ADAPTIVE REAL-TIME TOOL FOR HUMAN GAIT EVENT DETECTION USING A WEARABLE GYROSCOPE *

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The development of robust algorithms for human gait analysis are essential to evaluate the gait performance, and in many cases, crucial for diagnosing gait pathologies. This work proposes a new adaptive tool for human gait event detection in real-time, based on the angular velocity recorded from one gyroscope placed on the instep of the foot and in a finite state machine with adaptive decision rules. The signal was segmented to detect 6 events: Heel Strike (HS), Foot Flat (FF), Middle Mid-Stance (MMST), Heel-Off (HO), Toe-Off (TO), and Middle Mid-Swing (MMSW). The tool was validated with healthy subjects in ground-level walking using a treadmill, for different speeds (1.5 to 4.5 km/h) and slopes (0 to 10%). The results show that the tool is highly accurate and versatile for the detection of all events, as indicated by the values of accuracy, average delays and advances (HS: 99.96%, -7.95 ms, and 9.85 ms; FF: 99.48%, -4.95 ms, and 9.35 ms; MMST: 98.26%, -36.54 ms, and 16.38 ms; HO: 98.87%, -22.71 ms, and 18.62 ms; TO: 95.95%, -6.80 ms, 14.38 ms; MMSW: 96.06%, -3.45 ms; 0.15 ms, respectively). These findings suggest that the proposed tool is suitable for the real-time gait analysis in real-life activities.

1. Introduction

Accurate and efficient gait event detectors play an integral role in the design of controllers for many real-time therapies to restore lower limb progression [1]. Such therapies can be improved with devices capable of enhancing or restoring the lower limb motor function [2], such as orthoses or exoskeletons [3].

Many different sensors have been used for the human gait analysis. Most of them are embedded into the assistive devices and are directly used in advanced control algorithms (e.g., accelerometers, gyroscopes, and potentiometers) while

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others are mounted in the user's body to supplement the information available from the devices (e.g., foot-switches) [2]. Given the portability required by these systems [4], studies point out that the use of wearable inertial sensors which are considered an optimal solution for recording information, in real-time, correlated to locomotion [5]. Recent technological advances have made these sensors smaller, lighter, cheaper and with low-power consumption, making them suitable for long-term and outdoor ambulatory applications [6]. Additionally, inertial sensors have stood out by their versatility and accuracy, providing good trade-off between portability, cost and precision when compared with the golden standards.

For gait event detection, recent studies have been using one or multiple inertial sensors [1], [3], [5]–[10], or a combination of inertial with foot-contact sensors [2], [4]. Also, the choice of algorithm goes through finite state machines (FSMs) based on the specification of a set of decision rules, which can be implemented through functional data analysis [11], and machine learning techniques [9]. Moreover, the performance relies on the appropriate and accurate placement of the sensors in the body. Foot-contact sensors are placed on the foot [4], [7] while inertial sensors can be mounted in different parts of the body, such as foot [2], [9], shank [3], [5], [6] tight, arms [9], and trunk [8].

Studies have been focus on finding accurate solutions that describe the gait human pattern with a few number of sensor, easy to be mounted. Thus, this paper addresses a novel adaptive real-time tool for the gait event detection, suitable for distinct human walking conditions (speeds and slopes), based on a gyroscope placed in the instep of the foot, and in a FSM with adaptive decision rules to detect 6 gait events: the 4 well-established gait events (Heel Strike – HS, Foot Flat – FF, Heel-Off – HO, and Toe-Off – TO), plus 2 moments in the middle of each gait phase (Middle Mid-Stance – MMST, and Middle Mid-Swing - MMSW). The proposed algorithm uses as input the angular velocity aligned with the sagittal plane. This work extends the one performed in [10], that proposes a similar method to detect HS and TO on a humanoid robot and a biped model.

2. System Overview

To overcome the real-time and portability constraints, the proposed tool relies on a high-performance microcontroller (MCU) to run the algorithm (STM32F407VGT, STMicroelectronics) and in a wearable IMU to measure the kinematic data (Tech IMU v4, Technaid S.L.). The IMU integrates 3 distinct tri-dimensional inertial sensors, including an accelerometer (range: ± 16 g), a gyroscope (range: ± 34.9 rad/s), and a magnetometer (range: ± 8.1 G). Moreover, this IMU constitutes an optimal solution given its small size (11x26x36 mm), weight (10 g), admissible current consumption (70 mA) and its built-in calibration, only allowing communication through a control area network (CAN). The choice of the MCU was made regarding this protocol, since the STM32F4 MCU is incorporated with CAN controllers. In this application, data were only recorded from the gyroscope at 100 Hz. We have mounted this sensor in the instep of the foot (Figure 1) to have access to the direct measurement of the orientation angles of the user's foot, and restricted measurements of angular velocity to the sagittal plane, considering that previous studies have shown feasibility for real time event detection [12]. The gyroscope was chosen given its stability, low noise (accelerometers showed to be sensible to shocks, vibrations, gravity, and position) and immunity to magnetic environments (unlike magnetometers) [5], [9].

