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EEG Spectrum Analysis of Various Electrodes from Sleep Stages of Detection and Drowsiness with Monitoring Driving Performance of Estimation Control System

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Abstract: The growing number of traffic accidents in resent years has become a serious concern to society. Accidents caused by driver's drowsiness behind the steering 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. 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 study proposes methods for drowsiness estimation that combine the Electroencephalogram (EEG) log sub band power spectrum, correlation analysis, principal component analysis, Autoregressive (AR) Model and Liner 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.

Key words: Alertness, EEG, power spectrum, spectrum analysis, Autoregressive (AR) Model, Linear Regression Model

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% 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 (French, 2002; Wierwille *et al*., 1994; Amditis *et al*., 2002; Ueno *et al*., 1994; Pilutti and Ulsoy, 1999). 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 (Smith *et al*., 2000; Perez *et al*., 2001; Popieul *et al*., 2003). 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 (Makeig and Inlow, 1993; Makeig and Jung, 1996; Matousek and Petersen, 1983; Roberts *et al*., 2000; Wilson and Bracewell, 2000). 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 fluctuations in the subject performance (Roberts *et al*., 2000; Van Orden *et al*., 2001; Jung *et al*., 1997). While approaches based on EEG signals have the advantages for making accurate and quantitative judgments of alertness levels, most recent psycho physiological studies have focused on using the same estimator for all subjects (Roberts *et al*., 2000; Wilson and Bracewell, 2000). 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.

Oscillatory signal activities are ubiquitous in the biomedical signal (Buzsaki, 2006). Multi electrode recordings provide the opportunity to study signal oscillations from a network perspective. To assess signal interactions in the frequency domain, one often applies methods such as ordinary coherence and granger

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causality spectra (Chen *et al*., 2006) that are formulated within the frame work of liner stochastic process. Electroencephalogram (EEG) is one of the most important electrophysiological techniques used in human clinical and basic sleep research. Barlow (1979) proposed liner modeling system which has a long lasting history in EEG analysis. The models are mainly considered as a mathematical description of the signal and less as a Biophysical Model of the underlying neuronal mechanisms.

Franaszczuk and Blinowska (1985) proposed a model to interpret liner models as damped harmonic oscillators generating EEG activity based on the equivalence between stochastically driven harmonic oscillators and Autoregressive (AR) Models. There is a unique transformation between the AR coefficients and the frequencies and damping coefficients of the corresponding oscillators. In particular at times when the EEG is dominated by a certain rhythmic activity, on might expect that this activity will be rejected by a pole with a corresponding frequency and low damping. This idea was the starting point of the analysis (Olbrich and Achermann, 2004).

The sleep EEG is always not stationary, However, researchers demonstrated that the effects of non stationary become relevant only with scales >1s (Olbrich *et al.* 2003). Therefore, short segments with duration of around 1s are sufficiently described by linear models. The non stationary in longer time scales might be rejected by the variation of the AR-coefficient and thus by the corresponding frequencies and damping coefficients. Based on the above considerations, researchers propose an easy way to define oscillatory events. They are detected, whenever the damping of one of the poles of a 1s AR Model is below a predefined threshold.

In this research, the scope of the current study is to examine neural activity correlates of fatigue/drowsiness. The research investigates the feasibility of using multi channel EEG power spectrum and liner regression models to estimate non-invasively the continuous fluctuations in individual operators' changing level 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.

MATERIALS AND METHODS

VR-based highway driving simulator: In this study, researchers 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. Figure 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 highway scene changes interactively as the driver is driving the car at a fixed velocity of 100 km h^{-1} on the highway. The car is constantly and randomly drifted away from the center of the cruising lane, mimicking the consequences of a non-idea road surface.

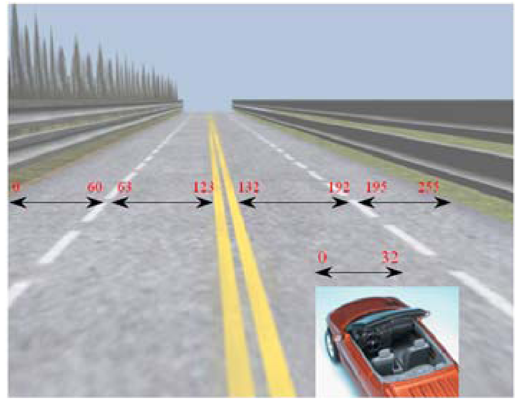

Fig. 1: VR based highway scene

Subjects: Statistical reports (Ueno *et al*., 1994) showed that the best time for doing the highway-drowsiness simulation is the early afternoon hours after lunch because drivers usually get drowsy within 1 h of continuous driving, a total of 16 subjects participated in the VR-based highway driving sessions on 2 separated days. On the 1st day, these participants started with a 15-45 min practice to keep the car at the center of the cruising with the steering wheel. After practicing, subjects began a 45 min 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 min driving session. Participants who demonstrated waves of drowsiness containing two or more micro-sleep in both sessions were selected for further analysis.

