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Estimation of driver attention using Visually Evoked Potentials

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Abstract— **We propose a system for estimating driver attention levels using Visually Evoked Potentials (VEP), computed from the EEG signals of the visual cortex. We investigate the use of both Steady State VEP (SSVEP) and Pattern Onset VEP (POVEP) for this purpose. The subject fixates on a flickering stimulus, generating a Steady State VEP (SSVEP). Occasionally, a random stimulus is flashed on the screen, and the subsequent POVEP is also analyzed. It is seen that the SSVEP is related to the attention levels of the subjects. The sudden stimulus also generates local maxima/minima values for the POVEP, at the P2 and N2 components. Entropy measures of the frequency response of both the responses could also be used to characterize the occurrence of stimuli. We also propose a system architecture for a Driver Alertness system, which fuses the above process and a vision based traffic analysis system, to alert the driver well in advance of any decrease in attention.**

Index Terms— **Driver Attention, Visual Evoked Potential, SSVEP, Brain Computing**

I. INTRODUCTION

Driver fatigue has been identified as the major cause of road accidents in recent years. According to the National Sleep Foundation, around 51% of drivers have driven a vehicle while feeling drowsy and 17% have fallen asleep behind the wheel [1]. Fatigue and the resulting lack of attention reduce the alertness levels of the driver and cause a huge increase in reaction times, which might be critical in tasks requiring immediate response.

Nowadays, the focus of road safety has shifted from collision protection to prevention. Many new accident avoidance techniques have been proposed, ranging from lane detection mechanisms [2], [3], traffic analysis vision systems [4], vehicular networks [5], [6], and tiredness estimation systems [7], [8]. Lane detection mechanisms rely on vision based systems, where cameras mounted on the side of the car track the separators painted on the road, to determine whether the driver is committing errors [2]. Traffic analysis systems [4] analyze the amount of traffic present on the highway. They can also identify objects, like pedestrians, in front of the car. Vehicular ad-hoc networks [6] rely on wireless sensors installed in every car on the road. These sensors 'talk' to each other, passing important information and avoiding collisions.

Other proposed techniques attempt to measure whether the driver is drowsy or feeling tired. This is done using either vision-based or physiological techniques. Vision based approaches rely on eye movements to estimate drowsiness levels [7]. Video cameras mounted in the car track the eye closure speed, saccadic eye movements, and the head movements of the driver [7], [9]. However, these techniques suffer from the limitation of varying light and driving conditions.

Physiological methods rely on heart rate, electro-oculographic (EOG), and electroencephalographic (EEG) signals [1], [10]–[12]. EOG studies have observed a decline in saccadic frequencies, and an increase in eye blink duration, with tiredness. EEG signals, especially the slow alpha waves, are shown to have a positive correlation with sleep patterns [1]. They have been shown to be more effective than eye-activity based methods in tracking instantaneous fluctuations, on shorter time windows.

EEG signals can help provide a reliable estimate of the driver alertness levels. Daimler-Chrysler have developed a driver alertness system, Distronic [19], which evaluates the EEG patterns of the driver under stress. Lin et.al. [1] propose a system using the EEG signals of the driver during a driving simulation. They perform Independent Component Analysis (ICA) on the various channels and correlate the alpha band (8 - 13Hz) frequency components with the performance of the driver, to show that these frequency bands have a high positive correlation with the drowsiness level of the driver. A possible drawback of this approach is that the driver may be fully awake, but still may not be paying attention to the road due to some other distractions, like cell-phones, passengers, music etc. The above system is not able to identify such cases, though these are also possible sources for driving errors.

