ENEE 639: Neural Engineering and Instrumentation

Project: Auditory Event-related Potential Discriminant

Name: Dingyi Pei and Ehsan Ahmed Dhrubo

Date: 05/ 26/ 2022

1. Introduction

Event-related potentials (ERPs) are very small voltages generated in the brain structures in response to specific events or stimuli, providing a powerful method for exploring the human mind and brain. Detecting event-related potentials (ERPs) from single trials is critical to the operation of many stimulus-driven brain-computer interface (BCI) systems. The low strength of the ERP signal compared to the noise (due to artifacts and BCI irrelevant brain processes) makes this a challenging signal detection problem.

ERP mainly deals with brain-related activity and it helps to eradicate problems created in brain regions. A brain-computer interface can be based on miniature-ERP induced by very small lateral visual stimuli [1]. Word expectancy and event-related brain potentials can be helpful during sentence processing [2]. Broadening the time-course of EEG and ERP components can be implicated in reward processing [3]. The N400 of ERP can be modeled as a change in a probabilistic representation of meaning and language processing [4]. An analysis of audio-visual cross-modal integration utilizing event-related potential (ERP) recordings can be done [5]. Structural encoding and recognition of biological motion can get evidence from event-related potentials and source analysis [6]. Semantic analysis of auditory input during sleep can be studied with event-related potentials [7]. Single-trial analysis of oddball event-related potential in simultaneous EEG-fMRI can be studied [8]. With the use of ERP Alcohol dependence syndrome, Schizophrenia, Bipolar affective disorder, Depression, Suicidal Tendency, lie testing, and panic disorder can be detected and can be fixed incorporate with research.

In this project, we included six types of sounds, where five of them were from daily life and one was out of daily life, to discriminate between each type of ERP evoked from different sounds using two methods.

2. Methodology

2.1 Auditory stimulation

The auditory stimulus involved five types of sounds from daily life (car horn, door lock, camera, dog bark, crash) and one out of daily life (gunshot). The resources were downloaded online and processed in MATLAB to make sure all the sounds were adjusted to the same volume level as well as the same range of duration. Each sound was considered as the target, and between each target sound, five seconds of periodic beeps were given to separate each target. Auditory stimulation was presented in 30 trials. At the beginning of each trial, the subject was first under the environment of periodic beeps, and the target sounds came in every five seconds. Each trial contained six sound targets ordered in a random sequence (as shown in Figure 1).

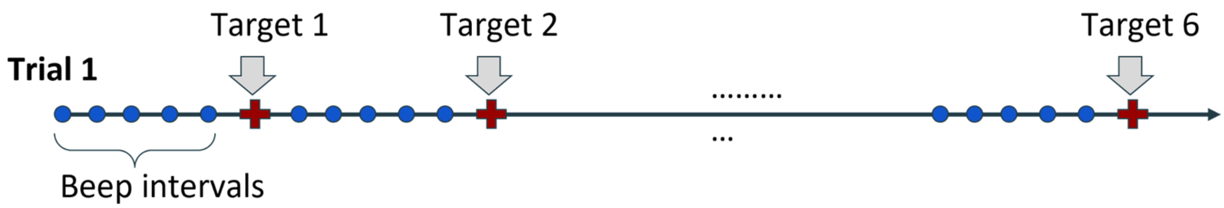

Figure 1 Auditory stimulus with six target sounds under periodic beep background

2.2 Experimental design and data collection

One healthy male subject participated in this experiment. During the experiment, the subject was asked to sit in front of the table and be relaxed. To avoid the interference of eye blinks /movements, the subject was asked to close the eye during the recording. The EEG signals were recorded using KT88 digital brain electric activity system with a 100 Hz sampling rate. There are 16 EEG channels placed under the 10/20 electrodes placement including Fp1, Fp2, F3, F4, F7, F8, C3, C4, T3, T4, T5, T6, O1 and O2, and the locations of the channels were shown in Figure 2. Two reference channels for each hemisphere were located over the ear.

