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MODELLING SOCIAL AND EMOTIONAL COMPONENTS IN SOCIAL ROBOTICS USING ROBOT ARTIFICIAL INTELLIGENCE

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Content

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“Live as if you were living already for the second time
and as if you had acted the first time as wrongly as you are about to act now.”
Victor Frankl

Introduction

The modeling of social and emotional components in social robotics using robot artificial intelligence has been an important area of research in an interdisciplinary field combining robotics, psychology, and computer science. The origins of social robotics can be traced back to the 1990s, when the potential of robots in a social, rather than just an industrial, context began to be recognized (Breazeal, 2002). This sub-discipline of robotics emerged in response to a growing demand for robots that could interact with humans more naturally and efficiently than their industrial counterparts (Fong et al., 2003). Early work in the field focused on exploring the applicability of robots in various social contexts, such as healthcare, education, and social interaction. During this time, it was also beginning to be recognized that traditional robot design methods, which focus on performance and precision, were insufficient in a social context. Thus, elements of social and emotional psychology began to be introduced into the robot design process (Dautenhahn, 1998). The introduction of these new elements also required advanced artificial intelligence techniques to enable robots to understand and interpret human emotions and behaviors. In this context, pattern recognition and machine learning algorithms began to be used to analyze sensory data, such as images and sounds, to identify human emotions and intentions (Picard, 1997). One of the first challenges in this area was emotion recognition. Research in this area initially focused on the analysis of facial expressions and tone of voice, but over time other modalities such as gestures and body posture were also considered (El Kaliouby et al., 2006). The use of facial recognition and speech analysis technologies has enabled robots to better understand the social context and adapt their behavior. In this context, various machine learning techniques such as support vector machines and neural networks have been used to classify emotions based on sensory data (Goodfellow et al., 2015).

Another important aspect was facial expressions and gestures, which play a key role in social interactions. Research in this area has focused on modeling these aspects in a way that humans can understand. To this end, advanced machine learning techniques and neural networks have been used to analyze and interpret these subtle forms of communication (Breazeal et al., 2005). For example, reinforcement learning algorithms have been used to optimize robot movements to better understand and interpret human gestures (Knox et al., 2013). As the technology has evolved, the need to integrate different sensory modalities to better understand social context has also been recognized. To this end, data fusion techniques from different sensors, such as cameras and microphones, have been used to create more complex emotional and social models (Paiva et al., 2017). The application of these advanced AI techniques to social robotics has created new opportunities, but also new challenges. On the one hand, advanced algorithms enable the creation of robots with increasing autonomy and social interaction capabilities. On the other hand, there is a need for further research into the ethics and social implications of these technologies (Sharkey, Skarkey, 2012). In the ethical context, questions have been raised about the impact of social robots on human relationships and interactions. For example, research has focused on the potential dangers of robots replacing human interactions, as well as the ethical implications of data privacy and security (Calo, 2015).

Modeling the social and emotional components of social robotics using artificial intelligence has become a key element in the development of the field. The use of advanced AI techniques, such as machine learning and neural networks, has contributed significantly to making robot-human interactions more efficient and natural. However, further research is needed to fully understand and optimize these interactions in a social and ethical context.

This dissertation is a series of 8 publications, thematically divided into 4 chapters. The series consists of the following papers (the following publication numbering is used consistently throughout the work):

1. Probierz, E., & Galuszka, A. (2022). Emotion detection based on sentiment analysis: an example of a social robots on short and long texts conversation. *European Research Studies Journal*, 25(2), 135-144. (100 points Ministry of Science and Higher Education)
2. Probierz, E., Galuszka, A., Grzejszczak, T., Galuszka, A. (2022) Ohbot social robots emotion modelling using markov chains and YOLOv5 neural network. In I. Work, E. Maia, P. & P. Geril (Eds.), *Modelling and simulation 2022: The European Simulation and Modelling Conference 2022. ESM'2022*, October 26-28. 2022, Porto, Portugal (103-110).EUROSIS-ETI. (70 points Ministry of Science and Higher Education)
3. Janiaczyk, W. A., Probierz, E., & Galuszka, A. (2020). On the recognition and analysis of selected emotional states in the artificial intelligence of social robots. In A. Nketsai, C. Baron, & C. Foucher, A. Nketsai, C. Baron, & C. Foucher (Ed.), Modelling and simulation 2020: *The European Simulation and Modelling Conference 2020. ESM'2020*, October 21-23, 2020, Toulouse, France (pp. 223-228). EUROSIS-ETI. (70 points Ministry of Science and

Higher Education)

4. Galuszka, A., & Probierz, E. (2021). On transformation of conditional, conformant and parallel planning to linear programming. *Archives of Control Sciences*, *31*. (100 points Ministry of Science and Higher Education)
5. Probierz, E., Galuszka, A., & Galuszka, A. (2023). Social robot response to negative emotions as a PDDL planning problem in the presence of uncertainty. *Przeglad Elektrotechniczny*, 2023(8). (70 points Ministry of Science and Higher Education)
6. Probierz, E., Bartosiak, N., Wojnar, M., Skowronski, K., Galuszka, A., Grzejszczak, T., & Kędziora, O. (2022, August). Application of Tiny-ML methods for face recognition in social robotics using OhBot robots. In *2022 26th International Conference on Methods and Models in Automation and Robotics (MMAR)* (pp. 146-151). IEEE. (20 points Ministry of Science and Higher Education)
7. Eryka Probierz (2023). On Emotion Detection and Recognition Using a Context-Aware Approach by Social Robots- Modification of Faster R-CNN and YOLO v3 Neural Networks, *European Research Studies Journal*, Volume XXVI Issue 1, 572-585. (100 points Ministry of Science and Higher Education)
8. Grzejszczak, T., Bartosiak, N., Wojnar, M., Skowroński, K., Probierz, E. (2022). Regulacja pozycji robota społecznego w sprzężeniu zwrotnym z systemem wizyjnym. In A. Świerniak, J. Krystek (Ed*.), Automatyzacja procesów dyskretnych, Teoria i zastosowania*, t. 1, ISBN 978-83-7880-854-1 (pp. 79-86). (20 points Ministry of Science and Higher Education)

In addition to published papers on social robotics activities, the conducted research has been presented at the following conferences:

1. 17th International Conference DisCo 2022: Empowering Digital and Entrepreneurial Competences through E-learning, 20-21.06.2022, Prague, Czech Republic. Presentation: The use of social robots in emotion modeling using Ohbots robots as an example.

2.The European Simulation and Modeling Conference 2022, ESM 2022, Porto, Portugal, October 26-28, 2022. Presentation: OHBOT Social Robots Emotion Modeling using Markov Chains and YOLOv5 Neural Networks.

3. The European Simulation and Modeling Conference 2020. ESM '2020, October 21-23, 2020, Toulouse, France. Presentation: On the detection and analysis of selected emotional states in the artificial intelligence of social robots.

4. 26th International Conference on Methods and Models in Automation and Robotics: MMAR 2022, August 22-25, 2022, Międzyzdroje, Poland. Presentation: Application of Tiny-ML methods for face recognition in social robotics using OhBot robots.

The research was awarded the Scientist of the Future 2021 Award in the Humanities, Arts and Society of the Future category for research on the use of machine learning methods for social science data processing, and nominated for this award for research on social robotics in the framework of emotion detection and recognition by social robots. A popular science article on social robotics was also published and won first place in the 2020 "On Human Science" competition, titled "A robot comes to the couch... Emotions and Morality of Social Robots".

Contribution

In the first paper (Probierz, Galuszka, 2022), the author of this thesis was responsible for developing and designing the methodology, performing the calculations, performing the experiments and data collection, and writing the first draft. The second author was responsible for study conception and revision, critical review of the manuscript, and overall supervision.

In the second paper (Probierz et al. 2022), the first author was responsible for preparing and building the models, performing the formal analysis, visualizing and presenting the data, and writing the first draft of the manuscript. The second author was responsible for the part related to the study design, especially in the context of the formulation of the research question. The third author of the paper was responsible for data collection and performing the experiments, and the fourth author of the paper was responsible for critical review and revision.

In the third paper (Janiaczyk, Probierz, Galuszka, 2020), the dissertation author was responsible for study conception regarding ideas and formulation of research questions and writing the first draft, the first author was responsible for perfoming the experiment and data/evidence collection, the third author was responsible for supervision and critical review and revision.

In the fourth paper (Galuszka, Probierz, 2021), the author of the present study was responsible for data/evidence collection, data curation, and writing the first draft. The first author was responsible for study design, methodology, and critical review and revision.

In the fifth paper (Probierz, Galuszka, Galuszka, 2023), the first author was responsible for the development and design of the methodology, data curation, and writing the first draft. The second author was responsible for study design and formal analysis. The third author was responsible for study design and critical review, revision, and supervision.

In the sixth paper (Probierz et al. 2022), the author was responsible for development and design of methodology, formulation of research questions, execution of experiments, and writing the first draft. The second, third, and fourth authors were responsible for data collection and data curation. The fifth and sixth authors were responsible for study design, critical review, revision, and supervision.

In the seventh paper, the author of this dissertation is the sole author (Probierz, 2023).

In the eighth paper (Grzejszczak et al., 2022), the author was responsible for formulating the research questions, developing and designing the methodology, conducting the experiments, and writing the first draft. The second, third, and fourth authors were responsible for performing the experiments, data collection, and data curation. The fifth author was responsible for project management and supervision.

In summary, in this publication cycle, the dissertation author is the sole author of one paper and the first author of four others. The above distribution of contributions was confirmed in Appendix 1 and 2 at the end of the dissertation by the supervisor/co-author of 6 papers and the co-author of paper number 8.

Dissertation thesis

Work in the field of social robots aims to improve human-robot communication and to enable the robot to better interpret the social situation in which it finds itself, so that it can adapt its response appropriately. The development of social robots is likely to increase their application in many fields, such as rehabilitation robots, helper robots for the elderly, support robots in therapeutic processes (e.g. for people suffering from depression), robots that support the development of children suffering from autism, and educational robots. The range of applications for social robots is very broad, and their relevance increases with the need for increased isolation (caused by Covid-19), incomplete access to medical care, or the phenomenon of an aging population.

A social robot has the chance to be a helper and a friend. It has the chance to collect the necessary data, to record routine behavior and, in case of unresponsiveness, to notify the necessary medical assistance. For this to happen, it is necessary to ensure the quality of this relationship, also understood as the correct interpretation and matching of statements with the emotions of the interlocutor. Social robots are becoming more and more sophisticated thanks to work related to the continuous analysis and improvement of human-robot interaction. The emphasis on the socialization of robots stems from studies that show that for a social robot to accomplish an assigned task, its cooperation with a human is essential. Humans, on the other hand, are more likely to cooperate with a robot the more it exhibits social characteristics and behaviors.

One of the most common solutions to socialize a robot is to implement solutions that allow it to recognize and respond to the emotions of the caller. Researchers point to solutions ranging from computer vision to audio or text analysis or medical indicator analysis. The topic of emotion detection is not very popular, and among the proposed solutions one can find both those based on deep neural networks and those that analyze only the geometry of the face. However, detecting and responding to the caller's emotions alone is not enough to create a fully social robot. This is because analyzing and reacting to emotions only concerns the interlocutor, the robot itself often does not show emotions or shows them in a very simplified way. Furthermore, it is pointed out that emotions are not the only important construct that indicates sociality.

As psychological theories suggest, what makes humans human, and what could to some extent make robots human, are complex phenomena such as emotional and social intelligence. These are sets of intertwined competencies that make people social beings who live in a social environment and consistently act according to its norms. Both constructs are highly heterogeneous in terms of their definition and the individual components they contain. Many researchers point to the great difficulty of studying them because of their complementary competencies and phenomena. However, regardless of how these phenomena are defined and understood, researchers agree that they play an important role in people's lives.

The purpose of this series of publications is to present a series of studies that address topics related to the analysis of emotions and social reactions, as well as the responsiveness and adaptation of robotic interactions to human behavior.

Based on the above, the thesis of the dissertation is proposed:

The proposed solutions for recognizing and modeling social and emotional components based on robot artificial intelligence allow for implementation and application in social robotics.

Dissertation structure

The series of publications received a total of 550 points from the Ministry of Science and

Higher Education. Due to the nature of the dissertation, it consists of this introduction, 4 chapters, discussion, practical application of the research, conclusion and bibliography. Each chapter consists of an introduction, a literature review of the chapter topic, a summary of published papers, original articles and a conclusion. The bibliography of the thesis is divided according to the chapters.

Chapter 1 of the thesis deals with the modeling of emotional response based on implementations of artificial intelligence and machine learning methods in robotics. It focuses on modeling emotional responses in robotics using artificial intelligence (AI) and machine learning (ML). Key elements include theories of emotion, emotion expression by robots, emotion recognition, and adaptive emotional responses. Various theories of emotion, such as affect theory, apresion theory, and basic emotion theory, serve as the basis for AI and ML algorithms. ML techniques, including neural networks, are used to generate and recognize emotional expressions. Adaptive emotional responses are modeled using various machine learning techniques, such as reinforcement learning. Applications of affective robotics are broad and include healthcare, education, therapy, and social interaction. These robots are designed to recognize and respond to human emotions, which has the potential to improve well-being and mental health. Two published articles focus on different aspects of this field. The first article examines emotion recognition in conversations with social robots in the context of Polish and English. The second article focuses on modeling emotions in social robots using Markov chains and the YOLOv5 neural network. Both articles demonstrate how AI and ML techniques can be effectively used to create advanced robotic systems capable of emotional interactions with humans.

Chapter 2 of the thesis deals with the modeling of emotional response based on action planning in the PDDL language. It focuses on the application of Planning Domain Definition Language (PDDL) in the context of emotion modeling in Artificial Intelligence (AI). PDDL, as a formal knowledge representation language, is used in automated planning, which is a key element in AI. In the context of social robotics, where robots need to interact with humans in dynamic environments, PDDL-based planning becomes relevant. The literature highlights the importance of automated planning and the ontology for emotion visualization. The results suggest that PDDL can be used to accurately model a robot's interaction with humans based on their emotional states. The three articles published in this chapter extend the knowledge in the field of emotion modeling, especially in the context of social robotics. The chapter highlights the importance of PDDL for modeling emotional responses in AI and social robotics. An analysis of the literature and key articles points to potential developments in this area.

Chapter 3 of the thesis deals with the modeling of social behavior of robots based on the application of neural networks in robotics. It focuses on the modelling of social behavior of robots with an emphasis on technologies such as machine learning and neural networks. The dynamics of social interactions, the impact of robots on human behavior in the context of special education, and the application of Lattice Computing (LC) models for behavioral analysis will be discussed. An interdisciplinary approach combining AI and cognitive theory leading to developmental robotics is highlighted. Challenges in data acquisition and new approaches to learning human-robot interaction models are also presented. Two key papers are developed within the chapter. The first focuses on the use of Tiny-ML in face recognition, with tests on YOLOv4-tiny and YOLOv5s networks, with superior performance of the latter. The second article focuses on emotion detection, using Faster R-CNN and YOLOv3 neural network models, with modifications to improve detection performance. The chapter highlights the importance of interdisciplinary approaches and advanced technologies in modeling robot social behavior. An analysis of the literature and key articles points to potential future directions in the field of social robotics.

Chapter 4 of the thesis deals with the modeling of selected social components using the PID controller in social robotics. It focuses on the application of the PID (Proportional-Integral-Differential) controller in social robotics. This controller is commonly used in automatic control and has been applied in various social robotics contexts, such as speed control of a mobile robot. Different nonlinear control techniques have been analyzed and compared. In the context of modeling social components, the continuous evolution of robots through interactions with the physical and social environment has been highlighted. One of the reviewed papers makes an innovative contribution by focusing on maintaining eye contact between robot and human. The application of a PID controller in this context has proven effective, using a face detection algorithm based on Haar cascades as a feedback signal. This article provides a practical approach to one of the most subtle but crucial aspects of human-robot interaction. The chapter highlights the variety of applications of the PID controller in social robotics, from speed control to subtle aspects of social interaction. The use of this controller opens up new possibilities in the field of robot-human interaction and is crucial for the further development of social robotics.

The dissertation concludes with a discussion, a practical application of the research, a conclusion, and a bibliography.

1. Modelling emotional response based on implementations of artificial intelligence and machine learning methods in robotics

1.1 Introduction

Modeling emotional responses in robotics is important for creating interactive and user-friendly systems. In recent years, artificial intelligence (AI) and machine learning (ML) have contributed to advances in the field of affective robotics, which aims to understand, model, and respond to human emotions. Within the development of the field, a number of key issues can be identified.

One of them is theories of emotions and their use in robotics. To model emotional responses, researchers use various theories of emotion, such as affect theory (Russell, 1980), apprehension theory (Scherer, 2001), or basic emotion theory (Ekman, 1992). These theories serve as the basis for creating AI and ML algorithms that can recognize and generate emotions. Affect theory (Russell, 1980) presents emotion as a combination of two dimensions - valence (pleasure) and arousal (activation). In this theory, emotions are represented in a two-dimensional space where each emotion has unique coordinates on the valence and arousal axes. Affect theory is used to model the emotional responses of robots by controlling their behavior based on levels of pleasure and activation. For example, a paper by McColl et al. (2016) proposed an approach based on affect theory to model emotion in social robots, in which the robot's movement parameters are changed to generate appropriate emotional responses. Affect theory describes emotion as the result of evaluating (salient) situations or events in the context of individual needs, goals, and values. In this theory, emotions are generated on the basis of various evaluation criteria, such as congruence with goals, consistency with norms, or controllability of the event. Appreciative theory is used to model the emotional responses of robots by evaluating situations and adjusting their behavior based on these evaluations. For example, the work of Am El Ayadi et al. (2011) presents an approach based on apresia theory for recognizing emotions from speech, where different speech features are analyzed for apresia and then classified into appropriate emotions. The basic emotion theory proposes the existence of six basic emotions (happiness, sadness, fear, anger, surprise, disgust) that are universal across cultures. These emotions have their own unique facial expressions that can be recognized by people around the world. Basic emotion theory is often used in robotics to model the emotional responses of robots, especially in the context of recognizing emotion from facial expressions. For example, a paper by A. Mollahosseini et al. (2016) presented an emotion recognition system based on convolutional neural networks (CNNs) trained on a dataset of facial expressions representing six basic emotions.

Another important aspect is the ability of robots to express emotions. Robots can express emotions through various channels such as speech, gestures, facial expressions, or body movements. Research in this area focuses on creating natural and believable emotional expressions (Breazeal, 2003; Canamero, 2005). Machine learning techniques are used to generate emotional expressions based on sensory data. Speech synthesizers can be adapted to generate different emotional features, such as intonation, tempo, or pitch. The work of E. Bevacqua et al. (2007) presents a system that can generate speech with different emotions using hidden Markov models and a speech synthesizer. Gestures are an important non-verbal communication channel for the expression of emotions. The work of S. Kopp et al. (2006) proposes a model for the generation of emotional gestures for social robots based on the analysis of motion features and gesture-related data corpora. Facial expressions are one of the most obvious and expressive ways to express emotions. A paper by M. Bartneck et al. (2005) describes how emotion expression can be modeled in social robots by manipulating facial parameters according to the underlying emotion theory. Body movements, such as posture or movement, can also be used to express emotion in robots. A paper by J. K. Olsen et al. (2021) describes a neural network-based approach to generating robot movements that are consistent with the underlying emotion. This system learns from human movement data and adapts it to the robot's movements to achieve natural and convincing emotional expressions.

Robot emotion recognition and adaptive emotional responses also deserve special attention. Emotion recognition is a key component of emotional interactions with robots. Various techniques such as feature-based classification (Kwon et al., 2019), convolutional neural networks (CNNs) (Mollahosseini et al., 2016), or recurrent neural networks (RNNs) (Li et al., 2017) are used in research to recognize emotions from data such as speech, facial expressions, or body movements. One approach to robot emotion recognition is speech feature analysis. The paper by El Ayadi et al. (2011) provides an overview of different speech features used for emotion recognition, such as pitch, intensity, or tempo. The authors also analyze different emotion classification techniques, such as neural networks, support vector machines, or hidden Markov models. Robots can recognize emotions by analyzing human facial expressions. A paper by A. Mollahosseini et al. (2016) presents an emotion recognition system based on convolutional neural networks (CNNs), trained on a dataset of facial expressions representing six basic emotions. Gestures and body posture also provide information about a person's emotions. A paper by H. Gunes et al. (2015) discusses various methods and techniques for recognizing emotions based on gesture and posture analysis, such as support vector machines, decision trees, or neural networks. Robots can also use physiological signals such as heart rate, skin temperature, or skin conductance to recognize emotions. A paper by R. W. Picard (1997) introduces the concept of "affective computing" and describes various methods for analyzing physiological signals to recognize emotions. The authors also discuss potential applications of these methods in robotics and human-computer interaction. The creation of adaptive emotional responses is based on the robot's ability to change its behavior based on the user's emotions. Various machine learning methods, such as reinforcement learning (Velásquez, 1998) or demonstration learning (Argall et al., 2009), are used in this research area so that robots can learn appropriate emotional responses in different situations.

The development of affective robotics is particularly relevant in terms of potential applications. Among them, the most frequently cited are healthcare - for example, assisting people with disabilities (Belpaeme et al., 2018; Uluer et al., 2023), education - supporting the learning process by adapting the robot's actions and reactions to the student's emotions (Kory & Breazeal, 2014), therapy (Scassellati et al., 2018), and social interaction (Tapus et al., 2007). Robots using AI and ML can adapt their behavior to better interact with humans, build trust, and facilitate communication. The potential of affective robotics to enhance human well-being is also being demonstrated. Robots can be designed to recognize and respond to people's emotions, which can help improve their wellbeing and overall mental health (Spitale, Gunes, 2022). Robots can also be used to improve the customer experience by adapting their actions and reactions to their emotions (Chen, Girish, 2023). The authors also identify a number of challenges and possible future directions. These include the personalization of affective robots (Churamani et al., 2022). These robots need to be able to adapt their actions and reactions to individual differences in human emotions, which requires advanced machine learning techniques. Interacting with different groups of people (Uluer et al., 2023) or interacting with other technologies (Hui et al., 2023), where the authors note that affective robotics must be able to integrate with other technologies such as the Internet of Things. This is challenging as it requires the development of complex models and algorithms that can manage many different data sources.

1.2. Literature review

Current research directions focus on designing and building robots capable of recognizing, expressing, and responding to human emotions. The article by Spitale and Gunes (2022) conducted a literature review on the application of affective robotics to improve human well-being. They also formulate a list of recommendations for future research in affective robotics and identify a research agenda for the field. The papers also consider the application of machine learning techniques to create robots capable of recognizing and responding to human emotions. The authors propose two models for continuous learning in affective robotics (Churamani et al., 2022). The article by Uluer et al. (2023) discusses the application of affective robotics in healthcare. A robotic assistance system with emotion recognition functions for hearing-impaired children was presented, while Hui et al. (2023) demonstrated the possible integration of affective robotics with the Internet of Things. The paper develops a dynamic model with affective robotics to improve emotional services.

Taveter and Kirikal (2022) proposed an architecture for robotic systems based on the theory of constructed emotions. The work focused on prototyping robotic systems capable of generating and expressing emotions. The proposed architecture aimed to enable robots to better understand and respond to human emotions, which is crucial for effective human-robot interaction. A number of analyses also examine tactile technologies in affective interactions between humans, robots, and virtual humans (Olugbade, He, Maiolino, Heylen, 2023). The analyses address how affective touch is used in human-robot interactions, how technology can mimic and respond to affective touch, and how it can be integrated with robotic technology. The literature review also provides solutions for mixing emotions and moods in artificial agents such as social robots (Fernández-Rodicio, Maroto-Gómez, et al. 2022).

In another research there are an affective architecture for a mini social robot that could express different emotional states was presented. The issue of recognizing human affective states in non-meaningful tasks is also analyzed (Jirak et al., 2022). The influence of the embodied robot on human affective states was confirmed, but it was also found that affective behavior was mainly related to the robot-free condition. This issue is also related to affective displacement and the potential automation of care (Lynch et al., 2022). The study offered a speculative reading of three affective displacements in human-robot interactions, analyzing the spatial and affective politics of social robotics. This work provided important insights into how affective robotics can affect human caregiving and how these interactions can affect caregiving experiences. The researchers also note that users' affective preferences for humanoid robot voices are not insignificant (Li et al., 2022). The study focuses on understanding how different features of a robot's voice can influence users' affective preferences. The research also explores how affective robotics can be used to improve human mental health (Axelsson, Spitale, and Gunes, 2023). This work has provided important insights into how robots can be designed to support mental health and how these interactions can affect human well-being. Interaction with a social robot is inextricably linked to physical touch from a robot caregiver (Mazursky, DeVoe, and Sebo, 2022). The analysis conducted provides valuable insights into how robotic touch can influence human-robot interactions and how these interactions can affect the caregiving experience. Many researchers also point to the oversimplifications of emotionality that are replicated in the context of affective robotics. To counter this, an analysis of processes for multidimensional decision making has been conducted by researchers. This has provided insights into how robots can be designed to mimic human decision-making processes and how these interactions can influence human-robot interactions (Ho, Hoorn, 2022). It is also worth noting that while many studies address the topic of single robot sensing, analyses of multisensory integration are also emerging. A study by Li et al. (2022) discussed the effect of multisensory integration of a humanoid robot's appearance and voice on users' affective preferences and visual attention. They focused on understanding how different features of the robot's appearance and voice could affect users' affective preferences.

Contemporary robots aim to leave limited industrial environments and explore unknown and unstructured domains in order to find widespread applications in the real world as service and social robots (Cavallo et al., 2018). Therefore, in addition to new physical boundaries, they also have to face human boundaries. This implies the need to consider the human-robot interaction from the very beginning of the design, the possibility for the robot to recognize the emotions of the users and in some way react and "behave" accordingly. This can play a key role in their integration into society. However, this capability is far from being achieved. Over the past decade, there have been many attempts to implement automatons for various applications outside of industry. However, very few applications have attempted to incorporate the user's emotional state into the robot's behavioral model, as this raises questions such as: How should human emotions be modeled to correctly represent their state of mind? Which sensor modalities and which classification methods are most feasible to obtain the desired knowledge? Furthermore, what are the most appropriate applications for a robot to have this sensitivity?

In a paper by Khan and colleagues (2022), the authors investigated the feasibility of using machine learning models to monitor emotions using robots. They pointed out that emotion monitoring could play a key role in the study of mental health disorders, which account for 14% of the world's illnesses. Currently, the mental health system is facing an increasing demand. The study examined existing machine learning (ML) models and signal data from various biosensors, evaluated the suitability of robotic devices to monitor various physiological and physical characteristics related to human emotions, and discussed their potential application in mental health monitoring. Among the selected 80 articles, the results were divided into two different emotional categories, namely discrete and valence-arousal (VA). By examining two different types of signals (physical and physiological) from 10 different signal sources, it was found that RGB images and CNN models outperformed all other data sources and models, respectively, in both categories. Of the 27 discrete image signals tested, 25 achieved accuracy greater than 80%, with the highest accuracy observed for face image signals (99.90%). In addition to imaging signals, brain signals showed greater potential than other data sources in both emotional categories, with accuracies of 99.40% and 96.88%. For both categories, discrete and valence-arousal, neural network-based models showed higher scores. Most of the neural network models achieved accuracies above 80%, ranging from 80.14% to 99.90% in the discrete category, 83.79% to 96.88% in arousal, and 83.79% to 99.40% in valence. It was also found that the performance of fusion signals (the combination of two or more signals) exceeded that of individual signals in most cases, demonstrating the importance of combining different signals for future model development. Overall, the potential implications of the study were discussed, considering both human computing and mental health monitoring. The current study will certainly serve as a basis for research in the field of human emotion recognition, with a particular focus on the development of various robotic tools for mental health monitoring.

Other available literature (Demaeght et al., 2022) indicates that the number of caregivers working in nursing homes and daily care services is decreasing in countries such as Germany and Italy, limiting time for interpersonal communication. In addition, as a result of the Covid-19 pandemic, social distance has become more important during contact restrictions, leading to an additional reduction in personal interactions. This social isolation can significantly increase emotional distress. Robotic assistance could help address this challenge on three levels: (1) by assisting caregivers in responding individually to the needs of patients and nursing home residents; (2) by monitoring the health and emotional state of patients; (3) by maintaining high standards of hygiene and minimizing human contact when necessary. To advance research on the emotional aspects and acceptance of robotic caregiving, the authors conducted two studies in which elderly participants interacted with the social robot Misa. Facial and vocal expression analysis was used to identify and measure the emotional state of the participants during the interaction. While interpersonal contact plays a key role in elderly care, the results show that robot assistance adds value for both caregivers and patients, and that they show emotion when interacting with it.

Also worthy of special attention are the scientific papers that indirectly correspond to the articles published in this chapter. The work on sentiment analysis and emotion points out that many approaches to this problem treat sentiment analysis and emotion recognition as two separate tasks, neglecting their interaction (Zhang et al., 2022). This research proposes an approach that treats emotion as an external expression of sentiment and sentiment as the essential nature of emotion. To this end, a multi-task representation learning network, called KAMT, is designed, which includes two attention mechanisms: inter-modal and inter-task, and an external knowledge augmentation layer. The external knowledge augmentation layer is used to extract a vector of the participant's gender, age, occupation, and general color or shape. The main purpose of inter-modal attention is to capture effective multimodal features. Inter-task attention is designed to model the correlation between sentiment analysis and emotion classification. Experiments were conducted on three commonly used datasets, and the experimental results confirmed the effectiveness of the KAMT model. The results indicate that considering the interaction between sentiment and emotion can significantly improve the effectiveness of learning sentiment and emotion representations.

Analyses also address the problem of sentiment and emotion recognition from speech using universal speech representations with speaker-aware pre-training models (Atmaja, Sasou, 2022). Understanding sentiment and emotion in speech is a challenge in the field of multimodal human language. In some cases, such as telephone conversations, only audio data can be obtained. In this study, sentiment analysis and emotion recognition from speech were independently evaluated using state-of-the-art self-directed learning models - universal speech representations with speaker-aware pre-training models. Three different sizes of universal models were evaluated on three sentiment tasks and one emotion task. The evaluation showed that the best results were obtained with a two-class sentiment analysis, based on both weighted and unweighted accuracies (81% and 73%). This binary classification using unimodal acoustic analysis was also competitive with previous methods using multimodal fusion. The models were unable to make accurate predictions in the emotion recognition task and in sentiment analysis tasks with more classes. The uneven nature of the data sets may also have contributed to the observed performance degradation in the six-class emotion, three-class sentiment, and seven-class sentiment tasks. It was also emphasized that machines should be able to recognize nonverbal information in human-machine communication, especially in sentiment analysis and emotion recognition. This capability is important for more natural human-machine interactions. If the robot is able to recognize people's affective states, it will also be able to show empathy and sympathy to people by acting, speaking, or showing different reactions. Since sentiment and emotion are similar concepts (sentiment is often represented as valence, which is an emotional attribute), it is reasonable to evaluate the use of the same model for both problems. The conclusions of the study indicate that unequal distribution is a key problem in sentiment analysis and emotion recognition based on deep learning. The computational load in this study was another problem; the experiments had to be run in a very small batch of two samples to avoid memory limitation errors. The size of the UniSpeech-SAT Large model, in addition to the size of the data, was responsible for this limitation. Future research can be directed towards overcoming these problems.

Another study focuses on the analysis of emotional features in human-robot interactions (Chen et al., 2023). A method for analyzing emotional features based on wide-deep networks is proposed, which divides emotion recognition into two layers. The first step is to extract emotional features from faces and gestures using wide-deep networks. The authors note that bimodal emotions are not completely independent of each other, so they use canonical correlation analysis (CCA) to analyze and extract correlations between emotional features. They then build a coupled emotion recognition network based on the extracted bimodal features. Both simulation and application experiments have been conducted. According to the simulation experiments conducted on the Face and Body Gesture (FABO) database, the recognition rate of the proposed method increased by 1.15 percent compared to the feature elimination method of the recursive support vector machine (SVMRFE) without considering the unbalanced feature contribution. In addition, the multimodal recognition rate of the proposed method is 21.22%, 2.65%, 1.61%, 1.54%, and 0.20% higher than that of the sparse autoencoder deep neural network (FDNNSA), ResNet-101 + GFK, C3D + MCB + DBN, hierarchical classification fusion strategy (HCFS), and convolutional cross-channel neural network (CCCNN), respectively. In addition, preliminary application experiments were conducted on the developed emotional social robot system, where the emotional robot recognizes the emotions of eight volunteers based on their facial expressions and body gestures. The results indicate that this method can significantly improve the efficiency of emotion recognition in human-robot interactions.

The topic of emotion recognition is also addressed in the context of defined societal problems. Many studies focus on the growing problem of an aging population in most European countries, leading to an increasing number of elderly people in need of care (Demaeght et al., 2022). At the same time, the number of caregivers working in nursing homes and on a daily basis is decreasing. This situation has been exacerbated by the Covid-19 pandemic, which has forced social distance and reduced personal interaction, leading to severe emotional distress due to social isolation. It has been suggested that robotic assistance can contribute to solving this challenge on three levels: (1) by assisting caregivers to respond individually to the needs of patients and nursing home residents; (2) by monitoring the health and emotional state of patients; (3) by maintaining high standards of hygiene and minimizing human contact when necessary. To further investigate the emotional aspects and acceptance of robotic assistance in care, two studies were conducted in which elderly participants interacted with the social robot Misa. Facial and vocal expression analysis was used to identify and measure the emotional state of the participants during the interaction. Although interpersonal contact plays a key role in the care of the elderly, the results show that robotic assistance adds value for both caregivers and patients, and that they show emotion when interacting with it. While pointing to the potential benefits of robots in caregiving, the study also highlights the need for further research in this area, especially in the context of emotional interactions and older people's acceptance of technology.

The characterization of emotions is also a complex problem due to their dynamic nature. Research on dynamic modeling of emotions and anomaly detection in conversations has the potential to make an important contribution to the development of social robotics. Research shows that social media conversation data contains a lot of useful information, and anomaly detection in conversations is an important research direction in the field of sentiment analysis (Sun, Zhang, Li, 2018). Each user has their own specific emotional characteristics, and by studying the distribution and sampling of users' emotional transitions, specific emotional transitions in conversations can be simulated. Anomaly detection in conversational data refers to the detection of unusual opinions and sentiment patterns of users, as well as special temporal aspects of such patterns. The proposed hybrid model, which combines a convolutional long short-term memory neural network (CNN-LSTM) with a Monte Carlo Markov method (MCMC), allows the identification of users' emotions, the sampling of users' emotional transitions, and the detection of anomalies according to the transition tensor. The sampling of emotional transitions is implemented by improving the MCMC algorithm, and the detection of anomalies is performed by calculating the similarity between the normal transition tensor and the user's current transition tensor. The experiment was conducted on four corpora, and the results showed that emotions can be well sampled according to the user's characteristics, and anomalies can be detected by the proposed method. The proposed model can be used in intelligent conversational systems, such as simulating emotional transitions and detecting abnormal emotions.

These solutions can be subsequently used in the context of automatic characterization of end users' emotions (Adikari et al., 2019). In this study, we use an AI-based cognitive model for emotion recognition in chatbots using Markov chains, word embedding, and natural language processing. The proposed model is able to extract emotions from conversations, detect emotional transitions over time, predict emotions in real time, and intelligently profile human participants based on their distinct emotional characteristics. In the study, experiments were conducted on a real end-user dataset to demonstrate the functionality of the proposed model. The results of the experiments confirmed the plausibility of the model for emotional awareness in industrial conversational agents.

The use of Markov chains in the context of studying the dynamics of affective states allows the operationalization of affect (Cipresso, Borghesi, Chirico, 2023). The Markov chain model is a stochastic process in which the probability of moving from one state to another is determined only by the current state and not by the sequence of events that preceded it. The study proposes that this model may be useful for understanding how different groups of individuals (e.g., patients versus controls) may express different transition matrices, i.e., different Markov processes that may highlight specific behavioral phenotypes. The study of Markov chains on affect dynamics can shed new light on phenotypic behavior related to emotional states through mathematical properties of data collected in experimental designs. It is suggested that such models can provide rich insights into how affect dynamics may be related to mental health outcomes, leading to improved understanding and targeted intervention.

1.3. Introduction to the publication

Two articles have been published within the chapter on modeling emotional response based on implementations of artificial intelligence and machine learning methods in robotics (1: Probierz, Gałuszka, 2022; 2: Probierz et al. 2022).

The goal of the first paper is to present a solution for detecting emotions from text in a conversation with a social robot. Emotions are detected using sentiment analysis based on the English and Polish lexicon. It was pointed out that texts derived from conversations are characterized by significant variability compared to continuous texts derived from blog posts, social networks or journalistic reports. Analyzing emotions in the context of a conversation is challenging because the intensity of both a particular emotion and several emotions at once can change as the conversation unfolds. An additional complication is the length of the utterance, which is often short. A single analysis of a short utterance may not be able to identify the correct emotion of the sentence, and only an analysis in a conversational context has the chance to highlight this context and this emotion. It is emphasized that the aspect of the analyzed language is particularly important here. While image analysis allows for universal solutions that can be applied almost independently of the cultural context, text analysis is strictly dependent on the language in which it is written and the cultural context. This significant difference means that most research on sentiment analysis and emotion detection is based on lexicons and the analysis of English texts. The universality and ubiquity of this language has allowed the development of a number of sophisticated methods for detecting and recognizing emotions in speech. The study analyzed the derived social robot conversations both in terms of a solution dedicated to the Polish language and after translation into English and analysis using an available solution for English. In order to achieve the set goals, the study used two lexicons and a collection of human-robot conversations divided into short and long conversations. The first lexicon used was the NRC Emotional Lexicon, which was created in 2011 and used Amazon's Mechanical Turk solution as an annotation method. The second lexicon was the Polish plWordNet, which is a lexicon based on the Princeton WordNet in English, and the version used is 4.2. In order to test and analyze emotional sentiment, 80 conversations were recorded with a social robot that has implemented a chat option that is emotionless and displays only neutral statements. In this way, the difficulty shown by other researchers in distinguishing between the emotions of the sender and the receiver was partially overcome. The conversations were further divided into long and short conversations. The criteria for short conversations were 8-10 messages from both sides, which translated into an average of 4 messages from the person talking to the social robot. Long conversations, on the other hand, were more than 16 messages and up to 30 messages, which allowed the analysis of an average of 14 utterances from one person. Conversations between 11 and 15 messages were considered medium length and were not analyzed in the study. The results obtained for short messages showed little or no discrepancy between the NRC lexicon and plWordNet. Similar results were obtained for long messages, with a maximum deviation of 2% for the emotions of disgust (NRC=10%, plWordNet=12%) and sadness (NRC-13% and plWordNet=11%). The conclusions of the study indicate that the results obtained show the same or similar distribution of emotions made by sentiment analysis using both plNetWord and NRC lexicons. However, the study is not without some limitations. Firstly, the analyses performed were carried out on a limited set of conversations, which will be extended to other types of conversations in further research. For a thorough analysis, a chat implemented in a social robot was used to minimize the influence of the listener's language. Further analysis will be done considering conversations between two people. The results obtained also contradict the part of the research that shows the important role of local lexicons created for specific languages.

The second article focuses on the growing field of social robotics, which combines solutions from robotics, computer science, psychology, and many other disciplines. Within this development, there is a particular focus on improving human-robot interaction by designing robots to be perceived as more social. The goal of this work is to implement a module that allows a robot's facial response to be matched to the current state presented by a person, and to predict and attribute a person's emotional style. The goal is to increase the reactivity of the social robot and to sensitize it to sudden changes in the emotions of the interlocutor. Neural networks and Markov chains have been used to accomplish this task. It is pointed out that social robotics is a complex subject, both because of its interdisciplinary nature and the variety of purposes for which these robots can be used. Social robots come in a wide range of sizes, from those that fit in the palm of your hand to human-sized, and in many shapes, from animal-like to humanoid. The purpose for which they are designed can also vary: robots can serve an educational, therapeutic, rehabilitative, or entertainment function. Regardless of their purpose, however, it is necessary to establish a relationship between humans and robots. The quality of this interaction and the way the human perceives the robot has a significant impact on the success of subsequent tasks. This is why work focused on increasing the "community" of social robots is such an important part of social robotics. The goal is to develop and implement solutions that enable human-robot interaction as quickly and efficiently as possible. One of the most common approaches is to try to model emotions based on the current social situation.

Many research has been devoted to modeling emotions using embedded chatbot solutions, which allow speech to be modified on the fly and adapted to the emotional state of the recipient. A less explored area of this research is work on adapting facial expressions or movements of a social robot. Most social robots have the ability to actively respond using a variety of servo systems. In this work, emotion modeling will focus on this set of elements that allow the emotions of the social robot to be modeled. This modeling is based on a constant interaction with the information transmitted by the social robot's camera and analyzed using a YOLOv5s neural network and a Markov chain. The designed solution has been implemented in the social robot OhBot, taking into account all the limitations and requirements (e.g. limited computational power). The theoretical proposal for matching the social robot's facial expressions to the speaker has been practically implemented and the effectiveness of the predictions made has been tested, reaching 82-70.5%. The results obtained in this paper can be transferred to other social robots, as well as to other IoT solutions that require emotion modeling. The theoretical background is also presented, introducing key techniques and methods used in the context of social robotics and emotion recognition. It is pointed out that they often represent different solutions from those commonly used. This is due to the dissimilarity of both software and hardware parts. The goal of most social robots is mobility and often small size. To achieve this, microcomputers with limited processing power are used, as well as sensors and servos of appropriate size. All this leads to the need for models that do not require complex and time-consuming processing or high computing power. To be fully functional, a social robot should respond appropriately, both in terms of the content of the message (be it voice or other) and the response time. Waiting too long for a response from the robot can lead to a loss of interest and thus motivation to continue the interaction on the part of the recipient. Therefore, solutions with satisfactory efficiency and speed are repeatedly used. A proposed model is also presented that is designed to be able to detect the emotion displayed by the caller, based on the analyzed image from the camera embedded in the robot. In addition to being able to determine the current emotional state, it is possible to track changes and transitions of subsequent emotions. The implementation of the presented architecture makes it possible to predict emotions based on previous data containing transitions of emotional states. The proposed architecture has been implemented in a social robot of the OhBot type to match the robot's facial expressions with the current and predicted emotional states of the interlocutor. Such matching allows for a better human-robot relationship and has the potential to improve and accelerate the goals to be achieved with the social robot. To ensure the validity of the proposed module, it is divided into three parts: the first is responsible for detecting emotions both from the current state and from previously obtained data, the next is designed to make predictions of emotions based on Markov models, and the last part of the solution allows matching the robot's facial expressions to the current state and to the emotional style of the interlocutor. The results obtained in the study suggest that sentiment analysis and emotion detection in social robot conversations is possible and can be performed with similar results for both Polish and English. However, it is worth to notice that further research is needed to understand the full range of possibilities and limitations of these techniques.

1.4. Summary of Chapter 1

Chapter 1 discusses the topic of modeling emotional responses in robotics, with an emphasis on the use of artificial intelligence (AI) and machine learning (ML) in this context. The relevance of this topic stems from the growing demand for interactive and user-friendly systems that can understand, model, and respond to human emotions. Within this theme, various aspects will be considered, including theories of emotion and their application to robotics, the ability of robots to express emotions, the recognition of emotions by robots, and adaptive emotional responses. All of these are key to creating effective robotic systems capable of interacting with humans on an emotional level. In the context of emotion theory, several approaches are discussed, such as affect theory, apresion theory, and basic emotion theory. These theories serve as a basis for the development of AI and ML algorithms that can recognize and generate emotions. For example, affect theory is used to model the emotional responses of robots by controlling their behavior based on pleasure and activation levels. Appreciative theory, on the other hand, describes emotions as the result of evaluating situations or events in the context of individual needs, goals, and values, and is used to model robots' emotional responses by evaluating situations and adjusting their behavior based on these evaluations. Core emotion theory posits the existence of six basic emotions that are universal across cultures and is often used in robotics to model emotional responses of robots, especially in the context of recognizing emotions from facial expressions. The possibility for robots to express emotions is also pointed out, highlighting different channels such as speech, gestures, facial expressions or body movements. Machine learning techniques such as neural networks are used to generate emotional expressions based on sensory data. Emotion recognition by robots is a key element of emotional interaction with robots. Various ML techniques such as feature-based classification, convolutional neural networks (CNNs), or recurrent neural networks (RNNs) are used in research to recognize emotions based on data such as speech, facial expressions, or body movements. The creation of adaptive emotional responses is based on the robot's ability to change its behavior based on the user's emotions. This research area uses various machine learning methods, such as reinforcement learning or demonstration learning, to help robots learn appropriate emotional responses in different situations.

