Available online at www.sciencedirect.com
ScienceDirect
Medical Engineering & Physics 29 (2007) 344–349
Medical Engineering & Physics
www.elsevier.com/locate/medengphy

Heart rate variability in mental stress aloud

Vesna Vuksanović *, Vera Gal

Institute of Biophysics, Faculty of Medicine, University of Belgrade, Višegradska 26/2, 11000 Belgrade, Serbia and Montenegro

Received 18 January 2006; received in revised form 3 April 2006; accepted 9 May 2006

Abstract

Previous investigations on arithmetic stress with verbalization showed that spectral measures of heart rate variability (HRV) did not assess changes in autonomic modulation, although the heart rate (HR) increased. In this study non-linear measures of HRV are determined and linear measures are re-examined in order to understand this apparent discrepancy between HR and HRV changes. In 23 healthy subjects 5-min electrocardiograms (ECGs) were recorded at rest and during arithmetic stress aloud. We determined non-linear (short-term scaling exponent, sensitivity to the initial condition and signal complexity) and linear (low-frequency and high-frequency spectral powers) measures. Our results showed that averaging concealed out an opposite effect of mental stress aloud on spectral measures and that this could be the main reason why the effect was not quantified. We found that increase of HR upon mental stress aloud could be achieved through the decreased as well as increased modulation in high-frequency band (HF). We also showed that non-linear measures distinguished this opposite effect of mental stress aloud on linear measures. Decreased HF power is associated with increase in short-term scaling exponent and decrease in signal complexity, while increased HF power increased sensitivity to the initial conditions. Apart from their opposite response to the mental stress, the two groups differed in baseline in sensitivity to the initial conditions. We suggest that variety of changes in HR dynamics upon different perturbation could be due to some differences in intrinsic properties of the system.

Keywords: Heart rate variability; Nonlinear time series analysis; DFA; Sample entropy; Largest Lyapunov exponent; Mental stress

1. Introduction

Influence of mental stress on heart rate (HR) and spectral measures of heart rate variability (HRV) has been well documented [1]. It has been reported that various types of mental stresses performed in laboratory conditions increase HR and decrease HRV [1–3]. The majority of the studies conclude that the reduction in overall variability is induced by the withdrawal of the highly frequent vagal activity [1]. However, in mental stress performed with verbalization an evident increase in HR was not followed by change in HRV [4,5]. The latter was explained by significant influence of altered breathing pattern upon speaking. Yet, it still remains unclear how could HR change without appropriate and assessable change in its autonomic modulation reflected on spectral characteristics of HRV. If there is a superposition of various effects these effects should be quantified.

Non-linear analysis methods of HRV have been developed to quantify its characteristics that cannot be distinguished by linear methods. Some of them are able to distinguish groups that do not differ in spectral measures [6,7]. The difference between subjects with major depression and control is in "the sensitive dependence on initial condition", quantified by the largest Lyapunov exponent [6], although the groups do not differ in spectral measures. The advantage of non-linear measures was reported in a follow-up study on various HRV measures in patients with coronary artery diseases. Short-term scaling exponent and approximate entropy change significantly during follow-up, while spectral measures do not [7]. The main observation of these studies is that non-linear measures are more sensitive than linear in detecting subtle changes in intrinsic properties of HR dynamics. Moreover, the nature of the non-linear measures is to quantify qualitative (non-linear interactions between regulatory

* Corresponding author. Tel.: +381 11 3615767.
E-mail address: vvesna@eunet.yu (V. Vuksanović).

1350-4533/$ – see front matter © 2006 Published by Elsevier Ltd on behalf of IPEM.
doi:10.1016/j.medengphy.2006.05.011

mechanisms) rather than quantitative (time- or frequency-domains) properties of the heart rate dynamics.

For these reasons, in this work we wanted (i) to investigate the possibility to assess changes in autonomic modulation of HR in mental stress aloud by non-linear measures and (ii) to re-examine the reasons for spectral measures' failure in doing that.

2. Subjects

Twenty-three volunteers (10 men and 13 women, mean age 33.6 ± 2.3 years) participated in the study. Ethical Committee of Faculty of Medicine approved the study. Informed consent was obtained from all subjects. Subjects were healthy with no previous symptoms of cardiovascular or any other chronic disorder. Mean value of body mass index was (22.5 ± 0.6) kg/m^2. All subjects were non-smokers and they were advised not to drink any coffeinated beverages in the morning prior to the study.

