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Efficient sleep stage recognition system based on EEG signal using *k*-means clustering based feature weighting

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ABSTRACT

Sleep scoring is one of the most important methods for diagnosis in psychiatry and neurology. Sleep staging is a time consuming and difficult task conducted by sleep specialists. The purposes of this work are to automatic score the sleep stages and to help to sleep physicians on sleep stage scoring. In this work, a novel data preprocessing method called *k*-means clustering based feature weighting (KMCFW) has been proposed and combined with *k*-NN (*k*-nearest neighbor) and decision tree classifiers to classify the EEG (electroencephalogram) sleep into six sleep stages including awake, N-REM (non-rapid eye movement) stage 1, N-REM stage 2, N-REM stage 3, REM, and non-sleep (movement time). First of all, frequency domain features belonging to sleep EEG signal have been extracted using Welch spectral analysis method and composed 129 features from EEG signal relating each sleep stages. In order to decrease the features, the statistical features comprising minimum value, maximum value, standard deviation, and mean value have been used and then reduced from 129 to 4 features. In the second phase, the sleep stages dataset with four features has been weighted by means of *k*-means clustering based feature weighting. Finally, the weighted sleep stages have been automatically classified into six sleep stages using *k*-NN and C4.5 decision tree classifier. In the classification of sleep stages, the *k* values of 10, 20, 30, 40, 50, and 60 in *k*-NN classifier have been used and compared with each other. In the experimental results, while sleep stages has been classified with 55.88% success rate using *k*-NN classifier (for *k* value of 40), the weighted sleep stages with KMCFW has been recognized with 82.15% success rate *k*-NN classifier (for *k* value of 40). And also, we have investigated the relevance between sleep stages and frequency domain features belonging to EEG signal. These results have demonstrated that proposed weighting method have a considerable impact on automatic determining of sleep stages. This system could be used as an online system in the automatic scoring of sleep stages and helps to sleep physicians in the sleep scoring process.

1. Introduction

In this article, we have addressed why automatic sleep staging systems need for sleep scoring and given some conducted studies by researchers in the automatic sleep staging systems. Sleep staging is a complex and difficult problem to be solved by researches. Therefore, a lot of methods have been proposed and applied to sleep staging problem.

Sleep is a losing state as temporary, partial, and periodic in the form of that can be returned with various forced stimulus of the communication of organism with environment. And also, sleep can be defined the decreasing of motor activity, the decreasing of response with stimulus, and to be easy recycling as behavioral (Polat, Yosunkaya, & Güneş, 2008; Rechtschaffen & Kales, 1968).

Sleep staging was done according to human sleep standard terminology and handbook prepared by Rechtschaffen and Kales (RK) in 1968 (Rechtschaffen & Kales, 1968). Scoring of sleep stages was done on the basis of RK standard (RKS) until recent dates and sleep stages in normal subject was divided into five stages including awake, N-REM 1 (non-rapid eye movement-1), N-REM 2, N-REM 3, N-REM 4, and REM (rapid eye movement). American Academy of Sleep Medicine (AASM) determined new rules in the scoring of sleep on the chairmanship of Dr. Iber Conrad. Nowadays, sleep staging is done according to these new rules. Sleep stages basically consists of two stages including N-REM (stage I, stage II, and stage III) and REM stages (Academy of Sleep Medicine Task Force, 1999; Dursun, 2008).

The process of sleep scoring consists of three steps as follows:

- There need epochs with 30 s to score the sleep stages.
- Each epoch is named with a sleep stage.
- If two stages take place in same epoch, it is called as that stage what stage is more than half of the epoch.

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In literature, there are many works regarding to sleep stage scoring. The used systems are generally on the basis of extracting features obtained from EEG, EMG, and EOG and on classifying them into one of the sleep stages, while trying to obtain similar results as the experts of visual scoring (Šušmáková & Krakovská, 2008). Few studies among these studies have been explained as follows.

In study of Estévez et al., an automated sleep scoring system has been demonstrated. Five patterns have been searched for: slow delta and theta wave predominance in the background EEG activity, presence of sleep spindles in the EEG, presence of rapid eye movements in an electro-oculogram, and the muscle tone in an electromyogram. Results on a test set have shown an overall accuracy of 87.7% between the automated system and the human expert (Estévez et al., 2002).

