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Research Article

Classification of Sleep Stages Using PSG Recording Signals

Yasin Koca[1], Seral Özşen[2*], Fatma Z. Göğüş[3], Gülay Tezel[4], Serkan Küçüktürk[5], Hülya Vatansev[6]

[1] Department of Electrical and Electronics Engineering, Konya Tech. Unv. Konya, Turkey
[2*] Department of Electrical and Electronics Engineering, Konya Tech. Unv. Konya, Turkey (ORCID: 0000-0001-5332-8665)
[3] Department of Computer Engineering, Konya Tech. Unv. Konya, Turkey (ORCID: 0000-0001-5035-7575)
[4] Department of Computer Engineering, Konya Tech. Unv. Konya, Turkey (ORCID: 0000-0003-1698-0106)
[5] Sleep Laboratory, Faculty of Medicine, Necmettin Erbakan Unv. Konya, Turkey (ORCID: 0000-0001-8445-666X)
[6] Sleep Laboratory, Faculty of Medicine, Necmettin Erbakan Unv. Konya, Turkey (ORCID: 0000-0002-8382-3904)

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Abstract

Automatic sleep staging is aimed within the scope of this paper. Sleep staging is a study by a sleep specialist. Since this process takes quite a long time and sleep is a method based on the knowledge and experience, it is inevitable for each person to show different results. For this, an automatic sleep staging method has been introduced. In the study, EEG (Electroencephalogram), EOG (Electrooculogram), EMG (Electromyogram) data recorded by PSG (Polysomnography) device for seven patients in Necmettin Erbakan University sleep laboratory were used. 81 different features were taken from the data in time and frequency environment. Also, PCA (Principal component analysis) and SFS (Sequential forward selection) feature selection methods were used. The classification success of the sleep phases in different machine learning methods was measured by using the received features. Linear D. (Linear Discriminant Analysis), Cubic SVM (Support vector machine), Weighted kNN (k nearest neighbor), Bagged Trees, ANN (Artificial neural network) were used as classifiers. System success was achieved with a 5 fold cross-validation method. Accuracy rates obtained were respectively 55.6%, 65.8%, 67%, 72.1%, and 69.1%.

Keywords: PSG, Sleep Stages, EEG, EOG, EMG, Bagged Trees.

PSG Kayıt Sinyalleri Kullanılarak Uyku Evrelerinin Sınıflandırılması

Öz

Bu çalışma kapsamında uyku evrelerinin sınıflandırılması amaçlanmaktadır. Uyku evreleme uyku uzmanları tarafından gerçekleştirilen bir çalışmadır. Bu süreç oldukça uzun sürdüğü ve uyku bilgi ve deneyimine dayalı olduğu için her bir kişi için farklı sonuçlar göstermesi kaçınılmazdır. Bunun için, otomatik uyku evreleme yöntemi tanıtılmıştır. Çalışmada Necmettin Erbakan Üniversitesi uyku laboratuvarındaki yedi hasta için PSG (Polisomnografi) cihazı ile kaydedilen EEG (Elektroensefalogram), EOG (Elektrookülogram), EMG (Elektromyogram) verileri kullanılmıştır. Verilerden zaman ve frekans ortamlarında 81 farklı özellik elde edilmiştir. Ayrıca, temel bileşen analizi (Principal component analysis -PCA) ve sıralı ileri seçim (Sequential forward selection-SFS) özellik seçme yöntemleri kullanılmıştır. Uyku evrelerinin sınıflandırma başarıları farklı makine öğrenmesi yöntemleri ve elde edilen özellikler kullanılarak ölçülmüştür. Sınıflandırıcı olarak Doğrusal D. (Doğrusal Diskriminant Analizi), Kübik SVM (Destek vektör makinesi), Ağırlıklı kNN (k en yakın komşu), Torbalı Ağaçlar, YSA (Yapay sinir ağı) kullanılmıştır. Sistem başarısı 5-kat çarpraz doğrulama ile elde edilmiştir. Elde edilen doğruluk oranları sırasıyla % 55.6, % 65.8, % 67, % 72.1 ve % 69.1'dir.

Anahtar Kelimeler: PSG, Uyku Evreleme, EEG, EOG, EMG, Torbalı Ağaçlar.

