Frequency-domain Heart Rate Variability Analysis Performed by Digital Filters

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Abstract

Short-term heart rate variability (HRV) analysis based on spectral methods has been widely applied to assessment of autonomic nervous system activities for many physiological and mental disorders. Recently, homecare devices designed for heart monitoring have attempted to include HRV analysis function. These homecare devices based on some microprocessors with low computational power might encounter difficulty in implementing HRV spectral analysis for real-time applications. Therefore simple and less computation consuming methods to calculate frequency domain HRV indicators are needed.

In this study, time-domain digital filters are proposed to solve this problem. The low-frequency (LF, 0.04-0.15 Hz) band and high-frequency (HF, 0.15-0.4 Hz) band signals of HRV are filtered from original 256 beats HRV signal. The variances of these two signals were considered as the equivalence of LF and HF powers derived from standard Fourier-based spectra respectively. Some finite and infinite impulse response (FIR and IIR) filters were tested to show their feasibility and find the optimal filter.

The results showed that the time-domain filter with simple modification can generate comparable LF and HF power of HRV. The FIR filter-based method just uses the convolution operator thus it can simplify the design and deployment of short-term HRV analysis in homecare devices and make the real-time applications easier.

1. Introduction

Heart rate variability (HRV) reflects autonomic nervous activities (ANA) and has been applied for many physiological and mental disorders [1-2]. HRV is measured from the sequential heartbeat interval series of normal beats. In general, HRV analysis is divided into time-domain and frequency-domain analysis [1]. The time-domain method uses long-term heartbeat intervals data mainly from 24-hr Holter monitor. In frequency-domain analysis, the power spectrum of the short-term (about 5 minutes) heartbeat intervals is divided into two main components: the low-frequency component (LF, 0.04~0.15 Hz) and the high-frequency component (HF, 0.15~0.4 Hz). The HF power is considered as an index of vagal tone, on the other hand, the LF power, is influenced by both sympathetic and vagal controls.

Because of easy setting, the frequency-domain measures of HRV have been widely used [3-6]. This method is based on the spectral analysis of heartbeat interval series. The spectra could be obtained by discrete Fourier transform (DFT) [3-5] or auto-regression (AR) model [7]. These analyses need complicated computational procedures and thus are generally performed by software programs run on a computer.

Recently, homecare devices designed for heart monitoring have attempted to include short-term HRV analysis [8-10]. These homecare devices based on microprocessors with low computational power might encounter difficulty in implementing HRV spectral analysis. Therefore simple and less computation consuming methods to calculate frequency domain HRV indicators need to be proposed for homecare application.

Although the frequency domain measures of HRV are calculated from spectra of heartbeat intervals, actually they are expressed as the sum of power within a frequency range. Thus it is possible to approximate LF and HF power by calculating the power of signals filtered from original heartbeat intervals signals within the ranges of LF and HF. In this study, we attempted to demonstrate the feasibility of using time-domain filter to get frequency-domain measures and to find the most suitable filter design for this purpose.

2. Methods and materials

In this study, we proposed a method to approximate he spectral power within a frequency band by calculating the variance of the signal filtered by a band-pass filter from original signal. Thus, in HRV analysis, the LF band and HF band signals of HRV are filtered from original 256 beats HRV signal. The variances of these two signals were considered as the equivalence of LF and HF powers derived from standard Fourier-based spectra respectively. In order to find the possible solutions to get the approximate power by proposed method, some finite impulse response (FIR) and infinite impulse response (IIR) filters were tested. The Matlab 7.0 software and its signal processing toolbox (Mathworks Inc., USA) were used to implement the relevant computation.

2.1. Filters design

The designed FIR filter was a Hamming-window based, linear-phase filter with normalized cutoff frequency. The cutoff frequencies of bandpass filters for LF calculation were 0.04 Hz and 0.15 Hz and those for HF power calculation were 0.15 Hz and 0.4 Hz. The 10-40orders of filters were chosen to test their feasibility.

