Using Signal Quality Assessment (SQA) to Help Sleep Stage Classification

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Abstract

Among all of the measured signals in polysomnography, ECG signal acquisition is one of the easiest to measure. We hypothesize that the signal quality (SQ) will be significantly different among sleep stages (awake, light, deep sleep, and REM). To check the hypothesis, the Sleep Heart Health Study visit 1 (SHHS1) dataset was used (6,441subjects) in this study. In this database, 4082 subjects had at least more than 5 consecutive minutes for each stage. As SQ assessment (SQA) features, we used the kurtosis, the skewness, the Shannon entropy, and the standard deviation of the signal after high-pass filtering using a cut-off frequency of 40 Hz. For each of the stages with a duration of more than 5 minutes, the features were estimated in epochs of 30 s using a sliding window with increments of 1 s from the start of the stage to its end. The prediction power of each feature between pairs of sleep stages was assessed using the area under the ROC curve (AUC). The observations showed that kurtosis provided on average, higher AUC than the other features. In a conclusion, ECG SQA features may help to improve the classification of sleep stages in automatic classification systems.

1. Introduction

Sleep is a necessary part of human existence; during sleeping, the body can clear debris and waste from the lymphatic system, which boosts the immune system [1]. Moreover, many vital sleeping processes such as protein synthesis, tissue growth, hormone release, and muscle, mostly happen in the deep sleep stage. The earliest study of the various stages of sleep was provided by Loomis et al. [2]. According to the National Heart, Lung, and Blood Institute, people with sleep deficiency have a greater risk of many health complications, such as heart disease, kidney disease, diabetes, stroke, high blood pressure, and obesity [3]. Accordingly, accurate classification of sleep stages can be useful for the evaluation of sleep quality. In sleep stage analysis, records are divided into 30 seconds pieces. Each divided piece is called an epoch. Each epoch is tagged as, awake (stage 0), light sleep (stages 1-2), deep sleep (stages 3-4), and rapid eye movement (REM) sleep (stage 5). In light sleep, the level of awareness becomes lower than in the awake state, the body temperature drops, eye movements stop, and the breathing and HR become more regular. In deep sleep the muscles are completely relaxed, the blood pressure drops, and breathing slows down. Deep sleep is the most essential stage of sleep, since replacing cells, building muscle tissue, and healing wounds are happening in this stage. In REM sleep, the brain lights up with activity, the body is relaxed and immobilized, the breathing becomes faster and irregular, the eyes move rapidly and the dreaming process develops.

The gold standard in terms of sleep analysis is overnight polysomnography (PSG) which refers to a systematic process employed to collect physiological signals during sleep [4]. PSG is presented by the recording of several physiological variables during sleep such as electroencephalogram (EEG), electrooculogram (EOG), electromyogram (EMG), electrocardiogram (ECG), respiratory effort, airflow, saturation of oxygen, and thoracic and abdominal effort [5]. The EEG signal is the most important signal for sleep stages classification. Nevertheless, out of the lab signal recording, and analysis of EEG signal presents us with some technical challenges [6]. On the other hand, ECG can be more easily acquired during home sleep monitoring. Electrocardiographic signals (ECG) can be processed to identify periodically occurring disturbances in the heart rhythm. As the most prominent peak in ECG signal is the R wave, RR intervals contain essential information regarding physiological regulation. It has been claimed that cyclic variations in RR intervals are associated with sleep apnea and sleep stages. Nevertheless, in this work, we focus on the unobtrusive approach to look for physiological correlates of sleep stages using the quantifiers of the quality of the raw ECG signals. One of the main challenges of ECG analysis in unobtrusive monitoring, such as signal recording in wearables, is that these signals are suffering from different kinds of noise and artifacts. Hence, automatic assessment

of the quality of ECG signals is increasingly demanded in reducing false alarms due to the presence of unacceptable levels of noise [7]. Here the hypothesis is that the deeper the level of sleep the lower the movements are, hence the quality of the recorded ECG would be higher. Accordingly, the quality of the ECG signal can be considered as a feature to classify sleep stages.

2. Method

In this section, the methodology which is applied to study the dependence of some ECG SQA indices with sleep stages is explained. To understand the main idea, the block diagram of processing steps is presented in Figure 1.

