# Machine Learning Approach to Measure Sleep Quality using EEG Signals

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**Abstract—Sleep quality has a vital effect on good health and well-being throughout a life. Getting enough sleep at the right times can help protect mental health, physical health, quality of life, and safety. In this study, an electroencephalography (EEG)-based machine-learning approach is proposed to measure sleep quality. The advantages of our approach over standard Polysomnography (PSG) method are: 1) it measures sleep quality by recognizing three sleep categories rather than five sleep stages, thus higher accuracy can be expected; 2) three sleep categories are recognized by analyzing EEG signals only using two EEG electrodes, so the user experience is improved because he/she is attached with fewer sensors during sleep. Using quantitative features obtained from EEG signals, we developed a new automatic sleep-staging framework that consists of a multi-class support vector machine (SVM) classification based on a decision tree approach. We used polysomnographic data from PhysioBank database to train and evaluate the performance of the framework, where the sleep stages have been visually annotated. The results demonstrated that the proposed approach achieves high classification performance, which helps to measure sleep quality accurately.**

## I. Introduction

Sleep quality plays an essential role in an individual's learning ability, physical movement, and performance [1]. With the rapid pace of modern life, millions of people suffer from sleep problems. Therefore, automated sleep quality measurement is of utmost interest and can help in evaluating the treatment progress in patients with common sleep disorders such as restless legs syndrome, insomnia, narcolepsy, and obstructive sleep apnea.

Sleep is characterized by continuous changes in brain, eye, muscle, respiratory and heartbeat activity. To evaluate the sleep quality, traditional polysomnographic (PSG) records different types of physiological data including the electroencephalogram (EEG), electrooculogram (EOG), electromyogram (EMG) and electrocardiogram (ECG). The PSG recording then divides into 30 sec sleep stages, which are subsequently classified as wakefulness (W), rapid eye movement (REM), stage 1 (S1); stage 2 (S2); and deep sleep, or slow wave sleep (SWS = S3+S4) according to the guidelines of American academy of sleep medicine (AASM) in 2007 [2]. Sleep stage scoring is the gold standard for the analysis of human sleep [1], [3]-[7] that helps to identify the sleep stages that are vital in diagnosing and treating sleep disorders [8]-[12].

Sleep staging is usually conducted by specialized experts. This process, however, is cumbersome, error prone, time consuming, and delays further data processing [13]. As a result many methods have been proposed for automatic sleep staging in order to reduce the time required, effort spent and number of errors [13]. In automatic sleep staging, classifiers are trained using features associated with each 30 sec segment of sleep data and its corresponding stage that is manually annotated by sleep specialists or neurologists. After training, the classifiers automatically determine the sleep stage corresponding to each segment.

The traditional PSG approach uses several sensors to measure EEG, EOG, EMG and ECG signals [14]. This can make users feel uncomfortable during sleep since a lot of sensors are attached on their body and scalp. On the other hand, the EEG signals are able to provide information about brain activities based on electrical recordings taken on the scalp of a subject. The EEG signals at different frequency sub-bands of beta, alpha, theta, and delta, show different characteristics during different sleep stages. Thus, EEG signals are the most important signals in sleep stage classification for both manual and automatic classification [1]. Therefore to improve the user experience, automatic sleep staging based on measuring only EEG signals has been of utmost interest among the sleep research community during the last decade [1],[3]-[6].

Many different machine learning-based methods for automatic sleep stage classification (ASSC) have been proposed in the past. Approximately 31% of the ASSC methods use classification schemes that are based on support vector machine (SVM) classifiers, 22% based on artificial neural networks (ANN) classifiers, 11% based on linear discriminant analysis (LDA), 10% based on K-nearest neighbor (KNN), 5% based on decision trees (DT) and the remaining 21% based on other types such as Naive Bayes (NB), Hidden Markov Model (HMM), fuzzy classification, and combined classification [1].

Among different sleep datasets, the publicly available dataset "Sleep-EDF Database [Expanded]" from Physionet website [14], [18] has been widely used in the

literature for training and evaluating the proposed automatic sleep staging methods. Here we briefly compare the performance of some of the most popular procedures based on "Sleep-EDF Database [Expanded]" dataset with highest classification performance among the available literature. We must note that comparison with the studies using other sleep databases and PSG signals is very difficult and is not considered in this study.

