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The detection of Freezing of Gait in Parkinson's disease patients using EEG signals based on Wavelet Decomposition

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Abstract— **Freezing of Gait (FOG) is one of the most disabling gait disturbances of Parkinson's disease (PD). The experience has often been described as "feeling like their feet have been glued to the floor while trying to walk" and as such it is a common cause of falling in PD patients. In this paper, EEG subbands Wavelet Energy and Total Wavelet Entropy were extracted using the multiresolution decomposition of EEG signal based on the Discrete Wavelet Transform and were used to analyze the dynamics in the EEG during freezing. The Back Propagation Neural Network classifier has the ability to identify the onset of freezing of PD patients during walking using these features with average values of accuracy, sensitivity and specificity are around 75 %. This results have proved the feasibility of utilized EEG in future treatment of FOG.**

I. INTRODUCTION

After Alzheimer's disease (AD), Parkinson's disease (PD) is the second most prevalent neurodegenerative disorder which increases with age [1]. It is a slowly progressive neurologic disorder caused by degeneration of dopamine and other sub-cortical neurons in the substantia nigra, an area in the basal ganglia of the brain. Dopamine is one of neurotransmitters which help transmit a message to the striatum in the central area of the brain to initiate and control movement and balance.

The freezing of gait (FOG) is defined as a 'brief, episodic absence or marker reduction of forward progression of the feet despite the intention to walk' [2]. It was found to be the most distressing symptom of PD. It is a common cause of fall, interferes with daily activities, makes people with Parkinson's lose confidence in walking and significantly impairs quality of life [3]. It is one of the least understood symptoms in Parkinson's disease and empirical treatments are of poor efficacy, making it an important clinical problem [2], [4].

In recent years, a few attempts have been reported on the detection and prediction of FOG. Since leg oscillations are so common in episodes of freezing, they are used as a sign of the freezing's onset and as an indication that special treatment to 'un-freeze' needs to be done immediately [2], [5]. Two major different approaches are based on characterizing freezing of gait using spatiotemporal kinematic parameter of gait (an increased cadence, decreased stride length, and decreased angular excursion of leg joints) and based on frequency analysis of leg movement [6]. Some works have also been reported using an Electromyographic (EMG) pattern to detect the onset of FOG [7], [8]. A wearable device using on-body acceleration sensors to measure the patients' movement has been developed [9]. Functional MRI and virtual reality-based walking tasks were utilized in recent research to identify direct neural correlate underlying freezing behavior in a patient with PD [4].

Electroencephalogram (EEG) has been used to identify and analyze brain dysfunctions including Alzheimer Disease (AD) [10], Epilepsy [11], monitoring cerebral injury and recovery [12] and Parkinson's Disease [13]. To the best of our knowledge, there is no implementation of EEG for FOG detection except in a preliminary experiment [14] . In this paper, we present a methods for detection of FOG using EEG signals based on Wavelet decomposition and patterns recognition techniques. The propose features, subband Wavelet Energy and Total Wavelet Entropy, were chosen as they were reported has significant advantages in detecting changes in a short segment of EEG signals [15]. Complemented with the Multilayer Perceptron Neural Network, they showed a significant change in the brain signals before freezing.

II. METHODS

A. Experimental Setup and Data Acquisition

Twenty-six patients (age 69.8 $\pm$ 8.41) with idiopathic Parkinson's disease with significant FOG were recruited from the Parkinson's Disease Research Clinic at the Brain and Mind Research Institute, University of Sydney. All patients underwent a structured series of video-recorded timed up-and-go tasks (TUG). Freezing episodes were defined as the paroxysmal cessation of a patient's footsteps during a TUG task and were analyzed by two independent raters.

The EEG signals were obtained using a-4 channel wireless EEG system developed by UTS with sensors are located at occipital one (O1-primary visual receiving area), parietal four (P4-navigational movement area), central zero (Cz-primary motor area) and frontal zero (Fz- supplementary motor area). Only the differential channels O1-T4 and P4-T3 were used in this study. Raw data were acquired at sampling rate of 500 Hz in 1 to 2 hours periods for each patient and an epoch of 1 second from individual freezing events was taken. Afterward

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EEGs data were divided into three groups. The first group was recorded prior to an onset of Freezing (normal walking). The second group is referred to a period of onset of FOG (5 seconds before freezing). The third group contains the EEG signals during the FOG. These data are then processed in three stages: preprocessing stage, feature extraction and selection stage, and classification stage.

