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Araştırma / Research

DALGACIK DÖNÜŞÜMÜ İLE YAPAY SİNİR AĞLARI KULLANILARAK UYKU EVRELERİNİN OTOMATİK SINIFLANDIRILMASI

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ÖZ

Bu çalışmada, Tıkayıcı uyku apnesi sahip kişilerden elde edilen polisomnografik uyku kayıtlarına dayanan otomatik uyku evresi sınıflandırma çalışması yapılmıştır. Çeşitli çalışmalarda, normal kişilerden elde edilen EEG kayıtlarına dayanarak uyku evreleri sınıflandırılmıştır. Tıkayıcı uyku apneli kişilerin uykusu gece boyunca sıklıkla kesintiye uğradığından, uyku bozukluklarının doğru skorlanması tanı için önemlidir. Otomatik uyku evrelerinin sınıflandırılması için sinyaller Amerikan Uyku Tıbbı Akademisi kriterlerine göre seçilmiştir. Otomatik uyku evrelerinin sınıflandırması için bu sinyal gücü değerlerinden oluşan özellik vektörleri, ANN (Yapay Sinir Ağları) girdileri olarak hesaplanmıştır. YSA'nın başarısını artırmak için geliştirilen algoritma ile sinyallerden elde edilen özellik vektör tablosunu yeniden sıralanmıştır. Bu çalışmada, YSA'nın eğitim ve test başarısı 10 kat çapraz doğrulama kullanılarak belirlenmiştir. YSA tarafından uygulanan otomatik uyku evre skorlaması çalışmasında, Uyanıklık, REM (Hızlı Göz Hareketi), NREM1 (Hızlı göz hareki olmayan), NREM2, NREM3'ün doğru tanıma oranı sırasıyla %95, % 93, % 91, % 86 ve % 92 olarak bulunmuştur. Bulgular, otomatik uyku evresi sınıflandırma eğitim ve test başarısının literatürdeki diğer çalışmalara göre daha iyi olduğunu göstermektedir.

Anahtar kelimeler: Polisomnografi, Dalgacık Dönüşümü, Yapay Sinir Ağları, Uyku skorlama, Uyku Evreleri

AUTOMATIC SLEEP STAGE CLASSIFICATION USING ARTIFICIAL NEURAL NETWORKS WITH WAVELET TRANSFORM

ABSTRACT

This study mainly focuses on automatic sleep stage classification based on polysomnographic sleep recordings obtained from obstructive sleep apnea subjects. Various studies have so far classified sleep stages based on EEG recordings obtained from normal subjects. Because obstructive sleep apnea subjects' sleep is often interrupted throughout the night, accurate scoring of their sleep disorders is important for diagnosis. The signals for automatic sleep stages classification were selected in accordance with American Academy of Sleep Medicine criteria. Feature vectors consisting of these signal power values for the automatic sleep stage classification were calculated as inputs of ANN (Artificial Neural Networks). We re-ordered the feature vector table obtained from signals via the algorithm developed to increase the success of the ANN. In this study, training and testing success of ANN were determined by using 10-fold cross-validation. In the study of automatic sleep stage scoring implemented by ANN, the correct recognition rate of Wakefulness, REM (Rapid Eye Movement), NREM1(Non REM1), NREM2, NREM3 were found as 95%, 93%, 91%, 86% and 92%, respectively. The findings suggest that training and test success of automatic sleep stage classification are better compared to the other studies in the literature.

Keywords: Polysomnogram, Wavelet transform, Artificial Neural Networks, Sleep scoring, Sleep stages

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1. INTRODUCTION

Sleep, which comprises one-third of human life, is an important part of daily life. It directly influences mental performance, learning ability, general physical and mental achievement. Sleep is necessary brain activity for the restructuring of memory, neural growth and psychological regeneration [1]. Sleep disorder, which can be defined as insufficient sleep, can cause problems such as forgetfulness, irritability and distractibility. Sleep disorders mostly decrease the quality of life and worsen the health. It is a public health problem which leads to traffic and occupational accidents. Some sleep disorders make it difficult to fall asleep and continue sleeping, and others cause excessive sleepiness. Thus, the diagnosis of diseases associated with sleep is important in sleep research.