Experiment was performed in a quiet surrounding between 10 a.m. and 2 p.m. ECGs were taken in supine position, at rest and during arithmetic mental stress. After attachment of the electrodes every subject relaxed for 10 min. Afterwards, 5-min ECG was taken in supine rest during spontaneous breathing. Immediately after, also in supine position, subjects performed arithmetic task for 5 min. Standard procedure of mental arithmetic test was performed [1,4,5]. Briefly, subjects subtracted 17 starting from 1000. They were instructed to subtract as accurate as possible. For a single subtraction time allowed was 5 s and was signalled by a sound. They told the result and after each answer subjects received verbal confirmation ("right" or "wrong"). They continued successive subtracting even when the result was wrong. The subjects did not talk during calculation between verbalization of the answers.

3. Analysis of HRV

3.1. Spectral analysis

A 256 consecutive RR intervals, extracted from the ECGs, all with the sinus rhythm, were used for the analysis. Spectral analysis of RR-interval time series was performed using Origin 5.0 program (Microcal Softwere Inc., Northampton, MA, USA), as previously reported [8]. Fast fourier transform (FFT) was used to transform time series in frequency domain. Sampling interval was 500 ms and Hanning window was used to attenuate leakage effect. Power spectral density was calculated and the powers were integrated in the low-LF; (0.04–0.15) Hz and high-HF; (0.15–0.5) Hz frequency bands for all RR-interval time series. An unequal increase of heart rate is normalized by mean RR-intervals. The coefficients of component variance (CCV) in LF and HF band were calculated. CCV-LF and CCV-HF were calculated as the square root of LF or HF power divided by mean RR.

Table 1
Estimated values of minimum embedding dimension (d) of unfiltered and filtered RR-intervals time series

	Baseline ($n = 23$)	Mental stress ($n = 23$)
d	15.83 ± 0.29	15.70 ± 0.29
d(LF)	12.48 ± 0.36	11.74 ± 0.30
d(HF)	13.48 ± 0.34	13.52 ± 0.27

Abbreviations—d(LF): minimum embedding dimension of time series filtered in LF band; d(HF): time series filtered in HF band.

3.2. Detrended fluctuation analysis

Detrended fluctuation analysis (DFA) method was used to quantify presence or absence of fractal-like correlation properties of the heart period (HP) time series [9]. For DFA, RR-interval time series is divided into equal windows, n. In each window, the data were first integrated and then detrended by subtracting the least-squares linear regression line. The mean square fluctuation of this integrated and detrended time series were measured within the observation windows of various sizes ($4 \leq n \leq 64$) and then plotted against the window size on log–log scale [9]. The scaling exponent α presents the slope of this line. Values of α are from 0 (excluding) to 1.5 (including) and indicate different correlation properties of time series [9]. For $0.5 < \alpha \leq 1$ time series is said to be long-range correlated. (The case of $\alpha = 1$ is a special one and corresponds to the $1/f$ behaviour.) Due to the length of the data series we calculated only short-term scaling exponent (α_1) from 4 to 11 beats.

3.3. Largest Lyapunov exponent

Largest Lyapunov exponent (LLE) was used to estimate the chaotic properties or sensitivity to the initial conditions of RR intervals dynamics. Presence of positive Lyapunov exponent indicates chaotic system sensitive to the initial conditions. (Quasi)periodic signals will have an exponent equal to zero. In order to estimate LLE we used software designed for non-linear data analysis TSTOOL V1.11 according to the following method (described also in our previous work [10]). In short, first step in calculation of LLE is reconstruction of an attractor from a given time series. To reconstruct the attractor, i.e. transform one-dimensional time series into d-dimensional vectors in phase space it was necessary to choose two parameters: time-delay and minimum embedding dimension (d). In our work the lag of 1 was used as most appropriate choice for time-delay. This value was based on previous studies and recommendations for analysis of discrete time series [11]. Minimum embedding dimension determines the number of phase space coordinates sufficient to unfold attractor. We estimated d by Cao's method [12], which is efficient for high-dimensional attractors acquired from time series with small number of data points. Estimated values of d are presented in Table 1 (We have not found any statistically significant difference in d between baseline and mental stress. However, values of d differed between non-filtered and filtered

time series, which is in accordance with the previous findings [6].) Dynamics reconstructed in this way allowed estimation of LLE by nearest neighbour's method [13]. Rosenstein et al. [14] re-examined this method and made it appropriate for small data sets. In order to reduce noise in data, RR-interval time series were filtered in LF and HF bands. LLE was calculated for both unfiltered and filtered time series as described by Yeragani et al. [6].

