

Gyroscope-based assessment of temporal gait parameters during treadmill walking and running

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Abstract Wireless sensing solutions that provide accurate long-term monitoring of walking and running gait characteristics in a real-world environment would be an excellent tool for sport scientist researchers and practitioners. The purpose of this study was to compare the performance of a body-worn wireless gyroscope-based gait analysis application to a marker-based motion capture system for the detection of heel-strike and toe-off and subsequent calculation of gait parameters during walking and running. The gait application consists of a set of wireless inertial sensors and an adaptive algorithm for the calculation of temporal gait parameters. Five healthy subjects were asked to walk and run on a treadmill at two different walking speeds (2 and 4 kph) and at a jogging

(8 kph) and running (12 kph) speed. Data were simultaneously acquired from both systems. True error, percentage error and ICC scores indicate that the adaptive algorithm successfully calculated strides times across all speeds. However, results showed poor to moderate agreement for stance and swing times. We conclude that this gait analysis platform is valid for determining stride times in both walking and running. This is a useful application, particularly in the sporting arena, where long-term monitoring of running gait characteristics outside of the laboratory is of interest.

Keywords Adaptive algorithm · Inertial sensor · Gait events · Heel-strike · Toe-off · Stride time · Stance time · Swing time

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1 Introduction

Recent advancements in wireless sensor technology have made continuous monitoring of physiological and biomechanical signals in a natural environment, a realistic prospect [5]. For example, the use of body-worn inertial sensors, such as gyroscopes, accelerometers and magnetometers, have become widespread in the analysis of human movement [18]. These sensors have been used in a variety of clinical applications [1, 20], and have been shown to be useful in certain instances in the sporting domain [4, 25]. Biomechanical evaluation of running has traditionally been undertaken in specialized gait laboratories where use of a treadmill enables the capture of large amounts of movement data [7]. Setup and operation of these costly systems can be time-consuming and training intensive in comparison to gait analysis using on-body sensors. In addition, athletes may not adopt their natural gait in such a setting. Recent research has focused on the

use of accelerometers as an extra-laboratory solution to these challenges [11, 14, 24]. This paper proposes the use of body-worn gyroscopes for this purpose.

The measurement device used in this study is a flexible, multi-sensing device, consisting of a triaxial accelerometer with options of add-on daughter boards with ECG and EMG measurement capabilities, in addition to triaxial gyroscope daughter boards (see Fig. 1) [2]. It is, therefore, a potentially attractive technology for sport and exercise scientists because of its ability to collect and store large amounts of diverse information. The purpose of the study was to investigate the utility of this device in gait analysis using a novel, fully automatic gyroscope-based algorithm. We have previously validated the performance of this algorithm against a force plate for the identification of gait events in normal and clinically impaired gait [8]. Furthermore, it has been implemented in the classification of fallers and non-fallers using the timed-up-and-go test [9]. However, it has not as yet been applied to sustained locomotion, particularly for running. It is possible that the higher impacts repeatedly experienced during running, along with the altered biomechanics, could degrade the performance of the algorithm. Identification of gait events, heel-strike (HS) and toe-off (TO) using inertial sensors, during faster speeds, has proven to be problematic in the past [16]. The algorithm presented here is novel, in that it adaptively calculates thresholds using each subject's individual data to determine HS and TO times from the angular velocity about the y-axis of a shank-mounted gyroscope (axes illustrated in Fig. 1). It also incorporates an artifact rejection routine which ensures more robust gait event detection, particularly important in running gait due to larger impacts.

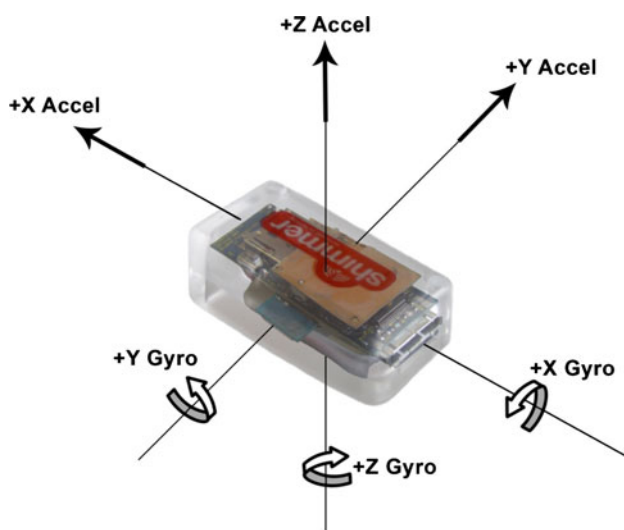


Fig. 1 Inertial sensor used to calculate temporal gait parameters. The angular velocity about the y-axis was used to identify heel-strike and toe-off points. This relates to movement in the sagittal plane

