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Enhancing the performance of motor imagery classification to design a robust brain computer interface using feed forward back-propagation neural network

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ABSTRACT

This paper proposes a feed forward back-propagation neural network (FFBPNN) based method to enhance the performance of the motor imagery classification. The dataset consists of fifty nine channels of EEG signals which are first normalised using minmax method and then given as input to the FFBPNN network. Experimental outcomes of the FFBPNN are recorded in term of '0's or '1's for two classes of motor imagery signals. The accuracy of the proposed FFBPNN method has been measured using confusion matrix, mean square error and percentage accuracy. However, accuracy of the FFBPNN based method is recorded up to 99.8%. Hence the proposed method gives better accuracy of the classification which will ultimately help in designing robust BCI.

1. Introduction

Brain computer interface is a system that enables the interface between brain activity and electronic device. Moreover BCI system generally takes bio-signal as an input and predicts a state of action. Traditional BCI enabled system is designed aiming at assisting sensory motor functions where primary aspect is classification of bio-signals. In last few decades various schemes have been proposed for bio-signal processing and classification some of which will be discussed below.

Filter bank common spatial pattern algorithm to optimize the subject-specific frequency band on datasets 2a and 2b of the BCI competition IV is suggested in [1]. Combining information coming from multiple sources and reducing the existing uncertainty in EEG signals using stack generalization is proposed in [2]. Methods based on statistical models that take into account the temporal changes in the electroencephalographic (EEG) signal for asynchronous brain–computer interfaces (BCI) based on imaginary motor tasks are proposed in [3]. A spatio-spectral filtering network for BCI to classify motor imagery data is suggested in [4]. A self-paced BCI based on a robust learning mechanism that extracts and selects spatio-spectral features for differentiating multiple EEG classes is proposed in [5]. BCI issues on hand movement using discrete wavelet transform is discussed in [6].

Different soft computing based methods such as artificial neural network, fuzzy-artificial neural network are also applied for BCI systems. Sub-band classification of decomposed single event-related potential co-variants for multi-class brain–computer interface is proposed in [7] which have an accuracy of 70%. Recurrent quantum neural network (RQNN) filtering procedure has been applied in a two-class motor imagery-based brain–computer interface is proposed in [8] where the objective was to filter EEG signals before feature extraction and classification to increase signal separability. Convolutional neural network (CNN) for the detection of P300 waves in time domain is suggested in [9]. Here seven classifiers are proposed from which four are single classifiers with different features set and three are multi-classifiers. An algorithm based on neural networks and fuzzy theory to classify spontaneous mental activities from EEG signals is suggested in [10] to operate a non-invasive BCI. A three-class mental task-based BCI that uses the Hilbert–Huang transform for the features extractor and fuzzy particle swarm optimization with cross-mutated-based artificial neural network for the classification is proposed in [11]. Recurrent self-evolving fuzzy neural network that employs an on-line gradient descent learning rule to address the EEG regression problem in brain dynamics is proposed in [12]. Brain dynamics of driver or

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Nomenclature-

ANN	Artificial Neural Network
BCI	Brain computer interface
ECoG	Electrocorticogram
EEG	Electroencephalogram
FFBPNN	Feed forward back-propagation neural network
MEG	Magnetoencephalogram

the cognitive states of drivers affect driving safety endangering both the individual and the public. A block sparse Bayesian learning algorithm for EEG-based driver's drowsiness estimation is proposed in [13]. All the above described methods have accuracy that can be enhanced ultimately improving the performance of the BCI system.

In this paper, a feed-forward back-propagation neural network (FFBPNN) based algorithm is proposed for motor imagery classification. The paper is organised as follows – Section 2 describes the basic concept of motor imagery, Section 3 contains the proposed method using FFBPNN, Section 4 describes the results of the proposed method, Section 5 contains the comparison of the different methods with proposed method, Section 6 contains the conclusion.

