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An Approach In Determining Fatigueness And Drowsiness Detection Using EEG

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Abstract:*Driver fatigue is a major exogenous cause of fatal road accidents and has implications for Malaysian road safety. The major aspect that causes human errors is fatigue/drowsiness due to task-induced factors or attitude/behavior of the driver. Therefore, it is necessary to identify significant index to detect driver fatigue and associate that index with the level of alertness, for road safety and for use by regulatory bodies. This can be carried out by observing the physiological behavior through the Event-related potentials (ERPs) and electroencephalography (EEG) measures. ERP's are very small voltage potentials that examine the information processing and characterize the brain structures in response to specific events or stimuli. Studies have shown EEG changes that are time-locked to sensory, cognitive or motor events are the most promising psychophysiological measures for assessing mental process and better indicators of fatigue. Hence, in this research work, to detect driver fatigue and associate with alertness, it is proposed to develop an adaptive fatigue identification algorithm based on the EEG frequency spindles. As for a preliminary work, two secondary set of EEG data from Physionet are used. The signals will be analyzed to extract discriminant features and for classification of the level of fatigue.*

KEYWORDS:*Driver fatigue, electroencephalography (EEG), event-related potential (ERP), multilayer neural network (MLNN), adaptive neuro-fuzzy (ANF).*

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I. INTRODUCTION

Fatigue, sleepiness, and stress while driving were common among the heavy vehicle and car drivers in Malaysia, with various possible causes: acute and chronic sleep deprivation, driving the vehicle for long hours and at different driving patterns, irregular schedule changes, and sleep disorders due to the driver's working conditions, especially at monotonous driving environment. Driving a vehicle under the influences of fatigue/drowsiness will cause longer response time, vigilance reduction and deficits in communication and information processing, which may lead to higher risk of collision and lacks correctness in decision-making, especially at high speeds. Statistics on fatal or injury-causing traffic accidents by Malaysian Institute of Road Safety Research (MIROS) shows that the death-to-population ratio stands at 23.8 to 100,000 Malaysian people, 80% of fatal accidents are due to human errors.

The available technologies for monitoring the driver's cognitive state are still in its infancy and the knowledge of understanding government policies (JPJ, PDRM, JKJR, MIROS, JKR) focusing on 4E (Engineering, Enforcement, Education and Environment) and vehicle manufacturer's strategies are yet not sufficient to prevent from fatal road accidents. In recent years, a variety of methods and approaches have been proposed by researchers for detecting driver fatigue/drowsiness based on eye movements, head movements, and biosignals. Among the various psychophysiological based approaches as an indicative measure, EEG perhaps being the most promising indicators of driver fatigue. However, there are some challenges in developing EEG based driver alertness systems, which includes, lack of a significant index for detecting fatigue and pervasive noise interferences while acquiring the EEG signals in a realistic and dynamic driving environment.

Furthermore, driver fatigue may also cause due to task-induced factors such as a high density of traffic, body posture and under exposure to vibration and noise that may not relate with sleepiness. At present, there are no adaptive models to discriminate the correlation between the physical and cognitive consequences of fatigue that relates to driver alertness. Hence, it is necessary to develop an adaptive driver fatigue identification model considering various environmental and behavioral aspects of the driver and evaluate the level of alertness. The Event-related potentials (ERP) observed from the drivers can be used to identify the cognitive state and fatigue index that may improve the driver's performance capacity and prevents from a catastrophic incident. However, there is limited information on the correlation between driver fatigues due to task-induced factors and attitude/behavior. Therefore, understanding the psychology of fatigue may lead to better fatigue-alertness model.

II. LITERATURE REVIEW

Heavy vehicles (E-class license) driver fatigue is a major exogenous cause of road accidents and has implications for Malaysian road safety (Lal et al., 2003; Lee Choon Fai, 2015; Mustafa, 2010). Statistics on fatal road accidents by Malaysian Institute of Road Safety Research (MIROS) shows that the death-to-population ratio stands at 23.8 to 100,000 people (10.3% (lorry) and 1.59% (bus)), compared to the world average of 18 to 100,000 people, human errors being 80% (Jonathan Lee, 2015). The major aspect that causes human errors are fatigue or drowsiness due to personality and temperament, lack of sleep, consumption of alcohol, long driving hours and driving patterns such as driving at midnight, early dawn, mid-afternoon hours and especially in the monotonous driving environment, personality and temperament may also influence fatigue (Stern et al., 1994; Wang et al., 2006). Therefore, preventing such catastrophic accidents is thus a major focus of government policies, vehicle manufactures strategies and research efforts in the field of automotive and safety research (Charbonnier et al., 2016; Mustafa, 2010; Wang and Wets, 2013).

