Received November 19, 2018, accepted January 2, 2019, date of publication January 17, 2019, date of current version February 4, 2019.

Digital Object Identifier 10.1109/ACCESS.2019.2892492

Cross-Correlation Aided Ensemble of Classifiers for BCI Oriented EEG Study

PARNIKA N. PARANJAPE[1], (Member, IEEE), MEERA M. DHABU[1], (Member, IEEE), PARAG S. DESHPANDE[1], AND AKSHAY M. KEKRE[2], (Member, IEEE)

[1]Department of Computer Science and Engineering, Visvesvaraya National Institute of Technology, Nagpur, India
[2]Department of Electronics and Communication Engineering, Visvesvaraya National Institute of Technology, Nagpur 440010, India

Corresponding author: Parnika N. Paranjape (parnika.paranjape@students.vnit.ac.in)

ABSTRACT Recently, Brain–computer interface (BCI) oriented electroencephalographic (EEG) studies have received due attention for decoding human brain signals corresponding to a specific mental state and providing an alternate solution to the disabled or paralyzed persons for communicating with the computer, robotic arm, or various neural prostheses. In this paper, we propose a two-phase approach to distinguish EEG signals of different mental tasks. The first phase combines the cross-correlation features and slow cortical potentials mean extracted from the most significant channels to form feature vectors. The second phase performs a classification of these feature vectors using SVM and KNN classifiers. It further boosts the classification performance by creating an ensemble of SVM classifiers trained with complementary feature sets extracted during the first phase. EEG signals generated for the same mental task are similar in shape to each other and dissimilar to other activities. The basic principle of cross-correlation is to measure the similarity in shape between two signals which makes it suitable for the EEG analysis. We test the performance of the proposed approach on the BCI competition II dataset Ia representing the cursor movement EEG data for a healthy subject. Experimental results on this dataset demonstrate a significant improvement in the classification accuracy compared to other reported results. Moreover, the proposed work requires fewer channels and features compared to the recent study, which uses all six channels and 42 features, manifesting the efficacy of the proposed work.

INDEX TERMS Brain-computer interface (BCI), cross-correlation, EEG classification, ensemble.

I. INTRODUCTION

Over the past few years, many researchers across the world have been analyzing the electroencephalographic (EEG) signals for various applications such as detection of brain disorders like Epilepsy [1], [2] and Alzheimer [3], emotion recognition [4], [5], sleep stage classification [6], [7], etc. Another type of EEG study involves developing brain-computer interface (BCI) systems which provide a platform for persons with disabilities or severe neurological disorders to control a computer or robotic arm through their brain signals.

In the BCI oriented EEG study, a subject (an individual) is stimulated to perform an imaginary task such as the movement of hand, tongue, limb, imagery cursor movement, etc. Simultaneously, the brain activities are recorded from the subject's scalp in the form of EEG signals. The analysis of these signals is then provided to the subject in visual or audial form for learning to produce distinguishable EEG signals for different mental tasks. These distinct signals are further analyzed in real time to decode the type of motor imagery activity performed by the subject. EEG signals are non-stationary, subject-specific, task-specific and usually contain artifacts like eye blinks, eye movements, muscle movements, etc. Therefore, each BCI application requires different features and classification methods for analyzing EEG signals.

In EEG-based BCI systems, EEG signals, particularly in the mu (8-14 Hz) or beta (14-30 Hz) frequency ranges [8]–[10] or event related potentials such as P300 [11], [12] or slow cortical potentials (SCP) [13], [14] have been widely used in the previous studies as they are highly distinctive. The accurate recognition of the mental activity from EEG signals mainly relies on the discriminative power of the features extracted from EEG signals. During EEG signal processing, features are commonly extracted from time, frequency, time-frequency or a combination of multiple domains. The most widely used feature extraction methods for motor imagery EEG signals are summarized as follows:

- Fast Fourier Transform (FFT):- Varsta *et al*. [15] and Polak and Kostov [16] extracted Fourier spectral features by applying Fourier transform over windowed signal segments.
- Autoregressive (AR) parameters:- An AR model is built for the input signal, and then the model coefficients are used as features [17]–[20]. Both AR and FFT methods assume that the input signal is stationary. However, the EEG signals are non-stationary. Therefore, AR and FFT methods may not give good results on EEG signals.
- Specific frequency band related features [21]–[25].
- Common spatial pattern (CSP):- This method builds the spatial filters to extract the features with a maximum variance between two classes [26], [27].
- Coefficients of wavelet transform:- In [28] and [29], researchers have used the wavelet transform coefficients of the desired frequency bands for EEG analysis.
- Wavelet packet decomposition (WPD):- Ting *et al*. [29] have used the specific sub-band energy and coefficients mean of the wavelet transform. Göksu [30] developed a method which computes the log energy entropy of the WPD coefficients for each frequency band.
- Cross-correlation:- This technique has been widely applied to the analysis of EEG signals related to brain disorders like Epilepsy [31] and EMG signals of neuromuscular diseases [32]. In the recent years, cross-correlation technique has been applied to the multichannel motor imagery EEG analysis, where the statistical features are extracted from the cross-correlation between signals of different channels. The cross-correlation technique offers low computational complexity and minimizes the effect of random noise present in EEG signals [32].

The dataset Ia of BCI competition II [33], described in Section II, has been analyzed by other researchers using different approaches. Mensh *et al*. [13], the winner of the BCI competition II on dataset Ia, combined the SCP measures extracted from the channels 1 and 2 with the gamma-band power estimated from the channels 4 and 6. They further trained a simple linear discriminant (LDA) classifier and reported an accuracy of 88.7% on the test data. Sun and Zhang [34] complemented the SCP measures of the channels 1 and 2 with the spectral centroid on channel 4 and improved the accuracy to 90.44%. Wang *et al*. [35] observed that the wavelet packet coefficients of the channels 4 and 6 in the beta-band show a significant cue-class difference. Therefore, they computed the average energy of the signals using beta-band wavelet coefficients for each of the channels 4 and 6. Further, they combined these features with SCP means of the channels 1 and 2. Finally, neural network and SVM classifiers were used to perform classification of these feature vectors, obtaining an accuracy of 91.47% on the test data. Ting *et al*. [29] applied wavelet packet decomposition to extract coefficient means and energy of 0-50 Hz sub-band from all the six channels to form a 17-dimensional feature vector. Ting *et al*. then used a probabilistic neural network (PNN) classifier and achieved 90.8% test accuracy. Kayikcioglu and Aydemir [36] introduced a method that fits a second order polynomial to the channel 1 signals. They extracted two features from the coefficients of the second order polynomial, followed by classification using KNN to improve the accuracy to 92.15% on the test data. Hu *et al*. [37] achieved 90.1% test accuracy using the coefficients mean and specific sub-band energy of WPD of all six channels. Nguyen *et al*. [38] performed a wavelet decomposition of the signals of each channel and extracted most informative wavelet coefficients from each channel. These features were combined to form a feature vector, followed by classification using interval Type-2 fuzzy logic system, achieving an accuracy of 90.1% on the test data. Recently, Göksu [30] proposed a method to extract log energy entropy of the wavelet packets from all six channels and trained an MLP classifier, improving the classification performance to 92.83%.

Most of the above methods, except the method proposed by Kayikcioglu and Aydemir [36], have extracted the features from EEG signals without considering the shape characteristics of these signals. Therefore, there is still some scope to enhance the classification accuracy by utilizing a fewer number of distinctive features. EEG signals vary in amplitude but exhibit similar shape characteristics for the same mental activity and different shape characteristics for different mental activities. Kayikcioglu and Aydemir fitted a second order polynomial to the EEG signals to capture the upward/downward curve pattern of these signals. However, their method utilized only one type of information extracted from a single channel for classification, producing only 92.15% test accuracy.

In this work, we propose to extract discriminative features from each cross-correlation sequence because the cross-correlation between two signals measures the similarity in shape between these signals. Reference signal selection is a solid criterion for performing cross-correlation. The proposed work performs intra-channel cross-correlation (i.e. cross-correlation between signals of the same channel), where the reference signal is not intuitive. Thus, it is challenging to select the suitable reference signal.

