

## DYNAMIC ANALYSIS ON THE HEART ELECTROMAGNETIC ACTIVITY

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*Dinamica ritmului cardiac a fost analizată utilizând teste computaționale dezvoltate pe baza teoriei haosului deterministic. Secțiunile Poincaré, dimensiunea de corelație și timpul de corelație ca și serile de date surogat au reprezentat principalele teste semi-quantitative discutate pentru două situații fizioleice distincte. Rezultatele au sugerat că tendința dinamică de mare complexitate evidențiată în activitatea inimii poate fi semnificativ influențată de stresul emoțional generat de modificările din metabolismul adrenalinei.*

*The heart beat dynamics was analyzed by using computational tools derived from deterministic chaos theory. Poincaré section, correlation dimension and correlation time as well as surrogate data series were the main semi-quantitative tests comparatively discussed in two distinct physiologic situations. The results suggested that the high complexity dynamic trend evidenced in heart activity might be significantly influenced by emotional stress loading generated by the changes in adrenaline metabolism.*

**Key words:** heart electromagnetic activity, deterministic chaos, stress loaded subjects

### 1. Introduction

Since the 90's the chaos theory was applied in the study of heart dynamics: one of the first applications of nonlinear methods to the analysis of emotions effect on heart physiology was reported in 1992 [1]. In the last years new reports regarding the non linearity of the electrocardiographic (ECG) signal have been published aiming to develop computational tools useful in clinical diagnostic [2-6]. In the next we present the results of the analysis of two ECG signal types recorded for health subjects in certain emotional situation, by applying specialized tests.

### 2. Theoretical background

(i) The portrait in the state space is basically constructed using all the system parameters but the re-construction from only one  $\mathbf{x}(t)$  parameter and its first

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derivative  $\mathbf{x}'(\mathbf{t})$ , measured at equal time steps, is largely utilized in the estimation of system complexity [7] as well as the reconstruction by using delay coordinates  $\mathbf{x}(\mathbf{t})/\mathbf{x}(\mathbf{t-1})$ . The qualitative interpretation of the attractor shape as well as the semi-quantitative interpretation, based on the fractal dimension can result in the assessing of the system dynamics to one of the limit cases: periodic-stochastic-chaotic. (ii) The return maps - cross-sections of the phase plane can offer new information on the system attractor complexity. In such representation known as Poincaré section, chaotic data will often appear in the form of a strange attractor having a fractal structure. (iii) The auto-correlation function:

$$\Psi(t) = \int_{-\infty}^{\infty} f(t+\tau)f(\tau)d\tau \quad (1)$$

informs about intrinsic connections between data. The value  $\tau$  at which the auto-correlation function reaches  $1/e$  ( $e=2.71...$ ) of its initial value represents the correlation time of the time series. (iv) The Fourier spectrum needs to be studied in the log-linear representation ( $\ln P/f$ ); Nyquist frequency may be considered, i.e. the inverse of the distance between two consecutive points). A flat shape of the graph  $\ln \mathbf{P}(\mathbf{f}(\mathbf{t}))$ , where  $\mathbf{P}(\mathbf{f})$  is spectral power indicates stochastic fluctuations, several dominant peaks correspond to quasi-periodic data, while a coherent decrease of  $\ln \mathbf{P}(\mathbf{f})$  is a hallmark of hidden determinism. When the evidence of determinism have been identified within the data suspected of chaotic trend, it is recommended to repeat the tests using surrogate data that resemble the raw data series but that lack determinism [8]. The strategy we followed for the analysis of the heart dynamics was mainly that proposed in [9].

