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## BIOMEDICAL ENGINEERING | RESEARCH ARTICLE

# Wavelet bispectrum-based nonlinear features for cardiac murmur identification

Dinesh Kumar<sup>1\*</sup>, Rajendrasinh Jadeja<sup>1</sup> and Sarang Pande<sup>2</sup>

**Abstract:** Cardiac or heart sound carries important diagnosis information for several cardiovascular diseases, such as natural or prosthetic valve dysfunction and heart failure. Hence, algorithms are required for the analysis of cardiac sound for computer-based automatic diagnosis. In the cardiac sound-based analysis, one of the tasks is to classify abnormal cardiac sounds, i.e. murmurs, caused by various cardiac anomalies. We introduce a new feature named *system response* which is chosen to be estimated using wavelet bispectrum over Fourier bispectrum because of non-stationary and non-Gaussian nature of cardiac sounds. System response essentially characterizes the cardiac structure responsible for the production of cardiac sounds which is later employed to automatically classify different types of cardiac murmurs. In cases of various types of cardiac murmurs, such as aortic regurgitation and mitral stenosis, system response of the cardiac structures is studied in this paper. Later, an artificial neural network-based classifier is constructed using the system response as a set of features to automatically classify murmur types. Performance of the classifier is obtained with the sensitivity of 93.57% and specificity of 94.24% which is comparable with the state of the art. Furthermore, system response computed from wavelet bispectrum shows 4% higher accurate classification than Fourier bispectrum.



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### ABOUT THE AUTHOR

Dinesh Kumar has been a faculty member within the Department of Electrical Engineering at the Marwadi Education Foundation's Group of Institutions, Rajkot, India, since 23 June 2014. His education includes undergraduate B. Tech. (2002) in Electrical Engineering from Indian Institute of Technology Kanpur, and PhD (2015) in Information Science and Technology (in the research domain of Biomedical signal processing) from University of Coimbra, Portugal. His main areas of interest are Signal Processing and Control, Image processing, Nonlinear Dynamics, Soft computing and Machine learning.

### PUBLIC INTEREST STATEMENT

In shifting paradigm of healthcare system from curative to preventive, it has been inevitable to capture health conditions via monitoring system over a significant time in order to avoid critical situation like surgery. In this attempt, personalized healthcare devices are being developed which enable acquiring of physiological signals and their analysis. Furthermore, with these systems patients can perform follow-up themselves. Heart sound is one of the potential and economic physiological signals which can be used to determine heart's conditions, namely in the cases of valvular dysfunction. Therefore, efficient analysis techniques are required to process heart sound and extract relevant information related to such diseases. Abnormal sounds are heard besides the regular heart beating sound in cases of heart-related problems. This paper proposes a new technique for abnormal heart sound analysis whereby presence of certain cardiac diseases can automatically be determined.

**Subjects: Biomedical Engineering; Medical Devices; Digital Signal Processing; Instrumentation, Measurement & Testing; Systems & Controls**

**Keywords: Cardiac sound; Bispectrum; cepstrum; system response; high order comulants**

## 1. Introduction

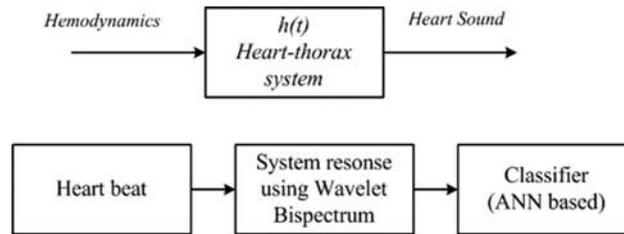
Auscultation is predominantly used in practice to determine heart valve disorders, heart failure and coronary artery diseases (Durand, Blanchard, Cloutier, Sabbah, & Stein, 1990). A computer-assisted version of cardiac sound analysis aids in preparing diagnosis of aforementioned cardiac disorders. One of the challenging tasks in cardiac sound analysis is to recognize the presence of murmur and its characteristics. These murmurs are originated due to numerous pathological conditions in the heart and hence show different characteristics (Erickson, 2003). Therefore, the next task in cardiac sound analysis is to classify the types of murmurs. To this end, a classifier based on some discriminative features of the cardiac murmurs has to be constructed.

Murmurs are often observed in systolic or diastolic region of a heart cycle (see Figures 2(a) and 4(a)). These sounds are originated due to some abnormalities in the heart. For instance, the most known causes of murmurs are backward regurgitation, forward flow through narrowed or deformed valve, and vibration of loose structures within heart and continuous blood flow through atrial-ventricular shunts (Erickson, 2003).

