Time-Frequency Distribution Analysis Of Electroencephalograms During Mental Arithmetic Task Performance

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DECLARATION

I declare that this thesis is the result of my own research, except as cited in the references, entitled "Time-Frequency Distribution Analysis of Electroencephalograms During Mental Arithmetic Task Performance". The thesis has not been approved for any degree and has not been applied for any other degree at the same time.

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Date : 5/7/2021

APPROVAL

I hereby declare that I have checked this report entitled "Time-Frequency Distribution Analysis of Electroencephalograms During Mental Arithmetic Task Performance" and in my opinion, this thesis it complies the partial fulfillment for awarding the award of the degree of Bachelor of Electrical Engineering with Honours.

Signature : ....

Supervisor Name : DR. EZREEN FARINA BINTI SHAIR

Date : 5/7/2021

DEDICATIONS

Dedicated to Hazlan Hussin my beloved father and mother, Roszita Ahmad. I would like to thank my sibling and my special friends for providing me with moral encouragement, cooperation, and empathy.

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ABSTRACT

Cognitive workload or mental workload refers to the sum of mental work needed to finish a job, such as problem-solving, reading, writing, and success of mental arithmetic. For the diagnosis and treatment of brain and mental illnesses, electroencephalograms (EEGs) have become an increasingly important measure of brain activity. EEGs recordings provide information regarding the brain's electrical activity. Through EEG records is one of the most important instruments for the detection of neurological disorders, such as epilepsy, brain tumor, head injury, sleep disturbance, etc, is base on the study of brain electrical activity.Feature extraction represents a distinguishing property, a familiar measurement, and a functional component obtained from a section of a pattern. Furthermore, they also simplify the sum of available resources to explain a large set of data accurately. The main aim of this project is to accurately evaluate the cognitive workload of EEG signals using the time-frequency distribution (TFD) during mental arithmetic task success. We can extract the EEG function by using time-frequency distribution (TFD) and use different types of classifiers, such as K-Nearest Neighbor (KNN), Support Vector Machine (SVM), and several more, to use the signal in a real-time application that requires information on both time and frequency. By integrating the EEG signal it can help to increase or improve the diagnosis of neurological in the future.

ABSTRAK

Beban kerja kognitif atau beban kerja mental merujuk kepada jumlah kerja mental yang diperlukan untuk menyelesaikan sesuatu pekerjaan, seperti penyelesaian masalah, membaca, menulis, dan kejayaan aritmetik mental. Untuk diagnosis dan rawatan penyakit otak dan mental, electroencephalograms (EEG) telah menjadi ukuran aktiviti otak yang semakin penting. Rakaman EEG memberikan maklumat mengenai aktiviti elektrik otak. Melalui rekod EEG, salah satu instrumen yang paling penting untuk mengesan gangguan neurologi, seperti epilepsi, tumor otak, kecederaan kepala, gangguan tidur, dan lain-lain, adalah berdasarkan kajian aktiviti elektrik otak. Pengekstrakan ciri mewakili sifat membezakan, pengukuran yang biasa, dan komponen fungsional yang diperoleh dari bahagian corak. Selain itu, mereka juga mempermudah jumlah sumber yang ada untuk menjelaskan sejumlah besar data dengan tepat. Tujuan utama projek ini adalah untuk menilai secara tepat beban kerja kognitif isyarat EEG menggunakan taburan frekuensi masa (TFD) semasa kejayaan tugas aritmetik mental. Kita boleh mengekstrak fungsi EEG dengan menggunakan taburan frekuensi masa (TFD) dan menggunakan pelbagai jenis pengklasifikasi, seperti Mesin Vektor Sokongan (SVM), K-Nearest Neighbor (KNN), dan beberapa lagi, untuk menggunakan isyarat secara nyata aplikasi masa yang memerlukan maklumat mengenai masa dan kekerapan. Dengan mengintegrasikan isyarat EEG, ia dapat membantu meningkatkan atau memperbaiki diagnosis neurologi pada masa akan datang.

