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Knee Joint Angle Measuring Portable Embedded System based on Inertial Measurement Units for Gait Analysis

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***Abstract*— Inside clinical research, gait analysis is a fundamental part of the functional evaluation of the human body's movement. Its evaluation has been carried out through different methods and tools, which allow early diagnosis of diseases, and monitoring and assessing the effectiveness of therapeutic plans applied to patients for rehabilitation. The observational method is one of the most used in specialized centers in Colombia; however, to avoid any possible errors associated with the subjectivity observation, technological tools that provide quantitative data can support this method. This paper deals with the methodological process for developing a computational tool and hardware device for the analysis of gait, specifically on articular kinematics of the knee. This work develops a prototype based on the fusion of inertial measurement units (IMU) data as an alternative for the attenuation of errors associated with each of these technologies. A videogrammetry technique measured the same human gait patterns to validate the proposed system, in terms of accuracy and repeatability of the recorded data. Results showed that the developed prototype successfully captured the knee-joint angles of the flexion-extension motions with high consistency and accuracy in with the measurements obtained from the videogrammetry technique. Statistical analysis (ICC and RMSE) exhibited a high correlation between the two systems for the measures of the joint angles. These results suggest the possibility of using an IMU-based prototype in realistic scenarios for accurately tracking a patient's knee-joint kinematics during a human gait.**

***Keywords*— IMU; gait analysis; motion analysis; knee-joint angle; kalman filter.**

I. INTRODUCTION

Human gait can be described as a sequence of events that occur rhythmically, that is, a repetitive pattern that allows the locomotion by combining several activities from the brain, nerves, and muscles. Gait analysis offers an opportunity for clinical evaluation of the act of walking and may reveal physical and psychological characteristics [1]–[4]. Observational gait analysis is an acquired skill that requires much practice and repetition. The process is complex and difficult because the physical therapist must learn how to look at the different body's joints while simultaneously compares the observed gait with normal gait features in three body planes (sagittal, frontal, and transversal) [5].

In effect, biomechanics gait data from knee joints are collected by laboratories using different technologies and instrumentation, such as [6], [7]. Moreover, it is possible to employ kinematics of rigid bodies for calculating the knee joint angle coming from the relative movement between the knee segments of the tibia and the femur [8], [9]. The data are reported in two-dimensional charts, where the abscissa defines the percentage of the gait cycle (GC), i.e., the time interval from heel contact of one foot to the next heel contact of the same foot, meanwhile the ordinate corresponds to the biomechanical measure of interest, that is, the knee-joint angle [10].

Gait analysis is commonly used to describe and identify normal gait but also to discover abnormal gait patterns [11], [12].The motion capture (MOCAP) system is one of the most used methods for gait analysis. It digitally records the body movements generating an accurate 3D measurement of joint kinematics. However, this method requires a controlled laboratory setup. In recent years, improvements in MOCAP systems have played an important role in clinical and bioengineering applications due to their effectiveness in identifying the patient's walking disability [13], [14]. An accurate diagnosis can provide crucial information for clinical decisions and the creation of optimal therapeutic strategies to improve the patient's health.

Normally, authors in the field tend to divide MOCAP systems for gait analysis into three main types [cita]: vision-based, sensors-based, and data fusion. Concerning vision-based, MOCAP utilizes data captured from optical sensors, usually from the visible spectrum, to obtain a quantitative measurement of human gait. Currently, there are many optical systems on the market for 2D and 3D gait analyses such as Vicon, Qualysis, and Optitrack; they are characterized by their high precision and repeatability. However, these systems become a non-viable option in clinical institutes in Colombia because of their high cost and complex technological infrastructure [15]–[17].

