Politécnico
de Viseu

Escola Superior
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Signal processing measurement of the results of the up-down hop test using sensors

Ticiana Carneiro Lopes Capris

Dissertação

Mestrado em Engenharia Informática - Sistemas de Informação

Trabalho efetuado sob a orientação de
Professor Doutor Carlos Cunha
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This thesis is dedicated to all the women who have dared to dream big and pursue their academic aspirations despite the challenges. May it serve as a testament to the power of resilience, hard work, and the unwavering belief in one's capabilities. To my family, for their unconditional love and support, you are my rock and my inspiration.

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Abstract

The advancement of mobile technology and sensor development has profoundly impacted several sectors, including physical therapy and rehabilitation sciences. This study focuses on measuring the Up-Down Hop Test findings with sensor technologies to improve clinical assessments and rehabilitation outcomes and contribute to the growth of sports science. By incorporating sensors into mobile devices, the study investigates novel techniques for objectively analyzing data from the Up-Down Hop Test, providing a complete understanding of the patient's lower limb function and stability. Using sensors, such as accelerometers, gyroscopes, and magnetometers, allows for the accurate capturing of movement data, which is essential for assessing the efficiency of rehabilitation programs and establishing an individual's readiness to resume physical activity.

The study describes the limitations of traditional ways of evaluating Up-Down Hop Test results, which rely on subjective assessments and physical measurements. The study uses sensor technology to overcome these issues, suggesting a more objective and efficient assessment process. This method improves the accuracy and reliability of test findings and facilitates the formulation of tailored rehabilitation plans based on quantitative data analysis.

A thorough literature analysis offers the study's theoretical underpinning, emphasizing the importance of the Up-Down Hop Test in physical therapy and the potential benefits of introducing sensor technology into its evaluation. Related works are discussed, contrasting various techniques and their clinical usefulness, highlighting the need for trustworthy, objective, and cost-effective tools for assessing athletic performance and healing.

The methodology section describes the methods used to execute and evaluate the sensor-based assessment of the Up-Down Hop Test, including sensor selection, data collection protocols, and analytic approaches. Pilot tests and statistical analysis have validated the suggested method's effectiveness, proving its ability to provide a complete knowledge of test results and guide rehabilitation efforts.

The study's findings support the viability of using sensor technology to correctly quantify Up-Down Hop Test outcomes. It provides valuable insights into the healing process and aids evidence-based decision-making in physical therapy practices. This study adds to the expanding body of knowledge about using sophisticated technology in healthcare, recommending future directions for developing more effective and

tailored rehabilitation treatments.

Keywords: Sensors; Physiotherapy; Rehabilitation; Jump up and down test; Mobile devices; Data analysis; Athletes' performance

Resumo

O estudo sobre a utilização da tecnologia de sensores para aprimorar a avaliação do Up-Down Hop Test em fisioterapia e ciências da reabilitação representa um avanço significativo na forma como abordamos a reabilitação física e a ciência do desporto. A utilização de acelerómetros, giroscópios e magnetómetros para capturar dados precisos de movimento pode revolucionar a objetividade e eficiência das avaliações clínicas, contribuindo, em última análise, para planos de reabilitação mais personalizados e eficazes. O foco em superar as limitações das avaliações subjetivas tradicionais com essas tecnologias aborda uma necessidade crítica de métodos mais confiáveis e quantitativos na avaliação da função e estabilidade dos membros inferiores.

A análise minuciosa da literatura fornece uma base sólida para a importância da integração da tecnologia de sensores nas avaliações de fisioterapia. Destaca a necessidade de ferramentas objetivas, confiáveis e custo-eficazes na avaliação do desempenho atlético e recuperação, pavimentando o caminho para uma aceitação e implementação mais amplas dessas tecnologias em ambientes clínicos.

A metodologia, incluindo a seleção de sensores apropriados, o estabelecimento de protocolos de coleta de dados e a utilização de abordagens analíticas para interpretar os dados, mostra uma abordagem bem pensada para a realização deste estudo. A validação da sua metodologia através de testes piloto e análise estatística reforça o potencial das avaliações baseadas em sensores em oferecer uma compreensão mais matizada dos resultados do Up-Down Hop Test.

Os resultados que destacam a viabilidade e eficácia da utilização da tecnologia de sensores para a quantificação precisa dos resultados da reabilitação são incrivelmente promissores. Esta abordagem não só ajuda no monitoramento do processo de cura, mas também melhora a tomada de decisões baseada em evidências nas práticas de terapia. Ao contribuir para o crescente corpo de conhecimento sobre a aplicação de tecnologias avançadas na saúde, o seu estudo aponta para direções futuras empolgantes para o desenvolvimento de intervenções de reabilitação mais eficientes e personalizadas.

Para contribuir ainda mais para este campo, poderia ser benéfico explorar a integração de algoritmos de aprendizagem automática com os dados coletados dos sensores para uma análise e modelagem preditiva ainda mais sofisticadas dos resultados da reabilitação. Além disso, investigar os impactos a longo prazo das avaliações baseadas em sensores na recuperação dos pacientes e o potencial para a integração dessas tecnologias em programas de reabilitação em casa poderia oferecer insights valiosos sobre a sua aplicabilidade e eficácia mais amplas.

Palavras-Chave: Sensores; Fisioterapia; Reabilitação; Teste de salto para cima e para baixo; Dispositivos móveis; Análise de dados; Performance dos atletas

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Chapter 1

Introduction

This chapter will introduce the thesis related to implementing a technological method for measuring the Up-Down Hop Test with sensors available in mobile devices. This chapter states the motivation of this thesis, which is supported by the contextualization of this subject related to innovative methods for physical therapy. Furthermore, the problem statement is explained, creating different objectives with expected results.

1.1 Motivation

The motivation for this Master's dissertation is to develop a new method for automatically analyzing sensor data related to the Up-Down Hop Test, encompassing aspects of improving clinical assessments, enhancing rehabilitation outcomes, and advancing technology in sports science. This project is based on the previous research of [Popovski et al., 2020]. Here are some main motivations:

1. Improve Precision and Objectivity in Clinical Assessments: Traditional methods for evaluating the results of the Up-Down Hop Test, frequently used to assess lower limb function, particularly following injuries or surgeries, rely mainly on subjective judgments and physical measurements. Creating an automatic analytic approach can considerably improve these assessments' accuracy, reliability, and objectivity.

2. Real-time feedback can be provided to clinicians and patients through automated sensor data processing. This real-time analysis can improve rehabilitation by allowing quick adjustments depending on acquired data, potentially leading to faster and more successful recovery times.

3. Increasing Accessibility and Usability: Automating the analysis makes it more accessible to a broader range of healthcare practitioners and situations. It can eliminate the requirement for specialist training to interpret the results, making the UDHT more applicable in various therapeutic settings.

4. Advancement of Rehabilitation Research The development of new ways for interpreting sensor data can help to expand the corpus of knowledge in rehabilitation science. It can enable more in-depth research on patient recovery patterns, the efficacy of various rehabilitation treatments, and the creation of individualized rehabilitation programs.

5. Promoting Patient Engagement and Self-Monitoring: Automated analytic tools can empower patients to closely monitor their development and better comprehend the rehabilitation process. Increased participation can lead to better outcomes and higher patient satisfaction. Integrating sensor technology with data analysis methodologies allows for the use of cutting-edge technologies such as machine learning and artificial intelligence to analyze physical therapy outcomes. It may lead to creating predictive models capable of forecasting recovery trajectories or identifying potential difficulties early in rehabilitation.

6. Improving Efficiency and Reducing Costs: Automating the analytical process can save healthcare professionals time and money compared to manual assessments. This efficiency allows more patients to be assessed in less time, potentially improving overall treatment quality.

In conclusion, the motivation for such a thesis stems from the potential to improve significantly clinical assessments, improve patient outcomes, and contribute to the growth of rehabilitation sciences through innovative technology.

1.2 Contextualization

Numerous sectors of human existence that were once formerly fully diverse are now beginning to share a growing number of characteristics due to the rapid advancement of technology [Anderson et al., 2016, Cornet and Holden, 2018, Salazar et al., 2013, Steinhubl et al., 2015]. The scope of this research has been expanded because of the appearance and development of sensor systems with ever more excellent capabilities and usefulness [Jung et al., 2012]. The Up-Down Hop Test is a widely used physical therapy test that measures an individual's lower limb function and stability.

The test's results are critical in determining the patient's progress in rehabilitation and assessing the effectiveness of the treatment. However, the current assessment process relies on manual measurement and subjective visual inspection, leading to errors and inconsistencies in the evaluation. Sensor technology can provide a more objective and accurate assessment of the Up-Down Hop Test's results. As a result, it is imperative to identify the limitations of the current assessment process and develop a problem statement that outlines the need for a more efficient and objective assessment of the test's results.

The market for mobile devices is gaining more features and embedded sensors are becoming mainstream, such as accelerometers, magnetometers, and gyroscopes [Haghi et al., 2017]. It presents itself as an excellent opportunity for the creation of the broadest range of solutions in the most varied spheres of human life [Pires et al., 2015]. The sensors in mobile devices provide broad capabilities due to their integration and simple application development capabilities, which enable the creation of chances to produce solutions in the most diversified fields of knowledge [Pires et al., 2020b].

Sensors are helpful in a variety of contexts. Physical therapy is one of the fields in which sensors can be helpful, along with mobile devices for data acquisition and automatic calculation of results, contributing to achieving more accurate identification of results in various tests [Mourad and Bertrand-Krajewski, 2002]. Sensors allow the acquisition of various physical and physiological parameters [Majumder and Deen, 2019], e.g., heart rate, respiration rate, steps, velocity, force, and others. The following are a few of the most popular physical therapy exams that may be conducted with sensors:

- The Heel-Rise Test is used to diagnose neurological and degenerative pathologies, chronic venous illness, leg dysfunction in the calf region, Achilles tendon ruptures or tendonitis, and sports injuries, among other pathologies [Furrer et al., 2015];
- The Functional Reach Test is intended to aid in the recovery of conditions related to upper-body injuries, degenerative neurological disorders, and athletic injuries [Allen et al., 2013, Merchán-Baeza et al., 2015];
- The Ten Meter Walk Test aims to speed recovery from pathologies associated with balance alterations, neurological and degenerative disorders, lower limb traumas, and chronic venous illness [Cuesta-Vargas et al., 2020, Konharn et al., 2016];
- The Eight Hop Test and Up-Down Hop Test aid in the rehabilitation of balance disorders and illness of the lower limbs [Mahaffey et al., 2016];
- The Side Hop Test and Single Hop Test aid in the rehabilitation from neurological system illness [Mahaffey et al., 2016];

- The Chair Stand Test aids in the rehabilitation from neurological diseases, balance disorders, and lower limb injuries [Adusumilli et al., 2017];
- The Arm Curl Test aids in the rehabilitation from neurological diseases and injuries to the upper limbs [Mahaffey et al., 2016];
- The Chair Sit and Reach Test helps patients recover from neurological pathologies as well as lower and upper limb abnormalities [Mahaffey et al., 2016];
- The Timed-Up and Go Test helps patients recover from chronic venous illness, neurological disorders, degenerative diseases, lower limb injuries, and balance-related pathologies [Barry et al., 2014, Beauchet et al., 2011].

This research is based on the Timed-Up and Go Test. During the six stages of the physiological therapy text, the individual sits on a chair, stands up, walks three meters forward, changes gait, walks three meters backward, and finally sits back in the chair [Barry et al., 2014, Beauchet et al., 2011, Givens et al., 2018, Milosevic et al., 2013].

1.3 Problem Statement

The current assessment process for the Up-Down Hop Test has several limitations that hinder its effectiveness. Firstly, the assessment process relies on subjective visual inspection, prone to errors and inconsistencies, leading to inaccurate results. Secondly, the manual measurement of the test's results could be more efficient, requiring a skilled professional to perform the evaluation. Finally, the current assessment process cannot provide a detailed analysis of the test's results, such as muscle strength, balance, and postural control, which are critical in determining the patient's progress in rehabilitation.

To overcome the limitations of the current assessment process, a more objective and efficient assessment process that can provide accurate and detailed results of the Up-Down Hop Test is needed. Sensor technology can provide an effective solution to this problem by measuring and analyzing the test's results objectively and efficiently. Sensor technology can provide a detailed analysis of the test's results, including muscle strength, balance, and postural control, which can help accurately identify the patient's rehabilitation progress.

The current assessment process for the Up-Down Hop Test has several limitations, including subjective visual inspection, manual measurement, and the inability to provide detailed results. Using sensor technology can provide an objective and efficient assessment of the test's results, which can help accurately determine the patient's progress in rehabilitation. This project aims to put into practice a technique for assessing the many data points gathered during the Up-Down Hop Test utilizing mobile device sensors. These sensors are used for data collection to calculate the various signal qualities later. In the end, techniques for artificial intelligence are employed to identify illnesses automatically. Therefore, the problem statement of this project is to explore the potential of sensor technology for measuring and analyzing the results of the Up-Down Hop Test, focusing on signal processing techniques for extracting relevant features from the sensor data. This project will contribute to advancing sensor technology in physical therapy and improve the accuracy and efficiency of the Up-Down Hop Test assessment process.

The Up-Down Hop Test is a critical physical therapy test that assesses lower limb function and stability. The limitations of the current assessment process, such as subjective visual inspection, manual measurement, and inability to provide detailed results, hinder the effectiveness of the test. Using sensor technology can provide an objective and efficient assessment of the test's results, which can help accurately identify the patient's progress in rehabilitation. The problem statement of this thesis focuses on the potential of sensor technology for measuring and analyzing the results of the Up-Down Hop Test, employing signal processing techniques and machine learning algorithms to develop an automated system for identifying lower limb pathologies and tracking patient progress in rehabilitation.

1.4 Research questions

This work was based on the following research questions:

- (RQ1) What are the benefits of evaluating the Up-Down Hop Test using wearable devices?
- (RQ2) How do sensor-extracted features improve monitoring and evaluation of Up-Down Hop Test findings?
- (RQ3) Which factors contribute to detecting patterns of lower limb unbalance?
- (RQ4) Which sensors expose the patterns that can identify body disbalance during the execution of the Up-Down Hop Test?

1.5 Objectives

It is challenging and requires many instruments to assess the effectiveness and outcomes of the Up-Down Hop Test. This project aims to use the Up-Down Hop Test findings in person, given the availability of numerous tools that enable the automated measurement of results, such as sensors and mobile devices. To improve the accuracy of diagnosis and identify illness patterns to aid medical professionals in their treatment, this sort of test apparatus presents a problem.

Mobile device sensors use movement data to uncover patterns that may be used to track movements. These possibilities have increased the likelihood of developing more precise illness detection techniques utilizing inexpensive tools, bringing up a variety of new investigations that formed the foundation for this dissertation. Given how simple it is to create mobile apps that enable the interaction of multiple motion detection sensors, they may be utilized to the advantage of medical practitioners to support diagnosis and track patient recovery.

To address this problem, a mobile application will be developed for data acquisition, and a method will be created to estimate the results of the Up-Down Hop Test automatically. This mobile application will be an essential tool for physiotherapists to obtain accurate and reliable data during the Up-Down Hop Test. It will allow for the automated measurement of results, making it easier to track patient progress and improve the accuracy of diagnosis.

The main objective of this research is to study and create a method for analyzing and processing sensor data from mobile devices to estimate the results of the Up-Down Hop Test. The ultimate goal is to provide a more accurate and efficient assessment process for the test and improve the effectiveness of physical therapy. By developing this mobile application and employing sensor technology, this research will contribute to advancing physical therapy and the healthcare industry.

More specifically, the objectives of this work are:

1. Research on the State-of-the-Art: It consists of a literature review to understand current methodologies, technologies, and tools used in physical therapy assessments, especially those involving motion analysis and sensor data. The existing mobile applications and sensor technologies used for medical diagnostics, physical therapy, and movement analysis were evaluated. It includes accelerometers, gyroscopes, and other relevant sensors in smartphones and wearable devices. In the end, the gait analysis was identified, identifying apps in the current state-of-the-art where the project can contribute. It could involve limitations in the accuracy, accessibility, or comprehensiveness of existing tools.

2. Performance of the Data Acquisition with Some Experiments: Pilot tests were conducted with a small group of participants to ensure the application's functionality and data collection processes worked as intended. A protocol for the performance of the Up-Down Hop Test was defined, ensuring consistency and reliability in data collection across different sessions and participants.

3. Processing of the Collected Data: Data cleaning methods will be implemented to remove outliers. The feature extraction was performed to identify and extract relevant features from the sensor data that can be used to assess the

Up-Down Hop Test results, such as acceleration patterns, jump height, and stability upon landing.

4. Analysis of the Collected Data: Different data processing methods will be implemented to identify patterns in the data that correlate with different assessment outcomes, such as tiredness and tremors. The statistical analyses were performed to validate the findings and ensure the reliability of the data analysis methods.

1.6 Expected results

The expected results of this research project on developing a mobile application for estimating the results of the Up-Down Hop Test using sensor data can be outlined as follows:

1. Development of a State-of-the-Art Mobile Application: The project is expected to create an advanced mobile application designed specifically for physiotherapists. This application will leverage the latest sensor technology to capture and accurately capture and analyze movements during the Up-Down Hop Test.

