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# Quantitative Gait Analysis of an Amputee Using Inertial Measurement Unit: A Case Study

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ABSTRACT

This study presents a quantitative evaluation of lower limb joint motion using inertial measurement units (IMUs) for gait analysis. IMU sensors were attached to six lower limb segments of thirty-two healthy participants to capture knee and ankle kinematics during one gait cycle. A Butterworth filter was selected as the optimal preprocessing method to reduce noise and enhance signal clarity. The joint angles obtained from IMUs were compared with those from the Kinovea motion analysis system, with synchronization performed on a single gait cycle for each subject. Agreement between both systems was examined using the intraclass correlation coefficient (ICC), yielding values of 0.822 (right knee), 0.881 (right ankle), 0.797 (left knee), and 0.773 (left ankle), indicating moderate to excellent consistency. A case study involving an amputee further highlighted reduced motion range and gait asymmetry in the prosthetic limb, particularly during the swing phase. These findings suggest that IMUs provide a practical and cost-effective alternative for gait assessment in non-laboratory environments.

## INTRODUCTION

Gait analysis is a fundamental tool in biomechanics and clinical assessment, providing essential information about human locomotion, rehabilitation progress, and prosthetic evaluation. Traditional motion capture systems and video-based analysis software, such as VICON system, are widely recognized for their accuracy; however, their high cost, reliance on laboratory environments, and complex setup limit their practical use in everyday applications.

In recent years, inertial measurement units (IMUs) have emerged as a promising alternative for motion analysis. IMUs are portable, cost-effective, and capable of capturing kinematic data in real-world conditions. Despite these advantages, IMU-based measurements face several challenges, including signal noise, sensor drift, and the need for appropriate filtering techniques to ensure accuracy. Previous research has explored IMU applications in joint angle estimation, yet questions remain regarding their reliability compared to conventional systems.

The objective of this study is to evaluate the accuracy and reliability of IMU-based joint angle estimation during gait analysis. Specifically, knee and ankle joint angles obtained from IMU sensors are compared with those derived from the Kinovea motion analysis system in healthy participants. Preprocessing of IMU signals was optimized using filtering techniques, and the degree of agreement between the two systems was statistically

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assessed through the intraclass correlation coefficient (ICC). Additionally, a case study involving an amputee subject was conducted to highlight differences in joint kinematics and gait asymmetry. The findings of this research highlight the potential of IMUs as a practical and affordable tool for gait assessment, particularly in non-laboratory and clinical settings, offering a valuable alternative to traditional motion capture systems.

Recent studies have investigated the use of inertial measurement units (IMUs) for gait analysis as an alternative to conventional motion capture systems. IMU-based approaches provide advantages in portability, affordability, and ease of use, enabling applications outside laboratory environments (Tao et al., 2020; Clermont et al., 2020). However, challenges remain, including signal drift, calibration issues, and the need for filtering techniques such as Butterworth and Kalman filters to reduce noise and improve accuracy (Salarian et al., 202; Abbas et al., 2021).

Several works have validated IMU systems against gold-standard optical motion capture or video-based tools, reporting moderate-to-excellent agreement in kinematic measurements such as joint angles, stride length, and step timing (Esposito et al., 2019; Tedesco et al., 2021). Nonetheless, limitations persist, particularly regarding stride length estimation, sensor misalignment, and the scarcity of studies involving clinical populations such as amputees (Wang et al.,2022). These gaps emphasize the need for research that evaluates IMU-based gait analysis in both healthy and impaired individuals, while comparing performance with widely available reference tools such as Kinovea.

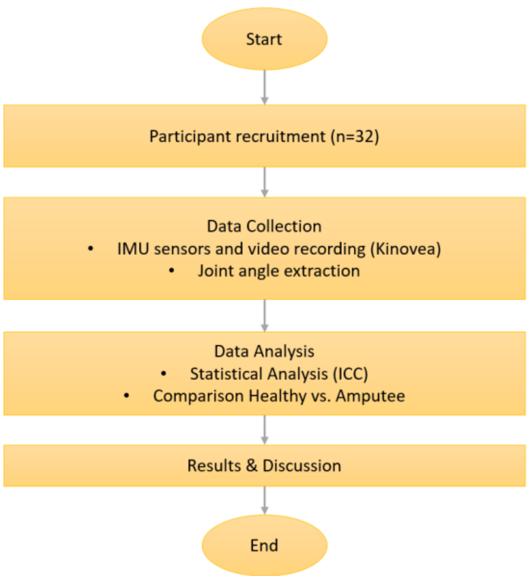



**Fig. 1** Workflow of the research

## MATERIALS AND METHOD

This section describes the design of the research methodology developed to achieve the study objectives. Inertial measurement units (IMUs) were employed to capture gait data from healthy participants, with a case study conducted on a lower-limb amputee. For validation, IMU-derived joint kinematics were compared with measurements obtained from the Kinovea motion analysis system in healthy individuals. The methodology is structured to present the framework for data collection, preprocessing, analysis, and evaluation procedures used to determine the accuracy and effectiveness of the proposed approach.

