A LOW-COST VISION-BASED ANALYSIS OF HUMAN WALKING

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Abstract: This paper presents a low-cost vision-based analysis of human walking, focusing on the evaluation using two motion capture technologies: Kinect and Inertial Measurement Units (IMU). The Kinect sensor provides a markerless, depth-based approach to motion tracking, while the IMU offers wearable motion sensing through accelerometers and gyroscopes. This integrated system improves analytical capabilities by capturing spatio-temporal gait parameters, supporting comprehensive biomechanical research. The proposed system highlights how the combination with results that can be used in the sensing devices of these technologies can offer valuable insight into human locomotion with low-cost efficient operation. A case of study is reported from laboratory experience to outline the characteristics and limits of the proposed system.
Keywords: Human Walking Analysis, Vision-Based Motion Capture, Wearable Sensors, Performance Evaluation.

1. Introduction

Human gait analysis is an essential field of study in biomechanics, health monitoring, physiotherapy, and rehabilitation. Provides important information on mobility, balance, and general health conditions, enabling the diagnosis and treatment of movement disorders and weakness, injuries, and neurological conditions. Traditional gait analysis systems, such as marker-based motion capture technologies such as Vicon [1], have set the gold standard for precision and reliability.

However, these systems are often expensive, require complex setups and are confined to controlled laboratory environments as cited in [2]. This suggests the development of vision-based motion capture systems, which offer low-cost, non-invasive, and portable solutions for analyzing human walking, as, for example, in [3]. The development of low-cost tools such as the Cassino Tracking System (CaTraSys) has significantly advanced human motion analysis by allowing accessible kinematic characterization of gait [4]. This system offers a cost-effective way to track posture and force during walking, making it valuable for clinical rehabilitation and diagnosis [5].

Vision-based motion capture systems leverage technologies such as depth-sensing cameras, structured light, and time-of-flight (ToF) sensors to track human movement and extract key gait parameters. Devices like Microsoft Kinect [6] and Intel RealSense [7] use depth sensing to create 3D skeletal models, allowing the measurement of key gait features such as stride length, joint angles, and walking speed. The transition from structured light to time-of-flight sensing in newer Kinect versions has improved accuracy and robustness, making them viable alternatives to traditional systems [8]. Vision-based systems are accessible, versatile and cost-effective, enabling naturalistic gait analysis and early detection of neurological conditions such as Parkinson's and Alzheimer's disease, especially in resource-limited settings [9]. Wearable sensors, such as inertial measurement units (IMUs), can complement vision-based systems by providing additional data on body motion and kinetics. IMUs measure acceleration and angular velocity. Studies have demonstrated the benefits of integrating wearable sensors with vision-based systems, creating a hybrid approach that enhances the accuracy and reliability of gait analysis like in [10]. For example, IMUs can compensate for occlusion-related errors in vision-based systems.

This paper presents low-cost vision-based systems as a low-cost tool in gait analysis, focusing on accessibility and potential to expand its clinical and research applications.

2. Requirements for Analysis of Walking

The analysis of human walking requires a comprehensive methodological framework to ensure adequate data acquisition, as noted in [2]. These Requirements cover both hardware and software aspects, data acquisition protocols, and analysis techniques as for main characteristics of walking, Fig. 1. Table 1 presents reference values for human walking, including ankle and knee movement, based on typical ranges observed in

healthy adults [11]. These values can vary according to age, gender, speed of walking, and physical condition. Understanding these parameters establishes a baseline for human walking analysis, allowing the assessment of movement patterns and joint dynamics. Walking speed, cadence, and step length indicate locomotion efficiency, while stance and swing phase reflect stability. Analyzing these values is crucial to detect abnormalities and improve mobility assessments. The selected systems, such as Kinect and IMU, must be able to capture human movement with sufficient spatial and temporal resolution. The Kinect sensor [6] needs proper calibration and placement to accurately track joint positions without markers. IMUs can be lightweight, portable, and capable of capturing angular velocity data. Figure 1 shows a conceptual scheme for the proposed system that integrates Kinect with IMU to satisfy the main requirements for a low-cost user-oriented system for analysis of human walking.
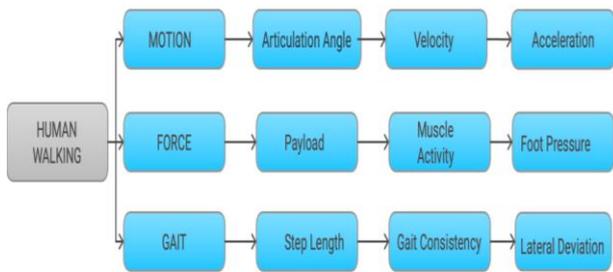

Fig. 1. Scheme of Requirements of a walking monitoring system, Table 1.