Several advanced signal processing techniques were widely applied in feature extraction to perform cardiac murmur classifications. For instance, wavelet transform (Corona & Torry, 1998), trimmed mean spectrogram (Leung, White, Collis, Brown, & Salmon, 2000), sub-band analysis using wavelet discrete transform (Gupta, Palaniappanb, Swaminathan, & Krishnan, 2007) and averaged Wigner-Ville distribution (Yoshida, Shinot, & Yana, 1997). These methods are capable to compute features like instantaneous frequency and energy in time-frequency domain. In some works, nonlinear and non-stationary nature of cardiac sound have been explored using nonlinear dynamics approach to identify features like chaos and complexity. For instance, complexity and chaotic behaviors were attempted to measure using fractal dimension and Lyapunov exponent, respectively (Carvalho, Gil, Henriques, Antunes, & Eugenio, 2005)(Ahlstrom et al., 2006). Another source for feature extraction is phase spectra; essentially, the information that can be extracted from the phase spectrum in lower order statistics (for instance second order, i.e. Fourier spectrum) may be incomplete as phase is distorted due to presence of noise; therefore, the undistorted phase information is gathered using high-order statistics (Nikias & Mendel, 2005). This approach, high-order statistics or Fourier bispectra, was applied in various cardiac murmurs in Hadjileontiadis & Panas (1997). Furthermore, a combined method of wavelet with high-order statistics was introduced to examine non-stationary and non-Gaussian background noise in heart sounds (Taplidou & Hadjileontiadis, 2006).

In most of the above-mentioned time-frequency-based transform techniques signals are assumed to be linear and stationary or non-stationary. Therefore, a new feature of cardiac murmur based on high-order statistics, i.e. wavelet bispectrum, is proposed in this paper which can be applied to nonlinear and non-stationary signals. The motivation behind applying high-order statistic approach is to extract nonlinear features while minimizing the effect of non-Gaussian noise in cardiac sound signals. Because of its advantage over second order or less order in terms of noise suppression and nonlinearity identification in signals, it is considered to use for feature extraction task in the process of cardiac murmur classification. The name of this new feature is system response (in fact this is the impulse response of the heart assuming that heart is a linear time-invariant system, described in Section 2), which is estimated via wavelet bispectrum. Later, based on this feature, cardiac murmurs of different types are classified using an artificial neural network technique-based classifier (see Figure 1 (bottom)). The classifier constructed based on system response feature exhibits classification with higher accuracy than the wavelet decomposition and power spectral-based features (Rios-Gutierrez et al., 2006)(Jiang, Samjin, & Wang, 2007)(Ververidis & Kotropoulos, 2004).

**Figure 1. (Top) Linear time-invariant model of heart-thorax resulting heart sounds. (Bottom) Steps in heart murmur classification.**



The paper is structured in four sections: second section contains a detailed description of the method for new feature; in the third section, the achieved results are shown; and some conclusions are drawn in the fourth section.

## 2. Methodology

In Reed, Reed, & Fritson (2004), heart was modeled as linear time-variant system with different time responses corresponding to S1 and S2. In a way, cardiac sounds are the outcomes of the cardiac system. The system response (impulse response if cardiac system is assumed to be a linear time-invariant system) can be an important feature based on which cardiac murmurs can be identified. Cardiac sounds exhibit nonlinearity and non-stationary characteristics (Tseng, Ko, & Jaw, 2012). Therefore, to deal with nonlinearity and non-stationarity in the estimation of system response, wavelet bispectrum is employed. Wavelet bispectrum-based method minimizes Gaussian noise effect in the estimated system response. In this section, heart’s simple linear model, system response identification using wavelet bispectrum and murmur classification are explained (see Figure 1).

Cardiac sound is produced as a result of hemodynamics of cardiac systems and propagates through the cardiac walls and layer of skin of chest. Human ear receives a convolved original signal with the system response of the medium it travels through. Hence, assuming this is a linear time-invariant (LTI)-based model which consists a nonminimum phase signal  $y(k)$  that is produced in the heart due to closing and subsequently vibrations of valves and  $h(k)$  the system response that is the inner and outer parts of the cardiac structure through cardiac sound propagates, the model is given by:

$$x(k) = y(k) * h(k) \tag{1}$$

Fourier transform-based bispectrum (FBS) is a background for wavelet bispectrum (WBS); therefore, a brief explanation is given here and in subsequent subsection, the system response computation is explained.

### 2.1. High-order spectrum:

If cardiac sound signals are considered as stochastic, zero mean, real-valued stationary time series  $x(k)$ , then its third-order moment sequence  $R(m, n)$  can be given as follows:

$$c_3(\tau_1, \tau_2) = E\{x(k)x(k + \tau_1)x(k + \tau_2)\}, \tag{2}$$

where  $E\{\cdot\}$  denotes the expected value. The respective bispectrum of  $x(k)$  is defined as follows with the double Fourier transform of third-order moments in (2):

$$B_x(\omega_1, \omega_2) = \sum_{m=-\infty}^{\infty} \sum_{n=-\infty}^{\infty} c_3(m, n) e^{-j(\omega_1 m + \omega_2 n)}, \tag{3}$$

where  $\omega_1 < \pi$  and  $\omega_2 < \pi$ .  $B(\omega_1, \omega_2)$  is periodic with the period  $2\pi$  in  $\omega_1$  and  $\omega_2$  and  $\omega_1 \geq 0, \omega_1 \geq \omega_2, \omega_1 + \omega_2 \leq \pi$ . Wavelet bispectrum uses wavelet coefficients as a central element of computation which is produced through the convolution of a scaled parent wavelet function  $\psi(k, n)$  with under analysis signal  $x(k)$ :

$$W_x(n, \omega) = \sqrt{\frac{\omega}{\eta}} \sum_{k=0}^{N-1} x(k) \psi^* \left[ \frac{\omega}{\eta} (k - n) \right], \tag{4}$$

where  $N$  is the number of samples in the signal  $x(k)$ , and  $a = \eta/\omega$  is the scaling term. Wavelet bispectrum can be formulated with the analogy of the previously written expression for Fourier bispectrum:

$$WB_x(\omega_1, \omega_2) = \frac{1}{N-1} \sum_{n=0}^{N-1} W_x(n, \omega_1) W_x(n, \omega_2) W_x^*(n, \omega), \tag{5}$$

where  $\omega = \omega_1 + \omega_2$  or inverse scale  $a^{-1} = a_1^{-1} + a_2^{-1}$ , is similar to frequency selection rule, i.e. as in Fourier transform-based bispectrum.

