COGNITIVE PERFORMANCE EVALUATION OF EARLY ONSET IN DEMENTIA: HYBRID EEG/EYE TRACKING DATA ANALYSIS

RASA BHATTARAI

A THESIS REPORT SUBMITTED IN PARTIAL FULFILLMENT
OF THE REQUIREMENTS FOR THE DEGREE OF
MASTER OF ENGINEERING IN COMPUTATIONAL INTELLIGENT SYSTEMS
INTERNATIONAL COLLEGE
KING MONGKUT'S INSTITUTE OF TECHNOLOGY LADKRABANG
ACADEMIC YEAR 2018

KMITL-2018-IC-M-11-07

COGNITIVE PERFORMANCE EVALUATION OF EARLY ONSET IN DEMENTIA: HYBRID EEG/EYE TRACKING DATA ANALYSIS

RASA BHATTARAI

A THESIS REPORT SUBMITTED IN PARTIAL FULFILLMENT
OF THE REQUIREMENTS FOR THE DEGREE OF
MASTER OF ENGINEERING IN COMPUTATIONAL INTELLIGENT SYSTEMS
INTERNATIONAL COLLEGE
KING MONGKUT'S INSTITUTE OF TECHNOLOGY LADKRABANG
ACADEMIC YEAR 2018

KMITL-2018-IC-M-11-07

Abstract

In the current era of growing population, there has been a significant increase in the number of people who are subjected to problem like dementia. This condition has become one of the major factor to be changed to an Alzheimer's disease at a later stage. The conditions majorly affects cognitive functioning of the body which eventually leads to the decline and dysfunction of the body parts to carry out normal activities. Many significant efforts has been carried out by medical teams and researchers to help in the preventive measures as well as providing medication for such critical conditions.

In this study, we have proposed a combined hybrid approach using electroencephalography (EEG) and eye tracking method to identify important features for the identification of an early stage of dementia which later has 80% chance for progress to Alzheimer's disease. Despite the presence of other imaging technologies which are expensive and not readily available, the use of the two biometric systems (EEG and eye tracking) prove to be a useful alternative to classify the Control group from cognitively impaired group or an early stage of dementia identification.

Acknowledgments

First of all I would like to thank my advisor Dr. Montri Phothisonothai for his supervision, encouragement and guidance in every little step that began since the start of this project. It would not have been possible for this project completion without his incredible support. I would also like to thank my other lecturers who have given me suggestions throughout this period to help improve upon many areas. Also a very special thanks to the elderly members (Subjects) and officials of Suthawas Elderly House Care, Nakhon Nayok, Thailand who devoted their time and contribution for the experiment.

In addition to the professional guidance provided by my lecturers of KMITL, I would also like to express my gratitude to Dr. Suchada Tantisatirapong, Srinakharinwirot University (SWU) for providing her time and ideas throughout this project. My gratitude also goes to Dr. Valentina Ticcinelli who came for 2 weeks to work in our lab and during that time provided her expertise on the project matter. Also, my very special thanks to my friend Ashmin Aryal who helped me with his incredible support and guidance during these two years.

Finally, I would like to mention the emotional support from my parents and family who always encouraged me to work hard, helped me to regain my confidence when I was low and inspired me to move on to strive for better.

Table of Contents

List of Figures

List of Tables

Chapter 1

Introduction

1.1 Background

1.1.1 Dementia

Dementia refers to a condition which is usually characterized by cognitive or memory impairments. The condition is often termed as 'Dementia of Alzheimer type (DAT)' whose characterization includes decline in cognitive and memory loss, inability in understanding words and an inability to do daily activities [1]. DAT is the most common form of dementia found in the elderly population. Research has shown that about 80 % of the people having dementia are most likely to progress having Alzheimer's disease at the later stage of their life [2]. Therefore, an early stage of Alzheimer's disease refers to the current condition of suffering from dementia.

1.1.2 Alzheimer's Disease

Alzheimer's Disease(AD) is a type of dementia that is characterized by gradual decline in cognitive and behavioral activities. The disease initiates it's beginning with the attack on nerve cells that are responsible for carrying out cognitive functions. The most common initial symptom is gradually worsening ability to remember new information. This occurs because the first neurons to be damaged and destroyed are usually in brain regions involved in forming new memories [3]. It eventually progresses to attack in other parts of the nerve cells that disables a person to carry out bodily functions. This leads to inability in eating, swallowing etc. which causes the immune system to function down thus making patients more exposed to infections. Ultimately, at the final stage of the disease the patient suffers from death [3].

Determining the diagnosis for Alzheimer's is very difficult as there has been no single test available. A number of cognitive tests, genetic/medical history, consultation with physicians, neurological specialists are obtained before one can conclude for diagnosis [3]. Medical community have been making a lot of efforts to find a cure to treat the disease completely. In spite of this, there is no complete treatment available. An initial diagnosis can be helpful in terms of precautionary measures such as providing medications and therapies. Also, the patient's family can be able to manage themselves for financial and mental stability as the disease progress for long term in the future [4].

Even with the difficulty to identify the presence of the disease during the earlier stage, many researchers have shown progressive improvement in this regard. Advanced medical imaging with computed tomography (CT) or magnetic resonance imaging (MRI), and with single-photon emission computed tomography (SPECT) or positron emission tomography (PET) are routinely used in clinical practices for newly diagnosed dementia patients. But there is still room for improvement since these technologies are very expensive and not readily available to all the diagnostic centers. In addition the neuroimaging techniques may not be suitable for those patients who have pacemaker or certain implants [5].

1.1.3 Mild Cognitive Impairment

Mild Cognitive Impairment (MCI) is the intermediate stage between the cognitive changes of normal aging and dementia. It is an important stage for cognitive processing because it constitutes a high risk for dementia [6]. MCI is a condition in which an individual has mild but measurable changes in thinking abilities that are noticeable to the person affected and to family members and friends, but they do not show any significant change in a person's ability to perform day to day activities. However, it has been seen that when for people who have MCI involving memory problems, people are more likely to develop Alzheimer's at some later point in life [3]. Sooner the condition regarding MCI is determined, sooner is the medications applied and the person can be less exposed to the risk of being in Alzheimer's disease category.

1.2 Problem Descriptions

For overcoming the financial barriers that withholds the use of expensive technologies like MRI, SPECT etc., many inexpensive and accurate methods have been discovered with the use of Electroencephalography(EEG) data and Eye scanning patterns. These methods are non-invasive and has an advantage of being affordable monitoring systems. It can be economically feasible for many hospitals and research centers to purchase the equipment for the diagnosis.

1.3 Research Objectives

This research comprises using the features of Eye tracking and EEG data in order to categorize the normal/control subjects from the early stage of dementia. The objectives are set as follows:

- To measure if the multimodal approach using two biometric system (EEG and eye tracking) can help in better classifciation of the normal subjects and early onset dementia subjects.
- To identify the key features that connects the presence of early stage of dementia for both EEG and Eye tracking system by analyzing the cognitive features.
- To enhance the effect of using low cost devices like EEG and Eye tracking method to ensure the feasibility of achieving low cost diagnosis system.

1.4 Scope of the Study

This research focuses on classification of the normal subjects from the early onset of dementia subjects. Data acquisition from both the sources EEG and Eye tracking are conducted separately.

1.5 Structure of the thesis

The thesis is organized into seven chapters:

- Chapter 2 provides background knowledge required to understand the basis of the thesis. It includes detailed description about Electroencephalography (EEG), Event Related Potential and Eye tracking systems.

- Chapter 3 provides a thorough understanding of previous related work in this field of study. It covers techniques that were previously used for EEG and eye tracking methods.
- Chapter 4 provides the methodology used in this experiment. It contains the experimental design and devices used during the data collection process.
- Chapter 5 provides the experiment setup, conducted experiment and results discussion. Two experiments (EEG and eye tracking) are covered in this section.
- Chapter 6 provides a brief discussion on the outcome of the results.
- Chapter 7 concludes the thesis and discusses possible future works.

Chapter 2

Background Knowledge

This chapter introduces various notions and concepts that is used in this research. Concise explanation, including fundamental information has been pointed out here.

2.1 Eye Tracking

Eye tracking is a method to measure different eye activities depending on the type of stimulus. It uses sensor technology to follow an individual's gaze and eye movement. The eye tracking device focuses where the person's eyes have been. There has been a numerous advantage on the type of eye tracking systems. Usually eye tracking technology has been helpful in video games, understanding human-machine interaction and in secure password protection systems. Also for the disabled community, such interactive system can help them by asking them to use just use their eye movements for any task. Thus they can replace the need for secondary devices like mouse or keyboard [7].

Studies have been conducted regarding the basic eye movements patterns such as Saccades (Prosaccades/Anti-saccades/Microsaccades), Smooth pursuit, Pupillary responses and Visual search.

- Saccades are fast darting movements of the eyes that shift gaze from one spatial location to another and can be either directed towards a target (Prosaccade) or away from a target (Antisaccade) [8]. The illustration is shown in Fig 2.1 [9].

- Smooth pursuit occurs when the eyes continuously follow or track a moving object [8]. The illustration is provided in Fig 2.2 [9].

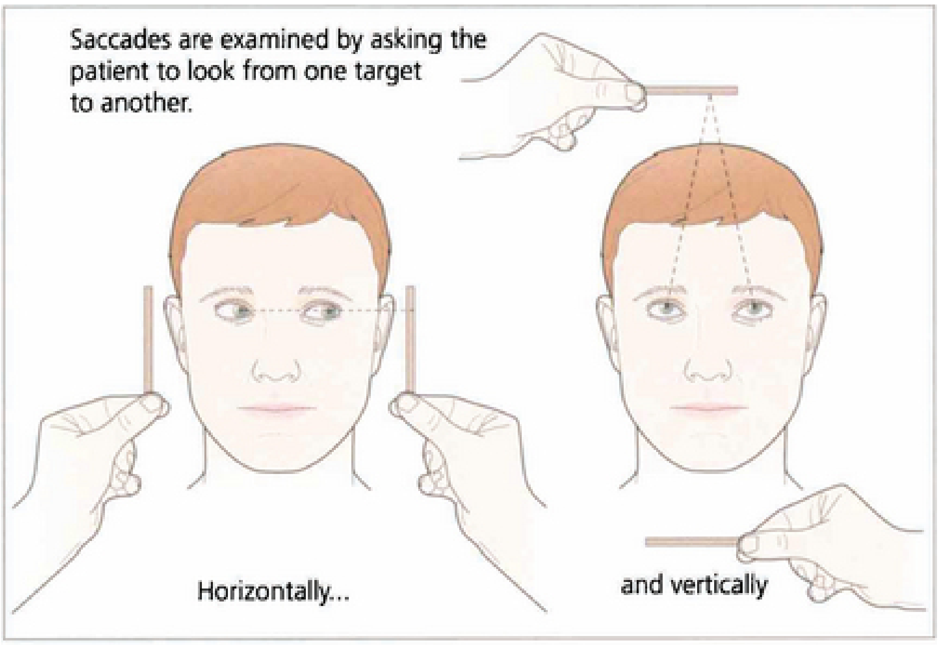


Figure 2.1: Saccades movement [9]

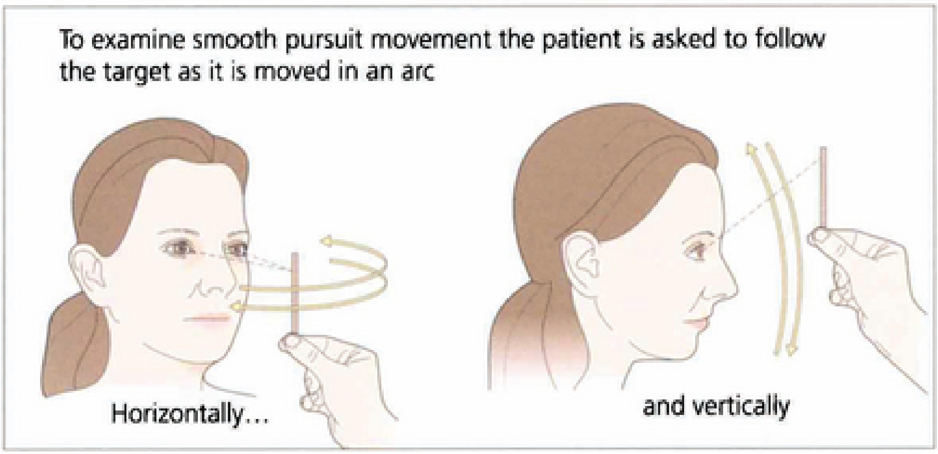


Figure 2.2: Smooth pursuit movement [9]

- Pupillary responses are the minute changes in pupils as dilation and constrictions of the pupil that are affected by central nervous system [8].

- Visual search is a goal directed search for a target object among a number of distractor objects [8]. An example is provided in Fig 2.3 [10].

Eye tracking movements show distinctive and unique behavior among every people. Such be-

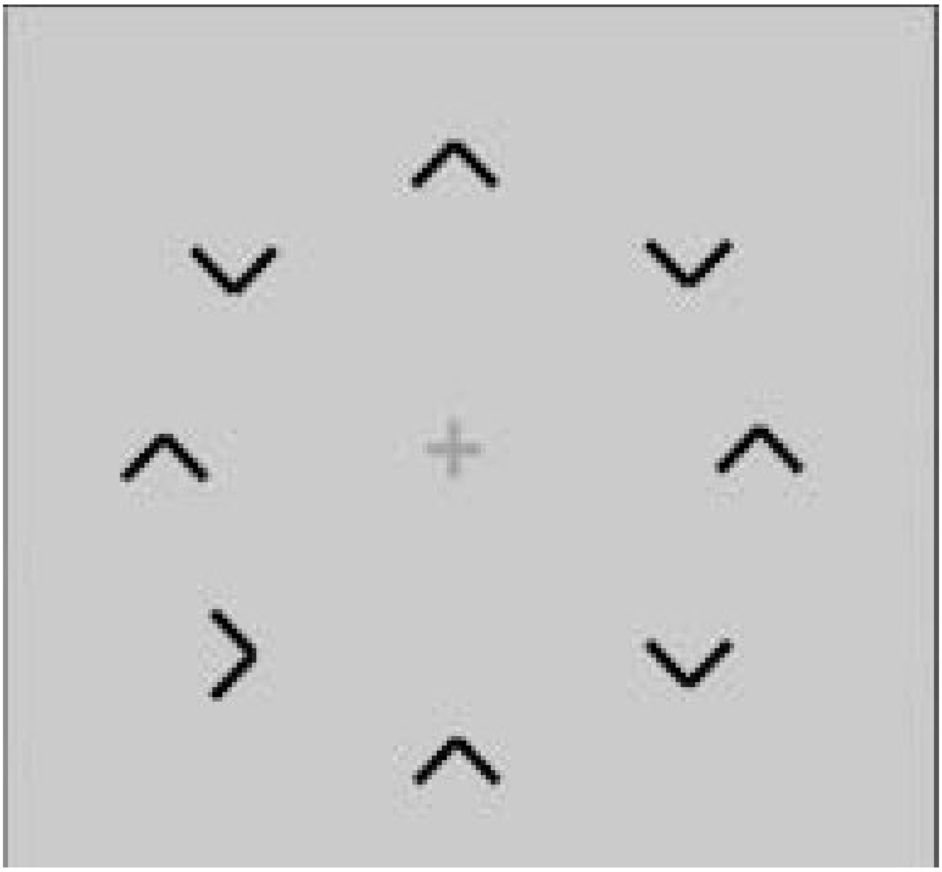


Figure 2.3: Visual Search example [10]

havior has been used for recognition in security systems, tracking of certain medical conditions in people etc. Studies have shown that occulomotor measures like saccades and smooth pursuit are specific among individuals and can even be used for biometric identification [11].

2.2 Electroencephalography (EEG)

Electroencephalography (EEG) is a method to obtain the electrical activity of the brain by placing electrodes on the scalp as per Standard convention of International 10-20 system. It is a non-invasive method. These electric potentials generated on the scalp is the result of multiple activities occurring within the brain. These activities can be any state of mind: Sleeping, resting, performing certain tasks or relaxing etc. The EEG signals are therefore rich with information about cerebral activities [12]. Therefore, they are highly reliable because of the direct measurement of such activities. A basic eeg recording structure is shown in Fig 2.4 [13].

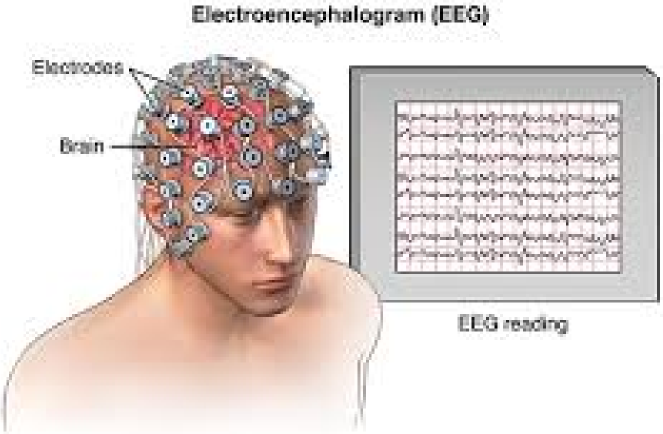


Figure 2.4: A recording of electroencephalography [13]

The high temporal resolution of EEG gives the most precise data with millisecond precision. The physiological information given out by the five different frequency bands (Alpha, Beta, Delta, Theta and Gamma) of EEG can be used for extrapolation of important features. The frequency range of these features is provided in Fig 2.5 [14]. The occurrence of these frequency bands are prominent in different region of the brain depending on the activity. Various medical conditions can be identified with the increase or decrease of the power occurring at these five different frequency bands.

EEG signals are filled with a number of artifacts arising from the various tasks assigned during the study. These artifacts are unwanted signals and does not provide any information to the desired condition under study. Biological signals contain multiple types of the signals caused by different internal mechanisms, such as EOG (electrooculogram) generated by the movement of eyeballs and eyelids and EMG (electromyogram) generated by muscular movements of body parts [15]. In the engineering field, EEG are used practically in brain-computer-interface technology. In those cases, the most serious artifact is ocular related potential, for example, eye movements and eye blinks [15].

Event Related Potential is the measured brain response that is the direct result of a specific sensory, cognitive, or motor event [16]. ERPs are scalp recorded voltage fluctuations that are time-locked to an event. These events/stimulus can be visual, auditory, olfactory etc. The ERP amplitude is usually smaller than the amplitude of background EEG so that the reliable ERP is obtained by averaging EEG fragments in multiple trials [17].

ERP studies usually comprises of oddball paradigm which is a behavioural task and is used for

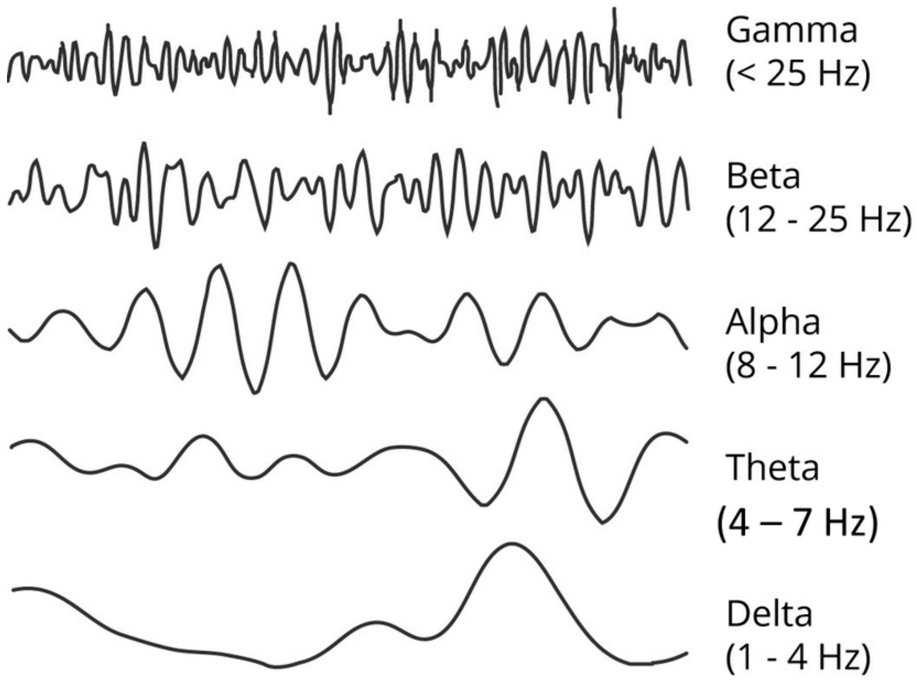


Figure 2.5: Frequency bands of EEG signal [14]

cognitive and attention measurement [18]. These paradigm helps to produce specific ERP component [19]. The statistical analysis of these values gives the significance of the ERP components for the condition that is being examined.