The Butterworth IIR filters were applied to test their feasibility in power calculation. The setting for cutoff frequencies was same as FIR filter design. The orders of IIR filters chosen in this test were 2-10.

2.2. Comparison with DFT-based method

The spectral analysis of HRV was performed by 256-points DFT. The sampling rate of the HRV signal was set as the reciprocal of mean of heartbeat intervals. Ten normal HRV data were used to compare the LF and HF powers obtained from DFT-based method and digital filter method. The root mean square error (RMSE) and correlation coefficient (CR) of filter-based vs. DFT-based method for each filter were used for the indicators to find the best filter design. Otherwise, LF/HF parameter was also compared.

3. Results

3.1. FIR filters

Total 31 FIR filters with 10-40 orders were generated to filter HRV data and get the LF and HF powers. Figure 1 showed the RMSE and CR of LF power obtained from 31 filters comparing with DFT-based method. It could be found that the RMSE decreased when order of filter increased and the CR had a peak at order 21. Figure 2 showed the RMSE and CR of HF power obtained from 31 filters comparing with DFT-based method. It could be found that the RMSE increased when order of filter increased and the CR had a valley at order 16. Since the solution should have the higher CR and the lower RMSE, the filter with order 21 was selected for LF power calculation and the filter with order 11 was selected for HF power calculation. The RMSE was about 30 ms^2 and the CR was over 0.8 in LF power approximation but only 0.6 in HF power approximation.

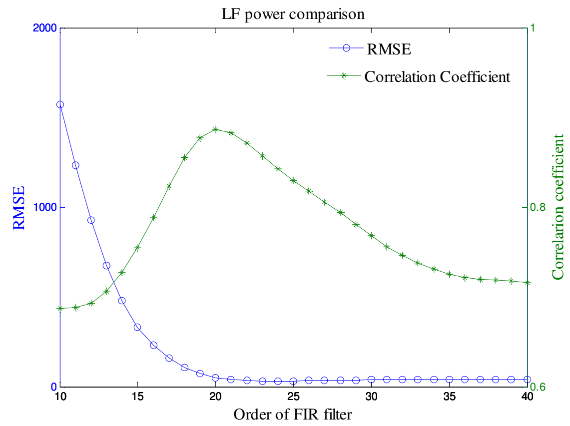

Figure 1. The RMSE and correlation coefficient of LF powers obtained from different orders of FIR filter comparing with DFT-based method in 10 normal HRV data.

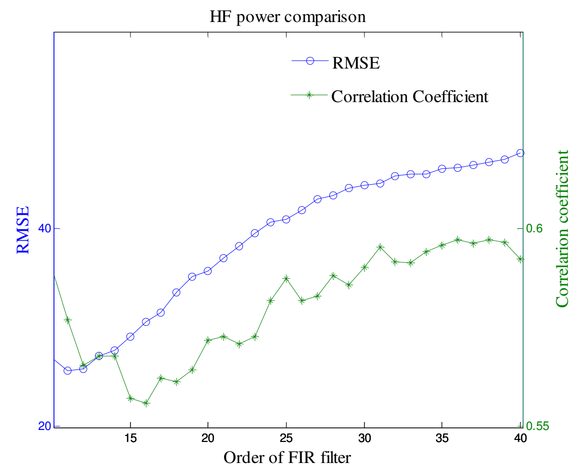

Figure 2. The RMSE and correlation coefficient of HF powers obtained from different orders of FIR filter comparing with DFT-based method in 10 normal HRV data.

Figure 3 showed the filtered signals from the selected LF and HF filters as well as original HRV signal and its spectrum of one sample.

