VIGILANCE ASSESSMENT USING EEG AND EYE TRACKING DATA FUSION

by

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Declaration of Authorship

I declare that this is my own work and, to the best of my knowledge and belief, it does not contain material published or written by a third party, except where permission has been obtained and/or appropriately cited through full and accurate referencing.

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Dedication

I dedicate my effort to my beloved husband, whose affection, encouragement, and prayers of day and night have made me reach where I am. Thank you for always believing in me …

Abstract

Vigilance describes the ability to maintain alertness while performing a task for a prolonged time. Maintaining vigilance is one of the requirements in many workplaces, especially those that rely on monitoring, such as: surveillance tasks, security monitoring, and air traffic control. These tasks necessitate a specific level of arousal, to provide an acceptable level of cognitive efficiency. Vigilance decrement could result in fatal consequences like accidents, loss of life, and system failure. In this thesis, we investigated the possibility of assessing the vigilance levels using a fusion of Electroencephalography (EEG) and eye tracking data. Vigilance levels are induced by performing a modified version of Stroop Color-Word Task (SCWT) for 30 minutes. Feature-level fusion based on the canonical correlation analysis (CCA) has been employed to enhance the classification accuracy for vigilance level assessment. In the feature level fusion, EEG and eye tracking features are concatenated into a single vector-feature-space and then fed as an input to the Support Vector Machine classifier. The results of the fusion showed that both modalities' accuracies have been enhanced. The highest accuracy for the fusion was using the EEG Delta band of 96.8± 0.6%, which is higher than using the EEG Delta band without the fusion (88.18±8.5%) or the eye tracking date alone (76.8 ± 8.4 %).

Keywords: Vigilance detection accuracy; vigilance assessment; Electroencephalogram (EEG); eye tracking; data fusion.

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List of Abbreviations

AC	Anatomical Connectivity
AFD	Average Fixation Duration
ANN	Artificial Neural Network
AOG	Area of Glance
AOI	Area of Interest
BCI	Brain Computer Interface
CBFV	Cerebral Blood Flow Velocity
CCA	Canonical Correlation Analysis
DT	Decision Tree
DWT	Discrete Wavelet Transform
EC	Effective Connectivity
ECoG	Electrocorticography
EEG	Electroencephalogram
ELMs	Extreme Learning Machines
EMG	Electromyogram
EOG	Electrooculogram
EOPs	Emergency Operating Procedures
ERPs	Even Related Potentials
FC	Fixation Count
FC	Functional Connectivity
FFT	Fast Fourier Transform
FIR	Finite Impulse Response

fNIRS	Functional Near Infrared Spectroscopy
FP	False Positive
FR	Fixation Rate
GMDH	Group Method and Data Handling
HbD	Hemoglobin D
HbO	Oxy-Hemoglobin
HF	Human Failure
HRV	Heart Rate Variability
IBI	Inter-beat Interval
ICA	Independent Component Analysis
KNN	k-Nearest Neighbours
LDA	Linear Discriminant Analysis
LOOCV	Leave-One-Out Cross-Validation
MSC	Magnitude Square Coherence
MVAR	Multivariate Autoregressive Models
NB	Naive Bayes
NPP	Nuclear Power Plants
PDC	Partial Directed Coherence
PDF	Probability Density Function
PSD	Power Spectral Density
rLDA	Regularized Linear Discriminant Analysis
SCWT	Stroop Colour-Word Task
SD	Spatial Density

SE	Spectral Entropy
SVM	Support Vector Machine
SWE	Shanon Wavelet Entropy
TCD	Transcranial Doppler
TP	True Positive
VD	Vigilance Decrement
VR	Virtual Reality
WE	Wavelet Entropy

Chapter 1. Introduction

1.1. Motivation

In today's world, emphasis is focused on reducing risks and eliminating the chances of accidents and errors. Vigilance level assessment in real-time is very important to avoid human errors. Critical working environments, like air traffic control, driving, quality control, and military surveillance, require the operator to be alert the whole time [1]. Such tasks necessitate a specific level of arousal to have an acceptable level of cognitive efficiency. Without attention, we cannot selectively operate and discriminate between useful information and noise. Being vigilant increases preparedness when danger arises. In a real-life application, it was observed that work overload, stress, time, and drowsiness are major factors that cause vigilance decrement [2]. Early research has shown that maintaining vigilance in a stressful environment requires hard mental work [3]. Studies have shown that it takes 30 minutes for the target detection performance to decrease by 15% while performing a hard mental task [4]. Reduction in performance level leads to an increased reaction time, error rate, and may cause fatal consequences. For example, personnel who are responsible for monitoring security cameras may miss some important targets that may increase the risk level. Furthermore, drivers' vigilance decrement could lead to traffic accidents. According to [5], 74% of European drivers suffer from fatigue while driving, and this may cause crashes; lower rates were reported amongst road users in North America (69%), Africa (64%), and Asia-Oceania (53%).

1.2. Background

Vigilance is the ability to sustain attention for an extended period of time [6]. It is very important to stay vigilant, maintain focus and respond to any occurring stimulus in real-life applications; some examples of these that require vigilance include: driving a car on long highways, conducting a quality inspection in manufacturing, or maintaining video surveillance of public areas, etc. It has been noted that vigilance decrement is a major risk factor for car crashes and many other crises [7]. Vigilance decrement may occur in many operational environments, but it is more common when there is a need for continuous concentration over a long period of time. Some reasons lie behind vigilance decrement, like a physiological need for neuronal stimulation or mental fatigue associated with completing a task for a long period of time, where the performance in recognizing and reacting to changes in the system state begins to degrade [8]. In specific activities, the rate at which this degradation occurs varies. Parasuraman et al. [3], argue that tasks can be differentiated from those requiring judgments against a memory value such as driving a car in an area with a defined speed limit, and those involving comparative judgments (oil temperature and oil pressure in an airplane). As an effect, on time-on-task vigilance decrement can result in a slow reaction time or an increase in error rate.

The term 'cognitive workload' has been described by Christopher Wickens as the "relation between the (quantitative) demands for resources imposed by a task and the ability to supply those resources by the operator" [9]. Bradley Cain defined it as "a mental construct that reflects the mental strain resulting from performing a task under specific environmental and operational conditions, coupled with the capability of the operator to respond to those demands" [9]. Using a multidimensional concept to describe workload, it appears to consist of four components: 1) Depletion factors, 2) Mental workload, 3) Performance, and 4) Task complexity [10]. According to Yerkes-Dodson Law, a negative quadratic relationship between arousal and performance was predicted. When the individual is performing a task, the level of interest and engagement will start to increase gradually with time until the individual reaches a point delivering the optimum performance. The performance will consequently start to decrease because of different factors, mainly increased or decreased cognitive workload (Vigilance decrement). In Figure 1.1, a relationship has been plotted describing performance vs. anxiety [11].

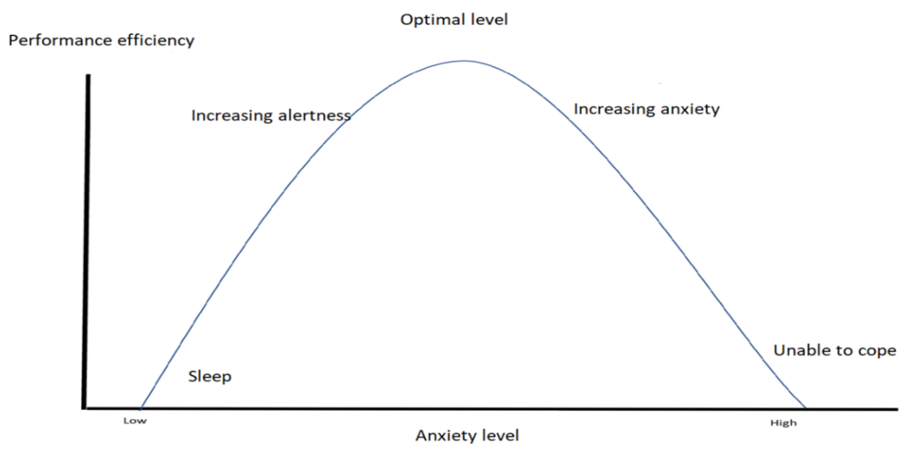

Figure 1.1: Yerkes-Dodson curve showing the relationship between anxiety and performance [11].

Many factors play a role in vigilance decrement such as: fatigue, distraction, boredom, task environment, and outside stressors [12]. Parasuraman et al. [13], related vigilance decrement to adverse environmental conditions and low motivation associated with lack of performance feedback. Schroeder et al. thought that the more involved the operator in decision-making and the more feedback the operator receives; the more aroused and alert (vigilant) the operator may be [14]. The fact that vigilance could decrease while performing a specific task in some critical monitoring environments can't be afforded; a slip in attention may have dire if not fatal consequences. For 31 out of 78 train accidents reported in the UK, studies have shown that the top 3 occurrence categories of railway accidents are human failure (HF) to collision, derailment, and level crossing occurrence. This study indicated that human failure is the main contributor to train accidents. Reasons behind the operator failure could vary; examples are distraction, perception, fatigue, and workload (time, pressure, and stress) [15]. Kristin M. Finkbeiner proved that the inclusion of different types of rest breaks could help in improving the overall performance when someone is doing a task for a long period of time. The breaks discussed in Finkbeiner's study were dog video breaks, robot video breaks, countdown breaks vs. continuous vigilance. The continuous group had the worst performance, while the other rest breaks helped in restoring attention and decreasing distress [16]. This study proves that operators may suffer from vigilance decrement and suggested some methods to improve it. However, to improve vigilance level, vigilance must be assessed accurately first.

Vigilance assessment is the first step to be done to enhance vigilance; assessing vigilance level accurately could help in any human failure in different work environments. There are three different methods to assess vigilance: subjective assessment, behavioral and objective assessment methods [9]. In the subjective assessment method, a person's perception of self-assessment may be considered. Self-assessment is usually measured by various techniques like surveys, questionnaires, or interviews. The problem with subjective measures is that it prevents us from understanding the multiple variations of workload during a task, in addition to being subject to a retrospective bias [17]. On the other hand, objective assessment is maintained when the measurement being identified uses quantitative data for specific task demands. It is very important to assess vigilance level and continuously monitor it using the best modalities; assessing vigilance level will help in evaluating the operator's mental state while performing a task [18].

1.3. Hypothesis and Thesis Contribution

Research in the field has shown that many studies proposed and designed new methods for vigilance level assessment. Such methods include heart rate variability, galvanic skin response [19], pupil diameter, eye blink frequency [1], and brain activity measurement, (EEG, EMG,... etc) [20]. Although all these modalities are considered effective in vigilance assessment, some limitations of modalities affect accuracy. Eye tracking features suffer from high intra-personal variability and are assumed to be sensitive to lighting conditions [21]. EEG and fNIRs provide poor spatial resolution [22]; EMG must be operated in a special environment for effective detection and it is very sensitive to movement [23], and ECoG is an invasive technique [24].

1.4. Thesis Organization

Across all the detection modalities mentioned in section 1.3, EEG is the most common modality used in vigilance assessment. Although EEG suffers from poor spatial resolution, it is still very popular for the following reasons [24]:

1. EEG has a high time resolution.
2. EEG is simple to operate, and it's a non-invasive detection method.
3. EEG cost is less than other modalities.
4. Event-related potentials (ERPs) features are provided by EEG signals. These features have proven their capability to be utilized in studying the changes that occur in the human brain with respect to time.

Eye tracking approach for data analysis is known to be friendly because of its ease of use, in addition to being non-intrusive. Research has shown that there are advantages of both EEG and eye tracking approaches; using eye tracking besides EEG could help in increasing the assessment accuracy [25].

This study hypothesizes that developing a fusion model to combine the EEG and eye tracking data can improve the accuracy of vigilance level assessment more than using either of the techniques alone. EEG and eye tracking possess several advantages as they are non-invasive, portable, less expensive, safe for long-term monitoring, and can be good complementarily [26]. The integration of these two modalities offers a mean to partially overcome the limitations of each of the individual modalities by combining their complementary aspects in one single analysis. We further hypothesize that the decrement in the power spectral density is EEG band-specific; therefore, the assessment on vigilance will utilize four different EEG frequency bands. To evaluate our hypotheses, we propose a novel protocol to assess vigilance level under alertness and vigilance decrement using a computerized version of the Stroop color-word task (SCWT). Besides, we present a fusion method using the EEG and the eye tracking data to enhance the vigilance classification accuracy. The experimental results showed that the proposed fusion model successfully increased the classification accuracy. All EEG bands showed a high classification accuracy when data fusion was employed.

1.5. Objectives

This thesis aims to achieve the following objectives:

1. To assess the level of vigilance based on EEG cortical activity and eye tracking data while performing a Stroop color work test.
2. To develop a fusion model of EEG and eye tracking data to discover the association across them and examine if the model can improve vigilance level assessment over individual modalities.

1.6. Thesis Layout

Chapter 1 introduced the motivation, background, hypotheses, and objective of this work. The rest of this thesis is arranged as follows: Chapter 2 provides a detailed literature review related to vigilance assessment using a single modality, followed by more literature review for the enhancement of vigilance assessment using a fusion of two modalities. Chapter 3 discusses details of the data collection paradigm. Chapter 4 discusses the processing techniques of EEG and eye tracking data fusion. Chapter 5 presents the results of the preprocessing applied on the EEG and the eye tracking data. Chapter 6 discusses the results of the vigilance assessment using the EEG as a single modality and the eye tracking alone. Chapter 7 discusses the results of vigilance assessment using the feature level fusion of both the EEG and the eye tracking data. Finally, conclusions and future work are highlighted in chapter 8.

