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A Novel Feature Selection Algorithm and Neural Network Classifier for Brain Computer Interface

K. Akilandeswari
Department of Computer Science,
Government Arts College (Autonomous), Salem-7, India
akilamanivelan@gmail.com
G.M.Nasira
Department of Computer Science,
Chikanna Government Arts College, Tirupur, India
nasiragm99@yahoo.com

Abstract

Brain-Computer Interface (BCI) measures specific brain activity features translating them into device control signals. Electrocorticography (ECoG) is a recording technique used in BCIs as it is robust. ECoG is acquired by placing electrodes beneath the skull, above (epidural) or below (subdural) dura matter. ECoG recordings balance fidelity and clinical practicality. ECoG signal extracted features are classified. BCI efficiency depends on the classifier's effectiveness. As feature vector dimensionality degrades BCI performance, Feature Selection (FS) methods are incorporated to improve classifier efficacy. FS is NP-hard. This study proposes a new FS method based on hybrid Particle Swarm Optimization (PSO). Selected features are classified using Neural Network (NN). Experiments showed that the new method outperformed conventional methods.

Keywords: Brain-computer interface (BCI), Electroencephalograph (EEG), Feature selection, Particle Swarm Optimization (PSO), Neural Network (NN)

Introduction

BCI is a communication method established on brain generated neural activity and is independent of normal peripheral nerves and muscles output pathways [1]. Neural activity in BCI is recorded using invasive and noninvasive techniques that measure specific brain activity features translating them into device control signals. The functional model of a Brain Computer Interface System is shown in Figure 1.

Features used in studies to date include P300 evoked potentials, slow cortical potentials, sensorimotor rhythms recorded from scalp, event-related potentials recorded on cortex, and neuronal action potentials recorded within cortex [2]. A BCI system detects specific patterns in a person's brain activity related to the person's intention to initiate control. BCI system translates patterns into control commands. Signal processing is important in BCI design, as it extracts meaningful information from brain signals [3].

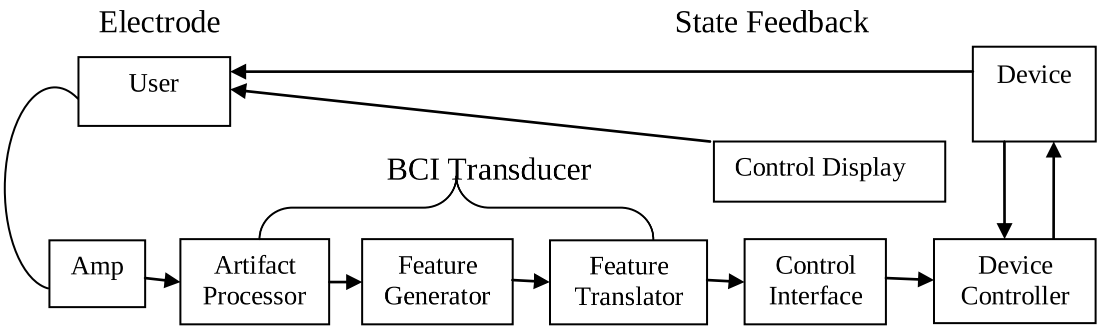

Figure 1: Functional model of a Brain-Computer Interface system

EEG is multivariate time series data measured through many sensors placed on a scalp, reflecting brain activity induced electrical potentials. EEG classification is an important BCI task providing a new dimension in human computer interface, directly linking a computer to human thinking [4]. EEG records electrical activity along the scalp produced by neurons firing within the brain. EEG records the brain's spontaneous electrical activity over a short time, usually 20–40 minutes, as recorded through electrodes placed on a scalp [5].

ECoG, which recently gained attention as a recording technique for BCI use, involves recording electrical signals from the brain's surface especially in patients being monitored before surgery [6]. ECoG is less invasive than neuronal recordings as the brain is not penetrated and so has a higher Signal-To-Noise Ratio (SNR) than EEG, and also higher spectral and spatial resolution.

