Modelling of P300 based Speller matrix BCI

Biosignal Processing and Modeling

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1 Motivation and goals

For many people with disabilities, to communicate with people around them through their attention is a very novel idea. In recent years, with the development of Brain Computer Interface (BCI), this idea is becoming possible. People can obtain the information the disabled want to express by extracting and recognizing the biosignal of them. The BCI speller paradigm is interesting because it is based on P300 Event Related Potentials (ERP) which are natural responses of the brain to some specific external stimuli. This is used in this paradigm and by this one can communicate through a computer using the P300 component of the event-related brain potential (ERP). This can be used as an aid to people who are unable to use any motor system for communication like 'locked-in' syndrome. Compared to other paradigms like motor imagery this P300 paradigm is fast, easy to identify the response and does not require even the movement of the eye muscle. We hope to complete the development and application of the BCI model[1] through experiments. As shown in Figure 1, we plan to design the paradigm to get the data, process the recorded data and design the application to get the feedback of the control.

More specifically, we choose to use the P300 speller instead of other BCI paradigms. Because the P300 speller is non-invasive and reliable with relatively high accuracies. Subjects only need relatively little training to use. Its limitation is its low information transmission rate, clinical practicability, etc. Through this project, we can explore a better and better method to process biosignals and build a reasonable model, which has a positive effect on the development of BCIs.

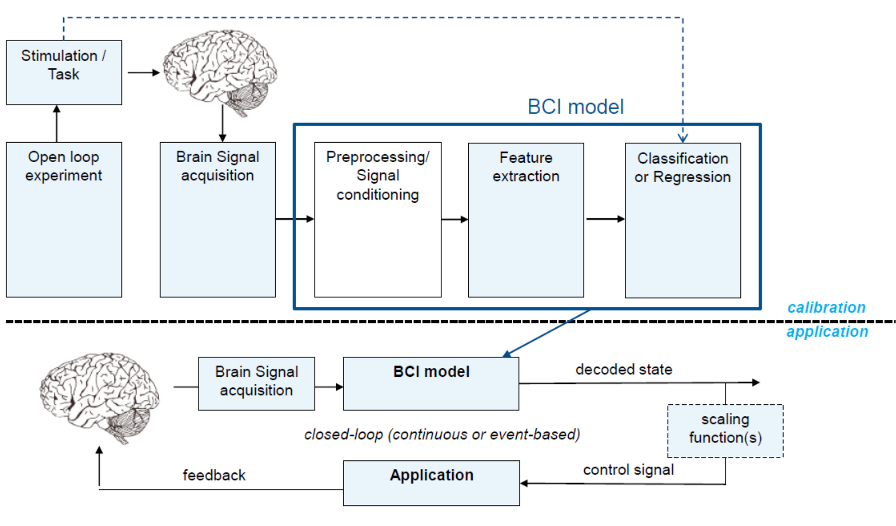


Figure 1: Development of BCI [1]

2 Methods

In this section, we will briefly introduce the process of our entire project and the specific methods adopted. The process of the entire project includes designing experimental paradigms for collecting data, processing biological signals and successfully recognizing them, and designing controllable robots to obtain feedback. In the subsection 2.2, we will introduce many different methods that we have tried, and compare their differences and pros and cons.

2.1 Designing the P300 speller paradigm

The P300 speller paradigm is based on the Farwell and Donchin P300 matrix speller[2]. This is a commonly used paradigm for Brain computer interface (BCI) systems. The P300 speller uses the oddball paradigm and elicits an event related potential (ERP) as a response. Oddball paradigm is based on the concept that attended target stimuli produce larger P300 potentials than attended non-target stimuli[3]. The ERP specific to this paradigm is P300 which is a positive deflection in EEG around 300ms. The matrix speller is composed of a 6x6 matrix of alphanumeric symbols from A to Z and 0 to 9 along with the symbol _ as shown in Figure 2 At a time one row or one column intensifies for a duration of 100ms and there was no intensification for 75ms. This is done for each row and each column and this is termed as a trial. The subject is made to think of a symbol based on a word during each trial and each trial is repeated 15 times as shown in Figure 3

