

# Stochastic Analysis and Classification of 4-Area Cardiac Auscultation Signals using Empirical Mode Decomposition and Acoustic Features

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## Abstract

*As cardiac murmurs do not generally appear in every area of auscultation, this paper presents an effective approach for cardiac murmur detection based on stochastic analysis of acoustic features derived from Empirical Mode Decomposition (EMD) and Hilbert-Huang Transform (HHT) of phonocardiographic (PCG) signals made up by the 4-Standard Auscultation Areas (SAA). The 4-SAA PCG database belongs to the National University of Colombia. Mel-Frequency Cepstral Coefficients (MFCC) and statistical moments of HHT were estimated over EMD components. An ergodic HMM was applied on the feature space, randomly initialized and trained by expectation maximization with a convergence at  $10e-6$  and a maximum iteration number of 1000. Global classification results for 4-SAA were around 98.7% with satisfactory sensitivity and specificity results, using a 30-fold cross-validation procedure (70/30 split). The representation capability of the EMD technique applied to 4-SAA PCG signals and stochastic analysis of acoustic features offered a high performance to detect cardiac murmurs.*

## 1. Introduction

Cardiac murmurs are generated when the blood flow becomes turbulent near damaged valves [1]. Heart mechanical activity can be appraised by auscultation recordings, i.e., phonocardiographic (PCG) signals, which is an inexpensive and non-invasive clinical procedure [2]. These heart sounds are commonly analyzed from 4-Standard Auscultation Areas (4-SAA), one for each cardiac valve, in order to thoroughly examine the state of the cardiac valves, as there are invisible murmurs for systems based on auscultation signals acquired from a single area [3].

Initially, taking advantage of the morphological changes in the signal shape caused by heart murmurs, different approaches based on energy and temporal measurements were proposed [4, 5]. However, cardiac murmurs

have a nonstationary nature and exhibit sudden frequency changes and transients [2, 6]. Other studies have considered the nonlinear nature of physiological signals, which has promoted the analysis of fractal features and the optimization of the embedding parameters in order to improve the training and classification stages [5, 7, 8], although the increment in processing time becomes a big problem for real-time applications. On the other hand, several approaches based on wavelets have been proposed taking into account the time-frequency disturbances associated with cardiac murmurs [9]. However, in contrast to approaches based on wavelets, which perform the analysis by projecting the signal under consideration onto a number of predefined basis vectors, other decomposition methods, such as Empirical Mode Decomposition (EMD) and Hilbert-Huang Transform (HHT), express the signal as an expansion of basis functions which are signal-dependent, and are estimated via an iterative procedure called sifting [10]. For example, in [11], an approach based on EMD was presented, where fetal heart sounds were extracted from a recorded single channel abdominal PCG [11]. Another interesting area is the acoustical disturbances caused by heart murmurs, which can be analyzed using Mel-Frequency Cepstral Coefficients (MFCC)[12, 13], but these procedures are very sensitive to artifacts or noises frequently involved in the acquisition stage [2]. For this reason, the combination between MFCC and statistical moments of HHT with appropriate EMD components would be suitable. Additionally, the inclusion of stochastic models, such as Hidden Markov Models (HMM), have successfully complemented procedures for cardiac murmur detection [14]. However, all these studies have been developed using a single auscultation signal, and fail when a murmur is missing or attenuated in the standard single derivation.

In this study, a classification approach based on the combination of HMM-MFCC-HHT from different EMD components of 4-SAA PCG signals is presented, in order to provide an objective and accurate mechanism for more reliable heart murmur diagnosis.

## 2. Materials and methods

### 2.1. Database

The database is made up of 143 de-identified adult subjects, who gave their formal consent, and underwent a medical examination with the approval of the ethical committee. The valve lesion severity was evaluated by cardiologists according to a clinical routine. 55 patients were labeled as normal, while 88 had evidence of cardiac murmurs (aortic stenosis, mitral regurgitation, etc). From each patient, 8 recordings were recorded according to the four standard auscultation areas (4-SAA), i.e., mitral, tricuspid, aortic and pulmonic areas, in the phase of post-expiratory and post-inspiratory apnea. Each recording lasts 8 s and was obtained with the patient standing in dorsal decubitus position. The signals were acquired at 44.1 kHz with 16-bits per sample with an electronic stethoscope (WelchAllyn<sup>®</sup> Meditron model). Finally, 400 individual beats were chosen, 180 normal and 180 with evidence of cardiac murmur. The individual beats picked out were the best from each cardiac sound signal, according to a visual and audible inspection by a cardiologists.

