SENN: Self-evolving Neural Network to Recognize Motor Imagery Thought Patterns

Stuti Chug[a] and Vandana Agarwal[b]

Department of Computer Science and Information Systems, BITS Pilani, Pilani Campus, India

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Abstract: The EEG-based motor imagery task classification has been a challenge for researchers due to the complex nature of EEG data. Human thoughts are a complex combination of different body limb activations and it is difficult to capture only one thought at a time. The data belonging to different motor imagery thought classes are also not separable linearly. In this paper, a novel technique for efficient and improved motor imagery task classification is proposed. Two major issues in motor imagery task classification of EEG data are addressed - channel selection and radial basis function neural network centers. The channel selection is posed as a combinatorial problem and an evolutionary nature-inspired algorithm PSOCS is proposed to select the most informative and discriminative channels using the Particle Swarm Optimization algorithm. The features are extracted using the selected channels and are subjected to classification. In this paper, a self-evolving radial basis functions neural network (SENN) is proposed based on sub-clusters within each motor imagery task class. The number, centers, and spread of hidden neurons are obtained by the k-means clustering algorithm. The proposed algorithm is validated using the benchmarked datasets BCI Competition IV 2a and BCI Competition IV 2b data set. The proposed technique outperforms some of the existing techniques and classifies the motor imagery tasks efficiently.

1 INTRODUCTION

The thought patterns are captured using a variety of sensors electroencephalogram (EEG), functional magnetic resonance imaging (fMRI), magnetoencephalography (MEG), and electrocorticography (ECoG). These signals are non-stationary and suffer due to multiple overlapping thoughts. A human with a neuromuscular disorder is provided assistance using a Brain-Computer Interface (BCI), in which the computational model recognizes the thought of imagination of movement of the body limb and translates the output to the control command such as movement of the prosthetic limb and robotic arms. The signals are captured using multiple receiving units, called channels of one or more types. Multiple units of these sensors are placed in different regions of the skull to capture the signals in the nearest portions of the brain. It becomes very difficult for a BCI to identify the best channels. Using a channel selection algorithm aims to enhance the classification accuracy by reducing overfitting issues and reducing computational complexity while using EEG data. Channel selection is considered part of the feature extraction process.

The channels are required to be selected in the most appropriate way so as to discriminate between thoughts resulting in the most correct recognition of the motor imagery thought patterns. Therefore, channel selection is viewed as a combinatorial problem that is solved using an optimization technique. Researchers have shown an interest in exploring the potential of Particle Swarm Optimization (PSO) in solving the channel selection problem. Binary quantum behaved particle swarm optimization (QBPSO) using Common Spatial Pattern (CSP), Fractional Order Darwinian Particle Swarm Optimization (FODPSO) algorithm and Binary Particle Swarm Optimization (BPSO) have been proposed in the literature. (Zhang and Wei, 2019; Sheoran and Saini, 2022; Kim et al., 2012). Other works include the Sequential Floating Forward Selection (SFFS) algorithm and Cohen's d effect size CSP (E-CSP) algorithm using z-score for channel selection (Baig et al., 2020; Qiu et al., 2016; Das and Suresh, 2015; Zhou et al., 2019).

Once the channels are selected, the most appro-

[a] https://orcid.org/0000-0002-9380-3923
[b] https://orcid.org/0000-0002-8942-5114

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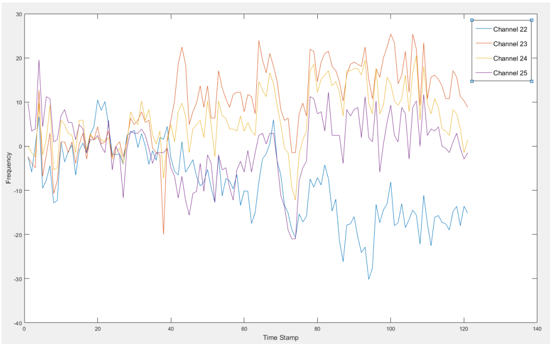
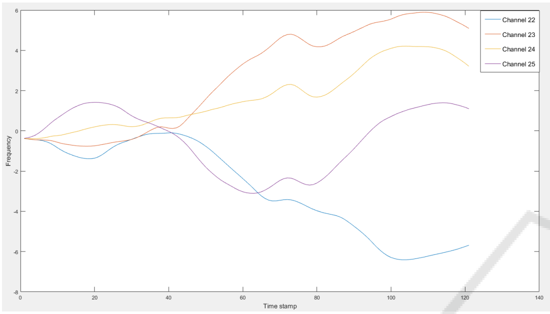


(a) Raw EEG signals.



(b) After preprocessing and standardization.

Figure 1: Raw, Preprocessed and standardized signals representation of Subject 5 of class 2 on BCI competition IV 2a dataset.

priate features are also extracted and subjected to the classification model. The classification model represents the decision hyperplane and needs to have the best parameters defining that. The selected features from each training data pair (x, y) form d-dimensional feature vectors $x = < x_1, x_2, x_3, ..., x_d >$. The raw EEG data from selected channels are subjected to standardization to overcome the non-stationary behavior of the signals (Ang et al., 2012). The effect of preprocessing using standardization is depicted for a few channels in Figure 1. The preprocessed data is then used for feature extraction using various methods such as Fourier transform, Discrete Wavelet transforms (DWT), and Haar wavelet (Nicolas-Alonso and Gomez-Gil, 2012).

