Sleep and Wakefulness activities: are they intrinsically different?

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Abstract

Wrist actigraphy is a well established procedure used to measure the activity of a subject for long time periods. It is a valuable tool to detect abnormal movement patterns associated with several sleep disorders, including insomnia, phase lag and periodic limb movements. A potential ability of the actigraphy data, together with other sources of physiological and behavioral information, is the discrimination between sleep and wakefulness states.

From a magnitude point of view it is usually simple to do a rough discrimination between these two states. However, the intensity alone can lead to misclassification in the presence of abnormal patterns or in the transition between states.

The different characteristics of the movements in sleep and awake states is not simply a matter of magnitude, it is much more that that. Here, the purposeless nature of the movement during the sleep state is assessed and differences, comparing with the wakefulness state, are characterized.¹

1 Introduction

The importance of healthy sleep habits receives increasing attention from the medical community. It is now well established that sleep loss and sleep disorders have an impact on public health and on the economy [5]. Sleep disorders can be related with diabetes, obesity, depression and cardiovascular diseases and affect both young and adult populations. The golden standard for the diagnosis of these disorders is the Polysomnography (PSG), which is a reliable but complex procedure. The advent of portable and cheap sensors has given importance to home and long term monitoring, which are of special relevance in sleep studies.

Actigraphy data, obtained with non invasive and portable 3D accelerometers, reflect the motor activity of the subjects. It has the ability to register behavioral data under normal life conditions and has received plenty of attention in the last years, in [1] an in depth review of several techniques and algorithms is made.

Several studies have compared the performance of Actigraphy and PSG, many focusing on the detection of the Sleep/Wakefulness (s/w) states. In [4] two studies are presented that optimize the sleep-detection algorithm, in [6] the performance of actigraphy is evaluated and 4 scoring algorithms are compared. In [3] the data was analyzed in terms of statistical properties, two distinct types of random magnitudes are considered, the times between successive groups of movements and the number of movements at each fixed time measurement epoch. In [2] the actigraphy data was segmented in several windows and modeled using Autoregressive models. The obtained clouds of coefficients were used to roughly discriminate the type of movement and thus the (s/w) state.

In this paper the nature of the predominant movements in each state is explored. While movements during sleep state are typically random and without a purpose, movements during wakefulness state are coherent and correlated. Here, the work from [2] is extended, presenting a new algorithm to compute the coefficients of the model and the estimated noise is used to assess the nature of the movements during each state.

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2 Problem Formulation

The actigraphy data is described here by using the following autoregressive (AR) model [7] is

\[ x(n) = \sum_{i=1}^{p} a_i(n) x(n-i) + \varepsilon(n) = X^T a(n) + \varepsilon(n) \] (1)

where \( p \) is the model order, \( a(n) \) is a \( p \) dimensional column vector with the coefficients of the model to be estimated and \( \varepsilon \) is white noise. This noise signal is the key issue of this paper and can be obtained from the original noisy data and from the estimated coefficients of the AR model according

\[ \varepsilon(n) = x(n) - X^T a(n) \] (2)

The analysis of these residues can be used to assess the goodness of fit (GOF) of the model to the observations and it is expected, in highly correlated time courses associated with coherent movements, smaller energies for the residues than in purposeless activities, typically associated with the sleep state, where the correlation between samples is smaller.

The estimation procedure of the coefficients of the model at each discrete time point \( n \), \( a(n) \), according the observation model 2, is formulated as an optimization task where the following energy function is minimized

\[ E(n) = (x(n) - X^T a(n))^2 + \alpha |a(n) - a(n-1)|^2 \] (3)

where the regularization term is needed because the system directly derived from (2), is undetermined and therefore is ill-posed. The regularization term forces similarity of consecutive coefficient vectors, \( a(n) \) and \( a(n-1) \), under the assumptions of smooth transitions between states.

