Discrete wavelet transform based freezing of gait detection in Parkinson's disease

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Abstract:

Wearable on body sensors have been employed in many applications including ambulatory monitoring and pervasive computing systems. In this work, a wearable assistant has been created for people suffering from Parkinson's disease (PD), specifically with the Freezing of Gait (FoG) symptom. Wearable accelerometers were placed on the person's body and used for movement measure. When FoG is detected, a rhythmic audio signal was given from the wearable assistant to motivate the wearer to continue walking. Long term monitoring results in collecting huge amounts of complex raw data; therefore, data analysis becomes impractical or infeasible resulting in the need for data reduction. In the present study, Discrete Wavelet Transform (DWT) has been used to extract the main features inherent in the key movement indicators for FoG detection. The discrimination capacities of these features were assessed using, i) Support Vector Machine (SVM) using a linear kernel function, and ii) Artificial Neural Network (ANN) with a two-layer feed-forward with hidden layer of 20 neurons that trained with conjugate gradient back- propagation. Using these two different machine learning techniques, we were capable of detecting FoG with an accuracy of 87.50% and 93.8%, respectively. Additionally, the comparison between the extracted features from DWT coefficients with those using Fast Fourier Transform (FFT) established accuracies of 93.8% and 81.3%, respectively. Finally, the discriminative features extracted from DWT yield to a robust multidimensional classification model compared to models in the literature based on a single feature. The work presented paves the way for reliable, real-time wearable sensors to aid people with PD.

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1 INTRODUCTION

PD is a chronic neurological disease linked to a decrease in dopamine levels, which causes abnormal brain activity leading to the signs of PD. There are many symptoms of PD, such as tremor, slowed movement, loss of automatic movement, impaired posture and balance, and changes in speech and writing (Mazilu *et al*., 2015). Motor blocks, or freezing is the most widespread negative effect of PD that affects the patient's legs during walking, and is termed FoG (Bächlin *et al*., 2010). The FoG has serious clinical and social effects as it is a precursor in falls, overlaps with daily activities, and extremely impairs quality of life. People with PD can be pervasively monitored using sensors and can receive stimulation to resume walking. Such a sensor may be part of a new healthcare technology in the field of wireless communications and networking aimed at interconnecting 'things' over the Internet, enabling machine to machine communications, and connectivity for the Internet of Things (IoT) (Sutagundar, & Hatti, 2017).

Research on PD has been very popular and attracts several researchers. Zabaleta *et al.* (2009) presented a method for detecting FoG using sensors to obtain 3-dimentional acceleration and 2-dimentional angular velocity to monitor the movements of shank, foot and thigh. Changes in the Power Spectral Density (PSD) in normal walking and freezing were determined using Short Time Fourier Transform (STFT). A freeze index (FI) has been employed as a classification variable using a linear classifier. The best classification results were obtained with a freeze index obtained from the horizontal axis acceleration of the heel, resulting in 82.7 % of valid FoG events being correctly detected. Moore *et al*. (2008) measured the left shank vertical acceleration over 6 second signal intervals for 11 people with PD, and analyzed the power spectra. During the FoG there are high leg movement's frequency components ranging from 3 to 8 Hz, which do not appear in the normal walking or standing. Moore *et al*. recognized the FI of the FoG offline, where the FI is calculated by dividing the power in the freeze band ranging 3–8 Hz by the no freezing power band ranging 0.5–3 Hz. A freeze threshold of the FI values is used in this work to detect the FoG, which is recognized above this threshold as a FoG event.

For assisting the PD patients, Bächlin *et al*. (2010) implemented a wearable device to monitor the FoG symptom. An analysis of the inherent frequency components in the movements has been used to automatically detect the FoG. The leg's motion has been sampled at 64 Hz using a rectangular window function of 4 seconds window length and 0.5 seconds steps. A 256 FFT points have been calculated in order to determine the PSD. The results of FoG detection established sensitivity and specificity of 73.1% and 81.6% values, respectively. Mazilu *et al.* (2013) compared the performance of using several feature extraction approaches based on statistical/time-domain features for the detection/ prediction of the FoG cases. Rezvanian and Lockhart (2016) identified the FoG using Continuous Wavelet Transform (CWT). The authors proposed an index from the CWT components, which discriminated the FoG in anterior posterior axis. A 2 seconds window size provided specificity and sensitivity of values 77.1% and 82.1%, respectively. Accordingly, the FoG detection techniques can be categorize into two main methods, namely FoG detection based on the freezing index with threshold algorithms and machine learning based FoG detection techniques. A wearable assistant has been proposed in practice to monitor people with PD for FoG detection (Jha, 2016). There are many data reduction techniques, including dimensionality reduction, and data compression (Han *et al*., 2011). Furthermore, DWT has been applied as a type of data reduction.

Accordingly, the foremost contribution of the current study is to apply DWT for feature extraction and data reduction as follows: 1) apply feature extraction approaches by using DWT to extract the main features, and 2) use ANN and SVM machine learning techniques to improve automated classification accuracy in order to distinguish between freezing and non-freezing events (Obaidullah *et al*., 2013). The discriminative features can then be used to build a more robust classification model than the models based on a single feature presented in the literature (Bibicu *et al*., 2013). The current work employed features of the sensor's data that can be used to distinguish between the occurrence of FoG from normal walking, so the FoG detection problem can be formulated as two class classification problems, namely true FoG versus a no freezing event (e.g. walking, standing or turning).

