Frequency domain analysis for the classification of Parkinson’s disease patients

S Kamalraj, K N Rejith and G K D Prasanna Venkatesan
Karpagam academy of higher Education, Coimbatore, India.
E-mail:1kamalrajec@gmail.com & rejith_kn@yahoo.com

Abstract: In this paper, Emotional recognition in Parkinson’s disease (PD) has been analyzed in frequency domain using Entropy, Energy-Entropy and Teager Energy-Entropy features. Classification results were observed using three classifiers namely Probabilistic Neural Network, K-Nearest Neighbors Algorithm and Support Vector Machine. Emotional EEG stimuli such as happiness, sadness, fear, anger, surprise, and disgust were used to categorize the PD patients and healthy controls (HC). For each EEG signal, the alpha, beta and gamma band frequency features are obtained for three different feature extraction methods (Spectral Entropy, Spectral Energy-Entropy, and Spectral Teager Energy-Entropy). The proposed Spectral Energy-Entropy feature performs well for all six emotions for different classifiers when compared to other features, whereas different features with classifiers give variant results for few emotions with highest accuracy of 96.8%.

Keywords: Electroencephalogram, Emotions, Fourier analysis, Multimodal stimulus, Non-linear methods, Parkinson’s disease, Spread factor, Teager Energy Entropy.

1. Introduction
Parkinson’s disease (PD) is a common progressive neurodegenerative disorder of the central nervous system [1]. Nowadays, PD affects about 1% of the world wide population over 55 years of age, and the number of PD patients in the elderly population has increased all the years’ record. The motor clinical symptoms of PD such as resting tremor, rigidity and postural instability, result from dopaminergic deficiency in the basal ganglia. In addition, PD is also characterized by the presence of non-motor impairments including cognitive dysfunction, even in the early stage of PD. However, the diagnosis of PD based on clinical symptoms is very difficult, especially in the early stage when there is no remarkable motor features and obvious cognitive dysfunction. Nonetheless, characterization of PD from the perspective of neuroscience provides us with an alternative way for exploring and quantifying corresponding brain functional neuronal mechanisms and improving diagnostic certainty.

Electroencephalograph (EEG) signals or brain signals are used widely in many applications such as to diagnose epilepsy, sleep disorders, depth of anesthesia, coma, encephalopathy, and brain death and also for detecting tumors, stroke and other focal brain disorders as front line method. In patients, emotional processing with disorder were analyzed using neuroimaging techniques such as functional magnetic resonance imaging (fMRI) and positron emission tomography (PET) and these techniques helps to identify the specific region of emotional functions [2]. It is also noted that the right hemisphere is involved with positive emotions such as happiness and surprise and the left hemisphere is involved with negative emotions such as sad, anger, fear, and disgust [3]. Various researchers have shown their interest on motor and cognitive impairments in neurological disorder people [4,5,6]. Later on, researchers have focused on investigating the emotional conditions in people with neurological disorders [7,8,9,10].
2. Protocol and data collection

Database of twenty non-demented PD patients and 20 healthy controls viewed emotional stimuli with fourteen-channel EEG recording were used in this study (Yuvaraj et al., [2016]). Twenty non-demented PD patients (10 men and 10 women) and 20 healthy controls (9 men and 11 women) matched for age (range from 40 to 65 years), education level, and gender participated in the study [11,12,13]. The PD patients were recruited through the Neurology Unit outpatient service at the Department of Medicine of the Hospital University Kebangsaan Malaysia (HUKM) medical center in Kuala Lumpur, Malaysia. All of them had been diagnosed with Idiopathic PD by a neurologist. Patients who had coexisting neurological disturbances (e.g., epilepsy, stroke) or who had undergone deep brain stimulation were not included in the study. The HC participants were recruited through the hospital community and/or from relatives of PD patients.

3. Feature extraction

Feature extraction processes are analyzed in frequency domain with three features namely, Spectral Entropy, Spectral Energy-Entropy, Spectral Teager Energy-Entropy. First the raw EEG data was preprocessed and then feature extraction was performed. The recorded signals were segmented into number of frames with an overlapping of 75%. Each frame has 1280 samples (corresponding to 10 second). The segmented signals were then filtered using pass band elliptic filters and the alpha (7 to 14 Hz), beta (14 to 21 Hz) and gamma (21 to 34 Hz) from all the 14 channels [14] were obtained.