On the other hand, sensor-based systems have a large offer of sensors to quantify the orientation of body segments and joint angles. The Inertial Measurement Units (IMU), composed by accelerometers, gyroscopes, and magnetometers, can provide data for motion tracking with enough accuracy and precision system [18]–[21]. The main advantage of IMU technologies is the ability to recording data with high sampling rates. Also, sensor fusion algorithms are proving to be a powerful method to overcome the limitations of vision-based capture systems in relation to marker occlusion and data loss [22], [23] technical advances in sensor devices have provided the opportunity of improving motion capture processes. Nevertheless, regardless of the technology used for data capture, there always is an inherently associated noise. This can generate inaccuracies when estimating parameters such as speed and acceleration. Therefore, it is necessary to develop methods to reduce noise, among them, Butterworth low pass filter [24], [25] and Kalman filter [7], [26]–[31] are the most used. Tannous et al. [32] incorporate IMU sensors in joint rotation axes to measure ankle and knee accelerations. They proposed a real-time orientation-based fusion scheme between Kinect and IMU sensors to improve the knee-joints kinematics during functional rehabilitation of the lower limb movement. They used a Kalman Filter to obtain accurate measures of joint angles since there are different types and sources of error that arise when placing these devices in the body.

This paper presents a data fusion study for the acquisition and processing of signals to measure the knee-joint angles during a human gait. The proposed system combines IMU sensors (gyroscope + accelerometer). This work is structured as follows: Section 2 describes the experimental procedure and methods for analyzing the signal of the knee-joint angle. Section 3 presents the main results and discusses them. Lastly, Section 4 explains the research conclusions and future directions. One of the contributions of this study is the development of a methodology that allows us to measure the knee angle of the IMU reliably and at a low cost, with a high possibility of expanding the use of this technology to other joints of the human body.

II. Materials and Methods

This section describes the methodology of the proposed system for all the stages, namely: acquisition, calibration, calculation of joint kinematics, preprocessing and data visualization. In order to enable a visual understanding, and explaining diagram of the proposed approach is shown in Fig. 1.

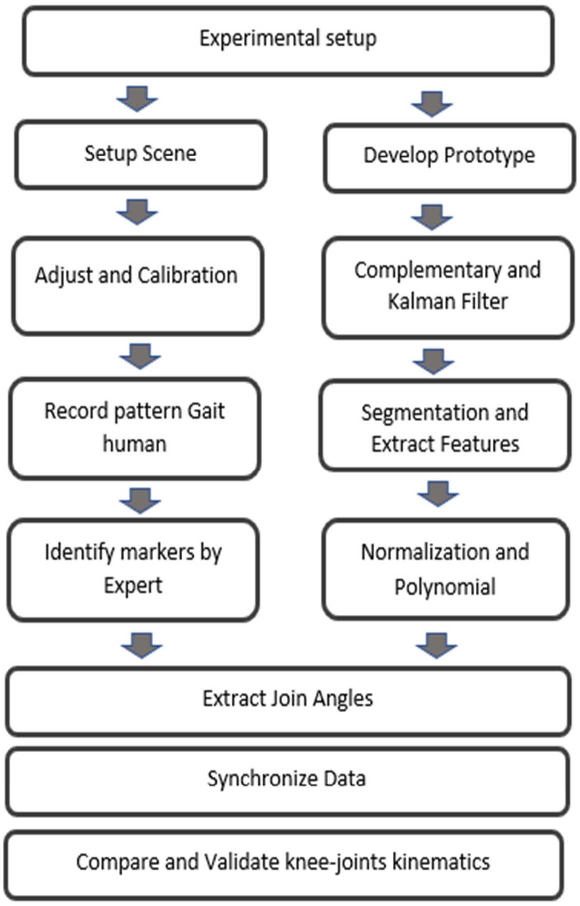

Fig. 1 Block diagram of the proposed methodology

A. Prototype Develop

The developed prototype consists of a lower limb motion system using two IMU sensors, type MPU6050 (gyroscope, accelerometer and triaxial magnetometer). IMUs were used to track the thigh and leg segments using Velcro, such can be seen in Fig. 2.

