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Detecting Distraction in Drivers using Electroencephalogram (EEG) Signals

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Abstract

Driver distraction is considered as major factors in most of the traffic accidents. Driving errors may arise due to the distraction of the drivers. The aim of this paper is to analyze the EEG signals to detect distractive driving. Data from 10 different subjects were obtained and categorised into different frequency bands. Distractive driving is related with Theta band, so the Theta frequency band were decomposed using Discrete Wavelet Transform (DWT) and 17 different features were extracted. By enabling Principle Component Analysis (PCA) the accuracy rate was found for Cognitive Distraction and Visual Distraction using different machine learning algorithms. K Nearest Neighbour (KNN) performed well when compared to other machine learning algorithms with a better accuracy rate of 71.1%.

Keywords: Electroencephalogram, Distraction, Cognitive, Visual, Theta band.

I. Introduction

Distracted driving is driving while performing secondary which leads to the chance of a motor vehicle crash[1]. To understand the driver behaviour it is significant to monitor their states [2]. A statistics indicates that there were 34,439 fatal crashes happened in US involved by 51,914 drivers, and 37,461 peoples lost their life's in the year 2016[3]. National Highway Traffic Safety Administration (NHTSA) had taken a necessary effort to save lives by preventing this dangerous behaviour [4]. Driver's inattention can be categorized into Distraction and Fatigue in [5]. Five types of driver distraction was considered in a study by American Automobile Association Foundation for Traffic Safety (AAAFTS) [6] namely attentive, Distracted, Looked but did not see, sleepy and unknown. In this paper, two categories of distraction namely Cognitive Distraction, which is looked but did not see and Visual Distraction is analysed using EEG signals.

Generally, distraction of the drivers is detected using Vehicular measures (pedal movement, braking, and lane deviation). Behavioural measures (Face Movement, Head Movement, Eye Movement, and Mouth Movement). In case of behavioural measures, and Physiological measures such as Electrooculogram EOG), Electrocardiogram (ECG), Electroencephalogram (EEG) etc. The percentage of eye closure measures the alert level of the drivers and the eye position was classified as open and close using classifiers such as support vector machine[7]. In[8] a stereo camera was used to monitor the driver distraction in real time by analysing the face gaze of a driver. The current driving state of the driver was indicated using an android-based Smartphone apps which receives physiological and facial data via wireless sensor network[9]. The alertness of the driver was continuously monitored and determined using the visual analysis of eye behaviour and head posture[10]. An innovative driver assistance system was proposed to find the alert state of the drivers which can measure the physiological signals and eye-blinking activities in a single device[11]. In[12] the eye and head tracking data were applied through advanced data processing methods. As an alternative of focussing the individual parts of the body by studying the upper body posture and motion as a whole overcomes the limitations of general purpose tracking algorithms[13].

II. Related Works

One challenge in the study of distraction driving is the wide range of distraction exposed to drivers. These distraction can induced the drivers to perform the secondary task such as using mobile, interacting with passengers, seeing ad boards, listening music etc[14]. To build up a real time approach for cognitive detection using driver's eye blink and driver's performance data were applied to Support Vector Machines (SVM) models and the result indicates that an accuracy rate of 81% was obtained for detecting the driver distraction[15]. A new framework by map viewing to predict the starting and ending time of a distraction was executed in[16], and the overall accuracy values were 81% and 70%, respectively for 24 subjects. Most researchers focussed on vehicular and behavioural based prediction for distraction detection. So in this study we are focussing on EEG based method to predict distraction.

III. Proposed Methodology

The proposed methodology using EEG for driver distraction detection is shown in Figure 1. The EEG data is acquired from different subjects are splitted into sub bands. Theta band which is suitable for distraction detection was pre-processed; features were extracted and classified as Visual and Cognitive Distraction.

