

PSD BASED SLEEP STAGE ANALYSIS USING NEURAL NETWORK CLASSIFIER

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Abstract

Sleepiness of drivers is a dangerous situation with hazardous consequences. Prolong and constant driving results in transient state of brain that resonates between awake and sleep. The brain signal pulses are studied to detect the state of sleepiness and alarm the driver about his condition. The Electroencephalogram (EEG) is the most common tool used in sleep research. This unit describes the methods for recording and analyzing the EEG. Detailed protocols describe recorder calibration, electrode application, EEG recording, and computer EEG analysis with power spectral analysis. This paper proposes a framework with power spectral density (PSD) and principal component analysis (PCA) as a feature vector using neural network (NN) classifier for sleep stage analysis.

Key Words: EEG, Sleep Stage Analysis, Neural Network, PCA, PSD

1 Introduction

Sleep is not a continuous phenomenon. When a person falls asleep, transits through different phases, namely, light sleep, deep sleep and sleep paradoxical generally associated with

revealing the quality of sleep. It makes it possible to highlight some of the pathologies. Thus, a good analysis of sleep inevitably passes through the classification of periods of the night in stadiums. To this end, several physiological variables (electroencephalogram, muscle activity, respiratory rhythm, etc.) are recorded during the night because they have different characteristics depending on the phase of sleep considered. Their most often performed by a human operator. This task is tedious and can take several hours. The objective of this work is to improve these techniques of automatic analysis of with special attention to the processing of artifacts. Moreover, this to compare different classification processes by validating their results on the database.

2 History

Historically, human beings have been fascinated by sleep. In 1937, the only physiological variable allowed Loomis and his collaborators to discern 5 stages of Sleep: A = alpha, B = low voltages, C = spindles, D = spindles + wide random potentials, E = wide random potentials [1]. The REM stage (Rapid Eye Movement) remained unnoticed until 1953, because it was confused with the awakening or the light sleep, was discovered. The association of the ocular activity with the activity EEG then allowed Nathaniel Kleitman and William Dement demonstrated, in 1957, the cyclical nature of sleep [2]. Then, the REM stage was accompanied by sluggishness in the cat. This was quickly verified in the man by Berger in 1962. Thus, muscle activity became ineluctably the third physiological variable to be taken in a sleep polygraph, a practice more commonly known as name of polysomnography (PSG). From that point on, a lot of studies were done in the field, but Lack of uniformity in methods and their nomenclature was highlighted by the Monroe in 1967 [3]. This prompted several scientists, including Allan Rechtschaffen and Anthony Kales, to write a standard manual for rating in sleeping stages [4]. It was published in 1968 and still today is a reference work. This paper distinguishes 5 main categories of EEG waves beta, according to their rhythms and amplitudes.

In the healthy young adult, the proportion of different stages of sleep overnight is approximately [5]: 2 to 5% for Stage 1; From 45 to 55% for stage 2; 3 to 8% for Stage 3; 10 to 15% for Stage 4; From 20 to 25% for the REM stage. However, the composition of sleep can be influenced by various factors like the individual himself, age, environment, ingestion of drugs and pathologies.

3 Automatic Analysis

At present, the analysis of polysomnographic signals is still often carried out by a human operator. However, the assignment of a sleep stage to each of the 1,500 periods on average one night of recording is a long and tedious task. Even for a trained operator this sometimes represents more than 2 hours of work. Thus, it is quite possible to imagine the advantage of using an automatic classification method. Its advantage is twofold: saving time (and therefore money), but also the guarantee of consistency of results. Indeed, human quotation shows high rates of inter and intra-cotter variability, due in particular to the difficulty of attributing a stage of sleep to transient periods. The automatic classification method makes it possible, because of its deterministic character, to guarantee a constant result for the same polysomnographic trace.

The automatic dimensioning in stages of sleep comprises 3 major steps: 1) Artifacts removal 2) Feature extraction 3) Classification. The first stage to remove artifacts of input EEG signals and then feature extraction is done with PCA (principal component analysis) and Power spectral density of a signal. This feature vector is further trained in neural network according to class. And test cases are applied to check the proposed system performance analysis.