ECoG or signal recorded from the brain's surface offers an opportunity to define what level of motor information is deciphered from human lateral cortex related to movements [7]. ECoG signal is more robust compared to EEG signals: its magnitude is 5 times larger, its spatial resolution related to independent signals is greater (0.125 versus 3.0 cm for EEG), and its frequency bandwidth is much higher (0-550 Hz versus 0- 40 Hz for EEG).

Feature Selection (FS) is a machine learning process where a features subset available from data is selected for a learning algorithm application. The best subset contains least dimensions that contribute to accuracy; the remaining are unimportant dimensions to be discarded [8]. FS is pattern recognition, statistics, and data mining community's active research area.FS selects a subset of d features from a set of D measurements, d<D, without degrading the recognition system's performance [9].

Optimization is a mathematical procedure to determine optimal allocation of scarce resources [11]. Optimization, and its special form, Linear Programming (LP) have found applications in almost all business facets, from advertising to production planning. FS is extensive and spreads through many fields, including data mining, text categorization, pattern recognition, and signal processing [12]. FS enhances accuracy in machine learning problems, which strongly indicates that it is necessary for ranking [13]. This study proposes FS based on PSO while NN classifies selected features. The rest of the study is organized as follows: Section 2 reviews related works in literature. Section 3 explains methodology. Section 4 discusses experimental results, and Section 5 concludes the work.

Literature Review

Genetic FS was used by Wei et al., [14] to find an EEG features subset that further improved estimation performance over correlation-based method reported in earlier studies. Features selected by genetic FS were different from those got by correlation analysis. Results prove that genetic FS was effective to optimize motion-sickness level estimation. This could lead to a practical system for non-invasive monitoring of individuals motion sickness in real-world environments.

A method, which obtained feature reduction and classifier selection based on software agents was presented by Castillo-Garcia et al., [15]. The obtained results found a topology represented as a neural model for adaptive BCI, with interrelated channels, features, and classifier. Features minimal subset and optimal classifier were obtained through adaptive BCI. Three EEG channels obtained a success rate of 93% for BCI competition III data set IVa.

He et al., [16] introduced an Empirical Mode Decomposition (EMD) in preprocessing which behaved as a filter bank to optimize band selection automatically for CSP and calculated instantaneous phase for PLV exactly. The new method was applied to public and recorded datasets (each n=4). Compared to conventional CSP, average classification accuracy increase was 5.4% (2.0% for public and 8.7% for recorded datasets), manifesting statistical significances ($p < 0.05$). The possibility of the proposed method's online realization was investigated showing results comparable with offline results.

A set of imagery-based cognitive tasks was evaluated by Soriano et al., [17], using functional Magnetic Resonance Imaging (fMRI) and EEG. Eleven healthy subjects (control group) and 4 stroke patients were evaluated with fMRI. Nine healthy subjects also underwent an EEG test. The fMRI results for control group showed specific and statistically differentiable activation patterns for motor versus music imagery (t-test, $p < 0.001$). Corroborating this, EEG results of FS to minimize classification error (using Davies-Bouldin index) found no common activation pattern though a well-defined meaningful electrodes set, and frequencies were found for some subjects.

An algorithm and all system constants were optimized to generate highest accuracy on a validation set by Tahmasebzadeh et al., [18]. The method was verified first through offline experiments on "BCI competition 2003" data set IIb and data was recorded by EmotivNeuro headset. The results were among the highest reported earlier but used few features from limited channels. The method was robust and did not need high computational power. So, it was implemented in an online P300 speller BCI and tested on 4 healthy subjects using an Emotive Neuro headset.

A new FS method based on PSO for EEG-based Motor-Imagery (MI) SBCI systems proposed by Zhiping et al., [19] included 2 steps: (1) an optimization algorithm, i.e. PSO selected EEG features and classifier parameters; and (2) a voting mechanism removed redundant features, produced by the optimization algorithm. The new method is used with GA. Experiment on single-trial MI EEG classification showed the proposed method’s effectiveness.

