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Statistical characterization of actigraphy data during *Sleep* and *Wakefulness* States

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***Abstract*— Human activity can be measured with *actimetry* sensors used by the subjects in several locations such as the wrists or legs. Actigraphy data is used in different contexts such as sports training or tele-medicine monitoring. In the diagnosis of sleep disorders, the *actimetry* sensor, which is basically a 3D axis accelerometer, is used by the patient in the non dominant wrist typically during an entire week. In this paper the actigraphy data is described by a weighted mixture of two distributions where the weight evolves along the day according to the patient *circadian* cycle. Thus, one of the distributions is mainly associated with the *wakefulness* state while the other is associated with the *sleep* state. Actigraphy data, acquired from 20 healthy patients and manually segmented by trained technicians, is used to characterize the acceleration magnitude during *sleep* and *wakefulness* states. Several mixture combinations are tested and statistically validated with conformity measures. It is shown that both distributions can co-exist at a certain time with varying importance along the *circadian* cycle.**

I. Introduction

Accurate diagnosis of sleep disorders is usually only possible in clinical facilities, where a *polysomnography* (PSG) exam is performed. Due to the complex setup associated to the PSG, the procedure strongly constraints the natural behavior of the patients and prevents long term monitoring of the processes needed for an accurate analysis of the sleep cycle. The wrist activity can be obtained with an *actimetry* sensor, also known as actigraph, the acquired data is an important tool in the assessment of the *circadian* cycle. Several disorders, characterized by abnormal patterns of activity and movement, can be diagnosed by the actigraphy data.

This low-cost and non-invasive method can be used to estimate the *sleep/wakefulness* (SW) state but with less accuracy than the PSG. Other important indicators are however impossible to obtain only from actigraphy data such as the detection of sleep stages [2], [3].

The main component of the *actimetry* sensor is a 3D axis accelerometer and the recorded data is usually the magnitude of the acceleration registered in a continuous basis during several days, *e.g.* an entire week. This small and portable device typically includes a microprocessor, an analog to digital converter, internal memory and a low energy wireless communication module. The acquisition rate, that can be adjusted, is typically set to 32 Hz.

In a common configuration the device outputs the number of movements during a given time interval, called *epoch* [7], [6]. However, this method does not capture relevant information such as movement intensity and dynamics.

In other configuration, the maximum acceleration magnitude during each epoch is registered. This configuration is very sensitive to noise, and non maximum, but relevant, peaks are not considered [5].

In the most common configuration the mean magnitude (or digital integration) of the activity is computed during each *epoch* [5].

The *actimetry* sensor is usually placed in the limbs. The most common location in long term monitoring procedures is the non-dominant wrist of the patient. Although the used device also registers the light and position of the patient along the time, in this work, the proposed mixture-distributions only take into account the actigraphy data.

The different pattern of movements observed during the circadian cycle can be easily used to roughly distinguish *wakefulness* and *sleep* states [2]. During the day (typically *wakefulness* state) the movements are usually very heterogeneous and dense. On the other hand, during the night (*sleep* state) the movements are more impulsive and sparse [4]. The difference resides not only in the intensity of the actigraphy signal but also in its statistical characterization. The differences on the actigraphy data in these two different states is related with the different *purpose* natures of them. During the day there is usually a goal and the corresponding movements have specific coherent and consistent purposes. On the other hand, during the *sleep* state the movements are involuntary and usually *purposeless* which make them impulsive non coherent and sparse.

In this paper the actigraphy data is described by a weighted mixture of two distributions where the weight evolves along the *circadian* cycle. One of the distributions of the mixture is mainly associated with the *wakefulness* state and the other is associated with *sleep* state. The difference between these two distributions is related with the characteristics associated to the different pattern of movements observed during *wakefulness* and *sleep* states. Real data in raw format, from 20 healthy subjects, is used to statistically characterize the *actimetry* signal and propose a mixture distribution model to describe it.

A common approach in the analysis of actigraphy is the description of data as a function of the number of

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recorded movements along each epoch. In [7] this analysis led to an exponential probability distribution to describe data during *sleep* state, and an activity dependent distribution for *wakefulness* state data. While activities such as running or walking can be described with a normal distribution, standing or laying is best described by Poisson or exponential distributions [8]. In [1], actigraphy data has been characterized using the magnitude for each epoch, in this work a Maxwell - Boltzan distribution was suggested to describe *wakefulness* state and poisson distribution for *sleep* state.

This paper is organized as follows. In section I, a small introduction is made about the techniques used to estimate the *Sleep/Wakefulness* state, the state of the art is revised and the paper organization described. In section II of the Methods, detailed information is given about the data sets and the analysis procedures for actigrahy data. Results are presented and discussed in section III and conclusions are drawn in section IV.

