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DOCTORAL DISSERTATION

Analysis of biomechanical and bioelectric parameters for the needs of automation of diagnostics and rehabilitation of patients

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Abstract

The complexities and challenges of patients' treatment inherent in the current rehabilitation and physical therapy landscape, highlight the critical role of accurate assessment, active patient participation, adherence to prescribed regimens, and continuous health monitoring for optimal outcomes of theraphy. It underscores the heavy reliance on the expertise of therapists and the challenges posed by patient engagement in repetitive exercises. The motivation behind this research is the pressing need to address these challenges amidst the growing demands on healthcare systems worldwide and the potential of advanced technologies, such as machine learning and robotics, to revolutionize diagnostics and rehabilitation through automation. The expert systems powered by AI to automate diagnostic and therapy parameters and the exploration of feedback loops within rehabilitation processes are highlighted as promising yet under-researched areas.

This dissertation tackled a significant scientific issue: the lack of conclusive evidence supporting the effectiveness of methodologies, assessments, and treatment protocols in robotic-assisted diagnostics and therapeutic interventions. The primary goal is to lay down the methodological foundation for an automated expert platform aimed at supporting, enhancing, and automating the diagnostic and rehabilitation processes. Utilizing machine learning and robotic technologies, the research develops a feedback mechanism that integrates electromyography (EMG), torque, and limb position data. This integration facilitates a more objective, efficient, and personalized approach to patient care. The study focuses on the analysis of upper limb movements, specifically elbow flexion and extension, involving the biceps and triceps muscles during isokinetic muscle force assessments, as well as tests for spasticity and muscle stiffness. Furthermore, there were explored the application of EMG biofeedback for pelvic floor muscles within a telerehabilitation framework and investigated EMG-triggered movement for knee rehabilitation using a rehabilitation robot.

The methodology centers on selecting established bioelectrical and biomechanical parameters and verifying their effectiveness and objectivity in diagnostic and therapeutic applications through robot-assisted techniques. This research aims to bridge the gap in evidence regarding the efficacy of robotic-assisted diagnostic and therapeutic interventions, proposing a novel approach that combines technological advancements with clinical practices to improve patient outcomes in rehabilitation. The research validates its hypotheses through extensive evaluations, comparing control and stroke groups for muscle force tests, assessing muscle spasticity in healthy and stroke survivors, and exploring the

effectiveness of telemedicine in urinary incontinence rehabilitation and EMG-triggered movement therapy for knee rehabilitation post-stroke. These researches focus on utilizing electromyography (EMG), torque, and positional data to derive biomechanical and bioelectrical parameters. By applying machine learning algorithms, the research aims to objectively evaluate and distinguish between healthy subjects and those with conditions, and to tailor rehabilitation exercises based on a feedback loop mechanism.

This comprehensive approach not only confirms the potential of robotic-assisted methods based on analysis of biomechanical and bioelectrical parameters in automatic diagnostic and therapeutic processes but also advances the field of biomedical engineering by providing a methodological framework for future developments in automated patient care.

Key words

analysis and processing of EMG signals, rehabilitation robot, neurorehabilitation, automatic diagnostics

Tytuł pracy

Analiza parametrów biomechanicznych i bioelektrycznych na potrzeby automatyzacji diagnostyki i rehabilitacji pacjentów

Streszczenie

Złożoność i wyzwania w procesie leczenie pacjentów, nieodłącznie związane z obecnym stanem rehabilitacji i fizjoterapii, podkreślają kluczową rolę dokładnej oceny, aktywnego udziału pacjenta, przestrzegania wyznaczonych schematów leczenia i ciągłego monitorowania stanu zdrowia w celu uzyskania optymalnych wyników terapii. Podkreśla to ogromną zależność od wiedzy specjalistycznej terapeutów i wyzwania, jakie stwarza zaangażowanie pacjenta w powtarzalne ćwiczenia. Motywacją badań zawartych w niniejszej rozprawie doktorskiej jest pilna potrzeba sprostania tym wyzwaniom w obliczu rosnących wymagań stawianych systemom opieki zdrowotnej na całym świecie oraz potencjałowi zaawansowanych technologii, takich jak uczenie maszynowe i robotyka, w zakresie zrewolucjonizowania diagnostyki i rehabilitacji poprzez automatyzację. Systemy eksperckie, wykorzystujące sztuczną inteligencję w celu automatyzacji procesów diagnostycznych i terapeutycznych, oraz mechanizmy pętli sprzężenia zwrotnego do zastosowań w rehabilitacji są uznawane za obiecujące, ale niedostatecznie zbadane obszary.

W niniejszej rozprawie doktorskiej poruszono istotny problem naukowy: brak jednoznacznych dowodów potwierdzających skuteczność metodologii, ocen i protokołów leczenia w diagnostyce i interwencjach terapeutycznych wspomaganych robotami. Podstawowym celem jest stworzenie podstaw metodologicznych dla zautomatyzowanej platformy eksperckiej, której zadaniem będzie wspieranie, doskonalenie i automatyzacja procesów diagnostycznych i rehabilitacyjnych. Wykorzystując technologie uczenia maszynowego i robotykę, w trakcie badań opracowano mechanizm sprzężenia zwrotnego, który integruje dane z elektromiografii (EMG), momentu obrotowego i pozycji kończyny. Integracja ta ułatwia bardziej obiektywne, skuteczne i spersonalizowane podejście do opieki nad pacjentem. W rozprawie skupiono się na analizie ruchów kończyny górnej, w szczególności zgięcia i wyprostu łokcia, angażujących mięśnie bicepsa i tricepsa, podczas oceny izokinetycznej siły mięśniowej, a także testów spastyczności i sztywności mięśni. Ponadto zbadano zastosowanie biofeedbacku EMG dla mięśni dna miednicy w ramach telerehabilitacji oraz przeanalizowano skuteczność wykorzystania ruchu wyzwalanego z poziomu sygnału EMG w rehabilitacji stawu kolanowego przy użyciu robota rehabilitacyjnego.

Metodologia koncentruje się na wyborze znanych parametrów bioelektrycznych i biomechanicznych oraz weryfikacji ich skuteczności i obiektywności w zastosowaniach diagnostycznych i terapeutycznych za pomocą technik wspomaganych robotem. Celem tych badań jest wypełnienie luki w dowodach dotyczących skuteczności interwencji diagno-

stycznych i terapeutycznych wspomaganych robotami, proponując nowatorskie podejście łączące postęp technologiczny z praktykami klinicznymi w celu poprawy wyników rehabilitacji pacjentów. Rozprawa potwierdza swoje hipotezy poprzez szeroko zakrojone oceny, porównanie grup kontrolnych i grup eksperymentalnych, pod kątem testów siły mięśni i oceny spastyczności mięśni u osób zdrowych i osób po udarze mózgu, a także badanie skuteczności telemedycyny w rehabilitacji nietrzymania moczu i terapii ruchowej wyzwalanej EMG w rehabilitacji stawu kolanowego po udarze. Badania te koncentrują się na wykorzystaniu danych elektromiograficznych (EMG), momentu obrotowego i położenia kończyny w celu uzyskania parametrów biomechanicznych i bioelektrycznych dla obiektywizacji diagnostyki. Zastosowanie algorytmów uczenia maszynowego, pozwoliło na obiektywną ocenę i rozróżnienie osób zdrowych od osób chorych. Natomiast, dostosowanie ćwiczeń rehabilitacyjnych w oparciu o mechanizm pętli sprzężenia zwrotnego pozwoliło uzyskać statystycznie lepsze wyniki testów po przeprowadzonej terapii.

To kompleksowe podejście nie tylko potwierdza potencjał metod wspomaganych robotem, opartych na analizie parametrów biomechanicznych i bioelektrycznych w automatycznych procesach diagnostycznych i terapeutycznych, ale także rozwija dziedzinę inżynierii biomedycznej, zapewniając ramy metodologiczne dla przyszłego rozwoju zautomatyzowanej opieki nad pacjentem.

Słowa kluczowe

analiza i przetwarzanie sygnałów EMG, robot rehabilitacyjny, neurorehabilitacja, automatyczna diagnostyka

Contents

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List of abbreviations and symbols

AI	Artificial Inteligence
ANN	Artificial Neural Network
amp	Amplitude
BP-ANN	Backpropagation Artificial Neural Network
Corr	Correlation
CC	Cross-correlation Torque and EMG
ch	Channel
CI	Confidence interval
CV	Coefficient of variability
Diff	Differen
DOF	Degree of freedom
dom	dominant
EMG	Electromyography
Exam	Examination
ext	Extension movement
flex	Flexion movement
imp	Impaired
ICC	Intraclass Correlation Coefficient
JPR	Joint Position Reproduction
JPS	Joint Position Sense

MAS	Modified Ashworth Scale
μV	micro Volts
Max	Maximum
Min	Minimum
ML	Machine learning
MNF	Mean Frequency
MDF	Median Frequency
Nm	Newton meters
non-dom	non-dominant
non-imp	Non-impaired
PFMs	Pelvic floor muscles
Pos	Position
PT	Physical therapist
Res	Researcher
RMS	Root mean square
ROM	Range of motion
S	Session
SD	Standard deviation
SEM	Standard Error of the Measurement
sEMG	Surface electromyography
SUI	Stress urinary incontinence
TENS	Transcutaneous Electrical Nerve Stimulation
T	Torque
UI	Urinary incontinence
ZC	Zero Crossing

Chapter 1

Introduction

Optimal outcomes in rehabilitation and physical therapy are achieved when there is an accurate assessment, active patient participation, adherence to the prescribed therapy regimen, and continuous monitoring of the patient's health state and progress. This involves a series of processes including physical examination, evaluation of the patient's condition, therapeutic intervention, continuous monitoring, and adjustments to the therapy plan aligned with the patient's progress in recovery. The success of conventional therapy largely hinges on the therapist's expertise, prior experience with comparable cases, and proficiency in devising effective rehabilitation strategies [62]. The rehabilitation process is typically demanding, time-intensive, and heavily reliant on the therapist's expertise. It also requires patient cooperation, often involving repeated exercises at home without professional supervision. The repetitiveness and lack of engagement in these tasks frequently lead to diminished patient participation. This issue stems from several factors: exercises not being tailored to individual capabilities, ineffective communication and interaction strategies, patients not clearly noticing their progress, and the absence of guidance and monitoring during home sessions. Tackling these challenges is crucial for enhancing therapeutic results and, notably, for minimizing the injury risk associated with incorrectly performed exercises.

1.1 Motivation

The motivation behind this research stems from the ongoing challenges in the current healthcare paradigm, particularly in diagnostics and rehabilitation. Traditional methods often rely heavily on subjective assessments and the expertise of healthcare professionals, which, while invaluable, can lead to variability in patient care. Moreover, the increasing demand on healthcare systems globally calls for innovative approaches to alleviate the burden on medical staff and resources. The integration of advanced technologies such as machine learning and robotics into healthcare practices presents an opportunity to address these challenges by automating and optimizing certain processes.

Efficient management of chronic diseases is essential for enhancing health outcomes, and quality of life, and ensuring cost-efficient healthcare. With the rising global prevalence of chronic conditions, the consequences of non-adherence to treatment regimens are becoming increasingly significant. Telemedicine solutions are progressively employed in healthcare and public health for patient communication, monitoring, education, and promoting adherence to chronic disease management. While telehealth tools show promise in facilitating better adherence to chronic disease management, the current evidence regarding their effectiveness is varied [49]. In the context of automating the diagnostic and rehabilitation process, the objective is to reduce the reliance on human intervention, specifically that of the rehabilitation professional, throughout the entire rehabilitation program, encompassing the initial assessment and exercise selection phase through to the meticulous monitoring of their execution and re-evaluation of the patient's health state. Hughes et al. [60] have emphasized the critical necessity for consensus on measurement instruments and assessment protocols. Additionally, they note that newly developed technology-based measurement tools possess the potential to complement clinical assessments of impairment, activity, and participation. However, these tools require thorough evaluation for their usability, validity, reliability, and responsiveness. Technologies are capable of providing assessment tools that are valid, reliable, and sensitive. When integrated with clinical measures, they can enhance clinical decision-making processes and contribute to a more detailed understanding of patient outcomes. Consequently, there is an evident need for established guidelines to assist clinicians and researchers in maximizing the effectiveness of technology-based assessments and the application of clinical metrics and procedures. The current technology requires the identification of a session or patient-specific therapy strategy where healthcare professionals have to account for and set several factors such as the physiological parameters, the daily condition of the patient, the seating position, the electrode locations, or other factors that might change between subjects and days, affecting the performance of the evaluation protocol and training. This procedure is time-consuming and scarcely repeatable. For instance, FES-cycling training requires initial setting of different parameters as the stimulation strategy, i.e., the on-off crank angular ranges of muscle stimulation, the pulse amplitude and duration of each stimulated muscle, and the stimulation frequency. In clinics, these parameters are usually identified manually through a time-consuming and scarcely repeatable procedure, potentially resulting in a sub-optimal training performance [6].

The healthcare sector is grappling with persistent staff deficits and ingrained systemic issues, further intensified by the COVID-19 pandemic. This situation has led to escalating work demands and stress for healthcare workers, contributing to heightened burnout levels and more frequent short- or long-term work absences. Elevated burnout among clinicians and medical staff carries significant professional consequences, potentially leading to increased medical errors and compromised patient care quality. Technical

and data-centric approaches can aid the healthcare workforce, yet their implementation encounters numerous obstacles. These include insufficient integration into clinical workflows, inadequate incorporation of healthcare professionals' feedback in their design, the necessity to improve health professionals' digital skills without increasing their workload, the absence of substantial benefits in solving clinically important issues, and issues arising from either too little or too much dependence on Artificial Intelligence(AI), potentially affecting clinical results [28, 107, 121].

The therapy supported by expert systems using AI enables healthcare professionals to automatically set every parameter for the patient's needs without their involvement. The exploration of automatization within rehabilitation processes through a feedback loop remains an area with limited research. The substantial expansion in medical data and advancements in data analytics hold the promise of enhanced care quality and improved health outcomes for patients, while potentially reducing costs for health systems. However, this growth also adds to the workload of healthcare professionals, primarily due to the significant training and documentation required for clinicians, among other factors. Additionally, while robot-assisted and automation technologies can augment the safety, quality, and efficiency of hospital workflows, including in surgical and other care settings, the challenge of balancing standardization through automation with the inherently unpredictable nature of healthcare work remains significant. Each patient may receive more therapy time due to automation, which is crucial for recovery, especially for neurological patients. Furthermore, although AI solutions are proposed for supporting clinical decision-making, operational optimization, patient empowerment, healthy lifestyle maintenance, and population health management, they still necessitate extensive testing and validation for effective implementation. While the path toward the practical integration of automated analysis and decision-making in medicine is extensive, it is crucial to continue and intensify research efforts at this stage to eventually realize their application in the future. This dissertation represents a significant stride in this ongoing journey.

1.2 Thesis statement and scope

The scientific problem addressed in this thesis is the absence of conclusive evidence validating the effectiveness of the methodologies and treatment protocols employed in robotic-assisted diagnostics and therapeutic interventions. The central objective of the research conducted in this dissertation is to establish the methodological essentials for an automated expert platform designed to aid, enhance, and automate the diagnosis and rehabilitation process.

The research utilized machine learning and robotic technologies to establish a feedback mechanism that integrates electromyography (EMG), torque, and limb position data, thereby enabling a more objective, efficient, and tailored patient care strategy. The re-

search primarily investigated upper limb movements, with a particular emphasis on elbow flexion and extension actions involving the biceps and triceps muscles, during isokinetic muscle force assessments and tests for spasticity and muscle stiffness. Additionally, another study explored EMG biofeedback of pelvic floor muscles in the context of telerehabilitation, employing a remotely conducted evaluation protocol. Furthermore, there was research on EMG-triggered movement knee rehabilitation involving rectus femoris and biceps femoris muscles with using of a rehabilitation robot.

To address the scientific issue, the approach involves choosing established bioelectrical and biomechanical parameters and confirming their effectiveness and objectivity in diagnostic and therapeutic processes through the use of robot-assisted methods.

Based on the motivation and the aim of this dissertation, the following hypotheses have been formulated:

I. **EMG signals complemented by torque and limb position, generated by patients during machine-assisted diagnostic procedures allow to objectively assess the patient's condition.**

II. **EMG, complemented by torque and position measurements, when applicable, provide a complete set of signals facilitating biofeedback-based effective rehabilitation, also in telemedicine solutions.**

The content of this thesis is structured as follows:

- Chapter 2 presents information about biomechanical and bioelectrical parameters and state of art in automatization in diagnostics and rehabilitation,
- Chapter 3 details the solution proposed in this thesis,
- Chapter 4 presents the outcomes of clinical trials pertinent to the hypotheses posited in this dissertation,
- Chapter 5 encompasses a comprehensive summary of the thesis and future work.

Chapter 2

Background and related work

This chapter provides a comprehensive overview of the existing body of knowledge relevant to the analysis of biomechanical and bioelectric parameters for the automation of diagnostics and rehabilitation.

2.1 Biomechanical and bioelectrical parameters in diagnostic and rehabilitation

The section begins by examining the latest advancements in electromyography, torque, and limb position assessments within the medical field, as well as their incorporation into machine learning and robotic technologies for enhancing patient treatment.

2.1.1 Torque measurement in musculoskeletal assessment

The force produced by muscles plays a crucial role in generating joint torque, which is essential for creating body movements, supporting joint stability, and maintaining posture. Isokinetic assessments, characterized by constant-speed limb's movement, are broadly applied in fields ranging from athletic performance to clinical rehabilitation and scientific research. Their popularity stems from their ability to provide uniform, replicable benchmarks, including controlled force-velocity factors of muscle performance, motion range, and testing procedures, coupled with their relative safety [34]. Consequently, they are often regarded as the definitive standard for strength evaluation [5, 139]. Strength, often measured as the peak (maximum) torque produced by a joint, is a key factor associated with human motion, as it represents the most straightforward, objective, and accurate indicator of an individual's maximum strength capacity, assessed in a practical and controlled physiological setting. This metric is frequently evaluated for clinical, rehabilitation, and research purposes to understand human performance. The maximum torque produced at a joint results from a multifaceted combination of muscle fiber con-

traction characteristics and the actual structure of numerous muscle fibers, connective tissues, and neural signals in the body. Factors like diverse muscle properties, the angle of muscle fibers, the effects of both series and parallel elasticity, variations in the moment arm, and involuntary neural inhibition [103], all contribute significantly. These elements lead to discrepancies between the overall joint torque-angle-angular velocity profile and the specific force-length-velocity profiles of individual muscles. Introduced in the 1960s, isokinetic dynamometry was developed to measure the torque or force moment produced by muscle group contractions during circular movements. Dynamometer enables precise evaluation of dynamic muscle contractions by strictly regulating the speed, resistance, and joint angle [54]. The ability to safely exert maximal effort in a regulated setting has established isokinetic dynamometry as the benchmark technique in research [82]. This has promoted the application of isokinetic dynamometers in training, rehabilitation, and assessment of musculoskeletal functions. The study by Ghroubi S et al. [41] demonstrated that a dynamic-resistance muscle strength training regimen, utilizing an isokinetic dynamometer, can enhance muscle strength and maximal oxygen uptake (VO_2max) in a safe manner –without inducing clinical symptoms, ECG alterations, or changes in arterial blood pressure—among patients recovering from coronary artery bypass grafting, without posing significant risks. In the study of Carlyle et al. [24], the peak of the EMG-force cross-correlation function and the peak latency were assessed for both limbs using root mean square (RMS) of surface electromyography (EMG_{RMS}) and isometric dynamometry, as follows:

- Cross-correlation EMG Torque peak (CC_{peak})

$$CC_{\text{peak}} = \max_{n} \left\{ \sum_{m=-\infty}^{\infty} \text{Torque}[m] \cdot EMG_{RMS}[n+m] \right\} \tag{2.1}$$

- Cross-correlation EMG Torque time (CC_{time})

$$CC_{\text{time}} = \frac{\arg\max_{n} \left\{ \sum_{m=-\infty}^{\infty} \text{Torque}[m] \cdot EMG_{RMS}[n+m] \right\}}{fs} \tag{2.2}$$

  where f_s is the sampling frequency.

2.1.2 Position tracking in movement analysis

Research on tracking human movement for rehabilitative purposes has been a dynamic area of study starting from the 1980s. In physical rehabilitation, measuring joint angles is a standard practice for assessing joint functionality. Position measurement enables one to set limb position in space, measure its velocity and range of motion, and mark events in accordance with the joint range of movement. Human body joints are characterized by

different structures, enabling a range of movement types and degrees of freedom (DOF). Every joint's DOF is associated with a specific range of motion (ROM), indicating the extent of angular rotation possible within a given time frame. ROM is frequently employed in physical rehabilitation to evaluate the functional capacity of a patient's joints [106].

A variety of wearable sensors are available to track movement and alterations in the position of limbs or the body. They encompass devices such as pedometers, goniometers, electromechanical switches or pressure sensors, magnetometers, and inertial sensors.

Proprioception - Joint Position Sense

Proprioception, also refered to as position sense (JPS), is the ability to determine body segment positions and movements in space and is based on sensory signals provided to the brain from muscle, joint, and skin receptors. The proprioceptive feedback plays also a crucial role in the reorganization and recovery of neuromotor systems [29]. This is why it also gains attention of engineers and physiotherapists, who create innovative rehabilitation devices for neurological patients. With technology, becoming more and more advanced, we can provide objective data to clinicians, which can be a base for assessing and planning the therapy process. One of the tests for proprioception, which gathered some attention, is joint position matching or joint position reproduction (JPR). An individual must replicate a reference joint angle with covered or closed eyes (ie, using proprioceptive information). The Goble at al. [45] point out however, that on the surface, this test might seem straightforward, but there are multiple insights gained from a recent series of position-matching studies that should be taken into consideration while implementing the proprioception test into the rehabilitation tool. Some research [9, 73] claim that JPR tests for proprioception have low testing validity because the proprioceptive information available during target position generation and the proprioceptive information available during target position reproduction are not the same. On the other hand, it is widely accepted that large matching errors can be a useful indicator of proprioceptive deficiency [45]. A recent survey reported that about 90% of occupational therapists and physiotherapists routinely assess for sensory loss but over 70% of them do not use standardized measures [111].

2.1.3 Electromyography

Electromyography (EMG), which involves the examination of muscle bioelectrical activity, furnishes insights into neural function and the associated muscle coordination patterns. The EMG signal is a representation of the electric potential field generated by the depolarization of the outer muscle-fiber membrane (the sarcolemma)[88]. Investigations into this domain commenced in the late 18th century, and it wasn't until 1890 that Etienne Marey achieved the first recorded EMG readings. The breadth of EMG's

applicability extends beyond mere muscular conditions like weakness or tension; it has been found to mirror changes across a spectrum of biological and physiological systems. Furthermore, EMG readings have been associated with autonomic functions, including the sympathetic nervous system, and cognitive processes like memory and emotion [66]. These findings suggest that EMG's utility lies in its ability to reflect a comprehensive, multi-level biopsychosocial response, positioning EMG data as a component of a broader, interconnected system of physiological and psychological responses.

Signal processing

In the context of this scientific investigation, it is important to recognize that the EMG signal exhibits characteristics of a non-stationary stochastic signal. Its specific attributes are contingent upon factors including the magnitude and duration of muscle contraction, the dynamic or static state of the muscles, their degree of fatigue, and the quality of electrode-skin contact. Notably, approximately 95% of the power spectral density in the surface EMG signal is ascribed to harmonics within the 0-400 Hz frequency range, with the residual 5% being attributable to noise stemming from electrode-related artifacts and the recording apparatus [151]. In accordance with the principles of the Kotelnikov-Shannon sampling theorem, it is imperative to maintain a minimum sampling frequency of at least twice the highest frequency present in the signal, a requirement that translates to a frequency of no less than 1000 Hz. In the realm of medical device standards, particularly those governing electromyographs, such as EN 60601-1 (Medical electrical equipment - General requirements for basic safety and essential performance), EN 60601-1-2 (Collateral Standard: Electromagnetic disturbances - Requirements and tests), and EN 60601-2-40 (Particular requirements for the basic safety and essential performance of electromyographs and evoked response equipment), there is an absence of specific directives pertaining to signal processing methodologies, stringent filtration criteria, or amplification prerequisites for surface electromyography. As a result, EMG signal processing predominantly relies on the implementation of band-pass filters. The high-pass filter serves the purpose of attenuating artifacts arising from patient movements and fluctuations in electrode-skin contact, while the low-pass filter is instrumental in mitigating electromagnetic interference and noise stemming from extraneous devices [151]. These artifacts typically fall within the 10-15Hz frequency range, with 10Hz representing artifacts caused by walking and 15Hz corresponding to those from rapid movements [114, 132]. Furthermore, it is customary to employ a filter operating at either 50 Hz or 60 Hz for the purpose of eliminating power line interference, which is a well-established practice in this domain. A sample filtered EMG signal is presented at Figure 2.1. To fully appreciate the capabilities and limitations of the data derived from Pelvic Floor Muscle Surface Electromyography in the context of The Glazer Protocol and biofeedback, clinicians must familiarize themselves with the technical intricacies of the instrumentation [44]. This includes understanding differential

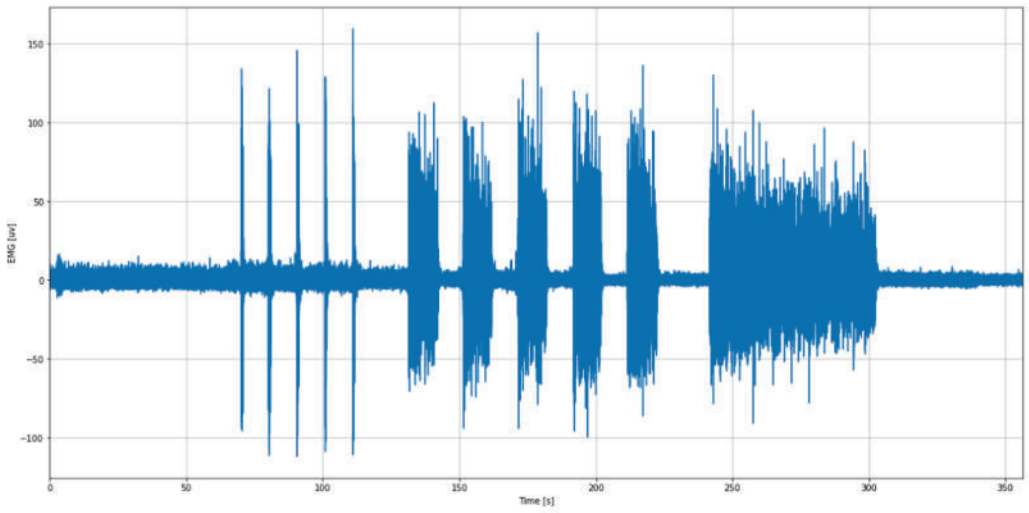


Figure 2.1: Filtered EMG signal

amplification, the importance of common mode rejection sensitivity, impedance characteristics, the process of rectification, the application of bandpass and notch filters, the nuances of analog-to-digital conversion, the methodology behind power density spectral frequency analysis through fast Fourier transformation, and the techniques for signal reintegration. This foundational knowledge is crucial for interpreting sEMG data accurately and effectively, as highlighted in Glazer's study [44].

EMG signal parameters

In scientific literature, various parameters are commonly utilized for the analysis of EMG signals. The primary parameters associated with surface EMG include aspects such as the amplitude and duration of muscle contractions, as well as propagation velocity[32]. EMG serves the purpose of elucidating the behavior, or patterns of activity, of a specific muscle, and can also be employed to assess the muscle's condition, whether it is normal, myopathic, or denervated/reinnervated [14]. Researches [2, 35, 59, 133, 147] reveal that muscle contraction intensity and fatigue are marked by a shift in the median power density spectral frequency towards lower frequencies is linked to subjective feelings of muscle fatigue, hypoxia, diminished blood circulation, and local inflammation, characterized by the release of various neurochemicals, which in turn heighten pain sensitivity. Parameters for EMG signal analysis are typically from: time domain, frequency domain, and time-frequency domain. The time domain is the most widely used category due to its simplicity, rapid computational nature, and reliance on signal amplitude. Spectral signal analysis is employed to investigate muscle contractions and infer alterations in the recruitment of motor units [100].

During sustained contraction, there is an increase in the low-frequency elements of the EMG, which isn't evident in the time-domain waveform. This rise in low-frequency com-

ponents signals muscle fatigue [80]. Mean frequency (MNF) and median frequency (MDF) are widely recognized as key indicators of musculoskeletal health [40, 68, 119, 149]. These parameters diminish in line with muscle strength, indicating muscle fatigue. Furthermore, the MNF of the EMG signal reflects the muscle's oxygen level, which decreases as muscle fatigue sets in Taelman's et al. study [135]. A representation in the time-frequency domain provides the ability to pinpoint signal energy in both the time and frequency domains, thereby offering a more precise description of the underlying physiological phenomena [151].

Among the various time-frequency representations, researchers commonly favor three: the Short-Time Fourier Transform (STFT), Wavelet Transform (WT), and Wavelet Packet Transform (WPT).

Time domain parameters are defined as follows:

- **Root Mean Square (RMS)** - the square root of the average power of the sEMG signals at a given analysis window, defined by the following:

$$\mathrm{RMS}_i(t) = \sqrt{\frac{1}{M}\sum_{k=1}^{M} \mathrm{sEMG}_i^t(k)^2} \tag{2.3}$$

  Where:

  i is the number of channels

  t is the number of analysis windows

  M is the number of all points in a window

  k is the point currently in the analysis window

- **Zero Crossing (ZC)** - the number of times that the sEMG signal crosses the 0 axis. It can be formulated as:

$$ZC = \frac{1}{M-1}\sum_{k=1}^{M-1} 1(\cdot)\left(\mathrm{sEMG}(k)\cdot \mathrm{sEMG}(k-1) < 0\right) \tag{2.4}$$

  where

  M is the total number of samples in the signal.

  sEMG(k) represents the k^{th} sample of the signal

  $1(\cdot)$ is an indicator function that returns 1 if the condition within the parentheses is true (i.e., if there is a change in sign between consecutive samples) and 0 otherwise.

- **Window Length (WL)** - the cumulative length of the sEMG signal over time. It can be calculated as follows:

$$WL_i(t) = \sum_{k=1}^{M} \left| \text{sEMG}_i^t(k+1) - \text{sEMG}_i^t(k) \right| \tag{2.5}$$

Where:

i is the number of channels

t is the number of analysis windows

M is the number of all points in a window

k is the point currently in the analysis window

- **Standard deviation (SD)** - a measure used to quantify the amount of variation or dispersion of a set of values, expressed as:

$$SD = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (sEMG_i - \mu_{sEMG})^2} \tag{2.6}$$

Where:

N denotes the total number of sEMG signal samples

$sEMG_i$ is the amplitude of each individual sEMG signal sample

μ_{sEMG} represents the mean amplitude of the sEMG signal across all samples.

- **Coefficient of variability (CV)** - the standardized measure of the dispersion of a probability distribution or frequency distribution, expressed as:

$$CV = \frac{SD}{\mu_{sEMG}} \times 100\% \tag{2.7}$$

Where:

SD is standard deviation of sEMG signal

μ_{sEMG} represents the mean amplitude of the sEMG signal across all samples.

- **Average peak amplitude** [µV] — the mean value from peaks in the defined window.

- **Average mean amplitude from rest phase** [µV] — the mean value between offset and onset.

- **Time before peak** [s] - the average duration from when the patient received the instruction to contract the muscle to the point of reaching the peak during the contraction phase.

- **Time after peak** [s] - the average duration from when the patient received the instruction to relax the muscle to the point of reaching the threshold (50% of the mean value of the signal).
- **Onset** [s] - the average duration from the point when the patient received the instruction to contract the muscle to the point of crossing the threshold.
- **Offset** [s] - the average duration from the point when the patient received the instruction to relax the muscle to the point of crossing the threshold.
- **Time of amplitude increase (onset to peak)** [s] — the average duration from when the patient crosses the threshold before the contraction (onset) to the point of reaching the peak during the contraction phase.
- **Time of amplitude decrease (peak to offset)** [s] — the average duration from the point of reaching the peak during the contraction phase to when the patient crosses the threshold after contraction (offset).
- **Contraction duration (onset to offset)** [s] — the mean value of time between onset and offset from contractions.
- **Average mean amplitude rest** [µV] — the mean value from the rest phase based on the onsets and offsets.
- **Average mean amplitude work**[µV] — the mean value from the work phase based on the onsets and offsets.

Frequency domain parameters are defined as follows:

- **Median Frequency** - frequency value at which the EMG power spectrum is divided into two regions with an equal integrated power [137], expressed as:

$$\sum_{j=1}^{MDF} P_j = \sum_{j=MDF}^{M} P_j = \frac{1}{2}\sum_{j=1}^{M}(j-1)P_j, \tag{2.8}$$

  where P_j is the EMG power spectrum at a frequency bin j and M is the length of the frequency bin.

- **Mean Frequency** - average frequency value that is computed as a sum of the product of the EMG power spectrum and frequency, divided by a total sum of spectrum intensity [137]. It can be expressed as:

$$MNF = \frac{\sum_{j=1}^{M} f_j P_j}{\sum_{j=1}^{M} P_j}, \tag{2.9}$$

  where f_j is a frequency value at a frequency bin j.

Transformations within the time-frequency domain, which serve as the foundation for calculating signal parameters, are characterized in the following manner:

- The spectrogram, which is derived from **the Short-Time Fourier Transform**, is represented as follows:

$$STFT\{x[n]\}(m,\omega) = X(m,\omega) = \sum_{n=-\infty}^{\infty} x[n]w[n-m]e^{-j\omega n} \tag{2.10}$$

  where x[n] - signal, w[n] - window.

- **The Wavelet Transform** produces a scalogram, and a significant portion of research indicates that the Daubechies wavelet family is particularly suitable for EMG signal analysis. This can be presented as:

$$DWT_x[n,a] = \sum_{m=0}^{N-1} x[m] \cdot \Psi_j[m-n] \tag{2.11}$$

  where $\Psi_j[n] = \frac{1}{\sqrt{a}}\Psi\left(\frac{n}{d}\right)$

- The **Wavelet Packet Transform** offers an alternative approach to the time-frequency representation of discrete signals, characterized by its dyadic decomposition of both the approximation and detail subbands. This decomposition can be executed across all levels, known as a full decomposition tree, or selectively at levels dictated by entropy, resulting in an optimal decomposition tree. In the scenario of optimal decomposition, the majority of the energy is concentrated in a minimal set of relevant coefficients. However, unlike the uniform structure of a full decomposition, the tree structure in optimal decomposition is irregular.

2.2 Automatization in diagnostic and rehabilitation

The introduction of automation into diagnostics and rehabilitation constitutes a pivotal shift in the healthcare sector. This chapter explores the transformative impact of automation, driven by developments in artificial intelligence (AI), robotics, and information technology, on the processes of diagnosis and the delivery of rehabilitation treatments. By incorporating these advanced technologies, the precision and speed of medical services are significantly improved, leading to better health results and expanded access to medical care for patients.

2.2.1 Clinical scales and protocols for patient assessment

Clinical scales serve as fundamental instruments in the healthcare sector, facilitating the assessment and quantification of diverse facets of a patient's health status. These

instruments offer a uniform approach to appraise the intensity of symptoms, functional capacities, and the overall effect of medical conditions on an individual's daily activities. This chapter aims to explore the mechanisms, uses, and importance of these scales in the context of patient management.

The Modified Ashworth Scale's (MAS) purpose is to grade muscle spasticity. The scale is defined in the following way [7]:

- 0: No increase in muscle tone
- 1: Slight increase in muscle tone, with a catch and release or minimal resistance at the end of the range of motion when an affected part(s) is moved in flexion or extension
- 1+: Slight increase in muscle tone, manifested as a catch, followed by minimal resistance through the remainder (less than half) of the range of motion
- 2: A marked increase in muscle tone throughout most of the range of motion, but affected part(s) are still easily moved
- 3: Considerable increase in muscle tone, passive movement difficult
- 4: Affected part(s) rigid in flexion or extension

The semi-quantitative characterizations within the MAS, such as "slight increase in muscle tone" (MAS 1, MAS 1+) and "more marked increase in muscle tone" (MAS 2), may result in potential ambiguities when distinguishing between "1 and 1+" and "1+ and 2," leading to potential interpretation challenges [105]. In the primary findings of Abiglou et al.'s study [3], it was observed that there is no substantial correlation between the quantitative evaluations of the impact of strokes on spastic joints and the clinical assessment of muscle tone, as indicated by the Ashworth scores. Hence, clinical scale reliability among different raters and within the same rater is a subject of debate, as these scores are derived from the subjective judgments of the examiner, which involve elements like muscle twitch observation, and heavily depend on the examiner's level of expertise. The absence of dependable and uniform subjective assessments highlights the necessity for an objective measurement method grounded in quantitative principles to precisely gauge spasticity [25]. Such objective measurements may prove more effective in evaluating and tracking the progress of treatment and rehabilitation for this condition.

The Lovett Scale, commonly referred to as the manual muscle testing method, is a clinical instrument designed for the evaluation of muscular strength. This technique emphasizes the assessment of collective muscle groups as opposed to isolated muscles. During the application of the Lovett Scale, a skilled examiner provides manual opposition to each muscle group and assigns a strength grade according to the subject's capacity to resist this force. The scale is defined in the following way [94]:

- Grade 0, LT: 0 (zero) - No evidence of contractility
- Grade 1, LT: T (trace) - Slight contractility, no movement
- Grade 2, LT: P (poor) - Full range of motion, gravity eliminated
- Grade 3, LT: F (fair) - Full range of motion with gravity
- Grade 4, LT: G (good) - Full range of motion against gravity, some resistance
- Grade 5, LT: N (normal) - Full range of motion against gravity, full resistance

The Brunnstrom Recovery Scale is a tool created to chronicle the progression of limb motor recovery following a stroke, tracing the evolution from initial flaccidity through to the resumption of almost typical movement patterns and coordination. Health professionals determine the patient's recovery phase by observing the extent of spasticity and movement. This scale encompasses three components that assess the arm, hand, and leg, each rated on a scale from one to six. For upper and lower limbs, the recovery stages are as follows [125]:

- **Stage 1:** The patient evidences flaccidity, with little or no resistance to passive motion and no initiation of voluntary movement.
- **Stage 2:** Spasticity begins to develop, and initiation of synergies is possible on voluntary effort or as an associated reaction.
- **Stage 3:** There is increased resistance due to spasticity, and limb synergies are performed voluntarily.
- **Stage 4:** Spasticity is less evident than earlier, and movement combinations that deviate from synergies are possible.
- **Stage 5:** There is minimal resistance from spasticity, and individual as well as complex movement combinations are possible independent of synergy.
- **Stage 6:** Spasticity is difficult to demonstrate unless movements are performed with rapidity, and synergies do not interfere with performance.

For hand, the stages are as follows [125]:

- **Stage 1:** Muscles are flaccid on the involved side.
- **Stage 2:** The patient evidences minimal spasticity, and little or no active finger flexion is possible.
- **Stage 3:** The patient is able to hold on to a handle placed in the hand but unable to release through voluntary finger extension. Reflex extension may be possible.

- **Stage 4:** The patient is able to release by lateral thumb movement with minimal finger extension or through normal functional synergy. That is, he or she is able to grasp with the fingers while the wrist is extended and able to release the fingers while the wrist is flexed.
- **Stage 5:** Voluntary mass extension of digits is possible, and the patient is able to control cylindrical and spherical grasp with limited functional use.
- **Stage 6:** The patient demonstrates voluntary extension of fingers, lateral, palmar, and three-point prehension and individual finger movements are possible.

The modified Rankin Scale score is recognized as the conventional metric for assessing disability outcomes in the context of stroke patient management and research studies [15]. The scale is characterized as follows:

- **0** no symptoms
- **1** No significant disability. Able to carry out all usual activities, despite some symptoms.
- **2** Slight disability. Able to look after own affairs without assistance, but unable to carry out all previous activities.
- **3** Moderate disability. Requires some help, but able to walk unassisted.
- **4** Moderately severe disability. Unable to attend to own bodily needs without assistance, and unable to walk unassisted.
- **5** Severe disability. Requires constant nursing care and attention, bedridden, incontinent.
- **6** Dead.

The Fugl-Meyer Assessment scale, a 226-point evaluative instrument, quantifies recovery stages post-hemiplegic stroke through a multi-item, ordinal scoring system across five domains: motor and sensory functions, balance, range of motion, and pain. Each item within these domains is rated on a scale from 0 to 2, reflecting the ability to perform specific tasks. The motor domain, for example, spans a range of movements and accounts for a substantial portion of the total score, with separate points allocated for the upper and lower extremities. This scale, requiring detailed assessment by a trained physical therapist, offers a structured 30-minute evaluation of a patient's functional capabilities [43].

The Barthel Index is a tool for evaluating self-sufficiency in activities of daily living (ADL), with the highest possible score being 100. It has been widely applied in studies

concerning stroke, with Granger et al. [47] affirming its reliability and agreement with other stroke assessments. The Index covers ten ADLs, as follows:

- FEEDING

  0 = unable

  5 = needs help cutting, spreading butter, etc., or requires modified diet

  10 = independent

- BATHING

  0 = dependent

  5 = independent (or in shower)

- GROOMING

  0 = needs to help with personal care

  5 = independent (face/hair/teeth/shaving implements provided)

- DRESSING

  0 = dependent

  5 = needs help but can do about half unaided

  10 = independent (including buttons, zips, laces, etc.)

BOWELS 0 = incontinent (or needs to be given enemas)

  5 = occasional accident

  10 = continent

- BLADDER

  0 = incontinent, or catheterized and unable to manage alone

  5 = occasional accident

  10 = continent

- TOILET USE

  0 = dependent

  5 = needs some help, but can do something alone

  10 = independent (on and off, dressing, wiping)

- TRANSFERS (BED TO CHAIR AND BACK)

0 = unable, no sitting balance

5 = major help (one or two people, physical), can sit

10 = minor help (verbal or physical)

15 = independent

- MOBILITY (ON LEVEL SURFACES)

  0 = immobile or < 50 yards

  5 = wheelchair independent, including corners, > 50 yards

  10 = walks with help of one person (verbal or physical) > 50 yards

  15 = independent (but may use any aid; for example, stick) > 50 yards

- STAIRS

  0 = unable

  5 = needs help (verbal, physical, carrying aid)

  10 = independent

The Frenchay Arm Test, which can be completed in under three minutes, involves five tasks assessed on a pass/fail(score 1/0) basis, with the patient earning a point for each task successfully performed. During the test, the patient begins each task seated at a table, starting with their hands resting in their lap. The tasks, aimed at evaluating the functionality of the affected arm or hand, include [50]:

- Stabilise a ruler, while drawing a line with a pencil held in the other hand. To pass, the ruler must be held firmly.

- Grasp a cylinder (12mm diameter, 5cm long), set on its side approximately 15cm from the table edge, lift it about 30cm and replace without dropping.

- Pick up a glass, half full of water positioned about 15 to 30cm from the edge of the table, drink some water and replace without spilling.

- Remove and replace a sprung clothes peg from a 1Omm diameter dowel, 15 cm long set in a 10 cm base, 15 to 30 cm from table edge. Not to drop peg or knock dowel over.

- Comb hair (or imitate); must comb across top, down the back and down each side of head.