Chapter 2. Literature Review

In this chapter, we discuss the different approaches used for vigilance assessment and highlight the most common objective measures. The objective measure includes physiological/ neurophysiological measures that can be used for cognitive workload assessment. The literature summarizes the vigilance assessment modalities that have been used in different research works, in addition, to summarize the approaches that has been utilized for the cognitive workload assessment using data fusion.

2.1. Vigilance Assessment Methods

Fatigue arises as a result of task factors; an example is task demand. In order to identify the fatigue level, both subjective and objective measures can be used. On one hand, the subjective measures depend on the operators reporting that they are tired or fatigued. To obtain a better assessment of fatigue level, measures that are more sensitive to changes in performance are required. On the other hand, objective measures can identify increased fatigue-related risks because of their sensitivity to changes across time, and under a range of different conditions.

Objective measures could be physiological, neurophysiological, or behavioral responses of the operator during a task. The neurophysiological measures include electroencephalography and near-infrared functional spectroscopy. Physiological measures include electrocardiography, while behavioral measures include the following: dynamics of the keystrokes, mouse tracking, and body positioning [27]. Researchers have compared subjective and objective mental workload assessment and suggested that objective measures can provide a more comprehensive, and richer understanding of the workload.

2.1.1. Vigilance assessment using subjective and behavioral approaches.

The assessment of cognitive state can be done using subjective, behavioral, and physiological measures [18]. The subjective measures are limited when the assessment is disruptive to the real-time task. A study [28] explained that humans may not have an accurate judgment when it comes to their cognitive states all the time. On the other hand, behavioral vigilance assessments are more task-based, and their evaluation for the cognitive state is a function of time [29]. Reaction time and target detection rate are some of the measures that can be obtained using the behavioral approach, where reaction time is the length of time it takes a person to respond to a given stimulus of an event, and the target detection rate refers to the number of hit events. It has also been found that the target detection rate and vigilance are directly related [30]; where target detection rate decreases with vigilance decrement.

2.1.2. Vigilance assessment using physiological and neurophysiological approaches. The physiological measures used in assessing cognitive workload are very important. They can improve cognitive state assessment by adopting approaches that measure changes in the central and peripheral nervous system due to their sensitivity to real-time information for the cognitive workload. Accuracy in assessing cognitive workload has been found to significantly increase when physiological data was utilized [31]. Studies have shown that changes in vigilance levels are related to physiological changes, these changes are controlled by the brain and nervous system. Various physiological measures were utilized for cognitive workload assessment; for instance, many studies in literature employed eye tracking measurements for cognitive workload assessment. Many eye tracking features such as fixations duration, saccades, pupil size, and scan paths can help us understand human behaviors when performing attentional tasks. One of the key reasons behind traffic accidents and poor driving is the suboptimal level of cognitive functioning (inattention, drowsiness) [18]. A study compared between physiological and behavioral measures assessing the cognitive workload while driving found that physiological measures were more sensitive to variation in the cognitive workload, while behavioral measures (steering wheel reversals, velocity, and lane-keeping) were not as sensitive [29]. Hence, the inclusion of the physiological data would complement and enhance the assessment besides the behavioral metrics. Many of the physiological changes while performing a task can affect psychophysiological measures such as: heart rate, skin conductance, and the electrical activity of the brain. The electrical activity of the brain is more sensitive to change in vigilance, since it reflects the physiological changes that the operator is experiencing, such as: workload, drowsiness, stress, etc.

Table 2.1 summarises the types of physiological/neurophysiological measures and the metrics that can be extracted to reflect the level of cognitive workload [32].

Table 2.1: List of physiological/neurophysiological measures used in required mental resources quantification [32].

Measure	Extracted metrics
ECG	Inter-beat interval (IBI)
	Heart rate variability (HRV)
EEG	SPDs for frontal theta, alpha, beta…etc
TCD	Bilateral CBFV in medial cerebral arteries
fNIR	Bilateral rSO_2 in the prefrontal cortex
Eye tracker	Mean fixation duration

2.2. Cognitive Workload Assessment

This section provides an overview of existing cognitive workload assessment contributions in the literature. The overview highlights different modalities that have been used to assess cognitive workload, in addition to different fusion techniques that have been utilized to increase the cognitive workload classification accuracy.

2.2.1. Cognitive workload assessment through a single modality. A study [33] compared 7 measures to evaluate the mental workload; these measures are: pupil size, blink rate, blink duration, heart rate variability, parasympathetic/sympathetic ratio, and total power. A simulated experiment of computerized emergency operating procedures (EOPs) of different levels was carried out for 18 participants. The results showed that the blink rate is sensitive to the task level, while the error rate is sensitive to the arousal level. Blink duration tends to increase for long task periods regardless of the task level. This study indicated that eye response measures are useful in detecting the temporal changes of mental workload. On the other hand, cardiac measures can distinguish between task levels and evaluate the overall workload. Hwang et. al in study [34] investigated the operator's mental workload and work performance of the nuclear power plants (NPP) environment. The experiment included two tasks: primary and secondary tasks; both tasks are simulation-based for the reactor shutdown procedure in the fourth nuclear power plants (FNPP). In this study, both subjective and physiological measures (HRV) have been assessed by comparing the error rate between the physiological measures and the NASA-TLX questionnaire. Group method and data handling (GMDH) (one of the better-known neural network methodologies) were utilized. In addition, the analysis of Pearson-product moment correlation was used to examine the relationship between two response variables (NASA-TLX scores and the error rates). The results showed an increase in the number of errors in the secondary task. This implies that the subjects were fatigued due to the heavy mental workload. The experiment also indicated that most of the participants' heart rate and LF/HF components increased for high-level tasks. However, the heart rate variability (HRV) decreased for the same level of tasks (complicated tasks).

Warm et al., [35] utilized Transcranial Doppler Sonography (TCD) measures. One of the TCD measures is the cerebral blood flow velocity (CBFV), which was used to diagnose the operator fatigue level. The study showed that vigilance decrement is reliably accompanied by the reduction of CBFV in the right hemisphere measured using TCD. Another study [36] investigated the level of blood oxygenation in frontal areas (measured by functional near-infrared spectroscopy (fNIRS)) in relation to mental workload. Results showed the sensitivity of fNIRS measures to mental task load and to the task level. This study also pointed the importance of employing fNIRS to monitor the hemodynamic changes in the brain areas for the operator in different fields.

Dean J. Krusienski [37] presented a user-state detection system in an active virtual reality (VR) environment, which monitors the user behavior through tracking physiological signs, like the electroencephalogram (EEG) via the use of a VR process. The study assessed cognitive workload using EEG while performing a traditional n-back task within an immersive VR environment. Fifteen participants performed the task, and the spatio-spectral EEG features were reviewed with respect to the job performance. Feature extraction was done using FFT and classified by rLDA with four-fold cross-validation. The results of the cognitive workload assessment gave an accuracy of 73.6 and 60.6%, for task-level 0 and 2, respectively. By employing a high-level task for the purpose of measuring cognitive workload using EEG, Pega Zarjam (2015) [38] has compared the accuracy of detection using subjective ratings and EEG-based method. Subjective rating (self-assessment) has often been a preferred measure because of its simplicity and its relative response to cognitive load types. Through the analysis, the researcher used 7 different levels of workload to investigate workload differentiation dependent on EEG signals. The entropy, power, and standard deviation of the wavelet coefficients were obtained from the segmented EEG signals, that were found to change continually in accordance with the level of load. By applying discrete wavelet transform (DWT) for the signals recorded from 32-channel EEG, results showed that high task load discrimination was primarily found inside the frontal lobe of the brain, corresponding to the delta frequency band. This is supported by relevant results emphasizing that the frontal lobe is important for maintaining and carrying out cognitive tasks because of its tight relationship with attention and working memory. This study has also shown that their cognitive load classification methodology outperformed self-ratings, by accomplishing an extremely high detection accuracy of 98% in discriminating seven load levels, compared to 31% classification accuracy of self-rating.

Although some tasks are described as low cognitive level tasks, still sustaining attention is very critical, even if performing an easy task. Drowsiness is defined as a transition state between being asleep and awake, and it may have severe consequences when occurring while a task is being performed. Yugang Liu (2017) [15] proposed a fatigue detection system for high-speed train safety; the system is based on monitoring train driver vigilance using a wireless wearable electroencephalograph (EEG). It helps in monitoring the alertness of the vehicle operators to prevent them from drifting off to sleep while driving. The system monitors the driver's face area using Haar feature classifiers, with a training set to quickly identify alterations in the face area of the driver. Data for 10 drivers was studied by applying FFT of 8-channels EEG and classified using support vector machines (SVM) classifier. The study showed that in the alert situation, lower frequency components were discovered in the region of the forehead and distributed in the occipital region. The system achieved an excellent classification efficiency of 90.70% for driver’s vigilance detection.

For a similar application, F. Sauvet (2014) [2] was interested in the fact that fatigue and sleepiness may reach high levels during long-haul overnight flights. Under these circumstances, voluntary or maybe even involuntary sleep periods could take place raising the chance of accidents. For 14 healthy pilots flying airplanes for flights with the length 10 ± 2.0 h, STFT approach was applied to the collected EEG signals and using Fuzzy logic fusion, an agreement of the relative power had been observed utilizing the ratio $(\alpha + \theta)/\beta$. The O1-M2 channel offered the finest classification. Using a detection threshold that is entirely independent, and did not need to be tuned per subject, they achieved a 98.3% accuracy of vigilance state detection.

Studies have used electroencephalography (EEG) to assess cognitive workload and reported that the higher the cognitive workload, the higher the theta band power and the lower the alpha band power. Many of those studies lacked consistency; in addition, they did not take the individual differences into consideration. Sebastien Puma (2017) in [39] used EEG to measure the cognitive workload in a multi-tasking environment, with 20 participants performing a task that is common in an airline pilot recruitment in addition to more sub-tasks. Subjective ratings, performance scores, pupil size, and EEG signals were used to measure the cognitive workload. Results indicated that EEG allows for discriminating cognitive load by showing a widespread in theta rhythm and localized increase in the alpha rhythm. The study also reported that the higher the performance, the lower the band power.

Although objective methods are better in detection compared to subjective ones, still their accuracy, temporal resolution, and latency need to be enhanced. The reason behind this is that these measures appeared to be sub-optimal when using objective approaches. In some cases, the system does not respond to changes in the task load because of the subject movement that could produce noise and artifacts. It is a big challenge facing researchers to overcome this problem, and to do that, the fusion approach of modalities in assessing cognitive workload has been suggested in many research papers in order to improve the detection accuracy. The literature illustrates some successful work for cognitive workload assessment by applying data fusion of two modalities.

2.2.2. Cognitive workload assessment through EEG-EMG fusion and EEG-fNIRs fusion. Data fusion is an incorporation of data taken from different sources for the purpose of inferring important information that cannot be obtained from a single modality. Data fusion is classified into three levels: feature level fusion, decision level fusion or hybrid models [9]. Even though the accuracy obtained was high using EEG in many of the cognitive workload assessment studies, in a real application the case is significantly different, because information becomes corrupted, disturbed, as well as delayed. In such instances, instead of dealing with single sensor weaknesses, and enhancing information quality/accuracy, the use of multiple modalities is needed. Multi-modal fusion techniques have proven their efficiency in other domains such as wireless sensor networks. Extensive work has been done in improving the estimation accuracy of cognitive workload utilizing different sensor modalities. In any case, the general execution of various approaches and strategies remains problematic in real-world applications. A few investigations in the literature showed that a single methodology may be adequate to evaluate cognitive workload, while in other applications it was not. Thus, data fusion can be used to increase the accuracy of evaluation. In some cases, due to subject movements, or the system suffering from noise and artifacts, the use of data fusion for two modalities may help in improving signal-to-noise ratio, reducing ambiguity and uncertainty, enhancing performance, and improving temporal and spatial coverage. In the cognitive workload assessment literature, fusion by using data from two sensors appeared to be effective for real-time measurement of cognitive workload.

According to Mehmet Akin (2008), in a study [40], earlier scientific studies made use of only EEG signals for estimating the vigilance level. The researcher aimed to estimate vigilance level by implementing both EMG and EEG signals for enhancing the accuracy of estimating vigilance level. The study developed a completely new strategy for estimating vigilance level by utilizing both EMG and EEG signals during transition state from wakefulness to sleep for 30 drivers. Extracting features from the sources has been done using DWT for efficient discrimination; chin EMG was used to eliminate movement artifacts, and ANN was used as a classifier. EEG signals showed less beta and alpha bands power when the individual is asleep. The study reported that the beta and alpha activities decreased during the shift from wakefulness to sleep stage when merging EMG and EEG. An accuracy of 98-99% was obtained for vigilance level assessment which outperformed another study that used only EEG with an accuracy of 95-96%.