Šušmáková et al. has researched the basic knowledge about classification of sleep stages from polysomnographic recordings. And also, they have reviewed and compared a large number of measures to find the suitable candidates for the study of sleep onset and sleep evolution. They obtained classification error of 23% on the most difficult decision problem, between S1 and REM sleep by measures computed from electromyogram led by fractal exponent (Šušmáková & Krakovská, 2008).

Caffarel et al. has compared sleep staging by an automated neural network system, BioSleep (Oxford BioSignals) and a human scorer using the Rechtschaffen and Kales scoring (RKS) system. On their study, sleep study recordings from 114 patients with suspected obstructed sleep apnea syndrome (OSA) has been analysed by ANN and by a blinded human scorer. They obtained poor (median $j = 0.305$) as overall agreement of automatic and manual scoring for the 114 studies for the classification including wake, light-sleep, deep-sleep, and REM while only a little better ($j = 0.449$) for the crude {wake|sleep} distinction (Caffarel, Gibson, Harrison, Griffiths, & Drinnan, 2006).

Zoubek et al. has focused on the problem of selecting relevant features extracted from human polysomnographic (PSG) signals to perform accurate sleep/wake stages classification. While they achieved an agreement of 71% with the whole database classification of two human experts using a simple set of features such as relative EEG powers in five frequency bands, 80% of agreement with the expert classification obtained using features extracted from the EEG, EOG and EMG signals (Zoubek, Charbonnier, Lesecq, Buguet, & Chapotot, 2007).

In this paper, we have proposed a novel data preprocessing method called *k*-means clustering based feature weighting to increase the classification ability of sleep stages using *k*-NN classifier and decision tree classifier. The purposes of KMCFW are (i) to transform the non-linearly separable dataset to linearly separable dataset and (ii) to gather the similar or closer data points. The proposed method to recognize the sleep stages comprises of three phases. In the first phase, for feature extraction, Welch spectral analysis method has been used to extract significant frequency features from EEG signal and obtained 129 features from EEG signal thanks to this phase. In order to reduce the number of features, we have used the statistical features including minimum value, maximum value, standard deviation, and mean value of 129 frequency domain features and decreased the number of feature from 129 to 4. By means of using statistical features instead of all features (129), the curse of dimensionality problem has been prevented. In the second phase, KMCFW method has been used to weight sleep stage dataset with four features as data preprocessing. In the third phase, *k*-NN and decision tree classifiers have been used to classify the sleep stages into six classes including awake, N-REM stage 1, N-REM stage 2, N-REM stage 3, REM, and non-sleep (movement time). In the classification of sleep stages, the *k* values of 10, 20, 30, 40, 50, and 60 in *k*-NN classifier was used and compared with each other. While sleep stages has been classified with 55.88% success rate using *k*-NN classifier (for *k* value of 40), the weighted sleep stages with KMCFW has been recognized with 82.15% success rate *k*-NN classifier (for *k* value of 40).

The material is presented in the next section. In Section 3, the used method is described. The experimental data and results to present the effectiveness of our method are given in Section 4. Finally, the conclusions are given in Section 5 with future directions.

2. Material

2.1. Subjects and data acquisition

All night polysomnographic records were made by using VIASY trademark PSG device on the sleep laboratory of Meram Medicine Faculty of Selcuk University. Polysomnography (PSG) device is a device that recorded electrophysical signals such as electroencephalograph (EEG), electrooculograms (EOG), Electromyography (EMG) etc. In this study, we have studied on five male subjects and their ages are 56, 31, 40, 46, and 36, respectively. The average age mean is 41.8. In automatic scoring of sleep stages, the EEG signals acquired from PSG device was used. The average recording time was 7 h and total recording time was 35 h. The EEG signals were recorded from standard surface electrodes placed on C4-A1 sites. The EEG signals vary between 5 μV and 400 μV. The sampling frequency of EEG signals is 128 Hz. A bandpass filter at the frequency ranges of 0.1–60 Hz was applied to EEG signals to remove the noise and artifacts from EEG signals. And also, notch filter at frequency of 50 Hz has been applied to EEG signals to alienate the network frequency (50 Hz).