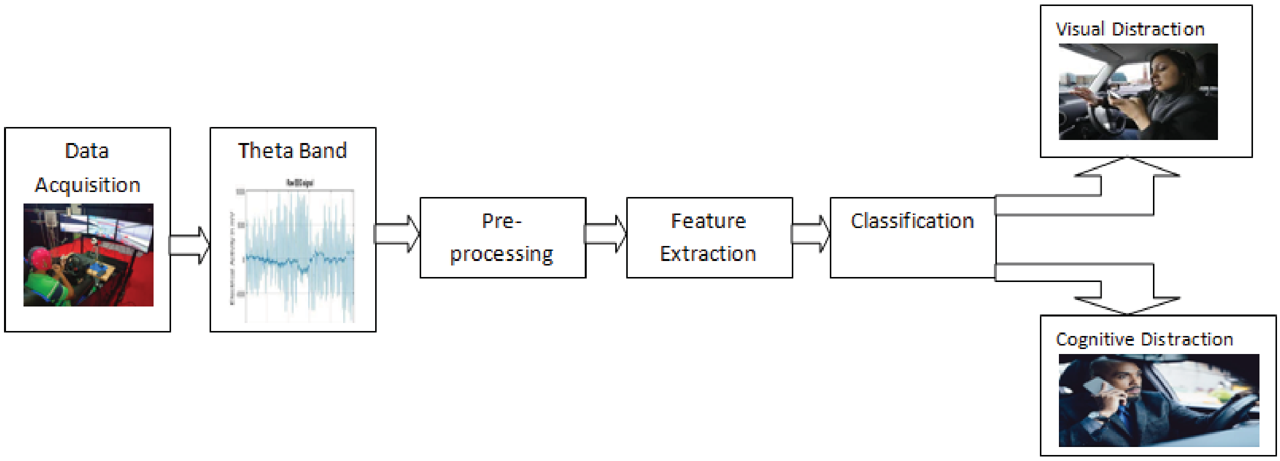

Figure 1: Proposed Methodology

A. Experimental Setup

A Virtual Reality based driving environment setup was installed in AI Research Lab at VISTAS. A speed dreams game was installed to make a feel of real road driving environment and the speed of the vehicle was set at a maximum of 60 Km/hr. A 21 channel EEG electrodes was used to obtain the data from 10 subjects in 3 different timings.Each participant has to participate the experiments in 3 different timings (midnight (01.00 am to 2.00 am); early morning (4.00 am to 5.00 am) and afternoon (2.00 pm to 4.00 pm). The experiments were held for 90- 120 minutes. An Infrared (IR) camera was used to capture the behavioural measures of the drivers. The subjects will be interrupted both visually (through messages) and cognitively (by phone call) while driving and the corresponding EEG data are recorded. The wall of the experimental area was covered with black cloth to have a feel of driving in night time. Figure 2 & Figure 3 represents the image taken during Cognitive Distraction & Visual Distraction

Figure2: Image taken during Cognitive distraction

Figure 3: Image taken during Visual distraction

IV. Signal Processing and Analysis

A band pass filter was set at a range of 0.5 Hz to 49 Hz to remove the noises and other artifacts like power line interference; eye movement etc from the raw EEG data. The filtered EEG data were categorized into different bands such as Delta (δ), Theta (θ), Alpha (α), Beta (β), and Gamma (γ). The distraction was related to Theta band (8-13 Hz), so only the theta band was used for further process. A wavelet analysis for the EEG was done and the Daubechies (DB4) fourth order Discrete Wavelet Transform was used to decompose the Theta band signals. The linear and nonlinear features such as Mean, Median, Maximum, Minimum, Standard Deviation, Kurtosis, Hurst, Root Mean Square, Trim Mean, Harmonic Mean, Nan Mean, Sample Entropy, Power, Energy, Mode and Variance were extracted for the theta band. Principle Component Analysis was enabled for features reduction. By using the classification learner tool the classifier accuracy for identifying the distraction type (Cognitive and Visual) was found using the following machine learning algorithms such as SVM and KNN.

V. Results and Discussion

A two class comparison between cognitive distraction and visual distraction was made using SVM and KNN algorithms. Table 1 shows the accuracy rate of 21 EEG channels for both cognitive and visual distraction using SVM and KNN.