In recent years, there are number of techniques and approaches have been proposed to recognize vigilance changes in the past such as physical changes during fatigue and measuring physiological changes of drivers, such as eye activity measurement, heartbeat rate, skin electric potential, and especially, brain wave activities as a means of detecting the cognitive states (Al-Sultan et al., 2013; Lee and Chung, 2012; Liang et al., 2005). Therefore, monitoring EEG signals during driver fatigue may be a promising variable for use in fatigue/drowsiness countermeasure systems(Mohamed et al., 2018). EEG based identification of alertness levels have the advantages of making an accurate and quantitative assessment and relatively shorter one to track second-to-second fluctuations in the driver's performance. However, EEG based monitoring fatigue and evaluating the significant index level are still in its infancy and there is lot to explore such as the EEG frequency spindles correlates of fatigue and drowsiness, as well as to evaluate what extent these cognitive-state related EEG activities can be efficiently incorporated into a real-time fatigue monitoring system (Charbonnier et al., 2016; Johnson et al., 2011; Lal et al., 2003; Touryan et al., 2016). Also, there are challenges in processing the EEG signals, which contains pervasive noise interferences while recording the brain responses in a realistic and dynamic driving environment (Yang et al., 2010).

Therefore, in this research work, it is proposed to develop anadaptive heavy vehicle driver fatigue and alertness model based on EEG frequency bands by combining signal processing algorithms and soft computing techniques such as Neuro-fuzzy algorithm to estimate the driver cognitive state while driving a vehicle in a virtual reality (VR)-based dynamic simulator under monotonous driving environment. To minimize the computational time, the features used for modeling should be minimal. Thus, in this research, it is proposed to minimize the number of features using soft computing techniques and classification using non-linear supervised classification algorithms. The proposed adaptive model identifies the discrimination between the driver's level of fatigue by recognizing whether the driver is fatigue due to task-induced factors or attitude/ behavior using the brain responses, then the level of fatigue is related with sleepiness (i.e. the level of alertness towards driving).

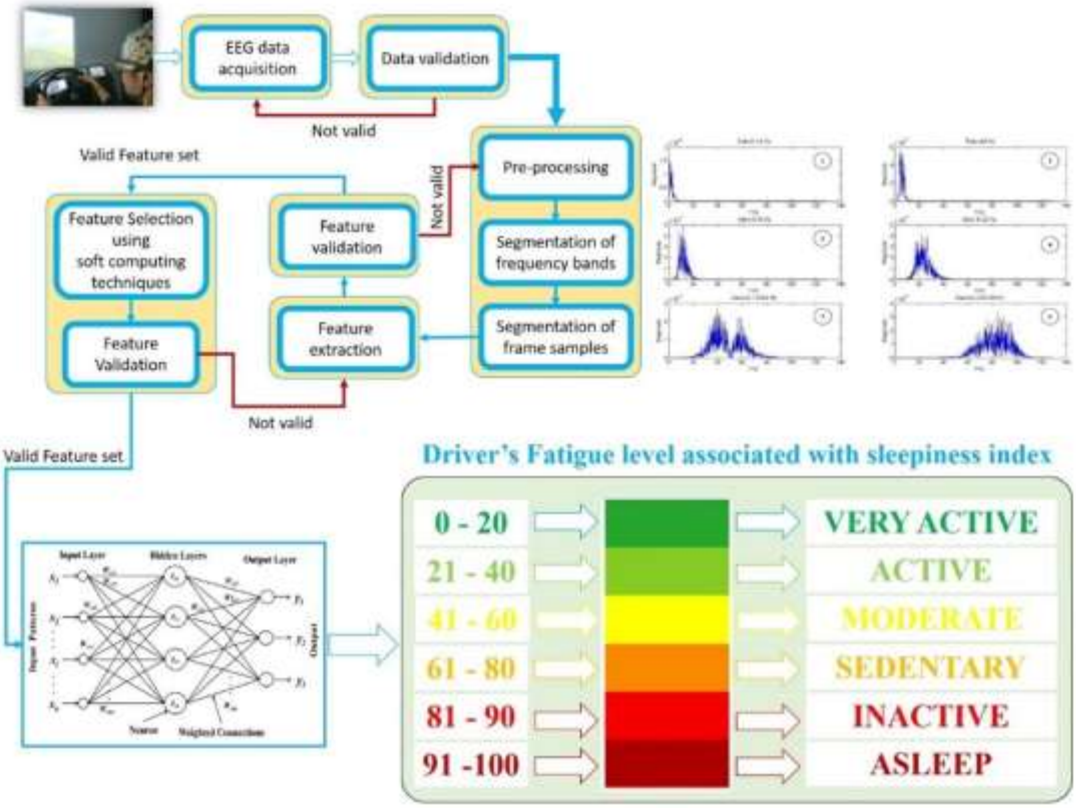
Further, the adaptive model can be utilized to alert drivers and regulators in optimizing the properties of the interface systems in identifying potential catastrophe. The proposed system alerts the driver during fatigue/drowsiness according to the recognition of cognitive state and produces the fatigue index and level of alertness. The proposed system also helps the driver to be more attentive and intuitive to prevent fatal road accidents.