4. Sample entropy

Sample entropy (SampEn), statistics described in work of Richman and Moorman [15], was used to quantify complexity/irregularity of RR-interval time series, or "how" chaotic the system is. Sample entropy is defined as the negative natural logarithm of conditional probability that sequences of length m that match pointwise within the tolerance r also match at the next data point. In another word, it quantifies extent to which a sequence of m RR intervals can predict the next RR interval duration, based on the knowledge of the degree of the similarity for sequences of length m to that for sequences of length $m+1$. A time series containing many repetitive sequences has relatively small SampEn and less predictable process has higher SampEn. SampEn was calculated with the fixed input parameters $m=2$ and $r=0.2$ of S.D. of the HP data.

4.1. Statistical analysis

Statistical analysis was performed by SPSS 10.0 statistical software. Results are presented as mean ± standard error (S.E.). Due to the skewness of the distribution LF and HF were analysed statistically after natural logarithmic transformation. Paired Student's t-test was used to compare baseline and mental stress results.

Analysis of covariance was used to test two different responses in HF upon mental stress.

5. Results

Table 2 presents results obtained from all subjects who performed arithmetic task aloud ($n=23$). In arithmetic stress aloud, there is a significant increase in HR, CCV-LF and α_1 and a decrease in LLE of HF time series. Spectral measures of HRV do not change ($p>0.05$).

However, during calculation of spectral characteristics of HRV in arithmetic stress, we noticed that in some subjects HF power increased while in the others decreased compared to the corresponding values in baseline. Increase of HF in arithmetic stress was found in 13 and decrease in 10 subjects. We supposed that when group was analysed as a whole this opposite response in HF cancelled out. Therefore, we formed two different groups: the A group consisted of subjects who responded to stress with the decrease and the B group consisted of subjects with the increase in HF power. We examined relationship between HF in mental stress and HF in baseline. We wanted to find out whether the relationship was different for these groups. Results of the analysis are given in Table 3 (a and b). We have not found interaction between the groups in response to mental stress ($b_3=-0.28$; $p>0.05$) and therefore the significance for the other two terms was reanalysed (Table 3b). The significance for both common slope ($b_1=1.03$; $p<0.001$) and different intercept ($b_2=0.91$; $p<0.001$) terms indicated parallel slope model. It means that there are two intercepts, one for each group, and one slope for parallel regression lines (Fig. 1).

Separate analysis of two newly formed groups showed some additional differences (Table 4). In the A group, during arithmetic stress, there was the significant increase in HR, LF/HF power ratio and α_1. In the B group the significant increase was determined in HR and LLE and the decrease in LLE of HF. Additionally, groups A and B differed in baseline in CCV-HF and LLE.

Table 2
Heart rate and measures of heart rate variability at rest and during mental stress

	Baseline	Mental stress	t	p-Value
HR (Hz)	1.24 ± 0.04	1.35 ± 0.05	4.425	<0.001
ln(LF) (ms^2)	5.96 ± 0.14	6.14 ± 0.16	0.833	ns
CCV-LF (%)	2.44 ± 0.15	3.04 ± 0.22	2.111	0.046
ln(HF) (ms^2)	6.39 ± 0.19	6.50 ± 0.25	0.441	ns
CCV-HF (%)	3.12 ± 0.24	3.85 ± 0.34	1.978	ns
LF/HF	1.08 ± 0.43	1.07 ± 0.24	0.003	ns
α_1	0.85 ± 0.04	0.97 ± 0.04	3.488	0.002
LLE	0.062 ± 0.004	0.065 ± 0.004	0.383	ns
LLE(LF)	0.105 ± 0.005	0.113 ± 0.007	0.726	ns
LLE(HF)	0.078 ± 0.004	0.066 ± 0.003	2.810	0.010
SampEn	1.77 ± 0.04	1.65 ± 0.06	1.827	ns

Abbreviations—HR: heart rate; LF: low-frequency power; HF: high-frequency power; CCV-LF: coefficient of component variance in LF band; CCV-HF: coefficient of component variance in HF band; LF/HF: low-frequency-to-high-frequency power ratio; α_1: short-term scaling exponent; SampEn: sample entropy; LLE: largest Lyapunov exponent; LLE(LF): series filtered in low-frequency band; LLE(HF): series filtered in high-frequency band.

