Non-Invasive Detection of the Freezing of Gait in Parkinson's disease Using Spectral and Wavelet Features

Kimia Nazarzadeh, Sridhar P. Arjunan, Dinesh K. Kumar and Debi Prasad Das

Abstract— **In this study, we have analyzed the accelerometer data recorded during gait analysis of Parkinson disease patients for detecting freezing of gait (FOG) episodes. The proposed method filters the recordings for noise reduction of the leg movement changes and computes the wavelet coefficients to detect FOG events. Publicly available FOG database was used and the technique was evaluated using receiver operating characteristic (ROC) analysis. Results show a higher performance of the wavelet feature in discrimination of the FOG events from the background activity when compared with the existing technique.**

I. Introduction

Parkinson's disease (PD) is a neurodegenerative disorder of the central nervous system with the average diagnosis age of 65 years and high prevalence of 10 million patients worldwide [1]. Freezing of Gait (FOG) is a symptom of PD in advanced stages where the feet are glued to the floor unexpectedly [2], [3]. The underlying mechanism of FOG is still unclear and its diagnosis is complex [4], [5]. Due to the daily, unpredictable and frequent occurrence of FOG events, they can drastically degrade the quality of life in patients with advanced PD [6]. It implies the necessity of developing accurate FOG detection algorithms towards improvement of living conditions in PD patients. As an important aspect of neurodegeneration process in the PD patients, accurate FOG detection can also be quite useful for diagnose and assessment of PD at different stages.

Some patients who suffer from PD are able to overcome FOG attacks by stimulating their sensory-motor cortex deliberately. For example, they can suppress the FOG onset by walking to a rhythm or music, shifting body weight or marching to a command [7]. It has given rise to the idea that gait pattern in patients with PD can be improved by presenting them with external auditory or visual stimuli through a biofeedback procedure [8]. To this end, external feedback can be presented to the patients in a closed loop, once the FOG onset is predicted [9]. Electromyogram (EMG) signals and acceleration data recorded from leg muscles are two non-invasive and affordable modalities which have been previously used to this end [10]–[12]. Between these two, however, accelerometer sensors may have more potential to be incorporated into a wearable device, a characteristic which could be of great benefit for PD patients [10], [13].

Variation of frequency components in acceleration of FOG and non-FOG situations is known to be an efficient feature for automatic FOG detection [10], [14]. There is evidence that the frequency interval of 3-8 Hz (or the freeze band) plays an integral role in FOG events in leg movement, while the frequency interval of 0.5-3 Hz is more dominant during non-FOG episodes (or the locomotor band) [10], [14]. In a pioneer work reported by Moore et al [14], the spectral information of the freeze and locomotor bands were used for automatic discrimination of the FOG and non-FOG events. Bachlin et al [10] reported a power spectral density based method by modifying the Moore's algorithm [14] with new improvements such as inclusion of an energy threshold to identify walking from normal standing. It led to a maximum sensitivity of 73.1% and specificity of 81.6% for FOG detection on a database of 10 PD patients, recorded by three tri-axial accelerometers attached to the shank, the thigh and a belt at the lower back [10].

In this paper, we propose an FOG detection algorithm using the wavelet coefficients of leg movement changes. After performing spectral filtering of the data, wavelet coefficients were obtained of the accelerometer data on the publicly available database. The data was classified to discriminate between FOG and non-FOG events in PD patients. We compare our results with the FOG detection algorithm reported by Bachlin et al [10] on a similar database through receiver operating characteristic (ROC) analysis.

II. Materials and methods

In this section, we explain the leg movement data, the PSD-based FOG detection algorithm, and our proposed modifications including the new wavelet feature for FOG detection.

A. Data

The database used in this study is a publicly available set (Daphnet Freezing of Gait Data Set) [15] of leg movement signals recorded by three acceleration sensors along x (horizontal forward), y (vertical) and z (horizontal lateral) axes [10]. All data were recorded using wearable assistant research hardware attached to the patient's leg at the shank (above the ankle), the thigh (above the knee) as well as the lower back [10]. Throughout this manuscript, we refer to these sensors as s1, s2 and s3 (shank, thigh and lower back, respectively). The original database included 10 subjects, but only 8 of them (2 female, the overall age range 59 – 75 years) experienced FOG events during the recording sessions. Also, 6 out of the 8 FOG-positive patients participated in more than one run. In this study, we chose the data of the first runs in 8 FOG-positive PD patients. All of these patients were at the advanced stages of PD (the Hoehn and Yahr scale [10] between 2 to 4). All signals were recorded at the sampling rate of 64 Hz [7].

