FRACTAL AND SYMBOLIC ANALYSIS OF HEART RATE VARIABILITY AND SLEEP STAGING

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Abstract: We apply fractal and symbolic nonlinear time series analysis methods for evaluation of heart rate variability in different sleep stages. This work is the first attempt to apply Higuchi's fractal dimension method and newly proposed symbolic dynamics method to analyze rhythmograms in wakefulness and sleep. We demonstrate that these methods are useful in evaluation of sleep patterns.

Introduction

Application of nonlinear algorithms for processing biological signals becomes more and more important [1]. Nonlinear and symbolic dynamics methods, including chaos theory and fractal geometry, have been applied to biomedical signal and image analysis ([2]-[4]). It was demonstrated that these methods are useful for understanding complex physiological phenomena such as electrophysiology of the heart [5], night sleep with its shifts of sleep stages observed in EEG-signals [6] and in sustained fluctuations of autonomic functions (temperature, blood pressure, heart rate, etc.) Clinical investigations reveals chaotic components in heart rate (HR) data previously described as periodic, sinus rhythm; the changes of Heart Rate Variability (HRV) during individual sleep stages were demonstrated [7].

In this paper we apply fractal and symbolic nonlinear time series analysis methods for evaluation of HRV in different sleep stages. This work is the first attempt to apply Higuchi's fractal dimension method and newly proposed symbolic dynamics method to analyze rhythmograms in wakefulness and sleep. We demonstrate that these methods are useful in evaluation of sleep patterns.

Materials and Methods

The contingent was 3 healthy subjects: one adolescent girl, 14 years old, one 27-year woman, and one 44-year man. HRV data (RR intervals) throughout all night sleep stages were registered in the Sleep Medicine Centre of the Institute of Psychophysiology and Rehabilitation in Palanga, Lithuania.

Polygraphic recordings of EEG, EOG, and EMG were obtained using polysomnography system Alice-4. A *rhythmogram* (a sequence of successive values of RR-intervals of ECG) was constructed from the ECG sampled at 500 Hz. Convenional computerized analysis of HR, including power spectrum analysis, was performed. Three major oscillatory components of HR power spectrum were used as a noninvasive instrument, reflecting autonomic HR control: (i) very low frequency component (VLFC), associated with thermoregulatory influence; (ii) low frequency component (LFC), reflecting predominantly sympathetic control; (iii) high frequency component (HFC), reflecting parasympathetic one [8]. Sleep structure was analyzed after visual identification of sleep stages according to Rechtschaffen and Kales [11].

EEG and other biosignals are usually very noisy and they remain stationary only during very short intervals.One often forgets that *linear methods* (like FFT or wavelet transform) *work properly only for stationary signals*.

Nonlinear analysis of the data collected in Palanga Sleep Medicine Center was performed in the Group of Biosignal Analysis Fundamentals (GBAF) of the Medical Research Center Polish Academy of Sciences, Warsaw. Both Centers are partners in the EU FP6. project SENSATION (IST 507231) (cf. [12]). In GBAF we apply mainly two nonlinear methods of biosignal (represented as a time series) analysis - Higuchi's fractal dimension method and a symbolic dynamics method. Both methods assess *signal complexity (*[13]-[14]).

A. Higuchi's fractal dimension method

Fractal methods were applied in analysis of HRV complexity [15] and HRV during sleep [16]. Higuchi's algorithm ([17]-[18]) calculates *fractal dimension* of a time series directly in the time domain. It is based on a measure of length, *L(k)*, of the curve that represents the considered time series while using a segment of k samples as a unit. If *L(k)* scales like

$$L(k) \sim k^{-D_f} \qquad (1)$$

the curve is said to show *fractal dimension* D_f. Because a simple curve has dimension equal *1* and a plane has

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dimension equal *2* value of D_f is always between *1* (for a simple curve) and *2* (for a curve which nearly fills out the whole plane). D_f measures *complexity* of the curve and so complexity of the time series of which this curve is a graphical representation.

