Performance Analysis of Wavelet Filters for Heart Rate Variability Analysis

Sarla and Dilbag Singh

Abstract Heart rate variability (HRV) analysis yields important insights into the understanding of physiological mechanisms. The HRV analysis is a powerful tool for risk prediction in heart diseases. Most common methods of HRV analysis are fast Fourier transform and autoregressive methods. However, these methods have limitations in the study of long-term nonlinear variations and transient analysis of heart rate variability. Wavelet transform-based HRV analysis overcomes these limitations. This paper identifies the characteristics of wavelet transform in heart rate variability analysis. The number of wavelet filters is suggested in the literature, but every wavelet filter has a specific category of application. To investigate the wavelet filters for heart rate variability analysis, RR tachogram extracted from five minutes of ECG signal recorded from a healthy volunteer. The appropriate wavelet filter should be adaptive to slow and fast variation in the HRV signal. The different wavelet filter performances are assessed, and the observations presented in the results revealed that Db-3 (Daubechies) with six-filter length is the most suitable wavelet filter for HRV analysis.

Keywords Heart rate variability · Wavelet transform · Filter · RR interval

1 Introduction

There are many mathematical tools which are used for heart rate variability analysis like Fourier transform, autoregressive method and wavelet transform. Discrete Fourier transform is a very popular technique in the frequency domain because it is simple and fast but valid only for stationary signal due to lack of its time resolution [1, 2], while wavelet transforms are used for both stationary and non-stationary kind of signals [3, 4]. Wavelet transform is used for time–frequency domain analysis, and it also works as a filter to take out time-dependent signals [2, 3]. Generally, wavelet

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decomposes data into distinct frequency component, and after decomposition, every component's resolution is matched to its scale [5, 6].

Heart rate variability (HRV) is a popular tool used for the calculation of cardiac autonomic modulations [7, 8]. Recently studies show that HRV can quickly become one powerful tool for risk prediction in heart disease [9, 10]. HRV provides insight understanding about the relationship between the autonomic nervous system (ANS) and arrhythmia and mechanisms of how ANS influence arrhythmia [11, 12]. The time-varying changes in the heart directly linked with time–frequency estimation HRV which can be easily quantified using time-scale methods, also known as wavelet transform [13, 14]. Wavelet has many shapes, and its aim is to get fit in the shape of the signal that can be analyzed for a good quantitative measurement [15]. Wavelet transform is capable of displaying information such as breakpoints, interference in high derivatives [16]. This work is facilitating a link between the filters used in wavelet transform and power spectral density for the estimation of HRV. From Fig. 1, it observed that there is a discrepancy in the choice of wavelet functions,

