Signal Stationarity Assessment for the Heart Rate Variability Spectral Analysis

AN Kalinichenko[1], MI Nilicheva[1], SV Khasheva[1], OD Yurieva[1], OV Mamontov[2]

[1]StPetersburg State Electrotechnical University, StPetersburg, Russia
[2]Federal Heart, Blood and Endocrinology Center, StPetersburg, Russia

Abstract

The results of experimental examination of different approaches to the signal stationarity assessment with regard to the heart rate variability spectral parameters estimation are presented. The following three approaches were considered: autoregressive parameters monitoring; analysis of detrended signal and assessment of generalized likelihood ratio.

The above methods were examined with the use of both artificially modeled signals and a set of real signal recordings. A combination of parameters providing least values of nonstationarity detection error was determined for each method. It was shown that the three methods demonstrate similar performance, while the obtained errors can be reduced by their joint use and also by taking into account some additional statistical indexes (such as signal mean value and variance).

1. Introduction

The technique of heart rate variability (HRV) analysis is based on statistical and spectral analysis of NN intervals (time intervals between adjacent heart beats of background rhythm). The signal formed by the series of NN intervals is nonstationary by its nature due to both physiological origin and to external factors influencing a patient in the course of the signal acquisition process [1]. Nevertheless some traditional techniques of random signals analysis, such as FFT based and autoregressive (AR) spectral analysis, are commonly used for the investigation of heart rate regulation physiological mechanisms [1, 2]. The use of the mentioned above methods suggests fulfillment of signal stationarity condition within the frames of the analyzed signal fragment. Otherwise the obtained results can not be considered as statistically consistent.

In practice when the spectral HRV parameters are calculated it is usually supposed that within the borders of the analyzed signal fragment the stationarity conditions are met. It can be ensured due to both correct procedure of the signal acquisition and human observation of the data to be analyzed [1]. Figure 1 shows example of heart rate signal obtained in the course of orthostatic testing. Two periods of local stationarity and a transient process corresponding to the patient's position change are clearly seen at the plot.

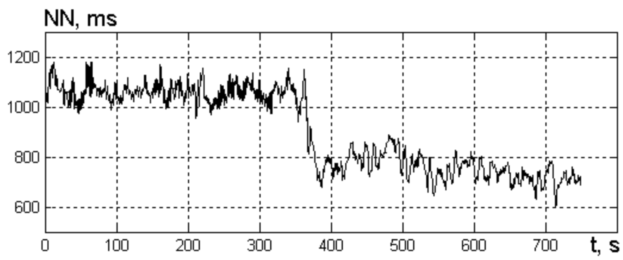

Figure 1. An example of HRV signal including two fragments of local stationarity and a transient process.

At the same time there are some practical applications where the signal is registered during long-time period and the assumption of the signal stationarity can not be valid. Besides, the instants of the stationarity violation are not known beforehand and can not be humanly supervised. These are such applications as bed-side cardiac rhythm monitoring, Holter ECG monitoring and some others. In order to obtain statistically valid estimations of HRV parameters some automatic procedure of the signal stationarity assessment is needed. Two different problems can be set:

- Calculation of some stationarity (or nonstationarity) index for the analyzed signal fragment to assess the degree of the obtained results reliability.
- Automatic segmentation of the signal recording into a number of locally stationary fragments to avoid calculation of erroneous parameters for the signal sections including some transient processes or noises.

The most well known methods of random process stationarity assessment are runs test and reverse arrangements test [3], based on division of the observed data recording into fragments of equal length and further statistical analysis of the obtained sequence. However this approach provides only an estimation of the signal nonstationarity in the whole and gives no possibility of detecting the signal sections that can be considered as locally stationary. More efficient way to solve this problem is to use more complicated techniques such as correlation, spectral analysis and parametric modeling of processes [4].

The aim of this study was examination of several different approaches to signal stationarity analysis with regard to the spectral HRV analysis and choice of the corresponding algorithms parameters.

2. Methods

Three different approaches were examined:

A. Autoregression coefficients monitoring [4]. This method consists in tracking of standard deviation of autoregression (AR) coefficient estimated for the consecutive signal fragments. As long as the data belong to the same kind of statistical distribution the standard deviation values are comparatively small. If two last analysed fragments of the data belong to different distributions, the stepwise increase of this index takes place due to abrupt change of the AR parameters values.

