PRE-POST ACCIDENT ANALYSIS RELATES TO PRE-CURSOR EMOTION FOR DRIVER BEHAVIOR UNDERSTANDING

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Abstract: - As a high rate of road accidents, a research study has been done on the causes of these accidents. Yet, driver behavior is one of the main reason for this predicament while emotion plays a vital role as it affect the driver behavior itself. However, studies on pre-cursor emotion and pre-post accident condition using Electroencephalogram (EEG) pattern are scarce. Hence, this paper proposed to analyze the pre-post accident analysis to determine the correlation between driver behavior and emotion through the 2-D affective space model: valance arousal approach (VAA). EEG machine has been applied to produce the brain waves that requires the drivers to drive in a different traffic condition by using driving simulator. The analysis results of VA for each driver exposed that pre- cursor emotion will affect the emotion in pre-accident whereas negative emotion appear frequently in post-accident compared to positive emotion. This exemplify that the understanding of pre-cursor emotion and its relationship towards driver behavior will help the driver to learn on how to control his/her emotions which can prevent an accident.

Key-words: Driver behavior, EEG, valance, arousal,VAA, pre-cursor emotion, pre-post accident

1 Introduction

A traffic collision is a matter of great concern to all of us. But regrettably, there is still a large number of road accident happened even the possible root causes has been identified such as over speed, congestion and bad road condition. Piotr Bojarand et.al [12] in their study revealed that for every 100 road accidents 80 were caused by improper behaviors of drivers. In addition, according to Rozhan and Ahmad [4], Malaysia road system has been classified among the finest roads system in *Asia* but unfortunately Malaysia still gain the highest rate of accidents.

Many reasons has contributed to an accident including condition of the road and the environment, which can affect the driver's action while driving. However, the change of driver behavior does not depend solely on the environment and in fact, stress plays an important role too. This observation has been supported by Stephens and Groeger [3] where they found that most drivers would feel angry and frustrated when they have to reduce speed because of traffic and subsequently retaliated by accelerating after the impending event. Interesting enough Md.Rizal et al. [2] indicated that most accidents are caused by human error, which possibly emerges from the driver behavior.

1.1 Emotion, valance (V) and arousal (A)

The valence arousal analysis (VAA) approach can help to understand in details on pre-cursor emotion of the driver in driving simulation task. In addition, the study of the driver emotional states with respect to the change of different driving environment may provide a better understanding of the effect on long term memory (LTM) towards early detection of highly emotional agitated driver which can prevent an accident [15].Emotional affect has been conceptualized along two dimensions of valence, which describes the extent of pleasure or sadness, and arousal, which describes the extent of calmness or excitation [5]. In this research, we proposed a novel approach to analyze and understand the driver behavior based on the affective space model (ASM) that enables emotions to be viewed in two different axes of the valance (V) and arousal (A). Figure 1 shows the affective space model with several emotions' labelled according to Russell [1] but details of the emotion can be referred to Russell's model.

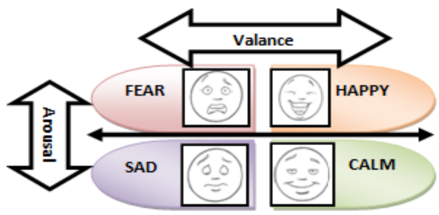

Fig.1: The Affective Space Model with the Different Position of Basic Emotions with Emotion Primitives Axis x for Valance, and y for Arousal.

1.2 Emotion and EEG

Quantifying emotion has never been an easy task but study by Al-Shibabi and Mourant [11] opined that human's feelings were actually the perceptible of bodily changes directly induced by compelling stimulus. In recent years a huge amount of research paper has been studied on emotions recognition by using EEG recordings [10]. Chanel et. al. tried to recognize only the arousal dimension of emotion from EEG and other physiological measures [6]. In other study, the wavelet based feature extraction of EEG signal in alpha band activity has proved to be successful in discretizing emotions from the EEG signals [13].