The first step towards solving these issues is to investigate the relation between attention levels of a user and the EEG signals generated in the visual cortex. In this paper we propose a system for estimating the attention levels of the subject. We make use of the Visual Evoked Potentials (VEPs) generated in the visual cortex for our system. VEPs have been used successfully in many Brain Computing devices [13]–[15]. Kremlacek et.al. [23] have also developed a model for VEP signals using three damped oscillators. Most Brain Computer Interfaces (BCI) systems use either the Steady State VEP (SSVEP) or the Flash VEPs (FVEP) for user interaction. SSVEP is a periodic response generated in the brain, at a presentation of a repetitive stimuli. The frequency of the response matches that of the stimulus, and extends over a very narrow bandwidth. SSVEP is a reliable measure of the user response, and has been used in many BCI systems for conveying commands or selecting options [13], [15]. The user makes a selection from the options displayed on the screen by concentrating on one of them, due to which the

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SSVEP shows a maxima at the target frequency. Flash-VEP (FVEP), on the other hand, are short responses to flash or OFF-to-ON stimuli, which occur only once. FVEPs are time and phase locked to the flash onsets of the input stimulus, and thus can be used to detect occurrence of stimuli. Lee et.al. [14] use FVEPs to control the movement of a cursor on the screen. Kramarenko [24] have also analyzed the validity of spectral analysis for VEPs.

In our approach, we use a flickering stimulus display to generate a SSVEP response from the subject, which is analyzed over the duration of the experiment. It is seen that the SSVEP is related to the attention levels of the subjects, At random time instances, an instantaneous stimulus is flashed on the screen, away from the central fixation point, and the corresponding response is also measured. It is found that the occurrence of the stimulus, causes a specific response in the EEG signals within 200 msec of the event. This response is also called the Pattern Onset VEP (POVEP), and is identifiable when the subject is attentive. Shannon and Renyi entropy measures of these frequency responses are used as an evaluation measure.

The rest of the paper is divided as follows: Section 2 describes the proposed Driver Alertness System, while Section 3 describes the experimental approach used in our work. The results are discussed in Section 4, and Section 5 discusses the conclusions and future work in this area.

II. PROPOSED DRIVER ALERTNESS SYSTEM

The Driver Alertness System is a combined multimodal system, utilizing vision based and physiological approaches for evaluating the alertness of the driver. The proposed system could be used in a Driving Test Simulator, under simulated levels of traffic and stress, to investigate the VEP response and feasibility of such a system in a near real-world environment.

The vision system consists of sensor cameras mounted outside the car, which analyze the traffic on the road, and identify any necessary signs or stimuli, that should be attended to by the driver. Yazdi [16] and Wang et.al. [2] have already proposed systems which monitor the outside traffic and lanes on the road for driver assistance. On similar lines, the proposed system can detect important signboards, another vehicle that suddenly cuts across the car, or the amount of traffic on the road. Thus the vision system can identify situations requiring driver attention, though such situations may or may not be dangerous in themselves. The Brain Computing Interface consists of a EEG neuro-data acquisition sensor placed over the driver's head. The unit continuously measures the EEG signals of the driver at different locations of the brain. Both the sensors convey data to a central fusion system, which fuses the information from the two and evaluates the performance of the driver. It can estimate whether the driver is paying attention or not, based on the combined information. To assist the system in stimulating EEG responses, there is a light source installed on top of the rear-view mirror targeted towards the driver's eyes. The whole setup is shown in Figure 1.

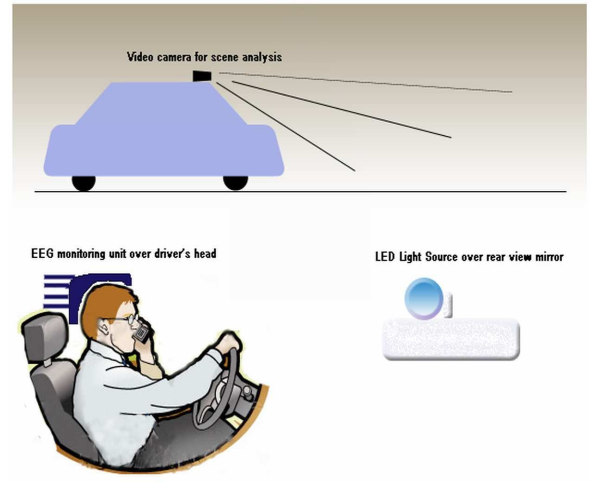

Fig. 1. The driver alertness system. It consists of the vision based traffic analysis systems, a light source for generating POVEP in the driver, and the EEG monitoring unit for collecting the brain response.

