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Statistical Characterization of Actigraphy Data for Sleep/Wake Assessment

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Abstract. Wrist actigraphy is a well established and very useful procedure for long term activity monitoring. Its lightweight and non-intrusive nature makes it not only a valuable tool in the detection of abnormal behavioral patterns, associated with certain sleep disorders, but also an unexpected source of basic information related with brain states, namely, wakefulness and sleep.

Here, the activity in the different states is assumed to be intrinsically different. These differences are not simply related with magnitude and movement counting, but due to real differences on the statistical distributions describing the actigraphy data across different states.

In this paper, the proposed methodology to characterize the actigraphy data is based on *Autoregressive* (AR) models. It is shown that the coefficients estimated in each state are organized into almost separable clusters on the feature space. This suggests the ability of the method to discriminate these states based only on the movements recorded on actigraphy data.

Keywords: Actigraphy; Autoregressive model; Pattern recognition; Sleep/Wake estimation

1. Introduction

Sleep disorders form a class of medical conditions, pathological or not, affecting millions of people across the world. They are characterized by changes in the normal pattern of the circadian cycle and even sleep disruption, with severe consequences for the general health condition of the subjects [Lger et al., 2007]. The detection, characterization and diagnosis of these disorders is usually performed with *polysomnography* (PSG), an expensive, complex and very intrusive exam,where several physiological variables are monitored, usually during a single night. This technology is not appropriated for long term monitoring because it is uncomfortable for the patient and strongly interferes with his mobility and normal routines.

For long term monitoring exams, alternative methods are preferred where other sources of data may be used, such as behavioral ones, e.g, *Sleep* and *Dream* diaries and *Actigraphy*.

Actigraphy (ACT), in particular, has been used with success in the last years in the diagnosis of several disorders like Insomnia [Siversten et al., 2006] and *Obstructive Sleep Apnea Syndrome* (OSAS) [Hedner et al., 2004].

ACT data is obtained with non invasive and highly portable accelerometer sensors, usually placed at the non dominant wrist, that measure the motor activity of the subjects during several days and nights. It is a valuable tool to gather behavioral information about the patients or sleep parameters such as sleep continuity and times, with a minimum intrusion and interference on normal daily routines [Sadeh et al., 1995].

It has been used with success in the estimation of the shape and characterization of the circadian cycle [Cole et al., 1992; Sadeh et al., 1994] but its use in the estimation of the sleep and wakefulness states is still an open discussion [Pollak et al., 2001].

In this paper we propose a statistical description of the movement based on *Autoregressive models* (AR) to show that movements during wakefulness and sleep states are intrinsically different.

Purposeless is the key concept of the paper. While movements during sleep state are typically random and without purpose, movements during wakefulness state are coherent and correlated. This empirical observation suggests that movements recorded during different states, apparently similar from temporal and intensity points of view, may present relevant differences from spectral or statistical distribution points of view.

Here, the work from [Domingues et al., 2010], where higher order statistics are computed with AR models, is refined to improve the discriminative power of the method for sleep staging purposes.

2. Material and Methods

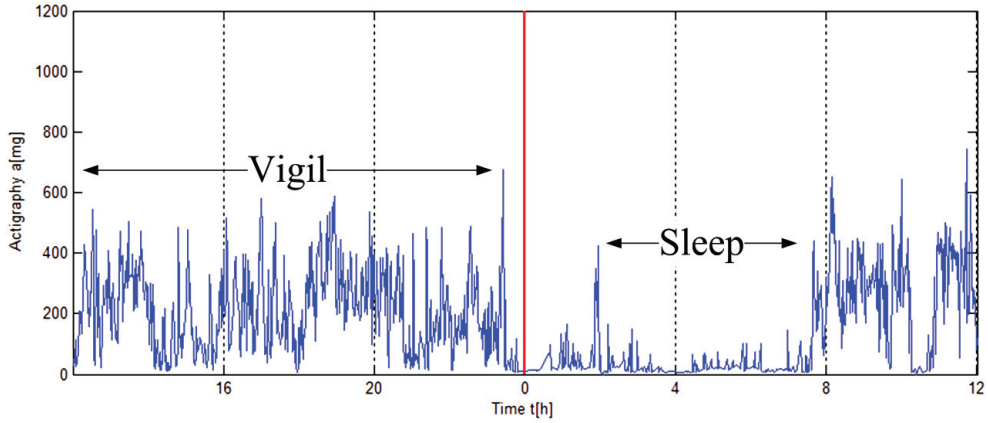

Figure 1 - Typical aspect of the actigraphy data recorded over one circadian cycle.

