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#### **Short Communication**

## A novel cardiac spectral envelope extraction algorithm using a single-degree-of-freedom vibration model



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#### ARSTRACT

A novel cardiac spectral envelope extraction method was developed to acquire the optimal envelope information in the frequency domain to differentiate normal heart sounds and valvular heart disorders for further analysis. This automatic algorithm was based on the vibration model of a mass–spring–damper system. To acquire the best spectral envelope information from both a normal heart sound signal and an aortic regurgitation murmur signal, the morphological influence of two analytical parameters, the natural frequency p (range: 1–100 Hz) and the damping factor  $\zeta$  (range: 10–500%), on the single-degree-of-freedom model was evaluated using the root mean square error. The cardiac spectral envelope curve could be optimized at the natural frequency of  $35\pm5$  Hz and the damping factor of  $70\pm8\%$ . The spectral envelope extracted by the single-degree-of-freedom model showed more informative and efficient morphological characteristics than that extracted by an autoregressive power spectrum density model reported previously.

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#### 1. Introduction

A spectral envelope is the shape of the power spectrum of a signal. It is an important tool for the identification of specific sounds or signals [1] and provides a simple and conspicuous representation of the intrinsic properties of a signal [2,3]. Various spectral envelope estimation methods, including linear predictive coding (LPC), autoregressive moving average modeling, cepstrum analysis, and the discrete cepstrum, have been proposed to extract the spectral envelope of a biomedical signal [4]. LPC is a method used to compute an autoregressive (AR) model to replicate a desired power spectrum as the transfer function of an all-pole filter with order p. This estimation falls below the true spectrum and exceeds the true spectrum in regions that drop suddenly. Therefore, there are considerable mismatching errors between a true spectrum and its corresponding LPC envelope [5].

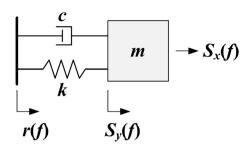
In a previous study [6], we reported a novel heart murmur classification method using the envelope curve of the power spectral

density (PSD) in the frequency domain. It shows obviously that the cardiac spectral information itself and its shape are determined by the activity and mechanical and geometric properties of the heart valves. The cardiac spectral shape can be used to evaluate the functions of the cardiovascular system [7]. The envelope was estimated by the normalized AR modeling of the PSD waveforms for a heart sound. This algorithm showed superior performance with high sensitivity and specificity. Furthermore, in order to extract single characteristic peaks from the spectral envelope, a multi-Gaussian model was used. Each Gaussian profile showed distinct cardiac hemodynamic sequences for normal heart sounds and murmurs [7]. However, we could not ignore the presence of a mismatch between the true spectrum and the extracted envelope. Although the order of the AR model was selected using the Akaike information criterion (AIC) [8], the mismatching error directly affects the single characteristic peaks. Therefore, a new spectral envelope method to decrease the number of mismatching errors is needed.

In a previous study [3], we developed a cardiac envelope extraction algorithm based on a single-degree-of-freedom analytical model in the time domain. This algorithm showed good performance compared to two popular envelope extraction algorithms, including the Shannon envelope, based on the normalized average Shannon energy, and the Hilbert envelope, based on the Hilbert transform [2]. Therefore, we developed a novel spectral envelope extraction algorithm based on a single-degree-of-freedom

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**Fig. 1.** A single-degree-of-freedom vibration model to extract the cardiac spectral envelope information. Here, m denotes the mass, c denotes the damping coefficient, k denotes the coefficient of the spring, r(f) denotes the rack displacement,  $S_x(f)$  denotes the input waveform, and  $S_y(f)$  denotes the output response.

vibration model controlled by the natural frequency and the damping factor. The proposed mass-spring-damper model was optimized by the root mean square error measure and its morphology was compared with the results of the AR-PSD estimation method.

#### 2. Cardiac spectral envelope extraction method

#### 2.1. Collection of cardiac sounds

Eight normal cardiac sounds were recorded from eight healthy subjects (aged  $28 \pm 9\,\mathrm{yr}$ ) with no history of heart complications using a self-constructed stethoscope system, and eight aortic regurgitation murmurs were selected from eight patients without other coexistent heart valvular disorders (aged  $72 \pm 16\,\mathrm{yr}$ ) in medical textbooks authorized by a cardiovascular specialist [2]. All signals had 16 bit-depth and a sampling frequency of 8000 Hz. Additional signal processing to eliminate a fundamental power interference of 60 Hz and its harmonics was not applied to any given signal x(t),  $t=1,\ldots,N$ , where N denotes the number of data points.