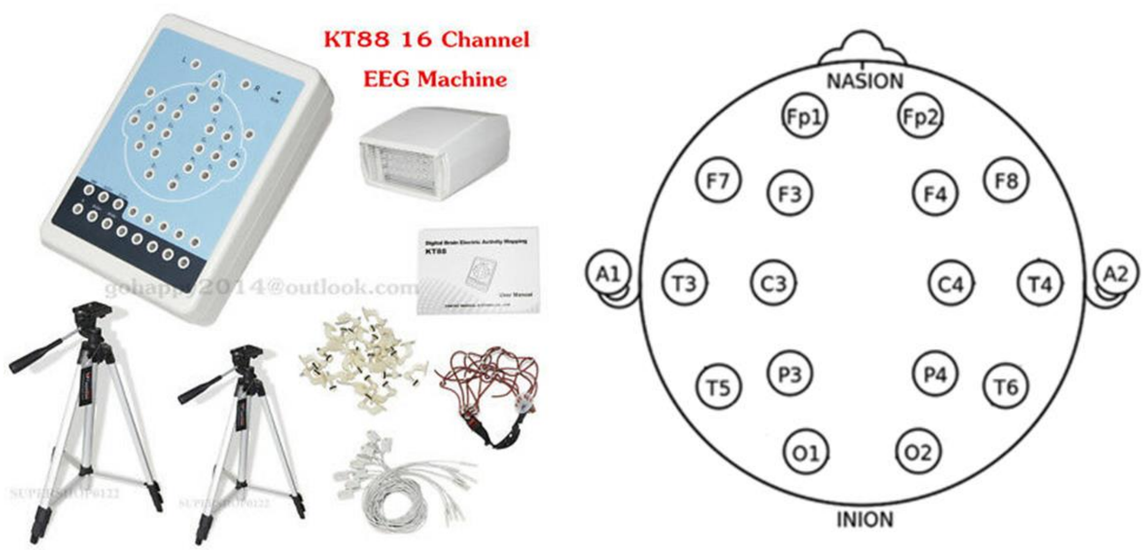

Figure 2 EEG collecting system (left) and EEG electrode locations (right)

2.3 Data analysis

The EEG data were first preprocessed to remove the global activity using spatial filter common average reference (CAR) for each channel, by subtracting the mean potentials from the other 15 channels. Then, the EEG signals were filtered to 0.1-8 Hz using a 5th-order Butterworth band-pass filter. As there were lots of alpha waves generated during the recording since the subject closed his eyes. Thus, the signals within the 8-12 Hz should be removed. Then, the EEG signals were segmented from the onset point of the auditory stimulus to 800 ms after stimulation. Since signal trial discriminant is still challenging, we attempted to obtain relatively purer ERP signals by averaging 15 random EEG trials for each sound. Eventually, a total of 20 trials of ERP were generated and ready to be analyzed.

Two methods were applied in this project. One is using averaged temporal ERP as a template and we introduced extended canonical correlation analysis (eCCA) to compare each ERP trial with the six templates which correspond to six sound targets respectively, and the target class was determined by the largest correlation coefficient. The other method was to extract ERP features using the autoregression (AR) model and reduce the dimensionality using principal component analysis (PCA). The six-class classifier was trained using linear regression analysis. Both of these two methods were evaluated by 10-fold cross-validation.

2.3.1 Method 1– Extended Canonical Correlation Analysis (eCCA)

Here, we applied a leave-one-out validation method to test the discriminant performance for each ERP trial. Each single ERP trial was considered as testing data (***X***), and we created ERP templates (***Y***) for each task by averaging the rest of the ERP trials. Extended canonical correlation analysis (eCCA) was introduced here to calculate the correlations between each testing trial with the ERP templates from every task to thereby determine which target task this testing trial belongs to. The traditional CCA is a method for exploring the relationships between two multivariate sets of variables (vectors), all measured on the same individual. Canonical variables usually first are identified with linear combinations of the variables of testing data (***X***) and template data (***Y***). Both ***X*** and ***Y*** matrices are *m*-by-*n*, where *m* is the number of EEG channels and *n* denotes the number of ERP samples. Then we have the canonical variables ***U*** and ***V*** defined as below:

$$U_1 = a_{11}X_{11} + a_{12}X_{12} + \ldots + a_{11}X_{1n}$$

$$U_2 = a_{21}X_{21} + a_{22}X_{22} + \ldots + a_{21}X_{2n}$$

…..

