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Development of a Brain-Machine Interface for Motor Imagination Task

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摘要

本研究以設計互動式腦控開關之大腦人機介面的主要方向，並設計出想像運動之訓練面板，可以即時的偵測給定的想像任務受測者是否有成功的執行。選擇大腦皮質區的運動感覺區上的 C3 與 C4 頻道為訊號量測源，利用想像前後左右腦的 μ 節率(μ rhythm)與 β 波會產生不對稱性，針對 Graz 大學所提供的腦波資料分析自迴規模型、能量頻譜熵值、小波包熵值、相位鎖定值與共同空間型態等特徵組合與事件相關移動平均來增加事件相關非同步與事件相關同步化的特性，再加入主成份分析與線性鑑別分析兩種特徵抽取方法，並且提出機器學習方法中的支持向量機器取代以往需要經過經驗法則來調整的閥值偵測。結果顯示特徵 AR 搭配 PLV、PSW 與 WPE 後，使用 3 筆資料片段的事件相關移動平均再經過 LDA 轉換後會有較好的效果，其平均的偽正率為 2.86%、偵測率為 96.79%、正確率為 96.13%。

關鍵詞：腦電波、事件相關移動平均、運動想像、特徵組合，支持向量機器。

Abstract

In this study, we designed the training panel for imaginary action for instantly detecting and it is detected with the difference in brain wave under relaxed state and imaginary state. Channels C3 and C4 of motor area of Cerebral Cortex are selected as signal measuring source. The asymmetry μ rhythm and β wave of left and right brain is used in brain wave analysis of Graz University, the Autoregressive Model (AR), Power Spectral Entropy (PSE), Wavelet Packet Entropy (WPE), Phase Locking Value (PLV) and Common Spatial Pattern (CSP) combined characteristic and event-related moving average to increase Event-Related Desynchronization (ERD) and Event-Related Synchronization (ERS) features and add Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) characteristics extraction method and proposed the Support Vector Machine (SVM) of machine learning method to replace the threshold detection adjustment with thumb rule. The results indicated that characteristic AR combined with PLV, PSW and WPE, use related moving average of 3 epochs and converted with LDA will have better effect. The average FPR is 2.68% and Detecting Rate is 96.79% and Accurate Rate is 96.13%

Keywords**:** Brain Wave; Event-Related Moving Average; Action Imagination; Characteristics Combination; Support Vector Machine.

I. Introduction

Brain-machine interface (BMI) is to provide people suffering severe motor disabilities with a channel that can be used to communicate with other people or to control outer devices by mean of brain activities [1, 2]. One type of BMI is based on detection of the change of EEG rhythms when subjects perform motor imagery tasks such as the imagination of right- and left-hand (or finger) movements. The change of the EEG rhythms means the frequency power decrease in the contralateral brain signals, known as event-related desynchronization (ERD). The ERD often occurs in mu (8-12 Hz) and beta (13-28 Hz) rhythms [3]. Based on the ERD effect occurred during motor imagery, useful BMI systems can be designed. One of the motor imagery-based BMI applications is the so-called brain-controlled switch [4-7].

When brain-controlled switch has been designed, the next step is to test the performance of the switch. Therefore, an experimental paradigm should be prepared in advance in order to evaluate the switch’s performance [4-7]. Before designing an experimental paradigm, two kinds of situations should be considered: 1) Subjects do not intend to operate the switch, and 2) Subjects intend to operate the switch. Hence, two kinds of states should be involved in the design of the paradigm: one is the “intentional control state”, and the other is the “no control state”. During the intentional control state, subjects will be asked to imagine the instructed movement when an auditory signal is provided. If the motor imagery is detected, the switch is turned. So, this state can be used to test how sensitive the switch is. On the contrary, subjects are asked not to perform any motor imagery tasks during the no control state: the switch should not be turned on. Therefore, the no control state can be used to test the stability of the switch. However, what should the subjects do during the no control state if they are asked not to imagine any voluntary movements?