Various classification algorithms are used for motor imagery task classification, such as linear classifier, nonlinear Bayesian classifier, nearest neighbor classifier, support vector machines (SVM), radial basis function neural network (RBFNN), deep neural network, and combination of classifiers (Baig et al., 2020; Nicolas-Alonso and Gomez-Gil, 2012; Davoudi et al., 2017; Agarwal, 2019; Alam et al., 2021; Bhatti et al., 2019; Zhao et al., 2020). Common spatial pattern (CSP) algorithm was also used in EEG classification (Zhang and Eskandarian, 2020; Miao et al., 2017; Ang et al., 2012). A pre-processing filter approach Subject Specific Multivariate EMD Filter (SS-MEMDBF) has been proposed where the filters based on MEMD reduce the non-stationaries caused by inter and intra-subject differences, thus obtaining enhanced EEG signals (Xie et al., 2016). For classification, Riemannian mean computation for all classes was used by the authors (Ko et al., 2018).

Of various classification models such as a k-nearest neighbor, support vector machines, and neural networks, the neural network has been used effectively in a variety of recognition tasks due to their capability to handle nonlinearity in training data effectively. The radial basis function neural network (RBFNN) is said to have the best approximation ability and is simple in its architecture with only one hidden layer (Haykin, 2005). The EEG data is highly complex and poses challenges in identifying the number of neurons in the hidden layer. Particle Swarm Optimization (PSO) has been used in different recognition tasks and is said to converge to the optimal solution provided the algorithm parameters are carefully chosen.

In this paper, the two main problems are addressed, channel selection and RBFNN design. A population of particles is initially randomly generated and moved in the search space using a guided heuristic, where each particle not only remembers its own best solution found (known as the cognitive part), also each particle knows the position in the search space which is the best among all particles (this is known as social intelligence). While many existing techniques tend to display a greedy approach of optimization leading to suboptimal solutions, PSO provides a mechanism to explore the search space effectively and to exploit the neighborhood. We are motivated by the computational efficiency of particle swarm optimization (PSO) and use it to address the issues appropriately.

Our Contribution in this Paper: In this paper, we propose a novel approach to classify the complex EEG signals for four motor imagery classes. The approach uses PSO to select the most informative EEG channels. The selected channels are used to extract Haar features. The proposed classifier design has self-evolving hidden layer where the number and centers of neurons are computed using K-Means and PSO algorithm. This algorithm finds sub-clusters with subjective similarities within each class. Based on the number of natural clusters the centers are computed.

This paper is organized as follows: Section 2 presents the basic framework and the proposed algorithm, section 3 describes the experimental part, section 4 discusses the results and section 5 presents the

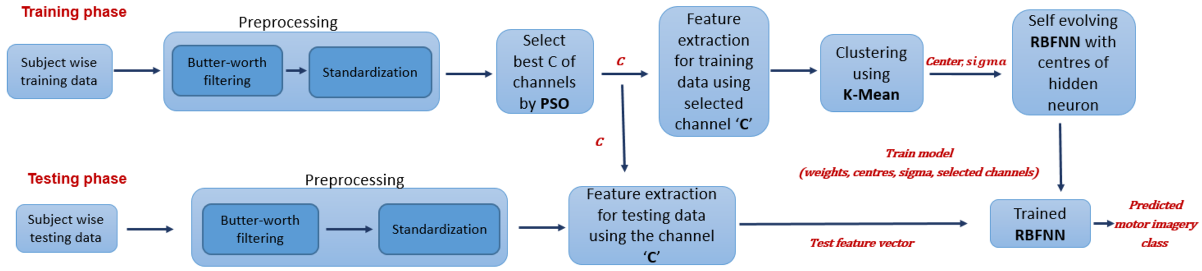


Figure 2: Flow diagram of proposed model.

conclusion and future work.

2 PROPOSED ALGORITHM

In this study, we propose a technique that uses PSO algorithm to capture the most informative channels from a large channel set. In this technique, the classification is done by self-evolving radial basis neural network. A self-evolving radial basis functions neural network is proposed based on sub-clusters within each motor imagery task class. The k-means and PSO clustering algorithms obtains the number, centers, and spread of hidden neurons.

In the proposed algorithm, first, we filter out artifacts from raw EEG signals with the help of Butter worth filter with a frequency cutoff between 4-38HZ after extracting appropriate features from prepossessing data. Then class-wise K-Means clustering is applied on selected features that provide center and spread (sigma) value for each neuron. The RBFNN model is generated, and each hidden layer neuron has its center and sigma value. Finally, the RBFNN model is used for classification based on selected features. Figure 2 represents the block diagram of the proposed approach.

