DYNAMICAL ANALYSIS OF HEART BEAT FROM THE VIEWPOINT OF CHAOS THEORY

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ECG signal computational approach was carried out in this paper aiming to reveal the complexity of the apparent periodic signal. In this respect, the numerical analysis of the raw data was accomplished in parallel with that of the data generated following the dominant frequency extraction. Power spectra, auto-correlation function and auto-correlation time, the portrait in the state space and its fractal dimension were the quasi-quantitative tests derived from the chaos theory that were applied for this complexity analysis of ECG signal.

Key words: heart beat, chaotic dynamics, computational tools.

1. INTRODUCTION

Application of chaos theory to the electroencephalographic signals [1] has generated the highest and earliest interest for computational studies in medicine – proving to be helpful in the emphasis of distinct degrees of complexity in the dynamics of normal *versus* epileptic subjects brains: dominant quasi-periodic behavior of brain was revealed in pathologic cases, while chaotic behavior was found in normal ones. Comparatively, in the case of the heart activity, the symmetrical appearance of the electrographic signal (ECG) strongly suggests the dominancy of the periodic rhytm but the modern physics challenges to interpret the heart muscle dynamics from the viewpoint of complex systems. Consequently one of the first applications of nonlinear methods to the analysis of the heart physiology was reported in the '90s by Reidbord and Redington [2] while heart beat variability was further studied in cases of arrhythmia or general anesthesia by Sleight [3], Pomfrett [4], Fortrat [5], Lass [6] and others. The theoretical investigation of turbulence and non- stationarity in human heart rhythm was accomplished by Lin *et al*., [7], Bernaola-Galvan *et al*., [8] and others, all considering heart bioelectrogenesis as mainly periodic phenomena. The statistic approach of heart dynamics was carried out by Stanley's group in both normal and pathological cases [9] with focus mainly on the interbeat interval variability[10], revealing the heart non-Gausian behavior [11] and underlying that the multifractal structure of healthy subjects is different than that of diseased subjects [12]. The analysis of the stochasticity in non-stationary data for the beat-to-beat fluctuations in the heart rates (Ghasemi *et al*. [13]) for healthy subjects, as well as for those with congestive heart failure proposing a potential diagnostic tool for distinguishing healthy subjects from those with congestive heart failure. The power spectrum method was applied in the statistical analysis of interbeat intervals during atrial fibrillation by Henning *et al*. [14] that proposed the decomposing the intervals into two statistically independent times, with different dynamical features while Staniczenko *et al*. [15] focused on power spectrum of cardiac ryhthmus succeeding to develop an algorithm useful for the rapid identification of frequency disorder in other rhythmic signals too. In some papers [12, 16–19] the detrended data were considered a useful tool in heart dynamics investigation but the investigated data series were composed of heart beat intervals without interest on the ECG amplitude fluctuations. In the next, a comparative analysis of raw ECG signal *versus* detrended data series– resulted following the extraction of dominant frequency – is presented by applying several computational tests based on chaotic determinism theory, including power spectra and fractal dimension of the system attractor.

2. THEORETICAL BACKGROUND

The analysis strategy followed by us was derived mainly from that proposed by Sprott and Rowlands [20]:

(i) The Fourier spectrum visualized in linear-log representation: Log P *versus* frequency (where P is the square of the amplitude); Nyquist frequency may be considered, i.e. the inverse of the distance between two consecutive points; for random and chaotic data broad spectra are obtained, several dominant peaks correspond to quasi-periodic data, while the coherent decrease of lgP(f) is a hallmark of hidden determinism (deterministic chaos), i.e. a more complex evolution.

(ii) Basically, the same information about the system dynamics that can be provided by the power spectrum can also be extracted studying the auto-correlation function:

$$\Psi(t) = \int_{-\infty}^{\infty} f(t+\tau)\, f(\tau)\, dt \tag{1}$$

but from a different point of view. The value τ at which the auto-correlation function reaches 1/e (e=2.71…) of its initial value is the correlation time of the temporal series. The function $\Psi(t)$ will drop abruptly to zero for highly random data, implying small correlation time, but also for some chaotic series containing data that are not apparently correlated with each other. For quasi periodic signals will have a correlation function that varies with τ but whose amplitude only slowly decreases. In the case of chaotic determinism the data are governed by strong connections and for them the auto-correlation function slowly decreases with time.

