Sleep/Wakefulness State from Actigraphy

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Abstract. In this paper a definition of the *activity* (ACT) variable is proposed and a method to estimate it from the noisy *actigraph* output sensor data is described. A statistical model for the *actigraph* data generation process is suggested based on its working physical principles and on physiological considerations about human activity. The *purposeless* nature of the sleeping movements is used to discriminate the *Sleep* and *Wakefulness* (SW) states.

The estimated ACT signal from the *actigraph* output signal is correlated with the data from a *Sleep Diary* to validate the SW oscillations, computed from the ACT. A *Sleep electronic Diary* (SeD) was implemented in the scope of this work to make it possible an accurate register of the patient activities relevant for the diagnosis of sleep disorders.

Examples using real data, illustrating the application of the method, have shown high correlation between the output of the proposed algorithm that characterizes the *activity* and the data registered in the SeD.

Keywords: Statistical Signal Processing, Human Activity, Actigraphy, Sleep Disorder, Sleep Diary, Statistical Mixture.

1 Introduction

Sleeping is a key factor for a healthy condition and the inability to fall asleep or stay asleep has important impacts on people's health [1]. Diabetes, obesity, depression or cardiovascular diseases are associated with sleep disorders. An accurate assessment of the patient activity (ACT) may be very helpful in the diagnosis of pathological sleep disorders. However, an objective and accurate definition of human activity is difficult and depends on each specific application context. *Actigraphy* data may be used to quantify and characterize the ACT variable [2].

The actigraphy data is usually acquired with an *actigraph* sensor that is wrist watch shaped[1]. The actigraph device, containing a three axis accelerometer [3], records the detected acceleration magnitude on the non dominant wrist typically for a period of one week.

The main goal of this technique is to register the activity during the patients daily routine, in their natural environment, without the complexity associated

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[1] In this work a SOMNOwatch^{TM} device from SOMNOmedics GmbH was used.

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with other more sophisticated techniques such as the polysomnography. Despite its simplicity it is able to distinguish sleep form wakefulness states in approximately 80% up to 90% of the cases depending on the algorithm [4,5,6].

In this paper, the analysis of the actigraph output signal has revealed a mixture of two dominant components, one associated with the day life activity and the other associated with the night activity. The evolution of the relative importance of these two components along the circadian cycle have shown a strong correlation with the *Sleep Diary* information for different patients. Therefore, the probability function associated with the actigraph output signal is modeled as a mixture of two distributions modeling the two observed components.

It is thought that the difference in both components reside in the *purposeless* characteristic of the movements during the sleep state. During the wake state the movements are usually purposeful, they are coherent and coordinated which leads to a statistical distribution of the actigraph signal different from the one obtained during the sleep state where the *purposeless* nature of the movements, more impulsive, non coherent and usually more sparsely distributed along the time, induces the generation of an actigraph output signal with different characteristics.

The two distributions used to model the output signal of the actigraph are a shifted Maxwell distribution, prevalent during the wakefulness state and a Poisson distribution prevalent during the sleep state.

The shifted Maxwell distribution arises if the three accelerometer components are *independent and identically distributed* (i.i.d.) non zero mean Gaussian distributed. The Poisson distribution is appropriated when the movements are mainly constituted by short duration and non correlated impulses [7] low pass filtered by the actigraph device and by the window based processing algorithm proposed here. The visual inspection of the histogram of the signal confirms the validity of this model. However, for sake of simplicity, in this paper, the Poisson component is approximated by a normal distribution.

The proposed algorithm estimates the parameters of the mixture at each moment by considering data from a sliding window centered at each sample. The process is repeated for all time instants and regularization and outliers rejection procedures are applied. The overall process is described in the next section.

The ACT signal and the corresponding estimated SW state are compared with the *Sleep Diary* data for validation purposes. A *Sleep Diary* is a registration media where the patient register the events, corresponding time stamps and observations, occurred during the day or night, relevant for the diagnosis of sleep disorders. An electronic *Sleep Diary*, called *Sleep e-Diary* (SeD), was designed and implemented specifically in the scope of this project in order to improve the register accuracy of the data provided by the patient. It is implemented in Python [2] and was designed to run in a mobile phone over the operating system Symbian from Nokia.

