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Developing a Few-channel Hybrid BCI System by Using Motor Imagery with SSVEP Assist

Li-Wei Ko, Shih-Chuan Lin, Meng-Shue Song, Oleksii Komarov

***Abstract*— Generally, Steady-State Visually Evoked Potentials (SSVEP) has widely recognized advantages, like being easy to use, requiring little user training [1], while Motor Imagery (MI) is not easy to introduce for some subjects. This work introduces a hybrid brain-computer interface (BCI) combines MI and SSVEP strategies — such an approach allows us to improve performance and universality of the system, and also the number of EEG electrodes from 32 to 3 in central area can increase the efficiency of EEG preprocessing to design an effective and easy way to use hybrid BCI system. In this study the Common Spatial Pattern (CSP) algorithm was introduced as a feature extraction method, which provides a high accuracy in event-related synchronization/desynchronization (ERS/ERD) -based BCI. The four most common classifiers (KNNC, PARZENDC, LDC, SVC) were used for accuracy estimation. Results show that support vector classifier (SVC) and K-nearest-neighbor (KNN) classifier provide better performance than others, and it is possible to reach the same good accuracy using 3-channel (C3, Cz, C4) hybrid BCI system, as with usual 32-channel system.**

Keywords – hybrid brain computer interface (BCI), Motor Imagery (MI), Steady State Visually Evoked Potentials (SSVEP), electroencephalogram (EEG) channel reduction.

I. INTRODUCTION

The brain-computer interface (BCI) system uses the brainwaves electrical signal acquisition to communicate between brain and some terminal device. The goal of BCI is not to determine a person's intent by eavesdropping on thoughts, but rather to provide a new channel of output for the brain that gives a way to direct some external activity. Usage of noninvasive electroencephalogram (EEG), which has a high temporal resolution, appropriate for measuring every thousandth of a second, is the most prevalent method of signal acquisition in modern BCI systems. Normally application of the BCI requires voluntary adaptive control by the user. However, BCI systems do not work for all users — approximately 20% of subjects do not exhibit adequate BCI performance for effective controlling, a phenomenon called "BCI illiteracy" by some groups. This is why development of new BCI approaches to improve of BCI universality is an important problem [11].

Based on these studies, the system also combines two typical BCI approaches as hybrid technique: Motor Imagery (MI) and Steady-State Visually Evoked Potentials (SSVEP) tasks.

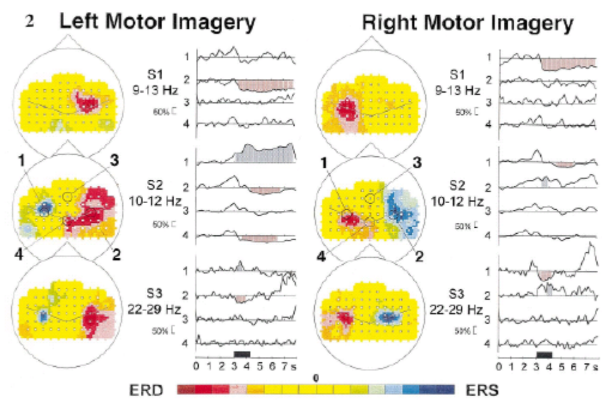

Figure 1 ERD/ERS maps and time courses of four selected recording sites

SSVEP is a natural response for visual stimulation at specific frequencies. It is characterized by signal amplitude, increasing at the stimulus frequency [1, 3, 4]..

A hybrid BCI is composed of two or more BCIs. This particular one recognizes at least two brain activity patterns in a simultaneous or sequential manner [11-18]. Using two or more patterns, the hybrid BCI can achieve certain goals in a more efficient way than conventional BCI systems [18]. For example, Allison et al. demonstrated that classification accuracy can be improved by detection of MI and SSVEP simultaneously, especially for BCI-blind subjects [11]. Pfurtscheller et al. proposed a hybrid BCI, where an MI-based brain switch was used to turn ON/OFF an SSVEP-based BCI [1,15,17]. This study uses a hybrid MI and SSVEP combined BCI to distinguish the patterns, based on time-frequency analysis, with higher accuracy.