III. METHODOLOGY

3.1 Development of Data Collection Protocols and Subject Selection

An EEG data acquisition protocol has to be developed for heavy vehicle driving based on driving simulation and interactive driving experiment. The development of EEG recording scheme involves monotonous driving scene, driver cabin simulator and EEG data acquisition system with real-life situations. The development of driving simulation requires broad areas of knowledge and learning. Further, the placement of electrodes for the EEG acquisition corresponding to the cognitive state involves different experimental observations. Further, selection of subject also important for the study that relates to the fatigue and alertness level. The data acquisition for driver fatigue and alertness measures requires subjects from various age groups.

Figure 1. Flowchart of EEG data processing procedures for the driver's fatigue level associated with sleepiness index



a) Driving simulator specification

Driving simulator system consists of the driving cockpit, steering wheel and pedal, a monitor, and a desktop computer. A custom-made driving cockpit will be build to recreate similar in-vehicle driving environment during the simulation. As for the input devices, Thrustmaster T500 RS GT6 Racing Wheel and Thrustmaster TH8A Gear Shift Add-On are chosen because of their mounting compatibility with the driving cockpit and compatible with the open source driving simulation software. Realistic wheel design with 30 cm diameter with brushed metal central spokes and can be detached allowing for future upgrades. This driving wheel can deliver ultra-precision steering motion with 16-bit resolution and would not decrease in the course of time thanks to the contactless magnetic sensor. It also came with a quick responding force feedback mechanism that will adjust the steering cornering force. With the realistic adjustable angle of rotation up to three full turns, it can imitate the real car steering maneuver. For the pedal set, it is adjustable and convenience to a suite for a different driver. The brake pedal is designed with 157 Nm pressure to give realistic braking operation. For the driving simulation system, a desktop computer will be used, which powered by 6th Generation Intel® Core™ i5-6500 Processor (6M Cache, up to 3.60 GHz), 16 GB of RAM, GeForce GTX 1060 graphics card, and Windows 10 64-bit operating system. An ultra-wide view angle of the 35-inch monitor is used to display visual for driving simulation.

