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A NEW APPROACH TO DETECT CONGESTIVE HEART FAILURE USING DETRENDED FLUCTUATION ANALYSIS OF ELECTROCARDIOGRAM SIGNALS

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Abstract

The aim of this study is to evaluate how far the detrended fluctuation analysis (DFA) approach helps to characterize the short-term and intermediate-term fractal correlations in the raw electrocardiogram (ECG) signals and thereby discriminate between normal and congestive heart failure (CHF) subjects. The DFA-1 calculations were performed on normal and CHF short-term ECG segments, of the order of 20 seconds duration. Differences were found in short-term and intermediate-term correlation properties and the corresponding scaling exponents of the two groups (normal and CHF). The statistical analyses show that short-term fractal scaling exponent alone is sufficient to distinguish between normal and CHF subjects. The receiver operating characteristic curve (ROC) analysis confirms the robustness of this new approach and exhibits an average accuracy that exceeds 98.2%, average sensitivity of about 98.4%, positive predictivity of 98.00%, and average specificity of 98.00%.

Keywords: Congestive heart failure, Detrended fluctuation analysis, ECG classification, Scaling exponents, Short-term and intermediate-term fractal correlations.

1. Introduction

Despite numerous recent advances in the field of medicine, congestive heart failure (CHF) has been difficult to manage with in clinical practice and mortality rate has remained high [1]. As a consequence the development of new methods and measures of mortality risk in CHF, including sudden cardiac death, is still a major challenge. Besides this, there is a need to reach remote and underserved communities with life saving healthcare. A reliable automated classification system combined with high-speed communication can resolve this issue. This work

Nomenclatures

$F(k)$	Scaling function
k	Specific scale
M	Average of the series $x(i)$, V
$x(i)$	Discrete time series, V
$Y_k(i)$	Detrended fluctuations, V
$y(i)$	Profile of $x(i)$, V
$y_k(i)$	Local trend in the box, V

Greek Symbols

α	Scaling exponent.

Abbreviations

AHA	American heart association
AUC	Area under curve
BIDMC	Beth Israel deaconess medical center
CHF	Congestive heart failure
CP	Crossover point
chfdb	CHF database
DFA	Detrended fluctuation analysis
ECG	ElectroCardioGram
EEG	ElectroEncephaloGram
HR	Heart rate
HRV	Heart rate variability
nsrdb	normal sinus rhythm database
PVC	Premature ventricular contraction
ROC	Receiver operating characteristic

is an attempt to develop such an automated system to discriminate between normal and congestive heart failure subjects.

There has been growing evidence that the output signals of biological, physical and physiological systems exhibit complex self-similar fluctuations (fractal) over a broad range of space and/ or time scales, i.e., small fluctuations at small scales have similar characteristics to large fluctuations at large time scales. Fractal properties have been observed in real-time ECG recordings of the heart [2], EEG recordings of brain waves, eye movements, as well as in recordings of human movements [3]. Fractal properties are an emergent property of the system dynamics, and to the extent that a given pathology disrupts those dynamics the resulting properties will be altered. Since the mechanisms which control the underlying interactions are nonlinear the output signals are typically nonstationary and the conventional methods such as power-spectrum and auto-correlation analysis are not suitable for such nonstationary signals. Poincare plot, approximate entropy, sample entropy, correlation dimension, sequential trend analysis, maximum Lyapunov exponents, and detrended fluctuation analysis (DFA) are some of the popular nonlinear methods that can be used.

The aim of this study is to quantify correlations across time scales in the nonstationary electrocardiogram (ECG) time series. Compared to other nonlinear methods, DFA is thought to be more robust to nonstationarity [3] and thus, is an

obvious choice. This application of DFA to raw ECG signal is motivated first, by the fact that heart is a highly complex system and second, by the difficulties in satisfying the assumptions of either linear or chaos analysis. DFA is a scaling analysis method which provides a quantitative parameter - the scaling exponent – that quantifies intrinsic fractal-like correlation properties of the dynamic system that generates the signal. One of the usual challenges is that scaling exponent is not always constant and crossovers often exist. This means the scaling exponent is different for different range of scales [4]. A change in the value of scaling exponent is usually due to change in fractal correlation properties of the signal at different scales, though it can be due to nonstationarities in the signal.