2.1 Prepossessing

EEG Brain signals are sensitive to noise, and removing artifacts from original signals is essential. Band-pass filtering and standardization are required before feeding the raw data into our model (Ang et al., 2012). As shown in Figure 1(a), the raw signal has high distortion, but after filtering out the artifacts using the Butterworth filter, signals are relatively smooth in [Figure 1(b)]. Based on(Ang et al., 2012), the Butterworth filter is engaged to filter out disentangle sensorimotor rhythms. Our model used a Butterworth filter ranging from (4-38 Hz) because it contains the most relevant information in motor imagery applications.

2.2 Standardization

Exponential moving standardization is employed to reduce non-stationary fluctuations (Ang et al., 2012). Electrodes standardization was used to standardize the band-pass filter data. The mathematical formulation is defined below:

$$s_t^{'} = \frac{s_t - \mu_t}{\sqrt{\sigma_2^t}} \tag{1}$$

$$\mu_t = (1-\alpha)s_t + \alpha\mu_{t-1} \tag{2}$$

$$\sigma_t^2 = (1-\alpha)(s_t - \mu_t)^2 + \alpha\sigma_{t-1}^2 \tag{3}$$

where $s_t^{'}$ and s_t are standardized signal and input signal at time t. μ_t and σ_t^2 denote mean and variance value of each electrode in a trial. The α is a parameter known as the decay factor. Standardization removes the occasional movements of the signals and protects each trial's trend from the past signal.

2.3 Channel Selection based on Particle Swarm Optimization

Particle swarm optimization (PSO) is an optimization algorithm based on animals/birds' behavior. In the PSO algorithm, swarm particles search for food in a cooperative way, and each particle in the swarm learns from its experience and another particle experience for updating the search pattern to find the food. PSO is a popular and effective global search technique. It is an appropriate algorithm for addressing feature selection problems for the following reasons: easy feature encoding, global search capability, reasonable computationally, fewer parameters, and easier implementation. PSO algorithm finds optimal solution from a multi dimensional search space. There are 25 (q say) channels in BCI competition IV 2a dataset of which only a few are significant in our application. The problem of finding p (say) best channels from q channels is an exponentially high combinatorial problem

Algorithm 1: PSOCS.

Input: feature matrix
Output: $Optimal\_channel\_set$
Initalize:
$P_i, velo_i, max\_iteration, Gbest, Pbest, c_1 c_2$
Generate random particles (p) and each particle range between [1 25]
for *i=1 to no of particles* **do**
  $calculatefitnessfunctionfit_i$
  $updatePbest, Gbest$
for *K=1 to max_iteration* **do**
  for *each particle i* **do**
    $r_1 = Generaterandom(0,1)$
    $r_2 = Generaterandom(0,1)$
      // Random number uniformly distributed between 0 and 1
    $w = \left(w_{max} - \frac{w_{max}-w_{min}}{I_{max}} * i\right)$
    for *each particle's dimension j* **do**
      $velocity\_part = w * velo_{ij}^{k}$
      $cognitive\_part = c_1 r_1 (Pbest_{ij}^{k} - P_{ij}^{k})$
      $social\_part = c_2 r_2 (Gbest_{j}^{k} - P_{ij}^{k})$
      $velo_{ij}^{k+1} = velocity\_part + cognitive\_part + sociaL\_part$
      $temp = P_{ij}^{k} + velo_{ij}^{k+1}$
        // Rounded values
      if $(temp <= 25 \&\& temp >= 1)$ **then**
        $P_{ij}^{k+1} = P_{ij}^{k} + velo_{ij}^{k+1}$
      $Calculatefitnessfunctionfit_J$
      $UpdatePbest, Gbest$
$Optimal\_channel\_set = Gbest\_channels$

and requires exponential time. In this paper, we use PSO for selecting an optimal number of channels for classification as described in Algorithm 1. In polynomial time the PSO algorithm starts with initialization of a population of particles randomly in channel search space. Every particle $Particle_i\{i = 1,2,...K\}$ has properties such as P_i, $velo_i$ and $Pbest$, where P_i is the position with velocity $velo_i$ and a memory of personal best position $Pbest$. The global best ($Gbest$) value defines the best particle found from all the particles. The population is a collection of particles where each particle represents the selected channel set, and each particle ranges between 1 and 25. The particle velocity ($velo$) is updated by eqn(4), which is a combination of three part namely: momentum $(w * velo_{ij}^{t})$ where w is weight inertia, $velo_{ij}^{t}$ is memory of previous t direction, (2) term is the cognitive part where it quantifies the performance relative to its past experience and (3) term is the social part where it quantifies the performance relative to its neighbour.

$$velo_{ij}^{k+1} = w * velo_{ij}^{k} + c_1 r_1 (Pbest_{ij}^{k} - P_{ij}^{k}) + c_2 r_2 (Gbest^{k} - P_{ij}^{k}) \quad (4)$$

Where k represents the previous iteration and k+1 is the current iteration. The right hand side of eqn(4) uses the values computed in the k^{th} iteration and the left hand side uses all to modify velocity of the particle in $k+1^{th}$ iteration. Position of particle P_{ij} is updated at $k+1^{th}$ iteration as given below

$$P_{ij}^{k+1} = P_{ij}^{k} + velo_{ij}^{k+1} \quad (5)$$

where w is weight inertia that is calculated by eqn(6). The acceleration coefficient c_1 and c_2 are set to range between 0 and 1. The parameters r_1, r_2 are random numbers uniformly distributed between 0 and 1. I_{max} and I are the maximum and the current iteration, and w_{max} =0.9 and w_{min}=0.4 are the initial and final value of weight inertia.

$$w = w_{max} - \left(\frac{w_{max} - w_{min}}{I_{max}} * i\right) \quad (6)$$

Each particle is designed to represent a vector of numbers from 1 to 25. They are randomly generated initial and later it moves to a position representative another set of channels. The particle can change the number of unique channels while it moves in the 25 dimensional space. The fitness function for channel selection problem is taken as the accuracy of classification.