2. Enhanced Data Acquisition Capabilities: The application will enable efficient and accurate data collection during the Up-Down Hop Test. Utilizing the sensors available in mobile devices will gather comprehensive movement data crucial for assessing patient performance and progress.

3. Sophisticated Data Processing Algorithms: The project aims to develop robust algorithms for processing the collected sensor data. These algorithms can filter noise, identify key movement patterns, and extract relevant metrics from the raw data.

4. Detailed Analysis of Physical Parameters: Through analyzing processed data, the project expects to identify critical parameters that influence the outcome of the Up-Down Hop Test. Parameters like tiredness and tremors will be quantitatively assessed, providing insights into the patient's condition and recovery progress.

5. Accurate and Efficient Assessment Process: The ultimate goal is to provide physiotherapists with a tool that offers a more accurate and efficient assessment of the Up-Down Hop Test. By automating the measurement and analysis process, the application will reduce the likelihood of human error and improve the reliability of the test results.

6. Improved Physical Therapy Outcomes: With the ability to track patient progress more accurately and identify specific areas of improvement, the application is

expected to contribute significantly to the effectiveness of physical therapy treatments. It will not only aid in faster recovery but also in the more personalized care of patients.

7. Contribution to Healthcare Research: The project is anticipated to contribute valuable insights and tools to the healthcare industry, particularly in physical therapy. Demonstrating the feasibility and benefits of using mobile device sensors for clinical assessments may pave the way for further research and development in this area.

8. Platform for Sharing and Comparing Results: Creating a platform to display and share the results related to the Up-Down Hop Test will facilitate better communication among medical professionals. It will also enable comparing patient progress over time and across different cases, fostering a collaborative environment for treatment planning and research.

In summary, the expected results encompass the development of a cutting-edge tool for physical therapy assessment, an enhanced understanding of patient mobility issues, and a significant contribution to the medical technology and healthcare field.

1.7 Work Schedule

The Work Schedule for the proposed Master's thesis outlines the milestones for completing the research project. This section serves as a comprehensive guide to the project's progression and helps to ensure that each milestone is met within the specified timeline. The work schedule is aligned with the research project's methodology and aims and objectives to ensure that all tasks are completed efficiently and effectively.

The work schedule is organized with columns for each month and rows for each section/subsection of the project, as table 1.1 presents. The "X" in each cell represents the planned completion of a section/subsection during that specific month. The work schedule starts with the proposal, which includes the summary, introduction, and state-of-the-art. Then, the project section will be developed, including the creation of the mobile application for data collection and the preliminary organization and analysis of the collected data.

In the results section, the focus will be on creating a hierarchical model for test result analysis and defining the sensor data collection method. Finally, the final delivery will include the thesis review and corrections.

This work schedule is a reference for tracking the project's progress and making necessary adjustments to meet the final deadline. Following the work schedule is essential to ensure the research project is completed on time and meets the desired outcomes. The work schedule is designed to align with the methodology, which includes data collection, data processing, and data analysis techniques, and the aims and objectives include developing a mobile application for data acquisition and creating a method for estimating the results of the Up-Down Hop Test. This work schedule will contribute to the success of the thesis completion and the realization of the desired results.

Table 1.1: Work Schedule

Section/ Sub-section	**nov/ 22**	**dec/ 22**	**jan/ 23**	**feb/ 23**	**mar/ 23**	**apr/ 23**	**may/ 23**	**jun/ 23**	**jul/ 23**	**aug/ 23**	**sep/ 23**	**oct/ 23**	**nov/ 23**	**dec/ 23**	**jan/ 24**	**fev/ 24**
1. Proposal	X	X	X													
1.1 Summary	X															
1.2 Introduction	X	X														
1.3 State of the Art		X														
1.4 Methodology		X	X													
1.5 Final Proposal		X	X													
2. Project			X	X	X	X	X	X	X	X	X	X	X	X	X	X
2.1 Dissertation Issuance			X	X	X	X	X	X	X	X	X	X	X	X	X	X
2.1.1 Definition of the Sensor Data Collection Method			X	X	X											
2.1.2 Creation of the Mobile Application for Data Collection					X											

Section/ Subsection	**nov/ 22**	**dec/ 22**	**jan/ 23**	**feb/ 23**	**mar/ 23**	**apr/ 23**	**may/ 23**	**jun/ 23**	**jul/ 23**	**aug/ 23**	**sep/ 23**	**oct/ 23**	**nov/ 23**	**dec/ 23**	**jan/ 24**	**fev/ 24**
2.2 Collected Data Preliminary Organization and Analysis						X	X	X	X							
2.3 Writing of the Collected Data Description paper							X	X	X	X	X	X	X			
2.4 Development of a Data Analysis Application							X	X	X							
2.5 Extraction of Test-related variables								X	X	X						
2.6 Development of Data Analysis methods										X	X	X	X			
3 Results													X	X	X	X
3.1 Creation of an Hierarchical Model for Test Result Analysis													X	X		

Section/ Subsection	**nov/ 22**	**dec/ 22**	**jan/ 23**	**feb/ 23**	**mar/ 23**	**apr/ 23**	**may/ 23**	**jun/ 23**	**jul/ 23**	**aug/ 23**	**sep/ 23**	**oct/ 23**	**nov/ 23**	**dec/ 23**	**jan/ 24**	**fev/ 24**
3.2 Definition of the Sensor Data Collection Method													X	X		
4 Final Delivery															X	X
4.1 Thesis Review															X	X
4.2 Final Corrections																X

In conclusion, the Work Schedule chapter serves as a road map for the entire project, outlining the milestones and deadlines for each section and subsection of the thesis "Signal Processing Measurement of the Results of the Up-Down Hop Test using Sensors". The table provides a comprehensive overview of the planned progression of the project, from the initial proposal to the final delivery of the thesis, including the research on the state-of-the-art study, the development of the mobile application for data collection, the processing and analysis of the collected data, and the identification of relationships between the results of the Up-Down Hop Test and various demographic and physical characteristics of the participants. By following this work schedule, the project is expected to stay on track and meet the desired objectives, leading to a more accurate and efficient assessment process for the Up-Down Hop Test and improving the effectiveness of physical therapy. The ultimate goal is to contribute to advancing physical therapy and the healthcare industry.

1.8 Thesis Outline

The thesis structure, as outlined, presents a clear and logical progression that's well-suited for a research thesis in signal processing, mainly focusing on the measurement of the Up-Down Hop Test. Each chapter builds upon the previous one, setting a solid foundation for your arguments and findings. The chapters are structured logically and concisely to provide an in-depth understanding of the project and its objectives.

The first chapter introduces the importance of signal processing in sports science, particularly in performance measurement and injury prevention. It outlines the research questions and hypotheses, highlighting the Up-Down Hop Test as a valuable measure and how signal processing can improve its accuracy and reliability. The project's scope includes specific aspects of signal processing and types of sensors, and the study's significance is discussed, highlighting its potential impact on sports science and rehabilitation.

The second chapter provides a comprehensive overview of the main topics in the project's scope, including signal processing and its applications in measuring the results of the Up-Down Hop Test. This chapter serves as a foundation for the subsequent chapters, providing a clear understanding of the main concepts and theories discussed throughout the document. It also presents a comprehensive literature review of the latest studies and research on signal processing techniques and algorithms for the Up-Down Hop Test. This chapter provides an overview of the current state of the art and references the proposed methodology.

Chapter three discusses the methodology for data collection in sports science, including the selection of sensors, signal processing techniques, and data collection and analysis process. It explains the chosen sensors, their accuracy, sensitivity, and practicality and outlines the experimental setup, participant selection, test procedures, and data analysis steps. This chapter outlines the steps and processes involved in collecting and analyzing the data and clearly explains the proposed methodology.

The fourth chapter presents the results of the proposed measurement. This chapter provides a comprehensive analysis of the results and a conclusion of the work done, highlighting the significance of the research and its contributions to the field of signal processing and the measurement of the results of the Up-Down Hop Test. It also provides a comparison with the related work and an analysis of the benefits and limitations of the proposed methodology.

Chapter Five summarizes the findings of the Up-Down Hop Test and signal processing in sports science, highlighting its novel aspects and potential impact on future studies. It also suggests areas for further investigation, such as new sensor technologies, advanced signal processing algorithms, or expanded test protocols, to build on the work.

Chapter 2

Literature Review

This chapter presents the theoretical framework of the study, that is, the theme and context are framed, demonstrating its relevance.

The literature review aims to gather relevant information about what has already been written and its analysis. This empirical part includes mention of the main conclusions that were measured by other authors, highlighting the contribution of the study being carried out.

2.1 Theoretical Framework

The Up-Down Hop Test is an important evaluative component in the field of sports medicine and rehabilitation, serving as a critical tool for measuring lower extremity function, stability, and recovery after injury. Based on a thorough theoretical framework, this test uses biomechanical principles to assess dynamic balance, proprioceptive ability, and the neuromuscular control required for effective locomotion and sports performance. By requiring an individual to do consecutive hops on a single leg, the test not only assesses physical traits such as strength and endurance, but also incorporates vital aspects such as coordination and agility. This multimodal method enables clinicians and researchers to gain valuable insights regarding an athlete's preparedness to return to sport, as well as an individual's rehabilitation process. As a result, the Up-Down Hop Test bridges the gap between theoretical knowledge and practical application, including kinesiology, biomechanics, and physical therapy concepts to inform evidence-based practice and improve patient outcomes.

2.1.1 Mobile devices

Mobile devices (e.g., tablets, smartphones, and wearable technology) have completely changed how people engage with the outside world and one another [Ometov et al., 2021]. These gadgets combine wireless connectivity and sophisticated computer power to let users do various tasks at any time and from any location, including work, entertainment, and communication [Poslad, 2011]. Sophisticated integrated circuits, sometimes known as microprocessors, are the brains behind mobile devices [Yan et al., 2024]. Advances in semiconductor technology, particularly the miniaturization of components through Moore's Law, which states that the number of transistors on a microchip doubles roughly every two years, increasing performance and lowering costs, have played a significant role in driving the evolution of mobile technology [Poslad, 2011].

Moreover, mobile devices use high-speed data networks, such as 4G LTE and 5G, to speed up data transfer and provide access to cloud services, expanding their usefulness beyond what can be done locally [Shafique et al., 2020, Hui et al., 2020]. These devices can interact with their surroundings thanks to the incorporation of sensors like GPS, accelerometers, and gyroscopes [Javaid et al., 2021, Caro-Alvaro et al., 2024]. It opens up possibilities for applications like fitness tracking, augmented reality, and location-based services [Kanade and Prasad, 2021]. Mobile gadgets significantly impact society, affecting consumer behavior, information availability, and communication habits [Pires et al., 2016, Javaid et al., 2021]. Yet, this widespread use gives rise to worries about security, privacy, and mental health, which has sparked continuous study into morally and environmentally responsible technology use [Ahram et al., 2017]. Future developments and difficulties in mobile technology will bring new inventions and changes to digital interaction and connectivity [Ling, 2004].

2.1.2 Sensors

Many sensors are built into mobile devices, which improves their functionality and interaction by allowing them to understand and react to their surroundings in sophisticated ways [Khan et al., 2012]. These sensors fall into three categories: location, motion, and environmental. Motion is detected using motion sensors, which include magnetometers, gyroscopes, and accelerometers [Pires et al., 2018, Pires, 2018, Lopez-Nava and Munoz-Melendez, 2016]. Devices with accelerometers may monitor acceleration forces and ascertain their orientation concerning Earth's gravity [Middlemiss et al., 2016]. It is crucial for applications such as step tracking and screen rotation [Pires et al., 2022]. Gyroscopes are used to assess rotational motion, which helps augmented reality experiences and navigation apps function more precisely [Daponte et al., 2014]. As digital compasses, magnetometers determine the device's orientation for the Earth's magnetic field, improving navigational capabilities [Goldenberg, 2006].

Barometers, thermometers, and hygrometers are environmental sensors that detect temperature, humidity, and air pressure. These sensors can help calibrate other sensors and supply data for weather-related applications [Sziroczak et al., 2022]. Position sensors, like the Global Positioning System (GPS), allow devices to pinpoint their location remarkably accurately, which makes location-based applications like tracking and mapping possible [Oguntala et al., 2018].

Additionally, proximity sensors, which can identify things nearby without making physical contact, are another characteristic of mobile devices [Khan et al., 2012]. These sensors are frequently used to turn off touch screen capabilities when the phone is held near the ear during a call [Lane et al., 2010]. Light sensors enhance readability and prolong battery life by adjusting screen brightness in response to ambient light [Yu et al., 2016]. More advanced sensors, such as LiDAR (Light Detection and Ranging), have recently been made available for use in augmented reality experiences and the creation of comprehensive spatial maps [Selleck et al., 2018]. Incorporating these sensors into mobile devices is a prime example of how cutting-edge technology and user-centered design can create new applications and services that improve accessibility and immersiveness of daily tasks [Kitson et al., 2018, Longo et al., 2017].

2.1.3 Ambient Assisted Living

By incorporating technology into their everyday lives, people who are elderly or disabled can live better thanks to the novel concept known as ambient assisted living (AAL) [Cicirelli et al., 2021, Maskeliūnas et al., 2019]. In the AAL ecosystem, mobile devices are essential since they serve as the user's interface for interacting with different assistive technologies [Maskeliūnas et al., 2019]. These gadgets use their built-in sensors, networking capabilities, and processing power to provide services that promote well-being, safety, and independence [Marques et al., 2019].

Mobile devices can provide location-based services through GPS and Wi-Fi positioning, allowing for real-time monitoring and support for users who might need emergency assistance or are prone to wandering because of illnesses like dementia [Ray et al., 2019]. These gadgets have motion sensors that can identify falls or abrupt movements and send alarms to medical staff or caretakers [Bhattacharjee and Biswas, 2021]. Additionally, mobile devices can be used to control smart home technologies, which lessens the need for physical mobility and increases comfort by enabling users to control lighting, heating, security, and entertainment systems with touch or voice commands [Fadhil et al., 2020].

Incorporating health monitoring programs into mobile devices makes it possible to continuously watch vital signs like blood pressure and heart rate, which helps identify possible health problems early and enhances the management of chronic disorders [Dias and Paulo Silva Cunha, 2018, Khan et al., 2016]. Mobile devices' intuitive user interfaces combined with applications that can be customized guarantee that AAL technologies are available and flexible enough to meet people's unique requirements and preferences, encouraging their participation and autonomy [Raffaeli et al., 2016].

Mobile devices, which integrate assistive functions into commonplace products and services, serve as a bridge that connects users with an intelligent ambient environment [Dunne et al., 2021, Kouroupetroglou, 2014]. This combination allows people with limited abilities to live more autonomous and satisfying lives [Moilanen et al., 2021]. It opens new opportunities for advancing inclusive technology solutions that meet the many needs of an aging world population [Warschauer, 2004].

2.1.4 Physical Therapy

The convergence of mobile devices, AAL, and physical therapy is a progressive approach to healthcare, especially for the rehabilitation and assistance of people going through recovery or those with physical impairments [Nascimento et al., 2020]. Through this integration, patients can receive individualized, effective, and easily accessible physical therapy treatments right in their homes by utilizing the widespread use and advanced technological capabilities of mobile devices inside the AAL framework [Memon et al., 2014, Nussbaum et al., 2019]. With many sensors built into them, mobile devices allow medical providers to monitor a patient's movements and physiological characteristics remotely, making it easier to evaluate the effectiveness of therapy [Malasinghe et al., 2019, Banos et al., 2014]. Accelerometers and gyroscopes, for example, can monitor the range of motion and the quality of motions during workouts, giving helpful information to customize rehabilitation programs to the patient's requirements [Díaz et al., 2019, Dobkin and Martinez, 2018].

By utilizing AAL technology, mobile devices can be smoothly incorporated into the patient's living space, facilitating the use of augmented or virtual reality applications to deliver interactive therapy sessions [Farooq et al., 2022]. These apps can motivate and engage patients as they complete activities, which may improve adherence to treatment plans [Pérez-Jover et al., 2019]. Furthermore, in situations where face-to-face interaction is not feasible, mobile devices can communicate between patients and therapists, facilitating telerehabilitation [Muñoz-Tomás et al., 2023]. This capability benefits those who have trouble moving around, live in remote locations or are in circumstances when face-to-face meetings are impractical, like during public health emergencies [Hjelm, 2017].

Integrating AAL, mobile technology, and physical therapy creates an atmosphere of ongoing education and support where patients may access educational materials, take control of their rehabilitation timetables, and get immediate feedback on their performance [Martínez de la Cal et al., 2021]. By actively empowering patients to participate in their rehabilitation process, this holistic approach not only improves the efficacy of physical therapy interventions but may also result in improved outcomes and a higher quality of life for patients [Yun and Choi, 2019, Pires et al., 2021]. Physical therapy will continue to push the envelope as technological advancements integrate creative solutions within the AAL framework, resulting in more individualized, easily accessible, and life-affirming outcomes for individuals who require it [Norman, 2021, Yin et al., 2021].