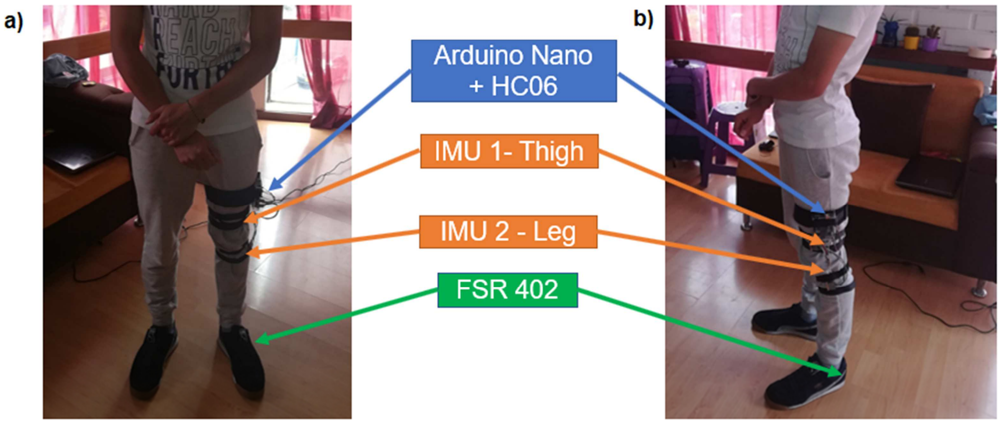

Fig. 2 Subject wearing develop system with IMU sensors: a) subject in front view; b) subject in sagittal view.

Each triaxial gyroscope was set to cover a range of 500 degrees per second. Each triaxial accelerometer range is set to 16G. Signals measured by both sensors are captured at a sampling frequency of 120 Hz. IMU sensors are connected to an Arduino Nano board (ATmega328P), through the I2C communication pins. Additionally, a force sensor resistor FSR402 is connected to the Arduino via a USB cable. The prototype data is transmitted to the PC through the Bluetooth module HC06 (See Fig. 3).

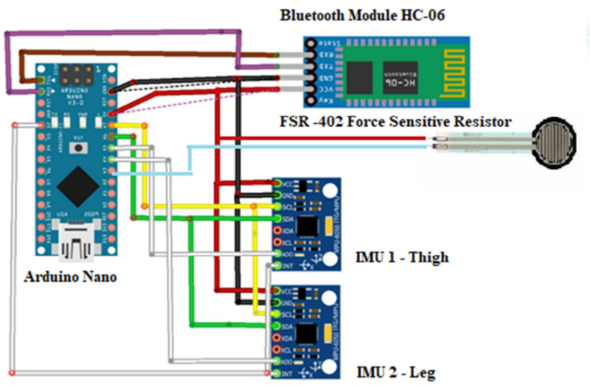

Fig. 3 The electronic scheme of the prototype developed to capture the measurements.

B. Experimental Setup

The methods and protocols used in this study are based on guidelines for the functional evaluation of human gait. The database considered in this study was obtained from recordings of signals from 12 volunteer subjects aged between 18 and 28. To validate the accuracy and repeatability of the measurements, a videogrammetry technique is used, together with a widely used criterion for the clinical-functional evaluation and measurement of knee flexion angles through the use of universal goniometers [33], [34].

The videogrammetry technique –applied for the gait analysis at the knee-joint- consists of placing a camera that captures the image of adhesive markers placed on the hip, knee and ankle joints. The here-used tool used for validation purposes is an optical motion capture system (cvMob), which is a free software used for the evaluation of two-dimensional human gait. Reliability and accuracy for knee-joint angle measurement have been compared to systems such as Vicon 3D as discussed in [35]. Therefore, the first step in the process was the selection of camera features to analyze. The camera used is a Logitech 920 Webcam, since it offers a high definition for video capture with a resolution of 1920x1080 pixels and 30 FPS. The camera calibration algorithm used is Zhang's algorithm [36], [37], which iteratively finds correspondences between the coordinates of some easily identifiable characteristic points of a known object (chessboard) both in the image plane and in the scene.