The effectiveness of treatment is highly contingent on an accurate diagnosis. In the context of pelvic floor rehabilitation, it is imperative that women receive precise guidance on executing proper pelvic muscle contractions. Previously, when a patient's ability to contract was not at least equivalent to a level 2 on the Oxford scale, the initial approach often involved electric stimulation therapy. Upon achieving the Oxford level 2, the treatment strategy shifted to active contractions coupled with biofeedback therapy[31]. However, the International Continence Society currently endorses a revised, more straightforward grading system that consists of four levels: absent, weak, normal (deemed as "moderate"), and strong. This new modified scale aims to encapsulate the comprehensive action of tightening, lifting, and squeezing [110]. Modified Oxford Scale for pelvic floor muscles assessment is as follows [110]:

- 0/5 No discernible contraction of muscles
- 1/5 Flicker or pulsation is felt, no discernible lifting or tightening
- 2/5 Weak contraction, no discernible lifting or tightening
- 3/5 Moderate, some lifting of the posterior wall and some tightening around the examiner's finger, contraction is visible
- 4/5 Good, the elevation of the vaginal wall is felt against resistance, drawing in of the perineum is felt, able to hold for 5 or more seconds
- 5/5 Strong resistance is felt, if 2 fingers are inserted, fingers will be approximated, able to hold for 10 seconds

The Glazer protocol for pelvic floor muscle assessment with electromyography, as outlined in paper [16], involves the patient lying down with the trunk and lower limbs forming an approximate angle of 135 degrees, and the feet turned outwards, leaving a small gap between the heels. This positioning is critical as the EMG signal strength from pelvic floor muscles varies with hip rotation. Such rotation activates the internal obturator muscles, which are connected to the front part of the pubococcygeus muscle, potentially enhancing the patient's perception of pelvic floor muscle contractions and mistakenly raising the baseline muscle tone. For a more comprehensive assessment, the patient's position may be switched to standing, offering better insights for stress incontinence and everyday situations. The original Glazer protocol consists of the following phases [16]:

1. Pre-baseline rest - 60 seconds of rest, allows the diagnosis of hypertonus. It informs about a lack of relaxation of the pelvic floor muscle while laying, reduced activation in standing, or the reduced co-activation of the obliquus internus.
2. Phasic contractions - five quick flicks with a 10-second rest, allow the diagnosis of muscular dysfunction or relaxation deficits. It informs about slow peak increase

within quick-flick bursts, slow relaxation after quick activation, a reduced peak activation level, the co-activation of the surrounding muscles, and the reduced co-activation of the obliquus internus.

3. Tonic contractions - five 10-second tonic contractions with a 10-second rest after each, allow muscular dysfunction, weakness, or relaxation deficits. It informs about a reduced pelvic floor activation level, a steep decrease of activity within 10 seconds, difficulty with contraction over 10 seconds, and a co-activation of the transverse abdiminis or gluteus.

4. Endurance contraction - one 60-second endurance contraction, allows for diagnosis of reduced endurance or innervation deficits. It informs about time domain changes due to fatigue, the constancy of the contraction level and the co-activation of the gluteus or rectus abdominal.

5. Post-baseline rest - 60-second rest, allows to diagnose hypertonus or relaxation deficits. It informs about increased activity at the rest or late rest line level.

The Sorensen test, also known as the Biering-Sorensen test, is a widely recognized method for assessing the endurance of the trunk extensor muscles, which are critical for spinal stability and may play a role in low back pain (LBP) [33]. It involves measuring the amount of time a person can maintain the upper body in a horizontal position while lying prone on an examination table, with the lower body secured. This position specifically targets the endurance of the trunk extensor muscles measured by EMG signal. In the analysis of EMG data, several key metrics — Median Frequency (MDF), Averaged EMG (AEMG), and Line Fit — are employed to assess muscle fatigue and recruitment dynamics. Median Frequency is indicative of muscle fatigue, with a decrease in MDF values suggesting fatigue onset. Conversely, Averaged EMG is utilized to evaluate the level of muscle recruitment during physical tasks. The Line Fit, represented by the slope of the linear regression line applied to the MDF over time, provides a quantitative measure of fatigue progression; a decreasing slope signifies muscle fatigue, while a slope that remains constant or increases indicates the absence of fatigue. It has gained considerable popularity for predicting low back pain within the next year in males and has become a reference tool for evaluating muscle performance in patients with LBP, notably before and after rehabilitation programs [33].

2.2.2 Rehabilitation robots

In recent years, there has been significant growth in the field of robotic technology applied to rehabilitation. Robots have been widely employed in various physical rehabilitation domains to aid in patient recovery. This includes assisting in the restoration of

movement post-stroke [65, 85], enhancing or replacing diminished functions [83], and facilitating mobility support [53]. Robotic devices designed for neurorehabilitation primarily leverage the principles of motor learning, which involve engaging patients in intensive, repetitive, and task-specific motor activities [21, 22, 79]. These robot-assisted rehabilitation systems have demonstrated their effectiveness in promoting functional recovery, including enhancements in gait and upper limb function, for individuals with conditions such as traumatic brain injury (TBI), stroke, spinal cord injuries (SCI), cerebral palsy, Parkinson's disease, and multiple sclerosis (MS) [21]. Technological solutions offer credible, consistent, and acute evaluation instruments. These, when employed in conjunction with clinical metrics, can enhance clinical judgment and yield more comprehensive data regarding patient results[27].

Figure 2.2: Examples of rehabilitation robots on the market: A) Biodex System 4 Pro [13] B) EGZOTech Sidra LEG [37] C) Hocoma Lokomat Pro 6 [92] D) Tyromotion Omego[141]

The Figure 2.2 presents rehabilitation robots available on the market. Presently, there is underscored the necessity for established guidelines that will aid clinicians and researchers in enhancing the utilization of technology-driven evaluations, as well as the implementation of clinical metrics and methodologies[122]. However, one of the primary barriers to the widespread adoption of robotic technologies in neurorehabilitation is the issue of reimbursement for medical treatments that utilize advanced technology. In the realm of

neurological rehabilitation, the choice of treatment and its duration is often influenced not by the patient's specific needs or medical requirements but by the reimbursement rates established by insurance companies [22].

In a comprehensive review of the economic implications of robotic rehabilitation for adult stroke patients conducted by Kenneth Lo et al.[79], it was found that robotic therapy offers superior cost-effectiveness when compared to conventional therapy. Particularly for individuals experiencing severe disability resulting from a significant stroke, the economic advantage of robotic therapy was strongly evident. This advantage can be attributed to the increased demand for one-on-one therapeutic intervention during conventional therapy sessions, necessary to achieve comparable health benefits to those provided by robotic therapy. Conventional therapy often involves physiotherapists manually assisting and exercising the impaired limbs of stroke patients, a physically demanding task, particularly for those with substantial motor deficits. As a consequence, therapists must allocate more time and effort towards limb exercises in conventional therapy to achieve the same number of repetitions as robotic devices, ultimately leading to elevated therapy costs.

Robot-assisted neurorehabilitation of the upper limb, thanks to its capacity to deliver high-intensity training protocols, has the potential for a greater impact on impairment and motor function both in subacute and chronic stroke [70, 87], and many different devices have been proposed for use in clinical and (optionally) home settings [83]. Sheng B. et al.'s [126] comprehensive analysis indicates that individuals undergoing training with robots designed for upper limb rehabilitation experience enhancements in their range of motion, muscle strength, and overall physical capabilities. Among the studies reviewed, only a few concluded that training both limbs simultaneously offers more benefits than training one limb at a time. However, the review also emphasizes a crucial limitation in the current body of research, which is the lack of definitive proof supporting the efficiency of the methods and treatment plans used in these robotic-assisted therapies.

In a study examining the impact of Continuous Passive Motion (CPM) on individuals with post-stroke upper limb disabilities, Song et al. [129] investigated the outcomes of robot-assisted wrist training using a one-degree-of-freedom rehabilitation robot, which was EMG-controlled. The study found that the application of assistive torque, governed by myoelectric signals, enabled stroke survivors to achieve an expanded range of motion while also experiencing a marked reduction in EMG activity from the agonist muscles. This approach allowed for targeted training within ranges previously unreachable, utilizing the residual voluntary EMG activity on the affected side. Following a regimen of 20 rehabilitation sessions, there was an observable, though not statistically significant, enhancement in the range of motion, accompanied by a notable decrease in the root mean square error (RMSE) between the actual and targeted wrist angles. Additionally, significant gains were observed in muscle strength and clinical assessment scores. In their research, Hu XL et al. [56] explored the impact of using an electromyography-driven robotic hand

for upper-limb rehabilitation post-stroke. Their study focused on assessing motor recovery and the effects of task-oriented training facilitated by the robotic hand (Figure 2.3). The findings revealed that such training could enhance muscle coordination, particularly

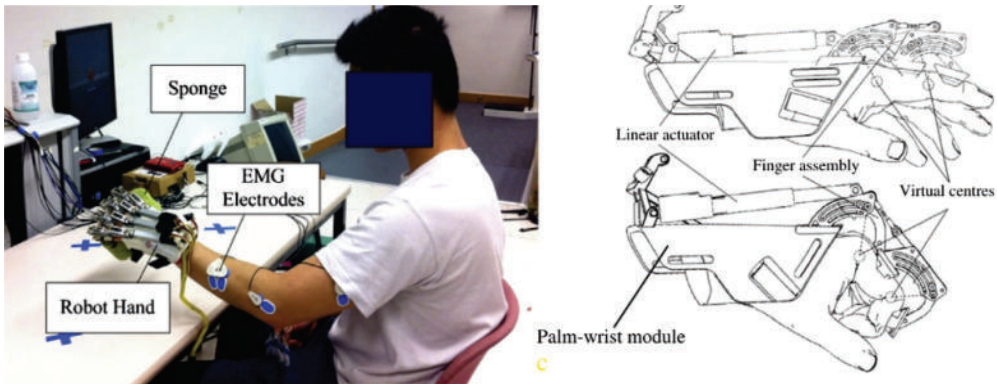


Figure 2.3: The setup for the experiment involving EMG-controlled robotic hand-assisted training of the upper limb, along with a diagram detailing the mechanical design of the robotic hand [56]

between the antagonist muscles of the fingers, namely the flexor digitorum and extensor digitorum. It was also found to decrease unnecessary muscle activity in the biceps brachii. The study utilized EMG to track changes in muscle coordination throughout the training sessions, offering a quantitative method to gauge training progress. Notably, a significant reduction in EMG activity was observed in both the flexor digitorum and biceps brachii, correlating with decreased spasticity in the finger and elbow joints. In a subsequent study [55], demonstrated that EMG-driven robotic hands could deliver prolonged, consistent, and precise therapy, aiding in fine motor control, such as finger movements. Improvements were noted in muscle coordination, as evidenced by reduced co-contraction in EMG signals, and a decrease in unnecessary biceps brachii activity. A decrease in finger spasticity was also recorded, and assessed using the Modified Ashworth Score, highlighting the potential of EMG-driven robotic aids in enhancing post-stroke rehabilitation outcomes. Trzmiel T. et al.'s research [140] showed the effectiveness of using EMG-driven robotic systems in rehabilitating patients suffering from post-COVID-19 fatigue syndrome. Incorporating robotic rehabilitation into traditional therapy routines did not detract from the overall outcomes. The findings suggest that integrating robotic rehabilitation into treatment plans for individuals with post-coronavirus fatigue syndrome is a viable approach. The clinical outcomes of robotic hand training in practical healthcare settings were found to be on par with those observed in controlled research environments, despite the clinical settings offering more flexible training schedules and less frequent sessions per week[57]. Additionally, patients undergoing treatment in the clinical setting experienced greater improvements in daily living independence and more significant reductions in muscle tone compared to those in the research lab setting.

In our study with Lewandowska-Sroka et al.[77], that is not an intefrated part of this

PhD research, the inclusion of the EMG-triggered neurorehabilitation robot in the patient's daily rehabilitation plan has a positive effect on the outcomes of the treatment. The study employed a prospective, randomized controlled trial with two distinct arms: the first group received standard physiotherapy combined with robotic-assisted exercises, while the second group was provided with standard physiotherapy alongside exercises using a lower limb rotor for 6 weeks. In seven parameters, there was a significant rise observed across successive measurements, while the Ashworth scale showed a notable decline. The outcomes with the posterior predictive averages for each treatment condition and observation are depicted in Figure 2.4. Initially, there was no significant difference between the groups regarding the overall parameter means, as evidenced by the lack of significant treatment effect parameters. Secondly, a significant weekly main effect was noted across all parameters, signifying that for seven parameters, there was a credible increase across successive observations. Conversely, for the Ashworth scale, there was a notable decrease. The most substantial alterations were noted in the measurements obtained using the Lovett scale. The most substantial alterations were detected in the measurements conducted using the Lovett scale. The mean circumference of the thigh, measured 5 and 15 cm above the knee, showed a more significant increase in the robot condition relative to the control condition. Furthermore, the reduction in Ashworth scores over time was statistically significant in both groups, but the decrease was more pronounced in the robot condition.

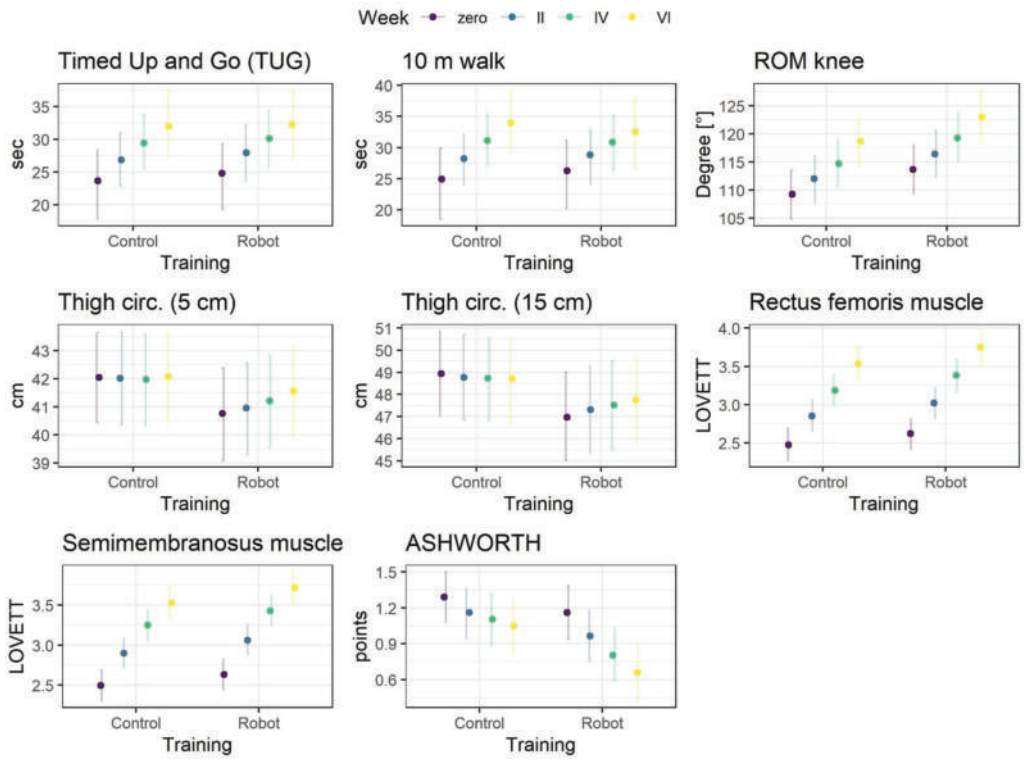


Figure 2.4: Posterior predictive means for each treatment condition and measurement for robot and control groups [77]

In a systematic review conducted by Singh H. et al.[127], focusing on rehabilitation through the use of robotic aids such as exoskeletons and end-effectors, it was concluded that individuals with mild to moderate impairments exhibited significant enhancements in both body structure/function and performance metrics. Initial findings indicate that robot-assisted rehabilitation is safe and practicable, and has the potential to decrease the level of active assistance required from therapists. In a prospective, randomized controlled trial, Jansen H. et al.[64] assessed the impact of using a controlled active motion device versus physiotherapy only in patients who underwent surgery for unstable ankle fractures. The clinical outcomes were evaluated at 6 and 12 weeks post-operation by two examiners who were aware of the patients' treatment group assignments. Various clinical metrics to evaluate foot and ankle, and dynamic pedography, were recorded. The findings indicated that the incorporation of a controlled active motion device significantly enhanced clinical results in patients with unstable ankle fractures who required partial weight-bearing.

In a randomized controlled trial conducted by Chen K. et al.[26], a comparison between home-based rehabilitation and laboratory-based rehabilitation using a portable rehabilitation robot for the ankle was made. The study found notable enhancements in the home-based group across all measured biomechanical and clinical parameters. These improvements included active dorsiflexion range of motion (identified as the primary outcome), along with mobility (evidenced by the 6-minute walk test and the timed up and go test), balance (assessed through the Pediatric Balance Scale), selective motor control of the lower extremity (evaluated by the SCALE), muscle strength, and joint stiffness. The only exceptions were passive range of motion and spasticity, which were measured by the Modified Ashworth Scale and did not show significant changes. The study by Morito K. et al.[89] investigated the effects of home training using a robotic device for ankle motion, supplemented by visual biofeedback, on two individuals with chronic hemiplegia. The findings suggest that training that includes visual biofeedback of force information can enhance the reciprocal inhibition of the tibialis anterior muscle and diminish co-contraction.

2.2.3 EMG biofeedback and gamification in rehabilitation

EMG biofeedback was first used and researched in 1976 to treat a group of patients with hemiparesis, torticollis, dystonia, and spinal cord or peripheral nerve injury [17]. The study conducted by Govil K. et al.[46] found that targeted EMG Biofeedback therapy on the gluteus maximus led to enhancements in EMG amplitude and several walking metrics, such as velocity and cadence. Furthermore, individuals receiving neurofeedback and EMG-biofeedback experienced improvements in hand function comparable to those undergoing traditional occupational therapy[115]. Cordo P et al.'s study [30] suggests that the combination of assisted movement and muscle vibration, accompanied by either EMG or torque biofeedback, can diminish upper limb impairments, enhance voluntary activation

of hand muscles, and partially restore hand functionality in individuals with significant hand disabilities resulting from chronic stroke. Additionally, research by Dosen S. et al. [36] illustrated that participants could effectively utilize real-time EMG biofeedback to monitor and adjust their myoelectric signals, resulting in more stable commands for myoelectric prosthetic devices. Yoo JW et al.'s study [146] represents the clinical trial to showcase the enhanced advantages of integrating EMG biofeedback with virtual reality (VR) exercise games for children diagnosed with spastic cerebral palsy. The findings from this study revealed that the combined use of augmented EMG and VR feedback resulted in superior neuromuscular balance control in the elbow joint compared to the use of EMG biofeedback in isolation.

Biofeedback can motivate patients who are frustrated over the inability to isolate pelvic floor muscles (PFMs) or who lack the sensation of muscle contraction [93]. Learning to properly engage pelvic floor muscles for effective outcomes can be challenging. In clinical settings, supplementary techniques like vaginal cones and biofeedback are often employed alongside exercises to enhance this process. Numerous research studies have confirmed the efficacy of these combined approaches in managing incontinence issues. Numerous studies have proved biofeedback to be effective in the treatment of incontinence [1, 20, 58]. Rett et al.[117] found that a brief period of pelvic floor muscle training, augmented with surface electromyography biofeedback, was effective in alleviating symptoms of stress urinary incontinence (SUI) in premenopausal women, offering a viable option for conservative treatment. However, the results of different studies and systematic reviews on whether PFMs training with biofeedback is better than PFMT alone are conflicting. The research [31] analyzed data from 390 female patients suffering from stress or mixed urinary incontinence. These individuals were trained to swiftly and effectively engage their PFMs using biofeedback guidance. They conducted one to two home-based training sessions lasting 10 minutes each, daily for a duration of 3 to 6 months. The training sessions were automatically recorded by an EMG-biofeedback device each time the exercises were performed, ensuring patient compliance was monitored. Follow-up consultations were scheduled every 4 to 12 weeks. The findings indicated a significant self-reported improvement rate (94%) and high levels of patient satisfaction with the therapy outcomes. Additionally, there was a notable enhancement in the strength of pelvic floor contractions, evidenced by an increase in Oxford scores from 2.9 to 4.1, and the electrical EMG potentials nearly doubled, rising from 11.3 μV to 21.5 μV, according to the data presented in [31]. In conclusion, the application of sophisticated sEMG technology for visualizing muscle-related phenomena, previously undetectable, exemplifies one of the ways in which biofeedback can integrate evidence-based medicine practices. This approach not only aids in the precise definition and management of disorders but also contributes substantial additional value to the field [44].

The aim of the feedback is to provide the users with an instant numerical assess-

ment of their performance in executing the movement as indicated for instance by the Game Score, along with a descriptive insight into their muscle activity based on EMG data. Additionally, EMG offers the practitioner a comprehensive view of the user's ongoing improvement in regaining mastery over their upper limb muscles. Interventions using game-based approaches have effectively facilitated motor recovery in the treatment of stroke [42, 116] and Parkinson's disease [52]. The Hung's et al. [61] study explores the efficacy and challenges of game-based rehabilitation systems for stroke survivors. Despite the proven benefits of repetitive rehabilitation exercises, patient adherence is low, primarily due to the monotonous nature of traditional exercises and lack of professional oversight in home settings. Game-based rehabilitation, while offering potential for greater engagement through entertaining and diverse games, faces limitations such as a narrow selection of games, lack of motivational elements, and high costs. Feedback from patients and occupational therapists highlights the need for systems that are not only engaging and diverse but also capable of providing therapeutic monitoring and feedback. The study suggests that carefully selected and tailored games, which balance entertainment with therapeutic objectives and include motivational features, could significantly improve patient adherence and recovery outcomes. The study [109] evaluates the effectiveness of game-based interventions in enhancing user control over standard myoelectric prostheses, comparing genres such as racing and rhythm-based games. Patients found racing games more enjoyable, while rhythm games offered better challenges for electromyography control, crucial for prosthesis manipulation. Key parameters for assessing control include muscle contraction strength and muscles activation capabilities. The study underscores the importance of proportional control in myoelectric prostheses, where signal strength dictates movement speed, necessitating varied muscle activation levels. EMG biofeedback, integral for patient motivation and awareness of muscular activity, has been effectively utilized in clinical settings. The racing game, with its simple controls and automatic acceleration, was highly favored for its fun, affinity, and motivational aspects. Overall, engaging with these games resulted in a more enjoyable and effortful experience compared to traditional myoelectric rehabilitation tools, indicating the potential of tailored game mechanics in prosthetic training and rehabilitation. Illustrations of rehabilitation games developed by EGZOTech are presented in Figure 2.5.

2.2.4 Artificial Intelligence in Rehabilitation

Artificial Intelligence utilizes advanced computational and inferential techniques to produce insights, allowing the system to engage in reasoning and learning, and enhances clinician decision-making by providing augmented intelligence. Machine learning (ML), a branch of artificial intelligence, allows healthcare professionals to utilize existing data to forecast outcomes. Furthermore, ML facilitates automated decision-making and generates

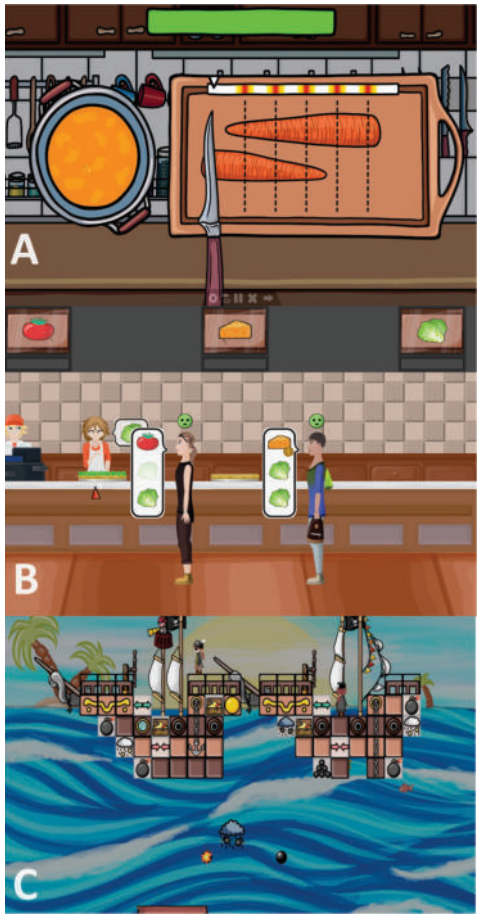


Figure 2.5: Example of rehabilitation games [37] A Slice and Dice, B Burger Mania C Brick Pirates

predictions using patient data, serving as a means to offer immediate preventive measures for individuals with particular health conditions. Through the utilization of machine learning algorithms, such systems acquire the capability to discern and adapt to the behavioral patterns and traits of individuals over a period, thereby enhancing their efficiency in minimizing the occurrence of false positives. In Alsobhi's at al. study [4], a majority (61.8%) of the investigated physical therapists reported being unaware of the use of AI in rehabilitation contexts.

Table 2.1 presents the usage and accuracy of supervised machine learning techniques for musculoskeletal applications [134]. In an investigation by Ye et al. [145], the efficacy of a ML-derived tool designed to assess the fall risk in elderly individuals was examined. The findings suggested that this ML-informed tool effectively generated early alerts, potentially mitigating fall incidents among this demographic. Given that patients suffering from orthopedic and neurological conditions often require prolonged and rigorous physical rehabilitation to ameliorate their functional impairments, physical therapists may encounter difficulties in crafting therapeutic strategies that accurately reflect patient progress. In these instances, employing an AI-based decision support system, underpinned by ML, could significantly aid PTs in diagnosing and tracking rehabilitation efforts. In

Table 2.1: Accuracy of supervised machine learning techniques for musculoskeletal applications.[134]

Ref	Classification Question	Data Source	Acc[%]	Algorithm Used
[97]	Is pathology present	X-ray	83	16 layer CNN
[63]	or not?	MRI	70.4	CNN
			75.4	
			95.4	
[23]	Can successful exercise	fMRI	92	SLR
[81]	performance be identified?		93	SVM, LR
[19]		Inertial sensor	99.4	CNN k-NN
			97.8	SVM
[67]	Can risk of injury be	Inertial sensor	94.1	10F-CV
	classified based upon		72	10F-CV
	movement quality?		90	LOSO-CV
			60	LOSO-CV
[101]	Can CLBP subgroups be	EHR	71.05	DT
	stratified accurately?		71.05	BT

10F-CV: 10-fold cross-validation.
BT-boosted tree.
CLBP- chronic low back pain.
CNN- convolutional neural network.
DT-decision tree.
EHR-electronic health records.
K-NN- k-nearest neighbour.
LOSO-CV- leave-one-subject-out cross-validation.
LR-logistical regression.
SVM-support vector machine.

a study conducted by Tageldeen et al.[136], a non-invasive human-machine interface was created, utilizing sEMG signals and a neuro-fuzzy classification system to estimate joint torques. The findings from this study highlighted that fuzzy logic inference systems have proven to be highly effective in real-time EMG/Torque estimation, and the optimization of membership functions through expert systems has led to reduced training durations and enhanced results. In research [128], a hierarchical control approach was employed, incorporating EMG data and wrist strength metrics. This control mechanism was realized through a Backpropagation Artificial Neural Network (BP-ANN), which was trained using data from exercises previously conducted with other patients. A key finding was that the control system could predict human actions with a lead time of about 0.2 to 0.3 seconds, enhancing the fluidity of exoskeleton operation by generating personalized maps for each patient. Notably, two studies by Wang et al. [144, 143] are prominent in the review for their innovative control strategies, utilizing Kalman filters and self-learning machines based on various neural network designs to identify patient intentions or abrupt movement shifts during upper limb rehabilitation exercises. These methods proved to be

effective in movement anticipation and learning rehabilitation paths for recurring therapies. Similarly, studies [78, 120, 74] introduced smart approaches by integrating signal processing of EMG and force-myographic data, among others. These studies proposed employing a straightforward ANN with a backpropagation learning algorithm, leading to the creation of both discrete and continuous motor control models for exoskeleton movement. The models were trained with labeled data in a supervised learning framework, and after training, the BP-ANN made predictions using unlabelled test data. Although the outcomes were promising, the potential for fuzzy systems to expedite the BP-ANN training process was identified as an area for enhancement [78]. In Lambelet et al. study [71], an adaptive position control system was developed, employing an admittance controller that reacts to an input force. The study found that incorporating surface electromyographic signals into the adaptive admittance control allows for the automatic modulation of assistance based on the characteristics of the input signal.

Gathering physiological data from patients is crucial in the advancement of robotic systems, as such information can significantly enhance robot control mechanisms [71, 120, 128, 136, 144, 143] or contribute to more accurate and objective evaluations that reflect the rehabilitative process and its benefits for users [10]. When it comes to the integration of data collection and fusion methodologies in the creation of exoskeletal or rehabilitation robotic systems, the reliability of EMG-based technologies stands out, making their integration a fundamental aspect in the evolution of forthcoming devices.

In Petersson et al.'s studies [107], healthcare leaders identify several challenges in implementing AI both within the broader healthcare system and their specific organizations. These challenges include external factors, internal capacity for strategic change, and the transformation of healthcare professions and practices. The findings suggest a need for developing implementation strategies across healthcare organizations to enhance AI-specific capabilities. Effective AI implementation also requires appropriate laws and policies. Furthermore, investment in implementation processes is crucial, along with collaboration between healthcare sectors, county councils, and industry partners.

Chapter 3

System design and implementation

This chapter outlines the system design and implementation framework developed for the analysis of biomechanical and bioelectric parameters, aimed at enhancing the automation of diagnostics and rehabilitation processes for patients. The integration of advanced sensing technologies (an electromyograph, a dynamometer, and a goniometer), data analysis methods, and machine learning algorithms forms the cornerstone of this innovative system, enabling precise and real-time monitoring and assessment of patient conditions.

3.1 General concept

The central aim of this dissertation is to explore and establish the foundational methodology for an automated expert platform that leverages biomechanical and bioelectric parameters for diagnosing and rehabilitating patients. By harnessing the power of machine learning and robotic systems, this research seeks to create a feedback loop that incorporates EMG, torque, and limb position measurements to facilitate a more objective, efficient, and personalized approach to patient care.

Drawing upon a comprehensive review of the literature, we formulated specifications for diagnostic and rehabilitation protocols to be integrated into the Luna EMG and Stella BIO devices. These protocols include but are not limited to, Force isometric test [5, 122], Force isokinetic test [5, 34, 41, 54, 82, 38, 138, 139], Joint position sense evaluation [9, 45, 73], Muscle spasticity test [3, 24, 25, 142, 148], Maximum Voluntary Isometric Contraction (MVIC) EMG test [35, 109], ROM measurement [106], the Glazer protocol [12, 16, 31, 44, 99], Muscle fatigue test [2, 27, 33, 35, 40, 59, 68, 119, 133, 135, 147, 149], and Luna EMG initial evaluation [14, 27]. Each protocol has implemented a detailed procedure with instructions about the used extension and muscle for EMG evaluation.

The Luna EMG initial evaluation constitutes an evaluation protocol designed for the initial examination of new patients. There was created a decision tree diagram, illustrated at Figure 3.1. This diagram was constructed based on the bioelectrical and biomechanical

parameters that I identified through the analysis of data from the Luna EMG device, outlining subsequent steps in patient rehabilitation. During, the Luna EMG initial eval-

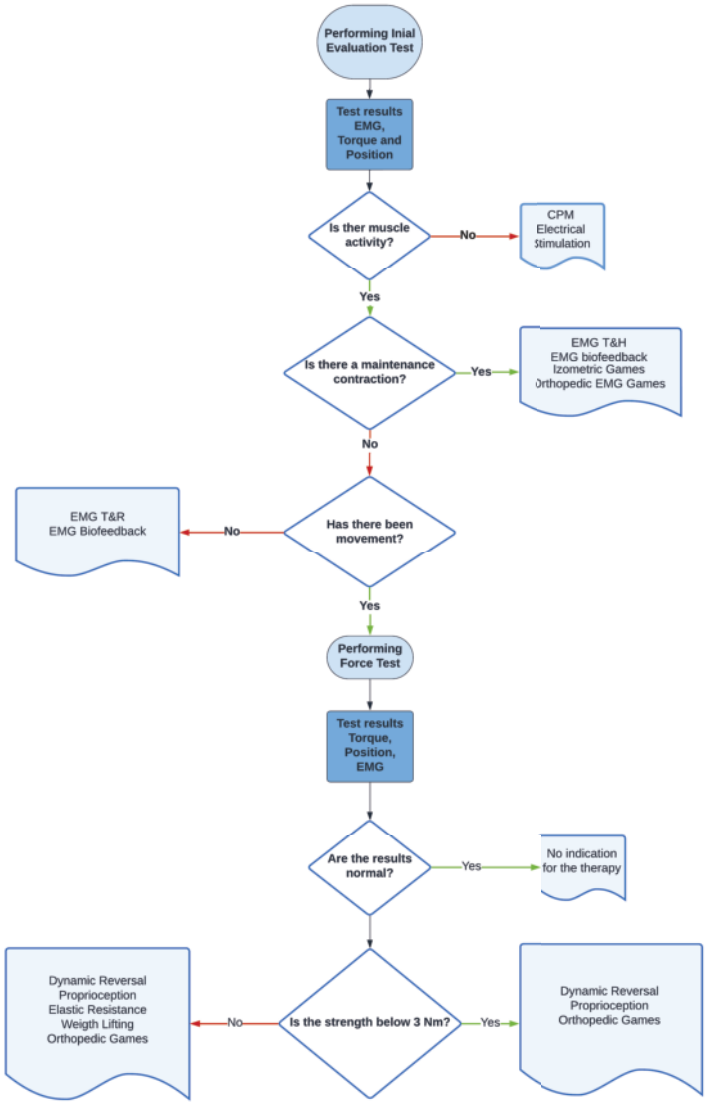


Figure 3.1: Initial Evaluation Decision Tree

uation, participants are required to be in a relaxed state at the start of the test. Upon hearing a "Contraction" audio cue, they must promptly execute the movement in the correct direction and maintain the contraction until the active phase concludes. Following a "Relax" audio cue, they should return to a relaxed state, allowing the limb to passively revert to its starting position. They must then await the signal to begin the next cycle. The test comprises three such repetitions. This protocol facilitates a rapid appraisal based on objective metrics, subsequently guiding the recommendation of tailored exercises utilizing the Luna EMG rehabilitation robot. The methodology of this expert system is delineated in Figure 3.1. The evaluation encompasses tests for muscle activation capability, the initiation of movement in an unladen limb, and the capacity to generate muscular force. In the context of biomechanical and bioelectrical analysis of the test, several key parameters are

quantified to evaluate performance and physiological responses. These include positional metrics such as the range of motion, and torque-related measurements encompassing the average torque exerted during active phases, the mean torque during rest intervals, and peak torque values. Additionally, electromyographic signals are researched, with emphasis on the mean signal amplitude during both work and rest periods, the initiation and relaxation of muscle activation (onset and offset), and the variability in the duration of activity and inactivity phases. The outcomes of the assessment provide insights into the innervation status of muscles, the capacity for sustained contraction, the potential for active movement, the ability to move through the complete range of motion, and the overall muscle strength.

To validate the hypotheses proposed in the doctoral dissertation, the ensuing evaluations of the formulated diagnostic and therapeutic procedures were conducted. The Muscle Force Test, studied on both a control group and a stroke group targeting the upper limbs, involved EMG recordings from the biceps brachii and triceps brachii muscles. This test is evaluated in the publication [118] and is elaborated upon in Section 4.1. The evaluation of the Muscle Spasticity Test, conducted on 68 healthy individuals and 116 stroke survivors focusing on the upper limbs, involved EMG assessments of the biceps brachii and triceps brachii muscles. This is detailed in Section 4.2. The evaluation of the Glazer Protocol was carried out on patients with stress urinary incontinence remotely using a telemedicine rehabilitation program. The patients after evaluation received treatment plans with EMG biofeedback exercises in the Stella BIO application. Details of the telemedicine-administered test and rehabilitation process are provided in Section 4.3. Additionally, Section 4.4presents research investigating the efficacy of EMG-triggered movement therapy in knee rehabilitation for patients post-stroke.

In a study examining fatigue among individuals with post-viral fatigue syndrome following COVID-19, the Muscle fatigue test was employed in our study with Zasadzka et al. [150]. The study confirms that the Application of an EMG-Rehabilitation Robot in Patients with Post-Coronavirus Fatigue Syndrome (COVID-19) is feasible and safe. The test protocol for muscle fatigue assessment with EMG from biceps brachii muscle was established with the upper limb fixed at a 90-degree angle of elbow flexion. It involved an initial 30-second period of relaxation, followed by a 30-second contraction phase, and concluding with another 30-second relaxation phase. In instances where a patient could not sustain a 30-second contraction, the algorithm was designed to determine the duration of muscle contraction using only the EMG signal. The muscle fatigue was assessed based on the Mean Frequency described in equation (2.9) and presented in Figure 3.2. In comparing pre- and post-intervention outcomes, both the Intervention Group and Control Group showed improvements across the majority of measured parameters. However, muscle fatigue, as assessed by EMG, did not follow this trend. The Intervention Group demonstrated non-significant enhancements, while the Control Group exhibited non-significant

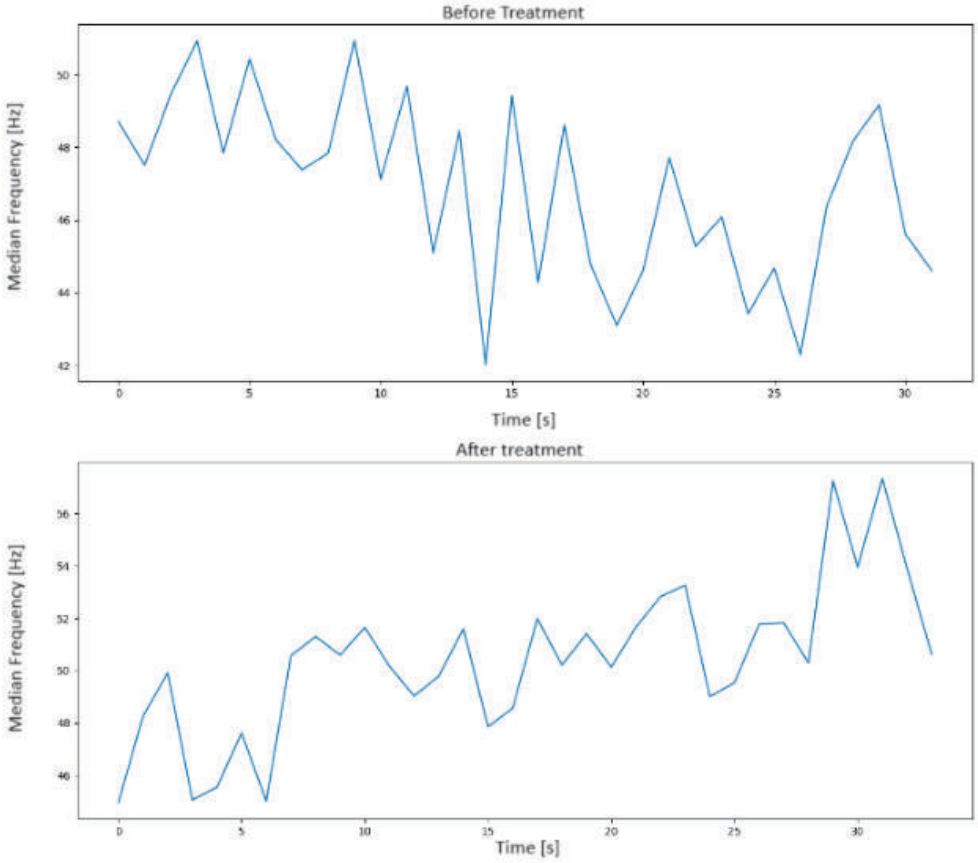


Figure 3.2: Example of median frequency of EMG signal from a patient with Post-Coronavirus Fatigue Syndrome (COVID-19) before (with visible shift to lower frequency due to fatigue) and after treatment

declines. The comparison of mean changes of measured parameters did not reveal any statistically significant differences between the study groups (Table 3.1). Muscle fatigue

Table 3.1: Comparison of mean pre-post changes of outcomes between groups [150]

Outcome Measure	**Intervention Group**	**Control Group**	**p**
FIM	26 (16–113)	23 (–27–54)	0.137
HGS	3 (0–10)	4 (–9–10)	0.367
BI	8 (4–14)	6 (–3–11)	0.233
FAS	–2 (–11–0)	–2 (–7–7)	0.412
Fatigue (EMG)	0 (–14.9–34.7)	2.80(–55.4–11.3)	0.909

FIM—Functional Independence Measure

HGS—Handgrip strength

BI—Barthel Index

FAS—Fatigue Assessment Scale

Fatigue (EMG)—muscle fatigue calculated from EMG measurement data, expressed as a percentage of the slope of the mean frequency curve.

dynamic test was described in the study [130]. The research confirms that the testing procedure with the rehabilitation robot can be a useful in the assessment of muscle fatigue, strength, and muscle activation during exercises among patients with Multiple Sclerosis. The main goal of the study was to create and test a special protocol, using Luna EMG, to assess fatigue and other related factors among patients with multiple sclerosis. The experiment was performed among 25 patients with multiple sclerosis on the elbow extension with EMG signal collected from biceps brachii and triceps brachii. The study protocol proceeded as follows: 2 minutes of passive motion exercise, 5 minutes of isokinetic exercise of elbow flexion and extension, 2 minutes of break, and 2 minutes of isokinetic exercise of the same joint 3.3. Data from the experiment shows that there is an average correlation

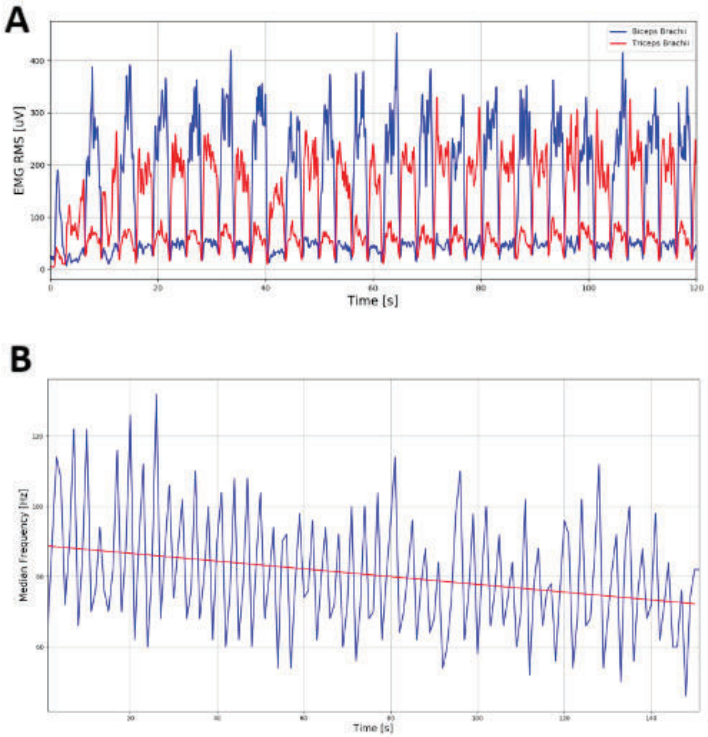


Figure 3.3: A EMG RMS signal of biceps and triceps muscles during 2 min isokinetic exercise B Median Frequency of EMG signal of triceps with linear regression (red) [130]

between triceps muscle fatigue and the amount of repetition, both for 5 minutes and 2 minutes of exercise. This could indicate that biceps brachii, got more tired in the second training, being followed by the exhausting first one. The high correlation between mean torque in flexion and MDF slope of biceps brachii during the 2 minutes of exercise was noted, higher mean force, correlated with higher fatigue.