CONTRIBUTIONS

- **Reference signal selection:** As the reference signal selection is critical for cross-correlation, we propose a unique approach to select the reference signal instead of randomly picking the reference.
- **Feature extraction:** After selecting the suitable reference signal, we extract discriminative features from each cross-correlation sequence. We then combine these features with the SCP means as the use of different types of information enhances the accuracy of classification [13], [35]. The features of only most significant channels are utilized in the proposed work as they produce better classification accuracy.

- **Reduced feature dimensionality:** The recent study by Göksu [30] extracts 42 features using all six channels. As opposed to this, the proposed approach utilizes only two channels and five features, reducing the feature dimensionality. Thus, the proposed approach leads to a relatively efficient classification model and makes it suitable for BCI oriented EEG analysis, where disabled persons can control the computer or various neural prostheses through their brain signals.
- **Classification:** Features extracted from different significant channels and multiple suitable reference signals may correspond to diverse characteristics which complement each other and enhance the overall classification accuracy. Therefore, we propose to construct an ensemble of base classifiers trained on complementary feature sets to further boost the classification accuracy. Experimental analysis demonstrates the superiority of the proposed approach compared to other reported studies on the dataset Ia of BCI competition II.

The rest of the paper is organized as follows. Section II briefly describes the EEG dataset used in this study. The details of the proposed approach are given in Section III. Section IV presents an experimental analysis and discussion. The proposed work is concluded in Section V.

II. DATASET

EEG signals used in this study are obtained from BCI competition II dataset Ia [33] available at the competition website.[1] The recordings were collected from a single healthy subject at the Institute of Medical Psychology and Behavioral Neurobiology, University of Tuebingen, Germany. The cortical potentials were measured when a subject moved a cursor up or down on a computer screen. The total duration of each trial is 6 seconds. The structure of the trial is shown in Figure 1. In each trial, the visual cue was presented by a highlighted goal at either the top or bottom of the screen to denote 'up' or 'down' activity from 0.5 seconds to 6 seconds. The subject received a visual feedback of his cortical potentials from 2 seconds to 5.5 seconds. Data from feedback phase of 3.5 seconds is made available for training and testing. As mentioned in [30], the vertical eye movement artifacts were removed from the SCP measurements. The upward/downward movement of the cursor on the screen indicates cortical negativity/positivity produced by the subject.

[1] https://www.bbci.de/competition/ii/tuebingen_desc_i.html

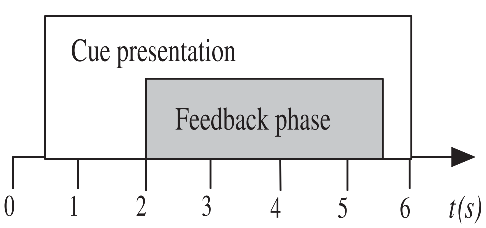

FIGURE 1. Trial structure.

EEG signals were collected from the six electrodes placed on the subject's scalp as per the International 10-20 system and are referenced to the Cz electrode as follows: Channel 1: A1 (left mastoid); Channel 2: A2 (right mastoid); Channels 3 and 5: 2 cm frontal of C3 and C4 respectively; Channels 4 and 6: 2 cm parietal of C3 and C4 respectively. The training set consists of total 268 trials: 135 from class '0' i.e. up and 133 from class '1' i.e. down. Test set consists of total 293 trials. Both training and test trials consist of data from only 3.5 seconds feedback phase. The goal of this study is to predict the class label as '0' or '1' for the EEG trials in the test set.

III. METHODOLOGY

As discussed in Section I, if a subject performs the same mental activity, then the generated EEG signals exhibit similar shape otherwise, the shapes of the signals produced for different mental activities are different. As the cross-correlation technique measures the similarity in shape between two signals, we propose to extract the features from the cross-correlation sequence between two signals. Moreover, the use of different types of features improves the class separability of different EEG signals. In this work, we propose a novel two-phase approach to classify the EEG signals of up and down cursor movement imagery data. The two phases are 1) feature extraction and 2) building the classification model. The first phase extracts the cross-correlation features and slow cortical potentials (SCP) means from the significant channels. Then, these features are integrated into a single vector which serves as an input to SVM and KNN classifiers. The second phase constructs an ensemble of SVM classifiers trained with complementary feature sets to boost the classification accuracy. The proposed approach is diagrammed in Figure 2 and the various steps involved are as follows:

A. PHASE I: FEATURE EXTRACTION

Cross-correlation is one of the feature extraction techniques in the time domain. This technique offers low computational complexity and it curtails the effect of random noise present in EEG signals while extracting features from the cross-correlation sequence. The cross-correlation between two signals $p(t)$ and $q(t)$ is calculated as shown in (1).

$$CC_{pq}[l] = \begin{cases} \sum_{t=0}^{N-l-1} p_{t+l} q_t & \text{if } l \geq 0 \\ CC_{qp}[-l] & \text{if } l < 0 \end{cases} \tag{1}$$

where, $l = -(N-1), \ldots, -2, -1, 0, 1, 2, \ldots, (N-1)$. The variable '$l$' denotes a lag or time shift parameter and $CC_{pq}[l]$ denotes the cross-correlation between two signals p and q with lag 'l'. For $l \geq 0$, signal $p(t)$ is leading the signal $q(t)$ by 'l' positions and for $l < 0$, $p(t)$ lags behind the signal $q(t)$. If 'N' is the finite length of the signals $p(t)$ and $q(t)$, then the number of samples in the resultant cross-correlation sequence is $2N-1$.

Selection of the reference signal is a solid criterion for performing the cross-correlation as the quality of classification

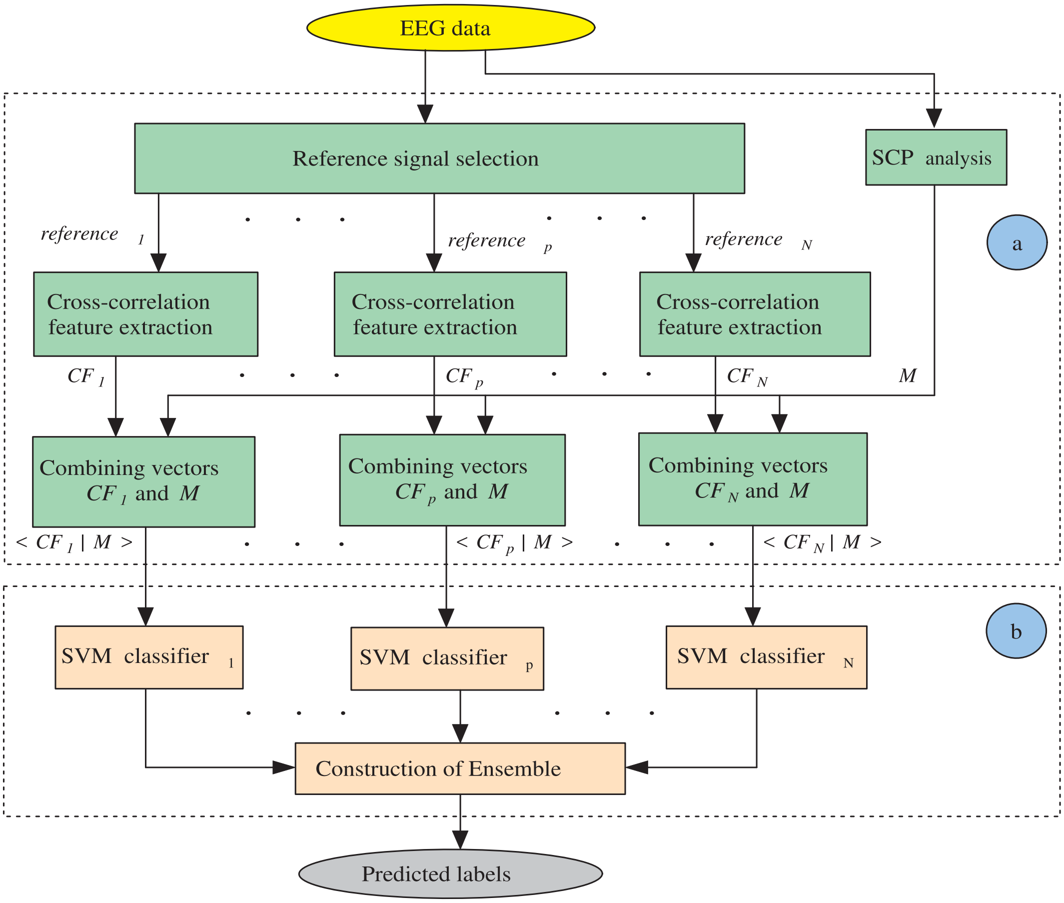

FIGURE 2. Flow diagram of the proposed approach. (a) Feature extraction. (b) building the classification model.

