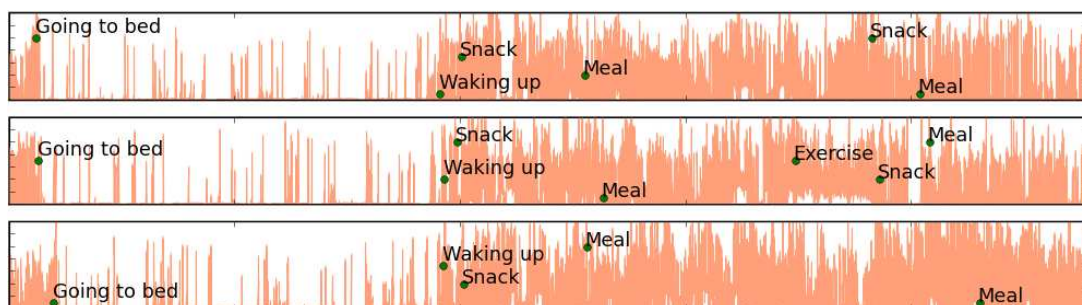




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Activity Characterization from Actimetry Sensor Data for Sleep Disorders Diagnosis

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Abstract

The *human activity* (HA) is one of the most important indicators used in assessing the sleep/vigil state and to estimate the sleep circadian cycle. Its accurate definition and measurement is very difficult. Usually only an indirect and noisy version is available, acquired with an *actigraph*, that is a device mainly composed by a three axis accelerometer.

In this thesis the actigraph signal is statistically processed and considered as a noisy observation of the unknown variable *Activity* (ACT). The activity signal is correlated with the data from a *sleep e-diary* (SeD) to estimate the sleep/vigil state and identify abnormal patterns on its circadian cycle. In the scope of this work a SeD was developed in a mobile phone to make it easier for patients to register the more relevant events in their daily routine.

The main goal of this thesis is to define the HA and to propose a method to estimate it from the actigraph data and from the SeD.

An observation model for the actigraph signal is proposed based on the physical working principles of the acquisition device. A Bayesian approach is used to estimate the activity and a segmentation algorithm based on *Graph-Cuts* is used to infer the sleep/vigil (SV) state.

Experiments using real data have shown two distinct statistical distributions of the actigraph signal, one space-shifted Maxwell distribution during the wake time, and a space-shifted Poisson distribution during the sleep time. The estimated activity and SV state are consistent with the SeD data.

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

Resumo

A *actividade humana* (AH) é um dos indicadores mais importantes para avaliar o estado sono/vigília e para estimar o ciclo circadiano. A sua definição e medição exactas são muito difíceis de realizar, sendo que normalmente apenas se conhece uma versão indirecta adquirida com um actígrafo, que é essencialmente um acelerómetro tri-axial.

Nesta tese, o sinal proveniente do actígrafo vai ser processado estatisticamente e considerado como sendo uma observação de uma variável desconhecida, a *actividade* (ACT). O sinal da actividade é então correlacionado com os dados obtidos através de um diário de sono electrónico, para estimar o estado sono/vigília e identificar padrões anormais no ciclo circadiano. No seguimento deste trabalho foi desenvolvido um diário de sono electrónico (DSE), implementável em telemóvel, com o objectivo de tornar mais fácil para os pacientes o registo dos eventos mais relevantes no seu dia-a-dia.

O principal objectivo deste trabalho é definir a AH e propôr um método para a estimar a partir dos dados do actígrafo e do diário de sono electrónico.

É proposto um modelo de observações para o sinal do actígrafo, baseado nos princípios físicos de funcionamento do dispositivo de aquisição. É usada uma aproximação Bayesiana para estimar a actividade e um algoritmo de segmentação, baseado em *Graph-Cuts*, para inferir sobre o estado sono/vigília (SV).

As experiências com dados reais mostraram duas diferentes distribuições estísticas do sinal do actígrafo, uma distribuição de Maxwell deslocada no espaço durante a vigília, e uma distribuição de Poisson também deslocada no espaço durante o sono. Os dados do DSE são consistentes com o estado SV estimado.

Palavras-chave: Distúrbios de sono, Processamento estatístico de sinal, Actigrafia, Actividade Humana, Diário de Sono, Mistura de Distribuições.

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Abbreviations

| | | |
|---------------|---|--|
| ACT | - | <i>Activity</i> |
| ASPS | - | <i>Advanced Sleep Phase Syndrome</i> |
| DSPS | - | <i>Delayed Sleep Phase Syndrome</i> |
| ECG | - | <i>Electrocardiogram</i> |
| EEG | - | <i>Electroencefalogram</i> |
| EKG | - | <i>Electrocardiogram</i> |
| EMG | - | <i>Electromiogram</i> |
| EOG | - | <i>Electroculogram</i> |
| FMUL | - | <i>Faculdade de Medicina da Universidade de Lisboa</i> |
| GC | - | <i>Graph-Cuts</i> |
| HA | - | <i>Human Activity</i> |
| IST | - | <i>Instituto Superior Técnico</i> |
| \mathcal{M} | - | <i>Maxwell distribution</i> |
| MSE | - | <i>Minimum Square Error</i> |
| \mathcal{N} | - | <i>Normal distribution</i> |
| PLMD | - | <i>Periodic Limb Movement Disorder</i> |
| REM | - | <i>Rapid Eye Movements</i> |
| RBD | - | <i>Rapid eye movement Behavior Disorder</i> |
| SeD | - | <i>Sleep electronic Diary</i> |
| SMS | - | <i>Short Message Service</i> |
| SV | - | <i>Sleep/Vigil</i> |
| SWSD | - | <i>Shift Work Sleep Disorder</i> |

Chapter 1

Introduction

The human body requires sleep to be healthy and the inability to fall asleep or stay asleep has important impacts on people's health. Diseases and conditions such as diabetes, obesity, depression or cardiovascular diseases are associated with sleep disorders. As noted by Damien Leger et al. [1], "Sleep disorders can have substantial impact on public health through the disruption of education, work, and the quality of life for affected patients. The substantial breakthroughs in sleep research and sleep medicine now being made are influencing public health approaches to these disorders."

The more common pathologies associated with sleep disorders are:

- Hypopnea syndrome, when at sleep there's a slow respiratory rate or the breathing is abnormally shallow.
- Narcolepsy, the condition of falling asleep spontaneously and unwillingly.
- *Periodic limb movement disorder* (PLMD), sudden involuntary movement of arms and/or legs during sleep.
- *Rapid eye movement behavior disorder* (RBD), acting out violent or dramatic dreams while in REM sleep.
- Situational circadian rhythm sleep disorders, jet lag and *shift work sleep disorder* (SWSD).
- Obstructive sleep apnea, when the airway is partially obstructed and the patient can't get enough deep sleep.
- Sleepwalking, engaging in activities normally associated with wakefulness, without realizing it.
- Sleep paralysis, this is characterized by temporary paralysis of the body shortly before or after sleep.
- *Delayed sleep phase syndrome* (DSPS), inability to awaken and fall asleep at socially acceptable times but no problem with sleep maintenance, a disorder of circadian rhythms. Other such disorders are *advanced sleep phase syndrome* (ASPS) and *Non-24-hour sleep-wake syndrome* (Non-24).

Some of these conditions may be diagnosed using actigraphy, especially the last three ones, the DSPS, ASPS and Non-24. The accuracy of the diagnosis of these pathological conditions may be improved with an accurate definition and estimation of the ACT variable.

The analysis of the actigraph output signal have 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 e-Diary* (SeD) information for different patients. This observation have inspired the method proposed in this thesis to define the *Activity* (ACT) variable and the corresponding approach to estimate it. 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.

It is thought that the difference in both components reside in *purposeless* characteristic of the movements during the sleep state. During the vigil state the movements have usually a purpose, they are coherent and coordinated which leads to a statistical distribution of the actigraph signal different from the one obtain 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 a very different distribution of the acigraph signal.

The proposed method models the output signal of the actigraph as a mixture of two distributions; a Maxwell distribution, prevalent during the vigil state, and a Poisson distribution prevalent during the sleep state.

The actigraph sensor is essentially a three axis accelerometer. The Maxwell distribution arises if the three components are assumed *independent and identically distributed* described by a non zero mean normal distribution, as shown in the appendix. The Poisson distribution arises if the three components present an impulsive behavior, where the movements are mainly constituted by short duration non correlated impulses. The time interval between these impulses is exponentially distributed as stated in. The integration process associated with the lowpass nature of the actigraph sensor and the window based processing algorithm used to process the signal suggest that the Poisson distribution is appropriated to describe the sleep component of the mixture. The visual inspection of this component reinforces this perception. However, for sake of simplicity, in this thesis, the Poisson component is approximated by a normal distribution.

The proposed algorithm estimates the parameters of the mixture at each moment by considering the 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 vector parameters of the mixture along the time, $\theta(n)$, is assumed here, to be a noisy version of the multidimensional ACT signal that is used to estimate the state. The new proposed definition for the ACT variable is more complete and accurate than the previous approaches where only accelerations intensities were considered. In fact, some sleep disturbances events can lead to larger intensities on the actigraphy output signal than calm tasks during the vigil state. As important as the actigraph intensity is the type of activity which may be infer from the relative importance of both mixture components.

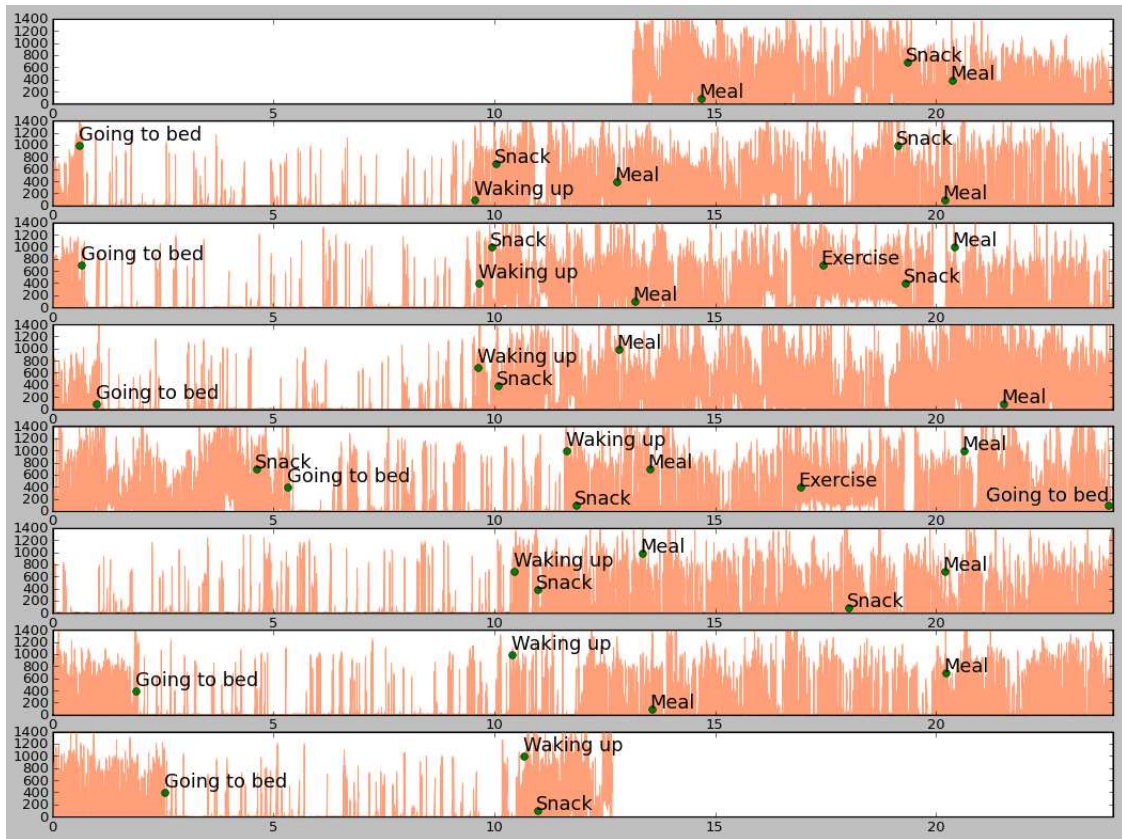


Figure 1.1: Joint graphical representation of the actigraphy and sleep diary data.

The ACT and SV signal are compared with the SeD data for validation purposes, as shown in Fig.1.1. The SeD used in this work is described in the next section, and was designed and implemented specifically in the scope of this work and displayed in Fig.1.2, in order to improve the accuracy of the data provided by the patient.



Figure 1.2: Main menu of the SeD implemented on a mobile phone.

1.1 Motivation and Objectives

Sleep disorders affect a large part of the population in the western countries. These disorders have several consequences like excessive daytime sleepiness, cognitive problems, motor vehicle crashes (especially at night), poor job performance and reduced productivity or even diabetes and hypertension. Helping to diagnose and treating these conditions is obviously a very strong motivation.

The objective of this work is to propose a method for analyzing the data from actigraphs, to provide a new, and hopefully better, way to diagnose these conditions mentioned above. This could be achieved by proposing a new way for characterizing the ACT variable, not by the accelerations intensity only, or its mean over any period, but through a whole set of variables that describe the histogram of those intensities at each moment. Additionally, in the scope of this work a SeD implemented on a mobile phone.

1.2 State of the art

There are mainly three methods for diagnosing sleep disorders: polysomnography, actigraphy and sleep diaries.

1.2.1 Polysomnography

Polysomnography consists of acquiring multiple biometrical signals such as EEG, air flow, EMG for chin and leg movements, EOG for REM detection, EKG, oxygen saturation and chest and abdominal wall movement. Some of these and other not mentioned may be optional considering the desired diagnosis. This method, normally performed during a single night, is very reliable in estimating the sleep states, but requires the patient to be all wired up, like the kid in Fig.1.3, and almost needs the patient to sleep in a strange environment. A typical result obtained from polysomnography is illustrated in Fig.1.3.

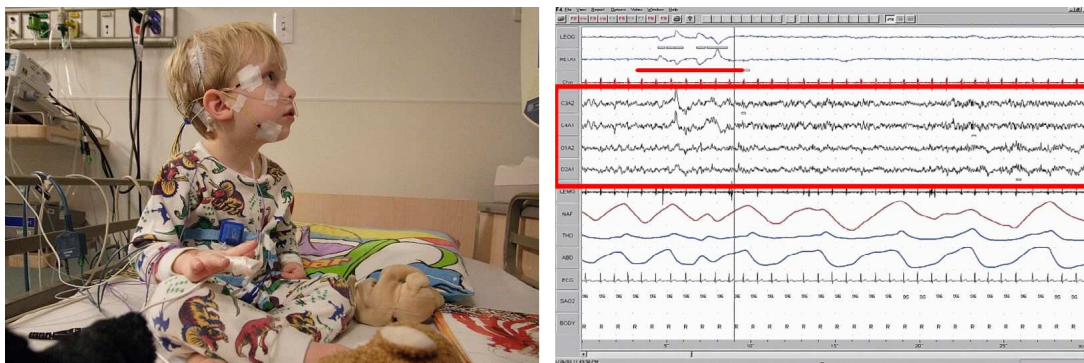


Figure 1.3: On the left is a patient prepared for a polysomnography, and on the right is an usual outcome.