Sleep disorders are diagnosed by using polysomnogram (PSG) records. PSG device saves biomedical signals such as brain activity, heart rate, muscle movements and oxygen saturation in the blood. The most important process in the diagnosis of sleep disorders is the accurate scoring of sleeping via the signals obtained from the PSG devices [2]. Sleep stages are scored visually by using the rules identified by Rechtschaffen and Kales in 1968. In 1990, these rules were revised at the annual meeting of the sleep studies community. According to these rules, automated scorings based on computer algorithms were developed [1, 3, 4, 5]. All polysomnography recordings were divided into 30 second epochs from onset to the end of the sleep, and each epoch was scored separately. Each score represents one of the basic stages of sleep. These stages are determined by examining electromyogram (EMG), electrooculogram (EOG) and electroencephalogram (EEG) recordings. In 2007, American Academy of Sleep Medicine (AASM) published new scoring rules which provide scoring standardization and sleep recording techniques, and they were finally revised in 2014 [2,4,5]. Today, according to AASM criteria, sleep records are divided into five stages: wakefulness, REM, which stands for rapid eye movements, NREM1, NREM2 and NREM3, which represent absent or slower eye movements. Sleep is visually scored by the doctor through examining based on AASM criteria, using 3 EEG signals from the human head, 1 EMG signal from the chin, and 2 EOG signals from the right and left eye [2, 4]. Sleep scored via visual inspection causes many errors and takes a long time. The signals in PSG recordings are very complex and some specific signal structures must be determined. Thus, it does not only vary depending on the doctor's skills and experience but also results in some subjectivity in sleep staging process. Researchers have so far developed many techniques by using various sleep scoring methods to help the doctor. Some of the proposed methods and techniques are described below.

In 2013, the energy properties of FPz-Cz EEG signal obtained from a single channel were removed by Yu-Liang Hsu et al. Thanks to these features, automatic sleep stages were scored via Recurrent Elman Artificial Neural Networks [3]. In 2007, Virkkala et al. extracted signal characteristics via Discrete Fourier Transform (DFT) by using EOG recordings, sleep staging was performed by decision tree [6]. In a study in 2011 by Huupponen et al., waking and deep sleep was determined by calculating EEG recordings. The EEG amplitude provided a good identification of deep sleep, which was 86.25%; however, it was relatively poor in the identification of wakefulness, which was 39.06%. Mean frequency provided a relatively good identification of deep sleep and awake with a rate of 84.66% and 77.67%, respectively [7]. In an article published in 2012 by Luay Fraiwan et al., a method based on time-frequency analysis by using a single channel EEG was proposed in order to automatically score sleep stages [8]. In an article published in 2014 by Shan Mota-Fakhra, signal processing techniques for human sleep EEG signals were explained comprehensively. In this study, preprocessing techniques applied in the EEG signals were briefly explained and the studies carried out up until now in order to identify and suppress artefact were summarized [9]. In a sleep study by Stepnowsky et al., sleep stages were scored based on sleep apnea patient records in 2013, and it featured extraction via spectral analysis by using frontal EEG signals. Sleep was scored by using these features [10].

In sleep analysis studies such as automatic apnea detection and sleep staging, ANN is the most frequently used method [3, 4, 7]. In numerous studies on automatic sleep scoring based on EEG signals, wavelet analysis and ANN, spectral analysis methods were used together or individually [7, 8, 11, 14]. One or several signals were used in many studies based on ANN in the literature [6, 7, 9, 11, 12].

In this study, a new computer algorithm was developed based on artificial neural network (ANN) method in order to automatically score sleep stage, and it was also analyzed based on visual scoring rules. In automatic sleep stage scoring, compatibility was provided via visual scorings by using the signals of 3 EEG, 2 EOG and 1 EMG which doctors use in sleep scoring. In this study, sleep staging was performed automatically based on scoring rules identified by the developed computer algorithm by using ANN method. In Section 2, signal preprocessing, feature extraction, the reordering of extracted features via the developed algorithm and three-layer feed-forward neural network are explained. Results and discussions are presented in Section 3. The conclusions are presented in Section 4.