### 2.2. Theoretical background

**A. Empirical Mode Decomposition (EMD)**– This method, reported in [15], adaptively decomposes a multi-component signal  $x(t)$  into a number  $L$  of Intrinsic Mode Functions (IMFs),  $h^{(i)}(t)$ ,  $1 \leq i \leq L$ ,

$$x(t) = \sum_{i=1}^L h^{(i)}(t) + d(t) \quad (1)$$

where  $d(t)$  is a remainder which is a non zero-mean slowly varying function with only few extrema. Each one of the IMFs, say the  $i$ th one  $h^{(i)}(t)$ , is estimated with the aid of an iterative process, called sifting, applied to the residual multi-component signal

$$x^{(i)}(t) = \begin{cases} x(t) & , i = 1 \\ x(t) - \sum_{j=1}^{i-1} h^{(j)}(t) & , i \geq 2 \end{cases} \quad (2)$$

According to this, during the  $(n + 1)$ th sifting iteration, the temporary IMF estimate  $h_n^{(i)}(t)$  is improved according to the following steps [10]: 1) Find the local maxima and minima of  $h_n^{(i)}(t)$ . 2) Interpolate, using natural cubic splines, along the points of  $h_n^{(i)}(t)$ , previously estimated, in order to form an upper and a lower envelope. 3) Compute the mean of the two envelopes. 4) Obtain the refined estimate  $h_{n+1}^{(i)}(t)$  of the IMF by subtracting the mean found in the previous step from the current IMF estimate  $h_n^{(i)}(t)$ . 5) Proceed from step 1 again unless a stopping criterion has

been fulfilled. For the first iteration,  $x^{(i)}(t)$  is used as temporary IMF estimate  $h_1(t)$ .

**B. Hilbert-Huang Transform (HHT)**– Instantaneous frequency and its magnitude of heart sound signals can be extracted by HHT, which is used to adaptively decompose non-stationary and nonlinear signals and extract the instantaneous frequency. In general, HHT consists of two steps: Empirical Mode Decomposition (EMD) and Hilbert transform. EMD is used to adaptively decompose the signal into a series of intrinsic mode functions (IMFs). Hilbert transform is then carried out to acquire the instantaneous frequency and amplitude of each IMF and constitute the time-frequency-energy distribution in the Hilbert-Huang spectrum of the signal [16].

**C. Mel-Frequency Cepstral Coefficients (MFCC)**– Psychophysical studies have shown that human perception of the frequency content of audio sounds does not follow a linear scale but as a Mel-warped frequency, which spaces linearly for low-frequency contents and logarithmical at high frequencies [2]. So, MFCC are a family of parameters that are estimated as [17]:

$$c[p] = \sum_{m=0}^{M-1} X_F[m] \cos(\pi p(m - 0.5)/M), \quad 0 \leq p \leq M \quad (3)$$

where  $X_F[m] = \ln\left(\sum_{i=0}^{N-1} |X[i]|^2 H_m[i]\right)$ . Here,  $X[i]$  is the Fourier transform of an input random sequence  $x[n]$  and  $H_m[i]$  is a triangular band-pass filter with central frequency in  $f[m]$ . Thus, in order to simplify the signal spectrum without any significant loss of data, a set of  $M$  triangular band-pass filters must be used, which are nonuniform in the original spectrum and uniformly distributed at the Mel-warped spectrum. Each filter is multiplied by the spectrum so that only a single value of magnitude is returned per filter.

