Statistics-based technique for automated detection of gait events from accelerometer signals

R.R. Torrealba, J. Cappelletto, L. Fermín-León, J.C. Grieco and G. Fernández-López

To control an intelligent knee prosthesis for above-knee amputees, an algorithm is developed to detect gait events directly from accelerometer signals captured on the prosthesis. Using this technique, several events are automatically detected along the gait cycle. The simplicity and effectiveness of the technique is demonstrated, showing automated adaptability even for amplitude and frequency variations in gait pattern, while solving problems inherent to calibration such as offsets and scale factors. Results are equally applicable to intact limbs and further applications are also possible for events detection on periodic signals with spikes.

Introduction: Control of intelligent knee prostheses for above-knee (A/K) amputees is based on characterisation of the gait cycle. These prosthetic devices use finite-state control, and characterisation of the gait cycle is required to determine the current state of the prosthesis during walking [1]. This characterisation is performed by the on-board microprocessor, detecting particular features classified as gait events from the signals captured on the prosthesis. Detecting as many stages as possible along the gait cycle is important so as to develop an accurate control for the prosthesis; independently a finite-state or a continuous strategy is intended. In the former case, every event detected indicates the beginning of a particular gait stage and consequently the corresponding control action is applied. In the latter case, events detected may be used to estimate gait frequency and also to couple a tracking system to the prosthesis.

Accelerometer signals captured on lower limbs during walking present a periodic spike pattern [2–4]. This Letter presents a statistics-based technique that takes advantage of such behaviour, by detecting those spikes as gait events. The method is based on thresholds applied on the accelerometer signals to isolate the spikes in an automated way, regardless of signal amplitude changes with gait speed and prosthesis' length [4]. As far as the authors are aware, it is the first time such a technique is used to automatically detect gait events from lower limb accelerations in real-time; furthermore, it shows reliable results also useful in other applications.

Methodology: The prosthesis instrumentation comprises two bi-axial accelerometers fixed at the knee and ankle joints in the sagittal plane. Knee accelerometer 'y'-axis is aligned with the femur whereas ankle accelerometer 'y'-axis is aligned with the tibia. During the trials, the prosthesis was worn by an A/K amputee walking on a treadmill. The accelerometers were connected to a data acquisition board carried by the patient, and the signals were sent to a PC via serial interface, with real-time control running in the PC. The tested controller applies an adaptive control signal proportional to the knee angle, however further details are outside the scope of this Letter. The sampling frequency was 60 Hz and the patient's walking speed ranged from 1.5 to 3 kph.

Algorithm: The technique here presented introduces a statistics-based gait event detector algorithm (SGEDA). The SGEDA works with the 'x' and 'y' acceleration signals captured at the ankle and the 'x' acceleration signal captured at the knee. First, the signal conditioning block (SCB) filters out high frequency electrical noise. The SCB outputs enter into the threshold level setting block (TLSB) and into the peak and valley isolation block (PVIB). The TLSB computes the threshold levels based on recent signal statistics; then, the PVIB applies such thresholds in order to isolate the peak and valley candidates, from which gait events are detected. Finally, the local minima (on valleys) or maxima (on peaks) of the signals are identified as the points with near-zero derivative, which become the events detected.

The keynote of the SGEDA is the TLSB applied to the accelerometer signals; this is based on the Kaplan-Meier cumulative distribution function (CDF) as implemented by MATLAB. The histogram and CDF of the accelerometer signals computed from 1000 samples are plotted in Fig. 1. As can be observed, the CDF is very steep for all the signals (see Figs. 1*d*–*f*), indicating that most of the data is close to the distribution mean (see Figs. 1*a*–*c*). The values located far from the mean correspond to CDF values near 0 or 1, which refer to valleys and peaks, respectively. The CDF of a signal represents the probability that a random variable X is lower than or equal to a value A (set by a percentile) in the sample space. Then, by setting convenient fixed percentiles, it is possible to adjust the level of the thresholds to isolate the peak and valley zones automatically.

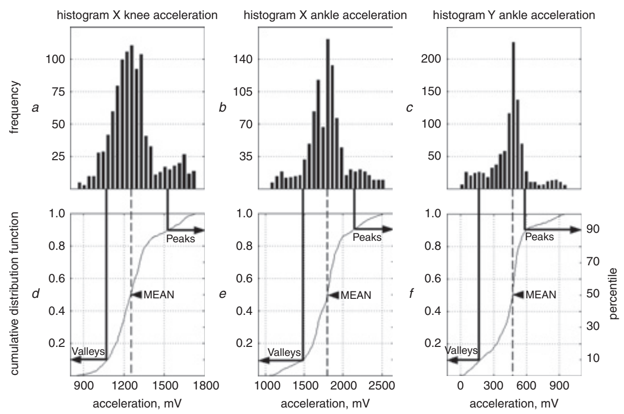

Fig. 1 *Histogram and cumulative distribution function of accelerometer signals captured with patient walking at 2 kph*

Results and discussion: The acceleration signals used by the SGEDA as conditioned by the SCB are shown in Fig. 2. These were captured with the patient walking at 2 kph and the thresholds (percentiles) and events detected in real-time are also shown. In Fig. 2*b*, two different valleys are detected for each gait cycle. The less deep valley corresponds to heel-strike (0% of gait cycle) and the deepest one to toe-off (~60% of gait cycle), the two most important events along the gait cycle which determine the start of stance and swing phases, respectively [3]. For a finite-state control, these results enable one to define different states in terms of percentages of gait cycle. Nevertheless, the control strategy being applied here used the events detected for gait frequency and phase estimation only. It must be noticed that the mean of the signals shown in Fig. 2 differ from each other but, in order to isolate the peaks and valleys and later detect these as gait events, percentiles are set absolutely regardless of the mean values. This is one of the major assets of the statistics-based technique shown here.