B. Data Preprocessing

Based on visual inspection on raw data, data from 10 patients were selected and 40 samples of data from each chosen subject were taken for each group (i.e.1200 samples). Afterwards, EEGs were filtered using band-pass and band-stop butterworth IIR filters in order to eliminate low frequency noise and high frequency noise (BPF 0.5-60 Hz) and cancel out the 50 Hz line frequency (BSF 50 Hz). Then, a simple threshold filter was applied for further eliminated noise, based on comparison of the signal data with its neighbor and the standard deviation of the data.

C. Feature Extraction and Selection

Compared to a traditional Fourier Transform, Wavelet Transform has the advantages of time-frequency localization, multiscale zooming, and multirate filtering for detecting and characterizing transients since its building block functions are adjustable and adaptable [16]. It gives an excellent feature extraction from non-stationary signals such as EEGs. In this research, the discrete wavelet transforms (DWT) based on dyadic scales and positions is used. The DWT is defined as,

$$DWT(j,k) = \frac{1}{\sqrt{|2^j|}} \int_{-\infty}^{\infty} x(t)\psi(\frac{t-2^j k}{2^j})dt \qquad (1)$$

where 2^j and $k2^j$ are the scale (reciprocal of frequency) and translation (time localization) respectively.

In the procedure of multiresolution decomposition of signal $x(t)$ based on the DWT, each signal is simultaneously passed through a complementary high pass filter (HPF) and low pass filter (LPF) and is down sampled by 2. The outputs of the high pass and low pass filters provide the detail D_j with the frequency band $[f_m/2 : f_m]$ and the approximation A_j with the frequency band $[0 : f_m/2]$, respectively. Frequency subbands are related to the sampling frequency of the original signal f_s in which f_m=$f_s/2^{(l+1)}$ where l is the level of decomposition.

The Wavelet decomposition for a given EEG signal $x(t)$ that shows the DWT with their coefficients could be written

$$x(t) = \sum_{k=-\infty}^{\infty} A(k)\varphi_k(t) + \sum_{j=0}^{\infty}\sum_{k=-\infty}^{\infty} D(j,k)\psi_{j,k}(t) \qquad (2)$$

The EEG signals then can be considered as a superposition of different structures occurring on different time-scales at different times. For EEG sampled at 500 Hz, a six level decomposition results in a good match to the standard clinical EEG subbands: *delta* (A_6: 0-3.9 Hz), *theta* (D_6: 3.9-7.8 Hz), *alpha* (D_5: 7.8-15.6 Hz), *beta* (D_4: 15.6-31.3 Hz), *gamma* (D_3: 31.3-62.5 Hz). Two of the highest resolution components are noises: D_2 (62.5-125 Hz) and D_1 (125-250 Hz). Daubechies (db4) wavelets are selected as the wavelet function due to their smoothing feature which is suitable for detecting changes of the EEG signals. Reconstruction of these signals into five constituent EEG subbands is depicted in Fig.1.

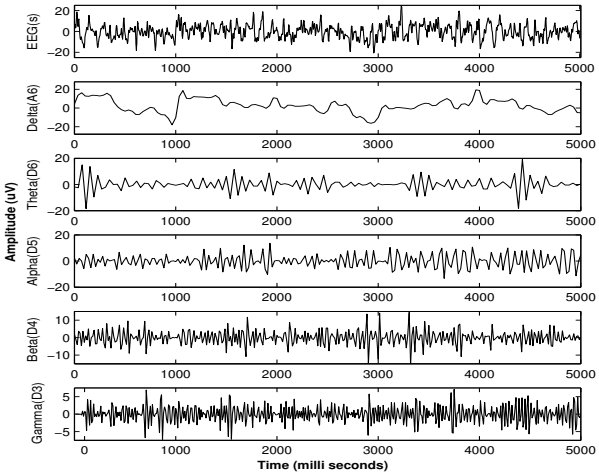

Fig. 1. Wavelet decomposition of EEG into five EEG subbands

The energy in these components and their wavelet coefficients are related to the energy of the original signal, according to Parseval's Theorm. This partition at different time (k) and in scale (j=1,....,l) can be presented as:

$$ED_j = \sum_{k=1}^{N} |D_{j,k}|^2, j = 1,....l \qquad (3)$$

$$EA_l = \sum_{k=1}^{N} |A_{j,k}|^2 \qquad (4)$$

where N is the number of the coefficients of the detail or approximation at each decomposition level.

The energy distribution diagrams of EEG subbands at channel O1 and P4 of three groups of signal: a) normal; b) onset; c) freezing shows that EEG wavelet energy increases before freezing in all subbands (Fig. 2). In comparison with the EEG signal from normal stage, subbands *alpha*, *beta*, and *gamma* of freezing stage have a bigger percentage of the values of the total energy of the signal.

