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Fractal Approach to Identify Quantitatively Intracardiac Atrial Fibrillation from ECG Signals

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ABSTRACT:
In this paper it has been studied how ECG signals show fractal pattern and thus it has been tried to find the fractal dimension of the ECG time series. For this we have used Hurst's Rescaled Range Analysis method. In this work, ECG signals are acquired from normal subjects. Intracardiac Atrial Fibrillation ECG time series data are collected from MIT-BIH Physionet database. From this analysis, we have tried to identify this type of disease by looking at the Fractal dimension.

I. INTRODUCTION

Electrocardiogram (ECG) is a graphic recording of the time variant voltages produced by the myo-cardiogram during the cardiac cycle. Time domain and frequency domain features of ECG signals can be extracted using Digital Signal Processing (DSP) techniques and these help to detect cardiac abnormalities. It has been seen that if there is fibrillation present in the ECG then this is indicated by the presence of distinct peaks in the range of 3 Hz-7 Hz in the frequency band of its frequency spectrum [1-2]. Noise elimination from ECG signals contaminated with background noise is a challenging task. Savitzky Golay filter works well in noise elimination [3-5].

Atrial fibrillation is a common type of arrhythmia. It is much common than atrial flutter, affecting 5-10% of elderly people. The basis of atrial fibrillation is rapid and chaotic depolarization occurring throughout the atria. No "P" waves are seen and the ECG baseline consists of low-amplitude oscillations. Although around 400-600 impulses reach the AV node every minute, only 120-180 of these impulses will reach the ventricles to produce QRS complexes [6]. Transmission of atrial impulses throughout the AV node is erratic, making the ventricular (QRS complex) rhythm "irregularly irregular". The erratic atrial depolarization leads to a failure of effective atrial contraction. Loss of "atrial kick" reduces ventricular filling and this leads to a fall of 10-15% in cardiac output [6]. The symptoms of atrial fibrillation include angina, breathlessness, dizziness, palpitation, syncope, weakness etc. Studies on scatter plots of normal, Intracardiac atrial fibrillation and other arrhythmic ECGs can be done using DSP techniques [7-9]. Normal and abnormal ECGs can be effectively studied in terms of Power spectrum Density [10]. These techniques of DSP can be considered as effective tools for identifying cardiac abnormalities. In this paper, attempts have been made to identify Intracardiac atria fibrillation from ECG time series in terms of Fractal Dimension.

It has been seen that many Physical, Bio-physical, Geo-physical signals are irregular and in many times these follow Gaussian distribution [11]. But many a times it is impossible to get a trend to these signals. Fractal statistics appears to be useful in studying this type of irregular signals. Bio-signals like ECG signals are non-stationary and they have shown a self-similarity pattern i.e. a fractal pattern [12-13]. This similarity can contain important information about the robustness of health and can indicate types of disease. Therefore, studying the irregularity is important.

Recently many methods were proposed to study this irregularity. The simplest method was the standard partition function method [14]. But it requires the data set to be stable and temporal. But heart rate of any healthy person is not constant even under ideal conditions and it changes throughout a day. Diseased heart also shows irregularity in the ECG pattern. To avoid this problem, Wavelet transform modulus maxima method was proposed [15], which was based on the wavelet analysis. But this method is difficult and requires large computation. Later on, Hurst developed Rescaled Range Analysis [16-18] which is a statistical method to analyze long range data set by choosing discrete set of time series. There are many other methods namely ANN, DFA, MF-DFA etc which can also be used to study the fractal geometry.

Fractal geometry mathematically characterizes systems that are fundamentally irregular at all scales. A fractal structure has the property that if one magnifies a small portion of it, it would show the complexity of the entire system. In short, they are made of transformed copies of themselves. This property implies the absence of analytical regularity of the system.

Furthermore, fractals are divided into two categories: monofractal and multifractal. Monofractals are those whose scaling property is same in different regions of the system. Multifractals are more complicated self-similar objects. They consist of differently weighted fractals, with different non-linear dimensions .Thus the fundamental property is that the scaling property may be different in different regions of the system.

In an attempt to explore the underlying structure and the governing mechanism of manifestly aberrant appearance of the time series, fractal statistics have been pursued with time dependent experimental data. Hence, we will use Rescaled Range Fractal analysis method to study the ECG signals in this paper.

