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ScienceDirect
Gait & Posture 25 (2007) 469–474
GAIT & POSTURE
www.elsevier.com/locate/gaitpost

Automatic detection of gait events using kinematic data

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Received 13 December 2005; received in revised form 24 February 2006; accepted 20 May 2006

Abstract

The timing of heel strike (HS) and toe off (TO), the events that mark the transitions between stance and swing phase of gait, is essential when analysing gait. Force plate recordings are routinely used to identify these events. Additional instrumentation, such as force sensitive resistors, can also been used. These approaches, however, include restrictions on the number of steps that can be analyzed and further encumbrance of the subject. We developed an algorithm which automatically determines these times from kinematic data recorded by a motion capture system, which is routinely used in gait analysis laboratories. The foot velocity algorithm (FVA) uses data from the heel and toe markers and identifies features in the vertical velocity of the foot which correspond to the gait events. We verified the performance of the FVA using a large data set of 54 normal children that contained both force plate recordings and kinematic data and found errors of (mean $\pm$ standard deviation) 16 ± 15 ms for HS and 9 ± 15 ms for TO. The algorithm also worked well when tested on a small number of children with spastic diplegia. We compared the performance of the FVA with another kinematic method previously described. Our foot velocity algorithm offered more accurate results and was easier to implement than the previously described one, and should be applicable in a variety of gait analysis settings.

Keywords: Walking; Gait events; Heel strike; Toe off; Algorithm

1. Introduction

The definition of individual gait events is an essential starting point for nearly all aspects of gait analysis. By convention, initial foot contact is generally taken as the starting point of a complete gait cycle and marks the beginning of the stance phase. Termination of foot contact marks the beginning of the swing phase. In normal gait these events correspond to heel strike (HS) and toe off (TO), respectively. The timing information of these events is used in the analysis of temporal gait parameters such as stride time and periods of single and double support, and allows for the time normalization of data per gait cycle. This analysis is necessary for examining ensemble averages of kinematic, kinetic and EMG patterns over a number of gait cycles, and facilitates comparison between different subjects and conditions.

The gold standard method of defining gait events is based on the use of a force plate. A simple threshold on the force level can accurately provide the timing of HS and TO, provided a "clean" force plate hit has occurred, one in which a single foot lands entirely on the force plate. This method is generally restricted to a gait laboratory setting and the number of available force plates (often one or two) limits the number of consecutive gait cycles that can be analyzed. Researchers have developed alternative systems to overcome these restrictions such as instrumented walkways [1,2], using force sensitive resistors attached to the feet [3,4] or wearing specially instrumented shoes [5]. Timing

Abbreviations: AE, absolute error; FVA, foot velocity algorithm; HMA, Hreljac–Marshall algorithm; HS, heel strike; TE, true error; TO, toe off

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doi:10.1016/j.gaitpost.2006.05.016

information can also be extracted from the signals recorded from additional sensors such as accelerometers [6,7] or gyroscopes [8].

Motion analysis systems are often used to record kinematic data in gait analysis, based on trajectories of markers attached to landmark positions on the subject. Both experienced and untrained raters, following specific instructions, can generally identify HS and TO to within acceptable tolerances manually, by examining the marker trajectories and velocity plots [9,10]. Automatic algorithms which use thresholds on the height or velocity of markers have been used with more variable results [10,11]. Stanhope et al. [12] developed a method which accurately determined timing information using a kinematic model. However, this model was individual-specific and required a separate method, such as the use of a force plate, to determine the initial occurrence of gait events.

Hreljac and Marshall [13] developed algorithms for determining HS and TO based on the displacement, acceleration and jerk (the derivative of acceleration) of heel and toe markers. Their algorithms determined the location of characteristic peaks, troughs and zero crossings to determine HS and TO times. However, the location of the points had to be estimated first to ensure the correct points were identified. Their method also used optimal filtering [14] of each marker as an initial step. The results of such an algorithm were shown to be highly sensitive to the choice of cutoff frequency [15]. Other researchers have shown that various methods for determining the optimal cutoff frequency produce different results and have proposed the selection of different cutoff frequencies when higher derivatives of the displacement time data are to be calculated [16].

