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Detection of Sleep Spindles in Sleep EEG by using the PSD Methods

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Abstract

Background/Objectives: In this study, Fast Fourier Transform (FFT), Welch, Autoregressive (AR) and MUSIC methods were implemented to detect sleep spindles (SSs) in Electroencephalogram (EEG) signals by extracting features in frequency space. **Methods/Statistical Analysis**: A database from these signals of five subjects which were recorded at sleep laboratory of Necmettin Erbakan University in Turkey was ready for use. The database consisted of 600 EEG epochs in total. The number of epochs was 300 for both with and without SSs in this database. Comparison of the performances of these methods on SS determination process was performed by using Artificial Neural Networks (ANN) classifier. **Findings:** According to the test classification results, notable difference was obtained between the applied PSD methods. By using the extracted all features, maximum test classification accuracies were achieved as 84.83%, 80.67%, 80.83% and 80.33% with use of FFT, Welch, AR and MUSIC, respectively. To determine the SSs, Principal Component Analysis (PCA) also was utilized in this study. When PCA was applied, the results were 89.50%, 82.00%, 93.00% and 94.83% by use of the same PSD methods, respectively. **Application/Improvements:** As a result, the performance of PCA and MUSIC is better than the others. Hence, these methods can be used safely for automatic detection of SSs.

Keywords: AR, EEG, FFT, MUSIC, Sleep Spindle, Welch

1. Introduction

Sleep related troubles have affected the daily life of people more seriously at the present time. Sleep stage scoring is an inevitable method to detect the sleep related problems. To score sleep, was benefited from these signals such as EEG, Electrooculogram (EOG) and Electrocardiogram (ECG) during sleep by recorded PSG device and then these recordings are evaluated by sleep experts. There are some rules for staging sleep. The specific rules are defined by 1. According to the guideline, a night sleep is divided into five stages which are named as Awake (W), Non-REM1, Non-REM2, Non-REM3 and REM2.

SSs and K-complexes are important components for determination of the N-REM stage-2 in the sleep electroencephalogram (EEG)[2]. Sleep spindle consists of 10 - 16 Hz waves and its time interval is between 0.5 and 3 seconds[3–5].

In literature, many studies have been performed related to sleep spindle detection. In [6], an algorithm was proposed that models the amplitude-frequency sleep spindle. In [7], features were obtained from EEG in time and frequency domain and then the SSs were classified. Ventouras et al. was benefited from Artificial Neural Network (ANN) for the same purpose[8]. In other study, a system was introduced to detect SSs by using amplitude features of SSs[9]. Liang et al. developed a neuro-fuzzy system to find the SSs[10]. In other study, line length that is an effective feature was used for SSs[11]. In other research study[12], a method was introduced for SS detection that is using gaussian systems.

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Parekh et al. put forward a SS detection system by processing the EEG[13]. In [14], the authors proposed a method that detects the SSs in sleep EEG by using Short Time Fourier Transform (STFT) for feature extraction. In [15], a study was realized for processing of EEG signals. Ahmed et al. presented a novel approach based on the energy operator and wavelet method[16].

In this study, four different PSD methods were used to detect sleep spindles (SSs) in the sleep EEG by extracting features in frequency space. A data set was composed with the EEG signals from five subjects The database comprise 600 EEG epochs in total. The number of epochs with SSs is 300 and the number of epochs without SSs is 300 in this database. Comparison of the performances of these methods on sleep spindle determination process was performed by using Artificial Neural Networks (ANN) classifier. According to the test classification results, notable difference was obtained between the applied spectral methods. Maximum test and training classification accuracies were achieved as 84.83%, 80.67%, 80.83% and 80.33%; 86.92%, 89.33%, 85.25% and 93.92% with use of FFT, Welch, AR and MUSIC, respectively. FFT and MUSIC methods have been shown to exhibit better performance than others. Also, for PCA method, maximum test and training classification accuracies were achieved as 89.50%, 82.00%, 93.00% and 94.83%; 100%, 99.67%, 99.92% and 99.58% with use of FFT, Welch, AR and MUSIC, respectively. When PCA was used, MUSIC and FFT methods have better performance for test and training in the order.

