Real-Time Tool for Human Gait Detection from Lower Trunk Acceleration

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Abstract. The continuous monitoring of human gait would allow to more objectively verify the abnormalities that arise from the most common pathologies. Therefore, this manuscript proposes a real-time tool for human gait detection from lower trunk acceleration. The vertical acceleration signal was acquired through an IMU mounted on a waistband, a wearable device. The proposed algorithm was based on a finite state machine (FSM) which includes a set of suitable decision rules and the detection of Heel-Strike (HS), Foot-flat (FF), Toe-off (TO), Mid-Stance (MS) and Heel-strike (HS) events for each leg. Results involved 7 healthy subjects which had to walk 20 m three times with a comfortable speed. The results showed that the proposed algorithm detects in real-time all the mentioned events with a high accuracy and time-effectiveness character. Also, the adaptability of the algorithm has also been verified, being easily adapted to some gait conditions, such as for different speeds and slopes. Further, the developed tool is modular and therefore can easily be integrated in another robotic control system for gait rehabilitation. These findings suggest that the proposed tool is suitable for the real-time gait analysis in real-life activities.

Keywords: Gait detection · Lower trunk · Acceleration · Real-time Wearable

1 Introduction

Walking is one of the most common human physical activities and plays an important role in our daily tasks. The term "gait" is used to describe the way of walking, consisting in consecutive cycles subdivided in a sequence of events triggering transitions from one gait phase to another [1].

Due to the high number of gait pathologies that currently exist, clinicians need a simple, robust and efficient method to quantify patients' gait abnormalities [2].

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These methods should work independently of the intra and inter gait variability of each patient and should allow a continuous evaluation. Accurate and efficient new tools for detecting gait events have been developed [2–4]. In fact, these new tools have proved to be important for the assistance and rehabilitation of the human gait, since they can be incorporated into devices, as orthoses or exoskeletons, which may be fundamental in the recovery of the patients' gait [1–4].

Previously, force platforms, stereo photogrammetric systems, optical bars, or video-analysis have been used to analyze the human gait [5, 6]. However, these devices present limitations making them not feasible for measurements on daily-life situations: they do not allow a complete analysis of the entire gait cycle, demand special environments and require long post-processing, especially when used for subjects with gait abnormalities [5]. Wearable sensors, such as Inertial Measurement Units (IMUs) which generally integrate accelerometers, gyroscopes and magnetometers, are an optimal alternative since they allow to evaluate gait in real-time without these restrictions. Furthermore, with the technological advances, these sensors are lighter and smaller, making them suitable to record gait information and be embedded in wearable devices for outdoor ambulatory applications [6].

The placement of IMUs in the body human for gait events identification, firstly considered the lower body segments (shank and foot). However, such approaches commonly require independent sensors for each lower limb, thus increasing the cost of the solution and interference in the users' daily lives [3]. In addition, the correct gait segmentation depends in many cases on the data of more than one of the sensors embedded in the IMU, which becomes more complex to the signal processing. Through the acquisition of lower trunk acceleration, placing an IMU in the lower vertebral column region (lower thoracic region and lumbar region) it is possible to obtain gait information from both lower limbs and from a single axis. In this way, the measurement of the lower torso acceleration is an efficient solution when it is intended to segment the human gait, using just one inertial sensor and without requiring large processing requirements [2].

In the last years, several systems have been developed to detect gait events, through the lower trunk acceleration based on the use of IMUs [2, 3, 7–14]. The development of these detection systems requires the use of sophisticated algorithms specially for real-time contexts, which are actually very important for gait laboratories and outside of rehabilitation environments towards assisted living environments. The implementation of these algorithms varied greatly from system to system and in general, heuristic rules and wavelet-based approaches were the most used. Further, most of the algorithms were constructed based on the antero posterior and vertical plane. In fact, through the study of the vertical acceleration signal (antero-posterior plane) it is possible to identify the follow gait events: the heel strike, foot-flat, toe-off, mid-stance and heel-off for each limb, as is depicted in Fig. 1 [2]. Also, González *et al.* [3] and Alvarez *et al.* [7] developed the only two systems which provided a real-time gait events detection, namely the initial and final contact events. The gait detection was based on heuristic roles and it were used two acceleration axes vertical and antero-posterior signals.