not only depends on the type of features extracted from the cross-correlation sequence, but also depends on the reference signal used to generate the cross-correlation sequence. Thus, in this work, we propose an approach to select the suitable reference signals for performing the cross-correlation. Steps involved in the feature extraction phase are as follows:

1) STEP 1: REFERENCE SIGNAL SELECTION

In certain EEG studies, the reference signal is intuitive. For example, identifying subjects with the epileptic seizure from a group of healthy subjects and subjects with epilepsy. In this case, signals of healthy subjects are quite different from the signals of the subjects with epileptic seizures [31]. However, in studies such as identification of different mental activities performed by the subject from his/her EEG signals, the EEG signals of different activities are not easily differentiable. In this work, we analyze these signals using intra-channel cross-correlation, where the selection of the reference signal is not trivial. One may randomly select the reference signal. However, randomness does not ensure the accurate results.

The dataset Ia of BCI competition II has EEG signals for two classes, viz. ‘up’ and ‘down’ cursor movements. In this case, a reference signal can be a representative of any one of these classes. After detailed analysis, we observe that if a signal, whose sample mean is either closer to or farther from the overall mean of the same class, but farther from the overall mean of the other class, is selected as a reference signal, then the extracted cross-correlation features give better accuracy. However, if a signal, whose mean value is closer to the overall mean of the other class, is selected as a reference, then the cross-correlation features degrade the classification performance. This scenario for channel 1 is depicted in Figure 3. In this figure, the channel 1 signals, viz. ‘$r1$’ and ‘$r2$’ are closest to and farthest from the overall mean of the ‘up’ activity, respectively but farther from the overall mean of the ‘down’ activity. These signals are shown in Figure 4. It can be seen from Figure 3 that the test accuracies achieved using ‘$r1$’ and ‘$r2$’ as the reference signal are higher than that obtained with other reference signals chosen randomly.

Let $\mathcal{T}$: set of training samples, $\mathcal{T}_u$: set of ‘up’ class samples, $\mathcal{T}_d$: set of ‘down’ class samples, p: # data points per signal, and j: channel index. We select the reference signal corresponding to a given channel from the ‘up’ activity as follows:

- $\forall\, r \in \mathcal{T}_u$, compute the mean and standard deviation as follows,

$$\mu_j^{u_m} = \frac{1}{p}\sum_{i=1}^{p} r_{ji}^{u_m},\ \sigma_j^{u_m} = \sqrt{\frac{\sum_{i=1}^{p}\left(r_{ji}^{u_m} - \mu_j^{u_m}\right)^2}{p-1}}$$

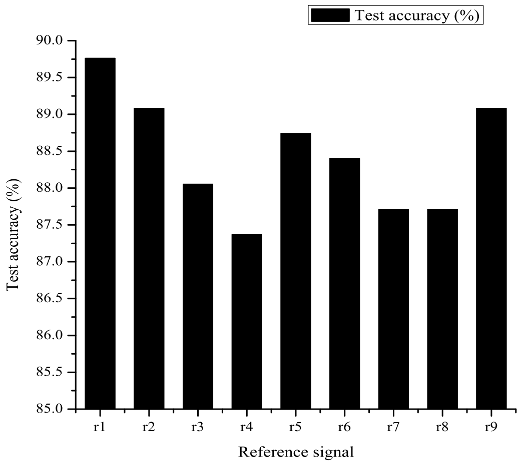

FIGURE 3. Test accuracies obtained with various reference signals of channel 1.

- $\forall\, r \in \mathcal{T}_d$, compute the mean and standard deviation as follows,
$\mu_j^{d_q} = \frac{1}{p}\sum_{i=1}^{p} r_{ji}^{d_q}$, $\sigma_j^{d_q} = \sqrt{\frac{\sum_{i=1}^{p}\left(r_{ji}^{d_q}-\mu_j^{d_q}\right)^2}{p-1}}$
- Compute the mean of 'up' class,
$\mu_j^{u} = \frac{1}{|\mathcal{T}_u|}\sum_{m=1}^{|\mathcal{T}_u|}\mu_j^{u_m}$
- Compute the mean of 'down' class,
$\mu_j^{d} = \frac{1}{|\mathcal{T}_d|}\sum_{q=1}^{|\mathcal{T}_d|}\mu_j^{d_q}$
- Let $r_j^{u_l} \in \mathcal{T}_u$ where, $\mu_j^{u_l}$ is either closest to or farthest from μ_j^{u} with smaller $\sigma_j^{u_l}$ and farther from μ_j^{d}. Then, $r_j^{u_l}$ becomes the candidate reference signal.

In this work, we experiment with both signals whose mean values are either closest to or farthest from the 'up' class mean. The reference signal selection process for channel 1 is depicted in Figure 4.

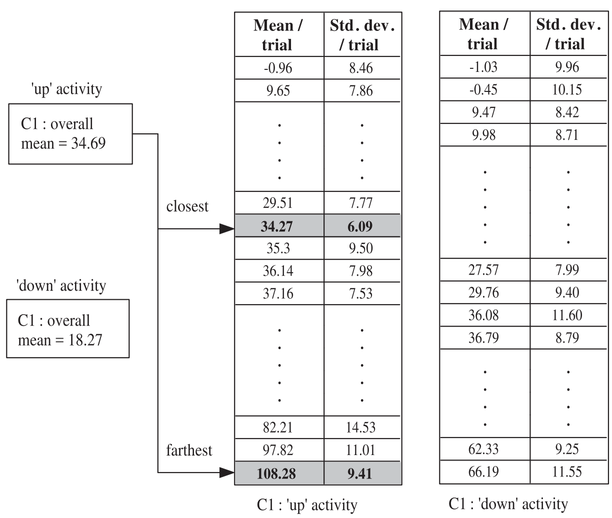

FIGURE 4. Reference selection for channel 1.

2) STEP 2: CROSS-CORRELATION FEATURE EXTRACTION

After selecting the reference signal, the remaining EEG signals of both 'up' and 'down' activity are correlated with the reference signal. The dataset Ia has EEG recordings from six different channels. Therefore, a reference signal is different for each channel. Bose *et al.* [32] and Krishna *et al.* [39] extracted different types of features, viz. Hjorth parameters, statistical features, etc. Chandaka *et al.* [31] extracted following features from the cross-correlation sequence for the detection of epileptic seizure and achieved promising results.

1) Peak / Maximum value:
2) Instant at which peak occurs:
3) Centroid (*cent*)

$$cent = \frac{\sum_{l=-(N-1)}^{(N-1)} l * CC[l]}{\sum_{l=-(N-1)}^{(N-1)} CC[l]} \tag{2}$$

4) Equivalent width (W)

$$W = \frac{\sum_{l=-(N-1)}^{(N-1)} CC[l]}{Peak\ value\ of\ CC[l]} \tag{3}$$

5) Mean square abscissa (*msa*)

$$msa = \frac{\sum_{l=-(N-1)}^{(N-1)} l^2 * CC[l]}{\sum_{l=-(N-1)}^{(N-1)} CC[l]} \tag{4}$$

Experimental results demonstrate that the aforementioned features are more discriminative than the statistical and Hjorth features for both channels 1 and 2. Hence, in the proposed work, we extract these features from each cross-correlation sequence corresponding to the channels 1 and 2. It is also observed that the cross-correlation features extracted from the channels 1 and 2 give better classification accuracies compared to those extracted from other channels. This is manifested in Section IV. Thus, we utilize the proposed cross-correlation features of the channels 1 and 2 only.

