Vigilance Monitoring System Using Brain EEG Signal Processing

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Abstract— For many human machine interaction systems, the operators need to retain high and constant level of vigilance to prevent accidents. Comparing with other techniques that used for vigilance monitoring such as face recognition; a new technique was emerged that based on using the electroencephalogram (EEG) signals from the brain to reflect the vigilance level much sooner and more accurately. However, many difficulties exist in this field such as; how to label the EEG data, how to remove the noise from the EEG data, what are the most effective features for this type of signal and then what is the optimum classification technique. This paper introduced a new experiment for vigilance monitoring using Brain EEG signal processing. EEG data are analyzed using Fast Fourier Transform to extract features corresponding to two distinct vigilance levels: awake and falling asleep. Unsupervised learning method using multi layer Neural Network trained by a standard back propagation algorithm is used to classify the two classes of vigilance levels. Our preliminary results for estimating different vigilance levels with EEG signals are quite promising. We reached to 96.4% classification rate for the two considered vigilance levels, the result that surpassed the results from other researches in the same application. This research can give a direction for the vigilance labeling and features selection for the real time vigilance monitoring system in future.

Key-Words: EEG signal processing, Vigilance monitoring system, Safety systems.

1 Introduction

Every year, around the world, the number of traffic accident deaths is more than 600 thousands, and the number of traffic accident injuries is more than 10 millions and billions in monetary losses. In 2002, the National Sleep Foundation (NSF) reported that 51% of adult drivers had driven a vehicle while feeling drowsy and 17% had actually fallen asleep [1]. During the past few decades, studies on vigilance (alertness) have shown that vigilance estimation is very useful for many human machine interaction systems in which the operator should retain vigilance above a constant level. For example, airway dispatchers, pilots and long-distance truck drivers need to retain a high level of vigilance. As a result, we need an effective method to measure the current vigilance level of the operator.

Previous studies have shown that information regarding alertness and cognition is available in EEG recordings [2][3].

The (EEG) signal is a recording of the electrical activity of the brain, directly from the scalp. Four types of rhythms for this type of signal are particularly important: Delta (0.5–4 Hz): These waves are primarily associated with deep sleep and may be present in the waking state. Theta (4–8 Hz): These waves have been associated with access to unconscious material, creative inspiration and deep meditation. It seems to be related to the level of arousal. Alpha (8–12 Hz): these waves have been thought to indicate both a relaxed awareness without any attention or concentration. Beta (12-30) Hz: It is most evident in the frontal region and associated with active busy or anxious thinking and active concentration [4].

Figure 1 explains the sleep cycle for a normal person. As shown in fig. 1 the sleep stages are: W (Awake or alert), Stages 1,2,3,4 (Known as NREM stages) and the fifth REM (Rapid Eye Movement) stage.

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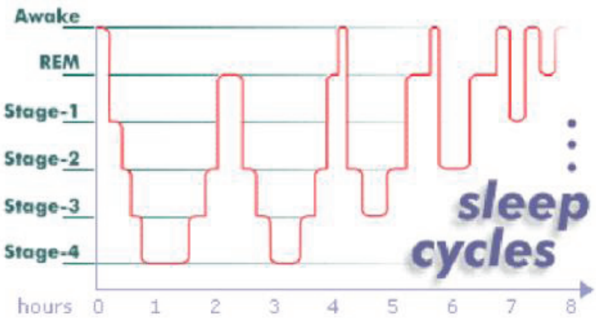

Figure 1. The Sleep Cycles Associated with on night's sleep [5].

During the earliest phases of sleep, you are still relatively awake and alert and the brain produces the Beta waves. As the brain begins to relax and slow down, slower waves known as Alpha waves are produced [6].

The Sequence of Sleep Stages: It is important to realize, however, that sleep does not progress through these stages in sequence. As shown in figure 1, sleep begins in stage 1 and progresses into stages 2, 3 and 4. After stage 4 sleep, stage 3 and then stage 2 sleep are repeated before entering REM sleep. Once REM sleep is over, the body usually returns to stage 2 sleep. Sleep cycles through these stages approximately four or five times throughout the night. On average, we enter the REM stage approximately 90 minutes after falling asleep.

This paper introduced a new experiment for vigilance monitoring using Brain EEG signal processing. 2 EEG channels data were analyzed using Fast Fourier Transform to extract features corresponding to two distinct vigilance levels: awake (w) and the first stage of falling asleep. Unsupervised learning method using multi layer Neural Network trained by a standard back propagation algorithm was used to classify the two classes of vigilance levels. Our preliminary results for estimating different vigilance levels with EEG signals are quite promising. We reached to 96.4% classification rate for the two considered vigilance levels, the result that surpassed the results from other researches in the same application.