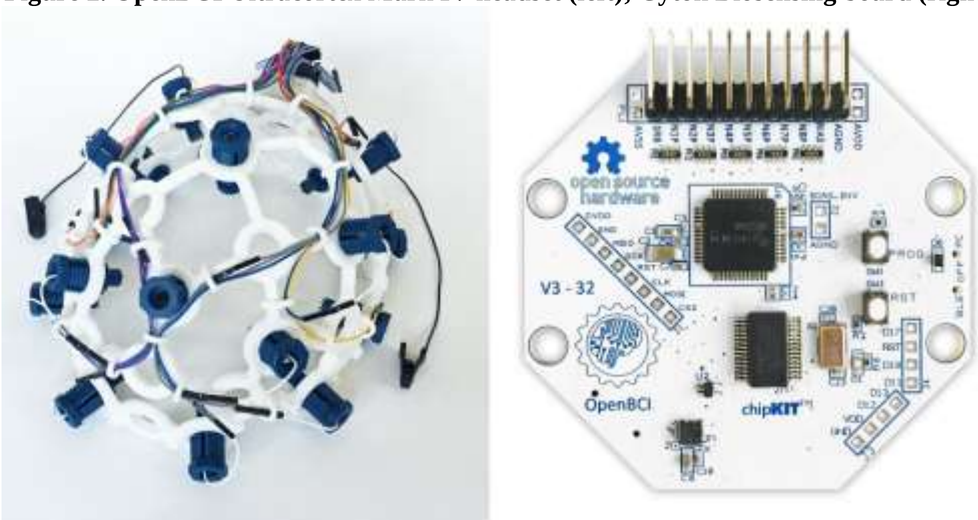
b) Soundproof cubicle

Recording EEG signal in normal surrounding condition will be affected by unwanted noise. This noise will result in the inconsistency and inaccuracy in data recording. To preclude this noise interference, a proper double-layer soundproof cubicle measure of 9 ft. by 9 ft. by 9 ft. will be built. A proper insulation material will be used, including acoustic foam and combining with egg trays. The reason for using egg trays because to reduce the cost of soundproofing. A door with a window, two transparent windows, three ventilation systems, two LED lights, and proper cable passages will be installed. The air ventilation system is carefully designed to reduced noise produced by the air conditioner fan. The chilled air from the air conditioner will flow through a soundproofing box before it enters the cubicle. This soundproof cubicle will be designed based on the commercial soundproof cubicle.

c) EEG data acquisition

When recording a physiological signal involving EEG, the biggest challenge is to record the signal with no surrounding noise interference. A research grade brain-computer interface (BCI), Ultracortex Mark IV EEG headset is used to record EEG signal during the experiment. It equipped with 8-channel dry electrodes and capable of recording high-quality brain signal. To sample the EEG signal, a Cyton Biosensing board is used. This board has an 8-channel neural interface with a 32-bit processor and it can communicate wirelessly with the computer using USB dongle.

Figure 2. OpenBCI Ultracortex Mark IV headset (left); Cyton Biosensing board (right)



d) Recruiting the potential subject

The subject screening for this research must go through a series of screening process to ensure whether the subject is qualified to participate in this experimentation. The screening process is an essential step before undergoing the experiment because there are few criteria need to be met: Age range of the desired subject is between 20 to 50 years old with at least two years of driving experiences, healthy person, did not have illness related to brain, heart, visual (other than corrected vision), hearing and not alcoholic. The subject who are interested may fill a form via printed copy and the selected subject will be informed via phone. A total number of 25 subjects are required for EEG database. After completion of this research, the developed adaptive heavy vehicle driver fatigue and alertness model will be tested by professional heavy vehicle drivers.

e) Ethics approval and subject consent

This research involves the non-invasive measurement of electroencephalography signals, it is necessary to register for National Medical Research Registration (NMRR) and obtain ethical committee approval from the Medical Research Ethics Committee (MREC) of Malaysia. A consent form will be given to the subject and needs to be signed in front of a witness, to confirm that a mutual agreement has been attained and the subject is aware of the risk possibility that might be happened during the experiment.

f) Driving simulation experimentation

An open source software, OpenDS will be used for the driving simulation (Green et al., 2014). Total of two sessions will be performed on the same day. Consuming caffeine and smoking were prohibited one day before the experimentation session. Subjects were advised to have sufficient sleep one night before coming for the morning session. The morning session will start at 9.00 a.m. and the afternoon session will start at 2.30 p.m. Statistical reports (Ueno et al., 1999) showed that the best time for doing the highway-drowsiness simulation is the early afternoon hours after lunch because drivers usually get drowsy within one hour of continuous driving.

