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Analyzing short-term measurements of heart rate variability in the frequency domain using robustly estimated spectral density functions

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ABSTRACT

To assess the variability of heart rate in the frequency domain, usually the spectral density function of the tachogram series is estimated. However, classical spectral density estimates are well known to be prone to outlying observations; hence, robustness is an issue. Therefore, the heart rate variability is assessed by robustly estimating the spectral density function of the tachogram series using a multi-step procedure based on robust filtering. This procedure is insensitive to outliers, and therefore provides fully automated signal processing which will facilitate reliable and reproducible heart rate variability analysis with minimal operator input. Moreover, it can also be used to identify and mark outlying observations. The proposed method is applied to short-term heart rate variability measurements of diabetic patients with different degrees of cardiovascular autonomic neuropathy.

1. Introduction

Frequency-domain analysis of short-term heart rate variability (HRV) recordings is a non-invasive method which has been increasingly used in medicine (cf. Task Force of The European Society of Cardiology and The North American Society of Pacing and Electrophysiology, 1996; Howorka et al., 1997, 1998; Hartikainen et al., 1998; Pumprla et al., 2002). To assess the variability of heart rate in the frequency domain, the spectral density function of the tachogram is estimated. The tachogram is the series of time intervals between consecutive heart beats. These time intervals are also called *R–R*-intervals, i.e., the periods between an *R*-peak and the next *R*-peak in an electrocardiogram (cf. Fig. 1). The intervals normally have a duration of about 750 ms corresponding to a heart rate of 80 beats per minute. In the tachogram (an example is displayed in Fig. 2), outlying observations can be caused by ventricular ectopic beats and other artifacts (cf. Hartikainen et al., 1998). Ectopic beats are usually premature and produce a very short *R–R*-interval followed by a compensatory delay and therefore a prolonged *R–R*-interval. Typical tachogram patterns caused by ectopic beats can be seen in Fig. 2 around heart beat numbers 90 and 1090. Correspondingly, missed beats result in erroneously prolonged *R–R*-intervals (sum of two consecutive *R–R*-intervals). Typical patterns caused by missed beats are visible in Fig. 2 around beat number 730.

These outlying tachogram measurements affect the spectral analysis of heart rate variability if classical spectral density estimators which are sensitive to outliers, are used. For details see Kleiner et al. (1979) or Martin and Thomson (1982). Therefore, we aim to assess the heart rate variability by estimating the spectral density function of the tachogram series using robust methods that are insensitive to outlying tachogram values caused by ectopic beats or other artifacts. Furthermore, as ectopic or missing beats do not affect successive heart beats, the additive outlier (AO) model (cf. Denby and Martin,

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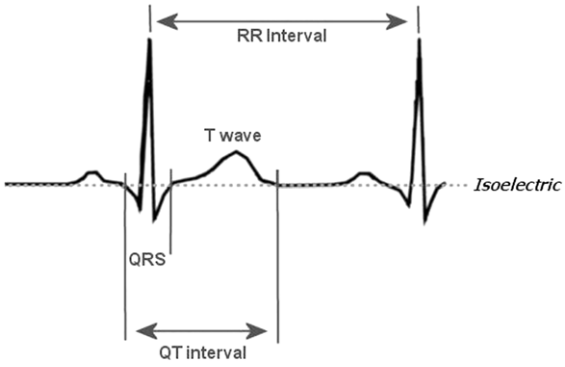

Fig. 1. Ideal electrocardiogram signal.

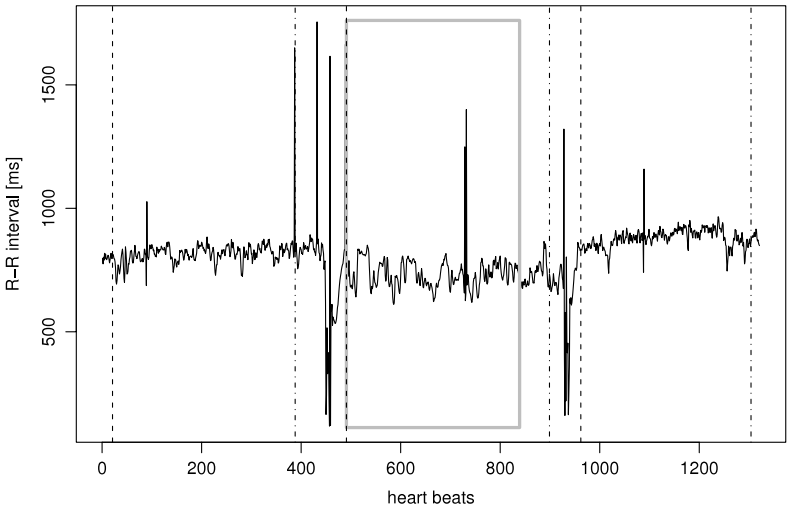

Fig. 2. Tachogram of 1321 consecutive heart beats.

1979; Fox, 1972) seems to be an appropriate model when analyzing heart rate variability data. The AO model consists of a stationary core process, x_t, to which occasional outliers have been added. The observed process y_t is said to have additive outliers if it is defined by

$$y_t = x_t + v_t \tag{1}$$

where the contaminations v_t are independently and identically distributed according to a contaminated normal distribution with a degenerate central component, i.e.,

$$\mathcal{C}\mathcal{N}(\gamma, 0, \sigma^2) = (1-\gamma)\mathcal{N}(0,0) + \gamma\mathcal{N}(0,\sigma^2), \tag{2}$$

where γ is small. $\mathcal{N}(\mu, \sigma^2)$ denotes the normal distribution with mean μ and variance σ^2. Hence, the core process x_t is observed with probability $1-\gamma$ whereas the core process plus a disturbance v_t is observed with probability γ. x_t and v_t are also assumed to be independent.

We do not compute the spectral density function of the entire tachogram, but calculate several estimates within overlapping windows (cf. Pumprla et al., 2002). This is to ensure stationarity in each window and to deal with signals whose frequency content changes over time. The result of the so called dynamic Fourier analysis applied to the tachogram series plotted in Fig. 2 is displayed in Fig. 3. Each slice parallel to the frequency-spectrum plane in Fig. 3 represents the spectral density estimate of the corresponding time window.

A high variability in heart rate indicates good adaptability, implying a healthy person with well functioning autonomic control mechanisms. Conversely, lower variability is often an indicator of abnormal and insufficient adaptability of the autonomic nervous system. Therefore, we do not use the entire tachogram series but several overlapping windows to assess the heart rate variability and only focus on an analysis in the frequency domain. We are neither interested in modeling the heart rate in the time domain nor in forecasting as this is often the aim in the context of online-monitoring.

In the following the problem of robust spectral analysis of short-term HRV data is considered. To obtain a robust estimate of the spectral density function we suggest to use the multi-step procedure proposed by Martin and Thomson (1982). This