Comparative Analysis of the Gait Cycle on Different Surfaces with the Use of Inertial Sensors

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Abstract. The current study aimed to compare the kinematics of the pelvic, quadriceps, knee and anterior tibial areas of the body, during walking on surfaces, regular, regular with forced and irregular gait, using low-cost wireless IMUs. Ten healthy individuals participated in this study and the 10MWT was used. The patterns measured by the sensors were analyzed and by means of a mathematical analysis of polynomial regression by least squares, predictive curves were obtained that were compared with models established in previous research, obtaining as a result a mean square error (RMSE) of 0.6925 ° between the predictions and the measures. In addition, a secondary RMSE of 4.2651 ° for the predicted curves and the database. These results indicate that the gait is different on each surface, due to factors such as the irregularities present in each terrain. Also, that the devices built can be used in medical fields.

Keywords: Biomechanics, gait cycle, characteristic curves, RMSE, Inertial motion unit.

1 Introduction

Inertial motion units (IMUs) are composed of inertial sensors that allow the measurement of linear acceleration (accelerometer), angular velocity (gyroscope) and magnetometer. This module allows to obtain information on the X, Y and Z axes, so they are appropriate to obtain data of the movement of the body, Losa et al. [1] and Kobsar et al. [2] They analyzed 82 studies using IMUs from different systems such as Xsens, Opal, Dynaport, and Shimmer, with a mean number of participants in the studies being 12 people. The study showed that IMUs have good validity and reliability when obtaining data on stride time, step length and that it can be used for the measurement of joint angle, data that will help obtain biomechanical results such as stability and segmental accelerations.

In the study conducted by Hu et al. [3] they concluded that, IMU devices with machine learning algorithms can facilitate, identify and intervene in fall risks. In their research, they conducted trials in 17 healthy older adults and 18 young people with average ages of 71.5 and 27, respectively. Participants walked on a flat, uneven brick surface, with a sensor located above the L5 vertebra. It was tested with four input models, the fully trained IMU sensor, only with signals from the accelerometer, gyroscope and magnetometer. The first model outperformed the others with an area under the receiver operator curve (AUC) of 0.97 and 0.96, respectively. In addition to having a high accuracy with values between 96.3 and 94.7%, an f1 score of 96.3 and 94.6%.

The purpose of this study is to verify the kinematic behavior of the lower part of the human body during walking on regular surfaces with forced gait (treadmill), regular (cement) and irregular (grass). Tests will be carried out on 10 people, using 5 units of distributed inertial movement, one in the L5 vertebra, one in each quadriceps and one in each anterior tibial muscle. These variables can be observed through an HTML interface where the data taken by the sensors with WiFi connection will be sent. Using polynomial regression with least squares. It is proposed to achieve characteristic curves that allow to know a similar pattern between the individuals during the walking cycle. In addition, this study shows literary reviews made by other authors, triaxial movement equations, methods to be applied, an analysis of results obtained from the measurements and a discussion about the effectiveness of the proposed system.

2 Methods

The tests will be conducted on 10 individuals who do not present lesions or pre-existing abnormalities diagnosed during walking (5 women and 5 men) with height, weight, age and body mass index (BMI) averages of 1.66 m, 65.23 kg, 25 ± 5 years and 23.64 $kg \cdot ^{m2}$, respectively. The individual parameters are detailed in Table 1. Each of these variables will deliver different characteristic curves, according to each participant. Where P corresponds to the trial individual and S to the sex of the individual.

The people who will collaborate with the rehearsals will make the march at their own speed and barefoot to avoid the influence of footwear. The 10-meter walking test (10MWT) will be used, a test used in the studies of Washabaugh et al. [4] and Nikaido et al. [5] Participants will march in a straight line and a section of 14 meters will be taken into account, the first two meters correspond to the acceleration phase and the last two to the deceleration phase [6].