In the morning, a baseline measurement will be performed: a measurement of the subject's biosignals when he is wide awake. Subjects will arrive early 30 minutes for a briefing and preliminary setup. The subject will be asked to drive for 30 minutes to rehearsal with the selected driving course. After that, the subject will drive for 60 minutes in the simulator.To induce fatigue, the subject will be asked to perform another driving session on the same day. After lunch, the subject has to complete another 60 minutes driving session. Continuously driving on the virtual road in 60 minutes will affect the performance of the driving, mental fatigue is hypothetical to increase with time-on-task (Charbonnier et al., 2016). During this period, drowsy data will be recorded. For ERP task, Reaction Test feature in OpenDS will be used. This task comprises a response experiment with instruction on screen. The subject has to react to suddenly appearing signs by braking and steering. After the drive, a PDF file with a bar chart will show up. The experiment will be conducted in a soundproof room with temperature-controlled between 25 ^{0}C to 27 ^{0}C and lighting will be kept at dim to encourage the subject concentrating on driving.

Subjective measurement of the subject's alertness will be performed using the Karolinska sleepiness scale (KSS) (Kaida et al., 2006). The participant will be asked verbally to indicate their sleepiness level at four different stage while driving, which is at the early of the driving, at the middle, and at the end of the driving session. This is a 9-point orally anchored scale with 1 = extremely alert, 2 = very alert, 3 = alert, 4 = rather alert, 5 = neither alert nor sleepy, 6 = some sighs of sleepiness, 7 = sleepy, but no difficulty remaining awake, 8 = sleepy, some effort to keep alert and 9 = extremely sleepy, fighting sleep.

3.2 Development of Algorithms for Validation and Pre-processing

The recorded EEG signals are subjected to random error due to the measurement protocols and experimental devices. This requires suitable data validation protocols for validating the recorded EEG signals. Further, the recorded stimuli should be enhanced and this requires the development of suitable data pre-processing techniques. Suitable data validation protocols based on statistical distribution functions and signal pre-processing techniques will be developed. The developed validation protocol will be applied to the recorded data and validation test will be performed. Subsequently, by applying the pre-processing methods the validated data will be enhanced. Further, the fatigue corresponding to the theta and alpha waves will be analyzed to enhance the classification system into the more robust system and minimize the computation time.

3.3 Development of Feature Extraction and Feature Optimization Algorithms

The dimensionality of the pre-processed EEG signals is very high and this requires a high computation cost while performing pattern recognition and clustering. Hence, suitable feature extraction techniques are to be developed for extracting the features that correlate the fatigue from the EEG signals. The developed feature extraction algorithm will be applied to the pre-processed signals and used to optimize the features using soft computing techniques. To have a better-generalized model and to minimize the computational time, the features used for modeling and clustering should be minimal. A soft computing based fusion of optimization algorithms will be developed to minimize the number of features. Sufficient features will be extracted from the proposed optimization algorithm. A database consisting of the selected features and the associated fatigue level, level of alertness and ability of the heavy vehicle driver will be formulated.

3.4 Developmentof Feature Classification Using Neural Networks

The fatigue and alertness of the drivers depend upon the dynamic environment and the simulator intention. A standard alertness level and sleep index should be formulated based on the observations by conducting a pilot study and the feedback of the subject involving EEG data collection protocol, the appropriate level of the index (Very active, active, moderate, sedentary, inactive and asleep) have to be formulated to enhance recognition system. This requires an intelligent pattern recognition model capable of generating a suitable alert/warning system and optimize the interfacing system in order to make the driver more attentive and instructive. To enhance the reliability of the system and minimize the training time, it is also proposed to develop a Bio-Inspired algorithm for classification.

