

Time-Frequency Analysis of Heart Rate Variability for Sleep and Wake Classification

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Abstract—This paper describes a method to adapt the spectral features extracted from heart rate variability (HRV) for sleep and wake classification. HRV series can be derived from electrocardiogram (ECG) signals obtained from single-night polysomnography (PSG) recordings. Traditionally, the HRV spectral features are extracted from the spectrum of an HRV series with fixed boundaries specifying bands of very low frequency (VLF), low frequency (LF), and high frequency (HF). However, because they are fixed, they may fail to accurately reflect certain aspects of autonomic nervous activity, which in turn may limit their discriminative power when using HRV spectral features, e.g., in sleep and wake classification. This is in part related to the fact that the sympathetic tone (partially reflected in the LF band) and the respiratory activity (modulated in the HF band) will vary over time. In order to minimize the impact of these differences, we adapt the HRV spectral boundaries using time-frequency analysis. Experiments conducted on a dataset acquired from 15 healthy subjects show that the discriminative power of the adapted HRV spectral features are significantly increased when classifying sleep and wake. Additionally, this method also provides a significant improvement of the overall classification performance when used in combination with some other (non-spectral) HRV features.

Keywords - heart rate variability; sleep and wake classification; time-frequency analysis; feature extraction.

I. INTRODUCTION

Sleep plays an important role in human health. Night-time polysomnography (PSG) recordings, along with manually scored hypnograms, are considered the “gold standard” for objectively analyzing sleep architecture and occurrence of sleep-related problems [1], [2]. PSG recordings are typically recorded and analyzed in sleep laboratories, and are usually split into non-overlapping time intervals (or epochs) of 30 seconds [1].

As shown in literature, monitoring heart rate variability (HRV) throughout the night during bedtime is helpful in sleep staging [2], [3], particularly to distinguish between rapid eye movement (REM) and non-rapid eye movement (NREM) [4], [5]. Spectral analysis of HRV, as derived from the length

variations of RR-intervals, has been widely employed in the assessment of autonomic activity during bedtime [2], [4], [6]. It traditionally involves the transformation of an HRV series into an HRV Power Spectrum Density (PSD). An HRV spectrum is typically divided into three bands, namely the very low frequency (VLF) band from 0.003 to 0.04 Hz, the low frequency (LF) band from 0.04 to 0.15 Hz, and the high frequency (HF) band between 0.15 and 0.4 Hz [7], [8]. These bands can then be used to compute certain properties such as the ‘spectral power’ of the VLF, LF, and HF components and the ratio of low-to-high frequency (LF/HF) components [2], [4], [9], [10]. It has been found that the VLF spectral power is mainly associated with long-term regulatory mechanisms; the LF spectral power is a marker of sympathetic modulation on the heart and it also reflects some parasympathetic influences when the respiratory frequency components partially fall into the LF band; the HF spectral power is related to parasympathetic activity mainly caused by respiratory sinus arrhythmia (RSA); the LF/HF ratio is an indication of sympathetic-parasympathetic balance [2], [8], [10], [11]. In particular, the HRV spectrum usually contains a peak centered around the respiration frequency that is located in the HF band; and another peak in the LF band which reflects, to a certain degree, sympathetic activation [7], [12], [13].

The parameters derived from HRV PSD can be used as features in automatic sleep staging systems [2], [3]. Previous work [3] has used HRV spectral features with fixed boundaries for sleep and wake classification. That classifier exploits the fact that sympathetic tone and the respiratory activity are modulated in different frequency bands of the HRV spectrum, and exhibit different properties during sleep and wake states, therefore allowing them to be a discrimination between them.

However, it is known that the HRV spectrum and the dominant (or peak) frequencies of the LF and HF bands are not constant but rather vary over time according to the autonomic modulations of the heart beats [8]. Hence, when fixed band boundaries are used to compute HRV spectral features, we might produce inaccurate estimates of cardiac autonomic activities. Since the discrimination of sleep stages (sleep and wake in our case), depend on these estimates, our classification accuracy will be affected. In order to avoid this issue, we will use a feature adaptation method while estimating the HRV features.