Table 1. Parameters of the individuals to be tested

P	S	Height [m]	Weight [kg]	Age [years]	ICM [$kg \cdot m^{-2}$]
1	F	1.64	66.9	30	24.87
2	M	1.80	78.6	29	24.26
3	M	1.77	67.3	20	21.48
4	F	1.54	58.3	26	24.58
5	F	1.54	59.2	22	24.96
6	F	1.67	64.1	30	22.98
7	M	1.68	59.8	28	21.18
8	F	1.49	55.1	25	24.81
9	M	1.61	64.2	23	24.76

10	M	1.87	78.8	27	22.53

For the study, 5 inertial sensors will be used located in the L5 vertebra, the quadriceps and in the anterior tibial muscle, as shown in Fig. 1 (a), (b) and (c). Three tests per person will be carried out on the different surfaces to rule out possible erroneous measurements and correct them by averaging the data obtained.

(a) (b) (c)

Fig. 1. (a) Frontal plane, (b) Lateral plane, (c) Posterior plane of the location of the IMUs in a trial individual.

The global reference system that will be represented in the signals consists of three components corresponding to the three X, Y and Z axes, which will form the sagittal, coronal, and transverse plane, which will be called as Antero-Posterior (AP), Medium-Lateral (ML) and Vertical (VT), respectively.

2.1 Walking cycle

Importance will be given to the gait cycle, called the stride, which is a sequence of events that occur from the contact of a heel with the surface, until its next contact with the same surface. This cycle consists of three phases such as the initial one that starts from rest, the second called rhythmic stage at constant speed and the third, which is the descent phase until returning to rest, Alvez et al. [7].

According to Agudelo et al. [8] during the gait cycle each lower limb goes through the support phase and the oscillation phase. The support phase occurs when the foot has contact with the surface, begins with the initial contact, ends with the take-off of the forefoot and corresponds to 60% of the cycle. The oscillation phase occurs when the foot is raised, while moving forward and preparing for the next support, begins with the takeoff of the forefoot, ends in the next contact with the ground and corresponds to the remaining 40% of the cycle.

2.2 Inertial motion units

The sensor system chosen to perform the tests is the MPU 9250 that allows motion tracking on 9 axes. This module features a gyroscope, accelerometer and magnetometer of 3 axes each, and integrates a digital motion processor (DMP) that allows motion capture. In addition, it has a voltage regulator at 3.3 V, an I2C serial communication protocol consisting of two pins, one of serial data and another of a serial clock (SDA and SCL), respectively. It also has a programmable scale range of 250, 500, 1000 and 2000 degrees$\cdot^{s-1}$ for the gyroscope, 2, 4, 8 and 16 g in the accelerometer and ±4800 μT of the magnetometer [9].

Mahony's complementary filter will be used to obtain a signal with minimal noise or alteration. This algorithm calculates the error by cross-multiplication between measured and estimated vectors, taking into account the acceleration and the magnetic field, thus allowing to correct the bias in the gyroscope signals, Ludwing and Burnham [10].

The values resulting from the filter correspond to angular coordinates that allow to specify the orientation of objects in space, known as Euler angles, called Yaw Ψ which is the rotation on the Z axis, Pitch θ around the Y axis and Roll φ represents the rotation on the X axis, shown in Equations 1, 2 and 3, respectively, Jouybari et al. [11].

$$\Psi = \text{atan2}(2q_2q_3 - 2q_1q_4, \qquad 2q_1^2 + 2q_2^2 - 1) \tag{1}$$

$$\theta = -sin^{-1}(2q_2q_4 + 2q_1q_3) \tag{2}$$

$$\phi = \tan^{-1}\left(\frac{\{2q_3q_4 - 2q_1q_2\}}{\{\, 2q_1^2 + 2q_4^2 - 1\}}\right) \tag{3}$$

Where q, correspond to the quaternies previously calculated in the filter and that allow a representation of the rotation and three-dimensional orientation of the objects, in this case of the parts of the body, Jouybari et al. [11].

Once the Euler angles of the quadriceps and the anterior tibial have been obtained, these are added together by Equation 4, proposed by Garza-Ulloa [12] to obtain the relative kinematic angles of the joints, in this case the knee θ_{knee} that corresponds to the rotational movement Pitch θ on the Y axis.

$$\theta_{knee} = \theta_{shank} + (180 - \theta_{thigh}) \tag{4}$$

θ_{shank}, corresponds to the angle of the anterior tibial and θ_{thigh}, is the angle of the quadriceps during the walking cycle, measured in °.

With the Euler angles, we proceed to identify and classify the walking cycles of the study subjects, so the data corresponding to each cycle are manually filtered, to rule out possible biases in the measurements.

