Original Article

Adaptive neuro-fuzzy method for sleep stages detection by PPG signal

Mohammad Mahdi Moradi [1], Mohammad H. Fatehi [2]*, Hassan Masoumi [1], Mehdi Taghizadeh [2]

[1] Department of Biomedical Engineering, Kazerun Branch, Islamic Azad University, Kazerun, Iran. [2] Department of Electrical Engineering, Kazerun Branch, Islamic Azad University, Kazerun, Iran.

Correspondence: Mohammad H. Fatehi, Department of Electrical Engineering, Kazerun Branch, Islamic Azad University, Kazerun, Iran.

ABSTRACT

Using a new method to detect sleep stages in medical applications for reducing the workload of physicians in the analysis of sleep data is one of the key issues in recent years. In this study, the PPG (Photoplethysmogram) signal is used for the detection of sleep stages. Using a new method (ANFIS) and a new signal (PPG) for sleep stage detection. The signal features extracted using the conventional methods and best features are selected using neighborhood component analysis for classification method. Finally, sleep steps are detected using valid methods: Neural network, linear discriminant analysis, KNN, support vector machine, and ANFIS. The accuracy of sleep stages detection was 57.72%, 70.75%, 69.72%, 93.35% and 99.48% respectively. The computation time is 3.79 sec, 1.21 sec, 1.43 sec, 21.15sec, and 36 sec, respectively. This study shows that the proposed method has separated the sleep stages with acceptable accuracy.

Keywords: ANFIS method, PPG signal, sleep stage classification, support vector machines, neural network, LDA.

Introduction

PPG Signal is one of the signals used to classify sleep stages. Proper sleep segregation is a major problem and a useful solution in the diagnosis of sleep disorders in patients. A standard method of sleep recording for patients during sleep on the CRIT-RIA and suggested by Rashtshafen and Kals (R&K) [1].
According to the R&K standard, sleep consists of six general stages: Awakening: REM and Awake, NREM, and Sleep: Stage 1 (S1), Stage 2 (S2), Stage 3 (S3), stage 4 (S4) [2].
Adaptive Neuro-Fuzzy Inference System (ANFIS) was first proposed by Jang. ANFIS can be easily implemented for a given input/output task and hence it is attractive for many application purposes.

Access this article online	
Website: www.japer.in	**E-ISSN:** 2249-3379

How to cite this article: Mohammad Mahdi Moradi, Mohammad H. Fatehi, Hassan Masoumi, Mehdi Taghizadeh. Adaptive neuro-fuzzy method for sleep stages detection by PPG signal. J Adv Pharm Edu Res 2020;10(S1):69-75. Source of Support: Nil, Conflict of Interest: None declared.

Another method is the process separation which is proposed by the American Academy of Sleep Medicine (AASM). This method combines the S3 and S4 stages of the R&K standard, known as slow-wave sleep (SWS) [3].
The traditional and manual method of classifying sleep stages are time-consuming and costly [4]. Also, this is done by trained professionals and possible human error may not be satisfactory [5]. Useful and reliable parameters for the analysis and classification of sleep stages have been extracted. Based on [1], entropy is used to calculate the fractality and regularity of PPG signals at different sleep stages.
In [6], the features of a Fast Fourier Transform (FFT) are used to classify sleep stages. Due to the non-stationary nature of the signal, continuous wavelet transform entropy has also been used to classification sleep stages [7].
In this paper, 51 features from PPG signals are extracted and the optimum features for classification of sleep stages are selected. The selected features are used for input feature to support vector machines, neural networks, LDA, and ANFIS for sleep stage classification. The experimental results have provided better classification accuracy to classify sleep stages from PPG signals is SVM. Data and classifiers are presented in Section 2. The experimental results and discussion for the sleep

stage classification using PPG signals are given in Section 3. Finally, section 4 concludes the paper.

Methodology

Dataset

This study uses the PPG dataset available at [8, 9]. Data recorded in a sleep laboratory of a Belgium hospital Brainnet TM System of MEDATEC, Brussels, Belgium. It consists of 12 channels of recordings from patients. EOG, EEG, EMG, ECG, nasal airflow (NAF), PPG was recorded. The standard European Data Format (EDF) was used and the sampling frequency was 200Hz.

