CLASSIFICATION OF COGNITIVE WORKLOAD LEVELS UNDER VAGUE VISUAL STIMULATION

by

Rwan Adil Osman Mahmoud

A Thesis Presented to the Faculty of the
American University of Sharjah
College of Engineering
in Partial Fulfillment
of the Requirements
for the Degree of

Master of Science in
Computer Engineering

Sharjah, United Arab Emirates

May 2016

Approval Signatures

We, the undersigned, approve the Master’s Thesis of Rwan Adil Osman Mahmoud.

Thesis Title: Classification of Cognitive Workload Levels under Vague Visual Stimulation

Signature	**Date of Signature** (dd/mm/yyyy)
___________________________ Dr. Tamer Shanableh Professor, Department of Computer Science and Engineering Thesis Advisor	_______________
___________________________ Dr. Hasan Al Nashash Professor, Department of Electrical Engineering Thesis Co-Advisor	_______________
___________________________ Dr. Gerassimos Barlas Professor, Department of Computer Science and Engineering Thesis Committee Member	_______________
___________________________ Dr. Hasan Mir Associate Professor, Department of Electrical Engineering Thesis Committee Member	_______________
___________________________ Dr. Assim Sagahyroon Head, Department of Computer Science and Engineering	_______________
___________________________ Dr. Mohamed El-Tarhuni Associate Dean of College of Engineering	_______________
___________________________ Dr. Leland Blank Dean of College of Engineering	_______________
___________________________ Dr. Khaled Assaleh Interim Vice Provost for Research and Graduate Studies	_______________

Acknowledgment

First, I am grateful to Allah for all the blessing he bestows upon me.

I would like to express my sincere gratitude to my advisors, Dr. Tamer Shanableh and Dr. Hasan Al Nashash, for their continuous support, immense knowledge and for their patience. This thesis would not exist at all without their guidance and encouragement. I am very privileged to have such dedicated supervisors. I am very thankful as I have learnt so much from them.

I would like to take this opportunity to express my sincere thanks to the American University of Sharjah and especially the Department of Computer Science and Engineering for granting me the assistantship that made pursuing Master degree possible. I am very thankful for the head of the Department Dr. Assim Sagahyroon for welcoming me and for his support and assistance. I am also grateful for all the professors that I had the pleasure to be one of their students. A special gratitude belongs to Ms. Salwa Mohamed for her valuable comments and suggestions.

Dedication

To my father, who spared no effort to educate us. May Allah have mercy on your soul and grant you a place in Firdaus.

To my role model, my mother, I hope you are proud of me and may Allah give you long healthy and happy life.

To my better half, Hisham, thank you for always supporting and believing in me.

Abstract

In most applications where humans are involved, it is important to augment the interaction between users and the components of these applications. One significant element is the cognitive state of the subjects involved. The cognitive state can be manipulated by the amount of cognitive workload allocated to the working memory. If the assigned cognitive workload is too low, the subject’s cognition will be underutilized. In contrast, if the workload is more than the subject's capabilities, he or she will be mentally overloaded. Thus, there is a serious need to accurately assess and quantify cognitive workload levels. In this work, a method for separating four different cognitive workload levels is presented. We use an existing data set that contains EEG signals recorded from sixteen subjects while experiencing four different levels of cognitive workload. Some of these workload levels is due to the degradation of visual stimuli. The proposed solution integrates preprocessing of EEG signals, feature extraction based on discrete wavelet transform and statistical features, dimensionality reduction using stepwise regression and multiclass linear classification. Experimental results show that the average classification accuracy of the presented method is 93.4%. The effect of EEG channel selection on the classification accuracy is also investigated. The results show that channels included in the brain frontal lobes are important in cognitive workload classification. By utilizing only 23 channels, most of them are located in the frontal region; the proposed solution provides an average classification accuracy of 91%. It is shown that the proposed solution is more accurate and computationally less demanding when compared to the existing work.

Search Terms: Cognitive workload, EEG, DWT, stepwise regression, channel selection

Table of Contents

List of Figures

List of Tables

Chapter 1. Introduction

1.1. Background and Motivation

Cognitive workload is the amount of mental resources and mental effort being used and required in the working memory at any given moment while performing any mental task. Its level is affected by many factors including the requirements of the task, the environment in which the task is being performed and the perceptual capabilities and the skills of the performer [1]. Many jobs are greatly influenced by extremely high or low cognitive workload. These include military, clinical, industrial, computer-based assistance [2], or even driving and gaming and all sensitive applications that require high level of vigilance. Thus, there is a serious need to accurately quantify the level of cognitive workload. The importance of measuring cognitive workload is to monitor and enhance the cognitive performance of users. This is in addition to reducing any degradation in performance caused by lack of attention or cognitive overload. This degradation can affect memory, learning process and decision-making. Internal and external factors, such as the level of noise in the environment, can affect the current cognitive state of the human user. This state, as well as the mental capacity of the user, must be taken into consideration in order to avoid any cognitive overload and to better utilize their cognitive capabilities [3]. The measurement of cognitive workload helps to better understand the internal processes of users. Thus, it helps to assess their abilities to process information and decide whether to trust decisions made in specific cognitive states. Moreover, in designing work environments, cognitive workload can be an important factor to consider in order to avoid any situations that may impose or result in demanding work conditions and to avoid cognitive overload [4].

In designing a method to measure or assess cognitive workload, many aspects must be taken into consideration. These include experience; unskilled or novices are expected to undergo more cognitive load implementing a task than those who are more familiar with it [5]. Stimuli type, such as visual, auditory or other type, determines the conscious perception. Additionally, how salient the stimulus is, has a great effect on the amount of mental resources needed to process information. Attention to the stimulus; saliency may not have an effect if the stimulus is not noticeable. Anticipation of a priori knowledge of the stimulus can influence the time to perceive information, which will therefore reduce the amount of cognitive workload placed on the brain [6]. Multitasking is directly related to the cognitive state and the mental resources required for completing each task.

Accurately measuring the cognitive workload can be a challenging task. However, some physiological and psychological indicators can help in quantifying different cognitive workload levels. In general, there are four main methods for assessing cognitive workload [7]:

Analytical methods: They are based on modeling workload. Examples: Time-Line analysis and Prediction (TLAP) [8].

Subjective methods: These methods rely on the subject rating for the different mental tasks, such as the NASA TLX [9] and the Friedman's Chi-Square test [10].

Performance methods: In these methods, the user's performance can help in determining the cognitive workload. For example, any deterioration in performance can indicate the increase of workload level. Metrics used in these methods include reaction time and accuracy.

Psychophysiological methods: The physiological methods measure physiological changes associated with different cognitive workload levels. In comparison with the previously mentioned methods, the physiological methods are found to be objective and have less interference with the main task [11]. Next, some of the most popular techniques in the psychophysiological methods are presented:

Eye-tracking: With the increasing potential of eye-tracking technologies, it is now possible to collect eye tracking data with high sampling rates. Unlike the previous generations of eye-trackers, nowadays the devices are non-invasive. This enables the collection of data without the interference with the subjects. Tracking the eye can offer two methods of assessing cognitive workload. The first one is done by utilizing the relation between eye movements and cognitive load. Eye-movements, especially small movements around the fixation points (called saccades) are highly modulated by visual attention. This relation between eye movements and attention offers a method of assessing mental workload. The second potential source for measuring cognitive workload offered by eye tracking is the size of the pupil. The pupil diameter has a direct relationship with the cognitive state, visual search, sentence processing, visuospatial memory and attention [12]. A well-known indicator for cognitive state is the Index of Cognitive Activity (ICA). ICA is the measure of sudden changes in the pupil diameter occurring in small time. One limiting factor of using pupil size as a measure of mental workload is the effect of light on the dilation of the pupil. The amount of light reaching the retina can directly affect the diameter of the pupil. Thus, the brightness of the environment must be controlled while measuring ICA, to overcome this issue.

Functional Near-Infrared Spectroscopy (fNIRS): fNIRS is the application of near-infrared (NIR) in determining the functioning areas of the brain. It takes advantage of the fact that the amount of light absorbed by oxygenated blood is less than the amount of light absorbed by deoxygenated blood. Using emitters and detectors of near-infrared light can allow for determining the hemoglobin concentrations in the different parts of the brain, consequently the functioning areas. fNIRS is also used as a method for measuring the cognitive workload by analyzing these functioning areas of the brain.

Heart rate variability (HRV): HRV is the variation in the interval separating heartbeats (beat to beat time). HRV reflects many of the social and mental characteristics such as stress [13], emotional strain and anxiety [14]. Moreover, HRV is used frequently in the field of psychophysiology. Additionally, HRV offers a method for separating different cognitive states.

Electroencephalogram (EEG): This is a noninvasive electrophysiological method for monitoring and measuring the electrical activities of the brain. EEG reflects the voltages produced by the ionic currents of the brain neurons [15]. It is used in many applications related to understanding or assessing the brain functionalities. These include sleep disorders, controlling the process of anesthesia, coma, epilepsy and brain death [16]. Additionally, EEG signals are very sensitive to changes and variations in alertness and attention. Thus, EEG is considered to be a powerful means in measuring the levels of vigilance and mental effort.

1.2. Problem Statement

The grand challenge of this work is the accurate quantitative assessment of cognitive workload. EEG signals are used in this work as a metric for classifying four levels of cognitive workload. An experiment was conducted to generate these different levels as a result of the degradation of visual stimuli, and EEG signals were recorded simultaneously. The dataset is reused from the existing work of K Yu *et al.* [17]. The classification system reported in [17] resulted in classification accuracy of

87%. The objective of this thesis is to develop another method for measuring cognitive workload that offers a higher classification accuracy. Another challenge that is considered in this work is the complexity of the developed system, in terms of processing time. Thus, a computationally efficient classification system is also developed in this work.

The classification system adopted consists of multiple steps. The first step is the pre-processing of EEG signals. The objective of this stage is to include only the frequency components that increase classification accuracy. Additionally, any sort of eye movements, such as blinking, during the recording of the EEG signals can result in contamination of the signals. Thus, it is important to remove such artifacts before conducting any processing. The second step of the classification system is extracting useful and non-redundant information from the preprocessed data. The extracted feature vectors are used to build a general model for classification. In this work, various statistical features are extracted from the discrete wavelet domain. The next step is dimensionality reduction of the extracted feature vectors, using stepwise regression. The final step of cognitive levels classification system is using a multiclass linear classifier to differentiate between the four levels.

In addition to the classification system, EEG channel selection was also investigated. Two methods of channel selection were examined to further reduce the computational complexity. The rest of this thesis is organized as follows:

Chapter 2 presents the work done in the area of cognitive workload assessment, especially using physiological methods. It includes two sections; the first one addresses the physiological methods in general. While the other focuses on the existing approaches that utilize EEG signals in cognitive workload classification. The last section in Chapter 2, explains the need for channel selection in cognitive workload classification. Additionally, it provides examples from the literature for EEG channel selection.

Chapter 3 explains the details of the experiment system. The paradigm along with the data acquisition system are detailed in this chapter. Additionally, Chapter 3 illustrates the different cognitive levels studied in details.

Chapter 4 explains the existing approach for cognitive workload classification under vague stimulation. It introduces the existing work as well as the proposed solution. Additionally, the various steps of the adopted classification system are explained in detail.

In Chapter 5, the evaluation of the proposed solution is provided. Also, Chapter 5 presents a comparison between the existing and the developed solutions.

Finally, Chapter 6 provides the conclusion of this thesis; it also includes the future work and recommendations.

Chapter 2. Literature Review

In comparison with the several methods available for cognitive workload assessment, physiological methods are found to be objective and to have less interference with the main task [11]. This chapter reviews existing studies in the topic of assessing and separating different levels of cognitive workload based on physiological methods. Firstly, different techniques are presented, then, this chapter focuses on EEG signals in cognitive levels classification. It also introduces EEG channel selection, and presents available approaches to implement it.

2.1. Cognitive Workload Classification using Different Physiological Methods

In [18], S. Tokuda *et al.* aimed to evaluate the Mental Workload (MWL) of individuals using a specific type of eye-movements called Saccadic Intrusions (SI) and accordingly, deciding subject's ability to safely drive a vehicle. The motivation behind using SI is that the previous methods of estimating MWL using pupil diameter are not efficient in applications such as driving. Unlike SI, the pupil diameter is very dependent on the environment around the subject and can easily change due to the brightness level variations. SI has many types including regular saccades, microsaccades, and saccadic intrusion. The main focus of the study was regular saccades. The characteristics that define SI are the amplitude and the dwell time. The amplitude (horizontal not vertical) is measured in degrees, and lies in the range of 0.4-4.1 degrees. The dwell time is the plateau of the rectangular pulse, and its value is usually in the range of 60-870 ms. For generating different levels of MWL, the participants were engaged in an experiment of three cognitive levels. The recorded eye movements were examined to find the gaze deviations with similar characteristics to SI. These eye behaviors were then represented in SI values. For each participant, the MWL versus the SI was compared. The results showed a high correlation between the MWL level and the level of SI detected. Additionally, the MWL was compared to the change of pupil diameter of the participants. The results showed that the SI is a better indicator than the pupil diameter in assessing cognitive load.

Oskar Palinko and Andrew L. Kun in [19] suggested a way to eliminate the effects of light on the size of the pupil diameter. The objective was to have more accurate results in assessing cognitive workload. This study, as the one reviewed previously, considered driving as an application for the measured cognitive workload.