### 3. Results and discussions

In fig. 1 the raw ECG data and the corresponding surrogate data series are presented. The ECG signal is normally characterized by the QRS wave triplet (a short duration and high amplitude depolarization between two rapid and small amplitude hyperpolarizations), preceded by the P wave and followed by a remarkable T wave [10]. In the normal ECG (fig. 2) the P wave, has small amplitude, being possibly screened by the recording noise while in the stressed subjects the P wave is higher, but because of the much shorter time interval between two consecutive signals (about three times less than in the ECG of a relaxed subject), it is partially overlapping onto the T wave of the previous ECG signal. In comparison to the normal ECG case, the graphs corresponding to emotional stress loading cases present obvious changes at the level of ECG amplitudes (P wave and QRS complex). (i) The portrait in the state space (reconstructed in delay coordinates,  $\mathbf{x}(\mathbf{t})/\mathbf{x}(\mathbf{t-1})$ ) revealed the pseudo-periodic trend

(fuzzy loop) with a higher area in the case of emotional subjects; the inner structure of the loop – more visible for stressed subjects (fig. 3) indicates the high complexity component of heart dynamics – the trend of chaotic determinism.

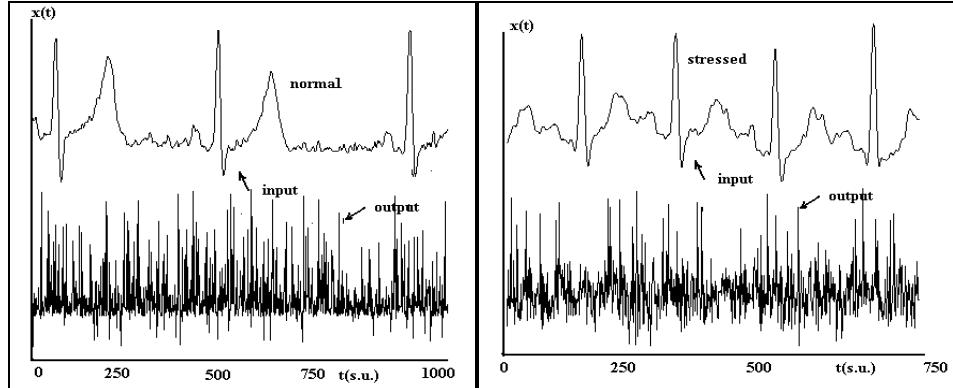


Fig. 1. a.-b ECG data (input) and surrogate data (output)

(ii) The Poincaré sections are rather similar (though exhibiting some differences regarding the point spreading along the first bisectrix) in the case of raw ECG data (fig. 4).

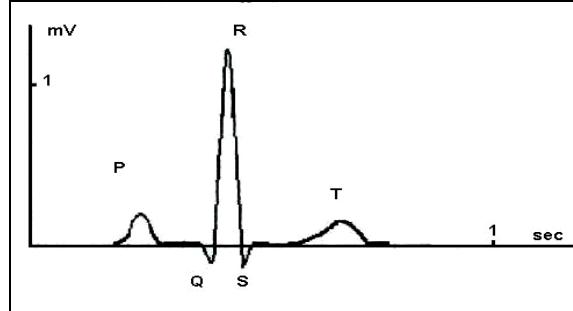


Fig. 2. The structure of ECG signal

There are the surrogate data that will make the difference in Poincaré section as shown further. (iii) The auto-correlation function tends to decrease slowly with wave like variations of its amplitude (Fig. 5) revealing clearly the pseudo-periodic trend, which seems to be dominant in both analyzed cases. In normal cases there is a slower diminution of the auto-correlation function amplitude in comparison to the stressed subject case where a more rapid decrease is visible, meaning that a stronger temporal correlation exists between the data representing the activity of a normally relaxed heart. The values of the auto-correlation time enable us to underline the quantitative difference between normal ( $\tau=73.42$ ) and emotionally stressed heart ( $\tau=9.39$ ) as presented in fig. 5 (the

difference between the average values corresponding to the two series of ten subjects each, being significant as well).

