March - April 2020
ISSN: 0193-4120 Page No. 9967 - 9973

Classification of Parkinson's disease using FBNN Algorithm

M.Bhuvaneswari[1], Anitha Antony[2]
[1]Asst Prof,Dept of ECE ,Karpagam Academy of Higher Education,India
[2]Asst Prof,Dept of ECE, Karpagam College of Engineering, India.
bhuvaneshwari.m@kahedu.edu.in

Article Info
Volume 83
Page Number: 9967 - 9973
Publication Issue:
March - April 2020

Article History
***Article Received**: 24 July 2019*
***Revised**: 12 September 2019*
***Accepted**: 15 February 2020*
***Publication**: 11 April 2020*

Abstract: Parkinson's Disease (PD) one of the movement disorders which occur in the neurological activities, but the diagnosis of disease is quite challenging. Sometimes the diagnosis methods are difficult at the time of considering a large number of motor and non-motor symptoms in PD patients. But it is highly risk to manage PD patients in medical management. To enhance that lot of research are focused on PD for long term approaches. Further this paper contributes the reviews and treatment of Parkinson's disease using MEG signals. Also it concluded with experimental analysis of Feed Back Neural Network (FBNN) with different parametric features.

Keywords: *Magneto encephalography, Parkinson's Disease, Feed Back Neural Network*

I. INTRODUCTION

Magneto encephalography (MEG) is a non-invasive technique which is used to measure the neural activity of brain by recording the magnetic fields generated by electrical current. The MEG is combined with MRI to get an accurate structural perspective and resolution of neuronal activity. This combination is called as magnetic source imaging (MSI). The magnetic field used in magneto encephalography is to measure the brain which is in the range of femto –tesla to pico – tesla. The Parkinson's disease (PD) is a growing neurological disorder which cause serious disability and reduce the quality of life [1].The features of cardinal motor and the response to the dopaminergic therapy are the characteristic signs of PD. The neuro physiological characters related toParkinson's disease (PD) are studied within the motor system and the whole brain using magneto encephalography. The accuracy of clinical diagnosis is around 80 to 90 % [2]. In the analysis of MEG the aim of motor networks are spatially limited to the motor cortex which is performed usually in source space.MEG helps to investigate the underlying mechanisms of hallucinations in PD patients. The frequency-specific neural oscillations in PD patients are studied using MEG with unimodel Visual Hallucination (VH) and compared with multimodal hallucination and without hallucination PD patients. The MEG data of PD patients are recorded using 306 channels (102 magnetometers, 204 gradiometers) with the sample frequency range of 1250Hz [3]. The origin of MEG signals are shown in fig 1 which representing the depolarisation of intracellular and extracellular currents.

II. LITERATURE REVIEW

Abbasi et.al [4],proposes the measures of spectral analysis in unilateral DBS in (both 130 Hz and 340 Hz) that leads to a lowering of alpha and beta power over both sensor motor cortices. These recordings took place the day after surgery with eyes closed and motor improvement was found without correlation. Luoma et.al[5],assigns the alpha lowering and beta band power during DBS ON, only during the resting state when the eyes were open. During eyes-closed or a motor task: No significant difference between ON and OFF stimulation. -Maximum CMC over sensor motor area contra lateral to extended hand.

Airaksinenet.al[6], suggests the STN-DBS modified the coherence of CMC with large inter individual variability, correlation with motor improvement was inconsistent. Hallet.al[7], shows the contra lateral M1 with resting-state beta power than ipsilateral M1 in PD. zolpidem normalized the ratio between left and right. Normalization correlated positively with improvement in UPDRS-III scores. M1 beta power differences during different phases of movement normalized after zolpidem.

Hirschmannet.al[8], cortical sources coherent with oscillations STN in PD DBS patients in the age of 11 to 26. It consists of two bands alpha band and beta band. In Alpha band Ipsilateral temporal regions are located, in beta band Ipsilateralsensor motor and adjacent premotor cortex are located. HeinrichsGraham et.al[9], proposes the PD (DRT OFF) vs. controls with the help of spectral analysis significantly at lower beta band power in bilateral motor regions. After DRT, this largely normalizes. The FC Increased synchronicity between motor and cortices are partially normalized by DRT. HeinrichsGraham et.al[10],suggests the amplitudes response which affects severely to the PD patients suffering from right-dominant disease.

