Detecting Gait Events from Outdoor Accelerometer Data for Long-term and Continuous Monitoring Applications

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Abstract- Detecting gait events is the key to many gait analysis applications which would immensely benefit if the analysis could be carried out using wearable sensors in uncontrolled outdoor environments, enabling continuous monitoring and long-term analysis. This would allow exploring new frontiers in gait analysis by facilitating the availability of more data and empower individuals, especially patients, to avail the benefits of gait analysis in their everyday lives. Previous gait event detection algorithms impose many restrictions as they have been developed from data collected in controlled, indoor environments. This paper proposes a robust algorithm that utilizes a priori knowledge of gait in conjunction with continuous wavelet transform analysis, to accurately identify heel strike and toe off, from noisy accelerometer signals collected during indoor and outdoor walking. The accuracy of the algorithm is evaluated by using footswitches that are considered as ground truth and the results are compared with another recently published algorithm.

Keywords-gait event detection; accelerometer; outdoor walking; wavelet transform;continuous monitoring

1. INTRODUCTION

In gait analysis, the two most relevant temporal gait parameters in a normal gait cycle are the initial heel contact or heel strike (HS) and terminal contact or toe off (TO); and other temporal parameters like swing, stance and stride time can also be computed from them [1]. Thus, accurately and robustly identifying these events is the key to many gait analysis applications. Majority of such applications would benefit from long-term monitoring where gait measurements could be taken and evaluated continuously. For example, many studies have shown that improper coordination within the neural-locomotor control system may lead to deviations from normal gait behavior, which makes gait parameters an important indicator for identifying and monitoring patients suffering from neuro-physiological disorders and impairments [2], risk of falling [3] [4] [5], etc. Such analysis might also require continuous monitoring of their gait cycles in response to periodic medicinal therapy. Apart from monitoring and evaluating long term effects, gait analysis can be used to design and optimize functional electrical simulation (FES) systems [6], develop clinical tools for diagnosis [7], access the quality of gait of amputees and rehabilitating patients [8], develop activity monitors and many more. While controlled indoor environments might be suited for some applications where information from a few steps might be sufficient, many others require the analysis to be carried out for longer periods of time in everyday life scenarios with semi or uncontrolled, outdoor environments.

The present state of practice is to perform advanced clinical gait analysis in controlled gait labs equipped with stationary sensor systems such as motion capture systems and force plates [9]. However they provide information of only a couple of steps and are highly expensive, immobile and require competence in maintenance, operation and execution. This renders them inadequate for outdoor applications. Furthermore, when patients are brought into such gait labs, the 'white-coat effect' might have a role to play as well, especially in determining the behavior of patients when one is measuring deviations from normal gait behavior [10]. Technological advancements have made inertial sensors such as accelerometers and gyroscopes, miniature, low-powered, durable, inexpensive, highly mobile and readily available [11]. This lead to the development of ambulatory systems that could be used outside gait labs but are currently restricted to controlled indoor environments. This is mainly due to the existing algorithms which have been developed by collecting data from controlled indoor experiments and laying a number of assumptions on the experimental conditions such as exact alignment of the sensors during the entire movement [6] [12], flat and inclined walking surfaces [13], etc. However these assumptions might not hold in real everyday life scenarios for long time periods. This motivates the need to develop robust and efficient algorithms such that gait analysis can be moved outdoors in more uncontrolled environments and implemented in various applications that involve long-term or continuous monitoring in everyday life. This would allow moving from a clinician's perspective to a more patient's perspective such that patients can be empowered to avail the benefits of gait analysis in their everyday lives.

Recently, wavelet transforms are being increasingly used to develop gait event detection algorithms as it supports simultaneous time frequency analysis of non-stationary signals and have been shown to be robust among peak detection algorithms [14]. While [15] have developed a method using gyroscopes, [13] have found it appropriate to use accelerometers. In the context of gait event analysis in uncontrolled environments, accelerometers seem to be a better choice than gyroscopes for developing automated gait event identification systems. Sudden movements like jerks or turns during walking would cause large gyro drift errors. Furthermore, gyroscopes have high power consumption, long reaction time and are very sensitive to temperature effects limiting their long term outdoor use [16]. Accelerometers, on the other hand, suffer from noise due to mechanical vibrations and calibration errors but these do not diverge in time and in many cases can be handled effectively. Some authors have used machine learning techniques [13] [17] but the difficulty with such algorithms is that they depend on labeled training data and the addition or exclusion of any parameter would require re-training the entire algorithm. All methods that have been reviewed in this paper have been developed by using data collected inside controlled indoor conditions. Thus it remains to be seen how they would perform when implemented directly on semi or uncontrolled outdoor environments.

