ENS 491-492 – Graduation Project

Final Report

Project Title: Analysis, Improvement and Deployment of an SSVEP BCI Speller system

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1. EXECUTIVE SUMMARY

The purpose of this project is to establish direct communication between the brain and the computer for individuals who need complete assistance for communication and develop a simulation that replicates the SSVEP (steady-state visually evoked potentials) to be used for training ML (machine learning) models or benchmarking different researches on this field. The first goal will be achieved by using the visual presentation of a matrix of characters/numbers through a computer interface. When exposed to a flickering image, the human brain generates signals with the same frequency. These brain signals called SSVEP can be observed by EEG (electroencephalogram) and allow subjects to type solely based on their brain signals. By applying FFT (Fast Fourier Transform) to SSVEP, one can determine the which image subject is looking at. Since EEG is a non-invasive data collecting method, the obtained signals involve an enormous amount of noise created by head movements, eye and muscle artifacts, etc. Therefore, a machine learning algorithm is used to classify the SSVEP data, so that words and sentences can be formed by utilizing BCI. There is a scarcity of data in the SSVEP community since data collection is a cumbersome process, thus we developed a simulation tool to generate SSVEP data with desired frequencies, number of harmonics, and time. The process consists of 4 steps. The first step is a simulation that aims to generate artificial data based on real SSVEP brain signals by using MATLAB. The second step is parameter tuning the SSVEP simulation by extracting features from widely used SSVEP datasets (Chen et al., 2014; Liu et al., 2020) utilizing ML algorithms. The third step is the analysis and optimization of the current SSVEP speller algorithm. The fourth step will be to deploy a real-time system with a portable EEG system that is called Emotiv. Currently, this architecture with Emotiv+ obtains more than 60% accuracy for binary classification of 5-second data. Consequently, we concluded that portable and weak EEG recorders like Emotiv+ can still be utilized for SSVEP based speller.

2. **PROBLEM STATEMENT**

Brain-Computer Interfaces provide direct communication between the brain and an external device, this connection can be utilized in multiple ways such as assisting or augmenting human cognitive functions by eliminating the need for intermediate bodily functions. Steady-state visually evoked potentials are electrical responses from the human brain to the flickering images with predetermined frequencies. These electrical responses can be observed by placing electrodes on the subject's head, usually on the occipital lobe since it is responsible for visual processing. This area of BCIs is valuable to investigate due to the non-invasive nature of collecting EEG data. By applying fast Fourier transform (FFT) to collected EEG signals one can classify which image the subject is looking at. The application of such technology is potentially limitless from smart environments to assisting disabled people.

In this project, we intend for the subject to be able to form complete sentences without typing or speaking, simply by looking at a screen. In Figure 1, you can see the characters' unique flickering frequencies and phases. Utilizing FFT and classifying the data we should be able to print the character on screen, composing words and sentences.

EEG recording is a cumbersome process since you need a laboratory. Emotiv is a portable EEG recording device and we thought it would be valuable to use the above-mentioned technology in our homes with the help of wearable technology. This would require a tool to extract meaningful data from Emotiv and present it in real-time. Non-invasive technologies such as SSVEP are noisy by nature. There are reasons why it is hard to get clean data using portable EEG devices.

- Unlike laboratory EEG devices, the number of electrodes that correspond to the visual lobe of the brain was drastically low. In Emotiv+ software only 2 electrodes O7 and O8 could be utilized.

- Unlike laboratory experiments, it was hard to find participants to train our model configured to their various brain patterns due to coronavirus. The sample size of our training was 8 participants with 2 sessions of recording which can be considered as unacceptable to conclude any statement.
- The external hardware device Emotiv+ was too sensitive to any type of movement which makes noise.
- Due to limited documentation and software advancements of Emotiv, experimental and non-stable software have been used. This also results in shifting the project from Matlab to Python.

In order to train a good classifying model one needs a lot of data, there are not many resources in this area and as mentioned above, collecting data is usually expensive and time-consuming. We thought simulating EEG data referencing datasets (Chen et al., 2014; Liu et al., 2020) would be useful. To develop such a simulation we had to research the intricacies of SSVEP data and the human brain, analyzing the parameters and optimizing them. As far as we know, such a simulation has not been made.

2.1) Objectives/Tasks

1. Generation of artificial brain signals. The intended result is the generation of noise added which is in 40 different frequencies and phases due to the number of characters in our matrix. And each equivalent frequency signal should be generated with different noises in order to simulate the randomness of data collection.

2. Adjusting parameters in the algorithm of brain signal simulation based on the evaluation of real brain signal data that is collected by the previous works in this

field. The intended result of this task is the optimization of parameters to generate artificial brain signals as much as being close to the real brain signals.

3. Development of real-time BCI system with Emotiv device. This requires creating a BCI with desired flickering frequencies, getting real-time data from the device with epochs, extracting artifacts, and applying a classification algorithm to form words and sentences.

4. Optimization of both tools to achieve efficient and re-usable results. Optimization requires utilizing different tools and communication between them.

2.2) Realistic Constraints

The one major constraint we have is the global pandemic. Due to COVID-19, we do not have access to laboratories our university provides. This means that we cannot get usable EEG data from multiple subjects. We are trying to solve this issue by building an artificial EEG signal simulation and conducting experiments with friends and family.

For the same reason, we opted for a remote wearable electroencephalography product, Emotiv EPOC+. To collect the data, we bought the student license.

3. **METHODOLOGY**

3.1) Simulation and dataset analysis

3.1.1) Linear Regression Analysis

Benchmark Dataset

SSVEP Benchmark Dataset was used in this project. The 5 × 8 stimulation matrix includes the 26 letters of the English alphabet, 10 numbers, and 4 symbols such as space, comma, period, and backspace. The frequencies for each letter range from 8.0 to 15.8 Hz with an interval of 0.2 Hz. The phase interval between two neighboring frequencies is 0.35π. There are 35 subjects in this dataset and 64 electrodes were placed on each subject, we focused on the 62nd electrode which is Oz.

In the dataset, the sampling frequency is 250 first and the last 0.5 seconds are not taken into account. There are 6 blocks for each character for a subject. For blocks we approached from 2 different perspectives: Taking each block separately and averaging 6 of them.

Linear Regression

The aim in the regression part of the project is to find A and h values since for each frequency f in the frequency domain, the amplitude of it can be represented as Ab^{-hf}.

To find A and h values, we used linear regression. Characteristic of SSVEP suggests we should see the multiples of the frequency we are looking at, in order to convert our equation into a linear function, we have taken the logarithm of Ab^{-hf}, and our representation has become $\log_b A - hf$ which is linear. To find $\log_b A$ and $-h$ values, $X.u = Y$ was solved for u, where $X \in R^{35Px2}$, $u \in R^{2x1}$, $Y \in R^{35Px1}$; P is a parameter representing how many peak values we are filling the matrices with, 35 is constant since there are 35 subjects in the dataset.

- The first column of the X is filled with f's based on parameter P and the second column is all 1’s to account for biases in linear regression.
- Column vector u is filled with our unknowns, $-h$ and $\log_b A$
- Column vector $Y$is filled with values corresponding to the subject's FFT value at that frequency f.

For instance, matrices for character 1 which has peaks at frequencies 8, 16, 24, 32, 40, 48, …

If we pick P as 5 matrices in that equation will look like this:

$$\begin{bmatrix} 8 & 1 \\ 16 & 1 \\ 24 & 1 \\ 32 & 1 \\ 40 & 1 \\ 8 & 1 \\ 16 & 1 \\ \dots & \dots \end{bmatrix} \quad \begin{bmatrix} -h \\ log_b A \end{bmatrix} \quad = \quad \begin{bmatrix} 0.0768019689376919 \\ 0.520011651135126 \\ -0.703916577796064 \\ -0.131058973360648 \\ -1.92646830254182 \\ 0.640103318908803 \\ 0.599553150384832 \\ \dots \end{bmatrix}$$

In order to get $-\ h$ and $log\ _b A$ values, we have used the least square method.

Theorem *Let X be an m×n matrix and let Y be a vector in* $R^{\ m}$*. For* $X.u\ =\ Y$ the *following are equivalent:*

$$\hat{u} = (X^T X)^{-1} X^T Y$$

Peak Value Analysis

After finding the values of A and h we generated the peak points for corresponding characters' frequency values to find the base value in the exponential form of Ab^{-hf}. As can be seen in figure 2.

Base Analysis

Since we found the values A and -h we tried different values for b, to find the best one we used mean square error values.

$$\text{MSE} = \frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)$$

We looked at the first 3,4 and 5 harmonics. Results can be seen in figure 3.

We also analyzed the mean square error with respect to frequencies, as can be seen in figure 4.

3.1.2) Linear Regression Simulation

The linear regression method has been achieved. We used the benchmark dataset as our reference. We have figured out the values of A which represents the amplitude of the signal and constant h values for each character. After the consideration of the Mean Squared Error and Mean Relative Error of the base values that range from 1.2 to 3.0, our best base value is decided as 1.4. For instance, when we refill the matrices of our linear regression problem based on the top 5 peaks in FFT of the average signal of each 6 blocks within 35 subjects in the Benchmark dataset, for the character 1 that has 8 Hertz frequency and use the least square method in order to find u values, u values would be -0.2022 and 3.1186. Therefore our h constant becomes 0.1446 and $log_{1.4}^{A}$ becomes 3.7584 and the amplitude of the signal is solved as 3.5416. When we generate an artificial signal based on these values such that it has a 3.5416 amplitude value, 5 harmonics with additional random phases.

Since the human eye would detect other character's flickering frequencies, these characters would affect our simulation signal based on their adjacency to the main character. In order to figure out the coefficients of the other character's effectiveness, we have created a distance matrix that demonstrates the effect coefficients based on their Euclidean distance to the main focused character. For instance, when we focus on the first character of the table (top left), the distance matrix can be seen in figure 5.

Other character's signal amplitudes are calculated as inversely proportional to their distances. A number of harmonics are kept as 5 and base amplitude is designed as 1. Amplitudes of other character signals can be also seen in figure 6.

There are other signals that are generated by the human brain and these signals are considered as noise in our model. In order to simulate these signals, we have added randomly generated signals into our final signal as white noise.

Another method for generating noise was using noise power spectral density, in reality not every frequency as effective as others, certain frequencies are more dominant. The resulting plots for both signals can be seen in the appendix, figure 7,8,9,10,11 and 12.

