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Indicators of Sleepiness in an ambulatory EEG study of night driving

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Abstract— **Driver sleepiness due to sleep deprivation is a causative factor in 1% to 3% of all motor vehicle crashes. In recent studies, the importance of developing driver fatigue countermeasure devices has been stressed, in order to help prevent driving accidents and errors. Although numerous physiological indicators are available to describe an individual's level of alertness, the EEG signal has been shown to be one of the most predictive and reliable, since it is a direct measure of brain activity. In the present study, multichannel EEG data that were collected from 20 sleep-deprived subjects during real environmental conditions of driving are presented for the first time. EEG data's annotation made by two independent Medical Doctors revealed an increase of slowing activity and an acute increase of the alpha waves 5-10 seconds before driving events. From the EEG data that were collected, the Relative Band Ratio (RBR) of the EEG frequency bands, the Shannon Entropy, and the Kullback-Leibler (KL) Entropy were estimated for each one second segment. The mean values of these measurements were estimated for 5 minutes periods. Analysis revealed a significant increase of alpha waves relevant band ratios (RBR), a decrease of gamma waves RBR, and a significant decrease of KL entropy when the first and the last 5-min periods were compared. A rapid decrease of both Shannon and K-L entropies was observed just before the driving events. Conclusively, EEG can assess effectively the brain activity alterations that occur a few seconds before sleeping/drowsiness events in driving, and its quantitative measurements can be used as potential sleepiness indicators for future development of driver fatigue countermeasure devices.**

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I. INTRODUCTION

Sleep loss and disturbed sleep can result in impaired performance [1]. Sleep deprivation can reduce attention and vigilance by 50%, decision-making ability [2], communication skills [3], and memory [4]. The most sensitive tasks are those, which are long and monotonous, such as driving, which become very vulnerable to the effects of sleep deprivation. Studies have affirmed that sleep-deprived drivers are just as dangerous as drunk drivers [5]. It has been shown that people who drive after being awake for 17 to 19 hours performed worse than those with a blood alcohol level of .05 percent [5]. Driver sleepiness due to sleep deprivation is a causative factor in 1% to 3% of all motor vehicle crashes [6]. Surveys of the prevalence of sleepy behavior in drivers suggest that sleepiness may be a more common cause of highway crashes than implying that by reducing the extent of drowsy driver problem may improving the safety of highways.

Detailed study of human fatigue has only occurred during the last twenty-five years. In recent studies, it has been identified the importance of developing driver fatigue countermeasure devices in order to prevent driving accidents and errors [7]. Evidence from the scientific literature suggests reasons for giving serious consideration to the implementation of technological countermeasures for driver fatigue [8]. The basic idea behind vehicle-based detection is to monitor the driver unobtrusively in order to detect when the driver is impaired by drowsiness.

Although numerous physiological indicators are available to describe an individual's level of alertness, the EEG signal has been shown to be one of the most predictive and reliable, since it is a direct measure of brain activity [9]. Recently, EEG driver simulator studies in drivers tried to describe the development of an EEG based fatigue countermeasure algorithm, and test the reliability of this algorithm to detect different phases of fatigue in 'offline data analysis' mode [10].

The main goal of the present study is to develop a reliable quantitative EEG-based method assessing significant brain activity alterations induced by driver's drowsiness in order to be used as a robust driving event predictor.

II. MATERIAL AND METHODS

A. Subjects and Experimental Protocol

Twenty-one subjects (20 males and 1 female) were participated in the present study. The subject s were average drivers (mean driving experience: 8.3 years), with a mean age of 26.5 years. The experiments were performed in CERTH, Thessaloniki, Greece, from 6 June till 27 July 2005.

It was asked from subjects to stay awake for at least 24 hours, and then to arrive at CERTH premises at around 22.00. Upon arrival and after passed the standard medical examination test, the subjects' level of sleepiness was estimated by using the Karolinska Sleepiness Scale (KSS) test, and their sleepiness behavior was scaled by the M.D. by using the Epworth Sleepiness test.

