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Automated elimination of EOG artifacts in sleep EEG using regression method

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Abstract: Sleep electroencephalogram (EEG) signal is an important clinical tool for automatic sleep staging process. Sleep EEG signal is effected by artifacts and other biological signal sources, such as electrooculogram (EOG) and electromyogram (EMG), and since it is effected, its clinical utility reduces. Therefore, eliminating EOG artifacts from sleep EEG signal is a major challenge for automatic sleep staging. We have studied the effects of EOG signals on sleep EEG and tried to remove them from the EEG signals by using regression method. The EEG and EOG recordings of seven subjects were obtained from the Sleep Research Laboratory of Meram Medicine Faculty of Necmettin Erbakan University. A dataset consisting of 58 h and 6941 epochs was used in the research. Then, in order to see the consequences of this process, we classified pure sleep EEG and artifact-eliminated EEG signals with artificial neural networks (ANN). The results showed that elimination of EOG artifacts raised the classification accuracy on each subject at a range of 1%–1.5%. However, this increase was obtained for a single parameter. This can be regarded as an important improvement if the whole system is considered. However, different artifact elimination strategies combined with different classification methods for another sleep EEG artifact may give higher accuracy differences between original and purified signals.

Key words: Artificial neural networks, electrooculogram artifact elimination, regression, sleep stage scoring

1. Introduction

Sleep staging is the most important process in the detection of sleep diseases. Therefore, the correct diagnosis and appropriate treatment of sleep disorders not only improve people's quality of life, but also allow them to live safer lives. Correct diagnosis leads to correct treatment; therefore, patient data must be collected and evaluated carefully for making accurate diagnosis.

Automatic sleep staging has been an active field of research area recently. Because the manual sleep staging process is time-consuming and a difficult task undertaken by sleep experts, some more efficient methods have been developed and applied partly to sleep stage classification. Many studies have emphasized that especially nonlinear methods include effective tools to understand the complexity of Electroencephalogram (EEG) signals [1–6]. However, different nonlinear algorithms might be used in the analysis of sleep EEG signals [7]. Some of them are higher-order spectra (HOS) [8], recurrence quantification analysis (RQA) [9], continuous wavelet transform (CWT) [10], discrete wavelet transform (DWT) [11], intrinsic time-scale decomposition (ITD) [12] and entropies [13]. On the other hand, many factors can be pointed here which degrade classification

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accuracy of these methods including the complex nature of EEG signals, noisy environment, and artifacts of EEG, electrooculogram (EOG), and electromyogram (EMG) signals that intervene each other.

The person experiences the sleep phases repeated periodically during sleep. The quality of sleep depends on the number of these stages and their actualization order. The names of the mentioned sleep stages are wakefulness (W), rapid eye movement (REM), non-REM-I (NREM-1), non-REM-II (NREM-2), and non-REM-III (NREM-3) stages [14]. The first few minutes of sleeping is the W stage. The first phase following the W stage is the NREM-1 and it can be termed as transitional sleep or light sleep. Meanwhile, the sleep continues, begins to deepen and then NREM-2 is seen. The most prominent feature at this stage is the presence of K complex and sleep spindle patterns. NREM-3 Stage is the deepest period of sleep. Finally, in the REM period, the presence of mental activities is observed [15]. Figure 1 shows all sleep stages during a one-night sleep and their approximate duration, respectively.

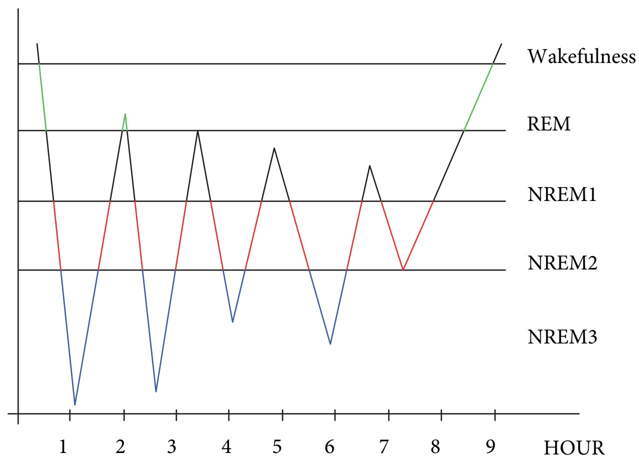

Figure 1. Change of sleep stages during a one-night sleep [16].