For the analysis, polynomial regression by least squares will be used, which aims to find a polynomial function of degree n, which best fits the measured data. This method is frequently used to analyze biomechanical patterns, as is the case with the authors, Bravo et al. [13] and Martínez-Solís et al. [14] To evaluate the effectiveness of the estimation model, the square root of the mean square error (RMSE) will be used. This index is determined with Equation 5.

$$\text{RMSE} = \sqrt{\frac{(Y_i - \widehat{Y}_i)^2}{n}} \tag{5}$$

Y_i, is the measured value of the angles of the body, is the value of the angle estimated by the polynomial regression and $\widehat{Y}_i n$, corresponds to the number of samples of the cycle.

3 Results and Discussion

The gait cycles corresponding to the sensors located in the L5 vertebra, quadriceps and anterior tibials were manually identified. Patterns that showed significant similarity were classified. Curves that had anomalies, noises or that did not have similarities were discarded. It was decided to obtain average curves of each pattern to make a proportional estimate.

A total of samples was recognized for the pelvic obliquity patterns of 12, 11 and 10 for the data measured on the regular surface with forced, regular, and irregular gait respectively, obtaining maximum values up of 6 ° and down of -7.8 °. By modeling in MATLAB, the pelvic obliquity patterns and the average curves corresponding to each sample were obtained.

With the sensors located in the quadriceps, the most obvious patterns that develop in the sagittal plane during the walking cycle were obtained, these are the flexion and extension performed by the thigh. A total of 15 similar samples were classified for the data measured on the three surfaces, obtaining maximum bending values of 23, 24.5 and 24.8° and an extension of -22.4, -22.2 and -23.8 °, respectively for each surface.

As with the quadriceps, the data from the sensors located in the anterior tibials in the sagittal plane in which the angles of flexion and extension performed by the leg are obtained was prioritized.

For these curves a total of similar samples of 14, 15 and 14 were obtained on the surface of regular with forced, regular, and irregular march, a maximum bending angle of 15 ° and an extension of -58 °, on the three surfaces, were obtained.

It is important to denote that the angles obtained by the quadriceps and the anterior tibial serve to calculate the angle that the knee performs during the walking cycle, so Equation 4 is used to obtain the patterns resulting from the union. Like the previous patterns, the angles corresponding to the flexion and extension of the knee were projected.

For these curves it was decided to use 14 samples, which is the minimum number obtained from the previous patterns. Maximum bending angles of 22 ° and extension of 68 ° were obtained on all three surfaces.

With the obtaining of the average curves of the march cycles, a polynomial regression by least squares was carried out to estimate a polynomial function that fits the data measured by the sensors. The analysis was performed in Matlab using the polyfit(x,y,n) command that returns the coefficients for a polynomial p(x) of degree n that has an acceptable fit to the variables entered. Additionally, a confidence band was made that details the maximum and minimum range of movement of the body parts with the adjustment of the curves by least squares.

As a result of the polynomial adjustment, the RMSE of the data measured by the sensors was obtained, with respect to the predictions for each part of the body on the different surfaces, these values are found in Table 2, where the RMSE for A, B and C correspond to the regular surface with forced, regular, and irregular gait, respectively.

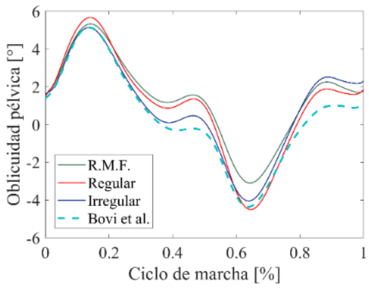
Table 2. – Value of the square root of the mean square error of curve adjustment.

Walking cycle	RMSE [°]		
	To	B	C
Pelvic obliquity	0.0358	0.0528	0.0288
Pelvic rotation	0.0409	0.0440	0.0201
Flex/Ext quadriceps	0.5042	0.294	0.3266
Anterior tibial flex/ext	0.624	0.6925	0.5167
Flex/Ext knee	0.5669	0.5564	0.6720

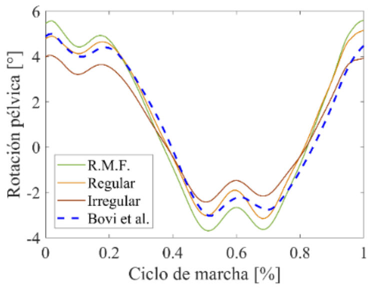
As can be seen in Table 2, the RMSE values obtained are close to 0, with the range of minimum and maximum values being between 0.0288 and 0.6925 ° respectively, indicating that the curves have been satisfactorily adjusted with the least square's method.

