Automatic Detection of Slow-Wave-Sleep Using Heart Rate Variability

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Abstract

In this study, we used heart rate variability parameters to first characterize, and then automatically detect Slow-Wave-Sleep (SWS). First, a wavelet transform was used to decompose equally sampled RR interval series into their time dependent spectral components: Very Low Frequency (VLF) 0.005-0.04Hz, Low Frequency (LF) 0.04-0.15Hz, and High Frequency (HF) 0.15-0.45Hz.

Then, the known decrease in LF power during SWS sleep was confirmed, and a linear relation between the average LF/HF balance throughout the night, and the balance during SWS, was found. Also similar behaviour was found with VLF power and VLF/HF ratio.

Finally, a decision algorithm with two criterions was defined using a training set of ECG recordings, and applied on a test set. Results summed to 80% correct identification of SWS. Limitations of the study, as well as inherent differences between SWS definitions based upon EEG and ECG, are discussed.

1. Introduction

Nocturnal sleep time is subdivided into cycles. Each cycle repeats 4-5 times a night in healthy subjects, and each consists of a cascade of sleep stages, normally in the same order of occurrence (but with different proportions during the night). Sleep stages are determined according to a set of rules defined by Rechtschaffen and Kales (R&K) [1] based on 3 bio-signals: electroencephalogram (EEG), electromyogram (EMG), and electrooculogram (EOG). It is accustomed to define 3 stages of existence: Wake, REM sleep and Non-REM sleep. The later is further subdivided into Light Sleep (LS - sleep stages 1 and 2), and Slow Wave Sleep (SWS - sleep stages 3 and 4).

The assessment of the normality of sleep and sleep structure are commonly done in a sleep laboratory, using an expensive, and uncomfortable sleep study (polysomnography), which involves the recording of various bio-signals including EEG, EOG, EMG, ECG, pulse oximetry, and various breathing related signals. These tedious studies are the reason for the wide search for alternative methods of sleep assessment, and for screening tests that might partially reduce number of full sleep studies [2,3].

In this search of alternative methods, studies have already shown that the ECG signal alone contains relevant information regarding sleep (e.g. sleep onset and arousals from sleep during the night [4]), sleep disturbances (e.g. detection of apneic events during the night [5]), and sleep structure (e.g. differences between SWS and other sleep stages [6]). The information regarding sleep structure can be uncovered by spectral analysis of the RR interval signal. Studies have shown that HF percentage of total power is increased during SWS at the expense of a reduction in the LF power percentage [6]. Also, studies have shown that the balance of powers LF/HF during the night is usually above unity, but during SWS it decreases below unity in normals, and remains above unity in apneic subjects [6,7]. However, in these studies, measurements were made on isolated segments of sleep that had first been clearly identified as belonging to a certain sleep stage, and then analysed.

In the present study we are trying to do the opposite, i.e. first measure the spectrum continuously during the entire night, with no a priory knowledge of sleep stages. Then, analyse the power distribution as a function of time in general, and specifically during SWS, and finally try to identify SWS from temporal spectral behaviour.

2. Methods

The study included 34 adult subjects (age 35±15, 20 males, 14 females), arbitrarily selected from the typical adult population referred to a sleep study for a multitude of reasons. Only children (under 15 years of age) and subjects with any heart related disease were rejected. Data from 17 (arbitrarily chosen) served for the development of the algorithm (training set) and the other half served to validate the detection method (test set).

All subjects underwent a full sleep study including recordings of the following signals: 2 central EEG (digitised at 100Hz), 2 occipital EEG (100 Hz), chin and tibialis EMG (100 Hz), left and right EOG (100 Hz), ECG (200 Hz), abdomen and thorax effort (10 Hz), oxygen saturation (1 Hz), nasal air flow (100 Hz). All studies were monitored off-line and sleep stages were determined according to standard R & K criteria by a sleep expert. Apnea events and other sleep disturbances were also marked. This staging was the reference against

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which we later examined our automated SWS detection algorithm.

The automated algorithm consisted of the following steps: (1) Detect R wave peaks in all ECG files using an automated algorithm. Create an equally sampled RR intervals series (RRI). (2) Time-dependant spectral analysis of the RRI series using the wavelet transform algorithm described in [8,9]. The results of the transform created 3 arrays which describe the development in time of the: VLF power (0.005-0.04Hz), LF power (0.04-0.15Hz), and HF power (0.15-0.45Hz). (3) Derive and define a set of rules for automated detection of SWS, from the training set arrays. (4) Apply the set of rules on both, the training and the test sets.

3. Results

The output of the wavelet transform of the RRI series of subject L03 is shown in figure 1, together with the sleep stages as determined by standard R &K criteria. The plot shows the LF power, as well as its ratio with respect to the HF power, as function of time (the time unit is a sleep epoch = 30 seconds). Note that during SWS (stages 3 & 4 – marked bold), the LF/HF balance, and LF power, reach their lowest values.