The distribution of sleep epochs belonging to five subjects is shown in Table 1. Fig. 1 presents the EEG signals with 30 s belonging to each sleep stages including awake, N-REM stage 1, N-REM stage 2, and N-REM stage 3, and REM stages recorded on a healthy subject.

Let us explain how the individual sleep stages are described in RKS (Rechtschaffen & Kales, 1968; Šušmáková & Krakovská, 2008).

Awake (W) is described by a low voltage (10–30 mV) and mixed frequency EEG. Possible features of this stage are considerable alpha activity in EEG and relatively high tonic EMG (Šušmáková & Krakovská, 2008).

N-REM S1 is characterized with low voltage and mixed frequency EEG with the highest amplitude in the range of 2–7 Hz. In this stage, alpha activity does not take more than 50% of an epoch. Vertex sharp waves with amplitudes of around 200 mV may happen. S1 after wakefulness can be accompanied by slow eye movements (Šušmáková & Krakovská, 2008).

N-REM S2 is characterized by limited proportion of slow waves, by sleep spindles and by *K*-complexes on a relatively low voltage, mixed frequency background activity. Sleep spindles are bursts of brain waves of 12–16 Hz. A *K*-complex is a sharp negative wave followed by a slower positive wave. This stage is part of the

Table 1
The distribution of sleep stages on full dataset.

Sleep stages	Awake	N-REM-1	N-REM-2	N-REM-3	REM	Non-sleep	Total
Number of epochs in stages	438	206	2295	196	776	285	4196

The duration of each epoch is 30 s.

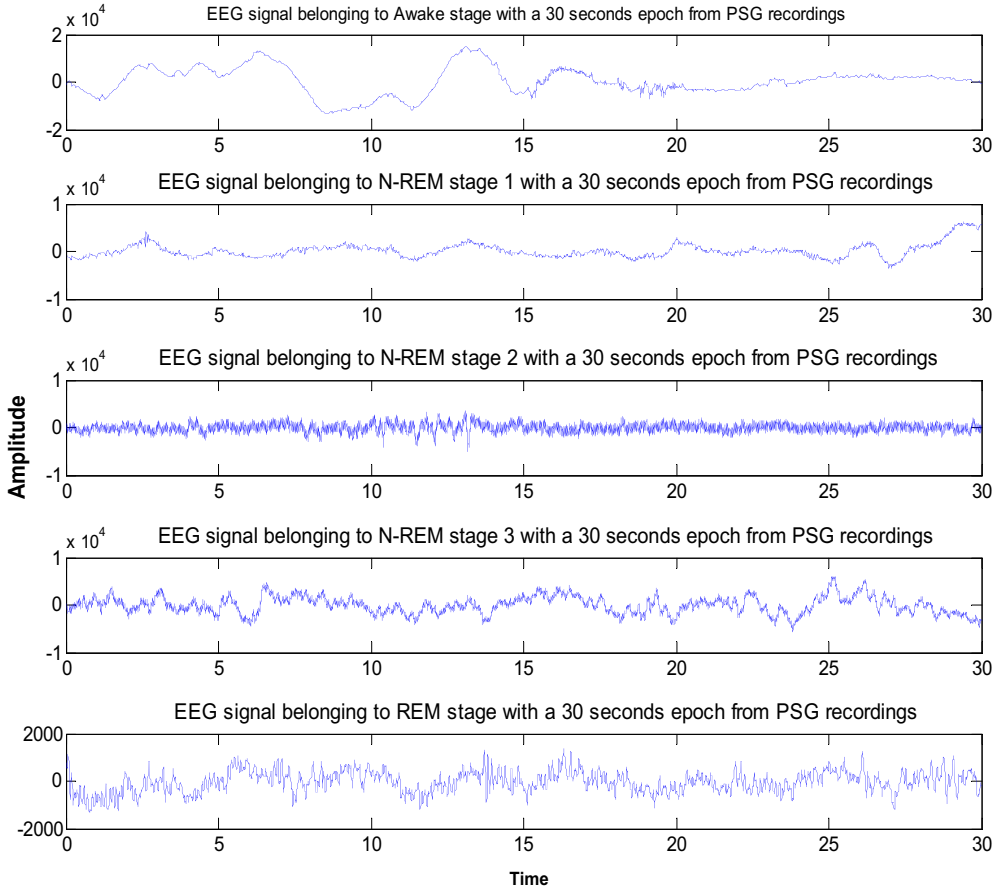

Fig. 1. The EEG signals with 30 s belonging to each sleep stages including awake, N-REM stage 1, N-REM stage 2, and N-REM stage 3, and REM stages recorded on a healthy subject.

