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Prediction of Freezing of Gait (FOG) Episodes in Parkinson's Disease patients by Gait Analysis

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ABSTRACT: Freezing of Gait (FOG) is an incapacitating gait disorder in Parkinson's disease (PD) patients that manifests as disruptions in walking with an abrupt and transient nature. Eventhough the patients with earlier stages of PD have been reported experiencing FOG, it becomes more frequent in later stages of PD. It is very exhausting and decrease the quality of life of PD patients. If FOG can be effectively detected before it happens, external cues can be provided to aid the patients to avert the freezing phenomenon. The proposed method analyses the accelerometer signals using wavelet decomposition and extract significant features to train the classifier to accurately predict the FOG episodes.

KEYWORDS: Freezing of gait (FOG); parkinson's disease (PD); gait analysis; accelerometer; gait disturbance.

I. INTRODUCTION

Parkinson's disease (PD) is a neurodegenerative disorder that results from the progressive loss of dopaminergic neurons and other sub-cortical neurons [3]. The dopaminergic neurons produce dopamine which is responsible for the normal movements in humans. So the degeneration of these neurons impair movement and manifest as resting tremor, bradykinesia, a forward stooped posture, postural instability, rigidity, and freezing. The cause of PD is unknown (idiopathic), and although there is no complete cure, there are treatment options like medications and surgery available to manage the symptoms. Around 10 million people in the world are suffering from PD. Age is considered to be one of the most important risk factor. As the quantity of elderly people increase in the society, PD is considered to be a major health problem and the number of patients with parkinsons (PWP) may increase in the future years.

Gait and balance disorders are a major therapeutic challenge in PD. These symptoms respond poorly to dopaminergic treatments, except in the early stages of the disease [2]. Freezing of gait (FOG) is one of the typical symptom that is more prevailing in the later stages of PD and is more than just a sign of advanced parkinson's disease. It is defined as, "a brief, episodic absence of marked reduction of forward progression of the feet despite the intention to walk". During FOG the patients' gait is halted with a feeling of "the feet being glued to the ground"[1]. FOG lasts for less than a minute, but unlike normal people they experience: start hesitation, turn hesitation, hesitation in tight squares-FOG through narrow space, destination hesitation, and open-space hesitation [4].

Falls occuring in patients with advanced PD can be related to FOG. As the disease progresses the shaking or tremor, freezing and other symptoms may begin to interfere with the daily life and It significantly reduces the quality of life. Above 40% of patients with postural imbalance have multiple falls that can often lead to injuries and fractures that need medical care. It reduces the productivity and the fear of walking results in social isolation [5].

The factors commonly induce FOG are turning, fatigue, confined spaces, stressful situations, and emotional factors. Since dopaminergic treatment partially assauges FOG, there are other strategies are developed to help the patients to overcome it. Somatosensory cues have been found to improve walking, with visual or attentional cues proposing more impact, followed by tactile, emotional and auditory cues [6], [8]. It is also found that demand cueing (only given when FOG episodes are detected) is more efficient than continuous cueing [7]. Cueing can also be used to overcome other mobility problems such as gait initiation failure and shuffling [6].



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In clinical assessment, evaluation of PD is done based on the patient's diaries, self reports, and patient report by doctors. However, these methods are subjected to perceptual and recall bias [9]. These offer limited benefit to the doctor to make their decisions and direct observation is not practical as the symptoms cover a time span of several hours. Hospital stay or frequent visits to hospitals may be difficult and contribute to increase in financial cost. Due to this problem several rating scales have been developed such as, Unified Parkinson's Disease Rating Scale (UPDRS), Activities of Daily Living (ADL), which rates symptoms on a scale of 0 (no sign of severity) to 4 (highest sign of severity) based on patient history[10]. In addition, the symptoms vary significantly during daytime, and this scales provide the valuation over a particular moment. It is difficult to elicit FOG patterns experienced by the PWP at their homes in a clinical environment [4].

To address shortcomings, various methods have been proposed using wearable sensors such as, force sensing resistors [11], [12], 3D marker [13], inertial sensors [14]. With the substantial drop in cost and weights of sensors, a number of systems using wearable accelerometers were proposed [3], [14], [15]. Ease of extraction of signals from the patients as they go on about their daily life made the wearable technology more acceptable.