This paper addresses the development and validation of a novel adaptive real-time tool for the gait event detection. The proposed system consists of one inertial sensor, in particular, an accelerometer placed in the lower trunk at the T2-L1 inter-vertebral space.

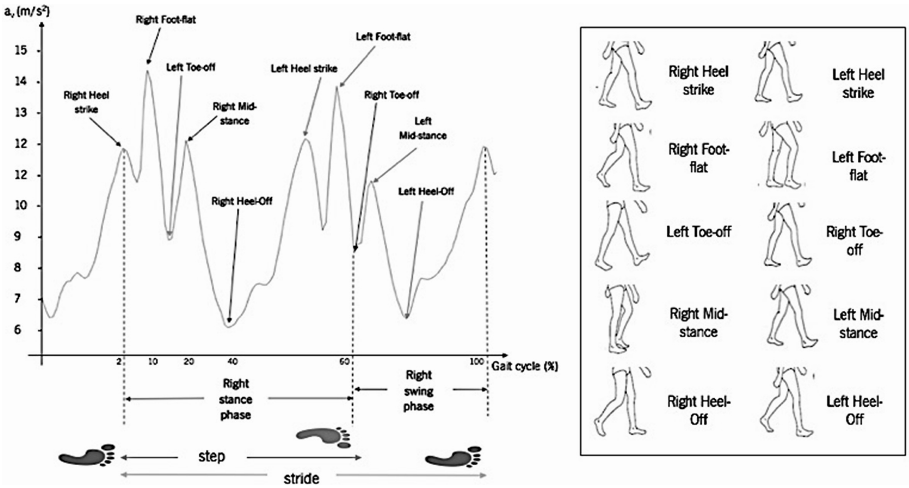

Fig. 1. Vertical acceleration over one stride. Adapted from [2].

Further, it includes a novel tool for gait detection through the lower trunk acceleration signal implemented by a Finite State Machine (FSM) with decision rules and adaptive thresholds. This tool is able to detect five gait events for each leg: Heel Strike (HS), Foot Flat (FF), Mid-Stance (MS), Toe-Off (TO) and Heel-Off (HO). This system follows the idea of implementing a wearable system based on the use of only one IMU, in order to minimize the use of several devices and simplify its use by the user. Lastly, note that the algorithm only uses one acceleration axis - the vertical orientation, aligned with the earth's gravitational axis, in contrast to what was presented in the literature, and especially the two systems developed for real-time segmentation of the gait [3, 7].

2 Methods

2.1 System Overview

In order to achieve all the requirements of portability and ergonomics, the system consisted of a processing unit and an inertial acquisition system embedded in an adjustable waistband for any abdominal diameter, represented in Fig. 2. In addition, it was implemented a data storage system in order to save the inertial gait acquired data in each trial, in a microSD card. These data were storage in the microSD card via SPI protocol.

The processing unit relies on a high-performance microcontroller Atmega 2560 (Arduino Mega) and for the acquisition system it was used an IMU, particularity, the MPU-6050. The MPU-6050, which was the world's first integrated 6-axis motion tracking device, combines 3-axis gyroscope (range: ±2000°/s) and 3-axis accelerometer (range: ±16 g) in a small 4 × 4 × 0.9 mm package. In this particular system, data were only recorded from the accelerometer, in particular the vertical acceleration, with a full-scale range of ±2 g (enough to detect gait events through a lower trunk acquisition) at a sampling frequency of 100 Hz (sufficient to measure one gait cycle).

Fig. 2. Gait detection system developed on a waistband: the bag on the left houses the processing unit and the data storage system, whereas the gait acquisition system, the IMU, has been embedded so as to be placed in T2-L1 inter-vertebral space.