This paper is organized as follows: Sec 2 presents the related work; Sec 3 presents the vigilance monitoring system architecture and methodology; Sec 4 present the experiment setup and the experimental results. Finally conclusions and future work are drawn in Sec 5.

2 Related Work

In EEG-based vigilance research field, most effort was focused on the evoked potential (EP) response under different vigilance levels [7]-[12]. Recently, the group mean performance of EEG signals under different vigilance levels was used. According to the mean performance during a fixed time period, vigilance levels can be estimated. Then the relation between EEG and vigilance can be analyzed.

In [13] an EEG-based drowsiness estimation technology based on ICA (independent component analysis), power-spectrum analysis, correlation analysis, and the linear regression model was proposed and evaluated in a VR (Virtual reality) based driving environment. The proposed analysis methods were feasible to accurately estimate individual driving error accompanying loss of alertness by linear regression model applied to ten subband log power spectra near Alpha bands of 2 ICA components as inputs. Averaged accuracies of within- and cross-session estimation for five subjects were 86.2% and 88.2%, respectively. They also compared the results to those obtained by linear regression models applied to two best drowsiness-related EEG channels located at central electrodes of the corresponding ICA components. Average accuracies of within- and cross-session estimation for five subjects were 84.6% and 82.4%, respectively.

[14] Considered the problem of selecting relevant features extracted from human polysomnographic (PSG) signals to perform accurate sleep/wake stages classification. extraction of various features from the electroencephalogram (EEG), the electro-oculogram (EOG) and the electromyogram (EMG) processed in the frequency and time domains was achieved using a database of 47 night sleep recordings obtained from healthy adults. Four EEG channels (C3-A2, P3-A2, C4-A1, and P4-A1), one transversal EOG and one chin EMG were registered and digitized at a sampling frequency fs=128 Hz. The EEG leads were attached onto the scalp according to the International 10-20 EEG System of electrodes placement. Multiple iterative feature selection and supervised classification methods were applied together with a systematic statistical assessment of the classification performances. The results showed that using a simple set of features such as relative EEG powers in five frequency bands yields an agreement of 71% with the whole database classification of two human experts. These performances are within the range of existing classification systems. The addition of features extracted from the EOG and EMG signals makes it possible to reach about 80% of agreement with the expert classification. The most significant improvement on classification accuracy is obtained

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on NREM sleep stage 1, a stage of transition between sleep and wakefulness.

In [15] the researchers analyzed the EEG data and extract features corresponding to two extreme vigilance levels: awake and sleeping and avoid the middle levels. 64 channels of signals including 4 channels of EOG are recorded. 20 channels of EEG data recorded from electrodes located at the center of the head were used. Short-time Fourier Transform (FT) was used to transform the original EEG data directly to the frequency field. And a second method used the FT to transform the results of the CSP (Common Spatial Patterns) transform to the frequency field. The EEG signals of frequency between 2Hz and 30Hz were used to analyze. Then PCA (Principal Component Analysis) was used to reduce the dimensions. Several clustering methods such as Normalized cut [16], Soft clustering [17] and K-mean were used to cluster the EEG data. They conclude that, CSP transform could greatly increase the accuracy of the clustering of the EEG data.

In [18] EOG features, mainly slow eye movements (SEM), to estimate the human vigilance changes during a monotonous task. In particular, SEMs were first automatically detected by a method based on Discrete Wavelet Transform (DWT), then linear dynamic system was used to find the trajectory of vigilance changes according to the SEM proportion. The performance of this system was evaluated by the correlation coefficients between the final outputs and the local error rates of the subjects. The result suggested that SEMs perform better than rapid eye movements (REM) and blinks in estimating the vigilance. Using SEM alone, the correlation can achieve 0.75 for off-line, while combined with a feature from blinks it reached 0.79.

In [19] 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 (PSD) 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, and 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 was done with neural networks. The detection results obtained with this technique were 86.5 % for drowsiness stage and 81.7% for alertness segment.