3.1.3) Nonlinear Regression Analysis

In order to have a better understanding of the Benchmark dataset and generate the artificial stimulation signal more precisely, we broaden our viewpoint and decided to approach our problem with a nonlinear regression analysis solution. It is the type of regression analysis that nonlinear combination of the model parameters models the data. In that analysis, we assumed that EEG signals are the combination of $\alpha f^2 + \beta f + \gamma$. For the purpose of finding α, β,and γvalues, $X.u = Y$ was solved for u, where $X \in R^{35Px3}$, $u \in R^{3x1}$, $Y \in R^{35Px1}$; P is a parameter representing how many peak values we are filling the matrices with, 35 is constant since there are 35 subjects in the dataset.

The first column of the X is filled with the squared frequency based on parameter P values of the block's averaged signal. The second column is filled with the frequency based on parameter P values of the blocks averaged signal and the third column is all 1's to account for coefficients.

- Column vector $u$is filled with the unknown coefficients of α, β,and γ.
- Column vector $Y$is filled with values corresponding to the subject's FFT peak value at that frequency f.
- For instance, matrices for character 1 which has peaks at frequencies 8, 16, 24, 32, 40, 48,…

If we pick P as 5 and our focused character is 1, matrices in that equation will look like:

$$\begin{bmatrix} 64 & 8 & 1 \\ 256 & 16 & 1 \\ 576 & 24 & 1 \\ 1024 & 32 & 1 \\ 1600 & 40 & 1 \\ 64 & 8 & 1 \\ 256 & 16 & 1 \\ 576 & 24 & 1 \\ 1024 & 32 & 1 \\ 1600 & 40 & 1 \\ \cdots & \cdots & \cdots \end{bmatrix} \begin{bmatrix} \alpha \\ \beta \\ \gamma \end{bmatrix} = \begin{bmatrix} 1.08803746966259 \\ 1.77055169513704 \\ 0.461473151853326 \\ 0.865902469424027 \\ 0.105728467458992 \\ 2.02025829524239 \\ 1.93223325078395 \\ 0.895237729580729 \\ 1.14582842050193 \\ 0.404855009489007 \\ \cdots \end{bmatrix}$$

In order to get α, β,and γ values, we have used the least square method as we did on linear regression analysis.

After finding the values of α, β,and γ we generated the peak points for corresponding characters' frequency values to generate a simulation signal in the form of $\alpha f^2 + \beta f + \gamma$. After the generation of new peak points, we have measured the error between the FFT of the formed signal's peak points and the FFT of the real benchmark dataset's signal by using the mean squared error measure.

Our MSE values based on the frequencies for the top 3, 4, and 5 peaks can be seen in figure 13, notice the scale of the y axis, which is 1e-25. Resulted MSE values are relatively less than the MSE values for linear regression analysis.

3.1.4) Nonlinear Regression Simulation

After finding the α, β,and γ values, we have become able to generate our artificial simulation signal. We have first revealed out the magnitude of the signal by using $\alpha f^2 + \beta f + \gamma$. For instance, let's say we would like to generate the signal for character 1 that has 8 Hertz frequency for the top 5 peaks. Therefore our α, β,and γvalues based on the solution for nonlinear analysis would be 0.0016, -0.1431, and 3.4078, and the amplitude of the base signal would be 2.7158.

Since frequency values would be changed in each harmonic due to the base formula of $\alpha f^2 + \beta f + \gamma$,amplitude magnitude needs to be recalculated in each additional harmonic. FFT of harmonics added signal can be seen in the appendix.

Hence, other character's signals would affect the signals that are collected from EEG, other character's signals assumed as noise, and the same approach in the linear regression simulation is applied. The same distance matrix is used for the calculation of the amplitudes of the other character's signal and the same signals generated as the noise of other characters.

Randomly generated white noise and power spectral density noise is added as done in the linear regression simulation. The final signal and its FFT result can be found in figure 14. As can be seen in the figure, amplitudes of the harmonics don't decrease logarithmically as we expect in an SSVEP. Nonlinear simulation is worth exploring in the future of this project due to less error in the regression.

3.1.5) Dataset Creation

We have created artificial signal datasets for the LDA machine learning model using our linear model simulation. We have tuned the parameters of the linear regression model according to the results that are explained above. We have generated our dataset by using a linear regression model, with 5 harmonics. White noise and power spectrum noise have been chosen for the creation of the datasets. Power spectrum noise is generated thanks to Yeung et al. (2018).

Each dataset has distinct coefficient values from 5 to 50, increasing by 5 for both noise model datasets. Each dataset consisted of a total of 8000 signals. Since we have 40 flickering characters with different frequencies, 200 distinct signals for each frequency have been simulated. Random phases used for 5 harmonics. Each noise has been created randomly and multiplied by the selected coefficient. Therefore, each signal has become distinct from the other. FFT and plotted final signal for the power spectrum noise coefficient for 1 and 45 can be seen in Figures 9 and 11.

3.1.6) Linear Discriminant Analysis and benchmark of simulation

Each dataset has been used to train and test out the LDA model. we have 40 characters, each of them representing a different class. LDA is a multi-class classification machine learning algorithm, it is fast and supports categorical labels. We have used a 5 fold cross-validation method in order to test and train our datasets. The input was the FFTs of signals.

We trained the model with different noise coefficients, to determine the best one we also put the benchmark dataset into the model. We also analyzed our simulation datasets and the benchmark dataset with respect to the seconds the trial is conducted. The benchmark datasets' accuracies with respect to seconds can be seen in figure 15, as seconds increase so does the accuracy, as expected. LDA mean accuracies of white and power spectrum noise can be seen in Figures 16 and 17, as coefficients of the noise increase, accuracy decreases.

We looked at second by second and compared each to the benchmark dataset to decide the best coefficient for our simulation. As can be seen in Figures 18 and 19, the best one is between 20 and 25.

We also tried combining white noise with power spectrum noise and compared the accuracies with the benchmark dataset and BETA dataset, figure 20 suggests the best combination of the coefficient is 15 for both power spectrum and white noise. Trial second is 3 seconds in this figure since the BETA dataset's block duration of the trial is 3 seconds for the subjects S16–S70. We cropped the benchmark dataset down to 3 seconds, then added zeros padding to hit the 0.2 Hz spectral resolution.

3.1.7) Channel Analysis

We chose the oZ channel as our reference point for our simulation after conducting channel analysis to the Benchmark and BETA dataset. Both datasets use 64 channels, we looked at the occipital lobe since SSVEP signals are the most evident there, LDA was used due to the same reasons mentioned in the report. PZ, PO3, PO5, PO4, PO6, POz, O1, Oz, O2 channels were analyzed. As can be seen in figures 21 and 22, the best accuracy was achieved by Oz and POz. BETA dataset gives less accuracy than the benchmark dataset, this may be due to the duration of the trial second being shorter in the BETA dataset as we investigated in 3.1.6.

Also, we concatenated Oz with POz to test if we get better accuracies in the ML model. For the benchmark, accuracy was 0.91 as opposed to the best result being 0.89 for just Oz. For the BETA, accuracy was 0.72 as opposed to the best result being 0.68 for just Oz.

3.2) EMOTIV and Real-time experiment tool

3.2.1) Experiment

Until the second phase, all of the experiments were conducted on Hakan which means all of the EEG data is coming from one subject. After the promising results, a small group of participants within age 21-27 (n=9 (6 male, 3 female), std=1.15, mean=23.3), are selected by the author's social network. Each participant performed two consecutive sections of the experiment. Within each section, 20 ‘C’ letters and 20 ‘G’ letters (10 and 14 Hz respectively), randomly shuffled and clued in order. Each letter flickers for 5 seconds (after 0.5-second clue and 0.5 seconds faze out, total 6 seconds), which corresponds to 640 data points with 128 Hz sampling frequency mode of Emotiv+. Letters are epoched and recorded with the clock of the local computer with 5-millisecond error tolerance.

One experiment takes approximately 5 minutes. For display, 60 Hz - Lenovo Y520 Legion computer has been used. In experiments, the distance between the monitor and participants’ eyes is measured approximately 57 cm, which is the standard visual unit in cognitive neuroscience. Before the experiment, all participants were informed about the possible risks and the aim of the study. Even though the experiment is arguably safe, all participants signed the consent form to avoid any risk of health issues due to the fact that flickering objects can trigger epilepsy crises.

For recording, the BlueTooth connection of Emotiv+ and Cykit software has been used. Before starting the recording, each electrode is carefully immersed with lens solution for better conductivity and placed as Emotiv software suggests. All records and timestamps are saved in the cloud system to avoid any type of loss.

3.2.2) Classification

In the current classification step, the data of 5 participants have been used. Each participant performed 2 sessions of the 40 letter experiment therefore, 400 times 5-second data of EEG were used in classification models. Likewise, the other EEG classification papers, LDA (linear discriminant analysis), and LR (logistic regressions) models have been trained. Unfortunately, all the hyperparameters were not manipulated/tuned and left for future works. As feature extraction, 3 different strategies have been followed. First, the full spectrum of frequency domains between 7.8 Hz and 16 Hz (reminder: All the letter frequencies are between 8 Hz-15.8 Hz) selected as feature vector; secondly, only frequencies that are closer than 1.3 Hz to information frequencies (10 Hz and 14 Hz) have been selected; Lastly, like the previous selection but additionally, 2 more harmonic frequencies have been chosen as information frequency (10, 20, 30 Hz and 14, 28, 42 Hz).

3.2.3) Results of classification

For classification accuracies, 10-fold cross-validation has been performed. In other words, 90% train and 10% test split have been utilized 10 times. There are still tests to be done, however, the results are shown in figure 23.

Reminder: Even though the results do not seem promising. We would like to remind the reader that there are some steps that can increase accuracy. Some explanations could be; The dataset is too small, artifact cleaning is suspended, no optimization algorithm was not run yet, etc.

4. RESULTS & DISCUSSION

As far as we know there isn't any SSVEP EEG simulation on the field. We started this project out of necessity and found new approaches as we went along. The initial objective was generating data that is indistinguishable from a benchmark dataset in terms of classifying letters. Upon completing the tasks for simulation we found areas we could improve such as adding a distance matrix and using two different methods for generating noise. It was a challenge since this was an uncharted territory with no guidelines to follow. Thanks to weekly meetings with our supervisors we realized weak components of simulation and implemented them successfully. In the end, we ran two classifying algorithms on our simulation dataset with different coefficients for noises and compared the results from the benchmark dataset to find the optimal noise coefficient. We believe our simulation does what it is intended to do.

Similarly, there is no real-time SSVEP experiment tool, we achieved what we wanted. There is still room for improvement with regard to classification algorithms used.

