Toward Robust and Platform-Agnostic Gait Analysis

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***Abstract*—Biometric gait analysis using wearable sensors offers an objective and quantitative method for gait parameter extraction. However, current techniques are constrained to specific platform parameters, and hence significantly lack generality, scalability and sustainability. In this paper, we propose a platform-independent and self-adaptive approach for gait cycle detection and cadence estimation. Our algorithm utilizes physical kinematic properties and cyclic patterns of foot acceleration signals to automatically adjust internal parameters of the algorithm. As a result, the proposed approach is robust to noise and changes in sensor platform parameters such as sampling rate and sensor resolution. For the evaluation purpose, we use acceleration signals collected from 16 subjects in a clinical setting to examine the accuracy and robustness of the proposed algorithm. The results show that our approach achieves a precision above 98% and a recall above 95% in stride detection, and an average accuracy of 98% in cadence estimation under various uncertainty conditions such as noisy signals and changes in sampling frequency and sensor resolution.**

Keywords—gait analysis; wearable sensors; reliability; stride detection; cadence estimation; robustness

I. INTRODUCTION

Gait study in various application fields has recently attracted considerable attentions. With growing popularization of body-worn sensors, gait cycle detection using wearable sensors, such as accelerometer, gyroscope and force sensitive resistor, has become a trend in various application fields [1-6]. Spatiotemporal gait parameters such as stride time, cadence, and stride length provide useful information pertaining to a wide range of applications including authentication [1-4], physical impairments diagnosis, and rehabilitation monitoring [5,6].

A gait cycle (e.g., single stride) is defined as a sequence of functions taken by one limb, which begins with the reference foot contacting the ground, follows by leg swing, and ends with subsequent ground contact of the same foot [8]. General parameters specific to gait activity can be estimated using gait cycle detection in a certain walking distance.

Early studies have reported that, the shape of the acceleration curve recorded for one gait cycle is repeating throughout a continuous walk; therefore, it is possible to determine gait events by studying the acceleration signal throughout the gait cycle [9,10]. Furthermore, several important spatiotemporal gait parameters, including cadence, step length, velocity and symmetry, can be obtained from acceleration data [11].

As a result, numerous approaches for gait cycle detection and recognition using inertial sensors have been developed and utilized on various domains. They have been proven to be well-designed and practically accurate [12-16]. Major problem with these approaches, however, is that each requires a number of tuning parameters that need to be adjusted according to the platform used or the context within which the system is utilized. Our focus in this paper is to develop a gait analysis algorithm that is platform-independent and can be easily adopted in various settings.

In this paper, we introduce a reliable and robust approach for gait cycle detection and cadence estimation which uses acceleration signals from the foot during a normal walk. The main advantages of our approach are as follows: 1) it is robust to noisy signals and changes of sensor platform parameters including sensor resolution and sampling frequency, 2) the internal parameters are self-adapted based on physical kinematic measurements and acceleration signal patterns, with zero dependency on the experiment setup, 3) it takes calibrated tri-axial acceleration signals from the foot as the input, and does not require any sophisticated signal pre-processing procedure.

II. RELATED WORK

In this subsection we discuss some of the current gait analysis techniques. Generally speaking, the current approach toward gait cycle detection requires a number of predefined parameters or thresholds adjustments based on the specific experimental analysis or even manual observations. This limitation results in a potentially poor performance on new sensor platforms with different sampling frequency, sensor dynamic range, etc.

For example, in some step-counting applications mentioned in [12], each step is recognized according to a predefined threshold on the vertical acceleration peak in accelerometer readings. Such a peak is a result of the ground repulsive force when the foot hits the floor in the heel strike event. However, the pre-specified threshold is not reliable considering various types of walking surface.

In [13], a motion detection approach using accelerometer is introduced. The authors have successfully differentiated the actual walking portion from the standing-still portion by comparing the acceleration data with two specific values corresponding to the starting/stopping points of the movement. However, these two values were empirically found in their experiment, which may not function accurately once a different type of accelerometer sensor with a potentially different sensitivity/range is employed.