### 2.2. System response by wavelet bispectrum

In order to determine the system response using bispectrum, the absolute magnitude spectrum of the  $h(k)$  is required. The two measure assumptions have been suggested in the proposed model: first is the whiteness of  $y(k)$  and the second is the existence of a third-order cumulation for its distribution. Now, (1) can be written in discrete form as follows:

$$x(k) = \sum_{s=0}^{\infty} h(s) y(s - k). \tag{6}$$

For bispectrum computation, (6) can be written in a simple form if  $y(k)$  is assumed independent:

$$c_3(\tau_1, \tau_2) = \gamma^3 \sum_{s=0}^{\infty} h(s) h(s + \tau_1) h(s + \tau_2), \tag{7}$$

where  $\gamma^3 = E(y^3(k))$  and  $h(s) = 0$  for  $s < 0$ . When the Fourier transform is applied on (7), the bispectrum can be given as below:

$$\begin{aligned} B_x(\omega_1, \omega_2) &= \gamma^3 \sum_{\tau_1=-\infty}^{\infty} \sum_{\tau_2=-\infty}^{\infty} \sum_{s=-\infty}^{\infty} h(s) h(s + \tau_1) \\ & h(s + \tau_2) \exp(-j(\omega_1 \tau_2 + \omega_2 \tau_2)) \\ &= \gamma^3 H(\omega_1) H(\omega_2) H(-\omega_1 + \omega_2) \\ &= \gamma^3 H(\omega_1) H(\omega_2) H^*(\omega_1 + \omega_2), \end{aligned} \tag{8}$$

where  $H(\omega) = \sum_{k=0}^{\infty} h(k) \exp(-jk\omega)$ . In continuous wavelet transform, the wavelet functions are used that can be written as  $\psi(k) = g(k) \exp(i\eta k)$ . In order to estimate the system response, WBS of (6) is obtained in the same way as bispectrum based on Fourier transform has been formulated in (8):

$$WB_x(\omega_1, \omega_2) = \gamma^3 WB_h(\omega_1) WB_h(\omega_2) WB_h^*(\omega_1 + \omega_2) \tag{9}$$

Absolute values relationship of (9) can be given as:

$$|WB_x(\omega_1, \omega_2)| = |WB_h(\omega_1)| |WB_h(\omega_2)| |WB_h^*(\omega_1 + \omega_2)|, \tag{10}$$

$$\log |WB_x(\omega_1, \omega_2)| = \log |WB_h(\omega_1)| + \log |WB_h(\omega_2)| + \log |WB_h^*(\omega_1 + \omega_2)|. \tag{11}$$

Magnitude of the WBS of system response is estimated according to the algorithm used for phase estimation described in Matsouka & Ulrych (2008). For convenience, we assume  $\omega_1 = u$  and  $\omega_2 = v$ , and logarithm of the absolute values of WBS of signal  $x(k)$  and system response are  $T$  and  $S$ , respectively, then (11) can be written as:

$$T(u, v) = S(u) + S(v) + S(u + v), \tag{12}$$

where  $u = 1, 2, \dots, N/2$  and  $v = u, u + 1, \dots, N - u$ . By varying values of  $u$  and  $v$  a sparse matrix is constructed:

$$\begin{aligned} T(1, 1) &= S(1) + S(1) + S(2) \\ T(1, 2) &= S(1) + S(2) + S(3) \\ &\vdots \\ T(N/2, N/2) &= 2S(N/2) - S(N) \end{aligned} \tag{13}$$

which can also be written as:

$$\begin{aligned} T &= AS \\ S &= (A'A)^{-1}A'T. \end{aligned} \tag{14}$$

The unknown magnitude vector  $S$  is determined using least-square solution of (14) (Matsouka & Ulrych, 2008). The magnitude of  $S$  estimates the system response of the cardiac structure.

### 2.3. Murmur classification

From the above-extracted system response of the cardiac murmur production system, type of murmur is classified using simple feed-forward network. In this process, first, heart beats are identified, which was performed using high-frequency signature of diastolic cardiac sound (S2 sounds) method developed in Kumar et al. (2006). Then, each heart beat (or cycle) is taken for feature extraction, i.e. computation of system response, process.

## 3. Implementation and evaluation of simulation results

The cardiac sound samples were collected from <http://egeneralmedical.com/listohearmur.html>. Their sampling frequency is 8000 Hz, and they have been digitized with 16-bit resolution. The prepared database of heart murmurs includes 23 patients with 2 main classes of lesion, i.e. stenosis and regurgitation.