The method realization:

1. The input data series is divided into K overlapping fragments $y_k(n), n = 1,...,N$ having duration N samples each and advancing by the step S.
2. AR model is determined for each fragment
$$\tilde{y}_k(n) = -\sum_{p=1}^{P} a_{p,k}\ y_k(n-p), n = P+1,...,N ,$$
where P is the model order, and $a_{p,k}$ are the coefficients.
3. The standard deviation is calculated for each pair of successive fragments:
$$d_{\mathrm{A}}(k) = \sum_{p=1}^{P}\left[a_{p,k}^2 - a_{p,k-1}^2\right], k = 2,...,K .$$
4. Consequence of the values $d_{\mathrm{A}}(k), k = 2,...,K$ forms a function that can be examined for the presence of sharp spikes indicating the instances of the stationarity violation. The adjusted parameters are N, P and S.

B. Detrended signal analysis.

A simplified version of detrended fluctuation analysis (DFA) technique is used in this method [5].

The method realization:

1. The initial sequence $x(m), m = 1,2,...,M$ is divided with the use of step S into fragments of equal duration N samples:
$$y(l,k) = x[(l-1)S + k], k = 1,...,N, l = 1,...,L ,$$
where L is total number of obtained fragments.
2. Every fragment $y(l,k)$ is divided into J nonoverlapping sections containing $n = N/J$ samples each.
3. Least square linear trend is determined for each section [3]. The sequence of the obtained trends samples for the whole fragment l is denoted here as $y_n(l,k), k = 1,...,N$.
4. The calculated signal $y_n(l,k)$ is subtracted from the fragment samples $y(l,k)$ and mean square value is calculated:
$$F(l) = \sqrt{\frac{1}{N}\sum_{k=1}^{N}[y(l,k) - y_n(l,k)]^2}, l = 1,...,L .$$
5. Then the following values are defined:
$$a(l) = \frac{\ln\left[F(l)\right]}{\ln(n)}, l = 1,...,L ,$$

the modules of first differences of which
$$d_{\mathrm{B}}(l) = \left|a(l+1) - a(l)\right|, l = 1,...,L-1 ,$$
are used as indexes of the signal nonstationarity. The adjusted parameters are N, n and S.

C. The generalized likelihood ratio based method.

The method based on the generalized likelihood ratio [4] uses three data windows: the growing reference window (the step of growing is S), the sliding test window of constant duration and a pooled window formed by concatenation of the two. Distance measures are then derived using AR model prediction error computed for the three data sets.

Let $\varepsilon(m:n)$ represent the prediction error energy within an arbitrary data set or window with boundaries m and n.
$$\varepsilon(m:n) = \sum_{i=m}^{n} e^2(i) = \sum_{i=m}^{n}\left[x(i) + \sum_{k=1}^{P} a_k x(i-k)\right]^2 ,$$
where $x(i)$ are the samples of the analyzed signal, a_k are AR model coefficients, determined for the given signal fragment, and P is the AR model order.

The log likelihood measure for the window is defined as
$$H(m:n) = (n-m+1)\ln\left[\frac{\varepsilon(m:n)}{(n-m+1)}\right].$$

Three measures are computed for the three data sets described above: $H(1:m-1)$ for the growing reference window, $H(m:n)$ for the sliding test window of duration $N = n - m$, and $H(1:n)$ for pooled window. The index of the signal nonstationarity is defined as

$$d_C(n) = H(1:n) - \left[H(1:m-1) + H(m:n) \right].$$

This index $d_C(n)$ represents a measure of total square error increase in case the test window is added to the growing window. The adjusted parameters are N, P and S.