The development of affective robotics is particularly relevant in terms of potential applications. The most frequently mentioned are healthcare - e.g. assisting people with disabilities, education - supporting the learning process by adapting the robot's actions and reactions to the student's emotions, therapy and social interaction. Robots using AI and ML can adapt their behavior to better interact with humans, build trust and facilitate communication. The potential of affective robotics to improve human well-being is also being demonstrated. Robots can be designed to recognize and respond to people's emotions, which can help improve their well-being and overall mental health. Social robotics is also full of challenges and possible directions for development. Issues include the personalization of affective robots. These robots need to be able to adapt their actions and reactions to individual differences in human emotions, which requires advanced machine learning techniques. Interaction with different groups of people or with other technologies, where it is suggested that affective robotics must be able to integrate with other technologies such as the Internet of Things. This is challenging as it requires the development of complex models and algorithms that can manage many different data sources. The published articles are part of a stream of ongoing research. The first article focuses on emotion detection based on sentiment analysis in the context of conversations with social robots. Conversational text is characterized by significant variability, which poses a challenge for sentiment analysis. In the study, texts derived from conversations with social robots were analyzed both in terms of a dedicated Polish language solution and after translation into English and analysis using an available English language solution. The results of the study suggest that sentiment analysis and emotion detection in social robot conversations is possible and can be performed with similar results for both Polish and English. The second article focuses on modeling social robot emotions using Markov chains and the YOLOv5 neural network. The article points out that social robotics is a complex issue, both because of its interdisciplinary nature and the variety of purposes for which these robots can be used. In the study, the implemented module allows to adapt the robot's facial reaction to the current state presented by the person, as well as to predict and attribute the person's emotional style. The results obtained in this paper can be transferred to other social robots, as well as to other IoT solutions that require emotion modeling. In summary, both articles show how AI and ML techniques can be used to create robots capable of emotionally interacting with humans. The first article shows how sentiment analysis can be used to detect emotions in conversations with social robots, highlighting the importance of context and language. The second article shows how techniques such as Markov chains and neural networks can be used to model the emotions of social robots, emphasizing the importance of adaptive emotional responses. Both articles are relevant to the development of affective robotics, showing how AI and ML techniques can be used to create advanced systems that can understand, model, and respond to human emotions.

1.5. Publications

1. Probierz, E., & Galuszka, A. (2022). Emotion detection based on sentiment analysis: an example of a social robots on short and long texts conversation. European Research Studies Journal, 25(2), 135-144.
2. Probierz, E., Galuszka, A., Grzejszczak, T., Galuszka, A. (2022) Ohbot social robots emotion modelling using markov chains and YOLOv5 neural network. In I. Work, E. Maia, P. & P. Geril (Eds.), *Modelling and simulation 2022: The European Simulation andModelling Conference 2022. ESM'2022, October 26-28. 2022, Porto, Portugal (103-110).*EUROSIS-ETI.

Article 1

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Emotion Detection Based on Sentiment Analysis: An Example of a Social Robots on Short and Long Texts Conversation

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Abstract:

Purpose: *The aim of this paper is to present a solution to detect emotions from text obtained in a conversation with a social robot. Emotions will be detected using sentiment analysis based on the English and Polish lexicon.*
Design/methodology/approach: *Data from social robot conversation records will be converted into text and then split into short and long speech. The original language utterances will then be analysed using the Polish lexicon, while the translated texts will be analysed using the English emotional lexicon.*
Findings: *The results obtained indicate the same or similar distribution of emotions made by sentiment analysis using both plNetWord and NRC lexicons.*
Practical Implications: *The results obtained can be used for further research addressing the creation and development of lexicons based on the selected language. They are also applicable to the implementation of solutions for detecting and responding to conversational emotions by social robots.*
Originality/Value: *The analyses so far mostly take up the subject of textual analysis in English. The aim of the present study is to analyse a Polish text and to compare the results obtained with those for English texts. The analysis of differences in the emotional sentiment of utterances may lead to the construction of more effective models based on the chosen language.*

Keywords: *Sentiment analysis, emotion detection, social robots.*

JEL classification: *D12, D47, D53.*

Paper type: *A research study.*

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1. Introduction

Texts derived from conversation are characterised by significant variation compared to continuous texts derived from blog posts, social networks or journalistic reporting. Conversational text poses a challenge in the context of emotion analysis because as the conversation unfolds, there can be a change in the intensity of both a particular emotion and several emotions at once. An additional difficulty is also the length of the utterance, which is very often short. A single analysis of a short utterance may not allow to determine the correct sentiment of the sentence, and only an analysis in the context of the conversation has a chance to highlight this context and this emotion.

The analysis of conversational sentiment is useful from the point of view of many areas of analysis (Agarwal and Toshniwal, 2018). It can be applied to statements related to finance, economics, everyday conversations, or, as in the case under review, based on conversations with a social robot.

The aspect of language analysed is also particularly relevant here. While image analysis allows for universal solutions that can be applied almost independently of the cultural context, yes, text analysis is strictly dependent on the language in which it is written and the cultural context. It is this significant difference that makes the vast majority of studies on sentiment analysis and emotion detection rely on lexicons and analyse English texts. The universality and ubiquity of this language has allowed the creation of many advanced methods to detect and recognise emotions in utterances (Burnap *et al.*, 2015).

However, such popularity is not enjoyed by other languages, for which individual lexicons have to be created anew. Some approaches propose to translate the analysed texts into English and then process them using the available methods. Other researchers suggest creating lexicons dedicated to a particular language, including both emotional valence and word interrelationships (Kiritchenko, Zhu, and Mohammad, 2014).

In this paper, the analysed texts coming from conversations with social robots will be analysed both in terms of a solution dedicated to the Polish language, will be translated and then analysed by a solution available from the English language.

2. Literature Review

Based on the conducted analysis of theoretical reports, many researchers have taken up the topic of detecting and analysing the sentiment of utterances using lexicons. The main reason for such research is the phenomenon that the emotional information conveyed by the sender is distributed more in the text/voice channel than in the visual channel. This means that although many effective methods are available to detect emotion based on image/video, it may be an insufficient source and may not allow for a deeper analysis of an individual's emotions.

The extreme difficulty of combining the two approaches is also pointed out, as well as the phenomenon of confusing emotion analysis between listener and sender and the difficulty of distinguishing between the utterances of the individuals in question during sentiment analysis. It should also be noted that the analysis of text in relation to the analysis of sound leads to simplification and reduction of a lot of information that sound carries.

Based on the text it is not possible to notice modulations, pauses or changes in the tone of voice. Nevertheless, this represents an important and needed solution, as these types of records are widely used in both social networks and streaming platforms. Within the available solutions, some trends can be observed, which are systematically developed.

One of the most widely developed solutions is the approach using Deep learning methods (Gu *et al.*, 2018). The use of neural networks to process and analyse emotions is one of the most popular solutions. Such methods, with particular emphasis on LSTM Networks and R-CNN Networks, are used in image analysis and in some work on text analysis. They allow satisfactory performance for given classes of observations. In the context of text analysis, one of the biggest challenges is to ensure a sufficiently large and diverse dataset. As mentioned earlier, image analysis can be carried out almost independently of the cultural and linguistic context. Which means that the same data sets can be used to train networks that will then be used in a variety of social settings.

However, such a transfer is not possible in the case of text analysis. Text is strictly dependent on the language in which it is written. This means that for a specific language, it would be necessary to create a large enough database to train a network that would recognise, for example, Polish conversation. This is not an impossible task, but it requires time and money due to the lack of currently available databases that would have a representative sample of data for the given emotional categories.

Another branch developed in the field of emotion detection are methods that do not use neural networks, but make use of machine learning solutions (Dhaoui, Webster, and Tan, 2017). These work by searching for specific features and then creating appropriate representations from them to be applied to classification methods. Many researchers undertake such work using SVM method, Naive Bayes Method or Decision Trees Method.

According to research, such a solution allows the detection of a wide range of solutions, but for a number of reasons it often has a lower accuracy than other solutions. The main reason for this is the exceptional multimodality of the display of emotions, which is realised through many channels, such as image, sound, text of utterance, but also the absence of utterance or the use of emoticons (Khoo and Johnkhan, 2018). Such diversity leads to difficulties in accurately classifying a given emotion.

The last type of research that is conducted in the context of sentiment analysis is rule-based approaches (Drus and Khalid, 2019). They are based on the comparison of the obtained data to sets containing already once described data together with the assigned emotion (Muhammad, Kusumaningrum, and Wibowo, 2021; Sadia, Khan, and Bashir, 2018). The main disadvantage of these approaches is the necessity to have or develop a given lexicon, i.e. a reference to which the data will be compared. What is important, a given lexicon is dependent on the language analysed, which translates into a multitude of lexicons for English and their underrepresentation for other languages (Khan *et al.*, 2016). It is this approach that will be presented later in the study, where both Polish and English lexicons will be used.

3. Materials and Methods

In order to achieve the set objectives, the paper uses two lexicons and a collection of human-robot conversations divided into short and long conversations.

The first lexicon used was the NRC Emotional Lexicon, which was created in 2011, and Amazon's Mechanical Turk solution was used as the annotation method (Mohammad and Turney, 2013). The dictionary that served as a base for the analysed words was the 1911 Roget Thesaurus. This thesaurus allows grouping related words into categories that have similar contexts or sense of expression. Importantly, if a word can be assigned to more than one category, it is marked as ambiguous and has more than one meaning.

Based on this solution, a near-synonyms system was then developed, which allowed synonyms to be assigned to a word. The system created had a certain degree of randomisation. The material thus prepared was then evaluated by annotators, who rated the synonyms presented to them. The developed lexicon consists of about 24 thousand pairs of words of similar meaning. These word pairs were then used to elaborate emotional connections and to create a proper lexicon of emotional connections consisting of 14 thousand word types. It allows to identify negative or positive sentiment and to detect 8 different emotions such as anger, anticipation, disgust, fear, joy, sadness, surprise and trust.

Another lexicon used was the Polish plWordNet lexicon (Janz *et al.*, 2017; Rudnicka *et al.*, 2019). This is a lexicon based on Princeton WordNet in English, and the version used was 4.2. It consists of over 224 thousand words divided into verbs, nouns, adverbs and adjectives. The network allows for the study of emotional collocations, i.e. frequently occurring connections between words with emotional overtones. The resulting lexicon consists of approximately 180,000 words having an emotional annotation to one or more emotions.

The lexicon makes it possible to identify basic emotions such as joy, trust, looking forward to something expected (anticipation), sadness, anger, fear, disgust and surprise at something unexpected (Maziarz *et al.*, 2016). In addition to emotions, it is possible to detect universal values such as usefulness, the good of others, truth, knowledge, beauty, happiness, non-usefulness, harm, ignorance, error, ugliness, unhappiness. In addition, the lexicon makes it possible to identify emotional attitudes, i.e., values ranging from strongly negative to strongly positive. It also takes into account neutral and weakly negative and positive attitudes.

3.1 Conversation Data

In order to test and analyse emotional sentiment, a recording was made of 80 conversations with a social robot having a chat bot option implemented, which is devoid of emotion and shows only neutral statements. This approach made it possible to partially overcome the difficulty shown by other researchers, i.e., distinguishing the emotions of the sender from the listener. Conversations were further divided into long and short ones. The criteria for short conversations were taken to be 8 - 10 messages coming from both sides, which on average translated into 4 messages from the person talking to the social robot.

Long conversations, on the other hand, were taken to be more than 16 messages till 30 messages, which on average allowed the analysis of 14 utterances from the person. Utterances between 11 and 15 messages were treated as medium length and were not analysed in the study. This made it possible to obtain 36 short messages, 31 long messages and 13 medium messages. The long and short messages were then translated into English from the Polish language in order to be analysed using the English lexicon.

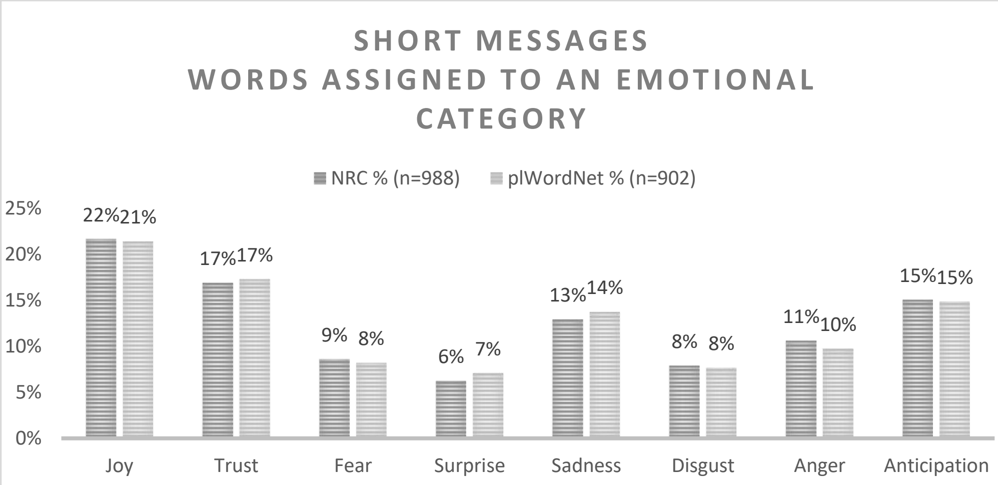
4. Results

Thirty-six short and 31 long messages were developed for analysis. Each set was compiled in Polish and English. The short messages contained a total of 1724 words in Polish and 1604 words in English. The analyses showed that the short messages contained 988 emotionally charged Polish words and 1027 emotionally charged English words. The long messages contained 21786 Polish words and 13449 emotionally charged Polish words.

In English there were a total of 20441 words for long messages and 14211 emotionally charged words. Both lexicon allowed the division of emotionally charged words into 8 categories representing each basic emotion. The obtained results are presented in Figures 1 and 2.

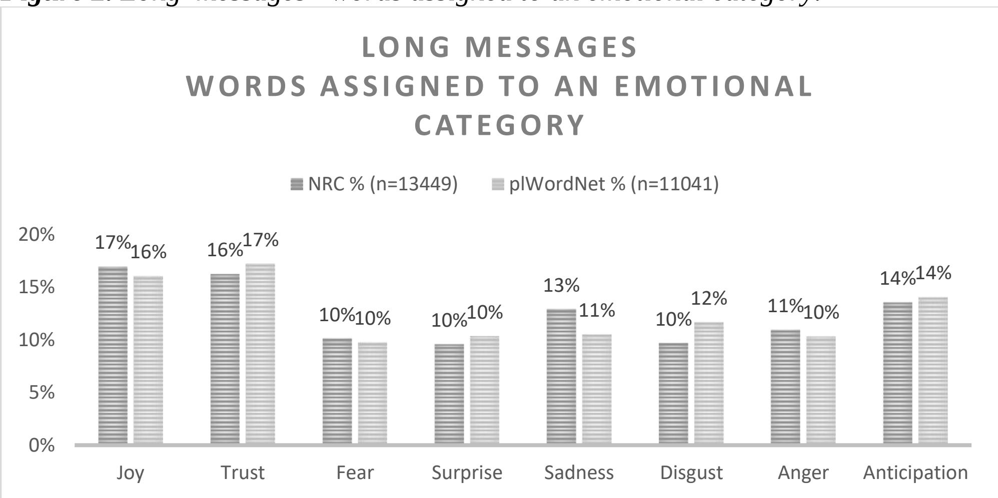
The results obtained for short messages showed no or little discrepancy between the NRC lexicon and plWordNet. Similar results were also obtained for long messages with a maximum discrepancy of 2% for the emotion disgust (NRC=10%, plWordNet=12%) and emotion sadness (NRC-13% and plWordNet=11%).

Figure 1. *Short messages - words assigned to an emotional category.*



Source: *Own elaboration based on research.*

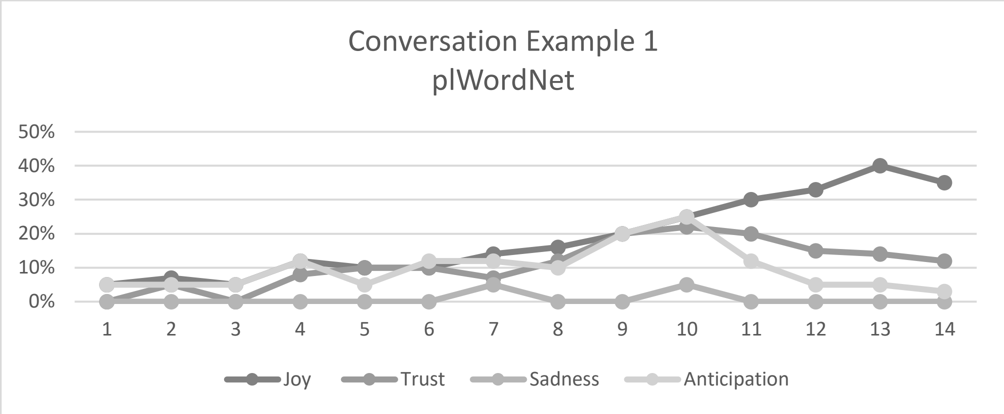
Figure 2. *Long messages - words assigned to an emotional category.*



Source: *Own elaboration based on research.*

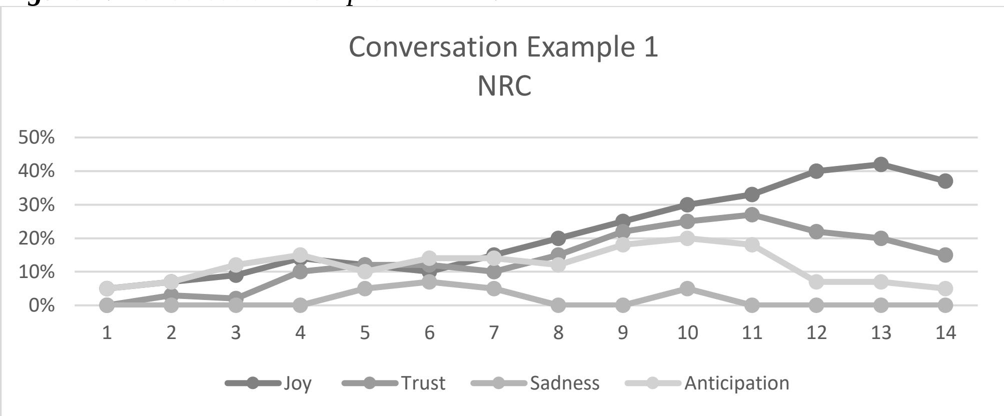
In addition to the results obtained for the pooled analysis of both long and short conversations, changes in conversations based on the individual utterances analyzed were also analyzed. For these analyses 3 examples are presented, both for the analysis of the Polish text based on plNetWord, but also for the English text based on NRC. The examples are presented in Figuress 3 to 8. The first example concerns waiting for the arrival of friends. The second example is about a conversation after failing an exam at university. Example three is about waiting for the publication of the results of admission to a master's degree program.

Figure 3. *Conversation example 1 – plWordNet.*



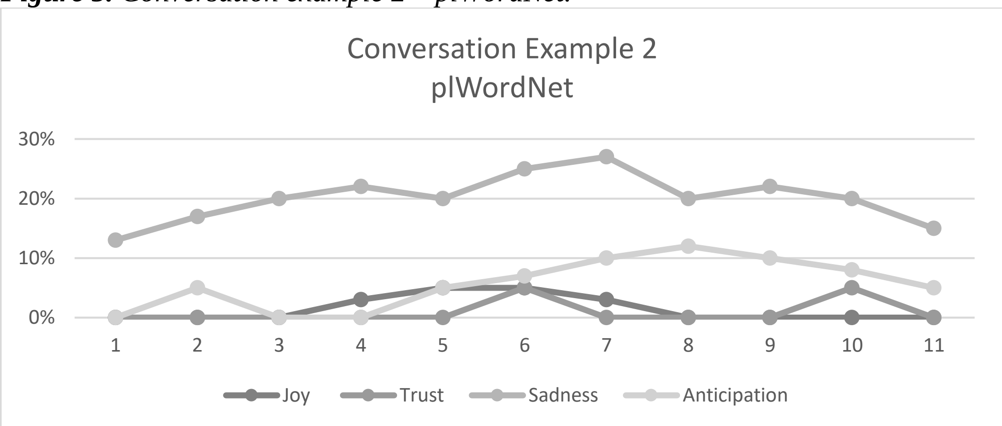
Source: *Own elaboration based on research.*

Figure 4. *Conversation example 1 – NRC.*



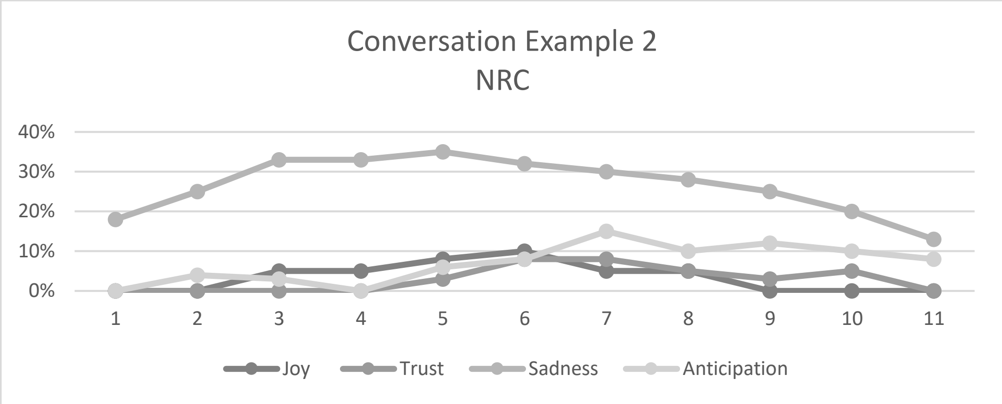
Source: *Own elaboration based on research.*

Figure 5. *Conversation example 2 – plWordNet.*



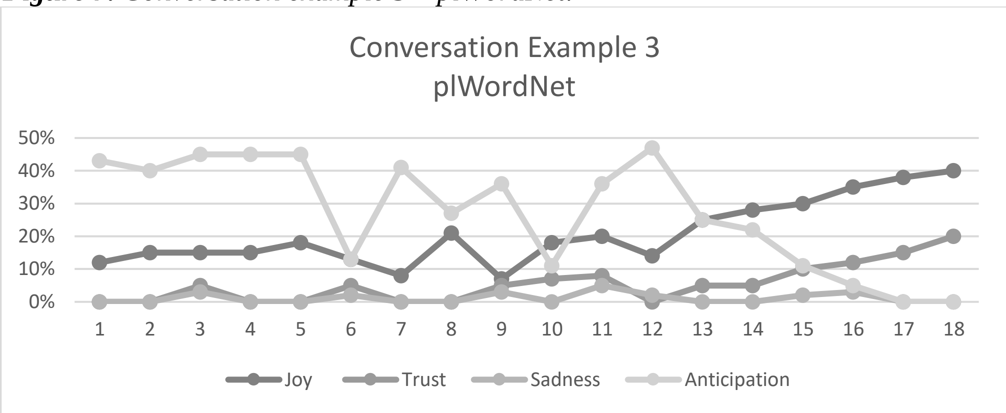
Source: *Own elaboration based on research.*

Figure 6. *Conversation example 2 – NRC.*



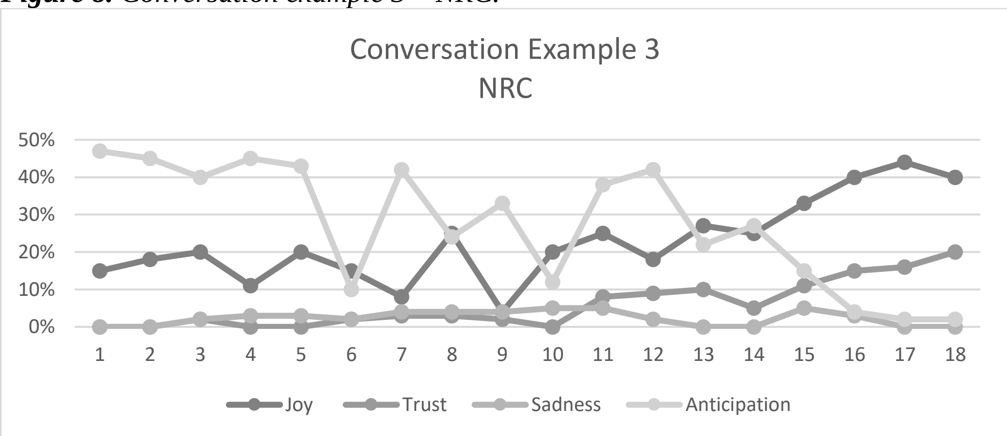
Source: *Own elaboration based on research.*

Figure 7. *Conversation example 3 – plWordNet.*



Source: *Own elaboration based on research.*

Figure 8. *Conversation example 3 – NRC.*



Source: *Own elaboration based on research.*

Based on the examples presented, one can see a replication of the trend associated with the 4 most widely represented emotions, i.e., joy, trust, sadness and anticipation.

5. Discussion and Conclusion

The purpose of this paper was to present sentiment analyses on data derived from conversations held with a social robot. Data were prepared in Polish and English versions, and divided into long and short conversations. Then, sentiment analyses were conducted collectively for short and long conversations taking into account two different lexicons, i.e., NRC and plWordNet. The next step was to perform cross-sectional analyses on the selected long conversations in order to analyze changes in the selected four dominant emotions. The results obtained indicate the same or similar distribution of emotions made by sentiment analysis using both plNetWord and NRC lexicons.

However, the conducted study is not free from some limitations. Firstly, the conducted analyses were carried out on a limited set of conversations, which in further research work will be extended to other types of conversations. For a thorough analysis, a chat bot implemented in a social robot was used to minimize the impact of the listener's speech. Further analysis will be conducted considering conversations between two people. The obtained results also contradict the part of the research that shows the important role of local lexicons created for particular languages.

The results obtained did not allow for a difference analysis because the results obtained showed little variation. Further work is to test these results on a larger sample of data to see if using targeted lexicons for a particular language shows more emotional diversity than when translating texts into English and using available lexicons for English.

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OHBOT SOCIAL ROBOTS EMOTION MODELING USING MARKOV CHAINS AND YOLOV5 NEURAL NETWORK

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Social robots, Emotion modelling, Markov models, YOLO neural network, OhBot Robot

ABSTRACT

Social robotics is a strongly developing and multidisciplinary field that combines solutions from robotics, computer science, psychology and many other disciplines. Within its development, there is a particular focus on enhancing human-robot interaction, by constructing robots in such a way that they are perceived as more social. The aim of this paper is to implement a module that allows a robot's facial reaction to be matched to the current state presented by a person, and to predict and attribute a person's emotional style. The aim is to increase the reactivity of the social robot and to sensitise it to sudden changes in the emotions of the interlocutor. Neural networks and Markov chains were used to complete the task. The use of YOLOv5s networks made it possible to analyse and label both single emotions and their sequences based on the acquired image of the interacting person. The implementation of a second-order Markov chain enabled the prediction of sequences of emotional states, taking into account previously acquired data and user characteristics. The designed solution was implemented into a social robot of the OhBot type, taking into account all the constraints and requirements this brings (e.g. limited computing power). The theoretical proposal for matching the social robot's facial expressions to the speaker was practically implemented, and the effectiveness of the predictions carried out was tested, which reached 82-70.5%. The results obtained in this publication can be transferred to other social robots, as well as to other IoT solutions that require emotional modelling.

INTRODUCTION

Social robotics is a complex issue. Both because of its interdisciplinary nature and the multitude of purposes for which these robots can be used, it poses a challenge to both researchers and the industry at large (Caic et al., 2019). Social robots come in a wide range of sizes - from those that fit in the palm of the hand, to human-sized, and in many shapes - from those resembling animals to humanoid shapes. The purpose for which they are designed can also vary: robots serve an educational, therapeutic, rehabilitative or entertainment function (Formose, 2021). However, regardless of their intended use, a human-robot relationship is necessary for this to occur. Also, the quality of this interaction and the way the human perceives the robot has a considerable impact on the success of further tasks (Leite et al., 2013). This is why work focusing on increasing the 'community' of social robots is such an important part of social robotics. Their aim is to develop and implement solutions that allow human-robot interaction to take place in the fastest and most efficient way possible (Lambert et al., 2020). One of the most common approaches used here is to try to model emotions based on the social situation at hand. A lot of research has been devoted to modelling emotions using embedded chat bot solutions, which allow for ongoing modification of speech and matching it to the emotional state of the recipient (Satake et al., 2009; Edwards et al., 2019). A less explored part of this research is work on matching facial expressions or movements of a social robot (Liu et al., 2017). The vast majority of social robots have the ability to actively respond using a variety of servo systems. In this thesis, emotion modelling will focus on this group of elements that allows for the modelling of a social robot's emotions. This modelling will be based on constant contact with the information transmitted from the social robot's camera and analysed by means of a YOLOv5s (Ahmad et al., 2020) and Markov chain neural network. The implemented model will be tested on a developed set of emotion sequences, and robot matching will be done not only by analysing the current situation, but also by assigning to a specific emotional state. The paper is divided as follows: the next section contains a theoretical introduction to social robotics, emotion modelling and the use of Markov chain models. Next, a model of the implemented architecture will be presented along with a description of the individual components. The fourth section consists of the results obtained, taking into account information such as the database, the sequence of emotions or their prediction. The article closes with a section on the summary and discussion and the possibility of developing the model with further research and work.

THEORETICAL BACKGROUND

The aim of this theoretical review is to introduce the key techniques and methods used in the context of social robotics and emotion detection. It should be noted that these often represent different solutions from those widely used. This is due to the dissimilarity of both the software and hardware part. The goal of most social robots is their mobility and often their small size. In order to achieve this, microcomputers with limited computing power are used and sensors and servos of an appropriate size are employed. All of this leads to the need for models that do not require complex and time-consuming processing or high computing power. A social robot, in order to fulfil its full purpose, should respond appropriately both in terms of the content of the message (whether voice or any other) and the response time. Waiting too long for a response from the robot may result in a loss of interest, and thus motivation to continue the interaction in the recipient. To this end, solutions with satisfactory efficiency and speed are repeatedly used. This theoretical introduction does not provide an exhaustive summary of all the methods used, but only identifies those that are widely used in social robotics and represent the latest and most up-to-date solutions to the problem of emotion modelling.

Social robots

The wide range of applications and the way social robots are constructed makes it difficult to create solutions that are universal enough to be applied to most of them. The social robot market is highly heterogeneous in many respects and it is not possible at the moment to distinguish dominant trends or implementations. This causes some limitation of the suggested method. This thesis aims to demonstrate a method to process an image to label it with a given emotion and then use it for prediction methods based on Markov chains. The robot shows facial expressions attributed to a given emotion, which are consistent with those presented by the interlocutor and matched to a specific emotional style. Therefore, robots with the ability to modify, control and adjust facial expressions, regardless of their complexity, can benefit from the proposed method. Since the aim of this work, in addition to creating a model that allows the generation of robot facial expressions based on the interlocutor's reactions, is also to implement it into a target solution, a brief characterisation of OhBot social robots will be presented below.

Emotion modelling

Emotion modelling is an important element in social robotics as well as in other fields. It should be emphasised that it has been repeatedly demonstrated that participants in a social situation who behave similarly to us, who present a similar type of both facial expression rate and emotional expression, are perceived as people with whom more interaction and contact can be made. These methods, designed to mimic a person's chosen behaviours to achieve specific goals, are widely used. They are used in business psychology to build brands, attract customers and investors. They are used in psychological and psychotherapeutic methods aimed at matching the person of the client/patient, so that it is possible to create a safe space for such a person to reflect and to remove stimuli that block the process. People who behave in a similar way are perceived as more trustworthy, they are also the ones with whom contact is more likely to be made and with whom it becomes possible to achieve goals more quickly. It is for these reasons that the use of mechanisms for modelling and imitating emotions, as well as other behaviours, by social robots is thoroughly supported by psychological theories. The primary goal of interaction with a social robot is to achieve an intended task, which, in order to be realised, requires the establishment of robot-human contact (Sabanovic, Chang, 2016). It is the quality of this contact that determines a great many factors, such as motivation or involvement of the other person (Becker, 2006). All these aspects point to the importance, in the process of building and constructing social robots, of taking into account issues such as processes that mimic certain behaviours of the interlocutor. It is worth noting that the way a person expresses themselves, shows emotions and reacts can be defined in more general dimensions leading to the possibility of defining an emotional style (Roberts et al., 2012). Emotional style is a set of characteristics that allows one to describe the nature of a person's emotional expression. According to research, it is insufficient to analyse only at the current level of a given emotion and, in order to be more effective, it is also necessary to take into account the interconnections between emotions and the style in which they are presented (Yildrim et al., 2011; Kesebir et al., 2019).

Markov chains

Here we introduce the notion of Markov Chain (MC) assuming that there are given:

1) Q - state space,
2) A - transition matrix,
3) a_{ij} – a probability of transfer from the state i to state j in a single step, where $\sum_j a_{ij} = 1$,
4) x_0 – an initial state (or distribution X_0 for initial state derivation),
5) t – step (time) index.

If we know the state at time t, the transition to step $t + 1$ does not depend on the state in steps i - 1, i - 2 ... (what is called *Markov property*). So MC is a stochastic process (i.e. a series of random variables), such as the probability of being in step t in state x depends only on the state of the chain in step (t-1) is (Markov 1971):

$$P(x_t \mid x_{t-1}, x_{t-2}, \dots, x_1) = P(x_t \mid x_{t-1}) \qquad (1)$$

Among the applications of modeling with MC one can distinguish: random walk, modeling biological, physical and social processes, statistical tools, simulating financial markets, reasoning with uncertain knowledge, e.g. in Bayesian networks, generation algorithm from any distribution (e.g. Metropolis-Hastings) and simulated annealing type algorithms (Omer and Woldegebreal 2022).

Markov chains in social robotic

The use of Markov chain methods for social robotics is a new issue, while a number of papers can be found that successfully combine the two aspects. Particularly noteworthy is an article addressing the topic of emotion prediction based on text, natural language processing and second-order Markov chain, the application of which was based on chatbots (Adikari et al., 2019). This is a solution not directly dedicated to social robots, but whose elements can be successfully transferred to this field. It is worth noting that emotion detection here is based on text analysis, which is ultimately intended to be used to construct emotion-dependent responses of a chat-bot system. Another paper uses Markov decision processes to develop emotional behaviour about assistive robots (Yu et al., 2008). The resulting model allows for emotional state matching, but had to be optimised due to its computational requirements. Importantly, the described work does not take into account a real-world implementation into a social robot, which does not allow for performance comparisons under real-world machine conditions. Such use also appears in the consideration of robots assisting in exercise (Shao et al., 2019), accompanying in dance (Peng et al., 2015), performing collaborative instrument-playing sessions (Weinberg et al., 2009) or adapting their behaviour to social situations. Due to the rapid development of the field and the lack of a specific technological and theoretical paradigm, it should be noted that some of the solutions are only theoretical and do not consider practical implementation into a social robot (Nogueiras et al., 2001). Some of the solutions can only be applied to a narrow group of social robots and there is no possibility to use the proposed solutions in other fields. Nevertheless, conducting research and publishing the obtained results has the potential for further, more structured development of social robotics (Langer, Levy-Tzedek, 2021).

PROPOSED MODEL ARCHITECTURE

The proposed model is designed to be able to detect the emotion the interviewee is displaying, based on an analysed image from a camera embedded in the robot. In addition to being able to determine the current emotional state, it is possible to trace the changes and transitions of successive emotions. The implementation of the architecture presented in Fig. 1 makes it possible to predict emotions based on previous data containing transitions of emotional states. The proposed architecture has been implemented in a social robot of the OhBot type in order to match the robot's facial expressions with the current and anticipated emotional states of the interlocutor. Such matching allows for a better human-robot relationship and has the potential to enhance and accelerate the goals to be achieved with the social robot. In order to ensure the correctness of the proposed module, it is divided into three sections: the first one is responsible for detecting emotions both from the current state and from previously obtained data, the next one has the task of making a prediction of emotions based on Markov models, and the last part of the solution allows matching the robot's facial expressions to the current state and to the emotional style of the interlocutor.

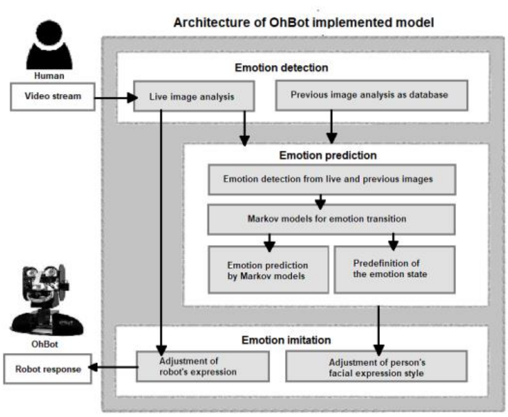


Figure 1: Architecture of OhBot Implemented Model

Emotion detection
The purpose of the emotion detection section is to process the image acquired from the camera implemented in the social robot. This image is processed for two purposes. The first purpose is to determine the current emotional state of the interlocutor, the second purpose is to determine the sequence of changes in the emotional states of the interlocutor from the beginning of the conversation until the end.

Emotion prediciton
The aim of the emotion prediction section is to detect emotions from both the current state and previous images, perform transition modelling and then predict emotions and the emotional state sequence.

Emotion detection by neural network.
In order to carry out the task of emotion detection based on the acquired image, it was decided to use a neural network previously trained on appropriately classified images. The choice of neural network was closely related to the need for its target implementation on the microcomputer present in the social robot. This means that the implemented network, in addition to satisfactory performance, should have a suitably small and simplified architecture that does not require a large amount of computing power. Based on solutions from the Tiny-ML range, it was decided on the YOLOv5s network, which is the newest network in the YOLO family and the smallest (s - small). In order for the network to detect emotions correctly, it was trained on a database: AffectNet (Mollahosseini, 2017). This is a database of approximately 220,000 images, each with an annotation assigned to one of eight categories. Among the emotions recognised are neutral state, anger, disgust, fear, happy, sad, surprise and anticipation. Due to the uneven and lowest representation of labels for the anticipation emotion, it was decided not to include it in the final model. Training of the neural network showed that it obtained the lowest image-based detection performance relative to the other emotions. In fig. 2, however, shows the final detection performance of the other seven emotions based on the YOLOv5s network trained on the AffectNet image collection.

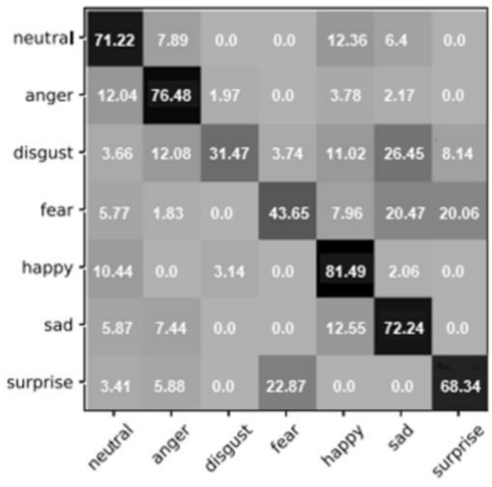


Figure 2: Accuracy of 7 Emotions Trained on YOLOv5s Neural Network

Markov model for emotion transition

The use of emotions as a series of consecutive states represents one of the less frequently used constructs. Such solutions have already been defined using Markov Models and Finite State Machines (FSM) (Davies, 2018). The proposed solutions provide an important substrate for the implementation and practical aspects of solution implementation. An important solution combining both Markov Models and practical implementation to a chatbot solution was applied using NLP Natural Language Processing (NLP) solutions, thus allowing the tailoring and personalisation of chatbot utterances (Adikari et al., 2019). The present application of Markov models is intended to allow the matching of the robot's mimic response to detected emotions, which are received via a video channel and analysed by a neural network.

In order to develop a model of transitions between emotional states, the following assumptions must be made:

The emotion space is defined as:

$$Q = \{q_i : \mathrm{i} = 1,2, \ldots \mathrm{n}\} \qquad (2)$$

where $n=7$, as number of emotional states.

When one emotion changes to another we can describe is as changes between states, eg. transitions. In contrast, the probability with which one emotion can change to another emotion is referred to as transition probablilities. By having records of individual changes of emotional states, it is possible to identify interactions between the states in question. These interactions are modelled using a matrix of emotional states (A).

$$A = \begin{pmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{pmatrix} \qquad (3)$$

n – number of emotional states,

a_{ij} – emotional transition from $q1$ to $q2$, which denotes in:

$$a_{ij} \in [0,1], i,j \in [1,n], \qquad \sum_{j=1}^{n} a_{ij} = 1, i = 1,2 \ldots n \qquad (4)$$

The emotions held and the transition model was based on the results of the image analysis. The analysed image sequences labelled with the given emotional states were stored in the conversation base. The analysis of the image in terms of the emotion of the interlocutor starts from the moment the conversation with the robot starts, then the images are analysed at specific time intervals, $t=15s$. If a given emotion is the same as the previous one, the result of the analysis is not stored, but if a given image is labelled with a different emotion, this information is stored in the database. The sequence of changes in emotional states is recorded until the conversation between the human and the social robot stops. Obtaining a sufficient number of state sequences allows certain characteristics of the interlocutor to be specified, which allows generalisations to be made and assigned to a certain group with certain characteristics.

Predefinition of the emotional states.

Based on the implemented mechanism for building a baseline of emotion change during conversation with the robot and the developed emotion transition matrix with associated possibilities, it is possible to infer the emotional characteristics of the interlocutor reflecting general tendencies related to the manifested emotions, which can be to some extent reproduced and imitated by the social robot to match the emotional state of the human. Research to create an emotional profile of a person has also been conducted by Amato et al. (2019). However, it is worth noting that they focused on the utterances of the subject and the emotions extracted from the analysis of the text that made up the utterance. The developed result was to modify the responses of the chatbot, whereas in the present study its task is to match the facial expressions of the social robot with the peeled video cues. One of the most significant differences is the ability to detect a neutral state in the implemented solution. In previous studies conducted, the neutral state was shown to be the most common state and, based on conversation analysis with the social robot, it prevailed 70% of the time. It is also worth noting that the variability of the emotions presented and their diversity, is not only due to the intrinsic characteristics of the interlocutor, but also to the length of the conversation. This means that the choice of overall emotional style to predict the robot's facial expressions is also dependent on the assumed length of the interaction. Due to the analysis and detection of emotions, it is possible to determine the frequency of emotion change and, based on emotion categories, to determine a preference for positive or negative emotions. According to research, most emotions last for about 90 seconds, and are rarely maintained for longer. Instead, it can be replaced more quickly by another emotion. Based on the relationships presented, an emotional style assignment scheme was developed (Fig. 3).

Algorithm for selecting emotional characteristic

n_p=number of detected positive emotions
n_n=number of detected negative emotions
n_{all}=number of all detected emotions
t = time

MIN($t > 120s$)
1. If $n_p > \frac{3}{4} n_{all} \cup n_{all} > 4$
2. then return *positive vivid*
3. otherwise return *positive steady*

4. If else $n_n > \frac{3}{4} n_{all} \cup n_{all} > 4$
4. then return *negative vivid*
5. otherwise return *negative steady*

6. If else $\sim\left(n_n > \frac{3}{4} n_{all} \cup n_p > \frac{3}{4} n_{all}\right) \cup n_{all} > 4$
7. then return *neutral vivid*
8. otherwise return *neutral steady*

9. End if

10. Repeat every t=120s until $n_{all} = 0$

Figure 3: Algorithm for Selecting Emotional Characteristic.

Based on the above schema, 6 emotional styles can be distinguished based on whether a person presents more neutral, positive or negative emotions and how often these are changed during interaction with the robot. These 6 styles form the basis of the robot's behaviour and prediction of its facial expressions.

Emotion prediction by Markov models.

The overarching aim of this solution is to make a prediction of the following emotion based on an emotion transition matrix and an emotion sequence pool on emotional characteristic styles. As can be seen on examples of participants interacting with social robots there are certain patterns of emotional styles. In order to read these patterns correctly, it is possible to refer to the transition likelihoods developed with markov chains. Higher order Markov chains will be used for this purpose. In general, they allow the probability of a given state to be developed based on the probability of a previous state. However, in their simplest structure, their 'memory' only extends to one previous state. To expand the number of states on which the prediction is to be based, the n^{th} order Markov model should be used, with the following structure:

$$P(x_t \mid x_{t-1}, x_{t-2}, \dots, x_1) = P(x_t \mid x_{t-1}, \dots, x_{t-n}), \quad t>n \qquad (5)$$

It should be noted, however, that although higher order models allow one to base their predictions on a larger number of historical data, the number of parameters required for estimation then increases exponentially. This means that the higher the order, the less reliable the estimated parameters become. Based on the above, it was decided to use a second-order Markov model, allowing the development and estimation of predictions based on the two prior emotions detected.

Emotion imitation

The above implementations aim to match the facial response of the social robot to the emotional style of the person and the current emotion presented. This means that the robot is sensitive to and adapts to changes in the social environment. The implementation of dynamic mimicry allows the creation of more realistic and tailored robot responses and does not require the implementation of pre-defined ready-made scenarios, which were much less resistant to change.

TEST RESULTS

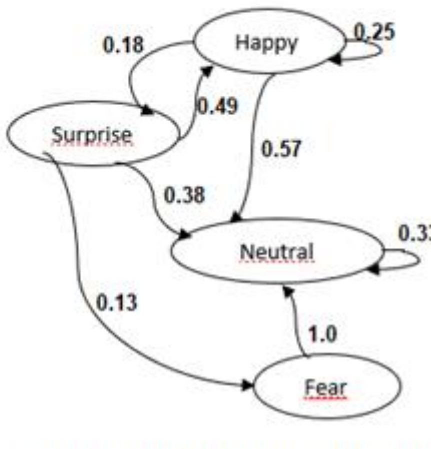
In order to test the developed model, a series of tests were implemented into a robotic OhBot head. This was possible, not least because of the possession of previous data, on human-robot interaction, which included sequences of detected emotions during a single conversation. The implementation for testing included the full proposed model, including emotion modelling, emotion style detection and final prediction.

