An Adaptive Real-Time Algorithm to Detect Gait Events Using Inertial Sensors

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Abstract—**This study aimed at developing an adaptive algorithm to detect in real time temporal gait events, based on data acquired from inertial and magnetic measurement units.**

Trials on 9 healthy subjects were performed to select the best body locations for the sensors out of 8 different possibilities, trying to optimize system portability, data inter-variability and real-time algorithm simplicity. Subjects walked over the GaitRite mat at different self-selected speeds: normal, fast, and slow. Results showed a significantly low variability ($p<0.05$) of the shank angular velocity in the sagittal plane, reducing the number of sensors required for the real-time algorithm to two (the ones placed on the shanks).

The detection of the Initial Contact (IC) and the End Contact (EC) was based on the shank angular velocity and flexion/extension angle. The gait events were identified as local minima on the sagittal-plane angular velocity. Features extracted from the signals of the previous steps were used to improve the events localization. These features were self-calibrated at the beginning of the trial and updated every step.

The algorithm was validated against the GaitRite system and was compared to two other real-time algorithms available in the literature to assess its reliability and performance. F1-scores of 0.9987 for IC and 0.9996 for EC were obtained. Our algorithm detected the gait events with a mean (SD) delay of 68.6 (15.1) ms for IC and 7.8 (23.6) ms for EC, with respect to the GaitRite, for the self-selected normal speed. These values were significantly lower than those obtained by other published algorithms.

Results indicated that the system is suitable for real-time gait monitoring, assessment and ambulatory rehabilitation, based on biofeedback or neuroprostheses.

Keywords—**Gait temporal parameters, Real-time processing, IMMS, Ambulatory system.**

I. INTRODUCTION

Gait and balance disorders are common in older adults and neurological patients. Thus, the detection of temporal gait parameters is crucial for monitoring or assessment purposes [1]. A real-time detection of gait temporal parameters, such as the initial contact (IC) and end contact (EC), is also needed to develop goal-oriented rehabilitation treatments based on biofeedback [2] or on Functional Electrical Stimulation (FES) [3,4].

Different sensors can be used to provide real-time information in ambulatory clinical settings. Body-mounted Inertial and Magnetic Measurement Systems (IMMS), combining data from tri-axial gyroscopes, accelerometers and magnetometers, have arisen as the optimal solution [1]. IMMS are small, light, easy to don and doff and, thanks to data fusion, they provide drift-free angles, angular velocities and linear accelerations with minimal latency. Accelerometers and gyroscopes have been widely used, but their output is strongly influenced by drift and, in the case of accelerometers, also by gravity and heel-strike vibrations [1]. Footswitches have also been used, especially to control FES. Their processing is very simple, but they do not provide as much gait information and they have been reported to cause discomfort, to be prone to mechanical failure and to be unreliable when used with patients with drop-foot or shuffling-feet [5].

Several algorithms have been proposed for gait assessment. Generally wavelet analysis [6] and low-pass filters have been applied to the signals to prepare it for derivatives, integration [7] or detection of peaks correlated to the desired event [6–8]. Most of the proposed offline algorithms have provided good reliability, but they're unsuitable for real-time applications. On the other hand, most of the proposed real-time algorithms are tested on a restricted sample, lack adaptability and introduce detection delays due to the processing.

The present study proposes a real-time, adaptive algorithm to provide accurate gait-event detection. To reach this aim, sensor placement was optimized, trying to minimize the number of sensors, the subject inter-variability and the software complexity. The developed algorithm was validated against the gold standard and compared to other real-time methods proposed in the literature.

II. ALGORITHM DESIGN

A. Data Collection

Nine healthy subjects participated in the experiments (8 women and 1 man; age: 27.1 ± 4.4 years; height: 169.0 ± 8.8 cm; weight: 56.3 ± 10.3 kg). Eight IMMS (MTx sensors from Xsens technologies B.V., Netherlands) were placed over the sternum, S1 vertebra, mid-point of the external part of both thighs and calves, and on the insteps. They were fixed using Velcro and double-sided adhesive

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tape, minimizing motion artifacts. The sensors, sampled at 50 Hz, were synchronized with the GaitRite System (CIR Systems Inc., United States), sampled at 120 Hz.

Before starting the trials, the subjects were asked to keep an upright position in order to perform the initial coordinate alignment calibration of the Xsens system, according to [9]. Then, they were asked to walk over the GaitRite mat, at three different self-selected speeds: normal, fast and slow. Each condition was repeated 12 times.