Actigraphy data was collected with a Somnowatch device, from Somnomedics, placed at the non-dominant wrist of the subjects with a sampling rate of 1Hz. The core of these devices is a 3D accelerometer that measure the acceleration along 3 orthogonal axis with a configurable output format. Here, the output of the actigraph is the acceleration magnitude. A typical time course of approximately one circadian cycle is displayed in Fig. 1.

The actigraphy data used in this study was jointly acquired with PSG data for validation purposes. The hypnogram, obtained from the PSG data by trained technicians, is used as ground truth to identify the sleep and wakefulness states in each epoch.

2.1. Pre-processing

Two pre-processing operations are performed on the data: i)Magnitude normalization and ii)activity segmentation. The proposed method is not intensity dependent, magnitude normalization is needed to minimize the interpatient and intra-patients variability effects. The normalization step is simply a mean subtraction and variance normalization procedure according to

$$x(n) = \frac{y(n) - \mu_Y}{\sigma_Y} \tag{1}$$

where μ_Y and σ_Y are the mean and standard deviation of the data, respectively.

The second operation, movement segmentation, is performed since the large segments of immobility are useless for activity characterization and sleep staging. They constitute a source of noise and confound factors in the training process of the staging classifier.

A simple threshold based detector was implemented to detect movement and extract the corresponding actigraphy data. Fig. 2 displays an example of pre-processed data. Fig. 2.a) shows the

normalized actigraphy signal and the movement indicator and Fig. 2.b) the corresponding hypnogram segment.

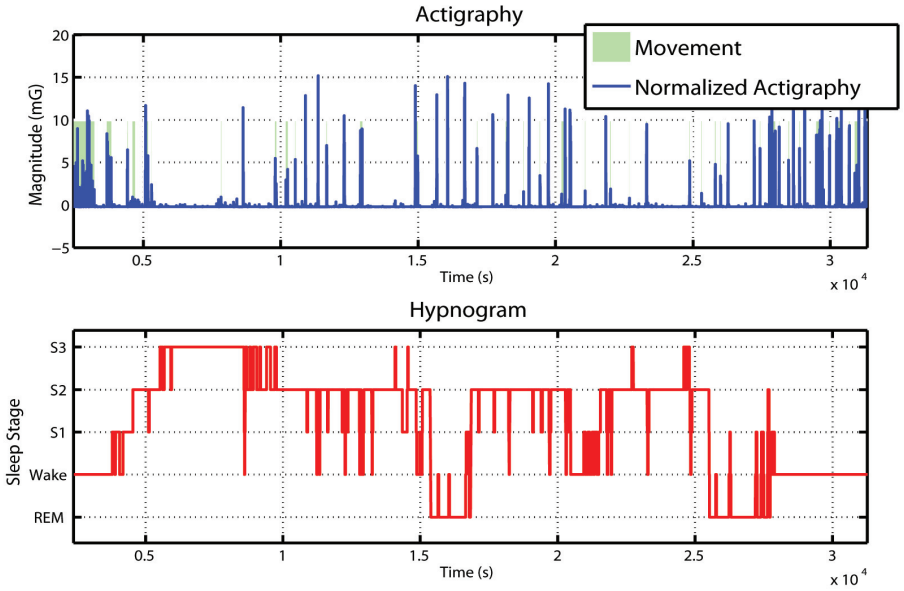

Figure 2: a) Actigraphy data and detected movements (top) and b) Hypnogram (bottom)

Data acquired from ten patients was used for analysis. After normalization and movement detection the segments corresponding to *sleep*, s, and *wakefulness*, w, states were concatenated into two large arrays respectively.

2.2. Correlation measures

As explained in Section 1 the work developed was based on the assumption that movements during sleep and wake states have different statistical properties. This claim can be easily confirmed by two simple measures; the auto-correlation and power spectral density of the two (**s**/**w**) arrays.

Fig. 3 shows the plot of the autocorrelation coefficients for the two arrays, obtained for a maximum delay of 300 seconds. It is clear that wakefulness movements are more correlated than sleep movements.