$$U_{m1} = a_{m1}X_{m1} + a_{m2}X_{m2} + \ldots + a_{m1}X_{mn}$$

$$V_1 = b_{11}Y_{11} + b_{12}Y_{12} + \ldots + b_{11}Y_{1n}$$

$$V_2 = b_{21}Y_{21} + b_{22}Y_{22} + \ldots + b_{21}Y_{2n}$$

…..

$$V_{m1} = b_{m1}Y_{m1} + b_{m2}Y_{m2} + \ldots + b_{m1}Y_{mn}$$

Then, we obtained two canonical coefficient matrices ***A*** and ***B***, corresponding to ***X*** and ***X*** respectively, where ***A*** and ***B*** maximize the Pearson correlation coefficient ***ρ***(***U***, ***V***). Here, these two coefficient matrices were considered as spatial filtering matrices and we projected the testing trial ***X*** as well as template trial ***Y*** to canonical space.

$$U = AX,\ V = BY$$
$$U_A = AX,\ V_A = AY$$
$$U_B = BX,\ V_B = BY$$

And the correlations between the testing trial and template trial were determined by the mean of three correlations of $\rho(U, V)$, $\rho(U_A, V_A)$ and $\rho(U_B, V_B)$. Each testing trial was correlated to every template from six targets, and the testing trials belonged to the target which held the largest extended canonical coefficient value.

2.3.2 Method 2 – Autoregression (AR) + Principal Component Analysis (PCA) + Linear Discriminant Analysis (LDA)

Autoregressive (AR) methods have been used in a number of studies for different analyses such as feature extraction and classification tasks. AR is used to model EEG data by representing the signal at each channel as a linear combination of the signal at previous time points. As shown in the equation below:

$$y(t) = \beta_0 + \beta_1 y(t-1) + \beta_2 y(t-2) + \ldots + \beta_n y(t-n)$$

In this project, the AR formulated the ERP signals in the time domain as a linear prediction problem and the rules used for calculating the least square values using the geometric mean of forward and backward squared prediction errors during minimization. The AR coefficients $\boldsymbol{\beta}$ calculated from each channel were considered as features, representing the time sample correlations of the ERP signals. We applied an AR model for all 16 channels, 20 trials and 6 tasks. We attempted different orders of the AR model and the best order was determined by the best classification performance.

Next, the PCA was employed to reduce the dimensionality of current features. First, the data were divided into training data (⅘ of data) and testing data (⅕ of data). And then we prepared the training data in a *p*-by-*q* matrix, where *p* represents the number of trials from all tasks, and *q* denotes the number AR features of all 16 channels. After applying PCA to the training data, the principal components were sorted according to the descending order of the eigenvalues of covariance of the training data. The first *m* PCs were selected which represented the largest variance across various trials, where *m* was determined by the classification performance. After the PCs were calculated, we projected both training data and testing data to the PC space by multiplying the PC matrix. Then, we started training a six-class classifier using the PC features from the training data using linear discriminant analysis (LDA), a linear transformation of the data which maximizes the variance between classes whilst minimizing the variance within each class.

3. Results

3.1 ERP components

ERP components can be simply defined by their polarity (positive or negative-going voltage), timing, scalp locations, and sensitivity to the task. Different ERP components emphasize different aspects of features. Some components are triggered by the presence of a stimulus, and some reflect neural processes that are entirely task-dependent, and others are associated with the preparation and execution of a given motor response. Figure 3 shows the averaged ERP signals evoked by six target sounds, and multiple ERP components can be observed here, including P1, N1, P2, N2 and P3. P1 is usually considered as sensory gating, as indicated by the pink dashed lines, representing the

