# Analysis of the Breathing Pattern in Elderly Patients Using the Hurst Exponent Applied to the Respiratory Flow Signal*

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***Abstract*— Due to the increasing elderly population and the extensive number of comorbidities that affect them, studies are required to determine future increments in admission to emergency departments. Some of these studies could focus on the relation between chronic diseases and breathing pattern in elderly patients. Variations in the fractal properties of respiratory signals can be associated with several diseases. To determine the relationship between these variations and breathing patterns, and to quantify the fractal properties of respiratory flow signals, we estimated the *Hurst* exponent ($H$). Detrended fluctuation analysis (DFA) and discrete wavelet transform-based estimation (DWTE) methods were applied. The estimation methods were analyzed using simulated data series generated by *fractional Gaussian noise*. 43 elderly patients (19 patients with a non-periodic breathing pattern - nPB, and 24 patients with a periodic breathing pattern - PB) were studied. The results were evaluated according to the length of data and the number of averaged data series used to obtain a good estimation. The DWTE method estimated the respiratory flow signals better than the DFA method, and obtained *Hurst* values clustered by group. We found significant differences in the $H$ exponent ($p = 0.002$) between PB and nPB patients, which showed different behavior in the fractal properties.**

## I. INTRODUCTION

The aging of the developed world population affects future planning in emergency departments, and increases interest in chronic disease studies. According to the study of United Nations [1], at present, people over 69 years old represent 22% of the total population, and is estimated an increasing to 35% by 2100. The most common diseases in the elderly are of a cardiac or respiratory nature, although an extensive number of comorbidities can affect the prognosis and diagnosis of this population.

Elderly breathing patterns can differ with health and age, and abnormalities may develop, such as periodic modulations that could be interspersed with apnea. This modulation is referred to as a Periodic Breathing pattern. In our previous studies [2], [3], we classified patients into three groups according to the presence of this modulation. Patients without modulation were classified as the non-Periodic Breathing group (nPB), and those with modulation were classified as the Periodic Breathing group (PB). In the PB group, patients with apneas between modulations were classified as the Cheyne-Stokes Respiration group (CSR). PB patterns are related with aging, heart failure and respiratory diseases [4].

Biomedical systems exhibit complexity and nonlinear structures in measured signals. A fractal analysis allows us to evaluate the complexity, self-similarity and characteristic length of the signals. Several studies present the relation between alterations in physiological parameters and changes in the fractal properties of their systems, which could be associated with the clinical diagnosis and/or treatment of diseases [5], [6], [7], [8]. The study of fractal variability in cardiorespiratory diseases has become a method of growing interest to describe and characterize its dynamic patterns.

The Hurst exponent ($H$), which is used to quantify the fractal properties of a system, is a measure of long-term memory in time series. In the literature, there are numerous comparative analysis of the $H$ exponent using simulated data, and the exponent is estimated by different methods to evaluate the error. *Fano factor* and *Aggregate variance* methods are widely used to measure the fractal properties of signal [9], [10], [11]. However, estimators like *detrended fluctuation analysis* (DFA) and *discrete wavelet transform-based estimation* (DWTE) method have proved more efficient and allow better long-range dependence (LRD) detection and quantification [12].

Some studies of the immature newborn respiratory system describe the presence of apneas and modulations in breathing pattern. Similar alterations can occur in the elderly breathing pattern. The inter-breath interval (IBI) signal extracted from the respiratory flow signal is analyzed as a function of the long-rate dependence [8], [13].

In this study, we analyzed the respiratory flow signal of elderly patients admitted to the short-stay unit. We aimed to characterize the IBI signal through the $H$ exponent, by applying DFA and DWTE estimators, in order to find differences in the fractal behavior between PB and nPB patterns. This performance can involve physiological changes in dynamics breathing regulations, related with age and/or several diseases [14].

## II. DATASETS

### A. Registered signals

Respiratory flow signals were recorded from 45 elderly patients (aged 82±6 years) admitted without specific diseases to the short-stay unit, at the Hospital de la Santa Creu i Sant Pau in Barcelona, Spain. All subjects were included in the study according to a protocol approved by the local

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ethics committee (Ref. IIBSP-VEN-2012-168). The protocol for respiratory flow signal acquisition is described in [2], [3].

The patients were classified into two groups according to the presence of periodic modulation in the respiratory flow signal, which was validated by clinicians: 19 patients had a non-periodic breathing pattern (nPB) and 24 patients had a periodic breathing pattern (PB). Additionally, the patients in the nPB group were classified as a function of the respiratory rate into the following groups: nPB slow ($nPB\_slow < 20 resp/min$) with 12 patients, and nPB fast ($nPB\_fast > 20 resp/min$) with 7 patients. Within the PB group, 11 patients were classified as CSR and 13 patients as without apnea. The remaining 2 patients were excluded from the study due to problems with the records.

