Changes in Detrended Fluctuation Indices with Aging in Healthy and Congestive Heart Failure Subjects

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Abstract

Detrended Fluctuation Analysis (DFA) aims to quantify the fractal correlation properties in nonstationary time series, and it has successfully been applied in the assessment of the Heart Rate Variability (HRV) for cardiac risk stratification purposes. However the physiological meaning of DFA indices and its relation with aging have not yet been completely established. Given that a loss of complexity in the physiological regulation of elderly subjects has been reported in the literature, we hypothesized that DFA indices could be modified by aging. In this work we computed the Hurst exponent (estimated using DFA method) and DFA indices α_1 and α_2 to assess the HRV in healthy and Congestive Heart Failure (CHF) subjects, and we studied the dependence of these indices on aging for both healthy and CHF subjects. We found that only α_2 and Hurst exponent, and only in the case of healthy subjects, have significant discrimination capability to distinguish between young and elderly groups, and also that these indices have a steady increase with aging. Therefore, we can conclude that the loss of complexity due to aging can be quantified by changes in the values of α_2 and Hurst exponent.

1. Introduction

Healthy human heart rate has been shown to exhibit complex dynamics, which consists of both short-term and long-term temporal correlations [1]. The Detrended Fluctuation Analysis (DFA) is a method for quantifying the fractal correlation properties in non-stationary physiological time series [2], and has widely been applied for Heart Rate Variability (HRV) signals. Although a loss of complexity in the physiological regulation due to aging has been conjectured, the effect of the aging on complex heart rate dynamics in humans, and hence the physiological meaning of the changes in DFA indices and its relationship with aging, have not yet been fully elucidated [3, 4].

The purpose of this paper is to study the relationship between age and the changes in Hurst exponent and DFA indices. In order to obtain an adequate quantitative description of this relationship, we analyzed DFA indices for both healthy and Congestive Heart Failure (CHF) subjects.

The structure of the paper is as follows. In the next section we summarize the DFA algorithm for HRV analysis. In Section 3, we describe the patient data sets used in the study, as well as the scheme of the data analysis. Then, in Section 4, we present the main results obtained in terms of aging behavior and discrimination properties of the DFA indices. Finally, the conclusions and discussion are presented.

2. DFA indices and Hurst exponent

The DFA is a well-established method for assessing and quantifying short-term and long-term correlations in time series with non-stationarities [2]. This algorithm determines the scaling behavior of the time series based on the computation of a scaling exponent, α, from a discrete-time process with length N samples. For HRV signals, $x(n)$ is the n-th RR-interval between consecutive beats in an ECG. The DFA procedure consists of four steps. In the first step, the time series is integrated as follows,

$$y(k) = \sum_{i=1}^{k}(x(i) - \bar{x}) \qquad (1)$$

where $\bar{x}$ is the average RR-interval. In the second step, the integrated time series $y(k)$ is divided into N_s non-overlapping segments of equal length s. In the third step,

a least squares linear regression is fitted to each segment. Coordinate y of the fitted line is denoted by $y_s(n)$, and it represents the linear trend for each given segment. In the last step, the root-mean square fluctuation, $F(s)$, of the detrended integrated series is quantified by

$$F(s) = \sqrt{\frac{1}{N}\sum_{k=1}^{N}(y(k) - y_s(k))^2} \qquad (2)$$

This computation is repeated over all scales, i.e., segment lengths, yielding a relationship between $F(s)$, the averaged root-mean square fluctuation, and the segment length s. If the data $x(n)$ is self-similar, the fluctuation function $F(s)$ increases by following a power-law, that is,

$$F(s) \propto s^{\alpha} \qquad (3)$$

where the fluctuation exponent α is related to the Hurst exponent, H, by $\alpha = H + 1$. Therefore, it is possible to estimate H using the DFA method.

Index α quantifies the correlation properties of a time series. For instance, a value $\alpha = 1.5$ ($H = 0.5$) indicates that the successive increments in the RR-interval time series are uncorrelated, corresponding to the Brownian motion [5]. Values of $1 < \alpha < 1.5$ ($0 < H < 0.5$) indicates anti-persistent behavior, i.e., the successive increments in the time series are negatively correlated. In contrast, $1.5 < \alpha < 2$ ($0.5 < H < 1$) indicates persistent long-term correlations, i.e., the successive increments are positively correlated. The scaling exponent α can be estimated as the slope of the regression line fitted to the log-log plot of the root-mean squate fluctuation function, $F(s)$ vs. s.

HRV signals have been found to show, at least, bi-scaling (bi-fractal) behavior. Therefore, two scaling exponents are needed in order to characterize the fractal correlations properties of the HRV signal, one for short-term, denoted by α_1, and the other for long-term, denoted by α_2. Practically, α_1 is estimated by fitting a regression line to $\log F(s)$ vs. $\log s$, for $4 \leq s \leq 16$ (i.e less than 16 beats), whereas, α_2 is similarly obtained for $16 \leq s \leq N/4$. For very large scales, $s > N/4$, $F(s)$ becomes statistically unreliable because the number of segments N_s for the averaging procedure becomes very small [6].