The concept of DFA was first introduced by Peng et al. [5] in 1995 and since then has been successfully used to quantify fractal correlation properties of nonstationary biological, physical and physiological signals. It has found applications in diverse research fields like, in medicine, for example, for DNA sequences, cardiac dynamics, temperature fluctuations [6], and even, economics [7]. In the past extensive work has been carried out by applying DFA on heart rate variability (HRV) signals and it was found to be useful in distinguishing between normal and arrhythmia subjects [8-12]. However, not much is found in the literature where DFA is tried on raw ECG signals. In one of the approaches ECG readings were analyzed using DFA along with unassisted K-means clustering algorithm [13]. But the success rate of CHF classification was only 86.7%. Lai et al. performed automatic ECG classification into normal and premature ventricular contraction (PVC) beats using fractal and cross correlation analyses [2]. They claim an accuracy of 100% on only some of the American heart association (AHA) ECG records. Multifractal properties of two-channel ECG patterns of patients suffering from congestive heart failure have been studied and compared with those of healthy subjects by Dutta [14]. The degree of correlation was compared between the two groups using Holder exponent. He found the normal group to have a higher correlation compared to the CHF group.

In another attempt, Wang Jun et al. used a single scaling exponent to distinguish between congestive heart failure and sudden cardiac death [15]. But no details about accuracy and specificity are available. Recent HRV studies have shown that some indices describing cardiac dynamics, such as fractal scaling exponents, may provide useful prognostic information in various clinical settings and their reproducibility may be better than traditional indices. For example, the short-term DFA scaling exponent, α_1, has been shown to be a good marker in the process of aging [16] and reliable predictor of mortality in post-myocardial infarction patients [17]. Timo et al. have shown that altered short-term fractal scaling exponent of heart rate (HR) dynamics is a strong predictor of cardiac death, particularly, of sudden cardiac death in an unselected elderly population [18].

For the purpose of this study, a DFA algorithm similar to the original DFA algorithm [5] and short-term DFA scaling exponent to characterize the fractal correlations in the ECG signal is adopted and a classification into normal and CHF subjects is performed.

For practical purposes, clinical investigators are usually interested in using substantially shorter time series and since DFA is directly applied on raw ECG signals, this new approach is highly suitable to clinical investigators.

2. Methods and Materials

2.1. ECG records

Since age and gender of subjects influence upon results of DFA, before any comparison between normal and CHF groups, one should make sure that the groups are both age- and sex-matched. All the ECG records used are from the benchmark PhysioNet databases [19]. For sake of comparison and validation, two groups, named, I and II are used. Group-I comprises 5 normal sinus rhythm ECG records from MIT-BIH normal sinus rhythm database (nsrdb) and 5 CHF ECG records from Beth Israel Deaconess Medical Center (BIDMC) CHF database (chfdb). Group-II comprises 5 normal sinus rhythm ECG records from Fantasia normal sinus rhythm database (fantasia) and 5 CHF ECG records from BIDMC CHF database (chfdb) of PhysioNet. Details of databases from PhysioNet, subjects, and their ECG records, used to form Groups I and II, are shown in Table 1. The sampling frequency of nsrdb database used in Group-I is 128 Hz, that of fantasia used in Group-II is 250 Hz and chfdb database used in Groups I and II is 250 Hz.

Table 1. Details of PhysioNet databases, subjects and their ECG records used to form Group-I and Group-II.

Database	Group-I	Group-II
Normal	nsrdb	fantasia
Subjects	men 3 and women 2	men 4 and woman 1
Age, years	38-50	68-71
Channel used	1 (modified lead II)	2 (modified lead II)
Record length, hours	0.5	2
Sampling frequency, samples/s	128	250
CHF	chfdb	chfdb
Subjects	men 3 and women 2	men 4 and woman 1
Age, years	22-54	63-71
Channel used	1 (modified lead II)	1 (modified lead II)
Record length, hours	20	20
Sampling frequency, samples/s	250	250

Since the sampling frequency does influence upon the calculated indices it is necessary to have the same sampling frequency for both the normal and CHF databases. For this reason ECG signals from normal database (nsrdb) in Group-I are first re-sampled at 250 Hz. However, since the sampling frequency is the same for both the fantasia and chfdb databases (250 Hz), there is no question of re-sampling in the Group-II. Each record, from Groups I and II, is divided into segments of equal time duration (20 s), with 5000 samples per segment, for analysis. A total of 3510 segments from normal sinus rhythm and an equal number of segments from CHF data base are analysed.