In order to test the described methods a set of artificially generated model signals (resembling the HRV signals obtained in the course of orthostatic testing) was formed. Duration of each model realization was chosen equal to 12 minute (two locally stationary segments and a 20 second transition fragment between them). A power spectral density (PSD) function was defined for each segment as a sum of three Gaussian curves centered to the three frequency ranges used for HRV analysis: VLF, LF and HF [2, 6]. Specifying the area under each portion of this curve one can obtain the PSD function having any needed values of total power within VLF, LF and HF ranges. Then the magnitude spectrum was calculated from PSD function and its values was used further as amplitudes of sine signals with corresponding frequencies and random phases (evenly distributed within the range 0–2π) to compose model signal realization. To avoid signal leap at the point of two segments junction a smoothing function was used to provide gradual transition from the first segment to the second. Then a constant value (simulating mean NN interval duration) was added to the function and the obtained signal (with sampling rate 4 Hz that meets the requirements of HRV analysis [1]) was considered as a model of heart rate control function.

Figure 2 shows an example of PSD plots (upper plots) for two segments of the model signal realization (lower plots). The HRV spectral parameters (VLF, LF and HF) for this signal are also shown on the PSD plots. This relationship between HRV parameters of two segments is similar to the typical situation of HRV decrease in the course of orthostatic testing procedure. Several different model recordings were generated that simulated various variants of LF and HF power sudden change.

A set of real HRV signal recordings was also formed that includes 36 realizations (11 to 17 minute long) obtained in the course of orthostatic testing procedures at the Federal Heart, Blood and Endocrinology Center (St.Petersburg, Russia). Each of the recordings selected for the set includes at least two 5 minute segments of local stationarity separated by a transient period. All recordings were manually verified: the borders of stationary segments and transient periods were marked (by visual examination). The data set was then randomly split into two subsets: a training set (16 recordings) and a test set (20 recordings).

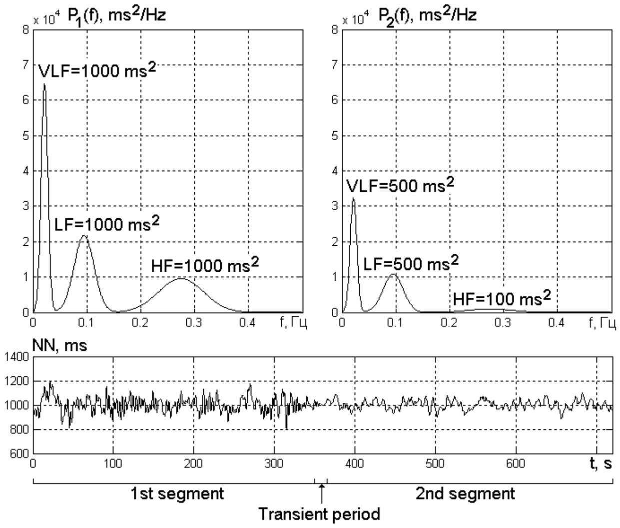

Figure 2. PSD plots (upper plots) for two segments of the model signal realization (lower plots).

The goal of the algorithms examination was estimation of the stationary segments borders detection accuracy. The stationarity violation was considered as detected, if the used nonstationarity index value in the vicinity of the corresponding time instant was at least two times greater than maximum value of this index at the preceding stationary segment.

The value of the detection error at the crossing point of type I and type II error curves was used as a criterion for the algorithms parameters optimization procedure. The mentioned two types of errors were defined as follows:

- Type I error – no stationarity violation was detected near the marked transient period;
- Type II error – false detection of stationarity violation within a fragment marked as stationary.

3. Results

The examination of all three methods with the use of model signals provided the ranges of the methods parameters that give satisfactory results. The final optimization of these parameters was implemented with the use of the training data set. Combinations of parameters that produce least values of nonstationarity detection error were determined. Then the algorithms performance was estimated with the use of the test data set. The determined combinations of the methods parameters and the values of errors for both data sets are presented in table 1.

Figure 3 shows an example of real signal analysis by all three methods with the use of the determined parameters combinations. It is seen that each examined method produce sharp spike of the nonstationarity index near the point of the stationarity violation.

Table 1. The determined combinations of the methods parameters and the error values for the training and the test data sets.

