Heart Rate Based Sleep Staging

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Abstract

Sleep plays a vital role in health and well-being by maintaining health, quality of life, and productivity. Millions of people worldwide exhibit inadequate sleep due to modern lifestyle behavior or physical illness. Sleep stages identification and evaluation is fundamental in determining sleep quality and diagnosing sleep disorders and their severity. Usually this task is performed by the mean of Polysomnography studies. The current development in nanotechnologies, data exchange methods and recording systems could allow this procedure to be carried out with simpler modalities and shorter preparation times, making possible to obtain a reliable sleep scoring from a home-recorded night of sleep. The main objective of this project is to develop a classification model which can be employed for automatic classification of sleep stages starting from parameters related to Heart Rate Variability extracted from ECG data alone. Data collected from several subjects during sleep studies were available. A total of 25 full night of polysomnographic visual sleep staging records constituting 25 different records have been employed. A pre-processing step was crucial in order to improve signal quality, allowing the detection of the most accurate number of R wave peaks. The obtained tachograph were processed to remove outliers and provide information related to 30s epochs. At this point 27 HRV-related features were extracted, some of them selected to explain sleep stages changes during night. A classifier was used to automatic detect sleep stages with an accuracy of 54 ± 3.5. The distinctive contribution brought by this work consists mainly in the more precise subdivision of sleep stages classification and a greater generalization capability, being able to operate for both healthy and pathological subjects. The main limitation of this algorithm is the intrinsic presence of motion and respiration artifacts which often compromise the ECG signal without possible processing improvements. A further direction of improvement would be the employment of plethysmography records for deducting Heart Rate Variability measures increasing HRV measurement robustness and reliability when used with ECG or further easing the sensors setup when used alone.

1 PROBLEM AND MOTIVATION

According to the latest *Sleep Scoring Manual* proposed by the AASM Visual Scoring Task (1), which refined the first ever *Sleeping Scoring Manual* defined by R&K (2), sleep stages are defined based on the measurement of electrical activity arising from different regions collected during a complex, long and expensive procedure (polysomnography) which involves the recording of several biological signals including EEG, EOG, EMG, ECG, pulse oximetry, and various breathing related signals. The three most important signals are the EEG collected on the scalp, the EOG produced by the ocular muscular activity and the EMG recorded through electrodes placed above and below the chin; these are employed by the current visual sleep scoring method, allowing alone to define sleep stages. The *Manual of Sleep Scoring* classifies sleep as consisting of 4 stages. The American Academy of Sleep Medicine (3) has later refined the Visual Sleep Scoring providing a large amount of data collected from different scorers in order to better underline the areas of disagreement which appear to be the scoring stages N1 and N3. Lately more and more methods for scoring and defined sleep stages have been sought in order to either improve detection accuracy or ease the signal collection methodology. Heart Rate Variability measure is a parameter which can be collected with a relatively high precision from both ECG measurements or Plethysmography. The purpose of this project is to first analyze the Heart Variability in relation to the sleep cycle then identify features of interest in order to classify sleep stages based on the changes in HRV re-

flected by key parameters. This could constitute a tool to increase the robustness of sleep stages detection through polysomnogarphy or a method to automatic classify them in order to provide a reliable estimate of the sleep cycle through a more comfortable and less expensive setup.

