Detection of motor imagery (MI) event in Electroencephalogram (EEG) signals using artificial intelligence technique

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***Abstract*— With the recent development of technology and acquisition devices, the research of detection and classification utilizing EEG signals is rapidly increasing. One of the critical research in the field of the brain-computer interface includes an accurate detection of motor neuron behavior called motor imagery (MI) events. Due to the increased number in people with inabilities (e.g. paralyzed people, autism, and elderly people), accurate detection of MI events can of great help. In this work, a method for the detection of the MI events using the electroencephalogram (EEG) signal is proposed. Data from thirteen random subjects from a publicly available dataset was utilized. Firstly, the EEG signals were preprocessed and then a combination of time domain and frequency domain features were extracted from the signals. The number of features was reduced and selected using a minimum-redundancy-maximum-relevance (MRMR) algorithm and forward feature selection. On the subject level with leave-one-subject-out cross-validation, MI events were recognized with an average F1-score of 68.69% using the Support Vector Machine classification model. The best individual performance was obtained with an F1-score of 79%. These results suggest that the proposed approach is able to identify MI events in the EEG signal and thus the method may potentially be integrated into devices that can assist people with inability. Further improvement in the performance of the method can be done by carrying out testing in a wider population.**

Keywords—Electroencephalograph (EEG), motor imagery (MI), movement, Support Vector Machine (SVM), prediction, classification

I. Introduction

Advances in electroencephalogram (EEG) signal processing and sophisticated computing capabilities have potential possibilities to diagnose underlying diseases in humans. One of the uses of the EEG signal is to understand and diagnose the motor imagery (MI) events, the mental processing of imagining movements without incurring any actual physical movements [1]. Specifically, the motor imagery information can be useful for the paralyzed/elderly people who have the inability to perform physical movements at their old age and/or during rehabilitation. Therefore, it is important to analyze the MI events in EEG signals in order to explore potential solutions to assist physically handicapped and/or elderly people.

Recent efforts are focused on analyzing and studying MI events signals and trying to understand the signals in-depth in order to develop potential systems that can assist treating patients or the people who are unable to express themselves [2] - [3]. Different groups of patients under different clinical conditions are studied using motor imagery EEG signals towards solving the underlying issues. Several studies worked on MI events to study stroke patients and explored whether the motor recovery can be gained through mental practice or not. It was observed that the MI events can be helpful to activate the brain motor area. But the acute stroke patients may not be benefitted from mental practice [2]. Neurofeedback can help patients to learn the MI strategy and can increase the MI effectiveness to improve the health conditions [4]. The study of MI events was also shown to be very useful to learn a new sport more efficiently through mental practice in combination with physical practice [3]. The work in [3] showed that imagery rehearsal can be very effective in the improvement of learning a new sport and it was far better than the only physical practice or without practice. Notable research works observed that the event-related motor imagery EEG signals can be suggested to bring improvement in the area of rehabilitation. Motor imagery movement can also be helpful to assist physically handicapped patients. The MI based movement can be implemented instead of physical movement to reduce the problems of expressing the needs of such individuals.

With a goal of developing an accurate MI detection system, numerous researchers are trying to improve the algorithms to get better and efficient recognition. In [5], the authors showed the advantages of the improved back propagation (BP) neural network over the traditional BP neural network in MI event detection by solving the low signal-to-noise ratio and unclean filtering issues. The work presented in [6] proposed an optimized motor imagery paradigm where significant improvement was found in classification accuracy and usability. The imagery data of the hand movement of the writing pattern of a Chinese character was used as motor imagery data. Then the common spatial pattern (CSP) method was utilized to extract the features and support vector machine (SVM) was used for the classification. The authors in [7] proposed a method to detect the motor imagery movement using linear discriminant analysis (LDA) classifier. In [8], the work proposed an empirical mode decomposition (EMD) based method to detect the mu rhythm during motor imagery hand movement. In a recent study [9], the authors used a method to detect motor imagery left and right hand movement using support vector machine (SVM) classifier where independent component analysis (ICA) was used to remove noise signals of motor disable person. For control and stroke rehabilitation, EEG based strategies are also studied to detect MI events. The study of [10] used the filter bank common spatial pattern (FBCSP) algorithm to decompose the EEG into multiple frequency pass bands and later on the common spatial pattern algorithm was used to extract the features for the band pass frequency ranges. Despite the existing work on MI events detections, the accuracy of the detection is yet to be improved. Due to the dynamic nature of the EEG signal and dependency of the subject's compliance, further improvement in the method of MI event detection is critical. In the present work, a method to predict the MI events from the movement of the hand and different fingers is proposed. The work also demonstrates how feature selection algorithm can affect the recognition accuracy. To improve accuracy, the best feature set from the feature selection algorithm is finalized. Finally, several key points from the results are discussed in detail.