5. **IMPACT**

Brain Computer Interfaces has a lot of potential uses in various fields such as medical diagnosis and detection, smart environments with the integration of IoT, and even video games and entertainment. SSVEP being a non-invasive method makes it a highly invested and investigated alternative to other methods. We believe that our work has the potential to help the future works of SSVEP BCI research on two fronts.

SSVEP data gathering takes lots of time and needs suitable lab environments. Finding reliable data is difficult, this hinders the development of other technologies. With the simulation, we developed you can get any amount of samples with various frequencies and noises. For example, you are developing a classification system. To train the algorithm you need data and if you want your model to be successful you want variance in data to accounting for the noisy nature of non-invasive data gathering. Our simulation generates artificial EEG data with various coefficients for noise, thus making the data “difficult” as needed. Without worrying about the data gathering, researchers could focus on their work, even if they have the tools for data gathering they could test their work on different datasets with the parameters they wish.

With the help of devices such as Emotiv, BCIs with SSVEP usage can become mobile. Acquiring meaningful data is a difficult and time-consuming process with the Emotiv interface. The tool we developed, Xavier, bypasses all the hassle and gives an easy-to-use alternative tool to researchers who do not have access to laboratories. The advancements we made help the future development of SSVEP technologies by eliminating the need for laboratories and trained subjects.

6. **ETHICAL ISSUES**

One possible ethical problem could be, our solution uses different software to sustain integration between the BlueTooth connection of Emotiv hardware and recording software. The experimental software named Cykit is free-licensed and used to record EEG data. However, even if there are no patent or license records, the authors personally emailed to designed or Cykit software for user-agreement form. The Cykit team explicitly stated that our software is totally free and some researchers already used it without any problem. Apart from that, there are two main ethical issues; consent of participants and Epilepsia risk.

Recording brain waves and publishing the data anonymously could still be problematic due to the fact that this data could be used for irrelevant intentions. Therefore, we assure each participant that they understand we have all the right to share your data anonymously. Only, participants that allowed and gave consent, conducted the experiment after they signed the user agreement and consent form.

Our experimental design has to flashlight at high frequencies into the eyes of the participants. Unfortunately, this flickering can trigger some health problems. Some participants diagnosed with epilepsy or those with suspected epilepsy, intentionally excluded from the experiment due to the fact that they can harm by having an epilepsy attack. On the consent form, we also ensure that not every participant with a family history of epilepsy does the experiment.

7. **PROJECT MANAGEMENT**

Future tasks in previous reports have been displayed via Gantt charts, as can be seen in Figures 24 and 25. During the initial phase of the project, implementing and developing the Generative Adversarial Networks, or GANs for short, had been set as a future plan. Hence, there is a time limitation, this task would not be accomplished in the required time. Therefore, we have decided to remove the developing GANs task. Other tasks such as channel analysis were added instead. Another removed task was training Emotiv data with transfer learning. Removal of this task had been decided also for the same limited time reason.

Project management is the process of making use of teams and resources to complete project activities within the boundaries of time, cost, and scope. The initiation phase of our project has been achieved successfully. In order to understand our problem better and construct a better solution, we have read and discussed the related articles that were determined by the supervisors of our project. Therefore, in the first few weeks, we focused on a better understanding of the problem statement and solution.

The project definition and planning section was the step after the initiation phase. We designated the future tasks and made an estimation of the required time for each task. After that, we have scheduled our project according to these tasks. That planning section has been repeated in each quarter of the project due to required reports of the project. We have divided our project problem into 2 parts such as simulating EEG signals and SSVEP usage with a portable EEG system called Emotiv. Both parts need to be carried out simultaneously. Therefore, we have decided to divide the team into 2 groups to achieve that simultaneous management process of the project. We have conducted weekly meetings with our supervisors and required tasks assigned for each person/team during those meetings. In

We have learned the significance of the definition of the scope of the projects during the initiation phase. Furthermore, we have figured out what we want to achieve, set the project objectives. The importance of time schedules was learned. During the time of the creation of the project plan, estimation of the required time for each task along with our project is important, and that outcome has been gained from the management of the project.

Resource and tool determination should be done after the initiation phase. It is important for ease of preparation at the start of the project. Assessing the resources and required tools is necessary to determine any bottlenecks in the project execution. That step is also important for the risk management of the project.

Another learning outcome of project management is the substantiality of communication within the team. In order to achieve division of tasks and focus on the nitty-gritty of the tasks, communication is essential.

The significance of monitoring the project has been also learned during project management. Monitoring has been accomplished by the weekly meeting with supervisors.

8. **CONCLUSION AND FUTURE WORK**

As a result of our project, a real-time SSVEP system and artificial signal simulation with satisfying results have been achieved.

As the next step of the project, classifying algorithms that have been used for simulation should be optimized. As we discussed before, we aimed to test our system with GANs deep learning model. Due to constraints in time, this task wasn't achieved. Therefore, this task can be assigned as future work. If the expected outcomes would be sustained by GANs, our project would run fast and the real-time system would become more efficient and fast. Nonlinear simulation can also be assigned as future work.