Table 3
Analysis of covariance for estimation of two different responses to mental stress aloud

Term	Estimate	S.E.	t	p
(a) $R^2=0.822$, $p<0.001$; $Y=-1.119+1.16G+2.75X-0.28GX$				
b_1	1.16	0.16	7.34	<0.001
b_2	2.75	1.0	2.63	0.016
b_3	−0.28	0.16	−1.77	0.092
(b) $R^2=0.792$, $p<0.001$; $Y=-0.203+1.03G+0.91X$				
b_1	1.03	0.15	6.98	<0.001
b_2	0.91	0.13	7.25	<0.001

Abbreviations—Y: HF power in mental stress; X: HF power in baseline; G: group (values are 1 for group A and −1 for group B); b_1: refers to the total group regression of Y and X; b_2: adjust the intercepts for each group; b_3: homogeneity of the slopes.

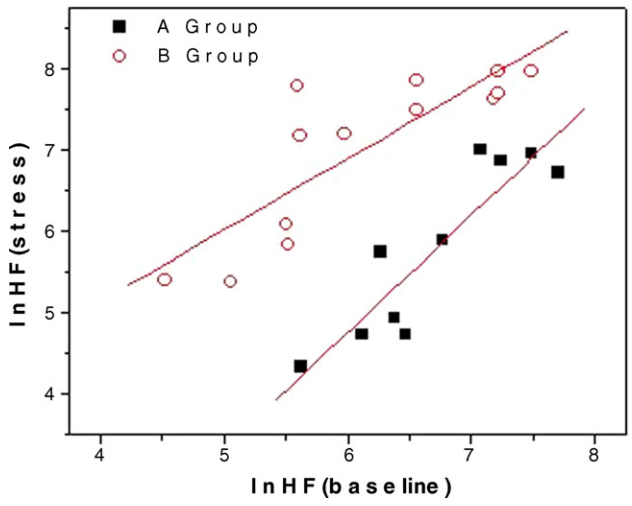

Fig. 1. Regression lines for the groups with the opposite response to the mental stress (A denotes subject with decrease in HF in mental stress and B subjects with the increase in HF in mental stress). Regression line for group A: ln HF(stress) = −3.86 + 1.44 ln HF(baseline); regression line for group B: ln HF(stress) = 1.62 + 0.88 ln HF(baseline).

6. Discussion

Our results showed that non-linear measures could detect the influence of arithmetic stress aloud on autonomic modulation of the heart rate. We also showed that the spectral measures also quantify the effect, but only after taking into account the fact that the response does not need to be unique.

At the beginning of the study we only confirmed previously reported data, which stated that HR in a group of subjects could change without a change in spectral HRV measures [4,5]. It seems that vocalization of answers during the task interfered with the analysis and concealed out the changes in HRV (Table 2). On the other hand, previous investigations showed that altered breathing and talking change HR and the spectral characteristics of HRV [5,16,17]. It was also found that respiratory and heart rate variability spectra, from short-term ECGs, are synchronized [5,17]. Therefore, we assumed that measurement of respiratory rate could not provide any better insight into the apparent discrepancy between HR and spectral HRV changes. Our approach was to investigate non-linear HR dynamics in response to the mental stress aloud in order to get better insights into its qualitative properties.

