

Detection of REM in Sleep EOG Signals

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Abstract

Background/Objectives: Sleep staging is very important phase for diagnosing respiration and sleep diseases. Nowadays, Electroencephalogram (EEG), Electromyogram (EMG), Electrooculogram (EOG) signals are particularly used together in studies on sleep staging. **Methods/Statistical Analysis:** Associating only EOG signals to sleep staging was distinctly purposed. So, this paper deals with extraction features and classifying for determining REM-NREM states from the EOG signals. In this study, left eye (LEOG) and the right eye (REOG) signals were used. After EOG signals were obtained, 21 different features were extracted from LEOG and REOG in time and frequency domain according to rules of American Academy of Sleep Medicine (AASM). **Findings:** Artificial Neural Networks (ANN) was adopted on features as method of classification with 3-fold cross validation technique and reached conclusion with the maximum test classification accuracy as 88.05%. To obtain higher classification accuracies, Sequential Backward Selection (SBS) method was used. According to results of SBS, number of the best features combination was determined as 13 and the maximum classification accuracy was obtained as 89.62%. The optimum value of hidden layer node number of ANN was determined as 15 for the best features. **Application/Improvements:** When looking from the viewpoint of percentage of classification accuracy of this study, a result can be seen that is non-negligible value for literature.

Keywords: Artificial Neural Networks, EOG, Feature Selection, SBS, Sleep Stage

1. Introduction

Nowadays, Sleep stage scoring take an important place in determination of sleep related problems. Many studies have been doing to date on the sleep stage scoring. Because, even if sleep staging can be applied automatically, accuracy of implementing is low and insufficient. So, studies are going on using different methods.

Sleep staging is labelling according to sleep stages by the help of biological markers obtaining from sensors¹. These biological markers are obtained from

Polysomnographic (PSG) recordings during the sleep in sleep laboratory. PSG can record Electroencephalogram (EEG), Electromyogram (EMG), Electrooculogram (EOG) signals and other signals sensing from parts of body. Sleep staging is implemented in compliance with some rules determined in 2007 and revised in 2014 by American Academy of Sleep Medicine (AASM). According to modern-day AASM rules, sleep consists of 5 stages named as Wake, Non-REM I, Non-REM II, Non-REM III, REM (Rapid Eye Movement) and recorded signals is separated to 30 seconds long epochs².

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Many studies were done and are going on related to sleep stage scoring. In ³, researchers extracted time domain features from the EEG, EOG and EMG signals and calculated coefficient of correlation. They reached as a result that standard deviation of EOG signals is more interrelated than the other features. In the other study, researchers used ANOVA (analysis of variance) for investigating relation of features from recorded EEG, EOG and EMG signals⁴. When looking at the other study, time and frequency domain features were extracted from the EEG, EOG and EMG signals and used Sequential Feature Selection Method for selecting features⁵. In ⁶, they chose ANN with 10-fold cross validation method for study and obtained classification accuracy as 90.4% and 90.8%. Finally, kappa coefficients calculated from decision tree using the EEG, EOG and EMG signals and obtained 86.68% classification accuracy⁷.

As it seen, EEG, EOG and EMG signals were generally used together in above mentioned studies. In this study, EOG signal was only used different from aforementioned investigations. 21 different features were extracted from epochs of EOG signals that were labelled as REM and NREM recorded by PSG. For classification, ANN was implemented with 3-fold cross validation and the best combination of features were selected by using Sequential Backward Selection (SBS). Maximum test accuracy was recorded as 89.62%. Process steps were implemented as shown in Figure 1. Firstly, data was obtained from polysomnography test device in preparing dataset stage and these data were separated according to AASM rules and process that will be implemented. After feature extracting process, dominant features were selected. End of these process, classification methods were implemented and results were obtained.

2. Material and Methods

2.1 Preparing Dataset

In this study, the used data was obtained Left Eye Electrooculogram (LEOG) and the Right Eye Electrooculogram (REOG) signals from polysomnography test device at Meram Medicine Faculty of Necmettin Erbakan University in Konya/Turkey. EOG signals were sampled at a rate of 128 Hz.

EOG signals were separated to 30-second-long epochs that were labelled as REM and NREM by a sleep expert and then each epoch was separated 5-second-long windows of signal for increasing accuracy of classification. 318 REM signal windows and 318 NREM signal windows were selected equally as data sets.