Similarly, in [20], the authors examined the ability to separate the response of the pupil size to the cognitive task from the reflex of the pupil to light. In both studies, they were successful in separating the Task Evoked Pupillary Response (TERP) from the effect on the pupil resulting from the change in light. However in [20], the stimulation of the cognitive workload was originating from visual and auditory sources, while in the later work, the stimulation was produced from two visual tasks (one for the simulation of driving and the other for the simulation of the participant's interaction with a device). Having two stimuli that use the same channel (the visual channel), complicates the process of separating TERP from the pupil's reflex to light. They conducted three-task experiments on 12 subjects. The first task is to study the effect of light on the pupil size. The second task is to study the effect of TERP on the pupil size. The last one is to separate the effect of TERP from the effect of illumination. Since the third task is a combination of the first two tasks, the authors subtracted the average pupil diameter of the first experiment from the pupil diameter of the third experiment. This is in order to separate the effect of illumination from the recorded size of the pupil. The resulted diameter was very similar to that of the second task. This indicates the possibility of separating the TERP effect from the illumination effect on the pupil diameter.

S. Marshall in [21] studied the ability of index of cognitive activity (ICA) in measuring the cognitive workload. ICA is the measure of sudden changes in the pupil diameter. The relation between ICA and cognitive workload was studied using 4 different settings of tasks. The different settings were to test all the different combinations of light and darkness, with and without cognitive effort. The results showed that ICA level is different when comparing the cognitive effort vs. the absence of cognitive effort. This is regardless of the amount of light in the environment. In contrast, ICA has no differences in levels, or remains almost constant if the level of cognitive load is constant. This is true even if the environment undergoes a change in light. Thus, the study concluded that ICA is not affected by the brightness of the environment and therefore, can be used in cognitive workload assessment.

In [22], M. Bartels and S. Marshall evaluated different types of eye-tracking devices. They assessed the performance of these devices in measuring cognitive workload using ICA. The procedure included three different workload tasks and four different eye-tracking hardware systems with at least one eye tracking hardware for each participant. For each of the hardware systems, the measured ICA had a strong correlation with the level of difficulty of the cognitive task. As the level of the difficulty increases, the level of ICA increases accordingly. The results show that regardless of the hardware used, ICA can be considered a good metric in evaluating cognitive workload.

In the work done by E. Solovey *et al.* in [23], cognitive workload was assessed in order to better understand the internal state of brain computer interface (BCI) users. The objective was to design efficient systems and user interfaces with improved task switching and utilized multitasking processes. Functional near-infrared spectroscopy (fNIRS) sensors were used to measure signals from a subject's brain. The measured signals reflect the oxygenated and deoxygenated blood in different parts of the brain. First, they conducted an experiment with three different multitasking scenarios that are common to BCI. The results verified that different cognitive states could be distinguished using the signals measured from fNIRS sensors. A real-time system was then developed to use the feedback from the cognitive workload classification system. This feedback is used to improve the behavior of a user interface application with integrated multitasking conditions.

In the subject of HRV and cognitive workload, A. Luque-Casado [24] studied this relation and compared it to the fitness level. He conducted an experiment to compare the HRV of two groups while performing three different cognitive tasks. The first cognitive task was designed to test the sustained attention of the participants. The second task aimed to test the ability of the participants to build-up expectancies about the occurrence of a certain event. In the last experiment the subjects were requested to discriminate between the duration of two visual stimuli. The members of the first group were of high levels of fitness, while the members of the second group were of normal levels of fitness. The purpose of this experiment was to prove the relation between cognitive performance of the participants and their HRV. The results compared the response time, the accuracy, HRV and the fitness level. They show that the performance of the high-fitness group was better in tasks that require sustained attention. Additionally, HRV was proven to have a strong correlation with cognitive load, especially, for tasks with high perceptual demands. Another work done on the relation between memory workload and HRV was conducted by M. Suriya-Prakash *et* *al.* in [25]. The results were similar to the previous one. As the memory workload increases, the HRV decreases. Also, from the conducted experiment, it was noted that subjects who performed better in completing the cognitive tasks had lower values of HRV than those who had poor performance.

E. Haapalainen *et al.* compared the performance of many sensors in measuring and assessing cognitive workload. They used different stimuli that require elementary cognitive processes. Then, using the multiple psycho-physiological sensors, they were able to decide which metrics are most helpful in determining the cognitive state. The experiment included 20 participants who implemented 6 different cognitive tasks. The sensors included in the experiment were a contactless eye-tracker to track the eye-gaze and measure the pupil size, a Body-Media armband to measure electrocardiogram signal (ECG) and galvanic skin response (GSR), wireless EEG headset to measure EEG signal, and a wireless heart rate monitor. Statistical features such as mean, median, spectral power and variance were extracted from the signals recorded by the different sensors. The results indicated that the best features in assessing cognitive workload were the median of the ECG signals and the mean of the heat flux, with a classification accuracy of over 80%.

2.2. Cognitive Workload Classification using EEG Signals

As mentioned previously, EEG signals are very sensitive to changes and variations in alertness and attention. This makes EEG signals a powerful means in cognitive workload classification. Following are some of the studies carried out in the area of cognitive workload classification using EEG signals. This review focuses on the various techniques used for EEG pre-processing, feature extraction and classification used.

P. Zarjam et al. in [26] aimed to classify 7 levels of cognitive workload using EEG signals. The source of the cognitive workload was arithmetic tasks with different levels of difficulty. Signals contaminated with EOG artifacts were discarded from the analysis. The remaining signals were then filtered with a band-pass filter of 0.5-30Hz. For feature extraction, the discrete wavelet transform (DWT) was applied to the signals and then entropy measurements were calculated to construct the features. For classification, Artificial Neural Network (ANN) classifier was used. One important thing to be noted in this study is the use of source localization to reduce the number of channels used in the analysis. The algorithm used for source localization was cortical source imaging using a minimum norm estimate. With 7 channels form the Frontal region, the average classification results of the entropy measurements were 94.7%.

In the work done by C. L. Baldwin and B.N. Penaranda in [27], EEG signals recorded from fifteen subjects were used to classify cognitive workload. The signals were collected at 500 Hz sampling rate, with ground at the second EEG channel (FPz). The experiment included three different working memory tasks, with two levels of difficulty each. After visually inspecting the EEG signals to remove noisy channels, the remaining subset of EEG channels was further reduced. The EEG subset included channels ‘F3’, ‘Fz’, ‘F4’, ‘C3’, ‘Cz’, ‘C4’, ‘P3’, ‘Pz’, ‘P4’ and ‘Oz’ only. These signals were filtered using a high-pass filter with cutoff frequency of 0.1 Hz and a 70 Hz low-pass filter. In this study, the feature vector that consisted of the power, was calculated from five frequency bands. These bands were delta (0.01–3 Hz), theta (4–7 Hz), alpha (8–12 Hz), beta (13–30 Hz), and gamma (31–42 Hz). Artificial neural networks (ANNs) were used for classification. The data was split equally between the training and testing phases. The average classification result in this study was 85%.

EEG signals were also used by Christian Mühl*et al.* in [28] in order to classify two levels of mental workload. After removing the (EOG) artifacts, the signals were divided into six frequency bands. The bands were delta (1–4 Hz), theta (4–8 Hz), alpha (8–12 Hz), beta (12–30 Hz), gamma (30–47 Hz), and high gamma (53–90 Hz). The spectral powers of these frequency bands were used as features. Additionally, features were also extracted from spatially filtering the signals using common spatial pattern (CSP) filter to calculate the spectral power of these filtered signals. The resulting feature vectors were reduced in size using maximum Relevance Minimum Redundancy (mRMR) feature selection algorithm. Finally, the classification was implemented using Linear Discriminant Analysis (LDA) classifier.

In [29], Shreyasi Datta *et al.* recorded EEG signals from 10 electrodes. These electrodes were FP1, FP2, F3, F4, O1, O2, P3, P4, T3 and T4. The recorded signals were used in the classification of three cognitive activities, in an experiment that included four subjects. Elliptical Band pass filter with bandwidth of (13-30 Hz) was used for filtering the EEG signals. Additionally, in order to remove the interference of adjacent channels, common average referencing method was performed on the recorded EEG signals. For feature extraction, several methods were used in this study. These are Automatic Autoregressive parameters, computed using Kalman filter, Hjorth Parameter, Hurst Exponents and Approximate Entropy. Interval Type 2 Fuzzy System was used for classification. Using the combination of all features, the average classification accuracy reported, reached 85.33%.

Wireless EEG signals were explored in [30] to assess memory workload. The workload levels of an n-back task were classified for 9 subjects. The system proposed in this paper included automatic artifacts removal, feature extraction, feature scaling, feature selection and classification. Four groups of feature extraction techniques were employed. These are spectral power density, statistical features, morphological features and time–frequency features based on four-level DWT. The statistical features included were mean, variance, skewness, and kurtosis. The morphological features included in this work were curve length, number of peaks and average non-linear energy. The wavelet entropy was employed for decreasing the dimensionality of the features. The classification was carried out using support vector machine classifier, which was used in this work. For the n-back cognitive levels, the system proposed in this study resulted in an average classification accuracy of 82%.

2.3. Channel Selection

Altahat *et al.* in [31], collected EEG data from 64 channels. This data was used for person authentication. The dataset included the EEG signals of 106 subjects performing six different mental tasks. The recorded signals were filtered using a bandpass filter of (4-52 Hz) pass band. For each channel, the PSD of six frequency bands with a resolution of 8 Hz was extracted as features. For channel selection, the data of 50 participants only was included in the analysis. The feature vectors of all subjects for a given mental task alongside all channels were assumed to have a Gaussian distribution. The channels were ranked based on their stability, then, a sequential forward selection procedure was implemented to find the best subset of EEG channels. The suggested subset of EEG channels for person authentication included 8 EEG channels.

Common Spatial Pattern (CSP) is another method for channel selection which was presented in [32]. The idea of CSP method is to project the channels into low-dimensional subspace to maximize the variances of two classes. CSP is based on the simultaneous diagonalization of the covariance matrices of both classes. In [32], the authors are assuming that the two channels corresponding to the maximal coefficients of the spatial pattern vectors are the channels with the most correlation to the task specific sources. The reported average classification accuracy reached around 92.6% for two subjects, using a subset of four EEG channels only.

In order to optimize the previous method of channel selection, the authors of [33] proposed the Sparse Common Spatial pattern (SCSP) method for channel selection. The proposed method reduces the number of EEG channels by sparsifying the common spatial filters within the classification accuracy constraint. SCSP method which outperformed the CSP method, in terms of classification accuracy, especially when the number of selected channels is relatively small.

This chapter provided a review for the different techniques in cognitive workload clsassification. EEG signals, as explained above, are used in many studies as a metric for classifying the cognitive levels. In this thesis, EEG signals are used for classifying four levels of cognitive workload. The experiment conducted to generate these levels is explaind in the following chapter.

Chapter 3. Experimental Setup

In this chapter, the details of the experimental procedure are described. The experimental setup and data collection, illustrated in Figure 1, were performed as explained in [17]. They are described in this thesis for completeness.

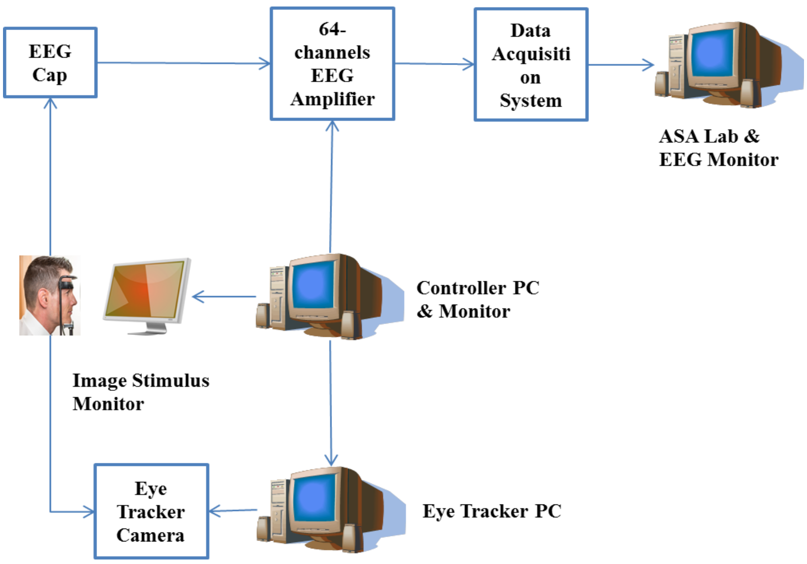

Figure 1: System setup

3.1. Participants

The experiment included 16 healthy subjects, with normal or corrected-to-normal vision. These subjects were tested for color blindness and had to go through the dominant eye test. The history of the participants shows that they were not on medication and had not experienced any neurological or cardiovascular diseases. Additionally, the participants did not suffer from any psychiatric disorders or hypertension. NASA task load index (NASA TLX) questionnaire, which is a subjective workload assessment, was completed by every participant before and after the experiment. This assessment is based on different subscales that act as sources of workload demand. These subscales are Mental Demands, Physical Demands, Temporal Demands, Own Performance, Effort and Frustration [9].

3.2. Protocol

The main focus of the experiment is the cognitive workload for visual perception. The experiment was conducted using a 24” monitor to display the visual stimuli, and was performed in a quiet room with controlled brightness. The total time of the experiment was around 90 minutes (including the preparation time). Four levels of cognitive workload were tested, with each level lasting for about 10 minutes. During that time, and while the experiment was being performed, EEG signals were recorded from 64 channels.

For each level of the cognitive tasks, the subjects were asked to identify the human face (the target) displayed on the monitor, by pressing the letter ‘Q’. Otherwise, to identify the non-target images (i.e. anything displayed other than a human face), they were asked to press the letter ‘P’. The difficulty level of the cognitive tasks increased from level 1, as the easiest, to level 4, as the most difficult cognitive task.

