Assessment of Inertial Measurement Units for Estimating Kinematic Data in Gait Analysis

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Abstract— Accurate measurement of human joint angles during gait is crucial for understanding movement biomechanics and assessing musculoskeletal conditions. Inertial measurement units (IMUs) have become popular for capturing joint kinematics due to their portability, affordability, and ease of use. In this paper, a system with four IMU sensors was designed and tested to compare joint angles obtained from IMUs with those from a 3D motion capture system. The experiments showed that an excellent correlation (r = 0.9) in hip and knee joint angles, outperforming the state-of-the-art systems.

Keywords— Gait Analysis; Inertial Measurement Unit; Accelerometer; Gyroscope; Validation against Optical Capture System.

I. INTRODUCTION

Gait analysis is routinely conducted in a clinical setting, as a subjective assessment tool to evaluate the health of cardiopulmonary, neurological, and musculoskeletal systems. The kinematic data of gait is a significant indicator for assessment and follow-up the patients with chronic heart failure, hemiplegia, and knee osteoarthritis [1, 2, 3].

While gait analysis offers valuable insights, its effectiveness in a clinical setting can be limited by inherent subjectivity. Visual observation by clinicians, though honed by experience, can be prone to inconsistency between practitioners. Additionally, time constraints during clinical appointments may restrict the comprehensiveness of gait assessments. This can be particularly challenging for conditions requiring detailed analysis of movement patterns [4]. To address these limitations, research is exploring more objective and quantitative methods for gait analysis.

One of the most objective and sophisticated systems for gait analysis is vision-based three-dimensional motion tracking such as VICON and SIMI Motion systems [5]. Such systems use optoelectronic, force plates, and surface electromyography to measure the kinematic, kinetic and muscle activity for the gait analysis. However, for these systems to be widely adapted these systems have several challenges: (i) the cost of such systems, (ii) the technical expertise needed to operate them, (iii) they usually require long time for set up and calibration (typically more than one hour) [6], and (iv) they are stationary system thus they cannot be used in outdoor setting.

Alternatively previous studies used sensor-based systems for the analysis. These systems utilised Micro Electromechanical Systems (MEMS) and Inertial Measuring Units (IMUs) for motion analysis. IMUs are widely used for robotics and hand-held applications such as monitoring athlete performance during sports training sessions. They proved successful and precise tracking results to provide attitude information for static and slowly moving systems [7] [8].

The IMU unit consists of three main parts, accelerometers, magnetometer and gyroscopes. Roll and pitch information is usually obtained by accelerometers and gyroscope data fusion, whereas heading information is usually obtained from magnetometer aiding integrated gyroscope measurement [9].

Although this unit is portable, simple, and cheap compared to the 3D motion-capturing systems, its systematic errors may affect the accuracy of outcomes due to overestimation or underestimation of the measurements. These errors may occur by gyroscope unit due to the integration of the velocity variable and the angle calculation over time [10, 11]. In addition to that, the noise, and imperfections within the electronic components in the amplifier may accumulate errors and interfere with data analysis or interpretation. Moreover, the material quality of the components of the sensors can affect the susceptibility to noise and the overall reliability of the IMU system [12].

In the literature, several studies attempted to validate such a sensor-based system. Park and Yoon [13] evaluated the validity of IMUs compared to motion-capture systems (Mocap) for gait analysis on lower-extremity joint angles. The results showed that IMU-based measurements demonstrated good validity for hip-joint angles throughout walking. However, significant differences were observed in knee and ankle joint angles, particularly during the swing phase. The study suggested caution when using IMUs for joint angle measurements during that phase of gait, emphasising the need for further refinement in IMU-based systems for the whole gait cycle.

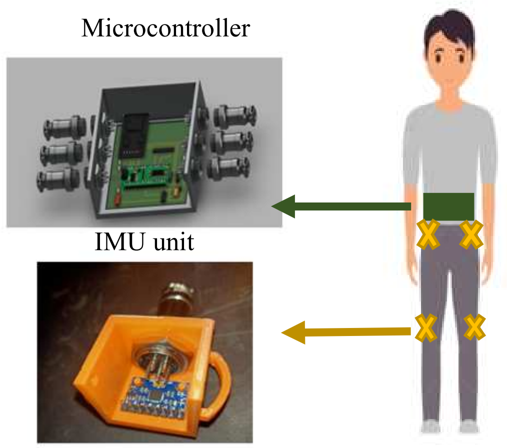


Fig. 1: Interconnection between main port control protocol and Sub IMU units.