We developed a new algorithm for determining HS and TO that is based on a simple velocity curve derived from heel and toe marker trajectories, filtered with a single cutoff frequency. We validated the algorithm by comparing it to the timing of the same gait events as determined with the use of a force plate, for both normal gait and a limited number of patients with spastic diplegia.

2. Methods

2.1. Normal children

Kinematic and force plate data from 54 normal children (33 males, 21 females, age 2–13 years, mean $\pm$ standard deviation 7.6 ± 2.5 years) were obtained from a normal gait database [17], at the gait laboratory of the University of Virginia. The children walked barefoot and all walking trials which contained consecutive clean force plate hits on both the left and right sides were included (between 1 and 3 trials per child, 126 in total). Kinematic data were collected using a four-camera system (Motion Analysis Corporation, Santa Rosa, CA) with a sampling frequency of 60 Hz, using the 15 marker Helen Hayes Hospital set, although only the heel and toe (metatarsal head II) markers were used in this analysis. Two force plates (Kistler, Winterthur, Switzerland) recorded ground reaction forces of consecutive steps with a frequency of 600 Hz.

2.2. Clinical data

Three patients, diagnosed with either spastic diplegia or asymmetric spastic diplegia, completed barefoot walking trials (2 males, 1 female, age 8–12 years). One patient displayed an equinus pattern during gait on both sides; physical examination revealed static contracture of the soleus and gastrocnemius on the left side and bilateral dynamic calf tightness but no foot deformities. The other two patients showed no equinus during gait but physical examination revealed pes planus, with an abducted forefoot and valgus rearfoot in both and dynamic calf tightness in one case. The data were collected at the Hugh Williamson Gait Analysis Laboratory, Royal Children's Hospital, Melbourne. Kinematic data were recorded using the Vicon system with a sampling frequency of 120 Hz. Data from heel and toe (metatarsal head II) markers were used in this study. Two force plates (AMTI, Watertown, MA, USA) were used to record the ground reaction force of two consecutive steps with a sampling frequency of 1080 Hz.

All experimental procedures were conducted in accordance with the declaration of Helsinki and approved by the Research Ethics Committees of the two Institutions.

2.3. Force plate method to determine gait events

HS and TO times were automatically determined from the force plate data as the times at which the resultant force exceeded a threshold of 10 N and fell below a threshold of 5 N, respectively. The sharply rising force at HS means that using a 10 N threshold provides an accurate estimation of the time when the force rises above zero, and this threshold is widely used either with resultant force or the vertical force component [9,10,13,15]. A lower threshold was used for the detection of TO because of the more gradual reduction in force at TO [9,15].

2.4. Foot velocity algorithm (FVA)

The input signals for the algorithm are the displacement–time data for heel and toe markers gathered by a motion analysis system. Such data generally come with 3D coordinates representing the distance traveled in the direction of progression, vertical and medial–lateral location. The FVA only requires the vertical information, however, and it would work equally well with 2D sagittal kinematics. The signals are low pass filtered with a cutoff frequency of 7 Hz using a zero phase fourth order Butterworth filter. A new signal, representing the foot centre, is created by calculating the midpoint of the heel and toe marker locations. The vertical velocity of the foot centre is calculated by taking the first