Database

In order for the proposed model to work correctly, it was necessary to use a dataset containing sequences of emotions. It was decided to use an in-house dataset that had been developed and acquired as a result of previous work carried out in social robotics. This means that each state sequence recorded was derived from an actual human-robot interaction. This is important, due to the fact that most studies use externally available collections to analyse emotional sequences, such as: analyses of excerpts from films or TV series (image-based emotion detection) or analyses of social media and posts there (text-based emotion detection). Such an approach is necessary in the absence of an in-house collection, but it takes into account a certain assumption that the acquired data will be able to reflect the emotional behaviour of individuals in relation to interactions with robots. Due to the above, it was decided to base the research conducted on an in-house dataset. The dataset is a record of the changes in emotion that the camera recorded, which were then labelled by the YOLOv5s network based on 7 emotion categories. The data was collected from 11.2021 to 06.2022, allowing for a satisfactory number of interactions. It should be noted that the recorded data only contains the sequences of change of emotion, from the start to the end of the interaction, and in no way the images based on which these emotions were classified are stored. This is in order to fully animate the data, and thus the people interacting with the social robot. The emotion state sequence database contains 982 people whose emotion state sequence was recorded. In order to develop accurate analyses, it was decided to analyse and discard from the collection those records that were shorter than 2 minutes and those that were longer than 20 minutes. After cleaning, 746 sequences of emotional states were included in the target solution. The base developed and prepared was used to analyse and generate an emotion matrix per participant.

Transition analysis for emotion states

The developed emotion chains for each person, based on the base prepared for the study were used to analyse and calculate Markov probability matrices. The developed matrices contained the sequence of changes between the 7 available emotions, together with the probability of their occurrence. Two emotion state transitions were included to demonstrate an example emotion chain, one for an interaction lasting 3:43 min and the other for an interaction lasting 11:25 min. Figure 4 shows these example analyses.



Short human-robot interaction - emotion transition

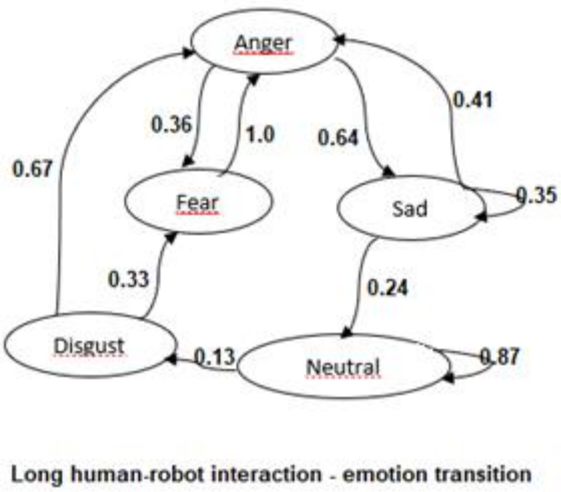


Figure 4: Examples of emotion transition interaction.

Based on the above analyses, a high diversity of emotions occurring during the interaction with the robot can be observed. The diversity is also manifested in the length of the interaction itself and in the nature of the emotions observed. Self-looping means that the person tended to return to the same emotion as before. Above and beyond this, it should be noted that most interactions do not show all emotions, only a selection of those analysed, while the most frequently recurring emotion in all diagrams is the neutral state.

Emocjonal style attribution

Based on the developed algorithm (Figure 3), the obtained emotion transition for each participant will be used for analyses related to emotional style. Aspects such as the total number of emotions, the number of self-loops or the interaction time with the robot were taken into account here. Assignment to a given emotional style allowed for predictions regarding the nature of the next emotion - whether it would be negative, neutral or positive, as well as the vividness of a given interaction. Although neutral is the predominant emotion, it is important to note that it is the occurrence of other strong emotions that determines the need for feedback from the robot. Matching the facial expressions of a social robot to a person showing sadness or fear allows for non-verbal support and speeds up the process of proper human-robot interaction. The ability to assign people to a specific emotional style has the potential to allow for more accurate and personalised robotic responses, thus leading to greater motivation and faster establishment of planned goals.

Emotion prediction

An implemented second-order Markov chain was used to predict the emotion that should be reflected using facial expressions. For each emotion in the transition state, a probability of occurrence was assigned, and the second-order model allowed a probability analysis up to two emotions backwards. This made it possible to make a prediction for the next emotion. In order to do this, a database containing consecutive emotions with time stamping was used. Using this database as the data needed for validation, it was divided into a training set of 80% and a test set of 20%. The potential emotion was then analysed based on the data held, building on the previous two. The data was designed to predict both the missing emotion in the middle of the conversation with the robot and at the end of the conversation. To test the effectiveness of the prediction, a positive or negative category was assigned for each emotion, and both categories were assigned for the neutral state. It was then possible to calculate the prediction performance of both the specific emotion and the overall characteristics. The results obtained are as follows:
82% effectiveness of detecting the negative category,
77.5% efficiency in detecting the negative category without the neutral state,
72% positive category detection efficiency,
70.7% efficiency in detecting a positive category without a neutral state.
The next step was to analyse the effectiveness of direct emotion prediction. The results obtained are as follows:
neutral - 76.4%; anger - 78.9%; disgust - 54.5%; fear - 68.4%; happy - 75.2%; sad - 73.8% and surprise - 71.9%.
Due to the fact that only the last two emotions were analysed, no selection of the base was made in terms of the length of the entire interaction with the robot, meaning that it is effective for interactions lasting between 2 minutes and 20 minutes. It is presumed that as the base grows, the accuracy of the prediction carried out will increase. It should also be noted that the effectiveness of predicted emotions is higher than the effectiveness of emotion detection by YOLOv5s when training based on the AffectNet database. This allows us to conclude that the use of combined prediction methods has the potential to build models with higher precision and accuracy without incurring higher computing power costs. Figure 5 contains a schematic of how the entire model implemented for OhBot social robots works, and Figure 6 contains an example of the robot's facial reactions presented as an avatar.

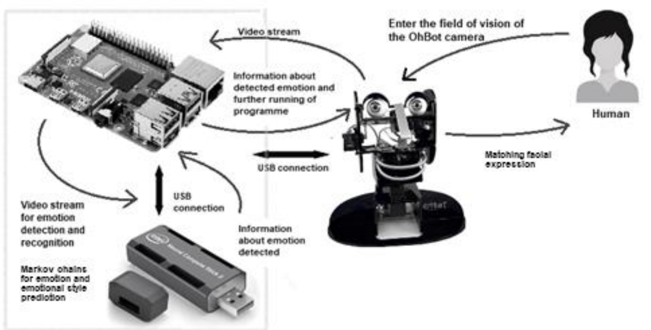


Figure 5: Implementation model.

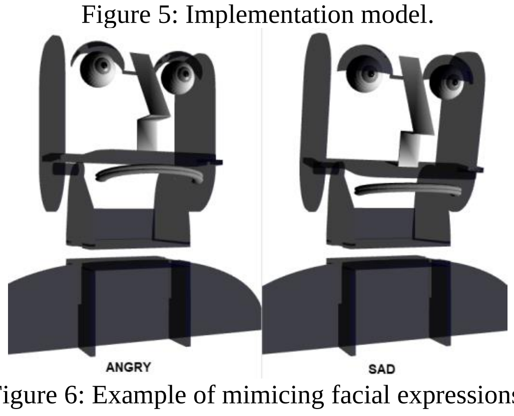


Figure 6: Example of mimicing facial expressions.

CONCLUSION AND DISCUSSION

The aim of this paper was to present and implement a model that allows mimicry of the facial expressions of a person interacting with a social robot. Mimicry of facial expressions is understood as the replication of detected and labelled emotions (Amato et al., 2019). In order to realise the above, a model combining solutions from neural networks and Markov chains was prepared. The developed model allows the prediction of individual emotions in a satisfactory manner, as well as the assignment of a person to an emotional state. The developed predictions were based on an in-house developed database containing sequences of emotion changes, which were recorded using a social robot. The proposed model was then implemented into OhBot social robots allowing for real-time modelling of the robot's facial expressions in real time based on the emotion predictions made. The effectiveness of the implemented predictions was also tested and satisfactory results were obtained for most of the 7 predicted emotions. The developed model and its implementation can be implemented in most social robots having and able to generate a facial reaction. It can also be modified to suit mobile robots, thus predicting a response with individual limbs or posture. The implementation of this solution allowed the robot to move away from previously developed mimicry response patterns and implement a solution that responds to and adapts to sudden changes in the caller's emotions. The use of a combination of two methods allowed the solution to be implemented despite the limited computing power and other constraints posed by social robots. It is also worth mentioning that this is not the only process implemented simultaneously in the social robot under test. With reference to previous work addressing the topic of modelling emotions, it should be noted that it is possible to model them both with an image (as was done in this paper), but also with text (Adikari et al., 2019). The latter of which poses a separate challenge due to linguistic diversity. It is conjectured that a combination of both approaches would produce even more accurate results related to emotion prediction. It is also worth noting that the number of predicted emotions in different research papers varies and depends on a number of factors. In the present study, the specification of 7 emotions was dictated by previous training of the network based on the AffectNet dataset. It is not excluded that results developed on a different group of emotions (probably larger) could have differed significantly from those obtained. Finally, it should be noted that a second-order Markov chain was used here. Using other solutions from the Markov family could have led to a broader probability analysis and a deeper understanding of the changes that occur between emotional states.

FUTURE RESEARCH

A number of activities centred around the further development of emotion modelling in social robots are planned as part of further research (Probierz, Gałuszka 2022). This work focuses on a number of factors and solutions, while for this article, as mentioned above, the use of other types of Markov models is a planned next step. It is also extremely important to expand the database, which is possible due to the continuous use of social robots within the university, and which will allow further analyses to be carried out and results to be compared with a larger number of recorded emotional states. The number of emotions detected also plays an important role; it is indicated that the satisfactory detection performance of 7-8 emotional categories decreases significantly when this set is enlarged to include more complex emotional reactions. In order for it to be appropriate to label and then predict more emotions, work is planned to combine a combination of image-based emotion detection together with text-based emotion detection. As shown above, this approach has the potential for higher prediction performance, but is also model-dependent on the language for which the text will be analysed. This means that a model that processes someone's speech in the context of searching for emotionally charged words may differ significantly depending on the language for which it was developed. As the results obtained show, the modelling of social robot facial expressions is feasible and practically implementable, but it does not exhaust a wide range of possibilities for further development and the pursuit of the highest possible prediction performance.

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2. Modelling emotional response based on action planning in PDDL language

2.1. Introduction

In artificial intelligence (AI), planning refers to the automation of reasoning about plans, and in particular the reasoning that underlies the formulation of a plan to achieve a particular goal in a given situation. A key element of planning in AI is modeling: the planning system takes as input a description (or model) of the initial situation, the actions available to change it, and the end state, and then generates a plan consisting of those actions that, when executed from the initial situation, will achieve the goal (Haslum et al., 2019). The Planning Domain Definition Language (PDDL) is a formal knowledge representation language designed to express planning models. It was developed by the planning research community to facilitate the comparison of systems. It has become the de facto standard input language for many planning systems, although it is not the only modeling language for planning. Over the years, several variants of PDDL have emerged to describe planning problems of different nature and complexity, with a focus on deterministic problems (Haslum et al., 2019). In the more than two decades that PDDL has existed as a standard modeling language in the automatic planning research community, the language has undergone several revisions and extensions. The specification of the syntax and semantics of the various subsets of PDDL is scattered across many publications and is not readily available. Although PDDL is intended to be a high-level modeling language, the art of modeling planning problems in PDDL is not easy to master. There is a lot of practical knowledge, such as idioms for modeling typical situations, 'tricks' for dealing with the limitations of the language, and pitfalls to avoid, that is rarely documented (Haslum et al., 2019).

Social robots must interact autonomously with humans in dynamic and uncertain environments. A common way to control such robots is to use finite state machines (FSMs), where each state corresponds to a particular situation during the interaction, and transitions between states depend on both actions taken by the robot and information received from sensors. FSMs are simple and fast mechanisms for controlling a robot, especially in structured environments, but in more advanced applications, identifying and correctly specifying all the possible states that can occur and the transitions between them can be a really difficult task. In addition, adding or modifying features once the robot is deployed can be very difficult because all behaviors are highly encoded (Fuentetaja et al., 2020). An important aspect here is action-based planning. It allows modeling the actions that the robot can perform and the possible states of the system using a language based on predicate logic, the Planning Domain Definition Language (PDDL).

In the context of emotion modelling, automatic planning plays a key role, especially in the social robotics problem of recognizing or responding to human emotions. It is pointed out that the problem of automatic planning in artificial intelligence is to find sequences of agent actions that transform the agent's initial environment into a desired target situation. This problem becomes more complicated when the information about the modeled world is not sufficient to determine all the facts necessary to describe the initial state of the world. In such a context, human emotions, which are regulatory processes activated in response to various stimuli, are a source of additional uncertainty. In this context, the PDDL language can be used to describe the domain and planning tasks, allowing accurate modeling of the robot's interactions with humans based on their emotional states.

2.2. Literature review

In the context of the growing popularity of using automated planning to control robotic architectures, Fuentetaja and colleagues (2020) highlighted the ability to define tasks to be performed in a declarative manner. However, as the authors noted, classical planning tasks, even in the basic standard Planning Domain Definition Language (PDDL) format, were difficult for non-expert engineers to formalize, especially when the modeled case was complex. Human-Robot Interaction (HRI) was such a complex environment. In their manuscript, the authors described an approach to designing a planning model capable of controlling autonomous social robots interacting with humans. The results showed that the model was able to capture all relevant aspects of human-robot interaction in the scenarios analyzed. In the context of education, one of the many purposes for which social robots are designed is to support the learning process.

Rohlfing and colleagues (2022) highlighted that learning can be supported in a variety of ways, as the learner can engage in different activities that promote learning. The authors highlighted the differences in social relationships between humans and robots during language learning by children interacting with a social robot. This study aimed to identify differences in social relationships between humans and robots during children's language learning. Sonderegger (2022) discussed the use of language models in education, pointing out the limitations of current social robot and chatbot systems, which often rely on rule-based and retrieval-based methods. The author presented an approach for using generative language models to enhance interactive learning with educational social robots. The model combined the technological capabilities of generative language models with the educational tasks of a social robot in the role of tutor and learning partner. Van den Berghe (2022) discussed the use of social robots in trans-language pedagogy, i.e., using the full linguistic repertoire of students in schools. The author conducted a review of research on the use of robots in second language learning, analyzing whether students' languages were used strategically to support the learning of another language. The conclusions of the review include recommendations for the future use of social robots in trans-language pedagogy.

The research conducted by Rebecca Z. Lin et al. (2018) focused on creating an ontology for visualizing emotions. In this research, a Visualized Emotion Ontology (VEO) was created to semantically define 25 emotions based on recognized models. This research has shown that visual representations of emotions, such as shapes, lines, and colors, can be effectively used to model and recognize emotions. The results of these studies suggest that modeling techniques such as those used in the PDDL can be used to create more sophisticated models of emotion. Subsequent studies have focused on analyzing and modeling emotions in the context of attitudes and sentiments (Schuff et al. 2017). In these studies, modeling techniques were used to analyze subtle emotions based on Ekman and Plutchik's definitions. The results of this research indicate that modeling techniques, such as PDDL, can be used to analyze and recognize emotions in social media. The aforementioned studies have provided valuable insights into the role of social robots in various aspects of education and human interaction. The use of technologies such as language models in combination with social robots can provide significant benefits in the context of education and social interaction.

The topic of modeling emotional responses using the PDDL language is not as popular as other branches of social robotics development, but nevertheless, several articles can be found that address the topic. The article by Pérez-Pinillos, Fernández, and Borrajo (2011) addresses the topic of modeling emotional responses in agents. The article discusses a long-term reasoning model that integrates emotions, drives, preferences, and personality traits in autonomous agents based on AI planning. The emotional state was represented as two functions: valence and arousal. This two-dimensional model was chosen for its simplicity and ability to provide a representation similar to other emotional models. It was found that the deliberative model outperformed the reactive model when the personality tended to be more neurotic. This works because the effects of actions are increased and drives increase more. A long-term reasoning model was also proposed, integrating emotions, drives, preferences, and personality traits in autonomous agents based on AI planning. The emotional state was represented as two functions: valence and arousal. This two-dimensional model was chosen for its simplicity and ability to provide a representation similar to other emotional models. The authors suggested that their model is able to account for future rewards in an integrated way with the agent's other goals. The quality of plans was discussed for different types of agents, such as methodical, stable, neurotic, and receptive. Graphs showing the quality of plans for these agents showed that the deliberative model was more effective than the reactive model, especially for agents with more neurotic personalities.

In the context of agents who plan their actions in the future, it is important for them to consider their needs, even if they are not necessary at the moment (Pérez-Pinillos, Fernández and Borrajo, 2013). For agents with a conscientious personality, this is particularly important because they take more time to perform actions. As a result, conscientious agents take less time to execute plans than negligent agents. In recent years, a number of emotion-focused systems have been developed, usually based on Frijda's theory of emotion. This theory posits that emotion is the tendency of an individual to adopt a particular behavior according to his or her needs. Emotions also involve the interaction of the individual with the environment. For example, people try to move away from objects that threaten their survival, while moving closer to objects that satisfy their needs. The study proposes a model for long-term reasoning that integrates emotions, drives, preferences, and personality traits in autonomous agents based on artificial intelligence planning. The goal is to generate plans that maximize valence while satisfying the agent's needs or drives. Experiments have shown that the quality of solutions (measured as valence value) is higher when a deliberative model is used compared to a reactive one. This implies a more realistic agent behavior. The proposed model is a first step towards the development of a more advanced and complex architecture.

The problem of modeling emotions using the PDDL language is also relevant in the context of experience management in interactive narratives (Hernandez, Bulitko, & Hilaire, 2014). The research discusses the different techniques used in PACE, such as emotion modeling, narrative planning, and adaptation. The importance of emotion modeling in the context of interactive narratives is highlighted, emphasizing that emotions are key to understanding player reactions and adapting the experience to their needs. Research also points out that there are many models describing human behavior in different domains, but there is a lack of a unified modeling approach (Yordanova, 2011). Human behavior can be modeled for a variety of reasons, such as simulation, prediction, filtering, and smoothing. Simulation involves generating samples of the future trajectory, while prediction defines the probability distribution in the action space. Relevant models include the PECS reference model, the Belief-Desire-Perception model, the GOMS model, the Markovian task model, and natural language. Among the above mentioned models, the PDDL also plays an important role, which can be used to represent knowledge about what actions are available to a person in a given state of the world, what their effects are, and what conditions must be met for an action to be performed. Yordanova's (2011) research shows that one of the main strengths of PDDL is its expressiveness and ability to represent complex cause-effect relationships. However, PDDL can be difficult to use in dynamic environments where information changes rapidly because it requires clearly defined pre- and post-conditions for each action. In addition, PDDL is not ideal for modeling human behavior in real-world, unstructured environments, where people often act on incomplete or inaccurate information.

Some studies also focus on the application aspect of PDDL. The design of a robotic system that operates autonomously in a naturalistic play environment is addressed (Charisi et al., 2017). At the same time, the goal is a social human-robot interaction focused on children. Utilizing existing child development theories and emotion models, a dynamic interaction framework for natural child-robot interaction is designed. In this dynamic framework, social human-robot interaction is defined by the system's ability to take into account the social-emotional state of the user and plan accordingly by selecting appropriate strategies to execute. The robot needs a temporal planning system that combines the characteristics of task-oriented activities with the principles of human-robot social interaction.

An important aspect is also the possible unpredictability of human behavior, which forces one to re-plan a change of state (Izquierdo-Badiola, 2022). As research shows, the main challenge in human-robot communication is dealing with the stochastic nature of the dynamic human environment. Humans become uncontrollable agents, making flexibility and adaptability key features in planning collaborative goals. Human-human collaboration allows humans to plan ahead, but they are typically unable to automatically adapt to changes in the dynamic and uncertain real world by reassessing the current state of the world and the partner, and replanning to achieve the goal. It has been suggested that existing approaches to task planning do not meet the requirements of adaptability in human-robot collaborative tasks. Many researchers believe that the main problem is the lack of modeling of the partner and its integration into the automated task planning system. Therefore, plans have been presented that solve the human-robot collaboration task by dealing with the unplanned behavior of the human partner. The hypothesis was that by taking into account the agents' states (physical and mental) in the generation and execution of the plan, the robot can better understand and react to unplanned human behavior, adding the ability to adapt and anticipate unpredictable situations through modeling and replanning. To this end, the focus was on integrating human state with AI planning to anticipate and avoid failures caused by human behavior in human-robot collaborative tasks. The main objective was to answer the research questions of how to improve HRC plans in terms of success rate and avoidance of action failures by integrating the agent state model into the planning stage, and whether an appropriate and balanced task distribution among agents can be achieved in this case. The agent state is defined in terms of skills, knowledge, and motivation. The system generates two parallel action sequences assigned to a robot and a human.

Children's coping with painful and stressful medical procedures in clinical settings is also addressed in the context of potential applications (Lindsay et al. 2022). It is suggested that children regularly experience pain and distress in clinical situations, which may have negative short and in both the short and long term. While there are many techniques to help manage such situations, recent research has shown that social robots can be used to help manage children's pain and stress during medical procedures. In response to these challenges, an automatic planning-based system was developed that uses observed social cues combined with the robot's state to select appropriate behaviors. The main goal of the system was to adapt to different roles during interventions. The robot could act as a facilitator introducing or explaining parts of the procedure, as an assistant performing activities together with humans, or as a teacher/interviewer at the end of the procedure in the debriefing phase. The system architecture consisted of several components, including social signal processing, an interaction manager, a scheduling system, and a robotic platform. The challenges of integrating social signals into the planning model, the need for reliability, the challenges of learning predictive models, and the difficulties of integrating social signals into the planning model were highlighted. The need to consider the emotional state of the patient in the decision-making process was also highlighted as being critical to the appropriate selection of interventions.

The issue of PDDL language use also arises in the context of recently implemented ontology-based standards (Gonçalves, Bernardo, Sousa, 2023). This study highlights recently developed ontology-based standards (IEEE 1872-2015; IEEE 1872.2-2021; IEEE 7007- 2021) and those currently under development (IEEE P1872.1; IEEE P1872.3). The goal of these standards is to improve the performance of robots in performing tasks. It has been pointed out that elderly care has specific characteristics related to human-robot interactions in a single space. Robots must respect social and ethical standards (according to IEEE 7007-2021). The EUROAGE projects aimed at developing technologies to support an active and healthy life for the elderly. Different tasks have been developed, such as educational games, cognitive games with robots, and robots for elderly care. A smart home environment where robots perform their tasks was also described. A key element of the presented system was the ontology-based control architecture. In this context, a description of the robot and a description of the smart home were presented. It was noted that the robots were developed according to the IEEE 1872-2015 standard. A global knowledge engine architecture was also presented, which allows the robot to plan its actions using relevant semantic information from the environment. To this end, the focus was on the application of standard ontologies in a specific social robot scenario for the elderly. As part of the presented approach, the robots had the ability to plan their actions based on semantic information from the environment. For this purpose, the Planning Domain Definition Language (PDDL) was used to define problems and domains. This made it possible to automatically generate action plans for the robots based on the current state of the environment and available semantic information.

The issue of appropriate behavior modeling is also relevant to trust in social robots (Koeszegi, Vincze, 2022). The book points out that robots are becoming increasingly present in our daily lives, populating our living and working spaces. It is hoped that robots will be able to relieve humans of routine, dangerous, or monotonous tasks. It is believed that they can make our lives more comfortable, easier and even more enjoyable by providing companionship and care. However, with the increasing autonomy and influence of robots in our lives, there are concerns about losing control of these machines.

Another important area of research is intelligent robotics (Tonk et al. 2023). This involves the development of robotic systems that can autonomously navigate their environment, efficiently plan actions, and communicate naturally with humans. As a result of these advances, the fields of navigation, planning, and human-robot interaction have experienced significant breakthroughs. Robots have become capable of navigating complex environments thanks to reliable navigation algorithms. They can now use planning strategies to make intelligent decisions and act autonomously. In addition, research in human-robot interaction has focused on creating user-friendly interfaces that enable seamless collaboration between humans and robots. In the context of navigation, it has been emphasized that robots must be able to navigate their environment in order to perform various tasks. Techniques such as simultaneous localization and mapping (SLAM), path planning, and obstacle avoidance were mentioned. Thanks to these techniques, intelligent robots can now operate in a variety of environments, such as homes, hospitals, warehouses, or outdoor spaces. Another key element of intelligent robotics is planning. Various planning techniques have been mentioned, such as classical planning, probabilistic planning, and hierarchical planning. By combining planning methods with navigation algorithms, robots can plan and execute their tasks autonomously, increasing their efficiency and flexibility.

Previous articles have demonstrated the applied value of social robots in areas such as education or support in stressful situations. Another area is the use of social assistive robots (SARs) in therapy (Bettosi et al. 2023). In human-to-human therapy, experts often communicate the thought process behind the decisions they make to promote transparency and build trust. As we move toward incorporating more complex decision models into these robots, the ability of SARs to explain their decisions becomes more challenging. In the context of decision making in SARs, it has been pointed out that treatment sessions can be thought of as sequential decision-making processes, where prior data often influences future actions of the system. The mechanisms that drive these processes can use a variety of techniques, from simple rule-based approaches to complex machine learning algorithms. Several studies in this area were mentioned, including the use of reinforcement learning in various therapeutic contexts. A key aspect was the issue of transparent communication of decisions in SAR-guided therapy. In human-to-human therapy, experts communicate transparently, which leads to trust building. In robots, trust is derived from the integrity of the software that guides their complex decisions. Therefore, transparent decision communication can help alleviate trust concerns while providing clearer insight into the robot's motivations and intentions. To this end, the Planning Domain Definition Language (PDDL) was used in the context of physical therapy. One scenario focused on upper extremity therapy, where the SAR made decisions based on an automated planning mechanism developed using PDDL. Therapists described unique poses for each patient, and the decision support system then created a plan that the robot executed as sequential actions in the real world. If the actions failed, the plan was regenerated.

2.3. Introduction to the publication

Three articles have been published under the chapter modeling emotional response based on action planning in the PDDL language (3: Janiaczyk, Probierz, Gałuszka, 2020; 4: Gałuszka, Probierz, 2021; 5: Probierz, Gałuszka, Gałuszka, 2021).

The first paper was entitled "On the recognition and analysis of selected emotional states in the artificial intelligence of social robots". The aim of the study was to investigate the possibility of using automatic planning tools in the presence of uncertainty to analyze a person's emotional state and influence the diagnosed state by a social robot. The main goal of the emotional state analysis was to create a database of characteristic facial expressions, the combination of which was used to determine a given emotion. PDDL (Planning Domain Definition Language) was used to describe the domain and the planning tasks. The ACL (Allegro Common Lisp) platform was used as the compiler, with Sensory Graphplan as the planning algorithm. The authors based their research on the 6-7 universal emotions defined by Paul Ekman. The problem of automatic planning in AI is to find a sequence of agent actions that transforms the agent's initial environment into a desired target situation. The problem becomes more complicated when the information about the modeled world is not sufficient to determine all the facts necessary to describe the initial state of the world. Emotions are regulatory processes that are triggered when a person is confronted with stimuli whose meaning is important to the organism or personality. There are four types of emotion triggers: endogenous and exogenous stimuli, physiological correlates, cognitive appraisal, and motivational properties. This paper proposes a set of examples and solutions to planning problems in artificial intelligence for modeling a social robot's response to a human emotional state. It was assumed that the robot is communicating with a human with an unknown emotional state, which is a source of uncertainty. It was also assumed that the robot would be able to analyze five negative emotions based on the facial expressions shown in Section 3. It was assumed that one of the tasks of the social robot is to respond to the emotional state of the person in such a way that when a negative emotion is detected, it can be reduced or not escalated. This paper focuses on the possibilities of using automatic planning tools in the presence of uncertainty to analyze a person's emotional state and influence the diagnosed state by a social robot. The authors present a methodology based on the PDDL language and the ACL platform, and describe different facial expressions specific to each emotion. The paper also proposes modeling the social robot's response to the human's emotional state as a conditional planning task.

The paper, entitled 'On transformation of conditional, conformant and parallel planning to linear programming', focuses on the transformation of conditional, conformant and parallel planning problems to linear programming. The paper presents heuristics for the transformation of these planning problems, based on an extension of the transformation presented in previous work. The motivation for this approach is that linear programming problems are known for their ease of computation. In the introduction to conditional, conformal, and parallel planning problems, basic definitions and examples are presented. The planning problem is assumed to consist of four sets: conditions, actions, initial state, and final state. For a conformal planning problem, there are no sensory actions, which leads to two possible worlds: the first in which a condition is true, and the second in which it is false. The solution is a plan that solves the problem regardless of which world we are in. The section on transforming planning problems shows how to transform planning problems into linear programming. For a conditional planning problem, if l is the number of planning steps, the variables for the conditions are specified in a finite way. For the actions, the variables are also specified in a certain way. The initial state can be transformed from a set of possible initial states to a set of equations with the values of the variables for the unknown conditions equal to 1. The target state is reached if the condition is true in the last planning step. The sample results section shows the transformation results for the examples presented in the previous sections. There are two possible situations for the conformal planning problem. In the first, the bomb is in the first package, but it is not known if it is in the second package. In the second situation, the bomb is not in the second package, but it is not known if it is in the first package. The values of the variables for the actions are binary, so the solution can be interpreted directly as a plan. In the section Remarks on the Computational Complexity of Transformed Planning Problems, the complexity classes P and Σ P are introduced. For the conformal planning problem, the problem belongs to class Σ 2P and is a complete problem. The complexity of the heuristics presented in this paper is due to the size of the LP problem, i.e., the number of variables and constraints for the problem.

A recent paper presented the use of automatic planning methodology in the presence of uncertainty to analyse the emotional state of a person and the possible reactions of a social robot. The main emotions considered are sadness, fear, anger, disgust and contempt. The scenarios take into account uncertainty modelling in emotion detection. The result of the work is a set of two planning domains with illustrative examples. The assumption was that when negative emotions are detected, the robot should react in such a way as to reduce or not escalate them. The introduction to the problem concerned automatic planning in artificial intelligence, which is formulated as a search for a sequence of agent actions that transforms the agent's initial environment into a desired goal-oriented situation. The problem becomes more complicated when the information about the modelled world is not sufficient to determine all the facts necessary to describe the initial state of the world. In such a case, we say that the initial state of the problem is uncertain. One of the ways people communicate is through facial expressions. Theability to recognise emotions is important in the context of social robots, as it allows the tone of the conversation to be adapted to the mood of the interlocutor. The interaction between human and robot should be seamless, and the robot should be able to adapt to the current situation and extract as much information as possible based on the analysis of the user's face. Human emotion recognition can be implemented by analysing facial expressions, sound or body language. This paper focuses on emotion recognition using facial expressions. Seven basic emotions are detected: fear, anger, happiness, sadness, surprise, disgust and neutrality. Two planning domains are presented in this paper. The first domain, named 'basic emotion', deals with the task of recognising and responding a social robot to two related emotions: sadness and anguish. The second domain, named 'complex emotions', is an extended version of the previous one, in which the social robot's task is to respond to a complex emotionally uncertain initial situation. In the simulation research section, a number of tests were conducted using the newly created planning domain. The results show the suitability of classical automatic planning methods for analysing emotional states. It should be noted that the examples considered are only illustrative of the applicability of the methods presented and are not intended to provide a ready-made solution fora specific social robot. In summary, the paper presents an approach to modelling and analysing a social robot's response to negative human emotions in the presence of uncertainty. The presented approach may be useful for social robot designers who wish to incorporate the robot's ability to recognise and respond to human emotions in their designs. However, further research is needed toadapt the presented approach to specific applications in real-world social robotics environments.

2.4. Summary of Chapter 2

The chapter entitled "Planning Domain Definition Language (PDDL)-based emotional response modeling" focuses on the use of the Planning Domain Definition Language (PDDL) to model emotional responses in the context of artificial intelligence (AI). In AI, planning refers to the automation of reasoning about plans, and in particular the reasoning that underlies the formulation of a plan to achieve a specific goal in a given situation. A key element of planning in AI is modeling. The PDDL language was developed as a formal knowledge representation language for expressing planning models. Over the years, it has become the standard input language for many planning systems, although it is not the only modeling language for planning. In the more than two decades of PDDL's existence, the language has undergone several revisions and extensions. Although PDDL is intended to be a "high-level" modeling language, modeling planning problems in PDDL is not easy to learn. Social robots, which must interact autonomously with humans in dynamic and uncertain environments, often use finite state machines (FSMs) for control. However, in more advanced applications, it can be difficult to identify and correctly specify all possible states and transitions between them. In this context, action-based planning such as PDDL becomes crucial, especially in the context of emotion modeling.

In the context of emotion modelling, automatic planning plays a key role, especially in the social robotics problem of recognizing or responding to human emotions. Human emotions, which are regulatory processes triggered in response to various stimuli, represent an additional source of uncertainty. In this context, PDDL can be used to describe the domain and planning tasks, allowing accurate modeling of the robot's interaction with humans based on their emotional states. In the literature, Fuentetaja and colleagues (2020) have highlighted the ability to define tasks to be performed in a declarative manner in the context of automatic planning to control robotic architectures. Human-robot interaction (HRI) was one such complex environment. Research conducted by Rebecca Z. Lin et al. (2018) focused on the creation of an emotion visualization ontology, where a Visualized Emotion Ontology (VEO) was created to semantically define 25 emotions based on established models. The results of this research suggest that modeling techniques, such as those used in PDDL, can be used to create more sophisticated models of emotions. The three articles published in this chapter represent an important expansion of knowledge in the field of emotional response modeling in the context of artificial intelligence, particularly as it relates to social robotics. Each makes a unique contribution to this growing field of research, highlighting different aspects and challenges of detecting, analyzing, and responding to emotional states in social robot interactions.

In summary, this chapter focuses on the use of the PDDL language to model emotional responses in the context of artificial intelligence. The relevance of the topic in the chapter title is highlighted by the growing interest in modeling emotions in the context of human-robot interaction. An analysis of the literature on the subject and the three key articles described in the introduction to the publication indicate the importance of PDDL in this area and potential directions for development in the field of emotional response modeling.

2.5. Publications

3. Janiaczyk, W. A., Probierz, E., & Galuszka, A. (2020). On the recognition and analysis of selected emotional states in the artificial intelligence of social robots. In A. Nketsai, C. Baron, & C. Foucher, A. Nketsai, C. Baron, & C. Foucher (Ed.), Modelling and simulation 2020: The European Simulation and Modelling Conference 2020. ESM'2020, October 21-23, 2020, Toulouse, France (pp. 223-228). EUROSIS-ETI.

4. Galuszka, A., & Probierz, E. (2021). On transformation of conditional, conformant and parallel planning to linear programming. Archives of Control Sciences, 375-399.

5. Probierz, E., Galuszka, A., & Galuszka, A. (2023). Social robot response to negative emotions as a PDDL planning problem in the presence of uncertainty. Przeglad Elektrotechniczny, 2023(8).

ON THE RECOGNITION AND ANALYSIS OF SELECTED EMOTIONAL STATES IN THE ARTIFICIAL INTELLIGENCE OF SOCIAL ROBOTS

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AI in simulation, AI planning, conditional planning, PDDL language, social robotics

ABSTRACT

The aim of the study was to examine the possibility of using automatic planning tools in the presence of uncertainty to analyze the emotional state of a person and exert influence on the diagnosed state by a social robot. The purpose of the emotional state analysis was to create a base of characteristic facial expressions, which combination was used to determine a given emotion. The result of the work is a set of examples and solutions of artificial intelligence planning problems regarding modeling the social robot's response to human emotional state. It is assumed that in the case of detection of negative emotions, the robot should react in a way that leads to its reduction or lack of escalation. The PDDL planning language and Allegro Common Lisp software were used in the implementations and simulations.

INTRODUCTION

The problem of automatic planning in artificial intelligence is formulated as a search for a sequence of agent actions (called a plan) that transforms the initial agent environment (called the initial state of the planning problem) into the desired goal situation (e.g. [8]).
The problem becomes more complicated if information about the modeled world is not enough to determine all the facts necessary to describe the initial state of the world. We say then that the initial state of the problem is uncertain, but it can be represented by a set of possible initial states. The problem resolution plan can take the form of conditionally implemented actions based on new information that appears during plan search. This approach is called conditional planning ([16, [17]).
The aim of the study was to examine the possibility of using methods of searching for a conditional plan to analyze the emotional state of a person and exert influence on the diagnosed condition. The uncertainty taken into account concerned the human emotional state in interaction with the robot. For the needs of emotional state analysis, a base of characteristic facial expressions was used, which appropriate combination was used to determine emotions. The research involved modification of one of the classic planning fields, taking into account uncertainty about the patient's state of health [12, http://web.cs.wpi.edu/~nth/cs534/resources/SensoryGraphPlan/sgp/domains/]. The modification consisted in matching actions representing taking medications and performing laboratory tests to actions modeling human emotional states and performing facial expression analyzes.
PDDL (Planning Domain Definition Language) [1], [3] was used to describe the domain and planning tasks. The ACL platform (Allegro Common Lisp) was used as the compiler, in which the planning algorithm is Sensory Graphplan [7].
The authors base their research on the 6-7 universal emotions as defined by Paul Ekman. But in real life people show usually blended emotions. Instead of using emotional states it is maybe more appropriate to use emotional dimensions as valence, arousal dominance etc. as defined by Russel for example in his circumplex model.

PDDL AS A REPRESENTATION OF CONDITIONAL PLANNING TASK

Following Bylander (1994) it is assumed that action planning Π (called STRIPS planning) consists of four sets $\Pi=\{C, O, I, G\}$:

- C is a finite set of *conditions*,
- O is a finite set of actions, where each action $o \in O$ takes the form $c^+, c^- \rightarrow c_+, c_-$, where:
  - $c^+ \subseteq C$ are so called *positive preconditions*,
  - $c^- \subseteq C$ are so called *negative preconditions*,
  - $c_+ \subseteq C$ are so called *positive postconditions*,
  - $c_- \subseteq C$ are so called *negative postconditions*,
- $I \subseteq C$ is an *initial state*,
- $G = \{G_+, G_-\}$ is a *goal situation*, where $G_+ \subseteq C$ are positive conditions (i.e. are true) and $G_- \subseteq C$ are negative conditions (i.e. are false).

In order to include the information that some conditions are unknown (assume k conditions can be true or false) in the description of the current problem state, one can introduce so called *k-states* proposed by Baral et al. (2000). In simple terms *k-state* is a pair (S, Σ), where S is the current problem state, and Σ is a set that consists of all possible states. For unknown initial state set Σ consists of all states S, for which:

- condition $c \in C$ is true in the initial state (i.e. $c \in I$),
- condition $c \in C$ is false (i.e. $\neg c \in I$),

- if it is unknown whether condition $c \in C$ is true or false in the initial state then set Σ includes both states for which this condition is true and false.

The initial state I can be potentially any state from states included in set Σ.

Intelligent robotic systems are often equipped with sensors of different kind that are used to determine different properties of robot's environment. This information can be mapped to truth degree of conditions that define current problem state. Usually it is done by introducing special actions called *sensory actions* (Weld et al. 1998, Oglietti 2005). As there is no formal extension of STRIPS planning by sensory actions (Baral et al. 2000, Son and Baral 2001), below the definition of these actions for k unknown conditions, as a special subset of STRIPS actions, is proposed.

Definition. For k unknown conditions set of sensory actions $O_s \subseteq O$ is a finite set of actions, where for each sensory action o_s it is needed to introduce two STRIPS sensory actions

$\{ o_s^t, o_s^f \} \in O_s$ that take the form:

- $o_s^t : c^+, c^- \rightarrow c_i$, if condition c_i is true after performing action o_s,
- $o_s^f : c^+, c^- \rightarrow \neg c_i$, if condition c_i is false after performing action o_s,

for $i = 1,2\ldots k$. It follows that the number of STRIPS sensory actions $|O_s| = 2k$.

The result of applying action to the current state depends whether the action is ordinary or sensory. Description of this result is presented below, is based on (Baral 2000) and is adopted to STRIPS problem.

For action o, *k-state* is described by a set $\{Result(S,\{o\}), Result(\Sigma,\{o\})\}$, where $Result(S,\{o\})$ is the same like incase with complete information, e.g.:

$$Result(S, \{ \}) = S, \quad (1)$$

$$Result(S, \{o\}) = \begin{cases} (S \cup c_+) \setminus c_- & \text{if } c^+ \subseteq S \wedge c^- \cap S = \varnothing; \\ S & \text{in opposite case,} \end{cases} \quad (2)$$

$$Result(S, \{o_1, o_2,\ldots, o_n \}) = Result(Result(S, \{o_1\}), \{o_2,\ldots, o_n\}), \quad (3)$$

and:

$$Result(\Sigma,\{o\}) = \{ Result(S',\{o\}) \mid S' \in \Sigma \}. \quad (4)$$

For sensory actions o_s, current state S remains the same, whereas the set Σ is reduced to set of states, for which condition $c_i \in S$:

$$Result(\Sigma,\{o_s\}) = Result(\Sigma',\{o_s\}) , \quad (5)$$

where: $\Sigma' = \{S' \in \Sigma \mid (c_i \in S' \leftrightarrow c_i \in S)\}$.

It follows that planning problem with incomplete information about initial state takes the form:

$$\Pi = \{C, O, \Sigma, G\}. \quad (6)$$

EXPRESSION OF NEGATIVE EMOTIONS

Emotions are regulation processes that are triggered when a person comes into contact with stimuli whose meaning is important for the body or personality [14]. There are four types of emotion-inducing factors:

i. Endogenous (arising in the mind) and exogenous (arising in the surrounding world) stimuli.

ii. Physiological correlates, i.e. the action of the central peripheral nervous system.

iii. Cognitive assessment, i.e. the assessment of events by the person giving them meaning.

iv. Motivational properties, i.e. goals and aspirations that are accompanied by emotions.

Emotions differ from feelings in that they occur suddenly and are intense, which causes immediate action. Emotional processes are mental activities that rely on the relationship with reality. Each emotion can be described by characterizing its 3 main components:

- intensity
- mark (affect)
- content

The intensity of the emotional process depends on how important the stimulus will be for the person. The higher its stimulation, i.e. the greater its activation, the greater the mobilization of energy to act, i.e. the stimulus is more intense [18]. The sign of the emotional process is influenced by the direction of the reaction to which the stimulus stimulates a person. There are two types of emotions:

- positive (positive), i.e. pleasant
- negative (negative), i.e. unpleasant

Emotions vary in quality, depending on the factor causing them and the type of reaction they are prompted to. These factors create the content of the emotional process. Negative emotions were selected for the research, indicating how a social robot can react to them in order to reduce them.

Sadness

Sadness is felt as a result of losing someone important or failure to achieve a goal. He is accompanied by bad humor and feelings of distress [18]. A gesture characteristic of sadness is raising and tightening the eyebrows shown in Fig. 1b. This photo also shows that the upper eyelids fall slightly and the lower eyelids are slightly tightened. Fig.1c shows a combination of all signs of sadness. The eyebrows are raised and pinched towards each other, so that their inner corner is raised, the upper eyelids fall slightly, the corners of the lips are lowered and the cheeks are raised. The last of these microgests shapes wrinkles (called nasolabial folds) running from the nostrils, beyond the corners of the mouth. The muscle responsible for lifting the cheeks also creates these furrows and pushes up the skin under the eyes, which results in their narrowing.

(a) zdjęcie 1 (neutralne) (b) zdjęcie 2 (c) zdjęcie 3

Fig.1. Pictures showing microexpressions of sadness [source: Ekman, P., & Białas, W. (2012). Emotions revealed: Discover what people want to hide from you and learn more about yourself. Helion]

Fear

Fear is felt when the source of the anticipated threat or danger is known. The inability to identify this source causes fear [18]. Fear is a person's response to a real, direct and

physical threat to the physical self. Anxiety occurs as a result of feeling an indefinite threat to one's own self and personality [9].
When the tension of the lower eyelids occurs with the elevation of the upper, while the rest of the face is expressionless, it is highly likely that the person feels fear, as shown in Fig. 2b. The eyebrows in Fig.2c are drawn together and raised, when you add the upper eyelid lift, which usually appears with the tension of the lower eyelids, you will again get a scared expression.

(a) zdjęcie 1 (neutralne) (b) zdjęcie 2 (c) zdjęcie 3

Fig. 2: Pictures showing fear microexpressions [source: the same like in fig.1]

Anger
Anger occurs when thwarting our goals. For the most part, it targets people who we love or like, and not those we don't like [18]. Anger is associated with aggressive behavior.

(a) zdjęcie 1(neutralne) (b) zdjęcie 2 (c) zdjęcie 3

Fig. 3: Pictures showing microexpressions of anger [source: the same like in fig.1]

In Fig. 3b, the lower eyelids are slightly strained and the upper ones are raised, which gives the effect of a glaring look with slightly lowered and tightened eyebrows, which shows inhibited anger. Fig.3c shows the higher intensity of the previously described expressions, which is already a clear sign of anger.