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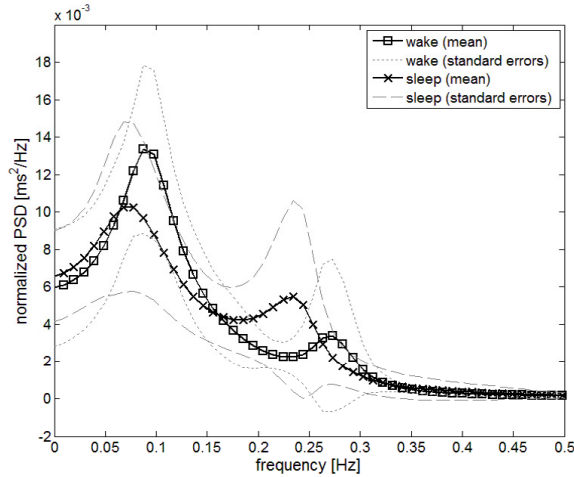


Fig. 1. An example of the mean HRV PSDs (with standard errors) for sleep and wake states of a subject.

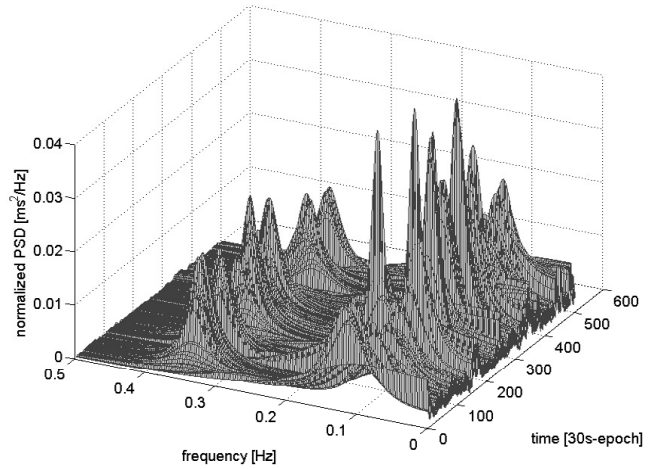


Fig. 2. An example of the normalized HRV PSD versus time (30-s epoch) of a subject.

Our method is based on “time-frequency analysis” of HRV data that has been employed in other areas such as stress detection [14], [15] and anesthesia analysis [16]. It has been widely suggested that the LF and HF boundaries are related to the peak frequency in the traditional LF band (called “LF peak frequency”) and the peak frequency in the traditional HF band (called “HF peak frequency”), respectively [15], [16]. In practice, these two peak frequencies can be estimated by determining the frequency of local maximum in the band between 0.003 and 0.15 Hz (i.e., the traditional VLF band and LF band) and in the band from 0.15 to 0.4 Hz (i.e., the traditional HF band), respectively. The working assumption is that the peaks always fall within those two bands. By centering the new bands around these peaks, instead of using fixed boundaries, we can compensate for their time-varying behavior. This should help, to some extent, to reduce within-subject and between-subject variability in the way these features express sympathetic activation and respiratory activity, and ultimately help improving sleep and wake classification. Fig. 1 illustrates an example of the mean HRV PSDs with standard errors (standard deviations) for sleep and wake states of a subject. It can be observed that, although their standard errors overlap a lot, their mean values perform not the same in different frequency ranges. This might provide an opportunity of discriminating between sleep and wake states. Fig. 2 illustrates the time variation of the HRV PSD for a subject. It visually shows that the HRV PSD is varying over time.

II. METHOD

Fig. 3 illustrates a block diagram describing the feature adaptation method proposed in this paper used for sleep and wake classification. Each block will be explained further in the remainder of this section.

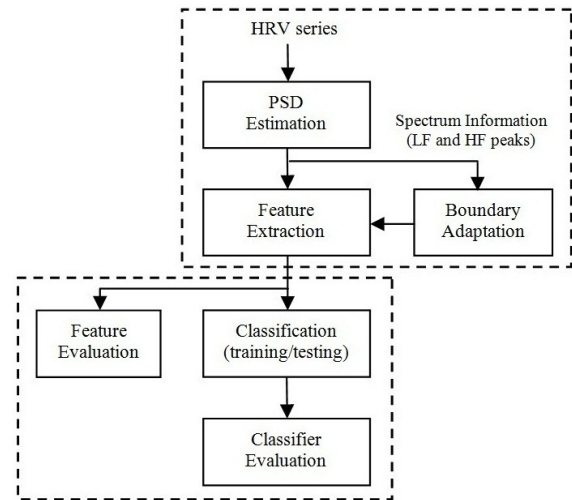


Fig. 3. Block diagram of the feature adaptation method, used for sleep and wake classification.