90 min cycle and occupies approximately 45–60% of sleep (Šušmáková & Krakovská, 2008).

N-REM S3 is scored when 20–50% of the epoch of EEG contains 2 Hz or slower waves with amplitudes above 75 mV. Sleep spindles and *K*-complexes may also be show (Šušmáková & Krakovská, 2008).

REM stage presents low voltage and mixed frequency EEG. Saw-tooth wave pattern and beta waves are frequently demonstrate. There exist cases when sleep spindles or *K*-complexes characteristic for S2 alternate with some typical features of REM stage. REM stage composes 20–25% of a normal nights sleep (Šušmáková & Krakovská, 2008).

Movement time: If the EEG signal is not clear in more than half of an epoch due to amplifier blocking or muscle activity, the epoch is counted neither as sleep nor as waking, but is labeled as movement time. It is not the same as the discrete body movements, which could be very short and that can be a part of a sleep stage (Šušmáková & Krakovská, 2008).

3. Method

3.1. The proposed method

In this paper, the proposed method to classify the sleep stages comprises of three stages. In the first stage, Welch FFT (Fast Fourier Transform) spectral analysis has been used to extract important frequency features from EEG signal and obtained 129 features from EEG signal thanks to this phase. In order to reduce the number of features, we have used the statistical features including minimum value, maximum value, standard deviation, and mean value of 129 frequency domain features and decreased the number of feature from 129 to 4. In the second stage, KMCFW method has been used to weight sleep stage dataset with four features as data preprocessing. In the third stage, *k*-NN and decision tree classifiers have been used to classify the sleep stages into six sleep stages including awake, N-REM stage 1, N-REM stage 2, N-REM stage 3, REM, and non-sleep. Fig. 2 presents the flowchart of proposed method. We have explained the subsections of proposed method in following sections.

3.1.1. Welch spectral analysis method: feature extraction process

As feature extraction process, we have used Welch spectral analysis method to transform EEG signals from time domain to frequency domain. Welch method is described as classical method based on FFT. Welch method is the second modification of periodogram spectral estimator, which is to window data segments before computing the periodogram (Evans, 2000; Evans, McDicken, Skidmore, & Woodcock, 1989; Latifoğlu, Polat, Kara, & Güneş, 2008; Muller, Ciccotti, Reiche, & Hagen, 2001; Saini, Nanda, & Maulik, 1993; Sigel, 1998; Vaitkus, Cobbold, & Johnston, 1988). If ready for use information on the signal composes of the samples $\{x(n)\}_{n=1}^{N}$, the periodogram spectral estimator is provided as follows:

$$\widehat{P}_{PER}(f) = \frac{1}{N}\left|\sum_{n=1}^{N} x(n)\exp(-j2\pi fn)\right|^2 \quad (1)$$

where $\widehat{P}_{PER}(f)$ is the estimation of periodogram. In Welch method, signals are divided into overlapping segments, each data segment is windowed, periodograms are calculated and then average of peri-

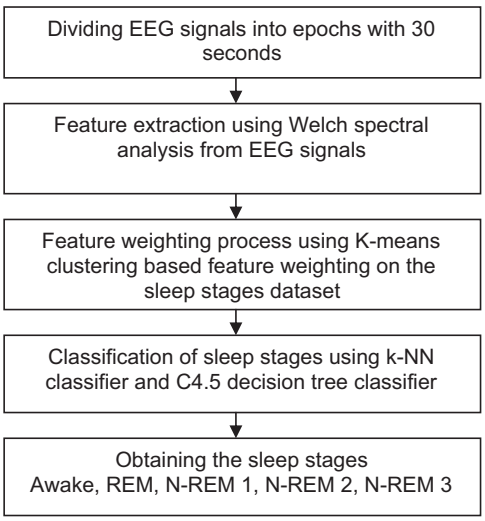

Fig. 2. The flowchart of proposed method.