In another study [14], the authors have presented an gait recognition approach based on 3D acceleration data during walking. Gait cycles are detected from the zero-normalized vertical acceleration signal by finding the zero points. There is, however, a limitation that the first zero point requires to be visually detected, which makes the method not fully automatic.

C. Nickel et al. [15] have presented another method for accelerometer-based gait recognition by computing both min-salience and max-salience vectors of the signal, and using two predefined thresholds to determine the start point of each gait cycle. However, these two parameters were chosen to achieve the best result according to the experimental data. Such an approach may not be generalized for use in other practices with potentially different platform settings.

Another study [16] has developed an algorithm to detect stride from the filtered acceleration and angular velocity signals. The authors used several thresholds to find the start points and end points of a stride based on the variance of signal vector magnitudes calculated from sensor readouts. Although this algorithm has been proved to achieve a high accuracy, it requires several predefined platform-dependent parameters.

III. Algorithm Overview and Preliminaries

It is suggested and proved by many former studies that using foot mounted accelerometers is an effective and practical approach for ambulatory gait monitoring and gait parameters assessment [17-19]. Due to its advantage, our algorithm extracts gait information from the three-axial acceleration signals of the foot in the ambulation.

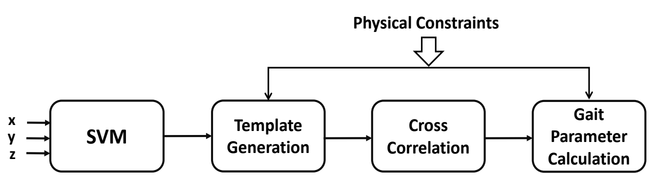

Fig. 1. Algorithm Overview

Figure 1 gives an overview of the proposed algorithm. Signal Vector Magnitude (SVM) is adopted for data processing in order to get around manual mapping from three axes of the sensor output to the orientations of device placement. Cross correlation function takes templates generated from SVM signal to continuously determine the similarity of the signal with its past without any predefined threshold. Two gait specific parameters are extracted from the cross correlation output.

There are several physical constraints introduced in the template generation and gait parameter calculation phases to automatically adjust the internal parameters.

Different gait parameters can be naturally constrained by physical constraints of human movements. Such constraints have been previously studied and can be used to limit various expected gait parameters in our algorithm.

Cadence, normally measured in steps per minute, is generally considered as an independent variable of walking, which can be used to determine the magnitudes of other kinematic characteristics of gait [20]. There are many studies examined the cadence for specific groups of subjects, and the normal range can be fairly large [8,21,22].

An early study in [22] examined the cadence of natural walk and showed that the cadence is 107 (steps/min) for young adults and 104 (steps/min) for the elderly. In another study [8], the normal cadence ranged from 100 (steps/min) to 115 (steps/min), while another stride analysis [21] posted a much wider range of cadence, from 60 (steps/min) to 132(steps/min).

Table I summarizes the general measurements for normal cadence, and the parameters used in our algorithm are adjusted according to the given values.

TABLE I. Normal Cadence Measurements

Normal Cadence	Steps/min	Strides/min
Mean	100	50
Range	80 – 130	40 – 65
Over Rate	140	70

In the traditional definition, one gait cycle is composed of a stance phase followed by a swing phase [12], which has been further divided into eight events, as it shown in the figure 2 from Vaughan's book [20].

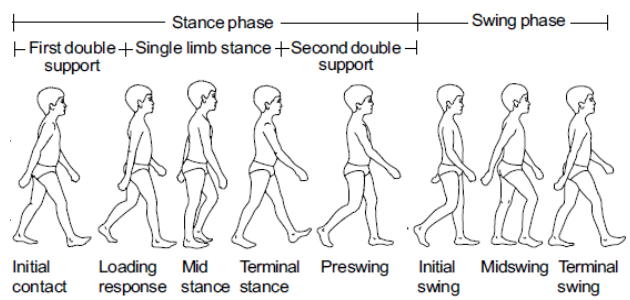

Fig. 2. The Normal Gait Cycle of an 8-Year Old Boy [20]

In the perspective of acceleration signals from single foot in a normal walk, gait cycle is recorded as a periodically repeating pattern consisted of a fierce fluctuation representing the period from swing phase till loading response and a relatively flat curve referring to the mid-stance phase [12,20].