### B. Simulated data

Simulated data was obtained to evaluate the response of $H$ exponent estimators with different time-series lengths, generated by the fractional Gaussian noise (fGn) model. The *circulant matrix embedding* method [15] was used to generate simulated IBI signals with different defined $H$ values. The *adjusted fourier transform* method [16] was used to reproduce the real IBI signals and preserve the statistical properties (surrogate data series).

An fGn can be seen as a Gaussian process, with the stationary increment of self-similar stochastic processes by Hurst parameters. Consequently, fGn is a zero-mean stationary process characterized by two parameters: the Hurst exponent $H \in (0,1)$ and its variance $\sigma^2$.

An incremental process $X = \{X_k, k \in Z\}$ of fractional Brownian motions can be defined as fractional Gaussian noise if it satisfies

$$X_k = B_H(k+1) - B_H(k), \tag{1}$$

and its autocorrelation function is given by

$$\rho(k) = \frac{1}{2}\left[|k+1|^{2H} - 2|k|^{2H} + |k+1|^{2H}\right] \tag{2}$$

$$\rho(k)_{k\to\infty} = H(2H-1)k^{2H-2}. \tag{3}$$

As can be seen from (3), the Hurst exponent is a measure of the long-term correlation between the discrete time series. The LRD behavior is observable in the $X_k$ process, due to the slow decay in the correlation for $1/2 < H < 1$, and means that the process is positively correlated or has a long memory. When $H = 1/2$, the process is uncorrelated and is defined as *white noise*. Finally, for $0 < H < 1/2$ means that the process is negatively correlated and has *short-range dependence*.

The fGn data show similar behavior to the LRD with the real IBI signals and $H$ controlled values. Surrogate series allow reproduction of the IBI signals, and preserve certain statistical and fractal properties. These series are useful to reduce the dispersion error in the $H$ estimation in real IBI signals, and to compare the effectiveness of the applied methods.

## III. METHODOLOGY

### A. Inter-breath interval signal extraction

Inter-breath interval signals (IBI) are obtained from the time period for each breath cycle duration. The respiratory flow signal represents the cyclical activity that consists of inspirations and expirations repeated over time. Everyone of these cycles is measured by inspiratory time ($T_I$), expiratory time ($T_E$), and breath duration ($T_{Tot}$), as the sum of $T_I + T_E$.

The time series of the breath durations were extracted automatically using an algorithm based on the inflection points and the zero-crossing of the respiratory flow signal power. Thereafter, they were visually inspected and, if necessary, edited.

The IBI signal is a discrete sequence of the $T_{Tot}$ intervals. In order to determine possible apnea episodes, an adaptive threshold corresponding to three breath duration intervals ($T_{Tot} \geq 3$) was defined. These episodes are characteristic of the CSR pattern. Fig. 1 illustrates the performance of the aforementioned in an example of the respiratory flow signal acquired from a CSR patient. This figure shows the results of the time series marks (Fig. 1b,c), and the IBI signal (Fig. 1d).

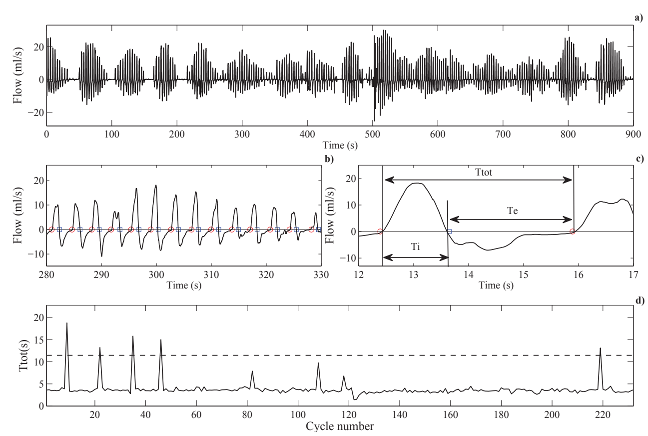


Fig. 1. (a) Respiratory flow signal acquired from a CSR patient, (b) a signal excerpt showing the detection of $T_I$ and $T_E$ intervals, (c) definition of inspiratory time, expiratory time and breath duration within a respiratory cycle, and (d) the resulting IBI signal with the apnea threshold marked ($T_{Tot} \geq 3$).