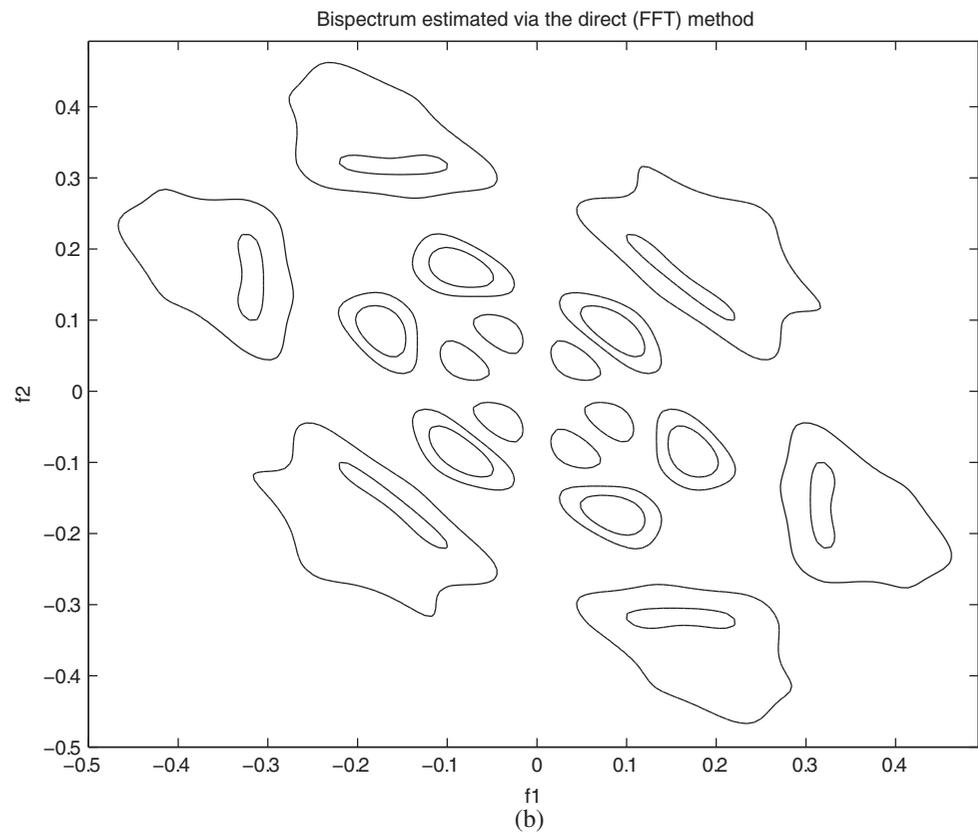
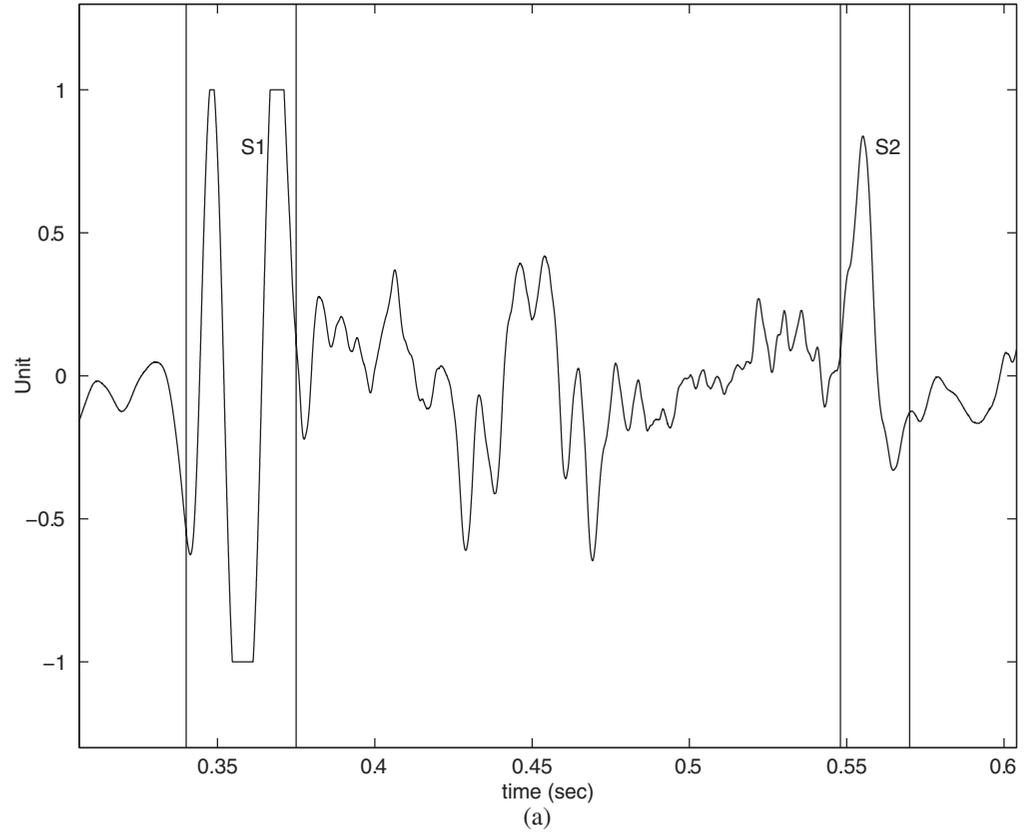
### 3.1. Bispectrum and system response computation

Classification performance was tested with the system response computed using FBS as well as WBS. The demarcated segments of heart murmur are divided into several segments by 45 samples window with 50% overlap. Each segment is 128 points Fourier-transformed. Some examples of bispectrum can be seen in Figures 2(b) and 4(b). From Figures 2(b) and 4(b), it can be deduced that frequency couplings are present mainly in lower positive frequencies, while other quadratures are resultant of symmetry property of Fourier transform.