The aim of this study was, therefore, to compare the performance of the adaptive gyroscope-based algorithm (referred to hereafter as AGA) to a marker-based motion capture system for the detection of HS and TO and associated temporal parameters during sustained walking and running. The experiment was accordingly carried out on a treadmill where bouts of locomotion at four different speeds—two walking speeds, one jogging speed and one running speed—were performed. Firstly, we calculated HS and TO points from a marker-based motion capture system using two different, previously reported algorithms to successfully identify HS and TO. The first method is an algorithm proposed by Hreljac and Marshal (HMA) [12]. This algorithm is based on the values of the vertical and horizontal components of jerk equal to zero for HS and TO, respectively. The authors reported absolute value errors in measuring HS of 4.7 ms and TO of 5.6 ms during walking, when compared to a force plate. The second method is an algorithm proposed by Zeni et al. (ZA) [27] for HS and TO detection in treadmill walking. It is based on the change in the horizontal component of the velocity vector from positive to negative. It has been shown by the authors to determine 94 % of gait events within 16.7 ms of the force-plate value. We then compared the results obtained using these algorithms to the results obtained using the AGA. Finally, we compared the algorithms to each other to assess the differences across all three methods. We hypothesize that the level of agreement between the temporal gait parameters as calculated by two previously reported algorithms [quantified by intraclass correlation coefficients ICC(2,k), true error and percentage error] would not be higher than the levels of agreement observed between those methods and the AGA presented here.

2 Methods

2.1 Experimental setup

The gait of five normal healthy subjects (4M, 1F, age range 26–32 years) was measured on a treadmill using two gait measurement technologies simultaneously: the SHIMMER wireless sensor platform (SHIMMER research, Dublin, Ireland) and the optical marker-based Cartesian Optoelectronic Dynamic Anthropometer (CODA) motion analysis system (Charnwood Dynamics Ltd, Leicestershire, UK). The purpose of the study was explained to each subject before they were asked to give their consent to take part in the study. Subjects wore their own training shoes. There were four different treadmill speeds used in the study: 2, 4, 8 and 12 kph. 2 and 4 kph were classed as walking speeds, and 8 and 12 kph were classed as jogging and running speeds, respectively. The subjects were given time to

familiarize themselves with the treadmill and the different speeds. Data were recorded whilst each subject performed two trials of 20 s duration at each speed. Eight trials were completed for each of the five subjects. Two trials were excluded from subsequent analysis due to visibility difficulties with the infrared markers. The experimental setup is detailed graphically in Fig. 2.

2.2 Gyroscope data acquisition

Gyroscope data were acquired using two shimmer wireless inertial sensors attached to the shank of the left and right leg. Each sensor contained a triaxial gyroscope daughterboard, sampling each of the three axes at 102.4 Hz. Data were acquired from the inertial sensors using a custom-built application, developed using the BioMOBIUS software development environment (<http://www.biomobius.org>) [3]. The inertial sensors and the optical marker-based acquisition system were synchronized using a dedicated trigger output from the CODA system, as described previously [8].

All signal processing and data analysis were carried out off-line using the MATLAB® [<http://www.mathworks.com/> (Natick, VA, USA)] environment. A standard calibration procedure was used to calibrate all gyroscopes [6]. Before further processing, the raw gyroscope signal was low pass filtered with zero-phase fifth order Butterworth filter with a 50.2 Hz corner frequency. Figure 3 shows the angular velocity signal about the y-axis obtained from the shank-mounted gyroscope at two different speeds: 2 and 12 kph for one subject. The HS and TO points are indicated.