3.2. IIR filters

Total 9 IIR filters with 2-10 orders were generated to filter HRV data and get the LF and HF powers. Figure 4 and 5 showed the RMSE and CR of LF and HF power, respectively, obtained from 9 filters comparing with DFT-based method. It could be found that the RMSE increased and the CR decreased when order of filter increased. Therefore we selected the IIR filter with order 2 as the optimal solution in order to have higher correlation and less error.

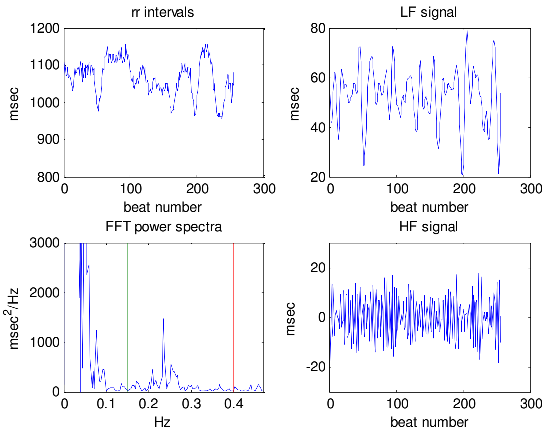

Figure 3. Illustrations of signals by FIR filtering of one sample. Original HRV signal (top left), spectrum of HRV (bottom left), the filtered signal from LF filter with order 21 (top right) and the filtered signal from HF filter with order 11 (bottom right).

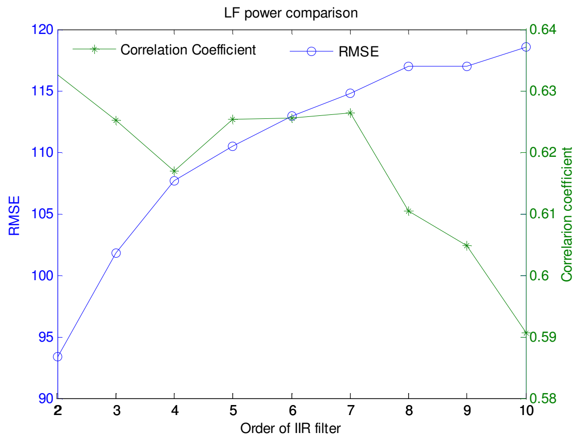

Figure 4. The RMSE and correlation coefficient of LF powers obtained from different orders of IIR filter comparing with DFT-based method in 10 normal HRV data.

The RMSE was about 90 ms^2 and the CR was about 0.6 in LF power approximation. In HF power approximation, the RMSE was about 50 ms^2 and the CR was also about 0.6. Figure 6 showed the filtered signals from the selected LF and HF filters as well as original HRV signal and its spectrum of one sample.

Table 1 showed the RMSE and CR of final selected FIR and IIR filters. Both LF and HF powers computed by our method were larger than those obtained from DFT-based method. However, the correlation is significant, especially, in LF using FIR filter. Figure 7 showed the scatter plot of LF and HF power for our method vs. DFT method. The regression lines were also presented in the figure. The regression analysis revealed that the HF power from filter method was 3-4 times that from DFT method.

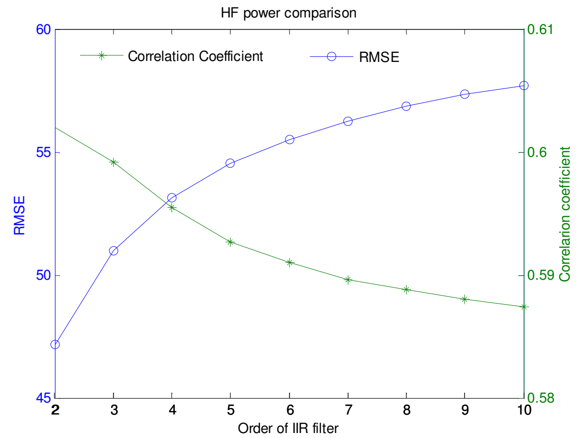

Figure 5. The RMSE and correlation coefficient of HF powers obtained from different orders of IIR filter comparing with DFT-based method in 10 normal HRV data.

