# EEG Processing System for Detecting a State of Drowsy Driving

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***Abstract*—By exploiting a database of 109 persons including two states to detect: sleepy or not, we have designed a system for automatically detecting drowsiness of a driver at the wheel. By filtering the alpha wave and by using the power spectral density of that same wave, our data were analyzed using the percentiles as measures of dispersion. A threshold discriminating the two states was found, which helped to highlight the area of the brain responsible for the state of drowsiness for driver. Thus, number of EEG signals to be analyzed will reduce and processing time of this system will be decreased. With cross validation technique, data are trained and tested, to get result with accuracy of 80% or higher. It shows that the EEG could be used helping experts in the development of an intelligent system for detecting state of drowsy driving with only ten signals by person.**

***Index Terms*—EEG, DSP, drowsiness, α wave, percentile**

## I. Introduction

Nowadays sleepiness at the wheel is a problem that affects to the society at large rather more than it at first seemed. One of the tasks performed by analysis of electroencephalogram (EEG) is the problem of recognizing the state of somnolence, characterized by lower level of attention and the extension of reaction time to any external stimuli.

Vigilance is a state when a person has open eyes and solves a mathematical problem. Relaxation is a state of rest with closed eyes. Somnolence can be described as a state with closed eyes, characterized by attention declining and reduced level of information assessment.

The value of alpha band energy is a good marker of the relaxation state. However, it is possible to distinguish the states of somnolence and vigilance only by the changes in the energy of alpha range.

On the other hand, there are a lot of studies done on this area, have led to the development of neural network-based systems to assess vigilance levels using electroencephalogram (EEG) signals [1]-[5]. All these systems ensure the vigilance quantification more or less successfully with a monitoring analysis capability. In [2], T. P. Jung and colleagues suggested a method based on the spectral component analysis and a multilayer neural network. The aim was to study on the one hand the correlation between the EEG signal spectrum and the vigilance level quantified by an auditory test, and on the other hand, the automatic classification of vigilance states from the spectrum of the same EEG signal performed by a neural network. In [4], a Radial Basis Function (RBF) neural network made it possible to classify the vigilance levels. The considered parameters are the coefficients of an autoregressive model (AR). Kohonen Self-organizing maps were used to make the cartography of the awakening-sleep transition over EEG epochs [5].

In this paper EEG signals from 109 persons are analyzed and the feature extraction is carried out through the methods of Fast Fourier Transform (FFT), digital filtering and power spectra. After that, the signals are classified to get the best result. To do this, our data were analyzed using the percentiles as measures of dispersion. The data are trained and tested to get a result with an accuracy of 80% or higher. It shows that EEG data could be used helping experts in the development of an intelligent system to detect a state of drowsy driving.

## II. Data Bank

The establishment of two banks EEG data: Analytical work was conducted on a database [6] totaling 109 individuals. Subjects performed different motor/imagery tasks while 64-channel EEG were recorded using the BCI 2000 system. Each subject performed 2 experimental runs: two one-minute baseline runs (one with eyes open, one with eyes closed). The data are provided here in EDF+ format (containing 64 EEG signals, each sampled at 160 samples per second, and an annotation channel).

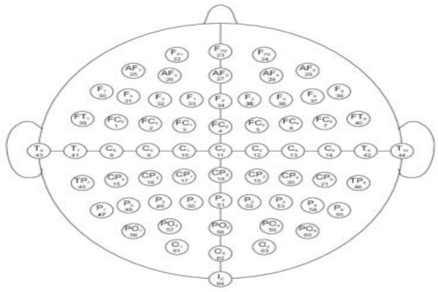

Figure 1. Electrode configuration.

The EEGs were recorded from 64 electrodes as per the international 10-10 system (excluding electrodes Nz, F9, F10, FT9, FT10, A1, A2, TP9, TP10, P9, and P10), as shown in Fig. 1. The numbers below each electrode name

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indicate the order in which they appear in the records; note that signals in the records are numbered from 0 to 63, while the numbers in the figure range from 1 to 64.