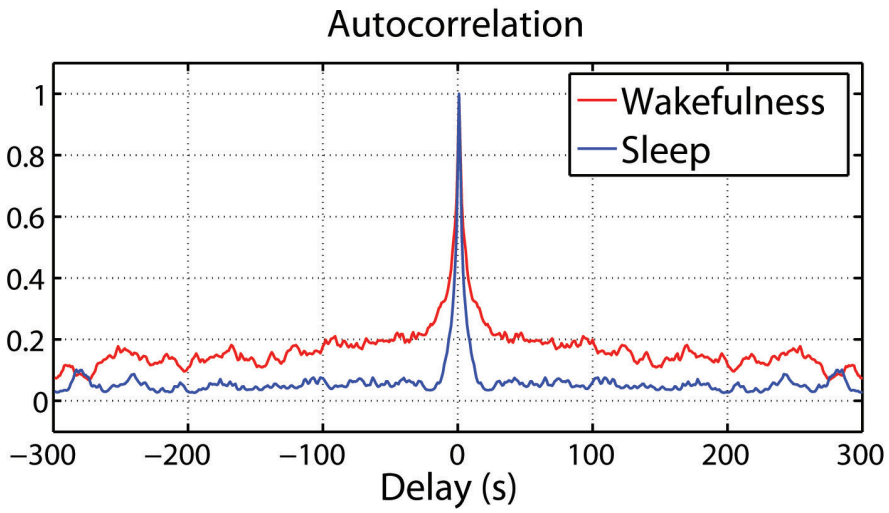

Figure 3 - Autocorrelation coefficient for sleep and wakefulness states.

Fig. 4 shows the Power Spectral Density (PSD), estimate via Yule-Walker's method [Takalo et al., 2005]. It can be seen that the bandwidth for wakefulness movements is higher than for sleep movements, thus confirming the initial guess.

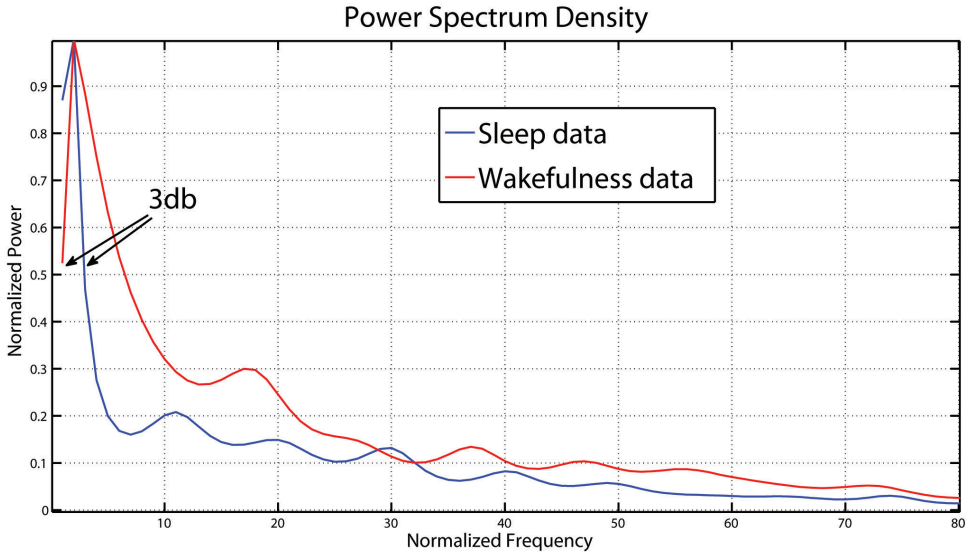

Figure 4 : Power Spectral density of the ovements during wakefulness (red) and sleep (blue) states.

2.3. Autoregressive coefficients estimation

The coefficients of *Autoregressive models* (AR) constitute the set of features used for sleep/wakefulness detection, a method already proposed before by the authors in [Domingues et al., 2010] to roughly discriminate sleep and wakefulness states from actigraphy data.

The estimation of the AR coefficients described in the previous work is performed on a block basis, introducing a heavy filtering effect. Here, the AR coefficients estimation is performed on a per sample basis, thus increasing time resolution and a ground truth (hypnogram) is available to quantify the performance of the method.

The overall idea is to estimate the coefficients of a p order AR model based on the current sample, on the $p-1$ previous samples and on the previous estimated set of coefficients, obtained in the previous sample. By doing this, the estimation of the coefficients are strongly guided by the previously estimated coefficients, incrementally updated with the information provided by the new sample.