[20] Recorded 19 EEG channels signals from 10 volunteers while they were playing a virtual driving game. Recordings were band pass filtered between 0.5 and 30 Hz. Then, they extracted some chaotic features (include Higuchi's fractal dimension and Petrosian's fractal dimension) and logarithm of energy of signal. Feed forward Artificial Neural Network (ANN) was used as a classifier to classify the two classes of vigilance; alert and drowsy (first stage of sleep). The result showed that, the Ability of each feature has been evaluated and the maximum accuracy of classification was 75.5%. While the accuracy of classification with all three features for the nineteen channels was about 83.3%.

In [21] a total of 19 features were computed from only one EEG channel to differentiate the alertness and drowsiness stages. After a selection process based on lambda of Wilks criterion [22], 7 parameters were chosen to feed a Neural Network classifier. Eighteen EEG records were analyzed. The method gets 87.4% and 83.6% of alertness and drowsiness correct detections rates, respectively.

This paper introduced a new experiment for vigilance monitoring using Brain EEG signal processing. Two distinct vigilance levels: alert (awake) and the first stage of falling asleep (drowsy) were classified in our system. 2 EEG channels only were used in our experiment. Frequency components corresponding to Alpha and Beta bands [8-32 hz] of the EEG signals were extracted using Fast Fourier Transform (FFT) and used as features. Thus we have 23 features for each channel and a total of 46 features from the 2 channels for every state. Unsupervised learning method using multi layer Neural Network trained by a standard back propagation algorithm was used to classify the two classes of vigilance levels. Our preliminary results for estimating different vigilance levels with EEG signals are quite promising. We reached to 96.4% average classification rate for the two considered vigilance levels, the result that surpassed the results from other researches in the same application.

3 System Methodology

This research presented an EEG-based vigilance monitoring system. Vigilance monitoring system can be embedded in the cars to prevent accidents. The methodology of such systems is simply as follows. EEG signals of the subject are collected and transferred to the embedded CPU within the car for analyzing. Then the feedback from the computer is used to operate a siren system that's embedded within the car if the first stage of asleep is recognized.

The Methodology used for the process of the EEG signal classification is divided into the following four steps as shown in Fig 2. Firstly, recording large amount of EEG data and the corresponding vigilance levels. Secondly, perform preprocessing to the EEG data such as noise reduction and artifacts removal. Thirdly, transform the EEG signals and extract features from these signals. At last, analyze the EEG signals to classify the two vigilance levels these signals belong to. The detailed techniques used for each step are discussed below.

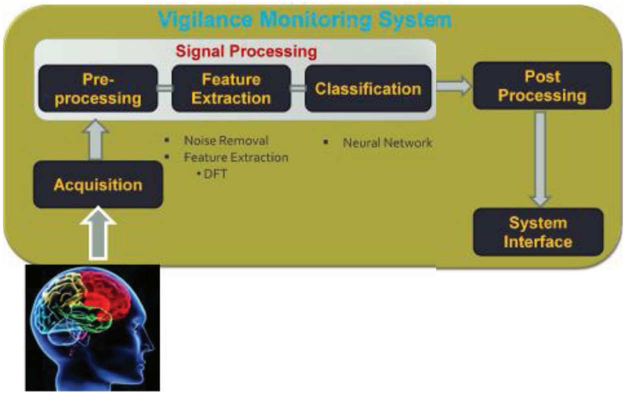

Fig 2. System Methodology

3.1 Signal Acquistion

In our experiment of this research we used a data set from [23]. The recordings were obtained from 8 Caucasian males and females (21 - 35 years old) without any medication; they contain horizontal EOG signal, FpzCz and PzOz (2 EEG signals), and an event marker. Each channel signal sampled at 100 Hz. The sleep stages were coded in the file as binaries 0, 1, 2, 3 and 4. The recordings were obtained from ambulatory healthy volunteers during 24 hours in their normal daily life, using a modified cassette tape recorder. Subjects, recordings are described in [24].

Signal was recorded using a head set consisting of 64 electrodes as shown in Fig 3 using a standard 10/20 electrodes position. The Two bipolar EEG channels only were used: Fpz-Cz and Pz-Oz.

Data for one subject only was used in our experiment to classify the two vigilance states: awake (W) and first stage of falling asleep (stage 1). 16 minutes epochs was used for each state. Then we have 16*60*100= 960 samples for each channels and a total of 1920 samples from the two EEG channels for each state. 70% of the data samples were used for training, 15% were used for validation and the remaining 15% were used for testing. 98 iterations were used for each state.