2.4 Clustering

Clustering is the process of dividing a set of data points into groups so that data points in the same group are more similar than data points in other groups. In other words, the goal is to separate groups with similar characteristics and assign them to clusters. K-means clustering is simpler and has a linear time complexity with data size (less expensive). The class-wise K-Means Clustering Algorithm starts by initializing the k number of centers randomly and assign the data point x to one of the K subsets in p^{th} class. It then uses a procedure to end up with a partition of the data points into K disjoint clusters $clust$ in p^{th} class. Then we combine all class cluster data points T and check that the sum of the distance of each cluster member to its cluster center should be minimized.

$$J = min \sum_{i=1}^{k} \sum_{d \varepsilon clust_j} \left\| X^d - C_j \right\| \quad (7)$$

Algorithm 2: SENN.

Input: Feature matrix[features extracted using channels selected by PSOCS (Algorithm 1)], class label
$Class\_cluster\_no = n$;
`// Create Class_cluster_no random center class wise`
for *i=1 to no. of classes* **do**
  class_cluster= class i^{th} training data;
  for *j=1 to Class_cluster_no* **do**
    Pos= random position in class_cluster
    $center = class\_cluster(Pos)$
  center= Concatenate all class cluster's center
  cluster_info=class information of all cluster
while *True* **do**
  for *i=1 to no. of training sample* **do**
    $class\_i\_cluster =$ all center whose class is same as class label i
    for *j=1 to no. of class_i_cluster* **do**
      $Dist_j =$
      $distance(x\_data_i, class\_i\_cluster_j)$
    $Min\_dist = min(Dist)$
    cluster_index=cluster index whose distance is minimum
    $count(cluster\_index) = count + 1$
    $sum(cluster\_index) = sum(cluster\_index) + x\_data(i)$
    $cluster\_no = cluster\_index$
  `// find new center`
  for *i=1 to center* **do**
    `// only consider those cluster whose count is not equal to zero`
    if $count \neq 0$ **then**
      $mean(i) = sum(i)/count(i)$
  $center\_new = mean$
  `// Sigma value`
  for *i=1 to center* **do**
    for *j=1 to i^{th}cluster* **do**
      $\sigma_i = \frac{1}{p} \sum \left\| cluster_j^i - Center_i \right\|^2$
  `// stopping condition`
  if *center_new==center* **then**
    break;
  $center = center\_new$
for *i=1 to no of training sample* **do**
  for *j=1 to no of center* **do**
    $\phi_j(x) = e^{\frac{-\left\|x\_data_i - center_j\right\|^2}{2\sigma_j^2}}$
Output: ϕ

where C_j is the mean of the data points in set $clust_j$ given by

$$C_j = \frac{1}{T_j} \sum_{d \varepsilon clust_j} X^d \tag{8}$$

Iteratively searching the closest mean C_j to each data point x_p reallocating and the data points to the associated clusters $clust_j$, and then recomputing the cluster means C_j. The K-means clustering terminates when no data points change their cluster from one to another. Multiple runs can be carried out to find the local minimum with the lowest J.

2.5 Self Evolving Radial Basis Functions Neural Network Design

RBFNN is a single hidden layer network with an input layer fully connected to a hidden layer. Then, the output of the hidden layer performs a weighted sum of input features to get the output. Unlike the Multi Layer Perceptron (MLP), calculating weights for layers in RBFNN is very different; even the interpretation role of hidden layer nodes is easy. The RBFNN topological diagram is explained in Figure 3. The hid-

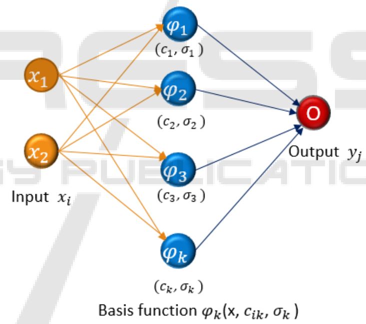


Figure 3: RBFNN structure.

