# MULTIFRACTAL ANALYSIS OF ACTIGRAPHY DATA

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**Abstract:** The actigraphy is a non-invasive technique that allows the assessment of individual's activity over time. Fibromyalgia is a partially disabling condition characterized by persistent pain, affective disturbances and fatigue, leading to reduced physical activity. Although the influence of pain on physical functioning is well-accepted, the understanding of how pain affects individuals' temporal dynamics of activity patterns remains a challenging task. The multifractal approach is a suitable tool for pattern analysis that describes the dataset with dimension spectra. The aim of this work was to apply a multifractal approach to quantify the complex dynamics of actigraphy data in patients with fibromyalgia. Data were collected by an actigraphy device to the wrist of fifty four individuals during a period of about four weeks. Data were analysed by using Fast Fourier Transform (FFT) of the time-series. In addition, a multifractal approach was applied. The FFT analysis revealed that there were no differences between the groups, and the physical activity presented a non Gaussian distribution for all individuals. By contrast, the multifractal analysis revealed asymmetrical spectra and a qualitative distinction between healthy and fibromyalgia patients.

**Keywords***:* multifractal, variability, actigraphy, fibromyalgia, dynamic of physical activity.

## Introduction

The actigraphy is a non-invasive technique that allows the assessment of an individual's activity. A clock-like device is used on the wrist, or on the leg, in order to register the activity level as the individual performs his daily tasks. As a result, the movement time series (Figure 1) is stored and can be analysed with several methods in order to unveil the dynamic of physical activity over time, e. g., wakefulness and sleeping periods. [5][6]

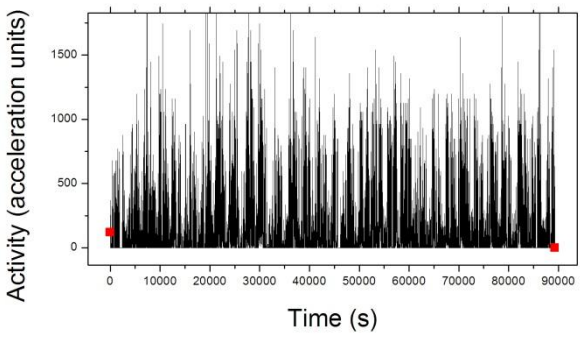


Figure 1 – Activity series of an individual. The activity is presented in acceleration units and the Time in seconds.

A fractal is a shape, in which, the parts are similar to the whole and presents a Hausdorff-Besicovitch dimension that exceeds the topological dimension. [2]

The fractal geometry has been successfully used to the analysis of physiological signals, showing differences on heartbeat time-series between healthy individuals and congestive heart failure patients. [7][8]

However, sometimes the pattern cannot be characterized only by one fractal dimension index, such as it occurs when fractal dimension presents huge variations over time. For these cases, a multifractal approach might be an appropriate tool for pattern analysis. Given that multifractals can describe a dataset with dimension spectra, it provides a suitable method for analysing this kind of data. [9]

Multifractals have already been used on physiological data (heartbeat dynamics), providing evidence about the scale invariance and nonlinear properties of heart rate and the differentiation between healthy and pathological heart rate variability [4][9]. Furthermore, although it has been recognized that multifractal formalisms are appropriate for explaining human performance and behaviour [10], research on variability of physical activity by using multifractals is still scarce.

The multifractal spectra of a signal represent the distributions of the correlation properties of the phenomena under study.

Fibromyalgia is a chronic pain condition that exhibits widespread pain, fatigue, sleep disturbances, psychological disorders and other minor symptoms [1]. Although the etiology of fibromyalgia is still unknown,

it has been suggested that persistent pain in fibromyalgia may lead to altered physical functioning as it occurs in other chronic pain syndromes. [7]

The aim of this work was to apply a multifractal approach to the analysis of actigraphy data in order to unveil the dynamics of physical activity in patients with fibromyalgia.