2.1.5 Physical Therapy Tests

Physical functional tests are crucial tools in assessing an individual's physical capabilities, providing valuable insights into their overall health, functional mobility, and risk of injury or falls [Brown, 2019]. These tests are widely used in clinical settings, rehabilitation, sports medicine, and geriatric care to design appropriate treatment plans, monitor progress, and evaluate the effectiveness of interventions [Kang et al., 2022, Choi et al., 2023]. Key physical functional tests include the Timed Up and Go (TUG) Test, which assesses mobility, balance, and the risk of falling [Ponciano et al., 2020, Oliveira-Zmuda et al., 2022]. The 6-Minute Walk Test (6MWT) evaluates aerobic capacity and endurance, with longer distances indicating better cardiovascular fitness and endurance [Kim et al., 2023, Zhang et al., 2023].

The Gait Speed Test measures the speed at which an individual walks over a short distance, usually 4 meters [De la Cámara et al., 2020, Gabriel et al., 2023]. Higher scores indicate better balance. The Sit-to-Stand Test evaluates lower body strength by counting the number of times an individual can stand up from a seated position in 30 seconds [Vilarinho et al., 2024, Spangler et al., 2023]. The Berg Balance Scale (BBS) is a simple yet powerful test that measures static balance and fall risk through various tasks such as standing from sitting, standing on one foot, and reaching forward while standing [Xu et al., 2023]. Functional Reach Test measures an individual's stability by assessing the maximum distance they can reach forward while standing in place without losing balance [Francisco et al., 2024, Pires et al., 2020a].

Hand Grip Strength Test measures the maximum isometric strength of the hand and forearm muscles, which has been associated with nutritional status, cognitive performance, and cardiovascular health [Neto et al., 2023]. The Short Physical Performance Battery (SPPB) assesses lower extremity function using three subtests - a balance test, a gait speed test, and a chair stand test [Naugle et al., 2022].

The Functional Independence Measure (FIM) is a comprehensive tool used in rehabilitation settings to assess an individual's level of disability and their need for assistance in performing daily activities [Spangler et al., 2023]. The Balance Error Scoring System (BESS) is primarily used in sports medicine to assess an individual's ability to maintain balance in various positions [Zarei and Norasteh, 2023].

The Senior Fitness Test evaluates physical fitness components crucial for independent living, including strength, flexibility, agility, endurance, and balance [Pucci et al., 2019]. Tests include the chair stand test for lower body strength, arm curl test for upper body strength, chair sit-and-reach test for lower body flexibility, back scratch test for upper body flexibility, 8-foot up-and-go test for agility and dynamic balance, and 6-minute walk test for aerobic endurance [Horbacz et al., 2023].

The Step Test for Aerobic Fitness measures cardiovascular endurance by stepping up and down on a platform at a set pace for a determined time [Mendes Jr et al., 2016]. The Dynamic Gait Index (DGI) evaluates an individual's ability to modify balance while walking in the presence of external demands [Pintado-Izquierdo et al., 2020]. The Y Balance Test is an extension of the SEBT, measuring risk for lower extremity injury by measuring an individual's reach in three directions while standing on one leg [Pires and Camargo, 2018].

Stair Climb Test measures the time it takes an individual to ascend and descend a set of stairs, providing insight into leg strength, endurance, and cardiovascular fitness [Davis and Powers, 2010]. Push-Up Test counts the maximum number of push-ups an individual can perform without rest [Müller et al., 2021]. Sit-and-Reach Test measures hamstring and lower back flexibility, while Two-Minute Step Test measures aerobic endurance [Cancela et al., 2018].

Functional Movement Screen (FMS) is a screening tool that identifies limitations or asymmetries in seven fundamental movement patterns, which are key to functional movement quality. It is used to target problems and reduce the risk of injury [Krysak et al., 2019]. Other tests include 30-Second Chair Stand Test, Lateral Step Test, Standing Long Jump Test, Functional Squat Test, Single-Leg Stand Test, Single-Leg Hop, Triple Hop, Cross-Over Hop Test, 6-Meter Timed Hop Test, Single-Leg Vertical Hop Test, Eight Hop Test, Heel-Rise Test, Arm Curl Test, and Side Hop Test [Pimenta et al., 2022, Petrica et al., 2023, Fernandes et al., 2016, Dos Reis et al., 2015, Silva, 2019, Matos et al., 2024, Popovski et al., 2020].

These tests assess an individual's gait, balance, agility, coordination, speed, agility, and endurance [Cuenca-Garcia et al., 2022]. They are designed for elderly populations, focusing on gait and balance ability, gait and balance, and fall risk [Sebastião et al., 2017]. The 30-Second Chair Stand Test measures lower body strength by counting the number of stands a person can complete in 30 seconds [Gonçalves et al., 2015, Gonçalves et al., 2014]. The Lateral Step Test assesses lateral movement and agility [Cuenca-Garcia et al., 2022]. The Heel-Rise Test is designed specifically for older adults to measure physical attributes such as strength, flexibility, agility, and endurance, helping to determine their fitness level and functional age [Pires et al., 2020c, Monteiro et al., 2013]. The Standing Long Jump Test assesses lower body strength and power by measuring the distance an individual can jump forward from a standing position [Hobold et al., 2017, Cuenca-Garcia et al., 2022].

Healthcare professionals use hop tests to evaluate an individual's physical function, allowing them to tailor interventions to improve their quality of life and reduce the risk of injury or health deterioration [Cuenca-Garcia et al., 2022]. They measure the number of repetitions, and time during the performance of the test, where the equilibrium is also evaluated [Cuenca-Garcia et al., 2022]. These tests are based on the individual's health status, functional level, and specific assessment objectives. The choice of test depends on the individual's health status, physical capacity, and the assessment's objectives [Sousa et al., 2014]. The tests provide valuable insights into an individual's physical health, guide intervention strategies, and monitor progress over time [Duarte et al., 2023]. They are commonly used in the assessment of athletes, particularly after lower limb injuries, to determine their ability to perform complex and strenuous movements safely [Noakes, 2011]. The results can guide rehabilitation progress, inform return-to-sport decisions, and help design training programs to address identified weaknesses or asymmetries [Preatoni et al., 2022]. Hop tests provide a quantitative measure of an individual's functional recovery, ensuring a safe and effective return to pre-injury activity levels [Di Trani, 2017].

In conclusion, functional movement screening tools help identify limitations or asymmetries in seven fundamental movement patterns, reducing the risk of injury and improving overall health [Krysak et al., 2019].

2.1.6 Up-Down Hop Test

The Up-Down Hop Test, is used to evaluate a person's lower extremity strength, power, endurance, and coordination [Reiman and Manske, 2009]. It is beneficial for athletes recuperating from leg injuries. The test requires the participant to hop in place on one leg continuously [Davies et al., 2020]. Specifically, they must leap from a specified line on the ground forward and upward, then instantly hop backward to the starting position [Hay, 1993]. Depending on the protocol, this procedure is repeated as often as feasible for a predetermined time, usually between 30 and 1 minute.

The Up-Down Hop Test's primary goal is to assess a person's capacity for high-impact, repetitive activity on a single leg, simulating the explosive and dynamic movements frequently needed in sports and daily activities [Rosen et al., 2019, Wang et al., 2023, Popovski et al., 2020]. It assesses balance and proprioceptive abilities in addition to the functional performance of the lower limbs in terms of power and agility since sustained hopping action necessitates a high degree of control and stability [Docherty et al., 2005].

The number of complete hops completed in the allocated time or the total distance traveled can be used to evaluate performance on the Up-Down Hop Test statistically [Melam et al., 2018]. To identify impairments and asymmetries that may point to an incomplete recovery or an increased risk of re-injury, it can be helpful to compare the data obtained from the injured leg to the uninjured leg or, if available, to baseline values [Van Der Horst et al., 2017].

This test is beneficial in rehabilitation, where it may be used to track advancement over time, direct the emphasis and intensity of therapy, and support evidence-based decision-making regarding an athlete's preparedness to resume sports [Mithoefer et al., 2012, McCrea and Guskiewicz, 2014]. The Up-Down Hop Test offers valuable information on the lower extremities' functional capability and resilience, which is essential for guaranteeing safe and efficient rehabilitation outcomes [Eckert et al., 2017, Henderson, 2023]. It reduces the likelihood of recurrence of injuries and enhances long-term athletic performance [Smith, 1994].

Using sensors to measure the Up-Down Hop Test outcomes entails leveraging contemporary technology to gather precise, impartial data about a person's performance [Tan et al., 2021]. This method can improve the assessment by offering in-depth insights into the mechanics of each hop, the limb symmetry, and the overall effectiveness of the action [Holsgaard-Larsen et al., 2014]. An athlete's lower limb (such as the ankle or shoe) can be fitted with tiny, light sensors like gyroscopes and accelerometers [Steijlen et al., 2021, O'Reilly et al., 2018, Mendes Jr et al., 2016]. These sensors provide information on each hop's height, speed, and smoothness by measuring the acceleration and angular velocity, respectively [Steijlen et al., 2021, O'Reilly et al., 2018, Mendes Jr et al., 2016].

Through the analysis of this data, practitioners can evaluate the quality of motions and the quantity of hops, including compensatory patterns that may not be readily apparent [Steijlen et al., 2021, O'Reilly et al., 2018, Mendes Jr et al., 2016]. The ground response forces produced during each hop can be measured using force plates in a more fixed configuration. Standing on a force plate, the athlete completes the Up-Down Hop Test, which records the vertical force applied during each landing and takeoff [Ghulam, 2016]. By calculating the hops' power and symmetry and evaluating the landings' stability, this data can be utilized to determine the likelihood of damage or the degree of recovery following an injury [Paterno et al., 2010].

The body's three-dimensional movements can be tracked during the test using highly accurate motion capture systems. Important anatomical landmarks on the athlete's body are marked with reflective markers, and cameras positioned all around the testing area record the movement of these markers [Lapinski et al., 2019]. With this configuration, the biomechanics of the hop, including joint angles, limb alignment, and balance during the test, can be thoroughly examined [Dos Reis et al., 2015]. The athlete can quantify the force and distribution of pressure applied by their foot with pressure-sensitive insoles inserted inside their shoes during each hop [De Fazio et al., 2023]. To detect imbalances and direct specific rehabilitation activities, they offer important information on foot placement, loading patterns, and the symmetry of force application between hops [Bishop et al., 2022].

IMUs (inertial measurement units) offer full information on the orientation, acceleration, and rotational speeds of the limb they are attached to by combining accelerometers, gyroscopes, and, occasionally, magnetometers [Reyes Leiva et al., 2021, García-de Villa et al., 2023]. When utilized in the Up-Down Hop Test, they can provide a comprehensive image of limb mechanics, including rotational dynamics and acceleration patterns, providing an in-depth look into the lower extremities' functional capacities [Stergiou, 2020].

Through the utilization of several sensors and technologies, professionals can acquire a comprehensive dataset from the Up-Down Hop Test, facilitating a detailed evaluation of an individual's performance. This methodology measures the results in terms of distance traveled or hops accomplished and adds biomechanical insights to the assessment, opening the door to highly individualized and successful training and rehabilitation regimens.

2.2 Related Work

This section intends to present the literature review related to the implementation of technological methods for the analysis of sensors' data acquired during the performance of the Up-Down Hop Test.

The authors of [Ahmadian et al., 2020] used of a wearable system with three inertial measurement units (IMUs) for measuring 3D knee and ankle angles during the triple single-leg hop test. This system was validated against a camera-based system and evaluated for its applicability in clinical research settings. The method involved ten able-bodied participants for technical validation and a clinical research application with 22 participants with unilateral sport-related knee injuries and 10 uninjured participants. The results showed that the estimated angles had a high degree of accuracy, with median root-mean-square errors of less than 2.3 and 3.2 degrees for knee and ankle joints, respectively, and correlation coefficients above 0.92 when compared with the camera-based system. The study concluded that the wearable system could accurately capture post-injury modifications in hopping kinematics and reveal significant differences in range of motion, offering a practical tool for clinical research environments.

In [Kockum and Annette, 2015], the study assessed the reliability of a test battery designed to measure hop performance and leg muscle power in athletes. It involved 14 healthy athletes performing three hop tests, two leg-power tests, and a single-leg squat jump. The study found good to excellent intra-class correlation coefficients (ICC) ranging from 0.84 to 0.98 for all tests, indicating high reliability. The standard error of measurement (SEM) and the smallest real difference (SRD) were calculated, showing the precision and minimum detectable change for each test. The conclusion highlighted the test battery's utility for evaluating athletic function, especially in the context of power and jumping abilities, suggesting its potential applicability in determining readiness to return to sport post-injury.

The authors of [Soares et al., 2022] investigated the correlation between isometric muscle strength and kinematics of the pelvis, hip, and knee during functional tasks in women with patellofemoral pain. Conducted on thirty-five women, it explored the relationships between the strength of hip abductors, lateral rotators, and knee extensors against the range of motion during various tasks. Results showed a weak correlation between knee extensor strength and knee range of motion during a single-leg hop test's landing phase, and a moderate correlation between hip abductor strength and pelvic obliquity during stair ascent. The study concludes that there isn't a strong correlation between isometric muscle strength and kinematic changes during the evaluated tasks, suggesting the complexity of patellofemoral pain's bio mechanical factors.

In [Cacolice et al., 2020], the study aimed to generate predictive models for ground reaction forces (GRFs) from clinical and functional tests in a healthy and active college-age population. It examined how well simple clinical measures and functional tests could predict vertical and posterior GRFs in 42 active college-age individuals through a series of tests including Fat Free Mass (FFM) assessment, Ankle Dorsiflexion Passive Range of Motion (DPROM), and Single-Leg Triple Hop (SLTH), among others. The results indicated that specific combinations of these tests could predict GRFs with significant accuracy, highlighting their potential utility in identifying individuals at elevated risk for ACL injury without the need for costly and specialized equipment.

The authors of [Chang et al., 2017] investigated the characteristics of intratendinous microcirculation shortly after an Achilles rupture and its relationship with treatment outcomes. Conducted on thirteen subjects, it measured microcirculation values in injured Achilles tendons post-surgery and correlated these with functional outcomes at 3 and 6 months. The findings revealed significant correlations between early microcirculatory changes and both symptoms and functional symmetry post-repair, suggesting that early microcirculation assessment could provide valuable prognostic information for rehabilitation and healing outcomes.

In [Castillo et al., 2022], the study explored the impact of muscle fatigue on the invertor and evertor muscles of the ankle on functional jump tests and postural control. Involving 30 active young adults, it evaluated their performance pre- and post-inducing fatigue through isokinetic dynamometry. The results demonstrated that muscle fatigue led to decreased performance in functional activities and postural control, except for speed in a bipedal stance with eyes open. The study underscores the utility of functional jump tests as low-cost, clinically relevant measures for assessing the effects of muscle fatigue.

The authors of [Ford et al., 2016] aimed to objectively identify preferred landing legs in athletes with and without anterior cruciate ligament reconstruction (ACLR) during a drop vertical jump task. It included 158 participants, comparing those with a history of ACLR to uninjured controls. The research found no significant difference in the distribution of preferred landing legs between groups. However, ACLR subjects who preferred to land on their uninvolved limb showed decreased limb symmetry in hop tests, indicating this preference might reflect confidence and readiness to return to sport.

Table 2.1 presents a summary of the advantages and disadvantages of the presented studies.

Table 2.1: Comparison of Methods from Selected Studies

Study	**Advantages**	**Disadvantages**
Ford et al. [Ford et al., 2016]	Objective method to classify preferred landing leg, indicating potential for return-to-sport assessments.	Requires specific equipment and analysis software, potentially limiting applicability.
Castillo et al. [Castillo et al., 2022]	Demonstrates practicality of functional jump tests to assess muscle fatigue's influence on postural control and performance.	Focus on a specific young adult population may limit generalizability to other groups.
Kockum & Heijne [Kockum and Annette, 2015]	Provides a reliable test battery for evaluating leg muscle power in athletes, with good to excellent ICC values.	Methodological errors must be considered, and standardization during testing is crucial.
Chang et al. [Chang et al., 2017]	Offers insights into the role of microcirculation changes in tendon healing, potentially aiding in treatment strategies.	Limited by a small sample size and focuses on early post-surgery periods, which may not provide a full picture of long-term healing.
Cacolice et al. [Cacolice et al., 2020]	Demonstrates the potential of using clinical measures and functional tests to predict GRFs, key indicators of ACL injury risk.	Predictive models account for only a moderate amount of variance in GRFs, suggesting additional factors might influence injury risk.

Ahmadian et al. [Ahmadian et al., 2020]	Introduces an accurate method for measuring 3D joint angles during dynamic activities, suitable for clinical research and injury recovery assessment.	Measurement accuracy may be influenced by initial sensor orientation; further validation needed for broader clinical practice.
Soares et al. [Soares et al., 2022]	Highlights the relationship between muscle strength and kinematic changes, contributing to understanding of patellofemoral pain syndrome.	Focus on women with patellofemoral pain limits generalizability; only weak to moderate correlations suggest other factors also play significant roles.

The papers reviewed offer a diverse range of methodologies and insights into the evaluation of athletic performance and injury recovery. Ford et al. [Ford et al., 2016] and Castillo et al. [Castillo et al., 2022] emphasize the importance of objective assessments in determining athletes' readiness for return-to-sport, highlighting the need for practical, low-cost tools in clinical settings. Kockum & Heijne [Kockum and Annette, 2015] and Chang et al. [Chang et al., 2017] further underscore the relevance of reliable testing batteries and non-invasive methods for monitoring recovery, respectively.