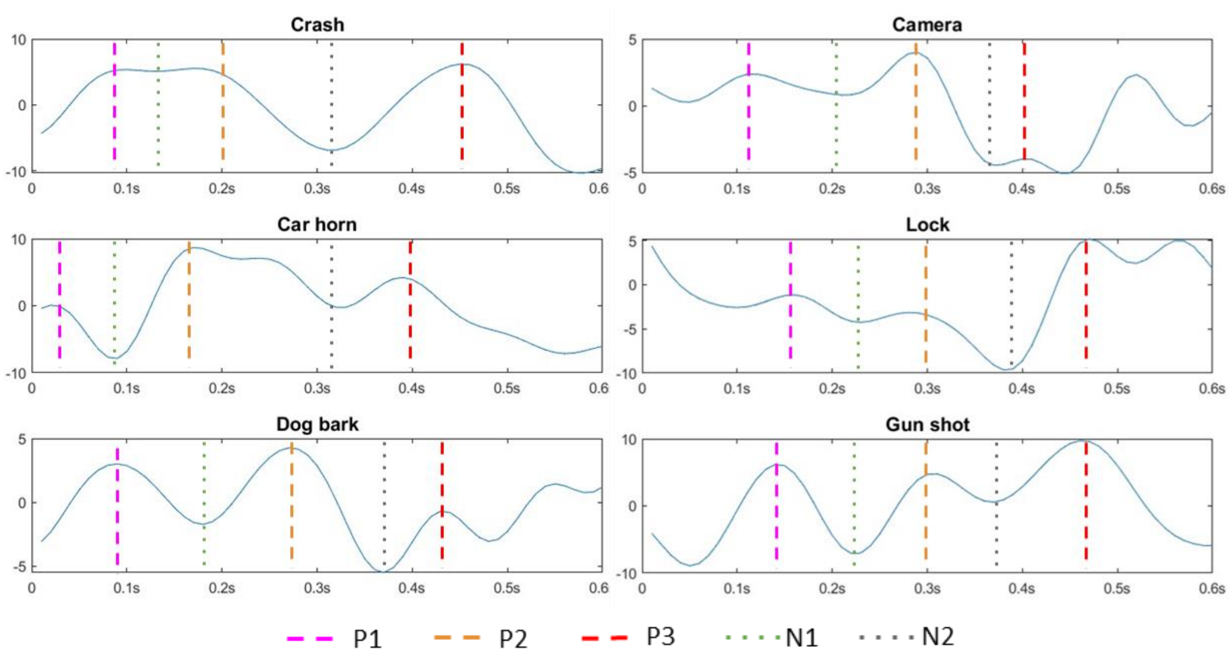

Figure 3 ERP patterns of six types of auditory stimulus and corresponded ERP components recorded from P3 electrode. Positive potentials are indicated by dashed lines and negative potentials are illustrated by dotted lines.

early selection mechanism involving the automatic filtering of sensory stimuli. N1(green dotted lines) is sensitive to attention or response selection. However, this component is not apparently observed in all tasks. P2 (orange dashed lines) can be observed from ERP patterns corresponding to stimulation of camera, dog bark and gunshot. The exact functionality of P2 is not that clear but it suggests that P2 may correlate with fairly simple stimuli compared with P3. Since each target sound was embedded in the periodic beeps, N2 waves reflect automatic responses to target auditory stimuli that differ from the preceding beeps, and this component can be recognized from ERPs of all targets (indicated by gray dotted lines). As for the P3, it is one of the most widely used components in ERP research and responds to the infrequent (target) stimuli, or arbitrarily complex targets. The P3 potentials (illustrated in red dashed lines) are not as apparent in camera and dog bark responses as in other types of target stimuli.

Since each ERP component wave has various scalp distributions, Figure 4 shows how the ERP potentials change across time. It is obvious that the dynamic changes of ERP potentials and distributions vary from different tasks. The N1 and P2 waves are apparently observed from task “crash”, while P1 and P3 are dominant in tasks “car horn” and “door lock”. The “gunshot” evoked P3 has longer latency than other tasks. Average lower amplitude generated from “camera” evoked ERPs, and it may be because this type of sound is more common in daily life. It is also surprising that positive and negative potentials are located on different hemispheres of the scalp and a possible reason may be the resources of stimulation came from the right side of the subject.

