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Wearable Electronic Device for Comparative Evaluation of Human Gait in Controlled and Standardized Environments

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Abstract— This project presents the development of a portable system designed to analyze gait patterns in healthy individuals, simulating alterations characteristic of knee osteoarthritis through controlled movements. The project responds to the need for accessible tools for biomechanical analysis in non-clinical settings, overcoming the mobility and cost limitations associated with conventional technologies. Real-time data are collected and processed using motion sensors and an integrated system to identify biomechanical differences between standardized gait patterns and pain simulations. The methodology was based on VDI 2206, following a spiral design approach to wearable device development. Progressive iterations were implemented with validations in controlled and standardized environments, allowing comparative evaluation of human gait using integrated sensors and biomechanical data processing techniques. The results highlight the system's effectiveness in capturing variations in tilt angles and validating altered gait patterns, with potential applications in rehabilitation and early diagnosis. This system represents an innovative, practical, and cost-effective solution to study human gait and improve the quality of life of people affected by biomechanical disorders.

Keywords: Wearable device, Human gait, IMU sensor, Butterworth filter, VDI 2206 methodology.

I. INTRODUCTION

Walking is a fundamental activity for a person, as it can reflect their overall health status [1]. Alterations in how a person walks can lead to problems throughout their life, such as pain, discomfort, limitations, or even disability. These alterations can be due to various internal factors, such as joint problems, or external factors like the physical environment and/or lifestyle [2]. Studying human gait is essential to identify anomalies and develop possible solutions to mitigate their long-term effects [3].

Osteoarthritis is a common degenerative joint disease characterized by the gradual deterioration of cartilage, causing pain, stiffness, and altered walking patterns, often resulting in an antalgic gait [4]. It is a leading cause of disability, particularly among older adults. In low-income countries, limited access to specialists and rehabilitation services exacerbates the impact of such conditions [5]. Conversational agents—AI-based virtual assistants—offer a promising solution by supporting patients with pain management, exercise, medication adherence, and mental health guidance. These tools can help address healthcare gaps, promote early detection of symptoms, and reduce the disease burden of underserved populations [6].

Despite technological advances in clinical monitoring, current tools often provide limited and less accessible analysis of gait patterns in non-clinical environments [3]. This makes early detection and continuous monitoring of biomechanical alterations affecting human gait difficult [7]. The lack of portable, low-cost solutions that integrate ergonomic technology and real-time analysis systems represents a significant limitation in managing this condition [8].

As a possible solution to this scenario, the present project proposes developing a portable ergonomic diagnostic system to detect gait patterns in healthy individuals and later simulate characteristic alterations of knee osteoarthritis through controlled exaggeration of specific pain-related movements. This approach aims to facilitate the study of abnormal patterns, supporting the development of personal, low-cost diagnostic and rehabilitation strategies. It holds great potential to control the impact of this condition on mobility and quality of life in the future.

A. Problem Situation

As previously mentioned, walking is an essential activity for our physical health. However, alterations in walking patterns, such as those caused by knee osteoarthritis, can significantly affect mobility and quality of life, potentially leading to a risk of disability throughout one’s life. This problem affects many older adults around the world and, increasingly, younger individuals due to external factors such as being overweight or premature joint degeneration [9].

Understanding gait biomechanics is essential, as it allows us to identify abnormal movement patterns in people, which are often related to diseases [10]. Without this understanding, developing personalized solutions for treatment and early diagnosis becomes more difficult. For example, the lack of accessible tools to analyze a person's gait in real time limits healthcare professionals’ ability to perform early interventions or design effective rehabilitation programs. This gap affects patients and healthcare systems, which must face higher costs due to complications from this condition [11].

The implementation of portable technology for gait analysis has emerged as a promising alternative to overcome this difficulty. Devices such as inertial sensors (IMUs) record kinematic parameters in real environments, making it easier to perform objective and continuous movement evaluations. Integrating these systems with signal processing algorithms and biomechanical models enables the early detection of gait anomalies, thereby improving clinical and personalized decision-making for each patient's treatment [12].

Moreover, this technology benefits healthcare professionals and enhances patient confidence by providing more detailed information about their condition. Through intuitive user interfaces, individuals can monitor their progress and see the current state of their condition, allowing them to adhere more effectively to rehabilitation programs. This dramatically improves therapeutic outcomes and reduces osteoarthritis progression, promoting greater autonomy and quality of life in those who suffer from this disease [13].

