

Differentiating between light and deep sleep stages using an ambulatory device based on peripheral arterial tonometry

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Abstract

The objective of this study is to develop and assess an automatic algorithm based on the peripheral arterial tone (PAT) signal to differentiate between light and deep sleep stages. The PAT signal is a measure of the pulsatile arterial volume changes at the finger tip reflecting sympathetic tone variations and is recorded by an ambulatory unattended device, the Watch-PAT100, which has been shown to be capable of detecting wake, NREM and REM sleep. An algorithm to differentiate light from deep sleep was developed using a training set of 49 patients and was validated using a separate set of 44 patients. In both patient sets, Watch-PAT100 data were recorded simultaneously with polysomnography during a full night sleep study. The algorithm is based on 14 features extracted from two time series of PAT amplitudes and inter-pulse periods (IPP). Those features were then further processed to yield a prediction function that determines the likelihood of detecting a deep sleep stage epoch during NREM sleep periods. Overall sensitivity, specificity and agreement of the automatic algorithm to identify standard 30 s epochs of light and deep sleep stages were 66%, 89%, 82% and 65%, 87%, 80% for the training and validation sets, respectively. Together with the already existing algorithms for REM and wake detection we propose a close to full stage detection method based solely on the PAT and actigraphy signals. The automatic sleep stages detection algorithm could be very useful for unattended ambulatory sleep monitoring assessing sleep stages when EEG recordings are not available.

Keywords: peripheral arterial tonometry, deep sleep stages, light sleep stages, REM sleep, sleep apnea, minimum least-squares optimization

Introduction

Non-rapid eye movement (NREM) sleep was traditionally classified into four stages, where stage 1 was defined as drowsiness (just falling asleep), stage 2 as light sleep, and stages 3 and 4 as deep sleep, which is considered the more refreshing sleep. Both stages 1 and 2 NREM sleep, classified as light sleep, are characterized by theta EEG activity. In stage 1 NREM there may be slow vertical eye rolling while stage 2 of NREM is characterized by sleep spindles and/or K complexes, no eye movements and reduced EMG activity. Stages 3 and 4 NREM sleep, classified as deep sleep, are characterized by delta EEG activity (which is the reason for the common term describing these stages as slow-wave sleep), no eye movements (although the EOG channels commonly show EEG artifacts) and even further diminished EMG activity (Lavie *et al* 2002, Rechtschaffen and Kales 1968). Given the more restorative nature of deep sleep, and the common findings of increased deep sleep following sleep deprivation or treatment for sleep disorders, it may be of substantial clinical importance to distinguish between light and deep sleep stages.

Recently, the AASM Visual Scoring Task Force re-examined these rules and came up with a new terminology for sleep stages. Since no evidence was found to justify dividing slow-wave sleep into two stages, i.e. stages 3 and 4 of NREM sleep, it was proposed to combine these into a single stage of deep sleep (Silber *et al* 2007). However, despite coming up with new scoring criteria, as with its predecessor (Rechtschaffen and Kales 1968) the activity of the autonomic nervous system (ANS) still does not play a major role in scoring sleep stages, despite increasing evidence for substantial and differential activities of this system in the various sleep stages. In other words, regardless of the EEG changes measured via surface electrodes, light and deep sleep seem to differ by autonomic activations manifested predominantly as higher and more stable parasympathetic activity in deep sleep than light NREM sleep (Dvir *et al* 2002, Herscovici *et al* 2007, Lavie *et al* 2000, Narkiewicz *et al* 1998a, 1998b, Penzel *et al* 2000, 2003, Pressman and Fry 1989, Villa *et al* 2000, Virtanen *et al* 2007). Thus, ANS such as heart rate, heart rate variability or peripheral arterial tone may be of significant importance in evaluating the quality of NREM sleep.

The Watch_PAT100 (WP100) is an ambulatory sleep recorder, which is based predominantly on recordings of the peripheral arterial tone (PAT) signal and pulse rate (two important outputs of the autonomic nervous system), actigraphy and pulse oximetry (Bar *et al* 2003, Penzel *et al* 2004a, 2004b, Pillar *et al* 2003). It has been shown to accurately detect sleep versus wakefulness (Hedner *et al* 2004) as well as to detect REM sleep (Dvir *et al* 2002, Herscovici *et al* 2007, Lavie *et al* 2000). Given the well-established changes of the autonomic nervous system characteristics in patients with obstructive sleep apnea (Aydin *et al* 2004, Brooks *et al* 1999, Jo *et al* 2005, Narkiewicz *et al* 1998, Narkiewicz and Somers 1997, Penzel *et al* 2000, 2003, Pepin *et al* 1994), the WP100 has been tested on both normal subjects and patients with OSA (Bar *et al* 2003, Dvir *et al* 2002, Hedner *et al* 2004, Herscovici *et al* 2007, Lavie *et al* 2000, Penzel *et al* 2004a, 2004b, Pillar *et al* 2003). However, the ability to distinguish between light sleep and deep sleep based on autonomic nervous system outputs monitored by the WP100 has not been examined. Since deep sleep has been shown to be associated with increased parasympathetic activity (such as heart rate and heart rate variability), and more regular and stable heart rate (Berlad *et al* 1993, Bonnet and Arand 1997, Brandenberger *et al* 2005, Burgess *et al* 1999, Busek *et al* 2005, Elsenbruch *et al* 1999, Ferri *et al* 2000, Kirby and Verrier 1989, Kodama *et al* 1998, Liguori *et al* 2000, Monti *et al* 2002, Negoescu and Csiki 1989, Noll *et al* 1994, Okada *et al* 1991, Penzel *et al* 2003, Pressman and Fry 1989, Somers *et al* 1993, Takeuchi *et al* 1994, Trinder *et al* 2001, Villa *et al* 2000), we sought to develop an algorithm which will allow detecting and distinguishing light from deep