Darren J. Leamy in study [41] approached dual-modality techniques that are very important to brain-computer interface (BCI) researchers, these techniques used to instigate the possibility of improving classification accuracy by demonstrating enhancements to imagined-movement based BCIs. It was thought that the fusion analysis is going to lead to more precise BCIs. The modalities used were EEG and fNIRS, with which they recorded concurrent and co-locational electrical, and hemodynamic responses in the motor cortex during an imagined movement task participated by 2 subjects. An analysis and classification of fNIRS and EEG data was carried out using leave-one-out cross-validation (LOOCV), along with linear discriminant analysis (LDA). Each subject performed 40 experimental trials, and the accuracy for each of the two subjects was 58% and 66% for classification during an imagined movement-based task. Siamac Fazli (2012) in a study [42] applied the same two modalities for data fusion (fNIRS and EEG) motivated by the non-invasive Brain-Computer Interfaces (BCI) since many reports on applications with electroencephalography (EEG) clearly showed a need for better accuracy and stability for the BCI systems. For that reason, the study investigated whether near-infrared spectroscopy (NIRS) could be utilized to improve the EEG classification. 14 subjects performed motor imagery and executed movements tasks to test how the classification of the NIRS will enhance the ongoing real-time EEG classification. The results obtained from 16 NIRS detectors and 37 EEG electrodes were classified by both cross-validation and LDA classifiers. The results demonstrated that measurements of EEG and NIRS can greatly enhance the classification accuracy of motor imagery in more than 90% of the subjects, as well to increase classification accuracy for the performance by 5% on average. In addition to the previous two studies, Xuxian Yin (2015) in study [43] tried to boost the number of states categorized by a brain-computer interface (BCI); Yin used a motor imagery task where the persons imagined both speed and force of hand clenching. The time-phase-frequency feature was obtained from EEG, and the HbD [the distinction of oxy hemoglobin] (HbO) was obtained from fNIRS. Deoxyhemoglobin (Hb) attribute was utilized to enhance the accuracy of fNIRS strategy. The BCI was utilized to instantly capture electroencephalographic (EEG) and functional near-infrared spectroscopy (fNIRS) signals. Features were extracted by applying the Hilbert transform and complex wavelet convolution and then classified by extreme learning machines (ELMs). Classification accuracy for the decoding motor imagery task of 89% was obtained in addition to an enhancement by 1% to 5 % over the single EEG modality or the single fNIRS modality.

2.2.3. Cognitive workload assessment through EEG-ECG fusion. Sudarshan Kriya Yoga (SKY) is a kind of rhythmic breathing exercise, a significant kind of Pranayama that expresses physical, emotional, mental, and interpersonal well-being. SKY was the task adopted in S. Chandra (2016) study for 25 subjects [44]. The goal of the study was to quantitatively measure if SKY is going to increase workload tolerance. The study also aimed at verifying the result of meditation in regulating stress and increasing task efficiency. DWT and Pan-Tompkins algorithms were used for extracting features of the EEG and the ECG signals. The study reported that the results of the fusion classified by ANN showed better accuracy in comparison with the SVM classifier, and reached up to 90%. The study did not share any information about the system outperforming the sole EEG. According to XueWang (2017) [45], a mental workload classification accuracy of 90% was been obtained when 10 subjects performed an n-back task over 3 different levels. The accuracy mentioned was the result of the feature level fusion for both EEG and ECG modalities. Furthermore, and for the same study, an accuracy of 91% was obtained for the classifier level fusion. Features were extracted using Welch's method and HRVAS and were classified by SVM. However, the study reported that fusion models did not show significant performance over single modality models.

2.2.4. Cognitive workload assessment through EEG-eye tracking fusion. Eye response metrics, such as dilation of the pupils, blink frequency, and length of the blinks, correspond with cognitive workload regardless of the workload level. It was indicated by previous studies that blink frequency and blink length decrease with the high task demand and high cognitive load periods. Yifei Lu and Wei-Long Zheng (2015) in study [46] have confirmed this through a study combining EEG and eye movement to enhance emotion recognition. The objective of the paper was to examine emotionally linked sixteen eye movements and describe the intrinsic patterns for the movement of the eye in three emotional states: positive, neutral, and negative. Another objective for the study was to combine EEG and eye movement for the purpose of analyzing various fusion modality approaches. Subjects were asked to watch some video clips, and the data was collected using 62-channels electrode. Feature extraction was done by applying STFT and classified by both SVM and LDS. Yifei Lu and Wei-Long adopted fuzzy integral fusion strategy that showed a high accuracy of 87.59%. This was in comparison to the single EEG modality or the single eye movement modality for emotion recognition with accuracies of 77.80% and 78.51%, respectively. Meanwhile, David Rozado (2015) [47] combined EEG and pupillometry for a high-level task. In his study, 23 participants took a mental arithmetic task; the data was collected from 62-channel electrodes, and the features were extracted and classified by both LDA and SVMs classifiers. For simple arithmetic operations, an error rate of 17% for the fusion was calculated compared to an error rate of 26.1% for pupillometry alone and 24.1% for EEG alone. They achieved the workload assessment classification accuracy of 83.25% for the fusion approach. Brouwer (2017) in a study [48] investigated the cognitive workload assessment method when participants were conducting monitoring tasks. She has proposed that EEG and eye pupillometry could complement each other in order to reach a higher degree of understanding that none of the modalities would achieve independently. The eye monitoring approach has shown effectiveness to differentiate between hits and misses, whereas EEG has also shown to better help differentiate between goals and non-targets. Therefore, integrating the characteristics of both styles into one model improved the overall accuracy. Nonetheless, no statistical analyses have been recorded in the study. Jung-Hoon Kim (2017) in a study [49] tried to optimize the efficiency of the cognitive assessment methodologies by demonstrating a correlation between EEG and eye tracking data. Subjects performed simulated baggage screening task, and both eye tracking and EEG data were obtained. Results have indicated a significant correlation between cognitive workload metrics based on EEG and eye tracking measurements. In addition, Fares Al-Shargie [50] reviewed vigilance enhancement by applying conventional and unconventional means. The study illustrated that unconventional means are effective in enhancing vigilance decrement. It has also shown that the unconventional means of enhancement depend on many factors, such as time-on-task and overall experimental protocol.

Al-Shargie et. al. in [51] illustrated that the speed of reaction time, and accuracy to a specific stimulus decrease when the time on task increases. The experiment in this study was a Stroop color-word task (SCWT), and the enhancement part was based on audio stimulation with a pure tone of 250 Hz. The study applied partial directed coherence (PDC) and graph theory analysis (GTA) to determine the coupling between brain regions under vigilance and enhanced mental states. Results showed that PDC is very sensitive to vigilance decrement, and thus, when the time on in task increases, the brain connectivity network decreases, $p < 0.5$. The study stated that enhancement using audio simulation is effective since the brain connectivity remained high compared to the vigilance phase. Another study [52] utilized "challenge integration" as a strategy to enhance vigilance; the task used in the study was a primary surveillance task integrated with a challenging stimulus for the purpose of detecting the changes in vigilance levels during the task. EEG and eye tracking data of 12 subjects were analyzed. Frontal midline theta power and frontal theta to parietal alpha power ratio showed an increment for the challenge integration, while the delta band power of EEG decreased on the frontoparietal and occipital cortices due to challenge integration ($p < 0.05$). Saccade amplitude, saccade velocity and blink rate obtained from eye tracking data exhibited significant changes for the challenge stimulus as well.

Fusion of modalities in studying cognitive workload assessment has shown an improvement in accuracy through some of the studies mentioned above, regardless to the level of task performed. The fusion of modalities was successful in different types of cognitive workload, whether it was a memory load task, perception channel discrimination task, mental arithmetic task, psychomotor or emotion recognition task. A challenge to be presented is proving that the accuracy of vigilance assessment can be enhanced by the fusion of two modalities. According to a recent paper [9] published in 2019, only 27% of the studies combined EEG and fNIRS, and 4 out of the 10 studies showed significant improvement with the fusion; all of these 4 studies applied the decision level fusion. For the studies that applied the feature level fusion, there was no improvement over the single EEG modality. As a result, decision level fusion for EEG and fNIRS data is better compared to the single EEG modality. ECG and EEG fusion were only performed by 8% of all studies that adopted the fusion approach; the fusion of EEG and ECG at the feature level didn't improve performance. Three studies have combined EEG and ECG, and none of them showed any better results for the fusion at the feature level. For this reason, the fusion of EEG and ECG is to be eliminated.

This Thesis aims to study the possibility of enhancing vigilance assessment through the fusion of two modalities: eye tracking and EEG. The goal is to develop an adaptive vigilance model for monitoring vigilance. Eye movements are selected as the primary inputs of the proposed model since they can be continuously monitored and measured. Studies have shown the existence of a relationship between sustained attention and eye movement [53]. Both, blink frequency and blink duration increase with vigilance decrement [54]. EEG is the second modality proposed for assessing vigilance; studies showed that prefrontal and parietal brain areas play important roles in regulating vigilance [55]. Vigilance decrement as a problem lies in the brain region; the fusion of EEG and eye tracking as two close sources to the problem are the best to be used. The literature for the EEG and eye tracking fusion for cognitive workload supports the idea of the proposed fusion approach. According to Essam Debie (2019) in [9], combining EEG with pupillometry has been done by only 6 studies of which 2 only have recorded statistically significant improvement over the single EEG; these 2 studies have applied the feature level fusion [9].

Chapter 3. Experiment and Data Collection

3.1. Data Collection

The details of the experiment and the data collection are discussed in the following three sections, covering information about the participants in the experiment, experiment setup, and the procedure and the task sequence.

3.1.1. Participants. In this study, 9 healthy volunteers who are students at the American University of Sharjah (age = 24.5 ± 5.5 years) were recruited to obtain EEG and eye tracking signals. All the participants met the predefined inclusion criteria of having normal hearing, normal/corrected to normal vision, no history of psychiatric or cognitive disorders, no symptoms of drug addiction or abuse, and no intake of long-term medications. In addition, all recordings were performed in accordance with the medical ethical standards. In order for the experiment not to get affected by the potential circadian influences, the experiment took a place between 3.00 P.M. and 7:00 P.M. Participants have been informed about the experiment procedure's nature, and each participant gave informed written consent. The experiment protocol was designed following the declaration of Helsinki and was approved by the Institutional Review Board (IRB) of the American University of Sharjah.

3.1.2. Experimental setup and physiological data acquisition. The experiment took place at the Biomedical Engineering Laboratory at the American University of Sharjah. The lab has a controlled level of both light and temperature. EEG and eye tracking were recorded during the experiment; the brain activity was measured using the 64-channel ANT Neuro EEG system at a sampling rate of 500 Hz. A wearable cap according to the standard 10-20 layout, and connected to a 64-channel EEG amplifier, was used, and data acquisition was done using ASA software. The cap consists of a set of 64 Ag/AgCl scalp EEG electrodes. The same software was also used to check the electrode impedances by applying a conductive gel layer and maintained below 10 KΩ. The AFz electrode is set as the system ground, and all other electrode signals are referenced to the mastoid electrodes M1 and M2. The subject's response to the experiment was labelled as either "Correct", "Incorrect", or "Time is up". Responses were collected using a parallel interface between the stimulus representation PC and the EEG recording PC [51]. Figure 3.1 shows the EEG electrode distribution according to the 10-20 system layout that have been used in the experiment, and Figure 3.2 shows the experiment protocol including the SCWT interface.

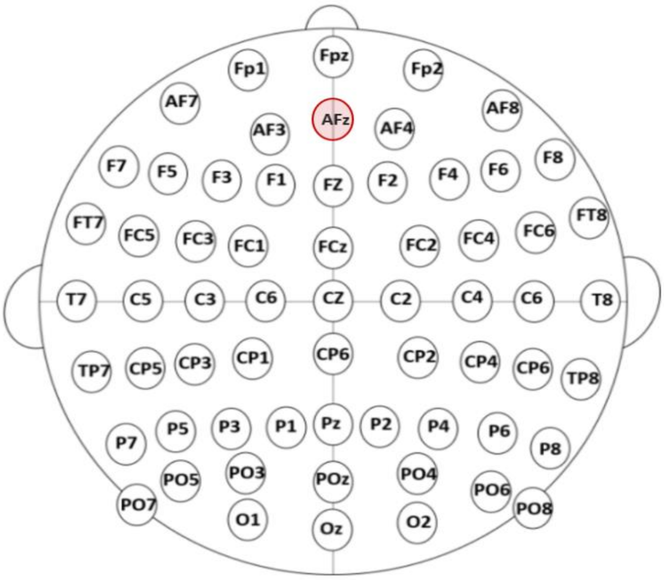

Figure 3.1: EEG electrode distribution according to the 10-20 system layout [55].

Eye movement data from eye tracking glasses provide various eye tracking detailed parameters. The data was collected using the EyeLink Portable Duo system at a sampling rate of 500 Hz. This system is designed to use an infra-red camera to record non-invasively the gaze position and pupil diameter. Absolute stabilization of the participant's head is unnecessary; therefore, instruction was given to the participant to reduce head movement to obtain better quality for both the eye tracking and EEG data.

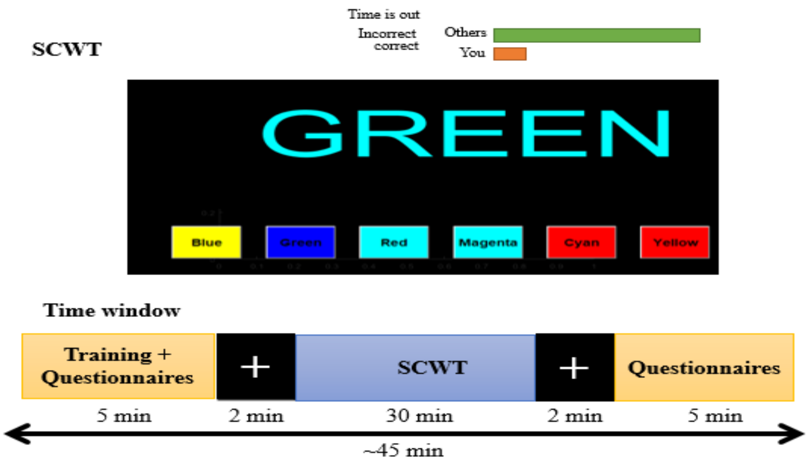

Figure 3.2: Experimental protocol (**a**) stroop color-word task (SCWT) presentation interface and (**b**) timing window. In the timing window, the plus sign in black background is for the pre- and post-baseline. Thirty (30) min SCWT for vigilance group.