Table 1. PPG signal Specifications in database

Name	Sampling Frequency	Age	Apnea/hypopnea index	Recording duration	Nr of hypopnea scored by theexpert	Nr of Abstractive apnea scored by the expert	Nr of central apnea scored by the expert	Nr of mixed apnea scored by the expert
Excerpt1	200Hz	51	50.9/h	09:32:00	249	194	3	6
Excerpt2	200Hz	64	16.1/h	08:27:20	47	66	0	1
Excerpt3	200Hz	70	49.3/h	09:33:40	38	340	0	0
Excerpt4	200Hz	50	95/h	08:36:00	333	389	0	1
Excerpt5	200Hz	41	809/h	09:22:40	189	350	17	144
Excerpt6	200Hz	54	25.1/h	09:12:30	151	66	0	0
Excerpt7	200Hz	60	51/h	07:32:00	113	209	1	9
Excerpt8	200Hz	50	7.4/h	09:05:20	12	39	0	0
Excerpt9	200Hz	54	21.2/h	08:35:20	37	128	0	0
Excerpt10	200Hz	51	55.5/h	08:00:00	62	131	69	108
Excerpt11	200Hz	51	46.7/h	08:02:40	172	116	1	0
Excerpt12	200Hz	51	59.1/h	08:02:00	37	51	43	136

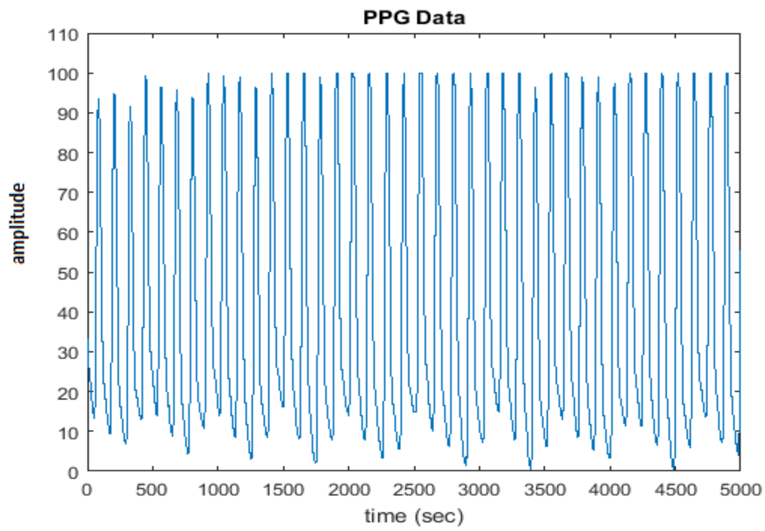

Figure 1. PPG data in 5000 sample: 25 sec

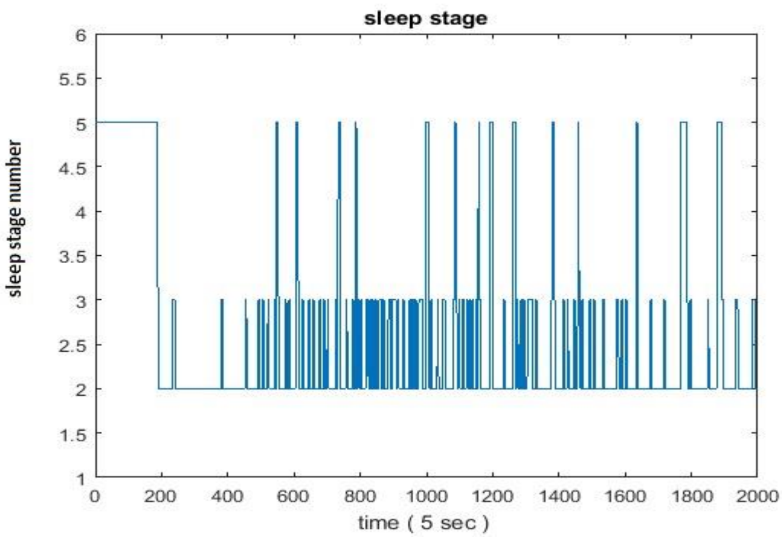

Figure 2. Sleep stage with 5 sec in a step

These numerical values correspond to the sleep stage (one value per 5 sec) annotated by the expert according to the Rechtschaffen and Kales criteria. Table 2 presents the sleep stages and their labels.