2 METHODOLOGY

2.1 Data set

The used dataset was recorded for many freezing events, which is available at https://archive.ics.uci.edu/ml/datasets/Daphnet+Freezing+of+Gait. It was acquired by using wearable device that combines 3-dimentional accelerometers placed on the ankle (shank), above the knee on the thigh, and on the hip. The movements are sampled at 64Hz, where the data is transmitted over a Bluetooth link for further processing. People with PD were asked to perform many tasks including walking in straight line, walking with many turns, perform number of the activities of everyday living, where patients went into several rooms while opening doors, fetching drinks, and other daily activities. Data was recorded for ten people over an 8 hrs and 20 min period. In the experiments, eight patients had FoG and two patients did not experience any freezing events.

The dataset contains ten files for ten patients collecting the time of each sample, the horizontal (forward), horizontal (lateral) and vertical acceleration for each of the 3 sensors (ankle, thigh and hip), and annotations of '0' for not part of experiment, '1' for no freeze event and '2' for a freeze event. The vertical acceleration of the sensor at the ankle (shank) was used in this work as in Bächlin *et al*. (2010). Subsequent feature selection and extraction was needed for each patient to distinguish between the freeze and no freeze events.

2.2 Freezing of gait feature extraction

The main features of both FoG and normal movements must be extracted in order to distinguish between them. The used feature extraction approach aims to construct the representation of the data in a subspace with a reduced dimension (Webb, 2003). Pattern recognition machine itself does not directly operate on the raw sensor data. Instead, firstly, a representation of data is built in terms of feature variables and then classification is performed. In addition, for efficient classification, the used features should be with high information content. In this article, the DWT is used as a data reduction technique applied to the raw sensor data.

The DWT is a linear signal processing technique, where the data vector is transformed to a wavelet coefficients' vector of the same length. The main advantage of DWT is its availability to truncate the transformed data to extract the most significant wavelet coefficients, which also reduced the data dimensionally and compress the data by replacing the other coefficients by zero. The representation of the resultant data is therefore very sparse. Thus, the operations in the wavelet space becomes computationally efficient, which enables DWT to build a robust multidimensional classification model compared to any other transforms which provided single feature. Moreover, DWT is useful in the applications that based on the analysis of time-series data. These characteristics lead to the superiority of using DWT in long time monitoring of the PD individuals as it creates a large amount of data and subsequently needs data reduction while keeping the integrity of the original data. The original data approximation of can be reconstructed by performing the inverse DWT for the given set of coefficients (Han *et al*., 2011).

The DWT is evaluated at translations and discrete scales. The discrete scale is stated as $s = s_0^i$ with an integer '*i*', and fixed dilation step ($s_0 > 1$). In addition, the discrete translation factor $\tau = k\,\tau_0 s_0^i$ with a translation that depends on the dilation step s_0^i is used. The resulting discrete wavelets are:

$$w_{i,k}(t) = s_0^{-i/2} h(s_0^{-i}(t - k\tau_0 s_0^i)) = s_0^{-i/2} h(s_0^{-i} t - k\tau_0) \qquad (1)$$

The wavelet coefficients are a sequence of the approximation and detail coefficients. The low frequency components of the signal (high scale) are the approximations, and the high frequency components (low scale) are the details. The most basic level of the filtering process is shown in Figure 1.

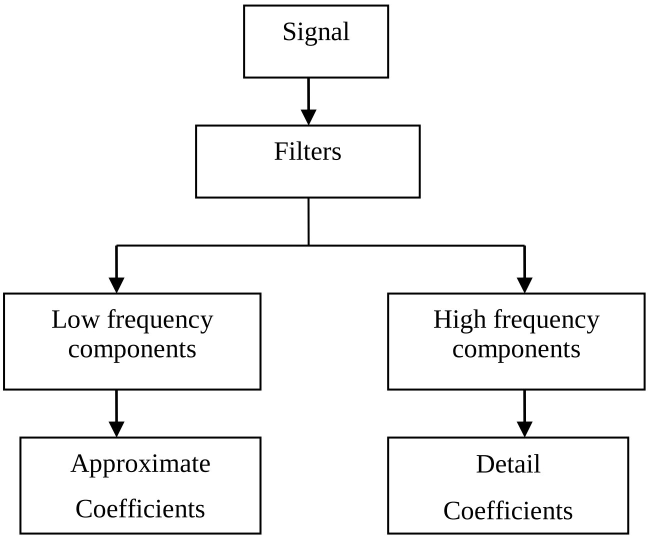


Figure 1 The filtering process for wavelet coefficients

The features can be extracted using DWT from raw sensor data. The basic feature extraction steps are, i) decomposing the signal using DWT to obtain the approximation and detailed coefficients using filtering process, and ii) using the approximate and detail coefficients of DWT to extract the features. The extracted features from the DWT coefficients of the raw sensor data are considered useful features for input into classifiers. The extracted features from the signal are as follows:

1) The mean, which is the average value of the DWT coefficients that computed once for approximate coefficients and another for detail coefficients. It can be expressed as:

$$\overline{x} = \left(\frac{1}{n}\right)\sum_{i=1}^{n} x_i \qquad (2)$$

where $\overline{x}$ is the mean, x is a sequence of coefficient, n is the number of the coefficients sequence.

2) The variance, which is a measure of the spread of data in a data set, which is given by:

$$V = \frac{1}{n-1}\sum_{i=1}^{n}(x_i - \overline{x})^2 \qquad (3)$$

3) The mean of energy, which is given by:

$$\overline{E} = \left(\frac{1}{n}\right)\sum_{i=1}^{n} x_i^2 \qquad (4)$$

4) The maximum amplitude, which is defined as the maximum value of the sequence of coefficients.

5) The minimum amplitude which is defined as the minimum value of the sequence of coefficients.

6) The mid-frequency, which is the obtained frequency value when the power spectral density is at the maximum value.

7) The maximum energy, which is the highest energy value obtained from the sequences of coefficients.

8) The minimum energy, which is the lowest energy value obtained from the sequences of coefficients.