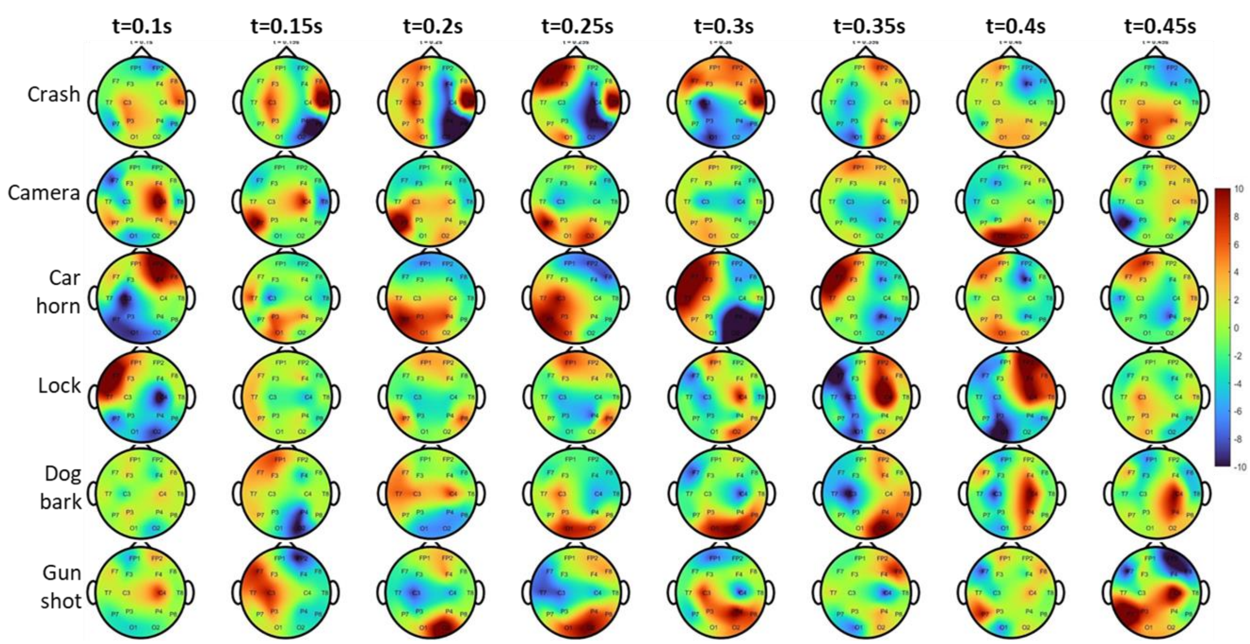

Figure 4 The dynamic changes of six types of auditory-evoked ERP potentials over time.

3.2 eCCA

For validation, out of 20 samples, 1 sample is considered as the testing trial and the average of the rest of 19 samples out of 20 samples is considered as the training trial. Here we did 10-fold cross-validation to evaluate our method. We found the accuracy, recall and precision of eCCA-based classification for our project which is depicted in Figure 5. We plotted the accuracy bar chart for all of the classes in Figure 6.

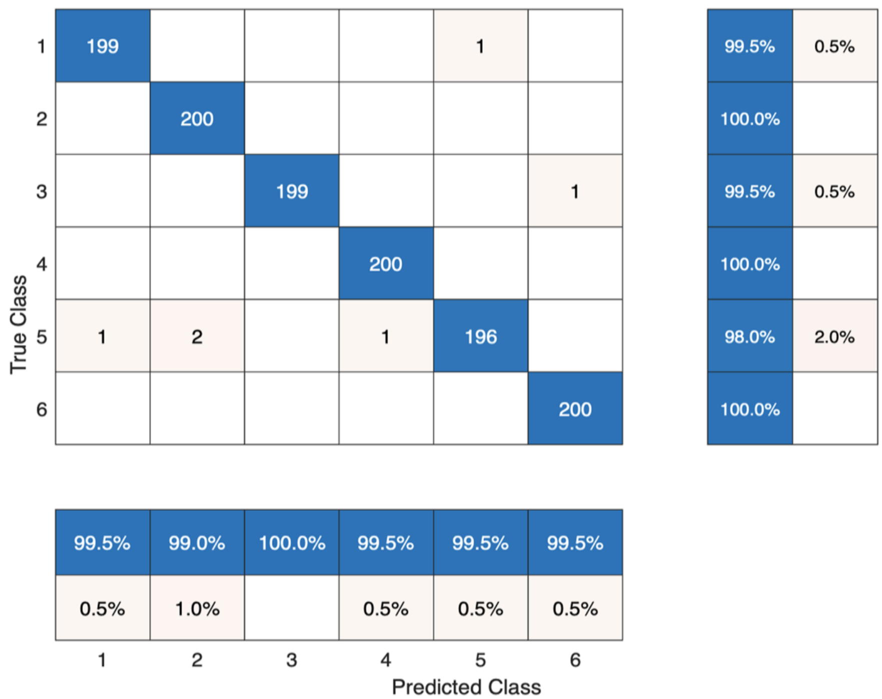

Figure 5 Confusion matrix for eCCA showing accuracy, recall and precision for all the classes