The ultimate goal of a brain-controlled switch is self-paced (asynchronous) [8]. A fully self-paced brain-controlled switch allows subjects to perform any mental tasks other than the motor imagery tasks for the “intentional control”, or just keep relaxed when they do not intend to operate the switch. In [9], subjects asked to count the number of times that a ball bounced off the monitor’s screen during the no control state, while subjects were asked to keep relaxed during the no control state in [7].

It is known that the ERD has patterns in certain frequency bands, and can be observed when subjects perform motor imagery tasks over motor areas contralateral to the hand imagined [10, 11]. Features that can effectively represent the ERD when subject perform motor imagery tasks are considered useful features. Therefore, how to extract such features from EEG signals becomes crucial. Therefore, a great variety of features have been proposed/adopted to design motor imagery-based BMIs, such as amplitudes of EEG signals [12], band power [13], power spectrum density (PSD) [5], [7], [14] autoregressive (AR) and adaptive AR (AAR) parameters [15], [16], time-frequency features [17], inverse model-based features [18-20], power spectrum entropy (PSE), [21], [22], and phase-locked value (PLV) based on Hilbert transform [23],[24]. These features have shown promise in those works.

In [25], a supervised feature mining (SFM) method based on genetic algorithms (GAs) and fuzzy measure theory has been proposed. The SFM method is general method for automatic feature evaluation and selection. It is able to find the optimal feature subset and remove the redundant ones from a large amount of feature candidates without taking trial-and-error. The success has been shown in the EMG feature selection [25] and the attribute selection for semiconductor manufacturing [26]. In this article, we will utilize the SFM method to identify the optimal feature subset from the existing features that have been used in the motor imagery-based BMIs [7, 12-24]. In addition to the feature evaluation on the existing EEG features, one may ask: are there any other possible features that outperform the existing ones? To achieve better performance of brain-controlled switch, it is necessary to search for other possible features and include them in the SFM-based feature evaluation process. That will be very helpful, and will be one of the major tasks. We propose in this article a promising solution, introduced as follows.

We plan to use a set of features: the input to the detector will be a vector. Therefore, a motor imagery detector can automatically determine an appropriate threshold (more precisely, a decision boundary in a high-dimensional space) that can effectively distinguish positive data from negative ones.

True positive rate (TPR) and false positive rate (FPR) are performance indices for evaluating the detector's performance. A robust motor imagery detector should be able to achieve a high TPR so that the brain-controlled switch has a high sensitivity. In addition, it should be able to achieve a low-enough FPR so that the brain-controlled switch can remain stable when subjects keep relaxed. In this article, an advanced machine learning technique called kernel Principal Component Analysis (kernel PCA) is adopted as the motor imagery detector.

It is known that Principal component analysis (PCA) is a popular subspace analysis method for pattern representation and reconstruction. Due to its linear nature, its performance is sometimes limited. Recently, a nonlinear version of PCA has been proposed, called kernel PCA [30]. KPCA first maps the input data into a higher dimensional feature space via a nonlinear mapping, and then performs the linear PCA in that space to find a set of eigenvectors that are nonlinearly related to the input data. Thus, kernel PCA can capture the nonlinear relationships between pixels in an image, and extract more discriminating features from an image and reduce the dimensionality of the input image. In pattern recognition studies, e.g. [31, 32], kernel PCA has shown to have better performance than PCA in terms of feature extraction. More recently, kernel PCA has been extended to a brand-new topic called novelty detection/outlier detection [33]. Kernel PCA novelty detector uses the reconstruction error in feature space as a novelty measure. A test data point is rejected as an outlier if its feature-space reconstruction error is larger than a threshold. Thus, the decision boundary of the kernel PCA detector is the reconstruction-error boundary. Our recent work on defect detection for liquid crystal displays (LCDs) [34] has proven the effectiveness of the kernel PCA in terms of detection accuracy. Therefore, we adopt the kernel PCA as the motor imagery detector, which is a novel method in the brain-controlled switch application.