The system works as follows: the vision sensors continuously analyze the traffic conditions and the road signs and other driving cues. The system is able to classify various scenes, and identify important cues. The EEG sensor, placed over the visual cortex of the driver at occipital sites O1 and O2, monitors the EEG signals at all times to analyze the steady-state VEP. Whenever the vision system identifies a situation requiring driver attention, like heavy traffic or pedestrians on the road, it sends a signal to the system, which activates a low-brightness light source, placed over the rear-view mirror. A flash of light is pointed towards the driver at a suitable eccentricity. The resulting Visually Evoked Potential, Pattern-Onset VEP (POVEP), is measured and averaged over several successive instances.

The SSVEP can potentially be used to estimate the attention level of the driver. In addition, an alert driver would show a definite response to the POVEP stimuli every time such a flash is shown. Thus the presence of POVEP could help indicate the driver alertness state. If the person is drowsy or distracted due to some reason, the system would not register any such response over time. The proposed system is potentially more robust for a driving scenario, since a driver may be awake, but might not be attentive to the road. Since such a case may also be a potential cause of dangerous driving, it is beneficial to identify such scenarios and give feedback to the driver by way of a mild beep or jolt.

To test the feasibility of such a system, it is necessary to first investigate the effect of steady state and flash stimuli on a subject's EEG response. In this paper, we have explored the effects of such stimulus on the VEP response of subjects in a dark-room laboratory environment. We analyze the steady state response continuously. We also attempt to identify the POVEP in the presence of SSVEP. It is seen that both the SSVEP and POVEP could be potential measures for estimating the alertness levels of subjects. The details of the experiment are given in the next section.

III. SETUP TO EVALUATE POVEP RESPONSE

The experimental setup was designed to evaluate the response of a subject to Pattern-Onset VEP, in a laboratory environment, to determine the suitability of such an approach for further tests in driving simulators.

A. Experimental Setup

Subjects were seated about 56 cm from a CRT monitor. The refresh rate of the monitor was fixed at 60 Hz. The steady-state stimulus consisted of a rectangular grating, with alternate white and black bars. This pattern was presented for 5 frames, and the negative of this pattern (the bars interchange their colors) was presented for 1 frame, giving a flicker rate of 10 Hz. This frequency was chosen because it showed a high signal-noise ratio [13]. At random time instants, a visual stimulus, a letter between A-H, was shown for 100 msec. The stimulus was situated at a random location $10°$ to the central fixation point, lying in the peripheral vision of the subject. The width of the stimulus was kept at $1°$. This visual stimulus generated a pattern-onset VEP in the visual cortex. A screen-shot of the stimulus is shown in Figure 2.

Most Event Related Potential studies require target detection or spatial localization. The user responds to the target stimuli by pressing a button [17], or has to concentrate on a desired target out of a number of possible options [13]. In our experiment, visual stimuli in the form of letters were used as a measure of accuracy. The subjects were instructed to count the number of times a stimulus was shown. This gave us an approximate estimate of the alertness of the subject during each session.

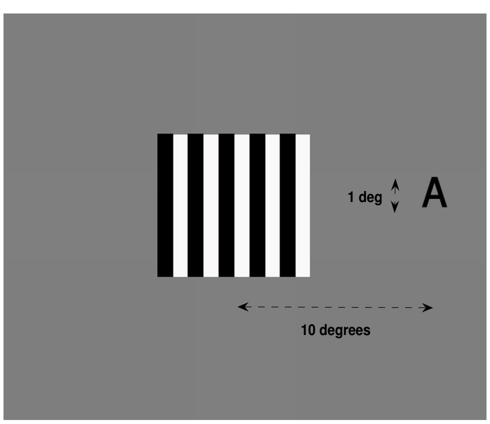

Fig. 2. The stimuli used for measuring the response of the subjects to the visual stimuli. The central pattern is flickering at a frequency of 10 Hz. The visual stimulus (a letter between A-H) is shown for 100 msec. The duration is thus chosen so as to reduce the effects of saccadic eye movements.