During feature extraction the Common Spatial Pattern (CSP) algorithm shows high efficiency in calculation of spatial filters for ERD/ERS detection [18]. This study uses CSP function for simultaneous direction determination by

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diagonalizing the two covariance matrices, associated with two classes of motor imagery conditions [18]. With application of the CSP function, the average accuracy can reach more than 85%. The average accuracy of hybrid method can reach up to 99%, which is higher than both MI and SSVEP methods apart.
In this study the 3-channel (C3, Cz and C4) EEG-based hybrid BCI system was designed based on the observable SSVEP pattern in central area. The system exhibits accuracy up to 97% — higher than only MI or SSVEP sessions. Proposed approach provides a simpler way to measure the MI and SSVEP response.

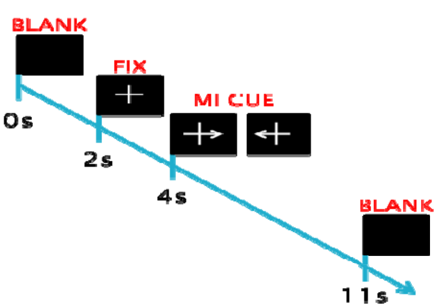
II. Material and Methods

A. Subjects

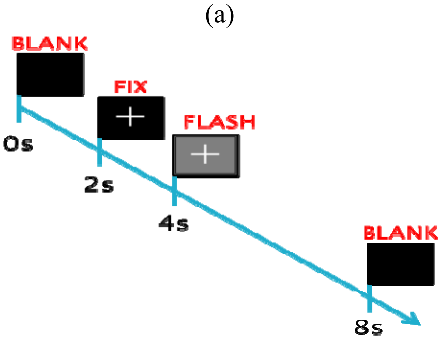
For EEG experiment 11 right-handed volunteers were selected - 8 males and 3 females, aged between 21 and 29 years (mean age 24±3 years), with normal or corrected to normal vision. Subjects had no history of gastrointestinal, cardiovascular, neurological or psychological disorders, were healthy and had no prior experience with EEG-based BCI experiment. Each experiment was performed in accordance with actual country laws and IRB regulations. One female volunteer felt uncomfortable during the experiment, thus her data was excluded from data analysis. In total, the study was conducted on 11 subjects.

B. BCI experiment paradigm

After EEG recording setup had been performed, subjects were seated in a comfortable position, and were instructed to follow the experiment rule. The records for one subject had been taken continuously in one day. In this study, the experiment was divided in three sessions, as shown on Fig.2



(a)



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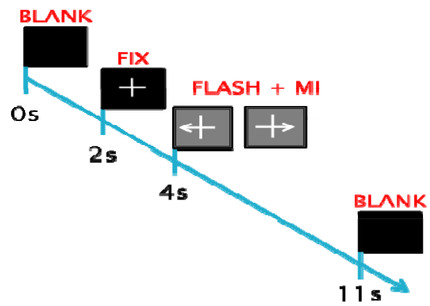

(c)

Figure. 2. The experiment procedure. (a) presents the procedure of MI task. (b) presents the procedure of SSVEP task. (c) presents the procedure of hybrid task(MI+SSVEP)

a. MI Task Experiment Design

In the MI task session (see Figure. 2-(a)), there were five blocks in one session; duration of each imagery session was 7 seconds, when a left hand arrow appeared, the subject need to imagine grasping his/her left hand. In the first block, subjects were asked to either squeeze left or right hand in real action. Then they were instructed to squeeze left or right hand in imagery starting from the second block. The data for analysis includes three runs without the second run, totally 45 trials were collected for each subjects.