The work in this paper is divided into three stages. 1) The analysing of 3D accelerometer sensor signals using wavelet decomposition 2) significant features selection and quantization of feature vectors 3) prediction of the FOG events on their onset.

II. RELATED WORK

Several researchers are proposed techniques to detect FOG using wearable technologies. They used sensors like inertial sensors [11], [13], [15], [18], [20], Electroencephalography [16], [17], electromyography [12], [19]. Some authors calculated the freeze index (FI) which is defined as the power in freeze band (0.5-3 Hz) to that of power in locomotor band (3-8 Hz) and a threshold limit is chosen to detect FOG [1], [3]. During the onset of freezing episodes there are dynamic physiological changes in the brain. A. M. Ardi Handojoseno et al. [16], [17] utilizes wavelet decomposition features of EEG to use as a potential bio marker for detecting FOG. In [18] the authors looked into the use of time- domain and statistical features, together with FFT features.

III. DATASET

To study the usefulness of accelerometer signals for predicting FOG, Daphnet freezing of gait dataset is collected from UCI machine learning repository. This dataset is devised to use as a benchmark to model automatic methods to detect FOG episodes from wearable accelerometer sensors placed in hip, trunk and ankle. The data gathering is done by the collaboration between the Laboratory for gait and neurodynamics, Tel Aviv Sourasky Medical Center, Israel and the Wearable Computing Laboratoy, ETH Zurich, Switzerland. The study was approved by the local Human Subjects Review Committee, and was performed in accordance with the ethical standards of the Declaration of Helsinki. The data was gathered from 10 PD patients, 7 males and 3 females ranging from the age of 59 to 75 years with different stages of PD. Two patients had frequent FOG episodes. During data acquisition, apart from the aforementioned two patients, all patients were on the off stage of their medication cycle.

The protocol is based on two sessions, one without RAS feedback and the other one with RAS feedback. Each session consisted of three basic walking tasks designed to represent different aspects of daily walking. The walking tasks are; 1)Walking back and forth in a straight line, 2)random walking with several 360° turns, and 3)walking simulating the activities of daily living which involves deliberate moving from room to rooms, such as picking up a glass of water and back. All the trails were recorded by a physiotherapist on a digital camera. Another assistant therapist labeled the current activities of the patient as standing, walking, turning and freezing. After the trails the video was analysed along with the manual labelings to correctly identify the start times, end times and duration of FOG episodes [15].

The dataset comprises of 3 wearable wireless accelerometer sensors recording 3D acceleration at 64 Hz. The sensors are placed at the ankle(shank), on the thigh just above the knee, and on the hip. An accelerometer measures the acceleration and orientation of the patients in three axes, namely X, Y and Z axes. The X-axis measures the horizontal forward acceleration and Y-axis measures the vertical (upward and downward) acceleration. The Z-axis measures the horizontal lateral acceleration.



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In annotation, the activities like standing, turning and walking are labeled as 'no freeze'. As a result, the final ground truth labels for each 3D accelerometer sensor signals are either labeled as 'no freeze' or 'freeze'. Out of the 10 PD patients who participated in the test, 2 did not have any freeze [15].

IV. DATA ANALYSIS

The file of each patient comprises data in matrix format, with one line being sample and one column being channel. The 11 channels are respectively, the time of samples in millisecond, ankle acceleration-horizontal, vertical and horizontal lateral, upper leg acceleration-horizontal, vertical and horizontal vertical, trunk acceleration-horizontal, vertical and horizontal vertical, annotations. The annotations makes it easy to understand the FOG episodes. The patients 4 and 10 had no FOG episodes. The FOG data and normal walking data of each patient is seperated to get clear analysis to detect the differences that can be used to differentiate the two, thereby making the prediction possible.

A) WAVELET DECOMPOSITION

There are two types of wavelet transforms; Continuous Wavelet Transform(CWT), and Discrete wavelet transform (DWT). Discrete wavelet transform (DWT) algorithms have become standards tools for processing of signals and images in several areas in research and industry. A mother wavelet is needed to perform the transform. It is achieved through the dilation and translation of mother wavelet. Here, dyadic wavelet is used to extract features from the signal for FOG prediction.