D'Croz-Baron et al., [20] proposed identifying left/right hand motor imagery as part of a BCI experiment. Feature vector was formed by sixth order Autoregressive Coefficients (AR) or sixth order Adaptive Autoregressive coefficients (AAR) represented by EEG signals from C3 and C4 channels, according to EEG 10-20 standard. The signal analyzed considered 1 second windows with 50% overlapping. FS based on Fisher Criterion (FC) removed irrelevant and noisy information. Classification results obtained with 2 AR methods, Burg and Levinson-Durbin, and one AAR LMS were presented.

Machine learning techniques were used for FS on a self-recorded data set by Jenke et al., [21]. Results regarding performance of different FS methods, use of selected feature types, and electrode location selection was presented. Features selected by multi-variate methods outperformed uni-variate methods slightly. Advanced feature extraction techniques had advantages over common spectral power bands. Results suggested locations preference over parietal and centro-parietal lobes.

Master-worker implementations of 2 different parallel evolutionary models, parallel computation of cost functions for individuals in a population, and parallel execution of evolutionary multi-objective procedure on subpopulation were proposed by Kimovski et al., [22]. Experiments on varied benchmarks, including those related to FS in EEG signals classification for BCI applications, showed benefits of parallel processing not only for decreasing running time, but for improving solution quality.

An ensemble FS scheme combining 2 sample t-test, MCCA, and Support Vector Machine (SVM) with Recursive Feature Elimination (SVM-RFE) result in optimal group-discriminating feature for each modality was suggested by Sui et al., [23]. Classified power was between 2 groups based on selected features through 7 modality-combinations. Results showed that fMRI-sMRI-EEG combination ensured top classification accuracy in training (91%) and prediction rate (100%) in testing data, validating effectiveness, and advantages of multimodal fusion in discriminating schizophrenia.

A FS strategy including channel selection by fisher ratio analysis in frequency domain and time segment selection by visual inspection in time domain presented by Prasad et al., [24] achieved an improvement of 7.5% misclassification rate compared to a baseline system using wavelet coefficients as features and SVM as classifier.

Peng and Lu [25] reduced features, that a classifier deals with and improved classification accuracy using automatic FS. EEG signal was decomposed into 5 sub-band components by discrete wavelet transform. Features were extracted as input to train 3 classifiers (NB, SVM, kNN and LDA) and to judge whether EEG signal was epileptic. Results showed that selected features based classification accuracy was significantly higher than on original features. Each feature’s relative importance was also analyzed.

A statistically-motivated electrode and FS procedure, based on Cohen's effect size f2 proposed by Jenke et al., [26] compared inter- and intra-individual selection on a self-recorded database. Classification evaluation was through use of Quadratic Discriminant Analysis (QDA). Both f2 based FS versions yielded comparable results. While highest accuracies of 57.5% (5 classes) was reached by applied intra-individual selection, inter-individual analysis successfully located features performing with lower variance in recognition rates across subjects than combinations of electrodes and features as suggested in literature.

Nasehi and Pourghassem [27] proposed FS based on Statistical-Principal Component Analysis (S-PCA) and Wavelet Transform (WT) features in medical and BCI applications. Signals were sent to 6 sub-bands by 4 mother wavelet (sym6, db5, bior1.5, and robio2.8). Then 5 features (like number of zero coefficients, smallest and largest coefficients, mean and standard deviation of coefficients) were extracted from sub-bands as feature vectors. kNN classifier and 7 different brain activity signals evaluated the new method. Results indicated improved classification performance compared to present methods.

Performance of forward, backward, and branch and bound FS algorithms when applied to electroencephalography and electromyography data was compared by Johnson et al., [28]. Results showed that forward selection algorithm outperformed other techniques for specific problems. Also, time domain features were selected primarily over frequency domain features. The selected subset's validation suggested the approach as appropriate for future investigation.

A framework that closely integrates spatial FS and weighting within a classification task was proposed by Jrad et al.,[29]. Spatial weights were considered as hyper-parameters for an SVM to learn. The resulting spatially weighted SVM (sw-SVM) was designed to maximize the margin between classes while reducing generalization error. Experiments on 8 Error Related Potential (ErrP) data sets, illustrated sw-SVM's efficiency from physiological and machine learning points of view.

Methodology

This study used Walsh-Hadamard Transform (WHT) for feature extraction and FS using PSO. Multi-layer Perceptron Neural Network (MLPNN) classifier is used for feature classification.