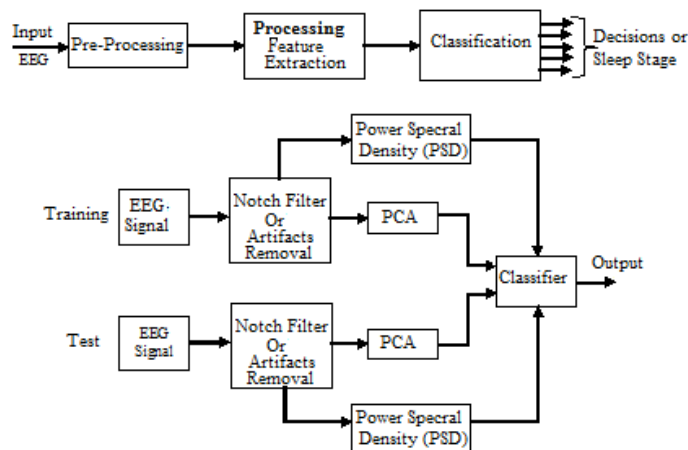


Figure 1: Stages of Automatic Classification in Stages of Sleep

4 Proposed Methodology

The methods of detecting artefacts encountered in the literature are very varied. Several of them use adaptive autoregressive models to detect sudden changes in EEG signal stationarity ([6], [7]). Others calculate the existing correlation between two polysomnographic signals to detect, for example, the presence of EOG interference on the EEG ([8]). Some methods use a non-linear energy operator to deduce a certain number of variables then confronted with limit values ([9],[10]). Finally, several methods directly compare the amplitudes of polysomnographic

[8] [11].

Concerning the correction of artifacts, the number of works dealing with the subject appeared to us more limited. Some studies focus on correcting EOG artifacts on EEG [7], but most of the work encountered concerns the correction of the cardiac interference present on the other ECG signals.

Artifact Removal Processes: The In this work we have extended the meaning of the word artefact to anything that might interfere with the extraction of discriminating characteristics for automatic classification into sleep stages. This includes, in particular, the peak waves which appear during epileptic seizures and which are not, as such, phenomena of artificial or accidental origin.

Among these artefacts, we distinguished between those of short duration not exceeding a few seconds (most artefacts) and those of longer duration, which may persist for several hours or even overnight. Cardiac interference and slow corrugation artifacts.

In the first case, the interferences produced are highly random, which makes it difficult or even impossible to correct them. On the other hand, the duration they occupy within the time to classify is generally low. Thus, we have chosen to simply remove them from the classification process by considering only the remaining part of the signal for the characteristic extraction step. In the second case, artefacts cannot be treated in the same way because they occupy practically all the epochs of the polysomnographic recording.

Artifacts Removal by Adaptive Notch Filter : In Filtering is a complex and often poorly understood and incorrectly used aspect of EEG and ERP processing, and ERPLAB is designed to make it easy for users to filter their data properly. Filtering is done slightly differently depending on whether you are filtering continuous EEG, epoched EEG, or averaged ERPs.

Conventional filtering is done to restrict the frequency band to the required range. It involves the following:

- Notch Filter at 50Hz to eliminate the power line interference.
- Butterworth high pass filter at 0.5Hz and low pass filter at 30Hz to restrict to delta (0.5Hz-4Hz), theta (4Hz-8Hz), alpha (8Hz-13Hz) and beta (13Hz-30Hz) frequency range.

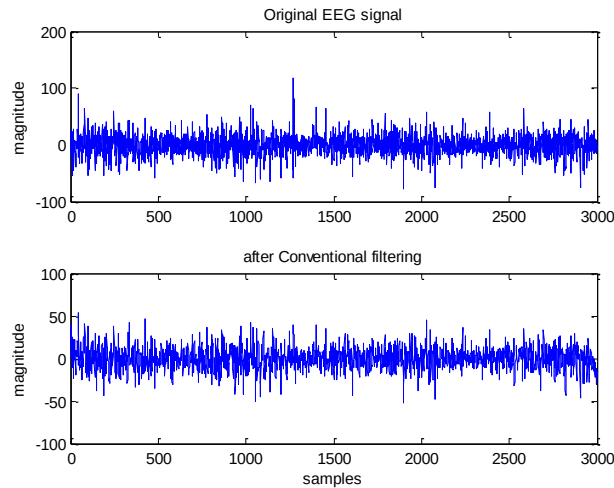


Figure 2: EEG signal after conventional filtering

Removing the trend (mean) from the signal:

Characteristic Extraction Process: The panel of extracted characteristics is therefore much diversified.