Yeo and Park [15] and Piche et al., [16] investigated also the accuracy of an IMU system for gait analysis compared to an optical motion capture (OMC) system. They found no significant differences in Spatio-temporal parameters between the two systems with similar measurements for knee joint angles. However, there were significant differences in hip joint angles. They also acknowledge the small sample size with limitations in the generalizability of findings to real-world environments.

In this paper, we propose a Wearable Gait Analysis system (WGA) that utilizes IMU sensors. It is a sensor-based system that is low cost and can be used both indoors and outdoors, furthermore, its calibration time is significantly shorter in comparison to the vision-based systems. WGA was tested and its results were validated with optoelectronic motion capture to improve the kinematic angle outcomes, and hence can be used for further clinical assessment and rehabilitation.

This paper is organised as follows: section II presents the proposed methodology. Section III presents the experiments results, and section V concludes this paper.

II. METHODS

A. *WGA Overview*

WGA system includes four IMU sensors, a microcontroller, a battery, a power supply, and an SD card. The system overview is shown in Fig. 1. has four cabled IMU units interconnected with the main port. The IMUs collect the kinematic data from knees and hip joints of both right and left sides. WGA main components are presented in Tabel 1.

Calibration of the inertial sensors is important to ensure the accuracy of MEMS – IMU. A precise turntable was utilized to provide reference rotation rates for gyroscope calibration. Also, a fixed static position tests were employed in six different orientations for accelerometer calibration to calculate the scale factor and bias [16, 17].

TABLE 1: WGA MAIN COMPONENTS.

Item	***Description***
Microcontroller	ATmega328/ Arduino Nano
IMU	MPU-6050, Six-Axis (Gyro + Accelerometer) MEMS MotionTracking™ Device/ TDK
Card reader	Micro SD Storage Board TF Card Reader Memory Shield Module SPI Port
Power supply	9 volts rechargeable / micro-USB

B. *Angles estimation*

The readings of gyroscopes and accelerometers were integrated and processed using the Kalman filter in (MATLAB R2022a). The Kalman Filter (KF) is a mathematical algorithm commonly used for data smoothing and filtering, particularly in removing noise from sensors' data. The algorithm follows three stages: Prediction, measurement, and correction to decrease the rate of noise within the electronic components and correct the noise and drifting due to the integration the velocity all over the gait cycle [18, 19].

For each IMU, a two states KF is used (as shown in Fig. 2), to estimate the orientation angle (ψ), as follows:

First, the states have been defined:

$$X = \begin{bmatrix} \delta\psi \\ \delta\dot{\psi} \end{bmatrix} \tag{1}$$

where $\delta\psi$ is the error between the angle calculated by accelerometer and angle calculated by gyro measurement integration and $\delta\dot{\psi}$ is the rate of change of this error.

Second, the prediction model is calculated as follows:

$$X_{k+1} = \Phi_{k+1,k} X_k + G_k w_k \tag{2}$$

Where $\Phi_{k+1,k}$ is the transition matrix from time k to $k+1$, w_k represents the noise and G_k distribution matrix. Using the state definition in Eq(1) , and substitute for the transition matrix, Equation (2) can be rewritten as follows:

$$\begin{bmatrix} \delta\psi \\ \delta\dot{\psi} \end{bmatrix}_{k+1} = \begin{bmatrix} 1 & \Delta t \\ 0 & 1 \end{bmatrix} \begin{bmatrix} \delta\psi \\ \delta\dot{\psi} \end{bmatrix}_k \tag{2}$$

where k is the index for the current state vector and $k+1$ is the next state vector to be predicted, and Δt is the time step between the current and predicted states.

Then in the correction phase, the accelerometers calculated angles based on gravity components were used to correct the gyro calculated angles based on rates integration. The used model is using error in angle $\delta\psi$ instead of the angle itself and the measurement in this case is the difference between two angles as in following equations:

The measurement vector at time k is calculated as follows:

$$Z_k = H_k X_k + \eta_k \tag{4}$$

where:
Z_k represents the measurement vector at time k.
H_k is a row vector [1 0], indicating that the measurement directly corresponds to the first element of the state vector X_k
X_k represents the state vector at time k.
η_k is the measurement noise, which accounts for errors or uncertainties in the measurement process.
Thirdly, X_{k+1} is updated as in Eq (5) where K is the Kalman gain [19]. $\hat{X}_{k+1}$ is the final optimal estimate of the states.

$$\hat{X}_{k+1} = X_{k+1} + K[Z_k - H_k X_{k+1}] \tag{5}$$

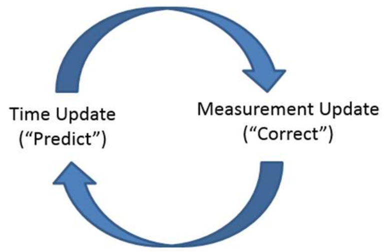


Fig 2: Schematic diagram of Kalman filter process.