Figure 2 illustrates the sequence of the visual stimuli displayed on the monitor. Each trial started by displaying a fixation cross (+) that lasted for 500 ms, after which a digit (Digit 1) was displayed for 300 ms. Following that, another digit (Digit 2) was displayed for 300 ms before an image of 256x256 pixels was displayed for 300 ms. Finally, a maximum time window of 3000 ms is left for the subjects to respond (wait for response). The next trial is initiated immediately after the response. The previous sequence was repeated for all the levels. The difference between the levels was the definition of the target image. The four cognitive levels are described in the following levels:

Level 1: In this level, the definition of the target is simply an image of a human face. This target can easily be distinguished from the image itself, regardless of the values of the two digits.

Level 2: In this level, the target is defined as the human-face image that is preceded by either two odd numbers or two even numbers.

Level 3: The target of this level is the same as the previous one. Only in this level the signal to noise ratio (SNR) of the images was reduced to 0 dB. The objective of reducing the SNR is to increase the amount of cognitive workload imposed on the subjects.

Level 4: This level is similar to the previous two levels. However, the SNR of the images was decreased more than the previous level. The images had SNR of -5dB, again. This is to increase the cognitive workload placed on the subjects.

Figure 3 provides examples for the target sequences of each of the cognitive levels. The order in which the levels were presented was random so as to avoid any adaptation that could affect the perception of the subjects during the experiment.

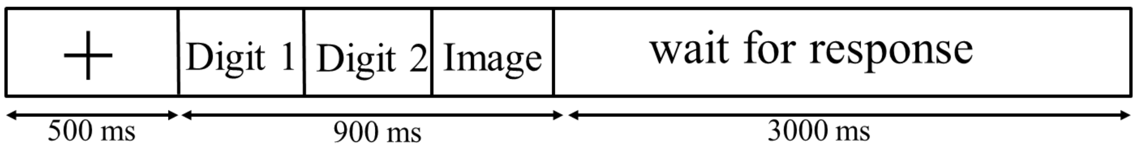

Figure 2: The sequence of visual stimuli

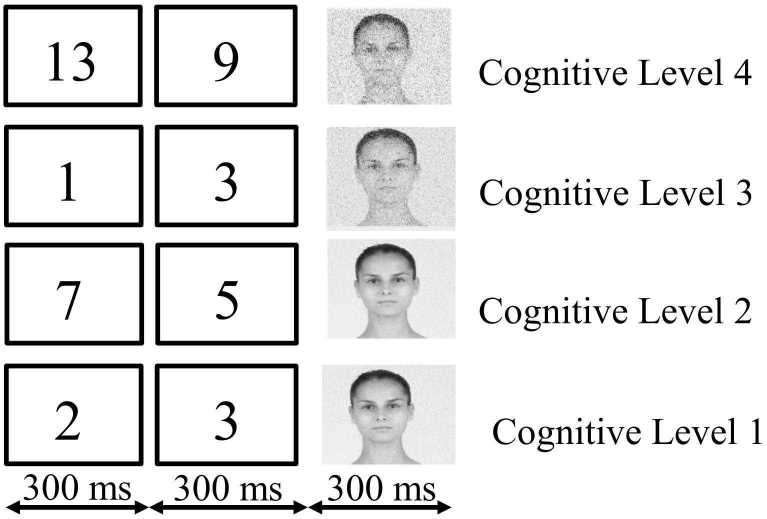

Figure 3: Sample targets for each of the four workload levels

3.3. Data Collection

The recorded EEG data was collected from 62 different channels. These channels were referenced to the two channels recorded from the ears. Additional to the EEG signals, one channel electrooculogram (EOG) and one channel electrocardiogram (ECG) were also recorded simultaneously. ANT waveguard caps (Waveguard, ANT B.V., Enschede, The Netherlands) were used for the data collection, with the 64 electrodes arranged in a 10-10 international system. All the signals were collected and sampled using the ANT amplifier (ANT B.V., Enschede, Netherlands) at 512 Hz sampling rate.

Figure 4 presents an example of EEG signals from 16 channels. The x-axis represents the time (temporal aspects of the channels), while the y-axis represents channels locations (spatial aspects). Figure 5 illustrates the locations of the electrodes on the subject’s head. These electrodes are explained in more details in Chapter 4.

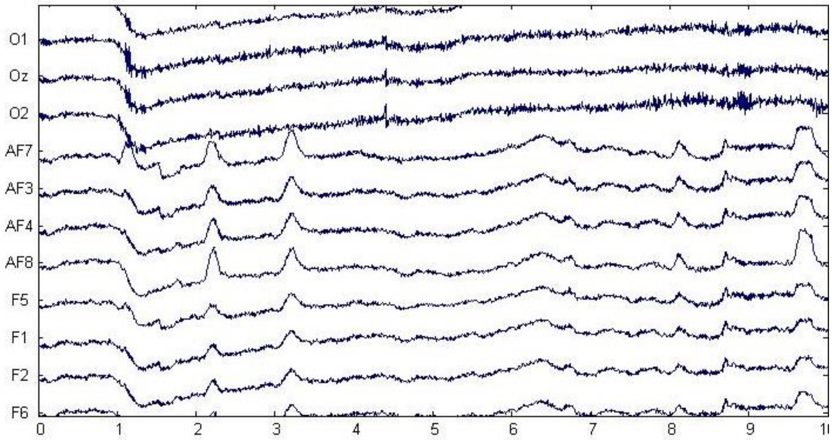

Figure 4: Example of EEG signals

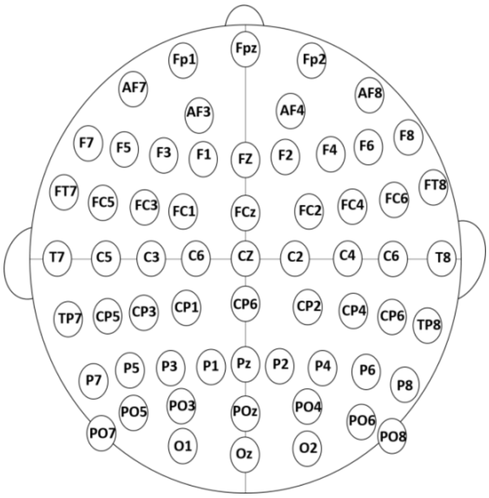

Figure 5: The locations of EEG channels

This chapter illustrated the experiment conducted to generate the four cognitive levels and the differece between these levels. Additionally, this chapter explained the data collected during the experiment. The following chapter illustrates the steps of the exisiting method for cognitive workload classification, as well as the method proposed in this thesis.

Chapter 4. Methodology

This chapter introduces the various steps of the classification system. The first section summarizes the approach used in the existing work of [17], for cognitive workload classification. In the second section of this chapter, the proposed techniques for preprocessing, feature extraction, dimensionality reduction and classification are presented. Additionally, EEG channel selection is presented as an optional step in the classification system. The last section in this chapter presents the stationarity test for EEG signals.

4.1. Existing Work

This section reviews the preprocessing, feature extraction and classification used in the existing work of Yu *et al.* [17].

4.1.1. Pre-processing. The EEG signals were passed through a second-order blind identification "SOBI" filter [34] to remove the effect of eye blinks on the EEG signals. The signals were also filtered using "pop_eegfiltnew" [35] with pass-band of (0.3-40 Hz).

4.1.2. Feature extraction. Two methods of feature extraction were used. The first one was Power Spectral Density (PSD) method. In this method the feature vector was the average of the spectral powers across the 62 channels. The power of each channel was calculated in the frequency bands: α (8-12 Hz), θ (4-7) Hz and σ (0.5-3 Hz). Then, these values were used as features. The second method of feature extraction was bilinear common spatial pattern (BCSP). In this method, the feature vector contained 2 spatial projections and 4 temporal projections. The projections were calculated using the BSCP objection functions:

$$max_{W,V} \frac{\det(W^T X_+ V V^T X_+^T W)}{\det(W^T X_- V V^T X_-^T W)} \tag{1}$$

$$max_{W,V} \frac{\det(W^T X_- V V^T X_-^T W)}{\det(W^{\ T} X_+ V V^T X_+^T W)} \tag{2}$$

where W and V are the spatial and the temporal projections respectively. *det(.)* is the determinant operator. X_+ and X_- are the EEG data belonging to different classes (different level of cognitive workload). W and V can be found by solving (3) and (4), respectively [36].

$$X_+VV^TX_+W = X_-VV^TX_-W\Lambda \tag{3}$$

$$X_+WW^TX_+V = X_-WW^TX_-V\Lambda \tag{4}$$

where Λ is a diagonal matrix. V is initially assumed to be known and set to be a full rank square matrix.

4.1.3. Classification. For classification, a one-against-one method was used. For each combination of two classes (two levels of cognitive workload), a binary Support Vector Machine (SVM) classifier [37] was generated. Six classifiers were needed for the four levels to cover all different combinations. Each binary classifier would deliver one result and each result was considered as one vote. Then, the majority voting was used for determining the classification result. Probabilistic values of each classifier were used in the case of even scores.

4.2. Proposed Solution

This section introduces the proposed solution for cognitive level classification. It demonstrates the proposed preprocessing technique, channel selection approaches, feature extraction schemes and linear multiclass classification. Figure 6 illustrates the general steps of the proposed solution. The first step is the preprocessing of EEG signals using filtering techniques. The next step is channel selection. This step is optional in the classification. However, if added, channel selection can reduce the computational overhead in the rest of the classification system. Two methods for channel selection are explained in this section, where the effect of these methods on the classification system will be explained in Chapter 5. The following step in the proposed system is feature extraction based on Discrete Wavelet Transform (DWT) and statistical measures. The dimensionality of the feature vectors is then reduced by using the stepwise regression procedure. Lastly, a simple linear classifier is used to predict the cognitive levels.

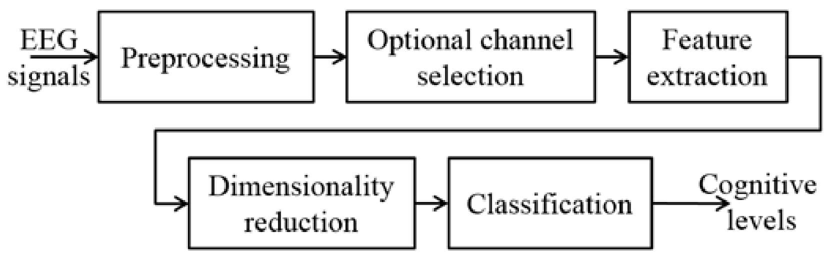

Figure 6: Proposed cognitive workload classification solution

4.2.1. Pre-processing. In this step, two filters were used. First, the signals were filtered using Hamming windowed sinc FIR filter. The function "pop_eegfiltnew" was used to implement this filter with a pass-band of (0.1-60 Hz). These values are typical in processing EEG signals to remove noise (frequencies below 0.1 Hz) and unwanted higher frequencies (above 60 Hz). The purpose of the second filter was to remove the EOG artifacts. This was implemented using "SOBI" filter.

4.2.2. Channel selection. Channel selection is the process of selecting the relevant channels that contain the major features of cognitive states. Channel selection reduces the processing and data acquisition complexity. It can also help in improving the performance of classification by reducing the amount of overfitting that may occur due to the utilization of unnecessary channels [38].

In this work, the effect of channel selection on the overall classification accuracy was studied. To achieve that, we applied two approaches for channel selection prior to the proposed feature extraction and classification steps. The first approach examined is based on selecting EEG channels that correspond to the different regions of the human brain. The cerebral cortex of the human brain consists of four lobes. These are the Frontal, Parietal, Occipital and Temporal as illustrated in Figure 7. The Frontal lobes are associated with reasoning, planning and problem solving [39]. The parietal lobes are related to movements and perception of stimuli [40], while the occipital lobes are related to visual processing [38]. The temporal lobes, located on both sides of the brain and just above the ears, control the hearing and contain the auditory cortex [41]. In this work, the selection of EEG channels was examined based on their locations as illustrated in Figure 8, i.e. channels in the same region comprise a subset. The objective of this experiment is to identify the region of the brain that contributes most to the classification of cognitive levels. Figure 8 shows the 16 channels for the Frontal lobes (red electrodes in Figure 8), 9 channels for the Parietal lobes (yellow), 10 channels for the Occipital lobes (blue) and 6 channels for the Temporal lobes (purple). The Central channels are treated as a separate region (grey) with 7 channels. As illustrated in Figure 8, there are 7 channels shared between the Frontal and Central regions. These were considered as part of both the Frontal and the Central subsets. Similarly, the 7 channels shared between the Central and the

Parietal regions were considered as part of both the Central and the Parietal subsets. Thus, the total number of channels in the Frontal, Parietal, Occipital, Temporal and Central regions is 23, 16, 10, 6 and 21, respectively.