However, careful analysis showed that spectral measures of HRV could assess influence of mental stress aloud. The influence was reflected on HF spectral power, which either decreased or increased upon mental stress aloud. Both changes lead to the increase in HR (Table 4). LF power did not change significantly indicating that slower cardiovascular rhythms maintain their activity during short-term regulation of HR [18]. HF power represents influence of respiration on HR and it is assigned to parasympathetic activity [19]. When highly frequent parasympathetic modulation (that slows down HR) withdrawals, it results in HR increase. That probably happens in mental stress aloud too (when HF power decreases). Increase of HF together with the increase of HR is more difficult to explain. It could be an influence of complex respiratory pattern but it also might include different co-activation mechanisms. Terkelsen et al. [20] reported similar results on the lack of change in spectral HRV measures in pain-induced increase of HR. They suggested that it could be caused by compensatory sympatho-adrenal activation with catecholamine release into the circulation. Furthermore, in standing that elicits similar response in HRV as found in mental stress [18], it has been reported that yohimbine, α_2-adrenergic antagonist, increases LF as well as HF (which is exclusively vagaly mediated) [21]. These authors suggested that the effect might be caused by the increase in cholinergic activity. We suppose that similar mechanisms occur in mental stress aloud. It might mean that some subjects handle stress by the simple withdrawal of parasympathetic activity while the others exhibit an additional anti-andrenergic effect.

Some of the non-linear HRV measures identified differences between baseline and mental stress aloud (Table 2).

Table 4
Heart rate and measures of HRV in two different groups

	A ($n = 10$)		B ($n = 13$)	
	Baseline	Mental stress	Baseline	Mental stress
HR (Hz)	1.23 ± 0.05	1.43 ± 0.06**	1.18 ± 0.06	1.28 ± 0.06**
ln(LF) (ms^2)	6.07 ± 0.12	5.82 ± 0.28	5.87 ± 0.24	6.38 ± 0.15
CCV-LF (%)	2.58 ± 0.12	2.76 ± 0.28	2.34 ± 0.25	3.26 ± 0.32
ln(HF) (ms^2)	6.71 ± 0.21	5.79 ± 0.33***,†	6.16 ± 0.26	7.04 ± 0.27***
CCV-HF (%)	3.67 ± 0.37¶	2.83 ± 0.39***,†	2.69 ± 0.27	4.64 ± 0.51***
LF/HF	0.62 ± 0.11	1.51 ± 0.46*	1.42 ± 0.16	0.77 ± 0.09
α_1	0.86 ± 0.07	1.05 ± 0.05**	0.84 ± 0.05	0.91 ± 0.05
LLE	0.074 ± 0.006¶	0.064 ± 0.006	0.054 ± 0.004	0.067 ± 0.004*
LLE(LF)	0.111 ± 0.008	0.110 ± 0.008	0.099 ± 0.006	0.115 ± 0.010
LLE(HF)	0.074 ± 0.007	0.066 ± 0.003	0.080 ± 0.004	0.067 ± 0.004**
SampEn	1.81 ± 0.58	1.53 ± 0.09**	1.74 ± 0.06	1.73 ± 0.07

A denotes subjects with decrease of HF power and B subjects with increase of HF power upon mental stress. Abbreviations are as in Table 3. Difference between baseline and mental stress within the same group: $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$. Difference between A and B groups at rest: $^{\P}p < 0.01$. Difference between A and B groups in mental stress aloud: $^{\dagger}p < 0.01$.

They also point to dissimilarities between groups with the opposite response to mental stress. Arithmetic stress with speaking increased short-term scaling exponent only in the group with the decrease in HF (Table 4). This is in agreement with findings that the reduction in vagal activity, reflected on HF power, increases correlation properties of the HR time series [22,23]. It also concurs with the expected withdrawal of parasympathetic activity in mental stress [4]. Our results point out that α_1 does not change when HF increases, implying that only pronounced autonomic activity could alter correlation properties of HR dynamics. This is also consistent with the finding that α_1 correlated with the LF/HF power ratio [24,25].

Complexity measure (SampEn) is not related to the variation at any particular frequency band but to an overall complexity of a signal. Our results on SampEn showed that it depended on the magnitude of the modulation in HF band. Significant decrease in HF power decreases complexity of the signal too (Table 4, A group). This was also found in active standing [10], healthy aging [10,26] and serious heart diseases [27,28], but also in free-running conditions in healthy subjects [25]. This dependence can also explain the lack of difference in SampEn between baseline and mental stress in the group with increased HF power.