From a given time series

$$X(1),\ \ldots,\ X(r),\ \ldots,\ X(N)$$

the algorithm constructs k new time series

$$X^k_m:\ X(m),\ X(m+k),\ X(m+2k), \ldots,\ X(m+i)$$

$$i = \text{int}\,[(N-m)/k) * k] \quad \text{for} \quad m=1,2,\ldots,k$$

where m – initial time, k – time interval, and int*[.]* – denotes integer part of its real argument.

For example, for $k=4$ and $N=1000$ the algorithm produces 4 time series:

$$X^4_1 : X(1), X(5), X(9), \ \ldots, X(997)$$
$$X^4_2 : X(2), X(6), X(10), \ldots, X(998)$$
$$X^4_3 : X(3), X(7), X(11), \ldots, X(999)$$
$$X^4_4 : X(4), X(8), X(12), \ldots, X(1000)$$

The 'length' $L_m(k)$ of each curve X^k_m is then calculated as:

$$L_m = \frac{1}{k}\cdot\left[\left(\sum_{i=1}^{\text{int}\left(\frac{N-m}{k}\right)}\left|X(m+i\cdot k)-X(m+(i-1)\cdot k)\right|\right)\cdot\frac{N-1}{\text{int}\left(\frac{N-m}{k}\right)\cdot k}\right] \quad (2)$$

where N – the total number of samples

$L_m(k)$ is not the 'length' in Euclidean sense, it represents the normalized sum of absolute values of difference in ordinates of pair of points distant k (with initial point m).

The length of curve $L(k)$ for the time interval k is then calculated as the mean of the k values $L_m(k)$ for $m=1, 2, \ldots, k$

$$L(k) = \frac{\sum_{m=1}^{k} L_m(k)}{k}$$

The value of fractal dimension, D_f is calculated by a least-squares linear best-fitting procedure as the angular coefficient of the linear regression of the log-log graph of (1):

$$\ln\,[L(k)] \sim \ln\left(\frac{1}{k}\right) \quad (3)$$

according to the following formulae:

$$D_f = \frac{n*\sum(x_k * y_k) - \sum x_k \sum y_k}{n*\sum\left(x_k^{\,2}\right) - \left(\sum x_k\right)^2}$$

with standard deviation:

$$S_{Df} = \sqrt{\frac{n\left[\sum y_k^{\,2} - D_f * \sum x_k y_k - \bar{b} * \sum y_k\right]}{(n-2)*\left[n*\sum x_k^{\,2} - \left(\sum x_k\right)^2\right]}}$$

where $x_k = \ln\left(\frac{1}{k}\right)$, $y_k = \ln\,[L(k)]$, for $k = k_1, \ldots, k_{max}$ and n denotes the number of k-values for which the linear regression is calculated ($2 \le n \le k_{max}$). Higuchi's fractal dimension is a quantifier which can be evaluated without reconstruction of the system's phase space [13]. Contrary to other methods e.g. correlation dimension it requires only short time intervals – a window containing 100 data point is enough to calculate one value of Higuchi's fractal dimension. The algorithm is also highly resistive to noise [18]. The algorithm is fast and may be implemented in real time even on a PC.

We have been using Higuchi's method for analysis of EEG-signals ([6], [14], [18]). The method was applied recently to HRV analysis of twenty-four-hours ECG [19]. But this work is the first attempt to apply Higuchi's method to analyze rhythmograms in wakefulness and different sleep stages. So, we analyze time series $X(r)$, where index r numbers heart cycles (beats) and X denotes the length (in milliseconds) of the r-th RR-interval of ECG.

We use moving window of length $W=100$ points (beats) that is moved $w=1$ point at each step (i.e. overlapping segment is equal 99), and D_f value calculated in the window is attributed to the first point (beat) following that window. The value $k_{max} = 8$ is used that should be proper for such a length of the window (cf. [18]).