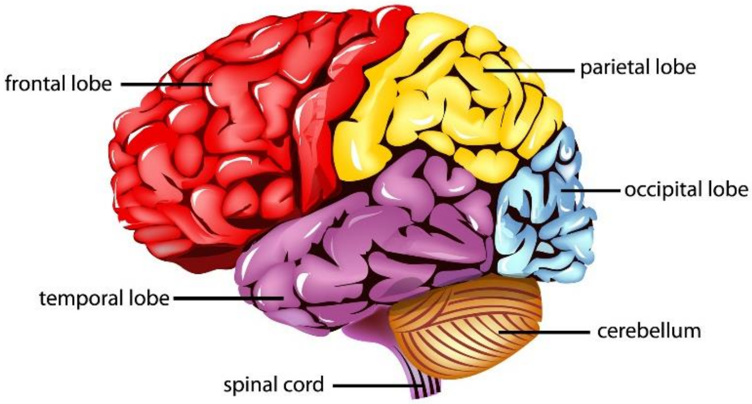

Figure 7: The cerebral cortex

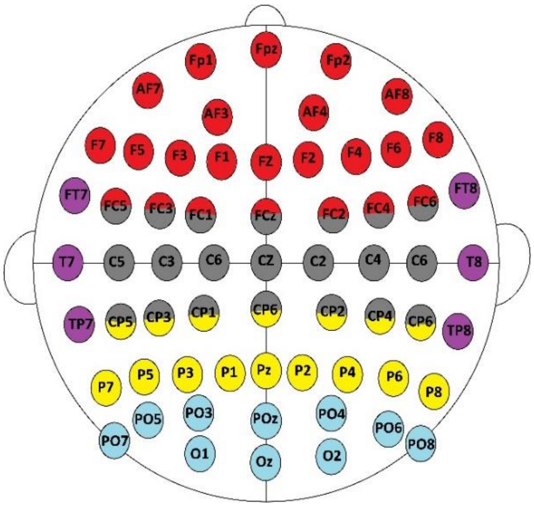

Figure 8: The locations of the EEG electrodes based on the lobes of the human brain

The second method examined in this work for channel selection is the approach reported by [31]. The reviewed algorithm was proposed for a human authentication system, in this work however, we use it in the overall system of cognitive load classification. In the Experimental Results chapter, channel selection algorithm is applied to the data and the locations of the top selected channels are visualized. In this section, the channel selection algorithm proposed by [31] is reviewed for completeness. The experiment reported in [31] included the data for 64 EEG channels from 50 subjects. The subjects performed six mental tasks, for the purpose of person authentication. For each channel of the EEG signals, the PSD of six frequency bands with a resolution of 8 Hz was extracted as features. The feature vectors of all subjects for a given mental task alongside all channels were assumed to have a Gaussian distribution. The channels were ranked based on their stability. Then, a sequential forward selection procedure was implemented to find the best subset of EEG channels. The stability of each channel was calculated using:

$$S_i = DB_i - DW_i \tag{5}$$

where DW_i is the within-subject distance. In our work of cognitive level classification, this can be calculated using the Mahalanobis distance between the means of the feature vectors' distributions, of different cognitive levels for the same subject at a given channel. DB_i is the inter-subject distance. In this work, this can be calculated as the Mahalanobis distance between the means of feature vectors' distributions of different subjects for the same cognitive level and EEG channel. The Mahalanobis distance is a measure of the distance between a point and a distribution, taking the correlation of the data set into account [42], and defined as follows [43]:

$$D_M(\underline{x}) = \sqrt{\left(\underline{x} - \underline{\mu}\right)^T C^{-1}(\underline{x} - \underline{\mu})} \tag{6}$$

where $D_M(\underline{x})$ is the Mahalanobis distance of an observation $\underline{x} = (x_1, x_2, x_3, \dots, x_N)^T$ from a set of an observations with means $\underline{\mu} = (\mu_1, \mu_2, \mu_3, \dots, \mu_N)^T$ and covariance matrix C.

4.2.3. Feature extraction. The output of the pre-processing step is filtered signals of 62 EEG channels. The second step in the proposed system is feature extraction. In this step, only useful and non-redundant information will be selected from the raw EEG data in order to build a general model for classification. In this work, the filtered signals from the 62 channels are treated as a 2-D image, then, a discrete 2-D wavelet transform (DWT) is applied. We use the Haar wavelet transformation for its simplicity and speed. For image transformations, matrix operations are used as expressed in (7):

$$Y_n = H_n X_n H_n^T \tag{7}$$

where X_n is the input *nxn* image, and H_n are the Haar basis functions. In general, the Haar basis functions $H_k(x)$ is defined for x between 0 and 1, and k is an integer between 0 to $N-1$, where N is the length of the input. The integer k can be computed as the $\Sigma 2p + q - 1$ where $p = 0,\ldots,n-1$ and q is either 0 or 1 if $p = 0$, and between 1 and $2p$ otherwise. The Haar basis functions are therefore defined as:

$$h_{00}(x) = \frac{1}{\sqrt{N}}\,, \qquad for\ 0 \le x \le 1 \tag{8}$$

and

$$h_{pq}(x) = \frac{1}{\sqrt{N}}\begin{cases} 2^{p/2}\,, & \frac{q-1}{2^p} \le x < \frac{q-\frac{1}{2}}{2^p}, \\ -2^{p/2}, & \frac{q-1/2}{2^p} \le x < \frac{q}{p}, \\ 0, & otherwise\ for\ x \in [0,1] \end{cases} \tag{9}$$

Applying DWT on the EEG signals results in four subbands. These subbands contain the approximation coefficients matrix ($\boldsymbol{Y_{0,0}}$) and the detail coefficients matrices of the horizontal ($\boldsymbol{Y_{0,1}}$), vertical ($\boldsymbol{Y_{1.0}}$) and diagonal ($\boldsymbol{Y_{1,1}}$) edges. With a one level wavelet transformation, the dimensions of each subband are half of the input, namely, 62/2 rows and 257/2 columns. The number of columns pertains to the length of each epoch. Statistical features are then extracted from the vertical edges matrix ($\boldsymbol{Y_{1.0}}$). This matrix is chosen because it represents the temporal dynamics of the EEG signals. The extracted statistical features included:

i. Spatial and temporal means of the $\boldsymbol{Y_{1.0}}$ EEG subband.
ii. Spatial and temporal standard deviations of the ($\boldsymbol{Y_{1.0}}$) EEG subband
iii. Spatial and temporal entropy of the $\boldsymbol{Y_{1.0}}$ EEG subband.
iv. The spatial covariance matrix of the $\boldsymbol{Y_{1.0}}$ EEG subband

The entropy can be considered as the average uncertainty associated with an event, and is defined as:

$$E = -\sum_{i=1}^{n} P(x_i) log_2 P(x_i) \tag{10}$$

where the length n is 62/2 and 257/2 for spatial and temporal measures respectively. $P(x)$ is the probability of encountering the value x and can be approximated through relative frequencies of the input data.

For a matrix A_{nxm}, the covariance matrix of A is C_{nxm}. Each c_{ij} element in C is the covariance of the i^{th} and the j^{th} columns in A. In general, the covariance of the variables Y and Z is defined as:

$$cov(Y,Z) = \frac{\sum_{i=1}^{n}(Y_i - \bar{y})^*(Z_i - \bar{z})}{n-1} \tag{11}$$

where n is the length of vector Y and Z, $\bar{y}\, and\, \bar{z}$ are the means of Y and Z respectively. In our case, Y and Z are 2 different columns of the $\boldsymbol{Y_{1,0}}$ EEG subband. Hence, the size of the covariance matrix is 31x31. Since the covariance matrix is symmetrical, then only the values above the main diagonal are retained and represented as a vector.

Figure 9 illustrates the process of feature extraction used in this work. The filtered EEG signals are combined as an image, and transformed using DWT. Statistical features are then extracted from the vertical subband $\boldsymbol{Y_{1,0}}$ as explained above.

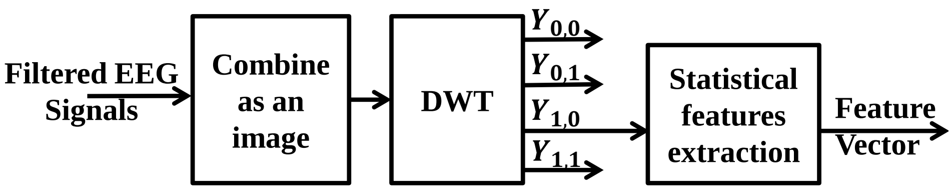

Figure 9: Proposed feature extraction process

The outcome of feature extraction is feature vectors that represent the data samples. Thereafter, normalization is needed to ensure that the different features are on similar scales. This is crucial to make the features have the same impact on the classification model.

Z-score, also known as zero-mean normalization, is a method used for normalization of feature vectors. It measures the distances between data points and the mean (μ) in terms of standard deviations. A z-score can be either positive, negative or zero. A z-score of zero indicates that the data point has the same value as the mean (μ). A positive z-score indicates that the data point is above the mean, and a negative z-score results from a data point below the mean. The unit of measure is in standard deviations (σ). For a feature vector X the z-score of data point x_i is defined as:

$$z = \frac{(x_i - \mu)}{\sigma} \tag{12}$$

where μ and σ are the mean and standard deviation of X, respectively. In terms of implementation, the z-scores are applied to the train dataset only. The resultant means and standard deviations of which are then used to normalize the test dataset.

4.2.4. Dimensionality reduction. The dimensionality of the resultant feature vectors is detailed in Table 1. The total length of each feature vector is 945 variables. Such a dimensionality is considered high, and can affect the performance of the classifier if not enough feature vectors are available in the training phase, causing what is known as "curse of dimensionality" [44]. Therefore, in this work, we used stepwise regression to reduce the dimensionality of the feature vectors, whilst retaining the most important variables.

Table 1: Description of the feature vector content and size

Features	No. of variables
Mean of subband $\mathbf{Y}_{1,0}$ columns	129
Standard deviation of subband $\mathbf{Y}_{1,0}$ columns	129
Mean of subband $\mathbf{Y}_{1,0}$ rows	31
Standard deviation of subband $\mathbf{Y}_{1,0}$ rows	31
Entropy of subband $\mathbf{Y}_{1,0}$ columns	129
Entropy of subband $\mathbf{Y}_{1,0}$ rows	31
Spatial covariance matrix	465

Stepwise regression is a method of variable selection, but it can be used for dimensionality reduction as proposed by [45]. Dimension reduction or model selection procedures are usually either forward or backward. Forward selection starts with the simplest model of all (i.e. one feature variable), then, adds suitable variables one at a time until the "best" model is reached. Backward elimination works with the most general model, and drops variables one at a time until the "best" model is reached. Stepwise, on the other hand, is a combination of both forward and backward methods, where variables can be dropped and added. For a set of variables x_1, x_2… x_k, f_{in} is the F-random variable for adding a variable to the model and f_{out} is the value of the F-random variable for removing a variable from the model. The stepwise regression is defined by the following steps [46].

Step 1: All the variables are examined one by one to generate a one-variable model in the form of:

$$h(x) = \theta_0 + \theta_1 x_1 \tag{13}$$

where $h(x)$ denotes the hypothesis that the included variables are needed for the classification of the cognitive level. x_1 is one of the different k variables that gives the highest F-statistics.

Step 2: For the remaining *k-1* variables the variables are examined to choose the second best variable such that the model in Equation (14) gives the best classification result. Here, x_2 is added such that its statistic f_2 is greater than f_{in}.

$$h(x) = \theta_0 + \theta_1 x_1 + \theta_2 x_2 \tag{14}$$

f_2 is calculated by:

$$f_2 = \frac{SS_R(\theta_1|\theta_2\theta_0)}{MS_E(x_1, x_2)} \tag{15}$$

SS_R denotes the regression sum squares error and MS_E denotes the mean square error. After x_2 is chosen, the algorithm rechecks if x_1 is to be removed. This is done by comparing f_1 to f_{out}. If f_1 is less than f_{out} x_1 is removed from the model. f_1 is calculated using the Equation (16):

$$f_1 = \frac{SS_R(\theta_2|\theta_1\theta_0)}{MS_E(x_2, x_1)} \tag{16}$$

Step3: For the remaining (*k*-*2*) variables, the third best variable is included by testing 3-variables model such that the model in Equation (17) which has the best classification result. x_1 and x_2 are the variables chosen in the previous steps and x_3 is chosen from the remaining (*k*-*2*) variables. Similarly, x_3 is chosen using the F-statistics.

$$h(x) = \theta_0 + \theta_1 x_1 + \theta_2 x_2 + \theta_3 x_3 \tag{17}$$

This algorithm continues until no more variables can be included or removed from the model.

Figure 10 illustrates the process of feature vector dimensionality reduction. Stepwise regression is applied to the feature vectors of the training dataset. The output from the stepwise regression is the indices of the retained feature variables. These indices are stored and used to reduce the number of features in the test dataset.

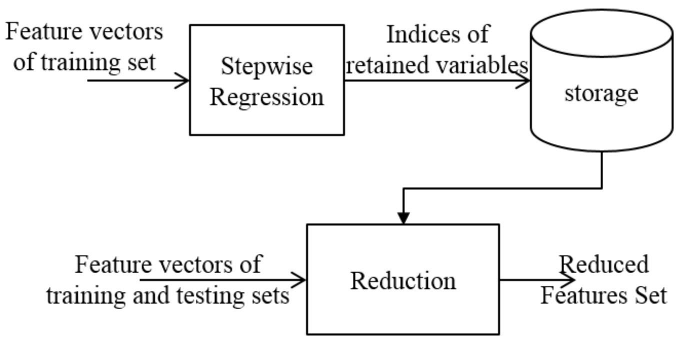

Figure 10: Dimensionality reduction of feature vectors using stepwise regression

4.2.5. Classification. In this work, both linear and non-linear classification approaches were examined. We found that linear classifiers worked best with the proposed feature extraction approach. In linear classifiers, the class is determined by a linear combination of features with predetermined weights. The weights are the attributes of the model, thus, the hypothesis or the predicted class will be:

$$h(x) = \theta_0 + \theta_1 x_1 + \theta_2 x_2 + \cdots + \theta_N x_N \tag{18}$$

where θ_j*'s* are the attributes of the model. For k classes we can define the input matrix X as:

$$X = [X_1, X_2, \dots X_k]^T \tag{19}$$

where X_i is a matrix with all the feature vectors belonging to class i, with M features, the size of X_i is N_i*M. The optimum set of weights for the i^{th} class is defined as:

$$\theta_i^{opt} = argmin_{\theta_i} \|X\theta_i - y_i\|_p \tag{20}$$

with:

$$y_i = [\, 0_{N_1}, 0_{N_2}, .. 1_{N_i}, .. 0_{N_k}]^T \tag{21}$$

where y_i is the ideal output vector for class i, which should be all zeros except when the input feature vector belongs to the same class. N_i is the number of training examples of class i. The $\|.\|_p$ operator in this work is the second norm ($p=2$).