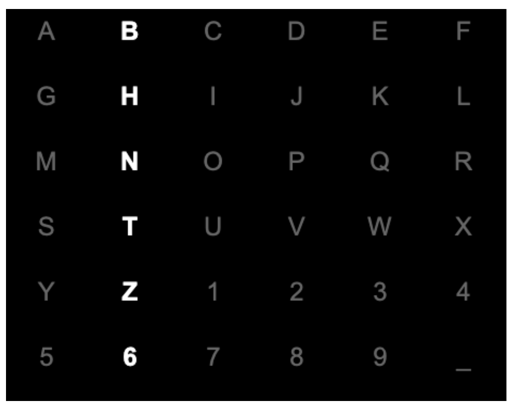


Figure 2: 6x6 matrix showing an intensification of the row

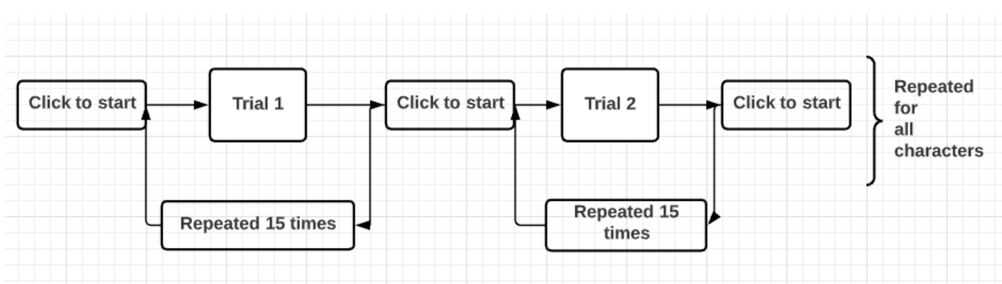


Figure 3: The paradigm for P300 speller matrix

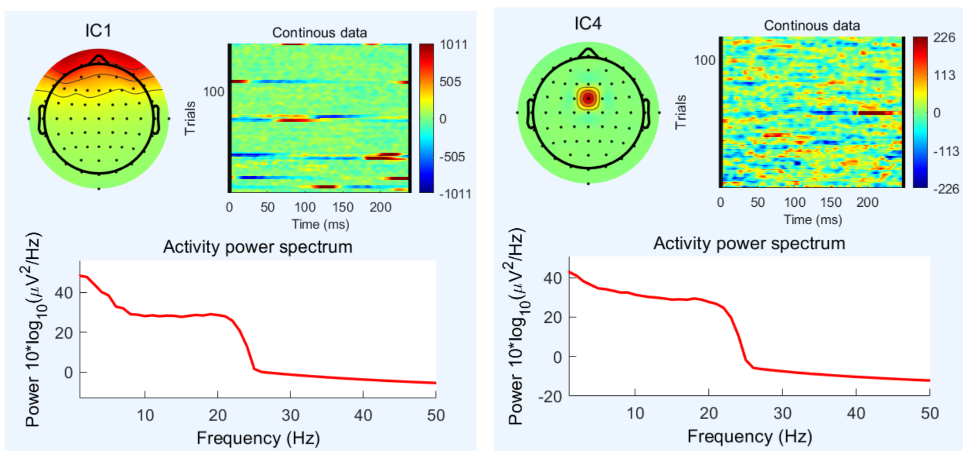
2.2 Processing the recorded data

2.2.1 Signal preprocessing

In order to improve the classification accuracy, we need to get clean EEG signals in the first step. This part can be done on the EEGLAB platform in MATLAB. In this project, mainly two steps of pre-processing are required as follows.

First, a bandpass filter with passband 1-20Hz is applied to avoid slow Baseline drift and high-frequency noise. Since the P300 ERP we mainly focus on in this project are usually below 10Hz, there's no risk to use this filter.