Dataset

Data Set I from BCI Competition III evaluated the ECoG dataset. A subject performs imagined left small finger or tongue movements in BCI experiments. Recordings were at a rate of 1000Hz. Recorded potentials were microvolt values after amplification. All trials had an imagined tongue or finger movement recorded for 3 seconds. Recording intervals started 0.5 seconds after visual cue end to prevent data reflecting visually evoked potentials. A data set is a brain signal record from BCI experiments in BCI technology labs split into 2s: one part labeled data ('training set') and the unlabeled data ('test set').

Walsh-Hadamard Transform

WHT is a popular non-sinusoidal orthogonal transform, which is used widely in digital signal processing as its application is easy and shortens processing time.The coefficients of such extension point to the effectiveness of occurrence of analogous structure at a specific position. Such coefficients are normalized by dc coefficient of an expansion, i.e., local image’s average gray value, then measuring a local structure independent of modality. Walsh basis functions correspond to local structure, as positive/negative going horizontal/vertical edge, corner of certain types, etc. [30].

WHT of a signal x, of size $N = 2^n$, is matrix-vector product $\mathbf{WHT}_{N\cdot x}$, as in equation (1) where [31]

$$WHT_N = \bigotimes_{i=1}^{n} DFT_2 = \overbrace{DFT_2 \otimes \ldots \otimes DFT_2}^{n} \tag{1}$$

Matrix $\mathrm{DFT}_2 = \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix}$ is 2-point DFT matrix and $\otimes$ denotes tensor or Kronecker product. Tensor product of 2 matrices is obtained by replacing each entry of first matrix by that element multiplied by second matrix.

Particle Swarm Optimization (PSO) Based Feature Selection

Kennedy and Eberhart introduced PSO, an evolutionary algorithm in 1995, inspired by animals’ social and cognitive interactions with one another, and with the environment. PSO operates by iteratively directing particles to an optimum using social/cognitive components [32]. Particles location denoted by $x_{i,j}$, are influenced by a velocity component in n-dimensional search space, denoted by $v_{i,j}$, where i represents particle's index, and j is search space dimension. Particles are considered possible solutions in PSO; they fly through virtual space having maximum velocity limitations denoted by v_{max}. Particles are attracted to positions yielding best results.

Velocity and particle update equations (2) [33]:

$$\begin{aligned}
V_{i,j}(t) &= \omega \times V_{i,j}(t-1) + C_{i,j} + S_{i,j} \\
C_{i,j} &= c_1 r_{1,j} \times (Pbest_{i,j}(t-1) - x_{i,j}(t-1)) \\
S_{i,j} &= c_2 r_{2,j} \times (\mathrm{G}\,best_{i,j}(t-1) - x_{i,j}(t-1)) \\
x_{i,j}(t) &= x_{i,j}(t-1)) + V_{i,j}(t)
\end{aligned} \tag{2}$$

$r_{1,j}$ and $r_{2,j}$ are distinct random values ranging between 0 and 1; c_1 and c_2 are acceleration coefficients controlling the effectiveness of social (S) and cognitive (C) components, and w the inertia weight, t is current iteration, i particle index in a population and j the dimension. PSO Algorithm [34] is given in figure 2.

Input: Randomly initialized position and velocity of the particles: X_i 0 and V_i 0

Output: Position of the approximate global optima X^*

Begin

While terminating condition is not reached do

Begin

for i = 1 to number of particles

Evaluate the fitness: =f(X_i);

Update p_i and g_i;

Adapt velocity of the particle;

Update the position of the particle;

increase i;

end while

end

Figure 2: PSO Algorithm

Hybrid PSO algorithm begins with an initial K particles swarm. Every particle vector corresponds to underlying problem's candidate solution. All particles repeatedly move till maximum iterations are passed. During each iteration, a particle individual best and swarm's best positions are determined. A particle adjusts position based on individual experience (pbest) and swarm's intelligence (gbest) as seen in the equations. To expedite convergence speed, particles are updated using a hill-climbing heuristic before entering the next iteration. When the algorithm is terminated, an incumbent gbest and corresponding fitness value are output. They are considered as optimal task assignment and minimum cost (equation 3). The proposed hybrid algorithm's flow is given in figure 3.