Zhu et al. used multiclass SVM classifier to classify the six sleep stages of W, S1, S2, S3, S4, and REM, which achieved 87.5% classification accuracy [3]. Liu et al. [4] performed sleep stage classification based on ANN classifier. They achieved an optimal classification accuracy of 89.5% to classify W, S1 + REM, S2, and SWS. Sanders et al. [5] used LDA classifier for sleep stage classification. Their proposed method correctly classified the five stages of W, S1, S2, SWS, and REM with an average accuracy of 75%. Phan et al. [6] used KNN to develop an ASSC system to classify the four sleep stages of W, S1 + REM, S2, and SWS. The classifier provided 94.49% accuracy. Aboalayon et al. [1] compared the performance of DT, SVM, ANN, and KNN to classify six sleep stages of W, S1, S2, S3, S4, and REM. DT classifier obtained the best overall classification accuracy with an average of 93.13%. In terms of classification accuracy, the DT was followed by the SVM (92.37%), ANN (91.70%), and KNN (89.38%).

In order to reliably estimate sleep disorders, it is essential to precisely estimate sleep quality parameters [17]-[20]. Three main parameters can be calculated to measure sleep quality: 1) sleep latency, 2) sleep efficiency, and 3) percentage of deep sleep [20]. Sleep latency is the time that it takes to finish the transition from wakefulness to the first sleep stage. Sleep efficiency is the ratio of time spent asleep to the time spent in bed. Percentage of deep sleep is the ratio of deep sleep to the all sleep stages. In order to calculate these parameters, only three sleep categories need to be distinguished: wakefulness, light sleep + REM (S1, S2, REM), and deep sleep (S3, S4). Consequently, the scope of measuring sleep quality involves determining how to recognize these three sleep categories. Furthermore, the definition of sleep stages and the sleep literature show that EEG signals are similar in S1 and REM sleep [21]. Additionally, high variability in the EEG signals between and within subjects has been found, especially in stages S1 and REM sleep [22], [23]. Therefore, we attempted to classify the three sleep categories based on the EEG signals alone. We used an automatic sleep staging framework that consists of a multi-class SVM classification based on a decision tree approach. We first trained the SVM classifier by using polysomnographic data of first night of 8/67 healthy subjects from PhysioBank database with annotated sleep stages [16]. Then we evaluated the performance of the classifier using the remaining 110 data (nights) from 67 subjects. The rest of the paper is organized as follow. Section 2 describes the dataset and the method. The classification results are discussed in Section 3. Conclusions are given in Section 4.

## II. METHOD

### A. Subjects

In this study we used sleep data from SC Sleep-EDF Database [Expanded] that is freely available through Physionet for training and testing purposes [16]. We selected EEG signals recorded from 67 healthy subjects (female (n=34, 50.74%), male (n=33, 49.25%), mean age of 57.13years (age range: 25-101 years with the standard deviation of 23.03years)) without any medication for 24 hours sampled at 100 Hz. For each subject the EEG data were recorded for two nights. However, we considered one-night data for 13 of the subjects, since the data from the other night were noisy due to the poor electrode connections in most of the recording time and could not be considered in the study. Also 3 of the subjects had just one-night data. Thus the total number of data is 118. Sleep stages have been scored manually according to Rechtschaffen & Kales (R & K) criteria [24] based on 30 sec segments of recordings. We selected Fpz-Cz and Pz-Oz EEG electrodes in our evaluations.

### B. Data Pre-Processing

EEG signals are typically contaminated by a number of artifacts that may be caused by eye movement, eye blinks, electrode movement, muscle activity, movements of the head, sweating, breathing, heartbeat, electrical line noise, etc. One approach to extract and cancel artifactual signals is independent component analysis (ICA). This approach is based on the hypothesis that an artifact is statistically independent from the rest of the signals [25]. However, ICA performance depends on the length of the data because the larger the data processed, the higher the probability that the effective number of sources will overcome the number of EEG electrodes and therefore that we are dealing with overcomplete ICA. In this case, ICA will not be able to separate the artifact from the rest. Moreover, often artifacts involve a very narrow frequency range and exploiting these features in the frequency domain would help, but ICA operates in time domain. This means that, even when the separation is good, some useful EEG information content can be seen in the component accounting for the artifact, thus the cancellation would cause information loss. One way to overcome this problem is wavelet enhanced ICA method (wICA) [26] that applies a wavelet thresholding not to the observed raw EEG but to the de-mixed independent components as an intermediate step. It allows recovering the neural activity present in "artificial" components. In this study in order to minimize the effect of the artifact we first bandpass-filtered each sleep segment between