For Spectral Entropy (SEN) feature extraction process, from the filtered values, \( x(q) \) were first Fourier transformed to \( Y(m) \) using the equation (1),

\[
Y^k_m = \sum_{q=1}^{N} x^k_q \cdot w_n^{(q-1)(k-1)}
\]

where \( w_n = e^{-2\pi i n/N} \) is the complex exponential and \( N \) is the total number of data in the filtered signal.

From the Fourier transformed signal \( Y(m) \), the SEN value is calculated using equation (2),

\[
H^k_j = -\sum_{m=1}^{N} Y^k_j(m) \ln(Y^k_j(m))
\]

where \( N = 128 \), is the number of samples.

Spectral Energy-Entropy (SEEN) value is calculated using the power values of Spectral entropy. From the filtered values, the SEEN feature is calculated using the equation (3),

\[
S^k_j = -\sum_{m=1}^{N} (Y^k_j(m))^2 \ln(Y^k_j(m))^2
\]

Teager Energy (TE) is a powerful nonlinear operator proposed by Kaiser, capable to extract the signal energy based on mechanical and physical considerations. The continuous form of the TE is given as

\[
\phi [y(t)] = \left( \frac{d}{dt} y(t) \right)^2 - y(t) \frac{d^2}{dt^2} y(t)
\]

From the Fourier transformed signal, Spectral Teager Energy Entropy feature (STEEN) is calculated using equation (4),

\[
H^k_j = -\sum_{q=1}^{N} [\phi Y^k_j(m) \ln(\phi Y^k_j(m))]
\]
Similarly, the features corresponding to the PD and HC performed by all the twenty subjects (for all trials) were extracted using fourteen channels. Each frame has 42 (14 channels x 3 bands) feature values and it is given as input to the network.

4. Feature classification

4.1. K-nearest neighbor algorithm. K nearest neighbor (KNN) is a simple algorithm, which stores all cases and classifies new cases based on similarity measure. KNN algorithms have been used since 1970 in many applications like statistical estimation and pattern recognition. In KNN classification, the output is a class membership. An object is classified by a majority vote of its neighbors, with the object being assigned to the class most common among its k nearest neighbors (k is a positive integer, typically small). If k = 1, then the object is simply assigned to the class of that single nearest neighbor. For this KNN model same 42 input values were given and the accuracy results of each emotion (happiness-E1, sadness-E2, fear-E3, anger-E4, surprise-E5, and disgust-E6) and the corresponding smoothing parameter (K) ranges from 1 to 10 were found.

4.2. Probabilistic neural network. To discriminate the PD and HC for six different emotions, probabilistic neural network (PNN) has been developed. A probabilistic neural network (PNN) is a feed forward neural network, which is widely used in classification and pattern recognition problems. In the PNN algorithm, the parent probability distribution function (PDF) of each class is approximated by a Parzen window and a non-parametric function. By this method, the probability of mis-classification is minimized. In a PNN, the operations are organized into a multilayered feed forward network with four layers. PNN is a supervised neural network proposed by Donald F. Specht[15, 16] and it is a kind of radial basis network suitable for classification problems. The only factor that needs to be selected for training is the smoothing factor/spread factor which affects the classification accuracy. The network structure of PNNs is similar to that of back propagation; the primary difference is that it uses exponential activation function instead of sigmoid activation function and also the training time is lesser compared to multi-layer feed forward network trained by back propagation algorithm. In this paper, PNN architecture and the feature extraction process are constructed and analysed using MATLAB software. This problem requires 42 input neurons. The accuracy results of each emotion and the corresponding best smoothing parameter (K) ranges from 0.55 to 0.65 were found.

