Diagnosis of Parkinson's Disease Using EEG and fMRI

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Abstract

Parkinson's disease is a brain disorder that leads to shaking, stiffness, and difficulty with walking, balance, and coordination. Parkinson's symptoms usually begin gradually and get worse over time. As the disease progresses, people may have difficulty walking and talking. In this system, an Architecture is proposed for Parkinson’s disease detection by investigating the topological properties of functional brain networks within fMRI and EEG Signals of Healthy Control (normal) and PD patients. For fMRI the functional whole-brain connectome was constructed by thresholding partial correlation matrices of 160 regions from Dosenbach brain atlas. 160 x 160 functional correlation matrix was constructed using the Pearson correlation. From the graph theory approach, network metrics were analysed. For EEG spatial and Bispectrum features are extracted. Finally, Adaboost Classifier is used to classify whether it is normal or PD.

Introduction

Parkinson's disease (PD) is a progressive nervous system disorder that affects movement because of less dopamine secretions in human Brain. An estimated seven to 10 million people worldwide have Parkinson's disease. The prevalence of the disease ranges from 41 people per 100,000 in the fourth decade of life to more than 1,900 people per 100,000 among those who are 80 and older. There is no homogenous and large epidemiological data on PD from India. The prevalence rate of 14.1 per 100,000 amongst a population of 63,645 from rural Kashmir in the northern part of India. The prevalence rate over the age of 60 years was 247/100,000. A low prevalence rate of 27/100,000 was reported from Bangalore, in the southern part of India, and 16.1/100,000 from rural Bengal, in the eastern part of India. The prevalence rate of 328.3/100,000 among a population of 14,010 Parsis living in colonies in Mumbai, Western India.

The main aim of this work is to analyse Parkinson’s disease detection by investigating the topological properties of functional brain networks within fMRI and EEG Signals of Healthy Control (normal) and PD patients.

Related Works

Martin Gottlich et al. [8] used graph-theory based technique to measure whole-brain intrinsic connectivity. The network parameters used in this study would be helpful to track disease state and characterize subtypes of PD patients related to cognitive dysfunctions or other non-motor symptoms. Hugo-Cesar Baggio et al. [9] reported that complex network analysis through resting-state fMRI is very helpful in investigating functional changes related to cognitive decline in PD. Yongbin Chen et al. [16] had used whole-brain functional connectivity as a classification feature to identify PD patients and healthy controls. The performance of this method had yielded an accuracy of 93.62%.

Zhang D et al. [17] reported that they had used network centrality, seed-based functional connectivity, and network efficiency analyses for full map of abnormal connectivity networks in PD with tremor that is distributed over cortical, subcortical, cerebellum, and brainstem sites and observed the functional changes were recorded.

Abhishek M.S et al. [1] reported that voice signals played a major role in predicting Parkinson's disease and concluded that genetic algorithm is the most common method used to extract features voice signal properties. Athanasios Tsanas et al. [5], the authors had used **132 dysphonia measures from sustained vowels and this work could be** used to discriminate PD subjects from healthy controls and was tested. Alex Frid et al. [2] developed an automatic system for quantification and classification of Parkinson's disease directly from natural speech using the Machine Learning technique

Jens Barth et al. [10] developed a method by combining hand and gait motor function impairment to differentiate between PD patients and healthy controls. Sama et al. [4] presented a method to detect dyskinesia and to characterize motor states for PD patients. Shyamal Patel et al. [14]) had used accelerometer data to estimate the severity of symptoms and motor complications for the patients in Parkinson's disease