Let us consider $y(n)$, the n^{th} actigraph sample, generated according to the following p-order AR model

$$y(n)=\sum_{k=1}^{p} a_k(n)\,x(n-k)+\varepsilon(n)=\boldsymbol{x}_p^{\boldsymbol{T}}(n)\,\boldsymbol{a}(n)+\varepsilon(n) \tag{2}$$

where $\boldsymbol{x}_p=\{x(n-1),x(n-2),\ldots,x(n-p)\}^T$ is a column vector containing the p previous samples, $\boldsymbol{a}(n)=\{a_1(n),a_2(n),\ldots,a_p(n)\}^T$ is the column vector of coefficients to be estimated at sample time n and $\varepsilon(n)$ is the residue.

The vector of coefficients is obtained by minimizing the energy of the residue

$$\varepsilon^2(n)=[\,y(n)-\boldsymbol{x}_p^{\boldsymbol{T}}(n)\,\boldsymbol{a}(n)]^2 \tag{3}$$

which is an ill-posed problem [Curtis et al., 2002], thus a regularization term is needed.

Let us consider the following energy function with regularization

$$E(n)=[\,y(n)-\boldsymbol{x}_{\boldsymbol{p}}^{\boldsymbol{T}}(n)\boldsymbol{a}(n)]^2+\alpha\|\boldsymbol{a}(n)-\boldsymbol{a}(n-1)\|_2^2 \tag{4}$$

where the quadratic term, $\|\boldsymbol{a}(n)-\boldsymbol{a}(n-1)\|_2^2$, is a prior that forces similarity between consecutive model parameters. The constant α tunes the strength of that similarity and was selected to be 150 on a trial and error basis. The stationary point of (4) with respect to $\alpha(n)$ is computed as

$$\nabla_{a(n)}E=\boldsymbol{x}_p(n)\cdot(\boldsymbol{x}_p^T(n)\boldsymbol{a}(n)-y(n))+\alpha\cdot[\boldsymbol{a}(n)-\boldsymbol{a}(n-1)]=0 \tag{5}$$

leading to

$$\hat{a}(n)=(\boldsymbol{x}_{\boldsymbol{p}}(n)\boldsymbol{x}_{\boldsymbol{p}}^{\boldsymbol{T}}(n)+\alpha I_p)^{-1}(\boldsymbol{x}_{\boldsymbol{p}}(n)y(n)+\alpha\,\boldsymbol{a}(n-1)) \tag{5}$$

Where I_p is the $p\times p$ identity matrix.

The optimal order of the model, p = 50, was obtained using Akaike information criterion [Akaike, 1969], allowing a good fit of the model to the data and an acceptable computation time.

By stacking the N vectors $\hat{\boldsymbol{a}}(n)$, obtained for each sample, from (6), and for each state, **w**akefulness and **s**leep, two $N\times p$ matrices are obtained, $\boldsymbol{A}_\tau,\tau=\{w,s\}$ .Each line $\boldsymbol{a}_l^\tau(n),0\le n\le N$, corresponds to the vector of p coefficients computed for the n^{th} sample and each column $\boldsymbol{a}_c^\tau(n),0\le i\le p$, corresponds to the i^{th} coefficient computed for the N samples.

For the sake of computational efficiency, a data dimensionality reduction is performed. For that, the 3 most discriminative components of $\hat{\boldsymbol{a}}(n)$ were selected performing an adapted forward search [Novovicov et al., 1994] according to the following procedure.

Let us consider the following metric function to measure the distance between specific sets of homologous columns, $\boldsymbol{a}_{\boldsymbol{c}}^{\boldsymbol{w}}(i_{1,}..,i_r)$ and $\boldsymbol{a}_{\boldsymbol{c}}^{\boldsymbol{s}}(i_{1,}..,i_r)$ from matrices $\boldsymbol{A}^{\boldsymbol{w}}$ and $\boldsymbol{A}^{\boldsymbol{s}}$ respectively,

$$d(i_{1,}i_{2,}..,i_r)=\frac{\left\|\mu_{\boldsymbol{a}_c^w}(i_{1,}..,i_r)-\mu_{\boldsymbol{a}_c^s}(i_{1,}..,i_r)\right\|}{\left\|\Sigma_{\boldsymbol{a}_c^w}(i_{1,}..,i_r)\right\|_F+\left\|\Sigma_{\boldsymbol{a}_c^s}(i_{1,}..,i_r)\right\|_F} \tag{6}$$

where μ and Σ are the mean and the covariance matrix of the selected columns and $\|x\|_F$ is the Frobenius norm.