Each feature is calculated for both approximate and detail coefficients for freeze and no freeze events, the significant features which are giving good discrimination of the two classes (freeze and no freeze) that considered as the main parameters will be tabulated and analyzed for classification.

2.3 Detection of gait

From each signal, the selected extracted features were used as input to ANN and SVM according to their popularity (Saba *et al.*, 2016) to classify data based on their extracted statistical information or prior knowledge from the raw data (Karamizadeh *et al.*, 2014). SVM classifies by finding a decision boundary, also referred to as a hyper-plane. SVM searches for maximum marginal hyper-plane, where the hyper-plane with a large margin can classify more accurately than that with smaller one. Support vector points are the data points that lie on the margin and the linear combination of only these points is represented the solution (Kotsiantis *et al.*, 2007). Comparing ANN to SVM, the sequential training procedures is the essential characteristic of ANNs that gives it the ability to learn complex nonlinear input/output relations with adapting according to the data. The proposed PD detection technique is shown in Algorithm 1 that is explained in detail in the next section.

Algorithm 1 :PD detection

Start

Read vertical acceleration of the sensor at ankle Pi (: ,3) = S

Read annotation Pi (: , 11)

if annotation=2 then

S= freeze

else if annotation =1 then

S= no freeze

Compute DWT for S

Display DWT coefficients (CAF , CDF) for freezing & (CANF , CDNF) for no freezing

Compute features for all DWT coefficients

Set a target value 0 for freeze & 1 for no freeze

Apply the computed features and target to ANN

Train the network to classify the inputs according to the target using scaled conjugate gradient back-propagation

Detecting of freezing cases

End

2.4 Proposed system

In the current work, a dataset was created to host the signals captured from the wearable on body sensors in the experiments. The dataset is for post processing in order to test several classification algorithms to detect PD FoG. Nine signals were acquired from the three sensors; each signal contains freezing and no freezing events. As compared to the literature (Bächlin *et al*., 2010), the vertical acceleration of the sensor at the ankle (shank) was used, which has been shown to give the best result in FoG detection. The Dataset contains ten files for ten patients, where 8 patients out of ten exhibited FoG during the study, the data of 8 patients is used to separate freezing and no freezing events, to apply DWT to each case for data reduction and then extract the main features from the DWT coefficients in order to distinguish between the two classes of freeze and no freeze. The primary steps of the proposed system are, i) data acquisition, ii) apply DWT, iii) feature selection, and finally iv) feature extraction and classification, as shown in Figure 2.

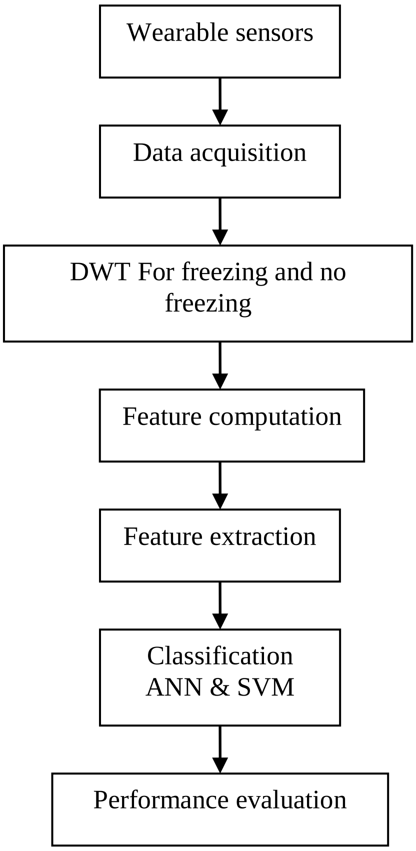


Figure 2 Proposed system block diagram

Firstly the approximate and detail coefficients, CA and CD are computed for each signal as shown in Figure 3.

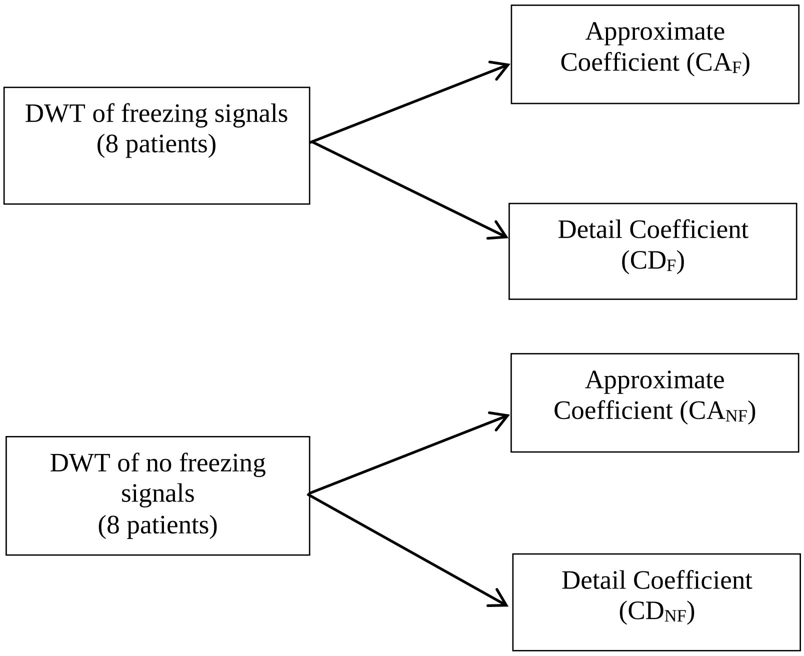


Figure 3 Approximate and detail coefficients for freezing and no freezing signals

There are eight features extracted (as discussed in section 2.2) from the DWT coefficients, but only five significant features were finally used being the Variance, Maximum amplitude, Minimum amplitude, Maximum energy and Minimum energy. The feature vector is built with 16 samples to train and test the ANN and the SVM classifiers.

