Classification of Motor Imagery EEG Signals for Using in Neuro-Rehabilitation Applications

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Abstract— **Brain computer interfaces which are developed for the rehabilitation systems decode motor imagery EEG signals to control external devices. However, the extraction of the features from the EEG imagery signals and classification of it is an important problem. In this paper, common spatial pattern analysis, which is widely used in motor image applications, was preferred for getting features.**

As a classifier, the accuracy performances of Artificial neural network (%93), Convolutional Neural Network (%91), Support Vector Machine (%84) and K- Nearest Neighbour Algorithm (%90) were compared. As a result of the comparison, Artificial Neural Network method was the most successful classifier with %93.9 accuracy.

Keywords-- Motor Imagery EEG, common spatial pattern, deep learning, machine learning, classification

I. Introduction

Stroke is a health problem related to brain damage and occurs when the blood vessels that feed the brain stop flowing. In stroke, damage occurs to the spinal cord, which is located in the lower brain region and functions in transmitting signals from the motor cortex to the body. As a result, voluntary muscle movements are lost. However, in the cortex, which is located in the upper brain region, where EEG waves are produced, commands for normal functioning of brain activity and muscle activity continue to be produced. Only, these commands cannot be transmitted to the relevant muscles of the body through the damaged spinal cord. In summary, in the case of paralysis, the brain produces commands for the hand, leg and face muscles, but these commands are not sent to the related muscles due to the damage cannot reach. As a result of a stroke, a locked-in situation occurs in patients. In this disorder, while all voluntary muscles are paralyzed, cognitive consciousness does not turn off. The patient can hear his/her surroundings and perform vertical eye movements and blinking. Brain Computer Interface (BCI) technologies have emerged to provide rehabilitation of such patients and increase their interaction with the environment.

The recent developments in imaging and signal processing techniques, more effective techniques have been made available in BCI applications [1]. One of these is motor imagery (MI). It is known that MI EEG signals are becoming active when the subject planning to execute a movement even though there is no movement in the limbs. [2]. The studies have shown that MI based BCI's are a good candidate for closed loop rehabilitations [3]. There are invasive and non-invasive methods that is developed to record MI EEG signals from the brain. Invasive methods derive brain signals directly from human brain by surgery, while in non-invasive methods electrodes placed on the human scalp to measure brain activity. Because of its cheap and better resolution ability, the EEG is preferable type of non-invasive BCI methods [4].

MI BCI combines 4 main stages, namely: data collection, pre-processing, signal processing and translation to device commands. In the first stage, signals are collected, digitalized and stored with the help of EEG recorder and electrodes. In pre-processing stage collected signals involved to be filtered, cleaned and transformed and so on. Signal processing stage itself combine feature extraction and classification phases. To discriminate EEG signals, feature extraction is used. To determine the classes corresponding to different mental states, extracted features then pass to classification phase. Finally, categorized signals are translated to device commands such as wheelchair, drone or robotic rehabilitation systems etc. To obtain better classification results in this research area, many studies have been done, and offered various methods. The difficulty in determining the right commands using MI based BCIs come from the differences in motor learning functions, brain topology and variety between persons. In this paper, Common Spatial Patterns (CSP) were used as a feature for the MI tasks [6].

Next, we compared the performances of some machine learning and deep learning classifiers that are used as a final step to predict the correct command.

II. Materials and Methods

A. Dataset

The proposed method was evaluated using the BCI Competition IV Dataset I, which was recorded from 4 human subjects using Ag/AgCl electrode cap non-invasively while performing motor imagery tasks. Here we used only motor images of person d out of 4 human subjects (a,b,c,d). The EEG

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recordings included a total of 59 channels that mostly were distributed over sensorimotor areas. Each subject contributed in two sessions: a calibration session and an evaluation session [1]. In the calibration session, each subject performed a total of 200 motor imagery tasks. These imagery tasks include left hand and right hand imaginary movements [1]. Training data was collected in the calibration runs. In the recordings, left, right or down pointing arrows were used as cues to represent left hand or right-hand movement imaginations. After a focus sign(cross) was shown to the subject for 2 s, the direction sign was given to the screen for 4 s. Then the screen was blank for 2 s. In the study, we use the 100 Hz down sampled version of the data [1].

