Algorithm for Sleep/Wake Identification From Actigraphy

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Abstract. We describe a novel algorithm for identification of sleep/wake periods based on actigraphy signals designed to be used for a proper estimation of ambulatory blood pressure monitoring (ABPM) parameters. Automatic and accurate determination of sleep/wake periods is critical in cardiovascular risk assessment applications including the evaluation of dipper vs non-dipper status and diagnosis of hypertension. The algorithm is based on adaptive rank-order filters, rank-order decision logic, and morphological processing. The algorithm was validated on a database of 104 subjects including actigraphy signals for both the dominant and non-dominant hands (i.e. 208 actigraphy recordings). The algorithm achieved a mean performance above 94% with an average number of 0.04 invalid transitions per 48 hours.

1 Introduction

Ambulatory Blood Pressure Monitoring (ABPM) has been widely used over casual office readings to improve the diagnosis and treatment of hypertension, and to assess cardiovascular risk [1]. ABPM is a fully automated technique in which blood pressure (BP) measurements are taken at regular intervals (usually every 15 to 30 minutes) over a 24 or 48 hour period, providing a continuous BP record during the patient's normal daily activities. The use of ABPM has allowed for the observation of a circadian BP pattern. Typically, there is a decrease in systolic and diastolic BP levels during periods of sleep. Subjects who exhibit a nocturnal BP drop of at least 10% are classified as dippers, the ones who do not show this drop are called non-dippers. Recent studies have shown that non-dipper BP patterns are associated with an increased frequency of cardiovascular events, as well as target-organ damage, and cardiovascular morbidity and mortality [2, 3, 4, 5, 6].

The correct assessment of dipper vs. non-dipper requires the ability to accurately identify activity and rest cycles. Traditionally, determination of activity and rest cycles has been performed by either assuming a fixed schedule (with the sleep period spanning from 23:00 to 7:00 hours, and the wake period from 23:00 to 7:00 hours, for instance) [7], or requiring patients to keep a diary of their going to sleep and wake up times. In practice, both of these methods have proven inaccurate due to differences in sleep habits and unreliabity of subjective diaries. Recent studies indicate that an accurate identification of activity/rest cycles can be obtained through the use of actigraphy, which provides an inexpensive and non-obtrusive method to discriminate between activity and rest periods based on recorded activity levels. The typical actigraphs are wrist-worn devices that use accelerometers to measure and record movement counts at uniform time intervals with low sampling frequencies (e.g. 1 sample per minute). The actigraphy signal can be used to identify sleep/wake periods [8, 9, 10], but an automatic algorithm is needed that will perform this identification objectively and accurately. In this paper, we propose an algorithm to perform automatic sleep/wake identification based on actigraphy.

2 Methods

Fig. 1 shows a block diagram of the proposed algorithm. The algorithm is comprised of two stages: (1) a *Pre-processing stage*, and (2) a *Processing and Decision stage*. The aim of the first stage is to produce an initial estimate of the activity and rest periods from the actigraphy signal. The second stage processes the actigraphy signal using information from this initial estimate to produce a binary signal with the final identification of the activity and rest periods,

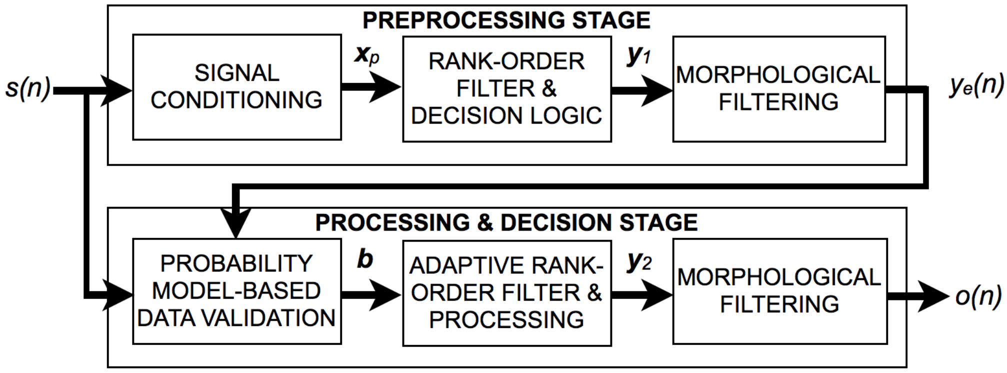

Fig. 1: Algorithm block diagram. The algorithm takes an actigraphy signal $s(n)$ as an input and produces a binary signal $o(n)$ as an output, where rest periods are represented as binary 0, and wake periods as binary 1. The algorithm consists of two stages. The purpose of the preprocessing stage is to produce an initial estimate of the sleep/wake periods from the original actigraphy signal, $y_e(n)$. The processing and decision stage processes the original actigraphy signal using information derived from the initial estimate of sleep/wake periods generated in the preprocessing stage, to produce the final identification of sleep/wake periods.