Joint position sense evaluation was utilized in these researches [75, 76, 99]. Throughout the procedure, the limb of the participant is secured to the robotic extension and unweight. Subsequently, the researcher establishes the motion range, selecting between passive or active modes, and determines whether the movement would involve flexion or extension. Additionally, adjustments are made to the speed, force, and duration of the position held.

The researcher then defined the target position, the robot moves to position and sustains the participant's limb in the designated posture. In the passive mode, the participant notified the researcher upon the robot reaching the set position. Conversely, in the active mode, the participants themselves maneuvered their limb to the specified position.

The results from our study with Oleksy et al. [98] demonstrate that the evaluation performed on the rehabilitation robot is reliable for joint position sense assessment in both knee flexion and extension, in active and passive modes as well on the right as on the left sides. Twenty-four male students, in good health and aged between 18 and 30 years, participated in the study as volunteers. In the study, JPS tests for the right and left knees were conducted using the Luna EMG rehabilitation robot during both flexion and extension movements in active and passive modes. The assessment of JPS assessment involved conducting four successive tests on each lower limb. For the active joint position assessment, the knee under examination was passively guided to a specific target position. This position was held for 5 seconds, allowing the participant to memorize it, before being passively returned to the starting position. After a 3-second pause at the starting position, the participant then actively moved their knee to align with the remembered target position, signaling verbally when they believed the knee had reached the target, at which point the device recorded the position. In the passive mode of JPS measurement, the procedure began by passively moving the knee to a set target position for evaluation. The knee was held at this target position for 5 seconds to enable the participant to memorize the position. It was then passively returned to the starting position. Following a 3-second hold at the starting position, the knee was again passively moved towards the target position, and the movement was halted based on the participant's indication when they felt the knee had attained the target position. These tests were conducted in two distinct sessions, spaced one week apart. The reliability of knee flexion and extension measurements in both modes was high, with ICC values ranging from 0.866 to 0.982 and Standard Error of Measurement (SEM) between 0.63 and 0.31. The average JPS angle error showed no significant difference between the right and left limbs ($p < 0.05$), and there was no notable correlation between the limbs ($r = 0.21$–0.34; $p > 0.05$). There were used Bland–Altman plots, a statistical method used to visualize the agreement between two quantitative measurements by plotting the differences between the measurements against their averages. The plots indicated a minimal bias between limbs, albeit with relatively large limits of agreement 3.4.

Consequently, the JPS test procedure and Luna EMG rehabilitation robot were deemed a reliable instrument for assessing knee JPS in both active and passive modes. While the JPS angle error did not show significant variance between the left and right sides in this study, a slight asymmetry was noted, as evidenced by a broad level of agreement exceeding 5° in the Bland–Altman plots. This suggests that for healthy individuals, such as active athletes, proprioception assessment should be conducted on both sides.

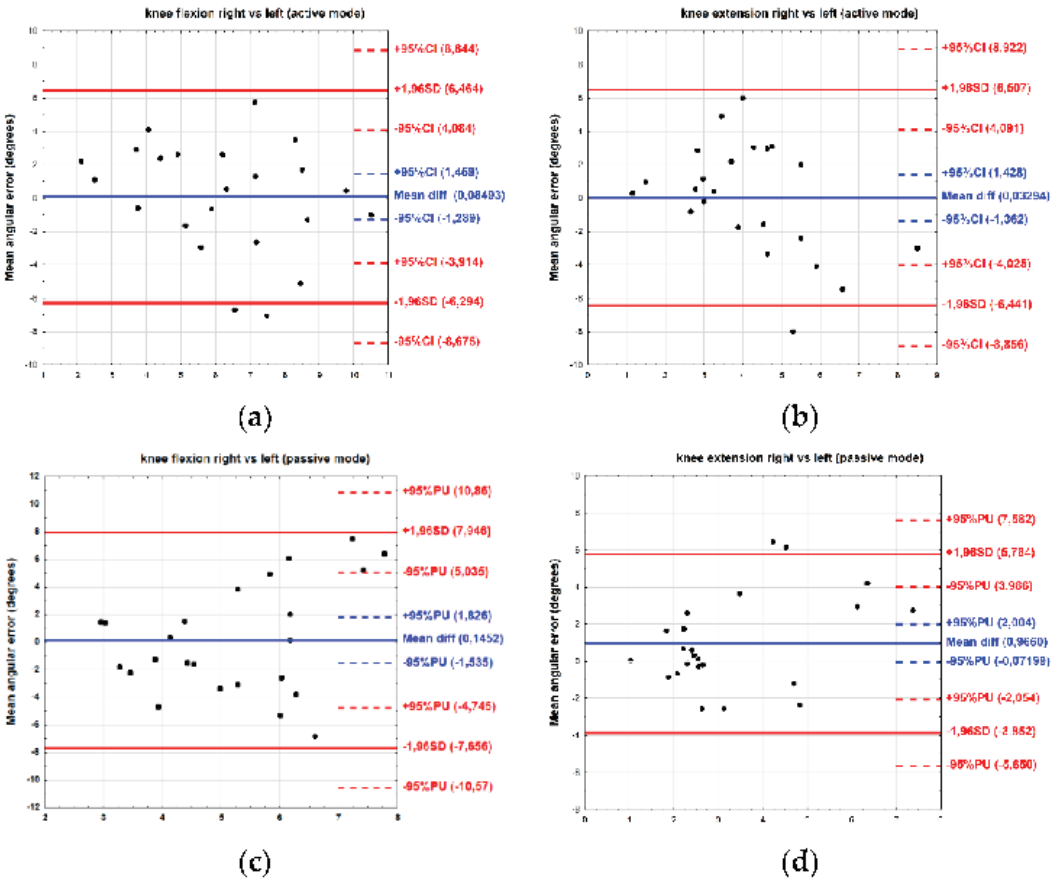


Figure 3.4: Bland–Altman plot showing agreement between right and left sides for active (a,b) and passive (c,d) modes of joint position sense [99]

Additionally, our other study [75] presents findings on the JPS test performed on the rehabilitation robot, highlighting its capability to provide dependable assessments of upper limb proprioception. Each upper extremity was subjected to four rounds of measurements for the active mode in the group of 102 healthy young adults. For the assessment of active joint flexion, the elbow under examination was passively maneuvered to a predetermined target position. This position was maintained for five seconds, allowing subjects to memorize it, before being passively returned to the initial position. After holding the initial position for three seconds, subjects were then instructed to actively move their limb to achieve the target position. The study reveals a high degree of consistency in measurements, as indicated by the interclass correlation coefficient (ICC) values ranging from 0.969 to 0.997, underscoring the reliability of the agreement between the two assessments. There was significant congruence between researchers for both upper limbs (right limb: P=0.3484 [Exam 1]; P=1.0000 [Exam 2]; left limb: P=0.1092 [Exam 1]; P=0.7706 [Exam 2]), as well as across different examinations (right limb: P=0.1127 [Researcher 1]; P=0.2113 [Researcher 2]; left limb: P=0.0087 [Researcher 1]; P=0.1466 [Researcher 2]). Furthermore, Bland-Altman analysis demonstrated minimal inter-rater variations, with deviations around 0.05° in the initial examination for the left upper limb and 0.04° for the

right upper limb, with the largest discrepancy observed in the left upper limb between examinations being just 0.08°. Through the device's application, evaluations conducted on the proprioceptive senses of the upper limbs in a group of 102 healthy young adults demonstrated notable consistency, both internally and externally. This consistency in measurement underscores the device's effectiveness and reliability in proprioceptive evaluation, suggesting its potential utility in clinical and research settings for assessing upper limb sensory functions.

Moreover, the latest our research [76] was carried out with participants who were in the late phase after stroke. A group of 126 individuals was involved, comprising 78 females and 48 males, with a median age of around 60. The methodology adopted in this study mirrors that outlined in prior research [75]. Assessment of proprioception for both the left and right upper limbs was conducted using the Luna EMG rehabilitation robot. The evaluation was executed by two researchers in two sessions, spaced two weeks apart. Comparative analysis of the data was done both inter-researcher and intra-research, presented in Table 3.2 and Table 3.3. Results indicated a high degree of reliability in the measurements obtained for the right hand, as evidenced by interclass correlation coefficients (ICC) ranging from 0.996 to 0.998, and for the left hand ranging from 0.994 to 0.999. Pearson's linear correlation also showed a consistently high level of agreement ($R = 1.00$) for both hands, across both comparisons between the different examinations (Exam) and the researchers (Res) who conducted the tests with the participants.

Table 3.2: Proprioception (right upper limb) [76]

Exam	Res	$\bar{x}$	SD	Diff $\bar{x}$	SD	p	R	ICC	CV	SEM
I	1	5.80	3.22	-0.04	0.18	0.0220	1.00	0.998	55.54	0.29
I	2	5.77	3.18					(0.998-0.999)	55.19	0.28
II	1	5.72	3.15	0.01	0.20	0.7921	1.00	0.998	55.18	0.28
II	2	5.72	3.18					(0.997-0.999)	55.56	0.28
I	1	5.80	3.22	-0.09	0.23	0.0001	1.00	0.997	55.54	0.29
II	1	5.72	3.15					(0.996-0.998)	55.18	0.28
I	2	5.77	3.18	-0.05	0.27	0.0578	1.00	0.996	55.19	0.28
II	2	5.72	3.18					(0.995-0.998)	55.56	0.28

$\bar{x}$ - mean of the absolute difference between the target and replicated position

SD - standard deviation

Diff - difference between examination $\bar{x}$

p - the dependent-samples t-test result

R - Pearson Correlation

ICC - Interclass correlation coefficients

CV - Coefficient of variable

SEM - Standard error of measurement

Table 3.3: Proprioception (left upper limb) [76]

Exam	Res	$\bar{x}$	SD	Diff $\bar{x}$	SD	p	R	ICC	CV	SEM
I	1	6.65	3.52	0.02	0.25	0.4487	1.00	0.998	52.98	0.31
I	2	6.67	3.53					(0.997-0.998)	52.99	0.31
II	1	6.55	3.43	-0.01	0.18	0.4027	1.00	0.999	52.34	0.31
II	2	6.54	3.45					(0.998-0.999)	52.82	0.31
I	1	6.65	3.52	-0.10	0.28	0.0002	1.00	0.996	52.98	0.31
II	1	6.55	3.43					(0.995-0.997)	52.34	0.31
I	2	6.67	3.53	-0.13	0.35	0.0001	1.00	0.994	52.99	0.31
II	2	6.54	3.45					(0.992-0.996)	52.82	0.31

$\bar{x}$ - mean of the absolute difference between the target and replicated position

SD - standard deviation

Diff - difference between examination $\bar{x}$

p - the dependent-samples t-test result

R - Pearson Correlation

ICC - interclass correlation coefficients

CV - Coefficient of variable

SEM - Standard error of measurement

3.2 Research equipment

The research equipment employed in the design and implementation of the system for analyzing biomechanical and bioelectric parameters is pivotal to the success of this project. This section details the specialized hardware and software components selected for data acquisition, processing, and analysis, ensuring the highest standards of precision, reliability, and scalability in the study of patient diagnostics and rehabilitation.

3.2.1 Computer unit and software

The computer used to conduct the simulation ran on Microsoft Windows 11 x64. Activities related to data processing and analysis, performing simulations, as well as preparing materials for the dissertation were performed using software written in the Python 3.11 programming language [112]. The numerical libraries NumPy v1.24.3 [95] and pandas v2.0.1 [104] were used as the basis for handling numerical data, the SciPy v1.10.1 library [124] as a tool for basic signal processing and statistical analysis, the scikit-learn v1.2.2 library [123] providing machine learning methods, the pingouin v0.5.4 library [113] for statistical analysis, as well as the Matplotlib v3.7.1 library[86] as a tool for performing graphical data analysis.

3.2.2 Luna EMG

Luna EMG, manufactured by EGZOTech Sp. z o.o. (registration number/TNP/MDD 0373/4038/2021), is a multi-use rehabilitation robot - rehabilitation exercise device, intended for medical purposes of rehabilitation, physiotherapy, and occupational therapy, including both therapy and evaluation of the patient's state. Luna EMG includes motor and extension components, which are modular mechanical elements for upper and lower limbs, including occupational therapy, or trunks. These parts are affixed to the patient either through straps or grips. Luna EMG is equipped with a position sensor, a dynamometer, and an electromyograph. The head's rotation position accuracy is $\pm 2°$ and the maximal speed is $100°/s$. Torque measurement has accuracy ± 0.2Nm with maximal head rotation 60 Nm. The presence of a negative sign in torque values indicates that the force applied is in a counterclockwise direction. The electromyograph has 6 channels with simultaneous sampling of up to 1000 samples per second with 24-bit accuracy. Luna EMG has a baseline noise is below $0.5\mu V$ RMS and an accuracy of electromyography of $1\mu V$. The device's movement is programmable and guided by an array of sensors. Operational control of Luna EMG is executed via a Windows-based application on a tablet, utilizing a User Interface (UI). Luna EMG is engineered to support various fundamental control algorithms, encompassing isokinetic movement, isotonic movement, and isometric exercises. Study tests were performed using of Luna EMG rehabilitation robot with Upper Limb Extension, presented in Figure 3.5. Luna EMG may operate in the following modes:

Figure 3.5: Luna EMG with Upper Limb Extension with Mezos SIT examination and treatment chair [37]

- Continuous passive motion - the robot moves the patient's limb with constant velocity and limited resistance
- Isokinetic movement - the patient has to move the robot extension with constant velocity but resistance is variable.
- Isotonic movement - the patient exercises with constant resistance
- Isometric movement - the robot extension is fixed in one position
- Electromyography measurement and biofeedback
- EMG triggered movement - trigger and hold, where the patient has to keep contraction with muscle activity above the threshold to robot movement; trigger and release, where the patient only has to cross the threshold to robot movement in the whole range of movement
- Proprioception - joint position reproduction for assessment and therapy
- Rehabilitation games - works with 3 operation modes as: isokinetic movement, EMG triggered movement (trigger and hold) and EMG biofeedback.

3.2.3 Stella BIO

Stella BIO, manufactured by EGZOTech Sp. z o.o. (registration number TNP/MDD 0373/4038/2021), is indicated for assessing electromyography signals from the pelvic floor and surface muscles and for providing EMG signals to be used in biofeedback. Additionally, that medical device is designated for the treatment of pelvic floor disorders and is also a transcutaneous electrical nerve stimulator and external functional neuromuscular stimulator. That electromyography biofeedback device with electrical stimulation is a battery-powered, mobile, and connected to the computer unit or smartphone via WiFi (Figure 3.6). The software to control the device and collect the data is a web browser application, available at https://app.egzotech.com/. The Stella BIO application enables telerehabilitation processes by allowing specialists to establish evaluation protocols and treatment exercises while providing them with continuous access to patient outcomes. A patient employs the Stella BIO device through an application on their personal computer or smartphone to conduct therapy sessions. The bioelectrical signal could be collected from up to 8 channels at a simultaneous sampling rate of 1000Hz. The baseline noise is below 0.5µV RMS and the measurement resolution ±6000 µV is 0.1 µV. Stella BIO is may operate in the following modes:

- EMG biofeedback,
- electrical muscle stimulation,

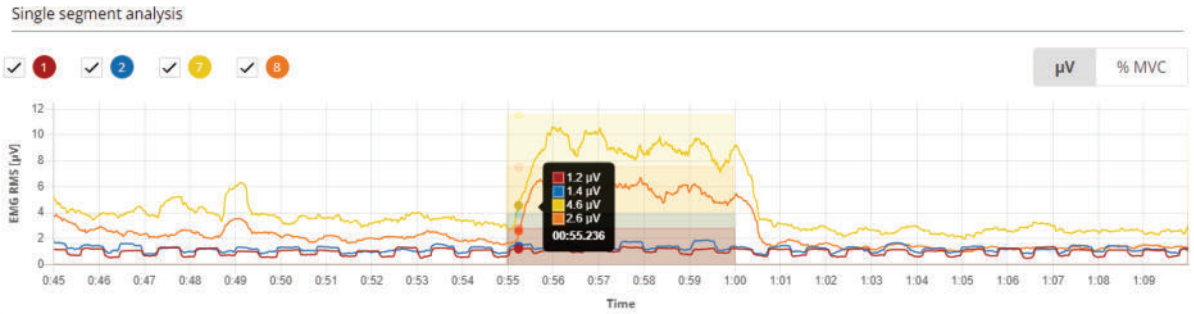
- functional electrical stimulation,
- EMG - triggered electrical muscle stimulation,
- transcutaneous Electrical Nerve Stimulation (TENS),
- rehabilitation games control with EMG signal.

Figure 3.6: Stella BIO device during pelvic floor muscle training [37]

3.3 Practical implementation in healthcare

In the research project of The National Centre for Research and Development (NCBR) "Development of innovative methods of automatic diagnostic and rehabilitation using robots and bioelectric measurements" POIR.01.01.01-00-2077/15, I contributed as a Product Engineer, overseeing the development of the Luna EMG rehabilitation robot, detailed described in Section 3.2.2. My duties also encompassed the research, innovation, and development of the Stella BIO electromyography biofeedback device, which incorporates electrical stimulation elaborated in detaild in Section 3.2.3, and the Mezos SIT examination and treatment chair, presented in Figure 3.5. This work involved designing diagnostic and therapeutic programs, data analysis techniques 3.7, and automation concepts in rehabilitation 3.8. The NCBR acknowledged the successful completion of this project both in terms of its objectives and financial management. The Stella BIO device received EC certification as a medical device on July 27, 2020, with the registration number TN-P/MDD 0373/4038/2021, and was granted an industrial pattern (Rp.26591) on January 25, 2021, followed by FDA approval under 510(k) (number K210002) on October 1, 2021.

The Mezos SIT, categorized as a Class I medical device, was certified under the 2017/745 MDR (certification of free sale no 224/2022 dated April 25, 2022), Moreover, the technology developed in Mezos SIT has 2 application patents: P.440692 Chair to rehabilitation exercises from 21.03.2022 and P.440693 Positioning mechanism for a chair to rehabilitation exercises from 21.03.2022. Between 2019 and 2023, sales of the Luna EMG reached 338 units (Fig.3.9), Stella BIO saw 106 units sold from 2020 to 2023, and Mezos SIT achieved 115 units sold from 2022 to 2023.

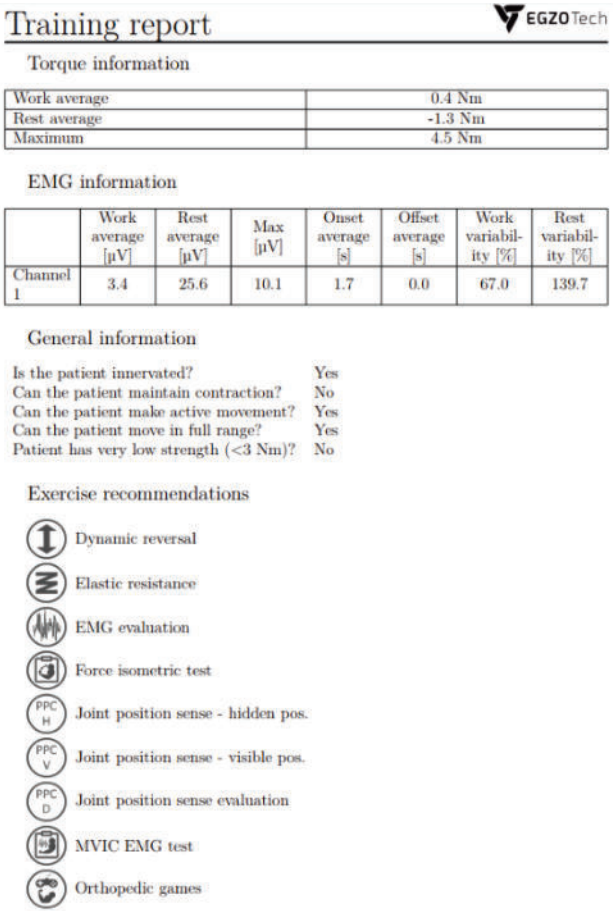


	Work/Rest Cycle	Min [µV]	Max [µV]	Average [µV]	Deviation [µV]	Coefficient of variability	Onset time	Release time	Activation time [s]	Relaxation time [s]	Linear regression [µV/s]	% comparison max. values	% comparison avg. values
1	Work	-	-	-	-	-	-	-	-	-	-	-	-
	Rest	-	-	-	-	-							
2	Work	-	-	-	-	-	-	-	-	-	-		
	Rest	-	-	-	-	-							
7	Work	3.84	10.65	8.71	1.22	14%	00:55.242	01:00.515	0.74	0.50	-0.38	59%	58%
	Rest	2.68	4.66	3.48	0.32	9%							
8	Work	2.58	6.71	5.52	0.65	12%	00:55.296	01:00.514	0.41	0.46	-0.15		
	Rest	1.52	3.31	2.09	0.30	14%							

Figure 3.7: Part of EMG signal analysis in Stella's BIO report after exercise

In another research project of the NCBR "Development of an innovative rehabilitation splint for the lower limbs for neurological and orthopaedic patients using electromyography and electrostimulation" POIR.01.01.01-00-0855/20, I held the roles of Research and Development Project Manager and Biomedical Engineer. The Sidra LEG, a lower limbs rehabilitation robot, was certified under the EU Regulation 2017/745 MDR (TNP/MDR/0015/4038/2023) on November 28, 2023, and is subject to a patent application no P.445951.

Furthermore, in the project of "Development of an innovative robot for automated hand neurorehabilitation and occupational therapy using electromyography" POIR.01.01.01-00-1859/20, where I served as a Biomedical Engineer, the Meissa OT, an upper limb rehabilitation robot, obtained certification under the same EU regulation on November 28, 2023. This technology is also pending patent protection no P.445950. In 2023, sales figures indicated that 87 units of Sidra LEG and 43 units of Meissa OT were distributed to end-users.



Training report

EGZO Tech

Torque information

Work average	0.4 Nm
Rest average	-1.3 Nm
Maximum	4.5 Nm

EMG information

	Work average [µV]	Rest average [µV]	Max [µV]	Onset average [s]	Offset average [s]	Work variability [%]	Rest variability [%]
Channel 1	3.4	25.6	10.1	1.7	0.0	67.0	139.7

General information

Is the patient innervated?	Yes
Can the patient maintain contraction?	No
Can the patient make active movement?	Yes
Can the patient move in full range?	Yes
Patient has very low strength (<3 Nm)?	No

Exercise recommendations

- Dynamic reversal
- Elastic resistance
- EMG evaluation
- Force isometric test
- Joint position sense - hidden pos.
- Joint position sense - visible pos.
- Joint position sense evaluation
- MVIC EMG test
- Orthopedic games

Figure 3.8: Initial Evaluation Test Report with exercise recommendations

Figure 3.9: Luna EMG with the patients in the clinical center [37]

Chapter 4

Automatization of diagnostics and selected rehabilitation procedures

This chapter is dedicated to assessing the effectiveness of automated systems used for diagnosing and rehabilitating patients with conditions such as urinary incontinence and stroke-induced muscle stiffness and spasticity, alongside the utilization of force isokinetic testing. The aim is to corroborate the proposed hypotheses that involve the employment of electromyography signals, torque, and measurements of limb positions for the objective evaluation of patient states, including within telemedicine frameworks, and to examine how these metrics can be integrated into a biophysical feedback loop to improve the outcomes of rehabilitation.

4.1 Automatisation in diagnostics - Force Isokinetic Test

Motor skills are significantly impacted by stroke, underscoring the need for accurate and sensitive methods to assess muscle strength and activity. The evaluation techniques are crucial for understanding muscle function in individuals with neurological conditions to prepare individual precise treatment plans. The objective of this research is to examine the effects of impairments in individuals who have experienced a stroke and in healthy participants on the outcomes of isokinetic dynamometry and surface electromyography assessments. Furthermore, this section explores the effectiveness and reliability of the prepared assessment procedure and rehabilitation robots in evaluating neurological conditions.

4.1.1 Materials and methods

In this scientific investigation, an examination was conducted involving two groups of participants: one comprising ten individuals afflicted by a neurological disorder due to stroke (referred to as Group 1), and the other consisting of ten healthy subjects (referred to as Group 2). The characteristics of both groups can be found in Table 4.1 and the Histograms of Lovett Scale for patients with the neurological disorder is presented in Figure 4.1. Group 1 participants had experienced a stroke ranging from 0.5 to 18 years before the study. Owing to the relatively small size of this group, they were not subdivided further, based on the time elapsed since their stroke.

Table 4.1: Subjects' characteristic [118]

	Group 1	Group 2
Number of subjects	10	10
Age (years)	55,50 ±16,42	52,40 ±10,62
Sex (male, female)	5 M 5 F	6 M 4 F
Handedness	9 right 1 left	9 right 1 left
Impaired upper limb	7 right 3 left	- -

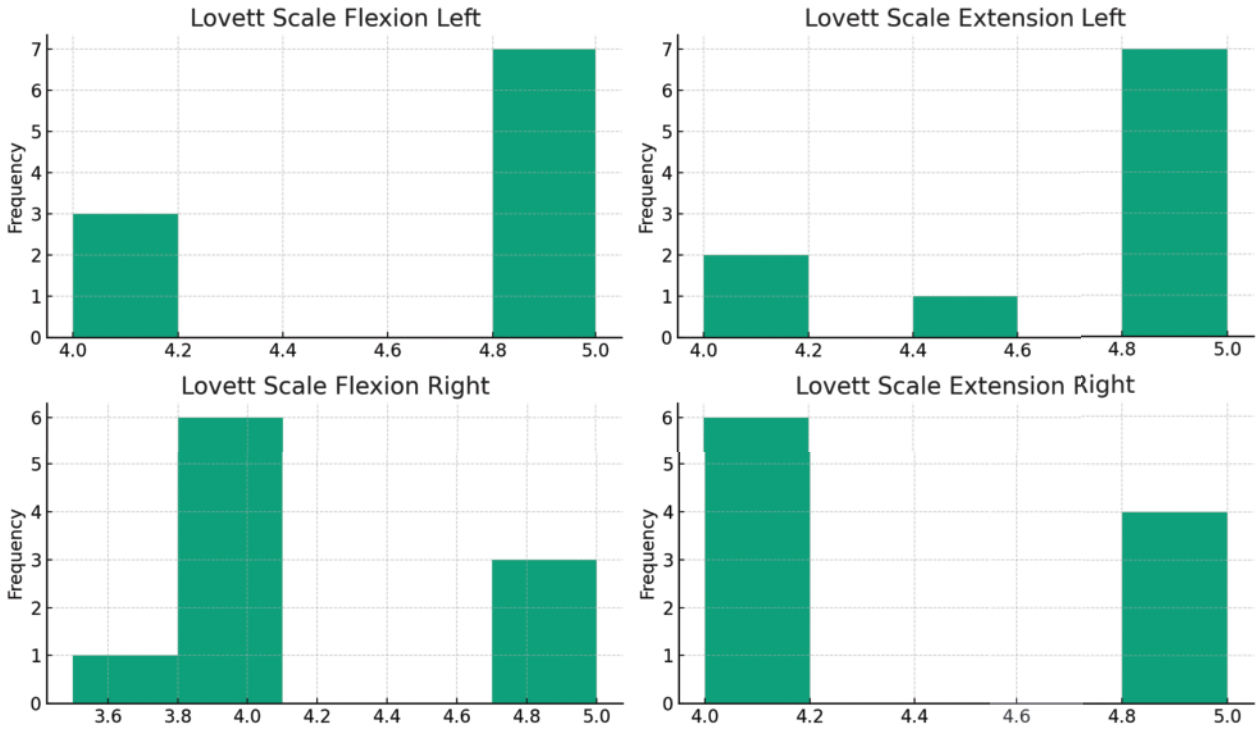


Figure 4.1: Histograms of Lovett Scale for the stroke survivors group

The exercise tests were divided into three distinct sessions, with two of them occurring on the same day (S1 and S2), and the third session (S3) conducted several days later. Importantly, all subjects were not concurrently engaged in any other forms of therapy or

physical exercise, and their functional conditions remained stable throughout the study. Each subject received a comprehensive briefing on the study's objectives and procedures and subsequently provided informed consent to participate. All testing procedures were carried out at the "AMED" Rehabilitation Clinic in Katowice, Poland.

Measurements in the study were conducted using the Luna EMG rehabilitation robot, which is outfitted with both a dynamometer and a unit for acquiring surface electromyography (sEMG) data. The research equipment and Python software to analyze data are detailed described in 3.2. During the entire testing process, the EMG signal was captured using the Luna EMG system at a sampling rate of 500 Hz. To refine the signal, both bandstop and bandpass filters were applied, with the bandstop filter having a cutoff range of 48 to 52 Hz and the bandpass filter allowing frequencies between 28 to 138 Hz to pass through. The root mean square (RMS) values of the electromyography signals were calculated using a time window of 100 milliseconds (Equation 2.3). Participants were positioned in a seated posture, with their upper limbs securely attached to the apparatus (as depicted at Figure 4.2). The robot was adjusted to either the left or right side, contingent upon the limb undergoing evaluation. The elbow joint's range of motion was configured to span from 30 degrees to 150 degrees, resulting in a total ROM of 120 degrees. The bioelectrical activity was monitored for the triceps brachii (CH1) and biceps brachii (CH2) muscles in adherence to the SENIAM recommendations [51], utilizing surface electrodes from Sorimex, based in Toruń, Poland. The testing protocol included three one-minute

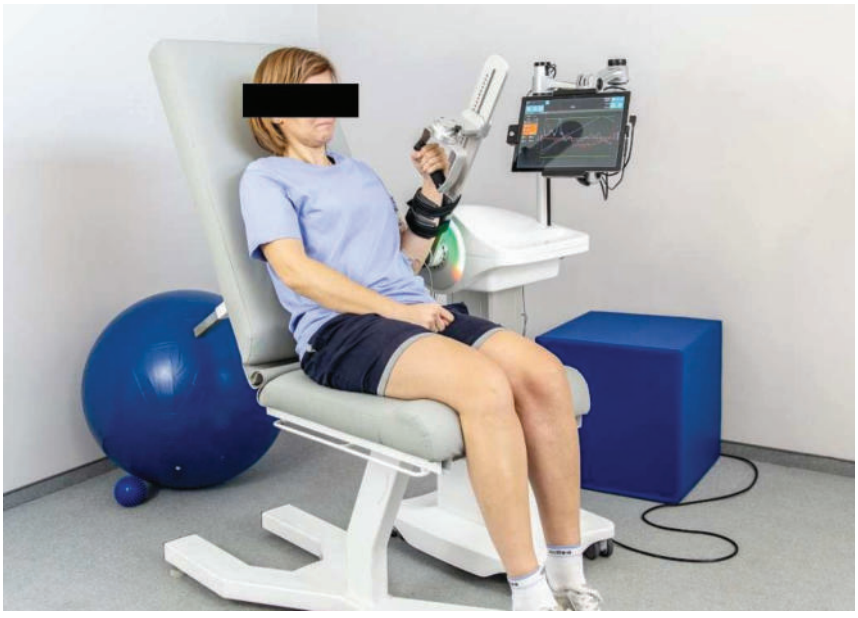


Figure 4.2: Subject during the Force Isokinetic Test [118]

sessions of continuous passive motion exercises at velocities of 10°/s, 30°/s, and 50°/s to facilitate participant warm-up, followed by a one-minute rest period. Subsequently, an isokinetic assessment was performed, comprising five cycles of maximal flexions and extensions at the elbow joint at a speed of 50°/s, interspersed with a one-minute rest

period. The Luna EMG isokinetic test precisely measures the elbow joint's angle and the torque exerted by the participant, adjusting the dynamometer's resistance to maintain a constant velocity. Figures 4.3 and 4.4 showcase a data chart representing a patient's neurological condition and healthy subject, respectively.

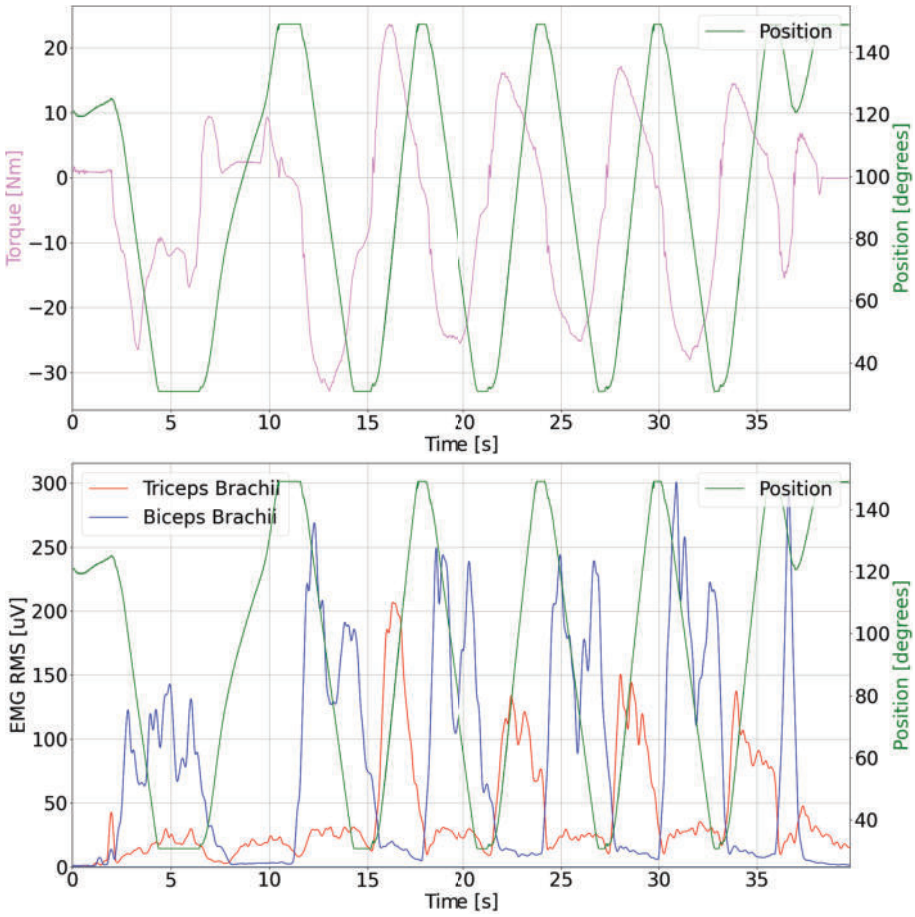


Figure 4.3: Sample measurement results of an isokinetic test for a patient with neurological disorder: Torque and Position (upper panel), EMG of triceps brachii and biceps brachii and Position (lower panel) [118]

4.1.2 Results

For the dominant upper limb (Table 4.2), high reliability (ICC $>$ 0.90) were observed in EMG channel 1 triceps muscle during flexion, and mean torque for extension across S1 and S2 sessions, and in peak torque flexion measurements across all sessions. Moderate to good reliability was noted in several other parameters, including EMG channel 2 extensor and flexor muscles and torque extension measurements. In the non-dominant upper limb (Table 4.3), high reliability was consistently observed in torque measurements, particularly in mean torque extension and flexion across different sessions. EMG measurements showed moderate to good reliability, with the highest ICC value noted in EMG channel 1 extensor muscles between S1 and S3 sessions. In terms of statistical significance, the p-value analysis

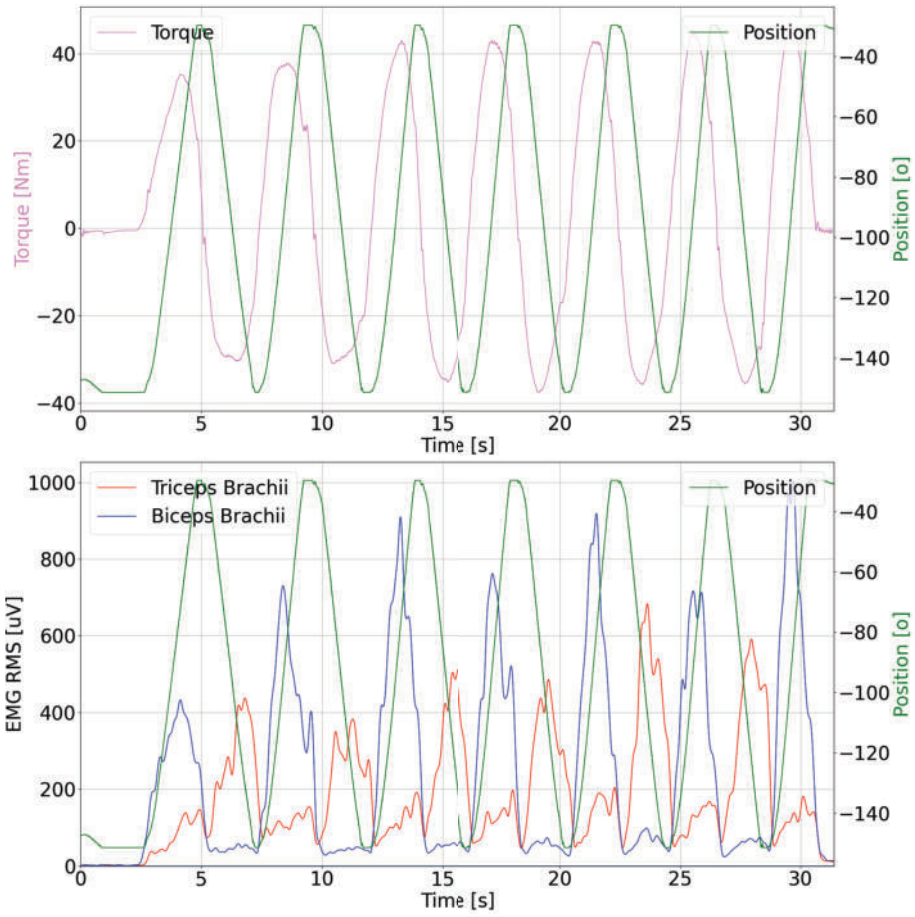


Figure 4.4: Sample measurement results of an isokinetic test for a healthy subject: Torque and Position (upper panel), EMG of triceps brachii and biceps brachii and Position (lower panel)

revealed varied outcomes across different parameters and sessions. Notably, EMG channel 1 during flexion movement between S1 and S2 sessions in the dominant upper limb showed significant differences ($p = 0.0273$), indicating a potential influence of session variability on these measurements. Conversely, several parameters, such as torque measurements in both dominant and non-dominant limbs, demonstrated no significant differences between sessions ($p > 0.05$), reinforcing the repeatability of these assessments.

In the healthy cohort, superior outcomes were observed across all measured parameters. However, no significant disparities were noted in the electromyography signal of the triceps brachii (EMG CH1) during extension or the EMG recordings of the biceps brachii (EMG CH2) in flexion when comparing the unaffected arm of subjects with neurological disorders to the bilateral arms of the healthy subjects.

Moreover, the EMG readings of the biceps brachii (EMG CH2) during extension did not exhibit notable differences between the impaired arm of neurological subjects and the non-dominant arm of healthy individuals (as indicated in Table 4.4).

Significant disparities were observed in all metrics related to the affected limbs when compared to the healthy group, besides EMG Ch1 in extension movement for dominant

Table 4.2: Reliability and repeatability for the healthy group dominant upper limb

Parameters	S	Mean	SD	CV(%)	SEM	p	Corr	ICC3
EMG CH1 ext	S1	146.54	97.28	66.39	30.76	0.2547	0.85	0.79
	S2	210.28	141.01	67.06	44.59			
EMG CH1 flex	S1	79.90	63.42	79.37	20.05	0.0273	0.95	**0.96**
	S2	96.20	75.72	78.70	23.94			
EMG CH2 ext	S1	60.98	42.40	69.53	13.41	0.0645	0.70	0.87
	S2	79.30	57.60	72.63	18.21			
EMG CH2 flex	S1	204.15	84.92	41.60	26.86	0.3028	0.62	0.58
	S2	254.98	125.50	49.22	39.69			
Torque ext	S1	11.07	4.37	39.48	1.38	0.1565	0.92	**0.91**
	S2	14.14	4.93	34.82	1.56			
Torque flex	S1	-16.88	7.97	-47.24	2.52	0.3121	0.84	0.81
	S2	-21.13	10.19	-48.21	3.22			
Peak T ext	S1	23.63	8.51	36.00	2.69	0.2531	0.82	0.81
	S2	28.56	10.07	35.28	3.19			
Peak T flex	S1	-28.67	12.86	-44.86	4.07	0.3674	0.95	**0.93**
	S2	-34.53	15.36	-44.50	4.86			
EMG CH1 ext	S1	146.54	97.28	66.39	30.76	0.016	0.93	0.77
	S3	200.64	178.37	88.90	56.40			
EMG CH1 flex	S1	79.90	63.42	79.37	20.05	0.469	0.89	0.47
	S3	56.87	27.42	48.22	8.67			
EMG CH2 ext	S1	60.98	42.40	69.53	13.41	0.031	1.00	0.84
	S3	71.46	41.39	57.92	13.09			
EMG CH2 flex	S1	204.15	84.92	41.60	26.86	0.469	0.86	0.81
	S3	222.51	132.02	59.33	41.75			
Torque ext	S1	11.07	4.37	39.48	1.38	0.156	0.86	0.75
	S3	13.96	8.74	62.62	2.76			
Torque flex	S1	-16.88	7.97	-47.24	2.52	0.219	0.96	0.89
	S3	-18.43	11.57	-62.79	3.66			
Peak T ext	S1	23.63	8.51	36.00	2.69	0.031	0.96	0.88
	S3	27.42	13.91	50.71	4.40			
Peak T flex	S1	-28.67	12.86	-44.86	4.07	0.156	0.96	**0.93**
	S3	-28.70	14.65	-51.03	4.63			
EMG CH1 ext	S2	210.28	141.01	67.06	44.59	0.156	0.93	0.77
	S3	200.64	178.37	88.90	56.40			
EMG CH1 flex	S2	96.20	75.72	78.70	23.94	0.219	0.89	0.39
	S3	56.87	27.42	48.22	8.67			
EMG CH2 ext	S2	79.30	57.60	72.63	18.21	0.297	0.82	0.76
	S3	71.46	41.39	57.92	13.09			
EMG CH2 flex	S2	254.98	125.50	49.22	39.69	0.938	0.68	0.84
	S3	222.51	132.02	59.33	41.75			
Torque ext	S2	14.14	4.93	34.82	1.56	0.938	0.89	0.79
	S3	13.96	8.74	62.62	2.76			
Torque flex	S2	-21.13	10.19	-48.21	3.22	0.938	1.00	**0.94**
	S3	-18.43	11.57	-62.79	3.66			
Peak T ext	S2	28.56	10.07	35.28	3.19	0.813	0.96	0.84
	S3	27.42	13.91	50.71	4.40			
Peak T flex	S2	-34.53	15.36	-44.50	4.86	0.578	0.96	**0.98**
	S3	-28.70	14.65	-51.03	4.63			

extremity (refer to Table 4.6 and Table 4.7). Additionally, the performance metrics for the affected arm were consistently lower than those for the unaffected arm, except for the average EMG values of the triceps brachii during elbow extension and the peak torque values for both flexion and extension (as shown in Table 4.8).