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LIST OF SYMBOLS AND ABBREVIATIONS

FKE : Faculty of Electrical

UTeM : Universiti Teknikal Malaysia Melaka

EEG : Electroencephalogram

TFD : Time-frequency domain

MAV : Mean Absolute Value

STFT : Short Time Fourier Trasform

WL : Waveform Length

WPT : Wavelet Packet Trasform

WT : Wavelet Trasform

MNF : Mean Frequency Power Spectrum

MNF : Mean Frequency Power Spectrum

KNN : K- Nearest Neighbor

SVM : Support Vector Machine

FYP 1 : Final Year Project 1

FYP 2 : Final Year Project 2

RMS : Root mean square

V_{rms} : Voltage root mean square

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CHAPTER 1

INTRODUCTION

1.1 Background

Cognitive workload or mental workload refers to the level of mental effort required to do a task. The high cognitive workload could contribute to cognitive exhaustion for a sustained period. In cases where high levels of continuous focus are required, this results in problems such as a reduction in the efficiency of a task. In cognitive neuroscience and other real-world applications, the recognition of mental workload tasks is, therefore, an important field [1]. In various case studies, the commonly used cognitive workload measurement consists of a series of tasks such as arithmetic tasks, visual perception tasks, or several types of simulation.

The experimental research was performed to investigate the possibility of using the EEG signal in time-frequency domain analysis and classification of cognitive workload during an arithmetic task performance. Based on the authors in previous work [2], we analyzed the relationship between the EEG signal in arithmetic task difficulty level. The result of the analysis indicates the possibility of using different task levels to identify the classification group's base on the EEG signal. The aim of this work is to introduce or implement the extracted EEG signal feature in time and frequency and to determine the accuracy of difficult tasks group's by using several classifiers.

1.2 Motivation

Although people seem to take task such as concentration and problem solving for granted, they are so woven into the fabric of our daily lives. Cognitive disturbances can cause chaos in several aspects of the life of a person due to this behavior. Consider, for example, how your health and happiness can interfere with negative events. Even relatively minor memory problems can find it harder to cope with the demands of daily activities. There are several other types of impact correlated with the issue of cognition, such as Alzheimer's disease, dementia, or memory loss cognitive for a psychological illness and many more. Estimates of the number of deaths attributed to Alzheimer's in 2018 by state are included in Figure 1.1. This data is gathered from death certificates and represents the illness reported by the doctor as the main cause of death.

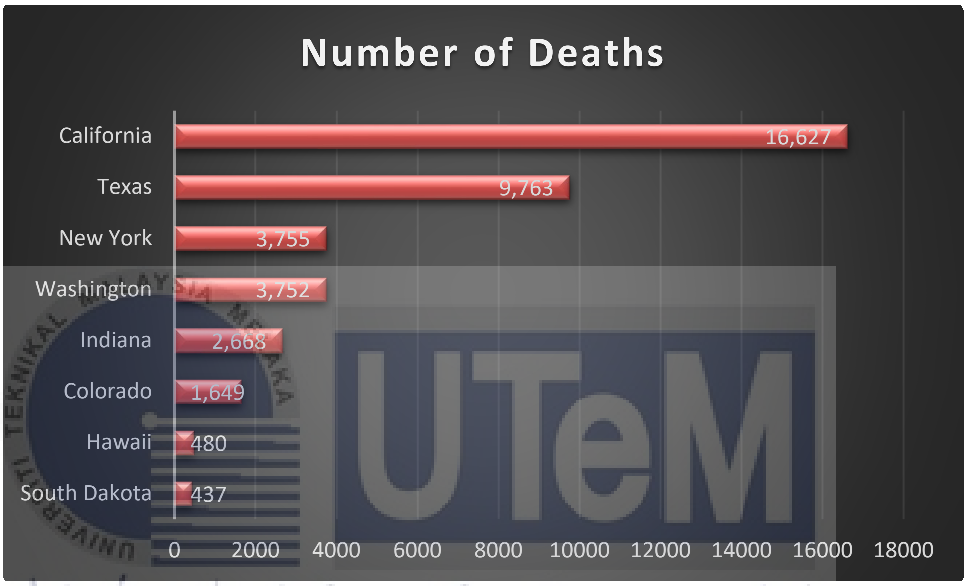

Figure 1.1 Number of Deaths Due to Alzheimer's Disease by different State in the world , 2018.

EEG signals from the human brain are clinically the best and most common signal to represent brain activities in the field of medicine or engineering. Even though the majority of researchers use the EEG signal to a non-stationary characteristic, a good processing technique is important in order to extract the important features to achieve better performance of the classification for pattern recognition [3].

