Testing the Presence of Non Stationarities in Short Heart Rate Variability Series

A Porta[1], G D'Addio[2], S Guzzetti[3], D Lucini[4], M Pagani[4]

[1]DiSP LITA di Vialba, Universita' degli Studi di Milano, Milan, Italy
[2]S. Maugeri Foundation, IRCCS, Rehabilitation Institute of Telese, Italy
[3]DiSC, Universita' degli Studi di Milano, Medicina Interna II, Milan, Italy
[4]DiSC, Universita' degli Studi di Milano, Medicina Interna I, Milan, Italy

Abstract

The study proposes a test to evaluate stationarity over short beat-to-beat variability series of heart period (about 300 samples). This test checks the steadiness of mean and variance (i.e. a restricted form of weak stationarity). Artificial series, in which changes of the mean and variance are simulated, are utilized to set the analysis parameters and to evaluate the performance of the method. Next, the test is applied to beat-to-beat series variability series of heart period derived from humans at rest, during controlled respiration at different breathing rates (10, 15 and 20 breaths/minute) and during 80° head-up tilt. The application proves the difficulty to find stationary periods in short term recordings of heart period variability and prompts for an assessment of the effect of non stationarities on traditional linear and non linear indexes assuming stationarity as a requirement.

1. Introduction

Heart period fluctuations are intensively studied over a time window of about 5 minutes (i.e. short term analysis) because they are believed to provide important information about cardiovascular control mechanisms [1]. Two main categories of tools are traditionally exploited. Tools evaluating the amplitude of the heart period variations like e.g. the power spectrum [2] and those quantifying complexity (or its opposite, regularity) of the heart period changes like e.g. different types of entropies [3]. These methods assume that the series are stationary (i.e. the statistical quantities are invariant to translation of the time origin), or at least weakly stationary (i.e. mean is constant over time and autocorrelation function depends only on the time separation between two samples, thus implying also the stability of the variance over time). Usually, weak stationarity is not checked even in the most restricted form (i.e. steady mean and variance). Short-term recordings of heart period variability are conventionally considered stationary as a result of carefully controlled experimental settings that should guarantee the absence of important transients.

The aim of this study is to propose and evaluate a simple test to check steadiness of the mean and variance (restricted weak stationarity, RWS) over heart period variability series of about 5 minutes (i.e. about 300 samples).

The RWS test was evaluated on autoregressive (AR) processes: they simulated gradually increasing changes in the amplitude of oscillations close to 0 cycles/sample and/or larger and larger amplitude modulations. When evaluated over a finite time window, very slow tends produced changes of the mean, while amplitude modulations induced modifications of the variance.

The RWS test was applied to data extracted from 9 healthy young subjects undergoing ECG recordings at rest in supine position, during controlled respiration at 10, 15 and 20 breaths/minute and during 80° head-up tilt. Initially, we checked stationarity on sequences of 300 samples utilized in a previous study [3] to understand whether a stationarity analysis carried out by visual inspection by an experienced researcher and a fully automatic method performed similarly. Subsequently, we randomly picked up sequences of 300 samples from the entire heart period series (from 550 to 800 samples) and we carried out the RWS test to understand how easy it was to detect stationary periods on short term heart rate variability recordings.