II. Methods

In this study 20 healthy patients wore an actimeter in the non dominant wrist for a period of approximately 14 days/nights in normal quotidian life. Light intensity and position were also acquired and stored by the actimeter.
The epoch length was set to 60 seconds, the sampling rate 32Hz and the resolution 12 bits. Light intensity and position were stored in an adaptive sampling rate basis, according to a variation criterion, with a maximum period rate of one minute. This additional information, together with patient's position and a *sleep e-Diary* [1] was used in the segmentation process of the actigraphy data. This process was supervised by trained technicians. Fig. 1 shows an example of segmented actigraphy data.

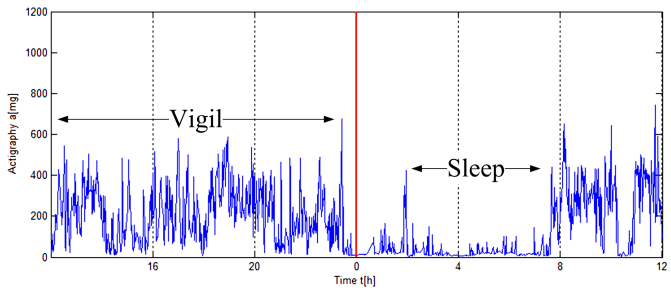

Fig. 1. *Sleep* and *wakefulness* states are characterized by different patterns of movements

For each patient, the segmented actigraphy was grouped according to the corresponding state, *wakefulness* or *sleep*, thus two large data arrays were obtained per patient. The histograms of these two arrays were computed and several different distributions were fitted to assess the best representation for each data type, according to

$$\hat{\theta}_k = \arg\min \|p_k(x,\theta) - h_k(x)\|^2 \tag{1}$$

where $p_k(x,\theta)$ is the distribution used to fit the real histogram $h_k(x)$ obtained from the k^{th} subject.

The fitting error was computed according to

$$e_k = \frac{\sum |p_k(x,\theta) - h_k(x)|}{\sum p_k(x,\theta)} \tag{2}$$

where k is the subject index, $p(x,\theta)$ is the distribution to be fitted and $h(x)$ is the histogram.

It was shown that, while some single distributions can fit the data with acceptable error, a mixture of two distributions fits better the actigraphy data. Thus, several mixtures of two different distributions were tested in order to identify the combination that best describe the actigraphy data during the two states. The probability distribution functions of the mixture distribution is the following

$$p(x) = \alpha \cdot p_s + (1-\alpha) \cdot p_w \tag{3}$$

where α is a weight coefficient and p_s, p_w are the probability function for *sleep* and *wakefulness* states respectively. In order to estimate the optimal values for the parameters of the distribution functions, nonlinear curve-fitting problems were solved by using the function *lsqcurvefit* from *Matlab*. From the initial histogram fitting process, four distributions were chosen, two for the *sleep* state and two for the *wakefulness* state. The optimal mixture was then found by combining these distributions, as shown in Table I.

TABLE I
Table of mixture distributions

p_w	p_s
Maxwell distribution	Gamma distribution
Maxwell distribution	Inverse Gaussian distribution
Rician distribution	Gamma distribution
Rician distribution	Inverse Gaussian distribution

The assessment of the fitting process was done through the fitting error, by the Kolmogorov-Smirnov p-value test (KS) and by the Kullback-Leibler distance (KL).

Finally, to infer the performance of the algorithm in non-segmented data, the evolution of α was observed along the circadian cycle for several days. Assuming that the actigraphy data can be modeled by a mixture distribution and that each distribution has a variable weight, depending on the period of the circadian cycle, then α from (3) should increase during the night and decrease during the day. This can be used to infer *Sleep/Wakefulness* state.

Due to the large size of the data sets, the algorithms were implemented using overlapping sliding windows. The window size was set to 100 samples (1 sample = 1 minute) and with a sliding step of 100 samples. The histograms were computed for each window and the parameters of distribution functions were estimated.

III. Results

Tests performed with the 20 actigraphy data sets and several distributions have shown that the Gamma distribution (G) and the Inverse Gaussian distribution (IG) are the most appropriated to describe the actigraphy data during sleep.