9. **APPENDIX**

Figure 1: Frequencies and phases of the characters

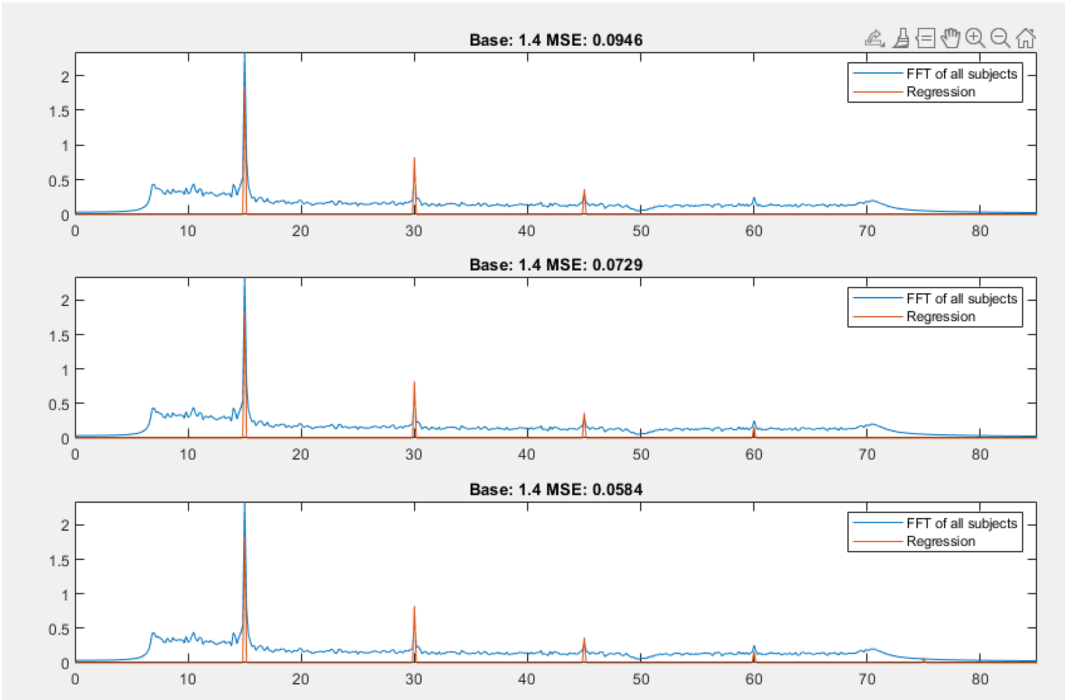

Figure 2: Generated peak points with the values achieved from linear regression

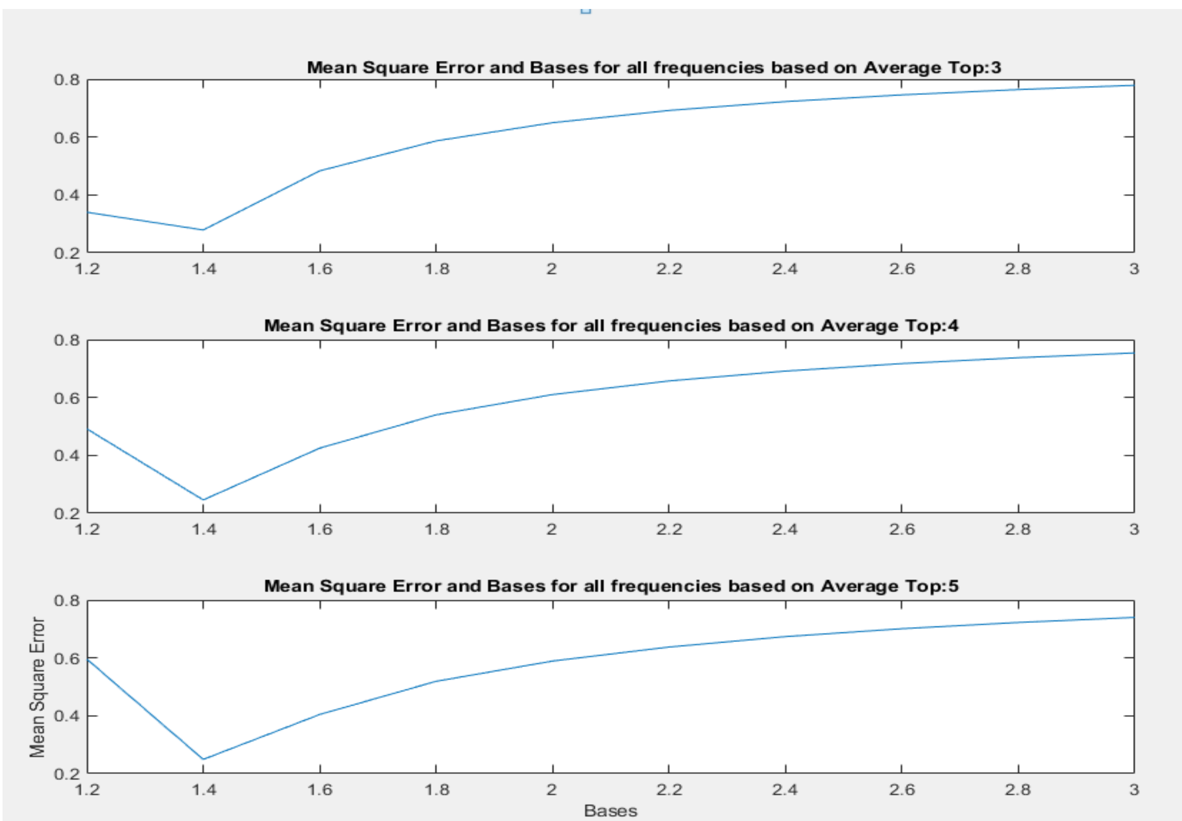

Figure 3: Base analysis

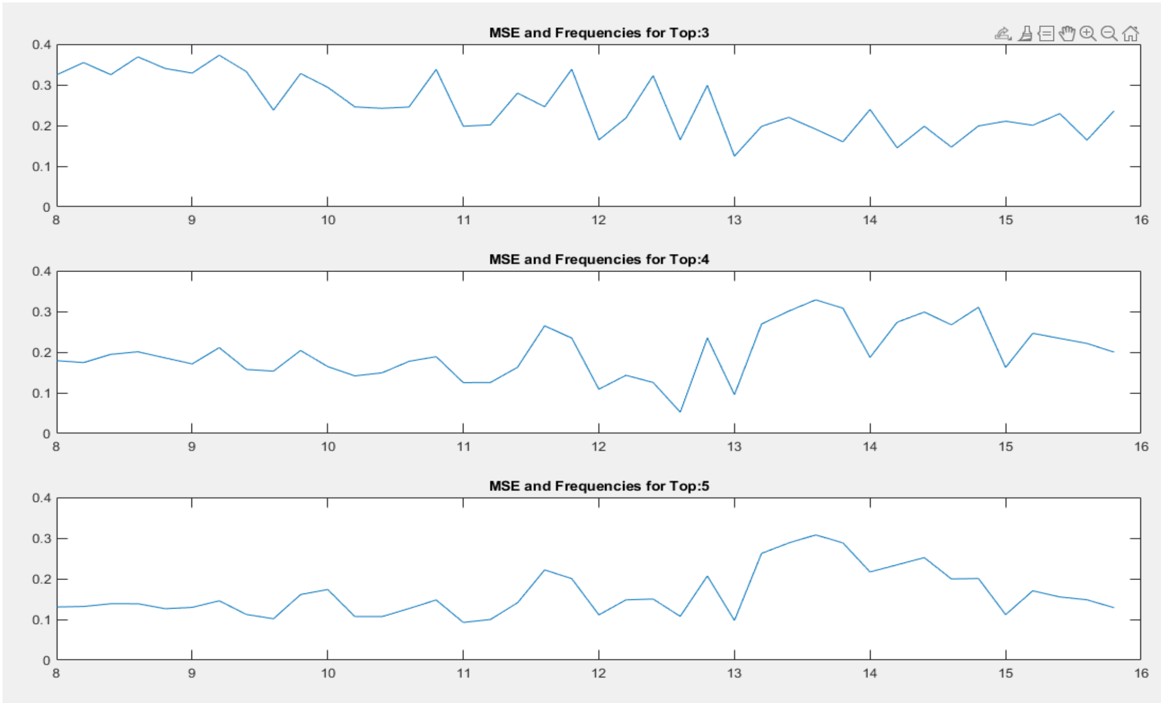

Figure 4: MSE and Frequencies

1	1	2	3	4	5	6	7
1	1.4142	2.2360	3.1622	4.1231	5.0990	6.0827	7.0710
2	2.2360	2.8284	3.6055	4.4721	5.3851	6.3245	7.2801
3	3.1622	3.6055	4.2426	5	5.8309	6.7082	7.6157
4	4.4721	4.4721	5	5.6568	6.4031	7.2111	8.0622

Figure 5: Distance matrix when the focused character is 1 (top left)

1	0.7142	0.5102	0.3644	0.2603	0.1859	0.1328	0.0948
0.7142	0.6213	0.4712	0.3450	0.2497	0.1798	0.1291	0.0926
0.5102	0.4712	0.3860	0.2972	0.2220	0.1633	0.1190	0.0863
0.3644	0.3450	0.2972	0.2399	0.1859	0.1405	0.1046	0.0771
0.2603	0.2497	0.2220	0.1859	0.1490	0.1159	0.0883	0.0663

Figure 6: Amplitude matrix when the focused character is 1 (top left)

