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Original article

Effect of reflexological stimulation on heart rate variability

Effet de la stimulation reflexe sur la variabilité du rythme cardiaque

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Abstract

Analysis of heart rate variation (HRV) has become a popular non-invasive tool for assessing the activities of the autonomic nervous system (ANS). HRV analysis is based on the concept that fast fluctuations may specifically reflect changes of sympathetic and vagal activity. It shows that the structure generating the signal is not simply linear, but also involves non-linear contributions. These signals are essentially non-stationary and may contain indicators of cardiac health. This work is an attempt made to do a quantitative study on the effect of reflexology on the heart rate variability (HRV) during reflexologic stimulation. The non-linear parameters are evaluated for this study and the results obtained for 20 subjects are tabulated.

Résumé

L'analyse de la variation de fréquence cardiaque (HRV) est devenue un outil non invasif très répandu pour évaluer les activités du système nerveux autonome. L'intérêt de la HRV réside dans le fait que les fluctuations rapides peuvent spécifiquement refléter des changements d'activité des systèmes sympathique et vagal. Elle prouve que la structure produisant du signal n'est pas simplement linéaire et met en jeu des fonctionnements non-linéaires. Les signaux sont essentiellement non stationnaires et peuvent refléter des dysfonctionnements cardiaques. Ce travail tente de faire une étude quantitative de l'effet des stimulations réflexologiques sur la variabilité de la HRV. Les paramètres non linéaires sont évalués dans cette étude et les résultats obtenus pour 20 sujets sont présentés.

Keywords: Heart rate; Reflexology; Correlation dimension; Largest Lyapunov exponent

Mots clés : Rythme cardiaque ; Réflexologie ; Dimension de correlation ; Exposant de Lyapunov

1. Introduction

Reflexology is the art and science of working on specific reflex points (areas) on the hands, feet, and ears to relax and relieve stress and pain in the body. In clinical terms, reflexology is the application of pressure, primarily, but not limited to the feet hands or ears which causes a physiological response in the body. Reflexology originated in China about 4000 BC. First recorded history of reflexology is in 2330 BC in Egypt. They were masters in setting bones, caring for wounds and treating illness. They recorded the medical practices through drawings of surgical operations and medical treatments. The movement is traced from India to China and then to Japan. Reflexology is a science based on the principles that reflexes or areas on the hands, feet and ears of the body relate to internal organs and other structures of the body. It was introduced to the west by Dr. William Fitzgerald [25]. In reflexology the feet, hands and ears are seen as a perfect microcosm of the body, with somatic replications of all organs, glands and muscles of the body on an area or

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reflex point. As a science, it is the study of relieving pain and stress in the body through touch using alternating pressure.

Reflexology embraces all body systems and organs, physical: by unlocking, stimulating and improving circulation; mental: through the application of touch and its therapeutic affect on the body; and emotional: the universal connection at the subtle level with client to relieve pain and relax the body. We have used non-linear signal processing parameters to estimate the quantitative difference between the two HRV signals: one without reflexology and the other one under reflexological stimulation. Reflexology being a healing art working on the subtle planes of the human body, we are using subtle tools for investigating the same.

Siev-Ner et al. [37] have evaluated the effect of reflexology on the subjects with symptoms of multiple sclerosis. They successfully showed that the specific reflexology treatment (manual pressure on specific points at feet and massage of calf area) alleviates the motor, sensory and urinary symptoms in multiple sclerosis subjects. Frankel [11] has showed the positive effects of reflexology on the baroreceptor reflex sensitivity, blood pressure and sinus arrhythmia. Grealish et al. [29] have shown the effect of foot massage and reflexology on decreasing the anxiety, pain and nausea in patients with cancer. Bishop et al. [4] have proved that reflexology is an effective method of treating encopresis and constipation patients. Christ Stormer has clearly explained the healing effect of reflexology on respiratory, circulatory, and cardiac disorders. Most recently, Jennifer et al. [15] have studied the impact of foot massage and guided relaxation following the cardiac surgery.

