EEG SUBJECT IDENTIFICATION USING PORTABLE DEVICES

A THESIS

Submitted by

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for the award of the degree

of

Master of Technology (M.Tech)

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

INDIAN INSTITUTE OF TECHNOLOGY MADRAS

CHENNAI-600036

JUNE 2020

THESIS CERTIFICATE

This is to certify that the thesis entitled **"CHANNEL REDUCTION FOR SUBJECT IDENTIFICATION"** submitted by **Karthikeswaren R** to the Indian Institute of Technology, Madras for the award of the degree of **Master of Technology** is a bona fide record of research work carried out by him under my supervision. The contents of this thesis, in full or in parts, have not been submitted to any other Institute or University for the award of any degree or diploma.

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ACKNOWLEDGEMENTS

I would like to thank Prof. Hema A. Murthy, and Prof. Umesh S. for guiding and co-guiding my project, respectively. Their guidance and support has been of immense importance.

My lab mates Mari Ganesh Kumar, Rini Sharon, Saranya M S, Sidharth Aggarwal, Srihari M, Vinay Kashyap, and Rajat Chawla have helped in different ways. They introduced me to the domain of EEG Signals, which happened to be a great advantage for my project. Data collection for my experiments would have been a great hassle if it weren't for them.

ABSTRACT

Subject identification involves the subject accessing the biometric system and gets identified based on features that are unique to him/her. In EEG subject identification we identify the subject based on brain signals recorded by an EEG device. This project is aimed at reducing the number of channels required to get a meaningful result on subject identification. It is a tedious task to process data streaming from over one hundred channels and then identify the subject. Previously, by reducing the channel count to nine, a result close to that of using all 128 channels of the EEG system has been achieved.

In the first part of the project we will go through some of the methods used in speaker identification and try to apply them in the context of EEG. Techniques such as feature switching will be implemented on channels to see if the performance could be improved. Later, we will explore different channel setups and switching them based on the type task can give us good results.

The second part introduces the Muse device which is a portable device for recording EEG signals. It is a commercial product that can also be used for research. It has only four channels that are located at important areas (frontal and temporal lobes) of the brain. This device gives us advantage over the 128 channel system in multiple ways. For instance, this device is cheaper, and easier to wear. In this part we will be able to observe that task is not a requirement while testing for any given subject using this device.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

EEG: Electroencephalogram

GMM: Gaussian Mixture Models

UBM: Universal Background Models

KLD: Kullback Leibler Divergence

JFA: Joint Factor Analysis

AR 1: All Regions 1

CHAPTER 1
INTRODUCTION

1.1. INTRODUCTION

At present, biometric systems exist in various forms and have their own advantages and drawbacks. One particular drawback is that almost all biometric systems are physically hackable without the presence of the subject in different ways. For instance, a biometric system incorporating facial recognition can be hacked by face masks or photos. To add to that, a finger-print scanner can be bypassed by an artful usage of chewing gum, or clay. Since, there is no way to physically emulate a subject's brain signals, this problem can be overcome by EEG based biometrics.

EEG biometric systems have their limitations as well. To begin with, they come with a heavy price tag. Also, it is computationally expensive to process the signals from a large number of channels. To top it off, the design of the system isn't very elegant, or compact.

Figure 1.1: 128 Channel EEG System in this project[1]

[1] Mari Ganesh Kumar, EEG signals and task-independent person-specific signatures, PhD Seminar

1.2. MOTIVATION OF THE WORK

Reducing the number of channels can pave the way to overcome all of the above mentioned shortcomings. Previously, it has been shown that using just 9 channels will give us similar results as when all of the channels were used [5]. Well-educated guesses were the basis for selecting the channels to obtain those results. The first part of the project will explore the following two questions.

First of all, will selecting those channels in a quantitatively justifiable way ensure better results? The brain is a very complex organ made of tens of billions of neurons. In addition, the asymmetric nature of the brain makes the task of identifying the subject specific signatures even harder. Even if the assumptions made to arrive at the previous results were right, the possibility that even slight changes in the location of channels giving us better results cannot be dismissed. Hence, a scoring mechanism could enhance the result, and lead us to answer the question.

Secondly, are subject specific signatures located at different locations for different subjects? Since, every human's brain structure is different from each other, it wouldn't be surprising to see locations associated with prominent subject specific signatures not coinciding across subjects. Therefore, channel switching is an idea that has to be explored to address this question.

In the second part of the project, the 128 channel system was replaced by Muse device. This device covers the limitations of the 128 channel EEG system in terms of both expenditure, and elegance. Hence, any practical result on subject identification will be of some significance.