Second, we try to remove some artifacts based on ICA decomposition. Actually, after using the above bandpass filter, some high-frequency artifacts such as power line noise are already removed. So in this step we mainly need to find out and remove those low-frequency artifacts. Typical examples are the artifacts caused by eye-blinks and channel noise, whose topoplots and corresponding temporal and spectral information are shown in the following figures.



(a) Eye-blinks artifacts

(b) Channel noise artifacts

Figure 4: Example Artifacts

2.2.2 Basic Method

The data from the signal preprocessing is used to train and build a model to classify attended and unattended events. For this we tried 2 different methodologies. In this section we briefly describe the first methodology we tried, which was also named basic method.

Filtering and standardization of data The preprocessed data was filtered using a Butterworth 8th order bandpass filter with cut-off frequencies at 0.1 and 10 Hz. This data was further decimated to the highest frequency thus each single channel had 7 sample points only [3] Mirghasemi et al., proposed that there could be a Visually Evoked potential interference at 5.7Hz. So, a notch filter was added to remove the interference at 5.7Hz. Each channel data is then baseline corrected and normalized between -1 to +1.

Feature extraction After filtering and processing the data, each data was epoched from the start of the intensification 0ms to 667ms [3]. This is because those evoked potentials, P300 around 300ms and this window is used to extract all the necessary time features for efficient classification.

Feature reduction and classification A recursive channel elimination uses a classifier's performance according to the score based on the number of true positives, false positives and false negatives. This method was deemed to be a good way to do the feature reduction. The downside of this is the computation energy needed. Using this method 448 features were reduced to 48 features as shown in Figure 5

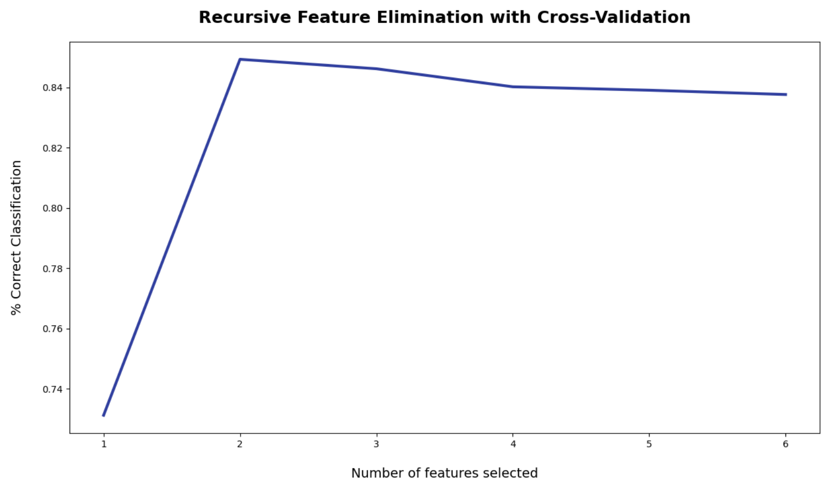


Figure 5: Recursive feature elimination scores for cross validation

Classification models With this reduced spatial feature matrix, we trained our LDA model using a grid search to hyper tune the parameters to find the best model. Various solver for the LDA was compared and it was found that singular value decomposition was the best with cross validation accuracy 87.6%. When tested this model 27/31 characters were predicted correctly giving an accuracy of 87.09%. Followed by another classifier namely random classifier with maximum depth as 10. This model gave much lesser validation accuracy of only 85%. With the same features we tried finding the best parameters for an SVM and we found that with 'C': 0.01, 'gamma': 1, 'kernel': 'poly' we get a maximum validation accuracy as 86.1%. In conclusion we understood that the accuracy couldn't be just improved by changing the models since the input to the models lacked some characteristic.

So, we concluded that the spatial feature alone was not enough to get the best accuracy even though it did give us a good average accuracy of 87%. So, in the next methodology we tried to extract the spectral feature to improve the model's learning.

2.2.3 Improved Method

Feature extraction In this part of Methodology 2, we need to extract the temporal and spectral features that can bring the best separation between stimulus and non-stimulus EEG signals. First of all, we should carefully analyze and compare the time course of both signals. For example, the time course of averaged signals across all training data (session 10 and 11) at channel Cz is shown below.