II. Materials and Methods

A. Data Acquisition

The raw motor imagery EEG data were obtained from publicly available "GigaDB" database [11]. The dataset contains EEG recordings of both hands MI tasks. The data were acquired using 64 channel Ag/AgCl active electrodes at the sampling rate of 512 Hz. A total of 13 subjects were considered randomly from the dataset for this study. Apart from MI EEG data, the database also includes non-MI tasks such as eye blinking, eyeball movement, etc. However, only the MI event data were considered for the study. A summary of the data protocol is presented in Fig. 1.

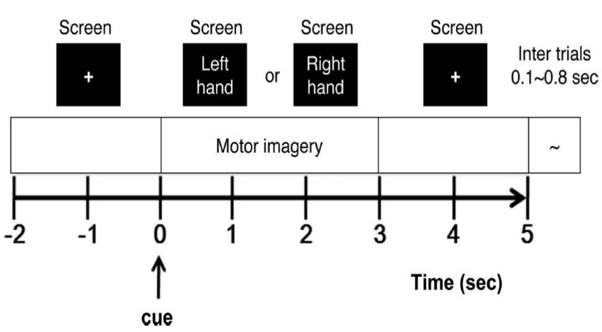

Fig. 1. Setup for each trial [11]

A total of 100 trials were taken for MI data. Each trial duration was 7s where a black screen appeared for the first 2s, motor imagery activity occurred for 3s and a black screen reappeared for the next 2s (shown in Fig. 1). Therefore, the total duration of 100 trials was 700s. A total of sixty-four electrodes were used to form motor imagery data and each electrode consisted of imagery data of 700 seconds. The data was organized into MI data from left hand movement and right hand movement as MI-left and MI-right respectively [11]. In the present work, only MI-left was utilized for the development of the classification model and validation.

B. Data Processing and Annotation

Firstly, the bad trials were identified by using the band-passed filter, and later a high-pass filter above 0.5 Hz was used to remove drifts from all EEG trials. Next, the data was divided into consecutive non-overlapping frames. The raw EEG data for 3 electrodes obtained from the MI tasks is illustrated in Fig.2. The dynamic nature of EEG signals is evident from the electrode data. Next, the data annotation was performed to mark the MI events and the period of non-MI events and/or idle. The onset of the MI events was first spotted and then for a period of 3s was marked as MI events. The rest of the data in one trial was assumed as non-MI events. Since the annotation was done by human raters, the annotation reliability was assessed with the kappa coefficient. A good kappa coefficient of 0.80 suggested a reliable annotation.