C. Statistical Analysis

Data acquired by the developed prototype as well as videogrammetry technique were recorded as video samples. When performing the trials, 12 subjects are instructed to walk a set distance of 6 meters at a slow walking speed. An effective distance between 2.1 - 4.1 meters was captured with the camera range. For determining the reliability and repeatability of the system, statistical analysis of recorded data by IMU is carried out using Octave 4.4.1. The mean and standard deviation of the Root Mean Square Error (RMSE) are the statistical measures used for making comparisons. On the other hand, the Intraclass Correlation Coefficient (ICC) allows assessing the repeatability of the instrument under identical conditions. Thus, in this paper, ICC evaluates the consistency of two recording sessions (executed within 10 days). Statistical analysis rejects the null hypothesis if the alpha value associated with the observed result is equal to or less than a significance level of 0.05. Finally, the intra- and intertester validation criteria are methods to estimate significant parameters as well as a reference for measures of maximum active knee flexion and extension with universal goniometers.

D. Knee-Joint Angle Measurement Model

The MPU-6050 integrated 6-axis MotionTracking device that combines a 3-axis gyroscope (wx, wy, wz) and 3-axis accelerometer (ax, ay, az). The angle is calculated from a data fusion model that incorporates the gyroscope and accelerometer measurements of both sensors. The sensor alignment also enables more accurate data fusion, when data from both sensors are aligned to the terrestrial reference systems and frameworks, the data extracted can then be fused reliably.

The proposed algorithm accumulates several measurements against a fixed reference orientation and proceeds to estimate an adjustment value within a time interval in order to measure the gyroscope and accelerometer at zero. The offsets are calculated for a total of 200 measurements and then averaged in order to obtain the 6 adjustment parameters.

In the *Tait-Bryan* convention, the angle of the sagittal plane is represented by the symbol ρ . This angle can be calculated from a complementary filter, which consists of a weighted sum between the gyroscope and accelerometer measurements such as detail in Eq.1. Where k_1 y k_2 is a constant between [0-1] and was established experimentally.

$$\rho = k_1[\,\rho^- + \int_t^t w_x(t)dt] + \; k_2.atan\left(\frac{a_y}{\sqrt{{a_x}^2+{a_z}^2}}\right) \quad (1)$$

Since the angle of the knee-joint corresponds to the relative angle between the consecutive segments of the thigh and leg, two mpu-6050 are placed as follows: The first sensor is fixed between the Hip-Knee (ρ^{hk}) joints and the second between the Knee-Ankle (ρ^{ka}).

$$\rho = \rho^{hk} - \rho^{ka} \quad (2)$$

Finally, the knee-joint angle ρ shown in Eq. 2 is calculated as the difference of the segments, provided that the sensors are oriented with respect to the same reference systems.

E. Kalman Filter

This section describes the process of filtering the data obtained to improve the quality of the IMU data. The proposed filter is Kalman, which is mainly used to filter and predict measurements in linear systems where noise can take on are Gaussian-distributed. This filter contains a process model and a measurement model, where equations Eq. 3 and Eq. 4 correspond to the equation of the process and the measurement.

$$\hat{x}_k{}^- = A\hat{x}_{k-1} + Bu_k + w_k \quad (3)$$

$$z_k = Hx_k + v_k \quad (4)$$

The matrix A relates the state at the previous time step k−1 to the state at the current step k, the matrix B relates the optional control input and he matrix H relates the state to the measurement z_k. The random variables w_k and v_k represent the process and measurement noise respectively [38]. When these equations are applied for the filtering of measures can be considered $A = B = H = 1$; $w_k = v_k = 0$ and $x = \rho$, corresponding to the knee-joint angle [39] .

In addition, the equations for the Kalman filter can be divided into two groups: time update equations and measurement update equations. The complete operation of the proposed Kalman filter is described in Fig. 4.