$$\begin{aligned} v_{ij} &\leftarrow v_{ij} + c_1 rand_1 (pbest_{ij} - particle_{ij}) + c_2 rand_2 (\mathrm{gbest}_j - \mathrm{particle}_{ij}) \\ \mathrm{particle}_{ij} &\leftarrow particle_{ij} + v_{ij} \end{aligned} \tag{3}$$

1. Initialize.

1.1 Generate K particles at random.

1.2 Generate velocities v_{ij}, 1 £ i £ K and 1 £ j £ r, where v_{ij} is randomly drawn from [0.0, 1.0].

2. Repeat until a given maximal number of iterations is achieved.

2.1 Evaluate the fitness of each particle.

2.2 Determine the best vector pbest visited so far by each particle.

2.3 Determine the best vector gbest visited so far by the whole swarm.

2.4 Update velocities v_{ij} using (1) restricted by a maximum threshold v_{max}.

2.5 Update particles, vectors using (2).

2.6 Improve the solution quality of each particle using the embedded hill-climbing heuristic.

Figure 3: Hybrid PSO Algorithm

Multi-Layer Perceptron Neural Network (MLP NN) Classifier

MLP model is a feed-forward artificial NN classifier. The connections between perceptrons in an MLP (in figure 4) are forward, and all perceptrons are connected to all next layer perceptrons except the output layer that produces the result. A non-linear activation function in most cases is applied to data and result is the input to next layer up to output layer [36].

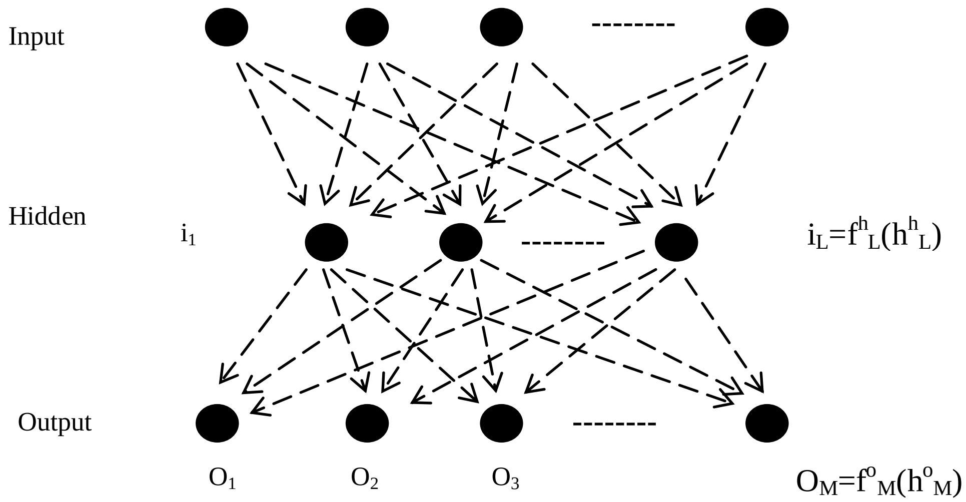

Figure 4: Multi-Layer Perceptron Neural Network

NN and thus MLP, are universal approximators, i.e. when having enough neurons and layers, they approximate any continuous function. The fact that they can classify any number of classes makes NN highly flexible classifiers that adapt to various problems. So, MLP, which is a popular NN used for classification, were applied to all BCI problems like binary or multiclass, synchronous or asynchronous BCI. But, the fact that MLP are universal approximators makes them sensitive to overtraining, especially with noisy and non-stationary data as EEG. Hence, careful architecture selection and regularization are needed.

An MLP without hidden layers is called a Perceptron [37]. Interestingly, a Perceptron is equal to Linear Discriminant Analysis (LDA) and so is sometimes used for BCI applications. MLP networks have an input layer, one/more intermediary or Hidden Layers and an output layer. A weight matrix is defined for each layer. ANN topology solves classification problems with non-linearly separable patterns and is used as a universal function generator [38]. MLPs have training and execution phases. It is impossible to use delta rule directly for training, as it does not permit weight recalculation for subterranean layers with such network topology.