II. DATA SELECTION

Normal ECG signals are recorded using POLYPARA module with a sampling rate of 200 samples per second. Intracardiac Atrial Fibrillation ECG signals are collected from MIT-BIH Physionet database [19]. This database is a large and growing archive of well-characterized digital recordings of physiologic signals and related data. Physio-Bank currently includes databases of multi-parameter cardiopulmonary, neural, and other biomedical signals from healthy subjects and patients with a variety of conditions with major public health implications including sudden cardiac death, congestive heart failure, epilepsy, gait disorders, sleep-apnea and aging (Goldberger et al., 2000).

In MIT-BIH Physionet database all the Intracardiac atrial fibrillation ECG signals were recorded using a decapolar catheter with 2-5-2mm spacing (7mm spacing between bipoles). This catheter was placed in four separate regions of the heart. In each region, the 5 bipolar signals were recorded along with 3 surface ECG leads [19]. Data were digitized at 1 kHz. Catheter bipoles are labeled (distal to proximal) as CS12, CS34,..., CS90 [19]. The catheter positions in the relevant regions of the heart are shown in Fig-1.

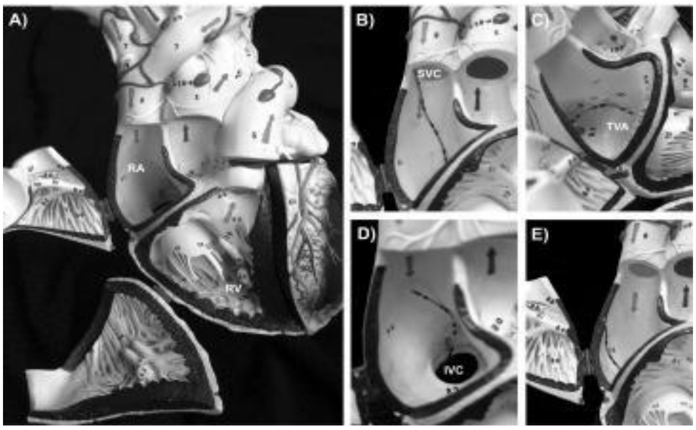

Fig-1: Catheter Positions in the Four Regions of the Heart [19]

At “SVC”, the distal tip of the catheter (CS12) is close to the annulus of the superior vena cava.
At “IVC”, the proximal tip of the catheter (CS90) is close to the annulus of the inferior vena cava
At “TVA”, the distal tip (CS12) is close to the tricuspid valve annulus
At “AFW”, the entire catheter rests against the atrial free wall.

III. MATHEMATICAL ANALYSIS:

RESCALED RANGE ANALYSIS:

The rescaled range analysis is simple yet robust non-parametric method for fast fractal analysis. This is performed on the discrete time series data set x_t of dimension N by calculating the mean $\tilde{x}(N)$;the standard deviation S(N) and the cumulative departure X(n,N),where,

$$\tilde{x}(N) = \sum \frac{x_t}{N} \tag{1}$$

$$S(N) = [\frac{1}{N}\sum (x_t - \tilde{x}(N))^2]^{\frac{1}{2}} \tag{2}$$

Range of cumulative departure of the data is

$$R(N)=\max[x(n,N)]-\min[x(n,N)] \tag{3}$$

Where cumulative departure is given by

$$X(n,N) = \sum (x_t - \tilde{x}(N)), \quad 0 \le n \le N \tag{4}$$

The associated R/S analysis for the ECG signals is discussed in detail in the Result section of this paper. It is computed as

$$\frac{R}{S} = n^H \tag{5}$$

The slope of the plot of log (R/S) vs. log (n) gives rise to H. The magnitude of H indicates whether a time series is random or successive increments in time series.

The fractal dimension D [20-21] is determined as

$$D = 2-H. \tag{6}$$

The correlation 'ρ' [21] between two successive steps or increment is given by

$$\rho = 2^{2H-1}-1 \quad (7)$$

. If H = 0.5 then ρ = 0. For this the time series represents random walk and each observation is totally independent of the prior observations. If ρ is positive then 0.5<H<1, meaning the time series is persistent and has long memory effect, that is the preceding observations has a positive correlation with the successive observations. On the other hand if ρ is negative then 0<H<0.5, meaning the observations are non-persistent and the each value has negative correlation with the previous value [17].