The DWT of a function f(x) is given by

$$DWT_{\varphi}f(j,\tau) = \int_{-\infty}^{+\infty} f(x)\varphi_{j,\tau}^{*}(x)dx \tag{1}$$

Where $\varphi_{j,\tau} = \frac{1}{2^j} \cdot \varphi\left(\frac{x-\tau}{j}\right)$, $j \in Z$ is the dilation or scale, $\tau \in Z$ is the translation and $\varphi^*(...)$ is the complex conjugate of the mother wavelet. The mother wavelet is given by $\varphi(x)$ and when scaled with j, yields a scaling function φ_j .

DWT decomposes a signal into fine and coarse wavelet co-efficients at different resolutions or scales. Multi-Resolution Analysis (MRA) using DWT can be accomplished by employing the algorithm proposed by Mallat [10]. The decomposition of a sequence or signal starts at a scale $J = \log 2$ (N)-1, where N is the length of the sequence. With this representation, the signal is analyzed at each scale j, DWT yields a fine coefficient called the approximation coefficient a j and a coarse coefficient termed the detail coefficients correspond to the low pass filter h while the detail coefficients correspond to the high pass filter g. For more information, the signal has to be processed at a different scale. So the algorithm iteratively moves from a higher scale j to a scale j - 1 until it reaches j=0. At each lower scale j - 1, the signal is subdivided into low pass signal and high pass signal, and they are then down-sampled. Down-sampling involves the reduction of the number of samples of the signal by half of its original size.



Fig 1: Subband energies of approximation coefficients in ankle sensor

a) Feature Selection: In this work, to extract the features, we seperated the 3D accelerometer sensor data into 1D signals to analyze it thoroughly. 7 level decomposition is done on the 1D signals in order to obtain a clear analysis. The subband energies of wavelet coefficients at each level are obtained and it is used to determine the



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features to be selected for furthur analysis. Fig 1 and 2 shows the subband energy comparison of both FOG time series and normal walking time series. It can be seen from the Fig 1 that difference in energy between the normal walking and FOG data is predominant in levels from j=4 to j=7. So the approximation coefficient energy of level j=4 to j=7 are good to be taken as feature vectors. Similarly, comparing the detail coefficient subband energy of each patient, concluded that levels j=4 to j=1 gives good results. Here, the results from patient 9 is given in Fig 2.



Fig 2: Subband energies of detail coefficients in ankle sensor

We repeat the same MODWT decomposition of the resultant time-domain accelerometer signals for the other sensors, and extract signature feature vectors that can be utilized to effectively differentiate an FOG episode from a normal movement time series.

b) Feature vector selection: By the careful and diligent analysis of the sensor data to extract features that helps to differentiate FOG time series and normal walking time series, it is observed that there is significant difference in subband energies of approaximation and detail coefficients.

Approximation coefficients: The subband energies in levels j=7 to j=4 can be used to differentiate FOG time series and normal walking time series. Energies at j=4 is selected because they are less susceptible to noise and to detect FOG at its onset, the analysing should be less time consuming(large size of dataset) and accurate.

Detail coefficients: The PD movement time series spans a frequency range from 0.5 to 8Hz. Detail coefficients can give more information about the unique features that can be used to differentiate between normal and FOG time series. The subband energies from j=4 to j=1 is significantly higher for FOG series. So we used detail coefficients from j=4 to j=1, compute their subband energies and use them as feature vectors for prediction of FOG episodes.

B) VECTOR QUANTIZATION

We selected the subband energies of approximation coefficients from j=4 and subband energies of detail coefficients from j=4 to j=1 as the feature vectors. From each 1D sensor we get five feature vectors. There are three sensors, so a total of 15 vectors for each patient is selected for furthur analysis. We used only the ankle sensor data for rest of the work. We employed vector quantization to remove the redundancy and to study the linear and non-linear relationships between the feature vectors.