As we can see in the Figure 6, there is a significant peak (P300) around 330ms after the onset of the stimulus. So, this point is highly likely to be an outstanding feature. What's more, as discussed in the lecture, N100, which is evoked due to the unexpected stimulus around 100ms after the onset, can also be a potentially useful feature, although the effect is not obvious enough in Figure 6. So, we should also take N100 into account and evaluate its separation power later. In this methodology, all signals are averaged across all trials before classification to reduce the variation of EEG. The averaged topoplot of P300 and N100 are as Figure 7.

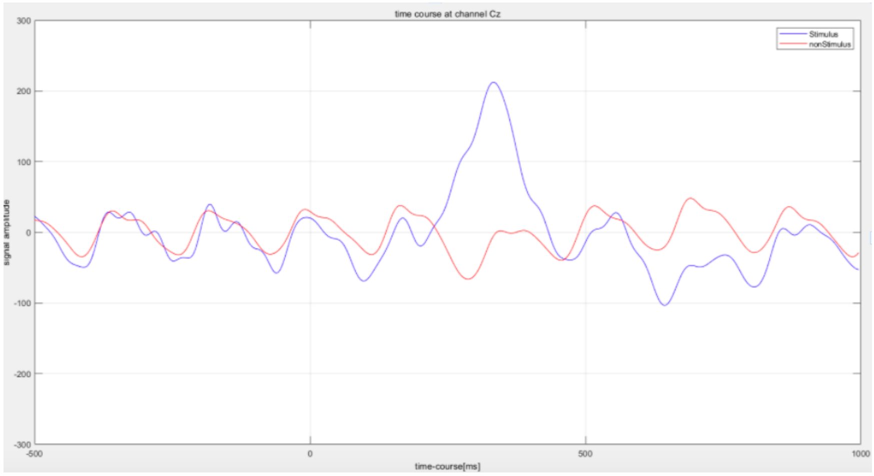


Figure 6: Averaged time course at channel Cz

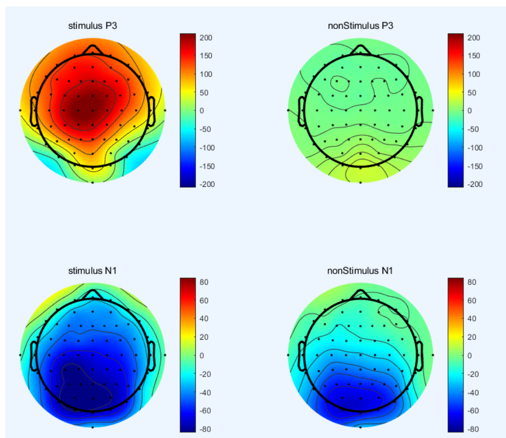


Figure 7: Averaged topoplot

After roughly determining the time range when to extract the features in the time course, we can analyze the temporal features more precisely. For P300, the methodology works as follows: first, we take a small window around 330ms after the onset and find the peak value in this window. Next, we take a second window around the found peak and take the average within the window. This averaged value is then considered as the temporal feature of P300. In this way, we can reduce the effect of instability and uncertainty of EEG signals to some extent and guarantee to find the optimal value to temporally represent P300. The temporal feature of N100 can be extracted in a similar way.

When extracting frequency features, we apply fft() to the signal around P300 with the frequency resolution of 1Hz. In order to avoid the impulse effect after padding zeros in fft(), the extracted signal fragment is extended to the desired length by mirroring. Then we can plot and observe the amplitude difference of all frequencies. The following figure compares the frequency component between stimulus and non-stimulus signal at channel Cz, where a significant difference at 3Hz can be observed as shown in Figure 8. This indicates that the frequency feature of P300 is highly likely to lie in the range around 3Hz. The actual separation power of this spectral feature is also to be evaluated later.