1.1. Heart rate variability

Electrocardiography deals with the electrical activity of the heart. Monitored by placing sensors at the limb extremities of the subject, electrocardiogram (ECG) is a record of the origin and propagation of the electric potential through cardiac muscles. It is considered a representative signal of cardiac physiology, useful in diagnosing cardiac disorders. The state of cardiac health is generally reflected in the shape of ECG waveform and heart rate. It may contain important pointers to the nature of diseases afflicting the heart. However, bio-signals being non-stationary signals, this reflection may occur at random in the time scale. Therefore, for effective diagnostics, the study of ECG pattern and heart rate variability (HRV) signal (instantaneous heart rate against time axis) may have to be carried out over several hours. HRV is a useful signal for understanding the status of the autonomic nervous system (ANS).

Past 20 years have witnessed the recognition of the significant relationship between autonomic nervous system and cardiovascular mortality including sudden death due to cardiac arrest [7,24,26,36,39]. Because of the significant results obtained in this area, a task force was set up by the Board of European Society of Cardiology and was co-sponsored by the North American Society of Pacing and Electrophysiology. Numerous numbers of papers appeared in connection with HRV-related cardiological issues [2,18,23,27] which reiterate the significance of HRV in assessing the cardiac heath. The interest in the analysis of HRV (that is, the fluctuations of the heart beating in time) is not new. Much progress was achieved in this field with the advent of cheap and massive computational power, which provoked many recent advances.

HRV is a non-invasive measurement of cardiovascular autonomic regulation. Specifically, it is a measurement of the interaction between sympathetic and parasympathetic activity in autonomic functioning. There are two main approaches for analysis: time domain analysis of HRV for standard deviation of normal to normal intervals (SDNN); and frequency domain analysis for power spectrum density (PSD). The latter provides high frequency (parasympathetic activity) and low frequency (sympathetic activity) and total power (sympathetic/parasympathetic balance) values. Spectral analysis is the most popular linear technique used in the analysis of HRV signals [1,33,42]. Spectral power in the high-frequency (HF: 0.15–0.5 Hz) band reflects respiratory sinus arrhythmia (RSA) and thus, cardiac vagal activity. Low frequency (LF: 0.04–0.15 Hz) power is related baroreceptor control and is mediated by both vagal and sympathetic systems. Very low-frequency (VLF: 0.0033–0.04 Hz) power appears to be related thermoregulatory and vascular mechanisms, and renin-angio tension systems.

Physiological signals often vary in a complex and irregular manner. Analysis of linear statistics such as mean values, variability measures, and spectra of such signals generally does not address directly their complexity and thus may miss potentially useful information. Since the underlying mechanisms involved in the control of heart rate mainly non-linear, the application of non-linear techniques seems appropriate [8,14,21,28].

Recently, new dynamic methods of HRV quantification have been used to uncover non-linear fluctuations in heart rate that are not otherwise apparent. Fell et al. [10] and Radhakrishna Rao et al. [34] have tried the non-linear analysis of ECG and HRV signals, respectively. Several methods have been proposed: correlation dimension (CD) [35] and Poincare plot geometry [31].

In one's life time, the legs and feet are under the pressure of the body's weight for approximately two thirds of time. The feet are the furthest extension of the body from the heart. Consequently, the blood which is pumped from the heart to feet and recirculated back to the heart will have an increase in difficulty in its ability to circulate. This may lead to various ailments in the legs and feet. The reflexology will allow the repeated movement of muscles to produce a very prominent overall pressuring action on the walls of the blood vessels in the lower extremities. These blood vessels will have more strength to contract and expand and will enhance circulation of blood back to heart. The heart will in turn have a greater supply of blood to nourish the body. Hence, there will be more variation in the heart rate and becomes more chaotic. In this work, three non-linear parameters CD, entropy and Poincare geometry (SD2) are used to find the effectiveness of the reflexology on the HRV signal.

2. Materials and methods

The ECG of 20 normal subjects (age between 17 and 21 years) was taken 20 min in lead II configuration in the relaxed sitting position. After this, the same subject was given reflexological stimulation just below the toes of both feet by a mechanical reflexological device (Massager-scroller type) in the same relaxed sitting for another 20 min. And the ECG was recorded using Power Lab/16SP system (ADI Instrument). The data are sampled at a sampling rate of 400 sps with a resolution of 12 bits/sample and stored in a random access file. *RR* interval is then found out [16,41].