where rest periods are represented as a 0 and activity periods as a 1. During the first stage, the algorithm processes regions of consecutive zeroes corresponding to invalid data using a combined activity/rest probability model. A rank-order filter is then applied to the signal, and based on an adaptive threshold, a binary signal is generated, where a 0 or a 1 indicate sleep or wake periods, respectively. A morphological filter is finally applied to the binary signal to eliminate invalid transitions. The second stage takes the original actigraphy signal, and using the initial estimate of sleep/wake periods from the pre-processing stage, applies separate probability models to estimated sleep and wake zones in order to eliminate regions of invalid zeroes. This signal validation and conditioning process is followed by an adaptive rank-order filtering and thresholding operation, which produces a binary signal corresponding to a more refined estimate of sleep/wake periods. Finally, a morphological filter is applied to the binary signal to eliminate invalid transitions and obtain the final sleep/wake identification signal.

The algorithm was validated on a database containing actigraphy recordings of 48 hours for 104 subjects. The study took place in Galicia (Spain), and it was approved by the State Ethics Committee of Clinical Research. All subjects gave written informed consent. The subjects were diurnally active and nocturnally resting healthy young adult volunteers, 22.43 ± 1.66 years of age. All participants wore two actigraphs (Mini-Motion-Logger, Ambulatory Monitoring Inc., Ardsley, New York, USA), one on each wrist, to monitor their physical activity every minute. This compact (about half the size of a wristwatch) device uses accelerometers to determine the level of activity in counts per minute. During this experiment, ABPM was also monitored on the non-dominant arm, with ABPM measurements being taken every 20 minutes between 7:00 and 23:00 hours, and every 30 minutes between 23:00 and 7:00 hours. The same computer was always used to synchronize the internal clocks of the two actigraphs. For every subject, the assessment database includes two actigraphy signals, corresponding to simultaneous recordings for the dominant and non-dominant hands, respectively (i.e., 208 recordings). The participants agreed to keep an accurate diary of the times when they went to sleep and woke up for the duration of the experiment. This diary was used as the reference for the assessment and evaluation of the algorithm's performance. This assessment was based on three performance metrics (PM). PM1 was defined as the coincidence between the algorithm output and the diary in 1-minute epochs, PM2 represents the coincidence between the algorithm