2.2 Feature Extraction and Selection

21 features were extracted in time and frequency domain from 318 REM windows and 318 NREM windows of EOG signals. When looking at the studies about sleep staging, these features can be seen that have importance in studies of sleep staging^{5,7}. These features are listed below:

2.2.1 Time Domain

1. Absolute mean of signal:

$$X_m = \frac{1}{N} \sum_{n=1}^N x(n) \quad (1)$$

2. Energy of signal:

$$X_{energy} = \sum_{n=1}^N x(n)^2 \quad (2)$$

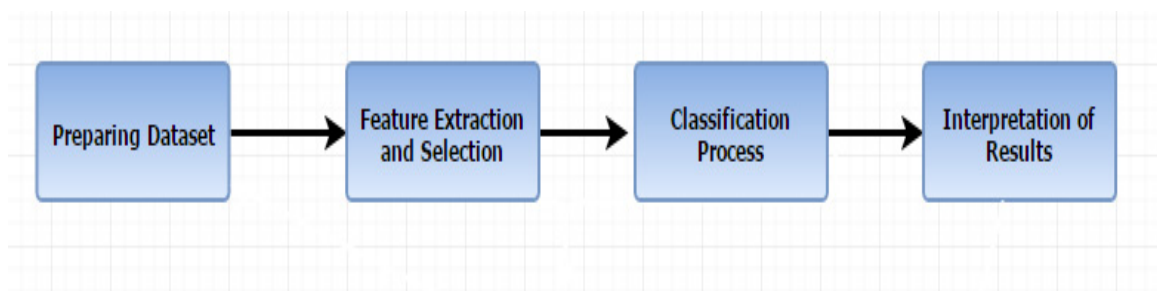


Figure 1. The performed process steps.

3. Form factor of signal:

$$SF = \frac{x_{rms}}{\frac{1}{N} \sum_{n=1}^N \sqrt{|x(n)|}} \quad (3)$$

4. Standard deviation of the signal:

$$X_{std} = \sqrt{\frac{\sum_{n=1}^N (x(n) - x_m)^2}{N-1}} \quad (4)$$

5. Skewness of signal:

$$X_{skw} = \frac{\sum_{n=1}^N (x(n) - x_m)^3}{(N-1)x_{std}^3} \quad (5)$$

6. Kurtosis of signal:

$$X_{krt} = \frac{\sum_{n=1}^N (x(n) - x_m)^4}{(N-1)x_{std}^4} \quad (6)$$

7. The ratio of signal energy to that of the previous window
8. The ratio of signal energy to that in the next window
9. The ratio of signal energy to power of all epochs
10. The ratio of signal energy to energy of all signals
11. The ratio of signal form factor to form factor of all epochs
12. The ratio of signal form factor to form factor of all signals
13. The ratio of signal standard deviation to standard deviation of all epochs
14. The ratio of signal standard deviation to standard deviation of all signals

2.2.2 Frequency Domain

1. Relative energy-1 in 0-2Hz (energy of signal/energy of all epochs)

2. Relative energy-2 in 0-2Hz (energy of signal/energy of all signals)
3. Relative energy-1 in 2-4Hz (energy of signal/energy of all epochs)
4. Relative energy-2 in 2-4Hz (energy of signal/energy of all signals)
5. Absolute mean of $\Delta EOG = EOGL - EOGR$
6. Absolute standard deviation $\Delta EOG = EOGL - EOGR$
7. Energy of $\Delta EOG = EOGL - EOGR$

21x318 size feature matrix as REM labelled and 21x318 size feature matrix as NREM labelled was formed in the result of the feature extraction process.

SBS process was applied to find out which features are dominant in classification procedure. While SBS was implementing, ANN was again applied with 3-fold cross validation technique. LR, ITNUM, MC parameters were fixed at values 2, 1000 and 0.8 respectively. Only HLNN was used as changeable and the number of optimum hidden layer node number was found by changing HLNN between 1 and 100.

2.3 Classification Process

After extracting features, k-fold cross validation technique was used. K-fold cross validation technique is reliable and determinant technique. In⁸, it seems that k-fold cross validation technique reduces errors of classification.