In order to development a better brain controlled interface, this article used imagery and relaxation data from Graz data, features combination, Even-Related Moving Average, PCA, LDA, and SVM to investigate and comparison those results. And the online experiments will be used to test the efficient of the proposed method.

II. System Architecture and Experimental Design

A. System Architecture

The equipment used to measure EEG signal is developed by our lab. The 32-channel Electro-Cap is produced by company "Neuroscan" and those electrodes are placed according to international 10-20 brain electrode system. By using the circuit and soft developed in our lab, the brain signal can be acquired and analyzed. Figure 1 shows the experiment equipment. The electric transmission gel: By using the gel, the electric signal can be transmit from brain skin to electrode. 1A shows it. Electrode cap: It is produced by Neuroscan used to transmit the electric signal from brain. Figure 1B shows the picture in real. Brain signal acquisition equipment: through the 16 channels and 16 bit Analog to Digital Card "NI USB-6212", the brain signal can be measured and used in the computer. Figure 1C show it.

The amplification circuit: This circuit is designed in our lab and used for brain signal amplification and noisy removing. In order to analyze brain signal, the software "MATLAB" is used as offline analysis for data rearrangement, feature extraction, figure plot, and classification. The OS is 32-bit Windows Vista Home Premium, Intel(R) Core(TM)2 Quad Processor, 2G RAM, and 22-inch Acer LCD.

There are five healthy subjects, their ages are from 21 to 25, and all of their dominant hands are right hand. They didn`t have any brain leisure and any brain control training before.

Figure 1 Experiment Equipment A：the electric gel。B：36-channel electrode cap。C：NI USB-6212 analog to digital card。D：16-

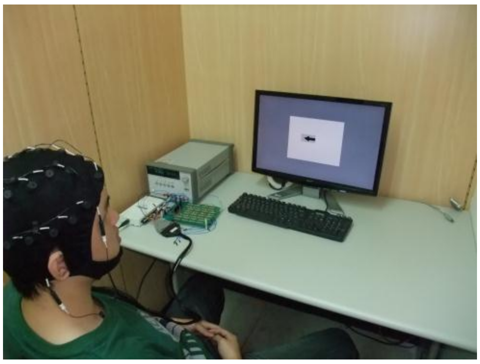

Figure 2 The actual situation in experiment

B. Experimental Design

There are two main session in our experiment design. The first one is Calibration Session which is used to collect the EEG data in relation state. The second one is Online Training Session which is included two Motor Imagery Task and two states, Intentional Control State and System Silence State.

Calibration Session

There is a short Calibration Session before each experiment, shown as Figure 3. The subjects don`t need to pay attention on any Motor Imagery Task and just relax. The time duration of this stage is 2 minutes. In the first session, the panel will show "Please Keep Relax" to tell the subject this session is beginning and show "END" to tell this session is finished. Through Session 1, there are 30 EEG data collected in relaxation state. The Power Spectral Density (PSD) is used to calculate the density of energy for those data and the average and standard deviation value will be calculated and be used as the estimation principle value in second session.

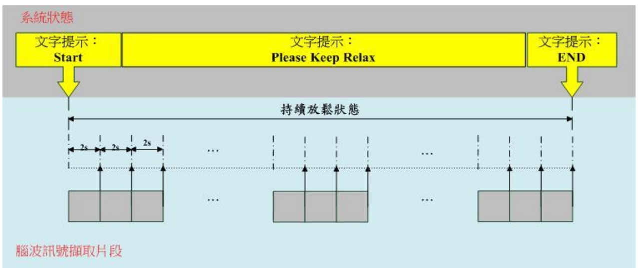

Figure 3 Calibration Session

Online Training Session

The second session is Online Training Session. All the subjects will participate in 5 experimental sessions. During the sessions, the subjects were asked to perform a particular motor imagery task and system silence task. In the motor imagery task, the figure "+" appears in first second and last two seconds. It means the subject needs to perform the imagery task. The motor imagery task can be right hand movement or left hand movement. The subject needs to perform one of them according to the direction of arrow before the arrow disappears. Then Silence State will begin and it is used to display the result of motor imagery task. There are 30 data in one session totally. Figure 4 show the details of Online Training Session