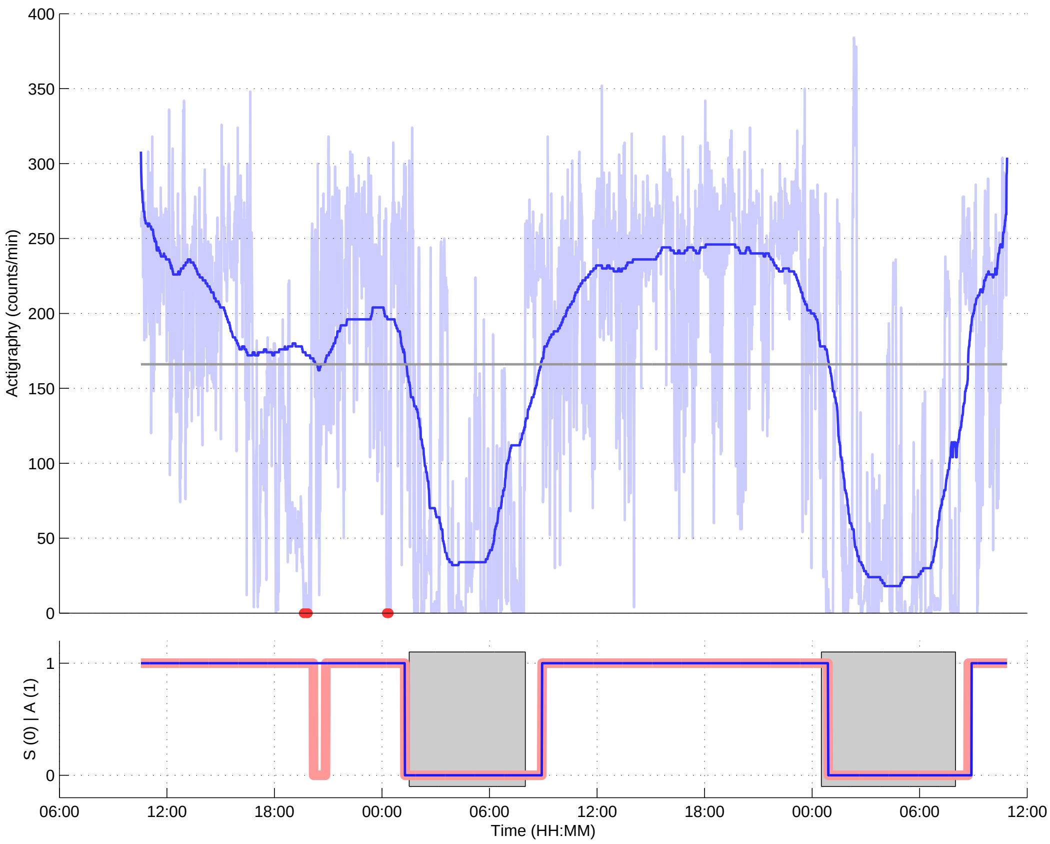

Fig. 2: Example of results illustrating the performance of the algorithm on a real actigraphy signal collected with a wrist actigraph. This figure illustrates the robustness of the algorithm when dealing with periods of low activity and disconnections of the actigraph during a wake cycle, such as the period between the 18:00 and 00:00 hours of the first day, due to the ability of the morphological filter to eliminate invalid transitions.

	Performance Metrics		
	PM1 (Dominat)	PM1 (Non-Dominant)	PM2 (Dom vs Nond)
Median (%)	94.8	94.8	97.3
Mean (%)	94.3	94.1	96.6
Std Dev (%)	3.3	3.2	2.4
Max (%)	99.1	99.1	99.7
Min (%)	80.6	81.5	86.9
Avg. Inv. Trans. (PM3)	0.02	0.02	0.04

Tab. 1: This table shows the results of the assessment study. The values shown correspond to the performance metrics PM1 trough PM3. For PM1 and PM2, the algorithm displays mean and median values above 94%, standard deviation no greater than 3.3%, and a range of performance (min to max) better than or equal to 80.6% to 99.1%. In every case, the average number of invalid transitions per 48 hours (PM3) is less than or equal to 0.04.

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output for the dominant and non-dominant hand signals in 1-minute epochs, and PM3 is the number of invalid transitions per 48-hour period.

3 Results and Discussion

Fig. 2 provides an illustrative example of algorithm performance on a real actigraphy signal. On the top plot, a representative 48 hour actigraphy signal is shown in light color. The large dots on the x-axis correspond to sequences of consecutive zeroes that the algorithm has determined to be invalid data (i.e. actigraph removal). The filtered signal appears superimposed on the original actigraphy signal in a darker color . The horizontal line around 160 counts per minute represents the adaptive threshold calculated by the algorithm for this particular signal. Based on this adaptive threshold, a binary signal is produced, which appears in a light color on the bottom plot, where sleep regions are represented with a 0, and wake periods with a 1. Finally, a morphological filter is applied to eliminate invalid transitions, such as the one occurring at around 21:00 hours on the first day. The binary signal showing the final sleep/wake identification also appears in the bottom plot in a darker color, showing that the invalid transition has been eliminated. The two gray squares on the bottom plot correspond to the manually annotated sleep regions. The desired algorithm output would be 0 inside those regions and 1 everywhere else.

Performance metrics PM1-PM3 were calculated for every subject in the database. The results for every metric are shown in Table 3. The mean value for PM1 was 94.3%, with a standard deviation of 3.3% when using the dominant hand actigraphy signal, and 94.1% with a standard deviation of 3.2% with the non-dominant hand signal. The range of values for either hand over the 104 subjects in the database was between 80.6% and 99.1%. In the case of PM2, the mean was 96.6% with a standard deviation of 2.4% and a range of 86.9% to 99.7% over the entire database. The average number of invalid transitions per 48 hours was no greater than 0.04.

4 Conclusions

We described a novel algorithm for the identification of sleep/wake periods based on actigraphy to be used in ABPM applications. The algorithm uses adaptive rank-order filters, rank-order decision logic, and morphological filters. The algorithm was validated on a database containing 48-hour actigraphy recordings for 104 subjects. The algorithm achieved a mean coincidence with the reference signal above 94%, with less than 0.04 invalid transitions per 48 hours, on average.

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