Data collection During each driving session, participants were fitted with 33 EEG/EOG channels using sintered Ag/AgC1 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.

An EEG amplifier measures voltage differences between points on the scalp. This implies that each channel is connected to two electrodes. Usually, measurement is "unipolar" rather than "bipolar" which means that the second electrode is identical for all channels and called "reference" (Ref). Also, amplifier inputs must be kept within a small voltage range relative to the amplifier's zero (ground) voltage level. This is achieved by connecting yet another electrode, a "ground" (Gnd) electrode, to the subject's scalp.

EEG electrodes are small metal plates that are attached to the scalp using a conducting electrode gel. They can be made from various materials. Most frequently, tin (Sn) and silver/silver-chloride (Ag/AgCl) electrodes are used but there are gold (Au) and platinum (Pt) electrodes as well.

While Sn electrodes have the advantage of being cheap, they introduce a large amount of low-frequency noise ("drifting") below 1 Hz. For low-frequency recordings such as slow cortical potential measurements or low-noise ERP recordings, Ag/AgCl electrodes are typically used.

Important but often neglected: using electrodes made from different materials in the same recording will result in DC voltage offsets between electrodes due to electrochemical contact potentials. Such contact potentials are generally larger than what a typical amplifier tolerates. The result will be a zero or much diminished signal amplitude and a bad signal to noise ratio. This applies to all amplifier inputs, i.e., channels, reference and ground electrodes must all be made from the same material.

The driving performance and EEG/EOG/ECK signals are simultaneously recorded. Before data acquisition, the contact impedance between EEG electrodes and cortex was calibrated to be <5 kΩ. The EEG data were recorded with 16 bit quantization level at sampling rate of 500 Hz and then re-sampled down to 250 Hz for the simplicity of data processing. Researchers also defined a subject's driving performance as the deviation between the center of the vehicle and the center of 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, the car deviation increases and vice versa. The recorded driving performance time series were then smoothed using driving performance time series were then smoothed using a causal 90 sec square moving-averaged filter advancing at 2 sec steps to eliminate variance at cycle lengths <1-2 min since the cycle lengths of drowsiness level with fluctuates were >4 min (Makeig and Inlow, 1993; Jung *et al*., 1997).

AR Model: The parametric description of the EEG signal by means of the AR Model makes possible estimation of the transfer function of the system in the straight forward way. From the transfer function it is easy to find the differential equation describing the investigated process. The detection algorithm is based on modeling 1 sec segments of the EEG time using Autoregressive (AR) models of order p. From the AR (p) Model:

$$\sum_{j=0}^{p} a_j x_{n-1} = \varepsilon_n \tag{1}$$

Where:

a_j = Coefficients of the model ($a_0 = 1$)
x_n = The value of the sampled signal at the moment n
ε_n = Zero mean uncorrelated white noise process

Applying the z transform to Eq. 1 we obtain:

$$A(z)X(z) = E(z) \tag{2}$$

Where:

$$A(z) = \sum_{j=0}^{p} a_j z^{-j} \tag{3}$$

X (z) = The Z transform of the signal x
E (z) = The Z transform of the noise

If the system is stable, there exists $A^{-1}(z)$ and researchers get:

$$X(z) = A^{-1}(z)E(z) \tag{4}$$

In the z domain, this filter is expressed by the Eq. 4 where A^{-1} (z) is the transfer function. Denoting it by H(z) and writing if explicitly, researchers obtain:

$$H(z) = A^{-1}(z) = \frac{1}{\sum_{j=0}^{p} a_j z^{-j}} \tag{5}$$

Multiplying numerator and denominator z^p, researchers get:

$$H(z) = \frac{z^p}{\sum_{j=0}^{p} a_j z^{p-j}} \tag{6}$$

Factorizing the denominator gives equatiopn:

