Complexity Analysis of Electrocardiographic Signals

I. Neacsu[1], D. E. Creanga[2] and Fl. M. Tufescu[2]

[1] *University Al. I. Cuza, Faculty of Biology, 20A Bd. Carol I, Iasi, Romania*
E-mail: ineacsu@uaic.ro
[2] *University Al. I. Cuza, Faculty of Physics, 11A Bd. Carol I, Iasi, Romania*

Abstract. Two types of electrocardiographic data series were investigated using appropriate tests based on a selection of semi-quantitative analysis algorithms. Distribution histograms, power spectra, auto-correlation functions, state-space portraits, Lyapunov exponents and wavelet transformations were applied to electrocardiograms of normal and stressed subjects. Statistical analysis using the Student's *t*-test revealed significant and non-significant alterations in stress-loaded cases compared to normal ones. Higher levels of adrenaline may account for a more complex dynamics (deterministic chaos) revealed in the stressed subjects.

Key words: Electrocardiographic data — Deterministic chaos — Stressed subjects

Introduction

Recordings of electrical activity of the main vital organs are important physiological investigation tools for medical researchers, but also for biophysicists. Electroencephalograms, electrocardiograms, electromyograms and electroretinograms (May 1991; Goldberger 1999; Arita 2001; Dafilis et al. 2001; Arita et al. 2002) are more or less present in day-to-day diagnostics of numerous patients. Application of chaos theory to the electroencephalographic signals (May 1991) has generated the highest and earliest interest in both medicine and physics (for instance the emphasis of distinct degrees of complexity in normal and epileptic subjects: dominant quasi-periodic behavior of brain was revealed in pathologic cases, while chaotic behavior was found in normal ones).

One of the first applications of nonlinear methods to analysis of the effect of emotions on heart physiology was reported in the 1990s (Reidbord and Redington 1992).

Among the most recent reports regarding the non-linearity of the electrocardiographic (ECG) signal we mention:
– the study of cardiac arrhythmia (Lass 2002),

Correspondence to: Dorina Creanga, University Al. I. Cuza, Faculty of Physics, 11A Bd. Carol I, Iasi, Romania. E-mail: dorinacreanga@yahoo.com

– the evidence of changes in heart rate variability during induction of general anesthesia (Pomfrett 1999; Sleight and Donovan 1999),
– the study of respiratory influences on the non-linear dynamics of heart rate variability (Fortrat et al. 1997),
– the study of heart rate variability in different generations (Yoshikawa and Yasuda 2003),
– the discrimination of healthy patients from those with cardiac pathology based on wavelet analysis of heartbeat intervals (Thurner et al. 1998),
– the theoretical investigation of turbulence (Lin and Hugson 2001) and non-stationarity in human heart rhythm (Bernaola-Galvan et al. 2001).

In this paper, we present the results obtained in the analysis of two series of ECG signals recorded on healthy subjects in different emotional conditions.

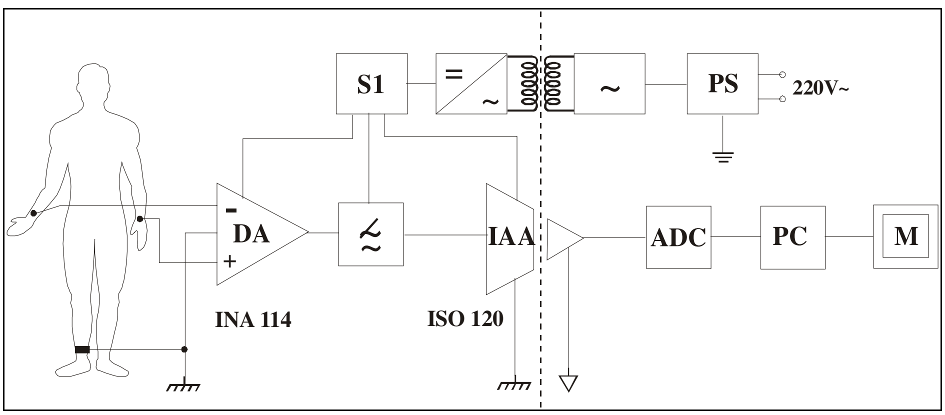
Materials and Methods

A laboratory device was designed and assembled to record electrocardiograms (Creanga et al. 2000) in digital version (signal sampling with a frequency of 500 Hz).

According to Scheme 1, the input signal is amplified (by a specialized low-noise amplifier) and passed through a low-pass filter (to improve the signal-to-noise ratio) and further processed by an analogue-digital converter connected to a PC system.

The input part is completely galvanically separated from the output part to ensure absolute protection of patients.

Two lots of ten recordings each were taken for comparative investigation in normal and emotionally stressed subjects. (Normal physiological state was assigned



Scheme 1. The block scheme of the ECG recording device: DA, input amplifier (INA 114 type element from Burr-Brown (Texas Instruments)); IAA (ISO 120), insulator amplifier; ADC, analogue-to-digital converter (ADS 7808); PC, computer system; PS, stabilized power supply; S1, specialized stabilizer for the input circuits; M, display unit (computer monitor).

to young healthy students invited as volunteers for ECG recording, while emotional stress was induced in the same subjects by subjecting them later to a non-announced test of evaluation of their activity). The linear and non-linear computational tests have been applied to series of 10,000 data each. The paired two-tailed Student's t-test was applied using the MS Excel program to compare the normal and stress-loaded cases.