odograms is found. $\{x_l(n)\}$, l = 1, ..., S are data segments and each segment's length equals M. The overlap ratio is frequently chosen as 50% ($M/2$) (Latifoğlu et al., 2008). The Welch spectrum estimate is given by:

$$\widehat{P}_w(f) = \frac{1}{S}\sum_{l=1}^{s}\widehat{P}_l(f) \tag{2}$$

$$\widehat{P}_l(f) = \frac{1}{M}\frac{1}{P}\left|\sum_{n=1}^{M} v(n)x_l(n)\exp(-j2\pi fn)\right|^2 \tag{3}$$

where $\widehat{P}_l(f)$ is the periodogram estimate of lth segment, $v(n)$ is the data-window, M is window sequence. P is total average of $|v(n)^2|$ and given as $P = 1/M\sum_{n=1}^{M}|v(n)|^2$, $\widehat{P}_w(f)$ is the Welch PSD estimate, M is the length of each signal segment and S is the number of segments (Latifoğlu et al., 2008).

Later, evaluation of $\widehat{P}_w(f)$ at the frequency samples fundamentally demands the computation of the following discrete Fourier transform (DFT).

The FFT algorithm can calculate the Welch PSD. Variance of an estimator is one of the measures often used to characterize its performance. For 50% overlap and triangular window, variance for the Welch method is provided by Latifoğlu et al. (2008);

$$\mathrm{var}(\widehat{P}_w(f)) = \frac{9}{8S}\mathrm{var}(\widehat{P}_l(f)) \tag{4}$$

where $\widehat{P}_w(f)$ the Welch PSD is estimate and $\widehat{P}_l(f)$ is the periodogram estimate of each signal interval (Evans et al., 1989, 2000; Latifoğlu et al., 2008; Muller et al., 2001; Saini et al., 1993; Sigel, 1998; Vaitkus et al., 1988).

In feature extraction from EEG signals, 129 data segments (windows) for EEG signal have been used and obtained a sleep stage dataset comprising 129 features in the end of Welch method for EEG signals.

In order to reduce the dimension of sleep stage dataset with 129 features, the statistical measures have been used. The used statistical features are minimum value, maximum value, standard deviation, and mean value belonging to each feature in sleep stage dataset. The dimension of sleep stage dataset is decreased from 129 to 4 features for EEG signals. The used statistical features are shown in Table 2, where $x(n)$, $n = 1, 2, \ldots, N$ is a time series. N is the number of data points.

3.1.2. k-Means clustering based feature weighting (KMCFW): data preprocessing

Clustering algorithms are used widely not only to collect similar or dissimilar data, but also useful for data compression and data reduction. The most used clustering algorithms are k-means clustering (MacQueen, 1967), fuzzy C-means clustering (Bezdek, 1981), the mountain clustering (Yager & Filev, 1994), and subtractive clustering (Chiu, 1994). In this paper, we have chosen k-means clustering as weighting process since this method is widely used in literature.

In k-means clustering based feature weighting method, at first the clusters of each feature are found using k-means clustering (KMC) and calculated the distance between its cluster and mean value of that feature. According to calculated distance, features are weighted.

The goal of feature weighting method is to map the features according to their distributions in a dataset and also transform from non-linearly separable dataset to linearly separable dataset. Feature weighting method works based upon principle that decreasing the variance in features forming dataset. Thanks to this weighting method, the similar data in same feature are gathered and the discrimination ability of classifier is increased.

In this study, a new weighting method (KMCFW) is proposed. The k-means clustering is briefly explained and then explained the proposed weighting method.

k-Means clustering also known as C-means clustering has been applied to a variety of areas including image segmentation, speech data compression, data mining etc (Rui & Donald, 2005). The working of KMC can be summarized as follows (Guldemır & Sengur, 2006):

Stage 1: Choose K initial cluster centers $z_1, z_2, \ldots, z_K$ randomly from the n points $\{X_1, X_2, X_3, \ldots, X_n\}$.

