International Journal of Master of Engineering Research and Technology, 2394-6172-(O)
Volume-7, Issue-12, December 2020

Analysis of Motor Imagery EEG Classification Based on Neural Network

Abhilash Lilhore
M. Tech. Scholar
Digital Communication
PCST, Bhopal (M.P.)

Prof. Jitendra Mishra
Associate Professor & HOD
Department of Electronics & Communication
PCST, Bhopal (M.P.)

ABSTRACT

. This paper proposed the neural network-based classification algorithms for the prediction of EEG signals bands. The neural network algorithm is a variant of a multilayer neural network for the extraction of features used discrete wavelet transform function. The discrete wavelet transform function decomposed the electroencephalogram signal in different sub-bands for the processing. The represent bands into varied frequency range. The proposed algorithms are simulated in MATLAB software and used the standard dataset of BCI competition-IV dataset for the analysis of performance. The proposed algorithm compares with machine learning classifiers for disease detection. The performance of the proposed algorithms improved the efficiency of the brain-computer interface system.

'**Keywords: -** EEG classification, ALS, DWT, Neural Network, Deep learning

Introduction

The immediate goal of a BCI system is to provide these users with basic communication capabilities, so that they can express their wishes to caregivers or even operate word processing programs or neuropores theses. It is obvious that a BCI system could improve their quality of life, while at the same time reduce the cost of intensive care. Although some non-invasive technologies provide a higher spatial resolution (e.g. fMRI), the EEG has proved to be the most popular method due to direct measures of neural activity, inexpensiveness, and portability for clinical use. EEG measures electrical brain activity caused by the flow of electric currents during synaptic excitations of neuronal dendrites, especially in the cortex, but also in the deep brain structures. The electric signals are recorded by placing electrodes on the scalp. EEG signals have been used to control devices such as wheelchairs and communication aid systems[2, 3, 4]. During the past decade, EEG methods have also become a promising approach in controlling assistive and rehabilitation devices. EEG signals could provide a pathway from the brain to various external devices resulting in brain-controlled assistive devices for disabled people and brain-controlled rehabilitation devices for patients with strokes and other neurological deficits. The soft computing algorithms play an important role in classification of EEG classification. The classification process categories the signal group and easily decode the behaviors of human brain. The feature extraction and selection are also major challenge in motor imagery EEG signals. For the extraction of features used various transform function such as fast Fourier transform function, DWT function and many others function [5, 6]. In the rest part of this paper, divided into five sections: section II-feature extraction, section III-proposed methodology, section IV-result analysis & discussion and finally discuss the conclusion & future work in section V.

II Feature Extraction

Feature extraction of EEG data is basic phase of motor imagery classification. For the extraction of features used wavelet transform function. The wavelet transform function is collection of to represent or approximate signals or methods[7, 15]. This process of function derived from basic wavelet transform function is called mother wavelet transform function. The transform coefficient can be approximated to the original signal. The wavelet transform describes the local nature of signals in both time and frequency domains. The continuous wavelet transforms function of signal x(t) is defined as

$$WTx(a,\tau)\frac{1}{\sqrt{a}}\int_{-\infty}^{\infty}x(t)\psi\left(\frac{t-\tau}{a}\right)dt \dots\dots\dots(1)$$

Where a represent scale factor, τ represent time factor and $\psi(t)$ is a wavelet basis function, including all family of wavelet transform function.

EEG data signal are non-stationary signals, so DWT are good option for discreet wavelets. The DWT function define as

$$WT_{x(J.k)=\int x(t)\psi j,k(t)dt} \dots\dots\dots\dots\dots\dots\dots.(2)$$

According to the process of sampling, the maximum frequency of the signal is fs/2. If the signal is decomposed by lower order, the complete frequency signal decomposed into L+1 sub band. The wavelet decomposition layer shown in figure