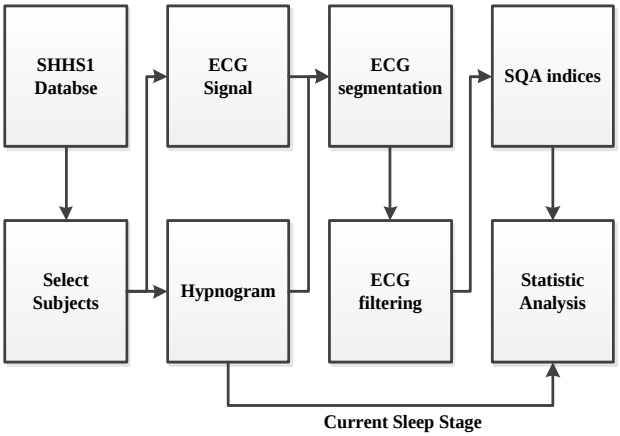

Figure 1. The block diagram of sleep study by using SQA.

2.1. Database

The Sleep Heart Health Study visit 1 (SHHS1) dataset was utilized in this work [8],[9]. The Sleep Heart Health Study (SHHS) is a multi-center cohort study implemented by the National Heart Lung & Blood Institute to determine the cardiovascular and other consequences of sleep-disordered breathing. In all, 6,441 men and women aged 40 years and older were enrolled between November 1, 1995, and January 31, 1998, to take part in SHHS Visit 1. In our study, 4082 subjects from SHHS1 with more than 5 consecutive minutes for each stage were selected. Also, here the light sleep labeled as stage 1 was not analyzed since it is quite similar to the awake stage so for light sleep only stage 2 was considered. Deep sleep was treated by pooling stage 3 and stage 4. Subjects with more than 5 minutes of recording in each stage of awake (stage 0), light sleep (stage 2), deep sleep (stage 3 or 4), and REM sleep (stage 5) were identified and included in this study. The ECG signal in this database was sampled at 125 Hz.

2.2. Signal Quality (SQ) indices in ECG

Since the ECG signal has low frequency and amplitude, it is vulnerable to noise. Therefore, the first step for an accurate ECG analysis is to carry out signal filtering. In these terms, the ECG signal is corrupted by two major noises generated by biological (such as base-line drift, motion artifacts, muscle contraction, EMG interface, etc.) and environmental resources (such as power-line interference, instrumentation noise generated by electrical devices, etc.). Electrocardiogram signal quality assessment (SQA) plays a critical role in improving the diagnostic accuracy and reliability of ECG signals. This work uses SQ indices kurtosis, Shannon entropy, and skewness. All those indices are frequently used [10],[11]. Moreover, an additional SQA assessment is employed: the standard deviation of the ECG after high-pass filtering as a surrogate measure of the EMG that accompanies the ECG signal. Next, we briefly introduce the different SQA measures,

Kurtosis

Kurtosis is a measure of the "tailedness" of the probability distribution. The standard measure of a distribution's kurtosis is a scaled version of the fourth moment of the distribution. When this parameter is biased is estimated as,

$$Kurt[x] = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^4}{(\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2)^2} \quad (2)$$

Before kurtosis estimation, the ECG has been filtered using a second-order band-pass filter with a cut-off frequency between 15 to 30 Hz to enhance the QRS complex.

Skewness

Skewness is a measure of the asymmetry of the probability distribution of a real-valued random variable about its mean. The standard measure of a distribution's skewness is a scaled version of the third moment of the distribution. When the skewness is biased, it is estimated as,

$$skew[x] = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^3}{(\sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2})^3} \quad (2)$$

Before skewness estimation, the ECG signal was filtered using the same filter that was employed for the kurtosis.

Shannon Entropy

The Shannon entropy measures the average level of information (bins) provided by a random process. Given a discrete random variable *X*, with possible outcomes $x_1,...,x_n$, which occur with probability $P(x_1),...,P(x_n)$ the entropy of *X* is defined as,

$$H(X) = -\sum_{i=1}^{n} P(x_i)\log P(x_i) \quad (3)$$

In this work, this parameter is calculated from the empirical probability distribution by selecting the number of bins equal to the square root of the number of points in the *X* variables.

Prior to estimation, the ECG signal has been filtered using the same band-pass filter that has been employed for kurtosis and skewness estimation.

EMG noise level

EMG is a signal with a wideband content, high above the bandwidth of the ECG. Hence, a surrogate of the EMG level can be obtained by high-pass filtering the signal using a cut-off frequency high enough to reduce most of the ECG wave contents. Therefore, the standard deviation of the signal after high-pass filtering can be used as an index of EMG level and as an additional SQA index. Here, a cut-off frequency of 40 Hz was selected. After this, the standard deviation of the filtered ECG has been employed as an additional SQA index.