2.2. Detrended fluctuation analysis (DFA)

The prime advantages of using DFA over conventional methods (e.g., spectral-, auto-correlation-, and Hurst-analysis) is that it permits the identification of intrinsic self-similarity, or fractal correlation, embedded in a seemingly nonstationary signal and also avoids spurious detection of long-range correlations that are actually an artifact of nonstationarity. For a proper study of intrinsic dynamics of the system it is necessary to discard the trends exogenous to the system.

The DFA method eliminates nonstationarities which are due to trends not necessarily related to cardiac dynamics. For example, the first-order DFA eliminates constant trends from the original time series, the second-order DFA eliminates linear trends from the original time series, and n^{th} order DFA eliminates the $(n-1)^{th}$ order polynomial trends in the time series. In this work, it is found that a 1^{st} order DFA is suitable for discrimination of the raw ECG signals into normal and CHF.

DFA is a modified form of root-mean square analysis of random walk which provides scaling exponents corresponding to short-term, intermediate-term and long-term correlations in the time-varying signals [4]. The scaling exponents obtained from DFA have prognostic and diagnostic values [16, 17]. The calculation of scaling exponents involves the following steps:

(1) Starting with the ECG time series $x(i)$, where, $i = 1,2,\ldots,N$ and N is the length of the signal the first step in DFA is to integrate $x(i)$ to arrive at a new time series $y(i)$, usually called profile,

$$y(i) = \sum_{n=1}^{i}[x(n) - M] \tag{1}$$

$$M = \frac{1}{N}\sum_{n=1}^{N} x(n) \tag{2}$$

where M is the average of the series $x(i)$.

(2) The integrated time series, profile $y(i)$, is then divided into boxes of equal length k. In each box k, $y(i)$ is fitted with a linear function $y_k(i)$ which corresponds to the local trend in that box (using least-square fit). A polynomial fit of order-l results in a DFA-l (For $l = 1$, DFA-1; for $l = 2$, DFA-2 and so forth).

(3) Next, the integrated profile $y(i)$ is then detrended by subtracting the local trend $y_k(i)$ in each box k.

$$Y_k(i) = y(i) - y_k(i) \tag{3}$$

(4) Next, the root-mean squares of the detrended fluctuations $Y_k(i)$ are calculated for each value of k.

$$F(k) = \sqrt{\frac{1}{N}\sum_{i=1}^{N}[Y_k(i)]^2} \tag{4}$$

This computation is repeated for varied box lengths to yield $F(k)$ as a function of k (usually, $\log F(k)$ as a function of $\log k$).

For scale invariant signals with power-law correlations there exists a power-law relation between $F(k)$ and the scale k.

$$F(k) \sim k^{\alpha} \tag{5}$$

Because the power-laws are scale invariant $F(k)$ is sometimes called scaling function and the parameter α is called scaling exponent. A plot of $F(k)$ vs. k on a log-log scale (that is, log $F(k)$ against log k, usually called DFA plot) reveals a linear relationship with the slope as the scaling exponent, α. The value of α represents the degree of correlation in the signal: if $\alpha = 0.5$ the signal is uncorrelated (white noise); if $0.5 < \alpha < 1.0$ the signal is positive-correlated (increments in the time series are likely to be followed by increments and vice versa); if $0 < \alpha < 0.5$ the signal is negative-correlated (increments in the time series are likely to be followed by decrements and vice versa); If $\alpha = 1.0$, it corresponds to 1/f noise (pink noise), $\alpha = 1.5$ corresponds to Brownian noise (the integral of white noise is Brownian noise or random walk) and $1<\alpha<1.5$ correspond to different types of noise.

For this work, in specific, first-order DFA is chosen, as it can accurately quantify fractal-like correlations in the nonstationary ECG signals and distinguish between normal and CHF subjects.

2.3. Time variation of scaling behavior and crossover phenomenon

One of the usual challenges is that scaling exponent is not always constant and crossovers often exist. This means the scaling exponent is different for different range of scales [4]. A change in the value of scaling exponent is usually due to change in fractal correlation properties of the signal at different scales, though it can be due to nonstationarities in the signal.