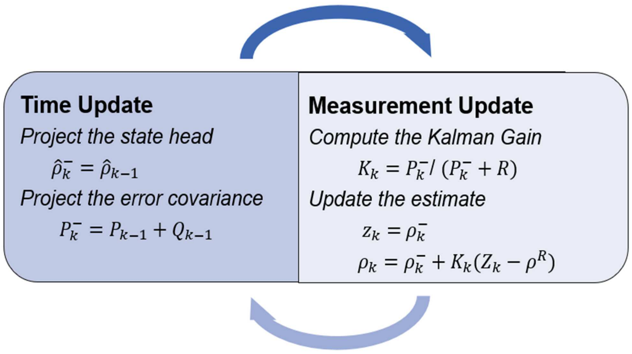

Fig. 4 Kalman Filter Equations.

In practice, Q represents the process noise covariance and R is the measurement noise covariance. Finally, a *posteriori* estimate covariance matrix $P_k{}^-$, the *a priori* estimate covariance matrix P_{k-1} and K_k is the Kalman gain.

F. Feature Extraction and Segmentation

In this stage, the segmentation of the signal is performed which consists of extracting a complete cycle from the gait pattern. For this, the maximum points P_j of the signal are located as illustrated in Fig. 5.

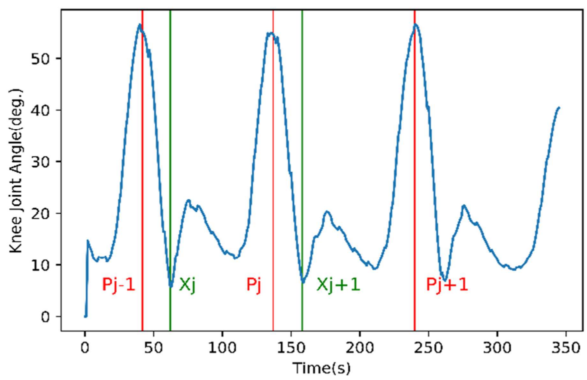

Fig.5 Gait pattern segmentation

Because it can cause changes in the interval of separation of the peaks, from the central maximum the maximums are located P_{j-1} and then P_{j+1}. The intervals can be found at ΔP_{j-1} and then ΔP_{j+1}can be calculated from equations Eq. 5 y Eq. 6.

$$\Delta P_{j-1} = |P_j - P_{j-1}| \quad (5)$$

$$\Delta P_{j-1} = |P_{j+1} - P_j| \quad (6)$$

Similarly, the interval from the central maximum P_j to the minimums X_j and X_{j+1} calculated as shown in Eq. 7 y Eq. 8.

$$\Delta X_{j-1} = |X_j - P_j| \quad (7)$$

$$\Delta X_{j+1} = |X_{j+1} - P_j| \quad (8)$$

After, from this data, it is possible to define the size of the window S_{seg} signal interval by calculating the variables C_1 and C_2 (Eq.9, Eq.10, and Eq. 11).

$$C_1 = \Delta X_{j+1}/\Delta P_{j+1} \quad (9)$$

$$C_2 = \Delta X_{j-1}/\Delta P_{j-1} \quad (10)$$

$$S_{seg} = S[P_j - C_1\Delta P_{j-1},\ P_j + C_2\Delta P_{j-1}] \quad (11)$$

G. Dynamic Time Warping and Polynomial Regression

The dynamic time warping (DTW) method uses a cost function for estimating the warping function for aligning and normalize two signals. This approach is useful and widely used because of the different sampling frequency that recording devices can have for collecting data from the same event. In effect, linear time normalization scales the shorter data so that the two vectors can have the same length, making thus possible the comparison. In this way, for reducing the dissimilarity between two signals, the shorter signal must be interpolated until it coincides with the length of the larger one. After the segmentation and normalization of the gait patterns, it is necessary to establish a set of patterns of the repetitions performed by each subject to obtain an adjustment curve using the polynomial regression method with a 95% confidence interval.