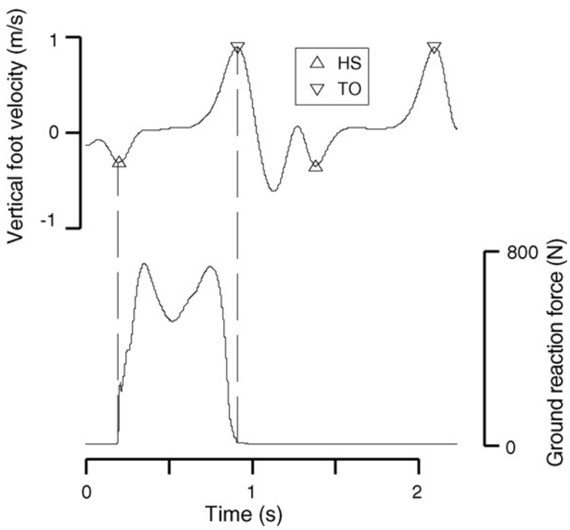

Fig. 1. The vertical velocity of the foot centre of a man walking [17], with triangular markers indicating the timing of heel strike (HS) and toe off (TO) as determined by the foot velocity algorithm, and a simultaneous recording from a force plate which provides the ''true'' times for HS and TO for one step, which are marked with dashed lines.

derivative of the vertical coordinates using finite difference equations. This signal is interpolated using a cubic spline method to match the force plate data which are generally gathered with a higher sample frequency.

This vertical velocity of the foot centre has a simple characteristic shape repeated for each gait cycle during normal gait (Fig. 1). In Fig. 1, a simultaneous force plate recording has been shown to identify the HS and TO events for one gait cycle, and it can be seen that the vertical velocity curve has easily identifiable features – maxima and minima – occurring at these times. The algorithm is designed to identify the correct HS and TO times automatically.

The major peaks in the vertical velocity curve are identified by searching for the maximum values within a window of the order of one gait cycle, 0.8 s, which provides the timing of the TO events.

The troughs in the signal are identified using a smaller window size, 0.08 s, which provides a set of possible HS times. The correct trough for the HS event is identified by imposing a constraint on the possible HS times: that the heel marker must be close to the ground at the time of heel strike. A threshold level on the height of the heel marker, set at 35% of the range of heel heights encountered during the trial, excludes the major trough in the foot velocity signal which occurs during the swing phase of gait, and can be seen between the first TO and the second HS in Fig. 1. Smaller subsequent troughs which may be identified during the stance phase, between HS and the following TO, are disregarded.

2.5. *Description of Hreljac–Marshall algorithm (HMA)*

The method described by Hreljac and Marshall [13] utilizes the kinematic data for heel and toe (metatarsal head V), although in this study the toe marker was placed at metatarsal head II. The 3D coordinate data are smoothed using a fourth order, zero lag, Butterworth filter with optimal cutoff frequencies determined using the residual method of Wells and Winter [14]. Second and third derivatives of the position–time data are calculated to provide acceleration and jerk using finite difference equations.

The time of HS is estimated to occur at the time of a local maximum in the vertical acceleration of the heel marker. Linear interpolation is used to determine the exact time when the jerk equals zero. Hreljac and Marshall suggested by Hreljac and Marshall that the local maximum in the vertical acceleration of the heel marker will precede the minimum vertical displacement of the heel marker by 2–10% of the stride time, and that this event be used as a starting point to locate the local maximum in the vertical acceleration of the heel marker that represents HS.

The time of TO is estimated to occur at the time of a local maximum in the horizontal acceleration of the toe marker. Linear interpolation is used to determine the exact time when the jerk equals zero. Hreljac and Marshall stated that the TO always follows the minimum vertical displacement of the toe marker by 10–15% of the stride time, allowing this event to be used as a starting point to locate the local maximum in the horizontal acceleration of the toe marker that represents TO.

When we implemented the algorithm as suggested by Hreljac and Marshall we found very poor performance in HS estimation. We investigated the large errors which occurred with an apparent bi-modal distribution, and found that they arose from the variability of the vertical acceleration curves for the heel markers. There are multiple peaks in the acceleration curves and in most cases the algorithm was not able to identify the appropriate peak. We found that the appropriate acceleration peak often occurred after the time of the minimum vertical displacement of the heel marker, and adapted the algorithm to improve the results significantly. We tuned the algorithm to search for the acceleration peak working backwards from a starting point of 50 ms after the minimum vertical displacement of the heel marker as this significantly improved the results.