Each individual has been a measure of brain activity (EEG) and thus we have for each individual 64 signals, eyes closed signals (YF) and 64 signals, eyes open signals (YO), corresponding to the 64 electrodes placed on the scalp of the individual. So a total of 218x24 EEG signals. Recording of each signal period is 60,994 seconds, with a sampling frequency of 160Hz

## III. Features Extraction

Fig. 2 shows the steps we will follow to achieve this application. These steps are: Filtering, Fourier transformation, power spectrum and maximum detection.

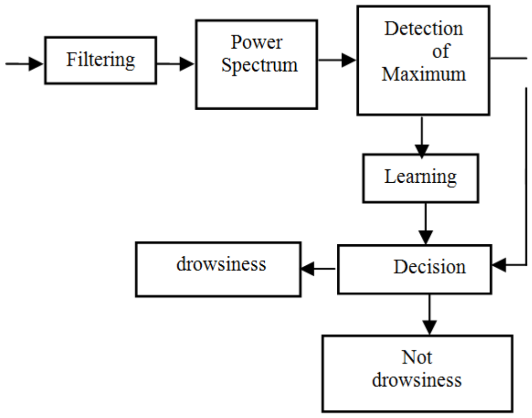



Figure 2. Steps of application.

### A. Filtering

As the wave α contains information that would allow us to distinguish between the two states (drowsiness or not). This step is to filter the EEG signal in order to maintain specific information of α wave.

Let x(n) signal before the filter and y(n) the output of the FIR filter, so y(n) is defined by:

$$y(n)=\sum h(k)\, x(n-k) \tag{1}$$

where $N$ is the order of the FIR filter and $h(k)$ are the coefficients of this filter.

### B. Fourier Transform and Power Spertrum

EEG signals have non stationary character. Therefore it is appropriate to examine its spectral composition in time-frequency domain using the Short-Time Fourier Transform (STFT).

The power spectrum of EEG signals can be estimated as:

$$S_i(k) = \frac{|X_i(k)|^2}{N} \tag{2}$$

where $N$ is the length of time, $X_i(k)$ is the spectrum of individual segment signal, $x_i(n)$, n=0, N-1, usually derived using the discrete Fourier transform (DFT).

$$X_i(m) = \sum_{n=0}^{N-1} x_i(n) e^{-2\pi jnm/N} \qquad \text{m= 0, N-1} \tag{3}$$

### C. Detection of Maximum

After using the filter for α wave and determining its spectral density, the search for the maximum amplitude of the entire spectral distribution of the frequency of this wave is important for the discrimination of two states detecting.

### D. Learning

This step will define the decision rule that will allow us to detect drowsiness. A statistical analysis based on the concept of quartile and using percentiles as measures of dispersion we found a threshold for two states: drowsiness or not. Thus, the indicators developed to analyze the data and especially to define a decision criterion to decide on the state of drowsiness are.

- Calculation of the first quartile;
- Calculation of the third quartile;
- Calculation of the inter quartile (Q3-Q1) away;
- And setting a lower bound and an upper bound, with:

Bound_low = Q1-(1.5 * (Q3-Q1)).
Bound up = Q3 + (1.5 * (Q3-Q1)).

### E. Decision

Once the decision rule established a simple threshold comparison test found previously, we will decide on drowsiness or not the person driving.

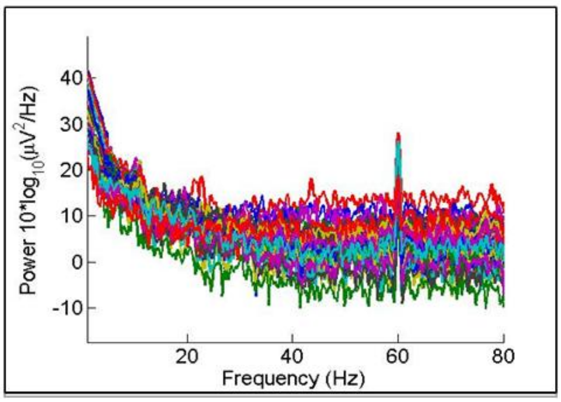
## IV. Results

The aim of this section is to achieve filtering of alpha wave between 8Hz and 12Hz. Infinite Impulse Response Filter (FIR) is used it order is 66. After filtering 64 EEG signals of each person, it is possible to conduct a spectral analysis. Fig. 3 and Fig. 4 show the visualization of the 64 spectral power of the 54th person before and after filtering and this for eyes open and eyes closed.