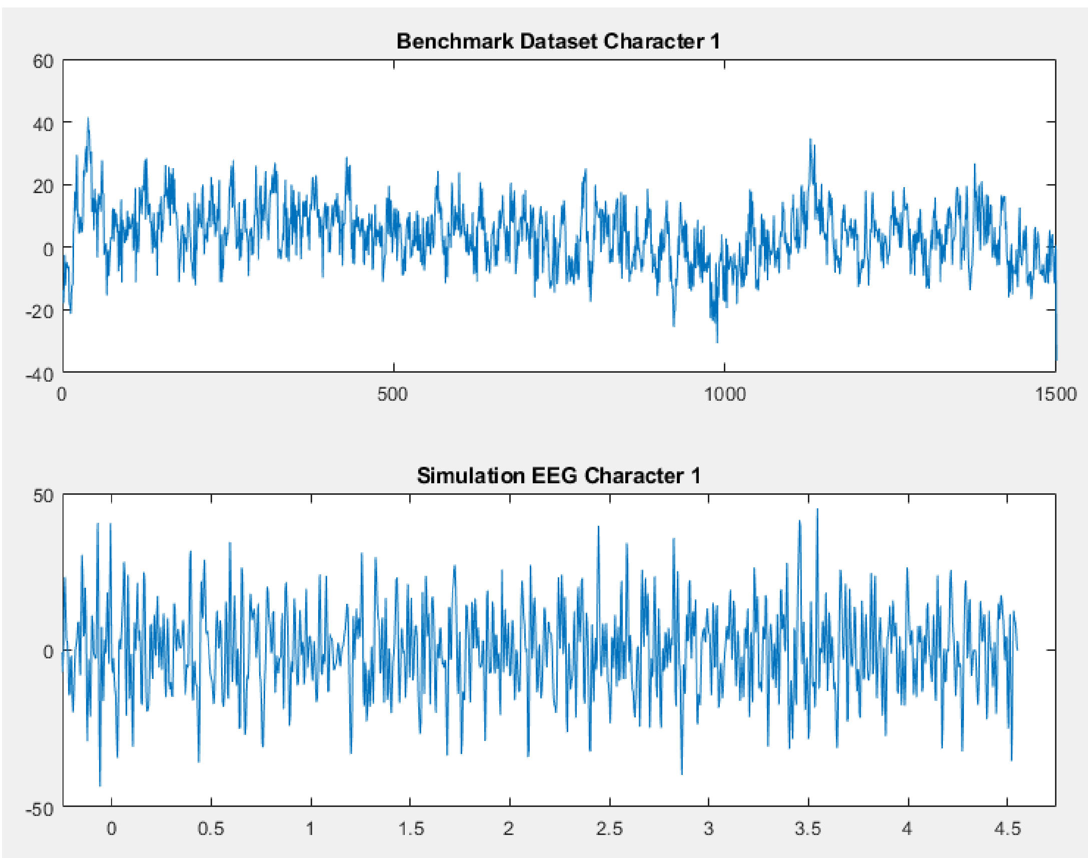

Figure 7: EEG signals of benchmark dataset and simulation

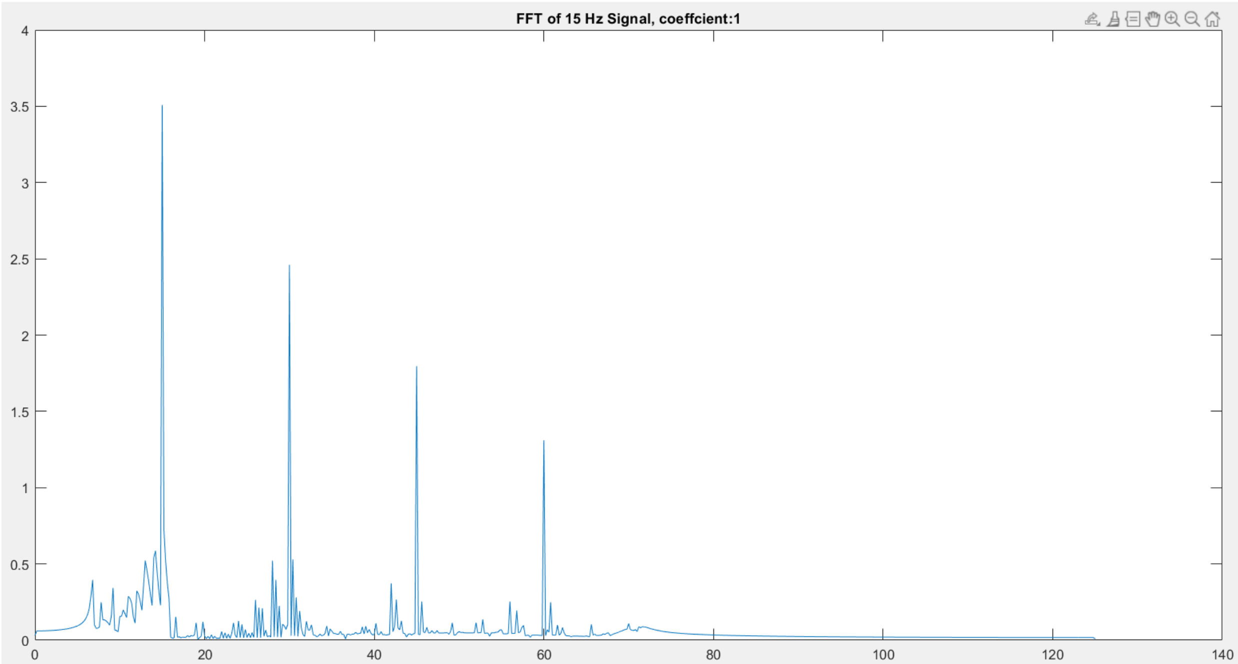

Figure 8: FFT of 15 Hz Power Spectrum Noise Signal with coefficient 1

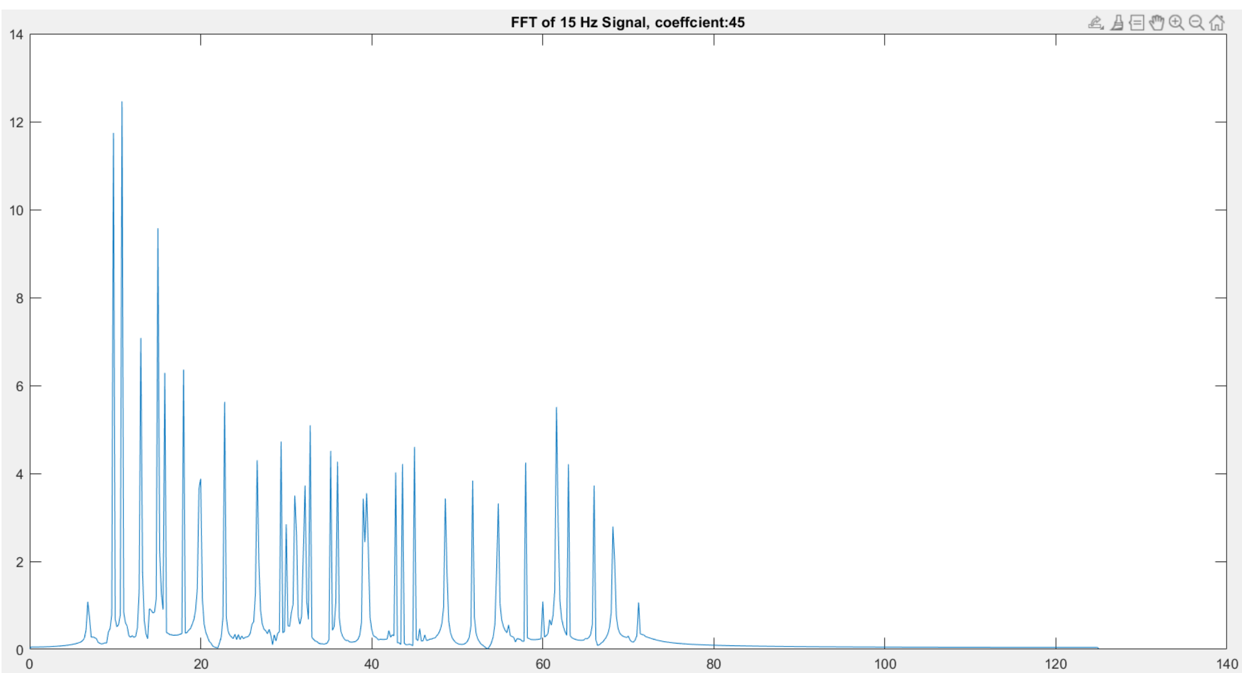

Figure 9: FFT of 15 Hz Power Spectrum Noise Signal with coefficient 45

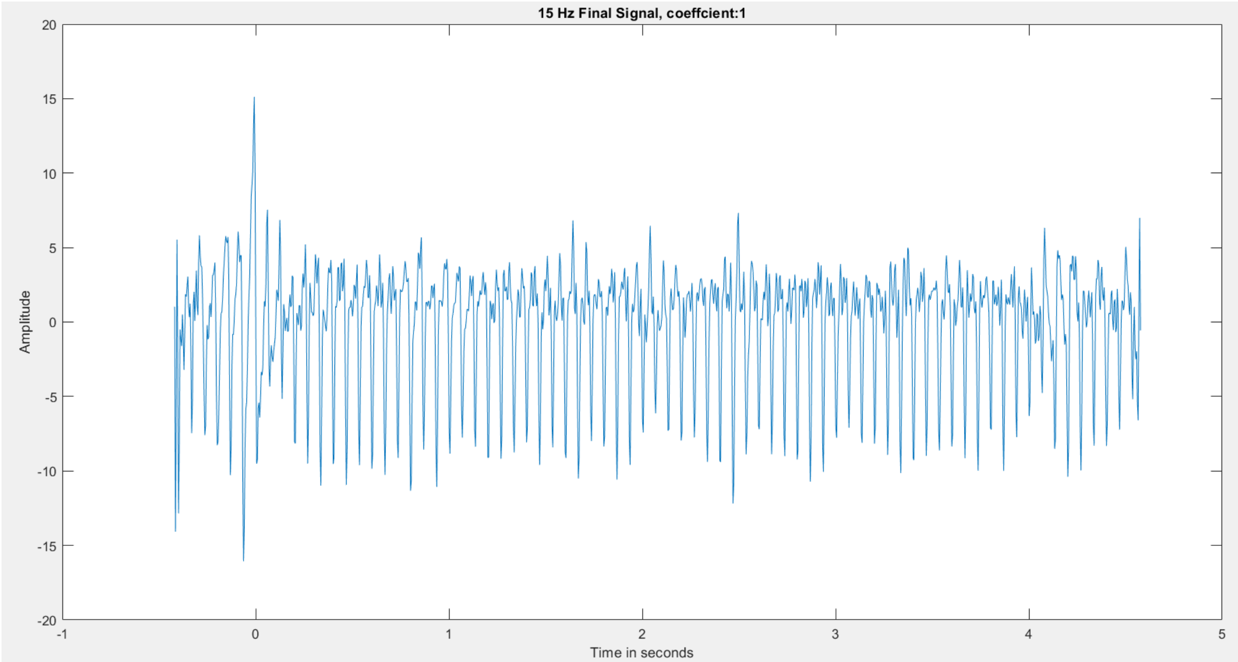

Figure 10: Final Signal of 15 Hz Power Spectrum Noise Signal with coefficient 1

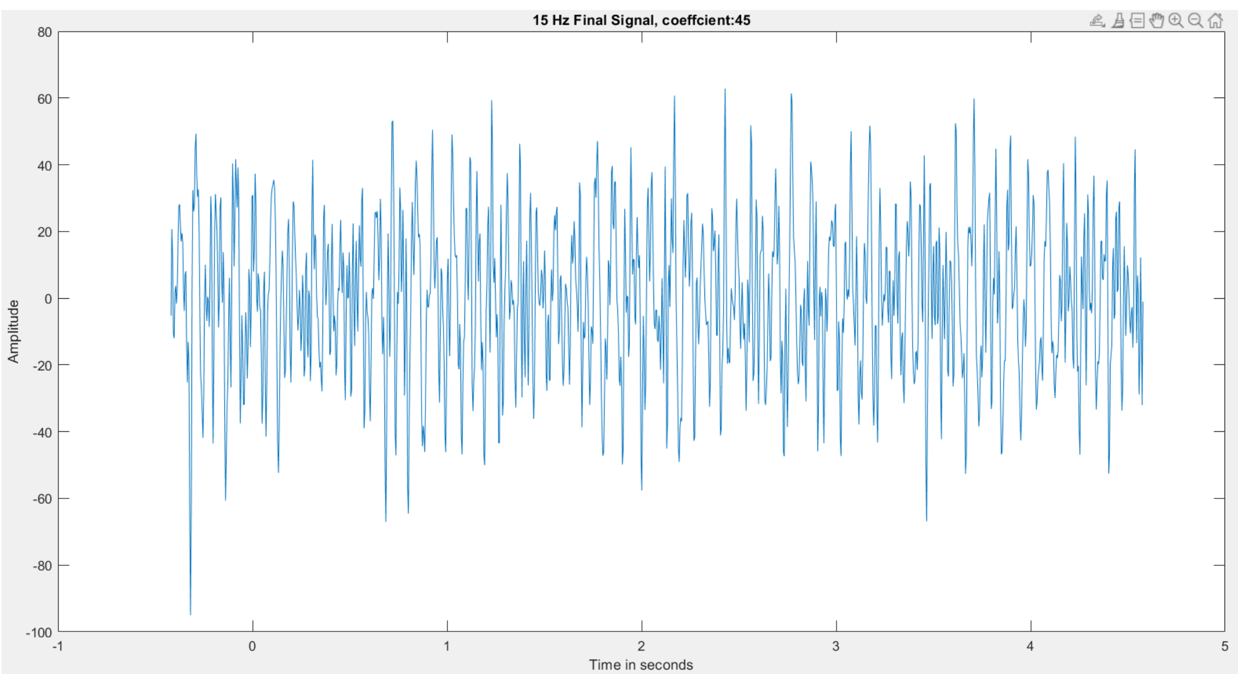

Figure 11: Final Signal of 15 Hz Power Spectrum Noise Signal with coefficient 45

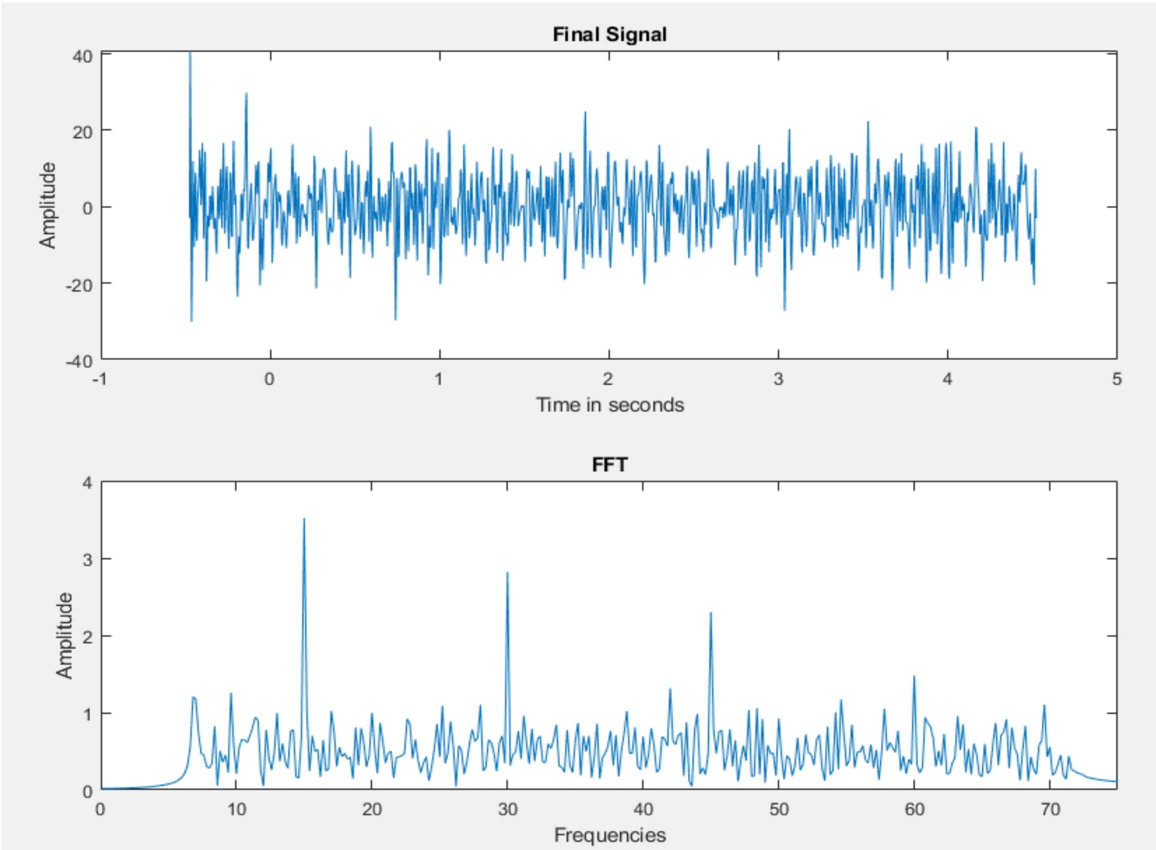

Figure 12: White noise signal with coefficient 15 and FFT of signal with frequency 15