Experimental Results

The experiments are conducted to calculate accuracy and RMSE. Precision and Recall are calculated for finger and tongue. The proposed NN parameters used are given in Table 1. Table 2 to 4 and figure 5 to 8 shows the classification accuracy and RMSE, Precision and Recall for Finger and Precision and Recall for Tongue.

Table 1: MLPNN Parameters Used

Number of layers	**3**
Number of hidden layers	1
Number of neurons in hidden layer	30
Number of neurons in output layer	2
Activation function used	Sigmoidal
Learning algorithm used	Back propagation

Table 2: Classification accuracy and RMSE

Techniques	**Classification accuracy**	**RMSE**
PSO- MLP with BP training	96.43	0.1864
Hybrid PSO- MLP with BP training	97.02	0.1721
Hybrid PSO - MLP with Hybrid PSO training	97.62	0.1703

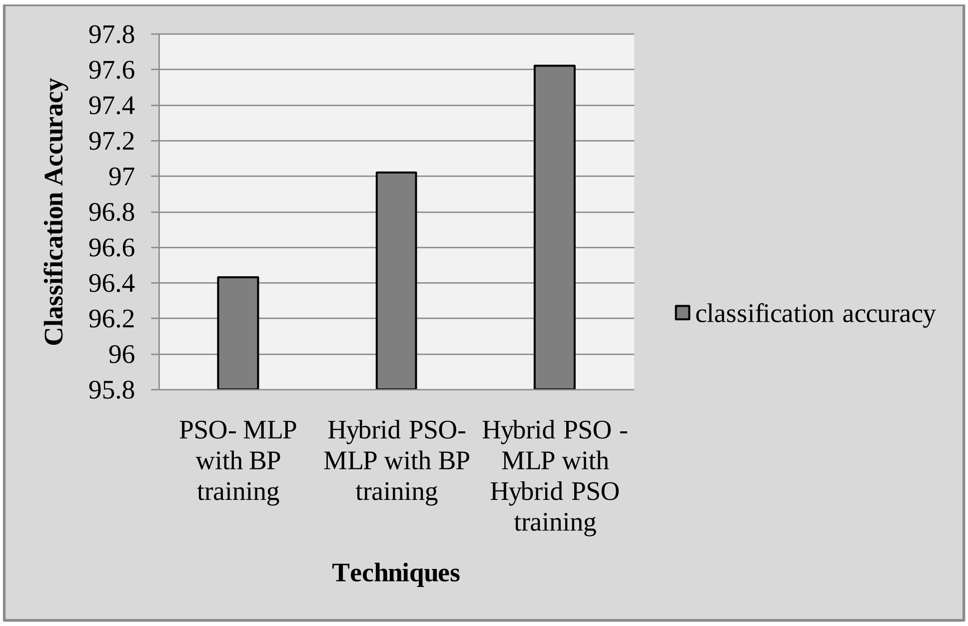

Figure 5: Classification Accuracy

From figure 5, the proposed hybrid PSO with MLP- hybrid PSO training has improved classification accuracy by 1.2265% when compared with PSO-MLP-BP training.