Table 1. Demographic and sleep data for the training and validation sets.

| | Training set ($N = 49$) | Validation set ($N = 44$) | P value |
|------------------------|---------------------------|-----------------------------|-----------|
| Mean RDI | 26.9 ± 19.09 | 34.0 ± 30.28 | NS |
| Mean age | 44.7 ± 13.58 | 43.5 ± 14.67 | NS |
| Mean BMI | 27.4 ± 5.31 | 28.7 ± 6.23 | NS |
| Mean arousal index | 33.0 ± 22 | 26.6 ± 14.0 | NS |
| Mean deep (%) | 21 ± 9 | 20.9 ± 10 | NS |
| Mean REM (%) | 21 ± 7 | 19.4 ± 6 | NS |
| Total sleep time (min) | 351 ± 49 | 357 ± 61 | NS |
| Mean SaO ₂ | 86 ± 19 | 84 ± 21 | NS |
| Desaturation index | 22 ± 23 | 21 ± 23 | NS |
| Sleep efficiency | 0.83 ± 11 | 0.84 ± 15 | NS |

sleep solely based on the PAT signal (i.e. the vascular tone and the pulse rate both are channels of the WP100). This allowed us to test the hypothesis that autonomic nervous system output changes are sleep-stage dependent.

Materials and methods

Subjects

The study group consisted of two separate sets: a training set, used to develop the algorithm, and a separate validation set, used to validate the algorithms. The training set consisted of 49 adult patients (27 males) referred to the Technion Sleep Disorders Center for evaluation of presumed obstructive sleep apnea syndrome (OSAS), and an additional 6 young healthy volunteers (3 males) without any complaints of sleep disruption, daytime sleepiness, or snoring, recruited via advertisements in the Faculty of Medicine of the Technion, Haifa. The healthy volunteers were free of any disease and were on no medications. The exclusion criteria for the suspected OSAS patients were permanent pacemaker, non-sinus cardiac arrhythmias, peripheral vasculopathy or neuropathy, severe lung disease, S/P bilateral cervical or thoracic sympathectomy, finger deformity that precluded adequate sensor application, use of alpha-adrenergic receptor blockers (24 h washout period required), alcohol or drug abuse during the last 3 years.

The validation set consisted of 44 adult OSAS patients (30 males) and 10 young healthy volunteers (8 males) recruited in the same manner as the training set and according to the same inclusion and exclusion criteria. The study was approved by the Rambam Medical Center Committee for studies in human subjects, and patients signed an informed consent form prior to participation.

The training and validation groups did not differ statistically in RDI, age, BMI desaturation index, mean SaO₂ values, arousal index, percentage of deep sleep, percentage of REM sleep and total sleep time (see table 1).

Protocol

All participants underwent a whole night polysomnography (PSG, Embla system, Flaga HF, Iceland) with simultaneous recordings of the Watch-PAT100 (WP100) device (Itamar-Medical Ltd, Caesarea, Israel). The PSG and the WP100 were synchronized using a continuous synchronization bi-level signal generated by the WP100 and recorded on both devices. The two

sets of signals (the one from the PSG and the other from the WP100) were then synchronized to compensate differences in internal clock of the two systems. The final error in synchronization time does not exceed 20 s. By the end of the recording, the two data files (in PSG and in Watch-PAT) included the same synchronization signal and could thus be aligned exactly offline for head-to-head comparisons.

Prior to the study, patients completed a sleep questionnaire including physical data (e.g. weight and height), general health condition and medical history, medication usage and sleep habits. Lights off were no later than midnight, and lights on at 06:00 AM. The mean start time of the test was 11 PM \pm 30 min and the end of the test was 6:00 \pm 45 min and the mean duration was 7.99 \pm 42 min.

The WP100 was attached to the forearm of the dominant hand of the patient. The PAT probe was mounted on the index finger and the oximetry probe on the adjacent finger. Recording started with lights off and continued in a synchronized mode till lights on. The data quality of both the WP100 and the PSG was quite good and the signals recorded were valid for about 90% of the study.

The PSG files were scored for apnea–hypopnea index using Chicago criteria. Data were blindly double scored for stages to assess inter-scorer variability. The Kappa coefficient for the stages double scoring was 0.83, which is considered ‘almost perfect agreement’ according to Landis and Koch (1977).