Method	Parameters	Error, %	
		Training set	Test set
A	$N=100$ $P=8$ $S=20$	14	17
B	$N=100$ $n=10$ $S=20$	23	27
C	$N=50$ $P=6$ $S=20$	31	34

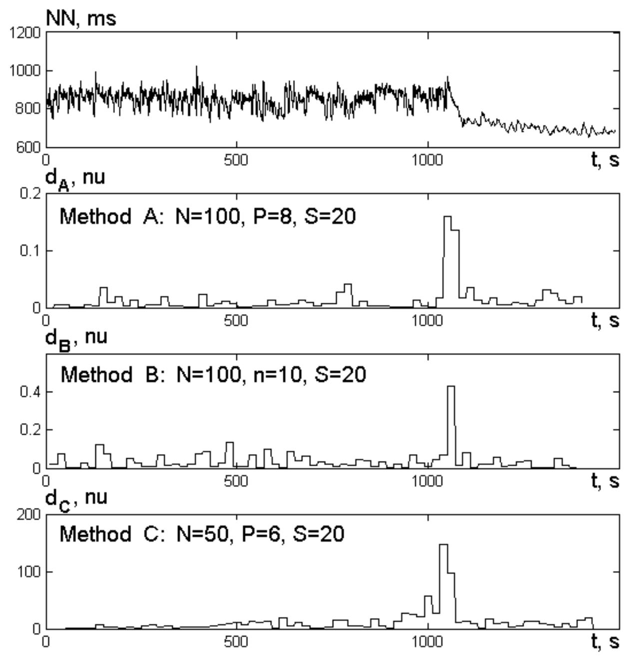

Figure 3. An example of real HRV signal analysis.

4. Discussion and conclusions

The following conclusions can be made as a result of the presented above examination:

Method A based on autoregression coefficients monitoring produces clearly expressed spikes near the signal portions where some nonstationarity takes place, but in cases of the signal change from lower frequency to higher frequency this method reacts to the transient process earlier than in the opposite situation due to the dominating influence of higher frequency components on AR parameters.

Method B based on the detrended signal analysis is more mathematically simple than two others but similar to the method A turns out to be too sensitive to the higher frequency components appearing in the analyzed signal.

Method C based on generalized likelihood ratio produces more accurate localization of transient processes but does not give such distinct spikes as the method A.

Besides, as it is seen from the table 1, the error estimations obtained for all three methods are comparatively high. The best results were shown by the method based on AR model monitoring approach (the method A). At the same time the error level can be substantially reduced by means of joint use of different alternative methods and also by taking into account some other statistical parameters, such as mean value and variance. For instance, one can see that the stationarity violation taking place in signals shown at figures 1 and 3 affects not only frequency content of these signals but also manifests itself in clearly expressed change of both mean value and variance of the signal.

The proposed methods can be used as additional means of the HRV parameters statistical consistency enhancement in the devices, systems and software packages for automated HRV analysis both in real-time and off-line modes.

References

[1] Task Force of the European Society of Cardiology and North American Society of Pacing Electrophysiology. Heart rate variability: standards of measurement, physiological interpretation and clinical use. Circulation 1996;93:1043–1065.

[2] Clifford GD, Azuaje F, and McSharry PE, editors. Advanced Methods and Tools for ECG Analysis. Artech House Publishing, Boston/London. 2006. 384 pp.

[3] Bendat, Julius S., and Piersol, Allan G., Random Data: Analysis and Measurement Procedures, 3nd ed. Wiley-Interscience, 2000 – 594 p.

[4] Rangaraj .M. Rangayyan. Biomedical Signal Analysis. IEEE Press, Wiley-Interscience, 2002 - 516 p.

[5] Peng C-K, Buldyrev SV, Havlin S, Simons M, Stanley HE, Goldberger AL. Mosaic organization of DNA nucleotides. Phys Rev E Stat Phys Plasmas Fluids Relat Interdiscip Topics. 1994;49:1685–1689.

[6] Kalinichenko AN. On the Accuracy of Heart Rate Variability Spectral Parameters Estimation. St.Petersburg, Russia. Informative and Control Systems 2007; 6: 41–48.

Address for correspondence:

Alexander Kalinichenko
Biomedical Engineering Department,
St.Petersburg State Electrotechnical University,
5 Prof. Popov Str., St.Petersburg, 197376, Russia
ank-bs@yandex.ru