Monitoring Changes in Daily Actigraphy Patterns of Free-living Patients

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Abstract. The current development of actigraphs integrated in small and discrete devices allows noninvasive recording of patient activity over several days or even months. The information obtained by these devices allows the analysis of daily activity patterns and therefore may be a useful tool to monitor the status of out-patients in diseases such as major depression. However, the full exploitation of this information requires automated systems that reduce the inherent complexity of these data and facilitate their interpretation by the clinicians. Thus in this paper a Daily Activity Monitoring System (DAMS) is presented based on functional data analysis algorithms for signal alignment and non-linear dimensionality reduction techniques based on manifolds. The DAMS allows robust processing of actigraphy data, and visual detection of changes or anomalies in routine activity.

Keywords: Actigraphy, monitoring, manifolds, functional data analysis

1 Introduction

Over the last decades the actigraps technology has improved substantially by developing smaller sensors, increasing battery life, and improving data storage capacity.These improvements have led to the possibility of integrating these actigraphs in small and discrete devices, allowing long time noninvasive studies of free living-patient activity.

By collecting information on motor activity of patients we can get a picture of the daily sleep-wake cycles and routines. This information can be very useful for the diagnosis and evaluation of several clinical sleep disorders and treatment outcomes. Different studies studies suggest that the information provided by actigraphy can be used to monitor the progress of patients with mood disorders such as major depression [1–4], or patients with dementia [5, 6].

Despite the advantages of actigraphy, extracting useful information from the signals is not easy, and even more if we consider long-term studies, that require evaluating changes in daily activity patterns and detection of anomaly activity signals. In this sense, automated systems that reduce the inherent complexity of these data and facilitate their interpretation by the clinicians are required. To contribute to this purpose, a Daily Activity Monitoring System (DAMS) is presented in this work. A DAMS is a system that visually presents daily activity patterns recorded on the same patient, helping to detect changes or anomalies in their routine activity.

2 Materials and Methods

The DAMS, processes the signal recorded by the actigraph through the following stages (see Figure 1): 1) in the first stage, missing data detection is performed by applying filtering based techniques over the actigraphy signal. 2) Subsequently, gaussian mean imputation was used to replace missed values. 3) Once the data were preprocessed, the daily actigraphy signals were registered in order to align the main activity peaks. To do so, the time warping algorithm based on functional data analysis [7, 8] using b-spline basis was applied. 4) A nonlinear dimensionality reduction technique based on Isomap manifold algorithm was used to visualize data in 2D plot. 5) Finally an anomaly detection algorithm based on the concept of nearest neighbors distances was applied.

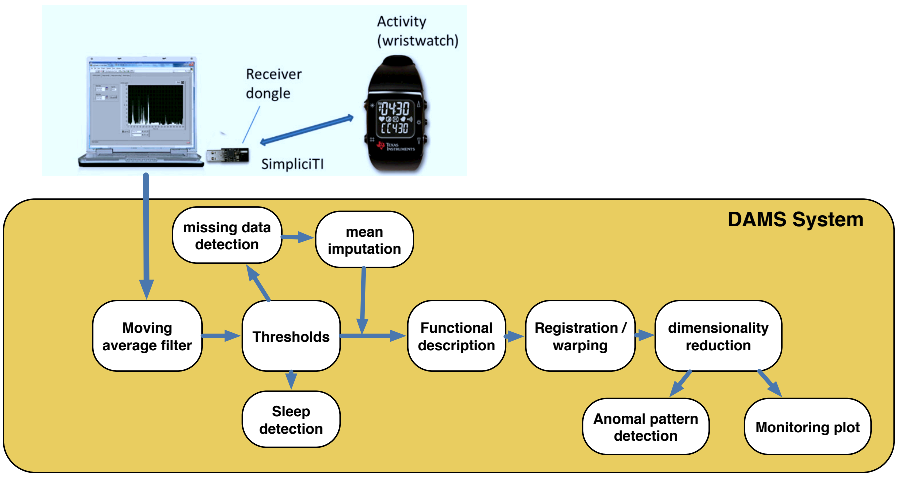

Fig. 1. Schema of the DAMS system.