Recording of the ECG followed the non-invasive standard technique and the human subjects have given their consent to take part in the study.

Theoretical Background

The strategy we followed in our analysis was mainly that proposed by Sprott and Rowlands (1994):

Graphic plot of data series

First, the graph of the studied data series $f(t)$ must be visualized and interpreted; numerical smoothing can be applied if appropriate, but some loss of intrinsic information may be expected together with the noise reduction.

Power spectrum

Further, the Fourier spectrum is to be studied in the linear-log representation ($\log P$ *versus* frequency, P being the power, i.e. the square of the amplitude; Nyquist frequency may be considered, i.e. the inverse of the distance between two consecutive points). For different mathematical representations of studied signals, different definitions of the Fourier transform should be used; considering the intrinsic periodicity of heart signals, the next formula have been chosen:

$$f(t) = \sum_{-\infty}^{\infty} a_n \exp(i\omega_n t)$$

$$a(\omega) = (\omega/2\pi) \int_0^{2\pi/\omega} f(t) \exp(-i\omega t)\mathrm{d}t$$

where f is the decomposed signal, and a_n or $a(\omega)$ are amplitudes of the Fourier transform.

A flat shape of the graph $\ln P(f(t))$, where $P(f)$ is spectral power (the square of the amplitude a_n of the harmonic component with frequency ω_n) indicates random fluctuations, several dominant peaks correspond to quasi-periodic data, and a coherent decrease in $\ln P(f)$ is a hallmark of hidden determinism (deterministic chaos), i.e. a more complex evolution. Basically, the power spectrum provides the same details about the system as the auto-correlation function, $\Psi(t) = \int_{-\infty}^{\infty} f(t+\tau)f(\tau)\mathrm{d}\tau$, but from a different point of view.

Auto-correlation function

While power spectrum is focused on the main frequencies, auto-correlation function informs about intrinsic connections between data. The value τ at which the auto-correlation function reaches $1/\mathrm{e}$ ($\mathrm{e} = 2.71\ldots$) of its initial value is the correlation time of the time series. The function $\Psi(t)$ decreases rapidly to zero for random data but also for some chaotic series formed by data that are not apparently correlated with each other. Nevertheless, there are chaotic data governed by strong connections and for them the auto-correlation function slowly decreases with time lag.

The portrait in the state space

The state-space portrait: in case of a dissipative system, the state space is an m-dimensional hyperspace formed by all system parameters, but the state-space portrait can be reconstructed using a single variable (measurable at equal time steps), $x(t)$ (Takens 1981). Often the computational algorithms used in investigations 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 torus for a quasi-periodic system, and a complicated object (yet with a discernible shape) for a more complex dynamics.

The correlation dimension

The fractal dimension attached to the 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) (Grassberger and Procaccia 1983). This is usually done by calculating the distance between every pair of N data points and sorting them into bins of width $\mathrm{d}r$ proportional to r. The correlation dimension is given by

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

where one must consider r tending to *0*, and N tending to infinity.

The embedding dimension

Beside the “fractal dimension”, another non-conventional meaning of the term “dimension”, useful in the analysis of system dynamics is the “embedding dimension”, which can be used to examine the geometrical structure formed in the state hyperspace similarly to microscopic investigation of a real object. Such as different details of a small spot become distinguishable on different microscope scales (or, on the contrary, a different set of neighbour points become a single spot), in the case of embedding dimension equal to m, for instance, successive m tuples of data are treated as points in the m-space. According to Kumar et al. (1999), the embedding dimension (m) measures the density of the attractor finding the probability of one point within a certain distance R from another point. When the correlation dimension of the attractor (measuring the number of pairs of points that are within the limit of distance R) stabilizes to a certain value for m, then the system is chaotic (if no stabilization occurs, then randomness is suspected to govern the system dynamics).

Trajectory divergence

Lyapunov exponents represent a way of measuring the dynamics of an attractor by means of divergence of close trajectories. If two close points x_n and $x_n + \mathrm{d}x_n$ at a certain time step (let us say n^{th} step) are belonging to two close orbits, then at the next time step $(n+1)$ they will evolve to x_{n+1} and $x_{n+1} + \mathrm{d}x_{n+1}$, respectively, so the measure of their divergence is:

$$\lambda = \lim_{N \to \infty} \frac{1}{N} \sum_{i=1}^{N} \ln \left(\frac{\mathrm{d}x_{n+1}}{\mathrm{d}x_n} \right)$$

When $\mathrm{d}x_n$ is infinitesimally small, the use of the Taylor series expansion becomes appropriate which involves the utilization of the derivatives.

