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Comparison of multi-class motor imagery classification methods for EEG signals

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Abstract

This paper presents a comparative study of EEG-based multiclass motor imagery classifiers based on Kullback-Leiber regularised Riemann Mean and support vector machine, hybrid one versus one classifier, linear discriminant analysis, and convolutional neural network. The paper is felt to be of interest to those researchers working in the motor imagery classification of EEG signals. The work presented in this paper helps to understand the basics of different multi-class motor imagery classifiers, their accuracy, and the number of channels involved.

1. Introduction

In Brain-computer interfacing (BCI), Motor imagery (MI) is a process in which the human brain imagines that a person is performing a movement without actual involvement of peripheral nerves and muscles and without even tensioning the muscles. MI-based BCI is an independent system with higher classification accuracy. The BCI helps to convert inputs from the brain into commands or directives due to the user's desire and sends them to external devices such as computers or prostheses. Among various non-invasive BCI methods, electroencephalography (EEG) is one of the best methods to record or test brain activity due to its excellent time resolution and portability and requires less expensive equipment. Therefore, it is more convenient and practical to use EEG signals as input in BCI systems (Wang, S. Gao, and X. Gao). The BCI system consists of 3 components-input signal, processing unit, and control command. The processing unit takes EEG signals as input signals. The bioelectric signals resulting from electrical activity in the brain are captured by EEG equipment (Safitri, Djamal, and Nugraha). These bioelectric signals captured by EEG signals need to be classified using a suitable classifier for further study/processing. Classifiers are helpful because they enable us to decide whether a left (or right) hand movement or left (or right) foot movement command is initiated. Therefore, the classifier plays a vital role in motor imagery signal classification (Thang and Temiyasathit Sharbaf, Fallah, and Rashidi Du, Liu, and Tian). To improve classification accuracy, the feature extraction technique is crucial. Feature extraction strategies are critical for enhancing MI signal classification rates.

In this paper, we have compared EEG-based MI classification methods and found ways to give good performance in terms of accuracy, channel count, and complexity. The organization of the paper is as follows. In section 2, classification methods that have been considered for the study have been presented. Section 3 is dedicated to the observations and discussion. Finally, section 4 is the conclusion section of the paper.

2. Methods for Classification

In this section, we have presented four classifier methods, namely Kullback-Leiber regularised Riemann mean (KLRRM) (Mishra et al.) in combination with linear support vector machine (SVM), Naïve Bayes (NB) (Sharbaf, Fallah, and Rashidi), linear discriminant analysis (LDA) (Thang and Temiyasathit), convolutional neural network (CNN) (Du, Liu, and Tian). Each method has its advantages, and some are better than others in terms of channel count used, complexity, the accuracy of classifiers, etc. The details of the classifiers are as follows:

2.1. Linear Discriminant Analysis (LDA)

LDA is a linear classifier commonly used to classify linearly separable data. In LDA, nominal statistics maximize the likelihood of discrimination between two classes. LDA can also project high-dimensional data onto a low-dimensionality feature space (Kim, S.-K. Lee, and B. Lee). Over the past decades, LDA has been extensively used to reduce dimensionality, recognize patterns, and classify data. LDA has been used by Thang and Temiyasathit (Thang and Temiyasathit) to boost the accuracy of signal categorization in BCI by using the regularizing multi-bands common spatial patterns approach (RMCSP). Using a high number of channels as recording devices restricts the BCI system. RMCSP is developed to use EEG for research signals with fewer channels. Five FIR filters were used to filter the EEG data into five distinct frequency sections. The RMCSP technique's operation has two steps, as shown in Fig 1.

a) In the first step, five FIR filters were used to span five different frequency bands, and spectral characteristics that characterize event-related synchronous events from the brain were extracted using these filters.

b) The second step learns spatial patterns to different spectral data by regularizing common spatial patterns. The one versus rest (OVR) CSP approach is used in this strategy.

The RMCSP filters log variances of features were employed to input LDA, which is used as the classifier. The output is then combined from the four-class classifiers via a voting tactic based on the majority, which assigns the class label given to the classifier with the highest likelihood (Thang and Temiyasathit).