4.1.3 Discussion and conclusions

The results shown in Tables 4.2 and 4.3 underscores the potential benefits and obstacles associated with employing isokinetic dynamometry and surface electromyography tests for assessing muscle strength and activity. This clinical research aimed to assess neurological deficits to elucidate the impact of such disorders the isokinetic test outcomes

Table 4.3: Reliability and repeatability for the healthy group non-dominant upper limb

Parameters	S	Mean	SD	CV(%)	SEM	p	Corr	ICC3
EMG CH1 ext	S1	187.17	132.80	70.95	41.99	0.625	0.83	0.64
	S2	208.07	163.33	78.50	51.65			
EMG CH1 flex	S1	77.91	42.84	54.98	13.55	0.952*	0.60*	0.59
	S2	79.02	38.87	49.19	12.29			
EMG CH2 ext	S1	57.92	39.72	68.57	12.56	0.770	0.45	0.60
	S2	63.01	47.62	75.57	15.06			
EMG CH2 flex	S1	185.30	114.12	61.59	36.09	0.730*	0.69*	0.66
	S2	201.05	84.53	42.05	26.73			
Torque ext	S1	-13.14	6.55	-49.85	2.07	0.638*	0.91*	**0.91**
	S2	-14.58	6.96	-47.70	2.20			
Torque flex	S1	12.95	6.27	48.43	1.98	0.369*	0.95*	**0.95**
	S2	15.64	6.80	43.51	2.15			
Peak T ext	S1	-23.40	10.69	-45.69	3.38	0.531*	0.95*	**0.95**
	S2	-26.36	10.05	-38.12	3.18			
Peak T flex	S1	25.68	12.01	46.79	3.80	0.688*	0.83*	0.83
	S2	27.87	12.03	43.15	3.80			
EMG CH1 ext	S1	187.17	132.80	70.95	41.99	0.156	0.93	**0.95**
	S3	199.90	151.10	75.59	47.78			
EMG CH1 flex	S1	77.91	42.84	54.98	13.55	0.469	0.39	0.39
	S3	60.16	21.36	35.51	6.76			
EMG CH2 ext	S1	57.92	39.72	68.57	12.56	0.469	0.89	0.86
	S3	49.12	30.01	61.11	9.49			
EMG CH2 flex	S1	185.30	114.12	61.59	36.09	0.469	0.79	0.70
	S3	177.57	111.17	62.61	35.16			
Torque ext	S1	-13.14	6.55	-49.85	2.07	0.375	0.71	0.86
	S3	-14.19	8.31	-58.55	2.63			
Torque flex	S1	12.95	6.27	48.43	1.98	0.031	0.71	0.50
	S3	15.42	7.83	50.79	2.48			
Peak T ext	S1	-23.40	10.69	-45.69	3.38	0.297	0.82	0.87
	S3	-24.56	11.01	-44.86	3.48			
Peak T flex	S1	25.68	12.01	46.79	3.80	0.047	0.68	**0.91**
	S3	25.97	10.98	42.29	3.47			
EMG CH1 ext	S2	208.07	163.33	78.50	51.65	0.156	0.86	0.70
	S3	199.90	151.10	75.59	47.78			
EMG CH1 flex	S2	79.02	38.87	49.19	12.29	0.375	0.50	0.61
	S3	60.16	21.36	35.51	6.76			
EMG CH2 ext	S2	63.01	47.62	75.57	15.06	0.469	0.57	0.44
	S3	49.12	30.01	61.11	9.49			
EMG CH2 flex	S2	201.05	84.53	42.05	26.73	0.813	0.86	0.64
	S3	177.57	111.17	62.61	35.16			
Torque ext	S2	-14.58	6.96	-47.70	2.20	0.469	0.86	0.83
	S3	-14.19	8.31	-58.55	2.63			
Torque flex	S2	15.64	6.80	43.51	2.15	0.297	0.79	0.78
	S3	15.42	7.83	50.79	2.48			
Peak T ext	S2	-26.36	10.05	-38.12	3.18	1.000	0.89	**0.92**
	S3	-24.56	11.01	-44.86	3.48			
Peak T flex	S2	27.87	12.03	43.15	3.80	0.297	0.86	0.75
	S3	25.97	10.98	42.29	3.47			

Table 4.4: T student test results of the non-impaired limb of neurological patients G1 vs non-dominant limb of healthy group G2

		MEAN		t	df	p	N		SD	
		G1	G2				G1	G2	G1	G2
EMG CH1	flex	45.54	73.72	-3.24	55	**0.002**	30	27	28.99	36.48
	ext	148.69	198.21	-1.48	55	0.14524	30	27	108.27	143.85
EMG CH2	flex	177.88	189.13	-0.30	55	0.76630	30	27	171.21	99.65
	ext	47.02	57.52	-1.03	55	0.30683	30	27	37.25	39.62
Torque	flex	10.99	14.59	-2.09	55	**0.04153**	30	27	6.26	6.74
	ext	9.21	13.95	-2.94	55	**0.00480**	30	27	5.18	6.92
Peak T	flex	19.50	26.57	-2.53	55	**0.0143**	30	27	9.73	11.35
	ext	18.15	24.80	-2.66	55	**0.0102**	30	27	8.65	10.21

Table 4.5: T student test results of the non-impaired limb of neurological patients G1 vs dominant limb of healthy group G2

		MEAN		t	df	p	N		SD	
		G1	G2				G1	G2	G1	G2
EMG CH1	flex	45.54	79.97	-2.74	55	**0.008**	30	27	28.99	61.61
	ext	148.69	184.17	-1.10	55	0.278	30	27	108.27	135.57
EMG CH2	flex	177.88	227.73	-1.29	55	0.204	30	27	171.21	111.70
	ext	47.02	70.48	-2.09	55	**0.041**	30	27	37.25	47.23
Torque	flex	10.99	18.86	-3.70	55	**0.0005**	30	27	6.26	9.61
	ext	9.21	12.96	-2.55	55	**0.014**	30	27	5.18	5.90
Peak T	flex	19.50	30.85	-3.58	55	**0.0007**	30	27	9.73	14.03
	ext	18.15	26.44	-3.27	55	**0.0019**	30	27	8.65	10.48

Table 4.6: T student test results of the impaired limb of neurological group G1 vs dominant limb of healthy group G2

		MEAN		t	df	p	N		SD	
		G1	G2				G1	G2	G1	G2
EMG CH1	flex	31.5	79.97	-3.96	53	**0.0002**	28	27	18.25	61.61
	ext	113.78	184.17	-1.95	53	0.0563	28	27	131.89	135.57
EMG CH2	flex	97.17	227.73	-5.19	54	**0.000003**	29	27	74.22	111.70
	ext	30.69	70.48	-4.19	54	**0.0001**	29	27	19.08	47.23
Torque	flex	8.20	18.86	-5.02	54	**0.000006**	29	27	5.98	9.61
	ext	6.50	12.96	-4.24	54	**0.00009**	29	27	5.47	5.90
Peak T	flex	14.71	30.85	-5.10	54	**0.000005**	29	27	9.35	14.03
	ext	14.88	26.44	-4.23	54	**0.00009**	29	27	9.98	10.48

Table 4.7: T student test results of the impaired limb of neurological patients G1 vs non-dominant limb of healthy group G2

		MEAN		t	df	p	N		SD	
		G1	G2				G1	G2	G1	G2
EMG CH1	flex	31.85	73.72	-5.41	53	**0.000002**	28	27	18.25	36.48
	ext	113.78	198.21	-2.27	53	**0.027**	28	27	131.89	143.85
EMG CH2	flex	97.17	189.13	-3.93	54	**0.0002**	29	27	74.22	99.65
	ext	30.69	57.52	-3.26	54	**0.002**	29	27	19.08	39.62
Torque	flex	8.20	14.59	-3.76	54	**0.0004**	29	27	5.98	6.74
	ext	6.50	13.95	-4.48	54	**0.00004**	29	27	5.47	6.92
Peak T	flex	14.71	26.57	-4.28	54	**0.00008**	29	27	9.35	11.35
	ext	14.88	24.80	-3.68	54	**0.0005**	29	27	9.98	10.21

and to determine how healthcare providers can track patient advancement throughout rehabilitation. Notable disparities were observed between the performance of impaired and unimpaired limbs, with the exception of the mean EMG RMS amplitude for the triceps brachii during extension movements and the peak torque values. The compromised condition of the limb was found to affect the consistency of test results across different sessions, particularly in terms of electromyography metrics. Moreover, when comparing the unaffected arm in the neurological cohort with either arm in the healthy control group, across

Table 4.8: T student test results of impaired limb (G1) vs non-impaired limb (G2) of group with neurological disorder[118]

		MEAN		t	df	p	N		SD	
		G1	G2				G1	G2	G1	G2
EMG CH1	flex	31.85	45.54	-2.13	56	**0.03720**	28	30	18.25	28.99
	ext	113.78	148.69	-1.11	56	0.27390	28	30	131.89	108.27
EMG CH2	flex	97.17	177.88	-2.34	57	**0.02311**	29	30	74.22	171.21
	ext	30.69	47.02	-2.11	57	**0.03944**	29	30	19.08	37.25
Torque	flex	-8.20	10.99	-12.040	57	**2.71E-17**	29	30	1.097	0.8092
	ext	6.50	-9.21	11.328	57	**3.20E-16**	29	30	1.116	0.7707
Peak T	flex	14.71	19.50	-1.93	57	0.05893	29	30	9.35	9.73
	ext	-14.28	-18.15	1.52	57	0.13523	29	30	10.83	8.65

all evaluated parameters there were detected only a few significant differences. The isokinetic dynamometer stands as a tool for the precise quantification of muscle power, offering an evaluation of dynamic muscle contractions with strict control over speed, resistance, and joint positioning. Although it delivers accurate measurement data, its effectiveness is limited when muscle activity falls below a certain threshold. To bridge this gap, surface electromyography serves as a non-invasive alternative, capable of tracking muscle status in individuals whose muscle activity might not be discernible through conventional clinical evaluations [131]. Isokinetic testing techniques have proven to be reliable and sensitive, particularly for evaluating the lower extremities (knees and ankles) in patients with orthopedic conditions [138]. The review by El Mhandi L et al. [38] highlights the significance of isokinetic testing in the detailed evaluation and treatment of neuromuscular disorders. However, the application of isokinetic assessments in patients with neurological impairments has received less attention. Given its widespread use in health and athletic settings, such evaluations could offer valuable insights for professionals in the field of rehabilitation. This study has provided strong arguments for the utilization of isokinetic assessments via rehabilitation robots that enable both measurements, offering valuable metrics for monitoring the progression of neurological disorders, which is beneficial for clinical practitioners. By integrating isokinetic testing with a comprehensive review of the patient's medical history, a physical examination, and an assessment of functional ability, healthcare practitioners can significantly enhance the management, rehabilitation, and patients' functioning in daily life dealing with neuromuscular diseases.

4.2 Automatization of diagnostics of stroke patients - Muscle stiffness and spasticity

Spasticity is a frequently encountered manifestation associated with upper motor neuron lesions, characterized by augmented muscular tautness and rigidity, and heightened

reflexive excitability leading to uncontrolled muscle contractions or abrupt motions. The most often used definition of spasticity comes from Lance [72] and is formulated as follows: “a velocity-dependent increase in tonic stretch reflexes with exaggerated tendon jerks, resulting from hyper-excitability of the stretch reflexes”. Spasticity manifests across a spectrum of intensities, thereby impeding the daily functioning, locomotion, or vocalization of an afflicted individual, often inducing discomfort or pain [91]. Although subjected to thorough research, the etiological underpinnings of neuromuscular irregularities linked with spasticity remain inadequately elucidated. The traditional approaches for assessing spasticity involve utilizing clinical scales or analyzing the biomechanical and neurophysiological aspects of limb resistance during passive or voluntary motions.

Spasticity represents a common clinical manifestation observed in individuals who have suffered a stroke[148]. Based on study [142], after a 6-month from the acute stage of stroke reassessment of 211 patients. It was found that 42.6% (90 individuals) experienced spasticity. Of the total patient group, 15.6% exhibited a more severe level of spasticity (Modified Ashworth Scale 3). While the occurrence of spasticity was similar in both upper and lower limbs, the upper limbs were more often (18.9%) affected by higher degrees of spasticity compared to the lower limbs (5.5%). Furthermore, patients with spasticity had lower scores on the Barthel Index.

This section aims to evaluate the system to automatically diagnose muscle stiffness and spasticity based on a test procedure performed on the Luna EMG rehabilitation robot. The first step was the pilot study of the muscle stiffness and spasticity test. The second one was checking the reliability and repeatability of the prepared diagnostic test improved based on the results and conclusions of the pilot study. The third one was to find appropriable biomechanical and bioelectrical parameters and high-accuracy algorithms to classify the subject as healthy subject or stroke survivor.

4.2.1 Pilot study

The pilot study results were presented during a poster session at the European Congress of NeuroRehabilitation 2019 in Budapest [108]. The study aimed to establish a protocol for assessing joint stiffness, employing a robotic device to measure torque in the elbow joint during continuous passive motion of a patient’s limb. The evaluation involved two distinct groups, each comprising ten individuals: one group consisted of neurological patients who had experienced an ischemic stroke, and the other group was made up of healthy individuals with no movement impairments related to central nervous system disorders. The research was performed in the "AMED" Rehabilitation Clinic in Katowice, Poland. Each participant was thoroughly informed about the aims and methodologies of the study before giving their informed consent to take part. To ensure the test’s effectiveness as an assessment protocol and to gather accurate data for reliability testing,

only patients without spasticity (Ashworth Scale = 0) were selected for this phase of the research.

Participants from both groups underwent a test involving continuous passive motion in the elbow joint at three different speeds: 10°/s, 30°/s, and 50°/s, with each speed maintained for 60 seconds. The test was conducted twice in one day (S1 and S2) and then once again the following day (S3), for both arms, specifically focusing on the elbow joint, with the range of motion (ROM) set to 120 degrees.

In the study, correlations were observed within the healthy group across different velocities — 10°/s for the right arm and 30°/s and 50°/s for both arms—concerning both mean and maximum torque values during flexion and extension movements, as detailed in Table 4.9. Among the neurological patients, the repeatability of the tests was primarily noted in the maximum torque values at speeds of 30°/s and 50°/s for both the affected and unaffected arms, covering both flexion and extension movements, as shown in Table 4.10. However, for neurological patients, the mean torque values displayed variability across nearly all tests.

Table 4.9: Stiffness and Spasticity Test Pearson R Correlation between sessions results for healthy group [108]

	Right			Left		
	S1 vs S2	S1 vs S3	S2 vs S3	S1 vs S2	S1 vs S3	S2 vs S3
Velocity 10°/s						
T Mean Extension	0.34	**0.54**	**0.77**	**0.74**	**-0.92**	**-0.56**
T Mean Flexion	**0.91**	**0.96**	**0.90**	**0.68**	**-0.74**	-0.37
T Peak Extension	**0.84**	**0.95**	**0.82**	**0.62**	**-0.69**	**-0.54**
T Peak Flexion	**0.95**	**0.84**	**0.73**	**0.75**	**-0.64**	-0.36
Velocity 30°/s						
T Mean Extension	**0.91**	**0.60**	**0.70**	**0.67**	**0.72**	0.28
T Mean Flexion	**0.83**	**0.83**	**0.81**	**0.90**	**0.82**	**0.88**
T Peak Extension	**0.82**	**0.69**	**0.69**	**0.84**	**0.72**	**0.61**
T Peak Flexion	**0.63**	0.35	0.49	**0.93**	**0.85**	**0.91**
Velocity 50°/s						
T Mean Extension	**0.92**	**0.77**	**0.83**	**0.70**	**0.73**	0.45
T Mean Flexion	**0.90**	0.69	**0.84**	**0.90**	**0.87**	**0.89**
T Peak Extension	**0.68**	**0.94**	**0.68**	**0.87**	**0.81**	**0.86**
T Peak Flexion	**0.97**	**0.60**	**0.63**	**0.65**	**0.90**	**0.80**

The proposed protocol was rigorously tested to confirm the reliability of the data measured by the rehabilitation robot and test results to ensure its applicability in clinical settings. The testing revealed consistent data among healthy participants, particularly in terms of maximum and mean torque values, and among stroke patients regarding mean torque values. Notably, even though the stroke group was clinically identified as free from spasticity, the mean torque values frequently varied with each test, particularly at a speed of 10°/s for both the affected and unaffected sides. This suggests that muscle stiffness might change even during the 60-second test, potentially due to the muscles relaxing

Table 4.10: Stiffness and Spasticity Test Pearson R Correlation between sessions results for stroke survivors [108]

	Affected			Unaffected		
	S1 vs S2	S1 vs S3	S2 vs S3	S1 vs S2	S1 vs S3	S2 vs S3
Velocity 10°/s						
T Mean Extension	0.15	0.45	0.45	0.39	-0.31	-0.26
T Mean Flexion	0.27	-0.33	-0.24	0.47	0.04	0.42
T Peak Extension	**0.57**	0.49	0.48	**0.51**	0.24	**0.63**
T Peak Flexion	0.33	-0.07	**0.72**	0.36	0.32	**0.59**
Velocity 30°/s						
T Mean Extension	0.06	0.39	0.41	0.04	**0.50**	0.17
T Mean Flexion	-0.29	0.01	-0.24	**0.60**	0.42	0.44
T Peak Extension	**0.59**	**0.77**	**0.61**	**0.77**	**0.83**	**0.75**
T Peak Flexion	**0.71**	**0.73**	**0.70**	**0.71**	**0.81**	**0.80**
Velocity 50°/s						
T Mean Extension	0.28	0.44	0.46	0.49	0.26	**0.66**
T Mean Flexion	0.12	0.00	-0.38	**0.59**	0.25	0.42
T Peak Extension	**0.58**	**0.77**	**0.61**	**0.60**	**0.65**	**0.86**
T Peak Flexion	**0.84**	**0.79**	0.49	**0.83**	**0.64**	**0.74**

from the passive motion, indicating a need for a shorter test duration. Alternatively, the mean values in stroke patients might be affected by other factors not present in healthy individuals. Further investigation and data collection, especially adding electromyography measurements, are necessary to clarify these issues and optimize the protocol for clinical use.

4.2.2 Materials and methods

The clinical study was carried out following the ethical rules of the Helsinki Declaration, and approved by the Local Bioethics Commission of the University of Rzeszow (consent no. 2022/036/W). The research was registered in the clinical trials register at ClinicalTrials.gov (registration number NCT05486052). The study was performed in the Spa and Rehabilitation Hospital "Excelsior" in Iwonicz-Zdroj, Poland and the Innovative Biofeedback Methods Laboratory at the University of Rzeszów, Poland.

The study was run in a group of 116 post-stroke subjects (Group 1) around the age of 60, including 76 women and 40 men, and a group of 68 healthy young adult subjects (Group 2) - 47 women and 21 men. Inclusion Criteria for the stroke survivors were as follows: Participants eligible for this study must have experienced their first ischemic stroke and provided informed and voluntary consent. Eligible individuals should possess basic gripping ability and exhibit a degree of paresis of the upper limb and hand rated 4-5 on the Brunnström scale. Additionally, participants should have a disability degree of 3 on the Rankin scale, exhibit spastic tension in the upper limb, and have a paresis of the hand rated no more than 3 on the modified Ashworth scale. Lastly, candidates must

have a current health condition, as confirmed by a medical examination, that allows for safe participation in tests and exercises. Exclusion Criteria for post-stroke patients were as follows: This study precludes the participation of individuals who do not provide informed and voluntary consent. Additional exclusion factors include individuals who have experienced a second or subsequent stroke, hemorrhagic stroke, or strokes specifically affecting the brainstem and cerebellum. Further criteria exclude participants with cognitive impairments that hinder understanding and performance of exercise tasks, visual field defects, mechanical or thermal injuries impairing hand function, and concurrent neurological, rheumatological, and orthopedic conditions, such as permanent contractures, that could impact grasping capabilities and mobility. For the control group, the study excluded individuals presenting with upper limb impairments, such as those resulting from injuries (e.g., dislocations, sprains, fractures), as well as participants with burns, contractures, abnormal muscle tone, muscle wasting, and conditions related to neurology, orthopedics, and rheumatology that compromise upper-limb functionality. Participants with unstable medical conditions, metal or electronic implants, women during menstruation, and individuals with epilepsy are also excluded from this study. The results from the physical test for Group 1 were presented in Table 4.11. The clinical scales and assessment were described in detail in Section 2.2.1. Due to the ambiguity associated with the "1+" category in the Modified Ashword Scale results, the score of "1+" was redefined as 1.5 to enhance clarity and consistency.

Table 4.11: Clinical scales assessment measured by physical therapist in stroke survivors group

	Median	**SD**	**MAX**	**MIN**
Burnnstrom	5	0.52	5	3
Rankin	2	0.50	3	2
Modified Ashword Scale	1.5	0.25	2	1.5
Barthel Index	75	4.24	85	65
Frenchay Arm Test	6	0.59	6	4
Fugl-Meyer Assessment Scale	8	0.86	10	6

Procedures

The procedure was performed with the Luna EMG rehabilitation robot, which enables simultaneously measuring the kinematic, biomechanical, and electrophysiological responses of spastic stretch reflexes. The participant was seated on a couch and securely fastened to the apparatus via straps. The range of movement was fixed between around 90° and 180° of elbow flexion (Figure 4.5). Before the procedure, the rehabilitation robot weighs the upper limb to level its impact on torque measurements. The minus sign in torque informs about the counterclockwise direction of the applied force. The EMG

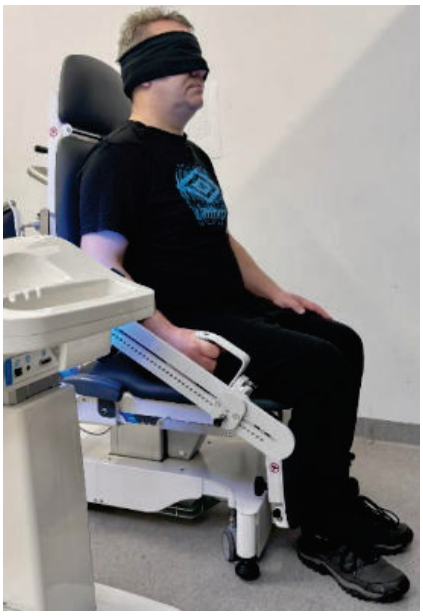


Figure 4.5: Subject during Spasticity Test

signals were measured from surface electrodes on Biceps Brachii – channel 1 and Triceps Brachii – channel 2. The measurements adhere to the standards outlined in the SENIAM guidelines [51]. Initially, the device sets the limb to a resting position depending on the movement under examination (flexion or extension). Subsequently, it executes a singular movement at a velocity of 10°/s and reverts to the resting position at an identical pace. Following this operation, a resting interval of 60 seconds ensues. Analogous movements are then carried out at speeds of 50°/s and 100°/s. Subjects were instructed to remain relaxed during the test. Figure 4.7 and Figure 4.6 present examples of data acquisition during the performed spasticity test by a stroke survivor and a healthy person. The assessments were conducted for both the right and left upper extremities, involving motions of elbow flexion and extension. The test of muscle spasticity and stiffness was performed twice in one day. Additionally, for the healthy group, the study was repeated after two week in the same condition to check the repeatability of the test.

Data Analysis

Data was analyzed with software in Python, described in Section 3.2 with the calculation based on the equations the Sections 2.1.1 and 2.1.3. The presented Tables in Section 4.2.3 consist of biomechanical and bioelectrical parameters: Torque (T), EMG RMS from channel 1 (Ch1), and EMG RMS from channel 2 (Ch2), Positon (Pos) for Maximal or Minimal Torque (T) and EMG RMS (CH1 or CH2), all parameters are displayed with numbers 10,50, and 100 meaning velocity of movement.

Data on repeatability and reliability were evaluated using the Wilcoxon or t-student test, with the latter applied to variables exhibiting a normal distribution (denoted by "*"

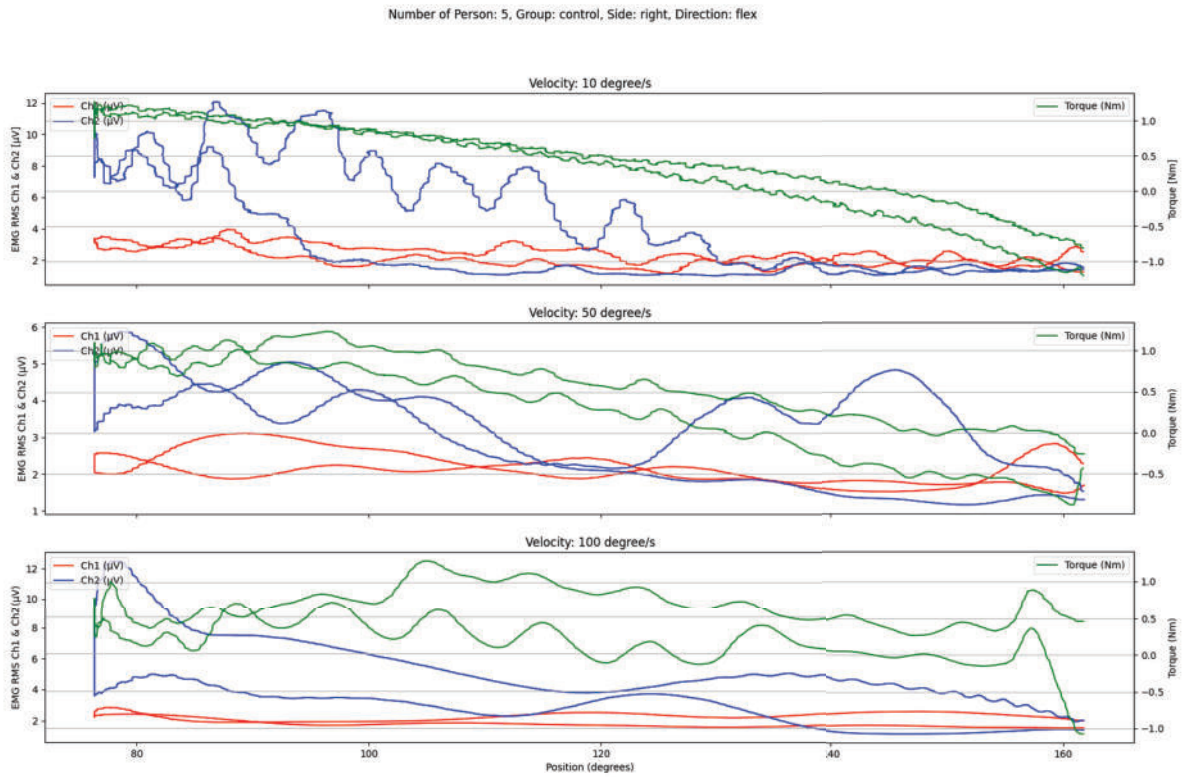


Figure 4.6: Example of data from control group

Figure 4.7: Example of data from stroke

in the tables) and p-values exceeding 0.05 suggesting a lack of significant disparity, Spear-

man Correlation or Pearson Correlation with the latter applied to variables exhibiting a normal distribution (denoted by "*" in the tables) and Intraclass Correlation Coefficient (ICC). The analysis of the ICC followed the guidelines proposed by Koo et al. [69], categorizing the ICC values as follows: less than 0.50 indicated poor reliability, 0.50 to 0.75 suggested moderate reliability, 0.75 to 0.90 denoted good reliability, and values greater than 0.90 were considered to reflect high reliability. Data set variability was characterized through the calculation of arithmetic means, standard deviations (SDs), and 95% confidence intervals (CIs) for ICC value, along with the computation of coefficients of variation (CVs) and the standard error of measurement (SEMs).
To assess differences between the post-stroke and healthy groups, the normality of the distribution was first verified using the Shapiro-Wilk test, followed by the application of either the Mann-Whitney U or t-student test with p-values indicating the level of significance. All data were analyzed using software written in Python 3.11 including, but not limited the scipy and pingouin libraries, ensuring rigorous examination of differences between groups.

4.2.3 Results

Repetability and reliability of the test

The statistical test outcomes for repeatability and reliability with ICC3 from 0.50 are presented in Tables 4.12, 4.13, 4.14, 4.15, and 4.16 for the control group, and in Tables 4.17, 4.18, 4.19, and 4.20 for the group of stroke survivors.

In the control group, a comprehensive analysis of limb movements was conducted to establish a baseline for normal function and assess the repeatability and reliability of machine-assisted diagnostics.
Right Limb Extension (Table 4.12): Analysis of the right limb extension revealed notable variability in torque measurements. Despite this, a moderate level of reliability was observed in some variables, and the absence of significant differences between sessions suggested good repeatability of these measurements. Several variables demonstrated high reliability, with ICC values greater than 0.75, suggesting that measurements for these variables are consistent across sessions. This includes T10 Min, Ch1 10 Zero Crossing, Ch1 50 Mean, and Ch1 100 Mean. There were significant changes between sessions for certain variables, with p-values less than 0.05. This includes variables such as T50 Position Min (Pos Min), Ch1 50 Mean, and Ch1 50 Cross-correlation Torque EMG Peak (CC Peak), indicating significant differences between sessions for these measures.
Right Limb Flexion (Table 4.15): High variability in some measurements, especially at lower velocities, could challenge the reliability of using these variables for objective assessments of patient conditions. The right limb flexion movements mirrored the extension

Table 4.12: Control right limb extension movement

Parameters	S	Mean	SD	CV(%)	SEM	p	Corr	ICC3
T10 Min	1	-1.72	1.99	-116.07	0.30	0.31	0.76	0.84 (0.72-0.91)
	2	-1.41	1.38	-97.79	0.21			
T50 Min	1	-1.33	1.45	-108.77	0.22	0.49	0.63	0.54 (0.29-0.72)
	2	-1.21	0.87	-71.23	0.13			
T10 Pos Min	1	158.94	18.00	11.33	2.68	**0.05**	0.58	0.58 (0.34-0.74)
	2	162.61	17.55	10.79	2.62			
T100 Pos Min	1	123.62	36.86	29.82	5.50	0.11	0.50	0.54 (0.30-0.72)
	2	133.74	38.01	28.42	5.67			
T10 Min	1	7.53	1.84	24.38	0.27	0.87	0.63	0.57 (0.33-0.74)
	2	7.39	1.80	24.37	0.27			
Ch1 10 Mean	1	18.86	13.31	70.58	1.98	0.06	0.68	0.75 (0.59-0.86)
	2	22.36	42.89	191.80	6.39			
Ch1 10 Max	1	61.87	40.88	66.08	6.09	0.47	0.67	0.65 (0.44-0.79)
	2	79.46	148.10	186.38	22.08			
Ch1 10 ZC	1	2651.20	920.26	34.71	137.18	**0.05**	0.79	0.82 (0.69-0.90)
	2	2751.07	808.01	29.37	120.45			
Ch1 50 Mean	1	18.62	19.13	102.72	2.85	**0.03**	0.65	0.83 (0.72-0.90)
	2	15.48	16.77	108.31	2.50			
Ch1 50 Max	1	62.35	71.34	114.43	10.64	**0.05**	0.67	0.75 (0.59-0.86)
	2	46.77	50.09	107.10	7.47			
Ch1 50 MNF	1	277.61	9.06	3.27	1.35	0.20	0.49	0.66 (0.45-0.80)
	2	278.30	8.00	2.87	1.19			
Ch1 100 Mean	1	22.53	29.47	130.78	4.39	0.99	0.79	0.78 (0.63-0.87)
	2	20.11	18.47	91.85	2.75			
Ch1 100 Max	1	73.06	111.66	152.83	16.65	0.80	0.75	0.64 (0.42-0.79)
	2	62.77	53.44	85.14	7.97			
Ch1 100 CV	1	0.89	0.35	39.36	0.05	0.44*	0.64*	0.62 (0.40-0.77)
	2	0.85	0.29	33.45	0.04			
Ch1 100 Time Min	1	1.07	0.71	66.20	0.11	**0.01**	0.49	0.51 (0.26-0.70)
	2	0.80	0.70	87.46	0.10			
Ch1 100 MNF	1	277.88	9.52	3.43	1.42	0.91	0.53	0.66 (0.45-0.80)
	2	278.77	9.27	3.33	1.38			
Ch2 10 Mean	1	7.58	12.80	168.75	1.91	0.90	0.48	0.62 (0.39-0.78)
	2	6.77	6.50	96.00	0.97			
Ch2 10 Min	1	1.46	0.94	64.73	0.14	0.17	0.74	0.57 (0.32-0.75)
	2	1.33	0.81	60.79	0.12			
Ch2 50 Mean	1	8.97	10.47	116.71	1.56	0.29	0.63	0.53 (0.27-0.71)
	2	8.20	7.04	85.88	1.05			
Ch2 50 Pos Min	1	122.96	28.68	23.33	4.28	0.63	0.52	0.50 (0.24-0.69)
	2	123.84	28.55	23.05	4.26			
Ch2 50 MNF	1	293.07	13.76	4.69	2.05	0.75	0.60	0.65 (0.44-0.79)
	2	293.72	14.20	4.83	2.12			
Ch2 50 MDF	1	77.30	35.14	45.46	5.24	0.39	0.58	0.66 (0.45-0.80)
	2	82.14	35.79	43.57	5.34			
Ch2 100 Mean	1	10.19	9.85	96.73	1.47	0.19	0.73	0.51 (0.25-0.70)
	2	9.96	9.15	91.91	1.36			
Ch2 100 Min	1	1.85	1.19	64.62	0.18	0.62	0.56	0.72 (0.54-0.84)
	2	1.86	1.18	63.13	0.18			
Ch2 100 CV	1	0.74	0.33	44.94	0.05	0.77*	0.55*	0.54 (0.29-0.72)
	2	0.72	0.36	49.50	0.05			
Ch2 100 MNF	1	292.06	12.56	4.30	1.87	0.51	0.62	0.67 (0.47-0.81)
	2	292.26	15.70	5.37	2.34			
Ch2 100 MDF	1	75.04	32.67	43.54	4.87	0.18	0.67	0.71 (0.53-0.83)
	2	78.30	38.89	49.67	5.80			
Ch2 100 ZC	1	575.68	117.35	20.38	17.49	0.60*	0.69*	0.69 (0.50-0.82)
	2	568.20	120.68	21.24	17.99			

* means T-student test results for p-vaule and Pearson R Correlation for Corr

movements in terms of high variability. However, these movements also demonstrated moderate reliability and repeatability across sessions, indicating a consistent performance pattern. The moderate to high reliability of some variables, like Ch2 100 Zero Crossing (ICC of 0.80), supports the potential for using EMG signals and torque measurements in objective assessments, provided that variables with higher reliability are prioritized.

Left Limb Extension (Table 4.13 and 4.14): For left limb extension, the control group

Table 4.13: Control group left limb extension movement

Parameters	S	Mean	SD	CV[%]	SEM	p	Corr	ICC3
T10 Min	1	-1.31	1.28	-97.82	0.19	0.31	0.48	0.66 (0.46-0.80)
	2	-1.45	1.00	-68.86	0.15			
T50 Min	1	-1.38	1.19	-86.42	0.18	0.60	0.51	0.57 (0.34-0.74)
	2	-1.36	0.84	-61.41	0.12			
T100 Min	1	-1.63	1.04	-63.94	0.15	0.28	0.50	0.50 (0.24-0.69)
	2	-1.67	0.75	-44.55	0.11			
T50 Pos Max	1	224.52	35.92	16.00	5.30	0.19	0.49	0.55 (0.32-0.73)
	2	231.79	35.97	15.52	5.30			
T50 Time Max	1	2.38	1.28	53.93	0.19	0.35	0.66	0.63 (0.42-0.78)
	2	2.51	1.36	54.25	0.20			
Ch1 10 Mean	1	32.88	43.67	132.83	6.44	0.07	0.81	0.66 (0.45-0.80)
	2	24.88	31.59	126.98	4.66			
Ch1 10 Max	1	94.11	118.51	125.92	17.47	0.55	0.70	0.69 (0.49-0.82)
	2	84.91	107.92	127.10	15.91			
Ch1 10 MNF	1	279.33	14.32	5.12	2.11	0.91	0.68	0.78 (0.64-0.88)
	2	279.84	11.74	4.20	1.73			
Ch1 10 MDF	1	51.11	35.61	69.68	5.25	0.84	0.65	0.77 (0.62-0.87)
	2	50.78	26.15	51.49	3.86			
Ch1 10 CC Peak	1	541878.80	1988098.25	366.89	293129.10	0.65	0.52	0.80 (0.67-0.89)
	2	602070.40	3495951.01	580.65	515449.85			
Ch1 10 ZC	1	2638.62	963.55	36.52	142.07	0.09	0.61	0.74 (0.57-0.85)
	2	2812.33	1024.40	36.43	151.04			
Ch1 50 Mean	1	23.14	21.38	92.41	3.15	**0.03**	0.75	0.68 (0.48-0.81)
	2	19.10	17.69	92.62	2.61			
Ch1 50 Max	1	68.64	52.22	76.08	7.70	0.08	0.68	0.53 (0.28-0.71)
	2	62.98	57.22	90.85	8.44			
Ch1 50 CV	1	0.87	0.33	37.42	0.05	0.09	0.37	0.55 (0.31-0.73)
	2	0.96	0.39	41.05	0.06			
Ch1 50 MNF	1	280.56	12.78	4.55	1.88	0.64	0.66	0.70 (0.52-0.82)
	2	279.97	10.35	3.70	1.53			
Ch1 50 ZC	1	736.51	239.06	32.46	35.25	**0.002**	0.79	0.76 (0.60-0.86)
	2	776.57	211.41	27.22	31.17			
Ch1 100 Mean	1	24.99	25.02	100.12	3.69	0.18	0.74	0.59 (0.36-0.75)
	2	22.71	24.17	106.45	3.56			
Ch1 100 MNF	1	280.65	12.49	4.45	1.84	0.75	0.75	0.72 (0.55-0.84)
	2	280.25	11.33	4.04	1.67			
Ch1 100 MDF	1	54.71	28.30	51.73	4.17	0.43	0.61	0.66 (0.46-0.80)
	2	50.68	24.49	48.32	3.61			
Ch1 100 ZC	1	454.46	147.57	32.47	21.76	0.14*	0.66*	0.66 (0.46-0.79)
	2	481.93	150.69	31.27	22.22			

* means T-student test results for p-vaule and Pearson R Correlation for Corr

exhibited consistent performance across sessions. Despite the variability, certain variables showed moderate to high reliability, and the lack of significant session-to-session differences pointed to the movements' good repeatability.

Left Limb Flexion (Table 4.16): The left limb flexion movements displayed a similar pattern to the extension movements, with stable performance across sessions. High reliability was noted in key variables, affirming the consistent measurements despite inherent assessment variability.

The analysis extended to stroke survivors to evaluate the diagnostic procedures' sensitivity and applicability in a rehabilitation context.

Right Limb Extension (Table 4.17): The lack of significant changes between sessions for most variables suggests that the measurements are repeatable, which is crucial for assessing the progression or improvement of stroke survivors' conditions over time. The variability in certain variables underscores the need for careful consideration when interpreting these measurements, as high variability could affect the reliability of assessments.

Table 4.14: Control group left limb extension movement cont.

Parameters	S	Mean	SD	CV[%]	SEM	p	Corr	ICC3
Ch2 10 Mean	1	7.41	6.51	87.86	0.96	0.39	0.62	0.65 (0.44-0.79)
	2	6.97	9.24	132.48	1.36			
Ch2 10 MNF	1	291.18	15.93	5.47	2.35	0.25	0.69	0.69 (0.50-0.82)
	2	292.21	13.72	4.69	2.02			
Ch2 10 MDF	1	74.49	44.11	59.21	6.50	0.18	0.63	0.73 (0.57-0.84)
	2	77.98	39.40	50.53	5.81			
Ch2 10 CC Peak	1	101494.25	284086.89	279.90	41886.33	0.69	0.56	0.61 (0.39-0.77)
	2	131470.69	682251.34	518.94	100592.47			
Ch2 50 Mean	1	9.28	8.19	88.23	1.21	0.10	0.75	0.67 (0.47-0.80)
	2	8.58	7.95	92.69	1.17			
Ch2 50 Max	1	36.38	46.16	126.88	6.81	0.09	0.67	0.71 (0.53-0.83)
	2	33.52	43.29	129.15	6.38			
Ch2 50 CV	1	0.82	0.37	44.97	0.05	0.28	0.55	0.62 (0.41-0.77)
	2	0.79	0.43	54.14	0.06			
Ch2 50 Pos Min	1	224.56	30.64	13.64	4.52	0.07	0.49	0.52 (0.28-0.71)
	2	234.30	29.88	12.75	4.41			
Ch2 50 MNF	1	290.65	16.50	5.68	2.43	0.86	0.52	0.59 (0.36-0.75)
	2	290.77	12.84	4.42	1.89			
Ch2 50 MDF	1	75.41	47.10	62.47	6.95	0.77	0.50	0.56 (0.33-0.73)
	2	72.05	31.81	44.15	4.69			
Ch2 50 ZC	1	869.41	223.67	25.73	32.98	**0.002**	0.70	0.61 (0.38-0.76)
	2	916.91	199.44	21.75	29.41			
Ch2 100 Mean	1	9.71	8.48	87.27	1.25	0.17	0.82	0.70 (0.51-0.82)
	2	9.48	8.94	94.27	1.32			
Ch2 100 Max	1	30.47	31.68	103.98	4.67	0.53	0.78	0.61 (0.39-0.76)
	2	33.65	41.61	123.65	6.14			
Ch2 100 CV	1	0.73	0.30	41.18	0.04	0.18*	0.53*	0.53 (0.28-0.71)
	2	0.80	0.34	42.39	0.05			
Ch2 100 MNF	1	288.33	14.13	4.90	2.08	0.32	0.58	0.60 (0.38-0.76)
	2	290.24	13.98	4.82	2.06			
Ch2 100 MDF	1	66.55	34.46	51.77	5.08	0.56	0.53	0.56 (0.33-0.73)
	2	73.05	35.81	49.01	5.28			
Ch2 100 ZC	1	532.87	128.04	24.03	18.88	0.13*	0.53*	0.53 (0.28-0.71)
	2	561.46	131.52	23.43	19.39			

* means T-student test results for p-vaule and Pearson R Correlation for Corr

The moderate to high reliability of certain variables (e.g., T10 Max, Ch2 100 CC Time with an ICC of 0.73) supports the use of these measurements in objectively assessing the condition of the patient after stroke.

Right Limb Flexion (Table 4.19): A few variables, such as T10 Max, T50 Max, Ch1 10 CC Peak and Ch1 ZC showed statistically significant changes between sessions with p-values of 0.04 or 0.02, suggesting significant differences in these measurements between sessions. The Intraclass Correlation Coefficient (ICC) values vary across variables, with some showing moderate to good reliability, such as Ch2 100 Zero Crossing with an ICC of 0.86, indicating consistent measurements across sessions for these variables. Despite the significant variability, certain variables exhibited high reliability, highlighting their potential in reliably assessing condition changes over time.

Left Limb Extension (Table 4.20): Stroke survivors' left limb extension movements demonstrated stable performance across sessions based on the minimal changes in mean values for most variables and the lack of significant differences between sessions for most parameters. The high reliability of certain variables, such as T10 Min, T50 Min, and T100 Min (ICC of 0.88, 0.89, and 0.87 respectively), underscores their potential usefulness in objectively assessing and monitoring the condition of stroke survivors over time.

