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ON-LINE DETECTION OF DROWSINESS USING BRAIN AND VISUAL INFORMATION

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Abstract: In this paper we propose the on line detection of drowsiness using brain and visual information to monitor the driver attentiveness in cars. Our Embedded paper is to design and develop a low cost feature which is based on embedded platform for finding the driver drowsiness. Specifically, our Embedded System includes a webcam placed on the steering column which is capable to capture the eye movements and EEG placed at the forehead of the Driver to find out the brain activity. If the driver is not paying attention on the road ahead and a dangerous situation is detected, the system will warn the driver by giving the warning sounds. Our Embedded System uses ARM9 32-bit micro controller has a feature of image processing technique as well as Analog to Digital Conversion and S3C2440 based micro controller to process the brain and visual information of driver.

Keywords: EEG, ARM9, S3C2440.

1. INTRODUCTION

A drowsiness detection system using both brain and visual activity is presented in this paper. The brain activity is monitored using a single electroencephalographic (EEG) channel. An EEG-based drowsiness detector using diagnostic techniques and fuzzy logic is proposed. Visual activity is monitored through blinking detection and characterization. Blinking features are extracted from an electrooculographic (EOG) channel. Features are merged using fuzzy logic to create an EOG-based drowsiness detector. The features used by the EOG-based detector are voluntary restricted to the features that can be automatically extracted from a video analysis of the same accuracy. Both detection systems are then merged using cascading decision rules according to a medical scale of drowsiness evaluation. Merging brain and visual information makes it possible to detect three levels of drowsiness: "awake," "drowsy," and "very drowsy." One major advantage of the system is that it does not have to be tuned for each driver. The system was tested on driving data from 20 different drivers and reached 80.6% correct classifications on three drowsiness levels. The results show that EEG and EOG detectors are redundant: EEG-based detections are used to confirm EOG-based detection and thus enable the false alarm rate to be reduced to 5% while the true positive rate is not decreased, compared with a single EOG-based detector.

For the last few decades, driver drowsiness has been monitored with two kinds of systems. The first one is "vehicle oriented" . Drowsiness is detected by analyzing the driver's behavior using information measured by sensors located in the vehicle, such as its position on the road, steering wheel movements, pressure on the driving pedals or the variability of the car's speed. The main disadvantage of this approach is that driving behavior may be very different from one driver to another. This makes it difficult to construct a "correct driving" model that can be used to detect variations in driving behavior. This model has to be learnt for each driver. The second kind of system is the "driver-oriented" systems.

2. MATERIAL AND METHOD

The database used in this study was provided by the Centre d'Etudes de Physiologie Applique (CEPA) from Strasbourg, France. The data were obtained using the "Poste d'Analyse de la Vigilance en Conduite Automobile Simule" (PAVCAS) driving simulator. PAVCAS is a moving base driving simulator made up of a mobile base with four degrees of liberty (vertical and longitudinal movements, swaying, and pitching) and a real-time interactive visualization unit. The visualization unit reproduces the driving conditions on a freeway by day or night very well. Images are shown on five screens in front of the vehicle and are arranged in semicircle.

The database is made up of 40 recordings from 20 subjects. Each subject was recorded while driving for 90 min, firstly while perfectly rested and secondly while suffering from sleep deprivation (the subject slept only 4 h the previous night) in diurnal conditions. The database is thus composed of 60 h of driving data. Each recording includes four EEG channels [left frontal (F3), central (C3), parietal (P3), and occipital (O1)], one EOG channel and a video of the driver's face. Data acquisition of physiological signals was performed at 250 Hz. Objective sleepiness was evaluated on each recording by an expert doctor using the scale described in Table I. The expert classified nonoverlapping intervals of 20 s (epochs) using the four EEG channels and the EOG channel simultaneously. The database contains 5512 epochs classified as level 0 of drowsiness, 949 epochs as level 1, 663 epochs as level 2, 407 as level 3, and 26 epochs as level 4. This expertize of the data represents the ground truth as the doctor expertize is actually the surest evaluation of drowsiness. Moreover, self-assessment of drowsiness is often wrong.
Half the data, randomly chosen, were used to select and tune certain parameters of the drowsiness detectors, such as the length of the analysis windows, the optimal values for the thresholds used and the choice of different

features. This dataset is named data-set 1. The different parameters are empirically tuned on this data-set using ROC curves. ROC curves display the ratio of correct detections in function of the ratio of false alarms. Hence, to tune each parameter, we made its value vary. The value corresponding to the point of the ROC curve the closest to the optimal one (100% true detections, 0% false alarms) was then selected. The other half was used to evaluate the system. This data-set is named data-set 2. Each data-set contains data recorded on different drivers and the same distribution between awake and drowsy states.