In this study, we classified the BCI Competition IV Dataset I with the following algorithms; Artificial Neural Network, Convolutional Neural Network, Support Vector Machine (SVM) and the K-Nearest Neighbour (KNN) algorithm.

B. *Common Spatial Patterns(CSP)*

The CSP algorithm is based on the simultaneous diagonalization of two covariance matrices. It calculates a spatially filtered signal Z which is maximizes the difference in the variance of the two classes [7]. The normalized spatial covariance matrix of the EEG signal is calculated as follows:

$$M = \frac{DD^T}{trace(DD^T)} \tag{1}$$

where, M denotes normalized covariance matrix and D denotes the pre-processed EEG signal matrix in the two conditions with dimensions CxS matrix (C is the number of channels and S is the number of samples). Trace is the sum of the diagonal elements of (DD^T). The composite covariance matrix Mc was obtained by summing two matrices $(\overline{\mathrm{M}}_1, \overline{\mathrm{M}}_2)$ which belongs to the two classes (Eq. 2). $\overline{\mathrm{M}}_1$and $\overline{\mathrm{M}}_2$ are the spatial covariance matrix and represents the averages of the trials of each class respectively.

$$\mathrm{Mc} = \overline{\mathrm{M}}_1 + \overline{\mathrm{M}}_2 \tag{2}$$

Mc can be decomposed as

$$Mc = E_c \lambda_c E_{\mathbb{C}}^T \tag{3}$$

where λ_c is a diagonal matrix of eigenvalues and E_c is a corresponding eigenvector. Using the formula of whitening transformation for simultaneous diagonalization:

$$W = \sqrt{\lambda_c^{-1}} E_c^T \tag{4}$$

W was used to transforms the average covariance matrices as

$$K_1 = W\overline{M}_1 W^T \text{ and } K_2 = W\overline{M}_2 W^T \tag{5}$$

Then K_1 and K_2 share common eigenvectors, and the sum of the corresponding eigenvalues for the two matrices is always equal to 1, such that

$$K_1 = U\lambda_1 U^T, \quad K_2 = U\lambda_2 U^T, \qquad \mathrm{I} = \lambda_1 + \lambda_2 \tag{6}$$

Where I is the identity matrix. Assuming that eigenvalues are sorted in a descending order, the feature vectors of two population of EEG can be discriminated by the first and the last eigenvectors of U which proof discriminative ability of spatial filtering [8]. We can then obtain projection matrix W from the whitened covariance matrices of EEG as following:

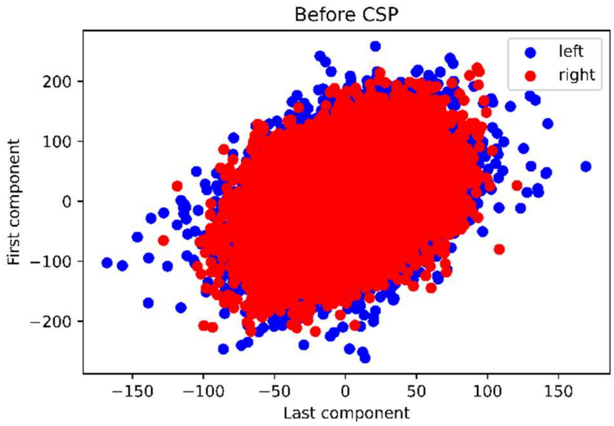
$$\mathrm{Z} = \mathrm{W'U'} \tag{7}$$

where rows of Z are the stationary spatial filters and columns of the Z′ is called the common spatial patterns [9].

