Quantification of Wavelet Band Metrics for Assessing Heart Rate Variability

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Abstract— **Because of its physiological and clinical importance, heart rate variability (HRV) has been investigated with many techniques, including time-frequency methods. In this study, time-varying frequency changes in the lower bands of continuous wavelet transforms directly computed from ECG signals are quantified with statistical and information-theoretic measures. These metrics are compared for resting and lower body negative pressure (LBNP) conditions, and with standard HRV metrics. Although the latter confirm the expected lower variability in the LBNP condition, metrics from the main frequency band in the wavelet transform corresponding to the observed range of heart rate (0.5–1.25 Hz) exhibit statistically significant higher variability than baseline conditions. It is proposed that a more complete HRV analysis can emerge when lower-band variability metrics of ECG in the time-frequency domain is used in conjunction with more traditional time and frequency domain approaches.**

Keywords— **Heart rate variability, ECG, continuous wavelet transform, entropy, approximate entropy.**

I. Introduction

Numerous approaches have been developed to analyze how heart rate variability (HRV) is linked to underlying autonomic nervous system (ANS) activity by quantifying time and frequency domain aspects of HRV [1]. The high frequency (HF) (0.15-0.40 Hz) component is associated with parasympathetic activity, whereas low frequencies (LF) (0.04-0.15 Hz) are produced by mostly sympathetic and some parasympathetic nerve activity. The LF/HF ratio has been proposed to quantify the dynamic relationship between sympathetic and parasympathetic activity [2].

While traditional Fourier transform (FT) HRV analysis generally relates HRV to experimental conditions, some difficulties arise. First, HRV signals are generated, post hoc, from the original RR intervals of electrocardiograms (ECGs), and usually undergo resampling and other post-processing to obtain a uniformly-sampled signal suitable for frequency analysis. The resulting HRV is susceptible to artifacts introduced during these processes [3].

Second, HRV frequencies do not directly correspond to the actual frequency of important ECG features [4]. The standard very low, low, and high frequencies (VLF, LF, HF, respectively) are useful because numerous studies have correlated known physiological stressors with FT results. The relationship, while meaningful, is indirect.

Third, with the FT, it is difficult to assess when the changes in the heart rate occur, and to detect transient events [5]. As a result, investigators are turning to time-frequency approaches, such as wavelet transforms, to assess the dynamic characteristics of HRV [5, 6].

The most plentiful source of information about heart activity is found in the original ECG, for which many analysis and interpretation techniques in both the time and frequency domains are available [5, 6]. In this paper, a complementary approach is proposed to enhance understanding of the HRV-ANS relationship. Specifically, it is suggested that HRV can also be studied directly in the time-frequency domain from ECG by quantifying variability metrics of instantaneous changes in frequencies in a continuous wavelet transform (CWT) in a specific frequency band corresponding to the heart rate. The standard RR interval measures are complemented with analogous fluctuations in frequency in the time-frequency domain, as changes in frequency correspond to beat-to-beat variation.

The experiments performed in the current study used a known orthostatic stressor – lower body negative pressure (LBNP) – to increase sympathetic tone. It was hypothesized that corresponding changes in heart rate variability can be statistically quantified in terms of ECG signal roughness, entropy, and approximate entropy, through the CWT.

II. Materials and Methods

A. Subjects and experimental protocol

Nine healthy subjects (7 men, 2 women) participated in this study. The participants were 27 ± 5 years of age, 171 ± 3 cm in height, and 79 ± 9 kg in weight (means ± SE). All subjects provided informed, written consent for the experimental protocol as approved by The University of Western Ontario (UWO) Health Sciences Research Ethics Board.

Subjects reported to the laboratory at UWO on two separate occasions within a one-week period. During the first session, subjects participated in an orientation session in which they experienced LBNP. During the experiments, subjects – having refrained from food (two hours), caffeine

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and nicotine (12 hours), and exercise (at least 12 hours) – lay on their backs with the lower torso to the iliac crest enclosed in an LBNP chamber, and completed the baseline and LBNP (–20 mmHG) experimental five-minute conditions in a supine posture.

Analog signals for ECG (standard three-lead, sampled at 1 KHz), as well as other parameters, were collected as part of a larger study with an on-line data acquisition and analysis system (PowerLab, ADInstruments; Castle Hill, NSW, Australia). ECG signals were bandpass filtered at 10-25 Hz.

B. Continuous wavelet transform

The CWT captures time-frequency information at arbitrary resolutions, with frequency content better resolved at low frequencies, and transient events better resolved at high frequencies. Specific wavelets, $\psi(t)$, where t is time, can be selected for different applications. The Morlet wavelet, used in this study and in many others, has been found to be particularly useful, as its scale has a straightforward linear relationship to the Fourier period, and is expressed as [7]:

$$\psi(t) = \frac{1}{\sqrt{b\pi}} \exp\left(-\frac{t}{b}\right)^2 \exp\left(j2\pi f_c t\right) \tag{1}$$

where $j = \sqrt{-1}$, f_c is the centre frequency (the position of the global maximum of the Fourier transform of $\psi(t)$), and $b > 0$ is the bandwidth parameter. The bandwidth b and centre frequency were set to 1, so that frequency = signal sampling frequency / wavelet scale ($f = f_s / a$). The CWT using the basis function in Eq. 1 was calculated for 128 frequencies to a maximum of 2.4805 Hz, with $\Delta f = 0.0195$ and $f_s = 1$ KHz.