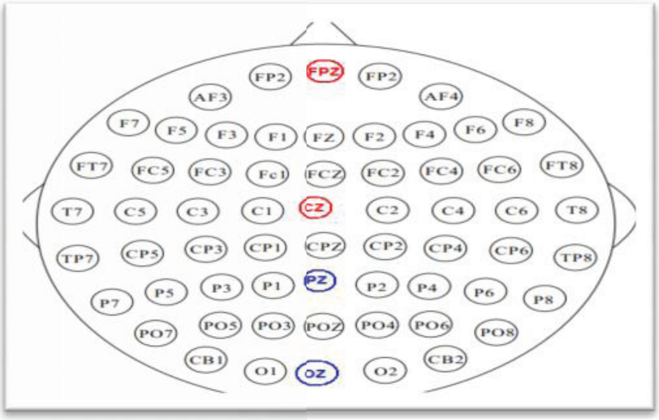

Fig 3: Electrodes Distribution over the scalp according to the Standard 10/20 electrodes placement.

3.2 Signal preprocessing

Originally, the EEG signals contain a lot of artifacts and unrelated signals. Generally speaking, there are two types of artifacts [13]. The first type is the extra cerebral source artifact which is recorded together with EEG, such as electrooculo-gram (EOG), electromyography (EMG), and ECG. The second type is the technical artifact resulting from the EEG recording system, such as signal drift and decay. In our experiments, a 2-channels System is used to record EEG signals. The EEG Signal are extracted using a 3rd order band pass filter for the frequency range [0.5 - 45 Hz] which is the range of the EEG Signal only.

3.3 Feature Extraction

Besides the artifacts we talked about in the previous section, there exist a lot of background signals which are unrelated to vigilance change. So we need a decomposition method which can extract the EEG signals we interested in. As we know, there are a lot of classical or effective decomposition methods. But unfortunately, as the energy of background signals is much greater than the energy of the signals we interested in, most of them are not suitable under this situation. Here we use Discrete Fourier Transform (DFT) to transform Signal from the time domain to the frequency domain.[25]

DFT can be formulated as:

$$X(k) = \sum_{j=1}^{N} x(j)\, \mathbf{w}_N^{(j-1)(k-1)} \qquad (1)$$

Where

$W_N = e^{(2\pi i)/N}$

Is the N^{th} root of unity, is used herein to compute the DFT of each epoch. In our experiment, N is equal to 100 (sampling frequency =100 Hz).

Amplitude values for the frequency components corresponding to the frequency band [8-30Hz], which corresponding to the Alpha and Beta bands of the EEG signal, were used as features in our experiment. Alpha and Beta bands are the two bands of frequency that associated with the two considered vigilance states in our experiment as we mentioned before[6]. Thus we have 23 features for each channel and a total of 46 features for each state.

3.4. Classification

Neural network has been used by many researchers to classify the EEG signal [26]. In this research Multi-layer Perceptron Neural Network (MLP) was used as a classifier. The learning algorithms used were Feed-Forward and Back-Propagation. The data collected were randomly divided into training, validation and testing sets. The dimension of the data was: 16(min)*60=960 seconds data for each state. In each epoch the data are divided as follows:

- 70% Training patterns
- 15% Validation patterns
- 15% Testing patterns

The MLP NN consists of an input layer, N hidden layers and an output layer. The number of neurons in the input layer equals the length of the features vector which are 46 features in our experiment. The output layer should contain one neuron used to classify the two states of vigilance (Awake and falling asleep (stage 1).

4 Experiment and Experimental Results

Experiment is down using one subject data from the dataset at [23]. EEG data recorded using a head set consisting of 64 electrodes using a standard 10/20 electrodes position. 2 EEG channels recordings only were used in our experiment Fpz-Cz and Pz-Oz. Each channel signal sampled at 100 Hz. The recordings were obtained from ambulatory healthy volunteers during 24 hours in their normal daily life, using a modified cassette tape recorder. 16 minute data recordings were used for the two considered states (Awake and falling asleep stage 1). Thus we have 16*60=960 seconds data for each state and a total of 1920 seconds of data for the two states. (DFT) were used to analyze the data. The amplitude values for the frequency components for the frequency band from 8-30Hz (Alpha and Beta bands) for each channels were used as features. Thus we have 23 features for each channel and a total of 46 features for the 2 channels used.

Multi-layer Perceptron Neural Network trained by a standard back propagation algorithm is used for classification. 70% of the data (1344 patterns) were used for training, 15% (288, 144 patterns for each class) were used for validation and the remaining 15% were used for testing. The configuration of the MLP NN was as follows:

- Number of input neuron=46
- Number of hidden layer=1 with 100 neurons
- Number of output neuron=1
- The activation function used was the sigmoid function.
- The learning rate was 0.01.