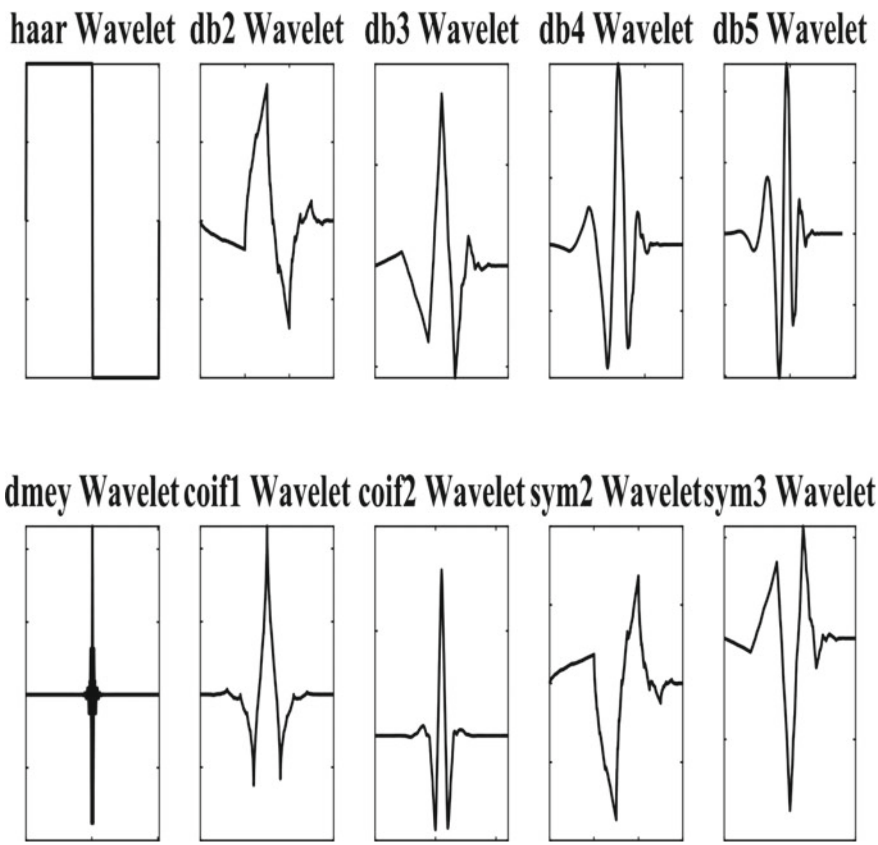

Fig. 1 Selected different wavelet transform

and the selection criteria adopted in their commands are often not reasonable, and performance evaluations are almost absent. Thus, it is required to study this matter of HRV analysis by wavelet. In this paper, the comparison of different types of wavelets is presented with a representation of the instantaneous power of the HRV spectrum.

2 Materials and Method

2.1 Physiological Recordings

To evaluate wavelet filter performance for HRV analysis, ECG data recorded from a single healthy young volunteer (male, age 23 years) in the supine position in Biomedical Lab in Dr. B R Ambedkar National Institute of Technology, Jalandhar (Punjab) using Biopac® BSL system MP36 and BSL version 3.7.6 Pro.

The acquisition of the ECG signal was performed under dim light conditions and in a noise-free environment. The duration of the ECG recording was 5 min. The subject included for the study possess no history of diabetes mellitus, hypertension, alcohol dependence and other diseases that can affect HRV. Temperature, pulse and blood pressure checked for the possibility of any abnormality. The informed consent form was signed the subject as per institute's Ethical committee guidelines for human subjects.

2.2 HRV and Wavelet Transform

Wavelet transform is a mathematical function which is used to divide the data into different frequency components and play an important role in the matching of components resolution with its scale [2, 6]. The large window in wavelet in a signal represents gross features and small window provides detail features. The equation of continuous wavelet transforms for signal $x(t)$ is–

$$W_a x(b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x(t)\Psi^*\left(\frac{t-b}{a}\right)\mathrm{d}t, \quad a > 0$$

where 'a' is dilation, 'b' is the translation (both are discretized), '*' denotes complex conjugate and Ψ is a wavelet function.

Dyadic wavelet transform of a signal $x(t)$ is–

$$\mathrm{DyWT}(a, b) = \frac{1}{2^j} \int_{-\infty}^{\infty} x(t)\Psi^*\left(\frac{t-b}{2^j}\right)\mathrm{d}t$$

In the discrete-time signal, the dyadic discrete wavelet transform can be a combination of a high-pass filter and low-pass filter. There were seven wavelet scales ($j = 7$) obtained from the wavelet decomposition of signal. During down sampling, the signal is divided into two parts: one is detail signal and other is approximation signal [2, 15]. Detail signal represents the high-pass filter while the approximation signal represents the low-pass filter (Fig. 2). At the moment, the detail coefficient of the filtration collected, while redistributing the approximation into two halves, one is high pass and the other low pass. High-frequency component is obtained from merging the detail signal at scales 5 and 6, while the low-frequency component is obtained from merging the detail signal at scales 3 and 4. The very-low-frequency component obtained from the detail signal at scale 7 (see Fig. 3).

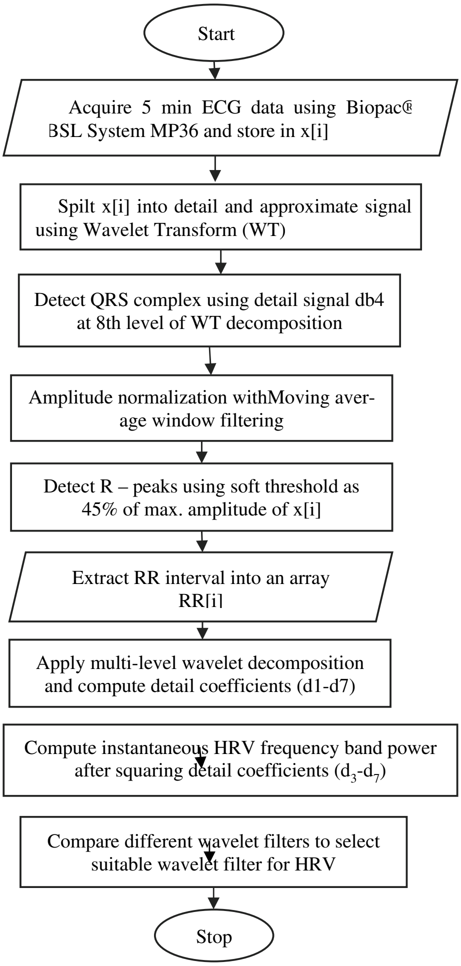

Fig. 2 Flow chart of wavelet transform-based filter bank evaluation of HRV analysis

