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An adaptive, real-time cadence algorithm for unconstrained sensor placement

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ABSTRACT

This paper evaluates a new and adaptive real-time cadence detection algorithm (CDA) for unconstrained sensor placement during walking and running. Conventional correlation procedures, dependent on sensor position and orientation, may alternately detect either steps or strides and consequently suffer from false negatives or positives. To overcome this limitation, the CDA validates correlation peaks as strides using the Sylvester's criterion (SC). This paper compares the CDA with conventional correlation methods.

22 volunteers completed 7 different circuits (approx. 140 m) at three gaits-speeds: walking (1.5 m s^{-1}), running (3.4 m s^{-1}), and sprinting (5.2 and 5.7 m s^{-1}), disturbed by various gait-related activities. The algorithm was simultaneously evaluated for 10 different sensor positions. Reference strides were obtained from a foot sensor using a dedicated offline algorithm.

The described algorithm resulted in consistent numbers of true positives (85.6–100.0%) and false positives (0.0–2.9%) and showed to be consistently accurate for cadence feedback across all circuits, subjects and sensors (mean ± SD: 98.9 ± 0.2%), compared to conventional cross-correlation (87.3 ± 13.5%), biased (73.0 ± 16.2) and unbiased (82.2 ± 20.6) autocorrelation procedures.

This study shows that the SC significantly improves cadence detection, resulting in robust results for various gaits, subjects and sensor positions.

1. Introduction

All forms of human locomotion are cyclic in nature. Understandably, the detection of the fundamental movement frequency (cadence) is of interest and has served as a basis for physical activity assessment [1,2], activity recognition [3,4] and detection of spatiotemporal events within the gait cycle (e.g. initial contact, toe-off) [5–8]. In addition, cadence is related to energy expenditure in running [12], swimming [9], skating [10] and rowing [11] and impact forces [13] in running. The use of electronic devices, such as sport watches and smartphones, is rapidly increasing [14]. These devices are commonly equipped with tri-axial accelerometers used to provide feedback on cadence. However, the devices are carried at many different locations on the body, while sensor orientation and position may have a large impact on the accuracy of cadence detection. Especially the smartphone is often loosely fixated and carried with variable orientation. Cadence detection is further challenged by gait transitions and variation between activities, such as walking, running and climbing stairs and by gait-related interruptions, such as stopping, going through a fence, or stepping over an obstacle. Lastly, the algorithms are expected to provide real-time feedback and consequently computation on the device is required. Clearly, the diverse usage of devices in everyday conditions challenges algorithms for accurate cadence detection.

Different approaches to estimate cadence have been proposed. Approaches can be divided in clustering, time-domain and frequency-domain techniques [15]. Each approach has specific advantages and disadvantages. The clustering techniques require training of a model, which makes generalization and quick adaptation across various situations and sensor orientations difficult. In the time-domain, acceleration signals are typically first low-pass filtered before detection of peak or zero-crossings [15,16]. The disadvantage is that variations in sensor position, sensor fixation, terrain and activity require dynamic thresholds for peak detection. Sensor position and movement intensity alter the signal-to-noise ratio, which makes peak detection in the time-domain prone to false positives or negatives [17].

Alternatively, the cadence can be estimated in the frequency domain using the Fast Fourier Transformation (FFT) [6,17–19]. Disadvantage of the FFT are resolution problems that occur

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depending on the choice of the (time) window length [15]. With long windows, the accuracy of the frequency estimate is reduced and feedback will be delayed [17]. On the other hand, short windows reduce the relative power at the dominant frequency and consequently the reliability of the estimate. Wavelet analysis has been introduced as an alternative [21]. However, the optimization process underlying the wavelet analysis makes the computational load relatively high [21] and therefore wavelet analysis is considered to be less useful for real-time analysis and on-sensor processing.

Correlation procedures share advantages and disadvantages with frequency domain techniques, but the correlation spectrum corresponds directly with the time-domain (Figs. 2 and 3). In walking and running, peak correlation coefficients are found when the original signal and its time-delayed copy (autocorrelation) have an overlap of one step or stride, depending on the sensor position and orientation. The correlation peaks represent the average periodicity over the chosen window. Crucial steps in correlation procedures are the choice of the window length, selection of the signal and the procedure to detect the peak that represents the true fundamental movement frequency. As an alternative to autocorrelation, cross-correlation procedures are used for template matching [16,20], where an online or offline defined template is correlated to the signal. A disadvantage of template-matching is that the template has to resemble the signal quite closely for accurate detection and therefore is prone to suffer from mismatches. Cross-correlation procedures [15,22,23] can also be applied without a pre-defined template, which may improve generalizability and adaptiveness. Cross-correlation procedures without pre-defined templates compare sequential movement traces.