2. Methods

2.1. RWS test

Giving the series x={x(i), i=1, …N}, Kolmogorov-Smirnov goodness-of-fit test is utilized to assess the normality of the distribution ($p<0.05$). If the null hypothesis is rejected, the data undergo a log-transformation and Kolmogorov-Smirnov test is applied again. Next, N-L+1 ordered sequences of length L are constructed as $x_L(i)=(x(i),x(i+1),\ldots,x(i+L+1))$. The sequence $x_L(i)$ is actually a pattern derived from x. M patterns are randomly selected from the set of N-L+1 possible patterns (all the patterns have the same probability to be selected). The RWS test checks if mean and variance remain constant over the M patterns. If the null hypothesis of a normal distribution of x cannot be rejected, the test on the stability of the mean is performed via analysis of variance (F-test statistics), otherwise it is performed via Kruskal-Wallis test (both tests with an assigned level of confidence p). The test on the stability of the variance is performed via Bartlett test when the hypothesis of a normal distribution cannot be rejected, otherwise it is performed via Levene test using the median (more suitable than the mean in the case of skewed distributions) and less sensible than the Bartlett test to departures from normality (both tests with the same level of confidence p as that utilized to test the stability of the mean). If the normality test is passed, the test about the homogeneity of the variance via Bartlett test must be passed to check the stability of the mean via analysis of variance. See e.g. [4] for the practical implementation of the above-mentioned well-established tests.

2.2. Parameter setting

In addition to the level of confidence p, three parameters should be set before performing the RWS test: the series length N, the pattern length L and the number of patterns M. N is set to 300 samples (i.e. the traditional sequence length in short term analysis of heart period variability). L and M are less easy to be decided. L should be sufficiently large to observe several cycles (at least 5) of the slowest time scale that it is considered an expression of a stationary phenomenon inside the series of N samples. As the slowest rhythmicity in heart period variability that has been considered as a repetitive and stable phenomenon in short term recordings is the low frequency oscillation (LF, around 0.1 Hz [1,2]) L is set equal to 50 (i.e. about 5 cycles of LF with a mean heart period equal to 1 second). M is set equal to 8 to guarantee that, with a random selection of the patterns, it is likely to analyse almost all the samples of series. Fig.1 shows an example of M=8 patterns of L=50 samples (small-size panels) drawn at random from the entire series of N=300 samples (full-size panel).

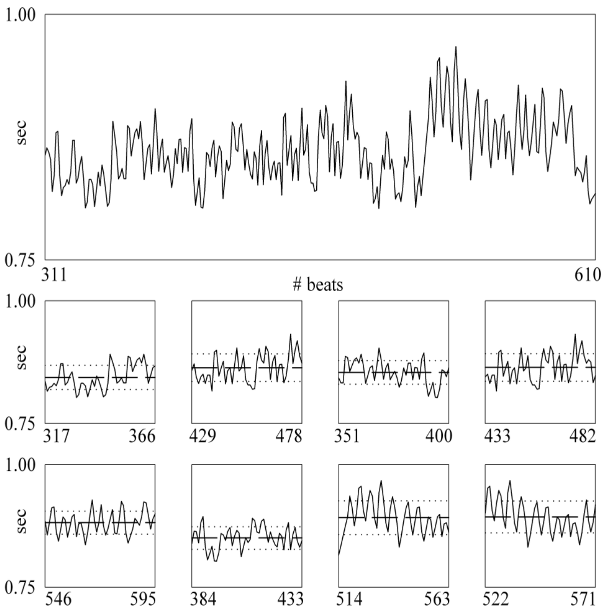

Figure 1. Full-size panel: RR interval series of 300 samples. Small-size panels: sequences of 50 samples derived randomly from the entire series (the means is represented by a long dashed line, while the interval of 1 sd around the mean is indicated by two dotted lines). Mean changes are found significant.

2.3. Simulations

To evaluate the performance of the RWS test two types of artificial series have been utilized. Both types of series were built such a way that: i) they were stationary processes over a time window of infinite length; ii) they could be considered stationary processes for certain values of a parameter when observed over a window of finite length; iii) they exhibited more and more evident non-stationarities while increasing one parameter value when observed over a window of finite length.