2.5 Evaluation metrics

Nine metrics are measured to evaluate the proposed method, where the assessment of the classifier accuracy performance was computed by using the confusion matrix (Altman, & Bland, 1994). In addition, in order to check the quality of classifiers, the Receiver Operating Characteristic (ROC) curve has been used being a comparison of two operating characteristics, the True Positive Rate (TPR) and the False Positive Rate (FPR) (Swets, 2014). The closer each curve is to the left and top edges of the plot, the better the classification. The following metrics for the binary classification in the present study are calculated from the confusion matrix:

1) Sensitivity (TPR) is also known as the true positive rate, or probability of detection. It is used to identify the classification accuracy. The sensitivity of the test is defined as the ratio between the individuals who have positive test results for the disease and those who have the disease, which is given by:

$$TPR = \frac{TP}{P} = \frac{TP}{TP + FN} \tag{5}$$

where TP is the number of true positive cases, P is the number of real positive cases in the data, and FN is the number of false negative cases.

2) Specificity (TNR), also called the true negative rate. In a medical test, it is the ratio between healthy patients known not to have the disease and who will test negative for it, which is given by:

$$TNR = \frac{TN}{N} = \frac{TN}{TN + FP} \tag{6}$$

where TN is the number of true negative cases, N is the number of real negative cases in the data, FP is the number of false positive cases.

3) Precision, or Positive Predictive Value (PPV) is the ratio of true positives to combined true and false positives, which is given by:

$$PPV = \frac{TP}{TP + FP} \tag{7}$$

4) Negative Predictive Value (NPV) is the ratio of true negative to combined true and false negatives, which is given by:

$$NPV = \frac{TN}{TN + FN} \tag{8}$$

5) Miss rate, or False Negative Rate (FNR) is the ratio between the false negative cases and the real positive cases in the data, which is given by:

$$FNR = \frac{FN}{P} = 1\text{-}TPR \tag{9}$$

6) Fall out, or False Positive Rate (FPR) is the ratio between the false positive cases and the real negative cases in the data, which is given by:

$$FPR = \frac{FP}{N} = 1\text{-}TNR \tag{10}$$

7) False Discovery Rate (FDR) is the ratio of the false positives to combined true and the false positives which is given by:

$$FDR = \frac{FP}{FP + TP} = 1\text{-}\ PPV \tag{11}$$

8) False Omission Rate (FOR) is the ratio of false negatives to combined true and false negatives which is given by:

$$FOR = \frac{FN}{FN + TN} = 1\text{-}\ NPV \tag{12}$$

9) Accuracy (ACC) refers to the ability to differentiate the diseased patient and the healthy cases correctly. In a medical test, the accuracy of a test is the proportion of the cases correctly identified as patient and the cases correctly identified as healthy in all evaluated cases, which is given by:

$$ACC = \frac{TP + TN}{P + N} = \frac{TP + TN}{TP + TN + FP + FN} \tag{13}$$

3 RESULTS AND DISCUSSION

In this paper, the vertical acceleration signal of the sensor at the ankle (shank) from dataset in section 2.1 had been used. As the performance of using different types of classifiers for FoG detection of PD patients using the features extracted from DWT coefficients was analyzed. Then, we compared the performance of using features extracted from FFT coefficients and extracted from DWT coefficients.

3.1 Performance metrics using the ANN and SVM

Figure 4 illustrates the signal of the vertical axis of the sensor at the ankle the PD patient, freezing signal and no freezing signal and the corresponding DWT coefficients of them.

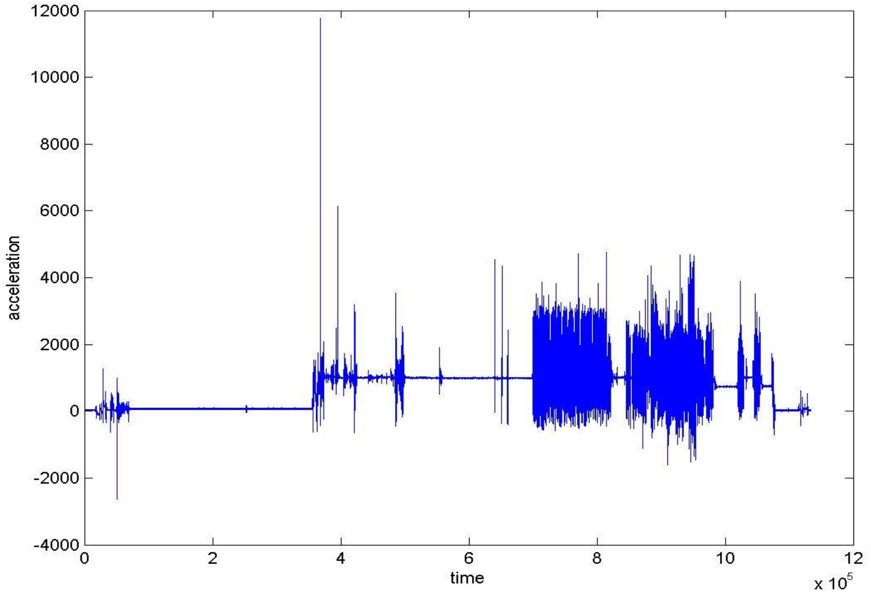
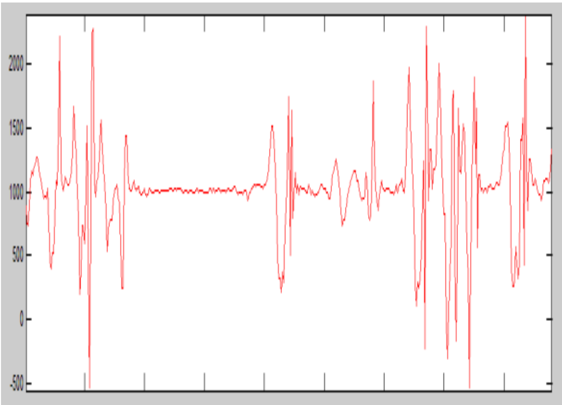
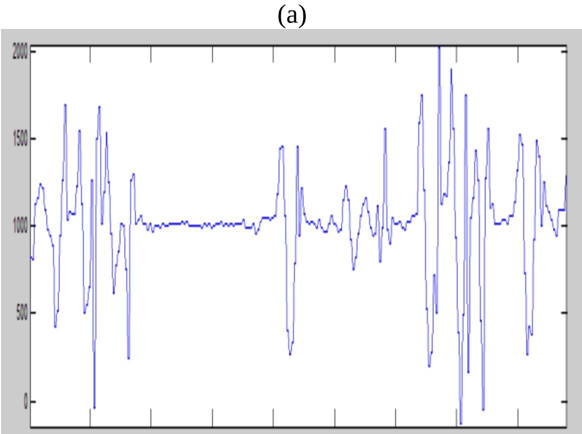