[*] Corresponding Author: Konya Technical University, Faculty of Engineering and Natural Sciences, Department of Electrical and Electronics Engineering, Konya, Turkey, ORCID: 0000-0001-5332-8665, sozsen@ktun.edu.tr

1. Introduction

The process of sleep staging is carried out by an expert by examining the electroencephalogram (EEG), the electrooculogram (EOG), and electromyogram (EMG), electrocardiogram (EKG) tracings received from patients throughout the night (6-8 hours) and some other signals and by identifying stages of sleep in different parts of time called epoch (30-second parts). The process is executed by a sleep expert and takes quite a long time. Making these processes done automatically reduces processing load and provides convenience for sleep expert in the diagnosis process and shortens the diagnosis period. Among the signals examined, Elektroensefalogram (EEG), right and left eye Elektrookülogram (EOG) and the chin Elektromiyogram (EMG) signals are the most frequently used ones (Iber, Ancoli-Israel, Chesson & Quan, 2007).

In spite of fact that EEG, EOG and EMG tracings are used basically in sleep staging, especially the density of EEG signal in staging process and the power in detecting stages higher than the other signals. There are five sleep stages: Awake (W), Non-REM1, Non-REM2, Non-REM3 and REM (Iber, Ancoli-Israel, Chesson & Quan, 2007).

In literature, many scientific researches has been done using automatic sleep staging methods relating to sleep staging process. Among them, Yücelbaş et al. (2015) went for the purification of EEG signals for a healthy evaluation due to the noises of EEG, EOG, EMG signals during recording and measured the staging success between the pure EEG signal and the impure EEG signal using ANN (Yücelbaş et al., 2015). Huang et al. (2020) have suggested a signal pre-processing and feature scanning method. They classified the features which are obtained with SVM method (Huang et al., 2020). Jiang et al. (2019) in the study, has presented multimode signal decomposition and feature extraction in order to obtain effective features from sub-band signals of single-channel EEG data (Jiang, Lu, Ma & Wang, 2019). Liu et al. (2020) in order to combine spectral information, have visualized sleep dynamics by employing diffusion geometry based sensor fusion algorithm and suggested an algorithm for automatic sleep staging (Liu, Lo, Malik, Sheu & Wu, 2020). Diykh et al. (2020) has divided each epoch of EEG signal into the blocks using sliding window technique and has extracted statistical features and presented to least-squares support-vector machine (LS-SVM) classifier (Diykh, Li & Abdulla, 2020). Abdulla et al. (2019) proposed a technique to classify sleep phases by using correlation graphics from sleep EEG signals (Abdulla, Diykh, Laft, Saleh & Deo, 2019). Fan (2018) has proposed automatic sleep staging system using combination of Multi scale entropy (MSE) and Principal components Analysis (PCA) (Fan, 2018). Savareh et al. (2018) used wavelet tree analysis (Savareh, Bashiri, Behmanesh, Meftahi & Hatef).

In this study, the process of classification sleep stages has been performed using Linear D., Cubic SVM, Weigted kNN, Bagged Trees, ANN. The performances of these methods in sleep stage classification has been evaluated.

2. Material and Method

2.1. Data Used

In the study, PSG (Polysomnography) recording data sampled with 200 Hz sampling frequency of 7 people recorded in the sleep laboratory of Necmettin Erbakan University Meram Medical Faculty was used. Taken from 7 patients; EEG signal (0.5-35 Hz bandpass filter Butterworth, 6th order), EMG signal (1-45 Hz bandpass filter Butterworth, 6th order), R / LEOG signal (0.3-30 Hz bandpass filter Butterworth, 6th degrees) filtered and divided into epochs. 6000 data correspond to each 30 sec epoch of the signal recorded with 200 Hz. The distribution of the total number of epochs for all signal recordings (EEG, REOG, LEOG, and EMG) by stages is given in Table 1.

Table 1. Distribution of sleep stages

Stages	Number of epoch
Awake(W)	1072
Non-REM1(N1)	420
Non-REM2(N2)	2863
Non-REM3(N3/SWS)	385
REM	650
Total	5390

For the classification process to proceed in a healthy way, 400 epochs randomly selected from other stages were taken on the basis of N3 (385) stage, which has the lowest epochs number of sleep stages. Thus, it is aimed to minimize the effect of stages on each other during the classification stage.

2.2. Frequency Estimation Methods

Plotting a signal in the time domain is expressed in time-amplitude representation. But depending on the nature of the signals, often discernible important information is kept secret in frequency components. In the study, features were extracted from all signal records (EEG, REOG, LEOG, EMG) in time and frequency environment. Welch method, which is one of the spectrum estimation methods, was used for all signal records in the frequency environment.