A. Data

Fifteen healthy subjects, including 5 males and 10 females with age 31.0 ± 10.4 (mean \pm standard deviation), were recruited to participate in the experiment. A subject was considered “healthy” if his/her Pittsburgh Sleep Quality Index (PSQI) was less than 6. Among the 15 subjects, 9 were monitored in the Sleep Health Center, Boston, USA in 2009 and 6 subjects were monitored in the Philips Experience Lab, Eindhoven, the Netherlands in 2010. Full PSG (Alice 5 PSG, Philips Respironics) was recorded for each subject according to the American Academy of Sleep Medicine (AASM) guidelines [17]. ECG data was recorded with a modified V2 lead, sampled at 500 Hz. Sleep stages were manually scored by an expert according to the AASM guidelines. Based on the scores of the 15 participants, we recorded a sleep efficiency of $92.3\% \pm 3.8\%$.

B. HRV Spectrum

In order to calculate the HRV PSDs, RR-intervals must first be computed from the ECG signals. In our study, the following steps can be performed in order to obtain an RR interval series:

- A peak detector, based on the filter-bank algorithm [18], is used to locate the R peaks, yielding an RR-interval series.
- The very short (less than 0.3 seconds) and long (more than 2 seconds) RR intervals (usually caused by ectopic heart beats, misidentification of R peaks, or badly attached electrodes during measurement) are removed.
- The RR-interval series is normalized with respect to its average amplitude (divided by the mean value).
- The resulting series is then “re-sampled” at 4 Hz by using linear interpolation.
- Finally, the PSD is estimated with an autoregressive (AR) model, where the order is adaptive and automatically determined by Akaike’s information criterion (AIC) [19] and is limited to 15.

C. Time-Frequency Analysis

As explained in Section I, the use of the fixed boundaries in HRV spectrum may not be appropriate to accurately represent different states of the autonomic nervous system and further to classify sleep and wake. The respiratory frequency, and therefore the corresponding peak in the HF band vary in time; likewise, the peak corresponding to the sympathetic tone in the LF band also varies, reflecting differences in the autonomic activation during sleep. By applying a time-frequency analysis the boundaries which define each band can be dynamically adapted so that the frequency components can be more correctly assigned to the corresponding bands. The boundary adaptation was performed in a relation with the LF and HF peak frequencies (changing over time) that can be estimated before feature extraction. Fig. 4 illustrates an example of a filled contour plot of the HRV spectrum versus time, in which the LF peak and the HF peak frequencies vary over time.

By re-defining the boundaries of the LF and HF bands for each epoch, we can overcome the issues mentioned above. This can be achieved in the following way:

- The new HF* band is centered on the HF peak frequency [14], [15] with a constant bandwidth of 0.1 Hz [20]. This choice reflects the observation found after analyzing the HRV PSDs of all 15 subjects that most of the frequency components related to RSA lie within a bandwidth of 0.1 Hz. A larger bandwidth (usually 0.25 Hz) was used in other work [14], [21], but we found that in some occasions it also includes the overlapping components from its adjacent band (i.e., the LF band).
- The new LF* band is centered on the dominant frequency that is found in the traditional LF band, with a bandwidth of 0.11 Hz (similar to the traditional definition).
- The VLF* band is defined from its traditional lower limit of 0.003 Hz up to the lower limit of the LF band.

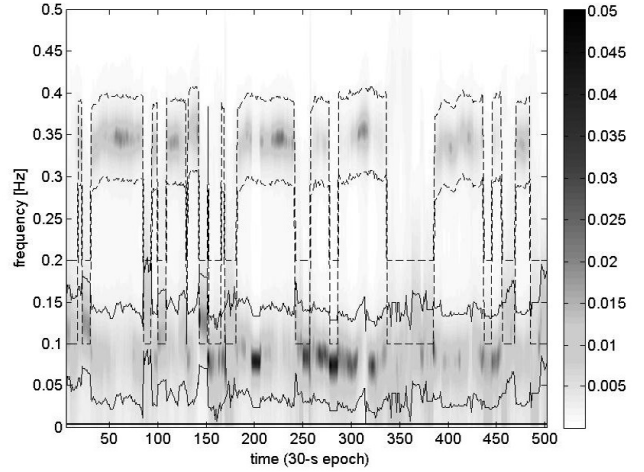


Fig. 4. HRV spectrum versus time (30-s epoch) of a subject. The limits of the new HF* and LF* bands are plotted in dash and solid curves, respectively. The lower boundary of the new VLF* band (at 0.003 Hz) is plotted as a bold-solid line.