Stage 2: Assign point X_i, $i = 1, 2, \ldots, n$ to the cluster $C_j, j \in \{1, 2, \ldots, K\}$

$$\text{if } \|X_i - z_j\| < \|X_i - z_p\|, \quad p = 1, 2, \ldots, K \quad \text{and} \quad j \neq p$$

Stage 3: Compute new cluster centers as follows:

$$z_i^{new} = \frac{1}{n_i}\sum_{X_j \in C_i} X_j, \quad i = 1, 2, \ldots, K$$

where n_i is the number of elements belonging to the cluster C_i.

Stage 4: If $\|z_i^{new} - z_i\| < \varepsilon$, $i = 1, 2, \ldots, K$, then terminate. Otherwise continue from phase 2.

This weighting method works as follows: firstly the cluster centers are calculated using KMC method. After computing the centers of features, the ratios of means of features to their centers are calculated and these ratios are multiplied with data point of each feature. Fig. 3 demonstrates the flowchart of KMCFW method.

3.1.3. Used classifier algorithms: sleep stage classification process

After KMCFW applied to sleep stages dataset, the weighted sleep stages were classified using k-NN classifier and C4.5 decision

Table 2
The used statistical measures.

1. Minimum value: $x_p = \min\|x(n)\|$
2. Maximum value: $x_p = \max\|x(n)\|$
3. Standard deviation: $X_{std} = \sqrt{\frac{\sum_{n=1}^{N}(x(n)-x_m)^2}{N-1}}$
4. Mean value: $X_m = \sum_{n=1}^{N} x(n)N$

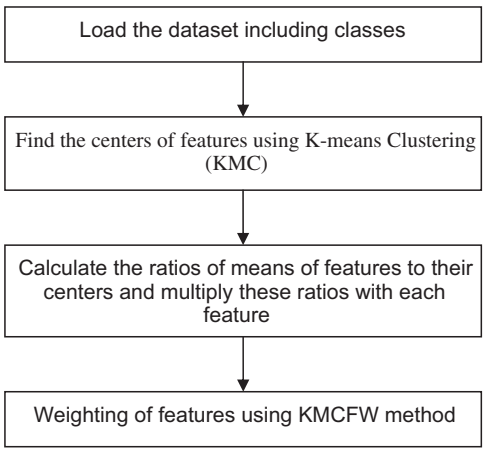

Fig. 3. The flowchart of KMCFW method.

tree into six sleep stages including W, REM, N-REM S1, N-REM 2, N-REM S3, and non-sleep.

3.1.3.1. k-Nearest neighbor (k-NN) classifier. The *k*-nearest neighbor algorithm is one of the simplest algorithms among all machine learning algorithms. In *k*-nearest-neighbor classification, the training dataset is used to classify each data of a "target" dataset. The structure of the data is that there is a classification variable of interest and a number of additional predictor variables. *k*-NN algorithm works as follows: (Dasarathy, 1991; http://www.resample.com/xlminer/help/k-NN/knn_intro.htm (last accessed 2009); Shakhnarovich, Darrell, & Indyk, 2005):

(a) For each row in the target dataset (the set to be classified), locate the *k* closest members (the *k* nearest neighbors) of the training dataset. A Euclidean distance measure is used to calculate how close each member of the training set is to the target row that is being examined.
(b) Examine the *k* nearest neighbors – which classification do most of them belong to? Assign this category to the row being examined.
(c) Repeat this procedure for the remaining rows in the target set.
(d) The user select a maximum value for *k*, builds models parallel on all values of *k* up to the maximum specified value and scoring is done on the best of these models.

In training and testing process of sleep stage dataset using *k*-NN classifier, the values shown in Table 3 are used.

3.1.3.2. C4.5 decision tree classifier. Decision trees have been successfully used in solving problems related to machine learning and classifier systems. A decision tree is induced from sample training dataset and each sample is composed of feature values and class label. Decision trees are general classification method based on inductive inference. They can work with noisy data and missing data in dataset. Decision trees search in the hypothesis space that is fully explained. In constructing of decision tree, small trees are generally preferred to big trees (Mitchell, 1997; Quinlan, 1986).