2.3 Marker-based data acquisition

Two CODA cx1 units were used to acquire data, one placed at either side of the treadmill. Previous studies have validated this system as a reliable platform for gait measurements [17, 19]. Two infrared light-emitting diode

markers were placed on the left and right foot. Markers were positioned on the inferior lateral aspect of the heel and the lateral aspect of the fifth metatarsal head on the exterior of the subjects' training shoes. The data were collected at a sampling rate of 200 Hz. Kinematic data were analyzed using the CODAmotion analysis software. Two separate, previously reported methods for the calculation of HS and TO from kinematic data were used for comparison with the gyroscope-based method, as described previously (HMA, ZA).

2.4 Temporal parameters

Temporal parameters of gait were derived using a previously reported algorithm (AGA) [8], which applies an adaptive threshold approach to determine HS and TO events from the angular velocity signal about the sensor y-axis. Each gyroscope sensor is positioned such that its y-axis is parallel to the floor, in a medio-lateral direction. The HS and TO characteristic points derived using both the gyroscope-based and optical motion capture systems were used to calculate stride, stance and swing times. Stride was defined as HS to HS of the same foot, stance was defined as HS to TO of the same foot and swing was defined as TO to HS of the same foot.

2.5 Statistical analysis

HS and TO points derived from the gyroscope using the AGA were compared against those derived from the HMA and the ZA. Comparisons were made for individual steps, and the left and right leg data were merged. This yielded 1,378 HS and 1,426 TO points for comparison altogether across all speeds. The true error was defined as the difference in time (in milliseconds) between the temporal parameters calculated using the three methods. The percentage error (%) was defined as the mean difference

Fig. 2 Experimental setup

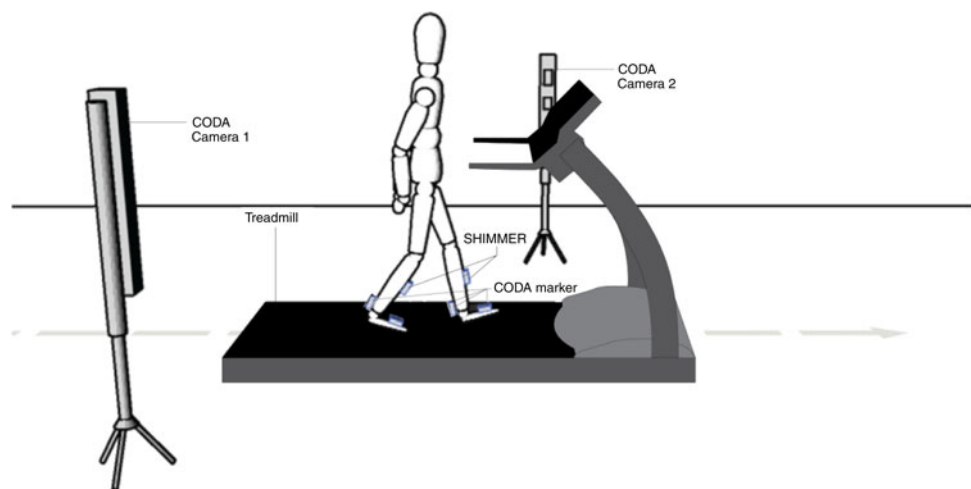
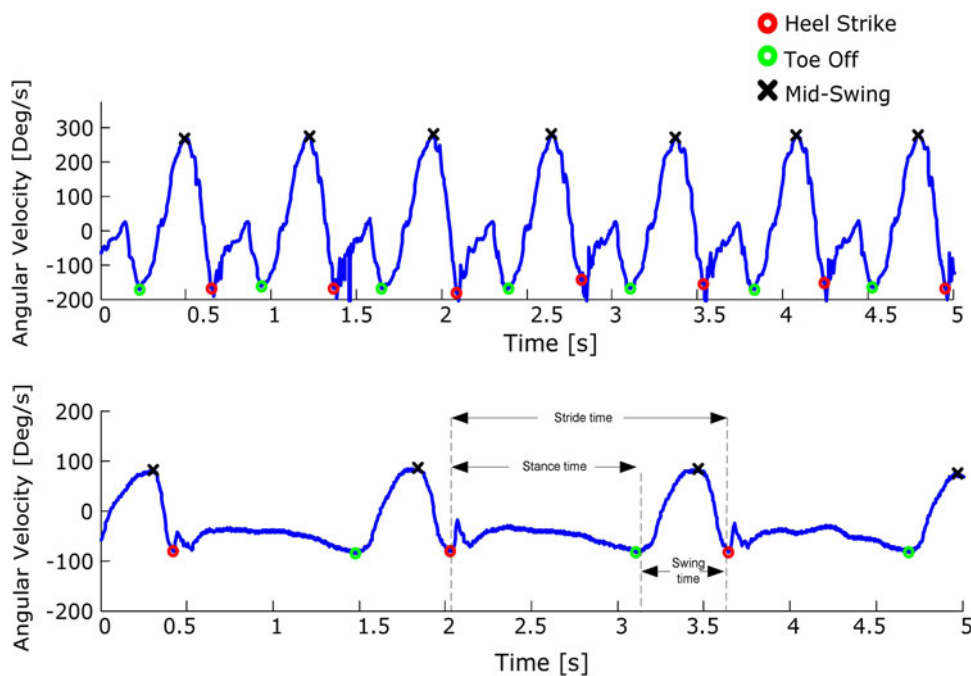