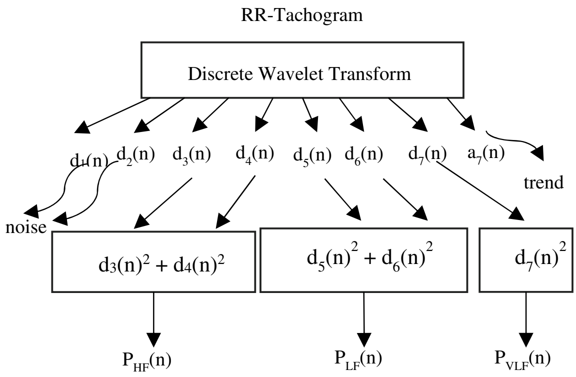

Fig. 3 Wavelet decomposition of RR tachogram signal to calculate instantaneous HRV frequency bands power [6]: VLF (very low frequency) = d_7 (0.01875 − 0.0375 Hz); LF (low frequency) = $d_5 + d_6$ (0.0375 − 0.15 Hz); HF (high frequency) = $d_3 + d_4$ (0.15 − 0.6 Hz

Figure 2 represents the detailed methodology used for this study. In this work, four types of wavelet families are described: Haar Wavelet (HW), Daubechies Wavelet (DW), Discrete Meyer Wavelet and Symmlet Wavelet (SW) [2]. Each wavelet family has different orders of the filter. Daubechies is an orthogonal wavelet that is fully supported [2, 6]. Filter order decides the length of the filter [6]. Higher-order filters provide a higher degree of smoothness in a signal and can be tailored to localize better frequencies, which increases energy compaction. Lower-order filters have a good time localization and save important edge information [6]. Wavelet-based HRV analysis requires a good balance between filter length, degree of smoothness, computational complexity, due to which it prioritizes good localization of time and frequency.

3 Results and Discussion

Wavelet transform is a good choice for HRV analysis of ECG because it is orthogonal, smooth and nearly symmetric. In this paper, many standard wavelets were tried but used the one that creates the good performance over a particular application. Figure 4

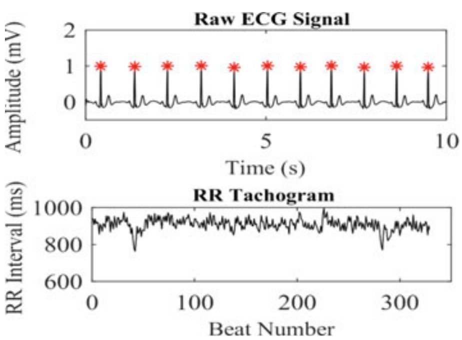

Fig. 4 A representative sample of 10 s ECG signal with R peak marked as '*' sign and corresponding RR tachogram of complete five-minute ECG recording selected for wavelet-based HRV analysis

shows the raw ECG signal and RR tachogram extracted from five minutes of ECG data. The selection of a particular wavelet depends on a particular application. So, the scaling function related to a good wavelet usually resembles that of a given signal. Other important factors like noise sensitivity and errors are to be recognizable. Filter length is one of the factors that affect all decomposition levels of detail coefficient.

The DWT analysis of wavelets such as Db-1 (Haar), Db-2, Db-3, Db-4, Db-5, Dmey, Coif-01, Coif-02, Sym-2 and reporting of results given in Table 1 with Fig. 6 that are representing the instantaneous PSD decomposition of Db-3 wavelet by increasing wavelet order. Instantaneous PSD decompositions are detected to be almost same at VLF, LF and HF levels. Low-order wavelets are needed to identify temporary episodes and higher-order wavelets are a great choice for long-lasting information. Different basis and order distribute the power between different frequency bands. The total PSD is roughly in the same span for all wavelets, and the diffusion of power in the spectral band depending on the wavelet or on order, which also proved from mean and SD values. Figure 5 shows wavelet decomposition of RR tachogram of five-minute ECG signal recorded under resting state in the supine posture, with db3 wavelet filter and d_1, d_2, …, d_7 detail signals extracted.