Cacolice et al.[Cacolice et al., 2020] and Ahmadian et al.[Ahmadian et al., 2020] introduce predictive models and wearable sensor technologies, showcasing the potential of integrating clinical measures with advanced technology for real-time, dynamic assessments. Soares et al. [Soares et al., 2022] adds to this by linking isometric muscle strength with kinematic changes, suggesting a comprehensive approach that considers multiple factors in injury prevention and rehabilitation.

2.3 Research Gap

Integrating these insights could significantly inform the development of a technological method for analyzing Up-Down Hop Test. A potential approach could combine wearable sensors for real-time joint angle measurement, functional jump tests to assess muscle fatigue's impact, and predictive models to identify risk factors. This method would offer a comprehensive, accessible, and effective tool for clinicians and researchers, enhancing injury prevention strategies and rehabilitation protocols by leveraging the strengths of each study's findings.

This research project aims to develop a mobile application for physiotherapists to estimate the results of the Up-Down Hop Test using sensor data. The application will use advanced sensor technology to capture and analyze movements during the test, enabling efficient data collection. Robust algorithms will be developed to filter noise, identify key movement patterns, and extract relevant metrics. The analysis of processed data will identify critical parameters influencing the test outcome, such as tiredness and tremor. The application will automate the measurement and analysis process, reducing human error and improving test reliability. The application will also contribute to healthcare research by demonstrating the feasibility of using mobile device sensors for clinical assessments. The platform will facilitate better communication among medical professionals and facilitate comparison of patient progress.

Chapter 3

Methodology

The project aims to improve Up-Down Hop Test results measurement using innovative sensor technology. A comprehensive literature review and technological development strategies will be used to identify existing methodologies and gaps. The project will focus on designing, developing, and validating sensor-based systems for precise performance metrics measurement. This holistic approach aims to address current limitations and provide a more objective, efficient, and detailed assessment tool for clinical and athletic settings.

3.1 Literature Review Methodology

The bibliographic search employed a Natural Language Processing (NLP) framework is based on the "Preferred Reporting Items for Systematic Reviews and Meta-Analyses" (PRISMA) methodology [Moher et al., 2010]. Relevant articles are found using specific inclusion and exclusion criteria and well-defined search phrases. The results are filtered to remove duplicates, unconnected or incomplete publications, and papers that have undergone extensive screening. Next, a qualitative examination of manually chosen, high-quality articles is performed [Moher et al., 2015]. This thesis evaluates contemporary research on executing certain tests with wearable or mobile devices. A natural language processing (NLP) toolbox was automatically used to aid in the effective search of the literature databases [Zdravevski et al., 2019].

3.1.1 Search Strategy

This research analyzes Up-Down Hop Test-related content published between January 2010 and November 2022, using the PRISMA search technique, to answer the fundamental question of "What are the most commonly used systems for measuring Up-Down Hop Test results?". We employed an automated strategy to search for papers published by the following publishers in their respective digital libraries: IEEE Xplore, Elsevier, Springer, Multidisciplinary Digital Publishing Institute (MDPI), and PubMed Central. The publishers are processed automatically using a technology that conducts a thorough search of the libraries using the search phrases provided. The NLP toolset analyzes every articles returned by the separate systems, automatically eliminating irrelevant ones. Zdravevski et al. [Zdravevski et al., 2019] provide detailed information on the NLP toolkit components.

The NLP framework's input parameters include keywords (phrases) and requirements for identifying relevant articles. This study used the following search phrases: "up down hop test with sensors" OR "up down hop test with mobile devices" OR "up down hop test". As a result, the software conducted three different searches in all digital libraries using these terms, and then deleted the duplicates based on the identifiers. Furthermore, the remaining publications were evaluated using the inclusion criteria outlined in the next subsection.

3.1.2 Inclusion criteria

The majority of publications of interest focused on wearable technologies for analyzing the Up-Down Hop Test. This multidisciplinary research combines computer, electrical, and health sciences. The studies were examined, the sensors were classified, and the information was mapped in order to extract relevant information from the numerous studies analyzed and connect it to the medical business.

The following criteria were considered when selecting studies for this systematic review: (1) studies that utilize wearables to measure the test results; (2) studies that employ mobile devices to measure the test results; (3) studies that clearly articulate their objectives; (4) studies that describe the population's characteristics; (5) studies that provide specific findings related to the test; (6) original research studies published between 2010 and 2022; (7) studies published in English language.

3.2 Analysis of functional and non-functional requirements

The functional requirements 3.2.1 are those with which the user interacts directly and performs all actions of the method, being necessary for the proper functioning of the solution according to the stipulated objectives. The non-functional requirements 3.2.2 are those that serve to support the functional requirements of the solution.

3.2.1 Functional requirements

The proposed solution will entail the development of a mobile application designed for smartphones running the Android operating system. This application will facilitate patient data input, collect information pertinent to the Up-Down Hop Test, and present the gathered data. Functional requirements for the mobile application, from the perspective of an ordinary user, include:

1. Record data about user characteristics, such as weight, height, and age, among other relevant parameters.
2. Provide the option to select from a range of inertial sensors (including accelerometer, and gyroscope) for use in conducting the test. Ideally, all available sensors should be utilized in optimal conditions.
3. Capture data from the selected sensors.
4. Enable the initiation of sensor data capture for test analysis.
5. Displaying detailed test results showcasing metrics such as the number of steps taken, duration, average speed, total distance covered, and other relevant indicators.

3.2.2 Non-functional requirements

Non-functional requirements, as implied by their name, do not directly pertain to the specific functions of the application. Consequently, the following considerations have been factored in:

1. Implement the use of buttons conducive to effortless finger interaction.
2. Utilization of user-friendly and easily navigable forms.
3. Provision of the option to switch between English and Portuguese languages.
4. Presentation of data clearly and concisely for optimal comprehension.
5. Ensure that the application is extensible, thus enabling the seamless addition of new features in subsequent iterations.
6. Mandate a 10-second waiting period after pressing the button to initiate the test.

3.3 Solution Modeling

Modelling employs graphical representation, utilizing various models to articulate the problem at hand, thus facilitating a clearer understanding of how the application will operate and how it should be developed.

3.3.1 Context Diagram

The context diagram, presented in figure 3.1, delineates the data flows between the system and external entities (users), facilitating the identification of various modules, relationships, and elements external to the application. Consequently, this diagram serves as a validation tool for project requirements. Figure 3 illustrates the context diagram of the mobile application, which encapsulates the requirements outlined in subsections 3.2.1 and 3.2.2 (functional and non-functional requirements). It delineates the data flow and communication direction between the application and the actor (Patient).

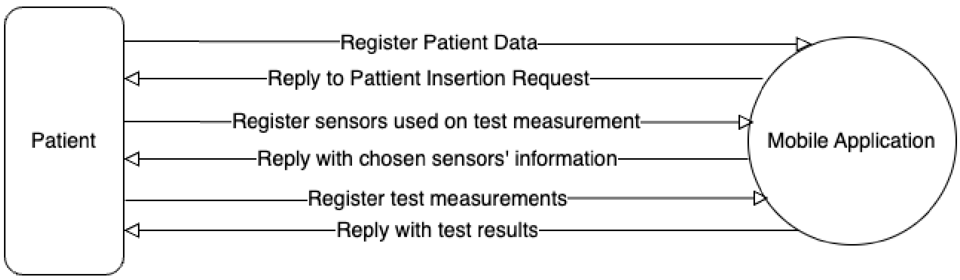

Figure 3.1: Context Diagram of the application

3.3.2 Use Case Diagrams

The use Case Diagrams identify the main user interaction moments with the system, in a manner that it is possible to obtain the necessary steps to obtain the specific objective.

Figure 3.2 corresponds to the use case diagram, where it is possible to visualize the System frontier that bounds the use cases that will be developed, as well as the responsibilities of each system actor. The application will have a single actor, designated as "Patient", which represents the application user.

3.3.3 Actors and Respective Use Cases

The Table 3.1 aims to define the actors and use case they take part (according to the context diagram). The presented use cases defined the requirements of the application.

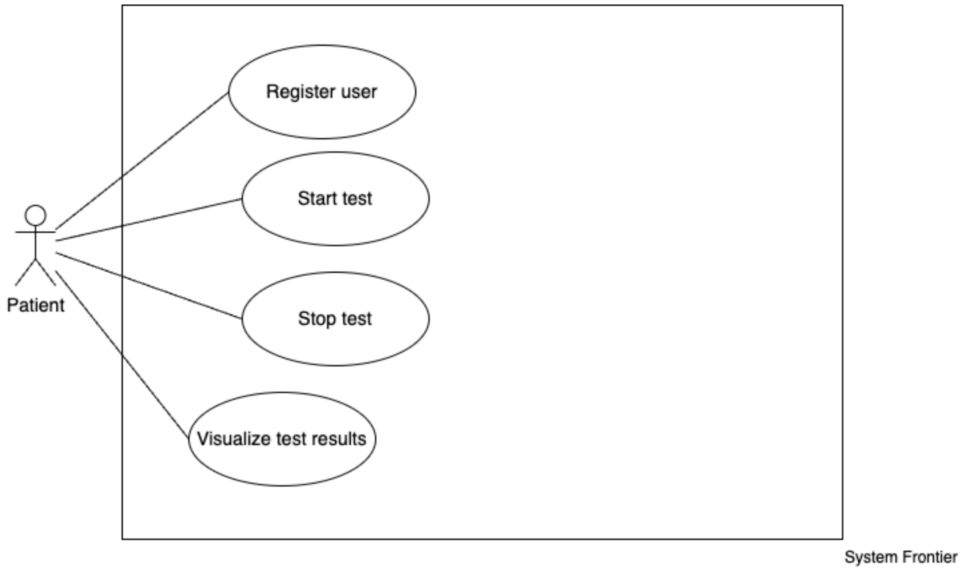

Figure 3.2: Use Case Diagram of the application

Table 3.1: Actors and respective use cases

Actor	**Use Case**	**Objectives**
Patient	Register user	The objective is to enable the user/patient to insert its own data, e.g., identity, age, weight, height
	Start Test	The objective is to enable the user/patient to perform a hop test
	Stop test	The objective is to enable the user/patient to end a hop test
	Visualize results	The objective is to enable the user/patient to visualize the result of a hop test

3.3.4 Use cases Description

In the description of a given use case it is assumed that things go according to plan (main path). However, it may be necessary to perform descriptions of alternative situations, that is, alternative paths. This subsection presents, in a more detailed form, the description of the use cases, using tables. Each table contains several fields, such as:

- Name - indicates the name of the use case.
- Description - provides a description of the use case.

- Precondition - indicates if there is a condition that must be met in order to start the current use case.
- Main Path - describes the several stages of the use case between the actor and the system.
- Supplements or Adornments - Indicates the concrete test cases that can be issued to validate use case operation.
- Post Conditions - If they are present, describes any operation issues after the use case terminates.

Table 3.2: "Register User" use case description

Name	Register User
Description	The objective is for the user to be able to insert data about himself.
Precondition	The mobile device must be identified and registered.
Main Path	1. The use case begins when the user selects the "Inserir Dados" button. 2. The application shows a form with all the data fields related to the patient (ID, age, height, weight, physical test and gender). 3. The user fills the form, uses the "Guardar" button to store entries. 4. The application validates and stores the form entries.
Supplements or Adornments	Perform several tests to verify if: √ The user can insert a new patient.
Post Conditions	The application stores the new patient on the database.

Table 3.3: "Start Test" use case description

Name	Start Test

Table 3.3: "Start Test" use case description

Description	The objective is for the user to start a hop test.
Precondition	The user must perform the use case entitled "Register User". The user must allow access to its physical activity on the device.
Main Path	1. The use case begins when the user selects the "Iniciar Captura" button. 2. The user waits 10 seconds. 3. The application emits a sound alert and exhibits the waiting message. 4. The application starts data collection. 5. The application exhibits the message that is capturing data.
Supplements or Adornments	Perform several tests to verify if: √ The user can start a test.
Post Conditions	The application stores sensors' values.

Table 3.4: "Stop Test" use case description

Name	Stop Test
Description	The objective is for the user to stop a hop test.
Precondition	The user is performing a test.
Main Path	1. The user presses the button "Parar Captura". 2. The application stops data collection. 3. The application exhibits the detailed information of the test performed.

Table 3.4: "Stop Test" use case description

Supplements or Adornments	Perform several tests to verify if: √ The user can stop a test. √ The parameters collected during the test are correct.
Post Conditions	The application shows the test's results.

Table 3.5: "Visualize Test Results" use case description

Name	Visualize Test Results
Description	The objective is for the user to visualize hop test results.
Precondition	The user stopped a test.
Main Path	1. The user reads the results.
Supplements or Adornments	Perform several tests to verify if: √ The application presents the test's results.
Post Conditions	None.

3.4 Development

The previous sections were aimed at the design of the mobile application; with this section, we intend to describe the process of developing and implementing it. The technologies that best suited the project context were selected to develop and implement the mobile application. Therefore, below is a brief explanation of each of the technologies used and details of why they were chosen to create the mobile application. To develop an application, following specific standards and criteria is necessary, thereby speeding up the development process. There are different types of development methodologies to facilitate these tasks, such as structured methodology and agile development methodologies. We chose the agile development methodology, more precisely, the Scrum framework. In section 3.3.2, the selected process (Scrum) for the development of the mobile application is described, as well as a description of how user stories (daily tasks) were managed.

3.4.1 Selected Tools and Technologies

Before and throughout the creation of this project report, various tools and technologies were utilized, as detailed below.

Android Studio

Android Studio serves as the designated Integrated Development Environment (IDE) for crafting applications tailored to the Android operating system. An IDE amalgamates diverse tools and functionalities crucial for software and/or mobile application development, streamlining the process significantly. The primary programming languages employed within Android Studio are Java and XML (Extensible Markup Language) [Chaubey and Sharma, 2023].

Java

Java stands as a high-level, object-oriented programming language renowned for its safety and extensive array of resources. Supported by a vast community of enthusiasts and programmers, its wealth of available information on the web enables swift access to answers and solutions. Widely adopted globally, Java is predominantly employed in crafting the functional components of applications.

XML

XML is a markup language for generating files encompassing various functionalities [Nečaskỳ, 2008]. Among its prevalent uses are: Incorporating predefined texts intended for use in Java classes. Designs the interface of application screens, encapsulating the layout of all screen elements, including text boxes, buttons, images, and more. Defines the items within an application's menu. Represents the hexadecimal codes for specific colours. Specifies the standard dimensions for objects such as buttons, screens, and images. Facilitating the creation of graphic components such as outlines, buttons, fills, and more.

Agile Development Approach: Scrum

Scrum embodies an iterative and incremental approach to enhance project timelines and mitigate risks. Its purpose is to furnish a framework conducive to developing products and projects [Srivastava et al., 2017].

Within Scrum, three primary roles exist: the Development Team, the Product Owner, and the Scrum Master. The Development Team assumes responsibility for product/project development, striving to deliver a fully functional increment at the end of each sprint. Teams operate in a structured and self-organizing manner. In Scrum-managed projects, the team size typically ranges from 3 to 10 members.

The Product Owner assumes the role of the product's visionary and owner, overseeing the product backlog (a compilation of all project functionalities) and validating the team's work at the end of each sprint through acceptance or rejection.

The Scrum Master is tasked with maintaining the development team's productivity, ensuring they possess the requisite resources for project development, and facilitating communication between the Product Owner and the team. Additionally, the Scrum Master conducts diagnostic assessments of the team's performance in each sprint.

Scrum also encompasses specific artefacts: the Product Backlog, the Sprint Backlog, and the Definition of "Done." The Product Backlog serves as a prioritized list of all functional requirements yet to be implemented, managed by the Product Owner with assistance from the Scrum Master. These requirements are typically represented as user stories and encompass features, functions, improvements, and corrections slated for future product versions. The Sprint Backlog, on the other hand, is a collection of tasks selected for a given sprint, crafted during sprint planning. These tasks contribute directly to achieving the functional objectives of the product backlog items. The Definition of "Done" outlines the criteria for completing a product backlog item.

Projects in Scrum are segmented into cycles known as sprints, each representing a time-boxed period dedicated to executing project-related activities. Traditionally lasting 2 to 4 weeks, sprints operate under the purview of the Product Owner, who maintains a product backlog listing all project activities. Over time, this list is prioritized, creating a sprint backlog encompassing tasks slated for development during the sprint. Daily meetings are conducted to synchronize team efforts and swiftly address emerging issues [Sachdeva, 2016].

This iterative approach enables the timely detection and resolution of problems, culminating in tangible results at the end of each sprint, whether in the form of functional increments or completed products, as outlined in the sprint backlog planning. Figure 3.3 illustrates the flow of the Scrum process.