This paper proposes a robust algorithm to accurately detect gait events of HS and TO by effectively analyzing noisy gait data, collected using accelerometers, from both indoor and outdoor environments. The proposition is an improvement of a previously published algorithm [18] and adopts a new approach in order to generalize the algorithm by making fewer assumptions and eliminating thresholds. The algorithm uses continuous wavelet transform analysis to obtain the temporal location of gait events in the given signal and provide features that are used to classify the identified gait events into HSs and TOs. Prior knowledge of temporal relations that exist in human gait is used to correct the misclassified events. The accuracy of the algorithm is evaluated by using footswitches that are considered as ground truth and the performance is compared by applying the methodology adopted in [13], on both the indoor and outdoor datasets.

2. Experiments

Fifteen healthy volunteers participated in the experiments with informed prior consent. Each subject had two Shimmer (3-axis) accelerometers (sampling at 128 Hz) attached to both their ankles using Velcro straps. The subjects were instructed to walk for about 25 minutes at their preferred walking speed on an outdoor street. A previously published dataset which was collected from 6 subjects walking inside a laboratory is used as the indoor walking dataset [19]. This experiment used two Shimmer 3-axis accelerometers (sampling at 50 Hz) positioned at the ankles and a 6m long Gold GaitRite pressure sensitive mat (sampling at 60 Hz) which had its own software for detecting HS and TO. The pressure-mat data was used as the ground truth.

3. Methodology

The ability of wavelet transform to give the time localization of the spectral components in a non-stationary signal has rendered it a powerful tool for processing of biosignals like EEG, EMG and ECG [20]. The Continuous Wavelet Transform or CWT of a signal, $x(t)$, is given as [20]:

$$CWT(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} x(t) \psi^* \left(\frac{t-b}{a} \right) dt \qquad (1)$$

where ψ^* is the complex conjugate of the wavelet function $\psi(t)$ and a and b are the dilation and location parameters of the wavelet, respectively. The dilation or scale is inversely proportional to the spectral components. Low scales or high frequencies provide more local information while high scales or low frequencies provide relatively more global information about the signal. Depending on the type of walker, the multi-resolution property of CWT helps the algorithm to adapt to changes in individual gait behavior, making it appropriate for gait analysis. Fig. 1a shows the resultant acceleration signal calculated from the individual accelerations of the 3-axis accelerometer and the CWT is applied on this signal[1]. CWT coefficients indicate the similarity between the chosen wavelet and the signal and this similarity is in terms of the matching frequency component. Thus sym-4 wavelet is chosen (Fig. 1b) as it highly matches the HS regions giving higher coefficients in comparison to the TO regions, thus providing a better separation between them at the same scales (Fig. 2).

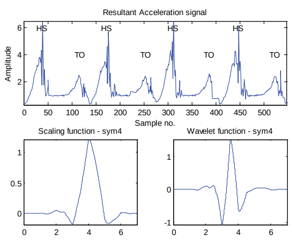

Figure 1. (a) HS and TO regions in the resultant acc. signal from outdoor walking. (b) Sym-4 wavelet function.

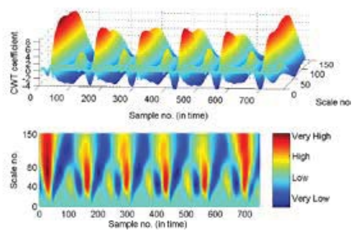

Figure 2. CWT coefficients of the resultant acceleration signal.

[1] Henceforth the term ‘signal’ shall be used to represent the resultant accelerometer signal.

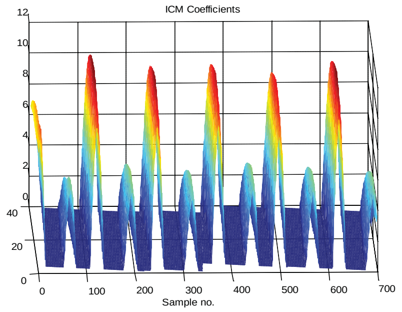

Figure 3. Separate HS and TO regions.

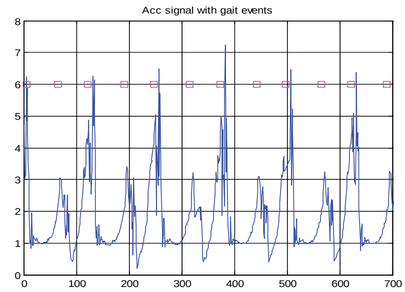

Figure 4. Temporal location of individual gait events.

The scales corresponding to the major frequency component of the signal, i.e. scales corresponding to ‘High’ and ‘Very High’ coefficients (refer Fig. 2) are extracted using an adaptive weighted technique where higher weights are assigned to the scales with higher coefficients and vice versa. All non-positive CWT coefficients are then set to zero to effectively separate the HS and TO regions as shown in Fig. 3. The sharp ridges that form in the separated HS and TO regions are obtained by computing the local maxima along the temporal axis. The median of each of these ridges gives the temporal location of individual gait events, shown as squares in Fig. 4.

