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Analysis of Motor Imagery EEG Classification methods based on Feature Optimization

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***Abstract*— Motor Imagery (MI) electroencephalography (EEG) is widely studied for its non-invasiveness, easy availability, portability, and high temporal resolution. As for MI EEG signal processing, the high dimensions of features represent a research challenge. It is necessary to eliminate redundant features, which not only create an additional overhead of managing the space complexity, but also might include outliers, thereby reducing classification accuracy. In order to improve the brain-computer interface, I am using the neural network model's feature selection and reduction procedure. In this research, deep learning-based classification algorithms for ALS illness prediction were developed. A multilayer neural network variation, the deep learning technique uses the discrete wavelet transform function to retrieve information. 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 ALS diseases for the analysis of performance. The proposed algorithm compares with Bayesian-based neural network and ensemble-based machine learning classifiers for ALS disease detection. The performance of the proposed algorithms improved the efficiency of the brain-computer interface system.**

Keywords*— Motor Imagery,Electroencephalography, Brain–Computer Interface, ALS,BCI,MATLAB.

I. INTRODUCTION

Brain computer interface provides platform for the analysis of human physical and kinetics behaviours analysis. Motor imagery based BCI is a very productive communication method for people with motor disabilities. Motor Imagery (MI) is a mental process wherein the subject imagines that he is performing a specific motor action such as a hand or foot movement without otherwise performing it in reality. Electroencephalogram (EEG) signals are used as inputs to BCI systems. EEG signals are feature extracted in order to overcome the contaminations of noise and artifacts in them. Soft computing algorithms are then used in the classification of different brain patterns obtained upon performing different motor imagery tasks. A BCI system measures brain activity and translates it into control signals. These control signals can be used to construct new augmentative technologies. People with motor disabilities need augmentative technologies corresponding to natural ways of communications. Those who are totally paralyzed, or locked-in, cannot use conventional augmentative technologies, since some measure of muscle control is required[1]. 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]. 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 behaviours of human brain.

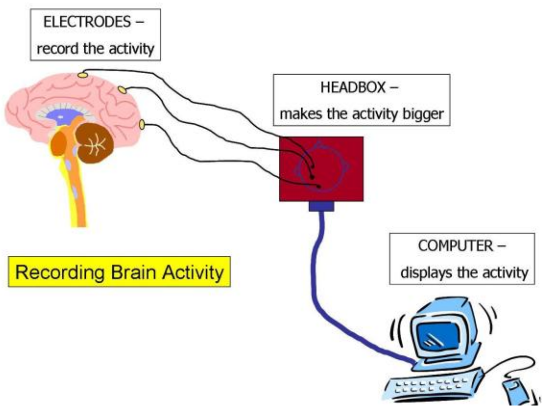

Figure 1.1: EEG Process Diagram.

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].

II. CLASSIFICATION

The algorithm is trained for a set of data (EEG signals) which is been already taken from different subjects for two tasks. Since the task is clear identification and grouping of signal pattern, classification algorithms are preferred to regression methods. Out of the different classification algorithms like LDA, KNN, SVM, LVQ, NN, Neuro-Fuzzy etc, we select classifiers with higher adaptability and precision; i.e. ANFIS[21-22].

III. PROPOSED METHODOLOGY

In this dissertation proposed a feature optimization and feature selection technique for multi- level classification technique. The multi-level classification technique suffered a problem of feature selection and feature optimization. The process of feature optimization reduces the unwanted and unused feature of data during the process of classification. For the optimization of feature used Teacher Learning Based Optimization technique. Teacher Learning Based Optimization technique well knows optimization technique. The process of Teacher Learning Based Optimization technique followed the principle of biological ants.

IV. 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

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

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

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

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

V. TEACHER LEARNING ALGORITHM (TLBO)

The extracted Features of EEG data passes through Teacher learning algorithm (TLBO) for the process of optimization and removal of redundant features of EEG signals data. The processing of TLBO algorithm describe here[14].The teacher learning based optimization algorithm is population and dynamic selection of constraints of EEG data for the process of noise removal. The algorithm has three phases for the processing of data. Teacher phase, learner phase and finally terminated the condition of maximum iteration define by the process of algorithm. The following terminology used for the process of algorithm[14, 15].

N: define the population size.

D: number of features for the processing of optimization

MAXIT: condition for iteration.

The random distribution of population of extracted feature of DWT in terms search space of features and learner.

$$x^{0}_{(i,j)=x_j^{min}} + rand\times\left(x_j^{max}-x_j^{min}\right) \quad \ldots\ldots(3)$$

The generation of new feature is

$$X^{g}_{(i)} = \left[x^{g}_{(i,1)}, x^{g}_{(i,2)}, \cdots\cdots\cdots\cdots\ldots x^{g}_{(i,j)}\ldots\ldots\ldots, x^{g}_{(i,D)},\right] \ldots.(4)$$

The mean parameter Mg of each subject of the learners in the class at generation g is given as

$$M^{g} = \left[m_1^{g}, m^{g}_{2,}\ldots\ldots\ldots\ldots m_j^{g}\ldots\ldots\ldots\ldots m_D^{g}\right] \ldots.(5)$$

The new feature set generation after the processing of mean.

$$Xnew^{g}_{(i)=X^{g}_{(i)+rand\times\left(X^{g}_{Teacher}-TFM^{g}\right)}} \quad \ldots\ldots\ldots..(6)$$

TF is feature optimization function. The value of function is 1 or 2.