Figure 5 depicts a reference signal which is a representative of 'up' activity, whereas the typical 'up' and 'down' activity signals are shown in Figures 6 and 7 respectively. These signals correspond to channel 1. Figures 8 and 9 depict a cross-correlation between the reference signal and

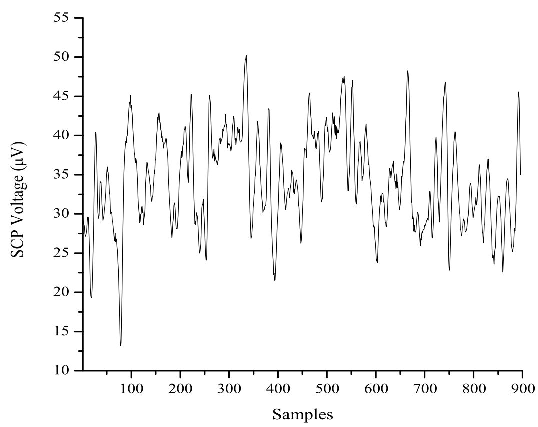

FIGURE 5. Reference signal of channel 1.

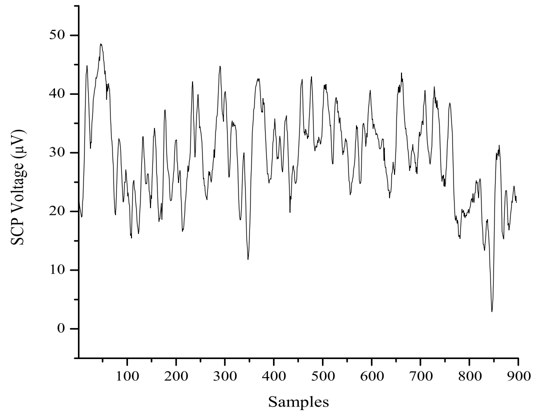

FIGURE 6. Typical 'up' activity signal of channel 1.

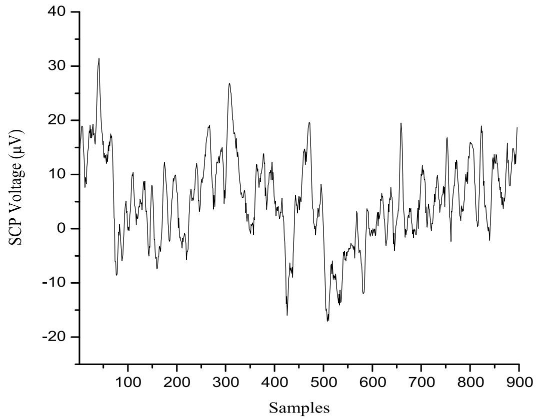

FIGURE 7. Typical 'down' activity signal of channel 1.

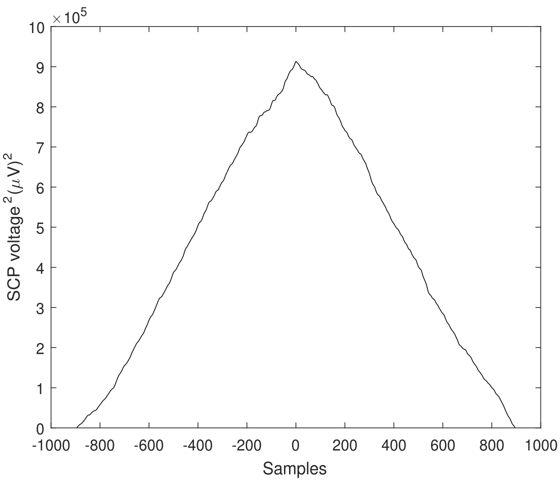

FIGURE 8. Crosscorrelogram of the reference and 'up' activity.

the typical 'up' and 'down' activity signals respectively. The cross-correlograms of some trials of the 'up' and 'down' activities may be somewhat different from their typical cross-correlograms due to noise in SCP measurements.

3) STEP 3: SLOW CORTICAL POTENTIALS (SCP) ANALYSIS

In [13], the winner of BCI competition II dataset Ia demonstrated that the channels 1 and 2 show a significant

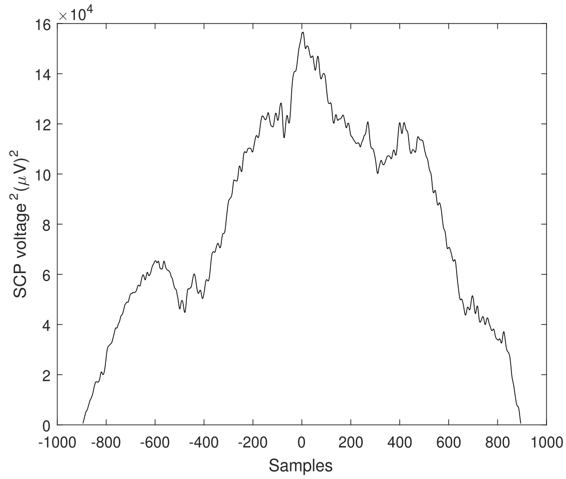

FIGURE 9. Crosscorrelogram of the reference and 'down' activity.

difference between the cue class means. It can be seen from Figures 10 and 11 that the cue class difference is 20-30 μV for the channels 1 and 2, except an initial transient which may be due to the inception of feedback phase. Therefore, for each trial, the SCP voltages of the channels 1 and 2 are averaged from 0.5s to 3.5s ignoring the initial transient. Cue class differences are marginal for the remaining four channels.

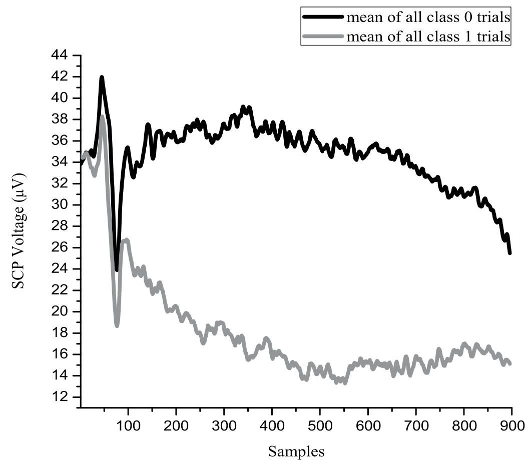

FIGURE 10. SCP analysis of the channel 1, training samples.

4) STEP 4: CONSTRUCTION OF FEATURE VECTOR

The use of different types of information enhances the performance of the classifier [13], [35]. Hence, we propose to combine the discriminative cross-correlation features of the significant channel and SCP means of the channels 1 and 2, forming a feature vector for each trial.

B. PHASE II: BUILDING THE CLASSIFICATION MODEL

Several different types of classifiers such as SVM, KNN, neural network, LDA, etc. have been employed in the EEG signal classification. SVM and KNN classifiers are most widely

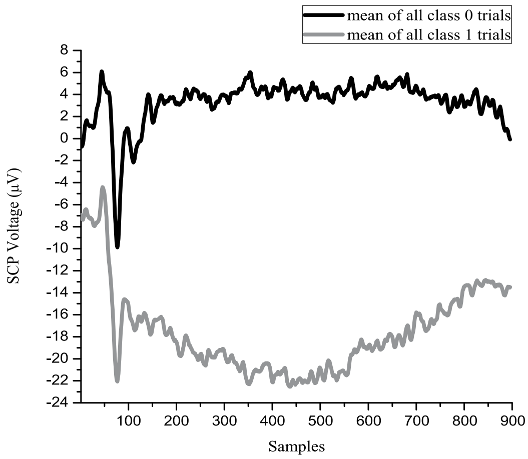

FIGURE 11. SCP analysis of the channel 2, training samples.

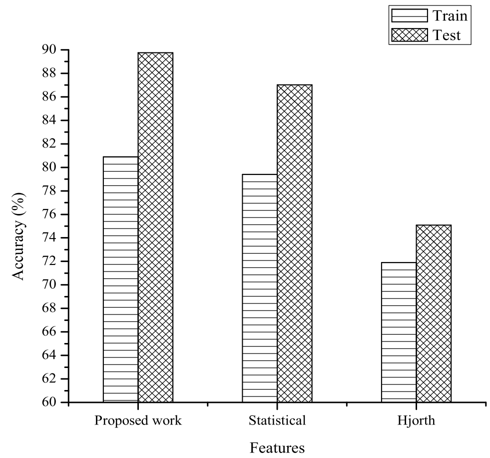

FIGURE 12. Performance of classifier built using different types of features extracted from the cross-correlation sequences for channel 1.

used and shown to be effective in the EEG classification. The following subsections describe the steps involved in the phase II.