3.4.2 Project Management

The success of managing and developing a software project hinges on effective and efficient planning from its inception. A well-structured initial project plan lays the groundwork for addressing a significant portion of the challenges that may arise during the project's lifecycle [Sachdeva, 2016]. In the context of the Scrum methodology, strict adherence to the predefined framework was not observed, as certain events outlined in the method were not executed during the development process. Furthermore, given that the application serves as its product (rather than being developed for an external client), the roles of the development team, Product Owner, and Scrum Master were consolidated into a single individual—the author of this

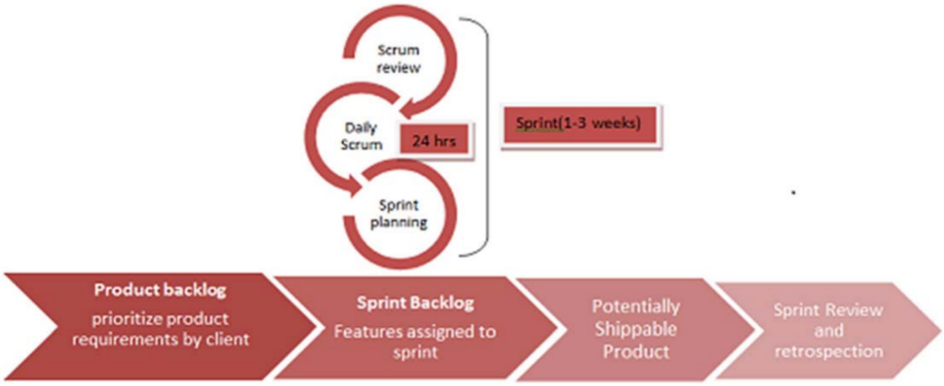

Figure 3.3: Scrum cycles

project report [Cao et al., 2009]. Before commencing application development, the Product Backlog was meticulously defined, encompassing all features discussed in the Requirements Analysis section 3.2. With a comprehensive list of features established in section 3.2.1, development of the mobile application commenced. Notably, a departure from the traditional Scrum methodology was observed, as the project was structured around individual functionalities (Issues) rather than distinct Sprints. Meetings akin to Sprint Planning sessions were conducted to determine the following functionality to be developed and its targeted completion date. The planning phase of the mobile application initiative commenced with an analysis of the previously identified requirements [Liu et al., 2019]. This comprehensive analysis facilitated the definition of the mobile application's structure and functionalities.

3.5 Development

The Up-Down Hop Test is a complete sensor-based assessment of lower body strength. This protocol describes the actions and parameters required to test and analyze the data collected. The research presents a preliminary yet novel strategy that incorporates sensor technologies in the early stages of the Up-Down Hop Test methodology. The method for the data acquisition and process of the data is illustrated in Figure 3.4.

3.5.1 Equipment

The equipment comprises selecting and using sensors included in off-the-shelf mobile devices to acquire the data required for test analysis. The following devices were utilized:

- A smartphone with built-in accelerometer, and gyroscope sensors, running a dedicated data acquisition application.

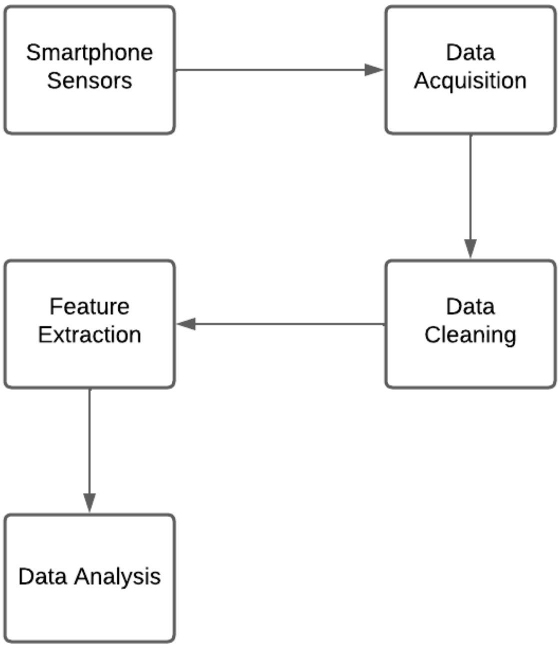

Figure 3.4: Proposed Methodology

- A smartphone holder or strap to secure the device on the participant's waist (e.g., an adjustable belt with a pouch, a dedicated armband, or a waist-mounted harness).
- A flat, non-slip surface for test execution, preferably with a marked jump area and stable floor.

3.5.2 Test Procedure

The test protocols comprise a data collection stage in which the subject is informed about the test's purpose, process, and safety precautions. They are told to wear comfortable clothes and adequate footwear. The smartphone holder or strap is positioned in the center of the waist. The subject is next instructed to stand on a flat, non-slippery surface with their feet shoulder-width apart. The test findings can provide useful information about lower body strength.

They are then told to stand on one leg, preferably the dominant leg, with their hands on their hips and the other leg slightly elevated off the ground. The mobile app collects data from the smartphone's sensors and any additional sensors. The participant is encouraged to do a vertical jump as high as possible while maintaining a straight posture and landing on the same leg. After landing, the participant is instructed to reestablish balance and control before ceasing data recording on the mobile application. To reduce fatigue, participants are allowed to rest for 30-60 seconds.

The subject is then asked to repeat the procedure for the other leg. Two further experiments were conducted for each leg, rotating between them and following the processes outlined above. The subject is urged to take adequate rest between trials in order to reduce tiredness and maintain the quality of the test results. Throughout the test, the mobile application collects data from the smartphone's accelerometer, and gyroscope sensors.

3.5.3 Integrative Sensor Technology for Enhanced Mobility and Fall Risk Assessment in Older Adults

The data processing varies depending on the sensors employed, and it also includes the fusion of the various sensors to acquire the results of the participants' tests. This section concludes with the data analysis used to reach these results.

Advanced sensor technology has transformed how we monitor and comprehend older persons' bodily conditions and motor skills. Mobility tests, such as the Up-Down Hop test, use data from gyroscopes, and accelerometers to evaluate dynamic balance. An integrated analysis approach examines data from numerous sensors at the same time, resulting in a comprehensive picture of the subject's physical condition. This method checks data from gyroscopes, and accelerometers at the same time, allowing researchers to better comprehend the intricacies of senior movement and stability while also giving illuminating trends.

Gyroscope data patterns show persistent change, which could imply continuous movement in elderly persons due to reduced stability or neurological disorders. Isolated spikes indicate fast corrective moves, whereas flat-lining graphs represent periods of stability or repose. The accelerometer data indicates peaking at rest, sudden changes, and oscillating patterns, indicating stationary motions. Magnetic data patterns reflect important changes, such as shifts in closeness to magnetic objects or in the magnetic surroundings. Signal stability exhibits minimal change, pointing to a low magnetic interference environment. Stability-seeking periods may mirror times when older persons seek stability, and magnetic objects may alter readings if they use assistive equipment.

Advanced data fusion techniques combine sensor data to generate a comprehensive image of movement and orientation, allowing for the detection of tiny changes. Longitudinal monitoring and trend analysis aid in detecting slow changes, but environmental contextualization and behavioral correlation are essential for comprehensive health assessments. Understanding individual patterns aids in the development of individualized care methods for older persons, such as fall prevention, increased safe mobility, and improved life quality.

The data analysis included Time Domain Analysis and Statistical Analysis. The time-domain study entails determining peak acceleration and deceleration during a hop, evaluating total duration to assess speed and functional performance, and examining the rate at which hops are executed to assess endurance and rhythmic consistency. For data distribution and prediction, statistical analysis uses descriptive statistics such as mean, median, mode, and standard deviation, as well as inferential statistics.

Chapter 4

Results and Discussion

4.1 Accelerometer results

This section presents a comprehensive analysis of the results obtained from accelerometer sensors during a series of dynamic tests. Accelerometers, known for their sensitivity to movement and capability to capture multi-directional acceleration, offer a granular view of motion and intensity. Through a meticulous examination of the data, we aim to uncover patterns, intensity fluctuations, and potential anomalies across different phases of activity. Each sensor's output provides a unique perspective on the motion it captures, allowing us to piece together a detailed narrative of the physical dynamics at play. Given the precise nature of the Up-Down Hop Test, a singular accelerometer was employed for each subject. The data collated herein reflects not only the vigor and rhythm of the activities performed but also hints at the positional and contextual factors contributing to the observed results.

Figure 4.1 presents the readings from an accelerometer during an Up-Down Hop Test, combining the acceleration vector at any given time. The chart is useful for examining high-intensity points of the Up-Down Hop Test and could be used to assess performance, consistency, and effort. There is variability in readings, with many peaks and troughs, likely representing moments of high activity or movement. The range of accelerometer values ranges from 0 approximately over 50, suggesting moments of significant acceleration followed by periods of rest or less intense activity. There are no visible patterns representing motion change that could unveil unbalance.

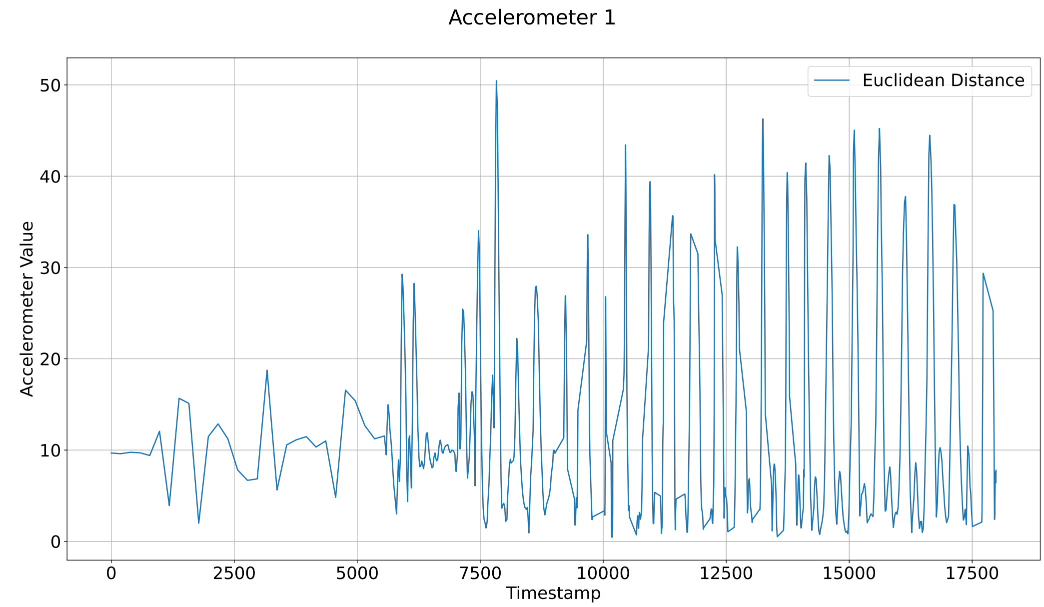

Figure 4.1: Chart of accelerometer sensor results - first patient

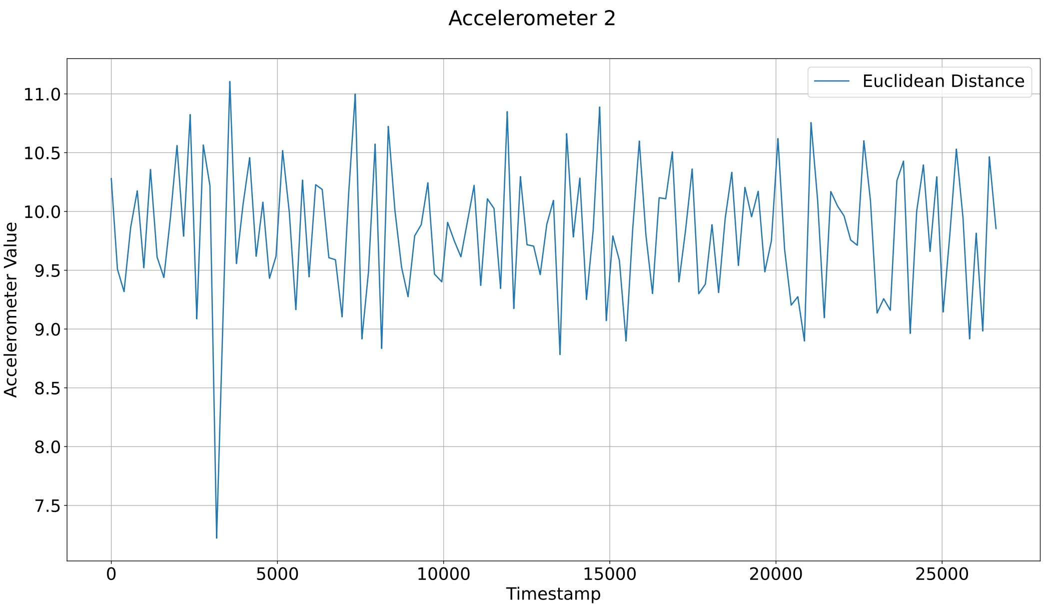

Figure 4.2: Chart of accelerometer sensor results - second patient

Figure 4.2 shows data from a second accelerometer sensor, the readings on this chart are more consistent, suggesting less variable and more uniform motions. The Euclidean Distance line is smoother, implying more steady and less dynamic movements. The timestamp scale ranges from 0 to approximately 28,000, making it difficult to determine the duration of the test or time between readings. The patient in this test was unable to successfully execute the test due to physical limitations.

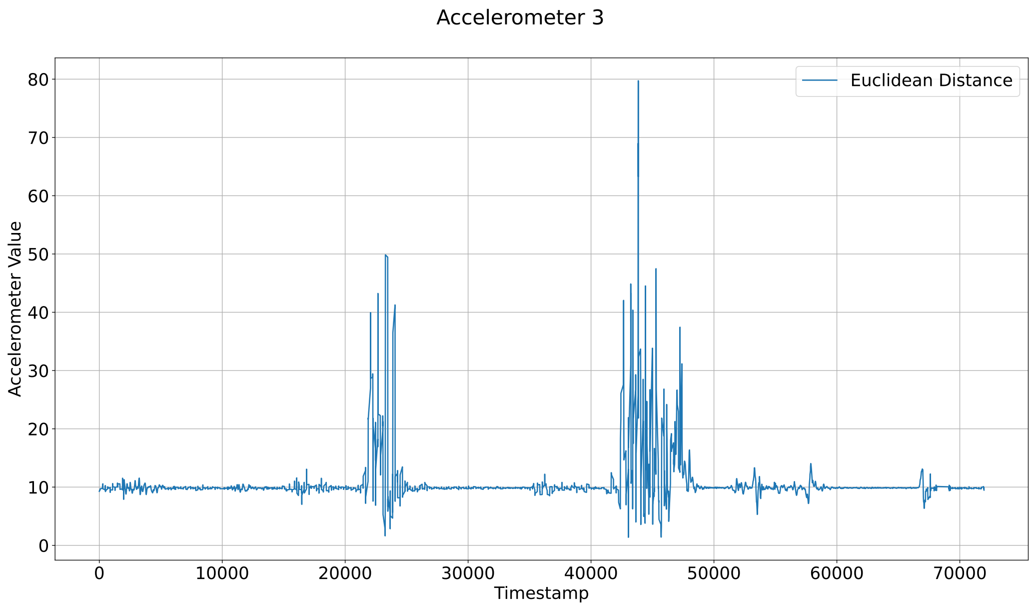

Figure 4.3: Chart of accelerometer sensor results - third patient

Figure 4.3 presents data from the third patient accelerometer results. The chart shows dramatic fluctuations in accelerometer values, indicating periods of high activity and inactivity. The taller spikes suggest high acceleration events, indicating rapid position change, such as hard landings. Activity intervals appear in bursts, with clusters of tall spikes around timestamps 23,000 and 45,000. The graph does not show patterns of body unbalance, mainly because the physical condition of the person disallowed continuing the test after two steps.

Figure 4.4 displays data from a fourth patient accelerometer sensor. It demonstrates variability in readings, with spikes indicating moments of activity. The data patterns are not immediately discernible, suggesting unpredictability of the physical activity being measured. The distribution of spikes throughout the timestamp suggests an uneven distribution over time, with significant variation in intensity. In comparison to other charts, Figure 4.4 appears to show a different profile of activity, possibly due to different movement types, body parts, or conditions. Finally, in this test, it is still not visible any pattern of unbalance.

Figure 4.5 represents data from a series of accelerometer sensors. It shows fluctuations between approximately 6 and 20. The accelerometer consistently records values around 8 to 12, with intermittent spikes deviating from this range. The spikes in this chart suggest the sensor is capturing a range of movement intensities, but without additional context, it's difficult to draw precise conclusions about the activities these movements represent. The consistent occurrence of the offset error suggests a need for calibration or a review of data collection methodology.

