Comparisons between Motor Area EEG and all-Channels EEG for Two Algorithms in Motor Imagery Task Classification

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Abstract. This article reports on a comparative study to identify electroencephalography (EEG) signals during motor imagery (MI) for motor area EEG and all-channels EEG in the Brain Computer Interface (BCI) application. In this paper, we present two algorithms: CC-LS-SVM and CC-LR for MI tasks classification. The CC-LS-SVM algorithm combines the cross-correlation (CC) technique and the least square support vector machine (LS-SVM). The CC-LR algorithm assembles the cross-correlation (CC) technique and binary logistic regression (LR) model. These two algorithms are implemented on the motor area EEG and the all-channels EEG to investigate how well they perform and also to test which area EEG is better for the MI classification. These two algorithms are also compared with some existing methods which reveal their competitive performance during classification. Results on both datasets, IVa and IVb from BCI Competition III, show that the CC-LS-SVM algorithm performs better than the CC-LR algorithm on both the motor area EEG and the all-channels EEG. The results also demonstrate that the CC-LS-SVM algorithm performs much better for the all-channels EEG than for the motor area EEG. Furthermore, the LS-SVM based approach can correctly identify the discriminative MI tasks, demonstrating the algorithm's superiority in classification performance over some existing methods.

Keywords- Brain Computer Interface (BCI); Electroencephalogram (EEG); Motor imagery; Cross-correlation; least square support vector machine; Logistic regression.

1. Introduction

The ability to communicate with the outside world is one of the most indispensible assets that people have. Our hands, legs and other limbs are essential for performing our daily activities. Unfortunately, these abilities can be lost due to accidents or diseases (e.g. amyotrophic lateral sclerosis (ALS), brainstem stroke, mitochondrial disease, spinal-cord injury, traumatic-brain injury and even later-stage cerebral palsy etc) [1]. These diseases can disrupt the neuromuscular channels through which the brain communicates with its environment and exerts control. Therefore, it is impossible for the people who are motor disabled, to live and meet their daily needs without external help.

The Brain Computer Interface (BCI) is a well known emerging technology and research field, in which people are able to communicate with their environment and control prosthetic or other external devices by using only their brain activity [2]. It promises to provide a way for people to communicate with the outside world using *thoughts* alone. A motor imagery based BCI translates a subject's motor intention into a command signal through real-time detection of motor imagery states, e.g. imagination of left hand or right hand movement. Motor imagery (MI) is a common mental task in which subjects are instructed to imagine themselves performing a specific motor action (such as a hand or foot movement) without an overt motor output [1, 3]. Among various techniques, Electroencephalography (EEG) is the most studied potential technique to capture MI brain activities for non-invasive BCI designs due to its excellent temporal resolution, non-invasiveness, usability, and low set-up costs [4, 5].

A BCI system, by extracting EEG signals directly from the brain, might help to restore abilities to patients who have lost sensory or motor function because of their disabilities. The major purpose of BCI is to translate a brain activity into a command to control an external device [6]. Users produce different brain activity patterns that will be identified by the system and translated into commands. In most existing BCI, this identification relies on a classification algorithm [6], i.e. an algorithm that aims at automatically estimating the class of data as represented by a feature vector. BCI applications are considered to be pattern recognition problems that signal processing, feature extraction and pattern classification techniques are attempting to solve.

Recently, cross-correlation (CC) technique has become popular in biomedical research for feature extraction from time series data. This method has been successfully used in many applications like ECG beat detection [7, 8], gait signal processing [9, 10], emotional speech recognition [11], heart rate variability classification [12], signal to noise enhancement [13] and seizure prediction [14]. This study intends to apply the CC technique for feature extraction from the MI EEG data as all the channels on the head do not provide independent information and there are high correlations between the channels in EEG [15]. EEG signals are also typically very noisy and not directly usable in BCI applications. The CC technique can reduce noise by means of correlation calculation because of the characteristics of signal periodicity [16].

This paper focuses on two classifiers, least square support vector machine (LS-SVM) and binary logistic regression (LR) for classifying the cross-correlation's features because the LS-SVM is a robust intelligent technique for classification in BCI applications and the LR is increasingly popular in machine learning, due to its similarity with support vector machines (SVMs). The LS-SVM and LR classifiers are employed separately on the cross-correlation features and then compared to see which classifier performs better for the cross-correlation features. Thus this study develops the two algorithms for classifying MI EEG signals, namely cross-correlation based least square support vector machine denoted by CC-LS-SVM algorithm and cross-correlation based logistic regression presented as CC-LR algorithm. In the CC-LS-SVM algorithm, a CC technique is used for feature extraction and the LS-SVM method is employed to classify the features. On the other hand, in the CC-LR method, we apply a CC technique to extract representative features from the MI EEG data and use a LR logistic regression for classification.