$$H(z) = \frac{z^p}{\prod_{j=1}^{p} (z-z_j)} \tag{7}$$

where, $z_j = r_k e^{i\varphi k}$. Using the above equation to estimate the frequencies $f_k = \varphi_k/(2\pi\Delta)$ and damping coefficients $\gamma_k = \Delta^{-1}\ln r_k$ (Δ denotes the sampling interval). Researchers assume that there are only single poles of H(Z) which can be written in the form:

$$H(z) = \sum_{j=1}^{p}\left(\frac{z}{z\text{-}z_j}\right) \tag{8}$$

For the single pole coefficients c_j can be found according to the equation:

$$c_j = \lim_{z\to z_j}\frac{(z-Z_j)H(z)}{z} \tag{9}$$

By means of the inverse transform $-z^{-1}$ from the Eq. 8 the impulse response of the system: h (n) can be found. Since, from the properties of the z^{-1} transform we know that $z^{-1}(z/z\text{-}z_j) = \exp(n.\ln z_i)$, researchers obtain:

$$h(n) = z^{-1}(H(z)) = \sum_{j=1}^{p} c_j \exp(n.\ln z_j) \tag{10}$$

If the sampling interval Δt was chosen according to the Nyquist theorem we can express the impulse response as continuous function and write it in the form:

$$\begin{aligned} h(t) &= \sum_{j=1}^{p} c_j \exp\left(\frac{t}{\Delta t}\ln z_j\right) \\ &= \sum_{j=1}^{p} c_j \exp(a_j t) \end{aligned} \tag{11}$$

Where:

$$t = \Delta t \times n a_j = \frac{\ln z_j}{\Delta t}$$

Laplace transform of the Eq. 11 which corresponds to the transfer function H(s) of the continuous system is given by the equation:

$$H(s) = \sum_{j=1}^{p} c_j \frac{1}{(s\text{-}a_j)} \tag{12}$$

The above expression can obtained directly from Eq. 8 by means of the integral transform z. Equation 12 can be written as a ratio of two polynomials of the order p-1 and p:

$$H(s) = \frac{b_{p-1}s^{p-1}+\ldots.+b_1 s+b_0}{c_p s^p+\ldots..+c_1 s+c_0} \tag{13}$$

The polynomial coefficients can be readily calculated from c_j and a_j. This form of the transfer was found also by Freeman. It leads directly to the differential equations describing the system. The transfer function is the ratio of the Laplace transform of input y(t) and output x(t) functions:

$$H(s) = \frac{X(s)}{Y(s)} = \frac{L(x(t))}{L(y(t))} \tag{14}$$

Since, variable s corresponds to the operator d/dt, from Eq. 13 and 14, researchers get:

$$c_p\frac{d^p}{dt^p}x(t)+\ldots+c_1\frac{d^1}{dt^1}x(t)+c_0 x(t) = \frac{d^{p-1}}{dt^{p-1}}y(t)+\ldots+b_1\frac{d^1}{dt^1}y(t)+b_0 y(t) \tag{15}$$

In this way, researchers have obtained the differential equation describing the system which is free of the arbitrary parameters. Its order is determined by the characteristic of the signal and may be found from the criteria based on the principal of the maximum of entropy.

BLOCK DIAGRAM OF EEG SIGNALS

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 min simulated driving session, the EEG data were first preprocessed using a simple low-pass filter with a cut-of frequency of 50 Hz to remove the line noise and other high-frequency noise. Then, researchers calculate the moving-averaged log power spectra of all 33 EEG channels by using a 750-point Henning window with 250 point overlap. The windowed 750 point epochs were further sub-divided into several 125 point sub windows using Hanning window was extended to 256 points by zero padding for a 256 point FFT. A moving median filter was the 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

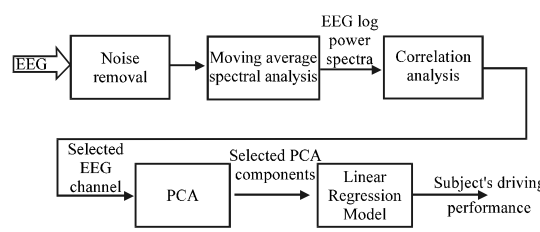

Fig. 2: Block diagram of driving performance of sleep stages for monitoring control system

spectrum for each session consisted of 33 channel EEG power spectrum estimated across 40 frequencies stepping at 2 sec time intervals.

