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Monitoring Driver's Alertness Based on the Driving Performance Estimation and the EEG Power Spectrum Analysis

S. F. Liang[1, 2*], C. T. Lin[1, 2], R. C. Wu[1, 2], Y. C. Chen[1, 2], T. Y. Huang[1, 2], and T. P. Jung[3]
[1]Brain Research Center, University System of Taiwan.
[2]Department of Electrical and Control Engineering, National Chiao-Tung University, Hsinchu, Taiwan.
[3]Institute for Neural Computation, University of California San Diego, La Jolla, CA, USA.

Abstract—Preventing accidents caused by drowsiness behind the steering wheel is highly desirable but requires techniques for continuously estimating driver's abilities of perception, recognition and vehicle control abilities. This paper proposes methods for drowsiness estimation that combine the electroencephalogram (EEG) log subband power spectrum, correlation analysis, principal component analysis, and linear regression models to indirectly estimate driver's drowsiness level in a virtual-reality-based driving simulator. Results show that it is feasible to quantitatively monitor driver's alertness with concurrent changes in driving performance in a realistic driving simulator.

Keywords—Alertness, EEG, power spectrum, correlation analysis, linear regression model.

I. INTRODUCTION

Accidents caused by drowsiness at the wheel have a high fatality rate because of the marked decline in the driver's abilities of perception, recognition and vehicle control abilities while sleepy. Driver's fatigue has been implicated as a causal factor in many accidents, e.g., the National Transportation Safety Board found that 58 percent of 107 single-vehicle roadway departure crashes were fatigue-related in 1995. Preventing such accidents is thus a major focus of efforts in the field of active safety research [1-5]. A number of methods have been proposed to detect vigilance changes in the past. One focuses on physical changes during fatigue, such as the inclination of the driver's head, sagging posture, and decline in gripping force on steering wheel [6-8]. The others focuses on measuring physiological changes of drivers, such as eye activity measures, heart beat rate, skin electric potential, and particularly, electroencephalographic (EEG) activities as a means of detecting the cognitive states [12-16]. Although the eye blink duration and blink rate typically increase while blink amplitude decreases as function of the cumulative time on tasks, those eye-activity based methods require a relatively long moving averaged window aiming to track slow changes in vigilance, whereas the EEG-based method can use a shorter one to track second-to-second fluctuations in the subject performance [10-12]. While approaches based on EEG signals have the advantages for making accurate and quantitative judgments of alertness levels, most recent psychophysiological studies have focused on using the same estimator for all subjects [15-16]. These methods did not account for large individual variability in EEG dynamics accompanying loss of alertness, and thus could not accurately estimate or predict individual changes in alertness and performance.

In this paper, the scope of the current study is to examine neural activity correlates of fatigue/drowsiness. Our research investigates the feasibility of using multi-channel EEG power spectrum and linear regression models to estimate non-invasively the continuous fluctuations in individual operators' changing levels of alertness indirectly by measuring the driver's driving performance expressed as deviation between the center of the vehicle and the center of the cruising lane in a very realistic driving task. This paper is organized as follows. Section II describes the details of the EEG-based drowsiness experimental setup. Data analysis is given in Section III. In Section IV, we explore the relationship between the alertness level and the EEG power spectrum. Behavioral data are used to evaluate estimation performance of our alertness-monitoring model. Finally, we conclude our findings in Section V.

II. METHODOLOGY

A. VR-based Highway Driving Simulator

In this study, we developed a Virtual-Reality (VR)-based interactive highway scene. The continued construction of highway and monotonous operation of driving make it easy for drivers to feel drowsy within hours. Fig. 1 shows the VR-based highway scene displayed on a color XVGA 15" monitor including four lanes from left to right to simulate the view of the driver. The distance from the left side to the right side of the road is evenly divided into 256 parts (digitized into values 0-255). The highway scene changes interactively as the driver is driving the car at a fixed velocity of 100 km/hr on the highway. The car is constantly and randomly drifted away from the center of the cruising lane, mimicking the consequences of a non-ideal road surface.