III. Result and Discussion

This paper presented the use of both the IMU prototype and videogrammetry data capture protocol to create an affordable and portable system to analyze human gait. Fig 6 shows the results of the Kalman filter applied to the knee angle signal from subject 1. Afterward, the features extraction process consisted of locating the maximum and minimum values of each signal using an algorithm.

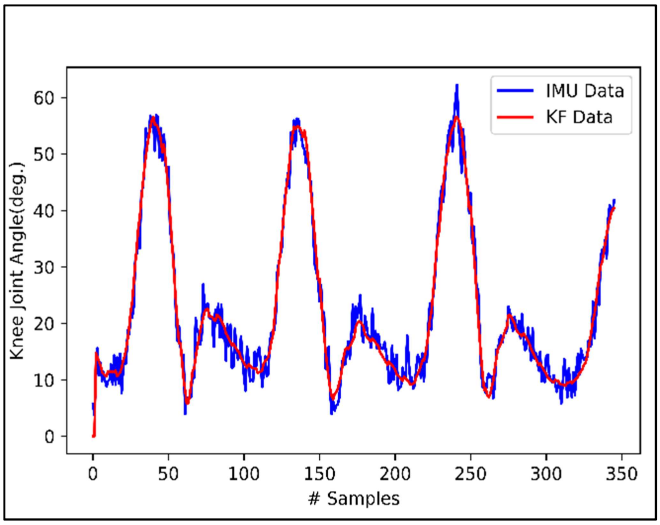

Fig. 6. Kalman Filter and Knee Angle Estimation Model

This approach automatically detects the peak-peak intervals, and therefore, the C1 and C2 values for the signal segmentation (see Fig. 7).

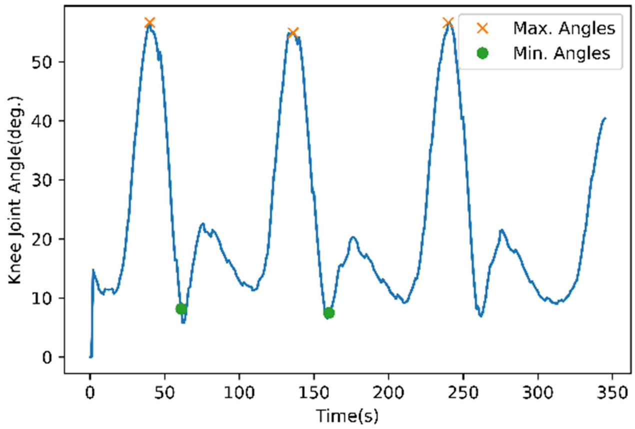

Fig. 7 Identification of maximum and minimum peaks.

The minimum values correspond to the time in which the foot encounters the ground (contact phase), identified by the information from the FSR force sensors on the heel of the foot. Fig. 8 presents the result of the signal segmentation, showing up the identified phases of human gait: initial contact, load response, terminal support, and balance.

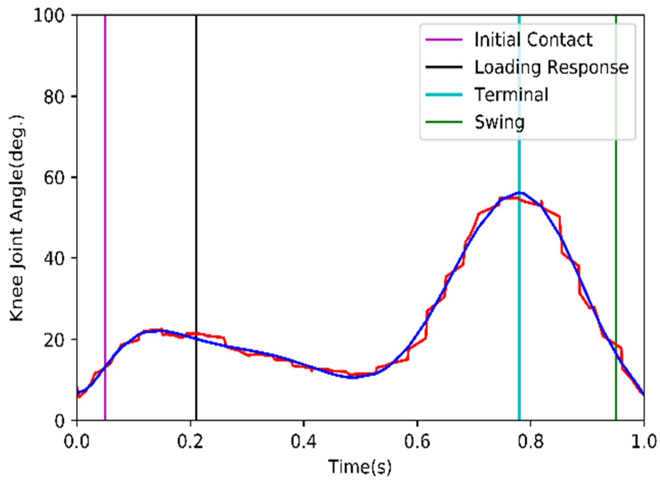

Fig. 8 . Segmentation and identification of the human gait phases.