[2] See Python Programming Language Official Website (http://www.python.org/)

2 Problem Formulation

The main component of the actigraph sensor is a 3D axis accelerometer and the output of the sensor is its acceleration magnitude. Inspection of the experimental data histogram have shown clearly two components, one more important during the day, $p_d(r)$, and the other more important at night, $p_n(r)$.

The first, $p_d(r)$, is modeled as a shifted Maxwell distribution, where the three acceleration components are assumed independent and identically non zero mean Gaussian distributed, $p(a_x) = p(a_y) = p(a_z) = \mathcal{N}(\mu, \sigma^2)$. Under these assumptions the acceleration magnitude, $r = \sqrt{a_x^2 + a_y^2 + a_z^2}$ may be modeled by a shifted *Maxwell* distribution, $\mathcal{M}(c_\mathcal{M}, \sigma_\mathcal{M}^2)$,

$$p_d(r) = \sqrt{\frac{2}{\pi}} \frac{(r - c_\mathcal{M})^2}{\sigma_\mathcal{M}^3} e^{-\frac{(r-c_\mathcal{M})^2}{\sigma_\mathcal{M}^2}}. \tag{1}$$

The second component, $p_n(r)$ is assumed to be generated from involuntary movements, less coordinated and more impulsive [8] [7]. Here, for sake of simplicity, a Gaussian distribution is used to describe this component, $\mathcal{N}(c_\mathcal{N}, \sigma_\mathcal{N}^2)$. Therefore the following mixture is proposed to describe the output signal of the actigraph sensor,

$$p(r, \theta) = \alpha \sqrt{\frac{2}{\pi}} \frac{(r - c_\mathcal{M})^2}{\sigma_\mathcal{M}^3} e^{-\frac{(r-c_\mathcal{M})^2}{\sigma_\mathcal{M}^2}} + \beta \frac{1}{\sqrt{2\pi}} \frac{1}{\sigma_\mathcal{N}} e^{-\frac{(r-c_\mathcal{N})^2}{2\sigma_\mathcal{N}^2}} \tag{2}$$

where the time varying parameter column vector,

$$\theta(n) = \{\underbrace{\alpha(n), \sigma_\mathcal{M}(n), c_\mathcal{M}(n)}_{\theta_\mathcal{M}(n)}, \underbrace{\beta(n), \sigma_\mathcal{N}(n), c_\mathcal{N}(n)}_{\theta_\mathcal{N}(n)}\}^T \tag{3}$$

is estimated to characterize the activity at each discrete instant n.

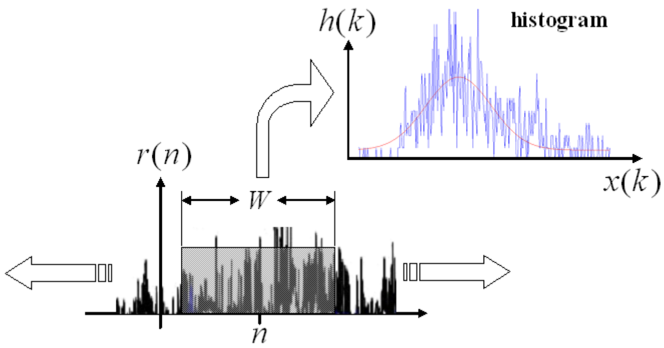


Fig. 1. Windowing parameter estimation with histogram fitting

The estimation of $\theta(n)$ at each instant n is performed by solving the following equation

$$\theta(n) = \arg\min_{\theta} \sum_{k=1}^{L} (h_n(k) - p(x_k, \theta))^2 \tag{4}$$

where $0 < n \leq N$, $\mathbf{h}_n = \{h_n(1), ..., h_n(L)\}$ is the L dimensional histogram, with bins centered at locations $\mathbf{x} = \{x_1, x_2, ..., x_L\}$, computed in a W dimensional window centered at the n^{th} sample and $p(x_k, \theta)$ is the function (2) computed at locations x_k, as shown in Fig.1.

The relative importance of each distribution along the circadian cycle is obtained from the parameters $\alpha(n)$ and $\beta(n)$. In most cases both distributions are present, but in some cases only one of them is present. During the night $p_n(r)$ is prevalent and during the day the more important distribution is usually $p_d(r)$. The multidimensional signal $\theta(n)$, here called *Activity* (ACT), provides a more complete and accurate characterization of the patient activity than the usual simple acceleration magnitude.