2. Motor imagery and its applications

People with physical disability need an alternative assistive device or method to perform a motor task or interact with the entire environment. BCI has had an elongated antiquity centered on motor control applications such as paralyzed body parts, robotic arms, cursors, etc. Many of the applications are centered on the needs of the disabled community. In that context motor imagery BCI can be useful. Basically each of the human brain hemispheres is segmented into four lobes with different functions. The lobes are separated by fissures (sulcus). The primary somatic sensory Cortex (Parietal lobe) and the primary motor cortex (Temporal lobe) are the most important regions for BCI research.

Motor imagery includes the movement of several parts of the body generates from sensory motor cortex activation. Using some algorithmic process and BCI based tool one can be able to classify EEG signal characteristics or pattern and also design a feedback enabled assistive device (in real time or single trial basis). Many machine learning techniques that have been used are Bayesian learning method, artificial neural network, fuzzy-art neural network, linear discriminant analysis, support vector machines etc. In this work FFBPNN is used for two class motor imagery classifications which will be described in Section 3.

3. FFBPNN-based scheme for motor imagery classification

Proposed FFBPNN based scheme uses supervised learning for classification of motor imagery data. Different steps involved in the proposed FFBPNN based scheme are shown in Fig. 1. Detail description of each of the steps are given in subsection below.

3.1. Dataset used

There are various single trial EEG dataset or other bio-signal dataset available of different research group such as BCI competition IV dataset I (contains EEG signals), dataset 2 (contains EEG), dataset 3 (contains MEG signals) and dataset 4 (contains ECoG signals) which can be used to test a BCI model. In this work motor imagery EEG Data set used is provided by the Berlin BCI group [14]. The dataset consists of two sub datasets, calibration data

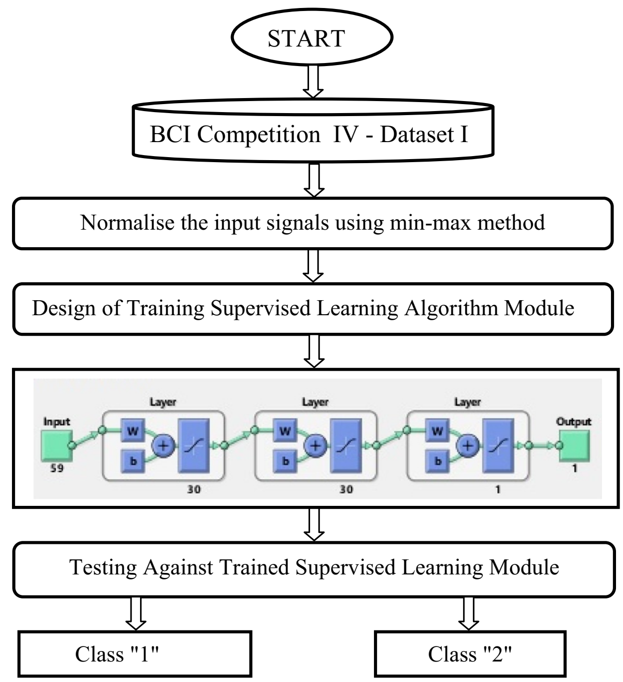

Fig. 1. Flowchart of the proposed scheme.

and evaluation data. Here calibration EEG datasets are used which were recorded from healthy subjects. For each subject two classes of motor imagery were selected from the three classes left hand, right hand, and foot. Out of three varieties of recorded EEG signal namely left hand, right hand and foot where subject are namely a, b, c, d, e, f, and g. Only two classes are selected for each healthy subject namely left, foot. Using the EEG amplifier of BrainAmp MR plus the signals is sampled at 100 Hz. The fifty nine channels are AF3, AF4, F5, F3, F1, Fz, F2, F4, F6, FC5, FC3, FC1, FCz, FC2, FC4, FC6, CFC7, CFC5, CFC3, CFC1, CFC2, CFC4, CFC6, CFC8, T7, C5, C3, C1, Cz, C2, C4, C6, T8, CCP7, CCP5, CCP3, CCP1, CCP2, CCP4, CCP6, CCP8, CP5, CP3, CP1, CPz, CP2, CP4, CP6, P5, P3, P1, Pz, P2, P4, P6, PO1, PO2, O1, and O2 [14]. Subject 'a' chose {left, foot}, subject 'b' chose {left, right}, subject 'f' chose {left, foot}, subject 'g' chose {left, right}. Spatial patterns of motor imagery from different subjects are shown in Fig. 2 [4]. In Fig. 2 black dots indicate positions of electrodes on the hemisphere. Some specific motor imagery frequency band feature of respective classes mentioned subject wise on each plot in Fig. 2.