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B. PSD-based FOG detection algorithm

The original FOG detection method [10] is based on extraction of the mean PSD from sliding windows of the leg movement signals. To this end, continuous output of each acceleration sensor is segmented into 4 s successive windows with 3.5 s overlap. Mean PSD of each window is then computed within two frequency bands of 0.5-3 Hz (locomotor band) and 3-8 Hz (freeze band) leading to two feature time series of non-FOG and FOG information, respectively. Summation of these spectral features is discriminative of walking and standing situations (very low values of total PSD shows that the subject has been standing with no walking activity). Also, the ratio of the freeze band's PSD over the locomotor band's PSD (*the Freeze Index*) is indicative of FOG events. The higher ratio represents the higher probability of FOG occurrence in a window.

C. Noise filtering of accelerometer recording

Extraction of PSD from short-length segments (4 s) may be affected by the edge effect and spectral leakage. In order to alleviate this issue, we performed spectral filtering of the recordings prior to segmentation. We decomposed the continuous signal into expert segmented locomotor and freeze signals after using Butterworth filter of order 5. Segmentation with the previous parameters (4 s length with 3.5 s overlap) was then applied on the filtered signals. Fig.1 illustrates the block diagram of the analysis procedure.

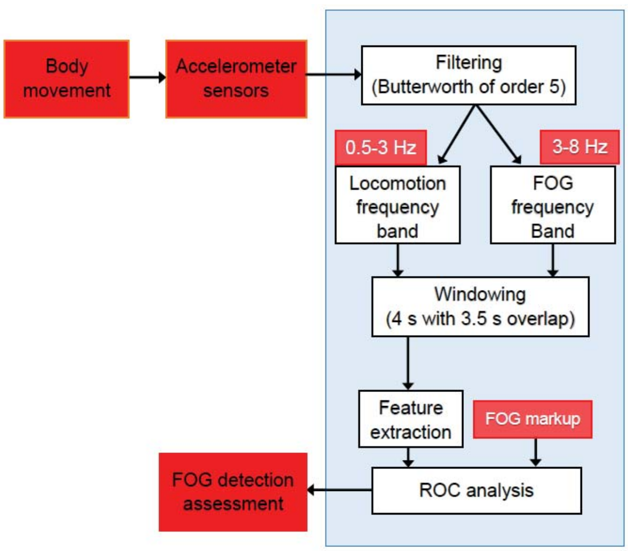


Fig.1. Block diagram of the modified FOG detection algorithm. The blue-shaded box is where the original FOG detection algorithm has been changed.

D. FOG detection algorithm with wavelet coefficients

Wavelet transform has the advantage of simultaneously providing spectral and temporal support. This is important for this analysis because FOG episodes have short temporal locations and small spectral changes, and having variable scale. We extracted Haar wavelet coefficients with 5 decomposition levels from the segmented locomotor and freeze band signals (the block 'Feature extraction' in Fig.1). Absolute value of the wavelet coefficients over all 5 scales was computed for each segment leading to a wavelet feature time series over the entire recording time span. We chose the Haar mother wavelet because it can detect sudden transient changes in the signals, potentially introduced by FOG occurrences.

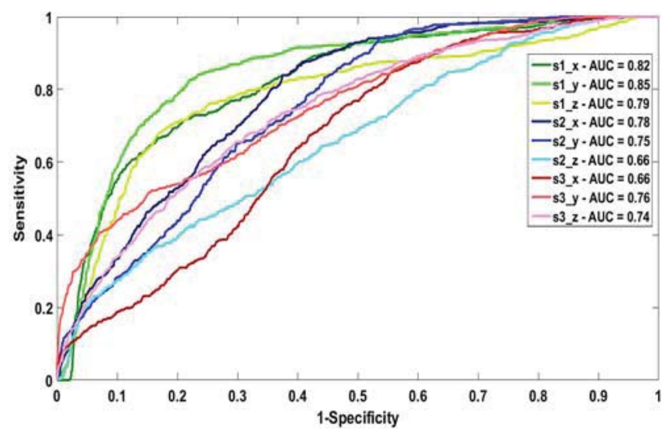
E. ROC analysis and statistical testing

Evaluation of the modified FOG detection algorithm was performed through ROC analysis. All feature time series along with the FOG markup (made by the expert) were fed into the ROC analysis block where the specificity and sensitivity of comparisons were estimated at different thresholds leading to the ROC. The area under the curve (AUC) of each ROC plot was computed for each sensor-axis (totally 9 for each subject). It yielded 9 distributions of 8 AUC values over all subjects and for the two techniques; wavelet and PSD based.