B. Scope and Limitations

1) Scope: This project aims to design and implement a portable system to analyze human gait patterns in healthy individuals and then simulate the characteristic alterations of knee osteoarthritis through controlled exaggerations. The system will include the following:

Features:

- A portable device based on inertial motion sensors (IMUs), which capture and record biomechanical gait parameters in real time.
- Embedded software that processes the collected data, applies a digital filter, and generates detailed reports on movement patterns.
- A simple and intuitive visualization interface for the results, adapted to non-clinical environments.

Work Volume:

- Development and integration of an ergonomic system composed of hardware (sensors and mechanical structure) and software for data processing.
- Experimental validation of the system through real tests with captured samples from healthy individuals, simulating pain through exaggerated and controlled alterations in non-clinical environments.
- Generation of a detailed report documenting the detected biomechanical differences.

Factors Considered:

- Only gait patterns related to the lower limbs will be analyzed, focusing on parameters such as knee flexion and extension.
- The analysis will be limited to young and older adults without other comorbidities that could significantly influence gait biomechanics.

2) Limitations:

Aspects Not Considered:

- The analysis of joints beyond the lower limbs will not be included.
- The development of a device for use in sports or high-performance activities is not considered.

Feasibility and Resources:

- The project will be developed using commercially available inertial motion sensors (IMU 6050) and open-source platforms to ensure low cost and high accessibility.
- Access to testing facilities, laboratory equipment, and analysis software provided by the educational institution is available.
- Qualified human resources are available for the system's design, development, and validation.

C. Expected benefits

The proposed system will compare gait patterns in individuals with healthy knees by simulating the characteristic alterations of osteoarthritis through controlled exaggerations. The purpose is to analyze and understand the biomechanical differences associated with this condition. This analysis will contribute to understanding how alterations in human gait affect biomechanics, providing valuable information for developing rehabilitation strategies.

The portable ergonomic diagnostic system performs real-time gait inspection in non-clinical environments, facilitating the collection of accurate and reliable data in non-clinical contexts and daily life. This makes it a more accessible and practical tool for studying gait biomechanics in healthy and affected individuals, providing essential data for ergonomic research and clinical applications.

II. Literature Review

Knee osteoarthritis significantly affects a person's walking ability and biomechanical movement patterns [14][15]. Recent studies indicate the role of portable technologies in improving diagnosis and continuous monitoring [16]. In this context, wearable electronic devices have become promising tools for real-time gait analysis, as they offer portability, low cost, and robustness in controlled environments [17]. These systems use IMU sensors, which are composed of accelerometers and gyroscopes, to accurately capture kinematic data without limiting the natural movement and fluidity of walking. This literature review highlights key advancements in gait analysis and their relevance to the design of portable systems for comparative evaluation, emphasizing measurement accuracy, data processing, and future clinical applications.

This study analyzed knee motion in healthy individuals using an interesting portable system, highlighting the importance of establishing a baseline to evaluate biomechanical deviations in affected populations. The results showed that osteoarthritis significantly alters flexion and extension angles during walking, resulting in irregular patterns that affect overall stability and mobility [7].

Furthermore, emerging literature on healthy and osteoarthritic knee phenotypes based on the Coronal Plane

Alignment of the Knee (CPAK) classification is vital for understanding how anatomical variations affect human gait, an essential aspect for developing medical and surgical interventions.

People with disabilities are at high risk of inactivity, which can lead to health issues. This study found that walking longer distances is linked to better physical ability and well-being, highlighting the importance of encouraging walking to improve health outcomes in this population [1].

Knee osteoarthritis (KOA) is a common degenerative joint disease in people over 45. It is caused by cartilage deterioration and leads to symptoms like pain, stiffness, and swelling. Traditional diagnosis using X-rays, MRI, and CT scans is often time-consuming. To improve efficiency, this study applied deep learning models—CNN, AlexNet, ResNet34, and ResNet50—to predict KOA severity. A deep stack ensemble approach achieved a high accuracy of 99.71% [5].

