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An automatic detector of drowsiness based on spectral analysis and wavelet decomposition of EEG records

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***Abstract*— An algorithm to detect automatically drowsiness episodes has been developed. It uses only one EEG channel to differentiate the stages of alertness and drowsiness. In this work the vectors features are building combining Power Spectral Density (PDS) and Wavelet Transform (WT). The feature extracted from the PSD of EEG signal are: Central frequency, the First Quartile Frequency, the Maximum Frequency, the Total Energy of the Spectrum, the Power of Theta and Alpha bands. In the Wavelet Domain, it was computed the number of Zero Crossing and the integrated from the scale 3, 4 and 5 of Daubechies 2 order WT. The classifying of epochs is being done with neural networks. The detection results obtained with this technique are 86.5 % for drowsiness stages and 81.7% for alertness segment. Those results show that the features extracted and the classifier are able to identify drowsiness EEG segments.**

I. INTRODUCTION

DROWSINESS is the stage between been awake and been asleep. During this stage the capacity of been alert and take quickly decisions considerably decreases. This situation is a serious problem if a subject is performing a task which needs attention, like driving. In many countries drowsiness is responsible for many car accidents. The National Highway Traffic Safety Administration (NHTSA) conservatively estimates that 100,000 police-reported crashes are the direct results of driver fatigue each year [1]. For this reason it is important to develop automatic detectors of this state.

Most of the automatic detection methods are based on studying the driver behavior to detect abnormal doing [2], or using image processing to detect its head or blink movements [3], [4]. Drowsiness can be also detected in a electroencepholographic (EEG) recording, because this signal reflect very well the loss of alertness [5].

The Electroencephalography is the most used technique to measure the electrical activity of the brain [6]. Different signal processing techniques, like Neural Networks (NN) [7],[8], Means Comparison Test [9], Wavelet Transform (WT) [5],[10], Independent Component Analysis [7] and Fussy Logic [11], have been proposed to detect drowsiness in EEG signals. However, the last two techniques need a large number of EEG channels, which are unpleasant for the driver.

In this work, we proposed a method to detect the drowsiness stage using only one EEG channel. In order to classify the data, NN has been used. Classifications of drowsiness with NN had obtained good results [7], [8]. The key of a good operation of them is the feature vector-in, which represents the drowsiness stage. Different feature extraction methods may affect the classification result significantly. In this work vectors are building combining the best features obtained from the Power Spectral Density (PSD) in a previous work [14], with features extracted from WT signals [5], [10].

Figure 1 shows an example of awake (or alertness) and drowsiness activity in ten seconds EEG segment.

II. MATERIALS

EEG records of ten subjects were selected from the MIT-BIH Polysomnographic Database (Patients 3, 4, 14, 16, 48, 59, 60, 61, 66, 67) [12]. Their ages are between 32 and 56 years old. Some of the patients of the database suffered some kind of sleep disorder. This database contains over 80 hours of four-, six-, and seven-channel polysomnographic recordings. The single available EEG signal was acquired between C3 y O1 positions on 10-20 montage system with a sample frequency of 250 Hz. The sleep stages were visually scored by experts for 30 seconds epochs, according to the criteria of Rechtschaffen and Kales [13]. In this work there have been used epochs corresponding to "Awake stage" (alertness) and "Stage I" (drowsiness). Figure 1 illustrates an example of two 10 s EEG segments for both stages.

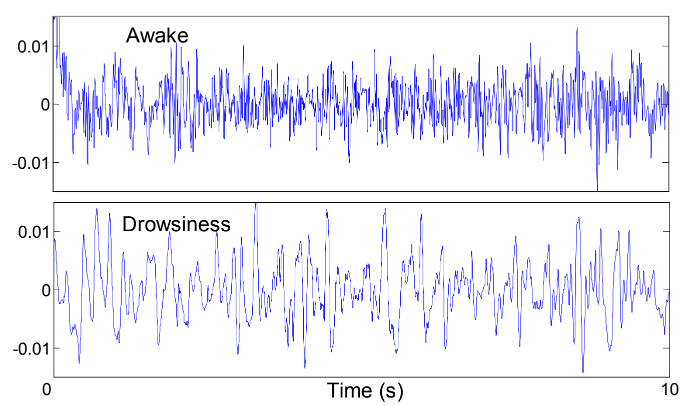

Figure 1. Alertness and drowsiness EEG segments taken between C3 and O1.