2.6. *Comparison of force plate method with kinematic algorithms*

Data were processed offline with algorithms developed in MATLAB™. For each trial the HS and TO event times were determined using the force plate data and estimated using the two kinematic methods. The true errors (TE) and absolute errors (AE) were calculated for each of the algorithms using

$$\mathrm{TE} = \text{event time} - \text{estimated time} \quad (1)$$

$$\mathrm{AE} = |\text{event time} - \text{estimated time}| \quad (2)$$

The distributions of TEs and AEs were plotted in histogram form and tested with the Shapiro–Wilk normality test. If the test rejected normality ($p < 0.05$), normal quantile–quantile plots were examined to determine the nature of the deviation from normality and the skewness was calculated. Although skewness was detected in all distributions for the normal children's data, where the W statistic was greater than 0.97 the distributions were assumed to be approximately normal ($W = 1$ for the normal distribution). Results are reported as mean ± standard deviation for normal distributions and median (range) otherwise. Data analysis was completed within the statistical program R [18].

3. Results

3.1. Normal children

Our foot velocity algorithm performed very well in estimating HS and TO times in comparison with the force plate timings, providing a reasonable estimate for the gait events for each trial. The distributions of TEs for HS and TO are presented as histograms in Fig. 2(a and b), respectively. The distributions of errors are close to that of the normal distribution ($W > 0.97$), and the gait events are accurate on average to within one frame of the kinematic data. HS was detected by the algorithm 16 ± 15 ms later than determined by the force plate while TO was detected 9 ± 15 ms later than determined by the force plate. The absolute errors were 15 (0–65) ms for HS and 11 (0–72) ms for TO.

The distributions of the TEs for the Hreljac–Marshall HS and TO algorithms are presented in Fig. 2(c and d). The distribution of errors in the estimation of HS was non-normal ($W = 0.82$), with a median error of 8 ms early and a range of errors between 104 ms early and 109 ms late. The distribution of errors in the estimation of TO was approximately normal ($W > 0.97$), TO being detected 24 ± 15 ms later than determined by the force plate. The absolute errors were 20 (0–109) ms for HS and 24 (0–76) ms for TO.

3.2. Clinical data

The two methods were both able to determine HS and TO for each of the clinical gait data files. It should be borne in mind that Hreljac and Marshall never claimed their algorithm was applicable in clinical cases [13], but the results of both algorithms are presented here for comparison in histogram form in Fig. 3. On average HS was detected by our foot velocity algorithm 3 ± 9 ms earlier than determined by force plate while TO was 6 ± 26 ms earlier, with average absolute errors of 7 ± 6 ms for HS and 23 ± 10 ms for TO. On average, the Hreljac–Marshall algorithm detected HS