Table 1 shows the comparison of different wavelet filter performance for heart rate variability analysis. In the spectral approximation, the inter-wavelet PSD variance decreases with increasing frequency/scale. Normalized spectral powers continue unobstructed by the order or type of wavelet. Considering the filter length which changes the time-period of all band power after wavelet decomposition and the P_{VLF} time-period decreased by higher-order filter. There was no signal addition used to ignore the accuracy of results. So, it observed that Haar and symlet-3 are not fitted well in the case of PSD. Figure 6 shows instantaneous PSD for respective HRV frequency bands using wavelet decomposition of RR tachogram of five-minute ECG signal recorded under resting state in the supine posture, with db3 wavelet filter. Now, another concept transient episode detection was focused on many protocols for variable HRV analysis. It can be seen evidently the difference in LF/HF ratio. So, it is obvious that Db-3 wavelet with six-coefficient and minimum filter length represents a good result of variable HRV. So, taking into account the filter length and wavelet coefficients, Db-3 is used in the remaining analysis of HRV.

4 Conclusion

This study discussed the comparison of different wavelets and wavelet orders for HRV analysis. Wavelet transform is found to be a tool to analysis transient variation of heart rate variability. The wavelet transform shows spectral changes for specific interval, and it was noted from the observations that db3 as mother wavelet for HRV analysis due to clear changes in LF/HF ratio with lowest filter coefficients, i.e. six. Thus, db3 wavelet filter proposed best fit for heart rate variability analysis.

Table 1 Comparison of different wavelet filter performance for heart rate variability analysis

Wavelet	P_{d3}	P_{d4}	P_{d5}	P_{d6}	$P_{d7} = P_{VLF}$	P_{LF}	P_{HF}	P_{Total}	P_{nLF}	P_{nHF}	P_{LF}/P_{HF}
db1	3657.22	3470.87	7632.52	9594.37	18,973.51	6562.17	5425.40	30,961.08	54.74	45.26	1.21
db2	5209.68	4681.89	4566.17	12,695.22	2835.33	7781.99	7678.31	18,295.63	50.34	49.66	1.01
db3	4084.72	3536.58	3577.17	11,416.62	10,901.14	6408.67	6008.12	23,317.93	51.61	48.39	**1.07**
db4	4255.62	3794.83	4342.67	6910.13	9224.81	5884.64	6349.32	21,458.77	48.10	51.90	0.93
db5	5080.87	3316.91	4193.36	9418.20	9797.20	7589.13	6960.45	24,346.78	52.16	47.84	1.09
dmey	4247.45	3799.28	4343.53	6936.92	9225.19	5887.02	6343.61	21,455.82	48.13	51.87	0.93
coif1	4254.61	3122.22	3016.40	11,918.78	11,303.25	6600.97	5952.66	23,856.88	52.58	47.42	1.11
coif2	3831.75	3571.34	3264.91	7006.49	4797.11	5344.49	5905.43	16,047.03	47.51	52.49	0.91
sym2	5209.68	4681.89	4566.17	12,695.22	2835.33	7781.99	7678.31	18,295.63	50.34	49.66	1.01
sym3	4084.72	3536.58	3577.17	11,416.62	10,901.14	6408.67	6008.12	23,317.93	51.61	48.39	1.07
sym4	4118.55	3198.14	3584.67	8941.82	14,046.97	6189.46	5883.04	26,119.46	51.27	48.73	1.05

Bold indicates db3 behaves as a mother wavelet due to clear changes in LF/RF ratio with lowest filter coefficient
P_{dj} = Mean power of the detail signal at jth decomposition level
P_{LF} = Mean power of the low-frequency component (0.0375 − 0.15 Hz).
P_{HF} = Mean power of the high-frequency component (0.15 − 0.6 Hz)
P_{nLF} = Normalized low-frequency power, $P_{LF}/(P_{Total} - P_{VLF})$
P_{nHF} = Normalized low-frequency power, $P_{HF}/(P_{Total} - P_{VLF})$
$P_{Total} = P_{VLF} + P_{LF} + P_{HF}$
P_{VLF} = Mean power of the very-low-frequency component (0.01875–0.0375 Hz); LF (low frequency) = $d5 + d6$ (0.0375–0.15 Hz); HF (high frequency) = $d3 + d4$ (0.15–0.6 Hz)
P_{LF}/P_{HF} = The ratio between the power of LF and HF component