3.1.3. Procedure and task sequence. Participants performed a thirty minutes computerized Stroop color-word task (SCWT). EEG and eye tracking data were simultaneously recorded while participants were performing the SCWT. Before recording the EEG and eye tracking data, participants practiced the task for three minutes to get familiar with the SCWT task and were asked to fill a Brunel Mood Scale questionnaire [56]. After completing the task, the participants were asked to fill the same questionnaire again. Vigilance level will be assessed using the fusion of EEG and eye tracking data. The proposed computerized SCWT is briefly described.

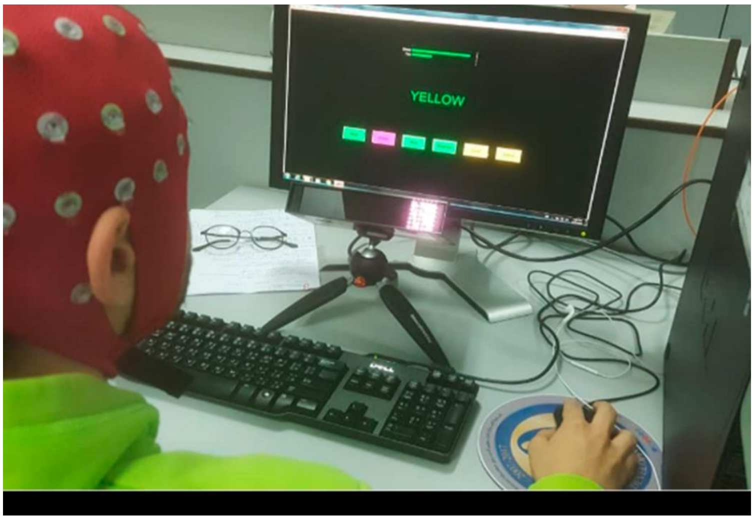

Figure 3.3: EEG data acquisition and experimental set up.

An interactive and computerized SCWT was developed and presented using MATLAB with Graphical User Interface [51]. The SCWT used in this experiment involved displaying six basic colors: blue, green, red, magenta, cyan, and yellow. Figure 3.4 shows the interface of the SCWT. One word was displayed at a time, and the answers of the color word to be matched to are presented in random sequences in the computer screen monitor. The displayed color word on the monitor screen was written in a different color than the word’s meaning, and the correct answer is the color in which the word is displayed (e.g.: if Green is written in Cyan then Cyan is the correct answer). The participants picked their answers as quickly and accurately as possible by left-clicking the mouse on one of the six answering buttons. To eliminate the participant’s habituation, the challenge level has been increased by setting the background color of the button in a random way. The reaction time recorded during the training phase was used to determine the maximum time for each trial. The response for each trial performed was displayed by a feedback message of “correct “or “incorrect” answer in addition to the recorded reaction time. In case the participant consumed all the time given for the trial with no response, the feedback message was “Time is up”.

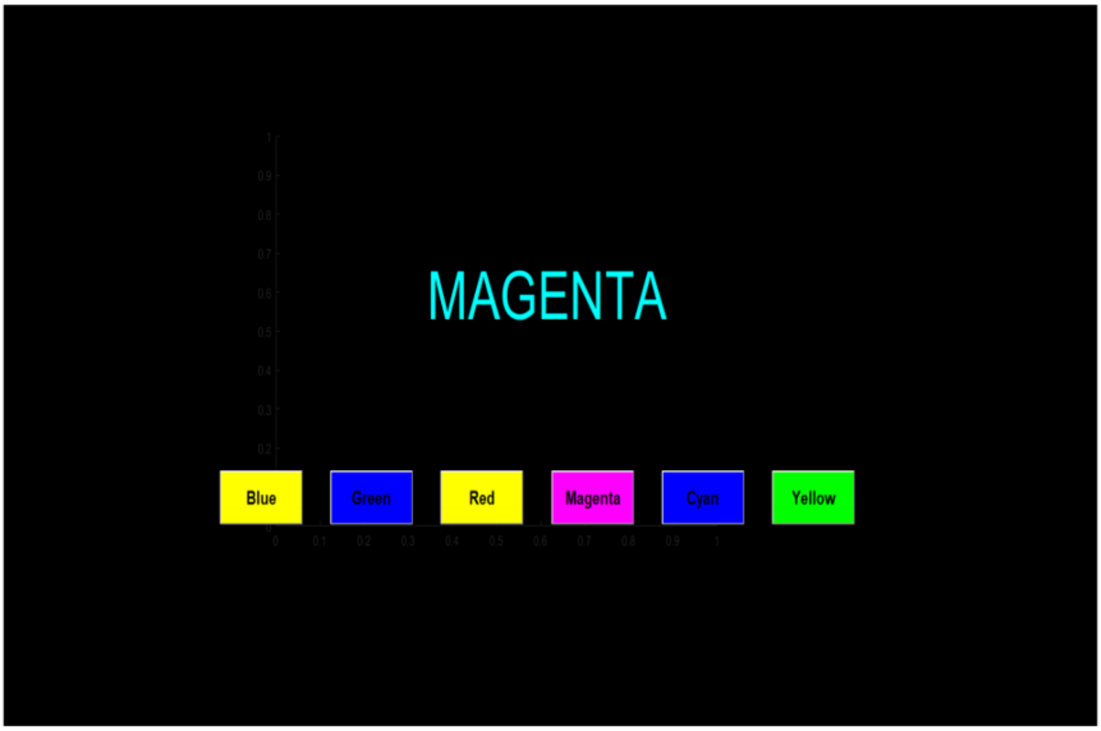

Figure 3.4: Main view of the developed SCWT.

Chapter 4. Data Analysis

4.1. EEG and Eye Tracking Data Preprocessing

The acquisition session of the EEG signals is usually divided into periods or epochs; once the data has been acquired, a preprocessing package is used to filter the signals as detailed. Signal preprocessing is considered a key factor for obtaining good classification rates. After signal filtering, machine learning classification algorithms are used to ass the level of vigilance [57] . This section discusses the preprocessing steps that have been applied to both the EEG and eye tracking data.

Preprocessing of EEG signals involved the following steps:

1. Import raw data.
2. Read channel locations.
3. Apply high pass filtering at a frequency of 0.1 Hz to remove background signal and DC offset.
4. Carry out independent component analysis (ICA) to remove artifacts.
5. Apply low pass filtering at a frequency of 40 Hz.
6. Re-reference the EEG data into the average of all channels.
7. Segment the EEG data into target-related EEG epochs of 1200 ms.
8. Perform baseline extraction and removal using the whole duration of each epoch.
9. Band-pass the clean EEG signals into four frequency bands corresponding to, delta (< 4 Hz), theta (4–8 Hz), alpha (8–13 Hz), and beta (13–30 Hz) frequency bands.

Preprocessing of the eye tracking data involved steps which have been performed using the EyeLink Data Viewer software; the Data viewer software is a tool that allows users to display, filter, and create output reports from the EDF data files recorded with EyeLink Portable Duo. Additional filtration for the eye tracking data can also be done using MATLAB [58] [59]. In addition, reports in an excel format for the eye tracking features can be created using the EyeLink Data Viewer software. The researcher has used the EyeLink Data Viewer software to extract the following features: fixation duration, pupil size, saccade duration, saccade amplitude, saccade velocity, and blink duration. The mentioned features were preprocessed as follows:

1. Prepare the raw data by having it in time series and convert the standard format of the eye tracker output for both eyes.
2. Filter the raw data to avoid any invalid samples; the filtering process will reject any of the following samples: (a) dilation speed outliers and edge artifacts, (b) trend-line deviation outliers, and (c) temporally isolated sample.
3. Merge nearby fixations with an amplitude threshold of 1.0°.
4. Set a high pass filter of 100 ms and 20 ms for both fixation duration, and saccade duration, respectively.
5. Set a low pass filter for saccade duration at 200 ms.
6. Apply extending blinks technique by removing the data points that correspond to the 100 ms before, and after a blink is created.
7. Set a high pass filter for saccade velocity of 30°/s.
8. Set a high pass filter for saccade amplitude of 0.1°

4.2. EEG Feature Extraction Method

Vigilance reflects the interaction of multiple brain regions; this interaction can be detected to provide a quantitative and rich insight about the cognitive process in the brain. Many features can be used to assess vigilance level for subjects performing critical tasks in various working environments. In our study, we have employed the power spectral density as a feature to assess vigilance level.

4.2.1. Power spectral density. The EEG data analysis can be done with Fast Fourier Transformation to obtain the PSD, at which power is plotted versus frequency. The PSD has been performed by dividing the signal sequence into segments, and then multiply the segment with an appropriate window. Let $xd(n)$ be the sequence, the signal intervals represented by d = 1, 2, 3…L and M is interval length. Thus, power spectral density extraction is defined in equation (1) by [60]:

$$\hat{pd}(f) = \frac{1}{MU} \left| \sum_{n=0}^{M-1} xd(n)w(n)e^{-j2\pi fn} \right|^2 \quad (1)$$

The normalization factor (U) for power in window function follows equation (2):

$$U = \frac{1}{M} \sum_{n=0}^{M-1} w^2\,(n) \quad (2)$$

where $w(n)$ is the hann window function.

4.3. Eye Tracking Feature Extraction Method

Researchers seek adequate eye tracking metrics to represent their studies. Eye tracking metrics are divided into four types of metrics: (1) metrics based on fixations, (2) metrics based on saccades, (3) metrics based on scanpaths, and (4) metrics of pupil size and blink rate.

4.3.1. Metrics based on fixation. Metrics based on fixation are dived into two groups, the first group is metrics based on the number of fixations, and the second group is metrics based on the duration of the fixation, where Fixation Count (FC) is the total number of fixations in each area of interest (AOI). Study [61] reports that a higher number of fixations to a stimulus is an indication to inefficient information. Fixation rate (FR) is calculated using Equation (3):

$$\mathrm{FR} = \frac{\text{Total Number of Fixations in AOI}}{\text{Total Number of Fixations in AOG}} \quad (3)$$

Total number of fixations in the area of glance (AOG) mentioned in the equation (3) reflects one of the following: (AOG) where it can be either the whole stimulus, meaning that you calculate the ratio of the total number of fixations in one AOI to all fixations, or it can be to another AOI, to show the ratio of fixations between two different AOIs. Fixation Spatial Density (SD) represents the number of cells containing at least one fixation, divided by the total number of cells when the stimuli are being presented by a grid. Equation (4) calculates the SD, where n is equal to the number of cells in the grid, and ci is equal to 1 if the cell number i is visited, and equal to zero otherwise. The indication of SD is the "coverage of an area"; it also calculates the dispersion of the participant's fixations. If SD is low, this is an indication of a small coverage area [62].

$$SD = \frac{\sum_{i=1}^{n} c_i}{n} \tag{4}$$

Some metrics are based on the Duration of Fixations; the duration of fixations is equal to the required time to analyze a stimulus “the depth of processing”. Measuring FC is not enough; some cases showed that even if you have low FC, you still can have a high duration of fixation. Thus, combing both metrics is important in the analysis process. Average Fixation Duration (AFD), also called Mean Fixation Duration, is equal to the total of the durations of all the fixations divided by the number of fixations. Equation (5) expresses mathematically AFD:

$$AFD(AOI) = \frac{\sum_{i=1}^{n}(ET(F_i) - ST(F_i))\ inAOI}{n} \tag{5}$$

where ($ET(F_i)$, and $ST(F_i)$ are the end time and start time for a fixation F_i. The n is the total number of fixations in a given AOI [63].

4.3.2. Metrics based on saccades. The Higher numbers of saccades indicate more searching and effort while performing a task [62], and the regressions rate indicates the percentage of backward saccades of any length. For an example, good readers will have few regressions, thus higher regressions rates indicate that the readers are having difficulty in reading and understanding a stimulus [64].

4.3.3. Metrics based on scanpaths. Attention switching expresses the participant focus change between different AOIs. The attention switch frequency can be measured by calculating the total number of switches between a set of AOIs per minute. The attention switching frequencies can be represented by a transitional matrix [65]; equation (6) represents the frequency transitions between AOIs:

$$TM = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} c_{i,j}}{n^2} \tag{6}$$

where $c_{i,j}$ is equal to 1 if the AOI is visited and 0 otherwise. A comparison between two transition matrices can be done by calculating the transition density. Transition density reflects the ratio between non-zero cells to the total cells of the matrix, where high transition density indicates an inefficient response to a given stimulus [65].

4.3.4. Pupil size and blink rate. Pupil size metrics and blink rate metrics are associated with measuring cognitive workload, where the lower the blink rates mean higher workload and higher attention. Higher blink rates indicate loss of attention and fatigue. If the pupil size is large, then this is an indication of more effort being done by the participant [64]. In this thesis we have utilized six eye tracking features based on their importance in cognitive workload assessment as mentioned in the literature, the eye tracking features extracted were: Fixation duration, pupil size, saccade duration, saccade amplitude, saccade velocity, and blink duration. Using the EyeLink® Data Viewer software, features have been extracted and filtered. The software has a built-in algorithm for the eye tracking data preprocessing, it allows users to display, and create output reports from the EDF data files recorded with EyeLink Portable Duo. Reports in an excel format for the eye tracking features have been created using the EyeLink Data Viewer software. The Data Viewer software enables visualization options and also provides different types of analysis.