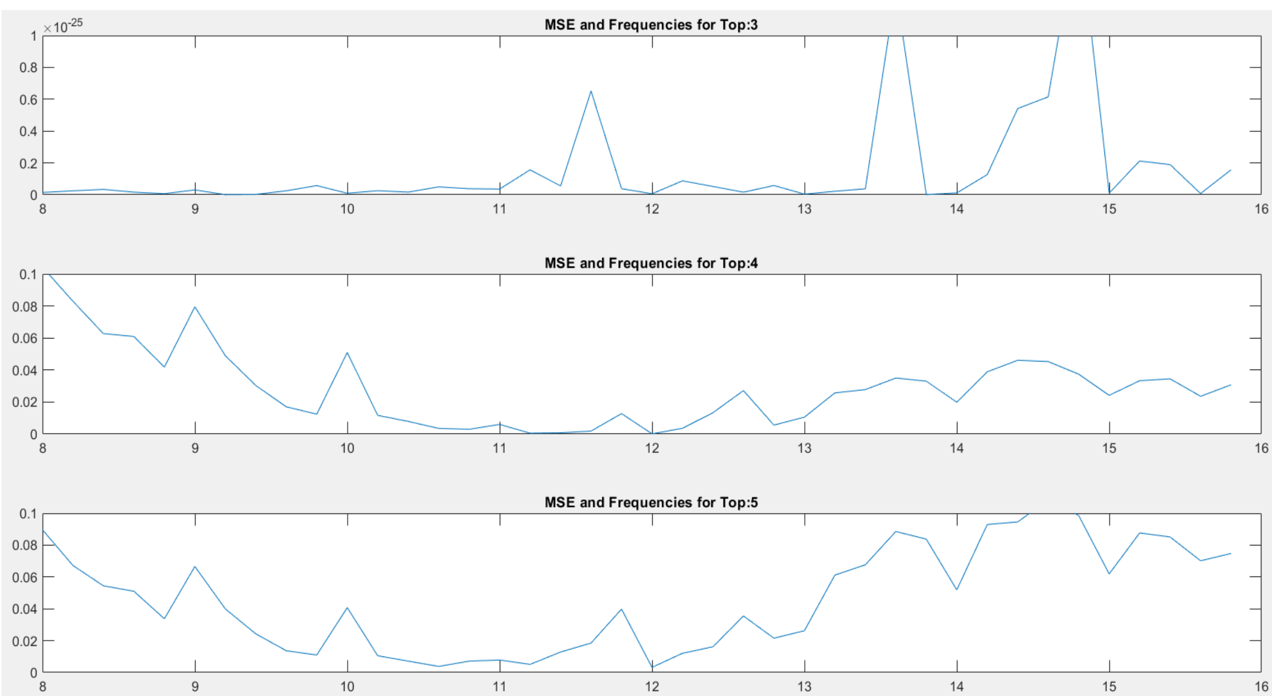

Figure 13: MSE of nonlinear regression wrt frequencies

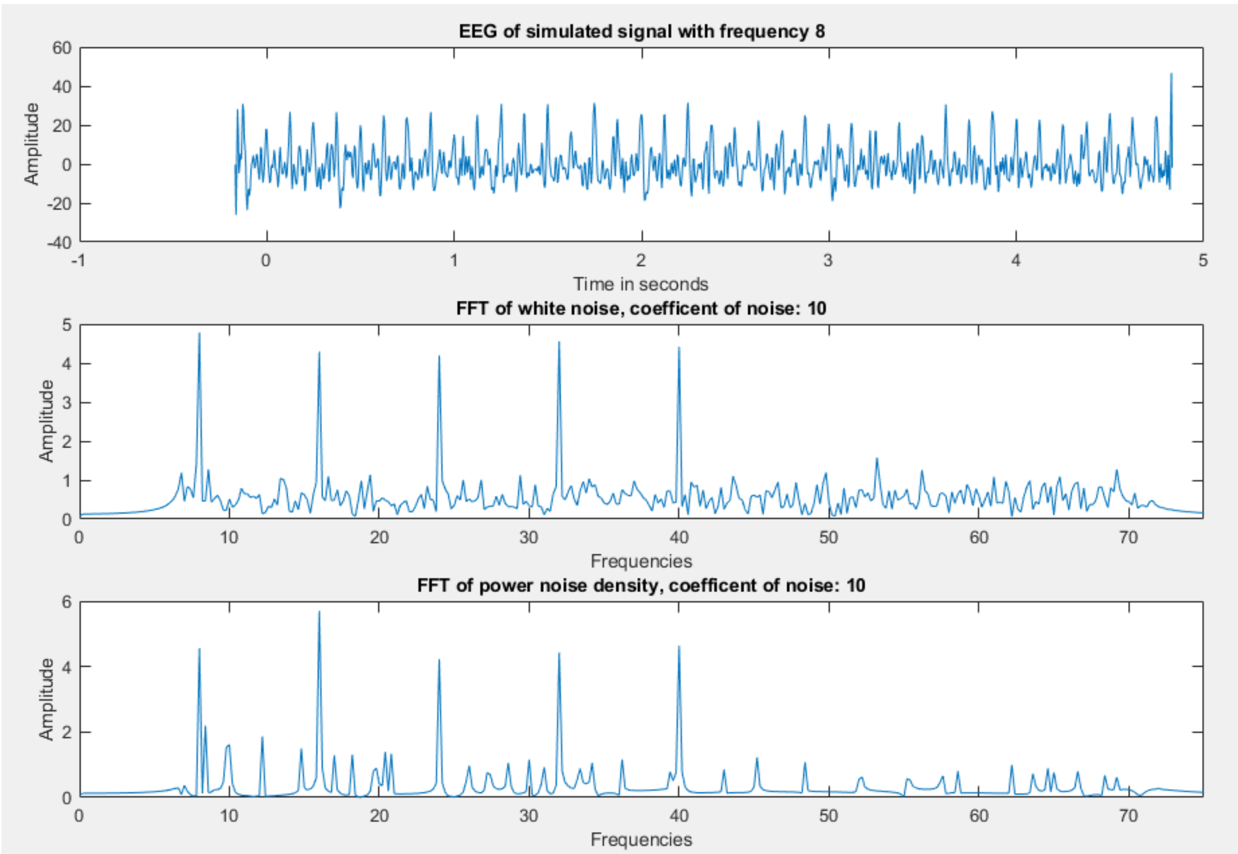

Figure 14: Nonlinear simulation model with power and white noise

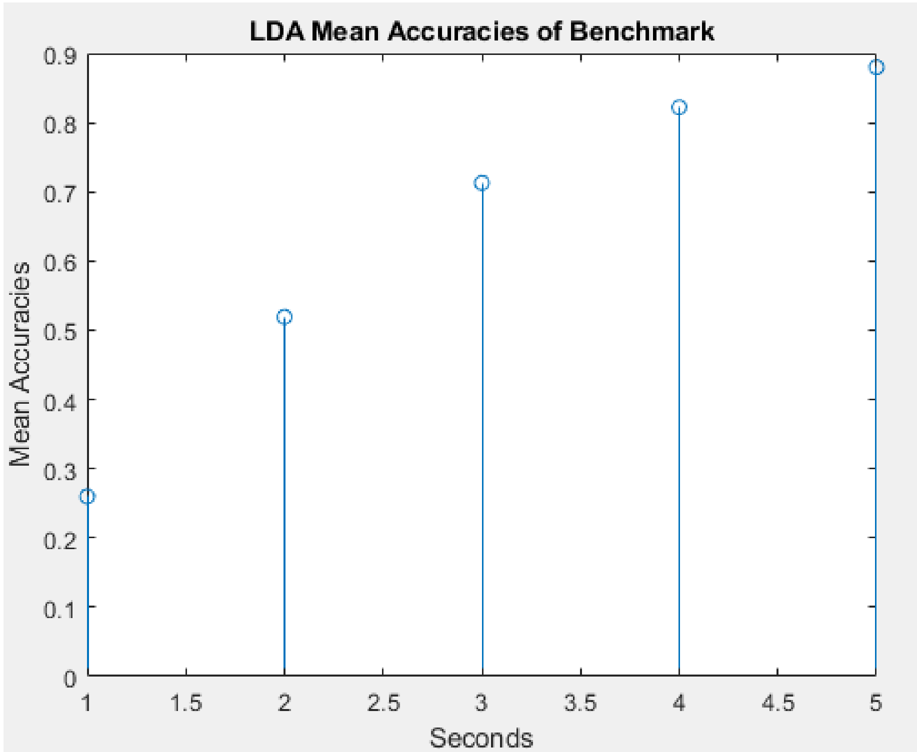

Figure 15: LDA Mean Accuracies of Benchmark dataset with respect to seconds

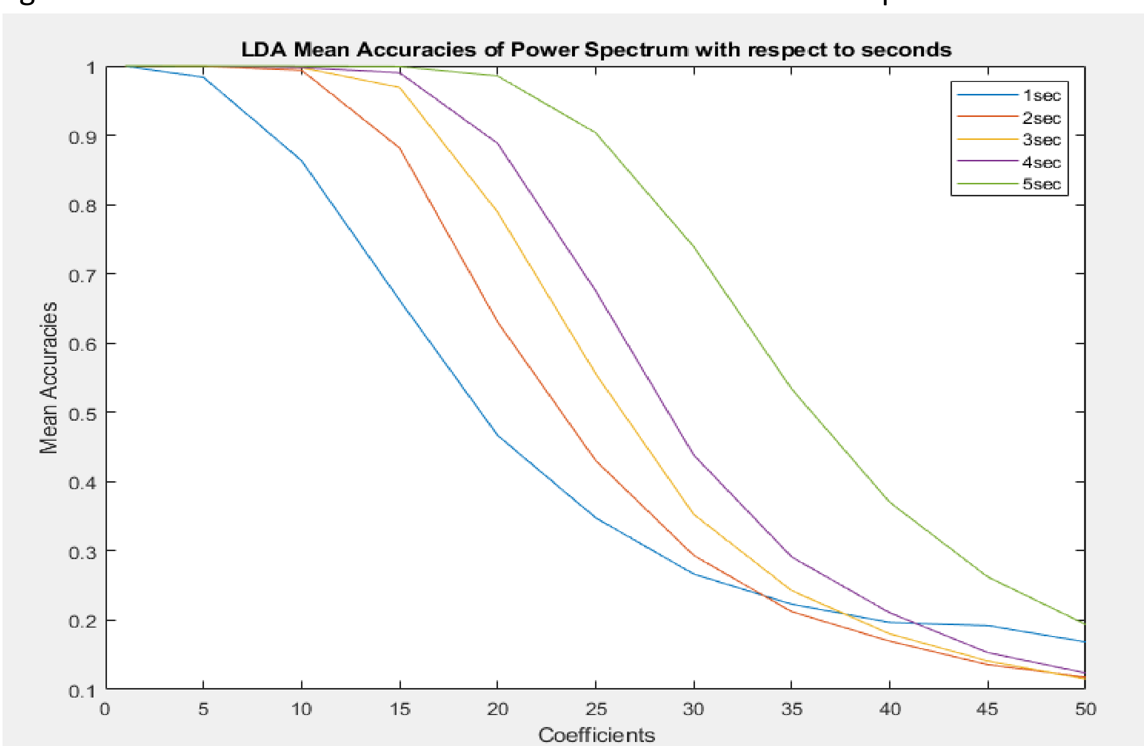

Figure 16: LDA Mean Accuracies of Power Spectrum noise with respect to seconds and coefficients

