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WAVELET AND FOURIER TRANSFORMS AS DIAGNOSTIC TOOLS IN AUTONOMIC NERVOUS STATUS TESTS

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Abstract - The objective of this study was to enable the assessment of modulated sympathovagal balance shifts in healthy subjects, provoked by a 30-min functional Combined Posture Test (CPT). Discrete wavelet transform (WT) and short-time Fourier transform were both performed to reveal very low frequency (VLF, 0.001-0.04 Hz) fluctuations in the heart rate variability (HRV). In our controlled experiments deep breathing-induced VLF peaks were detected by both methods. The VLF local maxima were more sharply outlined by the WT, which “zoomed in” on the lower frequencies with a satisfactory time resolution. STFT with a comparable frequency range generally showed smoother time-frequency representation in the high frequencies and between transients in the HRV signal, but responses to the non-stationarities during the test were blurred. Although not intended to replace entirely the classical STFT spectral analysis, but rather be used in a parallel way with it, the wavelet transform was shown to be diagnostically advantageous and appropriate for overall assessment of the rapidly changing autonomic balance during autonomic functional tests.

1. Introduction

Modulated response of the heart rate variability (HRV) to postural change and physical stress is believed to represent a major noninvasive indicator of the sympathovagal balance, which assists efforts for a qualitative diagnosis in a number of diseases, associated with deterioration of the autonomic control like myocardial infarction [1], diabetes mellitus [2] and sudden cardiac death [3]. If controlled perturbations such as posture changes [4] and deep breaths are applied, they may expose a hidden compensated saturation or deficiency mode of the autonomic tone, with a subsequent inability to adapt under stress.

Spectral analysis of heart rate variability (HRV) is widely used for identification of sympathovagal interaction disturbances [5], but measurement and evaluation of spectral components at critical time points of functional tests are controversial. However, exactly these quickly changing spectral patterns under stress conditions may help for a better understanding about the individual autonomic function status than conventional stationary spectral analysis alone [6]. Myers et al. addressed some of the problems of the non-stationarities in the heart rate [7], although solutions, apart from routine data segment rejection and short spectral window lengths, appear still largely limited. Recent adaptive short-time Fourier analysis techniques [8] present interesting alternatives, but the decision-making processes involved might greatly influence the compatibility and quality of the time-frequency decompositions.

The present study investigates the transitory sympathovagal spectral interplay in a new functional combined posture test (CPT), using two time-frequency/scale decomposition methods - a discrete wavelet transform (WT) and a short-time Fourier transform (STFT) with comparable frequency ranges.

2. Methods

2.1. Experimental protocol and data acquisition

Electrocardiograms (ECG) with 30-min duration and 250 Hz sampling rate (2 channels) were recorded from 12 healthy normotensive volunteers (24 ± 2 years). The subjects were asked to restrict their physical activity, food intake, smoking, etc. before the experiments. The recordings were carried out in an isolated experimental room. We applied a test protocol (Fig. 1), termed the Combined Posture Test (CPT), in order to evaluate the autonomic function. The CPT description follows below.

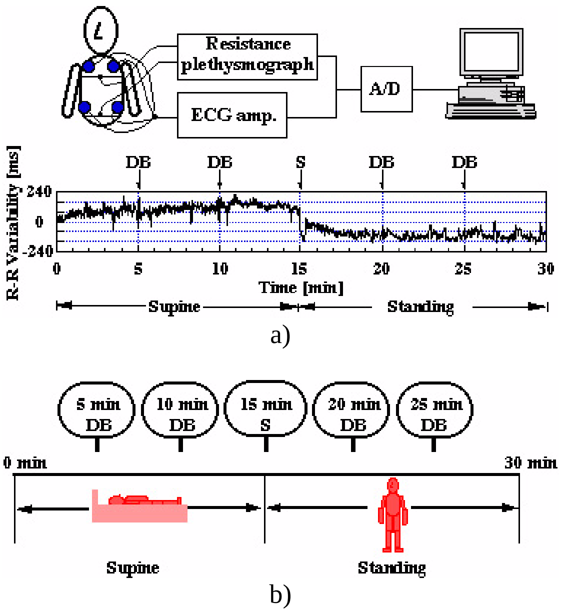


Fig. 1 Schematic outline of the Combined Posture Test (CPT). a) Data acquisition and b) experimental protocol.