B. Symbolic dynamics method

Symbolic and nonlinear methods find interesting application in ECG and HRV signal analysis ([20]-[25]). Our own symbolic method that is still under development ([6],[14]) differs from other ones that it is applied rather to the binary encoded time series 'derivative' than to the time series itself.

We represent the derivative time series in a binary form, with *'1'* corresponding to non-negative and *'0'* to negative value of the difference

$$Y(j) = \begin{cases} 1 & \text{if } [X(r+1) - X(r)] \ge 0 \\ 0 & \text{if } [X(r+1) - X(r)] < 0 \end{cases} \quad (4)$$

Then this binary series is encoded in a sequence of B-bit symbols, z_q :

$$Z(q) = Z\,[Y(j), Y(j+1), \ldots, Y(j+B-1)] \ \leftrightarrow\ z_q \in \mathbf{A} \quad (5)$$

$$q = 1, \ldots, Q = \text{int}[I/B]\,; \quad j = 1, \ldots, (qB+1), \ldots, BQ$$

where

$\mathbf{A} = \{a_0, \ldots, a_{L-1}\}$ - the *alphabet*; $\mathbf{L} = 2^B$

In particular,

$$z_q \in \mathbf{A} = \{ 0, 1, 2, 3, \ldots, (2^B - 1) \} \subset \mathbf{N}$$

that is the alphabet may consist of B-bit integer decimal numbers.

Symbolic series $z_1, \ldots, z_Q$ can be analyzed using *moving-window* - numbers of chosen symbols are counted in a W-symbols-long window and the window is then moved along $w \le W$ symbols again and again until the entire symbolic series is covered. This way *Running Symbols' Count Values* (RSCV) of counts of chosen symbols in the series $Z(q)$ are calculated, e.g. the counts L_{Bx0} of symbol *'decimal 0'* that encodes the B-bits sequence $Bx0$ (i.e.$[000\ldots]_B$) in the binary series $Y(j)$ (5); for $B=4$ this symbol is '*decimal 15'*. For analysis of rhytmograms we choose *4*-bits symbols ($B=4$); we use moving window of length $W=100$ symbols (i.e. *400* beats), that is moved in each step $w=5$ symbols (*20* beats), i.e. overlapping segment is *95* symbols (*380* beats) long. The greater the value of L_{4x0} the more persistently RR-interval length diminishes, i.e. the more persistently HR increases.

C. HR and HRV during sleep stages and cycles

In healthy subjects, HR markedly decreased in non-REM sleep and increased in REM sleep. Fig.1. shows the HR time course during night sleep for a subject displaying the typical HR sleep pattern. The transition from wakefulness to stage 1 and stage 2 was accompanied by a marked decrease of HR, which continuously progressed during stages 3 and 4.

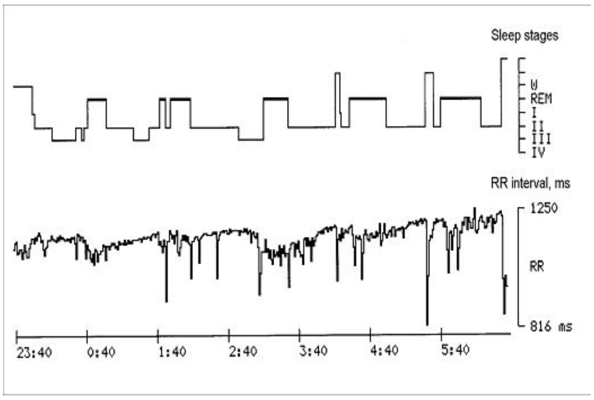

Figure 1: Heart rate (RR interval) during shifts of sleep stages.
Abscissa: time from the onset of experiment;
Ordinate: hypnogram reflecting sleep stages
(*W* – wakefulness; *REM* - rapid eye movement sleep;
I, II, III, and *IV* - NREM sleep stages);
heart period [msec] as measured by RR intervals (*RR*).