Chapter 3

Literature Review

This chapter is devoted for literature review, which includes past studies, related works and theories that involve in this research. Detailed information can be found in following sections.

3.1 Eye Tracking

Eye tracking provides a convenient and promising biological marker of cognitive impairment in patients with neurodegenerative disease such as Alzheimer's disease [20]. Fundamental ocular functions and viewing behavior are altered by AD. Since there is an intimate link between eye movements and cognition, changes in eye movement patterns can be used to infer AD related changes in cognitive processing. The basic eye movements patterns and their significance on cognitive impairment have been studied.

Numerous studies have shown that compared with healthy controls, patients show increased latency to initiate prosaccades and have lower prosaccade velocity and accuracy. Also, like other prosaccade test, participants in the gap/overlap task are required to prosaccade to a peripheral target [8]. Patients also show increased latency when executing antisaccade and making corrective saccades following an error. The result of both prosaccades and antisaccade is correlated with neuropsychological test scores including Mini-Mental State exam (MMSE) [8]. Patients with AD have smooth pursuit impairments like their saccadic dysfunctions. They show an increased latency to initiate smooth pursuit, lower initial acceleration, decreased velocity and decreased gain (Ratio of pursuit velocity to target velocity) [8].

Larry et al. studied changes in visual fixation and saccadic eye movements in Alzheimer's disease and has found that AD patients show increased latency to initiation of saccades at follow-up than at baseline [21]. William et al. studied dysfunction in the saccadic eye movements in Alzheimer's Disease and reported that latency of saccades were prolonged only when the visual target timing could not be predicted. Also, peak saccadic velocities were significantly slowed in patients with AD when the target timing was random [22]. Dmitry et al. used Visual Paired Comparison task which is a recognition memory test for the detection of memory impairments associated with MCI. For this paper some novel and repeated images were used to understand the movement behavior. They have applied various machine learning methods for the automatic detection of cognitive impairment and concluded Support Vector Machine (SVM) classified with accuracy of 87%, sensitivity of 97% and specificity of 77% [23].

Apart from basic oculomotor functions, AD patients have also been examined in regard to complex viewing behavior. It is reported that compared to healthy controls, patients are less accurate and have longer response times in visual search tasks [8]. Patients' eye movement patterns during visual search have been characterized as disorganized and stochastic along with longer duration of fixations while searching. Even though the patients can find search target they still have longer response times which reflects slower processing time in AD patients. In addition, studies have reported that patients with AD have been found to direct attention away from stimuli and allocate more eye movements to non-stimulus areas than control [8].

Basic oculomotor metrics was calculated for normal individuals and Alzheimer's subjects by Pavisic et al. The results confirmed that patients have abnormal eye movement patterns in fixation stability, saccades and smooth pursuit tasks compared to age-matched healthy controls [24]. Significant correlations between eye tracking metrics and standard visual cognitive estimates are reported. Nebes et al. study found that as dementia severity increased, so did the magnitude of slowing of the reaction time [25]. These studies confirms that eye tracking can be a very reliable and easy solution for the diagnostic phase of Alzheimer's disease.

3.2 Electroencephalography

Studies have shown that AD has at least three major effects on EEG: Slowing of the EEG, Reduced complexity of the EEG signals and perturbations in EEG synchrony. Summarizing study of these three effects, the conclusion states that EEG of MCI and AD patients seems to be more regular (reduced complexity) than of age-matched control subjects. AD is associated with increase of power in low frequencies and decrease of power in higher frequencies. Also, there is reduced statistical dependency between the EEG signals from different channels in MCI and AD patients [26].

Numerous studies have been conducted for detection of AD during resting state condition as the procedure is easier and does not require stimulation devices. When compared to resting state EEG rhythms of healthy normal elderly (Nold) subjects, AD patients showed an amplitude increase of widespread delta and theta sources and an amplitude decrease of posterior alpha (8- 13 Hz) and/or beta (13 - 30 Hz) sources confirming to the previous study [27]. However one study by Francisco et al. have concluded that the lack of Alpha rhythm discriminate mild AD much better than those presenting richer alpha content which is in contrast to the other studies [28].

Similarly, studies conducted with resting state EEG rhythms and MCI have demonstrated that increased delta/theta activity, decreased alpha and beta, and slowed mean frequency may be predictors of progression from MCI to dementia [29]. Apart from the resting state, EEG recordings can be performed in other conditions as well: While the subject is at rest (with open or closed eyes); While the subject performs working-memory or other tasks; While the subject is being stimulated with auditory, visual, tactile or other signals [26]. The different recording conditions may also lead to fine distinctions for MCI and AD. Study about components like N100, P200 and N200 components did not reach a statistical difference [30]. Findings from Gozke et al. using visual ERPs revealed that mean N200 and P300 latencies of mild cognitive impairment group were significantly longer than controls. However, no significant difference was observed between the two groups with respect to N200 amplitudes [31].

Geoffrey et al. utilized two methods for the detection of dementia using EEG. He proposed fractal dimension method for analyzing the EEG waveforms which demonstrates that appropriate fractal dimension could achieve 67% sensitivity to probable AD with specificity of 99.9%. Another method used was probability density function of the zero-crossing intervals to achieve 78% sensitivity to probable AD [32]. Santosh et al. present a method for differentiating AD patients from healthy ones based on their EEG signals using Benford's law and SVM with a Radial Basis Function (RBF) kernel [33]. Another review study by Noor et al. summarise that the effects of dementia on AD can be slowing and reducing of EEG complexity and synchrony. The author suggest SVM classifier as a suitable technique for classification of features of EEG signals [34].

Chapter 4

Methodology

This chapter introduces the methods used and conducted in this study.

4.1 Stimulus

In the proposed experiment, a stimuli regarding visual behavior is proposed and presented to the subjects. The stimuli presented to the subjects is categorized into three types: i.e., 1) Saccadic movement 2) Smooth Pursuit movement and 3) Face Recognition. For both the EEG and Eye tracking method, the experiment's visual stimuli is different but the type of eye movement behavior is the same. It is done so that the subject may not feel fatigue by looking at the same eye movement in both phases of the experiment.

4.1.1 Eye tracking

For the Saccadic experiment in our system, a circular object is initially shown at the center of the display monitor. The object stays at the center point location initially for 2 seconds. It then moves on to random direction in every 1 second. The range of the random direction is about 9 degrees top, bottom, left and right. The subject need to fix their gaze at the moving target object until the program halts with a message to stop their gaze focus and relax. This process is repeated two times for one subject. The illustration is provided in Fig 4.1.

For the Smooth pursuit task, an object is initially shown at the center of the screen for 2 seconds.

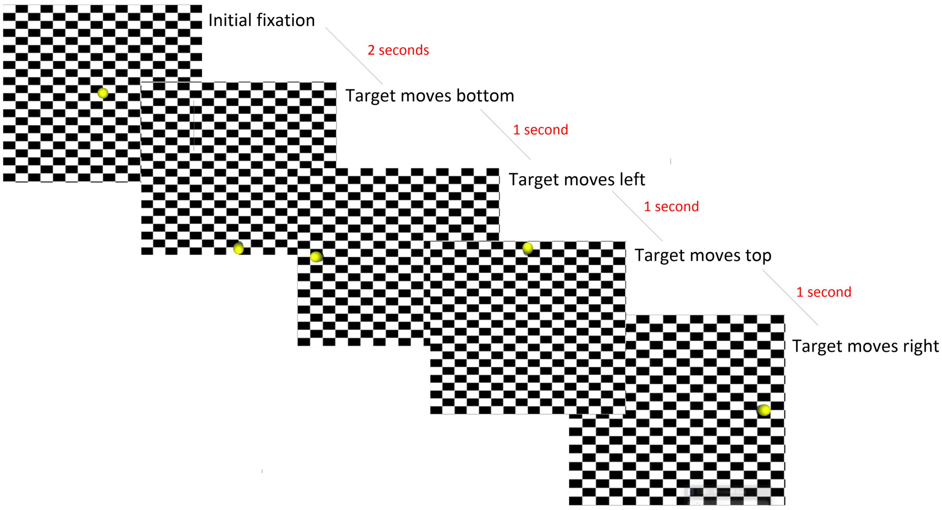


Figure 4.1: Saccadic movement in random 4 directions (top, bottom, left and right)

It is then moved towards the right side of the display device. Taking that extremity point as an initial value, the object starts making an elliptical motion. The elliptical motion is random. It moves up to a certain point in clockwise direction and again in anti-clockwise direction. Similar to the saccadic experiment, the subject need to fix their gaze and follow the moving target object. This process is also repeated two times for one subject. The illustration is provided in Fig 4.2.

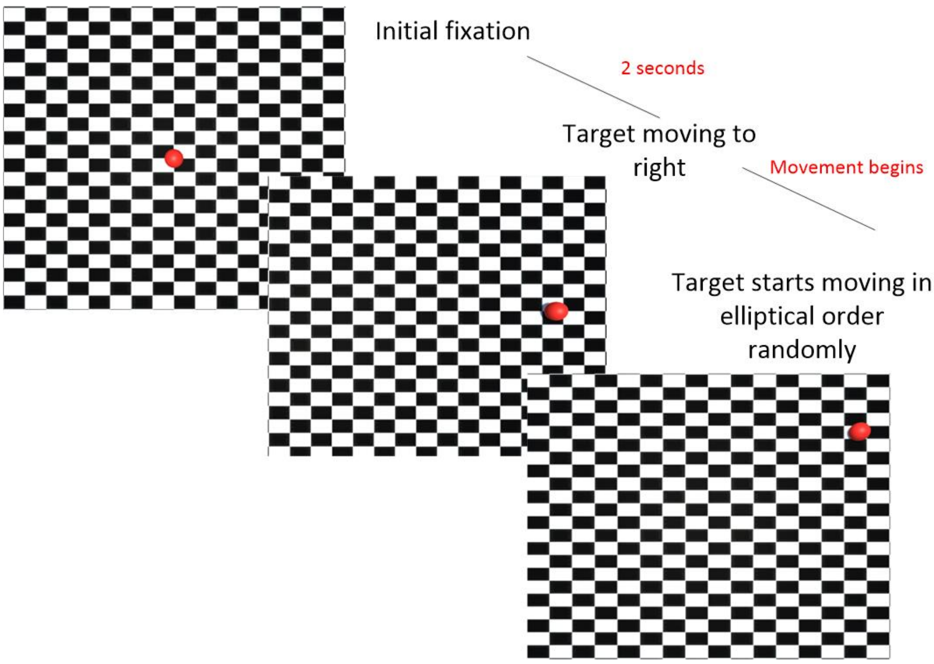


Figure 4.2: Smooth movement in elliptical order

Finally, for the face learning and recognition task, sample of images is taken from Karolinska

Directed Emotional Faces (KDEF) dataset. KDEF is a public database used for psychological and medical research purposes. There are two phases for face recognition: Learning and recognition. For learning phase, 10 images are shown to the subjects. Each image is displayed for 5000 ms with an interval of 2000 ms as a break to position the subject's eye at the center of the screen. During the 2000 ms interval a fixation point is displayed at the center of the screen. The placement of these images is randomized towards either left or right from the center of the screen. The intent of this learning of images is to know about their eye movements and what kind of features in the face do they look upon to remember the image.

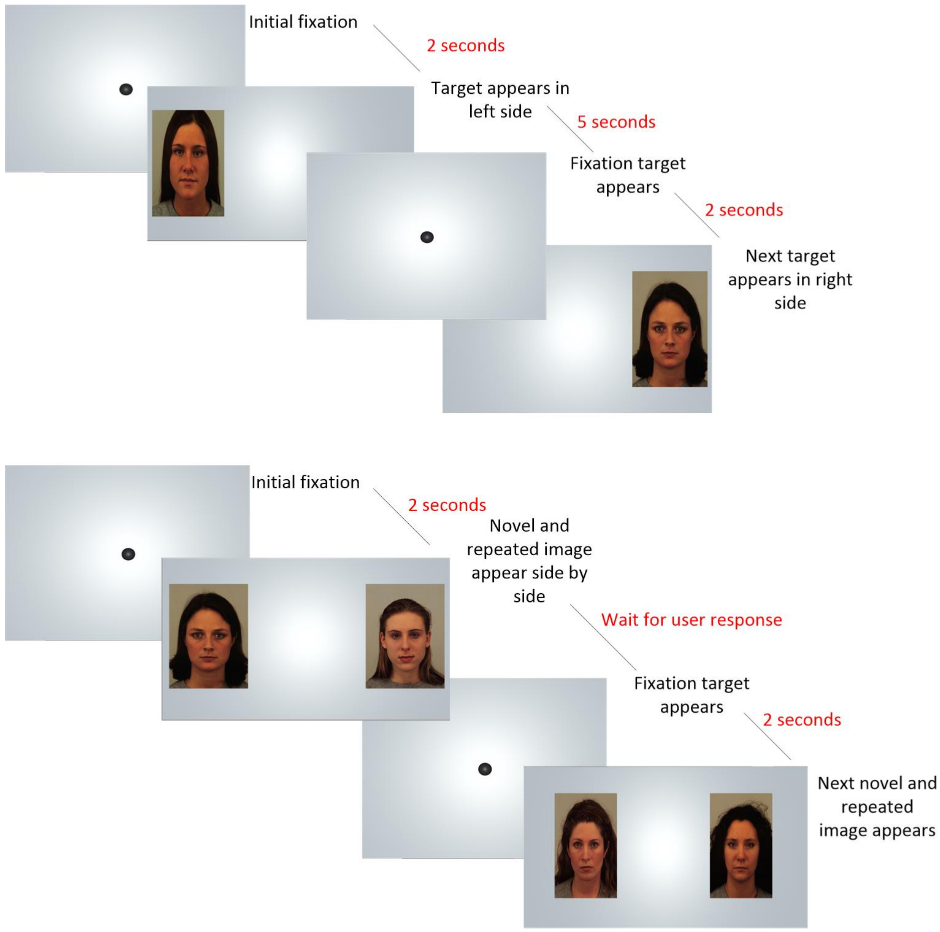


Figure 4.3: Face learning and Recognition

For recognition phase, 20 images (Among which 10 images are from learning phase and rest Novel images) is shown to the subjects. Subjects are instructed to confirm if the image was previously presented or not. The stimulus (image) will remain on the screen until the subject responds by pressing the button and move on to next stimulus (image) once the choice has been made. The illustration process for both the learning and recognition phase is shown in Fig 4.3.

Device: The device used to record eye tracking points is Tobii. It uses sensor technology to capture the eye movements direction. The Tobii Unity Software Development Kit (SDK)[1] provided by Tobii is compatible to be used with Unity for designing platform and Visual Studio for coding platform to develop custom applications. Therefore, we were able to track the gaze points (x and y coordinates) to ensure where the user is looking at what particular timestamp. The device is attached to the monitor to ensure that it's position is static. The device is shown in Fig 4.4 [35].

Figure 4.4: Eye tracker device [35]

4.1.2 EEG

For the Saccadic experiment in EEG, a circular object moves at different position on the screen. It's movement is completely random and unlike the saccadic movement of Eye tracking, it does not limit itself to 4 different position (top, right, bottom and left) of the screen as shown in Figure 4.1. The subject had to focus their attention on the places where these objects would appear. The sample of the movement is shown in Fig 4.5.

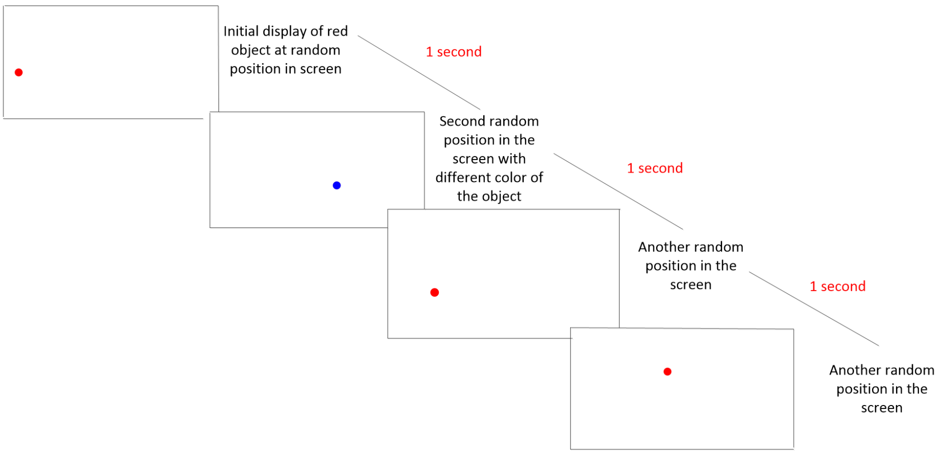


Figure 4.5: Saccadic movement in random directions

[1]SDK to implement eye tracking in Unity applications

For the Smooth pursuit task, a rectangular object moves towards left and right of the screen with a fixed axis. It changes it's color during the movement so that the subject will not feel tiresome during the experimentation process. The illustration is provided in Fig 4.6.

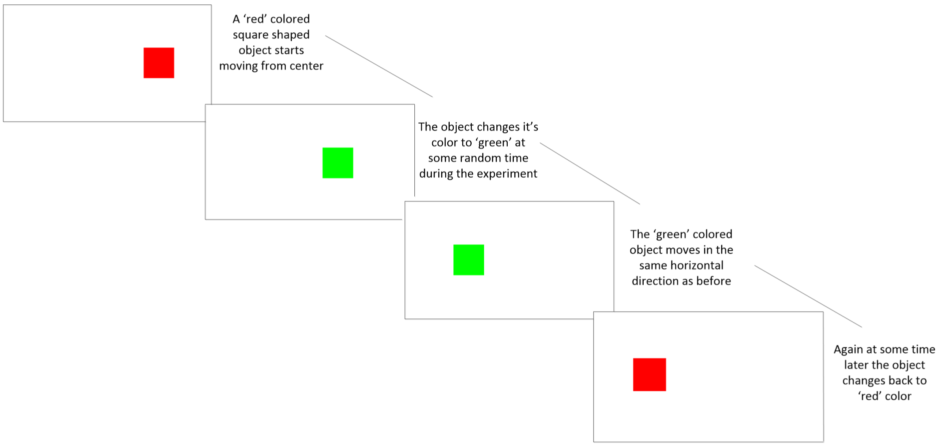


Figure 4.6: Smooth movement in horizontal directions

The face recognition task is the same as used for eye tracking. The subjects need to memorize the figure and identify the image in the recognition process. The illustration is provided in Fig 4.3.

Device: The device used to record EEG recordings is Bioradio ™(Great Lakes Neuro Technologies, OH, USA). It is a wearable device that acquires physiological data like ECG, EMG, EEG etc. This device can be programmed for 8 channels of EEG signal. It offers an application software BioCapture and a Software Development Kit (SDK) which is compatible with MATLAB to develop a custom application based on the needs of the user. For this experiment, this SDK has been utilized to stream the real time data obtained from the event related potential experiment. General function of the device is shown below in Fig 4.7 [36].

4.2 System workflow

The visual systems that are designed and explained above are proposed as a method to capture eye tracking information conducted from different visual tasks. The system workflow of the proposed method is provided in Fig 4.8.