A. Valli and Dr.G. Wiselin Jiji [6] developed a method by extracting properties from Striatum, substantia nigra to classify normal and PD controls. Peter Drotar et al. [11] had used different handwriting modalities to classify PD. Pereira et al. [7] reported that handwritten trace as features for automatic classification of PD. Salama A. Mostafa et al. [13] reported that they had used multiple feature evaluation and classification methods for improving the diagnoses of Parkinson's disease. Timothy J. Wroge et al. [15] reported that disease diagnosis and prediction is possible through automated machine learning architectures using only non-invasive voice biomarkers as features. A.M. Ardi Handojoseno et al. [3] stated that combining the spatial, spectral and temporal features of surface EEG had helpful in the FOG in PD. Rajamanickam Yuvaraj et al. [12] had used HOS features extracted from EEG signals for diagnosis of PD patients. Passos et al.[18] had used deep neural network called ResNet-50 to learn the patterns and extracted features from images draw by patients and produced 96% of identification rate. Prajapati et.al [23] reported that using topological properties of functional brain networks within healthy controls (HCs) and PD patients are extracted from fMRI images to diagnose PD or HC.

In this work, we have used by combining the features of fMRI & EEG signals and performed classification using AdaBoost classifier to accurately predict the target class for each case in the data.

Methodology

An Architecture is proposed for Parkinson's disease detection by investigating the topological properties of functional brain networks within fMRI and EEG Signals of Healthy Control (normal) and PD patients. Figure 1 shows the overview of Proposed Architecture. For fMRI the functional whole-brain connectome was constructed by thresholding partial correlation matrices of 160 regions from Dosenbach brain atlas. 160 x 160 functional correlation matrix was constructed using the Pearson correlation. From the graph

theory approach, network metrics were analysed. For EEG spatial and Bispectrum features are extracted. Finally, Adaboost Classifier is used to classify whether it is normal or PD.

Data Set Used:

The input images were taken from the OpenNEURO which is open science neuro informatics database storing datasets from human brain imaging research studies. The dataset contains raw fMRI scans, raw EEG in Brain Vision format where the subjects include fMRI of 100 patients with Parkinson's and 100 with Healthy control, EEG signals were recorded in closed eye resting state for 100 patients with Parkinson's and 100 with Healthy Control. In Parkinson's 25 Male patients and 75 Female patients and in Healthy Control 10 Female and 90 male patients were taken. Figure 2 and Fig. 3 for the input Healthy Control and PD and Fig. 4 and Fig. 5 are Input image EEG for Healthy Control and PD respectively.

Network Construction and functional Connectome

The two fundamental elements of the network are edges and nodes, where nodes represent the brain regions and edges depict the functional connectivity between two brain regions or nodes. The Region of interest for this category are frontoparietal, cingulo-opercular, sensorimotor, occipital, and cerebellum were selected from Dosenbach atlas[21] to draw functional connectome and the output is shown in Fig. 6.

GRETNA tool is used to find out the functional connectivity matrices from brain images [20] and edges for the connectivity has been calculated using Pearson corelation coefficients [19]. The output is shown in Fig. 7 and Fig. 8. Each region is considered as a node to construct the brain network and the output is shown in Fig. 9 and Fig. 10.

FEATURE EXTRACTION: fMRI

We have extracted [24] the parameters betweenness mean, betweenness standard deviation, page rank mean, page rank standard deviation, centrality degree mean, centrality degree standard deviation, clustering coefficient, assortivity, closeness, centrality closeness values from network created from fMRI.

Betweenness

$$c_{Betweenness} = \frac{\sum_{v \in \gamma}[c_{bet}\left(v^*\right) - c_{bet}(v)]}{n^3 - 4^{n^2} + 5n - 2}$$

1

Where,v^* is the node with maximum betweenness and $c_{bet}(.)$is the normalized betweenness.

Page rank

$$C_{PR} = (I - aAd^{-1})^{-1}1 = D(D - aA)^{-1}$$

2

Where, D is a diagonal matrix,I is an N x N identity matrix, a is weight on the edges from vertex v.

Centrality Degree

$$C_D(i) = K_i = \sum_{i \neq j} A_{ij}$$

3

Where, A is a matrix with vertices i ,j where$i \neq j$

Clustering Coefficient

$$C_{clustering}(v) = \frac{1}{d(v).\,(d(v) - 1)} \sum_{r,\, s \in N(v)} A_{rs}$$

4

Where, $d(v)$is the degree of vertex v,$N(v)$ is set of all nodes that are a distance 1 from a vertex v and A is the matrix.