b. SSVEP Task Experiment Design

During SSVEP session (see Fig.2-c), subjects were asked to gaze at the monitor flicker, until it stopped flashing. In order to determine the set of the most appropriate frequencies for flicker flashing, a special preliminary experiment was conducted. As a result, four flicker stimulus frequencies were selected: 13 Hz, 15 Hz, 17 Hz and 20 Hz. A 21-inch LCD monitor (60 Hz refresh rate, 1920x1080 screen resolution) was used for visual stimulation. In general, selected frequencies cannot be implemented with a fixed rate of black/white flickering pattern, due to limited refresh rate of the LCD screen. A special technique was developed to approximate target frequencies of SSVEP stimulus with variable black/white reversing intervals [1,9]. For example, 11 Hz target stimulus on a screen with 60 Hz refreshing rate can be implemented with 11 cycles of black/white alternating patterns lasting (3 3 3 2 3 3 3 2 3 3 2 3 3 3 2 3 3 3 2 3 3 2) frames per second. Using this approach, any stimulus frequency up to half of the screen refreshing rate can be realized. Totally, 10 trials per subject were collected in this session.

c. Hybrid Task Experiment Design

In this session two different stimulus were combined to obtain stronger response, determined by analysis of time-frequency power spectrum diagram. Subjects were instructed to focus on the fixation dot for 2 seconds. Then cue was showed for 7 seconds. Demonstration of the left cue was accompanied by 20 Hz flashing, demonstration of the right cue was accompanied by 15 Hz flashing. Totally 45 trials per subject were collected in this session.

Presentation® experiment program control software was used for stimulus presentation.

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C. *Data Recording*

To record EEG signal, an elasticated cap with 32 sensors was used (Contact Precision Instruments amplifiers, Neuroscan Acquire software). An electrodes placement strategy suggested by International 10/20 system was used in this study (Fig.3). Data was collected with a sampling rate of 500 Hz. The impedance of each channel was kept below 5 kΩ.

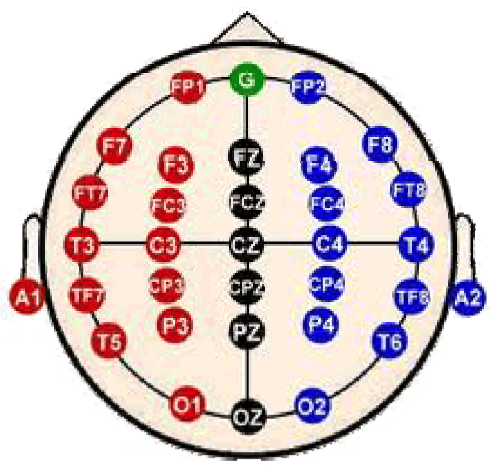


Figure 3 32-channel EEG position the data using

D. *Data Processing*

The data analysis process is listed below:

1. Bandpass filter 1~50 Hz was used to remove 60 Hz power line noise and other high frequency noise;

2. Noise/artifact removal was applied to avoid incorrect pattern determination;

3. Fixation time (2 sec) was used to record the baseline for normalization;

4. Epoch extraction to study the event-related EEG dynamics of continuously recorded data;

5. A Fast Fourier Transform with 1 second step (500 data points) overlapped by 0.5 seconds (250 data points), implemented by Hamming window;

MATLAB R2009b and EEGLAB (Delorme A & Makeig S, 2004) were used for data analysis