Figure 1.2: Muse Device[2]

1.3. ORGANISATION OF THE THESIS

There are three more chapters in this study. The thesis organization is as follows:

- In Chapter 2 (Literature Review), we will go through the various papers from which techniques and definitions were incorporated in this paper.
- Chapter 3 (Experiments and Observations) has a description of the experiments and the results obtained from them. It is split into two parts, on the basis of work done during the two semesters.
- Chapter 4 (Conclusion) wraps up the thesis with the relevance of the results and some possible future work on them.

[2] Official Muse Website

CHAPTER 2

LITERATURE REVIEW

2.1. INTRODUCTION

This chapter contains experiments and analysis that incorporated techniques from both speech and EEG signal related papers. Here we will go through previous work that laid the foundation of our project. Also, we will discuss the dataset collected by other members of CCBR, and the portable Muse device.

2.2. EEG SIGNALS

EEG signals mentioned in the first part of chapter 3 were collected using 128 channels with a sampling rate of 250 Hz. This system was manufactured by Electrical Geodesics, Inc. In the second part of the project, the Muse device with 4 channels was used to collect the data. Both these signals tend to have bands ranging upto 50 Hz. These dataset contained EEG signals collected from multiple subjects performing various elicitation protocols. They are made of subbands, namely delta, theta, alpha, beta, and gamma. This study mostly involves the later three among them.

- Alpha: The range of this band is between 3-15 Hz. When in a meditative state, this band will be dominant in the spectrum.
- Beta: This band falls between 15-30 Hz. When the subject is trying to focus on a given task, this band has a more significant magnitude.
- Gamma: This band has a range of 30 to 50 Hz. During REM sleep, and performing tasks requiring copious amounts of attention and focus.

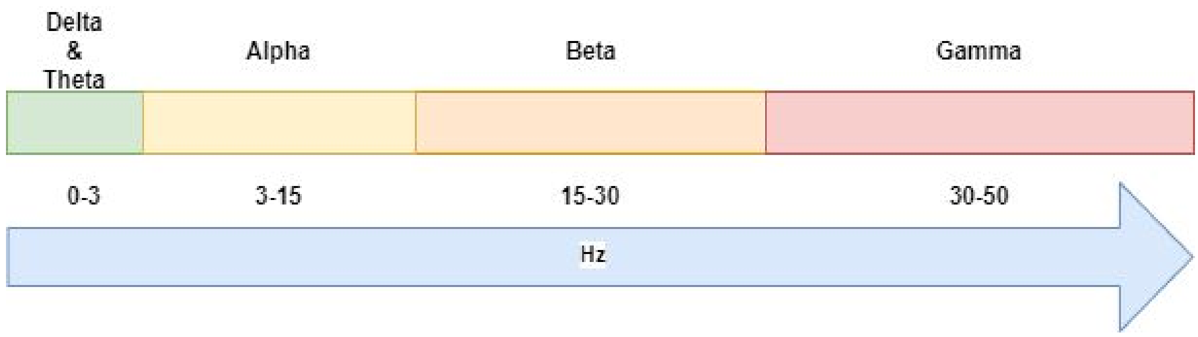


Figure 2.1: EEG Bands

2.3 DATASETS

2.3.1. 128 CHANNEL DATASET

There are over 80 subjects in the dataset. Our interest and focus will be mostly on the 30 subjects that have completed multiple sessions.

In previous research, subjects were made to go through a few elicitation protocols so that their EEG signals could be collected in a systematic way. Here is the list of all the elicitation protocols used to collect the dataset in [5]:

Table 2.1: Elicitation Protocols

S. No.	Experiment	Brief Description
1	Odd Ball	Subjects were instructed to differentiate non-target stimuli from explicitly distinguishable target stimuli. There are different ways in which these stimuli were shown: 1. Figures differing in shape and colour. 2. Audio beeps of frequencies identifiable from each other. 3. Audio beeps occuring on the left and right ear.
2	Familiar and Unfamiliar Words	Upon hearing a familiar word, subjects were asked to click on the mouse.
3	Imagining Binary Answers	Subjects were asked to answer 'yes' or 'no' to the questions using mouse click before imagining the answer in their mind.
4	Motor and Mental Imaginary	Subjects imagined various motor and mental tasks alternatively.
5	Passive Audio	To the subject listening passively, various audio clips were

		played. The audio clips included stories, sentences, words, phrases, and attention inducing sounds.
6	Steady State Visually Evoked Potential	A set of figures were displayed at various frequencies, after which the subjects were supposed to answer questions about the figure.
7	Passive Audio-Visual	Subjects were watching video clips followed by a question about each of them.

Visual form of Odd Ball, Steady State Visually Evoked Potential, Passive Audio-Visual required the eyes of the subject to be open. For the rest of the experiments the subjects had to keep their eyes closed.