Jha et.al [11], contributes the coherence between alpha and beta band at the age of 9 to 25. In Alpha band coherence between the PPN and posterior brain stem and cingulum. In Beta band coherence between PPN and medial frontal wall, SMA and primary motor cortex. Krause et al[12] , proposes the tACS of the motor cortex at beta frequency (20 Hz), but not at 10 Hz, attenuated beta band CMC during isometric contraction and reduced performance (amplitude variability) of a finger tapping task in PD, but not in controls. Further the performance of PD patients controls on motor task (motor sequence acquisition). During random presentation of the task there are no differences in beta band power. After learning a sequence the less training-related beta power suppression in motor cortex in PD versus HC. In addition, less training related theta activity in cortical motor regions, paralleling susceptibility to inference [13].

Oswal et.al[14], describe theAlpha band coherence between temporal cortical areas and the STN reduced following movement onset. The degree of suppression in is significantly greater ON DRT than OFF DRT.Oswalet.al [15],the DBS relatively selectively suppressed lower beta band synchronization of activity between STN and mesial premotor regions, including SMA. Then, the motor cortical regions “driving” STN in beta band with different delays for lower and higher beta band.TeWoerd et.al, suggest PD patients have demonstrated comparable auditory entrainment as controls. Therefore the deficient entrainment in PD patients concerns the motor circuits only.

March - April 2020
ISSN: 0193-4120 Page No. 9967 - 9973

III. DATA COLLECTION

In this study, data set was acquired to analyze the Parkinson's disease (PD). It consist of totally 161 subjects of which 79 subjects MEG signals with cognitive normal. Three different types of auditory signals were stimulated with 1 K Hz and 2 K Hz. Duration of the presentation of the stimuli is 30 minutes. 16 channel EEG is used to acquire the signal along with the sampling frequency of 256 Hz. The evoked potential response signals were averaged and classified with PD and Cognitive normal.

IV. FEATURE EXTRACTION

Parametric Function

Parametric modelling is a mathematical model that estimates the values of zeros and poles, which provides additional insight about the dynamics of EEG signal more directly. Further, it is also very useful in finding the transition between the normal AD and abnormal AD states. Autoregressive (AR) modelling is a parametric model that can be used to quantify the boundary limits between the AD and non AD transition states of a subject.

Step 1: Let T = { }. where T is a null set or a measure-zero set.

Step 2: For channel c = 1, 2, 3, ..., 19, do steps 3-10

Step3: Consider the EEG signals recorded for 10 seconds from each channel 'c' $x_i^c, i=1,2,3,\dots,2560$

Step 4: Normalize the AEP signals using Equation (1)

$$xn_i^c = \frac{0.8\left(x_i^c - x_{min}\right)}{\left(x_{max} - x_{min}\right)} + 0.1, i=1,2,3,\dots,2560 \quad (1)$$

where, xn_i^c is the normalized data value,

x_i^c is the data to be normalized,

x_{min} is the minimum value from EEG data,

x_{max} is the maximum value from EEG data.

Step 5: For the normalized EEG signals, formulate the AR model for the given order (k) and relation $d(z)$from Equation

$$d(z) = 1 + \sum_{k=1}^{p} a_k z^{-k}$$

V. CLASSIFICATION

The feedback neural network consists of arbitrary functions of neurons which have feedback interactions among different layers, but it is suitable for simple set of neurons. It consists of many feedback connections between the neurons. It is a dynamic network even at evolve in either continuous or discrete time. In general, the fig.1 shows the basic structure of a single-layer feedback network (or) Hopfield network. The loops are introduced in the network to guide their signals from one direction to another direction. Further, this network gives an impression in the input of earlier derived algorithms, and then FBNN will change repeatedly till it attains the state of equilibrium point. When the input of the network is changed then a new equilibrium will be farmed. The architecture of FBNN also referred as interactive or recurrent neural network which is often used to determine the feedback connections in a single layer organization. After, the feedback loops are allowed in networks that are used in content addressable memories.