2. MATERIALS AND METHODS

2.1. Data Acquisition and Preparation

The signals used in the study were obtained via the Empla S 4000 PSG device from the sleep apnea subjects staying in the Sleep Research Laboratory of Kahramanmaras Sutcu Imam University. EEG, EOG and EMG signals were sampled at a rate of 200 Hz. The signal records obtained from PSG devices were scored visually by doctors. Scored records were classified based on the type of apnea and apnea/hypopnea index (AHI) by the doctors. The records were classified based on the reported and scored records belonging to 30 patients, (AHI<5, normal; 5 <=AHI<15; mild, 15 <= AHI < 30, moderate; and AHI >30, severe) in accordance with AHI. Subjects were given names such as subject1, subject2 etc. 10 subjects suffering from obstructive sleep apnea (5=<AHI =< 15) that Apne/hipopne index were selected between 5 and 15 in order for ANN to perform automatic scoring. Signal processing was performed in order to prepare data by filtering, amplifying and cleaning. Given the possible existence of dc values in the signals, these signals were first purified of these dc values. The patient's movements during sleep caused unexpected noises on PSG signals. More often than not, these high-frequency noises were suppressed by low pass and band reject filters. Network noise was suppressed by PSG recording system. Unexpected amplitude changes (artefacts) may occur in the respiratory signals during sleep due to the movements of the patient or sensors. Statistical methods were used in order to prevent unexpected amplitude changes. Statistically, 95.45 percent of a normally distributed number sequence occurs at an interval of $\mu \pm 2\sigma$ [18] where μ represents arithmetic mean of a sequence and σ represents standard deviation. Amplitude value which is not between this ranges was considered as noise (artefact).

A total of 9808 epochs obtained from 10 subjects were used (1115 epochs for Wakefulness (W), 1939 epochs for REM (R), 312 epochs for NREM1 (N1), 3653 epochs for NREM2 (N2), 2789 epochs for NREM3(N3)) and scored by a doctor. Sleep stage information is given in Table 1.

Table 1. The distributions of the subjects' sleep stages

Subjects	AHI	W	R	N1	N2	N3
01	5	112	152	16	391	194
02	6	59	123	36	187	411
03	7	210	119	63	215	283
04	9	18	217	26	482	197
05	9	273	192	29	228	243
06	11	11	269	4	240	277
07	13	177	197	20	295	284
08	14	74	106	26	488	206
09	14	33	211	18	467	206
10	15	116	124	22	355	235
Total		1115	1939	312	3653	2789

In data preprocessing, the signals received from the subjects were converted into Matlab data formation from EBM data formation to be analyzed in time and frequency domain. These signals were filtered firstly by using band pass filters. 0.5-35 Hz band pass filters for EEG signals, 0.3-40 Hz band pass filters for EOG signals and 0.5-100 Hz band pass filters for EMG signal were used. In addition, we analyzed 30 second epochs which scored by doctor according to the AASM criteria. Evaluated signals (taken from the subjects 3 EEG signal, EMG signal from the chin, 2 EOG signal from right and left eye) were divided into epochs which are Wakefulness, REM, NREM1, NREM2, and NREM3.

2.2. Wavelet Transform

Wavelet transform (WT) is widely used in extracting features from EEG signals. WT is a signal based on transformation of basic components called wavelet. Wavelet may display in different shapes. Wavelets provide a useful tool for time-frequency analysis. Generally, the biological signal wave forms can be modelled coherently with temporal and spectral characteristics of a particular component of the selected wavelet.

Recent studies on the components of the wavelet focused on selecting the signal and enabling researchers to choose their own method of analyzing multiple wavelets. Many filters such as Haar, Daubechies, Biorthogonal, Coiflets, Symlets and Meyer use wavelet families. In this study, Daubechies structures of wavelet families were applied to the EEG Signals and db12 was determined as the optimal wavelet.

WT is one of the most popular transformation techniques for time-frequency transformations which divide the signal into varied frequency components and analyze every component with a resolution on that scale. WT of a signal which is a function of time depends on the variable frequency and time [14]. Wavelet series is a method applicable on different fields, including signal processing techniques. Wavelet method was used to extract the equal components of a signal, the resulting coefficient is often obtained via the threshold method, and the threshold was again used to create the discrete wavelet coefficients of the basic signal [12, 14].

$$\psi_{a,b}(t) = \frac{1}{\sqrt{|a|}}\psi\left(\frac{t-a}{b}\right) \quad (1)$$

b here represents the shift parameter. Set of functions ψa,b (t) is called a wavelet family. As for the parameters, (a, b) are continuous valued, which is called continuous wavelet transform. The description of classical wavelets expands as a function of tools, a <1 or narrow width corresponds at high frequency wavelets, while a >1 or is a wider width low frequency wavelet [14].