Fig. 3 Gyroscope data recorded from the left shank for subject 2. The *top graph* illustrates a portion of running at 12 kph. The *bottom graph* illustrates a portion of walking at 2 kph. Stance, stride and swing times are marked with *dotted lines*



(expressed as a percentage of the reference) between each method and associated reference. Temporal gait parameters derived using the AGA were compared against those derived from the other two marker-based algorithms using the mean true error, the mean percentage error and ICC(2, k). The smaller the true error and percentage error, the greater the agreement between algorithms in calculating temporal parameters. We interpreted the ICCs in two ways. One way was using benchmarks suggested by Shrout and Fleiss [23], i.e., >0.75 excellent reliability, $0.40\text{--}0.75$ fair-to-good reliability and <0.40 poor reliability. The other was by comparing ICC values obtained when comparing the two kinematic, optical marker-based methods against each other (HMA vs. ZA). The logic behind this approach implies that if ICCs observed in the AGA versus HMA and AGA versus ZA comparisons are as good as or better than those in HMA versus ZA, this suggests that the platform presented here can be accepted as a suitable tool for gait analysis.

3 Results

Observation of participants suggested that they all ran with a heel-strike pattern. The results indicated that HS and, therefore, stride time, as calculated by the AGA showed good to excellent agreement with the other two methods, while stance and swing times demonstrated poor agreement. Table 1 shows the mean and standard deviation (SD) of each temporal gait parameter as calculated by each method.

Table 1 Mean and standard deviation (SD) of stride, stance and swing times for each method

	AGA	HMA	ZA
2 kph			
Stride time (s)	1.68 ± 0.08	1.70 ± 0.05	1.69 ± 0.06
Stance time (s)	1.08 ± 0.07	1.20 ± 0.04	1.21 ± 0.05
Swing time (s)	0.60 ± 0.05	0.50 ± 0.03	0.47 ± 0.03
4 kph			
Stride time (s)	1.23 ± 0.02	1.23 ± 0.02	1.23 ± 0.01
Stance time (s)	0.74 ± 0.03	0.84 ± 0.04	0.84 ± 0.03
Swing time (s)	0.49 ± 0.03	0.41 ± 0.01	0.41 ± 0.01
8 kph			
Stride time (s)	0.81 ± 0.01	0.81 ± 0.01	0.81 ± 0.01
Stance time (s)	0.39 ± 0.03	0.44 ± 0.02	0.46 ± 0.01
Swing time (s)	0.46 ± 0.33	0.36 ± 0.01	0.34 ± 0.01
12 kph			
Stride time (s)	0.77 ± 0.02	0.78 ± 0.01	0.78 ± 0.01
Stance time (s)	0.45 ± 0.51	0.39 ± 0.06	0.42 ± 0.01
Swing time (s)	0.45 ± 0.02	0.39 ± 0.01	0.36 ± 0.01