Feature evaluation and dimension reduction We can evaluate the separation power of the extracted temporal and spectral features in all channels by calculating Fisher Criterion, which performs the evaluation based on minimizing the variance within one single class and maximizing the mean value between two classes. The evaluation results of the temporal features of N100 and P300 are as follows:

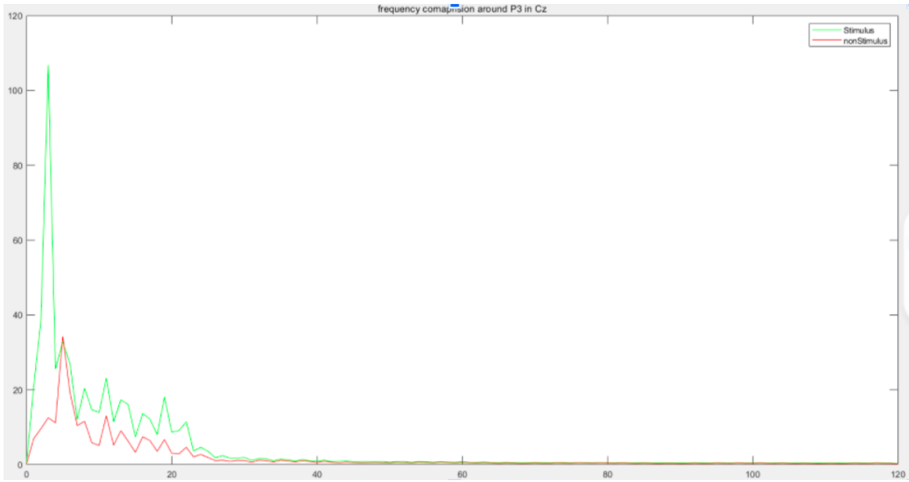
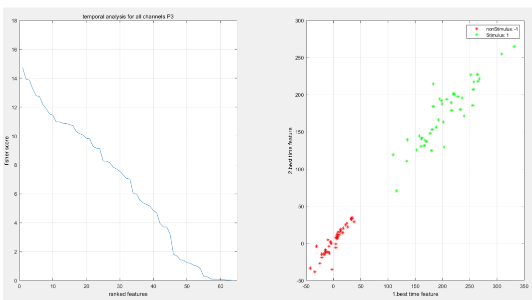
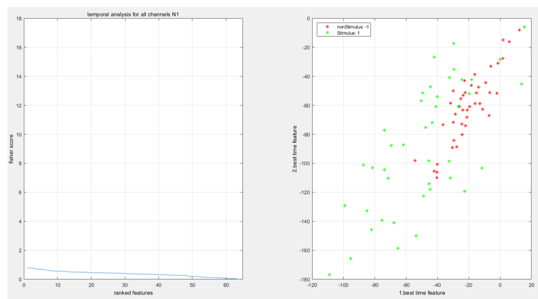


Figure 8: Frequency comparison of P300 at channel Cz



(a) Temporal feature analysis for P300



(b) Temporal feature analysis for N100

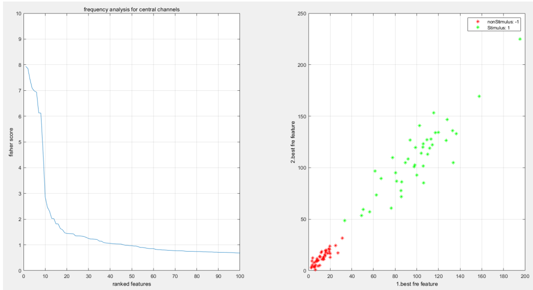
Figure 9: Temporal features(right) shows P300 and (left) shows N100

From the plotted result based on Fisher Criterion, we can now conclude that temporal features of P300 can bring a very nice classification, while temporal features of N100 are relatively overlapping, which means this kind of feature should be excluded. What's more, in the left hand side of the figure, we can also see sorted Fisher scores of all channels. In fact, only those channels in the central area of the skull show the strongest separation power. Therefore, we can choose P300 of those central channels as temporal features in this methodology.