2 BACKGROUND AND RELATED WORK

2.1 Sleep Stages Scoring

The American Academy of Sleep Medicine (1) identifies four different stages divided in Non-Rapid Eye Movements (NREM - three stages) and Rapid Eye Movements (REM - one stage). The most widely used classification reference is the *Visual Scoring Manual*, having revised the milestone work of R&K (2) , which consists of the analysis and scoring of biological signals gathered in short epochs (20-30 seconds) in order to define the sleep stage of the subject; although it can provide information sampled at a 30 second rate without giving a precise initial and final instant for each phase, this method can offer information precise enough with a much less effort with respect to a continuous scoring. Signal of interest are generally: brain waves (electroencephalogram, or EEG); eye movements (electrooculogram, or EOG); chin muscle activity (chin electromyogram, or EMG); air flow from the nose and mouth; chest and abdominal movement; blood oxygen levels (oximetry); heart rate and rhythm (electrocardiogram, or ECG); and leg movements (leg electromyogram, or EMG). The EEG, EOG, and chin EMG signals are necessary to determine whether a person is awake or asleep, and also to determine whether his or her pattern of sleep is normal (1). Collection of signal happens simultaneously during polysomnography at a laboratory or hospital; usually the preparation needed in order to perform polysomnography on a patient requires a long preparation (more than 45 min) and requires the patient to sleep in a unfamiliar environment potentially compromising the recordings (4).

2.2 Heart Rate Variability (HRV)

Heart rate variability (HRV) consists of changes in the time intervals between consecutive heartbeats called inter-beat intervals (IBIs). The oscillations of a healthy heart are complex and constantly changing, allowing the cardiovascular system to rapidly adjust to sudden physical and psychological challenges to homeostasis. HRV reflects regulation of autonomic balance, blood pressure (BP), gas exchange, gut, heart, and vascular tone, which refers to the diameter of the blood vessels that regulate BP, and possibly facial muscles (5). Heart Rate Variability metrics are derived from the ECG starting from the Inter Beats Interval (IBI) or from a plethysmograph, taking into account the pulse transmit time (PTT) which characterize the delay after each QRS complex. Several metrics can be inferred starting from IBIs over a period both in time and frequency domain as reported by Shaffer and Ginsberg in their *Heart Rate Variability Metrics and Norms Overview* (5). Sleep stages alternate throughout a normal sleep period and correlate with changes in HRV (6). According to Boudreau et al (7) the circadian and sleep stage-specific effects on heart rate variability are clinically relevant. A study from Xi Long, Pedro Fonseca et al (8) investigated the use of cardiac information and more specifically, heart rate variability (HRV), for automatic deep sleep detection throughout the night, achieving significant results. Sleep-related researches have employed Heart Rate Variability associated parameters to quantify modulation of the sympathetic and parasympathetic branches of the autonomic nervous system as stated by Blurr (9), who additionally provided a more efficient algebraic interpretation of HRV spectral components. Several studies have tried to automatically determine sleep stages either in detail or by macro areas (wake, NREM, REM) by the mean of different classifier using ECG alone (4), (10), (11), (12), (13), (14), (15) or gathering together different signal other than ECG such as EEG (16), (17), EDR (ECG-derived respiration) (18) or many more signals recorded by a wearable sensorized T-shirt (19). Particular attention has been paid to Bianchi A. M. works in HRV analysis for sleep staging; She conducted a series of studies on the existing relationship between sleep stages and autonomous nervous system (ANS) (20),(21), reporting several HRV analysis methodologies (22),(14), (23),(24) which have been briefly summarized in (25); other related works have been aimed to produce a reliable sleep staging classification based on HRV features using different types of sensors such as wearables devices (19), (26) and sensorized beds (27),(28). The research direction in this field is going toward the sought of a reliable and comfort-

able, other than less expensive procedure to measure biological signal in order to allow classification algorithm to automatically detect sleep cycles.

3 APPROACH AND UNIQUENESS

As reported in the previous paragraph, many developed algorithms were based on subject-specific validation or took into account only a distinction based on sleep macro-structure comprising sleep-wake, or deep-light sleep staging. The main objective of this project is to develop a classification model which can be employed for automatic classification of sleep stages starting from parameters related to Heart Rate Variability extracted from ECG data alone. This would be a subject independent classifier, able to discriminate sleep stages S1, S2, S3, S4 and REM sleep in both pathological and healthy subject. This would improve the quality and affordability of sleep monitoring, allowing potentially everyone to detect and record their sleeping dynamics from any place and environment.This improvement would allow subjects affected by sleep disorders to have an easier, more comfortable and more efficient method to monitor their sleep-behaviour. Without the necessity to rely on the presence of a laboratory, medical staff and instrumentation, more night-monitorings would be available allowing the collection of huge quantity of data for experts to have a more consistent subject-specific database for purpose related to diagnosis or study.

