Biomedical Signal Processing and Control 8 (2013) 542–550

Contents lists available at SciVerse ScienceDirect

Biomedical Signal Processing and Control

journal homepage: www.elsevier.com/locate/bspc

A new algorithm for wavelet-based heart rate variability analysis

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ARTICLE INFO

Article history:
Received 27 February 2013
Received in revised form 22 April 2013
Accepted 20 May 2013

Keywords:
Heart rate variability
Wavelet transform
Wavelet packets
RHRV

ABSTRACT

One of the most promising non-invasive markers of the activity of the autonomic nervous system is heart rate variability (HRV). HRV analysis toolkits often provide spectral analysis techniques using the Fourier transform, which assumes that the heart rate series is stationary. To overcome this issue, the Short Time Fourier Transform (STFT) is often used. However, the wavelet transform is thought to be a more suitable tool for analyzing non-stationary signals than the STFT. Given the lack of support for wavelet-based analysis in HRV toolkits, such analysis must be implemented by the researcher. This has made this technique underutilized.

This paper presents a new algorithm to perform HRV power spectrum analysis based on the Maximal Overlap Discrete Wavelet Packet Transform (MODWPT). The algorithm calculates the power in any spectral band with a given tolerance for the band's boundaries. The MODWPT decomposition tree is pruned to avoid calculating unnecessary wavelet coefficients, thereby optimizing execution time. The center of energy shift correction is applied to achieve optimum alignment of the wavelet coefficients. This algorithm has been implemented in RHRV, an open-source package for HRV analysis. To the best of our knowledge, RHRV is the first HRV toolkit with support for wavelet-based spectral analysis.

1. Introduction

Heart rate variability (HRV) refers to the variation over time of the intervals between consecutive heartbeats. Since the heart rhythm is modulated by the autonomic nervous system (ANS), HRV is thought to reflect the activity of the sympathetic and parasympathetic branches of the ANS. The continuous modulation of the ANS results in continuous variations in heart rate. One of the most powerful HRV analysis techniques is based on the spectral analysis of the time series obtained from the distances between each pair of consecutive heartbeats. The HRV power spectrum is a useful tool as a predictor of multiple pathologies [1,2].

Akselrod et al. [3] described three components in the HRV power spectrum with physiological relevance: the very low frequency (VLF) component (frequencies below 0.03 Hz), which is modulated by the renin–angiotensin system; the low frequency (LF) component (0.03–0.15 Hz), which is thought to be of both sympathetic and parasympathetic nature; and the high frequency (HF) component (0.18–0.4 Hz), which is related to the parasympathetic system. At present, there is no absolute consensus on the precise limits of the boundaries of these three bands. In the literature we can find authors who use slightly different bands' boundaries [4].

There exist several HRV spectral analysis techniques. These techniques may be classified as nonparametric and parametric [5]. The main advantage of the nonparametric methods is the simplicity and speed of the algorithm used (The Fast Fourier Transform). The main advantage of the parametric methods is that they give smoother spectral components. However, parametric methods present problems regarding to correct model order selection. Although these techniques are widely used, they have no temporal resolution. This severely limits their ability to analyze non-stationary signals and transient phenomena. To alleviate this limitation temporal windows are often used, so that small segments of the whole signal are analyzed. Among these techniques we may highlight the Short Time Fourier Transform (STFT) [6]. However, time–frequency resolution of the STFT depends on the spread of the window used. Thus, the STFT has fixed time–frequency resolution: high frequency resolution implies poor time resolution and vice versa. Conversely to Fourier, the wavelet transform performs time–frequency analysis and it is recognized as a powerful tool to study non-stationary signals [7].