Fig 9 presents the video sequence for a complete human gait cycle. The therapist performed an inspection and functional evaluation of the lower limb joints from 12 subjects to determine a normal human gait. The data fusion model used data from two IMU sensors at a sampling frequency of 120 Hz to estimate the knee angle. Also, the setup of the Kalman Filter included the calculation of both Q and R covariance matrices. Using the data captured during a time interval of the IMU sensor in a stable position, the value of R was 0.028; meanwhile, analyzing the signal response in function of Q values (0.1, 0.01 and 0.001) the estimation of the best-fit Q value for signal filtering was 0.001.

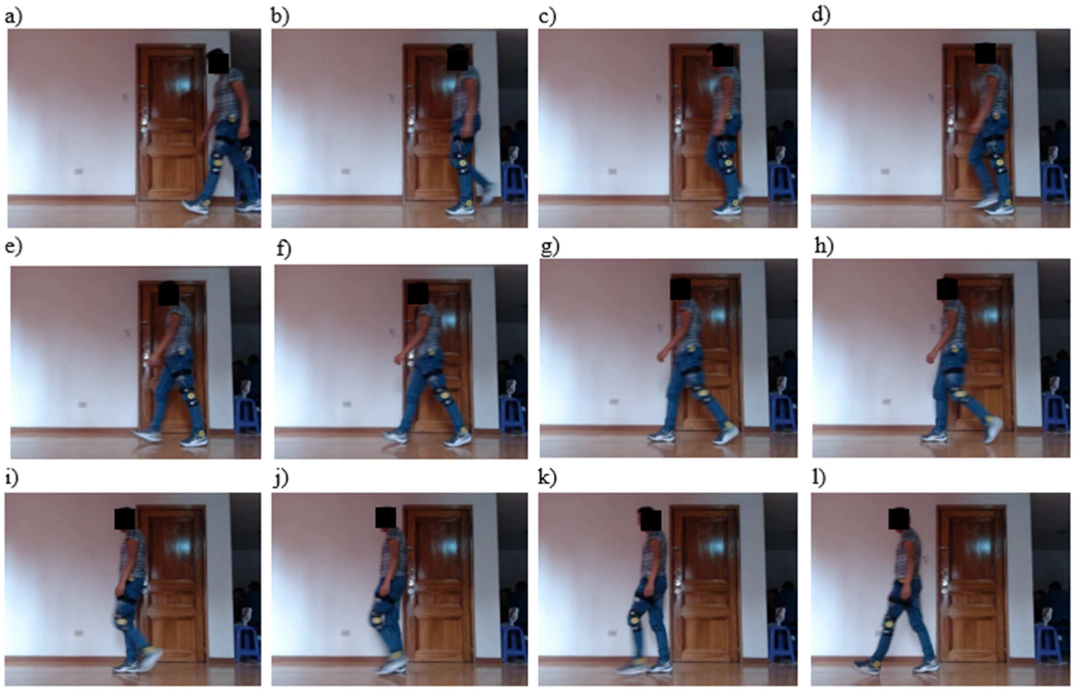

Fig. 9 video sequence captured from the camera for a complete cycle of human gait.

Due to the un-synchronized stored of gait patterns, it is necessary to use the DTW technique for a temporary normalization. From these patterns, it is possible to apply a curve of adjustment using the least-squares method; thus, with a polynomial of degree n=10 and a 95% confidence interval, the Fig. 10 shows the normalization of the signal.