Such acceleration signals contain detailed temporal information along with the gait ambulation. (1) and (2) reveal the relations between cadence and the number of signal samples used for recording one step/stride for a given sampling frequency

$$W_{step} = (60 \times Frequency) / Cadence \quad (1)$$

$$W_{stride} = 2 \times W_{step} \quad (2)$$

where W_{step} denotes the number of signal samples for recording one step, while W_{stride} refers to one stride, and *Frequency* is the sampling rate (Hz).

IV. Data Processing

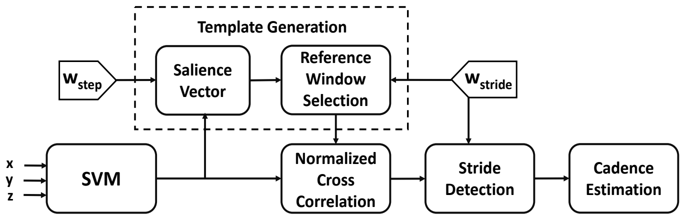

Fig. 3. Data Workflow

Our data analysis consists of several steps as shown in Fig. 3. The data workflow takes the tri-axial accelerometer reading as the input and ultimately detects the strides and outputs the cadence estimation in a real time manner. In this subsection we elaborate each processing step.

1) *Signal Vector Magnitude (SVM) calculation:* Tri-axial accelerometer generates signals in three orthogonal axes, which are commonly used to determine the acceleration in anterior-posterior (AP), medial-lateral (ML) and vertical (VT) directions. To avoid manual work of mapping the axes, we use signal vector magnitude (SVM) of tri-axial accelerometer data for gait cycle detection. The SVM reveals the degree of movement intensity in the gait behavior [16]. For any three-dimensional input (x, y, and z), SVM is given by

$$SVM(t) = \sqrt{x^2(t) + y^2(t) + z^2(t)} \tag{3}$$

2) *Salience vector construction:* Salience vector has already been adopted in several gait analysis researches [19, 23]. A minimum (or maximum) salience vector contains a value for each sample point of the signal, which is the number of consecutive following samples larger (or smaller) than the current one [23].

In our approach, salience vector is used to seek for the local minimum sample points (called salient points) which are spaced apart by repeated high intensity curves. Such curve relates to gait events covering one step, and hence, a parameter W_{step} is introduced here using the mean cadence (100 steps per minute), to ensure every two consecutive local minimum points have an adequate distance between them to record the movement of one step.

Figure 4 shows a SVM signal on the top and its corresponding min-salience vector on the bottom. The small circles indicate the salient points selected in this step.

3) *Reference window selection*: An ideal template should exactly capture one gait cycle movement; however, to trade off between the processing complexity and the accuracy, up to five approximate reference windows are selected from one SVM signal, each of which is determined by two consecutive salient points from previous step. Two parameters calculated using equation (2) with the range of normal cadence (strides/min) given in Table I are used here, to bind the distance of neighbor salient points. These windows were used as templates in the following cross-correlation function.

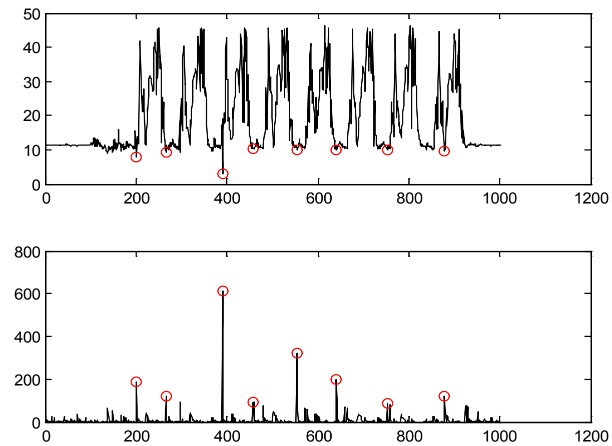

Fig. 4. SVM Signal and Salience Vector

4) *Cross-correlation function:* It is a flexible measure for the similarity degree between two signals with unequal lengths.