Table 1: Accuracy rate of detecting distraction using SVM and KNN classifiers

Channels	Classifiers	Visual Distraction	Cognitive Distraction	Total
FP2	SVM	26	81.8	53.3
	KNN	91.3	50	71.1
FP1	SVM	100	4	51.1
	KNN	63.6	60.8	62.2
F7	SVM	100	4	53.3
	KNN	56.5	45.4	51.1
F3	SVM	100	0	51.1
	KNN	95.6	40.9	68.9
FZ	SVM	95.4	17.3	55.6
	KNN	22.7	91.3	57.8
F4	SVM	100	4.5	53.3
	KNN	100	9	55.6
F8	SVM	95.6	22.7	60
	KNN	73.9	36.3	55.6
T3	SVM	40.9	78.2	60
	KNN	95.4	8.6	51.1
C3	SVM	100	9	55.6
	KNN	52.1	63.6	57.8
CZ	SVM	95.6	9	53.3
	KNN	78.2	27.2	53.3
C4	SVM	100	4.3	51.1
	KNN	72.7	34.7	53.3
T4	SVM	95.6	9	53.3
	KNN	72.7	43.4	57.8
M2	SVM	91.3	18.1	55.6
	KNN	13	100	55.6
M1	SVM	95.4	13	53.3
	KNN	59	47.8	53.3
T5	SVM	9	100	55.6
	KNN	54.5	52.1	53.3
P3	SVM	100	21.7	60
	KNN	72.7	56.5	64.4
PZ	SVM	95.4	8.6	51.1
	KNN	95.4	13	53.3
P4	SVM	100	8.6	53.3
	KNN	59	56.5	57.8
T6	SVM	95.6	9	53.3
	KNN	60.8	50	55.6

O1	SVM	4	100	51.1
	KNN	100	0	51.1
O2	SVM	45.4	73.9	60
	KNN	90.9	17.3	53.3

Figure 4 shows the Accuracy rate of distraction using SVM and KNN classifier. It is clear that KNN Classifier performs well when compared to SVM. FP2 channel has the highest accuracy of 71.1% when compared with all other channels.

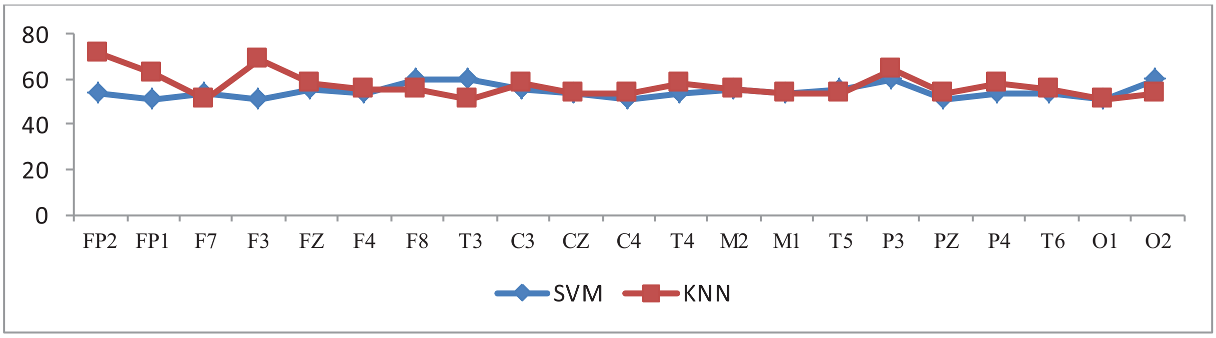

Figure 4: Total Accuracy rate of distraction using SVM and KNN classifier

The cognitive and visual distraction predicting percentage was also performed as shown in Figure 5 and Figure 6 respectively. Channels FP1, F3, F4, F7, C3, C4, P3 P4 and O1 has the accuracy rate of 100% for visual distraction and Channels M2, T5 and O1 have the highest accuracy rate of 100% for predicting cognitive distraction.