The Lyapunov exponent can be calculated for each dimension, but usually only the largest exponent is considered for dynamics interpretation. A positive exponent indicates a sensitive dependence on initial conditions, or that our forecasts can diverge fast when based upon different estimates of starting conditions. If a Lyapunov exponent is positive then the system is chaotic and unstable, the magnitude of the Lyapunov exponent being a measure of the sensitivity to initial conditions, the primary characteristic of a chaotic system. If the Lyapunov exponent is less than zero then the system attracts to a fixed point or stable periodic orbit (periodic orbits are identified by their negative Lyapunov exponent) and the absolute value of the exponent measures the degree of stability.

Wavelet maps

The wavelet transformation (Daubechies 1996) offers the possibility to reconstruct the function of interest $f(t)$ as a linear combination of soliton-like functions:

$$f(t) = \sum_{j,k} c_{jk} \Psi_{jk}(t)$$

The basis functions are obtained from a single soliton function (mother wavelet function) by translation and dilatation operations. Analogously to the Fourier transform coefficients, the wavelet transform coefficients are:

$$c_{jk} = [W_\Psi f]_{(1/2^j, k^{2/j})}$$

The projection of the wavelet transform in the (T, DT) plane (time and time scale or observation magnitude) is a 2-dimensional (2-D) picture with specific symmetry for chaotic, quasi-periodic, and random data. The stepwise Haar function was used as mother wavelet in this study:

$$\Psi(x) = \begin{cases} 1 & \text{when } 0 \le x < 1/2 \\ -1 & \text{when } 1/2 < x \le 1 \\ 0 & \text{otherwise} \end{cases}$$

and: $\Psi_{jk}(x) \equiv \Psi(2^j x - k)$, where j is a non-negative integer and $0 \le k \le 2^j - 1$. So the analyzed function can be reconstructed as a superposition of rectangular signals, while the Fourier transformation is based on harmonic functions. The wavelet transformation represents a generalization in 3-D coordinates of the Fourier transformation: it maintains the time (rather than the frequency) as abscissa; the 2-D projection involves time as abscissa and the time scale as ordinate. The wavelet analysis was successfully utilized in investigations of heart rate fluctuations, for example by Bracic-Lotric et al. (2000) and Kimura et al. (1998), while the studies of Toledo et al. (1998, 2003), Pichot et al. (2001) can be mentioned as examples of applications to clinical problems.

Return maps

Since a 2-D phase-space plot may be not sufficient to distinguish between random and chaotic data, it would be useful to visualize some cross-sections of the phase plane in order to reduce its dimension by one (Poincar sections). Every point has as coordinates the value of X at the time at which X' equals a constant *versus* the value of X at the previous time at which X' equaled the same (controlled) constant. After such an operation, chaotic data will often appear in the form of a strange attractor having a fractal structure.

Surrogate data

Besides the computational tests presented above, there are also some other possibilities to investigate non-deterministic complexity, among them surrogate data (Schreiber and Schmitz 2000) and recurrence plots (Webber and Zbilut 1994; Babinec et al. 2002), considered as the most promising approaches of chaos analysis.

Once you have found evidence of determinism in your data, it is recommended to repeat the tests using surrogate data that resemble the raw data series but that lack determinism. If the results are the same, then the conclusion formulated regarding the initial data can be taken as good. To generate surrogate data for analysis of nondeterministic complexity, the raw data values may be simply shuffled, this way the probability distribution does not change, though, in general, the power spectrum and correlation function change considerably.

Results and Discussion

According to the analysis strategy suggested by Sprott and Rowlands (1994), the ECG signals of relaxed and stressed subjects have been comparatively studied by means of a selection of linear and non-linear tests.

The discussion is focused on the semi-quantitative tests due to the convenient comparison of numerical data instead of qualitative description.

ECG graphs

The graphs of ECG signal amplitude *versus* time are given in Figure 1 (raw data); numerically smoothed data are also discussed in some paragraphs. In the normal, relaxed subjects (Fig. 1, left) the ECG signal exhibits the QRS wave triplet (a short duration and high amplitude depolarization between two rapid and small amplitude hyperpolarizations), followed by a remarkable T wave. The P wave, normally preceding the QRS triplet, has small amplitude, being screened by the recording noise.

In the stressed subjects (Fig. 1, right), 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 the T wave of the previous ECG signal.

ECG power spectra

The power spectrum is dominated in both situations by a large plateau in the range of high frequencies, which is characteristic of fluctuating signals. In the range of small frequencies, a high amplitude peak is present in both cases (Figure 2). But in the range of small and medium-small frequencies, one can see a rather linear decrease in spectrum amplitude with frequency in normal subjects (Fig. 2, left),

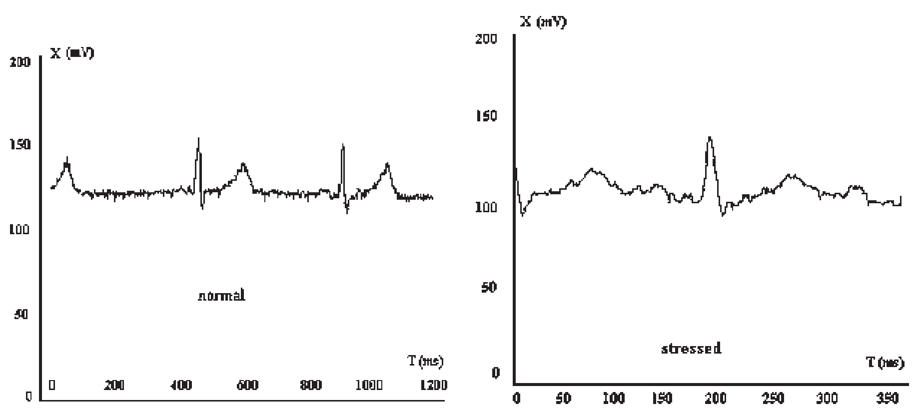


Figure 1. ECG signals in relaxed (left) and stress-loaded subjects (right). X, the electric potential; T, the time.