Figure 4.7: Bioradio device [36]

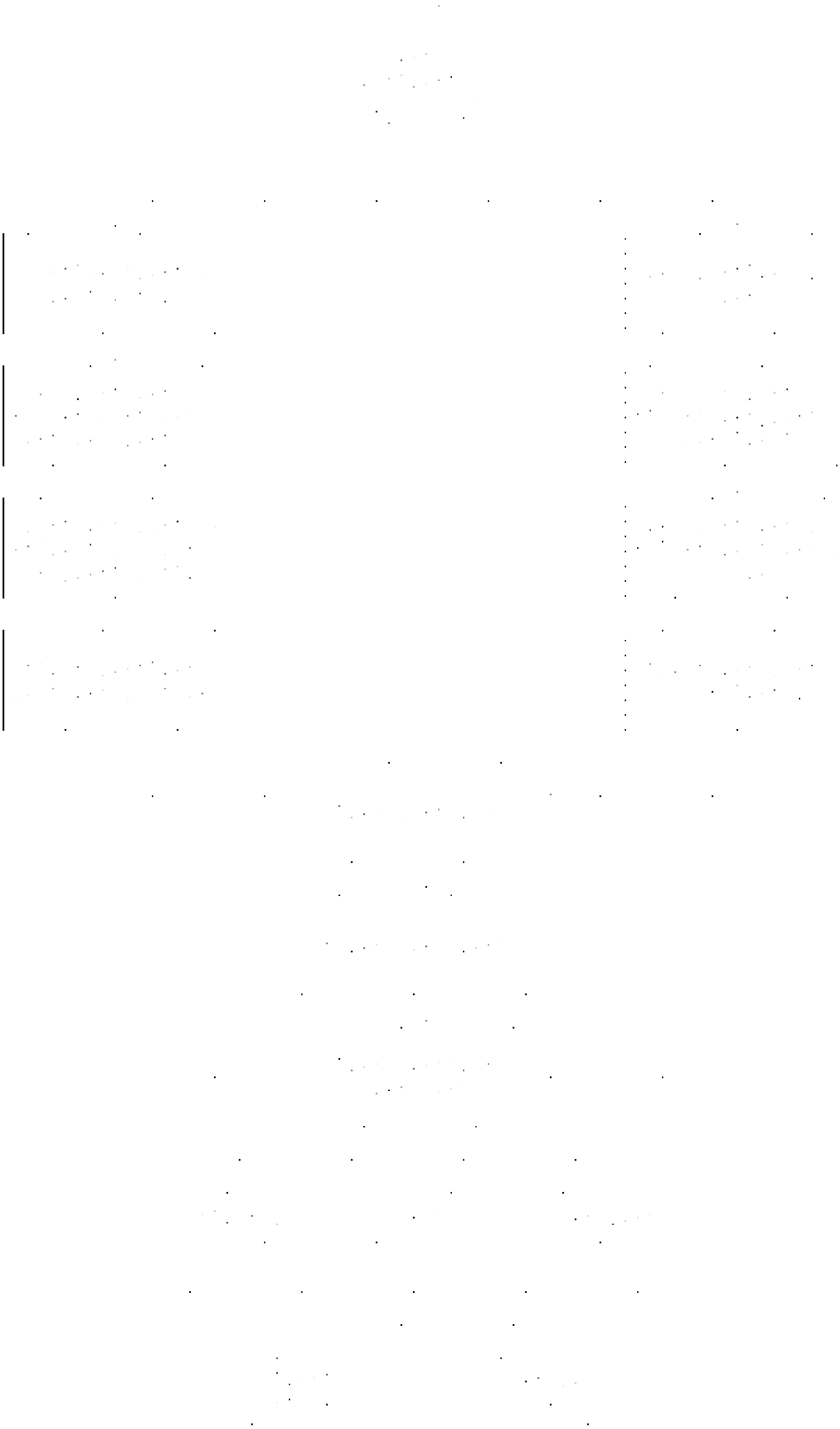


Figure 4.8: System overview of the proposed method

Chapter 5

Experimentation and Results

First, in this section, there will be explanation and list of environment and development tools used in this research. The results achieved in the experiment are summarized and discussed.

5.1 Development Environment

Processor	Intel(R) Core(TM) i7-6500U CPU @ 2.50GHz, 2 Core(s), 4 Logical Processor(s)
Physical Memory Capacity	8.0 GB
Operating System	Microsoft Windows 10 Pro
Screen resolution	1920 * 1080

Table 5.1: Specifications of the experimental computer

The stimuli preparation was done in both Unity and MATLAB. For eye tracking, Tobii Eye tracker's SDK was used for preparing stimuli using Unity as a development platform. For EEG, Bioradio SDK was used in MATLAB environment for preparing the stimuli. Both the experiments were placed in a computer with the specifications provided in Table 5.1.

5.2 Subjects

The data collection was done in Suthawas Elderly House Care situated at 999 Khrongkan Ban Khlong Om Mu 9 Rd, Tambon Sai Mun, Amphoe Ongkharak, Chang Wat Nakhon Nayok 26120, Thailand after the approval of research ethics. The total participant for the experiment were 15. A detailed description is provided in Table 5.2.

Condition	Number of subjects		Age (mean $\pm$ std.dev [years])		
	Female	Male	Female	Male	Total
Control	7	1	70.8571 ± 11.4372	57.00	8
Dementia	7	0	71.7142 ± 10.6099	0	7

Table 5.2: Subject's description

For additional verification purpose, Mini-Mental State Exam (MMSE) was conducted. MMSE is a widely used test to detect various cognitive functional abilities among the elderly group to detect their strength of cognitive behavior. It combines tests of orientation, attention, memory, language and visual-spatial skills [37]. It is commonly used as a part of process for diagnosis of dementia. It is a paper based test which has a maximum score of 30 with lower score indicative of more severe cognitive problems [38]. The Fig 5.1 shows the MMSE test being conducted for the subjects at the elderly care.

Figure 5.1: Mini-Mental State Exam (MMSE) test being taken for the subjects

5.3 Experiment 1: Eye tracking classification

5.3.1 Objective

This experiment is conducted to measure the cognitive abilities of people based on their eye movement patterns. Research has shown that every human perceive objects and system behavior with different observing patterns. These different perceiving of eye movement patterns is used as a tool to identify the cognitive behavior.

5.3.2 Experiment Setup

The subjects were asked to be seated comfortably at about 60cm distance from the monitor screen. The lightning and the temperature of the room was kept consistent across all the subjects. The Tobii device was well-mounted on the computer screen. Initially, for every different subject a calibration was done to check and improve the performance accuracy of the eye tracker. The calibration toolbox requires to enter the user information. It then proceeds to adjust the calibration as per different user. There are a total of 9 calibration points. These points have a fixed radius of dotted circles outside them. The subject needs to look at these 9 points and ensure that their gaze points lies within the dotted circles for good calibration. Once, they are calibrated the experiment can begin. The subject needs to just sit in that position and follow the experimental procedure. Since they might get fatigued, their position might change at the end of experiment. Calibration can be done again after completing one set of experiment to ensure the position of the subject is well-adjusted with respect to the computer screen. A demonstration of the experiment is shown below in Fig 5.2.

5.4 Experiment 2: Electroencephalography (EEG)

5.4.1 Objective

This experiment is conducted to measure the cognitive abilities of people based on their EEG features. Since EEG has been used before for the analysis and classification of various medical

Figure 5.2: Subject performing Face learning experiment

conditions, this experiment focuses to identify specific features for the evaluation of cognitive behavior.

5.4.2 Experiment Setup

The subjects were placed with electrodes on 4 locations on their scalp. A general outline of the structure of different positions of the electrode is shown in Fig 5.3 where the positions that have been used in the experiment is highlighted in red circles [14]. The Fp1 and Fp2 indicates Pre-frontal positions and O1 and O2 represent the Occipital positions. The odd numbers indicate position on the left and even numbers indicate position on the right side of the electrodes placement.

Before we adjusted the positions of different electrodes we had to make sure that there are no impurities on their surface. The electrodes location site was first cleaned with alcohol wipes and Nuprep skin prep gel to get rid of dirt and oil content. The position of the two electrodes was placed at the frontal region and two electrodes at the occipital region. After the surface was clean and dry the Gold cup electrodes were filled with Ten20 conductive EEG paste and placed in these locations. Also, the ground electrode was placed between the two frontal electrodes (FpZ) on the forehead. The reference was connected to the earlobe. A demonstration is shown below in Fig 5.4. Initially to check if all the electrodes are working and giving a normal EEG wave, it was confirmed by looking at the output obtained from BioCapture application program. It is an application software

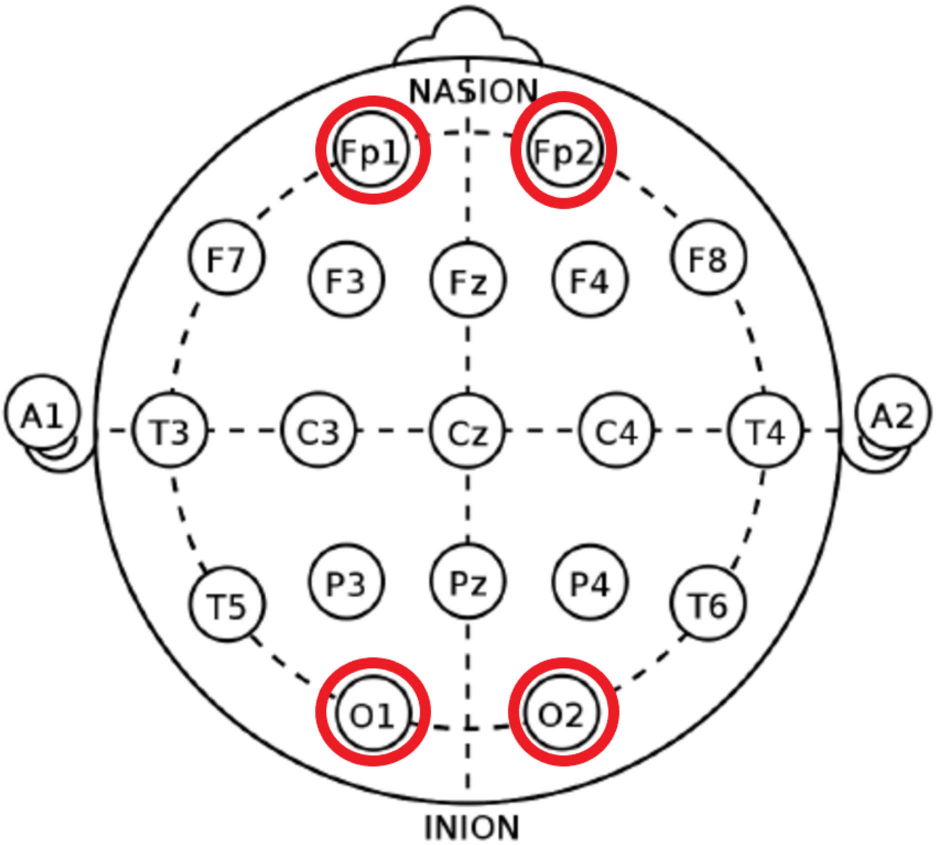


Figure 5.3: Standard 10-20 electrode system [40]

provided by the Bioradio manufacturer. Once the graph was obtained from the desired electrodes, the experiment began.

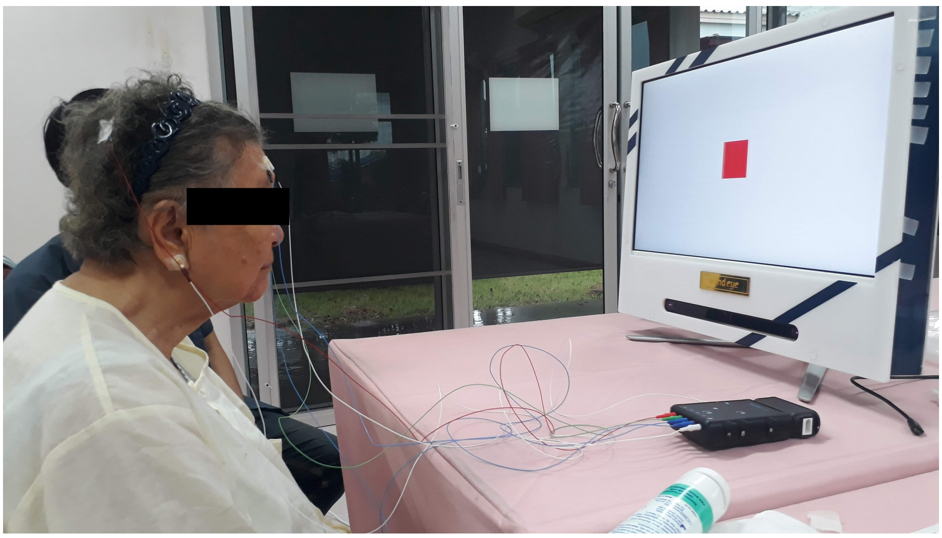


Figure 5.4: Subject performing the EEG experiment task

5.5 Analysis

5.5.1 Eye tracking data

The data obtained from the experiments of eye tracking was first processed using EyeMMV toolbox. It is a toolbox used for post experimental eye movement analysis [39]. The toolbox requires MATLAB environment for it's execution. It is open source and it can filter out noise while checking the samples of raw data [40].

Dispersion-Threshold Identification (I-DT) Dispersion-threshold identification (I-DT) is a method which states that since the fixation points have low velocity, they tend to form a cluster [41]. It identifies fixation as a group of consecutive points within a particular dispersion or a maximum separation. Due to the reason that fixation lasts for a duration of 100ms, the I-DT algorithms generally have a minimum duration threshold of 100-200 ms to consider account for equipment variability [42]. The pseudocode for I-DT algorithm is provided below [42].

Algorithm 1 I-DT algorithm

```
while there are still points, do
    Initialize window over first points to cover the duration threshold
    if dispersion of window points is less than or equal to threshold then
        Add additional points to the window until dispersion is greater than threshold
        Note a fixation at the centroid of the window points
        Remove window points from points
    else
        Remove first points from points
return fixations
```

The identification of fixations in the toolbox utilizes this concept of I-DT (dispersion-based) detection algorithms while making some modification with the introduction of spatial and temporal constraints [39]. In the EyeMMV toolbox, the fixation detection algorithm uses two spatial parameters and one temporal constraint. The first spatial parameter (t1) is the spatial range used for computation of fixations. t1 indicates maximum distance a point can have from the center of cluster. The second spatial parameter (t2) value can be defined in the case that the level of noise has been reported and measured in the eye tracking device. The temporal parameter (minimum duration) indicates a threshold point to be considered for fixation. Usually depending on the equipment variability, the minimum duration threshold is taken from 100-200ms [42]. The implementation of second spatial parameter is used to remove the noise of eye tracking data. For getting the fixation points, the following method is implemented in the toolbox [39].

1. Beginning from the first record obtained from the data, the mean points of horizontal (x) and vertical (y) coordinate is calculated. Then euclidean distance is computed between the mean point (x_{mean}, y_{mean}) and a record.

$$distance = \sqrt{(x_{\text{mean}} - x_i)^2 + (y_{\text{mean}} - y_i)^2}, \tag{5.1}$$

   where i = 1 to length of data samples.
   Until the euclidean distance is found to be greater than the first spatial parameter t1, every record is included to make a fixation cluster. The records which does not satisfy this condition is excluded and it proceeds on for formation of another fixation cluster.

2. After performing t1 criteria, the euclidean distance between the mean points of the cluster is computed with every records in that cluster.
   If the distance is found to be greater than the second spatial parameter t2, then that record is not considered and removed from that cluster. After every record in the cluster satisfy this criteria, fixation coordinates is computed as the mean value of the cluster.

3. Finally, the duration of fixation is evaluated by taking the difference of passing times between first record of the cluster and last record of the cluster. If this duration is less than minimum threshold, the cluster is removed.

A general representation of the input and output of the system is given in Figure 5.5 [39]

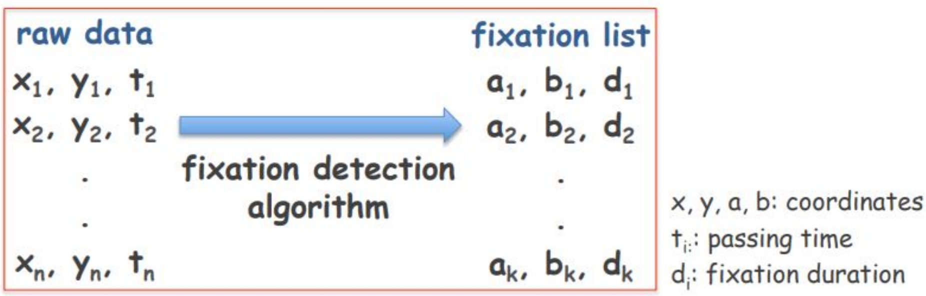


Figure 5.5: General data input/output after applying fixation detection algorithm [39]

By providing the spatial and temporal constraints, the following features were identified from the eye tracking data. These features have significance in terms of cognitive processing abilities and have been used as an important metric to study the effects of cognitive impairments in eye movement data.

- Total number of fixations - It is the total number of fixations performed by a subject in the region of interest during the period of experiment. Studies have shown that cognitive processing affects the fixational patterns [8]. It is calculated from the fixation list obtained after applying the algorithm as seen in Figure 5.5.

- Mean duration of fixations - It is the average of the total duration of fixations. For a visual search tasks, it can be seen that higher the duration of fixation, higher is the time the subject is taking to analyze the target on the screen. It is calculated from Step 3 of the fixation detection algorithm.

$$\text{Mean duration of fixations} = \frac{\sum \text{Total fixation duration in AOI}}{\text{Total number of fixations}} \tag{5.2}$$

- Total number of saccades - It is the total number of saccades obtained in the region of interest during the period of experiment. It indicates the amount of visual search on a display. Saccadic movements can be random if the subject is not able to focus clearly on the target due to the cognitive disability. It is calculated from Step 3 of the fixation detection algorithm by observing the eye movements occurring between fixations.

- Mean duration of saccades - It is the average of the total duration of saccadic movement. It has been found that saccades performed in dementia and alzheimer's subjects do not reach the target [8]. This indicates that cognitive impairment leads to an inability to disengage the visual attention from one target area to another.

$$\text{Mean duration of saccades} = \frac{\sum \text{Total saccadic duration in AOI}}{\text{Total number of saccades}} \tag{5.3}$$

- Mean saccadic amplitude - It is the average of the angular distance travelled by the eye during such saccadic movements [43]. There has been conflicting findings for the study of this metric and an explanation for such conflicts have been seen as the variation of condition severity [8].

$$\text{Saccadic amplitude} = \frac{\sum \text{Distance between consecutive fixations}}{\text{Number of fixations} - 1} \tag{5.4}$$

- Saccades/Fixation ratio (SF ratio) - It is the ratio which compares the time spent processing saccades component representations to the time spent processing fixation component [43]. Higher value indicate that the subject take time to search for the target than to be able to fixate or process the target.

$$\text{SF ratio} = \frac{\text{Total saccade time (Search time)}}{\text{Total fixation time (Processing time)}} \tag{5.5}$$

- Spatial density - It refers to the coverage of an interface due to search and processing of gazepoint samples [44].

$$\text{Spatial density} = \frac{\sum_{i=1}^{n} c_{\mathrm{i}}}{n^2} \tag{5.6}$$

  where, n is the number of cells in the grid,
  If the stimulus is considered as a layout of grid, the value of c_i is 1 if the cell i is visited and 0 otherwise [43].

- Transition matrix - It is the metric which measures the frequency of eye movement transitions between defined areas of interest [43]. If the value is higher, it indicate extensive search with inefficient scanning [43]. This concept can be used to check the difference in search pattern seen between the dementia and control groups.

$$\text{Transition matrix} = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} c_{\mathrm{i,j}}}{n^2} \tag{5.7}$$

  where, n is the number of fixations in the area of interest (AOI), c_i is 1 if the Area of Interest (AOI) is visited and 0 otherwise [43].