Then, researchers calculate the correlation coefficients between the smoothed subjects' driving performance and the log power spectra of all EEG channels at each frequency band to from a correlation spectrum. The log power spectra of 2 EEG channels with the highest correlation coefficients are selected. Researchers further applied the Principal Component Analysis (PCA) to decompose the selected 2 channel EEG log power spectrum and extract the directions of largest variance for each session. Projection of the EEG log spectral data on the subspace formed by the eigenvectors corresponding to the largest 50 eigen values were then used as inputs to train individual Linear Regression Model for each subject which used a 50 order liner 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 separated testing session from the same subject.

RESULTS AND DISCUSSION

Relationship between the EEG spectrum and subject alertness: To investigate the fluctuations in driving performance to concurrent changes in the EEG spectrum, researchers measured correlations between changes in the EEG power spectrum and driving performances to from a correlation spectrum. Researchers investigated the spatial distributions of these positive correlation spectra on the scalp at dominant frequency bins, 7, 12, 16 and 20 Hz, separately as shown in Fig. 3. The correlations are

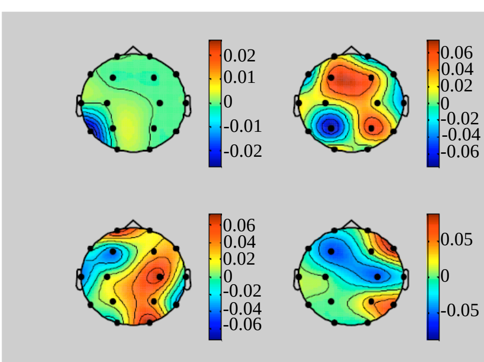

Fig. 3: Scalp topographies for the correlations between EEG power and driving performance at dominant frequencies 7, 12, 16 and 20 Hz, computed separately for 40 EEG frequencies between 1 and 40 Hz

particularly strong at central and posterior channels which are similar to the results of previous studies in the drowsy experiments (Makeig and Inlow, 1993; Makeig and Jung, 1996). The relatively high correlation coefficients of EEG log power spectrum with driving performance suggests that using EEG log power spectrum may 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, researchers believe it is adequate to use 2-channel EEG signals having the highest correlation coefficients to assess the alertness level of drivers.

Next, researchers 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 1 day to 1 week long for the selected five subjects. Figure 4 plots correlations 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 provided 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 by Makeig and Inlow (1993) and Jung *et al*. (1997). These finding 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 cable of adapting to individual differences in the mapping between EEG and alertness.

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 liner regression models with a least square error cost function is used. Researchers used only two EEG channels with the highest correlation

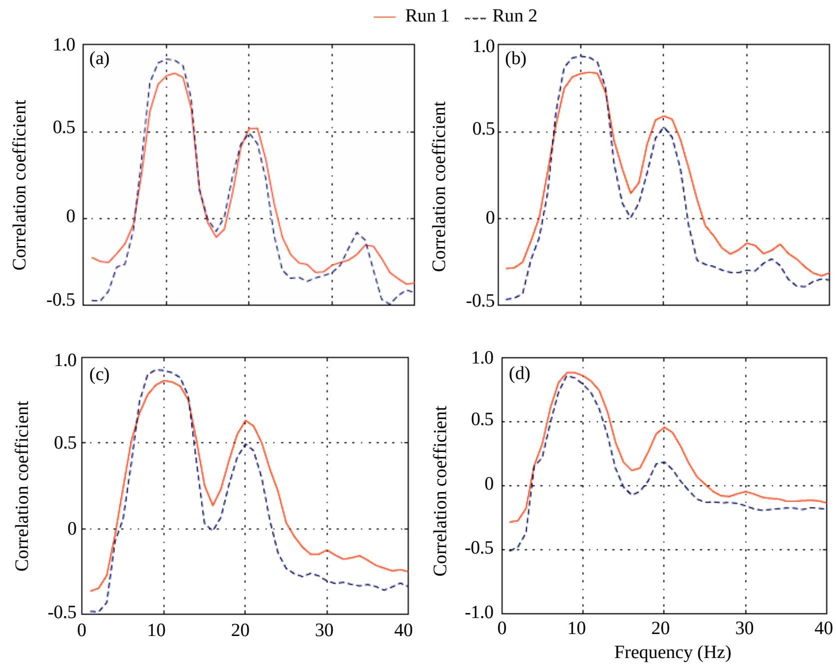

Fig. 4: Correlation spectra between the EEG power spectrum and the driving performance at a) Fz, b) Cz, c) Pz and d) Oz channels in two separate driving sessions with respect to subject A. Note that relationship between EEG power spectrum and driving performance is stable within this subject