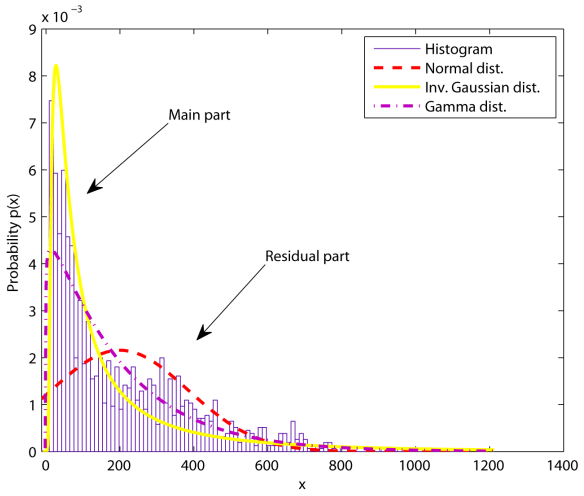

Fig. 2. Histogram for *sleep* state data fitted with different distribution

The Rician (R) distribution and the Maxwell - Boltzan distribution (M) are the more appropriated to describe the data during the *wakefulness* state. Fig. 2 and Fig. 3 plot the obtained results, when modeling the actigraphy data as a single distribution.

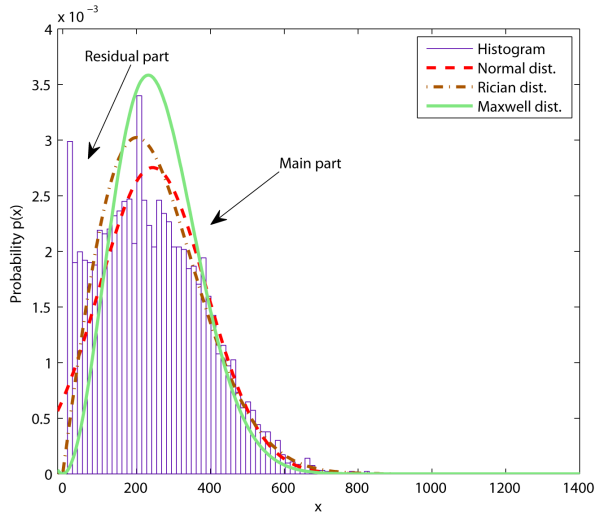

Fig. 3. Histogram for *wakefulness* state data fitted with different distribution

The mean and standard deviation values displayed in all tables were computed by using whole data from all subjects. On the contrary, the histograms displayed in all Figs in this section were computed from a single subject for illustration purposes only.

Fig. 2 shows the histogram obtained for the segmented sleep data. From the main part of the histogram it can be seen a small lobe which suggests the presence of other distribution. The same situation occurs in the *wakefulness* state histogram, plotted in Fig. 3, where before the main lobe there is a less pronounced peak.

TABLE II

MIXTURE DISTRIBUTION DURING *wakefulness* STATE

	Wakefulness					
Mix. dist.	$\bar{e}$	σ	*KL*	σ	*KS*	σ
M&G	0.112	0.032	0.236	0.101	0.012	0.034
M&IG	0.17	0.031	0.35	0.1	10^{-5}	10^{-5}
R&G	**0.095**	0.033	**0.182**	0.059	**0.027**	0.038
R&IG	0.134	0.04	0.313	0.175	0.004	0.011

TABLE III

MIXTURE DISTRIBUTION DURING *sleep* STATE

	Sleep					
Mix. dist.	$\bar{e}$	σ	*KL*	σ	*KS*	σ
M&G	0.19	0.05	0.067	0.403	0.005	0.02
M&IG	0.22	0.06	**0.10**	0.35	0.001	0.004
R&G	**0.188**	0.055	0.016	0.343	**0.019**	0.085
R&IG	0.226	0.093	0.151	0.362	0.001	0.006

The mixture distributions shown in Table I were tested with *Sleep* and *Wakefulness* data. During *wakefulness* state the minimum mean fitting error obtained with the Rician and Gamma distributions is $\bar{e} = 0.095$ and the corresponding standard deviation is $\sigma = 0.033$. For Maxwell and Gamma distribution mixture the minimum mean error is 0.112 with standard deviation 0.032, as shown in Table II.

For *sleep* state, the minimum mean fit error is $\bar{e} = 0.188$ with standard deviation $\sigma = 0.055$ for Rician and Gamma mixture distributions as shown in Table III.

The obtained results are supported by the Kolmogorov-Smirnov p-value test (KS) and the Kullback-Leibler distance (KL).

Fig. 4 and Fig. 5 show the histograms obtained for sleep and wakefulness data and the respective fit using two different mixture distributions. The data represented in the two histograms correspond to one single patient and all the data corresponding to *sleep* and *wakefulness* states respectively.

The mixture that lead to a smaller mean fitting error (0.265), Kullback-Leibler divergence (0.022) and Kolmogorov-Smirnov test p-value (0.044), is formed by the Gamma distribution for the *sleep* state and the Rician distribution for the *wakefulness* state (see table IV.).