A DFA plot, typically, exhibits three distinct regions with different slopes while studying the scaling behavior of the fluctuation function *F(k)* on small and large time scales in order to find out if there exist short-term, intermediate-term correlations and long-term correlations in the signal. The first and second straight lines with slopes α_1 and α_2, respectively, intersect at a crossover point (CP1). The second and third straight lines with slopes α_2 and α_3, respectively, intersect at a crossover point (CP2). The values of α_1, α_2 and α_3 are found using least-squares technique. Scaling exponent, α_1 reflects power related to short-term fluctuations (high frequency), α_2 reflects power related to intermediate-term fluctuations (low frequency) and α_3 reflects power related to long-term fluctuations (very lower frequency).

2.4. Short-term and intermediate-term fractal scaling exponents and t-tests

In some recent observational HRV studies, the short-term DFA scaling exponent, α_1, has been shown to be a good marker in the process of aging [16] and reliable predictor of mortality in post-myocardial infarction patients [17] and a strong predictor of cardiac death, particularly, of sudden cardiac death in an unselected elderly population [18].

Nevertheless, in this work, short-term fractal scaling exponent α_1 and intermediate-term scaling exponent α_2 are used and it is shown that short-term fractal scaling exponent α_1 alone is sufficient distinguish between normal and

CHF subjects. To assess the use of these parameters individual and pair-wise significance tests (Student's *t*-tests) are performed. To compare the scaling behavior of the fluctuation functions between the normal and CHF groups the mean and standard deviation of the difference between the corresponding scaling exponents, α_1 and α_2, of the two groups are computed. Parameters are regarded as statistically significant if $p < 0.05$.

2.5. Receiver operating characteristic (ROC) analysis and C-statistic

As mentioned above, individual and pair-wise significance tests (Student's *t*-tests) are used to evaluate the statistical differences between the scaling exponents, α_1 and α_2, for normal and CHF subjects. If significant differences between groups are found, then the ability of the non-linear analysis method to discriminate normal from CHF subjects is evaluated using receiver operating characteristic (ROC) plots in terms of C-statistics.

ROC curves are obtained by plotting sensitivity values (which represent the proportion of the patients with diagnosis of CHF who test positive) along the y axis against the corresponding (1-specificity) values (which represent the proportion of the correctly identified normal subjects) for all the available cutoff points along the x axis. Accuracy is a related parameter that quantifies the total number of subjects (both normal and CHF) precisely classified. The area under ROC curve (AUC), also called C-statistic, measures this discrimination, that is, the ability of the test to correctly classify those with and without the disease and is regarded as an index of diagnostic accuracy. The optimum threshold is the cut-off point in which the highest accuracy (minimal false negative and false positive results) is obtained. This can be determined from the ROC curve as the closet value to the left top point (corresponding to 100% sensitivity and 100% specificity). A C-statistic value of 0.5 indicates that the test results are better than those obtained by chance, where as a value of 1.0 indicates a perfectly sensitive and specific test.

3. Results and Discussion

To test for statistical significance of DFA approach, first the ECG data from normal and CHF subjects of Group-I (age and gender matched) are analyzed and it is shown that short-term fractal scaling exponent α_1 alone is sufficient to distinguish between normal and CHF subjects. Next, this approach is validated conducting another case study on normal and CHF subjects from Group-II (age and gender matched). Both α_1 and α_2 are analyzed from segments of 5000 samples and averaged to obtain mean values for the entire recording period. As mentioned earlier, a first-order DFA was chosen for this work as it can accurately quantify correlations in the nonstationary ECG signal and distinguish between the two groups. Both the normal and CHF subjects demonstrated short-term (small scales) and intermediate-term (large scales) correlations in the respective ECG signal.

The detrending procedure in the first-order DFA using linear fit is illustrated through two exemplary box sizes/ scales (k = 10 and k = 200) in Fig. 1, for a normal subject from Group-I. The least square linear fit (shown by dotted line

in each figure) to the profile (shown by solid line in each figure) is performed in each box at every scale. In this work for short-term 20 scales were used over the range $k = 10$ and $k = 100$ and for long-term 40 scales were used over the range $k = 100$ to $k = 500$. Comparing Fig. 1(a) with Fig. 1(b), it is clear that larger the scale value, k, larger the deviation of the linear fit from the profile. This also implies the scaling behavior of the fluctuation function $F(k)$ on small and large time scales.