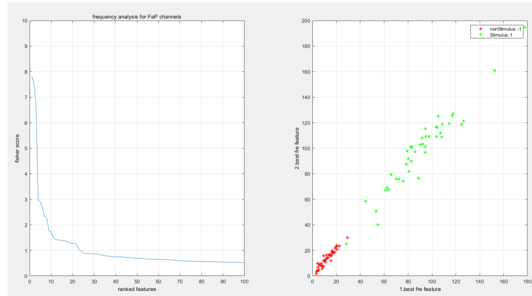
For spectral features, we can evaluate them in a similar way. But since so far we don't know which frequency to extract exactly, for simplicity we can mainly focus on the central channels that show the strongest separation power in terms of temporal features. Additionally, we can also analyze a few channels located in bit frontal and posterior areas such as Fz and Pz, which might also have a good separation power. The evaluation results are shown in the following figures.

From the evaluation results, we can see that both 3Hz and 4Hz can lead to a nice classification, but a bit worse compared to P300 temporal features. Therefore, we may take the average of the amplitude of 3Hz and 4Hz components, and consider this value as a spectral feature. And later in the classification phase, we'll test whether these additional spectral features can perform better than temporal features alone.

Moreover, we can reduce the dimension of features by means of LDA, which combines all the features together and weights more to the features with stronger separation power according to LDA. After this step, the dimension of features decreases to one because there are only two classes.



(a) Spectral feature analysis for P300 at central channels



(b) Spectral feature analysis for P300 at frontal and posterior channels

Figure 10: Spectral features at P300(right)central channels and (left)frontal and posterior channels

Classification First of all, considering that we take both temporal and spectral features into account and they have different units, and different features may have different statistical distributions, it's necessary to perform the normalization before dimensionality reduction and classification. To this end, we use z-score, which requires the mean and standard deviation of the data, to normalize the features.

After normalization, we can try various classification models (LDA and SVM in this methodology) and different features (1. temporal and spectral, 2. temporal alone) and check which may lead to the best performance on test data. Then we further reduce the number of trials from 15 to 1 to find out the minimum number that still can achieve an acceptable classification accuracy.

What's more, as mentioned above, since EEG signals are very unstable and have large variations, we need to take the average across all trials of one single row or column of the 6x6 matrix (Figure 2) before feature extraction and classification.

Results Session 12 as novel data is used to test the performance of this methodology. The result in Matlab shows that there is little difference in SVM and LDA, but additionally using spectral features can result in a remarkably better classification performance. The following figure compares the accuracy rate between these two feature selections, the blue curve represents the combination of temporal and spectral features, the red curve represents using temporal features alone.