3.2. Pre-processing of signals

EEG signals are collected from fifty nine channels for motor imagery classification. The EEG signals of all the channels are shown in Fig. 3(a). These signals are then normalized in the range of [−1, +1] using min–max method [18]. The signals are normalized using Eq. (1) and shown in Fig. 3(b). Both normalized signals and without normalized signals are then given as input to the

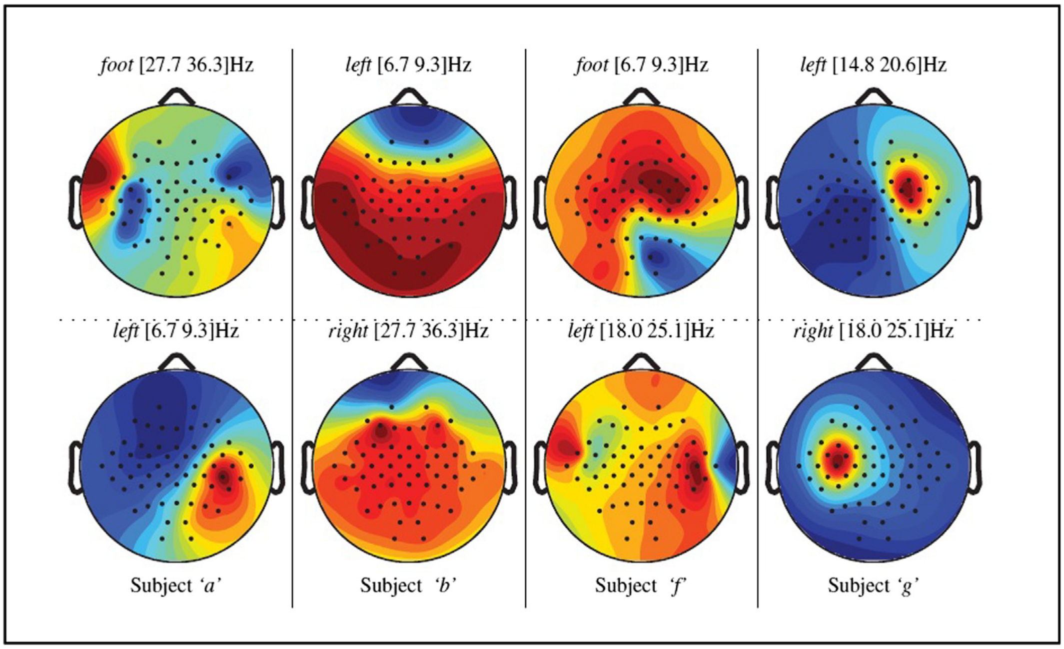

Fig. 2. Spatial pattern obtained from different subjects a, b, f and g [4].

FFBPNN module to classify motor imagery movement. The signals with the highest accuracy in classification are taken as final input.