1) STEP 1: BUILDING THE BASE CLASSIFIER USING FEATURE VECTORS CONSTRUCTED IN PHASE I

Using the feature vectors constructed in phase I, the proposed work builds SVM and KNN as the base classifiers. SVM classifier needs a regularization parameter C and the hyperparameters like degree for polynomial kernel and σ for RBF kernel. By harnessing a well-known method called grid search, we estimate the optimal hyperparameters and a suitable regularization parameter which yields the best accuracy for test samples. For KNN classifier, the best value of parameter 'k' is estimated by training the model with different 'k' values and selecting the one which gives the highest accuracy.

2) STEP 2: CONSTRUCTION OF AN ENSEMBLE OF BASE CLASSIFIERS

To boost the classification performance further, we employ an ensemble approach which can benefit from multiple models trained with complementary sets of features and the same base classifier. It is observed that the base classifier, trained with different feature sets, produces the results which correspond to diverse aspects of these features. We construct an ensemble of SVM classifiers trained with different feature sets obtained using different significant channels and multiple reference signals. The outcome of the ensemble model is determined using two different approaches: 1) majority voting, and 2) maximum probability where the class label with maximum posterior probability is predicted.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

All experiments have been conducted on an Intel Core 2 Duo machine with 3.17 GHz CPU, 4GB main memory and 64 bit Windows environment. The proposed approach is implemented in Matlab R2016a. The dataset used in this study is taken from BCI competition II dataset Ia where the goal is to differentiate the 'up' and 'down' cursor movements of a healthy subject. The performance metric for this dataset is classification accuracy.

In this work, we proposed to extract the cross-correlation features, viz. peak value, instant at which peak occurs, centroid ($cent$), equivalent width (W), and mean square abscissa (msa). We compare the classification accuracy of the classifier built using the proposed cross-correlation features and the classifier built using other types of features, viz. statistical [39] and Hjorth [32] extracted from the cross-correlation sequence by other researchers. Figures 12 and 13 for the channels 1 and 2 show that the proposed features are more discriminative than other types of features. In the experimental analysis, the channels 1 and 2 are found to be most significant in terms of the classification accuracy, see Figure 14. Therefore, we built the classifier using the proposed cross-correlation features extracted from the most significant channels 1 and 2.

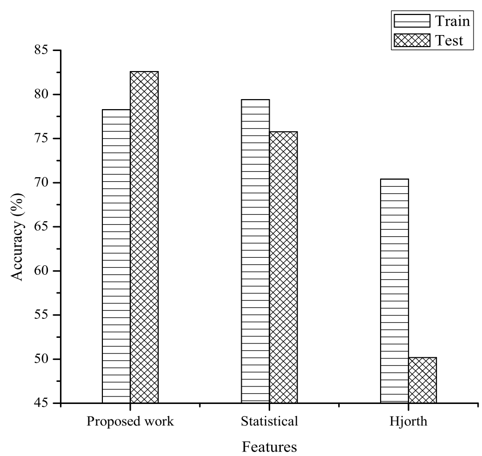

FIGURE 13. Performance of classifier built using different types of features extracted from the cross-correlation sequences for channel 2.

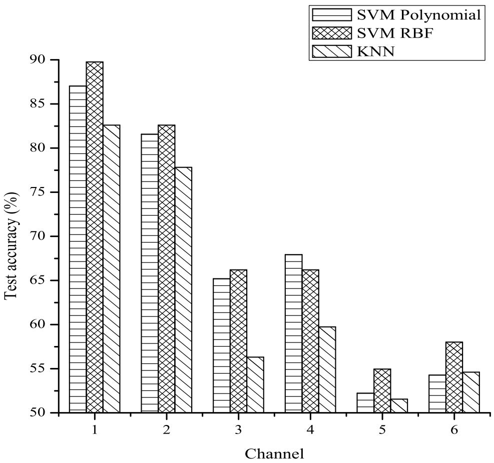

FIGURE 14. Test accuracies obtained using proposed cross-correlation features from each channel.

It can be seen from Figures 12 and 13 that the classification accuracy on the test samples is higher than that on the training samples for all types of features, except statistical and Hjorth features extracted from the channel 2. For the cases with higher test accuracy, the class separation power of the underlying features on the test samples is better than that on the training samples. Moreover, the previous studies [13], [35], [36] obtained better test accuracy than the training accuracy which also suggests that the test samples have better class separation than the training samples. We compute the class separability criterion J_3 [40] for both training and test samples using (5).

$$J_3 = trace\left(S_w{}^{-1} * S_B\right) \tag{5}$$

where,
S_w: within class scatter matrix.
S_B: between class scatter matrix.

Tables 1 and 2 suggest that the value of the criterion J_3 of the test samples is better than that of the training samples for most of the cases. Thus, for these cases, the test accuracy is higher than the training accuracy which is evident from Figures 12 and 13.

TABLE 1. Class separability criteria value for different types of features extracted from the cross-correlation sequences for channel 1.

J_3	Proposed work	Statistical features	Hjorth features
Train	0.212	0.516	0.241
Test	1.169	1.382	0.257

TABLE 2. Class separability criteria value for different types of features extracted from the cross-correlation sequences for channel 2.

J_3	Proposed work	Statistical features	Hjorth features
Train	0.234	1.299	0.179
Test	1.033	0.517	0.165

A detailed analysis of the most significant channels, viz. 1 and 2 with different combinations of discriminative features is given in the subsection IV-A. We also present an extensive analysis for the ensemble of classifiers trained with complementary feature sets in the subsection IV-B.

A. RESULTS FOR SIGNIFICANT CHANNELS

The classification accuracy for each channel obtained using the proposed cross-correlation features is shown in Figure 14. From Figure 14, it is evident that only the channels 1 and 2 achieved a desirable classification performance compared to other channels. Therefore, we only utilize the information from the channels 1 and 2 for classification. The classification power of the individual cross-correlation features of the channels 1 and 2 is depicted in Figures 15 and 16 respectively. It is evident from Figure 15 that the features, viz. 1 (peak value), 4 (equivalent width), and 5 (mean square abscissa) of the channel 1 are most discriminative as they perform well on the training as well as test samples. Figure 16 depicts that the fourth feature i.e. 'equivalent width' outperformed all other features of channel 2. The features 2 (centroid) and 3 (instant at which peak occurs) perform better on the test samples compared to the fifth feature i.e. 'mean square abscissa'. However, their ability to separate the training samples into two classes is very low compared to the fifth feature. Therefore, the features 2 and 3 may perform very well on the test samples, but at the cost of poor training accuracy. To address this issue, we prefer the fifth feature i.e. 'mean square abscissa' over the features 2 and 3 for channel 2.

Figure 15 for channel 1 suggests that the features 2 (centroid) and 4 (equivalent width) have higher test accuracy, whereas remaining features have higher training accuracy. To justify these results, the scatter plots for the channel 1 features, viz. 4 (equivalent width) and 5 (mean square abscissa) are shown in Figures 17 and 18 respectively. It can be seen that the fourth feature, i.e., equivalent width well separates the test samples into two classes than the training samples, whereas the fifth feature, i.e., mean square abscissa has better class separation for training samples compared to test samples. From Figures 17 and 18, it is evident that the range of

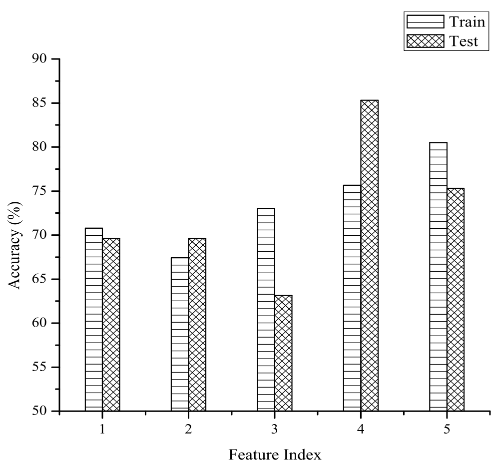

FIGURE 15. Classification accuracy of the individual cross-correlation features of channel 1.