Assortativity

$$\rho^D = \frac{\sum_{jk} jk(e_{jk} - q_j q_k)}{\sigma_q^2}$$

5

Where,e_{jk}refers to the joint excess degree probability for nodes with excess degrees j and k. $q_k$is a normalized distribution of a randomly selected node, given by $q_k = \frac{(k+1)\,p_k}{\sum_j j p_j}$ and σ_q is the standard deviation of the distributionq_k

Centrality closeness

$$C_{closeness}(v) = \frac{1}{\sum_{u \in v} d(u, v)}$$

6

Where, d (u, v) is the distance to all the other nodes in the network.

Feature Extraction: Eeg

The bispectrum is an advanced signal processing technique based on higher order statistics which considers both the amplitude and the degree of phase coupling of a signal. In contrast to traditional power spectrum, which quantifies the power of a time series over frequency, higher order spectral (HOS) analysis employs the Fourier transform of higher order correlation functions to explore the existence of quadratic (and cubic) non-linear coupling information (Rajamanickam Yuvaraj et al,2016).

The extracted bispectrum features are Bispectrum, Cumulant, Element frequency and Lag vectors. Spatial features include Wavelet Coherence mean, Wavelet Coherence SD, Wavelet Cross Spectrum mean, Wavelet Cross Spectrum SD[22].

Bispectrum

$$B(f_1, f_2) = F\left(f_1\right) * F\left(f_2\right) * F^*(f_1 + f_2)$$

7

Where, F denotes the Fourier transform of the signal, and F* its conjugate.

Cumulant

$$K_{nz} = \sum_{i=1-n} a_i^n k_{n, x_n}$$

8

Where, k_{nz} represents the nth order of the obtained variable (z). denotes the nth-order cumulant of the i^{th} component random variable.k_{n, x_n}

Lag vector

$$LV = \left|\langle sign\left[\Delta\emptyset(t_k\right]\rangle\right|$$

9

Where, sign is the signum function that discards phase difference of 0 mod π. The LV ranges between 0 and 1, with 0 indicating no coupling of instantaneous coupling due to volume conduction and 1 indicating true, lagged interaction.

Wavelet Cross spectrum

$$wcs_{jk}^n(t, s) = w_j^n(t, s)\, w_k^n(t, s)\, *$$

10

Where, t is the time and s is frequency (scale), as a result the WCS is complex valued

Wavelet Coherence

$$C(t, f) = \frac{|\sum_{i=-\Delta}^{\Delta} pw_{xy}(T, f, i)|}{\sum_i pw_{xx}(T, f, i) \sum_i pw_{yy}(T, f, i)}$$

11

Where T is the time around which the coherence is calculated, i is the current index, and f is the frequency. The summations are carried around a variable segment size Δ, which is inversely proportional to frequency

Classification

Using fMRI and EEG signal, we have performed classification operation, to identify whether the input is healthy control or Parkinson affected. In An AdaBoost classifier[24], we have used Naive Bayes classifier as base estimator. In this work, we have used n_estimators as 45 and learning rate as 1. The misclassified training samples get more weights, and the test error keeps decreasing even after 700 iterations.

Discussion

The proposed method performs the feasibility of a functional MRI and EEG based computational biomarker, which can quantify the functional connectivity patterns between healthy controls and PD patients. To differentiate PD and HCs, we utilized a novel graph theoretical approach to determine global and nodal measures from rs-fMRI data and Spatial, Bispectrum Features from EEG signals.

The present study examined the topological characteristics of brain functional connectomes among 100 PD and 100 HC subjects. The whole-brain functional connectome was constructed from rs-fMRI using a graph theory approach, which characterizes 160 regions from Dosenbach atlas. The mean correlation matrices were determined for both HC and PD groups. Features are extracted from both EEG and fMRI and given input to Adaboost classifier.