den layer to the output layer works in the same way as feed-forward MLP, with the sum of the weighted hidden unit activation given the output unit activation by eqn(10). The hidden unit activation functions are given by the basis function $\phi(x, c_j, \sigma_j)$, which depends on the center, sigma and the input data. The mathematical form of RBF Gaussian function

$$\phi_j(x) = e^{\frac{-\left\|x_i - c_j\right\|^2}{2\sigma^2}} \tag{9}$$

$$y_j(x) = \sum_{i=1}^{k} w_{ji} \phi_i(x)) \tag{10}$$

The sigma σ values are defined, usually with the p-closest neighbor method which alters the values to achieve overlapping of the response of every hidden and its neighboring unit. The function used is:

$$\sigma_j = \frac{1}{p}\sum \|X_i - C_j\|^2 \tag{11}$$

where c_j the p-closest neighbor of X_i

To explain the working flow of RBFNN, Suppose we have X data set with N samples and D dimension (x_data_i, y_i) where x_data_i is input data, and y_i is its class label. The output of the hidden unit activation function ϕ_j computed by eqn(9) is based on the distance between x_data_i and $center_j$. The spread of cluster is also used in the formation of ϕ_j. The weights between the hidden and output layers are calculated using Moore-Penrose generalized pseudo-inverse. Then, the output of the network is calculated using eqn(10).

2.5.1 Center Generation

Algorithm 2 discusses the implementation of self-evolving neural network (SENN) which finds centers of hidden neurons for RBFNN. These centers are based on the underlying structure of EEG data which uses K-Means clustering. Also, we experimented the evolution of RBFNN using the PSO algorithm to produce classwise centres. At first, random centres were chosen, and each center's dimensions were within a dimension-wise range. Then the particles move using eqn(4). The center dimension search space is $c*d$ where c is the number of centers and d is the number of dimensions. A particle P_i is moved by its velocity $Velo_i$ in the search space at time t is represented as P_i^t.

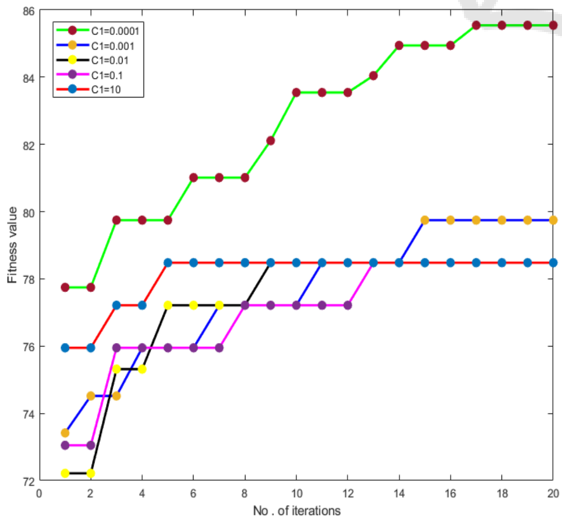


Figure 4: PSO convergence with respect to very small value of c1 on Subject 5 BCI competition IV datasetIIa.

The position of centers is updated according to the global and local best in $c*d$ search space where each row represents positions of sub-cluster centers. Let there be a population P of particles that search exploring and exploiting through their interactions. The mathamatical formation of velocity movement towards minima shown in eqn(4). The step size taken by particles is 0.0001 for C_1 and C_2. Both algorithms employ the same goal function for convergence as illustrated in eqn(7). We already covered K-Means centres generation part in section 2.4.

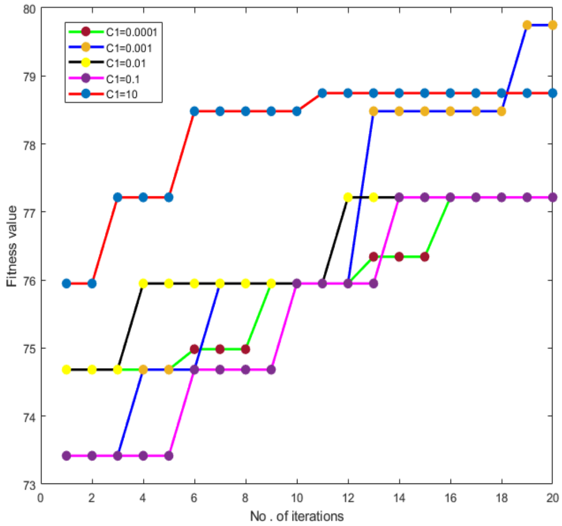


Figure 5: PSO convergence with respect to very small value of c2 on Subject 5 BCI competition IV datasetIIa.

3 DATASET AND EXPERIMENTAL DETAILS

3.1 Dataset Description

BCI Competition IV dataset IIa has four classes of motor imagery tasks. The EEG signals were collected from nine volunteers for four classes: left hand, right hand, tongue, and feet movement. Two sessions for motor imagery tasks were recorded from each subject, one for training and the other for testing. Each session contains 288 trials recorded with 25 channels (22 EEG Channels and 3 EOG channels). These channels are associated with right and left-hand motor imagery areas.

BCI Competition IV dataset IIb has two classes of motor imagery tasks. The EEG signals were collected from nine volunteers for two classes: left-hand and right-hand movements. Two sessions of motor imagery tasks were recorded from each subject, one for training and the other for testing. Each session contains 120 trials of data recorded with 3 channels (http://www.bbci.de /competition/iv/).

We categorized the BCI competition data set into two phases: the subject dependent dataset and the subject independent dataset. In the dependent dataset, data is used subject-wise, where each subject has training and testing data separately for each motor imagery class. There are nine subjects in the BCI competition IV IIa dataset, so we train the model subject wise and test its performance accordingly on the testing dataset.