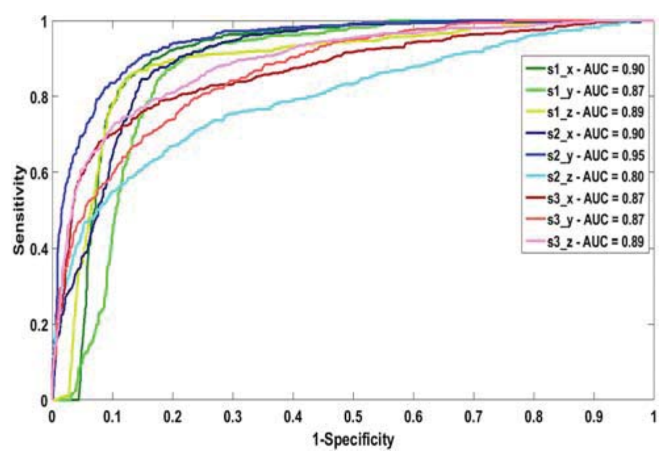
III. Results

A. ROC analysis results

For each subject, ROC curves were obtained after comparison of the FOG features with the expert's markups obtained at three sensors, three orientations and two methods described in section II. Fig.2 illustrates these ROC plots for an exemplary subject (no. 8) for the PSD-based FOG detection algorithm and the modified FOG detection algorithm with wavelet feature.



(A)



(B)

Fig.2. ROC curves of an exemplary subject (no. 8). Each curve is associated with a specific sensor (*s1*, *s2* and *s3*) and a specific orientation (*x*, *y* and *z*). (A) ROC curves of the PSD-based FOG detection algorithm, (B) ROC curves of the modified FOG detection algorithm with wavelet feature.

Table I summarizes the ROC analysis results of this study for two features described in section II. The results from the table suggest that the modified FOG detection algorithm with wavelet feature outperforms the original PSD-based FOG detection algorithm.

Table I: ROC analysis results of the two methods. The values in this table show the area under the curve (AUC) values associated with the ROC curves in Fig.2.

PSD-based FOG detection algorithm									
	Sensors								
Subject	***At the shank***			***At the thigh***			***At the lower back***		
	x	***y***	***z***	***x***	***y***	***z***	***x***	***y***	***z***
1	0.76	0.78	0.75	0.72	0.75	0.67	0.74	0.81	0.86
2	0.91	0.85	0.87	0.69	0.89	0.95	0.85	0.89	0.84
3	0.82	0.82	0.69	0.69	0.82	0.83	0.72	0.85	0.73
4	0.81	0.69	0.74	0.60	0.77	0.77	0.80	0.62	0.79
5	0.69	0.75	0.69	0.63	0.84	0.69	0.73	0.54	0.28
6	0.86	0.88	0.72	0.91	0.89	0.86	0.91	0.88	0.63
7	0.70	0.76	0.60	0.72	0.69	0.71	0.59	0.51	0.67
8	0.82	0.85	0.79	0.78	0.75	0.66	0.66	0.76	0.74
Mean	**0.79**	**0.79**	**0.72**	**0.71**	**0.80**	**0.76**	**0.74**	**0.73**	**0.69**
SD	**0.07**	**0.06**	**0.07**	**0.09**	**0.07**	**0.10**	**0.10**	**0.15**	**0.18**

Wavelet based FOG detection algorithm									
	Sensors								
Subject	***At the shank***			***At the thigh***			***At the lower back***		
	x	***y***	***z***	***x***	***y***	***z***	***x***	***y***	***z***
1	0.87	0.91	0.88	0.80	0.88	0.74	0.71	0.83	0.90
2	0.92	0.90	0.90	0.59	0.94	0.96	0.86	0.91	0.85
3	0.73	0.71	0.66	0.60	0.74	0.75	0.72	0.73	0.71
4	0.82	0.84	0.64	0.64	0.84	0.72	0.73	0.70	0.86
5	0.77	0.89	0.73	0.70	0.88	0.73	0.87	0.50	0.34
6	0.88	0.93	0.64	0.90	0.90	0.87	0.94	0.91	0.57
7	0.91	0.91	0.77	0.75	0.76	0.85	0.65	0.53	0.74
8	0.90	0.87	0.89	0.90	0.95	0.80	0.87	0.87	0.89
Mean	**0.85**	**0.86**	**0.76**	**0.73**	**0.86**	**0.80**	**0.79**	**0.74**	**0.73**
SD	**0.07**	**0.07**	**0.11**	**0.12**	**0.07**	**0.08**	**0.10**	**0.16**	**0.19**

Results from the Table I and Fig 3 show that there is a significant increase in the mean AUC values of wavelet based FOG detection method for each of the three sensors when compared with the PSD- based FOG detection method.