**Materials and methods**

The fluctuations in the time periods of extreme events return (EER) from actigraphy data were analysed by testing the heterogeneity in long-range dependence using Multifractal Detrending Moving Average (MFDMA).

MFDMA is an algorithm that aims to extract the multifractal spectra from time-series [3]. It is a reliable method that can be easily applied to physiological signals.

This procedure is briefly described as follows:

The first step consisted on generating the time periods of extreme events. Extreme events were defined as all those values that exceed a standard deviation plus the mean value of the activity. The time series of the periods of extreme events were calculated by computing the sequence of time lag between these extreme values, *x(i)*, i=1,2,....,*N*.

The second step was the integration of the EER time series

$$X(k) = \sum_{i=1}^{k} [x(i) - \acute{x}], k = 1, \dots, N \quad (1)$$

Next, the integrated series *X(k)* were divided into *Nn* non-overlapping segments of length *n* and in each segment *s* = 1….,*Nn* the local linear trend $X_s(k)$ was estimated and subtracted from *X(k)*. The q[th] order fluctuation function was calculated as

$$F_q(n) = \left\{ \frac{1}{N_n} \sum_{s=1}^{N_n} \left[ \frac{1}{N} \sum_{k=(s-1)n+1}^{sn} [X(k) - X_s(k)]^q \right] \right\}^{1/q} \quad (2)$$

where q can take any real value except for q = 0. When q = 0, we applied the L'Hôspital's rule [3].

Scaling the $F_q(n)$ function for different values of *n* we get

$$F_q(n) = n^{h(q)} \quad (3)$$

where *h(q)* is the generalized Hust exponent.

Appling the standard multifractal formalism the multifractal scaling exponent *τ(q)* is obtained as

$$\tau(q) = qh(q) - 1 \quad (4)$$

And finally applying the Legendre transform in (4),the multifractal spectra is estimated as

$$(q) = \frac{d\tau(q)}{dq}$$
$$f(q) = q - \tau(q). \quad (5)$$

The data of physical activity were collected by an actigraphy device attached to the wrist on fifty-four individuals. The devices were regularly worn by individuals during a period of about four weeks without interruption. Written informed consent was obtained from all participants in the study. The protocol of the study was approved by the official ethical committee of the Government of Balearic Islands (reference: 1431/10 PI).

The individuals were classified in two different groups: patients with fibromyalgia and healthy controls. Each group was also divided in two subgroups according to their menstrual cycle status: subjects with and without menopause.

Actigraphy data (acceleration units) were analysed in two different steps. The first one was the analysis of the activity distribution by using Fast Fourier Transform (FFT) of the time-series. A multifractal approach was also used to establish a classification criterion for the groups and to unveil the dynamics of the physical activity in patients with fibromyalgia and healthy controls.

Although patients with fibromyalgia are characterized by persistent chronic pain, they also report periods without pain. In these periods, one could expect a normalization of physical activity. Furthermore, we expected that significant differences between patients with fibromyalgia and healthy controls could be related to the timing among activity events. In order to evaluate these timing events, an EER analysis was performed.

For this procedure, only values bigger than one mean value plus a standard deviation were considered. Once these values were identified, the distance between them was calculated and a new time series was built as shown in figure 2:

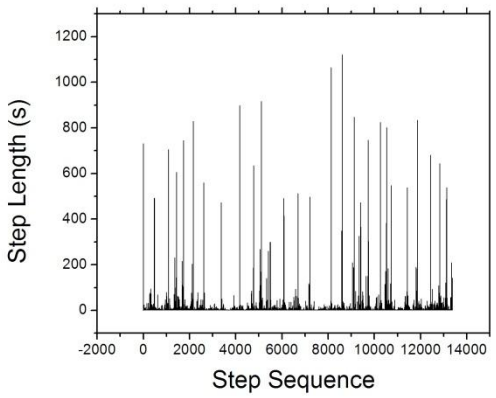


Figure 2 – The graph exhibit the extreme events returns. The Step length represents the time, in seconds, between two extreme events and the Step Sequence represents the order in which these extremes occur.