For validating our algorithm on the subject-independent dataset, we merge all subject's training data into one set and train the model. The testing is done on combined testing data. We do not know about the subject specification during training and testing in the independent phase. In the dependent dataset phase, the model's training is subject wise, but model training is subject-independent in the independent dataset phase.

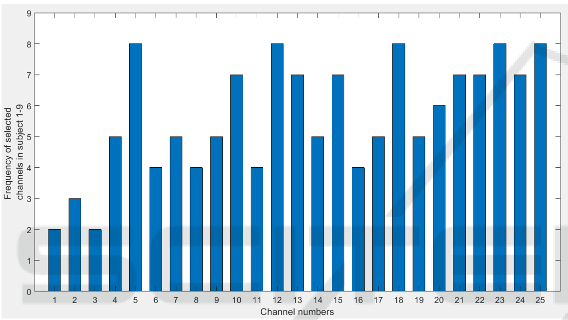


Figure 6: Number of times channel comes in selected channels set from subject 1-9 in BCI competition IV IIa dataset [Channels 6,12,18,23 and 25 are significant for 8 out of 9 subjects].

3.2 Experiment Evaluation

The performance of the proposed algorithm is evaluated on BCI Competition IV datasets IIa and IIb, as discussed above. The BCI Competition IV IIa dataset has nine subjects, as is mentioned above, and each subject data partitioned into training and testing. We train the model on the training dataset and validate the accuracy of the testing dataset. We find the best channels by using PSOCS; the population size of PSOCS is 20, and parameters c1 c2 are shown in Table I; for all subjects. Features were extracted using Haar wavelet with parameters n=5 and m=4 (where n and m are decomposition levels) from selected channels on the training dataset. We pass the data to the RBFNN_K-Means_classwise classifier for classification. In the RBFNN_K-Means_classwise classifier, first, we grouped similar thought patterns into sub-clusters and generated their center and spread values. We pass center and spread parameter to RBFNN model for classification. In the RBFNN_K-Means_classwise model, we start with k equal to the number of samples in the class, and at each iteration, we remove clusters with no single point. Two performance measures were used to evaluate the proposed algorithm; cohen's kappa coefficient(k) and accuracy (Acc). The accuracy (Acc) was computed as the ratio.

$$Acc = \frac{\sum_{t=1}^{n} n_1^t}{\sum_{t=1}^{n} n_2^t} * 100 \tag{12}$$

Cohen's kappa coefficient given below is used for evaluating the performance of the proposed algorithm.

$$\kappa = \frac{P_o - P_a}{1 - P_a} \tag{13}$$

$$P_a = \frac{1}{N^2} \sum_{t=1}^{n} n_1^t * n_2^t \tag{14}$$

where, P_o and P_a represent observed agreement and chance agreement on test samples respectively. N is the total number of test samples, n is the total number of classes, n_1^t is the total number of samples predicted to be belonging to class t and n_2^t is the total number of samples from actual class t.The proposed algorithm was implemented using MATLAB R2020b and all experiments were performed on Intel(R) Core(TM) i5-4590 CPU Processor(3.30GHz).

4 RESULTS AND DISCUSSION

In this section, we discuss the results of the proposed algorithm validates on datasets IIa and IIb from the BCI Competitions IV. *(i) Analysis of PSOCS() algorithm:* The PSOCS method was used to choose the best channels out of 25 channels, with the parameters c_1 and c_2 tuned between 0.0001 and 10. To explore the search space, the values of c_1 is varied from 0.0001 to 10 in multiples of 10 [Figure 4]. The convergence of the proposed PSOCS was investigated for subject 5 for 20 iterations. In algorithm this experiment, a population size of 20 particles was used. It is observed that the best accuracy of 85.5% is obtained with c_1= 0.0001. Figure 5 depicts the same experiment for dataset IV IIa and gives an accuracy of 79.8% with c_1= 0.001.

Subject-wise parameters and channel details are present in Table 1. For each subject, the best channels were obtained. In order to understand the significance of each channel across all 9 subjects, we computed the total number of subjects where a channel was selected. This number is plotted on y-axis in Figure 6. Channels such as 5,12,18,24 and 25 were selected by our algorithm for 8 (out of 9 subjects) emphasizing

Table 1: Parameters and channel details of every subject of BCI competition IV IIa dataset using PSOCS().