It is known that EEGs record brain activities as multichannel time series from multiple electrodes placed on the scalp of a subject. The different signals from different scalp sites do not provide the same amount of discriminative information. In this study, we are interested in investigating the performance of the EEG channels of the motor cortex area and the all-channels EEG data for the two algorithms. In the human brain, the motor cortex area is a very important area that controls voluntary muscle movements which are discussed in detail in Section 2. Current studies aim to improve the classification accuracy for the development of BCI systems and to investigate which area (motor area or the whole brain) is better for acquiring MI information for classification. In this paper, we also investigate the performances of LS-SVM and LR classifiers on the cross-correlation features in both areas.

The proposed two algorithms are implemented on datasets, IVa and IVb from BCI Completion III [17, 18]. The 3-fold cross validation procedure is used to evaluate the performance of the two algorithms on the basis of classification accuracy. In both datasets, the experimental outcomes demonstrate that the LS-SVM classifier performs much better than the LR classifier on the cross-correlation features in both areas. The classification accuracy of the CC-LS-SVM algorithm is higher for the all-channels data than the channels of motor area. The experimental results also show that the CC-

LS-SVM algorithm is superior to the existing methods for the motor area EEG and the all-channels EEG data.

The rest of the paper is organized as follows: Section 1.1 reviews the existing research. Section 2 describes the materials and methods that are introduced in this study. This section also describes about the experimental data and the implementations of these methods. The experimental results are presented in Section 3 and a brief discussion regarding experimental result is provided in Section 4. Finally Section 5 draws the conclusions of the study.

1.1. Review of the existing research

Over the last two decades, there have been numerous studies performed on BCIs for MI tasks classification for dataset IVa of BCI Competition III. A number of research groups have developed BCIs that employ brain signals from the motor cortex area, for example, Wang et al. [19] and Song et al. [20]. Some researchers introduced several methods for analysing the entire channels EEG data for BCI applications and investigated the physiological nature of the experimental paradigms, for instance, Blankertz et al. [17] and Wu et al. [21].

Wang et al. [19] introduced a technique based on independent component analysis (ICA) with constraints, applied to the rhythmic EEG data recorded from a BCI system to isolate the rhythmic activity for MI tasks over the motor cortex area. Their algorithm includes three parts: spatial filter generation, power feature extraction and classification. They used a spatial filter through the technique of spectrally constrained ICA (cICA) and extracted power feature in μ-rhythm frequency band as the major classification pattern. An advanced SVM was applied to classify the power features. The results demonstrated that the more advanced SVM with cICA based power features did not show a significant improvement in performance.

Song et al. [20] reported a framework to classify EEGs for BCI learning optical filters for dynamical system (DS) features. They used EEG signals as the output of a networked dynamical system (cortex) and exploited synchronization features from the DS for classification. They also proposed a new design for learning optical filters automatically from the data by employing a fisher ratio criterion on the motor cortex area. Experimental evaluations show that the dynamic system features combined with a filter learning approach is not enough to produce competitive performance on the motor cortex area for the MI signal classification in BCI applications. One of the disadvantages is that the parameters of their method were tuned manually.

The BCI III Winner algorithm in [17] involved an ensemble classifier based on three methods: (1) common special pattern (CSP) on even-related desynchronization (ERD) (2) autoregressive (AR) model on ERD and (3) Linear Discriminant Analysis (LDA) on temporal waves of readiness potential for dataset IVa. This algorithm was implemented for all-channels of EEG data. For subjects, ***aa*** and ***aw*** in dataset of IVa of BCI Competition, all three features (ERD feature by CSP analysis, ERD feature by a AR model and ERP feature by LDA on temporal waves) have been used and combined by a bagging method. For the other three subjects, ***al***, ***av*** and ***ay*** of the same dataset, only the CSP based feature was used. Furthermore, the Winner algorithm used the bootstrap aggregation and employed formerly classified test samples in subjects ***aw*** and ***ay***, to achieve the best performance.

Wu et al. in [21] reported an algorithm for classifying single-trial EEG during motor imagery by iterative spatio-spectral patterns learning (ISSPL). In their adopted framework, feature extraction and feature classification are treated as independent stages: spectral filters and the classifier are parameterized jointly in the maximal margin hyperplane for optimization, and thereby their generalization performance can be controlled for the all-channels data. The results for the all-channels data demonstrated the efficacy of ISSPL and the resultant spectral filters did not suffer from the potential overfitting problem and only a few steps of iterations were needed to obtain a satisfactory classification performance.

Although many methods have been developed in the past decade that yield impressive results in interpreting BCI data, the BCI technology is still not adequate for identifying the MI tasks from original data. This study addresses two questions: (i) what algorithm is the best for the MI classification? (ii) Which EEG data is better for the MI signal classification? Is it the motor area data or is it the all-channels data? To answer these two questions, this paper reports two algorithms based on the CC technique as described in Section 2.

2. Materials and methods

Two different approaches are developed in this study. One approach is the CC technique based LS-SVM called as CC-LS-SVM and the other one is the CC based LR denoted as CC-LR. The detailed descriptions of these methods are provided below. Fig. 1 (a) and Fig. 1(b) display the framework of the CC-LS-SVM algorithm and CC-LR algorithm respectively.