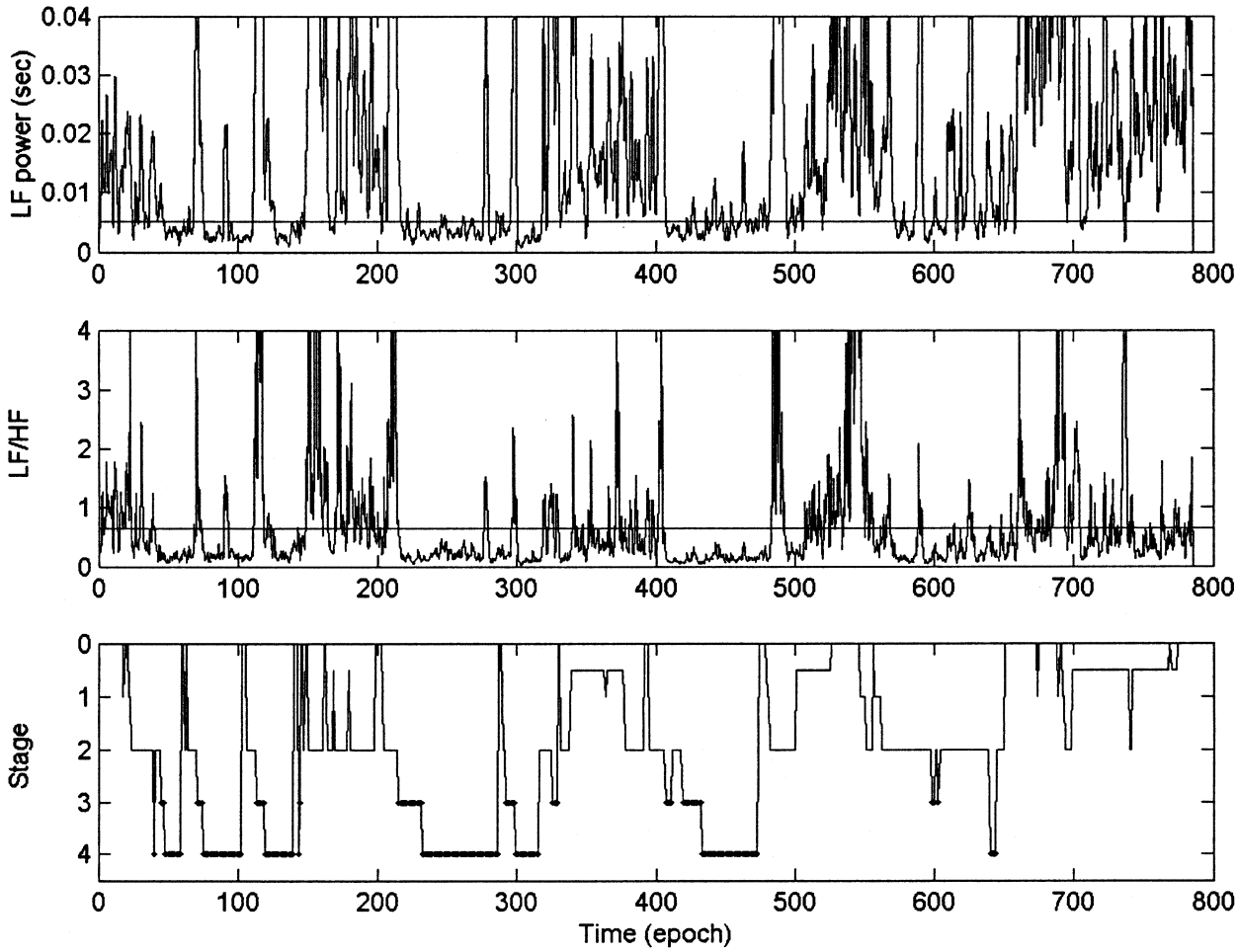

Figure 1: Graphic illustration of the limits set for the algorithm criteria. Top plot shows LF power as sleep progresses. Horizontal line indicates threshold below which is one third of LF values. Middle plot shows LF/HF ratio during the night. Horizontal line shows the calculated expected ratio according to whole night average ratio. Lower plot depicts sleep stage as a function of time as determined by R & K criteria (see text). 0 is for wake and movement time, 0.5 for REM, 1 and 2 for LS, and 3 and 4 for SWS. Note the good agreement between periods under the horizontal lines and SWS. Also note that sleep stage 2 at the end of night has boundary conditions with regards to algorithm criteria.

Table 1. Average absolute power values and standard deviation.

	SWS	LS	REM
VLF	0.014±0.009	0.031±0.021*	0.036±0.026*
LF	0.010±0.009	0.020±0.015*	0.021±0.013*
HF	0.013±0.014	0.016±0.016+	0.015±0.013

* Significant increase compared to SWS $p<0.001$
\+ Significant increase compared to SWS $p<0.05$

Average LF power and HF power during SWS have shown significant decrease ($p<0.001$, $p<0.05$ respectively) for all subjects, using one-tail-paired t-test. As shown in table 1, the VLF power exhibits a similar significant decrease in power during SWS.