1.3 Driver behavior and driving simulator

The correlation between emotion and driver behavior analysis must be embed together in this study to get a concrete understanding. Therefore, one of research study has proved that driver behavior can be identified and verified based on emotion.[14]. Vaa.T [9] in his research, aimed to collect and record driver behavior data on various driving situation by using the driving simulator. Imitation of real environment in town and residential area was designed to be used in his experiment. In addition, Dewinter et.al [16], found a correlation between fewer steering errors in the simulator and higher chance of passing the driving test for the first time. This research revealed the impact of driving simulation which can influence in the real time driving situation. Thus, driver behavior can be identified through a great use of driving simulator and emotion recognition.

2 EXPERIMENTAL DESIGN

2.1 Experimental Procedures

Firstly, subjects are briefed on the experimental procedures and signed an informed consent form for participating in this research. Then, subjects will be seated in a quiet, temperature controlled and lighted room due to the sensitive EEG signal. The electrodes are placed on the subject's scalp and the recording of the signals will be done by a program called BMC Acquisition. Before we start the experiment, the subject will be exposed to the driving simulator in order to get familiar with the devices. Next, subjects are instructed to open their eyes for one and half minutes followed by eyes close with the same duration. Eyes open was chosen as calm emotion since at this stage the subjects has not been burdened by any task. But, eyes close data has been used to analyze the pre-cursor emotion effect to the driver.

Afterwards, the 3 basic emotions movie clip will be displayed by using the International Affective Picture (IAPS), Bernard Bouchard's synthesized musical clips and Gross and Levenson's movie clips which can be used to elicit emotional responses [6] for one and half minutes per movie clip. Next, driving simulator 2009 has been used to synchronize with the real time driving situation. Thus, 3 different types of environment need to be completed for each subject; task 1 - easy driving, which embed with noisy sounds that might distract them while driving, task 2 – bulked driving, consist of an interview from the experimenter which purposely to identify their behavior while answering the question, and finally task 3- heavy driving, at this stage subjects need to deal with the traffic congestion where their driving skill will be defied. It will be conducted for 10 minutes. Finally, the recorded brainwaves are then saved for off-line preprocessing. This can be shown in figure 2.

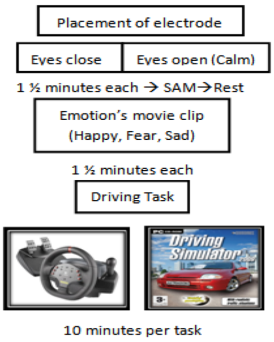

Fig.2: Experimental procedure

2.2 Electrode position

Five EEG electrodes were pasted on their scalp (C3, C4, T3, and T4) according to the "International 10-20" Standards and Cz as reference. These electrodes will then be plugged into the EEG head box to amplify the signals. Figure 2 shows the method that we use to analyze the brain signals and its spectrum for the subjects (driver).

2.3 Subjects

10 healthy subjects (6 female and 4 male) has been recruited from a final year student of International Islamic University of Malaysia (IIUM) who has met the criteria to get a concise result. Therefore, all the subjects must have at least 3 years driving experience and have a valid driving license. Moreover, they must be aged between 20 to 26 since the targeted group is the young driver.

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3 METHODOLOGY

Firstly, the raw EEG signals that has been collected before will be normalized to range [0, 1]. Since EEG contains a lot of noise from artifacts, body movement or eye blinks, noise removal was performed with low pass filter in the decimation function and then it will resample the resulting smoothed signal at lower rate. The matlab code below reduces the sample rate of *input* by a factor of 3. The EEG signal is processed as shown in figure 3.

input = decimate (input, 3);

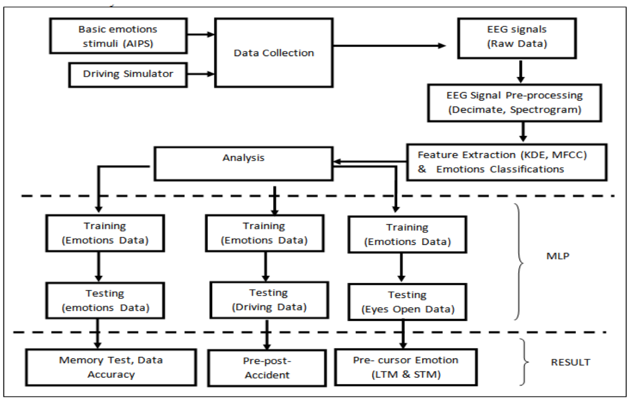

Fig. 3: Proposed method for analysis

3.1 Feature Extraction

3.1.1 Mel-frequency cepstral coefficients (MFCC)

The feature extraction approach that has been employed in our methodology is Mel-frequency cepstral coefficients (MFCC). MFCC is the most popular tool used for feature extraction in speech signals. Figure 4 is the block diagram of the conventional MFCC extraction algorithm [8].