LLE is a measure of chaotic properties of time series, i.e. its sensitive dependence to the initial conditions. We found that mental stress aloud increased LLE of unfiltered series and decreased LLE of HF time series (Table 4, B group). Significant increase in LLE of unfiltered series could be due to the increased non-linear interaction between variables that determine HR. Decrease in LLE of HF series is more difficult to explain. However, there is some evidence that it could decrease as a consequence of anti-cholinergic activity of the autonomic nervous system [29]. This might also occur in mental stress aloud. In addition, it was found only in the B group and concurred with previously discussed increase in HF power.

Complexity of the HR dynamics is additionally emphasized by dissimilarities in baseline HRV measures, found between groups with different response to mental stress (Table 4). Difference in CCV-HF was probably caused by individual differences in HR. However, we have not found statistically significant difference in mean HR in baseline. It seems that subtle individual differences in HR could be revealed by the measure of sensitivity to initial condition. Since LLE is focused on beat-to-beat behaviour of HR (not on its mean properties) it can point to some intrinsic characteristics of HR dynamics (e.g. individual differences in intrinsic HR, change in interaction between breathing and HR upon different perturbation of a system, etc.). Moreover, it could be that difference in LLE in baseline determines different behaviour in mental stress. It is possible that regulation of heart rate upon mental stress goes through the decreased parasympathetic activity but also through an additional anti-adrenergic effect, which are both reflected on HF interval of the modulation spectra. However, further investigations that include direct measurements are necessary to establish physiological background of non-linear measures and reveal variety of modulation of HR.

The limitation of this work is given by its purpose, which was to explain apparently contradictory findings on HRV measures in arithmetic stress aloud. We focused on various numerical approaches without deeper investigations of mental stress or other types of stress. Direct measurement combined with a variety of stresses and a much larger number of subjects, would certainly contribute to the better understanding of mechanisms involved in stress and their physical/physiological properties reflected on linear and non-linear measures.

7. Conclusion

In this study we demonstrated that change in autonomic modulation reflected on high-frequency spectral power is responsible for the increase of heart rate in mental stress aloud. We also demonstrated that magnitude and the direction of the change determines response of non-linear measures (or vice versa). Decrease in high-frequency modulation is connected with short-term correlation and complexity of the signal, and its increase is connected with the sensitivity to initial conditions. Our results indicate that there could be two distinctive behaviours in handling mental stress aloud.

References

[1] Pagani M, Lucini D, Rimoldi O, Furlan R, Piazza S, Biancardi L. In: Malik M, Camm AJ, editors. Heart rate variability. New York: Armonk, Futura; 1995. p. 245–73.
[2] Sloan RP, Shapiro PA, Bagiella E, Bioger JT, Lo ES, Gorman JM. Relationship between circulating catecholamines and low frequency heart period variability as indices of cardiac sympathetic activity during mental stress. Psychosom Med 1996;58:25–31.
[3] Shapiro PA, Sloan RP, Bagiella E, Kuhl JP, Anjilvel S, Mann JJ. Cerebral activation, hostility and cardiovascular control during mental stress. J Psychosom Res 2000;48:485–91.
[4] Sloan RP, Korten JB, Myers MM. Components of heart rate reactivity during mental arithmetic with and without speaking. Physiol Behav 1991;50(5):1039–45.
[5] Bernardi L, Wdowczyk-Szulc J, Valenti C, Castoldi S, Passino C, Spadacini G, et al. Effects of controlled breathing, mental activity and mental stress with or without verbalization on heart rate variability. J Am Coll Cardiol 2000;35(6):1462–9.
[6] Yeragani VK, Radhakrishna RKA, Smitha MR, Pohl RB, Balon R, Srinivasan K. Diminished chaos of heart rate time series in patients with major depression. Biol Psychiatry 2002;51:733–44.
[7] Jokinen V, Syvanne M, Makikallio TH, Airaksinen JK, Huikuri HV. Temporal age-related changes in spectral, fractal and complexity characteristics of heart rate variability. Clin Physiol 2001;21(3):273–81.
[8] Vuksanović V, Gal V, Kalanj J, Simeunović S. Effects of posture on heart rate variability spectral measures in children and young adults with heart disease. Int J Cardiol 2005;101(2):273–8.
[9] Peng C-K, Havlin S, Stanley HE, Goldberger AL. Quantification of scaling exponents and crossover phenomena in nonstationary heart beat time series. Chaos 1995;5:82–7.