This was contrasted by an increase of HR in REM sleep. The HR modifications correspond to cyclic modification of scored sleep stages. HR modification within a single sleep cycle were accompanied by changes in respiratory arrhythmias, which increased during non-REM sleep and decreased in REM sleep.

HRV during different sleep stages depends mainly on the changes of autonomic control. In all three healthy subjects the wakefulness was characterized by moderate HRV, normal HR frequency, and respiratory arrhythmia. The transition from wakefulness to stages 1 and 2 was paralleled by a progressive decrease of HR frequency and an increase of HRV and respiratory arrhythmia. The absolute values for each oscillatory component were equal during wakefulness. A decrease in total spectral power, largely accountable for by LFC was observed during non-REM sleep, especially in stage 4. In REM sleep an increase in total spectral power, largely accountable for by marked prevalence of LFC due to small contribution of MFC and HFC was observed. The relative contribution of LFC gradually diminished during non-REM sleep and increased in REM sleep. MFC contribution remained relatively constant throughout all the stages of sleep. The contribution of HFC gradually rising during non-REM sleep dropped markedly in REM sleep. Therefore we may suggest an increase of parasympathetic control and a decrease of sympathetic and metabolic ones during non-REM sleep, while this pattern of control is being reversed in REM sleep [8, 10].

Thus, the changes of autonomic control during individual sleep stages modify the HR and HRV structure. The question arises – can the non-linear methods of analysis reflect the HR modifications during sleep?

Results

HRV all night sleep data were analyzed using Higuchi's fractal dimension and our symbolic dynamics methods (Fig. 2.).

HRV analysis during all night sleep using Higuchi's fractal dimension demonstrates some scattering of D_f values throughout the night in a healthy adult male (Fig.2a). The maximal values of D_f are observed during slow wave sleep stages 3 and 4, while the minimal ones are prevalent during REM sleep and stage 1. The time-course trend of D_f during the night has an oscillatory structure which corresponds to the cyclic shifts of sleep stages and cycles. This is clearly evident in D_f plot during the first sleep cycle in male subject (Fig.2a). D_f values increases in stage 4 with mostly expressed parasympathetic input into the HR control and reach their nadir in REM sleep which is characterized by a withdrawal of vagal control [10].

The similar pattern of HRV analysis during night sleep was obtained using symbol dynamic method (Fig.2b). L_{4x0} , the counts of symbol *'4x0'* (decimal *'15'*), values modifications during sleep correspond the changes of sleep stages, although the changes have opposite direction. The L_{4x0} decreases during sleep stages 3 and 4 and increases in REM sleep.

The HRV analysis of all-night sleep in female (Figs. 2c and 2d) and adolescent girl (Figs. 2e and 2f) demonstrate the similar patterns of D_f and L_{4x0} values throughout the night. Although in adolescent girl, the changes of D_f and L_{4x0} values goes at the higher and lower baseline level, correspondingly. It might be explained by more expressed parasympathetic and sympathetic inputs to HR control seen in younger subjects [7, 9].

In Fig.3a we can see an increase of D_f values practically to 2.0 during the stages 3 and 4 of the first sleep cycle. Detail analysis of ECG during this period revealed the sinoatrial blockades, which are characteristic for teenagers and can be elicited by the augmented parasympathetic input into the HR control.

Thus, analysis of HRV using Higuchi's fractal dimension method and our symbolic dynamics method might be useful in detection of some HR disturbances and discrimination of the sinus rhythm from the abnormal one.