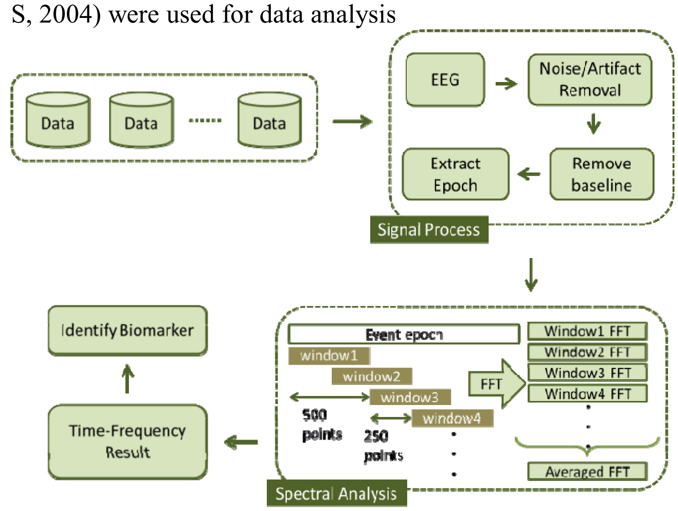


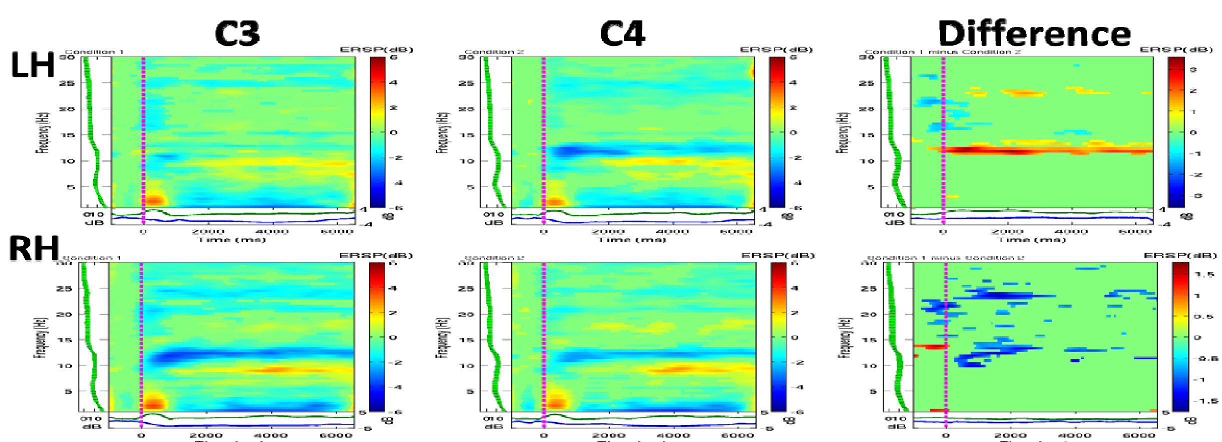
Figure 4. Paradigm of EEG data analysis.

III. RESULTS AND DISCUSSION

Fig. 5-a shows that, during imagery task, the results for right and left hands are opposite, which is consistent with previous studies. Pattern of MI response in time-frequency power spectrum diagram is based on ERD/ERS patterns, extracted from symmetric electrode pairs. This study shows that ERD pattern is presented in alpha band (8~12 Hz), and it occurs in C4 channel for left hand, and C3 for right hand, respectively. And vice versa, ERS occurs in C3 and C4 alpha band for left and right hands, respectively.

As shown in Fig.5-b, hybrid task combination of the signal patterns can be observed on C3 and C4 electrodes. The decrease of mu rhythm occurs on C4 for left hand imagery, and symmetrically on C3 for right hand. SSVEP power increases at 20 Hz and 15 Hz for left and right hand imagery, respectively.

Fig.5-c shows power increasing in frequency that corresponds to the one used in each type of stimulus flicker.



(a)

Figure 5-(a) According to previous study, power of EEG in alpha band and beta band in central area, obtained from the location of C3, C4 in the international 10–20 EEG system, which can provide power for discriminating and have high correlation with left and right movement imagery. The top two pictures present left hand (LH) imagery; the bottom two pictures presents right hand (RH) imagery.