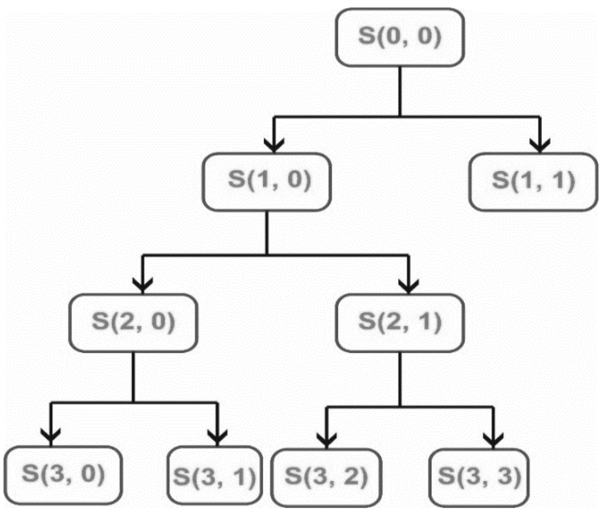

Figure 1: Describe the process of 3 level decomposition of EEG signals data with DWT transform function.

III Proposed Methodology

A neural network defines the relationship of nonlinear between two variables P and Pi+1 through network function. The process of function defines as

$$Pi + 1 = \delta(wpi + b) \dots\dots\dots\dots\dots\dots\dots\dots (1)$$

Where δ is activation function and matrix W and b is called model parameters. The variable P and Pi+1 is from of layers. the multilayer neural network argumenta with advance learning called deep neural network. The classification of network defines as y=f(u). the process of network function defines as

P1= δ1(w1u+b1)

P2= δ2(w2p1+b2)

….

………

Y= δL(wLpL-1+bL)

Where L is number of layers

Process of training of DNN.

The relation of neurons defines the process of EEG data

$F_k : R^{n_x} \rightarrow R^{n_x}$, where $x_k \in R^{n_x}$

Be the set of EGG data in neurons for the processing.

Hypothesis of error estimated by E

$$E_j = H_j\left(x_j\right) + v_j, \quad \forall\, k \le j \le k + A$$

where $H_j: R^{n_x} \rightarrow R^{n_y}$ is the relation of multilayer input?

estimate trained pattern

$$x_k = F_0 \rightarrow k(x_0) + \xi k$$

3 define learning factor as

$$x_k = arg\min_x \left\{ \|x - x_k\|\, B_k^{-1} + \sum_{j=k}^{k+A} \left\|H_j F_j(x) - y_j\right\| R_j^{-1} \right\}$$

Algorithm

Define $i = 0$

while $i < L$ do

process the TLBO optimal data of EEG signals and M is vector of convergence

$$\{x_k \text{ I } k \in [M.i, M.(i+1)]\}$$

$$x_k = arg\min_x \left\{ \|x - x_k\| P_k^{-1} + \sum_{k}^{k+p} \left\|H_j\, M_j, (x)\right\| p_j^{-1} \right\}$$

Generates the channel of ALS $= \{Fs(x_{k-1}),\ x_k\}$ with $k \in [i.M, (i+1).M]$