In this step, normalized cross-correlation is performed on SVM signal, and each reference window is used as a template sliding along SVM signal to automatically detect the similar portions. The result is normalized to eliminate the variance of signal amplitude. Figure 5 shows the output of one cross-correlation function. The peaks in the figure reflect the gait cycles recorded in SVM signal.

5) *Stride detection*: All the local maximum points are first picked using

$$C(t\text{-}1) < C(t) > C(t+1) \tag{4}$$

where $C(t)$ denotes the value of the entry at tag t in the normalized cross correlation curve.

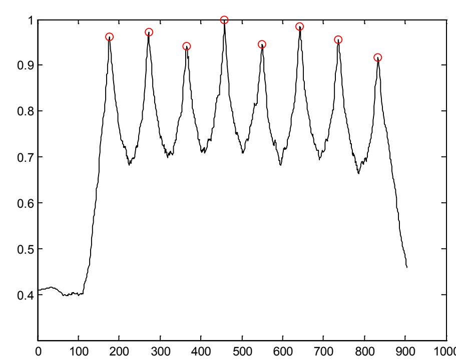

Fig. 5. Normalized Cross Correlation Result

The similarity degree can be directly measured by means of the value due to the normalized result. It is necessary to define a satisfactory similarity for declaring one stride. Considering the fact that gait is a dynamic movement, every stride made by the same foot may not have equal length during the walk. A shorter stride, which usually happened in the beginning and the end of a walk, indicates a shorter swing phase. According to the clinical study of human gait behavior, the time duration of swing phase is around 40% of one stride [20]. Therefore, the tolerance for determining a similar pattern of one stride is 0.6 in normalized cross correlation output. A local maximum point having value larger than 0.6 is first selected.

Another fact should also take into account is that, the cadence for a normal walk has an upper bound to distinguish it with other fierce movements, such as running, and hence there is a least W_{stride} number for recoding one stride in acceleration signals. Such W_{stride} can be estimated using the over rate cadence listed in Table I. As a result, for every two successive peaks with a distance less than that W_{stride}, the peak with smaller value is further eliminated.

In the end, the majority number of peaks detected from cross-correlation outputs using different templates is considered as the total number of strides recorded in the corresponding SVM signal.

6) *Cadence estimation*: Real time cadence can be estimated by means of temporal data related to each stride. After detecting the gait cycles from normalized cross-correlation curve, the cadence (steps/min) could be further calculated using

$$Cadence = 2 \times ((60 \times Frequency) / N) \qquad (5)$$

where *Frequency* denotes the sampling rate (Hz) and N is the number of sample points between two continuous strides determined in previous step.

The mean value of cadence for a series of strides is reported as the average cadence during the movement.

V. EXPERIMENTAL SETUP

A. Procedure

For validation purpose, we applied our approach on the acceleration datasets collected from 16 subjects in a clinical trial involving both health individuals and patients with glaucoma [27]. The acceleration signals were generated during 10-Meter-Walk [25] experiment. It is a standard test for gait parameter assessment, and 10-meter is a sufficient distance for the gait behavior to reach a steady state phase after acceleration period and before deceleration [5,25].

In this experiment, all the participants were required to walk for 10 meters three times at their comfortable speed while wearing a pair of sensor-equipped shoes. Two Shimmer [26] (Sensing Health with Intelligence, Modularity, Mobility and Experimental Reusability) sensor platforms were placed on the top of the shoes. The integrated tri-axial accelerometer (MMA7260Q) was used to generate acceleration data. The sampling rate for the output signal was 102.4Hz, and the sensitivity was set from -2g to 2g in their experiment [27]. The signals were calibrated before we used to reduce the complexity of raw data.

B. Data Acquisition

Over and above the accuracy evaluation, we also modified the original acceleration datasets to further test the robustness on several sensor platform parameters changes as well as the input with different amount of noise.