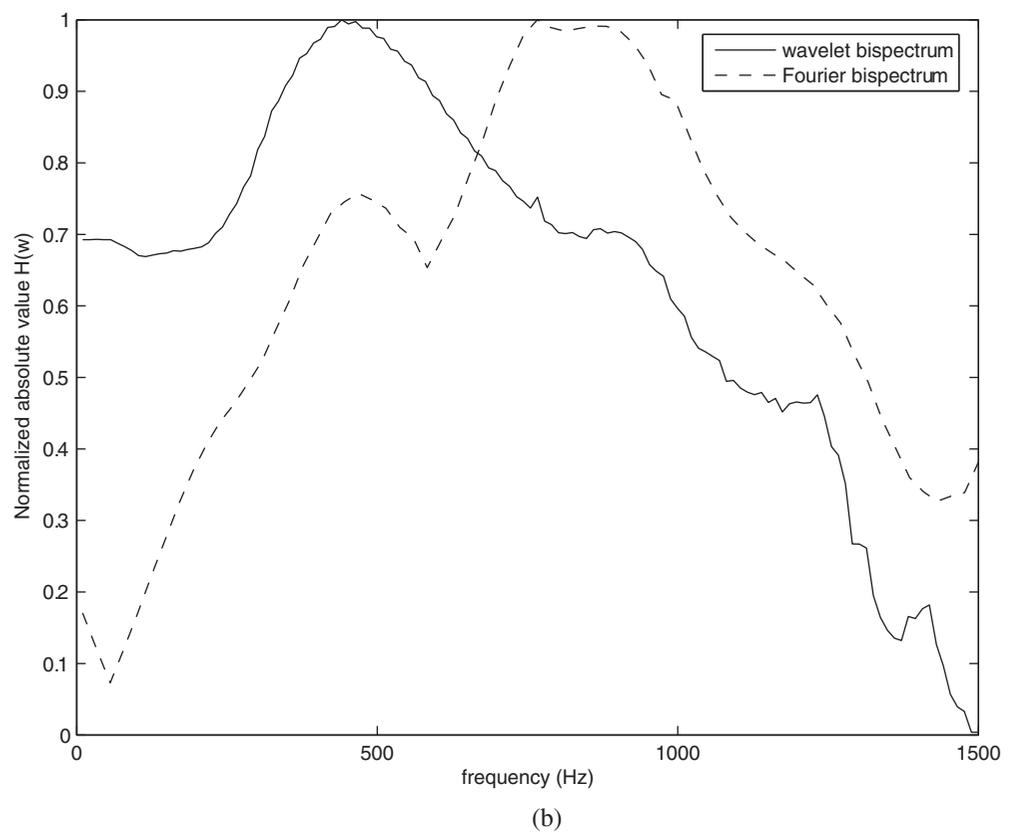
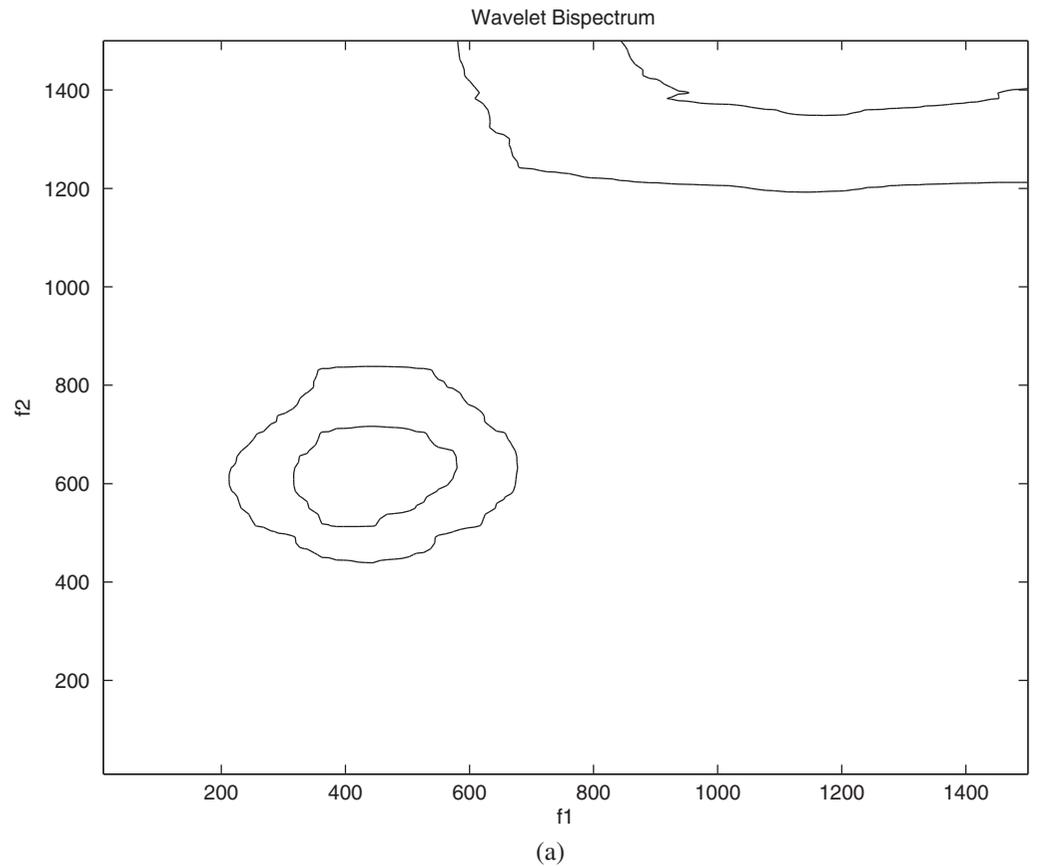
For WBS computation, Gaussian complex mother wavelet was chosen for continuous wavelet transform. It provides good time localization during wavelet transform due to its second-order exponential decay. Furthermore, it has also better ability to exhibit significant frequency (or phase) couplings in bi-frequency domain, as shown in Figures 3(a) and 5(a), where FBS misses to capture. In order to compute the WBS of a heart murmur, frequency range  $f(\omega = 2\pi f)$  is selected between 10 and 1500 Hz, and center frequency for Gaussian wavelet  $f_c = 0.8125$  (Taplidou & Hadjileontiadis, 2006). In the prepared database, it has been observed that heart murmurs originate in numerous cardiac disorders with the frequencies in that given range. However, in case of prosthetic valves the frequency range expands to 50 kHz which is absent in the database at this level.