Measure i for next step

end

Output: $EEG\ classifed$

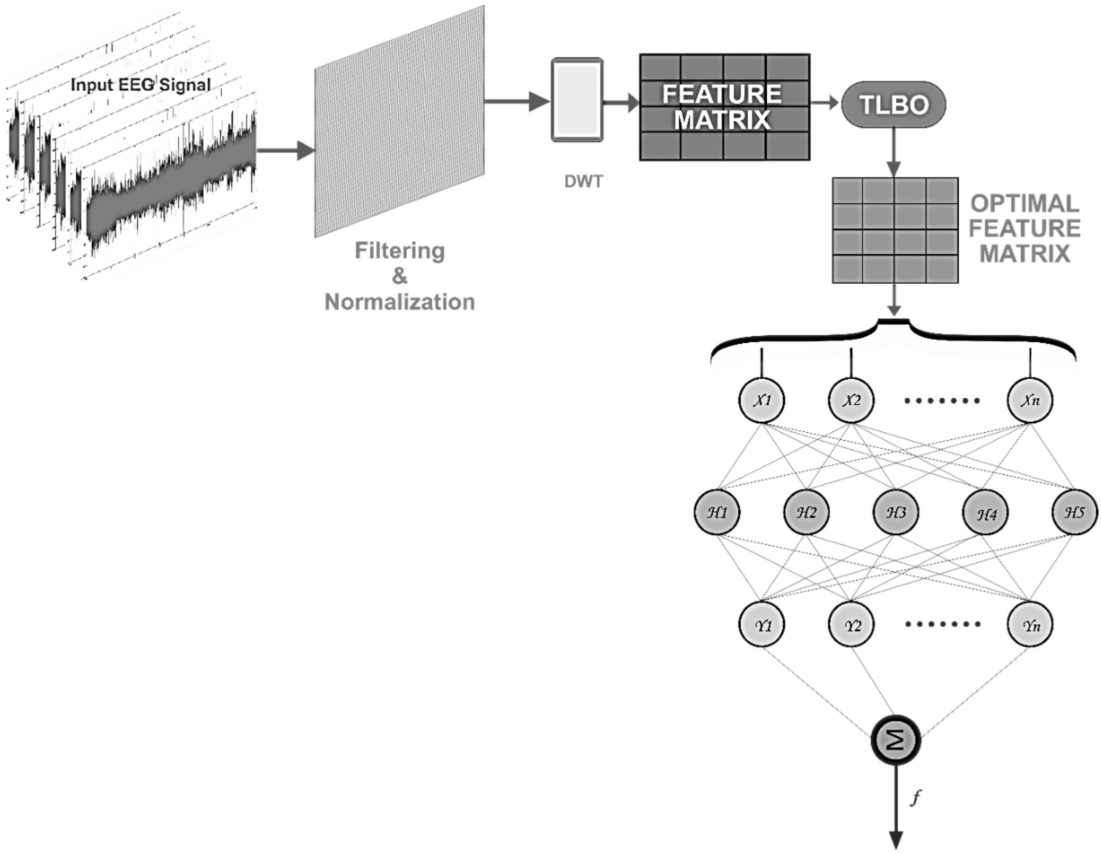

Figure 2: Process block diagram of EEG signal classification with deep neural network.

IV Result Analysis & Discussion

PERFORMANCE PARAMETERS

$$Accuracy = \frac{Total\ No.of\ Correctly\ Classified\ Instances}{Total\ No.of\ Instances} \times 100$$

$$Precision = \frac{TP}{TP + FP} \times 100$$

$$Sensitivity = \frac{TP}{TP + FN} \times 100$$

$$Specificity = \frac{TN}{TN + FP} \times 100$$

- TP: True Positive
- TN: True Negative
- FP: False Positive
- FN: False Negative

Analysis of EEG classification of data used three methods BN[18, 19], EBL[16, 17] and DNN[3]. The methods of classification used the optimal feature selection of different bands of data and raw signal as input for the process of classification[24, 25]. The description of classification result discusses here[26-30].

Signal	BN		EBL		DNN	
	16 DF (Dimension Features)	8 DF (Dimension Features)	16 DF (Dimension Features)	8 DF (Dimension Features)	16 DF (Dimension Features)	8 DF (Dimension Features)
Raw	88.69	89.91	90.26	91.25	93.61	94.52
Delta	86.38	88.34	89.34	90.42	93.44	95.64
Theta	89.47	91.22	92.24	93.34	95.51	96.02
Alpha	85.24	88.65	89.35	90.05	92.36	93.24
Beta	86.24	89.36	91.50	92.89	94.25	95.61

Table 1: Comparative analysis of Accuracy using BN(Bayesian networks), EBL(Ensembled Machine Learning) and DNN(Deep Neural Network) with 16-dimension and 8-dimension features. Here we all five signal bands: raw signal, delta signal, theta signal and beta single of electroencephalogram.

Signal	**BN**		**EBL**		**DNN**	
	16 DF (Dimension Features)	8 DF (Dimension Features)	16 DF (Dimension Features)	8 DF (Dimension Features)	16 DF (Dimension Features)	8 DF (Dimension Features)
Raw	75.56	78.67	79.64	82.65	85.45	88.48
Delta	76.44	79.24	80.55	81.34	84.45	90.35
Theta	78.41	83.12	84.08	86.25	87.47	92.47
Alpha	74.63	80.51	82.24	84.78	85.36	89.36
Beta	79.49	83.68	85.31	86.64	89.79	92.79

Table 2: Comparative analysis of Precision using BN(Bayesian networks), EBL(Ensembled Machine Learning) and DNN(Deep Neural Network) with 16-dimension and 8-dimension features. Here we all five signal bands: raw signal, delta signal, theta signal and beta single of electroencephalogram.