Table 4.15: Control group right limb flexion movement

Parameters	S	Mean	SD	CV[%]	SEM	p	Corr	ICC3
T50 Min	1	-1.22	1.25	-102.26	0.18	0.91	0.47	0.63 (0.41-0.77)
	2	-1.10	1.04	-94.35	0.15			
T10 Pos Min	1	153.38	24.42	15.92	3.60	0.24	0.64	0.55 (0.32-0.73)
	2	156.82	22.95	14.63	3.38			
Ch1 10 Mean	1	25.09	28.48	113.50	4.20	0.39	0.71	0.76 (0.60-0.86)
	2	20.03	24.56	122.64	3.62			
Ch1 10 Max	1	79.12	88.30	111.61	13.02	0.09	0.69	0.78 (0.63-0.87)
	2	63.53	74.17	116.74	10.94			
Ch1 10 Min	1	1.58	1.31	82.47	0.19	**0.003**	0.59	0.88 (0.80-0.93)
	2	1.35	1.36	100.42	0.20			
Ch1 10 CV	1	0.81	0.26	32.18	0.04	0.32*	0.53*	0.53 (0.28-0.71)
	2	0.77	0.25	31.98	0.04			
Ch1 10 MNF	1	277.22	5.83	2.10	0.86	0.78	0.57	0.63 (0.42-0.78)
	2	278.33	7.21	2.59	1.06			
Ch1 50 Mean	1	25.55	31.13	121.86	4.59	0.10	0.72	0.88 (0.79-0.93)
	2	20.85	25.37	121.69	3.74			
Ch1 50 Max	1	65.17	76.71	117.71	11.31	0.27	0.62	0.74 (0.58-0.85)
	2	52.22	64.67	123.83	9.53			
Ch1 50 Min	1	2.31	2.78	120.45	0.41	0.06	0.67	0.83 (0.71-0.90)
	2	1.86	2.24	120.62	0.33			
Ch1 50 MNF	1	277.04	5.74	2.07	0.85	0.71	0.57	0.58 (0.35-0.74)
	2	277.96	7.77	2.79	1.15			
Ch1 50 ZC	1	697.50	206.69	29.63	30.47	**0.05**	0.82	0.75 (0.59-0.85)
	2	734.63	220.29	29.99	32.48			
Ch1 100 Mean	1	26.77	39.51	147.62	5.83	**0.01**	0.81	0.81 (0.67-0.89)
	2	20.25	23.80	117.51	3.51			
Ch1 100 Max	1	63.08	117.86	186.85	17.38	0.23	0.75	0.66 (0.46-0.80)
	2	47.67	55.35	116.12	8.16			
Ch1 100 Min	1	2.61	3.22	123.70	0.48	**0.01**	0.59	0.62 (0.40-0.77)
	2	1.64	1.79	108.84	0.26			
Ch1 100 Time Max	1	1.39	0.55	39.54	0.08	0.74	0.39	0.52 (0.28-0.71)
	2	1.41	0.55	39.02	0.08			
Ch1 100 MNF	1	276.78	6.74	2.43	0.99	0.44	0.73	0.77 (0.62-0.87)
	2	277.48	6.81	2.45	1.00			
Ch1 100 MDF	1	44.86	11.61	25.88	1.71	0.49	0.66	0.61 (0.39-0.76)
	2	46.11	17.73	38.45	2.61			
Ch1 100 ZC	1	432.89	149.34	34.50	22.02	**0.03**	0.86	0.85 (0.74-0.91)
	2	445.22	140.99	31.67	20.79			
Ch2 10 Pos Max	1	142.43	27.08	19.01	3.99	0.18	0.72	0.67 (0.48-0.81)
	2	138.45	31.48	22.74	4.64			
Ch2 10 MNF	1	292.16	14.87	5.09	2.19	0.38*	0.74*	0.72 (0.55-0.84)
	2	291.61	12.90	4.43	1.90			
Ch2 10 MDF	1	78.19	37.91	48.49	5.59	0.68	0.66	0.63 (0.42-0.78)
	2	74.09	33.12	44.70	4.88			
Ch2 10 ZC	1	3108.64	836.42	26.91	123.32	0.46*	0.67*	0.63 (0.41-0.78)
	2	3199.18	583.12	18.23	85.98			
Ch2 50 Mean	1	6.99	6.75	96.50	0.99	0.49	0.47	0.63 (0.42-0.78)
	2	7.44	9.01	121.19	1.33			
Ch2 50 Min	1	1.86	1.27	68.45	0.19	**0.01**	0.69	0.59 (0.37-0.75)
	2	1.47	0.90	60.97	0.13			
Ch2 50 Pos Max	1	135.74	32.64	24.04	4.81	0.45	0.54	0.52 (0.27-0.70)
	2	130.20	35.40	27.19	5.22			
Ch2 50 MNF	1	286.72	10.29	3.59	1.52	0.34	0.66	0.53 (0.28-0.71)
	2	286.97	9.23	3.22	1.36			
Ch2 50 ZC	1	860.29	202.34	23.52	29.83	0.37	0.52	0.64 (0.42-0.78)
	2	875.36	171.08	19.54	25.22			
Ch2 100 Mean	1	8.23	8.77	106.56	1.29	0.11	0.68	0.67 (0.47-0.80)
	2	7.30	9.25	126.66	1.36			
Ch2 100 Pos Max	1	128.49	37.25	28.99	5.49	0.14	0.59	0.67 (0.48-0.81)
	2	124.23	34.25	27.57	5.05			
Ch2 100 MNF	1	284.75	10.57	3.71	1.56	0.14	0.59	0.58 (0.35-0.75)
	2	287.31	11.73	4.08	1.73			
Ch2 100 CC time	1	2.05	1.45	70.56	0.21	0.87	0.45	0.57 (0.33-0.74)
	2	2.01	1.35	67.29	0.20			
Ch2 100 ZC	1	535.62	134.41	25.09	19.82	**0.02**	0.69	0.80 (0.66-0.88)
	2	555.33	146.41	26.36	21.59			

Table 4.16: Control left limb flexion movement

Parameters	S	Mean	SD	CV[%]	SEM	p	Corr	ICC3
T10 Min	1	-1.27	1.20	-95.05	0.18	0.50	0.47	0.60 (0.38-0.75)
	2	-1.19	0.91	-76.27	0.13			
T100 Min	1	-1.76	0.90	-51.13	0.13	0.90	0.59	0.51 (0.26-0.69)
	2	-1.73	0.68	-39.20	0.10			
T10 Pos Max	1	218.32	38.57	17.66	5.63	0.19	0.61	0.63 (0.42-0.78)
	2	212.36	32.14	15.14	4.69			
Ch1 10 Mean	1	23.17	15.72	67.85	2.29	0.98	0.68	0.69 (0.50-0.81)
	2	22.21	17.87	80.46	2.61			
Ch1 10 Max	1	71.40	47.78	66.92	6.97	0.98	0.53	0.56 (0.32-0.73)
	2	71.37	59.29	83.07	8.65			
Ch1 10 Min	1	1.48	1.79	120.76	0.26	**6.31E-05**	0.65	0.63 (0.42-0.78)
	2	1.41	1.93	137.34	0.28			
Ch1 10 MNF	1	278.64	11.53	4.14	1.68	0.46	0.71	0.85 (0.75-0.92)
	2	278.63	13.98	5.02	2.04			
Ch1 10 MDF	1	51.31	34.00	66.26	4.96	0.38	0.61	0.87 (0.77-0.92)
	2	51.01	37.13	72.79	5.42			
Ch1 10 ZC	1	2668.57	813.70	30.49	118.69	**0.04**	0.71	0.82 (0.69-0.90)
	2	2793.94	929.05	33.25	135.52			
Ch1 50 Mean	1	25.14	19.31	76.83	2.82	0.48	0.56	0.52 (0.27-0.70)
	2	24.54	21.93	89.35	3.20			
Ch1 50 Min	1	2.59	4.78	184.17	0.70	**0.01**	0.52	0.59 (0.36-0.75)
	2	1.80	2.93	162.48	0.43			
Ch1 50 ZC	1	674.57	191.80	28.43	27.98	0.07	0.67	0.69 (0.50-0.81)
	2	730.13	240.70	32.97	35.11			
Ch1 100 Mean	1	25.52	24.24	94.95	3.54	0.37	0.68	0.67 (0.47-0.80)
	2	24.39	23.98	98.29	3.50			
Ch1 100 MNF	1	277.60	9.97	3.59	1.45	0.27	0.53	0.64 (0.44-0.79)
	2	278.15	10.32	3.71	1.51			
Ch1 100 MDF	1	49.30	25.66	52.06	3.74	0.86	0.31	0.68 (0.49-0.81)
	2	48.16	23.25	48.27	3.39			
Ch1 100 ZC	1	429.78	137.02	31.88	19.99	0.16	0.73	0.70 (0.51-0.82)
	2	457.64	152.09	33.23	22.19			
Ch2 10 Mean	1	8.38	10.04	119.91	1.46	**0.02**	0.77	0.91 (0.84-0.95)
	2	7.15	9.85	137.83	1.44			
Ch2 10 Min	1	1.38	0.68	49.56	0.10	**0.0001**	0.73	0.61 (0.38-0.76)
	2	1.21	0.77	63.69	0.11			
Ch2 10 MNF	1	288.86	13.12	4.54	1.91	0.71	0.76	0.68 (0.49-0.81)
	2	289.81	13.91	4.80	2.03			
Ch2 10 ZC	1	3339.89	1721.69	51.55	251.13	**0.01**	0.81	0.61 (0.39-0.76)
	2	3390.21	801.81	23.65	116.96			
Ch2 50 MNF	1	286.67	12.83	4.47	1.87	0.94	0.60	0.66 (0.46-0.79)
	2	286.25	11.45	4.00	1.67			
Ch2 50 MDF	1	63.46	37.86	59.66	5.52	0.99	0.63	0.73 (0.56-0.84)
	2	62.40	35.47	56.85	5.17			
Ch2 50 ZC	1	868.36	239.91	27.63	34.99	0.28	0.63	0.63 (0.42-0.77)
	2	890.28	196.56	22.08	28.67			
Ch2 100 MNF	1	285.54	11.32	3.97	1.65	0.98	0.74	0.65 (0.45-0.79)
	2	286.50	12.21	4.26	1.78			
Ch2 100 ZC	1	540.49	123.90	22.92	18.07	0.07*	0.72*	0.72 (0.55-0.84)
	2	566.26	133.59	23.59	19.49			

* means T-student test results for p-vaule and Pearson R Correlation for Corr

Left Limb Flexion (Table 4.19): Similar to the extension movements, left limb flexion in stroke survivors showed stable performance across sessions. High reliability in key variables, such as e.g. torque mean and maximal value for all velocities, was noted, suggesting the consistency of these measurements amidst inherent variability.

Groups differences

The Table 4.21, Table 4.22, Table 4.23, and Table 4.24 referenced to detail the outcomes from tests conducted on the flexion and extension movements of the left and right upper limbs, respectively. There was a notable decrease in the coefficient of variation

Table 4.17: Stroke right limb extension movement

Parameters	S	Mean	SD	CV[%]	SEM	p	Corr	ICC3
T10 Max	1	2.94	1.49	50.67	0.30	0.79	0.57	0.76 (0.53-0.89)
	2	2.90	1.47	50.66	0.29			
T100 Max	1	2.58	1.05	40.57	0.21	0.71	0.55	0.50 (0.14-0.74)
	2	2.71	1.25	46.16	0.25			
T10 Min	1	-2.55	3.79	-148.90	0.76	0.73	0.70	0.68 (0.40-0.85)
	2	-2.03	2.33	-114.90	0.47			
T50 Min	1	-1.58	2.27	-144.00	0.45	0.87	0.66	0.57 (0.23-0.78)
	2	-1.51	1.79	-118.23	0.36			
T100 Min	1	-1.86	2.57	-137.94	0.51	0.37	0.61	0.53 (0.18-0.76)
	2	-1.29	1.44	-111.60	0.29			
T50 Pos Max	1	124.09	28.98	23.35	5.80	0.94	0.47	0.53 (0.17-0.76)
	2	125.87	33.35	26.49	6.67			
T100 Pos Max	1	145.42	28.06	19.30	5.61	0.92	0.45	0.55 (0.21-0.77)
	2	138.96	34.72	24.99	6.94			
Ch1 10 Mean	1	26.15	23.32	89.18	4.66	0.11	0.85	0.84 (0.63-0.93)
	2	31.02	40.75	131.40	8.15			
Ch1 10 Max	1	112.88	141.86	125.67	28.37	0.35	0.81	0.78 (0.52-0.90)
	2	106.51	173.05	162.48	34.61			
Ch1 10 ZC	1	2784.67	723.22	25.97	144.64	0.87*	0.57*	0.56 (0.18-0.80)
	2	2814.90	935.33	33.23	187.07			
Ch1 50 Mean	1	21.11	17.28	81.85	3.46	**0.02**	0.84	0.83 (0.62-0.93)
	2	24.82	23.75	95.70	4.75			
Ch1 50 Max	1	60.13	54.28	90.26	10.86	**0.01**	0.79	0.72 (0.42-0.88)
	2	76.52	75.21	98.28	15.04			
Ch1 50 CC Peak	1	99437.66	113965.65	114.61	22793.13	0.06	0.57	0.53 (0.15-0.77)
	2	177607.14	329691.52	185.63	65938.30			
Ch1 50 CC Time	1	3.86	2.03	52.64	0.41	0.88	0.64	0.63 (0.29-0.83)
	2	3.62	2.15	59.23	0.43			
Ch1 100 Mean	1	22.05	17.83	80.86	3.57	0.14	0.56	0.62 (0.28-0.82)
	2	25.06	16.75	66.85	3.35			
Ch1 100 Max	1	61.28	46.91	76.56	9.38	**0.05**	0.61	0.59 (0.24-0.80)
	2	76.26	58.59	76.84	11.72			
Ch1 100 CC peak	1	66430.74	72495.46	109.13	14499.09	0.14	0.60	0.63 (0.32-0.82)
	2	83547.74	74137.86	88.74	14827.57			
Ch2 10 Mean	1	11.21	18.27	162.96	3.65	0.71	0.76	0.99 (0.96-1.00)
	2	13.01	19.66	151.20	3.93			
Ch2 10 Max	1	38.52	75.58	196.18	15.12	0.24	0.68	0.73 (0.34-0.90)
	2	59.87	103.76	173.33	20.75			
Ch2 10 CV	1	0.48	0.25	51.42	0.05	0.11*	0.80*	0.71 (0.30-0.89)
	2	0.66	0.44	67.20	0.09			
Ch2 10 MNF	1	290.62	11.86	4.08	2.37	0.99*	0.66*	0.62 (0.20-0.85)
	2	288.64	19.66	6.81	3.93			
Ch2 10 MDF	1	69.20	31.54	45.58	6.31	0.41*	0.63*	0.61 (0.20-0.84)
	2	73.58	44.60	60.61	8.92			
Ch2 10 CC Peak	1	226584.63	501100.38	221.15	100220.08	0.23	0.56	0.95 (0.87-0.98)
	2	303423.90	696293.78	229.48	139258.76			
Ch2 50 Mean	1	12.59	17.97	142.77	3.59	**0.003**	0.67	0.95 (0.89-0.98)
	2	17.31	24.13	139.44	4.83			
Ch2 50 Max	1	36.76	58.44	158.97	11.69	**0.008**	0.51	0.63 (0.28-0.83)
	2	77.33	152.46	197.14	30.49			
Ch2 50 Min	1	3.92	3.01	76.85	0.60	0.81	0.50	0.64 (0.30-0.84)
	2	3.84	2.63	68.50	0.53			
Ch2 50 CC Peak	1	76634.30	133078.40	173.65	26615.68	**0.05**	0.30	0.61 (0.26-0.82)
	2	140664.77	292785.53	208.14	58557.11			
Ch2 50 CC Time	1	4.14	1.96	47.31	0.39	0.06*	0.58*	0.58 (0.22-0.80)
	2	4.40	1.81	41.08	0.36			
Ch2 100 Mean	1	13.70	19.34	141.15	3.87	0.26	0.62	0.56 (0.21-0.79)
	2	16.71	20.80	124.49	4.16			
Ch2 100 Min	1	4.02	2.96	73.65	0.59	0.36	0.53	0.50 (0.12-0.75)
	2	3.96	2.46	62.20	0.49			
Ch2 100 Pos Min	1	131.37	26.54	20.21	5.31	**0.01**	0.53	0.56 (0.21-0.78)
	2	114.28	30.08	26.32	6.02			
Ch2 100 CC Time	1	2.69	0.97	36.20	0.19	**0.02**	0.69	0.73 (0.48-0.88)
	2	2.97	0.92	30.89	0.18			

* means T-student test results for p-vaule and Pearson R Correlation for Corr

(CV) for muscle activity (Ch1 CV and Ch2 CV) in stroke patients, indicating a more uniform response compared to the more variable response in healthy individuals. Signi-

Table 4.18: Stroke right limb flexion movement

Parameters	S	Mean	SD	CV[%]	SEM	p	Corr	ICC3
T10 Max	1	2.44	0.80	33.02	0.16	**0.04***	0.59*	0.52 (0.16-0.75)
	2	2.91	1.35	46.40	0.27			
Ch1 10 Mean	1	26.59	18.23	68.56	3.65	0.85	0.77	0.76 (0.52-0.89)
	2	25.68	17.54	68.29	3.51			
Ch1 10 CV	1	0.72	0.24	33.10	0.05	0.75	0.61	0.50 (0.12-0.75)
	2	0.69	0.27	39.47	0.05			
Ch1 10 CC Peak	1	470112.45	434853.94	92.50	86970.79	**0.04**	0.45	0.62 (0.30-0.82)
	2	705905.26	770123.07	109.10	154024.61			
Ch1 10 CC Time	1	17.02	5.68	33.36	1.14	0.14*	0.65*	0.63 (0.32-0.82)
	2	17.93	4.31	24.04	0.86			
Ch1 10 ZC	1	2655.96	920.61	34.66	184.12	0.51	0.56	0.70 (0.41-0.86)
	2	2809.12	878.31	31.27	175.66			
Ch1 50 Mean	1	26.44	22.58	85.40	4.52	0.39	0.67	0.77 (0.55-0.90)
	2	31.60	34.44	108.99	6.89			
Ch1 50 Max	1	57.45	51.00	88.78	10.20	0.26	0.70	0.71 (0.43-0.86)
	2	77.70	91.17	117.33	18.23			
Ch1 50 Time Min	1	1.23	1.73	140.55	0.35	0.07	0.34	0.53 (0.18-0.77)
	2	2.00	1.95	97.85	0.39			
Ch1 50 CC Peak	1	123082.64	129662.76	105.35	25932.55	0.44	0.21	0.53 (0.17-0.77)
	2	146887.56	148893.33	101.37	29778.67			
Ch1 50 ZC	1	724.50	202.10	27.90	40.42	0.47*	0.57*	0.57 (0.22-0.79)
	2	750.32	230.34	30.70	46.07			
Ch1 100 Mean	1	30.78	24.77	80.47	4.95	0.73	0.61	0.71 (0.44-0.87)
	2	32.28	26.98	83.58	5.40			
Ch1 100 Max	1	69.38	60.96	87.86	12.19	0.83	0.58	0.61 (0.28-0.81)
	2	76.59	72.36	94.48	14.47			
Ch1 100 ZC	1	389.36	111.43	28.62	22.29	**0.02***	0.65*	0.63 (0.32-0.82)
	2	441.60	137.49	31.13	27.50			
Ch2 10 Mean	1	9.79	10.39	106.20	2.08	0.28	0.75	0.64 (0.31-0.84)
	2	9.01	8.80	97.67	1.76			
Ch2 10 MNF	1	295.25	12.45	4.22	2.49	0.78*	0.67*	0.67 (0.35-0.85)
	2	293.68	12.62	4.30	2.52			
Ch2 10 MDF	1	81.32	28.58	35.14	5.72	0.87*	0.62*	0.62 (0.28-0.82)
	2	80.74	29.56	36.61	5.91			
Ch2 10 ZC	1	3510.86	947.18	26.98	189.44	0.61	0.73	0.83 (0.64-0.93)
	2	3388.72	925.52	27.31	185.10			
Ch2 50 Mean	1	8.07	9.90	122.62	1.98	1.00	0.59	0.60 (0.24-0.81)
	2	8.46	7.83	92.50	1.57			
Ch2 50 Pos Max	1	148.57	32.24	21.70	6.45	0.39	0.42	0.56 (0.21-0.78)
	2	142.60	32.88	23.05	6.58			
Ch2 50 MNF	1	292.09	11.46	3.92	2.29	0.42*	0.51*	0.51 (0.12-0.76)
	2	291.02	10.37	3.56	2.07			
Ch2 50 MDF	1	73.86	27.20	36.82	5.44	0.74*	0.54*	0.54 (0.16-0.78)
	2	74.61	25.68	34.43	5.14			
Ch2 50 ZC	1	945.27	234.83	24.84	46.97	0.89*	0.75*	0.75 (0.49-0.89)
	2	954.92	214.10	22.42	42.82			
Ch2 100 MNF	1	289.00	10.19	3.52	2.04	0.36*	0.58*	0.57 (0.21-0.80)
	2	288.52	12.09	4.19	2.42			
Ch2 100 MDF	1	68.45	24.05	35.13	4.81	0.31	0.40	0.50 (0.11-0.76)
	2	67.07	28.56	42.59	5.71			
Ch2 100 CC time	1	2.38	0.87	36.70	0.17	0.92*	0.55*	0.55 (0.17-0.78)
	2	2.35	1.00	42.51	0.20			
Ch2 100 ZC	1	551.41	134.75	24.44	26.95	0.69*	0.86*	0.86 (0.70-0.94)
	2	568.20	135.27	23.81	27.05			

* means T-student test results for p-vaule and Pearson R Correlation for Corr

ficant differences in torque values (left limb: T Mean and T Min, right limb: T Mean and T Max) across all speeds were observed, indicating higher resistance encountered by the robot from the limbs of stroke patients for flexion and extension movement. The minimum torque values were notably lower in the healthy group for right limb flexion movement, suggesting that these individuals were able to assist the robot. For extension movement of both limbs, EMG measurements revealed a notable rise in muscle activation for both biceps and triceps across all speeds, indicating increased activity in stroke patients com-

Table 4.19: Stroke group left limb flexion movement

Parameters	S	Mean	SD	CV[%]	SEM	p	Corr	ICC3
T10 Mean	1	-0.38	2.17	-564.42	0.41	0.31	0.45	0.83 (0.67-0.92)
	2	-0.67	1.75	-261.38	0.33			
T50 Mean	1	-0.43	2.18	-506.96	0.41	0.85	0.36	0.83 (0.66-0.92)
	2	-0.34	2.62	-763.02	0.49			
T100 Mean	1	-0.37	2.19	-597.57	0.41	0.87	0.28	0.81 (0.63-0.91)
	2	-0.36	2.95	-817.91	0.56			
T10 Max	1	2.92	6.66	228.14	1.26	0.26	0.51	0.83 (0.67-0.92)
	2	2.07	4.23	204.40	0.80			
T50 Max	1	2.08	5.21	250.14	0.98	0.44	0.36	0.94 (0.88-0.97)
	2	1.63	4.68	287.57	0.88			
T100 Max	1	2.03	4.71	232.10	0.89	0.90	0.01	0.91 (0.81-0.96)
	2	1.94	6.02	309.69	1.14			
T50 Time Min	1	2.33	1.19	51.03	0.22	0.81*	0.62*	0.62 (0.32-0.80)
	2	2.28	1.38	60.51	0.26			
T100 Time Min	1	0.95	0.98	103.32	0.19	0.78	0.60	0.51 (0.18-0.74)
	2	1.08	1.03	95.09	0.19			
Ch1 10 Mean	1	27.27	26.39	96.79	4.99	0.90	0.65	0.85 (0.67-0.93)
	2	30.91	33.86	109.54	6.40			
Ch1 10 Max	1	71.42	67.58	94.63	12.77	0.90	0.76	0.87 (0.72-0.95)
	2	91.40	109.71	120.03	20.73			
Ch1 10 MNF	1	278.60	8.37	3.00	1.58	0.71	0.51	0.54 (0.17-0.77)
	2	280.00	10.79	3.85	2.04			
Ch1 10 MDF	1	50.50	21.11	41.80	3.99	0.74	0.61	0.59 (0.24-0.80)
	2	50.43	17.50	34.70	3.31			
Ch1 10 CC Peak	1	928374.95	4105501.67	442.22	775866.89	0.78	0.34	0.98 (0.95-0.99)
	2	852986.63	3328661.84	390.24	629057.96			
Ch1 50 Mean	1	33.12	37.34	112.73	7.06	0.70	0.69	0.75 (0.50-0.88)
	2	34.68	34.73	100.13	6.56			
Ch1 50 Max	1	77.92	106.76	137.01	20.18	0.64	0.71	0.64 (0.33-0.83)
	2	77.61	76.61	98.71	14.48			
Ch1 50 Pos Max	1	245.18	29.17	11.90	5.51	0.44	0.62	0.77 (0.55-0.89)
	2	250.22	26.85	10.73	5.07			
Ch1 50 Time Max	1	1.84	1.02	55.35	0.19	0.12*	0.82*	0.82 (0.64-0.92)
	2	2.04	0.93	45.45	0.18			
Ch1 50 Time Min	1	1.64	1.91	116.36	0.36	0.17	0.58	0.55 (0.21-0.77)
	2	1.90	1.94	102.46	0.37			
Ch1 50 MDF	1	50.39	15.59	30.95	2.95	0.94	0.42	0.54 (0.18-0.77)
	2	52.38	18.84	35.96	3.56			
Ch1 50 CC Peak	1	392587.98	1277760.26	325.47	241473.99	0.83	0.54	0.72 (0.45-0.87)
	2	325201.51	1409828.96	433.52	266432.63			
Ch1 100 Mean	1	36.42	44.08	121.04	8.33	0.90	0.71	0.58 (0.24-0.80)
	2	33.44	35.15	105.12	6.64			
Ch1 100 Max	1	80.93	113.19	139.86	21.39	0.88	0.71	0.57 (0.22-0.79)
	2	69.78	66.10	94.73	12.49			
Ch1 100 Min	1	4.72	4.27	90.47	0.81	0.79	0.40	0.60 (0.27-0.81)
	2	4.69	3.39	72.36	0.64			
Ch1 100 Pos Max	1	254.30	24.96	9.82	4.72	0.33	0.29	0.81 (0.62-0.91)
	2	249.74	27.21	10.89	5.14			
Ch1 100 Pos Min	1	197.96	16.24	8.20	3.07	0.86	0.36	0.60 (0.29-0.80)
	2	200.21	18.52	9.25	3.50			
Ch1 100 Time Max	1	1.27	0.55	43.25	0.10	0.07*	0.82*	0.81 (0.62-0.91)
	2	1.42	0.63	44.54	0.12			
Ch1 100 MNF	1	278.19	6.68	2.40	1.26	0.58	0.38	0.67 (0.38-0.84)
	2	279.22	6.43	2.30	1.21			
Ch1 100 MDF	1	48.63	13.78	28.34	2.60	0.23	0.47	0.75 (0.50-0.88)
	2	51.05	14.09	27.59	2.66			
Ch1 100 CC Peak	1	237056.06	760793.59	320.93	143776.47	0.33	0.37	0.62 (0.30-0.82)
	2	283295.26	1358665.11	479.59	256763.57			
Ch2 50 CC Peak	1	66621.13	209932.50	315.11	39673.51	0.99	0.45	0.70 (0.41-0.86)
	2	46336.38	209723.51	452.61	39634.02			
Ch2 100 CC Peak	1	27547.54	87881.52	319.02	16608.05	0.71	0.27	0.63 (0.33-0.81)
	2	46214.29	212399.41	459.60	40139.72			

* means T-student test results for p-vaule and Pearson R Correlation for Corr

pared to healthy individuals for both average and minimum values. However, for flexion movement only electromyography of triceps muscle showed a significant increase in the obtained values (greater activity) between groups for the mean, maximum, and minimum

Table 4.20: Stroke left limb extension movement

Parameters	S	Mean	SD	CV[%]	SEM	p	Corr	ICC3
T10 Mean	1	-0.43	1.70	-393.43	0.30	0.43	0.46	0.68 (0.44-0.83)
	2	-0.49	2.12	-434.22	0.38			
T100 Mean	1	-1.05	1.77	-167.73	0.32	0.34	0.38	0.73 (0.51-0.86)
	2	-1.40	2.76	-196.90	0.50			
T10 Max	1	2.92	5.58	191.17	1.00	0.79	0.13	0.79 (0.61-0.89)
	2	2.84	8.61	302.83	1.55			
T10 Min	1	-3.16	3.71	-117.31	0.67	0.38	0.56	0.88 (0.76-0.94)
	2	-3.31	4.73	-142.99	0.85			
T50 Min	1	-2.93	3.03	-103.35	0.54	0.17	0.58	0.89 (0.79-0.95)
	2	-3.16	3.13	-98.91	0.56			
T100 Min	1	-2.87	2.94	-102.64	0.53	0.38	0.38	0.87 (0.76-0.94)
	2	-3.19	3.56	-111.60	0.64			
T100 Pos Max	1	237.72	36.74	15.45	6.60	0.72	0.41	0.54 (0.24-0.75)
	2	242.77	35.88	14.78	6.44			
T100 Time Min	1	1.52	0.80	52.41	0.14	0.62	0.57	0.62 (0.35-0.80)
	2	1.48	0.69	46.35	0.12			
Ch1 10 CV	1	0.77	0.29	38.05	0.05	0.83	0.54	0.67 (0.37-0.84)
	2	0.78	0.40	51.29	0.07			
Ch1 10 Pos Min	1	218.02	28.23	12.95	5.07	0.77	0.63	0.66 (0.38-0.83)
	2	219.45	28.98	13.20	5.20			
Ch1 10 CC Peak	1	1324067.85	4379136.19	330.73	786516.08	0.70	0.28	0.65 (0.35-0.83)
	2	1322726.58	6403066.88	484.08	1150024.76			
Ch1 100 CV	1	0.72	0.33	45.09	0.06	0.23	0.62	0.60 (0.29-0.80)
	2	0.66	0.26	39.88	0.05			
Ch2 10 Mean	1	14.25	18.62	130.67	3.34	0.39	0.51	0.94 (0.86-0.98)
	2	12.85	21.74	169.10	3.90			
Ch2 10 Max	1	75.57	137.36	181.76	24.67	0.35	0.40	0.84 (0.65-0.93)
	2	62.14	160.92	258.95	28.90			
Ch2 10 Min	1	3.55	2.20	62.05	0.40	**0.02**	0.27	0.51 (0.12-0.76)
	2	2.45	1.80	73.35	0.32			
Ch2 10 Time Min	1	5.03	4.39	87.36	0.79	0.29	0.65	0.63 (0.34-0.82)
	2	5.87	5.24	89.33	0.94			
Ch2 10 CC Peak	1	999847.88	4684645.89	468.54	841387.24	0.60	0.35	0.79 (0.57-0.90)
	2	1834563.57	9349350.50	509.62	1679192.92			
Ch2 50 Mean	1	18.94	29.80	157.37	5.35	0.24	0.62	0.86 (0.72-0.94)
	2	15.06	21.32	141.61	3.83			
Ch2 50 Max	1	58.48	101.38	173.37	18.21	0.57	0.49	0.92 (0.83-0.96)
	2	52.34	108.76	207.78	19.53			
Ch2 50 Pos Max	1	207.93	29.69	14.28	5.33	0.75	0.52	0.65 (0.38-0.82)
	2	209.85	33.27	15.86	5.98			
Ch2 100 Mean	1	20.39	24.42	119.78	4.39	0.69	0.46	0.63 (0.32-0.81)
	2	24.50	52.41	213.94	9.41			
Ch2 100 Max	1	63.10	86.16	136.55	15.48	0.53	0.37	0.64 (0.35-0.82)
	2	71.62	156.41	218.41	28.09			

* means T-student test results for p-vaule and Pearson R Correlation for Corr

values. Furthermore, the frequency parameter values for the EMG of the biceps (Ch1) were found to be significantly different for the extension movement of both limbs.

Overall, the study results suggest that stroke patients exhibit higher resistance and increased muscle activation during upper limb movements, with less variability in muscle response, compared to healthy individuals. The results indicate marked differences in muscle strength and control between stroke patients and healthy controls, with notable variations between flexion and extension movements as well as between the left and right upper limbs. The significant p-values across all performed tests underscore the statistical relevance of these findings. These disparities could reflect the extent of neurological and muscular impairment caused by stroke and underscore the importance of targeted rehabilitation strategies to address specific deficits in muscle function and motor control.

Table 4.21: Results from spasticity test of stroke survivors (G1) and control group (G2) for left limb flexion

Param	Velocity 10			Velocity 50			Velocity 100		
	$\bar{x}$±SD G1	$\bar{x}$±SD G2	p-value	$\bar{x}$±SD G1	$\bar{x}$±SD G2	p-value	$\bar{x}$±SD G1	$\bar{x}$±SD G2	p-value
T Mean	-0.81±1.51	-0.36±1.01	**7.81E-08**	-0.60±1.79	-0.34±1.05	**0.0002**	-0.62±1.85	-0.34±1.03	**8.47E-06**
T Max	1.70±3.69	1.19±1.20	0.531	1.42±3.47	0.91±1.15	0.696	1.45 ± 3.61	1.25±1.18	**0.044**
T Min	-2.65±1.98	-1.42±1.39	**5.72E-16**	-2.22±1.51	-1.38±1.22	**4.00E-11**	-2.50±1.31	-1.80±1.00	**7.01E-09**
T CV	-1.76±7.51	-0.82±17.98	0.256	0.14±7.41	-0.45±3.53	0.095	1.83±31.02	-0.13±10.30	**0.024**
T Pos Max	204.67±31.07	204.77±37.20	0.152	215.08±38.10	226.50±43.91	**0.006**	238.91±38.33	236.19±43.60	0.363
T Pos Min	244.49±24.75	243.69±29.73	0.972	235.28±28.74	225.91±36.37	**0.004**	210.62±28.76	206.85±33.28	0.294
T Time Max	9.57±6.83	9.87±5.91	0.586	2.15±1.69	2.72±1.29	**0.029**	1.86±1.24	1.68±0.72	**0.009**
T Time Min	9.18±2.90	8.22±3.13	**0.004**	2.70±4.94	2.39±1.38	0.554	1.07±1.22	1.55±1.17	**5.56E-05**
Ch1 Mean	25.83±23.58	20.61±18.90	**0.006**	31.06±30.80	24.40±22.46	**0.0006**	32.82±33.07	23.90±22.93	**0.0001**
Ch1 Max	71.66±71.33	67.30±63.79	0.356	70.81±75.56	64.28±63.84	**0.016**	71.22±73.58	59.69±60.79	**0.006**
Ch1 Min	3.72±2.93	1.34±1.46	**2.00E-24**	5.23±5.86	2.08±4.00	**3.02E-20**	5.39±4.62	2.40±4.73	**3.88E-19**
Ch1 CV	0.65±0.24	0.83±0.35	**3.61E-05**	0.58±0.21	0.74±0.32	**7.53E-06**	0.58±0.20	0.75±0.32	**9.77E-06**
Ch1 Pos Max	241.51±26.93	235.77±37.25	0.170	246.18±30.34	241.93±37.85	0.318	248.70±29.50	245.07±39.26	0.691
Ch1 Pos Min	210.34±22.42	212.34±22.97	0.401	197.32±19.87	199.59±24.76	0.072	196.64±18.26	199.03±23.86	0.200
Ch1 Time Max	6.01±3.12	6.30±3.36	0.622	2.03±1.62	2.45±5.05	0.788	1.41±1.09	1.87±5.03	0.281
Ch1 Time Min	7.68±5.98	9.66±4.96	**0.008**	1.91±2.31	1.88±4.57	0.465	0.73±1.15	1.01±4.42	0.608
Ch1 MNF	279.27±8.03	278.20±10.77	**2.48E-06**	278.51±6.26	277.98±8.57	**0.006**	278.08±6.36	277.56±8.78	**0.0002**
Ch1 MDF	50.11±18.05	48.75±28.88	**2.68E-06**	49.06±15.06	47.08±17.77	**0.001**	48.37±13.72	47.25±20.26	**0.0005**
Ch1 CC Peak	433257±2350270	200473±1200595	0.076	251641±1070676	47248±125174	0.169	121967±695064	35424±82349	**0.0007**
Ch1 CC Time	19.68±11.32	18.16±9.97	**0.034**	4.38±3.52	5.03±2.89	0.302	4.38±2.62	3.72±1.44	**0.001**
Ch1 ZC	3031±3500	2808±1169	0.473	1167±5484	929±2039	0.887	437±261	665±2060	0.432
Ch2 Mean	11.18±10.20	6.87±8.70	**2.87E-08**	9.20±6.40	6.59±9.37	**4.38E-07**	9.67±7.19	7.06±9.12	**2.47E-08**
Ch2 Max	43.27±58.68	32.26±41.70	0.058	31.00±64.29	22.68±30.27	0.056	26.95±36.56	22.80±33.75	**0.016**
Ch2 Min	3.47±2.40	1.29±0.84	**1.11E-23**	3.57±2.44	1.49±1.07	**6.91E-20**	4.02±3.35	1.60±1.34	**3.13E-19**
Ch2 CV	0.61±0.34	0.77±0.45	**0.0002**	0.50±0.39	0.64±0.33	**2.82E-06**	0.48±0.28	0.65±0.34	**1.45E-06**
Ch2 Pos Max	206.34±27.97	210.83±32.84	**0.032**	213.69±32.83	220.74±37.82	**0.009**	220.06±36.41	230.61±38.87	**0.013**
Ch2 Pos Min	218.99±26.21	218.34±26.99	0.995	203.77±24.60	202.41±28.08	0.388	207.13±30.82	203.65±30.26	0.793
Ch2 Time Max	8.08±6.33	6.78±5.57	0.132	2.63±5.44	2.88±7.05	0.909	1.44±1.08	2.16±7.03	0.485
Ch2 Time Min	7.54±5.47	8.79±4.78	**0.026**	1.45±2.25	1.93±5.49	0.102	0.90±1.14	1.28±5.40	0.931
Ch2 MNF	291.94±12.70	289.21±12.19	**0.008**	287.67±10.22	285.94±10.74	0.066	285.84±9.59	286.04±10.86	0.340
Ch2 MDF	76.58±32.27	68.00±33.00	**0.002**	67.51±23.67	60.82±30.52	**0.002**	62.42±21.94	60.27±27.15	**0.029**
Ch2 CC Peak	166384±826665	56071±233942	0.610	36323±140738	16136±104234	0.552	32401±166197	11585±42749	**0.005**
Ch2 CC Time	17.69±12.85	17.09±11.12	0.183	4.66±3.57	5.24±3.04	0.421	4.57±2.55	3.91±1.34	**0.0006**
Ch2 ZC	3509±3513	3321±1084	0.789	937.85±1085.90	1104.67±2182.18	0.468	531.97±228.30	784.27±2209.72	0.093

Table 4.22: Results from spasticity test of stroke survivors (G1) and control group (G2) for left limb extension

Parameters	Velocity 10			Velocity 50			Velocity 100		
	$\bar{x}$±SD G1	$\bar{x}$±SD G2	p-value	$\bar{x}$±SD G1	$\bar{x}$±SD G2	p-value	$\bar{x}$±SD G1	$\bar{x}$±SD G2	p-value
T Mean	-0.54±1.44	-0.28±1.05	**0.0001**	-0.72±1.90	-0.29±0.97	**3.68E-07**	-0.94±1.70	-0.24±0.94	**3.10E-09**
T Max	2.06±4.88	1.32±1.46	0.343	1.57±4.84	1.07±1.18	0.351	1.06±1.45	1.32±1.34	0.082
T Min	-2.81±3.03	-1.55±1.46	**2.78E-12**	-2.67±2.30	-1.49±1.38	**1.84E-15**	-2.67±2.33	-1.67±1.16	**2.73E-12**
T CV	-0.80±4.95	-0.34±14.77	0.429	-0.09±4.13	-0.69±6.08	0.833	0.04±20.03	-0.43±8.92	0.158
T Pos Max	202.10±26.03	203.33±29.13	0.793	223.52±39.25	219.75±36.01	0.302	240.05±37.09	244.98±32.79	0.531
T Pos Min	245.98±28.02	247.12±28.41	0.706	233.89±31.89	236.98±33.02	0.723	213.73±34.24	215.61±35.28	0.351
T Time Max	9.10±12.11	7.26±2.98	**7.49E-06**	3.05±3.45	2.36±1.20	**0.0002**	1.83±3.45	1.48±1.03	0.198
T Time Min	7.57±10.03	9.01±5.84	**0.016**	1.80±1.73	1.88±1.45	0.623	1.54±0.73	1.44±0.72	**0.036**
Ch1 Mean	27.68±24.70	26.68±31.96	0.170	22.96±18.95	19.91±17.68	**0.018**	23.84±19.39	22.01±21.70	**0.005**
Ch1 Max	87.85±101.70	85.08±95.19	0.497	69.13±60.79	61.77±50.63	0.345	66.47±60.00	68.52±61.10	0.998
Ch1 Min	4.21±3.44	2.06±5.05	**1.19E-21**	4.73±3.52	1.75±1.86	**2.28E-23**	6.17±6.26	2.30±4.11	**8.69E-24**
Ch1 CV	0.73±0.29	0.81±0.34	**0.010**	0.73±0.33	0.88±0.33	**5.55E-05**	0.67±0.28	0.91±0.33	**3.09E-09**
Ch1 Pos Max	244.70±26.29	240.74±25.47	0.060	249.62±27.04	246.14±28.35	0.089	250.70±27.69	246.60±30.18	0.146
Ch1 Pos Min	216.16±28.69	210.77±23.02	0.645	222.87±33.19	217.07±30.17	0.192	223.71±35.48	226.07±33.98	0.957
Ch1 Time Max	10.28±8.90	8.50±5.31	**0.013**	3.33±5.95	2.92±1.37	0.688	2.14±5.88	1.80±0.92	0.778
Ch1 Time Min	5.85±7.97	5.64±2.74	0.631	1.97±4.47	1.48±0.92	0.519	1.36±4.29	0.93±0.74	0.636
Ch1 MNF	277.71±6.00	278.89±12.31	**0.0003**	280.07±8.37	279.23±10.78	**0.0003**	280.23±8.02	279.04±10.63	**5.09E-05**
Ch1 MDF	46.33±13.55	49.85±28.20	**0.001**	51.51±18.00	51.62±28.87	**0.0006**	51.87±16.76	49.87±23.83	**1.51E-05**
Ch1 CC Peak	846994±3945636	421543±2204449	0.090	182278±1337794	37745±109848	**0.0006**	51835±215134	29030±57289	**0.002**
Ch1 CC Time	15.08±11.39	12.49±8.48	**0.009**	6.96±6.95	4.70±2.56	**2.70E-07**	3.90±6.84	2.53±1.76	**6.42E-05**
Ch1 ZC	3955±13978	2742±954	0.200	868±1136	750±232	0.056	556±1122	460±143	0.446
Ch2 Mean	12.70±15.38	6.82±7.37	**2.11E-09**	16.37±20.32	8.74±9.31	**7.11E-07**	20.00±29.03	9.29±10.02	**2.14E-09**
Ch2 Max	55.16±106.95	29.57±35.49	**0.006**	51.38±80.82	32.43±44.29	**0.001**	59.29±93.44	30.67±39.51	**1.53E-05**
Ch2 Min	3.41±2.06	1.32±0.81	**1.38E-21**	3.93±2.63	1.56±0.86	**1.06E-20**	4.51±3.06	1.80±1.40	**3.59E-20**
Ch2 CV	0.62±0.45	0.78±0.49	**0.006**	0.62±0.30	0.74±0.39	**0.036**	0.63±0.32	0.73±0.34	**0.015**
Ch2 Pos Max	222.18±34.57	215.27±29.15	0.297	212.77±34.43	215.43±32.96	0.292	211.34±34.65	216.92±35.06	0.057
Ch2 Pos Min	229.93±30.44	218.18±25.55	**0.001**	237.90±29.89	228.46±31.29	**0.002**	244.83±30.84	236.47±32.23	**0.004**
Ch2 Time Max	6.78±4.63	7.21±3.91	0.245	1.96±1.28	2.27±1.06	**0.025**	1.36±0.96	1.60±0.65	**0.006**
Ch2 Time Min	5.31±4.56	5.44±3.27	0.215	1.97±5.90	1.32±1.09	0.807	1.33±5.74	0.76±0.75	0.801
Ch2 MNF	288.07±13.81	291.54±13.73	0.093	291.74±14.79	290.05±13.60	0.282	291.00±13.64	289.45±13.78	0.540
Ch2 MDF	67.82±32.19	75.60±37.36	0.101	76.76±34.33	71.54±35.89	0.161	77.18±32.49	70.17±34.29	0.213
Ch2 CC Peak	886401±5452861	90605±414372	0.070	109888±767820	18540±45953	**0.001**	45044±294069	13118±30723	**0.002**
Ch2 CC Time	15.84±13.69	13.66±9.80	**0.041**	6.63±7.09	4.85±2.57	**4.09E-05**	3.48±6.97	2.53±1.81	0.076
Ch2 ZC	4319±13949	3381±1316	**0.044**	982±1176	881±212	0.712	608±1080	550±135	**0.013**