3. Patient data bases and DFA analysis

We applied the DFA method to the RR-intervals time series obtained from 24 hour Holter recordings in healthy and CHF subjects. All data were retrieved from Physionet (http://physionet.org) [7].

The dataset for normal control group contained 72 recordings from healthy subjects from 20 to 76 years old.

Table 1. *Mean$\pm$standard deviation for DFA indices and H exponent. Significant variation ($p < 0.001$) between young and elderly groups has been highlighted.*

	Young group	Elderly group	ΔMean
Healthy α_1	1.245 ± 0.162	1.272 ± 0.155	0.026
Healthy α_2	$\mathbf{1.005 \pm 0.052}$	$\mathbf{1.089 \pm 0.065}$	$\mathbf{0.084}$
Healthy H	$\mathbf{0.042 \pm 0.043}$	$\mathbf{0.124 \pm 0.046}$	$\mathbf{0.081}$
CHF α_1	0.929 ± 0.279	0.977 ± 0.237	0.048
CHF α_2	1.099 ± 0.115	1.118 ± 0.094	0.019
CHF H	0.113 ± 0.061	0.135 ± 0.060	0.022

The dataset of the CHF group contained 43 subjects from 22 to 79 years old.

All artifacts, missed detections, and ectopic beats, were excluded from the recordings, furthermore, the recordings were filtered and RR-intervals less than 200 ms and greater than 2000 ms were excluded. Also, RR-intervals were rejected if differed more than 20% from the previous and the subsequent (posterior) RR-interval [8].

We first studied the discrimination capabilities of DFA indices to distinguish between the young and the elderly subjects by splitting the dataset into two groups: Young group, from 20 to 50 years, and elderly group, from 51 to 80 years. The Student's t-test was used to check for statistically significant differences. The aim of this analysis was to elucidate whether the change in the indices between young and elderly subjects is significant or not, i.e., to elucidate whether the loss of complexity due to aging is reflected as significant variation of the fractal correlation properties.

Additionally, we studied the dependence of these indices on age for each healthy and CHF subject, by using linear regression of the indices vs. age, and then obtaining the slope (variation per year index) and its determination coefficient. The aim of this second analysis was to quantify the change of the fractal correlation properties of the HRV, i.e., to determine how evolves the change in the indices with aging.

4. Results

Mean values and standard deviations of DFA indices (α_1 and α_2) and H exponent for young and elderly subjects are summarized in Table 1.

The differences between young and elderly groups were significant only for H exponent and α_2, and only in the case of healthy subjects. None of the indices had significant differences in CHF. Though α_1 was found in the literature [9] and in our results to be the best index when discriminating between healthy and pathological subjects, it showed no significant variation between young and elderly, either in healthy or in CHF subjects. This result suggests that the loss of complexity with aging is mostly due
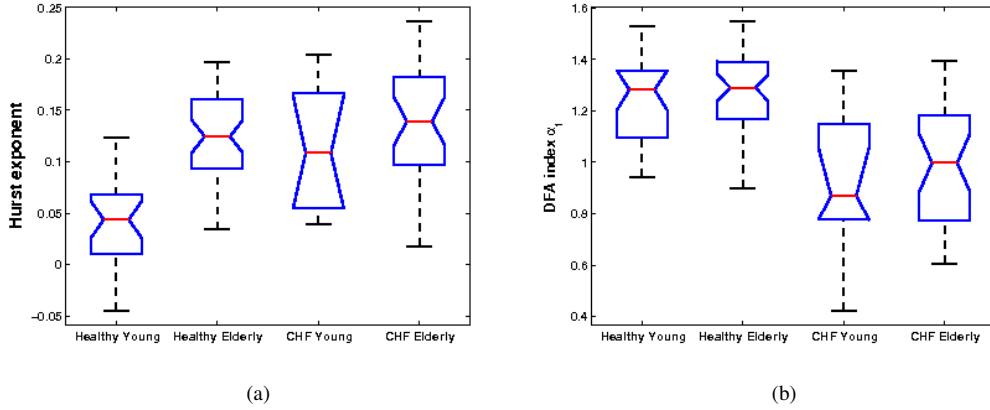
Figure 1. *Notched boxplot showing the distribution of H exponent (a), and DFA index α_1 (b) for young and elderly groups, for both healthy and CHF subjects. H exponent shows a significant difference between young and elderly for healthy subjects, that it is not shown by α_1. Instead, α_1 shows statistically significant differences between healthy and CHF subjects.*

to the breakdown on the long-term correlations, rather than to the short-term correlations.