In the first step of this feature selection procedure, the most discriminative coefficient is obtained by finding the two most distant homologous columns,

$$i_1=arg\,max_i\,d(i) \tag{7}$$

and in the next steps, the k^{th} most discriminative coefficient is obtained by

$$i_k=arg\,max_i\,d(i_{1,}i_{2,}i_{k-1},i) \tag{8}$$

where $i\in\{1,...,p\}\setminus\{i_1,.i_2,...,i_{k-1}\}$.

3. Results

The algorithm was first tested independently for each patient, two data sets were removed due to the lack of movement during sleep and noisy actigraphy data. The remaining 8 data sets were finally used to obtain the matrices of coefficients $\boldsymbol{A}^\tau$.

The three most significant coefficients, columns (50, 22, 23), are plotted in Fig.5 where the clouds of both states are clearly distinguishable.

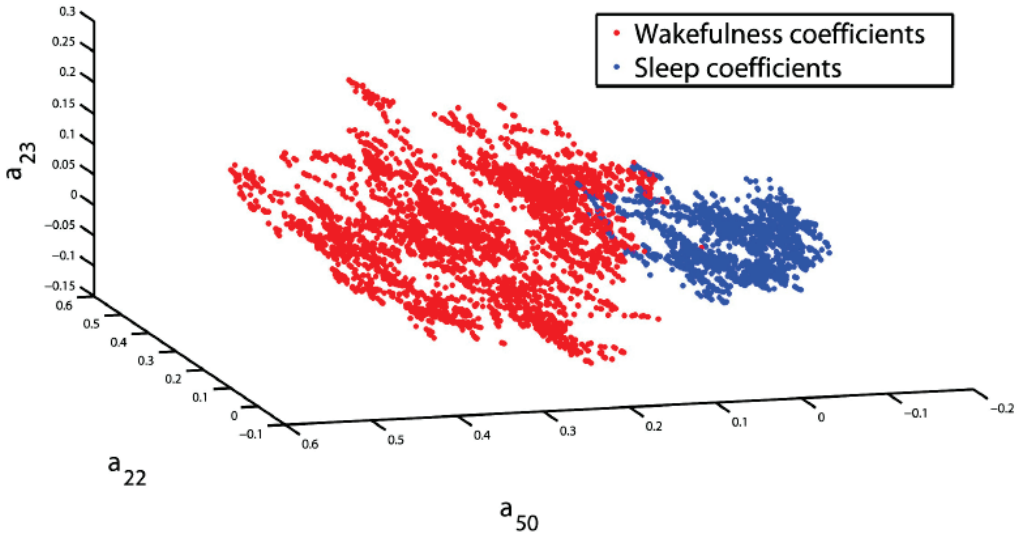

Figure 5 - The three most discriminative coefficients of the AR model yield almost separate clouds for Sleep (blue) and Wakefulness (red) states.

The separability and clustering nature of these clouds allows to use simple discriminative classifiers to discriminate the state and revels intrinsic differences on the movement characteristics between classes, which confirms the results obtained in [Domingues et al., 2010].

The modification of the algorithm to process the data on a per sample basis removes the lag and filtering effect on the previous method, allowing to detect subtle state changes.

The described method is robust but contains some user adjustable parameters, such as the movement detector threshold and model order, which strongly influences the results.

Although a special effort has been placed in the acquisition process and data selection, classifications errors in the hypnogram may persist. This is mainly related with human errors and inter operator variability Although a typical Polysomnography exam generates a large amount of data, only a small fraction, corresponding to movement periods, was used. Nevertheless, the eight data sets used in this study contained enough movement data to produce relevant results.

The obtained results are remarkable in the sense that using a simple device such as an actigraph, it is possible to do a rough estimation of the sleep/wake state of the patient. While these results alone are not sufficient for a standalone platform, they can be incorporated in existing frameworks to help improve the accuracy of sleep/wakefulness classifiers.

4. Conclusions

In this work the intrinsic properties of the movements during sleep and wakefulness are explored towards the development of a simple, portable and accurate sleep/wake estimator, based on actigraphy data and other physiological information.

AR coefficient based features and a *Forward Search* feature selection approach are used to discriminate wakefulness and sleep stages from actigraphy data.

With this method, it is shown that the movements during sleep and wakefulness states present different temporal correlation which is the basis for their discrimination.

Future work will combine the present work and features extracted from cardio-respiratory signals .

Acknowledgements

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