EEG based Driver Cognitive Distraction Assessment

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***Abstract*—The assessment of a drivers' cognitive distraction during driving is a challenging topic in research community. This paper states the ongoing research assessing driver's cognitive distraction using simulated driving. The driver's cognitive distraction detection is based on the analysis of EEG signal. A new analysis method based on Singular Value Decomposition (SVD) is introduced for the extraction of feature from the Electroencephalogram (EEG) signals. Hence, the results obtained consist in high accurate detection of the driver's cognitive state.**

***Keywords*- Cognitive Distraction, EEG, Simulated Driving, SVD, feature extraction.**

I. INTRODUCTION

Driver's cognitive distraction and inattention has been reported as one of the main causes of road accidents [1][2].Moreover, the study shows that drugs and alcohol present similar effect on driving performances. The driver's distraction caused 30% of the total amount of accidents between 2005 and 2009 as reported by the US National Highway Traffic Safety Administration (NHTSA) in 2011 [6]. As many road safety organizations, in Malaysia, according to the Jabatan Keselamatan Jalan Raya (JKJR) statistics, there were 414,421 accidents in 2010 with 6,871 deaths in total of all road users [1]. In addition, Malaysian Institute for Road Safety (MIROS) research statistics shows an increasing in crashes and fatalities. From 1995 to 2010 the number of fatalities caused by traffic accidents reached1160 deaths. Furthermore, a noticeable increase in the number of accidents has been reported in the same period ranging from 162,491 to 414,421 accidents [1][2].

Detecting driver's cognitive distraction while driving is a challenging topic in the researcher's community. However, the detection of the body's condition and mental state of drivers is a complex task which requires expertise in computer vision, Neurophysiological measurements and human features [3].The driver's cognitive state that may lead to accident may be one of following states: daydreaming, mind-wondering, thinking away of driving (mind-off-road) or practicing driving-unrelated cognitive task. Different instrumentations and technologies have been used to assess driver's distraction such as brain activity changes using EEG, Electromyography (EMG), Electrocardiography (ECG), video recording and computer vision.

This report is organized as follows; Section II includes the experiment scenario and data collection procedures. Section III presents the methodology used to address the research objectives. Finally, the experimental results and conclusions are given in Section IV and V, respectively.

II. EXPERIMENTAL APPARATUS

A. Dynamic Driving Environment

A virtual-reality (VR) based highway-driving environment was used to investigate the changes of EEG signals of drivers. City Car Driving 2.4.4 driving simulator was used as dynamic driving environment. This software provides a safe and low cost approach to study driver cognitive state changes under realistic driving events. One of the advantages consists in a realistic interaction between the subjects and the simulated environment. Thus, the subjects are provided with the most realistic driving conditions during the experiments.

A. Subjects

Forty-two healthy volunteers with no history of mental related disorders, body related problems, gastrointestinal, cardiovascular, or vestibular disorders participated in the experiment. The subjects are ages from 18 to 24 years with a 21.76 mean and 1.65 standard deviation.

B. Experimental Setup

Two sessions have been designed to investigate the effect of distraction on the behavioral performance and brain activities in a virtual environment.

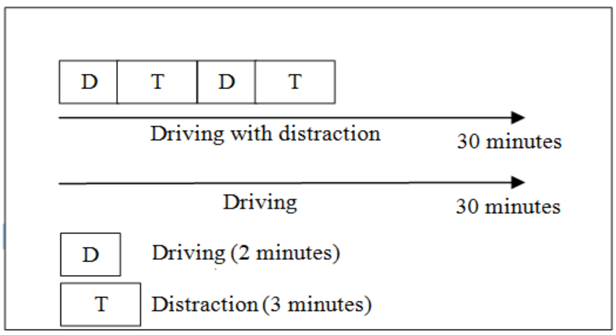

Figure 1. The experiment flow

The two designed sessions were developed to investigate the changes in driver cognitive state and driving performance. The first session, denoted A, consist in subjects driving for 30 minutes with no distraction. The second session, denoted B, consist in subjects driving with distraction. The distraction has been formulated as different logical reasoning (analogies) and real life problems as shown in Table 1.The distraction session (B) has been segmented as shown in Fig. 1 in order to assess the relaxation effect after distraction.

TABLE 1: EXAMPLE QUESTIONS IN THE SECONDARY TASK.

Question	**Answer**
Odometer is to mileage as compass is to: A. speed B. hiking C. needle D. direction	D
Elated is to despondent as enlightened is to A. aware B. ignorant C. miserable D. tolerant	B
Careful is to cautious as boastful is to A. arrogant B. humble C. joyful D. suspicious	A
Pride is to lion as shoal is to A. teacher B. student C. self-respect D. fish	D

C. Data Collection

In order to collect EEG signals, AGES 300 system with 128-channel Nets from EGI was mounted on the subject's scalp. 128 EEG electrodes used for physiological data acquisition with a Vertical reference at Cz electrode. The contact impedance between EEG electrodes and cortex was calibrated to be less than 5kΩbeforedata acquisition began. The EEG data were recorded with sampling rate of 500 Hz and then down-sampled to 250 Hz for data processing complexity reduction. Driving performance was defined as a linear combination of the deviation between the center of the vehicle and the center of the cruising lane, number of accidents and over speed limitation to indirectly quantify the level of subject's attention. The changes in driving performance has been used in the two performed sessions (driving and driving with secondary task) to give preliminary classification and ground truth of distraction events. When the subject is distracted (checked from subject's driving performance report), car deviation increase, speed awareness reduce and the probability to have an accident is higher than driving without distraction. Furthermore, the ability in solving the given task (logical reasoning (analogies) and real life problems) during and after the distraction session was investigated. This provides mean to assess the cognitive engagement of the subjects between driving and other cognitive activities.