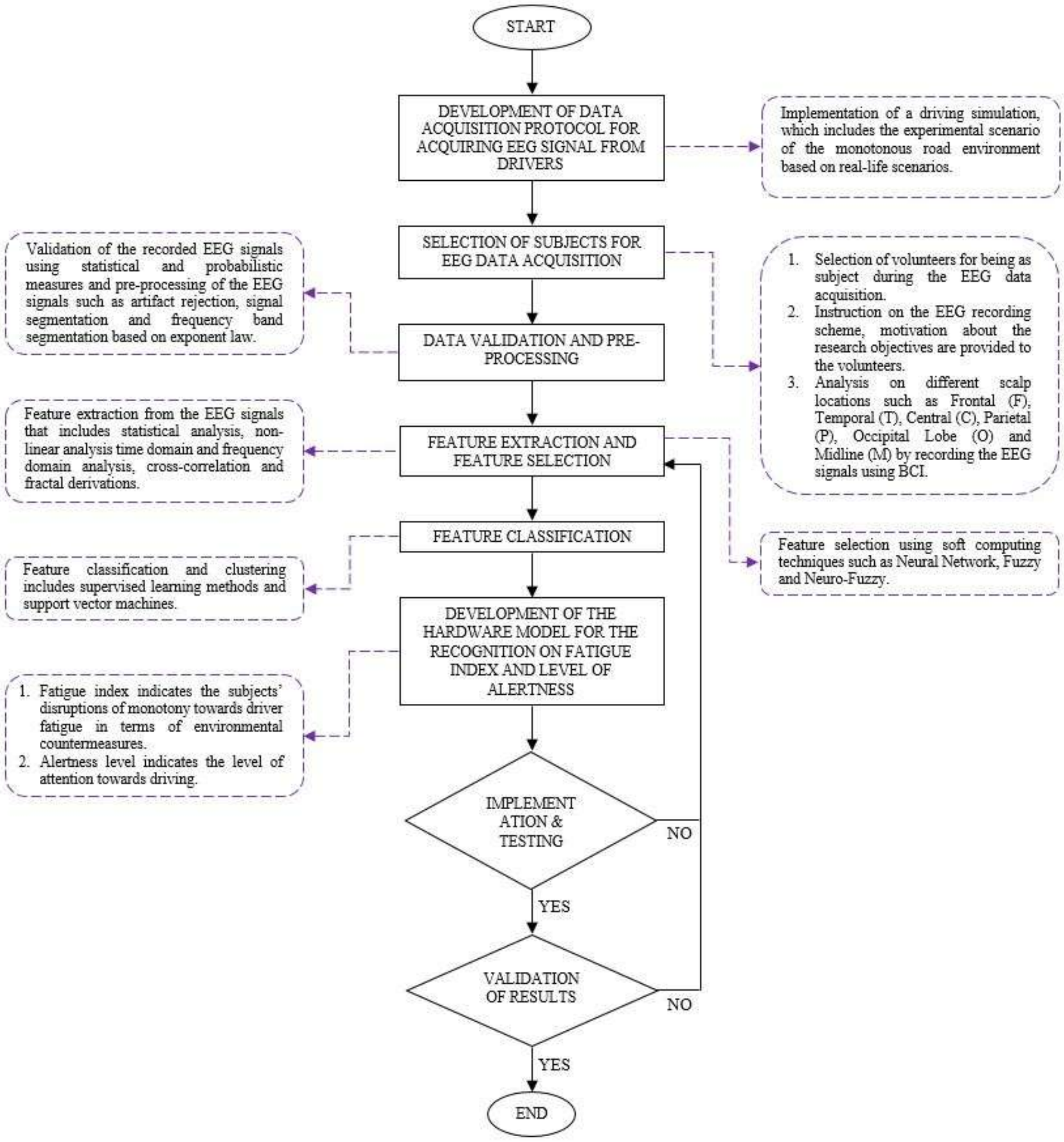
3.5 Development of Heavy Vehicle Driver Fatigue and Alertness Model

The embedded system comprises of four subsystems, namely, driver fatigue monitoring model, classification of alertness level, adaptive interfacing system and warning system. The monitoring system records the brain signal and estimates the level of fatigue and associates the command with the alertness index through the adaptive interface. Based on the alertness index, the system warns the driver and optimizes the environment and makes the driver attentive and instructive. The data pre-processing, feature extraction and data selection capabilities along with the intelligent classification model will be embedded into the interface system. The complete embedded arrangements along with the adaptive interface system will be fabricated.