Due the small size, low weight and low admissible current consumption (500 ± μA), this IMU is an optimal solution for the proposed system. The communication between the acquisition system and the processing unit was supported by the I2C protocol.

2.2 Proposed Algorithm

The proposed algorithm consists in five stages: acquisition, calibration, filtering, 1st derivative computation and finite state machine. For the calibration routine, were captured 500 samples which were used to calculate an offset that is withdrawn from each of the samples subsequently acquired.

Then, each acquired sample $(sample_n)$, after calibrated, was filtered with an exponential filter, which is ideal for a real-time implementation based on heuristic rules, since it does not cause delays in the signal and smooths the samples. Thus, each sample was filtered based on the following equation:

$$sample_{n_{filtered}} = \alpha.sample_n + (1 - \alpha).sample_{n-1}. \tag{1}$$

Where, α is the smoothing factor ($0 < \alpha < 1$), $sample_n$ corresponds to the current sample and $sample_{n-1}$ to the previous sample. α was set to 0.5 by trial and error.

After filtering the sample $\left(sample_{n_{filtered}}\right)$, the 1st derivative was determined to detect when the acceleration increases, decreases, or remains constant and, in order to deal with the noise, the derivatives below a threshold (near to zero but empirically set) were assumed as null. This allows to detect only the major variations, that usually are associated with the local peaks. The calculation of the 1st derivative was performed based on the following equation:

$$sample_{n_{diff\_derivated}} = sample_{n_{filtered}} - sample_{n-1_{filtered}}. \tag{2}$$

Once the 1st derivative $\left(sample_{n_{diff}\_derivated}\right)$ is calculated and the threshold applied, it follows the FSM implemented by means of a switch case statement, which changes the states in accordance with the decision rules.

All these stages, Acquisition, Calibration, Filtering, 1st Derivative and FSM, are presented in the flow chart depicted in Fig. 3. The FSM is constituted by eleven states that correspond to ten gait events and one of reset. Each of these events corresponds to a peak in the filtered acceleration acquired in the lower trunk, as represented in Fig. 1. To detect each of these events, ten decision rules have been implemented that allow to trigger from one state to other which are presented in the Table 1. Also, is indicated the gait event corresponding to the peak in the acceleration signal.

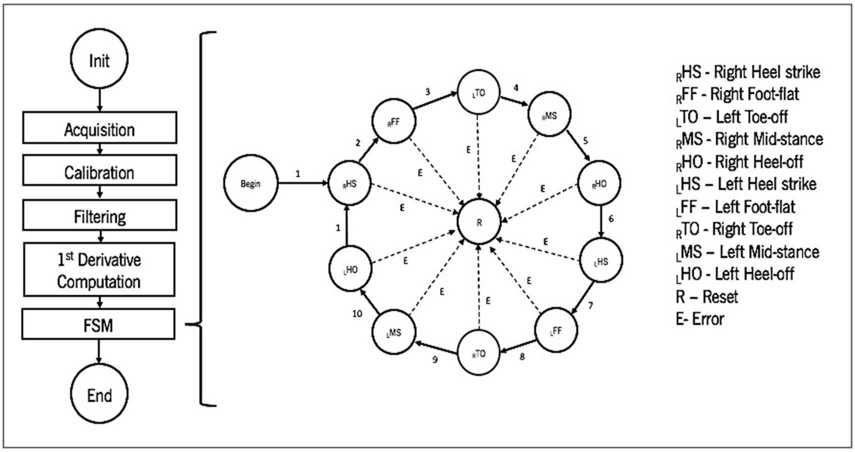

Fig. 3. Flow chart (left) and FSM (right) used to detect the gait events.

To increase the robustness of the algorithm, the thresholds used in the decision rules were adaptively calculated every three gait cycles and the first thresholds were set empirically. Also, after the occurrence of three gait cycles, each of the peaks corresponding to a gait event was detected based on its respective peak of the previous gait cycle, and must belong to a cadence calculated every three gait cycles. In this way, the peaks were only valid if they belonged to this calculated interval.