The work is compared with four different earlier works, and we found that our proposed work has received higher accuracy when compared with other works. Table 1 The Comparison of Sensitivity, Specificity, Precision and Performance of the reference papers with proposed paper has been organized and the detailed comparison table is shown below.

Table 1
Comparative analysis of Performance Measures

Work	Sensitivity	Specificity	Precision	Accuracy
Work [1]	75.0	82.5	77.9	75%
Work [3]	88.9	100	82.5	87.25%
Work [11]	88	88.5	97.6	89.75%
Work [12]	89	90.8	100	91.34%
Proposed Work	92.3	95.1	100	93.45%

Conclusion

In this work, by examining the topological organization of functional brain networks and EEG Signals, we have performed classification operation for Normal and PD patients using Adaboost classifier. We have got good accuracy when compared with other works. In future, we can extend the methodology for other psychological disorders. It can help the neurologists in faster and more accurate diagnosis during their screening itself.

Declarations

Conflicts of interest/Competing interests:

We have **no conflicts of interest** to disclose.

Funding:
NA.

Availability of data and material (data transparency): Data available on request from the authors. **Code availability (software application or custom code):** software application

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Figures

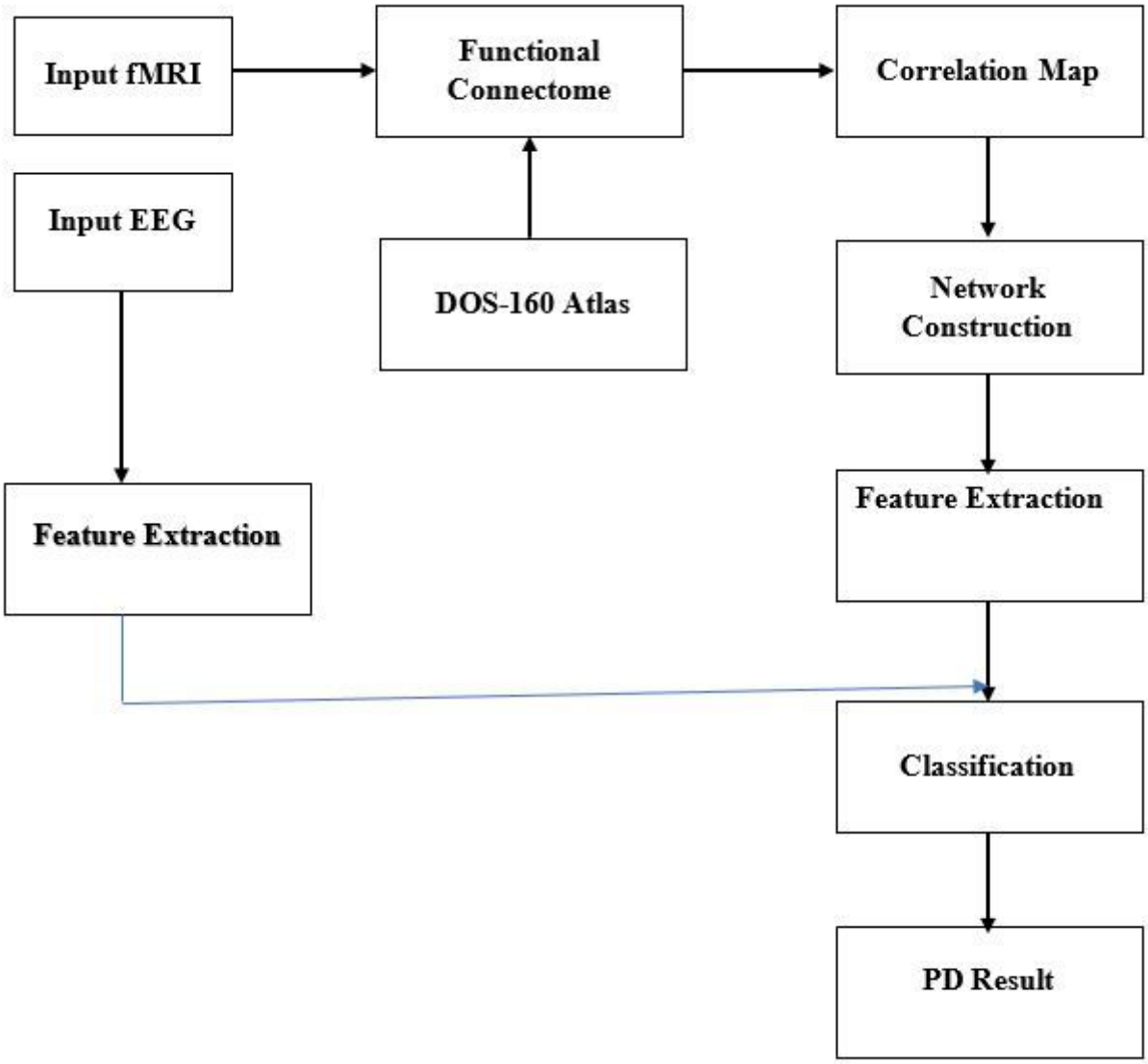

Figure 1

PROPOSED ARCHITECTURE

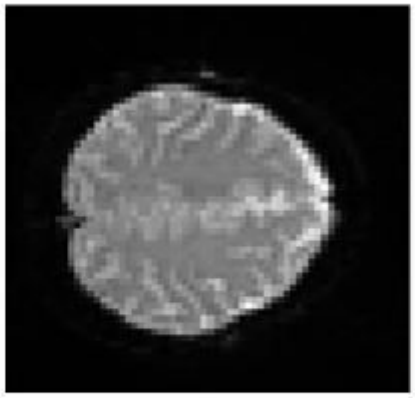

Figure 2

Input image fMRI (Healthy Control)

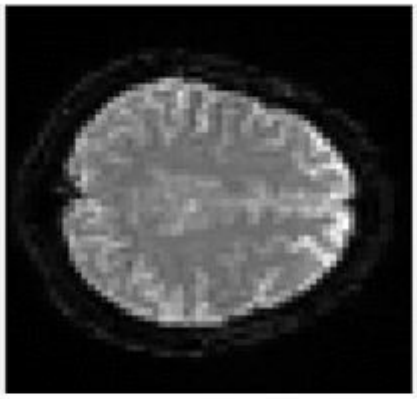

Figure 3

Input image(PD)