2.3.2 MUSE DEVICE CONFIGURATION & DATASET

In this section, we will examine the Muse device. The locations of the channels of the device will be mapped on the 128 channel setup here for later reference.

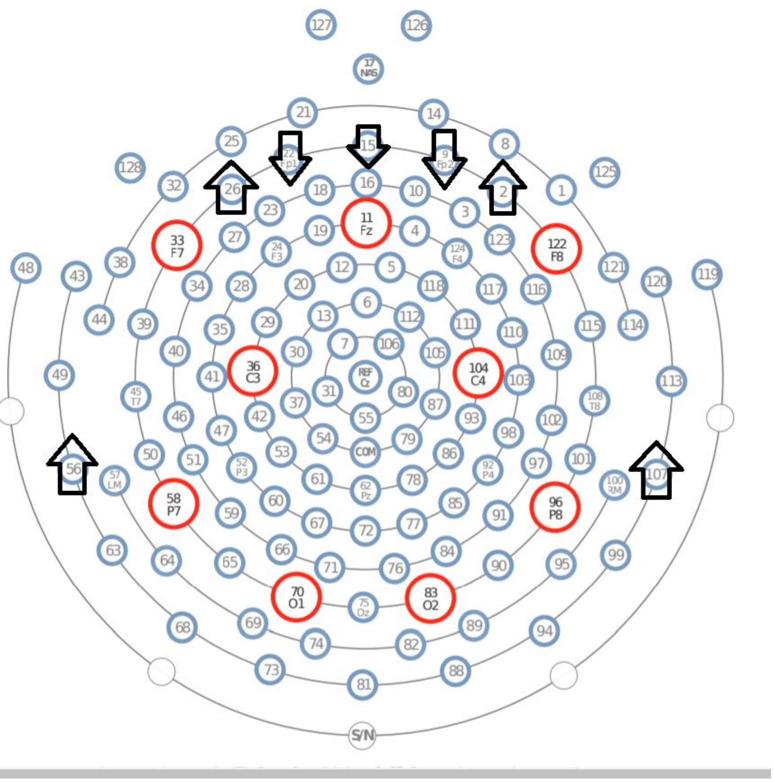


Figure 2.2: Muse Device Mapped on 128 Channel Device

In the above figure, the reference channels are marked with a downward arrow (22, 15, and 9). The upward arrows refer to the non-reference channels (26, 2, 56, and 107).

Two of those channels are situated around the frontal lobe. The other two are located around the temporal lobe.

We have collected data from 18 subjects with the device. Multiple sessions have been performed by 11 subjects. We used four elicitation protocols mentioned in 2.3.1. The dataset is also decently well distributed over both eyes-open and eyes-closed experiments.

2.4 PROCESSING THE EEG SIGNALS

The preprocessing involved splitting the data into chunks of 10 to 60 seconds. They were further split into windows of length 360 ms. Finally the PSD of those widows are computed and taken as features for UBM-GMM classification. This is very similar to the way in which data is preprocessed for speaker identification.

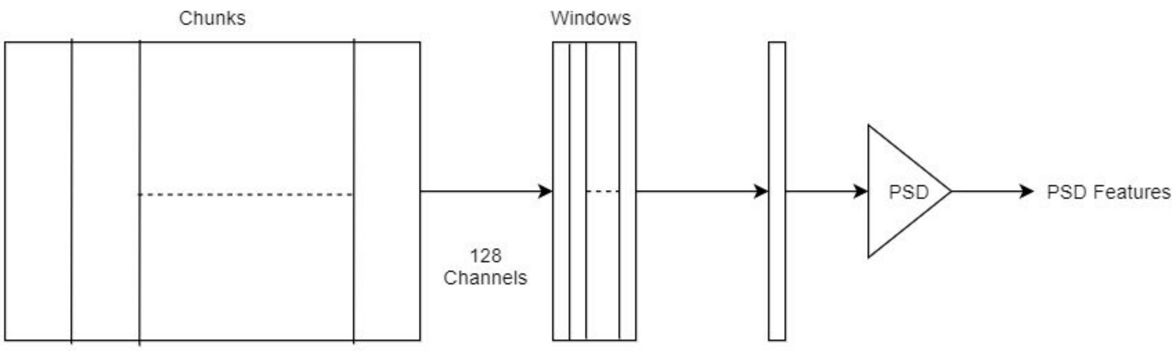


Figure 2.3: EEG Preprocessing Step

2.5 EEG SUBJECT IDENTIFICATION

2.5.1. DIFFERENT KINDS OF IDENTIFICATION

In this project, we will be taking a look at the following two types of subject identification:

1. Classical Identification: All chunks from every elicitation protocol and session were pooled together and shuffled. Then they were split into train, validation, and test data for identification.