It is emphasized that the filtering, as well as the calculation of the 1st derivative and the decision rules depend on the previous sample acquired, so this is always stored at the end of each stage (Acquisition, Calibration, Filtering, 1st Derivative and FSM). For the first sample acquired, it is assumed that the previous sample is zero at each of the different stages of the algorithm.

2.3 Validation

The validation of the proposed adaptive tool involved 7 healthy subjects (3 males and 4 females). These subjects present a mean age of 25.13 ± 1.01 years old, mean weight of 71.69 ± 5.84 kg and a mean height of 170.38 ± 3.48 cm. The subjects conducted

Table 1. Gait events detected and corresponding signal acceleration peaks

Gait event	Peak on acceleration signal	Decision rules
Right heel strike	1st Maximum local	$\left(sample_{n_{diff\_derivated}} < 0\right) \& \left(sample_{n-1_{diff\_derivated}} > 0\right) \& \left(sample_{n-1} > \mathrm{th}_{1st\ max\ local\ 1}\right)$
Right foot-flat	Maximum global	$\left(sample_{n_{diff\_derivated}} < 0\right) \& \left(sample_{n-1_{diff\_derivated}} > 0\right) \& \left(sample_{n-1} > \mathrm{th}_{max\ global\ 1}\right)$
Left toe-off	Minimum local	$\left(sample_{n_{diff\_derivated}} > 0\right) \& \left(sample_{n-1_{diff\_derivated}} < 0\right) \& \left(sample_{n-1} < \mathrm{th}_{min\ local\ 1}\right)$
Right mid-stance	2nd Maximum local	$\left(sample_{n_{diff\_derivated}} < 0\right) \& \left(sample_{n-1_{diff\_derivated}} > 0\right) \& \left(sample_{n-1} > \mathrm{th}_{2nd\ max\ local\ 1}\right)$
Right heel-off	Global minimum	$\left(sample_{n_{diff\_derivated}} > 0\right) \& \left(sample_{n-1_{diff\_derivated}} < 0\right) \& \left(sample_{n-1} < \mathrm{th}_{min\ global\ 1}\right)$
Left heel strike	1st Maximum local	$\left(sample_{n_{diff\_derivated}} < 0\right) \& \left(sample_{n-1_{diff\_derivated}} > 0\right) \& \left(sample_{n-1} > \mathrm{th}_{1st\ max\ local\ 2}\right)$
Left foot-flat	Maximum global	$\left(sample_{n_{diff\_derivated}} < 0\right) \& \left(sample_{n-1_{diff\_derivated}} > 0\right) \& \left(sample_{n-1} > \mathrm{th}_{max\ global\ 2}\right)$
Right toe-off	Minimum local	$\left(sample_{n_{diff\_derivated}} > 0\right) \& \left(sample_{n-1_{diff\_derivated}} < 0\right) \& \left(sample_{n-1} < \mathrm{th}_{min\ local\ 2}\right)$
Left mid-stance	2nd Maximum local	$\left(sample_{n_{diff\_derivated}} < 0\right) \& \left(sample_{n-1_{diff\_derivated}} > 0\right) \& \left(sample_{n-1} > \mathrm{th}_{2nd\ max\ local\ 2}\right)$
Left heel-off	Global minimum	$\left(sample_{n_{diff\_derivated}} > 0\right) \& \left(sample_{n-1_{diff\_derivated}} < 0\right) \& \left(sample_{n-1} < \mathrm{th}_{min\ global\ 2}\right)$

walking experiments on the ground at a comfortable speed, in a distance of 20 m on unobstructed hallway. Each participant performed 3 trials and between each trial repetition, the waistband was removed and then replaced to assess test-retest repeatability.