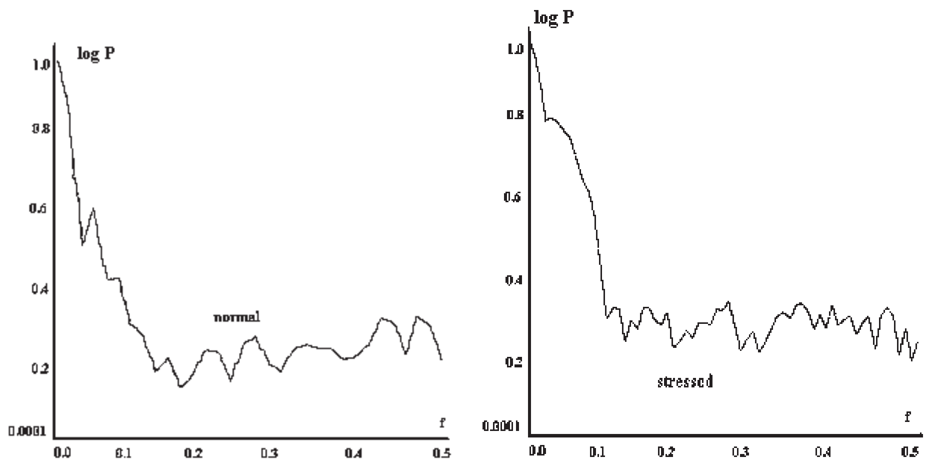


Figure 2. Power spectrum for normal subjects (left) and stress-loaded cases (right). log P, decimal logarithm of the power; f, the frequency.

while in stress loaded cases (Fig. 2, right) this quasi-linearity is not pronounced. Thus, a chaotic trend is evident in the small-medium frequency range for normal subjects, but not in the stressed ones. According to Takens (1981), power spectrum analysis is a linear analysis tool thus presuming that the ECG signal is a result of signals emitted by many generators (heart muscle cells), each producing a sine signal with different amplitude, frequency, and phase. Since the heart activity may be expected to be rather complex (in spite of its apparently periodic dominant), non-linear computational methods are of interest too.

Auto-correlation functions and auto-correlation times of the ECG signals

Auto-correlation functions tend to decrease slowly with wave-like variations of amplitude (Figure 3), revealing clearly the quasi-periodic trend, which is dominant in both analyzed groups. In normal cases (Fig. 3, left), there is a slower decrease in the auto-correlation function amplitude compared to stressed subjects (Fig. 3, right), 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 auto-correlation time τ (the time during which the auto-correlation function decreases to 1/e of its initial value) provides a quantitative measure of this situation. Indeed, there is a remarkable decrease in average values in the stressed heart: from 63.68 (normal condition) to 9.45 (emotional stress) (in Figure 3, the two example values are 67.170 and 8.579). This difference between the average values for two groups of ten subjects can be considered as significant: in the emotionally affected subjects, the average value is about seven times smaller than in the normal subjects (Table 1). Once again, the chaotic trend, i.e. a higher degree of complexity, is characteristic of a normal ECG signal, while for the other situation

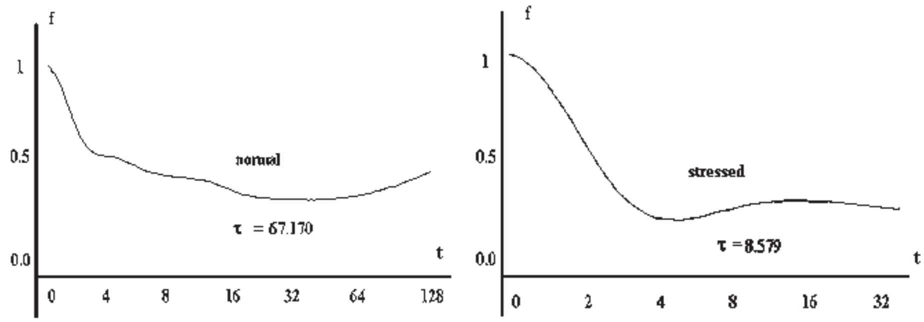


Figure 3. Auto-correlation function f and auto-correlation time τ in normal (left) and stress-loaded cases (right).