B. Sensor Selection

The choice of the sensors used to design the algorithm was a trade-off between system portability, low data inter-variability and real-time algorithm simplicity.

To analyze the inter-variability, the acquired signals were separated into cycles using the IC provided by the GaitRite system, and then normalized in time and amplitude. For each sensor, only data related to the plane of the movement and the line of progression was considered, i.e. anterior-posterior and vertical acceleration, sagittal-plane angular velocity and flexion/extension angle. These four signals were analyzed in terms of correlation with gait events, and the computational load required to process them in real time. Thus, the accelerations were discarded due to the high number of oscillations, caused by noise and vibrations. For the two remaining signals, the root mean square error (RMSE) between each cycle and the average cycle of the rest of the subjects was computed. Data resulted not normally distributed, thus a non-parametric Kruskal-Wallis test ($p<0.05$) was performed to compare the RMSE obtained for the eight sensors and two signals. Dunn-Sidak post-hoc tests were performed ($p<0.05$) to determine which pairs of effects were significantly different. Median and interquartile ranges of the RMSE are shown on Fig. 1.

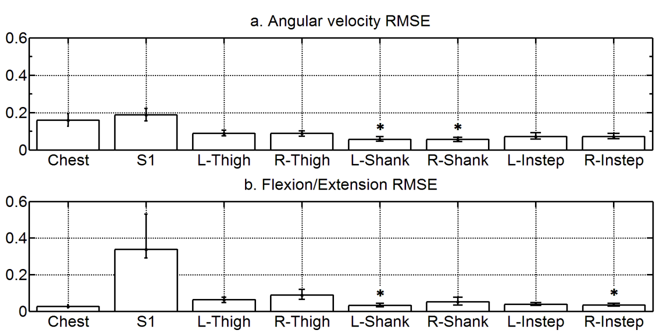

Fig. 1 Inter-variability of the angular velocity (a) and the Flexion/extension angle (b), in terms of normalized RMSE. L: Left; R: Right. * indicates that the sensor has a RMSE significantly lower ($p<0.05$) than all other sensors.

The sensors placed on the shanks were selected since they were characterized by the significantly lowest values of RMSE considering both the angular velocity and the flexion/extension angle. In addition, the shank angular velocity is highly correlated with the IC and EC [8], so the algorithm simplicity is also guaranteed. Thus, the algorithm was designed using, for each leg, the shank angular velocity and the shank flexion/extension angle.

C. Algorithm Description

An adaptive algorithm was designed to detect in real time the instants of the initial and end contact. As shown in Fig. 2, IC and EC were defined as two negative minima on the sagittal-plane angular velocity of the shank, as suggested by Lee et al. [8].

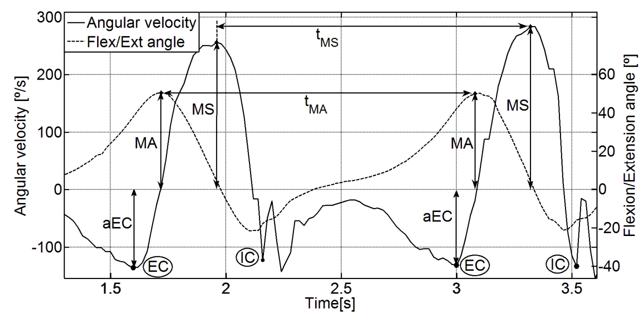

Fig. 2 Angular velocity and the flexion/extension angle of the shank used for event detection. Initial and End Contact as well as features extracted from the signals to optimize the localization of the events are highlighted.

The algorithm comprised four steps: signal conditioning, features initialization, peak detection and features update. The signal conditioning was a zero-delay, first-order FIR filter designed to reduce the noise.

The following features were defined (see Fig. 2): the peak of the flex/ext angle (Max-Angle, MA), the peak of the angular velocity (Mid-Swing, MS), their respective periods (tMA and tMS), and the value of the angular velocity at EC (aEC). These features were initialized during the first 3 steps of each leg and used to assure the robustness of the real-time event detection. IC was detected as the instant correspondent to the first negative minimum of the angular velocity after MS, within the 30% of t_{MS}. EC was detected as the instant correspondent to the minimum value of the angular velocity similar to aEC after the flex/ext angle reached the half of MA. After the event detection, the algorithm kept analyzing the signals, checking if the events were correctly detected. Thus, the features were updated every step with the true values, limiting the error propagation.