System response is computed using WBS. Some required values and parameter  $\gamma$  are initialized according to the described numerical technique for phase estimation in Matsouka & Ulrych (2008). WBS is better in exhibiting nonlinearity information, trade-off in computational cost between the other bispectrums such as Wigner, Fourier, and it also exhibits better frequency profile of system response (least variance), as shown in Figures 3(a) and 5(b). It is evident from the profiles of system response that WBS based estimation exhibits significant and wider difference between the two cardiac murmurs than FBS.

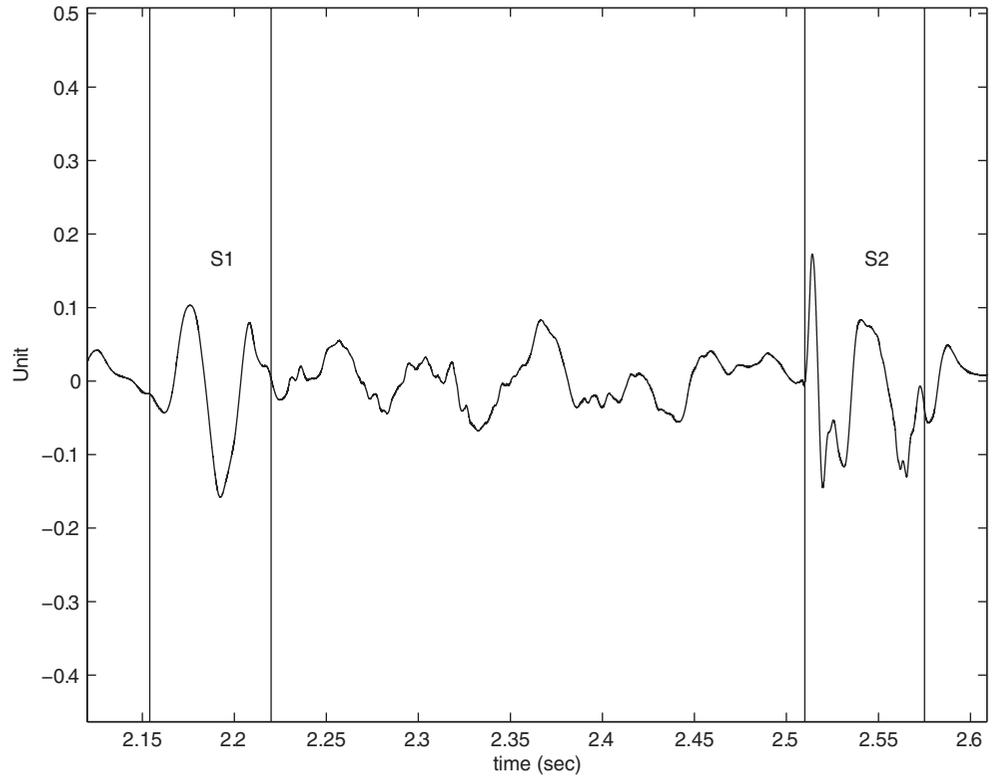
**Figure 2. Bispectrum analysis of segmented heart murmur systolic ejection case: (a) segmented heart cycle, (b) Fourier bispectrum.**