3.1 Material

Data collected from several subjects during sleep studies are available. A total of X hours of sleep constituting 25 different records are employed. Data include polysomnogrphic signals such as EEG, EMG, PPG, ECG, EOG, and others, as well as sleep scoring drawn up by experts. The sleep studies which constitute the source of the material employed in this project collect records from both pathological and healthy subjects and had been recorded at various laboratories, employing different instrumentation. No distinctions have been taken into account between these categories. For the aim of the project only the ECG signals have been considered and used to train the model.

3.2 Methods

The project has been developed using MATLAB software, while records were stored in EDF format. The first step required to visualize and reduce our records to the signals of interest only. These signals were characterize by different artifacts due to respiration, electric noise and other motion sources. For this reason a pre-processing step was crucial in order to improve signal quality, allowing the detection of the most accurate number of R wave peaks. Once the R wave peaks have been extracted from ECG signals using J. Pan and W. J. Tompkins algorithm (29), a further step of pre-processing was necessary in order to obtain a signal which does not present outliers and it's sampled at a uniform frequency. Then it's possible to work with a tachogram which plots R-R peaks interval as a function of heart beat number; signals have been divided in thirty-seconds-epochs and from prior five-minutes recording has possible to extract heart rate variability metrics for each epoch. More than 25 features were extracted and further filtered and selected in order to obtain best results. Finally, taking into account the feature selected, the choice and parameters tuning of a classification model has been carried out. The whole implementation sequence is reported in fig. 1.

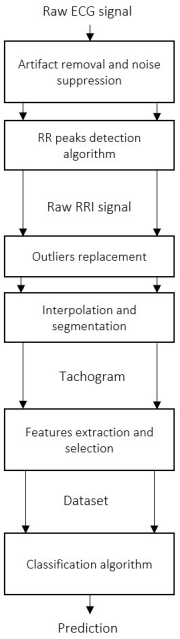

Figure 1: Software implementation scheme.

3.3 Proposed Solution

3.3.1 ECG Processing

The ECG signal has been firstly analysed employing the Discrete Wavelet Transform with the aim of reducing noise and artifacts contribution. De-

composition level was chosen according to the sampling frequency of the signals which range of values was 128 Hz, 256 Hz, 512 Hz. Each time the sampling frequency assumed a value which was the double of the previous one, the level has been increased by one starting from level 5 to level 7. In our work we exploited Symlet 4 mother wavelet which approximates well enough QRS-complex. The approximation coefficients, corresponding to frequency lower than 8 Hz were discarded in order to lower baseline wander and respiration artifacts, whereas detail coefficients level one were discarded in order to delete high frequency noise belonging to frequencies higher than 64 Hz. The result is reported in figure 2.

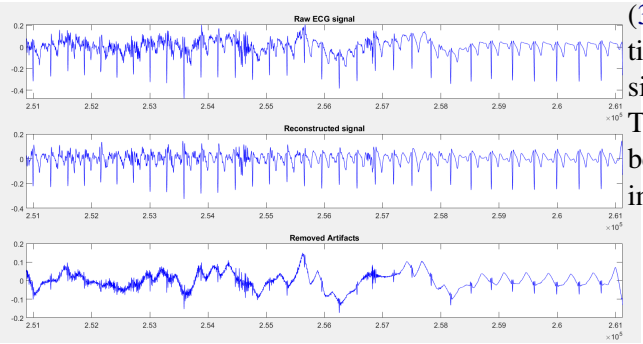

Figure 2: Pre-Processing on raw ECG data. The DWT allowed us to remove noise and artifacts in a different way with respect a BF filter.