To verify if the pattern of eye movement was per the visual stimulus, we applied the fixation detection algorithm as mentioned above. The figure 5.6 corresponds to the graph obtained after applying the algorithm. The maximum margin needed to be analysed is shown for x-axis, the horizontal resolution of the screen (1920) and for y-axis, the vertical resolution of the screen (1080). The red colored horizontal line corresponding to (0,0) indicates the minimum level of area where the fixation points need to be detected. The blue color represents the raw data and the plus'+' sign in red color represents the fixation centers obtained after the use of fixation detection algorithm. The green circles represents the points which are out of the area of interest and are not used for the analysis.

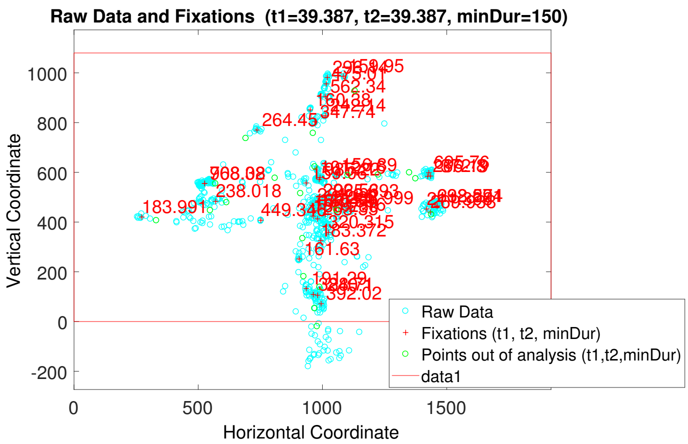


Figure 5.6: Fixation detection points in Saccadic movement

The fixation detection algorithm applied for the smooth pursuit movements is shown in Fig 5.7. We can see the points following a pattern same as that shown in the stimulus. Since, the stimulus corresponded to a fixation at the center and then following half of an elliptical motion, we can see the fixation points being detected at that region.

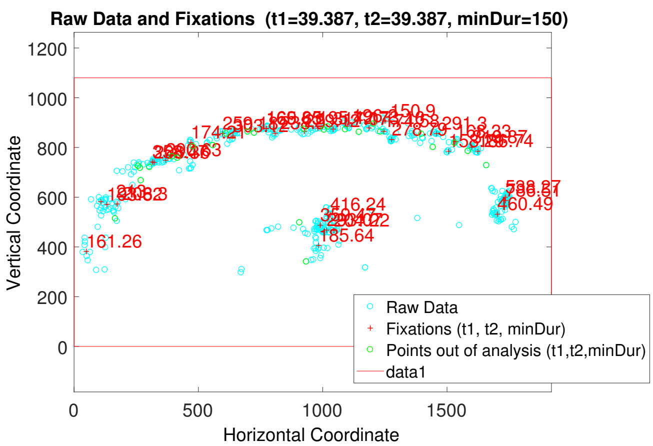


Figure 5.7: Fixation detection points in Smooth pursuit movement

Boruta Algorithm: For this research, we have used Boruta algorithm for the feature selection process. It works as a wrapper algorithm built around random forest. The random forest algorithm can give an estimate of the feature importance [45]. It is an ensemble based method where voting of multiple unbiased weak classifiers is done for classification. The Z score is used as a metric to determine feature importance and is calculated by diving the average loss by its standard deviation [45]. Thus, it compares the Z score of original and shadow features for every iteration. The feature is marked as important if the original features seems to perform better than the shadow feature. The pseudocode for Boruta algorithm is provided below [46]:

Algorithm 2 Boruta algorithm

Input: *originalData* - input dataset; *RFruns* - the number of random forest runs

Output: *finalSet* that contains relevant and irrelevant features

confirmedSet: ∅

rejectedSet: ∅

```
for each RFruns do
    originalPredictors ← originalData(predictors)
    shadowAttr ← permute(originalPredictors)
    extendedPredictors ← cbind(originalPredictors, shadowAttr)
    extendedData ← cbind(extendedPredictors, originalData(decisions))
    zScoreSet ← randomForest(extendedData)
    MZSA ← max(zScoreSet(shadowAttr))
    for each a ∈ originalPredictors do
        if zScoreSet(a) > MZSA then
            hit(a) ++
        end if
    end for
end for
for each a ∈ originalPredictors do
    significance(a) ← twoSidedEqualityTest(a)
    if significance(a) » MZSA then
        confirmedSet ← finalSet ∪ a
    else if significance(a) « MZSA then
        rejectedSet ← rejectedSet ∪ a
    end if
return finalSet ← rejectedSet ∪ confirmedSet
```

In the boxplot of Fig 5.8, we can see the Z-scores of all the attributes. Here, the blue box plot is labelled as shadow feature and is considered as benchmark for identifying how important and unimportant other attributes are. Ideally, the shadow attribute should not have any importance and usually has the value close to 0. The 3 blue box plots are labelled as minimum, mean and maximum importance for the shadow attribute. The 5 green plots are confirmed by boruta algorithm as important and the 2 red box plots are unimportant attributes and are rejected. The 1 yellow box plot is considered as attribute with tentative importance. To confirm the importance of this tentative attribute another function *TentativeRoughFix* from boruta package was applied which verified the attribute as important.

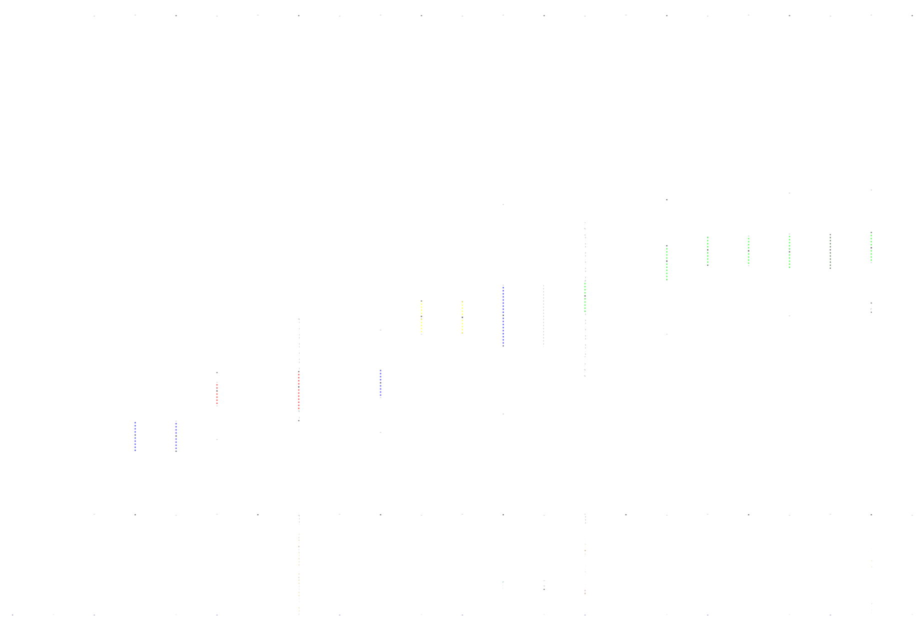


Figure 5.8: Boruta boxplot for eye tracking data

Applying boruta algorithm on the above features, it confirmed 6 features or independent variables as important for the classification and 2 features as unimportant. Therefore, we chose to do the classification with the 6 features. Finally the features that were used for the classification of eye tracking data were:

1. Total number of fixations
2. Mean duration of fixation
3. Total number of saccades
4. Mean saccadic duration

5. Saccades/Fixation ratio

6. Transition matrix

Due to the limited number of subjects with dementia, the data obtained for the experiments were limited. Therefore, to verify the classification procedure, Leave One Out Cross Validation method was used. Generally, cross validation refers to a statistical method to evaluate and compare learning algorithms by diving the data into two segments: Learn from one segment and validate from other segment [47].

Leave-One-Out Cross-Validation: Leave-One-Out Cross-validation (LOOCV) refers to the special kind of k-fold cross validation, where k equals to the number of instances in the entire dataset [47]. It takes all the instances except for one as training set in each iteration. For the test set, the single data is used. It's usage is considered to be suitable for cases where very few data instances are available such as in bioinformatics (A branch of science which combines biology and statistics or mathematical models to interpret the meaning of biological data). LOOCV was applied to the eye tracking dataset features with three different classifiers being tested.

For the eye tracking classification purpose we applied Support Vector Machine (SVM), Generalized Linear model (Logistic regression) and Naive Bayes classifier was with 6 input features. A detailed explanation of the classifier is provided at the final section of this chapter.

The performance of the classifier is given in Table 5.3.

Performance	**Classifier**		
	SVM Linear	GLM (Logistic)	Naive Bayes
Accuracy	**76.92**	73.07	71.15
Kappa	**0.65**	0.53	0.45

Table 5.3: Performance metric of classifiers on the eye tracking data

From the Table 5.3, we can see that the performance matrix shows the accuracy of SVM Linear to be higher with higher kappa value as well compared to the other classifiers.

Accuracy refers to the measure of how often a classifier is correct in it's predictions. It is generally evaluated by observing Confusion matrix as shown in Table 5.4. A Confusion matrix is a table that displays the output of the model predictions with the actual values [48].

<table>
<tr><th colspan="2">Confusion matrix</th><th colspan="2">Predicted</th></tr>
<tr><th colspan="2"></th><th>No</th><th>Yes</th></tr>
<tr><td rowspan="2">Actual</td><td>No</td><td>True negative (TN)</td><td>False positive (FP)</td></tr>
<tr><td>Yes</td><td>False negative (FN)</td><td>True positive (TP)</td></tr>
</table>

Table 5.4: Confusion matrix

In this way accuracy is computed by using these metrics obtained from the confusion matrix.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{5.8}$$

Kappa statistic value adjusts the value of accuracy by accounting for the possibility of a correct prediction by chance alone. The value for kappa ranges from 0 to 1, where the value 1 indicates perfect agreement between the model's prediction and true values [48]. A common interpretation for values less than one is defined as follows [48]:

- Poor agreement = Less than 0.2
- Fair agreement = 0.20 to 0.40
- Moderate agreement = 0.40 to 0.60
- Good agreement = 0.60 to 0.80
- Very good agreement = 0.80 to 1.00

The kappa statistic is calculated with the formula

$$\text{Kappa} = \frac{Pr_{\text{a}} - Pr_{\text{e}}}{1 - Pr_{\text{e}}} \tag{5.9}$$

where, Pr_a refers to the proportion of actual agreement, Pr_e refers to expected agreement between classifier and true values.

The face recognition task was conducted to identify the accuracy and the reaction times of the subject's during the task. This accuracy versus mean reaction times graph is shown in Figure 5.9. The control group is represented by Red colored squares whereas the dementia group is represented by Blue color diamonds. From the scatterplot, we can identify that for most of the control group the accuracy is above 0.6 to 1. They could identify the novel images from the previously studied images. However, for the dementia group, the subjects performed with low accuracy. The values ranges below 0.6. One outlier for the dementia group can be seen having the accuracy of 0.7. But for this outlier, we can notice that even if the accuracy for this subject was high compared to the other dementia subjects, the reaction time was very high.

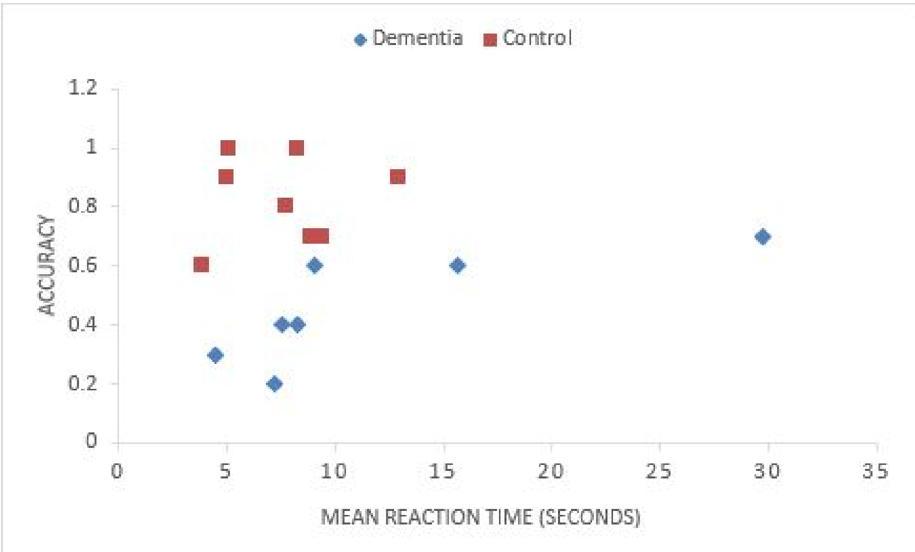


Figure 5.9: Comparison of Reaction times vs Accuracy in Face recognition task

For the face recognition task, we also decided to find out if there is certain difference in the pattern observed for recognising novel facial images and old images by the dementia subjects and normal subjects. The Figure 5.10 and 5.11 show the heatmaps obtained from the normal subjects and dementia subjects.

There was not much variation regarding the scanning pattern of the images. For the learned image (right side), there was no significant difference in the observation pattern. From the figure, we can see that the dementia group had shown more time fixating near the eyes than the control group for novel image (left side). The red color in the heatmap indicates the intensity of the fixation.

We have also evaluated the eye movement patterns and plotted them as a function of time (milliseconds). From the Figure 5.12, we can observe that the vertical and horizontal eye movements for the dementia group seems to be random and stochastic while the control group has smoother eye movement patterns and can follow the target object easily. Also, for the smooth pursuit task, we can observe similar response in both the groups with Control group having more organized pattern

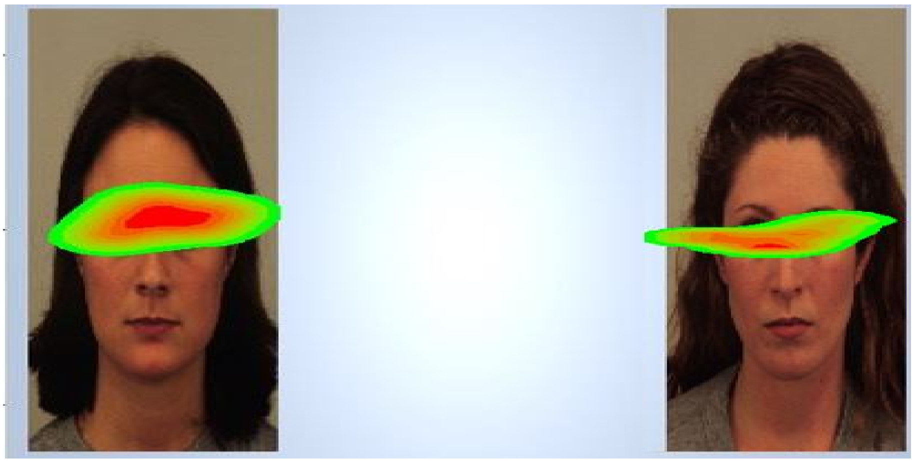


Figure 5.10: Heatmap for face recognition in Control group

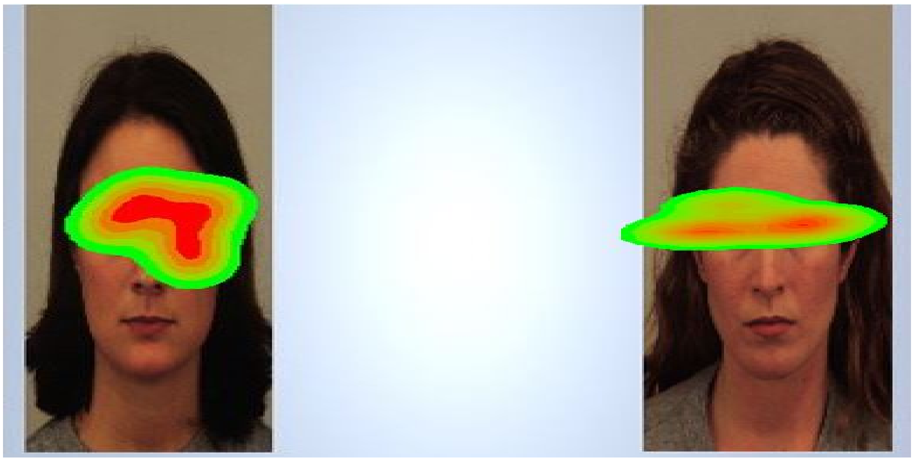


Figure 5.11: Heatmap for face recognition in Dementia group

than the dementia group. The graph shows that for either of the task the dementia group is having trouble following the target object smoothly as experiment proceeds.

5.5.2 EEG

The data obtained from the experiments of EEG was processed using MATLAB, EEGLAB toolbox. EEGLAB is an open source toolbox for the analysis of EEG data [49].

Moving average filter: Moving average filter is an efficient filter to remove noise from an EEG signal. It is a simple low pass FIR filter commonly used to smooth an array of sampled data. It operates by averaging a number of points from the input signal to produce each point in the output

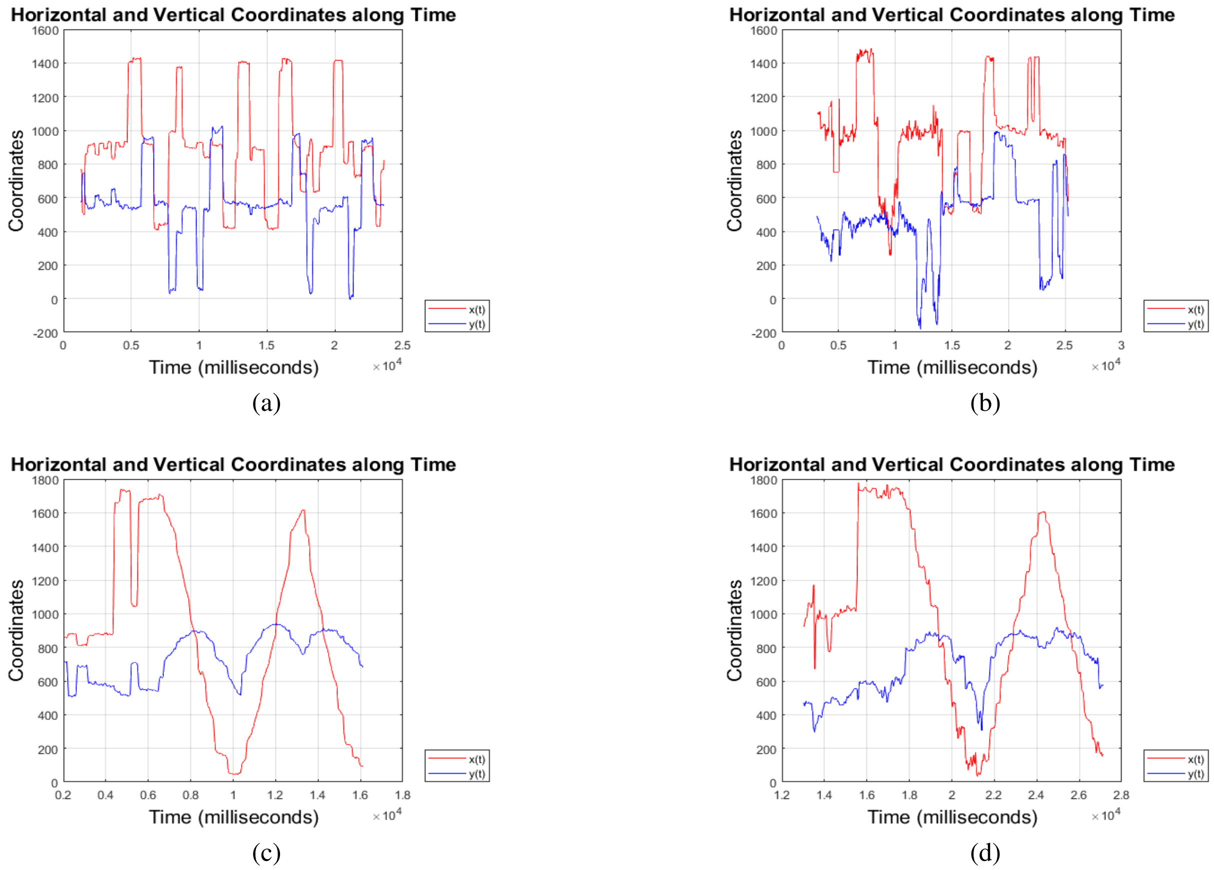


Figure 5.12: (a) Time vs co-ordinates saccades experiment eye movements for control group (b) Time vs co-ordinates saccades experiment eye movements for dementia group (c) Time vs co-ordinates smooth pursuit experiment eye movements for control group (d) Time vs co-ordinates smooth pursuit experiment eye movements for dementia group

signal. The equation is given as [50]:

$$y[i] = \frac{1}{M} \sum_{j=0}^{M-1} x[i+j] \tag{5.10}$$

where, x[ ] is the input signal, y[ ] is the output signal and M is the number of points chosen for the average. For example, for a 3-point moving average filter, the point 50 in the output signal is given by

$$y[50] = \frac{x[50] + x[51] + x[52]}{3} \tag{5.11}$$

The example of moving average filter for a raw data and after applying the filter is given in Fig 5.13 and Fig 5.14.