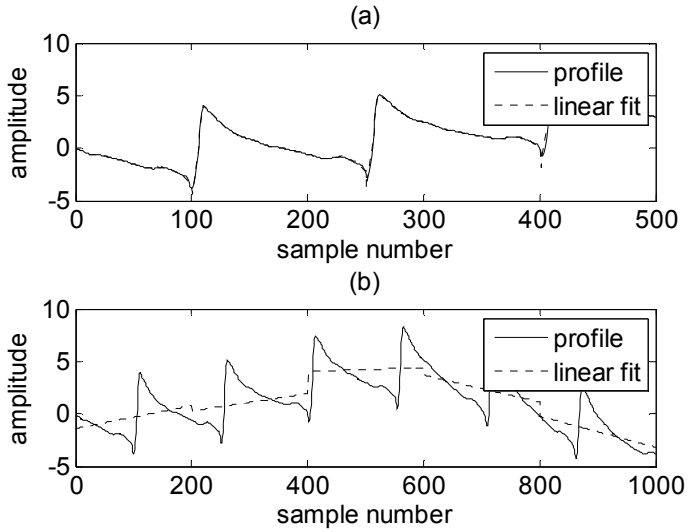

Fig. 1. Illustration of detrending procedure in the first-order DFA (DFA-1) for a normal subject from Group-I. (a) short-term ($k = 10$; number of windows=50) and (b) long-term ($k = 200$; number of windows=5). Solid line corresponds to profile and the dotted line corresponds to least square linear fit to the profile.

Figure 2(a) shows short-term DFA plot and Fig. 2(b) shows long-term DFA plot for both, a normal subject and a CHF subject, from Group-I. It is apparent that $F(k)$ increases with increasing k since deviations of the fit from the profile increase with increasing scale value, k. For the normal case $\alpha_1 = 0.7541$ and $\alpha_2 = 0.1001$ and for the CHF case $\alpha_1 = 1.3504$ and $\alpha_2 = 0.2016$. It is seen that in both the plots the CHF subject exhibits a deviation of the correlation exponents from those of the normal. But, α_1 in the normal subject is significantly smaller than α_1 in the CHF subject. The distribution of α_1 and α_2 for the normal and CHF groups (Group-I) are shown using Box-whiskers plots in Figs. 3(a) and (b), respectively. In Fig. 3(a) for α_1, the boxes (inter-quartile range) as well as the whiskers of normal and CHF subjects are apparently non-overlapping. In Fig. 3(b) for α_2, the boxes (inter-quartile range) as well as the whiskers of normal and CHF subjects are overlapping. These plots show that short-term fractal scaling exponent α_1 is sufficient to distinguish between normal and CHF subjects.

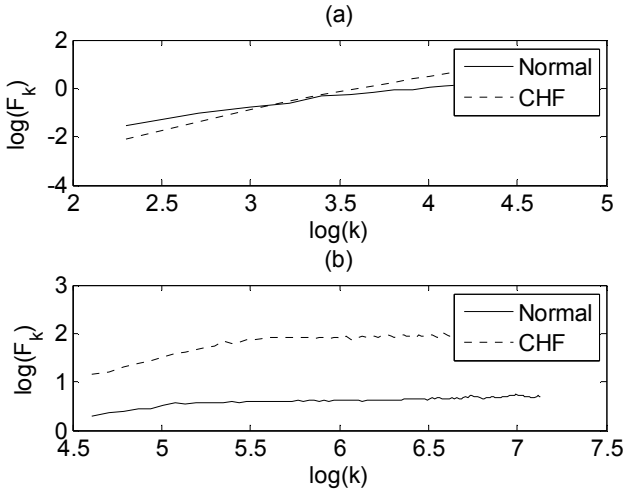

Fig. 2. (a) Short-term DFA plot for normal and CHF subjects from Group-I. Solid line corresponds to normal subject and the dotted line corresponds to CHF subject. (b) Long-term DFA plot for normal and CHF subjects from Group-I. Solid line corresponds to normal subject and the dotted line corresponds to CHF subject.