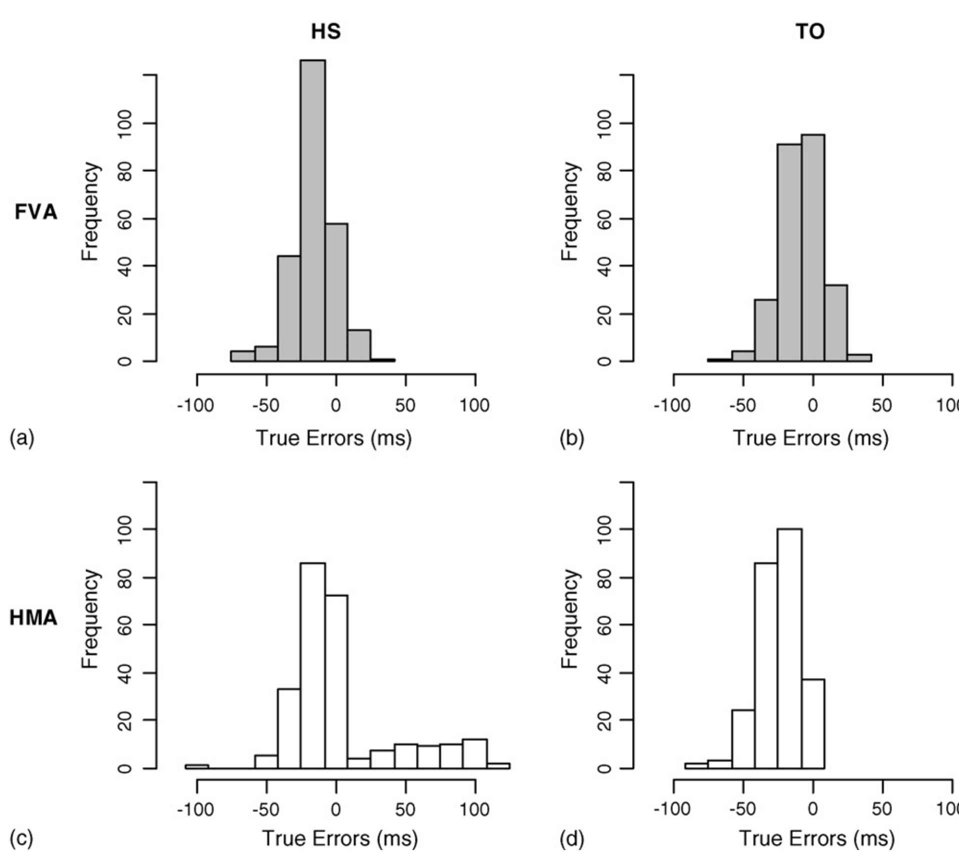

Fig. 2. Distribution of true errors (TEs)—the differences between the times of heel strike (HS) and toe off (TO) as determined by force plate and either the foot velocity algorithm (FVA, a and b) or the Hreljac–Marshall algorithm (HMA, c and d) for normal children's steps ($n = 252$, 126 trials with left and right steps).