Fig. 3 shows clearly after filtering α wave band, the difference between the EEG of a person with eyes closed and when his eyes are open. It appears a much larger maximum in the frequency band of α wave of the person with Closed Eyes (CE) from the same person with Open Eyes (OE). The same observation is present on all the signals of person of our data base.

The search this maximum is very important as it will allow us to realize the learning that will help our system to decide on the state of the person driving.

Before filtering (Open Eyes)



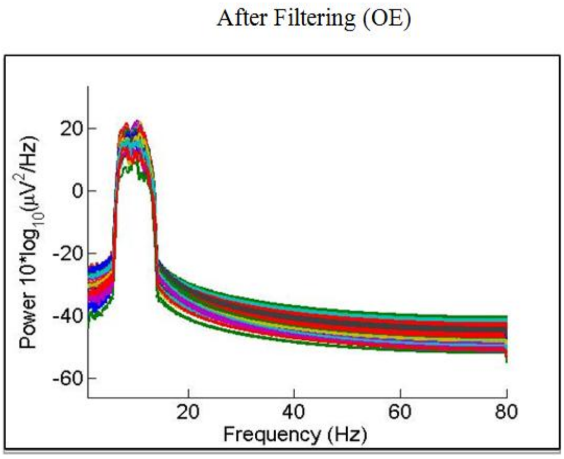



Figure 3. Spectrum power before and after filtering α wave (OY).

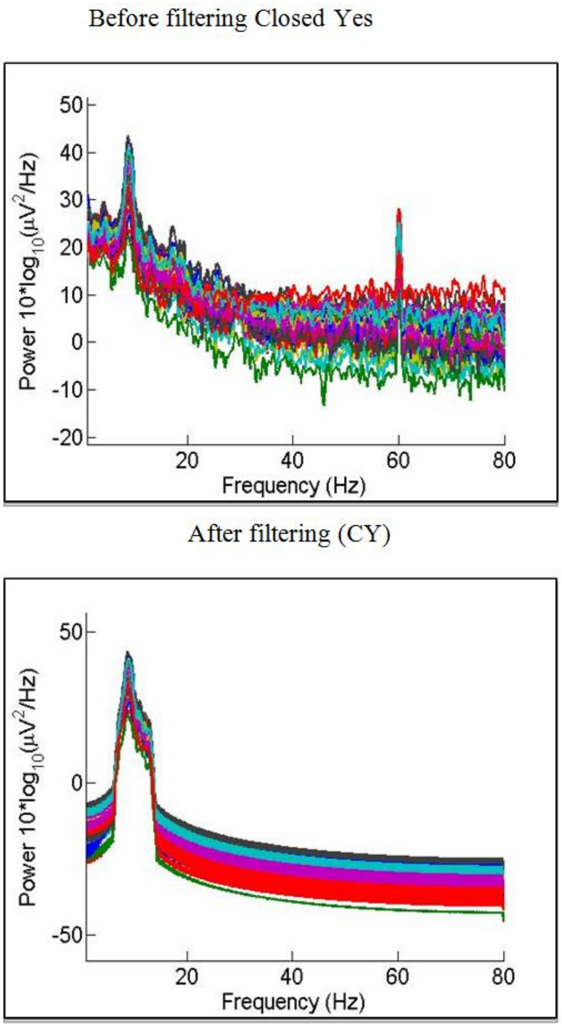



Figure 4. Spectrum power before and after filtering α wave (CY)

It should be noted that the position of the electrode corresponding to the maximum attained for each person, is not the same for all people in the database. Nevertheless, our study allowed us to locate the part of the brain responsible for this maximum. For 64 signals of the 54th person, Fig. 5 shows the energy distribution of the α wave on its frequency band.