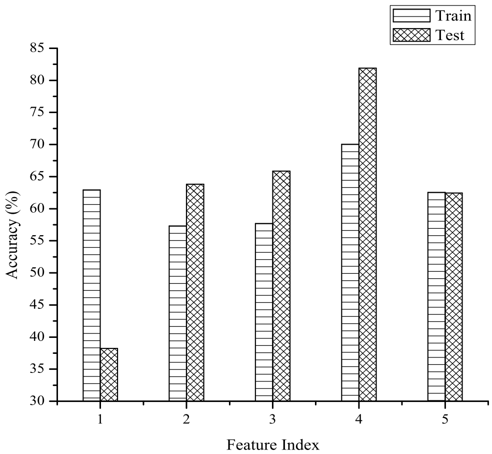

FIGURE 16. Classification accuracy of the individual cross-correlation features of channel 2.

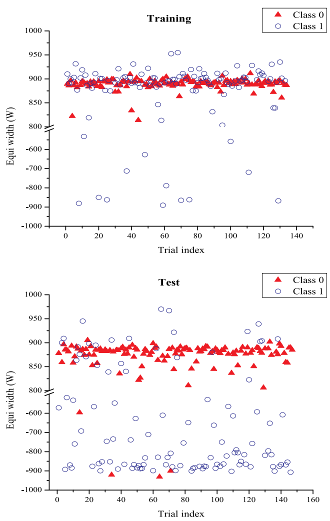

FIGURE 17. Scatter plot for values of equivalent width (*W*) of channel 1.

values of the features, viz. equivalent width and mean square abscissa in the test samples is close to their corresponding range of values in the training samples. Thus, if the ranges of values of a feature in the training and test samples are close enough and the feature has better class separation for test samples compared to that for training samples, then the test accuracy will be better than the training accuracy for a given feature. Similar behavior was observed for the channel 2 features depicted in Figure 16. In this figure, the test accuracy is better than the training accuracy for all features except the feature 1.

We performed experiments with different combinations of the discriminative cross-correlation features of the channels 1 and 2. In each experiment, significant cross-correlation features are combined with the SCP means of the channels 1 and 2 to form a feature vector for each trial which is then classified by SVM and KNN classifiers. SVM classifier with polynomial and RBF kernels are used, where the regularization parameter 'C' and the optimal hyperparameters 'degree' and 'σ' are estimated using a grid search method.

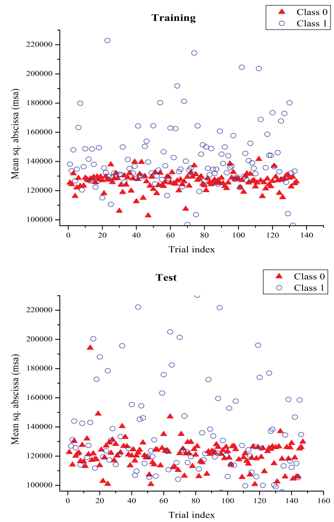

FIGURE 18. Scatter plot for values of mean square abscissa (*msa*) of channel 1.

The search range for 'C' is within $[1, 50]$ with a step size of 5 and the range for 'σ' is within $[2^{-2}, 2^5]$ with a step size of 2^1. For KNN classifier, the search range for parameter 'k' is $[1, 19]$ with a step size of 2. Separate training and test samples of the dataset Ia are provided by the BCI competition II [33], where the test accuracy is estimated using the entire training set. In this work, the training accuracy has been estimated using 10-fold stratified cross-validation. Both average accuracy and standard deviation for the training set have been reported in Tables 3, 5, and 7.

From Tables 3 and 4, it can be seen that the training as well as test accuracies obtained using the channel 1 features, viz. 1 (peak value), 4 (equivalent width), and 5 (mean square abscissa) are superior to the other feature combinations. It is also observed that SVM RBF classifier outperformed other classifiers in all the cases. When different types of features such as cross-correlation and SCP means are extracted from multiple channels, then there is a possibility that data samples with the same class label are scattered in multiple separate regions. KNN classifier can handle non-linearly separable data, but it usually works well when a lot of training samples are available. Polynomial kernel maps the input data to a finite dimensional feature space controlled by the degree parameter. Thus, the classification model learned from the data may get saturated after a certain point, limiting its performance. RBF kernel, on the other hand, maps the input

TABLE 3. Training accuracy and standard deviation for different combinations of discriminative features of channel 1.

Features	Classifier		
	SVM polynomial	SVM RBF	KNN
correlation (1,4,5) & SCP means	82.77 ± 5.52	**82.4 ± 7.95**	76.4 ± 7.71
correlation (1,2,4,5) & SCP means	79.78 ± 9.12	81.65 ± 6.36	76.4 ± 7.95
correlation (4,5) & SCP means	82.02 ± 5.77	81.65 ± 9.67	77.9 ± 7.83

TABLE 4. Test accuracies obtained with different combinations of discriminative features of channel 1.

Features	Classifier		
	SVM polynomial	SVM RBF	KNN
correlation (1,4,5) & SCP means	90.1 %	**93.52 %**	90.78 %
correlation (1,2,4,5) & SCP means	86.01 %	91.81 %	88.05 %
correlation (4,5) & SCP means	90.1 %	93.52 %	90.78 %

TABLE 5. Training accuracy and standard deviation for different combinations of discriminative features of channel 2.

Features	Classifier		
	SVM polynomial	SVM RBF	KNN
correlation (4,5) & SCP means	83.15 ± 9.39	$\mathbf{82.77 \pm 5.22}$	80.15 ± 6.28
correlation (3,4,5) & SCP means	76.78 ± 12.15	81.27 ± 8.04	79.78 ± 6.25
correlation (3,4) & SCP means	71.54 ± 6.96	76.78 ± 10.03	74.16 ± 11.08

TABLE 6. Test accuracies obtained with different combinations of discriminative features of channel 2.

Features	Classifier		
	SVM polynomial	SVM RBF	KNN
correlation (4,5) & SCP means	86.69 %	**91.81 %**	84.64 %
correlation (3,4,5) & SCP means	86.69 %	91.47 %	84.3 %
correlation (3,4) & SCP means	83.28 %	89.76 %	81.91 %

data to an infinite dimensional feature space, producing much complex decision boundaries compared to the polynomial kernel. Thus, the RBF kernel performs better for the data scattered in multiple separate regions.

Tables 5 and 6 show the training and test accuracies respectively, for the different combinations of the discriminative cross-correlation features of channel 2. The features 4 (equivalent width) and 5 (mean square abscissa) outperformed all other feature combinations for both training and test samples. Again, SVM RBF classifier performed better than SVM polynomial and KNN classifiers in all the cases.

B. RESULTS OF AN ENSEMBLE METHOD

The dataset Ia of BCI competition II contains the EEG signals from six different channels. In the proposed work, only the channels 1 and 2 are found to be most significant as they produced distinctive feature sets. It can be observed from the results in Tables 4 and 6 that the features, viz. peak value, equivalent width, mean square abscissa, and the SCP means are most discriminative for the channel 1, whereas the features, viz. equivalent width, mean square abscissa, and the SCP means are discriminative for the channel 2. It is also evident that SVM RBF classifier achieved the best results compared to SVM polynomial and KNN classifiers in all experiments. Based on the following observations, we propose to construct an ensemble of SVM RBF classifiers trained with complementary feature sets obtained from different significant channels which have multiple suitable reference signals.

- Training a classifier with different feature sets obtained from different channels produces the results that cover diverse aspects of these features.
- Training a classifier with feature sets obtained from multiple suitable reference signals of a given channel also boosts the classification performance.

We experimented with different number of models in the ensemble method. In each experiment, the same number of models were learned for both the channels to avoid bias towards a particular channel. We determined the outcome of an ensemble using two different approaches: 1) majority voting, and 2) maximum probability where the class label with maximum posterior probability is predicted. In case of a tie in majority voting, the class label with maximum posterior probability becomes the predicted label. In each experiment, we retain the best result from these two approaches. Table 7 shows the results of an ensemble method where, in each experiment, a different number of models were learned from the channels having different suitable reference signals. The best result of the ensemble method is marked in bold. This result corresponds to an ensemble designed with feature sets obtained from two best reference signals for each of the channels 1 and 2.

The different performance measures for the best result produced by an ensemble method are presented in Table 8.

TABLE 7. Results of ensembling significant channels with multiple reference signals.