[10] Vuksanović V, Gal V. Nonlinear and chaos characteristics of heart period time series: healthy aging and postural change. Auton Neurosci 2005;121:94–100.
[11] Mansier P, Clairambault J, Charlotte N, Medigue C, Vermeiren C, LePape G, et al. Linear and non-linear analysis of heart rate variability: a minireview. Cardiovasc Res 1996;31:371–9.
[12] Cao L. Practical method for determining the minimum embedding dimension of a scalar time series. Physica D 1997;110:43–50.
[13] Wolf A, Swift JB, Swinney L, Vastano JA. Determining Lyapunov exponents from a time series. Physica D 1985;16:285–317.
[14] Rosenstein MT, Collins JJ, De Luca C. Practical method for calculating largest Lyapunov exponents from small data sets. Physica D 1993;65:117–34.
[15] Richman JS, Moorman JR. Physiological time-series analysis using approximate entropy and sample entropy. Am J Physiol Heart Circ Physiol 2000;278:H2039–49.
[16] Badra JL, Cooke WH, Hoag JB, Crossman AA, Kuusela TA, Tahvanainen KUO, et al. Respiratory modulation of human autonomic rhythms. Am J Physiol Heart Circ Physiol 2001;280:H2674–88.
[17] Peng C-K, Henry IC, Mietus JE, Hausdorff JM, Khalsa G, Benson H, et al. Heart rate dynamics during three forms of meditation. Int J Cardiol 2004;95:19–27.
[18] Task Force of the European Society of Cardiology, the North American Society of Pacing and Electrophysiology. Heart rate variability: standards of measurement, physiological interpretation and clinical use. Circulation. 1996;93:1043–65.
[19] Akselrod S, Gordon 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;213:220–3.
[20] Terkelsen AJ, Molgaard H, Hansen J, Andersen OK, Jensen TS. Acute pain increases heart rate: differential mechanisms during rest and mental stress. Auton Neurosci 2005;121:101–9.
[21] Yeragani VK, Berger R, Pohl R, Srinivasan K, Balon R, Ramesh C, et al. Effects of yohimbine on heart rate variability in panic disorder patients and normal controls: a study of power spectral analysis of heart rate. J Cardiovasc Pharmacol 1992;20:609–18.
[22] Tulppo MP, Makikallio TH, Seppanen T, Shoemaker K, Tutungi E, Hughson RL, et al. Effects of pharmacological adrenergic and vagal modulation on fractal heart rate dynamics. Clin Physiol 2001;21:515–23.
[23] Hautala AJ, Makikallio TH, Seppanen T, Huikuri HV, Tulppo MP. Short-term correlation properties of R–R interval dynamics at different exercise intensity levels. Clin Physiol Funct Imaging 2003;23:215–33.
[24] Willson K, Francis DP, Wensel R, Coats AJS, Parker KH. Relationship between detrended fluctuation analysis and spectral analysis of heart-rate variability. Physiol Meas 2002;23:385–401.
[25] Platisa M, Gal V. Reflection of heart rate regulation on linear and nonlinear heart rate variability measures. Physiol Meas 2006;27(2):145–54.
[26] Pikkujamsa SM, Makikallio TH, Sourander LB, Raiha IJ, Puukka P, Skytta J, et al. Cardiac interbeat interval dynamics from childhood to senescence. Circulation 1999;100:393–9.
[27] Makikallio TH, Seppanen T, Niemala M, Airaksinen KEJ, Tulppo MP, Huikuri HV. Abnormalities in beat to beat complexity of heart rate dynamics in patients with a previous myocardial infarction. J Am Coll Cardiol 1996;28:1005–11.
[28] Makikallio TH, Ristimae T, Airaksinen KEJ, Peng C-K, Goldberger AL, Huikuri HV. Heart rate dynamics in patients with stable angina pectoris and utility of fractal and complexity measures. Am J Cardiol 1998;81:27–31.
[29] Yeragani V, Rao R. Effect of nortiptyline and paroxetine on measures of chaos of heart rate time series in patients with panic disorder. J Psychosom Res 2003;55:507–13.