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Comparison of EEG Pattern Recognition of Motor Imagery for Finger Movement Classification

Khairul Anam
Department of Electrical Engineering
University of Jember
Jember, Indonesia
khairul@unej.ac.id

Mohammad Nuh
Dept. of Biomedical Engineeering
ITS Surabaya
Surabaya, Indonesia
nuh@ee.its.ac.id

Adel Al-Jumaily
Biomedical Engineering
University of Technology, Sydney
Sydney, Australia
adel.al-Jumaily@uts.edu.au

***Abstract*— The detection of a hand movement beforehand can be a beneficent tool to control a prosthetic hand for upper extremity rehabilitation. To be able to achieve smooth control, the intention detection is acquired from the human body, especially from brain signal or electroencephalogram (EEG) signal. However, many constraints hamper the development of this brain-computer interface (BCI), especially for finger movement detection. Most of the researchers have focused on the detection of the left and right-hand movement. This article presents the comparison of various pattern recognition method for recognizing five individual finger movements, i.e., the thumb, index, middle, ring, and pinky finger movements. The EEG pattern recognition utilized common spatial pattern (CSP) for feature extraction. As for the classifier, four classifiers, i.e., random forest (RF), support vector machine (SVM), k-nearest neighborhood (kNN), and linear discriminant analysis (LDA) were tested and compared to each other. The experimental results indicated that the EEG pattern recognition with RF achieved the best accuracy of about 54%. Other published publication reported that the classification of the individual finger movement is still challenging and need more efforts to achieve better performance.**

Keywords*—*EEG, pattern recognition, finger movement

I. Introduction (*Heading 1*)

Bio-signal based classification for predicting a user intention has been developed for decades to control a therapy robot for rehabilitation [1][2][3]. Most of them utilize electromyography (EMG) signal and very few employ electroencephalogram (EEG)[4]. In fact, EEG signal is very beneficial especially for a patient who possesses a muscular problem. Therefore, for such people, a limb movement classification based on EEG signal is needed.

The stages of the classification of the limb movement using EEG signal is similar to that using EMG signal, but with more rich features [5]. Special for hand movement, the focus of the movement classification is to differentiate the left or right-hand movement [4][6][7]. In fact, the hand movement includes finger movement. Fortunately, the direction of brain-computer interface (BCI) heads to the finger movement detection [8][9][10][11].

The success of the BCI for finger movement recognition depends on the feature extracted from the EEG signal beside to the classifier. But the features are more important than the classifiers. Therefore, many EEG features have been developed such as common spatial pattern (CSP) [5][12], continuous wavelet transform[10] and so on. In addition, there are several classifiers have been tested and employed for EEG pattern recognition. Among them are support vector machine (SVM)[13], k-nearest neighborhood (kNN)[14], random forest (RF) [15], and linear discriminant analysis [9]

Unfortunately, most of the EEG pattern recognition on the limb movements focused on a binary classification that classifies either foot and hand movements, or right and left-hand movements[16]. Luckily, the trend has extended to finger movement [8][9][10][17]. To best of the author's knowledge, the multiclass classification for five individual finger movements or more is still rare[18].

This article presents the comparison of different pattern recognition methods for finger movement classification, especially for all five fingers. The multi-class classification for five individual finger movements is challenging. One publication reported that accuracy of around 43% was achieved when classifying five finger movements using event-related potential (ERP) feature and support vector machine (SVM) [16].

II. Material and Methods

A. EEG Pattern recognition

Fig. 1 shows the stages of EEG pattern recognition. It is started with the data acquisition of EEG signals. Then, the EEG signals are filtered and segmented in a specific window length. In this segment, several features are extracted and fed to the classifier. Finally, the classifier predicts the intended movement after undergoing the training phase.

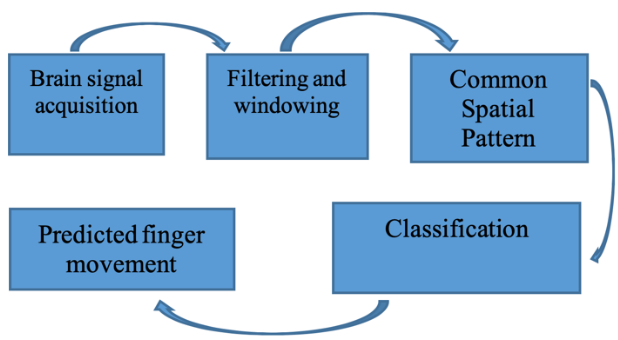

Fig. 1. EEG pattern recognition method for finger movement classification

B. Data Acquisition

The brain signal or so-called EEG signal is taken from [18]. The dataset used is a collection of EEG signal for finger movement taken from 4 intact subjects. The sampling frequency of the data acquisition is 200 Hz using EEG-1200 JE-921A from Nihon Kohden that is consisted of 19 EEG electrodes in the standard 10/20 system [18].