B. Subjects

Statistical reports [4] 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. A total of 16 subjects (ages from 20 to 40 years) participated in the VR-based highway driving experiments. Each subject completed simulated driving sessions on two separated days. On the first day, these participants started with a 15-45 minutes practice to keep the car at the center of the cruising with the steering wheel. After practicing, subjects began a 45-minute lane-keeping driving task. The driver's EEG signals and driving performance defined as deviations of the center of the car from the center of the third lane of the road were simultaneously recorded. Participants returned on a different day to complete the other 45-minute driving session. Participants who demonstrated waves of drowsiness containing two or more micro-sleep in both sessions were selected for further analysis. Based on these criteria, five participants (10 sessions) were selected for further modeling and cross-session testing.

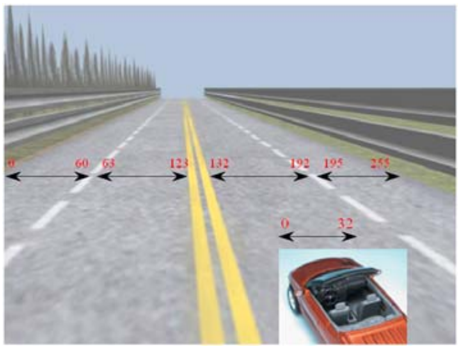

Fig. 1. VR-based highway scene.

C. Data Collection

During each driving session, participants were fitted with 33 EEG/EOG channels using sintered Ag/AgCl electrodes with an unipolar reference at right earlobe based on a modified International 10-20 system, and 2 ECG channels using bipolar connection placed on the chest. The driving performance and EEG/EOG/ECK signals are simultaneously recorded by the Scan NuAmps Express system (Compumedics Ltd., VIC, Australia). Before data acquisition, the contact impedance between EEG electrodes and cortex was calibrated to be less than 5kΩ. The EEG data were recorded with 16-bit quantization level at a sampling rate of 500 Hz and then re-sampled down to 250 Hz for the simplicity of data processing. We also defined a subject's driving performance as the deviation between the center of the vehicle and the center of the cruising lane to indirectly quantify the level of the subject's alertness. When the subject is drowsy (checked from both video recordings and subject's reports), the car deviation increases, and vice versa. The recorded driving performance time series were then smoothed using a causal 90s square moving-averaged filter advancing at 2s steps to eliminate variance at cycle lengths shorter than 1-2 minutes since the cycle lengths of drowsiness level with fluctuates were longer than 4 minutes [11-12].

III. Data Analysis

The flowchart of data analysis for estimating the level of alertness based on the EEG power spectrum is shown in Fig. 2. For each subject, after collecting 33-channel EEG signals and driving deviations in a 45-mininute simulated driving session, the EEG data were first preprocessed using a simple low-pass filter with a cut-off frequency of 50 Hz to remove the line noise and other high-frequency noise. Then, we calculate the moving-averaged log power spectra of all 33 EEG channels by using a 750-point Hanning window with 250-point overlap. The windowed 750-point epochs were further sub-divided into several 125-point sub-windows using Hanning window again with 25-point steps, and each sub-window was extended to 256 points by zero padding for a 256-point FFT. A moving median filter was then used to average and minimize the presence of artifacts in the EEG records of all sub-windows. The moving averaged EEG power spectra were further converted to a logarithmic scale for spectral correlation and driving performance estimation. Thus, the time series of EEG log power spectrum for each session consisted of 33-channel EEG power spectrum estimated across 40 frequencies (from 1 to 40 Hz) stepping at 2s time intervals.

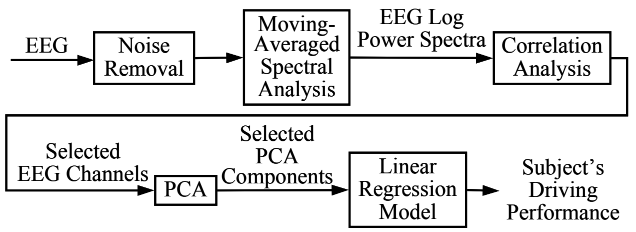

Fig 2: Analysis flowchart of the EEG signals.

