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LONG-TERM HEART BEAT VARIABILITY EVALUATION THROUGH DISCRETE WAVELET ANALYSIS

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Abstract-Evaluation of the long-term heart rhythm variability is essential not only in the clinical, but also in the preventive medicine. Routine spectral analysis techniques, utilizing time-frequency (FFT, STFT) or time-dependent modelling (ARMA, short-time AR) approaches, assume a priori quasi-stationarity of the input signal. The goals of this study were to demonstrate that signal decompositions, like the 3-D Discrete Wavelet Transform (DWT), are capable of tracking slow and abrupt changes in long-term heart rhythm variations, as well as to compare the performance of 7 unsophisticated wavelets and to investigate the compatibility and potential of DWT for evaluation of normal and pathological patterns in long-term electrocardiograms.

Introduction

Assessment of cardiac rhythm control receives recently well-deserved attention as the ultimate response of the autonomic nervous system to fluctuations in the human body homeostasis. Heart Rate Variability (HRV) studies, reflecting the cardiovascular control by the corresponding hypothalamic centers and the vasomotor feedback, become indispensable e.g. for prevention of sudden cardiac death, for early detection of diabetic neuropathy in children or for postsurgical follow-ups.

Using spectra of standard time-frequency distributions (Fourier Transform) or time-depend techniques (Autoregressive modeling) is recognized to give a most useful picture of the instantaneous interaction between the two autonomic nervous systems, which regulate major body functions. Although the exact mechanisms of this interplay are not yet very well understood and not all studies agree on the details, parasympathetic activity is considered to be correlated with High Frequency (HF) components of spectra, but both sympathetic and parasympathetic tonuses seem to determine the Low Frequency (LF) components of the HRV. The essential frequency bands in these spectra are well known [5]: 0-0.0167 Hz - dominated by physical activity and postural changes; 0.0167-0.05 Hz: Very LF (vasomotor and renin-angiotensin control systems - the thermoregulatory frequency is approx. 0.03 Hz); 0.05 Hz - 0.15 Hz: LF (oscillations of the baroreflex system - the Traube-Hering-Meyer frequency is approx. 0.1 Hz) and 0.15-0.4 Hz: HF (the respiratory arrhythmia frequency is 0.25 Hz for 15 breath/min; for normal free-breathing = 0.15-0.4 Hz). An established diagnostic method for neurocardiac control assessment is to compute the LF:HF ratio from the HRV spectra.

The physiological goal of our study was twofold: (1) to follow up the vegetative control status during a long-term session; (2) to detect significant singularities in the cardiac rhythm, in order to associate them with normal or pathological terms.

It should be considered, however, that the prevalently used spectral estimation techniques are bound to make a priori assumptions that the signal is at least quasi-stationary, which is unfortunately often not the case in the clinical practice.

Methods

J. Morlet [7] et al. first applied and developed (redefined) the theory of the Wavelet Transform (WT), an affine distribution, invariant to shift and dilatation. The continuos WT of a function $f(x)$, with respect to a mother wavelet $g(x)$ is defined as the modified convolution:

$$W(a,b) = |a|^{-\frac{1}{2}} \int_{-\infty}^{\infty} f(x) g\left(\frac{x-b}{a}\right) dx,$$

where a is a scale parameter and b is a translation parameter. The admissibility condition for $g(x)$ is (essentially):