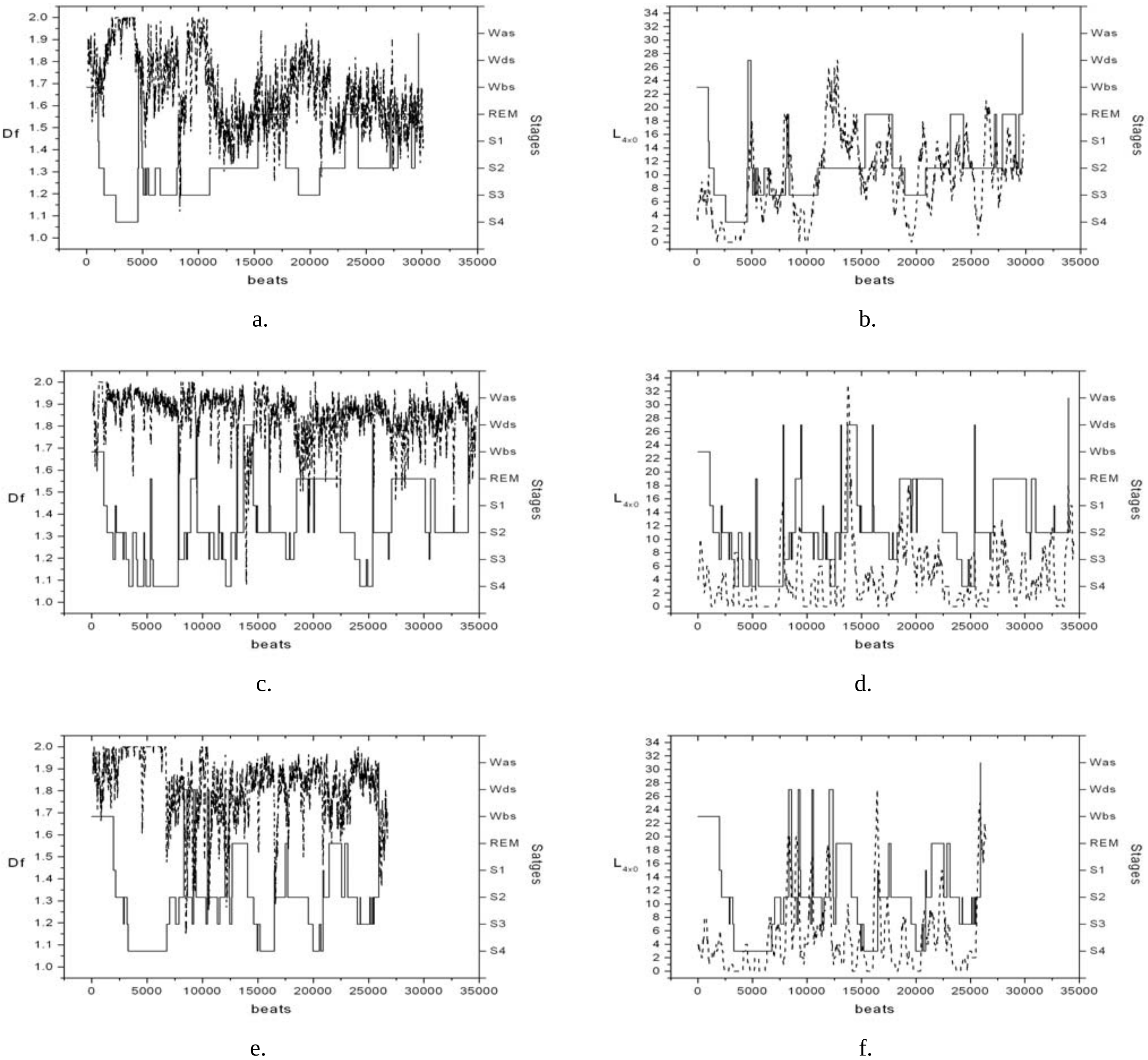

Figure 2: Hypnograms and results of HRV analysis during all-night sleep in three cases:
case 1 - 44-years old man (a., b.); case 2 - 27-years old woman (c., d.); case 3 - 14-years old adolescent girl (e., f.).
left (a., c., e.) – Higuchi's fractal dimension method; right (b., d., f.) – symbolic dynamics method;
S1, S2, S3, S4 denote non-REM sleep stages 1,2,3, and 4, respectively; *REM* sleep;
Wbs - wakefulness befor sleep; *Wds* - wakefulness during sleep; *Was* - wakefulness after sleep.