$$Z_i = \frac{(y_{max} - y_{min}) * (x - x_{min})}{(x_{max} - x_{min})} + y_{min} \tag{1}$$

where, Z_i= i^{th} normalized data

$y_{max} = +1$

$y_{min} = -1$

$x = (x_1, \cdots, x_n)$

$i = 1, 2, \cdots, n.$

3.3. Supervised learning using artificial neural network

Supervised learning algorithms have been used in most of the fields such as medical signal analysis [7–13], electrical signal analysis [15,16,19–21], intrusion detection etc. In this work supervised learning is used to classify two class motor imagery as classifier model is the most important part of the BCI system design. The intention of classification is to divide data from the preprocessor into different classes. Moreover, BCI system records the EEG signal and the preprocessor normally project static transformations whereas the classifier usually adaptive self-learning (or supervised learning) that is required to produce the minimum error based on a set of training sample. Several paradigms of adaptive software have been developed. One of the most popular and massively used paradigms is Artificial Neural network (ANN). ANN is used as supervised learning algorithms due to its ability to implicitly detect complex nonlinear relationships between dependent and independent variables, able to detect all possible interactions between predictor variables etc.

Computational process of artificial neural networks is designed based on a biological nervous system of the human brain. ANNs have been studied for more than three decades since Rosenblatt first applied single-layer perceptron to pattern classification learning in the late 1950s. From various type of neural network, feed-forward back-propagation neural network is chosen to carry out the classification task due to its ability of detecting the patterns correctly based on the works proposed in [15,16,19–21]. Feed-forward back-propagation neural network (FFBPNN) is the generalization of the Widrow-Hoff learning rule to multiple-layer networks and nonlinear differentiable transfer functions. Input vectors and the corresponding target vectors are used to train a network until it can approximate a function or associate input vectors with specific output vectors. A simple FFBPNN is shown in Fig. 4 with inputs, hidden layers, outputs etc.

The first step in the back propagation algorithm is to propagate the inputs forward [17]. The output of different layers is calculated using (2).

$$a^{n+1} = f^{n+1}\left(W^{n+1}a^{n+1} + b^{n+1}\right) \tag{2}$$

where a = network output
p = input to the first layer
W = Weight matrix of different layers
b = Bias matrix of different layers
f = Transfer function
$a_0 = p$
$n = 0, 1, \cdots, L-1$
L = Number of layers and
$a = a^L$ = last layer output

The next step in back propagation algorithm is to propagate the sensitivities backward through the network starting from the last layer as in (3),

$$s^L = -2\dot{F}^L(x^L)(t - a) \tag{3}$$

where s = Sensitivity,
x = Net Input,
t = Target

$$\dot{F}^L = \begin{bmatrix} \dot{f}^n(x_1^n) & 0 & \dots & 0 \\ 0 & \dot{f}^n(x_2^n) & \dots & 0 \\ \vdots & \vdots & \dots & \vdots \\ 0 & 0 & \dots & \dot{f}^n(x_{s^n}^n) \end{bmatrix}$$