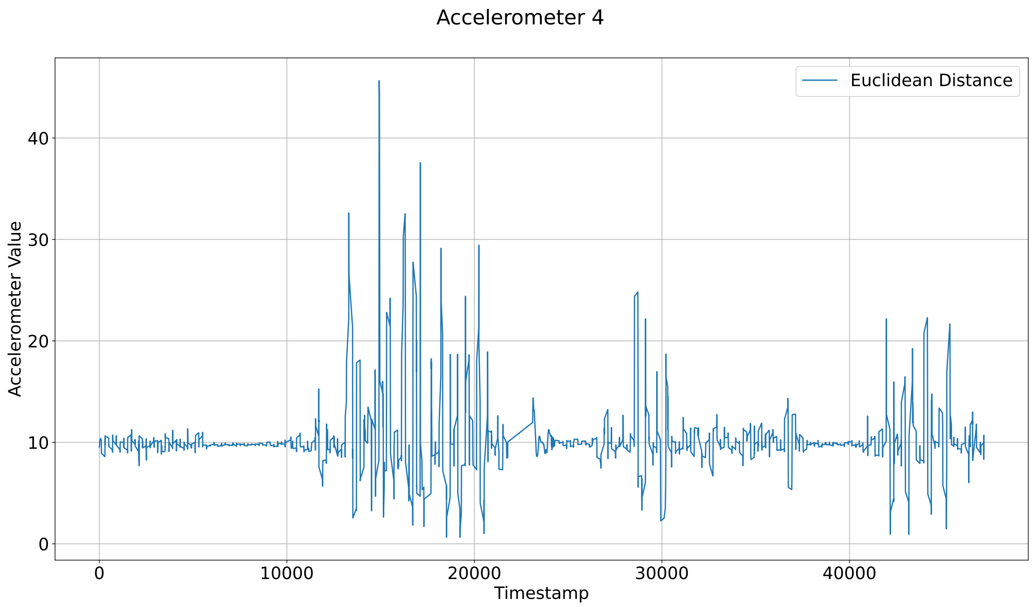

Figure 4.4: Chart of accelerometer sensor results - fourth patient

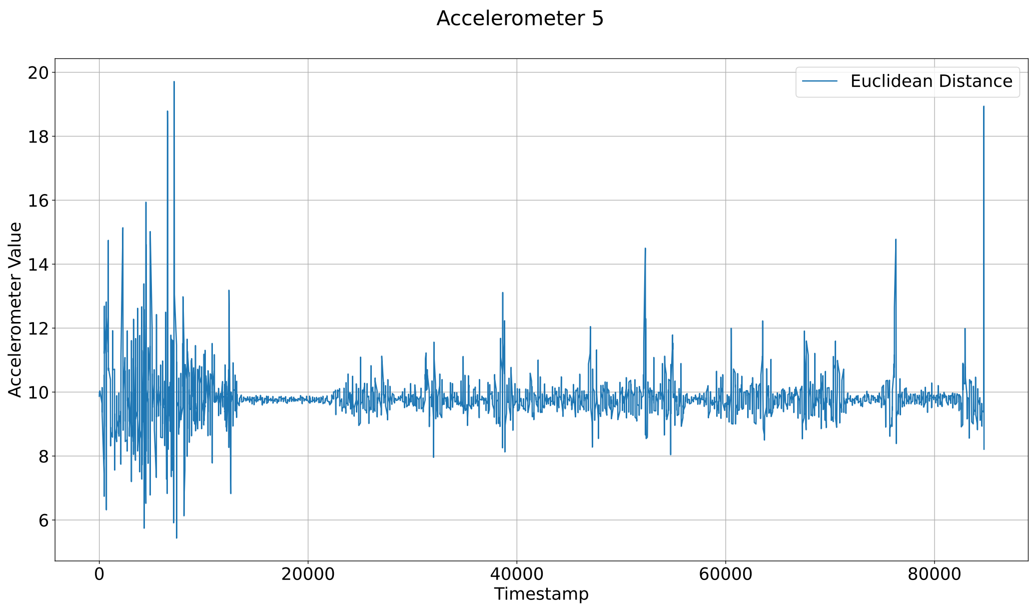

Figure 4.5: Chart of accelerometer sensor results - fifth patient

Figure 4.6 shows data consistent with previous charts, with activity ranges ranging from 5 to over 25, and spikes indicating significant movement or acceleration. The data could reflect specific test conditions with stationary or slow movement, with occasional bursts of intense activity. Understanding the accelerometer's placement and activities during data collection is necessary for full interpretation. However, there are visible patterns of unbalance at the end of the test.

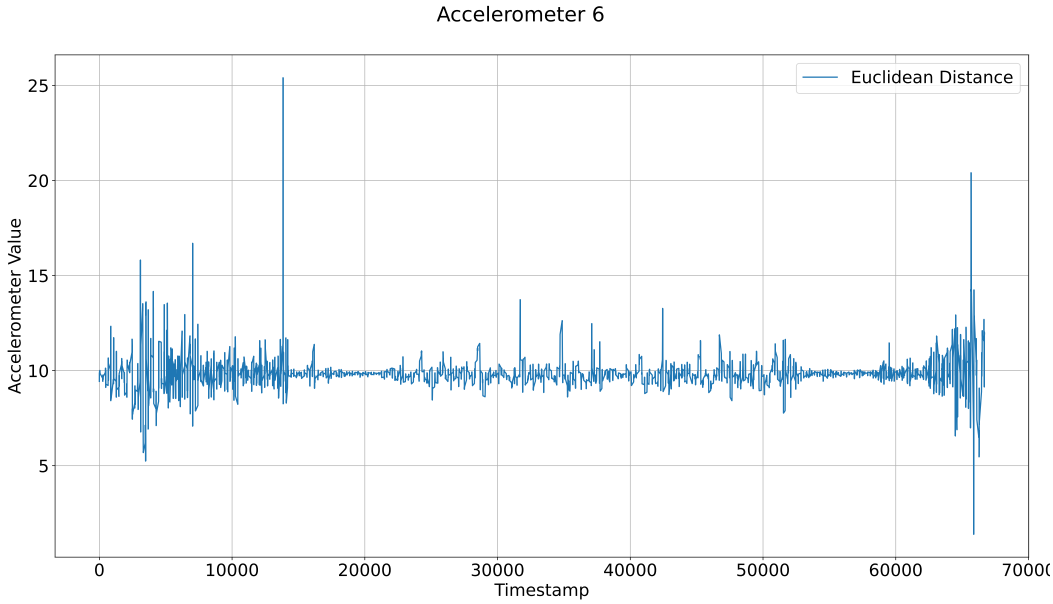

Figure 4.6: Chart of accelerometer sensor results - sixth patient

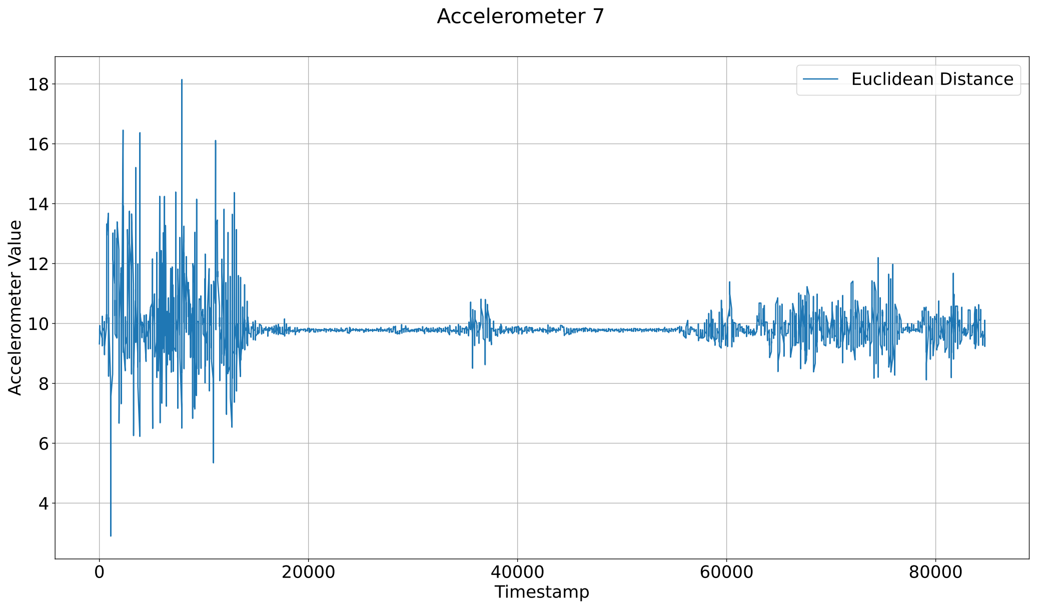

Figure 4.7: Chart of accelerometer sensor results - seventh patient

Figure 4.7 displays accelerometer sensor data for a seventh patient, with readings primarily between 4 and 18, with spikes indicating higher intensity motion. The graph shows a dense cluster of spikes in the beginning, up to around 17,000. This could indicate a period of high activity or varied movement, then settles into a more uniform pattern with fewer and lower spikes. A large positive constant value on the y-axis may indicate a systematic error in data logging or a placeholder value.

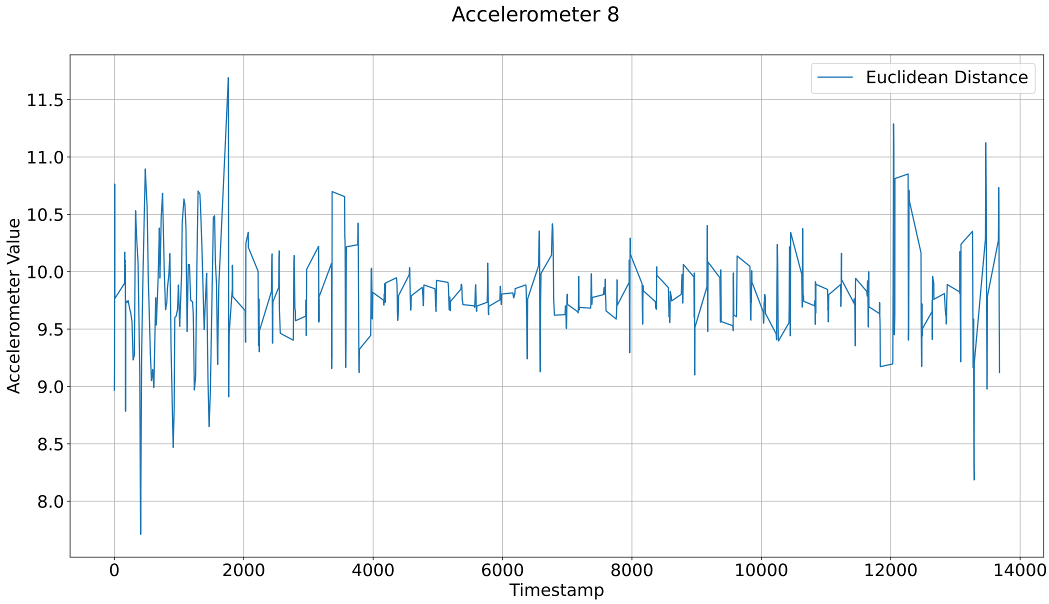

Figure 4.8: Chart of accelerometer sensor results - eighth patient

Figure 4.8 shows data from an accelerometer sensor with a less volatile pattern compared to previous charts. The data shows fluctuations mainly within the range of 8.5 to 11.5, suggesting moderate variability in the magnitude of movements detected by the sensor. The data generally clusters around the 9 to 11 mark, with occasional spikes that extend beyond this range. An anomaly or offset error is noted at the far right end, but with a pattern seen before on the test. The relatively stable range of accelerometer values may suggest less dramatic movement.

Figure 4.9 displays accelerometer sensor data over time, showing significant variability in values. The data shows pronounced spikes indicating sudden movements, suggesting sporadic motions. A consistent baseline movement around 10-12.5 indicates continuous movement, less intense than the spikes. The chart likely reflects a scenario where both low and high-intensity motions were recorded, possibly related to the same activity or test. The recurring anomaly suggests data post-processing operations are needed.

Figure 4.10 displays data from the tenth patient accelerometer sensor, ranging from 4 to 20 with most points clustering around 10. The chart shows noticeable spikes, suggesting rapid movement or high intensity. The middle section shows calmer activity with a denser cluster of smaller spikes, indicating a period of less intense or steady movements. The spikes early in the timeline may indicate a vigorous activity session, while the quieter middle phase could represent a rest, followed in the end with again more intense activity.

The data from ten accelerometer sensors is presented in a series of charts, each displaying varying levels and intensity of accelerometer values. The charts show

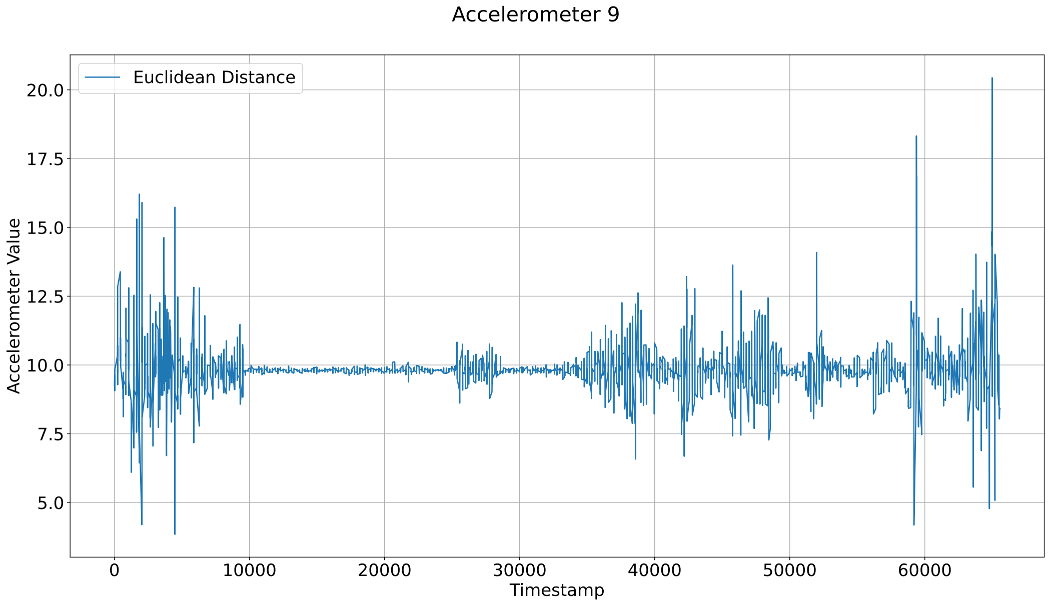

Figure 4.9: Chart of accelerometer sensor results - ninth patient

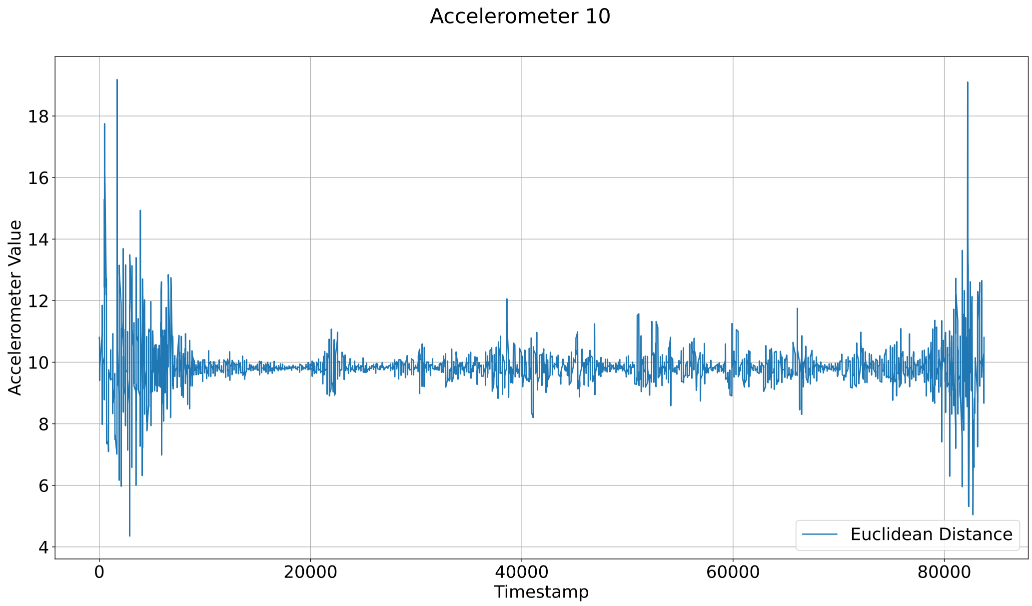

Figure 4.10: Chart of accelerometer sensor results - tenth patient

variability across sensors, with some registering more frequent spikes and others showing more consistent readings. Most charts show periods of intense activity, such as jumps or impacts during the Up-Down Hop Test, followed by rest periods or less intense movement phases. A consistent anomaly suggests a systematic issue in data recording or processing across all sensors. The timestamps increase linearly across all charts, indicating a continuous collection of data over time. The data is correlated with activity phases, with high spikes indicating the start of the test, less intense activity indicating a mid-phase, and a mix of calm and intense activity indicating the end phases of the test or activity. The consistent anomaly across the charts needs to be addressed to ensure data integrity for further analysis.

4.2 Gyroscope sensor results

This section present a comprehensive collection of graphs, related with a distinct part of a multifaceted narrative. These graphs track the Euclidean distance—representing the magnitude of angular velocity or orientation changes—against a series of time stamps, illustrating the dynamic response of the sensor during a series of physical tests.