0.5 and 50 Hz. EEG artifacts were then removed using wICA algorithm MATLAB code [27].

### *C. Feature Extraction*

As EEG signals are dynamic, sometimes transient (spikes/bursts), and mostly nonstationary for their practical analysis, we not only need to know their frequency components but also the times at which they occur. Time-frequency analysis is especially suitable for addressing such issues [28]. We usually need more time accuracy in locating transient waves (high frequency), and for slow waves, we may be more interested in frequency resolution. Such an analysis can be performed using wavelet transform (WT). A Wavelet Packet Tree (WPT) of depth 7 (7 levels) was designed for this purpose. In this study Daubechies wavelet of order 2 (db2) was applied to 30 sec segments of filtered and de-artifacted EEG signal [29]. The frequency ranges of the EEG signal were broken down into Delta (below 3.5 Hz), Theta (4-7 Hz), Alpha (8-13 Hz), and Beta (14-30 Hz) bands [30]. In the sleep EEG, because of presence of sleep spindles, there is another frequency band, that is, spindle frequency band. Out of the family of subbands, those containing frequency information of the following 6 bands were manually selected (Figure 1).

1. Delta: {0.39 - 3.13 Hz}, Wavelet coefficients = [$C_{38}$, $C_{30}$, $C_{31}$, $C_{32}$] = B1
2. Theta: {3.13 - 8.46 Hz}, Wavelet coefficients = [$C_{33}$, $C_{34}$, $C_{22}$, $C_{23}$, $C_{35}$] =B2
3. Alpha: {8.46 - 10.93 Hz}, Wavelet coefficients = [$C_{36}$, $C_{25}$] = B3
4. Spindle: {10.93 - 15.63 Hz}, Wavelet coefficients = [$C_{26}$, $C_{27}$, $C_{28}$] = B4
5. Beta1: {15.63 - 21.88 Hz}, Wavelet coefficients = [$C_{16}$, $C_{17}$] = B5
6. Beta2: {21.88 - 37.50 Hz}, Wavelet coefficients = [$C_{18}$, $C_5$] = B6

The following 32 statistical features were used to represent the time–frequency distribution of EEG signal

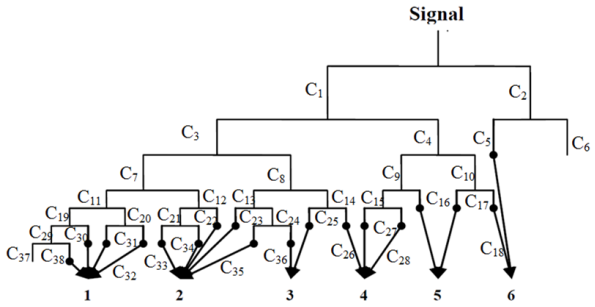


Figure 1. WPT and selected subbands.

for each electrode, therefore the total number of features are 2×32=64,

- Mean quadratic value or Energy (E1, E2, …, E6) of wavelet packet (WP) coefficients for each of the 6 bands (features 1-6)
- Total Energy (E7) (feature 7)
- Mean of the absolute values of the coefficients in each sub-band (features 8-13)
- Standard deviation of the coefficients in each sub-band (features 14-19)
- Ratio of different mean absolute values in different sub-bands (features 20-24)
- Shanon entropy of the vector B=[B1, B2, B3, B4, B5, B6] (feature 25)
- Permutation entropy [[31]]. (feature 26)
- Mean of each segment (feature 27)
- Maximum of each segment (feature 28)
- Minimum of each segment (feature 29)
- Median of each segment (feature 30)
- Standard deviation of each segment (feature 31)
- Mean of absolute differences (MAD) of each segment (feature 32)