$$\int g(x) dx \approx 0 \ .$$

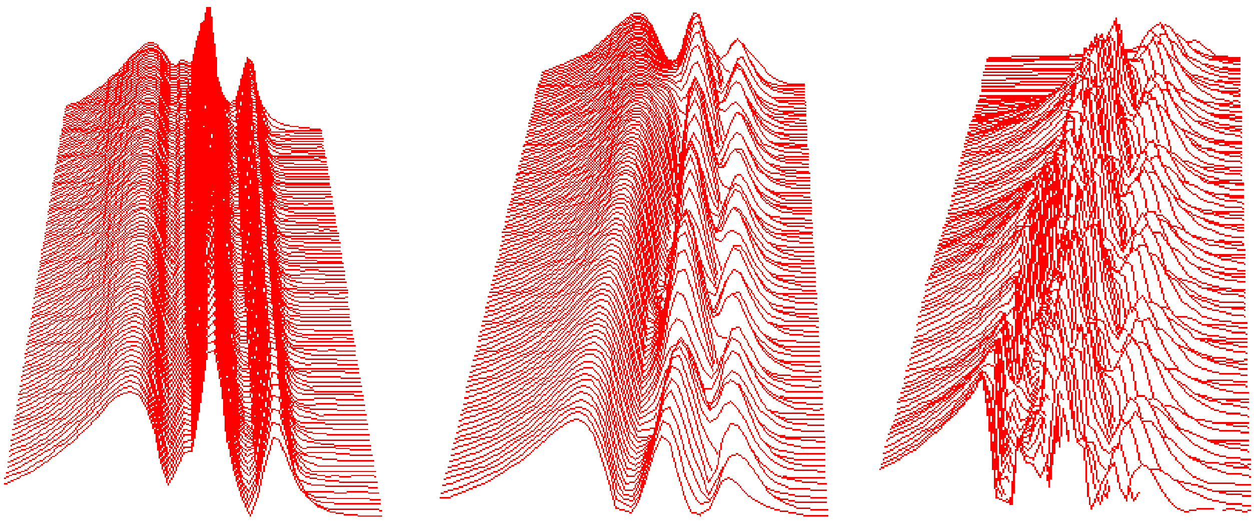
Increasing the scale a produces a family of dilated wavelets from a mother wavelet, while a shifts these wavelets within the data set. The energy normalization term of the WT allows equalizing the energies of the mother and all child wavelets. When the input signal is projected onto such a dilated and translated set of functions, the obtained two-dimensional surface of wavelet coefficients reflects essentially the frequency content of the signal, changing in time.

Although a tone is not admissible for a mother wavelet, the Fourier Transform (FT) can be represented as a special case of WT [8], where $g(x)=e^{jx}$, $a=\frac{1}{w}$ and $b=0$, so that:

$$W(\frac{1}{w},0)=\int_{-\infty}^{\infty} f(x)e^{-jwx}dx$$

The frequency and time resolutions of methods like the Short Time Fourier Transform (STFT) are fixed and the same bandwidth is maintained around each frequency, because the analyzing kernel is a tone function. However, the support of the wavelet function is proportional to the changing scale, ensuring constant ratio between the center wavelet frequency and the bandwidth (constant-Q processing). For higher frequencies the time resolution in WT becomes better and the frequency resolution - worse, while for low frequencies of $f(x)$ the opposite assertion is valid.

The gain of the WT is strongly dependent on how well the dilated and squeezed versions of the mother wavelet waveform match the signal as any correlator does. This means that the choice of the wavelet function is crucial for the wavelet characterization of the input data.



(a) (b) (c)

Fig.1. Discrete Wavelet Transform of a test signal - a sum of 3 tones: 0.005 Hz (testing the very low frequency limit - the thermoregulatory frequency of the vasomotor and renin-angiotensin control systems is approx. 0.03 Hz), 0.1 Hz (testing the WT response for the Traube-Hering-Meyer frequency of the baroreflex system) and 0.5 Hz (high frequency limit - the standard respiratory arrhythmia frequency is 0.25 Hz, corresponding to 15 breath/min; normal free-breathing = 0.15-0.4 Hz)
(a) WT with the Morlet wavelet; (b) WT with the Mexican Hat wavelet; (c) WT with the Haar wavelet

We tested 7 mother wavelets (Morlet with $\alpha=256, f=16Hz$, Mexican Hat, a Modulated Gaussian, a Gaussian Weighted Linear Frequency Modulated chirp, the 8.derivative of the Gaussian, Haar and Meyer), taking into account that (1) full frequency contents should be assessed as uniformly as possible over the entire frequency range; (2) more or less sharp transients in the HRV series should be detectable over the entire time range and (3) employed “voicing” resolution improvements should not lead to noise sensitivity.

For our application we chose WT parameters $a=a_0{}^m; a_0=2; b=1$, but considered a robust lattice. We selected non-orthogonal wavelets,because high levels of redundancy are typical for biomedical data. The necessary fine scale resolution required a “voicing” technique, i.e. employment of non-integer *m* values, so that we made use of a non-dyadic lattice of wavelets in spite of the dyadic scale base.

In order to study the WT response for different wavelets and to align the effective scale ranges we fed up, as an input signal, a sum of 3 tones: 0.005 Hz (testing the very low frequency limit), 0.1 Hz (testing the Meyer waves frequency) and 0.5 Hz (high frequency limit).