Figure 4 Signal of vertical axis of the sensor at the ankle

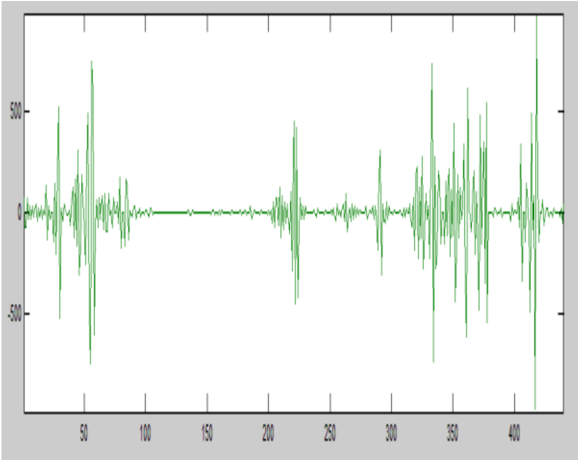
Figure 5(a) shows the freezing signal, which explains the movement of the patient at the freezing event. Figure 5 (b) and (c) shows the DWT approximate and detail coefficients of this signal, respectively. In addition, Figure 6 illustrates the no freezing signal and the approximate/ detail coefficients.



(a)

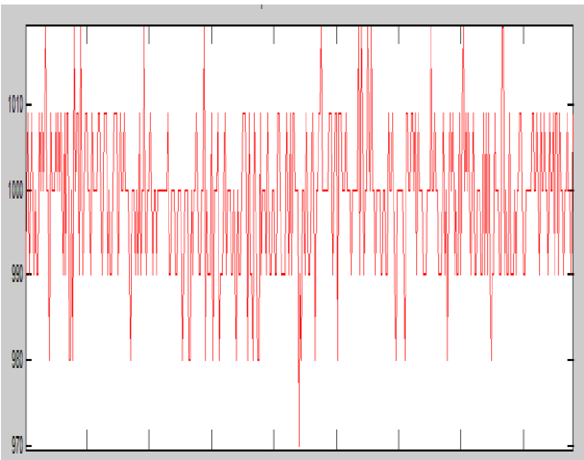


(b)

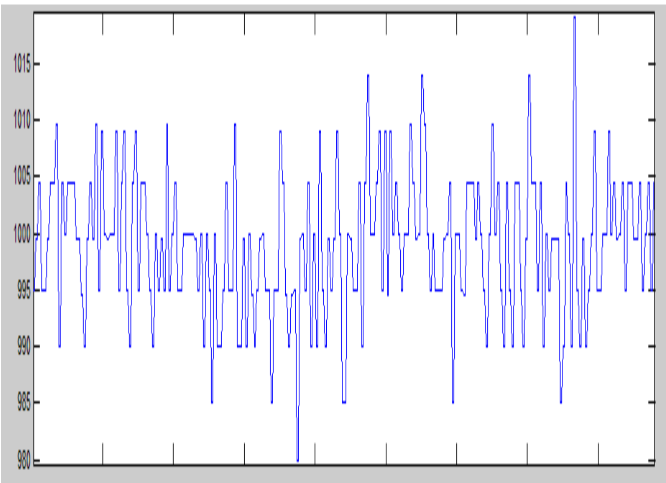


(c)

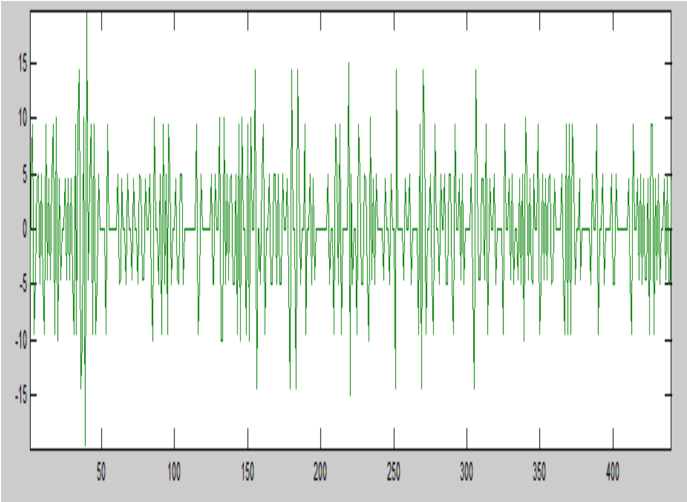
Figure 5 a) Freezing signal, b) Approximate coefficient, c) Detail coefficient



(a)



