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Automatic detection of wakefulness and rest intervals in actigraphic signals: A data-driven approach

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ABSTRACT

Actigraphy is an useful tool for evaluating the activity pattern of a subject; activity registries are usually processed by first splitting the signal into its wakefulness and rest intervals and then analyzing each one in isolation. Consequently, a preprocessing stage for such a splitting is needed. Several methods have been reported to this end but they rely on parameters and thresholds which are manually set based on previous knowledge of the signals or learned from training. This compromises the general applicability of this methods. In this paper we propose a new method in which thresholds are automatically set based solely on the specific registry to be analyzed. The method consists of two stages: (1) estimation of an initial classification mask by means of the expectation maximization algorithm and (2) estimation of a final refined mask through an iterative method which re-estimates both the mask and the classifier parameters at each iteration step. Results on real data show that our methodology outperforms those so far proposed and can be more effectively used to obtain derived sleep quality parameters from actigraphy registries.

1. Introduction

Actigraphy is becoming increasingly popular as a noninvasive technique for monitoring human activity/rest cycles. Recent commercially available devices provide real-time readings and wireless connectivity, spanning their applicability beyond simple assessment of life habits. In the last decades, the use of actigraphy with clinical purposes has been mainly limited to the assessment of the circadian rhythm and sleep quality [1–3]; however, recent contributions have shown that actigraphy is useful for the evaluation of some pathologies which affect the movement pattern; this is the case of, for instance, Attention Deficit and Hyperactivity Disorder (ADHD) [4–6], Infantile Colic [7], or Chronic Obstructive Pulmonary Disease (COPD) [8,9].

The specific application may require proper identification of the activity and rest intervals. For instance, sleep quality assessment is performed over the rest cycle, so that relevant parameters such as the sleep onset time or the number of awakenings can be obtained. On the other hand, diagnosis support methods, such as those presented in [4–6], rely on signal features that are computed either over the whole 24-h segment or only on the wakefulness or rest interval. Thus, the accuracy in the detection of these intervals is of paramount importance for the success of these methodologies.

Typically, the detection of the rest interval has been manually done by experts which, as every manual process, is time consuming and subject to variability; more recently, off-the-shelf devices may include a light sensor aimed at providing information to be used for the automatic detection of each interval at night time, so diurnal sleep periods, if any, may be lost. To the best of our knowledge, only a few contributions have focused on the detection procedures themselves, the most significant being described in Section 2. These contributions, however, rely on different parameters that are selected after a training process over a group of acquired signals. Thus, they are application (and population) dependent and prone to excessive generalization for specific registries. Additionally, the assumptions on which they are based may be objectionable.

This paper proposes a novel methodology to identify wakefulness and rest intervals in actigraphic records; as opposed to other proposals, all the parameters needed are estimated from the signal under analysis, so the aforementioned dependencies are avoided. After a preprocessing stage, the distribution of the data is modeled as a mixture of two Gaussians respectively accounting for each of the sought states. Based on this assumption, the identification is performed in two steps: an initial mask (binary classification) is

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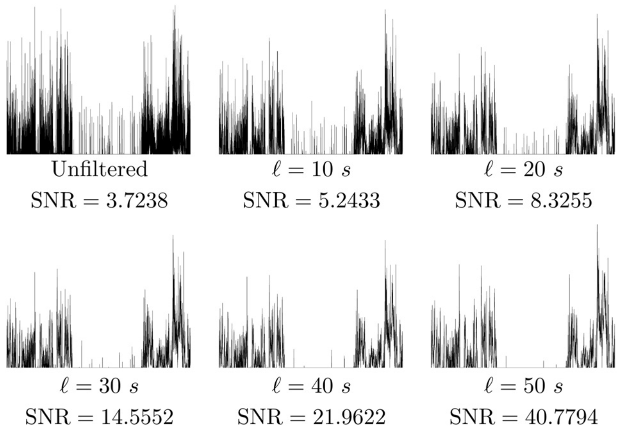

Fig. 1. Shape and signal to noise ratio of actigraphy signals for different filtering stages. ℓ denotes the length (in seconds) of the median filter.

obtained by comparing the sampling distribution of different data intervals with each of the Gaussians. An iterative method is then used to refine the initial mask by means of a linear classifier, the parameters of which are updated in every iteration step.