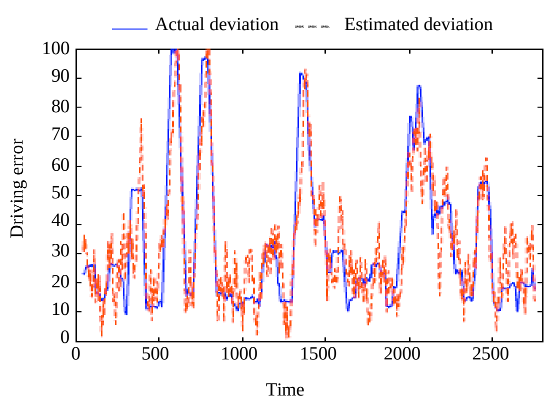

Fig. 5: Driving performance estimates for a session with respect to subject A, based on liner regression (red line) of PCA-reduced EEG log spectra at two scalp sites, over plotted against actual driving performance time series for the session (solid line). The correlation coefficient between the two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

coefficients in place of using all 33 channels to avoid introducing more unexpected noise. Figure 5 plots the estimated and actual driving performance of session. The liner regression model in Fig. 5 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 driving performance (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.

Electrode locations and names are specified by the international 10-20 system for most clinical and research applications. This system ensures that the naming of electrodes is consistent across laboratories. In most clinical applications, 19 recording electrodes are used. The brain machines use 2 or 4 channels and they monitor the frontal lobe at positions Fp1 and Fp2 (left and right above each eyebrow). Figure 7 and 8 show that the EEG spectrum performance of FP1 and FP2 electrodes. Figure 9 and 10 show that the EEG spectrum performance

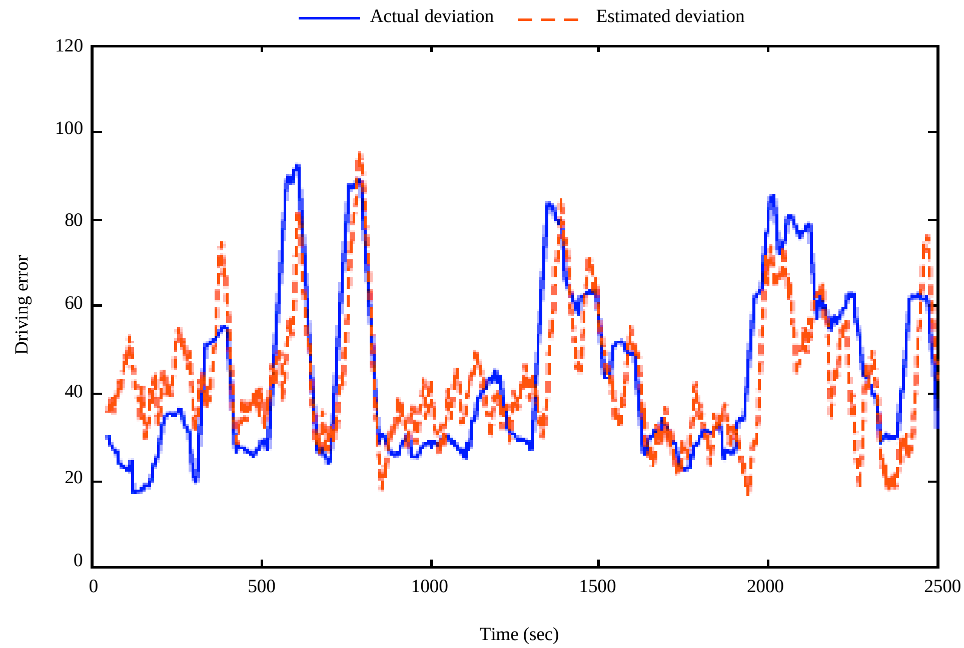

Fig. 6: Driving performance estimates for a test session based on a linear regression (red line) of PCA- reduced EEG log spectra trained from a separate training session with respect to the same subject, over plotted against actual driving performance time series of the test session (solid line). The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