Features such as peak value and difference in peak value are extracted from the matrix containing the coefficients representing the separated HS and TO regions. These features are used to separate the identified individual gait events into two clusters of HS and TO using k-means clustering, as shown in Fig. 6. Prior knowledge of temporal relations existing in normal human gait is used to identify the misclassified gait events. It is assumed that for a normal gait, a TO is always followed by a HS, resulting in the temporal relation of HS – TO – HS –TO and so on. Thus the difference in the indices in the vector of identified gait events for either TO or HS should be 2 as shown in Fig. 5. This model is utilized to identify and correct the misclassifications.

Event	HS	TO	HS	TO	HS	TO	HS…
Index	1	2	3	4	5	6	7…

Difference in HS indices = 2 *Difference in TO indices = 2*

Figure 5. Defined temporal relation for a normal gait.

4. Results

Preliminary results have shown that the algorithm was successful in correctly identifying gait events for both indoor and outdoor datasets. It was observed that a good quality signal with high SNR (signal to noise ratio) results in greater separation between the two clusters of HS and TO while one with poor SNR results in a poorer separation with more misclassifications as shown in Fig. 6 and 7. Utilizing this fact, it was observed that in comparison to indoor walking signals which had consistent level of noise, the outdoor signals from different subjects had varying levels of noise, with some being very noisier than the others. This gives an insight into the discrepancy between signals collected in controlled indoor environment versus uncontrolled outdoor conditions that could be investigated further.

5. Discussion

In recent years, gait analysis applications have grown manifold. There is an increasing need to develop robust and efficient systems such that gait analysis can be moved outdoors in more uncontrolled environments leading to long term analysis or continuous monitoring in everyday life. This would, in future, allow exploring new frontiers in gait analysis by facilitating the availability of more data and empower individuals and patients to avail the benefits of gait analysis in their everyday lives.

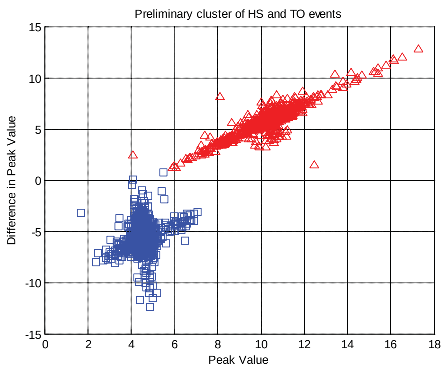

Figure 6. Clusters of HS (red) and TO (blue) of an outdoor signal with good SNR

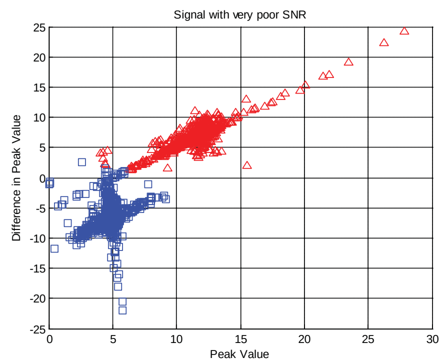

Figure 7. Clusters of HS (red) and TO (blue) of an outdoor signal with poor SNR

Previously published gait event detection algorithms have been developed by simulating an outdoor environment inside controlled indoor conditions and it remains to be seen how these algorithms shall perform when implemented in semi or uncontrolled environments for longer periods of time. Thus, the authors had previously proposed an algorithm based on prior knowledge of walking gait characteristics and wavelet transform that gave good results for both indoor and outdoor walking data [18]. However, it had certain drawbacks by laying assumptions on the shape of the HS and TO regions and maximum walking velocity along with utilizing some thresholds on wavelet coefficients in order to build a model that can identify events from noisy accelerometer signals.

The current algorithm adopts a different approach with minimal assumptions in order to have a generalized algorithm that can be directly implemented on noisy outdoor data. The resultant accelerometer signal is used for analysis which makes it invariant to individual axis alignment and insensitive to changes in the orientation of the sensor while walking, unlike many existing algorithms which assume that the sensor shall stay statically positioned during the entire movement. The proposed algorithm utilizes the temporal relation of normal gait, i.e. a HS is followed by a TO, in order to correct the misidentified events. This encourages the future possibility to adapt the proposed methodology to complex gait by altering or adding further sematic rules. The clusters of HS and TO events give an insight into the quality of the collected signal. A signal with high SNR results in a better separation between the clusters and vice-versa (Fig. 6 and 7). This could be used to define a data quality index that would prove useful to clinicians and researchers to determine the utility of the collected data. As part of future work, the accuracy of the proposed algorithm shall be evaluated by using footswitches that are considered as ground truth and the performance would be compared to the methodology proposed in [13].

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