1.2.2 Actigraphy

On the other hand, actigraphy consists only in using a device that is wrist watch shaped, like the one on Fig.1.4, on the wrist, usually in the non-dominant one, normally from 7 to 15 days. The device, called actigraph, has a tri-axial accelerometer and records the acceleration magnitude measured by it. Although

the acceleration is by far the most useful measure, some actigraphs may measure light intensity and the position of the actigraph as well. Meaning, the actigraphy is performed during the patients daily routine, in their natural environment, using a relatively more simpler and cheaper device than polysomnography. Additionally it is still quite reliable as it can distinguish sleep from wakefulness approximately between 80% and 90% of the time depending on the algorithm [2, 3, 4].



Figure 1.4: An actigraph used in raw data collecting.

Actigraphy is increasingly used mainly in sleep research, and in the clinical care of patients with sleep and circadian rhythm abnormalities [5, 6]. In sleep research the actigraphy is used in many subjects like the sleep onset [7], measures of children's sleep [8] or daytime naps in adolescent girls with chronic musculoskeletal pain [9]. Actigraphy is also used in issues not so related with sleep, like anesthesiology [10], chronic obstructive pulmonary disease [11] or hepatic encephalopathy [12].

1.2.3 Sleep diaries

Sleep diaries consist in a standard set of questions, that patients have to answer, usually for as long as they wear their actigraphs. At the beginning this questions and answers were registered on paper [13, 14], like the one that can be seen in Fig.1.5. More recently diaries started to be implemented on electronic devices. Those aim for a better compliance rate and accuracy in the times recorded by patients, because they are more portable. None the less, those SeD are devices exclusively dedicated to this task [15].

1.2.4 *Activity* (ACT) definition

Although there are some considerable solid classifications of sleep and wake states as REM, non-REM, etc. [16], there are few references in the literature describing statistical characterizations of the acceleration data measured with actigraphs. One of them is about statistical models of actigraphy where it is proposed a model for actigraph data only during sleep [17]. In these paper, the author modulates the movements during the sleep state as discrete events, with an exponential distribution for the inter-event intervals, which means a Poisson distribution for the number of movements in a given constant time interval. Other paper states that different activities result on different intensities distribution histograms [18], without defining these distributions.

Chapter 2

Problem Formulation

The main component of the actigraph sensor is a 3D axis accelerometer which output is the acceleration magnitude formed by two components, $d(n)$, dynamical component like vibrations and rapid movements, and $c(n)$, the static acceleration magnitude, e.g. gravity or long terms slow acceleration components [20]. 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 shift Maxwell distribution, derived at the appendix, where the three acceleration components are assumed independent, identically distributed with a normal distribution with the same mean, μ , $p(a_x) = p(a_y) = p(a_z) = \mathcal{N}(\mu, \sigma^2)$. Under these assumptions the acceleration magnitude, $d = \sqrt{a_x^2 + a_y^2 + a_z^2}$ may be modeled by a shifted *Maxwell* distribution, $\mathcal{M}(c_{\mathcal{M}}, \sigma_{\mathcal{M}}^2)$, where $c_{\mathcal{M}}$ is related with the static acceleration and $\sigma_{\mathcal{M}}$ is not necessary equal to σ , as shown at the appendix,

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

The second component, $p_n(r)$ is assumed to be generated from involuntary movements, less coordinated and more impulsive [21]. In sleep there are well defined intermittent peaks of activity at different intensities, then, the Poisson distribution is the more appropriated to describe this type of acceleration [17]. Here, however, for sake of simplicity, this component is described by a normal distribution, $\mathcal{N}(c_{\mathcal{N}}, \sigma_{\mathcal{N}}^2)$.

Therefore the distribution proposed in this paper to describe the actigraph output signal is the following mixture

$$p(r) = \alpha \mathcal{M}(c_{\mathcal{M}}, \sigma_{\mathcal{M}}^2) + \beta \mathcal{N}(c_{\mathcal{N}}, \sigma_{\mathcal{N}}^2) \quad (2)$$

or

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

where the time varying parameter column vectors, $\theta(n) = \underbrace{\{\alpha(n), \sigma_{\mathcal{M}}(n), c_{\mathcal{M}}(n)\}}_{\theta_{\mathcal{M}}(n)}, \underbrace{\{\beta(n), \sigma_{\mathcal{N}}(n), c_{\mathcal{N}}(n)\}}_{\theta_{\mathcal{N}}(n)}^T$ must be estimated to characterize the activity at each discrete instant n .

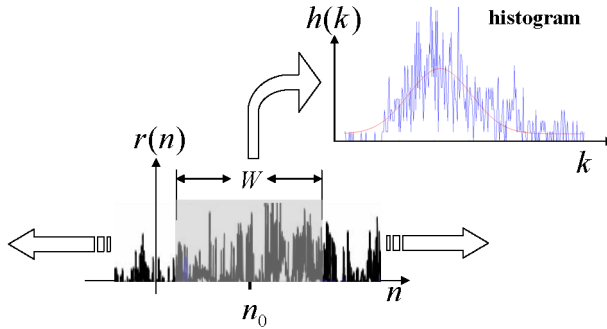


Figure 2.1: Windowing parameter estimation with histogram fitting.

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

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

where $0 < n \leq N$, $\mathbf{h}_n = \{h_n(1), \dots, h_n(L)\}$ is the L dimensional histogram, with bins centered at locations $\mathbf{x} = \{x_1, x_2, \dots, x_L\}$, computed in a W dimensional window centered at the n^{th} sample and $p(x_k, \theta)$ is the function (3) computed at locations x_k , as shown in Fig.2.1. 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 [22].

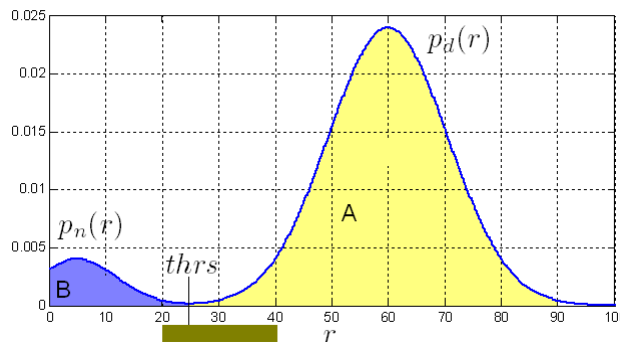


Figure 2.2: Distribution mixture.

The relative importance of the distributions and their characteristics change along the circadian cycle. The vector of parameters $\theta(n)$ is therefore a multidimensional signal that changes along the cycle and is proposed here to define the *Activity* (ACT) variable. 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 $p_d(r)$.

2.1 Estimation and filtering

The results of the iterative optimization algorithm depends on the initialization values and may not converge when only one distribution is present. This is because the algorithm tries to fit the absent distribution to a small amount of data, usually noise not related with the activity. To avoid these

difficulties the initialization of the parameters associated with the absent distribution must be zero. To detect if a distribution is absent, a local minimum of the smoothed histogram is searched around the value $thrs$, as displayed in Fig.2.2. If the percent of observations associated with $p_d(r)$ ($< thrs$) is less than $A\%$ or the percent of observations associated with $p_n(r)$ ($> thrs$) is less than $B\%$ the distribution is considered absent and the respective parameters are initialized to zero. The parameters $thrs$, A and B used are listed in Table 2.1. These parameters were obtained from typical bimodal histograms of real data, segmented manually. Table 2.2 shows the mean and standard deviation of the optimum thresholds, $thrs$, and the respective mean and standard deviation of A and B computed from real data of four patients.

| | | |
|------|--------|----|
| B | $thrs$ | A |
| 2.5% | 32 | 5% |

Table 2.1: Parameters used in the initialization procedure.

| | | B | $thrs$ | A |
|------------------|------|-------|--------|-------|
| Patient 1 | mean | 34.88 | 34.09 | 65.12 |
| | STD | 24.62 | 13.24 | 24.62 |
| Patient 2 | mean | 36.98 | 33.69 | 61.54 |
| | STD | 22.57 | 12.09 | 23.39 |
| Patient 3 | mean | 36.86 | 31.48 | 63.14 |
| | STD | 14.22 | 7.25 | 14.22 |
| Patients mean | mean | 36.24 | 33.08 | 63.27 |
| | STD | 20.75 | 11.10 | 21.08 |

Table 2.2: Mean and standard deviation of the parameter $thrs$ and respective values of A and B , computed from typical real histograms selected by hand.

Consider the parameter vector at n^{th} instant $\theta(n) = \{\theta_{\mathcal{N}}(n)^T \quad \theta_{\mathcal{M}}(n)^T\}^T$ as a stacked vector containing the parameters associated with the Normal, $\theta_{\mathcal{N}}(n)$, and Maxwell, $\theta_{\mathcal{M}}(n)$, distributions. These signals, $\theta_{\mathcal{N}}(n)$ and $\theta_{\mathcal{M}}(n)$, represent the evolution of each distribution along the time.

The initialization of the vectors $\theta_{\mathcal{N}}(n)$ and $\theta_{\mathcal{M}}(n)$, need for the fitting algorithm, is performed by partitioning the original histogram into two groups, h_{thrs}^- , associated with $p_n(r)$ and h_{thrs}^+ associated with $p_d(r)$ according the estimated threshold $thrs$. If n^- and n^+ are the number of samples of each set the initialization of mixture coefficients are

$$\alpha^0(n) = \frac{n^+}{n^- + n^+} \quad (5)$$

$$\beta^0(n) = \frac{n^-}{n^- + n^+}. \quad (6)$$

If the mean and standard deviation of h_{thrs}^- and h_{thrs}^+ are (μ_-, σ_-) and (μ_+, σ_+) respectively, then the initialization of $\theta_{\mathcal{N}}(n)$ is $\theta_{\mathcal{N}}^0(n) = \{\beta^0(n), \sigma^-, \mu^-\}$.

The initialization of $\theta_{\mathcal{M}}(n)$, $\theta_{\mathcal{M}}^0(n) = \{\alpha^0(n), \sigma_{\mathcal{M}}^0, \mu_{\mathcal{M}}^0\}$, is based on the assumption that $p_d(r)$ is a shifted Maxwell distribution. The mean and standard deviation of a Maxwell distribution with parameter a , $\mathcal{M}(a)$, (see appendix) are,

$$mean_{\mathcal{M}} = 2a\sqrt{\frac{2}{\pi}} \quad (7)$$

$$STD_{\mathcal{M}} = a\sqrt{\frac{3\pi - 8}{\pi}} \quad (8)$$

where $a = \sigma_{\mathcal{M}}$ in this case.

Therefore

$$\mu^+ - c_{\mathcal{M}}^0 = 2\sigma_{\mathcal{M}}^0\sqrt{\frac{2}{\pi}} \quad (9)$$

$$\sigma^+ = \sigma_{\mathcal{M}}^0\sqrt{\frac{3\pi - 8}{\pi}} \quad (10)$$

where $c_{\mathcal{M}}^0$ is the initial shifted value of the Maxwell distribution, which leads to,

$$\sigma_{\mathcal{M}}^0 = \sigma^+ \sqrt{\frac{\pi}{3\pi - 8}} \quad (11)$$

$$c_{\mathcal{M}}^0 = \mu^+ - \sigma^+ \sqrt{\frac{8}{3\pi - 8}} \quad (12)$$

Even with the previous pre-processing procedure to improve the convergence conditions of the fitting algorithm, about 2% of the estimated parameters are completely out of context and are considered outliers. They usually represent much larger values than the most part of the others, considered normal. Therefore after the fitting process another elimination procedure is performed in order to eliminate these outliers from the estimated signal.

The histogram of each component, $\{\theta_i(n)\}$, $h_i(r)$, is computed and the samples $\theta_{\mathcal{R}}(n)$, with $\mathcal{R} = \{\mathcal{N}, \mathcal{M}\}$, are rejected if at least one of the component belongs to the 2% upper portion of the respective histogram, that is, a complete sample $\theta_{\mathcal{R}}(n)$ is only accepted if its all components belongs to the 98% lower portion of the respective histogram. This mean that after this procedure some samples of $\theta_{\mathcal{M}}(n)$ are accepted and the homologous of $\theta_{\mathcal{N}}(n)$ may be reject, and the converse is also possible.

2.2 Kalman filter

The resulting signals $\theta_{\mathcal{N}}(n)$ and $\theta_{\mathcal{M}}(n)$, obtained in the previous step, are still noisy (non smoothed) with missing data. The Kalman filter is suitable to filter these signals and fill the gaps. The Kalman filter was proposed in the sixties of the twenty century [23] and its main goal is to recursively compute the *minimum square error* (MSE) state space unknown variable from the previous and present observations, where the following multidimensional model is assumed here [24]:

$$\mathbf{s}_{\mathcal{R}}(n+1) = \mathbf{s}_{\mathcal{R}}(n) + \mathbf{q}(n) \quad (13)$$

$$\theta_{\mathcal{R}}(n) = \mathbf{s}_{\mathcal{R}}(n) + \mathbf{r}(n) \quad (14)$$

where $\theta_{\mathcal{R}}(n)$ are noisy observation vectors, $\mathbf{q}(n) \sim \mathcal{N}(0, \sigma_q^2 \mathbf{I})$ and $\mathbf{r}(n) \sim \mathcal{N}(0, \sigma_r^2 \mathbf{I})$ are normal distributed multidimensional random variables with diagonal covariance matrices $\sigma_q^2 \mathbf{I}$ and $\sigma_r^2 \mathbf{I}$ respectively.

The estimated denoised signal is obtained from

$$\hat{\mathbf{s}}_{\mathcal{R}}(n) = \hat{\mathbf{s}}_{\mathcal{R}}^-(n) + \mathbf{K}(n) [\theta_{\mathcal{R}}(n) - \hat{\mathbf{s}}_{\mathcal{R}}^-(n)] \quad (15)$$

where $\hat{\mathbf{s}}_{\mathcal{R}}^-(n)$ and $\hat{\mathbf{s}}_{\mathcal{R}}(n)$ are denominated *a priori* and *a posteriori* estimates of $\mathbf{s}_{\mathcal{R}}(n)$ respectively. $\mathbf{K}(n)$, a 3×3 matrix in this case, is the so called *Kalman gain* and $(\theta_{\mathcal{R}}(n) - \hat{\mathbf{s}}_{\mathcal{R}}^-(n))$ is called *residue* or *innovation*. The *a priori* variable $\hat{\mathbf{s}}^-(n)$ is the optimum estimates before the last observation $\theta_{\mathcal{R}}(n)$ is acquired. This estimate is updated with the *innovation* term multiplied by the *Kalman Gain*, $\mathbf{K}(n)$, to produce the *a posteriori* estimate of $\mathbf{s}(n)$, $\hat{\mathbf{s}}(n)$. This is the optimum estimate of $\mathbf{s}(n)$ given the present and all previous observations.