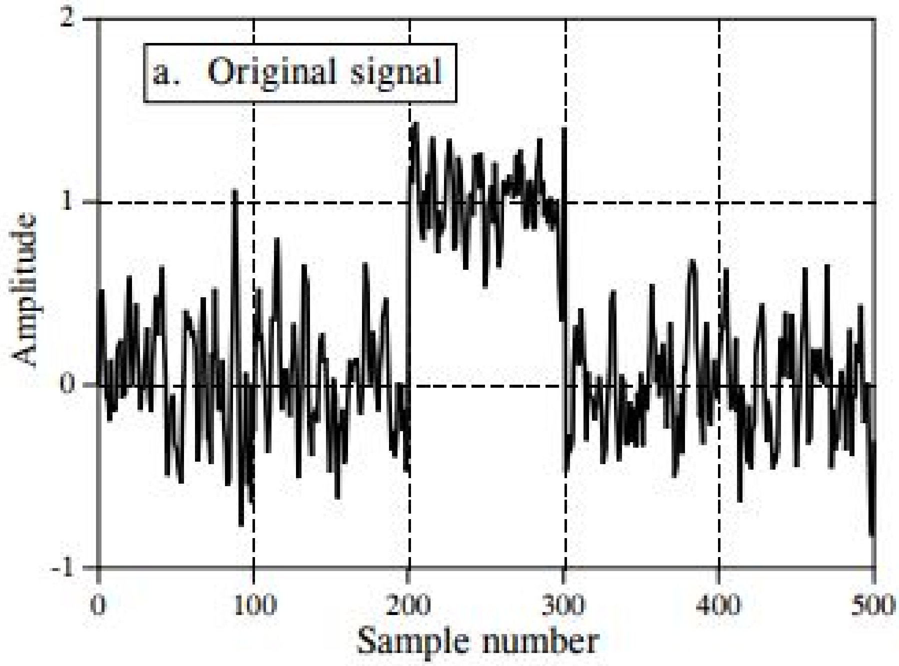


Figure 5.13: Moving average filter for a rectangular pulse buried in random noise [51]

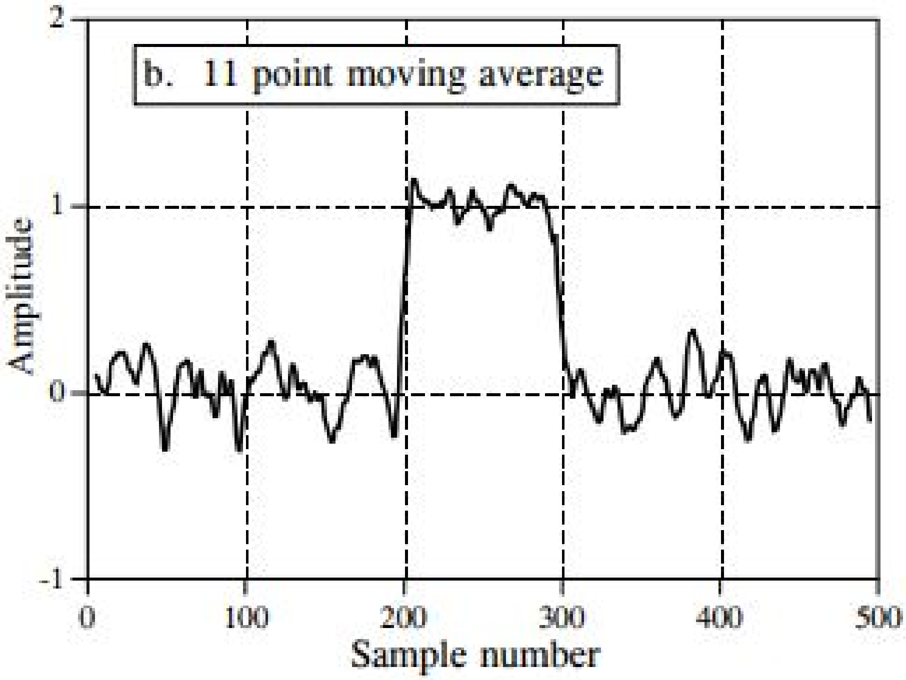


Figure 5.14: Filtering done by applying 11-point Moving average filter applied for the rectangular pulse [51]

The equation can also be written as below if the point is chosen symmetrically [50]:

$$y[i] = \frac{1}{M} \sum_{j=-(M-1)/2}^{(M-1)/2} x[i+j] \tag{5.12}$$

In this case, the 3-point moving average filter for the point 50 in the output signal is given by

$$y[50] = \frac{x[49] + x[50] + x[51]}{3} \tag{5.13}$$

.

Fourier transform: Fourier transform is a mathematical process which takes any time domain signal (periodic or non-periodic) and converts it to frequency domain. It is one of the several mathematical tools for analyzing the signals. The mathematical definition of a continuous Fourier transform is given as [51]:

$$X(\omega) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} x(t)e^{-j\omega t}dt \tag{5.14}$$

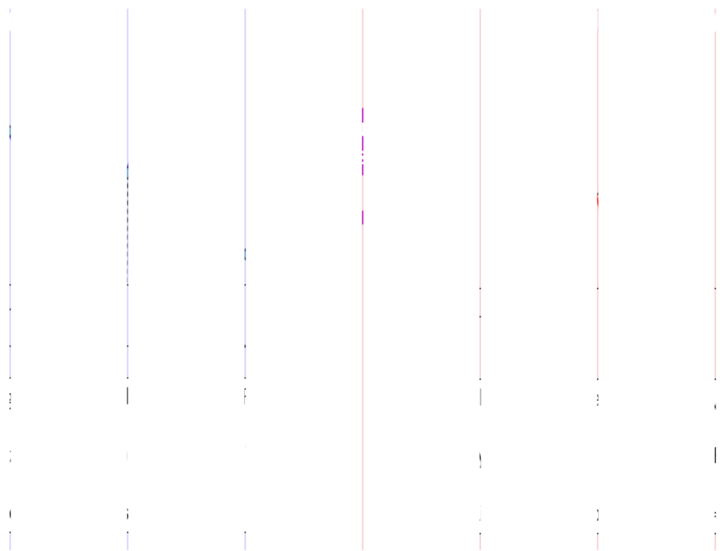


Figure 5.15: Fast fourier transform (Time and Frequency domain) [54]

Fast Fourier Transform (FFT): The fast fourier transform is an efficient algorithm to compute the Discrete Fourier transform(DFT) and it's inverse. Before the formulation of FFT algorithm, computation of finite DFT involve N^2 operations. It used to consume a lot of computation time and computation costs. Therefore, FFT has been a powerful computing algorithm [52]. A general representation is given in Fig 5.15 [53].

Band pass filters: Band pass filter as the name implies allow a certain band or range of frequencies to pass through it and rejects the signal which is outside that frequency range. An example of Band pass filter is shown in Fig 5.16 [54].

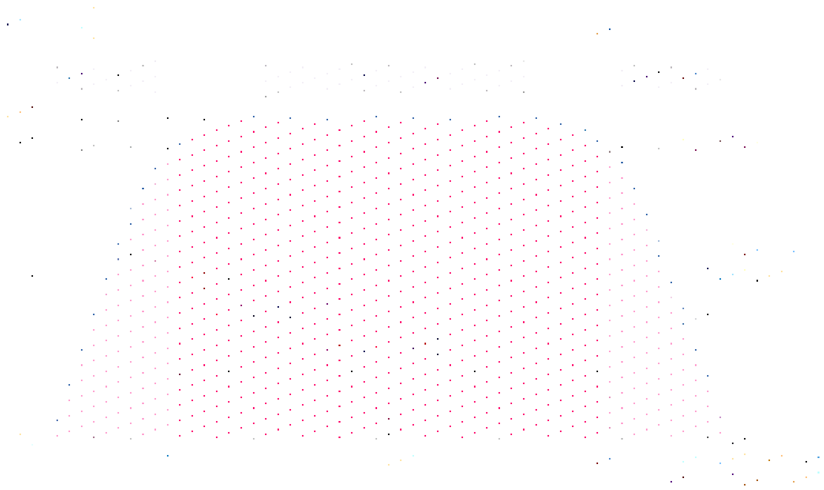


Figure 5.16: Band pass filter [55]

From the figure, we can see that f_L is the lower pass band value and f_H is the higher pass band value for the band pass filter. They are also called as lower and higher cut off frequency respectively. The width of the pass band is called Bandwidth. Therefore, the bandwidth can be calculated as the difference between upper and lower cut-off frequencies. All the frequency before f_L and after f_H is rejected. Only the frequencies which fall within f_L and f_H is allowed to pass through the filter.

The power of different frequency bands was thus extracted using the above methods and were used as features for the classification of EEG data. Moving average filter was used to remove the noise and make the data smooth. After the application of the filter, fft was used to view the data pattern in frequency domain and thus band pass filter was used to extract the average power of different frequency bands [1 - 30 Hz].

The features extracted from the EEG data are:-

- Average alpha band power: Alpha band power is generally correlated with memory and attention at all ages. The frequency range of alpha band is from 8 to 13 Hz [55].

- Average beta band power: Beta band power is generally observed during problem solving, decision making and active thinking state. The frequency range of beta band is from 13 to 30 Hz [55].

- Average delta band power: Delta band power highest in amplitude and has slow moving waves which usually occurs during sleep. The frequency range is from 1 to 4 Hz [55].
- Average theta band power: Theta band power is observed during relaxation. The frequency range of theta band is from 4 to 8 Hz [55].

The power of different frequency bands depicted some variation in the dementia and control subjects. The bandpower of alpha frequency in dementia subjects was comparatively lower than with the control subjects. Also, for theta and delta frequency range, dementia subjects showed higher power compared to control group. Representation of the 4 different band powers (Alpha, beta, delta and theta) obtained for the EEG signal is provided in the Fig 5.17.

Performance	**Classifier**		
	SVM Linear	**GLM (Logisitc)**	Naive Bayes
Accuracy	78.33	**81.67**	80.58
Kappa	0.66	**0.73**	0.70

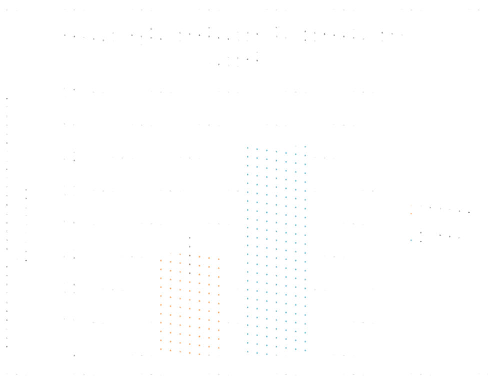
Table 5.5: Performance metric of classifiers on the EEG data

From Table 5.5, we can see that the logistic regression performed with good accuracy than the other two classifiers.

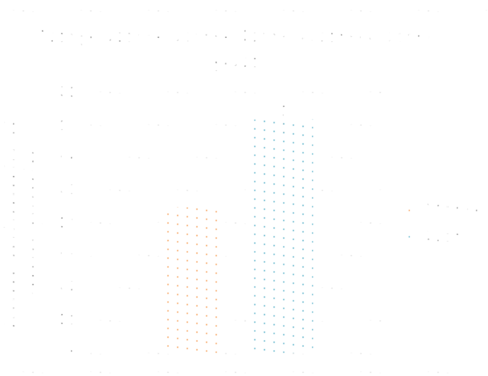
5.5.3 Modality fusion

Generally any system is observed with some data acquisition technique. In such case, each acquisition framework is denoted as modality and is associated with one data set. If data is required to be obtained from multiple modalities it is called multimodal [56].

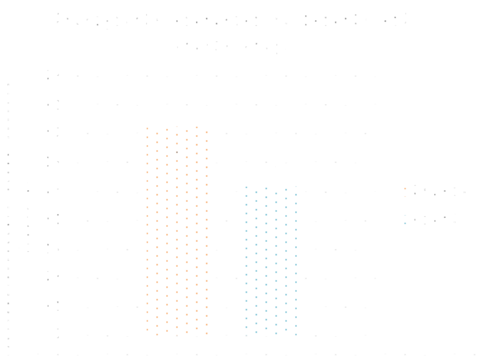
Multimodal systems takes data from multiple sources of biometric data for classification process. The necessary information could be obtained from any sources like eye and speech or fingerprint and retinal scan etc [57]. This concept was evolved to overcome the limitations of using



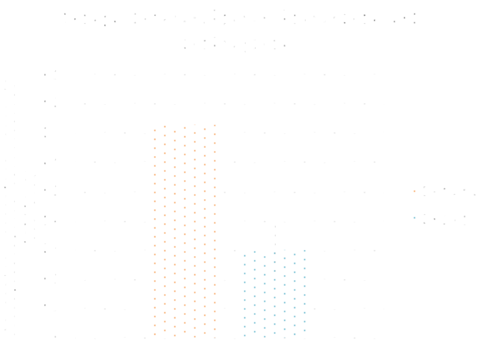
(a)



(b)



(c)



(d)

Figure 5.17: Group means of band powers representation for control and dementia group from the EEG experiments. Error bars represent Standard Error (SE)

single biometric system. For example if some data collection is being done using a source like retinal scan but the person cannot provide good data due to some surgery or injury. In such case having an alternative source of data is useful. Study conducted by Lu et al. using both EEG and eye tracking movements to enhance emotion recognition has shown that modality fusion could significantly improve emotion recognition accuracy compared to that of single modality [58].

Feature-level fusion: The information obtained through such different sources can be used to combine using fusion methods. There are different levels at which fusion can be implemented in such biometric analysis. Some of the examples are (i) sensor-level fusion (ii) feature-level (iii) score-level (iv) rank-level and (v) decision-level. Among the many fusion methods, the one which is mostly used is Feature-level fusion. It is the kind of fusion method where multiple features are extracted from the different modalities and then the extracted features are combined together into a final feature vector of higher dimension. The algorithm is mostly used by multiple biometric sources.

Generally feature level fusion is accomplished by concatenating the feature sets obtained from multiple input sources. Let us consider X = $\{x_1, x_2, x_3, ..., x_m\}$ and Y = $\{y_1, y_2, y_3, ..., y_n\}$ are the feature vectors that represent the features extracted from two individual sources [59]. The objective of Feature level fusion is to combine these two feature vector which is usually done by concatenating to yield a new feature vector say Z. However, to ensure that there is no such variation and distribution in the range of data obtained from the two feature vectors, the first step which is done before concatenation is Feature normalization. Usually min-max technique is used to perform this normalization.

$$x' = \frac{x - min(x)}{max(x) - min(x)} \tag{5.15}$$

The new feature vector of two individual sources which are now normalized can be represented as X' = $\{x'_1, x'_2, x'_3, ..., x'_m\}$ and Y' = $\{y'_1, y'_2, y'_3, ..., y'_n\}$. The final feature vector is obtained from the augmentation of the normalized vector Z' = $\{x'_1, x'_2, x'_3, ..., x'_m, y'_1, y'_2, y'_3, , , , , y'_n\}$ [59]. This new augmented feature vector may result in high dimensional(m+n) data and having an augmented vector does not necessarily improve the performance of the classifiers. Therefore, feature selection process is done to reduce the dimensionality of the problem which chooses minimum feature vector necessary to build a strong classifier. A number of feature selection algorithm such as Sequential Forward Selection (SFS), Sequential Backward Selection (SBS) etc [59].

From the boxplot of Fig 5.18, we can see the algorithm has marked 7 features as important while 3 features are rejected. It can be seen from the graph that the 3 features have lower Z score than that of maximum Z score of a shadow feature thus categorizing itself in the list of unimportant attribute.

In Figure 5.19, we can see the Z score stats for each of the 10 attributes. Hits are the values which occurs when a feature has higher Z score than the maximum Z score of it's shadow features. Here, in the normHits column, we can see that 100% of the time the attribute Alpha power and Beta power is found to be more important than the shadow attribute and we can see that the attribute is confirmed on the decision column. Similarly, 98% of the time delta power and theta power is found to be significant than the shadow attribute. But we can see that for 3 attributes Mean fixation duration,

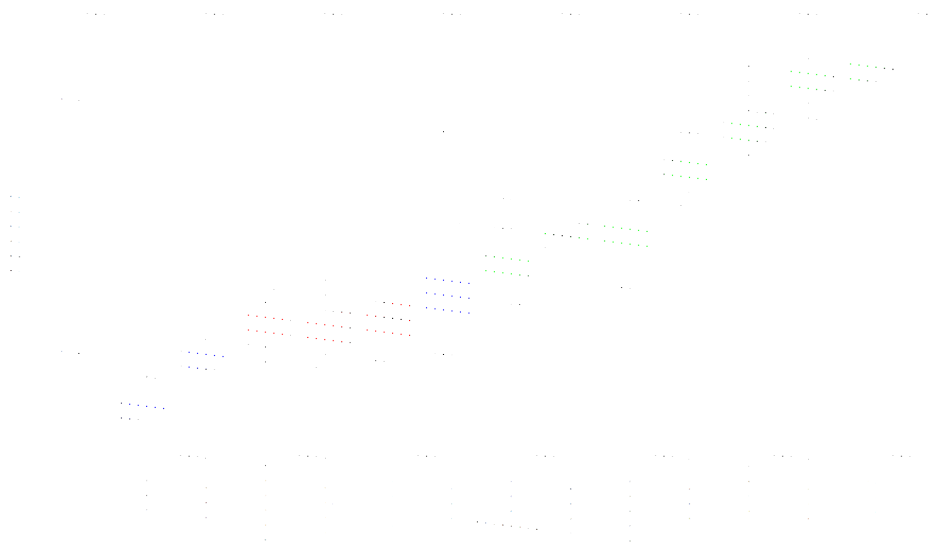


Figure 5.18: Boruta boxplot for modality fusion method

Mean saccadic duration and Saccades/Fixation ratio, the hit rate is very low and are rejected thus treated as unimportant.

Figure 5.19: Z-score statistics of each attribute

Finally a total of 7 features were selected as important and 3 other features were rejected. Therefore, we performed the final classification using these 7 features.

1. Average alpha band power
2. Average beta band power
3. Average delta band power
4. Average theta band power
5. Total number of fixation
6. Total number of saccades

7. Transition matrix

Modality feature level fusion method was used for the above EEG and Eye tracking dataset to view if the combination from multiple biometric sources provided a good classifier.

Performance	**Classifier**		
	SVM Linear	**GLM (Logistic)**	Naive Bayes
Accuracy	86.67	**89.98**	84.36
Kappa	0.72	**0.82**	0.72

Table 5.6: Performance metric of classifiers modality fusion

From Table 5.6, we can see that GLM (logistic classifier) was more accurate for the classification and performed better than SVM and Naive Bayes.

Classifier

A brief explanation on the classifiers is provided below.