2.1 Actigraphy Data

This study includes 27 days of activity monitoring data from one healthy person. The activity was recorded 24 hours a day allowing the analysis of the sleep activity and day time activity. The selected hardware platform for the actigraphy sensor was the Texas Instruments ez430 Chronos. The main technical specifications of the ez430 system used are: RF link at 868 MHz, automatic data downloading, more than a month battery life, memory without downloading to the PC up to 5 days storing one activity index per minute. Additional technical information on the hardware of the watch can be found in [9]. The selection of this device was done attending to their non-obtrusive and non-stigmatizing characteristics and their wireless and automatic synchronization capability. These characteristics are mandatory in free-living patients monitoring.

The ez430 Chronos was programmed to acquire the information from the three axis with a sampling frequency of 20 Hz. The device used applies a high pass second order Butterworth filter at 1.5 Hz on each axis signal. The activity was computed by using the value of time above a threshold (TAT) of 0.04 g for each axis in epochs of 60 seconds. Finally the resulting actigraphy value registered is the maximum TAT over the three axes in each epoch [10] .

2.2 Missing Data Detection and Imputation

Missing data are common in actigraphy records. Missing data could be due to different effects as can be; synchronization errors, left forgotten the actigraph, empty batteries, or empty memory. To minimize the effect of the missing data in the actigraphy analysis it is necessary their detection and imputation.

The missing data detection algorithm used in this work consists in two main steps: in the first step, a moving average filter is applied to the actigraphy signal s, consisting in a lowpass filter with filter coefficients equal to the reciprocal of the span. In this work a span of 120 minutes was used. When the actigraphy signal was filtered fs, a threshold was applied to detect regions with very low activity ($fs(t) \leqslant 2$) considered as missing data. Subsequently, gaussian mean imputation was used to replace missed values. An example of the results of the missing data detection algorithm are presented in Figure 2 (top).

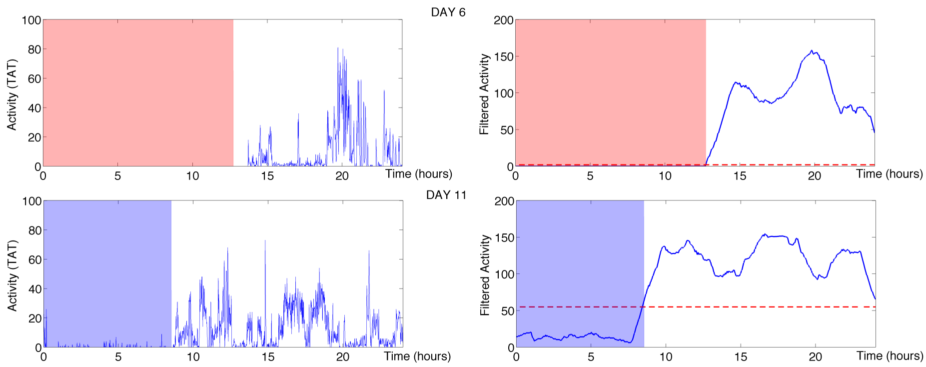

Fig. 2. Example of two daily actigraphy signals s (left), and their corresponding filtered signal fs (right). The red shaded region shows missed data, and the blue shaded region shows sleep periods.The thresholds values are presented as dashed lines.

2.3 Sleep Detection

The analysis of actigraphy during sleep, provides valuable information to assess the patient's condition as can be, sleep duration, stress or quality of sleep. To obtain this information from the data, the automatic detection of periods of sleep is mandatory. The same strategy used for the detection of missing data was applied, but the threshold values were changed. In this case a double threshold ($55 > fs(t) > 2$) has been applied. The double threshold allows us to detect periods with low activity but excluding missing data. An example of the results of the sleep detection algorithm are presented in Figure 2 (bottom).

2.4 Functional Description and Registration

The DAMS uses a functional description of the actigraphy signals based on B-spline functions (a compact support basis functions developed by de Boor [11]). The DAMS uses a B-splines basis of level 5 defined by 60 uniformly distributed knots. When using a B-spline basis of level n , the activity registered between two consecutive knots is approximated by a polynomial spline of $n-1$ degree, ensuring continuity and differentiability to the order $n-2$ in the knots.