### B. Hurst exponent estimators

Numerous methods for estimating $H$, using different approaches to quantify the self-similar behavior and the long-range dependence, have been reported and analyzed in the literature. In this study, methods such as the Rescaled Range or Fano factor were discarded, due to poor efficiency with our data set type. *Detrended Fluctuation Analysis* and *Discrete Wavelet Transform-based Estimation* methods were studied to estimate the $H$ exponents and characterize the analyzed signals [12], [13].

- *Detrended Fluctuation Analysis (DFA)*:
  DFA to estimate long-range dependence in non-stationary signals has already been used to quantify the fractal content in IBI series.

From time series of $N$ samples, the signal $B(i)$, $i = 1, \ldots, N$ is integrated according to [17]

$$y(k) = \sum_{i=1}^{k} (B(i) - B_{ave}) \tag{4}$$

where $B(i)$ is the IBI signal at time $i$, and $B_{ave}$ is the average value of the signal. Next, the data is divided into segments of equal length, $n$. The linear approximation $y_n$ is found for each separate segment, using least squares fit (representing the trend in that segment). The average fluctuation *F(n)* of the signal around the trend is given by

$$F(n) = \sqrt{\frac{1}{N} \sum_{k=1}^{N} (y(k) - y_n(k))^2} \tag{5}$$

*F(n)* is calculated for all $n$ segments considered. Afterwards, the relation between them and the size of segment $n$ is analyzed. In general, *F(n)* increases with the size segment. This relation is analyzed using a double logarithmic graph, with a log-log graph of *F(n)* versus $n$. A linear relationship indicates the presence of fractal scaling and self-fluctuations. Therefore, these fluctuations can be characterized by the slope of the line *F(n)*.

- *Discrete Wavelet Transform-based Estimation (DWTE)*: This method was proposed by Abry and Veitch [18], based on Wavelet decomposition to estimate $H$. It is considered a robust technique with non-stationarities, even when signals contain *short-range dependence*. The scaling properties of a wavelet basis optimally capture the scaling self-similar nature of LRD processes.
The decomposition of the studied time series studied $X_n$, provides the wavelet coefficients or details $d_x(j,k)$. Next, the variance of the wavelet coefficients ($E_j$) is estimated, according to scaling, by

$$E_j = \frac{1}{n_j} \sum_{k=1}^{n_j} |d_x(j,k)|^2 \tag{6}$$

where $n_j$ is the length of the detailed signal at $j$ level. A graph of $\log(E_j)$ against $j$ is created for computing $H$ by performing a weighted lineal regression over those scales.

## IV. RESULTS

Firstly, we studied the response of methods *DFA* and *DWTE* using simulated $H$ data. Secondly, we analyzed the results of these methods applied to the elderly breathing pattern, in order to identify possible differences between the groups of patients studied.

### A. Response of methods

In order to determine the response of both *DFA* and *DWTE* methods applied to IBI signals, we performed a study of 200 fGn data series, considering $H$ values between $0.5 < H < 0.95$ (20 data series to each $H$ value). Fig. 2 shows the estimation error for each $H$ value obtained applying the DFA and DWTE methods.

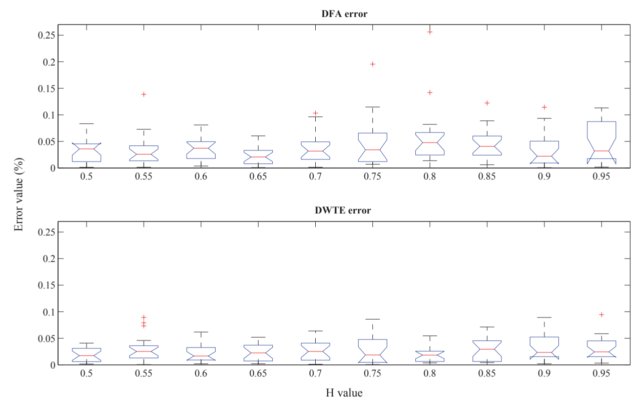


Fig. 2. Error estimation from different $H$ values applying (a) the DFA estimation method, and (b) the DWTE estimation method.

According to the results, the two methods showed an acceptable low error. On average, the $DWTE$ method presented the lowest error, less than 5%, whereas with the $DFA$ was around 7%.

In addition, we analyzed the relation between the error in the $H$ estimation, the number of surrogates averaged, and the data length (see Fig. 3). An increase in the number of surrogates averaged was directly related with a better estimation and lower dispersion values.