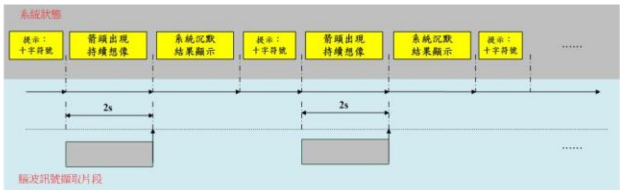

Figure 4 Online Training Seeeion

III. Brain Signal Collection and Pre-Processing

The scalp EEG signals are recorded from 32 electrodes placed according to the international 10-20 system with the left ear reference A1. The acquired EEG signals are amplified, filtered (0.1-100 Hz), and then digitized at a sampling rate of 250 Hz. During the EEG recording, subjects are seated in a chair, and asked to keep all muscles relaxed. In order to reduce artifacts, each subject will be instructed to avoid any eye-movements, blinks, body adjustments, or any body movements during the visual cue onset. During motor imagery, the electromyography (EMG) activity of each subject will be continuously monitored. Once EMG activity is detected, for example, once the EMG power within a specific frequency band is above a pre-defined threshold, the subject will be reminded to relax his/her muscles. The default frequency band for the EMG monitoring is 10-40 Hz, because mu and beta rhythms in the EEG signals are below 40 Hz. Epochs with EMG contamination will be excluded from offline neurophysiological analysis.

In practice, channel selection is still an ongoing research for BMI. As mentioned above, this article plans to use 32 channels to record EEG signals. However, it is known that motor imagery tasks evoke EEG signal changes on mu rhythm (8-12 Hz) and low beta rhythm (13-20 Hz). Therefore, motor cortex and somatosensory cortex would be the most important brain areas; hence it is expected that many of the 32 channels would be redundant. In this articlefigure, we will also try some channel combinations so that the number of channels can be greatly reduced, thus being able to increase the usability of the brain-controlled switch.

When the arrow appears, the subject begins the motor imagery until the arrow disappears. The ERD will appear in this duration and the Discrete Fourier Transform (DFT) will be used to transform the EEG signal in time domain to frequency domain.

Assume EEG signal x(t) is a function of continuous time，the equation is show as below。

$$X(\omega) = \int_{-\infty}^{\infty} x(t) e^{-j\omega t} dt \tag{1}$$

$$X(\omega) = \int_{-\infty}^{\infty} x(t) e^{-j2\pi ft} dt \tag{2}$$

$$e^{-j2\pi ft} = \cos(2\pi ft) + i\sin(2\pi f) \tag{3}$$

However, this EEG processing is a finite discrete signal transform. The continuous equation need to be fixed as finite discrete signal transform.

$$X(\omega) = \sum_{n=1}^{N} x[n] e^{-\frac{j2\pi f}{N}} \tag{4}$$

x [n] is nth point of EEG，N is the sample frequency, the total length of frequency spectrum is also N. After the EEG signal is transformed to frequency domain, it can be used to calculated the Power Spectral Density (PSD).

$$\hat{P}(\omega_i) = \frac{1}{N} |X(\omega_i)|^2 \tag{5}$$

ω_i is the ith value in frequency domain. N is the length of frequency spectrum. The PSD values of 8~20 Hz are summed.

$$P = \sum_i \hat{P}(\omega_i) \tag{6}$$

According to ERD and ERS, the PSD values of C3 and C4 can be calculated the difference, as $P_{diff}=P_{C4}-P_{C3}$ and used to observe the exist of ERD and ERS. Figure 5c shows the result of successful left hand imagination and the value of P_{diff} is almost lower than zero. The determination principle is that if the number of transition of positive and negative is less than two times, the system will determine the session is imagination session.