Then we calculate the correlation coefficients between the smoothed subjects' driving performance and the log power spectra of all EEG channels at each frequency band to form a correlation spectrum. The log power spectra of 2 EEG channels with the highest correlation coefficients are selected. We further applied the Principal Component Analysis (PCA) to decomposed the selected 2-channel EEG log power spectrum and extract the directions of largest variance for each session. Projections (PCA components) of the EEG log spectral data on the subspace formed by the eigenvectors corresponding to the largest 50 eigenvalues were then used as inputs to train the individual linear regression model for each subject, which used a 50-order linear polynomial with a least-square-error cost function to estimate the time course of the driving performance. Each model was trained using the features extracted from the training session and only tested on a separate testing session from the same subject.

IV. RESULTS AND DISCUSSIONS

A. Relationship between the EEG Spectrum and Subject Alertness

To investigate the fluctuations in driving performance to concurrent changes in the EEG spectrum, we measured correlations between changes in the EEG power spectrum and driving performance to form a correlation spectrum. We investigated the spatial distributions of these positive correlation spectra on the scalp at dominant frequency bins, 7, 12, 16 and 20Hz, separately, as shown in Fig. 3. The correlations are particularly strong at central and posterior channels, which are similar to the results of previous studies in the drowsy experiments [12-13]. The relatively high correlation coefficients of EEG log power spectrum with driving performance suggests that using EEG log power spectrum may be suitable for drowsiness (micro-sleep) estimation, where the subject's cognitive state might fall into the first stage of the non-rapid-eye-movement (NREM) sleep. To be practical for routine use during driving or in other occupations, EEG-based cognitive assessment systems should use as few EEG sensors as possible to reduce the preparation time for wiring drivers and the computational load for estimating continuously the level of alertness in near real time. According to the correlations shown in Fig. 3, we believe it is adequate to use 2-channel EEG signals having the highest correlation coefficients to assess the alertness level of drivers.

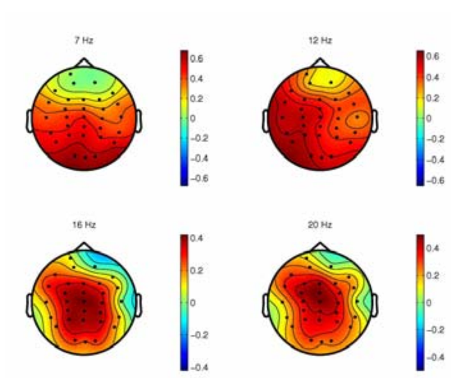

Fig. 3: Scalp topographies for the correlations between EEG power and driving performance at dominant frequencies 7, 12, 16, and 20 Hz, computed separately for 40 EEG frequencies between 1 and 40 Hz.

Next, we compared correlation spectra for individual sessions to examine the stability of this relationship over time and subjects. The time interval between the training and testing sessions of the lane-keeping experiments distributes over one day to one week long for the selected five subjects. Fig. 4 plots correlation spectra at cites Fz, Cz, Pz and Oz, of two separate driving sessions with respect to subjects A. The relationship between EEG power spectrum and driving performance is stable within the subjects, especially the spectrum below 20 Hz. These analyses provide strong and converging evidence that changes in subject alertness level indexed by driving performance during a driving task are strongly correlated with the changes in the EEG power spectrum at several frequencies at central and posterior cites. This relationship is relatively variable between subjects, but stable within subjects. It is consistent with the findings from a simple auditory target detection task reported in [11-12]. These findings suggest that information available in the EEG can be used for real-time estimation of changes in alertness of human operators. However, to achieve maximal accuracy, the estimation algorithm should be capable of adapting to individual differences in the mapping between EEG and alertness.