3. Monitoring System

A key requirement for effective walking analysis is the synchronization of the data acquired by the sensing systems. The Kinect provides video and depth data, while the IMUs capture motion through acceleration and angular velocity. Proper sensor setup is essential: the Kinect must be placed at a fixed height and angle, and IMUs must be securely attached to specific body parts. Post-processing techniques, including noise filtering and data normalization, help ensure accurate and reliable results. The proposed system consists of a pair of IMU sensors strategically placed between the knee and ankle, and between the ankle and toe, to measure lower limb motion during human walking. In addition, the Kinect sensor captures depth-based motion data to provide a comprehensive analysis of gait, as illustrated in Figure 2. Despite its simplicity, the proposed system maintains high data quality while remaining low cost, approximately €50 per unit, making it accessible to researchers, clinicians, and rehabilitation professionals.

The proposed monitoring system aims to evaluate the primary parameters of human walking, identifying motion defects in laboratory conditions. Kinect requires a dedicated testing space (4m × 2.5m) with a 2-meter distance from the subject to ensure complete body tracking, as shown in Figure 3.a. Measurement points are

captured as shown in Figure 3.b, while IMUs, placed on the shank and foot, as in Fig.4, collect inertial data essential for computing angles and torque during movement. The BMI160 sensor used in IMUs can detect 3-axis accelerations and angular velocities.

Tab. 1. Values of reference for human walking parameters [11], Figure 1

| Parameter (Units)	Reference Value
Walking Speed (m/s)	1.08 m/s (habitual), 1.55 m/s (fast)
Cadence (steps/minute)	116–122
Step Length (m)	0.7–0.82
Stride Length (m)	Double the step length
Double Support Time (% of cycle)	10–12%
Stance Phase Duration (% of cycle)	62%
Swing Phase Duration (% of cycle)	38%
Ankle Movement (Sagittal) (°)	Dorsiflexion: 10–15°; Plantarflexion: 20–25°
Knee Flexion Range (°)	Peak flexion: 60° (swing phase);20° (stance)
Flexion Range (°)	Peak flexion: 20°
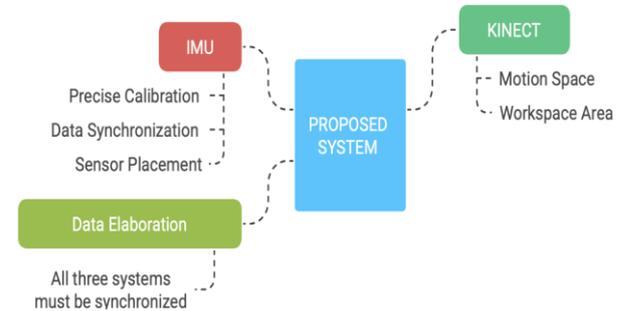
Fig. 2. Main requirements in design and operation of a walking monitoring system, Table 1.

a)   b)

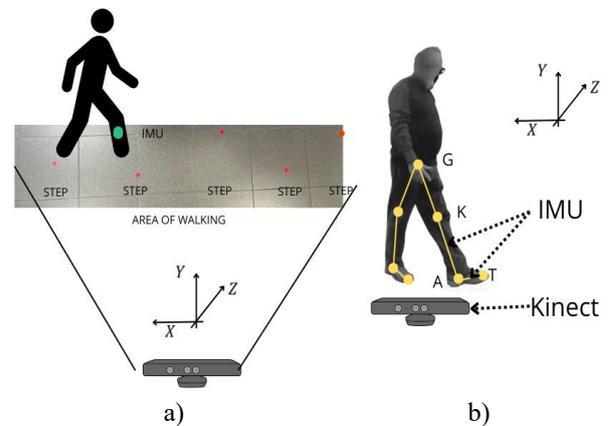**Fig. 3.** Suitable working area for Kinect: a) prescribed workspace b) marker set up.