(a) zdjęcie 1 (neutralne) (b) zdjęcie 2 (c) zdjęcie 3

Fig. 4: Pictures showing disgust microexpressions [source: the same like in fig.1]

Disgust
Disgust is caused by objects or situations that are repulsive to us. They can be seen in an infant after something bitter is put into the mouth. According to Paul Rozin, man's recognition of something as disgusting depends not only on the nature of the object, but also on its origin and social history, and what it resembles. Disgust can also be felt about immoral and socially unacceptable acts. This emotion does not create a person experiencing major problems, but while performing certain professions you must undergo desensitive training [9]. Disgust is signaled by two very different grimaces. The first is the wrinkling of the nose visible in Fig. 4b, the second is the lifting of the upper lip shown in Fig. 4c.

Contempt
Contempt has a lot to do with disgust, but there are differences that allow these emotions to be distinguished. "We feel contempt only for people and their behavior, not for smells, tastes or tactile sensations. Entering the dog's poop can be disgusting, but never contempt, the very thought of eating a calf's cerebellum can be disgusting, but it never arouses contempt. However, you can despise people who eat such disgusting things, because contempt contains an element of superiority felt relative to her object. Disrespectful dislike of people or their behavior makes you feel better than them (usually in a moral sense). Their behavior is degrading, but you don't have to run away from them immediately, which you would do in case of disgust" [5].

(a) zdjęcie 1 (neutralne) (b) zdjęcie 2 (c) zdjęcie 3

Fig. 5: Pictures showing contempt microexpressions [source: the same like in fig.1]

Contempt, despite the fact that it is classified as a negative feeling, can be nice to people when they feel it. This feeling may then go into embarrassment caused by realizing that you are experiencing pleasant sensations during that emotion. It particularly concerns people who are less sure of their status and who, by referring to contempt, try to emphasize their superiority towards others [5].
Contempt is the only emotion that is expressed on the face by one-sided expression. It is characterized by a tight and slightly raised corner of the mouth (Fig. 5b). The photo (Fig. 5c) can also signal contempt. It shows a slightly raised upper lip, but only on one side of the face.

REDUCTION OF NEGATIVE EMOTIONS AS A CONDITIONAL PLANNING TASK

This point proposes a set of examples and solutions to planning problems in artificial intelligence regarding modeling the social robot's response to human emotional state.
In the following scenarios, it was assumed that the robot communicates with a person with an unknown emotional state, which is a source of uncertainty, and it was assumed that the robot is able to analyze five negative emotions based on facial expression presented in point 3. It is assumed that one of the tasks social work involves reacting to a person's emotional state in such a way that when negative emotion is detected, it can be reduced or not escalated. A response adequate to a given emotion results in a reduction of its

level, while an inadequate response results in an escalation of negative emotion.

Based on the above assumptions, the following elements of the C and O sets of the planning problem were defined (6), which take into account the facial expressions detectable by the social robot, described in point 3:

C = {sadness, fear, anger, disgust, contempt, cheeks, eyelids, kacik_ust, eyebrows};

O = {face_expression_ analysis, face_expression detection, eyebrow_expression analysis, eyebrow_expression detection, reducing_working response},

which are presented in the PDDL language in Table 1

Table 1: Robot Conditions and Decisions in PDDL Language

(define (domain emotion_domain_2) (: requirements: conditional-effects: sensing) (: constants sadness fear anger upset contempt) cheeks - lifting cheeks eyelids - lifting of the lower eyelids and upper tension ; kacik_ust - lifting the mouth corner ; pulled_brows - pulling your brows towards you
(: action_expression_face analysis : parameters () : precondition () : effect (and (when (or (sad)) (cheeks)) (when (or (anger) (fear)) (eyelids)) (when (contempt) (kacik_ust))))
(: action face_expression detection : parameters () : precondition () : effect (and (observes (cheeks)) (observes (eyelids)) (observes (kacik_ust))))
(: action eyebrow_expression analysis : effect (and (when (or (sadness) (fear)) (sciagniete_brwi))))
(: action eyebrow_expression detection : effect (observes (sciagniete_brwi)))
(: action work_reduction_working : parameters (? emotion) : precondition (object? emotion) : effect (and (when (? emotion) (not (? emotion))) (when (not (? emotion)) (escalation_emotion))))))

Scenario 1. The robot is not sure whether a person expresses contempt or disgust. The goal is to reduce negative emotions and prevent them from escalating. Initial (uncertain) and target states are presented in Table 2.

Table 2: Initial and Target States in PDDL in Scenario 1

: init (not (cheeks)) (not (eyelids)) (not (kacik_ust)) (not (pulled_brows)) (oneof (contempt) (shame)) (not (sadness)) (not (anger)) (not (fear)) not (escalation_emotion)))
(: goal (and (not (sadness)) (not (fear)) (not (anger)) (not (upset)) (not (contempt)) (not (escalation_emotion)))))

Possible initial states {S1, S2} and the plan solving the problem are presented in Table 3. Achieving the goal is sufficient for analysis and detection of facial expression, and the relevant robot decisions result from the solution of the problem from scenario 1 (Table 3).

Scenario 2. The robot is not sure whether a person expresses contempt, anger or disgust. The goal is, as before, to reduce negative emotions and prevent their escalation. Initial (uncertain) and target states are presented in Table 4.

Achieving the goal is also sufficient for facial expression analysis and detection, and the relevant robot decisions result from the solution of the problem from scenario 2 (Table 5).

Table 3: Possible initial states and robot decisions in PDDL in scenario 1

Possible world 1	Possible world 2	Robot decisions
(object contempt) (object stop) (object anger) (object fear) (object sadness) (not (emotion_ Escalation)) (not (fear)) (not (anger)) (not (sadness)) (hate) (not (contempt)) (not (eyebrow pulled)) (not (corner of mouth)) (not (eyelids)) (not (cheeks))	(object contempt) (object stop) (object anger) (object fear) (object sadness) (not (escalation of emotions)) (not (fear)) (not (anger)) (not (sadness)) (not (shame)) (contempt) (not (eyebrow pulled)) (not (corner of mouth)) (not (eyelids)) (not (cheeks))	(((analysis facial expression))) (((detection facial expression))) (((robot reaction reducing contempt) if not the world 1) ((robot reaction reducing embarrassment) if not the world 2)

Table 4: Initial and target states in PDDL in scenario 2

(: init (not (cheeks)) (not (eyelids)) not (kacik_ust)) (not (eyebrow pulled)) oneof (contempt) (anger) (shame)) (not (sadness)) (not (fear)) (not (escalation_emotion)))
(: goal (and (not (sadness)) (not (fear)) (not (anger)) (not (upset)) (not (contempt)) (not (escalation_emotion)))))

Table 5: Possible initial states and robot decisions in PDDL in scenario 2

Possible world 1	Possible world 2	Possible world 3	Robot decisions
(object contempt) (object stop) (object anger) (object fear) (object sadness) (not (emotion_ Escalation)) (not (fear)) (not (sadness)) (hate) (not (contempt)) (not (anger)) (not (eyebrow pulled)) (not (corner of mouth)) (not (eyelids)) (not (cheeks))	object contempt) (object stop) (object anger) (object fear) (object sadness) (not (emotion_ Escalation)) (not (fear)) (not (sadness)) (not (shame)) (anger) (not (contempt)) (not (eyebrow pulled)) (not (corner of mouth)) (not (eyelids)) (not (cheeks))	object contempt) (object stop) (object anger) (object fear) (object sadness) (not (emotion_ Escalation)) (not (fear)) (not (sadness)) (not (shame)) (not (anger)) (contempt) (not (eyebrow pulled)) (not (kacik_ust)) (not (eyelids)) (not (cheeks))	((((face_expression analysis))) (((face_expression))) (((reaction_ of work_reducing contempt) 1 2) ((reaction_working_reducing shame) 2 3) ((reaction_working_reducing anger) 1 3)))

Scenario 3. The robot is not sure whether a person expresses sadness, fear, anger, contempt or disgust. The goal is, as before, to reduce negative emotions and prevent their escalation. Initial (uncertain) and target states are presented in Table 6.

Possible initial states {S1, S2, S3, S4, S5} and the plan solving the problem are shown in Table 7. Achieving the goal this time requires analysis and detection of both facial expression and eyebrow position (which results from the ambiguity of facial expression analysis) , and the relevant robot decisions result from the solution of the problem from scenario 3 (Table 7).

Table 6: Initial and target states in PDDL in scenario 3

: init (not (cheeks)) (not (eyelids)) (not (kacik_ust)) (not (pulled_brows)) (oneof (contempt) (shame)) (not (sadness)) (not (anger)) (not (fear)) not (escalation_emotion)))
(: goal (and (not (sadness)) (not (fear)) (not (anger)) (not (upset)) (not (contempt)) (not (escalation_emotion)))))

Table 7: Possible initial states and robot decisions in PDDL in scenario 3

Possible world 1	Possible world 2	Possible world 3
(object contempt) (object stop) object anger) (object fear) (object sadness) (not (emotion_ Escalation)) (contempt) not (sadness) not (fear) (Not (anger) (Not (disgust (Not (sciagniete_brwi)) Not(corner of mouth) not (eyelid) not (cheeks)	(object contempt)) (object stop) (object anger) (object fear) (object sadness) (not (emotion_ Escalation)) (not (contempt)) (hate) (not (sadness)) (not (fear)) not (anger)) not (eyebrow pulled)) (not (corner of mouth) (not eyelids (not (cheeks)	(object contempt) (object stop) (object anger) (object fear) (object sadness) (not (emotion_ Escalation)) (not (contempt)) (not (shame)) (anger) (not (sadness)) not (fear)) (not (eyebrow pulled)) (not (hang_account (not (eyelids)) (not (cheeks)
Possible world 4	**Possible world 5**	**Robot decisions**
(object contempt) (object stop) (object anger) (object fear) (object sadness) (not (emotion_ Escalation)) (not (contempt)) (not (shame)) (not (anger)) (fear) (not (sadness)) (not (eyebrow pulled)) (not (hang_account (not (eyelids)) (not (cheeks)	(object contempt) (object stop) (object anger) (object fear) (object sadness) (not (emotion_ Escalation)) (not (contempt)) (not (shame)) (not (anger)) (not (fear)) (sadness) (not (eyebrow pulled)) (not (hang_account (not (eyelids)) (not (cheeks)	((((face_expression analysis)) ((eyebrow_expression analysis))) (((face_expression detection)) ((eyebrow_expression detection))) (((Robot_Reaction_Re ducing Contempt) 2 3 4 5) ((Robot_Reaction_Red ucing Redemption) 1 3 4 5) ((Robot_Reaction_Red ucing Anger) 1 2 4 5) ((reaction_working_re ducing fear) 1 2 3 5) ((reaction_working_re ducing sadness) 1 2 3 4)))

CONCLUSION AND FUTURE RESEARCH

The research involved modification of the classical medical planning field, taking into account uncertainty about the patient's state of health. The modification consisted in matching actions representing taking medications and performing laboratory tests to actions modeling human emotional states and conducting psychological tests. The result of the modification is a new field of automatic planning containing the field definition and a set of planning problems.

In the part concerning the simulation research, a number of tests were carried out using the newly created planning domain. Research results indicate the usefulness of classic methods of automatic planning for the analysis of emotional states. It should be noted that the examples considered are very simple and indicate possible future directions of work development. Among them, we can distinguish the development of the field of planning taking into account the more complex emotional states of man and complex forms of reactions or psychological therapies conducted by social robots. There are potential possibilities to integrate classic automatic planning methods with visual facial expression recognition systems.

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On transformation of conditional, conformant and parallel planning to linear programming

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Classical planning in Artificial Intelligence is a computationally expensive problem of finding a sequence of actions that transforms a given initial state of the problem to a desired goal situation. Lack of information about the initial state leads to conditional and conformant planning that is more difficult than classical one. A parallel plan is the plan in which some actions can be executed in parallel, usually leading to decrease of the plan execution time but increase of the difficulty of finding the plan. This paper is focused on three planning problems which are computationally difficult: conditional, conformant and parallel conformant. To avoid these difficulties a set of transformations to Linear Programming Problem (LPP), illustrated by examples, is proposed. The results show that solving LPP corresponding to the planning problem can be computationally easier than solving the planning problem by exploring the problem state space. The cost is that not always the LPP solution can be interpreted directly as a plan.

Key words: planning, conformant planning, conditional planning, parallel planning, uncertainty, linear programming, computational complexity

1. Introduction

Artificial Intelligence can be understood as a study of design of intelligent agents. An intelligent agent is a system that acts intelligently on its environment. There are various problems which are being investigated by Artificial Intelligence, like knowledge, reasoning, learning and planning [20, 28]. Classical planning is a problem of finding a sequence of actions that will achieve a goal. Finding an optimal plan is generally a hard computational problem and needs a lot of resources. The situation becomes even more complicated when a planner does not have a complete set of information about an environment for which the plan should

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be created (e.g. [21]). This is called uncertainty and is essential for exact description of a real environment. There exist large number of different approaches and heuristics that try to deal with planning with uncertainty depending on its kind (e.g. [5]). One can find examples of planning applications in manufacturing, production planning (e.g. [25]), logistics and agentics (eg. [11]).

Planning should be distinguished from *scheduling* – well-known and frequently used technique of improving the cost of a plan. Planning is understood as causal relations between actions, while scheduling is concerned with metric constraints on actions [2, 4]. When all states of a planning problem (including an initial and a goal) are defined by a given set of conditions (also called predicates), then the problem is called STRIPS planning problem [23]. The planning systems have been successfully applied in planning modules of Deep Space One Spacecraft [31] and for elevators control in Rockefeler Center in New York [19]. One should mention STRIPS system is no longer used in its original form. The advanced version of STRIPS introduced in 1987 [24] is called Action Description Language (ADL) and other extensions of planning languages are standardized by Planning Domain Definition Language (PDDL) formalism ([15]. The latest PDDL extension is The Hierarchical Domain Definition Language (HDDL, [18]).

The problem becomes more complicated, if information about the modeled world is not sufficient to determine all facts necessary to describe an initial state of the world. Then, we say that the initial state of the problem is uncertain but can be represented by a set of possible initial states. A plan for solving such a problem may take the form of actions that are executed conditionally, based on new information emerging during the search for the plan. The inflow of new information is modeled by the so-called sensory actions, in such a way that the uncertainty of the information available is reduced by using information from the sensors. This approach is called conditional planning [30, 32].

In some cases, information from sensors may be unavailable e.g. sensors are damaged or broken down, receiving sensory information is too expensive or dangerous. Then, it is reasonable to search for a plan that is a solution to the planning problem independently of possible initial states. This approach is called conformant planning [30, 32]. Both conditional and conformant planning are more difficult to solve than a classical planning [17].

The cases, in which more than one action can be applied in one planning step, i.e. some actions can be performed simultaneously, constitute a large class of important planning problems. Such problem formulation allows to model multi-agent and multi-robot environments and is called parallel planning. Combining conformant and parallel planning leads to a problem, in which many agents interact in an uncertain environment with no possibility of performing sensing actions. Finding a solution to a parallel conformant planning problem is more difficult than for previous problems. To avoid this difficulty, in the paper we propose a heuristics for the transformation of the problem to a Linear Programming Problem (LPP), illustrated by examples.

1.1. Motivation

Finding a plan is generally a hard computational problem and needs a lot of resources. This hardness is especially characteristic for domain-independent algorithms [1] and it corresponds to difficulties with constructing general solvers. However, it should be noted that even for methods specific for certain domains (e.g. for block world), planning problems usually remain difficult [7]. The complexity of planning problems strongly depends on the complexity of the actions defined for the assumed domain (also [7]). Moreover in real-world applications knowledge about environment is incomplete, uncertain and approximate. It implies that planning in the presence of uncertainty is more complex than classical planning.

In general, planning with complete information is *PSPACE*-complete problem. Planning in the presence of incompleteness is much more complicated [6] and belongs to the next level in the hierarchy of completeness. Precisely speaking, if the uncertainty about the initial state is modelled by a set of possible initial states, then planning problem is NP^{NP}-complete or Σ_2P-complete [3]. High level of computational complexity of planning causes that practical applications of planning under uncertainty are based on heuristic algorithms (e.g. [16, 27]. The newest approach provides a way to combine a method that does not explicitly consider any problem structure with techniques that do [33].

One of the heuristics is a transformation of planning to LPP. LPP formulations in classical planning are under newest investigations: in [29] the post-hoc optimization heuristic uses LPP to determine a real-valued factor for each heuristic in a set of pattern database abstractions, and the cost partitioning is derived by multiplying the costs of all operators that affect an abstraction with that factor. Many other heuristics can be expressed with an LPP over variables that express how often an operator is used [26]. The idea of representing STRIPS planning problems by linear constraints and objective function is also not new in the literature (see e.g. [22]). In these cases the planning problem takes the form of binary integer linear program. It implies that the only allowed values of variables are '0' and '1' and they corresponds to false/truth values of planning problem predicates and actions. The computational efficiency of the approach is low (because of complexity of integer programming algorithms) and solution can be found only for small size planning problems. Another approach proposed by Bylander [8] is to introduce additional linear constraints to LPP. It allows to solve optimally some class of classical planning problems using LP polynomial algorithms [9]. The cost is that not always the LP solution can be interpreted directly as a plan (what is followed by assumption $P \neq NP$). Also, the size of LPP increased (polynomially) very fast with the number of planning problem variables.

1.2. Contribution

In this paper a heuristic of the transformation of conditional, conformant and parallel planning problems to LPP, basing on extension of the transformation given in [12], is proposed. This is done because LPPs are known to be computational easy [9].

The following problems are presented and analyzed:

- transformation of conditional planning to Linear Programming,
- transformation of conformant planning to Linear Programming,
- transformation of parallel conformant planning to Linear Programming,
- computational complexity of solving transformed planning problems.

1.3. Organization of the paper

The paper is organized as follow: In section 2 conditional, conformant and parallel planning problems together with examples are introduced. In section 3 planning problems transformations are proposed. In section 4 exemplary transformed problems are solved. Remarks on computational complexity are given in section 5. All is concluded and future works are suggested in section 6.

2. Conditional, conformant and parallel planning problems

Following Bylander [7] it is assumed that planning problem Π consists of four sets $\Pi = \{C, O, I, G\}$:

- C is a finite set of *conditions*,
- O is a finite set of actions, where each action $o \in O$ takes the form $c^+, c^- \rightarrow c_+, c_-$, where:
  - $c^+ \subseteq C$ are so called *positive preconditions*,
  - $c^- \subseteq C$ are so called *negative preconditions*,
  - $c_+ \subseteq C$ are so called *positive postconditions*,
  - $c_- \subseteq C$ are so called *negative postconditions*,
- $I \subseteq C$ is an *initial state*,
- $G = \{G_+, G_-\}$ is a *goal situation*, where $G_+ \subseteq C$ are positive conditions (i.e. are true) and $G_- \subseteq C$ are negative conditions (i.e. are false).

In order to include the information that some conditions are unknown (assume k conditions can be true or false) in the description of the current problem state, one can introduce so called *k-states* proposed by [3]. In simple terms *k-state* is a pair (s, Σ), where s is the current problem state, and Σ is a set that consists of all possible initial states I. For unknown initial state set Σ consists of all states s, for which:

- condition $c \in C$ is true in the initial state (i.e. $c \in I$),
- condition $c \in C$ is false (i.e. $\neg c \in I$),
- if it is unknown whether condition $c \in C$ is true or false in the initial state then set Σ includes both states for which this condition is true and false.

The initial state I can be potentially any state from states included in set Σ. The number of possible initial states is denoted by w and is limited by k such that: $w \leqslant 2^k$. Such planning problem with incomplete information about initial state is called *conformant planning problem* and takes the form:

$$\Pi_{\text{conf}} = (C, O, \Sigma, G). \tag{1}$$

The result of applying action to the current state depends whether the action is ordinary or sensory. Description of this result is presented below, is based on [3] and is adopted to STRIPS problem.

For action o, *k-state* is described by a set $\{Result(S, \{o\}), Result(\Sigma, \{o\})\}$, where $Result(S, \{o\})$ is the same like in case with complete information, e.g.:

$$\begin{aligned}
&Result(S, \{\ \}) = S,\\
&Result(S, \{o\}) = \begin{cases} (S \cup c_+)\backslash c_- & \text{if } c^+ \subseteq S \wedge c^- \cap S = \emptyset;\\ S & \text{in opposite case,}\end{cases}\\
&Result(S, \{o_1, o_2, \ldots, o_n\}) = Result(Result(S, \{o_1\}),\ \{o_2, \ldots, o_n\}),
\end{aligned} \tag{2}$$

and:

$$Result(\Sigma, \{o\}) = \{Result(S', \{o\}) |\ S' \in \Sigma\}. \tag{3}$$

Modern intelligent systems are often equipped with sensors of different kind that are used to determine different properties of robot's environment. This information can be mapped to truth degree of conditions that define current problem state. Usually, it is done by introducing special actions called *sensory actions* [32]. As there is no formal extension of STRIPS planning by sensory actions, below the definition of these actions for k unknown conditions, as a special subset of STRIPS actions, is proposed.

Definition 1 *For k unknown conditions set of sensory actions O_s is a finite set of actions, where for each sensory action $o_s \in O_s$ it is needed to introduce two STRIPS sensory actions $\{o_s^t, o_s^f\} \in O_s$ that take the form:*

$o_s^t : c^+, c^- \rightarrow c_i$, *if condition c_i is true after performing action o_s,*
$o_s^f : c^+, c^- \rightarrow \neg c_i$, *if condition c_i is false after performing action o_s,*
$i = 1, 2, \ldots, k$.

It follows that the maximal number of sensory actions $|O_s| = 2k$. The result of applying action to the current state depends on whether the action is ordinary or sensory. Such planning problem with incomplete information about initial state and sensory actions is called *conditional planning problem* and takes the form:

$$\Pi_{\mathrm{cond}} = (C, (O, O_s), \Sigma, G). \tag{4}$$

The *plan* $\Delta_C = \langle o_1, o_2, \ldots, o_n \rangle$ solves conformant planning problem if:

$$Result((S, \Sigma), \ , \Delta_C) = G. \tag{5}$$

Since all actions in Δ_C are ordered, Δ_C is called a *total order conformant plan*.

The *partial-order conformant plan* is denoted as $\Delta_{\mathrm{POC}} = \{\Delta_{\mathrm{SetC}}, \pi\}$, where $\Delta_{\mathrm{SetC}} = \{o_1, o_2, \ldots, o_n\}$ is the set of actions, and π is the non-returnable partial order defined on Δ_{SetC} (compare [2]). So, a *partial-order conformant plan* is a compact representation of a set of possible *total* ordered plans.

The *parallel partial-order conformant plan* is denoted as $\Delta_{\mathrm{PPOC}} = \{\Delta_{\mathrm{SetC}}, \pi, \#\}$, where $\{\Delta_{\mathrm{SetC}}, \pi\}$ is Δ_{POC}, while # is a symmetrical relation, defined on the set Δ_{SetC}. $\# \subseteq (\pi \cup \pi^{-1})$ is called a non-concurrency relation and it indicates which actions cannot be applied in parallel.

The *plan* Δ_{COND} solves conditional planning problem if:

$$Result((S, \Sigma), \ , \Delta_{\mathrm{COND}}) = G. \tag{6}$$

The plan consists of both classical ($o \in O$) and sensory actions ($o_s \in O_s$) and classical actions are performed conditionally and depend on the result of sensory action.

2.1. Example of conditional planning problem

Consider the problem of opening doors by the robot. It is assumed that robot can perform actions of pushing doors (*push_door*) and flipping lock (*flip_lock*). Additionally, it can perform sensory action of checking if doors are locked (*check_if_locked*). If doors are not locked (¬*locked*) and not jammed (¬*jammed*) then action *push_door* opens them. If doors are locked then action *push_door* jammed them. The goal is to open doors so condition *open* should be true in description of final problem state. Actions can be described as follow:

$$push\_door: \qquad \text{effect}: \ jammed \quad \text{if } \ locked, \tag{7}$$

$$\begin{array}{llll} \textit{push\_door}: & \text{effect}: \ \textit{open} & \text{if } \neg\textit{locked}, \neg\textit{jammed}, & (8)\\ \textit{flip\_lock}: & \text{effect}: \ \textit{locked} & \text{if } \neg\textit{locked}, & (9)\\ \textit{flip\_lock}: & \text{effect}: \ \neg\textit{locked} & \text{if } \textit{locked}, & (10)\\ \textit{check\_if\_locked}: & \text{determines} & \text{if } \textit{locked} \text{ is } \textit{true} \text{ or } \textit{false}. & (11) \end{array}$$

Action model in formulas (7)–(11) is different than classical cause-effect action. It is caused by the fact that actions effects in formulas (7)–(10) are formulated conditionally (action causes *set1_of_conditions* if *set2_of_conditions*) and action in formula (11) is formulated as a truth determination for unknown conditions). Both models can be translated into classical six cause-effect actions and take the form like in formulas (12)–(17):

$$o_1 = \textit{push\_door}: \quad \textit{locked} \rightarrow \textit{jammed}, \tag{12}$$
$$o_2 = \textit{push\_door\_1}: \quad \neg\textit{locked},\ \neg\textit{jammed} \rightarrow \textit{open}, \tag{13}$$
$$o_3 = \textit{flip\_lock}: \quad \neg\textit{locked} \rightarrow \textit{locked}, \tag{14}$$
$$o_4 = \textit{flip\_lock\_1}: \quad \textit{locked} \rightarrow \neg\textit{locked}, \tag{15}$$
$$o_5 = \textit{check\_if\_locked}: \ \{\text{no preconditions}\} \rightarrow \textit{locked}, \ \text{if } \textit{locked} \text{ is } \textit{true}, \tag{16}$$
$$o_6 = \textit{check\_if\_locked\_1}: \{\text{no preconditions}\} \rightarrow \neg\textit{locked}, \ \text{if } \textit{locked} \text{ is } \textit{false} \tag{17}$$

where $o_1, o_2, o_3, o_4 \in O$ and $o_5, o_6 \in O_s$.

Two separate actions are needed for one sensory action [32], so in the example $|O| = 6$. If the set of problem actions contains sensory actions it implies that the plan solving the problem is not a determined sequence of actions: if at least one action is sensory, then next actions depend on sensory action result. It leads to so called *conditional plans*. Assume in the example that in initial situation doors are closed and not jammed $\{\neg\textit{open}, \neg\textit{jammed}\}$, but it is unknown if they are locked. It leads to two possible initial problem states and theirs description is included in set Σ:

$$\Sigma = \{\{\neg\textit{open}, \neg\textit{jammed}, \textit{locked}\}, \ \{\neg\textit{open}, \ \neg\textit{jammed}, \ \neg\textit{locked}\}\}. \tag{18}$$

Remaining sets for STRIPS representation are:

$$C = \{c_1 = \textit{locked}, \ \ c_2 = \textit{jammed}, \ \ c_3 = \textit{open}\}, \quad I = \Sigma, \quad G = \{\textit{open}\}. \tag{19}$$

and conditional plan that solves the problem is:

$$\Delta = \{\textit{check\_if\_locked}, \ \ \text{if } \neg\textit{locked} \text{ then } \textit{push\_door}, \\ \text{if } \textit{locked} \text{ then } \textit{flip\_lock}, \textit{push\_door}\}. \tag{20}$$

2.2. Example of conformant planning problem

To illustrate conformant planning consider the following simple model of the action of taking medication [32]:

$$Medicate: \textit{no preconditions, effects}: (when\ I \neg I)\ \ (when\ \neg H D) \tag{21}$$

in which I means the patient is Infected, H means he is Hydrated and D means Dangerous health state. If the patient is Infected before the action then he will no longer be Infected but if the patient takes medication when he is not Hydrated then the result is Dangerous health state.

Action model in formula (21) is different than classical one. It is caused by a fact that actions effects are formulated conditionally with the general schema: action causes *set1_of_conditions* if *set2_of_conditions*. Please note that such defined action has no preconditions but action effects are formulated conditionally. It implies that preconditions are indirectly defined by effects, so action Medicate is equivalent to four classical cause-effect actions:

$$\begin{array}{lll} Med_1: & preconditions: (I\ and\ H), & effects: \neg I, \\ Med_2: & preconditions: (I\ and\ \neg H), & effects: (\neg I\ and\ D), \\ Med_3: & preconditions: (\neg I\ and\ H), & effects: \textit{no effects}, \\ Med_4: & preconditions: (\neg I\ and\ \neg H), & effects: D. \end{array} \tag{22}$$

As an example of conformant planning one can consider following problem Π_{Med} with two possible initial states:

$$\Pi_{Med} = \{C_{Med},\ O_{Med},\ \Sigma_{Med},\ G_{Med}\}, \tag{23}$$

where:

$$\begin{aligned} C_{Med} &= \{I,\ H,\ D\}, \\ O_{Med} &= \{Medicate: \textit{no preconditions, effects}: (when\ I \neg I)(when\ \neg H\ D); \\ &\qquad Drink: \textit{nopreconditions, effects}:\ H\}, \\ \Sigma_{Med} &= \{\{\neg I,\ \neg H,\ \neg D\},\ \ \{I,\ H,\ \neg D\}\}, \\ G_{Med} &= \{\neg I,\ \neg D\}. \end{aligned}$$

The plan that solves the problem cannot be just *Medicate* because we do not know whether the patient is hydrated or not. Conformant plan that solves the Π_{Med} problem is:

$$\Delta = \{Drink,\ Medicate\}. \tag{24}$$

2.3. Example of parallel conformant planning problem

To illustrate a parallel conformant planning problem consider the following simple *bomb in the toilet* problem with one action containing conditional effects:

$$\begin{aligned} Dunk(P): preconditions:\ & package(P),\ bomb(B), \\ effects:\ & if\ in(P,\ B)\ then\ defused(B), \end{aligned} \tag{25}$$

meaning that if there is a bomb B and there is a package P then action *dunk* causes that bomb B is defused if it was in package P. So if there is no bomb in package, the action *dunk* has no effects.

Action model in formula (25) is different than classical action. It is caused by a fact that actions effects are formulated conditionally with general schema: action causes *set1_of_conditions* if *set2_of_conditions*. Please note that an action defined in such way has no preconditions but action effects are formulated conditionally. It implies that preconditions are indirectly defined by effects, so action *Dunk* is equivalent to two classical actions:

$$\begin{aligned} Dunk_1(P):\quad & preconditions: package(P),\ bomb(B),\ in(P,\ B), \\ & effects:\quad defused(B), \\ Dunk_2(P):\quad & preconditions: package(P),\ bomb(B),\ not(in(P,\ B)), \\ & effects:\quad no\ effects. \end{aligned} \tag{26}$$

Now, let us consider the following problem Π_{BT} with two possible initial states (bomb is in package 1 or in package 2):

$$\Pi_{BT} = \{C_{BT},\ O_{BT},\ \Sigma_{BT},\ G_{BT}\}, \tag{27}$$

where:

$$\begin{aligned} C_{BT} &= \{package(P1), package(P2), bomb(B), in(P1, B), in(P2, B), defused(B)\}, \\ O_{BT} &= \{Dunk\}, \\ \Sigma_{BT} &= \{\{package(P1),\ package(P2),\ bomb(B),\ in(P1, B)\}, \\ &\quad \{package(P1),\ package(P2),\ bomb(B),\ in(P2, B)\}\}, \\ G_{BT} &= \{defused(B)\}. \end{aligned}$$

The conformant plan that solves the Π_{BT} problem is:

$$\begin{aligned} \Delta_{\mathrm{CBT}} &= \langle Dunk(P1),\ Dunk(P2)\rangle \qquad \text{or} \\ \Delta_{\mathrm{CBT}} &= \langle Dunk(P2),\ Dunk(P1)\rangle. \end{aligned} \tag{28}$$

The partial-order conformant plan that solves the Π_{BT} problem is:

$$\Delta_{\mathrm{POCBT}} = \{Dunk(P2),\ Dunk(P1)\}.(29) \tag{29}$$

If actions in Δ_{POCBT} can be performed in parallel ($\#_{BT} = \emptyset$), then $\Delta_{\mathrm{POCBT}} = \Delta_{\mathrm{PPOCBT}}$ and the problem is solved in one step.

3. Transformation to LP

Following [8], the transformation from planning to Linear Programming is based on mapping of conditions and operators in each plan step to variables. Truth values of conditions are mapped to ”0” and “1” for the planning without incompleteness, and to any values between “0” and “1” for planning with incomplete information.

Assume that if $c \in C$ is a condition and if the planning process is divided into l steps and i is the step index ($i = 0, 1, \ldots, l$) then $(l+1)$ variables are needed for this condition: $c(0), c(1), \ldots, c(l)$. If in turn $o \in O$ is an action, then we need l variables for each action: $o(0), o(1), \ldots, o(l-1)$. If $o_s \in O_s$ is a sensory action, then we need $2l$ variables for each sensory action: $o_s^t(0), o_s^t(1), \ldots, o_s^t(l-1)$, and $o_s^f(0), o_s^f(1), \ldots, o_s^f(l-1)$. Thus, the arguments for conditions c and operators o are extended by the index of the planning step.

The goal function reaches its maximum value if the value of the variable $c(l)$ corresponding to condition is: $c(l) = 1$ if $c \in G_+$ and $c(l) = 0$ if $c \in G_-$, i.e. the goal state is true in the last step of planning l.

Basing on above one can build LPP having vector of decision variables x:

$$x = \{c(0),\ o(0),\ o_s^t(0),\ o_s^f(0),\ c(1),\ o(1),\ o_s^t(1),\ o_s^f(1),\ \ldots,\\ c(l-1),\ o(l-1),\ o_s^t(l-1),\ o_s^f(l-1),\ c(l)\}.$$

Assume now that the set $G_+ = \{c_1^{\text{pos}},\ c_2^{\text{pos}},\ \ldots,\ c_n^{\text{pos}}\}$ and the set $G_- = \{c_1^{\text{neg}}, c_2^{\text{neg}}, \ldots, c_m^{\text{neg}}\}$, i.e. the goal consists of n positive and m negative conditions, so there are $(n+m)$ variables that constitutes LP objective function:

$$c^{\text{pos}}(l) = \left[c_1^{\text{pos}}(l),\ c_2^{\text{pos}}(l),\ \ldots,\ c_n^{\text{pos}}(l)\right];$$
$$c^{\text{neg}}(l) = \left[c_1^{\text{neg}}(l),\ c_2^{\text{neg}}(l),\ \ldots,\ c_m^{\text{neg}}(l)\right].$$

The objective function to be maximized is:

$$\text{Max} \leftarrow f((c^{\text{pos}}(l),\ c^{\text{neg}}(l)) = \left[\sum_{i=1}^{n}\left(c_i^{\text{pos}}(l)\right) + \sum_{j=1}^{m}\left(1 - c_j^{\text{neg}}(l)\right)\right]. \tag{30}$$

Since each component of (30) should be equal to 1 (one) if the goal is achieved, the optimal value of objective function (f_{opt}) to be maximized is known prior to solving LP problem and is $f_{\text{opt}} = (n + m)$. The optimization problem is formulated as:

Find minimal number of steps “l” for which $f_{\text{opt}} = (n + m)$.

Inequality constraints (of the form “greater or equal to”) express the property that actions can be applied if their preconditions are true. The left side of the inequality consists of variable corresponding to the precondition. If precondition is not satisfied then variable value for this condition is ‘0’. The right side of inequality is the sum of variables corresponding to all actions having the precondition. Thus, if left side is ‘0’ any action having the precondition cannot be applied. Dependently of the initial state representation and the number of actions taken in parallel inequalities differ in detail.

Equality constraints describe changes of variables value for conditions due to action application. Dependently of the initial state representation and the number of actions taken in parallel these equalities also differ in detail.

To model uncertainty about *truth* or *false* of unknown condition c it is proposed to use three-valued Kleen’s logic system. In this system logic values of condition are mapped into set $\left\{0,\ \frac{1}{2},\ 1\right\}$. Sentences $T(a) = 0$, $T(a) = 1$ and $T(a) = \frac{1}{2}$ denote that condition “a” is false, truth or that nothing can be said about truthfulness of “a” [10]. Following subsections introduce constraints dependently on the planning problem.

3.1. Conditional planning problem

For conditional planning problem (4) with two classical actions and one sensory action that checks the unknown c_3:

$$\begin{aligned}
o_1 :&\quad c_1 \rightarrow c_2\,,\\
o_2 :&\quad \neg c_1,\ \neg c_2 \rightarrow \neg c_3\,,\\
o^t_{s1} :&\quad \{\ \} \rightarrow c_3\,,\\
o^f_{s1} :&\quad \{\ \} \rightarrow \neg c_3\,,
\end{aligned} \tag{31}$$

the set of inequalities is:

$$\begin{aligned}
c_1(i) &\geqslant o_1(i),\\
1 - c_1(i) &\geqslant o_2(i),\\
1 - c_2(i) &\geqslant o_2(i),
\end{aligned} \tag{32}$$

and set of equalities is:

$$\begin{aligned}
c_2(i+1) &= c_2(i) + o_1(i),\\
c_3(i+1) &= c_3(i) - o_2(i) + \frac{1}{2}o^t_{s1}(i) - \frac{1}{2}o^f_{s1}(i).
\end{aligned} \tag{33}$$

One should note that the value c_3 in next planning step, $c_3(i+1)$, can be modified in two ways:

1) if c_3 is true in current planning problem state (i.e. $c_3(i) = 1$) than it can stay false in next step after applying action o_2;

2) if c_3 is unknown in current planning problem state (i.e. $c_3(i) = \frac{1}{2}$) than it can stay true or false in next step dependently of the sensory action result.

3.2. Conformant planning problem

In conformant planning there are no sensory actions, so for conformant planning problem (1) and two actions with unknown c_3:

$$\begin{aligned} o_1: &\quad c_1 \rightarrow c_2\,, \\ o_2: &\quad \neg c_1,\ \neg c_2 \rightarrow \neg c_3\,, \end{aligned}$$

there are two possible worlds: the first one in which c_3 is true and the second one in which c_3 is false. The solution is the plan that solves the problem independently of the world we are in. The set of inequalities is:

$$\begin{aligned} c_1^w(i) &\geqslant o_1(i), \\ 1 - c_1^w(i) &\geqslant o_2(i), \\ 1 - c_2^w(i) &\geqslant o_2(i), \end{aligned} \tag{34}$$

and set of equalities is:

$$\begin{aligned} c_2^w(i+1) &= c_2^w(i) + o_1(i), \\ c_3^w(i+1) &= c_3^w(i) - o_2(i), \end{aligned} \tag{35}$$

where $w = 1, 2$.

3.3. Parallel conformant planning problem

For parallel conformant planning problem (1) there is a possibility to perform many actions at the same planning step. One should note that actions o_1 and o_2 in (31) cannot be taken at the same step since their preconditions are mutually excluding. Assuming that r is the maximal number of actions performed in parallel one finds modifications in inequality (34):

$$r * c_1^w(i) \geqslant o_1(i).$$

4. Exemplary results

Below transformation results for examples introduced in sections 2.1, 2.2 and 2.3 are shown.

4.1. Transformation of conditional planning problem

If l is the number of planning steps then variables for conditions (19) are:

$$\begin{aligned} c_1(i) &= locked(i), \qquad & c_2(i) &= jammed(i), \\ c_3(i) &= open(i), & i &= 0, 1, \ldots, l, \end{aligned} \tag{36}$$

for actions (12)–(17):

$$\begin{aligned} o_1(i) &= push\_door(i), \\ o_2(i) &= push\_door\_1(i), \\ o_3(i) &= flip\_lock(i), \\ o_4(i) &= flip\_lock\_1(i), \\ o_5(i) &= check\_if\_locked(i), \\ o_6(i) &= check\_if\_locked\_1(i), \\ & i = 0, 1, \ldots l{-}1. \end{aligned} \tag{37}$$

The description of initial state can be transformed from the set of possible initial states Σ to set of equality constraints with variable values for unknown conditions equal to $\frac{1}{2}$:

$$\begin{aligned} c_1(0) &= locked(0) = 0.5, \\ c_2(0) &= jammed(0) = 0, \\ c_3(0) &= open(0) = 0. \end{aligned} \tag{38}$$

Goal state is reached if condition open is true in last planning step, so the objective function of LP is:

$$\max \leftarrow c_3(l) = open(l). \tag{39}$$

The planning problem is solved if the optimal value of f is equal to 1, meaning that one conditions is true. It leads to following formulation of optimization problem: *Find minimal number of planning steps l, such that* $f = 1$.

The set of constraints is:

– one action in one planning step (these are equality constraints):

$$\begin{aligned} & push\_door(i) + push\_door\_1(i) + flip\_lock(i) + flip\_lock\_1(i) + \\ & + check\_if\_locked(i) + check\_if\_locked\_1(i) = 1, \quad i = 0, 1, 2, \ldots l{-}1, \end{aligned} \tag{40}$$

– actions can be applied if preconditions are true (these are inequality constraints):

$$\begin{aligned} locked(i) &\geqslant push\_door(i) + flip\_locked\_1(i), \\ 1 - locked(i) &\geqslant push\_door\_1(i) + flip\_lock(i), \\ 1 - jammed(i) &\geqslant push\_door\_1(i), \quad i = 0, 1, 2, \ldots, l{-}1, \end{aligned} \tag{41}$$

– changes of variables for conditions due to action application (these are equality constraints):

$$\begin{aligned} jammed(i+1) &= jammed(i) + push\_door(i), \\ open(i+1) &= open(i) + push\_door\_1(i), \quad i = 0, 1, 2, \ldots, l{-}1. \end{aligned} \tag{42}$$

Constraints (41) and (42) are only formulas for actions (12)–(15). Now it is necessary to model the influence of sensory actions that will change the value of variable for uncertain condition $locked = \frac{1}{2}$:

$$\begin{aligned} locked(i+1) = locked(i) &+ 0.5check\_if\_locked(i) \\ &- 0.5check\_if\_locked\_1(i). \end{aligned} \tag{43}$$

Initially $locked(0) = \frac{1}{2}$. The condition locked can be determined by sensory action *check_if_locked* modeled by 2 actions $o_5 = check\_if\_locked$ that determines *locked* and $o_6 = check\_if\_locked\_1$ that determines $\neg\, locked$. Thus, the variable value of the action o_5 should increase the variable value of the condition $locked(i)$ from "$\frac{1}{2}$" to "1". Similarly, the variable value of the action o_6 should decrease the variable value of the condition $locked(i)$ from "$\frac{1}{2}$" to "0", what is expressed by (43). It should be noted that that other classical actions also influences the value of $locked(i)$. The variable of action $o_3(i) = flip\_lock(i)$ changes the $locked(i)$ value to "1" if it was "0". The variable of action $o_4(i) = flip\_lock\_1(i)$ changes the $locked(i)$ value to "0" if it was "1". Thus, the constraint (43) should also model these changes. It leads to:

$$\begin{aligned} locked(i+1) = locked(i) &+ 0.5check\_if\_locked(i) \\ &- 0.5check\_if\_locked\_1(i) + flip\_lock(i) - flip\_lock\_1(i). \end{aligned}$$

Last constraints are implications of the fact that sensory actions for each unknown condition are performed only once during planning process:

$$\Sigma check\_if\_locked(i) + \Sigma check\_if\_locked\_1(i) = 1.$$

Optimal solution *xopt* depends on the result of application of sensory action *check_if_locked*. If the door were locked, it would correspond to effects of action o_5, and it is modeled by introducing additional equality constraint to LP:

$$o_5(0) = check\_if\_locked(0) = 1, \tag{44}$$

and if the door were $\neg locked$, it corresponds to effects of action o_6, and is modeled by introducing additional equality constraint to LP:

$$o_6(0) = check\_if\_locked\_1(0) = 1. \tag{45}$$

In case (44) the number of planning steps that satisfies goal is $l = 3$ and the vector $xopt$ that maximizes (39) can be directly interpreted as a plan: $\Delta_1 = \{o_5, o_4, o_2\} = \{check\_if\_locked, flip\_lock\_1, push\_door\_1\}$. In the opposite case, one should apply additional heuristics or methods that leads to binary integer solution (see e.g. [12]). In case (45) the number of planning steps that satisfies goal is $l = 2$ and vector $xopt$ that maximizes (39) can be directly interpreted as a plan: $\Delta_2 = \{o_6, o_2\} = \{check\_if\_locked\_1, push\_door\_1\}$. Plans Δ_1 and Δ_2 correspond to conditional plan (7).

4.2. Transformation of conformant planning problem

If w is the index of possible initial world state, then variables of the problem (23) for conditions are:

$$\begin{gathered} c_1^w(i) = I^w(i), \quad c_2^w(i) = H^w(i), \quad c_3^w(i) = D^w(i), \\ i = 0, 1, \ldots, l, \quad w = 1, 2, \end{gathered} \tag{46}$$

for actions:

$$\begin{aligned} o_1(i) &= Med_1(i), \\ o_2(i) &= Med_2(i), \\ o_3(i) &= Med_3(i), \\ o_4(i) &= Med_4(i), \\ o_5(i) &= Drink(i), \quad i = 0, 1, \ldots, l{-}1. \end{aligned} \tag{47}$$

The initial state is a disjunction of two possibilities. It is modelled by a set of equality constraints:

$$\begin{aligned} &c_1^1(0) = I^1(0) = 0, \qquad c_2^1(0) = H^1(0) = 0, \\ &c_3^1(0) = D^1(0) = 0, \\ &c_1^2(0) = I^2(0) = 1, \qquad c_2^2(0) = H^2(0) = 1, \\ &c_3^2(0) = D^2(0) = 0, \end{aligned} \tag{48}$$

Goal state $G_{Med} = \{\neg I, \neg D\}$ is reached if conditions I and D are false in last planning step in each world, so the objective function of LP, mapping ¬c into variable value in step i equal to $(1 - c(i))$, is:

$$\max \leftarrow f = \left(1 - c_1^1(l)\right) + \left(1 - c_3^1(l)\right) + \left(1 - c_1^2(l)\right) + \left(1 - c_3^2(l)\right). \tag{49}$$

The planning problem is solved if the optimal value of f is equal to 4, meaning two conditions in both worlds are false. It leads to following formulation of optimization problem: *Find minimal number of planning steps l, such that* $f = 4$.