4.4. Data Classification

Many classification approaches are available in machine learning, such as: Navie Bayes classifier, Random Forest, K-Nearest Neighbors, and Decision Tree. Support vector machine classifiers are supervised learning models used in classification and regression analysis. SVM is a non-probabilistic binary linear classifier since it separates a binary set of training data and divides them by a clear gap as wide as possible [66]. In this study we have utilized the SVM classifier to classify different levels of vigilance; the kernel function of SVM in this study is the Radial Basis Function (RBF), and the learning method is minimal sequential optimization. For fine parameter tuning, we varied the soft margin regularization parameter C from the interval 10^{-2} to 10^{2} with the step of 10 based on cross-validation approach. The most suitable σ in the RBF kernel was searched in the range between 0.5 to 4 (step size of 0.5), and optimal values were set to $C = 1$ and $\sigma = 3$. The EEG, eye tracking data as well fusion of EEG + eye tracking data have been classified in the form of subject-independent classification where a 10-fold cross-validation approach with randomization was performed to each feature vector. In the 10-fold cross-validation, each of the EEG, the eye tracking, and EEG-eye tracking feature sets was divided into ten subsets. Nine of these subsets were used for classifier training, and the last tenth subset was used for estimation of classification accuracy, sensitivity, and specificity. This process was performed ten times with each subset having an equal chance of being the testing data, and the average classification accuracy, sensitivity, and specificity were then evaluated.

It is well known that the selected classifier is fast and successful in the field of brain-computer interface (BCI).

4.5. Data Fusion

In this study, we have utilized feature level fusion by using canonical correlation analysis. The details of the proposed fusion method are briefly described.

4.5.1. Feature level fusion. Feature level fusion is a fusion method where the data is represented by feature vectors. The features extracted from EEG and eye tracking data will be combined into a single fused feature vector. To produce the final feature vector, the vector must pass through appropriate feature normalization, transformation, and reduction schemes.

Table 4.1 shows the features extracted from both EEG data and eye tracking data.

Table 4.1: List of features extracted from both EEG and eye tracking data.

EEG features	Frequency domain features	The normalized magnitudes in the frequency domain at the specific frequency bands obtained by using the Fourier transform
	Time-domain features	kurtosis, skewness, minimum, maximum, variance, standard deviation and mean
Eye tracking features	Fixation duration, pupil size, saccade amplitude, saccade duration, saccadic mean velocity, and blink duration	

4.5.2. Canonical correlation analysis. The EEG signals have been band passed into four frequency bands (Delta, Theta, Alpha, and Beta). Our EEG provided 62 features; each corresponds to one of the 62 electrodes used in recording the signal. The eye tracking on the other hand has been processed to provide 6 features (Fixation duration, pupil size, saccade duration, saccade amplitude, saccadic mean velocity, and blink duration).The EEG and the eye tracking features were extracted for two time segments with a length of five minutes each. The first-time segment belongs to the first five minutes of the recording, and refers to the alertness state, while the second time segment belongs to the last five minutes of the recording and refers to the vigilance decrement state. Features from the two modalities have been extracted using a sliding window of 1 s. On one hand, 600 data points from the EEG were extracted, these data points refer to the power spectral density values extracted from both two windows (alertness and vigilance decrement) for each of the nine subjects. On the other hand, the eye tracking data was obtained by averaging the feature values in every 1s to obtain one data point at a time, this approach was performed for the two windows (alertness and vigilance decrement) with the length of five minutes each. Each subject data formed a matrix with a dimension of 600X 6, where 600 is the number of data points extracted from the two windows and the 6 refers to the number of eye tracking features. Our fusion approach was performed at the feature level. Suppose that we have two matrices of the features obtained from the two modalities: EEG and the eye tracking as follows, $A \in \mathbb{R}^{n\times p}\ and\, B \in \mathbb{R}^{n\times q}$, where A and B contains n samples, with p and q feature dimension, respectively. If $S_{aa} \in \mathbb{R}^{p\times p}$, $S_{bb} \in \mathbb{R}^{q\times q}$ are the variance matrices of A and B, respectively, and $S_{ab} \in \mathbb{R}^{p\times q}$ is the covariance matrix, where $S_{ab} = S_{ba}^{T}$. The canonical correlation (CCA) is used to obtain the $A^{*} = W_{a}^{T}A$ and $B^{*} = W_{b}^{T}B$ at which they represent the linear combination of the canonical variates [67] [68] [69]. The canonical variates provide the maximum correlation of shared variance between the two feature sets following equation (7):

$$\rho(A^{*}, B^{*}) = \rho(W_{a}^{T}A, W_{b}^{T}B) = \frac{W_{a}^{T}S_{ab}W_{b}}{\sqrt{(W_{a}^{T}S_{aa}W_{a})(W_{b}^{T}S_{bb}W_{b})}} \tag{7}$$

W_a and W_b are two arbitrary vectors that are not equal to zero, where $W_a \in \mathbb{R}^{p}$ and $W_b \in \mathbb{R}^{q}$. The below constraint must be placed to obtain the maximum correlation at which the two variances in the denominator are equal to 1:

$$W_{a}^{T}S_{aa}W_{a} = W_{b}^{T}S_{bb}W_{b} = 1 \tag{8}$$

Our model is summarized in equation (9), the maximization was calculated by applying the Lagrange multipliers on equation (7) by taking into consideration the constraint in equation (8), and noting that the canonical veritas A^{*} and B^{*} are uncorrelated within each data set with a mean of zero and a unit variance. On the other hand, the canonical veritas A^* and B^* have a nonzero correlation in their corresponding indices.

$$\text{Model} \begin{cases} max\rho(A^*, B^*) \\ W_a^T S_{aa} W_a = W_b^T S_{bb} W_b = 1 \\ W_a \in \mathbb{R}^p, W_b \in \mathbb{R}^q \end{cases} \tag{9}$$

$$L(A^*, B^*) = L(W_a^T A, W_b^T B) = W_a^T S_{ab} W_b - \frac{\lambda_1}{2}(W_a^T S_{aa} W_a - 1) - \frac{\lambda_2}{2}(W_b^T S_{bb} W_b - 1) \tag{10}$$

where λ_1 and λ_2 are the Lagrange multipliers.

Note that setting the partial derivative for $L(A^*, B^*)$ in equation (10) with respect W_a and W_b to be equal to zero, give us the following two equations:

$$\frac{\partial L}{\partial W_a} = S_{ab} W_b - \lambda_1 S_{aa} W_a = 0 \tag{11}$$

$$\frac{\partial L}{\partial W_b} = S_{ba} W_a - \lambda_1 S_{bb} W_b = 0 \tag{12}$$

And by multiplying both sides of the derivative with W_a^T and W_b^T under the condition mentioned in equation (8), then:

$$W_a^T S_{ab} W_b = \lambda_1 \, W_a^T S_{aa} W_a = \lambda_1 \tag{13}$$

$$W_b^T S_{ba} W_a = \lambda_2 W_b^T S_{bb} W_b = \lambda_2 \tag{14}$$

Let $\lambda_1 = \lambda_2 = \lambda$ then:

$$\rho(A^*, B^*) = W_a^T S_{ab} W_b = W_b^T S_{ba} W_a = \lambda \tag{15}$$

Equation (15) shows that the Lagrange multipliers λ_1 and λ_2 are equal to the correlation coefficients W_a^T and W_b^T; it is worth noting that substituting the partial derivative of the Lagrange multiplier with respect to W_a in the partial derivative of the Lagrange multiplier with respect to W_b will obtain the transformation matrices W_a and W_b using the eigenvalue's equations:

$$S_{aa}^{-1} S_{ab} S_{bb}^{-1} S_{ba} W_a = \lambda^2 W_a \tag{16}$$

$$S_{bb}^{-1}S_{ba}S_{aa}^{-1}S_{ab}W_b = \lambda^2 W_b \tag{17}$$

The transformation matrices W_a and W_b are the eigenvectors, and λ^2 is a vector of eigenvalues or squared of canonical correlations. The number of non-zero eigenvalues in each equation is stored in decreasing order. Finally, the final form of fusion is performed by concatenation of the transformed feature vectors within the associated components according to the following equation [67]:

$$F = \begin{pmatrix} A^* \\ B^* \end{pmatrix} = \begin{pmatrix} W_a^T A \\ W_b^T B \end{pmatrix} = \begin{pmatrix} W_a & 0 \\ 0 & W_b \end{pmatrix}^T \begin{pmatrix} A \\ B \end{pmatrix} \tag{18}$$

where F is the canonical correlation discriminant features.

To summarize, Figure 4.1 shows the experiment processing framework which is fourfold: First, obtaining signals from both the EEG and the eye tracking simultaneously while performing a SCWT. Second, extracting specific features from both modalities. Third, apply feature-level fusion based on canonical correlation for the features extracted from the EEG and the eye tracking. Fourth, classifying vigilance level using the SVM classifier.

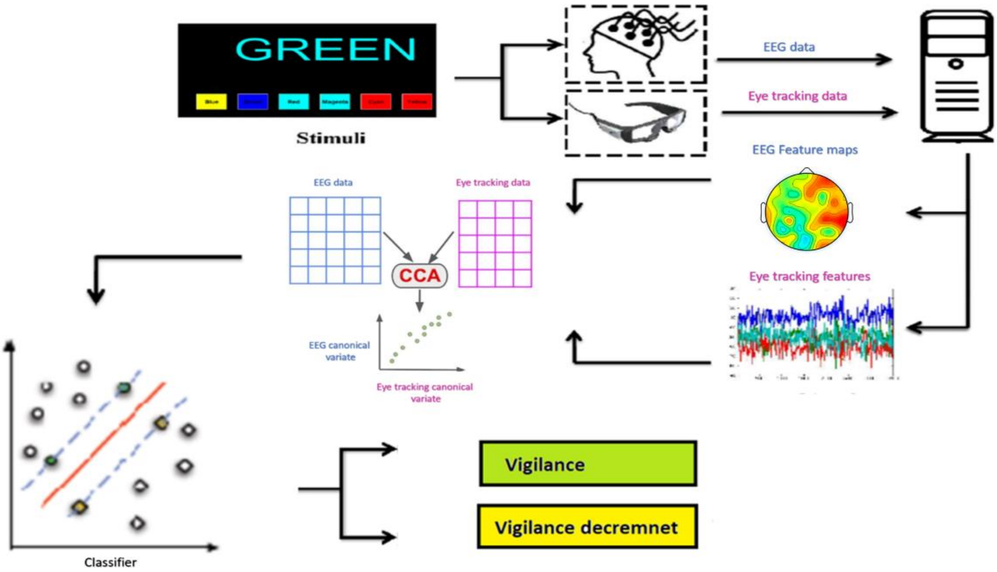

Figure 4.1: The framework of our experiment processing.

Chapter 5. EEG and Eye Tracking Preprocessing Results

Chapter five discusses the results of the preprocessing approach performed on the EEG data in section 5.1 and on the eye tracking data in section 5.2.

5.1. EEG Data Preprocessing Results

The raw EEG signals were filtered with a 0.5Hz - 40Hz bandpass filter, and all electrode signals were referenced to the mastoid electrodes M1 and M2. Using Independent analysis method, eye blinking artifacts were removed. For the eye blinking artifacts, components that appeared to contribute most to the artifacts were eliminated. For the EEG data, the processing is twofold: first, obtaining two windows with the length of five minutes each of the EEG data (alertness and vigilance decrement) . Second, FFT was used to convert the data from time domain to frequency domain to provide frequency information about the signals. Figure 5.1 shows the preprocessed EEG signal of subject 1 under alertness and vigilance decrement; the x-axis represents the time in milliseconds; the y-axis represents the electrodes, and the signal is divided into 4 epochs.

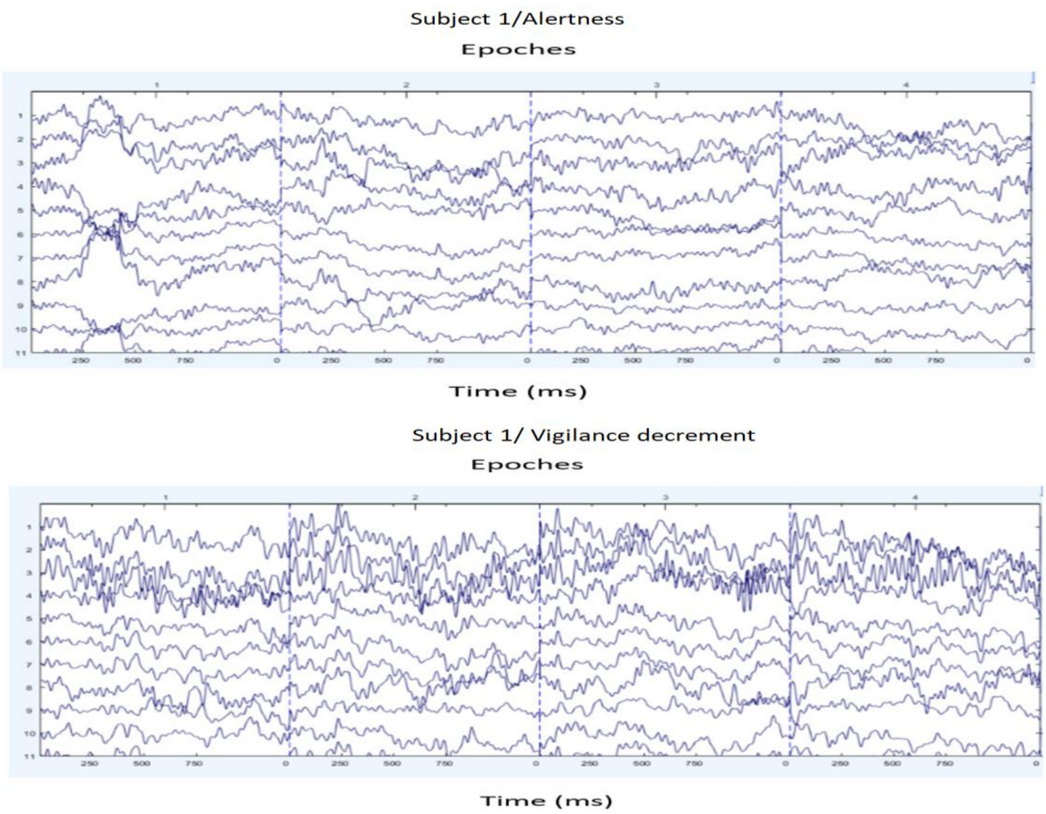

Figure 5.1: Pre-processed EEG signals for subject 1, from 11 electrodes and for 4 epochs.