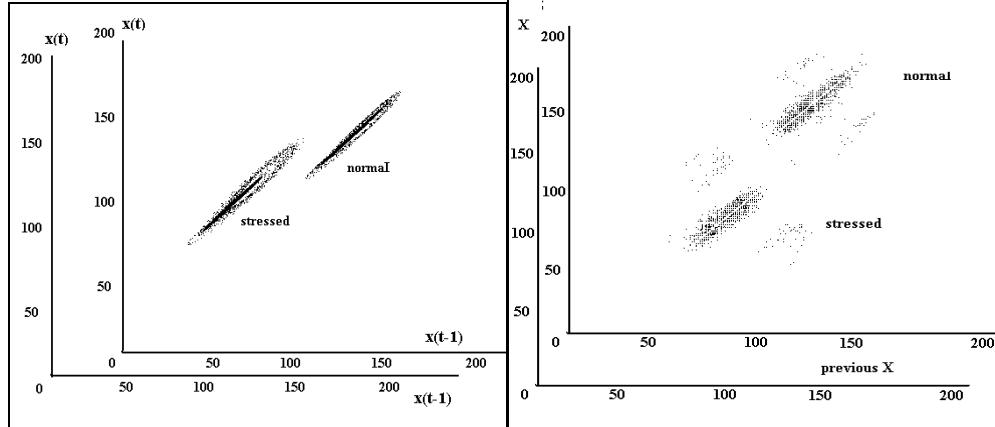


Fig. 3. The system attractor

Fig. 4. Poincaré sections for raw ECG data

So, the chaotic trend, i.e. the higher degree of complexity is characteristic to normal electrocardiographic signal while for the other situation smaller correlation between neighbor data was found.

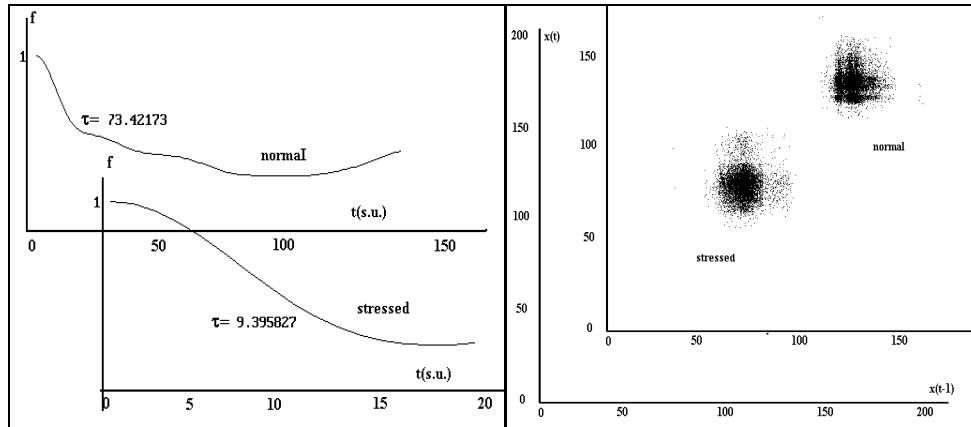


Fig. 5. The auto-correlation function (raw data)

Fig. 6. The attractors for the surrogate data

(iv) The surrogate data series (the output signals corresponding to the raw data inputs) are obviously lacking any periodic trend – which resulted in the dramatic change of the system attractor (fig. 6) – the stochastic trend seems to dominate in spite of obvious bilateral symmetry of the attractor points distribution. In figure 7 quite similar plots obtained for the correlation function are presented, the lack of determinism being evident from the rapid decreasing of the correlation function, i.e. the very small value of the correlation time (sub unitary values in both analyzed cases).