Each node in decision tree provides testing features belong to training set and each branch created from this node is suitable for a value of feature (Mitchell, 1997).

Decision trees are considered as a junction of disjunctions. C4.5 decision tree learning is a method for discrete-valued functions classifying, where a C4.5 decision tree depicts the learned function. Learned trees can be shown as sets of if-then rules. These learning methods are among the most popular of inductive inference algorithms and have been successfully applied to a broad range of tasks. C4.5 decision tree is a discovering method, hill climbing, not going backwards search through the space of all available C4.5 decision trees. The objective of C4.5 Decision tree learning is to partition recursively data into subgroups. For more information

Table 5
The effect of *k* value in *k*-NN classifier to classification of sleep stages using raw frequency domain features belonging to EEG signal without KMCFW.

k Value in *k*-NN classifier	Success rate (%)
10	52.68
20	53.68
30	55.41
40	**55.88**
50	55.15
60	53.85

Table 3
Training and testing dataset splits in *k*-NN classifier.

Sleep stages	Awake	N-REM stage 1	N-REM stage 2	N-REM stage 3	REM stage	Non-sleep (movement time)
Training set	138	56	295	46	176	85
Testing set	300	150	2000	150	600	200
Total	438	206	2295	196	776	285

The number of total epoch is 4196.

Table 4
The relevance coefficients between raw–weighted frequency domain features and sleep stages.

Used dataset	The name of relevance	Coefficient value
Raw frequency domain features belonging to EEG signal	The correlation between feature 1 (minimum value) belonging to EEG signal and sleep stages	−0.1383
	The correlation between feature 2 (maximum value) belonging to EEG signal and sleep stages	−0.09923
	The correlation between feature 3 (standard deviation value) belonging to EEG signal and sleep stages	−0.10707
	The correlation between feature 4 (mean value) belonging to EEG signal and sleep stages	**−0.13888**
Weighted frequency domain features belonging to EEG signal via *k*-means clustering based feature weighting	**The correlation between feature 1 (minimum value) belonging to EEG signal and sleep stages**	**−0.150499**
	The correlation between feature 2 (maximum value) belonging to EEG signal and sleep stages	−0.126657
	The correlation between feature 3 (standard deviation value) belonging to EEG signal and sleep stages	−0.135077
	The correlation between feature 4 (mean value) belonging to EEG signal and sleep stages	−0.167634

Table 6
The obtained confusion matrix from *k*-NN classifier using raw frequency domain features belonging to EEG signal on the classification of sleep stages (for *k* value of 40 in *k*-NN classifier).

Predicted sleep stages	Awake	N-REM stage 1	N-REM stage 2	N-REM stage 3	REM stage	Non-sleep (movement time)	Success rate (%)
Awake	85	0	130	2	78	5	28.34
N-REM stage 1	11	0	93	0	42	4	0.0
N-REM stage 2	54	0	1372	28	538	8	68.60
N-REM stage 3	0	0	71	15	64	0	10
REM stage	23	0	312	3	243	19	40.50
Non-sleep (movement time)	6	0	2	0	7	185	92.50

on C4.5 decision tree learning, the readers can refer to (Mitchell, 1997; Polat & Güneş, 2007; Quinlan, 1986).

In training and testing process of sleep stage dataset using decision tree classifier, 2-, 5-, 10-, and 15-fold cross validation methods have been used.

4. Results and discussion

In this particular work, we have proposed an efficient sleep stage recognition system based on EEG signal. This method has comprised of three stages. As feature extraction, Welch spectral analysis method has been applied to EEG signals with 30 s and obtained 129 frequency domain features from EEG signals. In order to reduce the complexity of classifier and to prevent the curse of dimensionality problem, the number of features of sleep stages dataset was reduced from 129 to 4 features using statistical measures including minimum value, maximum value, standard deviation, and mean value. As data preprocessing, *k*-means clustering based feature weighting has been used to weight the sleep stages dataset with four features. As classifier algorithms, *k*-NN classifier and C4.5 decision tree classifier have been used to classify the sleep epoch with 30 seconds into six sleep stages comprising awake, N-REM stage 1, N-REM stage 2, N-REM stage 3, REM, and movement time. The relevance coefficients between raw–weighted frequency domain features and sleep stages have been given in Table 4. When investigated these coefficients values, the most relevance feature to sleep stages is the mean value in raw frequency domain features with four features belonging to EEG signal. As for weighted frequency domain features belonging to EEG signal via *k*-means clustering based feature weighting, the most relevance feature to sleep stages is the minimum value feature.