2. Material and Methods

2.1Used Dataset

In this study, the used EEG signals recorded by a PSG equipment which its brand name is VIASY in sleep laboratory of Necmettin Erbakan University. Because the SSs are seen in only EEG signals, C4A1 and C3A2 channels of EEG were used in study. Sampling frequency of EEG signals was 128 Hz and the data were recorded for about 8 hours. And then the epochs (signal parts in 30 sec long) of the data were labeled by two sleep experts as W, Non-REM1-2-3 and REM. The experts determined 300 of 600 epochs as with-SS and the other 300 epochs as without-SS. The EEG signals are of high reliability. Example epochs of EEG signal with and without-SS are seen in Figure 1.

The epochs with & without SS are reported as seen in Table 1.

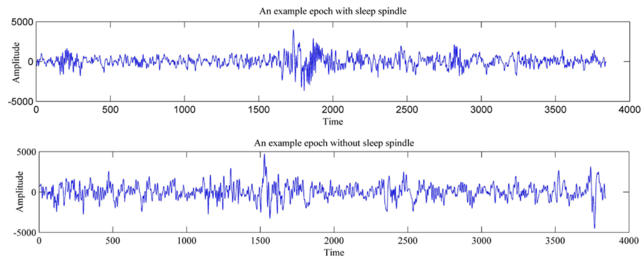

Figure 1. Instance epochs with and without SS.

Table 1. The epochs with & without SS in the dataset

	Epochs with SS		Epochs without SS	
	C4A1 channel of EEG	C3A2 channel of EEG	C4A1 channel of EEG	C3A2 channel of EEG
Subject-1	32	32	50	50
Subject-2	1	1	5	5
Subject-3	76	76	60	60
Subject-4	10	10	10	10
Subject-5	1	1	5	5
Subject-6	5	5	5	5
Subject-7	5	5	5	5
Subject-8	20	20	10	10
Subtotal	150	150	150	150
TOTAL	300		300	

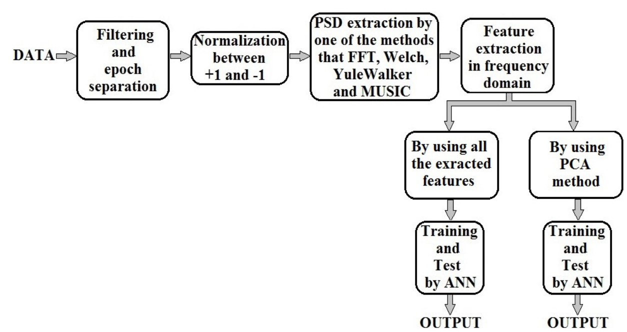

Figure 2. The performed process steps.

2.2 Preprocessing

The processing steps performed on the dataset are seen in the following Figure 2.

Data: In this study, EEG signals cleaned from of ECG artifacts were used. Firstly, the ECG artifacts were removed from uncleaned EEG signal before it was given to the system. To filter the ECG noises, firstly the ECG signals were splitted to the R-R intervals by using Pan-Tompkins algorithm[17]. After R peaks were identified, these peaks reflected EEG signal were taken away and the clear EEG signal was obtained as illustrated in Figure 3.

Data pre-processing: Filtering (bandpass filter in 0.5-35 Hz band) and eliminating artefacts were applied to the C3A2 and C4A1 channels of EEG signals belonging to five people. After that the epochs in 30 sec. length were prepared according to sampling rate.

Normalized: The used EEG signals were normalized between +1 and -1 values for feature extraction.

Feature Extraction: In this study, 10 different features were extracted in frequency domain according to the rules in [1].

Using the extracted features: Extracted all features ve PCA method were used to evaluate the performances of PSD methods. In [18,19], the PCA method was explained in detail.

Classifier: ANN was used as a classification system because of it has been chosen to classify SSs automatically[20,21].

PSD Extraction: Power spectral densities of EEG signals were obtained by performing FFT[22], Welch[23] (for this study, window type, length and overlap ratio were choosen as rectangular, 128 points and 50%, respectively), AR[24] (YuleWalker algorithm and 15 as model degree were utilized in this study) and MUSIC methods. The last PSD method which was used in this study is MUSIC (Multiple Signal Classification). In 1986, Schmidt put forward the MUSIC algorithm[25] which is one of the super-resolution techniques for array processing and generally used for frequency estimation and stationary signal analysis[26]. This algorithm is also a functional and forceful tool for non-stationary dispersion into matrix signal processing[27].

Training and Test: In this study, training and test steps were applied for the dataset. K-fold cross validation (cv) was used to separate data for training and test as 3-fold cv.