Table 1. Statistical analysis by means of the Student's t-test

	Computational results for two groups of ten subjects each					
No.	Correlation dimension		Auto-correlation time		Lyapunov exponent	
	Normal	Stressed	Normal	Stressed	Normal	Stressed
1	2.336	2.580	67.17	8.57	0.146	0.112
2	2.388	2.312	76.82	6.34	0.156	0.134
3	2.093	2.467	82.87	15.98	0.133	0.111
4	2.741	2.781	54.67	9.45	0.137	0.176
5	2.424	2.387	97.23	3.98	0.11	0.087
6	2.294	2.601	49.99	9.12	0.176	0.154
7	2.398	2.467	45.87	13.09	0.165	0.098
8	2.671	2.802	87.12	10.11	0.156	0.165
9	2.122	2.482	35.01	3.12	0.187	0.094
10	2.201	2.583	40.12	14.76	0.108	0.101
Average	2.151	2.314	63.68	9.45	0.147	0.123
Student's t-test probability p						
	0.010358		3.1967E-05		0.066212 (n. s.)	

n. s., non-significant

a smaller correlation between neighboring data is found. The t-test provides a high statistical significance of this difference ($p < 0.001$, where p is the probability that the statistical parameter t assumed the observed value by chance in case the two groups are in fact equal). After smoothing the raw data, the auto-correlation times increase by about 10 % in both groups.

ECG attractors

The state-space portrait, re-constructed (Crutchfield et al. 1986) using a single parameter of the system (ECG amplitude), is rather similar in the two groups of

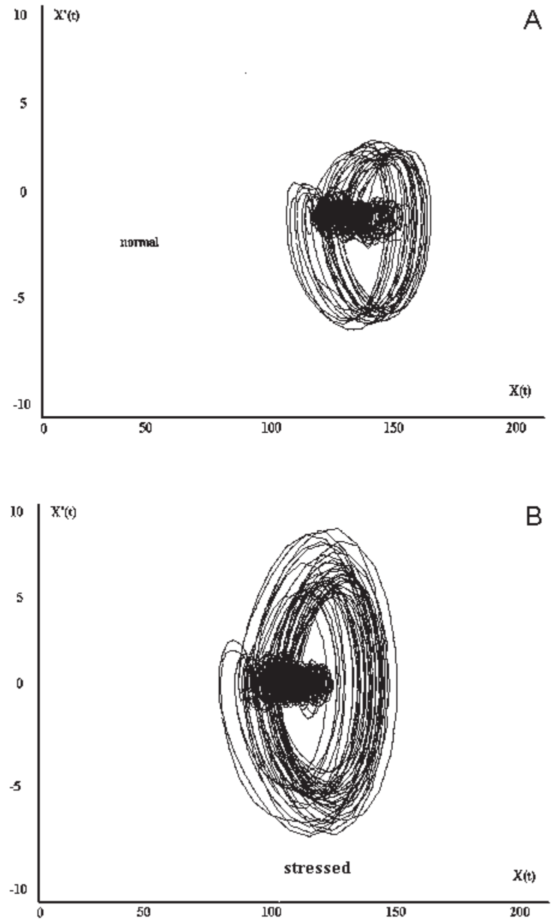


Figure 4A,B. The portrait in the state space: normal subjects (A), stressed patients (B). X, ECG potential; X', first derivative.

recordings for numerically smoothed data (Figure 4). A complex fuzzy loop seems to indicate the dominance of a quasi-periodic dynamics accompanied by certain fluctuations, either intrinsic to the heart complex activity or introduced by the recording noise. Thus the strange character of this signal attractor is not clearly visible (Fortrat et al. 1997) and neither is a difference between the two groups presented in Fig. 4A and B.

ECG fractal dimension

The non-linear dynamics of the ECG signal could be revealed by the correlation dimension expressing the fractal character of the complex object formed in the state space by the ECG attractor (Table 1). The correlation dimension may be

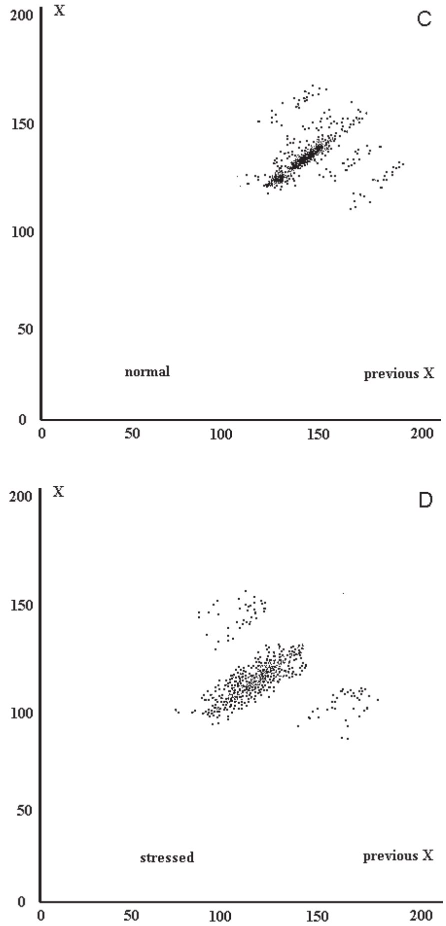


Figure 4C,D. The return maps (Poincaré sections): normal subjects (C), stressed patients (non-tracked points) (D).

used to describe system non-linearity (Igekuchi and Aihara 1997), a more complex system having a higher correlation dimension corresponding to a higher number of parameters or degrees of freedom necessary to describe the system features. Jing and Takigawa (2000) discussed the complexity of electric activity of the brain by calculating the correlation dimension for the electroencephalographic signal on twelve subjects and outlined the non-linear character of the neural system.