1.3 Problem Statement

The mental workload construct can be understood as the extent of cognitive engagement that directly affects the efficacy and quality of a learning process. The human brain creates electrical potential, and this electrical potential is captured by placing electrodes at different locations on the brain's cortical surface[4]. Recorded signals are called Electroencephalogram EEG signals.

There are a few factors that need to be considered when implementing the EEG signal due to the nonstationary signal. In the recent study they carry out the properties of brain activities base on different type of level difficulty of arithmetic task. The groups of arithmetic task is different in pattern based on the EEG signals and a specific technique is required to extract the features of the EEG signal. Time-domain and frequency-domain based techniques are not suitable for groups of arithmetic task classification [5]. In addition, different types of data reduce the quality of the classifier that require the search for the most accurate classifier for the electroencephalogram signal base on the arithmetic task [6].

1.4 Objectives

1. To analyze the EEG signal during mental arithmetic task Performance by using the time-frequency domain (TFD).
2. To classify the groups in arithmetic task performance base on the EEG signal in the TFD feature.
3. To compare the different performances of classifiers such as K-Nearest Neighbor, Support Vector Machine, and others in terms of accuracy and efficiency.

1.5 Scope

The research scope is limited to observe the different groups of mental arithmetic task levels in time-frequency distribution (TFD) and classify the signals of a subject by using surface EEG signals in Voltage root mean square (V_{rms}). The group is divided into 2 categories which are 'Good Count/Good' and 'Bad Count/Bad'. The scope will include data EEG signal, signal preprocessing, signal processing, and classification.

Next, the average of the EEG signals from the 10 subjects and the category's groups is taken to get the spectrogram of the signal processing. Lastly, the total of the EEG signals will be validated to get the accuracy of the different groups in arithmetic task and observe the categorized groups base on the arithmetic task.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

This chapter begins with a simple description of cognitive response electroencephalograms (EEG), followed by the extraction of features and various types of classifiers to be compared. Then, the suitable option or recommendation will be discussed along with an explanation of the literature review.

2.2 Cognition Response

In thought, perception, and senses the meaning of cognition refers to the conscious activity or method of learning information and comprehension. It covers many aspects of intellectual functions and procedures, such as concentration, judgment, reasoning, problem-solving, and language understanding [1]. Cognitive processes use and generate new knowledge from existing knowledge. This cognitive science also has practical applications, such as helping to cope with memory challenges, increasing the consistency of decision-making, identifying ways to help people recover from brain injury, treating learning disabilities, and structuring educational curricula to enhance learning [7]. As a reason, detecting mental workload during cognitive activities is a crucial topic of research in cognitive neuroscience and other real-world applications. The progress of a real-time assessment of cognitive workload could lead to the creation of smart systems that adapt training content and keep subjects in an optimal range of cognitive workload to ensure cognitive development, or even to constructively notify topics about their stress levels in those workload states [1].

2.3 Electroencephalograms (EEG)

A procedure used to measure the electrical activity in the brain is an electroencephalogram (EEG) [3]. It can be used to measure brain activity that occurs during an event such as the completion of a task or the presentation of a stimulus or even to measure the spontaneous brain activity that happens in the absence of a specific event. EEG signal findings reveal differences in brain function that could be helpful in diagnosing brain diseases, especially epilepsy and other seizure disorders [4]. As in the past research, some neurophysiologists have created a distinction between safe and unhealthy EEG signals based on visual examination, which was not a consistent method [5]. EEG signals hold a lot of data in the form of characteristics that are very hard to understand clearly by visual inspection. However, with the advent of digital technology, the study and detection of EEG signals can be performed effectively without much experience. The electrical signals in an EEG recording appear like wavy lines of peaks and valleys as shown in Figure 2.1.

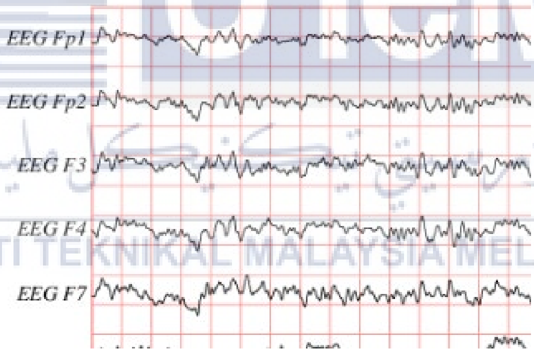

Figure 2.1 Raw EEG Signal

The EEG signals can be monitored using the (Ukraine,XAI-MEDICA) Neurocom monopolar EEG 23-channel device that is shown in Figure 2.2, regarding the previous author. Silver/silver chloride electrodes are connected mainly to the scalp of a human brain at Symmetrical anterior frontal (Fp1, Fp2), Frontal (F3, F4, Fz, F7, F8),Central (C3, C4, Cz),Parietal (P3, P4, Pz),Occipital (O1, O2) and Temporal (T3, T4, T5, T6)[2] .