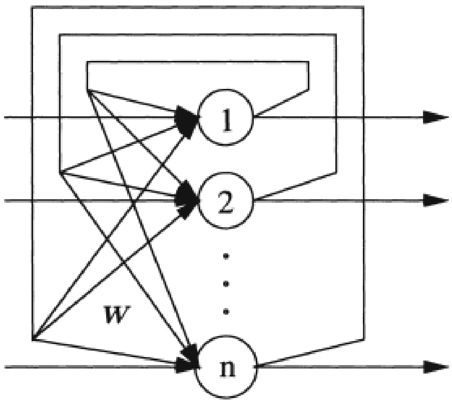

Fig. 1Diagram of Feed Back Neural Network (FBNN) [30]

TEST Engineering & Management

March - April 2020
ISSN: 0193-4120 Page No. 9967 - 9973

VI. RESULT AND DISCUSSION

In order to develop a generalized neural network model, the training samples are randomly selected from the total samples and a neural network is trained. 60% of dataset has been used for training the neural network and the remaining 40% of dataset has been used to test the performances of the neural network.

Table 1: Result analysis of Feedback neural network using MEG signals

Parametric Feature	Accuracy (%)	Sensitivity (%)	Specificity (%)	F measure (%)
AR Pole Tracking with 10^{th} order	89	92	90	88
AR Pole Tracking with 15^{th} order	96	95	93	92
AR Pole Tracking with 20^{th} order	94	92	95	94

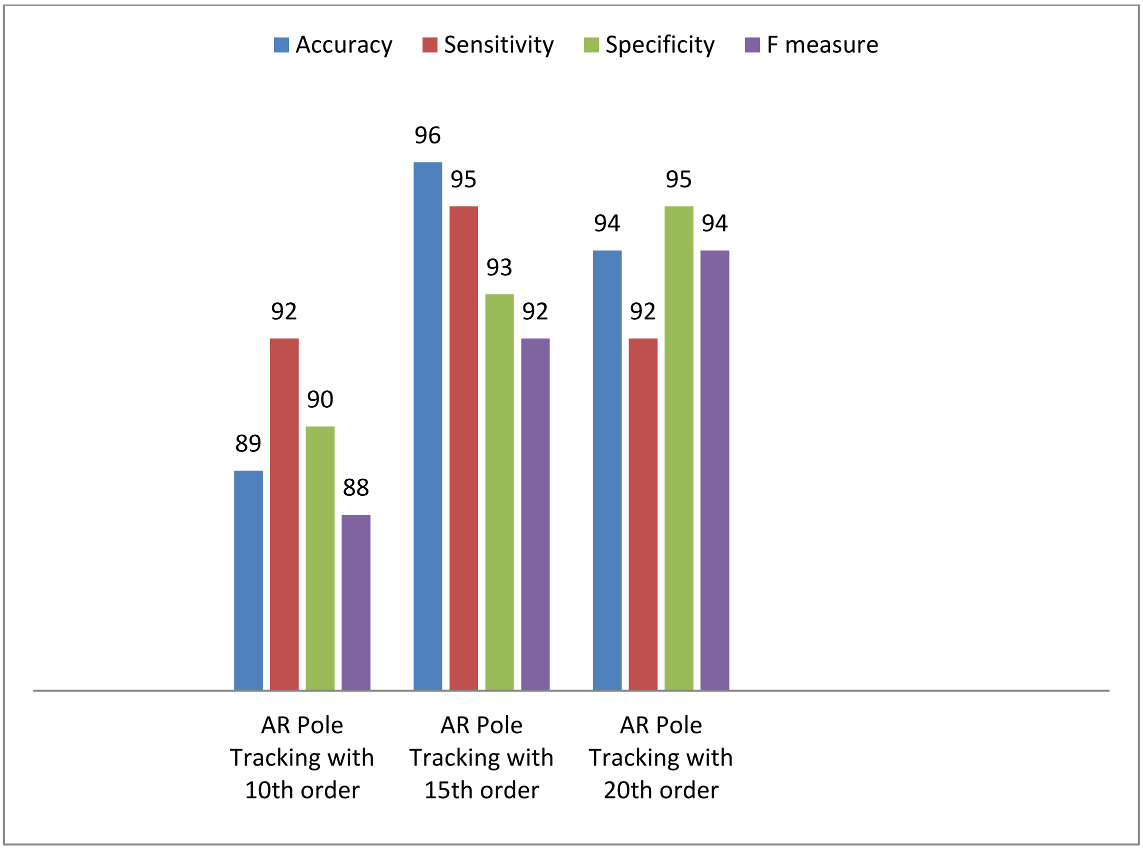

Fig. 2 Performance analysis of MEG signals using FBNN

Four intelligent classification designs are studied using the FBNN for three distinct hearing frequencies name 1 and 2 K Hz. Using feature extraction algorithms, four independent spectral