IV. RESULTS AND DISCUSSIONS

The plots for normal ECG and diseased ECG e.g. Intracardiac Atrial Fibrillation are shown in Fig-2 and Fig-3 respectively.

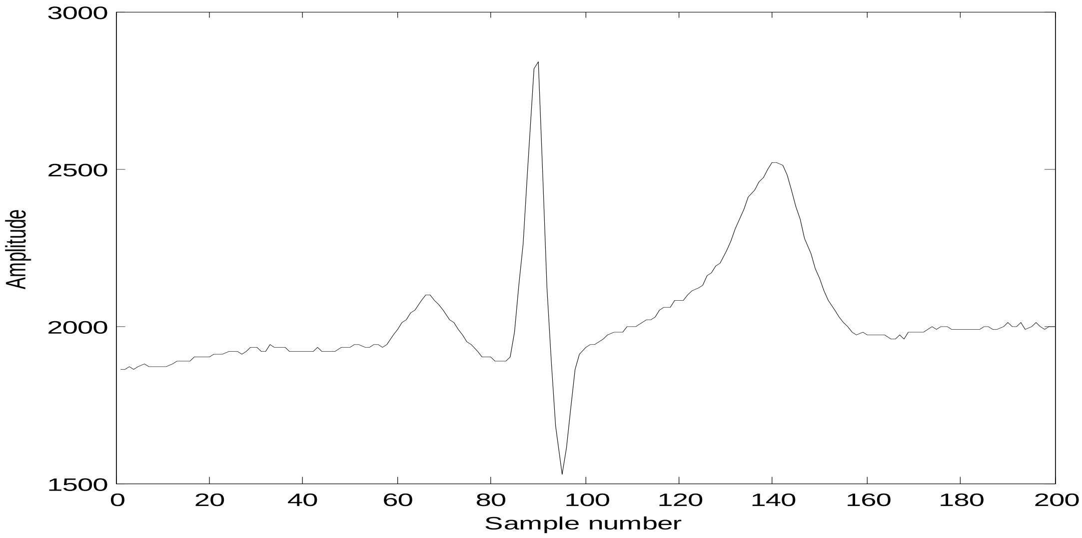

Fig-2: Normal ECG

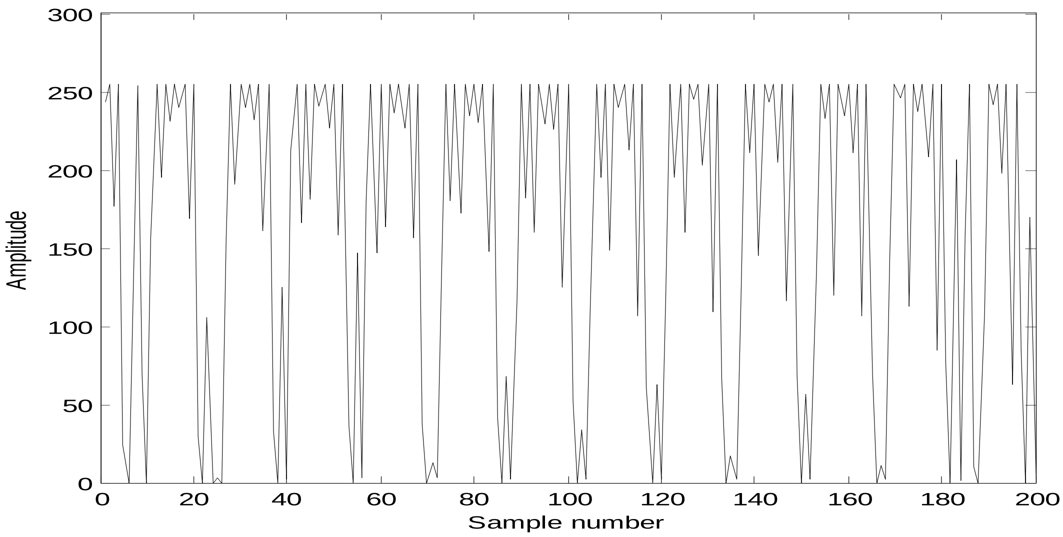

Fig-3: Intracardiac Atrial Fibrillation ECG

Normal ECG signals are recorded using POLYPARA module with a sampling rate of 200 samples per second. Both normal and diseased ECG time series are loaded on MATLAB platform. Rescaled range analysis method as explained in the earlier section is applied to these time series. For this method, we choose a set of dimension N (which is 200, in our case).Then the mean $\tilde{x}(N)$, standard