Signal	**BN**		**EBL**		**DNN**	
	16 DF (Dimension Features)	8 DF (Dimension Features)	16 DF (Dimension Features)	8 DF (Dimension Features)	16 DF (Dimension Features)	8 DF (Dimension Features)
Raw	85.26	88.49	89.55	92.64	95.37	98.48
Delta	86.41	89.26	90.34	91.47	94.61	96.45
Theta	88.26	93.26	94.62	96.62	97.34	98.47
Alpha	84.39	90.34	92.47	94.34	95.47	97.65
Beta	89.47	93.48	95.64	96.66	98.67	99.08

Table 3: Comparative analysis of Sensitivity using BN(Bayesian networks), EBL(Ensembled Machine Learning) and DNN(Deep Neural Network) with 16-dimension and 8-dimension features. Here we all five signal bands: raw signal, delta signal, theta signal and beta single of electroencephalogram.

Signal	**BN**		**EBL**		**DNN**	
	16DF (Dimension Features)	8 DF (Dimension Features)	16 DF (Dimension Features)	8 DF (Dimension Features)	16 DF (Dimension Features)	8 DF (Dimension Features)
Raw	83.56	84.74	86.63	87.95	90.68	93.48
Delta	80.65	86.41	89.36	92.58	94.48	96.67
Theta	82.55	88.72	89.24	92.26	95.52	98.62
Alpha	80.13	89.61	89.59	93.75	94.75	95.34
Beta	84.64	86.69	88.41	90.61	91.28	98.65

Table 4: Comparative analysis of Specificity using BN(Bayesian networks), EBL(Ensembled Machine Learning) and DNN(Deep Neural Network) with 16-dimension and 8-dimension features. Here we all five signal bands: raw signal, delta signal, theta signal and beta single of electroencephalogram.

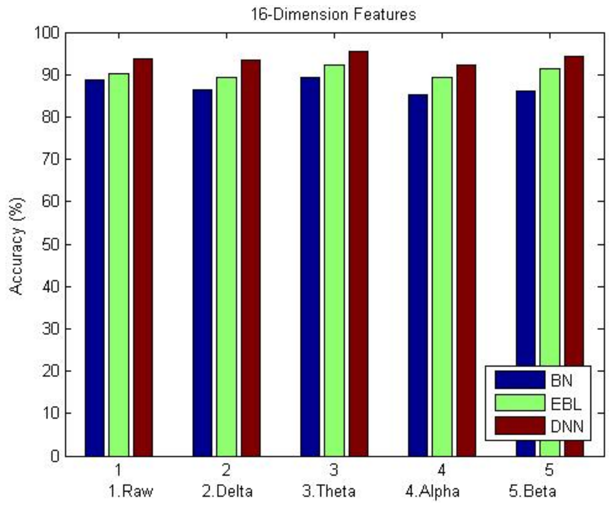

Figure 3: Comparative analysis of Accuracy using BN, EBL and DNN with 16-dimension features. Here we all five signal bands: raw signal, delta signal, theta signal and beta single of electroencephalogram with respect to accuracy. DNN has a higher accuracy in comparation of other two method BN and EBL.

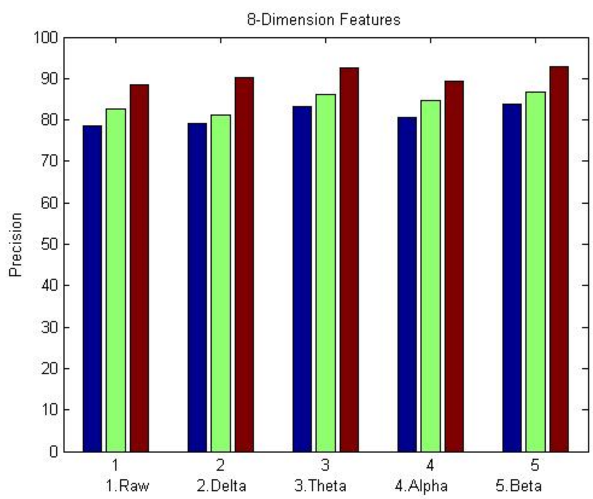

Figure 4: Comparative analysis of Precision using BN, EBL and DNN with 8-dimension features. Here we all five signal bands: raw signal, delta signal, theta signal and beta single of electroencephalogram with respect to Precision. DNN has a higher accuracy in comparation of other two method BN and EBL. The 8-dimension feature has more Precision in the scenario of 16-diamention features.