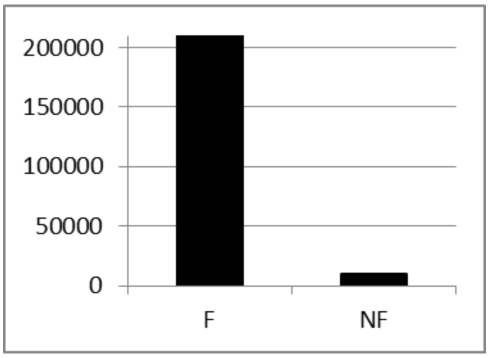
(b)



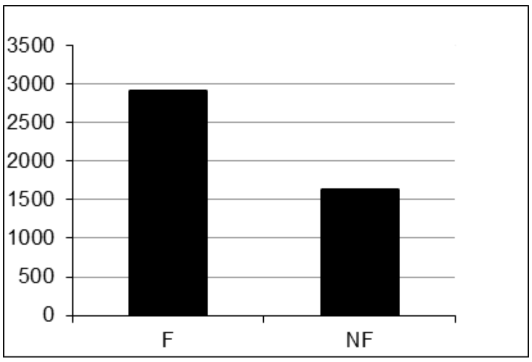
(c)

Figure 6 a) No freezing signal, b) Approximate coefficient, and c) Detail coefficient

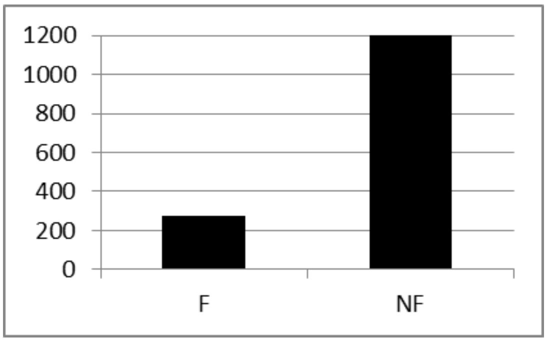
Figure 6(a) shows the no freezing signal, which explains the normal movement of a patient and when DWT taken to this signal, while Figure 6-b and 6-c show the form of the approximate and detail coefficient, respectively. The figures illustrate a great difference between the coefficients for freezing and no freezing, thus, we extract the features from these coefficients. The variation of the eight features as explained in section 2.2 with respect to each classes are analyzed and only five features are used which given faithful information. These features are the variance, maximum/ minimum amplitudes, maximum/ minimum energies. The average values of the significant features are calculated and plotted in graphs. The average feature values for the two classes in the y- axis and the class in the x-axis as (F mean freeze) and (NF mean no freeze) is shown in the following graph as Figure 7(a) through (e). Furthermore, Figure 7(a) shows that the variance has greater values in freezing than in no freezing.



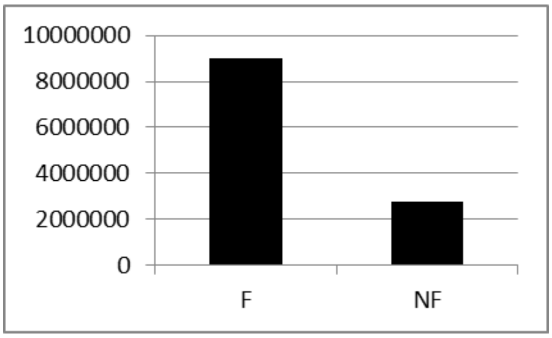
(a)



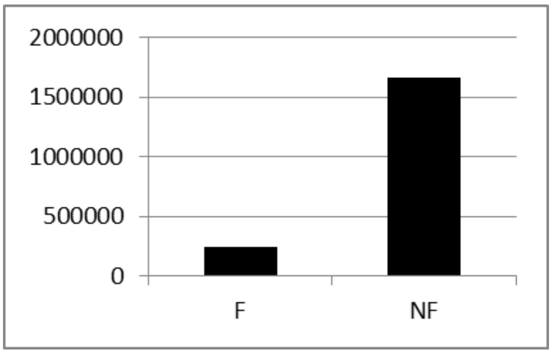
(b)



(c)



(d)



(e)

Figure 7 Illustrates the variation of (a): variance for two classes, (b) maximum amplitude for two classes, (c) minimum amplitude for two classes, (d) maximum energy for two classes, and (e) minimum energy for two classes

In Figure 7, the features give a clear difference between the freezing and no freezing, which are considered the main features to distinguish between the two classes. Figure 7(b) illustrates the variation of maximum amplitude is considered the significant feature to distinguish between the two classes as there is a difference in the values of freezing and no freezing. Figure 7(c) shows that the minimum amplitude has smaller values in freezing than in no freezing. This feature gives a clear difference between the freezing and no freezing, so it is considered the significant feature to distinguish between the two classes. Figure 7(d) shows that the variation of maximum energy gives a clear difference between the freezing and no freezing, so it is considered the significant feature to distinguish between the two classes. Figure 7(e) demonstrates that the variation of minimum energy gives a clear difference between the freezing and no freezing, so it is considered the significant feature to distinguish between the two classes.

In the present work, a two layer feed forward ANN with 20 neurons in its hidden layer was used. The network was trained with the default Scaled Conjugate Gradient back-propagation. As the extracted features applied to the network, the input was a 10×16 matrix and the target was a 1×16 matrix with ‘0’ for freezing and ‘1’ for no freezing. The input vectors and target vectors were divided randomly into three sets, namely 70% for training, 15% for validation, and the last 15% were used for testing. The network response is analyzed by a display of the confusion matrix that displays various types of errors that occurred for the final trained network. The accuracy was 93.8 % as shown in the confusion matrix in Table 1.