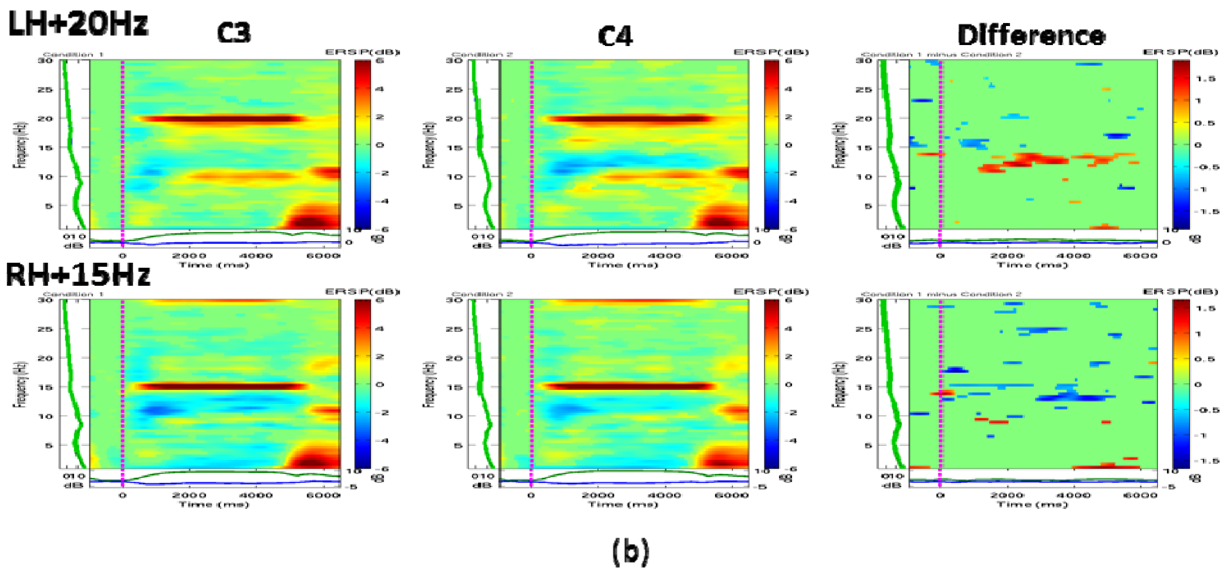


Figure.5-(b) The combination signal pattern in C3 and C4. An ERD occurred in contralateral brain and ERS occurred in ipsilateral side, and a power increase corresponding to flicker stimuli.

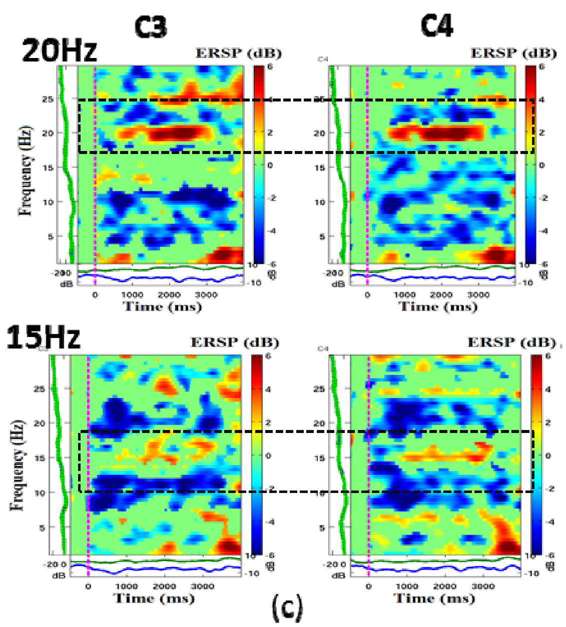


Figure 5-(c) shows 15 Hz and 20 Hz stimuli pattern in C3 and C4, the duration of flicker is 4s and the response manifests itself as an increase in amplitude of the stimulated frequency.