3. Proposed algorithm

3.1. *Adaptive Decision Rules*

Figure 1 shows the events detected throughout the angular velocity signal acquired by the gyroscope.

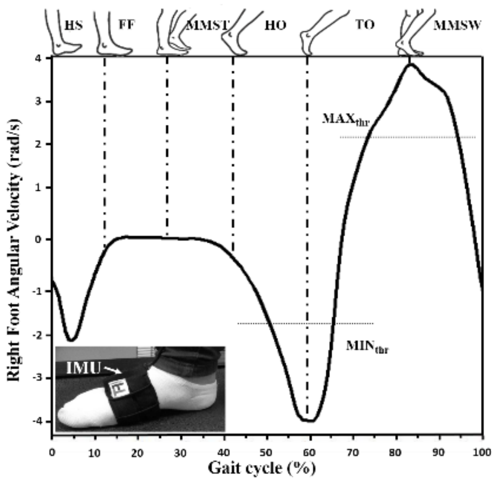

Figure 1. Representation of angular velocity of instep of right foot (continuous line) and gait events (HS, FF, MMST, HO, TO, and TO) during one gait cycle on healthy subject; adaptive thresholds to detect minimum and maximum (*MINthr* and *MAXthr*); and a real image of IMU mounted in user.

The criteria to define HS, HO and TO is based on foot plantar pressure measurements performed with force sensitive resistors (FSRs) placed on the heel and toe. Remaining events were defined based on simultaneous visualization of user's limb movement and the angular velocity recorded. Thus, we defined the decision rules, presented in Table 1, based on curve tracing techniques, such as thresholds crossing, local extrema detection and signal derivatives evaluation.

Table 1. Proposed decision rules using adaptive thresholds to detect the human gait events.

Condition	Decision Rule	State
1	$(\mathrm{gyro_n} > \mathrm{MAX_{thr}})$ AND $(\mathrm{derivative_n} < 0)$ AND $(\mathrm{derivative_{n-1}} > 0)$ AND $(\mathrm{gyro_{index}} - \mathrm{MAX_{index}} \in [0.7 * \mathrm{CAD_{Prev}}; 1.3 * \mathrm{CAD_{Prev}}])$	MAX / MMSW
2	$((\mathrm{HS\_thr_{mean}} - \mathrm{HS\_thr_{std}} < \mathrm{gyro_n} < \mathrm{HS\_thr_{mean}} + \mathrm{HS\_thr_{std}})$ OR 1st_gyro_min) AND 1st_gyro_max AND $(\mathrm{gyro_{index}} - \mathrm{MAX_{index}} \in [0; 0.4 * \mathrm{CAD_{Prev}}]))$	HS
3	$(\mathrm{derivative_n} \approx 0)$ AND $\lvert\mathrm{derivative_n}\rvert \leq 0.2$ AND 1st_gyro_min AND $(\mathrm{gyro_{index}} - \mathrm{MAX_{index}} \in [0.15 * \mathrm{CAD_{Prev}}; 1.0 * \mathrm{CAD_{Prev}}]))$	FF
4	$\mathrm{MMST\_counter} > (\mathrm{HO_{indexPrev}} - \mathrm{FF_{indexPrev}})/2$	MMST
5	$(\mathrm{gyro_n} < 0)$ AND $(\mathrm{derivative_n} < 0)$ AND $(\mathrm{derivative_{n-1}} < 0)$ AND $(\mathrm{derivative_n} > 0.9 * \mathrm{derivative_{n-1}})$ AND $(\mathrm{gyro_{index}} - \mathrm{MAX_{index}} \in [0.3 * \mathrm{CAD_{Prev}}; 1.0 * \mathrm{CAD_{Prev}}]))$	HO
6	$(\mathrm{gyro_n} < \mathrm{MIN_{thr}})$ AND $(\mathrm{derivative_n} = 0)$ AND $(\mathrm{derivative_{n-1}} < 0)$ AND $(\mathrm{gyro_{index}} - \mathrm{MAX_{index}} \in [0.5 * \mathrm{CAD_{Prev}}; 1.1 * \mathrm{CAD_{Prev}}])$	TO

As pointed out in Figure 1 and Table 1, the gait events were defined as: MMSW, the local maximum detected above an adaptive threshold (MAX_{thr}); HS, the angular velocity between a range empirically determined ($HS\_thr_{mean} \pm HS\_thr_{std}$) after occurring the maximum; FF, the angular velocity is approximately constant (n samples with 1st derivative almost null); MMST, *n* samples after FF occurred, where *n* corresponds to the duration of the last valid MMST; HO, the velocity becomes negative after a constant period; and TO, the 2nd minimum detected by an adaptive threshold (MIN_{thr}). The rules also have a condition dependent of the cadence (*CAD*) which establish adaptatively intervals where the events shall occur, allowing the algorithm to be sensible to changes in the pattern.