III. ALGORITHM VALIDATION

The algorithm performance was assessed using the GaitRite system as the goal standard.

A. Reliability Analysis

All true positives (TP), false positives (FP) and false negatives (FN) were counted; true negatives were omitted, due to the resulting unbalanced analysis dataset. TP, FP and FN were combined to compute the Precision (P), Recall (R) and F1-score metrics.

1193 IC events were correctly detected (TP), with 0 FP and 3 FN. In case of EC events, 1195 TP, 0 FP and 1 FN were obtained. This results in P_{IC}=1, R_{IC}=0.9975, P_{EC}=1 and R_{EC}=0.9992. The F1-scores were $F1_{IC}$=0.9987 and $F1_{EC}$=0.9996. All these values were above the 0.9 recommended by Rueterbories [1] for gait event detection reliability, in order to have a good system for ambulatory rehabilitation.

B. Agreement Analysis of Detection Timing

For all the TP, a Bland-Altman plot [10] was obtained for each speed condition to assess the agreement between the detection timing of the IC and EC events computed by the developed algorithm and the GaitRite (see figure 3). This agreement was evaluated as the difference between the GaitRite detection timings and the ones obtained by our algorithm. Thus, positive values corresponded to an early detection of our algorithm.

The mean values [95% Confidence Interval (CI)] of the difference between the detection timings were equal to -69.6 ms [-70.6, -68.6] for the slow self-selected speed, -68.6 ms [-69.5, -67.7] for the normal self-selected speed, and -71.0 ms [-72.0, -70.0] for the fast self-selected speed. For EC, the detection showed a mean difference [95% CI] of 3.3 ms [0.7, 5.9], -7.8 ms [-9.2, -6.4], and -7.8 ms [-9.1, -6.5] for slow, normal and fast self-selected speed, respectively. Limits of agreement are shown in Fig. 3.

The acceptable difference between both systems has to be defined taking into consideration the future application of the algorithm. Given that the sampling period is 20 ms, the mean difference in the detection timings are -3.49 samples in case of IC and -0.2 samples for EC. This makes the system suitable even for real-time applications.

Regardless of the detection timing variability, the proposed algorithm was always able to find the local minimum associated with IC. The differences in the detection timings came from the misalignment that sometimes happened between the local minimum of the angular velocity and the IC event detected by the GaitRite.

IV. COMPARISON WITH PREVIOUS PUBLISHED ALGORITHMS

The developed method was compared to two real-time algorithms previously published in literature [7,8]. The algorithm of Lee et al [8] used two shank-attached inertial sensors, detecting MS, IC and EC on a 3-Hz-filtered version of the raw signal. Its main drawback was the introduction of delays due to the filtering and the use of MS as reference for a previous event (EC). The algorithm of Gonzalez et al [7] used one sensor placed on the S1 vertebra, and located the IC and EC after a zero-cross on the 2-Hz-filtered version of the anterio-posterior acceleration. Both algorithms were assessed in terms of reliability and agreement analysis as explained in the section III.

For the reliability analysis, Lee's algorithm correctly detected all 1196 IC and EC events, but also extracted 3 false contacts (P=0.9975, R=1 and F1=0.9987). Gonzalez's algorithm worked perfectly (P=1, R=1 and F1=1).