C. Lower Limb Angle Calculation Using IMU Sensors

The kinematic hip (flexion - extension) angle was calculated by the inverse cosine X axis of the thigh segment, whereas the knee angle (flexion - extension) was calculated by summation of the inverse cosine X axis of the hip and leg segments as in Fig. 3.

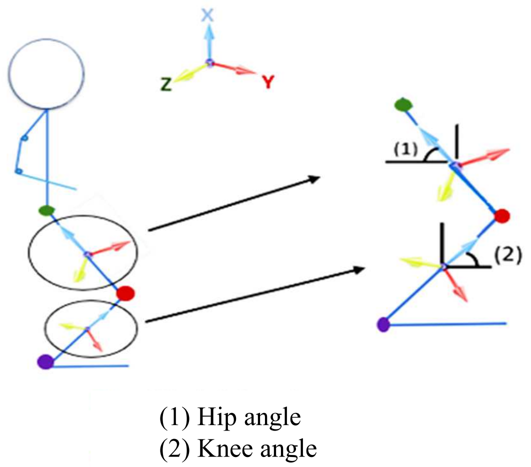


Fig 3: Schematic diagram of calculation the hip and knee angles

D. Measurements Validation

The results of IMU kinematic angles were validated by an optoelectronic motion capture system (Vicon gait lab) on a male – 27 years old at Ahram Canadian University, Egypt [1]. Vicon cameras were initially calibrated to ensure accurate spatial reconstruction of marker positions by a wand with reflective markers from six camera viewpoints. The calibration software uses these images to determine the intrinsic and extrinsic parameters of each camera, such as focal length, distortion coefficients, and camera positions. Then, reflective markers were set on lower limb bony landmarks based on Plug-In Gait Marker protocol as is shown in Fig. 4 [20].

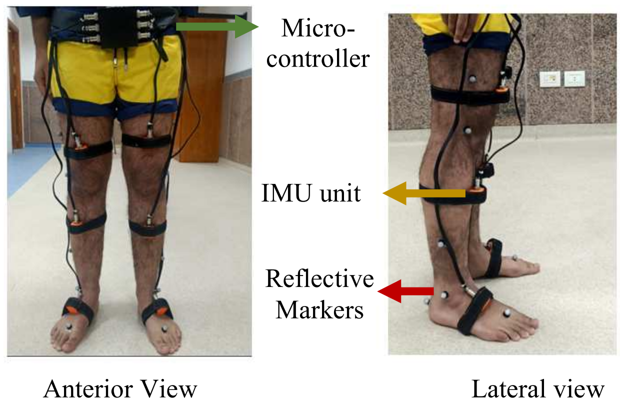


Fig 4: Reflective marker replacement on anatomical landmarks of the participant's body.

The participant was instructed to stand in a neutral pose or T-pose, with arms outstretched and feet shoulder-width apart to provide a standardized reference position for subsequent motion capture trials as shown in Fig. 5. Then, the dynamic analysis was performed with normal gait speed [21].

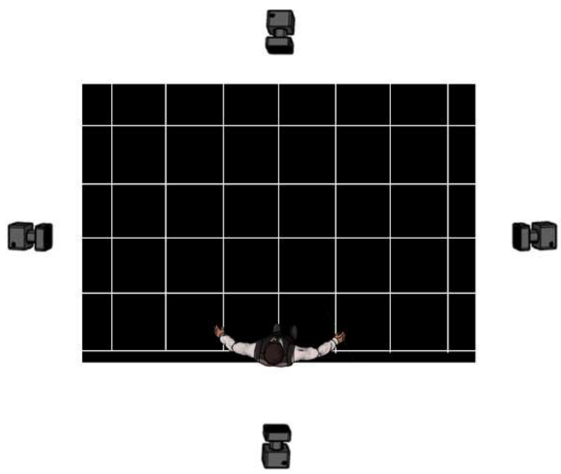


Fig 5: Experimental setup for motion capture using the capture Vicon system.

After data collection is complete, the raw motion capture data is processed using Vicon's proprietary software (Nexus).

[1] This study received ethical approval from the Institutional Review Board at Cairo University (Ethical Approval Number: P.T.REC/012/005067).

This involves identifying and labelling the markers in each frame of the captured video, reconstructing the 3D trajectories of the markers, and applying appropriate biomechanical models to calculate joint angles and segment kinematics.