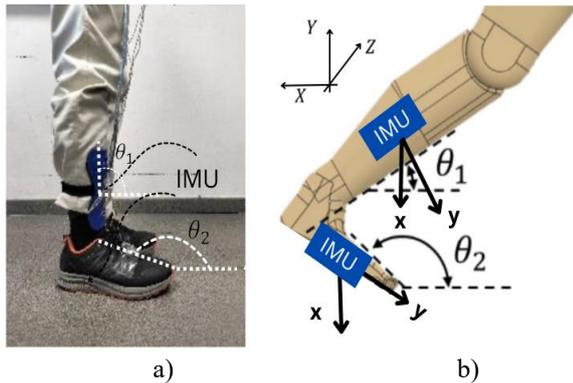<div align="center">a)   b)</div>

Fig. 4. Lab testing with IMU: a) lab test setup,
b) measured angle

Compared to traditional systems such as OptiTrack, which require high-end cameras priced at €2,200 each [13] and since the software costs €999 [14], this vision-based system is a highly cost-effective alternative. It allows accurate collection of gait metrics, such as step length, stride time, and joint angles, with minimal occlusion. During a straight-line walking, the participant is recorded in full by the Kinect, capturing spatio-temporal and angular metrics. This combination of Kinect and IMU data allows for an efficient, low-cost, non-invasive analysis of human walking suitable for both clinical and research environments.

4. Testing Mode

Testing procedure is designed to use the proposed system in Figs. 2-4 with a protocol in Fig. 5 follows a structured approach to ensure consistency and precision in data collection. Before the test, participants receive a detailed explanation of the procedure, sign a consent form, and provide relevant biometric and medical data. The volunteers are then instructed on the walking conditions, and the sensors are properly calibrated. During the test, participants walk in a straight line while the Kinect and IMU capture gait dynamics. Afterward, the collected data undergo post-processing, including visualization, storage, and report generation. This systematic process improves measurement reliability, reduces errors, and facilitates a comprehensive analysis of walking patterns for clinical and research applications.
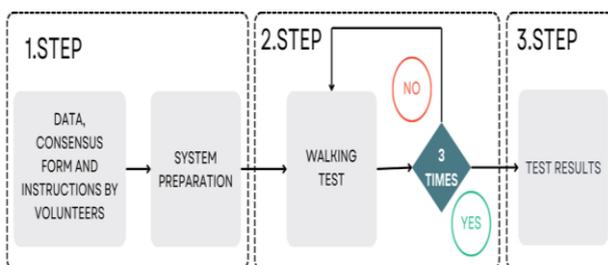

Fig. 5. Testing procedure according to designed protocol.

A properly designed protocol ensures proper testing planning by defining participant criteria, establishing conditions and synchronizing data, improving reliability, and minimizing measurement errors. The test protocol has been designed for the proposed as seen mentioned in Fig. 5 with the following steps.

1. Step: Pre-Test Measurements
   1.1. Explain the test to a volunteer.
   1.2. Give the consensus form to the volunteer and check that it is signed.
   1.3. Store the data obtained (age, height, weight and medical history relevant to the condition) from the volunteer in Table 2.
   1.4. Teach the volunteer to walk mode according to the timing and mode (slow or fast).
   1.5. Attach sensors (IMUs, foot pressure), calibrate and check the data acquisition of sensors; the Kinect sensor to capture the full walking cycle.
2. Step: Walking test
   2.1. The volunteer is asked to walk in a straight line.
   2.2. Data is acquired from sensors during the test.
3. Step: Post-processing
   3.1. Elaboration for visualization
   3.2. Storage and elaboration of row data
   3.3. Write a report with test results

5. Test Results

The feasibility evaluation and effectiveness of the proposed setup were assessed through walking tests conducted under controlled laboratory conditions. These tests involved an ongoing campaign with adult volunteers selected to represent a typical demographic, with heights ranging from 165 cm to 180 cm and weights between 70 kg and 100 kg. The experiments were conducted in a laboratory environment designed to reduce external variables, such as uneven surfaces, obstacles, and distractions. This controlled setting ensured that any variations in walking patterns could be attributed to individual biomechanical differences rather than environmental factors.

Each volunteer completed a walking trial lasting between 6 and 10 seconds, which included 5 minutes of setup time, depending on their natural walking speed and step length. Participants with longer strides completed the trial more quickly, while those with shorter steps took longer to finish. This variability highlighted the inherent challenge of achieving consistency in human gait testing, as differences in individual locomotion patterns significantly affected step synchronization and overall performance. During the tests, participants were instructed to walk naturally. This approach allowed the

system to capture genuine variations in walking behavior, which are essential for assessing real-world applicability.