- **SVM Linear**: Support vector machines or SVM is a type of supervised learning algorithm that can create a boundary known as hyperplane to classify data into groups of similar class values [48]. It makes a decision boundary in such a way as to maximise the separation between two classes wide as possible. SVM is compatible with both classification and numeric prediction task.

  Training a SVM with Linear kernel is faster than training with other kernel. A hyperplane in n-dimensional space is defined as $\vec{x} \, . \, \vec{w} + \boldsymbol{b} = 0$. where, w is a vector of n weights (w_1, w_2, ... w_n) and b is bias. For separating out the two classes as in this experiment, this formula is used to find a set of weights that specify two different hyperplanes: $\vec{x} \, . \, \vec{w} + \boldsymbol{b} \geq \pm 1$ and $\vec{x} \, . \, \vec{w} + \boldsymbol{b} \leq \pm -1$ [48].

- **GLM**: Generalized Linear Model (GLM) is a method to model the relationship between a variable whose outcome is to be predicted and one or more exploratory variable [60]. GLM can produce two categories of model: Classification and Regression. Logistic regression is the GLM that is used to perform binomial classification. This regression model is widely used in medical diagnosis systems like cancer detection etc [61].

Logistic regression uses a sigmoid function and it displays the output value between the range from 0 to 1. It is a predictive analysis and represents the relation between a categorical dependent variable and two or more independent variables. Based on the number of target output class, it can be categorized as Binomial (Two output class), Multinomial (Three or more possible output class) and Ordinal (Ordered categories) [61]. For this study we need to use Binomial classification which is given by:

$$P = \frac{e^y}{1 + e^y} \tag{5.16}$$

where, y = (β_0 + β_1x),

β_0 is the intercept, β_1 is the coefficient of x, x is single exploratory variable, y is the response variable.

- **Naive Bayes**: Naive Bayes classifier is based on the concept of Bayes theorem that uses conditional probability for events. Generally, Bayesian network (classifier) is used if we know about the relation between the features or if we can define which attributes are conditionally independent. Naive Bayes assumes that all the features are independent and equally important. However, in real world application where these assumption does not hold strongly, Naive Bayes still performs well due to it's versatility across many conditions [48]. It performs well with noisy and missing data and with any size of sample [48].

  Naive Bayes classifier is widely applied on the categorical attributes but there has been studies with the application of naive bayes on continuous variables by exploring probability distribution techniques like Gaussian distribution, Kernel density estimation, modified exponential distribution etc [62]. Therefore, for real-valued input variables we have assumed Gaussian distribution. This is an extension of naive Bayes method to handle continuous variables and is known as Gaussian Naive Bayes. It uses two parameters: mean μ and variance σ^2. The Probability Density Function of the Gaussian distribution is given by [62]:

$$P = \frac{1}{\sigma\sqrt{2\pi}} exp \frac{(-(x - \mu)^2)}{2\sigma^2} \tag{5.17}$$

  where μ and σ are the mean and variance for a continuous variable x.

Chapter 6

Discussion

Hybrid systems that incorporates the use of multiple sources to obtain data for classification has shown a significant approach in many other systems. A hybrid approach using modality fusion applied to the EEG and Eye tracking data for early detection of dementia shows that it performs better than compared with the use of a single modality. The findings indicate that seven statistics total number of fixation, total number of saccades, transition matrix and average EEG power of alpha, beta, delta and theta bands are important cognitive features to evaluate dementia and control group.

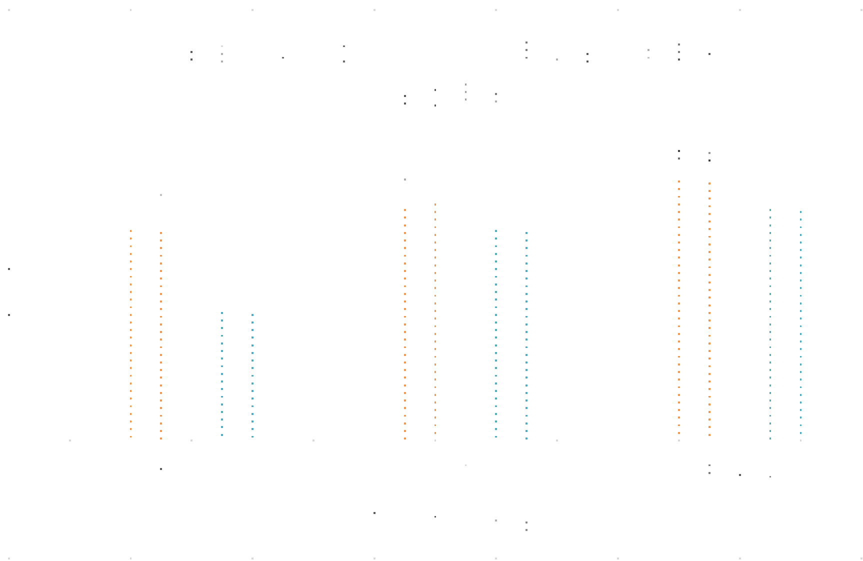


Figure 6.1: Performance comparison of single modality and multiple modality approach

The major contribution and findings obtained from the conducted research are as follows:

- The results obtained from the proposed multi-modal method confirms that hybrid systems overcomes the limitations due to single modal systems such as noise obtained with data collected from single source or being unable to provide data for a biometric modality.

- Average band power of alpha and beta band was observed lower in dementia group compared to control group. However, band power of delta and theta band was observed higher in dementia group compared to control group.

  The lowering of alpha power in dementia can be attributed to the fact that Alpha rhythms are seen to decrease as a function of age with even more lowering seen in neurodegenerative conditions like dementia, Alzheimer's disease etc [63]. The lowering of beta power in dementia can arise from the inability to have an active thinking and concentration state while performing the tasks.

- Average band power of delta and theta band was observed higher in dementia than in control. However, some studies demonstrate contradictory results with either a decrease or increase of these slow band frequencies. [27].

- The significant eye tracking metrics revealed that for the visual tasks, the number of fixations made by dementia group was lower compared to control group. The eye movements for dementia subjects were stochastic and random than compared to the control group.

  The inability to focus on the target object and disengage attention from one location to another on the screen is a lowering of cognitive processing ability [8]. These differences seen in search patterns can be interpreted as deficit in performing visuospatial tasks.

Chapter 7

Conclusion

This study is focused on the cognitive effects a person demonstrates if a person shows early signs of dementia. The effects are calculated from two biological methods: Eye tracking and EEG.

In this study, there are two experiment setups designed for each task. The task are related to visual movements of the stimulus presented on the screen. Both the EEG and Eye tracking method utilize this visual task experiment to collect the data. Separate classifiers are used for both EEG and eye tracking for unimodal system of classification. At last, the features are normalized, fused and feature selection algorithm is performed to obtain the final set of features necessary for multimodal system of classification. Important features that helps to explore and classify the cognitive states are examined. These features are applied to classification algorithm for categorizing dementia and control group.

From the conclusion of the study, it can be seen that multimodal approach turns out to be useful and effective in accuracy than unimodal systems. Studies using two different input modalities has been applied before for emotion recognition and to understand the dynamics of human cognitive processing. To our knowledge, there has been no study using the combined effects of EEG and eye tracking for the study of cognitive behaviour and classification of dementia subjects from normal group. The study concludes that multimodal systems or such hybrid approach using EEG and eye tracking systems have better classification impact than unimodal systems.

One limitation of the study is that the system would be more robust if we can obtain the data from the subjects who experience brain lesions. The lesion may be localised to some part of the brain or it can spread. The activity due to lesions might cause abnormality in the EEG data. Therefore, if we have another category of brain lesion the study could be expanded. Further, the method to diagnose a brain lesion subject involves using MRI or CT scanning which is an expensive technology.

Bibliography

[1] J. J. Jalbert, L. A. Daiello, and K. L. Lapane, "Dementia of the alzheimer type," *Epidemiologic reviews*, vol. 30, no. 1, pp. 15–34, 2008.

[2] D. P. Chapman, S. M. Williams, T. W. Strine, R. F. Anda, and M. J. Moore, "Dementia and its implications for public health," vol. 3, no. 2, 2006.

[3] "2017 alzheimer's disease facts and figures," *Alzheimer's & Dementia*, vol. 13, no. 4, pp. 325–373, 2017.

[4] Y. Watanabe, Y. Kobayashi, M. Tanaka, T. Asada, K. Ishii, and T. Yagi, "Analysis for alzheimer's disease using cross-correlation of eeg data," in *2017 10th Biomedical Engineering International Conference (BMEiCON)*. IEEE, 2017, pp. 1–5.

[5] A. H. Al-nuaimi, E. Jammeh, L. Sun, and E. Ifeachor, "Changes in the eeg amplitude as a biomarker for early detection of alzheimer's disease," in *2016 38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, 2016, pp. 993–996.

[6] Y. E. Geda, "Mild cognitive impairment in older adults," *Current psychiatry reports*, vol. 14, no. 4, pp. 320–327, 2012.

[7] A. Poole and L. J. Ball, "Eye tracking in hci and usability research," in *Encyclopedia of human computer interaction*. IGI Global, 2006, pp. 211–219.

[8] R. J. Molitor, P. C. Ko, and B. A. Ally, "Eye movements in alzheimer's disease," *Journal of Alzheimer's disease*, vol. 44, no. 1, pp. 1–12, 2015.

[9] Neuro opthamology. https://entokey.com/neuro-ophthalmology/. Accessed: 2019-05-20.

[10] A. Tales, J. Haworth, S. Nelson, R. J. Snowden, and G. Wilcock, “Abnormal visual search in mild cognitive impairment and alzheimer’s disease,” *Neurocase*, vol. 11, no. 1, pp. 80–84, 2005.

[11] G. Bargary, J. M. Bosten, P. T. Goodbourn, A. J. Lawrance-Owen, R. E. Hogg, and J. D. Mollon, “Individual differences in human eye movements: An oculomotor signature?” *Vision research*, vol. 141, pp. 157–169, 2017.

[12] T. Musha, “Fluctuations analysis of eeg signals allows detection of ad (alzheimer’s disease) in the early stage,” in *2015 International Conference on Noise and Fluctuations (ICNF)*. IEEE, 2015, pp. 1–4.

[13] Eeg, michigan advanced neurology center. http://drmridha.com/services/eeg. Accessed: 2019-06-27.

[14] S. Sakhavi, “Application of deep learning methods in brain-computer interface systems,” Ph.D. dissertation, National University of Singapore (Singapore), 2017.

[15] B. Singh and H. Wagatsuma, “A removal of eye movement and blink artifacts from eeg data using morphological component analysis,” *Computational and mathematical methods in medicine*, 2017.

[16] J. Lopez-Calderon and S. J. Luck, “Erplab: an open-source toolbox for the analysis of event-related potentials,” *Frontiers in human neuroscience*, vol. 8, p. 213, 2014.

[17] J. D. Kropotov, *Functional neuromarkers for psychiatry: Applications for diagnosis and treatment*. Academic Press, 2016.

[18] A. S. Malik and H. U. Amin, *Designing EEG Experiments for Studying the Brain: Design Code and Example Datasets*. Academic Press, 2017.

[19] B. Stemmer and H. A. Whitaker, *Handbook of the Neuroscience of Language*. Academic Press, 2008.

[20] T. J. Crawford, "The disengagement of visual attention in alzheimer's disease: a longitudinal eye-tracking study," *Frontiers in aging neuroscience*, vol. 7, p. 118, 2015.

[21] F. W. Bylsma, D. X. Rasmusson, G. W. Rebok, P. M. Keyl, L. Tune, and J. Brandt, "Changes in visual fixation and saccadic eye movements in alzheimer's disease," *International Journal of Psychophysiology*, vol. 19, no. 1, pp. 33–40, 1995.

[22] W. A. Fletcher and J. A. Sharpe, "Saccadic eye movement dysfunction in alzheimer's disease," *Annals of Neurology: Official Journal of the American Neurological Association and the Child Neurology Society*, vol. 20, no. 4, pp. 464–471, 1986.

[23] D. Lagun, C. Manzanares, S. M. Zola, E. A. Buffalo, and E. Agichtein, "Detecting cognitive impairment by eye movement analysis using automatic classification algorithms," *Journal of neuroscience methods*, vol. 201, no. 1, pp. 196–203, 2011.

[24] I. M. Pavisic, N. C. Firth, S. Parsons, D. M. Rego, T. J. Shakespeare, K. X. Yong, C. F. Slattery, R. W. Paterson, A. J. Foulkes, K. Macpherson *et al.*, "Eyetracking metrics in young onset alzheimer's disease: A window into cognitive visual functions," *Frontiers in neurology*, vol. 8, p. 377, 2017.

[25] R. D. Nebes and C. B. Brady, "Generalized cognitive slowing and severity of dementia in alzheimer's disease: Implications for the interpretation of response-time data," *Journal of Clinical and Experimental Neuropsychology*, vol. 14, no. 2, pp. 317–326, 1992.

[26] J. Dauwels, F.-B. Vialatte, and A. Cichocki, "On the early diagnosis of alzheimer's disease from eeg signals: a mini-review," in *Advances in Cognitive Neurodynamics (II)*. Springer, 2011, pp. 709–716.

[27] R. Lizio, F. Vecchio, G. B. Frisoni, R. Ferri, G. Rodriguez, and C. Babiloni, "Electroencephalographic rhythms in alzheimer's disease," *International Journal of Alzheimer's disease*, 2011.

[28] F. J. Fraga, E. F. Oliveira, and P. A. Kanda, "Eeg epoch selection: Lack of alpha rhythm improves discrimination of alzheimer's disease," in *2016 38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, 2016, pp. 2307–2310.

[29] C. Huang, L.-O. Wahlund, T. Dierks, P. Julin, B. Winblad, and V. Jelic, "Discrimination of alzheimer's disease and mild cognitive impairment by equivalent eeg sources: a cross-sectional and longitudinal study," *Clinical Neurophysiology*, vol. 111, no. 11, pp. 1961–1967, 2000.

[30] C. L. Lai, R. T. Lin, L. M. Liou, and C. K. Liu, "The role of event-related potentials in cognitive decline in alzheimer's disease," *Clinical Neurophysiology*, vol. 121, no. 2, pp. 194–199, 2010.

[31] E. Gozke, S. Tomrukcu, and N. Erdal, "Visual event-related potentials in patients with mild cognitive impairment," *International Journal of Gerontology*, vol. 10, no. 4, pp. 190–192, 2016.

[32] G. Henderson, E. Ifeachor, N. Hudson, C. Goh, N. Outram, S. Wimalaratna, C. Del Percio, and F. Vecchio, "Development and assessment of methods for detecting dementia using the human electroencephalogram," *IEEE Transactions on Biomedical Engineering*, vol. 53, no. 8, pp. 1557–1568, 2006.

[33] S. Tirunagari, D. Abasolo, A. Iorliam, A. T. Ho, and N. Poh, "Using benford's law to detect anomalies in electroencephalogram: An application to detecting alzheimer's disease," in *2017 IEEE Conference on Computational Intelligence in Bioinformatics and Computational Biology (CIBCB)*, 2017, pp. 1–6.

[34] N. K. Al-Qazzaz, S. H. B. Ali, S. A. Ahmad, K. Chellappan, M. Islam, J. Escudero *et al.*, "Role of eeg as biomarker in the early detection and classification of dementia," *The Scientific World Journal*, 2014.

[35] Tobii eyetracking. https://help.tobii.com/hc/en-us/articles/212814329-What-s-the-difference-between-Tobii-Eye-Tracker-4C-and-Tobii-EyeX-. Accessed: 2019-06-30.

[36] Great lakes neuro technologies. https://www.glneurotech.com/software-solutions-fd/. Accessed: 2019-06-30.

[37] Mini-mental state examination. https://www.ncbi.nlm.nih.gov/projects/gap/cgi-bin/GetPdf.cgi?id=phd001525.1. Accessed: 2019-06-29.

[38] S. T. Creavin, S. Wisniewski, A. H. Noel-Storr, C. M. Trevelyan, T. Hampton, D. Rayment, V. M. Thom, K. J. Nash, H. Elhamoui, R. Milligan *et al.*, "Mini-mental state examination (mmse) for the detection of dementia in clinically unevaluated people aged 65 and over in community and primary care populations," *Cochrane Database of Systematic Reviews*, no. 1, 2016.

[39] V. Krassanakis, V. Filippakopoulou, and B. Nakos, "Eyemmv toolbox: An eye movement post-analysis tool based on a two-step spatial dispersion threshold for fixation identification," *Journal of Eye Movement Research*, vol. 7, no. 1, pp. 1–10, 2014.

[40] K. Ooms and V. Krassanakis, "Measuring the spatial noise of a low-cost eye tracker to enhance fixation detection," *Journal of Imaging*, vol. 4, no. 8, p. 96, 2018.

[41] D. D. Salvucci, "An interactive model-based environment for eye-movement protocol analysis and visualization," in *Proceedings of the 2000 symposium on Eye tracking research & applications*. ACM, 2000, pp. 57–63.

[42] D. D. Salvucci and J. H. Goldberg, "Identifying fixations and saccades in eye-tracking protocols," in *Proceedings of the 2000 symposium on Eye tracking research & applications*. ACM, 2000, pp. 71–78.

[43] Z. Sharafi, T. Shaffer, B. Sharif, and Y.-G. Guéhéneuc, "Eye-tracking metrics in software engineering," in *2015 Asia-Pacific Software Engineering Conference (APSEC)*. IEEE, 2015, pp. 96–103.

[44] J. H. Goldberg and X. P. Kotval, "Computer interface evaluation using eye movements: methods and constructs," *International Journal of Industrial Ergonomics*, vol. 24, no. 6, pp. 631–645, 1999.

[45] M. B. Kursa, W. R. Rudnicki *et al.*, "Feature selection with the boruta package," *J Stat Softw*, vol. 36, no. 11, pp. 1–13, 2010.

[46] W. Paja, K. Pancerz, and P. Grochowalski, "Generational feature elimination and some other ranking feature selection methods," in *Advances in Feature Selection for Data and Pattern Recognition*. Springer, 2018, pp. 97–112.

[47] P. Refaeilzadeh, L. Tang, and H. Liu, "Cross-validation," *Encyclopedia of database systems*, pp. 532–538, 2009.

[48] B. Lantz, *Machine learning with R*. Packt Publishing Ltd, 2013.

[49] C. Brunner, A. Delorme, and S. Makeig, "Eeglab–an open source matlab toolbox for electrophysiological research," *Biomedical Engineering/Biomedizinische Technik*, 2013.

[50] S. W. Smith *et al.*, "The scientist and engineer's guide to digital signal processing," 1997.

[51] L. Saribulut, T. Ahmet, and M. TuMay, "Fundamentals and literature review of fourier transform in power quality issues," *Journal of Electrical and Electronics Engineering Research*, vol. 5, no. 1, pp. 9–22, 2013.

[52] A. P. Yoganathan, R. Gupta, and W. H. Corcoran, "Fast fourier transform in the analysis of biomedical data," *Medical and biological engineering*, vol. 14, no. 2, p. 239, 1976.

[53] S. Phenom. (2017) Digital signal processing:sampling rates,bandwidth, spectral lines, and more. https://community.plm.automation.siemens.com/t5/Testing-Knowledge-Base/Digital-Signal-Processing-Sampling-Rates-Bandwidth-Spectral/ta-p/402991. Accessed: 2019-05-25.

[54] Band pass filter. https://electronicspost.com/what-is-a-band-pass-filter-draw-and-explain-the-frequency-response-of-a-band-pass-filter/. Accessed: 2019-05-25.

[55] J. S. Kumar and P. Bhuvaneswari, "Analysis of electroencephalography (eeg) signals and its categorization–a study," *Procedia engineering*, vol. 38, pp. 2525–2536, 2012.

[56] D. Lahat, T. Adali, and C. Jutten, "Multimodal data fusion: an overview of methods, challenges, and prospects," *Proceedings of the IEEE*, vol. 103, no. 9, pp. 1449–1477, 2015.