#### 2.2. Wavelet-based pre-processing

The wavelet decomposition using the Daubechies mother wavelet (Db10) with nine scales was used to eliminate the uninteresting frequency components from an original signal. The approximations at three and nine scales were selected to eliminate high-frequency contents over 500 Hz and low-frequency contents below 7 Hz, respectively. The pre-processed signals had the frequency characteristics of 7–500 Hz. The normalization was applied by setting the variance of the signal to a value of 1.

#### 2.3. Single-degree-of-freedom vibration model

Consider a wide sense stationary (WSS) random process dataset x(t) with the autocorrelation function  $R_x(\tau)$ . The PSD of x(t) is given by the Fourier transform of its autocorrelation function as

$$S_{X}(f) = \int_{-\infty}^{\infty} R_{X}(\tau)e^{-j2\pi f\tau} d\tau.$$
 (1)

Consider a one-dimensional spring—mass—damper system (Fig. 1), where m denotes the mass, c denotes the damping coefficient, and k denotes the coefficient of the spring. This single-degree-of-freedom analytical model with the input  $S_x(f)$  and the output response  $S_y(f)$  is given by

$$m\ddot{S}_{V}(f) + c\dot{S}_{V}(f) + kS_{V}(f) = S_{X}(f), \tag{2}$$

where r(f) denotes the rack displacement r(f) = 0. Eq. (2) may be written as

$$\ddot{S}_{v}(f) + 2p\zeta \dot{S}_{v}(f) + p^{2}S_{v}(f) = S_{X}(f), \tag{3}$$

where  $p = \sqrt{k/m}$ ,  $\zeta = c/2\sqrt{mk}$ , and  $S_X(f) = S_X(f)/m$ . This vibration model could be controlled by two analytical parameters, p and  $\zeta$ , defined as the natural frequency (Hz) and the damping factor (%), respectively. The cross-correlation function was used to compensate for time delays by applying the low natural frequency to the cardiac spectral envelope. We compensated for the relative time delay by selecting the maximum peak of cross-correlation between two signals.

$$S_{Y}(f) = S_{V}(f - |\max(|CC(f)|)|), \tag{4}$$

where CC(f) denotes the cross-correlation between the input spectrum  $S_X(f)$  and output response  $S_Y(f)$ . A resulting signal was computed by applying the square root  $P(f) = e^{0.5 \ln S_Y(f)}$ , and the normalized waveform P(f) was called the cardiac spectral envelope curve. This automatic algorithm was implemented using the MATLAB software (MathWorks Inc., Natick, MA, USA).

#### 2.4. Validation

The proposed cardiac spectral envelope extraction algorithm was evaluated by the root mean square error (RMSE) between the input waveform  $S_X(f)$  and the output waveform P(f) on a single-degree-of-freedom vibration model as

$$RMSE = \sqrt{\frac{1}{M}} \int_{f=1}^{M} (P(f) - S_{x}(f))^{2},$$
 (5)

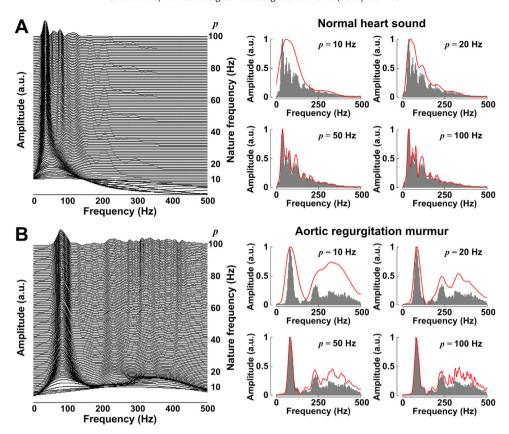
where M denotes the maximum frequency index of the target range M = 500 Hz. The optimal natural frequency and damping factor were selected by the derivative of RMSE (dRMSE).

#### 2.5. Statistical analyses

Quantitative data are expressed as means  $\pm$  standard deviations. Statistical analyses were performed using a two-tailed Student's t-test to compare the mean values obtained from two groups, using the frequency index of the maximum peak (Fmax) in the spectral envelopes [6]. P-values less than 0.05 were considered statistically significant.