The signal $\theta_{\mathcal{R}}(n)$ however is not defined where the samples were rejected. In this case the output of the Kalman filter is the *a priori* estimate, $\hat{\mathbf{s}}_{\mathcal{R}}^-(n)$. The whole filtering sequence is

$$\hat{\mathbf{s}}^-(n) = \hat{\mathbf{s}}(n-1) \quad (16)$$

$$\hat{\mathbf{P}}^-(n) = \hat{\mathbf{P}}(n-1) + \sigma_q^2 \mathbf{I} \quad (17)$$

$$\mathbf{K}(n) = \hat{\mathbf{P}}^-(n) (\hat{\mathbf{P}}^-(n) + \sigma_r^2 \mathbf{I})^{-1} \quad (18)$$

$$\hat{\mathbf{s}}(n) = \hat{\mathbf{s}}^-(n) + w(n) \mathbf{K}(n) [\theta_{\mathcal{R}}(n) - \hat{\mathbf{s}}^-(n)] \quad (19)$$

$$\hat{\mathbf{P}}(n) = [1 - w(n) \mathbf{K}(n)] \hat{\mathbf{P}}^-(n) \quad (20)$$

where $\hat{\mathbf{P}}^-(n)$ and $\hat{\mathbf{P}}(n)$ are the *a priori* and *a posteriori* estimates of the error covariance, respectively, and

$$w(n) = \begin{cases} 1 & \text{if } \theta_{\mathcal{R}}(n) \text{ was accepted} \\ 0 & \text{otherwise} \end{cases} \quad (21)$$

is a binary signal to indicate what samples are or not valid.

2.3 Sleep/vigil state estimation

The evolution of the parameters $\theta_{\mathcal{N}}(n)$ and $\theta_{\mathcal{M}}(n)$ along the circadian cycle may be used to characterize the type of activity of the patient. Here it is suggested that the relative importance of each distribution seems to be a promising indicator to estimate the *sleep/vigil* (SV) state of the patient. The *electroencephalogram* (EEG) is the more accurate indicator to estimate the state SV while the estimation based on *actimetry sensor* data is not so reliable. However, the analysis of the *actimetry sensor* data for SV estimation purposes is usually based only on the output signal intensity.

Here, it is proposed a new approach. It is suggested that the state SV is better estimated if the estimation is based on the relative importance of both distributions, $p_n(r)$ and $p_d(r)$, and not on the signal intensity. The reasoning for this approach is based on the fact that the observed movements during the sleep and vigil states are intrinsically different, not necessary related with its amplitude or intensity. A sedentary activity during the day may be much less intense than a pathologic very active sleep. The main concept that differentiate the two states is: *purposeless*. Our movements during the day have usually

an immediate purpose, are consistent and coordinated while during the *sleep* state they are involuntary and usually not controlled.

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

$$sv(n) = \alpha(n) - \beta(n) \quad (22)$$

where $\alpha(n)$ and $\beta(n)$ are the weights associated with $p_d(r)$ (vigil) and $p_n(r)$ (sleep) respectively in the mixture (2). This signal, represented at Fig.2.3, is an alternating signal according with the circadian cycle. Its analysis may be used to assess the regularity and phase shift of the sleep circadian cycle.

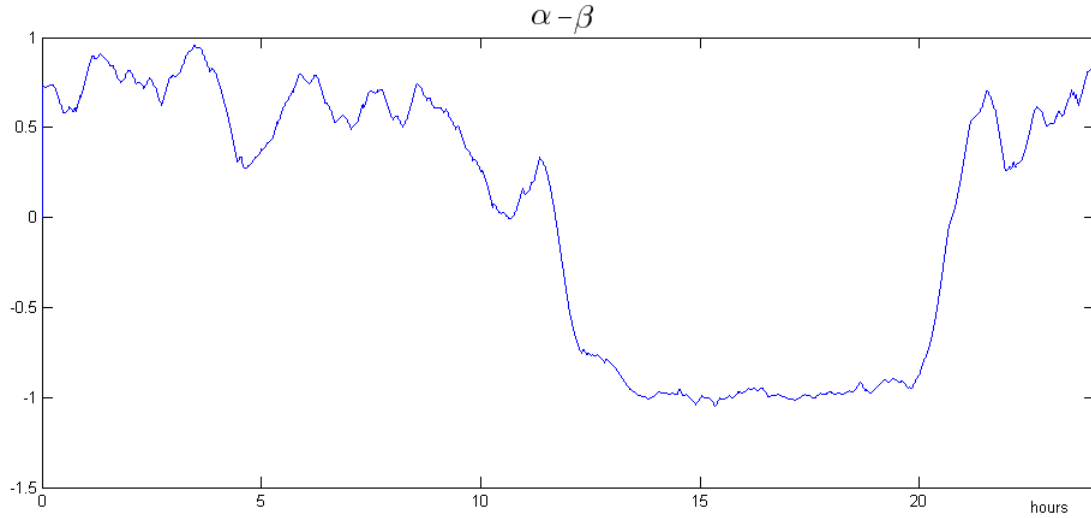


Figure 2.3: The signal $\alpha - \beta$ for a 24 hour cycle.

Let us define the following *Sleep/Vigil* (SV) binary state variable,

$$SV(n) = \begin{cases} 0 & \text{if sleep} \\ 1 & \text{otherwise} \end{cases} \quad (23)$$

The state variable $SV(n)$ may be estimated from the noisy signal $sv(n)$ as follows

$$\hat{\mathbf{S}}\mathbf{V} = \arg \min_{\mathbf{S}\mathbf{V}} E(\mathbf{sv}, \mathbf{S}\mathbf{V}) \quad (24)$$

where $\mathbf{S}\mathbf{V} = \{SV(1), SV(2), \dots, SV(N)\}^T$, $\mathbf{sv} = \{sv(1), sv(2), \dots, sv(N)\}^T$ and

$$E(\mathbf{sv}, \mathbf{S}\mathbf{V}) = \underbrace{\sum_n sv(n)(1 - 2SV(n))}_{\text{binarization}} + \alpha \underbrace{\sum_n |SV(n) - SV(n-1)|}_{\text{regularization}} \quad (25)$$

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

$$SV(n) = \begin{cases} 0 & \text{if } sv(n) < 0 \\ 1 & \text{otherwise} \end{cases} \quad (26)$$

because for each sample

$$sv(n)(1 - 2SV(n)) = \begin{cases} sv < 0 & \text{if } SV = 0 \text{ and } sv < 0 \\ -sv < 0 & \text{if } SV = 1 \text{ and } sv > 0 \end{cases} \quad (27)$$

is minimum.

The regularization term is used to force a stepwise constant solution with abrupt transitions by introducing temporal correlation between neighboring samples, $|SV(n) - SV(n - 1)|$, where differences between consecutive samples of \mathbf{SV} are penalized by α . As large is α as 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 the noise present in $sv(n)$.

The minimization of the energy function (25), formulated in (24), is a huge combinatorial optimization problem in the $\{0, 1\}^N$ high dimensional space where N is the length of \mathbf{SV} .

In [25] it is shown that several energy minimization problems in high dimensional discrete spaces can be efficiently solved by using *Graph-Cuts* (GC) based algorithms. The authors have designed a very fast and efficient algorithm to compute the global minimum of the energy function. However, the algorithm is not completely general which means that some energy functions cannot be minimized with the proposed method. In [26] the authors present a wide class of energy functions that may be minimized with the GC method. Fortunately, the function (25) belongs to that class.

The overall processing algorithm is therefore developed in the following steps

1. Processing of the actigraphy signal, $r(n)$,
 - (a) Computation of the histogram of a W length window located around each sample $r(n)$,
 - (b) Computation of the parameters of the mixture, $\theta(n) = \{\theta_{\mathcal{N}}^T, \theta_{\mathcal{M}}^T\}^T(n)$,
2. Elimination of the outliers in $\theta(n)$,
3. Smooth and fill the missing data in $\theta(n)$ by Kalman filtering to obtain $sv(n)$,
4. Estimate the state binary variable *Sleep/Vigil* (SV), $SV(n)$, from $sv(n)$ by using *Graph-Cuts*.

Chapter 3

Results and Discussion

3.1 Experimental results

In this section, experimental results with real data are presented. Four actigraph sequences are used but only for one there is accurate sleep diary information, acquired with a SeD implemented in the scope of this work. For other sequence there is also sleep diary information but acquired by the traditional paper based method and it is not totally reliable, presenting several obvious inconsistencies. For the other two sequences there are no sleep diary information at all.

A typical actigraphy sequence is represented in Fig.3.1 where the actigraph sensor output is registered during a week in a 24 hours basis.

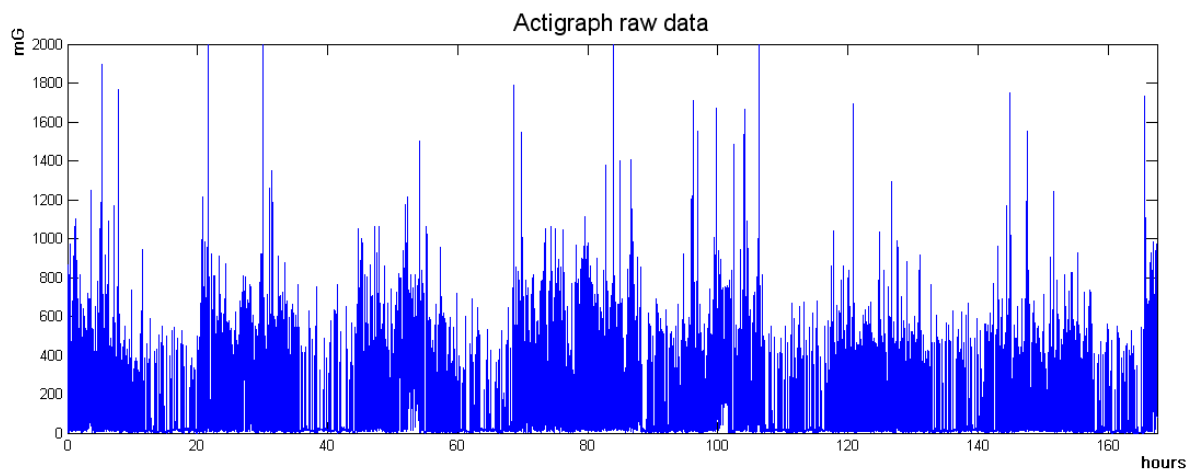


Figure 3.1: The raw data collected from the actigraph.

3.2 A sleep apnea case with SeD data

This study was performed for approximately 7 days, comprising about 167 hours. The Fig.3.1 displays the raw data where it is not possible clearly to distinguish between sleep and awake zones. This is in part due to movements during the sleep caused by the sleep apnea which prevent the patient to fall in

a deep sleep. In a normal sleep case both regions are more distinguishable but the proposed estimation algorithm still is helpful, mainly at the transitions, as it will be observed in the next cases.

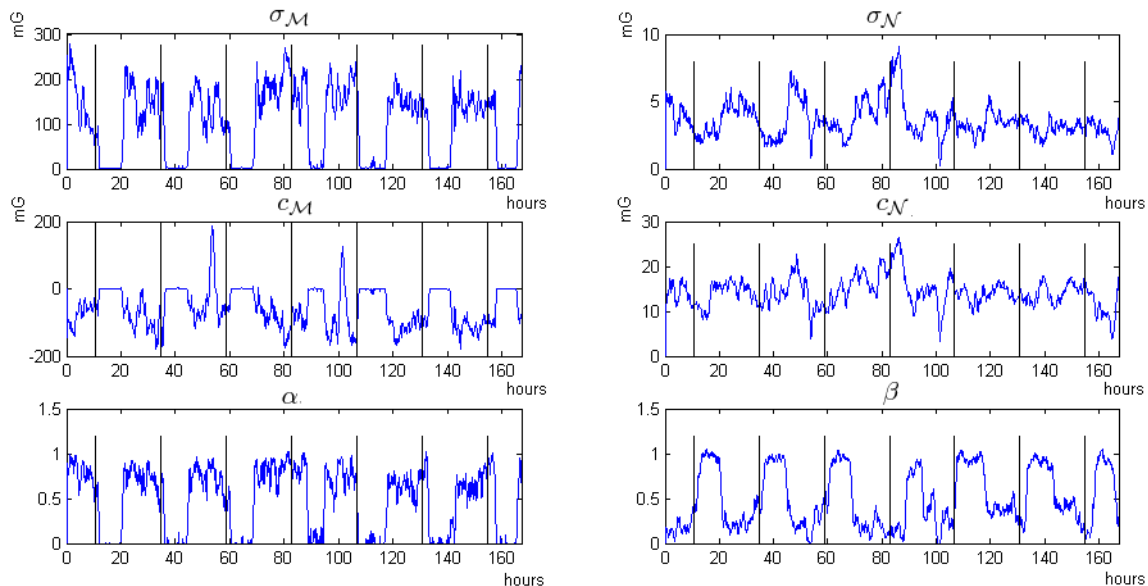


Figure 3.2: Typical result from the statistical analysis. On the left are the three parameters respecting the Maxwell distribution and on the right are the parameters relative to the Normal distribution. The black vertical periodic lines represent the midnight.

The six components of $\theta(n)$ estimated from the data displayed in Fig.3.1 are displayed in Fig.3.2. In this example they are visible the 7 periods corresponding to the seven consecutive days that the patient wore the actigraph sensor. The values of σ_M range from 0 to 300 mG with c_M ranging between -200 and 200 mG, thus representing the large and high intensities of the acceleration distribution, the Maxwell component. The values associated with $p_n(r)$, are smaller. σ_N ranges from 0 to 10 mG and c_M from 0 to 30 mG.

The signal $\alpha(n) - \beta(n)$, represented in Fig.3.3, is approximately one, with mean 0.98 and standard deviation 0.096, which mean that the mixture is able to describe the signal almost of the time. Other components than $p_n(r)$ and $p_d(r)$ are less important or it may be only noise.

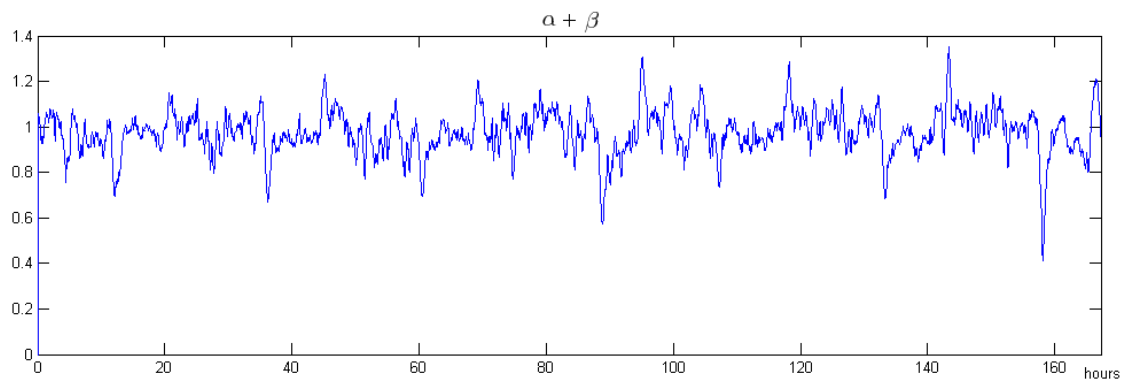


Figure 3.3: Plot representing $\alpha + \beta$ considering the case of Fig.3.2.