HRV analysis toolkits such as Kubios HRV [8] or aHRV [9] only enable HRV spectral analysis based on the Fourier transform or parametric methods. To the best of our knowledge, the only option for using the wavelet transform in HRV analysis is to manually implement the algorithms, probably with the support of some

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1746-8094/$ – see front matter
http://dx.doi.org/10.1016/j.bspc.2013.05.006

general wavelet library. This is tedious, and prone to error. Although some researchers have done this [10,11], many more (especially those with a medical background) choose to use Fourier-based tools, even when they know that the signal being analyzed is non-stationary. A query in the PubMed database with the terms "heart rate variability Fourier transform" returns 660 articles, while a query with the terms "heart rate variability wavelet transform" only returns 145 articles. The lack of tools for carrying out HRV analysis using the wavelet transform has made this potentially superior analysis technique underutilized in comparison with the Fourier transform.

In this paper we present an algorithm to perform HRV power spectrum analysis based on the Maximal Overlap Discrete Wavelet Packet Transform (MODWPT). The algorithm calculates the spectrogram in any frequency band, allowing a certain tolerance for the position of the band's boundaries. The algorithm has been validated over simulated and real RR series. Its capability for identifying fast changes in the RR series' spectral components has been compared with the STFT and a windowed version of the Burg method, showing that these techniques miss some transient changes that are successfully identified by the wavelet transform. We have implemented the algorithm in RHRV, an open-source package for HRV analysis publicly available on the Internet. A previous version of this algorithm was published in [12].

Section 2 starts with a brief review of the wavelet transform, with particular attention to the MODWPT, and then introduces our algorithm to perform HRV power spectrum analysis. Section 2.5 provides a short description of the implementation of the algorithm in the RHRV package. Section 3 presents a comparison between our algorithm, the STFT and the windowed Burg method over simulated and real RR series. Finally, the results of this paper are discussed and some conclusions are given.

2. Materials and methods

A brief review of some important wavelet concepts for our algorithm is now given. A wavelet is a small wave $\psi(t)$ (oscillating function) that is well concentrated in time. This function must have unitary norm $\|\psi\| = 1$ and verify the so-called admissibility condition: $\int_{-\infty}^{\infty} \psi(t)dt = 0$. $\psi(t)$ can be translated and dilated in time, yielding a set of wavelet functions:

$$\psi_{u,s}(t) = \frac{1}{\sqrt{s}}\psi\left(\frac{t-u}{s}\right), \quad (1)$$

where $s > 0$ is a dilation factor, and u is a real number representing the translations. As ψ generates all $\psi_{u,s}$ functions, it is called mother wavelet.

A continuous wavelet transform measures the time–frequency variations of a signal f by correlating it with $\psi_{u,s}$

$$Wf(u,s) = \int_{-\infty}^{\infty} f(t)\psi^*_{u,s}(t)dt. \quad (2)$$

In order to make the wavelet transform implementable on a computer, both dilation and translation factors must be discretized. This can be achieved as follows:

$$\left\{\psi_{j,n} = \frac{1}{\sqrt{2^j}}\psi\left(\frac{t-2^j n}{2^j}\right)\right\}_{j,n\ \in\ \mathbb{Z}.} \quad (3)$$

This family is an orthonormal basis of $\mathbf{L}^2(\mathbf{R})$. Orthogonal wavelets dilated by 2^j can be used to study signal variations at the resolution 2^{-j}. Thus, these families of wavelets originate a multiresolution signal analysis. Multiresolution analysis projects signals at various resolution spaces $\mathbf{V}_j$. Each $\mathbf{V}_j$ space contains all possible approximations at the resolution 2^{-j}. Thus, each decomposition level increases the spectral resolution of the decomposition, at the expense of losing temporal resolution. Let $\{\mathbf{V}_j\}_{j\in\mathbb{Z}}$ be a multiresolution approximation verifying $\mathbf{V}_{j+1} \subset \mathbf{V}_j\ \ \forall j \in \mathbb{Z}$ and let $\mathbf{W}_j$ be the orthogonal complement of $\mathbf{V}_j$ in $\mathbf{V}_{j-1}$: $\mathbf{V}_{j-1} = \mathbf{V}_j \oplus \mathbf{W}_j$. According to [13], the families