Subject	C1	C2	Channels	Accuracy(%)
Sub 1	0.0001	0.01	3 5 7 13 14 15 16 17 20 21 22 24 25	54.51±4.06
Sub 2	0.0001	0.001	4 5 6 8 10 11 12 13 14 15 18 21 23 24 25	49.65±3.12
Sub 3	0.01	0.1	5 7 8 9 10 11 12 14 16 18 19 21 22 23 25	59.13±2.51
Sub 4	0.001	0.1	4 5 9 10 12 13 15 17 18 19 20 22 23 24 25	53.48±3.96
Sub 5	0.0001	0.001	1 4 5 6 7 11 12 13 18 19 20 21 23 24 25	72.86±2.96
Sub 6	0.01	0.1	3 4 5 6 8 9 10 12 13 14 15 16 18 19 20 22 23 24 25	50.45±4.23
Sub 7	1	0.01	2 5 9 10 12 13 15 17 18 21 22 23 25	73.00±3.22
Sub 8	0.01	0.01	4 5 6 7 8 10 12 13 15 17 18 19 20 21 22 23 24 25	67.40±2.86
Sub 9	0.001	0.1	2 7 9 10 11 12 14 15 16 17 18 20 21 22 23 24	55.25±4.02

Table 2: Kappa values of the proposed PSOCS() algorithm and existing approaches for BCI competition IV IIa dataset.

Study	**Approach**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**Mean**
(Xie et al., 2016)	TSSM+LDA	0.77	0.33	0.77	0.51	0.35	0.36	0.71	0.72	0.83	**0.59**
(Miao et al., 2017)	DSFTP	0.63	0.43	0.74	0.54	0.19	0.26	0.63	0.62	0.69	0.53
(Zhang and Eskandarian, 2020)	TFCSP	0.62	0.36	0.76	0.40	0.29	0.34	0.59	0.57	0.62	0.51
(Ko et al., 2018)	RSTNN	0.69	0.29	0.68	0.34	0.09	0.30	0.57	0.49	0.56	0.45
(Ang et al., 2012)	FBCSP	0.68	0.42	0.75	0.48	0.40	0.27	0.77	0.75	0.61	0.57
Proposed Algorithm		0.58	0.49	0.57	0.52	0.72	0.48	0.74	0.67	0.54	**0.59**

Table 3: Accuracy and Kappa values for all subject on BCI competition IV IIb dataset using selected channels obtained by PSOCS().

Subject	Sub1	Sub2	Sub3	Sub4	Sub5	Sub6	Sub7	Sub8	Sub9
Accuracy (%)	52.12±2.16	58.37±3.56	58.7±5.86	52.13±4.77	73.63±2.34	53.78±4.35	49.14±3.06	59.13±4.06	58.37±2.98
Kappa	0.44±0.02	0.45±0.03	0.49±0.04	0.39±0.04	0.64±0.02	0.44±0.05	0.35±0.03	0.49±0.04	0.46±0.03

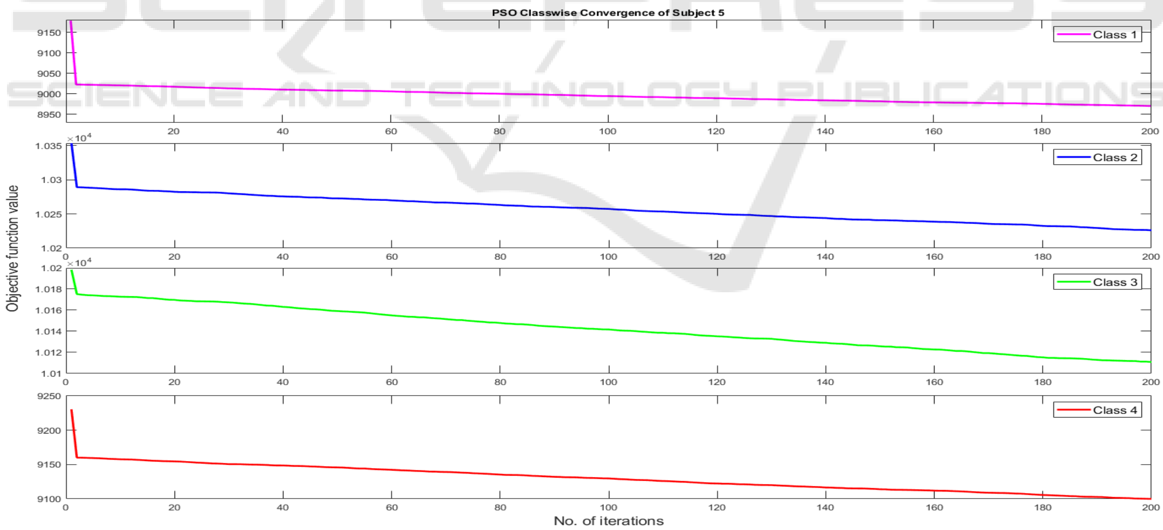


Figure 7: Convergence of PSOCS() algorithm on subject 5.

their importance in thought classification. The comparative analysis with previous studies of BCI competition IV dataset IIa shows that the proposed algorithm outperforms some of the existing techniques [Table 2]. Table 3 summarises the performance of our algorithm in terms of accuracy and kappa value of all subjects with all channels of BCI competition IV dataset IIb. Table 4 shows the confusion matrix for subject 1 of BCI competition IV dataset IIa.

(ii) Analysis of SENN: In Table 5 we can analyze the self-evolving property of the model by using K-means and PSO algorithm. Each class has, on an average, 60 samples per subject. In the beginning, we pass 60 clusters for each class, and after that clusters self-

Table 4: Confusion matrix for subject 1.