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III. METHODOLOGY

A. EEG filtering.

All EEG records were preprocessing with a 2^{nd} order, bidirectional, Butterworth, band - pass filter with cut-off frequencies of 0.5 and 60 Hz.

B. Temporal Segmentation

For the further analysis, a temporal segmentation of EEG signals was done. The reason for doing this is to assure statistical stationary to estimate the spectral density power. The duration of the blocks was of 1, 2, 5 and 10 seconds. Then the optimal duration was chosen from best result after testing the algorithm with the different length.

C. Signal Processing and Feature extraction

Electroencephalographic analysis has been widely adopted for the monitoring of cognitive state changes and sleep stages because abundant information in EEG recording reflects changes in drowsiness, arousal, sleep, attention, etc. The rhythmic activity of EEG is usually divided into frequency bands, named: Delta (0.5-4 Hz), Theta (4-8 Hz), Alpha (8-12 Hz), Beta (12-30 Hz) and Gamma (over 30 Hz). In this study, twelve features have been obtained from spectral analysis and wavelet decomposition of the EEG signal. The extraction was done in segments of 1, 2, 5 and 5 seconds.

1) Spectral analysis

For each signal segment, PSD was estimated with Burg method, which is appropriated for short duration signals. The mean value of each signal segment was previously removed before PSD computation. Based in a previous work of our group, an order = 20 was chosen [14]. In the same work the best features to detect the drowsiness in EEG records were analyzed. Those were used here and they are: Central Frequency (it contains the 50% of the power signal), First Quartile frequency (include the 25% of the power signal), Maximum Frequency (it contains the 95% of the power signal) and the Total Energy of Spectrum. The Power of Theta (4 to 8 Hz) and Alpha (8 to 12 Hz) EEG frequency bands were also calculated. [14]

2) Wavelet decomposition

WT allows for discrimination of no-stationary signals with different frequency feature [15].

The Daubechies 2 stationary WT was used to separate the EEG segments in five scales. In Subasi (2004) it was demonstrated that Daubechies wavelet of order 2 gives better classification efficiency than some of the others common wavelet [5]. At the sampling rate of 250Hz, the equivalent filters of scales 3, 4 and 5 have approximately the same frequency bandwidth as Beta, Alpha and Theta rhythms, respectively (see Table I). The D1 and D2 decomposition have not been used in this work due to their bandwidths do not include normal EEG components. Figure 2 shows the D3, D4 and D5 decomposition scales of WT for the alertness and drowsiness EEG segments showed in Fig 1.

TABLE I
FREQUENCY RANGES OF EQUIVALENT FILTERS

Scale	Frequency Range (Hz)
D1	62.5 – 125
D2	31.25 – 62.5
D3	15.62 – 31.25 (β)
D4	7.81 – 15.62 (α)
D5	3.9 – 7.81 (θ)

From the scales 3, 4 and 5 were extracted the zero crossing (ZC) and the integrated EEG (IEEG) as features of each segment. The IEEG is closely related to the energy of each rhythm. The ZC is the representation of the EEG clotting phenomenon. [10] For *i*-th scale decomposition D_i ($i=3,4,5$) the IEEG and the ZC are defined as follow:

$$IEEG = \sum_{k=1}^{N_i} \left| D_i[k] \right| \tag{1}$$

$$ZC = \sum_{k=1}^{N_i} \left[\operatorname{sgn}\left(-D_i[k].D_i[k+1] \right) \right] \tag{2}$$

where N_i is the number of samples of D_i and *sgn* is the signum function defined as

$$\operatorname{sgn}(x) = \begin{cases} 0, & if \quad x \le 0 \\ 1, & if \quad x > 0 \end{cases}$$