The optimization task described in equation (4) is performed by using the function *nlinfit* implemented in MatLab where the unknown parameters are obtained by estimating the coefficients of a nonlinear regression function using the least squares.

This optimization task is an *ill-posed* problem that is iteratively performed after pre-processing the raw data and post processing of the estimated results. Special care must be used with the initialization vector and in the post processing procedure, outliers on the estimated results are removed and replaced by interpolated ones.

3 Sleep/Wakefulness State Estimation

The evolution of the parameters $\theta_{\mathcal{N}}(n)$ and $\theta_{\mathcal{M}}(n)$ along the circadian cycle is used to characterize the type of activity of the patient. Here it is suggested that the relative importance of each distribution seems to be better in the estimation of the *sleep/wakefulness* (SW) state of the patient than the simple actigraph output signal intensity.

The following difference is used to assess the preponderant distribution at instant n

$$sw(n) = \alpha(n) - \beta(n) \tag{5}$$

where $\alpha(n)$ and $\beta(n)$ are the weights associated with $p_d(r)$ (wakefulness) and $p_n(r)$ (sleep) respectively in the mixture.

Let us define the *Sleep/Wakefulness* (SW) binary state variable as follows

$$SW(n) = \begin{cases} 0 & \text{if sleep} \\ 1 & otherwise \end{cases} \tag{6}$$

The state variable $SW(n)$ may be estimated from the noisy (non smoothed) signal $sw(n)$ as follows

$$\hat{\mathbf{SW}} = \arg\min_{\mathbf{SW}} E(\mathbf{sw}, \mathbf{SW}) \tag{7}$$

where $\mathbf{SW} = \{SW(1), SW(2), ..., SW(N)\}^T$, $\mathbf{sw} = \{sw(1), sw(2), ..., sw(N)\}^T$ and

$$E(\mathbf{sw}, \mathbf{SW}) = \underbrace{\sum_n sw(n)(1 - 2SW(n))}_{\text{binarization}} + \underbrace{\alpha \sum_n |SW(n) - SW(n-1)|}_{\text{regularization}} \tag{8}$$

where the first term forces the binarization of $sw(n)$ according

$$SW(n) = \begin{cases} 0 & \text{if } sw(n) < 0 \\ 1 & \text{otherwise} \end{cases} \tag{9}$$

The regularization term based on the L_1 norm is used to force a stepwise constant solution with abrupt transitions by introducing temporal correlation between neighboring samples, $|SW(n) - SW(n-1)|$, where differences between consecutive samples of $\mathbf{SW}$ are penalized by α. As larger α is as the large is the penalization and as stepwise constant is the solution. The value of α is manually chosen in order to keep the significant transitions related with changes on the state of the patient and to eliminate the transition due to the noise present in $sw(n)$.

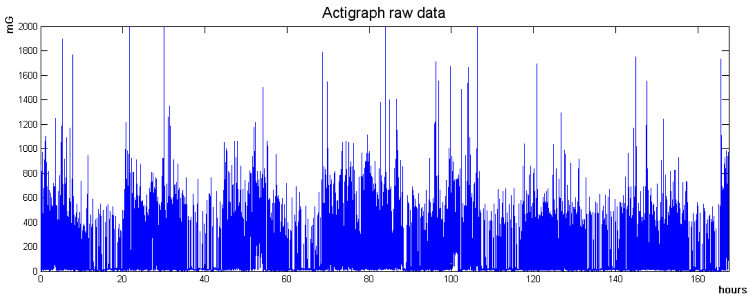
The minimization of the energy function (8), formulated in (7), is a huge combinatorial optimization problem in the $\{0, 1\}^N$ high dimensional space where N is the length of $\mathbf{SW}$. This minimization is solved by using a *Graph-Cuts* (GC) based algorithm, which is computational efficient providing the global minimum of (8) [9].

