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Wavelet Analysis to Detect Gait Events

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Abstract— **Manually detecting gait events by visual inspection of gait data is laborious. Currently, there are no robust techniques available to automate the process. However, detecting gait events is essentially a classification problem; an application for which wavelet analysis, a multiresolution technique, is well suited for. We employ wavelet analysis to classify heel strike- and toe off events using the ground reaction forces that are exerted during walking. We recorded the ground reaction forces for 30 unshod healthy subjects while they were stepping in place on a force platform for 30 s at a self-selected pace. Depending on the pace, each subject completed 14-26 gait cycles. We compared the timing of events detected with the wavelet analysis with the timing of events detected by analyzing the signal time-derivative. On average, the wavelet analysis detected the events 29 ms later. This difference corresponds to 1.2% of the average duration of the gait cycles, which was 2.4 s. Wavelet analysis shows promise for automated detection of gait events.**

I. Introduction

WALKING is a common everyday physical activity. Because gait is highly repetitive, abnormalities may signal pathology. Clinicians use gait analysis to diagnose motor disorders, or to evaluate the effect of medication or rehabilitation [1].

A. *Gait Analysis*

Heel strikes (HS) and toe offs (TO) determine the gait cycle. The starting-point for gait analysis is to determine the temporal locations of the HS and TO in the recorded signal. These HS- and TO times suffice to determine commonly used temporal- and spatial gait-parameters. The main method for gait analysis is to track the HS- and TO times through camera systems, which is laborious. The "gold standard" for determining the HS- and TO times is to use force platforms [2,3]; they record the vertical ground reaction forces (GRF) that the feet exert on their support surface during the step-phases in the gait cycle. The HS and TO show as short transients with small amplitudes that are embedded within the posturographic signal. However, the signal is non-periodic, non-stationary, and stochastic; both the frequency and amplitude of the HS and TO vary over time (Fig. 1) [4]. Hence, traditional signal analysis may erroneously interpret the HS- and TO related transients as signal artefacts if their amplitudes are too small. Wavelet analysis is a robust technique with successful applications in fields where non-periodic, non-stationary, and stochastic biological signals occur [5,6], but so far it has not been applied to gait time series recorded with force platforms.

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B. *Wavelet Analysis*

Wavelet transforms allow detecting specified frequencies at specified times, because the technique simultaneously resolves a signal in time- and frequency space. Convolving the signal x(t) over all time t with scaled and shifted versions of a mother wavelet ψ gives a matrix of wavelet coefficients [7]:

$$C(p,s) = \frac{1}{\sqrt{|s|}} \int_{-\infty}^{\infty} x(t)\psi\left(\frac{t-p}{s}\right)dt \tag{1}$$

The coefficients are functions of the scale factor s (which ψ was multiplied with, stretching or compressing it) and the wavelet's position p along the signal (ranging from t=0 to the end of the signal). Hence C(p,s) measures the similarity between the signal at time t and the scaled ψ – larger values indicate higher similarity.

A discrete wavelet transform samples C(p,s) on a dyadic grid (i.e. $s=2^j$ and $p=k2^j$). This reduces the requirements on computational speed and capacity without reducing accuracy (in time- and frequency space).

High pass filtering and low pass filtering the signal splits it into its high frequency components (i.e. details D) and low frequency components (i.e. approximations A). Iterating this process J times decomposes the signal s into:

$$s = A_{2^J} + D_{2^J} + D_{2^{J-1}} + ... + D_1 = A_J + \sum_{j \le J} D_j \tag{2}$$

where

$$A_{2^J} = A_{2^{J+1}} + D_{2^{J+1}} \tag{3}$$

The energy representation of s is:

$$E_J = \sum_{n \in Z} s_J^2(n) \tag{4}$$

Thresholding E_J separates consecutive envelopes in the representation.

C. *Purpose of Work*

This work examines wavelet analysis as a tool for detecting gait events from force platform posturographic recordings of gait time series.

II. SUBJECTS AND METHODS

A. Subjects

We tested the method on 30 volunteers (15 men and 15 women: mean age 27 (range 23-37); mean height 1.74 (SD 0.07) m; mean weight 74 (SD 11) kg; mean leisure exercise 2.8 (SD 1.5) h/week) at the Finnish Institute of Occupational Health. We assessed the subjects' health with a questionnaire; exclusion criteria were smoking, diagnosed balance- or sleep disorders, current leg- or back injuries, or current medication influencing sleepiness. Alcohol was prohibited 24 h prior to testing, whereas caffeine and exercise were prohibited 12 h prior to testing. Each subject gave their written informed consent before inclusion in the study.

B. Gait Testing

We tested gait with a custom-made force platform (∅ 0.43 m, [8]) on which the subject unshod stepped, in place, at a self-selected pace for 30 s. The platform sampled and low-pass filtered the ground reaction forces (GRF) at 33 Hz. The subsequent analysis used the total vertical GRF (converted to instantaneous weight in kg), and the lateral coordinates of its point of application (in cm) to the platform surface.