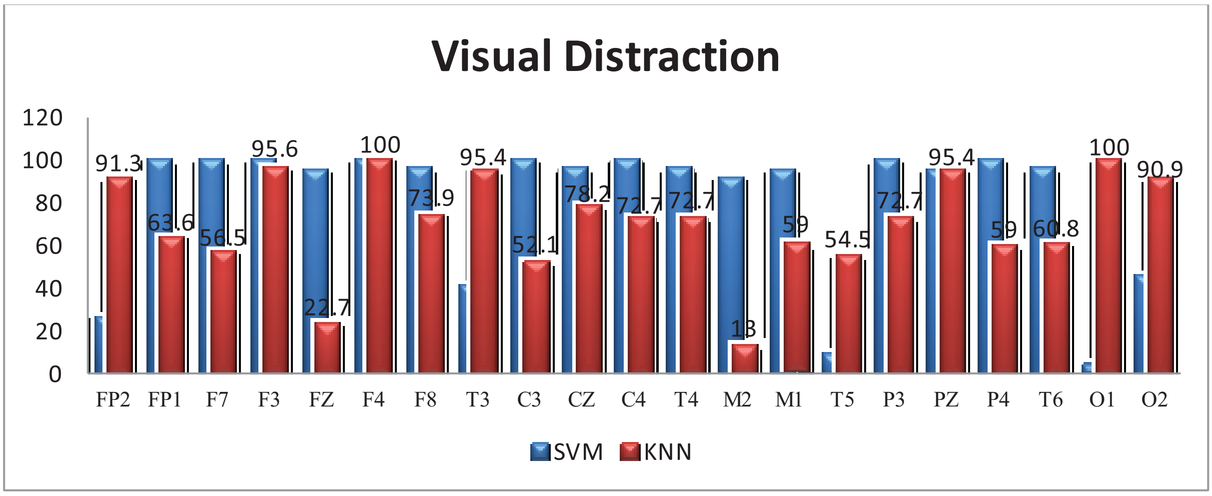

Figure 5: Comparison of Visual distraction using SVM and KNN classifier

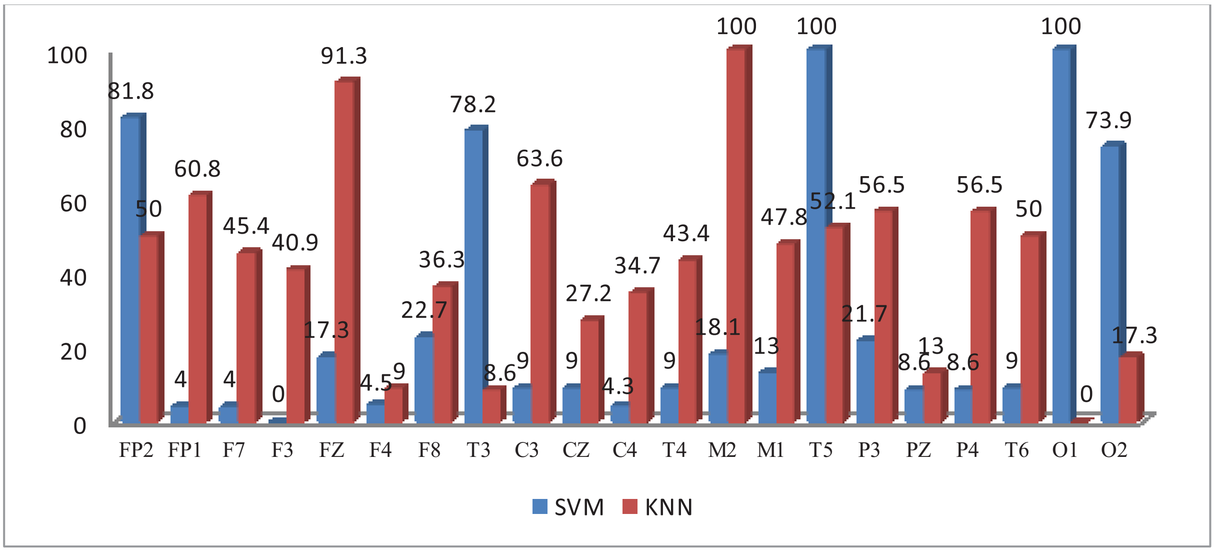

Figure 6: Comparison of Cognitive distraction using SVM and KNN classifier

In this study we implemented EEG based distraction detection. Based on our result the channels C3, C4, P3, P4, FP1, F7, F3, F4, and O1 has 100 % accuracy for predicting the visual distraction. While the driver is visually distracted he/she has to concentrate on the secondary task also (messaging while driving). But while in cognitive distraction the subjects view will not be affected, as he/she can see the road while talking on the phone. So the EEG signals will be more related to visual distraction when compared to cognitive distraction.

VI. Conclusion

In this paper, the results of both cognitive distraction and visual Distraction are compared, and it is found that channel FP2 has the highest accuracy rate of 71.1% for predicting distraction in drivers. An accuracy rate of 100% was obtained for predicting Visual distraction in 9 channels (FP1, F3, F7, F4, C3, C4, P3 P4 and O1). Similarly channels M2, T5 and O1 have the highest accuracy rate of 100% for predicting cognitive distraction. In future, using channel reduction techniques the channels can be reduced into a single channel or two channel electrodes for providing a compact model to alert the drivers from distraction.

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