The ECG signal is then ready to be processed for R-wave detection, being less affected by artifacts. The detection algorithm used is the one described by J. Pan and J. W. Tompkins in 1985 (29). For our MATLAB implementation we used the code provided by (30). In order to obtain a robust classifier it's mandatory to delete from the obtained tachograph out-of-range RR intervals deriving from artifacts or R-peaks algorithm inefficiency. Ectopic beats, arrhythmic events, missing data, and noise effects may alter the estimation of the PSD of HRV. Therefore a proper interpolation on preceding/successive beats on the HRV signal or on its autocorrelation function may decrease this error (31). All RR intervals greater than 2 seconds or lower than 0.35 seconds have been considered outliers and therefore have been removed prior to interpolation of data. The following step has been tachogram segmentation and subsequent interpolation using cubic spline at 4 Hz. This frequency has been chosen in order to guarantee high resolution in frequency domain for HRV frequency analysis (13). The segmentation consists of signal division in 30-seconds-epochs and 5 minutes overlapping records prior to each epoch.

3.3.2 Feature Extraction

Several features can be inferred from HRV variability, the ones examined for our purpose included traditional time domain features, frequency domain features, and some nonlinear analysis measures. A total of 28 features were extracted according to the most effective and explanatory among the others reported by (5), (31) and (32). Time domain features are reported in fig.3. For the aim of this project an AR model has been computed for each 5 minutes RR series; According to (33) the model order which allows an accurate estimation of the power spectrum of RR time series signal re-sampled at 4 Hz should be around 16. Thus the most representative spectral features have been computed and employed; these are reported in fig. 4.

Name	Description
RRm	Mean of 5 min RR inter-beat interval.
HRm	Mean of 5 min HR measure.
SDNN	Standard deviation of 5 min RR inter-beat interval.
RMSSD	Root mean square difference for successive RR intervals.
NN50	Number of RR intervals which differ more thann 50 ms.
CVRR	Coefficient of variation.
HTI	HRV Triangular Index.
RRmode	Mode of 5 min interbeat intervals.

Figure 3: Time domain HRV features used in this project.

HRV based on the methods of nonlinear dynamics might elicit valuable information for physiological interpretation of HRV (31). For this reason we decided to integrate some of them as explanatory variable of our model.A further step has been analyze, thus select relevant feature only. The criterion we employed in order to discriminate between relevant and non-relevant features was a correlation-based analysis. The criterion we employed in order to discriminate between relevant and non-relevant features was a correlation-based analysis. The correlation matrix C has been computed and visualized in order to seek for (1) most target-correlated features and (2) correlation be-

Name	Description
VLF	PSD computed in 0.0033 – 0.04 Hz band.
LF	PSD computed in 0.04 – 0.15 Hz band.
HF	PSD computed in 0.15 – 0.4 Hz band.
LF/HF	Low frequenncy to High frequency ratio.
Mean Frequency	Mean power density computed for each frequency band.
Spectral Entropy	Spectral Entropy measure computed for each frequency band.
Peak power	Peak power computed for each frequency band.
Peak frequency	Correspondent peak frequency computed for each frequency band.

Figure 4: Frequency domain HRV features used in this project.

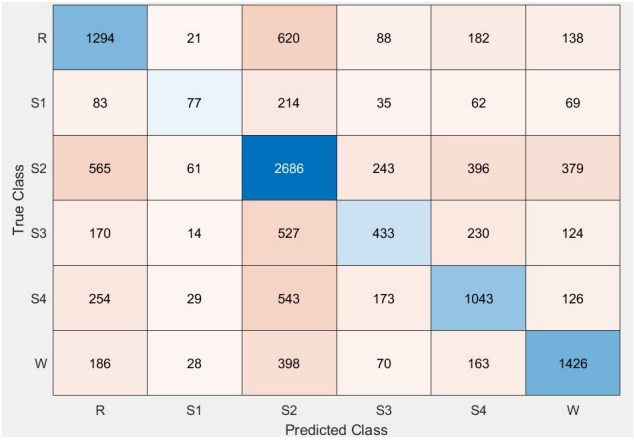

Figure 5: Confusion Matrix of our model.