We asked the subjects to breath at 15 breaths/min (0.25 Hz) throughout the recordings with 40% of time used for inspiration and 60% for expiration - synchronously with weak auditory signals from a computer. All experiments had two major phases - 15 min recording in a supine position and 15 min recording in a free standing position. Both supine and standing phases were combined with 2 deep breaths each in supine and upright posture, equidistantly 5, 10, 20 and 25 min after the start. Respiratory frequency of deep breathing was 6 breaths/min (0.1 Hz) and a controlled 4-fold tidal volume expansion was required during deep breathing, compared with the individual tidal volume in rest.. The tidal volume was continuously monitored and recorded throughout the recordings using two-belt chest-abdomen resistance plethysmograph.

2.2. Signal Processing

The first signal processing stage included adaptive recognition of the Q-, R- and S-waves and identification of all ectopic beats in the electrocardiogram through techniques described earlier [9]. The original R-R interval time series were then resampled through spline interpolation to generate equidistant time series with a sampling interval of 400 ms (w_s = 2.5 Hz). Further we applied and compared two decomposition methods:

A. Short-time Fourier transform (STFT: 6.8-min Blackman window, 0.8-s shift)

We performed a standard HRV analysis of the interpolated R-R interval series, mapping the signal into a time-frequency plane (τ, f) through the STFT:

$$\mathrm{STFT}_\tau f = \int x(t) g^*(t-\tau) e^{-2j\pi f t}\, dt \ ,$$

where $x(t)$ is the input HRV time series and $g(t)$ is a window function. The window length (1024 samples; at overall duration of 4096 samples) was set to match the lowest frequency we used with the wavelet transform. The time resolution had a tolerably low level for the purposes of this study, because the product of the time and frequency resolutions is lower bounded:

$$\Delta t \Delta f \geq \frac{1}{4\pi}.$$

The spectral window step was adjusted in such a way as to obtain a comparable number of spectra with the multiresolution wavelet transform over time. The STFT frequency decompositions were converted to compressed logarithmic spectral arrays for low frequency enhancement.

B. Discrete orthogonal wavelet transform (WT: Battle-Lemarie 16-tap wavelet, 12 scales available, 9 scales used)

The multiresolution wavelet representation [10] $(A_{2^{-j},i}x, (D_{2^{-j},i}x)_{-J\leq j\leq -1})$ decomposes an input signal $x(t)$ of length $N = 2^J$ at a time point i into J multiresolution levels of approximated $A_{2^{-j},i}x$ and detail $D_{2^{-j},i}x$ signals

$$A_{2^{j-1},i}x = \sqrt{2}\sum_k \tilde{h}_{k-2i} A_{2^j,k}x$$

$$D_{2^{j-1},i}x = \sqrt{2}\sum_k \tilde{g}_{k-2i} A_{2^j,k}x\,,$$

where $\tilde{g}_k = (-1)^k \tilde{h}_{-k+1}$. At each level j the halfband discrete quadrature mirror filters (QMF) H (low-pass) and G (band-pass), corresponding to particular scale and wavelet functions, are convolved with the approximated and subsampled input signal from the previous pyramid level. Thus the subband coding algorithm produces coarse and detailed output signals at the currently analyzed octave band and the wavelet expansion $D_{2^{-j},i}x$ splits the frequency space into non-overlapping dyadic blocks