[57] M. Singh, R. Singh, and A. Ross, "A comprehensive overview of biometric fusion," *Information Fusion*, vol. 52, pp. 187–205, 2019.

[58] Y. Lu, W.-L. Zheng, B. Li, and B.-L. Lu, "Combining eye movements and eeg to enhance emotion recognition," in *Twenty-Fourth International Joint Conference on Artificial Intelligence*, 2015.

[59] A. A. Ross and R. Govindarajan, "Feature level fusion of hand and face biometrics," in *Biometric Technology for Human Identification II*, vol. 5779. International Society for Optics and Photonics, 2005, pp. 196–205.

[60] M. Goldburd, A. Khare, and D. Tevet, "Generalized linear models for insurance rating," *Casualty Actuarial Society, CAS Monographs Series*, no. 5, 2016.

[61] P. Mugdil, M. Garg, V. Chhabra, P. Sehgal, and Jyoti, "Breast cancer prediction algorithm analysis," *International Journal of Advance Research, Ideas and Innovations in Technology*, vol. 5, no. 3, 2019.

[62] P. Yildirim and D. Birant, "Naive bayes classifier for continuous variables using novel method (nbc4d) and distributions," in *2014 IEEE International Symposium on Innovations in Intelligent Systems and Applications (INISTA) Proceedings*, 2014, pp. 110–115.

[63] J. P. Trammell, P. G. MacRae, G. Davis, D. Bergstedt, and A. E. Anderson, "The relationship of cognitive performance and the theta-alpha power ratio is age-dependent: An eeg study of short term memory and reasoning during task and resting-state in healthy young and old adults," *Frontiers in aging neuroscience*, vol. 9, p. 364, 2017.

Call for Papers

JCSSE 2019

July 10 - 12

The 16th International Joint Conference on Computer Science and Software Engineering

@Amari Pattaya

Pattaya Beach, Chonburi, Thailand

"Knowledge Evolution Towards Singularity of Man-Machine Intelligence"

Paper Submission

Papers should not exceed six (6) pages including results, figures, and references. All manuscripts must be written in English and prepared in the standard IEEE Conference Proceedings format in PDF. Manuscript templates are made available on the website. Only electronic submissions in PDF format will be accepted via Edas submission system. All submissions will be subjected to a double-blind review procedure. At least one of the authors must register to present the paper at the conference upon acceptance.

Conference website: http://jcsse.informatics.buu.ac.th

Topics (not limited to)

- Bio and Medical Informatics
- Computational Intelligence
- Emerging Intelligent Technologies
- Information Technology
- Intelligent Applications
- Intelligent Computer Networks and Systems
- Internet of Things
- Software Engineering

Important Dates

- Call for Papers: (Extended Final Call) April 16, 2019
- Notification of Acceptance: May 15, 2019
- Early-bird Registration: May 31, 2019
- Camera-ready Submission: May 31, 2019
- Conference Days: July 10 - 12, 2019

IEEE | IEEE THAILAND SECTION | IEEE Xplore® Digital Library

Organized by Department of Mathematics and Computer Science, Faculty of Science, Chulalongkorn University and Faculty of Informatics, Burapha University

Eye-Tracking Based Visualizations and Metrics Analysis for Individual Eye Movement Patterns

Rasa Bhattarai
International College
King Mongkut's Institute of Technology Ladkrabang
Ladkrabang, Bangkok 10520, Thailand
E-mail: 60610019@kmitl.ac.th

Montri Phothisonothai
International College
King Mongkut's Institute of Technology Ladkrabang
Ladkrabang, Bangkok 10520, Thailand
E-mail: montri.ph@kmitl.ac.th

***Abstract*—Uniqueness in the analysis pattern of objects by individual humans has a profound impact on the study of their visual learning and behavior. Eye movement patterns have been effectively emerging as a biometric based key for security systems, product recognition patterns, user identifications, as well as medical research purposes. The modern eye tracking systems are non-invasive and financially affordable. Therefore, in this paper, we proposed eye-tracking based visualizations and metrics analysis for individual eye movement patterns collected during any kinds of activities depending on the scope of the our experimental paradigms. Individuals can be aware of their own performances during certain task and improve upon their weak areas. The objective of the paper is to utilize the important visual metrics obtained from fixation, saccades and face recognition and use them to analyze for individual categorization. The obtained results shown that the specific features and patterns can be extracted the viewing aspect of individual subjects using naive Bayes classifier. We were successfully able to predict the individual eye movements with an accuracy of 90.22%.**

***Index Terms*—eye tracking, visual metrics, saccades, smooth pursuit**

I. INTRODUCTION

The way every human perceive objects and behavior of a system has different observant patterns. Since few decades, eye movements have been focused upon to understand the functionality of the viewing behavior of people. It has been used as a promising biomarker for security systems, automotive industry, virtual environment etc. Even graphical passwords are considered to be as an alternative to traditional passwords as it is easy to recall images [1]. One of the most practical application by using such eye movements can even be a major advantage for disabled people by helping them to interact with any interfaces directly without the need of secondary devices such as mouse or keyboard [2].

Eye tracking is a method identifying a person's eye movement which gives the measurements of the person's eye gaze positions and helps to know where the person is looking at [2]. Most of the modern eye tracking devices use infrared sensor technology to collect the individual's gaze pattern through the visual field [3]. Eye tracking systems being non-invasive have been in rapid growth these days. It is an easiest and convenient way to gather data for analysis of certain behavior. The decreasing cost, non-invasive procedure and financial availability has led many researchers to use such systems as a favorable tool for statistical analysis. Eye tracking systems obtains a stream of raw data, uses fixation detection algorithms which are either velocity-based, dispersion-based and area-based attributes as spatial characteristics to identify fixations, saccades and other metrics which can provide desired information depending on the research overview.

Therefore, in the proposed experiment, we initially aim to explore visualization patterns and evaluate eye tracking metrics like fixations, saccades, scanpaths etc. to understand movement mechanism for individual subjects.

II. LITERATURE REVIEW

Studies have shown that occulomotor measures like saccades and smooth pursuit are specific among individuals and can be used for biometric identification [4]. Biometric identification systems is a process to recognize an indiviudal through their biometric data by extraction of necessary features from the data which is later compared to the database verification sample [5]. The movement of every individual's eyes are considered to be unique thus making it as a good focus area for biometric authentication. This has led to the rise in new algorithms and techniques with ever increasing performance [6]. Similarly, there has been models that performed very well on keystroke and eye-tracking biometric data to identify user [7]. For such experiment which uses multiple bio-metric sources, the author encourages further study of eye tracking data since the models involving eye-tracking data are not successful [7].

Eye tracking patterns that can identify and select the desired object that can be useful for disabled or elderly people. Such metrics has also been used as an indicator for diseases like Alzheimers, Parkinsons etc. [8]. Overall, we can say that such visual metrics holds high potential to provide significant insights into any kind of platform that involves human interaction.

III. MATERIALS AND PROPOSED METHOD

In the proposed experiment, a simulation regarding visual behavior is presented to the subjects. The stimulation presented

978-1-7281-0719-6/19/$31.00 ©2019 IEEE

to the subjects is categorized into three types: i.e., 1) Saccades, 2) Smooth Pursuit and 3) Face Recognition. The stimulus is generated using Unity editor.

Saccades are the fast movement of eyes that shifts gaze location from one point to another. The movement is random and can occur in any direction. Such movements are used in many visual tracking experiments where a target object is shown and the subject are asked to either direct their gaze towards the target (prosaccade) or away from the target (antisaccade) [8]. For the Saccadic experiment in our system, a circular object is initially shown at the center of the display monitor as shown in Fig 1(1a). The object stays at the center point location for 2 seconds. It then moves on to random direction in every 1 second. The range of the random direction is about 9 degrees top, bottom, left and right. One complete trial takes 5 seconds and ends when the target object again reaches at the center of the display device. The subject need to fix their gaze at the moving target object until the program halts with a message to stop their gaze focus and relax.

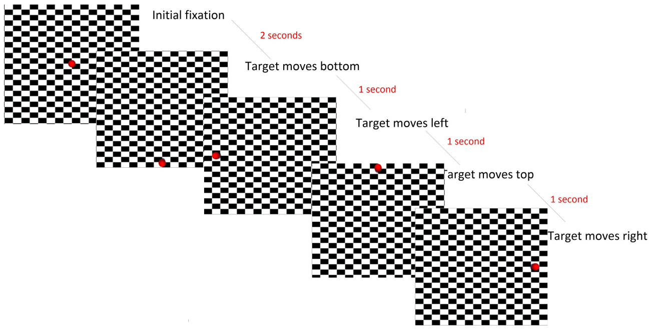
Smooth pursuit is the eye movement which is continuous and the objective is to follow a moving target object. The subject needs to hold their gaze on the target object that can begin from any point on the screen (either central or peripheral). For the Smooth pursuit task, an object is initially shown at the center of the screen for 2 seconds. It is then moved towards the right side of the display device. Taking that extremity point as an initial value, the object starts making an elliptical motion as shown in Fig 1(1b). The elliptical motion is random. It moves up to a certain point in clockwise direction and again in anti-clockwise direction. Similar to the saccadic experiment, the subject need to fix their gaze and follow the moving target object.

Finally, for the face learning and recognition task, a sample of images is taken from Karolinska Directed Emotional Faces (KDEF) dataset[1]. There are two phases for face recognition: Learning and recognition. For learning phase, 10 images are shown to the subjects. Each image is displayed for 5000 ms with an interval of 2000 ms as a break to position the subjects eye at the center of the screen as shown in Fig 1(1c). During the 2000 ms interval a fixation point is displayed at the center of the screen. The placement of these images is randomized towards either left or right from the center of the screen.

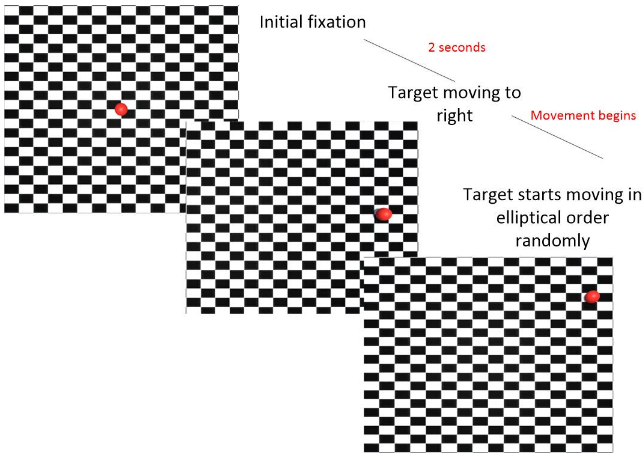
For recognition phase, 20 images (Among which 10 images are from learning phase and rest Novel images) is shown to the subjects. Subjects are instructed to confirm if the image was previously presented or not. The stimuli (image) will remain on the screen until the subject responds by pressing the button and move on to next stimulus (image).

IV. Data Acquisitions

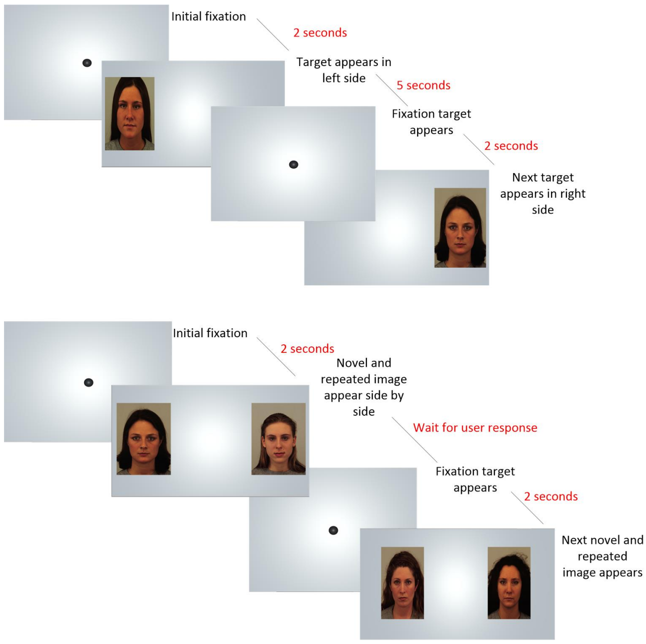
The experiment was conducted in a room with constant lightning conditions. The light was adjusted as to make the subject feel comfortable looking at the computer screen.



(a)



(b)



(c)

Fig. 1: (1a) Saccades: Target object moving randomly across screen (1b) Smooth Pursuit: Target object following an elliptical motion. (1c) Face recognition: Top fig: Learning phase Bottom fig: Recognition phase

[1]Karolinska Directed Emotional Faces (KDEF), a public database used for psychological and medical research purposes

The stimulus was shown on a monitor with a resolution of 1366×768, 8 GB RAM, Intel Core i7 Processor. The subjects volunteered by themselves for the experiment. They belonged to an age group in between 25 to 30. They were seated comfortably at an approximate distance of 60 cm from the monitor screen. They were explained about the procedure and were instructed to carefully follow the target object with less head movements as possible during the experimentation process. Breaks was provided to the subjects whenever it was needed.

V. Feature evaluation

For the obtained eye tracking dataset, a software analysis toolbox used for post-experimental analysis known as Eye Movements Metrics Visualizations (EyeMMV) was used [5]. The tool is used as a platform to provide fixations, saccadic values and scanpaths generated from the data for further analysis. The detection of fixation events was done with the use of an algorithm based on spatial and temporal constraints [9].

The experimental results obtained from 5 subjects (3 male and 2 female) are shown in Table I.

TABLE I: Comparison of EyeMMV results obtained from the experiment

EyeMMV	Sub A	Sub B	Sub C	Sub D	Sub E
Total no. of fixations	35	28	29	29	30
Mean fixation duration (ms)	913.0	988.0	974.7	939.9	947.2
Total no. of saccades	34	27	28	28	29
Mean saccadic duration (ms)	110.46	141.62	111.79	130.55	169.69
Mean saccadic amplitude	151.29	161.6	350.64	368	230.62
Scanpath length (pixels)	5144	4363.25	9818.03	10303.9	6687.86
Saccade by fixation	0.342	0.347	0.165	0.2	0.501

Eye tracking metrics shown in the above table are:

1. Total no. of fixations: The fixation detection algorithm returns a total number of fixation points from the raw data points. This metric returns a total number of fixations in the specified Area of Interest (AOI).

2. Mean fixation duration: The metric defines the average of the total fixation duration for one complete trial.

3. Total no. of saccades: The metric returns a total number of saccades extracted from the raw data in the specified AOI.

4. Mean saccadic duration: The metric defines the average of the saccadic duration for one complete trial.

5. Mean saccadic amplitude: The metric is the angular distance travelled by the eye during such saccadic eye movements.

6. Scanpath length: Scanpath is the sequence of eye movement gaze patterns while looking at the desired target field. The metric gives the total scanpath length value in pixels.

7. Saccade/fixation: The metric gives the ratio of the saccade/fixation.

The system overview of the system is given in Fig. 2.

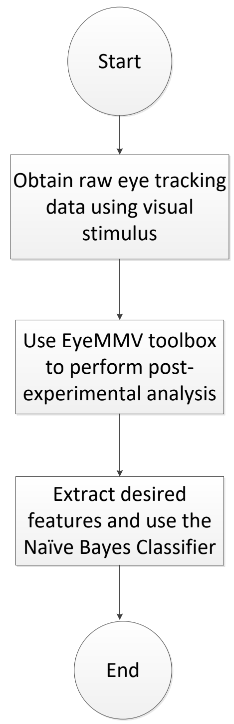
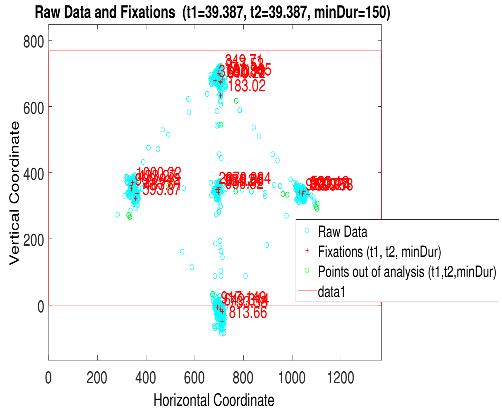


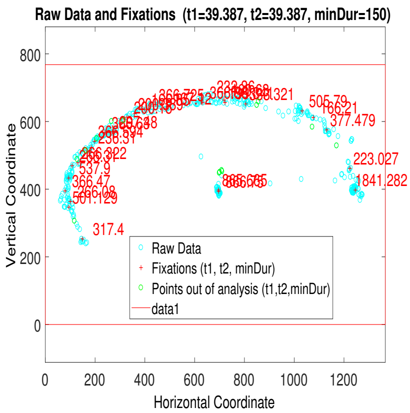
Fig. 2: System overview of the proposed method.

VI. Results and Discussion

The scanpath patterns for the saccade experiment for a single subject is shown in Fig 3(3a) as obtained from the subjects. The blue circles represent the raw data obtained from the overall experiment and the red points indicate the fixation points of the graph. Similarly, Fig 3(3b) shows the scanpath patterns for the smooth pursuit experiment. There is also an indication of the scanpath sequence as shown in Fig 4. The numbers indicated on the graph specifies the direction where the subject's eye gaze was following along the horizontal and vertical co-ordinates. Among a number of Machine Learning classifiers, reliable accuracy results was obtained from Naive Bayes algorithm. Naive Bayes classifier are based on Bayes theorem which utilize training data to calculate an observed probability of each outcome based on the evidence provided by the feature values. The classifier can then be applied to the unlabeled data which utilizes the observed probabilities value to predict their class [10].



(a)



(b)

Fig. 3: (3a) and (3b) Raw data points are shown in blue circles and fixation points shown in red plus (+) sign.

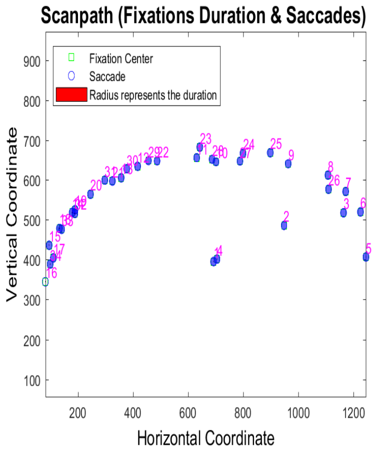


Fig. 4: Scanpath direction showing numbers within it, indicating the trace of direction.

Individual patterns were evaluated from the data obtained. The dataset was divided in the ratio of 70:30 for training and testing samples.The proposed machine learning classifiers, namely Naive Bayes, proved to show significant accuracy of 90.22%. The precision for the subjects (Sub A: 0.80, Sub B: 1, Sub C: 1, Sub D: 0.77 and Sub E: 0.85) has been obtained through the formula:

$$Precision = \frac{TruePositive}{(TruePositive + FalsePositive)}$$

VII. Conclusion and Future Work

From this paper, we have successfully shown a method to classify individual eye tracking patterns with the help of basic eye tracking metrics. From the data obtained through the evaluation, we can extend our study to analyze the patterns of eye tracking behavior specific to different situations. As mentioned earlier, such studies can provide potential data on the study of different medical condition. Evaluation of the features used in the system can be applied towards classification of a category for medical diagnosis.

References

[1] M. Mihajlov, M. Trapkova, and S. Arsenovski, "Eye tracking recognition-based graphical authentication", *International Conference on Application of Information and Communication Technologies (AICT)*, 2013.

[2] A. Poole, L. J. Ball, "Eye tracking in Human-Computer Interaction and Usability Research: Current Status and Future Prospects",*Encyclopedia of Human Computer Interaction, Pennsylvania: Idea Group, Inc*, 2005.

[3] P.A. Punde, M.E. Jadhav, and R.R. Manza, "A study of eye tracking technology and its applications", *International Conference on Intelligent Systems and Information Management (ICISIM)*, 2017.

[4] G. Bargary, J.M. Bosten, P.T. Goodbourn, A.J. Lawrence-Owen, R.R.Hogg, and J.D. Mollon, "Individual differences in human eye movements: An oculomotor signature ?", *Vision Research*, Vol. 141, pp 157–169, 2017.