Discrete Wavelet Transform (DWT), as well as reducing the computational load, provided enough information for the analysis of the basic signal. Digital signal representative of the time scale is obtained using digital filtering techniques. DWT operates two sets of functions, which are called wavelet functions and scaling functions, associated with low pass and high pass filters, respectively. The signal is decompositioned into different frequency bands via successive high pass and low pass filtering of the time domain signal [14]. The signal x(n) is passed as the first a half band high pass filter g(n) and the low pass filter h(n). Following the filtration, half of the samples can be eliminated by the Nyquist rule because the signal has the highest frequency of p = 2 radians in place of p. Thus, the signal can be subsampled by 2 by simply discarding each sample [14]. This procedure constitutes a level decomposition and can be expressed mathematically as follows:

$$Y_{high}[k] = \sum x(n)g(2k-n) \quad (2)$$

$$Y_{low}[k] = \sum x(n)h(2k-n) \quad (3)$$

Y_{high} [k] here represents the output of the high pass filters, and Y_{low} [k] is the output of low pass filters following subsampling by 2. This method is known as sub-band coding and might be repeated for further decomposition. At each level, filtering and subsampling can result in half of examples and spends half frequency band.

WT separates frequency bands of EEG signals and, thus, staging of sleep epochs helps us to identify the characteristic structure. In this study, while WT was applied to the EEG signals, the EMG and EOG signals were not applied. In the study, it was performed with Daubechies12 (db2) wavelet because it performed better in the analysis of EEG signals. WT was used to analyze and perform subband signals obtained from the signals conversion. Daubechies wavelet db12 model was used as the wavelet transform. 200 Hz sampling frequency of the recorded sleep EEG signals was reduced to 32 Hz sampling frequency in order to decrease processing time. The process of wavelet decomposition packet is shown in Figure 1.

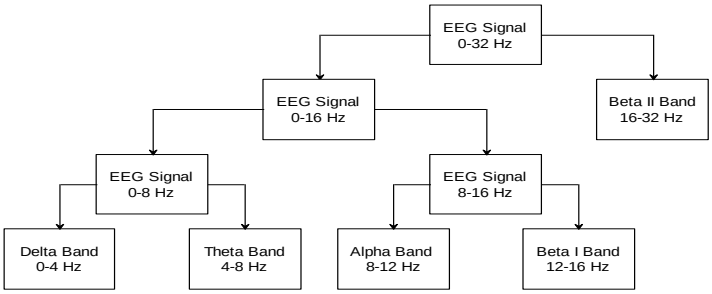

Figure 1. Third level wavelet packets

2.3. Feature Extraction

In this section, features of the signals (EEG, EOG and EMG) were extracted. For sleep stage scoring, EEG signals (C4, F4, O2), oculogram signals (E1, E2 taken from the right and left eyelid) and chin EMG signal (from chin) are used. Normally, EEG signals consist of the shaped of signals, delta (20-400µv amplitude, the frequency of 0.5-4 Hz band), theta (5-100 µv amplitude, the frequency of 4-8 Hz band),alpha (5-10 µv amplitude, the frequency of 8-12 Hz band, eyes closed), beta (1-5 µv amplitude, the frequency greater than 13 Hz, eyes open), sleep spindles (amplitudes about 75µv, the frequency of 12-16Hz band), K-complex (about 1 Hz frequency) and sawtooth wave (the frequency of 8-12 Hz band) [1, 2, 4, 5, 13]. EMG signal is located at the 10-5000 Hz frequency band. While amplitude of EMG signal is high in wakefulness, it is the lowest in REM and NREM3 stages [1, 2, 6, 8, 9]. While EOG signals a constant potential in the absence of eye movements, it has a variable potential in eye movement. This potential is determined while it is completely dark or eyes are closed. As for wakefulness and REM stages, their frequency and amplitude are high in NREM1 and NREM2, respectively; while their amplitude and frequency are low in NREM3 [1, 2, 4, 5].

For example, in the wakefulness stage, the amplitude of the EEG signal is around 20µV, and the frequency is higher than 8Hz. EOG signal is high frequency and high amplitude. EMG signal amplitude is around 10µV. Wakefulness stage is shown in Figure 2. Frequency distribution of EEG signal in the wakefulness stage obtained via Discrete Fourier Transform (DFT) is shown in Figure 3.