Set of constraints is:

– one action in one planning step (these are equality constraints):

$$\begin{aligned} &\sum_{k=1}^{n} o_k(i) = 1, \\ &\sum_{k=1}^{n} o_k(i) = 1, \quad i = 0, 1, 2, \ldots l-1, \end{aligned} \tag{50}$$

– actions can be applied if preconditions are true (these are inequality constraints):

$$\begin{aligned} I^w(i) &\geqslant Med_1(i) + Med_2(i), \\ (1 - I^w(i)) &\geqslant Med_3(i) + Med_4(i), \\ H^w(i) &\geqslant Med_1(i) + Med_3(i), \\ (1 - H^w(i)) &\geqslant Med_2(i) + Med_4(i), \\ & i = 0, 1, 2, \ldots l-1, \quad w = 1, 2; \end{aligned} \tag{51}$$

– changes of variables for conditions due to action application (these are also equality constraints):

$$\begin{aligned} I^w(i+1) &= I^w(i) - Med_1(i) - Med_2(i), \\ D^w(i+1) &= D^w(i) + Med_2(i) + Med_4(i), \\ H^w(i+1) &= H^w(i) + Drink(i), \\ & i = 0, 1, 2, \ldots l-1, \quad w = 1, 2. \end{aligned} \tag{52}$$

Last equality constraint in (52) should be studied more carefully. First action in plan (4) *Drink* applied to possible initial state when patient is hydrated leads to infeasible value of variable $H^2(1)$:

$$H^2(1) = H^2(0) + Drink(0) = 1 + 1 = 2,$$

so one should introduce additional balancing variable for each condition in each planning step to avoid infeasibility:

$$\begin{aligned} I^w(i+1) + I_b^w(i+1) &= I^w(i) - Med_1(i) - Med_2(i), \\ D^w(i+1) + D_b^w(i+1) &= D^w(i) + Med_2(i) + Med_4(i), \\ H^w(i+1) + H_b^w(i+1) &= H^w(i) + Drink(i), \\ & i = 0, 1, 2, \ldots l-1, \quad w = 1, 2. \end{aligned} \tag{53}$$

Basing on formulas (46) to (53) it is easy derive general formulas for any problem (1). Table 1 presents the optimal solution of (30) which is divided into sections that correspond to variable values of actions o_i and conditions c_i, where i is the index of planning step.

Table 1: Optimal solution *xopt* for transformation of the conformant planning problem example

world	variable	$i = 0$	$i = 1$	$i = 2$	add1	add2
$w1$	I	0	0	0	0	0
	H	0	1	1	0	0
	D	0	0	0	0	0
$w2$	I	1	1	0	0	0
	H	1	1	1	1	0
	D	0	0	0	0	0
O	med1	0	0	–	–	–
	med2	0	0	–	–	–
	med3	0	1	–	–	–
	med4	0	0	–	–	–
	drink	1	0	–	–	–

It should be noted that values of variables for actions are binary integer, so the solution presented in Table 1 can be directly interpreted as a plan: $\Delta = \{Drink, \ Medicate\}$. In the opposite case, one should apply additional heuristics or methods that leads to binary integer solution (see e.g. [12]).

4.3. Transformation of parallel conformant planning problem

If l is the number of planning steps and w is the number of possible initial world states then variables of the problem (27) for conditions are [14]:

$$\begin{aligned}&c_1(i) = package(P1, i), \quad c_2(i) = package(P2, i), \quad c_3(i) = bomb(B, i),\\ &c_4^w(i) = in(P1, B, i)^w, \quad c_5^w(i) = in(P2, B, i)^w, \quad c_6^w(i) = defused(B, i)^w,\\ &i = 0, 1, \ldots, l, \quad w = 1, 2,\end{aligned} \tag{54}$$

for actions:

$$\begin{aligned}&o_1^w(i) = Dunk_1(P1, i)^w, \quad o_2^w(i) = Dunk_2(P1, i)^w,\\ &o_3^w(i) = Dunk_1(P2, i)^w, \quad o_4^w(i) = Dunk_2(P2, i)^w,\\ &\qquad i = 0, 1, \ldots, l{-}1, \quad w = 1, 2.\end{aligned} \tag{55}$$

The initial state is a disjunction of two possibilities. It is modelled by a set of equality constraints:

$$\begin{aligned} &package(P1,0) = 1, \quad package(P2,0) = 1, \quad bomb(B,0) = 1, \\ &in(P1,B,0)^1 = 1, \quad in(P2,B,0)^1 = 0, \quad defused(B,0)^1 = 0, \\ &in(P1,B,0)^2 = 0, \quad in(P2,B,0)^2 = 1, \quad defused(B,0)^2 = 0.(56) \end{aligned} \tag{56}$$

Goal state G_{BT} is reached if condition (*defused* B) is *true* in last planning step in each world, so the objective function of LP is:

$$\max \leftarrow f = defused(B,l)^1 + defused(B,l)^2. \tag{57}$$

It leads to following formulation of optimization problem: *Find minimal number of planning steps l, such that* $f = 2$.

The set of constraints is given by:

– actions can be applied if preconditions are true (these are inequality constraints), so we have:

$$\begin{aligned} package(P1,i) &\geqslant Dunk_1(P1,i)^w + Dunk_2(P1,i)^w, \\ package(P2,i) &\geqslant Dunk_1(P2,i)^w + Dunk_2(P2,i)^w, \\ r * bomb(B,i) &\geqslant Dunk_1(P1,i)^w + Dunk_2(P1,i)^w + Dunk_1(P2,i)^w \\ &\quad + Dunk_2(P2,i)^w, \\ in(P1,B,i)^w &\geqslant Dunk_1(P1,i)^w, \\ in(P2,B,i)^w &\geqslant Dunk_1(P2,i)^w, \\ (1 - in(P1,B,i)^w) &\geqslant Dunk_2(P1,i)^w, \\ (1 - in(P2,B,i)^w) &\geqslant Dunk_2(P2,i)^w, \quad i = 0,1,2,\ldots,l{-}1, \quad w = 1,2, \end{aligned} \tag{58}$$

where r is a natural number indicating how many actions can be performed in parallel (in our example $r = 2$),

– changes of variables for conditions due to action application (these are equality constraints), so we have:

$$\begin{aligned} defused(B,i{+}1)^w = defused(B,i)^w + Dunk_1(P1,i)^w + Dunk_1(P2,i)^w, \\ i = 0,1,2,\ldots,l{-}1, \quad w = 1,2. \end{aligned} \tag{59}$$

The equality constraint (59) should be studied more carefully. If actions $Dunk_1(P1,i)^w$ and $Dunk_1(P2,i)^w$ are applied in parallel in the same planning step, then the value of condition $defused(B,i{+}1)^w$ becomes infeasible. In this case, one should introduce an additional balancing variable for each condition in each planning step to avoid infeasibility:

$$\begin{aligned} defused(B,i{+}1)^w + defused(B,i{+}1)_b{}^w = defused(B,i)^w + \\ +Dunk_1(P1,i)^w + Dunk_1(P2,i)^w, \\ i = 0,1,2,\ldots,l{-}1, \qquad w = 1,2. \end{aligned} \tag{60}$$

Table 2 presents the optimal solution of the parallel conformant planning problem as well as the two additional test problems with possible initial states given by set of equalities (61) and (62):

$$\begin{array}{rrr} package(P1,0) = 1, & package(P2,0) = 1, & bomb(B,0) = 1, \\ in(P1,B,0)^1 = 1, & in(P2,B,0)^1 = 0, & defused(B,0)^1 = 0, \\ in(P1,B,0)^2 = 1, & in(P2,B,0)^2 = 1, & defused(B,0)^2 = 0; \end{array} \tag{61}$$

$$\begin{array}{rrr} package(P1,0) = 1, & package(P2,0) = 1, & bomb(B,0) = 1, \\ in(P1,B,0)^1 = 1, & in(P2,B,0)^1 = 0, & defused(B,0)^1 = 0, \\ in(P1,B,0)^2 = 0, & in(P2,B,0)^2 = 0, & defused(B,0)^2 = 0.(62) \end{array} \tag{62}$$

Table 2: Optimal solution *xopt* for the parallel conformant planning problem (56) as well as (61) and (62) problems

world	LP variable	problem (56)	problem (61)	problem (62)
both	package(P1,0)	1	1	1
	package(p2,0)	1	1	1
	bomb(B,0)	1	1	1
world 1	in(P1,B,0)	1	1	1
	in(P2,B,0)	0	0	0
	defused(B,0)	0	0	0
world 2	in(P1,B,0)	0	1	0
	in(P2,B,0)	1	1	0
	defused(B,0)	0	0	0
world 1	Dunk1(P1,0)	1	1	1
	Dunk2(P1,0)	0	0	0
	Dunk1(P2,0)	0	0	0
	Dunk2(P2,0)	0	0	0
world 2	Dunk1(P1,0)	0	1	0
	Dunk2(P1,0)	0	0	0
	Dunk1(P2,0)	1	0	0
	Dunk2(P2,0)	0	0	0
world 1	defused(B,1)	1	1	1
world 2	defused(B,1)	1	1	0
–	objective f	2	2	1

In the first one (61) there is a bomb in first package but it is uncertain whether it is in the second package, in second one (62) there is no bomb in second package but it is uncertain whether it is in first package.

It should be noted that values of variables for actions are binary integer, so the solution presented in Table 1 can be directly interpreted as a plan:

$$\Delta_{\mathrm{PPOCBT}} = \{Dunk(P2),\ Dunk(P1)\}.$$

In the opposite case, one should apply additional heuristics or methods that lead to a binary integer solution.

5. Remarks on computational complexity of transformed planning problems

Let us introduce complexity classes $\boldsymbol{P}$ and $\Sigma_k\boldsymbol{P}$. Following [3], a decision problem is a problem of determining whether a given input w satisfies a certain property F (i.e., in set-theoretic terms, whether it belongs to the corresponding set $S = \{w|F(w)\}$). For every positive integer k, a problem belongs to the class $\Sigma_k\boldsymbol{P}$ if the formula $F(w)$ can be represented as:

$$\exists u_1\ \forall u_2\ \ldots\ F(u_1,\ u_2,\ \ldots,\ u_n,\ w),$$

where $F(u_1, u_2, \ldots, u_n, w)$ is a tractable property, and all k quantifiers run over words of tractable length (i.e., of length limited by some given polynomial of the length of the input).

5.1. Complexity of transformed conformant planning problem

Basing on above notation one can represent formula (1) for conformant planning as:

$$\exists\Delta\ \forall I\Pi\ (\Delta, \Pi(C, O, I, G))\,, \tag{63}$$

where the initial state I can be potentially any state from states included in the set Σ. It follows that conformant planning is in $\Sigma_2\boldsymbol{P}$. It is also a complete problem [3].

The complexity of the heuristic presented in the paper results from the size of LP problem, i.e. the number of variables and constraints for the problem (1). The number of variables depends on the number of conditions, actions and planning steps is:

$$p = w|C|(l+1) + w|O|l = p_1 + p_2\,, \tag{64}$$

where:

$p_1 = w|C|(l+1)$ – the number of variables corresponding to conditions,
$p_2 = w|O|l$ – the number of variables corresponding to actions.

The number of constraints is:

- $w|C|$ equality constraints to define the initial state, since the number of constraints needed to define the initial state for each belief state is $|C|$,
- $|C|l$ equality constraints to define the change of variable values after performing the action,
- $|C|l$ inequality constraints to define actions preconditions,
- $2p$ inequality constraints for variable values $\langle 0, 1\rangle$.

In a general case, for problems with the number of variables and constraints limited polynomially by the size of the planning problem, it can be shown [12] that transformation of planning to LP takes time: $\boldsymbol{T} = \boldsymbol{O}(nl)$, where n is the size of the problem, $n = (w|C| + w|O|)$. If, additionally, it is assumed that the number of planning steps does not increase exponentially with the size of the problem, then transformation of planning to LP is polynomial with complexity $\boldsymbol{T} = \boldsymbol{O}(n^3)$. The heuristics of the transformation of planning with incomplete information about initial state and determined effect of actions to LP has two properties:

a) one should introduce an additional balancing variable for each condition in each planning step to avoid possible infeasibility of variable values,

b) given any feasible solution of LP problem x connected with planning problem $\Pi = (C, O, \Sigma, G)$, it is easy to check (in polynomial time) whether the solution corresponds to plan that solves Π.

From the property a) it follows that polynomial time, depending on the problem size, is needed to solve LP problems that represents incomplete planning: $\boldsymbol{T} = \boldsymbol{O}(n^3)$. From the property b) it follows that the heuristic is in NP.

5.2. Complexity of transformed conditional planning problem

In general case, for STRIPS problems with number of variables and constraints limited polynomially by the size of planning problem, it can be shown [12] that transformation of planning to LP takes time:

$$\boldsymbol{T} = \boldsymbol{O}\left((|C| + |O|)l\right). \tag{65}$$

If additionally it is assumed that the number of planning steps does not increase exponentially with the size of the problem, then transformation of planning to LP is polynomial with complexity $\boldsymbol{T} = \boldsymbol{O}(n^3)$, where n is the size of the problem, $n = (|C| + |O|)$. The heuristic of the transformation of planning with incomplete information about initial state and determined effect of actions to LP has two properties:

c) for k sensory actions one should perform 2^k transformations to LP,

d) given any admissible solution of LP problem x connected with planning problem $\Pi = \{C, O, \Sigma, G\}$ it is easy to check (in polynomial time) whether the solution corresponds to plan that solves Π.

The property a) follows that it is needed polynomial time depended on problem size an exponential time depended on the number of sensory actions to solve LP problems that represents incomplete planning: $\boldsymbol{T} = \boldsymbol{O}(n^3 2^k)$. The property b) follows that heuristic is in NP.

6. Conclusion

In this paper the transformation and the computational complexity of conditional planning, conformant planning and parallel conformant planning problems to LP were presented and analyzed.

Important planning problems are those where more than one agent interacts with the problem environment simultaneously. They arise in multi-agent and multi-robot environments. Additionally, it is assumed here that maximal number of actions applied to current problem state is r. It can occur when r agents act on the same problem state or one agent is able to perform r actions at a time. It should be noted that in real-life problems application of an action to a problem state does not always lead to expected effects. It is particularly important in cases where action outcomes are uncertain, as well, and when a condition that is determined can become undetermined. Future works will be focused on introducing uncertain action outcomes to LP transformation.

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Article 5

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Social robot response to negative emotions as a PDDL planning problem in the presence of uncertainty

***Abstract**. We propose to use automatic scheduling in the presence of uncertainty methodology to analyze the emotional state of a person and possible responses of a social robot. The emotions considered were: Sadness, Fear, Anger, Disgust and Contempt. The scenarios considered include modelling uncertainty in emotion detection. The result of the work is a set of two planning domains with illustrative examples. It was assumed that when negative emotions are detected, the robot should react in such a way as to reduce or not escalate them.*

Streszczenie.** Proponujemy wykorzystanie metodologii automatycznego planowania w obecności niepewności do analizy stanu emocjonalnego osoby i możliwych reakcji robota społecznego. Rozważane emocje to: Smutek, Strach, Złość, Obrzydzenie i Pogarda. Rozważane scenariusze obejmują modelowanie niepewności w detekcji emocji. Efektem pracy jest zestaw dwóch domen planistycznych wraz z ilustrującymi je przykładami. Założono, że w przypadku wykrycia negatywnych emocji robot powinien reagować w taki sposób, aby je zmniejszyć lub nie eskalować. **(Reakcja robota społecznego na negatywne emocje jako problem planowania PDDL z uwzględnieniem niepewnej informacji).

Keywords: artificial intelligence planning, sensory planning, social robotics, emotion recognition.
Słowa kluczowe: planowanie w sztucznej inteligencji, planowanie sensoryczne, robotyka społeczna, rozpoznawanie emocji.

Introduction

The problem of automatic planning in artificial intelligence is formulated as a search for the sequence of the agent's actions (the so-called plan), which transforms the agent's initial environment (called the initial state of the planning problem) into a desired goal-oriented situation (eg [1]).

The problem becomes more complicated if the information about the modelled world is not sufficient to establish all the facts necessary to describe the baseline state of the world. We then say that the initial state of the problem is uncertain, but can be represented by a set of possible initial states. The problem resolution plan can take the form of conditionally implemented actions based on new information that appears when you search for the plan. This approach is called contingent planning ([2], [3]).

The idea of application of automated planning formalism in social robotics is not new but is the subject of ongoing research. One of the ways people communicate is through facial expression. The ability to recognize emotions is important in the context of social robots, as it enables the conversation tone to match the mood of the interlocutor. Human-robot interaction should be seamless, the robot should be able to adapt to the current situation and extract as much information as possible based on analysis of the user's face. Recognition of human emotions can be realized by analyzing facial expression, sound or body language. This paper focuses on emotion recognition using facial expression. Seven basic emotions are detected: fear, anger, happiness, sadness, surprise, disgust and neutrality. Analyzing emotional state based on facial expression is a complicated and complex task. Existing datasets are relatively small in scale, so the network must be taught a good representation using a limited number of training samples. The problem to be solved is Creating an efficient emotion detection algorithm that works in real time.

The study [4] contributes with the list of important aspects that must be taken into account while modelling a classical and deterministic PDDL domain for Social Robotics and executing the resulting plan in their highly dynamic and stochastic environments. In work [5] the Authors develop non-contact rehabilitation therapies for patients with physical impairments based on automated planning reasoning, but the deeper analysis of the problem one can find in [22].

The aim of this study was to investigate the possibility of using the methods of searching for a conditional plan to analyze the emotional state of a person and exerting an influence on the diagnosed state. The uncertainty taken into account was related to the emotional state of a person in interaction with the robot. For the needs of the emotional state analysis, a database of characteristic facial expressions was used, the appropriate combination of which was used to define emotions. The research consisted in modifying one of the classic planning fields, taking into account the uncertainty as to the patient's health [6]. The modification consisted in matching activities representing taking medications and performing laboratory tests to activities modelling human emotional states and performing facial expression analyses. PDDL (Planning Domain Definition Language) [7] has been used to describe the field and planning tasks.

PDDL as a representation of conditional planning task

Following [8] it is assumed that action planning Π (called STRIPS planning) consists of four sets $\Pi=\{C, O, I, G\}$:

- C is a finite set of *conditions*,
- O is a finite set of actions, where each action $o \in O$ takes the form $c^+, c^- \rightarrow c_+, c_-$, where:
  - o $c^+ \subseteq C$ are so called *positive preconditions*,
  - o $c^- \subseteq C$ are so called *negative preconditions*,
  - o $c_+ \subseteq C$ are so called *positive postconditions*,
  - o $c_- \subseteq C$ are so called *negative postconditions*,
- $I \subseteq C$ is an *initial state*,
- $G = \{G_+, G_-\}$ is a *goal situation*, where $G_+ \subseteq C$ are positive conditions (i.e. are true) and $G_- \subseteq C$ are negative conditions (i.e. are false).

In purpose of including in the characterization of the current state of the problem the information that some conditions are unknown (suppose that k conditions may be true or false), one might introduce the so-called k-states proposed by [9]. In simple terms *k-state* is a pair (S, Σ), where S is the current problem state, and Σ is a set that consists of all possible states. For unknown initial state set Σ consists of all states S, for which:

- condition $c \in C$ is true in the initial state (i.e. $c \in I$),
- condition $c \in C$ is false (i.e. $\neg c \in I$),
- if it is unknown whether condition $c \in C$ is true or false in the initial state then set Σ includes both states for which this condition is true and false.

The initial state I can be potentially any state from states included in set Σ.

Robotic intelligent systems are commonly armed with various types of sensors that are designed to determine various properties of the surrounding robot environment. This and other information can be represented to the degree of truth of the conditions that determine the current state of the problem. This is typically being done by implementing specialized operations referred to as *sensory actions* [9]. Since no formal extension of STRIPS planning to sensory actions exists, a definition of these actions for k uncertain conditions is being proposed below as a dedicated special subset of STRIPS actions.

Definition. For k unknown conditions set of sensory actions O_s is a finite set of actions, where for each sensory action o_s it is needed to introduce two STRIPS sensory actions
$\{ o_s^t, o_s^f \} \in O_s$ that take the form:

- $o_s^t : c^+, c^- \rightarrow c_i$, if condition c_i is true after performing action o_s,
- $o_s^f : c^+, c^- \rightarrow \neg c_i$, if condition c_i is false after performing action o_s,

for i = 1,2…k. It follows that the number of STRIPS sensory actions $|O_s| = 2k$.

The effect of the application of an action to the present state is determined by whether the action is conventional or sensory. The explanation of this result is given below, is on the basis of [2] and is mapped to the STRIPS problem.

For action o, *k-state* is described by a set $\{Result(S,\{o\}), Result(\Sigma,\{o\})\}$, where $Result(S,\{o\})$ is the same like in the case with complete information, e.g.:

(1) $Result(S, \{ \}) = S$,

(2) $Result(S, \{o\}) = (S \cup c_+) \setminus c_-$ if $c^+ \subseteq S \wedge c^- \cap S = \emptyset$; S in opposite case,

(3) $Result(S, \{o_1, o_2, \ldots, o_n\}) = Result(Result(S, \{o_1\}), \{o_2, \ldots, o_n\})$,

(4) $Result(\Sigma,\{o\}) = \{ Result(S',\{o\}) \mid S' \in \Sigma \}$.

For sensory actions o_s, current state S remains the same, whereas the set Σ is reduced to set of states, for which condition $c_i \in S$:

(5) $Result(\Sigma,\{o_s\}) = Result(\Sigma',\{o_s\})$,

where: $\Sigma' = \{S' \in \Sigma \mid (c_i \in S' \leftrightarrow c_i \in S)\}$.

It results that the planning problem with incomplete information on the initial state has a form of five sets of:

(6) $\Pi = \{C, O, O_s , \Sigma, G\}$.

Expression of negative emotions

Emotions are regulatory processes that are triggered when a person comes into contact with stimuli whose meaning is important for the body or personality [10]. There are four types of emotional triggers:

i. Endogenous (arising in the mind) and exogenous (arising in the surrounding world) stimuli.
ii. Physiological correlates, i.e. the activity of the central peripheral nervous system.
iii. Cognitive assessment, i.e. the assessment of events by the person who gives them meaning.
iv. Motivational qualities, i.e. goals and aspirations accompanied by emotions.

Emotions differ from feelings in that they come suddenly and are intense, causing immediate action. Emotional processes are mental activities that relate to reality. Each emotion can be described by characterizing its 3 main components:

- intensity
- sign (influence)
- contents

The intensity of the emotional process depends on how important the stimulus is for the person. The higher its stimulation, i.e. the greater its activation, the greater the mobilization of energy to act, i.e. the stimulus is more intense [10]. The sign of the emotional process is influenced by the direction of the reaction to which the stimulus stimulates the person. There are two types of emotions:

- positive, that is, pleasant
- negative or unpleasant

Emotions vary in quality depending on the factor that causes them and the type of reaction to which they are prompted. These factors make up the content of the emotional process. Negative emotions were selected for the study, indicating how the social robot could react to them in order to reduce them. The most popular division is made by Paul Ekman, who distinguish seven universal facial expressions (anger, contempt, disgust, fear, happiness, sadness and surprise). But, it is worth noting that studies concerning universal facial expression are steel continued and many researchers [11] suggests that people can represent even 16 complex expressions, that may be unified over the globe.

Sadness

Sadness is felt as a result of losing someone important or not achieving a goal. It is accompanied by a bad mood and a feeling of depression. Paul Ekman and Wally Friesen have suggested that sadness has two separate aspects - sadness and anguish [4]. The gesture characteristic of sadness is to raise and draw the eyebrows. Also the upper eyelids are slightly drooping and the lower eyelids are slightly tense. A combination of all the signs of sadness are: The eyebrows are raised and pulled together so that the inner corner is raised, the upper eyelids slightly droop, the corners of the mouth are lowered and the cheeks are raised. The last of these microgests shapes the wrinkles (the so-called nasolabial folds) that run from the nostrils, beyond the corners of the mouth. The muscle responsible for lifting the cheeks also creates these furrows and pushes the skin under the eyes, causing them to narrow.

Fear

Fear is felt when the source of the anticipated threat or danger is known. The inability to identify this source causes anxiety [12]. Fear is a person's reaction to a real, immediate, and physical threat to the physical self. Anxiety arises as a result of a feeling of an undefined threat to oneself and personality [13].

When the tension of the lower eyelids occurs along with the lifting of the upper eyelids, while the rest of the face is expressionless, it is very likely that the person is feeling fear. The eyebrows are pinched and raised, when you add the upper eyelid lift that usually occurs with lower eyelid tension, the scared expression reappears. Fear can also affects with mouth muscles leading to open mouth [14].

Anger

Anger occurs when we destroy our goals. It is aimed mainly at people we love or like, not those we don't like [12]. Anger is associated with aggressive behavior. The lower eyelids are slightly tense and the upper eyelids raised, which gives the effect of glaring eyes with slightly lowered and pulled eyebrows, which proves that anger is inhibited. Also staring intensely can be associated with anger [15].

Disgust

Disgust is caused by objects or situations that are repulsive to us. They can be seen in an infant after putting something bitter in their mouth. According to Paul Rozin, finding something disgusting by a person depends not only on the nature of the object, but also on its origin, social history and what it resembles. Disgust can also be felt towards immoral and socially unacceptable acts. This emotion does not cause major problems for the person experiencing it, but when performing certain jobs, one must undergo devout training [13]. Disgust is signalled by two very different grimaces: the first is the wrinkle of the nose, the second is the upper lip lift.

Contempt

Contempt has a lot to do with disgust, but there are differences that distinguish these emotions. “We only feel contempt for people and their behaviour, not for smells, tastes or tactile sensations. Walking into a dog's poop can be disgusting, but never contempt, the very thought of eating a calf's cerebellum can be disgusting, but never disdainful. However, it is possible to despise people who eat such disgusting things because contempt contains an element of superiority to its object; a lack of respect for people or their behaviour makes you feel better (usually in a moral sense) than them. is demeaning. but you don't have to run away from them right away, which you would do in case of disgust ”[4].

Contempt, although counted as a negative feeling, can be nice to people when they feel it. This feeling can then turn into the embarrassment of realizing that you are experiencing pleasant sensations during the emotion. This applies especially to people who are less confident in their status, who, referring to contempt, try to emphasize their superiority over others [4]. Contempt is the only emotion that expresses itself in a one-sided expression on the face. It is characterized by a tight and slightly raised corner of the mouth.

Automated recognition and reduction of negative emotions as a conditional planning problem

In this section we introduce PDDL domains for automated recognition and reduction of negative emotions by social robots, implemented on ACL (Allegro Common Lisp) platform [16], in which the Sensory Graphplan algorithm is the scheduling algorithm [17] that solves problems. Proposed domains address two problems:

Table 1 Actions with PDDL effects for “emotions basic” domain

Action	**Type of action**	**Effects of action**
test_check	with conditional effects	(and (when (sadness) (test_result_1)) (when (tornment) (test_result_2)))
emotion_analysis	sensory	(and (observes (test_result_1)) (observes (test_result_2)))
sadness_therapy	with conditional effects	(and (when (sadness) (not (sadness))) (when (not (sadness)) (depression)))
tornment_therapy	with conditional effects	(and (when (tornment) (not (tornment))) (when (not (tornment)) (depression)))

1. The first domain of planning problem, called “emotions basic”, concerns the task of recognizing and reacting a social robot to two related emotions: sadness and anguish. They are distinguished using the "*test_check*", which determines what score characterizes the emotion, while the sensory action "*emotion_analysis*" indicates the score obtained by the patient. Then, using the "*sadness_therapy*" and "*tornment_therapy*" actions, he is subjected to the appropriate, for his emotional state, treatment. It is assumed that an improperly selected therapy causes the patient's condition to deteriorate, which describes the corresponding conditional effect of the therapy actions. The domain is defined in Table 1 using PDDL formalism, where sets C and O of planning problem (6) are given as:

(7) C = {*sadness, tornment, test_result_1, test_result_2, depression*},

(8) O = {*test_check , sadness_therapy, tornment_therapy*},

(9) O_S = { *emotion_analysis* }.

2. The second domain, called “emotions complex”, is an expanded version of the previous one, in which the task of a social robot is to respond to a complex emotionally uncertain initial situation. It features 5 negative emotions, which are analyzed based on facial expressions. The action *face_expression_recognition* conditions on the basis of which facial expressions specific emotions are interpreted, while the action and *eyebrows_recognition* refine this result. The sensory actions *face_observation* and *eyebrows_expression_observation* indicate the expressions that have been noticed in the patient, thanks to them the appropriate therapy is selected. The wrong therapy results in the deterioration of the of the patient's condition. The domain is defined in Table 2. Conditions introduced are interpreted as follow: *cheeks* - lifting the cheeks; *eyelids* - lifting the lower eyelids and tightening the upper eyelids; *mouth_corner* - lifting the corner of the mouth; *eyebrows* - draw your eyebrows towards each other. The domain is defined in Table 2 using PDDL formalism, where sets C and O of planning problem (6) are given as:

(10) C = {*sadness, disgust, anger, fear, contempt, depression, cheeks, eyelids, mouth_corner, eyebrows*},

(11) O = {*face_expression_recognition, eyebrows_recognition, therapy*},

(12) O_S = {*face_observation, eyebrows_expression_observation*}.

Table 2 Actions with PDDL effects for “emotions complex” domain

Action	**Type of action**	**Effects of action**
face_expression_ recognition	with conditional effects	(and (when (or(sadness)(disgust))(cheeks)) (when (or(anger)(fear))(eyelids)) (when (contempt)(mouth_corner)))
face_observation	sensory	(and (observes (cheeks)) (observes (eyelids)) (observes (mouth_corner)))
eyebrows_ recognition	with conditional effects	(and (when (or (sadness)(fear)) (eyebrows)))
eyebrows_ expression_ observation	sensory	(observes (eyebrows))
therapy (?emotion)	with conditional effects	(and (when (?emotion) (not (?emotion))) (when (not (?emotion)) (depression)))

Scenarios for “emotions basic” domain

In the first planning problem, uncertainty applies only to sadness, so the uncertain construct was used to define it. The patient may feel sadness or not feel it (this means that he or she is in a state that does not require treatment). The goal is to bring him to a good emotional state, therefore it is necessary, with the help of action sensory action to diagnose the patient's condition in order to give him the right treatment. Wrong selected therapy results in worsening of the patient's condition.

The uncertainty about the sadness leads to two possible initial states. In the first, the patient does not feel any of the emotional states under study, while in the second he feels sadness. The *emotion_analysis* action determines whether to give the treatment or whether the patient is in world 1, i.e. does not require treatment. The problem is defined in Table 3 in PDDL formalism, i.e. the initial state of the problem and the set *G* from formula (6) are given. Resulting possible worlds (i.e. initial states, the set Σ in formula (6)) and the solution are presented in Table 4.

Table 3 The initial state of the first planning problem and the set G

Initial state of the first problem	**The goal state of the first problem**
(not (test_result_1)) (not (test_result_2)) (not (depression)) (not (tornment)) (uncertain (sadness)))	(and (not (sadness)) (not (tornment)) (not (depression)))

Table 4 Possible worlds and the solution of the first planning problem

Possible world 1	**Possible world 2**	**Conditional plan**
(not (sadness)) (not (tornment)) (not (depression)) (not (test_result_2)) (not (test_result_1))	(sadness) (not (tornment)) (not (depression)) (not (test_result_2)) (not (test_result_1))	1. test_check 2. emotion_analysis 3. sadness_therapy if not in world 1

In the second planning task, the patient may feel sadness, anguish or no feel any of the listed emotions, so uncertainty in the initial state was defined using the *oneof* construct. As in the previous task, the goal is to select the patient with the appropriate therapy to improve his emotional state; referring the patient to the wrong therapy will result in a worsening of his emotional state. The uncertainty about one of three possible emotional states leads to three possible initial states of the planning problem.

The problem is defined in Table 5 in PDDL formalism, i.e. the initial state of the problem and set *G* from formula (6) are given. Possible worlds (i.e. initial states, the set Σ in formula (6)) and the solution are presented in Table 6.

Table 5 The initial state of the first planning problem and the set G

Initial state of the second problem	**The goal state of the second problem**
(not (test_result_1)) (not (test_result_2)) (not (depression)) (oneof (and (sadness) (not (tornment))) (and (not (sadness)) (tornment)) (and (not (sadness)) (not (tornment)))))	(and (not (sadness)) (not (tornment)) (not (depression)))

Table 6 Possible worlds and the solution of the first planning problem

Possible world 1	**Possible world 2**	**Conditional plan**
(not (sadness)) (not (tornment)) (not (depression)) (not (test_result_2)) (not (test_result_1))	(sadness) (not (tornment)) (not (depression)) (not (test_result_2)) (not (test_result_1))	1. test_check 2. emotion_analysis 3. sadness_therapy *if not in world 1*

Scenario for "emotions complex" domain

In the third planning problem, the patient feels one of four negative emotions and it is the source of uncertainty. The problem has also an additional initial property in which the patient feels anger and this fact is true in the initial state. The problem is defined in Table 7 in PDDL formalism, i.e. the initial state of the problem and set *G* from formula (6) are given. Possible worlds (i.e. initial states, the set Σ in formula (6)) and the solution are presented in Table 8.

Table 7 The initial state of the third planning problem and the set G

Initial state of the third problem	**The goal state of the third problem**
(not (cheeks)) (not (eyelids)) (not (mouth_corner)) (not (eyebrows)) (oneof (sadness)(fear)(anger)(disgust)) (not (contempt)) (not (depression)))	(and (not (sadness)) (not (fear)) (not (anger)) (not (disgust)) (not (contempt)) (not (depression)))

Table 8 Possible worlds and the solution of the third planning problem

World 1	**World 2**	**World 3**	**World 4**	**Conditional plan**
(object contempt) (object disgust) (object anger) (object fear) (object sadness) (not (depression)) (not (contempt)) (disgust) (not (sadness)) (not (fear)) (not (anger)) (not (eyebrows)) (not(mouth_corner)) (not (eyelids)) (not (cheeks))	(object contempt) (object disgust) (object anger) (object fear) (object sadness) (not (depression)) (not (contempt)) (not (disgust)) (anger) (not (sadness)) (not (fear)) (not (eyebrows)) (not(mouth_corner)) (not (eyelids)) (not (cheeks))	(object contempt) (object disgust) (object anger) (object fear) (object sadness) (not (depression)) (not (contempt)) (not (disgust)) (not (anger)) (fear) (not (sadness)) (not (eyebrows)) (not(mouth_corner)) (not (eyelids)) (not (cheeks))	(object contempt) (object disgust) (object anger) (object fear) (object sadness) (not (depression)) (not (contempt)) (not (disgust)) (not (anger)) (not (fear)) (sadness) (not (eyebrows)) (not(mouth_corner)) (not (eyelids)) (not (cheeks))	1. eyebrows_recognition *or* face_expression_recognition 2. face_observation *or* eyebrows_expression_observation 3. therapy disgust *if not in worlds* 2 3 4 4. therapy anger *if not in worlds* 1 3 4 5. therapy fear *if not in worlds* 1 2 4 6. therapy sadness *if not in worlds* 1 2 3

It should be noted that for the third conditional plan problem the robot is able to perform some actions in parallel. It is caused by the fact that sets of actions are not *mutually excluded*, i.e. changing the order of applying the action, or apply them simultaneously does not lead to contradiction. In the plan presented in Table 8 actions *eyebrows_recognition* or *face_expression_recognition* can be performed in parallel or in any order. Similar property could be observed for sensory actions *face_observation* and *eyebrows_expression_observation*. The property of executing in parallel some of the decisions that are components of the plan can be used to reduce the execution time of the entire plan, in this case patient interaction (see e.g. [18]).

Discussion and conclusion

The research involved modification of the classical medical planning field, taking into account uncertainty about the patient's state of health. The modification consisted in matching actions representing taking medications and performing laboratory tests to actions modelling human emotional states and conducting psychological tests. The result of the modification is a new field of automatic planning containing the field definition and a set of planning problems.

In the part concerning the simulation research, a number of tests were carried out using the newly created planning domain. Research results indicate the usefulness of classic methods of automatic planning for the analysis of emotional states. It should be noted that the examples considered are very simple and indicate possible future directions of work development. Among them, we can distinguish the development of the field of planning taking into account the more complex emotional states of man and complex forms of reactions or psychological therapies conducted by social robots. There are potential possibilities to integrate classic automatic planning methods with visual facial expression recognition systems.

When building more complex automated planning systems one can be faced with the problem of efficient in time methods for searching the plan that is caused by the usually high computational complexity of planning problems especially in the presence of uncertainty [9]. The combinatorial and efficiency studies for emotion recognition as a planning problems has been studied in [19].

To overcome this difficulty we work for hybrid algorithms based on transformation of planning problems to linear programming. Our results indicate the usefulness of this approach [20] when integrating the planning system with OhBots expressing emotions robots interacting with human [21] within the Social Robots laboratory developed by Department of Automatic Control and Robotics at Silesian University of Technology.

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3. Modelling social behaviour of robots based on the application of neural networks in robotics

3.1. Introduction

The diversity of social behavior in robotics is a key area of research that is becoming increasingly important as technology and robot applications develop in society. This diversity is complex and multidimensional, encompassing different aspects such as behavior types, modeling methods, application contexts, and ethical challenges. In recent years, many different types of social behavior have been identified that can be modeled and simulated in robots. For example, robots can be programmed to show empathy and compassion by recognizing and responding to human emotions (Alves-Oliveira et al., 2019). Other research focuses on collaboration and teamwork between robots and humans, particularly in the context of team tasks and social interactions (Kim et al., 2018). In addition, there is a growing interest in understanding and modeling how robots can adhere to social norms and values across cultures and societies (Malle, Ullman, 2021). The diversity of social behavior requires different modeling methods. Artificial intelligence (AI) methods, especially neural networks and machine learning, are key tools in the field of social robotics, enabling robots to interact with humans in more complex and flexible ways. Neural networks are inspired by the structure and function of the human brain and are used to model complex patterns and relationships in data. In social robotics, neural networks are used in a variety of applications, such as recognizing emotions by analyzing facial expressions and speech, modeling subtle nuances of social interactions such as gestures, gaze, and posture, and adapting robot behavior to individual user preferences and needs (Zhang et al., 2020; Chen et al., 2020; Li et al., 2019). Machine learning, including deep learning, is a broad category of methods that enable robots to learn from data and experience. In social robotics, machine learning has many applications, including teaching collaboration using reinforcement learning, creating realistic simulations of social behavior in virtual environments, and modeling and understanding the ethical and social norms that influence robot behavior (Kim et al., 2013; Steels & Hild, 2012; Malle, Ullman, 2021). While neural networks and machine learning offer promising opportunities in social robotics, there are also challenges, such as creating models that are understandable and explainable to humans, and ensuring safety and privacy in the use of these methods, especially in the context of human interaction (Adadi et al., 2018; Sharkey & Sharkey, 2020).

The variety of artificial intelligence methods used is relevant to the different contexts of social robotics. In education, social robots are used to support teaching and interaction with students, using machine learning techniques to adapt to individual needs and learning styles (Belpaeme et al., 2018). In healthcare, robots can be used to monitor and assist patients, for example in elderly care, where neural networks can help to recognize patients' behavioral patterns and needs (Vianello et al., 2021). In industry, social robots are used for a variety of tasks, such as collaborating with humans in manufacturing environments. Machine learning and neural networks are used to create models that enable robots to collaborate and communicate effectively with humans and adapt to dynamic and complex work environments (Kim et al., 2013). In entertainment, social robots are used in games and interactive media, where AI techniques are used to create realistic and engaging interactions with users (Ribeiro et al., 2019). In different cultural and social contexts, social robots also need to take into account social norms and values that may influence their behavior and interactions. Research in this area focuses on understanding how robots can adhere to and adapt to different social and cultural norms, using AI methods to model and simulate these complex dynamics (Malle, Ullman, 2021).

This multifaceted nature of the problem leads to a number of issues and challenges. One of these is the need for an adequate dataset for training. Data quality has a direct impact on the quality of AI models. In medicine, medical data is mainly unstructured and lacks uniform and standardized annotation, which can affect the quality of medical AI algorithm models (Zhang & Zhang, 2023). In social robotics, the collection and processing of relevant data to train models, such as emotion recognition and social interaction, is crucial to the effectiveness of the systems. The issue of ethics is also often raised. Ethics in AI encompasses many aspects, such as privacy, security, discrimination, and responsibility. In the context of children, there is a need to protect children's rights in relation to the development of AI, especially in relation to privacy, security and discrimination (Hassan, 2022). In medicine, ethical challenges include issues such as data quality, algorithmic bias, opacity, safety, and accountability (Zhang & Zhang, 2023). In society, AI ethics also includes issues such as misuse of technology, racism, insecurity, and malicious algorithms with biases (Nasim et al., 2022). In addition to ethical issues, research often points to safety and liability issues. Safety in AI is crucial, especially in the context of autonomous robots and toys, where appropriate safety standards are required (Hassan, 2022). In addition, liability for AI-related accidents is not clear, which affects people's trust in the technology (Zhang & Zhang, 2023).

3.2. Literature review

In the context of modeling the social behavior of robots using neural networks, an analysis of the literature reveals several interesting approaches and methodologies. A popular direction is the detection of fake news, which is crucial to ensure the authenticity of information (Saikia et al. 2022). Therefore, auxiliary information based on social context has been investigated for the detection of fake news. Their approach focused on analyzing the social context of fake news detection using a hybrid graph neural network approach. This hybrid model was based on the integration of a graph neural network on message propagation and bidirectional encoder representations from a transformer model on message content to learn textual features. In this way, the approach learned both content and contextual features, allowing it to outperform baseline models. This allows for a potential implementation in social robotics to analyze the behaviors associated with fake news.

Considering the modeling of social behavior is important in the context of modeling robot navigation (Bachiller et al. 2021). To this end, a graph neural network was used to model navigation interference. The approach was based on the development of the SocNav1 dataset, which includes robot and human motion. This study highlighted the importance of including social interactions in modeling robot navigation so that robots are more aware of people in their environment. The subjects also studied social recommendation using a knowledge-aware coupled graph neural network (KCGN) (Huang et al. (2021). This model allowed encoding the relationship between a user and a higher-level object, using mutual information for global awareness of the graph structure. This approach could be useful for social robots that need to understand and respond to the preferences and behaviors of people in their environment.

Research is also investigating a biologically inspired motivational model for controlling the biological functions of autonomous robots that interact with and mimic human behavior

(Maroto-Gómez et al. 2023). This model aims to produce fully autonomous, natural behaviors that can adapt to both familiar and unexpected situations in human-robot interactions. The architecture mimics basic animal biological functions such as neuroendocrine responses, circadian and ultradian rhythms, motivation, and affection to generate biologically inspired behavior in social robots. A meta-analysis was also conducted to identify factors that influence children's trust in robots (Stower et al. 2021). This analysis aimed to understand how more human-like attributes influence trust in robot competence. The meta-analysis also revealed a bias toward underfunded research and differences in the methods and measures used to define trust. Attempts to predict the appropriate pose for a robot to participate in group formations typical of human social conversations, given the physical layout of the environment, are also the subject of ongoing research (Vázquez et al. 2022). This study suggests that different methods have different strengths. For example, the geometric approach was more effective at avoiding items generated in unoccupied areas of the environment, but the data-driven method was better at capturing the spatial variability of conversational formations.

Also very relevant are approaches that start from the analysis of human behavior and try to generate it in social robots. One of them is a bottom-up approach to the emergence of social behaviors resulting from the interaction between the curiosity drive, i.e. the intrinsic motivation to learn as much as possible, and the agent's environment (Gordon, 2019). The implementation of artificial curiosity algorithms in robots exploring human-like environments leads to the emergence of a hierarchical structure of learning and behavior. This structure resembles the sequential emergence of behavioral patterns in human infants, culminating in social behaviors such as face recognition, tracking, and attracting attention with facial expressions. It is emphasized that social interaction is the foundation of human society. It indicates our place in the community and provides information about what is happening in the environment. Human infants exhibit social behaviors very early in life, such as eye tracking, joint attention, and expressions of emotion designed to elicit a response from the caregiver. The article highlights that curiosity can be a precursor to many social behaviors when satisfied in a social environment.

The analysis of human behavior also makes it possible to take into account those social situations in which the robot must act in real time. Many articles point out that the creation of a new generation of robots that can move freely, make autonomous decisions, and interact directly with humans is crucial for the future of human-machine interaction (Antonucci et al. 2021).

These robots must not only be efficient, but also safe and predictable in their behavior. Humans have advanced mechanisms that allow them to move in socially acceptable ways, and creating algorithms that mimic these abilities is a major focus of human-robot interaction research. Research presents several approaches to predicting human motion, including physics-based models such as the Social Force Model (SFM) and neural network-based approaches. The SFM treats humans as particles under the influence of attractive and repulsive forces, providing a simple but effective representation of individual human motion. However, the model has some limitations, such as treating humans as particles, which does not distinguish natural motion patterns from less typical ones. Neural networks hold promise for predicting human intentions in a relatively simple way. However, their complex structures and training difficulties may mean that traditional models, such as the constant-velocity model, may outperform them for linear trajectories.