Sr. No	# Models/channel		Training accuracy	Test accuracy
	channel 1	channel 2		
1	1	1	81.95 ± 5.07	93.52 %
2	1	1	81.2 ± 4.72	93.52 %
3	2	2	81.5 ± 6.12	93.2 %
4	2	2	82.2 ± 6.1	93.52 %
5	**2**	**2**	$\mathbf{82.58 \pm 5.23}$	**94.54 %**
6	3	3	81.75 ± 6.54	93.17 %
7	3	3	82.13 ± 4.9	93.52 %
8	3	3	81.68 ± 9.55	93.86 %

TABLE 8. Performance measures for the best result from ensemble approach.

Dataset Ia	Accuracy	Sensitivity	Specificity	F-measure	Kappa
Training	82.58 %	0.7891	0.8717	0.8345	0.6518
Test	94.54 %	0.9226	0.9710	0.9470	0.8908

In Table 9, we present a comparison of the classification accuracy obtained by the proposed approach and other state-of-the-art methods developed for the dataset Ia of BCI competition II. It is evident that the proposed method significantly enhances the classification accuracy compared to other reported results on dataset Ia. We also outperform the winner of the BCI competition II on dataset Ia. Moreover, the proposed approach achieved the performance improvement with reduced feature dimensionality by harnessing only two channels and at the most five features.

TABLE 9. Performance comparison with other reported results.

Author	Accuracy (%)	# channels used	# features
Mensh et al. (Winner of BCI competition II) (2004) [13]	88.70 %	4	4
Sun and Zhang (2005) [34]	90.44 %	6	7
Wang et al. (2006) [35]	91.47 %	2	4
Ting et al. (2008) [29]	90.80 %	6	17
Kayikcioglu and Aydemir (2010) [36]	92.15 %	1	2
Hu et al. (2011) [37]	90.10 %	6	10
Nguyen et al. (2015) [38]	90.10 %	6	-
Göksu et al. (2018) [30]	92.83 %	6	42
Proposed method	**94.54 %**	**2**	**5**

C. STATISTICAL ANALYSIS OF THE RESULTS

Separate training and test samples of the dataset Ia are provided by BCI competition II. For this dataset, the test accuracy is estimated using the entire training set. Therefore, all previous approaches including the proposed work produced a single estimate of test accuracy as shown in Table 9. Two sets of accuracy results are required for conducting statistical analysis of the performance of classifiers. Thus, training and test samples are merged to yield a large dataset. We have implemented the recent approach by Göksu [30] and we are thankful to authors for guiding us for the implementation. As the implementations of other approaches are not readily available, we compare our results only with the recent approach by Göksu.

We performed 20 times 10-fold cross-validation on the merged dataset. The proposed approach produced 88.02 ± 0.4 accuracy and the approach by Göksu produced 77.76 ± 1.32 accuracy. The results are also statistically validated using the Mann-Whitney U-test which compares the two sets of accuracies produced by the proposed approach and the approach by Göksu. The two-sided p-value of this test is 6.431×10^{-8} which is smaller than 5% significance level. Therefore, this test rejects the null hypothesis that the results of two approaches belong to the same distribution at 5% significance level. This statistical test shows that the proposed approach is better than the recent method proposed by Göksu [30].

V. CONCLUSION

BCI oriented EEG studies have become extremely popular in the recent years as it assists the disabled or paralyzed persons to control the computer or neuroprosthetic devices through their brain EEG signals. The work proposed in this paper introduced a novel two-phase approach to distinguish the up and down cursor imagery movements of a healthy subject. As the brain produces similar signals for the same mental task and the cross-correlation technique measures the similarity in shape between two signals, we extracted the cross-correlation features in the first phase. We further integrated the most discriminative cross-correlation features with the SCP means for creating a feature vector. The second phase classified this vector using SVM RBF classifier whose performance is shown to be superior to SVM polynomial and KNN classifiers. It further employed an ensemble of SVM RBF classifiers trained with complementary feature sets to boost the classification performance. Extensive analysis of the dataset Ia of BCI competition II confirms the ascendancy of the proposed method compared to other reported results. Our method is also superior to the winner of BCI competition II dataset Ia. The proposed method is efficient as it achieved significant performance improvement with reduced feature dimensionality by employing only two channels and at the most five features compared with the recent study which uses all channels and 42 features.

The performance of the proposed approach confirms the potential of the cross-correlation features and also demonstrates the importance of using different types of features for improving the class separation power.

The future study involves working with more complex BCI oriented EEG signals, where the dependencies among different channels are responsible for different mental activities. One possible solution is to model the EEG signals as complex networks/visibility graphs to capture these dependencies among channels.

REFERENCES

[1] S. Supriya, S. Siuly, H. Wang, J. Cao, and Y. Zhang, "Weighted visibility graph with complex network features in the detection of epilepsy," *IEEE Access*, vol. 4, pp. 6554–6566, 2016.

[2] J. Saini and M. Dutta, "An extensive review on development of EEG-based computer-aided diagnosis systems for epilepsy detection," *Netw., Comput. Neural Syst.*, vol. 28, no. 1, pp. 1–27, Jan. 2017.

[3] R. Cassani, M. Estarellas, R. San-Martin, F. J. Fraga, and T. H. Falk, "Systematic review on resting-state EEG for Alzheimer's disease diagnosis and progression assessment," *Disease Markers*, vol. 2018, Oct. 2018, Art. no. 5174815.

[4] R. M. Mehmood, R. Du, and H. J. Lee, "Optimal feature selection and deep learning ensembles method for emotion recognition from human brain EEG sensors," *Cities*, vol. 4, p. 5, Jan. 2017.

[5] M. Hamada, B. B. Zaidan, and A. A. Zaidan, "A systematic review for human EEG brain signals based emotion classification, feature extraction, brain condition, group comparison," *J. Med. Syst.*, vol. 42, no. 9, p. 162, Sep. 2018.

[6] K. A. I. Aboalayon, M. Faezipour, W. S. Almuhammadi, and S. Moslehpour, "Sleep stage classification using EEG signal analysis: A comprehensive survey and new investigation," *Entropy*, vol. 18, no. 9, p. 272, 2016.

[7] R. Boostani, F. Karimzadeh, and M. Nami, "A comparative review on sleep stage classification methods in patients and healthy individuals," *Comput. Methods Programs Biomed.*, vol. 140, pp. 77–91, Mar. 2017.

[8] C. Guger, H. Ramoser, and G. Pfurtscheller, "Real-time EEG analysis with subject-specific spatial patterns for a brain-computer interface (BCI)," *IEEE Trans. Rehabil. Eng.*, vol. 8, no. 4, pp. 447–456, Dec. 2000.

[9] T. Wang, J. Deng, and B. He, "Classifying EEG-based motor imagery tasks by means of time-frequency synthesized spatial patterns," *Clin. Neurophysiol.*, vol. 115, no. 12, pp. 2744–2753, Dec. 2004.

[10] Y. Wang, Z. Zhang, Y. Li, X. Gao, S. Gao, and F. Yang, "BCI competition 2003-data set IV: An algorithm based on CSSD and FDA for classifying single-trial EEG," *IEEE Trans. Biomed. Eng.*, vol. 51, no. 6, pp. 1081–1086, Jun. 2004.

[11] E. Donchin, K. M. Spencer, and R. Wijesinghe, "The mental prosthesis: Assessing the speed of a P300-based brain-computer interface," *IEEE Trans. Rehabil. Eng.*, vol. 8, no. 2, pp. 174–179, Jun. 2000.

[12] U. Hoffmann, J.-M. Vesin, T. Ebrahimi, and K. Diserens, "An efficient P300-based brain–computer interface for disabled subjects," *J. Neurosci. Methods*, vol. 167, no. 1, pp. 115–125, Jan. 2008.

[13] B. D. Mensh, J. Werfel, and H. S. Seung, "BCI competition 2003-data set IA: Combining gamma-band power with slow cortical potentials to improve single-trial classification of electroencephalographic signals," *IEEE Trans. Biomed. Eng.*, vol. 51, no. 6, pp. 1052–1056, Jun. 2004.