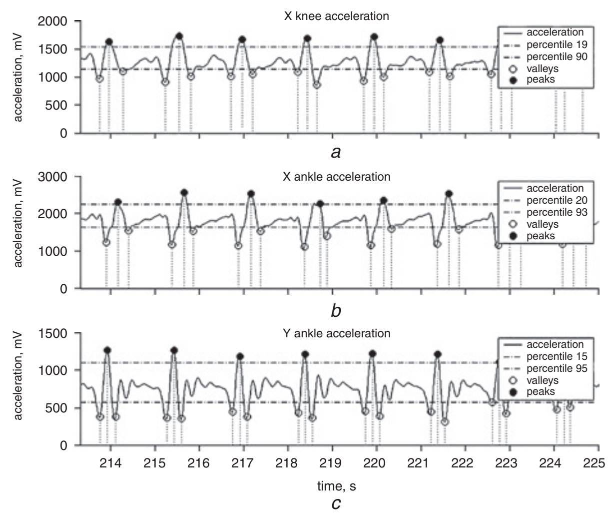

Fig. 2 *Signals, thresholds and events detected by algorithm*

To test the method, two thresholds were applied on the 'x' ankle acceleration while the amplitude of the signal is artificially varied. The thresholds were set at percentiles 7 and 93 to detect the deepest valley and highest peak of the signal only (see Fig. 3). The lower threshold was computed from 173 samples whereas the higher one was from 86, to evaluate the sample window size effect. No event was missed when the signal amplitude was doubled, but some were overlooked when it was reduced by half. As expected, the higher threshold responded faster than the lower one; this means that the lower the number of samples to determine the percentiles to set the thresholds, the faster the adaptive response of the SGEDA is and vice versa. These results make evident the other major asset of this technique, which is its capability to handle scale factors.

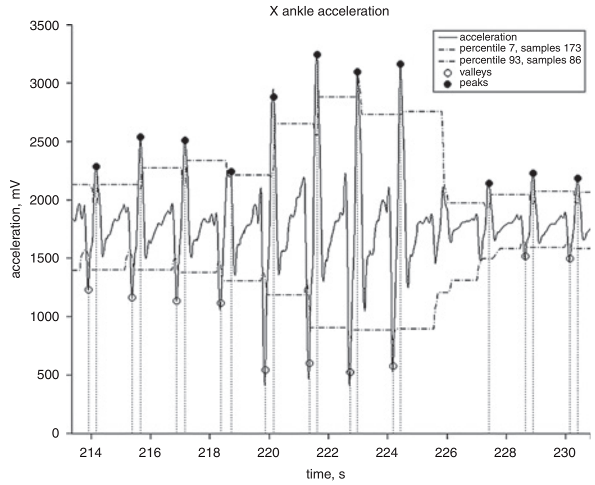

Fig. 3 *Adaptive response of algorithm to amplitude modulation*

Finally, frequency modulation is shown in Fig. 4 while the same previous two thresholds are applied on the 'x' ankle acceleration signal. It is observed that the deepest valley is always detected from the lower threshold regardless of the frequency modulation. However, the higher threshold fails to detect only the highest peak of the signal when it is modulated at half the sampling frequency (30 Hz). In this case, the threshold is adapted so fast that the second higher peak begins to be detected as well, as seen from 219 to 229 s. From the signal modulated at twice the sampling frequency (120 Hz), it is observed that the higher threshold detects only the highest peak of the signal again. In other words, a threshold applied according to a percentile set from a given number of samples at a certain frequency, will work for higher frequencies also but not necessarily for lower ones.

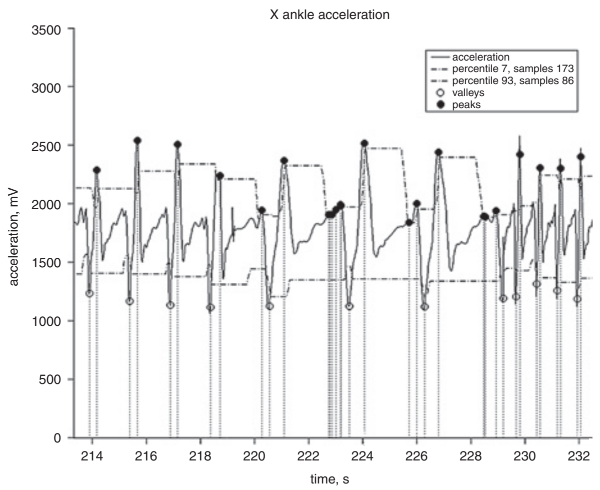

Fig. 4 *Adaptive response of algorithm to frequency modulation*

Conclusions: The capabilities of the technique here introduced to detect gait events from accelerometer signals have been shown. The two major assets of the technique presented are the automated setting of the thresholds used to isolate the spikes, regardless of the signal offset, and the easy-adaptive response of the thresholds to scale factors. The sensitivity of the algorithm depends on the number of samples taken into account to calculate the percentiles used to set the threshold levels. In general, the algorithm performance is accurate, however for safety reasons additional filtering might be included, to avoid any false or missing detection when controlling lower limb prostheses. Finally, the technique here developed is equally applicable to sound limbs [3, 4], and also has potential for other applications in which automated event detection is required from spiky pattern signals.

3 August 2010
doi: 10.1049/el.2010.2118

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