In-laboratory WP100 recording. The WP100 device has been previously described (Bar *et al* 2003, Hedner *et al* 2004, Margel *et al* 2003, Penzel *et al* 2004a, 2004b, Pillar *et al* 2003). Briefly, it consists of a battery-powered, wrist-mounted recording device and software for post-acquisition viewing and analysis of the recorded PAT data, which are derived from a specialized finger probe which records the arterial pulse. It records four signals: PAT signal (arterial pulse wave amplitude), pulse rate derived from the PAT signal, oxyhemoglobin saturation and wrist activity (derived from an accelerometer). The WP100 device contains a rechargeable power supply, preliminary signal conditioning hardware, 100 Hz data acquisition and data storage on a removable compact flash disk.

In-laboratory polysomnography. All subjects underwent a standard in-laboratory overnight PSG. Recorded signals included: EEG (C4-A1, C3-A2, O2-A1 and O1-A2), EOG, submental and bilateral tibial EMG, ECG, airflow (nasal pressure and thermistor), chest and abdominal motion (piezo bands), oxyhemoglobin saturation, positive airway pressure and body position. All physiological data were collected and stored on the digital polysomnography system (Embla, Flaga, Reykjavik, Iceland). PSG recordings were scored manually, with the scorer being blinded to the PAT signals. Sleep was blindly staged on the PSG according to standard R&K criteria and applying the updated AASM Visual Scoring Task Force criterion to combine the stages 3 and 4 into one deep sleep stage (Rechtschaffen and Kales 1968, Silber *et al* 2007).

PAT algorithms description

The WP100 system is already equipped with a set of algorithms, well described in the literature, detecting sleep, wake and REM stages using actigraphy and PAT signal, with an epoch-by-epoch high-resolution performance (Hedner *et al* 2004, Herscovici *et al* 2007). The newly developed algorithm described in the current study is intended to further separate the non-REM epochs and classify them into deep or light sleep epochs. The actigraph is used to differentiate

between sleep and wake periods only and not used for differentiation within the sleep periods between REM, deep and light sleep stages and neither is the oximeter.

A set of 14 normalized features in both the frequency and time domains was derived from the PAT signal amplitude (AMP) time series and the heart rate, i.e. inter-pulse period (IPP) time series. All the variables were scaled to their mean value so that they could be interpreted as a conditional probability. From each of the time series, a set of seven similar type of variables was derived, making it a total of 14 variables. Each such set of seven variables included scaling coefficients of a detrended fractal analysis (DFA), the mean value (mean Amp and mean heart rate) and four spectral components as well as the ratio between high and low frequency. All the variables and their conditional probabilities were computed within a 5 min sliding window advanced by 30 s epochs.

DFA is the scaling DFA exponent of the amplitude (in the Amp time series) and heart rate (in the IPP time series), LF is peak low frequency spectral density, ULF is the peak ultra low frequency spectral density, VLF is the peak very low frequency spectral density, HF is the peak high frequency spectral density and SpectRatio is the ratio of the peak low frequency density to the peak high frequency density. As said before, each such type of variable is derived from each of the two time series. The frequency ranges, corresponding to the respiratory, baro-receptor, thermoregulation and hormonal ranges, are 0.4–0.15 Hz (HF), 0.15–0.04 Hz (LF), 0.04–0.015 Hz (VLF) and 0.015–0.005 Hz (ULF) (Burgess *et al* 2004).

To combine and weigh each of the features we performed a two-step algorithm. The first step was to filter each of the features by defining a ± 5 min window around each epoch, allowing for smoothing around the epoch under consideration. This filter is defined as a neighboring filter (NF). The second step was done by choosing weightings that minimize the differences between the PSG staging and the PAT-derived staging. Each feature was examined for the degree to which it differentiates between light and deep sleep, prior to and after the filtering.

The total probability equation can be written as follows:

$$Y_{\text{est}}(n) = \sum_{j=1}^{14} \sum_{k=10}^{10} W_{jk} \times X_j(n+k) \quad (\text{PAT stages probability computation equation}) \quad (1)$$

where $Y_{\text{est}}(n)$ is the probability of an epoch n to be a deep sleep epoch, $X_j(n)$ is the value of each one of the fourteen features at epoch n , and W_{jk} is the 21 filter coefficient of each k features.

The weights are computed analytically to minimize the error in the identification process:

$$W_{jk} = \text{Min} \left(\sum_{n=1}^N Y_{\text{est}_n} - Y_{\text{actual}_n} \right)^2$$

(minimization criteria and weights computation method). (2)

where Y_{actual} is '1' if the n epoch is deep and '0' otherwise. $>W_{jk}$ is the least-squares error between the stage estimates Y_{est} and the PSG stages Y_{actual} (a vector of length N corresponding to the PSG sleep stage of each epoch).

Optimization was performed on a training set of 49 sleep studies. Rather than optimizing each estimator (W_{jk}) separately, the algorithm uses a single level of optimization wherein a linear classifier acts on an enlarged feature set composed of 20 epochs for every variable.

Analysis method. The algorithm accuracy was assessed by applying the weighted coefficient computed from the training set to the validation set.