For recording the EEG signals, a Grass bio-potential amplifier was used followed by a National Instruments DAQ system to digitize the signal at sampling rate of 512 Hz. The EEG signals were recorded using a Grass gold electrode from the O1 or O2 positions on the primary visual cortex, based on the international 10-20 system. The channel was referenced to the frontal site Fz, with the ground on the left earlobe. The measurement signal was amplified (50k), line filtered at 60 Hz to remove line noise, and then band-pass filtered over 1-100 Hz. This signal was then sampled by the DAQ unit and saved for further processing.

B. Procedure

Four subjects aged between 22 and 27 participated in the study. All had normal or corrected to normal vision. Each subject underwent 12 experimental trials, each lasting about 2 min. The trials were all conducted with very little time between them. This was done to induce monotony in the user, causing lack of attention in the latter sessions. No pattern onset visual stimulus was shown in the first 10 sec of every trial, to allow the subject to get accustomed to the steady state pattern, and to allow the SSVEP to stabilize. During the remaining duration in each trial, a visual stimulus (between A-H) was shown at random time instants at a distance of $10°$. Each such presentation of stimulus lasted for 100 msec. This was done to eliminate the effects of saccadic eye movements, which have a latency of around 100-200 msec [18]. The subject was required to count the number of times a visual stimulus was shown in each trial. No feedback about the subject's performance was given in between trials, so as not to bias or notify the subject.

C. Feature Extraction and analysis

The EEG signals are acquired over the 2 min trials, at a sampling rate of 512 Hz. The signal is low pass filtered at 60 Hz using a third order elliptic filter, to eliminate high frequency line noise. The resulting time series data is divided into 512 sample epochs with a 256 point overlap, denoting contiguous 1 sec frames of EEG data. The Fast Fourier Transform is computed for each frame and averaged over a trial for analyzing the steady state frequency spectra over the entire duration of the experiment. For the analysis of the stimulus response, POVEP, the time response for 250 msec after the occurrence of the each stimulus is extracted, and the frequency spectra is also computed for that time frame.

The Shannon and Renyi Entropies [21] have also been computed for the steady state response and the stimulus response, to analyze the responses and as possible measures for estimating attention. Entropy has also been used as a measure to eliminate artifacts from EEG signals in Greco et.al. [20]. In this paper we have used Shannon and Renyi entropies for analysis of the signals.

The standard shannon entropy measure over an incomplete probability distribution is defined as:

$$H_s(x) = \frac{-1}{w(p)} \sum_i p_i log_2 p_i \tag{1}$$

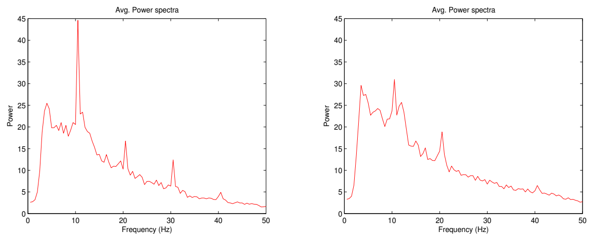

Fig. 3. Power Spectra plots for the steady state response for two trials. In the left trial, the accuracy of the subject was 0.91, while it was 0.65 for the right trial.

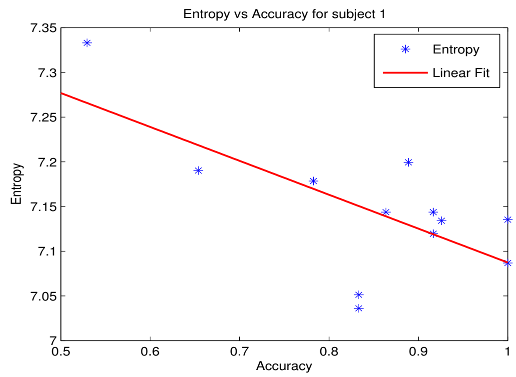

Fig. 4. Plot of the entropy of the SSVEP vs. accuracy for subject 1. The correlation between the two quantities is -0.67

where the total probabilities used in the entropy computation sum up to: $w(p) = \sum_i p_i \leq 1$.

Renyi entropy was proposed by Renyi as an alternate formula for computation of the entropy of incomplete probability mass distributions. The formula proposed by him for denoting the entropy of a a distribution is:

$$H_{\alpha}^{R}(p) = \frac{1}{1-\alpha} log_2 \frac{\sum_i p_i^{\alpha}}{\sum_i p_i} \tag{2}$$

The renyi entropy computation can be used in the same form for incomplete distribution also. The value of α is chosen as 3, since it has been shown to be an optimum value for time frequency signals by Baranuik et al. [21].