Once the functional basis to describe our spectra is defined, our data have to be fitted with the B-spline model. To do so, the smoothing algorithm described by Ramsay et al in [8] is used. This method estimates a curve x from observations $s_i = x(t_i) + \epsilon_i$. To avoid over-fitting, it introduces a roughness penalty to the least-square criterion used for fitting the observations, resulting in a penalized least squares criterion (PENSSE):

$$PENSSE_\lambda(x) = \sum_{i=1}^{length(s)} (s_i - x(t_i))^2 + \lambda J(x), \tag{1}$$

where $J(x)$ is a measure of roughness of x, and λ is a coefficient that controls the amount of penalty introduced due to roughness of x. Higher λ values mean a smoother model, and lower λ values mean better fitting.

In order to define a measure of roughness J, the concept of curvature or squared second derivative $(D^2x(t))^2$ of a function [8] has been used. Consequently, the measure of a function's roughness is the integrated squared second derivative

$$J(x) = \int (D^2x(t))^2 dt, \tag{2}$$

The smoothing depends on the λ parameter chosen. In order to automatically select a optimum λ value for a specific dataset, the Generalized Cross-Validation measure developed by Craven and Wahba [12] has been used.

As a result of the functional description, each daily activity signal was characterized by the coefficients of the B-spline basis.

The actigraphy signal has a strong daily pattern due to the daily routines based on work schedules, mealtimes, and sleep-wake cycles. However these pattern do not need to coincide exactly in time every day. This phenomena difficults the comparison between activity patterns as well as their automatic analysis using pattern recognition approaches. To solve this problem the daily activity signals need to be registered. That is, to transform the physical time scale used in each daily actigraphy by using a nonlinear registration algorithm, in order to align the different activity patterns that are slightly phase shifted. To do so, the time warping algorithm based on functional analysis and described by Ramsay in [8] was used. this algorithm is included in the FDA MATLAB toolbox [1].

The application of the daily actigraphy registration allows, between others, a better characterization of the mean actigraphy pattern. An example of the improvement in the characterization of the mean activity pattern can be seen in Figure 3. On this example it is easy to see how the registering processing allows the visualization of hidden activity patterns in the mean daily actigraphy related to daily activity routines.

2.5 Dimensionality Reduction and Visualization

Once we have the actigraphy data preprocessed we wanted to facilitate the visual comparison of the daily activity signals and their associated characteristics such as total daily activity recorded, the amount of lost data, or the number of hours slept. Thus we need to summarize the information contained in a record of daily activity in a very small set of variables to allow visual representation. To do so, a nonlinear dimensionality reduction algorithm based on Isomap manifolds [14] (using 14 euclidean neighbors) was chosen. The implementation of Isomap algorithm used was included in the MatlabToolbox for Dimensionality Reduction [2]

Once daily actigraphy signals are reduced to two dimensions, we can display them as circles in the 2D scatter plot. Moreover, it is possible to add other useful information for patient monitoring such as: the level of total daily activity, by varying the radius of the circle, or the amount of data lost, by varying alpha value (transparency) of the circle color.

2.6 Anomaly Detection

In this study an anomaly measure for each daily activity signal has been computed based on the concept of nearest neighbor analysis [13]. The anomaly score of a data instance, described by the two first manifold components, is defined as its distance to its kth nearest neighbor in a given data set . The key assumption of this method is that normal data instances occur in dense neighborhoods, while anomalies occur far from their closest neighbors. In this study we have considered the k value equal to the number of weeks included in the study (k=4). In this way we avoid that activity patterns that recur even once a week can be considered as anomalous. The anomaly score for each daily actigraphy signal was

[1] Available at `http://www.psych.mcgill.ca/misc/fda/software.html`

[2] Available at `http://homepage.tudelft.nl/19j49/Matlab_Toolbox_for_Dimensionality_Reduction.html`