III. Results and Discussion

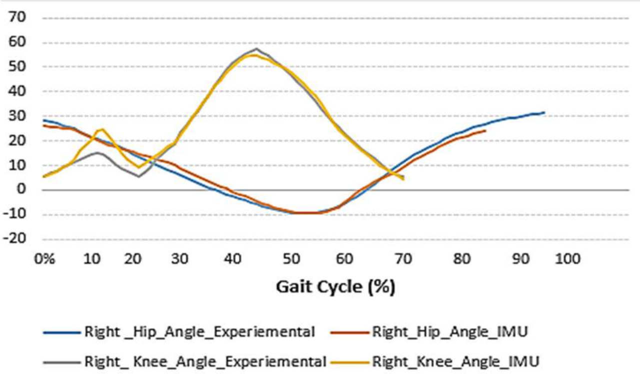
The study investigated the gait analysis accuracy using WGA and the Optical Motion Capture (OMC) system for gait analysis in the sagittal plane. The values of accelerometer and gyroscope bias are presented in Table 2, providing insights into the inherent systematic errors observed in the sensor readings.

TABLE 2: VALUES OF ACCELEROMETER AND GYROSCOPE BIAS

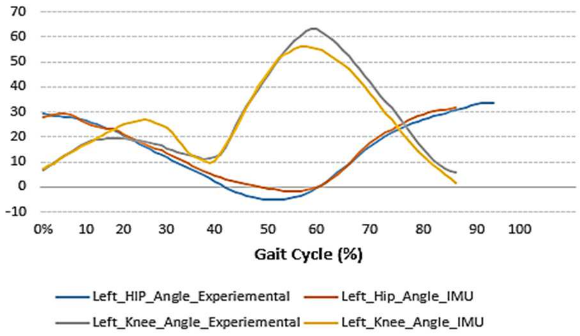
Segment	***Accelerometer bias (mGal)***	***Gyroscope bias (deg/s)***
Right Hip	0.0374	6.188
Left Hip	0.0307	5.571
Right Knee	0.0441	0.1767
Left Knee	0.0210	0.5278

Utilizing SPSS software, the Pearson correlation coefficient was calculated to assess the concurrent validity between IMU and capture system data. The correlation coefficients were excellent (0.993) for the hip angle and (0.987) for the knee angle, as shown in Fig. 6. Similarly, significant correlations were observed for the left side, with (0.994) for the hip angle and (0.974) for the knee angle.

Overall, the IMU system demonstrated comparable accuracy to the optical tracking system for hip and knee angles and showed strong agreement between the two systems across all phases of gait. By comparing the kinematic data obtained from both systems in the sagittal plane, we found an excellent correlation in hip and knee joint angles during walking, which was consistent with previous studies [22, 23, 24] which found an excellent correlation in the primary range of motion.



(a) Right Hip and Knee Results



(b) Left Hip and Knee results

Fig 6: Diagram represents right hip and knee angles with IMU and optical tracking in the sagittal plane.

The designed system with four IMU sensors demonstrates a marked improvement in measuring knee and hip joint angles compared to previous state-of-the-art systems. Bergmann et al., [1]; Piche et al., [15] and Yeo et al., [16] found a significant difference ($p < 0.05$) in maximum hip angle showing a lower accuracy for hip angle parameter. Besides that, WGA system demonstrated significant advantages over the system reported by Park et al., [14] which identified substantial discrepancies in the measurement of knee angles ($p<0.05$) especially in terminal stance, preswing, and terminal swing phases.

The demonstrated superiority of the IMU system represents a significant contribution to the field of biomechanics. This advancement is primarily due to its enhanced sensor technology, improved integration algorithms, and sophisticated calibration methods, which collectively result in more accurate and reliable measurements of hip and knee joint kinematics during gait. These technical improvements make the IMU system not only more effective but also highly efficient in capturing detailed joint movements. Additionally, the system's portability, affordability, and user-friendly nature significantly enhance its accessibility for widespread clinical and research applications. This accessibility ensures that high-precision gait analysis can be conducted in diverse settings, from advanced research laboratories to routine clinical practices, without compromising on measurement accuracy. Therefore, the IMU system offers a practical and impactful solution that addresses previous limitations and paves the way for more comprehensive and inclusive biomechanical assessments.

Conclusion

This study highlighted the potential of IMUs for capturing joint kinematics during gait, particularly at the hip and knee joints, where excellent correlation with a gold standard reference was observed. Future work can focus on wireless system development and refining algorithms to capture the joint kinematics more comprehensively, thereby advancing gait analysis capabilities for clinical assessment and treatment evaluation.

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