If the learner features are matched the condition of optimal value disturbed the population of features.

$$T_{F=round[1+rand(o,1)\{2--1\}]} \quad \ldots\ldots\ldots\ldots\ldots..(7)$$

New Generation set of optimal features

$$Xnew^{g}_{(i)=\{\begin{array}{l} x_i^{g}+rand\times(X_i^{g}-X_r^{g})\ if\ f(X_i^{g})<f(X_r^{g}) \\ x_i^{g}+rand\times(X_r^{g}-X_i^{g})\ otherwise\end{array}} \quad (8)$$

Else

Terminate the conditions.

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VI. 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

$$Pi + 1 = \delta(wpi + b) \quad \ldots\ldots\ldots\ldots(9)$$

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

$$F_k : R^{n_x} \rightarrow R^{n_x}, \text{ where } x_k \in R^{n_x} \quad \ldots(10)$$

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

Hypothesis of error estimated by E

$$E_j = H_j(x_j) + v_j, \quad \forall\, k \le j \le k + A \quad \ldots\ldots(11)$$

where Hj:Rnx → Rny is the relation of multilayer input?

estimate trained pattern

$$x_k = F_0 \rightarrow k(x_0) + \xi k \quad \ldots\ldots(12)$$

3 define learning factor as

$$x_k = \underset{x}{argmin}\left\{ \|x - x_k\|\, B_k^{-1} + \sum_{j=k}^{k+A} \|H_j F_j(x) - y_j\| R_j^{-1} \right\} \quad \ldots.(13)$$

Algorithm

Define i=0

while i < L do

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

$$\{x_k \ I \ k \in [M.i, M.(i+1)]\} \quad \ldots\ldots\ldots\ldots(14)$$

$$x_k = \underset{x}{argmin}\left\{ \|x - x_k\| P_k^{-1} + \sum_{k}^{k+p} \|H_j M_j,(x)\| p_j^{-1} \right\} \quad \ldots\ldots(15)$$

Generates the channel of ALS

$$ALS = \{Fs(x_{k-1}),\ x_k\} \text{ with } k \in [i.M, (i+1).M] \quad (16)$$

Measure i for next step

end

Output: ECG Classified

VII. SIMULATION AND RESULT ANALYSIS

The process of data collection of ALS patients is various tedious task. For the process of experimental task used bnci-horizon-2020 dataset of ALS patients with sample of 20, with parameters age, sex, position and value of sample[13, 21, 22]. The process of simulation used MATLAB16Ra software. And measure following parameters[15, 20, 23].

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

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

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

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

TP: True Positive

TN: True Negative

FP: False Positive

FN: False Negative

ASL	Age	Sex	ALSFRS-	Motion
1	708	M	43	Hands
2	576	F	42	Right upper
3	709	F	39	Left upper
4	649	M	43	Hands
5	721	F	44	Right upper
6	553	M	39	Right leg
7	780	F	29	Hands
8	721	M	46	Left foot
9	673	F	33	Left foot
10	708	M	39	Hands
11	600	M	43	Left foot
12	757	M	38	Hands
13	732	F	42	All four
14	661	M	43	Right hand
15	780	F	33	Left leg
16	804	M	40	Legs
17	624	M	31	Left upper
18	778	M	45	Right leg
19	699	M	46	Right Hand
20	765	M	33	Upper

Table 1: Individual ALS patient demographic information for ALS patients. Range of ASL subject, Age in month, sex (male or female), ALSFRS-R and motion[13].

RESULT ANALYSIS

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].

Table 2: 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.

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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 3: 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	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 4: 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	
	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 5: 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.

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

COMPARATIVE PERFORMANCE IMPROVEMENT

In this section the result of base paper method and proposed method are compared. Table 5 shows the percentage of improvement.

Table 6: Performance improvement of Proposed with other techniques.

	BN	EBL	DNN	IMPROVEMENT
Raw	88.69	90.26	93.61	5%
Delta	86.38	89.34	93.44	7%
Theta	89.47	92.24	95.51	5%
Alpha	85.24	89.35	92.36	7%
Beta	86.24	91.50	94.25	8%

Comparison tables shows that the proposed method got average 7% improvement in delta value,5% in thea,7% in alpha and 8 % in beta.it is clear that proposed method give better performance than previous method.

VIII. CONCLUSION

The motor imagery EEG signal classification is path of complex diseases analysis in medical science. Now a day's various authors and researcher used soft computing technique for the categorization of EEG signals. The feature extraction and selection of features in EEG signal play an important role. The extraction of features depends the raw data's behaviour. The feature of the EEG signal is a mixture of actual coefficient and noise coefficient. For the removal of noise using the TLOB algorithm, TLBO reduces the value of noise and gives the optimal feature set of EEG data. The optimal feature of EEG signals is fed into DNN. The design network of DNN estimates the proceeds data of the sample is ALS or not. The accuracy of DNN algorithms measures 99.9 % in some categories of a data sample. Good compression of the proposed algorithm with two algorithms one is NB and others are ELM, and both algorithms are machine learning-based for EEG data classification. The improved accuracy is increasing the efficiency of the brain-computer interface system in biomedical engineering. The proposed algorithm is reliable, cost-effective in terms of time complexity, and efficient for the detection of ALS disease based on EEG signal classification.

IX. FUTURE WORK

Motor imagery EEG signal classification method using machine learning algorithms that use brain activity captured by EEG to distinguish between various kinds of imagined movements. The development of brain-computer interfaces (BCIs), which enable people to operate external equipment with their thoughts, depends on this procedure. In future this method can be used for real time application.it will be very helpful in medical field.

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