The PAT studies were analyzed using the actigraph algorithm to separate the sleep and wake periods using previously described algorithms (Hedner *et al* 2004). The REM periods were detected using the previously described REM algorithm (Herscovici *et al* 2007). The non-REM periods were then separated into deep and light sleep periods using the newly developed algorithm. The oximetry measurement is not used to differentiate between deep and light neither the actigraph. The comparison was done based on a 30 s epoch by epoch comparison. Comparisons of performance in different OSA severity groups were made to show that the algorithm is not impaired by OSA severity effects on the PAT signal. The Algorithm performance was evaluated for each RDI group stratified by mild (0–20), moderate (20–40) and severe (more than 40).

The total sensitivity, specificity and agreement were measured using the whole 27 597 (20 555 light sleep and 7042 deep sleep) from the PSG epochs for training and 24 383 (18 320 light sleep and 6063 deep sleep) epochs for validation. Mean values of sensitivity, specificity and agreement based on per subject value were also computed as well as Kappa Cohen agreement.

Results

Training data set

Figure 1 shows the normalized histogram of the eight major contributive variables with the relative separation of each.

Figure 2 shows the combined histogram of all the variables (14 variables) for the combined data of all the patients for deep and light sleep, and illustrates the separation without filtration, and figure 3 shows the separation including the NF. The filtered data improve the separation between stages by 2% in sensitivity and 8% in specificity. Without filters the sensitivity/specificity is 72% and 77%, respectively (threshold -0.325). By adding the filter, the sensitivity and specificity increase to 74% and 85% when choosing the threshold at the intersection point (threshold -0.2).

The last step is to choose a threshold for the clinical application. The threshold was chosen in order to bring up the total specificity on an ROC curve to approximately 90% (threshold 0.1). The one chosen yields in the training set sensitivity, specificity and agreement values of 66%, 89% and 82%, respectively, for the whole training set. The per subject mean values of the sensitivity, specificity and agreement were ($63\% \pm$, $89\% \pm$, $0.83 \pm$) respectively, for the whole training set; the Kappa Cohen coefficient was 0.52 (moderate agreement). Mean value of Kappa averaging patients in each group is (0.52 ± 0.17 , 0.56 ± 0.20 and 0.55 ± 0.28) for light, moderate and severe RDI groups, respectively.

Figure 4 shows the total agreement of all the training set stratified to RDI categories. It can be seen that there is no substantial difference between the severe, mild and moderate OSA patient groups.

The Bland Altman plot in figure 5 shows no offset and no systemic error in the results.

Validation data set

In order to assess the accuracy of the algorithm it was tested on a separate validation set of 44 studies, reflecting a broad range of sleep apnea severity. The whole validation set shows 65%, 87% and 80% sensitivity, specificity and agreement values, respectively. The mean value of sensitivity, specificity and agreement of all the patients is 56%, 87% and 81%, respectively. The total sensitivity, specificity and agreement values for the validation set were very similar at 66%, 89% and 82%, respectively. The correlation of percentage of deep sleep over the night

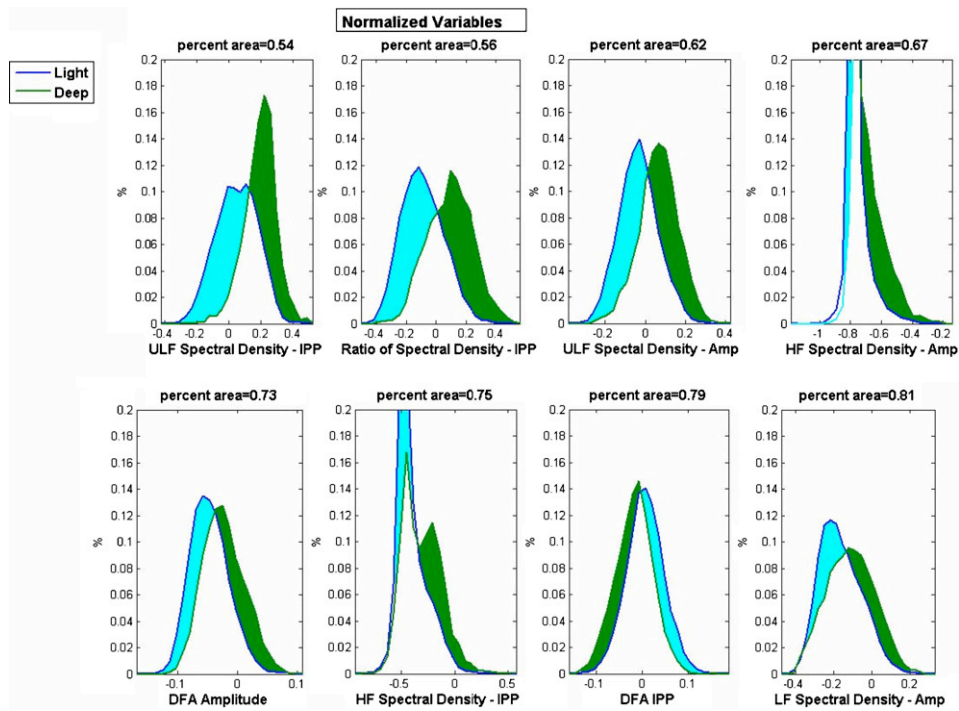


Figure 1. Histograms of separations for the variables that demonstrate the best separations (after NF). The best separation is given in the upper left panel and decreases clockwise. The dark green shaded region represents complete separation of deep sleep. The lighter blue shaded region represents complete separation of light sleep and the unshaded area in between represents unseparation (overlap of the two). The value on top of the graph represent the unseparated area relative to deep sleep complete separation area (a lower ratio means better separation).