With the adjusted gait cycles, the predictions on each surface are compared with the database of the research carried out by Bovi et al. [15] order to determine if the patterns have similarity.

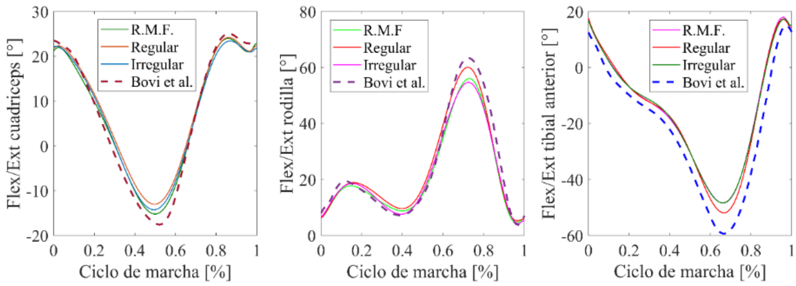
Fig. 3 shows the resulting gait cycles for pelvic obliquity (a), internal and external rotation of the pelvis (b), flexion and extension of the quadriceps (c), knee (d) and anterior tibial (e). In the legend R.M.F refers to the regular surface with forced march.



(a)



(b)



(c) (d) (e)

Fig. 2. Comparison of gait cycle patterns, obliquity (a), pelvic rotation (b), flexion and extension of the quadriceps (c), knee (d), anterior tibial (e).

To understand the difference between the least squares-adjusted patterns with respect to the database shown in Fig. 3, we chose to obtain the RMSE by comparing the adjustments of the patterns of pelvic obliquity and rotation, flexion and extension of the quadriceps, anterior tibial and knee, with the values of the natural gait cycles raised in the database of Bovi et al. [15] the p-value was obtained with the normal distribution curve, the results are detailed in Table 3. Where the RMSE and the p-value obtained with a significance level of 0.05 for A, B and C correspond to the studied surfaces, regular with forced, regular, and irregular gait, respectively.

Table 3. RMSE and p values for the predicted patterns with respect to the theoretical ones.

Walking cycle	RMSE [°]			P-value		
	A	B	C	A	B	C
Pelvic obliquity	1.0729	0.7574	0.7063	0.0019	0.1784	0.0734
Pelvic rotation	0.7108	0.5116	0.6622	0.4751	0.3112	0.4581
Flex/Ext quadriceps	1.6289	2.6202	2.0467	0.4291	0.2311	0.3776
Anterior tibial flex/ext	4.0357	2.9127	3.9038	0.1784	0.2406	0.1811
Flex/Ext knee	4.1830	3.3486	4.2651	0.1834	0.4488	0.2013

Looking at Table 3 it is stated that the RMSE with respect to the variables of the database are acceptable, because they are mostly low values or that tend to 0, the greatest affectation was obtained in the predictions of the anterior tibial, which leads to an affectation to the curves of the knee because their angles are dependent on the values of the anterior tibial and the quadriceps. With respect to p-values, these were obtained with a 95% confidence interval individually for the patterns of the gait cycle on different surfaces.

The values obtained from the pelvic obliquity in the three surfaces have a minimum variation between them, being the one with the greatest variation the regular surface with forced march with a value of 1.0729 ° ($p < 0.05$), the minimum variation was observed in the irregular surface with a value of 0.7063 ° ($p = 0.0734$).

On the regular surface with forced march, it is observed that the RMSE have irregular values with each other, having a maximum of 4.1830 ° ($p = 0.1834$) and a minimum of 0.7108 ° (p = 0.4751). In addition, when analyzing the values of the flexion extension of the quadriceps, tibial anterior and knee can be observed a considerable change between the regular surface with forced march and the regular surface, this is due to the resistance that each terrain presents.