Welch Method: In this method, the signal whose frequency spectrum is to be estimated is divided into overlapping (or not overlapping) windows. The FFT (Fast Fourier Transform) of each signal particle passed through the window is taken and the average of the FFTs of all windows gives the spectrum of the actual signal. The factors that affect performance are window type, window length and overlap amount (Welch, 1967).

2.3. Feature extraction and classification system

The block diagram of the system used for the classification of sleep stages is shown in Figure 1.

Figure 1. The block diagram of for automatic sleep staging

2.3.1. Feature generation

Features in Table 2 were generated from the EEG signal.

Table 2. Features of EEG signals

Number	Feature
1	Mean value of the EEG signal in time domain
2	Standard deviation of the EEG signal in time domain
3	Skewness of the EEG signal in time domain
4	Kurthosis of the EEG signal in time domain
5	Energy of the EEG signal in time domain
6	Hjorth mobility of the EEG signal in time domain (Hijorth, 1970)
7	Hjorth complexity of the EEG signal in time domain (Hijorth, 1970)
8	Sum of the powers of frequencies in alpha band (8-12Hz)
9	Sum of the powers of frequencies in Beta band (12-16Hz)
10	Sum of the powers of frequencies in theta band (4-8Hz)
11	Sum of powers of frequencies in delta band (0-8Hz)
12	Sum of powers of frequencies in 12–14 Hz (for sleep spindle detection)
13	Relative powers of frequencies in alpha band that is power of alpha band/power of whole spectrum
14	Relative powers of frequencies in beta band that is power of beta band/power of whole spectrum
15	Relative powers of frequencies in theta band that is power of theta band/power of whole spectrum
16	Relative powers of frequencies in delta band that is power of delta band/power of whole spectrum
17	Relative powers of frequencies in Spindle freq. band that is power of Spindle freq, band/power of whole spectrum
18	Power of alpha band in related epoch/power of alpha band in previous epoch
19	Power of beta band in related epoch/power of beta band in previous epoch
20	Power of theta band in related epoch/power of theta band in previous epoch
21	Power of delta band in related epoch/power of delta band in previous epoch
22	Power of Spindle freq, band in related epoch/power of Spindle ferq. band in previous epoch
23	Mean value of the EEG signal in frequency domain
24	Standard deviation of the EEG signal in frequency domain
25	Sum of the powers in frequency spectrum of EEG signal
26	Skewness of the left EEG signal in frequency domain
27	Kurthosis of the left EEG signal in frequency domain

Features generated from the Left/ Right and F (LEOG-REOG) EOG signal are shown in Table 3.

Table 3. Features of EOG signals

Number	Feature
28	Mean value of the L-EOG signal in time domain
29	Standard deviation of the L-EOG signal in time domain
30	Skewness of the L-EOG signal in time domain
31	Kurthosis of the L-EOG signal in time domain
32	Energy of the L-EOG signal in time domain
33	Hjorth mobility of the L-EOG signal in time domain
34	Hjorth complexity of the L-EOG signal in time domain
35	Mean value of the R-EOG signal in time domain
36	Standard deviation of the R-EOG signal in time domain
37	Skewness of the R-EOG signal in time domain
38	Kurthosis of the R-EOG signal in time domain
39	Energy of the R-EOG signal in time domain
40	Hjorth mobility of the R-EOG signal in time domain
41	Hjorth complexity of the R-EOG signal in time domain
42	Mean value of the F-EOG signal in time domain
43	Standard deviation of the F-EOG signal in time domain
44	Skewness of the F-EOG signal in time domain
45	Kurthosis of the F-EOG signal in time domain
46	Energy of the F-EOG signal in time domain
47	Hjorth mobility of the F-EOG signal in time domain
48	Hjorth complexity of the F-EOG signal in time domain
49	Sum of the powers of frequencies in 0,5–2 Hz for L-EOG
50	Relative powers of frequencies in 0,5–2 Hz that is power of 0,5–2 Hz/power of whole spectrum, for L-EOG
51	Power of 0,5-2Hz, band in related epoch/power of 0,5-2Hz band in previous epoch, for L-EOG
52	Mean value of the L-EOG signal in frequency domain
53	Standard deviation of the L-EOG signal in frequency domain
54	Sum of the powers in frequency spectrum of L-EOG signal
55	Skewness of the L-EOG signal in frequency domain
56	Kurthosis of the L-EOG signal in frequency domain
57	Sum of the powers of frequencies in 0,5–2 Hz for R-EOG
58	Relative powers of frequencies in 0,5–2 Hz that is power of 0,5–2 Hz/power of whole spectrum, for R-EOG
59	Power of 0,5-2Hz, band in related epoch/power of 0,5-2Hz band in previous epoch, for R-EOG
60	Mean value of the R-EOG signal in frequency domain
61	Standard deviation of the R-EOG signal in frequency domain
62	Sum of the powers in frequency spectrum of R-EOG signal
63	Skewness of the R-EOG signal in frequency domain
64	Kurthosis of the R-EOG signal in frequency domain
65	Sum of the powers of frequencies in 0,5–2 Hz for F-EOG
66	Relative powers of frequencies in 0,5–2 Hz that is power of 0,5–2 Hz/power of whole spectrum, for F-EOG
67	Power of 0,5-2Hz, band in related epoch/power of 0,5-2Hz band in previous epoch, for F-EOG
68	Mean value of the F-EOG signal in frequency domain
69	Standard deviation of the F-EOG signal in frequency domain
70	Sum of the powers in frequency spectrum of F-EOG signal
71	Skewness of the F-EOG signal in frequency domain
72	Kurthosis of the F-EOG signal in frequency domain

