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Performance Improved EEG based vowel recognition using Integrated PCA and Quadratic SVM

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Abstract

In this paper, performance improved EEG based vowel recognition using integrated Principal Component Analysis (PCA) with Quadratic Support Vector Machine (SVM) is developed with the help of a Graphical User Interface (GUI). The GUI displays Time-Frequency plot which shows suppression of alpha, beta and gamma rhythms. There is also a plot showing the Event Related Potential (ERP) of the patient. In addition to that, the GUI produces a topographical plot which shows the power of the electrical signals at the electrode. Data around the electrode is extrapolated. In the proposed system, data is collected by EEG device at sampling rate of 128Hz. This new sampling rate will produce lower samples for each recording, thus computational power and time required to train and test classifiers is reduced drastically. Further, five classifiers tested are built based on One Versus Rest (OVR) strategy, which are Fine Decision Tree (FDT), Linear Discriminant Analysis (LDA), Quadratic Support Vector Machine (QSVM), Weighted kernel Neural Network (WkNN) and also Subspace Discriminant Classifier (SDC). The performance for these classifiers are evaluated in recognizing the vowels imagined: “a, e, i, o , u”. QSVM is the best classifier among the five and shows that PCA has proven to improve the quality of classifier with 90.1% accuracy on 10 trials of 10 subjects tested. This improvement is significant as it boosts the performance for approximately 20% in accuracy. The system also allows specialist to monitor their patient’s brain activity which is recorded by the EEG device.

Keywords – EEG, OVR, speech, LDA, SVM, kNN

1. INTRODUCTION

Development in Brain Computer Interfaces (BCIs) have open doors for new strategies of movement recovery. The technological advancements in computer science and engineering has opened doors to better healthcare. BCIs are made to acquire electrical signals produced by brain and translate them into virtual movements [1]. Many different devices are can be used under the banner of BCI such as Electroencephalography (EEG), Magnetoencephalogram (MEG), Transcranial Direct Current Stimulation (TDCS) and Near Infrared Spectroscopy (NIRS). Each of this device has its own pros and cons. The researches done can be divided into two types which is clinical studies and methodology investigation [2,3].

Researchers [4] present recent developments in channel selection and evaluation algorithms for the purpose of processing of EEG signals in applications like early seizure detection, motor imagery, sleep state analysis, emotion and mental activity classification. Covering the usage of five different techniques for channel selection. The techniques are filtering method, wrapper method, embedded technique, hybrid method and also human-selection method. The advantages and disadvantages of this approach were discussed. Presented the usage of the techniques in the applications mentioned. The study discusses the use of four techniques for all the application. Focusing on the application of channel selection algorithm for motor imagery, filtering technique is commonly used in many researches. This is because it is able to improve the accuracy of the Brain-Computer Interface (BCI). Other techniques like wrapper technique and embedded technique has also yielded positive results. The study provides background knowledge on algorithms that can be deployed to select EEG channels, process and classify data received. Further work can be done to determine a channel selection technique that can produce the highest accuracy which can then be used in applications involving visual and auditory evoked memories. The channel selection methods are based on feature extraction of EEG data and therefore, the techniques have been used extensively in motor imagery application.

There are many classification algorithms being applied in BCI technology. Researchers [5] reviewed the modern classification algorithms for data produced by an EEG device. The algorithms are classified into four main methods, namely adaptive classifiers, matrix and tensor classifiers, adaptive learning classifiers and also deep learning classifiers. The researcher intends to update his/her previous work on classification algorithms commonly applied in the BCI field. This research discusses major issues faced in classifying EEG signals. The working principle, advantages and disadvantages of each classifier is explained thoroughly. In addition to that, the research also analyses properties of each classifier, i.e. stable or unstable, dynamic or static, regularized. Similar to the researcher's previous work [6]. This research also covers the suitability of the classifier based on the application. The research is concluded with future possibilities of the classifiers discussed

One of the gaps that still needs to be bridged is in increasing the accuracy of EEG feature classifiers [7]. There is a need for investigation of best performing classifier for each task and how they can be used collectively. Training trials required to achieve accurate results can be reduced [8-9].