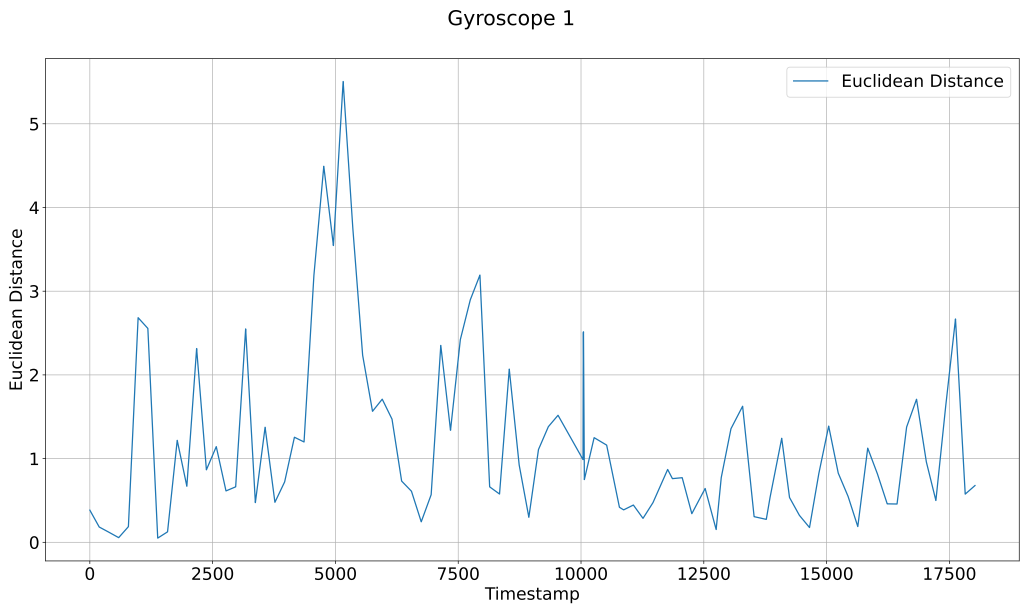

Figure 4.11: Chart of gyroscope sensor results - first patient

Figure 4.11 shows a line graph of Euclidean distance versus timestamp data from a gyroscope sensor during an Up-Down Hop Test. The data shows significant variability over time, with several peaks and troughs, suggesting uneven movements. Sporadic high peaking indicates moments of rapid movement or significant rotational change. Potential noise in the signal appears less extreme than the sharpest peaks, possibly indicative of smaller, more controlled movements. In summary, the chart provides a visual representation of movements detected by a gyroscope during an Up-Down Hop Test, but more context is needed to provide a detailed analysis.

Figure 4.12 shows the line graph of Euclidean distance measured by a gyroscope sensor on a second patient. The chart shows lower variability compared to the previous chart, with a maximum value just above 2.5, suggesting less intense movement

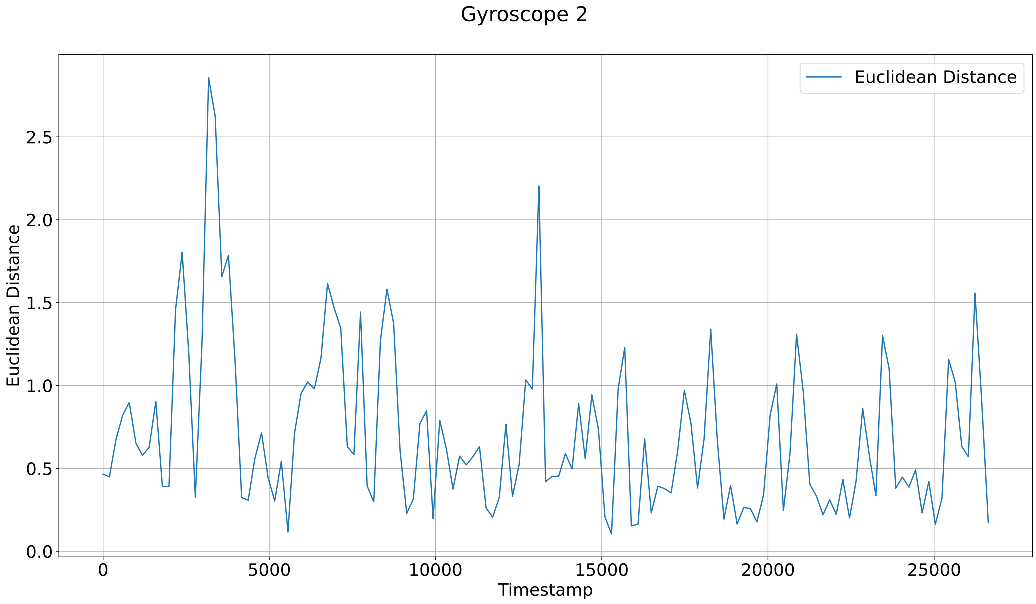

Figure 4.12: Chart of gyroscope sensor results - second patient

or rotations. The peaks are less pronounced and frequent, suggesting a lower intensity or more uniform motion during the hops. The graph exhibits a consistent oscillatory pattern with regular peaks and troughs, possibly corresponding to the rhythmic movements of hopping. The consistently lower Euclidean distance values suggest less dramatic movement, which could be of interest in analyzing the subject's performance or stability during the test.

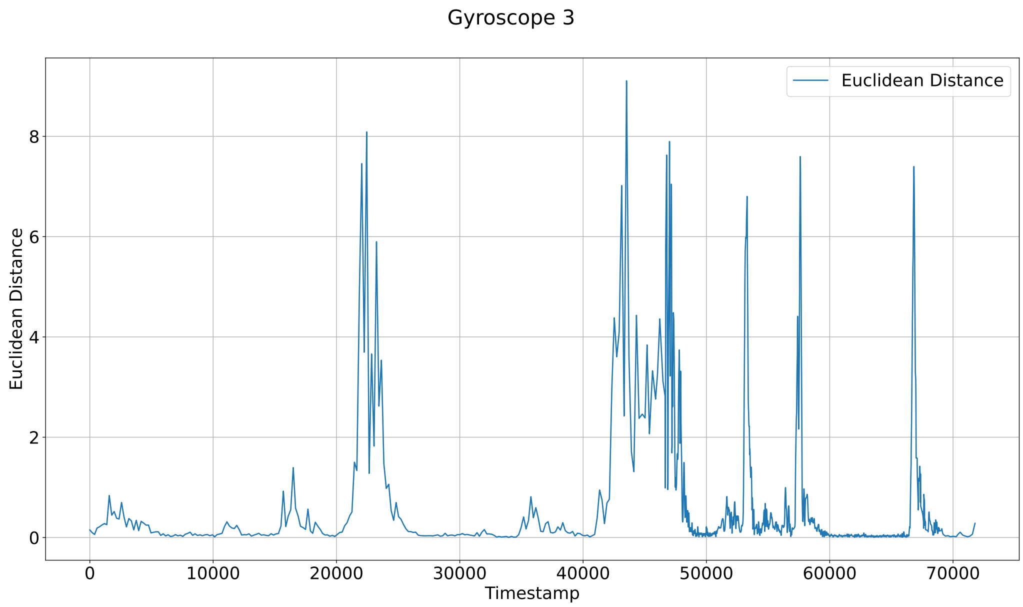

Figure 4.13: Chart of gyroscope sensor results - third patient

Figure 4.13 displays the Euclidean distance measured by a gyroscope sensor for a third patient. The graph shows higher peaks, indicating more significant movements or rotations detected by the gyroscope. Sharp spikes appear more frequently, suggesting a series of rapid and intense movements. The activity pattern is more intermittent, with long periods of low Euclidean distance punctuated by high spikes. Compared to the previous two graphs, this graph indicates more variance in movement intensity, possibly due to different test conditions, or individual performance. The data may be useful for analyzing quick changes in motion, detecting outliers in performance, or understanding sensor response to different movement intensities.

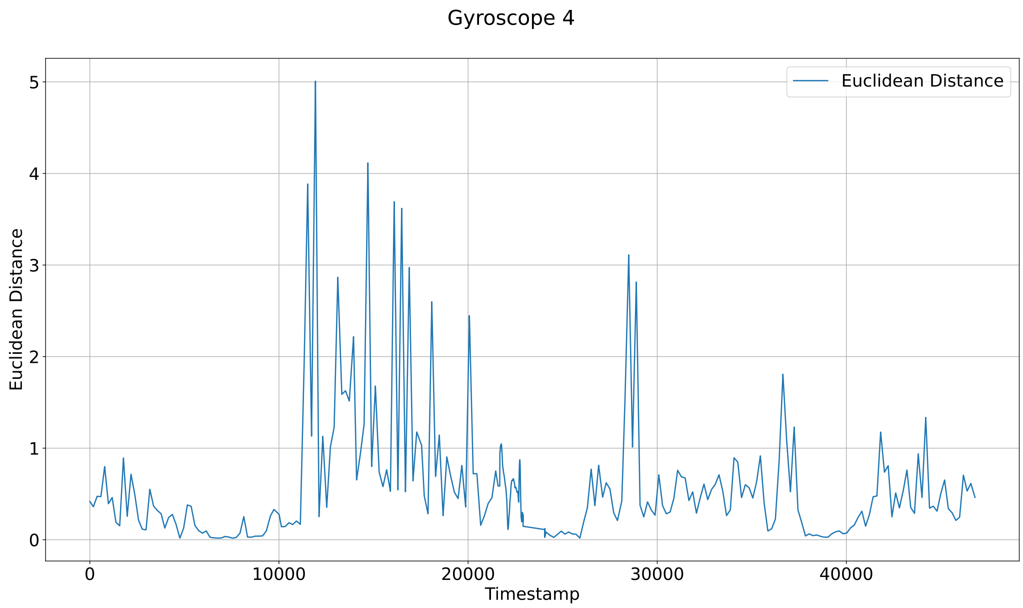

Figure 4.14: Chart of gyroscope sensor results - fourth patient

Figure 4.14 shows a moderate pattern of peaks and valleys in data collected on a test performed by a fourth patient . The graph's Euclidean distance values are generally below 5, suggesting less extreme movements. The consistent pattern of peaks and valleys aligns with repetitive motions like hopping. Activity phases include periods of calm activity and bursts of higher activity, possibly representing different phases or intensities of the Up-Down Hop Test. The graph may represent a balance between low-intensity and higher-intensity activity, possibly reflecting a state of moderate activity or a mix of different hopping intensities.

Figure 4.15 shows the Euclidean distance against timestamps for a fifth patient equipped with a gyroscopic sensor. It reveals activity patterns, with the distance hovering at lower levels, indicating less intense movements. A significant spike at the end of the time series may represent a sudden or large movement. The graph shows consistency with previous charts. The graph also shows more consistency in the lower range of Euclidean distance values, suggesting a steadier, more controlled

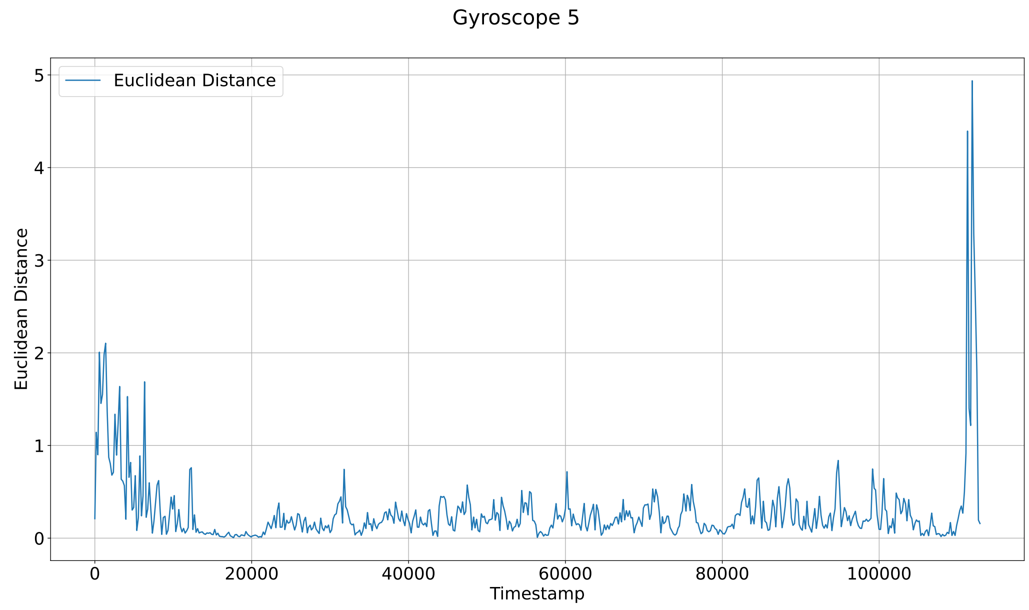

Figure 4.15: Chart of gyroscope sensor results - fifth patient

set of movements. Compared to Figure 4.14, this graph has fewer moderate spikes but ends with a dramatic increase in movement, possibly due to a final, intense phase, subject anomaly, or data collection issue.

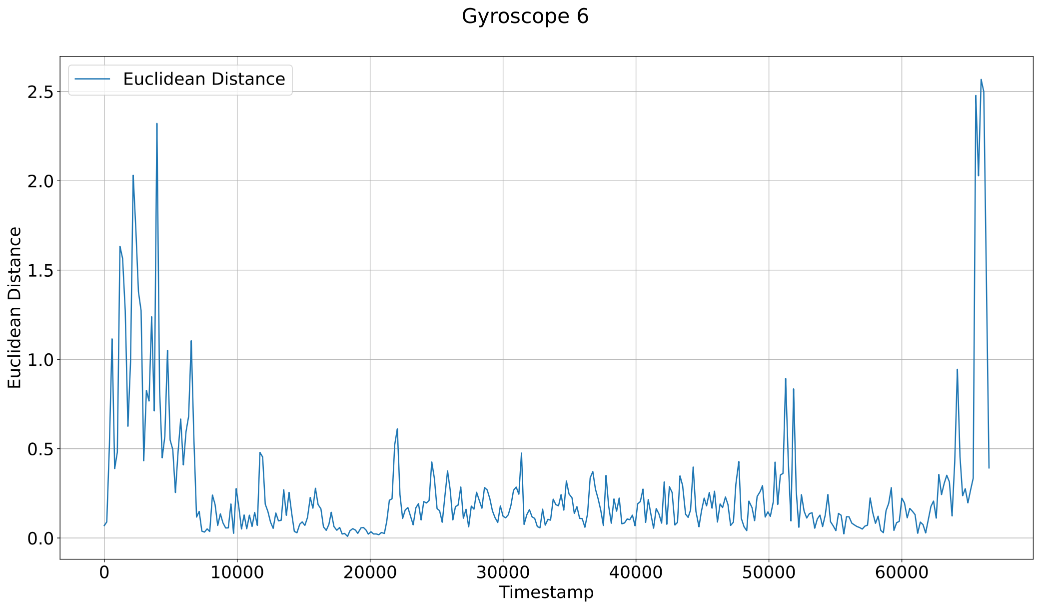

Figure 4.16: Chart of gyroscope sensor results - sixth patient

Figure 4.16 shows a pattern of Euclidean distances against timestamps from a gyroscope sensor. It shows varied intensities, with spikes indicating moments of higher movement or rotation. The graph shows lower Euclidean distance values with occasional spikes, with a significant spike toward the end. The graph ends with a high spike in Euclidean distance, possibly indicating an abrupt and significant movement. Comparing this graph to previous ones suggests an activity with less frequent but accordance in terms of high-intensity movements. The cause of these spikes could be a controlled session with occasional high activity bursts.

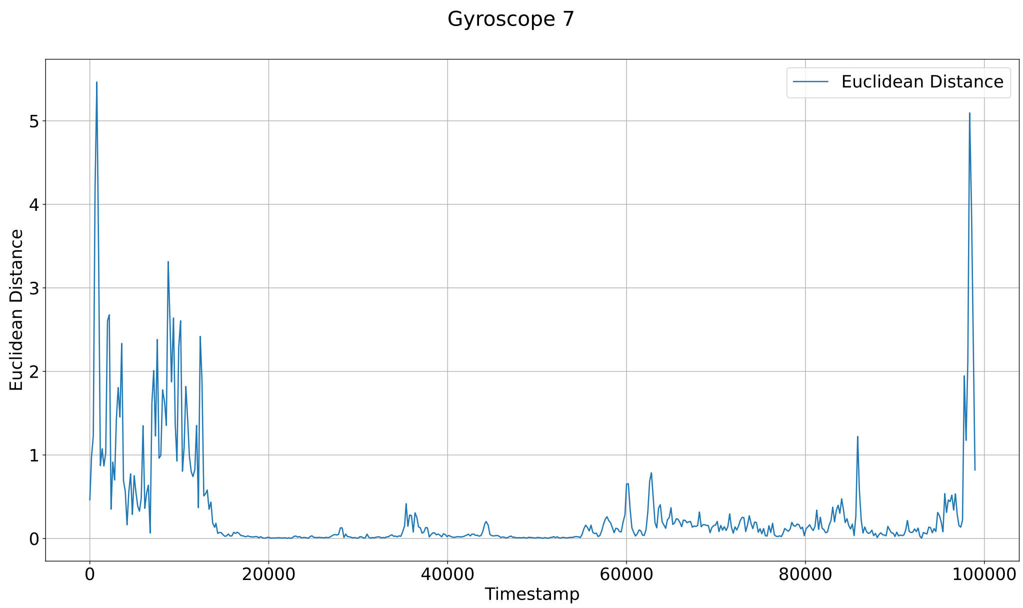

Figure 4.17: Chart of gyroscope sensor results - seventh patient

Figure 4.17 shows a series of Euclidean distance values from a gyroscope sensor against timestamps. The graph shows an initial high activity, followed by a period of lower activity. The Euclidean distance drops and maintains a moderate level with occasional spikes. A significant spike in Euclidean distance is observed at the end of the recorded data. The graph follows a pattern of intense activity followed by calmness, possibly as part of a warm-up and cool-down routine or a test examining reactions to stimuli. Correlating these movements with specific actions taken during the test is necessary to understand the data accurately.