Table 4 presents features generated from the EMG signal.

Table 4. Features of EMG signals

Number	Feature
73	Mean value of the EMG signal in time domain
74	Standard deviation of the EMG signal in time domain
75	Skewness of the EMG signal in time domain
76	Kurthosis of the EMG signal in time domain
77	Energy of the EMG signal in time domain
78	Hjorth mobility of the EMG signal in time domain
79	Hjorth complexity of the EMG signal in time domain
80	Sum of the powers in frequency spectrum of EMGsignal
81	The power of EMG signal in frequency domain for that epoch/The power of EMG signal in frequency domain for next epoch

2.3.2. Feature selection

Feature reduction was performed with PCA (Principal Component Analysis) (Smith, 2002) and SFS (Sequential forward selection) (Whitney, 1971) in order to determine the most appropriate feature number among the 81 features obtained. The classification process with PCA was carried out for 6, 8, 10… 20 features, respectively. 15 features have been determined with SFS. The best classification performance was tried to be achieved with the selected features.

3. Results and Discussion

In this study, 81 different features were obtained by Welch method in time and frequency environment for automatic sleep staging. PCA and SFS methods were used to increase system classification performance. Matlab, Classification Learn and Neural Network toolboxes were used to evaluate the classification performance of the obtained properties. Table 5 shows the classification success results for 81 features

Table 5. Classification success results for 81 features

Classifier	**Accuracy(%)**	**Sensitivity (%)**	**Precision (%)**
		W	**W**
		N1	**N1**
		N2	**N2**
		N3	**N3**
		REM	**REM**
Linear D.	55,6	45	55
		44	41
		52	42
		66	**79**
		72	68
SVM (Cubic)	65,8	60	62
		67	59
		47	50
		75	75
		81	**83**
kNN(Weigted)	67	60	67
		73	62
		43	60
		76	72
		83	**72**
Bagged Trees	**72,6**	69	71
		70	67
		56	63
		83	78
		86	**82**
ANN	69,1	60	69
		61	58
		57	62
		85	77
		83	**79**

If we look at the classification success of the 81 features in Table 5; we see the highest accuracy in the Bagged Trees algorithm. Then high success is seen in ANN. If we look at the sensitivity of class in the classification of 81 features, we see that N3 and REM phases are classified with a very good sensitivity. If we look at general Sensitivity, we see that the Bagged Trees algorithm gives the best sensitivity. If we look at the precision values, it is seen that the N3 and REM phases are still at high rates on the basis of class. Bagged Trees method gives the highest precision value among the methods used.

When we look at the table in general, we see that the Bagged Trees algorithm gives the best success among the methods as the highest accuracy, sensitivity and precision rates.

Classification results of 81 properties and properties selected with PCA are given in Figure 2, Sensitivity and Precision values are given in Figure 3 and Figure 4. Figure 5 shows the Accuracy rates for 15 features selected with SFS.