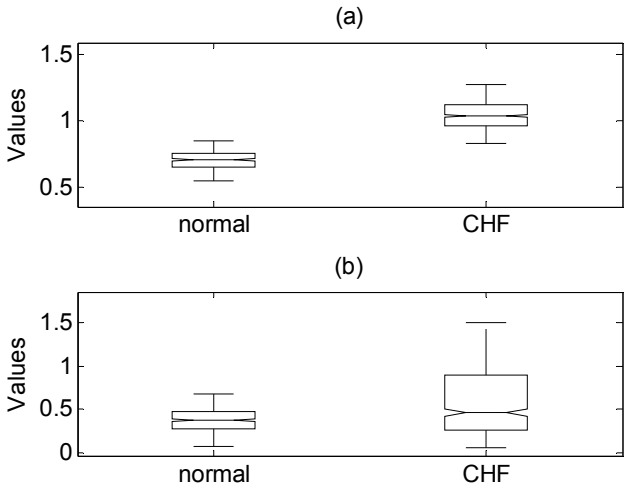

Fig. 3. The distribution of scaling exponents (a) α_1 and (b) α_2 using Box-whiskers plots (without outliers) for normal and CHF subjects from Group-I.

The results of statistical analysis of non-paired Student's *t*-test for normal and CHF groups of Group-I are depicted in Table 2. All values are expressed as mean ± Standard Deviation (median) [95% Confidence Interval]. For normal subjects, the following short-term and intermediate-term scaling exponents (mean ± S.D.):

α_1 = 0.6898 ± 0.1252 and α_2 = 0.4224 ± 0.2572, respectively, were found. For CHF subjects, on the other hand, the following short-term and intermediate-term scaling exponents (mean ± S.D.): α_1 = 1.0458 ± 0.1057 and α_2 = 0.5844 ± 0.4136 (both different from normal), were found. These distributions show that short-term fractal scaling exponent α_1 alone is sufficient to distinguish between normal and CHF subjects. It can be observed that both the groups show a larger value of α_1 as compared to that of α_2. This implies stronger correlations on short time scales compared to intermediate timescales.

Table 2. Descriptive results of DFA analysis for Group-I. All values are expressed as mean ± SD (median) [95% CI]. (non-paired Student's *t*-test; $p < 0.0001$).

Subject	alpha1	alpha2
Normal	0.6898 ± 0.1252(0.7068) [0.6787 0.7008]	0.4224 ± 0.2572(0.3757) [0.3998 0.4450]
CHF	1.0458 ± 0.1057(1.04) [1.0365 1.0551]	0.5844 ± 0.4136(0.4599) [0.5480 0.6207]

It is also found that α_1 and α_2 for normal group are always smaller than the respective values of the CHF group, the former being significantly smaller. This implies an increase in the correlations on short time scales, as well as, intermediate time scales in the CHF group, the former being more pronounced. Of course, experimental studies are necessary to confirm the mechanisms behind the increase in the correlation of the short-term records of CHF subjects.

The Student's t-test was also performed for the paired data. The results are tabulated in Table 3. Parameters are regarded as statistically significant if $p < 0.05$. The values of test statistic and p-value reveal that both the scaling exponents for both the groups are statistically significant, α1 being predominantly significant than α2. Next, the ability of the short-term fractal scaling exponents α1 and α2 to discriminate normal from CHF subjects (Group-I) is evaluated using receiver operating characteristic (ROC) plots, which are shown in Fig. 4. The diagonal line (dotted line) from 0 to 1.1 in Fig. 4 represents ROC curve that cannot discriminate between normal and CHF from Group-I. For the case of α2 (shown by dashed curved line), it is found that the area under the curve (AUC) is found to be 0.5968 with sensitivity = 54.4%, specificity = 68.4%, positive predictivity = 63.3%, and accuracy = 61.4%. For the case of α1 (shown by solid curved line), the area under the curve (AUC) is found to be 0.98755 with sensitivity = 98.4%, specificity = 98%, positive predictivity = 98.0%, and accuracy = 98.2%. These results substantiate the findings of this study that short-term fractal scaling exponent α1 alone is sufficient to distinguish between normal and CHF subjects.

Table 3. *p*-values and tstat (test statistic) values of paired *t*-test for α_1 and α_2 of healthy and CHF subjects from Group-I.