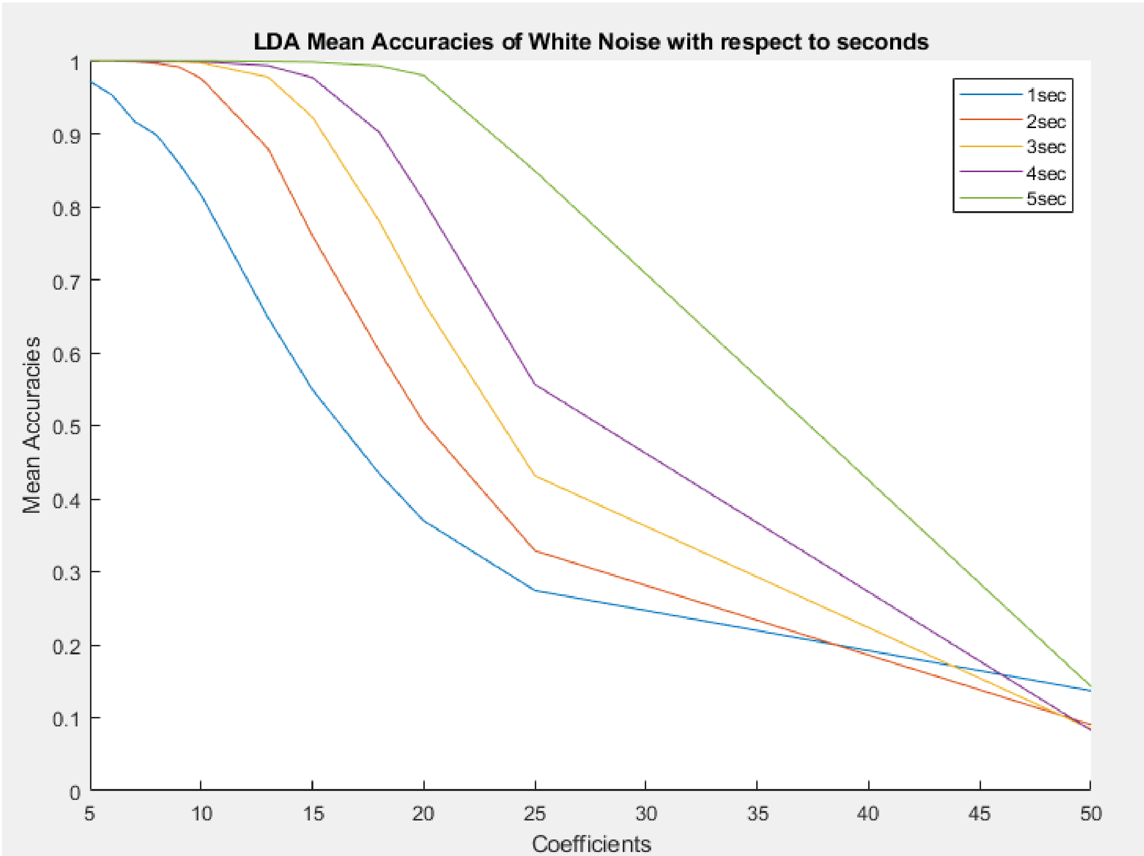

Figure 17: LDA Mean Accuracies of White noise with respect to seconds and coefficients

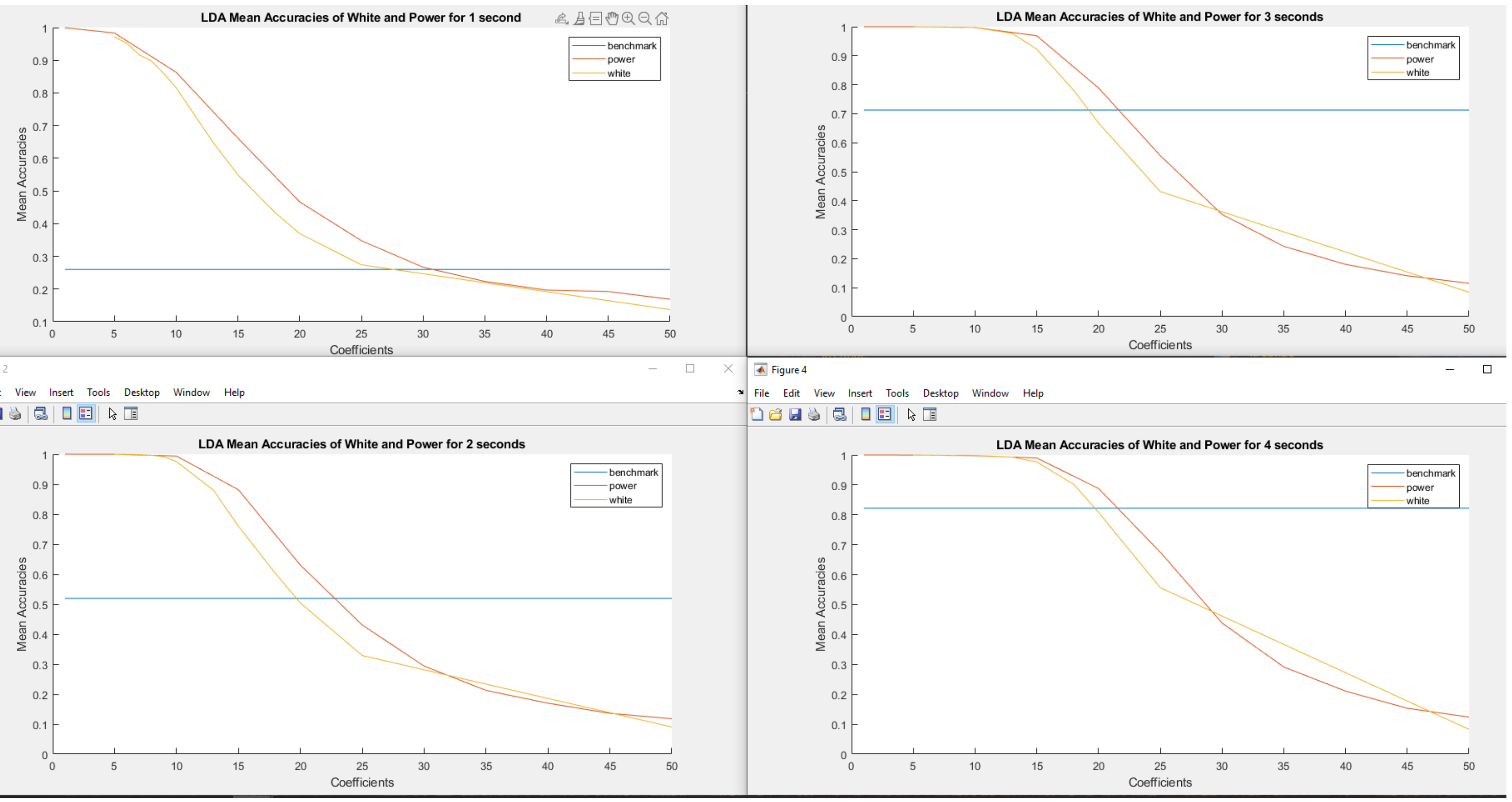

Figure 18: LDA Mean Accuracies of White and Power spectrum noise with different seconds observed, compared with the benchmark dataset accuracy

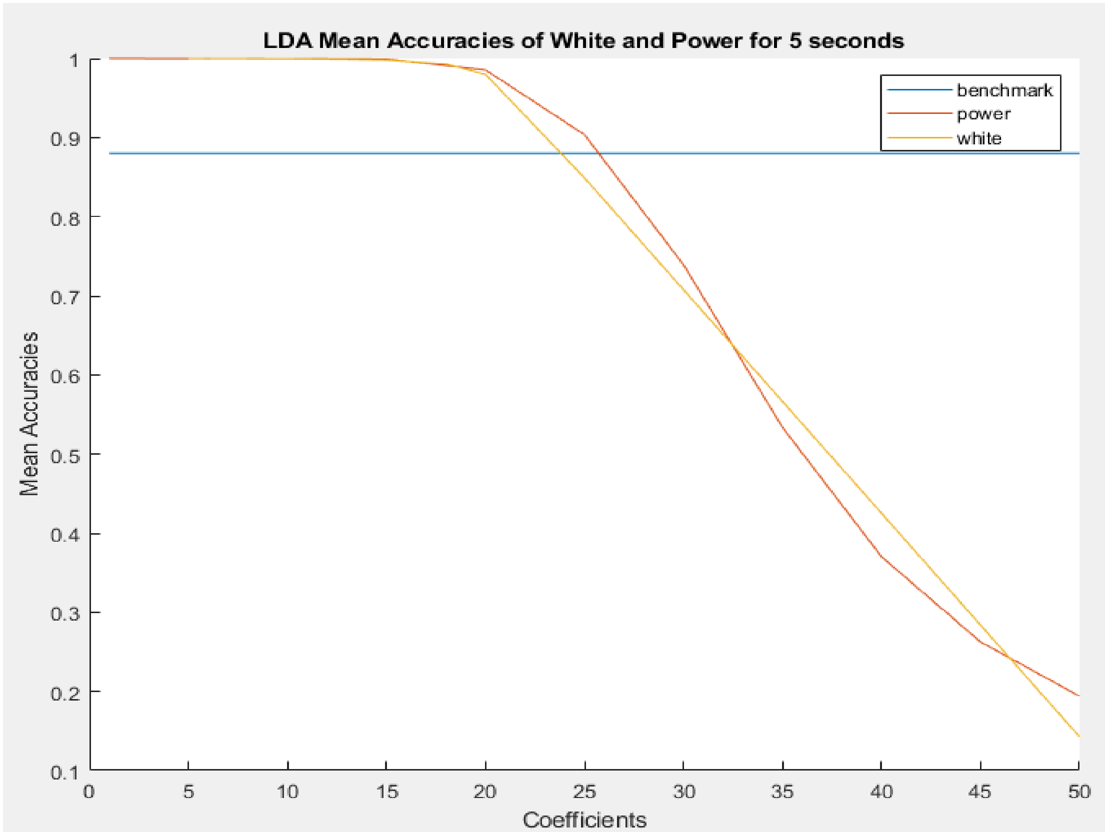

Figure 19: LDA Mean Accuracies of White and Power spectrum noise with 5 seconds observed, compared with the benchmark dataset accuracy