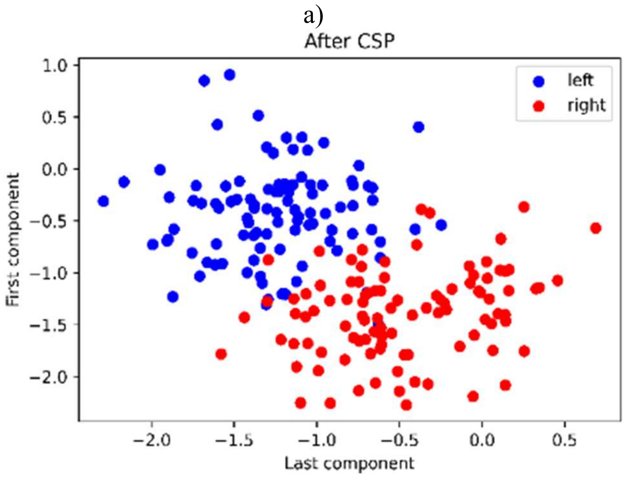
C. *Classification Algorithms*

In this study, the performances of 4 classifiers, which are widely used in the literature, are compared in terms of determining the classifier that makes the best classification in motor imagery signal classification. These classifiers are, Support Vector Machine (SVM), K- Nearest Neighbour (KNN), Artificial Neural Networks (ANNs) and Convolutional Neural Network (CNN). The parameters used in the classifier given as below. In SVM, linear kernel was chosen. In K-NN, Euclidian distance used as distance metric with the k-value is 3. The ANN has 3 layer architecture that consist of one input, one hidden and one output layer. The hidden layer has 512 neurons and the output layer has 2 neurons. The activation functions of hidden layer is RELU and output layer is Softmax. The data is divided as 70% training and 30% test. The CNN parameters are as follows: Sequential model, 1 dimension, 64 neurons at the input, 32 neurons at the hidden layer (first dense layer) and 2 neurons at the output neuron. The activation functions are RELU at the hidden layer and Softmax at the output layer.

III. RESULTS



a)



b)

Figure 1 : Scattering of right and left imagery before and after CSP.

In CSP, the first filter maximize the variation of the first class, while minimizing the variation of the second. The last filter maximize the variation of the second class, while minimizing the variation of the first. In order to see how well we can differentiate between the two classes, a scatter plot is a useful tool. Here both classes are plotted on a 2-dimensional plane: the x-axis is the first CSP component, the y-axis is the last. We applied the classifiers to this data. A classifier can be thought of as drawing a line in the above plot to separate the two classes [10]. To determine the class for a new trial, we just check on which side of the line the trial would be if plotted as above.

The data is split into a train and a test set. The classifier fits a model (in this case, a straight line) on the training set and use this model to make predictions about the test set (see on which side of the line each trial in the test set falls). Note that the CSP algorithm is part of the model so calculated using only the training data [11].

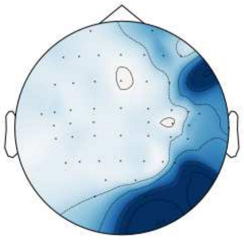


Figure 2: Scalp distributions for the subject performing right or left motor imagery.

In Figure 2, we see that there is no significant difference in the signal of most channels between the two classes. The CSP algorithm calculates channel mixes designed to maximize the difference in variation between the two classes. These mixtures are called spatial filters [12].

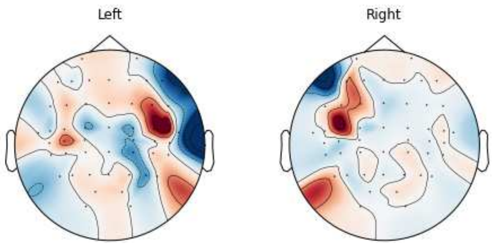


Figure 3: Active regions of the subject after applied CSP filter for the right and left motor imagery.