Clinical gait analysis traditionally requires expensive lab setups with high-resolution cameras and force platforms. This study explores a more portable and cost-effective alternative using a combination of Microsoft Kinect and Inertial Measurement Units (IMUs). While each sensor alone has limitations, their combined use improves reliability by complementing each other’s weaknesses. IMUs effectively capture gait kinematics, while the Kinect detects gait asymmetries between joints [18].

Also, this study explored a complementary approach using vision-based motion capture to analyze neurodegenerative diseases. Although their focus does not include osteoarthritis, their research highlights how integrating more advanced sensors facilitates the early detection of gait abnormalities. This element is key to developing our proposed system for this project [3].

III. METHODOLOGY

The development of advanced gait analysis systems follows a structured design methodology to ensure reliability, adaptability, and modular integration. The VDI 2206 standard (Fig. 1) systematically designs mechatronic systems; in this context, iterative development cycles integrating mechanical, electronic, and computational components are prioritized [19]. This methodology benefits from a structured process that improves accuracy, scalability, and real-time adaptability.

Accurate assessment of human gait in controlled environments requires a comprehensive understanding of the various subsystems that comprise the gait analysis system. Each subsystem is designed to capture specific aspects of human movement, from joint and muscle dynamics to the body's overall biomechanical responses. Integrating these subsystems facilitates a comprehensive assessment of biomechanical parameters and improves diagnostic capabilities. This enables the customization of medical interventions according to the specific needs of each individual. Each subsystem will be described below.

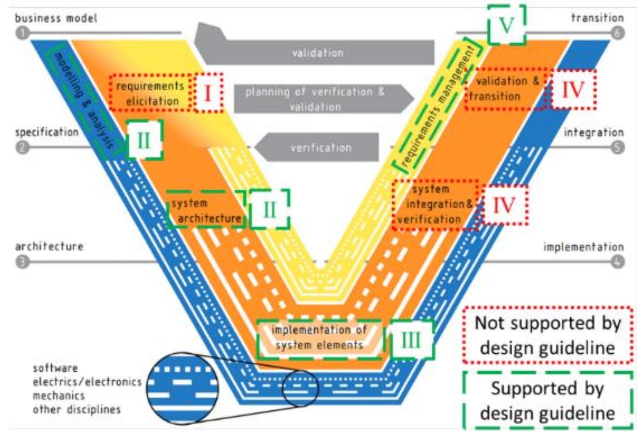

Fig. 1 Design Methodology 2206 [19].

1) Mechanical Subsystem: An acrylic enclosure was used for the mechanical subsystem that will protect the Arduino Mega. This will be mounted on a specifically designed harness for hip attachment. The design will ensure the device fits firmly against the user's body. This will provide stability during gait monitoring and allow for natural, interference-free movement. Additionally, the Arduino will be connected to three IMU (Inertial Measurement Unit) sensors strategically placed on the hip, knee, and instep. This allows for the precise capture of motion data at key points on the leg. The placement of these sensors has been determined through biomechanical studies to optimize motion tracking and minimize signal noise. This ensures high-fidelity data collection. The choice of acrylic for the enclosure provides both durability and lightness, protecting the electronic components from impacts and environmental conditions. The enclosure design also includes ventilation slots to prevent overheating and secure latches to stabilize the internal components during movement.

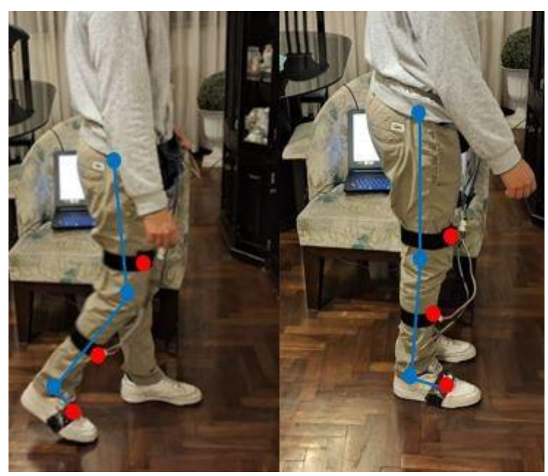

Fig. 2 Sensor placement.

2) Electronic subsystem: The cables establish the connections between the Arduino and the IMU sensors, ensuring the system's flexibility and portability. In addition, a multiplexer was integrated to manage communication with the three IMU sensors correctly. Fig. 3 presents a schematic diagram of the device's electronics, where the connections used in the components and the system's general architecture can be observed.