To sum up, in comparison with MI task, 9 of 11 subjects showed clearer patterns in SSVEP, and all subjects showed the clearest patterns in hybrid task. The strongest pattern of SSVEP starts from occipital area and decreases progressively to frontal area.

IV. Proposed Hybrid BCI Ssystem Using Three Central Electrodes

A. *Hybrid BCI System Design*

In consistency with previous results, strong phenomenon of SSVEP at C3, Cz and C4 was observed. Moreover, ERD/ERS of MI mainly focus in central area. This study proposes to reduce the number of channels, apply different classifiers, and compare results. Successful separation of left and right hand imagery results by machine learning technique is allowing to design a three-channel hybrid BCI system (Fig. 6). To estimate the system's accuracy, data of MI and SSVEP tasks was collected at C3, Cz and C4 channels. Furthermore, feature extraction, combined with classification, was performed.

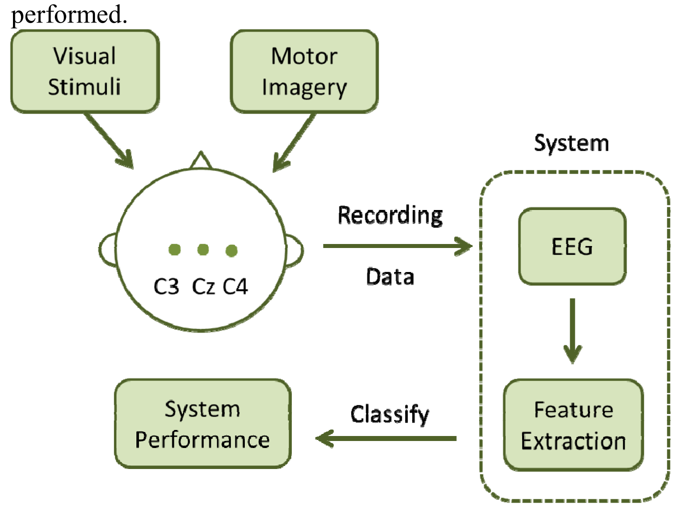


Figure 6. System paradigm of three channel BCI system

B. *Hybrid BCI Analysis*

This study extracted the 7 seconds imagery dataset and transferred it into 1~50Hz frequency as a feature. Also, the analysis of two different datasets was planned to compare the accuracy. The first dataset was based on the 32-channel sample dataset (which is shown in Figure 3), while the other dataset was based on the 3-channel (which is shown Figure 6) one. The goal of the analysis is to compare the accuracy between the two datasets.

a. Feature Extraction

This study designs spatial filters that lead to new frequency-domain data whose variances are optimal for the discrimination of two populations of EEG related to left and right motor imagery. The method is based on common spatial pattern, designed spatial filters using simultaneous diagonalization of two covariance matrix, was applied to the classification of imagining hand movement.

This study uses the frequency-domain data of a single trial, that presents as an N × H matrix E, where N is the number of channels and H is the number of frequency. The average spatial covariance of this data can be obtained from

$$\mathrm{C} = \frac{\mathrm{E}'\mathrm{E}}{\mathrm{N}} \tag{1}$$

where $'$ denotes the transpose operator. For separating two distributions, the spatial covariance is averaging over the trials of each group. The composite spatial covariance is calculated as

$$\mathrm{C_c} = \overline{C_l} + \overline{C_r} \tag{2}$$

C_c can be factored as $C_c = U_c\lambda_c U'_c$, where U_c is the matrix of eigenvectors and λ_c is the diagonal matrix of eigenvalues. The eigenvalues are assumed to be sorted in descending order in this section.