Sleep staging is performed by analyzing some signals and data from patients with the help of a polysomnography (PSG) device. Some of these signals are EEG, EOG, and EMG. They provide information about brain activity, eye movements, and chin movements respectively. These PSG records are divided into pieces of 10, 20, 30, and 60 s, which are called epochs. Sleep specialists evaluate and classify each epoch according to some special signal patterns. These assessments and classifications are done through important guides such as visual sleep scoring according to the classification developed by Rechtschaffen and Kales and scoring based on the new guidelines of the American Academy of Sleep Medicine [15]. These evaluations are made by sleep specialists with the help of special rules that are called manual sleep scoring. Manual sleep scoring is accepted to be more reliable than others by sleep specialists and sleep institutes; however, it has some negative aspects. First of all, it is a tiring and time-consuming task. Also, its correctness of classification highly depends on the experience and knowledge of the sleep expert. Hence, the sleep scores of two sleeping specialists evaluating the same episode may vary. These two negative factors constitute the basis of studies on automatic sleep scoring systems. When the literature about automatic sleep staging systems is reviewed, it is clearly seen that before designing such a system, several studies should be conducted in this field. The studies should focus on the following:

1. Preventing noise and artifacts by using some signal processing techniques,
2. Extraction of required properties to use in classification,
3. Classifier design with the ability to correct classifying of sleep stages.

The studies in the first category are related to recording the signals and include sampling rate arrangement, filtering process, elimination of artifacts related with body movements, and outlier removal. The signals used in automatic sleep stager should be cleaned out of these kinds of noises before processing. After signal cleaning, some valuable information from the recorded PSG signals can be extracted. Some of the time and frequency related features from EEG, EOG, and EMG signals are taken and the ones that carry more information in stage separation are selected among these features. Determination of feature extraction and selection methods is the main challenge in the second category [17]. The last part of automatic sleep staging process is the design of sleep stager. Many methodologies can be used here ranging from the statistical pattern recognition methods to artificial intelligence methods. Moreover, a specific rule-based system need to be developed [18]. Because the number of alternatives are very high, this step of sleep staging has been the most important and the hardest part of the automatic sleep staging process so far. Sometimes, it may be a true approach, but the researchers studying in signal processing field clearly know that obtaining a clean signal free from the noise and artifacts is a key point of the whole system. As it is known, EEG signals are recordings of the electrical activity of the brain and they are placed on the scalp in special positions. Likewise, EOG signals are also taken from the cross points on the eyes. An undesirable situation occurs here as a result of the action. EOG and EEG signals interfere with each other (see Figure 2).

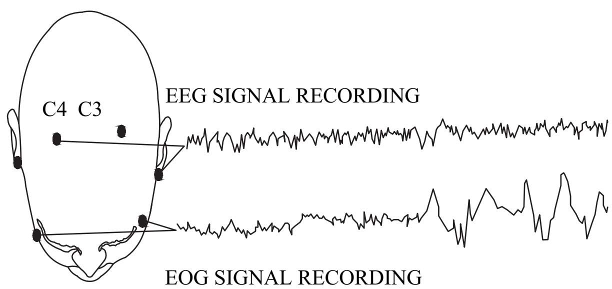

Figure 2. EEG and EOG signal recording in sleep [15].

1.1. Related works

EOG artifact elimination problem was addressed in different ways in EEG signal processing studies [19-21]. In another study, Manoilov found that these EOG artifacts featured in the frequency band of 8–13 Hz due to the blinking of the eyes [22]. In a different study, Manoilov and Borodzhieva found that the effects of eye blinks were seen more intensely at 3 Hz than at other test frequencies [23]. Bartels et al. reported that they achieved 70.8% correctness using blind source separation and support vector machine techniques [24]. In another study, Shah and Panse applied wavelet analysis to EEG signals for elimination of EOG signals. As a result of this study, they declared that wavelet analysis is an effective method for EOG artifact reduction [25]. Ghandeharion and Erfanian proposed a new method for eliminating EOG artifacts by combining wavelet analysis and independent component analysis [26]. Advantages and disadvantages of each method with respect to other methods have been examined in detailed in the literature [27–30].

These researches show that there are too many studies about artifact removal from clinic EEG whereas there are very few sleep EEG studies in the literature. In previous studies, the task of clearing EOG artifacts from the EEG data was performed by using clinical EEG data. Nevertheless, we have performed an artifact elimination in sleep EEG, which is different from the clinical EEG in terms of spectral properties. This is the greatest novelty of our work.

In the light of these, the purpose of this study was to examine the effect of EOG artifacts on the classification performance by discarding them from the sleep EEG. In our study, we deliberately used the review article of Croft and Barry [31] and performed an EOG artifact elimination study on seven patients' data. We analyzed the effects of this process for each frequency band and sleep stages. Then, we evaluated efficiency of stages and frequency bands in which the artifacts were more efficient. We performed another evaluation of EOG artifact elimination process on the classification of sleep stages. For this purpose, we extracted 16 EEG related features from the recorded raw EEG signals and artifact-eliminated EEG signals for each subject. Then, we used these two sets of data to classify sleep stages with artificial neural networks (ANN). By changing the network architecture and learning parameters, we found the optimum ANN giving the highest classification accuracy for two groups of data. According to the results, it is concluded that, EOG artifact elimination process raised classification accuracy by an average rate of 1.28% among the seven subjects.

The remainder of this paper is organized as follows: Section 2 introduces the data acquisition, method used, and material and system evaluation criteria. The results of EOG elimination with the proposed method is presented and the results of EOG elimination with regression and experimental and comparison of the results are shown in Section 3. Finally, conclusions and future work are presented in Section 4.