Values are expressed as mean \pm SD

Table 2 shows the mean true error (ms), percentage error and ICC(2, k) for all three comparisons across all speeds. The results for stride time (in bold) indicate that there was <1 ms of true error between each comparison across all walking and running speeds. Likewise, for percentage error, there was $<1.6\%$ error between each comparison across all speeds. This indicates that the AGA can calculate stride time with similarly high accuracy as the other two algorithms across all speeds. In contrast, true

Table 2 Mean true error (ms), percentage error (%) and ICC(2,*k*) for AGA versus HMA, AGA versus ZA and HMA versus ZA at 2, 4, 8 and 12 kph

	True Error (ms)			Error (%)			ICC(2, <i>k</i>)		
	AGA versus HMA	AGA versus ZA	HMA versus ZA	AGA versus HMA	AGA versus ZA	HMA versus ZA	AGA versus HMA	AGA versus ZA	HMA versus ZA
Walking									
2 kph									
Heel-strike	26.85	68.64	41.81	0.53	1.23	0.78			
Toe-off	-65.31	-56.36	22.38	1.37	1.18	0.47			
Stride time	-0.86	-0.31	0.29	0.97	0.83	1.09	0.96	0.97	0.94
Stance time	-111.49	-132.84	-20.42	9.62	11.12	2.13	0.66	0.59	0.85
Swing time	112.93	133.39	19.44	23.86	28.64	5.16	0.51	0.46	0.74
4 kph									
Heel-strike	14.62	45.74	30.87	0.35	1.06	0.76			
Toe-off	-63.15	-31.96	27.34	1.25	0.99	0.50			
Stride time	0.29	0.15	-0.12	0.66	0.45	0.66	0.87	0.94	0.83
Stance time	-99.27	-90.05	-3.49	11.83	12.39	2.01	0.33	0.33	0.72
Swing time	78.26	80.40	3.64	20.92	22.02	3.87	0.29	0.30	0.41
Running									
8 kph									
Heel-strike	33.43	64.17	32.17	0.81	1.50	0.79			
Toe-off	-32.43	-15.10	11.71	0.70	0.69	0.34			
Stride time	0.14	0.29	-0.07	1.54	1.27	1.12	0.55	0.57	0.53
Stance time	-66.37	-79.13	-20.83	15.22	19.78	5.91	0.32	0.26	0.32
Swing time	65.92	78.84	20.82	18.73	26.81	6.67	0.38	0.32	0.32
12 kph									
Heel-strike	24.09	61.74	37.74	0.54	1.41	0.97			
Toe-off	-28.79	-24.20	4.48	0.81	0.74	0.20			
Stride time	0.17	0.29	0.10	1.15	1.26	0.93	0.83	0.69	0.60
Stance time	-63.38	-90.15	-26.90	16.73	22.36	9.08	0.30	0.29	0.24
Swing time	54.84	89.99	33.25	16.55	26.35	8.57	0.32	0.28	0.26

error and percentage error were considerably larger for stance and swing times in comparisons that included the AGA, compared with the HMA versus ZA comparison. This suggests that the AGA identified TO at a different instant than the other methodologies. In terms of ICCs, all comparisons yielded excellent reliability (ICC > 0.75) for stride time in walking speeds. At 12 mph, comparisons that included the AGA resulted in higher levels of agreement (0.83, 0.69) than the HMA versus ZA (0.60) for stride time, while at 8 mph all comparisons yielded moderate levels of agreement. ICCs for stance and swing times show poor to moderate reliability for comparisons that included the AGA at all speeds.

4 Discussion

This study sought to examine the utility of a wireless body-worn gyroscope and an adaptive threshold-based algorithm

to calculate temporal gait parameters during sustained locomotion across a range of speeds from walking to running. Our hypothesis was partially supported: the level of agreement between stride time as calculated by optical motion capture-based algorithms, HMA and ZA, was not higher than the levels of agreement observed between those methods and the AGA across all four speeds. This indicates that the gait analysis system presented here is a valid tool for the measurement of stride time in both walking and running.