Figure 6 presents a sequence of snapshots from one of the walking tests. It shows the subject's movement alongside the corresponding skeletal model generated by the Kinect system. Key marker points associated with the lower limbs are highlighted, demonstrating the system's capability to track and represent joint motion effectively. The subject was positioned 2.5 meters away from the Kinect sensor, ensuring good tracking coverage and skeletal model accuracy within the sensor's field of view.
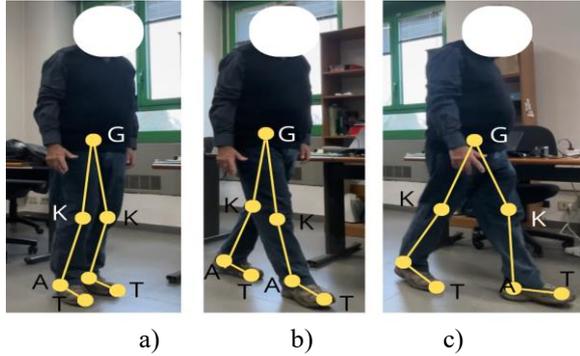

a)   b)   c)

Fig. 6. Snapshots of a human walking test: a) Start, b) First Step, c) Second Step

Figure 7 shows data captured from the Kinect sensor during the walking tests, illustrating lower limb motion from the sensor's perspective. Figure 7a shows the trajectory of the ankle marker in the X-Y plane, starting at positive X values, while Figure 7b shows the foot marker following a similar trajectory. These paths reflect the spatial progression of each marker throughout the walking cycle. It is evident that the effective range of the Kinect sensor with the previously described setup is approximately 2 meters. This pattern provides valuable insights into joint movement, gait patterns, and biomechanical variations across trials. The visualization of these parameters contributes to a comprehensive understanding of the subject's locomotion.

Figure 8 presents a comparison between data from the Inertial Measurement Unit (IMU) and the Kinect sensor for the joint angles defined in Figure 4, specifically focusing on the ankle and knee. The ankle angle is measured directly using the IMU, while the same angle, denoted as θ_2 in Figure 4b, can also be estimated from Kinect data using the spatial coordinates of the ankle (A) and toe (T) markers, by

$$\theta_{2\,Kinect} = \pi - tg^{-1}\frac{Y_A}{X_A - X_T} \qquad (1)$$

The knee angle (θ_1) in Fig. 4b) can be computed using the relative positions of the knee (K) and ankle (A) using Kinect tracking data as in the following equation

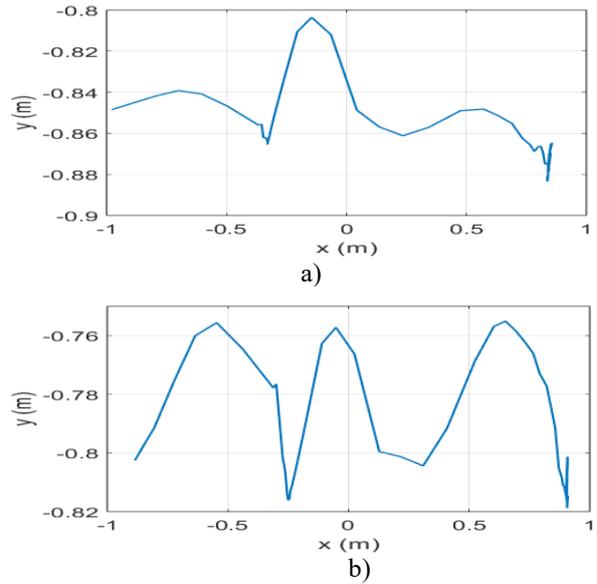$$\theta_{1\,Kinect} = tg^{-1}\frac{Y_K - Y_A}{X_K - X_A} \qquad (2)$$

a)

b)