Total energy of the wavelet coefficients will be

$$E_{tot} = EA_l + ED_j \qquad (5)$$

Normalization values of each subbands wavelet energy (WE) results in the Relative Wavelet Energy (RWE)

$$p_j = \frac{E_j}{E_{tot}} \qquad (6)$$

where E_j refers to ED_j and EA_l. Further analysis on the distribution energy using the Shannon information entropy theory reveals the shift of the degree of complexity of the signal. Based on distribution of the RWE, the total wavelet entropy (TWE) is defined as [15]:

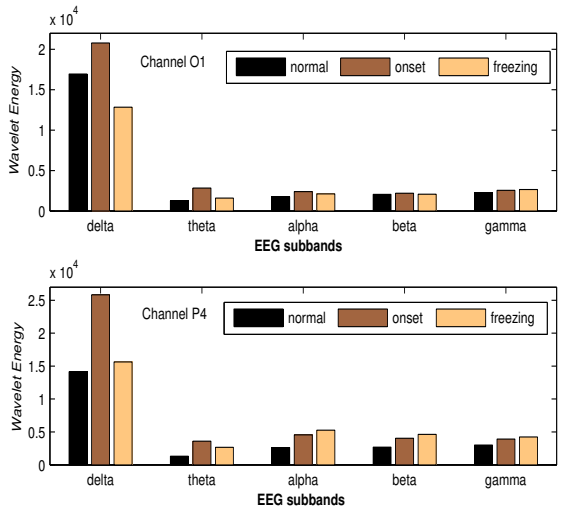

Fig. 2. Group means of wavelet energy of EEG subbands at O1 and P4

$$H(x) = -\sum_{j} p_{j,k} log p_{j,k} \quad (7)$$

Comparison of the TWE in three groups data (Fig.3) suggests that EEG activity in freezing stage is less regular (more complex) than in a normal condition in the occipital and parietal regions. Significant changes happen even between normal and onset with channel P4 appears as a stronger indicator of changing than channel O1.

Non-parametric statistical analysis the Wilcoxon Sum Rank Test was implemented to evaluate the statistical differences between those features of three groups of data and to select the significant one that differentiates those groups of data.

D. Classification

Based on the feature selection and their combination possibilities for classification, different Neural Networks with different set of inputs are developed. A three layer Back Propagation Neural Networks (BP-NN) is used, with 56% of the data trained by Levenberg Marquardt algoritm (25% and 19% of the data are used for validation and test, respectively). Tangent Sigmoid is chosen for activation function and training process is stopped by the validation set. The number of hidden nodes is selected between 4 to 7 depending on the number of inputs dimension and the number of training pairs. Twenty separated training and testing were done for each feature. Mean, standard deviation and the best result were recorded for further analysis.

III. RESULTS AND DISCUSSION

Statistical analysis indicates that group Normal differs from the other two groups (Onset and Freezing) at its Wavelet Energy subbands *delta*, *theta*, and *alpha* as well as their TWE (Table I). The higher subbands Wavelet Energy (*beta* and *gamma*) in channel O1 do not appear to be significantly different from each other as their confidence level less than

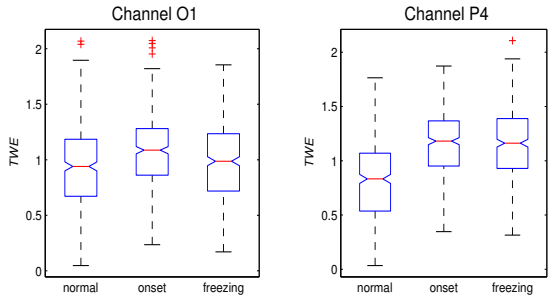

Fig. 3. The Box Plot of the TWE of three groups data of PD patients

99% (p-value >0.01). However, all subbands wavelet energy at channel P4 are statistically different, suggesting this region has been deeply affected by the FOG. The degree of order of wavelet energy significantly increased from onset stage to freezing stage at occipital region (O1) in contrast with continuous decreasing regularity at parietal region (P4) as the general trend of dynamic from normal to freezing. This trend was contrary to the pattern of EEG signal of AD and epileptic patients during seizure which becomes more organized and has less complexity and chaoticity [10], [11].

While the subband *delta* is likely to be affected by noise, it is observed that the *theta* subband wavelet energy shows the most considerable difference between all three groups. It is consistent with a previous study of spectral analysis using Fast Fourier Transform on the same data in which *theta* appears as the most significant EEG subband affected by freezing [14]. However, contrary to Palmer's study [17] in which *beta* band EEG is found to be more important for dual task performance in PD which may lead to FOG, in this study *alpha* has a more significant contribution to task performance than *beta*.