2.1. CC-LS-SVM algorithm

The CC-LS-SVM algorithm is a hybrid approach where the CC technique is used for the feature extraction and the LS-SVM is applied for the classification of the extracted features. Fig. 1 (a) presents the scheme of the proposed CC-LS-SVM algorithm. A brief description of this algorithm is provided below.

1. The C3 electrode position is considered as a reference channel.
2. The C3 channel is cross correlated with the data of the remaining channels and the cross-correlation sequences are obtained using the reference channel and any one of other channels. The detailed description of the CC technique is available in reference [7, 22].
3. The six statistical features, *mean, median, mode, standard deviation, maximum* and *minimum* are extracted from each cross-correlation sequence to characterize the distributions of EEG signals, which reduce the dimension of the cross-correlation sequence.
4. Extracted features are segmented as a training and testing set using a 3-fold cross validation process.
5. A two-step grid search technique [23, 24] is implemented on each three fold of a 3-fold cross validation method separately to select the optimum values of the hyper parameters (γ, σ^2) for the LS-SVM.
6. After selecting the optimal values of the hyper parameters, the training vector set is used to train the LS-SVM classifier with radial basis function (RBF) kernel and the testing vector set is applied as the inputs to evaluate the classification accuracy and effectiveness of the classifier with the selected parameters. The details of the LS-SVM algorithm could be found in reference [25-27].
7. The outputs of the LS-SVM algorithm provide the prediction results that directly assign the samples with a label +1 or -1 to identify which category it belongs to.

2.2. CC-LR algorithm

The CC-LR algorithm combines two techniques, cross-correlation (CC) and logistic regression (LR) for classifying the MI tasks in BCI applications. This algorithm performs in two stages: feature extraction and feature classification. The CC approach is employed to extract the features from the original MI data and the LR is used to distinguish the features. Fig. 1(b) depicts the proposed scheme for the CC-LR algorithm described as below.

1. This algorithm follows the steps 1-4 of the CC-LS-SVM algorithm to extract features by using the CC technique.
2. Then we employ the training and testing feature sets, separately, to the LR classifier as the inputs. The performance of the LR classifier is assessed based on the outcomes of the testing set. A detailed description of the LR method is available in [28, 29, 14].
3. The parameters of the LR model are estimated by maximum likelihood estimation (MLE) [14] for each of the three folds, separately.
4. The classification results are obtained at this stage. Based on the outcomes, we can decide how many values are predicted correctly for each of two classes by the algorithm.

In the following sections, we shall provide the details about the datasets used in the experiments and on how the experiments are set up. The implementations of these two algorithms are described in detail in Section 2.3. Then we present experimental results as well as discussions in Section 3.

2.3. Data and implementation

Two publicly available datasets, IVa and IVb of BCI Competition III, are used in this study to evaluate the efficacy of the proposed approach. All EEG data of these two sets were collected during motor imagery (MI) tasks.

Dataset IVa [17, 18] was recorded from five healthy subjects (labelled 'aa', 'al', 'av', 'aw', 'ay'), who performed right hand (RH) and right foot (RF) MI tasks. The subjects sat in comfortable chairs with their arms resting on armrests. This data set contains data from the four initial sessions without feedback. The EEG signals were recorded from 118 electrodes according to the international 10/20 system. There are 280 trials for each subject, i.e. 140 trials for each task per subject. During each trial, the subject was required to perform either of two MI tasks for 3.5 seconds. A training set and a testing set consisted of different sizes for each subject. Among 280 trials, 168, 224, 84, 56 and 28 trials composed the training set for subjects '***aa***', '***al***', '***av***', '***aw***', '***ay***' respectively. The remaining trials composed the test set. This study uses the down-sampled data at 100 Hz where the original sampling rate is 1000 Hz.

Dataset IVb [17, 18] was collected from one healthy male subject. He sat in a comfortable chair with arms resting on armrests. This data set has data from 7 initial sessions without feedback. The EEG data consisted of two classes: left hand (LH) and right foot (RF) MI tasks. Signals were recorded from 118 channels in 210 trials. 118 EEG channels were measured at the positions of the extended international 10/20 system. Signals were band-pass filtered between 0.05 and 200 Hz and digitized at 1000 Hz with 16 bit (0.1 μV) accuracy. The data was down-sampled at 100 Hz, which is used in this research.

In this study, we intend to implement our two methods on the electrodes of the motor cortex area of the brain and also on the all-channel electrodes for comparison.

The channels recorded from the motor area are chosen to investigate the activities of the motor cortex area of the brain for the proposed algorithms and the all-channels are considered to see how the classification algorithms handle feature vectors of relatively high dimensions. Actually we are interested to see the performance of the two algorithms on the two areas (motor area and all-channels data) and also to decide which algorithm is better for given areas of the brain. We know that only a particular part of the brain is activated in response to an MI task which is called the motor cortex. Motor cortex is one of the important brain areas most involved in controlling and execution of voluntary motor functions and this area of the brain is typically associated to the MI movements.