ECG return maps

The Poincaré sections (where the constant is equal to 0.5) are able to provide a supplementary view of the attractor structure, such as shown in Fig. 4C and D (consecutive data are not tracked between them in contrast with the graphs in Fig. 4A and B). In both discussed cases, the points are symmetrically disposed around the first bisectrix, bigger dispersion as well as enlarged substructure lobes of the attractor section being evident in the stressed heart (an observation in agreement with Fig. 4A and B, but more detailed).

Fractal dimension versus embedding dimension

The attractor fractal dimension, evaluated for smoothed data using the algorithm of the correlation dimension, is presented in Figure 5. Saturation tendency was remarked to the increase in the embedding dimension in the range of 1 to 10, the saturation value being smaller for normal subjects (for example 2.336, (Fig. 5, left) in comparison to 2.580, (Fig. 5, right) for two specific subjects).

According to Table 1, where average values are given, in the normal subjects the correlation dimension is 2.151, while in emotionally stressed patients the corresponding value is 2.314. The influence of signal noise was found remarkable, since in the raw data, the auto-correlation dimension was over 4, unacceptable for the size of the data series, so that smoothing was necessary. In Table 1, all the values corresponding to the two studied ECG groups are given. To see whether the difference between the average values is significant, the t-test was applied and the probability p was found equal to 0.010, meaning statistical significance at the level of 0.01.

ECG trajectories divergence

The largest Lyapunov exponent values seem to not differ much between the two groups of ECG recordings. The average values are 0.147 and 0.123, suggesting an increase in the stressed subjects, but the difference between the two average values does not seem to be significant statistically (Table 1).

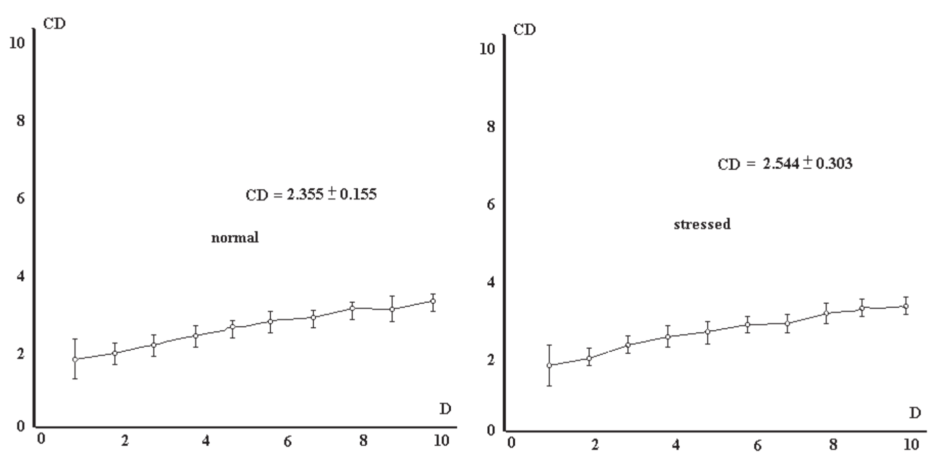


Figure 5. CD for ECG recorded in normal humans (left) and stressed ones (right) – numerical smoothed data. CD, correlation dimension; D, embedding dimension.

The t-test provided a small p value (0.061) exceeding the statistical significance level (0.05), so the difference cannot be considered statistically significant in this situation. We conclude that the computational test based on the largest Lyapunov exponent did not reveal the influence of stress on the heart activity.

ECG wavelet transformations

Wavelet analysis led to the Haar wavelet diagrams presented in Figure 6. The charts of this figure should be understood considering that the gray scale from white to black corresponds to the function values (on the third coordinate axis) ranging from zero to the maximum.

For low time scales (small DT values), the periodic trend is the dominant behavioral component in both cases whatever the time value is considered (grey fields alternating with white ones); for stressed subjects, the frequency of color fluctuation is higher. When the observation scale increases, the complexity of the 3-D function projection increases too: two structures shaped for low as well as for high time values corresponding to two peaks (black areas correspond to high wavelet function values) with crater shape (white areas surrounded by black ones). In the normal subjects (Fig. 6, left), the wavelet transform chart presents more symmetry and regularity, while for the stressed subjects (Fig. 6, right), the structures revealed by the wavelet diagrams are more contorted, corresponding to the higher degree of fluctuations visible also in Figs. 1 and 2.

It is difficult to say, however, if the apparently higher degree of symmetry in the normal ECG signal can be taken actually as an evidence of its higher complexity or not.

