Automatic sleep parameter computation from Activity and Cardiovascular data

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Abstract

Automatic computation of sleep parameters from data acquired with portable sensors, is a challenging problem with important clinical applications. In this paper, the Sleep Efficiency, and REM and Non-REM sleep percentages are automatically computed from ECG, Respiration and Actigraphy. The algorithm relies on two classifiers, designed to reject ambiguous data, and a regularization step that corrects the predicted number of samples on each of the considered classes. The described method achieves an estimation error of 4.5%, 9.9% and 5.5% on Sleep Efficiency, REM and NREM percentages respectively.

1 Introduction

Automatic computation of sleep parameters (SP), from data acquired in mobile environments, is an open issue that poses many challenges. Several approaches have been proposed to properly identify the different sleep stages, spectral analysis of the HRV plays a major role in many publications, where the frequency bands described in [3] have become the standard for HRV spectrum analysis. The estimation of sleep parameters/stages from multi-modal data is presented in some papers with promising results. In [4] the authors combine ACT and Cardio-Respiratory signals achieving high accuracies in Sleep and Wakefulness detection, although no proper validation data, (i.e. the hypnogram from the PSG), is used. In [5] the authors combine HRV with respiratory inductance plethysmography (RIP), achieving a k-index [1] of \( k = 0.45 \) for a 3 class discrimination (Wake, REM, NREM) and \( k = 0.57 \) for a simplified 2 class problem (Wake,Sleep).

This paper deals with the problem of automatically estimating three standard SP; i) SE, ii) REM\(_p\) and iii) NREM\(_p\) from ECG, Actigraphy (ACT) and RIP, which are easily acquired with portable sensors. The described method eliminates the need of a full Hypnogram by combining the rejection of ambiguous samples and a regularization operation.

2 Methods

The SP estimation method, displayed in Fig. 1, is composed by the pre-processing and feature extraction procedures, followed by a classification stage, designed to reject ambiguous features, and a regularization operation. The multi-modal dataset used in this work includes ECG and RIP data, obtained from PSG and ACT, acquired with a wrist actigraph, from 15 healthy volunteers. The pre-processing operations are required to reduce the movement artefacts, normalize the data across different patients and prepare it for feature extraction. After QRS complex detection, the RR signal is constructed from the detected R peaks, and downsampled to 2 Hz. Magnitude normalization and DC component removal are applied to both RIP and ACT signals.

After pre-processing, each dataset is divided in contiguous epochs of \( T = 30 \) seconds, synchronized with the ground-truth hypnogram provided by the medical staff. All the epochs corresponding to any of the 3 distinct Non-REM sleep stages were grouped into one single label. The feature vector includes the standard frequency and time domain RR features described in [3], the ACT features from [2] and mean and standard deviation of the respiratory rate. The statistical significance of the included features was assessed with a one-way ANOVA test.

The classification step relies on two classifiers that independently classify all samples into i) Sleep/Wakefulness (SW) and ii) REM/Non-REM (RN). Each classifier is designed to take into account a rejection factor (RF), rejecting a specified percentage of samples, whose classification is ambiguous. The rejection works by computing the true or estimate posterior probability of the winning class for each sample and rejecting those which are below the specified percentage.

Each classifier maps every sample into one of three labels: \( SW \in \{sl, wk, r\} \) and \( RN \in \{rs, ns, r\} \) where \( rs, ns, wk \) and \( r \) refer to REM, Non-REM, Wakefulness, Sleep and Rejected sample respectively.

During the training step, the two binary classifiers are trained with data from the 2 considered classes. However, during the test, they map samples belonging to 3 classes. Any sample from a class not predicted by the classifier will either be miss-classified or rejected. The Support Vector Classifier (SVC) with a quadratic kernel was chosen for both classification tasks.

Let us consider a binary classifier \( C \), with a reject option, which maps each sample into one of three labels \( l \in \{p,n,r\} \) where \( p, n \) and \( r \) denote Positive, Negative and Reject.

The confusion matrix\(^1\) is represented as

\[
A = \begin{bmatrix}
T_p & F_n & R_p \\
F_p & T_n & R_n
\end{bmatrix}
\]

where \( T_p, F_n, F_p, T_n, R_p \) and \( R_n \) are the True Positives, False Negatives, False Positives, True Negatives, Rejected Positives and Rejected Negatives respectively.