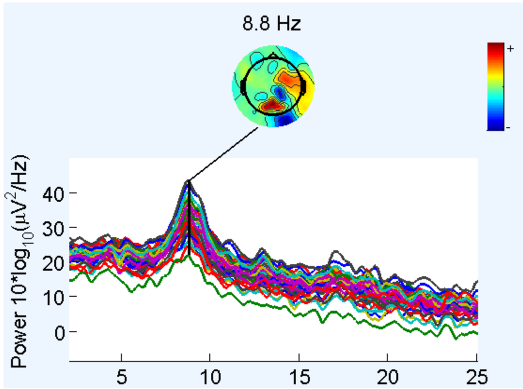



Figure 5. Energy distribution of the α wave for person N °54.

The maximum of spectral power corresponds to the frequency of 8.8Hz. Fig. 6 shows the energy localization throughout the brain. The red color shows the maximum reached. It is located in the occipital area. So for all individuals in the database we have established a close link between the state of drowsiness and EEG of the occipital part of the brain.

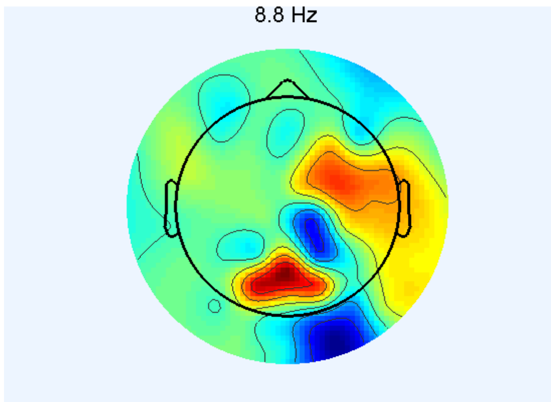



Figure 6. Energy localization throughout the brain (CY)N °54

The number of signals involved, becomes 10 signals. This is very important for our application, insofar as the number of signals responsible for the drowsiness will be reduced thus the time to real-time detection of this condition will automatically be reduced.

The maximum of 64 spectral powers corresponds to the frequency of 8.8Hz.

Fig. 5 shows the energy localization throughout the brain. The red color shows the maximum reached. It is located in the occipital area. So for all individuals in the database we have established a close link between the state of drowsiness and EEG of the occipital part of the brain.

Analysis of the results generated after filtering EEG signals, helped build a database of persons with a qualitative feature (eyes open or closed), and containing for each person the maximum amplitude of the spectral density on the α wave . These data were analyzed using indicators dispersion. Percentiles were preferred indicators of central tendency and dispersion classic because of the existence of peaks in the data set that distort their interpretation.

After determining the maximum of the spectral distribution of the band corresponding to alpha wave for all EEG signals from the database. To estimate the reliability of our proposed method, we use ten –foldcross validation method the total number of samples are sub-sampled into ten sets (k=10) such that each set contains approximately the same proportion of class samples as in the classification data set. Nine parts (90%) are used to train the classifier and one set (10%) for testing. The process is repeated ten more times such that every sub-partition is used as a testing set and the rest are used for classifier training.

Our indicator was developed on all available data (without reference to the state of the person) and led to the conclusion that if we consider that an individual is considered sleepy when the amplitude it is associated is greater than the lower bound, the results indicate that 64.2% of individuals with closed eyes are drowsy and 19.2% of persons are sleepy eyes open. Of the total 109 persons YO, 71 individuals were detected non drowsy or a percentage of 64.22% of correctly classified. For all 109 person YO, 88 sleepy states were detected with a rate of 80.73% correct classification.

## V. Conclusion

This current paper describes how it is possible through a judicious choice of one relevant feature, to develop a system for automatically detecting a state of drowsy driving. This feature is the maximum of the spectral density of the alpha wave. In addition, our study shows that it is possible to target only a specific part of the brain responsible for drowsy: the occipital part. This result will reduce the number of signals to be processed to reach the decision. Thus the number of signals to be processed to pass from 64 to 10 signals. The results obtained with respect to classification rate can be further improved by judicious a classification algorithm choice.

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