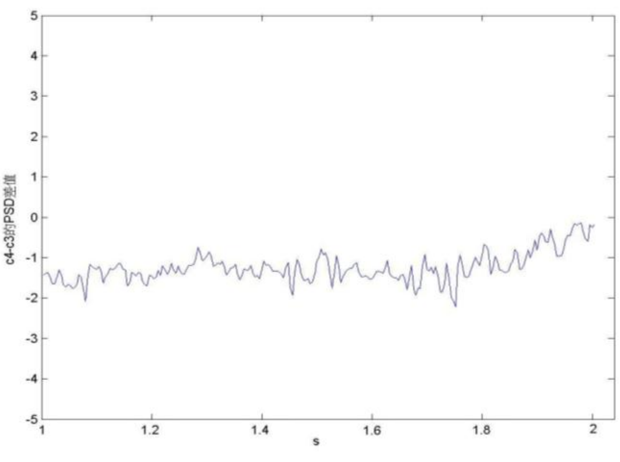

Figure 5 The results of PSD in three states

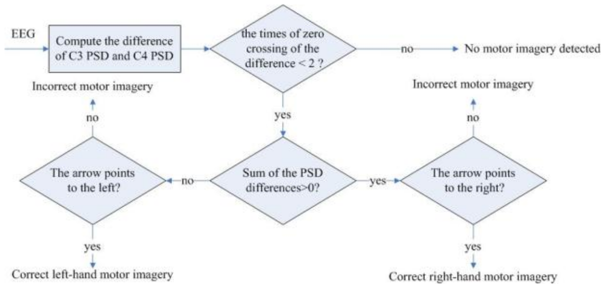

Figure 6 Experimental Follow Chart

If it is right arrow trail and the cumulative PDS value is higher than zero, it is successful right hand imagination. If it is left arrow trail and the cumulative PDS value is lower than zero, it is successful left hand imagination. The overall experiment follow is shown as figure 6.Although ERD is the phenomena of human active movement control but it has a large deviation between different subjects and trails. Therefore, the Even-Related Moving Average is used to filter out the natural noise. Figure 7 shows the method of Even-Related Moving Average and three continuous features are used to average.

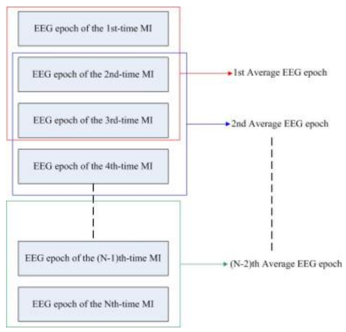

Figure 7 Even-Related Moving Average

A. Performance Index

In order to compare the performance between difference algorithm, there three performance indexes can be used to estimate the results. The equation is as below. FP is the number of detected as motor imagery in non-control state and TN is the number of detected as non-control state in non-control state. TP is the number of detected as motor imagery in Intention Control State and FN is the number of detected as non-motor imagery in Intentional Control State.

False Positive Rate (FPR)

$$FPR = \frac{FP}{TN + FP} \tag{7}$$

True Positive Rate (TPR)

$$TPR = \frac{TP}{TP + FN} \tag{8}$$

Accuracy

$$Accuracy = \frac{\#classified\ correctly}{\#nagative\ data + \#\ positive\ data} \tag{9}$$

TABLE 1 THE DESCRIPTION OF PERFORMANCE INDEXES

Performance Index	Description
FPR	The possibility of detected as motor imagery in Non-Control State
TPR	The possibility of detected as motor imagery in Control State
Accuracy	The overall accuracy in Control and Non-Control States

B. The Human-Machine Interface for Motor-Imaginary Training

In order to use the machine in real time, the human-machine interface for motor imaginary training is developed by using Microsoft Visual Studio 2008 in our lab. There are some parameters need to be setting shown as figure 8.