As we are looking for a response specifically in the motor cortex area, we manually select the 18 electrodes around the sensorimotor cortex based on the placement of international 10/20 system which includes the channels C5, C3, C1, C2, C4, C6, CP5, CP3, CP1, CP2, CP4, CP6, P5, P3, P1, P2, P4 and P6 from each of the two datasets. In [19], Wang et al. also considered the same electrodes for their research and their experimental results suggested that these electrodes are the best channels for getting the MI information.

As described before, the both datasets are originally recorded from 118 electrodes. Fig. 2 presents the locations of electrodes of datasets, IVa and IVb from BCI competition III. 118 electrodes are shown labelled according to the extended international 10/20 system. This figure was made in EEGLAB (MATLAB toolbox for processing data from EEG, magnetoencephalography (MEG), and other electrophysiological signals) and the electrode system is described in [30]. In [19], Wang et al. explained that the selected electrodes cover the motor cortex area. Thus, prior knowledge as well as the results of the following electrodes are investigated in this study.

In this study we firstly consider the electrode position C3 of the RH class as a reference channel from each subject of both datasets for the CC technique. This study uses the channel of the C3 electrode in the international 10/20 system as the reference channel. The C3 electrode is the best candidate for supplying the MI information about brain activities during the MI tasks in the international 10-20 system [31]. In each subject, the C3 channel is used as a reference channel for both the motor imagery EEG data and the all-channels EEG data.

Secondly, in the motor area data, the reference channel C3 of the RH class is cross-correlated with the data of the remaining 17 channels of that class and the data of all 18 channels of the RF class for each subject of both datasets. Thus total 35 cross-correlation sequences are obtained from the two classes of each subject. Then the mentioned six statistical features are calculated from each cross-correlation sequence and a feature vector set of 35×6 size is created. In the all-channels data, the reference channel C3 of the RH class is cross-correlated with 117 channels of this class and also 118 channels data of the RF class in each subject of both datasets. Thus we acquire a total of 135 cross-correlation sequences from the two-class MI data of a subject and then we extract previously mentioned six statistical features from each cross-correlation sequence to generate a feature vector set of 135×6 size.

Thirdly, we divide the feature vector set randomly as the training set and the testing set using the 3-fold cross-validation method [32, 33] in both the motor cortex set and the all-channels data, separately. In the 3-fold cross-validation procedure, a feature vector set is partitioned into 3 mutually exclusive subsets of approximately equal size and the method is repeated 3 times (folds). Each time, one of the subsets is used as a test set and the other two subsets are put together to form a training set. Then the average accuracy across all 3 trials is computed.

Finally, we employ these feature vector sets as the input to the LS-SVM and also to the LR. In the CC-LS-SVM algorithm, the training set is applied to train the LS-SVM classifier and the testing set is used to verify the effectiveness of the classifier for both datasets. As the result of the LS-SVM relies largely on the choice of a kernel, the RBF kernel is chosen after many trials. Before the classification, the two parameters (γ, σ^2) of the LS-SVM method are selected by applying a two-step grid search procedure [23] on each three folds for getting reliable performance of the method as these parameters play an important role in the classification performance. In the LS-SVM, the RF is treated as +1 and RH as -1 for dataset IVa, and the RF is considered as +1 and LH as -1 for dataset IVb.

In the CC-LR algorithm, we employ the training and testing sets as the inputs, separately, to the LR classifier; but we use the testing set to validate the classification accuracy of the classifier in both datasets. In the LR model, we consider independent variables x_1 as *mean* values, x_2 as *maximum* values, x_3 as *minimum* values, x_4 as *standard deviation* values, x_5 as *median* values and x_6 *as mode* values. We treat the dependent variable y as RH= 0 and RF= 1 for dataset IVa, and RF=0 and LR=1 for dataset IVb. The parameters of the LR model are obtained automatically using the maximum likelihood estimation (MLE) method.

3. Results

This section presets the experimental results of the proposed two algorithms for the motor area EEG and the all-channels EEG in datasets, IVa and IVb, and also reports a comparative study with the existing methods. As accuracy is a major concern in BCI systems, this study uses the classification accuracy as the criterion to evaluate the performance of the proposed method. The classification accuracy is calculated by dividing the number of correctly classified samples by the total number of samples [27, 32, 34]. It is worthy to mention that all experimental results for datasets, IVa and IVb, are presented based on the testing set. In this study, MATLAB (version7.7, R2008b) is used for mathematical calculations of the CC technique. The classification by the LS-SVM is carried out in MATLAB using the LS-SVMlab toolbox (version 1.5) [35] and the classification by the LR is performed using PASW (Predictive Analytics SoftWare) Statistics 18.