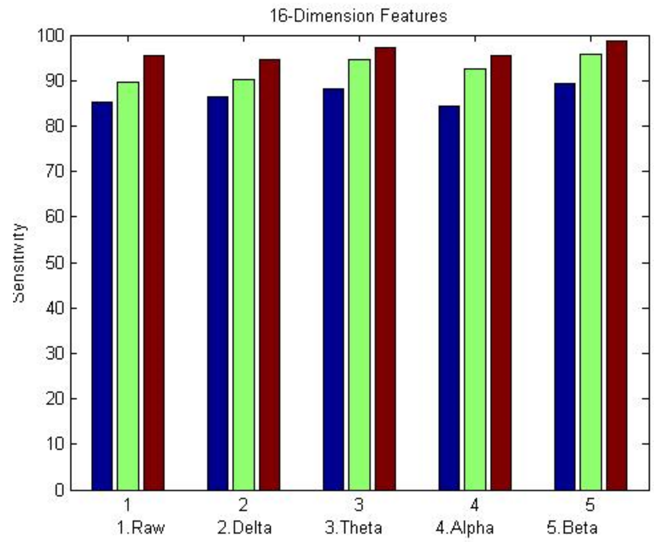

Figure 5: Comparative analysis of Sensitivity using BN, EBL and DNN with 16-dimension features. Here we all five signal bands: raw signal, delta signal, theta signal and beta single of electroencephalogram with respect to Sensitivity. DNN has a higher Sensitivity in comparation of other two method BN and EBL.

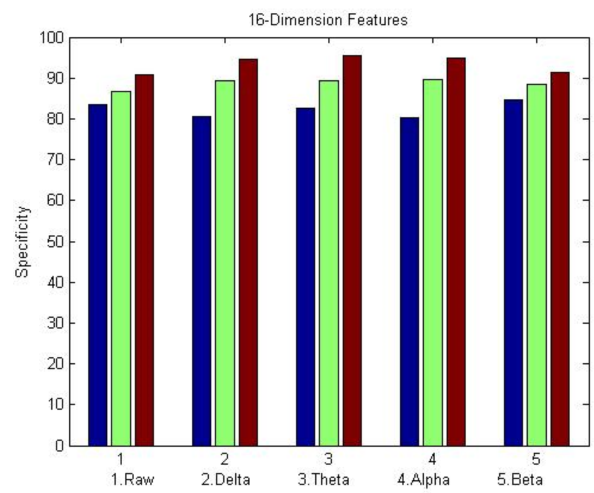

Figure 6: Comparative analysis of Specificity using BN, EBL and DNN with 16-dimension features. Here we all five signal bands: raw signal, delta signal, theta signal and beta single of electroencephalogram with respect to Specificity. DNN has a higher Specificity in comparation of other two method BN and EBL.

V Conclusion & Future Work

This paper proposed neural network-based methods for the classification of motor imagery EEG classification. the proposed algorithm is very efficient and increase the classification and detection ratio of EEG signals band with respect of target of alpha, beta, gamma and delta. The process of feature extraction based on discrete wavelet transforms methods. The methods of feature extraction compromised with noise intensity and deflect the classification ratio. In future minimize the noise of transform function and increase the classification accuracy.

References

[1] Yu Zhang, Guoxu Zhou, Jing Jin, Qibin Zhao, Xingyu Wang and Andrzej Cichocki "Sparse Bayesian Classification of EEG for Brain Computer Interface", IEEE, 2020, Pp 1-13.

[2] Leonard J. Trejo, Karla Kubitz, Roman Rosipal, Rebekah L. Kochavi and Leslie D. Montgomery "EEG-Based Estimation and Classification of Mental Fatigue", Psychology, 2019, Pp 572-589.

[3] Haider Raza, Hubert Cecotti and Girijesh Prasad "Optimising Frequency Band Selection with Forward-Addition and Backward-Elimination Algorithms in EEG-based Brain-Computer Interfaces", IJCNN, 2019, Pp 1-8.