The integration of necessary social behavior in social robots is a complex problem. This is evidenced by the variety of behavioral models used in different studies on the topic. To achieve seamless and effective human-like communication, robots need to integrate the necessary social behaviour for a given situation, using many of the behavioural patterns that humans use to achieve specific communication goals (Nocentini et al. 2019). Furthermore, robots should be equipped with the ability to understand the user's feelings, intentions, and beliefs, which are not only directly expressed by the user, but also shaped by physical signals (e.g., gaze, posture, facial expressions) and vocal signals (e.g., tone of voice and expressions). In educational human-robot interaction (HRI), it is widely believed that the behavior of the robot has a direct impact on the user's engagement with the robot, the task, and the partner in the case of a collaborative activity (Nasir et al. 2022). Increasing this engagement is responsible for increasing learning and productivity. Ongoing research focuses on the relationship between the robot's behavior and the user's state of engagement, assuming a linear relationship between engagement and the end goal: learning. However, the authors of this paper raise an important question: can it be assumed that in order to maximize learning, engagement must be maximized? Furthermore, traditional models of engagement based on supervision require people to annotate. This is not only labor intensive, but also introduces additional subjectivity into an already subjective construct of engagement. The paper highlights an implicit relationship that has been termed 'productive engagement'. It is theorized that a robot incorporating this knowledge would be able to discriminate between teams based on engagement that is conducive to learning, and adopt behaviors that lead to increased learning through productive engagement.

Novel social interaction is a dynamic process in which participants adapt, respond, and engage with their social partners (Eshed et al. 2021). To facilitate such interactions, people gather information about the social context and structure of the situation. The goal of this study was to deepen our understanding of the psychological determinants of behavior in novel social interactions. In the study, three social robots and a participant interacted nonverbally according to a pre-programmed "relationship matrix" that determined who favored whom. The participants' gaze was tracked during the interaction, and a measure of the participants' social information-gathering behavior was obtained using Bayesian inference models. The results reveal dynamics in a novel environment in which information-gathering behavior is initially predicted by psychological inflexibility and then, towards the end of the interaction, by curiosity.

Robot-human social interactions are also analyzed in the context of assessing the impact of these interactions on human inhibition. Research addresses the issue of tools for analyzing human behavior data in the context of robots supporting special education (Lytridis et al. 2022). The goal was to understand human behavior in response to different robot actions and to improve intervention design based on appropriate mathematical tools. To achieve these goals, the study used Lattice Computing (LC) models in combination with machine learning techniques to construct representations of the child's behavioral state. Using data collected during actual robotic interventions with children diagnosed with ASD and the aforementioned behavioral state representation, a time series of behavioral states was constructed. In this thesis, the causal relationship between specific actions of the robot and the observed behavioral states of the child was investigated to determine how different modes of interaction with the robot affected the child's behavior. The modeling of social behavior has enabled a shift in approach to the generation of human intelligence (Cangelosi, Schlesinger, 2018). The authors point out that the combination of advances in artificial intelligence and machine learning with established cognitive theory, which is at the intersection of AI and psychology, leads to the emergence of developmental robotics. It is an interdisciplinary approach, based on close collaboration between the disciplines of cognitive robotics and child psychology, to autonomously design behavioral and cognitive abilities in artificial cognitive agents, such as robots, that draw direct inspiration from developmental principles and mechanisms observed in children. The paper outlines the benefits of this approach and presents a detailed case study of the role of the body in early word learning, as well as an overview of several developmental robotics models for perceptual, social, and language development.

Adequate modeling of social behavior is also challenging in terms of obtaining relevant data. Research presents a novel approach for learning discrete models of human-robot interaction from small datasets (Zehfroosh et al. 2017). In a motivating application, human-robot interaction is an integral part of the pediatric rehabilitation paradigm, which involves a play-based social environment to improve the mobility of infants with mobility impairments. Designing interfaces in this context is challenging because to exploit and ultimately automate the social interaction between children and robots, a behavioral model is needed that captures the causality between the robot's actions and the child's responses. This paper adopts the Markov process (MDP) as such a model and selects transition probabilities using an empirical approximation procedure called smoothing. Smoothing has been successfully applied in natural language processing (NLP) and identification where, as in the current paradigm, learning from small data sets is crucial. The example of this research shows that conducting research in social behavior modeling also depends on the target application context.

In addition to generalizing social behavior, many studies analyze only selected specific behaviors. One frequently analyzed topic is empathy. Research highlights the importance of robots having the ability to empathize with humans and express appropriate emotions (Park, Whang, 2022). The cited article conducted a systematic literature review of empathy in human interaction, virtual agent, and social robot research. Based on the review, empathy in the context of human-robot interaction was defined as the ability of a robot to recognize a human's emotional state, thoughts, and situation and to generate appropriate affective or cognitive responses. On this basis, theories of empathy are presented and a conceptual model of empathy in human-robot interaction is developed, taking into account the process of empathy, the outcome of the interaction, and the characteristics of the observer and the person being empathized. This model is complemented by empirical research on empathic virtual agents and social robots. Key factors such as domain dependence, multimodality, and modulation of empathy that need to be considered in the design and study of empathic social robots are also identified.

The topic of empathy is addressed both from the point of view of the development of this trait in social robots, as well as in the context of how empathy can develop in humans when interacting with social robots. One study discusses the impact of communication with social robots on the development of empathy in children (Pashevich, 2022). Social robots are increasingly entering children's lives at a time when they are learning about social relationships and developing prosocial behaviors. These robots have the potential to influence the way children develop empathy. This paper presents a review of literature from 2010-2020 in the fields of human-robot interaction, psychology, neuropsychology, and robotics. A critical analysis of the evidence shows that while it is theoretically very likely that robots can influence the development of empathy in children, depending on their design, intensity, and context of use, there is uncertainty about the nature of the effect. Most of the studies reviewed that demonstrated the ability of robots to enhance empathy in children were not long-term studies. Therefore, there is a need for research on the effects of long-term, regular, and consistent communication with robots of different designs and in different situations on children's social and emotional development. In addition to empathy, another construct that has been analyzed is humor (Niculescu et al. 2013). The study examined how simple auditory/verbal speech features, such as voice characteristics (tone) and linguistic cues (expressions of empathy/humor), affect the quality of interaction with a social robot acting as a receptionist. Two robot characters were created in the experiment: Olivie, a more extroverted, enthusiastic, and humorous robot with a higher tone of voice, and Cynthia, a more introverted, calmer, and serious robot with a lower tone of voice. The results showed that tone of voice had a strong effect on ratings of the overall quality of the interaction, as well as the attractiveness of the robot and the overall enjoyment of the interaction. In addition, humor seemed to improve users' perceptions of task enjoyment, robot personality, and speaking style, while empathy influenced ratings of the robot's accepting behavior and ease of interaction.

3.3. Introduction to publication

Within the chapter modelling social behaviour of robots based on the application of neural networks in robotics, two articles were published (6: Probierz et al. 2022; 7: Probierz, 2023).

This paper presents the feasibility of using Tiny-ML methods in social robots for face recognition. Social robotics is one of the fastest growing areas of robotics, with companion, educational, and therapeutic robots entering people's daily lives. Social changes, such as an aging population, are leading to an increased need for robots to interact with humans. One of the key challenges in social robotics is the correct recognition of humans by robots, which is crucial for initiating human-robot contact. Social robots are tasked with interacting with humans, which requires real-time human recognition. Face recognition has become extremely important in the context of social robots. There are several approaches based on different technological solutions, such as distance sensors, lasers, cameras and microphones. High performance has been demonstrated for the recognition of visual objects using video recordings or image sequences. Classical high-performance solutions may not be feasible to implement in social robots with limited computational power. To avoid this problem, solutions based on Tiny Machine Learning are used, which promote the construction of fast, efficient, and computationally inexpensive machine learning and neural network solutions. Due to this limitation, a system consisting of an OhBot robot, a Raspberry Pi microcomputer and a Neural Stick is proposed. The goal is to implement facial recognition using tinyML solutions to quickly identify a person with whom the robot can engage in conversation or action. For this purpose, an implementation with YOLOv4 tiny networks as well as YOLOv5s using the OpenVINO solution was carried out. The tests were performed on a Raspberry Pi 4 model B WiFi DualBand Bluetooth 8GB RAM 1.5GHz microcomputer. The results show the superior performance of the YOLOv5s network compared to the YOLOv4-tiny network. After implementation, a series of tests were conducted focusing on detecting a person in an image to start a conversation and detecting the wearing of a face mask. In the case of person detection, the script was designed to automatically start a conversation when a person was detected at level 0.7. In the case of mask detection, the script was designed to automatically detect if people are wearing a mask or not, or if they are wearing it incorrectly. The resulting methods show that the YOLOv5s network performs better compared to YOLOv4- tiny, and the use of Neural Sticks significantly speeds up the face recognition process.

The second article deals with emotion detection and recognition in the context of human-robot interaction. The article points out that it is not enough to simply analyze a human face in order to recognize emotions. It is also crucial to understand the context in which the person is placed. Such a comprehensive analysis allows for a more accurate classification of emotions, which in turn leads to a more appropriate match between the robot's behavior and the social situation. Today's social robots, which are designed to interact with humans in a variety of scenarios, need to be equipped with advanced emotion recognition tools in order to effectively communicate and respond to human needs. For the analysis, the Emotic Database was used to identify 26 different emotions. This database was designed to recognize emotions based on the face and posture of a person, as well as the context of the image. The use of such a database allowed a more thorough investigation of the effectiveness of different emotion detection methods under different conditions. Two neural network models were used in the study: Faster R-CNN and YOLOv3. In the first stage of the analysis, both models were tested without any changes in their structure. Then, modifications of these networks were proposed, introducing the possibility of internal classification, which allowed to obtain more satisfactory results. The introduction of these modifications was aimed at increasing the efficiency of emotion detection under different conditions, which is crucial for improving the quality of human-robot interaction. The simulation results for both networks are presented in the form of tables that compare the effectiveness of emotion detection for different categories. These results show that both networks achieved similar results, although in some categories one network proved to be more effective than the other. Potential limitations of the methods and the need for further research in this area are also highlighted. In conclusion, the study provides insight into the potential of using neural networks for emotion detection and recognition in the context of human-social robot interaction. The results are highly relevant for the further development of social robot technology and can contribute to improving the quality of their interactions with humans. They also point to the need for further research in this area to better understand what factors affect the effectiveness of robot emotion recognition and how it can be improved.

3.4. Summary of Chapter 3

The chapter discusses various aspects of modeling robot social behavior, with a focus on robot-human social interactions and the use of technologies such as machine learning and neural networks to analyze and interpret these interactions. The dynamics of social interactions are presented, where information seeking behavior is predicted first by psychological rigidity and then by curiosity. The impact of robot interaction on human behavior has also been analyzed, especially in the context of special education. Lattice Computing (LC) models combined with machine learning techniques were used to construct representations of a child's behavioral state.

The causal relationship between the actions of the robot and the observed behavioral states of the child was investigated. An interdisciplinary approach combining developments in artificial intelligence and machine learning with cognitive theory leading to developmental robotics is of great importance. The benefits of this approach are presented with a case study of the role of the body in early word learning and developmental robotics models for perceptual, social, and language development. In the context of modelling social behavior, the challenge of acquiring appropriate data and a new approach to learning discrete models of human-robot interaction from small data sets are presented. The example of this research shows that conducting research in social behavior modeling also depends on the target application context. Next, the focus was on selected specific behaviors, such as empathy. It was analyzed how important it is for robots to be able to empathize with humans and to express appropriate emotions. The topics of humor and the influence of auditory/verbal speech features on the quality of social robot interaction were also addressed. Within the chapter, two articles have been developed that are part of the stream of research related to social behavior modeling in social robotics. The first article focuses on the use of tinyML methods in social robots for face recognition. It presents the use of tinyML technology to quickly recognize a person with whom the robot can engage in conversation or action. Tests conducted on different networks, such as YOLOv4-tiny and YOLOv5s, showed the superior performance of the latter. These results are relevant for initiating human-robot contact and can significantly speed up the facial recognition process (Probierz et al. 2022). In contrast, the second article focuses on emotion detection and recognition in the context of human-robot interaction. It emphasizes the importance of analyzing a person's context for more accurate emotion classification. It uses two neural network models, Faster R-CNN and YOLOv3, and presents modifications to these networks that improve the efficiency of emotion detection. These results have important implications for the advancement of social robot technology and could improve the quality of their interactions with humans.

In summary, the chapter focuses on an interdisciplinary approach to modeling robot social behavior using technologies such as machine learning and neural networks. The relevance of this topic is highlighted by the growing interest in social interactions between robots and humans and the need to understand and interpret these interactions. An analysis of the literature on the subject and of the two key papers described in the introduction of the publication shows the importance of the Tiny-ML technology and the modifications of the Faster R-CNN and

YOLO v3 networks in the field of face and emotion recognition, which could lead to innovative directions for development in the field of social robotics.

3.5. Publications:

6. Probierz, E., Bartosiak, N., Wojnar, M., Skowronski, K., Galuszka, A., Grzejszczak, T., & Kędziora, O. (2022, August). Application of Tiny-ML methods for face recognition in social robotics using OhBot robots. In 2022 26th International Conference on Methods and Models in Automation and Robotics (MMAR) (pp. 146-151). IEEE.
7. Probierz, E. (2023). On Emotion Detection and Recognition Using a Context- Aware Approach by Social Robots- Modification of Faster R-CNN and YOLO v3 Neural Networks, European Research Studies Journal Volume XXVI Issue 1, 572-585.

Article 6

Application of Tiny-ML methods for face recognition in social robotics using OhBot robots

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***Abstract*—The aim of this paper is to show the possible application of Tiny-ML family neural networks to social robots for face recognition. Social robotics is a constantly developing field that allows the production and development of robots whose task is to accompany humans, participate in social situations and perform specific educational, entertainment and therapeutic tasks. One of the fundamental problems of social robotics is the proper recognition of humans by robots. This poses a critical problem because it is the moment when human-robot contact is initiated. Widespread solutions, in addition to high efficiency, also require adequate computing power, which in social robots cannot always be provided. For this purpose, solutions from the Tiny-ML stream are used, i.e. such a construction of neural networks and machine learning that would be adapted to limited technological resources and, at the same time, equally effective. The paper uses a YOLOv4-tiny network, which was compared to a YOLOv5s solution, both in terms of efficiency and processing time. The proposed networks were tested on social robots of the OhBot type and with extended capabilities, by using Neural Sticks. The results obtained show the highest efficiency of the implemented YOLOv5s network using a Raspberry Pi along with an accelerator. The presented research is an opportunity to draw attention to the problem of computational complexity in robotic applications, and also has the potential to popularize social robots and their use in everyday life.**

Keywords—Social robots, OhBot robots, Face detection, Tiny-YOLO, Neural networks

I. Introduction

Social robotics is one of the fastest growing branches of robotics. Companion robots, educational robots or therapy support robots are the directions in which robots from the industrial hall are entering the everyday lives of ordinary people [1, 2]. The design, construction and implementation of social robots is a challenge that is being taken up by both research centres and large technology corporations. The changes that are taking place in society contribute to and reinforce the need for an increasing use of robots in everyday human contact [3]. One of the important factors is the ageing of the population, which leads to a change in the proportion of older people, who are becoming more numerous every year. As indicated, there is currently a lack of specialist staff in developing and highly developed countries who can provide adequate care for the elderly. This is where rehabilitation and companion robots come into play [4]. Also, global changes leading to the widespread migration of people are contributing to the increased use of educational robots [5]. As indicated, the main cause of children's educational problems is the lack of adequate education in a language that is not their mother tongue, in which education is currently provided. The use of a personal educational robot to accelerate language learning leads to equal opportunities and better education for children. Also children suffering from autism and Asperger's syndrome have a chance to benefit in a real way. According to research, the appropriate use of therapeutic robots contributes to improving their functioning in everyday environments, including with their peers [7]. However, regardless of the reasons that make social robots more widely used, some basic assumptions must be met to enable human-robot communication. The main purpose of this article is to implement neural networks from the Tiny-ML family to actual robotic system with all of its restrictions and limitations. The Tiny-ML neural networks are widely developed. Their main goal of this networks is to be able to implemented in microcomputers or other constrained systems. However, the solutions presented are not often tested on the target systems. The main novelty and purpose of this paper was not only to use networks from the Tiny-ML family but also to implement them into a real robotic system and to check the operation under such conditions.

The aim of this paper was to implement a tiny-ML version of the YOLO family of networks. These networks are widely used, but there are no many reports of their real-world implementation into robotic systems. The implementation has been carried out using a Raspberry Pi minicomputer and the Intel Neural Stick 2 computational optimiser. The results obtained indicate that despite the choice of tiny-ML networks, the use of the optimiser significantly speeds up network operation. This is particularly important in systems where not only the selected solution but also a number of other solutions are in operation. From the research conducted, one of the most important lessons learned is that the effectiveness and speed of the network when implemented end-to-end into a running robotic system can be significantly different from the isolated systems on which it was trained.

II. Related works

A. Social Robots

Social robots are robots whose task is to interact with humans. To make this possible, robots are required to perceive humans in real-time, both before, during and after a task. When a robot is having a conversation with a single human, it should be able to recognise the face of its interlocutor and follow it, even if the interlocutor changes location [7]. These requirements have made human face recognition, as an indirect feature of social robots, extremely important. Among the approaches used, it is important to distinguish those that are based on different technological solutions. Social robots recognise people using distance sensors, lasers, cameras or microphones. The different technological approaches have varying degrees of effectiveness. In terms of recognition of visual objects by means of video recordings or sequences of photographs, high effectiveness is demonstrated. As results from studies conducted by other researchers, the biggest challenge becomes face recognition in different conditions and the hardware and computational limitations of social robots in relation to standard computing computers [8]. Classical solutions with high performance may not be implementable to the limited power of social robots. In order to avoid this situation, solutions requiring fast response times and low computational power use the Tiny Machine Learning approach, a trend that promotes building fast, effective, and above all not computationally intensive machine learning and neural network solutions. This approach represents a new path of solutions, the combination of which is seen from 2020 [9].

B. Tiny-ML - origins and application

Tiny ML or machine learning and artificial intelligence solutions are a new trend present in technology. These solutions are often referred to as Edge AI [10]. Their main objective is the ability to perform calculations directly on microprocessors, even those powered by batteries. This marks a significant shift in the development of technology, which is moving from cloud computing operations directly to microtechnologies. Such a solution has several advantages, one of the most frequently mentioned being improved security - data is not sent, processed and transmitted back, but it also represents an opportunity to construct many solutions with new functions that were not available before. As pointed out, performing computations directly on microprocessors allows to ensure low latency, which in the context of social robot development, is a key issue [11]. TinyML solutions are already used in industrial predictive maintenance, allowing machines to be constantly monitored and faults to be predicted in advance. They are also being used in healthcare projects, such as the Solar Scare Mosquito project. This project uses tinyML to detect conditions conducive to the spread of mosquito-borne diseases, and thanks to constant solar power, it can operate for many years. Similar solutions are also being used in agriculture, where applications help detect disease found on plants without the need for an internet connection. This means that machine learning models are run directly on the device, and disease detection on a given plant can also take place in areas where there is no internet coverage. These and other applications to date point to the wide range of possibilities for using TinyML, including in social robotics [12,13]. Applying machine learning models directly to robots is a prospect that offers invaluable opportunities both by increasing responsiveness and by reducing the need to maintain a continuous internet connection.

III. System architecture

The system architecture consists of an OhBot-type robotic head, a Raspberry Pi-type microcomputer and a Neural Stick. The purpose of the designed system is to implement facial recognition using tinyML solutions, which will allow for the rapid detection of a person with whom the robot can enter into conversation or action. This solution allows the robot to search the environment almost continuously and only trigger further robot contact activation programmes when a face is detected. Thanks to the use of tinyML, a person who appears within the vision range of the camera located in the social robot will be recognised almost immediately, the robot will come to life and human-robot contact will take place. For the project, OhBot social robots were used, which were connected to RaspberryPi 4 minicomputer, whose computing power is supported by Intel Neural Stick 2.

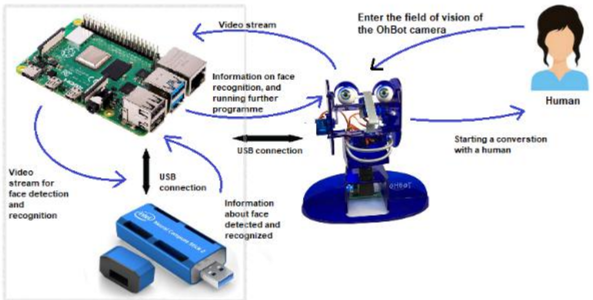

Fig. 1. System architecture diagram

The robot carries out a continuous analysis of the camera field. To detect a person in the field of view of the robot's camera, the visual data are sent to the minicomputer, where the pre-defended data are analysed by means of a neural network on the Neural Stick, whose task is to detect and recognise faces. The feedback the minicomputer receives is whether a face has been detected, in which case the minicomputer triggers a further sequence of actions to communicate between the robot and the human and sends this command to the social robot.

A. OhBot robots

OhBot social robots are technological solutions that resemble the human head. They consist of a series of servos allowing them to move their eyes, eyelids, mouth and even their entire head. The robots are fully programmable in Python, which enables the implementation of various tinyML solutions, also using the TensorFlowLite library. Fully integrated with other dedicated technological equipment, the robots are able to receive visual, auditory and tactile stimuli, detect tilt or light changes. Additionally, with the use of other extensions, it is possible to communicate not only via the Internet, but also via the telephone network and analyse data based on the LIDAR system. The robots are fully programmable, which means that both their movement, the sequence of their programmes or the overlapping of solutions must be programmed and implemented in the robot itself. This enables the continuous development of the social robot and makes it possible to analyse visual, audio and other data and create a robot that is able to respond adequately to the results of these analyses [14].

B. Face detection using neural networks

Face detection belongs to the broader concept of image-based object detection. The most commonly used solutions are those based on neural networks. The predominant choice is convolutional neural networks (CNNs), due to their predisposition to find patterns from images [15]. The structure of these networks allows the classification and labelling of detected objects, which determines their further potential. Some of the most popular networks for face detection are R-CNN, Fast R-CNN, Faster R-CNN and YOLO [16]. According to the literature review, YOLO networks are currently the most popular solution for face detection. It allows real-time face detection and achieves better time than other networks offering this feature [17]. The basic solution existing in YOLO is the generation of regions on which image bounding frames are formed. It is inside these frames that the classifier is triggered. In order to improve frame detection, enhancement methods are applied to post-processing so that duplicates are eliminated [18]. A given network analyses many frames and many similarities to a selected object class. It should be noted that there are many solutions of the YOLO family, in this work the tinyYolo solution is used, which allows implementation in solutions with limited computational power. This solution has been repeatedly used and tested on various datasets and shows satisfactory performance in face detection [19]. As an alternative to tinyYolo, it was decided to propose our own network, kept in the TinyML stream, which could combine all the advantages of the tinyYOLO network applied to social robots. It should be mentioned that in addition to the YOLO family of networks, R-CNN (Fast and Faster) networks are equally popular. In the conducted tests, it has been shown that R-CNN networks have similar or higher efficiency as YOLO family networks. In this paper, however, it has been decided to use the YOLO ones as there is no tiny-R-CNN equivalent currently available, which would allow implementation on microcomputers. The current architecture of the robot system includes a Raspberry Pi 4GB which is too little RAM to process non-tiny-R-CNN family networks.

C. Neural Stick

In order to optimise and accelerate the social robots, a solution of the types Intel Neural Compute Stick 2 (Intel NCS2) is integrated along with the minicomputer to extend AI inference by increasing performance [20]. This solution enables analysis and processing based on machine learning solutions and neural networks without the need for cloud computing and is compatible with the operating systems required for social robot programming. In addition, the solution distributes the OpenVINO toolkit, which allows the implementation of convolutional neural networks while ensuring low power consumption and real-time operation. An extensive library of functions and pre-optimised kernels are available in the solution and, most importantly, these toolkits are fully compatible with Raspberry Pi minicomputers [21].

IV. Tiny neural network design

For the analyses, it was decided to use two solutions based on neural networks. The first solution is a proposed network from the tiny-ML stream, tiny-YOLO v4, the second neural network is YOLOv5s. Both networks were trained on the same data sets, prepared in the same way, and then tested using a solution consisting of a social robot of the OhBor type, a Raspberry Pi minicomputer and a computation accelerator of the Intel Neural Stick type.

A. Neural networks architecture

It was decided to use and compare two YOLO network architectures with each other. The first one is YOLO v4 in a tiny version, the second one is YOLO v5 in a small version. The YOLO v4 version differs from the previous ones by minor changes [22,23]. The basic architecture consists of Backbone based on CSPDarknet53, Neck based on Spatial pyramid pooling and Path Aggregation Network and Head based on Class subnet and Box subnet. Head remained almost unchanged from YOLOv3. Leaky RELs were used as an activation function for the tiny model. YOLO v5 was proposed by other authors, including Glenn Jocher. YOLO v5 includes 5 models: *s*, *m*, *l*, *x* and *n*, which correspond to network size and increasing accuracy. In this research, the YOLOv5s version was chosen to offer the highest speed of the proposed models [24]. The YOLOv5 architecture is based on Backbone CSPDarknet53, Neck based on Path Aggregation Network and Head based on Yolo layer generating three feature map sizes to achieve multi-scale *[25].* Multi-scale detection is particularly important in the context of detecting objects with changing size due to a change in scale. In the case of social robots, an approaching human will first be detected with the smallest size (18x18), and as the human approaches the robot this size will increase to a large size (72x72).

B. Data preparation

The datasets were prepared using the Roboflow Tool. The prepared datasets were then imported into the tiny-YOLOv4 and YOLOv5s networks. Network training was implemented using Google Colaboratory Services. It provides 2 CPUs @ 2.2GHz (Intel Xeon), 13RAM and Nvidia Tesla K80 as GPU. Training was made on two datasets.

The first dataset was MS COCO [26]. This is a large-scale dataset that allows detection and segmentation, as well as labelling and classification of objects visible in images. COCO is an acronym for Common Objects in Context and its main purpose is to improve image recognition. Due to the wide applicability of this dataset for many state-of-the-art networks, it was decided to use it also in this study, so that the results obtained from training could be compared to the other results of both the same networks trained by other researchers and different solutions. The main features of the COCO collection are more than 200,000 labelled images, where the total number of all images is more than 300,000. The collection offers 80 object categories, i.e. instances that can be easily labelled (human, car), and 91 categories of things that may not have clear boundaries (e.g. sky, grass). In the whole collection there are approx. 250,000 people with marked key points necessary for person detection. The files was divided into Train images (about 18GB), Validation images (about 1GB) and Train to Validation annotations (241 MB). Training time on COCO dataset and Google Colaboratory Services was almost 13 hours.

Fig. 2. 17-key points to mark people in MS COCO

What is important from the point of view of the proposed solution and use in social robotics is the presence of 17 key points allowing to mark key points with values (x,y,z). The x and y values denote the coordinates of a given point, while v denotes its visibility (visible, invisible). The 17 points include: nose, left eye, right eye, left ear, right ear, left arm, right arm, left elbow, right elbow, left wrist, right wrist, left hip, right hip, left knee, right knee, left ankle, right ankle. A full depiction is shown in Figure 2.

The second dataset was a set that allowed the network to be trained to detect whether a person was wearing a mask, not wearing a mask, or wearing it incorrectly [27]. The collection consisted of 853 images. Both one and the other network were trained with a data split of 70:30. Division into 70:30 was applied to have the opportunity to compare results to other papers that also used this dataset. All of them decide on ratio 70 to 30. To analyse the results, we chose to include measures such as precision, recall and F1-measure (equation 1). Total training results (for both neural networks and both dataset) are given in Table I.

$$F_1 = 2 \cdot \frac{\text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}} = \frac{\text{tp}}{\text{tp} + \frac{1}{2}(\text{fp} + \text{fn})}. \quad (1)$$

TABLE I. Mean and 95% Confidence Intervals For Precision, Recall and F-measure over 10 Training and Evaluation Rounds

Network + Dataset	Precision	Recall	F-measure
YOLOv4-tiny, MS COCO	0.44 (0.51-0.37)	0.37 (0.31-0.43)	0.42 (0.45-0.39)
YOLOv4-tiny. Face Mask	0.89 (0.81-0.96)	0.77 (0.74-0.80)	0.83 (0.77-0.89)
YOLOv5s, MS COCO	0.49 (0.54-0.44)	0.41 (0.44-0.37)	0.45 (0.49-0.41)
YOLOv5s, Face Mask	**0.93**[a] (0.88-0.98)	**0.81**[a] (0.76-0.86)	**0.86**[a] (0.81-0.91)

a. Best performing model and dataset for each metric.

The trained networks were then developed as executables and transferred to the target device, a Raspberry Pi minicomputer. The results obtained in Table I indicate higher performance of the analysed metrics for the YOLOv5s network. This network obtained better performance in both one and the other dataset.

V. Implementation on Ohbot robots with neural sticks

The implementation was carried out with both networks using the OpenVINO solution. It was decided to use the two proposed solutions in order to test the network speed on a Raspberry Pi 4 model B WiFi DualBand Bluetooth 8GB RAM 1.5GHz microcomputer. Tests were conducted with and without Intel® Neural Compute Stick 2 (Intel® NCS2) accelerator. Based on the results of the tests carried out, it was decided on the final implementation tested experimentally on specific scenarios for OhBot-type robotic heads. The most important parameter for the implemented models was the value of frames per second (FPS), the full list of which can be found in TABLE II.

TABLE II. FPS Mean Frame Rates for Tested Models

Network + Dataset	Raspberry Pi	Raspberry Pi + Intel Neural Stick 2
YOLOv4-tiny, MS COCO	4.3 FPS	13.1 FPS
YOLOv4-tiny. Face Mask	7.1 FPS	24 FPS
YOLOv5s, MS COCO	5.7 FPS	17.1 FPS
YOLOv5s, Face Mask	8.3 FPS	31.2 FPS

The results obtained show the superiority of the YOLOv5s network, on both datasets. The highest results were obtained with the Intel Neural Stick 2, that is, by using the accelerator. This means that for the final tests YOLOv5s will be used and the Intel Neural Stick 2 will be plugged into the Raspberry Pi minicomputer.

VI. Experimental results

In order to implement the presented solution, it was decided to carry out a series of tests allowing the use of the YOLOv5s network allowing the detection of specific categories included in the MS COCO and in the set allowing the detection of face masks. Due to the prioritization of person detection by social robots, a series of tests centered around this theme were designed and extended based on the other capabilities of the network.

1. Detecting a person in an image to start a conversation

The aim of this task was to implement a function to automatically start a conversation when a person is detected at level 0.7. Also the value of 0.7 was decided because of the results obtained in Table I. In context of robots working with human, the precise classification is an important aspect. To prevent misdetection high value of threshold was set up. It should be noted that persons are detected by the network from level 0.5 onwards, but values lower than 0.7 indicate a greater distance between the person and the robot. When a person is detected, a script is activated which consists of the following steps:
1. Detection of a person at level 0.7.
2. Response of the robotic head: Good morning, would you like to talk to OhBot?
3. Waiting for a response.
4. Analysis of the person detection level, increasing the value means the person approaches closer, while decreasing it means moving away.
5. In case of a positive answer, switching to an automatic chat bot script.
6. When there is no answer or an unclear answer, the robotic head responds: Come closer so I can understand you better.
7. The moment the robot stops detecting a person the script is automatically cancelled.

2. Detection of face mask

The aim of this task was to implement a function to automatically detect whether people have a mask on or not, or whether they have it on incorrectly. Only values above 0.7 are analysed due to the same reasons as presented in scenario 1. The scenario script consists of the following steps:

I scheme:
1. Detection of a person wearing a mask at level 0.7.
2. Reaction of the robotic head: Good morning, thank you for wearing the mask!
3. Response of the robot:: Would you like to talk to OhBot?
4. If you get a positive answer, it switches to an automatic chat bot script.
5. If there is no answer or a negative answer, the script is terminated.

II scheme:
1. Detection of a person wearing a wrongly worn mask at level 0.7.
2. Response of the robotic head: Hello, I have an impression that your mask is not worn correctly. Could you please correct it?
3. Image analysis. If a person wearing the mask is detected at level 0.7, run the first scheme.
4. If OhBot again detects an incorrectly worn mask at level 0.7, repeat the request (point 2).
5. In case of detection of no mask at level 0.7 proceed to the third scheme.

III scheme:
1. Detection of a person without a mask at level 0.7.
2. Reaction of the robotic head: Good morning, I think you do not have your mask on, could you put it on?
3. Image analysis. If the person wearing the mask is detected at level 0.7, start the first scheme.
4. If the person is again detected not wearing a mask at level 0.7, repeat the request (point 2).
5. If an incorrectly donned mask is detected at level 0.7, the second scheme is started.

For the first scenario of the experiment, 40 trials were conducted. 36 times the robot correctly detected a person and initiated a conversation with them. 11 persons did not engage in further conversation, while the remaining 25 persons engaged in further conversation with the chat bot of the robotic head.

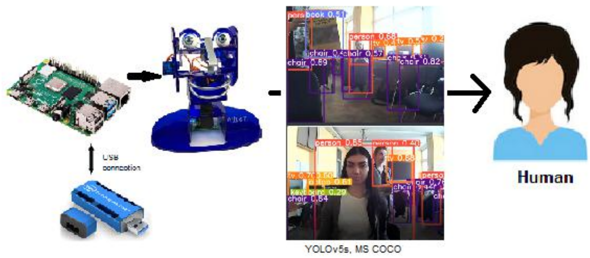

Fig. 3. Detecting a person in an image to start a conversation - architecture scheme.

For the second scenario of the experiment, 120 trials were conducted. 58 times the robot correctly detected the mask on, of which 33 people (57%) chose to continue the conversation with the OhBot. 7 times the robot did not correctly detect the mask being worn. 27 times the robot detected an incorrectly worn mask, of which 17 people (63%) corrected the mask. 10 people did not engage in conversation with the robot or correct the mask. 6 times the robot did not detect the incorrectly worn mask. 13 times the robot correctly detected people missing their mask, of which 4 people (31%) put on their mask and continued the conversation with the robot and the remaining 9 moved away. 6 times the robot incorrectly detected the absence of a mask on the person.

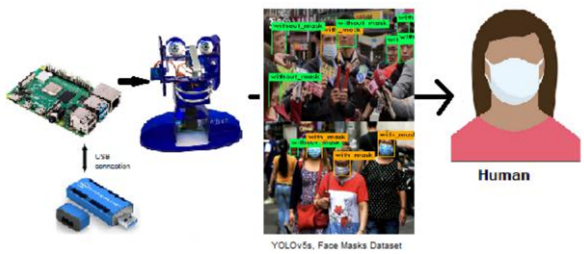

Fig. 4. Detecting of face mask - architecture scheme.

VII. Conclusion and Future Work

The aim of the research conducted was to analyse and implement available networks for person and face detection, for implementation in OhBot social robots. Two networks and two solution architectures were tested. The network demonstrating the highest efficiency and quality of operation turned out to be YOLOv5s, which best results were obtained on an architecture combining a minicomputer and a computational accelerator. Such a solution was integrated with a social robot, and then a series of tests were carried out to check the performance of a given solution in practice. The obtained results indicate that in most cases the implemented schemes worked and could be used in the activities connected with communicativeness and interactivity of social robots. One of the most important limitations of this study is that the tiny-YOLO network was tested only on Raspberry Pi microcomputers. It is necessary to compare the performance to solutions like Google Coral or Nvidia Jetson. Another limitation is the presence of additional processes that may interfere or disrupt the network. Further tests will be carried out comparatively: without and with the accompanying processes, so that it can be determined to what extent and in what way they affect the speed of the network. The proposed solutions are only one of many functionalities implemented in social robots, while they are particularly important due to their ability to start and open a conversation with a human. In further work, it is planned to implement social robot schemes for other classes and solutions allowing to have a conversation with more than one person.

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Article 7

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On Emotion Detection and Recognition Using a Context-Aware Approach by Social Robots– Modification of Faster R-CNN and YOLO v3 Neural Networks

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Abstract:

Purpose: *This paper points out that it is not sufficient only to analyze the human face, but it is also necessary to know the context. This allows for a more accurate classification of emotions, and thus a more appropriate match between the robot's behavior and the social situation in which it finds itself.*
Design/methodology/approach: *Proper situation assessment through a social robot is a fundamental and necessary skill at this point. In order for such an evaluation to be correct, it is necessary to distinguish certain criteria whose fulfillment can be responsible for the robot's better understanding of human intentions. One such criterion is the identification of the interlocutor's emotions. For the analysis, Emotic image database has been used, whose unique character allows to identify 26 emotions, understood as discrete categories. This database is constructed in such a way that it allows to detect emotions from both the face or posture of a person, as well as from the context that occurs in the picture.*
Findings: *The models chosen to solve the problem are Faster R-CNN and YOLO3 networks. In this paper a two-stage analysis is presented. Originally with no changes in the network structure along with the measurement efficiency. And then, as a next step, modifications to the aforementioned neural networks were proposed by introducing the possibility of an internal classifier that allowed for more satisfactory results.*
Practical Implications: *The analyzed solutions allow implementation in social robots due to the speed of operation, but show some hardware requirements. Nevertheless, they are an important support for social robots in social situations and have a chance to be the next step to their dissemination in everyday life.*
Originality/Value: *Emotion detection and recognition is an essential part of the human-robot relationship. Proper recognition increases the acceptance of robots by humans.*

Keywords: *Emotion recognition, emotion detection, neural network, Faster R-CNN, YOLOv3, social robots*

JEL classification: *D12, D47, D53.*
Paper type: *A research study.*

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1. Introduction

Social robots take part in a variety of social scenarios in which humans have certain needs.A set of assumptions about specific actions, attitudes, displayed emotions, or structure exists in a social context, and this knowledge is referred to as social intelligence (Mileounis *et al.*, 2015). The more a person accurately perceives and transmits a clear message, the more satisfying a particular social setting is for each participant since it allows for comprehension and proper communication.

How much a social robot has created social knowledge will influence how well it is gotten by individuals and how well it cooperates with them (Barchard *et al.*, 2020). When people communicate with one another, they send a variety of signals, including facial expressions, postures, the manner they speak, and what they say or do. The emotions that the interlocutor is experiencing at the time influence the content of the message.

When emotions are recognized correctly, the context of the statement is recognized correctly, and there is less information noise in communication (Qureshi *et al.*, 2016). A feeling is a psychological express that occurs when someone experiences or imagines a circumstance (Hirth *et al.*, 2011). The ability to correctly express and recognize emotions is linked to social intelligence, as well as the environment or culture in which a person was raised (Kim *et al.*, 2008).

Emotions are divided into numerous categories in order to classify and name distinct states. The divide between simple and complicated emotion (Thuseethan *et al.*, 2020) is the most common division. The term ”simple emotion” refers to a group of basic emotions that share a common denominator of universal occurrence (Paiva *et al.*, 2014; Rybka and Janicki, 2013).

Numerous endeavors have been made to discern basic emotions based on images (Tsiourti *et al.*, 2019; Leo *et al.*, 2015; Perez-Gaspar *et al.*, 2016), indicating that the methods used are highly accurate and effective. Composite emotions are variously defined as composites of many simple emotions with the addition of extra continuous characteristics like intensity (Wiem and Lachiri, 2017).

Ekman’s (Wiem and Lachiri, 2017) and Plutchik’s (Esau *et al.*, 2007) wheel models are the most popular. Deep neural networks face various difficulties in detecting and recognizing them. However, continuing research shows that emotion identification is extremely accurate (Ebrahimi Kahou *et al.*, 2015; Levi and Hassner, 2015; Jain *et al.*, 2019).

According to the aforementioned studies, there are numerous techniques to effectively detect simple and complicated emotions based on facial photos in the field of emotion detection. However, there are significant downsides to this technique, which become especially important when integrating the given algorithms into social robots. The first issue is that not every face, or even a portion of one, is available for examination. When there is no face in a snapshot, the algorithm is unable to analyze emotions. The key is to take a gander at both the faceposture and the setting of the photograph (Bendjoudi *et al.,* 2020). This method also allows for the consideration of more than one individual in the snapshot.

Because social robots are expected to participate in a variety of social contexts, it is necessary to consider that the robot will see a variety of interactions, including human-robot, human-human, and robot-robot interactions. Context analysis allows us to account for the links between the actors in a social context, reducing the possibility of artifacts that could lead to misinterpretation (Chen and Whitney, 2021). Social robots are already used in a variety of applications, indicating that further research could lead to improved robot-human interaction and, as a result, increased robot efficiency.

Currently, social robots are being successfully used in rehabilitation, supporting it, pushing people to be more methodical, and facilitating training monitoring (Kellmeyer *et al.,* 2018). Another application is for early diagnosis of depressive symptoms based on the study of patterns and routines of behavior, detection of changes in facial expression or speech, and maintenance of the therapeutic process in the treatment of mental diseases (Cao *et al.,* 2018). They can also help people age gracefully by helping with every day exercises, working with mental and actual wellbeing journals (Broekens *et al.,* 2009).

The use of robots in the development of social skills for people with autism spectrum disorders is a common application, as it allows for the development of certain competences based on a recurring pattern of behaviors and cause-effect correlations (Cabibihan *et al.,* 2013). The prospect of deploying social robots as private tutors is also mentioned in personalized education, allowing for the adaptation of the chosen subject matter to the level of development (e.g., children of immigrants who better their learning of a language that is not their native language) (Heerink *et al.,* 2016).

The work on enhancing the capabilities of social robots can possibly be not simply hypothetical, but also practical, due to the development opportunities mentioned. It is a broad field that provides for growth in many areas (Koziarski and Cyganek, 2018). Emotion discovery and acknowledgment dependent on both the faceposture and the specific situation visible in the image is the problem addressed in this study.

This is to allow for emotion recognition in photographs with multiple people or if faces aren't visible. The EMOTIC database, which comprises images of people in diverse places and scenarios, will be used for this purpose. Two algorithms will be used to examine the photos, allowing for quick calculations. For the use of emotion recognition and practical deployment of social robots, speed of operation is critical.

As a result, the EMOTIC picture database was trained using the YOLOv3 and Faster R-CNN algorithms, with extensive descriptions and results provided below. The results for the same collection of photographs but other algorithms were also analyzed.

2. YOLO v3

Darknet (Redmon and Farhadi, 2018) built the YOLO network, and v3 is the third and enhanced version of the network. YOLO stands for ”You Only Look Once.” This network employs one Darknet variation, consisting of 53 layers that were trained on a batch of ImageNet images. The number of these levels is placed on top of the 53 layers, totaling 106 layers, which is the YOLO v3 fundamental architecture.

The ability to identify at three different scales distinguishes this network from its predecessors. This means that detection can be done using a 1 x 1 kernel, but on three separate feature maps with varied sizes and locations throughout the network. The prediction is made at three scales that reduce the input image by 32, 16, and 8 percent, respectively.

Because theimage’s fine granularity is preserved, this property enables for the detection of small objects. This network supports cross-error based class prediction, i.e., utilizing logistic regression, as opposed to the prior version’s quadratic errors-based approach. A Softmax layer is not present in this network since its presence would suggest that each image must be assigned to only one class (Ju *et al*., 2019). Because this layer is missing, many labels can be applied to a single image; the greater the class score predicted using logistic regression, the higher the ranking.

3. Faster R-CNN

In 2015, the Faster R-CNN network was created as a follow-up to the R-CNN family of networks (Ren *et al.*, 2015). A region creation technique that locates an object on a map, feature generation for objects, classification of objects into classes, and a regression layer that allows for more accurate coordinates for specific objects are all common elements in all networks. The region proposal technique is what sets Faster R-CNN apart from the other networks in this family.

A selective search algorithm was previously proposed, but it required CPU calculation and was slower. RPN or convolutional network is utilized in Faster R-CNN to produce regions that will be evaluated later. This reduces analysis time while also allowing for the sharing of a given region between layers, which improves feature representation. The underlying network is made up of an RPN (region proposal algorithm) and a Fast R-CNN (detector). The network is anchor-based in both this framework and YOLO v3, and regression is used again. The most significant distinction is in the manner in which it operates.

YOLO v3 does regression classification of the bounding boxes simultaneously, whereas Faster R-CNN does it in two steps. This means that utilizing the YOLO v3 algorithm (Mao *et al.,* 2019) has no drawbacks.

Faster R-CNN is difficult to implement in real-time due to the two-step structure. On the other hand, the speed of the aforementioned algorithm is sufficient to be deemed a social robot functionality that does not require real-time. It was decided to conduct the investigation using the Faster R-CNN implementation (Ho *et al.,* 2019), which allows this model to be applied in real-time.

4. Experimental Results

4.1 EMOTIC Database

The EMOTIC database has 23,571 photos representing 34,320 people (Kosti *et al.,* 2019). It is a compilation of data from the COCO (Lin *et al.,* 2014) and Ade20K (Zhou *et al.,* 2017) databases. This database is unusual in that it comprises images of individuals in a variety of scenarios and scenarios, in a variety of settings, allowing for a diversified collection in terms of activities, social circumstances, and quantity of individuals.

