Characterization of inertial sensors signals of a smartwatch during walking

D Montero¹, S Salinas¹, G Laverde¹, S Sotelo², C Rueda¹, and M Altuve¹
¹ Facultad de Ingeniería Eléctrica y Electrónica, Universidad Pontificia Bolivariana, Bucaramanga, Colombia
² Departamento de Ciencias Básicas, Universidad Pontificia Bolivariana, Bucaramanga, Colombia
E-mail: danielfmontero@gmail.com

Abstract. Parameters of the human gait cycle are commonly used for the evaluation and diagnosis of motor and neurological disorders. Traditionally, biomechanical analysis is performed in specialized laboratories, but in these locations, the subject does not perform a natural gait and tends to hide or exaggerate their alterations. Therefore, in this paper, we characterized eighteen signals per experiment: six from gyroscopes and six from accelerometers of a smartwatch (Apple Watch Series 3) worn on each wrist, and three from gyroscopes of an inertial sensors placed on the ankles. Signals were collected from twenty young and healthy subjects without pathological history. Subjects walked naturally in a straight-line for 25 meters. Each subject performed the walking cycle several times for 6 minutes, 3600 signals were thus analyzed. Each signal was characterized using time domain, frequency domain and nonlinear measurements. Results show that angular velocity in the Z-axis contains relevant information to characterize human gait in both ankles and the wrist. Also, typical gait parameters were obtained from the smartwatch signals. The sample entropy showed that signals that have greater self-similarity are those that contain more information, such as angular velocity signals on the Z-axis in each ankle and wrist. This characterization could be useful for the automatic identification of the human gait cycle, the detection of pathologies and the recognition of people from human gait patterns using only the information extracted from sensors embedded in smartphones and smartwatches.

1. Introduction
Gait is the sequence of coordinated and alternating movements that humans use in his bipedal condition to move from one place to another. It is the most practiced physical activity, requiring the action and coordinated movement of different muscles. The biomechanical analysis of gait allows to identify gait disturbances and motor disabilities [1], is the basis for the systematic management of some diseases and pathological gait, and it is of great importance in the development of prostheses and orthoses [2].

Measurement and quantitative analysis of human gait cycle are traditionally carried out in specialized laboratories, equipped with a set of devices and tools, mainly infrared and conventional cameras, that allow capturing the dynamic and kinematic patterns of human movements in two-dimensional and three-dimensional forms [3]. However, a recent work reported that 15% fewer errors can be obtained to assess human gait using inertial sensors in the ankle
instead of traditional gait methods in laboratories based on infrared cameras [4]. Moreover, gait in specialized laboratories tends to be unnatural and motor disturbances can be hidden or exaggerated given the unrealistic conditions that occur in these confined spaces that restrict the number of steps (even a treadmill can affect the natural gait) [5]. Body-worn sensors are useful for gait assessment outside laboratories, over longer distances than those found in a typical gait laboratory, with different footwear conditions and walking surfaces, in short, in an environment suitable for a natural gait [6]. Gait parameters extracted from sensors embedded in smartwatches and smartphones can be used for authentication and indentation purposes [7]. Although gyroscopic and accelerometer signals on the wrist are not well correlated with those on the lower middle back [8], spatiotemporal gait parameters can be estimated from wrist-worn inertial sensors [9].

Since the distance traveled and the comfort of the user who wears the sensors affect the naturalness of the human gait cycle, in this work we characterize the signals obtained from the gyroscope and accelerometer sensors embedded in an Apple Watch Series 3 smartwatch that is worn on each wrist and gyroscope sensors worn on the ankles of 20 subjects who performed a 25 meters walk for 6 minutes. This characterization could be useful in future work for the automatic identification of the human gait cycle, the detection of pathologies and the recognition of people from human gait patterns using only the information extracted from sensors embedded in smartphones and smartwatches.