5.2. Eye Tracking Data Preprocessing Results

The raw eye tracking data is plotted in Figure 5.2 for one of the subjects; the plot shows the gaze position, the pupil size (µm), and a heatmap created to show the eye movement. The pupil size values were plotted in (µm) in Figure 5.2, while it was plotted in (AU) in figure 5.3. The heat map of the eye movement shows that the subject focused on a specific region of the screen which indicates an area of interest for the subject while performing the SCWT.

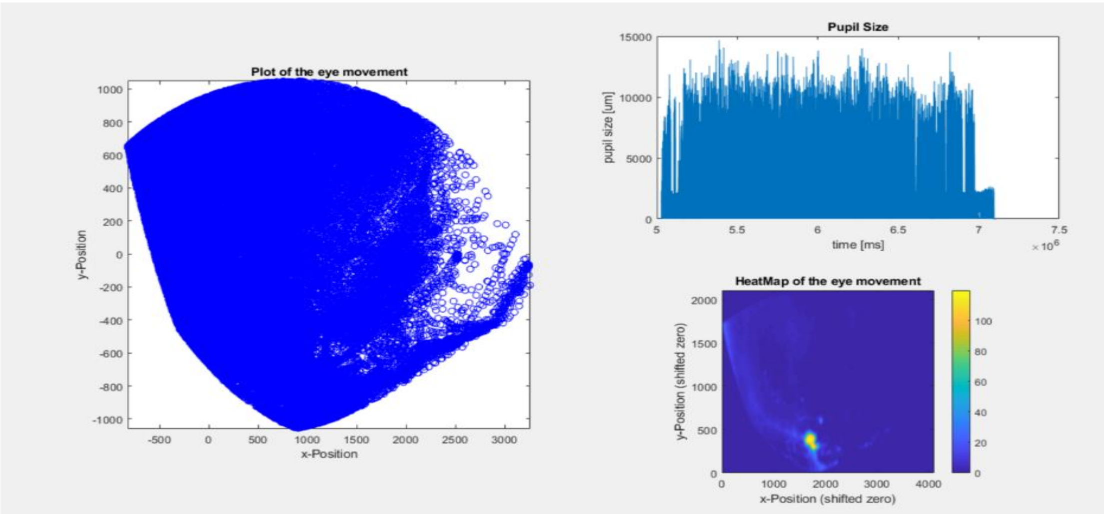

Figure 5.2: Eye tracking raw data for subject 1.

Six eye tracking features were extracted from the raw eye tracking data and have been pre-processed independently. Pupil size has been pre-processed by accepting only samples within a specific range based on the subject data. Figure 5.3 shows a sample histogram created for subject 1, providing the pupil size value (AU) with its frequency.

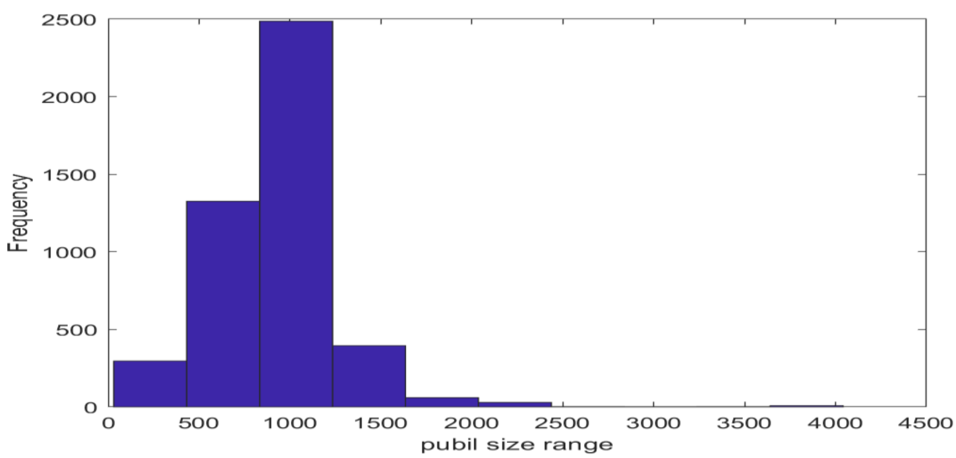

Figure 5.3: Subject 1 pupil size values and their frequencies.

The preprocessing of the pupil size values included accepting the values with the range (0-1500) for subject 1. Figure 5.4 shows the raw pupil size data and the preprocessed pupil values.

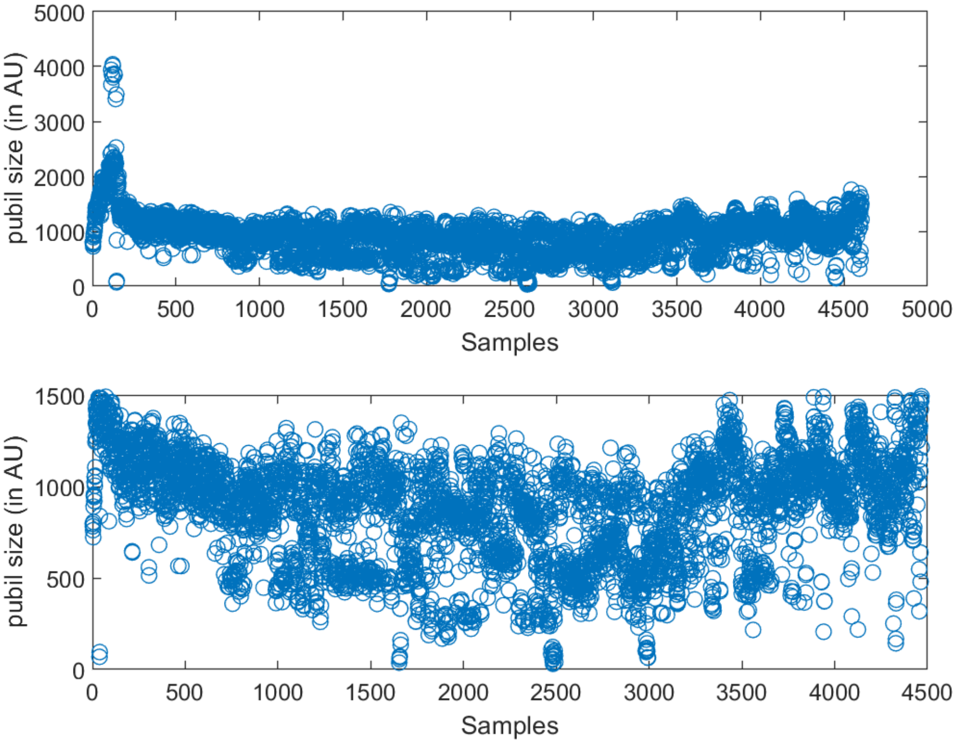

Figure 5.4: Subject 1 raw and preprocessed pupil samples.

Chapter 6. EEG and Eye Tracking Vigilance Level Assessment

6.1. EEG Vigilance Level Assessment

Our EEG vigilance assessment is based on the EEG band power, the power spectral density was extracted for four EEG frequency bands for two windows: alertness and vigilance decrement.

A comparison of PSD of all subjects under the two mental states (alert - vigilance decrement (VD)) for four frequency bands was done using a topographical map. For each of the four frequency bands, a topographical map was created for both alertness and vigilance decrement states. In addition to a topographical map based on the t-test between the states. This statistical t-test is useful in comparing the means of the PSD between alertness and vigilance decrement, it highlights the regions of the brain that are most sensitive to the change in the PSD. Figure 6.1 shows the topographical map created for both alertness and vigilance decrement states using the PSD values, in addition to the map showing the results of the t-test indicating the regions of the brain that are most sensitive to vigilance decrement.

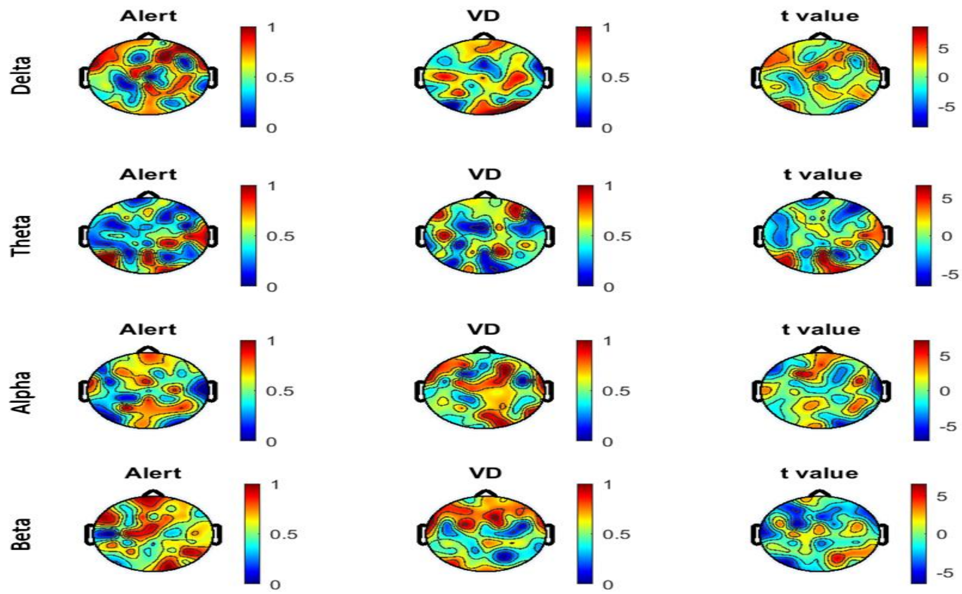

Figure 6.1: Comparison of PSD over all subjects under the two mental states (alert - vigilance decrement (VD)) in the four EEG frequency bands.

The classification accuracy of the vigilance assessment was obtained using SVM classifier for four EEG frequency bands. The SVM was set to 10 based on cross-validation to measure the EEG vigilance level classification performance for four EEG frequency bands. Figure 6.2 is showing the confusion matrix obtained for the classification of vigilance assessment using EEG.

Precited class: Alertness and Vigilance decrement

Actual class: Alertness and Vigilance decrement

Delta

2259	441
369	2331

Theta

2137	563
582	2118

Alpha

2178	522
594	2106

Beta

2460	240
215	2485

Figure 6.2: EEG vigilance assessment classification confusion matrix.

Table 6.1 shows the classification accuracy, sensitivity, and specificity for the two cognitive states: alertness and vigilance decrement for each of the EEG frequency bands.

Table 6.1: EEG bands classification accuracy, specificity, and sensitivity for vigilance assessment.

Band / Measure	Delta	Theta	Alpha	Beta
Accuracy	88.1±8.5%	81.4±11.2%	81.5±12.1%	92.0±7.3%
Sensitivity	86.8±10.3%	80.1±11.7%	80.9±13.0%	91.7±8.0%
Specificity	89.5±7.5	82.7±11.3%	82.2±11.6%	92.2±7.1%

6.2. Eye Tracking Vigilance Level Assessment

Our eye tracking vigilance assessment is based on six eye tracking features (fixation duration, pupil size, saccade duration, saccade amplitude, saccade velocity, and blink duration). These features were extracted for both alertness state and vigilance decrement state. The box plot representation in Figure 6.3 shows the mean change in the individual eye tracking feature between the alertness state and the vigilance decrement state, while, the box plot representation in Figure 6.4 shows the mean change in all eye tracking features between the alertness state and the vigilance decrement state. The six eye tracking features were fed to the SVM classifiers to investigate the classification accuracy of the vigilance level at which the classifier was set to 10 based on cross-validation to measure the eye tracking vigilance level classification performance.