IV. RESULTS AND DISCUSSION

A. Steady State Response

The power spectra of the steady state responses is shown in Figure 3. As mentioned earlier, the subjects are asked to count the number of times the visual stimulus is shown during a session. This gives an estimate of the attentiveness of the subject during a particular session. For an attentive subject, shown in Figure 3, the power spectra is narrow and is also characterized by a maxima at 10 Hz, the flicker rate of the steady pattern. For an inattentive subject, the peak at 10 Hz is no longer prominent. Also the SSVEP is more spread out over the spectrum.

This feature can also be observed in the comparison of the shannon entropy of the frequency spectra and the accuracy of the subjects. Since the SSVEP spectra is more spread out for inattentive subjects, the entropy values tend to be higher for trials with lower accuracy. The plot for entropy values and accuracy levels is shown in Figure 4. We see that increasing accuracy values correspond to lower entropy values. The correlation value between entropy and accuracy is -0.67. Thus the entropy of the SSVEP plots can be a potential measure of the attentiveness of the subjects.

TABLE I

THE CLASSIFICATION RESULTS FOR THE 4 SUBJECTS

Classification	Subject			
	1	2	3	4
Accuracy (%)	75	91	53	71

To investigate the feasibility of such an entropy-based measure as a means to characterize the attention levels, a basic classification model using feed forward neural networks was developed using a leave-one out cross-validation scheme [22]. The leave-one-out cross validation scheme is a simplified version of the popular k-fold cross validation method used by many researchers. In this method, each training case is omitted in turn and the network is trained on the remaining test set. The network is then tested using the omitted sample as the test case. This is repeated for all the cases.

In our test, we set an empirical threshold of 0.8 as a threshold attention level, resulting in a yes/no division of the test cases. The input feature vector for each trial consisted of the average Shannon entropy for that trial, averaged over contiguous time epochs of 512 samples, or 1 sec each, that constituted that particular trial. The classifier used was a back-propagation feed-forward neural network consisting of one hidden layer with 10 nodes in the hidden layer, with a tan-sigmoid transfer function. The results of the classification are shown in Table I.

The results are encouraging, though the classifier accuracy varied a lot across subjects, especially for subject 2. This could be due to the fact that the attention levels for subject 2 was very high across all trials, hence the test cases were not diverse enough. While the results show a definite potential for Entropy based characterization measures to be used for estimating attention, further and more detailed tests should be done using a larger subject base, to comprehensively estimate the attention measures.

It is also observed in our results that though the shape of the plots is similar, as can be seen from Figure 3, the magnitude of the power spectra varies between experimental sessions. This could be due to the different EEG activity levels in the subjects' visual cortex. This could be a further area for research, especially for Brain Computer Interfaces.

B. POVEP response to flashing stimuli

The POVEP has been analyzed as an added measure for estimating the attentiveness of the subjects. The EEG signal immediately after the presentation of the each pattern

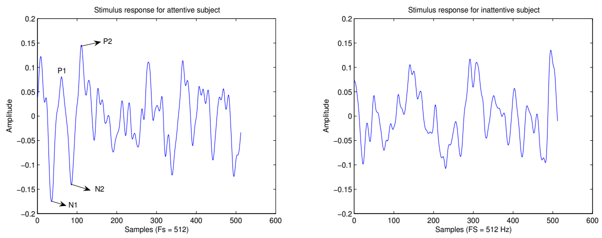

Fig. 5. The stimulus response of an attentive and inattentive subject to the pattern onset visual stimulus. The peaks P1, P2, and the valleys N1, N2 can be clearly seen in the left, while they are no longer prominent in the right.

onset stimulus has been recorded and averaged over all such occurrences of stimuli. Flash-VEP and POVEP induced by flash of visual stimuli consist of two major peaks and two corresponding valleys, within 200 msec of the onset of the stimulus [14]. These are termed as P1, P2, N1 and N2 respectively. Lee et.al. [14] have used the amplitude difference between N2 and P2, Amp_{p-v}, to identify target LED from an array of flashing LED sources.