Figure 2.2 EEG Systems NEUROCOM, NEUROLAB.

2.4 Feature Extraction

The feature extraction is an effective way to obtain valuable information found in EEG surface signals and to eliminate unwanted parts and interferences. EEG signal features are categorized as follows: the time domain, the frequency domain, and the time–frequency domain. Table 2.1 shows the advantages and disadvantages of the features.

Table 2.1. Types of "Feature Extraction".

Features	**Advantages**	**Disadvantages**	**Extracted features**
Time-domain	• Simple and efficient in EEG pattern recognition • Low noise environments [8]	• Non-stationary EEG signal properties	• Mean Absolute Value (MAV) • Mean Absolute Value Slope • Waveform Length (WL) [5]
Frequency domain	• Can estimate the EEG power spectrum in frequency form [9] • Reducing interference	• High noise environment • Weakness in the interpretation of non-stationary signals like EEG signal	• Short-time Fourier Transform (STFT) • Mean Frequency Power Spectrum (MNF) [4]
Time–frequency domain	• The limitation of time-domain and frequency-domain features can be resolved. [6]	• High dimensionality characteristics • High resolution of feature vectors [6].	• Wavelet Transform (WT) • Wavelet Packet Transform (WPT)

Although the time domain features have lower computational complexity and simplicity, interference could affect the initial EEG signal data as the calculation using this feature is based on the amplitude of the signal. While in "frequency distribution features," it may not have a good spectral estimation and cannot be employed for the analysis of short EEG signals [6].

In feature extraction, time-frequency analysis can gain that evaluation of signal in the time and frequency domain simultaneously using different time-frequency representations which gives the feasibility of examining great continuous segments of EEG signal. As the EEG signal is a non-stationary signal, the time-frequency approach may be suitable for the interpretation of the signal [10]. Time-frequency distribution has been widely used because of the dynamic characteristics of the EEG signal as it can provide temporal data and spectral data. In each feature extraction, the example and varying outcome graph are shown in Figure 2.3 below.

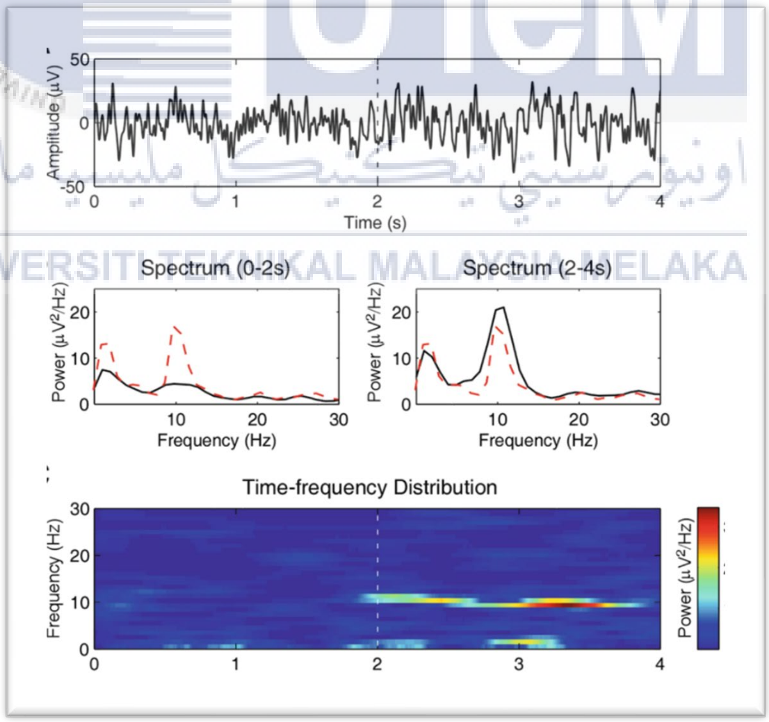

Figure 2.3 Diffrent type of "Feature Extraction".