This is the confusion matrix for eCCA which shows precision and recall for six classes of sound of test samples. Here the true class is represented as row wise and the predicted class is represented as column wise. For an example, we can consider the 5th row and the 5th column for demonstration. In the 5th row among 200 samples, 196 samples are predicted correctly as 5th class and 4 samples are predicted wrongly as other classes. So, out of 200 samples, 4 is the false negative for 5th class and (4/200) * 100% = 2% is the false-negative rate and 98% is the recall for 5th class which is shown just right to the 5th row. Similarly, in the 5th column among 200 samples, 196 samples are predicted correctly as 5th class and 1 sample is predicted as 5th class but it belongs to 1st class. So, out of 200 samples, 1 is the false positive for 5th class and (1/200) * 100% = 0.5% is the false positive rate and 99.5% is the precision for 5th class which is shown just below the 5th column. Thus we can calculate the precision, recall and accuracy of all the classes individually with the help of this confusion matrix.

Figure 6 shows the classification accuracy chart of test samples. From this graph, it can be seen that the accuracies for all of the classes are above 99% for eCCA classification method.

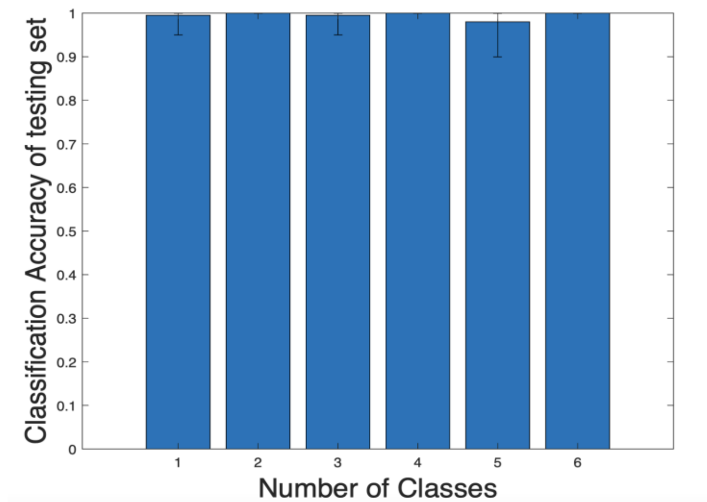

Figure 6 Classification Accuracy of testing samples of all the classes for eCCA

3.3 AR + PCA + LDA

In this method, we applied AR and PCA to extract ERP features to feed into the LDA classifier. The order of the AR model and the number of PCs were determined by the classification performance, as shown in Figure 7. The accuracy was averaged after 10-fold cross-validation.