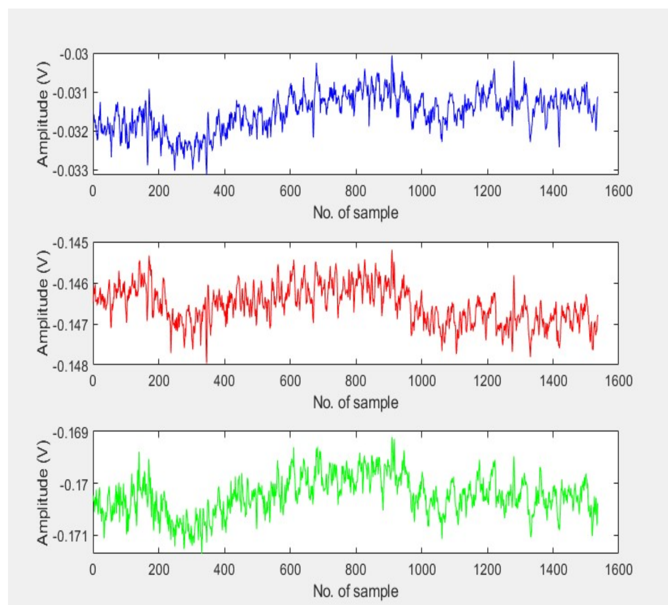

Fig. 2. Raw EEG data from MI tasks

C. Feature Extraction and Selection

Feature extraction and selection is an important step towards analyzing EEG data. A total of seventeen features are extracted from each of the non-overlapping epochs for each electrode which contains 700s of sensor data. Table I. presents the list of features that are used in this study. In order to eliminate any possible dimensional inconsistencies, the feature vector was normalized in the range of -1 to 1.

TABLE I. LIST OF FEATURES

No.	Features	No. of Electrode	Total features
1	Mean Value	64	$17 \times 64 = 1088$
2	Median Value		
3	Standard Deviation		
4	Mean Absolute Deviation		
5	Quantile25		
6	Quantile75		
7	Signal Interquartile Range		
8	Sample Skewness		
9	Sample Kurtosis		
10	Spectral Entropy		
11	Peak2Peak Value		
12	RMS Value		
13	Crest Factor		
14	Shape Factor		
15	Impulse Factor		
16	Margin Factor		
17	Signal Energy		

To minimize the cost and complexity of models, the feature set was reduced using feature selection procedures. Out of 13 subjects, 3 subjects were utilized for feature selection. To select the most important features, the minimum redundancy maximum relevant (MRMR) algorithm [12] was applied to rank the features sequentially based on mutual information. Different numbers of top features were checked (i.e. “k” values 10, 20, 30, and 40 where the k is the number of features that will be ranked sequentially to check). After ranking the features, Forward feature selection (FFS) was applied to find out the best sequence of the features from the ranked features. Linear discriminant analysis (LDA) was used during the forward feature selection process to find out the features in a sequence.

D. Classification

Different machine learning algorithms perform differently, based on the application of data sets. The Support Vector Machine (SVM) is one of the most important tools for machine learning and widely implemented in data classification. Out of several advantages, good generalization and regularization are two major powerful properties that outperform other classifiers. Due to these properties, SVM was utilized to detect and classify MI events. A linear kernel function was computed in this study for its simplicity and less complexity. MATLAB classification learner package is used to train and test the model. To test the performance of the classification model leave one subject out procedure was used to find out the performance of each subject where among the 10 subjects, 9 subjects were used to train the model and 1 subject was used to test the performance. This procedure was followed for all 10 subjects. Therefore, 10 training models were generated and the label for the 10 test data was predicted respectively. Finally, the predicted label of all 10 subjects was found.

E. Performance Evaluation

To validate the performance of the proposed method for the detection of the MI events, different performance metrics were measured. The parameters were positive (P) that defined epoch was MI event, negative (N) that defined epoch was non-MI event, true positive (TP) that defines epoch was positive and predicted to be positive, true negative (TN) that defines epoch was negative and predicted to be negative, false positive (FP) that defined observation was positive and predicted to be negative, and false negative (FN) that defined epoch was negative predicted to be positive [16]. The result was calculated by using the parameter from the data where it measured accuracy, sensitivity, specificity, precision, recall, and F1-score. The equations for the performance metrics were as below:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad [1]$$

$$Sensitivity = \frac{TP}{P} \quad [2]$$

$$Specificity = \frac{TN}{N} \quad [3]$$

$$Precision = \frac{TP}{TP + FP} \quad [4]$$

$$F - score = \frac{2TP}{2TP + FP + FN} \quad [5]$$

III. RESULTS

For different numbers of ranking features in MRMR, the best performance was obtained when the top 10 features where ranked by the MRMR algorithm. After the FFS, a total of 8 features were selected from the feature selection algorithm. The classification results for the different numbers of MRMR features (i.e. 10, 20, 30, and 40) in terms of the accuracy, sensitivity, specificity, precision, and F1-score are reported in Tables II -V. The mean values and the standard deviation are also given mentioned respectively.