The interface of experimental settings

A：the number of channels；B：the maximum and minimum voltage value of signal；C：the sample frequency of EEG signal；D：the filter band of digital filter；E：the PSD band；F：the setting of calibration time and open the panel；G：Setting the time of motor imagery or the appearance time of arrow；H：mode selection (cumulative and war mode). In the war mode, when the failure number is reached above maximum failure number, this system will stop.；J：the path of files。

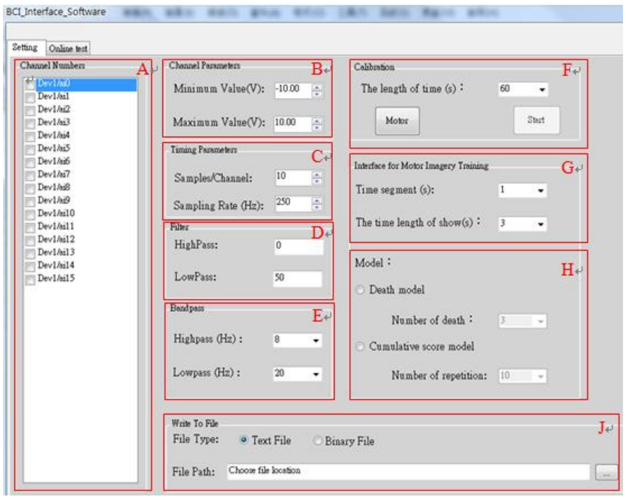

Figure 8 Design of Experiment Panel

Calibration Session Panel

The calibration panel is shown as figure 9 and the duration is setting in experimental panel. It will show “Please Keep Relax” until the system finish calibration session. Then it will show “END” and 30 data are collected for calibration.

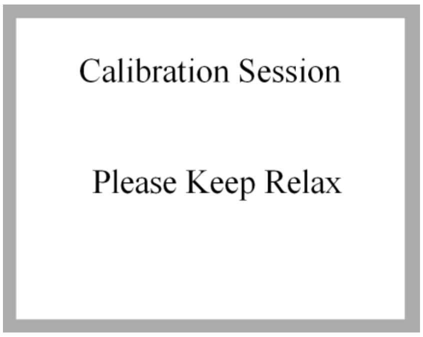

Figure 9 The Interface of Calibration Panel

Interface of Online Training

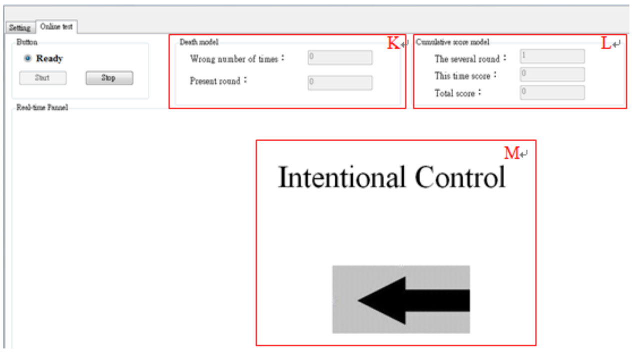

Figure 10 The Interface of Online Training

The main interface of BCI system is online training interface. It will show the signs, included “+”, “→”, and “←”, calculate the result and show it in real time. K：this block will show the failure number and total number in war mode；L：this will show the grade and the number of imagery in cumulative mode；M：this block is the position of arrow and it will become red ground when this trail is not successful.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

Expert the design of training interface, the more important purpose is investigate how to extract the useful signal of EEG for imaginary detection. Before the online training and data collection, the Graz Data from BCI competition 2003 are used to analysis the performance between different algorithm.

A. BCI competition 2003 Data Set III, Graz

The experimental data used in this paper are first published in BCI competition 2003. The data set consist of EEG signal (channel C3, Cz, C4) from a female normal subject (25 y). In experiment, the subject had to use the left/right hand imaginary movements to control a feedback system and each trial had a 9 second task an arrow cue was displayed on the screen to ask subject to control a bar to the cue direction.