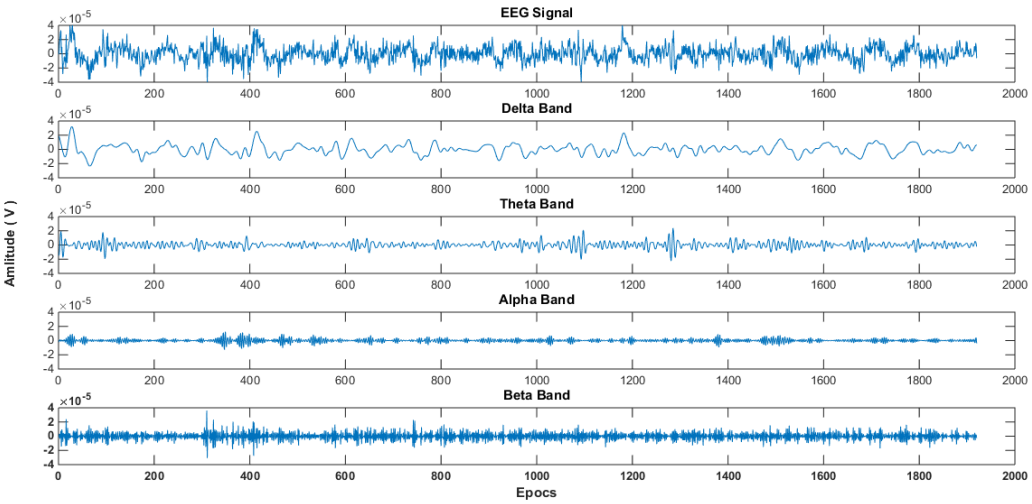

Figure 2. Wakefulness stage EEG signal and subbands of the EEG signal

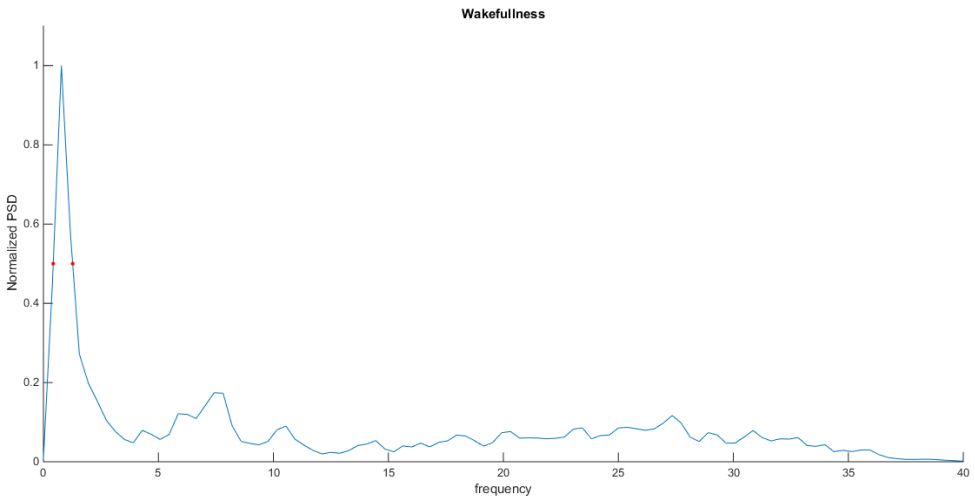

Figure 3. Wakefulness stage frequency band of the EEG signal

In the NREM3 stage, the amplitude of the EEG signal is high (around 100μV), while the frequency is low. The EOG signal displays high frequency and low-amplitude oscillations. EMG signal displays very low amplitude (around 0.2μV). NREM3 stage is shown in Figure 4. Frequency distribution of EEG signal in the NREM3 stage obtained via Discrete Fourier Transform is shown in Figure 5.