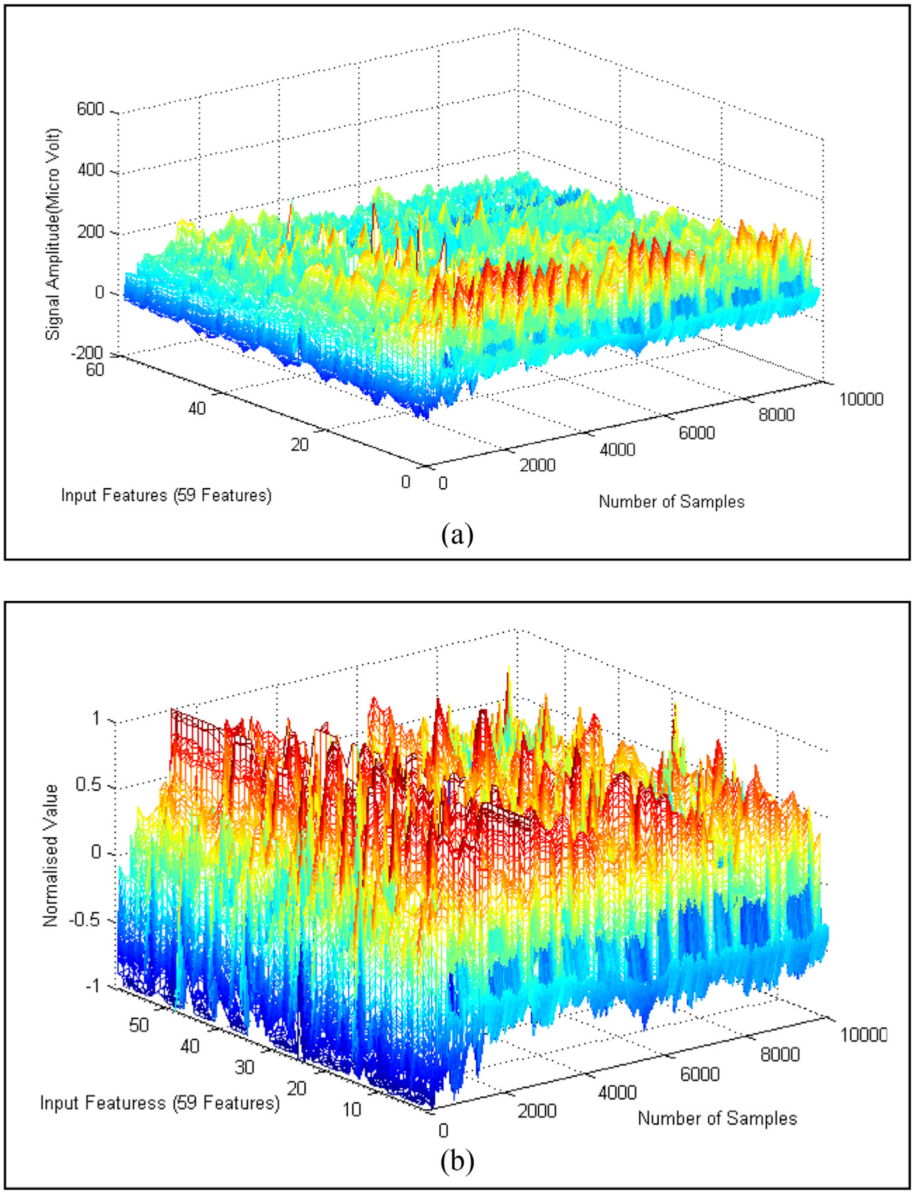

Fig. 3. EEG signals used (a) without normalization and (b) with normalization.

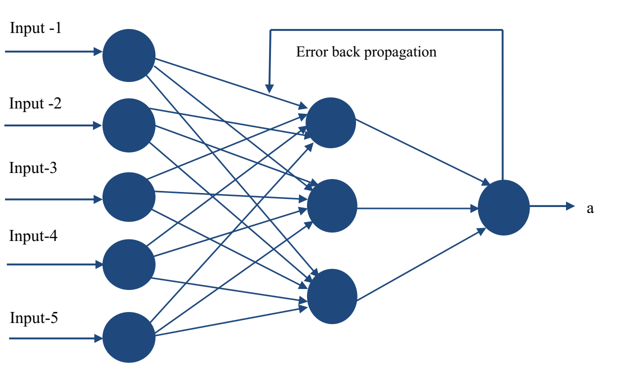

Fig. 4. Back-propagation neural network architecture.

From last layer the sensitivities are then back propagated to the first layer using (4),

$$s^n = \dot{F}^n(x^n)\left(W^{n+1}\right)^T s^{n+1} \tag{4}$$

Final step of back propagation algorithm is to update the weight and biases using approximate steepest descent rule as given in (5) and (6) respectively

$$W^n(k+1) = W^n(k) - \propto s^n (a^{n-1})^T \tag{5}$$

$$b^n(k+1) = b^n(k) - \propto s^n \tag{6}$$

where $\propto$ = learning rate.

In this work, FFBPNN is used to classify two class motor imagery data which is described in the next subsection.