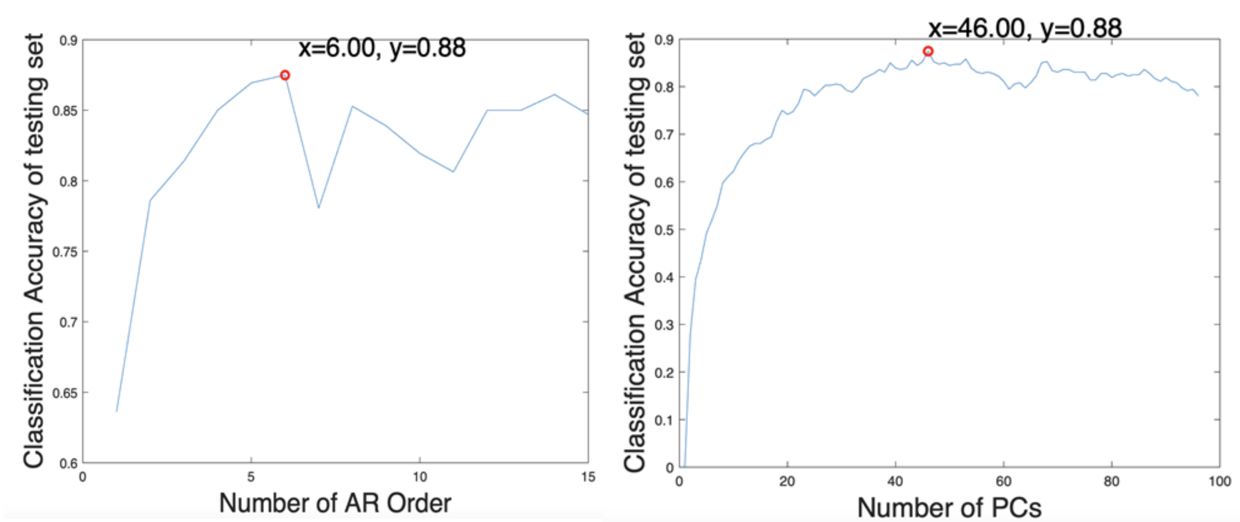

Figure 7 Optimal number of AR order and number of PCs determined by classification accuracy of testing samples

Here the number of AR orders was varied to find out the optimal AR order with the help of classification accuracy of test samples. From the figure, it can be seen that the optimal AR order for our project was 6. The number of principal components (PCs) was varied to find out the optimal number of PCs with the help of the classification accuracy of test samples. From the figure, it can be seen that the optimal number of PCs for our project was 46.

We found the accuracy, recall and precision of AR+PCA+LDA-based classification method for our project which can be observed in Figure 8. We plotted the accuracy bar chart for all of the classes in Figure 9.

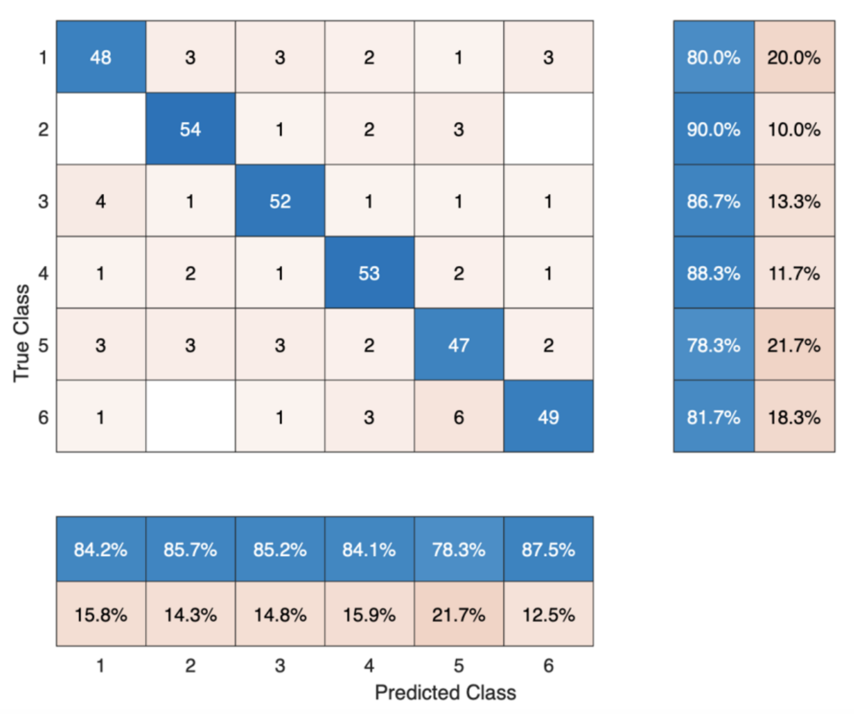

Figure 8 Confusion matrix for AR+PCA+LDA based classification method showing accuracy, recall and precision for all the classes

This confusion matrix shows precision and recall for six classes of the sound of test samples. Here the true class is represented as row wise and the predicted class is represented as column wise. For an example, we can consider the 5th row and the 5th column for demonstration. In the 5th row among 60 samples, 47 samples were predicted correctly as 5th class and 13 samples were predicted wrongly as other classes. So, out of 60 samples, 13 is the false negative for 5th class and (13/60) * 100% = 21.7% is the false-negative rate and 78.3% is the recall for 5th class which is shown just right to the

5th row. Similarly, in the 5th column among 60 samples, 47 samples were predicted correctly as 5th class and 13 samples were predicted as 5th class but they belonged to other classes. So, out of 60 samples, 13 is the false positive for 5th class and (13/60) * 100% = 21.7% is the false positive rate and 78.3% is the precision for 5th class which is shown just below the 5th column. Thus we can calculate the precision, recall and accuracy of all the classes individually with the help of this confusion matrix.