Table 2. The header of sleep stages in the database

Number sleep	Sleep stage
5	Wake stage
4	REM stage
3	S1 stage
2	S2 Stage
1	S3 Stage
0	S4 Stage
-1	movement
-2 or -3	unknown sleep stage

Features extraction

In this paper, time features such as maximum, minimum, average, and frequency characteristics such as power spectrum [10], maximum power, wavelet coefficients, and non-linear features [11] such as correlation and entropy and fractal [10, 12] are extracted. After extracting all features from signals, the best features are selected. In this study, 51 features are extracted from the data, as follows:

Max signal, Min signal, Mean signal, Beat count in min, Entropy [13], Wavelet features (db1, db2, db3, db4, db5), FFT feature (fftcoeff), Spectrum periodogram, Variance signal, Likelihood, and wavelet entropy.

Feature selection

Feature selection is based on Feature selection using neighborhood component analysis for classification (FSCNCA) method [14]. FSCNCA learns the feature weights by using a diagonal adaptation of neighborhood component analysis (NCA) with regularization. This method presented for reducing the number of features in achieve real-time processing and reducing computation time. At the end of the section, 2 features are selected.

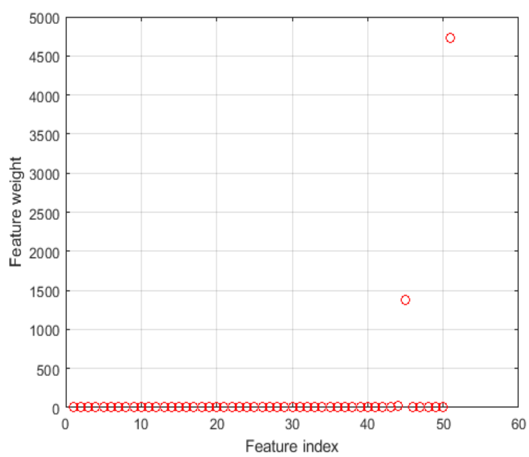

Figure 3. Feature selection output

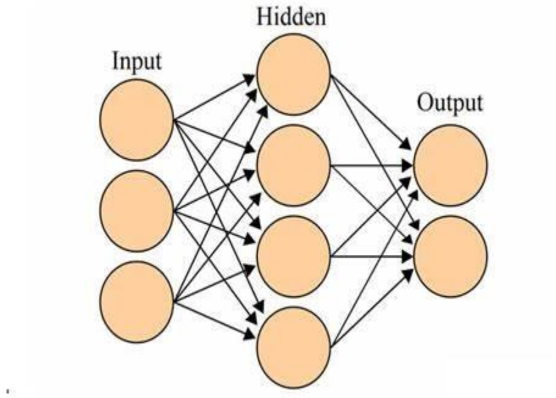

Figure 4. Neural network

Figure 4 shows a typical neural network. The Train network in the paper for processing results uses the Levenberg Marquardt (trainlm) method.

Classification

Neural network

In the designed network, the defined values are given below. The values change to zero before reaching the desired target or the desired gradient. The number of epoch is from 1 to 1000.The value of momentum changes from 1 to 10 ^ 10.

Jacobean is a function of efficiency in terms of weight and bias variables. The performance measures of the MSE. In this method, the error is measured by the mean squared error criterion. The network has an input layer and a hidden layer and one output layer.

Support vector machine

One of the methods for supervised classification is a support vector machine [15]. The original idea of this method was first introduced in 1979 by the Russian scholar Vladimir Vapnik and later used by him as a classifier in 1995 [15]. The basis of this view is based on the theory of statistical learning (SLT) and its implementation is similar to the neural network. This method designed to separate the data into two categories, and if you use multiple SVMs in parallel and different ways, then the method classifies data into more than two categories. In this study, SVM is used for classification and feature selection.