## Results

We found tthat the FFT output was not able to differentiate between the two groups.

The probability distributions *P(a)*, of activity data presented a non-Gaussian curve for all individuals and a high variability, as it can be seen on figures 3 and 4

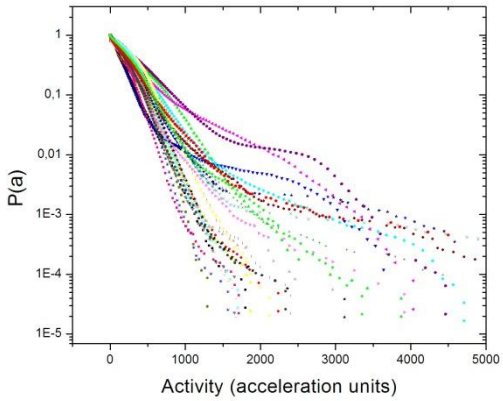


Figure 3 - Cumulative probability distribution for the physical activity in healthy individuals. The semilog plot shows the activity level and his normalize cumulative frequency.

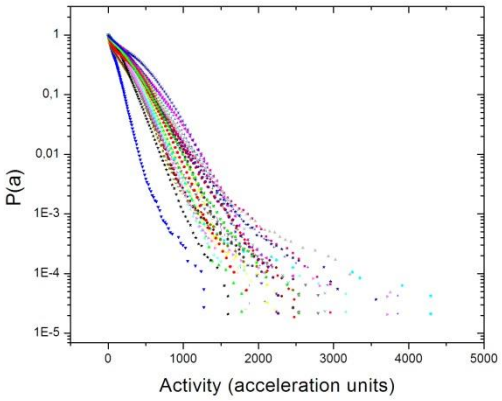


Figure 4 - Cumulative probability distribution for the physical activity in patients with fibromyalgia. The semilog plot shows the activity level and his normalize cumulative frequency.

The MFDMA analysis reported asymmetric multifractal spectra for the individuals, as it can be observed on the figures 5 and 6. No relationship was found between α values and the groups of participants.

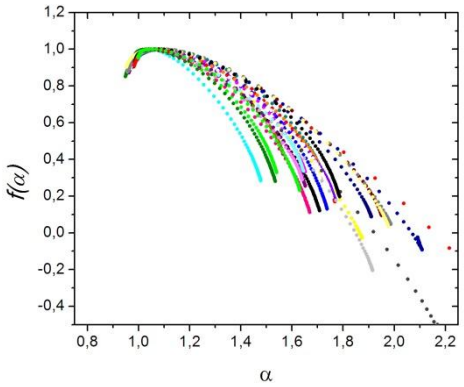


Figure 5 – Multifractal spectra for individuals of the fibromyalgia group. The α represents a fractal dimension presented by the time-series and the *f*(α) quantifies his occurrence.

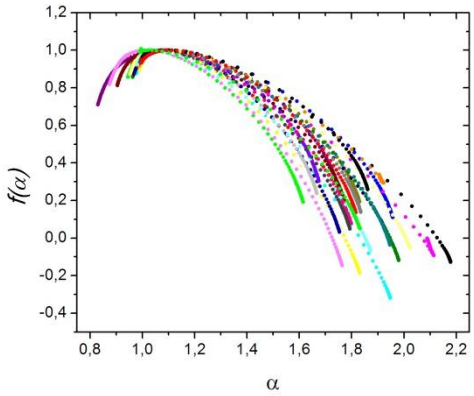


Figure 6 - Multifractal spectra for individuals of the healthy group. The α represents a fractal dimension presented by the time-series and the *f*(α) quantifies his occurrence.

The multifractal spectra showed a variability, revealing an individual pattern for each case.