Training stopped when the mean square error saturated at small values as shown in Fig.4. The training stopped at 98 epochs in our experiment as shown in Fig. 4.

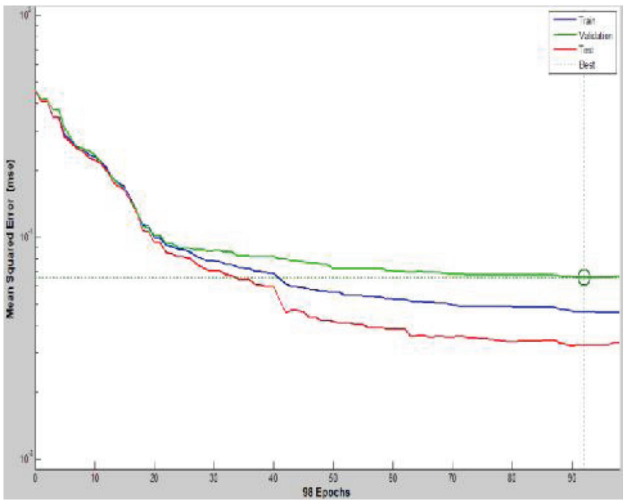

Fig. 4 Mean Square Error of Classification

Correct classification rate (CCR) for each class was calculated according to the following equation:

$$CCR = Cn/Tn * 100\% \qquad (2)$$

Where Cn is the total number of correct classifications and Tn is the total number of testing patterns). Correct classification rates representations for the two states of vigilance and the Total CCR are as shown in Fig.5. The confusion matrices for the learning and the testing processes are as shown in Fig.6. As shown in Fig.5, The proposed methodology in this research achieved a classification rate=93.8% for class 1 (awake state) and a classification rate=98.6% for the second class (falling asleep stage 1). The total classification rate for the two classes in our experiment was 96.2%, the results that surpassed the results from all the previous researches in the same applications.

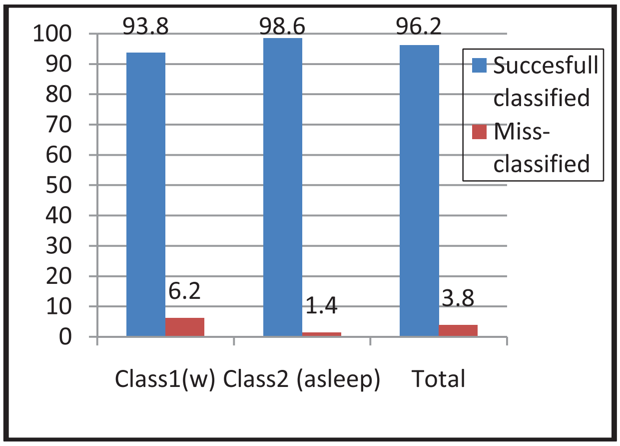

Fig 5. Classification Rates Representation

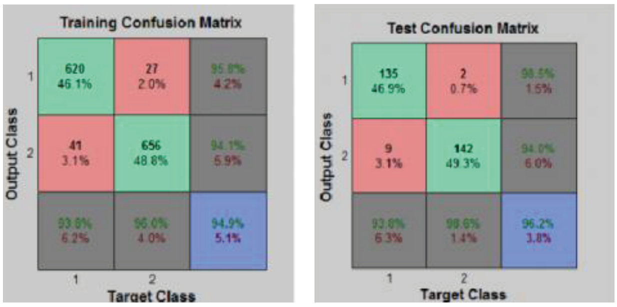

Fig 6. The Confusion Matrices for the Training and Testing.

5 Conclusion

This paper introduced a new experiment for vigilance monitoring using Brain EEG signal processing. Two distinct vigilance levels: alert (awake) and the first stage of falling asleep (drowsy) were classified in our system. 2 EEG channels only were used. Frequency components corresponding to Alpha and Beta bands [8-32 hz] of the EEG signals were extracted using Fast Fourier Transform (FFT) and used as features. Thus we have 23 features for each channel and a total of 46 features from the 2 channels for every state. Unsupervised learning method using multi layer Neural Network trained by a standard back propagation algorithm was used to classify the two classes of vigilance. We reached to 96.4% average classification rate for the two considered vigilance levels, the result that surpassed the results from other researches in the same application.

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