The largest and smallest eigenvalues in CSP decomposition forms the two filters. These CSP filters are used to represent right and left-hand imaginations as a scalp distribution. In Figure 3, red color shows higher activations. In accordance with the literature, the positions of the right- and left-hand motor imagery signals were observed on the brain appropriately. A spike of mu activity can be seen on each channel for both classes. At the right hemisphere, the mu for the left hand movement is lower than for the right hand movement. At the left hemisphere, the mu activity for the right-hand movement is reduced and at the central, the mu activity is about equal for both classes. The obtained results are consistent with the literature.

TABLE I. COMPARISON OF ALGORITHMS

Algorithm	Accuracy (%)
Support Vector Machine	0.841
The K-nearest neighbour algorithm	0.900
Neural Network Model	0.939
Convolutional Neural Network	0.905

IV. CONCLUSION

BCI based closed loop rehabilitation is proved more effective than classical rehabilitation. The critical point in closed loop rehabilitation is accuracy in classification and timing. In this study, we investigated the performances of the most common classifiers in the classification of the left hand and the right-hand motor imaginary signals. In MI signal classification, CSP is mostly preferred method for the feature extraction so we used this method in the study. The study shows that the ANN based classification algorithm is more successful than the other machine learning methods used in the research.

In some other studies, it was stated that CNN was more successful. However, CNN is a need more data for better training than ANN and it requires more processing time so it may cause problems in timing in the closed-loop rehabilitation.

REFERENCES

[1] C. E. Solórzano-Espíndola, E. Zamora, and H. Sossa, “Multi-subject classification of Motor Imagery EEG signals using transfer learning in neural networks”.

[2] M. M. Mashhad, “EEG-Based Brain-Computer Interfacing via Motor-Imagery: Practical Implementation and Feature Analysis,” 2019.

[3] S. Aggarwal and N. Chugh, “Signal processing techniques for motor imagery brain computer interface: A review,” *Array*, vol. 1–2, p. 100003, Jan. 2019, doi: 10.1016/j.array.2019.100003.

[4] X. Yu, K.-B. Sim, and P. Chum, “Analysis the effect of PCA for feature reduction in non-stationary EEG based motor imagery of BCI system,” *Optik-International Journal for Light and Electron Optics*, vol. 125, pp. 1498–1502, 2014, doi: 10.1016/j.ijleo.2013.09.013.

[5] X. Zhang and M. S. Eng, “Practical Electroencephalography (EEG) Applications in Stroke Rehabilitation: towards brain-computer interface (BCI) setup and motor function assessment,” 2009.

[6] Ö. Aydemir, “Common spatial pattern-based feature extraction from the best time segment of BCI data,” *Turkish Journal of Electrical Engineering and Computer Sciences*, vol. 24, no. 5, pp. 3976–3986, 2016, doi: 10.3906/elk-1502-162.

[7] D. H. Hubel and T. N. Wiesel, “Receptive fields and functional architecture of monkey striate cortex,” *The Journal of Physiology*, vol. 195, no. 1, pp. 215–243, Mar. 1968, doi: 10.1113/JPHYSIOL.1968.SP008455.

[8] "Theano Development Team, 'Convolutional Neural Networks (LeNet),' (accessed Apr. 14, 2022).

[9] D. Kim and A. S. Keene, "Automatic Artifact Annotator for EEG Waves Using Recurrent and Convolutional Neural Networks," 2019.

[10] N. Srivastava, G. Hinton, A. Krizhevsky, and R. Salakhutdinov, "Dropout: A Simple Way to Prevent Neural Networks from Overfitting," 2014.

[11] X. Xie, Z. Liang Yu, H. Lu, Z. Gu, and Y. Li, "Motor Imagery Classification based on Bilinear Sub-Manifold Learning of Symmetric Positive-Definite Matrices."

[12] H. Wang *et al.*, "Rehabilitation Treatment of Motor Dysfunction Patients Based on Deep Learning Brain–Computer Interface Technology," *Frontiers in Neuroscience*, vol. 14, Oct. 2020, doi: 10.3389/fnins.2020.595084.