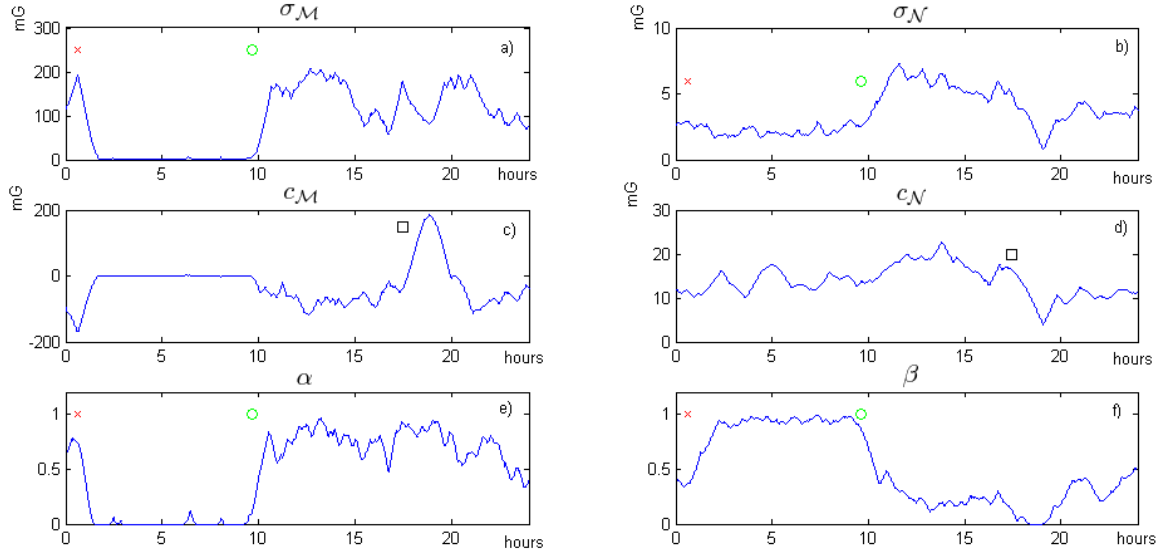


Figure 3.4: Zoom from Fig.3.2 overlapped with data collected with the SeD, on a), b), e) and f) the red x marks the time the patient went to bed, and the green circle is the respective time of awake. On c) and d), the black square represents the time of exercise.

Let us now consider only one single day of analysis from 12 am until 12 am of the next day as it is represented in Fig.3.4. It is clearly evident that the distribution function of accelerations intensities registered by the actigraph is altered depending on the actions taken by the patient. For instance it is visible that α is very close to zero between the x and the circle, where the patient is presumably sleeping, and so is the β between the circle and the next x. This indicates that the Maxwell distribution is predominant during the day time, as opposing to the Normal distribution that is predominant during the night.

Other alteration induced in the resultant analysis is the high values of c_M matching the time marked in the SeD as exercise by the subject. This is due to the relatively constant high acceleration intensities registered during pronounced exercise, as the Maxwell distribution component shifts to the right in the acceleration intensities distribution. This suggests that the activity intensity can be measured mainly through the c_M variable.

The fact of α is associated to the vigil state and the β to the sleep state suggests that SV state can be detected from the α and β signals. To assess this assumption the signal $\alpha(n) - \beta(n)$ is overlapped with the SeD data in the Fig.3.5.

However the circles appear to coincide with the sleep to awake estimated transition and specially the x's with the estimated awake sleep transition, there is in average a delay of about 20 min, and an example can be seen in Fig.3.6 The decreasing on the temporal resolution due the windowing method to estimate the vector of parameters decreases the accuracy on the estimation of this delay. More sophisticated methods may be used to try to estimate the sleep onset from these data which is an important clinical indicator for the insomnia.

In this case we have an almost complete information about the subject daily routine, so it is know

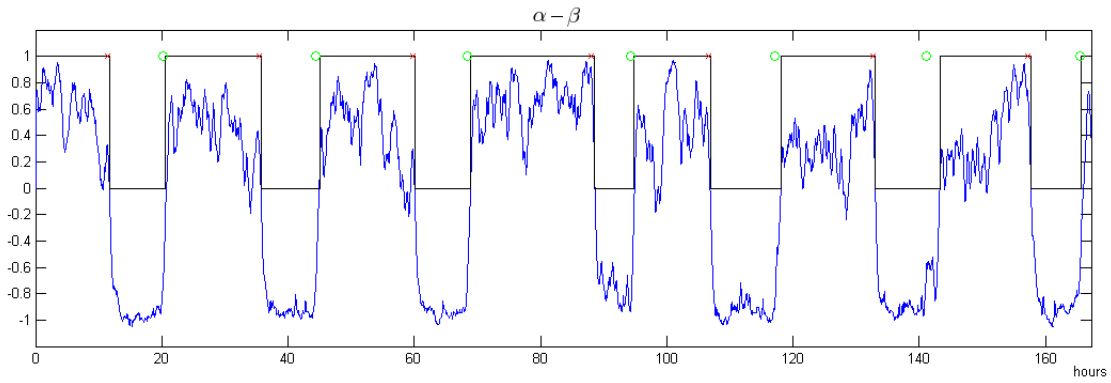


Figure 3.5: Representation of sleep/awake state estimation by the graph cut method. The red x's represent the going to bed time and the green circles the awake time, both from the SeD

that the analysis was performed from Monday until the next Monday morning, and it can be seen that in the last two complete days of analysis, corresponding to the weekend, the signal $\alpha - \beta$ is substantially different than in the other days, since it grows from morning until night, having its maximum before going to bed, and it is known that in these two days the subject had a quiet relaxing time at home. On the other hand, the first three days correspond to Monday, Tuesday and Wednesday, and they were normal days of work, with $\alpha - \beta$ having its maximum in the morning and decreasing until the patient has gone to bed, indicating more activity in the morning that decays along the day, as expected.

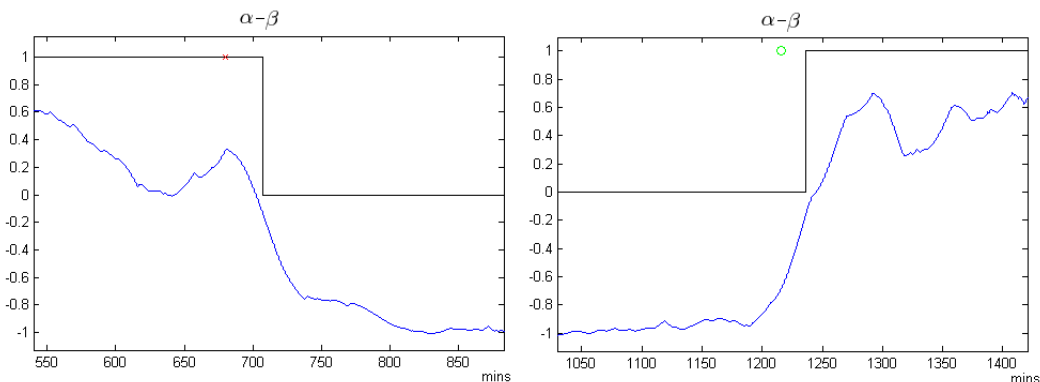


Figure 3.6: Zoom of the first day bed and awake times from the Fig.3.5

On the Thursday it was relatively normal day of work, but the patient stayed up until late, about 4 or 5 a.m., and so the $\alpha - \beta$ pattern of that day does not seem like one of the normal working days nor the weekend days. On the Friday was waking up late, some exercise and sleeping early, so $\alpha - \beta$ is again unusual, not low neither high.

3.3 Second case of disturbed sleep with SeD data

This second test was performed in 11 days and the sleep diary information was acquired with the developed SeD method. Fig.3.7 display the estimated parameters. The α and β parameters may seem a

little more noisy than in the last case, indicating that the SV pattern was not as regular as with the last case subject. Other remarkable difference is that c_M never goes over 50 mG except for one peak that reached about 100 mG, and since we have the SeD data available for this patient and it has no mark of exercise, this reinforces the correlation between exercise and the parameter c_M .

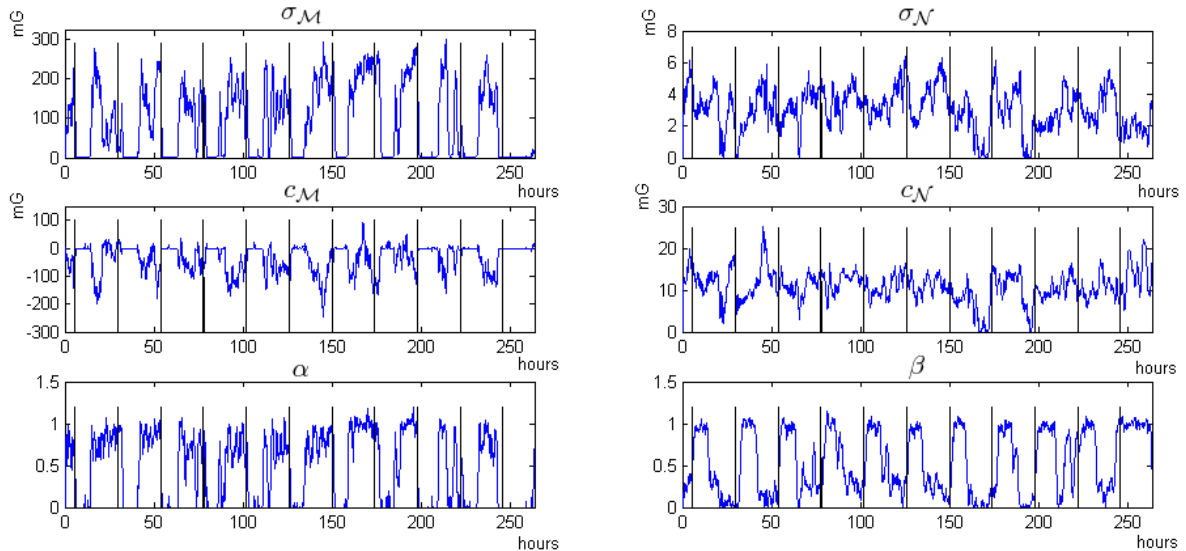


Figure 3.7: Second example of estimated parameters in a disturbed sleep condition.

Comparing the SeD data with the SV state estimation, it can be observed that sometimes the x's (the time that patient has marked as gone to bed) appear right before the awake to sleep transition, other times we have two consecutive marks and some days there are not marks at all, so although some marks confirm the sleep/awake transitions, others are not that reliable confirming the lack of accuracy of the traditional method to collect the sleep diary information.

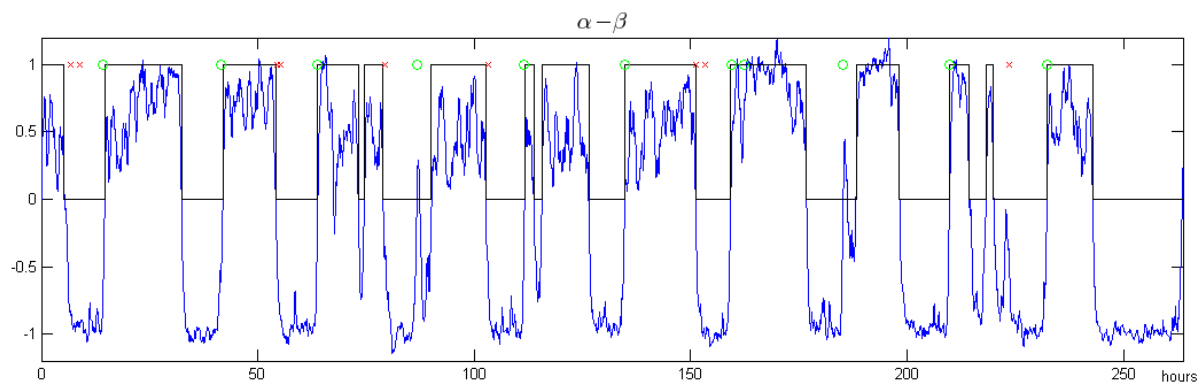


Figure 3.8: Sleep/awake state estimation respecting Fig.3.7 case.

The SV state variable shows clearly a non regular pattern along the circadian cycle with sleeping episodes during the day and short and irregular sleeping periods. The sleeping disorders of this patient are clearly revealed by the $sv(n) = \alpha(n) - \beta(n)$ signal.

3.4 An insomnia case

This example is about a diagnosed case of insomnia. Fig.3.9 displays the estimated parameters for this patient. Although the patient passes considerable time in bed, he can't get a good sleep, so he usually takes a nap during the afternoon. The sleeping time can easily be seen in the α and β coefficients.

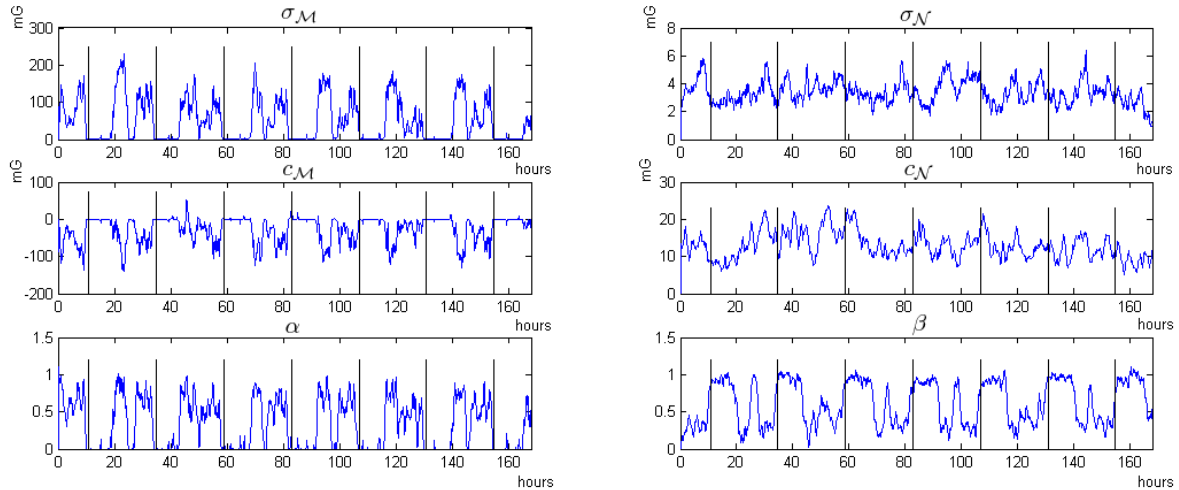


Figure 3.9: Parameters estimated from a case of insomnia.