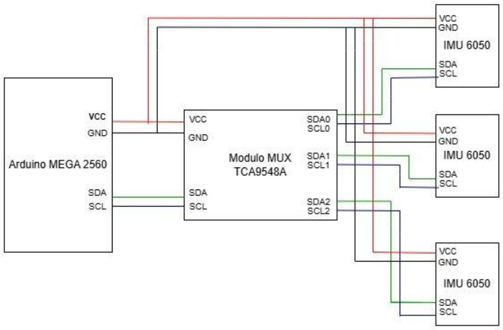

Fig. 3 Schematic diagram of the connections in the embedded system.

The I2C protocol was used to implement the system correctly. In this case, the Arduino played the master role, and the sensors were slaves. This facilitates data transmission efficiently and accurately, optimizing the system's synchronization and performance. Fig. 4 shows the sensors' connection to the embedded system and the wiring configuration.

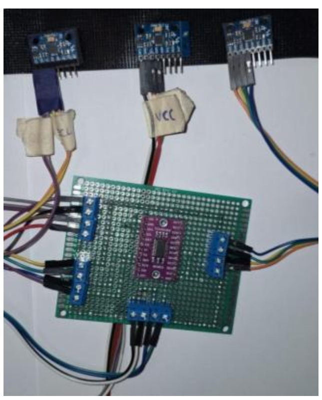

Fig. 4 Prototype of the electronic subsystem.

In addition, an Eagle PCB board was developed to reduce electrical noise and improve signal quality. This guarantees the system's more stable and reliable operation. Fig. 5 shows the circuit board layout and the routing of the connections.

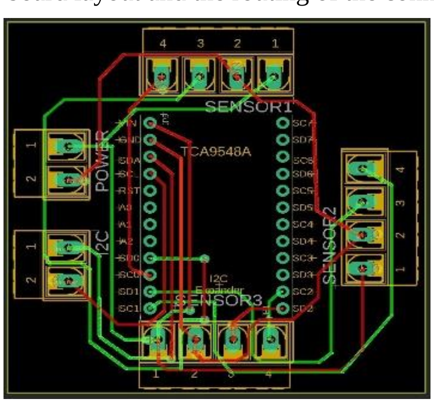

Fig. 5 Schematic design of the PCB.

3) Computer subsystem:

A comparative analysis was made between the Butterworth and extended Kalman filters to determine the most appropriate filtering technique. This comparison was intended to identify the method that offered the best noise removal and accurate signal estimation. Figs. 6 and 7 compare the signals with and without the extended Kalman and Butterworth filters.

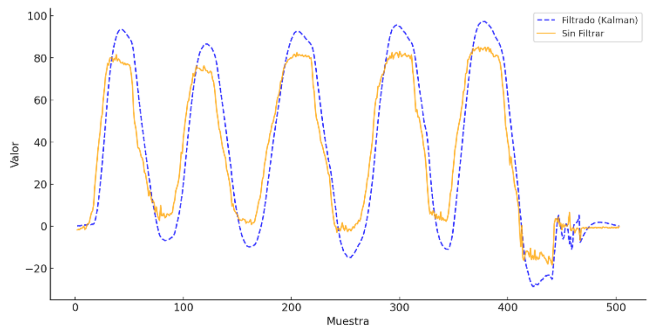

Fig. 6 Comparison of Filtered and Unfiltered Data Using the Extended Kalman Filter.

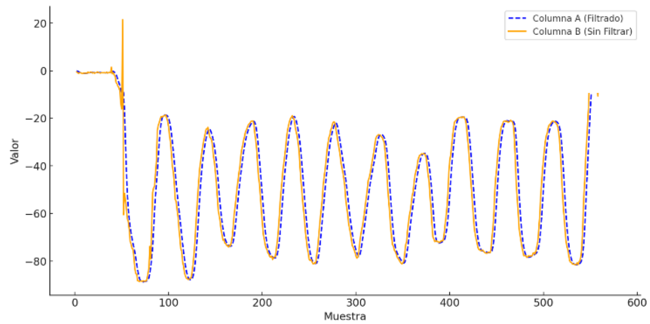

Fig. 7 Comparison of Filtered and Unfiltered Data Using the Butterworth Filter.