Fig. 4 illustrates an example of the adapted boundaries calculated for a given subject. It should be noted that the LF* and HF* bands may overlap in some epochs. This occurs when the LF and HF peaks are too close to each other or when there is no HF peak. The latter one often occurs during REM sleep [22] so that the new HF* band will be centered on the local maximum (according to our definition) that is usually the first frequency point in the traditional HF band since the spectral power in this band is usually decreasing over frequency.

D. HRV Feature Extraction

After determining the bands we can finally extract HRV-related features which can be used for sleep and wake classification. In our study we computed the logarithm of the spectral power in the VLF*, LF* and HF* bands (from here on indicated as HRV_VLF , HRV_LF , HRV_HF) and, in addition, the ratio between the spectral powers of the LF* and the HF* bands (HRV_LF/HF).

Note that, before computing the logarithm, the power of each band should first be normalized. This can be achieved by dividing the power in the VLF*, LF*, and HF* bands either by the total spectrum power [9], [23] or by the total spectrum power minus the power in the VLF* band [4], [6]. Since we did not observe any significant difference in the final result we will present the results obtained with the first definition.

E. Spectrum Information

As mentioned before, the determination of the new boundaries requires knowledge of spectrum information (here LF and HF peak frequencies), which must be obtained before extracting the spectral features. The LF peak frequency can be estimated by detecting the location of the peak in the HRV spectral range from 0.003 to 0.15 Hz. The HF peak frequency can be estimated from a respiratory effort signal simultaneously recorded with the PSG data or it can be derived

from the HRV series directly by searching for the peak in the range between 0.15 and 0.4 Hz. In this study, to avoid using an additional sensor modality, we used the latter approach.

F. Discriminative Power

A Hellinger distance metric [24] is employed to evaluate the discriminative power (i.e., separability) of the HRV spectral features in classifying sleep and wake. It is estimated by computing the amount of overlap between two probability density estimates in a binary class problem, expressed as:

$$D_H(p, q) = \sqrt{1 - \sum \sqrt{p(x)q(x)}} \quad (1)$$

where $p(x)$ and $q(x)$ are the probability density estimates of the feature values given class *sleep* and *wake*, respectively. In its most basic form, these density estimates can be computed by means of a normalized histogram with either a fixed number of bins or a specific bin size. In our study we computed histograms with 100 bins. A larger Hellinger distance reflects a higher discriminative power in separating the two classes.

G. Sleep and Wake Classification

It has been demonstrated that a Linear Discriminant- (LD-) based classifier is appropriate for the task of sleep and wake classification [3]. To assess the performance of this classifier, conventional measures of specificity (proportion of correctly identified actual wake epochs) and sensitivity (proportion of correctly identified actual sleep epochs) used in binary classification are not the most adequate criteria. The reason is that the number of epochs of one class (*wake*) during a whole-night recording will naturally be much smaller than the number of epochs of the other class (*sleep*), in what is usually called “imbalanced class distribution”. The Cohen’s Kappa coefficient of agreement κ [25] not only allows for a better understanding of the general performance of the classifier in correctly identifying both classes, but also allows for a better representation of the imbalanced problem [3]. Although it indicates, with a single metric, how well a classifier performs for both classes, evaluating a method with this single measure might not be sufficient. An alternative is to use an ROC curve which simply plots the “true positive rate” (i.e., sensitivity) versus “false positive rate” (i.e., one minus specificity) thus illustrating the classifier’s performance over the entire solution space by means of varying a decision threshold [26]. However, the ROC curve has been shown to be over-optimistic when there is a heavy imbalance between the two classes [27]. Hence, a so-called Precision-Recall (PR) curve is recommended instead. When comparing different classifiers, a larger area under the PR curve (AUC-PR) indicates a better performance. In this study, the two measures (κ and AUC-PR) were used to evaluate the performance of sleep and wake classification with and without HRV-band adaptation.

In addition, we combined the HRV spectral features with some other (non-spectral) HRV features selected from the feature set used in previous work [3], such as time domain features [2], [3], nonlinear measures extracted using Detrended Fluctuation Analysis (DFA) [28] and Sample Entropy [29].