The whitening transformation

$$\mathrm{P} = \sqrt{\lambda_c^{-1} U'_c} \tag{3}$$

equalizes the variances in the space spanned by U_c, i.e., all eigenvalues of $\mathrm{P}C_cP'$ are equal to one. If $\overline{C_l}$ and $\overline{C_r}$ are transformed as

$$S_l = \mathrm{P}\overline{C_l}P' \text{ and } S_r = \overline{PC_rP'} \tag{4}$$

Then S_l and S_r share common eigenvectors, i.e.,

$$S_l = B\lambda_l B'\ , S_r = B\lambda_r B'\ , \text{and } \lambda_l + \lambda_r = I \tag{5}$$

Where I is the identity matrix. Because the sum of λ_l and λ_r is always one, the eigenvector with largest eigenvalue for S_l has the smallest eigenvalue for S_r and vice versa. Eigenvectors B are useful for discriminating of these two distributions. The projection of whitened EEG onto the first and the last eigenvectors in B gives feature vectors that are optimal for discriminating.

With the projection matrix $\mathrm{W} = \mathrm{P'B}$, the mapping of a trial E is given as

$$\mathrm{Z} = \mathrm{WE} \tag{6}$$

The rows of W^{-1} are common spatial patterns.

For classification, the features used are obtained by filtering EEG according to (6). For these two imagined movement, the diagonals of only a small number m of signals are most suitable as features for constructing classifier. The signals Z'_P ($\mathrm{p} = 1 \cdots 2\mathrm{m}$) that maximize the difference of covariance of left versus right motor EEG are associated with largest eigenvalue λ_l and λ_r. These signals are the m first and last columns of Z due to the calculation of W.

$$f_P = \frac{diag(cov(Z'_P))}{N} \tag{7}$$

The feature vectors f_P of left and right trials are used to calculate a linear classifier. The average serves to approximate normalization [6].

b. Classifier

For classification, the study uses the following four classifiers: KNNC, PARZENDC, LDC and SVC respectively. The k-nearest-neighbor classifier is one of the most basic classifiers for pattern recognition or data classification. The principle of this method is based on the intuitive concept that data distances of the same class should be closer in the feature space. As a result, for a given data point x of unknown class, the study can simply compute the distance between x and all the data points in the training data, and assign the class determined by the K nearest points of x. Due to its simplicity, KNNC is often used as a base method in comparison with other sophisticated approaches in pattern recognition.

Linear Discriminant Classify (LDC) is a classification method originally developed in 1936 by R. A. Fisher. It is simple, mathematically robust and often produces models whose accuracy is as good as more complex methods, and A Support Vector Classifier (SVC) performs classification by finding the hyper-plane that maximizes the margin between the two classes. The vectors (cases) that define the hyper-plane are the support vectors.

PARZENDC is a technique for nonparametric density estimation, which can also be used for classification. Using a given kernel function, the technique approximates a given training set distribution via a linear combination of kernels centered on the observed points. In this work, we separately approximate densities for each of the two classes, and we assign a test point to the class with maximal posterior probability [19].

c. Validation

This study randomly divided dataset of each subject for 70% as training data, and 30% as testing data, and repeated it 100 times to eliminate the difference of sub-dataset. The training dataset was used to build a classifying module, which was used for testing dataset classification. Every subject got their own average accuracy and standard deviation of 100 repetitions. Then this study calculated average accuracy of each subject and the result is shown in the next paragraph.

C. Results

In the 32-chnnel dataset results, main features are extracted from MI task dataset to the 6 most important spatial patterns, which mean the steadiest accuracy was seen at m = 3 (in Eq. 7) and it's close to the highest accuracy. For the SSVEP and hybrid task, the best accuracy was achieved at m = 1. Detection the largest and smallest feature vector can be performed upon the two groups.

Figure 7 shows the comparison of different tasks' performances, this study compares three tasks (MI, SSVEP, hybrid task) accuracy by using KNNC, PARZENDC, LDC and SVC. Figure 7-a shows the result of 32-channel channel EEG classification of three tasks. The average accuracy performance display that MI task < SSVEP task < hybrid task.