3.6 Testing and Validation of Results

The developed model is to be tested and validated by heavy vehicle drivers in the various environmental situation at different patterns in the presence of a medical doctor and a psychology expert.

Figure 3. Flowchart of testing and validation of results



IV. PRELIMINARY RESULTS

The results can be used to assist the regulatory bodies (JPJ, PDRM, JKJR, MIROS, JKR) and medical practitioners in giving more understanding about driver fatigue and cognitive states. Furthermore, the developed model will warn the driver, while driving under the influence of fatigue/drowsiness and it can benefit in reducing the number of fatal accident due to the driver's fatigue. Since this research is required to procure new equipment, especially brain-computer interface (BCI), it will take some considerable time to obtain them. Despite not having BCI yet in for recording EEG signal, there is various publically available EEG data set can be obtained.

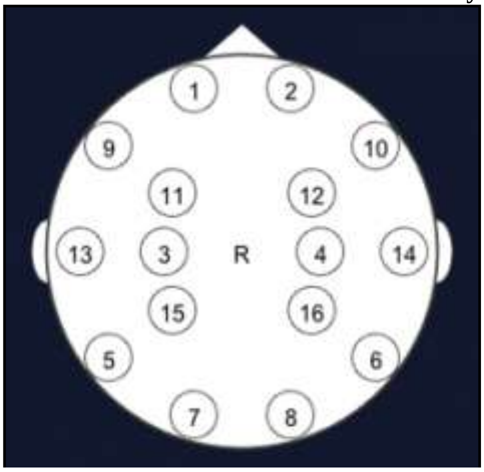
4.1 EEG Data Set

Two EEG data set is obtained from Physionet; EEG Motor Movement/Imagery Dataset (Schalk et al., 2004) is used as an awake dataset and MIT-BIH Polysomnographic Database (Goldberger et al., 2000) is used as drowsy data set. These data set are composed of multiple physiological signals, including electroencephalogram (EEG), electromyogram (EMG) and electrooculogram (EOG). For this preliminary work, only one channel of EEG signal from C4 electrode position is selected for analysis which is consists of 60 second signal from each of 16 subjects. The figure below illustrates the electrode position base on the 10-20 International System.

Table 1: List of channels and respective electrodes position

Electrode Position	Channel	Electrode Position	Channel
1	FP1	9	F7
2	FP2	10	F8
3	C3	11	F3
4	C4	12	F4
5	P7	13	T7
6	P8	14	T8
7	O1	15	P3
8	O2	16	P4

Figure 4. Electrodes location based on 10-20 system



4.2 Signal Preprocessing

Both datasetsare sampled at a different sampling frequency; Motor Movement/Imagery Dataset is sampled at 160 Hz and MIT-BIH Polysomnographic Database is sampled at 250 Hz. The Motor Movement/Imagery Dataset is resampled to 250 Hz. The raw EEG signals are filtered to remove noise using a notch filter at 50 Hz and removed artifacts below 0.5 Hz and above 32 Hz using 6th order Butterworth bandpass filter. The filtered signals are categorized into four frequency bands: Delta (δ) 0.1 - 4 Hz, Theta (θ) 4 – 8 Hz, Alpha (α) 8 – 16 Hz and Beta (β) 16 – 32 Hz. Each frequency band signal is segmented into 2s frame length having 500 samples per frame with 1s frame overlap.

4.3 Feature Extraction

Power spectrum density (PSD) using fast Fourier transform (FFT) is used to extract features from the four frequency band signals, namely Delta (δ), Theta (θ), Alpha (α) and Beta (β). The extracted features are mean power of Delta (δ), mean power of Theta (θ), mean power of Alpha (α) and mean power of Beta (β).

4.4 Classification

In this preliminary work, only two indexes of fatigue are classified, which are awake and drowsy. Multilayer neural networks (MLNN) and adaptive neuro-fuzzy (ANF) (Cetişli & Barkana, 2010) classifiers are used to classify between awake and drowsy. In MLNN, the model is organized with four input neurons, 20 hidden neurons and two neurons in the output layer. The network models were trained using different training function to evaluate the performance. The highest accuracy is obtained from Bayesian regularization backpropagation training function with 97.5% and 96.4% for training accuracy and testing accuracy respectively. Though the accuracy of Levenberg-Marquardt backpropagation is comparable to Bayesian regularization backpropagation.