4 Experimental Results

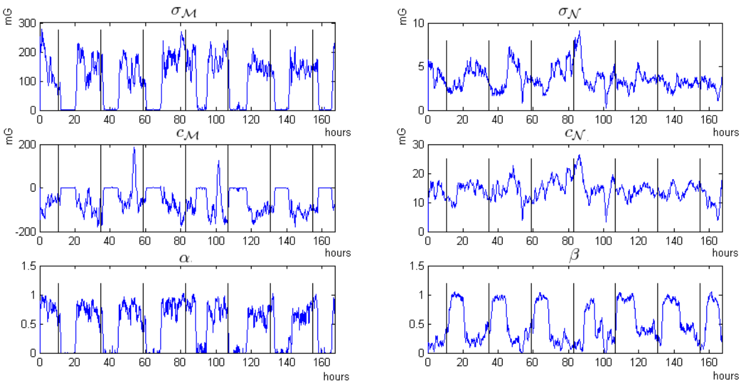
In this section an illustrative example using real data is presented. This study was performed for approximately 7 days, comprising about 167 hours. The raw data collected by the actigraph sensor is displayed in Fig.2.a). The six estimated components of $\theta(n)$ are displayed in Fig.2.b).

In this example are visible the 7 periods corresponding to the seven consecutive days that the patient wore the actigraph. The values of $\sigma_{\mathcal{M}}$ range from 0 to 300 mG with $c_{\mathcal{M}}$ ranging between -200 and 200 mG, representing the larger magnitude intensities of the acceleration distribution associated with the Maxwell component. The values associated with $p_n(r)$, are smaller. $\sigma_{\mathcal{N}}$ ranges from 0 to 10 mG and $c_{\mathcal{M}}$ from 0 to 30 mG.

The signal $\alpha(n) + \beta(n)$ is approximately one, with mean 0.98 and standard deviation 0.096, which mean that the mixture is able to describe the data most of the time.



(a) Raw data.



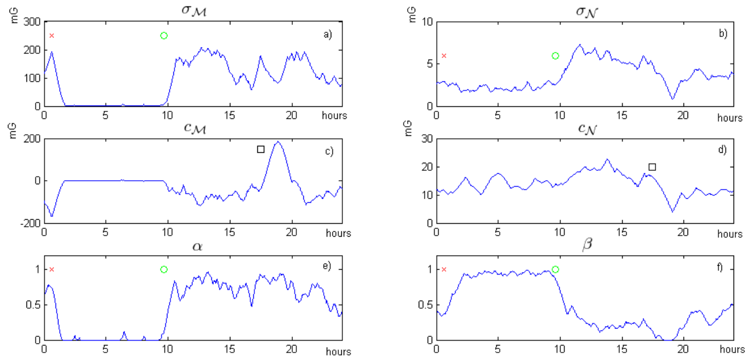
(b) Processed data.

Fig. 2. Real example acquired during 167 hours

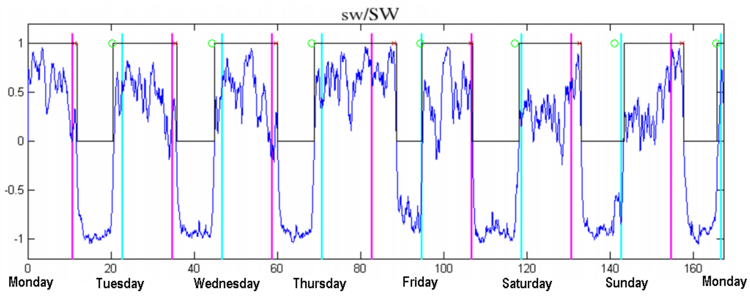
Fig.3.a) displays the estimated parameters on a single day between two consecutive midnights extracted from the graphs displayed in Fig.2.b). There are observed changes on the estimated parameters, according to the actions taken by the patient and with the moment that they happened. In these graphs α is very close to zero and β is clearly different from zero between the *"x"* mark (*go to bed* from the SeD) and the *"o"* mark (*get out of bed* from the SeD) where the patient is supposed to be sleeping. Out of this interval, at the same day, the situation is reversed, which indicates that the Maxwell distribution is predominant during the day time, while the Normal distribution is predominant during the night.

A relevant detail, observed in Fig.3.a), is the high values of $c_{\mathcal{M}}$ that match the time marked by the subject in the SeD as exercise. This suggests that the signal $\theta(n)$ may be used to detected specific activities or to measure activity intensity levels.