The closed form solution for Equation (20) that gives the optimum weights is defined as [45]:

$$\theta_i^{opt} = (\sum_{j=1}^{K} X_j^T X_j)^{-1} X_i^T 1_i \tag{22}$$

where $\mathbf{1}_i$ is the target vector of class i, which is comprised of zeros and ones, in the same manner as the ideal output vector. In this work, the result of the training phase is four sets of weights $\{\theta_1, \theta_2, \theta_3 and\ \theta_4\}$, with a set for each class (level of cognitive workload).

In the testing phase, the features of the testing sets are extracted, normalized and reduced in dimension. As explained above, the dimensionality reduction reuses the indices generated by the stepwise regression applied to the training dataset. Each feature vector from the testing set X_t is estimated against the four levels to calculate set of scores $\{s_i\}$ as follows:

$$s_i = X_t \theta_i^{opt} \tag{23}$$

The predicted level was determined by choosing the class that corresponds to the highest score. Finally, the classification rate (CR) is calculated using Equation (24).

$$CR = \frac{N_P}{N_T} \tag{24}$$

where N_P is the number of the correctly predicted testing examples and N_T is the total number of testing set.

The process of model generation and classification is illustrated in Figure 11. Based on the reduced feature vectors of the training set and their corresponding class labels, the training process generates the classification model. This model contains a weight set for each of the different levels of cognitive workload. Features are extracted from the testing dataset using the same process explained in Figure 9. Then, these vectors are reduced in dimensionality using the indices of the retained variables generated by the stepwise regression procedure. Linear classifier is then used for classifying the testing feature vectors using the generated models. The true labels of the testing feature vectors are then used to calculate the classification accuracy.

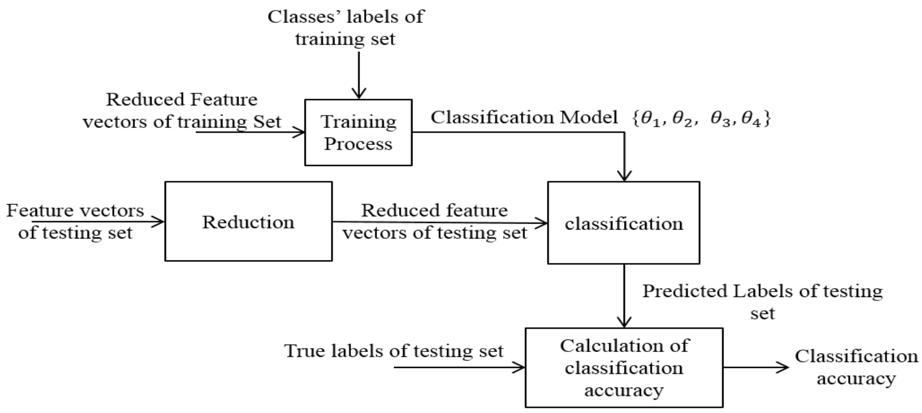

Figure 11: Block diagram of the proposed classification system

4.3. Stationarity Test

The developed system of cognitive levels classification is based on statistical features. These features determine the properties of the generated model. Thus, we clarify that these statistical features are independent on time, and that the generated model based on the training dataset is valid for classifying the test data set. This can be achieved by testing the stationarity of the EEG signals.

In general, a process $X(n)$ that is an ensemble of K sample functions $\{X_1(n), X_2(n), \ldots, X_K(n)\}$, is said to be stationary if the following conditions are met:

a- The mean of the process does not depend on time:

$$\mu_x(n) = \mu_x \tag{25}$$

b- The correlation function depends only on the time lag $\boldsymbol{l}$:

$$r_x(n, n-l) = r_x(l) \tag{26}$$

where $r_x(.)$ is the correlation function.

This chapter introduced the method proposed for cognitive levels classification. The next chapter presents the results of implementing the various steps of the classification system.

Chapter 5. Experimental Results

This chapter includes the experimental results carried out in this thesis. The first section provides a detailed description of the dataset used in this work. The second section presents the classification results of the four levels of cognitive workload. The section starts by the results of the existing work, then, presents the results of the proposed solution. Moreover, this chapter presents the analysis of applying the stepwise regression procedure on the proposed feature variables. The results of the computational complexity of both the existing and the proposed methods are presented in Section 5.4. Section 5.5 presents the effect of the two channel selection procedures examined in this thesis. The classification system proposed here was also evaluated in subject-independent cognitive levels classification. The results of this evaluation are presented in Section 5.6. Finally, the last section of this chapter examines the stationarity of the EEG signals.

5.1. Data Description

The training and testing examples comprised of one epoch each. Each epoch contains 62 EEG channels and recorded for 4400 ms with 512 Hz sampling frequency. Only the data from the onset of the second image to 500 ms, after the image was displayed, was included in the analysis. Hence, the total duration of the EEG signals is 1100 ms. Thus, each training or testing example contains 62 channels with 257 (512 Hz * 0.501 sec) samples.

Tables 2 and 3 describe in details the EEG-signals dataset used in both the existing and the proposed work:

Table 2: Dataset description

Subject	No. of epochs for level 1	No. of epochs for level 2	No. of epochs for level 3	No. of epochs for level 4	Total no. of epochs
1	210	210	210	210	840
2	210	210	210	210	840
3	210	210	210	210	840
4	210	209	210	210	839
5	210	210	210	210	840
6	210	210	210	210	840
7	210	210	187	201	808
8	210	210	209	210	839

Table 3: Continuation of dataset description

Subject	No. of epochs for level 1	No. of epochs for level 2	No. of epochs for level 3	No. of epochs for level 4	Total no. of epochs
9	210	210	210	210	840
10	210	210	200	210	830
11	210	210	210	210	840
12	210	210	210	210	840
13	210	210	207	210	837
14	210	210	210	208	838
15	210	210	210	210	840
16	210	210	210	210	840

5.2. Classification

A randomly selected 80% of the data is used in the training phase; the remaining 20% of the data was used for testing. This process was repeated 5 times, generating 5 different sets, and the average and standard deviation of the classification results are calculated. A similar approach was used in [17] as well.

5.2.1. Existing work. Figure 12 shows the classification results using the BCSP features and LIBSVM classifier reported in [17] for the 16 subjects. The x-axis represents the subjects, and the y-axis represents the average classification accuracy of the four cognitive levels for each subject. The classification rates for each of the four cognitive levels are presented in Figure 13. The overall average classification accuracy for this method is 87.6%.

The confusion matrix of classifying different cognitive levels using the reviewed work is reported in Figure 14. The rows represent the predicted cognitive levels, while the columns represent the true cognitive levels. The diagonal cells show how many of the cognitive levels were correctly predicted. Considering the misclassifications with error rates greater than 5%, the figure shows that cognitive level 1 is misclassified with level 4. Additionally, level 2 and level 3 are misclassified with level 1.

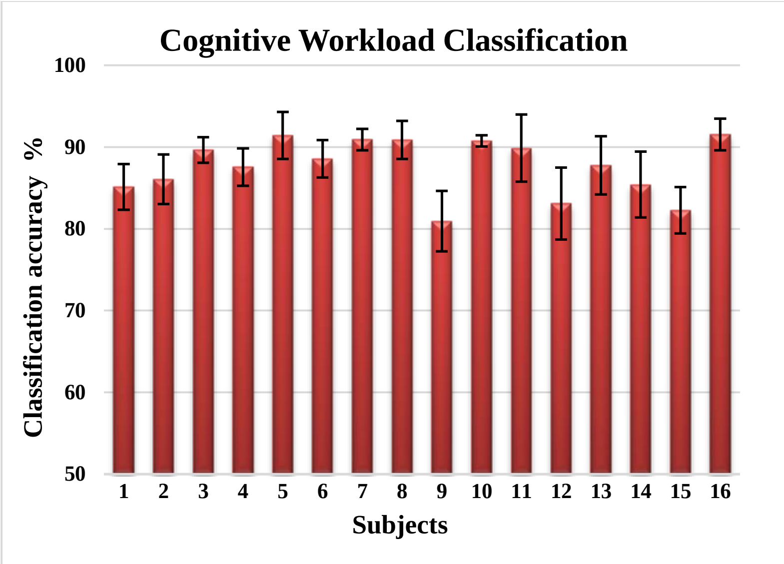

Figure 12: Cognitive workload classification results for the 16 subjects using the existing solution

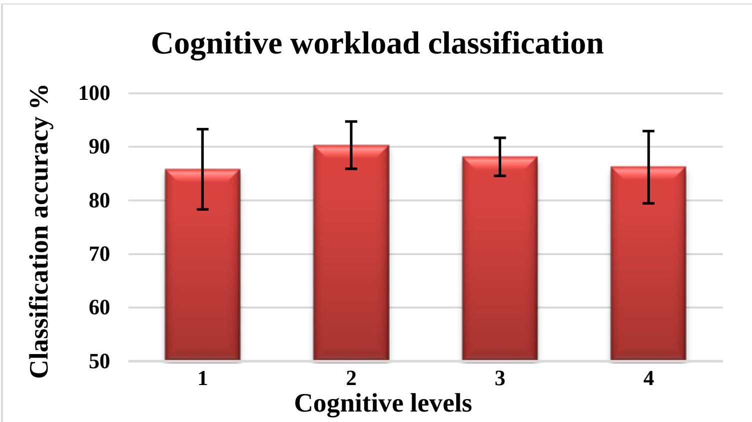

Figure 13: Classification results for the 4 cognitive levels using the existing solution

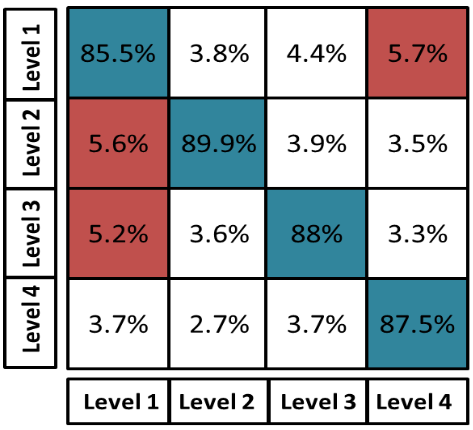

Figure 14: Cognitive levels classification confusion matrix (the existing solution)

5.2.2. Proposed solution. In order to determine the best method for cognitive workload classification, several approaches were studied in this work. The different steps of the classification system; preprocessing, features extraction and classification were examined. In addition to these steps, the effect of dimensionality reduction and channel selection processes on the performance of the classification system was inspected.

The first approach examined is based on statistical features, extracted from a single-level 2D DWT. The three subband of the horizontal, diagonal and vertical edges were examined separately, and the performance of each in cognitive workload classification was evaluated. The following steps summarize this approach.

i. The EEG signals are pre-processed using band-pass filter (0.3-40 Hz) and SOBI filter.
ii. The signals are combined into an image of dimensions 62x257.
iii. Statistical features are extracted from the three subbands ($\mathbf{Y}_{0,1}$, $\mathbf{Y}_{1,0}$ and $\mathbf{Y}_{1,1}$) of the DWT image.
iv. Feature vectors are normalized using the z-score method.
v. Stepwise regression is applied to reduce the dimensionality of the feature vectors.
vi. A linear classifier is used for classification.

The classification rates of this approach are presented in Figure 15. The y-axis represents the classification results for considering each of the three subbands in the feature extraction step. The average classification results over the 16 subjects, presented in the y-axis, are 85.7%, 86.2% and 84.0%, for feature extraction based on $\mathbf{Y}_{0,1}$, $\mathbf{Y}_{1,0}$ and $\mathbf{Y}_{1,1}$ subbands, respectively. $\mathbf{Y}_{1,0}$ which represents the vertical decomposition, as explained in section 4.2 provides the best classification rate. This frequency band contains the temporal EEG differences, which are important in cognitive level classification.

For the second approach, further analysis was performed in order to study the effect of applying two-level DWT in cognitive workload classification. This is realized by implementing a second level of the DWT to the $\mathbf{Y}_{0,0}$ (approximation) subband that resulted from the first level of the DWT. Then, the three subbands $\mathbf{Y}_{0,1}$, $\mathbf{Y}_{1,0}$ and $\mathbf{Y}_{1,1}$ were considered for features extraction. The following steps explain the sequence followed to implement this approach.

i. The EEG signals are pre-processed using band-pass filter (0.3-40 Hz) and SOBI filter.
ii. The signals are combined into an image of dimensions 62x257.
iii. The first level of DWT is implemented on the resulting image.
iv. The second level of DWT is implemented on the $\mathbf{Y_{0,0}}$ subband.
v. Statistical features are extracted from the three subbands ($\mathbf{Y_{0,1}}$, $\mathbf{Y_{1,0}}$ and $\mathbf{Y_{1,1}}$) of the second level of DWT.
vi. Feature vectors are normalized using the z-score method.
vii. Stepwise regression is applied to reduce the dimensionality of the feature vectors.
viii. A linear classifier is used for classification.