Different metrics, such as root mean square error (RMSE), mean absolute error (MAE), and root mean square value (RMS), were used to measure the effectiveness of each filter. These metrics provided a quantitative basis for estimating the accuracy and reliability of the filtered signals.

	MAE	RMSE	RMS	
			Filtered	No filtered
Filtro Kalman	11.07	12.96	52.83	48.12
Filtro Butterworth (2° orden)	5.13	7.41	53.3	53.37

Fig. 8 Comparison of Performance Metrics.

Experimental results indicated that the Butterworth filter is superior to the extended Kalman filter for this system. It shows better noise attenuation and better preservation of the original signal.

On the other hand, Fig. 9 shows the block diagram that summarizes the sequence of operations in implementing the Butterworth filter. This is applied to smooth the sensor data, providing a frequency response as flat as possible in the pass band to eliminate high-frequency noise. This preserves the signal's integrity and ensures that only relevant gait data is retained. This improves the accuracy of the motion analysis. As seen in the block diagram, the implementation is organized in steps to ensure a systematic approach to noise reduction and signal integrity [20].

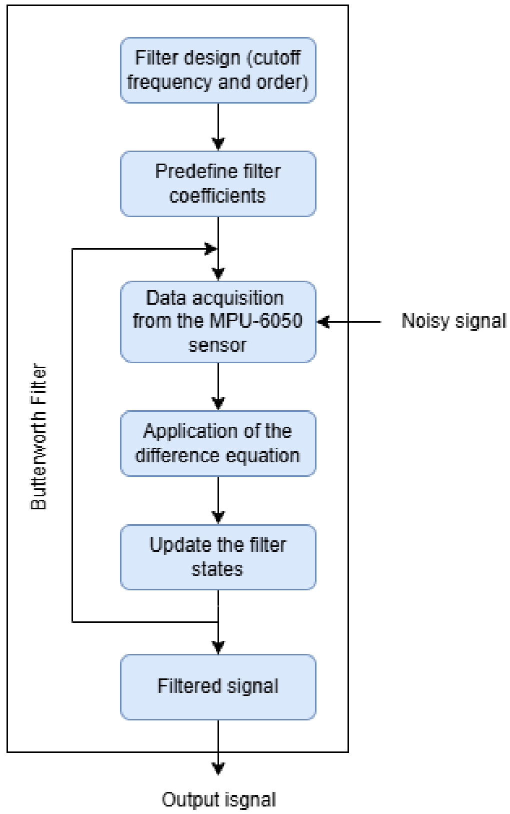

Fig. 9 Block diagram of the computer subsystem.

Here's an introduction to a series of steps in a block diagram:

a) System Initialization

- Set up the serial connection to send data to the monitor.
- Initiate the I2C communication and configure the MPU6050 sensor.
- Verify the sensor connection. If it is successful, display a confirmation message; if it fails, display an error.
- Set the sensor's sampling frequency to 500 Hz.

b) Start Main Loop

- The loop begins, which will run continuously.

c) Time Interval Control

- Check if the time elapsed since the last reading is greater than or equal to the interval of 2 ms (500 Hz).
- If the interval is correct, proceed to the next stage. If not, wait until the necessary time is met.

d) Sensor Data Reading

- Read the accelerations on the ax, ay, and az axes of the MPU6050 sensor.

e) Application of the Butterworth Filter (for each axis)

- For the X-axis:

$$filter_{ax} = b_0 ax + b_1 x[1] + b_2 x[2] - a_1 x[0] - a_2 x[1] \quad (1)$$

- For the Y-axis:

$$filter_{ay} = b_0 ay + b_1 y[1] + b_2 y[2] - a_1 y[0] - a_2 y[1] \quad (2)$$

The coefficients b_0, b_1, b_2, a_1, and a_2 of a second-order Butterworth filter determine its frequency response. They are calculated from the cutoff and sampling frequencies, using the bilinear transformation to move from the s-plane to the Z-plane. The coefficients in the numerator control the gains, while those in the denominator adjust the stability and frequency response. Proper selection of these coefficients is essential to meeting design specifications and ensuring filter stability.