This serves the purpose of examining whether the feature adaptation method described in this paper can help improving the classification performance when combined with other important features. Note that all these features were extracted from the same HRV series. Also, we compared the results with those obtained using actigraphy, a well-known feature for sleep and wake classification [3] and which is used as reference in this study.

III. RESULTS

A leave-one-subject-out cross validation (LOOCV) procedure was conducted to assess the discriminative power of the HRV spectral features and also to assess the performance of our classifier. Table I compares the discriminative power of the HRV spectral features computed using the traditional, fixed boundaries and using the adaptive boundaries. This table shows that, after using the method proposed in this paper, the discriminative power of the HRV spectral features are significantly increased (after a Wilcoxon Signed-ranks test with $p < 0.01$). For comparison, the table indicates the Hellinger distance of the actigraphy feature “activity count” (AC). Although the feature adaptation helps improving the discriminative power of the HRV spectral features, it is still relatively lower than that of the actigraphy feature.

Table II compares the classification performance obtained with and without boundary adaptation. It is interesting to note that the value of κ is similar when using HRV spectral features with and without adaptation. This seems to contradict the significant increase in discriminating power found with the Hellinger distance. Upon closer inspection we found that actually that occurs only for that single point in the solution space. In fact, when evaluating the performance over the entire solution space with AUC-PR we see an increase 0.30 to 0.36. The PR curves plotted in Fig. 5 clearly show that, in general, the adapted features are better than the original ones, particularly in the region when recall is lower than about 0.31. Note that the PR curves were obtained by pooling the LOOCV results of all subjects.

After combining the HRV spectral features with the additional HRV features indicated earlier, we see a significant increase in κ from 0.44 ± 0.25 (with fixed boundaries) to 0.48 ± 0.24 (with adaptive boundaries), where significance was tested with a paired Wilcoxon test ($p < 0.01$). Likewise, the pooled AUC-PR metric improves when using boundary adaptation. As the table indicates, the standard deviations of κ are relatively large compared to the mean values, indicating large between-subject variations in the classification results. The significance tests were performed pair-wise for each subject, thus indicating that boundary adaptation improved the classification performance in almost all subjects. Finally, for comparison purposes, the table also indicates the classification results using the actigraphy feature. As expected, it slightly outperforms the HRV features (with adaptation). Nevertheless, it should be kept in mind that although actigraphy is particularly adequate for sleep and wake classification, it requires the usage of an additional sensor [3].

TABLE I
COMPARISON OF DISCRIMINATIVE POWER

Feature	Hellinger Distance		Wilcoxon p value
	Without Adaptation (Fixed Boundaries)	With Adaptation (Adaptive Boundaries)	
HRV_VLF	0.19 ± 0.02	0.22 ± 0.01	0.001
HRV_LF	0.25 ± 0.01	0.26 ± 0.01	0.004
HRV_HF	0.23 ± 0.01	0.29 ± 0.01	0.001
HRV_LF/HF	0.22 ± 0.01	0.27 ± 0.01	0.001
AC	0.49 ± 0.01		/

TABLE II
COMPARISON OF CLASSIFICATION PERFORMANCE

	Actigraphy Feature	HRV Spectral Features*		HRV Features**	
		Without Adaptation (Fixed Boundaries)	With Adaptation (Adaptive Boundaries)	Without Adaptation (Fixed Boundaries)	With Adaptation (Adaptive Boundaries)
Accuracy	$94.8 \pm 2.7\%$	$90.3 \pm 9.0\%$	$89.3 \pm 10.7\%$	$89.9 \pm 8.5\%$	$93.1 \pm 4.2\%$
Sensitivity (Recall)	$46.8 \pm 19.6\%$	$32.7 \pm 14.1\%$	$33.9 \pm 13.8\%$	$50.6 \pm 13.4\%$	$49.7 \pm 19.2\%$
Specificity	$99.1 \pm 1.0\%$	$95.4 \pm 9.6\%$	$94.1 \pm 11.6\%$	$93.3 \pm 8.9\%$	$96.6 \pm 3.3\%$
Precision	$82.8 \pm 16.4\%$	$58.5 \pm 33.1\%$	$57.4 \pm 32.4\%$	$52.6 \pm 33.6\%$	$60.1 \pm 29.9\%$
Kappa Coefficient (κ)	0.53 ± 0.15	0.33 ± 0.18	0.33 ± 0.19	0.44 ± 0.25	0.48 ± 0.24
(Pooled) AUC-PR	0.67	0.30	0.36	0.51	0.54

*The HRV spectral features consist of HRV_VLF , HRV_LF , HRV_HF , and HRV_LF/HF .