[5] A. Bayat and M. Pomplun, "Biometric Identification through Eye-Movement Patterns", *International Conference on Applied Human Factors and Ergonomics*, 2018.

[6] M. Brooks, C. Aragon, and O. Komogortsev, "Identifying people by eye movements a potential replacement for passwords", *SPIE Newsroom*, pp.1–3, 2013

[7] D.L. Silver, and A.J. Biggs, "Keystroke and Eye-Tracking Biometrics for User Identification", *International conference on Artificial Intelligence (ICAI)*, June 26–29, 2006.

[8] R.J. Molitor, P.C. Ko, and B.A. Ally, "Eye movements in Alzheimer's Disease", *Journal of Alzheimer's disease*, vol. 44, No. 1, pp. 1–12, 2015.

[9] V. Krassanakis, V. Filippakopoulou, and B. Nakos, "EyeMMV toolbox: An eye movement post-analysis tool based on a two-step spatial dispersion threshold for fixation identification", *Journal of Eye Movement Research*, 7(1):1, 1–10, 2014.

[10] B. Lantz, "Machine Learning with R",*Packt Publishing Ltd., Birmingham B3 2PB, UK*, 2nd ed., pp 90-91, July, 2015.

Eye-Tracking Based Visualizations and Metrics Analysis for Individual Eye Movement Patterns

Rasa Bhattarai
International College
King Mongkut's Institute of Technology Ladkrabang
Ladkrabang, Bangkok 10520, Thailand
E-mail: 60610019@kmitl.ac.th

Montri Phothisonothai
International College
King Mongkut's Institute of Technology Ladkrabang
Ladkrabang, Bangkok 10520, Thailand
E-mail: montri.ph@kmitl.ac.th

***Abstract*—Uniqueness in the analysis pattern of objects by individual humans has a profound impact on the study of their visual learning and behavior. Eye movement patterns have been effectively emerging as a biometric based key for security systems, product recognition patterns, user identifications, as well as medical research purposes. The modern eye tracking systems are non-invasive and financially affordable. Therefore, in this paper, we proposed eye-tracking based visualizations and metrics analysis for individual eye movement patterns collected during any kinds of activities depending on the scope of the our experimental paradigms. Individuals can be aware of their own performances during certain task and improve upon their weak areas. The objective of the paper is to utilize the important visual metrics obtained from fixation, saccades and face recognition and use them to analyze for individual categorization. The obtained results shown that the specific features and patterns can be extracted the viewing aspect of individual subjects using naive Bayes classifier. We were successfully able to predict the individual eye movements with an accuracy of 90.22%.**

***Index Terms*—eye tracking, visual metrics, saccades, smooth pursuit**

I. INTRODUCTION

The way every human perceive objects and behavior of a system has different observant patterns. Since few decades, eye movements have been focused upon to understand the functionality of the viewing behavior of people. It has been used as a promising biomarker for security systems, automotive industry, virtual environment etc. Even graphical passwords are considered to be as an alternative to traditional passwords as it is easy to recall images [1]. One of the most practical application by using such eye movements can even be a major advantage for disabled people by helping them to interact with any interfaces directly without the need of secondary devices such as mouse or keyboard [2].

Eye tracking is a method identifying a person's eye movement which gives the measurements of the person's eye gaze positions and helps to know where the person is looking at [2]. Most of the modern eye tracking devices use infrared sensor technology to collect the individual's gaze pattern through the visual field [3]. Eye tracking systems being non-invasive have been in rapid growth these days. It is an easiest and convenient way to gather data for analysis of certain behavior. The decreasing cost, non-invasive procedure and financial availability has led many researchers to use such systems as a favorable tool for statistical analysis. Eye tracking systems obtains a stream of raw data, uses fixation detection algorithms which are either velocity-based, dispersion-based and area-based attributes as spatial characteristics to identify fixations, saccades and other metrics which can provide desired information depending on the research overview.

Therefore, in the proposed experiment, we initially aim to explore visualization patterns and evaluate eye tracking metrics like fixations, saccades, scanpaths etc. to understand movement mechanism for individual subjects.

II. LITERATURE REVIEW

Studies have shown that occulomotor measures like saccades and smooth pursuit are specific among individuals and can be used for biometric identification [4]. Biometric identification systems is a process to recognize an indiviudal through their biometric data by extraction of necessary features from the data which is later compared to the database verification sample [5]. The movement of every individual's eyes are considered to be unique thus making it as a good focus area for biometric authentication. This has led to the rise in new algorithms and techniques with ever increasing performance [6]. Similarly, there has been models that performed very well on keystroke and eye-tracking biometric data to identify user [7]. For such experiment which uses multiple bio-metric sources, the author encourages further study of eye tracking data since the models involving eye-tracking data are not successful [7].

Eye tracking patterns that can identify and select the desired object that can be useful for disabled or elderly people. Such metrics has also been used as an indicator for diseases like Alzheimers, Parkinsons etc. [8]. Overall, we can say that such visual metrics holds high potential to provide significant insights into any kind of platform that involves human interaction.

III. MATERIALS AND PROPOSED METHOD

In the proposed experiment, a simulation regarding visual behavior is presented to the subjects. The stimulation presented

978-1-7281-0719-6/19/$31.00 ©2019 IEEE

to the subjects is categorized into three types: i.e., 1) Saccades, 2) Smooth Pursuit and 3) Face Recognition. The stimulus is generated using Unity editor.

Saccades are the fast movement of eyes that shifts gaze location from one point to another. The movement is random and can occur in any direction. Such movements are used in many visual tracking experiments where a target object is shown and the subject are asked to either direct their gaze towards the target (prosaccade) or away from the target (antisaccade) [8]. For the Saccadic experiment in our system, a circular object is initially shown at the center of the display monitor as shown in Fig 1(1a). The object stays at the center point location for 2 seconds. It then moves on to random direction in every 1 second. The range of the random direction is about 9 degrees top, bottom, left and right. One complete trial takes 5 seconds and ends when the target object again reaches at the center of the display device. The subject need to fix their gaze at the moving target object until the program halts with a message to stop their gaze focus and relax.

Smooth pursuit is the eye movement which is continuous and the objective is to follow a moving target object. The subject needs to hold their gaze on the target object that can begin from any point on the screen (either central or peripheral). For the Smooth pursuit task, an object is initially shown at the center of the screen for 2 seconds. It is then moved towards the right side of the display device. Taking that extremity point as an initial value, the object starts making an elliptical motion as shown in Fig 1(1b). The elliptical motion is random. It moves up to a certain point in clockwise direction and again in anti-clockwise direction. Similar to the saccadic experiment, the subject need to fix their gaze and follow the moving target object.

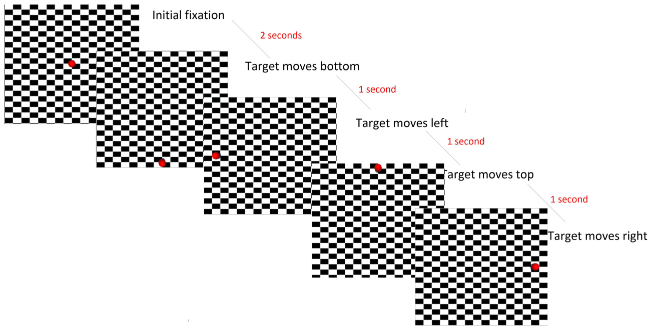
Finally, for the face learning and recognition task, a sample of images is taken from Karolinska Directed Emotional Faces (KDEF) dataset[1]. There are two phases for face recognition: Learning and recognition. For learning phase, 10 images are shown to the subjects. Each image is displayed for 5000 ms with an interval of 2000 ms as a break to position the subjects eye at the center of the screen as shown in Fig 1(1c). During the 2000 ms interval a fixation point is displayed at the center of the screen. The placement of these images is randomized towards either left or right from the center of the screen.

For recognition phase, 20 images (Among which 10 images are from learning phase and rest Novel images) is shown to the subjects. Subjects are instructed to confirm if the image was previously presented or not. The stimuli (image) will remain on the screen until the subject responds by pressing the button and move on to next stimulus (image).

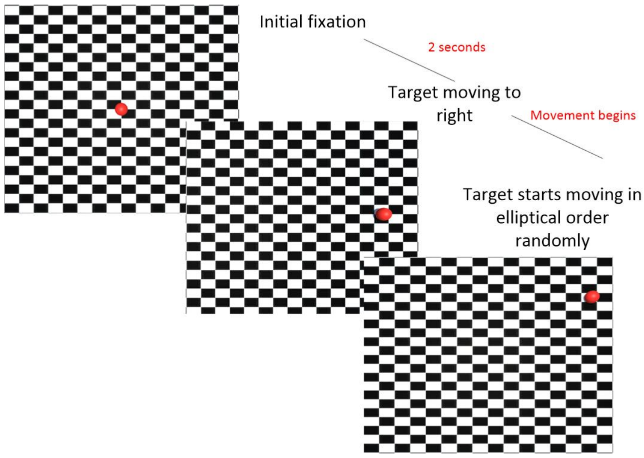
IV. Data Acquisitions

The experiment was conducted in a room with constant lightning conditions. The light was adjusted as to make the subject feel comfortable looking at the computer screen.

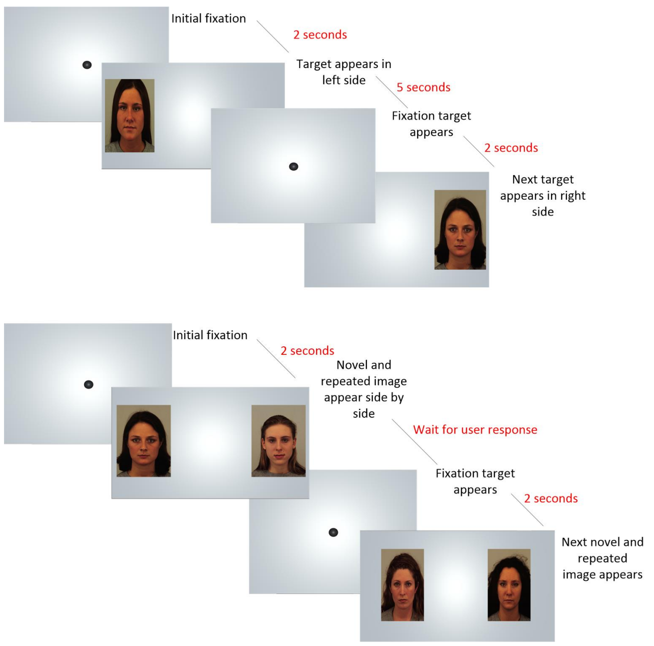
[1]Karolinska Directed Emotional Faces (KDEF), a public database used for psychological and medical research purposes



(a)



(b)



(c)

Fig. 1: (1a) Saccades: Target object moving randomly across screen (1b) Smooth Pursuit: Target object following an elliptical motion. (1c) Face recognition: Top fig: Learning phase Bottom fig: Recognition phase

The stimulus was shown on a monitor with a resolution of 1366×768, 8 GB RAM, Intel Core i7 Processor. The subjects volunteered by themselves for the experiment. They belonged to an age group in between 25 to 30. They were seated comfortably at an approximate distance of 60 cm from the monitor screen. They were explained about the procedure and were instructed to carefully follow the target object with less head movements as possible during the experimentation process. Breaks was provided to the subjects whenever it was needed.

V. Feature evaluation

For the obtained eye tracking dataset, a software analysis toolbox used for post-experimental analysis known as Eye Movements Metrics Visualizations (EyeMMV) was used [5]. The tool is used as a platform to provide fixations, saccadic values and scanpaths generated from the data for further analysis. The detection of fixation events was done with the use of an algorithm based on spatial and temporal constraints [9].

The experimental results obtained from 5 subjects (3 male and 2 female) are shown in Table I.

TABLE I: Comparison of EyeMMV results obtained from the experiment

EyeMMV	Sub A	Sub B	Sub C	Sub D	Sub E
Total no. of fixations	35	28	29	29	30
Mean fixation duration (ms)	913.0	988.0	974.7	939.9	947.2
Total no. of saccades	34	27	28	28	29
Mean saccadic duration (ms)	110.46	141.62	111.79	130.55	169.69
Mean saccadic amplitude	151.29	161.6	350.64	368	230.62
Scanpath length (pixels)	5144	4363.25	9818.03	10303.9	6687.86
Saccade by fixation	0.342	0.347	0.165	0.2	0.501

Eye tracking metrics shown in the above table are:

1. Total no. of fixations: The fixation detection algorithm returns a total number of fixation points from the raw data points. This metric returns a total number of fixations in the specified Area of Interest (AOI).

2. Mean fixation duration: The metric defines the average of the total fixation duration for one complete trial.

3. Total no. of saccades: The metric returns a total number of saccades extracted from the raw data in the specified AOI.

4. Mean saccadic duration: The metric defines the average of the saccadic duration for one complete trial.

5. Mean saccadic amplitude: The metric is the angular distance travelled by the eye during such saccadic eye movements.

6. Scanpath length: Scanpath is the sequence of eye movement gaze patterns while looking at the desired target field. The metric gives the total scanpath length value in pixels.

7. Saccade/fixation: The metric gives the ratio of the saccade/fixation.

The system overview of the system is given in Fig. 2.

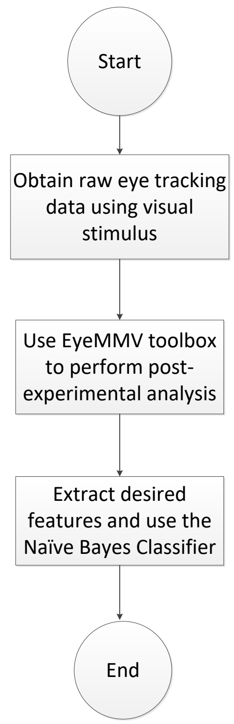
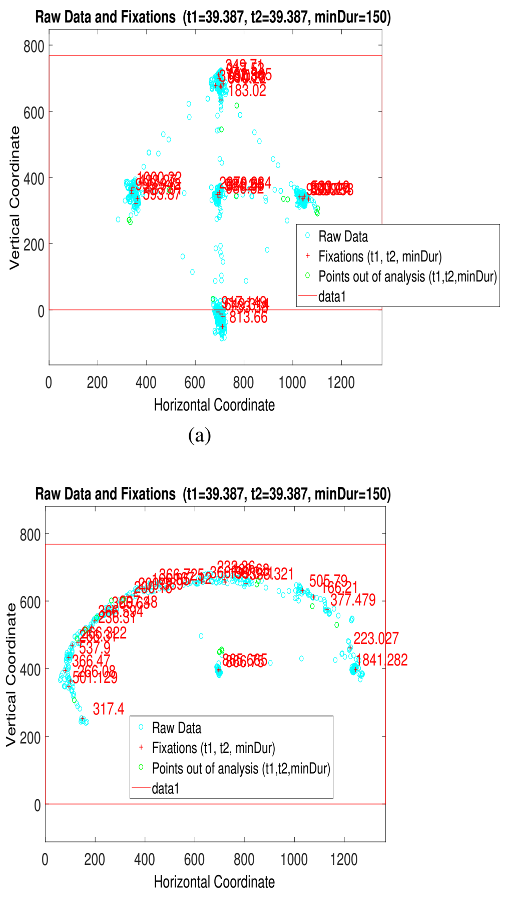


Fig. 2: System overview of the proposed method.

VI. Results and Discussion

The scanpath patterns for the saccade experiment for a single subject is shown in Fig 3(3a) as obtained from the subjects. The blue circles represent the raw data obtained from the overall experiment and the red points indicate the fixation points of the graph. Similarly, Fig 3(3b) shows the scanpath patterns for the smooth pursuit experiment. There is also an indication of the scanpath sequence as shown in Fig 4. The numbers indicated on the graph specifies the direction where the subject's eye gaze was following along the horizontal and vertical co-ordinates. Among a number of Machine Learning classifiers, reliable accuracy results was obtained from Naive Bayes algorithm. Naive Bayes classifier are based on Bayes theorem which utilize training data to calculate an observed probability of each outcome based on the evidence provided by the feature values. The classifier can then be applied to the unlabeled data which utilizes the observed probabilities value to predict their class [10].



(a)

(b)

Fig. 3: (3a) and (3b) Raw data points are shown in blue circles and fixation points shown in red plus (+) sign.

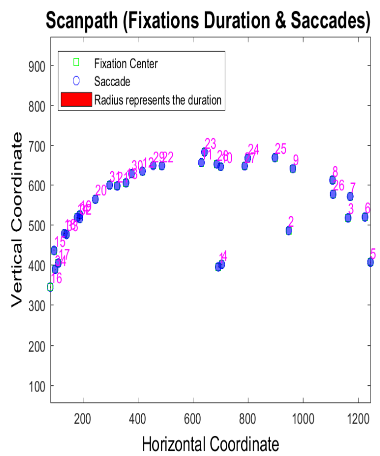


Fig. 4: Scanpath direction showing numbers within it, indicating the trace of direction.

Individual patterns were evaluated from the data obtained. The dataset was divided in the ratio of 70:30 for training and testing samples.The proposed machine learning classifiers, namely Naive Bayes, proved to show significant accuracy of 90.22%. The precision for the subjects (Sub A: 0.80, Sub B: 1, Sub C: 1, Sub D: 0.77 and Sub E: 0.85) has been obtained through the formula:

$$Precision = \frac{TruePositive}{(TruePositive + FalsePositive)}$$

VII. Conclusion and Future Work

From this paper, we have successfully shown a method to classify individual eye tracking patterns with the help of basic eye tracking metrics. From the data obtained through the evaluation, we can extend our study to analyze the patterns of eye tracking behavior specific to different situations. As mentioned earlier, such studies can provide potential data on the study of different medical condition. Evaluation of the features used in the system can be applied towards classification of a category for medical diagnosis.

References

[1] M. Mihajlov, M. Trapkova, and S. Arsenovski, “Eye tracking recognition-based graphical authentication”, *International Conference on Application of Information and Communication Technologies (AICT)*, 2013.

[2] A. Poole, L. J. Ball, “Eye tracking in Human-Computer Interaction and Usability Research: Current Status and Future Prospects”,*Encyclopedia of Human Computer Interaction, Pennsylvania: Idea Group, Inc*, 2005.

[3] P.A. Punde, M.E. Jadhav, and R.R. Manza, “A study of eye tracking technology and its applications”, *International Conference on Intelligent Systems and Information Management (ICISIM)*, 2017.

[4] G. Bargary, J.M. Bosten, P.T. Goodbourn, A.J. Lawrence-Owen, R.R.Hogg, and J.D. Mollon, “Individual differences in human eye movements: An oculomotor signature ?”, *Vision Research*, Vol. 141, pp 157–169, 2017.

[5] A. Bayat and M. Pomplun, “Biometric Identification through Eye-Movement Patterns”, *International Conference on Applied Human Factors and Ergonomics*, 2018.

[6] M. Brooks, C. Aragon, and O. Komogortsev, “Identifying people by eye movements a potential replacement for passwords”, *SPIE Newsroom*, pp.1–3, 2013

[7] D.L. Silver, and A.J. Biggs, “Keystroke and Eye-Tracking Biometrics for User Identification”, *International conference on Artificial Intelligence (ICAI)*, June 26–29, 2006.

[8] R.J. Molitor, P.C. Ko, and B.A. Ally, “Eye movements in Alzheimer’s Disease”, *Journal of Alzheimer’s disease*, vol. 44, No. 1, pp. 1–12, 2015.

[9] V. Krassanakis, V. Filippakopoulou, and B. Nakos, “EyeMMV toolbox: An eye movement post-analysis tool based on a two-step spatial dispersion threshold for fixation identification”, *Journal of Eye Movement Research*, 7(1):1, 1–10, 2014.

[10] B. Lantz, “Machine Learning with R”,*Packt Publishing Ltd., Birmingham B3 2PB, UK*, 2nd ed., pp 90-91, July, 2015.