3.2. *Finite State Machine*

To increase the robustness of the algorithm, our approach stands out by using adaptability given by the previous steps performed. This allows the continuous monitoring of the gait pattern to detect variations of step (duration of gait cycle) and speed (amplitude of angular velocity). This information is used to define intervals where the events must occur (conditions dependent of *CAD*) and to adjust the thresholds of the decision rules (MAX_{thr} and MIN_{thr}). Figure 2 shows the flow chart of the algorithm, which is composed by 5 steps executed sequentially in each iteration (100 Hz). The developed FSM, also depicted in Figure 2, presents 6 states, one for each gait event (MAX/MMSW, HS, FF, MMST, HO, TO), and

2 additional states (default state - DEF, and a reset state - R). The decision rules defined in Table 1 (1-6) and an exit condition (E) are used to trigger transitions.

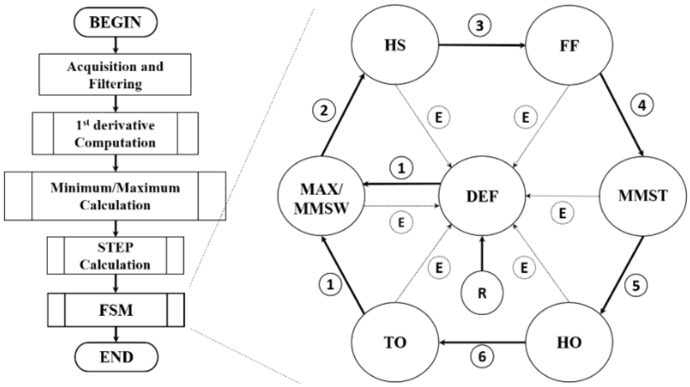

Figure 2. Flow chart of the proposed algorithm (left) and FSM (right) used to detect the gait events.

As indicated in Figure 2, the algorithm starts by measuring and filtering (1st order exponential Low-Pass filter) the angular velocity. The filtered sample is analyzed in 4 different stages in order to make the FSM adaptable for different walking conditions. First stage determines the 1st derivative, detecting when the velocity increases (positive signal), decreases (negative signal) or becomes constant (approximately zero). To deal with noise, the derivatives below a threshold (near zero) are set to zero. This allows to detect only the major variations, that usually are associated with the local peaks. The minimum/maximum calculation stage (2nd stage) is used to detected HS, MMSW, FF and TO, given their dependency to the local extrema. This stage also updates the MAX_{thr} and MIN_{thr} based on the current and previous peaks (60% of mean of 3 previous valid peaks). The 3rd stage, step calculation, computes adaptively the cadence, using the last 3 valid steps. For the first steps, initial conditions are used until a valid *CAD* is obtained. As referred, *CAD* is used in the algorithm to establish statistic decision limits where the events must occur. This strategy tailors the algorithm to work for distinct speeds, also allowing the FSM to restart in situations where an event was not detected (E condition). At final, the last stage implements the FSM by means of a switch case statement, which changes the states in accordance with the decision rules. As disclosed in Figure 2, the 1st state to run is the R state. Here, all variables are reset and the initial conditions (empirically tuned) are set. It follows a transition to DEF state. The FSM only leaves this state when the decision rule 1 is true (local maximum), transiting to MAX/MMSW. Note that the rule 1 only allows the transition to MAX state in the 1st detection. In the remaining situation, it detects the MMSW since the maximum corresponds to this event. The FSM is also adaptive in the calculation of the threshold for MMST (*MMST_counter*), which occurs approximately in the middle of the previous valid FF and HO, as showed in Table 1. We applied this strategy due to the unpredictability of MMST event.

At last, the tool is able to manage situations in which a user stands for a period of time without walking. In this case, the algorithm resets after a period without state changes (5**CAD*).

4. Validation

The validation of the proposed adaptive tool involved 11 healthy volunteers (7 males and 4 females), 6 in barefoot and 5 wearing shoes. The subjects present age of 28.27 ±4.17 years old, height of 1.70 ±0.08 m, and weight of 69 ±12.02 kg. The participants conducted walking experiments in a treadmill at different speeds (1.5, 2.5, 3.5, and 4.5 km/h; variable speed) and slopes (0, 5, and 10%). For each speed and slope, we asked the participants to perform 3 trials during 30 seconds. Globally, 3922 steps were analyzed and each gait event was evaluated regarding its accuracy, % of occurrence and duration of earlier and delayed detections. As ground truths, we used 2 FSR sensors placed on the heel and toe. This strategy was very effective to determine the performance parameters for HS, HO and TO. The remaining events were identified manually.