If we look at the midnight bars, it is almost always when the subject goes to bed, a decrease in α and an increase in β is observed, as expected, indicating that the patient is in the bed presumably sleeping. But then again, before the next midnight, it can be observed the same behavior indicating the nap.

The analysis of the SV state signal, displayed in Fig.3.9, allows to conclude that the very same method that was used to estimate the SV state in the first case, detects a sleep time between the night times in 4 out of the 7 days. Unfortunately there was no SeD available for this case, so it was impossible to confirm the going to bed time and the number of naps that patient really took.

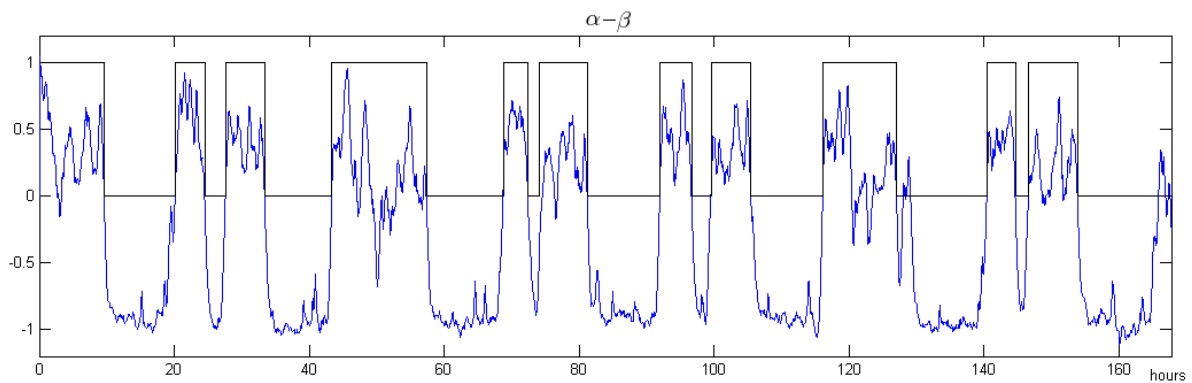


Figure 3.10: Graph cut sleep/awake estimation for the case of insomnia.

3.5 Model validation

In order to validate the Maxwell distribution in describing the day time actigraph sensor output signal statistical tests are performed and comparison with the normal distribution are made.

The tests consist in compute the fitting error when using the proposed mixture with a Maxwell and normal distributions with the fitting results by using a mixture of two normal distributions. The results are shown in Table 3.1.

Table 3.1: Percentage of $\epsilon_{\mathcal{MN}} \leq \epsilon_{\mathcal{NN}}$

| Case | Kolmogorov | Norm(r) | Kullback |
|------|------------|---------|----------|
| 1 | 66.2512 | 70.3785 | 69.3588 |
| 2 | 63.9847 | 60.4691 | 59.6275 |
| 3 | 61.2173 | 60.8583 | 61.5839 |

The first column corresponds to Kolmogorov-Smirnov test, the second one is the Euclidean norm of the residual vector, and the third one its from the Kullback-Leibler divergence. From the Table 3.1 can be seen that in a general way, the distribution consisting of two Normal ones, is a worst approximation for the data then the Normal-Maxwell one for about 60 to 70% of the samples. These tests and the fact of the Normal-Maxwell model has a physical foundation, suggests that the probability distribution function for the acceleration intensities composed by a Normal and a Maxwell distribution is an appropriated model for the actigraph data. However, the small advantage of using the Maxwell-Normal model over a pure mixture of Gaussians suggest that this last solution may be better because a lot of fast and optimized algorithms are described in the literature for fitting with Gaussian mixtures.

3.6 Toward a definition of human *Activity* (ACT)

The analysis of the results described in this section, makes it possible to conclude that the ACT may be characterized by a vector of parameters, e.g., $\theta = \{\alpha, \sigma_{\mathcal{M}}, c_{\mathcal{M}}, \beta, \sigma_{\mathcal{N}}, c_{\mathcal{N}}\}^T$, where α and β represent the importance of each distribution, or the prevalent vigil or sleep activity modes. The intensity of each type of activity is associated with the variables $c_{\mathcal{M}}$ and $c_{\mathcal{N}}$, the $c_{\mathcal{M}}$ was showed to be higher when intense exercise occurs, and in the same way, higher $c_{\mathcal{N}}$ values might be used to measure the sleep physical activity. Between the intense exercise category, each type of exercise may be distinguished by the set $c_{\mathcal{M}}$ and $\sigma_{\mathcal{M}}$.

Additionally, the ACT may be characterized by these parameters jointly with another physiological variables, such as the cardiac rhythm, breathing rate, EEG or even with non-physiological variables like luminosity or the actigraph orientation. The specific set of parameters used to characterize the ACT variable should depend on the objective of the study or the type of disorder.

Chapter 4

Conclusion

This thesis describes a methodology to the analysis of the actigraph sensor output signal in order to reveal relevant characteristics used in the diagnosis of sleep disorders. It is suggested that the actigraph signal may be accurately described by a mixture of a Maxwell and normal distributions. The derivation of the Maxwell distribution is based on assumption based on the physical principles of the device sensor and the normal distribution is an approximation of a Poisson distribution, derived from physiological considerations.

The key issue in this method is the concept of *purposeless* activity. During the vigil state the movements have usually a purpose, they are coherent and coordinated which leads to a statistical distribution of the actigraph signal different from the one obtain 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 a very different distribution on the acigraph signal.

It was shown that the vector, θ , containing the parameters of the distributions involved in the mixture is a promising candidate to this definition. In fact, more important than the signal intensity, the type of movements seems to be better in the characterization of the state *Sleep/Vigil* of the patient. However, the vector θ , allows also to extract the signal intensity, allowing to extract additional relevant information about the activity.

The process used to estimate ACT involves a fitting procedure, outliers removing and Kalman filtering of noisy signal with missing data.

The ACT signal is used to estimate the *Sleep/Vigil* (SV) state variable which is correlated with information extracted from a *Sleep e-Diary* (SeD) developed in the scope of this work. The correlation of both data have shown a good match suggesting that the proposed method to process the actigraph signal is useful in the diagnosis of sleep disorders.

Experimental results using real data from true patients are presented and confirm the ability of the method to detect abnormal pattern on the circadian cycle of the sleep.

Improvements on the method are needed in order to extract additional information, namely, quantification of the activity level during the sleep state or activity characterization during the vigil state.

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Appendices

A Maxwell distribution

Let us consider the acceleration vector $\mathbf{a} = \{a_x, a_y, a_z\}$ where the components are independent and normal distributed with mean μ_x, μ_y and μ_z respectively and variance σ^2 , $p(a_x) = \mathcal{N}(\mu_x, \sigma^2)$, $p(a_y) = \mathcal{N}(\mu_y, \sigma^2)$ and $p(a_z) = \mathcal{N}(\mu_z, \sigma^2)$, leading to,

$$p(a_x, a_y, a_z) = \frac{1}{(\sigma\sqrt{2\pi})^3} e^{-\frac{1}{2\sigma^2}((a_x-\mu_x)^2+(a_y-\mu_y)^2+(a_z-\mu_z)^2)} \quad (\text{A.1})$$

By using the following polar coordinates transformation,

$$\begin{aligned} a_x &= r \cos(\theta) \sin(\phi) \\ a_y &= r \sin(\theta) \sin(\phi) \\ a_z &= r \cos(\phi) \end{aligned} \quad (\text{A.2})$$

and the equality $p(r, \theta, \phi) = |J|p(a_x, a_y, a_z)$, where $J = -r^2 \sin(\phi)$, is the Jacobian of the transformation, it leads to

$$p(r, \theta, \phi) = \frac{1}{(\sqrt{2\pi})^3} \frac{r^2}{\sigma^3} e^{-\frac{r^2+T^2}{2\sigma^2}} |\sin(\phi)| e^{r \frac{\mu_z \cos(\phi) + t \sin(\phi) \cos(\theta-\alpha)}{\sigma^2}} \quad (\text{A.3})$$

where $T = \sqrt{\mu_x^2 + \mu_y^2 + \mu_z^2}$, $t = \sqrt{\mu_x^2 + \mu_y^2}$ and $\alpha = \arctan(\mu_y/\mu_x)$.

The distribution of the acceleration magnitude is $p(r) = \int_0^\pi \int_{-\pi}^\pi p(r, \theta, \phi) d\theta d\phi$,

$$p(r) = \frac{1}{(2\pi)^{3/2}} \frac{r^2}{\sigma^3} e^{-\frac{r^2+T^2}{2\sigma^2}} \int_0^\pi |\sin(\phi)| e^{\frac{r \cos(\phi) \mu_z}{\sigma^2}} \underbrace{\int_{-\pi}^\pi e^{\frac{rt}{\sigma^2} \sin \phi \cos(\theta-\alpha)} d\theta}_{2\pi I_0\left(\frac{rt}{\sigma^2} \sin(\phi)\right)} d\phi \quad (\text{A.4})$$

$$= \frac{2\pi}{(2\pi)^{3/2}} \frac{r^2}{\sigma^3} e^{-\frac{r^2+T^2}{2\sigma^2}} \int_0^\pi \sin(\phi) e^{\frac{r \cos(\phi) \mu_z}{\sigma^2}} I_0\left(\frac{rt}{\sigma^2} \sin(\phi)\right) d\phi \quad (\text{A.5})$$

where $I_0(x)$ is the zero order *Modified Bessel Function of the First Kind* [27] represented in Fig. A.1.

If $\frac{rt}{\sigma^2} \sin(\phi) < 1$ then $I_0\left(\frac{rt}{\sigma^2} \sin(\phi)\right) \approx 1$ which leads to the following simplification

$$p(r) = \sqrt{\frac{2}{\pi}} \frac{r}{\mu_z \sigma} \sinh\left(\frac{r \mu_z}{\sigma^2}\right) e^{-\frac{r^2+T^2}{2\sigma^2}} \quad (\text{A.6})$$

and if $\mu_x = \mu_y = \mu_z = 0$

$$p(r) = \sqrt{\frac{2}{\pi}} \frac{r^2}{\sigma^3} e^{-\frac{r^2}{2\sigma^2}} \quad (\text{A.7})$$

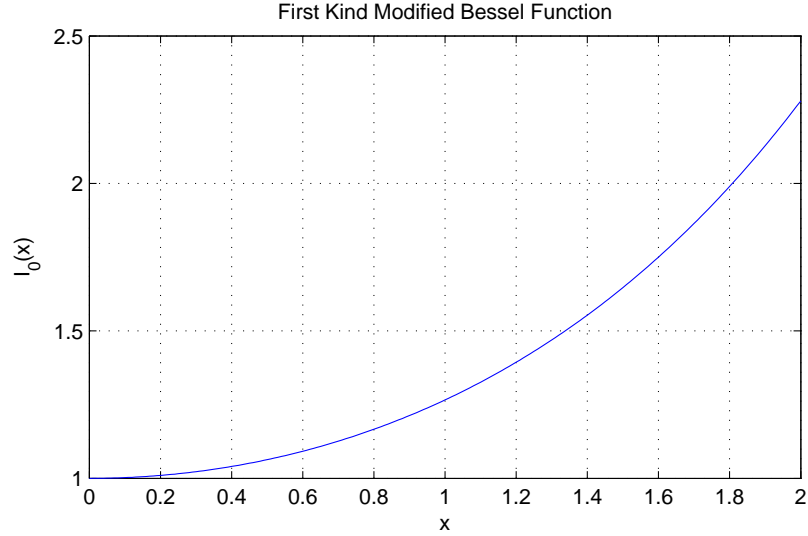


Figure A.1: *Modified Bessel Function of the First Kind.*

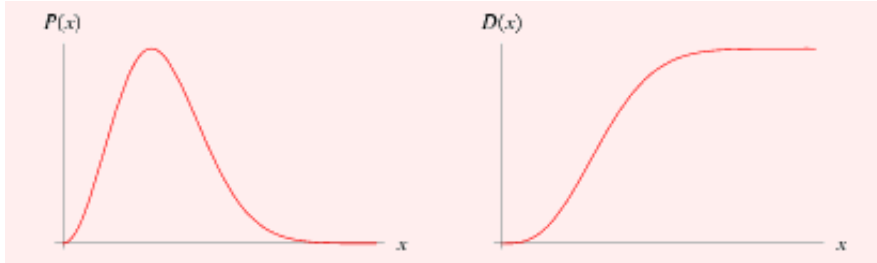


Figure A.2: Maxwell distribution.

which is the *Maxwell* distribution [27] represented in Fig. A.2 with the following mean and standard deviation,

$$\mu_{\mathcal{M}} = 2\sigma\sqrt{\frac{2}{\pi}} \quad (\text{A.8})$$

$$\sigma_{\mathcal{M}} = \sigma\sqrt{\frac{3\pi - 8}{\pi}} \quad (\text{A.9})$$

The distribution defined in (A.5) is displayed in Fig. A.3 for different values of $\mu_x = \mu_y = \mu_z = \mu = \{0, 1, \dots, 20\}$. As may be observed different values of μ leads to Maxwell like shape distributions with different shifting and spreadings. Therefore, the strategy adopted in the parameter estimation step to compute a shifting value $c_{\mathcal{M}}$ and a standard deviation $\sigma_{\mathcal{M}}$ of an arbitrary shifted Maxwell distribution is in accordance with the actigraph sensor model adopted in this work, described in this appendix.

B Sleep electronic diary

About the SeD developed, the main level block diagram of its operation is represented in Fig.B.1. It operates based on a list of events, in there are kept the events registered by the user and the list can be edited at will trough the main menu. At the same time, the alarm generator module analyzes the list and checks for possible missing events, like at least two meals a day, or at least one going to bed and

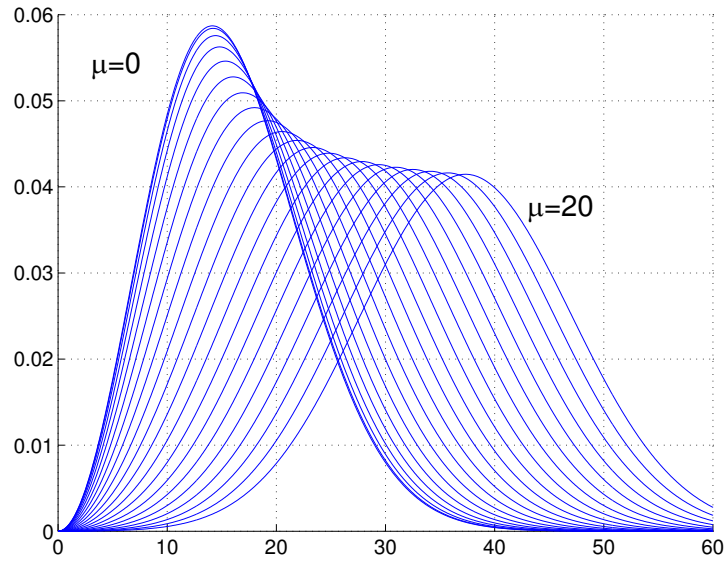


Figure A.3: Distribution function for different values of $\mu = \{0, 1, \dots, 20\}$.

awake mark per day, prompting the user if he didn't forget to introduce an event.