$$\left\{\phi_{j,n} = \frac{1}{\sqrt{2^j}}\phi\left(\frac{t-2^j n}{2^j}\right)\right\}_{n\in\mathbb{Z}} \quad \text{and}$$

$$\left\{\psi_{j,n} = \frac{1}{\sqrt{2^j}}\psi\left(\frac{t-2^j n}{2^j}\right)\right\}_{n\in\mathbb{Z}} \quad (4)$$

are an orthonormal basis for $\mathbf{V}_j$ and $\mathbf{W}_j$, respectively, for all $j \in \mathbb{Z}$. $\psi_{j,n}$ are the wavelet functions and $\phi_{j,n}$ are the scaling functions.

Thus, we can approximate any function $f \in \mathbf{L}^2(\mathbf{R})$ at resolution 2^{-j} as

$$P_{\mathbf{V}_j}f = \sum_{n=-\infty}^{\infty} \langle f, \phi_{j,n}\rangle \phi_{j,n} = \sum_{n=-\infty}^{\infty} a_j[n]\phi_{j,n} \quad (5)$$

and the orthogonal projection of f onto detail space $\mathbf{W}_j$ is:

$$P_{\mathbf{W}_j}f = \sum_{n=-\infty}^{\infty} \langle f, \psi_{j,n}\rangle \psi_{j,n} = \sum_{n=-\infty}^{\infty} d_j[n]\psi_{j,n}. \quad (6)$$

where $a_j[n]$ and $d_j[n]$ are called the approximation and detail coefficients, respectively.

Mallat proved [7] that both approximation and detail coefficients may be calculated using a filter bank. Let $h[n]$ and $g[n]$ be the FIR filters that will be used to compute the approximation and detail coefficients, respectively. It has been proven [13] that the filter $h[n] = \langle 1/\sqrt{2}\phi(t/2), \phi(t-n)\rangle$ and that $g[n] = \langle 1/\sqrt{2}\psi(t/2), \phi(t-n)\rangle$. $g[n]$ and $h[n]$ can be regarded as an approximation to a high-pass filter (the wavelet filter) and to a low-pass filter (the scaling filter), respectively. By applying recursively over the approximation coefficients the same filtering operation followed by sub-sampling by two, we obtain the multiresolution expression of f. This algorithm, known as the pyramid algorithm, is the most efficient way of computing the Fast Orthogonal Wavelet Transform (FOWT) [13].

2.1. MODWPT

Given that the filtering operation is only applied over the approximation coefficients, the FOWT only provides information on a limited set of frequency bands which need not be the ones used in the HRV analysis. A more suitable wavelet transform is needed for our algorithm: the wavelet packet decomposition (WPD). Instead of dividing only the approximation coefficients $a_j[n]$, both detail and approximation coefficients are decomposed successively by applying high pass and low pass filters to each set of coefficients.

Among the WPD transforms we have chosen the MODWPT [14] because it is less sensitive to the starting point of the time series and it is applicable to non dyadic sequences. Furthermore, the MODWPT avoids the sub-sampling step, and therefore it has the same number of wavelet coefficients in every decomposition level. This simplifies computations involving different decomposition levels.

The *jth* level of the MODWPT decomposes the frequency interval $[0, f_s/2]$, where f_s is the sampling frequency of the original signal f, into 2^j equal width intervals (see Fig. 1). Thus, the *nth* node (beginning at zero) in the *jth* level of the decomposition tree, the (j, n) node, is associated with the frequency interval $f_s/2^{j+1}[n, n+1]$. Each node will have N wavelet coefficients associated, N being the length of the sampled signal f. The N-dimensional vector $\mathbf{W}_{j,n}$ will denote the N wavelet coefficients associated with the (j, n) node.