5. Results and Discussion

The versatility and robustness of the algorithm for different walking conditions is highlighted by the results shown in Table 2, which indicate how much the proposed toll is accurate and time-effective in the real-time detection.

Table 2. Algorithm performance in terms of accuracy, % of occurrence and duration of delays (delayed detection) and advances (earlier detection) for each gait event.

	Accuracy	**Delay**		**Advance**	
	(%)	**%**	**ms**	**%**	**ms**
HS	99.96	15.78	7.95 ±7.13	14.36	9.85 ±11.21
FF	99.48	5.71	4.95 ±5.16	7.99	9.35 ±11.83
MMST	98.26	29.35	36.54 ±13.25	8.97	16.38 ±4.04
HO	98.87	30.80	22.71 ±21.07	15.38	18.62 ±9.63
TO	95.95	10.58	6.80 ±17.83	21.65	14.38 ±12.83
MMSW	95.06	5.95	3.45 ±3.36	0.15	0.90 ±2.42

By analyzing Table 2, we concluded that the proposed tool is accurate in the detection of all events for different speeds and slopes (accuracy > 95.06%). TO and MMSW constitute the events with less accuracy (95.95% and 95.06%, respectively) due to the existence of local maximums and minimums, respectively. Regarding the % occurrence and average duration of Delays (D) and

Advances (A), MMST (D: 29.35% and 36.54 ms; A: 8.97% and 16.38 ms) and HO (D: 30.80% and 22.71 ms; A: 15.38% and 18.62 ms) presented the worst results. For MMST, the prediction method is susceptible to the variations of the cadence, causing delays and advances when the cadence decreases or increases, respectively. For HO, instabilities of the signal during stance (not completely constant) can lead to delayed and earlier detections. Table 2 also points out high occurrence of early delays for TO. This results from the local minimums that occur very close to the global local minimum that truly identified the event. Moreover, the algorithm shows to be robust in barefoot and footwear conditions, even when different shoes types were worn. However, the IMU presents a better attachment when placed on the shoe (tends to slide in barefoot).

Regarding the adaptability provided to the algorithm, Figure 3 shows calculation of the adaptive thresholds (varies with previous global peaks) and the ranges that establish the limits where the events can occur (varies with cadence), for 2 steps of walking in an acceleration period. As disclosed, MAX_{thr} and MIN_{thr} are recalculated in each step (thresholds decrease in both cases). Additionally, the limits of each event (different between up and down limit defined in Table 1) varies with the cadence (all increase when the cadence increases).

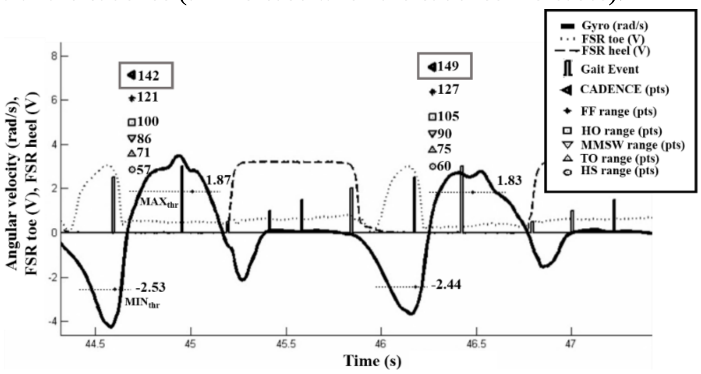

Figure 3. Representation (two steps) of gait events detection throughout the angular velocity and FSRs' output, value (points) of cadence, range (points) defined for each event, and value of MIN_{thr} and MAX_{thr}.

Lastly, these findings support that the proposed tool is a robust, adaptive, and effective strategy for the real-time gait analysis demanded either in assistive or diagnostic tasks.

6. Conclusion

The development of a real-time adaptive tool for human gait detection was described. The proposed algorithm stands out from the existing approaches since it uses a robust FSM triggered by adaptive decision rules and only one-axis from a gyroscope mounted in the instep of the foot. The algorithm, validated with healthy subjects, has shown to be very accurate and time-effective. Adaptability points enhanced the robustness of the proposed strategy, allowing its application at distinct walking conditions. Thus, the gyroscope has been valued to be a plausible device for gait monitoring systems, since it provides sufficient information for the segmentation and detection of human gait events. Future challenges include the validation of this algorithm with neurological subjects wearing assistive devices, such as orthoses and powered exoskeletons. Predictive techniques will also be a focus to tune the assistance with the user's gait pattern.

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