As it is seen in Figure 2, 3-fold cross validation technique was used in this study. 21x318 size feature matrix as REM labelled and 21x318 size feature matrix as NREM labelled were separated 3 group ratio of 2 to 1 as equal number of elements and 21x424 size training matrixes and 21x212 size test matrixes were obtained. Each training and test group was trained and tested three times. For ANN method, gradient descent learning algorithm (traingdx) was used as learning algorithm. Also, fixed Learning Rate (LR), Momentum Constant (MC) and Maximum Iteration Number (MAX_ITER) values were selected 2, 0.8 and 1000, respectively in MATLAB. Only optimum HLNN parameter of ANN was investigated for maximum accuracy in the process that was implemented single layer classifier. The other parameters were not changed, because these parameters could not affect accuracy of classification too much.

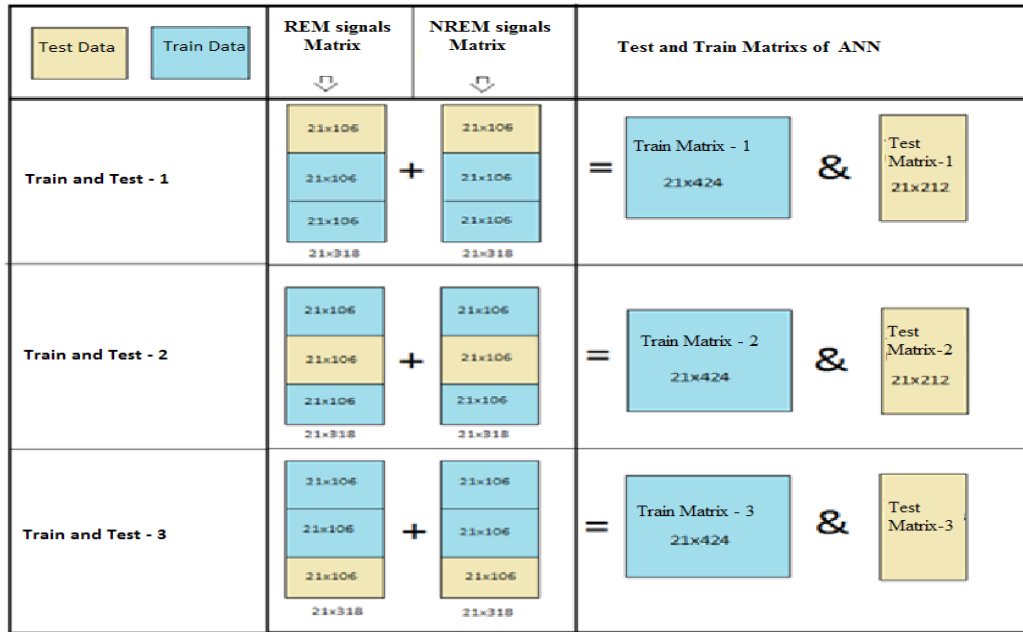


Figure 2. Selected train and test data groups.

3. Experimental Results

As mentioned above, when the previous studies were reviewed, there is not any study about sleep staging with only EOG signals. In this study, EOG signal was only used different from aforementioned investigations. Some of features after scanning the study of about sleep staging were specified and ANN method was implemented on EOG signal that was separated by the book. Optimum parameters of ANN on features were investigated and accuracy of classification was calculated. Then, dominant features were selected by using SBS and maximum accuracy of classification was landed up with this. Optimum parameters of ANN were investigated for maximum accuracy in the process that was implemented single layer classifier. The ranges of parameters were selected according to optimum parameters range that determined previous studies about sleep staging. Hidden Layer Node Number (HLNN), LR, MC and Iteration number (ITER) parameters were respectively changed in determined range. Process steps of fixed and variable values were:

Fixed values: LR=2; ITER=1000; MC=0.8;
Variable value: HLNN= [5:5:75]

Fixed values: HLNN=70; ITER=1000; MC=0.8;

Variable value: LR= [0.5:0.5:10]

Fixed values: HLNN=70; LR =3; MC =0.8;

Variable value: ITER= [100:100:1400]

Fixed values: ITER=1000; HLNN=70; LR =3;

Variable value: MC = [0.1:0.1:0.9]

Optimum parameter of ANN and classification accuracy is shown in Table 1.