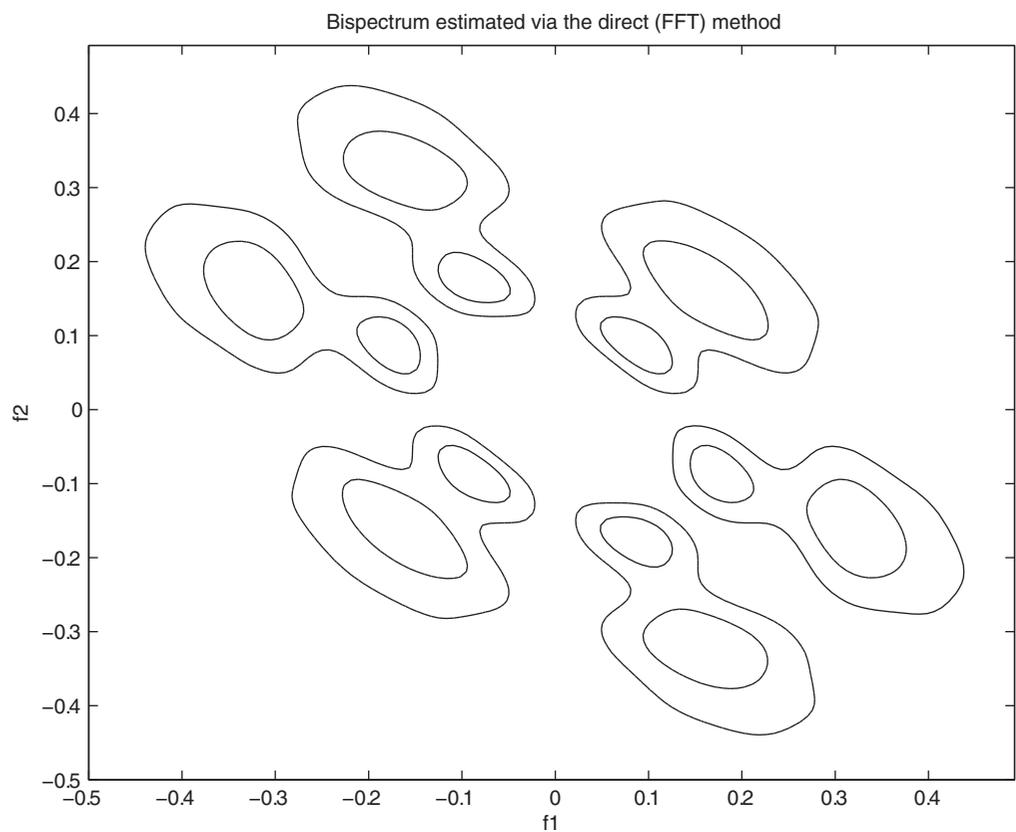
**Figure 3. Bispectrum analysis of segmented heart murmur systolic ejection case: (a) wavelet bispectrum, (b) system response.**



**Figure 4. Bispectrum analysis of segmented heart murmur in mitral regurgitation case: (a) segmented heart cycle, (b) Fourier bispectrum.**

