2006 IEEE International Conference on Systems, Man, and Cybernetics
October 8-11, 2006, Taipei, Taiwan

Driving Style Classification by Analyzing EEG Responses to Unexpected Obstacle Dodging Tasks

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Abstract—**Driving safely has received increasing attention of the publics due to the growing number of traffic accidents that the driver's driving style is highly correlated to many accidents. The purpose of this study is to investigate the relationship between driver's driving style and driver's ERP response. In our research, a virtual reality (VR) driving environment is developed to provide stimuli to subjects. Independent component analysis (ICA) is used to decompose the electroencephalogram (EEG) data. The power spectrum analysis of ICA components and correlation analysis are employed to investigate the EEG activities related to driving style. Experimental results demonstrate that we may classify the drivers into aggressive or gentle styles based on the observed ERP difference corresponding to the proposed unexpected obstacle dodging tasks.**

I. Introduction

Recently, driving safely has received increasing attention of the publics due to the growing number of traffic accidents. Some researches described that the driver's driving style is highly correlated to many accidents [1-3]. De Raedt et. al. [1] classified drivers' driving style as bad, average or good, based on a structured road test and they also proposed an active compensation strategy to reduce the accidents. Reymond et. al. [2] proposed a driver model that characterizes "normal" or "fast" driving styles based on the test track for on-board driver aid systems. Van Mierlo et. al. [3] described different vehicle parameters and driver's driving style could be taken to increase transport safety or to reduce traffic jams.

In another aspect, the use of driving simulation for vehicle design and driver perception studies is expanding rapidly. Keneny and Panerai [4] suggested that, in driving simulators with a large field of view, longitudinal speed can be estimated correctly from visual information. Thus, there was few research in physiological response quantization related to driving style. However, K. Eba and his group [5] introduced a driving experiment to observe the brain activities related to driving situation. In a car driving task with and without an unexpected dummy doll rushing out, they recorded the homodynamic activities of the frontal lobe by near infrared spectroscopy (NIRS). However, the study investigate physiological signal related to driving style was very few in previous researches.

In our previous researches [6-8], driver's cognitive state can be successfully estimated by the analyzing EEG response combined with virtual-reality (VR) technique. In this study, we want to investigate the EEG changes related to different driving style by designing the unexpected obstacle dodging experiments. We first construct a virtual-reality (VR) based interactive driving environment to provide obstacle dodging tasks. After collecting the multi-stream brain potentials, the independent component analysis (ICA) [9-12] is used to remove a wide variety of artifacts based on blind source separation and to extract the representative ERP spectra related to subject's driving behavior. Finally, we may classify the subject's driving style by analyzing EEG response during the driver dodges an unexpected obstacle task.

This paper is organized as follow. The experimental setup is given in Section II. In Section III, we explore the data analysis procedure. The experimental results are presented in Section IV. Finally, the conclusions of this paper are summarized in Section V.

II. Experimental Setup

In this study, we designed a VR-based interactive unexpected obstacle dodging experiment to investigate the EEG correlations of driving style. The developed VR-based driving simulation environment includes three major parts as shown in Fig. 1: (1) the virtual driving environment based on dynamic virtual reality technology, (2) EEG measurement system with 30-channel EEG sensors and 2-channels EKG sensors, and (3) the steering wheel for the subject to control a virtual car.

A. The VR Scene

A VR-based driving simulation environment is designed

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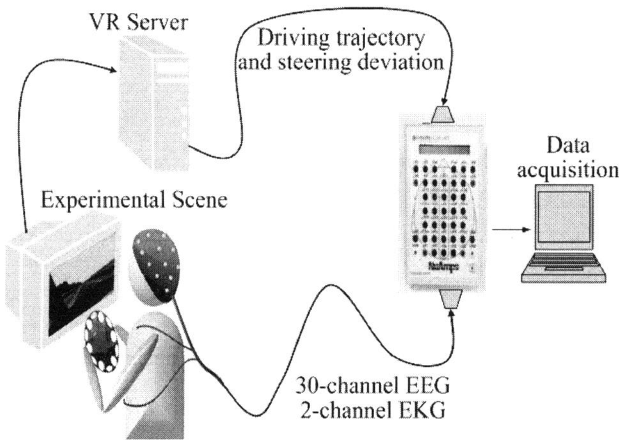

Fig. 1. Block diagram of the virtual-reality (VR)-based driving simulation environment and physiological signal acquisition system.