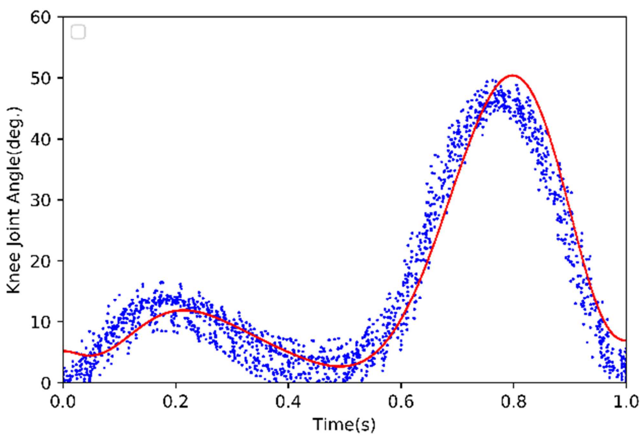

Fig. 10 Polynomial regression of normalized gait patterns.

The results showed that, for the 12 subjects, our motion tracking system successfully measured and recorded the knee flexion-extension (joint angles). Table 1 shows the accuracy of the joint angles measured from the two systems (proposed prototype and cvmob). The interclass correlation coefficient (ICC) between these systems was high for all subjects (> 0.97). Besides, RMSEs were low (2.2° – 4.1°) with a mean of 3.27. In previous studies of knee-joint angle measurement, especially in Knee Flexion Kinematics for Functional Rehabilitation Movements, Tannous et al. obtained ICC values around 0.96 – 0.98 and RMSE mean value of 3.96° from their lower limb fusion algorithm [32]. Also, Farrokh et al. estimated knee-joint angle in gait human with accelerometer and gyroscope sensors, obtaining ICC values from 0.99 to 1.0 and RMSE mean value of 3.58° [38]. Compared to previous studies, the proposed system can provide quantitative measurements of knee movements with high accuracy within the range of portable sensors. This system uses low-cost IMU sensors, providing remarkable improvements over earlier developed systems.

TABLE I
ACCURACY RESULTS OF THE TWO SYSTEMS FOR THE 12 SUBJECTS

Subject	RMSE	ICC
1	4.0	0.97
2	4.0	0.99
3	3.4	0.99
4	3.5	0.97
5	2.8	0.98
6	3.1	0.98
7	3.2	0.99
8	2.8	0.99
9	3.0	0.96
10	3.5	0.98
11	3.1	0.99
12	2.9	0.98

Table II shows the results (RMSE and ICC) over the two sessions (repeatability). It worth it to highlight that ICC, unlike Pearson, besides to establish the strength of the dependence between variables, it allows us to establish whether these are close to each other. For joint angles in the two sessions, ICC was high (> 0.97) for all subjects, presenting a strong correlation between the data sets from the two sessions. RMSEs for session 1 was around 0.5° – 2.1°, and for session 2, 1.0° - 2.7°.

TABLE II
REPEATABILITY OF THE TWO SESSIONS

Subject	RMSE Session 1	RMSE Session 2	ICC
1	1.3	2.7	0.97
2	1.0	1.0	0.99
3	1.6	1.8	0.99
4	0.5	1.4	0.97
5	1.2	2.6	0.98
6	1.2	1.9	0.98
7	1.2	1.1	0.99
8	0.9	1.2	0.99
9	2.0	2.3	0.96
10	0.5	1.2	0.98
11	2.1	3.0	0.99
12	1.0	1.1	0.98

IV. Conclusions

This study presented a portable prototype to measure knee angles using two IMUs connected to the thigh and leg, as well as the filtering process and data fusion model developed for estimating the knee joint angles. Specifically, for all subjects, the IMU-based system and the CvMOb yielded RMSE values around 2.2 °- 4.1 °, and ICC > 0.97. Recording data from 12 subjects, the findings demonstrated that the Kalman-based data fusion method (gyroscopes + triaxial accelerometers) allowed to mitigate and stabilize the accumulated errors of the IMU accurately. These results suggest that the prototype could use in realistically setups to accurately track knee movement to perform gait analysis. This system could also be an alternative to the current capture systems, and due to its low cost, it could have a high potential in clinical settings in emerging countries such as Colombia; however, additional experiments must validate the proposed system in clinical settings. Finally, it is possible to incorporate more IMU to track more body parts and joint angles, the authors are moving towards such a direction.

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