The measurements were performed in the CERTH experiment car. The subject was seated on the driver seat and the attached electrodes were connected to an ambulatory EEG monitoring system. A battery box with power supply independence time of approximately 3 hours supported the monitoring system. For the data acquisition, a sampling rate of 200Hz, for each channel of the recording, with amplitude range of ±20μV for EEG signals. The monitoring system hardware filters were adjusted to the band pass filtering option with a frequency range of 0.5 to 70Hz for EEG, with a notch filter at the 50Hz power supply component. EOG was derived bipolarly using two electrodes, one placed medially above and the other laterally below the right eye.

An experienced driving instructor was seated at the co-driver's seat (Fig. 1). At the back ther e was a technician monitoring the functioning of the recording equipment and a medical doctor monitoring the EEG.

Every subject drove the research vehicle for a maximum of 1 hour on a motorway. In eight cases, subjects' sleepiness level during driving was very high, and the driver instructor stopped the measurements after three or mo re consecutive sleepiness events (unintentionally cross the lane border). The traffic on the motorway was very low, and the task was monotonous enough to stimulate hypovigilance.

B. EEG Filtering and artifacts rejection

The EEG data were firstly filtered off-line by using a 3rd order Butterworth filter (band pass range: 0.5-45 Hz), and then the Infomax Independent Component Analysis (I-ICA) technique was used in order to remove eye movements and eye blinks [11]. ICA decomposition was performed on the EEG+EOG signals by using EEGLAB software [12]. Components contaminated by artifacts were rejected, and the remained components mixed and projected back onto the scalp ch annels [11]. The analysis was performed on the artifacts-free EEG data.

C. EEG Brain Waves Analysis

We analyzed only the data derived from subjects who manage to finish the task. The EEG signals were divided into 1-second segments (200 samples) and for each segment and each channel the relative band ratio (RBR) of typical brain waves were estimated. More specifically, there were estimated the percentage of delta waves (1-3.5 Hz), theta waves (3.5-7.5 Hz), alpha waves (7.5-12.5 Hz), beta (12.5-30 Hz) and gamma waves (30-60 Hz). The brain waves percentage was estimated for a time window with size 200 samples and without overlapping. For each measurement, the average percentage for each brain waves band was estimated for every 5 minutes of measurements.

D. Entropy Measures

We consider a discrete random variable having n possible outcomes x_k (k=1,…,n) with respective possibilities p_k, satisfying $p_k \geq 0$ and $\sum_{k=1}^{n} p_k = 1$. The Shannon entropy of p is defined as [13]:

$$H(p) = -\sum_k p_k \log p_k \quad (1)$$

Let us now suppose we have two different probability distributions: p={p_k} and q={q_k}. As K-L (Kulback-Leibler) entropy has been defined the quantity [14]:

$$K(p/q) = \sum_k p_k \log \frac{p_k}{q_k} \quad (2)$$

Fig. 1. The subject No. 1 in front of the wheel wearing the EEG cap before the experimental procedure. The driving instructor was seated next to the driver.

We estimated both Shannon entropy and K-L relative entropy for each EEG segment. As reference segment for K-L entropy, we used an EEG segment from the first minute of each recording.

III. RESULTS

We analyzed the data from the subjects who satisfied two criteria: i) Their KSS test was less than 10 and, ii) they managed to accomplish the one hour driving task. One-way ANOVA analysis was performed between the mean values of all estimated parameters: brain waves relative band ratios, Shannon Entropy, and K-L Entropy, between the mean values of the first and the last 5-minute periods of the experiment.

Comparing the mean values of relative band ratios of the first and the last 5 minute period we observed an increase of alpha RBR for the central and parietal channels (Fig. 2) that was statistically significant for the central channels: C3 ($p<0.03$), C4 ($p<0.02$) (Fig. 2). Theta RBR was also increased significantly by time for all channels ($p<0.05$ for all channels), and delta RBR was decreased but not significantly.