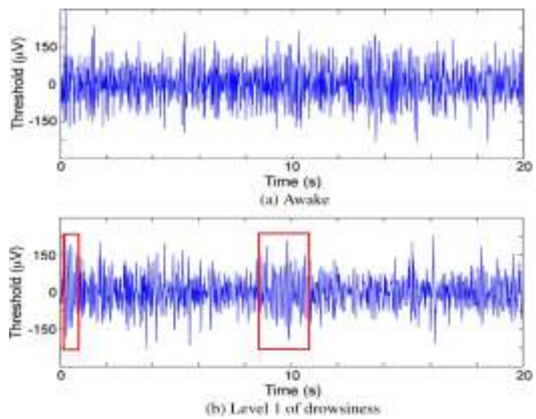

Figure 1Twenty seconds of EEG signal during (a) awakeness and (b) during

Drowsiness Detection From a Single EEG Channel

EEG is the measurement of the electrical activity of the brain by electrodes placed on the scalp according to the international 10–20 system. EEG is analyzed in the frequency domain, where rhythmic activities are measured in several physiologically significant frequency bands. Drowsiness is characterized in EEG by an increase of the α ([8–12] Hz) and θ ([4–8] Hz) activities, which are linked to relaxed and eyesclosed states, and a decrease of the β activity ([12–26] Hz) , which is linked to active concentration. A few studies have also shown modifications in the δ ([0.5–4] Hz) due to drowsiness but they mainly appears in advanced drowsiness state (δ activity is linked to deep sleep in particular) and the purpose here is to detect early signs of drowsiness. These variations of activity mainly appear in the parietal and central areas of the brain.

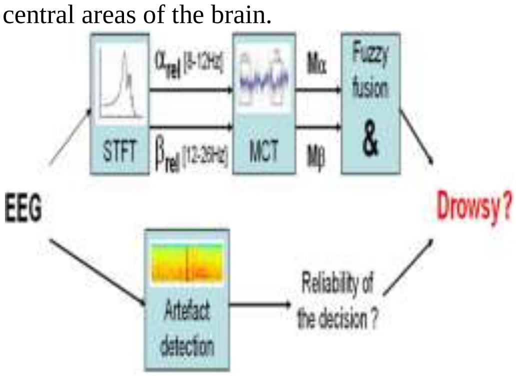

Figure 2EEG-based drowsiness detection method.

The purpose of the EEG-based detection system is to detect significant variations of activity in the relevant frequency ranges. The general principle of this system is shown in Fig. 2.

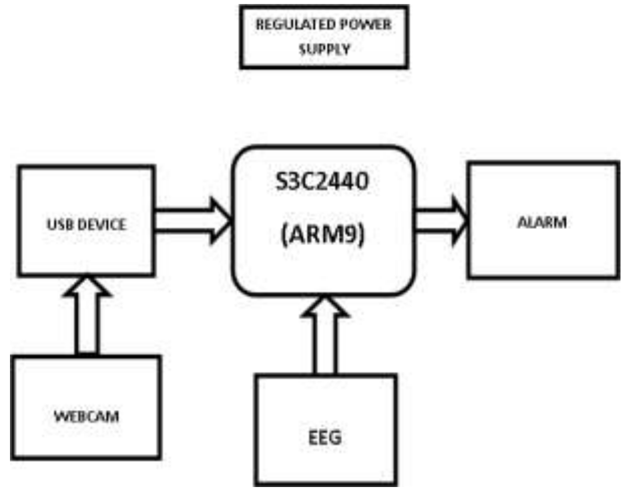

Figure 3 Block Diagram

The average relative power in α and β band, which is the ratio between the power computed in a specific frequency band and the total power of the EEG, is calculated from the EEG power spectrum, computed using a short time Fourier transform (STFT). They are respectively named αrel and βrel. Then, a mean comparison test (MCT) is processed on these energy signals. At the same time, a variance comparison test (V CT) is carried out to detect artefacts.