Fig. 3a shows the relation between the number of data series $H$ estimations that were averaged, and the error obtained in the estimation. Initially, the percentage error decreased quickly when the numbers of estimations increased. Error stabilized in both methods when 20 averages were used, but only the $DWTE$ method reduced the error to below 10%.

Fig. 3b illustrates the performance of the length dependence of both methods, as a function of the number of samples. Series with fewer than 250 samples had estimation error values of over 20%, while larger series led to errors of under 10%.

### B. Assessing the elderly flow signal

Using the Wilcoxon test to compare the values obtained with $DFA$ and $DWTE$ methods, we observed no statistically significant differences. Consequently, we found that the two methods were comparable. Subsequently, we applied the Kruskal-Wallis test to different groups of patients analyzed using the $DFA$ and $DWTE$ methods. Table I presents the results obtained as the mean and standard deviation of the estimated values for each group of patients, when we compared both methods.

According to the results, non-periodic breathing patients (with fast [$nPB\_fast$] and slow [$nPB\_slow$] respiratory rates) present the same variability with the $DFA$ method, whereas with the $DWTE$ method the value is lower for the slow rate, and slightly higher for the fast rate. When we compared the periodic breathing group (PB), the variability was higher with the $DWTE$ method than with the $DFA$ method. Finally, when

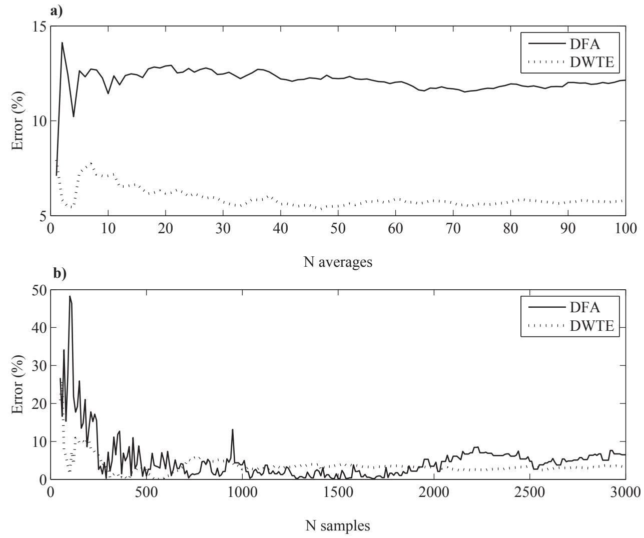


Fig. 3. (a) Error estimation of fGn data series that was generated, as a function of the number of $H$ estimations averaged using the *DFA* and $DWTE$ methods. (b) Relation between the percentage error and the number of samples in the generated data series, obtained with the *DFA* and $DWTE$ methods, respectively.

TABLE I
MEAN AND STANDARD DEVIATION OF DFA AND DWTE $H$ ESTIMATIONS FOR EACH GROUP OF PATIENTS

| Group | $n = 41$ | DFA | DWTE |
|---|---|---|---|
| nPB_slow | 12 | 0.67±0.10 | 0.63±0.16 |
| nPB_fast | 7 | 0.67±0.20 | 0.69±0.06 |
| PB | 13 | 0.72±0.13 | 0.78±0.13 |
| CSR | 11 | 0.67±0.20 | 0.57±0.13 |

$n$: number of patients in each group.

we compared the Cheyne-Stokes respiration group (CSR), this variability was significantly lower with the $DWTE$ method than with the *DFA* method.

The greatest differences in the $H$ parameter between the groups of patients were obtained with the $DWTE$ method ($p = 0.002$). Fractal behavior was higher in the $nPB\_fast$ group than in *nPB_slow* group. The PB group had the highest fractal performance. This could be associated with a high long-range dependence, while the CSR group showed the lowest fractality, with behavior close to white noise and short-range dependence

## V. CONCLUSIONS

*DFA* and $DWTE$ methods were used to study fractal behavior in inter-breath interval signals, and to evaluate the long-range dependence. Both methods were comparable on the basis of the $H$ exponent estimation.

With the $DWTE$ method, we obtained a better estimation of $H$, as a function of the average generated data series and with an error of less than 5%. Considering the number of samples, a generation data series of almost 20 surrogate data can reduce the error to less than 10%. Therefore, this method could be a useful tool for characterizing different respiratory patterns in elderly patients.

The results indicate that multifractal behavior occurs in this type of signals, which could describe the dynamic behavior of breathing patterns. These studies could help to investigate the relation between respiratory patterns and several diseases, especially in relation to the cardiac and respiratory system.

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