The classification results of this approach are presented in Figure 16. The average classification rates, represented in the y-axis, are 61.6%, 76.7% and 61.6%, for considering the $\mathbf{Y_{0,1}}$, $\mathbf{Y_{1,0}}$ and $\mathbf{Y_{1,1}}$ subbands respectively, in the feature extraction step. Analyzing these results reveals the following results. First, these results confirm the result of the previous approach, that the temporal differences contained in the $\mathbf{Y_{1,0}}$ are significant in cognitive workload classification. Also, the two-level DWT resulted in lower classification rate than the single level DWT. A reasonable justification for this is that the frequency bands used for feature extraction are from the second level of DWT. These are quarter of the size of their one-level transformation counterpart. Thus, some information is lost, and the feature vectors are therefore less accurate.

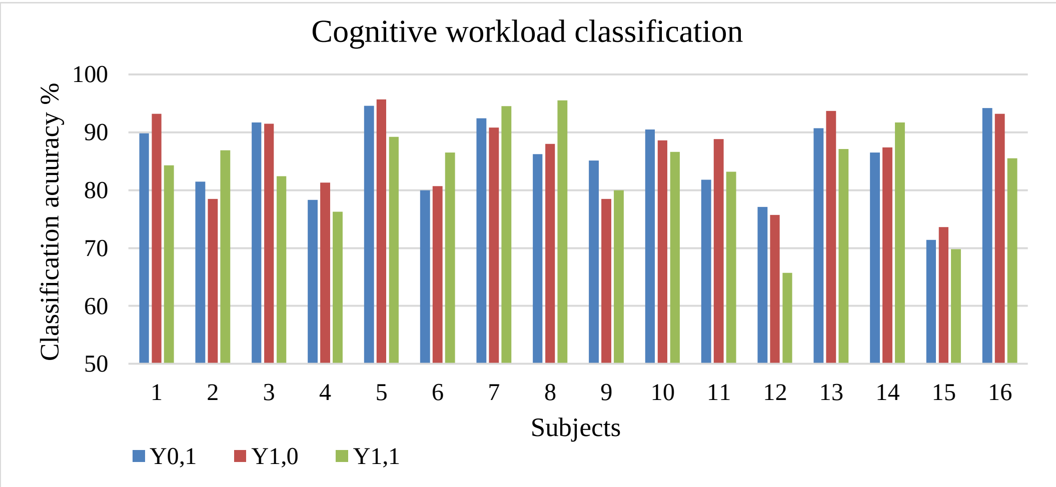

Figure 15: Cognitive workload classification accuracy of applying single-level DWT

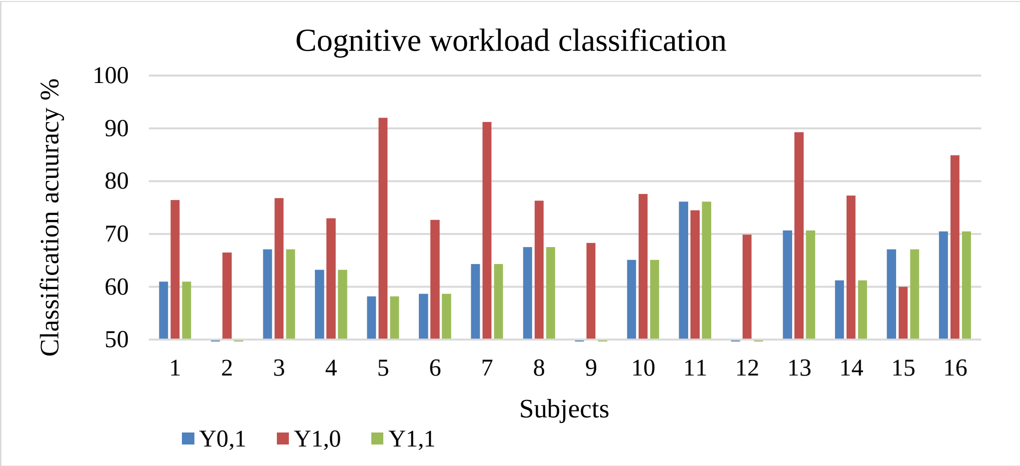

Figure 16: Cognitive workload classification accuracy of applying two-levels DWT

Since the vertical edge subband (**$Y_{1,0}$**) of a single-level DWT provided the best classification results so far, the next approach (Figure 17) examined is based on this information. However, as shown in Figure 17, more frequency components are included in this approach. As illustrated in the Figure **17**, the pass band of the first filter used in the preprocessing step was modified from (0.3-40Hz) to (0.1-60Hz). The following steps explain the implementation of this method.

i. The EEG signals are pre-processed using band-pass filter (0.1-60Hz) and SOBI filter.
ii. The signals are combined into an image of dimensions 62x257.
iii. Statistical features are extracted from the **$Y_{1,0}$** subband of the DWT image.
iv. Feature vectors are normalized using the z-score method.
v. Stepwise regression is applied to reduce the dimensionality of the feature vectors.
vi. A linear classifier is used for classification.

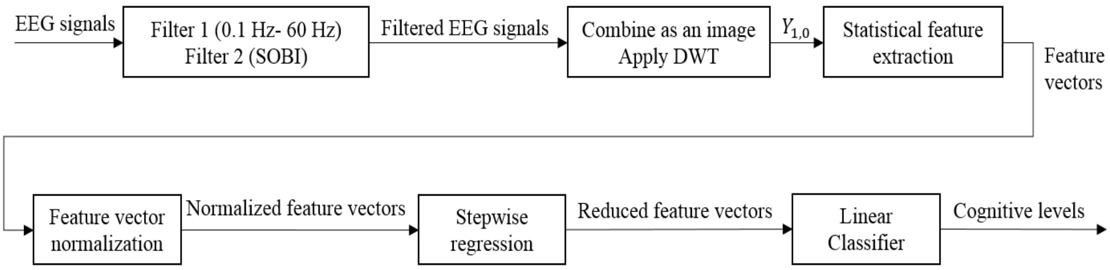

Figure 17: Block diagram of the proposed solution

The classification accuracy of this result is presented in Figure 18. For comparison reasons, the figure also presents the classification results of the existing work [17]. The error bars represent the standard deviations of the five runs per subject. From these results we can deduce the following results. Since the classification rate of the suggested approach is much higher than the previous approaches, this indicates that the band of frequencies (0.1-60 Hz) contains information that is important in separating the different cognitive workloads. Additionally, it is clear that the suggested approach achieves an average classification accuracy (93.4%) that is higher than the one achieved by the existing work (87.6%). Hence, the proposed classification system is more accurate. It is also shown that the proposed solution results in higher classification accuracy in nearly all subjects in comparison to the existing work. The variation between the five runs per subject which is represented by the error bars is also lower than the existing work. Figure 19 illustrates the average classification accuracy for each of the four cognitive levels, for both the proposed solution and the reviewed work [17]. The error bars represent the standard deviation of the classification accuracy resulting from the five runs of the experiment. It can be seen that the average classification accuracy of the proposed method, for all levels is above 93%. The lowest classification accuracy is 89% for Level 3, and the highest is 96% for Level 1. In general, the accuracies of Level 1 and Level 2 are higher than those of Level 3 and Level 4. This indicates that Level 1 and Level 2 are more separable than the other two levels. From the figure, it is clear that the proposed solution results in higher classification rate for each level than the existing work. Again, the variation between the five runs per subject which is represented by the error bars is also lower than the existing work.

The confusion matrix of classifying the 4 cognitive levels, using the proposed solution is presented in Figure 20. Again, considering the misclassifications with error rates greater than 5%, the figure shows that only level 4 is misclassified with level 3. This can be attributed to the similar nature of the cognitive workloads imposed by level 3 and level 4. The difference between these two cognitive levels is the increase in image distortion only. In comparison to the confusion matrix of the existing work (Figure 14), the proposed solution reduces the classification confusion to Level 3 and Level 4 only, which is a clear advantage.

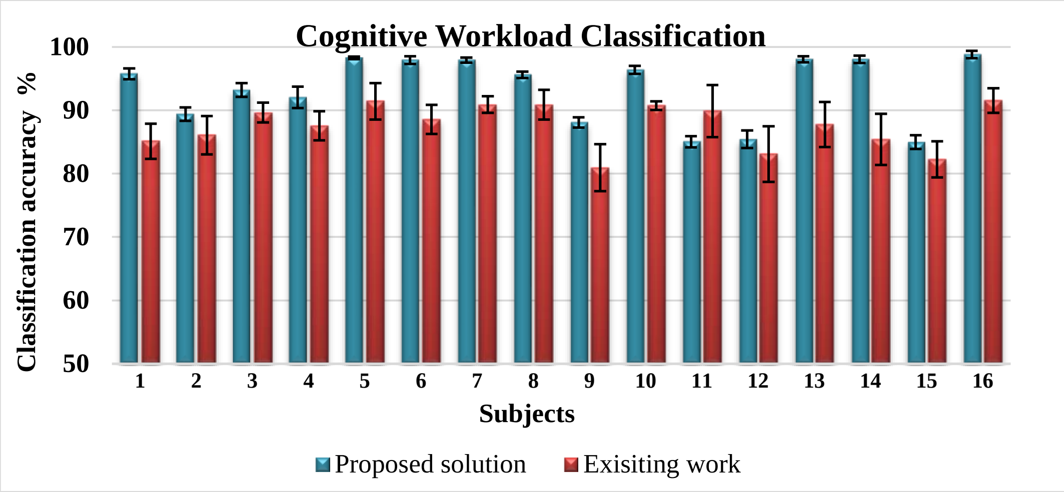

Figure 18: Cognitive workload classification results of the 16 subjects

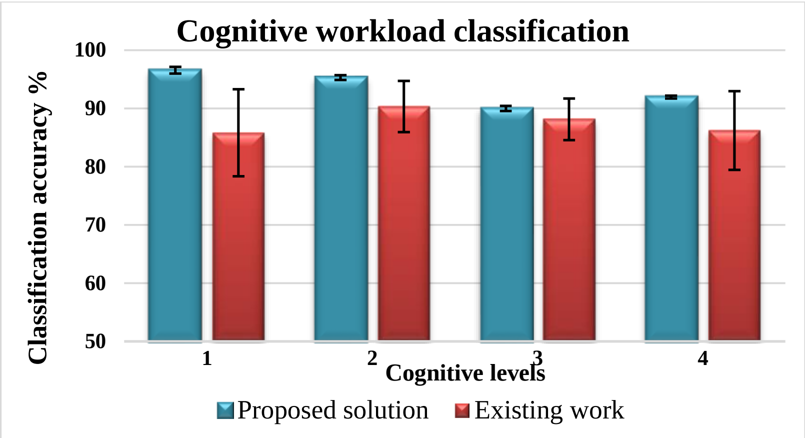

Figure 19: Cognitive workload classification results of the 4 cognitive levels

	Level 1	Level 2	Level 3	Level 4
Level 1	96.4%	2.5%	1.2%	1.5%
Level 2	1.2%	95.2%	2.5%	2.1%
Level 3	1.2%	1.7%	90.4%	4.3%
Level 4	1.2%	1.1%	5.9%	92.1%

Figure 20: Cognitive levels classification confusion matrix (the proposed solution)

5.3. Analysis of Stepwise Regression Results

The stepwise regression procedure is used in this work for dimensionality reduction. Its output is the indices of retained features. Table 4 provides an example of the stepwise regression output. The second column represents the number of variables before the stepwise regression. The third column represents the number of retained variables after applying the stepwise regression procedure.

Table 4: Features retained by the stepwise regression

Feature	Initial number of variables	Number of variables retained
Mean of subband $\mathbf{Y}_{1,0}$ columns	129	8
Standard deviation of subband $\mathbf{Y}_{1,0}$ columns	129	4
Mean of subband $\mathbf{Y}_{1,0}$ rows	31	0
Standard deviation of subband $\mathbf{Y}_{1,0}$ rows	31	3
Entropy of subband $\mathbf{Y}_{1,0}$ columns	129	0
Entropy of subband $\mathbf{Y}_{1,0}$ rows	31	0
Spatial covariance matrix	496	45

From the previous table we can reach the following conclusion. Since no variables were retained from the third feature (mean of subband $\mathbf{Y}_{1,0}$ rows), this indicates that EEG channels have the same or similar mean and are not useful for classification. Also, the entropy variables were not retained by the stepwise regression, which means that this feature is also not useful for classification purposes. The table also shows that the last feature (spatial covariance matrix) includes important information for classification of cognitive levels.

5.4. Computational Complexity

The computational time of the proposed solution (Figure 17) and the work reported in [17] are also measured. Table 5 presents the time required by each solution to extract features and perform classification. These measurements are conducted using MATLAB R2012a on an Intel core-i7 processor and 8.00 GB memory computer. The preprocessing of both methods is similar and requires almost the same time, thus, it was excluded from the comparison. It is shown in Table 5, that the proposed solution is much faster than the reviewed work of [17]. This is due to simple statistical features used in combination with a linear classifier.

Table 5: Time comparison between the existing work and the proposed solution

Method	Time in sec
Work presented in [17]	6515.25
Proposed solution (Figure 16)	784.75

5.5. Channel Selection

In this section, we present the effect of channel selection on the cognitive workload classification. Firstly, the intuitive approach of grouping EEG channels of the same brain region is examined. In Figure 21, we repeat the classification algorithm using each subset of channels individually. The objective of this experiment is to identify the region of the brain that contributes most to the classification of cognitive levels. The figure shows the resulting classification rates in the y-axis. It is clear that the subset of the Frontal channels achieved the highest classification accuracy of 84.3% using 23 channels only. This result is consistent with the decision making functionality of this brain area. This indicates that the EEG channels of the Frontal lobes are important in cognitive workload classification.