In order to obtain an effective strategy to determine the performance of the gait identification algorithm implemented, as a ground truth, it was used two FSR sensors (from Interlinks Electronics®) placed on the right heel and toe foot of each subject. The gait events detected were compared with the signals from the FSRs in each gait cycle, more properly the HS and TO. Thus, all participants' steps performed were analyzed

Table 2. Algorithm performance regarding its accuracy, percentage of occurrence and duration of delays (delayed detection) and advances (earlier detection) for HS, FF, TO, MS and HS gait events

Gait event	Accuracy (%)	Delayed (D)		Advanced (A)	
		%	(Mean ± SD) ms	%	(Mean ± SD) ms
HS	98.99	11.1	11.33 ± 2.52	8.33	9.69 ± 7.88
FF	99.98	6.03	2.17 ± 0.67	4.09	1.92 ± 1.24
TO	95.56	12.2	12.2 ± 3.29	5.75	4.81 ± 3.91
MS	93.94	21.8	11.8 ± 4.56	9.09	3.54 ± 1.34
HO	95.04	7.89	10.8 ± 3.55	5.43	9.03 ± 3.78

and HS, FF, TO, MS and HO events were evaluated regarding its accuracy, % of occurrence and duration of earlier and delayed detections.

3 Results and Discussion

The performance of the real-time algorithm is demonstrated in Table 2, where it is possible to analyze the accuracy of correct identification of HS, FF, TO, MS and HS event (considering both feet), in percentage. Besides the accuracy percentage, it is also presented the percentage of delayed and advanced gait events detection and the delay and advance delay times, comparing with the FSR data.

In Table 2, it is verified that the proposed algorithm for gait detection is accurate in the detection of all events, with an accuracy above 93.94%, being the HS and MS events with more accuracy (98.99% and 99.98%, respectively). On the other hand, MS and HS were the events with less accuracy due to changes in cadence and local and global peaks very close. Also, the accuracy is affected by the high susceptibility to noise when using the acceleration signal from the built-in accelerometer of the IMU.

Concerning to the percentage of occurrences of delays and advances, it is observable that the worst results were in the MS event (D: 21.8% and A: 9.09%). The MS corresponds to a maximum local in the trunk vertical acceleration signal, thus this observation is due to the fact that the algorithm detects local peaks that are very close to the local maximum which is supposed to be detected. Also, it was verified that the worst measured delayed (11.8 ms) and advanced (9.98 ms) results to this event does not contribute with significant delay and advanced time in the gait detection, since a normal gait cycle is 1.15 s [15].

It was also found that the delays measured for the initial and final foot-contact (HS - 11.33 ms and TO - 12.2 ms, respectively) were lower than those measured by the González' real-time algorithm proposed (117 and 34 ms, respectively) through the trunk acceleration [3]. These results are probably due to the filter implemented in [3], since it was used a low-order 11-order low-pass filter, which introduces an undesirable delay to the gait events detection, especially when it comes to a real-time implementation. On the other hand, in our tool it was implemented a filter exponential which only smooth the signal, not introducing delays in the real-time detection. Also, it is