C. Gait Event Detection with Wavelets

The aim of this work was to evaluate if wavelet analysis can extract heel strike (HS) and toe off (TO) from vertical GRF signals recorded during 30 s of walking on a force platform.

We chose the phase-linear Bior-wavelet (Wavelet Toolbox, Matlab) as mother wavelet to highlight the HS- and TO related transients. We based the choice on: 1) the visual similarity between the regions of interest of the original signals and the mother wavelet, and 2) the objective congruence between the results of a given wavelet and the results of the reference method (section *D*, eq. 5). Signal details at decomposition level J=2 highlighted the TO, and details at J=1 highlighted the HS (Fig. 1). The peak value within each envelope of E_2 (eq. 4) defined the TO times: $T(to_k)$ ($1 \leq k \leq N$, N number of gait cycles). The peak value within each envelope of E_1 within the intervals $T(to_{k-1})$:$T(to_k)$ defined the HS times: $T(hs_k)$.

D. Evaluation of Wavelet Performance

During gait the vertical GRF-signal resembles a square wave that abruptly changes sign when the body weight shifts from one leg to the other (Fig. 1). A time-derivative is sensitive to changes: it reaches its maximum when the change is maximal. Thus, as a reference method we used the maxima and minima of the signal derivative to detect the HS and TO times ($T(to_k)$ and $T(hs_k)$).

We compared the timing of the events detected by the wavelet method (T_{wav}) to the timing of the events detected by the reference (T_{ref}) according to [10]:

$$\Delta T = T_{wav} - T_{ref} \tag{5}$$

Student's t-test with $p \leq 0.05$ denoted significant differences between the methods. Pearson correlation with P 0.9 denoted high correspondence between the event times detected with the methods.

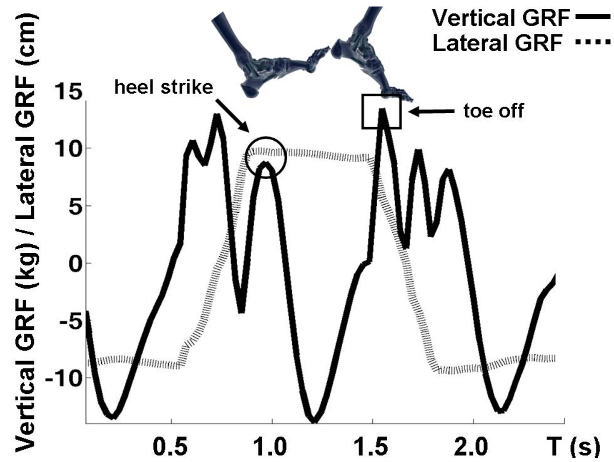


Fig. 1. The vertical GRF features transients during heel strike and toe off. The lateral coordinates of its point of application to the platform surface are positive during right foot stance, and negative during left foot stance. This figure exemplifies the step phase of the right leg during a gait cycle (between 1.0 and 1.5 s). To facilitate visual inspection both traces are centered on their geometrical mean (the vertical GRF typically fluctuates between 50 and 100 kg). This figure also shows that standard signals are laborious to analyze by hand.

III. RESULTS

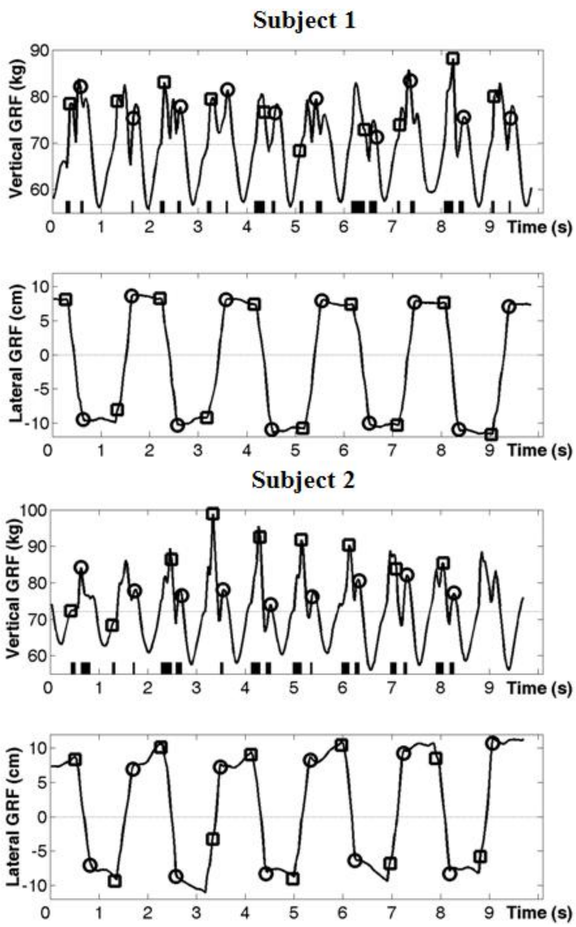
Each subject completed 14-26 gait cycles during a 30 s measurement. Figure 2 shows 5 consecutive gait cycles for 5 subjects. Figure 2 also shows that the gait signals exhibit highly individualized patterns: they vary in amplitude, frequency, and in the ratio of the amplitudes of the heel- and toe events. The figure also shows the HS and TO that the wavelet- and reference methods detected. The wavelet analysis detected the events 29 ± 67 ms later than the reference method (eq. 5). The difference was not significant, p=0.944. The difference 29 ms corresponds to 1.2% of the mean duration 2.4 ± 0.5 s of all the gait cycles. The correlation between wavelet events and reference events was high, P=0.993.