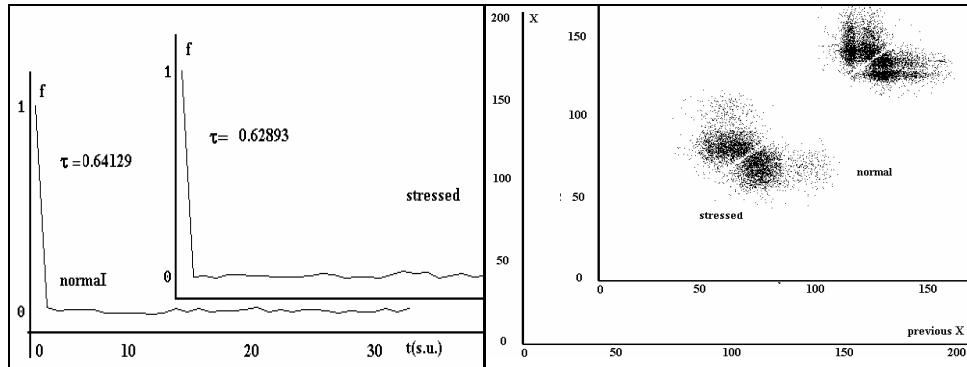


Fig. 7. Auto-correlation function for surrogate data

Fig. 8. Poincaré sections for the surrogate data

The Poincaré sections of surrogate data series (fig. 8) seem to bear more information on the chaotic trend in the heart dynamics. The differences between the relaxed and stressed heart may be described by saying that the structured object shaped in the plot corresponding to the normal heart exhibits more structural details (two pairs of lobes) than that corresponding to the stressed heart (one pair of fuzzy lobes).

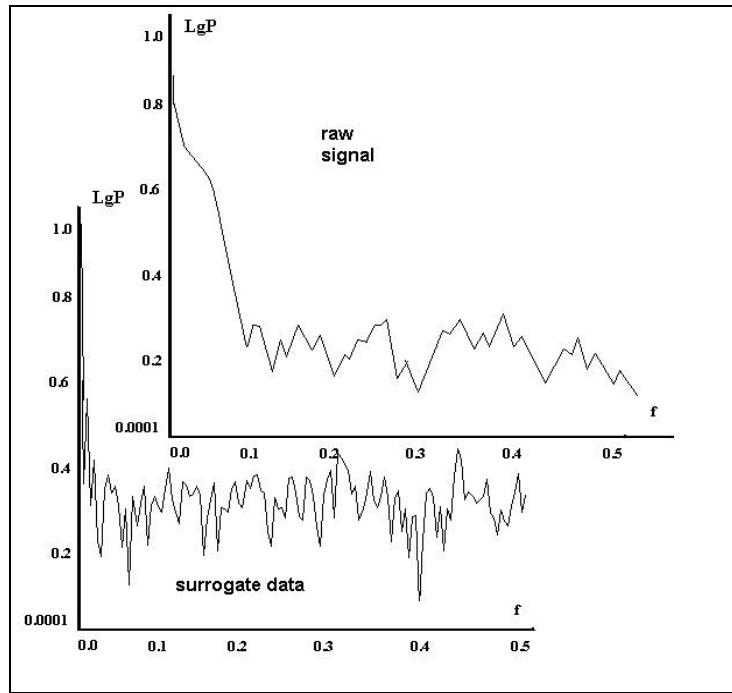


Fig. 9. Power spectra (logarithmic-linear view) for raw ECG signal and surrogate data

Enhanced adrenaline release is the main physiological feature of stress loading; heart beat is accelerated and blood pressure is increased.

However, it seems that not only the time duration of every ECG signal is shortened but other qualitative and quantitative changes of the main depolarization waves also occurred. One might say that the pseudo-periodic trend of heart beat dynamics is increased – the computational tests applied inhere sustaining this hypothesis. In Fig. 9 the power spectra are given for both raw signal and surrogate data series in the case of normal subjects. The large plateau with almost equal peaks corresponding to medium and high frequencies can be considered an indication of stochastic dynamical trend while the high peak at low frequency corresponds to the periodic dynamical component; more spurious appearance of surrogate data can be assigned to the increased stochastic trend. In surrogate data power spectrum the high peak from low frequency is no more distinct. In both studied situations (normal and stress loaded subjects) the power spectra shows the same qualitative features.

#### 4. Conclusion

Following the application of some computational tests to the analysis of ECG signals the overlapping of pseudo-periodic trend onto hidden deterministic one was evidenced. Enhanced adrenaline level in the emotionally stressed subjects has probably reduced the degree of complexity in the ECG series. So, the chaotic dynamical component of heart electromagnetic activity is better evidenced in normal relaxed subjects while in adrenaline loaded ones the pseudo-periodic trend seems to be enforced.

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