Table 2. Sensitivity, specificity and agreement mean values by subject for the three groups.

| | Group 1, RDI < 20 | Group 2, 20 < RDI < 40 | Group 3, RDI > 40 |
|-----------------|-------------------|------------------------|-------------------|
| Sensitivity (%) | 61 ± 26 | 55 ± 23 | 72 ± 32 |
| Specificity (%) | 89 ± 10 | 87 ± 13 | 87 ± 6 |
| Agreement (%) | 82 ± 7 | 78 ± 13 | 85 ± 6 |

with the PSG was $R = 0.51$ ($P < 0.05$) for the whole validation set. The per subject mean values of the sensitivity, specificity and agreement were $(56\% \pm, 87\% \pm, 0.81 \pm)$ respectively, for the whole training set the Kappa Cohen coefficient was 0.57 (moderate agreement). Mean value of Kappa averaging patients in each group is $(0.46 \pm 0.19, 0.42 \pm 0.1$ and $0.54 \pm 0.3)$ for light, moderate and severe RDI groups, respectively. Table 2 shows the mean values of sensitivity, specificity and agreement per RDI group for the validation set.

Figure 7 shows the Bland Altman plot of the percentage deep sleep for the validation set. There is no systemic error in percentage deep sleep.

Discussion

The major contribution of the current study is the development of a novel algorithm that can reasonably distinguish between light and deep sleep stages based solely on the PAT signal

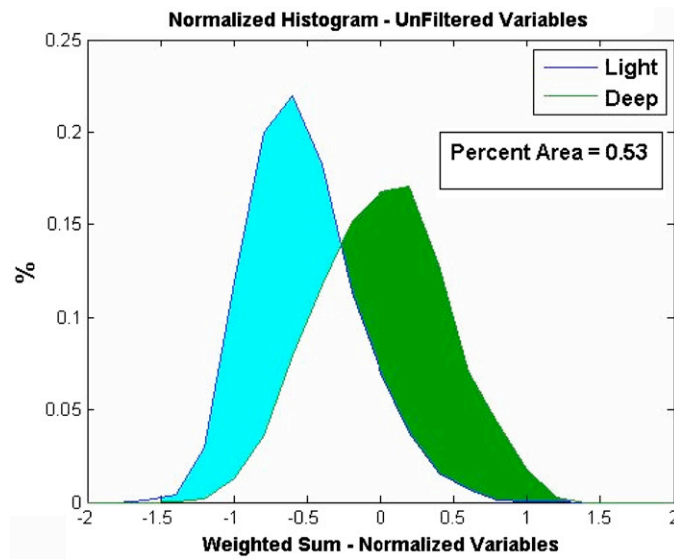


Figure 2. Weighted sum distribution without NF. Shaded and unshaded areas as in figure 1.

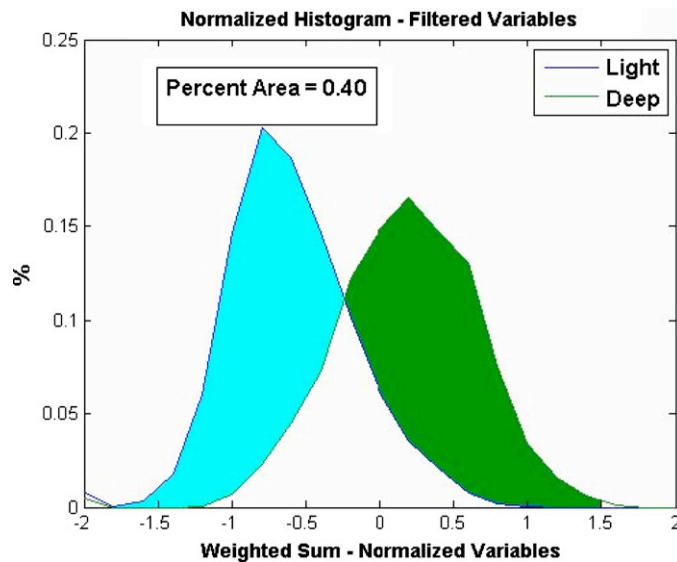


Figure 3. Weighted sum distribution with NF. Shaded and unshaded areas as in figure 1.

without depending on EEG monitoring. The agreement of this algorithm with PSG to identify standard 30 s epochs of light and deep sleep stages was validated to be 80%. Together with the previously described algorithms for wake and REM detection, the ambulatory WP100 is now capable of providing sleep stages without recording EEG, EOG and/or EMG channels. Thus, although WP100 cannot be utilized as a substitution for polysomnography, it can provide good assessment of sleep structure in the home setting.