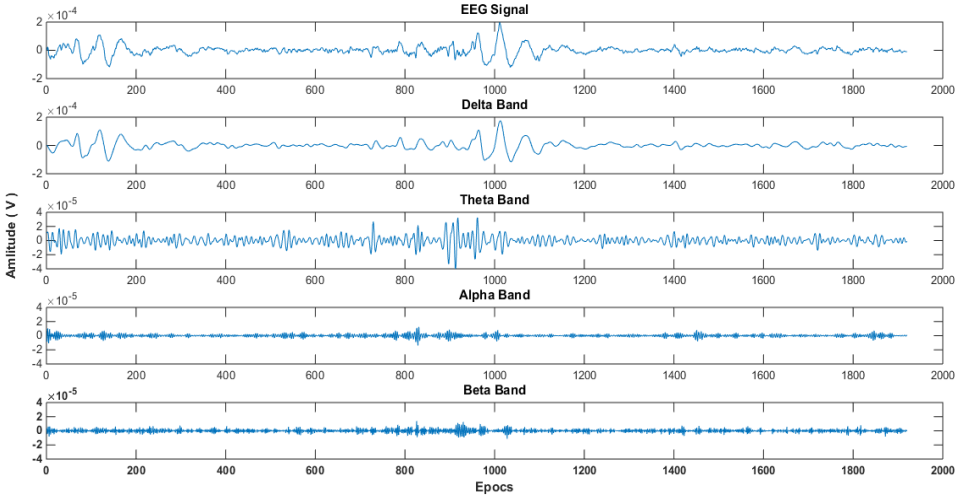

Figure 4. EEG signal and subbands of the EEG signal in NREM3 stage

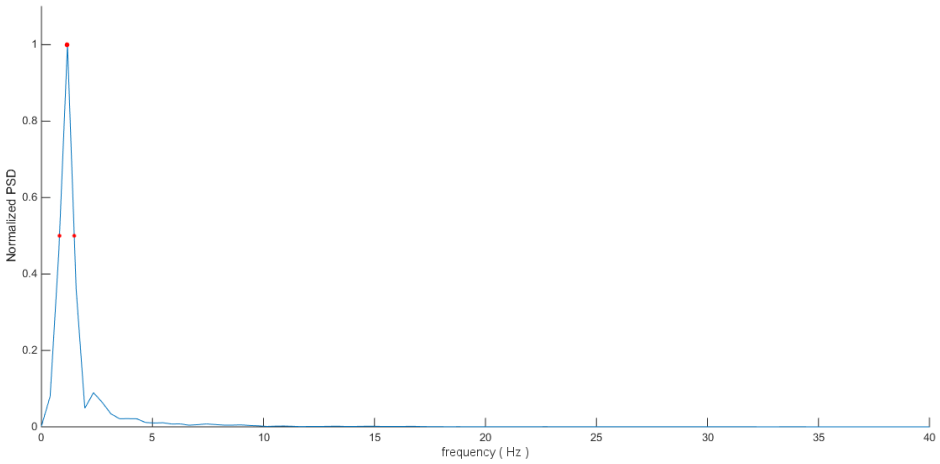

Figure 5. Frequency band of the EEG signal in NREM3 stage

Signal power, energy, effective value, mean value, standard deviation, band width and mean frequency of the signal are used in various studies [3, 6, 11]. These features give identifying information about the signals. In this study, subband of EEG signals was extracted by using WT. This subband power values were calculated in a way similar to Equation 4, and the power values of EOG and EMG signals were calculated for every 30-second epochs.

$$P = \frac{1}{N}\sum_{i=1}^{N}[x(i)]^2 \quad (4)$$

P is signal power, N is number of samples, and x(i) is time domain signal series.

Calculated 15 features of the 3 EEG signal, 3 features of 2 EOG and EMG signal are listed below.

1. Five features of each EEG signal (delta, theta, alpha, sigma and beta frequency bands) signal power (15 features)
2. EOG signal power of the right and left eyes (2 features)
3. EMG signal power of the chin muscles (1 features)

2.4. Artificial Neural Network Model

ANN is a structure used to model an unknown system. It is a quite useful method compared to other conventional classifiers and decision-making system with high calculation speed in the structure. ANN can be trained for several application examples and used for complex computer-based applications. There are many training procedures in the literature. Bayesian regulation backpropagation classifier yields the best performance. It minimizes a combination of squared errors and weights, and then determines the correct combination in order to produce a well generalizes ANN. ANN transfer functions offer a useful way in simulating event reaction using input and output. Tansig function, which is recommended for many applications, was also used in this study.