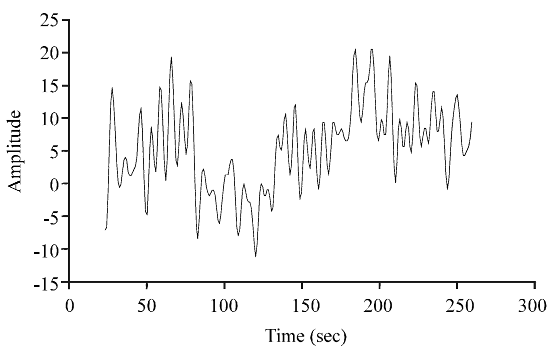

Fig. 7: EEG performance of FP1 electrode

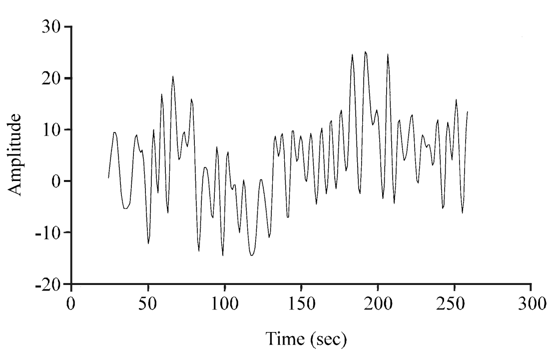

Fig. 8: EEG performance of FP2 electrode

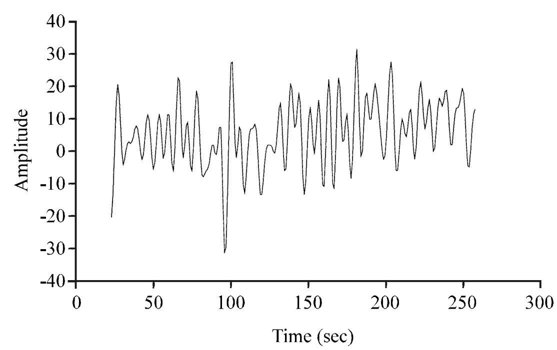

Fig. 9: EEG performance of F7 electrode

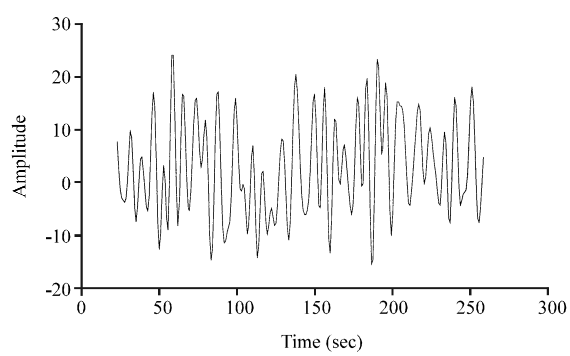

Fig. 10: EEG performance of F8 electrode

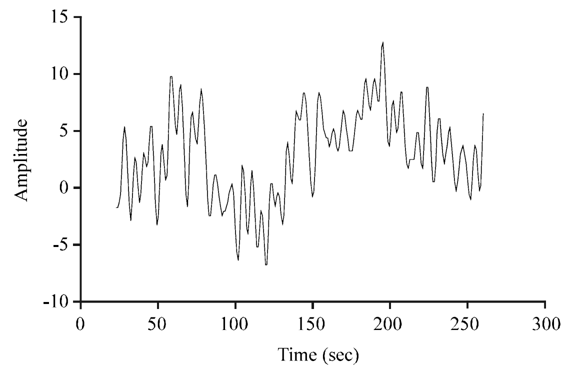

Fig. 11: EEG performance of AF1 electrode

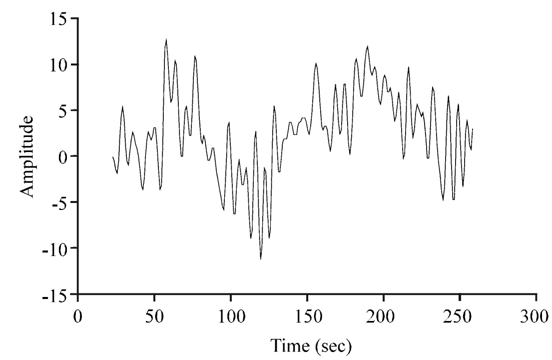

Fig. 12: EEG performance of AF2 electrode

of F7 and F8 electrodes. The recording of EEG spectrum performance of another electrode AF1 and AF2 are shown in Fig. 10-12.

CONCLUSION

In this study, researchers demonstrated a close relationship between minute-scale changes in driving performance and the EEG power spectrum. This relationship appears stable with in individuals across section but is some what variable between subjects. Researchers also combined EEG spectrum estimation, Pz, Cz, Tz, Oz, FP1, FP2, F7, F8 AF1 and AF2 estimation. AR Model analysis and linear regression to continuously estimate/predict fluctuations in human alertness level indexed by driving performance measurement, deviation between the center of the vehicle and the centre of the cruising lane. The results demonstrated that it is feasible to accurately estimate driving errors 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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