4.3 Support vector machine. A Support Vector Machine (SVM) is a discriminative classifier formally defined by a separating hyperplane. In other words, given labeled training data (supervised learning), the algorithm outputs an optimal hyperplane which categorizes new examples. In two dimensional space, this hyperplane is a line dividing a plane in two parts where in each class lay in either side. Support vector machines (SVM) are supervised learning models with associated learning algorithms that analyze data used for classification and regression analysis [17]. Given a set of training examples, each marked as belonging to one or the other of two categories, an SVM training algorithm builds a model that assigns new examples to one category or the other, making it a non-probabilistic binary linear classifier. Results of SVM for all six features were found.

5. Results and discussion

Emotional states of PD and HC using three features were investigated using three classifiers such as SVM, PNN and KNN models. The overall classification accuracies of three features for each emotion using three models were tabulated and shown in the figure (1), figure (2) and figure (3). For emotion E1, maximum accuracy of 96.8 is obtained using SEN with PNN and second highest accuracy of 95.97 using SEN with PNN. For emotion E2, maximum accuracy of 90.2 is obtained using SEN with KNN and second highest accuracy of 75.2 using SEN with KNN. For emotion E3, maximum accuracy of 95.07 is obtained using SEEN with KNN and second highest accuracy of 94.93 using SEEN with SVM. For emotion E4, maximum accuracy of 91.4 is obtained using SEEN with SVM and second highest accuracy of 87.16 using SEEN with KNN. For E5, maximum accuracy of 94.53 is obtained using SEEN with KNN and second highest accuracy of 88.04 using SEN with KNN. For E6, maximum accuracy of 88.18 is obtained using SEEN with SVM and second highest accuracy of 86.42 using SEN with KNN.
Figure 1: Overall results of SEN, SEEN and STEEN features using KNN

From figure 1, it could be observed that, the highest classification accuracy of 90.2% (for emotion E2) and the lowest classification accuracy of 80.68% (for emotion E4) were obtained for SEN feature using KNN. Then the highest classification accuracy of 95.07% (for emotion E3) and the lowest classification accuracy of 58.85% (for emotion E1) were obtained for SEEN feature using KNN. For STEEN feature using KNN, emotion E1 gives highest of 84.3% and emotion E4 gives lowest classification accuracy of 62.09%.

Figure 2: Overall results of SEN, SEEN and STEEN features using PNN

From figure 2, it could be observed that, the highest classification accuracy of 95.97% (for emotion E1) and the lowest classification accuracy of 67.69% (for emotion E3) were obtained for SEN feature using PNN. Then the highest classification accuracy of 96.8% (for emotion E1) and the lowest classification accuracy of 64.2% (for emotion E3) were obtained for SEEN feature using PNN. For STEEN feature using PNN, emotion E1 gives highest of 92.3% and emotion E4 gives lowest classification accuracy of 65.95%.

Figure 3: Overall results of SEN, SEEN and STEEN features using SVM.

From figure 3, it could be observed that, the highest classification accuracy of 90.2% (for emotion E2) and the lowest classification accuracy of 80.68% (for emotion E4) were obtained for SEN feature using SVM. Then the highest classification accuracy of 95.07% (for emotion E3) and the lowest classification accuracy of 58.85% (for emotion E1) were obtained for SEEN feature using SVM. For STEEN feature using SVM, emotion E1 gives highest of 84.3% and emotion E4 gives lowest classification accuracy of 62.09%.
From figure 3, it could be observed that, the highest classification accuracy of 95.54 % (for emotion E1) and the lowest classification accuracy of 64.86 % (for emotion E4) were obtained for SEN feature using SVM. Then the highest classification accuracy of 94.92 % (for emotion E3) and the lowest classification accuracy of 57.16 % (for emotion E1) were obtained for SEEN feature using SVM. For STEEN feature, emotion E1 gives highest of 94.19 % and emotion E2 gives lowest classification accuracy of 64.86 %.

