

Actigraphy-Based Sleep/Wake Detection for Insomniacs

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Abstract— This paper presents an actigraphy-based approach for sleep/wake detection for insomniacs. Due to its relative unobtrusiveness, actigraphy is often used to estimate overnight sleep-wake patterns in clinical practice. However, its performance has been shown to be limited in subjects with sleep complaints such as insomniacs. Quantifying activity counts on 30-s epoch basis, as usually done in regular actigraphy, may lead to an underestimation of wake periods where the subject shows reduced body movements. We therefore propose a new actigraphic feature to characterize the ‘possibility’ of epochs being asleep (or awake) before or after its nearest epoch with a very high activity levels. It is expected to correctly identify some wake epochs when they are very close to the high activity epochs, although they can be motionless. A data set containing 25 insomnia subjects and a linear discriminant classifier were used to test our approach in this study. Leave-one-subject-out cross validation results show that combining the new and the traditional actigraphic features led to a markedly improved performance in sleep/wake detection compared to that using the traditional feature only, with an increase in Cohen’s kappa from 0.49 to 0.55.

I. INTRODUCTION

Insomnia is one of the most common sleep disorders, and epidemiological studies have estimated a prevalence of ~30% of the world population suffering from insomnia symptoms [1]. Many factors can lead to insomnia, such as increased age, hyperarousals, daytime stress events, and sympathetic activity during the night compared with healthy subjects [2], [3], [4]. Diagnosis of insomnia symptoms and objective assessment of sleep quality often rely on retrieving and analyzing nocturnal sleep-wake patterns [5], [6]. Recommended by the American Academy of Sleep Medicine (AASM), polysomnography (PSG) with manual scoring on 30-s epoch basis is used to aid in the diagnosis of sleep/wake disorders [7]. However, PSG is usually required to be performed in a sleep laboratory with the use of many sensors with electrodes attached to the human body, not possible to provide a long-term monitoring of subjects with potential sleep problems, in particular the ones who suffer from insomnia. In addition, the first night or reverse first night effect of using PSG in a sleep lab would lead to under representation of usual sleep-wake patterns [8].

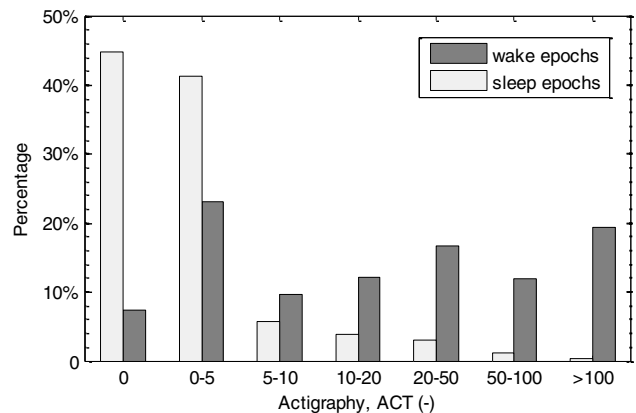
In practice, the unobtrusive, low-cost, and ease-of-use of wearable sensor technologies, such as wrist-worn actigraphy, enable sleep monitoring at home [9], [10]. In the past decade, a relatively high performance of sleep/wake detection using actigraphy has been achieved for healthy subjects without sleep disturbances [11], [12], [13], [14]. However, this is not yet the case for subjects with insomnia who have difficulty of

falling or maintaining sleep [6], causing increased wake periods and more ‘active’ sleep epochs.

Traditional actigraphy measures “activity counts” (ACT) per 30 s and thereby identifying wakefulness with reduced body movements (i.e., wake epochs with low physical activity or body motion) is one of the main challenges in achieving a reliable sleep/wake detector. This is in particular the case for insomniacs or subjects with insomnia symptoms who often have a large proportion of wake epochs during overnight sleep. Figure 1 plots the histogram of 30-s epoch-based ACT values, measured with Philips Actiwatch (Philips Respironics) during wake and sleep states from 25 insomniacs, annotated manually based on simultaneously recorded PSG. More than 40% of wake epochs are characterized by relatively low activity levels (e.g., $ACT < 10$), which seem difficult to be separated from sleep epochs. On the other hand, sleep epochs (with body movements or arousals [15] are also difficult to distinguish from wake epochs using ACT. To these matters, in addition to the traditional actigraphic feature ACT that quantifies activity counts only, we propose a new actigraphic feature in this study taking into account the ‘possibility’ of epochs being asleep or awake nearby (before or after) very high activity levels. This can be done by quantifying the time difference or distance between each epoch and its nearest epoch with lots of body motions (very high activity level), in correspondence to a large ACT value. The hypothesis here is that the epochs or periods closer to that with a very high level of activity (and therefore with a smaller time difference) are more likely to correspond to wake state, albeit possibly with less body movements.