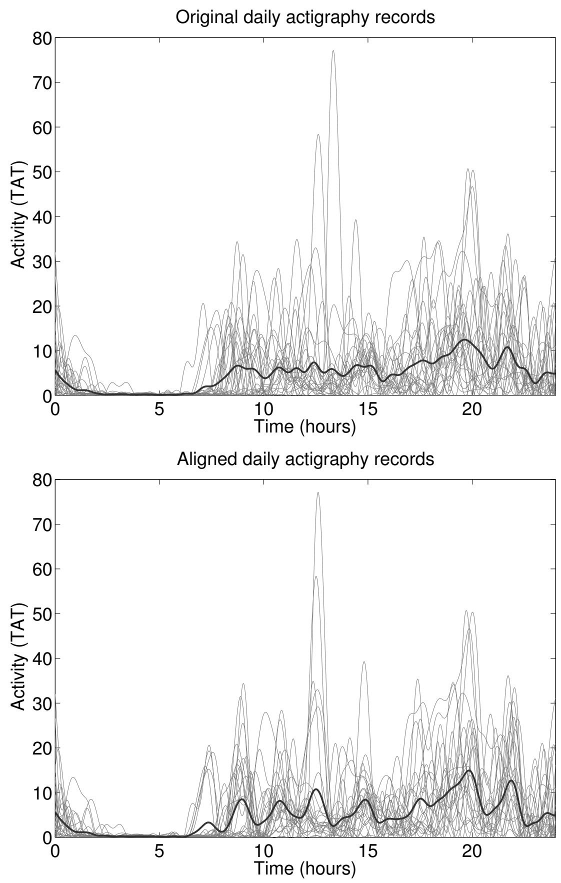

Fig. 3. Daily activity signals included in the study and their associated mean for both non-registered signals (left) and for registered signals (right).

included in the DAMS monitoring plot by changing the circle color according to a colormap as can be seen in Figure 4.

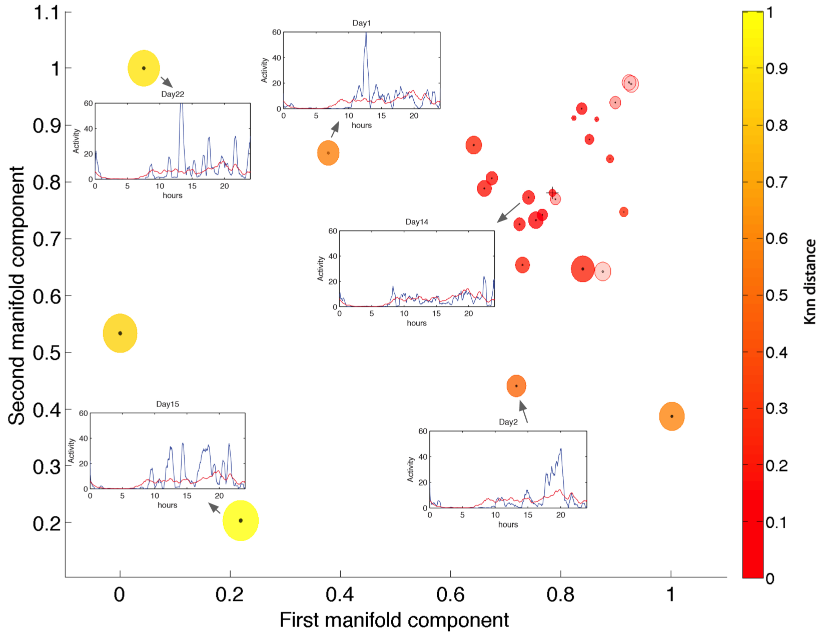

Fig. 4. DAMS visualization including 14 days samples represented as circles. The radius of the circle represents the total daily activity, and their transparency represents the amount of missing data. Moreover, the daily actigraphy signals (blue lines) are presented for some of the most representative days, including the mean actigraphy signal (red lines) for comparison purposes. The anomaly score for each daily actigraphy signal was included in the plot by changing the circle color according to the colormap. The median is indicated as + symbol.

3 Results and Conclusion

Figure 4 shows an example of the DAMS visualization using daily activity patterns obtained for the same person over 27 days. The DAMS visually define those days with normal activity pattern (in red color), as well as those with anomaly patterns (in yellow color) based on the distance to its nearest neighbors in the dataset. Moreover, the DAMS visualization organize the daily activity patterns according to their shape. The anomaly score based defined in this study is useful to characterize the differences of an specific day activity regarding the common activity patterns. Summarizing, the DAMS allows robust processing of actigraphy data and visual interpretation of daily actigraphy patterns for outpatients monitoring.

Acknowledgements

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