### Participants

Participants in this study were divided into two groups: healthy individuals (Table I) and individuals with lower-limb amputations (Table II). A total of thirty-two healthy participants were recruited, while one case study involved a unilateral lower-limb amputee.

**Table I** Demographic information of healthy participants (N=32)

| Variable | Mean ± SD | Range |
|---|---|---|
| Age (years) | 24.3 ± 6.2 | 15–46 |
| Height (cm) | 168.4 ± 9.8 | 155–197 |
| Body Mass (kg) | 71.2 ± 18.8 | 46–140 |
| Gender | 19 Female<br>11 Male | — |

**Table II** Case study demographic information

| Participant | Gender | Age (years) | Height (cm) | Body Mass (kg) |
|---|---|---|---|---|
| Healthy | Male | 55 | 163 | 80 |
| Transfemoral Amputee | Male | 53 | 160 | 86 |

### Materials and Instruments

In this study, Delsys inertial measurement units (IMUs) were employed to capture gait parameters. A total of six IMU sensors were strategically positioned on the lower limbs to ensure comprehensive and precise data acquisition. In addition, the Kinovea software was utilized in conjunction with a laptop and a high-resolution video camera to record motion data. The integration of IMU sensors with an optical motion tracking system enabled cross-validation of gait measurements, thereby enhancing the robustness and reliability of the overall movement analysis.

### IMU Sensor Placement

To capture lower-limb kinematics, six (6) inertial measurement unit (IMU) sensors were attached to standardized anatomical landmarks. Sensors were positioned at the mid-thigh, mid-shank, and dorsum of the foot on both the left and right limbs. This placement ensured accurate tracking of knee and ankle joint motion while minimizing measurement artifacts. The detailed placement of each sensor is summarized in Table III.

**Table III** Placement of the sensor

| Sensor ID | Placement Region | Body Side |
|---|---|---|
| S1 | Middle of Anterior Thigh | Front (Left Limb) |
| S2 | Middle of Anterior Shank | Front (Left Limb) |
| S3 | Middle of Anterior Foot | Front (Left Limb) |
| S4 | Middle of Anterior Thigh | Front (Right Limb) |
| S5 | Middle of Anterior Shank | Front (Right Limb) |
| S6 | Middle of Anterior Foot | Front (Right Limb) |

### Data Collection Protocol

Six sensors were used to collect IMU data. Each lower extremity (right and left) had three sensors: one on the thigh, one on the shank, and one on the foot. Measurements were performed at a sampling rate of 100 Hz. The raw IMU files (before cleaning) contained signals irrelevant to the study, such as EMG data and inconsistent column labeling, meaning column names were unclear or unrelated. To address this issue, Microsoft Excel was used to manually clean the data. After manual cleaning, Python code was used to systematically process the data and extract the desired signals (such as motion angles, acceleration, or rotation).

Videos were recorded using an iPhone 16 Pro camera. The footage was filmed from the side, showing clear joint movement. The software used for video analysis was Kinovea (version 0.9.5). Four joint angles were manually measured from the video: the right knee (RK), the left knee (LK), the right ankle (RA), and the left ankle (LA). These measurements were made by placing markers on anatomical landmarks on the body, i.e., specific locations on the joints used as reference for drawing the angles. Only one gait cycle was selected for each participant for each joint angle as shown Fig.2

The geometric relationships between the lower extremity segments (such as the thigh, leg, and foot) were used to calculate joint angles, based on data collected from the IMUs. To calculate the ankle angle, the orientation of the sensor on the foot was combined with the sensor on the shin (the part between the knee and ankle). To calculate the knee angle, the orientation of the sensor on the thigh was combined with the sensor on the shin. Curves were obtained that demonstrate how the knee and ankle angles change over time during a gait stride.