Table 4.23: Results from spasticity test of stroke survivors (G1) and control group (G2) for right limb flexion

Param	Velocity 10			Velocity 50			Velocity 100		
	$\bar{x}$±SD G1	$\bar{x}$±SD G2	p-value	$\bar{x}$±SD G1	$\bar{x}$±SD G2	p-value	$\bar{x}$±SD G1	$\bar{x}$±SD G2	p-value
T Mean	1.14±1.15	0.17±1.06	**3.95E-15**	1.16±1.16	0.17±1.03	**5.18E-15**	0.86±2.58	0.17±1.04	**1.75E-12**
T Max	2.85±1.57	1.56±1.45	**2.74E-15**	2.82±2.88	1.31±1.31	**1.20E-16**	2.85±1.80	1.49±1.20	**1.21E-20**
T Min	-1.49±2.33	-1.67±1.71	**0.015**	-0.85±1.43	-1.20±1.09	**0.0009**	-1.37±4.32	-1.40±1.17	**0.0008**
T CV	1.28±7.19	1.46±10.88	0.874	5.28±57.17	0.03±8.03	0.508	0.05±4.73	-12.14±116.33	0.125
T Pos Max	113.74±23.45	103.25±20.49	**1.01E-06**	121.24±28.82	114.96±26.36	**0.006**	141.50±29.75	137.29±29.17	**0.045**
T Pos Min	158.73±25.45	156.39±22.16	**0.003**	153.19±32.15	142.67±32.68	**3.18E-05**	129.27±39.08	129.53±37.50	0.549
T Time Max	9.31±5.79	7.52±2.27	**1.38E-08**	2.28±1.25	2.12±0.97	0.143	1.03±0.91	1.46±0.89	**2.89E-05**
T Time Min	8.88±6.86	9.18±6.05	0.342	2.23±2.13	2.81±1.42	**0.020**	1.97±0.80	1.93±0.68	0.118
Ch1 Mean	23.37±17.68	19.93±26.89	**0.0003**	26.11±26.24	21.74±24.60	**0.003**	28.98±23.76	22.18±27.54	**4.87E-05**
Ch1 Max	73.37±66.15	64.98±78.33	**0.029**	64.17±70.15	56.33±62.38	**0.023**	63.17±57.61	53.14±74.72	**0.004**
Ch1 Min	3.36±2.23	1.34±1.15	**3.36E-21**	4.40±4.52	1.93±2.45	**4.65E-18**	4.74±4.47	1.89±2.23	**1.31E-21**
Ch1 CV	0.70±0.26	0.83±0.30	**0.0005**	0.61±0.25	0.69±0.23	**0.002**	0.58±0.20	0.68±0.22	**0.0002**
Ch1 Pos Max	118.45±25.31	115.40±23.50	0.574	110.88±24.43	110.33±25.14	0.507	110.90±24.65	106.49±25.77	**0.002**
Ch1 Pos Min	147.03±23.06	141.87±21.71	**0.047**	160.13±20.95	159.73±15.66	**0.047**	160.66±22.43	158.40±16.33	**0.001**
Ch1 Time Max	6.26±3.36	5.83±2.83	0.112	2.03±1.14	2.02±0.90	0.361	1.40±0.66	1.41±0.53	0.342
Ch1 Time Min	8.38±5.82	8.83±4.84	0.540	1.48±1.80	1.39±1.71	0.648	0.56±0.88	0.49±0.79	0.715
Ch1 MNF	279.69±7.32	278.27±7.94	**0.002**	279.00±6.44	277.46±6.85	**0.0002**	278.43±6.38	277.09±6.65	**0.0001**
Ch1 MDF	50.98±15.73	47.43±17.66	**0.0003**	49.94±13.69	45.67±13.11	**2.50E-05**	48.78±13.90	45.67±13.87	**6.20E-05**
Ch1 CC Peak	640559±1073860	221155±461566	**1.26E-14**	168290±389844	55125±125686	**6.12E-15**	96644±171066	33350±75766	**5.77E-15**
Ch1 CC Time	17.85±5.79	14.37±7.06	**6.29E-06**	4.85±1.84	4.73±2.12	0.270	2.36±1.02	2.02±1.31	**0.011**
Ch1 ZC	3254±5899	2815±1157	0.364	734±265	716±211	0.230	441±202	444±145	0.937
Ch2 Mean	9.99±8.48	7.40±7.99	**6.60E-05**	9.24±7.66	6.77±8.47	**1.02E-05**	10.65±13.28	7.57±10.53	**1.15E-06**
Ch2 Max	45.12±102.02	33.14±47.04	0.373	26.19±35.31	23.21±29.87	0.093	31.01±85.36	21.44±28.23	**0.045**
Ch2 Min	3.47±2.36	1.45±0.95	**6.59E-18**	3.78±3.06	1.55±0.99	**2.22E-16**	4.00±3.47	1.74±2.40	**1.13E-18**
Ch2 CV	0.57±0.40	0.73±0.42	**0.0001**	0.47±0.30	0.65±0.36	**3.05E-06**	0.45±0.32	0.60±0.31	**3.93E-07**
Ch2 Pos Max	148.91±29.00	140.52±28.75	**0.010**	145.92±31.26	135.05±33.28	**0.005**	136.39±31.51	127.62±35.07	**0.001**
Ch2 Pos Min	136.31±26.85	134.22±23.56	0.362	151.73±27.35	152.62±22.81	0.215	153.59±28.45	152.50±21.65	**0.020**
Ch2 Time Max	7.60±6.15	5.90±5.01	**0.053**	2.34±1.98	2.32±1.44	0.404	1.46±0.96	1.40±0.84	0.731
Ch2 Time Min	7.25±5.02	8.11±4.42	0.110	1.30±1.52	1.28±1.54	0.816	0.71±0.95	0.62±0.83	0.519
Ch2 MNF	292.96±13.54	291.16±14.36	**0.021**	288.85±11.35	286.82±10.50	**0.030**	286.62±11.12	285.40±11.03	0.068
Ch2 MDF	77.91±31.56	74.72±38.49	**0.026**	69.50±26.31	62.50±26.53	**0.006**	64.58±26.20	58.86±27.86	**0.009**
Ch2 CC Peak	233756±331731	68283±125371	**9.77E-14**	58045±88109	13094±22427	**7.33E-16**	41804±80371	9389±18103	**2.56E-16**
Ch2 CC Time	15.37±4.56	14.25±7.07	0.889	4.60±1.82	4.66±2.22	0.876	2.46±1.03	2.11±1.42	**0.002**
Ch2 ZC	3868±6006	3163±843	**0.0008**	893±289	886±331	**0.061**	529±150	554±220	0.851

Table 4.24: Results from spasticity test of stroke survivors (G1) and control group (G2) for right limb extension

Param	Velocity 10			Velocity 50			Velocity 100		
	$\bar{x}$±SD G1	$\bar{x}$±SD G2	p-value	$\bar{x}$±SD G1	$\bar{x}$±SD G2	p-value	$\bar{x}$±SD G1	$\bar{x}$±SD G2	p-value
T Mean	0.89±1.00	0.13±0.95	**1.60E-15**	1.08±1.08	0.25±0.95	**2.28E-17**	0.99±0.99	0.08±0.86	**3.75E-20**
T Max	3.03±2.45	1.68±1.72	**2.07E-15**	2.86±1.99	1.65±1.54	**1.89E-14**	2.81±1.35	1.63±1.25	**1.92E-18**
T Min	-1.63±2.37	-1.60±1.43	**0.03**	-1.16±2.34	-1.26±1.05	**0.0002**	-1.27±1.82	-1.63±1.28	**9.82E-05**
T CV	0.92±3.26	-0.25±26.54	**0.02**	0.64±6.39	-3.11±30.68	0.19	0.42±26.66	0.65±10.26	**5.05E-05**
T Pos Max	111.88±23.19	106.61±26.02	**0.002**	122.86±31.19	112.08±31.63	**8.89E-05**	144.33±32.13	127.56±40.71	**5.41E-07**
T Pos Min	159.94±23.18	162.68±25.45	0.22	140.64±38.40	151.83±34.63	0.49	125.27±38.31	132.66±37.84	0.17
T Time Max	6.67±6.15	8.20±6.19	0.21	1.68±1.46	2.51±7.07	0.88	1.35±0.72	2.36±6.96	0.06
T Time Min	8.04±2.63	7.28±1.95	**0.0004**	2.67±1.27	2.57±2.34	**0.004**	1.59±0.98	2.24±7.06	**0.05**
Ch1 Mean	27.36±27.99	21.87±27.42	**0.03**	21.66±17.63	16.60±15.96	**0.0006**	23.26±17.65	21.04±21.12	**0.03**
Ch1 Max	95.78±121.12	78.63±98.99	0.24	60.49±51.46	54.44±53.96	0.11	65.97±55.27	67.66±72.48	0.997
Ch1 Min	4.49±5.73	1.46±1.43	**3.26E-22**	4.44±3.32	1.83±2.31	**5.42E-20**	5.17±3.27	2.34±2.61	**3.13E-18**
Ch1 CV	0.76±0.38	0.84±0.32	**0.01**	0.71±0.26	0.90±0.34	**1.13E-05**	0.69±0.31	0.91±0.36	**2.73E-07**
Ch1 Pos Max	110.30±20.92	115.28±31.77	0.45	106.73±21.28	111.96±32.05	0.20	108.60±22.70	117.06±34.19	**0.02**
Ch1 Pos Min	146.37±25.84	148.65±23.21	0.98	137.70±29.75	140.08±33.43	0.65	135.31±34.26	139.76±36.01	0.79
Ch1 Time Max	9.30±5.99	7.15±5.64	**0.0003**	2.86±1.73	3.27±3.57	0.46	1.81±1.07	2.60±6.96	0.16
Ch1 Time Min	6.20±3.49	5.20±2.42	0.06	1.53±1.09	2.28±6.35	0.90	1.05±0.79	1.66±6.10	0.66
Ch1 MNF	279.39±5.96	278.04±10.25	**6.36E-06**	279.58±7.71	277.77±8.49	**8.33E-05**	279.94±8.21	277.54±8.69	**5.63E-05**
Ch1 MDF	50.49±12.16	48.52±24.45	**1.77E-05**	49.92±15.34	47.66±20.52	**6.86E-05**	50.59±17.40	45.78±16.43	**0.0003**
Ch1 CC Peak	732004±1625995	250787±489479	**1.25E-14**	568625±4839900	66251±173069	**5.19E-15**	88708±129552	39292±89553	**1.36E-14**
Ch1 CC Time	11.45±6.06	13.52±8.69	0.44	3.77±1.76	4.59±12.01	**0.03**	2.57±1.13	2.89±1.54	0.17
Ch1 ZC	2755±707	2638±893	**0.019**	774±210	1087±2331	0.14	475±124	705±2128	**0.040**
Ch2 Mean	11.79±14.44	6.99±8.85	**6.97E-06**	14.15±15.29	8.53±9.53	**2.85E-06**	15.64±16.29	9.80±10.48	**1.19E-05**
Ch2 Max	43.13±75.38	27.69±37.67	**0.017**	44.47±74.64	28.47±35.76	**0.004**	42.65±70.59	32.01±42.48	**0.018**
Ch2 Min	3.63±2.44	1.40±0.84	**1.40E-18**	4.54±3.17	1.69±1.47	**1.52E-21**	5.08±3.56	1.84±1.34	**9.99E-22**
Ch2 CV	0.53±0.30	0.70±0.39	**0.0003**	0.59±0.36	0.73±0.35	**0.0008**	0.54±0.32	0.72±0.34	**1.05E-05**
Ch2 Pos Max	136.31±32.36	141.00±33.33	0.43	148.18±33.64	139.49±36.74	**0.004**	149.70±31.84	139.38±38.02	**0.001**
Ch2 Pos Min	131.66±29.46	139.32±26.76	0.054	124.99±27.87	127.27±33.88	0.57	118.68±29.43	119.32±35.48	0.86
Ch2 Time Max	6.30±4.43	7.27±4.07	**0.021**	2.07±1.12	2.95±5.63	0.055	1.30±0.67	1.62±0.70	**0.0003**
Ch2 Time Min	5.70±4.37	5.32±3.35	0.93	1.65±1.41	1.97±5.93	0.22	0.97±0.94	1.11±3.86	0.11
Ch2 MNF	290.16±14.82	293.54±14.13	0.29	293.62±14.60	292.69±14.71	0.26	293.40±14.31	291.57±13.86	0.19
Ch2 MDF	72.48±35.03	79.55±39.28	0.42	79.78±34.32	78.06±36.97	0.34	80.61±34.24	75.29±35.29	0.18
Ch2 CC Peak	258371±514724	57940±101545	**8.52E-11**	759498±7477994	41163±185168	**3.60E-16**	63319±88078	16677±33973	**1.07E-14**
Ch2 CC Time	13.38±5.29	14.60±8.94	0.46	4.18±1.51	4.02±5.19	**0.009**	2.79±0.89	2.94±1.45	0.94
Ch2 ZC	3229±1797	3383±1563	0.64	930±407	1232±2301	0.35	560±223	803±2046	0.83

Automated recognition of health state

This study employed machine learning techniques to predict categorical outcomes for post-stroke and healthy participants using classifiers from the scikit-learn library [123]. The objective was to define a set of parameters and a classification system capable of distinguishing between participant groups based on outcomes from the muscle spasticity assessment. The dataset consisted of various features related to torque, position, and electromyography measurements. Feature selection was performed to include a wide array of predictors such as 'Direction of movement', and 'Side', for each velocity: (10°/s, 50°/s, and 100°/s): 'T Mean', 'T Max', 'T Min', 'T CV', 'T Pos Max', 'T Pos Min', 'T Time Max', 'T Time Min', and for each channel (Ch1 - Biceps Brachii, Ch2 - Triceps Brachii): 'EMG RMS Mean', 'EMG RMS Max', 'EMG RMS CV', 'EMG RMS Pos Max', 'EMG RMS Pos Min', 'EMG MNF', 'EMG MDF'. The dataset was preprocessed to handle missing values using a SimpleImputer with a 'median' strategy. Categorical variables were transformed into numerical form through one-hot encoding. The data was then split into training and testing sets, with a test size of 20%, and the random state set to 42 for reproducibility.

A Random Forest Classifier is used as the base model, and GridSearchCV is employed to find the best hyperparameters from a defined grid. The best model from GridSearchCV is then used for further training. The trained model's performance is evaluated on the test set using accuracy as the primary metric. A classification report providing detailed metrics (precision, recall, f1-score) for each class and a confusion matrix for a visual representation of the model's performance are also generated. The results indicate that the best model achieved an accuracy of 58.78% on the test set. The classification report shows that the model performs better in predicting the healthy class with a precision of 57% and a recall of 97%, leading to a high f1-score of 72%. However, the model struggles with the post-storke class, achieving only 13% recall. This suggests that while the model is relatively effective at identifying the healthy group, it often misclassifies the post-stroke group as healthy one. After that to find better accuracy, there were used Decision Tree Classifier. Decision Trees are a type of supervised learning algorithm that is used for classification and regression tasks. They are desirable due to their simplicity and interpretability. The Decision Tree Classifier achieved an accuracy of 68.16% on the test data. The classification report provides a more detailed insight into the model's performance across the different classes: For the 'post-stroke' class, the model has a precision of 72% and a recall of 49%, resulting in an f1-score of 58For the 'healthy' class, the precision is slightly lower at 66%, but the recall is higher at 84%, leading to a higher f1-score of 74%. These results suggest that the Decision Tree Classifier is more effective in correctly identifying the healthy group compared to the post-stroke group, as indicated by the higher recall and f1-score for the healthy class. The overall accuracy of 68.16% indicates a moderate level of predictive power, but there might be room for improvement, possibly

through hyperparameter tuning, feature engineering, or trying more complex models like ensemble methods. Then, a grid search approach (GridSearchCV) was employed to optimize the hyperparameters of the HistGradientBoostingClassifier, considering 'learning rate' and 'max depth' as the parameters to tune. This classifier is a variant of the traditional Gradient Boosting Machines (GBM) and part of the family of algorithms that build an ensemble of decision trees in a sequential manner, where each subsequent tree aims to correct the errors of the previous ones. This model achieved the best accuracy of 92.24% on the test set. The classification report revealed a precision of 0.93 and 0.92 for the classes 'post-stroke' and 'healthy' respectively, with respective recalls of 0.90 and 0.94. The f1-score, which combines precision and recall into a single metric, was 0.91 for 'post-stroke' and 0.93 for 'healthy', indicating a robust performance of the model across both classes. Further diagnostics included a confusion matrix, visualized as a heatmap to better understand the classification errors in Figure 4.8. This allowed for the identification of instances where the model's predictions did not align with the actual values, providing insights into the model's performance and potential areas for improvement.

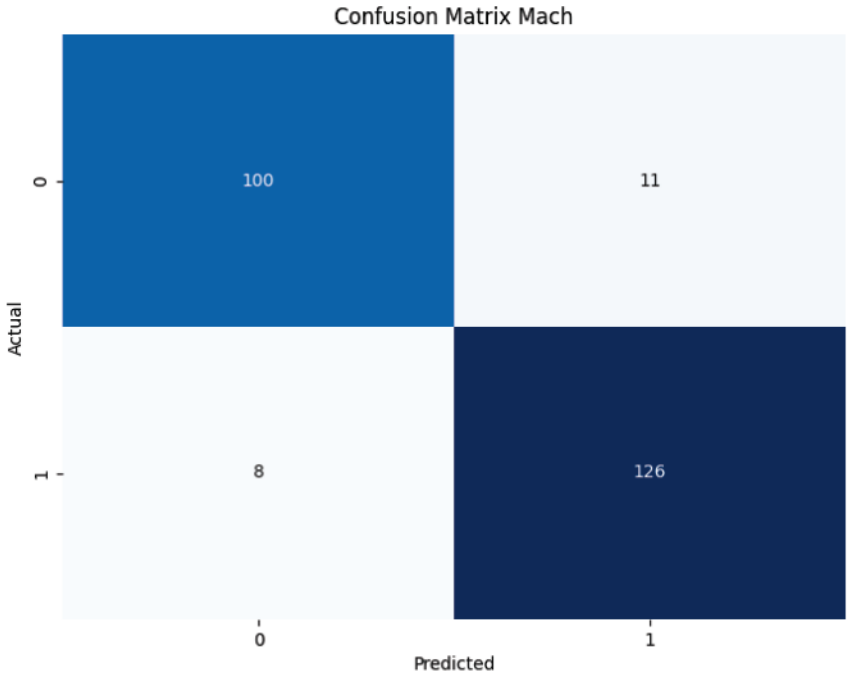


Figure 4.8: Confusion Matrix Mach

4.2.4 Discussion

This detailed summary shows that while some variables demonstrate moderate to good reliability between sessions (indicated by ICC values), the high coefficients of variation for some variables suggest considerable variability within the data. The p-values, pre-

dominantly higher than 0.05, generally indicate a lack of significant differences between sessions for most variables, supporting the repeatability aspect of the study hypothesis. The comparison between control groups and stroke survivors highlighted the potential of machine-assisted diagnostics in differentiating between healthy and affected limb functions. The high reliability in specific variables, particularly in stroke survivors, suggests that machine-assisted diagnostics can effectively monitor patient progress and condition over time.

The observed differences in EMG signals and torque between stroke patients and healthy controls substantiate the hypothesis that these measures can serve as objective indicators of spasticity. The variations across different movements and velocities underscore the complexity of spasticity as a multifaceted condition requiring personalized therapeutic approaches. The study's findings advocate for the integration of EMG and torque measurements in clinical practice, facilitating the objective assessment and monitoring of spasticity in stroke rehabilitation.

This study highlights the potential of machine learning (ML) techniques in the rehabilitation field, particularly in distinguishing between post-stroke and healthy individuals based on muscle spasticity assessment outcomes. The application of various classifiers from the scikit-learn library demonstrates the feasibility of predicting categorical outcomes using clinical measurement data. The progression from a Random Forest Classifier, through a Decision Tree Classifier, to a HistGradientBoostingClassifier underscores a methodical approach to enhancing model performance through algorithm selection and hyperparameter optimization. The initial use of a Random Forest Classifier, although providing a baseline accuracy of 58.78%, exhibited a significant imbalance in predictive performance between the classes. Specifically, its high recall but low precision for the healthy class indicated a tendency to misclassify post-stroke individuals as healthy, reflecting potential limitations in the model's ability to capture the nuances of the post-stroke condition. The transition to a Decision Tree Classifier, which achieved a higher overall accuracy of 68.16%, demonstrates the impact of model choice on prediction outcomes. The improved balance between precision and recall for both classes suggests that the simpler, more interpretable structure of decision trees may offer advantages in certain clinical applications. However, the still moderate accuracy and the disparity in class performance hinted at the need for further model refinement. The subsequent adoption of the HistGradientBoostingClassifier, achieving an impressive accuracy of 92.24%, represents a significant advancement in the study's objectives. The notable improvement in precision, recall, and f1-scores for both classes illustrates the efficacy of gradient boosting methods in dealing with complex, non-linear relationships in data. The model's robust performance across both post-stroke and healthy classes suggests that it effectively captures the underlying patterns distinguishing these groups, likely benefiting from the sequential correction of errors inherent in gradient boosting algorithms.

4.2.5 Conclusion

The presence of variables with significant changes and high reliability supports the thesis hypothesis (HI.) to some extent, suggesting that machine-assisted diagnostic procedures can provide objective assessments. The comparative analysis between the control group and stroke survivors highlights the potential of robot-assisted diagnostics in differentiating between healthy and affected limb functions. The control group's consistent performance across various limb movements provides a reliable baseline. In contrast, the observed variability in stroke survivors' measurements underscores the importance of selecting reliable variables for accurate assessment. The variability in both mean values and standard deviations across flexion and extension movements in both limbs suggests that spasticity and motor control issues manifest differently depending on the movement and the affected limb. This variability underscores the complexity of assessing and treating post-stroke spasticity and the importance of objective, quantitative measures like EMG and torque measurements. The data across all limbs and direction of movement, consistently show that there are measurable differences in EMG signals and torque between stroke patients and the control group, with stroke survivors generally exhibiting higher mean values and a broad range of variability. The significant disparities observed between stroke patients and healthy individuals across multiple movement parameters endorse the clinical utility of these metrics, offering a pathway toward more tailored and effective rehabilitation interventions. This comparative study confirms the effectiveness of EMG and torque measurements in objectively quantifying spasticity in stroke survivors. This study supports the hypothesis that EMG signals, torque, and limb position measurements can provide an objective basis for assessing patient conditions through robot-assisted diagnostics.

This research successfully demonstrates the application of machine learning techniques to differentiate between post-stroke and healthy individuals using muscle spasticity assessment data. The study's findings underscore the importance of selecting appropriate ML models and tuning their parameters to improve predictive accuracy in clinical settings. The superior performance of the HistGradientBoostingClassifier, evidenced by its high accuracy and balanced precision-recall across classes, highlights the potential of advanced ensemble methods in enhancing diagnostic processes. Moreover, the study emphasizes the role of feature selection and preprocessing in achieving optimal model performance. The inclusion of a wide array of predictors and the careful handling of missing values and categorical variables were critical in developing a reliable classification system.

The findings advocate for the judicious selection of reliable and repeatable biomechanical and bioelectrical parameters, considering the inherent variability in patient performances. Future work should focus on refining diagnostic procedures to enhance the reliability and objectivity of patient assessments, particularly in rehabilitation contexts.

Also, there could be explored further optimization of the HistGradientBoostingClassifier, experimentation with other advanced ML algorithms, and the integration of additional clinical parameters to enhance predictive capabilities. Additionally, the deployment of such models in real-world clinical environments could provide valuable insights into their practical utility and impact on patient care. Overall, this study contributes to the growing body of evidence supporting the integration of machine learning into rehabilitation, offering promising avenues for improving the accuracy and efficiency of medical diagnoses and interventions.

4.3 Automatization of diagnostics and rehabilitation of urinary incontinence patients

Urinary incontinence (UI) remains a largely unaddressed issue within the healthcare community, often overlooked and not openly discussed among healthcare providers. This condition adversely affects the daily life quality of individuals, although it is not considered life-threatening or hazardous. The 2016 Periodic Report by the European Commission CORDIS highlights that approximately 56 million individuals across Europe suffer from UI. A European study revealed a prevalence of 35% in women aged 18 to 99 [39].

The majority of UI cases go untreated, largely due to unawareness about available medical interventions and societal or cultural stigmas. Worldwide statistics from 2008 estimated 346 million people were living with some form of UI, a number projected to rise to 420 million by 2018. Various treatment strategies exist for managing both urinary and fecal incontinence, including pelvic floor muscle rehabilitation. This approach has shown efficacy in managing incontinence by improving the support of the perineal muscles, which is crucial for maintaining continence. In more severe instances, strengthening the pelvic floor can significantly enhance the success rates of surgical interventions aimed at correcting incontinence [18]. Additionally, biofeedback has emerged as a beneficial physical therapy technique for treating pelvic floor dysfunction. It employs subconscious and conscious cues, such as visual, auditory, or tactile feedback, to provide patients and clinicians with real-time information about physiological functions. This dual awareness facilitates the patient's ability to manage bodily responses previously outside their conscious control.

The pandemic, triggered by the coronavirus disease 2019 (COVID-19), has ushered in a profound transformation in healthcare. It heightened our awareness of the need for remote care and catalyzed significant efforts in harnessing information technologies to provide that care. In the realm of clinical practice, there remains an ongoing uncertainty regarding the methods healthcare professionals can employ to deliver remote rehabilitation for female pelvic floor dysfunction using telehealth [84].

A solution to the problem of the pandemic, the increasing cost of healthcare, and

the high number of patients falling within physiotherapy and exercises is the automation of diagnostic procedures and treatment. It can be done by providing the patient with the opportunity of remote exercises, consultation, and health status monitoring. The purpose of this research is to assess the effectiveness of EMG biofeedback exercises for telerehabilitation based on EMG biofeedback exercises with Stella BIO in stress urinary incontinence (SUI) in perimenopausal women (HII.).

4.3.1 Materials and methods

The inclusion criteria were as follows: women, stress urinary incontinence grade I or II, confirmed via USG examination, questionnaire of evaluation of frequency and intensity of SUI symptoms, quality of life questionnaire, in aged 40 to 65 years old. The exclusion criteria were pelvic organ prolapse, contraindication to use Stella BIO device or Perisphera H endovaginal electrode (Fig. 4.9). The participants have to have Internet access at home.

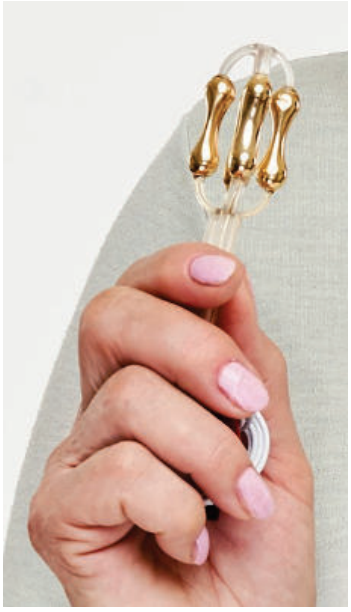


Figure 4.9: Endovaginal electrode Perisphera H [37]

In this study, we included 20 women with SUI aged 52 ±6.83. The project was approved by the Bioethics Committee KB-0012/22/2020 on 9 March 2020. Each participant was recruited with informed consent to participate in the study.

Procedures

Prior to starting a pelvic floor muscle training program with Stella BIO, the patients were examined by the urogynecological physiotherapist and received instruction on device usage. The participant completed the ICIQ-LUTSqol SF, a psychometrically robust patient-completed questionnaire evaluating the quality of life in urinary incontinent patients for use in research and clinical practice. Afterward, each patient was provided

with Stella BIO, along with an online training program for EMG biofeedback exercises to be performed independently at home for approximately 8 weeks. The initial and final exercises in the program involved the Glazer protocol, described in Section 2.2.1, to evaluate muscle health conditions. The EMG signal from the protocol was presented in Fig. 4.10.

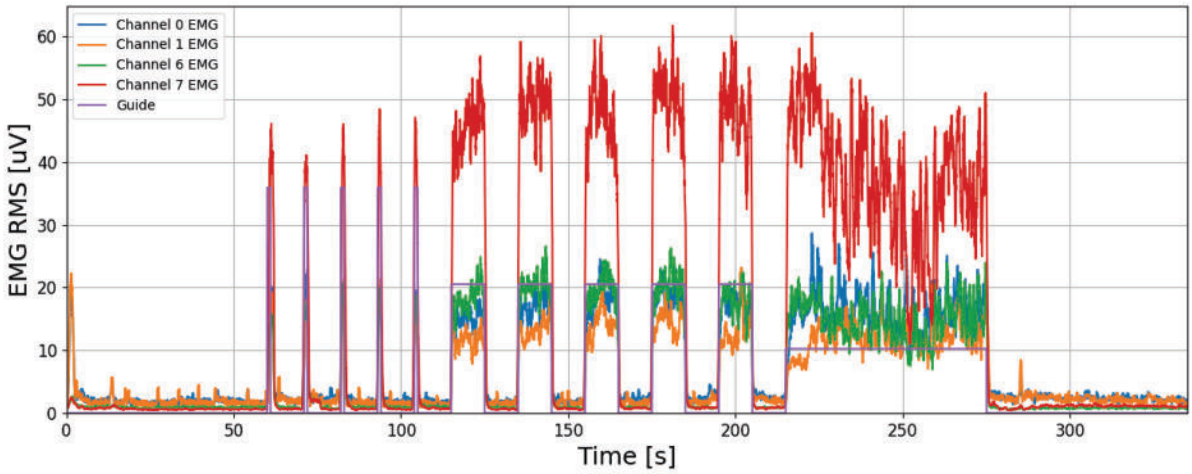


Figure 4.10: Example of EMG signals from Glazer protocol

Data Analysis

The bioelectrical activity of pelvic floor muscle was collected using the Perisphera H endovaginal electrode (BEACMED S.R.L., Italy) with Stella BIO (EGZOTech Sp. z o.o., Poland). The data was collected from 4 channels for the muscles: right transverse abdominal (ch 1), left transverse abdominal (ch 2), right pubococcygeal muscle (ch 7), and left pubococcygeal muscle (ch 8). The example of results from the software developed in Python (Sec. 3.2) was presented in Fig. 4.11. Statistical analysis was performed using STATISTICA 13.3 software (StatSoft, Poland). The Wilcoxon Signed-Rank Test was used to determine the significance of differences in the calculated parameters from the results before and after telemedicine treatment, with p-values exceeding 0.05 suggesting a lack of significant disparity.

The sEMG signal parameters, which are elaborated upon in Section 2.1.3, were computed in the manner described below:

1. Pre-baseline Stage:

    - Average mean amplitude [µV]—the value was calculated separately for the whole of stage signal and each of the 3 intervals: I-5s, II-5s, III-50s.
    - Mean amplitude variability [%]— the value was calculated based on standard deviation and mean of the data, separately for the whole of stage signal and each of the 3 intervals: I-5s, II-5s, III-50s.

2. Phasic contractions Stage:
    - Average peak amplitude [µV]
    - Average mean amplitude from rest phase [µV]
    - Time before peak [s]
    - Time after peak [s]
    - Time of amplitude increase (onset to peak) [s]
    - Time of amplitude decrease (peak to offset) [s]
    - Contraction duration (onset to offset) [s]
3. Tonic contractions Stage:
    - Average mean amplitude contraction [µV] — the mean value from 5 contractions phase based on the patient's instructions.
    - Average mean amplitude rest [µV]
    - Average mean amplitude work [µV]
    - Average peak amplitude [µV]
    - Mean amplitude variability [%]
    - Onset [s]
    - Offset [s]
    - Time before peak [s]
    - Time of amplitude increase (onset to peak) [s]
    - Time of amplitude decrease (peak to offset) [s]
4. Endurance Stage:
    - Average mean amplitude [µV] — the mean value from 6 intervals lasting 10 s each.
    - Mean amplitude variability [%]— the value was calculated based on the standard deviation and mean of the data from the whole contraction and 6 intervals lasting 10 s each.
5. Post-baseline Stage:
    - Average mean amplitude [µV] - the mean value of the whole stage signal
    - Mean amplitude variability [%] - the value calculated based on the standard deviation and mean of the whole signal

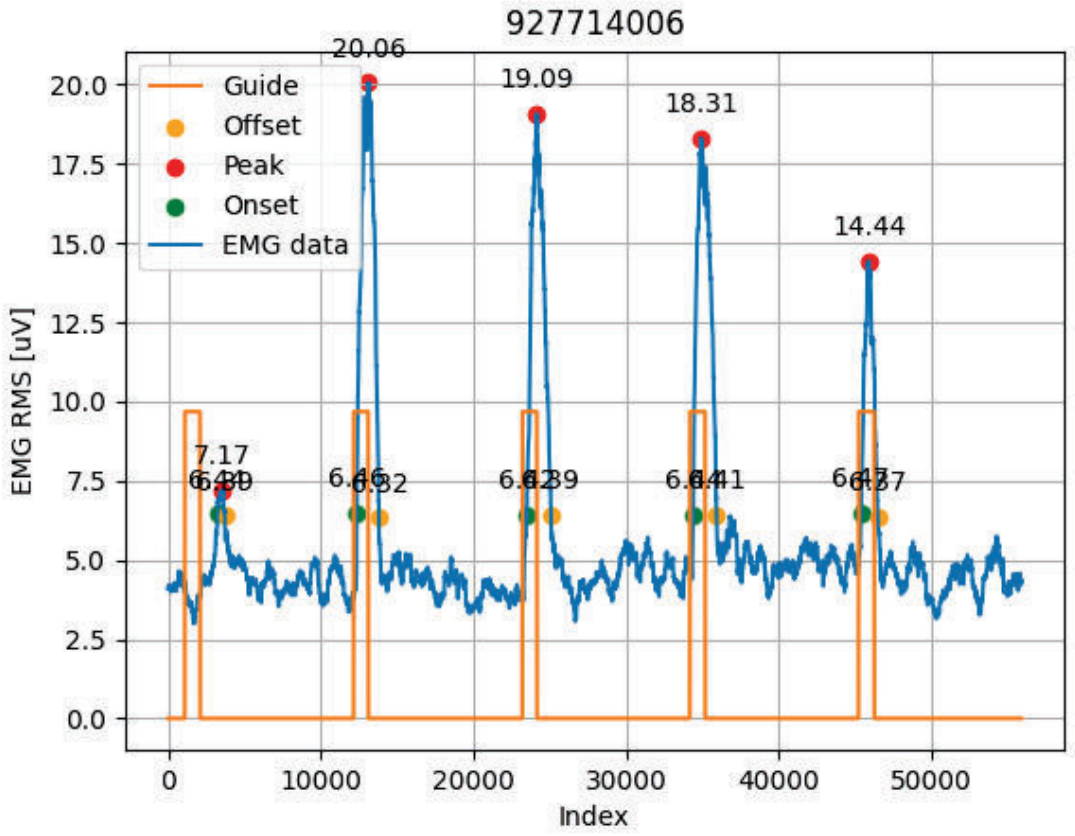


Figure 4.11: Example of Phasic Contraction Stage with detected peaks, onsets and offsets

4.3.2 Results

The results of ICIQ-LUTSqol SF are presented as follows, before treatment 10,93±3,47 after 6,46±3,95 with statistically significant difference between them ($p = 0.005$). The results are demonstrated as the mean, standard deviation (SD), and p from the Wilcoxon test pre-baseline stage in Tab. 4.25, phasic contraction stage in Tab. 4.26, tonic contraction stage in Tab. 4.27, endurance stage in Tab. 4.28, and post-baseline stage in Tab. 4.29. In the Tables, there were presented chosen parameters, especially with the significant changes after treatment. The digit in the bracket designates the channel number corresponding to the muscle. For the pre-baseline stage, there were significant improvements in the average mean amplitude for 7 channel for all intervals and the whole signal, in the Average mean amplitude for 8 channel only for II and III intervals, and the Mean amplitude variability II interval for 7 channel. The reduced mean amplitude suggests an improvement in muscle control and decreased involuntary muscle contraction. Improvements in parameters for the phasic contraction like average mean amplitude from the rest phase (Ch7 p=0.005 and Ch8 p=0.001), and time before peak (Ch7 p=0.049 and Ch8 p=0.009) are expected to reflect enhanced muscle function and control. Specifically, reductions in contraction duration and time of amplitude increase (Ch7 p=0.001 and Ch8 p=0.001), and shorter times

Table 4.25: Results of Pre-Baseline Stage

Parameter Name	Before		p	After	
	Mean	SD		Mean	SD
Average mean amplitude [µV] (6)	2.77	2.58	**0.001**	1.29	0.86
Average mean amplitude [µV] (6) - I-5s	2.66	2.04	**0.049**	1.58	1.12
Average mean amplitude [µV] (6) - II-5s	2.33	1.90	**0.004**	1.21	0.93
Average mean amplitude [µV] (6) - III-50s	2.83	2.74	**0.0003**	1.26	0.87
Average mean amplitude [µV] (7)	3.28	3.62	**0.006**	1.38	1.07
Average mean amplitude [µV] (7) - I-5s	2.61	2.10	0.171	1.84	1.40
Average mean amplitude [µV] (7) - II-5s	3.06	3.30	**0.030**	1.49	1.22
Average mean amplitude [µV] (7) - III-50s	3.36	3.95	**0.003**	1.32	1.06
Mean amp variability [%] (6) - I-5s	18.45	15.28	0.376	29.10	35.15
Mean amp variability [%] (6) - II-5s	14.44	12.96	**0.005**	9.49	3.47
Mean amp variability [%] (6) - III-50s	54.17	111.42	0.658	24.16	22.06
Mean amp variability [%] (7) - I-5s	19.81	18.79	0.520	22.47	21.10
Mean amp variability [%] (7) - II-5s	19.81	33.18	0.841	11.28	6.77
Mean amp variability [%] (7) - III-50s	46.11	91.08	0.295	22.68	19.66

The digit in the bracket designates the channel number corresponding to the muscle.

for muscle relaxation (time after peak) would indicate more effective muscle control and relaxation capabilities post-treatment. The mean peak amplitude observed in Channel 8 shows a notable decrease, while the post-treatment standard deviation is substantially lower, possibly indicating improved muscle control. In the tonic contraction stage, average

Table 4.26: Results of Phasic Contraction Stage

Parameter Name	Before		p	After	
	Mean	SD		Mean	SD
Average peak amplitude [µV](7)	11.67	10.68	0.053	30.62	62.41
Average peak amplitude [µV](8)	25.75	64.10	**0.027**	22.13	25.70
Average mean amp from rest phase[µV](7)	2.61	1.97	**0.005**	1.46	1.04
Average mean amp from rest phase[µV](8)	2.57	2.06	**0.001**	1.54	1.20
Time before peak[s] (7)	1.10	0.44	**0.049**	1.17	1.68
Time before peak[s] (8)	1.17	0.53	**0.009**	0.79	0.20
Time after peak[s] (7)	1.54	1.13	0.295	1.22	0.89
Time after peak[s] (8)	1.40	0.82	0.687	1.32	1.06
Time of amp increase (onset to peak)[s](7)	5.12	3.20	**0.001**	2.48	1.72
Time of amp increase (onset to peak)[s](8)	5.37	3.26	**0.001**	3.06	1.81
Contraction duration (onset to offset)[s](7)	6.49	4.15	0.064	4.21	2.26
Contraction duration (onset to offset)[s](8)	6.49	3.32	0.084	4.83	2.50

The digit in the bracket designates the channel number corresponding to the muscle.

mean amplitude work increased for the channels 7 and 8, although these changes were not statistically significant ($p = 0.421$ and $p = 0.391$, respectively). The Average Peak Amplitude of channel 7 saw an increase from 13.26 µV to 17.91 µV, and channel 8 from 15.88 µV to 16.91 µV, both indicating higher peak muscle contractions post-treatment. These changes were not statistically significant. A significant increase in median frequency

for channel 7 from 44.99 Hz to 72.85 Hz (p = 0.024), indicating potentially more efficient muscle fiber recruitment post-treatment. Channel 8 also showed an improvement from 44.92 Hz to 61.91 Hz, though not statistically significant (p = 0.320). A significant improvement in onset time for channel 7, from -0.22 seconds to -0.03 seconds (p = 0.003), suggesting faster muscle activation post-treatment. Offset time for channel 8 improved significantly from 0.22 seconds to -0.11 seconds (p = 0.030), indicating quicker muscle relaxation. Both channels showed a significant increase in the time from peak amplitude to offset, with channel 7 increasing from 6.41 seconds to 7.58 seconds (p = 0.048) and channel 8 from 6.27 seconds to 7.36 seconds (p = 0.017). This suggests a longer duration of muscle contraction post-treatment, potentially indicating improved muscle endurance.

Table 4.27: Results of Tonic Contraction Stage

Parameter Name	**Before**		**p**	**After**	
	Mean	**SD**		**Mean**	**SD**
Average mean amplitude work [µV] (7)	9.15	6.30	0.421	12.39	10.88
Average mean amplitude work [µV] (8)	10.94	10.47	0.391	11.23	7.81
Average peak amplitude [µV] (7)	13.26	9.11	0.277	17.91	13.87
Average peak amplitude [µV] (8)	15.88	14.64	0.241	16.91	10.60
Median frequency [Hz] (7)	44.99	18.04	**0.024**	72.85	36.81
Median frequency [Hz] (8)	44.92	17.25	0.320	61.91	30.81
Onset [s] (7)	-0.22	0.41	**0.003**	-0.03	0.22
Onset [s] (8)	-0.09	0.44	0.391	-0.003	0.41
Offset [s] (7)	0.03	1.66	0.639	-0.13	1.66
Offset [s] (8)	0.22	1.52	**0.030**	-0.11	2.23
Time of amp decrease (peak to offset)[s](7)	6.41	1.85	**0.048**	7.58	1.96
Time of amp decrease (peak to offset)[s](8)	6.27	2.27	**0.017**	7.36	2.34

The digit in the bracket designates the channel number corresponding to the muscle.