- Sampling frequency. We applied up-sampling and down-sampling methods on the original acceleration signals with a sampling frequency 102.4Hz, and acquired another five acceleration signal sets, which had sampling rates 8.5Hz, 17Hz, 34.1Hz, 51.2Hz and 204.8Hz, respectively.
- Sensor resolution. To obtain the signal sets with different amplitudes, we amplified the tri-axial signals to double and triple of their original amplitudes, and also attenuated it to the half.
- Signal-to-Noise ratio. To evaluate the performance of our algorithm on the noisy environments, we added white noise into the original tri-axial acceleration signals with the signal-to-noise ratio (SNR) 20db, 15db, 10db and 5db, respectively.

VI. RESULTS

In this section, we first report the accuracy of our algorithm on the collected data with fixed platform settings. We consider this performance as baseline. Next, we will present the performance of our algorithm in presence of noise and various platform changes, in order to demonstrate the potential of our framework in adapting to new unknown settings.

For measuring the performance of stride detection, a total of 49 trials from 16 participants were used; since every subject had two accelerometers mounted on both feet, this resulted in 98 signal datasets containing 811 strides overall.

A. Baseline Performance

Table II listed the performance of stride detection in terms of the recall and precision for each subject. The results show that among 16 subjects, our algorithm achieves a minimum recall of 95% for 13 subjects and a minimum precision of 95% for 15 subjects.

The performance on detecting strides for all the datasets has a recall of 96.05% and a precision of 98.98%.

TABLE II. INDIVIDUAL STRIDE DETECTION RESULTS

Performance	**Subject**															
	1	***2***	***3***	***4***	***5***	***6***	***7***	***8***	***9***	***10***	***11***	***12***	***13***	***14***	***15***	***16***
Recall (%)	98.67	100	100	95.74	95.74	96.08	98.04	92.16	97.92	91.67	92.86	97.83	95.56	90.57	96.30	96.30
Precision (%)	98.67	100	92.31	100	100	100	100	100	97.92	100	100	95.74	100	100	100	100

To evaluate the performance of cadence estimation, we first manually calculated the average cadence for each dataset by observing the temporal acceleration information. Then, we ran our algorithm and compared the automatically estimated output with the manual anotated numbers.

Figure 6 illustrates the average value and the range of the accuracy among the signal datasets from 8 individuals. As shown in this figure, our algorithm achieves an accuracy of 97% for individual cadence estimation. The average accuracy for the entire datasets is 99.17%.

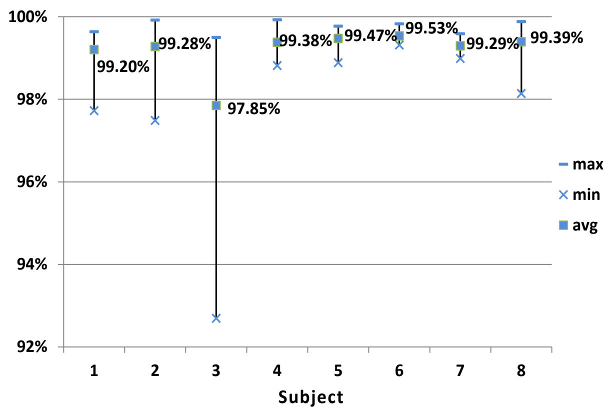

Fig. 6. Individual Cadence Estimation Results

B. Impact of Sampling Frequency

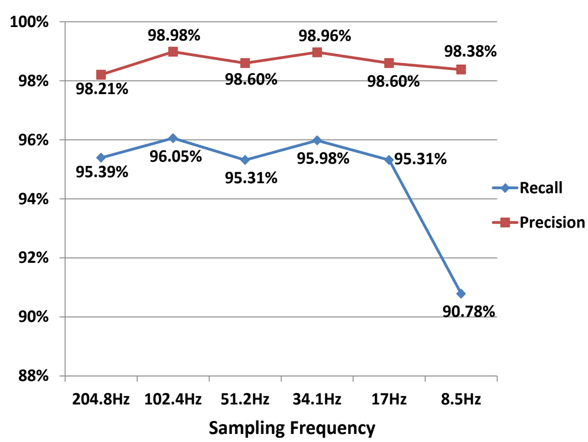

Fig. 7. Stride Detection Results on Frequency Changes

To validate the reliability of our algorithm, we first tested it using modified signal datasets with different sampling frequencies. Figure 7 shows the overall recall and precision values as a function of the sampling frequency.