6. Conclusion
The extracted features were associated to their respective emotions and the models were developed to discriminate the PD and HC individuals. The performance of the three models were tabulated and compared. In this paper, the frequency domain features SEN, SEEN and STEEN were extracted from the PD and HC EEG signals and the results were analyzed. From the analysis, it has been clearly observed that the entropy feature in frequency domain performs evenly well (above 80 %) for all six emotions for KNN. Energy entropy combination feature gives highest accuracy for most emotions but for different classifiers, whereas other features gives lower accuracy values of below 60% for few emotions. Emotions such as E1, E3, E4, E5 & E6 gives highest performance for features SEEN with KNN (96.8 %), SEEN with KNN (95.07 %), SEEN with SVM (91.42 %), SEEN with KNN (94.53 %), SEEN with SVM (88.18 %) respectively. Hence, the proposed spectral energy-entropy feature in frequency domain gives highest accuracy for all emotions except E2 but for different classifiers.

References

[1] Valls-Solé J and Valldeoriola F Neurophysiological correlate of clinical signs in Parkinson's Disease 2002 Clinical neurophysiology113792-805.

[2] Davidson RJ and Irwin W. The functional neuroanatomy of emotion and affective style. Trends in cognitive sciences. 1999 311-21.

[3] Alves NT, Fukusima SS and Aznar-Casanova JA. Models of brain asymmetry in emotional Processing 2008 Psychology & Neuroscience163.

[4] Bevilacqua V, D'Ambruoso D, Mandolino G and Suma M. A new tool to support diagnosis of neurological disorders by means of facial expressions. InMedical Measurements and Applications Proceedings (MeMeA), 2011 IEEE International Workshop on 2011 May 30 (pp. 544-49). IEEE.

[5] DeKosky ST, Heilman KM, Bowers D and Valenstein E Recognition and discrimination of emotional faces and pictures 1980 Brain and language9206-14.

[6] Mohr E, Juncos J, Cox C, Litvan I, Fedio P and Chase TN. Selective deficits in cognition and memory in high-functioning parkinsonian patients 1990 Journal of Neurology, Neurosurgery & Psychiatry53603-6.

[7] Zhao S, Rudzicz F, Carvalho LG, Márquez-Chin C and Livingstone SR. Automatic detection of expressed emotion in Parkinson's disease 2014InICASSP 4813-17.

[8] Pell MD and Leonard CL. Facial expression decoding in early Parkinson's disease 2005Cognitive Brain Research 23327-40.
[9] Baumgartner T, Esslen M and Jäncke L. From emotion perception to emotion experience: Emotions evoked by pictures and classical music 2006 International journal of psychophysiology 6034-43.

[10] Han CX, Wang J, Yi GS and Che YQ Investigation of EEG abnormalities in the early stage of Parkinson’s disease 2013 Cognitive neurodynamics 7351-9.

[11] Murugappan MN, Nagarajan R and Yaacob S. Comparison of different wavelet features from EEG signals for classifying human emotions 2009 In Industrial Electronics & Applications, ISIEA 2009. IEEE Symposium 2 836-841.

[12] Yuvaraj R, Murugappan M, Ibrahim NM, Omar MI, Sundaraj K, Mohamad K, Palaniappan R, and Satiyan M. Emotion classification in Parkinson's disease by higher-order spectra and power spectrum features using EEG signals: A comparative study 2014 Journal of integrative neuroscience 1389-120.

[13] Yuvaraj R, Murugappan M, Acharya UR, Adeli H, Ibrahim NM and Mesquita E. Brain functional connectivity patterns for emotional state classification in Parkinson’s disease patients without dementia 2016 Behavioural brain research 298248-60.

[14] Palaniappan, R., Raveendran, P., Nishida, S. and Saiwaki, N., 2000. Fuzzy atmap classification of mental tasks using segmented and overlapped EEG signals. In 2000 TENCON Proceedings. Intelligent Systems and Technologies for the New Millennium (Cat.No.00CH37119) 2 388-391.

[15] Sivanandam M. Introduction to artificial neural networks. vikas publishing House PVT LTD; 2009.

[16] Specht DF. Probabilistic neural networks. Neural networks. 1990 Jan 1;3(1):109-18.

[17] El-Naqa I, Yang Y, Wernick MN, Galatsanos NP and Nishikawa RM. A support vector machine approach for detection of microcalcifications 2002 IEEE transactions on medical imaging 211552-63.