The autonomic nervous system consists broadly of sympathetic and parasympathetic arms, the activities of which are generally elicited during different somatic states. While the

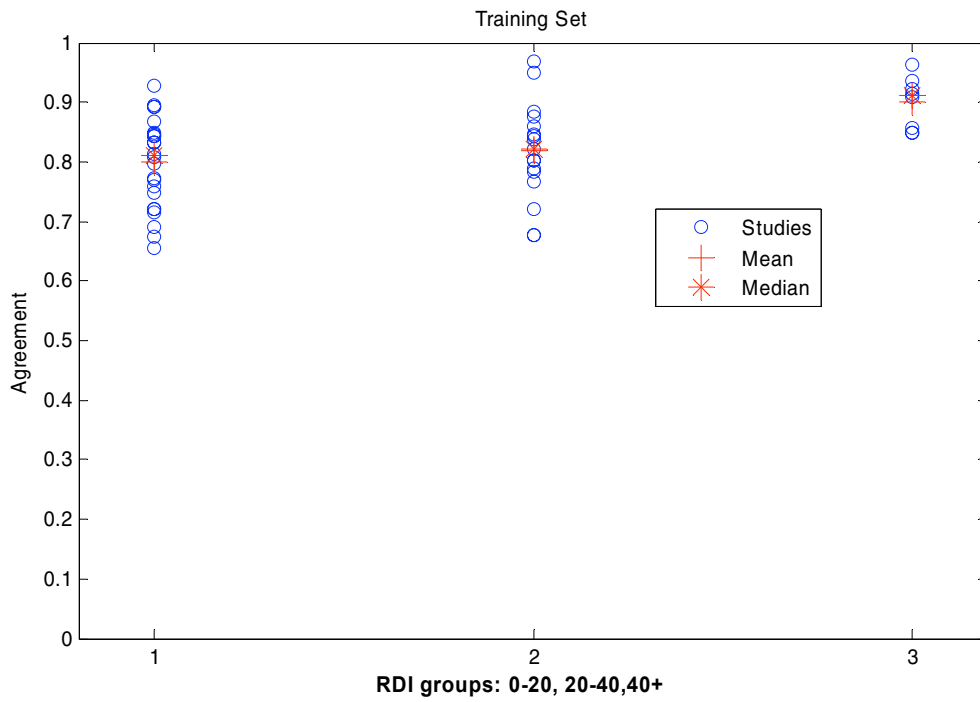


Figure 4. Agreement for mild (1), moderate (2) and severe (3) OSA training set.

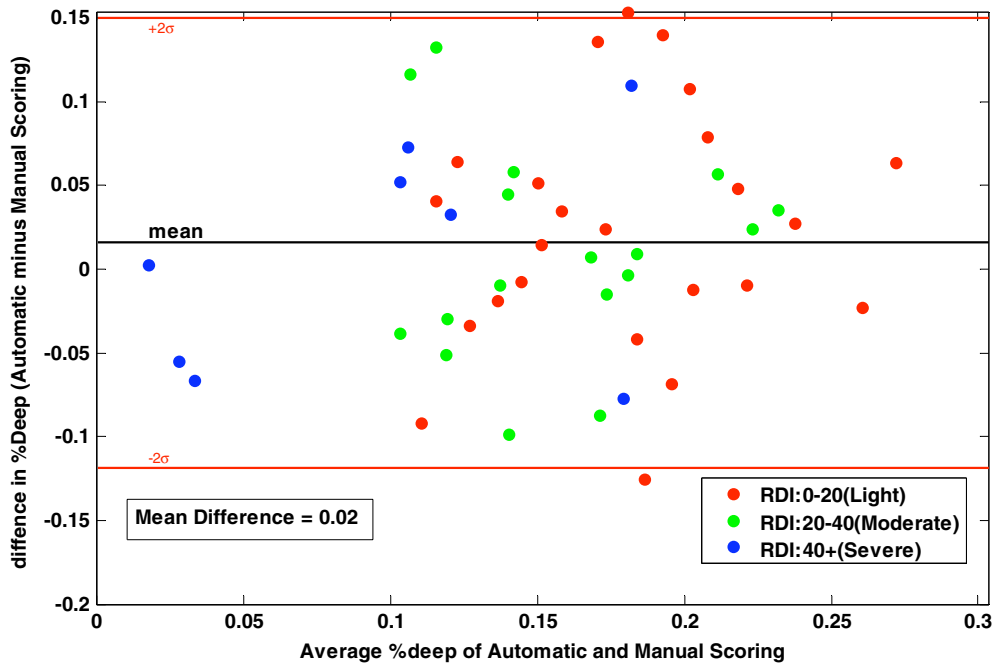


Figure 5. Bland Altman plot of error in % deep sleep stage detection (PSG versus algorithm) for the training set.