#### 3. Experimental results

The effects of two analytical parameters on the morphology of the cardiac spectral envelope were investigated to acquire the optimal spectral envelope information. We first evaluated the effect of the natural frequency p over a range of 1-100 Hz on the cardiac spectral envelopes for normal heart sounds (Fig. 2A) and aortic regurgitation murmurs (Fig. 2B) under setup conditions where the damping factor  $\zeta$  was 70.7%. A murmur led to a significant shift in Fmax (main peak) and a high density at a high frequency index (greater than 200 Hz) in the spectral envelopes compared to the normal heart sound ( $P < 0.0001 \ vs.$  the normal cardiac spectral envelope). These differences were due to the presence of a diastolic murmur, when the aortic valve was incapable of preventing the backflow of blood from the aorta into the left ventricle during ventricular diastole [7]. The normal cardiac spectral envelopes showed that a natural frequency p of 1–15 Hz led to a single main peak with  $Fmax = 77.24 \pm 18.51$  Hz, while a p of 18-100 Hz led to multiple peaks and Fmax =  $38.42 \pm 2.70$  Hz (P<0.0001 vs. that for p = 1-15 Hz). In particular, a p less than 15 Hz led to a dull envelope while a p greater than 18 Hz led to a low-noise sharp envelope.



**Fig. 2.** Effect of the natural frequency on a single-degree-of-freedom vibration model. Spectral envelopes were extracted for the natural frequencies p = 1 - 100 Hz and the damping factor ζ = 70.7% for a representative normal heart sound (A) and an aortic regurgitation murmur (B). The components colored gray indicate the PSD waveform. PSD, power spectrum density.

The natural frequencies greater than 100 Hz led to envelopes similar to the raw PSD waveform  $S_x(f)$ , but resulted in noisy envelopes. Most of the prominent peaks were concentrated in the low frequency range near 100 Hz. However, the cardiac murmur spectral envelopes showed a very low natural frequency (1-3 Hz) that led to a single main peak with  $Fmax = 297.73 \pm 35.59 \text{ Hz}$ . A p of 7-100 Hz led to a main peak with  $Fmax = 83.14 \pm 1.96 \text{ Hz}$  (P < 0.0001 vs. that for p = 1-3 Hz) and a considerable number of peaks in the high frequency range of 200-500 Hz. A p greater than 50 Hz led to a noisy envelope similar to the raw PSD waveform. The RMSE measure was used to select the optimal natural frequency for the single-degree-of-freedom vibration model for extracting an efficient cardiac spectral envelope (Figure S1A). The best natural frequency was calculated as  $p = 35 \pm 5 \text{ Hz}$  by applying the condition of dRMSE < 0.3 (Fig. 3A).

Fig. 4 shows the cardiac spectral envelopes for normal heart sounds (Fig. 4A) and aortic regurgitation murmurs (Fig. 4B) as a function of the damping factor, under setup conditions where the optimal natural frequency *p* was 35 Hz. These envelopes were

acquired by applying the damping factor  $\zeta$  over a range of 10–500%. Similar to the influence of the natural frequency, the cardiac murmur spectral envelopes exhibited a shift in the maximum peak compared to the normal ones. In the normal cardiac spectral envelopes, a 10% damping factor led to the fluctuation (underdamping) and negative components of a waveform, by misapplying the damping factor on a single-degree-of-freedom vibration model. This negative value was changed into a positive value for damping factors greater than 30%. However, spectral envelopes at  $\zeta$ of 30–60% went below the true spectrum and that at  $\zeta$  greater than 90% exceeded the true spectrum. A  $\zeta$  greater than 170% led to a significant shift in Fmax (P<0.0001; 72.31  $\pm$  13.04 Hz for  $\zeta > 170\%$  vs.  $36.88 \pm 0.67$  Hz for  $\zeta$  of 10–160%), resulting in difficulties discriminating between the normal sounds and murmurs in further analysis. Damping factors greater than 300% led to an over-estimated spectral envelope (over-damping) with an absence of inherent spectral properties. Therefore,  $\zeta = 70-160\%$  could be selected as a candidate of the critical damping factor for the normal heart sounds. The murmur spectral envelopes showed a

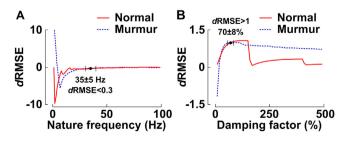
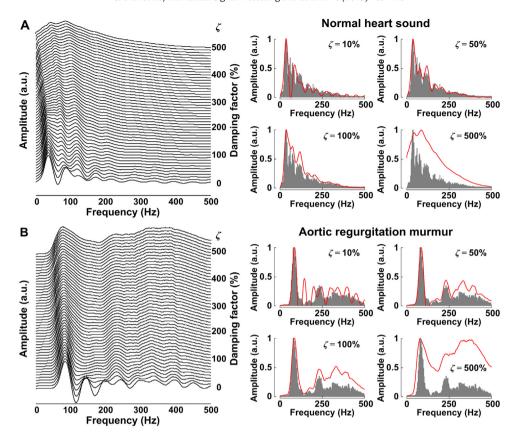


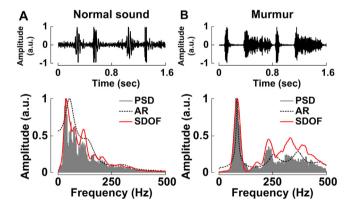
Fig. 3. dRMSE performance to select (A) the optimal natural frequency and (B) the optimal damping factor for the single-degree-of-freedom vibration model from the normal heart sound and aortic regurgitation murmur. dRMSE, derivative of root mean square error.