The stimuli response for POVEP for a time window of 1 sec following the occurrence of a visual stimulus is shown in Figure 5. The major peaks and valleys can all be observed within 200 msec of the stimulus. Thus, the first identifying feature of pattern onset VEP is the presence of these peaks. This approach has already been used in a few works in BCI [14]. In the case of a subject not paying attention (accuracy level of 0.65) to the visual stimulus, the extracted signal does not contain the target N1, N2, P1, P2 peaks within the 200 msec window, as seen in second plot of Figure 5. However, this observation is not very consistent over the various sessions, and in a few cases, subjects with very high accuracy levels also did not register the desired peaks. This is being investigated further, to improve its performance in estimating attention.

However, a major observation about the POVEP stimulus response is that it has predominantly low frequency components. To investigate this, we analyze the segments for 500 msec following the event. The fourier transform is computed for these segments, and the average shannon and renyi entropy values are computed for each session, over the frequency range 0-50 Hz. The entropy values for the steady state spectra are computed over the standard 1 sec windows and averaged over each session.

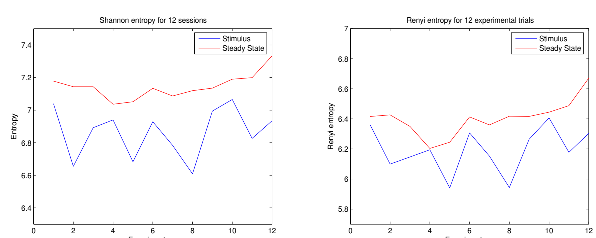

Fig. 6. Entropy plots for the a) Shannon and b) Renyi entropy values of FFT of the steady state user EEG over the entire trial and the average POVEP response on stimulus display.

The Entropy plots for all the 12 experiments for one subject are shown in Figure 6. The plots show the entropy levels over the entire session and the entropies for the POVEP averaged over the number of stimulus occurrences. It can be seen that in all the experimental sessions, both the Renyi and Shannon entropies are higher for the POVEP response, as compared to the steady state frequency response. This is to be expected since the pattern onset response has more power concentrated in the lower frequencies, hence the entropy is expected to be higher for the stimulus responses. This could be used as an added feature for identifying the response to sudden stimulus, and estimating the attention of the subject.

V. CONCLUSIONS AND FUTURE WORK

In this paper, we have proposed a system for estimating attention levels of subjects in performance based tasks. Such a system would be especially useful for alertness systems, like the proposed Driver Alertness System, for assisting and warning the driver well in advance. The Pattern Onset VEP might be used to characterize response to a sudden visual stimulus. The absence of such a stimulus response could generate a first stage of warning levels, wherein it can give a beep, or a mild jolt to the driver to ensure attention. The contributions of our work can be summed up as:

- Description of a potential Driver Alertness System for use in vehicles, especially during driving on highways.
- Development of a test bed for evaluating the subject attention in laboratory environment, in presence of a constant and monotonous flickering pattern.
- Analysis of steady state response and the stimulus response using frequency spectra and Shannon and Renyi entropy measures, to demonstrate the utility of these response in estimating attention.

However, the above system is not completely robust, and some inconsistencies, especially in POVEP response have been observed. Also the current test bed uses a flickering pattern to reinforce the subject's attention towards the test screen. For integration into an actual driver alertness system, the current approach would also have to provide results in a noisy environment. A few possible areas for future research are:

- Investigate VEP and EEG responses under simulated and near real-world conditions and using a large number of test subjects under varying levels of stress.
- Test the system in a Driving Simulator for estimating the efficiency of the approach for cluttered scenes and simulated traffic conditions.
- Enhance the robustness of the system, for accurate identification and characterization of stimuli responses. This can be done by using multiple channels, placed at different locations on the scalp, to gather more information about the VEP response. Independent Component Analysis (ICA) and Wavelet Decomposition are possible techniques for better analysis of the time-frequency characteristics of the signals.

- Explore the effect of different stimulus sizes, and varying eccentricities on the strength of the response.

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