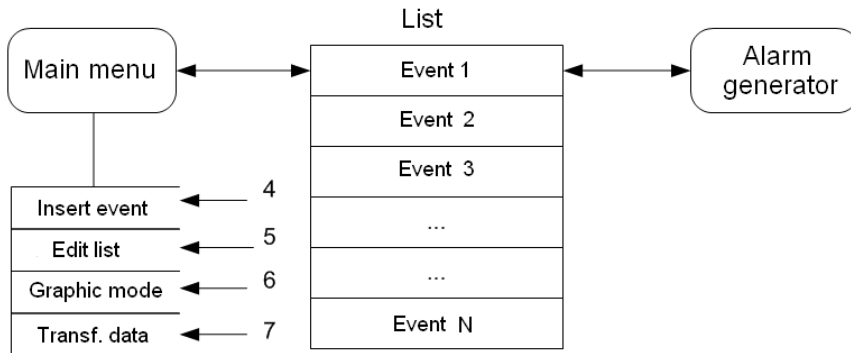


Figure B.1: Simple block diagram of the SeD operation

Now in the next Fig.B.1, is the block diagram for the SeD main menu, corresponding to the Fig.1.2. Entering the main menu there are 4 choices, insert event, edit list, graphic mode and transferring data.

The second choice, *edit list*, allows the user to search through the list of day with events registered, from where he can select one and see what events are in that day. Once the day is selected, the patient can either erase the event, or alter the type, date and time or intensity of the event.

Graphic mode is mainly to represent the events registered over a timeline, so that the user can have a better spatial perception of his events along the time.

Finally, when *transferring data* is selected, it leads to choosing the transferring method, which can be SMS, Bluetooth, E-mail or infrared, depending on the mobile phone capabilities. Once the user has chosen the desired method, then information is transferred in an encrypted text file, so it can be read by appropriate software.

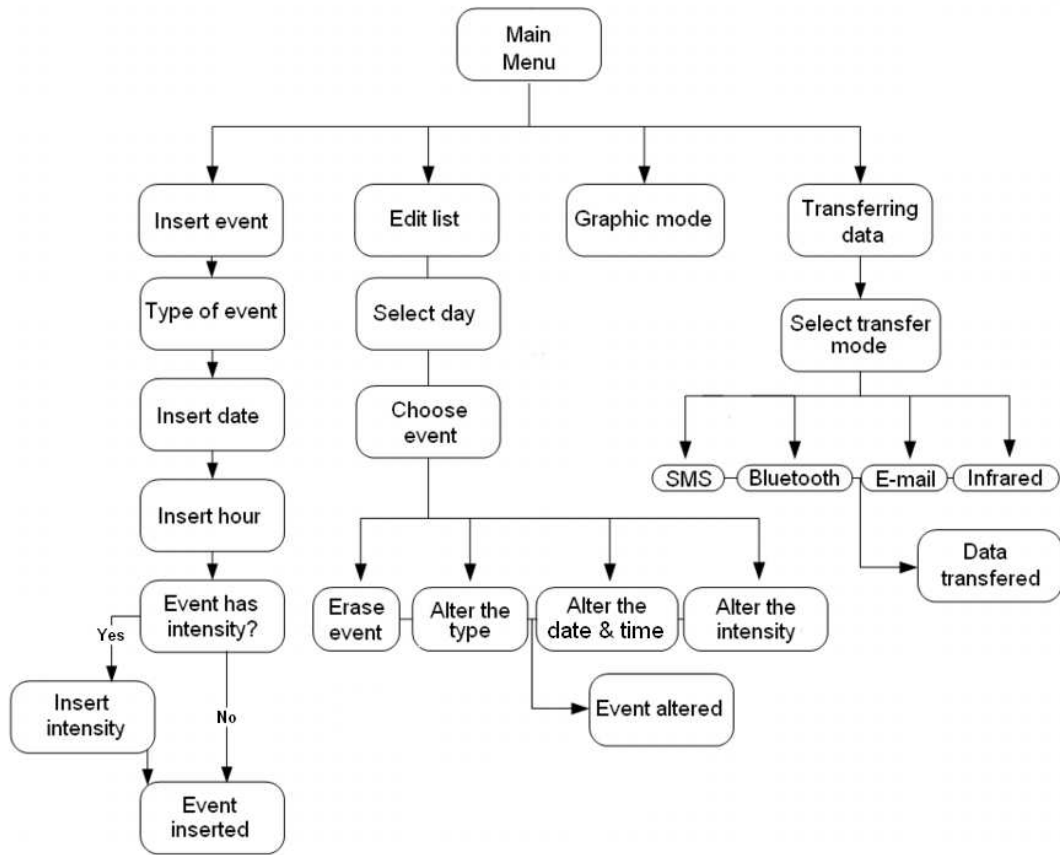


Figure B.2: Block diagram of the SeD main menu

C Submitted patent

Now, starting on the next page, it will be presented below the original text of the patent request n.º PT 104157 submitted on August 8, respecting the SeD. The text is written in Portuguese language, because that's how it had to be for submission.

Resumo

Sistema de registo de eventos em diário electrónico, implementado em telemóvel, para auxílio no diagnóstico de distúrbios do sono

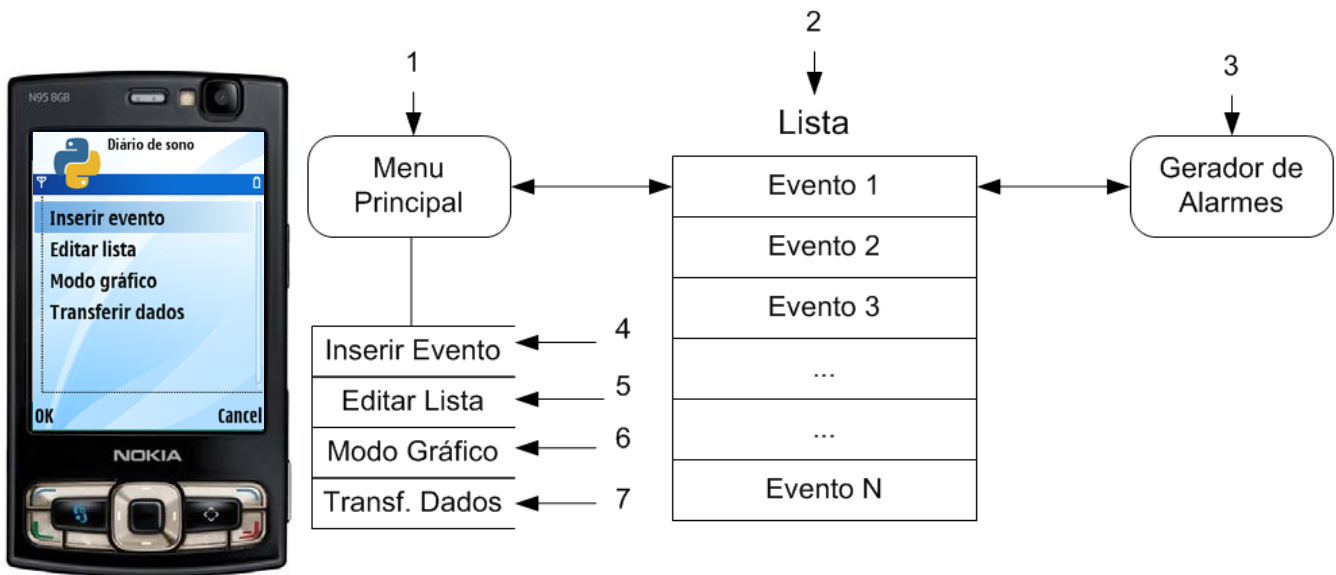
O presente evento é um diário electrónico do sono para registo de eventos quotidianos relevantes para o diagnóstico e análise de distúrbios do sono.

Este diário electrónico, desenhado para ser utilizado em telemóveis ou agendas electrónicas ("palmtops"), pretende tirar partido da crescente disseminação e contínuo aumento da capacidade computacional deste tipo de dispositivos. Desta forma pretende-se disponibilizar a baixo custo funcionalidades que tipicamente só estão disponíveis em equipamentos de alta tecnologia.

Os eventos, tais como deitar e acordar, são seleccionados pelo paciente a partir de uma lista pré-definida, facilmente configurável pelo médico, e registados. A inserção de eventos é guardada juntamente com o evento seleccionado de forma automática, tal como o dia e a hora da inserção, sendo no entanto possível inserir uma data e hora diferentes caso se trate de um evento esquecido e registado fora de tempo. Certos tipos de eventos, tais como dores de cabeça ou fadiga, podem ser adicionalmente caracterizados e guardados no telemóvel.

O sistema permite a inserção de eventos numa lista que pode ser editada e transferida por via electrónica para o médico para análise e aplicação no diagnóstico de distúrbios de sono.

Figura para publicação



Descrição

Sistema de registo de eventos em diário electrónico, implementado em telemóvel, para auxílio no diagnóstico de distúrbios do sono

O presente evento é um diário electrónico do sono para registo de eventos quotidianos relevantes para o diagnóstico de distúrbios do sono. No presente invento é apresentado um sistema de registo de eventos desenhado para funcionar em telemóveis ou agendas electrónicas ("palmtops"). O sistema permite a inserção de eventos numa lista que pode ser editada e transferida por via electrónica para o médico para análise e aplicação no diagnóstico de distúrbios de sono. A denominação do sistema é *diário electrónico de sono* ou em inglês, "*sleep e-diary*".

Palavras-chave

Biomedicina, diário do sono, diário electrónico, telemóvel, distúrbios sono

Estado da arte

O registo de eventos do dia-a-dia quotidiano é necessário em muitos contextos clínicos designadamente no diagnóstico de distúrbios de sono. Normalmente este processo é realizado manualmente anotando o evento em papel. Para esse efeito foram desenhados formulários específicos como por exemplo os que estão representados na Fig.1 ou na Fig. 2.

Mais recentemente, com o desenvolvimento das novas tecnologias, começaram a ser desenvolvidos diários electrónicos tais como os descritos nas patentes americanas D512042, 4385291 ou 4975842. Enquanto que estes diários são para registo de eventos diversos, há também diários desenvolvidos especificamente para os distúrbios de sono, como por exemplo o NASA AIRLOG (ROSEKIND MR, SMITH RM, GREGORY KB, MILLER DL, NASA AIRLOG: an electronic sleep/wake diary, Sleep Research 1996; 25: 525, <http://www.websciences.org/cftemplate/NAPS/archives/individ.cfm?ID=19960539>).

Os dispositivos electrónicos utilizados nos sistemas referidos são todos dedicados para efeito e o seu preço é elevado.

Antecedentes e descrição do invento

A estimação da actividade humana diária e a sua correlação com algumas variáveis fisiológicas ou eventos normais da actividade quotidiana é um procedimento fundamental no diagnóstico e tratamento de perturbações do sono que afectam uma grande percentagem da população dos países ocidentais.

As variáveis fisiológicas podem ser a temperatura, o electrocardiograma, o pulso ou o electroencefalograma (EEG). A actigrafia é particularmente útil neste contexto pois é uma medida directa da actividade humana. Os dados da actigrafia são obtidos a partir de um acelerómetro de 3 eixos colocado normalmente no pulso do paciente e que regista os movimentos do pulso durante a actividade diária e durante o sono.

A correlação dos dados do actígrafo com os eventos normais do dia-a-dia permite detectar padrões anormais de comportamento o que é fundamental no diagnóstico de alguns distúrbios do sono.

Nesta patente é descrito um sistema constituído por um diário electrónico do sono implementado num telemóvel. Este diário permite ao paciente registar facilmente eventos diários e respectivos marcadores temporais, tais como os momentos de deitar, acordar, das refeições, etc. A difusão generalizada de telemóveis, a sua cada vez maior capacidade de processamento, armazenamento e transmissão, torna este equipamento particularmente apropriado para esta aplicação.

Os dados do diário do sono são sobrepostos ao sinal do actígrafo de forma a correlacionar as actividades diárias e nocturnas como a informação da actividade.

Este diário electrónico, desenhado para ser utilizado em telemóveis ou agendas electrónicas ("palmtops"), pretende tirar partido da crescente disseminação e contínuo aumento da capacidade computacional deste tipo de dispositivos. Desta forma pretende-se disponibilizar a baixo custo funcionalidades que tipicamente só estão disponíveis em equipamentos de alta tecnologia.

A metodologia permite registar os eventos de forma simples, tais como deitar e acordar, seleccionando-os a partir de uma lista pré-definida. Esta lista é facilmente configurável pelo médico consoante as necessidades de cada paciente. Durante a inserção de eventos é guardada

juntamente com o evento seleccionado, e de forma automática, o dia e a hora da inserção, sendo no entanto possível inserir uma data e hora diferentes caso se trate de um evento esquecido e registado fora de tempo. Certos tipos de eventos, tais como dores de cabeça ou fadiga, podem ser adicionalmente caracterizados por uma intensidade que é também ela requerida ao utilizador e guardada no telemóvel.

Além da inserção de eventos, o diário permite também a sua visualização em modo de texto, devidamente organizados por dias, ou em modo gráfico, representados num eixo temporal, para uma melhor percepção da sua distribuição.

A lista de eventos pode ser editada permitindo a alteração do conteúdo de qualquer campo, a eliminação completa de um dado evento ou mesmo a inserção de novos eventos, sem ter que utilizar a interface normal.

Este diário possui ainda um alarme que alerta o utilizador para a não inserção de eventos que são espectáveis de ter um período relativamente bem definido, tais como o deitar/acordar ou refeições.

No fim ou durante o período de registo o ficheiro onde estão guardados os eventos pode ser transferido em formato digital por *Short Message Service* (SMS), Bluetooth, correio electrónico ou infravermelhos para um qualquer dispositivo remoto compatível, designadamente para o computador pessoal do médico.

Sistema de registo electrónico de eventos implementado num telefone celular

Este sistema é uma ferramenta utilizada no diagnóstico de distúrbios do sono e designa-se em inglês por *sleep e-diary*. O sistema é desenvolvido para telefones celulares ou agendas electrónicas ("palmtops") permitindo disponibilizar ao utilizador um sistema altamente sofisticado e desenvolvido a baixo custo, aproveitando a elevada capacidade computacional e disseminação generalizada destes dispositivos.

O sistema pode ser instalado no telemóvel ou na agenda electrónica do paciente que esteja equipado com o sistema operativo Symbian da Nokia ou Windows Mobile da Microsoft. Assim evita-se a utilização de equipamentos dedicados e dispendiosos que são utilizados normalmente neste tipo de aplicações.