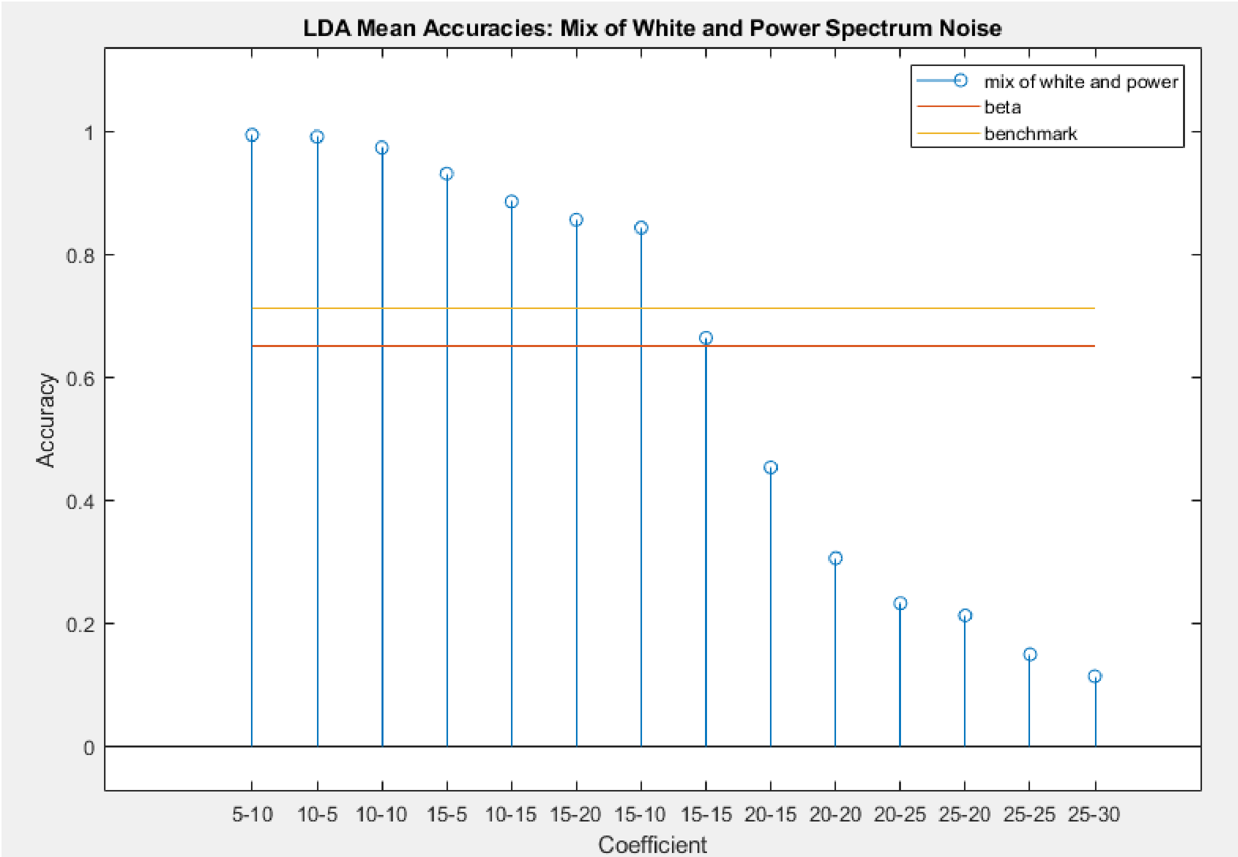

Figure 20: LDA accuracies of the combination of white and power spectrum noise compared with Benchmark and BETA datasets

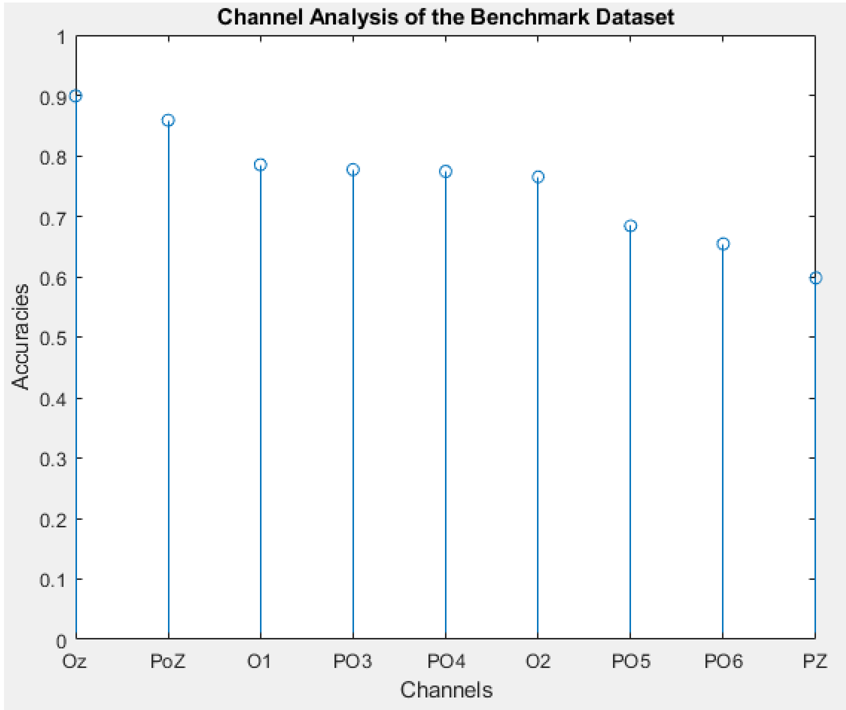

Figure 21: Channel analysis of the Benchmark Dataset

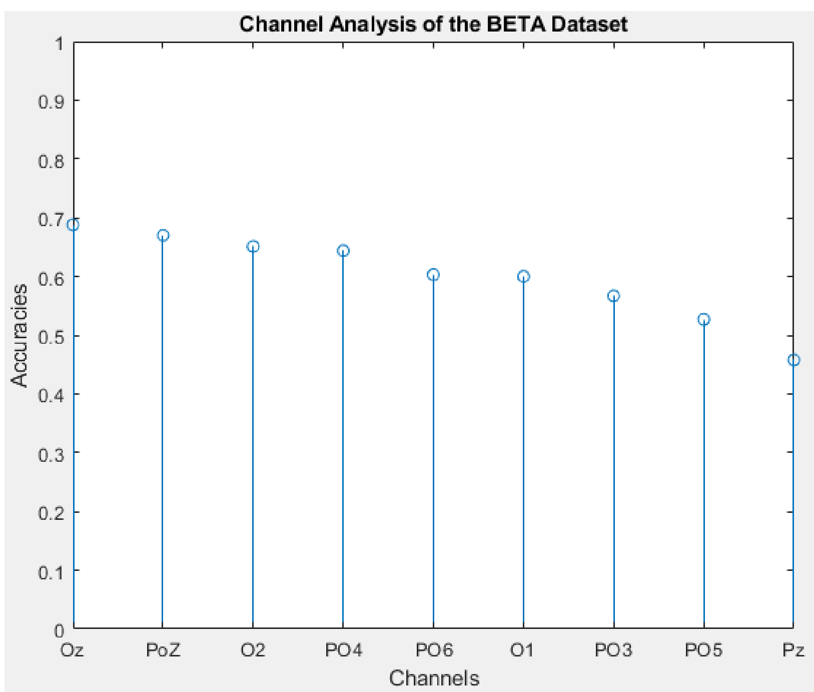

Figure 22: Channel analysis of the BETA Dataset

	Max	Mean	Min
LDA- Full Spectrum	61.75	58.71	54.36
LDA- 1.3 Delta	62.53	58.92	54.22
LR- 1.3 Delta	68.12	62.49	55.69

Figure 23: Results of Classification for Emotiv Experiments

						Week													
Tasks	Description	Duration (week)	Start	Finish	Person Responsible	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	Optimizing Hyper-parameters	2	22.02.2021	07.03.2020	Gorkem Gorkey/Nidanur Gunay														
2	Developing GAN	6	08.03.2020	18.04.2021	Gorkem Gorkey/Nidanur Gunay														
3	Try Previous model with Emotiv Data	2	22.02.2021	07.03.2020	Hakan Bugra Erentug														
4	Optimizing Previous model	4	08.03.2021	04.04.2021	Hakan Bugra Erentug														
5	Train Emotiv Data with Transfer Learning	6	05.04.2021	16.05.2021	n Bugra Erentug/Nidanur Gunay/ Gorkem G														

Figure 24: Gantt Chart of first Progress Report

						Week													
Tasks	Description	Duration (week)	Start	Finish	Person Responsible	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	Nonlinear Regression and new simulation model	4	1	5	Görkem,Nida														
2	Conducting experiments with Emotiv	2	4	6	Entire Group														
3	Classification algorithms: LDA, logistic regression	4	5	9	Entire Group														
4	Optimizing the classification algorithms	3	8	11	Entire Group														
5	Optimizing the BCI SSVEP algorithm	3	9	12	Entire Group														
6	Building and optimizing GAN	2	11	13	Entire Group														
7	Finalizing the report	2	13	15	Entire Group														

Figure 25: Gantt Chart of the second Progress Report

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