[14] S. Bengio, "HMM and IOHMM modeling of eeg rhythms for asynchronous bci systems," in *Proc. Eur. Symp. Artif. Neural Netw. (ESANN)*, 2004, pp. 199–204.
[15] M. Varsta, J. Heikkonen, J. del R. Millan, and J. Mourino, "Evaluating the performance of three feature sets for brain-computer interfaces with an early stopping MLP committee," in *Proc. 15th IEEE Int. Conf. Pattern Recognit.*, vol. 2, Sep. 2000, pp. 907–910.
[16] M. Polak and A. Kostov, "Feature extraction in development of brain-computer interface: A case study," in *Proc. 20th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, vol. 4, Nov. 1998, pp. 2058–2061.
[17] A. Schlögl, C. Neuper, and G. Pfurtscheller, "Estimating the mutual information of an EEG-based brain-computer interface," *Biomedizinische Technik/Biomed. Eng.*, vol. 47, nos. 1–2, pp. 3–8, 2002.
[18] G. Pfurtscheller, C. Neuper, A. Schlogl, and K. Lugger, "Separability of EEG signals recorded during right and left motor imagery using adaptive autoregressive parameters," *IEEE Trans. Rehabil. Eng.*, vol. 6, no. 3, pp. 316–325, Sep. 1998.
[19] D. P. Burke, S. P. Kelly, P. de Chazal, R. B. Reilly, and C. Finucane, "A parametric feature extraction and classification strategy for brain-computer interfacing," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 13, no. 1, pp. 7–12, Mar. 2005.
[20] C. Guger, A. Schlogl, C. Neuper, D. Walterspacher, T. Strein, and G. Pfurtscheller, "Rapid prototyping of an EEG-based brain-computer interface (BCI)," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 9, no. 1, pp. 49–58, Mar. 2001.
[21] G. Pfurtscheller, C. Neuper, D. Flotzinger, and M. Pregenzer, "EEG-based discrimination between imagination of right and left hand movement," *Electroencephalogr. Clin. Neurophysiol.*, vol. 103, no. 6, pp. 642–651, Dec. 1997.
[22] J. A. Pineda, B. Z. Allison, and A. Vankov, "The effects of self-movement, observation, and imagination on μ rhythms and readiness potentials (RP's): Toward a brain-computer interface (BCI)," *IEEE Trans. Rehabil. Eng.*, vol. 8, no. 2, pp. 219–222, Jun. 2000.
[23] G. Pfurtscheller and C. Neuper, "Motor imagery and direct brain-computer communication," *Proc. IEEE*, vol. 89, no. 7, pp. 1123–1134, Jul. 2001.
[24] T. N. Lal *et al.*, "Support vector channel selection in BCI," *IEEE Trans. Biomed. Eng.*, vol. 51, no. 6, pp. 1003–1010, Jun. 2004.
[25] D. J. McFarland, W. A. Sarnacki, and J. R. Wolpaw, "Brain–computer interface (BCI) operation: Optimizing information transfer rates," *Biol. Psychol.*, vol. 63, no. 3, pp. 237–251, Jul. 2003.
[26] G. Blanchard and B. Blankertz, "BCI competition 2003-data set IIa: Spatial patterns of self-controlled brain rhythm modulations," *IEEE Trans. Biomed. Eng.*, vol. 51, no. 6, pp. 1062–1066, Jun. 2004.
[27] S. Lemm, "Spatio-spectral filters for improving the classification of single trial EEG," *IEEE Trans. Biomed. Eng.*, vol. 52, no. 9, pp. 1541–1548, Sep. 2005.
[28] L. Qin and B. He, "A wavelet-based time-frequency analysis approach for classification of motor imagery for brain-computer interface applications," *J. Neural Eng.*, vol. 2, no. 4, pp. 65–72, Aug. 2005.
[29] W. Ting, Y. Guo-Zheng, Y. Bang-Hua, and S. Hong, "EEG feature extraction based on wavelet packet decomposition for brain computer interface," *Measurement*, vol. 41, no. 6, pp. 618–625, Jul. 2008.
[30] H. Göksu, "BCI oriented EEG analysis using log energy entropy of wavelet packets," *Biomed. Signal Process. Control*, vol. 44, pp. 101–109, Jul. 2018.
[31] S. Chandaka, A. Chatterjee, and S. Munshi, "Cross-correlation aided support vector machine classifier for classification of EEG signals," *Expert Syst. Appl.*, vol. 36, no. 2, pp. 1329–1336, Mar. 2009.
[32] R. Bose, K. Samanta, and S. S. Chatterjee, "Cross-correlation based feature extraction from EMG signals for classification of neuro-muscular diseases," in *Proc. IEEE Int. Conf. Intell. Control Power Instrum. (ICICPI)*, Oct. 2016, pp. 241–245.
[33] B. Blankertz *et al.*, "The BCI competition 2003: Progress and perspectives in detection and discrimination of EEG single trials," *IEEE Trans. Biomed. Eng.*, vol. 51, no. 6, pp. 1044–1051, Jun. 2004.
[34] S. Sun and C. Zhang, "Assessing features for electroencephalographic signal categorization," in *Proc. IEEE Int. Conf. Acoust., Speech, Signal Process. (ICASSP)*, vol. 5, Mar. 2005, pp. v/417–v/420.
[35] B. Wang, L. Jun, J. Bai, L. Peng, G. Li, and Y. Li, "EEG recognition based on multiple types of information by using wavelet packet transform and neural networks," in *Proc. IEEE 27th Annu. Int. Conf. Eng. Med. Biol. Soc. (IEEE-EMBS)*, Jan. 2006, pp. 5377–5380.
[36] T. Kayikcioglu and O. Aydemir, "A polynomial fitting and k-NN based approach for improving classification of motor imagery BCI data," *Pattern Recognit. Lett.*, vol. 31, no. 11, pp. 1207–1215, Aug. 2010.
[37] D. Hu, W. Li, and X. Chen, "Feature extraction of motor imagery EEG signals based on wavelet packet decomposition," in *Proc. IEEE/ICME Int. Conf. Complex Med. Eng. (CME)*, May 2011, pp. 694–697.
[38] T. Nguyen, A. Khosravi, D. Creighton, and S. Nahavandi, "EEG signal classification for BCI applications by wavelets and interval type-2 fuzzy logic systems," *Expert Syst. Appl.*, vol. 42, no. 9, pp. 4370–4380, Jun. 2015.
[39] D. H. Krishna, I. A. Pasha, and T. S. Savithri, "Classification of EEG motor imagery multi class signals based on cross correlation," *Procedia Comput. Sci.*, vol. 85, pp. 490–495, Jan. 2016.
[40] S. Theodoridis and K. Koutroumbas, "Feature selection," in *Pattern Recognition*, 4th ed. New York, NY, USA: Academic, 2008, pp. 261–322.

PARNIKA N. PARANJAPE received the M.Tech. degree in computer science from the Visvesvaraya National Institute of Technology, Nagpur, India, where she is currently pursuing the Ph.D. degree. Her research interests include data mining and analysis, graph mining, graph classification, and electroencephalographic classification.

MEERA M. DHABU received the Ph.D. degree from the Visvesvaraya National Institute of Technology, Nagpur, India, where she is currently an Assistant Professor with the Department of Computer Science and Engineering. She has 16 years of academic experience. She has co-authored a number of research articles in various journals, conferences, and book chapters. Her research interests include data mining and machine learning. She is a member of the ACM.

PARAG S. DESHPANDE received the M.Tech. degree from IIT Bombay, Mumbai, India, and the Ph.D. degree from Nagpur University, Nagpur, India. He is currently a Professor with the Department of Computer Science and Engineering, Visvesvaraya National Institute of Technology, Nagpur. He has 30 years of academic experience. He has co-authored a number of research articles in various journals, conferences, and book chapters. He has authored several books, including *C & Data Structure*, *Data Warehousing Using Oracle*, and *SQL/PL SQL for Oracle 11g* (Wiley). His research interests include databases, data mining, and pattern recognition. He is a member of ISTE and SAE-India. He was a recipient of prestigious awards and honors for his excellence in academics and research.

AKSHAY M. KEKRE received the M.Tech. degree in electronics engineering from the Ramdeobaba College of Engineering and Management, Nagpur, India. He is currently pursuing the Ph.D. degree with the Visvesvaraya National Institute of Technology, Nagpur. His research interests include the Internet of Things, machine-to-machine communications, and electroencephalographic classification.