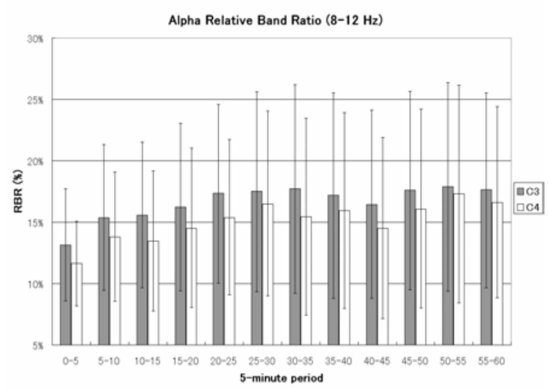

Fig. 2. The mean values of alpha relative band ratio - RBR (in percentage) for the channels C3 and C4 per 5-minute period.

A non-significant decrease of beta RBR that was more prominent for the frontal and central channels for both bands and a significant decrease of gamma RBR at parietal channels: P3 ($p<0.02$) and P4 ($P<0.05$) were also observed (Fig. 3).

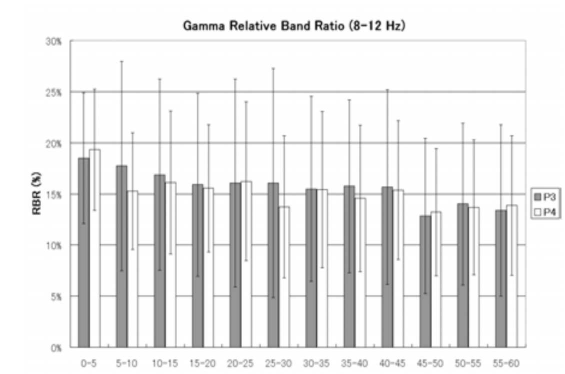

Fig. 3. The mean values of gamma relative band ratio - RBR (in percentage) for the channels P3 and P4 per 5-minute period.

Shannon Entropy was decreased at the last 5-minute period in comparison with the first 5-minute period but not significantly for all EEG channels. K-L Entropy was significantly decreased for the parietal and occipital channels of the left hemisphere: C3 ($p<0.04$) and O1 ($p<0.05$) (Fig. 4).

In five cases, more than one driving events were occurred during the experimental procedure. Subject No. 5, measured at 2[nd] of June 2005, was the most interesting case since he presented the highest level of KSS test (KSS<3). A significant increase of theta

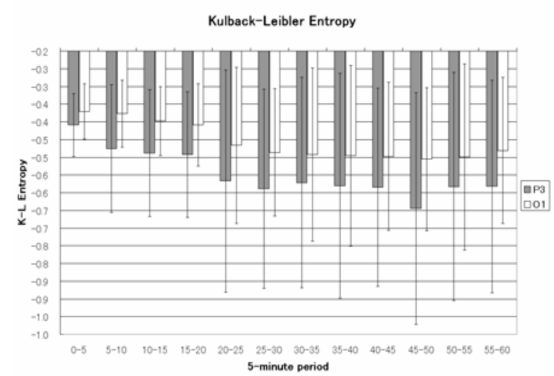

Fig. 4. The mean values of K-L entropy for the channels P3 and O1 per 5-minute period where the most significant differences were observed. As reference segment we used an EEG segment from the first minute of each recording.

and alpha waves was observed in all cases 4-5 seconds before the driving event (Fig. 5).

All EEG quantitative measurements that were selected for the present study, presented a significant change at least one minute before the driving event (Fig. 6), and this is in our opinion the most important finding of the present study. More specifically, a rapid increase of Shannon Entropy and a rapid transient increase of K-L Entropy were observed one minute before the driving event. In time-frequency analysis, there was a significant shifting of the power spectrum to lower frequencies (theta and alpha) (Fig. 6).