Table 1. Optimum parameter of ANN and classification accuracy

HLNN	LR	ITNUM	MC	CD (%)
70	3	1000	[0.1:0.9]	88.05

SBS method was used for selection of best features combination for maximum accuracy. Optimum value of HLNN, selected features and classification accuracy is shown in Table 2. As it is seen in the Table 2, in SBS method, each feature was omitted respectively and at the least affecting feature was put out of action. Column-1

of this table shows omitted feature and column-2 shows combination of features that implemented SBS. HLNN parameter was changed while SBS was implementing for maximum accuracy. Optimum HLNN is shown in column-3 and column-4 shows accuracy of this process step. According to results of SBS, number of the best features combination was determined as 13 and the maximum classification accuracy was obtained as 89.62%. The opti-

imum value of HLNN was determined as 15 for the best features.

The HLNN value with respecting of feature number is given in Figure 3. When Figure 3 is analyzed, feature number of 15 is seen that the best combination of HLNN.

Accuracies of classification with respecting of feature number are given in Figure 4. Accuracies of classifica-

Table 2. Selected features and classification accuracies

*Number of omitted Feature	*Numbers of Applied Features combination	Optimum Value of HLNN	Classification Accuracies (%)
17	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,18,19,20,21	20	88.67
12	1,2,3,4,5,6,7,8,9,10,11,13,14,15,16,18,19,20,21	50	88.36
20	1,2,3,4,5,6,7,8,9,10,11,13,14,15,16,18,19,21	15	88.20
21	1,2,3,4,5,6,7,8,9,10,11,13,14,15,16,18,19	10	88.67
2	1,3,4,5,6,7,8,9,10,11,13,14,15,16,18,19	55	88.52
1	3,4,5,6,7,8,9,10,11,13,14,15,16,18,19	75	89.15
13	3,4,5,6,7,8,9,10,11,14,15,16,18,19	40	88.52
10	3,4,5,6,7,8,9,11,14,15,16,18,19	15	89.62
8	3,4,5,6,7,9,11,14,15,16,18,19	25	88.52
16	3,4,5,6,7,9,11,14,15,18,19	20	88.36
7	3,4,5,6,9,11,14,15,18,19	55	89.15
4	3,5,6,9,11,14,15,18,19	20	88.67
6	3,5,9,11,14,15,18,19	35	89.46
5	3,9,11,14,15,18,19	25	88.36
11	3,9,14,15,18,19	55	87.73
9	3,14,15,18,19	5	87.57
3	14,15,18,19	50	87.42
18	14,15,19	25	85.06
15	14,19	60	83.49

*Features are numbered according to their sequence number in feature set.

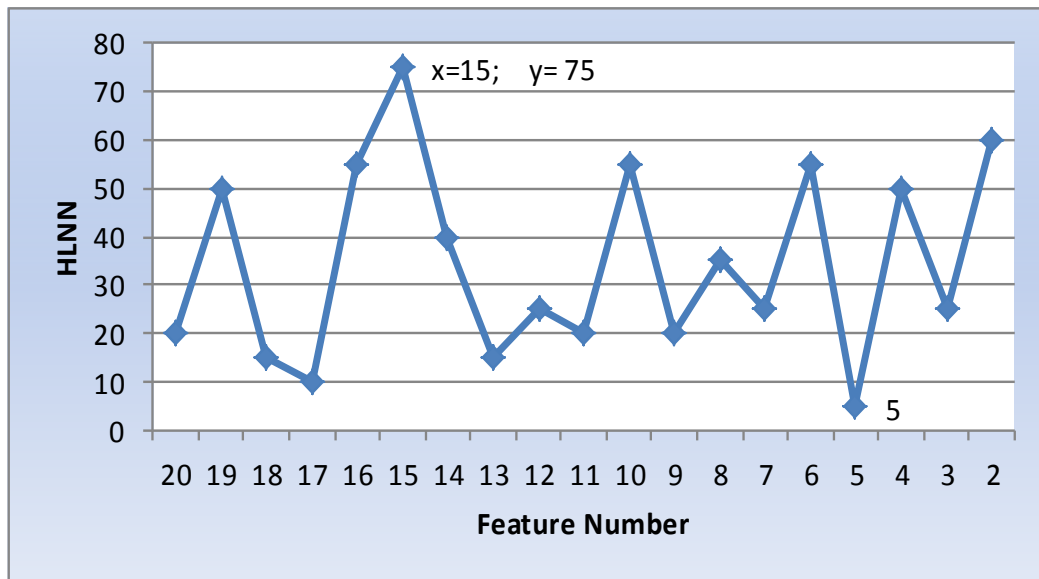


Figure 3. Change of HLNN according to feature number.

