A new approach for human gait evaluation through both computer vision and wearable inertial measurement devices

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Abstract. Accurate evaluation of human gait is essential for the timely detection of disorders and gait retraining. However, traditional methods have limitations in terms of precision, cost, and time. The integration of inertial sensors and computer vision systems offers automated, objective, and more detailed analysis. Our proposal is based on the collection of data from inertial measurement units connected via Bluetooth, which automatically estimate the range of motion, calculate velocity, step length, gait cycle, and cadence. Additionally, from each video frame obtained, the positions of the lower body are extracted using convolutional neural networks. A second estimation of the range of motion is then performed and processed using machine learning algorithms trained on features extracted from a database of approximately 2,300 images of healthy adults aged 20–25 years. This classification identifies the 8 stages of the gait cycle, achieving a minimum F1 Score of 0.89 ± 0.01 for mid-swing, a maximum of 0.96 ± 0.01 for mid-stance, and an overall accuracy of 0.936 $\pm$ 0.001. Both estimations are combined to generate new range of motion values, reducing uncertainty in separate measurements. The results are displayed through a graphical interface for an intuitive user experience. This implementation has the potential to generate low-cost tools that could be used by various specialized professionals as an additional resource to facilitate accurate diagnoses.

Keywords: Machine Learning Algorithms · Computer Vision · IMU · Human Gait

1 Introduction

Gait analysis is an essential tool for identifying changes or anomalies in movement patterns, which can be indicative of neurological, musculoskeletal, or systemic diseases [1]. However, conventional methods present limitations in precision, cost, and time, making their implementation in clinical settings challenging [2–4].

To address these limitations, various technological tools have been developed for movement monitoring, such as inertial sensors, optical motion capture systems, and computer vision. On one hand, computer vision stands out for its precision in controlled environments but can be affected by occlusions and variations in lighting [5]. On the other hand, inertial sensors offers high sampling frequency and portability; however, their reliability can be compromised by accumulated errors due to signal integration and data drift, affecting precise movement estimation over time [6]. This work proposes an integrated system that combines both computer vision and inertial sensors to overcome their individual limitations, providing more accurate measurements, leading to a practical and automated tool that facilitates patient diagnosis and monitoring.

2 Methods

One of the main goals of the system is to provide accurate joint range of motion measurements. To achieve this, we integrated two systems with different estimation processes, as seen in Figure 1.

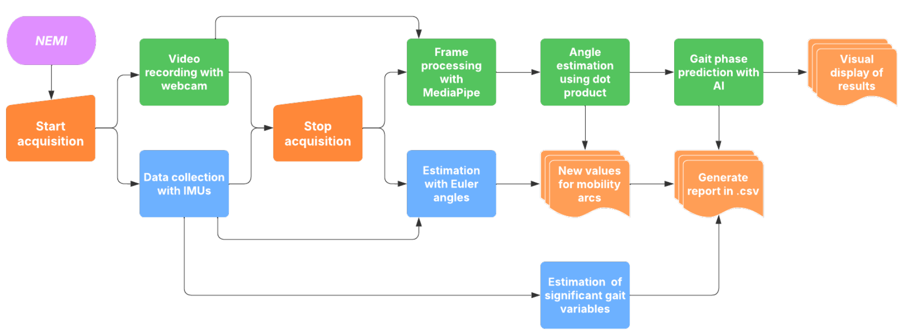

Fig. 1. Flowchart of our system; Nemi

First, using the interface developed in Unity, the user starts the gait cycle acquisition by simply pressing a button. At this point, the data (accelerations, Euler angles and time) obtained through the Bluetooth connection of the six *WT901BLE* IMU sensors is saved. Simultaneously, a video is recorded using the webcam until the user stops the acquisition, then the video is analyzed by artificial intelligence algorithms.

Secondly, with the estimation of joint range of motion, the wearable system converts the Euler angles into radians and constructs ZYX rotation matrices for each joint. Subsequently, the relative angles are calculated by multiplying the corresponding matrices.

After this, the captured frames are processed using *MediaPipe Pose* for the estimation, 10 key reference points. Each joint angle is calculated using the dot product, which takes as input the relative distances to the point of interest. *Example*, for the knee, the points of the shoulder and ankle are also used. Once both estimations with their respective timestamps are obtained, an average is calculated to generate new values and synchronize the measurements.

To take advantage of the benefits of each system, the features obtained from the IMUs are used to calculate the person's speed by integrating the accelerations measured, projecting them onto a common reference system, and averaging them. The cadence is calculated by counting the number of gait cycles per unit of time, using peaks in the angular signal to detect initial contact events. The step length is estimated from the relationship between speed and cadence.

The vision system uses significant features extracted from each frame to predict with a support vector machine (SVM) model the gait phase during which the data is collected. Therefore, we can compare the obtained results with ranges reported in the literature to identify values that fall outside the expected norms. These values are highlighted in a .csv file, while a video displaying the results is shown to make the information more intuitive for the user.