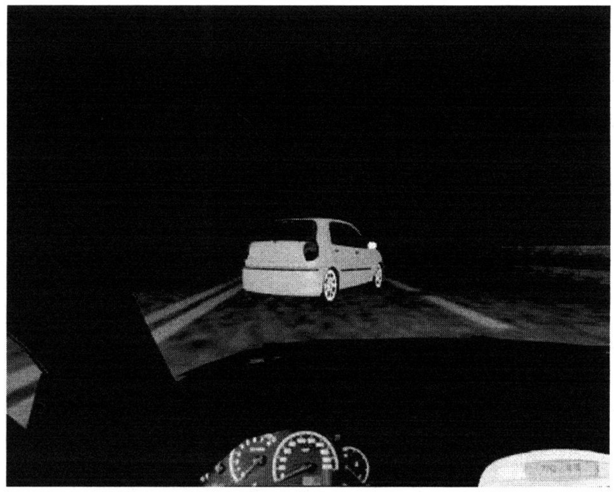

Fig. 2. The VR scene for obstacle dodging experiments.

and built up for interactive driving experiments. The appearance of an unexpected obstacle in the middle of the road during driving of the VR scene is designed as shown in Fig. 2. The VR scene was displayed on a color XVGA 42" Plasma Display Panel (PDP) to simulate a night time driving scene on freeway. The subjects are asked to sit in front of the PDP with the distance 60cm away from the displayer. The freeway VR scene we used in this study includes four lanes from left to right of the road. The distance from the left side to the right side of the road is equally divided into 256 points (digitized into values 0-255), where the width of each lane and the car are 60 units and 32 units, respectively. The frame rate of the scene changes as the driver is driving at a fixed velocity of 120 km/hr on freeway. The subjects are asked to keep the car in the VR scene in the middle of the third lane.

B. *Protocol of the Experiment*

The subject is asked to control the simulated car in the VR scene with the steering wheel and keep the car in the middle of the third lane. An obstacle task is provided to the subjects with a broken-down car appears in the middle of the road. The subjects are requested to dodge the broken-off car as soon as possible and avoid collision in the experiments. The Inter-trial intervals (ITIs) are set from 10 to 30 seconds, and differ from trial to trial randomly to avoid the anticipating effect of subjects.

Each subject participated in three driving experiments in three different days. The experiment start from a 1~5 minute training session and follows by two 30-min sessions including a 5 min break between these two experiment sessions. The EEG signals as well as the steering angle trajectory were recorded simultaneously during the experiments.

C. *Subjects and Data Collection*

Ten healthy volunteers (including seven males and three females) with no history of gastrointestinal, cardiovascular, or vestibular disorders participated in the experiments. They were requested not to smoke, drink caffeine, use drugs, or drink alcohol, all of which could influence the central and autonomic nervous system for a week prior to the main experiment. Three subjects' EEG data were excluded for further analysis because of the unexpected artifacts within the data. The EEG signals of seven subjects (one female and six males, ages from 21 to 26, all right-handed) with normal or corrected normal vision were further designed.

An electrode cap is mounted on the subject's head for signal acquisition on the scalp. The EEG electrodes were placed based on the 10-20 international system of electrode placement. Thirty (30) EEG channels (using sintered Ag/AgCl electrodes with an unipolar reference at right earlobe) and 2 ECG channels were measured in this experiment. The physiological signals and the event data from the scene as well as the steering angle trajectory were then sent through the Neuroscan biomedical signal amplifier to the data acquisition system.

III. Analysis Procedure

The angle variations of steering wheel and the trajectories of car movement are used to identify drivers' driving style. Fig. 3 shows two typical subjects' driving trajectories including the over-driving trajectory and the under-driving trajectory in this experiment.

The proposed data analysis procedure is given in Fig. 4. The driving style of each subject was identified according to the averaged driving trajectory and the steering deviation. Drivers were first classified into two categories: (1) the aggressive drivers (with over-driving trajectories), and (2) the gentle drivers (with under-driving trajectories). The event-related potentials (ERPs) of the subjects corresponding to the two types of driving style are extracted with the time interval [-500ms, 3000ms] respected the appearance of broken-off car. All ERPs are merged and analyzed with the independent component analysis (ICA) to decomposed ICA components for the feature extraction of the two subject's driving style. For each subject, the power spectrum of each ICA component in each epoch is first

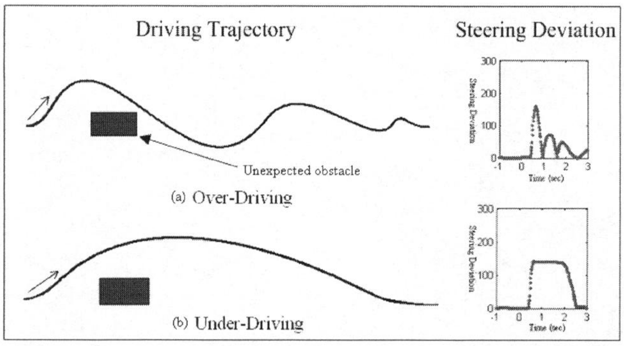

Fig. 3. Two typical driving trajectories related to two different driving styles.

calculated. The averaged power spectrum of each ICA component is next obtained by averaging the ICA power spectrum of all epochs.