		Predicted class			
		1	**2**	**3**	**4**
Actual class	**1**	**35**	16	13	8
	2	14	**44**	9	5
	3	8	8	**50**	6
	4	7	6	7	**52**

Table 5: Number of hidden neurons produced by SENN() evolved by Kmean and PSO algorithm in each class of subject 5 BCI competition IV dataset IIa.

	Kmean	**PSO**
Class 1	40 ±1.58	17.4 ±2.61
Class 2	39.2 ±2.95	17.8±1.48
Class 3	38 ±2.83	17.6±4.16
Class 4	37.8 ±2.49	19.4±0.89
Accuracy	73.0 ±3.22	65.8±2.59

evolve by using the K-means and PSO algorithms. A characteristic of each neuron in the RBFNN model is the center and spread information of those clusters. It is evident that the total number of evolved neurons is the sum total of clusters of all four classes.

(iii) Subject independent Analysis: Figure 7 demonstrates the convergence of the classwise clusters of subject 5 BCI competition IV dataset IIa using the PSO algorithm, with the parameters $c1$ and $c2$ set to 0.0001. In 200 iterations, the objective function's value decreases. If the $c1$ and $c2$ values are more than 0.0001, there is a high risk of local minima due to the cluster's rapid convergence.

In subject independent BCI competition IV dataset IIa, 11 channels [3,6,7,11,12,15,18,22,23,24,25] were selected with parameters c_1=0.1 c_1=0.6 and population size is taken as 20 on 50 iteration. Figure 8 shows the convergence of PSOCS on independent BCI competition IV dataset IIa.

Table 6 summarizes the cluster information for each class. Initially, we pass 100 clusters in each class and get the converged cluster 352 clusters out of 500. The convergence of Kmean clustering is shown in Figure 9, wherein the value of the objective function is minimized in each iteration. Table 7 summarizes all the parameters and accuracy of the independent dataset.

Table 6: Number of hidden neurons evolved in each class of subject independent BCI competition IV dataset IIa.

	Class 1	Class 2	Class 3	Class 4	Total
Initial no of Cluster	100	100	100	100	500
Obtained Cluster	81	89	88	90	352

Table 7: Accuracy of PSOCS() on independent BCI competition IV dataset IIa.

C_1	C_2	Channels	Accuracy
0.1	0.6	3,6,7,11,12,15,18,22,23,24,25	71.45%

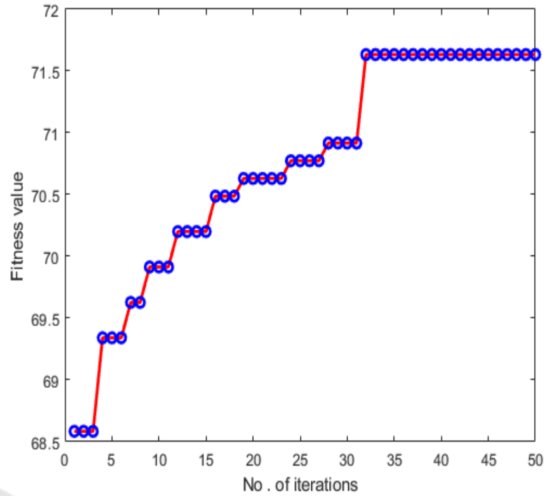


Figure 8: PSOCS() convergence on independent BCI competition IV IIa dataset.

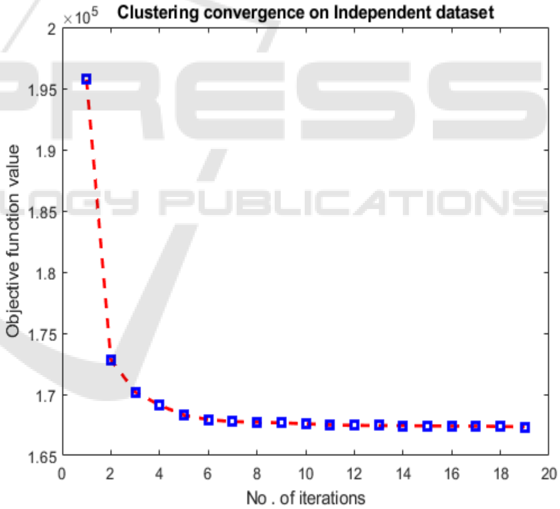


Figure 9: Clustering convergence on independent BCI competition IV dataset IIa [eqn 7 used for objective function value].

5 CONCLUSION AND FUTURE WORK

The proposed model learns from the underlying data and evolves the RBFNN hidden neuron in terms of numbers and locations of the centers. Therefore, the proposed work can easily be used in other applications independent of the domain-specific knowledge, given the feature vectors representing samples. The centers of the hidden neurons capture similar clusters of the training data from a given class. The complex phenomenon of thought patterns is handled efficiently using the proposed algorithm. Our algorithm outperforms those with an accuracy of 71.45% for subject-independent motor imagery task classification for the dataset IIa. The mean kappa value for subject-dependent task classification is obtained as 0.59 for the same dataset. The algorithm also performed well for dataset IIb. In the future, we will explore the potential of this algorithm to work with more complex thought classes such as music and mathematic problem solving. We plan to use the transfer learning methods for other mental activity recognition.

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