Linear discriminant analysis

In this method, the structure is similar to other classifier methods, with the exception that it is a completely linear method and has very low complexity. The method is designed to separate two data groups and data with parallel methods for the classification of several groups.

Adaptive Neuro-Fuzzy Inference Systems (ANFIS)

Adaptive Neuro-Fuzzy Inference System (ANFIS) was first proposed by Jang [3]. ANFIS can be easily implemented for a given input/output task and hence it is attractive for many application purposes. It has been successfully applied in different areas[3]. The first kind of NFS we apply for our data classification problem is the so-called Adaptive Neuro-Fuzzy Inference System (ANFIS) model, which hybridizes an ANN and a FIS into a kind of NFS with a homogeneous structure. That is, the ANFIS model integrates the ANN and FIS tools into a 'compound', meaning that there are no boundaries to differentiate the respective features of ANN and FIS[3].

Results

This paper uses five methods for classification and the classification results are expressed for each classifier. Feature Selection is done by the Sequential Forward Selection method. This method is used for reducing the number of Features and achieving real-time processing. The SVM classifier is used for feature selection.

Table 3. Results of feature selection

number	Feature #	feature
1	45	max_psd
2	51	wavelet entropy

Table 3 shows the results of the feature selection. After feature selection, sleep stages detection is performed using conventional methods. At this stage, the results of detection and calculation time are presented. Accuracy and calculation time of classifiers. First, using all features and then with selected features are detection.

Table 4. Results of time and accuracy of the LDA method with all features

time (sec)	accuracy	method
1.07	70.93 %	LDA

Table 4 shows the results of the accuracy and time of sleep stages detection using linear discriminate analysis with all the features.

Table 5. Results of time and accuracy of the LDA method with selected features

time (sec)	accuracy	method
1.21	70.75 %	LDA

Table 5 shows the results of the accuracy and time of sleep stages detection using linear discriminate analysis with selected features.

Table 6: Results of time and accuracy SVM method with all features

time (sec)	accuracy	method
21.4	93.35 %	SVM

Table 6 shows the results of the accuracy and time of sleep stages detection using Support Vector Machine with all features.

Table 7. Results of time and accuracy SVM method with selected features

time (sec)	accuracy	method
21.15	93.35 %	SVM

Table 7 shows the results of the accuracy and time of sleep stages detection using Support Vector Machine with selected features.

Table 8. Results of time and accuracy NN method with all features

time (sec)	accuracy	method
4.11	63.73 %	Neural Network

Table 8 shows the results of the accuracy and time of sleep stages detection using NN with all features.

Table 9. Results of time and accuracy NN method with selected features

time (sec)	accuracy	method
3.79	57.72 %	Neural Network

Table 9 shows the results of the accuracy and time of sleep stages detection using NN with selected features.

Table 10. Results of time and accuracy ANFIS method with all features

time (sec)	accuracy	method
52.64	94.09 %	ANFIS

Table 10 shows the results of the accuracy and time of sleep stages detection using ANFIS with all features.

Table 11. Results of time and accuracy ANFIS method with selected features

time (sec)	accuracy	method
36	99.48 %	ANFIS

Table 11 shows the results of the accuracy and time of sleep stages detection using ANFIS with selected features.

Table 12. Results of time and accuracy KNN method with all features

time (sec)	accuracy	method
2.58	69.72 %	KNN

Table 12 shows the results of the accuracy and time of sleep stages detection using KNN [16] with all features.

Table 13. Results of time and accuracy KNN method with selected features

time (sec)	accuracy	method
1.43	69.72 %	KNN

Table 13 shows the results of the accuracy and time of sleep stages detection using KNN with selected features.

Discussion and Conclusion

The previous chapters of this research include data collection, linear and nonlinear signal processing, and the results. At the beginning of this chapter, we discussed the results of different processing methods and then analyzing the results.

The main purpose of this study is to provide a new method for differentiating the sleep stages. The project attempts to distinguish the sleep stages using the PPG signal, which is much less expensive than other signals. This will largely prevent the waste of money. Various linear and nonlinear features such as temporal and statistical characteristics, violent coefficients, correlation dimensions, etc. extracted so that sleep stages are detected.