Several signal processing techniques were used on both the IMU data and the Kinovea software. The goal was to remove noise from the signals and obtain curves that realistically and logically represent motion (i.e., reflect the actual shape of the joints' motion). Filtering techniques included the Butterworth low-pass filter, the median filter, the Savitzky-Golay filter, and the moving average filter. All of these techniques helped reduce signal drift and high-frequency noise. Importantly, they did not alter the shape of the original motion curves, preserving the joint motion shape virtually unchanged. Ultimately, however, the Butterworth filter was chosen for the final analysis because it has a high ability to preserve the signal fidelity and realistically capture the biomechanical properties of the movement.

Synchronization is the next step after data filtering. This is because the IMU and Kinovea data were recorded at different sampling rates and on different timescales (i.e., they did not start at the same time). To synchronize, a distinct event in the gait cycle was manually identified in both data types. This event served as a reference point to standardize the timing of the two signals, such as heel strike or toe-off.

The acceleration values obtained from the IMU sensors mounted on the thigh and shank, the relative joint angles (ϕ) as shown in Fig. 2 were computed using the following equations;

$$(ax_1/az_1)\ atan2 = \alpha \qquad (3.1)$$
$$(ax_2/az_2)\ atan2 = \beta \qquad (3.2)$$
$$(\alpha + \beta) -180 = \phi \qquad (3.3)$$

Here, ax1ax1 and az1az1 represent the acceleration components along the x- and z-axes of the thigh sensor, while ax2ax2and az2az2 represent the acceleration components along the x- and z-axes of the shank sensor. These values were then used to calculate the relative knee joint angle during gait.

Signal processing was applied to enhance the quality of the recorded signals and to ensure accurate representation of joint motion. Several filtering methods were evaluated, such as the median filter, Savitzky–Golay filter, and moving average filter, all of which contributed to noise reduction and drift minimization. However, the Butterworth low-pass filter was ultimately selected, as it preserved the physiological characteristics of the gait cycle while effectively eliminating high-frequency noise.

The purpose of using the Intraclass Correlation Coefficient (ICC) as a statistical test is to measure the agreement between the results of the IMU and Kinovea systems. Therefore, the ICC value was calculated for each side of the body separately: the joint angles on the left side and the joint angles on the right side. When comparing the IMU results with the Kinovea (reference) data, the ICC results were as follows: 0.877 for the left side, meaning a good reliability degree, and 0.78 for the right side, meaning a medium to good reliability. This indicates that the estimation of joint angles using the IMU is reliable compared to the reference system.

At the end of this study, a graphical representation (graph) of the joint angle data was created after processing (e.g., filtering and smoothing). A separate curve was then drawn for each joint (e.g., right knee, left ankle, etc.), and each graphic showed a comparison between the two systems (IMU and Kinovea). These graphs were also used in a case study comparing a healthy person and a lower-limb amputee. The goal was to understand the asymmetries between the two sides and to detect range-of-motion limitations in the amputee.