f) Buffer update

- Shift the values in the buffer (history) of each axis to store the most recent filtered value:

$$x[2] = x[1],\ x[1] = x[0],\ x[0] = filter_{ax}$$

$$y[2] = y[1],\ y[1] = y[0],\ y[0] = filter_{ay}$$

$$z[2] = z[1],\ z[1] = z[0],\ z[0] = filter_{az}$$

g) Calculation of tilt angles

- Calculate the tilt angles on the X axis (ac_ang_x) using the filtered acceleration on the X, Y, and Z axis.

$$ac\_ang_x = arctan\left(\frac{filter_{ax}}{\sqrt{{filter_{ay}}^2 + {filter_{az}}^2}}\right) x \frac{180°}{\pi} \quad (3)$$

- Calculate the tilt angles on the Y axis (ac_ang_y) using the filtered acceleration on the X, Y, and Z axis.

$$ac\_ang_y = arctan\left(\frac{filter_{ay}}{\sqrt{{filter_{ax}}^2 + {filter_{az}}^2}}\right) x \frac{180°}{\pi} \quad (4)$$

h) Display the calculated angles

- Print ac_ang_x and ac_ang_y.

i) Update the time of the last reading

- Assign the current time to lastTime to control the interval in the next reading cycle.

j) Repeat process

- Return to step c) and continue with the next cycle, keeping the filter running to process data continuously.

Finally, after filtering the data using the Butterworth filter, proceed to export the processed information to a CSV file using MatLab.

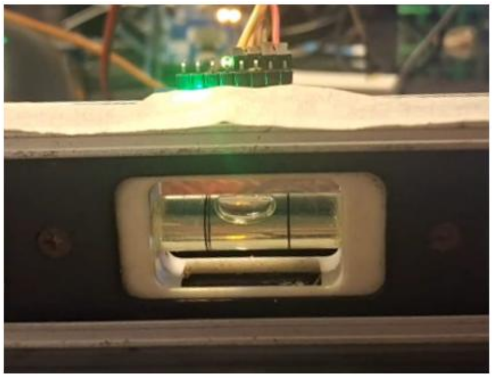

Fig. 10 Sensor compared with a bubble level

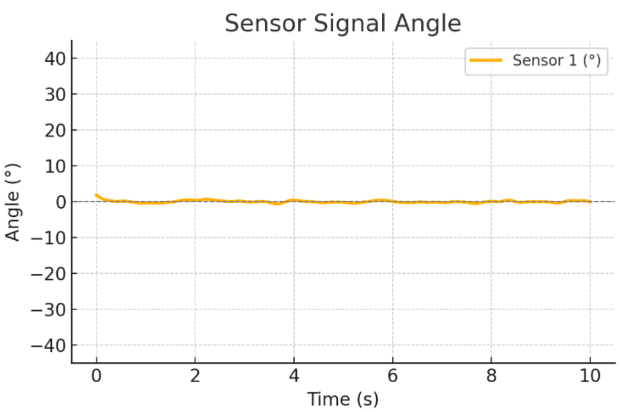

Fig. 11 Validation of the sensor using a bubble level

IV. RESULTS

The experimental test results were obtained with the system implemented on the test subject's leg. In this initial stage, the behavior and mobility of the leg in the resting state were analyzed to validate the correct operation of the system under controlled conditions and without active movement.

Fig. 12 shows the initial tests performed to evaluate the detection of the leg tilt angle at each sensor. At this stage, controlled movements such as flexion, extension, and slight rotations were performed to capture a wide range of angular displacements. The IMU sensors recorded real-time data on the orientation changes. This allowed assessment of tilt angles and smoothness of movement. The collected information was then processed to analyze signal stability, detect possible noise, and validate the accuracy of the angular motion tracking. These preliminary tests also helped to establish baseline references for further dynamic gait evaluations.

Fig. 12 Leg movement at rest

Fig. 13 shows the variations of the angles recorded when moving the leg consecutively and randomly. These initial tests established a baseline for more complex experiments such as standardized walks and pain gait simulations. The recorded angular variations provided information on the consistency of the sensor measurements, helping to identify possible signal deviations or inconsistencies. Analysis of these fluctuations made it possible to evaluate the system's responsiveness to dynamic movements and determine its reliability in capturing biomechanical changes in real time. These data constitute a reference to compare the deviations observed in pathological gait conditions.