The type-1 series was an AR process with one real pole (z=ρ with ρ≥0.0). When ρ=0.0 the AR process was a white noise (Fig.2a) and it was stationary even when observed over a window of finite length. By growing ρ from 0 to 1, the power was more and more concentrated around 0 cycles/samples and the amplitude of these fluctuations gradually increased. When this process was observed using an observation window of a finite length (N=300), non stationarities appeared as trends resulting

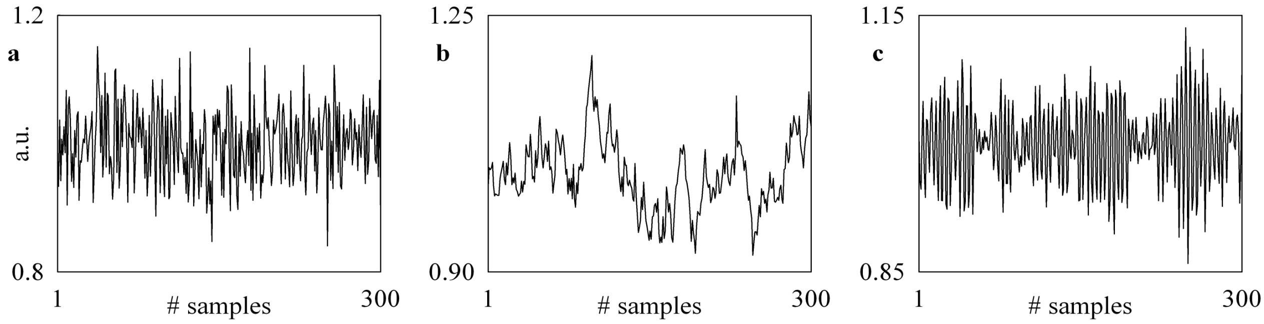

Figure 2. (a) Gaussian white noise. (b) AR(1) with ρ=0.91. (c) AR(2) with ρ=0.94 and φ=±π/2.

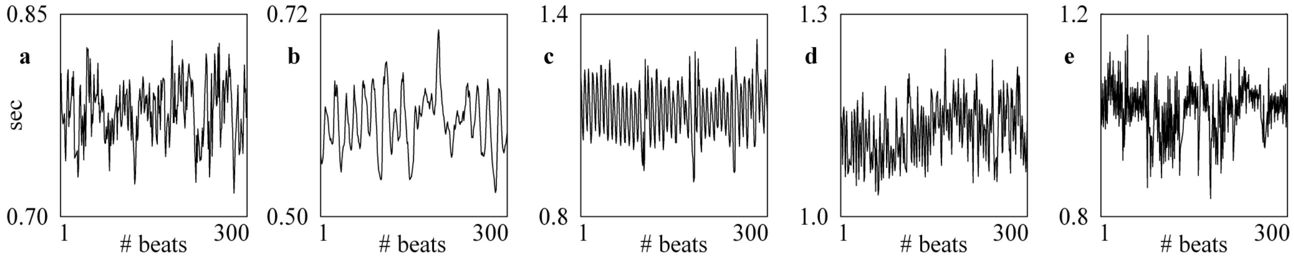

Figure 3. Examples of RR interval series at R, during T, R10, R15 and R20 (a-e respectively). The series in (a) and (c) are found stationary. Significant changes of the variance are detected in (b) and (e). Mean is not stable in (d).

from the shortness of the observation window with respect to the period of the dominant oscillation (Fig.2b). We generated 20 type-1 processes of 2000 samples while varying ρ from 0.01 to 0.99.

The type-2 series was an AR process with two complex and conjugated poles ($z=\rho e^{j\varphi}$ with $\varphi=\pm\pi/2$). Like in type-1 series the AR process was a white noise when $\rho=0.0$. By growing ρ from 0 to 1, the power was more and more concentrated around 0.25 cycles/samples, the amplitude of these fluctuations gradually increased and amplitude modulations became more and more evident without important changes of the mean (the amplitude of the oscillations around 0 cycles/sample decreased more and more). When this process was observed using an observation window of a finite length (N=300), non stationarities appeared as changes in variance due to the presence of amplitude modulations (Fig.2c). We generated 20 type-2 processes of 2000 samples while varying ρ from 0.6 to 0.98.