The original heart beat time series was obtained through adaptive wave detection procedures, which are described elsewhere [1]. After an extensive extrasystole identification all beat-to-beat intervals, associated with a recognized extrasystole were removed from further processing. The remaining R-R interval series (Fig.2) underwent time interpolation to achieve an equidistant sampling (4 Hz). The obtained in this way and demeaned data served next as the input signal function $f(x)$ of a Discrete Wavelet Transform routine [8], employing various mother wavelet functions as an analyzing kernel.

Results

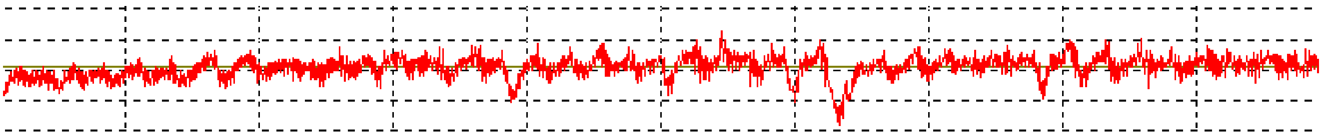


Fig.2. Original R-R interval variability time series of a patient with typical frequency fractions in the FFT heart rate variability spectrum.
Data is obtained after adaptive wave recognition procedures, described elsewhere [1]. After an equidistant time interpolation this series serves as an input to the Windowed Fourier and the Wavelet Transforms.
Vertical Grid is 100 ms, while series overall duration is 30 min.

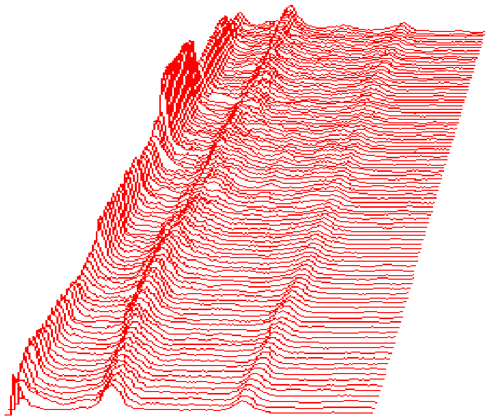
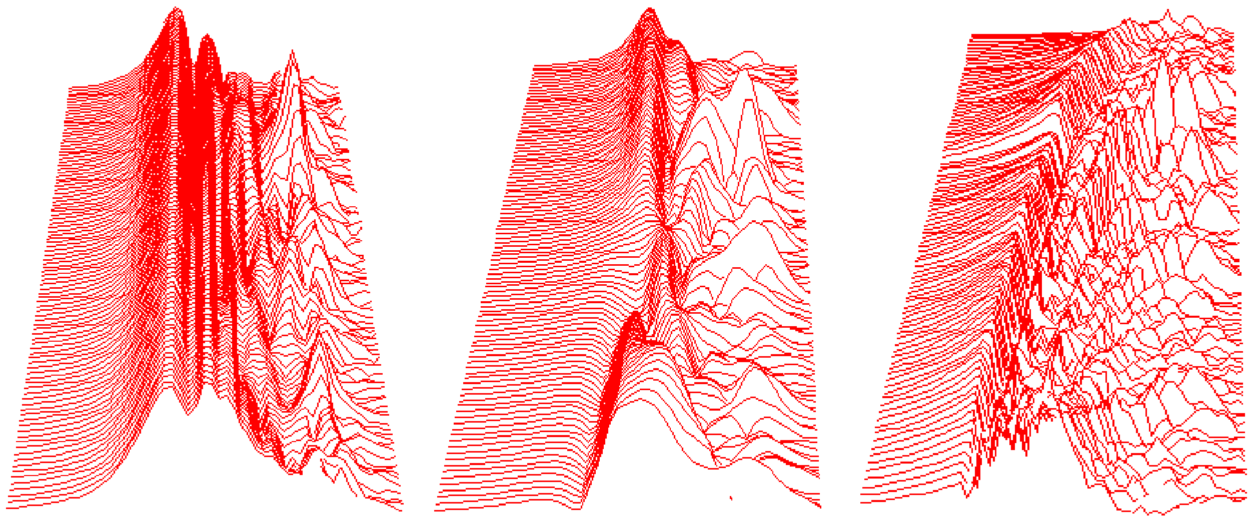


Fig.3. Moving Windowed Fourier Transform of R-R interval variations (Frequency range: 0.0039-0.5 Hz, Time range: 256 s, Data Windowing: Hamming window, FT Movement step: 16 s, Analyzed time range: 30 min).
The x-axis is the frequency, increasing from left to right side; the y-axis is the time, increasing in from front to back side; and the z-axis is the magnitude of the computed fourier coefficients.
Each horizontal curve reflects the stationary frequency distributions of the current data window.