2. Intersession Identification: For any given subject, chunks from the last few sessions (around 1-3) were taken for validation, and test purposes. The rest of the sessions (around 2-4) were used for training. This type of identification resembles the real world more.

In intersession identification is preferred more due to the robustness it can provide to the result.

2.5.2 UBM-GMM SUBJECT IDENTIFICATION

The UBM-GMM algorithm has been the foundation to analysing a lot of speech data. It has provided a solid basis for speaker identification problems. It is rooted in two important concepts, namely Gaussian Mixture Models (GMM's), and Bayesian Estimation [1].

First, a GMM is modeled on the entire training dataset. We call this the universal background model (UBM). After this the training dataset is separated based on the subject id. Then the UBM is adapted to each and every subject using bayesian estimation.

After training the UBM on the entire training dataset, for any given speaker, let's say $X = \{x_i, \ldots, x_T\}$ makes up the training dataset. Now we find the probability that a given training data-point belongs to mixture i in the UBM.

$$P(i|x_t) = \frac{w_i p_i(x_t)}{\sum_{j=1}^{M} w_j p_j(x_t)}$$

Using these computed probabilities, we can estimate other statistics that define the speaker's data.

$$n_i = \sum_{t=1}^{T} P(i \mid x_t)$$

$$E_i(x) = (1/n_i) \sum_{t=1}^{T} P(i \mid x_t)\, x_t$$

$$E_i(x^2) = (1/n_i) \sum_{t=1}^{T} P(i \mid x_t)\, x_t^2$$

To apply bayesian adaptation we have to define adaptation coefficient for every mixture as,

$$\alpha_i = \frac{n_i}{n_i + \gamma}$$

The new statistics of the mixture can be estimated using bayesian adaptation on the existing statistics of the speakers data.

$$\widehat{w_i} = \alpha_i n_i / T + (1 - \alpha_i) w_i$$

$$\widehat{\mu_i} = \alpha_i E_i(x) + (1 - \alpha_i)\mu_i$$

$$\widehat{\sigma_i^2} = \alpha_i E_i(x^2) + (1 - \alpha_i)(\sigma_i^2 + \mu_i^2) - \widehat{\mu_i^2}$$

The above steps are performed for each and every speaker. Using the speaker models $\lambda_i \; \{i = 1, ..., N\}$ and the UBM λ_{ubm} the likelihoods are calculated and the speaker is identified.

$$Speaker = argmax_i \sum_{t=1}^{T} [log(p(x_t \mid \lambda_i)) - log(p(x_t \mid \lambda_{ubm}))]$$

Applying UBM-GMM is a little different in the context of an EEG dataset, because we have to consider that the signals are received from multiple channels [2]. Here c refers to the channel number.

$$Subject = argmax_i \sum_{c=1}^{C} \sum_{t=1}^{T} [log(p(x_t^c \mid \lambda_i)) - log(p(x_t^c \mid \lambda_{ubm}))]$$

2.5.3 I-VECTOR SUBJECT IDENTIFICATION

Currently, i-vectors are one of the state of the art methods to solve speaker identification problems, and they can perform well when applied to EEG signals as well [4,5]. UBM-GMM laid the foundation to this method.

Prior to i-vectors, Joint Factor Analysis (JFA) used to be the go-to algorithm for speaker identification [3]. In JFA, a supervector (M) formed by a speaker's utterance can be separated as

$$M = m + Vy + Ux + Dz$$

In this equation U represents the subspace of the session (in case of multiple sessions) or the medium of the recording device. V and D are known as the eigenvoice matrix and diagonal residual, respectively. Combinedly, these matrices define the speaker subspace. Vector m is the supervector which is formed using the UBM.

i-vector method hypothesised that this equation can be reduced to

$$M = m + T w$$

Here T is called the total variability matrix. Our objective is to find w. First, we need to determine the Baum-Welch statistics of the utterance.

$$N_i = \sum_{c=1}^{C} \sum_{t=1}^{T} P(i \,|x_t^c, \lambda_{ubm})$$

$$F_i = \sum_{c=1}^{C} \sum_{t=1}^{T} P(i \,|x_t^c, \lambda_{ubm})(x_t^c - m_i)$$

These parameters are used to find the i-vector representing the utterance.

$$w = (I + T^T \Sigma^{-1/2} N T)^{-1} T^T \Sigma^{-1} F$$

These vectors are later used by a classifier such as SVM for identifying the speakers.