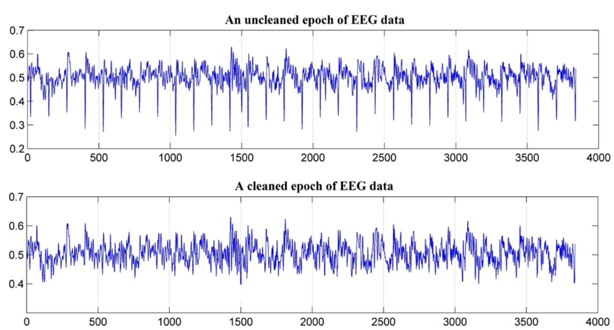

Figure 3. An sample of cleaned and uncleaned EEG signal.

2.3. Feature extraction

In this study, 10 different features in frequency space were taken out from the epochs with & without SS. x, L, rms and amv mean that PSD values, the length, root mean square and absolute mean value of the related epoch, respectively. These features are as following:

$$Feature\_1 = \frac{\text{the total power of } x \text{ in } 11\text{-}16 \text{ Hz}}{\text{the total power of } x} \quad (1)$$

$$Feature\_2 = \frac{\text{the total power of } x \text{ in } 10\text{-}16 \text{ Hz}}{\text{the total power of } x} \quad (2)$$

$$Feature\_3 = \frac{\text{the total power of } x \text{ in } 12\text{-}14 \text{ Hz}}{\text{the total power of } x} \quad (3)$$

$$Feature\_4 = \frac{\text{the total power of } x \text{ in } 9\text{-}16 \text{ Hz}}{\text{the total power of } x} \quad (4)$$

$$Feature\_5\ (\text{absolute mean value of } x) = \frac{\sum_{i=1}^{L} |x_i|}{L} \quad (5)$$

$$Feature\_6\ (\text{energy of } x) = \frac{\sum_{i=1}^{L} x_i^2}{L} \quad (6)$$

$$Feature\_7\ (\text{skewness of } x) = \frac{\sum_{n=1}^{L} \left(x(n) - x_m \right)^3}{(L-1)x_{std}^3} \quad (7)$$

$$Feature\_8\ (\text{kurtosis of } x) = \frac{\sum_{n=1}^{L} \left(x(n) - x_m \right)^4}{(L-1)x_{std}^4} \quad (8)$$

$$Feature\_9\ (\text{shape factor of } x) = \frac{x_{rms}}{x_{Amv}} \quad (9)$$

$$Feature\_10 = \text{standart deviation of } x \quad (10)$$

2.5. Training and Test

In this study, training and test processes were executed for the dataset. 3-fold cross validation was used to partition the training and test data in the following Table 2.

The training process of a classifier is performed to identify the parameters of the ANN which will give the best results. In the used ANN, one and then two hidden layers with nodes was trained with gradient descent algorithm. The momentum constant (mc), learning rate (lr), iteration number (itnum) and the node number of hidden layer (nnhl) parameters of ANN were evaluated in detail to obtain the highest classification accuracies.

3. Experimental results

3.1 Test and performance evolution

The sensitivity (SN), specificity (SP) and Average Recognition Rate (ARR) values have been used to evaluate the performances of the PSD methods in classification of sleep spindles. A confusion matrix as seen in Table 3 was formed for the calculation of these measurements.

And the SN, SP and ARR were computed according to the matrix with the following equations[28,29].

$$SN = TP / (TP + FN) \tag{11}$$

$$SP = TN / (TN + FP) \tag{12}$$

Also, classification accuracy was calculated with (13) as the following:

$$ARR = (SN + SP) / 2 \tag{13}$$

3.2 Results

In this study, 10 different features were extracted in frequency domain by applied some PSD methods that are FFT, Welch, AR and MUSIC to detect sleep spindles in sleep EEG, automatically. Evaluation and comparison of performances of these methods were performed by using ANN. PCA method has also been used to improve the system performance.

The classification results were given in Table 4. As seen in this table, by using the extracted all features, the highest classification accuracies for the database were obtained as 84.83%, 80.67%, 80.83% and 80.33% for test and 86.92%, 89.33%, 85.25% and 93.92% for training with use of FFT, Welch, AR and MUSIC methods, respectively. FFT and MUSIC methods have been shown to exhibit better performance than others. And also, for PCA method; maximum test and training classification accuracies were achieved as 89.50%, 82.00%, 93.00% and 94.83%; 100%, 99.67%, 99.92% and 99.58% with use of FFT, Welch, AR and MUSIC, respectively. When PCA was used, MUSIC and FFT methods have better performance for test and training in the order.