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Conclusions

Application of non-linear methods of analysis can be useful for evaluation of different states of HR control during sleep. Clear-cut differences might be seen in periodical structure of HRV data pictures corresponding different sleep stages. Plots of D_f and L_{4x0} values for time-course of night sleep demonstrate quasi-periodic oscillations, which correspond to the shifts of sleep stages during consecutive sleep cycles.

Changes of D_f and L_{4x0} values during night sleep can clearly reflect the transition from one to another state. The obtained results confirm the nonlinear structure evidence in HRV data. The non-linear analysis of HRV using fractal dimension and symbolic dynamics methods might be a useful tool for assessment of different states during night sleep and in qualitative evaluation of HR sleep pattern and the baseline level of autonomic HR control.

Considered nonlinear methods may find application in semiautomatic construction of hypnograms based on sleep HRV data.

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References

[1] CERUTTI, S., CARRAULT, G., CLUITMANS, P.J., KINIE, A., LIPPING, T., NIKOLAIDIS, N., PITAS, I., and SIGNORINI, M.G. (1996): 'Nonlinear algorithms for processing biological signals', Comp Met Prog Biomed, **51**, pp. 51-73

[2] PRINCIPE, J.C., YU, F.S. and REID, S.A. (1990): 'Display of EEG chaotic dynamics', Proceedings of the 1st Conference on Visualization in Biomedical Computing, IEEE Comput. Soc. Press., pp. 346-351, Los Alamos, CA, USA

[3] TANG, Y.Y., TAO, Y., and LAM, E.C.M. (2002): 'New method for feature extraction base on fractal behavior', Pattern Recognition, **35**, pp. 1071-1081

[4] KLONOWSKI, W. (2000): 'Signal and Image Analysis Using Chaos Theory and Fractal Geometry', Mach.Graph.Vis., **9,** pp. 403-431, http://hrabia.ibib.waw.pl/~lbaf/PDF_Doc/gkpo2000.pdf

[5] GOLDBERGER, A.L. (1992): 'Fractal mechanisms in the electrophysiology of the heart', IEEE Engng in Medicine and Biology, **47**, p. 53

[6] KLONOWSKI, W., OLEJARCZYK, E., STEPIEN, R., and SZELENBERGER, W. (2003): 'New Methods of Nonlinear and Symbolic Dynamics in Sleep EEG-Signal Analysis', in: Feng, D.D., and Carson, E.R.: 'Modelling and Control in Biomedical System', IFAC Publications, Elsevier, Oxford, pp. 241-244

[7] KLONOWSKI, W.. OLEJARCZYK, E., STEPIEN, R., and SZELENBERGER, W. (2004): 'Complexity of Polysomnogram Signals', WSEAS Transactions on Computers, **3**, pp. 1290-1294

[8] VARONECKAS, G., 'Heart rate and central hemodynamics during individual sleep stages and cycles' (1994) (Rus.), Fiziologija Cheloveka., **20**, pp. 76-83

[9] ZEMAITYTE, D., VARONECKAS, G., PLAUSKA, K. and KAUKENAS, J. (1986): 'Components of the heart rhythm power spectrum in wakefulness and individual sleep stages', Int. J. Psychophysiol., **4,** pp. 129-141

[10] ZEMAITYTE, D., VARONECKAS, G., DUONELIENE, D. I. , and DAUKSYS, R. (2000): 'Changes in the cardiovascular function in healthy subjects and patients with ishemic heart disease during sleep', Human Physiology, **26**, pp. 692-702, translated from Fiziologiya Cheloveka, **26**, pp. 50-61..