2. Materials and methods

Ethical approval was obtained for this study.

2.1. EOG artifact elimination from the EEG signals

Eye blinking and eye movements have a visible disruptive effect on EEG signals. At the same time, these movements affect the frequency components of EEG signals, too. In Figure 3, an effect of a big vertical eye movement on the EEG signal is presented [32].

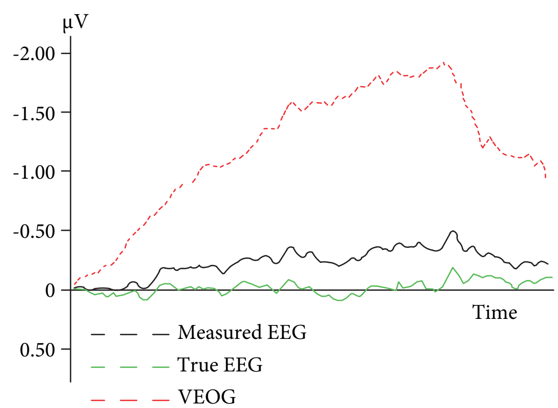

Figure 3. The disruptive effect of vertical EOG (VEOG) signal on EEG [32].

Sleep EEG shows different characteristics from the clinical EEG and therefore is affected by the EOG artifacts differently. The high frequency Beta activity (13–35 Hz) leaves its place to a lower frequency Alpha activity (8–12 Hz) in the W stage. Eye opening–closing, eye blinking, and eye movements are seen frequently in this stage. In the non-REM1 stage, alpha waves change to slower Theta waves (4–8 Hz), whereas they are not as frequent as in the W stage. Eye movements, especially those known as slow eye movements (SEM), are seen in this stage, too. Non-REM2 stage, however, is not characterized with specific eye movements. It is different from the SEM which is seen occasionally. Eye movements are not seen in this stage. In the non-REM3 stage, which includes the slowest waves (delta waves: 0–4 Hz) in sleep, it is possible to see eye movements. Finally, REM stage, as can be deduced from its name, characterized with Rapid Eye Movements with high amplitude.

In this study, we have benefited from Anderer et al.'s study [28] to eliminate EOG artifacts from the sleep EEG signals. According to this technique, the artifact elimination process is done as follows:

Let x and z denote left and right EOG channels and y denote to the EEG channel. Then a B value is calculated with the formula:

$$B_{yx.z} = \left(\left[r_{yx} - r_{yz}.r_{zx} \right] / 1 - r_{xz}^2 \right) .sd_y / sd_x, \tag{1}$$

where r_{yx} is the correlation between y and x (EEG and left EOG), r_{yz} is the correlation between y and z (EEG and right EOG), r_{zx} is the correlation between z and x (right EOG and left EOG), r_{xz} is the correlation between x and z (left EOG and right EOG), sd_y is the standard deviation of y (EEG), sd_x is the standard deviation of x (left EOG). Here, the calculated $B_{yx.z}$ constant is the effect of x (left EOG) on y (EEG) in the existence of z (right EOG). By using a similar equation, $B_{yz.x}$ constant is calculated to determine the effect of x on y in the existence of z. Then, for each data sample, the estimated EEG signal value is calculated through the following equations:

$$estTEEG_i = MEEG_i - (B_{yx.z}.EOG_{xi}) - (B_{yz.x}.EOG_{zi}) - C, \tag{2}$$

$$C = \overline{X} - (\overline{Y} * B_{yx.z}) - (\overline{Y} * B_{yz.x}), \tag{3}$$

where X represents the EOG and Y the EEG signal. B is calculated separately for left EOG and right EOG channel. The subtraction of C is to eliminate the EOG baseline effect from the sleep EEG.

2.2. Analysis of EOG artifacts on sleep EEG

The conducted study can be divided into two parts. One is to remove the EOG artifacts from the sleep EEG and see the effects of this procedure and the other one is to see the difference between the measured and the estimated (EOG-artifact-eliminated) EEG signals on sleep stage classification. However, before conducting these steps, we prepared and preprocessed the data.

2.2.1. Used dataset

In this study, we used the sleep EEG signal and left–right EOG signals of seven voluntary subjects. All subjects stayed in Meram Faculty of Medicine Sleep Laboratory, Necmettin Erbakan University during the recordings. First, a notch filter was applied to eliminate the 50-Hz electrical noise from the EEG and EOG records and then, the EEG and EOG signals of each subject were filtered by a 6th-order Butterworth band-pass finite impulse response (FIR) filter with cut-off frequencies 0.3–35 Hz. Second, outlier removal process was conducted on these signals to eliminate the unwanted effects of recording and for some other reasons. After this data cleaning process, all sleep signals were decomposed to epochs which are 30-s long pieces of signals. We used 6941 epochs in total in our analysis. This means that our dataset includes 6941 samples and such a dataset is sufficient for a scientific study.