In neuro-fuzzy classifier, the k-means algorithm is used to initialize the fuzzy rules. The data is equally divided to train and test sets. The first neuro-fuzzy classifier parameters are adapted by the scaled conjugate gradient method (SCG). The second classifier parameters are adapted by SCG method and the power values are applied to the fuzzy sets. The third classifier parameters also adapted with SCG and used least squares estimation (LSE) method for gradient estimation without using all training samples. The highest training accuracy and testing accuracy achieved using the first classifier with 91.2% and 91.5% respectively.

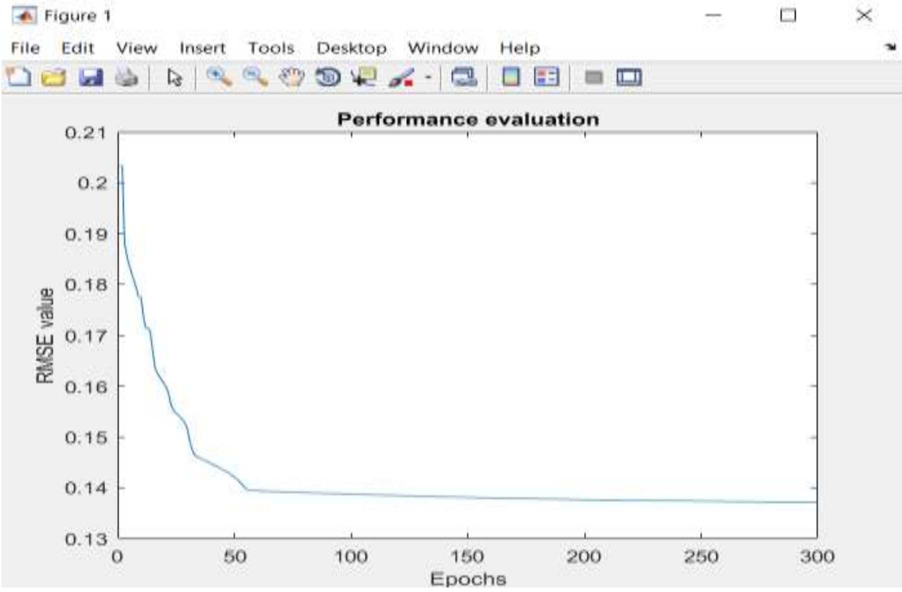
Table 2: Result of classification using MLNN

MLNN training function	Training accuracy (%)	Testing accuracy (%)
Levenberg-Marquardt backpropagation	97.2	95.9
Bayesian regularization backpropagation	97.5	96.4
Scaled conjugate gradient backpropagation	92.8	93.2
Resilient backpropagation	91.4	86.2

Table 3: Result of classification using neuro-fuzzy

Neuro-fuzzy classifier	Training accuracy (%)	Testing accuracy (%)
Conjugate gradient method (SCG)	91.2	91.5
SCG and power values	90.1	90.9
SCG and least squares estimation (LSE)	89.3	90.3

Figure 5. Performance evaluation of adaptive neuro-fuzzy



V. CONCLUSION

The goal of this research is to develop a fatigue and drowsiness detection model for drivers in order to provide effective methods to improve driving safety by using a new method on EEG frequency spindles based on neural net-fuzzy. Two secondary data set from Physionet are used and features are extracted using PSD. To minimize the computational time, only four features are extracted from the four frequency band signals. For this work, MLNN and ANF classifiers are used to evaluate their performance for fatigue and drowsiness detection.This researched study is registered and acquired approval from National Medical Research Registration (NMRR ID: NMRR-17-2767-36823(IIR)) and obtained Ethical approval from the Medical Research & Ethics Committee (MREC), Ministry of Health Malaysia (Ref.: KKM/NIHSEC/P17-2034(11-12)).In the future work, a heavy vehicle driver fatigue and alertness model will be developed to evaluate the performance of the system in real-time. The model will classify the fatigue index into six levels, namely very active, active, moderate, sedentary, inactive and asleep.

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