IV. DISCUSSION

The presented wavelet analysis detected heel strikes (HS) and toe offs (TO) in the ground reaction forces (GRF) that a force platform recorded while the subject was stepping in place on it for 30 s. The successful event-detection allows subsequent computation of temporal- and spatial gait-parameters used for gait evaluation.

We applied the wavelet analysis to the vertical GRF because this component often serves as the "gold standard" to determine gait events. We based the validation on the

HS- and TO times as determined from the lateral coordinates of the vertical GRF. The reason was that – at this point of the work when we focused on testing the wavelet technique on gait signals – it allowed a simple measurement setup. Moreover, the standard procedure to determine gait events with a force platform relies on one successful step on the platform *per walk*. Our protocol recorded data while the subject was stepping in place on the platform for 30 s. This allowed us to test the analysis on a gait signal with several gait cycles per subject. However, the recorded data is unlikely to match data recorded with standard gait-analysis equipments such as walkway- and treadmill based laborious video recordings [1,9] because the subjects were stepping in place on the force platform rather than walking. The event detection methods previously validated for use in normal gait show average errors ranging from 4.7 ms to 25 ms [2,3,10,11]. The average errors in this work were 29 ms, but the pros of the proposed technique are the simple measurement method and the automated detection of gait events. Next we need to validate the results against the results obtained with motion capture, the method used in other gait laboratories.



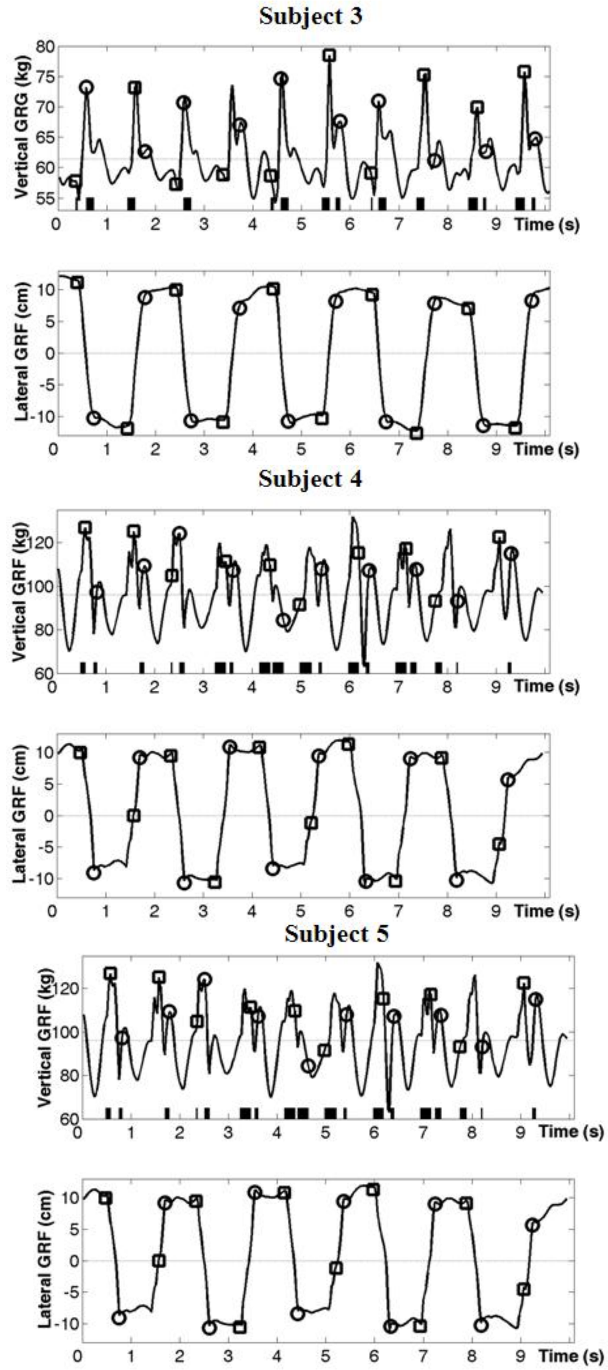


Fig. 2. Case studies of detected heel strikes (o) and toe offs (□) during 5 gait cycles for 5 subjects. Upper panes show the vertical GRF used for the wavelet-based gait event detection. Lower panes show the lateral GRF used for the reference gait event detection. In the upper panes, the horizontal lines show the geometrical mean of the full 30 s signals (the subject's weight), whereas the length of the black bars on the time-axis show the differences T between event times as detected with the wavelet- and reference methods. This figure shows that gait is highly individualized, and that automated gait event detection needs an analysis technique that is flexible enough to use on different gait patterns.

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