2.2. Naïve Bayes (NB) Classifier

NB classifier consists of a group of classification methods and is based on the Bayes theorem. The Bayes theorem determines the probability of a subsequent event based on the probability of a previous event. Bayesian classifiers work on the basic principle of probabilistic classification. NB has been used by Sharbaf et al. (Sharbaf, Fallah, and Rashidi). The authors recorded the EEG from 22 channels following the 10-20 international system with a sampling frequency of 250 Hz. These signals were band pass filtered within the 0.5 Hz -100 Hz (also used a 50 Hz Notch filter). The steps involved in the implementation of NB classifiers (Sharbaf, Fallah, and Rashidi) are as follows:

a) Following the least-square linear-phase filter, the signals were filtered.

b) As part of signal processing, a common spatial pattern (CSP) was used to distinguish between two signals based on differences in variance between them. The common spatio-spectral patterns (CSSPs) were used to embed an FIR filter into a spatial filter, and thus new channels were defined for delayed signals.

c) In shrinkage estimation for covariance matrix estimation, an estimate is made to minimize the mean square error by regularizing the covariance matrix. This method overcomes the disadvantages of conventional covariance matrix estimation, such as CSSP and CSP.

d) Mutual information best individual features (MIBIF) are used to select the relevant features.

e) One vs. one uses multiple classifiers in the N number class classification; each classifier distinguishes from one class to another.

f) To specify the trial's label if three classes win equally, the combined OVO extracted characteristics are accustomed to creating an NB classifier (Sharbaf, Fallah, and Rashidi).

g) Six linear SVM and four NB models have been used for four class classifications without ambiguity. The architecture is shown in Fig 2.

2.3. Shallow Convolution Network Architecture

For MI task detection and classification, researchers began to use deep learning techniques like CNN, which outperformed other traditional approaches. A

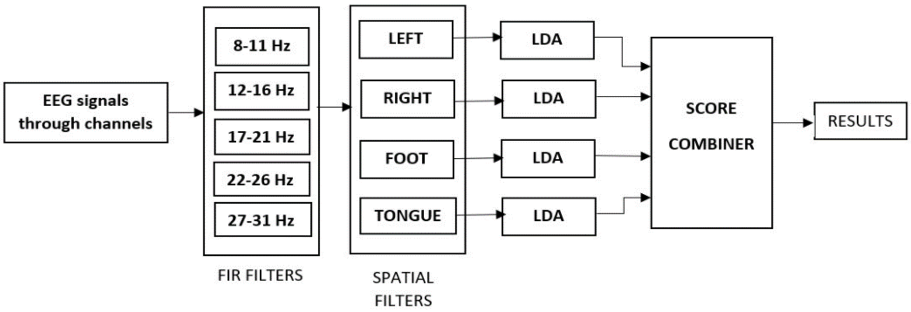

FIGURE 1. **Regularizing multi-band CSP architecture (Thang and Temiyasathit)**

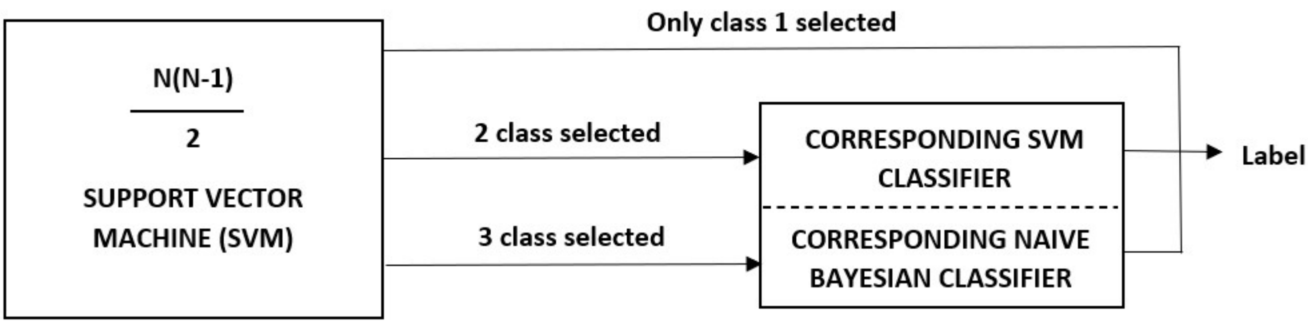

FIGURE 2. **Hybrid architecture of OVO and NB classifier (Sharbaf, Fallah, and Rashidi)**