(iii) The state space is generally an m-dimensional hyperspace constructed using all system parameters, but the state-space portrait can be reconstructed using a single variable x(t) (measurable at equal time steps) [21]. Often the computational algorithms used in the investigation of system dynamics are based on delay coordinates in the form x(t)/x(t–1) which are able to provide information on the system attractor – the equilibrium states toward which the system may evolve starting from different initial conditions but following the same laws. The attractor appears as a complex object having the shape of a loop for a periodic system, a thorus for a quasi-periodic system, or a more complicated object (yet with a discernible shape) for a complex dynamics governed by hidden determinism.

(iv) The fractal dimension of the system attractor may be calculated in many ways, for instance using the correlation dimension algorithm. The basic idea is to construct a function **C(r)**, which is the probability that two arbitrary points on the system trajectory shaped in the state space are closer together than r (r being the radius of a hypothetical hypersphere drawn to cover the attractor) [22]. The correlation dimension is given by

$$C_D = \lim_{dr \to 0} \frac{d(\log C(r))}{d(\log r)} \tag{2}$$

When calculated for increased values of the embedding dimension the correlation dimension should increase but eventually saturate at the correct value. Accordingly to Kumar [23] the embedding dimension (m) measures the density of the attractor finding the probability of one point within a certain distance R from another point enabling the examination of the geometrical structure shaped in the state hyperspace similarly with the microscopic investigation of a real object. Since generally none of the above mentioned tests (or others) is not sufficient to describe the system dynamics, one need to use an array of computational tools in order to conclude on the complex system behavior. Not only the raw data but also some data series generated from the initial signal can be very useful in the computational investigation. So, surrogate data or detrended data might be of interest in the case of chaotic or respectively quasi-periodic systems. The maximum-entropy method (that represents the data in terms of a finite number (N) of complex poles of discrete frequency) can be used in order to detrend the data by extracting the dominant frequencies – the most recent N points and the N poles being used to predict each next point. In the following we analyzed the whole ECG raw signal and its associated detrended data series on the basis of the above presented computational tests.

3. RESULTS AND DISCUSSION

In the next figures the numerically smoothed data are presented and analyzed (each data is replaced with the average of itself and its two nearest neighbors). A portion of about 1,000 points the whole ECG recording (about 10,000 points) is presented in Fig. 1a the corresponding detrended data being represented in Fig. 1 b. The characteristic ECG quasi-periodic structure can be seen in the raw data while a more complex graph – of detrended data – remained after dominant frequency extraction.

In Fig. 2 the power spectrum in logarithmic-linear representation can be seen. Instead of the quasi periodic signal, with low dominant frequency from Fig. 2a, a monotone decrease of the square amplitude to the increase of the frequency – for low and medium values is visible in Fig. 2b. For high frequencies – indicating noise or fluctuating behavior-the small peaks from the original signal appears amplified in the detrended data.

In Fig. 3 the auto-correlation function and correlation time are presented. After dominant frequency extraction from the original signal the correlation time has considerably diminished (more than twice) the correlation function decreasing more rapid to zero – which indicates the stronger chaotic feature of the detrended data.

The chaotic feature of the ECG data is better emphasized in Fig. 4 where the system attractors can be seen for both the raw signal and the detrended data.

The initial temporal series exhibit an attractor that can be described as a double fuzzy loop – suggesting the coexistence of quasi-periodic and chaotic dynamical trends. The detrended data series is characterized by a more complex attractor rather similar to the Lorenz's attractor which is typical for chaotic series [9]; however random tendency seems to be also present as suggested by the trajectories spreading around the central "eight" like object (aligned along the first bisectrix).