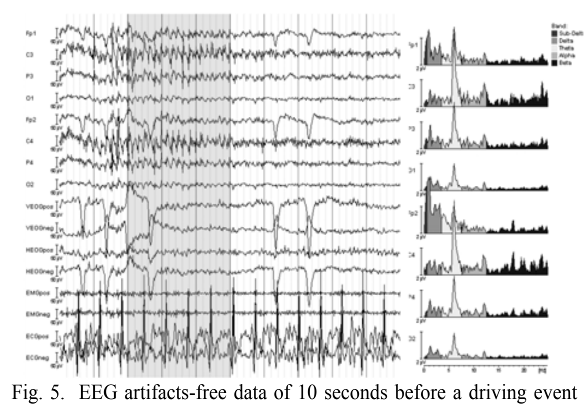

Fig. 5. EEG artifacts-free data of 10 seconds before a driving event accompanied by their power spectrum diagrams. On grey background are presented 3 seconds of a significant increase of theta waves.

IV. DISCUSSION

Research has shown that specific EEG changes are associated with driver fatigue due to sleep deprivation, and that fatigue is a major problem for both professional and non-professional drivers [9]. EEG has been proposed as the most prominent sleepiness indicator, since reflects in a direct way the effects of sleepiness to the central nervous system [9]. Studies have obtained EEG during driving in simulators and subjected it to a Fast Fourier Transform frequency analysis expressing it as power in the alpha and theta bands [10]. These frequency bands were found to be more prone to sleepiness [10], [15].

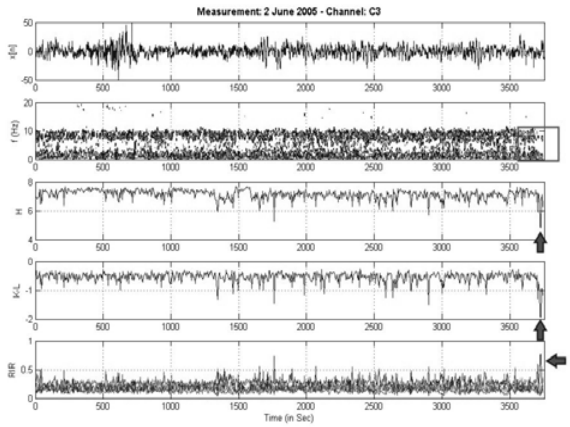

Fig. 6. The EEG recording of channel C3 (Subject: No5) accompanied by the quantitative EEG measurements that were estimated: time-frequency analysis (second panel), Shannon entropy (third panel), K-L entropy (fourth panel), and the RBR for all brain waves bands. At the end of the measurement (arrows), there was a serious driving event (cross the lane border to the right) due to sleepiness that was corrected immediately by the driver instructor.

In our study, we focus our interest on the analysis of both on-going brain activity during driving, and also of EEG segments derived before or during serious driving events that occurred during the experimental procedure. To our knowledge, it is the first time that such serious driving events capable to cause a serious car accident are studied. The EEG data were analyzed by using the standard EEG frequency bands and furthermore by using entropy measures since this category of measures have been found to classify with success different sleep stages, and seem proper candidate for detecting of fatigue and sleepiness [16] something that could be also done using non-linear methods [17].

We made the hypothesis that sleep deprivation together with the duration of driving would accentuate the deterioration in subjective and objective alertness. Our findings agree with previous studies that alpha band is one of the most prone frequency bands to sleepiness, since we observed a significant increase of alpha relative band ratio located at central and parietal brain areas. Gamma RBR and K-L entropy measures that were examined for the first time were also found to be sensitive enough in detecting sleepiness.

The rapid changes of both entropy measures (Shannon and K-L entropy) that were observed at least one minute before serious driving events support our notion that these measures are sensitive to sleepiness and can be used for detecting fatigue in drivers. This class of EEG measures could serve in the development of a prototype fatigue countermeasure device.

Although, our research data and methods provide convincing examples of feasibility of using a neurophysiological measure such as the EEG to develop an automated system to continuously track and compensate for variations in the alertness such as fatigue and drowsiness states of the human driver, further analysis of our data should be performed and further experimental research in real environment conditions is still needed to identify which EEG brain components linked with fatigue to be used in a fatigue-monitoring device during driving.

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