III. SIGNAL PROCESSING AND ANALYSIS

A. Analysis of Behavior Data

The software Statistical Package for Social Science (SPSS) was used to verify the significance of behavior data. The subject ability to answer the task given was analyzed to confirm the driver cognitive engagement in another cognitive task while driving. By using Paired-sample T-test, the significance of task response changes was tested.

B. EEG Data Analysis

Flowchart of data analysis for detecting the level of distraction based on EEG is shown in Fig. 2. For each participant, after collecting 128-channel EEG data from each session, the EEG data were first preprocessed using low-pass and high-pass filters with cut-off frequencies of 0.5 Hz to 50 Hz to remove the line noise and high frequency noise.

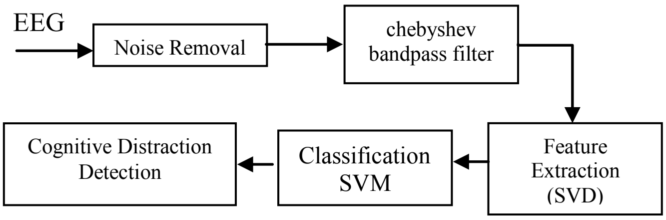

Figure 2. Analysis flowchart of the EEG signals.

In order to remove eye blinks and movements' artifacts, Gratton correction method has been used to detect and filter the contaminated useful EEG signal from the noisy raw data [16]. Then, the data from each subject for each session has been filtered by a chebyshev bandpass filterof order 6 in order to extract the EEG frequency bands (δ (0.5-4 Hz), θ (4-8 Hz), α_1 (8-11Hz), α_2(11-14Hz), β_1 (14-25Hz), β_2 (25-30 Hz)) in time domain. This frequency bands correspond to the brain rhythm and are usually used for data analysis in the domain.

From distracted driving session's data, one minute data has been extracted from each three minute segment, and one minute from time-equivalent segment from driving session's data. After data segmentation, the singular value decomposition (SVD) has been performed to extract features. Indeed, SVD have a predominant in representing the changes in EEG data related to the changes of driver cognitive distraction making it very efficient to investigate the driver cognitive distraction.

Support Vector Machine (SVM) classifiers from Waikato Environment for Knowledge Analysis (WEKA) has been used for classifying the data into distracted and non-distracted.

IV. Results and Discussion

A. Driver Problem Solving Ability Measures

To investigate the driving problem solving ability during driving and after driving, we have calculated the mean of correct answered questions during and after distraction session for all subjects as shown in fig. 3.

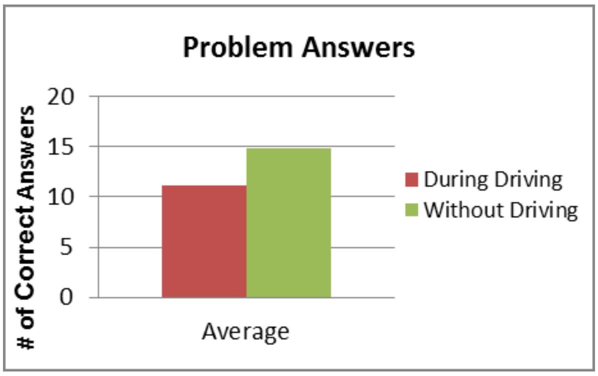

Figure 3. Driver Problem Solving Measurements

We can see from Fig. 3, that the subject ability to solve the given task has been significantly affected (distracted) as the driver is cognitively engaged during driving. This may consider as a confirmation that the experiment designed to assess the driver cognitive distraction has successful.

C. EEG- based Driver Cognitive Distraction

The singular values corresponding to each EEG frequency band from both experiment sessions for all subjects has been given to the classifier. The classification using SVM performed well by achieving an accuracy of 98.7% in distraction detection.
Previous studies have used many other features to represent the changes in driver's cognitive states; also many other classifiers have been used to classify the cognitive state of the driver. Table 2 gives an overview of the techniques (and their performances) used in the literature to position our current research. Table 2 shows that our technique provide a convenient solution to the distraction detection.

TABLE 2: OVERVIEW OF THE TECHNIQUES USED IN THE LITERATURE

Ref.	Features	Classifier	Accuracy Classification
[3]	PCA	Gaussian Maximum Likelihood Classifier (ML)	89.0%
[4]	PCA	Radial Basis Function neural network (RBFNN)	84.5%
[6]	NWFE	k-Nearest-Neighbor Classifier (kNN)	89.4%
[7]	NWFE	Support Vector Machine (SVM)	85.7
current	SVD	SVM	96.78

V. CONCLUSION AND FUTURE WORK

In this report, we have stated our research progress. The data collection and experiment procedures have been shown, as well as the methodology in analyzing and processing the EEG and behavior data. Some results shown as part of these study achievements. As a future plan, we are going to investigate the most dominant features related to distraction; that could be used as an index of distraction. A feature extraction and classification methods will be investigated.

The state-of-the-art experiments, methods in detecting the driver distraction have been illustrated. We have proposed a plan which it is consists of an experiment, data process and analysis method and results expected at the end of this study. The main aim of this study is to maximize the accuracy in detecting driver cognitive distraction by using a new experiment design and method applied for the first time for this research issue.

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