$$MAD = \frac{1}{N}\sum_k |x(k) - x(k-1)| \quad (1)$$

Features 1–13 show the frequency distribution of the signal, features 14–24 display the amount of transformation in the distribution of the frequency. Feature 25, Shannon entropy, is used to describe the energy distribution of the wavelet coefficients. Since Shannon entropy yields high values in wakefulness and REM sleep stages, and low values in SWS stages, it can also be used in sleep EEG signal processing [32]. Feature 26, permutation entropy, is used to get a quantitative complexity measure for a dynamical time series. Features 27-32 mainly consist of statistical measures applied directly to the time series.

### *D. Feature Pre-Processing and Dimension Reduction*

After extracting candidate features, the second step in the machine learning process is feature reduction, or feature selection, which is critical to the performance of the corresponding classifier. We wish to identify only a set of $N_r$ most salient features from the extensive list of candidate features which are relevant to distinguishing between the three sleep categories. The effective feature selection algorithm minimum redundancy maximum relevance (MRmR) [33] was used to select a set of most discriminating features between the three classes. MRmR algorithm tends to select a subset of features having the most correlation with a class (relevance) and the least correlation between themselves (redundancy).

In order to avoid choosing features that are dominant in just a few patterns, a stratified 10-fold cross validation procedure was used to select the best *N*r features, where the folds were selected so that each fold contains approximately the same number of segments for each

category. The 10-fold cross validation is an iterative process, where in each iteration, a single fold is retained as the validation data for testing and the remaining folds are used as training data. In the proposed feature selection scheme, for each iteration, a list of the best $kN$r, k > 1 features is determined using MRmR method. For this study the value of $k$ is chosen to be 2. After all iterations are completed, the $N$r features with the highest number of repetitions (probability of appearance) among the available lists were selected as the final set of selected features. It is desirable to use as small a number as possible so as to avoid over-fitting.

### *E. Dendrogram Multi-Class SVM*

In this study, we used a decision-tree-based support vector machine approach named Dendrogram-SVM (DSVM) for sleep categories classification [7]. The kernel function is Gaussian Radial basis function and the optimization technique is sequential minimal optimization [34] using the Statistics and Machine Learning Toolbox in MATLAB R2016. The rationale here is that associating decision tree architecture with binary SVMs combines the advantages of the efficient computation of decision trees and the high classification accuracy of SVMs.

### *F. Training the Classifier*

To train the classifier, we selected 8-night recorded EEG data from first night of 8 different subjects in the PhysioBank dataset. We then used 800 samples of each category from these 8 data for training to have the same number of samples for each category. Therefore, the total number of training samples was 3×800=2400. We then applied the MRmR procedure with 10-fold cross validation to the features from these 8 subjects to find the most discriminating features. Then we tested the trained classifier for the remaining 110 data (nights) from 67 subjects. We used bootstrap approach for training to find the best 8 training data that could give us the best test performance for the remaining 110 data. The number 8 was the least number of subjects with a best test performance (less over-fitting). In this study, $N$r = 15 features were selected. This value was determined on the basis that it is the lowest value which gave adequate performance. This number of features is much lower than 2400 training samples to prevent over-fitting (the feature to training sample ratio is 15/2400×100=0.625%)

## III. RESULTS

### *A. Dendrogram Generation*

The hierarchical cluster analysis step yielded the dendrogram shown in Figure 2. At the top of the tree (i.e. the root node), the first binary decision occurs for awake versus sleep. The Awake class is thus a terminal node and, when training SVM1, is considered to be a negative class, while the remaining merged two classes are

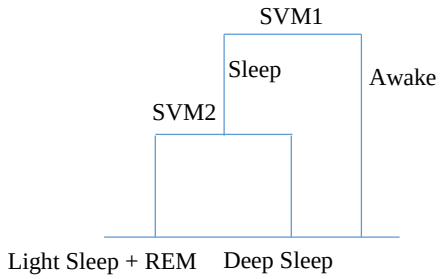


Figure 2. Dendrogram shows the multiple SVM classification generated for the three classes (awake, light sleep + REM, and deep sleep).

positive. Similarly, the second binary classifier in the tree (SVM2) is trained considering elements of deep sleep as negative and elements of light sleep + REM as positive. In this approach, the hierarchical cluster tree is created using the smallest distance between objects in the two clusters, where pairwise distance between pairs of observations is correlation, which is one minus the sample correlation between them.