For classification, four features of channel O1 were taken as they have a significantly high confidence level beyond criterium (p-value <0.01): WE *delta*, WE *theta*, WE *alpha* and TWE. All EEG subbands WE and TWE of channel P4 were implemented as inputs. Experiments were conducted for each location of brain (O1, P4) and combination of it.

The Back Propagation Neural Networks using Levenberg Marquardt algoritm for training shows a promising result in testing set as is indicated in Table II. Using only channel P4 has already given more than 76.57 % correct in classifying normal-onset. Performance was slightly increased in accuracy and specificity when it was combined with channel O1 to differentiate between normal and freezing. The success rate of differentiate between normal and onset (76.6 $\pm$ 3.4) is slightly higher than between normal and freezing (73.88 $\pm$ 79.6) implied that the neurological process of freezing in the brain started in 5 second periods before it appeared as freezing of gait. Compared to other works in different brain diseases such as AD and epilepsy which obtain accuracy up to 87.1 % [11] and sensitivity on average 83 % [18], clearly more research needs to be done to increase the performance of the system.

TABLE I

STATISTICAL CORRELATION ANALYSIS BETWEEN 3 DIFFERENT STAGES OF PD'S PATIENTS

Channel-Feature	mean±std Normal (N)	mean±std Onset (O)	mean±std Freezing (F)	*p*-value N-O	*p*-value N-F	*p*-value O-F
O1-WE δ	16939.779±26347.684	20781.927±28844.102	12840.539±21509.292	0.002	0.016	$\leq$ 0.001
O1-WE θ	1250.205±1496.056	2824.346±4010.260	1593.678±1997.817	$\leq$0.001	$\leq$0.001	$\leq$0.001
O1-WE α	1761.528±1828.380	2399.470 ±2168.370	2105.513±2200.471	$\leq$0.001	0.004	0.002
O1-WE β	2054.270±2776.284	2193.293±2729.281	2075.393±2411.743	0.028	0.174	0.290
O1-WE γ	2250.084±3129.022	2543.499 ±4003.021	2659.319±4233.292	0.339	0.083	0.373
O1-TWE	0.932±0.395	1.070±0.322	0.976± 0.353	$\leq$0.001	$\leq$0.001	$\leq$0.001
P4-WE δ	14132.911±20644.905	25843.544±32521.796	15637.085±18483.045	$\leq$0.001	$\leq$0.001	$\leq$0.001
P4-WE θ	1319.528±1366.631	3593.649±3857.009	2657.609±2045.397	$\leq$0.001	$\leq$0.001	0.002
P4-WE α	2622.983±2874.563	4546.447±3056.553	5271.596±3766.857	$\leq$0.001	$\leq$0.001	0.013
P4-WE β	2694.404±2835.144	4038.314±3000.283	4622.378±3257.461	$\leq$0.001	$\leq$0.001	0.007
P4-WE γ	3012.389±3562.820	3922.334±3108.741	4248.954±2950.425	$\leq$0.001	$\leq$0.001	0.020
P4-TWE	0.820±0.372	1.160±0.292	1.163±0.319	$\leq$0.001	$\leq$0.001	0.998

TABLE II

CLASSIFICATION RESULTS OF PROPOSED FEATURES USING BP-NN

Normal - Onset						
Inputs	Accuracy (%)		Sensitivity (%)		Specificity (%)	
	mean±std	best	mean±std	best	mean±std	best
O1	59.2±3.4	66.4	61.6±8.4	80.5	57.0±8.5	72.7
P4	76.6±3.4	81.6	74.2±6.8	86.8	78.9±7.3	89.7
O1,P4	75.0±3.4	80.3	72.0±7.0	87.3	77.2±5.4	88.6
Normal - Freezing						
Inputs	Accuracy (%)		Sensitivity (%)		Specificity (%)	
	mean±std	best	mean±std	best	mean±std	best
O1	52.1±3.9	57.9	54.2±11.9	74.4	50.2±9.4	76.3
P4	73.4±3.2	78.9	72.3±6.3	86.1	74.4±5.0	86.5
O1,P4	73.9±2.8	79.6	71.2±6.1	88.1	77.2±4.7	82.9

IV. CONCLUSIONS AND FUTURE WORK

We presented results of study of early detection of FOG in PD's patient using EEG signals. Complemented with special treatment such as sensory cuing, this classification system could be used in helping PD's patient with FOG to 'unfreeze' this symptom before it affected the movement. EEG subbands Wavelet Energy and Total Wavelet Entropy features can be used to represent changing during onset and freezing period. Classification done by BP-NN has a promising result and shows the feasibility of using EEGs for FOG detection. Moreover, this study support analysis of physiological brain dynamics during FOG. It may lead to better understanding of its underlying mechanism. Further exploration on other features, different area of the brain and classification methods will be our near future work before implementing it in a device.

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