2. State of the art

Contributions in this field could be classified in two main groups, namely, sleep scoring algorithms and the so-called change point detection methods [10,11]. About the former, they are intended to determine the quality of the sleep (sleep report) by the detection and analysis of the actual sleep periods within the rest interval [3,12–17]. Hence, they do not pursue the same goal as we do, but they pursue a second tier identification within the rest interval we mean to detect. We brought these methods up to avoid a misleading terminology, as the terms "rest" and "sleep" are often used interchangeably. Consequently, we concentrate on methods within the change-point detection group:

2.1. Change point detection methods

Despite this type of methods seem the most adequate to face the problem we deal with, its use on actigraphic registries is hampered by some characteristics of these signals, namely, non-stationarity, noisy/spiky nature, lack of prior knowledge and large inter-patient and intra-patient variability. This noisy/spiky behavior renders techniques usually applied to enhance biomedical signals (ECG, EMG, etc.) inappropriate in this application domain. Specifically, in Fig. 1, we show a typical scenario in which the aforementioned noisy/spiky nature is clearly visible; for the raw case (upper left corner) the Signal-to-Noise ratio (i.e., the power of the activity period divided by the power of the rest interval) is SNR=3.7238 dB. This value is much lower than the one usually obtained in the typical identification problem of ECG segments (approximately 15 dB for the estimation of the least visible —P— wave, see Fig. 2(a)[1]). If median filtering was used to improve SNR, SNR values comparable to those of more visible ECG waves could be obtained (Fig. 2(a)), at the price of artifacting the original signal, smearing the rest interval within the wakefulness interval and/or creating isolated false rest intervals in the activity period (Fig. 2(b)).

Despite these difficulties, some methods have been proposed in the early past.

2.1.1. Methods based on the discrete wavelet transform (DWT)

To the best of our knowledge, there is no contribution reported in literature apart from [7] that addresses this problem through the DWT. Despite the method performed reasonably well with newborn populations, the shift-variant nature of the DWT makes it inadvisable for pattern recognition applications. Current research pursues shift-invariance with limited redundancy and complexity [18] although no contributions have been so far proposed for the problem we here deal with.

2.1.2. Methods based on template matching

Template matching approaches may also be used for this objective; however, the definition of both the template and the similarity/error function are key issues for the success of the method and are usually very hardwired to the problem addressed. We are not aware of any contribution in this direction; however, in order to illustrate the difficulties associated to this methodology, we have implemented a naive template-matching approach for comparison purposes.

2.1.3. Methods based on statistical pattern recognition

The following contributions are worth mentioning:

(a) The method in [19] assumes that the actigraphic data consist of a mixture of two contributions resulting from intentional movements (during the wakefulness intervals $-\mathcal{W}-$) and spontaneous movements (during the rest intervals $-\mathcal{R}-$): considering the absolute activity value[2] r, the probability density function (pdf) may be expressed as

$$f_R(r) = p_{\mathcal{W}} \cdot pf_R(r|_{\mathcal{W}}) + p_{\mathcal{R}} \cdot pf_R(r|_{\mathcal{R}}), \tag{1}$$

where $f_R(r|_{\mathcal{W}})$ is a Maxwell (a specific case of the non-central χ^2) pdf and $f_R(r|_{\mathcal{R}})$ is a Gaussian pdf. The allocation to rest/wakefulness intervals is carried out for each signal interval, in which the parameters of the mixture are estimated using nonlinear least squares over the sample pdf in each window. Rest or wakefulness is assessed using a maximum likelihood classifier.

The nature of the first component in (1), relies on an assumption of independent and identically distributed Gaussian data for each signal recording channel.

These assumptions may be too stringent since in some applications, meaningful correlations could exist across the different channels and significative differences in the channel values may appear.

(b) The method in [20] uses the coefficients of an autoregressive (AR) model estimated over a sliding window. Classification is carried out by means of the maximum likelihood principle, in which the authors assume that the coefficients follow two different multivariate Gaussian models (one for wakefulness, one for rest). The parameters of each distribution are obtained following a training procedure over population data.

Although the results in [20] are promising, the length of the sliding windows (between 100 and 500 min, i.e., approximately between 2 and 8 h) compromises the temporal resolution of the method. In addition, the Gaussian assumption for the AR coefficients is not generally applicable as we have confirmed with our experiments. In this case, the classification performance decreases noticeably (see Section 4).

(c) Our proposal in [4,5] works on a low-pass version of the original signal obtained by means of a moving average using a 30-min rectangular kernel. Then each time instant is compared with a

[1] The SNR values for ECG wave segmentation have been obtained from a 5 min ECG acquisition on a healthy volunteer.

[2] $r = \sqrt{x^2 + y^2 + z^2}$, with x, y and z the three signal recording channels.