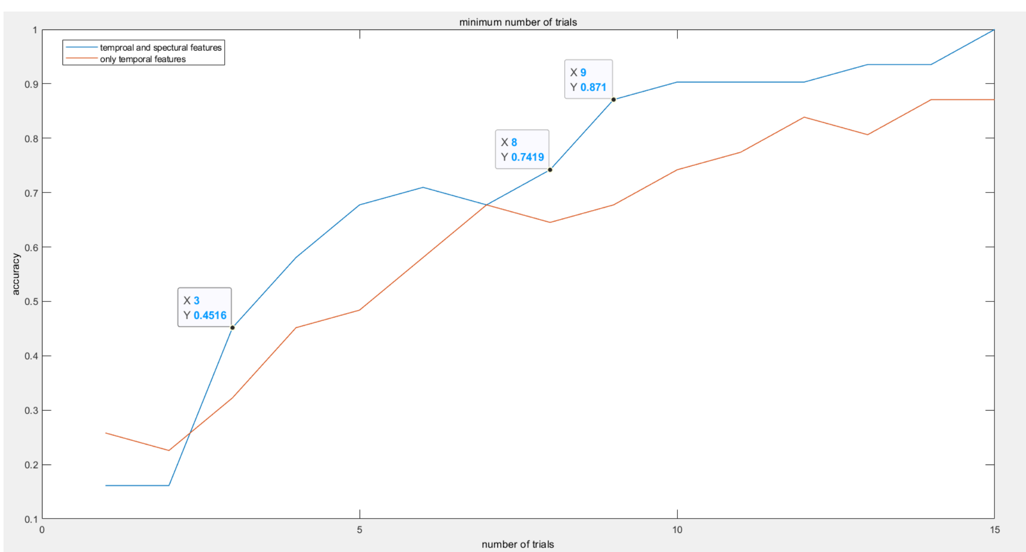


Figure 11: Comparison between two feature modes along number of trials

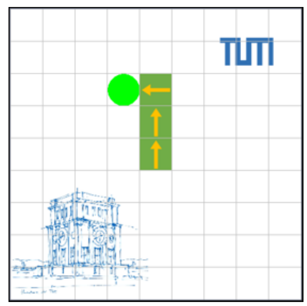
Moreover, we can see that in this methodology, 100% accuracy can only be achieved by 15 trials. But reducing the number of trials to 10, we can still achieve 90% accuracy. When the number of trials decreases to 8, there is a sharp accuracy reduction to 74%. If we continue to reduce the number of trials to 3, the accuracy rate will be lower than 50%. To conclude, the minimum number of trials to achieve a relatively high accuracy rate (at least 85%) is nine in this methodology using both temporal and spectral features with the LDA or SVM classification model.

3 Designing the movement of robot based on the corresponded prediction

In real-life applications, people with disabilities can control various devices such as robotic hands or wheelchairs through BCI. But for our experimental project, we just designed a visual situation of robot movement to simulate the input control after signal recognition and get the visible feedback. Specifically, we use the pygame library in python to design a game rendering interface. Then we use keyboard input as the control signal input and display different modes of game interface as the different operation of robot devices. We first draw a 9 x 9 grid in the interface, and then set the robot to move in the grid. By encoding different keyboard keys, we can then achieve different control functions for different input keys (Figure 11.a). Also, we marked the path of the position where the robot has moved in order to get a better feedback display (Figure 11.b).

Input:	Output:
A, G, M, S, Y, 5	move left
B, H, N, T, Z, 6	move up
C, I, O, U, 1, 7	move right
D, J, P, V, 2, 8	move down
E, K, Q, W, 3, 9	previous movement
F, L, R, X, 4	stay still

(a) Input signal and output action



(b) GUI

Figure 12: Design of moving robot based on the corresponded predict

4 Results and Discussion

Comparing the results by decreasing the number of trials

Number of trials/Accuracy of classifiers	6	9	12	15
LDA with basic features	9.6%	29.0%	51.6%	87.1%
Mixed LDA+SVM with basic features	12.9%	32.25%	67.7%	90.1%
Random forests with basic features	9.6%	29.0%	67.7%	83.8%
LDA with improved features	70.97%	87.10%	90.32%	100%
SVM with improved features	70.97%	87.10%	90.32%	100%

Table 1: The accuracy of each model with decreasing trials

As the above results show, we can draw the following discussion and conclusions:

- Pre-processing, which performs a bandpass filter and removes the artifacts based on Independent Component Analysis (ICA), is a very important step to get clean EEG signals and thus guarantee the recognition accuracy.

- In the feature extraction part, temporal features play the main role of recognition and the addition of special features can also improve the recognition accuracy.
- Since we set the steps of feature evaluation and feature dimensionality reduction, in the feature extraction part, we can extract as many good features as we think may exist. But for the paradigm part of the project, it will affect the complexity of the data collection process.
- Among the various dimensionality reduction methods, as the characteristics of Linear Discriminant Analysis stated, the features after LDA dimensionality reduction have the best distinguishability, which also means the best performance in the classification.
- In terms of classifier selection, both Support Vector Machine(SVM) and Linear Discriminant Analysis(LDA) classification methods have excellent performance.

5 Critical Reflection and Future Work

During our project, our goal has always been to improve the accuracy of pattern recognition as best as possible, so we tried many different methods to extract a variety of features and then used LDA to reduce the dimension. After getting almost 100% accuracy for the test dataset, we realized that the method of feature extraction is really complex.

For future work, we need to simplify the method of feature extraction without reducing the accuracy of recognition, such as reduction of necessary channels.

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