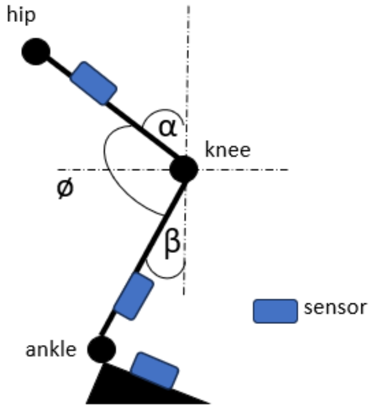



**Fig. 2** Measured joint angle and sensor placement.

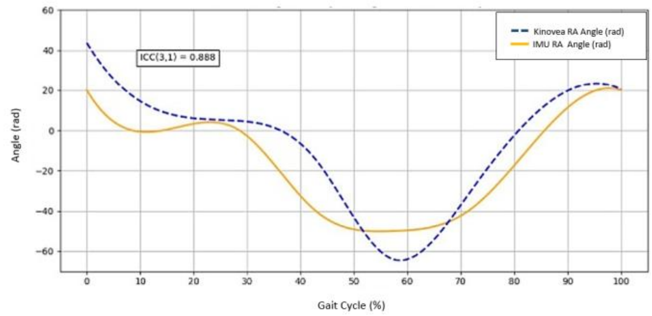
## RESULT AND DISCUSSION

### Joint Angle Measurement Using IMUs

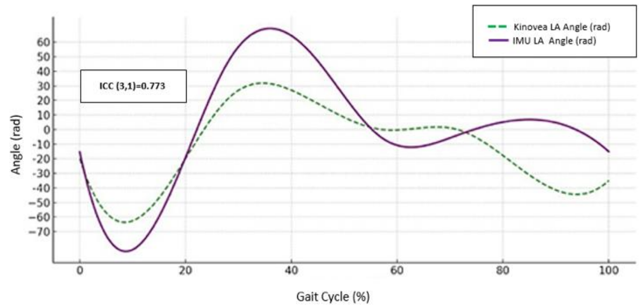
IMU data were collected from thirty healthy participants, with sensors placed on the thigh, shank, and foot of both lower limbs to capture knee and ankle joint motion. After acquisition, the raw signals were manually cleaned to retain only the X- and Z-axis accelerometer values relevant for angle computation. A Butterworth low-pass filter was then applied to suppress noise while preserving the biomechanical integrity of the gait signals, and one complete gait cycle was selected for each participant to ensure consistency. Joint angles for the right knee, right ankle, left knee, and left ankle were computed using custom Python algorithms, revealing inter-subject variations in amplitude and angular trajectories that reflect natural gait differences. The final smoothed joint angle curves, corresponding to one gait cycle per joint, are presented in Fig. IV and serve as the foundation for subsequent comparison and validation.

### IMU vs. Kinovea Joint Angle Comparison

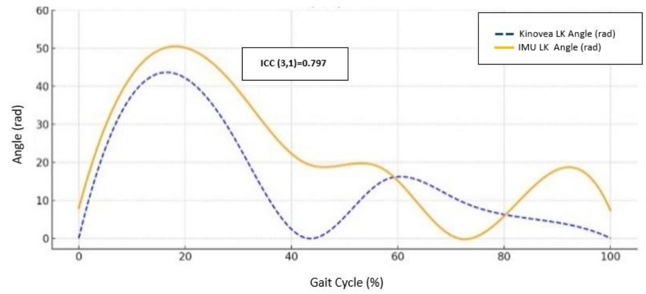
To evaluate the accuracy and agreement of the IMU-based system with the Kinovea video analysis method, joint angle measurements were compared using one representative gait cycle from the same participant. The analysis focused on the flexion and extension of the knee joints as well as the motion of the ankle joints. For each joint, IMU-derived and Kinovea-derived angles were plotted on a time-normalized scale (0–100% of the gait cycle), with the signals smoothed using a Butterworth low-pass filter to minimize noise while preserving motion characteristics. The Intraclass Correlation Coefficient (ICC (3,1)) was computed to quantify the level of agreement between the two systems, yielding ICC values of 0.822 (right knee), 0.881 (right ankle), 0.797 (left knee), and 0.773 (left ankle). These results indicate moderate to good reliability, with ankle joints exhibiting slightly higher consistency compared to knees. Although minor amplitude discrepancies were present—likely due to differences in measurement modalities and noise sensitivity—visual inspection of the superimposed curves confirmed that both systems captured comparable patterns of joint motion, as illustrated in the comparison plots presented in Fig. 4.



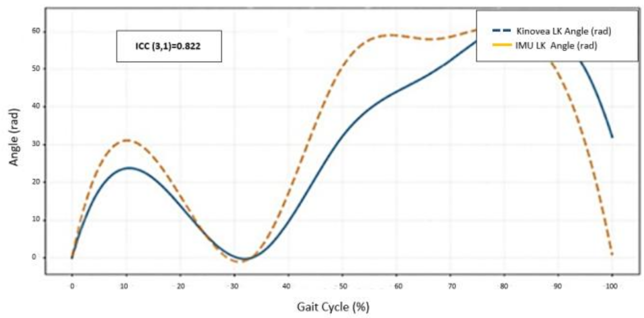

(a)




(b)




(c)



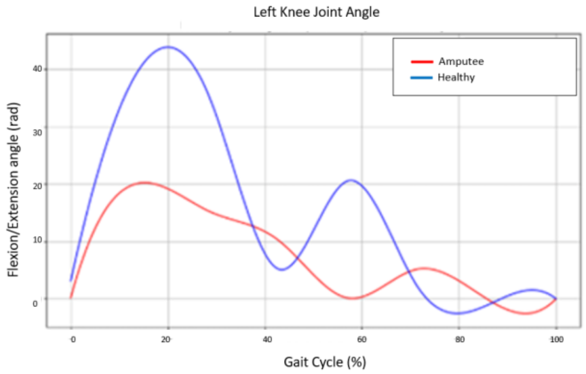

(d)

**Fig. 4** Comparison of a single participant's IMU and Kinovea joint angle measurement for (a) right ankle (RA), (b) left ankle (LA), (c) right knee (RK) and (d) left knee for a gait cycle.