When the orientation of the sensor is known, the vertical acceleration is often isolated [17,24] and used for the correlation procedure. Note that changes in sensor orientation during the activity may reduce accuracy. When the orientation is unknown, two solutions are often applied:

(i) The orientation of the sensor's local axes is re-aligned to match the global (earth) orientation. To this end, gyroscopes (and magnetometers) are often used. Note that the re-alignment should be representative throughout the movement. For real-time processing, the processing of multiple sensors simultaneously is disadvantageous for the computational load and battery life [15].

(ii) Alternatively, the magnitude of the acceleration signal is calculated [17,24]. Note that by calculating the magnitude, directional information is lost. Consequently, the signal frequency increases, which may increase the number of false positives. Without differentiation between half cycles (steps) versus whole cycles (strides) the algorithm is dependent on the sensor position. Centrally placed sensors will tend to detect steps, while sensors placed on the limbs will tend to detect strides. The sensors placed outside the midline but central on the body, such as sensors placed round the hip, will likely result in inaccurate cadence detection since they will inconsequently detect steps or strides. Moreover, when the goal is to detect steps, asymmetrical gait patterns, orientation, fixation and mediolateral placement will likely cause differences in left and right acceleration patterns. Such situations occur frequently in everyday conditions and may reduce the power of correlation between sequential steps. We reasoned that the correlation between two sequential strides may provide more stable cadence estimation and prevent step-stride confusions by verifying correlation peaks using the Sylvester's criterion (SC). The SC requires all directions of the reference signal to correlate positively with all directions of the incoming signal, this prevents the need to isolate a certain axis or to combine axes and makes the algorithm independent of sensor orientation.

Previous studies have described algorithms with reasonable to good results for the estimation of movement frequencies. These algorithms were often specifically designed for walking (e.g. [4,6,17,24]). Moreover, as argued by others, validation protocols have been often overly simplified and did not represent the variability of everyday conditions [2,15,17]. Furthermore, many algorithms rely on specific constraints, often sensor position and orientation have to be known and/or multiple sensors have to be used [4,6]. To our knowledge, there is no algorithm yet capable of dealing simultaneously with (i) unconstrained sensor placement; (ii) everyday conditions and (iii) real-time processing on the sensor. Therefore, the goal of the current study was to design and validate an algorithm that accurately detects strides and provides cadence feedback during walking and running under unconstrained conditions.

2. Material and methods

2.1. Subjects

Twenty-two healthy subjects (nine females, thirteen males, 28 ± 2.9 yrs, 178 ± 9.5 cm and 70 ± 10 kg) participated in this study. Subjects were recruited from the university population. All subjects provided written consent approved by the local ethics committee of the Vrije Universiteit Amsterdam in accordance with the guidelines set out in the Helsinki Declaration regarding human research.

2.2. Equipment

Accelerometer data were gathered from 3 Samsung Galaxy S4 phones (136.6 × 69.8 × 7.9 mm, 130 g (weight), 100 Hz, ±19.6 g (range)) and 7 small 9-DOF IMU's (MPU-9150, Invensense, San Jose, USA: 35 × 25 × 11 mm, ±12.5 g (weight), 500 Hz, ±16.0 g (range)). Sensor fixation differed per position, the sensors on the leg were strapped with elastic bands, shoe-sensors were taped, one phone was worn in the trouser pocket, the phones carried on the upper arm and around the waist (on the back) were placed in commercial neoprene belts and a dummy phone with a sensor was held in the hand. To measure speed, a GPS watch (Garmin Forerunner 620) was used. Activities were labelled afterwards using video footage (60 Hz) of three cameras. To enable actual implementation on the smartphone, the algorithm was simultaneously optimized for Java code and tested on Samsung Galaxy S4 phones. However, this paper focusses on the method and analysis performed offline in Matlab.

2.3. Protocol

Subjects had to walk or run outdoors back and forth on seven different circuits (distances of about 140 m, 210 m and 50 m) at three freely chosen gait speeds: walking, running, sprinting. Sprinting was performed under two conditions: with a sudden start and stop and with gradual acceleration and deceleration. Within each circuit, the regularity of the movement was interrupted by short gait-related activities, such as turns, jumping, slalom, speed ladder, answering the phone and stair walking. To further challenge the algorithm, most circuits were performed twice, once on paved and once on a grass surface (Table 1). Participants were free to fixate the 10 sensors in a way they felt comfortable for running. The researcher only assisted with the placement of these sensors. Prior to the measurements, participants were informed about the type of activity, without detailed instructions on the execution of the activity. The IMU's started sampling simultaneously once they were removed from their power source. To synchronize the smartphones with the IMUs and video footage, the participants were asked to make a jump prior to the actual experiment, which caused a clear peak in the acceleration signal that was used for synchronization.