The SW state, estimated by (7), and the SeD data, are overlapped and displayed in the Fig.3.b). Here we can see that the GC method successfully estimates the SW state and that it is well correlated with the SeD data. Other experiments performed with data collected from patients with sleep disorders have shown abnormal patterns on the estimated SW state that may be used in the diagnosis of these disorders.



(a) Zoom from Fig.2.b) overlapped with data collected with the SeD. *"x"* and *"o"* marks indicate the *"go to bed"* and the *"get out of bed"* events respectively registered in the SeD. On c) and d), the black square represents the time of exercise.



(b) Representation of the *Sleep/Wakefulness* (SW) state. Vertical magenta lines represent the midnight instants and the cyan ones represent the midday. *"x"* and *"o"* marks indicate the *"go to bed"* and the *"get out of bed"* events respectively registered in the SeD.

Fig. 3. Zoom and SW state

5 Conclusions

This paper proposes a new definition and method to estimate the *activity* (ACT) variable from actigraphy data. The *purposeless* nature of the movements during the sleep is the key concept used to model the actigraph sensor output by a mixture of two distributions. During the wakefulness state a Maxwell distribution is prevalent corresponding to movements that are usually coherent and fully purposiveness. During the sleep state the actigraph sensor output signal is better described by a Poisson distribution (here approximated by a Gaussian function) where the movements are impulsive, less coherent and usually *purposeless*.

This paper describes a method where a six dimensional vector of parameters of a two distribution mixture is estimated along the time and is proposed to describe the activity (ACT) that is used to estimate the *Sleep/Wakefulness* (SW) state variable.

An electronic *Sleep Diary*, here called *Sleep electronic Diary* (SeD), was developed in the scope of this work to run in a mobile phone. The goal is the improvement of the information accuracy registered by the patient for sleep disorders diagnosis purposes.

The estimated ACT signal from real patients and the corresponding data registered with the SeD have shown to be highly correlated which strongly suggests the usefulness of the method in the diagnosis of sleep disorders. The estimated SW state in patients with diagnosed sleep disorders have shown abnormal circadian patterns that may be used to identify that disorders without need of other more complex and sophisticated methods such as polysomnography.

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References

[1] Pandi-Perumal, S.R., Leger, D.: Sleep Disorders: Their Impact on Public Health, Informa Healthcare, UK (December 2006)
[2] Morgenthaler, T.I., Lee-Chiong, T., Alessi, C., Friedman, L., Aurora, R.N., Boehlecke, B., Brown, T., Chesson, A.L., Kapur, V., Maganti, R., Owens, J., Pancer, J., Swick, T.J., Zak, R.: Practice parameters for the clinical evaluation and treatment of circadian rhythm sleep disorders. Sleep 30(11), 1445–1459 (2007)
[3] Motoi, K., Tanaka, S., Nogwa, M., Yamakoshi, K.: Evaluation of a new sensor system for ambulatory monitoring of human posture together with walking speed. Transactions of the Japanese Society for Medical and Biological Engineering: BME 41(4), 273–279 (2003)
[4] Cole, R.J., Kripke, D.F., Gruen, W., Mullaney, D.J., Gillin, J.C.: Automatic sleep/wake identification from wrist activity. Sleep 15(5), 461–469 (1992)
[5] Paquet, J., Kawinska, A., Carrier, J.: Wake detection capacity of actigraphy during sleep. Sleep 30(10), 1362–1369 (2007)
[6] Jean-Louis, G., Kripke, D.F., Cole, R.J., Assmus, J.D., Langer, R.D.: Sleep detection with an accelerometer actigraph: comparisons with polysomnography. Physiology & behavior 72(1-2), 21–28 (2001)
[7] Gimeno, V., Sagales, T., Miguel, L., Ballarin, M.: The statistical distribution of wrist movements during sleep. Neuropsychobiology 38, 108–112 (1998)
[8] Vgontzas, A.N., Kales, A.: Sleep and its disorders. Annual Review of Medicine 50, 387–400 (1999)
[9] Boykov, Y., Veksler, O., Zabih, R.: Fast approximate energy minimization via graph cuts. IEEE Trans. Pattern Anal. Mach. Intell. 23(11), 1222–1239 (2001)