2. Analysis of the human gait cycle
The human gait cycle, commonly normalized according to its duration, begins when one foot makes first contact with the ground (0 %) and ends when the same foot touches the ground again (100%) [10], as illustrated in Figure 1. The two main components of the gait cycle are the stance phase and the swing phase, which represent 62 % and 38 %, respectively, of the gait cycle. In the stand phase, the foot touches the ground while in the swing phase the foot does not touch it. The simple stance phase occurs when only one foot is in contact with the ground whereas in the double support phase both feet are in contact with the ground, such as at the beginning and the end of the stance phase [11, 12]. The absence of a double support phase is typical of running. The temporal parameters generally used for the gait cycle analysis are cadence, period of support, swing, double support, and stride.

Figure 1. Phases involved in the human gait cycle.
The human gait cycle can be measured by the angular velocity in the mid-lateral axis of the leg ($z$-axis) as seen in Figure 2. The swing phase is characterized by a positive angular velocity that reaches its maximum value in the mid-swing phase. A negative angular velocity peak is associated with the last contact on the ground before the swing phase. At the end of the swing phase peak, a negative angular velocity peak represents the initial contact area of the ankle with the ground. Initial contact occurs when the heel touches the ground [13].

![Figure 2. Signal of the movement of the foot.](image)

3. Materials and methods

3.1. Hardware and software description

The data was acquired from four portable devices: two inertial sensors (Pololu MinIMU-9 v2) and two Apple Watch Series 3 smartwatches. The Pololu MinIMU-9 v2 is an inertial measurement unit (IMU) that packs an L3GD20 3-axis gyro and an LSM303DLHC 3-axis accelerometer and 3-axis magnetometer, each sensor measures the variable in three perpendicular directions ($x$, $y$ and $z$). The Apple Watch Series 3 has many sensors, but we only exploited and used the gyroscope and accelerometer sensors. The smartwatch has a 2.4 GHz dual-core processor, Wi-Fi connection and Bluetooth 4.2 for data transfer.

The IMU sensors acquire signals at a sampling frequency of 100 Hz, while smartwatches at 50 Hz. Raw signals (unprocessed) were obtained from the IMU and smartwatches sensors.

The inertial sensor data was exported using serial communication from its memory, while the smartwatch data was exported using an application developed in our laboratory. MATLAB® R2016a (The MathWorks, MA, USA) was used to process, store and visualize data.

3.2. Data acquisition and processing

In order to perform the characterization of the natural gait, data were obtained from 20 subjects, with no history of neuromuscular disorders or gait abnormality, between the ages of 18 to 32 years. Each subject naturally walked in a straight line for 25 meters, this experiment was repeated multiple times for 6 minutes. Pololu MinIMU-9 v2 sensors were placed on each ankle and Apple Watch smartwatches on each wrist, as shown in Figure 3. The data of each of the sensors were stored in its internal memory and then exported.

Accelerometers record linear accelerations $a$ in three different axes, $x$, $y$ and $z$. Similarly, gyroscopes record angular velocities $\omega$ in three different axes, $x$, $y$, and $z$. Therefore, six signals were collected for each smartwatch and three for each inertial sensor. A total of eighteen signals were thus characterized for each experiment. In the following, a superscript is used to indicate the location of the sensor (LA denotes left ankle, RA denotes right ankle, LW denotes left wrist and RW denotes right wrist) and a subscript is used to denote the axis of the measured variable ($x$, $y$ and $z$). For example, $w_{z}^{LA}$ denotes the angular velocity signal obtained from the left ankle in the direction given by the $x$ axis.

The beginning of the recording of the smartwatch was different from that of the inertial sensors. Therefore, the smartwatch signals were not synchronized (aligned) with those of the inertial sensors. For this reason, the cross-correlation between $\omega_{z}^{RA}$ and $a_{z}^{RW}$ was used to estimate the delay and have all the signals aligned (synchronized).
3.3. Characterization of the signals

We estimate different features of the human gait cycle signals using three different domains: time, frequency and nonlinear. In the time domain, we computed the mean, standard deviation, and kurtosis of the signals. In the frequency domain, we estimated the frequency of the two greatest peaks in the power spectral density of the signals. They were obtained through the fast Fourier transform algorithm. Finally, the sample and Shannon entropy of the signals were computed as a measure of information content.