3. Experimental protocol

Nine healthy young subjects underwent recordings of ECG (lead II) at rest (R) in supine position during spontaneous breathing. Next, three sessions of controlled respiration (according to a metronome) at 10, 15 and 20 breaths/minute were performed (R10, R15 and R20 respectively). The last recording was made during 80° head-up tilt (T). All the recordings lasted from 10 to 15 minutes. Heart period was extracted on a beat-to-beat basis from ECG as the temporal distance between two consecutive QRS complexes (RR interval).

4. Data analysis

Artificial series were analyzed as follows: we selected randomly 20 sequences of 300 samples inside the entire realization of 2000 samples and the RWS test was applied. The percentage of sequences found stationary with a $p<0.05$ was monitored as a function of ρ.

Real RR interval series underwent two different types of analysis. In the first type of analysis the RWS test was applied ($p<0.01$) on a unique sequence of 300 samples per subject classified as stationary by visual inspection in a previous study [3]. The percentage of stationary periods was monitored as a function of the experimental condition. This analysis aimed at comparing the performance of the automatic method with the most spread technique to check stationarity (i.e. visual inspection). The second type of analysis was performed by considering the entire RR series and by selecting randomly 15 sequences of 300 samples per subject. The RWS test ($p<0.01$) was, then, carried out on these 15 sequences and the percentage of stationary periods was monitored as a function of the experimental condition. This analysis aimed at evaluating how easy it was to find a stationary period in a given experimental condition.

5. Results

On both type-1 and type-2 simulated series we found that, while increasing ρ, it is less and less likely that the RWS test is passed, thus confirming the ability of the test to detect changes of the mean or variance.

Fig.3 shows examples of beat-to-beat sequences of 300 RR intervals judged by visual inspection as

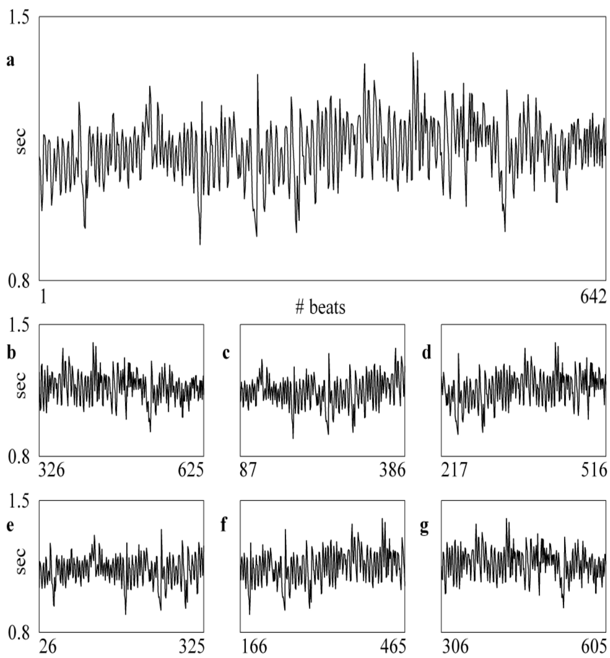

Figure 4. (a) Example of a complete RR interval series at R. (b-g) Six sequences of 300 beats derived at random from the entire series: only those shown in (b), (c) and (g) are classified as stationary.

stationary. The RWS test classified as stationary only those depicted in Fig.3a,c. Significant changes of the mean without modification in the variance were found in Fig.3d. Significant fluctuations in the variance were detected in Fig.3b,e. When the RWS test was applied to a unique sequence per subject judged as stationary by visual inspection, 67, 22, 78, 44 and 44 percent of the sequences were identified as stationary at R, during T, R10, R15 and R20 respectively. The percentage found during T was significantly smaller that that at R (χ^2 test with $p<0.05$).