The results show that except the signal set with a sampling rate 8.5Hz, our algorithm achieves a recall over 95% and a precision over 98% in stride detection across all the dataset trials. A prior study [28] on body sensors demonstrated that 17Hz is sufficient for physical movement monitoring applications, while the lower sampling frequencies may affect the accuracy due to inadequate information. Therefore, the drop in the recall when sampling frequency is reduced to 8.5Hz can be explained by insufficient information in the signal rather than the lack of robustness in our algorithm.

Table III lists the results of cadence estimation based on various sampling frequencies. The results show that our algorithm's performance continues to remain sufficiently high (e.g. > 98%) for the majority of test sampling frequencies.

TABLE III. CADENCE ESTIMATION RESULTS ON FREQUENCY CHANGES

Performance	Sampling Frequency					
	204.8Hz	*102.4Hz*	*51.2Hz*	*34.1Hz*	*17Hz*	*8.5Hz*
Accuracy (%)	99.04	99.17	99.23	99.09	98.51	95.92

C. Impact of Sensor Resolution

In addition to sampling frequency, we also evaluated the performance of our approach when signal amplitude changes. The outputs for stride detection and cadence estimation using doubled, tripled and halved signal datasets were exactly same as the results from the original signals.

This high level of robustness can be explained by the fact that we use normalized cross-correlation for gait feature detection. Therefore, our algorithm is not sensitive to the changes in the signal amplitude.

D. Impact of Environmental Noise

Besides the sensor platform parameters, we further tested our algorithm using signals with additive white noise varying from 20db to 5db. The results illustrated in figure 8 show that our algorithm maintains at least 96% of both recall and precision regardless of the amount of noise in the signals.

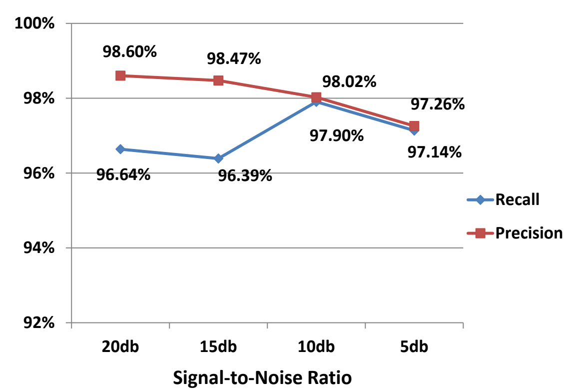

Fig. 8. Stride Detection Results on SNR Changes

Table IV below shows the accuracy of cadence estimation based on different SNRs. The average accuracy is over 98% across all the datasets.

TABLE IV. CADENCE ESTIMATION RESULT ON SNR CHANGES

Performance	Signal-to-Noise Ratio			
	20db	*15db*	*10db*	*5db*
Accuracy (%)	99.18	99.10	99.05	98.28

VII. Conclusion and Future Work

In this study, we proposed a self-adaptive gait detection algorithm for stride determination and cadence estimation; our approach is robust for the noisy acceleration signals and also independent of several sensor platform parameters such as sensor resolution and sampling frequency. We explained the underlying physical kinematic measurements used for automatic parameter adjustment. We proceeded with evaluation of our algorithm using clinical trial dataset in the changes of sensor platform parameters and environmental noise, and the results demonstrated the accuracy and robustness of this algorithm (98% precision and 95% recall in stride detection, and 98% in cadence estimation).

For the current study, we detect gait cycles using SVM signals in order to get around the manual axes mapping. However, it could potentially be regarded as a limitation since we are discarding specific gait information carried in separate axial signals. To address this shortcoming, our on-going study is to develop a more advanced algorithm to automatically detect the mapping between each axis and its actual direction. It will enable us to take full advantage of tri-axial readings for more accurate gait cycle detection as well as a more comprehensive feature extraction.

In addition to sampling frequency and sensor resolution, there are several other sensor platform parameters we are working on for the next stage, such as bit resolution and sensor sensitivity, to further enhance the generalizability and scalability of our gait analysis approach.

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