The interval between two successive QRS complexes is defined as the *r–r* interval (t_{r-r} s) and the heart rate (beats per minute) is given as

$$\mathrm{HR} = 60/t_{r-r}. \quad (1)$$

2.1. Correlation dimension analysis

Recent developments in the theory of non-linear dynamics have paved the way for analyzing signals generated from non-linear living systems [5,30]. It is now generally recognized that these non-linear techniques are able to describe the processes generated by biological systems in a more effective way. The non-linear dynamical techniques are based on the chaos and it has been applied to many areas including the areas of medicine and biology. The theory of chaos has been used to detect some cardiac arrhythmias such as ventricular fibrillation [22]. Efforts have been made in determining non-linear parameters like CD for pathological signals and it has been shown that they are useful indicators of pathologies. Methods based on chaos theory have been applied in tracking HRV signals and predicting the onset events such as ventricular tachycardia detecting congestive heart failure situations [6]. A novel method based on a phase–space technique to distinguish normal and abnormal cases has been proposed for cardiovascular signals [32]. The technique has been extended here to identify the abnormalities of different types.

In the phase–space plot shown *X*-axis represents the *heart-rate X*[*n*] and the *Y*-axis represents the *heart-rate after a delay X*[*n* + delay]. The choice of an appropriate delay is calculated using the minimal mutual information technique [12,13].

The method of estimating the embedding dimension from the phase–space patterns was proposed by Grassberger and Procassia [14]. Other authors have verified that the embedding theorem restriction is sufficient, but not a necessary condition for dynamic reconstruction [9]. Nevertheless, the dimensionality of the attractor is usually unknown for experimental data and, therefore, the corresponding embedding dimension is unknown. In the present work, an embedding dimension of five was chosen [17]. The software used for analysis is CDA Pro Data analyzer.

CD was calculated using the fundamental definition

$$\mathrm{CD} = \lim_{r \to 0} \frac{\log C(r)}{\log(r)} \quad (2)$$

where the correlation integral $C(r)$ is given by

$$C(r) = \frac{1}{N^2} \sum_{x=1}^{N} \sum_{y=1, x \neq y}^{N} \Theta\left(r - \left|X_x - X_y\right|\right) \quad (3)$$

where $X_x, X_y \rightarrow$ the points of the trajectory in the phase–space;
$N \rightarrow$ is the number of data points in phase–space;
$r \rightarrow$ is the radial distance around each reference point X_i;
$\Theta \rightarrow$ is the Heaviside function.

2.2. Entropy

Entropy is a thermodynamic quantity describing the amount of disorder in the system. From information theory perspective, the above concept of entropy is generalized as amount of information stored in more general probability distribution. The theory was supported by the contributions by Shannon, Renyi, and Kolmogorov. In this work, we adapt the entropy measure defined by Kolmogorov called Kolmogorov–Sinei entropy (KS entropy) [20].

Entropy is determined from the embedded time series data by finding points on the trajectory that are close together in phase–space (i.e., have small separation) but which occur at different times (i.e., are not time correlated). These two points are then followed into observe how rapidly they move apart from one another. These two points are then followed into the future to observe how rapidly they move apart from one another. The time it takes for point pairs to move apart is related to the so-called Kolmogorov entropy, *K*, by $\langle t_{\mathrm{div}} \rangle = 2^{-Kt}$ where $\langle t_{\mathrm{div}} \rangle$ is the average time for the pair to diverge apart and *K* is expressed in bits per second. Entropy reflects how well one can predict the behavior of each respective part of the trajectory from the other. Higher entropy indicates less predictability and a closer approach to stochasticity.

2.3. Poincare plot geometry

The Poincare plot is a technique taken from non-linear dynamics, portrays the nature of *RR* interval fluctuations. It is a graph of each *RR* interval plotted against the next interval (Fig. 1). Poincare plot analysis is an emerging quantitative-visual technique whereby the shape of the plot is categorized into functional classes that indicate the degree of the heart failure in a subject [43]. The plot provides summary information as well as detailed beat-to-beat information on the behavior of the heart [19].