It is evident from Table II that the six subjects show accuracy above 70% where 5 subjects show their F1-score value above 70%. The average accuracy and F1-score scores were 68.29% and 68.69% respectively. Table III shows that the average accuracy and F1-score scores were 69.01% and 68.55% respectively. In Table IV, the average accuracy and F1-score score were found to be 68.43% and 68.14% respectively. Finally, Table V exhibited that the average accuracy and F1-score score were found at 66.56% and 66.72% respectively.

TABLE II. PERFORMANCE OF THE SUBJECTS WITH MRMR FEATURE VALUE 10

Sub No.	Acc	Sens	Specs	Prec.	F1-score
1	71.00%	75.33%	67.75%	63.66%	69.01%
2	56.14%	95.67%	26.50%	49.40%	65.15%
3	53.29%	83.00%	31.00%	47.43%	60.36%
4	75.43%	92.00%	63.00%	65.09%	76.24%
5	82.14%	82.33%	82.00%	77.43%	79.81%
6	72.57%	81.33%	66.00%	64.21%	71.76%
7	77.71%	84.67%	72.50%	69.78%	76.51%
8	70.57%	81.00%	62.75%	61.99%	70.23%
9	59.43%	50.33%	66.25%	52.80%	51.54%
10	64.57%	81.33%	52.00%	55.96%	66.30%
Avg	68.29%	80.70%	58.98%	60.78%	68.69%
SD	9.10	11.52	16.76	8.90	7.97

TABLE III. PERFORMANCE OF THE SUBJECTS WITH MRMR FEATURE VALUE 20

Sub No.	Acc	Sens	Specs	Prec	F1-score
1	70.71%	74.67%	67.75%	63.46%	68.61%
2	59.29%	82.33%	42.00%	51.57%	63.41%
3	53.71%	78.33%	35.25%	47.57%	59.19%
4	75.86%	94.00%	62.25%	65.13%	76.94%
5	81.29%	82.33%	80.50%	76.00%	79.04%
6	72.71%	81.33%	66.25%	64.38%	71.87%
7	77.57%	84.00%	72.75%	69.81%	76.25%
8	72.43%	82.33%	65.00%	63.82%	71.91%
9	60.29%	48.33%	69.25%	54.10%	51.06%
10	66.29%	80.67%	55.50%	57.62%	67.22%
Avg	69.01%	78.83%	61.65%	61.35%	68.55%
SD	8.43	11.19	13.14	8.20	8.27

TABLE IV. PERFORMANCE OF THE SUBJECTS WITH MRMR FEATURE VALUE 30

Sub No.	Acc	Sens	Specs	Prec	F1-score
1	71.00%	76.67%	66.75%	63.36%	69.38%
2	57.14%	80.67%	39.50%	50.00%	61.73%
3	55.14%	86.67%	31.50%	48.69%	62.35%
4	69.43%	77.33%	63.50%	61.38%	68.44%
5	80.57%	84.00%	78.00%	74.12%	78.75%
6	72.29%	86.67%	61.50%	62.80%	72.83%
7	75.71%	86.33%	67.75%	66.75%	75.29%
8	73.29%	78.33%	69.50%	65.83%	71.54%
9	62.14%	44.00%	75.75%	57.64%	49.91%
10	67.57%	93.67%	48.00%	57.46%	71.23%
Avg	68.43%	79.43%	60.18%	60.80%	68.14%
SD	7.69	12.83	14.69	7.30	7.84

TABLE V. PERFORMANCE OF THE SUBJECTS WITH MRMR FEATURE VALUE 40

Sub No.	Acc	Sens	Specs	Prec	F1-score
1	66.14%	78.00%	57.25%	57.78%	66.38%
2	57.00%	79.33%	40.25%	49.90%	61.26%
3	53.00%	81.67%	31.50%	47.21%	59.83%
4	71.14%	77.67%	66.25%	63.32%	69.76%
5	72.14%	83.00%	64.00%	63.36%	71.86%
6	72.29%	85.33%	62.50%	63.05%	72.52%
7	77.43%	84.67%	72.00%	69.40%	76.28%
8	70.57%	84.67%	60.00%	61.35%	71.15%
9	60.71%	48.67%	69.75%	54.68%	51.50%
10	65.14%	81.33%	53.00%	56.48%	66.67%
Avg	66.56%	78.43%	57.65%	58.65%	66.72%
SD	7.29	10.26	12.26	6.44	7.00