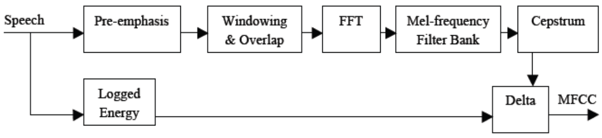

Fig. 4: Conventional MFCC Extraction Algorithm

Generally, the Mel scale frequency can be computed by the following equation:

i) $f_{mel} = k_{const.log_n}($

Also, from [10], other approximations of the Mel scale that were derived from the above equation make use of natural or decimal logarithm, which leads to different choice of the constant k*const.* The following two representations:

i) $f_{mel} = 2595_{\cdot log_n}(1+$

ii) $f_{mel} = 1127_{\cdot log_n}(1+ \frac{f_{inn}}{700}$

are widely used in the various implementations of the MFCC. These formulas provide a close approximation of the Mel scale for frequencies below 1000 Hz. In his research study, feature extraction needs to be performed on a non-speech signal. As such, we will be exploring on using MFCC to extract this low frequency signal. We are using 10 MFCC coefficients for capturing the relevant feature of the EEG. The final combined dataset from 4 channels gives a total of 40 features for classification.

3.1.2 Kernel Density Estimation (KDE)

KDE has been adopted as the second feature extraction purposely for a comparison in terms of performances. Thus, spectrogram has been performed first before we proceed with the KDE in order to represent the data in frequency domain. Thus, 256 nfft, 64 windows and 50 number of overlap has been applied in this study. The final data that we have for KDE are 525 instances and 100 features for each channel per emotion.

3.2 Classifier

3.2.1 Multi-layer perceptron (MLP)

Two classifiers were used in this research study to achieve the best result in term of accuracy level. First classifier was MLP which classify the extracted features to produce the result. Data fed into the input layer are the 40 features obtained from the previous stage. Then, each of the data is processed by the network by multiplying it with assigned weights in the hidden layers synapses. Moreover, 0.1 has been assigned as the mean-square error goal with 1 hidden layer consists of 10 number of neuron. Besides, we use tan-sig as the activation function for hidden layer and purelin as the output layer with 0.01 learning rate.

3.2.2 Adaptive Neuro-Fuzzy Inference Systems (ANFIS)

Another classifier that has been applied in this study is ANFIS which use a hybrid learning procedure. The proposed ANFIS can construct an input-output mapping based on both human knowledge (in the form of fuzzy if-then rules) and stipulated input-output data pairs [7]. The Sugeno fuzzy model was proposed for generating fuzzy rules from a given input-output data set. At this stage, we choose ANFIS wittingly to prove either it can give a better accuracy or not as ANFIS is good at mimicking human brain. Genfis2 and subtract clustering has been applied in this study to get a better accuracy.

3.2.3 K-Fold Cross Validation

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In order to get better results with high percentage of accuracy, we used the K-fold cross-validation for our global validation. The dataset and its desired result is randomized and sliced into 5 folds which mean that the process is repeated 5 times. This is required to eliminate any biasness towards the data [12]. Each dataset consist of 440 instances by which 352(80%) instances are used for training and the remaining 88 (20%) instances for testing. The data obtained from the subjects are tested against emotion data which is happy, calm, fear and sad .

4 RESULTS AND DISCUSSIONS

In this research study, the accuracy of the data gains importance to prove that the result will be more robust by using VA. Thus, memory test analysis has been applied to all subjects to see the level of accuracy, either it can be accepted or rejected. Then, 5fold validation was analyzed in order to obtain the intensity of the emotions per subject. In addition, based on this result, we will have a various number of subjects that achieve the highest intensity in certain emotion.