2.6 KULLBACK LEIBLER DIVERGENCE

KLD between any two probability distributions P and Q, assuming that the data follows the distribution P can be given by

$$D(P\|Q) = E_{X\sim P}(log(\frac{P(X)}{Q(X)}))$$

To compute this score between two GMMs, a theoretical approximation can be made.

$$D(P\|Q) = 0.5 \times [log(\frac{\Sigma_q}{\Sigma_p}) + Tr|\Sigma_q^{-1}\Sigma_p^{-1}| - d + (\mu_p - \mu_q)^T \Sigma_q^{-1}(\mu_p - \mu_q)$$

In UBM-GMM, if the subject MAP adapted GMM is well-separated from the UBM, then it indicates that the subject can be easily identified. If we select for channels that are the most well-separated from the UBM, then it could make the subjects easily identifiable. We can use KLD to solve this problem. To use KLD as a distance metric, it has to be commutative. To ensure this we can use the 2 sided formula that was used in [5,6].

$$Distance = 0.5 \times (D(P\|Q) + D(Q\|P))$$

CHAPTER 3

EXPERIMENTS AND RESULTS

3.1 PART - 1

3.1.1 BASELINE MODEL

In order to obtain baseline results, a small subset of the data with around 20 subjects from all 128 channels was taken for the purpose of classical identification. The dataset included about 1100 segments of EEG with each one being 15 seconds long. Then they were split into windows of 360 milliseconds. We tried a method which was unconventional. In this method instead of adapting the UBM to each subject and obtaining the subject-wise model, separate GMM's were trained on a subject-wise basis. As we can see in Table 3.1.1, The conventional UBM-GMM yielded better results.

Table 3.1.1: Baseline (Classical Identification)

Method	Accuracy %
GMM for each subject	60
UBM-GMM	90

For intersession identification, the baseline results were achieved with 30 subjects from all 128 channels, amounting to around 3500 chunks. The chunk and window sizes were retained from the previous analysis at 15 sec and 360 milliseconds, respectively. Table 3.1.2 suggests that having a higher number of mixtures around 150 gives us better performance.

Table 3.1.2: Baseline (Intersession Identification)

Mixtures	Accuracy %
50	55
150	72

3.1.2 CHANNEL SETUPS

Before we move further to more experiments it is important to lay out some channel setups that are associated with different parts of the brain. Here we will take a look at the different channel setups (figure 2.4 and 2.5) that have been used in [5] to prove that subject identification can be done utilizing only 9 channels instead of using all 128 channels.

Figure 3.1.1: Channel Setups 1

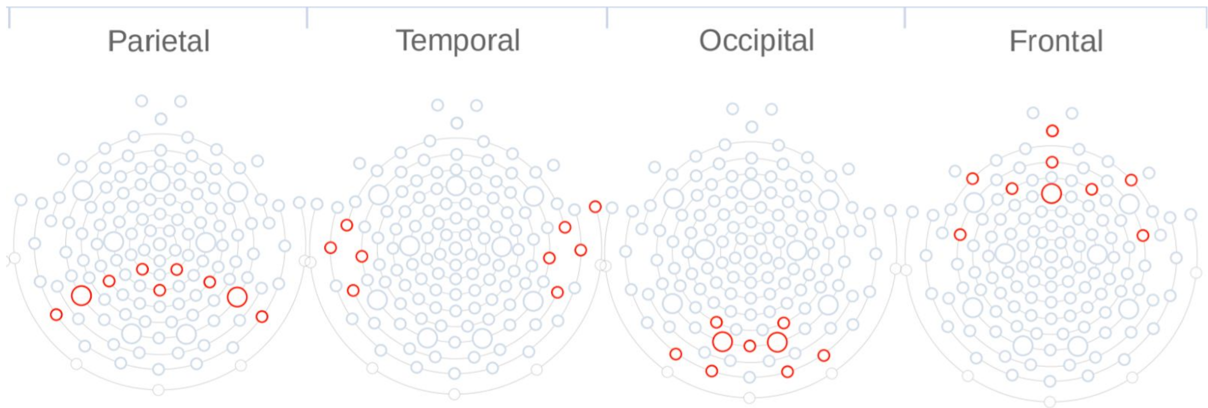


Figure 3.1.2: Channel Setups 2

The All Regions 1 (AR1) setup gave the best result when compared to the other setups [5]. On the intersession dataset, this setup gave an accuracy around 70%. The result given by using all 128 channels was 72% which is only slightly higher in comparison.

3.1.3 PARALLELIZATION OF UBM TRAINING

Since it took a long time to train the UBM, parallelizing the process across multiple cores became the apparent solution. Let's say we want to parallelize an M-mixture GMM algorithm to N cores. K-Means was applied to the entire dataset to split the dataset to the N cores. Within each core, applied GMM with M/N mixtures to obtain the weights, means, and covariances. This led us to obtain an accuracy of 70.69% with the 9 channels mentioned on the second chapter (AR 1) on intersession classification which is very similar to the 71.71% accuracy using all 128 channels (Table 3.1.3).