An example of entire RR series at R is shown in Fig.4a with 6 sequences of 300 samples (Fig.4b-g) drawn at random from the whole series. Only the sequences depicted in Fig.4b,c,g were found stationary. On the contrary, those in Fig.4d,f exhibited significant variations of the mean (no change of the variance) and that in Fig.4e revealed significant modifications of the variance. When the RWS test was applied to 15 sequences per subject drawn at random from the whole RR series, it identified as stationary 17, 6, 13, 20 and 11 percent of the sequences at R, during T, R10, R15 and R20 respectively. Again the percentage found during T was significantly smaller than that at R (χ^2 test with $p<0.05$).

6. Discussion

We propose a simple test checking the most restricted form of stationarity (steady mean and variance) on short heart rate variability series. This test is capable to give reliable results on artificial processes characterized by slow trends, simulating changes of the mean, and amplitude modulations, simulating variations of the variance.

The test is general but it is tailored to detect non stationarities in short-term recordings of heart rate variability by setting the parameters N, L and M to 300, 50 and 8 respectively. In this application the test considers any important oscillation slower than LF rhythm (around 0.1 Hz) as a non stationary phenomenon. If this phenomenon is capable to produce significant changes in the mean, the series is classified as non stationary. However, also series characterized by stable LF and/or higher frequency rhythms may be classified as non stationary. Indeed, it is sufficient that the amplitude of these oscillations is modulated such a way to produce significant changes in the variance.

The application of the test to segments classified as stationary by visual inspection suggests that judging stationarity by visual inspection may be inadequate. The least agreement between the proposed automatic method and a test based on visual inspection is found during T. In this experimental condition mean value appears to be quite constant but LF rhythms, usually present during T [2], appear to be amplitude-modulated (see e.g. Fig.3b). The underestimation of the importance of slow amplitude modulation phenomena in introducing non stationarities may be responsible for the bad performance of a test based on visual inspection.

The application of the test to segments randomly selected over the entire RR series suggests that finding a stationary sequence of 300 samples is not an easy task on short RR interval recordings (from 10 to 15 minutes). In addition, this task is less easy in specific experimental conditions (e.g. during T). During T, non stationarities are mainly attributed to changes of the variance due to the presence of remarkable slow modulations of the amplitude of the LF rhythm.

7. Conclusions

The proposed test checks the steadiness of mean and variance (a restricted form of weak stationarity) on short heart rate variability series. Its application to short term recordings of heart rate variability evidences that assessing stationarity by visual inspection may be unreliable and that stationary sequences may be difficult to be found even in well-controlled experimental settings. In addition, the difficulty to find stationary periods depends on the experimental condition. Therefore, it is important to assess to what extent the presence of non stationarities affects traditional linear and non linear indexes assuming stationarity as a prerequisite.

References

[1] Task force of the European Society of Cardiology and the North American Society of Pacing and Electrophysiology. Standard of measurement, physiological interpretation and clinical use. Circulation 1996;93:1043-1065.

[2] Pagani M, Lombardi F, Guzzetti S, Rimoldi O, Furlan R, Pizzinelli P, Sandrone G, Malfatto G, Dell'Orto S, Piccaluga E, Turiel M, Baselli G, Cerutti S, Malliani A. Power spectral analysis of heart rate and arterial pressure variabilities as a marker of sympatho-vagal interaction in man and conscious dog. Circ Res 1986;59:178-193.

[3] Porta A, Guzzetti S, Montano N, Furlan R, Pagani M, Malliani A, Cerutti S. Entropy, entropy rate and pattern classification as tools to typify complexity in short heart period variability series. IEEE Trans Biomed Eng 2001;48:1282-1291.

[4] Papoulis A. Probability, random variables and stochastic processes. McGraw-Hill, New York, 1984

Address for correspondence.

Alberto Porta, PhD
Universita' degli Studi di Milano
Dipartimento di Scienze Precliniche (DiSP)
LITA di Vialba
Via G.B. Grassi 74
20157, Milan,
Italy

E-mail: alberto.porta@unimi.it