4.1 Pre-emotion (memory test and 5-fold)

In this part, the accuracy has been calculated by using VA instead of directly getting the accuracy from MLP. As shown in figure 5, the memory test has been conducted by using KDE data which has a good accuracy for a certain emotions but some of them did not reach 50% accuracy.

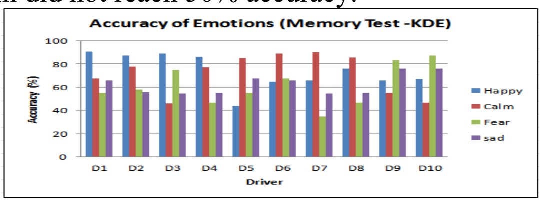

Fig. 5: Accuracy of emotion based on (KDE)

However, by using MFCC data, the basic emotions can be identified and it achieves more than 80% of accuracy and the best accuracy was at 0.1 of mean square error goal. It can be shown in figure 6.

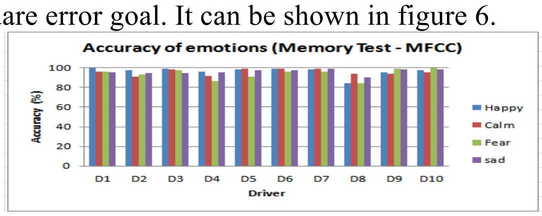

Fig. 6: Accuracy of emotion based on (MFCC)

Consequently, the emotions data can be used as the base for the driving task analysis by using MFCC data. Then, MFCC were selected for the k-fold test. In figure 7, it shows that each subject has their own highest intensity of emotion. It was obviously plotted according to the average k-fold percentage per subjects. This finding will be the interesting part, when the emotion that gains the highest intensity in k-fold has given the same result in memory test. In addition, there are 4 subjects has happy as the highest intensity of emotions, 4 subjects falls into calm , two subjects has fear as their pre-emotion and none of them engage to sad. The result proved that each subject has their own pre-emotion that may affect their driving behavior.

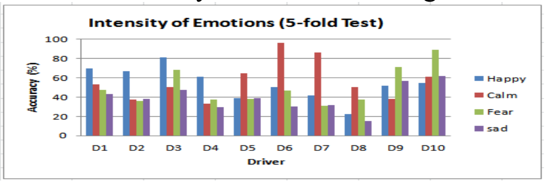

Fig.7: Intensity of emotions based on average accuracy of k-fold test

4.2 Pre and Post-accident analysis

Each task that given to the subject is wittingly to invoke stress, so we can identify the driver behavior while having the pressure situation. In this finding, it was identify that each subject has a diverse driving behavior. For subject 5, she has the same pre-cursor emotion since the beginning and change the emotion when the accident occurred but he manages to end the driving task with calm emotion. Besides, the subject took some spaces to get back to the pre-cursor emotion that she has. As we can see from figure 8-10, the horizontal black line represent that the accidents occurred while the subject drove the car. The movement of task 1 and 3 (figure 8 and 10) is mostly from calm to sad and vice-versa whereas for task 2(figure 9), he just stay sad for the whole task. This is the sign of give up, as she sigh a lot in order to manoeuvre the car while answering the question from the experimenter.

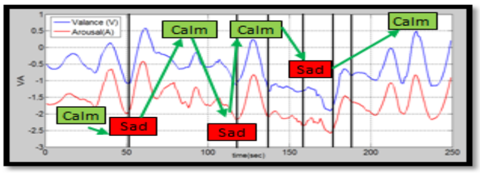

Fig. 8: Dynamic movement task 1, D5(driving & sounds)

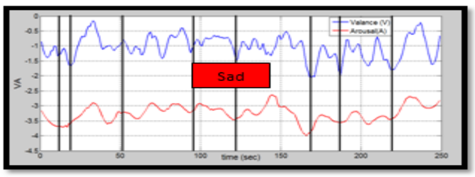

Fig. 9: Dynamic movement task 2, D5 (driving & interview)