**Fig. 4.** Effect of the damping factor on a single-degree-of-freedom vibration model. Spectral envelopes were extracted by the damping factors ζ = 10-500% and the natural frequency p = 35 Hz for (A) a representative normal heart sound and (B) aortic regurgitation murmur. The components colored gray indicate the PSD waveform.

similar pattern to the normal ones; a lower damping factor led to under-damped waveforms and a higher damping factor led to over-damped waveforms. A  $\zeta$  of 10% led to more fluctuation in a waveform than in the normal cardiac spectral envelopes, due to an increase in the vibration by high density at a high frequency index. The murmur spectral envelope at a  $\zeta$  of 10–60% showed a negative waveform, while it showed a positive waveform at  $\zeta$  greater than 70%. The murmur spectral envelopes led to no shift in Fmax according to the increase in the damping factor. Interestingly, a  $\zeta$  greater than 130% led to an over-damping phenomenon at a high frequency index for the spectral envelope; however, it possessed an inherent spectral property. Therefore, at  $\zeta$  of 70–120% could be selected as a candidate of the critical damping factor for the murmurs. Finally, RMSE measure was used to select the optimal damping factor for the single-degree-of-freedom vibration model (Figure S1B). The best natural frequency was calculated to be  $\zeta = 70 \pm 8\%$ by applying the constraint of dRMSE>1 to the candidates (Fig. 3B).

Finally, we compared the performance between the AR estimation algorithm and this study (Fig. 5). The optimal AR envelope was extracted by the order p=14 through the AIC method [6–8], and the proposed single-degree-of-freedom envelope (SDOF envelope) was extracted for the natural frequency p=35 Hz and the damping factor  $\zeta=70\%$ . It is obvious that, although the AR envelopes showed high performance with extremely high sensitivity and specificity, the AR spectral envelope included some mismatching errors such as a shift in Fmax and insufficient single characteristic peaks compared to an original PSD waveform. However, this study showed single characteristic peaks of the original PSD waveform clearly as well as lower RMSE and higher cross-correlation and single-to-noise ratio compared to AR spectral envelope (Table S1). Therefore, the single-degree-of-freedom spectral envelope was more informative and effective compared to the AR spectral envelope.



**Fig. 5.** Representative time waveforms and cardiac spectral curves for (A) a normal heart sound and (B) aortic regurgitation murmur. AR envelopes (dotted line) were extracted by the model order p=14. SDOF envelopes (red line) were extracted by the natural frequency p=35 Hz and the damping factor  $\zeta=70\%$ . AR, autoregressive; SDOF, single-degree-of-freedom. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of the article.)

#### 4. Conclusion

A new cardiac spectral extraction method based on a single-degree-of-freedom vibration model was introduced to produce the critical spectral envelope curve with the intrinsic property of a signal. The novelty of this study was a time variant single-degree-of-freedom vibration model to be applied in the spectral envelope extraction, using two analytical parameters. Normal heart sounds and aortic regurgitation murmurs were used as a testing dataset. The morphological variation in cardiac spectral envelope curves was investigated for the natural frequency range of 1–100 Hz and the damping factor range of 10–500% in a mass-spring-damper

system. The best cardiac spectral envelope curves were optimized at approximately 35-Hz natural frequency and approximately 70% damping factor. They clearly showed distinct cardiac hemodynamic sequences for the normal heart sound and the aortic regurgitation. A comparative study between this study and a previous study (AR parametric method) showed that the cardiac spectral envelopes extracted by the single-degree-of-freedom vibration model may be superior to the spectral envelopes produced by the AR method. Therefore, we anticipate that this stand-alone algorithm will be helpful to the field of spectral study and may become a frequently used envelope extraction approach. Finally, we plan to apply this algorithm to other valvular heart diseases as well as various biomedical signals, in combination with computer-aided classifier systems including the *k*-means algorithm, support vector machines, linear discriminant analysis, and *k*-nearest neighbor.

#### **Conflict of interest**

The authors have declared that no competing interests exist.

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#### Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.bspc.2014.12.010.

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