C. Wavelet metrics

High power areas in the CWT often appear as "blobs", or, in the present study, as thick "bands" (see Fig. 1). To determine the frequencies in the main CWT band, the ridge, (continuous maxima across the band) was identified through a ridge detection process in the 0.75-1.40 Hz range [8]. In a few cases, small gaps in the ridge were connected manually, based upon visual inspection of the CWT representation.

Three variability metrics, roughness, entropy, and approximate entropy, were calculated from ridges of the main power band of the CWT for the baseline and LBNP conditions, and compared. It was visually observed that the main bands in the LBNP CWTs were "wavier" and more complex than the corresponding baseline bands. All Morlet CWTs and CWT metrics were calculated in the Matlab environment (The Mathworks, Natick, MA).

Roughness (R) quantifies the departure from linearity of a time series, and is given as [9]:

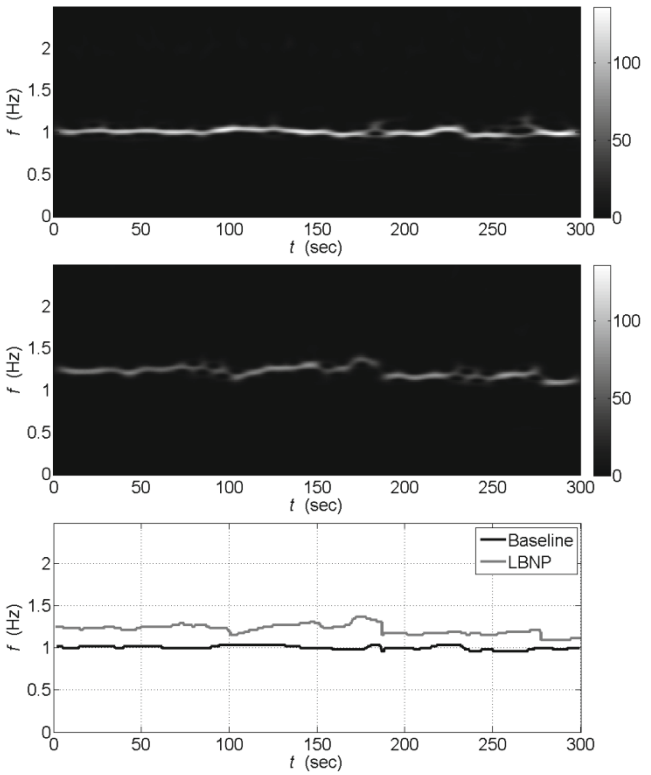

Fig. 1 Morlet CWT for baseline (top) and experimental (LBNP) (middle) conditions, and ridges extracted from the transforms (bottom)

$$R(x) = \frac{1}{N}\sum_{i=0}^{N-1}\left(x_i - 2x_{i-1} + x_{i-2}\right)^2, \quad i = \frac{t}{\Delta t} \tag{2}$$

Entropy (H) quantifies the unpredictability or disorder in a random variable [10]. In the wavelet domain, low entropies occur when the larger coefficient energies are concentrated at only a few discrete locations [6]. H is given as:

$$H(x) = -\sum_{i=0}^{N-1} p(x_i)\ln\left(p(x_i)\right), \quad i = \frac{t}{\Delta t}, \tag{3}$$

where N is the length of the ridge. $p(x)$ was computed with a Gaussian kernel with range 0.75-4.0 Hz, and with 200 equispaced points.

Approximate entropy (ApEn) is a measure of complexity that quantifies self-similarity, and has been applied to heart rate analysis [11]. To compute ApEn, a positive integer m (length of a sequence of data to be compared with other sequences of length m) and a radius $r \geq 0$ (self-similarity tolerance) are selected. The approximation of the correlation integral C for each i ($0 \leq i \leq N - m$) is computed as the mean of the number of times that the intra-sequence distance between two samples is less than r. ApEn is then [11]:

$$ApEn(m,r,N) = \frac{1}{N-m+1}\sum_{i=0}^{N-m}\log C_i^m(r) - \frac{1}{N-m}\sum_{i=0}^{N-m-1}\log C_i^{m+1}(r) \quad (4)$$

In the experiments performed here, $m = 5$, $r = 0.025$, and the original signal was down-sampled every 5th sample.

D. HRV time-and frequency-domain metrics

Standard HRV measures used in this study were: the standard deviation of normal-to-normal (NN) interval (SDNN), which reflects all the cyclic components responsible for variability in the periods of recording; the root mean square of successive differences in NN intervals (RMSSD), which quantifies parasympathetic nervous activity [5]; and the number of successive differences of intervals that differ by more than 50 msec (NN50). In the frequency domain, the LF/HF ratio was computed with a 1024-point FT applied with a 50% overlap Welch smoothing window. The maximum frequency analyzed was 0.5 Hz. Frequency bands were 0-0.04 Hz (VLF), 0.04-0.15 Hz. (LF), and 0.15-0.4 Hz (HF). All standard metrics were computed in the PowerLab environment.