Table 3.1.3: Parallelization Performance

Channels	Accuracy %
AR1	70.69
All Channels	71.71

3.1.4 APPLYING KLD TO OUR PROBLEM

The parallelized UBM was used for this part of the analysis as well. If the KLD score between UBM trained on a channel and the subject MAP adapted GMM is high, then the channel is a better representation of the subject compared to other channels. The weighted average KLD score across different subjects was calculated for each channel. All channels were ranked according to this score. The top channels were chosen and a UBM-GMM model was trained with these channels alone. The results (mentioned in table 3.1.4) were not as expected.

Table 3.1.4: KLD Channels Performance

Channels	Accuracy %
Top 9 KLD Channels	56.35
Top 20 KLD Channels	68.14
Top 30 KLD Channels	68.69

3.1.5 KLD AS A DISTANCE MEASURE

Due to the lack of commutativity, this score can't be used as a distance measure, possibly owing to lower accuracy. However, if KLD is calculated on both sides, it becomes commutative. Hence, 2-sided KLD was used from this part of the analysis.

In order to answer the second question mentioned in the motivation section of chapter 1 (section 1.2), we tried switching the channels according to each and every subject. To ensure uniformity of likelihood function for all subjects, all channels were used while training to score KLD and classification.

Table 3.1.5: Subject-wise Channel Switching using KLD

top_C	Accuracy (Top 9 KLD Channels)	Accuracy (Top 3 KLD Channels)	Accuracy % (AR1 Channels)
5	60.00 %	22.75%	73.33%
10	59.20 %	22.75%	72.94%

3.1.6 SANITY CHECKS

Since the results were not as close to the previously achieved baseline, a few sanity checks were performed. To check if KLD technique is working, results from previously well-established setups from the journal paper were cross-checked with KLD scores. In this analysis, only the channels of the corresponding setup were used to compute KLD and classification. To replicate the results on [5], we trained a UBM for each setup. In the end, no strong positive correlation was found between KLD and accuracy.

Table 3.1.6: Sanity Check 1

Setup	KLD	Accuracy %
AR 1	0.6349	71.10
AR 2	0.6206	64.31
AR 3	0.6052	69.41
Central	0.6120	69.41

Parietal	0.6809	67.06
Temporal	0.6084	57.65
Occipital	0.7886	67.65
Frontal	0.5206	61.96

This analysis was further broken to the subject level. Also, the results from subject-wise channel switching was included. Since channel switching is involved, an all channel UBM was used in order to enforce uniformity throughout this analysis. In addition to that, KLD was scored analytically also. The resulting accuracies for a random subject are mentioned below.

Table 3.1.7: Sanity Check 2

Setup	KLD (Theoretical)	KLD (Analytical)	Accuracy %
AR 1	0.4927	0.8739	70.0
AR 2	0.4365	0.8519	90.0
AR 3	0.4389	0.8060	80.0
Central	0.4358	1.2704	50.0
Parietal	0.5065	0.8496	10.0
Temporal	0.5077	1.4110	10.0
Occipital	0.8513	1.5822	60.0
Frontal	0.3021	0.9317	40.0
KLD Top 9	0.5824	NA	0.0

3.1.7 TWO LEVEL ADAPTATION ON UBM-GMM:

There is a possibility that the subject MAP model could also be adapted to the respective kld channels' signatures along with the subject-specific signature. This could be overcome by the use of two level adaptation on an UBM trained on all channels and subjects.

We will look at the execution of this method here. For every subject, the top channels were noted, and the UBM was adapted to those channels alone from the dataset containing all the subjects. This channel adapted UBM was further adapted to the respective subject. This adapted subject model and the UBM trained on all channels, and subjects were used for classification. Despite using this method, the accuracy was only 69.02%, which was no better than the 73.33% achieved in section 3.1.4 using the AR 1.

3.1.8 EYE OPEN VS EYE CLOSED EXPERIMENTS

Since KLD scoring was clearly not working, we performed a different experiment in this section. From the intersession dataset consisting 30 subjects, 14 subjects who completed both eye-open, and eye-closed experiments were selected. Among the 14 subjects, 11 have completed multiple sessions with eyes open, 13 have completed multiple sessions with eye-closed experiments. Various setups in section 2.8 were used to find the best set of channels. Also, a combination of these channel setups were used to get better results.

Table 3.1.8: Intersession Eye-Open

Region	Accuracy %
All Regions 1	89.47
All Regions 2	85.53
All Regions 3	89.47
Central	80.26
Parietal	84.21
Temporal	73.68
Occipital	69.73
Frontal	76.32

All the previously mentioned setups were used to arrive at the table above. Only the tasks which allowed the eyes to be open were taken for that experiment.