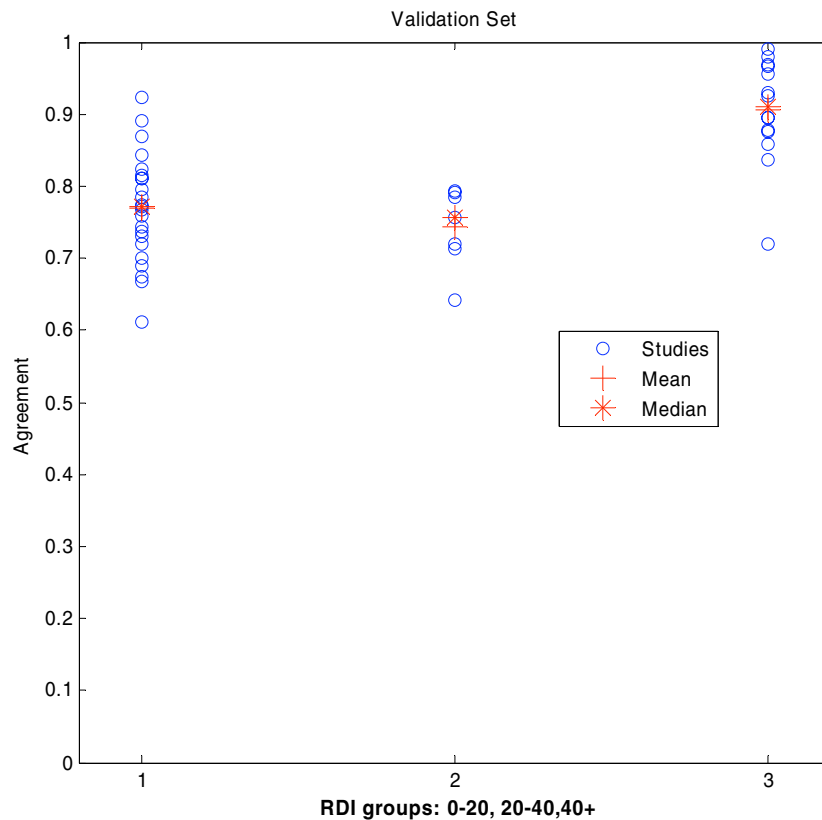


Figure 6. Agreement for mild (1), moderate (2) and severe (3) OSA validation set.

sympathetic system is active during stress, the parasympathetic arm dominates during relaxed periods. These systems have been very well studied during wakefulness, but to a much lesser extent during sleep. Spectral analysis of heart rate variability demonstrated that NREM is associated with high parasympathetic activity while REM is characterized by attenuated vagal tone and augmented sympathetic activity. The overall pattern during wakefulness showed an intermediate position between NREM and REM patterns; parasympathetic activity was lower than in NREM and higher than in REM, with an opposite trend for sympathetic activity (Berlad *et al* 1993, Futuro-Neto and Coote 1982, Levy and Pepin 2003, Liguori *et al* 2000). In an attempt to distinguish the circadian from the sleep effects on the autonomic nervous system it has been reported that there is a primarily circadian, but not sleep, influence on the parasympathetic nervous system activity, and primarily a sleep, but not circadian, influence on the sympathetic nervous system activity. While several studies demonstrated the differences of the autonomic nervous system activities between wakefulness, REM sleep and non-REM sleep (Berlad *et al* 1993, Futuro-Neto and Coote 1982, Levy and Pepin 2003, Liguori *et al* 2000, Somers *et al* 1993), the differences between light and deep non-REM sleep stages were only marginally studied. It was reported that stage 2 sleep shows some duality activity with a quiet period preceding slow-wave stage and an active period preceding REM sleep (Brandenberger *et al* 2005). Studying muscle sympathetic activity, it has been shown that light sleep (stage 2) is associated with around a 10% reduction of sympathetic activity