In this paper, we present a new method to automatically classify wake and sleep for insomniacs based on wrist-worn actigraphic data, where the inclusion of the new actigraphic feature is expected to help increase the classification accuracy. We use a linear discriminant-based classifier, which has been extensively used for sleep/wake detection in previous studies [11], [13], [16].

Figure 1. Normalized histogram of epoch-based actigraphy data (ACT) in different levels of activity. The data was measured from 25 insomniacs.



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II. METHODS

A. Subjects and Data

Single-night recordings from 25 self-reported insomniacs (11 females and 14 males) were included in this study. The subjects had a mean age of 45.0 ± 13.6 years and a mean body mass index (BMI) of 27.6 ± 3.8 kg/m². The collection of full PSG data (Alice 5 PSG, Philips Respironics) and actigraphy (Actiwatch, Philips Respironics) was performed at the Sleep Health Center, Boston, USA, in 2009. On average, 6.6 ± 0.9 hours' recorded data per subject was used, where sleep and wake epochs accounted for $71.5 \pm 0.17\%$ and $28.5 \pm 0.17\%$, respectively. Note that, for all continuous (non-overlapping) 30-s epochs, sleep stages were manually scored by an external sleep technician according to the AASM guidelines [7]. All subjects signed an inform consent.

B. Actigraphic Features

The existing actigraphic feature for each 30-s epoch was ACT. The new actigraphic feature proposed in this paper was obtained based on ACT. For each epoch, it calculated the logarithm of the distance to the nearest epoch with a very high activity level (DHAL). Assuming a series of n epoch-based ACT feature values $\mathbf{a} = \{a_1, a_2, \dots, a_n\}$, \mathbf{a}_T is a subset of \mathbf{a} in which feature values are larger than a threshold T , where the associated epoch indices are $\mathbf{e}_T = \{e_1, e_2, \dots, e_m\}$. Accordingly, $\mathbf{b} = \{b_1, b_2, \dots, b_n\}$ is a set of DHAL feature values from the same series. The value b_x at epoch x ($x = 1, 2, \dots, n$) can then be computed such that

$$b_x = \ln(\min\{|x - e_1|, |x - e_2|, \dots, |x - e_m|\}). \quad (1)$$

Here T was experimentally chosen as 100, indicating that an epoch with an ACT value larger than 100 was considered to be associated with a very high level of activity, probably during a wake state. In case the maximal ACT value of an overnight recording was not larger than 100, we used the 95% percentile of the ACT values over that recording instead. Furthermore, a moving averaging was applied to smooth the DHAL feature values for each overnight recording. We experimentally chose the moving averaging window size to be 40 epochs that could optimize the detection performance based on solely training data. As previously stated, to a certain extent, DHAL could reflect the possibility of being asleep of an epoch, by analyzing how far (i.e., absolute time distance) of that epoch to its nearest wake epoch with very high activity.

C. Sleep/Wake Detection

To automatically detect sleep or wake epochs, a linear discriminant-based classifier was adopted in this work. Note that the probabilities of being awake and asleep can vary over the night for this specific group of subjects showing insomnia symptoms. For example, the probability of being awake at the beginning of the night (after entering the bed and turning off the lights) should be much higher than that of being asleep. For that reason, we used a time-varying prior probability for each epoch, which used the time of night (or epoch index) to exploit those variations. It was computed by counting frequency of each epoch being scored as each state (sleep or wake). The

classifier used in this work was the same as that used in our previous work [13], [16].