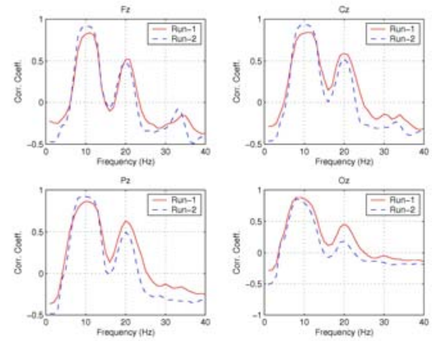

Fig. 4: Correlation spectra between the EEG power spectrum and the driving performance at Fz, Cz, Pz, and Oz channels in two separate driving sessions with respect to subject A. Note that the relationship between EEG power spectrum and driving performance is stable within this subject.

B. EEG-based Driving Performance Estimation/Prediction

In order to estimate/predict the subject's driving performance based on the information available in the EEG power spectrum, a 50-order linear regression models with a least-square-error cost function is used. We used only two EEG channels with the highest correlation coefficients in place of using all 33 channels to avoid introducing more unexpected noise. Fig. 5 plots the estimated and actual driving performance of a session with respect to subject A. The linear regression model in this figure is trained with and tested against the same session, i.e. within-session testing. As can been seen, the estimated driving performance matched extremely well with the actual driving performance (r = 0.91).

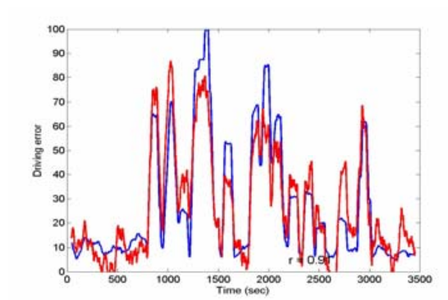

Fig. 5. Driving performance estimates for a session with respect to subject A, based on a linear regression (red line) of PCA-reduced EEG log spectra at two scalp sites, overplotted against actual driving performance time series for the session (solid line). The correlation coefficient between the two time series is r = 0.91.

When the model was tested against a separate test session with respect to the same subject, the correlation between the actual and estimated driving performance though decreased but remained high (r = 0.87) as shown in Fig. 6. Across 10 sessions, the mean correlation coefficient between actual driving performance time series for within-session estimation is 0.85 ± 0.11, whereas the mean correlation coefficient for cross-session estimation is 0.82 ± 0.07. These results suggest that continuous EEG-based driving performance estimation using a small number of data channels is feasible, and can give accurate information about minute-to-minute changes in operator alertness.

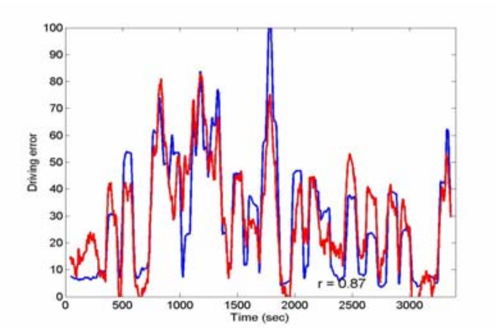

Fig. 6. Driving performance estimates for a test session, based on a linear regression (red line) of PCA-reduced EEG log spectra trained from a separate training session with respect to the same subject, overplotted against actual driving performance time series of the test session (solid line). The correlation coefficient between the two time series is r = 0.87. Note that the training and testing data in this study were completely disjoined.

V. Conclusion

In this study, we demonstrated a close relationship between minute-scale changes in driving performance and the EEG power spectrum. Our results demonstrated that it is feasible to accurately estimate driving errors based on multi-channel EEG power spectrum estimation and principal component analysis algorithm. Once an estimator has been developed for a driver, based on limited pilot testing, the method uses only spontaneous EEG signals obtained from the individual without requiring further collection or analysis of operator performance. The proposed methods thus might be practicable for applying to an online portable embedded system to perform a real-time alertness monitoring system.

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