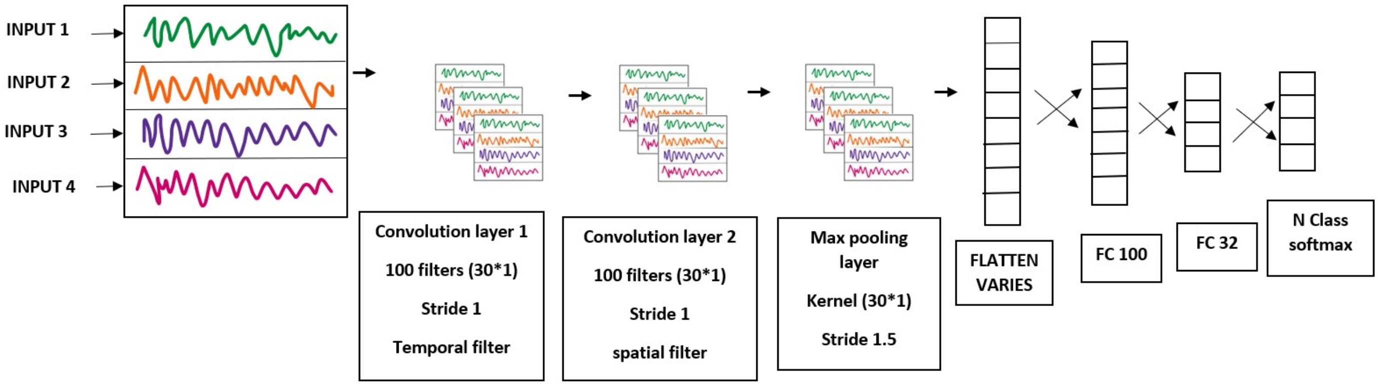

FIGURE 3. **The novel CNN architecture (Du, Liu, and Tian)**

shallow CNN architecture (Du, Liu, and Tian) was used with a unique signal-superposed data augmentation strategy to improve classification accuracy. The shallow CNN architecture (Du, Liu, and Tian) (Fig. 3) consists of three convolutional layers and four fully linked layers. The data augmentation method of superposing and normalizing the signals of the same labels across people and time is used to generate new artificial EEG data. This superimposed data augmentation strategy can help signals retain their intrinsic properties while also reducing signal drift over time and among patients. The classification result of the shallow CNN design is better than the preceding architectures, with an average accuracy of 91.06% for two-class classification tasks. The subject, when imagined moving any part of their body, and EEG data were recorded. Data augmentation was used to create more training data using a deep learning model in the training process. The author performed the following steps:

a) Transforming the real data is done by shifting, scaling, and rotating it. To tackle the problem of data scarcity, fresh data are generated artificially from existing training data. This technique is called data augmentation.

b) Four fully connected (FC) layers and three convolutional layers compose the novel CNN architecture.

c) For each EEG channel, the first layer conducts a linear pre-filtering as a function along the time axis.

d) By performing convolution along the axis of the EEG channel, the second layer can turn down the effects of the realm unrelated to movements.

e) The next layer provides the most robust architecture of all the layers.

f) Three layers are applied, linked after the convolutional layers, with the first FC layer containing approximately 6300 neurons. The last FC layer is the softmax layer, with the input being the data's total number of neurons to categorize (Du, Liu, and Tian).

2.4. Kullback-Leibler Regularized Riemannian (KLRRM mean and linear SVM

Feature extraction is more robust against noise and outliers by using Kullback-Leibler regularization. With KLRRM-based feature extraction, the classification accuracy is improved for almost all subjects. KLRRM and LSVM frameworks combined to achieve the highest accuracy for four subjects. Linear SVM (LSVM) is employed to categorize the data after calculating the distances to the Riemannian mean of all four classes. Mishra et al. (Mishra et al.) used this method to classify four class MI signals. A highly precise analog-to-digital converter with a 250 Hz sampling rate is used for digitizing the analog EEG signals. The authors adopted the methodology described below and also shown in Fig. 4.

a) Butterworth bandpass filter of sixth-order was used to filter the MI signals in the 8-30 Hz frequency range.

b) Feature extraction by using the KLRRM method was performed to improve the classification accuracy.

c) For all four MI classes, the Riemannian mean is derived based on regularisation in order to make feature extraction resilient against outliers.

d) Using the one vs. another mechanism of multiclass classification, the LSVM is trained. The subtest set's performance is examined using a trained LSVM and a regularized Riemannian mean matrix.

e) A similar procedure is repeated for all possible values of β (regularization factor), and the one with the greatest precision is considered ideal for the subject of interest. After that, the validation set is used to test the optimal beta (Q and Temiyasathit).