Fig. 7. Acquired trajectory of marker points, Fig. 3.b during a test like in Fig. 6 of: a) A for right ankle marker, b) T for right toe marker.
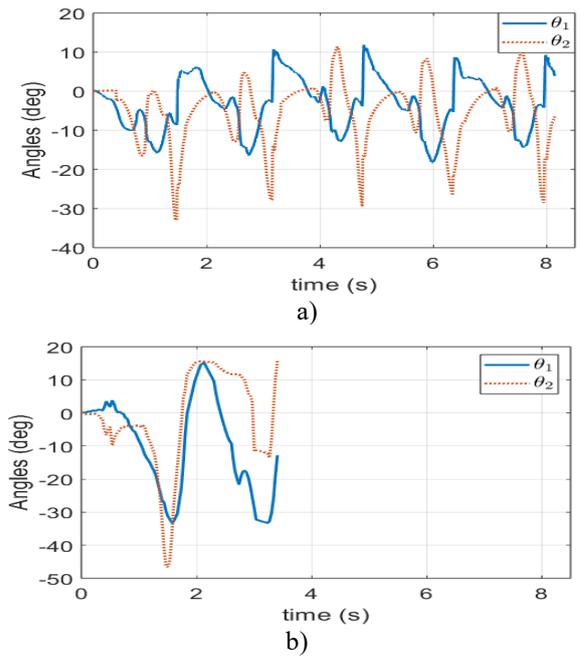

a)

b)

Fig. 8. Acquired angles θ_1 and θ_2 during a test like in Fig. 6: a) from IMU, Fig. 4.b, b) from Kinect-based calculation by Eqs. (1) and (2).

These angular measurements are essential for understanding limb articulation during gait cycles. Note that the Kinect sensor can acquire data from two steps, considering the setup previously explained, and captures motion from one meter to the left to one meter to the right, as shown in Fig. 7. In contrast, the IMU sensor can continue motion capture even if the body is no longer detected by the Kinect sensor.

Figures 9 and 10 show the acceleration data recorded during the human walking tests described in Fig. 6. Figure 9 focuses on the shank point, as defined in Fig. 4b), with Fig. 9a) showing the acceleration components along the x, y, and z axes, and Fig. 9b) showing the magnitude of linear acceleration after removing the gravity component. Similarly, Fig. 10 shows the acceleration data from the inertial measurement unit (IMU) attached to the foot, also identified in Fig. 4b), where Fig. 10a) shows the acceleration components, and Fig. 10b) shows the gravity-free magnitude of linear acceleration, as computed in Eq. (3)

$$a = \sqrt{a_x^2 + a_y^2 + a_z^2} - g \qquad (3)$$

These visualizations provide valuable insights into the dynamic motion patterns of the lower limb segments during walking. The gravity-compensated acceleration reveals a clear periodic structure associated with the walking cycle, as well as variations in impact intensity and timing between steps, which help characterize gait rhythm.

The data outlined above can be utilized for a numerical evaluation of walking performance when obtained through the proposed vision-based system, as illustrated in Figures 7 to 10. Each test was recorded using Kinect and inertial measurement units (IMUs). The Kinect captured 3D skeletal tracking, including the trajectories and angles of joint markers, while the IMU sensors gathered data on acceleration and angular velocity. The reported test results demonstrate that a Kinect-IMU multisensor setup effectively analyzes human walking. Table 2 lists the example data collected from a volunteer for the gait analysis tests, detailing individual characteristics and test conditions. Table 2 includes the test ID and date, which help track and organize the assessments for each participant. Additionally, it reports demographic and physical information such as gender, age (in years), height, weight, and detailed biometric measurements, providing a personalized baseline for gait comparisons. According to the established protocol for each volunteer, three tests were conducted to ensure proper statistical significance of their gait under consistent conditions. The presented walking tests were conducted on a male subject measuring 179 cm in height. To ensure accurate tracking, the Kinect's depth range was configured to a minimum of 2.5 meters. The walking sequence began with the left foot, followed by the right, making the initial step with the left foot effectively a half step. Due to the fixed position and limited field of view of the Kinect sensor, only two full steps of the instrumented right foot could be captured before the subject moved out of range. In contrast, the IMU sensors can continue recording data throughout the entire walking sequence without interruption. During the analysis, it was observed that the tracking accuracy of the Kinect is limited at the foot level due to the relatively small size of the foot, which can hinder reliable joint detection.
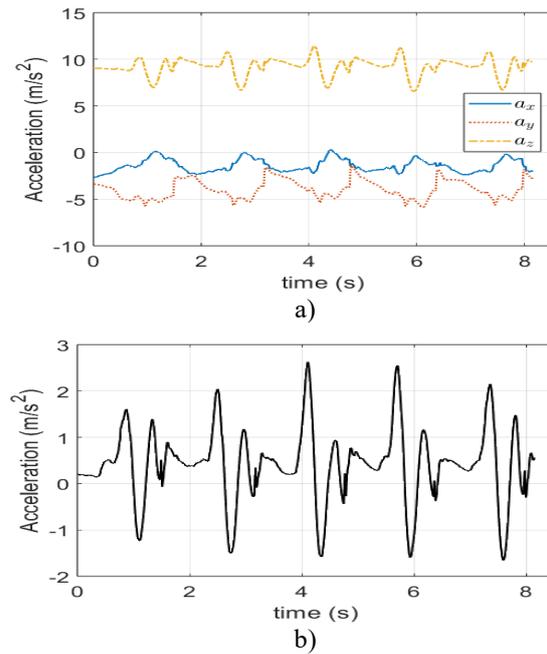

a)

b)