In the endurance stage, across all six intervals, both channels exhibited variations in average mean amplitude, which indicates the muscle's ability to maintain activity over time. Notably, for channel 8, there was a statistically significant increase in average mean amplitude in intervals 3, 4, and 5 (p-values of 0.020, 0.011, and 0.009, respectively), suggesting an enhancement in muscle endurance post-treatment. Channel 7 did not show statistically significant changes in amplitude, indicating possible variability in response to treatment or inherent differences in muscle characteristics between the channels. For both channels 7 and 8, there was a significant increase in mean amplitude variability (p-values of 0.033 and 0.022, respectively), indicating a greater fluctuation in muscle activity levels in the later stages of the endurance test. This could suggest adaptive responses in muscle activity to maintain function over prolonged periods, possibly reflecting an increase in neuromuscular control and endurance post-treatment. In interval 1, only channel 8 showed a significant increase in median frequency from 41.80 Hz to 73.12 Hz (p-value of 0.012), suggesting a shift towards higher frequency muscle fiber recruitment, which is often associated with improved muscle efficiency and endurance. In intervals 3 and

5, channel 8 exhibited significant increases in median frequency (p-values of 0.004 and 0.048, respectively), further supporting the notion of enhanced muscle function. Channel 7 did not show significant changes in median frequency, which might indicate a differential response to treatment or distinct physiological characteristics compared to channel 8.

Table 4.28: Results of Endurance Stage

Parameter Name	**Before**		**p**	**After**	
	Mean	**SD**		**Mean**	**SD**
Average mean amplitude interval 1 [µV] (7)	12.02	16.60	0.573	9.17	8.91
Average mean amplitude interval 1 [µV] (7)	12.02	16.60	0.573	9.17	8.91
Average mean amplitude interval 1 [µV] (8)	11.35	14.29	0.904	9.57	10.79
Average mean amplitude interval 2 [µV] (7)	6.29	4.76	0.629	8.49	7.94
Average mean amplitude interval 2 [µV] (8)	5.81	4.74	0.126	8.55	9.21
Average mean amplitude interval 3 [µV] (7)	7.62	6.04	0.376	9.82	6.40
Average mean amplitude interval 3 [µV] (8)	6.74	4.51	**0.020**	10.39	8.16
Average mean amplitude interval 4 [µV] (7)	7.28	4.98	0.334	9.60	6.00
Average mean amplitude interval 4 [µV] (8)	6.43	4.26	**0.011**	9.82	6.81
Average mean amplitude interval 5 [µV] (7)	7.35	5.97	0.171	9.42	5.66
Average mean amplitude interval 5 [µV] (8)	6.38	4.44	**0.009**	9.63	7.19
Average mean amplitude interval 6 [µV] (7)	7.65	4.43	0.683	9.51	8.46
Average mean amplitude interval 6 [µV] (8)	8.44	8.14	0.517	8.17	5.38
Mean amplitude variability interval 5[%] (7)	15.21	6.94	**0.033**	20.80	11.28
Mean amplitude variability interval 5[%] (8)	14.39	6.29	**0.022**	20.56	11.04
Median frequency interval 1 [Hz] (7)	43.62	23.47	0.542	54.94	26.23
Median frequency interval 1 [Hz] (8)	41.80	21.10	**0.012**	73.12	40.91
Median frequency interval 2 [Hz] (7)	50.39	24.27	0.094	43.63	26.52
Median frequency interval 2 [Hz] (8)	53.39	28.34	0.791	60.29	37.24
Median frequency interval 3 [Hz] (7)	54.44	29.06	0.893	55.21	39.71
Median frequency interval 3 [Hz] (8)	43.26	21.14	**0.004**	72.26	52.98
Median frequency interval 4 [Hz] (7)	38.24	19.51	0.340	55.79	34.38
Median frequency interval 4 [Hz] (8)	39.28	21.14	0.380	54.96	33.62
Median frequency interval 5 [Hz] (7)	39.69	20.13	**0.048**	64.25	46.21
Median frequency interval 5 [Hz] (8)	43.36	27.80	0.151	63.34	36.21

The digit in the bracket designates the channel number corresponding to the muscle.

The data show a reduction in mean amplitude post-treatment across all channels, suggesting a decrease in muscle activity at rest, although the changes were not statistically significant. This could indicate improved muscle relaxation and reduced involuntary muscle contractions, which are beneficial outcomes for patients with conditions like stress urinary incontinence.

4.3.3 Discussion

Bertotto et al. [12] and Hagen et al. [48] suggest that a program involving pelvic floor muscle exercises, with or without biofeedback, might be recommended for postmenopausal women experiencing stress urinary incontinence. This program shows potential in enhancing both the neurofunctional capacity of the pelvic floor and the overall quality

Table 4.29: Results of Post-baseline Stage

Parameter Name	Before		p	After	
	Mean	SD		Mean	SD
Average mean amplitude [µV] (1)	5.17	7.41	0.145	2.44	1.55
Average mean amplitude [µV] (2)	4.78	5.72	0.983	2.94	2.61
Average mean amplitude [µV] (7)	2.41	2.20	0.573	2.00	1.53
Average mean amplitude [µV] (8)	2.68	3.11	0.904	2.18	1.67

The digit in the bracket designates the channel number corresponding to the muscle.

of life in this demographic. Özlü et al. [102], in their study, found that both home exercises combined with intravaginal pressure biofeedback and home exercises with perineal EMG biofeedback are more effective than standalone home exercises in treating stress urinary incontinence among women. These methods exhibit similar efficacy and can serve as viable alternatives. In a randomized controlled trial, Aukee et al.[11] demonstrated a significant success rate of 68.8% using the home biofeedback method for pelvic floor training. The improvement in the leakage index after a 12-week training period was indicative of the effectiveness of this conservative treatment approach. However, Nunes et al.'s research [96] indicates that pelvic floor muscle training (PFMT) with biofeedback does not offer therapeutic benefits compared to alternative interventions such as no training, PFMT alone, and vaginal electrical stimulation for treating female stress urinary incontinence. Nevertheless, Arnouk et al.'s review [8] highlights the benefits of pelvic floor muscle physiotherapy and biofeedback for patients dealing with various dysfunctions including bladder issues (incontinence, overactive bladder), bowel problems (constipation - pelvic floor dyssynergia, fecal incontinence), pelvic organ prolapse, and sexual dysfunction (pelvic pain). Moreover, Moroni et al.'s research [90] combining biofeedback with PFMT shows uncertain effects on Quality of Life but demonstrates improved results on the pad test. Notably, group PFMT is as effective as individual treatment, and home PFMT does not consistently perform worse than supervised PFMT.

The results from our study provide compelling evidence of the efficacy of the treatment protocol on muscle control and function. The ICIQ-LUTSqol SF scores improved significantly from a mean of 10.93 to 6.46 post-treatment, with a p-value of 0.005, indicating a substantial enhancement in the quality of life related to lower urinary tract symptoms. This improvement underscores the clinical relevance of our intervention, emphasizing its potential to significantly ameliorate symptoms and improve patient outcomes. Moreover based on the Glazer Protocol outcomes, the treatment with EMG biofeedback telerehabilitation solutions has a impact on muscle control and function, as indicated by the improvements in various parameters measured across the pre-baseline, phasic contraction, tonic contraction, endurance, and post-baseline stages. The statistical analyses, particularly the use of the Wilcoxon test, underscore the robustness of these findings, with several parameters showing significant improvements post-treatment. In the pre-baseline

stage, the significant improvements in average mean amplitude across multiple channels and intervals suggest that the treatment effectively enhances muscle control. The reduction in mean amplitude is indicative of decreased involuntary muscle contractions, pointing to improved neuromuscular coordination and control. This is further supported by the changes in the mean amplitude variability in certain stage intervals, which suggest enhanced muscle response consistency. During the phasic contraction stage, notable improvements were observed in parameters such as average mean amplitude from the rest phase, time before peak, contraction duration, and time of amplitude increase. These changes are indicative of enhanced muscle function, including faster muscle activation (reduced time before peak), more efficient muscle control (reduced contraction duration and time of amplitude increase), and improved muscle relaxation capabilities. Such improvements are critical for the effective performance of daily activities and could significantly impact the quality of life for individuals with SUI undergoing treatment. The tonic contraction stage results, particularly the significant increase in median frequency for one of the channels, suggest more efficient muscle fiber recruitment post-treatment. This efficiency could translate into better muscle performance and endurance, essential for sustained muscle activities. Although not all changes in this stage were statistically significant, the trends observed indicate positive shifts towards improved muscle function. In the endurance stage, the significant increase in the time from peak amplitude to offset for both channels implies improved muscle endurance. This enhancement in endurance is crucial for daily activities and indicates that the treatment not only improves muscle control but also contributes to muscle endurance performance improvements. The consistent improvements across different stages and parameters of muscle function underscore the efficacy of EMG biofeedback in telemedicine in enhancing muscle control, reducing involuntary contractions, and improving overall quality of life for patients.

4.3.4 Conclusion

This study has highlighted the promise and challenges of using telerehabilitation for stress urinary incontinence treatment. The research demonstrates the effectiveness of the treatment protocol in significantly improving muscle control, function, and endurance, as evidenced by improvements in ICIQ-LUTSqol SF scores and various muscle performance parameters across pre-baseline, phasic, tonic, endurance, and post-baseline stages. The significant reductions in involuntary muscle contractions, enhanced muscle fiber recruitment, faster activation and relaxation times, and improved endurance collectively suggest that the treatment offers a promising approach to managing SUI patients' conditions affecting muscle control and function. Future research should aim to explore the long-term effects of this treatment and its applicability to a broader range of muscle-related conditions, with the ultimate goal of enhancing patient care and quality of life. Analyzing EMG

signal from pelvic floor muscles across each stage allows to dissect the rehabilitation program's effects on the pelvic floor muscles' endurance, rapid response capability, baseline conditions, and ability to maintain tonic contractions. This detailed stage-by-stage analysis helps identify specific areas of improvement or where further intervention may be needed, ultimately guiding more effective and targeted pelvic floor muscle rehabilitation strategies.

4.4 Automatization of rehabilitation - EMG-triggered movement exercises

This section aims to showcase the outcomes of therapy that utilized feedback exercises incorporating electromyography (EMG), torque, and positional data, facilitated by a rehabilitation robot (HII.).

4.4.1 Material and methods

The study received ethical clearance from the Bioethics Committee of the District Medical Chamber in Cracow, under the approval number NR 10/KBL/OIL/2019, on January 22, 2019. The results presented below constitute only an analysis of some of the data obtained in the research, as the pilot study. There was involved a research group comprising 7 individuals who had experienced an ischemic stroke. The study was performed in "Reh-Stab" Rehabilitation Clinic in Limanowa, Poland. The subjects participated in a two-week exercise regimen, engaging in sessions five times a week. Each session lasted between 90 to 120 minutes, tailored to the patient's specific condition. The rehabilitation approach combined personalized standard physiotherapy with sessions using rehabilitation robot. Therapeutic procedures focusing on the lower limb using Luna EMG rehabilitation robot consist of:

- A 5-minute session of Continuous Passive Movement (CPM) of the knee's flexion and extension movements.
- A 10-minute period of exercises initiated by electromyography, where the activity of the rectus femoris muscle (CH1) triggered the device's support for extension the knee.
- Another 10-minute session of electromyography-induced exercises, this time utilizing the biceps femoris muscle's (CH2) activity to engage the device's assistance for knee flexion.
- The regimen concluded with a 5-minute CPM session for lower limb

The testing protocol included a 1-minute EMG-triggered movement exercise for the rectus femoris muscle (CH1) presented in Figure 4.12, preceded 3-minute CPM for the knee to warm up the participant. The assessment was conducted upon admission (S1) and then again after a period of 2 weeks of therapy(S2). The comparison of the data before and after

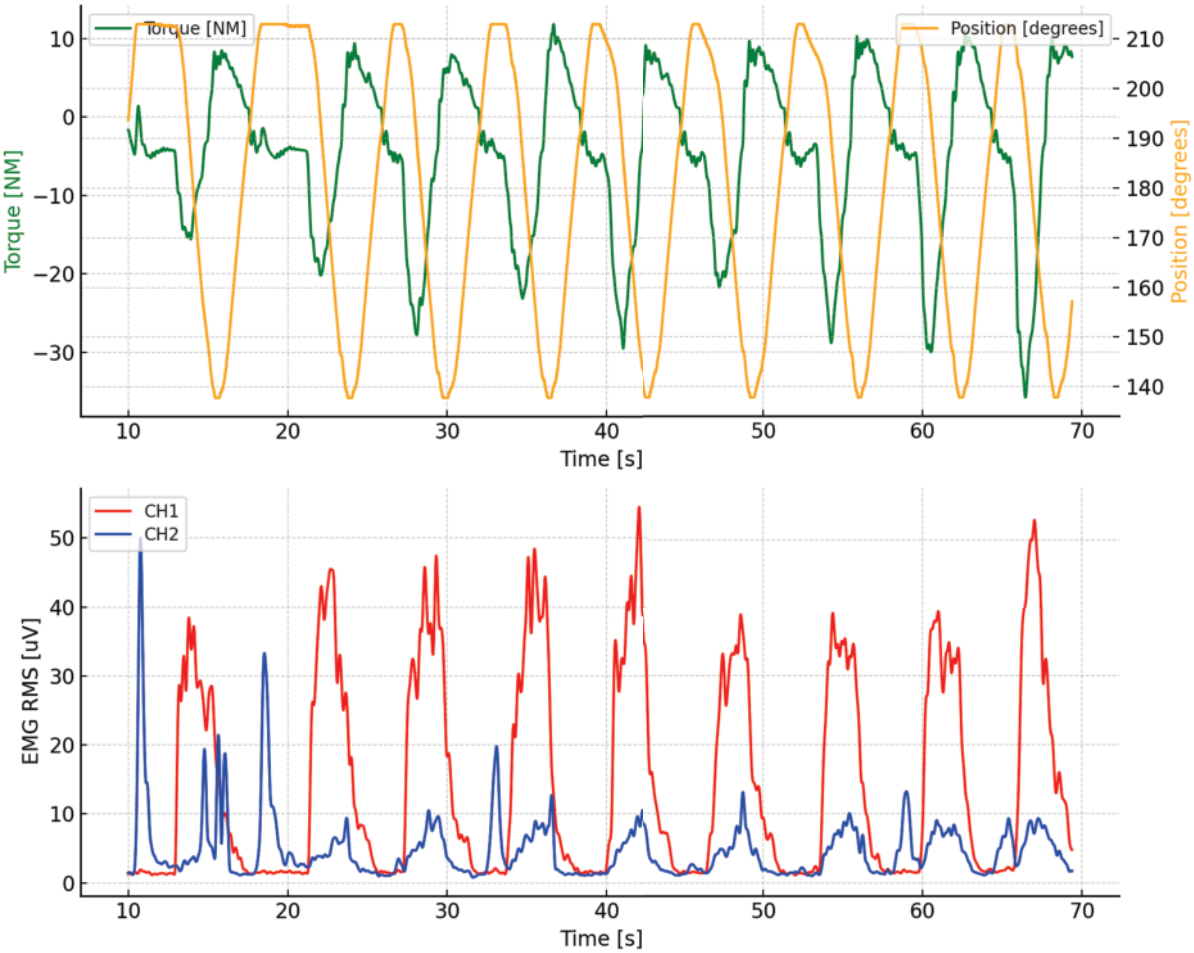


Figure 4.12: Example of EMG-triggered test results

treatment were assessed through the Wilcoxon or t-student test, with the t-test student being utilized for variables that followed a normal distribution (indicated by "*" in the tables). P-values greater than 0.05 indicated that there was no significant difference.

4.4.2 Results

The Table 4.30 summarizes the results of the test comparing measurements taken before (S1) and after 2 weeks of treatment (S2) across various parameters. The parameter calculation was separated on extension movement (ph1) and flexion movement (ph2) for knee joint. The study revealed significant improvements in specific parameters following two weeks of therapy utilizing feedback exercises with the Luna EMG rehabilitation robot. Notable changes were observed in the EMG readings and repetition times, indicating enhanced muscle activation and performance efficiency. Key findings include:

- A significant increase in EMG CH2 mean and max during phase 2 (p=0.022), suggesting improved activation of the biceps femoris muscle.
- Repetition (Rep) maximal time for both phases 1 and 2 showed significant reductions (p=0.047 and p=0.011, respectively), indicating quicker muscle response times and ability to hold the contraction.
- Repetition minimum in phase 2 also improved significantly (p=0.047), further supporting the enhanced efficiency in muscle responses and sustaining the contraction.

Despite these positive outcomes, some parameters such as EMG CH1 mean in phase 1 and Torque mean in both phases did not show significant changes, highlighting the variability in response to the therapy.

4.4.3 Discusion and conclusion

The current advancements, methodologies, and results of treatment with rehabilitation robots employing EMG-triggered movement are thoroughly detailed in the Section 2.2.2. The results underscore the potential benefits of integrating electromyography, torque, and positional feedback in rehabilitation exercises for stroke survivors. The significant improvements in EMG CH2 parameters and repetition times suggest that targeted exercises with the Luna EMG rehabilitation robot can enhance muscle activation and efficiency, which are crucial for the recovery of motor functions in post-stroke patients. The lack of significant change in some parameters may indicate the need for a longer therapy duration or the use of a different evaluation protocol to optimize rehabilitation outcomes. The findings also highlight the importance of incorporating technological advancements in rehabilitation practices to achieve better patient outcomes.

This pilot study demonstrates that rehabilitation exercises incorporating feedback mechanisms, facilitated by the Luna EMG rehabilitation robot, can lead to significant improvements in muscle activation and efficiency in individuals recovering from an ischemic stroke. The results suggest that such an approach could be a valuable addition to traditional stroke rehabilitation strategies. Future studies with larger sample sizes and longer therapy durations are recommended to further investigate the efficacy of this rehabilitation approach and to explore the potential for personalized therapy protocols.

Table 4.30: Results of test before (S1) and after 2 weeks of treatment (S2)

Parameters	S	Mean	SD	CV[%]	SEM	p-value
EMG CH1 mean ph1	S1	44.88	45.62	101.65	17.24	0.469
	S2	31.04	23.56	75.91	8.91	
EMG CH1 mean ph2	S1	35.64	13.76	38.63	5.20	0.882*
	S2	33.88	27.29	80.55	10.31	
EMG CH2 mean ph1	S1	12.88	4.19	32.54	1.58	0.219
	S2	21.35	12.80	59.93	4.84	
EMG CH2 mean ph2	S1	11.23	3.06	27.20	1.15	**0.022***
	S2	20.22	8.54	42.22	3.23	
Torque mean ph1	S1	8.72	11.61	133.09	4.39	0.938
	S2	8.02	6.02	75.03	2.27	
Torque mean ph2	S1	-4.74	6.08	-128.13	2.30	0.376*
	S2	-7.32	4.25	-58.03	1.61	
Rep time mean ph1	S1	4.31	2.03	47.05	0.77	0.109
	S2	3.22	0.34	10.55	0.13	
Rep time mean ph2	S1	3.22	0.53	16.41	0.20	0.209*
	S2	2.89	0.40	13.99	0.15	
EMG CH1 max ph1	S1	203.07	182.77	90.00	69.08	0.578
	S2	123.62	63.97	51.75	24.18	
EMG CH1 max ph2	S1	179.11	138.77	77.48	52.45	0.253*
	S2	111.66	53.61	48.01	20.26	
EMG CH2 max ph1	S1	41.07	13.49	32.84	5.10	0.131*
	S2	72.17	48.97	67.86	18.51	
EMG CH2 max ph2	S1	35.99	15.42	42.85	5.83	**0.022***
	S2	74.64	35.53	47.60	13.43	
Torque max ph1	S1	24.86	23.94	96.28	9.05	0.469
	S2	20.66	15.48	74.90	5.85	
Torque max ph2	S1	9.96	7.93	79.61	3.00	0.257*
	S2	6.17	2.88	46.77	1.09	
Rep time max ph1	S1	6.56	3.41	52.07	1.29	**0.047**
	S2	3.91	0.69	17.60	0.26	
Rep time max ph2	S1	5.95	1.93	32.52	0.73	**0.011***
	S2	3.55	0.82	23.09	0.31	
Number of rep	S1	10.00	3.16	31.62	1.20	0.497*
	S2	10.86	0.69	6.36	0.26	
Rep time min ph1	S1	2.27	2.10	92.40	0.79	0.600
	S2	2.38	1.07	44.82	0.40	
Rep time min ph2	S1	0.93	1.31	140.95	0.50	**0.047**
	S2	2.12	0.61	28.65	0.23	

* means T-student test results

Chapter 5

Conclusion and future work

This dissertation has addressed a critical scientific challenge: the absence of comprehensive evidence supporting the effectiveness of methodologies and treatment protocols in robotic-assisted diagnostics and therapeutic interventions. The primary goal of this research was to lay the foundational methodological principles for an automated expert platform that aims to augment, improve, and automate the processes of diagnosis and rehabilitation.

The distinctive contribution of the author primarily lies in the analysis of bioelectrical and biomechanical parameters based on muscle activity (EMG), torque, and position measurement and the application of machine learning for objective assessments: differentiating between healthy and affected individuals, and tailoring exercises to suit the patient's capacity based on the feedback loop. This integration enables a more objective, efficient, and personalized approach to patient care. The focus of the studies was primarily on upper limb movements, emphasizing elbow flexion and extension, and examining the roles of the biceps and triceps muscles in isokinetic muscle force assessments (Section 4.1), as well as in evaluating spasticity and muscle stiffness (Section 4.2). Furthermore, an another investigation delved into the application of EMG biofeedback for pelvic floor muscles within the scope of telerehabilitation, utilizing a protocol conducted remotely (Section 4.3). Moreover, research was conducted on the rehabilitation of knee movement, triggered by EMG, focusing on the rectus femoris and biceps femoris muscles through the use of a rehabilitation robot (Section 4.4).

The chosen bioelectrical and biomechanical parameters were validated for their effectiveness and objectivity in diagnostic and therapeutic processes through robot-assisted procedures. Table 5.1 displayed the parameters that demonstrated good reliability among individuals post-stroke and healthy groups, across different limbs or types of movement. Results shown for assessment procedures in Tables 4.2 and 4.3, and Tables 4.12-4.20 confirming the hipotesis HI., and treatment procedures in Tables 4.25 - 4.29 and Tables 4.30 confirming the hipotesis HII.. The findings from the adopted methodology indicate the feasibility of creating a cohesive system for the initiation and oversight of rehabilitation

Table 5.1: Biomechainal and bioelectrical parameters with good reliability

Test	**Parameters**	**Group**	**Limb and movement**	**Tables with results**
Muscle Force	Torque mean Peak torque	Healthy	Upper limb Ext and Flex	4.2 and 4.3
Muscle Spasticity	Ch1 10 MNF Ch1 10 MDF	Healthy	Left Upper limb	4.13, 4.14, and 4.16
Muscle Spasticity	Ch1 10 Mean Ch1 50 Mean	Healthy	Right Upper limb	4.12 and 4.16
Muscle Spasticity	Ch1 10 Mean Ch1 50 Mean Ch2 10 Mean	Post-stroke	Right Upper limb	4.17 and 4.18
Muscle Spasticity	T 10 Max T 100 Peak*	Post-stroke	Left Upper limb	4.19 and 4.20
Muscle Spasticity	Ch2 10 Mean Ch2 10 CC Peak Ch2 50 Mean	Post-stroke	Upper limb Ext	4.17 and 4.20
Muscle Spasticity	Ch1 10 Mean Ch1 50 Mean	Post-stroke	Upper limb Flex	4.18 and 4.19

*Torque Peak means T Min for extension and T Max for flexion

processes (automation). Before commencing exercises, individuals undergoing rehabilitation can undergo diagnostic evaluations. Subsequently, during the exercises, their movements can be scrutinized to ensure adherence to the prescribed exercise protocols (utilizing the feedback loop). This observation lends substantial support to the hypothesis proposed in the dissertation. This approach effectively addressed the outlined scientific problem by demonstrating the practicality and applicability of these parameters in enhancing patient care.

Based on the research conducted, the following hypotheses were confirmed:

I. **EMG signals complemented by torque and limb position, generated by patients during machine-assisted diagnostic procedures, allow to objectively assess the patient's condition.**

II. **EMG, complemented by torque and position measurements, when applicable, provide a complete set of signals facilitating biofeedback-based effective rehabilitation, also in telemedicine solutions.**

As we look to the future, it is clear that further research is needed to expand upon these findings, including larger scale clinical trials and the exploration of additional diagnostic and treatment protocols and parameters that could enhance the effectiveness of robotic-assisted interventions. Additionally, the potential for integrating these technologies into wider healthcare systems presents a promising avenue for improving access to and the quality of rehabilitation services.

In conclusion, this dissertation not only addresses a significant gap in the existing literature but also lays the groundwork for future innovations in the field of robotic-assisted healthcare and automatization. The methodologies and findings presented herein have the potential to significantly impact the way we approach diagnosis and rehabilitation, leading to more personalized, efficient, and effective patient care.

Bibliography

[1] Buket Aksac, Semih Aki, Ayse Karan, Onay Yalcin, Mete Isikoglu and Nurten Eskiyurt. 'Biofeedback and Pelvic Floor Exercises for the Rehabilitation of Urinary Stress Incontinence'. In: *Gynecologic and Obstetric Investigation* 56.1 (Aug. 2003), pp. 23–27. ISSN: 0378-7346. DOI: 10.1159/000072327. eprint: https://karger.com/goi/article-pdf/56/1/23/2866254/000072327.pdf. URL: https://doi.org/10.1159/000072327.

[2] E. Alfonsi, R. Pavesi, I. M. Merlo, A. Gelmetti, D. Zambarbieri, P. Lago, A. Arrigo, C. Reggiani and A. Moglia. 'Hemoglobin near-infrared spectroscopy and surface EMG study in muscle ischaemia and fatiguing isometric contraction'. In: *The Journal of sports medicine and physical fitness* 39.2 (1999), pp. 83–92.

[3] Laila Alibiglou, William Z. Rymer, Richard L. Harvey and Mehdi M. Mirbagheri. 'The relation between Ashworth scores and neuromechanical measurements of spasticity following stroke'. In: *Journal of NeuroEngineering and Rehabilitation* 5.1 (2008), p. 18. ISSN: 1743-0003. DOI: 10.1186/1743-0003-5-18. URL: https://doi.org/10.1186/1743-0003-5-18.

[4] M Alsobhi, F Khan, M F Chevidikunnan, R Basuodan, L Shawli and Z Neamatallah. 'Physical Therapists' Knowledge and Attitudes Regarding Artificial Intelligence Applications in Health Care and Rehabilitation: Cross-sectional Study'. In: *J Med Internet Res* 24.10 (Oct. 2022), e39565. DOI: 10.2196/39565.

[5] João Alvares, Rodrigo Rodrigues, Rodrigo Franke, Bruna Silva, Ronei Pinto, Marco Vaz and Bruno Baroni. 'Inter-machine reliability of the Biodex and Cybex isokinetic dynamometers for knee flexor/extensor isometric, concentric and eccentric tests'. In: *Physical Therapy in Sport* 16 (May 2014). DOI: 10.1016/j.ptsp.2014.04.004.

[6] Emilia Ambrosini, Simona Ferrante, Thomas Schauer, Giancarlo Ferrigno, Franco Molteni and Alessandra Pedrocchi. 'An Automatic Identification Procedure to Promote the use of FES-Cycling Training for Hemiparetic Patients'. In: *Journal of Healthcare Engineering* 5 (2014), p. 163457. ISSN: 2040-2295. DOI: 10.1260/2040-2295.5.3.275. URL: https://doi.org/10.1260/2040-2295.5.3.275.

[7] Noureddin nakhosin Ansari, Soofia Naghdi, Tahereh Arab and Shohreh Jalaei. 'The interrater and intrarater reliability of the Modified Ashworth Scale in the assessment of muscle spasticity: Limb and muscle group effect'. In: *NeuroRehabilitation* 23 (May 2008), pp. 231–7. DOI: 10.3233/NRE-2008-23304.

[8] Alex Arnouk, Elise De, Alexandra Rehfuss, Carin Cappadocia, Samantha Dickson and Fei Lian. 'Physical, Complementary, and Alternative Medicine in the Treatment of Pelvic Floor Disorders'. In: *Current Urology Reports* 18.6 (2017), p. 47. ISSN: 1534-6285. DOI: 10.1007/s11934-017-0694-7. URL: https://doi.org/10.1007/s11934-017-0694-7.

[9] JA Ashton-Miller. 'Proprioceptive thresholds at the ankle: implications for the prevention of ligament injury'. In: *Proprioception and Neuromuscular Control in Joint Stability*. Ed. by SM Lephart and FH Fu. Champaign, IL: Human Kinetics, 2000, pp. 279–290.

[10] Anand Asokan and M Vigneshwar. 'Design and Control of an EMG-based Low-cost Exoskeleton for Stroke Rehabilitation'. In: *2019 Fifth Indian Control Conference (ICC)*. 2019, pp. 478–483. DOI: 10.1109/INDIANCC.2019.8715555.

[11] Pauliina Aukee, Paula Immonen, David E. Laaksonen, Pekka Laippala, Jorma Penttinen and Olavi Airaksinen. 'The effect of home biofeedback training on stress incontinence'. In: *Acta Obstetricia et Gynecologica Scandinavica* 83.10 (2004), pp. 973–977. DOI: https://doi.org/10.1111/j.0001-6349.2004.00559.x. URL: https://obgyn.onlinelibrary.wiley.com/doi/abs/10.1111/j.0001-6349.2004.00559.x.

[12] Adriane Bertotto, Renata Schvartzman, Silvana Uchôa and Maria Celeste Osório Wender. 'Effect of electromyographic biofeedback as an add-on to pelvic floor muscle exercises on neuromuscular outcomes and quality of life in postmenopausal women with stress urinary incontinence: A randomized controlled trial'. In: *Neurourology and Urodynamics* 36.8 (2017), pp. 2142–2147. DOI: https://doi.org/10.1002/nau.23258. eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/nau.23258. URL: https://onlinelibrary.wiley.com/doi/abs/10.1002/nau.23258.

[13] *Biodex System 4 Pro*. Accessed on 2024-01-30. URL: https://www.polsl.pl/rib3/laboratoria-2/lbnrc/biodexsystem4pro/.

[14] Kari Bø. 'Measurement of pelvic floor muscle function and strength, and pelvic organ prolapse: Visual observation and palpation'. In: *Evidence-Based Physical Therapy for the Pelvic Floor: Bridging Science and Clinical Practice: Second Edition* (Jan. 2014), pp. 47–53. DOI: 10.1016/B978-0-7020-4443-4.00005-4.

[15] Joseph P. Broderick, Opeolu Adeoye and Jeffrey Elm. 'Evolution of the Modified Rankin Scale and Its Use in Future Stroke Trials'. In: *Stroke* 48 (2017). Epub 2017 Jun 16, pp. 2007–2012. DOI: 10.1161/STROKEAHA.117.017866.

[16] C. Brown, H. I. Glazer, V. Vogt, D. Menkes and G. Bachmann. 'Surface Electromyographic Biofeedback of Pelvic Floor Musculature'. In: *Contemporary OB/-GYN* (2011). Accessed: 2024-01-29. URL: https://www.contemporaryobgyn.net/view/surface-electromyographic-biofeedback-pelvic-floor-musculature.

[17] J Brudny, J Korein, BB Grynbaum, LW Friedmann, S Weinstein, G Sachs-Frankel and PV Belandres. 'EMG feedback therapy: review of treatment of 114 patients'. In: *Archives of physical medicine and rehabilitation* 57.2 (1976), pp. 55–61. ISSN: 0003-9993. URL: http://europepmc.org/abstract/MED/1259543.

[18] F.C. Burkhard, J.L.H.R. Bosch, F. Cruz, G.E. Lemack, A.K. Nambiar, N. Thiruchelvam, A. Tubaro et al. *EAU Guidelines on Urinary Incontinence in Adults*. Accessed: 2024-01-29. European Association of Urology. 2020. URL: https://d56bochluxqnz.cloudfront.net/media/EAU-Guidelines-on-Urinary-Incontinence-2020.pdf.

[19] David M Burns, Nathan Leung, Michael Hardisty, Cari M Whyne, Patrick Henry and Stewart McLachlin. 'Shoulder physiotherapy exercise recognition: machine learning the inertial signals from a smartwatch'. In: *Physiological Measurement* 39.7 (July 2018), p. 075007. DOI: 10.1088/1361-6579/aacfd9. URL: https://dx.doi.org/10.1088/1361-6579/aacfd9.

[20] Patricia Burns, Kevin Pranikoff, Thomas Nochajski, Evan Hadley, Kenneth Levy and Marcia Ory. 'A Comparison of Effectiveness of Biofeedback and Pelvic Muscle Exercise Treatment of Stress Incontinence in Older Community-Dwelling Women'. In: *Journal of gerontology* 48 (Aug. 1993), pp. M167–74. DOI: 10.1093/geronj/48.4.M167.

[21] Rocco Calabrò, Alberto Cacciola, Francesco Bertè, Alfredo Manuli, Antonino Leo, Alessia Bramanti, Antonino Naro, Demetrio Milardi and Placido Bramanti. 'Robotic gait rehabilitation and substitution devices in neurological disorders: where are we now?' In: *Neurological Sciences* 37, article 503 (Jan. 2016). DOI: 10.1007/s10072-016-2474-4.

[22] Rocco Calabrò, Claudia Müller-Eising, Maria Diliberti, Alfredo Manuli, Francesca Parrinello, Giuseppe Rao, Vincenzo Barone and Tamara Civello. 'Who Will Pay for Robotic Rehabilitation? The Growing Need for a Cost-effectiveness Analysis'. In: *Innovations in clinical neuroscience* 17 (Oct. 2020), pp. 14–16.

[23] Daniel Callan, Lloyd Mills, Connie Nott, Robert England and Shaun England. 'A Tool for Classifying Individuals with Chronic Back Pain: Using Multivariate Pattern Analysis with Functional Magnetic Resonance Imaging Data'. In: *PLOS ONE* 9.6 (June 2014), pp. 1–12. DOI: 10.1371/journal.pone.0098007. URL: https://doi.org/10.1371/journal.pone.0098007.

[24] Jennilee K. Carlyle and George Mochizuki. 'Influence of post-stroke spasticity on EMG-force coupling and force steadiness in biceps brachii'. In: *Journal of Electromyography and Kinesiology* 38 (2018). Neuromechanics of fine hand-motor tasks, pp. 49–55. ISSN: 1050-6411. DOI: https://doi.org/10.1016/j.jelekin.2017.11.005. URL: https://www.sciencedirect.com/science/article/pii/S1050641117300925.

[25] Yesung Cha and Arash Arami. 'Quantitative Modeling of Spasticity for Clinical Assessment, Treatment and Rehabilitation'. In: *Sensors* 20.18 (2020). ISSN: 1424-8220. DOI: 10.3390/s20185046. URL: https://www.mdpi.com/1424-8220/20/18/5046.

[26] Kai Chen, Yi-Ning Wu, Yupeng Ren, Lin Liu, Deborah Gaebler-Spira, Kelly Tankard, Julia Lee, Weiqun Song, Maobin Wang and Li-Qun Zhang. 'Home-Based Versus Laboratory-Based Robotic Ankle Training for Children With Cerebral Palsy: A Pilot Randomized Comparative Trial'. In: *Archives of Physical Medicine and Rehabilitation* 97.8 (2016), pp. 1237–1243. ISSN: 0003-9993. DOI: 10.1016/j.apmr.2016.01.029. URL: https://doi.org/10.1016/j.apmr.2016.01.029.

[27] Mario Cifrek, Vladimir Medved, Stanko Tonković and Saša Ostojić. 'Surface EMG based muscle fatigue evaluation in biomechanics'. In: *Clinical Biomechanics* 24.4 (2009), pp. 327–340. ISSN: 0268-0033. DOI: 10.1016/j.clinbiomech.2009.01.010. URL: https://doi.org/10.1016/j.clinbiomech.2009.01.010.

[28] Roger Collier. 'Medical technology often a burden if designed without physician input'. In: *CMAJ : Canadian Medical Association Journal* 190.36 (2018), E1091–E1092. DOI: 10.1503/cmaj.109-5656.

[29] Roberto Colombo, I Sterpi, A Mazzone, Carmen Delconte and F Pisano. 'Improving proprioceptive deficits after stroke through robot-assisted training of the upper limb: a pilot case report study'. In: *Neurocase* 22 (Nov. 2015), pp. 1–10. DOI: 10.1080/13554794.2015.1109667.

[30] Paul Cordo, Steven Wolf, Jau-Shin Lou, Ross Bogey, Matthew Stevenson, John Hayes and Elliot Roth. 'Treatment of Severe Hand Impairment Following Stroke by Combining Assisted Movement, Muscle Vibration, and Biofeedback'. In: *Journal of Neurologic Physical Therapy* 37.4 (2013). ISSN: 1557-0576. URL: https://

journals.lww.com/jnpt/fulltext/2013/12000/treatment_of_severe_hand_impairment_following.7.aspx.

[31] Christian Dannecker, Veronika Wolf, Renate Raab, Hermann Hepp and Christoph Anthuber. 'EMG-biofeedback assisted pelvic floor muscle training is an effective therapy of stress urinary or mixed incontinence: A 7-year experience with 390 patients'. In: *Archives of gynecology and obstetrics* 273 (Dec. 2005), pp. 93–7. DOI: 10.1007/s00404-005-0011-4.

[32] C.J. De Luca. 'Electromyography'. In: *Encyclopedia of Medical Devices and Instrumentation*. Ed. by John G. Webster. John Wiley & Sons, 2006, pp. 98–109.

[33] Christophe Demoulin, Marc Vanderthommen, Christophe Duysens and Jean-Michel Crielaard. 'Spinal muscle evaluation using the Sorensen test: a critical appraisal of the literature'. In: *Joint Bone Spine* 73.1 (2006), pp. 43–50. ISSN: 1297-319X. DOI: https://doi.org/10.1016/j.jbspin.2004.08.002. URL: https://www.sciencedirect.com/science/article/pii/S1297319X04001708.

[34] D. Didehdar and A. Kharazinejad. 'The Association Between Sprint Speed Test and Isokinetic Knee Strength in Healthy Male Volleyball Players'. In: *International Journal of Sport Studies for Health* 4.2 (2021), e126504. DOI: 10.5812/intjssh-126504. URL: https://brieflands.com/articles/intjssh-126504.html.

[35] George V. Dimitrov, Todor I. Arabadzhiev, Katya N. Mileva, Joanna L. Bowtell, Nicola Crichton and Nonna A. Dimitrova. 'Muscle Fatigue during Dynamic Contractions Assessed by New Spectral Indices'. In: *Medicine & Science in Sports & Exercise* 38.11 (2006), N/A. ISSN: 0195-9131. DOI: 00005768-200611000-00014. URL: https://journals.lww.com/acsm-msse/fulltext/2006/11000/muscle_fatigue_during_dynamic_contractions.14.aspx.

[36] Strahinja Dosen, Marko Markovic, Kelef Somer, Bernhard Graimann and Dario Farina. 'EMG Biofeedback for online predictive control of grasping force in a myoelectric prosthesis'. In: *Journal of NeuroEngineering and Rehabilitation* 12.1 (2015), p. 55. ISSN: 1743-0003. DOI: 10.1186/s12984-015-0047-z. URL: https://doi.org/10.1186/s12984-015-0047-z.

[37] Egzotech. *Egzotech Website*. Accessed on 2024-01-30. 2023. URL: https://www.egzotech.com/.

[38] Lhassan El Mhandi and François Bethoux. 'Isokinetic Testing in Patients with Neuromuscular Diseases: A Focused Review'. In: *American Journal of Physical Medicine and Rehabilitation* 92.2 (2013). ISSN: 0894-9115. DOI: 00002060-201302000-00009. URL: https://journals.lww.com/ajpmr/fulltext/2013/02000/isokinetic_testing_in_patients_with_neuromuscular.9.aspx.

[39] European Commission CORDIS. *Periodic Reporting for period 1 - WOMEN-UP (Cost effective self-management of urinary incontinence addressed to women across Europe)*. Tech. rep. Accessed: 2024-01-29. European Commission, 2016. URL: https://cordis.europa.eu/project/id/643535/reporting.

[40] A. Georgakis, L.K. Stergioulas and G. Giakas. 'Fatigue analysis of the surface EMG signal in isometric constant force contractions using the averaged instantaneous frequency'. In: *IEEE Transactions on Biomedical Engineering* 50.2 (2003), pp. 262–265. DOI: 10.1109/TBME.2002.807641.

[41] S. Ghroubi, W. Elleuch, L. Abid, M. Abdenadher, S. Kammoun and M.H. Elleuch. 'Effects of a low-intensity dynamic-resistance training protocol using an isokinetic dynamometer on muscular strength and aerobic capacity after coronary artery bypass grafting'. In: *Annals of Physical and Rehabilitation Medicine* 56.2 (2013), pp. 85–101. ISSN: 1877-0657. DOI: https://doi.org/10.1016/j.rehab.2012.10.006. URL: https://www.sciencedirect.com/science/article/pii/S1877065712013012.

[42] José-Antonio Gil-Gómez, Roberto Lloréns, Mariano Alcañiz and Carolina Colomer. 'Effectiveness of a Wii balance board-based system (eBaViR) for balance rehabilitation: a pilot randomized clinical trial in patients with acquired brain injury'. In: *Journal of neuroengineering and rehabilitation* 8.1 (2011), pp. 1–10.

[43] David J. Gladstone, Cynthia J. Danells and Sandra E. Black. 'The Fugl-Meyer Assessment of Motor Recovery after Stroke: A Critical Review of Its Measurement Properties'. In: *Neurorehabilitation and Neural Repair* 16.3 (2002). PMID: 12234086, pp. 232–240. DOI: 10.1177/154596802401105171. URL: https://doi.org/10.1177/154596802401105171.

[44] Howard I. Glazer and Claudia R. Hacad. 'The Glazer Protocol: Evidence-Based Medicine Pelvic Floor Muscle (PFM) Surface Electromyography (SEMG)'. In: *Biofeedback* 40.2 (June 2012), pp. 75–79. ISSN: 1081-5937. DOI: 10.5298/1081-5937-40.2.4. eprint: https://meridian.allenpress.com/biofeedback/article-pdf/40/2/75/1616888/1081-5937-40_2_4.pdf. URL: https://doi.org/10.5298/1081-5937-40.2.4.

[45] Daniel J. Goble. 'Proprioceptive Acuity Assessment Via Joint Position Matching: From Basic Science to General Practice'. In: *Physical Therapy* 90.8 (Aug. 2010), pp. 1176–1184. ISSN: 0031-9023. DOI: 10.2522/ptj.20090399. eprint: https://academic.oup.com/ptj/article-pdf/90/8/1176/31662089/ptj1176.pdf. URL: https://doi.org/10.2522/ptj.20090399.