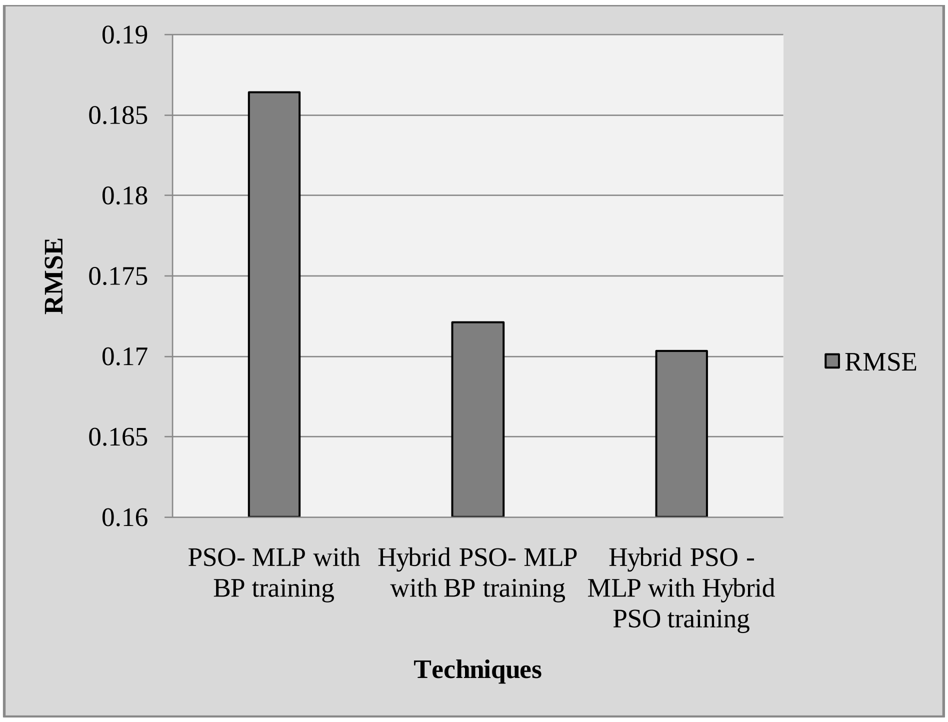

Figure 6: RMSE

It is observed from figure 6, that the proposed method reduced RMSE by 1.0514% when compared with Hybrid PSO-MLP-BP training and by 9.0272% when compared with PSO-MLP-BP training.

Table 3: Precision and Recall for Finger

Techniques	Precision	Recall
PSO- MLP with BP training	0.962025316	0.962025
Hybrid PSO- MLP with BP training	0.974358974	0.962025
Hybrid PSO - MLP with Hybrid PSO training	0.987012987	0.962025