The positive \( (\theta_{p,i}) \) and negative \( (\theta_{n,i}) \) correction factors and the fraction of rejected samples per class \( (\omega_{p,i} \) and \( \omega_{n,i} \) are computed for each

\(^1\)The positive detection rate is computed as \( \frac{T_p}{T_p + F_p} \) and the global accuracy as \( \frac{T_p + T_n}{T_p + F_p + T_n + R_p} \).
training dataset as

\[ \theta_{p,i} = \frac{\text{TP}_i + \text{FP}_i}{\text{TP}_i + \text{FN}_i} \]  

(2)

\[ \theta_{h,i} = \frac{\text{FN}_i + \text{TN}_i}{\text{FP}_i + \text{TN}_i} \]  

(3)

\[ \omega_{p,i} = \frac{\text{RP}_i + \text{RN}_i}{\text{RP}_i + \text{RN}_i} \]  

(4)

\[ \omega_{h,i} = \frac{\text{RN}_i}{\text{RP}_i + \text{RN}_i} \]  

(5)

with \( i \in \{1, \ldots, M\} \), and \( M \) the number of training datasets. The final values are obtained averaging over \( \theta_{(p,h)} \) and \( \omega_{(p,h)} \).

The number of estimated samples on each class can be improved by correcting the number of predicted samples as

\[ N(p) = \frac{N(p)}{\theta_p} \]  

(6)

\[ N(n) = \frac{N(n)}{\theta_n} \]  

(7)

where \( N(.) \) is a counting operator, and estimating the number of rejected samples from each class as

\[ N(r_p) = \omega_p N(r) \]  

(8)

\[ N(r_n) = \omega_n N(r) \]  

(9)

The expressions for the three SP can now be written as

\[ \text{SE} = \frac{N(sl)}{\theta_l (N(sl) + N(wk))} \]  

(10)

\[ \text{NREM}_p = \frac{N(ns) - \theta_n N(ns)}{N(ns) + N(rs) + N(r) \times \text{SE}} \]  

(11)

\[ \text{REM}_p = \frac{N(ns) - \theta_n N(rs)}{N(ns) + N(rs) + N(r) \times \text{SE}} \]  

(12)

where \( \text{SE} \) is computed from the output of the SW classifier and \( \text{NREM}_p \) and \( \text{REM}_p \) from the RN classifier.

3 Results

Each subject performed a standard nocturnal PSG exam at a sleep laboratory. The PSG data was jointly acquired with ACT using a SomnowatchTM device, from Somnomedics, placed in the non-dominant wrist of the subjects, acquiring with a sampling rate of 1Hz. The core of these devices is a 3D accelerometer that measures the acceleration along 3 orthogonal axes with a configurable output format. Here, the output of the actigraph is the acceleration magnitude.

The hypnogram, obtained from the PSG by trained technicians, is used as a ground truth to identify REM sleep, Non-REM sleep and wakefulness in epochs of 30 seconds.

Fifteen adult subjects (age 44.4 ± 11 years, 10 Males, 5 Females), with no pre-diagnosed sleep disorders, participated in this study.

The SE was computed from the hypnogram for each patient. All the values of SE fell within the range 85% – 95%. These values are within the accepted range for healthy subjects, usually above 85% [6].

The three SP and the estimation error\(^2\) were computed, for each dataset using the proposed method using a leave-one-patient-out cross-validation, where each patient dataset is tested after training the algorithm with the remaining data. Table 1 shows the average value and error for each parameter, computed for several different RFs. Using a RF of 10% the average values are almost coincident with the real values. The estimation errors are 4.5% for the SE, 9.9% for the REM\(_p\) and 5.5% for the NREM\(_p\).

\(^2\)Let \( \alpha \) represent a sleep parameter, the estimation error is given by

\[ E_{\alpha} = \frac{|\alpha_{\text{true}} - \alpha_{\text{estimated}}|}{\alpha_{\text{true}}} \]

In order to test the influence of the training and test sets and to assess the generalization capability of the algorithm the following steps were performed:

1. Ten datasets were randomly selected from the pool of 15 available datasets.
2. From these 10 datasets, 5 were randomly selected to train the algorithm.
3. The SP were estimated for the remaining 5 datasets and the average error computed.

This procedure was repeated 10 times resulting in average errors of 5.7 ± 0.12, 11.9 ± 4.3 and 4.4 ± 2.3 for SE, REM\(_p\) and NREM\(_p\) respectively. These values are very similar to the ones reported in Table 1 suggesting that the reported results should be extensible to other datasets.

4 Conclusion

In this paper we propose a new method to estimate sleep parameters from RR, RIP and ACT data. The method relies on two classifiers designed to reject ambiguous data and a regularization parameter based on the a priori informations from the classifiers performance and rejection patterns.

With this method the estimation errors are ≈ 5% for SE and NREM\(_p\) and ≈ 10% for REM\(_p\).

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References

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