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Origins of the power of the low frequency heart rate variability bandwidth^{☆,☆☆}

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ABSTRACT

Purpose: We hypothesized that heart period (HP) variability in the low frequency (LF) band is due to transient fluctuations of about 10 s in HP sequences, associated with fluctuations in blood pressure.

Methods: 10 healthy subjects, mean age 36 y, had HP and blood pressure acquired for 10 min each. Nonrandom HP fluctuations (ripples) lasting 6.7–20 s were detected using time-scrambled surrogate sequences as controls. **Results:** Ripples were 99 ± 40 ms in amplitude, in concatenates 23.4 ± 7.4 s long. They co-occurred with similar blood pressure ripples with amplitudes 5 ± 5 mm Hg, correlating with them with $r^2 = 0.68 \pm 0.10$, slope 23.9 ± 10.8 ms/mm Hg, at an optimum lag of 2.16 ± 0.63 beats. A second HP structure consisting of transient tachycardias of 140 ± 53 ms lasting 15.1 ± 6.1 occurred singly. Together the two structures contributed $84\% \pm 8\%$ of the total power in the LF band.

Conclusion: The LF band is caused by two types of HP structures that occur at discrete times.

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Introduction

Heart rate variability is often used to assess autonomic tone. The most common method to measure it is power spectral analysis, which models heart rate sequences as bands of frequency changes in heart rate. These analyses typically model an entire sequence, and they assume long-term continuous causes of heart rate changes such as physiologic oscillators. However, frequency transformations [1], non-linear predictability [2], correlation dimension [3], and information scaling [2] have shown that heart rate variability is not continuous. This prompted a fresh look at its causes.

We proposed a model in which heart rate sequences are linear assemblies of temporally localized events [4]. One potential use of the lexical approach is to be able to read physiology from ECG recordings, as the change over time. For this we first need to identify these subsequences, and map them to their physiologic sources. This approach requires understanding specific heart period subsequence shapes as they appear in time, and therefore analytic techniques such as spectral analysis are of limited use. Physiologic origins are known for the high frequency bandwidth, heart rate turbulence [5,6], the muscle-heart reflex [4], and SDANN and the ultralow frequency components [1,7].

Here we turned to the low frequency band in ECG recordings, centered at a frequency of about 0.1 Hz. The low frequency (LF) band

centred near 0.1 Hz is increased with orthostatic stress [8], partially abolished with both beta-blockers and atropine [9,10], and might reflect sympathetic tone or arterial baroreceptor function [11]. We assessed whether there are non-spurious local contributions to LF power in heart period sequences, and whether they correlate with accompanying blood pressures.

Methods

This study was approved by the Calgary General Hospital Research Ethics Committee.

Data acquisition

Ten healthy subjects (6 male; age 31 ± 9 y), lay supine for 10 min. All had ECG leads and the Finapres (Ohmeda, Madison, WI, USA) blood pressure finger cuff. Both outputs were passed through an analogue to digital device at 200 Hz, and over-read in CVSoft (Odessa Software, Calgary, Canada). We used the time of the first R-wave of each heart period as the time of that heart period value. Mean arterial pressure (MAP) values for each beat were calculated as $MAP = ((\text{systolic pressure}) / 3 + 2 \times (\text{diastolic pressure}) / 3)$. MAP and heart period sequences of 500 s duration were analyzed in Matlab (The Mathworks, Natick, MA, USA). A representative raw signal is shown in Fig. 1, top panel.

Isolating and parameterizing minibursts

Minibursts were identified on the basis of their large, one-sided excursion from baseline. Their low heart period values skew the distribution of heart period values (Fig. 2). To identify the miniburst beats

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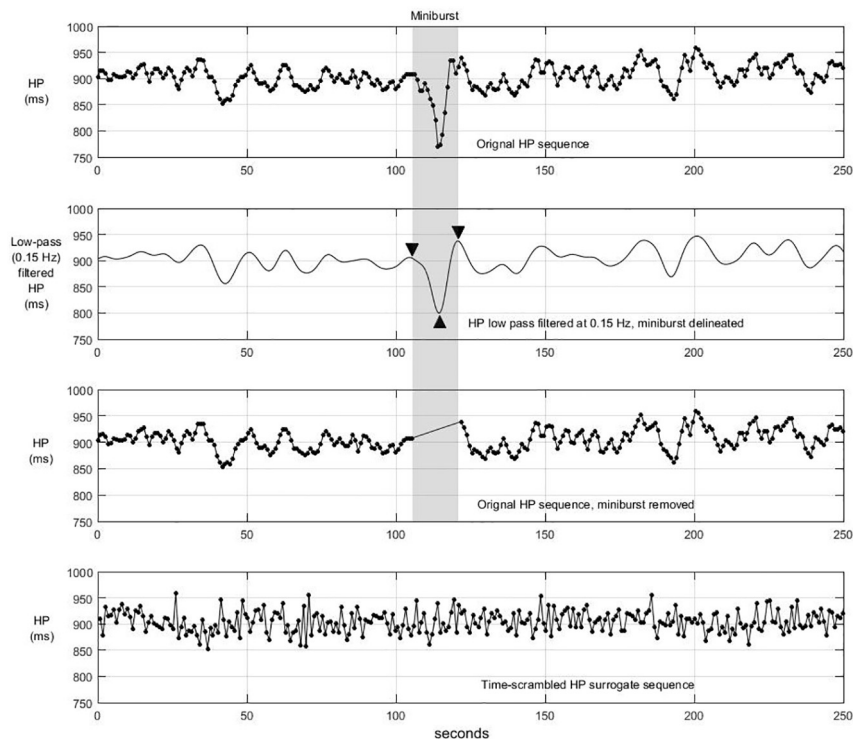