3.1 Results for dataset IVa

The complete experimental results for dataset IVa are summarized in Table 1. The table provides the classification performance as well as the overall mean of the CC-LS-SVM and CC-LR algorithms for the motor area EEG and the all-channels EEG. The results of each subject are reported in terms of mean ± standard deviation of the accuracy over a 3-fold cross-validation method on the testing set. In the motor area, the CC-LS-SVM algorithm yields the classification accuracy 100%, 94.19%, 100%, 96.97%, 94.45% for subject ***aa***, ***al***, ***av***, ***aw*** and ***ay***, respectively while these values are 88.9%, 77.0%, 75.0%, 100% and 100% for the CC-LR algorithm. The average accuracy rate is 97.12% for the CC-LS-SVM algorithm and 88.18% for the CC-LR algorithm for the motor area data. So, the CC-LS-SVM algorithm provides a 9.0% of improvement in the average performance over the CC-LR method. The standard deviation value of a subject describes the variation of the classification accuracies among the three folds. If the variation of the accuracies among the three folds is less, it indicates robustness of the method. For the motor area data, we can see that the standard deviation among the three folds in each subject is relatively small in the CC-LS-SVM algorithm, which indicates the strength of the CC-LS-SVM algorithm.

For the EEG data recorded from the all-channels, the CC-LS-SVM algorithm produced the classification accuracy of 99.57% for subject ***aa***, 94.88% for subject ***al***, 99.16% for subject ***av***, 97.45% for subject ***aw*** and 98.72% for subject ***ay***, whereas these values are 100%, 95.67%, 98.7%, 100% and 73.6%, respectively, for the CC-LR algorithm. The average accuracy was 97.96% for the CC-LS-SVM algorithm and 93.59% for the CC-LR method. Thus the average accuracy of the CC-LS-SVM algorithm was increased by 4.37% from the CC-LR method for the all-channels data. In the all-channels data, the standard deviation value in each subject was relatively low in both the algorithms. So, it can be claimed that the performance of the both algorithms are reliable. The results reveal that the CC-LS-SVM algorithm performs better on the both motor area and all-channels data than the CC-LR approach and the performance of the CC-LS-SVM method is better for the all-channels data than the motor area data.

Fig. 3 presents a comparison of the classification accuracy between the motor area EEG data and the all-channels EEG data for the CC-LS-SVM algorithm. From the figure, it may be seen that the CC-LS-SVM algorithm produces a higher performance for subject ***aa*** and subject ***av*** in the motor area EEG data than the all-channels data. On the other hand, the performance of the all-channels data is better for subject ***al***, subject ***aw*** and subject ***ay*** compared to the motor area data. Fig. 3 also illustrates that the overall classification performance of the algorithm is much better for the all-channels data than for the motor area data. Error bars of the motor area EEG data are also higher than the all-channels data. The error bars indicate the superiority of the CC-LS-SVM algorithm for the all-channels EEG data over the motor area data.

Fig. 4 displays the comparison of the classification accuracy between the motor area EEG and the all-channels EEG data for the CC-LR algorithm. It can be observed from the figure that the classification accuracy rates for the all-channels data are substantially higher for subjects, ***aa***, ***al*** and ***av*** and the same for subject ***aw*****,** compared to the motor area data. The motor area data provided better results only for subject ***ay*** over the all-channels data. The overall accuracy for the all-channels data is significantly higher than the motor area data for the CC-LR method. Fig. 3 and Fig. 4 depict that the EEG data recorded from the all-channels give the best result for both algorithms when compared to the data recorded from the motor cortex area.

Table 2 presents a comparison of the performances for the motor cortex area of the proposed CC-LS-SVM and CC-LR algorithms with the previously existing methods; SVM on constraints independent component analysis (cICA) power features [19] and SVM on dynamical system (DS) features [20]. These two existing methods are also implemented on the motor cortex area data for dataset IVa as discussed in Section 1.1. From Table 2, it can be seen that the highest accuracy was obtained by the CC-LS-SVM algorithm for subject ***aa*** and subject ***av***. The CC-LR method achieved a better performance for subject ***aw*** and subject ***ay***. The existing method, SVM on DS features produced the best performance only for subject ***al***. In Table 3, it is noted that the CC-LS-SVM algorithm provided the best result with an average classification accuracy of 97.12% while this value is 88.18% for the CC-LR algorithm, 85.64% for the SVM on DS algorithm and 84.06% for the SVM based on cICA approach. The CC-LS-SVM method achieves by 8.94% to 13.06% improvements for the motor area data over the three algorithms for dataset IVa.