4. Results

4.1. Gait events on the smartwatch

As a result of the data acquisition and processing section 3.2, the figures with the most relevant signals for the analysis of the human gait cycle are presented. Figure 4 and Figure 5 show an example segment of 3s of the linear acceleration and angular velocity signals for each sensor and the first 5 Hz of the frequency spectrum.

The ordinate axes of these figures were established in the same range to differentiate the magnitudes between the different signals, in the time and frequency domains. We can observe similar patterns and dynamics between the signals obtained from the smartwatch and those of the inertial sensors such as peaks, and positive and negative cycles. Moreover, frequency components around one, two and three hertz on the frequency spectrum are clearly observed in all signals. In which the first peak is the frequency at which the walk was made.

The events of the gait cycle are defined by the angular velocities in the z-axis of the inertial sensors in the ankles as shown in Figure 2 [13]. Therefore, signals in Figure 4(a) and Figure 5(a) were used as a reference to obtain the events of the gait cycle in the wrist. Each peak of $a_{zRW}$ and $a_{zLW}$ in Figure 4(a) occurs when each heel touches the ground (0% of human gait cycle). Zero crossings of $\omega_{zRW}$ in Figure 5(a) represent the change between the stance phase and the swing phase of the right leg, while the zero crossings of $\omega_{zLW}$ represents the change in the left leg. The positive $\omega_{zRW}$ cycle represents the swing phase of the right leg, while its negative cycle represents the left leg stance phase. In the same way it happens with $\omega_{zLW}$, the positive cycle is
the swing phase and the negative cycle is the right leg stance phase. Finally, the double support period can be measured taking into account the period in which the negative cycles of the $\omega_z^{RW}$ and $\omega_z^{LW}$ signals overlap.

![Graphs](image1.png)

**Figure 4.** Example of linear acceleration on the $x$-axis ($\alpha_x$) obtained from the four sensors. (a) Time domain, and (b) Frequency domain.

![Graphs](image2.png)

**Figure 5.** Example of angular velocity on the $z$-axis ($\omega_z$) obtained from the four sensors. (a) Time domain, and (b) Frequency domain.

Typical gait parameters were obtained from the smartwatch signals. An average cadence of 107.1 steps per minute, average left stance duration of 60.22%, average left swing duration of 39.77%, average left double support of 9.73%, average right stance duration of 59.72%, average right swing duration of 40.28% and average right double support of 10.25% were obtained among all the tests performed.

4.2. **Characterization of the signals**

Table 4.2 shows the features extracted for each signal of the smartwatch and IMU sensor in the time domain, frequency domain and nonlinear methods.
5. Discussion

We observed that the mean in Table 1 of angular velocities and linear acceleration signals on the $x$ and $y$ axes are very sensitive to the location of the sensors. For example, the displacement or rotation of the sensors in the ankle and the wrist orientation while walking produces differences in the signals acquired in the aforementioned axes. For this reason, angular velocity signals on the $z$ axis, where their similarities are more noticeable with a half-period of delay between them. The human gait cycle from the information obtained by the inertial sensors in the ankles was also observed in the smartwatch worn on the wrist, using the angular velocity signal of the lateral axis of the leg ($z$-axis) as reference. On one hand, the period of the gait cycle, determined from the peaks of the acceleration signal of the smartwatch on the $x$ axis, where each peak represents the contact between the heel and the ground, yielded an average period of 0.56 seconds. On the other hand, the periods of stance and swing phase of the right leg, calculated from the zero crossings of the angular velocity signal of the smartwatch on the $z$-axis, produced values of 0.451 seconds (40.28%) and 0.669 seconds (59.72%), respectively. While the periods of stance and swing phase of the left leg are 0.445 seconds (39.77%) and 0.674 seconds (60.22%). Moreover, the acceleration signals of the smartwatch on the $x$-axis on the right wrist (anteroposterior axis) and the angular velocity signals of the inertial sensor on the right ankle (middle lateral axis), allowed to know the cadence period, from the difference between the largest peaks, leading a value of 107.1 steps per minute, a normal spontaneous cadence in adults.