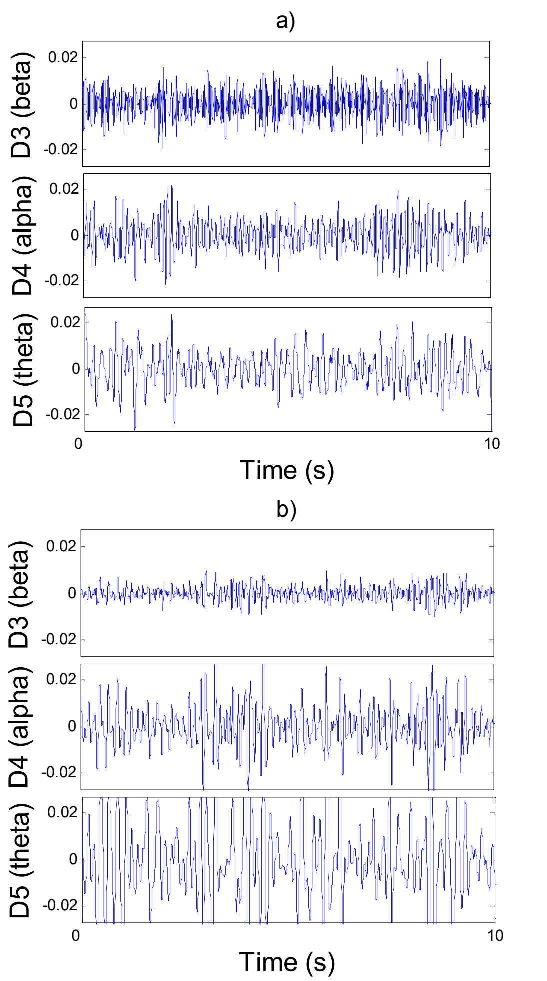

Figure 2. Scales D3, D4 and D5 of wavelet transform a) Alertness EEG b) Drowsiness EEG.

TABLE II
DETECTION RESULTS

	Number of neurons of hidden layer	10		15		20	
Time	%	Alertness	Drowsiness	Alertness	Drowsiness	Alertness	Drowsiness
1s	Alertness	90.55	9.45	90.08	9.92	89.98	10.02
	Drowsiness	54.77	45.23	57.88	42.12	58.7	41.3
2s	Alertness	71.79	28.21	84.9	15.1	84.94	15.06
	Drowsiness	37.4	62.6	46.68	53.32	47.78	52.22
5s	Alertness	88.7	11.3	89.5	10.5	**86.5**	**12.5**
	Drowsiness	36.7	63.3	24.8	75.2	**12.4**	**81.7**
10s	Alertness	90.35	9.65	89.2	10.8	90.1	9.9
	Drowsiness	16.55	83.45	13.85	86.15	11.2	88.8

D. *Classification*

A Neural Network (NN) is an interconnected group of artificial neurons that uses a mathematical or computational model for information processing. They change their structure based on external or internal information that flows through the network. They can be used to model complex relationships between inputs and outputs or to find patterns in data [16].

In this paper, it is proposed a NN as classifier. Twenty five NNs architectures were tested in this work to differentiate alertness and drowsiness stages. In all cases three layers were used, the first had 12 neurons (equal to the number of inputs vector), and the last had one neuron with tan-sigmoid transfer function. The hidden layer varied between 5 and 30 neurons.

The features vector set represent the NNs input. The out put categories were "0" to alertness stage and "1" to drowsiness stage.

The Levenberg-Marquardt backpropagation algorithm was used to train the different NNs. They were trained with aleatory set of data (30 %), and tested with the rest of them.