2.2.2. Analyzing the effect of EOG artifact elimination on sleep stage classification

As we stated above in the introduction section, sleep EEG signals should be purified from the EOG artifacts before the automatic staging process as its manual counterpart. Thus, besides seeing the effect of EOG artifact elimination process statistically, we also conducted some studies to see the effect of this process on sleep staging results. For this purpose, we prepared 16 features from the measured and estimated EEG signals for each subject and conducted a classification process by using these two groups of data with the aid of ANN. In essence, training ANN contains adjustable parameters to achieve maximum classification accuracy. Some of these parameters can be stated as hidden layer node numbers, training algorithm, determination of parameters in that algorithm, deciding when to stop training, etc. [33]. Before giving the details related to this experimentation procedure, an overview of this application can be seen in Figure 4.

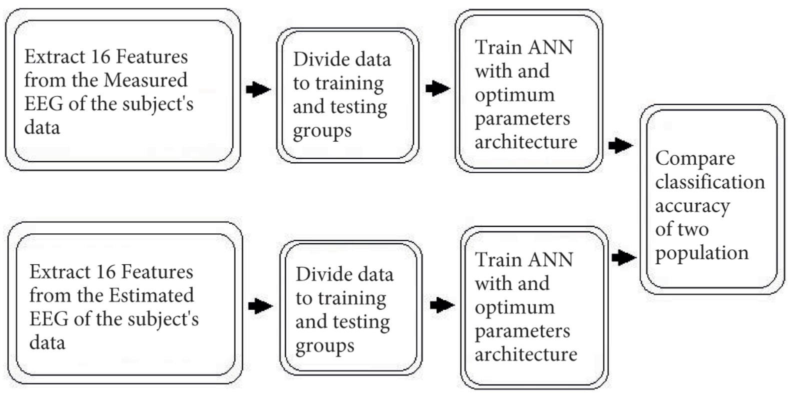

Figure 4. The main procedure in sleep stage classification for all EEG data.

The given procedure in Figure 4 was conducted for each subject's data. The extracted features from the measured and estimated EEG signals are:

1. Total power of alpha band in PSD of EEG signal
2. Total power of theta band in PSD of EEG signal
3. Total power of beta band in PSD of EEG signal
4. Total power of delta band in PSD of EEG signal
5. Ratio of alpha power to the power of whole frequencies in PSD
6. Ratio of theta power to the power of whole frequencies in PSD
7. Ratio of beta power to the power of whole frequencies in PSD
8. Ratio of delta power to the power of whole frequencies in PSD
9. Ratio of theta power to alpha power
10. Ratio of alpha power in current epoch to alpha power of previous epoch
11. Ratio of alpha power in current epoch to alpha power of next epoch
12. Mean absolute value of time domain EEG signal
13. Standard deviation of time domain EEG signal
14. Ratio of Mean value to standard value of time domain EEG signal
15. Skewness of the EEG signal
16. Kurthosis of the EEG signal.

Features 15 and 16 are calculated with the given formulas:

$$x_{skewness} = \frac{\sum\limits_{n=1}^{N} \left(x(n) - x_m\right)^3}{(N-1){x^3}_{std}}, \tag{4}$$

$$x_{kurthosis} = \frac{\sum\limits_{n=1}^{N} \left(x(n) - x_m\right)^4}{(N-1){x^4}_{std}}, \tag{5}$$

where N is the length of the signal x, x_m is the mean and x_{std} is the standard deviation of x.

After the feature extraction procedure, the training and test data to be used in the classification are separated. The 70% of data from each stage was taken for training data and the remaining 30% was reserved as the test data. The same epochs were used in this division for both types of EEG signals (measured and estimated). That is, the labels of epoch were the same in measured-EEG-training and estimated-EEG-training procedures. An example of this division process for a subject is given in Table 1.

Table 1. A sample of training and testing partitioning (subject 1).

	W	Non-REM1	Non-REM2	Non-REM3	REM	TOTAL
Training	55	18	291	54	113	531
Testing	24	8	166	23	49	270
TOTAL	79	26	457	77	162	801

$16 \times hn \times 5$ architecture was used in training process. Where 'hn' shows the number of hidden nodes in the formed one-layer ANN.

The optimum number of hn is found by changing hn from 5 to 50 with a step size of 5. In each of the experiments hn, ANN was trained and tested while other parameters were fixed. The value of hn reaching the minimum test error is determined as the optimum number of hn. In training ANN, the gradient descent learning algorithm with momentum was used and the minimum test error delivered to optimum value for maximum iteration number (max_iter) as above.

Calculating test accuracy was obtained using the following formula:

$$Classification\_accuracy = \frac{N_t}{N_T} \times 100, \tag{6}$$

where N_t is the number of data that classified correctly and N_T is the total number of test data. The obtained results in this stage are given in Section 3.2.