O sistema possui uma lista pré-definida pelo médico com os eventos necessários para o diagnóstico que o paciente pode seleccionar facilmente a partir de um menu com a lista dos eventos.

A selecção de um evento conduz ao seu armazenamento num ficheiro juntamente com a hora e a data em que foi armazenado. Durante o processo, o utilizador pode alterar a data e a hora presentes apresentadas, caso esteja a introduzir um evento que já tenha ocorrido.

Para alguns tipos de eventos também é pedido ao utilizador um valor de intensidade, como por exemplo, dor de cabeça ou sonolência, de forma a caracterizar a intensidade do evento que se está a registar.

O Utilizador pode em qualquer altura editar a lista armazenada, acrescentando eventos de que se tenha

esquecido, apagar eventos ou alterar os dados a eles associados. Pode ainda acrescentar comentários a cada registo/evento.

O sistema permite a visualização da lista em modo de texto, por dias ou em modo gráfico em que os vários eventos são representados em modo gráfico sobre uma linha temporal com os marcadores das horas e dos dias.

O sistema permite, em qualquer momento, a transferência da lista, em formato digital, por *Short Message Service* (SMS), Bluetooth, correio electrónico ou infravermelhos para um qualquer dispositivo remoto compatível, designadamente para o computador pessoal do médico para análise.

O sistema possui um mecanismo inteligente automático de análise da lista que gera alarmes quando inconsistências são detectadas ou acontecimentos esperados não acontecem. Por exemplo, quando alguns eventos periódicos não são introduzidos ou o evento "deitar" aparece duas vezes de seguida sem o evento "levantar" pelo meio.

Diagrama de blocos (Fig. 3)

A estrutura do sistema está representada na Fig. 3. O sistema é constituído pelo menu principal (1) e pelo módulo gerador de alarmes (3) que operam sobre uma lista guardada em formato de texto no telemóvel onde estão guardados os eventos (2). No menu principal estão disponíveis as opções que permitem alterar a lista de eventos já armazenados, tais como inserir um novo evento (4) ou editar um evento já existente (5). No menu principal acede-se também ao modo gráfico (6) e ao módulo de transferência de dados (7). O módulo gerador de alarmes apenas analisa os eventos guardados na lista e gera alarmes em caso de

inconsistências na lista existente, como por exemplo quando existem dois eventos de "deitar" sem haver nenhum de "acordar" pelo meio, ou se não houver nenhum evento de refeição num dia. Ou seja, em qualquer situação anormal que seja possível detectar e que resulte provavelmente de um esquecimento ou engano do paciente.

Diagrama de blocos do menu principal (Fig. 4)

O esquema detalhado do sistema está representado na Fig. 4. A partir do menu principal (1) existem quatro opções. Selecionando a primeira, "Inserir evento" (4), passa-se para a lista dos eventos disponíveis (8) cujo um exemplo está na Fig. 5 (27). A lista dos eventos que aparecem disponíveis é configurável consoante o tipo de diário que o médico necessite e onde também é possível indicar quais os eventos que têm uma característica de intensidade associada. Selecionado que está o evento que se quer registar é agora pedido que se insira a data (9) e (28) e de seguida a hora (10) e (29). Por fim, caso o evento esteja na lista de eventos disponíveis como um evento ao qual esteja associada uma intensidade, no caso de ser uma dor de cabeça por exemplo, é então requerido ao utilizador que introduza uma intensidade de 1 a 5 por questões de conveniência e padronização (12) e (30).

Selecionando "Editar lista" (5) a partir do menu principal aparece uma lista com os dias em que existem eventos registados (14) como está exemplificado na Fig. 6 (31), e ao seleccionar o dia pretendido aparece uma outra lista com os eventos registados nesse dia (15) e (32). Ao seleccionar o evento pretendido é então possível apagar o evento (16), alterar o seu tipo (17), alterar a data e/ou hora a que

este ocorreu (18) ou alterar a intensidade (19), caso aplicável.

Escolhendo o "Modo gráfico" (6) é possível visualizar os eventos distribuídos ao longo de uma linha temporal.

Por último, ao seleccionar "transferir dados" (7) passa-se ao menu com os meios de transferência possíveis (21) exemplificado na Fig. 7 (33).

Lisboa, 18 de Julho de 2008

Reivindicações

- 1) Sistema de registo electrónico de eventos implementado num telefone celular para diagnóstico de distúrbios do sono, caracterizado por um sistema operativo [Symbian da Nokia](#) ou [Windows Mobile da Microsoft](#) instalado num telemóvel ou agenda electrónica ("palmtop"), possuindo uma lista pré-definida e configurável com os eventos necessários ao diagnóstico, acessibilidades na inserção dos dados e registo automático dos mesmos juntamente com o dia e a hora da inserção dos dados registados, sendo o registo gerado pela selecção, editável, e com transferência da informação por via electrónica para um outro equipamento, constituída por: menu principal (1), lista de eventos (2) e gerador de alarmes (3).
- 2) Sistema de registo electrónico de eventos de acordo com a reivindicação 1, caracterizado por o Menu Principal e conter os seguintes características e funções:
 - a) Inserir Evento (4), definindo o tipo de invento (8), a data, a hora, e a intensidade (11), e finalizando (output) com evento inserido (13);
 - b) Editar Lista (5), definindo o dia e o evento, podendo este ser apagado, alterado no tipo, alterado na hora e/ou alterado na intensidade, e finalizando (output) com o "evento alterado"
 - c) Modo gráfico(6)
 - d) Transferência de dados (7), definindo a selecção do meio de transferência, nomeadamente "SMS", "Bluetooth", "E-mail", e "Infravermelhos" e finalizando com os dados transferidos.

- 3) Sistema de registo electrónico de eventos de acordo com as reivindicações 1 e 2, caracterizado por passos complementares e opcionais, nomeadamente:
 - a) Certos tipos de eventos, tais como dores de cabeça ou fadiga ou sonolência, poderem ser adicionalmente caracterizados por uma intensidade e guardados no telemóvel e posteriormente transferidos;
 - b) Possibilidade de inserir uma data e hora diferentes caso se trate de um evento esquecido e registado fora de tempo;
 - c) Possibilidade de acrescentar comentários a cada registo/evento.
- 4) Sistema de registo electrónico de eventos de acordo com as reivindicações 1 e 2, caracterizado pela transferência da lista, em formato digital, por *Short Message Service* (SMS), Bluetooth, correio electrónico ou infravermelhos para um qualquer dispositivo remoto compatível, designadamente para o computador pessoal do médico, para análise.
- 5) Sistema de registo electrónico de eventos de acordo com as reivindicações 1 e 2, caracterizado por a visualização da lista em modo de texto, por dias ou em modo gráfico em que os vários eventos ser representados em modo gráfico sobre uma linha temporal com os marcadores das horas e dos dias.
- 6) Sistema de registo electrónico de eventos de acordo com as reivindicações 1 e 2, caracterizado por um mecanismo inteligente automático de análise da lista que gera alarmes aquando de inconsistências ou acontecimentos inesperados.
- 7) Sistema de registo electrónico de eventos de acordo com as reivindicações 1, caracterizado pela sua visualização

conjunta no telemóvel com os dados de actigrafia obtidos a partir de um actígrafo de 3 eixos colocado normalmente no pulso do paciente e que regista os seus movimentos durante a sua actividade diurna e nocturna.

Lisboa, 8 de Agosto de 2008

TWO WEEK SLEEP DIARY

INSTRUCTIONS:

1. Write the date, day of the week, and type of day: Work, School, Day Off, or Vacation.
2. Put the letter "C" in the box when you have coffee, cola or tea. Put "M" when you take any medicine. Put "A" when you drink alcohol. Put "E" when you exercise.
3. Put a line (|) to show when you go to bed. Shade in the box that shows when you think you fell asleep.
4. Shade in all the boxes that show when you are asleep at night or when you take a nap during the day.
5. Leave boxes unshaded to show when you wake up at night and when you are awake during the day.

SAMPLE ENTRY BELOW: On a Monday when I worked, I jogged on my lunch break at 1 PM, had a glass of wine with dinner at 6 PM, fell asleep watching TV from 7 to 8 PM, went to bed at 10:30 PM, fell asleep around Midnight, woke up and couldn't get back to sleep at about 4 AM, went back to sleep from 5 to 7 AM, and had coffee and medicine at 7:00 in the morning.



| Today's Date | Day of the week | Type of Day Work, School, Off, Vacation | Noon | 1PM | 2 | 3 | 4 | 5 | 6PM | 7 | 8 | 9 | 10 | 11PM | Midnight | 1AM | 2 | 3 | 4 | 5 | 6AM | 7 | 8 | 9 | 10 | 11AM |
|--------------|-----------------|---|------|-----|---|---|---|---|-----|---|---|---|----|------|----------|-----|---|---|---|---|-----|---|---|---|----|------|
| sample | Mon. | Work | | E | | | | | A | | | | | | | | | | | | | C | M | | | |
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Fig. 1



Sleep Diary

| ANSWER IN THE MORNING AFTER WAKING FOR THE DAY | | | | | | |
|--|--|--|--|--|--|---|
| | At what time did you first go to bed last night? | Approximately how long did it take you to fall asleep? | About how many times, if any, did you awaken during the night? | Overall, about how many hours did you sleep? | At what time did you wake up (for the last time) this morning? | In general, how did you feel when you woke up? |
| DAY 1 | | | | | | <input type="checkbox"/> Very refreshed <input type="checkbox"/> Somewhat refreshed <input type="checkbox"/> Fatigued |
| DAY 2 | | | | | | <input type="checkbox"/> Very refreshed <input type="checkbox"/> Somewhat refreshed <input type="checkbox"/> Fatigued |
| DAY 3 | | | | | | <input type="checkbox"/> Very refreshed <input type="checkbox"/> Somewhat refreshed <input type="checkbox"/> Fatigued |
| DAY 4 | | | | | | <input type="checkbox"/> Very refreshed <input type="checkbox"/> Somewhat refreshed <input type="checkbox"/> Fatigued |
| DAY 5 | | | | | | <input type="checkbox"/> Very refreshed <input type="checkbox"/> Somewhat refreshed <input type="checkbox"/> Fatigued |
| DAY 6 | | | | | | <input type="checkbox"/> Very refreshed <input type="checkbox"/> Somewhat refreshed <input type="checkbox"/> Fatigued |
| DAY 7 | | | | | | <input type="checkbox"/> Very refreshed <input type="checkbox"/> Somewhat refreshed <input type="checkbox"/> Fatigued |