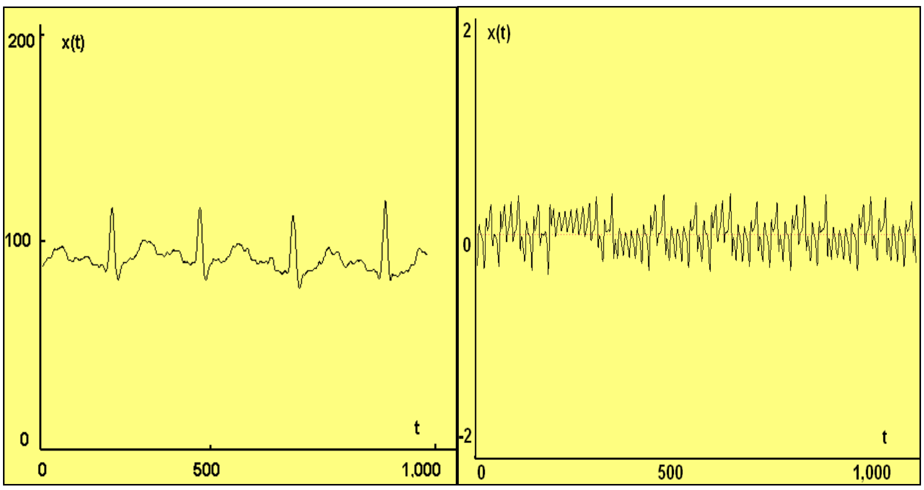

Fig. 1 a-b. The ECG signal (left) and the detrended data (right).

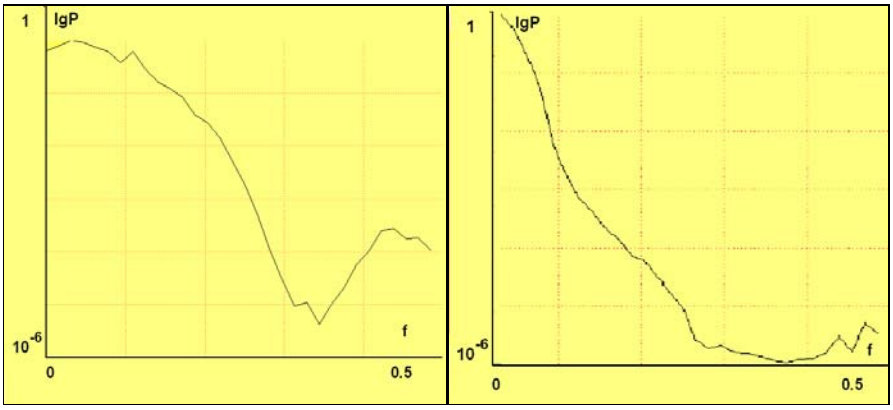

Fig. 2 a-b. Power spectrum (in linear-logarithmic representation) corresponding to ECG signal (left) and detrended data (right).

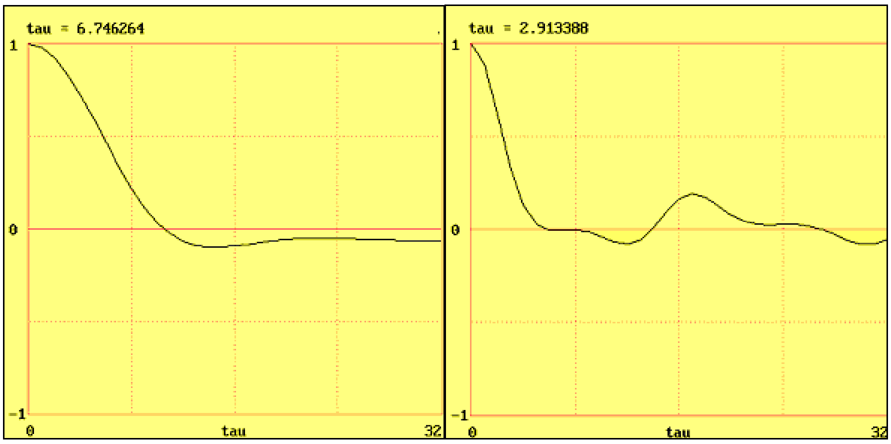

Fig. 3 a-b. The correlation function of ECG signal (left) and detrended data (right).