3.4. Proposed motor imagery classification based on FFBPNN

In this section aims to determine the class of motor imagery signals accurately. The proposed FFBPNN based method is divided into two stages, learn by examples and testing with unknown samples. First the network is trained with the help of target samples and then tested with unknown samples. The training neural network is chosen as FFBPNN after studying various literature [19–21]. Input given to the FFBPNN is the EEG signals obtained from the fifty nine channels. Corresponding targets are designed for each class of motor imagery. Training neural network is designed after varying different neurons, hidden layers, transfer function, algorithm, performance error goal (mean square error) etc. Final neural chosen is a feed-forward back-propagation neural network with two hidden layers and 30 neuron in each hidden layers. Transfer function chosen for the method is tan-sigmoid transfer function. All the signal processing and algorithm design works has been carried out using MATLAB [18] on a PC with Intel Core i3- 2120T CPU @2.60 GHz processor with 8 GB RAM.

Final artificial neural network obtained after training is shown in Fig. 5. Fig. 5(i) shows the structure of the neural network where x{1} is the inputs given and y{1} is the outputs obtained. Fig. 5(ii) shows the different layers of feed forward neural network where a{1} is the output of layer 1 which is given as input to layer 2, a{2} is the output of layer 2 which is given as input to output layer and y{1} is the outputs obtained. Fig. 5(iii) shows the general calculation performed inside a layer where p{1} is the inputs given, IW{1,1} is the weight, b{1} is the bias, net-sum is the net output and a{1} is the outputs of layer 1 after applying obtained. After the neural network is trained, the network is tested using various test fault cases.

4. Results and discussions

The performance of proposed FFBPNN based supervised learning method is evaluated varying error goal (mean square error), number of neurons, number of hidden layers, transfer function, training functions, with and without normalised inputs. Accuracy of the proposed FFBPNN method is calculated using a confusion matrix, mean square error and percentage accuracy. A confusion matrix is a table that is used to describe the performance of a classification model on a set of test data for which the true values are known. Results of the proposed FFBPNN based method are discussed in following subsections.

4.1. Performance varying error goal

The proposed FFBPNN based supervised learning method for motor imagery classification is tested varying different training error (mean square error) goal. Table 1 shows performance of the proposed method varying error goal 10^−1, 10^−2, 10^−3, 10^−4 etc. Accuracy of the proposed method is 99.8%with a performance goal of 10^−2. Hence proposed FFBPNN based method is able to classify the motor imagery data with a better accuracy.

4.2. Performance varying number of hidden layer

The proposed FFBPNN based classification method is tested varying number of hidden layers to find the optimum number of hidden layers require to design the training ANN module. Table 2 shows performances of the proposed method for different number of hidden layers such as 1, 2, 3 etc. Training accuracy and testing accuracy is highest in case of 2 hidden layers. There are no changes in training or testing accuracy even if the numbers of hidden layers are increased. Hence the number of hidden layers is set to two in the proposed FFBPNN method in the final neural network architecture.