The perks of using EEG is that it is inexpensive compared to other medical devices, non-invasive and can be portable [10-12]. Therefore, EEG is widely used to study neuroplasticity changes in many areas. EEG can also be used for early prediction and more research is required to be carried out considering the types of lesion, time taken for rehabilitation and larger sample size of patients [13-15].

2. PROPOSED SYSTEM

Figure 1 shows the proposed block diagram of the enhanced EEG based vowel recognition system integrating PCA and quadratic SVM. Data is collected by EEG device at sampling rate of 128Hz. This new sampling rate will produce lower samples for each recording, thus computational power and time required to train and test classifiers is reduced drastically. The recording of each activity will contain 256 samples. The system employs the usage of Principal Component Analysis (PCA) instead of Common Spatial Features (CSP), this is because PCA will transform data in rotation and find the direction with highest degree of variance. This method is suitable for data that does not epoch all the trials.

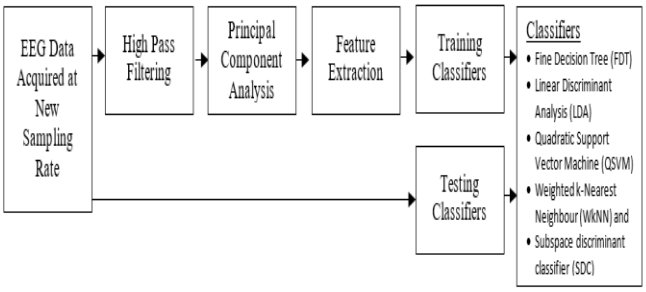

Fig. 1. Proposed block diagram of the enhanced EEG based vowel recognition system integrating PCA and quadratic SVM

The whole system starts with the EEG device. There are 16 sensors on the EEG device, and these sensor locations are fixed using the 10-20 system. Two of the 16 sensors are used as reference points. These two sensors will be placed behind the ears on mastoid bones. The rest of the 14 sensors are located at AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8 and AF4. Data collected by each of these sensors are considered as a separate channel. The sensors will measure the potential difference of the electrical signals fired by the neurons in the brain. The unit used by the sensors is micro-volts.

The computing device receives data from EEG device via Bluetooth connection. The data received has 25 channels which has additional nine channels. These nine channels contain other data such as timestamp, counter, marker signal, synchronization signal, gyro values and etc. The data from the EEG device is collected every 0.0078125 second based on the sampling rate of 128Hz. At the end of the two second recording, 256 samples are collected and tabulated in a matrix form. The dimensions of the matrix would be 256×25. A high pass filter is then used to reduce the effects of DC offset and also filter out low frequency noises that may exist in the signal. The high pass filter has roll-off frequency of 5Hz. Data is saved into the computing device in matrix format allowing the files to be accessed on MATLAB during classifier training.

Before the classifier can be trained, the matrix files need to be labelled and merged. Now there are five matrices all of size 2304×26. The five matrices are merged into one table, creating a table size of 11520×26. This table is located in the workspace of MATLAB and is ready to be used to train classifiers. 14 columns which hold the data from EEG sensors are used as predictors. The final column is used as response.

Classifiers are trained with PCA. Data on the predictor columns are mapped to the response column. Initially five classifiers are trained, which are Fine Decision Tree (FDT), Linear Discriminant Analysis (LDA), quadratic Support Vector Machine (SVM), Weighted k-Nearest Neighbour (WkNN) and Subspace Discriminant (SD) classifier. PCA will find the direction with highest variance of data making it easier for these classifiers to classify the data. The classifiers are set to train the data with 5-fold cross validation. This meant that the original data is divided into five sets where training happens on one of the set and validation on the other. The classifier is then improved and then validated on the next set. The iteration continues till the classifiers validates with the last set and learn new value of weights, concluding the training process. From the data, one classifier model is saved and used for prediction.

After several recording sessions and training of classifiers, one final recording is done to test the classifiers. The data is filtered and stored. The stored data is then directly used with the saved classifier model for prediction. The classifier model will return a number one to five indicating its prediction of activity. The prediction and actuation process runs continuously till stopped by the user.