The second method of channel selection examined in this work, is the one reported in [31]. After sorting the EEG channels based on their stabilities using Equation (5). The classification is then carried out using a varying number of channels ranging from 1 to 62. Figure 22 illustrates the effect of channel selection on the classification accuracy. In the figure, the classification results are reported using the proposed solution and the reviewed work of [17]. The maximum classification accuracy achieved by the existing work is 87% which requires the complete set of 62 EEG channels. On the other hand, the same classification accuracy is achieved by the proposed solution, with only 15 EEG channels. Additionally, considering the top-ranked 23 EEG channels, the proposed solution achieves 91% classification accuracy, while the existing work results in 72% accuracy.

Figure 23 visualizes the top-ranked 23 channels. It is clear that most of these channels reside in the Frontal region. Interestingly, this confirms the result obtained by the intuitive channel selection approach that we reported in Figure 21 above.

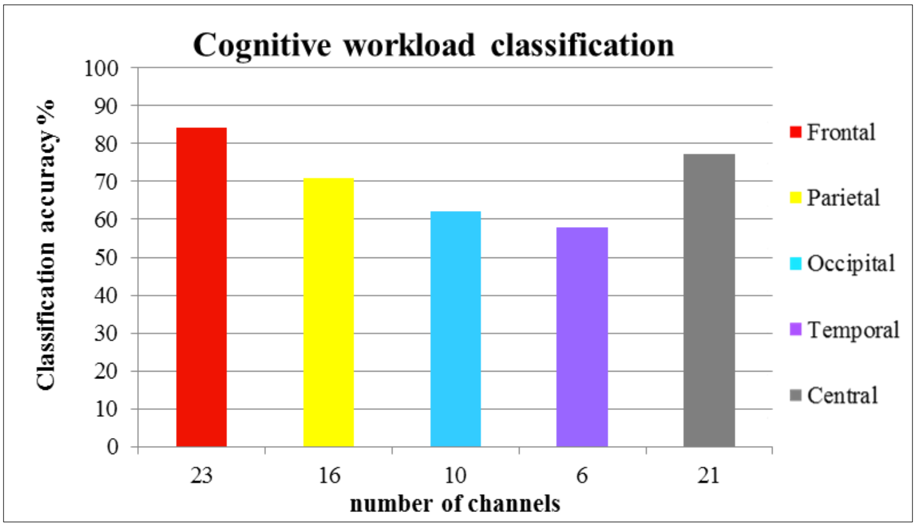

Figure 21: Classification results including channel subsets according to the brain regions

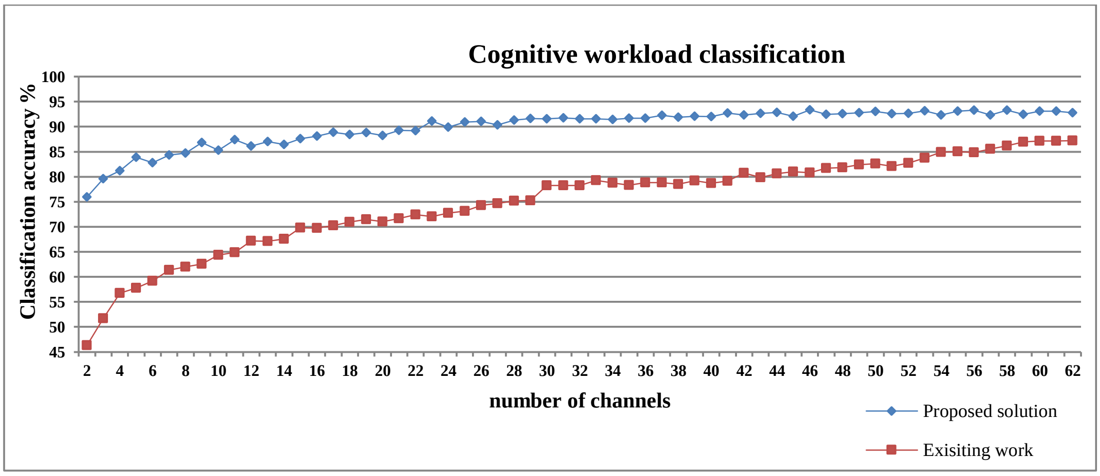

Figure 22: Classification results by varying the number of selected channels ranked by channels stability.

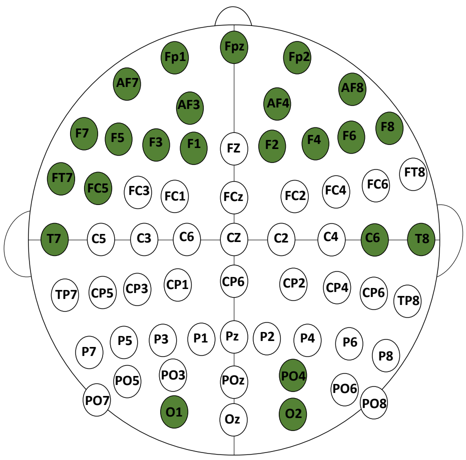

Figure 23: The locations of the first 23 channels with the highest stability

5.6. Subject-Independent Classification

In this thesis, EEG signals were evaluated for subject-independent cognitive workload classification. Figure 24 presents the results of repeating both the existing and the proposed methods for cognitive workload classification. However, in this experiment both the training (80%) and testing (20%) datasets are randomly selected from the combined data of EEG signals from all the subjects. This is considered semi-subject-independent, as the train set contains data from all subjects including the one being examined. As shown in the figure, the classification rate of the proposed solution is above chance (75%), while the classification rate of the existing work is 25% only. The low classification rates can be attributed to the unique information related to the human identity, shown by the EEG signal. This makes the subject-independent classification based on EEG signals very challenging.

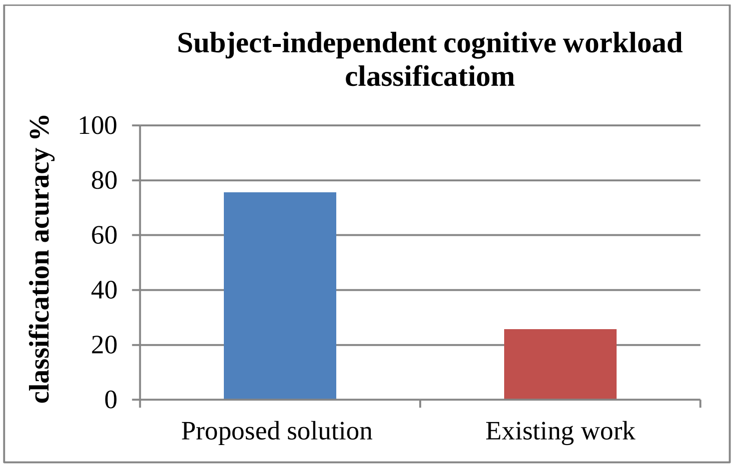

Figure 24: Subject-independent cognitive workload classification

5.7. Stationarity Test

The stationarity of the EEG signals was evaluated in this thesis in order to insure that the classification system developed, based on statistical feature, is time independent. It is worth mentioning that the stationarity is tested under certain constraint; which is that the EEG signals must belong to the same subject and the same cognitive level. Otherwise, the stationarity cannot be insured.

In this work, the stationarity was tested using two approaches as explained in the following.

i. The first approach considers the human head as the source of the process to be tested for stationarity. In this case, each process is one epoch, which consists of 62 realizations (62 channels), with 257 time samples for each realization. For the first condition of stationarity to be true, the mean of each time sample must be constant across all epochs. It was found that, by taking random time samples, the mean values of the 62 EEG channels at each time sample have values with a small standard deviation, as represented in Figure 25. In this figure, the x-axis represents the time sample, and the y- axis represents the mean and standard deviation of the values. The small values of the deviations thus confirm the first stationarity condition. For the second condition of stationarity to be true, the correlation between time samples depends only on the time lag. When the difference between correlations with the same time lag was calculated, the results were found to be around zero. This was done for different time lags as depicted in Figure 26. The x-axis represents the time lag for which the correlation was calculated, and the y-axis represents the mean and standard deviation of the correlations differences.

ii. The second approach considers all signals from one channel as a stochastic process. Since there are 62 EEG channels, the number of processes in each cognitive level is 62. Each process consists of 210 realizations, equivalent to the number of epochs in one cognitive level. To examine the first condition of stationarity, the mean values of each process are calculated. The y-axis of Figure 27 shows the means and standard deviations of these values, while the x-axis represents the different processes (channels). The figure indicates that the means are almost the same. This confirms the first stationarity condition. For the second condition to be realized, the difference of correlations of the same time lag must be zero or close to zero. Figure 28 presents the calculated differences of correlations with different lags. Here, the x-axis represents the time lag, while the y-axis represents the average differences and standard deviations. Similar to the first approach, the differences have values around zero. These results, combined with the previous ones, indicate the stationarity of the EEG signals used in this work.

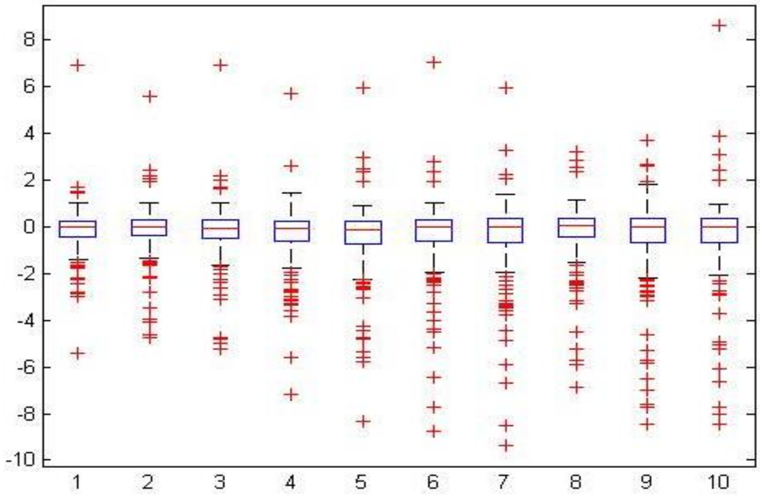

Figure 25: Ensemble mean of 10 time samples

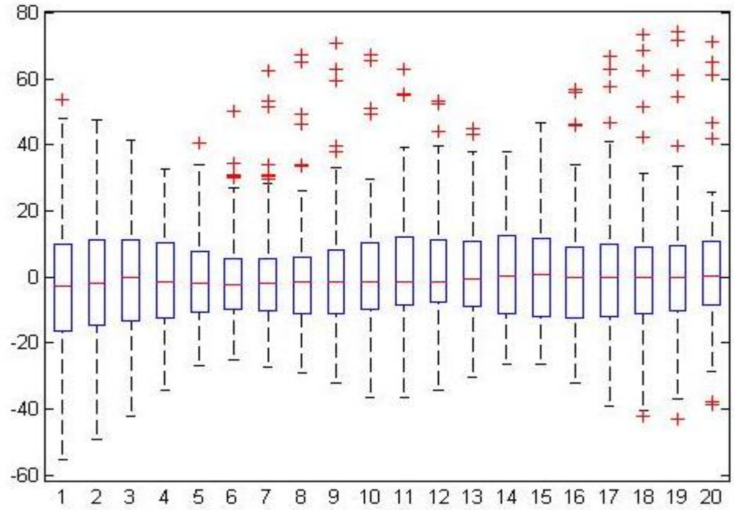

Figure 26: Mean of correlations differences

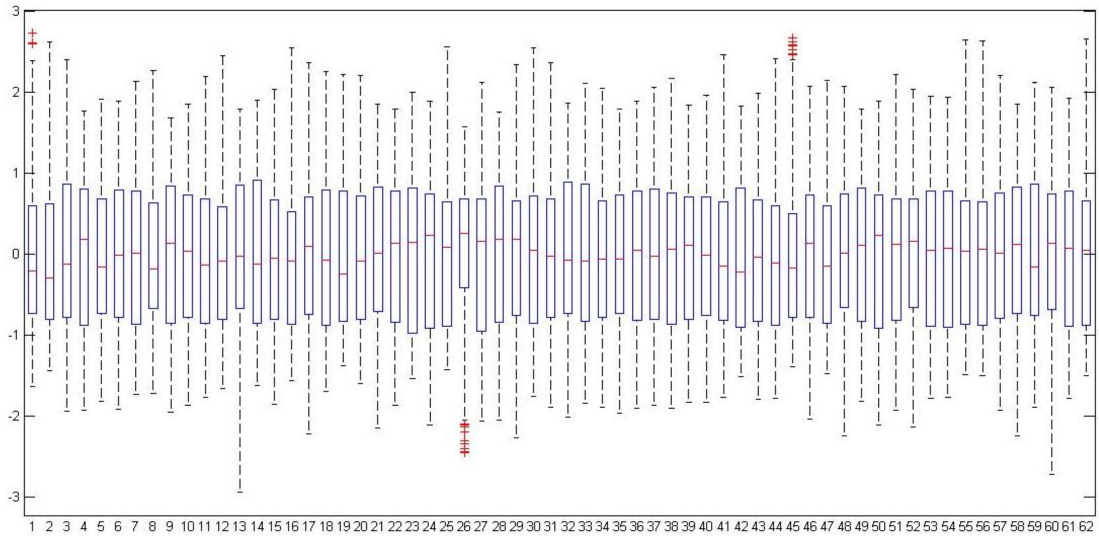

Figure 27: Ensemble mean for the 62 channels

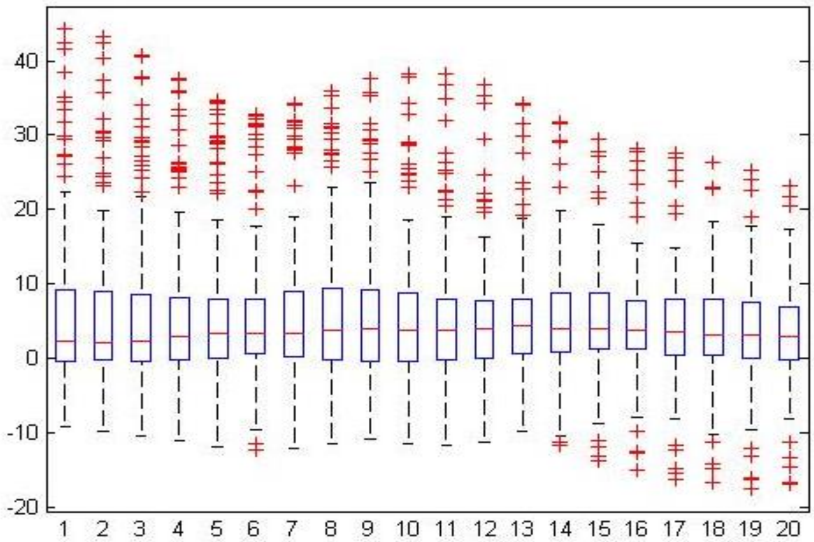

Figure 28: Mean of correlations differences

Chapter 6. Conclusion

Classification of four cognitive workload levels was examined in this thesis. EEG signals from 16 subjects were used in the classification. The stationarity of these signals was tested to validate the generated model. A novel feature extraction method based on DWT was developed in this work. Statistical features were extracted from the vertical subband of single level DWT. The high dimensionality of the features was then reduced using stepwise regression procedure. The classification was carried out using linear classifier. For 16 subjects and 4 levels of cognitive levels, this approach resulted in an average classification accuracy of 93.4%. This indicates that the temporal differences contained in the vertical subband are important in cognitive levels classification.