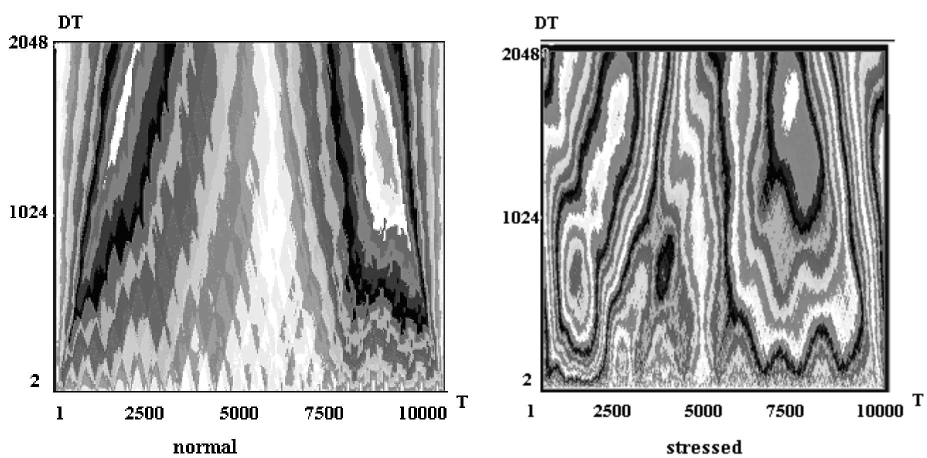


Figure 6. Wavelet transform for normal subjects (left) and for stressed subjects (right). T, time; DT, time scale.

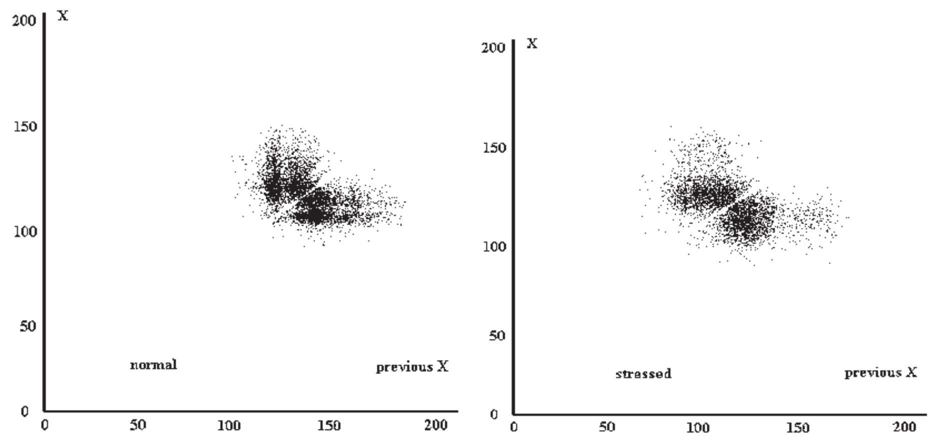


Figure 7. The surrogate data. Return maps (Poincaré sections): normal subjects (left), stressed patients (right).

Surrogate data of ECG signals

In comparison to the initial data series, the surrogate data exhibited different power spectra, wavelet graphs and correlation functions, as expected following the raw data shuffling. The Poincaré sections seem to be the most helpful graphs (Figure 7), since the discernable shape of the system attractor is revealed in both cases, while for the stressed subjects (Fig. 7, right) the fuzzy feature is more visible than for the normal subjects. We may say that more symmetry in the structure of the Poincaré section is visible in the case of normally relaxed subjects (Fig. 7, left), which is in accordance with the smaller value of the attractor fractal dimension.

In conclusion, the above results indicate that the complex dynamics of heart activity is significantly influenced by stress load as shown by means of the correlation dimension, Poincaré sections, and auto-correlation times.

The physiology of the stress hormone, adrenaline, might be invoked for a physiological comment related to the interpretation of the results of the semi-quantitative analysis carried out on electrocardiogram data.

Conclusion

Though the semi-quantitative tests applied to the ECG signal analysis are not able to provide specific information regarding the intrinsic mechanisms of the heart, they might lead to a more "coloured" picture of the modifications induced by the physiological condition of stress. The human heart remains a complex system with non-stationarity features, though the classical view is focused on the quasi-periodic character of its activity. The interpretation based on chaos theory seems to be rather adequate for the theoretical approaches of heart non-linear pulsation and the future could show us clinical diagnostic and prognostic applications derived from new semi-quantitative tests that are expected to be devised.

References

Arita S. (2001): Chaotic index of electrogastrograms responses with stress and its clinical applications. Proceedings of 2nd International Symposium on Advanced Intelligent System, VJMED **2**, 108—111

Arita S., Yoshii K., Ishihara S., Takeda T. (2002): Time series analysis of electrocardiogram and pulse wave responses. Int. J. Chaos Theory Appl. **7**, 81—84

Babinec P., Zemanová L., Babincová M. (2002): Randomness and determinism in human heart-beat dynamics: recurrence plot analysis. Phys. Med. **17**, 63—66

Bernaola-Galvan P., Ivanov P. Ch., Amaral L. A., Stanley H. E. (2001): Scale invariance in the nonstationarity of human heart rate. Phys. Rev. Lett. **87**, 168105—168109