deviation S(N), range R(N), cumulative departure X(n ,N) are found using eqns. 1, 2, 3, and 4 respectively. Subsequently, (R/S) value is calculated. A graph $\log_{10}$(R/S) vs. $\log_{10}$(n) is then plotted, where 'n' is the length of the data set. Hurst exponent is then found from the slope of this plot using eqn. 5. The graph $\log_{10}$(R/S) vs. $\log_{10}$ (n) for a normal ECG time series is shown in Fig-4 as a sample plot.

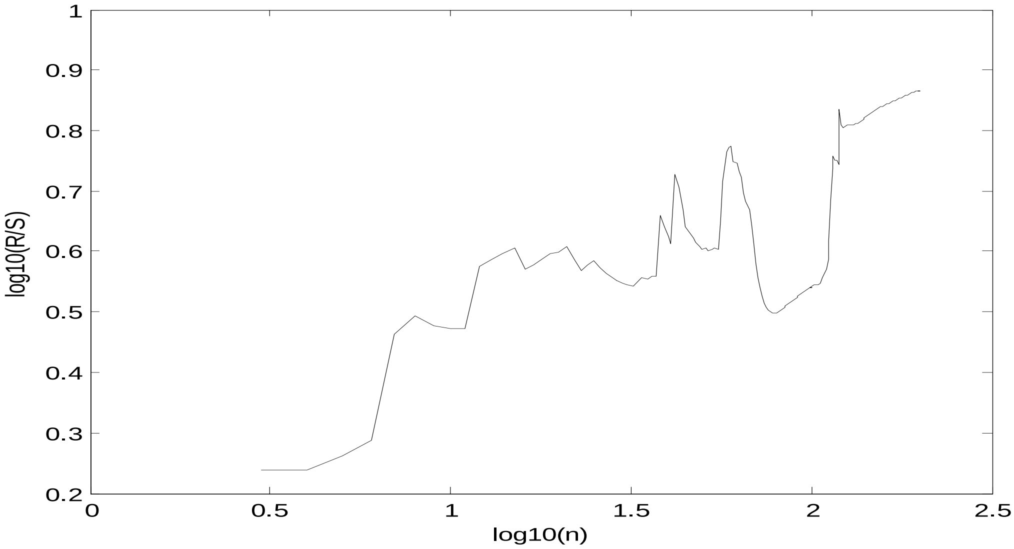

Fig-4: log $_{10}$(R/S) vs log $_{10}$(n) for a normal ECG time series

Similarly, the graph $\log_{10}$(R/S) vs. $\log_{10}$ (n) for an Intracardiac Atrial Fibrillation ECG time series is shown in Fig-5 as a sample plot.