Non-linear features allowed the characterization of the signals concerning their amount of information, and their self-similarity or amount of noise or irregularity. The sample entropy showed that the signals that have greater self-similarity (lower sample entropy) are those that contain more information (greater absolute value of Shannon’s entropy), such as angular velocity
signals on the $z$-axis in each ankle (normally used to estimate the gait parameters) and the angular velocity in the $z$-axis in the wrist.

6. Conclusion
This study shows that angular velocity signals on the $z$ axis both from the inertial sensors and the smartwatch provide valuable information to obtain parameters of the human gait cycle. Smartwatches, wireless and wearable devices, offer alternative solutions to specialized laboratories for the analysis of the human gait cycle, since they allow walking longer distances in open spaces and in more realistic conditions [6].

In this study, signals were acquired from a group of twenty people with no pathological history. In future projects, we will focus on collecting signals from healthy people and people with pathologies. In order to characterize the gait cycle from the wrist to make an automatic detection of anomalies or pathologies through smartwatches.

References
[1] Agudelo A I 2013 Marcha: descripción, métodos, herramientas de evaluación y parámetros de normalidad reportados en la literatura Revista CES Movimiento y Salud 1(1) 29
[2] Caballero J A 2011 Análisis del movimiento en el deporte (Sevilla: Wanceulen Editorial)
[3] Haro D M 2014 Laboratorio de análisis de marcha y movimiento Revista Médica Clínica Las Condes 25(2) 237
[4] Vargas L, Caicedo P, Salinas S, Sierra W and Rodriguez L 2017 Protocolo de evaluación de un sistema para medición de parámetros de tiempo de la marcha humana IX Congreso Iberoamericano de Tecnologías para Apoyo a la Discapacidad (IBERDISCAP) (Bogotá: Editorial Escuela Colombiana de Ingeniería) p 32
[5] Najafi B, Helbostad J L, Moe-Nilssen R, Zijlstra W and Aminian K 2009 Does walking strategy in older people change as a function of walking distance? Gait & Posture 29(2) 261
[6] Najafi B, Khan T and Wrobel J 2011 Laboratory in a box: Wearable sensors and its advantages for gait analysis Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC) (Boston: IEEE)
[7] Johnston A H and Weiss G M 2015 Smartwatch-based biometric gait recognition IEEE 7th International Conference on Biometrics Theory, Applications and Systems (BTAS) (Arlington: IEEE)
[8] Farah J, Lemaire E and Baddour N 2016 Comparison of inertial sensor data from the wrist and mid-lower back during a 2-minute walk test IEEE EMBS International Student Conference (ISC) (Ottawa: IEEE)
[9] Liu J, Lockhart T and Kim S 2018 Prediction of the spatio-temporal gait parameters using inertial sensor Journal of Mechanics in Medicine and Biology 18(7) 1
[10] Willems P, Schepens B and Detrembleur C 2012 Marcha normal EMC-Kinesiterapia-Medicina Física 33(2) 1
[11] Agudelo M, Bruíne T, Guarín V, Ruiz J and Zapata N 2013 Gait: Description, methods, assessment tools and normality parameters reported in the literature CES Movimiento y Salud 1(1) 1
[12] Henry O J and Hernandez V M 2013 Bases para el entendimiento del proceso de la marcha humana Archivos de Medicina (Col) 13(88) 1
[13] Salarian A, Russmann H, Vingerhoets F J G, Dehollain C, Blanc Y, Burkhard P R and Aminian K 2004 Gait assessment in parkinson’s disease: Toward an ambulatory system for long-term monitoring IEEE Transactions on Biomedical Engineering 51(8) 1434