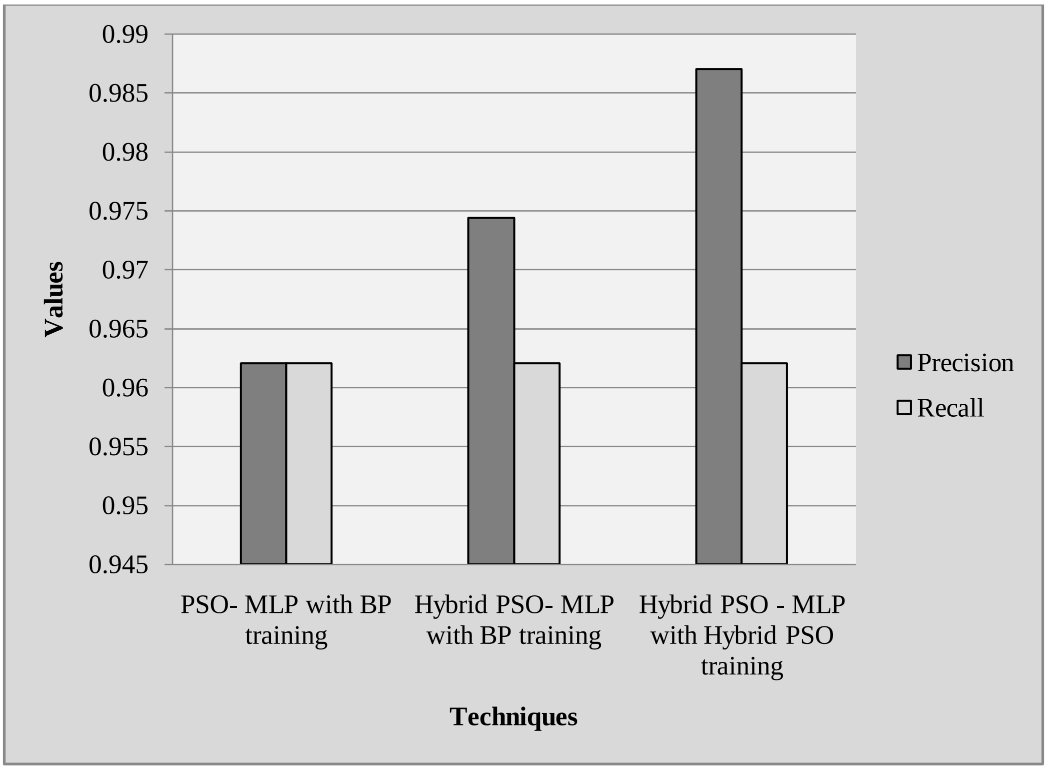

Figure 7: Precision and Recall for Finger

The precision for finger is improved 2.5641% by proposed method when compared with PSO- MLP with BP training is observed from figure 7.

Table 4: Precision and Recall for Tongue

Techniques	Precision	Recall
PSO- MLP with BP training	0.966292135	0.966292135
Hybrid PSO - MLP with BP training	0.966666667	0.97752809
Hybrid PSO - MLP with Hybrid PSO training	0.967032967	0.988764045

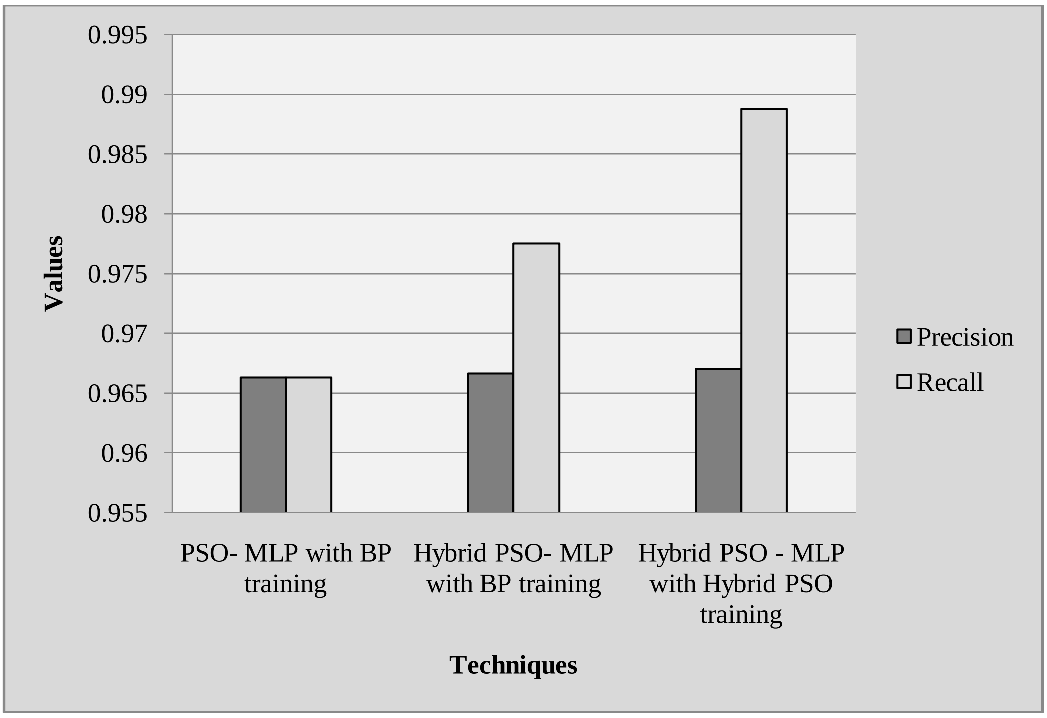

Figure 8: Precision and Recall for Tongue

The figure 8 shows that the proposed method improved precision for tongue by 0.0766% when compared with PSO- MLP with BP training. The recall improved by 2.2989% when compared with PSO- MLP with BP training.

Conclusion

BCI is a communication method based on the brain generated neural activity and is independent of peripheral nerves and muscles normal output pathways. BCI neural activity is recorded using invasive and noninvasive techniques. ECoG is presently generating growing excitement for its potential to support basic neuro-scientific investigations and is clinically practical for BCI systems. This study proposed a Hybrid PSO based FS with MLP. Experiment results proved that the new method outperformed MLP-BP with PSO based FS.

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