We calculate the correlation coefficients of the power spectrum of different ICA components corresponding to two groups of subject for aggressive drivers and gentle drivers, respectively, as Eqs. (1) and (2),

$$R^{j}_{under-driving} = corrcoef(PSD^{j}_{1}, PSD^{j}_{6}), \quad (1)$$

$$R^{j}_{over-driving} = corrcoef(PSD^{j}_{5}, PSD^{j}_{8}), \quad (2)$$

where j indicate the jth independent component, PSD^{j}_{i} represents ith subject power spectrum of ICA component j. The averaged power spectrum of different ICA component can be calculated by Eqs. (3) and (4),

$$\overline{PSD}^{j}_{under-driving} = avg(PSD^{j}_{1}, PSD^{j}_{6}), \quad (3)$$

$$\overline{PSD}^{j}_{over-driving} = avg(PSD^{j}_{5}, PSD^{j}_{8}). \quad (4)$$

For component j, if $R^{j}_{under-driving} > 0.8$ and $R^{j}_{over-driving} > 0.8$ and the correlation coefficient between $\overline{PSD}^{j}_{under-driving}$ and

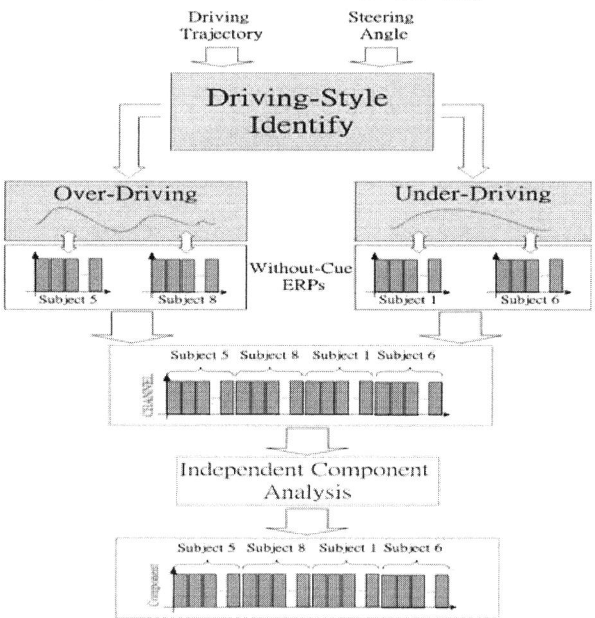

Fig. 4. The flowchart of driving style analysis.

$\overline{PSD}^{j}_{over-driving}$ is smaller than 0.5, this component is selected as a significant component related to driving style. According to the analysis, the 3th component shown in Fig. 5 is selected as the significant component.

IV. Experimental Results

According to Fig. 5, we average the power spectrum of all trials corresponding to ICA component 3. We can find the obvious power difference at 10Hz and 20Hz between aggressive and gentle drivers as shown in Fig. 6. Blue lines are the ERP spectrum of subject 5 and 8 who were identified as aggressive driver according to their driving trajectory. Red lines are the ERP spectrum of subject 1 and 6 with respect to ICA component 3 who were identified as gentle driver according to their driving trajectory. The aggressive driver's ERPs (Over-Driving drivers) have higher power at 10Hz and the gentle driver's ERPs (Under-Driving drivers) have higher power at 20Hz. We can use this observation to classify the driver's driving style by ERP analysis.

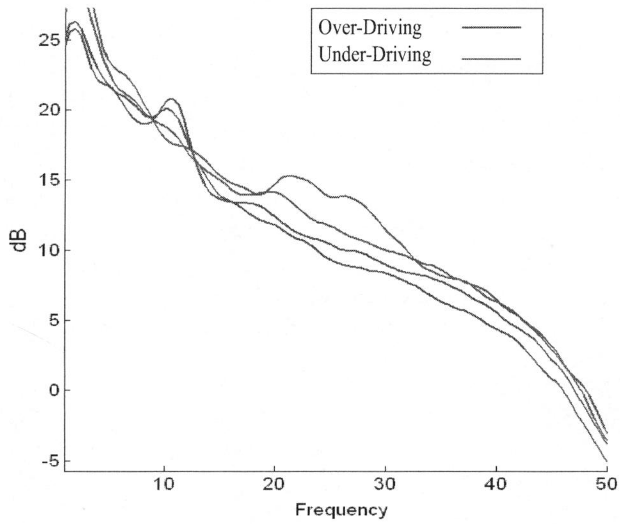

Fig. 5. The comparison waveform of ERP power spectrum

V. Conclusions and Discussions

In this study, the relationship between driver's driving style and driver's ERP response is discovered. After the comparison between steering deviation, driving trajectory, and the driver's ICA spectrum, we can find the obvious difference of power spectra magnitudes at 10Hz and 20Hz between aggressive and gentle drivers. We may classify the drivers into aggressive or gentle styles based on ERP difference. In the future, steering wheel can be designed to compensate the aggressive drivers' control for safety driving for the further application.

ACKNOWLEDGMENT

The authors would like to thank Mr. Tzyy-Ping Jung, Jeng-Ren Duann, and Ruey-Song Huang for their great help with developing and operating the experiments. This work was supported in part by the Brain Research Center in University System of Taiwan and National Chiao-Tung University, under Contrast 93E001, and National Science Council, Taiwan, under Contrast NSC 94-2213-E-009-096.

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