3. Experimental results

3.1. Statistical analysis of EOG artifact elimination from the EEG signals

The first part of the study involves the elimination of EOG artifacts from the measured EEG signals. This process was conducted for each subject and for each epoch. The effects of this elimination process were then analyzed statistically for each stage. In the time domain signals of left and right eye EOGs, measured EEG and estimated (EOG-artifact-eliminated) EEG are given in addition to their fast fourier transform (FFT) curves. As shown in Figure 5 (especially from the FFTs of signals), after the EOG artifact elimination process, EOG-based movements in the measured EEG signals are cleaned to some degree. Frequency contents of the measured and estimated EEG signals of each subject were obtained using the FFT method. The total powers in delta, theta, alpha, and beta bands were then calculated from the FFTs. Using these total powers, mean values of powers in related bands in each stage were found through averaging epochs in related stages. For example, if we analyze the first subject, it is seen that the subject has 79 W epochs, 26 NREM1 epochs, 457 NREM2 epochs, 77 NREM3 epochs, and 162 REM epochs. By using FFT of the measured and estimated EEG signals in each epoch, powers of theta, alpha, and beta bands were calculated. The average power of each band for each stage was calculated by using the related values in the related stages. As an example, let $Delta_{W measured}$ be the average power of delta band of the measured EEG signal among the epochs belonging to the W. Then, this value was calculated by:

$$delta_{W\_measured} = \frac{1}{N_W} \sum\nolimits_{i \in W} delta\_power\_measured_i, \tag{7}$$

where N_W is the number of W epochs.

As a result, the average powers of theta, alpha, and beta bands for the measured and estimated EEG signals in W, NREM1, NREM2, NREM3, and REM stages were calculated for each subject. These values were then categorized according to the stages. This process was conducted for each subject. For the W stage, these values are shown in Table 2 and Figure 5 in their box-plots.

Table 2. The average power spectral density values belonging to each frequency band for measured and estimated sleep EEG signals for W stage with seven subjects.

Subjects	For W stage							
	Delta		Theta		Alpha		Beta	
	Meas.	Est.	Meas.	Est.	Meas.	Est.	Meas.	Est.
Subject 1	0.2644	0.194	0.0587	0.0515	0.0756	0.0599	0.1002	0.0775
Subject 2	0.2772	0.241	0.0522	0.0481	0.0908	0.0857	0.1073	0.1023
Subject 3	0.368	0.0312	0.0729	0.0721	0.1022	0.0988	0.1214	0.1162
Subject 4	0.2907	0.2805	0.0577	0.0611	0.0819	0.083	0.0861	0.0857
Subject 5	0.4434	0.3546	0.0758	0.0743	0.1121	0.1036	0.1404	0.1285
Subject 6	0.5372	0.4717	0.1025	0.1034	0.1506	0.1424	0.2044	0.1885
Subject 7	0.7657	0.6805	0.1303	0.1398	0.1856	0.1802	0.261	0.2561

Meas.: measured, Est.: estimated.

The distribution of averaged frequency values of delta, theta, alpha, and beta bands among seven subjects for the W stage was plotted for the measured and estimated EEGs in Figure 6a. In Table 3, on the other hand, the differences between the measured and estimated values for each band in W stage were shown in percentage format. As seen in Table 3, the most remarkable change is seen in the delta band. In W stage, the frequency content of EEG signals is high in the order of 8–35 Hz. These frequencies in delta band are rarely seen (almost