The database has been tagged, allowing for the assignment of several emotions from 26 distinct categories to each individual. Unlike traditional emotion detection databases, this database contains not only photographs of faces, but the entire picture of a scene. The database's creators identified the 26 emotions based on a review of dictionaries and psychiatric texts, allowing for the formation of clusters of terms with comparable meanings.

From these clusters, 26 categories were chosen, taking into account the element of emotion distinguishability based on the photo, as well as six basic emotions that have been studied previously. The level of agreement for the tagged photos was also evaluated so that the information gathered could be used as a valid reference source.

The categories were: affection, anger, annoyance, anticipation, aversion, confidence, disapproval, disconnection, disquietment, doubt/confusion, embarrassment, engagement, esteem, excitement, fatigue, fear, happiness, pain, peace, pleasure, sadness, sensitivity, suffering, surprise, sympathy, and yearning.

The developers of the database (Kosti *et al.,* 2019) provided detailed definitions for the different categories. Among the database's fundamental statistics, it should be mentioned that 66% of the characters are male and 34% are female. The majority of the characters are adults (83%) although there are also youngsters (10%) and teenagers (7%) (Kosti *et al.,* 2019).

Figure 1. *Example of a image from EMOTIC database*

Source: *Kosti et al., 2019.*

4.2 Simulation Results on YOLOv3

YOLO v3 was the model used. TensorFlow 2 (Lin *et al.,* 2014) does this, allowing the network to be trained on a GPU. The annotations for the EMOTIC database were converted using convert2Yolo (Zhou *et al.,* 2017), which creates a text file with class assignment information and image dimensions. The text files were placed in a label folder, while the processed photos were placed in a directory.

After that, a 70:30 split was used to construct a training and test set. The executable was constructed by first creating a file with the names of 26 emotion categories, and then using the dataset that had been constructed. The batch parameter was set to 64, and each network layer’s line classes were adjusted to correspond to the 26 emotions. The filter values were also changed as a result.

The entire network is based on a Darknet 53 structure consisting of 53 convolutional network layers (Lee *et al.,* 2020). Anchors are employed in this model to identify areas, and the entire network is based on a Darknet 53 structure consisting of 53 convolutional network layers.

Table 1*. Performance scores (AP) for emotic dataset*

Labels	CNN (Kosti *et al.*, 2019)	GCN (Zhang *et al.*, 2019)	EmotiCon (Mittal *et al.*, 2020)	YOLO v3	Faster R-CNN
Affection	26,01	**46,89**	45.23	31.12	29.47
Anger	11,29	10,87	**15.46**	14.74	11.29
Annoyance	16,39	11,27	**21.92**	18.41	21.16
Anticipation	58,99	62,64	**72.12**	67.25	71.18
Aversion	9,56	5,93	17.81	**18.81**	14.39
Confidence	81,09	72,49	68.65	77.53	**86.84**
Disapproval	16,28	11,28	19.82	**20.54**	18.46

Disconnection	21,25	26,91	**43.12**	33.02	27.56
Disquietment	20,13	16,94	18.73	17.42	**23.21**
Doubt/Confusion	33,57	18,68	35.12	31.89	**35.47**
Embarrasement	3,08	1,94	14.37	**17.22**	6.04
Engagement	86,27	88,56	**91.12**	89.11	87.26
Esteem	18,58	13,33	23.62	**25.55**	22.73
Excitement	78,54	71,89	93.26	**95.62**	92.19
Fatigue	10,31	13,26	16.23	18.41	**19.47**
Fear	16,44	4,21	**23.65**	19.92	17.52
Happiness	55,21	73,26	74.71	76.70	**77.41**
Pain	10,00	6,52	13.21	11.29	**14.12**
Peace	22,94	32,85	34.27	30.12	**36.87**
Pleasure	48,65	57,46	**65.53**	29.99	24.36
Sadness	19,29	25,42	23.41	24.20	**26.07**
Sensitivity	**8,94**	5,99	8.32	8.46	6.71
Suffering	17,60	23,39	26.39	**27.44**	25.81
Surprise	21,96	9,02	17.37	16.74	**24.12**
Sympathy	15,25	17,53	34.28.	31.85	**36.44**
Yearning	9,01	10,55	**14.29**	12.81	9.47
mean	28,33	28,42	**35.48**	33.31	33.29

Source: *Own study.*

4.3 Simulation Results on Faster R-CNN

Initial assumptions were required by the model (Ho *et al.*, 2019). Along with cuDNN, a CUDA package was installed, enabling for GPU processing. This made it possible to train the Faster R-CNN network on a GPU with 8GB of RAM (using cuDNN). The network uses the default anchor solution, which consists of 256 image channels and nine potential windows (anchors) produced by multiplying three areas by their coefficients.

This corresponds to three areas, 1252, 2562, and 5122, respectively, for coefficients 1:1, 1:2, and 1:3. The anchor placements and parameters can be determined using a mixture of classification and regression layers. For the region proposal network, determining these is critical (RPN). A pre-trained network (Gao *et al.*, 2018) is used in the model to detect features in the image.

Because the initial layers differentiate edges or color patches that are universal independent of the implemented set, this is achievable. The computed regression coefficients for the envelope were used to change the generated anchors (i.e., windows). This enables us to generate foreground and background windows that will be used by the region proposal network (RPN).

The threshold value distinguishes between background and foreground anchors; if the value is higher, it is a foreground anchor; if the value is lower, it is a background anchor. The default settings specified by the authors were used to train the model, namely a threshold of foreground anchors above 0.7, background anchors below 0.3, and batchsize for RPN 256. The next step was to examine the above layer's Region of Interest (ROI) to determine the foreground and background ROIs.

Foreground ROIs are utilized above 0.5, whereas background ROIs are used between 0.5 and 0.1, and the batchsize for ROIs is 128. Furthermore, a fraction factor of 0.25 is employed, implying that the number of foreground ROIs cannot exceed batchsize fraction. The final stage is a classification layer, which allows a class to be assigned to a certain window. A detection threshold is set that permits as many envelopes to be drawn in the image as there are classes assigned to a window. Articles by the developers and modified versions of Faster R-CNN (Jiang and Learned-Miller, 2017; Chen *et al.,* 2018; Fan *et al.*, 2016) provide a more detailed discussion of the architecture.

Similar findings were achieved in all of the tests. The average score for both networks was 33. This isn't the finest score in the literature, but it's close to the 35.48 (Mittal *et al.,* 2020) score. The emotions produced the best outcomes for the Faster R-CNN network: confidence, disquietment, doubt/confusion, fatigue, happiness, pain, peace, sadness, surprise and sympathy. To be used on the YOLO v3 network. The emotions that produced the best results were aversion, disapproval, embarrassment, esteem, enthusiasm, and suffering. For YOLO v3, the results were similar for both networks. Faster R-CNN outperformed Faster R-CNN in 14 areas.

Table 2. *Performance scores (AP) for emotic dataset on modified neural networks*

Labels	CNN (Kosti *et al.*, 2019)	GCN (Zhang *et al.*, 2019)	EmotiCon (Mittal *et al.*, 2020)	YOLO v3	Faster R-CNN
Affection	**45.23**	31.12	29.47	30.14	41.41
Anger	**15.46**	14.74	11.29	12.12	13.88
Annoyance	21.92	18.41	21.16	16.48	**27.48**
Anticipation	72.12	67.25	71.18	69.44	**82.04**
Aversion	17.81	**18.81**	14.39	18.44	14.02
Confidence	68.65	77.53	86.84	71.79	**88.44**
Disapproval	19.82	20.54	18.46	**21.88**	19.43
Disconnection	**43.12**	33.02	27.56	31.94	38.25
Disquietment	18.73	17.42	23.21	15.47	**27.81**
Doubt / Confusion	35.12	31.89	35.47	36.44	**39.44**
Embarrasement	14.37	**17.22**	6.04	17.02	14.70
Engagement	**91.12**	89.11	87.26	90.78	89.38
Esteem	23.62	25.55	22.73	**26.77**	25.31
Excitement	93.26	**95.62**	92.19	91.45	94.15
Fatigue	16.23	18.41	19.47	19.44	**22.66**
Fear	**23.65**	19.92	17.52	18.40	19.12
Happiness	74.71	76.70	77.41	72.88	**79.49**
Pain	13.21	11.29	14.12	10.61	**16.77**
Peace	34.27	30.12	36.87	29.11	**45.63**

Pleasure	**65.53**	29.99	24.36	31.25	40.47
Sadness	23.41	24.20	26.07	22.22	**28.08**
Sensitivity	8.32	8.46	6.71	6.55	**9.09**
Suffering	26.39	27.44	25.81	26.05	**29.12**
Surprise	17.37	16.74	24.12	22.18	**31.71**
Sympathy	34.28.	31.85	36.44	27.44	**38.43**
Yearning	**14.29**	12.81	9.47	11.03	14.22
mean	35.48	33.31	33.29	32.59	**38.09**

Source: *Own study.*

4.4 Comparison

It was chosen to compare the collected results to three previously published solutions. The authors of the EMOTIC database (Ho *et al.*, 2019) proposed the classic CNN, as well as graphical modification (Zhang *et al.*, 2019) and the EmotiCon solution (Mittal *et al.*, 2020). CNN (Kosti *et al.*, 2019) is made up of two feature extractions.

The first contains feature extractions from highlighted text, while the second has feature extractions from the entire image. After they've been distinguished, they're joined using the Fusion network, and their emotion category scores are calculated. The graph network (Zhang *et al.*, 2019) has two branches, one of which is a convolutional network and the other of which employs RPN to highlight image windows. Then, taking into account the interrelationships between the highlighted windows, an emotional graph is built for them.

This information is then combined with the convolutional network, and emotion categories are highlighted.. The last answer achieved the best result in the comparison. Each of these networks uses the strategy of identifying and classifying images based on their collation of selected windows.

The network presented by the base authors had the best sensitivity result; it is also worth mentioning that the results of Faster R-CNN were comparable to CNN. For affection, the graph network based on the convolutional network produced the best results. The Emoti-Con network had the greatest performance in this category: anger, annoyance, anticipation, disconnection, engagement, fear, pleasure and yearning.

4.5 Simulation based on Modified Faster R-CNN with Classifier

Based on the literature analysis, it was decided to modify the Faster R-CNN network with the approach proposed for vehicle detection (Nguyen, 2019). In this approach, a soft non-maximal suppression (NMS) algorithm is used at the anchor generation stage of the RPN, allowing better results for repeated positions. The use of a soft solution is important here, since a classical one could lead to complete item removal.

The soft solution allows the ROI to be updated with neighbor proposals and the winning proposal based on objectivity evaluations. In practice, this means that when, for example, two context elements or two face elements are superimposed on each other in a photo, the algorithm will distinguish them, then evaluate which one is the neighbor and which one is the winning item with an assumed cross-validation factor of 0.5 (Hu *et al.,* 2018).

Another element that modifies the network is the use of context-dependent ROI fields (Nguyen, 2019). Using this mechanism allows the proposal size to be adjusted to a fixed size, but without the occurrence of inaccurate representations in forward propagation and the occurrence of increased errors in backward propagation.

That is, if the proposal size is larger than the predetermined feature map size, it will be reduced to the item size from the fixed size using the output feature map. If the proposal image is smaller then a deconvolution operation will be applied, allowing the proposal size to grow to a fixed value. The final element of the change is the application of a classifier allowing the extracted features to be used for classification. This allows the classification of propositions into an emotion class and an emotion class for context (Nguyen, 2019).

4.6 Simulation based on Modified YOLOv3 - YOLO-tiny

In order to improve the results for the YOLO3 network, it was decided to use a simplified model of this network called YOLO-tiny (Lestari *et al.,* 2019). This model in contrast to its larger counterpart contains only 7 convolutional layers (not 53) and 6 max-pooling layers. This network uses a CBL or Convolutional Batch Normalization Leaky Relu model which allows to combine several functions, i.e., convolutional layer, batch normalization layer and Leaky Relu (Zhang *et al.,* 2020).

This allows for a significant speed up of the model, however, the risk of inappropriate feature extraction is indicated, which may lead to inaccurate classification.

The results obtained indicate that the use of YOLO-tiny did not achieve higher performance than YOLO3, or other models tested. The lack of accurate feature extraction, due to the reduced size of the model, is probably indicated as the reason for the results obtained. In contrast, the modified Faster R-CNN model obtained satisfactory results, allowing for higher performance in detecting the indicated emotions not only compared to the classic Faster R-CNN, but also to the model presenting the highest performance to date (Mittal *et al.,* 2020).

Importantly, the modified network no longer exhibits the biases seen in the classical solution. That is, it has increased both those scores that, in similar network arrangements, also came out quite high, but most importantly it has managed to obtain higher recognition performance for other emotions that previously had a much lower recognition rate by the Faster R-CNN network.

5. Discussion and Conclusion

This research examines the use of neural networks to recognize emotions in social robots as a means of assisting in the right interpretation of social situations and its participants. Two networks were chosen for this purpose, YOLO v3 and Faster R-CNN, both of which can be implemented in real time. EMOTIC images were used to train the architects, which allowed them to detect and assign 26 different emotions.

While no average greater than the EmotiCon network was obtained, the results are promising. Therefore, it was decided to modify both networks and undertake recalculations for their modified versions. While the YOLO-tiny network did not obtain satisfactory results, the modified Faster-R-CNN network allowed higher scores for the detected emotions. Nonetheless, this outcome is satisfactory for several emotion categories. Others will need to put in more time studying and training the network.

However, the gathered data can provide a crucial component for a social robot, which might combine the results of picture and text analysis and make judgements about the emotions displayed in a given social context based on the two aspects.

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4. Modelling selected social components using the PID controller in social robotics

4.1. Introduction

Social robotics focuses on the interactions between robots and humans, and how robots can be integrated into various aspects of society. In the context of social robotics, controlling the speed of a mobile robot using an algorithm inspired by the social optimization of a spider based on a PID controller has become an important issue (Khan et al., 2023). Here, kinematic modeling is used to understand the mechanical behavior of the robots, and motor speed control is achieved using a PID controller that adjusts the appropriate parameters to achieve precise control of the robot's speed. Also in the field of social robotics, the use of different nonlinear control techniques is important to ensure adequate tracking of the trajectory and velocity profile that performs the movements of the humanoid robot's arms and head (Gomez-Quispe et al., 2023). In this case, different nonlinear control techniques such as nonlinear proportional derivative control with gravity compensation, backstepping control, and sliding mode control are analyzed and compared to achieve adequate trajectory tracking. With respect to modeling social components, it is also important to understand how robots can continuously evolve through interactions with their physical and social environment, mimicking human learning processes and cognitive development (Taniguchi et al., 2023). In this context, the concepts of world models and predictive coding are key to understanding how cognitive systems learn to model their environment, predict future sensory observations, and optimize their control strategies.

The PID (Proportional-Integral-Differential) controller is a commonly used tool in automatic control. It works by continuously calculating the error between the setpoint and the actual output and applying a correction based on the proportional, integral, and differential components of the error1. In the case of mobile robots, these three components are adjusted to achieve precise motor speed control. In the work of Khan et al. (2023), a Social Spider Optimization (SSO)-inspired algorithm was used to tune the parameters of the PID controller, which enabled precise control of the robot's speed, especially in the presence of disturbances and uncertainties. In the context of social and assistive robotics, the PID controller can be used in a variety of applications. In Social Assistive Robots (SARs), which aim to provide social interaction to users in different assistance scenarios, such as medication reminders or monitoring of daily activities, there is a need to adapt the robot's behavior to different health conditions and user contexts. In the work of Benedictis et al. (2022), an approach based on a user model and a novel control architecture was proposed to synthesize personalized training sessions for elderly people, adapting the robot's verbal behavior to the user's characteristics. For industrial applications such as Automated Guided Vehicles (AGVs), the PID controller can be optimized using different algorithms such as Particle Swarm Optimization (PSO) and Beetle Antennae Searching (BAS) to better control the robot's trajectory in different paths such as circles, ellipses, or spirals. In a study by Xiong and Wang (2022), a fuzzy adaptive PID control strategy was applied to synchronize the collaborative trajectories of two industrial robots, demonstrating the effectiveness of the method and greater flexibility in the distributed control mode. In conclusion, the PID controller plays a key role in modeling selected social components in social robotics. Its application in different contexts, from controlling the speed of a mobile robot to adapting social interactions in assistive robots, opens new possibilities in the field of robot-human interaction. This research sheds light on several dimensions of social robotics that are crucial for its further development and application.

4.2. Literature review

Research on modeling selected social components using the PID controller in social robotics has identified several key aspects that address the topic of PID controllers and social robotics. One study looked at combining two optimization algorithms, atom search optimization and particle swarm optimization, to create a hybrid algorithm called hybrid atom search particle swarm optimization (h-ASPSO) (Izci, Ekinci, Hussier, 2023). This algorithm was applied to the design of a proportional-integral-differential (PID) controller for automatic voltage regulators and wind turbines based on a double-fed induction generator. The results showed that h- ASPSO outperformed the original atom search optimization in terms of convergence speed and solution quality, providing promising results for various higher order engineering systems. Another study presented speed control of a wheeled mobile robot using a PID controller (Khan et al. 2023). In this work, the Social Spider Optimization (SSO) algorithm was applied to the PID controller.

The main objective of the work was to demonstrate the effectiveness of the proposed approach in achieving precise control of the robot speed, especially in the presence of disturbances and uncertainties. Another study investigated the introduction of a dual-design PID controller architecture process to improve system performance by reducing overshoot and saving electrical energy (Chotikunnad, Chotikunnan, 2023). The results showed that the dual-design PID controller was more effective in reducing overshoot and saving electricity. The paper also reports on an adaptive, robust Jacobian-based controller for controlling position tracking in the task space of robotic manipulators. The controller structure was built on a traditional PID framework and an additional control signal was synthesized to compensate for internal and external disturbances in the robot dynamics (Nguyet, Ba, 2023). A new approach to controlling the position of a microrobotic system using a PID controller is also presented (Ghith, Tolba, 2022). Using the sparrow search algorithm (SSA), optimal PID controller rates were obtained using a new objective function called integral square time multiplied square error (ISTES). Simulation and experimental results showed that the SSA PID controller based on the ISTES cost function achieved the best performance compared to different techniques, and the error was reduced by 50% compared to other experiments.

One possible use of PID controllers is to study and model the handshake in robot-human interactions (Avelino et al., 2018). The article presents the handshake as a key element of physical interaction between humans, which has different connotations in different cultures. The authors focus on investigating the grip strength for a comfortable handshake, conducting three sets of experiments with different groups of humans. The experiments are conducted with a social robot whose hands are equipped with tactile sensors to provide skin sensation. The goal is to learn the preferred grip closure for each user group, analyze the tactile sensor feedback for each closure, and develop and evaluate a hand grip controller based on the previous data. The study is based on a social robot whose hands are equipped with a total of 15 tactile sensors that measure the force distribution at multiple contact points. These sensors use changes in the magnetic field to estimate force, and a silicone cover gives them a more human-like feel. The authors conducted two tests: one with predefined finger configurations to gain initial insights, and another in which users had control of the robot's fingers. The robot described, Vizzy, was designed as a human assistant for social interaction tasks. The robot's hands are similar to those of an adult human, but with only four fingers capable of grasping objects. The tactile sensors are capable of detecting minimal forces of 10 mN. The experiment in the study involved a series of handshakes between the user and the robot, with different grip forces labeled "weak," "medium," and "strong. Participants were asked to rate each handshake in terms of strength and comfort. This work adds physical human-robot interaction to the robot's repertoire of social skills, fulfilling a previously identified need of many robot users.

An important study linking the PID controller to social robotics is a project on the control and ability to express emotions by a robot called EMYS (EMotive headY System) (Kedzierski et al. 2013). This is a robot head designed and built as part of the EU FP7 LIREC project to provide technology for the design of companion robots. These robots are designed to accompany humans in different places and situations, and a key capability of social robots is to interact with humans. EMYS is a three-disk structure equipped with a pair of movable eyes with eyelids mounted on a movable neck. The robot head is equipped with a speaker for speech purposes, a CMOS camera, a Kinect sensor, and a microphone for speech recognition. This allows it to visually perceive its environment, track objects and people with its eyes, make and maintain eye contact, pay attention, express emotions, recognize speech and speak. EMYS uses different types of servo motors to control different parts of the head. The robot's neck is driven by Robotis digital servo motors, while eye and eyelid movements are realized by Hitec analog micro servo motors. The robot is controlled by a Freescale microcontroller, which generates control signals for all the servomotors and potentiometers in a PID control loop. The robot is controlled by three levels of control, consisting of a lowest level that implements the basic hardware abstraction, a middle level that implements the robot's capabilities, and a top level that may include a dedicated decision making system, state machines, or a complex software system that simulates some functions of the human mind. EMYS is a valuable contribution to the field of social robotics, offering new possibilities for human-robot interaction and the expression of emotions by machines.

Part of the research focuses on an innovative approach for social robots to express emotions and internal states by changing their skin texture. The authors present a new non-verbal channel for social robots inspired by biological systems that often express their internal states by changing their skin texture. The importance of expressing internal and emotional states in social robotics is highlighted. Most systems achieve this through facial expressions, gestures, movements, and tone of voice. However, a new channel of expression through skin texture changes is proposed, inspired by phenomena such as goosebumps in humans or moulting in animals. It is noteworthy that despite developments in the field of soft robotics, skin texture change as an expression channel remains unexplored. This study presents the design and fabrication of a soft robot skin that can be modulated to express emotions and other internal states through texture change. Two forms of expressive texture change are presented, inspired by skin texture changes found in nature: goosebumps and spikes. A key element of the design is a multi-layered elastomeric skin that changes its surface texture under pressure. The authors use an H-bridge circuit combined with a pulse-width modulation (PWM) signal to control the flow that inflates or deflates the device. Pressure sensors are used as feedback for the closed-loop PID control of the system. After implementing this solution to control different texture states, the authors identified several problems with this approach, such as limited response time, low control accuracy, inefficiency due to air leakage, and noise. To address these challenges, the authors present an alternative control system based on a propeller displacement pump that allows precise volume control and minimizes leakage. In this context, the PID controller is a key element in controlling the fluid system to enable precise control of the robot skin texture.

Another study focused on the impact of the robot's social behavior on human creativity and their perception of the robot as a co-creator (Hu et al. 2021). The authors developed an interactive system to facilitate human-robot collaboration in creative activities. The study involved 12 adults who took turns with the robot to create compositions using tangram projectors on a shared workspace. The paper identifies four human behaviors associated with creativity: accepting the robot's ideas as inspiration, delegating a central role in creation to the robot, communicating creative intentions, and being playful in the creation process. The results suggest that too much control by the robot over the creative process can be counterproductive, and that playfulness plays an important role in the creative process. In this paper, a PID controller is applied to the navigation process of the robot. The PID controller is used to calculate the linear and angular velocity of the robot to reach certain waypoints. This is a key element in controlling the robot's motion to enable precise movement in the projected space, which in turn affects user interaction and collaboration. The above research shows that the PID controller, combined with advanced optimization and modeling techniques, provides a robust and flexible approach to control in social robotics. This allows not only precise control of individual robot components, but also integration into more complex systems, which is crucial for the development of effective and intelligent social robots.

4.3. Introduction to the publication

One article regarding this chapter was published (8: Grzejszczak et al. 2022). The theme article of this chapter focuses on the application of the PID controller in the context of social robotics. The main objective of the study was to maintain eye contact between the robot and the human, which is a key element in human-robot interaction (HRI). For this purpose, a vision system with a face detection algorithm was used as a feedback signal for the PID controller. The distance of the detected face from the center of the image was treated as an error to be minimized by the controller. The testbed consisted of a robot head called OhBot, to which a USB camera was attached. The robot software was written in Python using dedicated libraries. The vision system was based on the OpenCV library and used a face detection algorithm based on Haar cascades. The PID controller was implemented using the simple_pid library. The paper also describes the characteristics of the control system, including its tracking and latency. The use of servomotors in the robotic head introduced some latency, but this was considered negligible in the context of the overall system. The PID controller settings were selected using the Ziegler-Nichols method, resulting in very good control system performance. The authors found that the controlled object could be well represented by inertia with delay, which met the assumptions of the Ziegler-Nichols method. In the context of a vision system, the algorithm for face detection in an image consisted of several steps, including taking an image from the camera, detecting the face, and determining the center of the rectangle surrounding the face. All of these values were then scaled to the interval [0,10], which was the specification of the ohBot library for servo control. The authors also noted that the problem of scaling and geometric distortion due to the physical properties of the camera lens would be the subject of further research. The conclusions of the paper summarized the practical problems encountered in the physical implementation of the system. Nevertheless, this research represents an important step towards understanding and implementing effective control systems in social robotics, especially in the context of maintaining eye contact in human-robot interactions. The use of a PID controller in combination with an advanced vision system demonstrates that it is possible to effectively and accurately control a social robot under dynamically changing human interaction conditions.

4.4. Summary of Chapter 4

Chapter 4, entitled "Modeling selected social components using the PID controller in social robotics", focuses on the application of the PID (proportional-integral-differential) controller in the context of social robotics. The PID controller is a commonly used tool in the field of automatic control that works on the principle of continuously calculating the error between the desired and actual output and applying a correction based on the proportional, integral, and differential components of the error. In the context of social robotics, the use of the PID controller has become an important issue, especially in the speed control of a mobile robot (Khan et al., 2023). Various nonlinear control techniques such as nonlinear proportional derivative control with gravity compensation, backstepping control, and sliding mode control have been analyzed and compared (Gomez-Quispe et al., 2023). In the context of modeling the social components, it was also important to understand how robots can continuously evolve through interactions with their physical and social environment, mimicking human learning processes and cognitive development (Taniguchi et al., 2023). Several key aspects of modeling social components using a PID controller have been reported in the literature. One study looked at combining two optimization algorithms, atom search optimization and particle swarm optimization, to create a hybrid algorithm called hybrid atom search particle swarm optimization (h-ASPSO) (Izci, Ekinci, Hussier, 2023). This algorithm was applied to the design of a PID controller for automatic voltage regulator and wind systems based on a doubly fed induction generator. The results showed that h-ASPSO outperformed the original atom search optimization in terms of convergence speed and solution quality.

In the context of the chapter's theme, which focuses on the application of the PID controller in social robotics, the article under review makes an important contribution to the field of human-robot interaction (HRI). The article stands out because it focuses on a very specific aspect of HRI, namely maintaining eye contact between robot and human. This is a key element in social interactions that has not been fully explored in the context of social robotics. The use of the PID controller in this context was innovative and effective. This controller was used to minimize the deviation of the detected face's distance from the center of the image, which is important for maintaining eye contact. The use of a face detection algorithm based on Haar cascades as a feedback signal for the PID controller was a key element of the system. This combination of vision technology and process control was a unique contribution to the social robotics literature. Compared to the other studies discussed in this chapter, which also focused on the application of the PID controller in different social robotics contexts, the reviewed article offered a practical approach to one of the most subtle but crucial aspects of human-robot interaction. Its significance lies in the fact that it not only theoretically, but also practically demonstrates how the PID controller can be applied to control a social robot in dynamically changing human interaction settings. The conclusions of the article highlight that despite the practical problems encountered, such as latency and scaling, this research represents an important step towards understanding and implementing effective control systems in social robotics. In this context, the article is an important and innovative contribution to the field, opening up new opportunities for further research and practical applications.

In summary, Chapter 4 focused on the diverse applications and capabilities of the PID controller in the context of social robotics. From speed control of a mobile robot, to applications in socially assistive robots, to research on handshaking in robot-human interactions, the PID controller plays a key role in modeling selected social components. Its application in different contexts opens new possibilities in the field of robot-human interaction and is crucial for the further development and application of social robotics.

4.5. Publication

8. Grzejszczak, T., Bartosiak, N., Wojnar, M., Skowroński, K., Probierz, E. (2022). Regulacja pozycji robota społecznego w sprzężeniu zwrotnym z systemem wizyjnym. In A. Świerniak, J. Krystek (Ed*.), Automatyzacja procesów dyskretnych, Teoria i zastosowania*, t. 1, ISBN 978-83-7880-854-1 (pp. 79-86).

Article 8

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REGULACJA POZYCJI ROBOTA SPOŁECZNEGO W SPRZĘŻENIU ZWROTNYM Z SYSTEMEM WIZYJNYM

Streszczenie. Utrzymanie kontaktu wzrokowego jest ważnym aspektem w interakcji człowieka z robotem (HRI). Artykuł przedstawia implementację i procedurę strojenia regulatora PID. Jako sygnał sprzężenia zwrotnego użyty jest system wizyjny umożliwiający wykrywanie twarzy. Odległość wykrytej twarzy od środka obrazu traktowana jest jako uchyb. We wnioskach podsumowano praktyczne problemy napotkane podczas fizycznej implementacji.

POSITION REGULATION OF THE SOCIAL ROBOT IN FEEDBACK WITH THE VISION SYSTEM

Summary. Maintaining eye contact is an important aspect of Human-Robot Interaction (HRI). The paper presents the implementation and tuning procedure of the PID controller. A vision system with a face detection algorithm is used as a feedback signal. The distance between the detected face and the center of the image is an error. The conclusions summarize the practical problems encountered during physical implementation.

1. Wstęp

Robot społeczny to autonomiczny robot, który wchodzi w interakcje i komunikuje się z ludźmi lub innymi autonomicznymi obiektami, przestrzegając zachowań społecznych i reguł związanych z jego rolą [2,3]. Ważnym zadaniem podczas konstrukcji robotów społecznych jest implementacja odpowiednich algorytmów planowania trajektorii, czyli zmiany położenia, prędkości i przyspieszenia w celu sprawienia by interakcja człowieka z robotem (ang. *Human Robot Interaction - HRI*) przebiegała w sposób naturalny [4]. Jednym z aspektów HRI mających na celu polepszenie jakości interakcji jest utrzymanie kontaktu wzrokowego. Udowodniono, że uczestnicy wykazali bardziej skoordynowane i zsynchronizowane multimodalne zachowania między mową a spojrzeniem, gdy z powodzeniem nawiązano i utrzymano większy kontakt wzrokowy [8]. Utrzymanie kontaktu wzrokowego odbywa się najczęściej za pomocą systemu wizyjnego wyposażonego w algorytmy wykrywania twarzy. Najbardziej popularnym algorytmem dającym zadowalające wyniki jest algorytm bazujący na kaskadach Haara który z powodzeniem można zastosować do

HRI [5]. W poniższym opracowaniu zastosowano system wizyjny umożliwiający detekcję twarzy jako sygnał sprzężenia zwrotnego regulatora PID, który wyznacza pozycję robotycznej głowy. Głównym aspektem badawczym jest dostosowanie nastaw regulatora działającego w sposób dyskretny z próbkowaniem zależnym od czasu przetwarzania sygnału wizyjnego [6,7]. Dodatkowo układ posiada 2 wejścia i wyjścia: dla rotacji poziomej i pionowej. Nastawy regulatora dobrano zgodnie z metodą Zieglera Nicholsa [1]. Podobne zastosowania regulacji trajektorii z zastosowanie PID można odnaleźć w przykładach robotów śledzących i podążających za użytkownikiem [9].

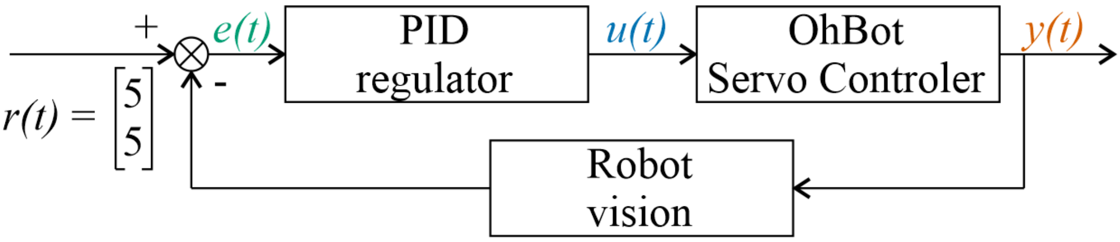
2. Opis stanowiska

Stanowisko robota społecznego składa się z robotycznej głowy, czyli gotowego urządzenia o nazwie OhBot, do którego przymocowano kamerę USB. Stanowisko zaprezentowane jest na rysunku 1. Oprogramowanie robota wykonano w języku Python z pomocą dedykowanych bibliotek. Głównymi elementami stanowiska są:

- Robotyczna głowa w której skład wchodzą serwomotory, kontroler serwomotorów oparty o bibliotekę ohbot, oraz konstrukcja imitująca głowę.
- System wizyjny z kamerą Logitech c920 bazujący na bibliotece *OpenCV*
- Regulator PID zaimplementowany z pomocą biblioteki *simple_pid*

Rys. 1. Stanowisko robota społecznego *OhBot* z kamerą

Postawione zadanie regulacji polega na imitacji kontaktu wzrokowego z użytkownikiem. Celem systemu wizyjnego jest wykrycie twarzy użytkownika a celem regulatora jest korekcja pozycji robota tak aby wykryta twarz znalazła się na środku obrazu. W tym celu utworzono pętlę sprzężenia zwrotnego, zgodnie z rysunkiem 2.



Rys. 2. Schemat blokowy układu regulacji

Układ ma własności nadążne w związku z zastosowaniem serwomotorów. Zastępcza transmisja serwomotoru jest inercją z małym opóźnieniem wynikającą z taniej konstrukcji robotycznej głowy (np. luzy na plastikowych zębatkach). Zakłada się jednak, że opóźnienie jest pomijalne a obiekt dla jakiego będzie projektowany regulator PID jest inercją z opóźnieniem. W rozdziale 4 opisano sposób doboru nastawy regulatora zgodnie z syntezą Zieglera-Nicholsa, jednak alternatywą jest wyznaczenie parametrów dla obiektu zastępczego. Dokonując syntezy regulatora PID zgodnie z regułami Zieglera-Nicholsa zaobserwowaliśmy bardzo dobre własności układu sterowania. W związku z tym, że obiekt może być reprezentowany przez inercję z opóźnieniem, co spełnia założenia metody, wybrana procedura doboru parametrów PID jest metodą referencyjną. Zatem można wnioskować, że inercja z opóźnieniem jest dobrą aproksymacją obiektu sterowania.

Warto zauważyć, że zgodnie ze specyfikacją biblioteki *ohBot*, sygnałem sterującym serwomotorami jest ich pozycja docelowa w przedziale [0,10], dlatego wartością zadaną jest środek przedziału, czyli $r(t)=[5,5]^T$. Każdy pozostały sygnał również jest rozpatrywany w przedziale [0,10].

W związku z tym, że system wizyjny zwraca błąd w osi pionowej i poziomej a sygnał sterujący również przesyłany jest do 2 serwokontrolerów modyfikujących położenie głowy w pionie i poziomie, układ posiada 2 wejścia i 2 wyjścia. Jednak ze względu na brak zależności skrośnych, pętla regulacji jest układem typu 2 x SISO (ang. Single Input Single Output). Każdy z powyższych sygnałów jest wektorem 2 wymiarowym.

3. System wizyjny

Ważnym elementem umożliwiającym pomiar błędu i regulację pozycji robota jest system wizyjny. Opracowany algorytm przetwarzania obrazów składa się z algorytmu detekcji twarzy na obrazie za pomocą kaskad Haara. Testy prowadzono na domyślnych wagach dostarczonych wraz z biblioteką *OpenCV*. Algorytm składa się z następujących punktów:

1. Pobranie klatki z kamery
2. Detekcja twarzy na obrazie (pozycji prostokąta okalającego)
3. Dla twarzy o najwyższej pewności, detekcji wyznaczenie środka prostokąta okalającego (x_F,y_F)
4. Sprowadzenie wyniku do przedziału [0,10]

Należy pamiętać, że wynikiem układu sterowania jest pozycja serwomotoru, czyli $y(t)$, Pozycja ta wpływa bezpośrednio na pole widzenia kamery. Pozycja wykrytej twarzy jest w układzie współrzędnych kamery, więc przed wyznaczeniem uchybu należy proporcjonalnie zmienić wyjście systemu wizyjnego poprzez przemnożenie wartości przez 10 i dzieląc przez wymiary klatki obrazu.

Obliczenia w układzie kamery powinny uwzględniać skalowanie oraz zniekształcenia geometryczne wynikające z właściwości fizycznych soczewek. Są to jednak prace przewidziane w dalszych badaniach mających na celu poprawę jakości. Problem skalowania bezpośrednio przekłada się na wzmocnienie graniczne, co zaobserwowano przy doborze parametrów. Dla wyeliminowania tego problemu założono stałą odległość użytkownika od kamery wynoszącą 1m.

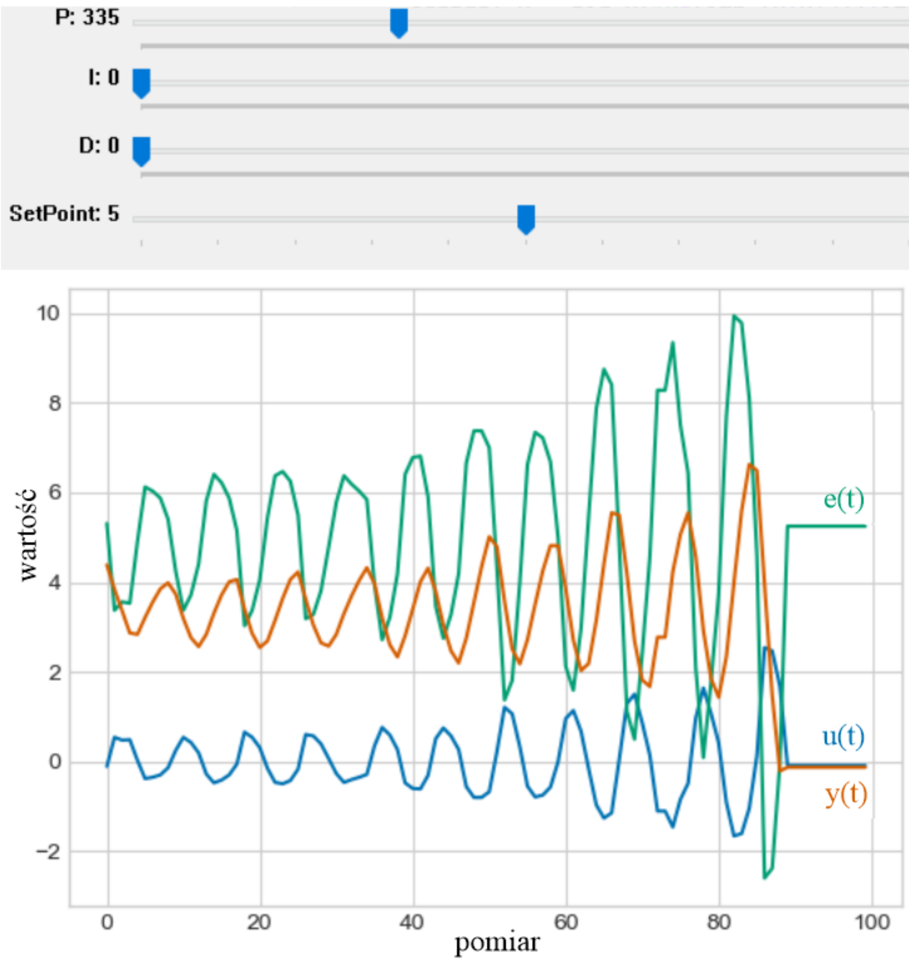
4. Nastawy regulatorów

W celu dobrania odpowiednich parametrów regulatora PID wybrano metodę Zieglera-Nicholsa. Biorąc pod uwagę wzór regulatora

$$K_r(s) = k_r(1 + \frac{1}{T_i s} + T_d s) \tag{1}$$

należy wyznaczyć wzmocnienie regulatora k_r, oraz stałe czasowe elementu całkującego T_i oraz różniczkującego T_d. Program obsługujący system wizyjny i kontroler wyposażono w suwaki, które umożliwiały na bieżąco modyfikacje parametrów regulatora oraz obserwację 100 ostatnich pomiarów. W związku z ograniczeniami implementacyjnymi, wartości PID widoczne na rysunku 3 są dzielone przez 1000, co definiuje dokładność pomiarową.

Pierwszy krokiem metody Zieglera-Nicholsa jest wyznaczenie wzmocnienia granicznego, przy którym w układzie występują nie gasnące oscylacje (układ na granicy stabilności).

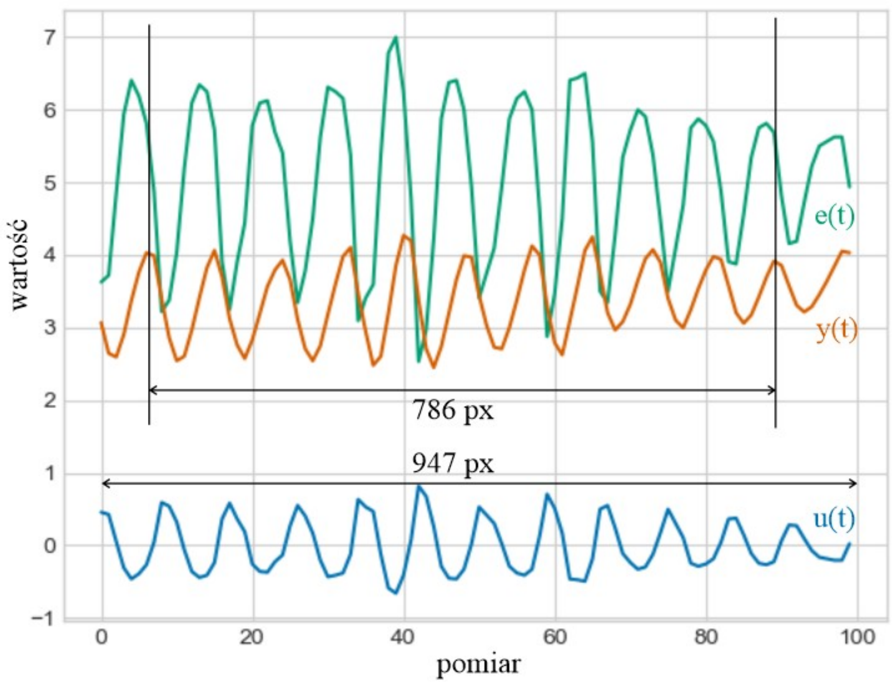


Rys. 3. Destabilizacja układu po próbie ustawienia wzmocnienia granicznego

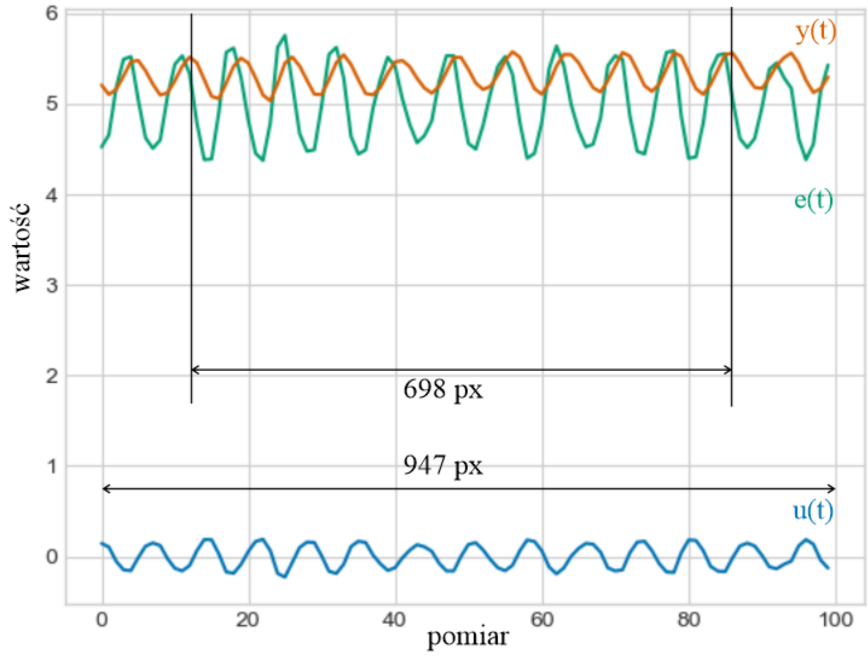
Wartości graniczne to $k_{gr} = [0,301\ 0,331]^T$, dla których przedstawiono przebiegi na rysunkach 4 i 5. W trakcie testów to zadanie okazało się trudne w związku z kilkoma efektami. Po pierwsze układ wymaga dwóch oddzielnych nastaw dla sterowania w pionie jak i poziomie ponieważ zakres ruchu robotycznej głowy w poziomie wynosi 180^{O} natomiast w pionie 90^{O} . Ponadto pole widzenia kamery również jest różne gdyż dostarczany obraz jest w proporcjach 16:9. Innym zaobserwowanym efektem była różna wartość wzmocnienia granicznego w zależności o odległości użytkownika od kamery. Czym dalej znajdowała się osoba tym układ był bardziej wrażliwy. Efekt spowodowany był różnicą między dostępnym ruchem a polem widzenia kamery oraz możliwym zakresem ruchu. Ostatecznie, wszystkie testy wykonywano w odległości 1m od kamery.

Kolejnym krokiem jest wyznaczenie stałych czasowych. W trakcie tego eksperymentu również zaobserwowano ciekawe wnioski wynikające z dyskretnego charakteru układu. Na prezentowanych przebiegach przedstawianych jest 100 ostatnich pomiarów. W zależności od mocy obliczeniowej komputera, pomiary te mogą zajmować zróżnicowany czas. Wykonano trzykrotny pomiar czasu przetwarzania pętli odpowiedzialnej za obsługę serwokontrolera, systemu wizyjnego, regulatora PID i modułu generującego przebiegi czasowe dla generacji 100 pomiarów i uzyskano średnią 9,06 s. Oznacza to, że program operuje średnio z częstotliwością 11 klatek na sekundę, a każdy pomiar na wykresie to około 0,09 s. Istnieje jednak obawa, że dla komputera o innej mocy obliczeniowej obliczenia należy powtórzyć.