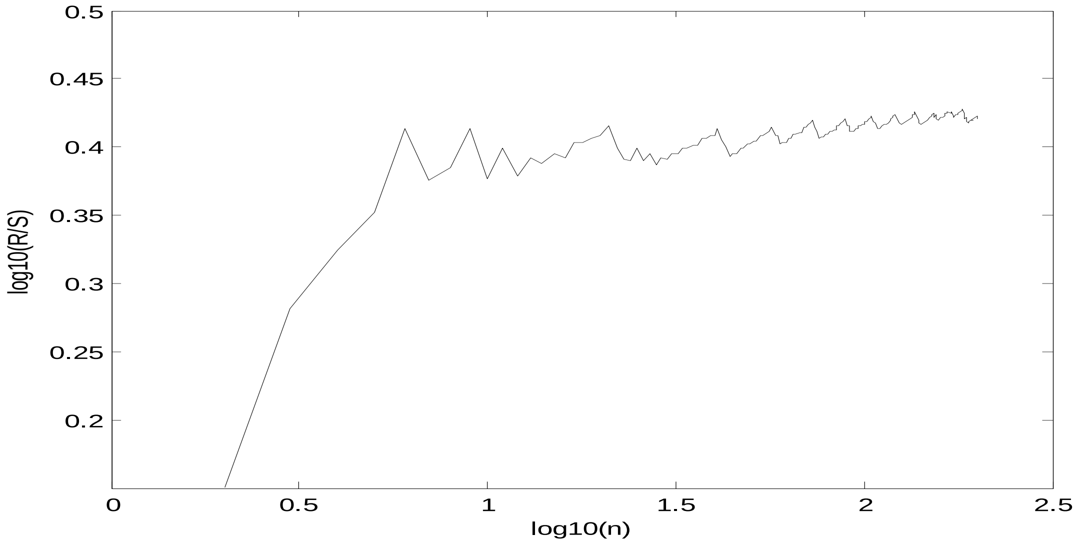

Fig-5: log $_{10}$(R/S) vs log $_{10}$(l) for an Intracardiac Atrial Fibrillation ECG time series

In all these plots, it appears that there is no linear dependency, thus ensuring the fact that, multifractal nature is present in all the cases. Now random Brownian motion produces a value H=0.5. Generally a value above this indicates positive autocorrelation in the signal .That is, it indicates an increased likelihood that the next value in the series will be in the same direction as the current value and that the direction of movement of the signal will continue or persist. On the other hand a value less than 0.5 indicates a negative correlation and it implies that the next values will be in the opposite direction. Hurst exponents may vary between 0 and 1.

As in our case, Hurst exponent is found to be below 0.5; there will be increasing irregularity or 'roughness' to the curve.

Now Fractal Dimension of each data set are obtained using eqn.(6), which is D = 2-H. We also find the correlation between two successive steps by using equ. (7), i.e. $\rho = 2^{2H-1}-1$.

Fractal dimension values obtained for normal and Intracardiac Atrial Fibrillation ECG time series are tabulated in Table-1 and Table-2 respectively as sample results.

Table 1: For Normal ECG Time Series

S. No.	H	D	ρ
1	0.3603	1.6397	-0.1761
2	0.3603	1.6397	-0.1761
3	0.4053	1.5947	-0.1230
4	0.3569	1.6431	-0.1799
5	0.3475	1.6525	-0.1905
6	0.3962	1.6038	-0.1340
7	0.3603	1.6397	-0.1761

Table 2: For Intracardiac Atrial Fibrillation

S. No.	H	D	ρ
1	0.2309	1.7691	-0.3114
2	0.2285	1.7715	-0.3136
3	0.2068	1.7932	-0.3340
4	0.2291	1.7709	-0.3131
5	0.2480	1.7520	-0.2949
6	0.2240	1.7760	-0.3179
7	0.2365	1.7635	-0.3061

Mean and Standard Deviation are obtained from the whole data set considered in this work and these results are tabulated in Table-3 for normal and Intracardiac Atrial Fibrillation ECG time series. These results are compared.

Table-3: Fractal Dimension for Normal and Intracardiac Atrial Fibrillation ECG Time Series.

Time Series Type	Mean	Standard Deviation	Maximum limit	Minimum limit	Mean-Std	Mean + Std
Normal	1.6271	0.0260	1.6525	1.5824	1.6011	1.6530
Intracardiac Atrial Fibrillation	1.7725	0.0126	1.7968	1.7410	1.7599	1.7851

V. CONCLUSION

Fractal Dimension of Intracardiac Atrial Fibrillation ECG time series lies in between 1.7725 ± 0.0126. Whereas, the Fractal Dimension of normal ECG time series is 1.6271 ± 0.0260. It is observed that the Fractal Dimension value is higher for the case of Intracardiac Atrial Fibrillation ECG time series as compared to that of normal ECG time series. Moreover, the variation of Fractal Dimension amongst the data set for Intracardiac Atrial Fibrillation ECG time series is small as compared to that of normal ECG time series. This analysis does have a significant clinical advantage. So, this range of Fractal Dimension for Intracardiac Atrial Fibrillation ECG time series can be used as a disease index to identify this disease.

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