This experiment compares the results between Event-Related Average with feature extraction and without feature extraction and different epochs. The number of maximum epochs is 4. And it is because 5 epochs cost 10 second and it is too slow. Table 2 shows the result between Event-Related Average with and without feature extraction (PSE) and different epochs. The classification method is K-nearest neighbor (KNN) algorithm. The result shows

Table 2 The results of Event-Related Moving Average

Data Type	FPR(%)	TPR(%)	Accuracy(%)
Raw data	47.14286	72.85714	62.85714
PSE without Event-Related Average	38	62.5	63.53
PSE with two epchos	28.92	66.57	68.1
PSE with three epchos	18.28	68.5	73.69
PSE with 4 epchos	16.88	68.95	74.19

Through above result, the Event-Related Moving Average is a method to increase the TPR and decreasing FPR. But there are still some methods can be used to improve the accuracy in advance. Figure 11 shows the energy of time-frequency spectrum. There is not obviously difference between C3 and C4 under non-imagery state and the 8~20 Hz band have larger difference under imagery state. Therefore, PSE and WPE can be used to determine the difference. Figure 12 shows the phase locking value between imagery and non-imagery. The value of non-imagery state us lower than the value of imagery. Therefore, some other feature method will be used to analyze the data and we will compare it and integer the most useful feature to get the best results.

The methods for feature extraction are Power Spectral Entropy (PSE), Wavelet Packet Entropy (WPE), Phase Locking Value (PLV), Autoregressive model (AR), and Common Spatial Pattern (CSP). PSE and WPE are calculated the difference in frequency domain. The main differences are PSE from discrete Fourier transform and WPE from wavelet transform. Phase locking value is calculated from Hilbert transform and the difference of phase between C3 and C4 is the phase locking value. Autoregressive model is the linear transform to get the model parameters and the model is used to get the filter predict date. CSP is use the linear optimization method to get the most difference vector in the feature space.

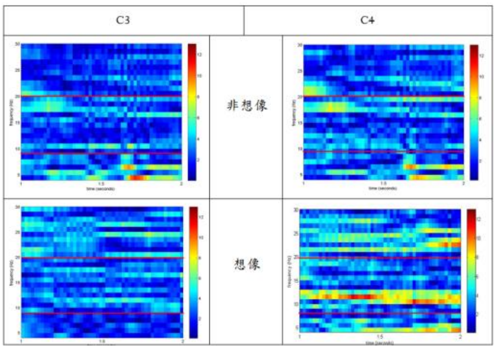

Figure 11 The C3 and C4 energy of time-frequency spectrum under imagery and non-imagery states

Finally, we can find the best method is LDA-SVM and the 7 best combinations are shown as below.

1. AR and PSE
2. AR and WPE
3. PSE and WPE
4. AE、PLV and PSE
5. AR、PSE and WPE
6. PLV、PSE and WPE
7. AR、PLV、PSE and WPE

Then, the SVM method is used to instead KNN methods and the LDA-SVM results are shown as table 3. The average results of LDA-SVM are 5% better than LDA-KNN, 20% better than raw data. The average value is higher than 80%. Therefore, the 7 features are used in our EEG signal analysis.

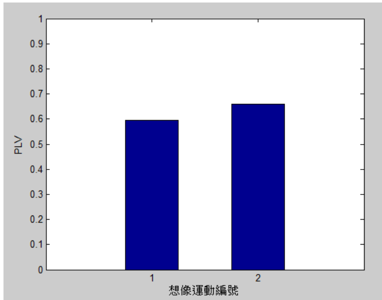

Figure 12 The average value of phase locking value. 1：Relaxation；2：right hand imagery。