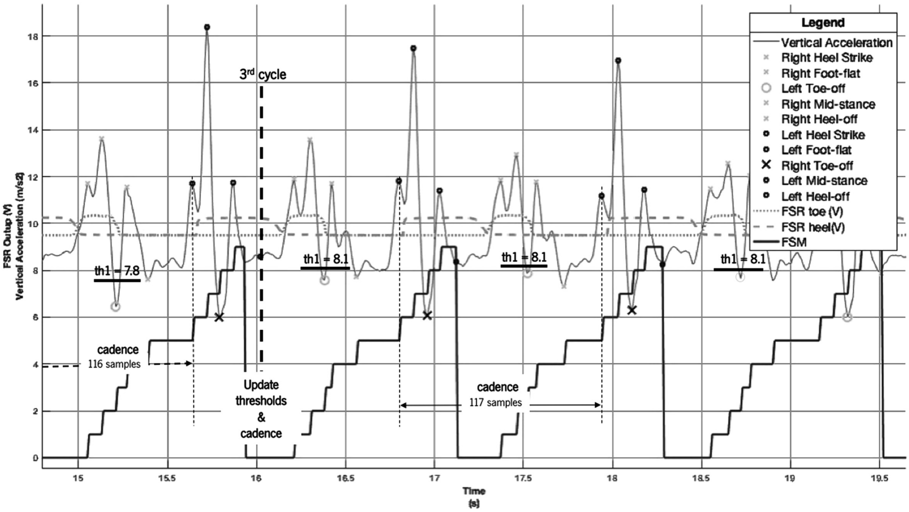

Fig. 4. Representation of gait events detection throughout the vertical acceleration (m/s^2) and FSRs output, in three-steps of a subject. It is pointed out the value of the adaptive thresholds (in this example for the TO detection for the right and left foot, a local minimum) and the value of the cadence (a specific defined range for each gait event) for the HS event.

emphasized that our tool it is based on a set of decision rules implemented by a FSM, depending only on the acquisition of the signal on a single axis. Thereby, the delay is smaller when compared to the algorithm presented in [3], which is based on a set of heuristic rules (zero-crossing) through the analysis of two acceleration axes.

Figure 4 depicts the gait events detection in three-steps of a subject. It is verified that the implemented algorithm detects the right/left heel strike (HS - 1st local maximum), right/left foot-flat (FF - global maximum), right/left toe-off (TO - local minimum), right/left mid-stance (MS - 2nd local maximum), and right/left heel-off (HO - global minimum), for the right and left limb, respectively. These detections provide an innovative character to the proposed tool since all the real-time gait detection algorithms on the literature only detected the initial and final foot-contact on the ground [3, 7].

Note that at the end of a third gait cycle, the threshold and cadence calculation is adapted based on the previous detected values, for each leg. In Fig. 4, it is only represented the threshold for the TO detection for the right limb and the cadence for the HS for the left leg. At the end of the third cycle, the threshold for the TO detection on the left leg (th1) goes from 7.8 to 8.1 and remains with this value during the following three cycles. Also, the calculation of the cadence for HS event was adapted according to the detection of the events during the three previous gait cycles, going from 116 to 117 samples. Thus, we prove the additivity of the implemented tool to detect gait through the vertical acceleration with a single-axis.

Lastly, it can also be verified that the HS and TO events, that the signal from the FSRs detect, are in accordance with the respective events identified through the signal of the trunk acceleration: the event HS corresponds to a rise in the signal of the FSR placed in the heel, which matches with the peak corresponding to the HS in the signal of the acceleration (1st local maximum); and the event TO corresponds to a decrease in the signal of the FSR placed in the toe, which beats with the peak corresponding to the signal of the acceleration (local minimum).

4 Conclusions

A real-time tool for human gait detection from lower trunk acceleration was developed and validated. The vertical acceleration signal (a single axis) was acquired by implementing an IMU on a waistband.

The proposed algorithm was based on a finite state machine using a set of suitable decision rules to detect HS, FF, TO, MS and HS for each leg. The algorithm was validated considering accuracy and time-effectiveness with 7 subjects walking at comfortable walk speeds on the ground. Results allowed to conclude that the projected tool is accurate and time-effective in real-time detection. Moreover, we introduce a new and real-time tool which detects all gait events of the stance-phase, through a single axis by a wearable system with an IMU.

The adaptability of the algorithm has also been verified, indicating the tool will be easily adapted to some gait conditions, such as for different speeds and slopes. Besides that, the implemented algorithm is modular since it can easily be integrated in another robotic control system for gait rehabilitation.

These are the future challenges. In the future, it will be addressed the validation of this algorithm considering different environments and conditions. These validations, besides healthy and (non)-elderly subjects, will include patients with neurological pathologies as Parkinson's Disease or Multiple Sclerosis. Thereby, the algorithm developed will be embedded in a more robust and ergonomic wearable system which will allow the gait monitoring, a special contribution to clinicians in order to facilitate diagnostic techniques but above all, allow to trace paths of motor symptoms' improvements for these devastating diseases.

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