Furthermore, two methods of EEG channels selection were examined in this thesis, and their effect on the classification was evaluated. Using a subset of 23 EEG channels only in the proposed system resulted in an average classification accuracy of 91%. These channels are Fpz, Fp1, Fp2, AF3, AF4, AF7, AF8, F1, F2, F3, F4, F5, F6, F7, F8, FT7, FC5, T7, T8, C6, PO4, O1 and O2. This subset is comprised mainly (16 channels) of channels in the Frontal region. This indicates the strong relation between the Frontal lobes and the working memory.

In comparison of the existing method in cognitive workload classification reported in [17], to the method presented in this thesis, we can conclude the following. The developed method resulted in higher classification accuracy, with and without channel selection. Additionally, the proposed solution reduces the classification confusion between the four cognitive levels to the highest two levels only. In terms of computational speed, the experimental results showed that the proposed method is more than eight times faster than the existing method. Thus, the objectives of this thesis were met, by developing classification system that is more accurate and less computationally complex.

For future work, other techniuques for dimensionality reduction and channel selection can be studied.

References

[1] S. G. Hart and L. E. Staveland, "Development of NASA-TLX (Task Load Index): Results of empirical and theoretical research," *Advances in psychology,* vol. 52, pp. 139-183, 1988.

[2] S. Wang, J. Gwizdka, and W. A. Chaovalitwongse, "Using Wireless EEG Signals to Assess Memory Workload in the n-Back Task," *IEEE Transactions on Human-Machine Systems,* vol. PP, pp. 1-12, 2015.

[3] D. Erdogmus *et al.*, "Cognitive State Estimation Based on EEG for Augmented Cognition," in *2nd International IEEE EMBS Conference on Neural Engineering, 2005,* Arlington, VA, 2005, pp. 566-569.

[4] D. E. Kieras, "Towards a practical GOMS model methodology for user interface design," *Handbook of human-computer interaction,* pp. 135-157, 1988.

[5] J. R. Anderson, C. F. Boyle and B. J. Reiser, *Cognitive Principles in the Design of Computer Tutors,* Pittsburgh: John Wiley and Sons, 1984.

[6] L. Melloni, C. M. Schwiedrzik, N. Muller, E. Rodriguez, and W. Singer, "Expectations Change the Signatures and Timing of Electrophysiological Correlates of Perceptual Awareness," *Journal of Neuroscience,* vol. 31, pp. 1386-1396, 2011.

[7] K. G. Seeber, "Cognitive load in simultaneous interpreting: Existing theories—new models," *Interpreting,* vol. 13, pp. 176-204, 2011.

[8] K. J. Sarno, "Role of multiple resources in predicting time-sharing efficiency: Evaluation of three workload models in a multiple-task setting," *The International Journal of Aviation Psychology,* vol. 5, pp. 107-130, 1995.

[9] T. NASA, "Website http://humansystems. arc. nasa. gov/groups," ed: TLX.

[10] D. Jensen, "Friedman's Chi-Square Test," *Encyclopedia of statistical sciences,* New York: John Wiley & Sons, 1983.

[11] J. Frey, C. Mühl, F. Lotte and M. Hachet, "Review of the Use of Electroencephalography as an Evaluation Method," in *PhyCS International Conference on Physiological Computing Systems,* Lisbonne, 2013.

[12] S. P. Marshall, "Identifying cognitive state from eye metrics," *Aviation, space, and environmental medicine,* vol. 78, pp. B165-B175, 2007.

[13] P. Nickel and F. Nachreiner, "Sensitivity and diagnosticity of the 0.1-Hz component of heart rate variability as an indicator of mental workload," *Human Factors: The Journal of the Human Factors and Ergonomics Society,* vol. 45, pp. 575-590, 2003.

[14] P. Jönsson, Samhällsvetenskap, P. Department of, u. Lunds, S. Social, p. Institutionen för, *et al.*, "Respiratory sinus arrhythmia as a function of state anxiety in healthy individuals," *International Journal of Psychophysiology,* vol. 63, pp. 48-54, 2007.

[15] F. L. da Silva, "EEG: origin and measurement," in *EEG-fMRI*, ed: Springer, 2009, pp. 19-38.

[16] B. A. Khalil and K. Misulis, "Atlas of EEG & Seizure Semiology," ed: Elsevier, Butterworth Heinehmann Edition, Philadelphia, 2006.

[17] K. Yu, I. Prasad, H. Mir, N. Thakor, and H. Al-Nashash, "Cognitive workload modulation through degraded visual stimuli: a single-trial EEG study," *Journal of Neural Engineering,* vol. 12, pp. 1-9, 2015.

[18] S. Tokuda, G. Obinata, E. Palmer and A. Chaparro, "Estimation of mental workload using saccadic eye movements in a free-viewing task," in *2011 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, Boston, MA, 2011, pp. 4523-4529.

[19] O. Palinko and A. Kun, "Exploring the effects of visual cognitive load and illumination on pupil diameter in driving simulators," *Proceedings of the Symposium on Eye Tracking Research and Applications,* New York, NY, 2012, pp. 413-416.

[20] O. Palinko and A. L. Kun, "Exploring the influence of light and cognitive load on pupil diameter in driving simulator studies," in *Proceedings of the Sixth International Driving Symposium on Human Factors in Driver Assessment, Training and Vehicle Design*, Lake Tahoe, CA, 2011, pp. 329-336.

[21] S. P. Marshall, "The index of cognitive activity: Measuring cognitive workload," in *proceedings of the 2002 IEEE 7th conference on Human factors and power plants*, Scottsdale, Arizona, 2002, pp. 7-5-7-9.

[22] M. Bartels and S. P. Marshall, "Measuring cognitive workload across different eye tracking hardware platforms," in *Proceedings of the symposium on eye tracking research and applications*, Santa Barbara, CA, 2012, pp. 161-164.

[23] E. T. Solovey, F. Lalooses, K. Chauncey, D. Weaver, M. Parasi, M. Scheutz, *et al.*, "Sensing cognitive multitasking for a brain-based adaptive user interface," in *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, Vancouver, 2011, pp. 383-392.

[24] A. Luque-Casado, M. Zabala, E. Morales, M. Mateo-March, and D. Sanabria, "Cognitive performance and heart rate variability: the influence of fitness level," *PloS one,* vol. 8, p. e56935, 2013.

[25] M. Suriya-Prakash, G. John-Preetham, and R. Sharma, "Is heart rate variability related to cognitive performance in visuospatial working memory?," *PeerJ PrePrints,* vol. 3, p. e1711, 2015.

[26] P. Zarjam, J. Epps, F. Chen, and N. H. Lovell, "Estimating cognitive workload using wavelet entropy-based features during an arithmetic task," *Computers in biology and medicine,* vol. 43, pp. 2186-2195, 2013.

[27] C. L. Baldwin and B. Penaranda, "Adaptive training using an artificial neural network and EEG metrics for within-and cross-task workload classification," *NeuroImage,* vol. 59, pp. 48-56, 2012.

[28] C. Mühl, C. Jeunet, and F. Lotte, "EEG-based workload estimation across affective contexts," *Frontiers in neuroscience*, vol. 8, pp. 1-15, 2014.

[29] S. Datta, A. Khasnobish, A. Konar, and D. Tibarewala, "Cognitive Activity Classification from EEG Signals with an Interval Type-2 Fuzzy System," in *Advancements of Medical Electronics,* ed: Springer, 2015, pp. 235-247.

[30] S. Wang, J. Gwizdka and W. A. Chaovalitwongse, "Using Wireless EEG Signals to Assess Memory Workload in the n-Back Task," in *IEEE Transactions on Human-Machine Systems,* vol. 46, pp. 424-435, 2016.

[31] S. Altahat, M. Wagner, and E. Martinez Marroquin, "Robust electroencephalogram channel set for person authentication," in *2015 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP),* Brisbane, Australia, 2015, pp. 997-1001.

[32] Y. Wang, S. Gao, and X. Gao, "Common spatial pattern method for channel selelction in motor imagery based brain-computer interface," in *2005 IEEE Engineering in Medicine and Biology 27th Annual Conference,* Shanghai, 2005, pp. 5392-5395.

[33] M. Arvaneh, C. Guan, K. K. Ang, and C. Quek, "Optimizing the channel selection and classification accuracy in EEG-based BCI," *IEEE Transactions on Biomedical Engineering,* vol. 58, pp. 1865-1873, 2011.

[34] A. Belouchrani, K. Abed-Meraim, J.-F. Cardoso, and E. Moulines, "A blind source separation technique using second-order statistics," *IEEE Transactions on Signal Processing,* vol. 45, pp. 434-444, 1997.

[35] A. Delorme and S. Makeig, "EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis," *Journal of neuroscience methods,* vol. 134, pp. 9-21, 2004.

[36] K. Yu, K. Shen, S. Shao, W. Ng, and X. Li, "Bilinear common spatial pattern for single-trial ERP-based rapid serial visual presentation triage," *Journal of neural engineering,* vol. 9, p. 046013, 2012.

[37] C.-C. Chang and C.-J. Lin, "LIBSVM: A library for support vector machines," *ACM Transactions on Intelligent Systems and Technology (TIST),* vol. 2, p. 27, 2011.

[38] T. Alotaiby, F. E. A. El-Samie, S. A. Alshebeili, and I. Ahmad, "A review of channel selection algorithms for EEG signal processing," *EURASIP Journal on Advances in Signal Processing,* vol. 2015, pp. 1-21, 2015.

[39] J. M. Fuster, *Prefrontal Cortex*: Springer, 1988.

[40] L. Fogassi and G. Luppino, "Motor functions of the parietal lobe," *Current opinion in neurobiology,* vol. 15, pp. 626-631, 2005.

[41] R. S. Snell, *Clinical anatomy for medical students*: Little, Brown Medical Division, 1995.

[42] P. C. Mahalanobis, "On the generalized distance in statistics," *Proceedings of the National Institute of Sciences (Calcutta),* vol. 2, pp. 49-55, 1936.

[43] R. De Maesschalck, D. Jouan-Rimbaud, and D. L. Massart, "The mahalanobis distance," *Chemometrics and intelligent laboratory systems,* vol. 50, pp. 1-18, 2000.

[44] A. K. Jain, R. P. Duin, and J. Mao, "Statistical pattern recognition: A review," *IEEE Transactions on Pattern Analysis and Machine Intelligence,* vol. 22, pp. 4-37, 2000.

[45] T. Shanableh and K. Assaleh, "Feature modeling using polynomial classifiers and stepwise regression," *Neurocomputing,* vol. 73, pp. 1752-1759, 2010.

[46] D. C. Montgomery and G. C. Runger, *Applied statistics and probability for engineers*: John Wiley & Sons, 2010.

Vita

Rwan Adil Osman Mahmud was born in 1991, in Khartoum, Sudan. She graduated from Asmaa Abd-Alraheem High School in Khartoum in 2008. She joined the University of Khartoum in 2008 and awarded the degree of Bacholr of Science (Honours) in Electrical and Electronic Engineering, with First Class in 2013. After graduation, Ms. Mahmoud worked as a teaching assistant in the University of Khartoum for one year. She then joined the American University of Sharjah in 2014, where she was granted a graduate assistantship to pusue a Master's program.

Ms. Mahmoud co-autherd a paper, titled "*Aggregate path Monte-Carlo method for single electron circuit simulations*", published in the ICCNEEE-2015 conference held in Khartoum, Sudan. In addition, she is the first author of a paper published in the 10th International Conference for Internet Technology and Secured Transactions (ICITST-2015) held in London, UK, titled "*Internet of things (IoT) security: Current status, challenges and prospective measures*".