Because the samples were dependent (the baseline and experimental data were collected from the same subject), the paired differences t-test was performed on the mean of baseline metric minus the mean of the LBNP metric, compared at $\alpha = 0.05$. Additionally, because of the dependence of the two samples and the small sample size, the non-parametric two-tailed Wilcoxon signed rank test was performed. All analyses were performed in SPSS (IBM).

III. Results

The CWT variability measures of the ridge of the main 0.5-1.25 Hz frequency band are shown in Table 1. The CWT power is significantly less linear (*R*), more disordered or unpredictable (*H*), and more complex (ApEn) in the experimental LBNP condition than in the baseline readings, contrasting with the HRV metrics, which exhibit the expected behavior of less variability in the experimental condition. The Wilcoxon *p* values support the t-test results.

For the standard HRV time- and frequency-domain metrics, the statistical analysis of the nine signals per condition is also shown in Table 1. Of these metrics, only SDNN was not significant ($p = 0.441$). This result is not surprising, as SDNN reflects long-term measurement of HRV. The non-parametric Wilcoxon tests also corroborate the significance of the HRV metrics. The LF/HF ratio (frequency domain) was also significant, with a higher LF content in the LBNP experiments, and a decrease in variability, as expected [12].

Table 1 CWT and HRV variability measures

Baseline – LBNP	Mean	Std. Dev.	2-tailed *p*	Wilcoxon *p*
CWT				
R	-1.341[a]	1.657[a]	0.041	0.002
H	-0.629	0.357	0.001	0.002
ApEn	-4.433[b]	3.401[b]	0.004	0.002
HRV				
SDNN	-4.881	19.223	0.468	0.441
RMSSD	22.781	24.366	0.023	0.038
NN50	55.222	50.791	0.011	0.028
LF/HF	-2.027	2.051	0.018	0.008

[a] $x \times 10^{-5}$, [b] $x \times 10^{-3}$

IV. Discussion

While important features may be present in all CWT bands, especially in the regions associated with low and high frequencies (< 0.4 Hz), the experiments in this paper focus on the band around 1 Hz, which contains the greatest power, and corresponds directly to the heart rate. The standard time and frequency domain HRV metrics are different, but complementary, to those obtained from the CWTs, and generally agree with the results of similar studies [13]. Careful analysis of the differences between the these metrics is necessary, however, to avoid misinterpretation. For example, the control LF/HF ratio was significantly lower than in LBNP, meaning that LBNP causes decreased high frequency and/or increased low frequency power. Thus, researchers may erroneously conclude that increased sympathetic tone should result in a more regular power band in the CWT plots. However, variability increases with sympathetic nerve activation, as seen in the CWT plots.

The large deviations (spikes in LBNP CWT) from the mean heart rate may correspond to transient adjustments of the ANS to compensate for fluctuations in blood pressure. With low blood pressure, afferent baroreceptor firing rates decrease, resulting in increased efferent sympathetic innervation and decreased parasympathetic innervation to the heart. The net result is an increase in heart rate and stroke volume. Peripheral resistance is also increased due to constriction of blood vessels via sympathetic innervation. It is possible that with LBNP, the initial ANS response overcompensates, which in turn activates antagonistic pathways. It is known that muscle sympathetic nerve activity during LBNP increases irregularly [14], possibly supporting the notion of phase-lag ANS regulation of blood pressure during LBNP. During nonhypotensive LBNP (-5 mmHg), muscle sympathetic nerve activity does increase, but a direct link to changes in heart rate is unclear [15]. As the link between ANS activation and heart rate activity is complex, the traditional metrics used in HRV cannot capture the time

at which these transient fluctuations occur (and therefore their correspondence with specific events cannot be determined), nor their rate of occurrence.

Although the current study treats variability measures over the entire length of the signal, how the signal evolves over time can also be investigated with the CWT. For studies where the most powerful CWT bands correspond to traditional bands, quantification of CWT metrics, as described in this paper, become particularly useful.

V. Conclusion

The variability measurements (*R*, *H*, and ApEn) computed from the CWT band corresponding to the heart rate provide an alternative, complimentary analysis of the ECG–ANS relationship. Clinicians and researchers using these techniques have the ability to visually inspect the CWT plot and to subsequently determine time points of interest and to relate those features to physiological events.

Future research will investigate dynamic change, which cannot be accurately measured by traditional HRV techniques. Transient changes in physiological response can be easily identified with the CWT. Additionally, in assessing changes over time, a rigorous method of choosing CWT parameters and basis functions is required. Whether the centers of gravity of the main bands are increasing or decreasing in dynamic conditions may provide further insight into various disease states, and may thereby enhance clinical usefulness of time-frequency techniques.

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Conflict of Interest

The authors declare that they have no conflict of interest.

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