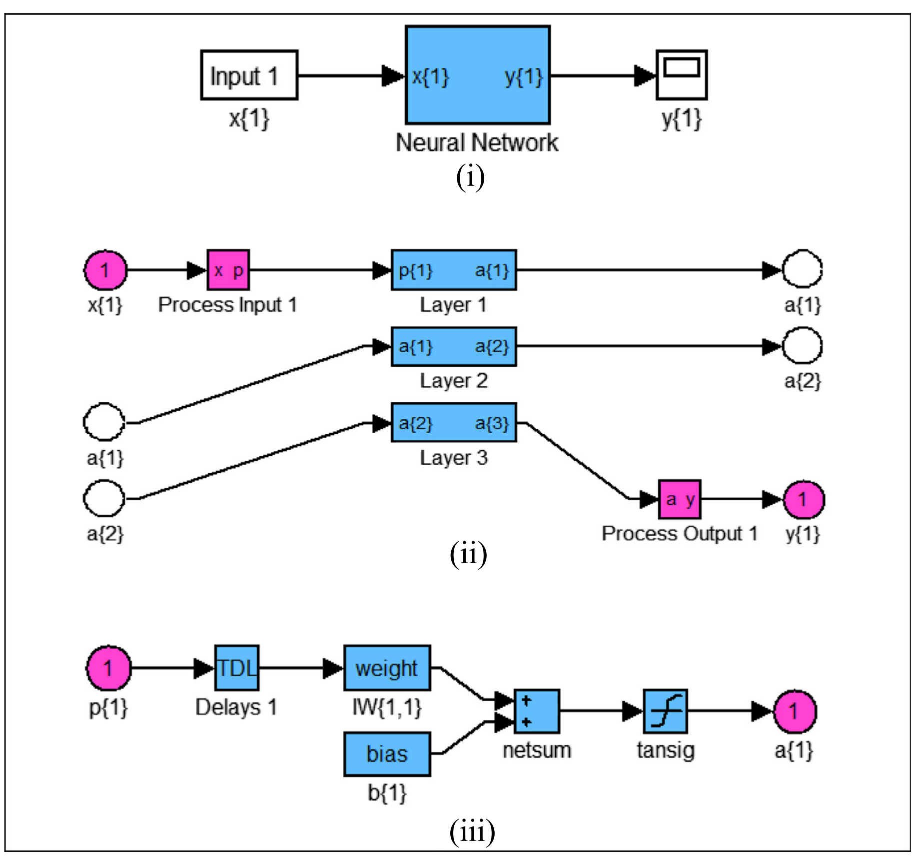

Fig. 5. Training neural network obtained for the proposed method.

Table 1
Performance of the method varying error goal.

Error goal	Performance	
	Time (s)	Accuracy (%)
10^−1	54 min	95%
10^−2	5 h 38 min	99.8%
10^−3	7 h 22 min	99.7%
10^−4	3 h 26 min	98.8%

Table 2
Performance of the method varying number of hidden layers.

Number of hidden layers	Performance	
	Time (s)	Accuracy (%)
1	9 h 25 min	99.8%
2	5 h 38 min	99.8%

Table 3
Performance of the method varying transfer function.

Number of neurons	Performance	
	Time (s)	Accuracy (%)
Purelin	14 min	49.6%
Log-sig	7 h 6 min	99.7%
Tan-sig	5 h 38 min	99.8%

Table 4
Performance of the method with and without normalized inputs.

Input	Performance	
	Time (s)	Accuracy (%)
Without normalised	12 h 28 min	99.5%
Normalised with minmax method	5 h 38 min	99.8%

4.3. Performance varying number of neurons

The proposed FFBPNN based classification scheme is tested varying number of neurons. Fig. 6 shows accuracy of the proposed FFBPNN method for different number of neurons used for training such as 11, 21, 31, 41, 51, 61, etc. Testing accuracy obtained is more in case of the network trained with 61 numbers of neurons in test sample estimate. There are no changes in training or testing accuracy even if the numbers of neurons are increased. Hence the number of neurons is set to 61 (30 in two hidden layers and 1 in the output layer) in the proposed method in the final neural network architecture.

4.4. Performance varying transfer function

The proposed FFBPNN based classification scheme is tested varying transfer function. Table 3 shows performances of the proposed method for different transfer function such as purelin, log-sig, tan-sig etc. Testing accuracy obtained is more in case of the network trained with tan-sig transfer function. Hence the transfer function used in the proposed method in the final neural network architecture is tan-sig.

4.5. Performance with and without normalised input

The proposed FFBPNN based motor imagery classification scheme is tested with and without normalized inputs. Table 4 shows performances of the proposed method with and without normalized input. Testing accuracy obtained is more in case of the network trained with normalized input rather than not normalized. Hence the normalized input is used in the proposed FFBPNN based method in the final neural network architecture.