The stride time interval is a very important phase to accurately identify in gait analysis, as it is used to delineate gait cycles. In the deterministic model of running proposed by Hay and Reid [10], running performance is determined by two biomechanical variables: stride length and stride frequency which is a direct outcome of stride time. Stride time variability has recently become an interesting gait parameter in running. In a study by Nakayama et al. [21],

the authors showed that differences in gait variability between trained and non-trained runners, as measured by stride-interval time series, suggested that expert runners can reduce variability in the trained movement without losing dynamical degrees of freedom for spatio-temporal organization of the gait pattern. Jordan et al. [13] confirmed the presence of long range correlations in running, again using the stride-time interval, thus elucidating the pathways of adaptive control of locomotion. By examining variability characteristics delineated by stride times, it may be possible to monitor sensorimotor function of athletes. Variability measurements in walking and running requires large amounts of data to be collected in a steady state, which up to now has been difficult with laboratory-based methods. The wireless body-worn gyroscope-based gait analysis system presented here can be considered a functional, cost-effective alternative to these traditional methods, allowing an individual's performance to be monitored continuously in a natural environment.

The stance and swing times calculated using the AGA yielded poor to moderate ICCs across all speeds. In a study carried out by Lee et al. [14] where an accelerometer was placed on the sacrum and used to extract temporal parameters of running gait, they also found strongest agreement between stride times and reduced agreement in stance time, although not to the same extent as the stance times reported here. In a study by Heiden and Burnett [11], they established that the location of the sensor greatly affected the ability of the sensor to accurately determine when HS and TO occurs. They found that the closer the sensor was to the foot, the more accurate the results. In our study, the sensor was worn on the upper shank. The algorithms applied to the marker data that were obtained from the optical motion capture system used the acceleration or velocity of the toe marker to calculate TO. Due to the physical separation of our sensor from the toe, it is reasonable to expect a time lag between the peak in the shank angular velocity signal associated with TO and that of the marker data, as the shank segment moves earlier than the foot as the toe comes off the ground. This is substantiated by the consistently longer swing times calculated by the AGA across all speeds compared to the HMA and ZA (Table 1). This problem is not encountered in the identification of HS as there is a more pronounced and synchronous change in momentum at HS in both the shank and foot segments. The angular velocity signal in Fig. 3 qualitatively illustrates how the TO point is clearly identifiable across a series of steps at both the walking and running speeds using the AGA. These observations lead us to conclude that poor stance and swing times reported here are not due to random errors in TO detection. Rather, they are more likely due to the positioning of the sensor on the upper shank, and the resulting earlier detection of TO,

compared to the TO times calculated from the toe markers. If this is the case, then simply moving the position of the sensor should greatly improve estimates of stance and swing times. Further work is required to confirm this.

While previous researchers (including the authors) have presented gyroscope-based algorithms for the calculation of HS and TO during walking [1, 8, 22], few attempts have been made to implement approaches for running. Previous studies have shown that an accelerometer can be used to analyze running gait [14, 15, 24]. An advantage of using a gyroscope for this purpose is that the signal is less influenced by gravity and by the orientation of the sensor. Yang et al. [26] used a shank-mounted gyroscope to calculate locomotion speeds between 5.5 and 7.8 mph, resulting in a 2.8–5.8 % underestimation of speed, approximately. The authors stated the importance of identifying gait characteristics from inertial sensor measurements as the key to developing effective gait speed estimation methods for walking and running. However, they do not report data for gait event detection. To the author's knowledge, this is the only study that has used on-body wireless gyroscopes to successfully calculate stride times in running speeds as high as 12 mph.

Some limitations in the study must be highlighted. The algorithms chosen for comparison (HMA, ZA) have previously been presented for walking. It is not known if using these algorithms to determine gait events during running would have affected our results. The fact that all subjects ran with a heel-striking gait pattern may have moderated this risk. A second limitation is that neither method used for comparison is considered a true "gold standard". However, all three algorithms used in this study have separately been validated against a force plate for walking in previous studies. The three-way comparison was implemented in an effort to make the analysis more rigorous in light of these limitations.

We conclude that the gyroscope-based gait analysis platform presented here is a useful tool in calculating stride times in both walking and running. The gyroscope board could ultimately be combined with the ECG/EMG boards for physiological and biomechanical wireless monitoring of an athlete. Different sensor locations need to be investigated in an effort to improve the accuracy of stance and swing times. Ideally, the performance of this system would be tested for a range of running speeds using a force plate embedded in a treadmill for a true "gold standard" comparison.

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