After training and cross-validation each NN, the result was compared. The classification results presented are the average of four training sets for each NN. In the following section, the most appropriate NN to differentiation both stages is explained.

The WT and de NN training were performed using the toolboxes available in MATLAB©.

IV. RESULTS

The quantitative analysis of the algorithm was done in 2315 EEG epochs (1625 alertness epoch and 690 drowsiness epochs). Each signal in database was validated by an expert in 30sec epochs. In this work, they were divided in segments of 1, 2, 5 and 10 seconds to extract the mentioned feature.

In order to evaluate the performance of the proposed algorithm, some statistical parameters have been calculated. The results of classifying segments are divided in four detection categories the % of drowsiness segments that the algorithm detects correctly, the % of alertness segments that the algorithm recognizes correctly, the % of alertness segments that the algorithm detecs erroneously as drowsiness and the % of drowsiness segments that the algorithm does not detect. The results of these values for different length segments and some NN architecture (hidden layer with 10, 15 and 20 neurons) are indicated in Table II. The results of each classification are compared with expert marks available in the database.

Considering that 5s long is better length time to take a decision in a real time than 10s, and the detection results with this segmentation are good, the 5s is considered as the most appropriate length-segment to extract feature, and NN(12-20-1) is the best architecture to discriminate both stages. It gets 86.5% of alertness stage detection and 81.7 % of drowsiness stage detection.

V. DISCUSSION AND CONCLUSION

Drowsiness is one of the leading reasons for accidents. Therefore, accident prediction through different method is crucial to improve safety.

In this work it is proposed to detect drowsiness using different feature extracted only from one EEG channel. The EEG has abundant information of sleep stages and reflects changes in drowsiness, arousal, sleep, and attention. The advantage of using only one EEG channel is that the driver could use only one sensor in the head instead of using an uncomfortable cap with a lot of electrodes. The EEG signal reflects very well the loss of alertness, so is appropriate to detect drowsiness [5], [19].

Based on previous studies [14],[10], we computed different EEG features: the Central frequency, the first quartile frequency, the Maximum frequency , the total Energy of Spectrum, the Power of Theta and Alpha bands, the number of Zero Crossing and the integrated EEG for the scales 3, 4 and 5 of Daubechies 2 wavelet transform.

In a previous work [14], the results obtained with the Central frequency, the first quartile frequency, the Maximum frequency, the power of Theta and Alpha bands and discriminate analysis were of 73.6 % of good drowsiness segment detection. Adding new features (ZC and IEEG) [10] and classifying the data with NNs the results improve. In this work it has been obtained an average 84.1% of good segments detection in both stages. The algorithm was tested in 2315 EEG 30-seconds epochs (1625 alertness epoch and 690 drowsiness epochs), which were divided in 1, 2, 5 and 10 seconds. Those segments belong to 10 subjects. The results show that the features extracted and the classifier are able to identify drowsiness EEG segments. We have observed that the most appropriate length-segment to extract feature in a short time and the best architecture of the NN to discriminate both stages are 5s and 12-20-1.

Similar works in literature detect drowsiness using EEG records and different techniques. Lin *et al.* in [11], [17], [18] use the EEG signal to detect the loss of alertness in drivers, whit good results. Arjuan in [19] identified changes in EEG recording in response to changes in alertness of the subjects. Those works show that the changes in EEG could be used to discriminate drowsiness from alertness in subjects. Pai Yuang in [10] obtained 90 % of drowsiness detection, using similar techniques present in our work, but using an active dry electrode system to obtain the EEG signal. In this work the signal used were obtained with common electrodes and the results are good too.

It could be found a few difference between drowsiness stages in EEG takes in polysomnographic records and in driving situations. However, the algorithm developed here could be also used in drowsiness driving detection.

In a future work, we will test the proposed drowsiness detector in new EEG signals obtained in our laboratory with a driver simulator in order to validate the algorithm with those new signals.

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