5. Comparison with other schemes

BCI datasets has been classified using various methods by researchers. The BCI competition IV dataset has been classified by various researchers [1,8,11]. Motor imagery classification is done using EEG BCI competition IV datasets I and datasets II. Accuracy of the proposed FFBPNN method is compared with other the schemes as shown in Table 5 in terms of fold of cross validation and accuracy. Fold of cross validation means data set is divided into equal parts and only one part is used for testing and all other parts used for training. All the methods used 10 or 5-fold testing where proposed method uses only 2-fold testing (means 50% data is used for training and 50% for testing). The proposed algorithm is designed with less training pattern but it provides better accuracy i.e. 99.8%. The reason for better accuracy of the proposed method is that back-propagation neural networks is very simple and it efficiently compute the gradient in a neural network. back-propagation neural networks with Lavenberg-Marquardt algorithm has faster rate of convergence which helped to increase the accuracy of the method. As the proposed method uses only 50% data in training, compared to other method it has more adaptability than other methods. Hence there are more chances that the efficiency of the proposed method will be better when it will be tested with EEG signals.

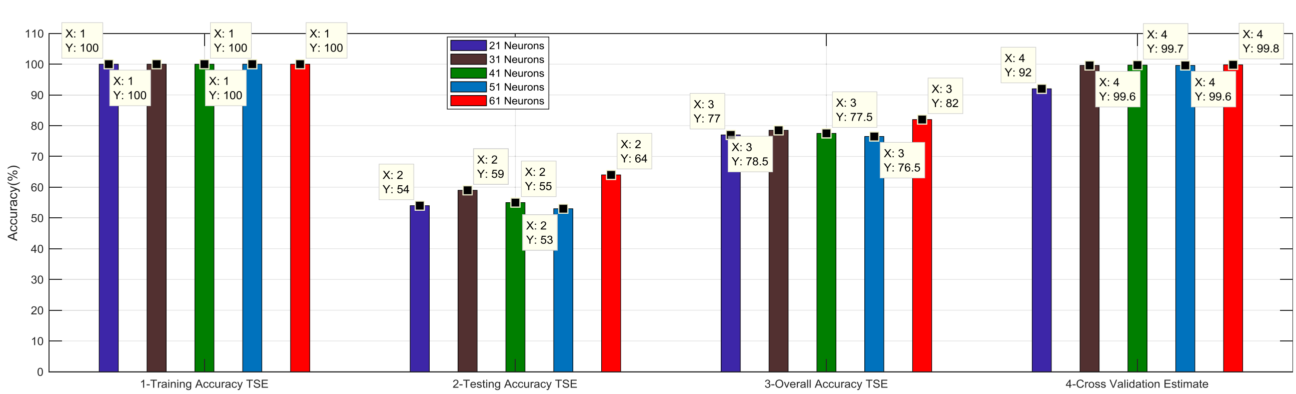

Fig. 6. Performance of the method varying number of neurons.

Table 5
Comparison of different schemes.

Suggested by	Dataset used	Algorithms used	Accuracy
Ang et al. [1]	BCI competition IV Datasets 2a and 2b	Filter bank common spatial pattern	Accuracy obtained using 10 fold cross validation
Nicolas-Alonso et al. [2]	BCI Competition IV dataset 2a	Stacked regularised linear discriminant analysis	Accuracy obtained using 5 fold cross validation (kappa value 0.74)
Zhang et al. [4]	BCI Competition IV dataset-I	Optimum spatio-spectral filtering network for brain–computer interface	Accuracy obtained using 10 fold cross validation (89.9%)
Gandhi et al. [8]	BCI competition IV data set 2a	Recurrent quantum neural network	Accuracy obtained using 10 fold cross validation
Proposed method	BCI competition dataset I	Feed forward back-propagation neural network with Lavenberg-Marquardt algorithm	Accuracy obtained using 2 fold cross validation (99.8% accuracy)

6. conclusions

BCI established a bridge between behavioural and clinical theories. The advent of this may returned a new look in the field of learning to human and computer for the cognitive state classification that reflects the functioning a human brain with its unique capacities for symbolic transformation and organisation into an electrical signal (motor imagery). On the other hand, soft computing has a collection of methodologies that helps to exploit above cognitive state classification into definite prediction. This paper includes a supervised learning algorithm using FFBPNN for motor imagery classification. The paper concludes with following:

- This paper proposes a FFBPNN based motor imagery classification scheme.
- Highest accuracy of the method is up to 99.8%.

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