According to these results, there is remarkable difference between using the extracted all features and using the PCA method. The test outcomes are also given in Figure 4, graphically.

4. Discussion and Conclusion

Sleep spindle is one of the significant parameters scoring N-REM-2. The stage forms approximately 50-60% of the full night sleep so determining of this stage is very

Table 2. The distribution of SSs according to 3-fold cross validation

	Epochs with SS	Epochs without SS	Training dataset	Test dataset
Fold-1	100	100	400	200
Fold-2	100	100	400	200
Fold-3	100	100	400	200

Table 3. An example confusion matrix

		Predicted Class	
Actual Class		YES (SS)	NO (Not-SS)
	YES (SS)	True Positive (TP)	False Negative (FN)
	NO (Not-SS)	False Positive (FP)	True Negative (TN)

Table 4. The classification results of these methods

AVERAGE OVERALL RESULTS (= (FOLD1 + FOLD2 + FOLD3)/3)															
METHODS	By Using The Extracted All Features							By Using The PCA Method							
	Training Results (%)			Test Results (%)			ANN Parameters	Training Results (%)			Test Results (%)			DNFM	ANN Parameters
	SN	SP	ARR	SN	SP	ARR		SN	SP	ARR	SN	SP	ARR		
FFT	82.83	91	86.92	86	83.67	84.83	nnhl= 73 itnum= 100 lr= 5.5 mc= 0.25	100	100	100	90.33	88.67	89.50	10	nnhl= 8 itnum= 6600 lr= 1.4 mc= 0.9
WELCH	86.17	92.50	89.33	84	77.33	80.67	nnhl= 55 itnum= 1000 lr= 1.9 mc= 0.8	99.67	99.67	99.67	84.33	79.67	82	9	nnhl= 10 itnum= 6700 lr= 1.5 mc= 0.8
AR	79.50	91	85.25	84	77.67	80.83	nnhl= 79 itnum= 120 lr= 4.1 mc= 0.8	100	99.83	99.92	92.67	93.33	93	7	nnhl= 10 itnum= 2300 lr= 3.2 mc= 0.9
MUSIC	93.50	94.33	93.92	92	68.67	80.33	nnhl= 79 itnum= 7000 lr= 2 mc= 0.8	99.83	99.33	99.58	96	93.67	94.83	8	nnhl= 8 itnum= 1200 lr= 1.8 mc= 0.9

SN:Sensitivity - SP:Specificity - ARR:Average Recognition Rate - DNFM:Dimension Number of Feature Matrix for PCA - nnhl: node number of hidden layer - itnum: Iteration Number - lr:Learning Rate - mc:Momentum Constant

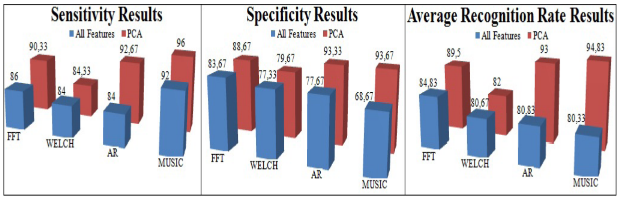

Figure 4. The comparison of these methods graphically

important for sleep experts. To determine the SSs in EEG signal, extracted features in frequency domain was evaluated by using FFT, Welch, AR and MUSIC methods.

Also, the performances of these methods were evaluated and compared by ANN. When the extracted all features were used, the best test and training results were recorded as 84.83%, 80.67%, 80.83% and 80.33%; 86.92%, 89.33%, 85.25% and 93.92% for FFT, Welch, AR and MUSIC methods, respectively. FFT and MUSIC methods have been shown to exhibit better performance than others. Other than this, by using PCA method the maximum test and training outcomes were obtained as 89.50%, 82.00%, 93.00% and 94.83%; 100%, 99.67%, 99.92% and 99.58% with use of these methods in the order. According to these results, MUSIC and FFT methods have better performance for test and training, respectively. The performance of the PCA-FFT-MUSIC methods have showed that it could be used in automatic detection of SSs.

The most important risk associated with EEG is artefact. It is possible that get higher classification accuracies by removing artefacts from EEG and adjusting better system parameters of ANN. And also, these methods can be used for automatic systems in the future scope.

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