Table 3 lists a comparison study for the all-channels data of our two algorithms with BCI III Winner [17] and iterative spatio-spectral patterns learning (ISSPL) [21] for dataset IVa. A brief description of BCI III Winner [17] and ISSPL [21] methods are provided in Section 1.1. The CC-LS-SVM algorithm produced an excellent result for subject ***av*** and subject ***ay*** where the CC-LR algorithm achieved the best results for subject ***aa*** and subject ***aw***. The BCI III Winner method gave the best performance for subject ***al*** and subject ***aw***. Both BCI III Winner and ISSPL methods achieved 100% accuracy for subject ***al***. Obviously, the average classification accuracy of the CC-LS-SVM method is excellent for the all-channels data. Table 3 depicts that the CC-LS-SVM algorithm is able to increase the classification accuracy by 4.37% from the CC-LR algorithm, by 3.76% from BCI III Winner and by 3.75% from the ISSPL.

3.2 Results for dataset IVb

Table 4 reports the classification results of the CC-LS-SVM algorithm and the CC-LR algorithm on the motor cortex area data and the all-channels data for dataset IVb. These results are listed in Fig. 5. For the CC-LS-SVM algorithm, the classification accuracy reaches 94.45% in the motor cortex area data while this value is 88.9% for the CC-LR algorithm. For the all-channels data, the CC-LS-SVM method is able to yield the accuracy of 98.72%, where the CC-LR method produces 96.83%. Therefore the performance for the all-channels data is 4.27% higher for the CC-LS-SVM and 7.93% higher for the CC-LR method than the performance of the motor area data. For the both algorithms, the standard deviations among the three folds are relatively lower for the all-channels data than for the motor cortex area data. The lower value of the standard deviation proves the reliability of those two methods in the all-channels data.

Fig. 5 shows a clearer picture of the performance for the CC-LS-SVM and CC-LR algorithms applied to the motor cortex area and the all-channels data for dataset IVb. From Fig. 5, it is observed that the both algorithms produce better results on the all-channels data than on the motor area data and the classification accuracy of the CC-LS-SVM method is slightly higher for the all-channels data than for the motor area data. Note that we could not compare the results of the CC-LS-SVM and CC-LR algorithms with any other previously existing methods for this dataset because there are no reported research results available.

4. **Discussions**

In this study, we have two queries. First one is: what algorithm is the best for the MI classification? Second one is: which EEG data (the motor area data or the all-channels data) is better for the MI signal classification? The experimental results for both datasets, IVa and IVb, demonstrate that the CC-LS-SVM algorithm is the best method for the motor cortex area data and the all-channels data in the MI signal classification. The results also indicate that the all-channels data is better to provide the excellent performance for the MI signal classification.

This study results are also compared with the existing methods shown in Table 2 and Table 3. Generally, it can be observed from Table 2 and Table 3 that there is an improvement in performance of the CC-LS-SVM algorithm for both the motor cortex area data and the all-channels data over the previously existing methods. Based on these results, it can be concluded that the LS-SVM method outperforms the existing methods for the MI tasks EEG signal classification on the motor cortex area data and the all-channels data and the CC-LS-SVM method performs better on the all-channels data than on the motor area data.

5. Conclusions

In this paper, we have presented the CC-LS-SVM and CC-LR algorithms for classifying the EEG data during motor imagery. The CC-LS-SVM algorithm assembles CC technique and LS-SVM, and the CC-LR algorithm combines the CC technique and LR model for MI tasks classification. In order to investigate the effectiveness of these two algorithms, we have implemented them individually on the EEG data recorded from the motor cortex area and also the all-channels EEG data. The results on two datasets, IVa and IVb of BCI Competition III, demonstrate that the CC-LS-SVM method produces better accuracy for the all-channels EEG data and the motor area EEG data than the CC-LR algorithm. The performance of the CC-LS-SVM algorithm is higher for the all-channels data than for the motor area data for the MI EEG signal classification. The results also suggest that the CC-LS-SVM algorithm outperforms the some of the previously existing algorithms in the literature for both the motor area and the all-channels data. Thus, it can be concluded that the CC-LS-SVM algorithm is the best algorithm for the MI EEG signal classification and the all-channels EEG can provide better information than the motor area EEG for the MI classification. In the future, we will extend these algorithms for online analysis.