The geometry of the Poincare plot is essential. A common way to describe the geometry is to fit an ellipse to the graph [3]. The ellipse is fitted onto the so called line-of-identity at

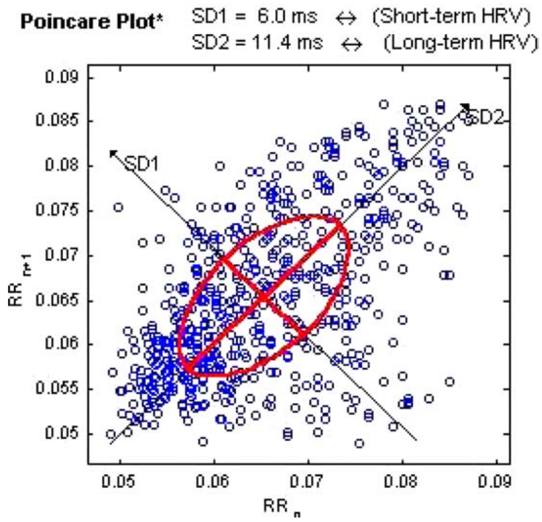

Fig. 1. The Poincare plot for a subject with reflexology.

45° to the normal axis. The standard deviation of the points perpendicular to the line-of-identity denoted by SD1 describes short-term variability which is mainly caused by RSA. The standard deviation along the line-of-identity denoted by SD2 describes long-term variability.

Statistically, the plot displays the correlation between consecutive intervals in a graphical manner. Non-linear dynamics considers the Poincare plot as the two-dimensional (2-D) reconstructed *RR* interval phase–space, which is a projection of the reconstructed attractor describing the dynamics of the cardiac system [38]. The *RR* interval Poincare plot typically appears as an elongated cloud of points oriented along the line-of-identity. The dispersion of points perpendicular to the line-of-identity reflects the level of short-term variability. The dispersion of points along the line-of-identity is thought to indicate the level of long-term variability.

To characterize the shape of the plot mathematically, most researchers have adopted the technique of fitting an ellipse to the plot, as figure details. A set of axis oriented with the line-of-identity is defined [40]. The axis of the Poincare plot is related to the new set of axis by rotation of $\theta = \pi/4$ rad

$$\begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix} \begin{bmatrix} RR_n \\ RR_{n+1} \end{bmatrix}. \quad (4)$$

In the reference system of the new axis, the dispersion of the points around the x_1 axis is measured by the standard deviation denoted by SD1. The quantity measures the width of the Poincare cloud and, length of the cloud and therefore indicates the level of short-term HRV [19]. The length of the cloud along the line-of-identity measures the long-term HRV and is measured by SD2 which is the standard deviation around the x_2 axis [19]. These measures are related to the standard HRV measures in the following manner:

$$SD1^2 = \mathrm{Var}\left(x_1\right) = \mathrm{Var}\left(\frac{1}{\sqrt{2}}RR_n - \frac{1}{\sqrt{2}}RR_{n+1}\right) \quad (5)$$

$$SD1^2 = \frac{1}{2}\mathrm{Var}\,(RR_n - RR_{n+1}) = \frac{1}{2}\,SDSD^2. \quad (6)$$

Thus, the SD1 measures of Poincare width are equivalent to the standard deviation of the difference between successive intervals, except that is scaled by $1/\sqrt{2}$. This means that one can relate SD1 and SD2 to the autocovariance function

$$SD1^2 = \Phi_{RR}(0) - \Phi_{RR}(1) \quad (7)$$

$$SD2^2 = \Phi_{RR}(0) + \Phi_{RR}(1). \quad (8)$$

By adding the above two Eqs. (7) and (8), we get

$$SD1^2 + SD2^2 = 2SDRR^2. \quad (9)$$

Finally,

$$SD2^2 = 2SDRR^2 - \frac{1}{\sqrt{2}}SDRR^2 \quad (10)$$

where $SDRR = \sqrt{E\,[RR_n^2] - \overline{RR}}$ is the square root of the variance of the *RR* intervals. The standard deviation of the successive differences of the *RR* intervals, denoted by SDSD

$$SDSD = \sqrt{E\,[RR_n - RR_{n+1}{}^2]} \bullet SDSD. \quad (11)$$

3. Results

The variations of the above parameters with and without parameters are tabulated in Table 1.