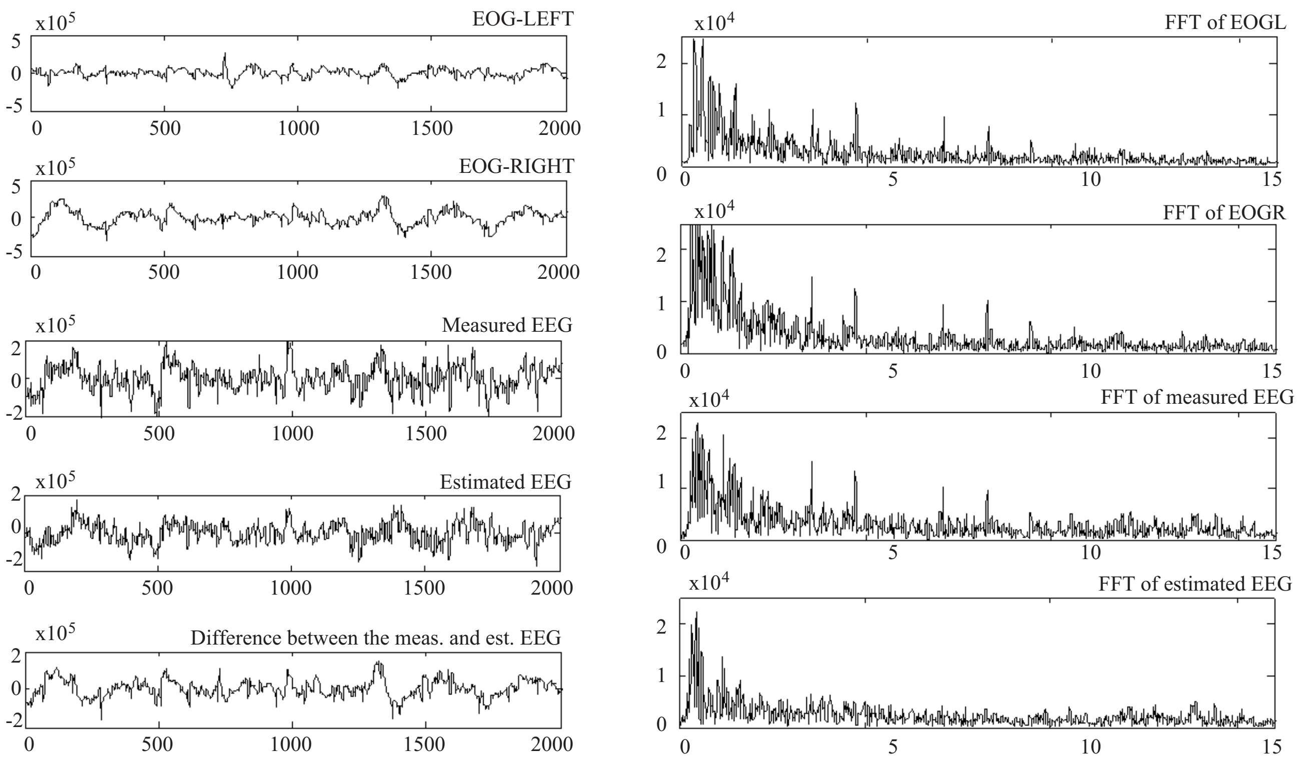

Figure 5. Time and frequency domain EOGL (left-eye EOG), EOGR (right-eye EOG), measured EEG and estimated EEG (after EOG artifact elimination) signals in an epoch.

never seen). Thus, any signal in that band should be originated from the EOG signals as found in our results shown in Table 3. Because there are rare EEG signals in delta band in the W stage, the B coefficients calculated by Eq. (2) are high with respect to the other bands. Thus, difference in that band in the measured and estimated EEG signals found to be highest for the W stage. This does not mean that EOG artifact mostly affects delta band in the W stage. The W stage mostly involves alpha and beta band frequencies, and according to Figure 6, it can be deduced that beta and then alpha bands are the most affected frequency bands in the W stage as expected (after ignoring delta band effect). This is because eye movements and eye blinks are very effective in this stage.

For the NREM1 stage, however, alpha waves leave their places to theta waves. As it is pointed in Section 2.1, other than SEM waves, no characteristic eye movements are seen in this stage. The changes in measured and estimated EEG signals are seen in Figure 6b and Table 3 for each frequency band.

Again, it is seen in Figure 6b and Table 3 that the delta band is the most affected band from the EOG signals. However, compared with the W stage, this effect is less because of diminished eye movements. When it comes to the alpha and theta bands, the differences in the NREM1 stage for the measured and estimated EEGs are higher than those in the W stage due to the fact that alpha and theta waves increase in this stage with respect to the W stage.

Results for the NREM2 stage are shown in Figure 6c and Table 3. The differences between the measured and estimated EEG signals are lower than their counterparts in the NREM1 and W stages. This is because eye movements are rarely seen in this stage. Thus, effects of EOG are lower in this stage in all bands.