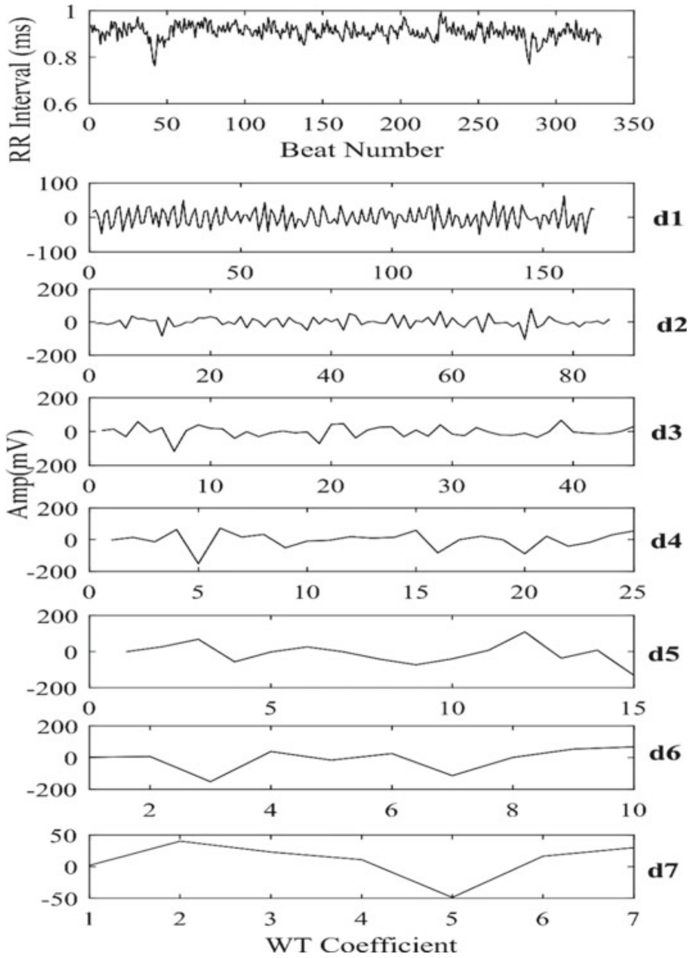

Fig. 5 Wavelet decomposition of RR tachogram of five-minute ECG signal recorded under resting state in the supine posture, with db3 wavelet filter. Where $d1$, $d2$, …, $d7$ indicate detail signals extracted from wavelet decomposition of RR tachogram

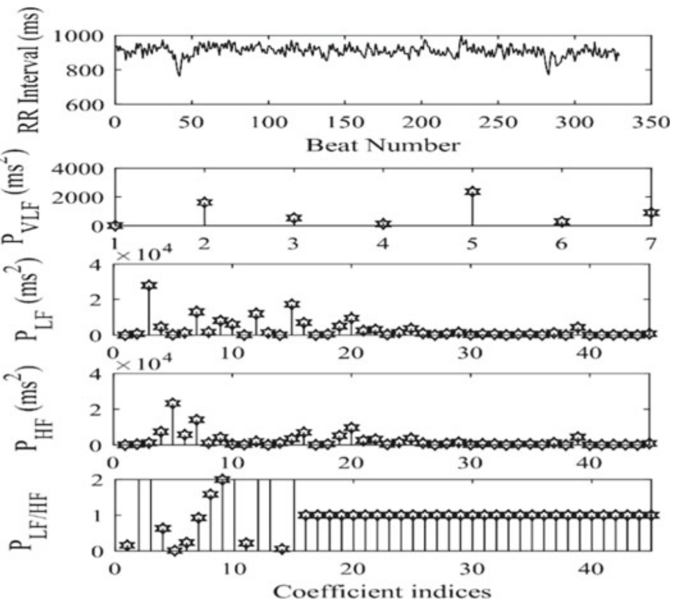

Fig. 6 Wavelet decomposition of RR tachogram of five-minute ECG signal recorded under resting state in the supine posture, with db3 wavelet filter where P_{VLF}, P_{LF} and P_{HF} indicates instantaneous PSD for respective HRV frequency bands: VLF (very low frequency) = $0.01875 - 0.0375$ Hz; LF (low frequency) = $0.0375 - 0.15$ Hz; HF (high frequency) = $0.15 - 0.6$ Hz

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