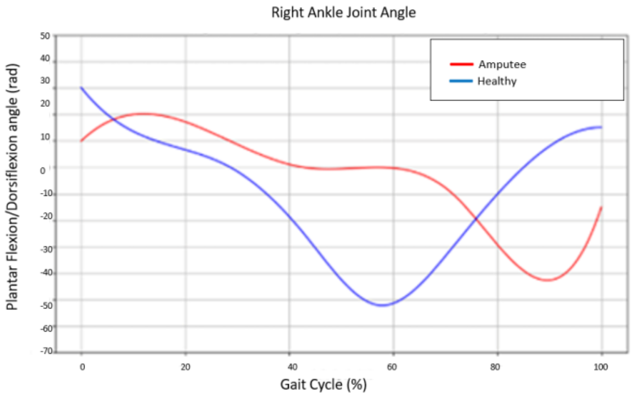
### A Case Study – Healthy vs. Amputee Comparison

A case study was conducted to examine gait asymmetry and joint motion limitations by comparing a healthy participant with a lower-limb amputee. To reduce the influence of confounding factors such as weight, height, and age, both individuals were selected to be comparable in these characteristics. IMU sensors were used to collect gait data, focusing on knee and ankle joint angles during one representative gait cycle. The analysis revealed notable asymmetries between the prosthetic and intact limbs, particularly during the swing and pre-swing phases, where the prosthetic limb exhibited reduced naturalness and restricted motion compared to the healthy participant. These findings highlight the potential of IMU-based analysis in identifying gait deviations and functional limitations in amputee populations.

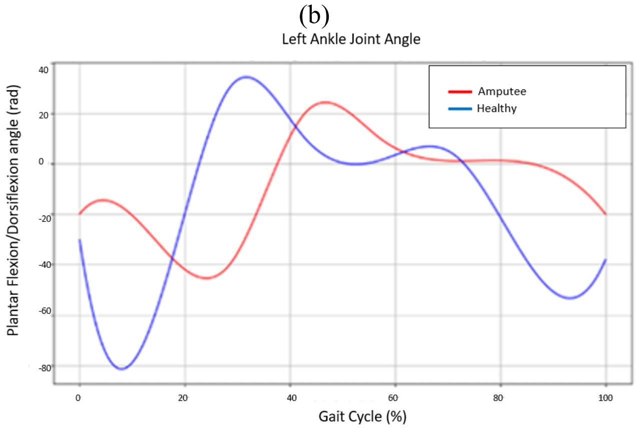
These results showed that an amputee exhibited an asymmetric gait compared to a healthy person. This study supports the usefulness of IMU in helping to detect differences in movement and measure angles, which will help in the future in designing a better prosthetic limb that improves the quality of life of the amputee.




(a)




(b)




(c)

**Fig. 5** Comparison of lower limb joint angle between healthy and an amputee throughout a gait cycle.

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## CONCLUSION

Six IMU sensors were employed to acquire lower-limb joint motion data from healthy participants. Four joint angles were extracted, and the signals were filtered using a Butterworth low-pass filter to reduce noise while preserving physiological patterns. Data preprocessing and visualization were performed in Python. For consistency, a single gait cycle was selected from each participant and compared with Kinovea measurements. The intraclass correlation coefficient (ICC) demonstrated moderate to excellent agreement between the IMU and Kinovea systems. In addition, a case study comparing a healthy subject and a lower-limb amputee revealed gait asymmetry and reduced prosthetic limb motion, particularly during the swing phase.

This study introduced a cost-effective method for estimating lower-limb joint angles using IMUs and proposed a comparative framework with Kinovea video-based motion analysis. The approach can serve as an alternative in clinical and research settings where advanced motion capture systems are unavailable.

The results provide clinically relevant information for assessing gait, supporting the development of rehabilitation strategies for amputees. The system's portability, low cost, and ease of use make it suitable for both laboratory and non-laboratory applications.

The study was limited by noise and signal drift in IMU measurements, which can be influenced by environmental conditions, sensor displacement, and gravitational effects. Furthermore, the participant pool consisted of 30 healthy subjects and one amputee, restricting the generalizability of the findings.

Future work should expand the participant population to include diverse clinical groups, such as stroke patients and amputees with different prosthetic designs. Combining IMU measurements with 3D motion capture systems could improve accuracy, while machine learning techniques applied to larger datasets may enhance gait classification and analysis.

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