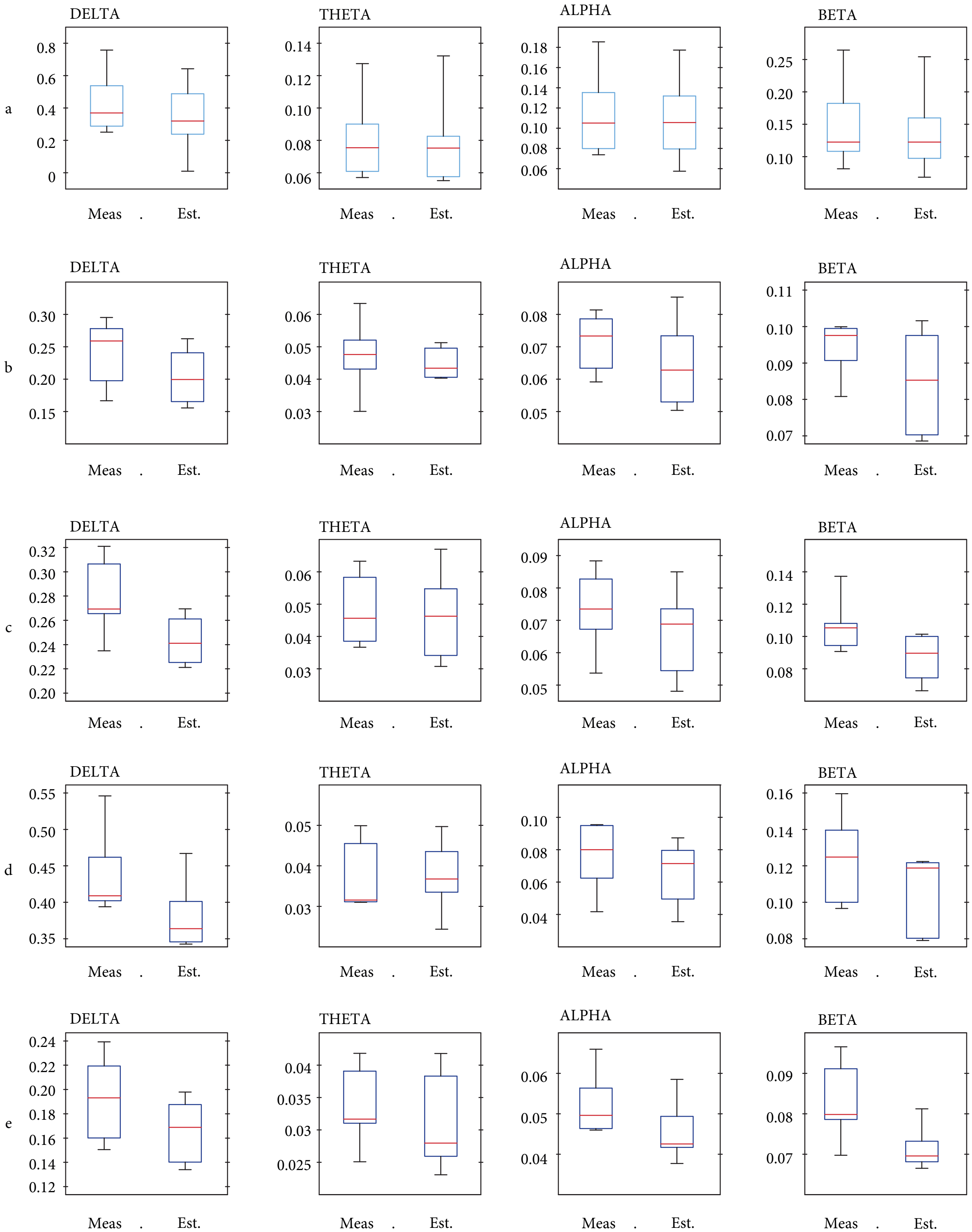

Figure 6. Change in the measured and estimated EEG powers in each frequency band among the seven subjects for 6a, W stage; 6b, NREM1 stage; 6c, NREM2 stage; 6d, NREM3 stage; 6e, REM stage.

Table 3. The difference between the measured and estimated values for each band in all sleep stages.

Stages	Frequency bands							
	Delta		Theta		Alpha		Beta	
	Meas.	Est.	Meas.	Est.	Meas.	Est.	Meas.	Est.
W	100	82,29	100	100	100	94,26	100	93,23
NREM STAGE I	100	84,17	100	95,04	100	90,88	100	87,28
NREM STAGE II	100	97,83	100	97,63	100	97,50	100	99,05
NREM STAGE III	100	92,46	100	98,65	100	97,54	100	94,38
REM	100	97,29	100	94,56	100	95,2	100	97,78

Meas.: measured, Est.: estimated.

When it comes to NREM3 stage, changes shown in Figure 6d were recorded. The frequency content of this stage is very low and very few differences are observed for the alpha, theta, and beta bands. Eye movements are not typical for this stage. However, when the delta band is compared to those of other stages, it is seen in Table 3 that the difference in this band is higher than that in the NREM2 but lower than that in the other stages. This means that eye movements are seen more frequently in this stage than in the NREM2 but less than in the NREM1 and W stages.

As a last step of this application branch of study, results for the REM stage were obtained (see Figure 6e). As it can be deduced from its name, the REM stage includes rapid eye movements. Therefore, frequency content of EOG signals is a bit higher than those of other stages. This can clearly be seen in Figure 6e and Table 3. The most evident differences are seen in the theta and alpha bands. EEG frequencies are in the order of 2–6 Hz in the REM stage, so the theta band is the most affected band from the eye movements which can be also inferred from the comparisons with other stages: the highest difference in the theta band is seen in this stage because of REM waves.

3.2. Analyzing effects of EOG elimination from the sleep EEG signals on sleep stage classification

The other objective of this study was to analyze the effect of EOG artifact elimination process on automatic sleep stage classification. For this purpose, seven training and testing procedures with ANN were conducted on the data of seven subjects as explained in Section 2.2 (see Figure 4 for explanation of the application). After conducting training and testing procedures on the measured and estimated EEG signals separately, the following results given in Table 4 were obtained.

According to these results, by using the estimated EEG signal, an average increase of 1.28% in classification accuracy was recorded among seven subjects. Surely, this is not sufficient for such a process but the selected features, using classifier, and artifact elimination method applied are major players in this kind of studies. Thus, different artifact elimination methods combined with different features and different classifiers would give better performances.

4. Conclusion and further studies

Studies on effective automatic sleep stage scoring are continuing increasingly. Still, there is not a practically applicable automatic scoring system because their low classification performance is under acceptable limits.

Table 4. The experimental results obtained from classification application for the measured and estimated datasets.