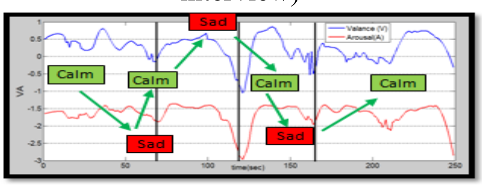

Fig. 10: Dynamic movement task 3, D5 (driving & congested traffic)

As we can define from figure 11, the dynamic movement is moving from fear to sad for task 1 whereas for task 2 he just stay sad. Perhaps, at this stage the subject was nervous to drive for the first task but after a lot of accidents, he just gave up and started to have sad emotion. It is obviously shown in figure 12. Then, he started with calm emotion for task 3 and fear when accident occurred but after accident he was happy. Therefore, he might have some interest after a long duration of driving but still remains the pre-cursor emotion even he felt happy previously. This illustrate that the subject easily feels fear even he is in a good mood.

Fig.11: Dynamic movement task 1, D9 (driving & sounds)

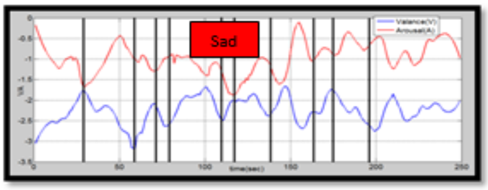

Fig. 12: Dynamic movement task 2, D9 (driving & interview)

Fig.13: Dynamic movement task 3, D9 (driving & congested traffic)

Consequently, we can conclude that each subject has their own pre-cursor emotion that affect to the driving behavior. Pre-cursor is the emotion that already inbuilt for the subject because of previous experience or emotions that he/she already had before the experiment.

4.3 Pre-cursor emotion

Based on the previous result, eyes close data has been analyzed in order to identify the correlation between pre-cursor emotion with the pre-post accident. The significant of this finding is to have a better understanding on long term memory (LTM) effect or short term memory (STM) effect to the driver behavior. Eye close has been consumed as the pre-emotional state that the subject has before they were invoke by any task. Therefore, it is important to know what kind of emotion that the drivers have before they start the task. After we plotted the dynamic movement of each subject, it shows that each subject has their own pre-cursor emotion that mostly giving high impact to the subject's emotion during the task's completion. As shown in figure 14, driver 5 has high intensity in calm emotion rather than happy and sad. Thus, this driver perhaps is a calm person since long time ago as it exists in his long term memory or he just has a calm emotion before he attend the experiment session.

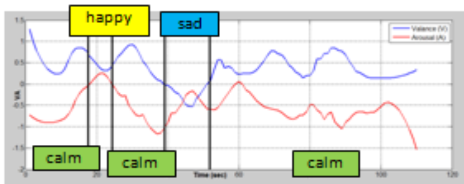

Fig. 14: Dynamic movement neutral state (eyes close), D5

Fig. 15: Dynamic movement neutral state (eyes close), D9

In contrast with driver 9, he already has fear emotion at this neutral stage which shows that he might afraid of anything even it is normal to the other driver. It can be shown in figure 15. These findings show that LTM or STM will give impact to the driver behavior. Thus, further analysis in this area should be continued for the next research study as it can determine the emotion of the driver while driving in a different circumstances.

5.4 ANFIS analysis

In previous memory test analysis, we found that MLP is not a stable classifier as it only gives a good accuracy for verification but not for identification. Thus, ANFIS has been selected to see the differences. Yet, ANFIS has given a better accuracy for memory test by achieving more than 90% accuracy and can be converged quite faster than MLP. This can be shown in figure 16.

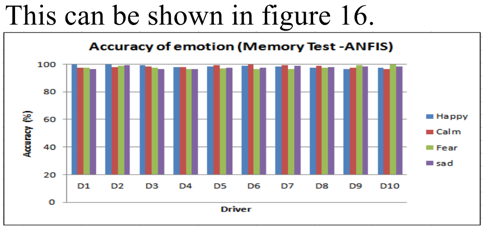

Fig. 16: Dynamic movement neutral state (eyes close), D5

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5.CONCLUSION & FUTURE WORK

Result from our experiment has proved that it is possible to correlate between pre-cursor emotion and driver behavior. Hence, unstable emotion may lead to an accident and the driver might easily change their positive emotion to the negative emotion. Thus, there are possibilities to determine the emotion especially for the agitated driver to control their emotion while driving in any situation. Consequently, an analysis which focus on the subject's background will be conducted in future work purposely to identify the effect towards driver behavior. Besides, we will apply ANFIS as the classifier since it gives a better result rather than MLP.