The classification accuracy of six classes is shown in Figure 9. From this graph, it can be seen that the accuracies for all of the classes are above 80% for eCCA classification method. Class 2 (sound camera) performed best among all six classes with average accuracy of 90%; the class 5 (sound dog bark) yielded the accuracy of other classes.

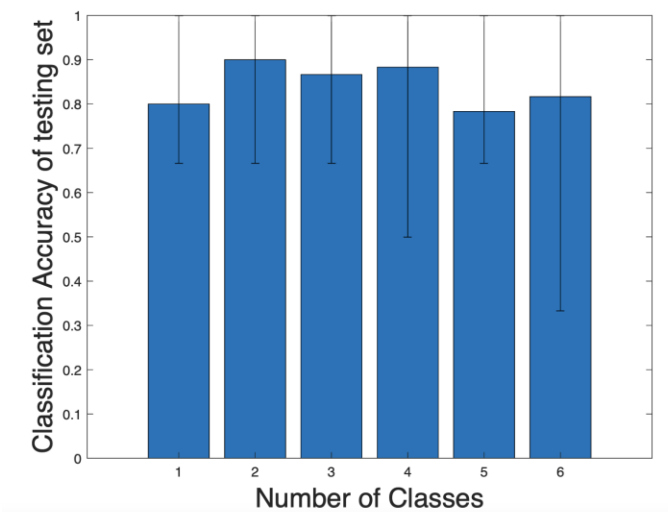

Figure 9 Classification Accuracy of testing samples of all the classes for AR+PCA+LDA based classification method

4. Discussion and Conclusion

In this project, we employed two methods to discriminate six types of the auditory stimulus and temporal ERP classification using extended CCA achieved over 99% of accuracy AR + PCA + LDA achieved up to 85% of accuracy, still yielding eCCA. Classical CCA can only be safely employed if the number of observations is much larger than the dimensions of either of the two random vectors. In this project, the dimension of samples is much higher than the number of observations, eCCA was performed as a spatial filter of both training trial and testing trial and improved the performance of target identification. The limitations of our project are that we collected only 30 trials for each auditory task, more trials are needed for future research for reliable results and Alpha waves affect ERP waves a lot, we need to improve the experiment protocol in the future which mainly focuses on the temporal ERP. We will employ other methods to derive spectral features.

5. Reference

[1] Wang, K., Xu, M., Wang, Y., Zhang, S., Chen, L., & Ming, D. (2020). Enhance decoding of pre-movement EEG patterns for brain–computer interfaces. *Journal of neural engineering*, *17*(1), 016033.

[2] Kutas, M., Lindamood, T. E., & Hillyard, S. A. (1984). Word expectancy and event-related brain potentials during sentence processing. *Preparatory states and processes*, *1984*, 217-237.

[3] Glazer, J. E., Kelley, N. J., Pornpattananangkul, N., Mittal, V. A., & Nusslock, R. (2018). Beyond the FRN: Broadening the time-course of EEG and ERP components implicated in reward processing. *International Journal of Psychophysiology*, *132*, 184-202.

[4] Rabovsky, M., Hansen, S. S., & McClelland, J. L. (2018). Modelling the N400 brain potential as change in a probabilistic representation of meaning. *Nature Human Behaviour*, *2*(9), 693-705.

[5] Teder-Sälejärvi, W. A., McDonald, J. J., Di Russo, F., & Hillyard, S. A. (2002). An analysis of audio-visual crossmodal integration by means of event-related potential (ERP) recordings. *Cognitive Brain Research*, *14*(1), 106-114.

[6] Jokisch, D., Daum, I., Suchan, B., & Troje, N. F. (2005). Structural encoding and recognition of biological motion: evidence from event-related potentials and source analysis. *Behavioural brain research*, *157*(2), 195-204.

[7] Bastuji, H., Perrin, F., & Garcia-Larrea, L. (2002). Semantic analysis of auditory input during sleep: studies with event related potentials. *International Journal of Psychophysiology*, *46*(3), 243-255.

[8] Bénar, C. G., Schön, D., Grimault, S., Nazarian, B., Burle, B., Roth, M., ... & Anton, J. L. (2007). Single-trial analysis of oddball event-related potentials in simultaneous EEG-fMRI. *Human brain mapping*, *28*(7), 602-613.