ANN is performed in three steps: modeling, training and simulation. In the modeling step, the number of layers to be used, the transfer functions of neurons and the number of neurons to be used in each layer are selected. Although these parameters are very important in the success of ANN model, the selection of feature vectors and their correct sequences proved to be important in testing. The order of feature vectors is common in accordance with implementation order of sleep stages [3, 10]. However, the feature vector table ordered in this way leads to convergence about learning artificial intelligence. For example, to classify the Rem stage, feature vectors were ordered as RNRNRN where R is REM stage and N is non-REM stage. The table of feature vectors was reordered in other sleep stages by similar ordering. Thus, the feature vectors were reordered based on sleep stages instead of time order. In the experiments carried out by this order, it was found that artificial intelligence learning increases success.

ANN was used in many studies with wavelet analysis [3, 10, 14]. ANN inputs formed coefficients by using the raw signals. Signal powers were obtained from subband of EEG signals by using wavelet analysis, the signal powers of the EOG and EMG were used as the input to the ANN.

Three-layer structure was used for neural network modeling. Number of neurons was selected 18, 9 and 1 for each layer via trials. After the feature vectors were reordered, 10 subject records were applied to the network. We compared the results of network for each subject with sleep stages scored by the doctor. The trained network was tested for each stage.

3. FINDINGS AND DISCUSSION

3.1. K-Fold Cross Validation

K-fold cross-validation is recommended as a criterion for the training and testing of an ANN. The original dataset is randomly divided into k equal size sub-datasets, which can be performed out in various forms. A single sub-dataset of the k sub-datasets is retained as the validation data in order to test the model, and the remaining k−1 sub-datasets are used as training data. The k results from the folds can then be averaged to produce a single estimation. The most preferred separation process in the literature is 10-fold cross-validation [3, 15]. 10-fold cross-validation was used to test the feature of classification system in this study.

3.2. Measuring Error

Taking a random set of initial weights, ANN output may differ from the desired classification. While the ANN is trained, the system is repeatedly adjusted to reduce weight the difference between the network output and the desired output of the system. It is expressed as difference error and may be measured in various ways. The most general measurements are mean square error (MSE) and sum square error (SSE). MSE measures the average of the squares of the errors. SSE is the average of the squares of the difference between each output and the desired output [11].

3.3. Performance Analysis of ANN

The performance of ANN classifier based on visual analysis was determined by calculating sensitivity, specificity and accuracy. These assessments are used as a common method of classification in pattern recognition applications. Sensitivity, specificity and accuracy are defined as follows:

$$\text{sensitivity} = \frac{\text{TP}}{\text{TP+FN}} \text{ x } 100\ \% \tag{5}$$

$$\text{specificity} = \frac{\text{TN}}{\text{TN+FP}} \text{ x } 100\ \% \tag{6}$$

$$\text{accuracy} = \frac{\text{TP+TN}}{\text{TP+FP+TN+FN}} \text{ x } 100\ \% \tag{7}$$

TP, FP, TN and FN here indicate the number of true positives, false positives, true negatives and false negatives, respectively [17].

For example, wakefulness: TP represents an output which was detected as the wakefulness stage that was also scored by the doctor as wakefulness stage. FN represents an output which was detected as other sleep stages that was scored by the doctor as wakefulness stage. FP represents an output which was detected as wakefulness that was scored by the doctor as other sleep stages. TN represents an output which was detected as other sleep stages that was scored by the doctor as other sleep stages.

The sensitivity, specificity and accuracy of the ANN are given in Table 2. The summary of rate of sleep stages is shown in Table 2 (Wakefulness, REM, NREM1, NREM2 and NREM3).

Table 2. Wakefulness, REM, NREM1, NREM2 and NREM3 stage classification test performance of the ANN

Sleep Stage	Sensitivity (%)	Specificity (%)	Accuracy (%)
Wakefulness	89	96	95
REM	85	93	93
NREM1	42	94	91
NREM2	79	87	86
NREM3	89	93	92

Another evaluation here is related with the misclassifications given in the confusion matrix. The ANN performance measures were calculated based on the confusion matrix. Each sleep stage classification was compared with other 4 stages considered as a single class (negatives). Epoch-by-epoch confusion matrix for the ANN is shown in Table 3.

Table 3. Confusion matrix for the classification of the test data based on ANN

	Sleep stages determined by doctor					
Automatic score	Stage	W	R	N1	N2	N3
	W	1058	98	16	21	2
	R	33	1805	8	142	63
	N1	19	19	284	58	5
	N2	4	11	3	3147	160
	N3	1	6	1	285	2559
Test classification error		5.11	6.91	8.97	13.85	8.24

In automatic sleep staging, the accuracy rates of Wakefulness (W), REM (R), NREM1 (N1) NREM2 (N2) and NREM3 (N3) were found as 95%, 93% 91%, 86% and 92%, respectively. The proposed neural network model was successful with the obtained classification rates.