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1. Diagrams of the proposed two algorithms: (a) CC-LS-SVM (b) CC-LR
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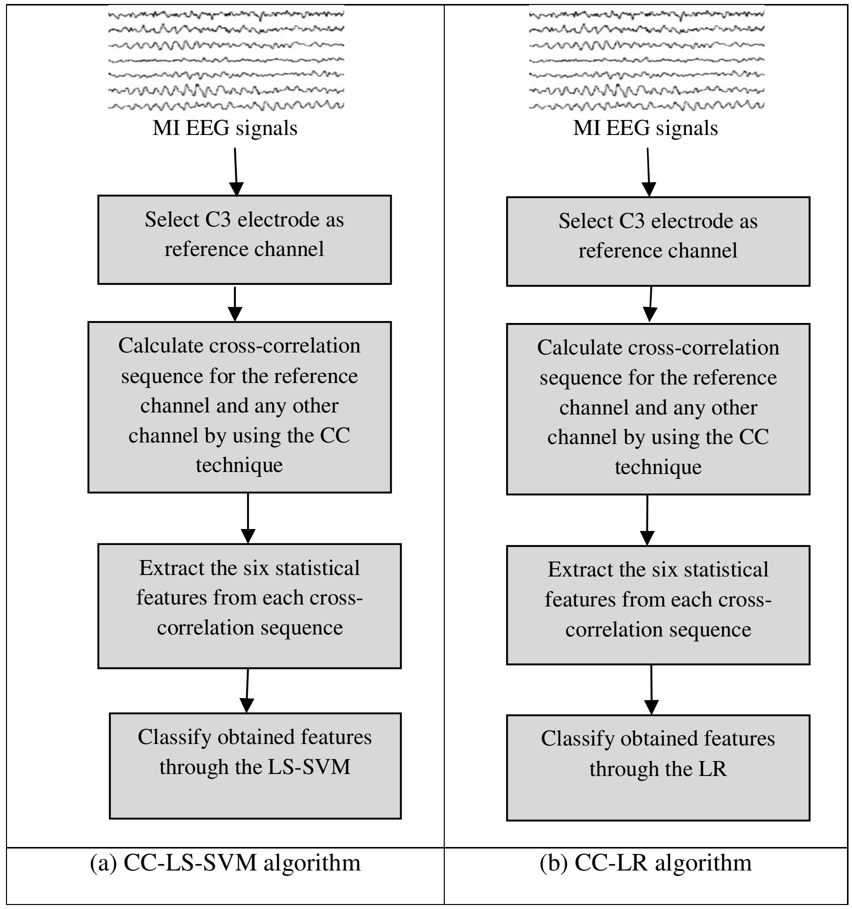

Fig. 1: Diagrams of the proposed two algorithms: (a) CC-LS-SVM (b) CC-LR

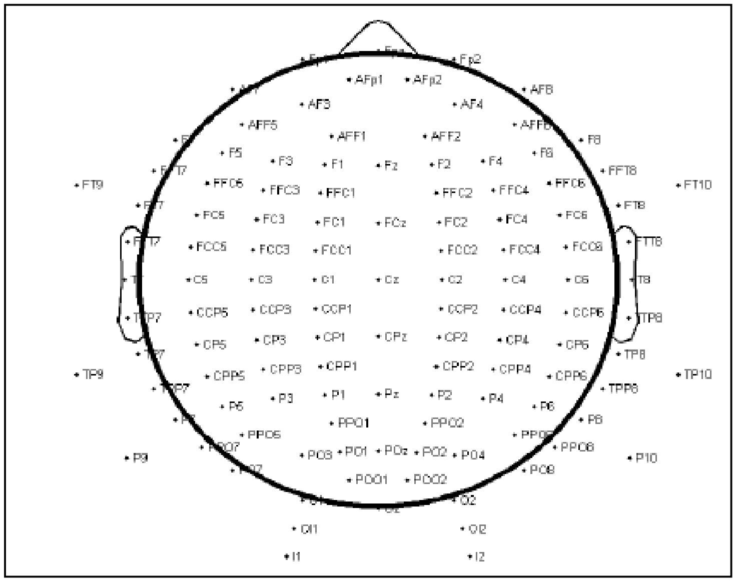

Fig. 2. Locations of electrodes for datasets IVa and IVb in BCI Competition III. 118 electrodes are shown labelled according to the extended international 10/20 system described in [30].

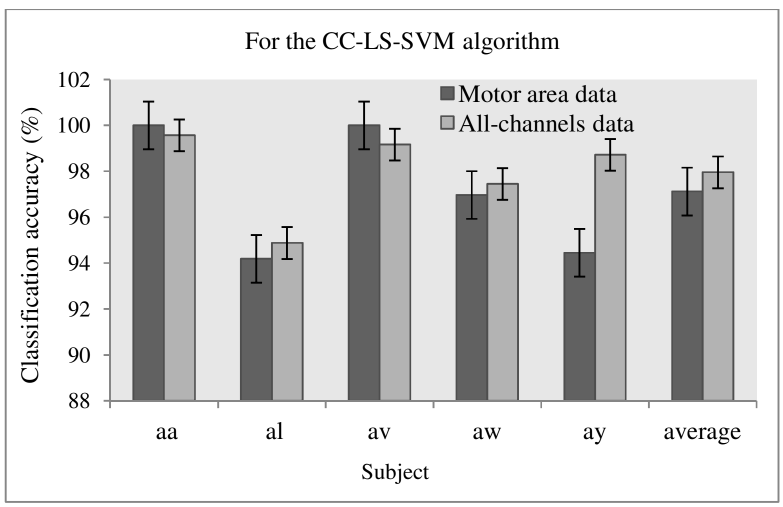

Fig. 3. Comparison of the performance between the motor area EEG and the all-channels EEG data for the CC-LS-SVM algorithm. The vertical lines show the standard errors of the test accuracies.