[4] Jeong-Hwan Lim, Jun-Hak Lee, Han-Jeong Hwang, Dong Hwan Kim, Chang-Hwan Im "Development of a hybrid mental spelling system combining SSVEP-based brain computer interface and webcam-based eye tracking" Biomedical Signal Processing and Control, 2019, Pp 99-104.

[5] Laura Acqualagna, Sebastian Bosse, Anne K Porbadnigk, Gabriel Curio, Klaus-Robert Müller, Thomas Wiegand and Benjamin Blankertz "EEG-based classification of video quality perception using steady state visual evoked potentials (SSVEPs)", J. Neural Eng., 2020, Pp 1-17.

[6] Dilshad Begum, K. M. Ravikumar, James. Mathew and Sanjeev Kubakaddi "EEG Based Patient Monitoring System for Mental Alertness Using Adaptive Neuro-Fuzzy Approach", Journal of Medical and Bioengineering, 2019, Pp 59-66.

[7] James J. S. Norton, Dong Sup Leeb, Jung Woo Leed, Woosik Lee, Ohjin Kwon and Phillip Won "Soft, curved electrode systems capable of integration on the auricle as a persistent brain computer interface", PNAS Early Edition, 2020, Pp 1-6.

[8] Feifei Qi, Yuanqing Li and Wei Wu "RSTFC: A Novel Algorithm for Spatio-Temporal Filtering and Classification of Single-Trial EEG", IEEE, 2019, Pp 3070-3082.

[9] Minho Kim, Byung Hyung Kim and Sungho Jo "Quantitative Evaluation of a Low-Cost Noninvasive Hybrid Interface Based on EEG and Eye Movement", IEEE, 2018, Pp 159-168.

[10] Oana Diana Eva and Anca Mihaela Lazar "Comparison of Classifiers and Statistical Analysis for EEG Signals Used in Brain Computer Interface Motor Task Paradigm", International Journal of Advanced Research in Artificial Intelligence, 2019, Pp 8-12.

[11] Chi Zhang, Li Tong, Ying Zeng, Jingfang Jiang, Haibing Bu, Bin Yan and Jianxin Li "Automatic Artifact Removal from Electroencephalogram Data Based on A Priori Artifact Information", Hindawi Publishing Corporation, 2018, Pp 1-9.

[12] Younghak Shin, Seungchan Lee, Minkyu Ahn, Hohyun Cho, Sung Chan Jun and Heung-No Lee "Noise Robustness Analysis of Sparse Representation based Classification Method for Non-stationary EEG Signal Classification", IEEE, 2020, Pp 1-10.

[13] Huijuan Yang, Siavash Sakhavi, Kai Keng Ang and Cuntai Guan "On the Use of Convolutional Neural Networks and Augmented CSP Features for Multi-class Motor Imagery of EEG Signals Classification", IEEE, 2019, Pp 1-4.

[14] Ye Liu, Qibin Zhao and Liqing Zhang "Uncorrelated Multiway Discriminant Analysis for Motor Imagery EEG Classification", International Journal of Neural Systems, 2019, Pp 1-14.

[15] Amirhossein S. Aghaei, Mohammad Shahin Mahanta and Konstantinos N. Plataniotis "Separable Common Spatio-Spectral Patterns for Motor Imagery BCI Systems", IEEE, 2018, Pp 15-29.

[16] Luis F. Nicolas-Alonso, Rebeca Corralejo, Javier Gomez-Pilar, Daniel Ãlvarez and Roberto Hornero "Adaptive Stacked Generalization for Multiclass Motor Imagery-based Brain Computer Interfaces", IEEE, 2019, Pp 1-11.

[17] Noman Naseer, Nauman Khalid Qureshi, Farzan Majeed Noori and Keum-Shik Hong "Analysis of Different Classification Techniques for Two-Class Functional Near-Infrared Spectroscopy-Based Brain-Computer Interface", Hindawi Publishing Corporation, 2020, Pp 1-12.

[18] Hongfei Ji, Jie Li, Rongrong Lu, Rong Gu, Lei Cao and Xiaoliang Gong "EEG Classification for Hybrid Brain-Computer Interface Using a Tensor Based Multiclass Multimodal Analysis Scheme", Hindawi Publishing Corporation, 2020, Pp 1-16.