Fig. 9. Acquired acceleration of the shank point, Fig. 4.b, during a test like in Fig. 6: a) components, b) magnitude.
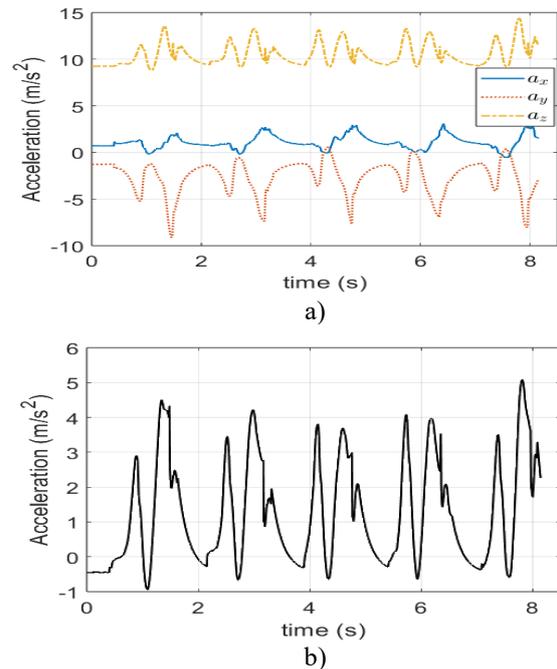

a)

b)

Fig. 10. Acquired acceleration of the foot point, Fig. 4.b, during a test like in Fig. 6: a) components, b) magnitude.

Table 3 summarizes the data obtained during a representative walking test, as shown in Fig. 6. It includes both angular and spatial measurements. Specifically, the variables $\theta_{1\,Kinect}$ and $\theta_{2\,Kinect}$ represent joint angles captured using the Kinect sensor, likely corresponding to the knee and ankle joints, respectively. Similarly, $\theta_{1\,IMU}$ and $\theta_{2\,IMU}$ denote angular data measured by the inertial

measurement units (IMUs), providing a complementary dataset for validating motion dynamics. The STEP parameter reflects the step length or time, essential for evaluating gait rhythm and consistency. Minimum and maximum values for each parameter are presented, offering insights into the range of motion and variability across the test. These data are critical for assessing joint mobility, synchronization between sensors, and the overall biomechanical performance of the participant during the walking cycle.

Table 2. Collected data from volunteers for walking analysis.

ID Test	Date	Gender	Age (years)	Height (cm)	Weight (kg)	Biometrics (cm)	Health status	Health problems
1	2025-01-1	M	34	179	82	45	GOOD	NO

ID Test	Date	Test Device	Test type	Foot angle (°)	Ankle angle (°)	Knee angle (°)	Thigh angle (°)	Sampling time (s)
1	2025-01-1	KINECT	01	16	30	23	41	5
2	2025-01-1	IMU	02	16	32	NA	NA	5

Table 3. Summary of main data acquired during a test like Fig. 6.

Parameters	Min	Max
$\theta_{1\,Kinect}$ (°)	15.1	33.3
$\theta_{2\,Kinect}$ (°)	15.7	46.5
$\theta_{1\,IMU}$ (°)	11.9	18.2
$\theta_{2\,IMU}$ (°)	11.3	33.0
STEP (cm)	45	58

6. Conclusions

This paper presents the design and implementation of a low-cost vision-based system for human gait analysis, using such sensors as Kinect and IMU sensors. The Kinect sensor's depth-sensing capabilities provide robust motion capture and spatiotemporal gait parameters, while the IMUs enhance motion tracking accuracy by capturing acceleration and angular velocity. The system addresses key challenges in gait analysis by offering an accessible, precise, and cost-effective solution for clinical and research applications. The proposed system can be an attractive solution for a wide range of applications, including clinical rehabilitation, evaluation of sport performance, and health monitoring, especially in resource-limited settings.

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