3. RESULTS AND DISCUSSION

The EEG-based detection system, the EOGbased detection system, and the drowsiness detection merging the two decisions are validated on the second part of the database, data-set 2, which was not used to tune the parameters of the different detectors. The results obtained are compared with the expert doctor classification.

The drowsiness detection system based on the EEG analysis reaches 84.6% correct detections of "drowsy" states, which corresponds to a level of drowsiness greater or equal to 1 in the OSS scale and 17.9% false alarms (epochs classified 0 by the expert and detected as "drowsy" by the system). These results are presented in Table I.

Table 1 Confusion matrix of the eeg-based method

		Expert	
		"Awake" (level 0)	"Drowsy" (level ≥ 1)
EEG-based system	"Awake"	82.1%	15.4%
	"Drowsy"	17.9%	84.6%
	Samples	2753	1025

The results obtained by the fusion system on the detection of "drowsy" and "very drowsy" states are

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shown in Table II . The results of the drowsiness detection are good with 72.6% correct detections of "drowsy" states (level 1 in the OSS scale) and 79.6% correct detection of "very drowsy" states (level ≥ 2 in the OSS scale). The discrimination of "awake" states (level 0 in the OSS scale) is also good with 82.1% correct detections. The overall true decision percentage, which is the rate of epochs correctly classified in the three classes ("awake," "drowsy," and "very drowsy"), is 80.6%, which proves that the detection system is efficient.

The rate of "awake" epochs which are misclassified is the same as the one obtained with EEG-based detection (17, 9% = 14, 5% + 3, 4%). Indeed, considering the false alarm rate for the "awake" state (percentage of epochs classified 0 by the expert and detected as "drowsy" or "very drowsy" by the system), the EEG/EOG system performance is limited by the performance of the EEG-based detection system. When the EEG system detects an epoch as "drowsy," the decision cannot be changed into "awake" by the EOG-based system. It can only be confirmed as "drowsy" or detected as "very drowsy." Then, any false alarm generated by the EEG detection system ("awake" epochs detected as "drowsy") remains a false alarm for the EEG/EOG system.

Table 2 Confusion matrix the eeg/eog detection

		Expert		
		"Awake" (level 0)	"Drowsy" (level 1)	"Very drowsy" (level ≥ 2)
EEG/EOG system	"Awake"	82,1%	14,0%	3,7%
	"Drowsy"	14,5%	72,6%	16,7%
	"Very drowsy"	3,4%	13,4%	79,6%
	Samples	2753	477	548

It can be seen in Table II that the EEG-/EOG-based detection leads to very good discrimination between "awake" and "very drowsy" states since only 3.4% of "awake" states are misclassified as "very drowsy" and only 3.7% of "very drowsy" states are misclassified as "awake."

Mix-ups mainly appear between adjacent classes. Indeed, most of the misclassified "awake" states are classified in the "drowsy" class (14.5%) and not in the "very drowsy" class (3.4%). The misclassified "drowsy" states are mixed up with both "awake" (14.0%) and "very drowsy" (13.4%) classes. The misclassified "very drowsy" states are classified in the "drowsy" class (16.4%) and not in the "awake" class (3.7%). On average, the percentage of confusion in adjacent classes is about 15%, which is probably close to inter-expert disagreement (percentage of epochs classified in different classes by different experts). This is quite understandable as the transition between two adjacent classes is not clear and immediate and it can occur in the middle of an epoch.

4. CONCLUSIONS

The paper "ON-LINE DETECTION OF DROWSINESS USING BRAIN AND VISUAL INFORMATION" has been successfully designed and tested. It has been developed by integrating features of all the hardware components and software used. Presence of every module has been reasoned out and placed carefully thus contributing to the best working of the unit. Secondly, using highly advanced ARM9 board and with the help of growing technology the project has been successfully implemented.

This system uses cascading rule decision to merge two drowsiness detection systems, an EEG-based detector, and an EOG-based detector. The EEG detection system is applied by merging several features extracted from a single EEG channel analysis using fuzzy logic. Drowsiness detection using visual information of the driver is carried out by using fuzzy logic merging several features extracted from the blinking analysis of one EOG channel. The final system merges these two systems according to medical rules to evaluate drowsiness. The method proposed allows drowsiness to be detected with three different levels ("awake," "drowsy," and "very drowsy"). It reaches an overall correct detection rate of 80.6%.

Finally, the analysis of literature has shown that contextual information and vehicle mechanical information are also really relevant. The integration of this information in the final system could increase the accuracy of the system.

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Biography

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