Furthermore, figure 2 shows the average LF/HF balance during SWS, against the average balance throughout the entire night. Each subject is represented by one point in the graph. As shown by the regression line, a linear relation exists between the two average balances. This relation was later used to predict the expected LF/HF balance during SWS from the average balance values during the night. Similar relations (but with different slope values) exist between the balance during other sleep stages and whole night average. A summary of these results can be found in table 2. Note again that the ratio VLF/HF has similar stage-dependent behavior, but with slightly different slopes.

Using these results, we formulated two criteria by which our algorithm defines SWS. The first criterion requires that the balance between the locally averaged LF (or VLF) power and the locally averaged HF power be below a limit determined per each subject. The limit was set between the expected balance during SWS and the expected balance during LS.

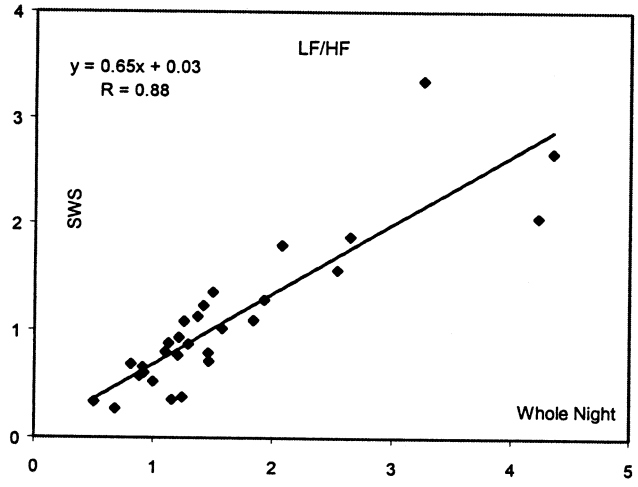

Figure 2: Linear regression of LF/HF ratio during SWS and the ratio during whole night for all subjects in training set.

Expected values were calculated using the relations found (by linear regression) between whole night balance and the balance during the sleep stage (different for SWS and LS – see table 2). The second criterion is based on the significant LF (or VLF) power decrease during SWS, and on the typical abundance of SWS, which is about one quarter of total sleep time. Taking the LF power measured during the night, the second criterion was met when LF (or VLF) power was within the lower third of values. - Any period in time that met both criterions, was marked as SWS.

Applying the two criteria on signals recorded during the whole night gave 82% and 80% correct identification in the training set and test set, respectively (See table 3 for test set results). Most of missed classifications (~70%) of non-SWS were during stage 2 (13% out of 19% in test set), typically at the second half of night. The lower correct classification per subject was 65%.

Table 2. Linear regression (R value)

	LF/HF	VLF/HF
SWS vs. Whole night	y = 0.65x + 0.03 (R = 0.88)	y = 0.52x + 0.14 (R = 0.91)
LS vs. Whole night	y = 1.01x + 0.02 (R = 0.98)	y = 0.84x + 0.31 (R = 0.95)
REM vs. Whole night	y = 1.35x - 0.27 (R = 0.89)	y = 1.33x - 0.31 (R = 0.84)

4. Discussion

In this study, a wavelet transform was used to decompose RRI series into its spectral components as a function of time. Power in each of 3 bands VLF, LF, and HF was calculated and used to confirm the known results of significant LF power decrease during SWS (as-well-as non-significant HF power decrease). In addition we found that VLF power also significantly decreases during SWS.

A linear relation between LF/HF or VLF/HF balance during the whole night and the balance values during SWS, as well as during other sleep stages, was found. A combination of these results was used and allowed for correct classification of 80% of SWS and non-SWS epochs during the night, in the test set.

The same results were obtained when regrouping our subjects into apneic subjects and non-apneic subjects.

In some subjects we noted that changes in HRV parameters preceded the SWS related changes in EEG, by 1-3 epochs. This time difference may be explained by the different origin of the EEG and ECG signal, although some of the upper centers of the central nervous system that are active through human sleep also play a role in the autonomic functioning. This difference may pose an inherent limitation on the maximum agreement that can

be reached between the two methods, as the autonomic nervous system is also affected by sources not directly related to the central nervous system.

A non-inherent limitation in this study was the relatively low ECG sample rate (200Hz), which was imposed by the available sleep laboratory system. Also, improvement may be achieved by defining thresholds that adapt during the night to the changing LF power and LF/HF balance. This may especially help with the miss-classification in late episodes of SWS where it seems that LF power as well as LF/HF balance increase (on average).

Further work is yet needed to characterize the difference between LS and REM using HRV parameters. However, the promising results obtained in previous studies (using similar time dependent spectral tools) that showed detection of sleep onset [4], arousal periods during sleep [10], and apnea events [5], together with the results presented in this study, may be combined to build an alternative description of sleep structure and sleep disturbances, using HRV parameters. This description might provide a physiological interpretation of sleep stages.

Table 3: Classification results for the test set:

R & K Algorithm results	SWS	Non-SWS (stage 2)
SWS	78	19 (13)
Non-SWS	22	81

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