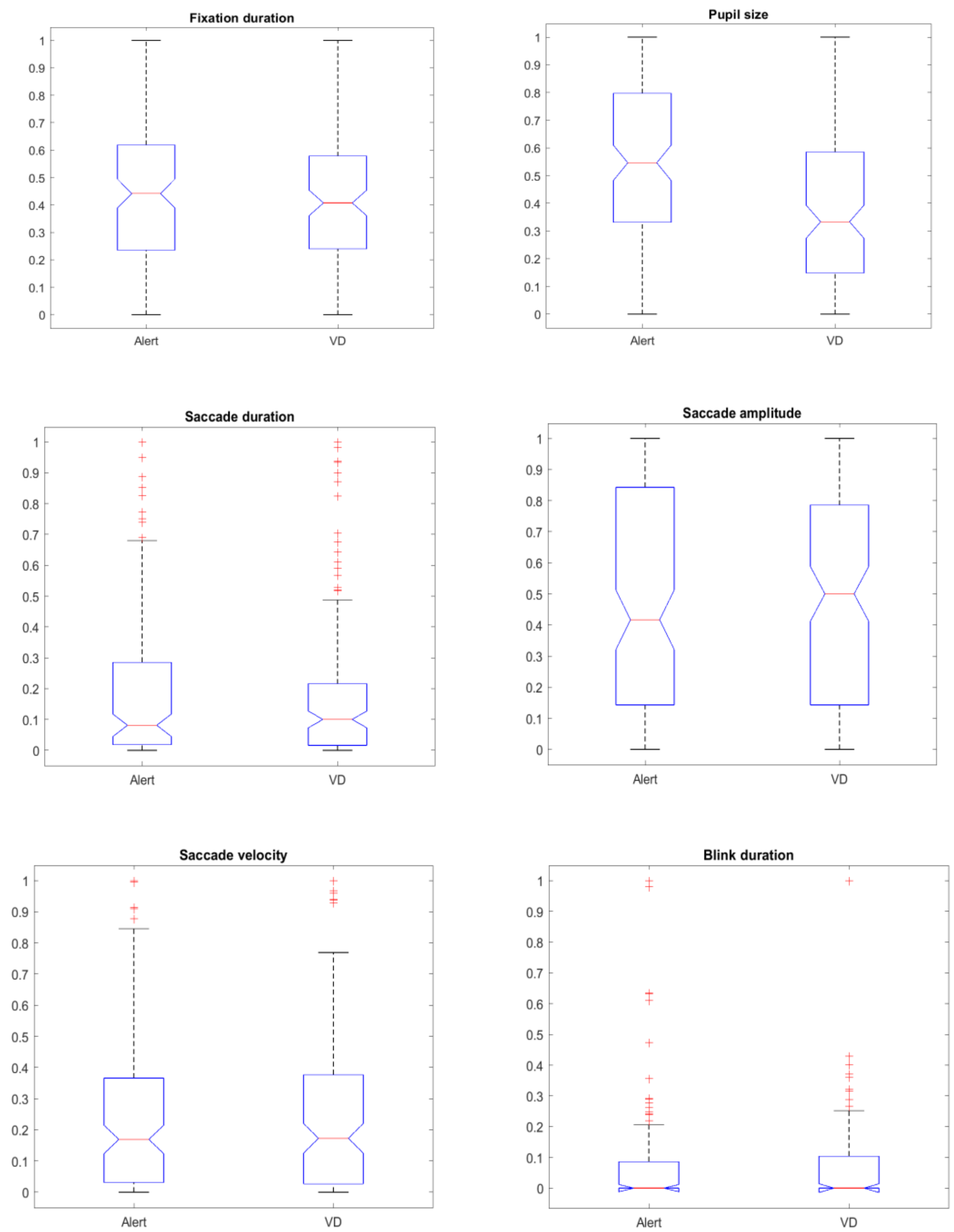

Figure 6.3: Mean change in the individual eye tracking features between alertness and vigilance decrement.

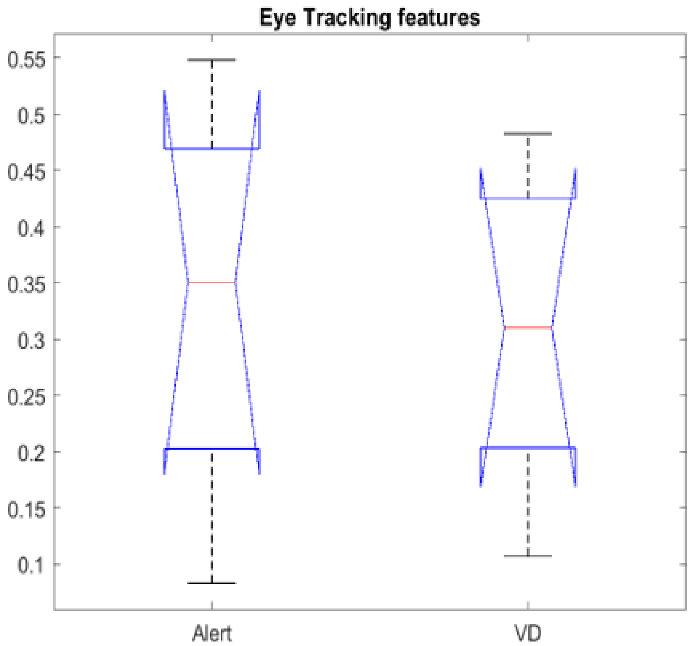

Figure 6.4: Mean change in all the eye tracking features between alertness and vigilance decrement.

Figure 6.5 is showing the confusion matrix obtained for the classification of vigilance assessment using the eye tracking modality. The achieved accuracy, sensitivity, and specificity for vigilance level classification using the eye tracking features are summarized in table 6.2.

	Predicted: Alertness	**Predicted: VD**
Actual: Alertness	2084	636
Actual: VD	617	2083

Figure 6.5: Eye tracking vigilance assessment classification confusion matrix.

Table 6.2: Eye tracking features classification accuracy, sensitivity, and specificity for vigilance assessment.

Measure / Feature	Accuracy	Sensitivity	Sepecificity
All features	76.8 ± 8.4%	76.4 ± 11.2%	77.1 ± 8.5%
Fixation duration	60.9 ± 11.6%	57.0 ± 12.2%	64.7 ± 12.5%
Pupil size	71.8 ± 13.0%	68.1 ± 15.5%	75.4 ± 10.9%
Saccade duration	58.8 ± 10.5%	54.1 ± 11.9%	63.4 ± 13.1%
Saccade amplitude	57.5 ± 9.6%	56.3 ± 10.9%	58.8 ± 9.9%
Saccade velocity	59.3 ± 8.8%	57.3 ± 13.2%	61.3 ± 10.3%
Blink duration	56.5 ± 3.1	48.9 ± 27.4	64.1 ± 26.5

Chapter 7. EEG and Eye Tracking Fusion Vigilance Level Assessment

In this chapter, we summarise the results of the vigilance assessment using the CCA feature level fusion. To enhance the accuracy of vigilance assessment, we have evaluated the feature sets from both the EEG and the eye tracking using feature-level fusion based on the canonical correlation analysis. Our target of the fusion is to seek the maximum correlation of shared variance between the feature matrices. The extracted feature matrices from the EEG and the eye tracking were utilized as inputs for the fusion, this fusion approach helped us to explore the correlation between the eye tracking data with the EEG data in different frequency bands. Machine learning classification analysis was employed to evaluate the effectiveness of detecting vigilance decrement based on the fusion of PSD features and the eye tracking features. Our primary focus was to enhance the vigilance level assessment based on the fusion of EEG and eye tracking data. Our SVM algorithm was set to 10 based on cross-validation for final classification.

In Figure 7.1 we displayed the mean values of the correlation coefficient obtained from EEG-eye tracking CCA for each of the four-frequency bands beside a heat map for the cross-subject correlation matrix. We have analyzed the covariance matrices of the feature sets from the two modalities (EEG and eye tracking). The criteria of selection were based on the correlation level of components from the transformed feature vectors, discarding those with small canonical correlations. The canonical correlations of the eye tracking features and the EEG features for vigilance assessment were obtained by applying CCA to the entire data sets arranged in descending rank order. These canonical correlations were computed from the estimated joint covariance matrix. From in Figure 7.1, the correlation varies with the component used, where the components of the x-axis refer to the six EEG-eye tracking features, where the higher the correlation value, indicates a higher change in vigilance level. Figure 7.1 also displaying the cross-subject source correlation matrix (map). The cross-subject source correlation matrix is determined by calculating the correlation coefficients of the subjects and then averaging the correlation coefficients across all. The matrix shows the consistency in inter-subject correlation between the two modalities.

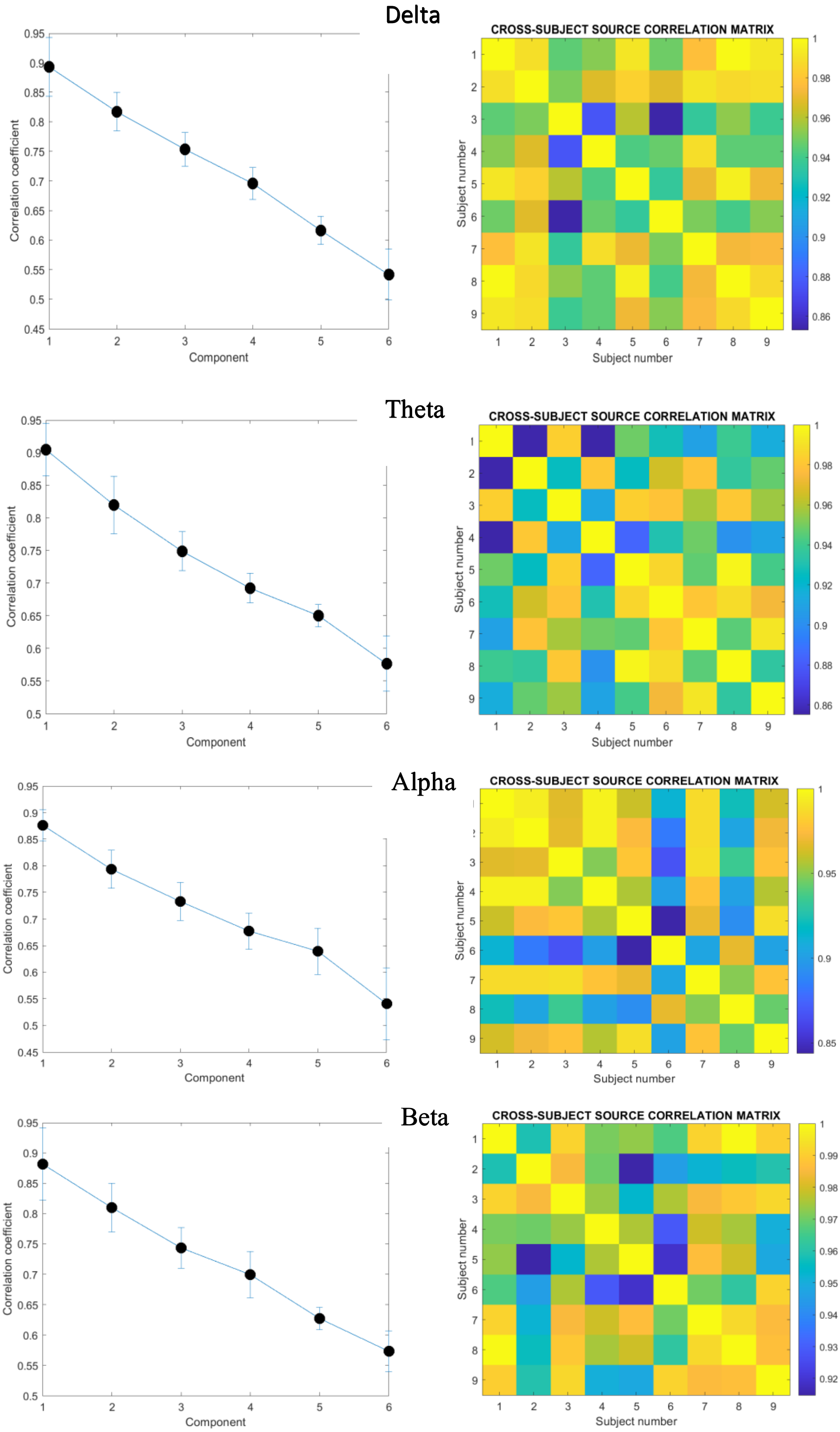

Figure 7.1: Values of the correlation coefficients for the EEG-Eye tracking CCA, and the cross-subject correlation heat map per EEG frequency band.

Figure 7.2 is showing the confusion matrix obtained for the classification of vigilance assessment using the fusion of the EEG and the eye tracking.

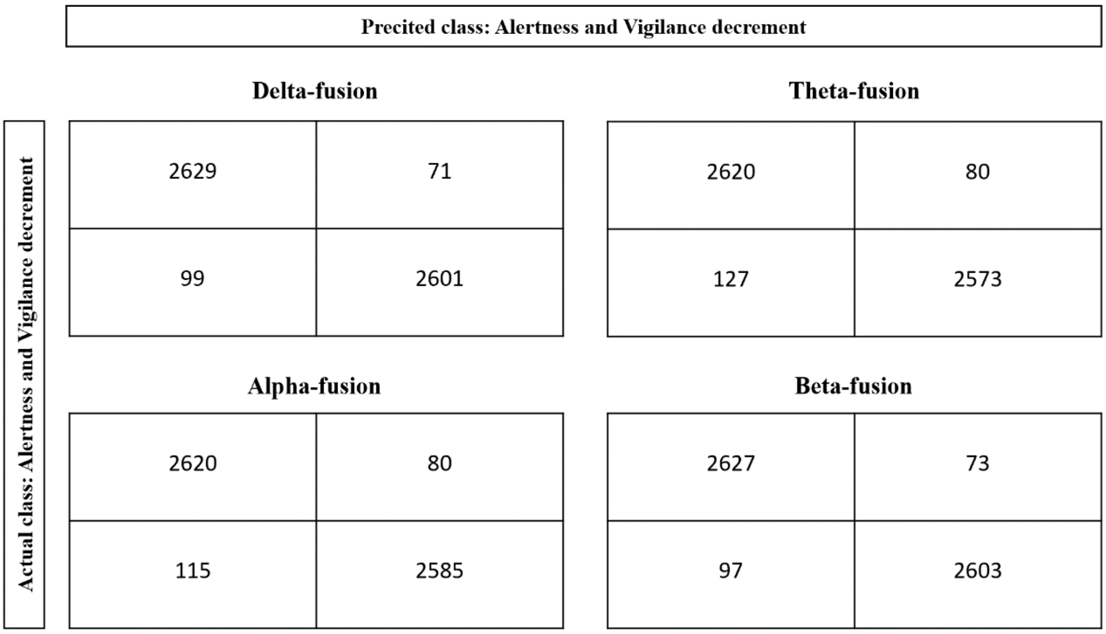

Figure 7.2: EEG-eye tracking data fusion vigilance assessment classification confusion matrix.