Stałe czasowe wyznaczono dokonując pomiaru szerokości cykli na wyświetlanym obrazie. Zapisany obraz z przebiegami posiadał określoną rozdzielczość. Wyliczono, że 100 pomiarów zajmuje na obrazie 947 pikseli, które trwają 9,06 sekundy. Zatem skoro 10 okresów oscylacji ma szerokość 786 pikseli, to trwały one 7,52 sekundy. Zatem okres oscylacji dla osi pionowej wynosi 0,752 s. Podobnie obliczenia dla osi poziomej dają wynik 0,670 s. Zatem $T_{osc} = [0{,}670\ 0{,}752]^T$.



Rys. 4. Układ granicznie stabilny w osi *oy* dla $k_{gr} = 331/1000$



Rys. 5. Układ granicznie stabilny w osi *ox* dla k_{gr} = 302/1000

Implementacja regulatora PID w bibliotece *simple_pid* odbywa się przez podanie trzech wzmocnień $\{k_P, k_I, k_D\}$, natomiast regulator przybiera postać

$$K_r(s) = k_P + \frac{k_I}{s} + k_D s. \tag{2}$$

Zatem w celu wyznaczenia zestawu 3 wzmocnień należy zastosować przekształcenia zgodnie z metodą Zieglera-Nicholsa

$$k_r = k_P = 0.6 k_{gr}\ , \tag{3}$$

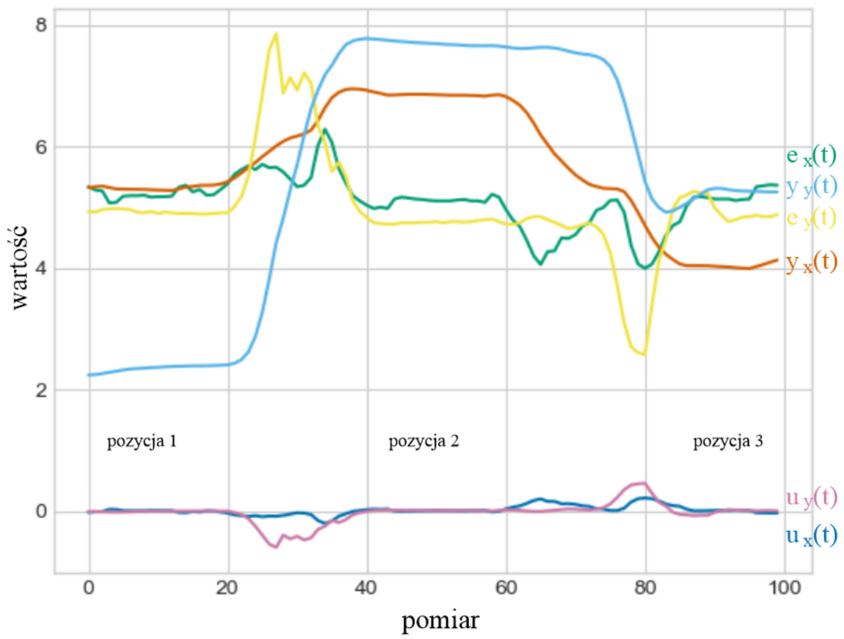
$$T_i = 0{,}5\, T_{osc}\ , k_I = \frac{2\, k_r}{T_{osc}}\ , \tag{4}$$

$$T_d = 0.125\, T_{osc}\ , k_D = 0{,}125\, k_r\ \ T_{osc}\ . \tag{5}$$

Po zastosowaniu przekształceń (3-5), dla przedstawionego przykładu, uzyskano nastawy regulatora $k_P = [0{,}180\ \ 0{,}199]^T$, $k_I = [0{,}0090\ \ 0{,}0088]^T$ oraz $k_D = [0{,}00056\ \ 0{,}00055]^T$. Demonstracja układu regulowanego znajduje się na rysunku 6. W trakcie demonstracji użytkownik zmienił swoją pozycję 3 krotnie, zmieniając wartość wyjścia z układu *y(t)* dla obu osi *ox* i *oy*.

5. Wnioski

Przedstawiona metoda z sukcesem umożliwia śledzenie użytkownika i imitacje utrzymywania kontaktu wzrokowego przez robota społecznego. Robot podąża wzrokiem za twarzą użytkownika. Dobrane nastawy regulatora gwarantują szybką reakcję. Analizując przebiegi można zaobserwować szybką redukcję błędu przy zmianie pozycji trwającej około 1 sekundę (około 7-15 pomiarów), co wskazuje na dobre własności dynamiczne układu. W układzie nie występuje przesterowanie. Scenariusze symulacyjne zostały dobrane w taki sposób aby nie osiągały wartości granicznych [0,10].



Rys. 6. Odpowiedzi układu regulowanego

Problem jednak pojawia się w przypadku gdy na obrazie znajduje się wiele twarzy lub nie wykryto żadnej. W przypadku wielu twarzy robot przełącza się losowo pomiędzy różnymi użytkownikami sprawiając wrażenie niestabilnego. Zastosowano algorytmy poprawiające występujące negatywne efekty takie jak anti-windup dla kumulacji błędu przy niewykryciu twarzy oraz ważenie pewności wykrytej twarzy i podążanie za twarzą o największej pewności wykrycia w przypadku wykrycia wielu.

Ostatni zauważony efekt wynika z geometrii kamery i został opisany w rozdziale 4 przy okazji wyznaczania k_{gr} . Efekt dotyczy wpływu odległości użytkownika od kamery na wzmocnienie graniczne.

6. Dalsze prace

Należy zaznaczyć, że zaproponowana metoda nie jest wolna od wad. Dalsze prace będą skupiać się na uniewrażliwienie systemu na zmienne niezależnie od bodźców zakłócających. Jedną ze zmiennych, która posiada niebagatelne znaczenie jest moc obliczeniowa jednostki. Należy zbadać wpływ osiąganej liczby klatek na sekundę na stałą czasową T_{osc}. Jest to znaczące, ponieważ dalsze prace prowadzone będą w celu maksymalnego uproszczenia systemu, tak aby był on równie wydajny w jednostkach o ograniczonych zasobach obliczeniowych. Kolejnym równie istotnym aspektem jest analiza odległości użytkownika od ekranu. Roboty społeczne wchodzące w interakcje z człowiekiem analizują i przetwarzają dane osób będących w ich bliskiej odległości (w większości do 10m), niemniej analiza i rozróżnienie odległości stojącej osoby lub osób pozwoliłaby na odróżnianie aktywnego rozmówcy od innych uczestników spotkania, a także na wykrywanie osób zbliżających się lub odchodzących od robota.

W celu identyfikacji tych parametrów należy zmierzyć 2 zmienne w systemie i uzależnić parametry PID od ich wartości. Zmiennymi są czas przetwarzania pętli, czyli jednego punktu pomiarowego z wykresu oraz wielkość prostokąta okalającego wynikającego z wykrywania twarzy, świadczący o odległości użytkownika od kamery.

PODZIĘKOWANIA

Praca TG została częściowo wsparta przez Politechnikę Śląską poprzez dotację na utrzymanie i rozwój potencjału badawczego w 2022 roku oraz poprzez dotację na utrzymanie i rozwój potencjału badawczego w 2022 roku dla młodych naukowców numer 02/060/BKM22/0041. Praca NB i MW była wspierana przez Program Mentorski realizowany przez Politechnikę Śląską (Program Mentorski – „Rozwiń Skrzydła") i opłacany z rezerwy Prorektora ds. Studenckich i Kształcenia: MPK: 60/ 001 GŹF: SUBD. Praca PE była wspierana częściowo przez Unię Europejską poprzez Europejski Fundusz Społeczny jako stypendium w ramach Grantu POWR.03.02.00-00-I029, a częściowo przez Politechnikę Śląską poprzez dotację na utrzymanie i rozwój potencjału badawczego w 2022 roku dla młodych naukowców numer 02/060/BKM22/0036.

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Discussion

The topics covered are the subject of a broad discussion on a number of related aspects. These issues are the subject of much research, including interdisciplinary research combining robotics, ethics, psychology, and law. This discussion will describe the difficulties, problems, and risks identified by the authors of the research papers that pose challenges to the development of social robotics in the areas covered in the four chapters above. In the context of social robotics, the misrecognition of emotions by social robots is a serious problem that can have far-reaching consequences. The application of social robotics in various life domains, such as healthcare, education, or social interaction, makes accurate emotion recognition crucial for the effectiveness and safety of these systems (Saganowski, 2022; Khan, 2022; Staff et al. 2020). In this context, errors in emotion recognition can lead to inappropriate responses from the robot, which in turn can trigger negative emotions in the humans with whom these robots interact.

One of the main challenges in emotion recognition is the complexity of the phenomenon of emotions themselves. They are a fundamental part of human life and influence most of our decisions (Saganowski, 2022). Emotions are complex states that bridge different disciplines such as psychology, electronics, signal processing, and machine learning (Saganowski, 2022). Therefore, there is no single, universally accepted definition of emotions, which complicates the task of recognizing them by social robots. In practical applications, misrecognition of emotions can lead to a number of problems. For example, in the context of healthcare, misrecognition of a patient's emotions can lead to inappropriate medical intervention (Khan, 2022). In education, misreading students' emotions can lead to ineffective teaching methods and student frustration (Staff et al. 2020). In social interactions, errors in emotion recognition can lead to misunderstandings and conflicts (Staff et al. 2020). Sensor technologies and machine learning play a key role in emotion recognition. Different modalities can be used to recognize emotions, but first the appropriate sensors must be used to capture these modalities (Saganowski, 2022). Among physiological signals, EEG provides the highest accuracy for emotion recognition (Saganowski, 2022). However, due to the sensitivity of EEG electrodes, it is currently impossible to use EEG in practical applications. Therefore, researchers are focusing on wearable devices that provide various biosynchronous and other environmental data (Saganowski, 2022). In the context of social robotics, the misrecognition of emotions can also affect people's trust in technology. Trust is a key element in human-robot interactions and is essential for the widespread adoption of these technologies2. Errors in emotion recognition can undermine this trust and limit the effectiveness of social robots in various applications (Staff et al. 2020). In summary, emotion misrecognition by social robots is a major challenge that requires further research and development. The complexity of emotions, the technological limitations, and the potential negative consequences of emotion recognition errors make this a critical area for the future development of social robotics (Saganowski, 2022; Khan, 2022; Sttaff et al. 2020).

The security of data analyzed by social robots is also becoming an increasingly important issue. As social robots gain popularity in various areas of life, such as healthcare, education, and social interaction, their ability to collect and analyze personal data and sensitive information is increasing (Yang et al., 2018; Mavrogiannis et al., 2021; Bao et al., 2018). While this data collection capability is beneficial in terms of functionality and efficiency, it also creates new challenges and risks related to data security. One of the key challenges is protecting data from unauthorized access. Social robots are becoming increasingly sophisticated and capable of processing large amounts of data, which in turn increases the risk of data breaches by third parties (Yang et al., 2018). For example, data collected by social robots can be used for marketing purposes, which raises the risk of it being used in an unethical or illegal manner. Data privacy is critical in this context, as data security breaches can lead to serious consequences, such as privacy violations, identity theft, or even threats to public safety (Bao et al., 2018). Another challenge is to ensure data integrity. This means that the data collected and analyzed by social robots must be protected from unauthorized modification (Bao et al., 2018). Data integrity is crucial to ensure the reliability and accuracy of the data, which is particularly important in the context of decisions made by social robots. For example, if human behavioral data is modified by third parties, this may affect the analysis results and decisions made by social robots. In this context, technologies such as blockchain can be used to ensure data integrity, but its implementation in social robotic systems is still under investigation (Yang et al., 2018). The issue of data security in social robotics is also linked to ethical and regulatory concerns. As social robots become more advanced and capable of processing large amounts of data, there is a need to develop ethical standards and regulations for the collection and processing of data by these systems (Mavrogiannis et al., 2021). For example, it is necessary to define what data can be collected by social robots and for what purpose, and how this data can be stored and processed in a legal and ethical manner. In conclusion, the security of data analyzed by social robots is a key challenge that requires further research and development. This includes both aspects of protecting the data from unauthorized access and ensuring its integrity. Furthermore, as social robots become more advanced and capable of processing large amounts of data, it is necessary to develop new methods and technologies to ensure their security, as well as to develop ethical standards and regulations in this regard (Yang et al., 2018; Mavrogiannis et al., 2021; Bao et al., 2018).

Another issue is ethics, which is one of the most complex and controversial. On the one hand, social robots have the potential to significantly improve people's quality of life by providing assistance in various fields such as healthcare, education, and social interaction. On the other hand, their ability to interact with humans on an emotional and social level raises many ethical dilemmas and challenges (Yang et al., 2018). One of the main concerns is the issue of emotional manipulation. Social robots are becoming increasingly sophisticated in recognizing and responding to human emotions, which raises the risk of emotional manipulation. For example, robots can be programmed to elicit specific emotions in humans to achieve specific outcomes, such as increasing sales in retail stores. This is an ethical issue, as emotional manipulation can have negative consequences for the psychological well-being of individuals (Desposato, 2015). Another challenge is the issue of privacy and data confidentiality. Social robots are capable of collecting large amounts of data about people, including sensitive data such as medical information or personal preferences. Protecting this data and ensuring its confidentiality is a key ethical challenge. Breaches of privacy can have serious consequences, such as stigmatization or discrimination (Mavrogiannis et al., 2021). Another issue is accountability for the actions of social robots. As robots become increasingly autonomous, questions arise about who is responsible for their actions, especially in situations where they may have a significant impact on people's lives. For example, in the context of healthcare, social robots may be used to monitor the health of patients and make therapeutic decisions. In such cases, the question of responsibility for errors or failures in robot performance becomes an ethical issue of great importance (Akalin & Loutfi, 2020). In the context of ethics in social robotics, there is also a need to consider cultural and social differences in perception and interaction with robots. Different cultures and communities may have different norms and expectations of social robots, which may affect their acceptance and use. Therefore, the design and implementation of social robots needs to take these differences into account and respond to them ethically (Yang et al., 2018). Ethics in social robotics is a complex and multidimensional issue that requires further research and analysis. It ranges from aspects related to emotional manipulation, privacy, accountability for actions, and consideration of cultural and social differences. As social robots become more advanced and ubiquitous, it is necessary to develop new research approaches and methodologies to understand and address these challenges in an ethical manner (Yang et al., 2018; Desposato, 2015; Mavrogiannis et al., 2021; Akalin & Loutfi, 2020).

Another important aspect is that the problem of social and cultural stereotypes (biases) is a significant challenge that can affect the interaction between robots and humans, as well as the perception of robots in society. These stereotypes can be the result of both machine learning processes and cultural influences, making them difficult to eliminate. Starting with language models, Nangia et al. (2020) note that language models, especially pre-trained ones, exploit cultural biases present in the data on which they are trained. They present the CrowS-Pairs dataset, which aims to measure different forms of social bias in language models. This study shows that these models favor sentences that express stereotypes, which may have a negative impact on their application in social robotics. A Social Categories and Stereotypes Communication (SCSC) framework is also proposed, which integrates different areas of the literature and explains the linguistic processes through which social stereotypes are perpetuated (Beukeboom, Burgers, 2019). They identify two main types of biases in language use that affect perceptions of social categories: biases in the linguistic labels used to describe categories, and biases in the description of the behaviors and characteristics of people in categorized groups. These mechanisms may also be present in interactions with social robots, affecting their ability to interact with humans in an unbiased manner. Mass media and popular culture play an important role in shaping social perceptions of dementia, which in turn influences the stigmatization of people with dementia. Similar mechanisms may affect social perceptions of social robots, especially if they are programmed in ways that perpetuate negative stereotypes (Low, Purwaningrum, 2020). All of this leads to the conclusion that social and cultural stereotypes are deeply embedded in various aspects of society and culture, and their impact on social robotics cannot be ignored. They affect not only the way robots are programmed and how they learn, but also the way they are perceived and accepted in society. Therefore, there is an urgent need for further research in this area to understand how to minimize the negative impact of these stereotypes on the development and implementation of social robots.

Also worth considering are standards and certification, which are key elements in ensuring the safety and efficiency of robots. However, there are a number of challenges and difficulties associated with these aspects that require in-depth analysis and understanding. The first challenge is the complexity and variety of standards that social robots must comply with. It is pointed out that introducing an external standard into an organization can lead to different results depending on the existing norms and practices in the professional community. In one case, it can lead to a culture of cynicism and chaotic working practices, while in another it can lead to a system of standardized practices that are willingly followed (Sandholt, 2012). Another problem is the lack of consideration of the specific safety requirements of the different contexts in which social robots operate. It is also noted that current standards, such as EN ISO 13482:2014, are not adapted to ensure the safety of people in public spaces. This standard does not take into account aspects such as crowds, social norms and principles of proxemics, or inappropriate human behavior (Salvini et al., 2021).The third challenge is compliance with ethical and social norms. It is also pointed out that social robots, especially those used in elderly care, must be compatible with the values of caregivers, such as respect, compassion, and dignity. The introduction of robots that are not in line with these values may lead to resistance from workers and negatively affect the quality of care (Parviainen, Turja, 2021). In the context of these challenges, there is a need to develop more integrated and flexible standards and certification schemes that take into account the diversity of contexts and requirements related to social robotics. This may require both the modification of existing standards and the creation of new, dedicated standards that better address the specific needs and challenges of this rapidly growing field. Implementing such changes will require the involvement of a variety of stakeholders, including robot manufacturers, certification organizations, health and social care professionals, and robot users themselves. Only then will the full benefits of social robotics be realized, while minimizing potential risks and negative impacts. These findings point to the need for further research and discussion to understand and address these challenges. This includes both empirical and theoretical research that can help identify best practices and strategies for standards and certification in social robotics.

The discussion of challenges and issues in social robotics covers many aspects, from emotion recognition by robots, privacy issues, ethics, social and cultural stereotypes, to standards and certifications. Each of these aspects has its own unique challenges that require deep understanding and analysis. Emotion recognition by social robots is critical to their effectiveness in various domains such as healthcare, education, and social interaction (Saganowski, 2022; Khan, 2022; Staff et al., 2020). The problem lies in the complexity of emotions, which is an interdisciplinary phenomenon involving psychology, electronics, signal processing, and machine learning. Errors in emotion recognition can lead to negative consequences, such as inappropriate medical interventions or ineffective teaching methods. Sensor technologies and machine learning play a key role in this context, but they are subject to limitations, such as the sensitivity of EEG electrodes, which hinders their practical application (Saganowski, 2022). Data security in social robotics is another challenge that is becoming increasingly important as robots become more capable of collecting and analyzing data (Yang et al., 2018; Mavrogiannis et al., 2021; Bao et al., 2018). Protecting data from unauthorized access and ensuring its integrity is critical. Data security breaches can have serious consequences, such as privacy violations or threats to public safety. Technologies such as blockchain can be used to ensure data integrity, but their implementation in social robotics systems is still under investigation. Ethics in social robotics is a complex and controversial issue that encompasses many aspects, from emotional manipulation to data privacy and accountability for robot actions (Yang et al., 2018; Desposato, 2015; Mavrogiannis et al., 2021; Akalin & Loutfi, 2020). Emotional manipulation and invasion of privacy are ethical dilemmas that can have negative consequences for the psychological well-being of individuals. Accountability for the actions of robots, especially in the context of health care, is an ethical issue of great importance. Cultural and social differences in perception and interaction with robots also need to be considered in the design and implementation of social robots. Social and cultural stereotypes are another challenge that can affect robot-human interactions (Nangia et al., 2020; Beukeboom, Burgers, 2019; Low, Purwaningrum, 2020). Language models may favor sentences that express stereotypes, which may negatively impact their application in social robotics. These mechanisms may also be present in interactions with social robots, affecting their ability to interact with humans in a non-convex manner. Standards and certifications in social robotics are crucial to ensure the safety and effectiveness of robots, but there are numerous challenges and difficulties related to these aspects (Sandholt, 2012; Salvini et al., 2010; Desposato, 2015). These standards need to be flexible to adapt to different contexts and applications, but at the same time stringent enough to ensure safety and efficiency. Certifications, such as CE in Europe, are key to bringing robots to market, but their use in social robotics is still being researched. The results of this research are key to understanding and solving challenges and problems in social robotics. Each of these aspects needs to be deeply understood and analyzed, and their solution will have a long-lasting impact on the development and application of social robotics in various fields.

Practical application

Social robotics is becoming increasingly popular due to the variety of practical applications in which robots can be used. The variety of environments, roles, and social contexts that can occur indicates a high potential for application, but also the need to adapt and adapt to many very specific conditions. One of the most frequently cited areas where social robotics is being successfully implemented is in healthcare. It focuses on many aspects such as patient care, operation in medical environments, and responses to ethical and privacy issues. Social robots equipped with an emotion recognition framework can monitor patients' emotional states and alert medical staff when intervention is needed. This is particularly useful in psychiatric wards and for patients with emotional or mental disorders (Reddy Devaram et al., 2022). Robots can be programmed to have therapeutic conversations with patients, provide emotional support, and even conduct cognitive-behavioral therapy sessions. This is particularly beneficial for patients who may feel uncomfortable interacting with humans (Reddy Devaram et al., 2022). Emotion modeling can help robots understand when a patient is in pain, allowing for timely administration of medication or other interventions (Reddy Devaram et al., 2022). Robots can also promote patient engagement in their healthcare by providing information, medication reminders, and even facilitating communication between the patient and healthcare providers (De et al., 2021). It is also possible to collect data on a patient's behavior and symptoms, which can be analyzed to improve healthcare delivery. This is particularly useful in chronic disease management (De et al., 2021). Another role may be to act as a facilitator in telehealth consultations, providing a more interactive and emotionally engaging experience than standard videoconferencing (De et al., 2021). It is worth noting, however, that as the use of artificial intelligence and robotics in healthcare increases, so do concerns about the privacy and security of patient data. Advanced algorithms are being developed to ensure the secure exchange of medical data (Khan et al., 2022). There is also the issue of intelligibility, which makes it difficult for healthcare providers to fully trust the technology. Explainable Artificial Intelligence (XAI) is emerging to address this issue (Yang, 2022).

Another practical application is the use of social robots in education. Social robots can be used to monitor the emotional state of students in real time. There is also a practical focus on promoting social interaction and cooperation among students. For example, robots can initiate games and team activities that require cooperation and communication (Reddy Devaram et al., 2022). In an educational context, social robots use advanced emotion and social behavior modeling technologies to tailor their interactions to individual students. Through the use of emotion recognition technologies, such as facial expression analysis and voice analysis, robots are able to monitor students' emotional states in real time (Cavallo et al., 2018). These robots not only diagnose emotions, but also provide emotional support through verbal and nonverbal interactions. They are programmed to respond to students' emotions in ways that promote positive behavior and social skills (Graterol et al., 2021). In addition, robots can adapt instructional materials and methods based on students' emotional state and engagement. For example, if the robot detects that a student is anxious, it can use relaxation techniques before continuing the lesson (Heredia et al., 2022). In the context of special education, social robots can be used as therapeutic tools for children with autism spectrum disorders (ASD). By modeling emotions and social behaviors, robots can tailor their interactions to the individual needs of these children, for example, by simulating emotions and social responses (Cavallo et al., 2018). Robots can also be used for emotional therapy, helping students to understand and express their emotions more effectively (Graterol et al., 2021). In terms of distance learning, social robots can provide personalized materials and assignments tailored to the needs and emotions of individual students (Reddy Devaram et al., 2022). They can also increase interaction and engagement in distance learning, for example by providing Q&A sessions, quizzes, and other interactive activities. Robots can also help teachers monitor student engagement and progress by providing valuable data and analytics. Ultimately, the use of social robotics in education opens up new possibilities for personalized learning and emotional support. Modeling emotions and social behavior in social robots can have a significant impact on the quality of education and the student experience. However, there are also ethical and technical challenges that require further research and regulation.

Another important area where the practical application of social robotics has been recognized is in customer service. The use of these robots in customer interactions opens up new opportunities for personalizing services and improving customer satisfaction. With advanced emotion recognition technologies, such as facial expression analysis and voice analysis, robots are able to monitor customers' emotional state in real time and customize their interactions (Cavallo et al., 2018). Studies show that customers' experiences with service robots are largely positive, evoking emotions such as joy, love, surprise, interest, and excitement (Filieri et al., 2022). Dissatisfaction occurs mainly when robots do not work properly. It is also worth noting that robots evoke more emotions when they move. In the context of telephone service, speech-based emotion recognition technologies can be used to identify a customer's emotional state and adjust interactions with them (Han et al., 2020). For example, if a robot detects that a customer is anxious or upset, it can use techniques to de-escalate the conflict or transfer the call to a more experienced operator. However, the use of social robotics in customer service also raises some ethical and technical challenges. For example, there is a need to ensure a high level of security and privacy of customer data. In addition, the use of advanced algorithms to model emotions and social behavior raises issues of intelligibility and accountability.

The usefulness of social robotics has also been recognized in the area of public safety. The introduction of these robots into public interactions opens up new opportunities for crisis management and enhanced security. With advanced emotion recognition technologies, such as facial expression analysis and voice analysis, robots are able to monitor people's emotional state in real time and adapt their interactions (Cavallo et al., 2018). Studies show that emotions and community attention play a key role in risk perception during the COVID-19 pandemic (Dyer and Kolic, 2020). Social robots can be used to monitor community emotions and attention in real time, which can help with crisis management and communication with the population. For example, if the robot notices that the community is concerned or disturbed, it can apply conflict de-escalation techniques or redirect communication to a more experienced operator. Ultimately, the application of social robotics in public safety opens up new possibilities for crisis management and increased security. Modeling emotions and social behavior in social robots can significantly improve the quality of interactions with the public and their experience of emergency management.

In the context of rehabilitation, social robots are becoming an increasingly important tool capable of modeling emotions and social behavior. Using these robots to interact with patients opens up new possibilities for individualizing therapy and increasing the efficiency of the rehabilitation process. Thanks to advanced emotion recognition technologies, such as facial expression and voice analysis, robots are able to monitor the emotional state of patients in real time and adapt their interactions (Esposito, Fortunati, & Lugano, 2014). Studies show that children with autism can interact more easily with a social robot than with a human peer because the robot's actions are less complex and more predictable (Pennazio, 2017). Social robots can be used to teach children with autism basic social skills, imitation, communication, and interaction. This encourages them to transfer the learned skills to human interactions with adults and peers. In the context of elderly rehabilitation, social robots can be used to monitor emotions and attention in real time, which can help guide therapy and communication with patients. For example, if the robot notices that a patient is anxious or worried, it can apply conflict de-escalation techniques or redirect communication to a more experienced therapist (Graterol et al., 2021). Continuing the analysis, it is worth noting that social robots in rehabilitation serve not only as tools to support therapies, but also as systems capable of adapting and profiling the user. For example, the NAOTherapist project has been developed to monitor a patient's condition and generate models of the user's profile, allowing therapies to be tailored to the patient's individual needs (Martín et al., 2020). The COVID-19 pandemic has also influenced the development of social robotics in rehabilitation. Given the limited access to rehabilitation centers, social robots can be used in home-based therapy, especially for patients with post-intensive care syndromes. A key element in the success of such therapy is remote monitoring of patient engagement and progress (Manjunatha et al., 2021).

In the case of tourism, social robots can be used as guides in museums or amusement parks. For example, one study used social robots in museums, where the robots were able to detect visitors' emotions and adjust their descriptions of exhibits based on the audience's reactions (Graterol et al., 2021). In the context of entertainment, social robots can be used in interactive games, amusement parks, or even movie theaters. Thanks to their ability to recognize emotions, these robots can adapt the difficulty of a game or type of entertainment to the emotional state of the user, increasing the immersion and satisfaction of the experience (Mishra et al., 2021). It should also be noted that social robots in the context of entertainment and tourism are becoming increasingly complex systems capable of interacting with groups of people. For example, the system proposed by Cosentino et al. (2018) makes it possible to recognize the emotions of a group of people by analyzing facial expressions. As a result, these robots can adapt their behavior to the overall mood of the group, which is particularly important in the context of mass entertainment, such as concerts or live performances. In the context of tourism, live streaming has become one of the tools that can help minimize losses in the tourism industry, especially during pandemic periods. Qiu et al. (2021) note that live streaming content mainly evokes positive emotions, which can be used by social robots as a form of interactive remote guidance. The motivation of tourists to participate in various forms of entertainment and tourism is also an important aspect that can be modeled by social robots. Jiang et al. (2021) note that the need for uniqueness, the need for social interaction, and the need for entertainment and leisure are important motivating factors that can be incorporated into social robot algorithms.

In the context of military work, the application of such robots can range from logistical support to interacting with soldiers under difficult emotional conditions. One of the key challenges in this context is to ensure effective interaction between the robot and the human. Kowalchuk and Chubenko (2016) note that emotions can play a role in the design of intelligent autonomous systems, such as military robots. For example, emotion modeling can be used to better understand and predict soldier behavior, which can be critical in situations that require rapid response. In research on modeling the impact of emotions in social networks in a military context, such models can be used to analyze and predict the impact of emotions on group behavior, which is particularly important in the context of team missions (Wang et al., 2015).

The last of the more widespread practical applications is the use of social robots as domestic helpers. One of the key challenges in this context is to ensure effective interaction between the robot and the human. The ability of robots to recognize human emotions can play a key role in their integration with humans. In the home context, such a capability can be used to monitor people's emotional state and adjust the robot's actions in response to these observations (Esposito et al., 2014). It is also suggested that smart home environments can use multi-agent systems to manage various aspects of home life, such as health and safety. Emotion modeling can be used to better understand and predict the behavior of household members, which can be critical in situations that require quick responses (Augusto et al. 2010). Research on the application of social robotics in the context of smart homes highlights that such systems can be used to manage various aspects of home life, from health to security. In this context, modeling emotions and social behavior can play a key role in ensuring effective interaction between the robot and household members (Rodriguez et al., 2008).

Social robotics has applications in a variety of fields, from healthcare to education to customer service. In healthcare, these robots monitor patients' emotions and adjust their actions, which is particularly beneficial in chronic disease management and psychiatric care. In education, social robots promote social interaction and cooperation among students by tailoring their interactions to the needs of individual students. In customer service, these robots increase customer satisfaction by personalizing services. In public safety, these robots can be used to manage emergencies and enhance security. In rehabilitation, social robots adapt therapies to individual patients' needs, which is particularly beneficial for therapy management and patient communication. In tourism, these robots can be used as guides in museums or amusement parks, adapting their descriptions of exhibits based on the audience's response. In a military context, these robots can be used to provide logistical support and interact with soldiers under difficult emotional conditions. In a domestic assistance context, these robots can be used to monitor the emotional state of individuals and adjust the robot's actions in response to these observations. In each of these contexts, there are ethical and technical challenges that require further research and regulation.

Summary and conclusions

In this dissertation, a series of studies were conducted on modeling emotions and social reactions in social robotics using artificial intelligence. The research conducted was subsequently published in the form of a publication list. The list consists of 8 publications, which are grouped into 4 thematically aligned chapters as part of the description in this paper.

The first chapter focused on modeling emotional responses in robotics using artificial intelligence and machine learning. Various theories of emotion, such as affect theory, fear theory, and basic emotion theory, were discussed as a basis for developing algorithms for emotion recognition and generation. The ability of robots to express emotions through various channels, such as speech, gestures, and facial expressions, has been considered. Machine learning techniques, including neural networks, were used to generate emotional expressions from sensory data. Special attention has been given to emotion recognition and adaptive emotional responses. Various machine learning techniques, such as convolutional and recurrent networks, have been applied to recognize emotions from data such as speech, facial expressions, and body movements. Potential applications of affective robotics in areas such as healthcare, education, and social interaction were also discussed. Challenges and possible directions for future research were highlighted, including the need to personalize affective robots and integrate them with other technologies such as the Internet of Things. The first article focused on emotion recognition from text in social robot conversations, both in English and Polish. The second article focused on the growing field of social robotics, with particular emphasis on improving human-robot interaction by designing robots that are perceived as more social. Neural networks and Markov chains were used to model emotions and predict a person's emotional style. A success rate of 70.5-82% was achieved. Both papers highlighted the need for further research to fully understand the capabilities and limitations of these techniques.

In the second chapter, in the context of modeling emotional responses in social robotics, the research focused on using the Planning Domain Definition Language (PDDL) to automatically plan the robot's actions in the face of uncertainty related to the emotional state of humans. PDDL, which is a formal knowledge representation language, was used to describe the planning domain and tasks, allowing precise modeling of the robot's interactions with humans based on their emotional states. The research used several planning algorithms and platforms, such as Sensory Graphplan and Allegro Common Lisp (ACL), to analyze and respond to emotions as defined by Paul Ekman. One article focused on the potential of using automated planning tools in the face of uncertainty to analyze a person's emotional state and influence the diagnosed state by a social robot. A methodology based on the PDDL language and the ACL platform was used to describe different facial expressions characteristic of each emotion. The second article presented the transformation of conditional, conformal, and parallel planning problems to linear programming, highlighting the computational ease of linear programming problems. The last article presented the application of the automatic planning methodology in the face of uncertainty to analyze the emotional state of a person and the possible responses of a social robot. The main emotions considered were sadness, fear, anger, disgust, and contempt. The result of the work is a set of two planning domains with illustrative examples. The assumption is that when negative emotions are detected, the robot should react in a way that reduces or does not escalate them. In conclusion, this research provides an approach for modeling and analyzing a social robot's response to negative human emotions in the face of uncertainty. These methods may be useful for social robot designers who wish to incorporate the robot's ability to recognize and respond to human emotions. However, further research is needed to adapt the presented approach to specific applications in real-world social robot environments.

The third chapter covered research focused on a variety of social behavior and modeling methods, including the use of neural networks and machine learning. Neural networks have been used to recognize emotions by analyzing facial expressions and speech, and to model the subtle nuances of social interactions. Machine learning has been used to teach cooperation through reinforcement learning and to create realistic simulations of social behavior. These methods have been applied in a variety of contexts, including education, healthcare, and industry, where social robots must adapt to dynamic and complex work environments. One of the challenges has been the need for appropriate datasets for training, especially in terms of ethics and data quality. This paper presents the use of Tiny-ML methods in social robots for face recognition, taking into account computational limitations. Test results showed superior performance of the YOLOv5s network compared to the YOLOv4-tiny network, especially in the context of recognizing people wearing masks. The second article focused on emotion detection and recognition in the context of human-robot interaction. Two neural network models were applied: Faster R-CNN and YOLOv3, which were modified to increase the efficiency of emotion recognition under different conditions. The results indicate that the two networks were similarly effective, although in some categories one network proved to be more effective than the other. In conclusion, this research provides insight into the potential of using neural networks and machine learning in social robotics, while highlighting the need for further research to understand and address ethical, security, and data quality challenges.

The last chapter dealt with the use of a PID controller to model selected social components. The PID controller, commonly used in automation, was used to precisely control the speed of a mobile robot. An algorithm inspired by the social optimization of the spider allowed to tune the parameters of the controller, especially in the presence of disturbances and uncertainties. In different contexts, such as social assistants or industrial robots, the PID controller was optimized using different algorithms, such as particle swarm optimization or beetle sensor search, which allowed better control of the robot's trajectory. The main topic of this chapter focused on maintaining eye contact between the robot and the human, which is a key element of human-robot interaction. For this purpose, a vision system with a face detection algorithm was used as a feedback signal for the PID controller. The tests were conducted on an OhBot robot head with a USB camera attached. The robot software was written in Python using dedicated libraries. The vision system, based on the OpenCV library, used a face detection algorithm based on Haar cascades. The settings of the PID controller were chosen using the Ziegler-Nichols method, which resulted in a very good performance of the control system. In conclusion, this research represents an important step towards understanding and implementing effective control systems in social robotics, especially in the context of maintaining eye contact in human-robot interactions. The use of a PID controller combined with an advanced vision system demonstrates that it is possible to effectively and accurately control a social robot under dynamically changing conditions of human interaction.

The thesis concludes with a discussion and practical application of social robotics. This dissertation is a series of publications on the topic of modeling emotions and social reactions in social robotics using artificial intelligence. Each of the papers presented deals with a selected aspect of social robotics. It is a subject area in the field of robotics, in the broad discipline of automation, electronics and electrical engineering. The presented articles are placed in the context of the available literature on the subject and in the context of possible applications.

Based on the presented series of publications and the guide to them, it is concluded that this dissertation provides robust evidence supporting the thesis, that AI-based solutions, including machine learning algorithms, planning languages, control system are not only feasible but also effective for recognizing and modeling social and emotional component in social robotics. It should be noted, however, that social robotics itself is a relatively young branch of robotics that is developing in many directions at once. It is also important to note that social robotics is a fascinating field of research at the intersection of many scientific disciplines, such as computer science, psychology, ethics, social science, and engineering. It is a field that focuses not only on the technical aspects of robot design and programming, but also on understanding the complex interactions between robots and humans and their impact on society. In this context, artificial intelligence methods, including neural networks and machine learning, are used to model and simulate the social behavior of robots, enabling them to interact with humans in more sophisticated and flexible ways. At the same time, psychological aspects such as empathy, nonverbal communication, and understanding of social context are being taken into account to create robots that can be considered more "social" and "understandable" to humans. Ethics and social science provide a framework for understanding and addressing the challenges of deploying social robots in various contexts, such as healthcare, education, or industry. Issues of privacy, safety, and responsibility, as well as the potential impact of robots on social structures and human relationships, become critical. All of this requires an interdisciplinary approach that combines advanced technologies with a deep understanding of human psychology and social dynamics. Therefore, social robotics is not only an engineering challenge, but also an ethical and social one, requiring an integrated approach to research and development. It is this interdisciplinarity and multiplicity of practical applications that allows social robotics to specialize in a specific research path, but also shows how much research and opportunities can be realized.

It is the potential for the future and development of human-robot interaction that represents a particular challenge, since the ultimate goal is to create social robots that are not only technically advanced, but also ethically and socially responsible.

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Appendix 1
Gliwice, 15.09.2023

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I declare that the information contained in the introduction of this thesis, in the contribution section is true and allows me to distinguish and demonstrate the independent contribution of the above-mentioned work.

List of publications:

1. Probierz, E., & Galuszka, A. (2022). Emotion detection based on sentiment analysis: an example of a social robots on short and long texts conversation. *European Research Studies Journal*, 25(2), 135-144.
2. Probierz, E., Galuszka, A., Grzejszczak, T., Galuszka, A. (2022) Ohbot social robots emotion modelling using markov chains and YOLOv5 neural network. In I. Work, E. Maia, P. & P. Geril (Eds.), *Modelling and simulation 2022: The European Simulation and Modelling Conference 2022. ESM'2022*, October 26-28. 2022, Porto, Portugal (103-110).EUROSIS-ETI.
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Appendix 2
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I declare that the information provided in the introduction of this thesis, in the contribution section, is true and allows to distinguish and demonstrate the independent contribution of the forementioned work.

Concern publication:

Grzejszczak, T., Bartosiak, N., Wojnar, M., Skowroński, K., Probierz, E. (2022). Regulacja pozycji robota społecznego w sprzężeniu zwrotnym z systemem wizyjnym. In A. Świerniak, J. Krystek (Ed.), Automatyzacja procesów dyskretnych, Teoria i zastosowania, t. 1, ISBN 978-83-7880-854-1 (pp. 79-86).

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Summary in Polish

Streszczenie pracy doktorskiej napisanej pod kierunkiem naukowym
dr hab. inż. prof. Pol. Śl. Adama Gałuszki
„Modelling social and emotional components in social robotics
using robot artificial intelligence”
Dr Eryka Probierz

Dysertacja ta stanowi cykl publikacyjny badań nad modelowaniem emocji i reakcji społecznych w robotyce społecznej przy użyciu sztucznej inteligencji. Badania te zostały opublikowane w formie listy ośmiu publikacji, pogrupowanych w cztery tematycznie spójne rozdziały.

Pierwszy rozdział koncentruje się na modelowaniu odpowiedzi emocjonalnych w robotyce za pomocą sztucznej inteligencji i uczenia maszynowego. Omówione są różne teorie emocji, które stanowią podstawę dla opracowania algorytmów rozpoznawania i generowania emocji. Zastosowano techniki uczenia maszynowego, w tym sieci neuronowe, do generowania wyrazów emocjonalnych z danych sensorycznych. Szczególną uwagę poświęcono rozpoznawaniu emocji i adaptacyjnym odpowiedziom emocjonalnym. Potencjalne zastosowania robotyki afektywnej w takich obszarach jak opieka zdrowotna, edukacja i interakcja społeczna również zostały omówione.

Drugi rozdział skupia się na wykorzystaniu języka Planning Domain Definition Language (PDDL) do automatycznego planowania działań robota w obliczu niepewności związanej ze stanem emocjonalnym ludzi. PDDL, będący formalnym językiem reprezentacji wiedzy, pozwala na precyzyjne modelowanie interakcji robota z ludźmi na podstawie ich stanów emocjonalnych. Wynikiem pracy jest zestaw dwóch domen planowania z ilustracyjnymi przykładami, zakładając, że robot powinien reagować w sposób redukujący negatywne emocje.

Trzeci rozdział obejmuje badania skoncentrowane na różnorodnych metodach modelowania zachowań społecznych, w tym wykorzystaniu sieci neuronowych i uczenia maszynowego. Metody te zostały zastosowane w różnych kontekstach, w tym w edukacji, opiece zdrowotnej i przemyśle. Jednym z wyzwań jest potrzeba odpowiednich zestawów danych do treningu, zwłaszcza pod względem etyki i jakości danych.

Ostatni rozdział dotyczy wykorzystania kontrolera PID do modelowania wybranych komponentów społecznych. Kontroler PID, powszechnie używany w automatyce, został użyty do

precyzyjnego sterowania prędkością mobilnego robota. Głównym tematem tego rozdziału jest utrzymanie kontaktu wzrokowego między robotem a człowiekiem, co jest kluczowym elementem interakcji człowiek-robot.

Dysertacja kończy się dyskusją i praktycznym zastosowaniem robotyki społecznej. Jest to dziedzina badawcza na styku wielu dyscyplin naukowych, takich jak informatyka, psychologia, etyka, nauki społeczne i inżynieria. W tym kontekście metody sztucznej inteligencji, w tym sieci neuronowe i uczenie maszynowe, są wykorzystywane do modelowania i symulowania zachowań społecznych robotów. Robotyka społeczna nie jest tylko wyzwaniem inżynieryjnym, ale również etycznym i społecznym, wymagającym zintegrowanego podejścia do badań i rozwoju. Jest to interdyscyplinarność i mnogość praktycznych zastosowań, która pozwala na specjalizację w konkretnej ścieżce badawczej, ale również pokazuje, jak wiele badań i możliwości może być zrealizowanych. Niniejsza rozprawa doktorska stara się choć w części odpowiedzieć na tę lukę w badaniach oraz wnieść dodatkową wiedzę dotyczącą modelowania emocji i reakcji społecznych w robotyce społecznej.

Summary in English

Summary of the doctoral thesis written under the scientific direction of
Assoc. Prof. Eng. Adam Gałuszka, Professor of the Silesian University of Technology
„Modelling social and emotional components in social robotics
using robot artificial intelligence"
PhD Eryka Probierz

This dissertation is a series of papers on modeling emotions and social responses in social robotics using artificial intelligence. This research has been published as a list of eight papers grouped into four thematically consistent chapters.

The first chapter focuses on modeling emotional responses in robotics using artificial intelligence and machine learning. Various theories of emotion are discussed, which form the basis for the development of algorithms for emotion recognition and generation. Machine learning techniques, including neural networks, are applied to generate emotional expressions from sensory data. Special attention is given to emotion recognition and adaptive emotional responses. Potential applications of affective robotics in areas such as healthcare, education, and social interaction are also discussed.

The second chapter focuses on the use of Planning Domain Definition Language (PDDL) to automatically plan a robot's actions in the face of uncertainty related to human emotional states. PDDL, which is a formal knowledge representation language, allows precise modeling of the robot's interactions with humans based on their emotional states. The result of the work is a set of two planning domains with illustrative examples, assuming that the robot should respond in a way that reduces negative emotions.

The third chapter covers research focused on a variety of methods for modeling social behavior, including the use of neural networks and machine learning. These methods have been applied in a variety of contexts, including education, healthcare, and industry. One challenge is the need for appropriate datasets for training, especially in terms of ethics and data quality.

The final chapter discusses the use of the PID controller to model selected social components. A PID controller, commonly used in automation, has been used to precisely control the speed of a mobile robot. The focus of this chapter is on maintaining eye contact between the robot and the human, which is a key component of human-robot interaction.

The thesis concludes with a discussion and practical application of social robotics. Social robotics is a research area at the intersection of many scientific disciplines, such as computer science, psychology, ethics, social science, and engineering. It uses artificial intelligence methods, including neural networks and machine learning, to model and simulate the social behavior of robots. Social robotics is not only an engineering challenge, but also an ethical and social one, requiring an integrated approach to research and development. It is interdisciplinary and has a variety of practical applications, which allows specialization in a specific research path, but also shows how much research and opportunities can be realized. This dissertation aims to at least partially fill this research gap and bring additional knowledge to the modeling of emotions and social reactions in social robotics.