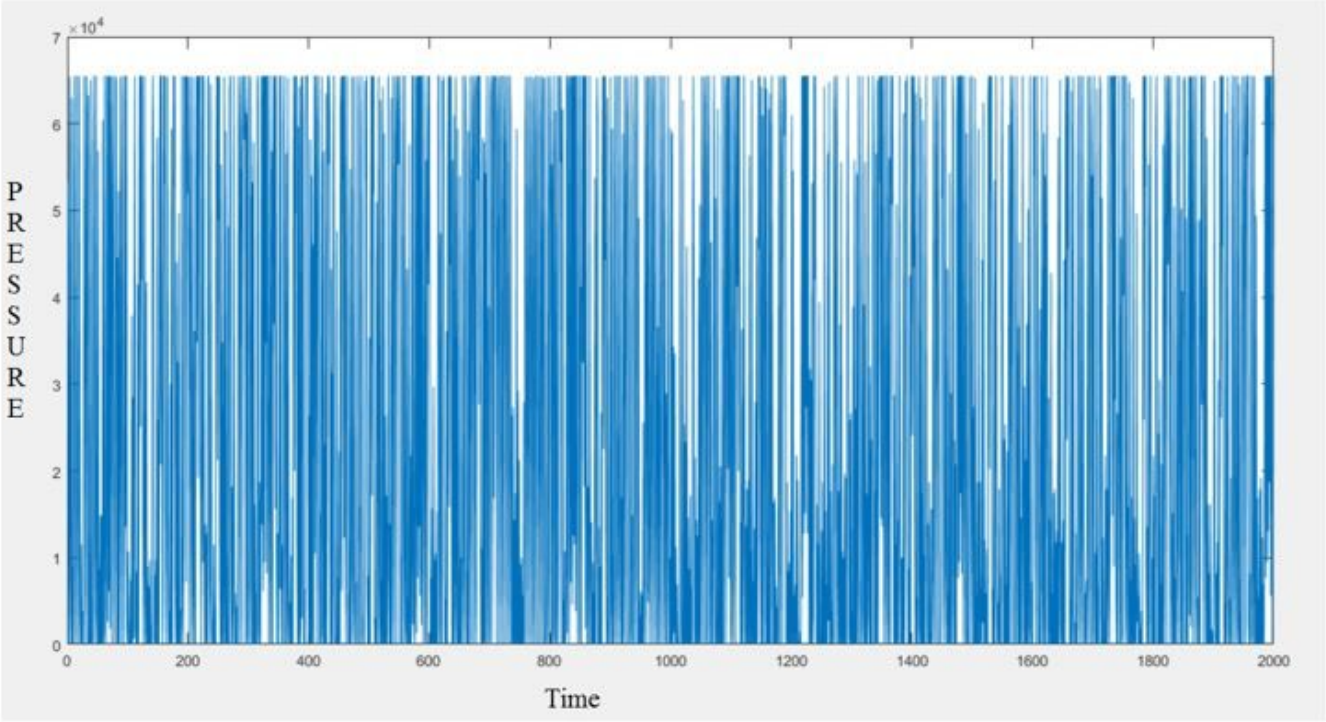

Figure 4

Input image EEG for Healthy Control

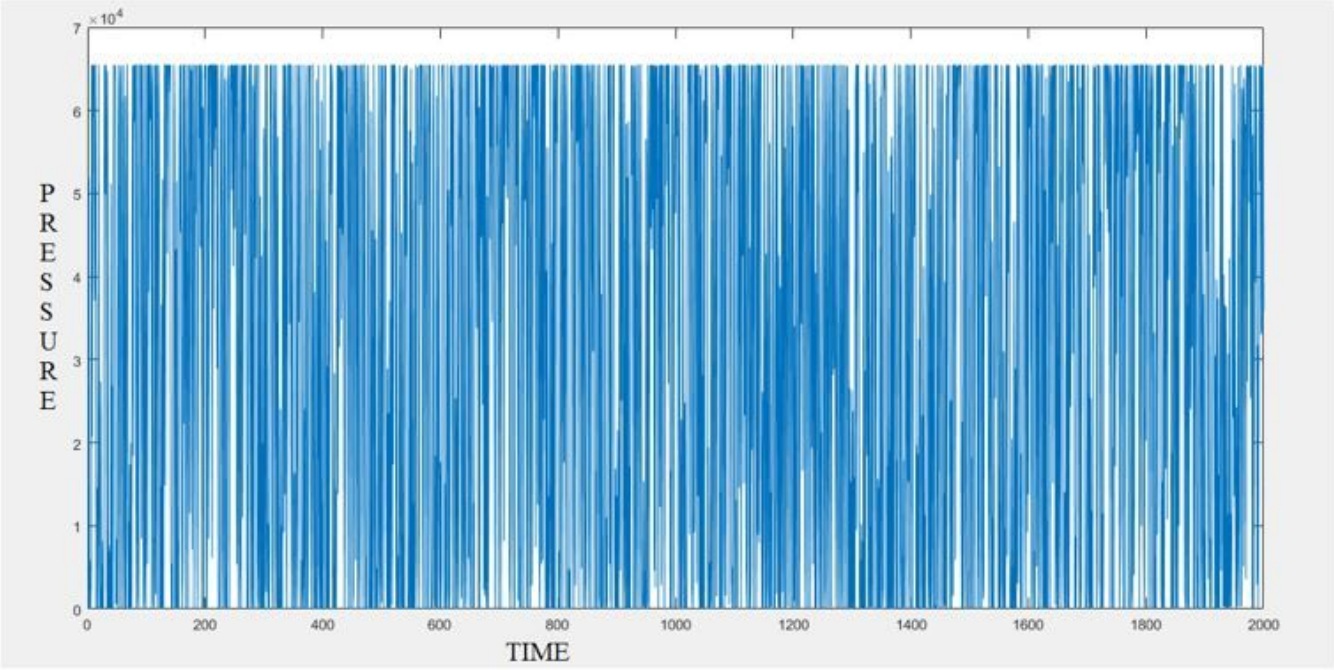

Figure 5

Input image for PD

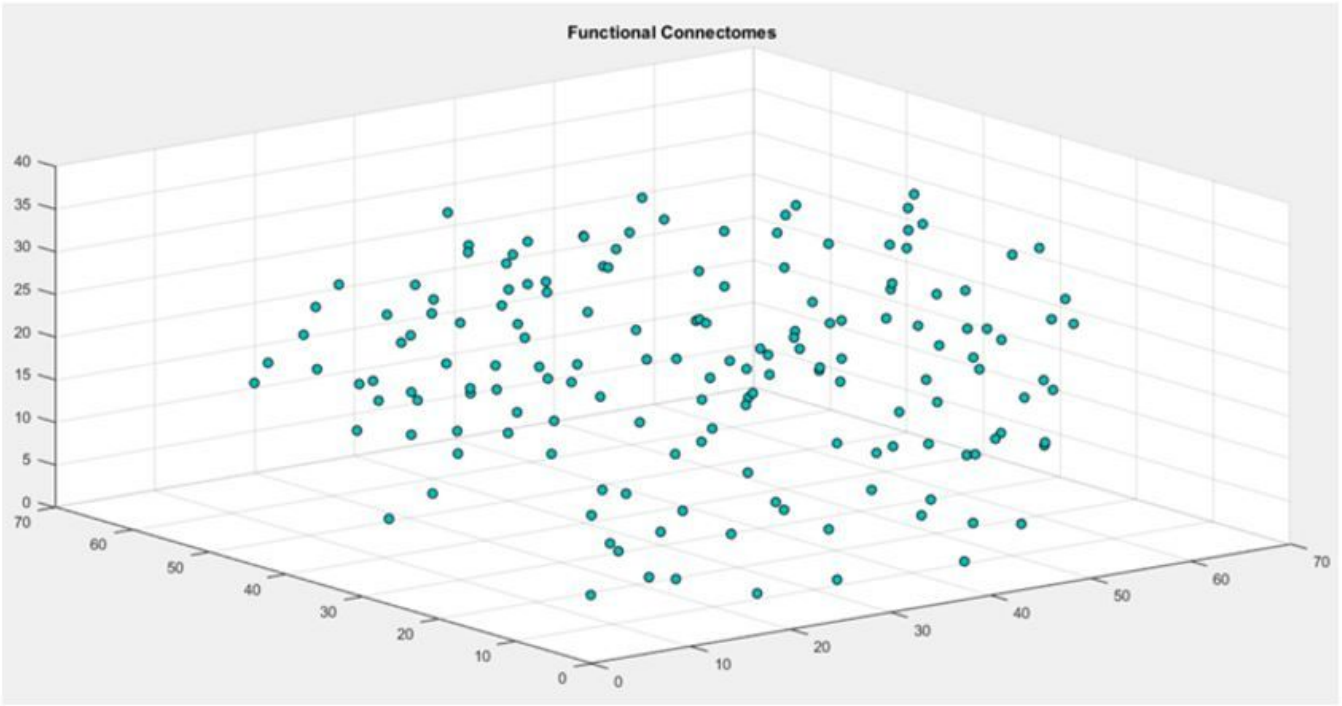

Figure 6

Functional Connectome

Figure 7

Functional Connectivity Matrix for Healthy Control

Figure 8

Functional Connectivity Matrix for PD

Figure 9

Network Construction for Normal case

Figure 10

Network Construction for PD

Figure 11

Analysis of Performance Measure