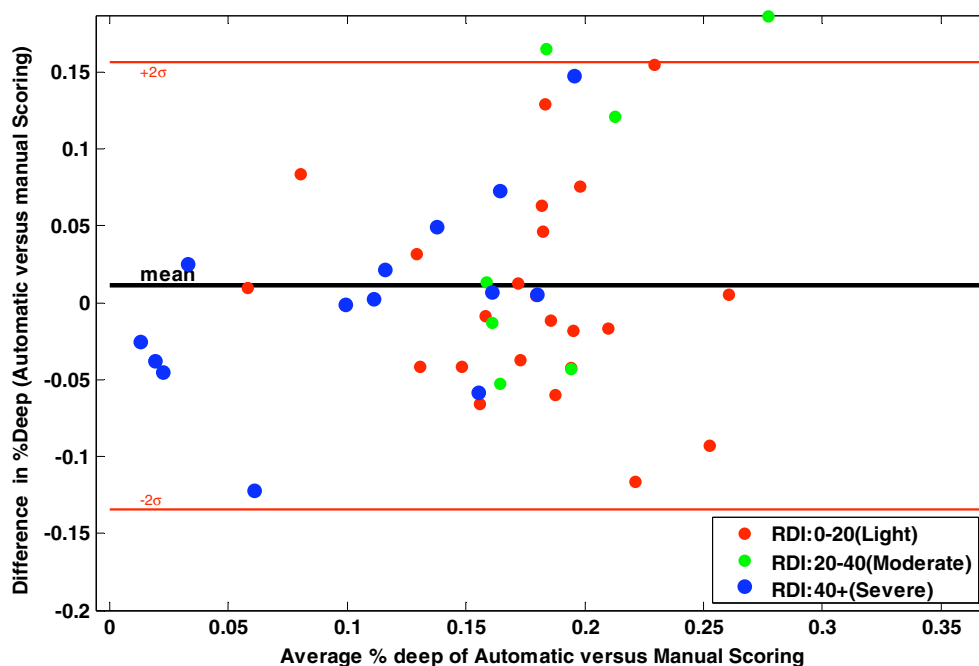


Figure 7. Bland Altman plot of error in % deep sleep stage detection (PSG versus algorithm) for the validation set.

(of wakefulness values) while deep sleep (stages 3–4) resulted in greater sympathetic activity decrement of 29% of the awake value (Hornyak *et al* 1991). Our current study, by showing that it is possible to accurately differentiate light sleep from deep sleep based on autonomic signals, further supports the presence of substantial changes in the output of the autonomic system during these two non-REM sleep stages. It should be kept in mind, however, that the sample in this study consisted of 93 adult patients with suspected OSA and 16 healthy adult volunteers. Thus, the findings may not be applicable for children or patients with other disorders for example insomnia

OSA has a substantial influence on both autonomic nervous system and sleep staging. While generally OSA is associated with increased sympathetic activation (Aydin *et al* 2004, Brooks *et al* 1999, Jo *et al* 2005, Narkiewicz *et al* 1998, Narkiewicz and Somers 1997, Penzel *et al* 2000, 2003, Pepin *et al* 1994), the breathing disorder is also known to result in decreased proportions of deep sleep stages (Malhotra and White 2002, Pillar *et al* 2000). The accuracy of the current algorithm in detecting light and deep sleep across a large variety of apnea severity suggests that sleep staging and autonomic nervous system changes may result from a similar patho-physiologic mechanism. The somewhat higher accuracy of the algorithm to distinguish between light and deep sleep in more severe OSA (figures 4 and 6) suggests that the strong effect of the sleep disordered breathing on the autonomic nervous system makes it easier to stage sleep in these patients.

In the era of emerging need for simple, easy, fast and accessible home diagnosis of OSA, the current study is of considerable importance. The WP100 is a simple device located solely on the hand and recording autonomic signals from a finger, with actigraphy and oximetry. Its ability to accurately detect wakefulness, REM sleep and non-REM sleep (Dvir *et al* 2002,

Hedner *et al* 2004, Herscovici *et al* 2007, Lavie *et al* 2000), as well as light/deep sleep (current findings), opens new horizons for the home diagnosis of OSA.

Until now the ability to stage sleep in the home was only possible using home PSG (Chesson *et al* 2003, Flemons *et al* 2003); however, the results of the current development and study described in this paper show for the first time the ability to stage sleep using a simple device based on PAT and actigraphy signals. Thus, we show that the PAT signal, which was previously used to separate REM from the non REM sleep, is rich in information regarding the further stratification of sleep stages, specifically the separation between deep and light sleep stages. In this respect, it could be argued that the 80–82% agreement reported here is insufficient for clinical usage. However, these results are within the range of variability between registered PSG scorers, as was reported by Collop (2002). Norman *et al* (2000) reported even worse results. The mean epoch by epoch agreement between scorers was 73% (range 67–82%). Agreements were higher in the normal subset (mean 76%, range 65–85%) than in the OSA subset (mean 71%, range 65–78%). Since our cohort consists of patients with OSA, we believe our results of 80–82% agreement accedes those of the inter-observer variability in scoring PSG by the traditional way. Furthermore, in a recent paper which evaluated the standard scoring to several combinations of automated scoring with partial review by a technologist (Morpheus and Somnolyzer 24 × 7 systems) the results were substantially lower (agreements of 70–72%) and were considered acceptable (Svetnik *et al* 2007). Thus, again, we believe that the current results are within the acceptable range for clinical usage.

Limitations

The current study has several limitations. First, the cohort size used is not large enough to ensure accuracy of the system. The algorithm has been developed on 49 records and validated on 44. Although by looking at epoch-by-epoch-based comparisons, the sample size is in the order of thousands, still further studies to test this algorithm on large population are required. Second, the cohort did not include other sleep disorders such as insomnia or parasomnia, some of which are known to affect the autonomic nervous system. Thus, the results of the current study should be at this time limited to patients with suspected OSA. Finally, the system is supposed to be utilized in the home, while in the current study it was tested in the lab. Thus, again, further studies are required to validate this system in the home settings.

Conclusions

Despite the above-mentioned limitations, we believe our study convincingly shows that an algorithm which is based on the PAT signal is capable of detecting light and deep sleep stages. It is not suggested that the WP100 can substitute the polysomnography, but together with the previously described algorithms to detect wake non-REM and REM sleep we believe that the current study shows a useful method to comprehensively stage sleep when EEG recording is not available, based on actigraphy and autonomic nervous system signals derived from the PAT signal.

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