$$[-2^{-j+1}\pi,\ -2^{-j}\pi] \bigcup [2^{-j}\pi,\ 2^{-j+1}\pi]$$

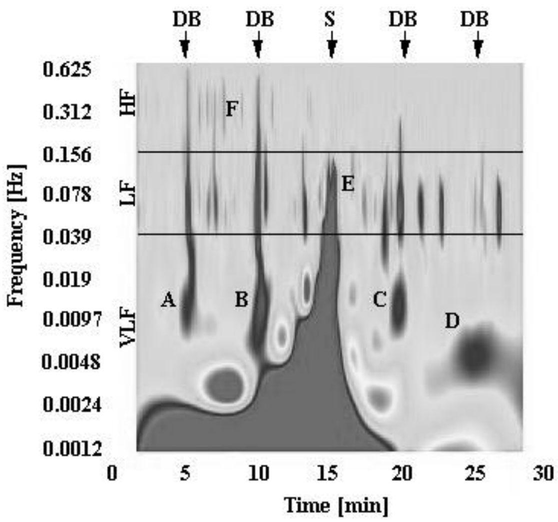
with a constant size on the logarithmic scale. For low frequencies the frequency resolution grid of the pyramidal WT becomes better and the time resolution - worse, while for high frequencies the opposite assertion is valid [10]. We tested the performance of a number of wavelets (Daubechies, Meyer, Coifman, Battle-Lemarie, etc.) with various filter lengths. Regular orthonormal spline wavelets performed best for HRV analysis and in this study we used the symmetric exponentially decaying Battle-Lemarie 16-tap wavelet.

The spectral frequency bands were commonly defined as: Very low frequency (VLF): 0.001 - 0.04 Hz; Low

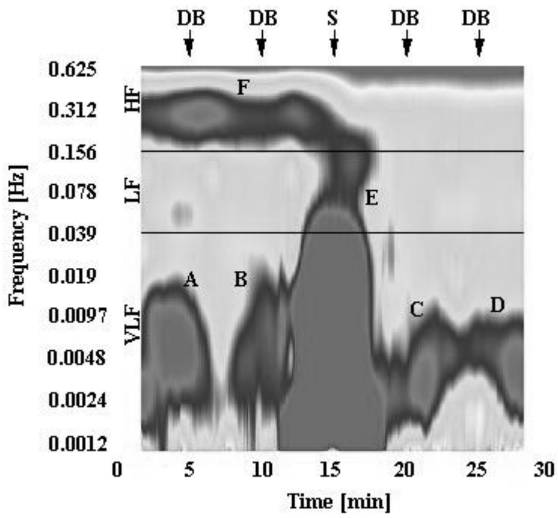
frequency (LF): 0.04 - 0.15 Hz; High frequency (HF): 0.15 - 0.6 Hz. Within these bands we used 0.005, 0.05 and 0.1 Hz test sinusoidal and chirp signals to verify the performance of the transforms at physiologically relevant frequencies.
Finally local frequency maxima at crucial CPT time points in all spectral regions were tracked down for identification and evaluation purposes.
The software for this study was written with the Borland C++ 4.5 for MS Windows compiler (Borland International) and the Mathematica software package (Wolfram Research, Inc.) was used partly for visualization.