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References:

[1] Russell JA. A circumplex model of affect. J Pers Soc Psychol 39:1161-1178, 1980.

[2] Md Rizal Othman, Zhong Zhang, Takashi Imamura and Tetsuo Miyake, "A Study of Analysis Method for Driver FeaturesExtraction", 2008.

[3] Stephen, A.N., 7 Groeger, J.A, do emotional appraisals of traffic situations influence driver behavior? Paper presented at the behavioral studies seminar, Bath, UK, 2006.

[4]Rozhan, M.I. and Ahmad H.M. (2002)."Universiti Sains Malaysia." In Reddy, V. Venugopal and Manjulika, S. (eds.). *Towards Virtualisation Open and Distance Learning*.Kogan Page, New Delhi, pp. 266–274.

[5] Ekman P. & Heider, K. "the University of a Contempt Expression: A replication. Motivation and emotion", Psychological Bulletin, 12, pp. 3030-308,1998.

[6] G. Chanel, J. Kronegg, D. Grandjean, and T. Pun, "Emotion assessment: Arousal evaluation using eeg's and peripheral physiological signals", Computer Vision Group, Computing Science Center, University of Geneva, Tech. Rep.05.02, 2005.

[7] L. A. Zadeh. Fuzzy sets. Information and Control, 8:338-353, 1965.

[8] W. Han, C. Cheong-Fat, P. Kong-Pang, "An Efficient MFCC Extraction Method in Speech Recognition", Circuits and Systems, 2006, ISCAS 2006.

[9] Vaa .T (2001). Cognition and emotion in driver behavior models: some critical viewpoints, International Cooperation on Theories and Concept in Traffic Safety Workshop. Caserta, Italy, 2001(1779):9-16.

[10] W. Heller, J.Nitschike, and d.Lindsay (1997), "Neuropsychological coorelates arousal in self-reported emotion," Neuroscience letters, vol. 11, no.4, pp.383-402.

[11] Al-Shibabi.T and Mourant.R.R.(2001), "A Framework for Modelling Human-Like Driving Behavior for Autonomous Vehicles in Driving Simulators", AGENTS '01 Proceedings of the fifth International Conference on Autonomous Agents.

[12]Piotr Bojar, Łukasz Muślewski, Maciej Woropay, Janusz Szpytko (2010). Influence of Human Factor on Transport System Safety. In N. Mastorakis, V.Mladenov and Z.Bojkovic, LATEST TRENDS ON APPLIED MATHEMATICS,SIMULATION MODELLING, (pp.227-231.) .Corfu Island, Greece: Wseas Press.

[13]M.Murugappan, M.Rizon, R.Nagarajan and S.Yaacob (2008), EEG Feature Extraction For Classifying Emotions Using Fcm and Fkm. In Qing Li, S.Y Chen, Anping Zu and Ming Li, RECENT ADVANCES IN SYSTEMS, COMMUNICATIONS & COMPUTERS, (pp.299-304). Hangzhou, China:Wseas Press.

[14] Norzaliza Md Nor, Abdul Wahab (2010),Driver Identification and Driver's Emotion Verification using KDE and MLP Neural Networks, Proceeding 3rd International Conference on ICT4M 2010,Jakarta, Indonesia,3:96-101.

[15]Norzaliza Md Nor, Abdul Wahab, Norhaslinda Kamaruddin, and Hariyati Majid (2011). Post Accident Analysis of driver Affection, 15thIEEE Symposium on Consumer Electronics, ISCE 2011, Singapore.

[16] De Winter, J. C. F., de Groot, S., Mulder, M., Wieringa, P. A., Dankelman, J. and Mulder, J.A.(2008) 'Relationships between driving simulator performance and driving test results',Ergonomics, Oct 28:1- 24.