[46] Kanika Govil and Majumi M. Noohu. 'Effect of EMG biofeedback training of gluteus maximus muscle on gait parameters in incomplete spinal cord injury'. In: *NeuroRehabilitation* 33 (2013), pp. 147–152. ISSN: 1878-6448. DOI: 10.3233/NRE-130939.

[47] Carl V Granger, Leland S Dewis, Nancy C Peters, Carol C Sherwood and James E Barrett. 'Stroke rehabilitation: analysis of repeated Barthel index measures'. In: *Archives of physical medicine and rehabilitation* 60.1 (1979), pp. 14–17.

[48] Suzanne Hagen, Andrew Elders, Susan Stratton, Nicole Sergenson, Carol Bugge, Sarah Dean, Jean Hay-Smith, Mary Kilonzo, Maria Dimitrova, Mohamed Abdel-Fattah, Wael Agur, Jo Booth, Cathryn Glazener, Karen Guerrero, Alison McDonald, John Norrie, Louise R Williams and Doreen McClurg. 'Effectiveness of pelvic floor muscle training with and without electromyographic biofeedback for urinary incontinence in women: multicentre randomised controlled trial'. In: *BMJ* 371 (2020). DOI: 10.1136/bmj.m3719. URL: https://www.bmj.com/content/371/bmj.m3719.

[49] Saee Hamine, Emily Gerth-Guyette, Dunia Faulx, Beverly B Green and Amy Sarah Ginsburg. 'Impact of mHealth Chronic Disease Management on Treatment Adherence and Patient Outcomes: A Systematic Review'. In: *J Med Internet Res* 17.2 (Feb. 2015), e52. ISSN: 1438-8871. DOI: 10.2196/jmir.3951. URL: http://www.ncbi.nlm.nih.gov/pubmed/25803266.

[50] A Heller, D T Wade, V A Wood, A Sunderland, R L Hewer and E Ward. 'Arm function after stroke: measurement and recovery over the first three months.' In: *Journal of Neurology, Neurosurgery & Psychiatry* 50.6 (1987), pp. 714–719. ISSN: 0022-3050. DOI: 10.1136/jnnp.50.6.714. URL: https://jnnp.bmj.com/content/50/6/714.

[51] Hermie J Hermens, Bart Freriks, Catherine Disselhorst-Klug and Günter Rau. 'Development of recommendations for SEMG sensors and sensor placement procedures'. In: *Journal of Electromyography and Kinesiology* 10.5 (2000), pp. 361–374. ISSN: 1050-6411. DOI: https://doi.org/10.1016/S1050-6411(00)00027-4. URL: https://www.sciencedirect.com/science/article/pii/S1050641100000274.

[52] Nathan B. Herz, Shyamal H. Mehta, Kapil D. Sethi, Paula Jackson, Patricia Hall and John C. Morgan. 'Nintendo Wii rehabilitation ("Wii-hab") provides benefits in Parkinson's disease'. In: *Parkinsonism & Related Disorders* 19.11 (2013), pp. 1039–1042. ISSN: 1353-8020. DOI: https://doi.org/10.1016/j.parkreldis.2013.07.014. URL: https://www.sciencedirect.com/science/article/pii/S135380201300268X.

[53] Renée J. F. van den Heuvel, Monique A. S. Lexis, Gert Jan Gelderblom, Rianne M. L. Jansens and Luc P. de Witte. 'Robots and ICT to support play in children with severe physical disabilities: a systematic review'. In: *Disability and Rehabilitation: Assistive Technology* 11.2 (2016). PMID: 26330097, pp. 103–116. DOI: 10.3109/17483107.2015.1079268. URL: https://doi.org/10.3109/17483107.2015.1079268.

[54] HJ Hislop and JJ Perrine. 'The isokinetic concept of exercise'. In: *Physical Therapy* 47.2 (1967), pp. 114–117.

[55] X. L. Hu, K.Y. Tong, X. J. Wei, W. Rong, E. A. Susanto and S. K. Ho. 'Coordinated upper limb training assisted with an electromyography (EMG)-driven hand robot after stroke'. In: *2013 35th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*. 2013, pp. 5903–5906. DOI: 10.1109/EMBC.2013.6610895.

[56] X.L. Hu, K.Y. Tong, X.J. Wei, W. Rong, E.A. Susanto and S.K. Ho. 'The effects of post-stroke upper-limb training with an electromyography (EMG)-driven hand robot'. In: *Journal of Electromyography and Kinesiology* 23.5 (2013), pp. 1065–1074. ISSN: 1050-6411. DOI: https://doi.org/10.1016/j.jelekin.2013.07.007. URL: https://www.sciencedirect.com/science/article/pii/S1050641113001764.

[57] Yanhuan Huang, Will Poyan Lai, Qiuyang Qian, Xiaoling Hu, Eric W. C. Tam and Yongping Zheng. 'Translation of robot-assisted rehabilitation to clinical service: a comparison of the rehabilitation effectiveness of EMG-driven robot hand assisted upper limb training in practical clinical service and in clinical trial with laboratory configuration for chronic stroke'. In: *BioMedical Engineering OnLine* 17.1 (2018), p. 91. ISSN: 1475-925X. DOI: 10.1186/s12938-018-0516-2. URL: https://doi.org/10.1186/s12938-018-0516-2.

[58] Markus Huebner, Katja Riegel, Heidemarie Hinninghofen, Dr. Diethelm Wallwiener, Ralf Tunn and Christl Reisenauer. 'Pelvic floor muscle training for stress urinary incontinence: A randomized, controlled trial comparing different conservative therapies'. In: *Physiotherapy research international : the journal for researchers and clinicians in physical therapy* 16 (Sept. 2010). DOI: 10.1002/pri.489.

[59] F. Hug, M. Faucher, T. Marqueste, Ch. Guillot, N. Kipson and Y. Jammes. 'Electromyographic signs of neuromuscular fatigue are concomitant with further increase in ventilation during static handgrip'. In: *Clinical Physiology and Functional Imaging* 24.1 (2004), pp. 25–32. DOI: https://doi.org/10.1046/j.1475-0961.2003.00525.x. URL: https://onlinelibrary.wiley.com/doi/abs/10.1046/j.1475-0961.2003.00525.x.

[60] Ann-Marie Hughes, Sofia Barbosa Bouças, Jane H. Burridge, Margit Alt Murphy, Jaap Buurke, Peter Feys, Verena Klamroth-Marganska, Ilse Lamers, Gerdienke Prange-Lasonder, Annick Timmermans and Thierry Keller. 'Evaluation of upper extremity neurorehabilitation using technology: a European Delphi consensus study within the EU COST Action Network on Robotics for Neurorehabilitation'. In: *Journal of NeuroEngineering and Rehabilitation* 13.1 (2016), p. 86. ISSN: 1743-0003. DOI: 10.1186/s12984-016-0192-z. URL: https://doi.org/10.1186/s12984-016-0192-z.

[61] Ya-Xuan Hung, Pei-Chen Huang, Kuan-Ta Chen and Woei-Chyn Chu. 'What Do Stroke Patients Look for in Game-Based Rehabilitation: A Survey Study'. In: *Medicine* 95.11 (2016), e–00027. DOI: 00005792-201603150-00027. URL: https://journals.lww.com/md-journal/fulltext/2016/03150/what_do_stroke_patients_look_for_in_game_based.27.aspx.

[62] Tiziano Innocenti, Diego Ristori, Simone Miele and Marco Testa. 'The management of shoulder impingement and related disorders: A systematic review on diagnostic accuracy of physical tests and manual therapy efficacy'. In: *Journal of Bodywork and Movement Therapies* 23.3 (2019), pp. 604–618. ISSN: 1360-8592. DOI: 10.1016/j.jbmt.2018.08.002. URL: https://doi.org/10.1016/j.jbmt.2018.08.002.

[63] Amir Jamaludin, Meelis Lootus, Timor Kadir, Andrew Zisserman, Jill Urban, Michele C. Battié, Jeremy Fairbank, Iain McCall and The Genodisc Consortium. 'ISSLS PRIZE IN BIOENGINEERING SCIENCE 2017: Automation of reading of radiological features from magnetic resonance images (MRIs) of the lumbar spine without human intervention is comparable with an expert radiologist'. In: *European Spine Journal* 26.5 (May 2017), pp. 1374–1383. ISSN: 1432-0932. DOI: 10.1007/s00586-017-4956-3. URL: https://doi.org/10.1007/s00586-017-4956-3.

[64] Hendrik Jansen, Martin Jordan, Sönke Frey, Stefanie Hölscher-Doht, Rainer Meffert and Timo Heintel. 'Active controlled motion in early rehabilitation improves outcome after ankle fractures: a randomized controlled trial'. In: *Clinical Rehabilitation* 32.3 (2018). PMID: 28805066, pp. 312–318. DOI: 10.1177/0269215517724192. URL: https://doi.org/10.1177/0269215517724192.

[65] Michelle Jillian Johnson, Roshan Rai, Sarath Barathi, Rochelle Mendonca and Karla Bustamante-Valles. 'Affordable stroke therapy in high-, low- and middle-income countries: From Theradrive to Rehab CARES, a compact robot gym'. In: *Journal of Rehabilitation and Assistive Technologies Engineering* 4 (2017). PMID: 31186929, p. 2055668317708732. DOI: 10.1177/2055668317708732. URL: https://doi.org/10.1177/2055668317708732.

[66] D. W. Kauff, O. Kempski, K. P. Koch, S. Huppert, K. P. Hoffmann, H. Lang and W. Kneist. 'Continuous intraoperative monitoring of autonomic nerves during low anterior rectal resection: an innovative approach for observation of functional nerve integrity in pelvic surgery'. In: *Langenbeck's Archives of Surgery* 397.5 (2012), pp. 787–792. ISSN: 1435-2451. DOI: 10.1007/s00423-011-0900-x. URL: https://doi.org/10.1007/s00423-011-0900-x.

[67] Rezvan Kianifar, Alexander Lee, Sachin Raina and Dana Kulić. 'Automated Assessment of Dynamic Knee Valgus and Risk of Knee Injury During the Single Leg Squat'. In: *IEEE Journal of Translational Engineering in Health and Medicine* 5 (2017), pp. 1–13. DOI: 10.1109/JTEHM.2017.2736559.

[68] Gyutae Kim, Mohammad A Ahad, Mohammed Ferdjallah and Gerald F. Harris. 'Correlation of muscle fatigue indices between intramuscular and surface EMG signals'. In: *Proceedings 2007 IEEE SoutheastCon* (2007), pp. 378–382. URL: https://api.semanticscholar.org/CorpusID:44958005.

[69] Terry K Koo and Mae Y Li. 'A guideline of selecting and reporting intraclass correlation coefficients for reliability research'. In: *Journal of chiropractic medicine* 15.2 (2016), pp. 155–163.

[70] Gert Kwakkel, Boudewijn J. Kollen and Hermano I. Krebs. 'Effects of Robot-Assisted Therapy on Upper Limb Recovery After Stroke: A Systematic Review'. In: *Neurorehabilitation and Neural Repair* 22.2 (2008). PMID: 17876068, pp. 111–121. DOI: 10.1177/1545968307305457.

[71] Charles Lambelet, Mingxing Lyu, Daniel Woolley, Roger Gassert and Nicole Wenderoth. 'The eWrist — A wearable wrist exoskeleton with sEMG-based force control for stroke rehabilitation'. In: *2017 International Conference on Rehabilitation Robotics (ICORR)*. 2017, pp. 726–733. DOI: 10.1109/ICORR.2017.8009334.

[72] James W. Lance. 'The control of muscle tone, reflexes, and movement'. In: *Neurology* 30.12 (1980), pp. 1303–1303. ISSN: 0028-3878. DOI: 10.1212/WNL.30.12.1303. eprint: https://n.neurology.org/content/30/12/1303.full.pdf. URL: https://n.neurology.org/content/30/12/1303.

[73] Judith I. Laszlo. 'Chapter 2 Motor Control and Learning: How Far Do the Experimental Tasks Restrict Our Theoretical Insight?' In: *Approaches to the Study of Motor Control and Learning*. Ed. by Jeffery J. Summers. Vol. 84. Advances in Psychology. North-Holland, 1992, pp. 47–79. DOI: https://doi.org/10.1016/S0166-4115(08)61682-9. URL: https://www.sciencedirect.com/science/article/pii/S0166411508616829.

[74] Zhang Lei. 'An upper limb movement estimation from electromyography by using BP neural network'. In: *Biomedical Signal Processing and Control* 49 (2019), pp. 434–439. ISSN: 1746-8094. DOI: https://doi.org/10.1016/j.bspc.2018.12.020. URL: https://www.sciencedirect.com/science/article/pii/S1746809418303197.

[75] J. Leszczak, A. Wolan-Nieroda, M. Drużbicki, A. Poświata, M. Mikulski, A. Roksela and A. Guzik. 'Evaluation of Reliability of the Luna EMG Rehabilitation Robot to Assess Proprioception in the Upper Limbs in 102 Healthy Young Adults'. In: *Medical Science Monitor: International Medical Journal of Experimental and Clinical Research* 30 (2024), e942439. DOI: 10.12659/MSM.942439. URL: https://doi.org/10.12659/MSM.942439.

[76] Justyna Leszczak, Bogumiła Pniak, Anna Poświata, Anna Roksela, Michał Mikulski, Mariusz Drużbicki and Agnieszka Guzik. 'Assessment of external and internal compliance of the Luna EMG robots as a tool for assessing upper limb proprioception in people after stroke'. In: *Międzynarodowe Dni Rehabilitacji w Rzeszowie*. Poster presented at the Międzynarodowe Dni Rehabilitacji w Rzeszowie, 8-9 February 2024. 2024.

[77] Patrycja Lewandowska-Sroka, Rafał Stabrawa, Dominika Kozak, Anna Poświata, Barbara Łysoń-Uklańska, Katarzyna Bienias, Anna Roksela, Marcin Kliś and Michael Mikulski. 'The Influence of EMG-Triggered Robotic Movement on Walking, Muscle Force and Spasticity after an Ischemic Stroke'. In: *Medicina (Kaunas, Lithuania)* 57 (Mar. 2021), p. 227. DOI: 10.3390/medicina57030227.

[78] Xinwei Li, Su Liu, Ying Chang, Sujiao Li, Yuanjie Fan and Hongliu Yu. 'A Human Joint Torque Estimation Method for Elbow Exoskeleton Control'. In: *International Journal of Humanoid Robotics* 17.03 (2020), p. 1950039. DOI: 10.1142/S0219843619500397. URL: https://doi.org/10.1142/S0219843619500397.

[79] Kenneth Lo, Matthew Stephenson and Craig Lockwood. 'The economic cost of robotic rehabilitation for adult stroke patients: a systematic review'. In: *JBI Database of Systematic Reviews and Implementation Reports* 17 (Apr. 2019), pp. 520–547. DOI: 10.11124/JBISRIR-2017-003896.

[80] R. Lopes and N. Betrouni. 'Fractal and multifractal analysis: A review'. In: *Medical Image Analysis* 13.4 (2009), pp. 634–649. ISSN: 1361-8415. DOI: https://doi.org/10.1016/j.media.2009.05.003. URL: https://www.sciencedirect.com/science/article/pii/S1361841509000395.

[81] Marina López-Solà, Choong-Wan Woo, Jesus Pujol, Joan Deus, Ben J. Harrison, Jordi Monfort and Tor D. Wager. 'Towards a neurophysiological signature for fibromyalgia'. In: *PAIN* 158.1 (2017). ISSN: 0304-3959. URL: https://journals.

lww.com/pain/fulltext/2017/01000/towards_a_neurophysiological_signature_for.7.aspx.

[82] H. Lund, K. Søndergaard, T. Zachariassen, R. Christensen, P. Bülow, M. Henriksen, E. M. Bartels, B. Danneskiold-Samsøe and H. Bliddal. 'Learning effect of isokinetic measurements in healthy subjects, and reliability and comparability of Biodex and Lido dynamometers'. In: *Clinical Physiology and Functional Imaging* 25.2 (2005), pp. 75–82. DOI: https://doi.org/10.1111/j.1475-097X.2004.00593.x. URL: https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1475-097X.2004.00593.x.

[83] Paweł Maciejasz, Jörg Eschweiler, Kurt Gerlach-Hahn, Arne Jansen-Troy and Steffen Leonhardt. 'A survey on robotic devices for upper limb rehabilitation'. In: *Journal of NeuroEngineering and Rehabilitation* 11.1 (9th Jan. 2014), p. 3. ISSN: 1743-0003. DOI: 10.1186/1743-0003-11-3. URL: https://doi.org/10.1186/1743-0003-11-3.

[84] Kyannie Mata, Rafaela Costa, Ébe Carbone, Marcia Maria Gimenez, Maria Bortolini, Rodrigo Castro and Fátima Fitz. 'Telehealth in the rehabilitation of female pelvic floor dysfunction: a systematic literature review'. In: *International Urogynecology Journal* 32 (Nov. 2020). DOI: 10.1007/s00192-020-04588-8.

[85] Maja J. Matarić, Jon Eriksson, David J. Feil-Seifer and Carolee J. Winstein. 'Socially assistive robotics for post-stroke rehabilitation'. In: *Journal of NeuroEngineering and Rehabilitation* 4.1 (19th Feb. 2007), p. 5. ISSN: 1743-0003. DOI: 10.1186/1743-0003-4-5. URL: https://doi.org/10.1186/1743-0003-4-5.

[86] Matplotlib Developers. *Matplotlib 3.7.1 Documentation*. Accessed: 2024-01-29. 2023. URL: https://matplotlib.org/stable/contents.html.

[87] J Mehrholz, A Hädrich, T Platz, J Kugler and M Pohl. 'Electromechanical and robot-assisted arm training for improving generic activities of daily living, arm function, and arm muscle strength after stroke'. In: *The Cochrane Database of Systematic Reviews* 6 (2012), p. CD006876. DOI: 10.1002/14651858.CD006876.pub3.

[88] T. Moritani, D. Stegeman and R. Merletti. 'Basic Physiology and Biophysics of EMG Signal Generation'. In: *Electromyography*. John Wiley & Sons, Ltd, 2004. Chap. 1, pp. 1–25. ISBN: 9780471678380. DOI: https://doi.org/10.1002/0471678384.ch1. URL: https://onlinelibrary.wiley.com/doi/abs/10.1002/0471678384.ch1.

[89] Kazuya Morito, Yuri Hasegawa, Keisuke Kubota and Toshiaki Tsuji. 'Visual Biofeedback of Force Information for Eccentric Training of Hemiplegic Patients'. In: *2019 IEEE 16th International Conference on Rehabilitation Robotics (ICORR)*. 2019, pp. 524–529. DOI: 10.1109/ICORR.2019.8779383.

[90] Rafael Mendes Moroni, Pedro Sergio Magnani, Jorge Milhem Haddad, Rodrigo de Aquino Castro and Luiz Gustavo Oliveira Brito. 'Conservative Treatment of Stress Urinary Incontinence: A Systematic Review with Meta-analysis of Randomized Controlled Trials'. In: *Revista Brasileira de Ginecologia e Obstetrícia / RBGO Gynecology and Obstetrics* 38.02 (2016), pp. 097–111. ISSN: 0100-7203, 1806-9339. DOI: 10.1055/s-0035-1571252. URL: http://www.thieme-connect.com/products/ejournals/abstract/10.1055/s-0035-1571252.

[91] Aditi A. Mullick, Nadine K. Musampa, Anatol G. Feldman and Mindy F. Levin. 'Stretch reflex spatial threshold measure discriminates between spasticity and rigidity'. In: *Clinical Neurophysiology* 124.4 (2013), pp. 740–751. ISSN: 1388-2457. DOI: https://doi.org/10.1016/j.clinph.2012.10.008. URL: https://www.sciencedirect.com/science/article/pii/S1388245712006931.

[92] Neurorehabilitacja. *Hocoma Lokomat Pro 6*. Accessed on 2024-01-30. URL: https://neurorehabilitacja.com.pl/rozwiazania/terapia-i-reedukacja-chodu-i-balansu/hocoma-lokomat-pro-6/.

[93] Diane Newman. 'Pelvic Floor Muscle Rehabilitation Using Biofeedback'. In: *Urologic nursing* 34 (July 2014), pp. 193–202. DOI: 10.7257/1053-816X.2014.34.4.193.

[94] Szymon Nitkiewicz, Michael Smieja, Tomasz Gogolewski, Andrzej Majchrowski, Łukasz Grabarczyk and Wojciech Maksymowicz. 'Objectication of Diagnostic Symptoms in Examination of Nervous System Damage by Static Interactions and Kinematic Parameters of Ankle Joint'. In: *Acta Physica Polonica Series a* 125 (Apr. 2014), A27–A30. DOI: 10.12693/APhysPolA.125.A-27.

[95] NumPy Developers. *NumPy v1.24.3 Documentation*. Accessed: 2024-01-29. 2024. URL: https://numpy.org/doc/1.24/.

[96] Erica Feio Carneiro Nunes, Luciana Maria Malosá Sampaio, Daniela Aparecida Biasotto-Gonzalez, Reny Costa dos Reis Nagano, Paulo Roberto Garcia Lucareli and Fabiano Politti. 'Biofeedback for pelvic floor muscle training in women with stress urinary incontinence: a systematic review with meta-analysis'. In: *Physiotherapy* 105.1 (2019), pp. 10–23. ISSN: 0031-9406. DOI: 10.1016/j.physio.2018.07.012. URL: https://doi.org/10.1016/j.physio.2018.07.012.

[97] Jakub Olczak, Niklas Fahlberg, Atsuto Maki, Ali Sharif Razavian, Anthony Jilert, André Stark, Olof Sköldenberg and Max Gordon. 'Artificial intelligence for analyzing orthopedic trauma radiographs'. In: *Acta Orthopaedica* 88.6 (Nov. 2017), pp. 581–586. DOI: 10.1080/17453674.2017.1344459. URL: https://actaorthop.org/actao/article/view/9748.

[98] Łukasz Oleksy, Aleksandra Królikowska, Anna Mika, Pawel Reichert, Monika Kentel, Maciej Kentel, Anna Poswiata, Anna Roksela, Dominika Kozak, Katarzyna Bienias, Marcel Smoliński, Artur Stolarczyk and Michael Mikulski. 'A Reliability of Active and Passive Knee Joint Position Sense Assessment Using the Luna EMG Rehabilitation Robot'. In: *International Journal of Environmental Research and Public Health* 19 (Nov. 2022). DOI: 10.3390/ijerph192315885.

[99] Łukasz Oleksy, Anna Mika, Iwona Sulowska-Daszyk, Ewelina Dušek, Renata Kielnar and Artur Stolarczyk. 'The Reliability of Pelvic Floor Muscle Bioelectrical Activity (sEMG) Assessment Using a Multi-Activity Measurement Protocol in Young Women'. In: *International Journal of Environmental Research and Public Health* 18 (Jan. 2021), p. 765. DOI: 10.3390/ijerph18020765.

[100] Mohammadreza Oskoei and Huosheng Hu. 'Myoelectric Control Systems - A survey'. In: *Biomedical Signal Processing and Control* 2 (Oct. 2007), pp. 275–294. DOI: 10.1016/j.bspc.2007.07.009.

[101] Wendy Oude Nijeweme-d'Hollosy, Lex van Velsen, Mannes Poel, Catharina G.M. Groothuis-Oudshoorn, Remko Soer and Hermie Hermens. 'Evaluation of three machine learning models for self-referral decision support on low back pain in primary care'. In: *International Journal of Medical Informatics* 110 (2018), pp. 31–41. ISSN: 1386-5056. DOI: https://doi.org/10.1016/j.ijmedinf.2017.11.010. URL: https://www.sciencedirect.com/science/article/pii/S1386505617304240.

[102] Aysun Özlü, Necmettin Yıldız and Özer Öztekin. 'Comparison of the efficacy of perineal and intravaginal biofeedback assisted pelvic floor muscle exercises in women with urodynamic stress urinary incontinence'. In: *Neurourology and Urodynamics* 36.8 (2017), pp. 2132–2141. DOI: https://doi.org/10.1002/nau.23257. eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/nau.23257. URL: https://onlinelibrary.wiley.com/doi/abs/10.1002/nau.23257.

[103] Matthew T.G. Pain and Stephanie E. Forrester. 'Predicting maximum eccentric strength from surface EMG measurements'. In: *Journal of Biomechanics* 42.11 (2009), pp. 1598–1603. ISSN: 0021-9290. DOI: https://doi.org/10.1016/j.jbiomech.2009.04.037. URL: https://www.sciencedirect.com/science/article/pii/S0021929009002553.

[104] pandas development team. *pandas 2.0.1 Documentation*. Accessed: 2024-01-29. 2023. URL: https://pandas.pydata.org/pandas-docs/version/2.0.1/.

[105] A D Pandyan, G R Johnson, C I M Price, R H Curless, M P Barnes and H Rodgers. 'A review of the properties and limitations of the Ashworth and modified Ashworth Scales as measures of spasticity'. In: *Clinical Rehabilitation* 13.5 (1999). PMID: 10498344, pp. 373–383. DOI: 10.1191/026921599677595404. eprint: https://doi.org/10.1191/026921599677595404. URL: https://doi.org/10.1191/026921599677595404.

[106] Ana Pereira, Vânia Guimarães and Ines Sousa. 'Joint angles tracking for rehabilitation at home using inertial sensors: a feasibility study'. In: May 2017, pp. 146–154. DOI: 10.1145/3154862.3154888.

[107] Lena Petersson, Ingrid Larsson, Jens M. Nygren, Per Nilsen, Margit Neher, Julie E. Reed, Daniel Tyskbo and Petra Svedberg. 'Challenges to implementing artificial intelligence in healthcare: a qualitative interview study with healthcare leaders in Sweden'. In: *BMC Health Services Research* 22.1 (2022), p. 850. ISSN: 1472-6963. DOI: 10.1186/s12913-022-08215-8. URL: https://doi.org/10.1186/s12913-022-08215-8.

[108] Anna Poświata, Anna Roksela, Magdalena Kłyk, Valery Tsinda Labou, Marcel Smoliński, Marcin Kliś and Michał Mikulski. 'A protocol for joint stiffness assessment using a rehabilitation robot'. In: *European Congress of NeuroRehabilitation 2019 (ECNR)*. ePoster Presentation. Budapest, Hungary: Budapest Congress Center, Oct. 2019.

[109] Cosima Prahm, Fares Kayali, Agnes Sturma and Oskar Aszmann. 'PlayBionic: Game-Based Interventions to Encourage Patient Engagement and Performance in Prosthetic Motor Rehabilitation'. In: *PM&R* 10.11 (2018), pp. 1252–1260. DOI: https://doi.org/10.1016/j.pmrj.2018.09.027. URL: https://onlinelibrary.wiley.com/doi/abs/10.1016/j.pmrj.2018.09.027.

[110] Heidi Prather, Sheila Dugan, Colleen Fitzgerald and Devyani Hunt. 'Review of Anatomy, Evaluation, and Treatment of Musculoskeletal Pelvic Floor Pain in Women'. In: *PM&R* 1.4 (2009), pp. 346–358. DOI: https://doi.org/10.1016/j.pmrj.2009.01.003. URL: https://onlinelibrary.wiley.com/doi/abs/10.1016/j.pmrj.2009.01.003.

[111] Lloyd U. Pumpa, Liana S. Cahill and Leeanne M. Carey. 'Somatosensory assessment and treatment after stroke: An evidence-practice gap'. In: *Australian Occupational Therapy Journal* 62.2 (2015), pp. 93–104. DOI: https://doi.org/10.1111/1440-1630.12170. URL: https://onlinelibrary.wiley.com/doi/abs/10.1111/1440-1630.12170.

[112] Python Software Foundation. *Python 3.11.7 Documentation*. Accessed: 2024-01-29. 2023. URL: https://docs.python.org/3.11/.

[113] Raphael Vallat. *Functions - Pingouin 0.5.4 documentation*. https://pingouin-stats.org/build/html/api.html. Accessed: 2024-01-29. 2024.

[114] Gregory Rash and Edd. 'Electromyography Fundamentals'. In: *International Encyclopedia of Ergonomics and Human Factors* (Jan. 2002).

[115] S. M. Rayegani, S. A. Raeissadat, L. Sedighipour, I. Mohammad Rezazadeh, M. H. Bahrami, D. Eliaspour and S. Khosrawi. 'Effect of Neurofeedback and Electromyographic-Biofeedback Therapy on Improving Hand Function in Stroke Patients'. In: *Topics in Stroke Rehabilitation* 21.2 (2014). PMID: 24710974, pp. 137–151. DOI: 10.1310/tsr2102-137. URL: https://doi.org/10.1310/tsr2102-137.

[116] David J. Reinkensmeyer and Sarah J. Housman. '"If I can't do it once, why do it a hundred times?": Connecting volition to movement success in a virtual environment motivates people to exercise the arm after stroke'. In: *2007 Virtual Rehabilitation*. 2007, pp. 44–48. DOI: 10.1109/ICVR.2007.4362128.

[117] Mariana T Rett, Jose A Simoes, Viviane Herrmann, Cristina LB Pinto, Andrea A Marques and Sirlei S Morais. 'Management of Stress Urinary Incontinence With Surface Electromyography–Assisted Biofeedback in Women of Reproductive Age'. In: *Physical Therapy* 87.2 (Feb. 2007), pp. 136–142. ISSN: 0031-9023. DOI: 10.2522/ptj.20050318. eprint: https://academic.oup.com/ptj/article-pdf/87/2/136/31669100/ptj0136.pdf. URL: https://doi.org/10.2522/ptj.20050318.

[118] Anna Roksela, Anna Poswiata, Jarosław Śmieja, Dominika Kozak, Katarzyna Bienias, Jakub Ślaga and Michael Mikulski. 'Evaluation of Neurological Disorders in Isokinetic Dynamometry and Surface Electromyography Activity of Biceps and Triceps Muscles'. In: Sept. 2023, pp. 325–338. ISBN: 978-3-031-38429-5. DOI: 10.1007/978-3-031-38430-1_25.

[119] Tsugutake Sadoyama and H. Miyano. 'Frequency analysis of surface EMG to evaluation of muscle fatigue'. In: *European Journal of Applied Physiology and Occupational Physiology* 47 (2004), pp. 239–246. URL: https://api.semanticscholar.org/CorpusID:23432723.

[120] Sohail Sangha, Ahmed M. Elnady and Carlo Menon. 'A compact robotic orthosis for wrist assistance'. In: *2016 6th IEEE International Conference on Biomedical Robotics and Biomechatronics (BioRob)*. 2016, pp. 1080–1085. DOI: 10.1109/BIOROB.2016.7523775.

[121] Hannes Schlieter, Lisa A Marsch, Diane Whitehouse, Lena Otto, Ana Rita Londral, Gisbert Wilhelm Teepe, Martin Benedict, Joseph Ollier, Tom Ulmer, Nathalie Gasser, Sabine Ultsch, Bastian Wollschlaeger and Tobias Kowatsch. 'Scale-up of Digital Innovations in Health Care: Expert Commentary on Enablers and Barriers'. In: *J Med Internet Res* 24.3 (Mar. 2022), e24582. ISSN: 1438-8871. DOI: 10.2196/24582. URL: http://www.ncbi.nlm.nih.gov/pubmed/35275065.

[122] S.R. Schwid, C.A. Thornton, S. Pandya, K.L. Manzur, M. Sanjak, M.D. Petrie, M.P. McDermott and A.D. Goodman. 'Quantitative assessment of motor fatigue and strength in MS'. In: *Neurology* 53.4 (1999), pp. 743–743. DOI: 10.1212/WNL.53.4.743. URL: https://www.neurology.org/doi/abs/10.1212/WNL.53.4.743.

[123] scikit-learn developers. *scikit-learn 1.2.2 Documentation*. Accessed: 2024-01-29. 2023. URL: https://scikit-learn.org/stable/versions.html#v1-2-2.

[124] SciPy Developers. *SciPy v1.10.1 Documentation*. Accessed: 2024-01-29. 2023. URL: https://docs.scipy.org/doc/scipy-1.10.1/reference/.

[125] S. K. Shah, S. J. Harasymiw and P. L. Stahl. 'Stroke Rehabilitation: Outcome Based on Brunnstrom Recovery Stages'. In: *The Occupational Therapy Journal of Research* 6.6 (1986), pp. 365–376. DOI: 10.1177/153944928600600604. URL: https://doi.org/10.1177/153944928600600604.

[126] Bo Sheng, Yanxin Zhang, Wei Meng, Chao Deng and Shengquan Xie. 'Bilateral robots for upper-limb stroke rehabilitation: State of the art and future prospects'. In: *Medical Engineering and Physics* 38.7 (2016), pp. 587–606. ISSN: 1350-4533. DOI: https://doi.org/10.1016/j.medengphy.2016.04.004. URL: https://www.sciencedirect.com/science/article/pii/S1350453316300480.

[127] Hardeep Singh, Janelle Unger, José Zariffa, Maureen Pakosh, Susan Jaglal, B. Catharine Craven and Kristin E. Musselman. 'Robot-assisted upper extremity rehabilitation for cervical spinal cord injuries: a systematic scoping review'. In: *Disability and Rehabilitation: Assistive Technology* 13.7 (2018). PMID: 29334467, pp. 704–715. DOI: 10.1080/17483107.2018.1425747. URL: https://doi.org/10.1080/17483107.2018.1425747.

[128] Ho Chit Siu, Ana M. Arenas, Tingxiao Sun and Leia A. Stirling. 'Implementation of a Surface Electromyography-Based Upper Extremity Exoskeleton Controller Using Learning from Demonstration'. In: *Sensors* 18.2 (2018). ISSN: 1424-8220. DOI: 10.3390/s18020467. URL: https://www.mdpi.com/1424-8220/18/2/467.

[129] Rong Song, Kai-yu Tong, Xiaoling Hu and Wei Zhou. 'Myoelectrically controlled wrist robot for stroke rehabilitation'. In: *Journal of NeuroEngineering and Rehabilitation* 10.1 (2013), p. 52. ISSN: 1743-0003. DOI: 10.1186/1743-0003-10-52. URL: https://doi.org/10.1186/1743-0003-10-52.

[130] Krystyna Stańczyk, Anna Poświata, Anna Roksela and Michał Mikulski. 'Assessment of Muscle Fatigue, Strength and Muscle Activation During Exercises with the Usage of Robot Luna EMG, Among Patients with Multiple Sclerosis'. In: *Information Technology in Biomedicine*. Ed. by Ewa Pietka, Pawel Badura, Jacek Kawa and Wojciech Wieclawek. Cham: Springer International Publishing, 2019, pp. 117–128. ISBN: 978-3-030-23762-2.

[131] K. M. Steele, C. Papazian and H. A. Feldner. 'Muscle Activity After Stroke: Perspectives on Deploying Surface Electromyography in Acute Care'. In: *Frontiers in Neurology* 11 (2020). DOI: 10.3389/fneur.2020.576757. URL: http://dx.doi.org/10.3389/fneur.2020.576757.

[132] Foster B. Stulen and Carlo J. De Luca. 'Muscle Fatigue Monitor: A Noninvasive Device for Observing Localized Muscular Fatigue'. In: *IEEE Transactions on Biomedical Engineering* BME-29.12 (1982), pp. 760–768. DOI: 10.1109/TBME.1982.324871.

[133] Masanobu Tachi, Motoki Kouzaki, Hiroaki Kanehisa and Tetsuo Fukunaga. 'The influence of circulatory difference on muscle oxygenation and fatigue during intermittent static dorsiflexion'. In: *European Journal of Applied Physiology* 91.5 (2004), pp. 682–688. ISSN: 1439-6327. DOI: 10.1007/s00421-003-1024-y. URL: https://doi.org/10.1007/s00421-003-1024-y.

[134] Chris Tack. 'Artificial intelligence and machine learning | applications in musculoskeletal physiotherapy'. In: *Musculoskeletal Science and Practice* 39 (Nov. 2018). DOI: 10.1016/j.msksp.2018.11.012.

[135] Joachim Taelman, Joke Vanderhaegen, Mieke Robijns, Gunnar Naulaers, Arthur Spaepen and Sabine Van Huffel. 'Estimation of Muscle Fatigue Using Surface Electromyography and Near-Infrared Spectroscopy'. In: *Oxygen Transport to Tissue XXXII*. Ed. by Joseph C. LaManna, Michelle A. Puchowicz, Kui Xu, David K Harrison and Duane F. Bruley. Boston, MA: Springer US, 2011, pp. 353–359. ISBN: 978-1-4419-7756-4.

[136] Momen Kamal Tageldeen, N. Perumal, I. Elamvazuthi and T. Ganesan. 'Design and control of an upper arm exoskeleton using Fuzzy logic techniques'. In: *2016 2nd IEEE International Symposium on Robotics and Manufacturing Automation (ROMA)*. 2016, pp. 1–6. DOI: 10.1109/ROMA.2016.7847838.

[137] S. Thongpanja, Angkoon Phinyomark, P. Phukpattaranont and Chusak Limsakul. 'Mean and Median Frequency of EMG Signal to Determine Muscle Force Based on Time-Dependent Power Spectrum'. In: *Elektronika ir Elektrotechnika* 19 (Mar. 2013), pp. 51–56. DOI: 10.5755/j01.eee.19.3.3697.

[138] B. Tiffreau, I. Ledoux, B. Eymard, A. Thévenon and J. Y. Hogrel. 'Isokinetic Muscle Testing for Weak Patients Suffering from Neuromuscular Disorders: A Reliability Study'. In: *Neuromuscular Disorders* 17.7 (2007), pp. 524–531. DOI: 10.1016/j.nmd.2007.03.014. URL: http://dx.doi.org/10.1016/j.nmd.2007.03.014.

[139] Vanessa van Tittelboom, Ipek Alemdaroglu-Gürbüz, Britta Hanssen, Lieve Heyrman, Hilde Feys, Kaat Desloovere, Patrick Calders and Christine Van den Broeck. 'Reliability of Isokinetic Strength Assessments of Knee and Hip Using the Biodex System 4 Dynamometer and Associations With Functional Strength in Healthy Children'. In: *Frontiers in Sports and Active Living* 4 (2022). ISSN: 2624-9367. DOI: 10.3389/fspor.2022.817216. URL: https://www.frontiersin.org/articles/10.3389/fspor.2022.817216.

[140] Tomasz Trzmiel, Renata Marchewka, Anna Pieczyńska, Ewa Zasadzka, Igor Zubrycki, Dominika Kozak, Michał Mikulski, Anna Poświata, Sławomir Tobis and Katarzyna Hojan. 'The Effect of Using a Rehabilitation Robot for Patients with Post-Coronavirus Disease (COVID-19) Fatigue Syndrome'. In: *Sensors* 23.19 (2023). ISSN: 1424-8220. DOI: 10.3390/s23198120. URL: https://www.mdpi.com/1424-8220/23/19/8120.

[141] Tyromotion. *Tyromotion Omego Plus*. Accessed on 2024-01-30. URL: https://tyromotion.com/en/products/omegoplus/.

[142] Peter P. Urban, Thomas Wolf, Michael Uebele, Jürgen J. Marx, Thomas Vogt, Peter Stoeter, Thomas Bauermann, Carsten Weibrich, Goran D. Vucurevic, Astrid Schneider and Jörg Wissel. 'Occurence and Clinical Predictors of Spasticity After Ischemic Stroke'. In: *Stroke* 41.9 (2010), pp. 2016–2020. DOI: 10.1161/STROKEAHA.110.581991. URL: https://www.ahajournals.org/doi/abs/10.1161/STROKEAHA.110.581991.

[143] Wang Wendong, Li Hanhao, Xiao Menghan, Chu Yang, Yuan Xiaoqing, Ming Xing and Zhang Bing. 'Design and verification of a human–robot interaction system for upper limb exoskeleton rehabilitation'. In: *Medical Engineering & Physics* 79 (2020), pp. 19–25. ISSN: 1350-4533. DOI: https://doi.org/10.1016/j.medengphy.2020.01.016. URL: https://www.sciencedirect.com/science/article/pii/S1350453320300394.

[144] Wang Wendong, Lei Qin, Xiaoqing Yuan, Xing Ming, Tongsen Sun and Yifan Liu. 'Bionic control of exoskeleton robot based on motion intention for rehabilitation training'. In: *Advanced Robotics* 33.12 (2019), pp. 590–601. DOI: 10.1080/01691864.2019.1621774.

[145] Chengyin Ye, Jinmei Li, Shiying Hao, Modi Liu, Hua Jin, Le Zheng, Minjie Xia, Bo Jin, Chunqing Zhu, Shaun T. Alfreds, Frank Stearns, Laura Kanov, Karl G. Sylvester, Eric Widen, Doff McElhinney and Xuefeng Bruce Ling. 'Identification of elders at higher risk for fall with statewide electronic health records and a machine learning algorithm'. In: *International Journal of Medical Informatics* 137 (2020), p. 104105. ISSN: 1386-5056. DOI: https://doi.org/10.1016/j.ijmedinf.2020.104105. URL: https://www.sciencedirect.com/science/article/pii/S1386505619314522.

[146] Ji Won Yoo, Dong Ryul Lee, Young Joo Cha and Sung Hyun You. 'Augmented effects of EMG biofeedback interfaced with virtual reality on neuromuscular control and movement coordination during reaching in children with cerebral palsy'. In: *NeuroRehabilitation* 40.2 (2017), pp. 175–185. ISSN: 1878-6448. DOI: 10.3233/NRE-161402.

[147] Y. Yoshitake, H. Ue, M. Miyazaki and T. Moritani. 'Assessment of lower-back muscle fatigue using electromyography, mechanomyography, and near-infrared spectroscopy'. In: *European Journal of Applied Physiology* 84.3 (2001), pp. 174–179. ISSN: 1439-6327. DOI: 10.1007/s004210170001. URL: https://doi.org/10.1007/s004210170001.

[148] Song Yu, Yan Chen, Qing Cai, Ke Ma, Haiqing Zheng and Longhan Xie. 'A Novel Quantitative Spasticity Evaluation Method Based on Surface Electromyogram Signals and Adaptive Neuro Fuzzy Inference System'. In: *Frontiers in Neuroscience* 14 (2020). ISSN: 1662-453X. DOI: 10.3389/fnins.2020.00462. URL: https://www.frontiersin.org/articles/10.3389/fnins.2020.00462.

[149] Marcus Yung, Svend Mathiassen and Richard Wells. 'Variation of force amplitude and its effects on local fatigue'. In: *European journal of applied physiology* 112 (Mar. 2012), pp. 3865–79. DOI: 10.1007/s00421-012-2375-z.

[150] Ewa Zasadzka, Sławomir Tobis, Tomasz Trzmiel, Renata Marchewka, Dominika Kozak, Anna Roksela, Anna Pieczyńska and Katarzyna Hojan. 'Application of an EMG-Rehabilitation Robot in Patients with Post-Coronavirus Fatigue Syndrome (COVID-19) - A Feasibility Study'. In: *International Journal of Environmental Research and Public Health* 19.16 (2022). ISSN: 1660-4601. DOI: 10.3390/ijerph191610398. URL: https://www.mdpi.com/1660-4601/19/16/10398.

[151] Massimiliano Zecca, Silvestro Micera, M.C. Carrozza and Paolo Dario. 'Control of Multifunctional Prosthetic Hands by Processing the Electromyographic Signal'. In: *Critical reviews in biomedical engineering* 30 (Feb. 2002), pp. 459–85. DOI: 10.1615/CritRevBiomedEng.v30.i456.80.

Appendices

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