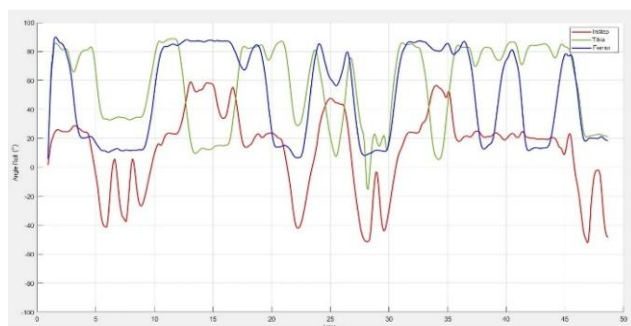

Fig. 13 Graph of leg movement at rest

Fig. 14 shows the system implanted in the test subject's leg during a standardized gait. Data was captured in real time, allowing the leg displacement to be recorded and analyzed. The system comprises IMU sensors strategically placed at the hip, knee, and instep. It continuously monitors angular variations and movement patterns. The system configuration allowed accurate tracking of joint dynamics, providing information on gait characteristics such as stride length, cadence, and asymmetry. The recorded data were also processed to evaluate the system's accuracy in detecting biomechanical deviations. In addition, the data are essential for applications in rehabilitation and clinical diagnostics.

Fig. 14 Monitoring system implementation.

Fig. 15 shows the graph corresponding to the obtained displacement pattern. This graph shows the variations in leg movement over time. Key parameters such as angular displacement, velocity, and acceleration are also highlighted. The recorded data provide information on the subject's gait dynamics. This allows different movement patterns to be identified as potential irregularities and biomechanical deviations. Furthermore, the displacement curves are a reference for comparing normal and altered gait conditions.

Fig. 15 System tests in standardized walking.

Fig. 16 presents the graph corresponding to the human gait of the same subject simulating pain during walking. This analysis allows us to observe how the gait pattern varies in response to the simulated conditions. The recorded data reveal altered stride length, cadence, and joint angles, reflecting compensatory mechanisms such as reduced loading on the affected limb or asymmetric movement patterns. These variations provide valuable information about how pain influences motor control and stability. This provides a basis for future studies on pathological gait and rehabilitation strategies. Furthermore, comparing this graph with previous standard gait data allows us to identify key biomechanical deviations associated with discomfort or injury.

Figs. 16 and 17 show that the lean angles differ significantly between standardized gait and gait simulating pain. The main variation is that the instep sensor records a greater lean angle when simulating pain. At the same time, the sensor placed on the femur detects a decrease in the angle of inclination. These differences reflect the subject's biomechanical adaptations in response to the pain simulation.

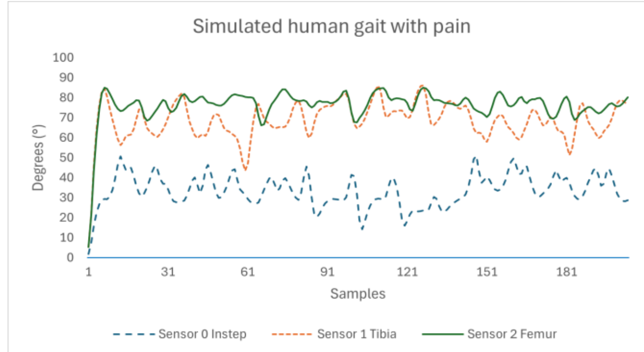

Fig. 16 System tests in walking, simulating pain

V. Conclusion

The implemented system demonstrated its ability to analyze gait patterns accurately, identifying significant differences in tilt angles between standardized walking and pain simulations, which validated its effectiveness in non-clinical environments. Additionally, the combination of inertial sensors and digital filtering algorithms, such as the Butterworth filter, enabled the acquisition of reliable, noise-free data essential for real-time biomechanical analysis. Moreover, the system's portability and ergonomic design ensure its practical use in various clinical, educational, and research contexts, making it accessible and cost-effective.

Furthermore, the results obtained in this project establish a solid foundation for developing advanced tools for the early diagnosis and personalized rehabilitation of individuals with osteoarthritis or other conditions affecting gait. By addressing a technological need in gait biomechanics, this project also contributes to public health by offering an efficient and cost-effective solution for monitoring and analyzing movement patterns. Ultimately, the presented system represents a significant advancement in integrating portable technology for human gait analysis, paving the way for future improvements in diagnosing and treating biomechanical disorders.

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