During the data acquisition, the subjects were seated in the front of the computer screen displayed the finger picture that should be imaged to move. The subject was asked to image the correspondence individual finger movement for 1 second and had a rest for 1.5 – 2.5 second. The experiment involved five individual movements, i.e., thumb (T), index (I), middle (M), ring (R), and pinky (P) fingers. Each movement was repeated 300 times. In total, there are about a duration of 25 minutes for whole experiments.

C. *Filtering and windowing*

EEG signal contains noises that can influence the performance of the pattern recognition. Therefore, the signal was filtered using a band-pass filter of 0.53 – 70 Hz and a notch filter of 50 Hz to overcome the electric power interference. Furthermore, the pattern recognition system was applied to each segment with one second of the window length overlapped every 0.1 seconds.

D. *Common spatial pattern*

In addition to the hardware filter, the EEG signal underwent spatial filtering using a common spatial pattern (CSP). CSP method is proven to divide the neural signal into different components related to task-common and task-specific component [19]. CSP is optimally employed for binary classification problem. This article involves five different classes. Therefore, an extension of CSP for the multiclass problem was used as indicated in [20]. We used five components of CSP led to the classifier, as shown in Fig. 2 and Fig. 3. It means, nineteen EEG signals out of nineteen EEG channels are projected and reduced to five data only. These five outputs will be the input of the classifier.

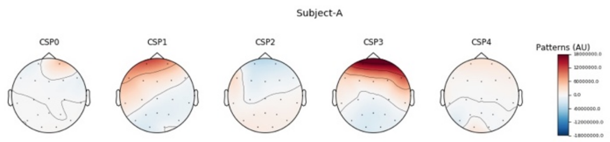

Fig. 2. Plotting of five components of CSP on Subject A

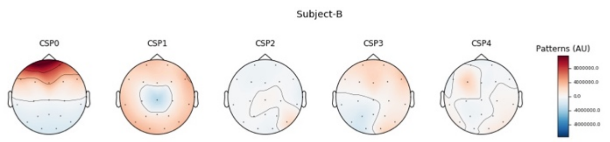

Fig. 3. Plotting of five components of CSP on Subject B

E. *Classification*

This paper compares different pattern recognition methods by evaluating different classifiers. There are four classifiers involved in the experiments i.e., support vector machine (SVM)[13], k-nearest neighborhood (kNN)[14], random forest (RF) [15], and linear discriminant analysis [9]. As for SVM, the radial basis function (RBF) kernel with C = 1.0 dan gamma = 0.2. Meanwhile, in kNN, we selected k = #feature in which 5. For the random forest, we set 100 trees. The experiments were run on the cloud server using python programming on Google Colab. The server computer has 12.72GB of RAM and GPU.

III. Result and Discussion

Data were divided into two groups i.e., training data and testing data using 5-cross-validation. The results of the training phase are depicted in Table 1. It can be seen from this table that random forest classifier is the most accurate one. It achieved 100% accuracy. Probably, the RF experienced overfitting. The testing result will confirm this prediction.

If we omit RF, kNN is the most accurate classifier on the training phase across four subjects. Fig. 4 shows this fact clearly. Furthermore, SVM and LDA are very close to each other.

TABLE I. Training accuracy using 5-cross validation

SUBJECT	SVM (%)		kNN (%)		RF (%)		LDA (%)	
	Mean	STD	Mean	STD	Mean	STD	Mean	STD
A	43.8	0.3	69.3	0.5	100	0.0	40.0	0.1
B	41.7	0.3	66.0	0.2	100	0.0	39.4	0.2
C	40.6	0.2	69.6	0.3	100	0.0	37.1	0.4
D	35.8	0.2	69.8	0.3	100	0.0	31.6	0.2
AVERAGE	40.5	0.2	68.6	0.3	100	0.0	37.0	0.2

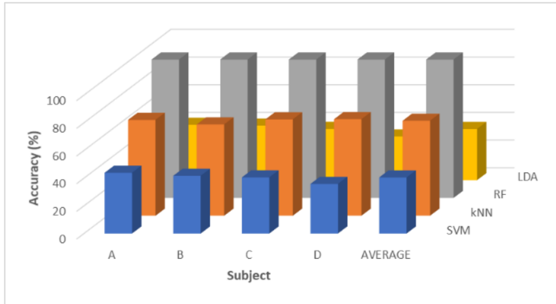

Fig. 4. Averaged accuracy of four classifiers on training stage

Different from the results on the training stage, the accuracy of the testing stages is close to each other, especially for kNN and RF, as seen in Table II. These results confirm what we said before that RF underwent overfitting. Nevertheless, RF attained the best testing accuracy of about 54%.

The trend is still the same as the training results. LDA is the worst but it is very close to SVM accuracy. Fig. 5 presents clearer information about accuracy comparison among these classifiers.