Table 1: Confusion matrix of ANN using DWT coefficient

Output Class

8 50.0%	1 6.3%	88.9% 11.1%
0 0.0%	7 43.8%	100% 0.0%
100% 0.0%	87.5% 12.5%	93.8% 6.3%

0

Target Class

Table 1 reports that the sensitivity, specificity, precision or PPV, and NPV of the ANN in the proposed method have the values of 100%, 87.5%, 88.9%, and 100%; respectively. Furthermore, the FNR, FPR, FDR, FOR and the ACC have values of zero, 12.5%, 11.1%, zero, and 93.8%; respectively. These all metrics are explained in Table 2. The Receiver Operating Characteristic (ROC) of ANN using DWT coefficients is shown in Figure 8.

Table 2 Evaluation metrics using DWT coefficient

Performance Metric	**Metric value using DWT**
Sensitivity	100%
Specificity	87.5%
Precision	88.9%
NPV	100%
FNR	0%
FPR	12.5%
FDR	11.1%
FOR	0%
ACC	93.8%

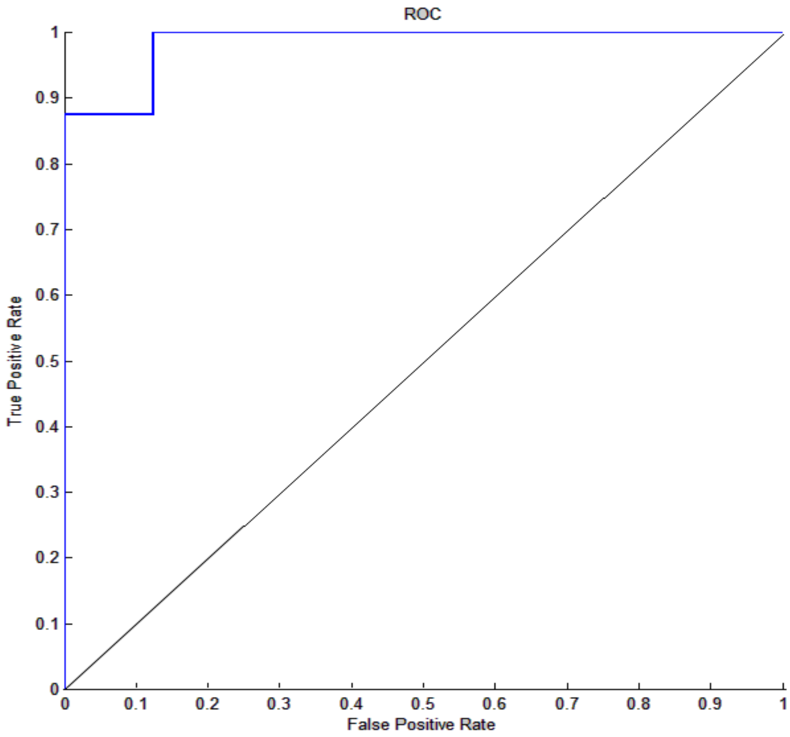


Figure 8 ROC of ANN using DWT coefficients

The extracted features were then applied to the SVM classifier to train the SVM classifier using a linear kernel function. The SVM achieved 87.50 % accuracy. The performance of the two classifiers is reported in Table 3. Table 3 establishes that the accuracy obtained using the ANN is higher than the obtained value using the SVM. Consequently, the ANN was used for the remaining elements of the current study.

Table 3 The performance of ANN & SVM using DWT coefficients

Classifier	Classification accuracy (%)
ANN	93.80
SVM	87.50

3.2 Comparison between using DWT and FFT

An FFT was applied to the freezing and no freezing signals to compute the same features extracted from DWT coefficients, namely variance, maximum amplitude, minimum amplitude, maximum energy, and minimum energy. Then, a two layer feed-forward ANN was applied with 20 neurons in its hidden layer. The network was trained with the default scaled conjugate gradient back propagation method. The extracted features were then applied to the network which has the following structure 5×16 input and 1×16 at the output (target) layer. The accuracy of detecting FoG, or distinguishing between freezing and no freezing was 81.3 % as shown in confusion matrix in Table 4.

Table 4: confusion matrix of ANN using FFT coefficient

Output Class

6 37.5%	1 6.3%	85.7% 14.3%
2 12.5%	7 43.8%	77.8% 22.2 %
75.0% 25.0%	87.5% 12.5%	81.3% 18.8%

Target Class

The confusion matrix in Table 4 established that the sensitivity, specificity, precision, or PPV and NPV of the ANN using FFT coefficient are 75.0%, 87.5%, 85.7% and 77.8%, respectively. Furthermore, the FNR, FPR, FDR, FOR and the ACC have values of 25.0%, 12.5%, 14.3%, 22.2% and 81.3%, respectively. These all metrics are explained in Table 5.

Table 5 Evaluation metrics using FFT coefficient

Performance Metric	**Metric value using FFT**
Sensitivity	75%
Specificity	87.5%
Precision	85.7%
NPV	77.8%
FNR	25%
FPR	12.5%
FDR	14.3%
FOR	22.2%
ACC	81.3%

The ROC of ANN using FFT coefficients is shown in Figure 9.

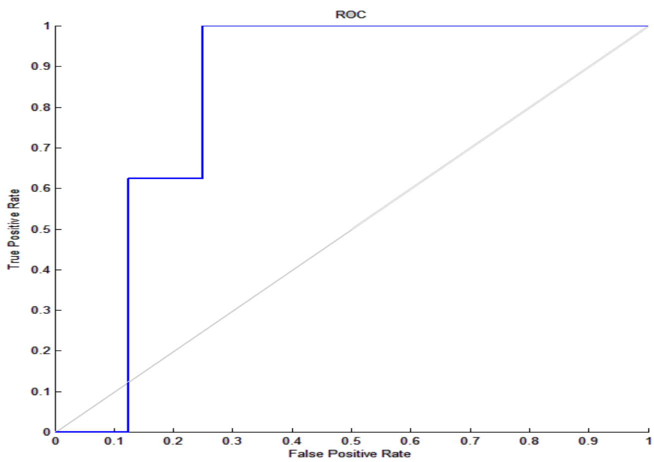


Figure 9 ROC of ANN using FFT coefficients

The performance of using features extracted from FFT coefficients and extracted from DWT coefficients is reported in Table 6.