Figure 4.18 shows a subdued range of Euclidean distance values from a gyroscope sensor plotted against timestamps. The graph shows low-intensity movements, regular small spikes, and consistent timestamp range from 0 to almost 14,000. The end behavior is consistent throughout the range, with no major fluctuations. The consistent yet low Euclidean distances could indicate a period of steady, moderate activity or a series of smaller, controlled movements. This consistent pattern could indicate a different type of activity in the testing protocol, a cool down phase after more intense exercise, or the sensor's precision and sensitivity in detecting subtle movements.

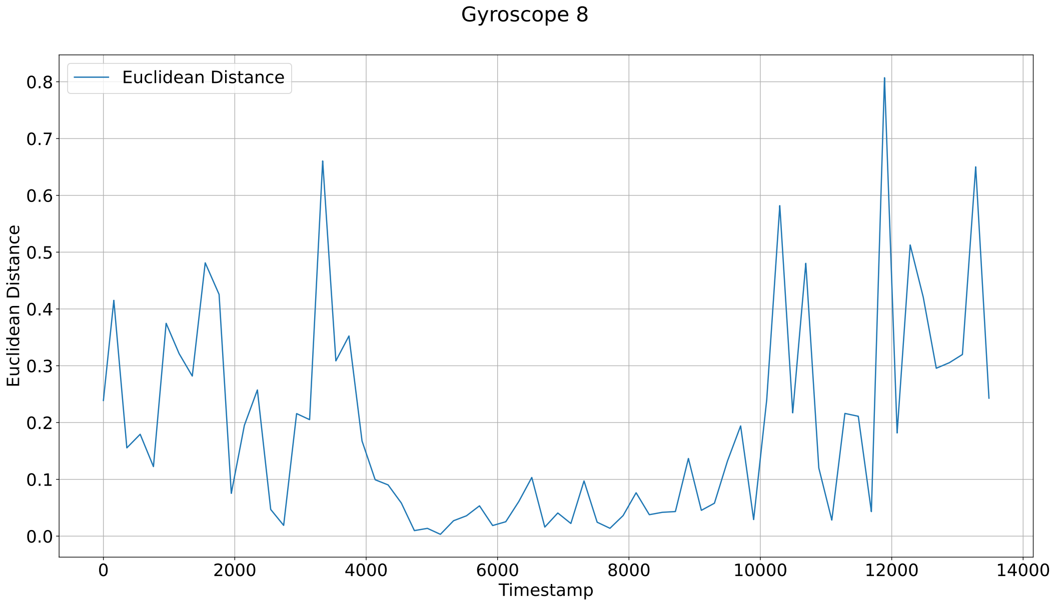

Figure 4.18: Chart of gyroscope sensor results - eighth patient

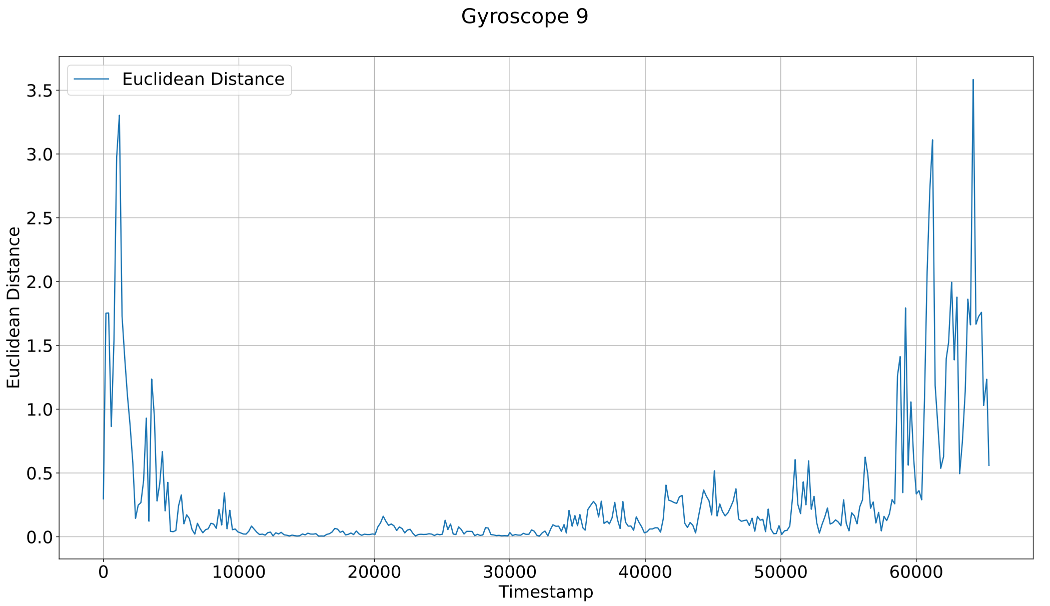

Figure 4.19: Chart of gyroscope sensor results - ninth patient

Figure 4.19 displays a pattern of Euclidean distance measurements from a gyroscope sensor on a ninth patient. It begins with high spikes indicating a quick series of movements, followed by lower levels. The graph then shows a gradual increase in activity, culminating in a series of high spikes towards the end. The graph ends with significant activity, suggesting an intense movement phase at the end of the recording period. The graph provides insights into the subject's movements, the test's structure, and the sensor's capacity to capture a wide range of motion intensities.

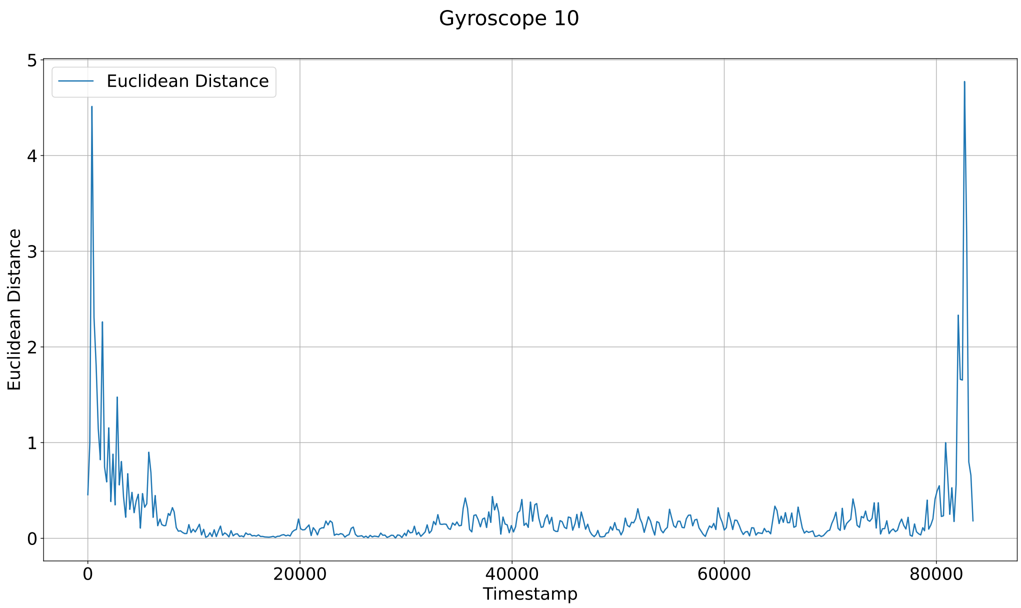

Figure 4.20: Chart of gyroscope sensor results - tenth patient

Figure 4.20 displays Euclidean distance data from a gyroscope sensor over a series of timestamps. The graph shows sharp spikes in Euclidean distance at the beginning, suggesting periods of intense movement or rapid angular changes. The graph levels out with minor fluctuations, indicating steadier, less dynamic movements. The significant spike at the end may represent an event or movement of particular interest, possibly indicating a concluding intense activity in a testing protocol or an abrupt reaction. The graph provides a visual storyline that might offer insights into the dynamics of movements captured by the sensor.

From 4.11 through 4.20 provides a detailed view of motion during a series of physical tests. The graphs show Euclidean distance measurements from a gyroscope sensor, plotted against timestamps, likely representing the sensor's readings during a physical activity test. Each graph exhibits peaks and valleys, corresponding to moments of activity (hops) and rest or less intense activity. The peaks vary in magnitude, suggesting differences in the intensity or range of motion for the hops. Some charts show consistent low-intensity activity with occasional high peaks, possibly indicating a period of rest or preparation followed by explosive movements. Several charts, especially later ones like 4.15, 4.16, and 4.19, end with a significant spike in the Euclidean distance, possibly denoting a final strenuous activity or a concluding action in the test. The continuity of the timestamp values suggests that the tests were part of a series, possibly capturing different phases or sessions of an ongoing experiment or monitoring over time.

4.3 Discussion

Correlating the data from accelerometer and gyroscope sensors gives a thorough picture of the hop test. During the Takeoff, the accelerometer data would show a big spike as the legs pushed off the ground. If the hop involves rotation or a posture shift, the gyroscope may report a change.

In the mid-air period, accelerometer readings would briefly normalize in the absence of ground contact, perhaps collecting solely gravity's force. Gyroscope data may show stability or continuing rotation based on body movements in the air.

During Landing, upon impact with the ground, the accelerometer would detect another spike. The gyroscope would most likely exhibit a quick change when the body adjusts to the landing. Analyzing the patterns across these sensors, particularly if they are time-synchronized, reveals not only the intensity and timing of each hop, but also the body's stability and technique. For example, a consistent pattern over hops indicates a regulated and repeatable action, whereas excessive fluctuation may indicate weariness or technique inconsistencies. Sharp spikes in gyroscope data may potentially indicate intentional rotational movements or a need for improved control to prevent excessive rotation during hops.

The present work started with the formulation of three research questions, presented in Chapter 1.

Regarding RQ1, "What are the benefits of evaluating the Up-Down Hop Test using wearable devices?", wearable devices can significantly improve the assessment of lower limb function in rehabilitation settings and sports performance monitoring. They could provide objective data on parameters like jump height, ground contact time, and symmetry between limbs, reducing reliance on subjective evaluation methods. The sensors and technology embedded in wearable devices enhance precision and reliability, leading to more reliable assessments. Remote monitoring and assessment are possible, allowing practitioners to monitor patients' progress outside clinical settings. The data collected can also help identify physical limitations, enabling tailoring preventative strategies. The technology also increases motivation and engagement, allowing for personalized rehabilitation and training programs. Automated data collection and analysis save time and resources for practitioners. The availability of mobile devices with such sensors enable the patient to perform multiple tests unobtrusively, with minimal effort and financially effective.

Concerning RQ2, "How do sensor-extracted features improve monitoring and evaluation of Up-Down Hop Test findings?", sensor-extracted features improve the monitoring and evaluation of Up-Down Hop Test findings by providing detailed, objective, and accurate measurements. These features include detailed bio mechanical analysis, objective and quantitative data, early detection of imbalances and asymmetries, progress monitoring over time, enhanced feedback for performance optimization, data-driven decision making, remote monitoring capabilities, and predictive analysis for injury prevention. Sensor technology eliminates subjectivity and variability associated with visual assessments and manual timing, leading to more reliable and consistent evaluations. Real-time data provided by wearable sensors can be used to correct technique, improve performance, and reduce injury risk. These features also enable remote monitoring, making them beneficial for continuous monitoring and individuals without regular access to clinical facilities.

Based on the RQ3, "Which factors contribute to the detection of patterns of lower limb unbalance?", lower limb unbalance can be identified by examining various factors affecting an individual's bio mechanical and physiological characteristics. Intrinsic factors include muscle strength and endurance, flexibility, neuromuscular coordination, proprioception, anatomical structure, previous injuries, age, and degenerative changes. Extrinsic factors include physical activity and training, environmental surfaces, occupational hazards, and lifestyle factors. Imbalances can lead to compensatory movement patterns, impacting gait and functional movements. Poor coordination, proprioception, and structural differences in bones, joints, and tissues can exacerbate unbalance. Age-related degenerative changes and repetitive movements in certain occupations can also contribute to imbalances. On an accelerometer data result (Figure 4.6) an unbalance pattern was visible at the end of the test. Although a single test, the idea that the measure of acceleration can lead to the detection of unbalance on lower limbs on the Up-Down Hop test is promising.

In addressing RQ4, "Which sensors expose the patterns that can identify body disbalance during the execution of the Up-Down Hop Test?", which concerns the identification of patterns indicating body disbalance during the execution of the Hop Test, it's noted that conditions of physical fitness can limit some individuals' ability to perform the test, as observed in the initial four subjects. For the remaining participants, analysis revealed a discernible pattern that commenced with an initial adaptation to the test, succeeded by a stabilization phase, and concluded with a detectable period of unbalance towards the test's end. The investigation found that both gyroscope and accelerometer sensors yielded similar outcomes in terms of identifying these phases. However, the accelerometer was particularly effective in pinpointing the unbalance pattern in subject number five. It is imperative to delineate these three distinct phases when analyzing sensor data to accurately interpret the results and assess balance and performance during the Hop Test. This segmentation is crucial for leveraging sensor technology in diagnosing and monitoring balance issues and overall physical condition in a clinical or sports performance context.

The study aims to develop a sensor-based method to analyze the Up-Down Hop Test results using smartphones. The method uses accelerometers, gyroscopes, and other sensors to measure and analyze movements during the test. This approach overcomes traditional subjective assessment methods, providing a more accurate, reliable, and efficient process. The goal is to enhance clinical assessments, rehabilitation outcomes, and understanding of an individual's lower limb functionality and stability. The research could provide real-time feedback, increase accessibility, and facilitate tailored rehabilitation plans. This could contribute significantly to physical therapy, sports science, and healthcare technology.

4.4 Limitations

When examining up-down hop test charts from accelerometers and gyroscopes, the sensor's location on the body can have a substantial impact on the data. For example, a sensor positioned on the foot will detect different accelerations and rotations than one placed on the waist or wrist. If the sensors' sample rate is too low, they may fail to effectively capture the rapid changes of the hop test, resulting in aliasing or an incorrect portrayal of the movement's frequency and intensity.

Sensors can detect noise, whether random or systematic. Gyroscopes can experience drift over time, in which the sensor's reported orientation deviates from the true orientation despite no actual movement. Without adequate calibration, the sensors may not deliver reliable readings. This includes zero-offset errors and scaling factors, which might impair data quality. External elements such as the type of surface the subject is hopping on or the footwear can influence test outcomes but are not directly monitored by the sensors.

Sensors only provide data from one specific viewpoint. Plus, human movement is complex, and hopping requires the coordination of multiple joints and muscles. The employed sensors may not catch all component of this intricacy. Finally, the raw data must be accurately understood. High peaks in accelerometer data may be attributable to actual vigorous movement or to distortions caused by sensor saturation or abrupt changes in direction.

To overcome the previously identified limitations, it is common to use multiple sensors placed at different body locations, high sampling rates, proper calibration routines, noise-reducing filtering methods, and sophisticated data analysis techniques.

Understanding the physical conditions of participants before conducting tests that utilize sensor technology is essential. This step ensures individuals are physically capable of safely engaging in activities required by the test, such as those in a hop test. Sensors are highly effective in gathering data but do not have the capability to assess a person's health status, recognize potential risks, or identify physical limitations on their own. A detailed pre-test evaluation of a participant's physical condition is therefore crucial. It ensures that all participants can safely perform the test activities and that the data collected reflects their actual performance capabilities. This approach not only safeguards the well-being of the participants but also enhances the integrity and applicability of the research findings.

Chapter 5

Conclusion

The aim of this work was to access the feasibility of using sensors present on a mobile device to register 'Up-Down Hop' test results. A state-of-the-art revision was performed to answer the main question "What systems exist that can measure the results of the Up-Down Hop test using sensors". A mobile application was developed that enables the user to register a patient, perform a test, and visualize the results obtained form the sensors.

Distinct patterns were observed in each sensor through meticulous analysis of detailed sensor data during the 'Up-Down Hop' test. The gyroscope exhibited device orientation and angular velocity fluctuations, mirroring the movements performed during the test. Similarly, the accelerometer depicted changes in acceleration, capturing both steady movements and sudden impacts or movements. This information is pivotal for comprehending the interplay between device dynamics and environmental factors throughout the Up-Down Hop test.

Upon analyzing gyroscope data during the 'Up-Down Hop' test, the following observations were made. Activity varied across trials, indicating different degrees of rotational movement. Some tests exhibited heightened gyroscope activity, signifying substantial fluctuations in device orientation. Conversely, in other instances, activity levels were more subdued, suggesting minor movements or periods of rest. Fluctuations such as spikes and dips in the data denoted rapid movement or abrupt shifts in device orientation.

In terms of accelerometer data many trials depicted the device at rest or moving at a constant velocity, as evidenced by values approximating 9.8. Significantly higher or lower acceleration values in specific trials indicated instances of acceleration or deceleration. Abrupt deviations in the data, such as spikes and dips, implied sudden movements or impacts during the test.

These conclusions highlight the intricate interplay between device dynamics (as captured by the gyroscope and accelerometer) during the Up-Down Hop test. Understanding these patterns is crucial for comprehending the behavior of the device in different scenarios and environments.

In terms of future work, the derived data can be processed further to enable automatic or at least semi-automatic information about the conditions of the patient, such as physical-related status. To enable such classification, one would have not only to collect sensor data, but also have an expert clinician log patient's details that are relevant, enabling cross-validation. For further exploration of data one could employ convolutional neural network (CNNs) approaches.

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