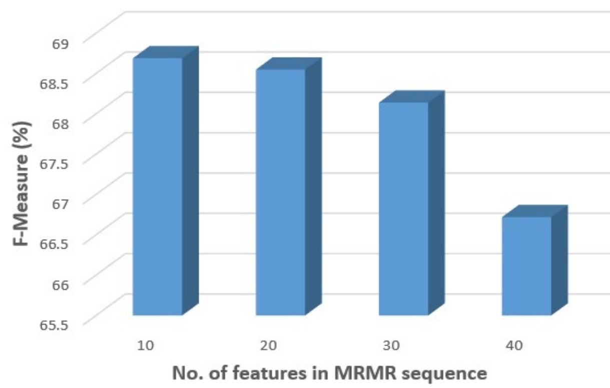

Fig. 3. Average F1-score score with different no. of MRMR sequence

It was evident that the best average F1-score of 68.59 was in case of taking 10 top features at the MRMR mutual information ranking stage. It was also evident from the results that the standard deviation of the F1-score tends to decrease as the increase of MRMR features. Fig. 3 illustrates a comparison in the F1-score with the different number of features in the MRMR sequence.

IV. DISCUSSION

The aim of the current work was twofold: i) to develop a method of the detection of the MI events in EEG signal and ii) identify the best set of feature and how the number of feature set affect the performance of the model. To the end, the investigation led to a method that can detect the MI-events almost 70% correctly. Also, the work provided an analysis of how the number of features can affect performance.

It is to be noted that the signal strength of EEG is very low and at some point, it goes below the threshold of noise. Therefore, it was extremely difficult to process the signal with such dynamic behavior. However, the current method could mostly remove the noise and was able to process the signal towards the detection of the MI-events.

The best results were found to be on an average F1-score of around 70% which may be suitable for brain-computer interface with limited applications. It was also evident that some of the subjects exhibited an F1-score of almost close to 80% which leads to a positive direction of further improving the performance. One of the interesting results from the classification model is the narrow standard deviation. It is always expected to have a narrow standard deviation in accuracy provided that the models don't get over fitted.

Another contribution of the current work was that the analysis of the number of features initially selected using mutual information. From the performance of the subjects with MRMR feature value 10, 20, 30, and 40 it was observed that the results are pretty much around the corner. It was evident that the best performance was obtained when the MRMR algorithm selected the top 10 ranked features. As the number of features increased, the performance of the model started to fall off. One potential reason could be the quality of the extracted features. There could be features those are highly correlated to each which in turn contributes to error. The best performance was obtained using only 8 features. This small number could potentially help to direct real-time analysis.

The method presented in the paper considers non-overlapping epochs of 512 samples. To obtain optimal performance, overlapping epochs can be considered in future studies. Since MI-events are dynamic, there are possibilities that tiny epochs would perform better compared to a big window.

While the method presents accurate detection of MI-events, the study was not free from limitations. One of the major limitations was that the method was to validate on a wider range of populations. The number of subjects can be increased to test and validate the model. Future work should be done considering more participants with more variety in MI events. Different classifier's performance can be explored to detect the MI-events. Further analysis can be carried out to detect which electrodes affect the performance of the classifier the most. This finding may lead to process fewer number of electrodes which eventually decrease the computational complexity.

V. Conclusion

In this study, a method for detecting motor imagery (MI) events in EEG signals was introduced using machine learning algorithm. On an average of ~70% F1-score was found from 10 subjects trials. The minimum redundancy maximum relevant (MRMR) algorithm followed by the forward feature selection (FFS) reduced the feature set drastically which helps to gain computational time. The initial results could potentially be helpful to develop a brain-computer interface that can contribute to help people with disabilities such as paralyzed people, elderly people, autistic people, etc. Of course, the accuracy can be improved further, however, the method provides a positive direction toward developing a more accurate algorithm. Further works can be done using more participants, different domains feature, and different classifiers.

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