By using three epochs Event-Related Moving Average, PCA, and SVM, the average results of FPR is lower than 5%, TRP is high than 90%, and the accuracy is higher than 90%. The best results of subject1 is by using PSE &WPE features：FPR is 6.25%、TPR is 98.33%、accuracy is 95.2%；the best results of subject2 is by using AR &WPE features：FPR is 1.83%、TPR is 96.91%、accuracy is 96.7%；the best results of subject3 is by using AR, PLV, PSW & WPE features：FPR is 0.83%、TPR is 96.67%、accuracy is 97.08%；the best results of subject4 is by using AR &WPE features：FPR is 2.91%、TPR is 98.33%、accuracy is 96.88%；the best results of subject5 is by using AR &WPE features：FPR is 2.5%、TPR is 93.75%、accuracy is 94.79%.

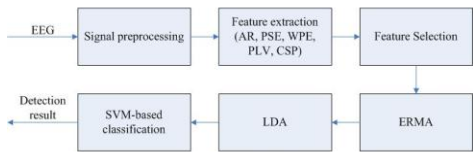

Figure 13 the LDA-SVM method for Graz data

Table 3 The results of different features by using LDA-SVM.

Features	FPR(%)	TPR(%)	Accuracy(%)
AR+PSE	12.86	84.32	85.73
AR+WPE	26.02	88.16	81.06
PSE+WPE	8.89	73.67	82.38
AR+PLV+PSE	14.85	84.04	85.59

AR+PSE+WPE	12.94	86.61	86.83
PLV+PS+WPE	10.8	74.19	81.69
AR+PLV+PSE+WPE	15.7	86.83	85.55

B. The Analysis of Online Experiment

There are 5 subjects in our experiment. According to the design of experiment, there are 4 times experiments for each subject. The average scores are shown as table 4.

Table 4 The average scores of experiments

Subject	Left Success	Right Success	Success /Total	Average Score
1	153	166	319/ 600	7790.49
2	146	213	359/ 600	100730
3	111	204	315 / 600	8978.65
4	204	120	324/ 600	15046.28
5	163	142	305/ 600	13643.66

The Gaze data results show some features cannot increase the accuracy, such as CSP. The result of CSP is even worse than raw data and it is because CSP need more channels to perform his effect. Expert to CSP, combination of the other feature and using PCA or LDA algorithm can make accuracy improved. Through the acquiring the EEG signal from the equipment in our lab and feature extraction, the online results are acceptable and considerable. But the results of PCA are better than LDA. Figure 14 shows the WPE & PSE result. Figure 15 shows the LDA result of WPE & PSE of subject. After LDA, the dimension is 1-dimension and two groups have some overlapped. Therefore, PCA has better results than LDA in our experiment.

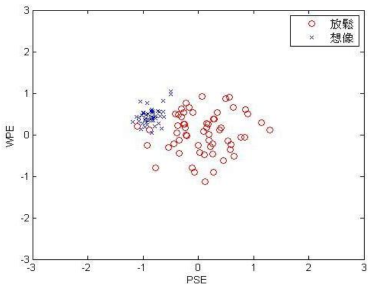

Figure 14 WPE & PSE results of subject 1

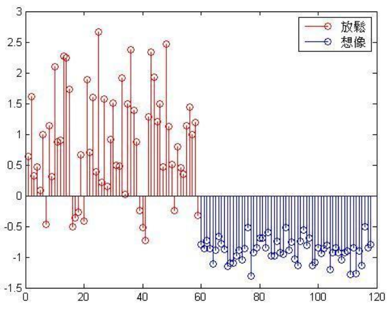

Figure 15 LDA results of WPE & PSE of subject 1

V. Conslusion

Finally, this article use imagery and relaxation data from Graz data, features combination, Even-Related Moving Average, PCA, LDA, and SVM to get better results for classification. And this article concluded seven useful feature combinations for motor imagery task. In the future, the online Brain Controlled Switch needs to be tested in real. In order have better results and decrease the times of imagery, the more data from more channels are also needed to be collected.

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