In classification of sleep stages using *k*-NN classifier without KMCFW, the obtained results are shown in Table 5. The *k* values of 10, 20, 30, 40, and 50 in *k*-NN classifier have been used and compared with each other. The *k* value of 40 in *k*-NN classifier has obtained best classification accuracy on the classification of sleep stages using raw frequency domain features belonging to EEG signal without KMCFW. In addition of this, we have given the confusion matrix of *k*-NN classifier for *k* value of 40 on the classification of sleep stages in Table 6.

In recognition of sleep stages using *k*-NN classifier with KMCFW, the achieved results are presented in Table 7. The *k* value of 30 in *k*-NN classifier has obtained the best success accuracy on the classification of sleep stages using weighted frequency domain features belonging to EEG signal with KMCFW. And also, the confusion matrix of *k*-NN classifier has been provided for *k* value of 30 on the classification of sleep stages in Table 8.

Sleep stages have been classified using C4.5 decision tree classifier. In training and testing of classifier, the number of 2-, 5-, 10-, and 15-fold cross validation methods were used. The obtained results for C4.5 decision tree classifier on the classification of sleep stages dataset are demonstrated in Table 9.

As can be seen from above results, the proposed feature weighting method has obtained better results on the automatic classifica-

Table 7
The effect of *k* value in *k*-NN classifier to classification of sleep stages using weighted frequency domain features belonging to EEG signal with *k*-means clustering based feature weighting method.

k Value in *k*-NN classifier	Success rate (%)
10	81.12
20	81.47
30	**82.21**
40	82.15
50	81.12
60	79.74

Table 9
The obtained results from C4.5 decision tree classifier on the classification of sleep stages using both raw frequency domain features belonging to EEG signal and weighted frequency domain features belonging to EEG signal with *k*-means clustering based feature weighting method.

Used dataset	The number of fold in decision tree classifier	Success rate (%)
Raw frequency domain features belonging to EEG signal	2	43.95
	5	43.66
	10	50
	15	54.96
Weighted frequency domain features belonging to EEG signal with *k*-means clustering based feature weighting method	2	54.91
	5	59.92
	10	68.91

Table 8
The obtained confusion matrix from a hybrid system based on combining *k*-means clustering based feature weighting and *k*-NN classifier using frequency domain features belonging to EEG signal on the classification of sleep stages (for *k* value of 30 in *k*-NN classifier).

Predicted sleep stages	Awake	N-REM stage 1	N-REM stage 2	N-REM stage 3	REM stage	Non-sleep (movement time)	Success rate (%)
Awake	240	26	6	26	0	2	80
N-REM stage 1	81	11	52	6	0	0	7.33
N-REM stage 2	34	5	1778	0	183	0	88.90
N-REM stage 3	50	2	0	98	0	0	65.34
REM stage	2	0	80	0	486	32	81
Non-sleep (movement time)	7	0	5	4	2	182	91

tion of sleep stages. This data preprocessing method could be confidently used together classifier algorithms on efficient sleep stages classification.

5. Conclusions

In this paper, we have proposed a new hybrid system comprising of Welch spectral analysis, *k*-means clustering based feature weighting, and classifier algorithms (*k*-NN classifier and decision tree classifier) to automatic score the sleep stages and to help to sleep physicians on sleep stage scoring. To score the sleep stages as online, *k*-NN classifier has been used because this classifier method does not need to any learning method. Therefore, the proposed method with *k*-NN classifier could be used as online on the automated classification of sleep stages. The cause of using KMCFW is that a non-linearly separable dataset can be transformed to a linearly separable dataset by this weighting method. And so, the classification ability of classifier algorithms could be increased. In future, beside EEG signals, chin EMG (electromyography) and EOG (electrooculogram) signals could be together used in the automatic classification of sleep stages.

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