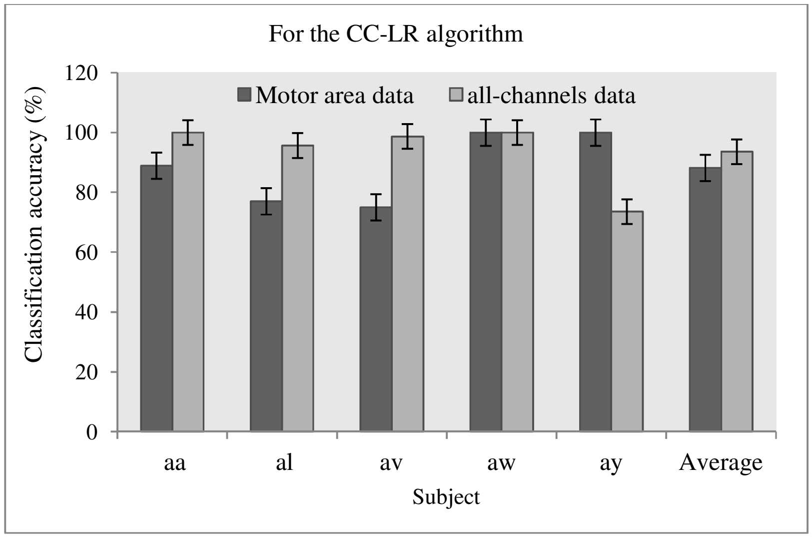

Fig. 4. Comparison of the performance between the motor area EEG and the all-channels EEG data for the CC-LR algorithm. The vertical lines show the standard error of the test accuracies.

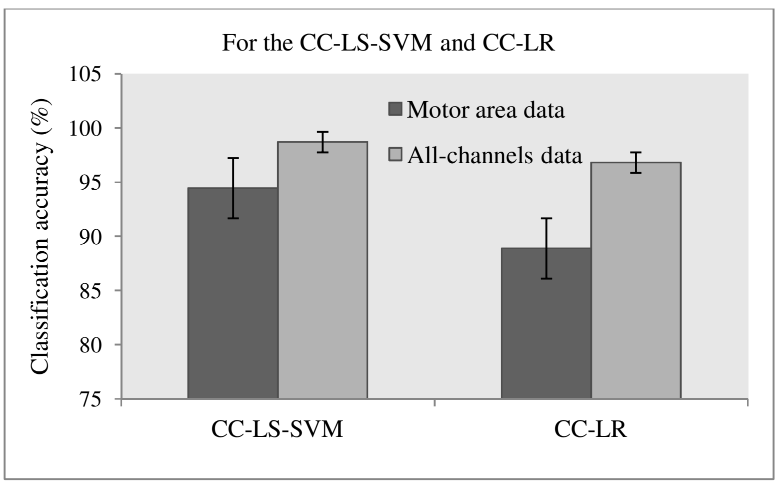

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Table 1: Experimental results of the two algorithms reported in percentage (mean ± standard deviation) for dataset IVa.

Subject	Motor area data		All-channels data	
	CC-LS-SVM	CC-LR	CC-LS-SVM	CC-LR
aa	100±0.0	88.9±19.22	99.57±0.74	100±0.0
al	94.19±5.04	77.0±21.18	94.88±4.45	95.67±4.45
av	100.0±0.0	75.0±22.05	99.16±1.46	98.7±2.25
aw	96.97±5.25	100±0.0	97.45±1.26	100.0±0.0
ay	94.45±4.81	100±0.0	98.72±1.28	73.6±3.20
Average	97.12±3.02	88.18±12.49	97.96±1.84	93.59±1.98

Table 2: The comparison of our two proposed algorithms with two existing methods for the motor area data in dataset IVa.

Subject	Classification accuracy on the motor area data (%)			
	CC-LS-SVM	CC-LR	SVM on cICA power features [19]	SVM on DS features [20]
a	100.0	88.9	85.7	83.3
al	94.19	77.0	89.3	96.3
av	100.0	75.0	75.0	72.7
aw	96.97	100.0	85.3	86.9
ay	94.45	100.0	85.0	89.0
Average	97.12	88.18	84.06	85.64

Table 3: The comparison of our two proposed algorithms with two existing methods for the all-channels data in dataset IVa.

Subject	Comparison of accuracy on the all-channel data (%)			
	CC-LS-SVM	CC-LR	BCI III Winner [17]	ISSPL [21]
aa	99.57	100	95.5	93.57
al	94.88	95.67	100.0	100.0
av	99.16	98.7	80.6	79.29
aw	97.45	100	100	99.64
ay	98.72	73.6	97.6	98.57
Average	97.96	93.59	94.20	94.21

Table 4: Experimental results of the two proposed algorithms reported in terms of the 3-fold cross validation accuracy (mean ± standard deviation) for dataset IVb.

	Classification accuracy (%)	
Method	Motor area data	All-channels data
CC-LS-SVM	94.45±4.81	98.72±1.28
CC-LR	88.9±19.22	96.83±0.72