3. EXPERIMENTAL RESULTS

The EEG is responsible to collect data emitted by the cortical cortex of the brain. The EEG will have 16 electrodes which would be placed according to 10-20 system. The EEG device would have to communicate wirelessly to the laptop and therefore other additional components to support the functions of the EEG device would be required. The EEG that is used is 'Emotiv EPOC+ as shown in Fig. 2.

Fig. 2. Emotive EEG device

A Graphical User Interface (GUI) is designed to provide information on the signals captured by the EEG and provided the basic control of the experiment. Fig. 3 shows the format of the GUI that is developed. A total of 16 waveforms will be displayed with the head plot which will provide an overall view on the pattern of brain activity.

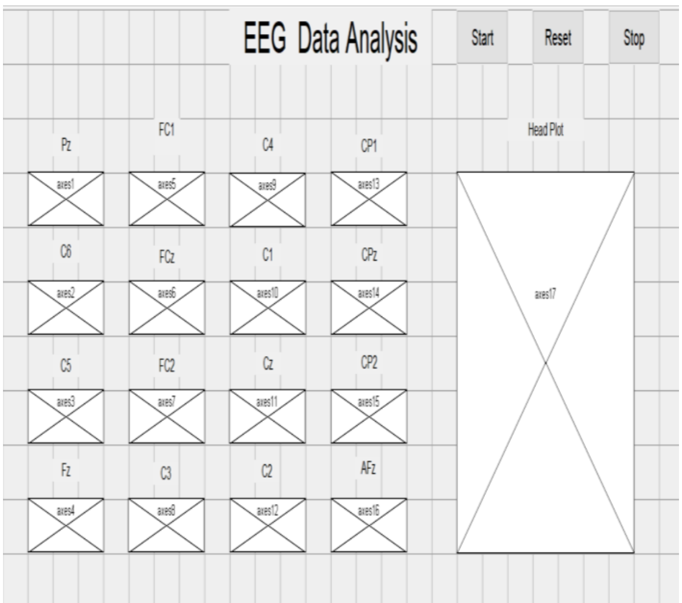

Fig. 3. GUI for EEG Data Analysis

The sections of GUI were separated into multiple GUIs. In this way the main GUI will open the necessary GUI based on the user interaction. The user is able to focus on the information/instructions displayed on screen. The three division of GUI design is training of classifier, testing of classifier and analysis of recorded EEG. The training GUI is constructed to open in full screen mode. Thus the participant is not distracted with other things that is running on the computing device. The other two GUIs open in normal mode with sufficient space between the contents. Fig. 4 shows the main framework constructed for the three GUIs.

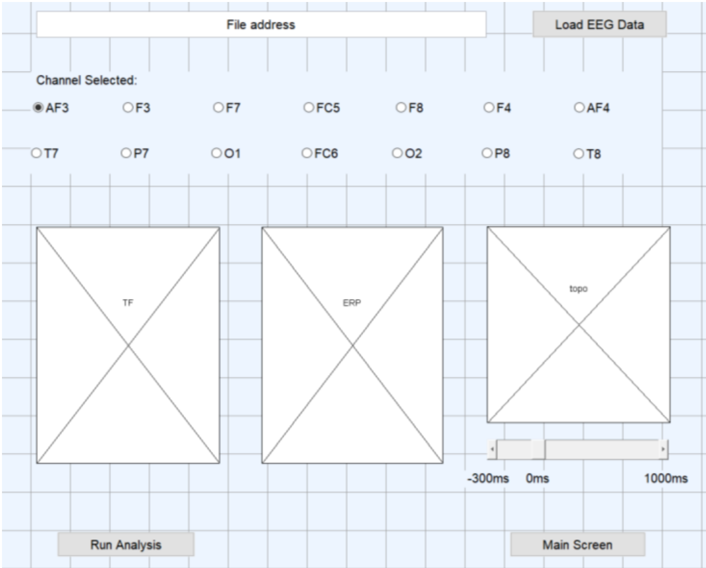

Fig. 4. GUI Analysis framework

Fig. 5 shows the results of the project which is displayed on the GUIs. The first image shows the GUI display, when user selects to train the classifier when trying to utter a word. The next image shows when a classifier is tested, and the final image shows the analysis of the recorded EEG data.