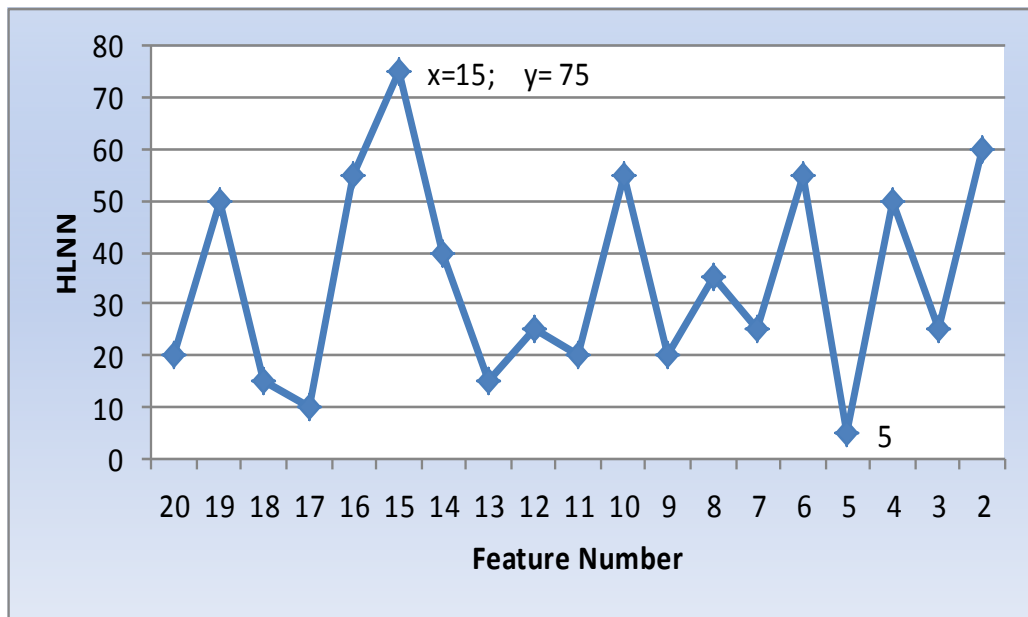


Figure 4. Accuracy of classification according to feature number.

tion nearly diminished when ineffective feature omitted sequentially can be observed.

As a conclusion, the best obtained features in this study are shown Table 3. As a basis, features of form factor, standard deviation (std), skewness, kurtosis, signal energy of EOG signal, relative and absolute mean of

Δ EOG energy have importance for classification of EOG signals as REM and NREM. When this table is analyzed, features about energy of signal like ratio of signal energy and relative energy are encountered with. So, energy of signal is dominant in both time domain and frequency domain. Also, absolute mean of difference of EOGL

Table 3. Best features combination

*Number of Feature	Name of Feature	Classification Accuracy (%)
3	Form factor of signal	89.62
4	Std of the signal	
5	Skewness of signal	
6	Kurtosis of signal	
7	The ratio of signal energy to that of the previous window	
8	The ratio of signal energy to that in the next window	
9	The ratio of signal energy to power of all epochs	
11	The ratio of signal form factor to form factor of all epochs	
14	The ratio of signal std to std of all signals	
15	Relative energy-1 in 0-2Hz	
16	Relative energy-2 in 0-2Hz	
18	Relative energy-2 in 2-4Hz	
19	Absolute mean of $\Delta\text{EOG}=\text{EOGL}-\text{EOGR}$	

and EOGR can be seen that among of results. Form factor, standard deviation, skewness, kurtosis is element of dominant features in our study too, as it is in many sleep staging studies.

4. Conclusion

Generally, EEG, EMG and EOG signals are particularly used together utilizing time domain and frequency domain features of these signals in studies on sleep staging. However, in this study, left eye and right eye EOG signals were only used to classify REM and NREM signals by extracting 21 features in time and frequency domain. The classification accuracy was recorded as 88.05% by using the 21 features. To obtain higher classification accuracies, Sequential Backward Selection SBS method was used. According to results of SBS, number of the best

features combination was determined as 13 and the maximum classification accuracy was obtained as 89.62%. When literature was investigated; a study about sleep staging by using only EOG signals was not seen. Also, when looking from the viewpoint of percentage of classification accuracy of this study, a result can be seen that is non-negligible value for literature. Additionally, for this study, sleep staging using different methods on EOG signals was performed. So, this study can be basis for future similar studies.

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