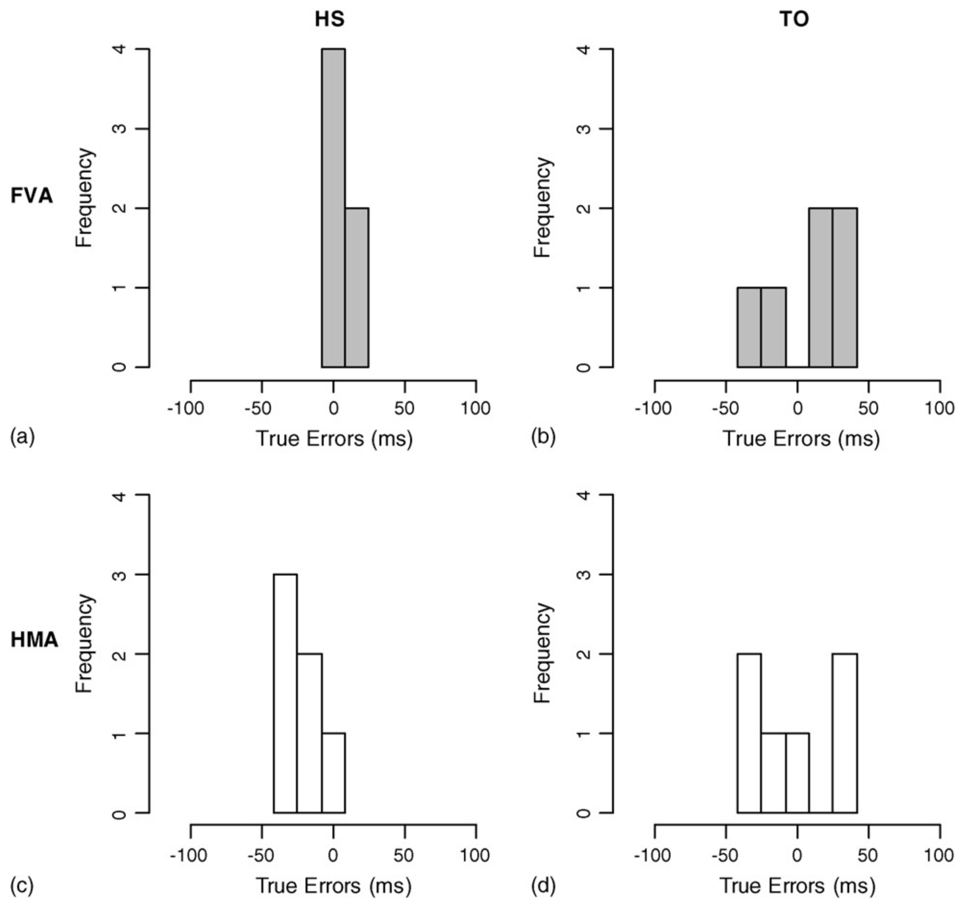

Fig. 3. Distribution of true errors (TEs)—the differences between the times of heel strike (HS) and toe off (TO) as determined by force plate and either the foot velocity algorithm (FVA, a and b) or the Hreljac–Marshall algorithm (HMA, c and d) for children with spastic diplegia ($n = 6$, 3 subjects with left and right steps).

24 ± 15 ms later than determined by force plate while TO was 4 ± 30 ms later, with average absolute errors of 24 ± 15 ms for HS and 24 ± 15 ms for TO.

4. Discussion

The usefulness of a reliable algorithm, such as the FVA is obvious, in that it allows for rapid and accurate division of gait cycles into stance and swing phase for any kinematic recordings in which heel and toe markers are included. While other algorithms have been proposed for this purpose, e.g. the HMA described in this paper, we found their accuracy lower than originally reported [13] and insufficient, particularly in the identification of heel strike (Fig. 2(c)). Hreljac and Marshall's results were based on two adult subjects, who walked at three different speeds wearing their own athletic shoes, and with the toe marker on metatarsal head V rather than II. These differences, in particular the small data set used in that paper, could explain the difference between the reported accuracy and our findings.

From the numerical point of view, a lower degree of differentiation is preferable when dealing with kinematic data. The FVA uses a single differentiation and looks at a velocity signal rather than the acceleration signals used in the HMA. The simplicity of the foot velocity signal and the ease of identifying the features corresponding to heel strike and toe off are definite advantages. Despite tuning, the multiple peaks in the acceleration curve confounded the HMA and led to a large spread in the errors associated with HS estimation (Fig. 2(c)). We also found that the FVA was robust over a range of filter cutoff frequencies, so simple filtering of the kinematic data was a viable option and the selection of an optimal cutoff frequency for each signal, which is a prerequisite for the HMA, was not necessary.

There are some limitations to this study. The FVA was only validated for subjects walking barefoot, although we would not expect the wearing of shoes to alter the foot velocity characteristics significantly. We did not control for the walking speed and, therefore, we do not know how the method would perform at very slow or fast speeds. The range of TEs found when testing the data with the FVA for the normal children's walking did not have any extreme outliers. It is probably the result of small variations in marker placement, individual variation in walking characteristics, and the fact that a large number of children over a range of ages was being tested. The FVA does show a bias towards detecting the gait event times slightly later than the force plate. If required, a correction for this could be incorporated in the algorithm.

The sampling rate of the tracking cameras must be sufficient to accurately capture the kinematic characteristics of the gait at whatever speed the subject is walking. Most gait laboratories gather their data at 50 Hz or 60 Hz, although some now routinely use cameras operating at 120 Hz or even 200 Hz. With standard consumer video cameras that run at 25 Hz or 30 Hz (the PAL and NTSC systems, respectively), the gait events will often occur between frames. Provided Nyquist's sampling theorem has been satisfied, methods can be employed to provide a better estimate of the location of a turning point in a signal when this lies between two sample points. We used spline fitting and interpolation to match the sampling frequency of the force plate data in this comparative study. There are, however, other methods to provide the best estimate of the location of a peak in a signal, such as using linear interpolation to find the zero-crossing of the derivative of the signal [13].

The FVA was tested on a small number of patients with spastic diplegia, and was shown to provide a fairly accurate estimation of gait event times despite altered gait characteristics in these patients. In clinical gait analysis, patients with neuromuscular disorders such as cerebral palsy, stroke and spinal cord injury may display more severe gait deviations, which may prevent the application of the FVA. This would have to be assessed on an individual case basis.