[11] ZEMAITYTE, D., VARONECKAS, G., SOKOLOV, E. (1984): 'Heart rhythm control during sleep', Psychophysiology, **21**, pp. 279-289

[12] RECHTSCHAFFEN, A., and KALES, A. (1968): 'A Manual of Standardized Terminology, Techniques, and Scoring for Sleep Stages in Human Subjects', Wash. D.C., U.S. Government Printing Office

[13] PENZEL, T., BECKER, H.F., BEKIARIS, E. and AMDITIS, A. (2004): 'Monitoring of sleepiness in the traffic and work environment', Medicon and Health Telematics 2004, 31 July – 5 August, 2004, Ischia, Italy, IFMBE, Vol. 6, 2004. Paper 234, ISBN: 88-7780-308-8, ISSN:1727-1983

[14] KLONOWSKI, W. (2002): 'Chaotic dynamics applied to signal complexity in phase space and in time domain', Chaos, Solitons and Fractals, **14**, pp. 1379-1387

[15] KLONOWSKI, W., OLEJARCZYK, E., STEPIEN, R. (2004): 'Complexity of Polysomnogram Signals', WSEAS Transactions on Computers, **3**, pp. 1290-1294

[16] SASSI, R. (2000): 'Analysis of HRV complexity through fractal and multivariate approaches', PhD Thesis, Politecnico di Milano, Italy

[17] TOGO, F. and YAMAMOTO, Y. (2001): 'Decreased fractal component of human heart rate

variability during non-REM sleep', American Journal of Physiology, Heart and Circulatory Physiology, **280**, pp. H17-H21

[18] HIGUCHI, T. (1988): 'Approach to an irregular time series on the basis of the fractal theory', Physica D, **31,** 277-283

[19] OLEJARCZYK, E., (2003): 'Analysis of EEG signals using fractal dimension', PhD Thesis, Thesis Supervisor: Prof. KLONOWSKI, W. Institute of Biocybernetics and Biomedical Engineering, Polish Academy of Sciences, Warsaw

[20] D'ADDIO, G., .ACCARDO, A., PINNA, G.D., MAESTRI, R., and RENGO, F. (2004): 'Twenty-four-hour fractal dimension analysis of heart rate variability in noltisalis database', Medicon and Health Telematics, 31 July – 5 August, 2004, Ischia, Italy, IFMBE, Vol. 6, 2004. Paper 509, ISBN: 88-7780-308-8, ISSN:1727-1983

[21] HONGXUAN, Z. and YIESHENG, Z. (2002): 'Qualitative chaos analysis for ventricular tachycardia and fibrillation based on symbolic complexity', Med. Eng. Phys., **23**, pp. 523-528

[22] WESSEL, N., SCHWARTZ, U., SAPARIN, P.I., KURTHS, J. (2002): 'Symbolic Dynamics for Medical Data Analysis', in: Klonowski W.: 'Attractor, Signals, and Synergetics', pp. 45-61, Proceedings of the 1st European Interdisciplinary School on Nonlinear Dynamics for System and Signal Analysis EUROATTRACTOR2000, Pabst Science Publishers, Lengerich, Berlin

[23] ZEBROWSKI, J.J. (2002): 'Types of Dynamical Order and some Physiological Processes', in: Klonowski W.: 'Attractor, Signals, and Synergetics', pp. 243-255, Proceedings of the 1st European Interdisciplinary School on Nonlinear Dynamics for System and Signal Analysis EUROATTRACTOR2000, Pabst Science Publishers, Lengerich, Berlin

[24] BARBI, M., CHILLEMI, S., and DI GARBO, A. (2003): 'Time Series Analysis by Nonlinear Prediction and Application to the Heart Rhytm', in: Klonowski, W.: From Quanta to Societies, pp. 123-129, Proceedings of the 2nd European Interdisciplinary School on Nonlinear Dynamics for System and Signal Analysis EUROATTRACTOR2001, Pabst Science Publishers, Lengerich, Berlin

[25] SÄKKI, M., KALDA, J., VAINU, M., and LAAN, M. (2004): 'On the Zipf's Law in Human Heartbeat Dynamics', in: Klonowski, W.: Simplicity behind Complexity**,** 211-219, Proceedings of the 3rd European Interdisciplinary School on Nonlinear Dynamics for System and Signal Analysis EUROATTRACTOR2002, Pabst Science Publishers, Lengerich, Berlin,.

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