March - April 2020
ISSN: 0193-4120 Page No. 9967 - 9973

features are extracted for distinct hearing frequencies. For each hearing frequency, using the same spectral energy features extracted from the 16 channels, a neural network model was developed to distinguish the normal and abnormal AD states. While developing this model the same spectral band feature is extracted from each channel and fed as input to the network model. The developed neural network model has 16 input neurons and an output neuron. Through simulation the number of hidden neurons is chosen. First, using too many neurons in the hidden layer results in over fitting and using few neurons in the hidden layer results in under fitting. The hidden neurons and output neurons are activated using log sigmoid activation functions. Training is conducted until the average error falls below 0.01 or reaches a maximum epoch limit of 10000. Testing error tolerance is set at 0.1. For each trial, the network is trained for ten times using the dataset and the classification performance is observed.

From the Table 1, it can be observed that AR pole tracking with 15^{th} order using MFNN reported the highest classification accuracy of 97.5 per cent and the AR pole tracking with 5^{th} order using FBN reported the lowest classification accuracy of 88 per cent. It was also noted that AR pole tracking with 15^{th} order using FBNN has obtained specificity 97%, sensitivity 94% and F measure 91%. From the Table 1, it indicates that AR pole tracking with 5^{th} order using FBNN has obtained specificity 90, sensitivity 88% and F measure 84%.

The performance analyses graph as shown in Fig.3. It observes the values of accuracy, sensitivity, specificity and F measure which obtained from the parametric feature of Feedback Neural Network (FBNN).

VII. CONCLUSION

Parkinson's disease (PD) one of the movement disorder which occur in the neurological activities, but the diagnosis of disease is quite challenging. However, this paper represents the review and experimental analysis on Parkinson’s disease using FBNN algorithm.

REFERENCES

[1]. Gómez, Carlos,Dubbelink, Kim ,Stam, Cornelis,Abásolo, Daniel,Berendse, Henk, Hornero, Roberto, Complexity Analysis of Resting-State MEG Activity in Early-Stage Parkinson’s Disease Patients,Annals of biomedical engineering,Vol.39.2011.

[2]. Sanjay P Singh, ‘Magnetoencephalography: Basic Principles’, 2014.

[3]. Victor J Geraedts, Arjan Hillebrand, ‘A systematic review of MEG-based studies in Parkinson’s disease: The motor system and beyond’, 2019.

[4]. M Dauwan, E M Vriens, ‘Aberrant resting-state oscillatory brain activity in Parkinson’s disease patients with visual hallucinations: An MEG source-space study’, 2019.

[5]. Jarkko Luomaa, Eero Pekkonenb, ‘Spontaneous sensorimotor cortical activity is suppressed by deep brain stimulation in patients with advanced Parkinson’s disease’, 2018.

[6]. Katja Airaksinen , Jyrki P Mäkelä , ‘ Cortico-muscular coherence in advanced Parkinson’s disease with deep brain stimulation’,2014.

[7]. Emma L. Hall, Siân E. Robson, Peter G. Morris, ‘the Relationship between MEG and MRI: A Review Article for the Special Issue of NeuroImage on Multi-Modal Data Fusion ‘, 2014.

[8]. Hirschmann J, Ozkurt TE, ‘Distinct oscillatory STN-cortical lopps revealed by simultaneous MEG and local field potential