Table 3.1.9: Intersession Eye-Closed

Region	Accuracy %
All Regions 1	82.22
All Regions 2	70.00
All Regions 3	75.55
Central	54.44
Parietal	75.55
Temporal	82.22
Occipital	81.11
Frontal	74.44

The only difference from the previous table is that the tasks chosen required the eyes of the subject to be closed.

We wanted to see if a combination of the setups mentioned in the second chapter could give us good results. So we chose two setups at a time and fixed the channel count to nine.

Table 3.1.10: Intersession Eye-Open (Combined Setups)

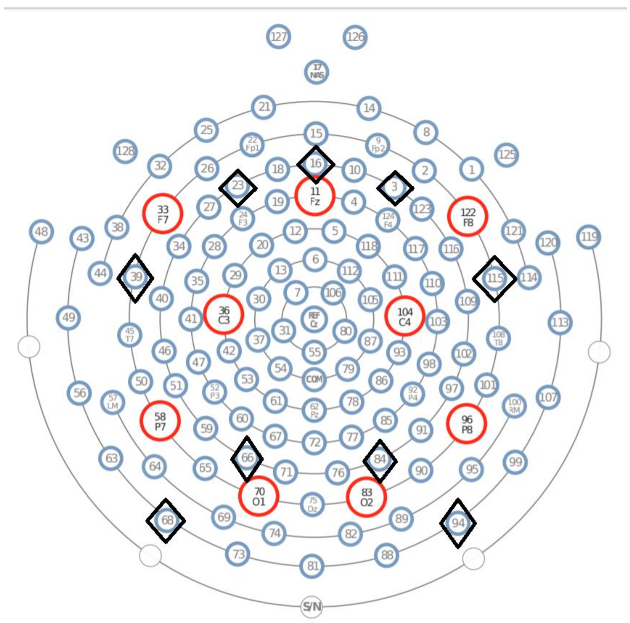
Region	Accuracy %
Central + Parietal	82.89
Central + Temporal	86.84
Central + Occipital	81.58
Central + Frontal	73.68
Parietal + Temporal	82.89
Parietal + Occipital	86.84
Parietal + Frontal	81.58
Temporal + Occipital	73.68
Temporal + Frontal	76.32
Occipital + Frontal	84.21

Table 3.1.11: Intersession Eye-Closed (Combined Setups)

Region	Accuracy %
Central + Parietal	78.89
Central + Temporal	80.00
Central + Occipital	78.89
Central + Frontal	81.11
Parietal + Temporal	78.89
Parietal + Occipital	80.00
Parietal + Frontal	78.89
Temporal + Occipital	81.11
Temporal + Frontal	80.00
Occipital + Frontal	83.33

From the four tables mentioned in this section, all regions 1 gave the best accuracy when the subject's eyes were open. Whenever the subject's eyes were closed, a combination of the occipital, and frontal lobes came out to be the best option.

Figure 3.1.3: Frontal + Occipital



3.2 PART 2

In this part we will move over from the 128 channel EEG system to the 4 channel Muse device. Here we will take a look at the data collected using the device and the Data from 18 subjects in total were collected, out of which 11 subjects have completed more than one session.

A good mix of both elicitation protocols with the eyes open and closed were used for data collection. Visual form of Odd Ball, audio frequency version of Odd Ball, Passive Audio-Visual, and Passive Audio were the elicitation protocols used for collecting with this device. In total, subjects went through around 100 elicitation protocols. The device covers only the frontal and temporal lobes. This information provides us a strong reason to choose these tasks that mostly involve the use of these two lobes.

3.2.1 MUSE DATA BASELINE

There were 18 subjects in the dataset of whom 11 have completed multiple sessions. With the chunk size and window size fixed at 15 seconds and 360 milliseconds respectively, the number of mixtures was set to 128. Only the PSD between 3 to 30 Hz were used. The results for both classical identification, and intersession identification are mentioned on Table 3.2.1.

Table 3.2.1: Muse Baseline

Mixtures	Types of Classification	Accuracy
128	Classical Identification	55.65 %
128	Intersession Identification	49.33 %

The chunk size was varied to see if the accuracy could be improved. As we can observe in Table 3.2.2, the intersession accuracy was the highest when the chunk size was 30 seconds long.

Table 3.2.2: Chunk Size vs Accuracy

Chunk Size	Accuracy %
15 sec	49.33
30 sec	51.75
60 sec	51.67

From now on, the chunk size was fixed at 30 seconds. There seems to be a negative return on investment after a certain chunk length.

3.2.2 BAND COMBINATIONS

Combinations of the following band frequencies alpha (3 to 15 Hz), beta (15 to 30 Hz), and gamma (30 to 50 Hz) were tried out to get the best band range in table 3.2.3. Alpha and beta bands together gave the best result, which is the same as the 128 channel EEG system.