Fig. 1. Processing of unfiltered original heart period signal with a miniburst and ripples through an example of a surrogate scrambled sequence. Top panel, raw signal. Second panel, low pass signal with miniburst annotated. Third panel, raw signal with miniburst excised. Bottom panel, time-scrambled surrogate sequence of the raw signal with the miniburst excised.

in each sequence, we successively removed the lowest heart period values until the skewness no longer differed from zero. The removed beats were deemed to be part of miniburst structures. To avoid respiratory influences, we used the 0.15 Hz low-pass filtered HP sequence to delineate the beginning and end of the miniburst structure. The immediately preceding and succeeding local maxima were deemed the start and end of the miniburst, respectively. ΔHP_{onset} was defined as the difference between the lowest miniburst heart period and the first heart period in the 0.15 Hz low-pass filtered sequence. $\Delta HP_{\text{offset}}$ was defined as the difference between the lowest miniburst heart period and the final heart period in the 0.15 Hz low-pass filtered sequence.

Surrogate analysis

We distinguished non-spurious local structures related to short-lived physiological changes from local structures due to processing artifacts and/or random elements using surrogacy. First, we randomized the original sequences after excision of minibursts to create 1000 surrogate sequences of each, then obtained measures of local structure of all the spurious local structures, thereby establishing their probability distribution (Fig. 1). Surrogate sequences [2,3] and thresholds were established for each original sequence. We then derived a significance threshold (>95th percentile) for spurious structures, and applied this to measures of local structure in the original sequences. Local structures exceeding this threshold were considered to be non-spurious local structures.

Locating non-spurious local LF contributions

To identify all non-spurious local contributions to LF band spectral power we performed Short Time Fourier Transforms (STFTs) on the interpolated original and surrogate sequences. Fast Fourier Transforms (FFTs) were performed on detrended, Hanning-windowed subsequences within a 20-s window that was moved along the interpolated sequences at an interval of 10 s. The power spectral density measure in the LF (0.05–0.15 Hz) spectral bin for each 20s window was determined and those subsequences whose LF-contribution exceeded the surrogate's 95th percentile threshold were considered non-spurious.

Quantifying local LF contributions

We first located the non-spurious subsequences in the interpolated original sequence, then replaced these subsequences with the corresponding subsequences from the corresponding 0.05 Hz low-pass filtered sequence. The LF power of this sequence was then compared with the LF power obtained from the interpolated original sequence to determine the contribution of the local structures. Two families of non-spurious subsequences contribute to LF power (Fig. 1). One family

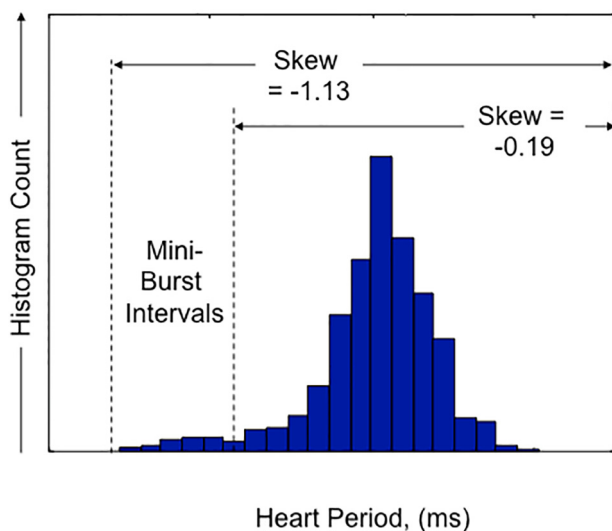


Fig. 2. Identification and excision of minibursts. Histogram of the differences between these local minima and maxima.

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