### *B. Classification Performance*

The set of 15 most relevant features selected by the MRmR procedure is shown in Table 1, sorted in terms of the optimized MRmR value. These selected features were then used for the two binary classifications in Figure 2. The classification performance of the proposed methodology for three sleep categories of awake, light sleep + REM, and deep sleep using the remaining 110 nights of 67 subjects are shown in Table 2. From Table 2 the classifier is capable of discriminating the tree categories with the accuracy of 91.4%. This confirms that the over-fitting has not occurred. Comparing with the preceding works using the same database and EEG signals[1], [3]-[6], the performance of the proposed procedure obtained high accuracy rate. The slightly higher performance in studies [6] and [1] can be due to the use of a portion of sleep stages of same subjects for training and another portion for testing in the form of leave one out or $k$-fold cross-validation and bootstrapping approaches in comparison to our case where the test data are from 110 nights that are not used for training.

## IV. CONCLUSIONS

In this paper, we developed a machine-learning algorithm based on *Dendrogram Multi-Class SVM* to detect the three sleep categories of light sleep+REM, deep sleep, and awake. Considering that standard PSG system may make users feel uncomfortable, our approach is specifically designed to recognize three sleep categories from two EEG electrodes only. We trained the machine-learning algorithm using only 8-night recorded EEG data from first night of 8 subjects available in Physiobank

sleep database. We then evaluated the algorithm using the remaining 110 data from 67 subjects. The results demonstrated that our approach can achieve high accuracy though only two EEG electrodes are used. The three parameters— sleep latency, sleep efficiency and percentage of deep sleep —can then be calculated to automatically monitor users' sleep quality at night. This can help in diagnosing sleep disorders and evaluating the treatment progress.

Table 1. The Nr = 15 discriminating features

| Feature # | Feature | MRmR |
|---|---|---|
| 1 | Standard deviation of each segment (Pz-Oz) | 0.9245 |
| 2 | Standard deviation of sub band S6 (Pz-Oz) | 0.9238 |
| 3 | Mean quadratic value or Energy in sub band S6 ( Pz-Oz) | 0.9220 |
| 4 | Mean quadratic value or Energy in sub band S1 ( Pz-Oz) | 0.8989 |
| 5 | Max of the segment ( Pz-Oz) | 0.8906 |
| 6 | Mean absolute value of sub band S5 ( Pz-Oz) | 0.8895 |
| 7 | Sum of absolute differences of each segment (Pz-Oz) | 0.8867 |
| 8 | Mean absolute value of sub band S4 ( Pz-Oz) | 0.8841 |
| 9 | Mean absolute value of sub band S1 ( Pz-Oz) | 0.8816 |
| 10 | Mean quadratic value or Energy in sub band S2 ( Pz-Oz) | 0.8199 |
| 11 | Permutation entropy ( Fpz-Cz) | 0.7602 |
| 12 | Permutation entropy ( Pz-Oz) | 0.7446 |
| 13 | The ratio of mean absolute value of sub band S3 to sub band S4 (Pz-Oz) | 0.7013 |
| 14 | The ratio of mean absolute value of sub band S5 to sub band S6 (Fpz-Cz) | 0.6752 |
| 15 | Mean absolute value of sub band S6 ( Fpz-Cz) | 0.5428 |

Table 2. SVM classification performance using 91285 light sleep + REM, 10022 deep sleep, and 133246 awake segments for 110 test Data

| Class | LS + REM | DS | AW | SE | SP | TA |
|---|---|---|---|---|---|---|
| LS + REM | 76914 | 6729 | 7642 | 84.3 | 96.1 | 91.4 |
| DS | 991 | 8960 | 71 | 89.4 | 96.9 | |
| AW | 4548 | 178 | 128520 | 96.4 | 92.4 | |

SE: Sensitivity, SP: Specificity, TA: Total accuracy, AW: Awake, DS: Deep sleep, LS+REM: Light sleep + REM.

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