Table 4 details the values obtained from variance σ, Pearson correlation coefficients R and coefficients of determination R2 of the patterns corresponding to the predictions made on the surfaces, regular with forced gait A, regular B and irregular C.

Table 4. Values of variance, Pearson correlation coefficient and pattern determination coefficient.

Walking cycle	σ			R			R^2		
	A	B	C	A	B	C	A	B	C
Pelvic obliquity	4.903	7.057	6.132	0.988	0.986	0.981	0.976	0.973	0.962
Pelvic rotation	11.522	8.983	5.435	0.988	0.999	0.998	0.976	0.998	0.997
Flex/Ext quadriceps	190.342	173.966	180.923	0.999	0.998	0.998	0.998	0.997	0.997
Anterior tibial flex/ext	416.846	458.606	411.644	0.994	0.997	0.996	0.989	0.994	0.992
Flex/Ext knee	254.486	294.166	248.669	0.993	0.987	0.986	0.987	0.975	0.986

Table 4 shows that the mathematical analysis performed with polynomial regression by least squares has an acceptable correlation with respect to the patterns proposed by Bovi et al. [15] obtaining maximum values of 0.999 in patterns such as pelvic rotation and flexion extension of the quadriceps on the regular and regular surface with forced gait, respectively. The minimum Pearson correlation value obtained was in the pelvic obliquity pattern on the irregular surface with a value of 0.981. Among the coefficients of determination obtained the maximum was 0.998 and a minimum was 0.962 in the patterns and surfaces mentioned above. These values confirm that the adjustment of curves by polynomial regression obtained reliable results that can be compared with different mathematical methods used for the study of the kinematics of the human body during walking.

4 Conclusions

By performing the measurements and analysis using least squares it is concluded that the sensors manufactured with an MPU9250 module and Wi-Fi communication are reliable to analyze the biomechanics of the human body. They could be improved to obtain minimal data loss and a more user-friendly interface that performs the calculations and approximations that were performed manually in this study.

Thanks to the mathematical analysis carried out in Matlab, it is affirmed that the predictions made with polynomial regression are effective, given that a maximum RMSE of 0.6925 ° was obtained in the pattern of the characteristic curve of the anterior tibial on the regular surface, while for the curves of the obliquity and rotation of the pelvis the maximums were respectively 0.0528 and 0.0440 °, on the same surface, for the movement of the quadriceps was 0.5042 ° on the regular surface with forced gait and from the knee the maximum was 0.6720 ° on the irregular surface, showing that a correct degree of polynomial was considered for the adjustment of each curve.

A great similarity was obtained between the angles measured by the manufactured sensors and the database of Bovi et al. [15], given that a minimum and maximum variation of between 0.7063 ($p = 0.0734$) and 1.0729 ° ($p < 0.05$) was obtained, for pelvic obliquity in the three terrains. The maximum RMSE was 4.2651° ($p = 0.2013$) between the theoretical curve of natural knee movement and the curve predicted for the irregular surface. Likewise, maximum RMSE values of 0.6622 ($p = 0.4581$), 2.6202 ($p = 0.2311$) and 4.0357 ° ($p = 0.1784$) were obtained for the rotation curves of the pelvis on the irregular surface, quadriceps movement on the regular surface and movement of the anterior tibial on the regular surface with forced gait, respectively.

The maximum variation between surfaces occurred during flexion extension of the quadriceps with a maximum of 2.6202 ° ($p = 0.2311$), in regular terrain and a minimum of 1.6289 ° ($p = 0.4291$) in the regular surface with forced march, in the anterior tibial the largest difference was between 4.0357 ($p = 0.1784$) and 2.9127 ° ($p = 0.2406$) on the same surfaces and for the knee the most notable variation occurred between the regular and irregular terrain with values of 3.3486 ($p = 0.4488$) and 4.2651 ° ($p = 0.2013$), respectively.

One of the most influential factors of variation in the regular surface with forced march is the resistance that is generated according to the height of the gram, which being higher generates a greater resistance, causing an affectation in the measurements The patterns obtained on the three surfaces show a variation during the cycles of the barefoot gait of people, this difference is the result of factors such as irregularities that a surface such as grass has with another regular with forced march such as the treadmill, the speed of each person's own gait, the loss of data due to Wi-Fi communication or the presence of noises in the signals.

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