Parameter	alpha1-CHF	alpha2-CHF
alpha1-normal	$p = 3.1379 \times 10^{-265}$; tstat = -48.5852	
alpha2-normal		$p = 2.2160 \times 10^{-13}$; tstat = -7.4369

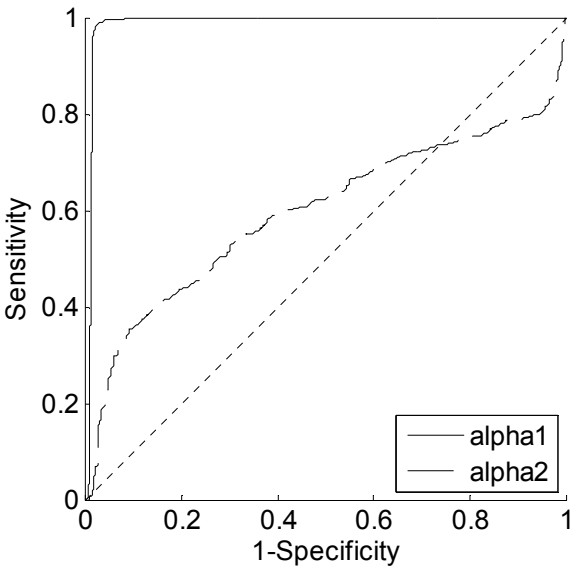

Fig. 4. ROC curve for α_1 (solid line) and α_2 (dashed line). The diagonal line (dotted line) from 0,0 to 1,1 represents ROC curve that cannot discriminate between normal and CHF from Group-I.

A scattergram of α1, with subjects along x-axis and the value of scaling exponent along y-axis for 5 normal (shown by 'o') and 5 CHF subjects (shown by '+') are shown in Fig. 5. In Fig. 5, the solid line corresponds to a linear function that separates the two groups.It is interesting to see the separation of α1 values between normal and CHF subjects (Group-I) and also nonoverlap of α1 values in both normal and CHF subjects. This means α1 exhibits variability large enough to separate intra-individuals of the respective groups, but small enough to separate normal from CHF. These results again confirm the finding that short-term fractal scaling exponent α1 has potential in discriminating normal and CHF subjects and thus can significantly add to the prognostic value of traditional cardiac analysis.

Finally, this approach is validated conducting another case study on normal and CHF subjects from Group-II (age and gender matched). The results of statistical analysis of non-paired Student's *t*-test for normal and CHF groups of Group-II are depicted in Table 4. All values are expressed as mean ± Standard Deviation (median) [95% Confidence Interval]. For normal subjects, the following short-term and intermediate-term scaling exponents (mean ± S.D.): $\alpha_1 = 0.8637 \pm 0.0841$ and $\alpha_2 = 0.5743 \pm 0.2035$, respectively, were observed. For CHF subjects, the following short-term and intermediate-term scaling exponents (mean ± S.D.): $\alpha_1 = 1.1330 \pm 0.2302$ and $\alpha_2 = 0.6416 \pm 0.3594$ (both different from normal), were found. These distributions show that short-term fractal scaling exponent α_1 is sufficient to distinguish between normal and CHF subjects.

The Student's *t*-test for paired data was also performed to ascertain the results. The results are tabulated in Table 5. Parameters are regarded as statistically

significant if $p < 0.05$. The values of test statistic and p-value reveal that both the scaling exponents for both the groups are statistically significant, α_1 being predominantly significant than α_2.

Table 4. Descriptive results of DFA analysis for Group-II. All values are expressed as mean ± SD (median) [95% CI]. (non-paired Student's *t*-test; $p < 0.0001$).

Subject	alpha1	alpha2
Normal	0.8637 ± 0.0841(0.8744) [0.8513 0.8760]	0.5743 ± 0.2035(0.5652) [0.5444 0.6043]
CHF	1.1330 ± 0.2302(1.045) [1.1009 1.1651]	0.6416 ± 0.3594(0.5268) [0.5915 0.6917]

Table 5. *p*-values and tstat (test statistic) values of paired *t*-test for α_1 and α_2 of healthy and CHF subjects from Group-II.