Bracic-Lotric M., Stefanovska A., Stajer D., Urbancic-Rovan V. (2000): Spectral components of heart rate variability determined by wavelet analysis. Physiol. Meas. **21**, 441—457

Creanga D. E., Ursu D., Gheorghiu M., Radu C. (2000): An insight in the electrocardiographic signal by means of wavelet analysis. 2nd European Symposium in Biomedical Engineering and Medical Physics (Patras, Greece), Abstract book BME 18

Crutchfield J. P., Farmer J. D., Packard W. (1986): Chaos. Sci. Am. 254, **12**, 46—51

Dafilis M. P., Liley D. T., Cadusch J. (2001): Robust chaos in a model of the electroencephalogram: implications for brain dynamics. Chaos **11**, 474—479

Daubechies I. (1996): Where do wavelets come from? Proceedings of the IEEE (Special Issue on Wavelets) **84**, 510—513

Evans D. J., Cohen E. G., Morris G. P. (1990): Viscosity of a simple fluid from its maximal Lyapunov exponents. Phys. Rev., A **42**, 5990—5997

Fortrat J. O., Yamamoto Y., Hughson R. L. (1997): Respiratory influences on non-linear dynamics of heart rate variability in humans. Biol. Cybern. **77**, 1—10

Goldberger A. L., West B. J. (1999): Chaos in physiology: health or disease? NATO ASI Ser. A, Life Sci. **138**, 143—156

Grassberger P., Procaccia I. (1983): Characterization of strange attractors. Physica D **9**, 198—208

Igekuchi T., Aihara K. (1997): Estimating correlation dimension on biological time series with a reliable method. J. Intell Fuzzy Syst. **5**, 33—52

Jing H., Takigawa M. (2000): Low sampling rate induces high correlation dimension on electroencephalograms from healthy subjects. Psychiatry Clin. Neurosci. **54**, 407—412

Kimura Y., Okamura K., Watanabe T., Yaegashi N., Uehara S., Yajima A. (1998): Time-frequency analysis of fetal heartbeat fluctuation using wavelet transform. Am. J. Physiol., Heart Circ. Physiol. **275**, H1993—1999

Kumar K., Tan C., Ghosh R. (1999): A hybrid system for financial trading and forecasting. S. Asian J. Manage. **5**, 1—8

Lass J. (2002): Biosignal interpretation: study of cardiac arrhythmias and electromagnetic field effects on human nervous system (PhD thesis), pp. 13—16, TTU press, Tallin

Lin D. C., Hughson R. L. (2001): Modeling heart rate variability in healthy humans: a turbulence analogy. Phys. Rev. Lett. **86**, 1650—1653

May R. (1991): Le chaos en biologie. Recherche **232**, 588—594

Pichot V., Buffiére S., Gaspoz J. M., Costes F., Molliex S., Duverney D., Roche F., Barthlmy J. C. (2001): Wavelet transform of heart rate variability to assess autonomic nervous system activity does not predict arousal from general anesthesia. Can. J. of Anaesth. **48**, 859—863

Pomfrett C. J. (1999): Heart rate variability, BIS and depth of anaesthesia. Br. J. Anaesth. **82**, 559—661

Reidbord S. P., Redington D. J. (1992): Psychophysiological processes during insight-oriented therapy. Further investigations into nonlinear psychodynamics. J. Nerv. Ment. Dis. **180**, 649—657

Schreiber T., Schmitz A. (2000): Surrogate time series. Physica D **142**, 346—382

Sleight J. W., Donovan J. (1999): Comparison of bispectral index, 95% spectral edge frequency and approximate entropy of the EEG, with changes in heart rate variability during induction of general anaesthesia. Br. J. Anaesth. **82**, 666—671

Sprott J. C., Rowlands G. (1994): Chaos Data Analyzer. American Institute of Physics, NY, USA

Takens F. (1981): Detecting Strange Attractor in Turbulence. In: Dynamical Systems of Turbulence (Eds. D. A. Rand and L. S. Young), Vol. 898, pp. 366—381, Springer Verlag, Berlin

Thurner S., Feurstein M. C., Teich M. C. (1998): Multiresolution wavelet analysis of heartbeat intervals discriminates healthy patients from those with cardiac pathology. Phys. Rev. Lett. **80**, 1544—1547

Toledo E., Gurevitz O., Hod H., Eldar M., Akselrod S. (1998): The use of a wavelet transform for the analysis of nonstationary heart rate variability signal during thrombolytic therapy as a marker of reperfusion. Comput. Cardiol. **25**, 609—612

Toledo E., Gurevitz O., Hod H., Eldar M., Akselrod S. (2003): Wavelet analysis of instantaneous heart rate: a study of autonomic control during thrombolysis. Am. J. Physiol., Regul. Integr. Comp. Physiol. **284**, R1079—1091

Webber C. L. Jr., Zbilut J. P. (1994): Dynamical assessment of physiological systems and states using recurrence plot strategies. J. Appl. Physiol. **76**, 965—973

Yoshikawa Y., Yasuda Y. (2003): Non-linear dynamics in heart rate variability in different generations. Bull. Toyohashi Sozo College **7**, 63—78

Final version accepted: April 21, 2006