Table 7.1 shows the SVM classification accuracies for vigilance assessment obtained using the EEG for four frequency bands, the eye tracking, and the EEG-eye tracking feature level fusion.

Table 7.1: EEG, eye tracking, and EEG-eye tracking fusion SVM classification accuracies for all subjects

Modality / Subject	Eye Tracking	EEG-Delta	EEG-Theta	EEG-Alpha	EEG-Beta	Fusion Delta	Fusion Theta	Fusion Alpha	Fusion Beta
Sub.1	86.5	91.3	84.5	85.6	97.6	96.10	95.8	95.6	98.8
Sub.2	81.8	92.3	82.1	79.8	90.8	97.0	96.3	96.6	96.0
Sub.3	73.3	77.0	72.8	73.3	82.6	95.8	96.0	95.5	95.8
Sub.4	60.6	99.0	99.5	99.8	100.0	98.0	98.6	99.1	98.6
Sub.5	69.5	96.8	95.6	96.0	98.8	96.5	96.8	95.8	96.6
Sub.6	72.5	93.5	86.8	90.8	99.6	97.5	94.8	95.8	96.0
Sub.7	83.1	76.1	70.1	70.1	81.1	96.8	96.1	96.8	96.3
Sub.8	75.3	87.6	72.1	65.6	87.0	97.0	95.1	96.0	96.3
Sub.9	88.3	80.0	69.1	72.8	90.1	96.8	95.6	96.0	97.0

Table 7.2 shows the classification accuracy, sensitivity and specificity obtained using the SVM classifier when data from every EEG frequency band was fused with the six eye tracking data to evaluate vigilance level.

Table 7.2: EEG-eye tracking fusion classification accuracy, sensitivity, and specificity for vigilance assessment

Band / Measure	Delta-eye tracking fusion	Theta-eye tracking fusion	Alpha-eye tracking fusion	Beta-eye tracking fusion
Accuracy	96.8±0.6%	96.1±1.1%	96.3±1.1%	96.8±1.1%
Sensitivity	97.3±1.0%	97.0±1.2%	97.0±1.1%	97.2±1.0%
Specificity	96.3±0.9%	95.2±1.3%	95.7±1.6%	96.4±1.2%

Figure 7.3 is a box plot classification accuracy obtained for the EEG and the eye tracking, in addition to showing the p-value calculated using the paired sample t-test. F-D, F-T,F-A, and F-B in the figure refer to Data fusion using delta band, theta band, alpha band , and beta band, respectively.

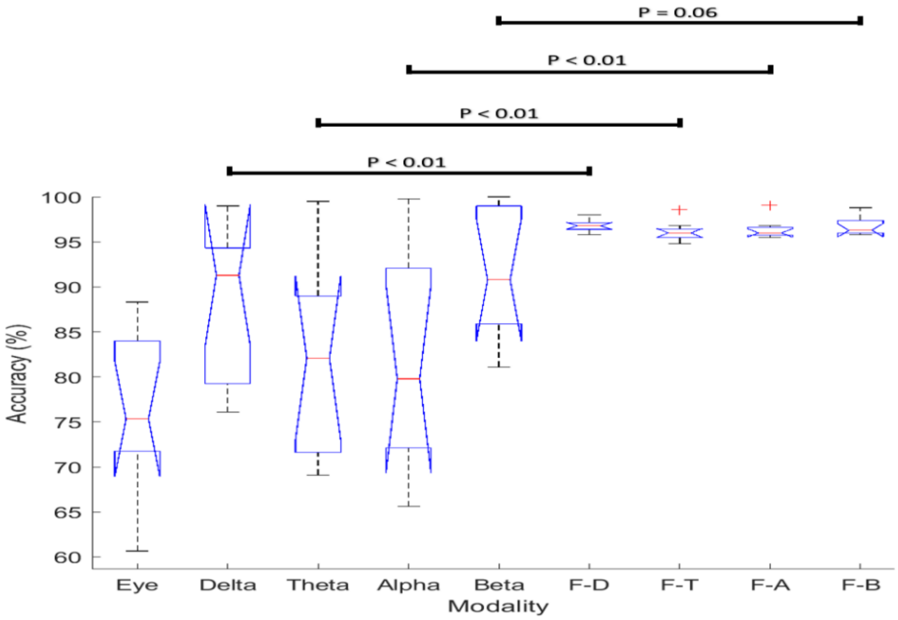

Figure 7.3: Boxplot classification accuracies obtained by the EEG and the eye tracking data, as well as CCA fusion. P-values were calculated the paired sample t-test.

Chapter 8. Conclusion and Future Work

This thesis covers three main sections in assessing vigilance. The first relates to assessing vigilance using a single modality (EEG), where the data has been processed and analyzed to detect alertness and vigilance decrement using EEG only. In the second section, eye tracking data has been utilized to assess vigilance level. In the third section, eye tracking and EEG data have been fused for the same purpose of improving vigilance assessment. The thesis hypothesis according to the literature in chapter 2 is that the detection accuracy will increase using the fusion approach. The data for the analysis was obtained from 9 subjects who performed a Stroop color- word task, and the fusion approach utilised in this study is the feature level fusion based on the canonical correlation analysis.

8.1. Major Findings

In this study, the study aimed at investigating the accuracy of adopting the EEG or the eye tracking for vigilance assessment. It was also the aim of the study to investigate if the fusion of bimodality (EEG-eye tracking) could enhance vigilance assessment. The approach adopted in the study was based on conducting data by simultaneously measuring the EEG and eye tracking of nine subjects. Subjects were asked to perform a SCWT for 30 minutes, our statistical analysis was performed on two-time segments of the recording; the first-time segment refers to the alertness state of the subjects, and the second refers to vigilance decrement. Four EEG frequency bands were utilized for vigilance assessment; the results of the EEG indicated that the Beta band provided the highest classification accuracy of 90.1±7.38%; Delta band followed with a close accuracy of 88.18±8.5%, While Alpha and Theta showed the lowest classification accuracy for vigilance assessment between the two states: alertness and vigilance decrement. Beta wave is known to be associated with alertness state and normal waking consciousness [70], [71]. Analysis of different cognitive processes like recognition tasks and informational differentiation processes are highly associated with the Beta range of the human EEG signals [72]. Delta wave is associated with sleep, deep sleep, and unconscious state. Study [73] reported that the Delta frequency band has a main role in carrying most of the information related to working memory load as it appeared to be related to the increment in the subjects' concentration during the experiment. Delta EEG band with its low-frequency activity contains significant electrophysiological correlates of cognitive processing and should receive more attention in future studies. In our study Beta and Delta bands were most sensitive to the change in the vigilance level due to their characteristic of being extremely related to either alertness or deep sleep. The SCWT requires high attention in recognizing colors in addition to a high memory strength to respond fast and minimize the reaction time. Figure 6.1 showed a significant change in the PSD across some areas of the brain between the alertness states to vigilance decrement for all of the four EEG frequency bands using a topographical map. We can notice that the occipital and the frontal brain regions were most sensitive to vigilance decrement. The occipital brain region is associated with the processing of visual activities, memory formation, distance, and depth perception; in addition, it is assumed to be responsible for color determination, and the frontal brain region is responsible for high-level cognitive functions such as memory, emotions, impulse control, problem-solving, social interaction, and motor function [74]. The topographical map supports the results of the EEG classification since both Beta and delta waves are captured in the frontal lobes of the brain [75].

Likewise, the eye tracking data showed a lower classification accuracy for vigilance assessment of 76.8 ± 8.4% when six eye tracking features were utilized. A possible justification of the low accuracy obtained from the eye tracking data is that the eye tracking system is very sensitive and that the system suffers from a limitation at which it requires the eye of the subject to be held still and on-axis with respect to the eye tracking camera. In addition, eye tracking features are very sensitive to light; light control can improve the classification accuracy using the same features [76]. A comparison between all the six eye tracking features was done to check the contribution of every feature in vigilance assessment; as a result, the highest classification accuracy was obtained using the pupil size (71.8 ± 13.0%); many studies have reported high classification accuracy obtained using the pupil size feature [77], [78]. The box plot in Figure 6.4 shows the mean change in the eye tracking features between alertness and vigilance decrement. Vigilance decrement appeared to have less spread a lower mean compared to the alertness.

A feature level fusion has been employed by grouping the temporal information of features for two modalities (EEG-eye tracking). Our fusion approach is based on the canonical correlation analysis; CCA is a very common method to explore the correlation between two modalities [68], [69]. It is known that CCA is a flexible and powerful tool for finding associations among the various data types. It also helps in eliminating the redundancy in features and provides a feature vector with effective discriminant information [79]. The EEG and the eye tracking data are dissimilar in nature, which makes it very hard to perform the analysis on both types together. Therefore, fusing the data using canonical correlation analysis helped in reducing both modalities to a feature corresponding to alertness and vigilance decrement. The task was then to explore associations across these feature datasets by taking advantage of the intersubject covariations to measure the association across the two modalities [80], [81]. Table 7.2 shows that all-EEG bands displayed better accuracy with the fusion; the Delta band obtained the highest fusion accuracy of 96.8± 0.6%, and all the other bands obtained a close fusion accuracy to Delta. Delta band appeared to be the most sensitive to vigilance decrement, and thus the results of data fusion are consistent with the researcher's expectations, as this band is associated with the deepest level of relaxation. In addition, it shows an increase in brain activity in the frontal leads during mental tasks as reported in [82]. A possible explanation for the contradiction between the increase of Delta waves during the SCWT task and the fact that Delta waves have been reported by many studies to be a result of sleep/deep sleep conditions has been justified as researchers argue about the presence of an inhibition that gets activated during a mental task to selectively suppress inappropriate or non-relevant neural activities [82]. Although the focus was very little on the low frequencies when it comes to the cognitive workload assessment, Study [83] has reported that the Delta band is associated with cognitive processes related to attention and the detection of motivationally salient stimuli in the environment as well as in behavioral inhibition. On the other hand, a study entitled [84] that the oscillation of the electric field in the brain determines the neural pool involved; this could explain why Delta wave oscillations may have a significant role in cognitive workload processing. The paper reported that during mental tasks, neural networks that are located away from the frontal lobes may be modulated by Delta that originates in the frontal cortex.

Although the data fusion enhanced the classification accuracy for EEG all bands when all subject's data was utilized, Table 7.1 showed that particularly, each subject had a different result of the fusion, where not all received the same enhancement. For example, subject four accuracy has not been enhanced during the fusion, this could be justified with the low eye tracking classification accuracy obtained for this subject (60.6%). On the other hand, subject nine had a high eye tracking classification accuracy of (88.3%) which contributed much in showing great enhancement for the EEG classification accuracies using the fusion approach. Subsequently, we can say that our fusion approach enhancement accuracy is dependent on the accuracies obtained from both inputs (EEG and eye tracking).

We have shown a box plot classification accuracy obtained for the EEG and the eye tracking in Figure 7.2, in addition to showing the p-value calculated using the paired sample t-test. A significant difference appeared to be between the EEG Delta band and the fusion using the EEG Delta band (F-D) with a $p < 0.01$, the same result was obtained for the Theta and the Alpha bands. Beta band on the other hand showed of $p = 0.06$ for the difference between utilizing it alone and through our fusion approach (F-B). These results are an indication that the CCA enhances the accuracy significantly.

8.2. Conclusion

This study employs fusion strategy by combining the eye tracking technology with the EEG technology for the target of vigilance assessment. The stimulus was a SWCT, where the beginning of the task corresponds to the alertness state, and the end of the task corresponds to the vigilance decrement state. Vigilance assessment is based on a Feature-level fusion of both EEG and eye tracking features using canonical correlation analysis. Nine healthy subjects experimented; results showed that both modalities' accuracies have been enhanced using the fusion. The highest accuracy for the fusion was using EEG Delta band of 96.8± 0.6%, which is higher than using the EEG Delta band without the fusion (88.18±8.5%%) or the eye tracking date alone (76.8 ± 8.4 %).

8.3. Recommendations and Future Research Directions

Due to the COVID 19 constraints, one of the main limitations of this thesis was the small sample size. A larger sample size is required to ensure adequate statistical analysis and further support to our findings. Discussed are several future research recommendations provided based on this work:

- Connectivity patterns and graph theory analysis is very informative features that have been utilized in [85] for vigilance assessment. These features have shown a good classification accuracy and proven their effectiveness in mental state discrimination contexts. These features are worth investigation using a data fusion approach that utilizes the connectivity patterns and the eye tracking data. This method could enhance the classification accuracy obtained for vigilance assessment.

- In this work, we have utilized the SVM classifier, other classifiers namely, KNN, LDA, NBC, and DT are known to be fast and successful in the field of brain-computer interface (BCI), Future studies could consider investigating and comparing different classifiers to assess vigilance based on fused modalities.

- In this work, the vigilance assessment was based on the data fusion between the EEG and the eye tracking modalities. Fusion was performed on the feature level using canonical correlation analysis. Feature level fusion provided a high classification accuracy. However, decision level fusion is worth investigation to compare the results and support our finding. Although feature level fusion based on the canonical correlation analysis is very effective and common, other fusion techniques would provide an advantage in vigilance assessment such as the group sparse canonical correlation analysis (GSCCA) method which helps in exploring the correlation of the group structure between the two modalities. Future studies could consider investigating and comparing the different fusions approaches for vigilance assessment.

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