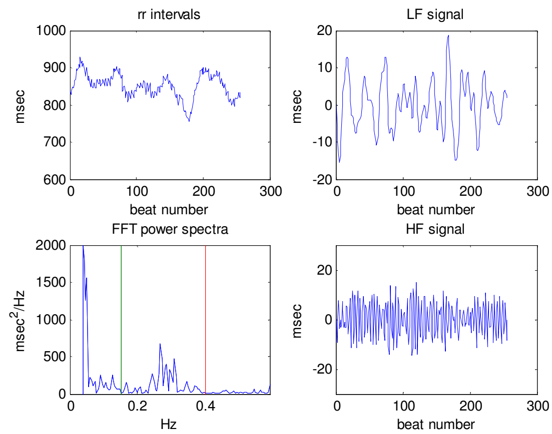

Figure 6. Illustrations of signals by IIR filtering of one sample. Original HRV signal (top left), spectrum of HRV (bottom left), the filtered signal from LF filter (top right) and HF filter (bottom right) with order 2.

Table 1. The RMSE and CR of final selected FIR and IIR filters and the mean of 10 HRV data from our method vs. DFT method

	Our method	DFT method	RMSE	CR
LF (FIR)	133.17	104.70	39.51	0.88
HF (FIR)	55.53	36.02	25.63	0.58
LF (IIR)	179.83	104.70	93.39	0.63
HF (IIR)	83.06	36.02	47.16	0.60

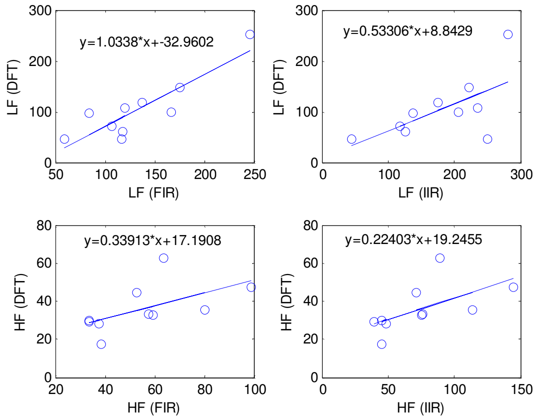

Figure 7. Scatter plot of LF and HF power for our method vs. DFT method including regression lines.

4. Discussion and conclusions

The LF and HF powers derived from our filtering method had obvious correlation to the DFT-based method, but there was difference between two methods. From table 1, the errors from FIR method is 37.5% in LF power (RMSE/DFT, 39.51/104.70) and 80% in HF power (25.63/36.02) that are better than IIR method. Although the result seems not good for being an alternative short-term HRV analysis, it is possible to improve the solution by modification according to regression analysis of figure 7 because of the good correlations. However, the difference also exists between well-known DFT-based spectral method and AR model based spectral method [7]. Thus our method should be validated by the discriminability on clinical application rather than only by the comparison with DFT-based method.

The optimal filters selected by approximating the data from DFT-based method in this study were FIR filter with order 21 for LF power calculation and order 11 for HF power calculation. The two filters could be easily implemented in a homecare application using software [8] or hardware [9] environment. Thus the real-time application of HRV analysis could be expected.

Moreover, our previous study [2] revealed that HRV modulated by vagal activity with HF oscillation and by both sympathetic and vagal activities with LF oscillation. The filtered LF and HF signal in figure 3 and 6 may provide a new insight for autonomic assessment by HRV analysis and need further investigation.

In conclusion, we proposed a filter-based method as an alternative for HRV spectral analysis and evaluated its feasibility by comparing with DFT-Based method. The results showed that our method with simple modification would generate comparable LF and HF power of HRV. This method will simplify the design and deployment of short-term HRV analysis in homecare devices and make the real-time applications easier.

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