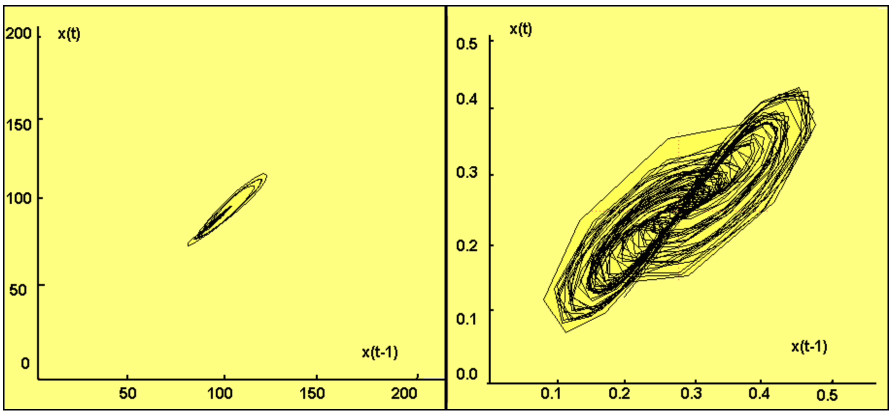

Fig. 4 a-b. The portrait in the state space: the ECG signal (left); the detrended data (right).

The attractor fractal dimension, expressed as correlation dimension, in Fig. 5 is presented. The chaotic dynamical component of ECG signal is clearly visible in the case of detrended data where the correlation dimension saturates to a non-integer value equal to 2.38; the difference between this value and that corresponding to the raw data (2.37) is not significant but the saturation tendency is present only in the second case – so one might say that the chaotic evolution of ECG signal is best emphasized by the data generated by dominant frequency extraction from the initial signal.

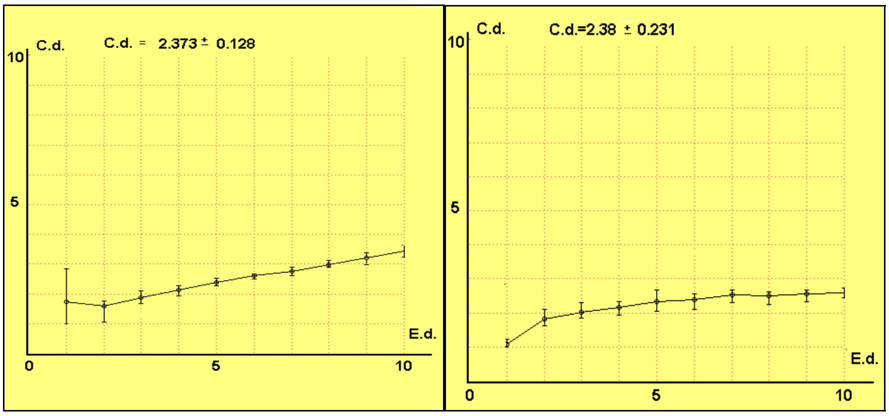

Fig. 5 a-b. The correlation dimension (C.d.) *versus* embedding dimension (E.d.) in ECG signal (left) and detrended data (right).

So, the ECG data series presents quasi-periodic dynamical trend overlapped onto chaotic dynamical component, the analysis of detrended data being particularly helpful in revealing this complex dynamics.

4. CONCLUSION

Heart activity, when analyzed by means of computational interpretation of whole ECG signal, can be described by complex dynamical evolution, as resulted from applying chaos theory approach. In comparison to most of the literature studies dedicated to heart rhythmus analysis, in this article not only the heart beat intervals were considered for the dynamical analysis but the whole ECG signal, since some fluctuations could also appear at the level of the biological signal amplitudes. The analysis of the heart dynamics revealed that the quasi-periodic component is overlapped onto a more complex dynamical component that may be assigned as a deterministic chaotic trend. The chaotic ECG evolution was revealed mainly following the dominant frequency extraction from the raw data series. In the future project new computational tests are going to be applied aiming to get additional information upon the heart dynamics not only in normal physiological cases but also in disturbed or pathological ones.

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