IV. Discussion

A. *Modified FOG detection algorithm in contrast to the original version*

Higher performance of the modified FOG detection algorithm in contrast to the original version highlights the importance of an optimum order in the segmentation and filtering steps of FOG detection. Band-pass filtering applied prior to the segmentation and on the continuous signals can reduce the noise, minimize the spectral leakage and increased the accuracy of the PSD estimates. However, PSD estimation over the entire recording session may ignore possible non-stationarity of the signals. Therefore, a new definition of the locomotor and freeze bands, not only based on their frequency contents (0.5-3 and 3-8 Hz), but according to their non-stationary properties seems necessary. In this regard, time-frequency distributions and wavelet transforms can be very useful [16].

B. *Non-stationary nature of the FOG events*

Based on the results of the modified FOG detection algorithm, wavelet feature has higher performance than the original FOG detection algorithm. It may imply that the FOG changes in the leg movement signals occur at multi scales and are better presented by wavelet coefficients rather than PSD estimates. Again, it emphasizes on the non-stationary nature of the FOG events. In the modified FOG detection algorithm, band-pass filtering (i.e., decomposition of the locomotor and freeze bands) is applied before wavelet feature extraction to reduce the noise of the signal.

V. Conclusion

In this paper, a modified version of the FOG detection algorithm is proposed for FOG detection in Parkinson's disease. This technique has performed filtering of the noise of the recordings and performed wavelet transform of the data in place of PSD analysis. The use of spectral filtering prior to the analysis is important to reduce noise, while the use of wavelet transform has the advantage that it provides localization in time and spectral domain, which is important for localizing the FOG events. Evaluation of the method using ROC analysis implies higher performance for the wavelet coefficient feature. One observation from the results is that there appears to be insignificant difference between the ROC results obtained from three leg movement sensors and with the combination of all the sensors. Thus, it may be possible to use only one sensor in place of the three that have been used in this database, which could be extremely useful when the intent is to develop wearable FOG detection systems.

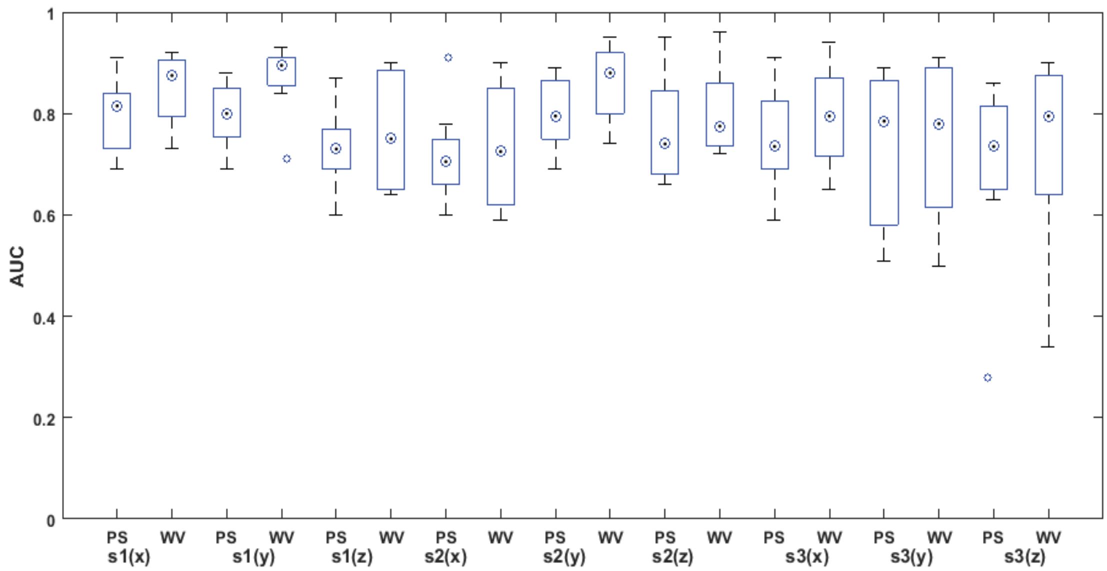


Fig.3. Boxplots of AUC values over all subjects and sensor-axis combinations. Each box is associated with the distribution of the AUC values at a specific sensor (*s1, s2* and *s3*) and a specific orientation (*x, y* and *z*). *PS* denotes the features are based on PSD in the original FOG detection algorithm and *WV* denotes the wavelet coefficients in the modified FOG detection algorithm.

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