Table 3.2.3: Band vs Accuracy

Bands	Accuracy %
Alpha	50.00
Beta	36.84
Gamma	31.57
Alpha, Beta	51.75
Beta, Gamma	35.96
Gamma, Alpha	39.47
Alpha, Beta, Gamma	40.35

Perhaps, alpha and beta were the dominant during the tasks that were performed by the subjects in these experiments.

3.2.3 USE OF I-VECTORS

In this section, i-vectors were used to check if the accuracy could be improved further. In previous research, i-vectors are known to have improved the performance over UBM-GMM in subject identification [5]. In the table 3.2.4 we have listed the accuracies achieved with different numbers of UBM mixtures.

Table 3.2.4: i-vector Accuracy

Mixtures	Accuracy %
16	46.37
32	45.97
64	39.52
128	52.02
256	33.47

The results didn't improve by much. This could be due to less amount of training data (only four channels) to feed a complex algorithm such as i-vector and SVM classification.

3.2.4 TASK VS REST

For this experiment, we took the entire dataset with 18 subjects. irrespective of the number of sessions the subject has completed. The training dataset only included the time spent on tasks. The validation dataset was switched between task data, and a dataset resting state data. The resulting split was 60:20:20 between the training, task validation and rest validation datasets.

Table 3.2.5: Task vs Rest Performance

State	Accuracy %
Rest	39.90
Task	47.32

As expected, in the table above we can see that the task dataset outperformed the rest dataset, but not by a lot. The reason for this is still unclear at the moment. It can be explored as a future work. This is a result worth pondering over.

3.2.5 UBM POOLING

We went back to intersession testing and tried to increase the training dataset. From the 128 channel dataset, we took the corresponding channels that are used in Muse and then re-referenced them. The re-referencing was done in two ways.

In the 128 channel system, all the channels are referenced from channel 0 (a.k.a. channel Cz).

$$\overline{V_0} = 0$$

$$\overline{V_1} = V_1 - V_0$$

$$\overline{V_2} = V_2 - V_0$$

.

.

$$\overline{V_{128}} = V_{128} - V_0$$

In order to re-referenced to channel *x,*

$$\overline{V_0} = V_0 - V_x$$

$$\overline{V_1} = V_1 - V_x$$

.

.

$$\overline{V_x} = 0$$

.

.

$$\overline{V_{128}} = V_{128} - V_x$$

We only take channels 2, 26, 56, and 107 because only those are mapped on Muse device.

Single Channel Re-Referencing: We take the middle reference channel (channel 15) and then use it for re-referencing.

$$V_x = V_{15}$$

Three Channel Re-Referencing: We take an average of all three reference channels (channel 22,15,9) and then use it for re-referencing.

$$V_x = (V_{22} + V_{15} + V_9)/3$$

Table 3.2.6: Re-Referencing

Method	Accuracy %
Single Channel Re-Referencing	18.70
Three Channel Re-Referencing	44.66

After the dataset was re-referenced they were normalized to follow the distribution of the other, both datasets together were then used for UBM training. Then they were adapted with Muse training dataset. The reason for this lack-lustre result could be owed to the fact that 128 channel data is entirely different from that of Muse data. The collecting electrodes are different. Almost none of the subjects overlapped between the two datasets. These reasons might have influenced the performance.

CHAPTER 4

CONCLUSION

In spite of all the complex methodologies used in the first part, modest results were the final product. Scoring the channels with KLD didn't bring any positive results. Perhaps, there is a better scoring mechanism. Also, these results don't mean channel switching as an idea should be completely devalidated from EEG signal analysis. EEG signals are extremely susceptible to environmental conditions that are out of the experimenter's control, such as the plasticity of the brain. Hence, these methods shouldn't be dismissed altogether, as they might work elsewhere in a totally different scenario.

Since we had some success with the intersession eye open and eye closed experiment, maybe more well-educated guesses should be looked into. Probably, extending these heuristics to incorporate the asymmetry of the brain could bring us good results as well.

In the second part of the project, we directed our attention towards Muse device. It has only four channels, rendering most of the drawbacks of the 128 channel system obsolete. So far, over 35 sessions, and 100 elicitation protocols were taken using this device. The results we have might not be great, but they were way better than the performance of a random number generator. There were some areas of improvement. For instance, we could have gone back to the 128 channel system and check if the Task vs Rest experiment can yield a similar result. In the re-referencing experiment we could have tried two level adaptation for the Muse data, and then to the subjects separately.

The Task vs Rest experiment is something to be noted. In practice, there could be some complications when the subject is asked to go through an elicitation protocol. This experiment shows us that the necessity to make the subject perform an elicitation protocol is not as important as it was previously thought to be.

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