3. Results

Deep breathing sessions in supine and standing postures cause instantaneous increase in all frequency bands (VLF, LF and HF), as shown in Fig. 2. VLF reaches peak power values at about 0.007 Hz in supine position (A and B in Fig.2) and 0.003 Hz under prolonged free standing (C and D in Fig.2) during deep breaths. These local maxima are better revealed by the WT, while the fixed time-frequency resolution grid of the STFT (optimized for maximal frequency resolution) doesn't allow their unambiguous identification. On the other hand the LF band power, mainly due to the Traube-Hering-Meyer baroreflex oscillations, is clearly present throughout the recordings in both methods. It increases in deep breathing, as expected, because the respiratory frequency is reduced to 0.1 Hz (6 breaths/min). Due to differences in the analyzing kernels of both transforms, WT enhances the non-stationarities in the LF, while STFT manifests weaker, but more regular decomposition for continuous oscillations. Finally, the HF is also elevated during deep breathing and supine posture enhances its power. Time resolution of the WT in case of transitory LF and HF peaks is well above that of the STFT, but its frequency resolution is inferior for the HF.
During the posture change at min 15 both WT and STFT register increases in all spectral bands, although the growth in the VLF and LF bands is most powerful (E in Fig.2). Vagally mediated HF variations (F in Fig.2) diminish substantially after standing, as expected. Generally the STFT demonstrates a significant advantage in the stationary demarcation of the HF variations.
Deep breathing sessions in standing posture at min 20 (C in Fig.2) and min 25 (D in Fig.2) of the test generally provoke a shift in the VLF peaks towards lower frequency, when compared to supine values (A and B in Fig.2). This VLF peak shift in standing is dependent upon the duration of orthostatic stress, manifesting a small, but significant decrease in frequency (Table 1) of the CPT-induced VLF peaks at min 25 (D in Fig.2), when compared to the peak at min 20 (C in Fig.2).



a)



b)

Fig. 2 Time-frequency/scale decompositions of 30-min HRV data in 12 healthy subjects during autonomic control combined posture tests were averaged and plotted. a) Orthogonal wavelet transform, using the Battle-Lemarie 16-tap wavelet and b) short-time Fourier transform (compressed logarithmic spectral array) using 6.8-min Blackman window and 0.8-s window shift.
The frequency axis on the WT plot a) implies band frequencies as opposed to discrete frequencies on the STFT plot b), so that WT plot axis labels in a) indicate upper scale band frequencies. Consequently characteristic peaks may appear slightly shifted in frequency in a), when compared to b).

Table 1 Peak frequency decrease of the very low frequency (VLF) component in the HRV during deep breathing in upright posture, as compared to the mean supine value.

	5 min after standing	10 min after standing
VLF Shift [%]	15.84±10.2	19.02±6.26
p (n = 12)	$< 2.54*10^{-4}$	$< 7.34*10^{-7}$

4. Discussion

The STFT demonstrated advantages for periodic stationary HRV signals between the test maneuvers, while the discrete WT is well suited for the characterization of short non-stationary signal “events” and has an improved frequency resolution in the VLF spectral region.

The frequency resolution of the WT in the HF band is very low, although the time resolution is excellent. In contrast the time-frequency resolution grid of the standard STFT is constant. These great disparities in resolution are the reason why we were unable to use and compare the LF / HF index in our study as an indicator of the sympathovagal interaction at any time point.

Our results showed the presence of VLF peaks in the sinus rhythm in response to deep breaths during supine and upright postures, as well as a shift of their peak frequency during prolonged postural stress. Posture change reflexes are initially mediated by the autonomic nervous system. However, under prolonged postural stress slow humoral mechanisms get increasingly involved in the blood pressure control [8]. That is why we suggest that the VLF maxima shift in the HRV during deep breaths under prolonged orthostatic stress is at least partly the manifestation of a slow compensatory renin- angiotensin-vasoconstriction control influence on the peripheral vasomotor tone in healthy subjects. Further research is necessary to clarify the origin of this effect, its reproducibility and. the impact of factors like aging and gender, in order to determine its diagnostic value in autonomic dysfunction.

5. Conclusion

In the present study we aimed to compare the performance of the WT and STFT for HRV signals during a posture change autonomic test, combined with controlled deep breathing. Mainly due to intrinsic features of the wavelet transform, we were able to identify weak, but consistent VLF peaks in the heart rhythm variations during deep breaths, which were relatively blurred in the STFT time-frequency decomposition.

It is concluded that WT performs more precisely in locating transient very low frequency peaks in the HRV during autonomic function tests, while respiratory arrhythmia and other stationary components of the HRV are better exposed by the STFT.

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