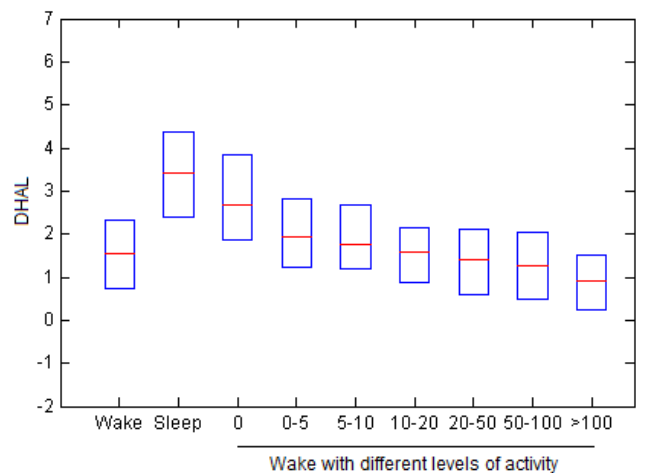
In regard to the performance evaluation of sleep/wake detection, we used the traditional metrics of accuracy, specificity, sensitivity, and precision. Moreover, due to the data imbalance in our data set (<30% wake epochs), we used the receiver operating characteristic (ROC) curve that can provide an overview detection performance when choosing different classifier decision-making thresholds. Additionally, we also calculated the Cohen's kappa coefficient (κ), a metric that compensates for chance agreement. In clinical practice, to objectively assess nocturnal sleep quality, sleep parameters per night (such as sleep efficiency or SE, sleep onset latency or SOL, and wake after sleep onset or WASO) are often derived from the estimated sleep-wake pattern.

A leave-one-subject-out cross validation (LOOCV) was employed to train and validate the classification performance. Performance results were pooled over all 25 subjects. Note that the final classifier decision-making threshold was selected to optimize average kappa value over all iterations of LOOCV based on training data.

III. RESULTS AND DISCUSSION

In Figure 2, we plot DHAL feature values (median and inter-quartile range, pooled over all subjects) in sleep and wake states as well as in wake state with different activity levels, i.e., ACT = 0, 0-5, 5-10, 10-20, 20-50, 50-100, >100. It shows that the wake epochs with higher activity correspond to a smaller DHAL value, indicating that they were closer to their nearest epoch (possibly wake) with a very high level of activity. We also see in the figure that this new feature seems capable to separate sleep epochs and some wake epochs having a relatively low activity level while they could not be distinguished with ACT. Compared with sleep epochs, those low activity wake epochs correspond to a smaller DHAL value. Nevertheless, we can also see in the figure that discriminating between sleep and wakefulness with no body motion is still difficult.

Figure 2. Boxplots of DHAL feature values in sleep and wake states as well as wake state with different levels of activity (i.e., ACT) from data pooled over all 25 insomniacs. Median and inter-quartile range are shown and outliers are removed for readability.



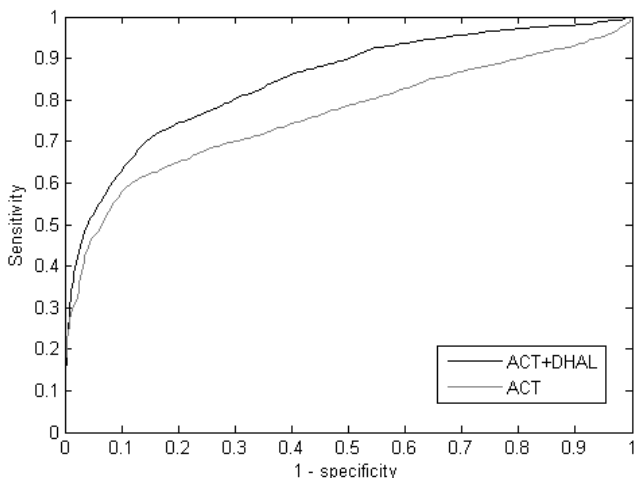
The LOOCV results of sleep/wake detection are presented in Table I. The table indicates that, when combining the existing actigraphic feature ACT and the new feature DHAL proposed in this work, the sleep/wake detection performance was markedly improved compared to that when using ACT only (Cohen’s kappa coefficient from 0.49 to 0.55). This can also be seen in Figure 3 that plots the pooled ROC curves using the two feature sets (ACT and ACT+DHAL). Note that, for each feature set, the ROC curve was generated by varying the classifier’s threshold simultaneously for all iterations during the LOOCV procedure. The figure illustrates the overview performance of sleep/wake detection in the entire thresholding solution space of the classifiers. A larger area under the ROC curve (AUROC) of 0.85 was achieved when using the combined feature set (ACT+DHAL) in comparison with that of 0.76 when using ACT feature set. Interestingly, we observed that adding the new feature DHAL to the feature set resulted in a clearly decreased false negatives and an increased sensitivity.