Parameter	alpha1-CHF	alpha2-CHF
alpha1-normal	$p = 0$; tstat = -14.8313	
alpha2-normal		$p = 0.0276$; tstat = -2.2119

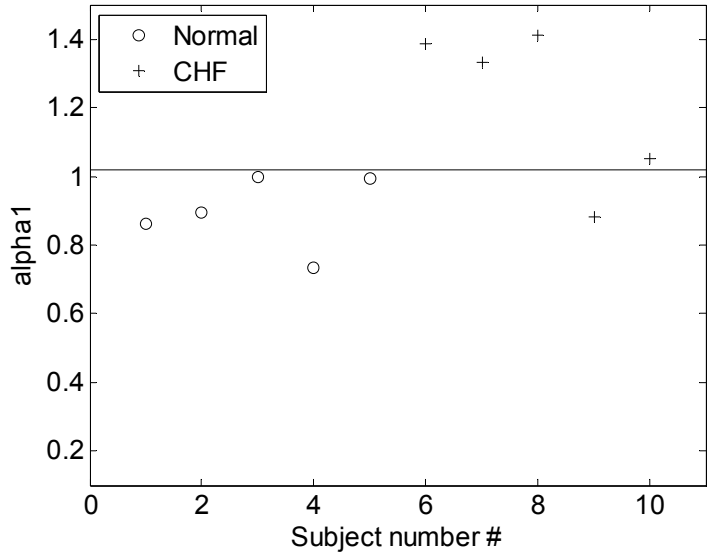

Fig. 5. Scatter plot of scaling exponents α_1 for normal subjects (o) and CHF subjects (+). Solid line corresponds to a linear function that separates the two groups.

Next, the ability of the short-term fractal scaling exponents, α_1 and α_2, to discriminate normal from CHF subjects (Group-II) is evaluated using receiver

operating characteristic (ROC) plots, which are shown in Fig. 6. For the case of α_2 (shown by dashed curved line), it is found that the area under the curve (AUC) is found to be 0.4897. For the case of α_1 (shown by solid curved line), the area under the curve (AUC) is found to be 0.85083 with sensitivity = 71.5%, specificity = 87.8%, positive predictivity = 86.7%, and accuracy = 79.2%. These results substantiate the finding of this study that the short-term fractal scaling exponent α_1 alone is sufficient to distinguish between normal and CHF subjects. The decrease in accuracy and other measures, on Group-II can be attributed to age differences, and differing male-to-female ratios between groups I and II.

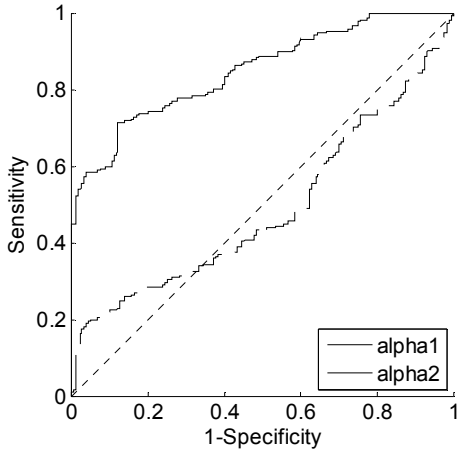

Fig. 6. ROC curve for α_1 (solid line) and α_2 (dashed line). The diagonal line (dotted line) from 0,0 to 1,1 represents ROC curve that cannot discriminate between normal and CHF from Group-II.

4. Limitations

The foremost limitation of this study is the small sample size. Although this study reports DFA to yield a very sensitive measure based on the *p*-value generated from the *t*-statistics, factors like high variance, age differences, and slightly differing male-to-female ratios between groups will have an impact on the results when statistical analyses are carried out on small sample sizes. Nevertheless, the results of this study provide sufficient evidence to warrant the execution of larger studies that can provide more statistically robust confirmation of the application of DFA as a sensitive measure of cardiac health.

5. Conclusion

In this study, DFA was applied to nonstationary raw ECG time series from normal and CHF subjects. It is found that this approach can identify the scaling behavior of the fluctuation function on small and intermediate time scales and separate out short-term and intermediate-term fractal correlations in the ECG signals. The quantified short-term scaling exponent is found to have potential in

discriminating normal and CHF subjects and thus can significantly add to the prognostic value of traditional cardiac analysis.

The short-term scaling exponent can easily be analyzed from ambulatory ECG recordings without time consuming preprocessing and hence, may have practical implications for risk stratification. In real time applications the value for specificity is more important than the value for sensitivity and with this approach average specificity is about the same order of sensitivity (98%).

The DFA method applied to HRV series usually demands long term series, at times of 24 hours length. Acquiring 24 hour record just for screening purpose is not amenable. Although, the ECG data used contains both 30 minutes and 20 hours duration records, this method uses short-term segments, of the order of 20 seconds duration. Hence the method is suitable for screening large populations in a short time.

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