Fig. 2

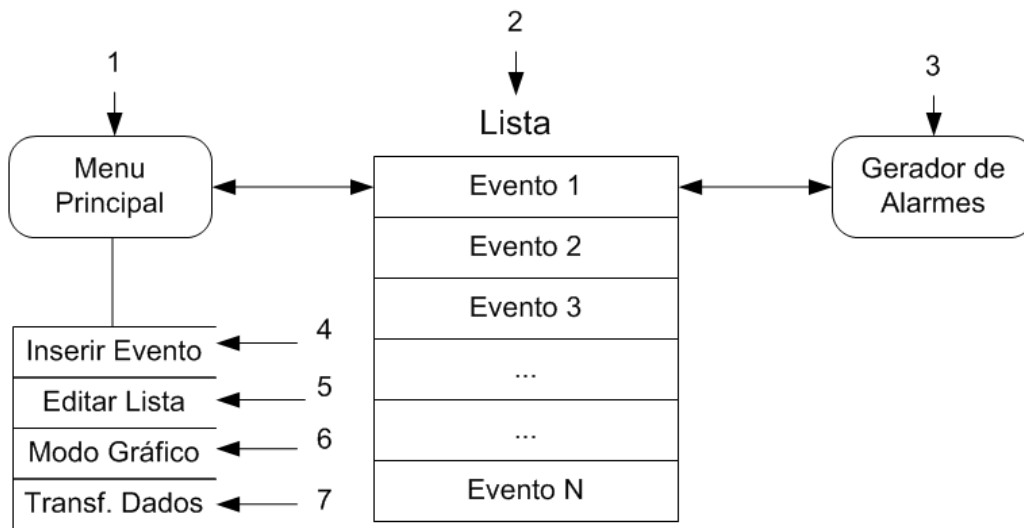


Fig. 3

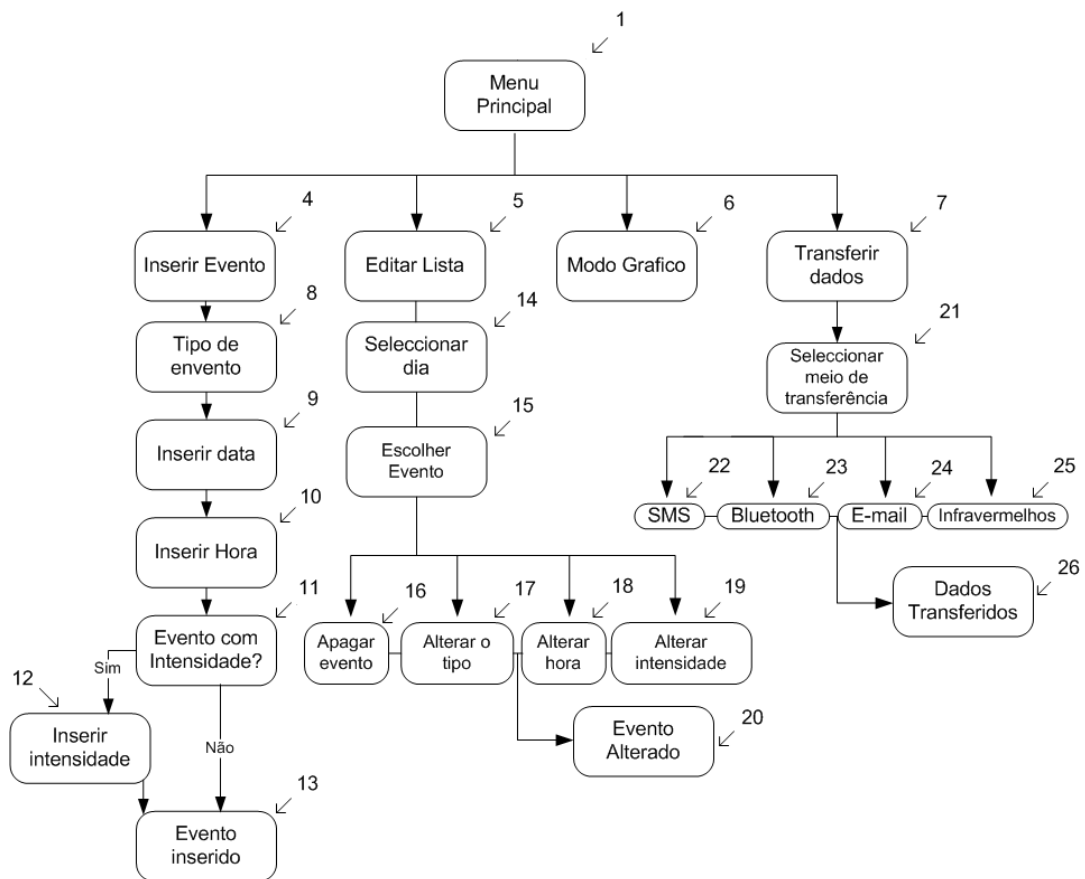


Fig. 4



Fig. 5



Fig. 6

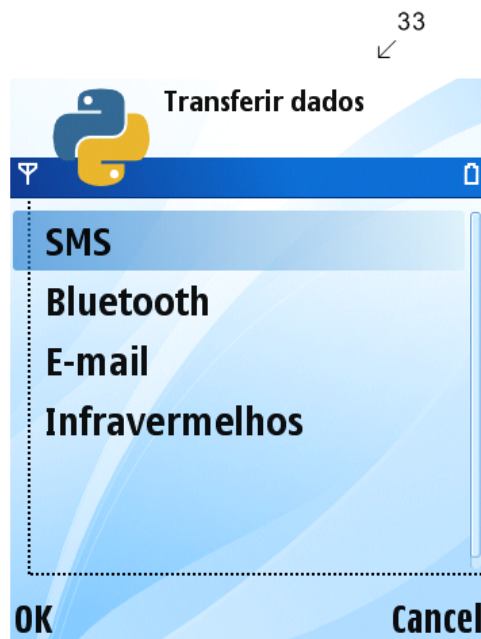


Fig. 7

D Code

All of the code here represented was written on Python, next follows the code for the sleep e-diary to work on a cell phone.

```
import socket, appuifw, e32
from e32db import format_time
from time import *

f = open(u'c:\\data.txt', 'a')
f.close()

def lereventos():
    f = open('c:\\sleepsetup.txt', 'r')
    eventos = []
    iev = []
    s = f.readline().decode("iso-8859-1")
    while s != '':
        if s[0] == '$':
            iev.append(1)
        else:
            iev.append(0)
        if s[len(s)-1] == '\n':
            eventos.append(s[1:len(s)-2])
        else:
            eventos.append(s[1:len(s)])
        s = f.readline().decode("iso-8859-1")
    f.close()
    return [iev, eventos]

def neventos():
    f = open(u'c:\\data.txt', 'r')
    ma = 0
    buf = f.read(17)
    while buf != '':
        ma = max(ma, int(buf[0:4]))
        buf = f.read(17)
    f.close()
    return ma

def listadias():
    f = open(u'c:\\data.txt', 'r')
    lis = []
    buf = f.read(17)
    while buf != '':
        num = int(buf[6:16])
        a2 = gmtime(num)
        flag = 1
        for day in lis:
            if (day[0] == a2[0]) and (day[1] == a2[1]) and (day[2] == a2[2]):
                flag = 0
        if flag:
            lis.append((a2[0], a2[1], a2[2]))
        buf = f.read(17)
    f.close()
    return [map(lambda x: unicode("%d-%d-%d" % (x[2], x[1], x[0])), lis), lis]

def ajuda(x):
    global I
    te = gmtime(x[2])
    s1 = str(te[3])
    if te[4] < 10:
        s2 = "0" + str(te[4])
    else:
        s2 = str(te[4])
    if I[0][x[1]] == 1:
        return "%s:%s, %s: %d" % (s1, s2, I[1][x[1]], x[3])
    else:
        return "%s:%s, %s" % (s1, s2, I[1][x[1]])

def listaeventos(day):
    f = open(u'c:\\data.txt', 'r')
    temp = mktime((day[0], day[1], day[2], 0, 0, 0, 0, 0))
    temp = temp + 3600
    lis = []
    buf = f.read(17)
    while buf != '':
        num = int(buf[6:16])
        if ((num - temp) < 86400) and ((num - temp) >= 0):
            lis.append((int(buf[0:4]), int(buf[4:6]), int(buf[6:16]), int(buf[16])))
        buf = f.read(17)
```



```

f.close()
return [map(lambda x: x[0], lis), map(ajuda, lis)]

def apagar(iden):
    f = open(u'c:\\data.txt','r')
    ap = 1
    st = ""
    buf = f.read(17)
    while buf != '':
        if int(buf[0:4]) != iden:
            st += buf
        buf = f.read(17)
    f.close()
    f = open(u'c:\\data.txt','w')
    f.write(st)
    f.close()

def bt_send():
    try :
        file=(u'c:\\data.txt')
        addr, services = socket.bt_obex_discover()
        service = services.values()[0]
        socket.bt_obex_send_file(addr,service,file)
        appuifw.note(u"Dados enviados","info")
    except Exception, e :
        appuifw.note(u"Erro: %s" %e, "error")

def inserir(n, ev, tempo, nivel):
    f = open(u'c:\\data.txt','r')
    buf = f.read(17)
    flag = 1
    st = ""
    while buf != '':
        if flag and tempo < int(buf[6:16]):
            st += u"%4d%2d%10d%d" % (n, ev, tempo, nivel)
            flag = 0
        st += buf
        buf = f.read(17)
    f.close()
    if flag:
        st += u"%4d%2d%10d%d" % (n, ev, tempo, nivel)
    f = open(u'c:\\data.txt','w')
    f.write(st)
    f.close()

L = [u'Insert event', u'Edit list', u'Graphic mode', u'Transferring data']
T = [u'SMS', u'Bluetooth', u'E-mail', u'Infrared']
I = lereventos()

nev = neventos()

while(True):
    appuifw.app.title=u"Sleep Diary"
    index = appuifw.selection_list(choices=L , search_field=1)
    if index == None:
        break
    if index == 0:
        appuifw.app.title=u"Insert event"
        while(True):
            ind = appuifw.selection_list(choices=I[1] , search_field=1)
            if ind == None:
                break
            if type(ind) == int:
                data = appuifw.query(u"Insert date:", "date", time() - altzone)
                if type(data) == int or type(data) == float:
                    hora = appuifw.query(u"Insert time:", "time", time() - altzone)
                    if type(hora) == int or type(hora) == float:
                        nev += 1
                        if I[0][ind] == 1:
                            intensi = appuifw.query(u"Insert intensity (1 to 5):", "number")
                            while (not (intensi > 0 and intensi < 6)):
                                intensi = appuifw.query(u"Insert intensity (1 to 5):", "number")
                            inserir(nev, ind, int(data + hora - altzone), intensi)
                            appuifw.note(u"Event saved", "conf")
                        else:
                            inserir(nev, ind, int(data + hora - altzone), 0)
                            appuifw.note(u"Event saved", "conf")
            else:
                inserir(nev, ind, int(data + hora - altzone), 0)
                appuifw.note(u"Event saved", "conf")
    if index == 1 or index == 2:
        if index == 1:
            appuifw.app.title=u"Edit list"
        else:
            appuifw.app.title=u"Graphic mode"
        [dias, nums] = listadias()
        esc = 0
        while esc != None:

```

```

esc = appuifw.selection_list(choices=dias , search_field=1)
if type(esc) == int and esc >= 0:
    appuifw.app.title=dias[esc]
    [indices, horas] = listaeventos(nums[esc])
    escd = appuifw.selection_list(choices=horas , search_field=1)
    if index == 2 and type(escd) == int:
        if appuifw.query(u"Are you sure?", "query"):
            apagar(indices[escd])
            appuifw.note(u"Event erased", "conf")
if index == 3:
    appuifw.app.title=u"Transfer data"
    indext = appuifw.selection_list(choices=T , search_field=1)
    bt_send()

```

Here is the code for the reader software that generated the Fig. 1.1:

```

from pylab import *
from easygui import fileopenbox
from time import *

f = fileopenbox(msg=None, title='Actigraphy data', argInitialFile=None)
while f == None:
    f = fileopenbox(msg=None, title='Actigraphy data', argInitialFile=None)
f = open(f, 'r')

s = f.readline()
hora = int(s[23:25])
minuto = int(s[26:28])
segundo = int(s[29:31])
tempo = 86400 - (3600*hora + 60*minuto + segundo)

for i in range(6):
    s = f.readline()

act = []

if len(s) > 10:
    while s != '':
        act.append(int(s.strip('\n')[14:len(s)-1]))
        s = f.readline()
    f.close()
else:
    while s != '':
        act.append(int(s.strip('\n')))
        s = f.readline()
    f.close()

ndias = int((len(act)-tempo)/86400) + 2
ns = len(act)

if ndias > 8:
    nc = 2
    if ndias % 2:
        (ndias/2) + 1
    else:
        nl = int(ndias/2)
else:
    nc = 1
    nl = ndias

xlbl = arange(0.0, 24.0, (24.0/86400.0))

f = fileopenbox(msg=None, title='Events set', argInitialFile=None)
while f == None:
    f = fileopenbox(msg=None, title='Events set', argInitialFile=None)
f = open(f, 'r')
I = []
inte = []
s = f.readline().decode("iso-8859-1")
while s != '':
    if s[0] == '$':
        )
    else:
        te.append(0)
    if s[len(s)-1] == '\n':
        I.append(s[1:len(s)-1])
    else:
        I.append(s[1:len(s)])
    s = f.readline().decode("iso-8859-1")
f.close()

f = fileopenbox(msg=None, title='Diary data', argInitialFile=None)

```

```

while f == None:
    f = fileopenbox(msg=None, title='Diary data', argInitialFile=None)
f = open(f, 'r')
buf = f.read(17)
lis = []
while buf != '':
    lis.append((float(buf[0:4]), float(buf[4:6]), float(buf[6:16]), float(buf[16])))
    buf = f.read(17)
f.close()

comp = len(lis)
temp = localtime(lis[0][2])
if (86400 - (3600*temp[3] + 60*temp[4])) <= tempo:
    xs = map(lambda x: (x[2] - lis[0][2] + 3600*temp[3] + 60*temp[4])/86400, lis)
else:
    xs = map(lambda x: (x[2] - lis[0][2] + 3600*temp[3] + 60*temp[4])/86400 + 1, lis)
ys = map(lambda x: x[1], lis)
zs = map(lambda x: x[3], lis)

n = 0
esc = (0,2,1,3)
for d in range(ndias):
    pl = subplot(nl, nc, d+1)
    xa = []
    ya = []
    aa = []
    ia = []
    if d == 0:
        xd = list(zeros(86400-tempo, dtype = int))
        xd.extend(act[0:tempo])
        pl.plot(xlbl, xd, '#FFA07A')
        pl.set_xlim(0.0, 24.0)
        pl.set_ylim(0.0, 1400.0)
    elif d == ndias-1:
        xd = act[tempo + (d-1)*86400: ns]
        xd.extend(list(zeros(86400-(ns-(tempo + (d-1)*86400)), dtype = int)))
        pl.plot(xlbl, xd, '#FFA07A')
        pl.set_xlim(0.0, 24.0)
        pl.set_ylim(0.0, 1400.0)
    else:
        pl.plot(xlbl, act[tempo + (d-1)*86400:tempo + d*86400], '#FFA07A')
        pl.set_xlim(0.0, 24.0)
        pl.set_ylim(0.0, 1400.0)

    for j in range(comp):
        if int(xs[j]) == d:
            xa.append((xs[j]-d)*24.0)
            ya.append(ys[j])
            aa.append(100 + 300*esc[(n-(int(n/4)*4)])])
            ia.append(zs[j])
            n = n + 1
    pl.plot(xa, aa, 'go')
    pl.set_xlim(0.0, 24.0)
    pl.set_ylim(0.0, 1400.0)
    compa = len(xa)
    for k in range(compa):
        if ia[k] == 0:
            text(xa[k], aa[k], I[int(ya[k])], color = 'k', fontsize=16)
        else:
            text(xa[k], aa[k], '%s: %d' % (I[int(ya[k])], ia[k]), color = 'k',
            fontsize=16)

show()

```

Here at last is the code for reading the SeD data only to generate a text output:

```

from pylab import *
from easygui import fileopenbox
from time import *

f = fileopenbox(msg=None, title='Events set', argInitialFile=None)
while f == None:
    f = fileopenbox(msg=None, title='Events set', argInitialFile=None)
f = open(f, 'r')
I = []
inte = []
s = f.readline().decode("iso-8859-1")
while s != '':
    if s[0] == '$':
        inte.append(1)
    else:
        inte.append(0)
    if s[len(s)-1] == '\n':

```

```

        I.append(s[1:len(s)-1])
    else:
        I.append(s[1:len(s)])
    s = f.readline().decode("iso-8859-1")
f.close()

fpath = fileopenbox(msg=None, title='Diary data', argInitialFile=None)
while fpath == None:
    fpath = fileopenbox(msg=None, title='Diary data', argInitialFile=None)
f = open(fpath, 'r')

buf = f.read(17)
lis = []
while buf != '':
    lis.append((float(buf[0:4]), float(buf[4:6]), float(buf[6:16]), float(buf[16])))
    buf = f.read(17)
f.close()

def listadias():
    f = open(fpath, 'r')
    lis = []
    buf = f.read(17)
    while buf != '':
        num = int(buf[6:16])
        a2 = gmtime(num)
        flag = 1
        for day in lis:
            if (day[0] == a2[0] and day[1] == a2[1] and day[2] == a2[2]):
                flag = 0
        if flag:
            lis.append((a2[0], a2[1], a2[2]))
        buf = f.read(17)
    f.close()
    return [map(lambda x: unicode("%d-%d-%d" % (x[2], x[1], x[0])), lis), lis]

def ajuda(x):
    global I
    te = gmtime(x[2])
    s1 = str(te[3])
    if te[4] < 10:
        s2 = "0" + str(te[4])
    else:
        s2 = str(te[4])
    if x[1] > 4:
        return unicode("%s:%s, %s: %d" % (s1, s2, I[x[1]], x[3]))
    else:
        return unicode("%s:%s, %s" % (s1, s2, I[x[1]]))

def listaeventos(day):
    f = open(fpath, 'r')
    temp = mktime((day[0], day[1], day[2], 0, 0, 0, 0, 0, 0))
    lis = []
    buf = f.read(17)
    while buf != '':
        num = int(buf[6:16])
        if ((num - temp) < 86400 and ((num - temp) >= 0) :
            lis.append((int(buf[0:4]), int(buf[4:6]), int(buf[6:16]),
            int(buf[16])))
        buf = f.read(17)
    f.close()
    return [map(lambda x: x[0], lis), map(ajuda, lis)]

dias = listadias()
ndias = len(dias[0])
if ndias <= 9:
    nl = 3
    nc = 3
else:
    nl = 4
    nc = 4

figure(facecolor = 'w')
for d in range(len(dias[0])):
    pl = subplot(nl, nc, d+1)
    axis('off')
    eventos = listaeventos(dias[1][d])
    title(dias[0][d], color = 'blue', fontsize = 14, fontweight = 'bold')
    pl.set_ylim(0.0, 14.0)
    for j in range(len(eventos[1])):
        text(0.1, 12 - j, eventos[1][j], color = 'black', fontsize = 13)

show()
title(u'Sleep e-diary')

```