The estimation of each coefficient is obtained by computing the gradient of (3) with respect to \( a(n) \) and solving for \( a(n) \)

\[ a(n) = (X(n)X^T(n) + \alpha I)^{-1}X(n)x(n) + \alpha a(n-1) \] (4)

3 Experimental Results

The data available for this study was gathered from 30 subjects, who wore the actigraph for approximately 14 days. An initial analysis of the data excluded non-healthy subjects and datasets exhibiting abnormal behavioral patterns, resulting in 23 datasets. The used actigraphs, from Somnomedics, are composed by a 3D axis accelerometer and record the mean magnitude of the acceleration in each epoch, set to 1 minute in these experiments. The 23 datasets were manually segmented into sleep and wake periods by trained technicians with the help of the information logged on Sleep Diaries, maintained by the subjects during the study. Periods corresponding to day time, with the obvious exceptions of naps during the day, and continued movements during the night longer than one minute were classified in the wakefulness class. All other periods, with the exception of small transition intervals, were classified in the sleep class.

Two different experiences were made to test the algorithm and to assess the variation of the noise during s/w states. The first experience used a single dataset, corresponding to approximately 14 days of continuous data from one patient. This experience was repeated several times for different patients to ensure that the algorithm is robust.

The second experiment uses two large datasets composed by the concatenation of all the manually segmented sleep and wakefulness periods respectively. This second experiment aims to reproduce the work from [2].

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and to give a direct comparison between sleep and wakefulness data. In order to make the noise, obtained from (2) independent from the magnitude, all the data was normalized before computing the AR coefficients. The normalization is given by (5).

\[ \tilde{x}(n) = \frac{x(n) - \mu}{\sigma} \]  

(5)

Where \( \tilde{x}(n) \) is the normalized sample, \( \mu \) and \( \sigma \) are the mean and standard deviation respectively. In the first experiment both \( \mu \) and \( \sigma \) are obtained incrementally while in the second they are computed for the two datasets. The parameter \( \alpha \) from (3) controls the weight given to the previous estimate, when estimating a new vector of coefficients, this parameter was set on trial and error. The results shown on the next section were obtained with \( \alpha \) set to 150. The order of the model was set to 5, resulting in a good compromise between processing performance and the expected results.

Figure 1 shows the plot of a portion of actigraphy data, from a single patient, and the noise resulting from the AR model fitting. From the figure it is clear that the noise resulting from the AR fitting has peaks corresponding to the movements during the night, thus confirming that the model is unable to describe these movements.

On the second experiment two large arrays of coefficients were obtained, \( a_{\text{wake}}^{N,p} \) and \( a_{\text{sleep}}^{N,p} \). Where \( p \) is the model order and \( N \) the size of each array of data. The first 3 coefficients of each array were plotted in a 3D plot resulting in the two clouds shown in Figure 2. This Figure also shows the plot of the two arrays of noise for sleep and wakefulness data respectively. The standard deviation of both arrays of noise was computed, yielding \( \sigma_{\text{sleep}}^{\text{noise}} = 1.2 \) and \( \sigma_{\text{wake}}^{\text{noise}} = 0.68 \), confirming the results obtained graphically. Finally, the normalized histograms of the two arrays of noise were computed and are shown in Figure 3. The need for a normalization arises from the fact that the two data sets have different sizes, resulting in arrays of noise with different number of samples.

4 Conclusions

The standards of Actigraphy analysis normally rely on the magnitude of the movements and number of occurrences to discriminate between sleep and wakefulness states. In this paper we show that this discrimination can also be made analyzing the correlation between successive movements, i.e. movements during the sleep state normally do not have a purpose, on the other hand movements during the wakefulness state normally have an objective, thus resulting in different characteristics that can be assessed using the actigraphy data.

While the described method alone is not able to discriminate the two states, it supports the claim that the purposeless nature of the movements during sleep can indeed be used, together with other features, to classify data into s/w states. Further work will try to isolate occurrences of movement during sleep/wakefulness and do this processing on a per movement basis.

References