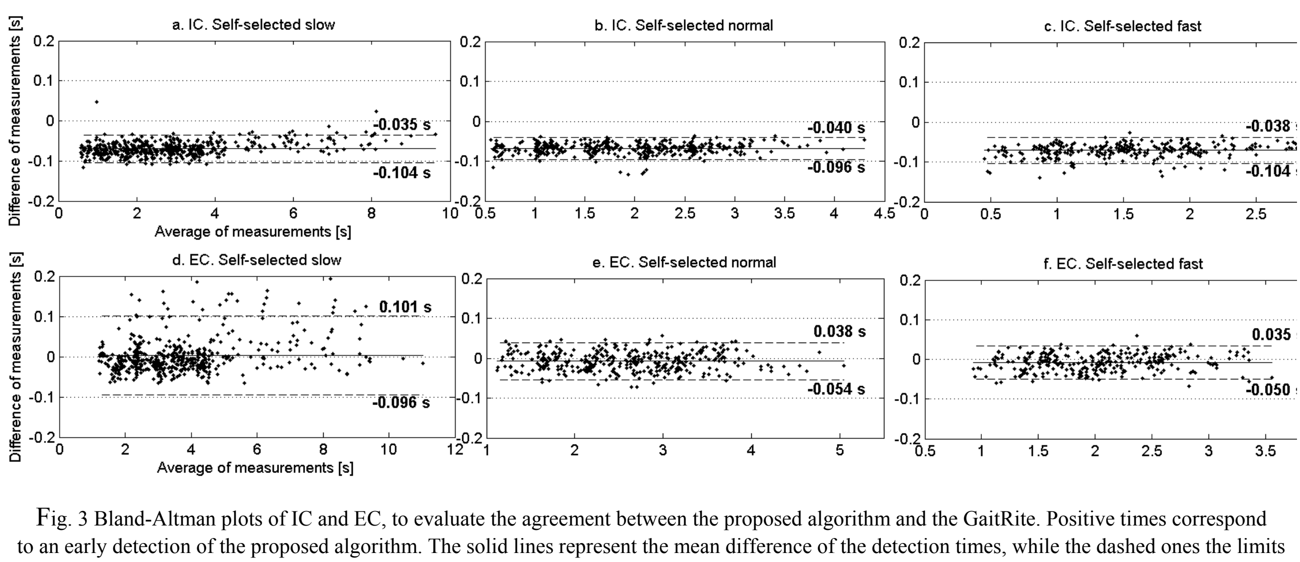

Fig. 3 Bland-Altman plots of IC and EC, to evaluate the agreement between the proposed algorithm and the GaitRite. Positive times correspond to an early detection of the proposed algorithm. The solid lines represent the mean difference of the detection times, while the dashed ones the limits of agreement (mean ± 1.96SD). Limits of agreement are reported in the figure.

For the timing agreement, a statistical analysis was done to compare the performance of the three algorithms in terms of detection timing. After verifying that all data was not normally distributed (Kolmogorov-Smirnov test), a non-parametric Kruskal-Wallis test ($p<0.05$) was performed. Six separate tests were used to analyze the two time events for the three speed conditions. Dunn-Sidak post-hoc tests were performed ($p<0.05$) to determine which pairs of effects were significantly different. Figure 4 shows the median and interquartile ranges of the detection timings obtained by the three algorithms, which were different for all speed conditions. The differences in the detection timings with respect to the GaitRite system obtained by the here proposed algorithm were always the lowest. Additionally, EC was sometimes detected in advance, which is tremendously useful for closed-loop rehabilitation treatments.

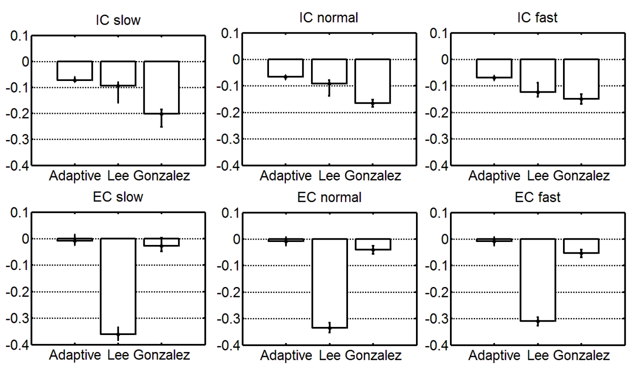

Fig. 4 Comparison between the 3 algorithms in terms of detection timing. Negative timings correspond to detections in delay with respect to the GaitRite.

V. CONCLUSION

This study presented a novel adaptive algorithm to detect gait events in real-time, using only two IMMS attached to the shanks. Its accuracy and reliability have been proved, indeed, from the comparison with the gold-standard system, where F1-scores of 0.9987 for IC and 0.9996 for EC were obtained. Our algorithm detected the gait events with a mean (SD) delay of 68.6 (15.1) ms for IC and 7.8 (23.6) ms for EC, with respect to the GaitRite, for the self-selected speed. These values were significantly lower than those obtained by other published algorithms. The obtained results suggested that the algorithm can be used to develop gait treatments based on biofeedback or neuroprostheses. The algorithm is adaptive and thus it can potentially be used for long-time applications. Additionally, since it used only information of the ipsilateral leg, it might be suitable for subjects with an asymmetrical gait. Further experiments are needed to validate the algorithm on a wider variety of ages and pathologies, such as elderly and post-stroke patients.

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