Biomed Tech 2013; 58 (Suppl. 1) © 2013 by Walter de Gruyter · Berlin · Boston. DOI 10.1515/bmt-2013-4170

Quantification of heart beat nonstationarities by nonparametric segmentation

Maik Riedl[1], Sabrina Camargo[1], Celia Anteneodo[2,3], Jürgen Kurths[1,4,5], Niels Wessel[1]

[1]Department of Physics, Humboldt-Universität zu Berlin, Germany

[2]Department of Physics, PUC-Rio, Brazil
[3]National Institute of Science and Technology for Complex Systems, Rio de Janeiro, Brazil

[4]Potsdam Institute for Climate Impact Research, Germany
[3]Institute for Complex Systems and Mathematical Biology, University of Aberdeen, United Kingdom

Maik.riedl@physik.hu-berlin.de

Abstract: *The standard parameter of heart rate variability (HRV) requires weak stationarity. We perform a nonparametric segmentation to HRV data of congestive heart failure patients as well as young and elderly healthy subjects where the signal is split into stationary epochs. By finding stationary segments we are able to quantify the nonstationarity by means of statistical values of segment length and jump size. We found high correlations between the measures of nonstationarity and standard values of HRV and a connection to results of detrended fluctuation analysis. The segmentation applied to heart rate time series detects aging and pathological conditions effects on the nonstationary behaviour of the analyzed groups, promising to contribute in complexity analysis and providing risk stratification measures.*

Keywords: *Heart rate variability, nonstationarity, segmentation*

Introduction

It has been a long time since studies on heart rate variability (HRV) have become as popular as the many devices available to record the cardiac activity [1]. As reported in literature, several diseases, as myocardial infarction, and diabetic neuropathy, point to a connection between healthiness and heart rate complexity. Also, the effects of aging are known to present higher HRV in younger individuals, compared to elderly ones [1]. As a standard tool of HRV analysis, the spectral analysis relies on the assumption of weak stationarity, where the mean value is constant and the covariance is only dependent on a time shift, but even in controlled environments, it is questionable whether the efficiency of such control ensures these conditions. The idea of the segmentation applied to time series is to provide patches of the signal where stationarity is verified. Instead of testing only the difference for the mean [2], we perform a nonparametric segmentation [3], taking into account the whole distribution, with all moments, especially mean and variance. We also use the known amplitude-frequency coupling of the dominant short-term oscillation [4], the respiratory sinus-arrhythmia, which connects the changes in the variance with the time-dependent covariance, implying nonstationarity.

Methods

For analysis, we consider 24 hours measurements of the electrocardiogram of three groups consisting of 15 young (YH; 11 females, 4 males, age 31±6 years) and 18 elderly subjects (EH; 11 males, 7 females, age 50±7 years), and 15 patients suffering from congestive heart failure (CHF; 11 males, 4 females, age 56±11 years) [5,6]. The series of time intervals between consecutive heart beats, the beat-to-beat intervals, are extracted from the electrocardiograms. All resultant signals were filtered in order to avoid ectopic beats [7].

After that these time series are segmented as follows: given a segment of a time series, a sliding pointer is moved in order to compare the two fragments, on the left (L) and the right (R) side of the pointer i. Then one selects the position i_{max} that maximizes the normalized Kolmogorov-Smirnov (KS) statistics:

$$D_i = D_{KS}\left(1/n_L + 1/n_R\right)^{-1/2} \qquad (1)$$

where D_{KS} is the distance between the cumulative distributions of the samples in the left and the right fragment. After determining the position i_{max}, one checks the statistical significance (at a chosen significance level α=0.05) of a potentially relevant cut at i_{max} by comparison with the result that would be obtained for a random sequence. The critical value is given by

$$D_{crit}^{\max}(n) = a(\ln n - b)^c \qquad (2)$$

where (a, b, c) is (1.52, 1.80, 0.14) in our case. The potential cut ticks the first stage if D^{max} exceeds its critical value for the selected significance level. If each resulting segment is greater than a defined minimum L_0, then the pointer is set and the procedure is recursively applied starting from the left patches until no patch is segmented. See Ref.[3] for further details. We performed the KS-segmentation with L_0=30 sample points in correspondence to the defined higher edge frequency of the very low frequency (VLF) band of heart rate with 0.03 Hz [1] providing at least a half period of this frequency in each segment.

Results

To quantify the nonstationarity, we obtain statistical values of the segmentation, which include not only segment length and jump size but also more sophisticated ones like the number of segments greater than 300, $L_{>300}$, and $\%\mu_{50}$ (Fig. 1). $L_{>300}$ corresponds to approximately 5 min, the shortest required segment length of HRV analysis and $\%\mu_{50}$ reflects the percentage of differences of the mean of two consecutive segments $|\mu_{i+1}- \mu_i|$>50ms in an analogy to the standard HRV measure pNN50, the percentage of consecutive RR intervals differing by more than 50ms [1].