Except three subjects, there is an increase in the CD in all the rest of subjects with reflexology (Fig. 2). This clearly shows the positive aspect of reflexology. Considering the consciousness planes of the psychophysical being, reflexology enhances the awareness as the CD value increases, since anesthesia decreases the CD. The CD is a measure of the complexity for the underlying attractor. Larger the dimension, the greater the degree of randomness of the data. The

Table 1
Showing the variation of non-linear parameters with and without reflexology

Parameters	Without reflexology (mean ± SD)	With reflexology (mean ± SD)	"*P*" value
CD	4.225 ± 0.28	4.29 ± 0.24	0.0503
Entropy	0.491 ± 0.07	0.54 ± 0.05	0.0256
SD2 (m s)	79.32 ± 32.74	66.37 ± 37.89	0.128

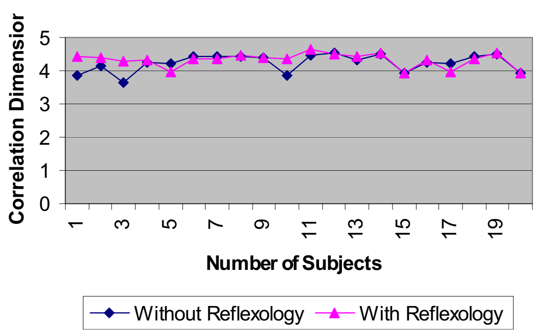

Fig. 2. Variation of CD with and without reflexology.

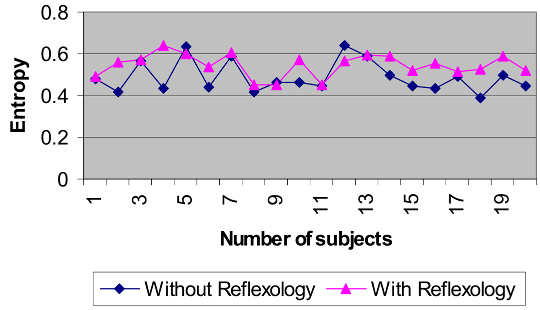

Fig. 3. Variation of Entropy with and without reflexology.

above result shows that the HRV becomes more random with reflexology, hence the CD increases.

Fig. 3 shows the entropy for all the subjects during relaxed sitting and during reflexological stimulation. In 17 cases, we see the increase of entropy with the reflexology. Entropy gives us a measure of the disorder of time series. We note here the fact that the value of entropy has increased, which indicates that the signal becomes more random with reflexology. The entropy becomes greater than 0.5 after the reflexology. In a majority of the cases, the time series shows the tendency to towards random walk during the stimulation. Again this is a positive aspect.

The randomness in the HRV increases with reflexology, hence the entropy increases.

Fig. 4 shows the SD2 for all subjects with reflexology and without reflexology. Here, we find a very interesting fact that at except in four subjects, in all the rest of the subjects under consideration the SD2 decreases. SD2 quantity measures the length of the Poincare cloud along the line-of-identity and it indicates the standard deviation around the x_2 axis. A decrease in SD2 shows an increase in the trend towards chaos. Physiologically it is a very good symptom as far as the HRV is considered. Fluctuation in heart is essentially a positive aspect, as far as the cardiac dynamics is concerned. These fluctuations are regulated by multiple control processes including neurohormonal regulation and local electrochemical factors.

4. Conclusion

The CD, entropy and SD2 in most of the cases under study due to the effect of reflexological stimulation have changed

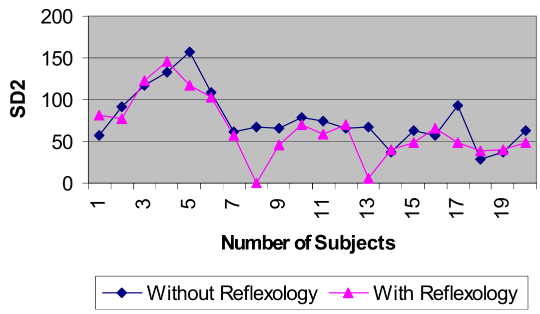

Fig. 4. Variation of SD2 (m s) with and without reflexology.

significantly (Table 1, Figs. 1–3). Among the three parameters taken for consideration, CD and entropy are more effective. The “*P*” value in the case of CD is 0.05 and entropy is 0.02 and even the SD2 is 0.12 (lower the “*P*” value, better is the result in “*t*” test). By studying, large number of population, the result may improve further. From the non-linear dynamics point of view, we know that complex trajectories are information generators. Hence, the more is the complexity of attractors, the higher the information content. This leads to the fact that a diseased state is a state of lesser information content and a healthier state is a state of high information content. Hence, reflexological stimulation could increase the complexity of HRV signal which is a better state. Hence, the HRV becomes more chaotic due to reflexological stimulation.