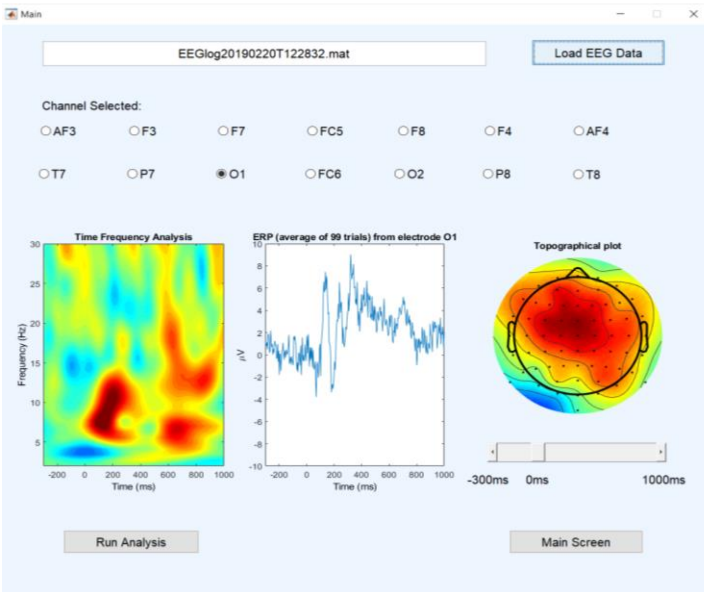

Fig. 5. Recorded EEG Signal

4. EXPERIMENTAL TEST RESULTS

For a start, the age group of volunteers selected to carry out testing is diversified. Ten subjects are selected, of which 4 of them are aged 20 years ± 2 years, 2 of them are 65 years ± 5 years and the remaining 4 are 40 years ± 5 years. Although the system is not tested on patients with speech disability, it is better to test the system on volunteers coming from different age group so that the system proposed is useful. Thus, it can be concluded that the system designed has potential to treat speaking disability patients regardless of their age.

The participants are not encouraged to blink or close their eyes as this will cause large fluctuations in alpha rhythm, eventually leading to lower quality of classifiers. 10 recording sessions are carried out for each subject. The tenth recording session is done with the sole intention of testing the classifiers designed. The change in the number of recording sessions is made in order to obtain better validation results of the classifiers. Five letters are being tested: “a”, “e”, “i”, “o” and “u”.

Each action will be iterated once only, unless there were disturbances during recording or the participant blinks or the participant is not satisfied with his/her performance. Participants are awarded with five seconds of rest time in between the recording of each action. Therefore, the recording sessions take up to 30 seconds, where 10 seconds of it is for recording of speech movements and 20 seconds for total break time. With this schedule of recording, lesser samples are processed, training and prediction time can be reduced. The participants are also more focused during recording.

4.1. Accuracy of classifiers trained with 1 trial

This test is conducted to investigate the performance of the classifiers when trained with singe trial or one recording session only. This challenges the idea of achieving a stable and accurate classifier with minimal training time. The classifier needs to be robust enough to accept the small changes in data collected. All the five classifiers are trained with first recording session of Subject 1 as shown in Table 1.

Table 1. Accuracy of classifiers trained with 1 trial.

Classifier	**Accuracy**
Fine Decision Tree	80.6%
Linear Discriminant Analysis	81.3%
Quadratic SVM	88.1%
Weighted kNN	80.6%
Subspace Discriminant	86.8%

4.2. Accuracy of classifiers trained with 9 trials

The objective of this test is to examine the role of PCA in improving the performance of classifiers and also how the classifiers improve with a larger training data. This test will also tell if it is possible to draw conclusions on direct relations on the availability of training data and performance of classifiers as shown in Table 2. Similar to previous test, data of Subject 1 is used.