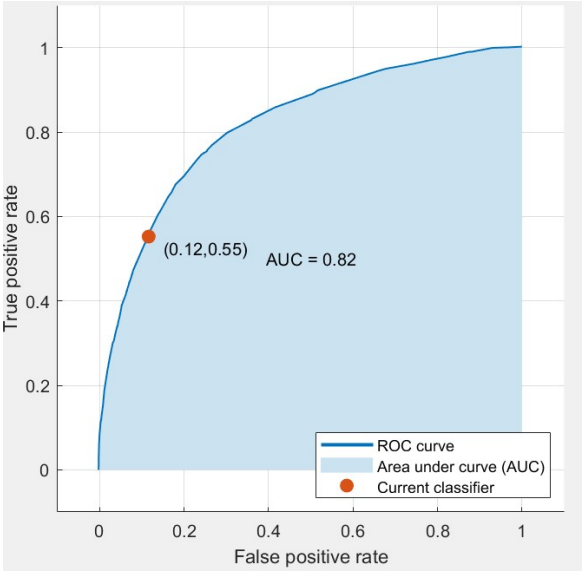

Figure 6: ROC curve of our model.

tween variables.

3.3.3 Classification

A six-classes classification problem, where classes corresponds to hypnograms drawn by experts. Classes are Wakeness 'W', Sleepstage one 'S1', sleep Stage two 'S2', Sleep stage three (or deep sleep) 'S3', stage four'S4' and REM sleep 'R'. We divided our records in a train set, corresponding to the 70% of the observations, and a test set constituting the remaining 30%. We employed then the cross-validation methodology with the aim to drastically reduce the model over-fitting, avoiding the generation of a data-dependant performances, and then a classifier, evaluating it based on its accuracy.

4 RESULTS AND CONTRIBUTIONS

After having trained and tested several classifiers and features sets, each one tuned with the best model parameters, the evaluation metrics of the best one for are reported. Our model is a KNN classifier trained with a train dataset of about 13 000 observation and tested over a set of about 5 500 observations. The accuracy reached is 54±3.5 %; The confusion matrix and ROC curve are reported in fig.5 and fig.6 respectively.

5 DISCUSSION AND CONCLUSIONS

Data collected from several subjects during sleep studies were available. A total of 25 full night of polysomnographic visual sleep staging records (hypnograms) constituting 25 different physiological signals records have been employed. Both time and frequency HRV-related features were extracted, some of them selected to explain sleep stages changes during night. A classifier was used to automatic detect sleep stages with an accuracy of . In order to improve the developed algorithm, information about a larger sample of individuals would be used, allowing better performances under several point of views. It would be possible to better evaluate the performance of the algorithm by training it on a wider set of samples which would allow to (1) create a balanced dataset, because reduction of most frequent target classes would be possible. Also a larger dataset would allow to (2) study more subjects, making it a more exhaustive research, increasing generalization capabilities. Finally a deeper research of Heart Rate Variability measures and more complex features could have explored and improved in our model as explanatory for the phenomenon.

A further direction of improvement would be the employment of plethysmography records for deducting Heart Rate Variability measures, as it is insensible to electrodes-motion artifacts, which instead characterize ECG measurements. Plethysmography directly measures blood flow and it's usually actuated through light-based sensors which constitute a pulse-oxymeter (or photoplethysmograph (PPG)). The advantage of this technique relies also in the reduced setup needed to collect the signal. Several study investigate the comparison between HRV parameters extracted from Electrocardiogram and Photoplethismogram; a classification model able to discriminate sleep stages which extract information from PPG or both ECG and PPG would be an interesting development.

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