In this paper, to receive the desired result, we tried to find the correct and reliable method. Although using more sophisticated systems may increase accuracy in some cases, but the system complexity leads to more computations and therefore to avoid real-time processing. In this paper, a variety of statistical, frequency[17], linear, and nonlinear time characteristics were investigated separately and using NN, SVM, KNN, ANFIS, and LDA classifiers. Considering the need for real-time process and accuracy and sensitivity, this method using for processing and classification.

Table 14. Accuracy results for all classifiers

LDA	SVM	NN	ANFIS	KNN		classifier
70.93 %	93.35 %	63.73 %	94.09 %	69.72 %	All features	accuracy
70.75 %	93.35 %	57.72 %	99.48 %	69.72 %	selected features	

Table 14 shows the results of three classifications with all features and features selected.

Table 15. Time of classification results for all classifiers

LDA	SVM	NN	ANFIS	KNN		classifier
1.07	21.14	4.11	52.64	2.58	All features	Time of classification
1.21	21.15	3.79	36	1.43	selected features	

Table 15 shows the results of calculating time are presented in three classifications with all and selected features.

Table 16. Total ranking for all classifiers.

LDA	KNN	ANFIS	SVM	NN	classifier
3	4	1	2	5	classifier of accuracy
1	2	5	3	4	classifier of processing time

As in Table 16, each classifier has advantages and disadvantages. Given the fact that ANFIS has higher accuracy than other classifiers. These are the major obstacle to real-time processing. According to table 15, the neural network has lower accuracy. Due to the above reasons, the ANFIS method has been selected. sleep steps are detected using valid methods: Neural network, linear discriminant analysis, KNN, support vector machine, and ANFIS. The accuracy of sleep stages detection was 57.72%, 70.75%, 69.72%, 93.35% and 99.48% respectively.

Regarding the high accuracy of the ANFIS method, this method is suggested for sleep processing.

The practical results, according to valid data, show that the ANFIS method is accurate and reliable for separating sleep stages.

Compare and contrast

The comparison of this paper results with published works in the literature is shown in table 17.

Table 17. Shows accuracy of sleep stage detection using all signal and the proposed method.

Reference	[18]	[19]	[20]	proposed method
Signal classified	W REM	long-term sleep monitoring	W,REM, S1,S2,S3,S4	W,REM, S1,S2,S3,S4
Signal use	one EMG and two EEG	R-R intervals and (ECG).	EEG	PPG
sensitivity	82 - 92%	68.71%	15 – 98.8%	99.48%
accuracy	82 - 93.86%,	89.97%	78.8 – 98.8%	99.48%

The methods presented divided into two general groups. The first group correctly detects the stages of sleep (S1, S2, S3, and S4) and wake, and the second group only detect sleep/wake stages.

In the first group, the signals used are either EEG signals or multiple signals.

But in the second group, with using the EEG signal, the accuracy improves, and if using other signals such as PPG and ECG, separately or together, the sleep and wake stages are detection incomplete.

The proposed method in this paper is employing of PPG signal alone for complete detection of the sleep stages with acceptable accuracy.

As it is obvious from Table 17, many signals used for sleep stages detection, but the PPG signal is a low-cost and easy to record and processing signal. For these causes, this signal is suggested for sleep stage detection.

In this study, due to the use of a mean-validation method, the system sensitivity is high and near accuracy.

This paper presents a novel method for extracting all stages of sleep. In this method, all sleep stages (W, S1, S2, S3, and S4) are detected using the PPG signal alone with high accuracy, specificity, and sensitivity.

Proposals to continue

In the end, there are suggestions for future work.

1. To increase the accuracy of the results, it is suggested to use more methods for classification. In this research, a patient's terminal has been used.
2. Depending on the interaction of the body finches with each other, other signals can be used to separate the sleep stages.