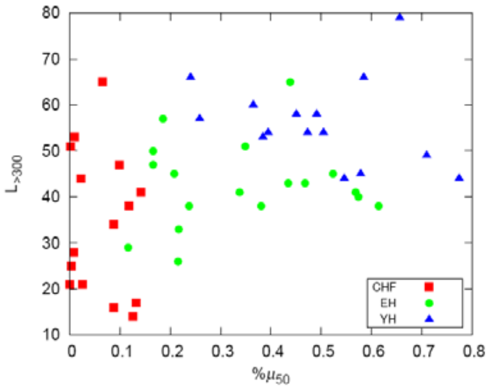

Figure 1: $L_{>300}$ and $\%\mu_{50}$ in the three groups

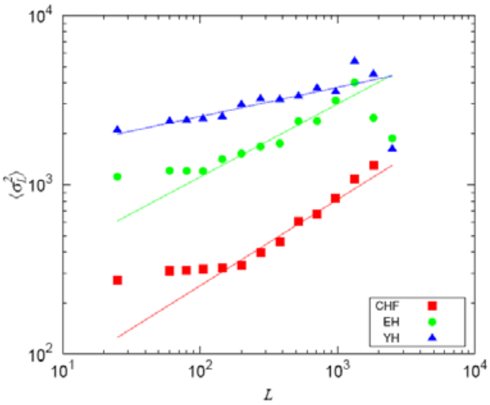

Figure 2 Mean variance of the segments of given segments length. The scaling exponents are indicated by solid lines (CHF:0.6, EH:0.4, and YH:0.2).

We found high positive correlations of about 0.9 between %μ50 and the overall standard deviation as well as a negative correlation around 0.8 between $L_{>300}$ and the normalized very low frequency power, VLF/P, linking the segmentation outcomes to standard measures.

In order to understand the scaling behaviour of the extracted trends in the time series, we compute the mean variance of the segments given a segment length (Fig. 2) which indicates a power function.

Discussion

In this paper we present the analysis of nonstationarities in heart rate by means of a nonparametric segmentation algorithm, being able to display differences between CHF and age-matched EH, as well as CHF and YH (Fig. 1). Also, differences between YH and EH can be detected, showing the aging effect in the loss of complexity of the heart rate (Fig.1).

The high positive correlation between $\%\mu_{50}$ and sdNN shows that the latter one is dominated by the large jumps. A negative correlation between $L_{>300}$ and VLF/P could reflects the reduction of longer segments by means of respiratory disorders which are prevalent in 30% to 50% of patients with CHF.

It is worth to mention here the similarity of Fig. 2 with plots given by detrended fluctuation analysis (DFA) [8]. In comparison to these results scaling exponent 0.6 in CHF indicates that random walk fluctuations dominate the dynamics of this group. For the EH and YH groups, the both exponents, 0.4 and 0.2, indicate power law correlations associated to the interchange of large and small RR intervals.

Through the outcomes of segmentation we have access to time characteristics of the signal that were no longer available, making possible a different approach to quantify nonstationarities in HRV analysis. Results are in agreement with previous knowledge and do not require arbitrary thresholds or excludes fragments of the time series. The individual risk stratification ability of this method relies in further applications to cardiological data bases.

Acknowledgement

We acknowledge Prof. Schirdewan for providing data. SC and CA acknowledge CNPq (Brazilian agency) for financial support. MR, NW and JK acknowledge the Deutsche Forschungsgemeinschaft, grant numbers DFG RI2016/2-1, WE 2834/5-1, KU837/29-2, and KU837/35-1.

Bibliography

[1] Task Force: Guidelines - heart rate variability, European Heart Journal vol. 17, pp. 354, 1996.

[2] Bernaola-Galvan, P., Ivanov, P. Ch. et al.: Scale invariance in the nonstationary of human heart rate, Phys. Rev. Lett. vol. 87, pp. 168105, 2001.

[3] Camargo, S., Queiros S. M. D. et al.: Nonparametric segmentation of nonstationary time series, Phys. Rev. E vol. 84, pp. 046702, (2011).

[4] Hirsch, J., B. Bishop: Respiratory sinus arrhythmia in humans: how breathing pattern modulates heart rate, American Journal of Physiology-Heart and Circulatory Physiology vol. 241, pp. H620, (1981).

[5] Goldberger, A. L., Amaral, L. A. N. et al.: http://circ.ahajournals.org/cgi/content/full/101/23/e215

[6] Wessel, N., Schirdewan, A. et al.: Intermittently decreased beat-to-beat variability in congestive heart failure, Phys. Rev. Lett. vol. 91, pp. 119801, 2003.

[7] Wessel, N., Malberg, H. et al.: Nonlinear methods of cardiovascular physics and their clinical applicability. International Journal of Bifurcation and Chaos vol. 17, pp. l3325, 2007.

[8] Peng, C. K., Havlin S. et al.: Quantification of scaling exponents and crossover phenomena in nonstationary heartbeat time series, Chaos vol. 5, pp. 82, 1995.