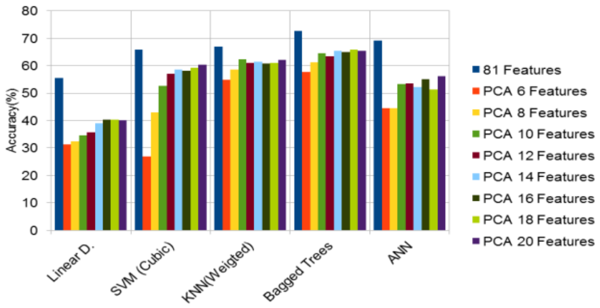

Figure 2. 81 features and PCA accuracy values

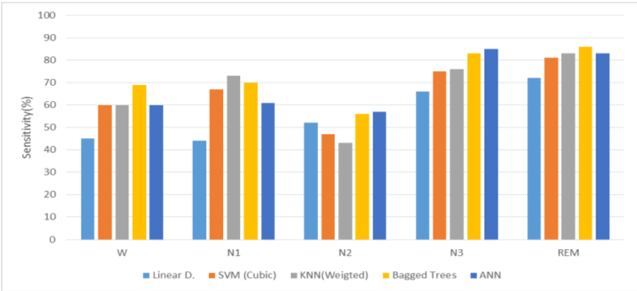

Figure 3. Sensitivity rates for each class

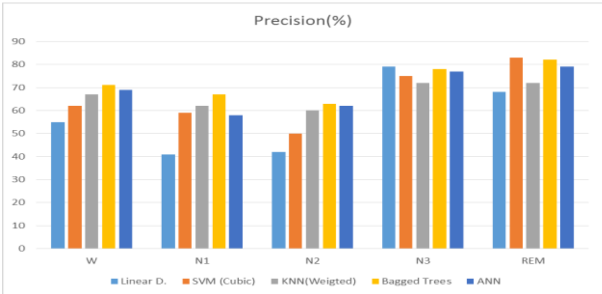

Figure 4. Precision rates for each class

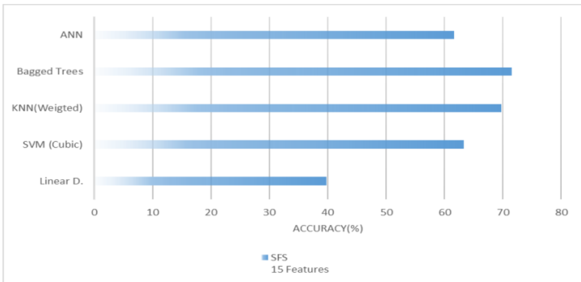

Figure 5. Accuracy rates for 15 features selected with SFS

In Figure 2, if we look at the status of 81 features and the features selected with PCA, it is seen that 81 features show high accuracy success.

When we look at Figure 3, the best classification in terms of sensitivity is seen in the REM stage and we see that the method that classifies the REM stage with the best sensitivity is Bagged Trees. When we look at the N3 stage, we see the best sensitivity rate in the ANN method. It is seen that the universe where the methods used have the lowest sensitivity is N2.

In Figure 4, we see that the applied methods classify the N3 and REM stages with high precision. If we look at the REM phase, we see that the method that classifies the highest is SVM (Cubic).

The SFS method was used to select the most suitable feature among the 81 features we extracted and the most suitable success was achieved with 15 features. In the SFS method, the most suitable feature search process starts with a blank feature set. As a result of the evaluation (the accuracy rate obtained with the kNN algorithm was used.) The best feature is added to the subset. Adding that feature continues until the stop criteria are met.

As a result of SFS transaction; 11, 7, 2, 65, 36, 41, 34, 63, 55, 57, 21, 10, 50, 33, 40 numbered features were obtained. When we look at Figure 5, we see the accuracy rate of 15 features selected by the SFS method. Here we see that the highest accuracy rate is taken by the Bagged Trees method. Confusion Matrix is given for the highest accuracy achieved in Table 6. Maximum values are given in bold.

Table 6. Classification success results for 81 features

		Predicted Class					
		W	N1	N2	N3	REM	
True Class	W	272	58	36	11	23	68%
	N1	70	266	35	13	16	67%
	N2	42	52	227	47	32	57%
	N3	9	14	26	331	5	**86%**
	REM	26	15	20	3	336	84%
		65%	66%	66%	**82%**	**82%**	**72.1%**

When we look at the confusion matrix in Table 6, we see that the Bagged Trees method achieved 72.1% accuracy with 15 features. If we examine the Bagged Trees method on a class basis, it shows the highest sensitivity in N3 stage and the highest precision in N3 and REM stages.

4. Conclusions

As can be seen in Figure 2, the best classification success appears for 81 features. When PCA is applied, the success of the system is generally expected to increase, but this has not been the case in this data set. The reason is the relation of the data that the classes have. Data loss is noticeable when applying PCA. It has been observed that the success in the PCA has increased with the increase of the features processed. It can be seen in Figure 5 that the 15 features selected with SFS give close results with 81 feature accuracy rates. When we look at all classes as Accuracy, Sensitivity and Precision, we can say that the Bagged Trees algorithm is the most successful algorithm in this study.

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