2.3. Data processing

To process the SHHS1 database, MATLAB ® version 2022a had been used to analyze a total of 4082 subjects. ECG segments that correspond to sleep stages 0, 2, 3, 4, or 5 that were longer than 5 minutes were included in the analysis. SQA indices were calculated using epochs of 30 s and updated by sliding the epoch in increments of 1 s from the start of the stage to its end. After obtaining the ECG SQA parameters, the median and interquartile were computed for each sleep stage. Moreover, pairwise comparisons between sleep stages were used for each SQA index to assess the classificatory power as measured using the area under the ROC curve (AUC).

3. Results

The results of the study are presented in the tables. Table 1 shows the median ± interquartile range values for the pooling of all the 4082 subject's SQA indices disclosed for each sleep stage. In Table 2 we can see the results of the median ± interquartile range of the AUC for SQA parameters when comparing one stage of sleep to the other.

4. Discussion and conclusion

In this study, 4082 subjects with more than 5 consecutive minutes for each stage of sleep (awake, light sleep, deep sleep, and REM sleep) from the SHHS1 database were analyzed. The SQA indices such as kurtosis, skewness, Shannon entropy, and one more proposed index, the standard deviation of the high-pass filtered ECG signal for each stage were obtained.

As reflected in Table 1, the median of kurtosis and the absolute value of skewness in the awake stage have the lowest value since the asymmetry of HRV distribution can be affected by the movement of the subject during this stage. However, the absolute value of skewness for the different sleep stages is quite similar. Shannon entropy has the highest value in the awake stage because the predictability is lower than in sleeping conditions due to the presence of a large amount of noise. The standard deviation of the high-pass filtered ECG (μV) has the highest value in the awake stage because the chances to find a high noise level are higher than sleeping due to motion artifacts and muscle activities. However, because these results are obtained by pooling the observations of each stage for all of the subjects, the intrasubject change of the indices may be blurred.

According to the result of Table 2, the kurtosis while the subject is awake compared with the light sleep showed the best performance of classification. However, the light sleep vs REM sleep showed poor classification efficiency when using SQA parameters such as the skewness, the Shannon entropy, and the standard deviation of the high-pass filtered ECG signal. Since the AUC value for all of these parameters is higher than 50%, it means that they have useful information for the classification of sleep stages. Consequently, and from the obtained results, kurtosis has the highest AUC values when comparing different stages of sleep while the skewness had the lowest values compared to the other SQA indices. These results are in accordance with previous studies. Sanchez del Rio et al. [2] assessed eleven different methods for the estimation of ECG signal quality. According to their result, the kurtosis parameter gave the best performance overall in the test. It gave a high correlation with the signal SNR (0.95±0.00) and a high correlation with the output of a beat detector (Positive Predictively=0.97±0.00) and high resolution in time (10 seconds of signal length). Moreover, Zhao et al. [11] proved that kurtosis can be used as an efficient SQA index in ECG quality analysis. Consequently, the SQA indices which are calculated here can be used to help to classify awake and sleep stages. However, more studies should be carried out to accurately categorize the different sleep stages. Therefore, for further studies, the result of SQA parameters can be applied to more sophisticated algorithms such as Machine Learning (ML) in automatic systems.

Table 1. The median ± interquartile range SQA indices.

	Kurtosis	Skewness	Shannon Entropy	The standard deviation of the HP filtered ECG(μV)
Awake	14.70 ± 1.68	-0.19 ± 0.05	2.97 ± 0.31	4.0 ± 2.6
Light sleep	16.48 ± 0.87	-0.21 ± 0.07	2.72 ± 0.14	2.8 ± 1.0
Deep sleep	15.88 ± 0.79	-0.20 ± 0.05	2.75 ± 0.13	2.7 ± 0.6
REM sleep	16.01 ± 0.86	-0.20 ± 0.06	2.76 ± 0.14	2.8 ± 0.9

Table 2. Median ± interquartile range AUC (%) for SQA indices.

	Awake vs light sleep	Awake vs deep sleep	Awake vs REM sleep	Light vs REM sleep	Light vs deep sleep	Deep vs REM sleep
Kurtosis	86 ± 21	80 ± 26	77 ± 25	67 ± 19	71 ± 21	71 ± 25
Skewness	70 ± 22	75 ± 26	72 ± 24	63 ± 16	66 ± 19	70 ± 24
Shannon Entropy	79 ± 22	78 ± 25	76 ± 24	63 ± 16	65 ± 18	69 ± 22
The standard deviation of the HP-filtered ECG	82 ± 24	83 ± 26	84±25	62±15	66±20	70 ± 24

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