References

1. Rechtschaffen, A., Kales, A. A Manual of Standardized Terminology, Techniques, and Scoring System for Sleep Stages of Human Subjects, Public Health Service, U.S.Govern. Printing Office, Washington, DC, 1968.
2. Aboalayon KA, Faezipour M, Almuhammadi WS, Moslehpour S. Sleep stage classification using EEG signal analysis: a comprehensive survey and new investigation. Entropy. 2016 Sep;18(9):272.
3. Loganathan C, Girija KV. Cancer classification using adaptive neuro fuzzy inference system with runge kutta learning. International Journal of Computer Applications. 2013 Jan 1;79(4).
4. Collop NA. Scoring variability between polysomnography technologists in different sleep laboratories. Sleep medicine. 2002 Jan 1;3(1):43-7.
5. Norman RG, Pal I, Stewart C, Walsleben JA, Rapoport DM. Interobserver agreement among sleep scorers from different centers in a large dataset. Sleep. 2000 Nov 1;23(7):901-8.
6. Doroshenkov LG, Konyshev VA, Selishchev SV. Classification of human sleep stages based on EEG processing using hidden Markov models. Biomedical Engineering. 2007 Jan 1;41(1):25-8.
7. Fraiwan L, Lweesy K, Khasawneh N, Fraiwan M, Wenz H. Classification of sleep stages using multi-wavelet time frequency entropy and LDA.
8. Al-Salman W, Li Y, Wen P, Diykh M. An efficient approach for EEG sleep spindles detection based on fractal dimension coupled with time frequency image. Biomedical Signal Processing and Control. 2018 Mar 1;41:210-21.
9. Ghimatgar H, Kazemi K, Helfroush MS, Aarabi A. An automatic single-channel EEG-based sleep stage scoring method based on hidden Markov Model. Journal of neuroscience methods. 2019 Aug 1;324:108320.
10. Weiss B, Clemens Z, Bódizs R, Halász P. Comparison of fractal and power spectral EEG features: Effects of topography and sleep stages. Brain research bulletin. 2011 Apr 5;84(6):359-75.
11. Acharya R, Faust O, Kannathal N, Chua T, Laxminarayan S. Non-linear analysis of EEG signals at various sleep stages. Computer methods and programs in biomedicine. 2005 Oct 1;80(1):37-45.
12. Pereda E, Gamundi A, Rial R, González J. Non-linear behaviour of human EEG: fractal exponent versus correlation dimension in awake and sleep stages. Neuroscience letters. 1998 Jun 19;250(2):91-4.
13. Chouvarda I, Rosso V, Mendez MO, Bianchi AM, Parrino L, Grassi A, Terzano M, Cerutti S. Assessment of the EEG complexity during activations from sleep. Computer methods and programs in biomedicine. 2011 Dec 1;104(3):e16-28.
14. Marcano-Cedeno A, Quintanilla-Domínguez J, Cortina-Januchs MG, Andina D. Feature selection using sequential forward selection and classification applying artificial metaplasticity neural network. InIECON 2010-36th annual conference on IEEE industrial electronics society 2010 Nov 7 (pp. 2845-2850). IEEE.
15. Iber, C., Ancoli-Isreal, S., Chesson Jr., A.L., Quan, S.F. The AASM Manual for Scoring of Sleep and Associated Events-Rules: Terminology and Technical Specification, American Academy of Sleep Medicine, 2007.
16. Güneş S, Polat K, Yosunkaya Ş. Efficient sleep stage recognition system based on EEG signal using k-means clustering based feature weighting. Expert Systems with Applications. 2010 Dec 1;37(12):7922-8.
17. Vural C, Yildiz M. Determination of sleep stage separation ability of features extracted from EEG signals using principle component analysis. Journal of medical systems. 2010 Feb 1;34(1):83-9.
18. Kassiri H, Chemparathy A, Salam MT, Boyce R, Adamantidis A, Genov R. Electronic sleep stage classifiers: A survey and VLSI design methodology. IEEE transactions on biomedical circuits and systems. 2016 Jun 16;11(1):177-88.

19. Yoon H, Hwang SH, Choi JW, Lee YJ, Jeong DU, Park KS. Slow-wave sleep estimation for healthy subjects and OSA patients using R–R intervals. IEEE journal of biomedical and health informatics. 2017 Jun 7;22(1):119-28.
20. Zhu G, Li Y, Wen P. Analysis and classification of sleep stages based on difference visibility graphs from a single-channel EEG signal. IEEE journal of biomedical and health informatics. 2014 Feb 6;18(6):1813-21.