March - April 2020
ISSN: 0193-4120 Page No. 9967 - 9973

recordings in patients with Parkinson's disease',2011.
[9]. Elizabeth Heinrichs Graham, Max J Kurz, 'Hypersynchrony despite pathologically reduced beta oscillations in patients with parkinson's disease: a pharmaco Magnetoencephalography study', 2014.
[10]. Elizabeth Heinrichs Graham, Pamela M Santamaria, 'The cortical signature of symptom laterality in Parkinson's disease', 2017.
[11]. Ashwani Jha, Vladimir Litvak, 'Functional Connectivity of the Pedunculopontine Nucleus and Surrounding region in Parkinson's Disease', Vol.27, 2017.
[12]. Vanessa Krause, Claudia Wach, 'Cortico muscular coupling and motor performance are modulated by 20 Hz transcranial alternating current stimulation (tACS) in Parkinson's disease', 2013.
[13]. Sarah Nadine Meissner, Vanessa Krause, 'the significance of brain oscillation in motor sequence learning: Insights from Parkinson's disease', 2018.
[14]. Ashwini Oswala b, Peter Browna , 'Synchronized neural oscillations and the pathophysiology of Parkinson's disease', 2013.
[15]. Ashwini Oswal, Martijn Beudel, 'Deep brain stimulation modulates synchrony within spatially and spectrally distinct resting state networks in Parkinson's disease', Vol.139, 2016.
[16]. Revathi, P., &Hemalatha, M. (2012, December). Classification of cotton leaf spot diseases using image processing edge detection techniques. In 2012 International Conference on Emerging Trends in Science, Engineering and Technology (INCOSET) (pp. 169-173). IEEE.
[17]. Perumal, P. C., Sowmya, S., Pratibha, P., Vidya, B., Anusooriya, P., Starlin, T., ...&Gopalakrishnan, V. K. (2014). Identification of novel PPARγ agonist from GC-MS analysis of ethanolic extract of Cayratiatrifolia (L.): a computational molecular simulation studies. J App Pharm Sci, 4, 006-011.
[18]. Suganya, S., Narmadha, R., Gopalakrishnan, V. K., &Devaki, K. (2012). Hypoglycemic effect of Costuspictus D. Don on alloxan induced type 2 diabetes mellitus in albino rats. Asian Pacific Journal of Tropical Disease, 2(2), 117-123.
[19]. Kumar, R. S., Ali, M. A., Osman, H., Ismail, R., Choon, T. S., Yoon, Y. K., ...&Manogaran, E. (2011). Synthesis and discovery of novel hexacyclic cage compounds as inhibitors of acetylcholinesterase. Bioorganic & medicinal chemistry letters, 21(13), 3997-4000.
[20]. Kalaiselvi, C., &Nasira, G. M. (2015). Prediction of heart diseases and cancer in diabetic patients using data mining techniques. Indian Journal of Science and Technology, 8(14), 1.
[21]. Ramkumar, S., SatheshKumar, K., &Emayavaramban, G. (2016). EOG signal classification using neural network for human computer interaction. International Journal of Computer Theory and Applications, 9(24), 223-231.
[22]. Wan, X., Zhang, K., Ramkumar, S., Deny, J., Emayavaramban, G., Ramkumar, M. S., & Hussein, A. F. (2019). A Review on Electroencephalogram Based Brain Computer Interface for Elderly Disabled. IEEE Access, 7, 36380-36387.
[23]. Emayavaramban, G., &Amudha, A. (2016). sEMG Based Classification of Hand Gestures using Artificial Neural Networks. Indian Journal of Science and Technology, 9(35), 1-10.
[24]. Fang, S., Hussein, A. F., Ramkumar, S., Dhanalakshmi, K. S., &Emayavaramban, G.

(2019). Prospects of Electrooculography in Human-Computer Interface Based Neural Rehabilitation for Neural Repair Patients. IEEE Access, 7, 25506-25515.

[25]. Emayavaramban, G., &Amudha, A. (2016). Recognition of sEMG for Prosthetic Control using Static and Dynamic Neural Networks. International Journal of Control Theory and Applications, 2(6), 155-165.

[27]. Krishnan, M. S., Ragavi, S., RamKumar, M. S., &Kavitha, D. (2019). Smart Asthma Prediction System using Internet of Things. Indian Journal of Public Health Research & Development, 10(2), 1103-1107.

[28]. G. Emayavaramban, A. Amudha*, Rajendran T., M. Sivaramkumar, K. Balachandar, T. Ramesh. “Identifying User Suitability in sEMG Based Hand Prosthesis Using Neural Networks” in Current Signal Transduction Therapy , (Pubmed& Scopus Indexed) **DOI** : 10.2174/157436241366618060410054 2

[29]. MP Paulraj, SB Yaccob, A Hamid, B Adom, K Subramaniam, CR Hema , EEG based hearing threshold classification using fractal feature and neural network, , 2012 IEEE Student Conference on Research and Development (SCOReD), 38-41,2012

[30]. KamalrajSubramaniam, Nisheena V Iqbal, Classification of fractal features of uterine EMG signal for the prediction of preterm birth, Biomedical and Pharmacology Journal, VOI 11, 369-374, 2018.

[26]. Ramkumar, S., Emayavaramban, G., Kumar, K. S., Navamani, J. M. A., Maheswari, K., &Priya, P. P. A. (2020). Task Identification System for Elderly Paralyzed Patients Using Electrooculography and Neural Networks. In EAI International Conference on Big Data Innovation for Sustainable Cognitive Computing (pp. 151-161). Springer, Cham.