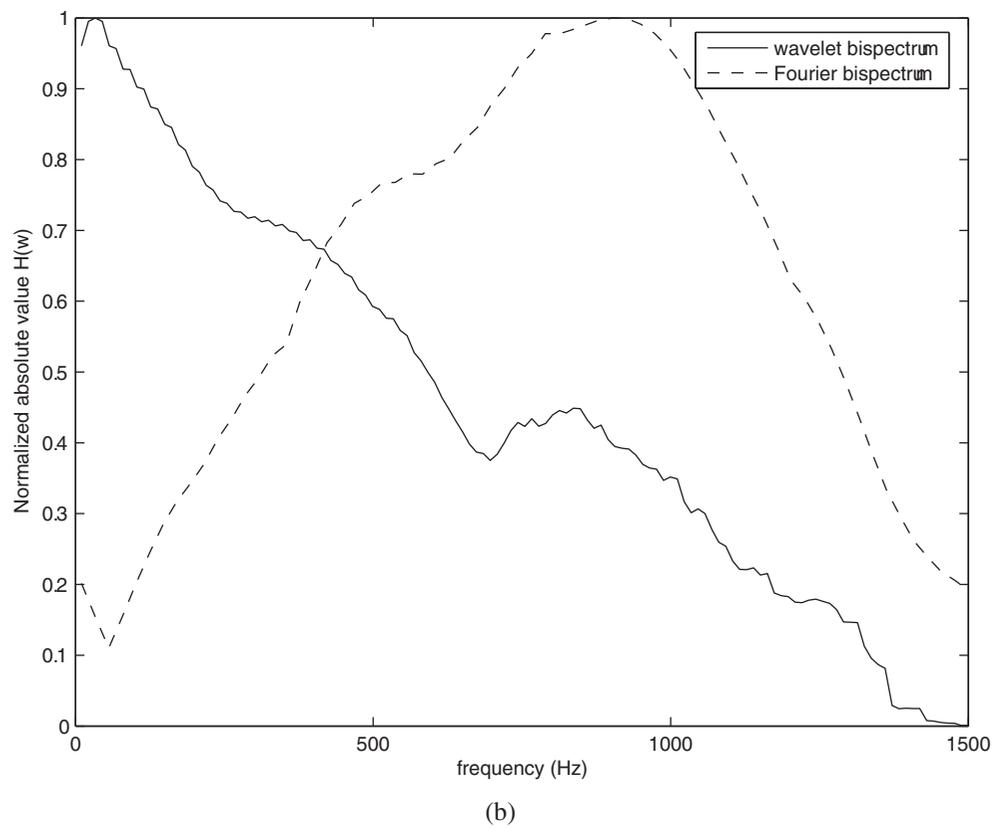
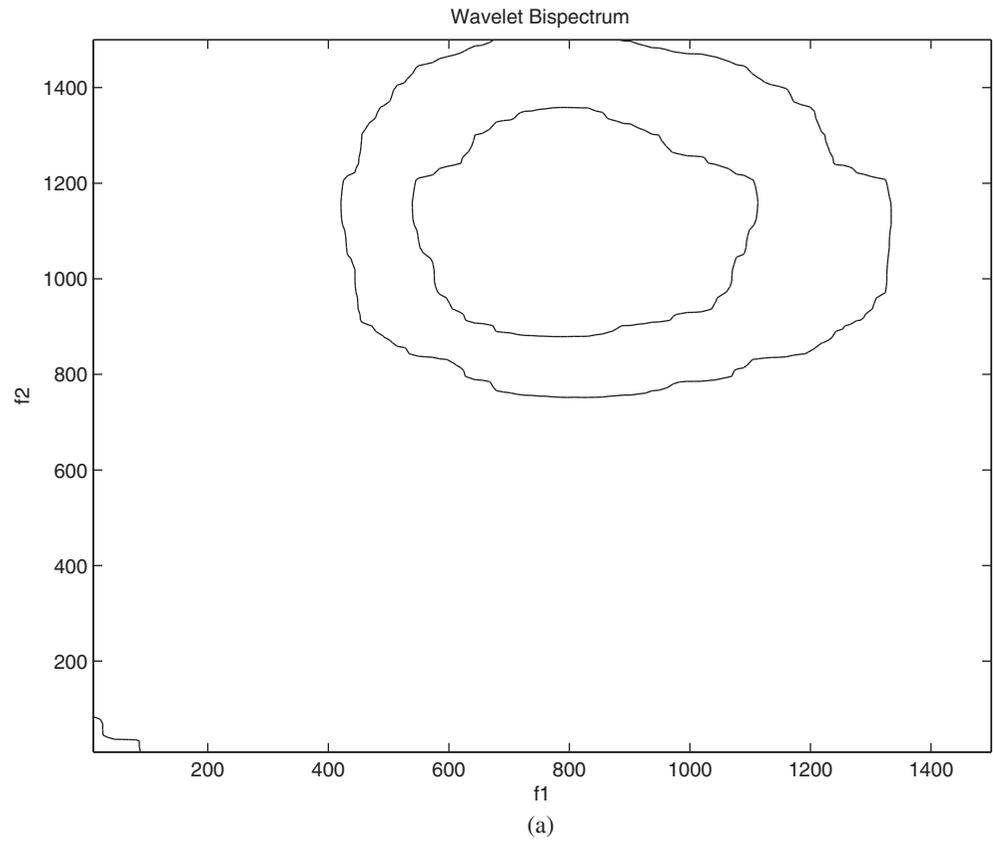


(a)



(b)

**Figure 5. Bispectrum analysis of segmented heart murmur in mitral regurgitation case: (a) wavelet bispectrum, (b) system response.**



**Table 1. Some results of lesions' murmur classification based on the features, system response**

Murmur type	Detected	Wrong-detected
	FBS/WBS	FBS/WBS
Aortic stenosis	152/160	28/20
Aortic regurgitation	117/122	25/20
Pulmonary stenosis	31/29	14/16
Systolic ejection	45/46	15/14
Mitral stenosis	51/52	7/6
Mitral regurgitation	164/174	26/16

### 3.2. Artificial neural network for murmur classification

A simple feed-forward network with three layers is used to classify the types of murmurs. The prepared network architecture includes 10 input points in the input layer, 10 neurons in three multi hidden layer and 6 neurons in output layer. For training the network, system response of 30 heart cycles of each lesion's murmur is taken. Total 675 non-contaminated heart cycles from available database are selected.

The achieved results of murmur classification are shown in Table 1. The overall sensitivity of classifier over FBS is 88.96% while with WBS is 93.57%. Specificity of the classifier with the system response obtained from WBS is determined as 94.24%. Hence, WBS has advantage of 4% accuracy with respect to FBS for the given classifier.

### 4. Conclusions

A new feature named as *system response* based on wavelet bispectrum was introduced for heart sounds, namely with murmur, classification. The feature was inspired by the presence of non-linearity and non-Gaussian background noise in cardiac sound signals. In this process, cardiac murmur production system was considered as a linear time-invariant system where the system response was computed using wavelet bispectrum. System response estimated using wavelet bispectrum was found to have capacity to discriminate different types for cardiac murmur better than Fourier bispectrum. Using system response as a set of features in a neural network-based classifier, a classification with significant accuracy was achieved.

For future work, database will be strengthened with more number of subjects as well as with diverse cardiac patients. More nonlinear features based on high-order statistics are planned to investigate in attempt to improve over sensitivity of murmur classification.

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