## Discussion

The non-normality of physical activity data makes difficult a conventional analysis of periods of rest and activity through mean and standard deviation. In our case, we further observed that the curves do not seem to present any index that can differ among the groups.

The individual variability plays an important role in the individual dynamics. It can be easily seen on the great differences among the curves behaviours in figures 3 and 4, as they intersect themselves several times. In order to evaluate this variability an exponential model was fitted to these curves and the correlation coefficient R estimated. The R values for the group with fibromyalgia are significantly different from the healthy group (Mann-Whitney test α=0.05) ranging from 0.849 to 0.996 for fibromyalgia and from 0.698 to 0.997 for healthy group. Indicating that the fibromyalgia group presents less variability than healthy group.

Concerning the data, we observed higher variability in healthy controls than in patients with fibromyalgia. The asymmetrical multifractal spectra also reveal a high heterogeneity in the scaling of the fractal dimensions for the time-series.

The spectra in figures 5 and 6, presented a similar behaviour for the parabola left side in all the individuals with fibromyalgia. These values of the spectra are associated with fluctuations of physical activity that occur over long time periods.

When it comes to the big intervals between extremes, the result presented by the spectra accords with the distributions of physical activity, expressing a bigger variability for healthy individuals, if we consider that these ones occur in larger periods of time.

We analysed the left side taking his length in both x and y axes, defined by the difference of the α with the maximum value of *f* and the lower value of α ($\alpha_0$ and $\alpha_+$), in x axis, and the difference of the *f* values for the mentioned alphas ($f(\alpha_+)$ and $f(\alpha_0)$), in y axis. The standard deviations for these values are presented on figure 6. It can be easily seen that the healthy individuals exhibit a bigger variability (bigger deviation), the result accords with the previous findings.

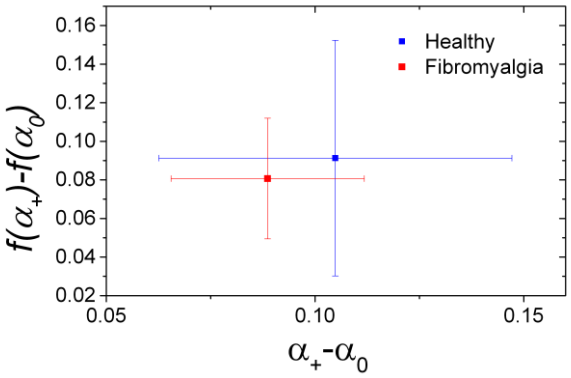


Figure 6 – Mean and standard deviations for the individuals of the two groups for the parabola left side on the x and y axes. It can be seen that the fibromyalgia group values are lower than the healthy group ones.

The phenomenon can be, possibly, explained by the syndrome symptoms. According to the literature, patients with fibromyalgia are characterized by reduced physical activity. [6] These individual might exhibit a reduction on these long time period fluctuations, breaking the similarity of the curves for those values.

In summary, our data suggest that a multifractal approach could be an appropriate method for explaining the high variability and the non-linear dynamics of human physical activity. Furthermore, our work provides evidence that multifractal formalisms are useful to distinguish between healthy and pathological physical activity, as displayed by patients with fibromyalgia. In this sense, our study is in agreement with recent findings suggesting that meaningful information is contained in the temporal dynamics of activity patterns [11].

## Conclusion

The observation of the multifractal spectra and the distributions of activity curves show a clear difference in terms of variability among the individuals.

The connection between the loss of individual variability and the pathological state was already shown on literature. [8] Although a group variability reduction was not suggested yet.

The results give rise to ideas and insights about the human physical activity and fibromyalgia mechanisms, bringing hypothesis that still need to be evaluated.

## Acknowledgments

We thank Dr. Dante R. Chialvo for providing us with the actigraphy devices for the study. Research was supported by the Spanish Secretary of State for R+D (grant# PSI2010-19372) and the Brazilian CAPES (grant# A002_2013) to PM.

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