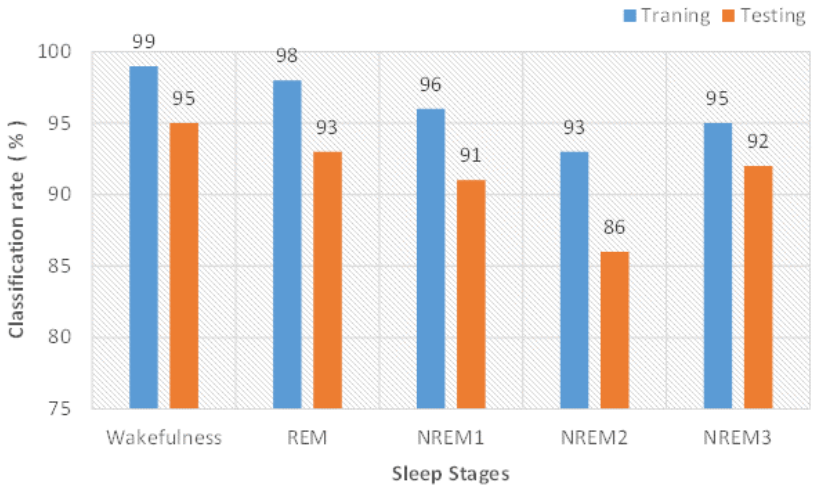

Figure 6. Classification rate for sleep stages using the ANN

A decline was observed in the classification performance in NREM2 stage because of the frequent interruption of sleep. Hence, classification success in NREM2 stage is slightly lower compared to other stages. However, the system proposed in this study displayed very well learning success compared to the other studies in the literature [3, 10, 16].

Most of the proposed systems about sleep stage deal with the sleep stages classification problem. Many methods in the existing studies were proposed for sleep stage classification. Yu-Liang Hsu et al. recurrent Elman neural classifier for a sleep stages, however, reported [3] that the classification rates did not exceed 88%. Huupponen et al. conducted a study on waking and deep sleep by calculating EEG recordings in 2011 [7], and concluded that the classification rates were approximately 80%. Thus, the ANN test classification results of classifier for the reordering feature vectors were very good. In addition, we calculated the precision of the classification compared to the results of the researchers who used EEG, EOG and EMG signals. The training and test classification rate of ANN for sleep stages are shown in Figure 6. The overall classifier accuracy of the classifier was obtained as 92%. Compared to existing studies in the literature, this rate is not only higher than an average of 1-3% ANN but also displays very good learning success. The results were obtained in a much shorter time as demonstrated by doctor examination, and it was more successful compared to existing studies in the literature [3].

4. RESULTS

In this study, a method for sleep stage recognition system based on visual scoring rules was proposed. The method consists of three steps. In the first step, which is called feature extraction, we applied DWT to EEG signals with 30-second epochs. Similarly, EOG and EMG signal power were calculated individually for the 30-second epochs. In the second step, we re-ordered features vector using developed algorithm. In the third step, we used reordered features as input to ANN. Thus, we were able to distinguish between Wakefulness, REM, NREM1, NREM2 and NREM3 stages. The experimental results obtained via 9808 epochs from nine different subjects demonstrated the validity of the proposed method.

Automatic sleep stage scoring was performed by using open database or recordings of healthy volunteers in the existing studies in the literature. AHI <15 patients were selected in order to provide compatibility with other studies. This automatic sleep stage scoring study based on u visual scoring rules is expected to offer a significant solution to sleep disorders examined by doctors. The following conclusions can be drawn based on the test results of this study.

- Unlike other studies, sleep stages were determined by using the sleep stages belonging to subjects with OSA.
- EMG, EOG 2 and 3 EEG signals were used in the automatic sleep stage classification.
- It was observed that classification performance of ANN with reordering of the feature vector was improved.
- A decline was observed in the classification performance in NREM stage observed because of the frequent interruption of sleep.

- Since many signals were recorded with PSG devices, using more signals instead of a single channel EEG signal improves the success of classification.

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