Acknowledgements

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References

[1] Akselrod S, Gordan D, Ubel FA, Shannon DC, Barger AC, Cohen RJ. Power spectrum analysis of heart rate fluctuation: a quantitative probe of beat-to-beat cardiovascular control. Science 1981;213:220–2.

[2] Berger RD, Akselrod S, Gordon D, Cohen RJ. An efficient algorithm for spectral analysis of heart rate variability. IEEE Transactions on Biomedical Engineering 1986;33:900–4.

[3] Brennan M, Palaniswami, Kamen P. Do existing measures of Poincare plot geometry reflect nonlinear features of heart rate variability? IEEE Transactions on Biomedical Engineering 2001;48(11):1342–7.

[4] E. Bishop, E. McKinnon, E. Weir, D.W. Brown, Reflexology in the management of encopresis and chronic constipation, Pediatric Nursing 15 (3) 20–21.

[5] Bruce JW. Fractal Physiology and Medicine: Studies of Nonlinear Phenomena in Life Science, 1. World Scientific Publishing Co. Pvt Ltd, Singapore; 2000.

[6] Cohen ME, Hudson DL, Deedwania PC. Applying continuous chaotic modeling to cardiac signal analysis. IEEE Engineering Medicine Biology 1996;15:97–102.

[7] Corr PB, Yamada KA, Witkowsky FX. Mechanisms controlling cardiac autonomic function and their relation to arrhythmogenesis. In: Fozzard HA, Haber E, Jennings RB, Katz AN, Morgan HE, editors. The Heart and Cardiovascular System. New York: Raven Press; 1986. p. 1343–403.

[8] Cysarz D, Bettermann H, van leeuwen P. Entropies of short binary sequences in heart period dynamics. American Journal of Physiology Heart and Circulatory Physiology 2000;278:H2163–72.

[9] Ding M, Grebogi E, Ott E, Sauer T, Yorke JA. Estimating correlation dimension from a chaotic time series: when a plateau occur? Physica D 1993;69:404–24.

[10] Fell J, Mann K, Roschke J, Gopinathan MS. Nonlinear analysis of continuous ECG during sleep I. Reconstruction. Biological Cybernatics 2000;82:477–83.

[11] Frankel BSM. The effect of reflexology on baroreceptor reflex sensitivity, blood pressure and sinus arrhythmia. Complementary Therapies in Medicine 1997;5:80–4.

[12] Fraser AM. Information and entropy in strange attractors. IEEE Transactions on Information Theory 1989;35:245–62.

[13] Fraser AM, Swinney HL. Independent coordinates for strange attractors from mutual information. Physical Review A 1986;33:1134–40.

[14] Grassberger P, Procassia I. Measuring the strangeness of strange attractors. Physica D 1983;9:189–208.

[15] Jennifer H, Lindy K, Peter G. The impact of foot massage and guided relaxation following cardiac surgery: a randomized controlled trial. Journal of Advanced Nursing 2002;37(2):199–207.

[16] Jiapu P, Willis JT. Real time QRS detector algorithm. IEEE Transactions on Biomedical Engineering 1985;32(3):223–30.

[17] C.S. Julian, R. George, Chaos Data Analyzer: The Professional Version, American Institute of Physics, USA.

[18] Kamath MV, Fallen EL. Correction of the heart rate variability signal for ectopics and missing beats. In: Malik M, Camm AJ, editors. Heart Rate Variability. Armonk: Futura; 1995. p. 75–85.

[19] Kamen PW, Krum H, Tonkin AM. Poincare plot of heart rate variability allows quantitative display of parasympathetic nervous activity. Clinical Science 1996;91:201–8.

[20] Kantz H, Schreiber T. Nonlinear Time Series Analysis. Cambridge University Press; 1997.

[21] Kantz H, Kurths J, Mayer-Kress G. Nonlinear Analysis of Physiological Data. first ed. Berlin: Springer; 1998.

[22] Kaplan DK, Cohen JR. Searching for chaos in fibrillation. Annals of the New York Academy of Science 1991:367–74.