Figure 1 shows the notched boxplots for H exponent (a) and for DFA index α_1 (b). The distribution of H exponent was very similar for healthy elderly group and CHF young and elderly groups, whereas for healthy young subjects the values were significantly lower. This indicates that the loss of complexity due to CHF and aging has similar effects in the change of the H exponent value. DFA index α_1 provided the best discrimination capability between healthy and CHF subjects. However, the distributions of young and elderly groups, for both healthy and CHF subjects, were very similar, that is, there were no significant differences between young and elderly. This suggests that the loss of complexity due to CHF has the effect of a breakdown on the fractal correlation characterized by α_1, which affects young and elderly groups in a similar way, whereas the loss of complexity due to aging quantified by α_1 provides no statistically significant differences, that is, aging seems to preserve the fractal correlation properties quantified by α_1 for healthy subjects.

The variation vs. year index and the determination coefficient of DFA indices (α_1 and α_2) and H exponent in terms of their dependence on age are summarized in Table 2. H exponent and α_2 indices were the only ones that reveal a steady increase (linear relationship) with aging, and again only for the case of healthy subjects. DFA index α_1 shows a constant value with aging, (α_1 increase ≈ 0 units/year), wich suggests that the fractal correlation properties quantified by this index are preserved with aging, confirming the previous analysis (Figure 1(b)). All the indices have a variation for CHF subjects that can not be explained by aging in a linear way. Figure 2 shows the dependence of the estimate H exponent (a), and DFA index

Table 2. *Variation/year index and determination coefficient for DFA indices and H exponent for both healthy and CHF subjects. Significance ($p < 0.001$) has been highlighted.*

	Variation/year Indx.	Determination coef.
Healthy α_1	$9.5690e-004$	0.010
Healthy α_2	**0.0023**	**0.264**
Healthy H	**0.0023**	**0.398**
CHF α_1	-0.0011	0.003
CHF α_2	1.017	0.041
CHF H	1.071	0.041

α_1 (b), on age for healthy subjects.

5.   Discussion and conclusions

We used DFA indices α_1 and α_2, together with H exponent, in order to study the dependence of the changes in these indices on aging, for both healthy and CHF subjects. First, we studied the differences between young and elderly subjects. We found that α_2 and H exponent provided statistically significant differences between young and elderly group, but only in the case of healthy subjects, whereas α_1 provided no significant differences. This suggest that the loss of complexity due to aging causes a breakdown in the fractal properties characterized by α_2 and H exponent, i.e long-term correlations, whereas it preserves the fractal properties characterized by α_1, i.e. short-term correlations. Finally, we studied how the change of these indices evolves with age. We found that α_2 and H exponent exhibit a steady increase with age, whereas α_1 exhibits a constant behavior, and only in the case of healthy subjects. We can conclude that the fractal correlation prop-
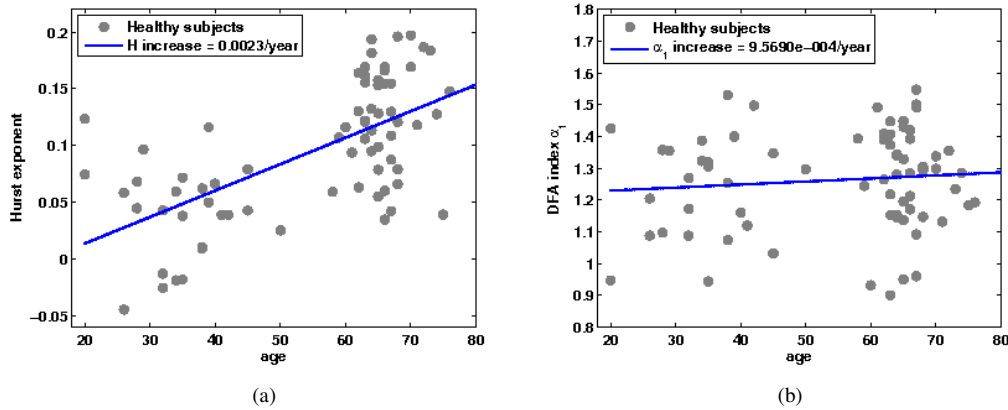
Figure 2. *Dependence of estimated scaling exponents H (a), and α_1 (b), on age for healthy subjects. H exponent shows a steady increase, whereas α_1 shows a constant behavior.*

erties in healthy subjects characterized by α_1 are preserved with aging, whereas those characterized by H exponent and α_2 are not preserved.

Further studies with much larger healthy populations are needed in order to obtain a better and more accurate description of the changes in scaling exponents (DFA indices and H exponent) due to aging, which will allow, ideally, to build an aging-curve of these indices for healthy subjects. Moreover, the aim is to determine the physiological relationships between the changes in the indices and the physiopathological causes, in order to use them not only as numerical indices, but rather in the clinical practice. For this purpose, the use of mathematical models that contain a detailed physiological description of circulatory system regulation processes should be considered, in order to improve our knowledge of the correlation between the information provided by the fractal indices and this regulation processes [10].

Acknowledgements

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