Given that $x = \{x_1, x_2, ..., x_d\}$ is our d-dimensional real-valued wavelet feature vector where d = 15, vector quantization is the process of mapping the wavelet feature vectors x to another d-dimensional real-valued vector y. At such, we say x is quantized by y. y is called a codeword and a finite set of codewords is called a codebook C = $\{y_i : i = 1,2,3,\dots,L\}$. The size of the codebook is denoted by L and it corresponds to the number of codewords in a codebook C. Each codeword y_i corresponds to the centroid of a region or cell called the voronoi region.

For each region C_i , we quantize any wavelet feature vectors in that region as codeword of y_i of C_i . That is, we represent all feature vectors within a region with the codeword of the region. In the next section, during the prediction of the onset of an FOG episode, all wavelet feature vectors will be represented by their nearest neighboring codewords.



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C) FOG PREDICTION

For the FOG prediction problem, the continuous random field(CRF) is modelled as follows. Given a dataset D consisting of all low level Parkinson's disease accelerometer sensor readings, after extracting signature spectral features through dyadic wavelet transform and the vector quantization of the extracted spectral feature vectors has been performed, each wavelet feature value is replaced with its corresponding centroid. Given a training dataset consisting of multiple sequence of spectral centroids that originate from 3 accelerometer sensors, the CRF learns the characteristics of the underlying data by searching hidden patterns. That is, it searches for elusive patterns from each sequence of centroids by investigating the Markov property between two random centroid variables. If a sequence occurs frequently and always result to the same output y_i , the behavior is stored using the feature function f and the behavior is investigated in other centroid sequences. At the end of the data exploration process by the CRF, numerous characteristics detected by different feature functions are found. If a feature occurs, it is embedded into CRF by assigning a real value number of 1. Otherwise, zero is added.

V. **RESULTS**

The daphnet dataset was extracted from 10 PD patients. [15] mentioned that Patient 4 and Patient 10 did not experience any FOG episode during the 8.5 hours period when the data was collected. Even though, we included the data from Patient 4 and Patient 10, and conducted our experiments using data from all the 10 PD patients. We allocated 75% of the data to the training set while the remaining 25% is used as the test set. We train our model on the training set while the test set is employed to predict a normal movement or FOG episode.

	Code Book Size 64		
Patient 6	Precision	Recall	F1- Measure
Normal	98.24	100	99.7
FOG	100	80	66.67
Overall	98.24		
Patient 9	Code Book Size 64		
	Precision	Recall	F1- Measure
Normal	100	95.35	97.62
FOG	87.5	100	93.33
Overall	96.49		
Patient 8	Code Book Size 64		
	Precision	Recall	F1-
			Measure
Normal	97.87	100	98.92
FOG	100	90.9	95.23
Overall	96.49		

TABLE I: Window size 256: FOG evaluation for patient

Table I. depicts the prediction results of patient 6, 9, 8 for a window size of 256. For the codebook size 64, we observe that our technique delivers an optimal recall of 100 % for the FOG label in case of patient 9. The normal label attains a 95.53 % recall. For the normal label, our approach achieve a precision of 98.24% and an F1-Measure of 99.7%. The FOG label has a 100 % precision and a 66.67 % F1-Measure. For patient 9, the actual number of FOG episodes are 14, and our technique predicted 16. While the actual normal walking events are 43, it predicted 41 events correctly. So in normal case there were 41 true positives(TP) and 2 true negatives(TN) and no false positives(FP). Precision and recall are calculated by the equations; $Precision = \frac{TP}{(TP+FP)}$ and $Recall = \frac{TP}{TP+FN}$. F1-measure is the harmonic mean between precision and recall. It is given by; $F1 - measure = \frac{2precision*Recall}{(Precision+Recall)}$.



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VI. CONCLUSION

Our proposed predictive model for FOG employs wavelet transform for extracting features and CRF for training and prediction. The subband energies of certain wavelet coefficients are given as the feature vectors to train the CRF. CRF then learns the unique features that can be used to identify the FOG episodes at its onset. Our technique gives overall performance above 95% for the window size 256. Since the dataset is very large, data redundancy methods can be used in real-time applications. Also using dedicated softwares like python, java and R, the performance can be improved.

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