3 Artificial vision for dynamic estimation of joint range of motion during human gait

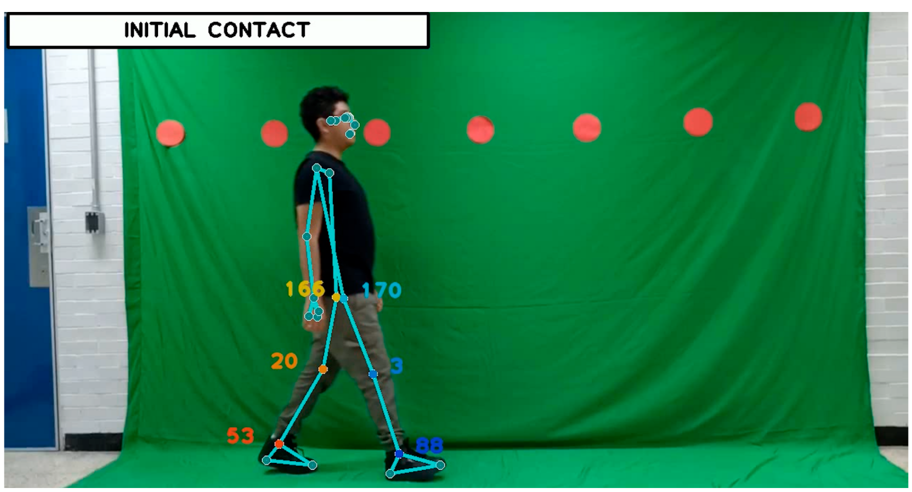

Fig. 2. Example of the processed gait analysis video

To enhance visualization and the understanding of the results, we integrated the *MediaPipe Pose* skeleton tracking model with their specific range of motion values displayed next to the joints in the same color and a phase prediction shown in the top-left corner of the screen (see Fig. 2).

To achieve this, we compared measurements taken with goniometers and range of motion estimations obtained by processing images from one of our databases. The absolute error derived from this comparison was 6.44%.

Finally, videos of individuals performing a complete human gait cycle were recorded at 244 fps, from which 2300 frames were extracted and processed to categorize them into the different gait phases, recovering key characteristics to train an SVM model, achieving an F1 Score ranging from 89% for mid-swing to 96% for pre-swing, with an overall accuracy of 94%, demonstrating the model's high reliability in classifying gait phases.

4 An IMU based wearable system to improve dynamic estimation of data in human gait phases

Once the IMU sensor data is recorded in CSV files, the ranges of motion are calculated and then smoothed using a Butterworth low-pass filter. Then the joint range of motion over time is plotted (see Fig 3), facilitating the visualization of the behavior of the hip, knee, and ankle angles throughout the gait cycle, allowing for dynamic movement analysis.

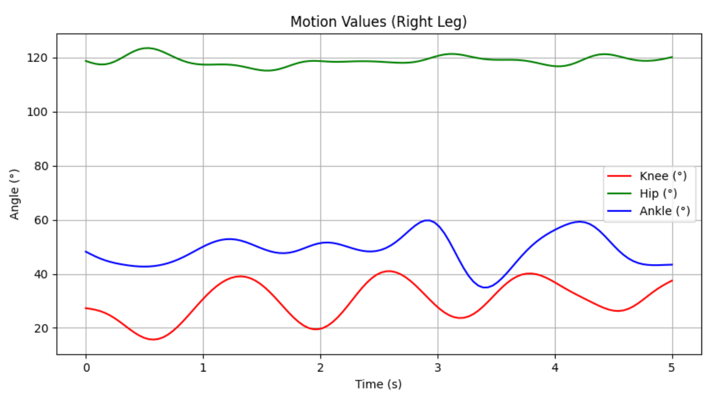

Fig. 3. Mobility arcs of each joint of the right leg

The IMU data are also used to calculate key parameters of human gait, such as speed, cadence, and stride length, which, along with the integration of results from the computer vision system, are combined into a table, showing important values to provide a comprehensive representation of human gait behavior over time, facilitating its analysis through the integration of both systems.

5 Discussion

The integration of computer vision and sensor-based systems has demonstrated significant advantages in terms of cost reduction and accessibility. By avoiding the need for specialized equipment, this approach makes gait analysis more accessible compared to traditional methods, which often rely on expensive tools like motion capture cameras.

One of the main achievements of this integration is the improved estimation of joint range of motion in the lower limbs, computer vision system obtained an absolute error of 6.4% and the use of IMU sensors reduced even more uncertainty by providing another estimation, which enhanced the reliability of the results.

The trained SVM model achieved an accuracy of 94% in classifying gait phases, demonstrating its robustness in predicting gait dynamics. This, combined with the implementation of dynamic parameter calculations such as gait speed, cadence, and step length, enables a comprehensive and detailed analysis of human gait. Providing an intuitive visualization of results and a detailed report of the human gait cycle in .csv format.

6 Conclusion and perspectives

The SVM model for gait phase classification achieved an accuracy of 94%, indicating reliable predictions. By integrating IMU data, the system reduced uncertainty and provided a more robust analysis of dynamic gait parameters. The implementation in Unity offers an intuitive and accessible interface for specialists, eliminating the need for high-cost equipment. This work has the potential to generate a low-cost tool capable of facilitating precise gait diagnostics. Future efforts should focus on extending the system's capabilities to analyze more complex or pathological gait patterns.

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