TABLE II. Testing accuracy using 5-cross validation

SUBJECT	SVM (%)		kNN (%)		RF (%)		LDA (%)	
	Mean	STD	Mean	STD	Mean	STD	Mean	STD
A	42.6	0.4	52.3	0.6	55	0.7	39.8	0.2
B	41.1	0.1	48.9	0.4	51	0.5	39.0	0.4
C	39.5	0.5	51.6	0.4	56	0.6	36.8	0.7
D	34.8	0.8	52.5	0.2	54	0.6	31.4	0.3
AVERAGE	39.5	0.5	51.3	0.4	54	0.6	36.7	0.4

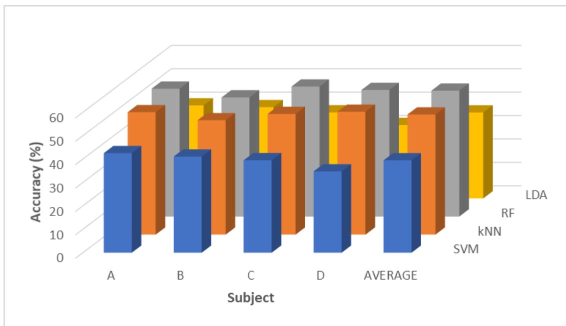

Fig. 5. Averaged accuracy of four classifiers on the testing stage

To analyze the classification performance on the individual finger, we investigate the confusion matrix of the classifier. In this case, two best classifiers were investigated as shown in Fig. 6 and Fig. 7. These figures present the normalized confusion matrix in which number “1” shows the accuracy 100%. Fig. 6 shows that the pattern recognition using RF classified the thumb movement by the accuracy of about 63%. However, the system misclassified the index movement as the thumb movement by the accuracy of 22% in which it is the worst accuracy compared to the rest finger movements. Probably, this fact is influenced by the closeness position of thumb and index fingers. This analysis is supported by the fact on the other finger movements. For example, the worst accuracy of the index finger movement occurred on the thumb and the middle finger in which their position is close to each other.

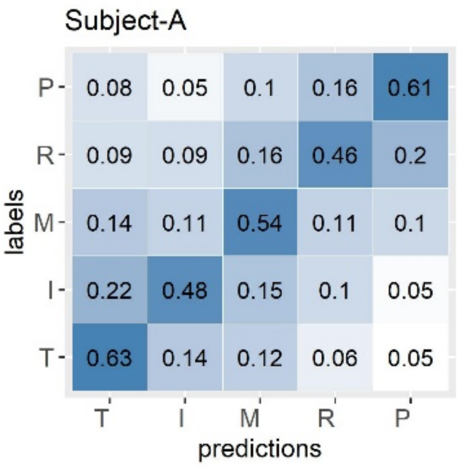

Fig. 6. Normalized confusion matrix resulted from Random Forest on 5-cross validation on Subject A

Similar to the RF, the best performance of the EEG pattern recognition occurred when it classified the thumb movements. However, the system misclassified the index finger movement as the thumb movements by the accuracy of 22%. As for the other individual movements, the most misclassified fingers occurred on the closest to the intended fingers. This fact can be seen clearly in the case of the index and middle finger movements. The index finger was misclassified mostly to the thumb and middle fingers movements. Meanwhile, the middle finger was misclassified to the index and ring finger movements.

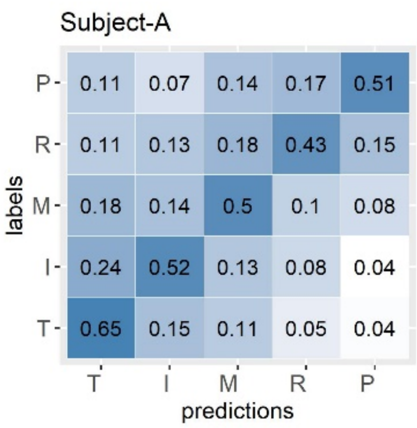

Fig. 7. Normalized Confusion matrix resulted from kNN on 5-cross validation on Subject A

If we just look at the results in this article, we conclude that the performance of the pattern recognition is not acceptable. However, to be fair, we need to compare the results with another reported publication that was using the same dataset with the same purpose. Murata et al. [18] had developed an EEG pattern recognition to classify these five finger movements. The EEG pattern recognition utilized SVM and event-related potential (ERP) and or event-related desynchronization (ERD) features. The attained accuracy was about 43%. This comparison indicates that decoding individual finger using EEG is challenging.

IV. Conclussion

This article presents the comparison of various EEG pattern recognition methods for classifying the five individual finger movements. The EEG pattern recognition consists of common spatial pattern for feature extraction and compares four different classifiers i.e., SVM, random forest, kNN, and LDA. The experimental results on 5-fold cross-validation show that the random forest achieved the best accuracy of about 54% but it is very close to the accuracy of kNN. However, the Random forest experienced overfitting. As for the LDA and SVM, their accuracy was the first and second-worst among the tested classifiers. The SVM’s performance can be improved by optimizing the parameters of the kernel. Compared to the published work, the performance achieved in this article is acceptable. The classification of individual finger movement is still challenging.

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