	Best ANN parameters for measured EEG1	Best ANN parameters for estimated EEG1	Accuracy with measured EEG(%)2	Accuracy with estimated EEG(%)2	Difference (meas. EEG and est. EEG) (%)
Subject 1	hn: 35 max_iter:420	hn: 45 max_iter:210	78.89	79.63	0.74
Subject 2	hn: 30 max_iter:380	hn: 310 max_iter:170	80.89	81.25	0.36
Subject 3	hn: 45 max_iter:370	hn: 30 max_iter:330	85.47	86.85	1.38
Subject 4	hn: 10 max_iter:890	hn: 10 max_iter:720	80.86	81.52	0.66
Subject 5	hn: 45 max_iter:870	hn: 45 max_iter:900	76.46	77.37	0.91
Subject 6	hn: 50 max_iter:270	hn: 50 max_iter:210	64.18	67.29	3.11
Subject 7	hn: 45 max_iter:730	hn: 25 max_iter:210	68.25	70.03	1.78
Mean			76.42	77.7	1.28

[1] *hn*: hidden node number, lr : 2 (learning rate), mc: 0.8 (momentum constant), max_{iter} : maximum iteration number

[2] calculated with equation 6

Several reasons can be mentioned for this failure ranging from the design of classifier systems to the extraction and selection of features from the sleep signals. However, the main problem lies behind the processing of EEG, EOG, and EMG signals. Especially EEG signal processing is a hard problem even in sleep EEG or clinical EEG.

EEG frequency bands contain important information for using classification of sleep EEG signals because each stage has its own frequency band and some special signal patterns. If there is an EOG artifact in the EEG signal, these artifacts are evaluated as the EEG frequency component in the base frequency components. Thus, the stage is scored incorrectly and every misscored stage reduces the accuracy of the classification of the system. As a result, the reliability of the designed automatic sleeping system remains low.

In this study, we aimed to analyze the effects of EOG signal on sleep EEG through eliminating EOG artifacts with regression method. It is very useful for real-time applications such as automated sleep staging systems. The most important advantage of the proposed method is that the proposed model works quickly in real-time applications and performs the staging process in a short time.

We analyzed sleep stages and frequency bands which have higher effects. According to the results, each stage was affected by the EOG artifact elimination process differently. For example, in the W stage, eye movements and eye blinks are frequent, and therefore this stage was considerably affected by the EOG artifacts. Frequency in the delta band in this stage was found to be the highest. However, as it is known, frequency content in this stage covers the alpha and beta bands. Thus, frequency components in the delta band surely should come from the EOG signals. In manual scoring process, experienced sleep experts know this and ignore EOG artifacts by looking at time domain EOG and EEG signals. However, automatic scoring systems can score W stages as non-REM3 because the delta band energy is the highest. These kinds of problems affect automatic sleep staging processed more than it is thought. Density of frequencies of eye movements change from stage to stage and this should be taken into consideration.

According to the obtained results, in the W stage, the frequency content of EEG signal involves alpha and beta waves and the effect of EOG artifact elimination process is moderate for this stage. For the NREM1 stage, SEM waves are seen in EOG channels and because of them, this stage, which majorly includes alpha and theta waves, is a bit affected by the process. In the NREM2 stage, however, eye movements are seen rarely. Thus, a minimum effect of EOG artifact elimination is seen in this stage. The NREM3 stage, on the other hand, involves delta band in EEG signals and some low-frequency eye movements. This is the reason why the delta band is the most affected band in this stage. Lastly, rapid eye movements, seen in the REM stage, effect theta and alpha bands because of their little high frequency when compared with other eye movements in sleep.

Besides evaluating the effects of EOG artifacts on EEG signals, we also conducted a classification procedure to see the effect on sleep stage classification performance. For this purpose, we trained and tested ANN architectures with gradient descent learning algorithm for two groups of dataset: one was derived from original measured EEG signals and the other was formed by estimated (artifact eliminated) EEG signals. Comparison of two training and testing processes were conducted on each of the seven subjects respectively and an average classification accuracy by using the measured EEG was found to be 76.42% while this accuracy was obtained as 77.70% for the estimated EEG. EOG artifact elimination process raised classification accuracy by an average rate of 1.28% among the seven subjects.

When the effect of the study on the classification accuracy is evaluated, it can be said that this value is low. However, it should be taken into account that increasing the classification accuracy of the automatic sleeping system does not depend solely on the EOG artifacts on the EEG. Hence, all other artifacts must be cleaned effectively in order to achieve high classification accuracy since the small increments to be obtained from each of the other parameters will increase the overall classification accuracy more effectively. Actually, it is seen that the accuracy of classification obtained in this way provides a reasonable improvement in the design of automatic sleep staging systems.

When the study is evaluated clinically, it is possible to use it as a part of automatic sleep staging system because this study is intended as an auxiliary signal restoration module to increase the classification accuracy in the automatic sleep staging system. Automatic sleep staging systems will be able to perform sleep staging, which is a difficult and laborious process, in a short time and with high accuracy. This will reduce the workload of doctors and staging will be a standard procedure for all clinics.

In the future, a system will be designed by combining different methods on the EOG artifact elimination. It is aimed to further increase the accuracy of the classification of the designed system.

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