Principal Component Analysis (PCA): Steps for performing a principal component analysis

1. Take the entire dataset containing D -dimensional samples.
2. Calculate the D -dimensional mean vector (i.e., the mean for every dimension of the whole dataset)
3. Calculate the covariance matrix of the entire dataset
4. Calculate the eigenvectors ($E_1, E_2, \dots, E_D$) and corresponding eigen values ($Y_1, Y_2, \dots, Y_D$)
5. Categorise the eigenvectors by reducing eigen values and select n eigenvectors with the largest eigen values to form a $D \times n$ dimensional matrix M (where every column represents an eigenvector)
6. Utilize this $D \times n$ eigenvector matrix to convert the samples onto the new subspace. This can be summarized by the mathematical equation: $Y = M^T \times x$ (where x is a $D \times 1$ -dimensional vector representing one sample, and Y is the transformed $n \times 1$ -dimensional sample in the new subspace.)
7. Find standard deviation using the following formula:

$$\sigma = \sqrt{\frac{1}{N} \sum_{i=1}^N (x_i - \mu)^2} \quad (1)$$

Power Spectral Density: The power spectral density of a random signal is the Fourier transform of its autocorrelation function. In the case of a discrete time signal, the autocorrelation function is also discrete time, and the power spectral density is reduced to a TFTD (Time Frequency Threshold-Dependent):

$$S_{xx}(F) = \sum_{n=-\infty}^{\infty} \varphi_{xx}(n) e^{-jn2\pi f} \quad (2)$$

symmetry, the power spectral density is purely real. If, moreover, the random variable x is real, then the autocorrelation function is real even, and the power spectral density is also real.

The inverse TFTD of the power spectral density is of course:

$$\varphi_{xx}(n) = \int_{-\frac{1}{2}}^{\frac{1}{2}} S_{xx}(F) e^{jn2\pi f} dF \quad (3)$$

The power spectral density is quadratic, i.e. it is independent of the phase of the signal. Moreover, it is always real and positive.

Set of Feature Vectors for Training:

$$(X; S_{xx}(F), \sigma) \quad (4)$$

5 Artificial neural networks

The multilayer perceptron method is used for classification. It is a particular architecture of artificial neural networks where neurons are grouped in layers. The number of input units is imposed since it must correspond to the number of selected attributes. Similarly, the quantity of neurons output must be identical to the number of classes considered (6 in our case: awakening, S1, S2, S3, S4 and REM). On the other hand, the number of intermediate layers (called hidden layers) and the optimal quantity of neurons they contain are to be determined empirically. The main advantage of this method lies in its computation time required for identification. Indeed, although this is related to the complexity of the neural network, the propagation of the input to the output is done almost instantaneously (on the order of a millisecond). On the other hand, this method requires a very long learning and a good classification is obtained only if the training database is important.

6 Simulation Results

Performance of proposed research work is carried out using:

$$Accuracy = \frac{TP+TN}{P+N} \quad (5)$$

Where, TP=True Positives

TN=True Negatives

$P + N$ = Total population.

Results: The sleep signal stages are taken from Mayela E. Zamora [12] for detection of sleepiness. Based on the characteristics of 3rd column, the stages are classified in 5

found in respective reference [12].

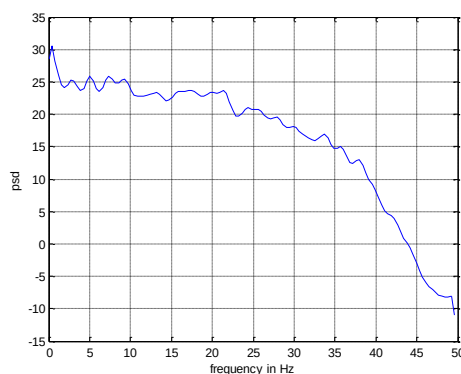


Figure 3: PSD v/s Frequency graph for sleep stage 1

Reference	Signal	Method	Classifier	Accuracy
Zamora M.E[12]	EEG	WT	Sparse Representation Method 3 Classes	94.2%
Mousa etal.[13]	EEG	WT+FFT	Fuzzy 4 Classes	84.4%
Proposed	EEG	PCA+PSD	BPNN	97.8%

Table 1: Comparision With Previous Work

7 Conclusion

This paper proposed a complete system of automatic classification in stages of sleep including the stages of elimination of artefacts, extraction of characteristics and classification itself in stages of sleep. The evaluation of their results was carried out and they appear to be quite satisfactory. The proposed framework has been implemented by Neural Network tool box of MATLAB and six stages of sleep classed are realized. This research work utilized 60-40 split case for testing and training of classifier. The accuracy obtained by this approach is 97.8%.

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