In conclusion, we have presented an algorithm which accurately identifies the timing of heel strike and toe off events using the kinematic data of heel and toe markers during walking. The algorithm was developed using data from adult walking (Fig. 1), and then validated using a large database of normal children's walking. The FVA is simpler, more accurate and reliable than an alternative algorithm presented in the literature. It was shown to work well with normal individuals as well as a limited number of patients with gait deviations.

Acknowledgements

We acknowledge the financial assistance of The Wellcome Trust, Enterprise Ireland and the Medical Research Council of South Africa. One of us (CLV) held an Ernest Walton Fellowship, funded by Science Foundation Ireland, when this research was conducted.

The authors would like to thank Dr. Anthony Schache from the Hugh Williamson Gait Analysis Laboratory, Royal Children's Hospital, Melbourne, Australia, for his assistance in providing clinical data.

Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at doi:10.1016/j.gaitpost.2006.05.016.

References

[1] Hansen AH, Childress DS, Meier MR. A simple method for determination of gait events. J Biomech 2002;35:135–8.

[2] Kyriazis V, Rigas C. A cheap telemetric system for analyzing gait. Hum Mov Sci 2001;20:867–74.

[3] Skelly MM, Chizeck HJ. Real-time gait event detection for paraplegic FES walking. IEEE Trans Neural Syst Rehabil Eng 2001;9:59–68.

[4] Chau T, Rizvi S. Automatic stride interval extraction from long, highly variable and noisy gait timing signals. Hum Mov Sci 2002;21:495–514.

[5] Nilsson J, Stokes VP, Thorstensson A. A new method to measure foot contact. J Biomech 1985;18:625–7.

[6] Mansfield A, Lyons GM. The use of accelerometry to detect heel contact events for use as a sensor in FES assisted walking. Med Eng Phys 2003;25:879–85.

[7] Auvinet B, Gloria E, Renault G, Barrey E. Runner's stride analysis: comparison of kinematic and kinetic analyses under field conditions. Sci Sports 2002;17:92–4.

[8] Aminian K, Najafi B, Bula C, Leyvraz PF, Robert P. Spatio-temporal parameters of gait measured by an ambulatory system using miniature gyroscopes. J Biomech 2002;35:689–99.

[9] Mickelborough J, van der Linden ML, Richards J, Ennos AR. Validity and reliability of a kinematic protocol for determining foot contact events. Gait Posture 2000;11:32–7.

[10] Ghoussayni S, Stevens C, Durham S, Ewins D. Assessment and validation of a simple automated method for the detection of gait events and intervals. Gait Posture 2004;20:266–72.

[11] Karcnik T. Using motion analysis data for foot-floor contact detection. Med Biol Eng Comput 2003;41:509–12.

[12] Stanhope SJ, Kepple TM, McGuire DA, Roman NL. Kinematic-based technique for event time determination during gait. Med Biol Eng Comput 1990;28:355–60.

[13] Hreljac A, Marshall RN. Algorithms to determine event timing during normal walking using kinematic data. J Biomech 2000;33:783–6.

[14] Wells RP, Winter DA. Assessment of signal and noise in the kinematics of normal, pathological, and sporting gaits. In: Proceedings of the special conference of the Canadian Society of Biomechanics; 1980. p. 92–3.

[15] Tirosh O, Sparrow WAT. Identifying heel contact and toe-off using forceplate thresholds with a range of digital-filter cutoff frequencies. J Appl Biomech 2003;19:178–84.

[16] Giakas G, Baltzopoulos V. A comparison of automatic filtering techniques applied to biomechanical walking data. J Biomech 1997;30:847–50.

[17] Vaughan CL, Davis BL, O'Connor JC. Gait Analysis Laboratory, a Windows 98/NT software package with a large database of gait data. Cape Town, South Africa: Kiboho Publishers; 1999, ISBN: 0 620 23560 8.

[18] R Development Core Team. R: a language and environment for statistical computing. Vienna, Austria: R Foundation for Statistical Computing; 2005, ISBN: 3-900051-07-0, http://www.R-project.org/.