TABLE I. PERFORMANCE COMPARISON (LOOCV) OF SLEEP/WAKE DETECTION USING DIFFERENT FEATURE SETS, WHERE DETECTION RESULTS ARE POOLED OVER ALL 25 INSOMNIACS

Metric*	Feature set	
	ACT	ACT+DHAL
Sensitivity	0.53	0.60
Specificity	0.92	0.92
Precision	0.71	0.72
Accuracy	0.82	0.84
Kappa	0.49	0.55
AUROC	0.76	0.85

* Sensitivity: true positive rate, specificity: true negative rate, precision: positive predictive value, accuracy: percentage of correctly detected epochs, Kappa: Cohen’s kappa coefficient of agreement, AUROC: area under the receiver operating characteristic (ROC) curve.
Note that here wake was considered positive class and sleep negative class.

Figure 3. ROC curves of sleep/wake detection using the two feature sets ACT and ACT+DHAL, detection results were pooled over all 25 insomniacs after LOOCV.



The absolute errors of estimating the sleep parameters SE, SOL, and WASO are given in Table II, in which mean and standard deviation results over all 25 insomnia subjects are computed. It shows that using the feature set ACT+DHAL resulted in a better performance in estimating SOL but a worse performance in estimating SE and WASO compared with the use of ACT only. Moreover, large standard deviations between subjects can be seen in the table. In general, the absolute estimation errors in estimating the sleep parameters for insomniacs are still larger than those for healthy subjects [11], [12]. It should be noted that, in this work, the decision-making threshold of the sleep/wake classifier was chosen to optimize Cohen’s kappa coefficient. However, in order to optimize the performance of estimating a certain sleep parameter, the classifier’s threshold should be selected to minimize the estimation error of that sleep parameter. This merits further investigation.

TABLE II. ABSOLUTE ERRORS OF ESTIMATING SLEEP PARAMETERS (SE, SOL, AND WASO), WHERE THE ESTIMATION RESULTS ARE COMPUTED AS MEAN ± STANDARD DEVIATION OVER ALL 25 INSOMNIACS

Sleep parameter*	Feature set	
	ACT	ACT+DHAL
SE (%)	9.2 ± 10.6	10.7 ± 10.5
SOL (min)	24.1 ± 34.7	19.8 ± 39.5
WASO (min)	28.9 ± 28.8	31.0 ± 26.5

* SE: sleep efficiency - ratio between total sleep time and total time in bed, SOL: sleep onset latency - the time it took before the subject fell asleep (i.e., the period between the beginning of a recording and the first epoch that is annotated or classified as sleep according to the AASM guidelines [4]), WASO: wake after sleep onset - total wake time after sleep onset time.

Although the addition of the proposed actigraphic feature DHAL improved the performance in sleep/wake detection for insomnia subjects, it is still inferior to that reported for healthy subjects (kappa value of 0.58 in [13]). As shown in Figure 2, the main challenge of actigraphy-based sleep/wake detection is to separate wakefulness with low activity and sleep in which a similar level of activity was found. In fact, in order to improve the detection performance, many previous studies have shown the effectiveness of incorporating cardiac and respiratory features in addition to actigraphy for healthy subjects [11], [13], [16], [18]. These features exploit the relation between sleep stages and autonomic cardiorespiratory activity [19], [20]. Yet the benefit of using these features in sleep/wake detection for insomniacs or for subjects suffering from comorbid insomnia symptoms still needs to be investigated in the future.

A relatively small data set was considered in this study, possibly producing a detection model that is not robust for a wide range of characteristics such as age, severity of insomnia (e.g. mild, moderate, and severe), type of insomnia (e.g. onset, maintenance, and terminal), or factors that causes insomnia symptoms (e.g. daytime stress, anxiety, jetlag, and diet) [1], [2], [21]. Therefore, training sleep/wake detection models that are specified according to these categories based on a larger data set merits further exploration. In that case, a pre-screening

procedure is required to obtain those characteristics before the sleep/wake detection.

An important limitation of this study is related to the data set used to test the algorithm being limited to subjects suffering from insomnia. In a practical clinical application, if this technology were to be used in the screening, assessment or even to aid diagnosis of insomnia, it is not known a priori if the subject actually suffers from the disorder or not. The evaluation of this technique on a control group of subjects with other, or even without any sleep disorders warrants further research.

IV. CONCLUSION

An actigraphy-based approach of automatic sleep/wake detection for insomniacs was described. In addition to the traditionally used actigraphy feature that quantifies activity counts in 30-s epochs, we propose a new feature in order to characterize the possibility of occurrence of sleep or wake state before and after the epochs with a very high level of activity. This feature was demonstrated to help correct some false negatives (i.e. the wake epochs that were misclassified as sleep epochs). As a result, an increased sensitivity was achieved that resulted in an improved detection performance accordingly, promising a reliable sleep/wake detector for insomnia patients or subjects with insomnia symptoms.

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