(a) (b) (c)

Fig.4. Discrete Wavelet Transform of the heart rhythm variability for 30 min.
The x-axis is the scale, decreasing from left to right side (corresponding to wavelet central frequency, increasing from left to right side); the y-axis is the delay (time), increasing from front to back side; and the z-axis is the magnitude of the computed wavelet coefficients.
Time resolution between two successive scale curves in this case is 18 s. Each horizontal curve reflects the match of the momentary wavelet frequencies with the whole data set.
(a) WT, employing the Morlet wavelet; (b) WT with the Mexican Hat wavelet; (c) WT with the Haar wavelet

The responses of three selected wavelet functions to the test tone sum are shown on Fig.1. The natural constant-Q property of the WT caused the observed effect of “zooming in” on higher frequencies and “panning out” on low frequency signal components [3], the decreased gain corresponding to the inherently smaller wavelet support for higher frequencies.

Further we analyzed 20 long-term ECGs (30 min, SR=250 Hz, 2 channel Holter Data). The corresponding windowed FT (0.0039-0.5 Hz, Hamming window) of a normal subject for a time interval of 30 min. is shown on Fig.3. The obtained wavelet-transformed trains for different HRV patterns, indicated more information components than the analogous FTs. Fig. 4 shows the wavelet characterization of the R-R intervals of the same healthy subject.

The overall spectral patterns in the FT and the WT were similar, especially when using wider and “slower” wavelets like the Mexican Hat wavelet (Fig.4b). In general, wavelets “zoom” in the higher frequencies, but the lower central frequency of this wavelet allowed more sensitivity in the important LF range. However, wavelets with a higher central frequency like a fast version of the Morlet wavelet ($\alpha = 256, f = 16 Hz$) shifted the event-related signal contents to the high frequency range (Fig.4a). Steep-edged wavelet functions like the Haar wavelet predictably proved inefficient for this principally slowly changing signal (Fig.4c).

The transient events, almost entirely ignored by the FT spectra, were clearly detected by the WT. Their time localization, duration and magnitude were reflected more distinctly by short and fast wavelets - Morlet, Modulated Gaussian, Gaussian Weighted Linear Frequency Modulated chirp (especially the last one). On the other hand, when slower transients were also to be kept track of, the Mexican Hat wavelet provided an optimal performance, while still detecting the faster events.

Discussion

In this study we performed signal decomposition of the cardiac rhythm variations and tested a new optimal environment for the evaluation of the vegetative balance. A signal analysis method like the Wavelet Transform matches closely natural phenomena, because it can handle its input through constant-Q processing over several octaves and the required assumptions (e.g. “mother” waveform) are milder. If a multiresolution approach is applied, the WT is able to analyze both relatively unknown processes through wideband, long enough mother wavelets and then match them closely only through changing the analyzing kernel.

Frequently in the WT applications local maxima assessment methods try to reduce the plethora of wavelet coefficients to a small set of significant ones, aiming to a feature extraction or event localization [6]. This is not reasonable in the case of a heart rhythm study, because all frequencies are important. A further consideration is that a direct transition from the well recognized frequency ranges (quasi-stationary spectral methods) to WT scale ranges is not possible. A systematic error would be involved if done so, because each dilated and translated wavelet (analyzing kernel) performs a match for a variable frequency band around its shifting central frequency, while the analyzing tone of the FT, for example, matches a single shifting central frequency. Nevertheless work is underway to overcome the problem and to transfer the significant accumulated physiological knowledge to this advanced technique.

The current study showed the advantages of the frequency-time resolution capabilities of the Digital Wavelet Transform. This method demonstrated immunity to noise and non-stationarity, controlled resolution, helpful redundancy and increased information potential as a practical diagnostic aid in the evaluation of the highly unpredictable heart beat rhythm variability signal.

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