Table 2. Accuracy of classifiers trained with 9 trials.

Classifier	Accuracy (without PCA)	Accuracy (with PCA)
Fine Decision Tree	69.2%	86.6%
Linear Discriminant Analysis	71.2%	88.7%
Quadratic SVM	69.5%	90.1%
Weighted kNN	74.8%	87.0%
Subspace Discriminant	56.8%	88.8%

4.3. Accuracy of classifiers in classifying each vowel

The theory is that each classifier performs differently in recognizing the vowels. For example, a quadratic SVM may be better at classifying the vowels “a, e, i” while a LDA is better at classifying “o, u” as shown in Table 3. The classifiers are trained using OVR concept where the classifiers try to separate the preferred response class for all the rest.

Table 3. Accuracy of classifiers in classifying each task.

Vowels	Fine Decision	Linear Discriminant	Quadratic SVM	Weighted kNN	Subpace Discriminant
a	81.2%	88.2%	95.0%	85.3%	88.2%
e	85.3%	88.7%	90.0%	88.6%	87.1%
i	86.9%	85.9%	90.0%	88.3%	88.2%
o	87.0%	90.0%	89.5%	84.9%	89.3%
u	86.4%	89.2%	87.3%	87.1%	88.2%

4.4. Inter subject testing

This final test is conducted to investigate how similar is one volunteer to the other and will it be logical to train classifiers on healthy volunteers but use the testing on disable speech patients in the future as shown in Table 4. If volunteers are almost the same, it is possible that the classifier is able to make correct predictions with the data of the other volunteer.

Table 4. Inter Subject Testing.

	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
S1	-	25%	41%	61%	85%	63%	29%	69%	45%	65%
S2	28%	-	42%	28%	22%	20%	40%	82%	65%	93%
S3	41%	43%	-	45%	43%	90%	24%	66%	88%	66%
S4	62%	26%	46%	-	100%	29%	45%	82%	41%	47%
S5	82%	22%	46%	89%	-	46%	66%	45%	69%	86%
S6	63%	25%	95%	40%	45%	-	49%	65%	41%	45%
S7	47%	80%	44%	87%	68%	44%	-	48%	86%	45%
S8	45%	60%	81%	48%	80%	45%	65%	-	60%	82%
S9	46%	63%	80%	45%	69%	47%	63%	66%	-	67%
S10	61%	95%	63%	45%	80%	40%	45%	87%	82%	-

Quadratic SVM is the best classifier among the five. It also shows that PCA has proven to improve the quality of classifier. This improvement is significant as it boosts the performance for approximately 20% in accuracy. The fourth test results show how each classifier perform for each task. In general, Quadratic SVM classifier dominates the classification process algorithms. The difference intra-classifier for the tasks is not much. More complex systems can adopt classifier switching strategy but the increase in performance is about 5%. The final test results are to measure how similar is one participant's thought processes to the other. It can be summarised that participant 2 and participant 10 are alike and also participant 3 with participant 6.

5. CONCLUSION

Thus in the proposed integrated PCA and QSVM for EEG based vowel recognition, the data was collected by EEG device at sampling rate of 128Hz. This new sampling rate produced lower samples for each recording. Thus computational power and time required to train and test classifiers is reduced drastically. Further, five classifiers tested are built based on One Versus Rest (OVR) strategy, which are Fine Decision Tree (FDT), Linear Discriminant Analysis (LDA), Quadratic Support Vector Machine (QSVM), Weighted kernel Neural Network (WkNN) and also Subspace Discriminant Classifier (SDC). The performance for these classifiers are evaluated in recognizing the vowels imagined: "a, e, i, o , u". QSVM is the best classifier among the five and shows that PCA has proven to improve the quality of classifier. This improvement is significant as it boosts the performance for approximately 20% in accuracy. The system also allows specialist to monitor their patient's brain activity which is recorded by the EEG device. Despite all the advantages of the system, it is limited to usage of data from 14 channels. Therefore, future work may include research on EEG devices with higher number of electrodes and/or a neural network combining the simple classifiers stated and switching from one to the other type based on the data.

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