The algorithm was finally tested with non-segmented data, according to (3), in order to observe the evolution of α through the circadian cycle. Fig. 6 plots the actigraphy data and the corresponding evolution of α during a period

TABLE IV

MIXTURE DISTRIBUTIONS ALONG THE CIRCADIAN CYCLE

	Along the circadian rhythm					
Mix. dist.	$\bar{e}$	σ	*KL*	σ	*KS*	σ
M&G	0.289	0.08	**0.018**	0.012	0.039	0.066
M&IG	0.281	0.057	0.034	0.018	0.023	0.025
R&G	**0.265**	0.061	0.022	0.009	**0.044**	0.068
R&IG	0.268	0.039	0.029	0.016	0.035	0.042

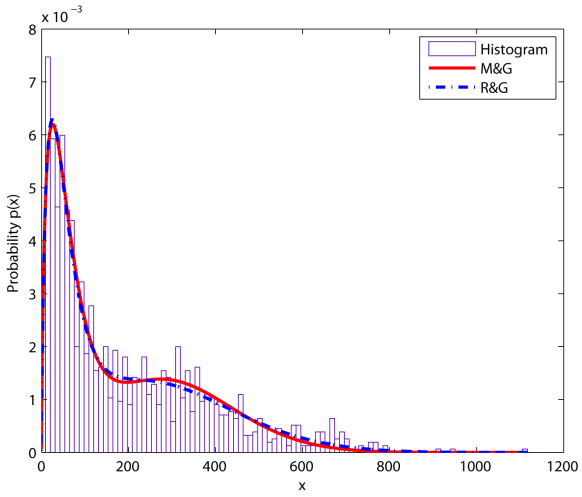

Fig. 4. The mixture distribution and the *sleep* histogram.

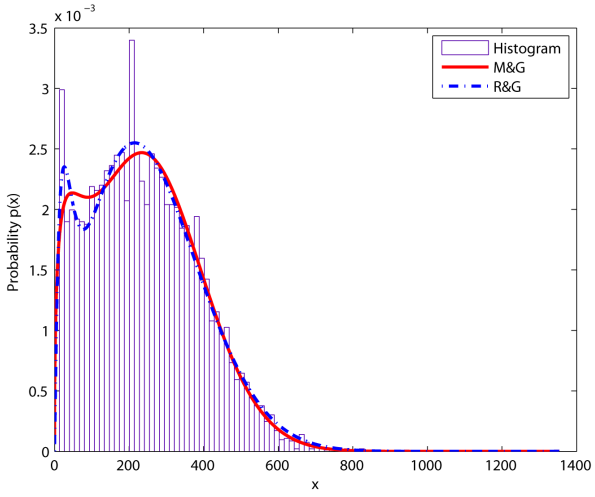

Fig. 5. The mixture distribution and the *wakefulness* histogram

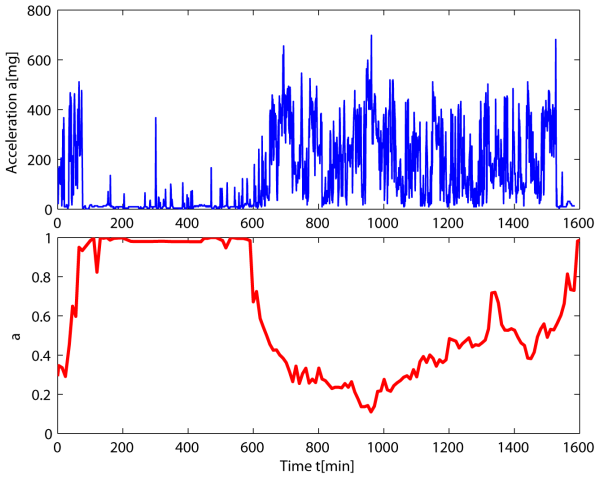

Fig. 6. Evaluation of α along the Circadian Cycle

of approximately 26 hours. As expected, the weight of the two distributions evolves according the circadian cycle. While during sleep, the dominant distribution is the Gamma distribution and the value of α is close to 1, during the day the dominant distribution is the Rician distribution with α presenting smaller values, as expected.

IV. Conclusion

This paper proposes a new statistical distribution to describe the different statistical characteristics of the wrist actigraphy during *sleep* and *wakefulness* states. It is shown that the global activity can be described by a mixture of two distributions; one associated with movements during *sleep* state and other associated with movements during *wakefulness* state. The main reason for the differences observed between both types of activities resides in the *purposeless* nature of the movements during *sleep* state.

During *sleep* state the movements are mainly described by the Gamma component of the mixture while for *wakefulness* state the Rician distribution is dominant. These two distributions co-exist with varying importance during the whole circadian cycle. The weight coefficient of the mixture, α, evolves along the circadian cycle and may be used to help in the estimation of the *Sleep/Wakefulness* state.

In the next steps of this work other physiological parameters and data will be used, jointly with the α parameter, to accurately estimated the SW state, characterize the sleep behavior and diagnosis some sleep disorders.

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