**The HRV features consist of the HRV spectral features and the other HRV features selected from the feature set used in [3].

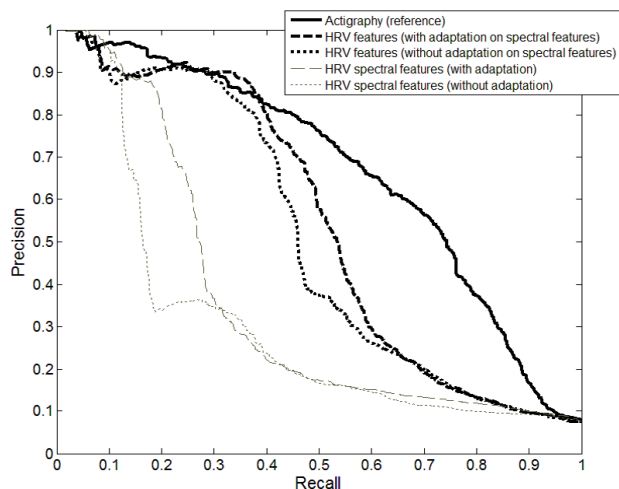


Fig. 5. Comparison of pooled PR-curves for sleep-wake classification using actigraphy (bold-solid curve), HRV features containing the spectral features with adaptation (bold-dash curve) and without adaptation (bold-dot curve), and HRV spectral features with adaptation (dash curve) and without adaptation (dot curve). Here *wake* is considered as the positive class.

IV. DISCUSSION

The method described in this paper shows a time-varying adaptation of the HRV spectral features that offer higher discriminative power in classifying sleep and wake states. The features are used as inputs to a sleep-wake classifier. We re-defined the spectral boundaries which are adapted to the

spectrum information (related to autonomic activity) that can be obtained before feature extraction. This is due to that we aim at defining a band that can better capture certain aspects of physiology during sleep, for example, respiratory activity (in the HF band) and sympathetic activation (in the LF band). For this purpose, we used an HF* bandwidth of 0.1 Hz instead of the 0.25 Hz used in the traditional HF band. Alternatively, rather than using a constant HF bandwidth (0.1 Hz) in this study, it could be determined by measuring and analyzing respiratory effort signals [15], but the use of an additional sensor is required.

Additionally, we observed that the LF and HF bands can overlap under different circumstances: when the peak in the LF and in the HF band are close to each other, when there is no clear peak in the HF band, or when the respiratory-frequency peak is below 0.15 Hz and therefore lies in the traditional LF band. The overlaps could be observed in Fig. 4. In these situations, the overlapped part of the spectrum components will actually be taken in the features computed for both the LF* and the HF* bands. This may have an impact in the classification process, reducing the accuracy of the classifier. Therefore, a more accurate method is needed for defining a threshold which separates the two bands rather than just using fixed bandwidths.

Finally, as we mentioned, the respiratory information was derived from the HRV data. Although this may not be as good an estimation as a direct measure of respiratory effort, it has been proven to be an accurate estimate of respiratory rate [2], [3]. More importantly, it does not require using an

additional sensor modality in this type of applications. Besides, the respiration rate can also be estimated from the ECG-derived respiratory (EDR) signal (i.e., the “envelope” of the ECG signal that reflects the respiration-induced modulation) [30]. This method is suggested to be further investigated.

V. CONCLUSION

In this study, we used a feature adaptation method based on the time-frequency analysis to adapt HRV spectral features. It aims at providing more accurate estimates of the sympathetic and respiratory activities in order to obtain a better sleep and wake classification. By adapting the spectral boundaries according to the peaks found in high- and low-frequency bands of the HRV PSD, the adapted features will have a larger discriminative power in distinguishing between sleep and wake states. Moreover, the adaptation also improves classification performance, especially after combining the HRV spectral features with the other existing HRV features, achieving a Cohen’s Kappa coefficient of 0.48 ± 0.24 (overall accuracy of $93.1 \pm 4.2\%$, sensitivity of $49.7 \pm 19.2\%$, specificity of $96.6 \pm 3.3\%$, and precision of $60.1 \pm 29.9\%$). However, since occasionally the adapted boundaries (and the HF* bandwidth) may still overlap, it is suggested to further explore a method that can better optimize these boundaries.

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