Table 6 The performance of DWT versus FFT

Extracted feature using	**Accuracy (%)**
DWT	93.80
FFT	81.30

The DWT is used to extract five features from the approximate coefficients and another five features from the detail coefficients concluding a total of ten extracted features. These features are used further with the ANN and provided efficient results. However, using FFT provided only 5 features, which applied also to ANN. The comparative study of the performance accuracy of using DWT versus FFT depicted that DWT achieved about 93.8% accuracy, while FFT achieved 81.3% due to the more extracted significant features. Thus, DWT enables to build a robust multidimensional classification model compared to the one based on FFT.

3.3 Comparison with related studies

The performance of using different types of classifiers for the FoG detection was analyzed for evaluated using the dataset of eight patients by extracting the features using DWT coefficients. This proposed method achieved much higher sensitivity and specificity values compared to the studies in (Bächlin *et al*., 2010) and (Rezvanian, & Lockhart, 2016), which used the same dataset. Bächlin *et al*. (2010) used FFT to extract the PD information from the frequency domain of the acceleration signal to detect FoG cases. This was realized by analyzing the frequency components inherent in these movements and the FoG was detected using a freeze index and threshold algorithm. This system detected the FoG events with 73.1% and 81.6% values of the sensitivity and specificity, respectively. Furthermore, Rezvanian and Lockhart (2016) used CWT for features extraction from the acceleration signal, which provided information in both the frequency and time domains and defined an index for identifying the FoG. This method achieved 82.1% and 77.1% values of the sensitivity and specificity, respectively.
However, the previous systems in the literature depended on only a single feature, the freeze index, the proposed system in this paper has used five features extracted from DWT coefficients (for both approximate and detail), which were then input to the ANN and SVM machine learning techniques to distinguish between freezing and not freezing event. A comparison of the three systems using sensor placed at shank are reported in Table 7.

Table 7 Comparison between proposed and other systems

Work	Dataset	Feature and method	sensitivity	Specificity
Bächlin *et al*. (2010)	The same dataset used in these three studies. 3 accelerometer sensors placed at the ankle (shank), on the thigh just above the knee, and on the hip capable of measuring 3D acceleration of the movement. The data were recorded in 8h and 20 min, for ten patients, eight patients exhibited FOG during study and two did not have any freeze events.	Use FFT, freeze index and threshold algorithm to detect FoG	73.1%	81.6%
Rezvanian and Lockhart (2016)		Use CWT and novel FoG index to detect FoG	82.1%	77.1%
Proposed system using the DWT and ANN		Use DWT and extract many features and use machine learning method to detect FoG	100%	87.5%

Table 7 indicates that the use of machine learning techniques, primarily the ANN significantly improve the automated classification accuracy, as the discriminative features extracted from DWT to build a significantly more robust multidimensional classification model than the models based on a single feature in the literature. Due to the superiority of the proposed method, it is recommended to detect the FOG using the proposed extracted features with other classifiers (Hore *et al*., 2016; Dey,& Ashour, 2016; Wang *et al*., 2016; Sharma, & Virmani, 2017; Ahmed *et al*., 2017; Li *et al*., 2017; Hemalatha, & Anouncia, 2017; Sghaier *et al*., 2018).

4 CONCLUSIONS

This paper has presented a novel and improved system for freezing of gait detection in people with PD. The system uses DWT and ANN to distinguish between the occurrence of freezing and no freezing events. The paper has demonstrated that a combination of features including variance, maximum amplitude, minimum amplitude, maximum energy and minimum energy, enables the extraction of information about the signals.

The results established the ability of the proposed system to detect FoG events with sensitivity and specificity of 100% and 87.5%, respectively, with significantly improved performance compared to other systems in the literature of 73.1% and 81.6% (Bächlin *et al*., 2010) and 82.1% and 77.1% (Rezvanian and Lockhart, 2016), respectively. Additionally, the results demonstrated that features extracted from DWT coefficients provided higher accuracy of freezing event detection than features extracted from FFT coefficients with resulting accuracy of 93.8% and 81.3%, respectively. Therefore, the system performance using ANN classifier was superior compared to using a freezing threshold used in previous work. Furthermore, extracted features from DWT coefficients gave higher detection accuracy than the features extracted from FFT coefficients. Generally, the use of machine learning techniques improves the automated classification accuracy, as the discriminative features extracted from DWT build a more robust multidimensional classification model than the models based on a single feature, and paved the way for simple and reliable wearable devices to aid PD.

Future studies can be conducted on other types of classifiers as imbalance classifier. Those classifiers can combine also all the signals from the three sensors put on ankle, on the thigh and on the hip then extract features from this combined signal. Also, we can extend our work by using deep neural network for FoG detection and use another type of transformation. A comparative study with other types of classifiers, such as the K- NN for detecting the FoG can be conducted. Predict the FoG before its occurrence and use the freeze index with other extracted features. In addition, since the freezing index is a proportion between the power in the freezing band [3–8 Hz] and the power in the locomotion band [0.5–3 Hz]. It is recommended in the future work to use the freeze index along with other extracted features during the classification process. Furthermore, since the main advantages of DWT include its ability for data reduction and its efficiency in several applications that based on time-series data analysis. These advantages are suitable to handle the long time monitoring of individuals having PD as large amount of data are acquired from the sensors and subsequently data reduction becomes essential needs while keeping the integrity of the original data. Accordingly, it is recommended to use several transform domains and compare with the use of DWT in the future work.

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