This study also compares the hybrid task performance between 3-channel and 32-channel EEG classification, and the result is shown as Figure 7-b. The blue chart indicates the 32-channel classification result (n =11), and the red one indicates the 3-channel result. Similar to the 32-channel, the best accuracy of the 3-channel can be reached up to 95% in the KNNC and SVC results, respectively.

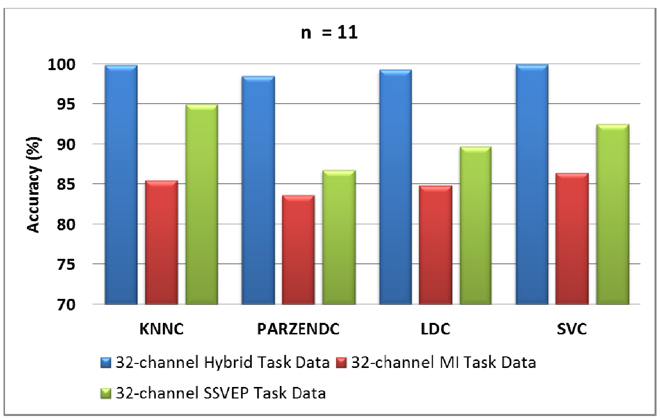


Figure 7-(a) Comparison of accuracy in MI, SSVEP and hybrid session

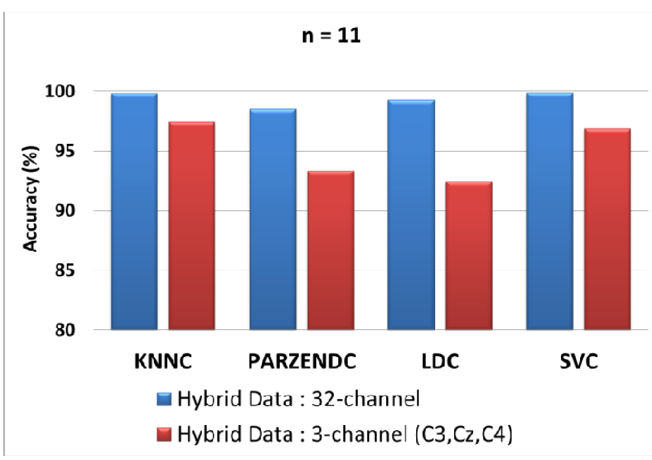


Figure 7-(b) The comparison of accuracy of 32-channel and 3-channel in hybrid session

In this case, the 4 common classifiers (KNNC, PARZENDC, LDC and SVC) are compared, and the result shows that for each of the classifiers, the accuracy can reach up to 90%.

Figure 7-b shows the accuracy comparison between 32-channel and 3-channel dataset in hybrid task. Results show that using 3-channel EEG signals from central area can keep as good performance as the accuracy from using 32-channel EEG channels. With KNNC and SVC classifiers can perform better accuracies than the other two classifiers. In the most results showed in the figure 7-(b), all the classification accuracy can be reached over 90%. It means that the proposed hybrid system can have a good classification performance than only using SSVEP or MI techniques to do the BCI system.

D. Discussion

As a result, MI task performance would be lower than the SSVEP task performance. At hybrid task session, the features of MI and SSVEP tasks are combined, which results in more specific pattern to recognize.

In the results, SSVEP approach showed higher accuracy than MI for 9 of 11 subjects, but the best accuracy has been reached for everyone with hybrid task. Thus, in accordance with previous studies, hybrid task indeed promotes universality of BCI.

This study showed that accuracy of the 3-channel system can reach up to 97%, that is just a little lower than the best possible accuracy of the full 32-channel system. One of the advantages of the 3-channel BCI system, proposed in this study, is reduced EEG preprocessing time. In addition, it becomes possible to use 3-channel brainwave-detecting devices like MINDO for this task.

Hybrid data showed the best performance in this study supposedly due to exhibition of more specific features than SSVEP and MI tasks separately. In the future, this method will be extended in order to research the cross-subject classification, design the real-time BCI and estimate its performance.

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