[23] Kobayashi M, Musha T. 1/f fluctuation of heart beat period. IEEE Transactions on Biomedical Engineering 1982;29:456–7.

[24] Levy MN, Schwartz PJ, editors. Vagal Control of the Heart: Experimental Basis and Clinical Implications. Armonk: Future; 1994.

[25] Lipsitz LA, Goldberger AL. Loss of "complexity" and aging: potential applications of fractals and chaos theory to senescence. JAMA 1992;40:543–6.

[26] Lown B, Verrier RL. Neural activity and ventricular fibrillation. New England Journal of Medicine 1976;294:1165–70.

[27] Malik M, Camn AJ. Components of heart rate variability—what they really mean and what we measure. American Journal of Cardiology 1993;72:821–2.

[28] Malik M. Heart rate variability. Current Opinion in Cardiology 1998; 13:36–44.

[29] Grealish L, Lomasney A, White-Man B. The effects of foot massage and reflexology on decreasing anxiety, pain, and nausea in patients with cancer. Cancer Nursing 2000;23:237–43.

[30] Metin A. Nonlinear Biomedical Signal Processing Dynamic Analysis and Modeling, II. New York: IEEE Press; 2001.

[31] Mohamed I, Owis, Ahmed H, Abou-Zied, Abou-Bakr M, Youssef, Yasser MK. Study of features on nonlinear dynamical modeling in ECG arrhythmia detection and classification. IEEE Transactions on Biomedical Engineering 2002;49(7):733–6.

[32] Narayana Dutt D, Krishnan SM. Application of Phase Space Techniques to the Analysis of Cardiac Signals. 1999 Proceedings of IEEE EMBS Conference, Atlanta, USA.

[33] Pomeranz B, Macaulay RJB, Caudill MA, Kutz I, Adam D, Kilborn KM, Barger AC, Shannon DC, Cohen RJ, Benson H. Assessment of autonomic function in humans by heart rate spectral analysis. American Journal of Physiology 1985;248:H151–3.

[34] Radhakrishna Rao KA, Vikram Kumar Yergani, Narayana Dutt D, Vedavathy TS. Characterizing chaos in heart rate variability time series of panic disorder patients. Proceedings of ICBME, Biovision 2001, Bangalore, India. December 2001. p. 163–7.

[35] Rajendra Acharya U, Subbanna Bhat P, Iyengar SS, Ashok Rao, Summet Dua. Classification of heart rate using artificial neural network and fuzzy equivalence relation. Pattern Recognition 2003;36: 61–8.

[36] Schwartz PJ, Priori SG. Sympathetic nervous system and cardiac arrythmias. In: Zipes DP, Jalife J, editors. Cardiac Electrophysiology from Cell to Bedside. Philadelphia: W.B. Saunders; 1990. p. 330–43.

[37] Siev-Ner I, Gamus D, Lerner-Geva L, Achiron A. Reflexology treatment symptoms of multiple sclerosis: a randomized controlled study. Multiple Sclerosis Journal 2003;9(4):356–61.

[38] Takens F. Detecting strange attractors in turbulence. In: Rand DA, Young LS, editors. Dynamical Systems and Turbulence ser Lecture notes in Mathematics, 898. Berlin Germany: Springer-Verlag,; 1981. p. 366–81.

[39] Task Force of the European Society of Cardiology and North American Society of Pacing and electrophysiology. Heart rate variability: standards of measurement, physiological interpretation and clinical use. European Heart Journal 1996;17:354–81.

[40] Tulppo M, Makikallio TH, Takala TES, Seppanen, Kuikuri H. Quantitative beat-to-beat analysis of heart rate dynamics during exercise. American Journal of Physiology 1996;71:H244–52.

[41] Wariar R, Eswaran C. Integer coefficient bandpass filter for the simultaneous removal of baseline wander, 50 and 100 Hz interference from the ECG. Medical and Biological Engineering and Computing 1991: 333–6.

[42] Weissman MW, Markowitz JS, Ouelette R, Greenwald S, Hahn JP. Panic disorder and cardiovascular/cerebrovascular problems. American Journal of Psychiatry 1990;147:1504–7.

[43] Woo MA, Stevenson WG, Moser DK, Trelease RB, Harper RH. Patterns of beat-to-beat heart rate variability in advanced heart failure. American Heart Journal 1992;123:704–10.