3. Discussion

In this paper, we have reviewed various EEG-based multi-class MI classifiers like LDA, LSVM, CNN, and hybrid one vs. one (OVO). The performance comparison of these classifiers is summarized in Table 1. The limitation of conventional OVO is when more than one class is labeled as the trial label. This condition arises when multiple classes have almost equal chances when compared to other classes. The hybrid OVO classifier system was proposed to overcome this type of limitation. The novel shallow CNN architecture was proposed to overcome the limitation of conventional CNN architecture as the conventional architecture is suitable for 2 class classification only, but the Novel CNN architecture is suitable for four-class classification and more suitable for real-time brain-computer interface (BCI) systems and better than some of the traditional machine learning-based approaches. The limitation of the BCI system is that it uses a large number of channels that are used as recording devices. RMCSP is designed in such a way that it can handle EEG signals with a smaller number of channels. LDA shows classification accuracy better than conventional CSP by 10%. KLRRM framework provides good accuracy for poor or noisy channels, which shows its robustness towards noise and outliers, and at the same time, it can maintain the accuracy of good subjects also. The KLRRM and LSVM mechanism provides better performance for both good and poor subjects.

4. CONCLUSION

One of the main reasons for the high misclassification rate is noise in the EEG data. Classification of MI signals is a very delicate and complex process because the intervention of noise and outliers are also there, which makes the classification process more vulnerable (Brigham and Kumar Zanini et al.). KLRRM and LSVM are one of the best methods which take into account the effect of noise and outliers. According to Mishra et al. (Mishra et al.), for the four-class classification method, an accuracy of 74.73% was provided for channels that are not affected by noise and 51.53% accuracy for noise-

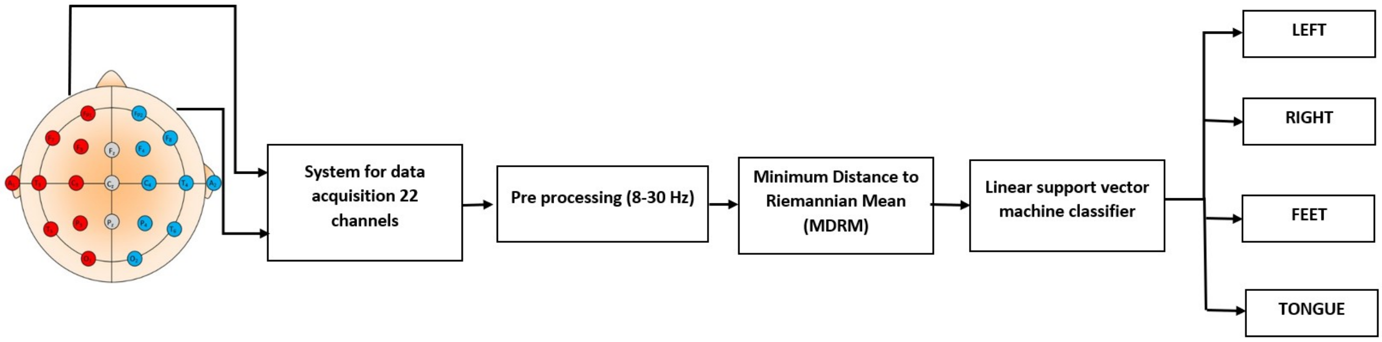

FIGURE 4. Architecture of KLRRM and LSVM (Mishra et al.)

TABLE 1. Performance comparison

Author Name	Pre-processing + feature extraction+ classifier	Number of channels used	Accuracy
Thang and Temiyasathit (Thang and Temiyasathit)	FIR filters + Regularising CSP +OVR CSP + LDA	22	Outperform normal CSP by 10%
Sharbaf et al. (Sharbaf, Fallah, and Rashidi)	FIR filters + CSP+ CSSP+ MIBIF+ hybrid OVO	22	Improvement in kappa score to 0.61
Du et al. (Du, Liu, and Tian)	Data augmentation+ CNN	16	average cross-validation accuracy of (global) 66.73%, (subject model) 76.78% [for 4 class classification]
Mishra et al (Mishra et al.)	Bandpass filter + KLRRM+MDRM+LSVM	22	74.43% and 51.53% for both good and noisy channels.

dominating channels which is quite a good result when we are dealing with such delicate MI signals where classifiers play a vital role in the overall process. The four-class classification method is quite promising and implementable. This method can be made more advanced and accurate for a real-time MI classifier.

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