**D. Hidden Markov Models (HMM)** – HMM is an extension of Markov chains, where each state does not correspond to an observable event, but is connected to a group of probability distributions of the state. In some applications, the states may have a certain physical meaning attached to the states or the sets of states [18, 19]. There are several well-known training criteria, such as Maximum Likelihood Estimation (MLE), Maximum Mutual Information (MMI), among others, however, this study has focused on applications based on the MLE criterion, given its good performance in previous studies [20]. Let  $\mathbf{X} = \{\boldsymbol{\varphi}_r^{n\varphi_r} : r = 1, \dots, R\}$  a training set of  $R$  samples, with categories  $\mathbf{C} = \{c_r^{n\varphi_r} : r = 1, \dots, R\}$  for  $M$  different classes, i.e.,  $c^r \in \{c_m : m = 1, \dots, M\}$ . Also, each sample  $\boldsymbol{\varphi}_r^{n\varphi_r}$  is represented by a sequence of feature vectors of length  $n\varphi_r$ ,

so,  $\boldsymbol{\varphi}_r^{n\varphi_r} = \{\varphi_{r,t} : t = 1, \dots, n\varphi_r\}$ . The total set of parameters of the HMM is denoted by  $\Theta$  and is composed of  $M$  models, i.e.,  $\Theta = \{\lambda_m\}$ , where  $\lambda_m$  denotes the set of parameters of the HMM corresponding to class  $c_m$ . The training procedure based on MLE criterion is carried out taking into account the following objective function:

$$f_{MLE}(\Theta) = \sum_{r=1}^R \log(P(\boldsymbol{\varphi}_r^{n\varphi_r} | \mathbf{c}^r)) \quad (4)$$

The optimization of (4) is achieved by adjusting the parameters of each model separately, relying on the training observation data, so that expression (4) gets a maximum value. This procedure includes the Expectation Maximization (EM) algorithm which is a well-known method for finding the maximum-likelihood estimate of the parameters of an underlying distribution from a data set when the data are incomplete or have hidden parameters [21].

### 2.3. Proposed procedure

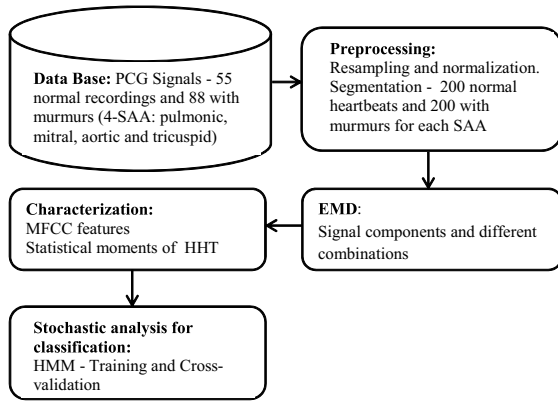


Figure 1. Block diagram – general proposed procedure

According to Figure 1, the 4-SAA PCG recordings were resampled to 4410 Hz by applying a FIR low-pass anti-aliasing filter. Next, the signals were normalized in [-1, 1]. Features derived from the acoustic and time-frequency analysis were estimated from different combinations of signal components obtained by the EMD technique. The IMFs were estimated using the sifting algorithm, with the following parameters: resolution 40 dB, residual energy 40 dB and the gradient step size 0.01. Particularly, a Mel-scaled filter bank was used to calculate the Mel-warped spectrum, so the first 8 and 12 MFCC were estimated using 24 Hamming shaped filters and a sliding hamming window (50% overlap) over different combinations of EMD components derived from the whole beats. Additionally, the first 10 statistical moments in function of the instant frequency and instant amplitude obtained by HHT were also considered, using the same combinations of EMD components. The representation space was normalized in order

to improve the classification performance. The stochastic analysis of the feature space in order to recognize the beat samples was carried out by a classifier type ergodic HMM initialized with a random parameter vector. The training stage was developed using an EM algorithm in order to estimate the maximum likelihood parameters (i.e., MLE criterion) with a convergence at 10e-6 and a maximum iteration number of 1000. The classification stage was carried out by a 30-fold cross-validation procedure using a 70/30 split, where consistency and representation capability of the feature space were analyzed.

### 3. Results and discussion

Table 1 presents the classification accuracy of a cardiac murmur detection system for 4-SAA PCG signals based on HMM, where sets of 8 and 12 MFCC were tested over two sets of constructions based on IMFs (EMD components), which were considered after making several different combinations: IMF-C1 = {3, 5, 7} and IMF-C2 = {1, 3, 5, 7}. Additionally, the first 10 statistical moments of HHT were included in these feature sets. These results show that MFCC 9, 10, 11 and 12 of the IMF 1 contain relevant acoustical information related to heart valve damages. Table 2 presents statistical measures of the HMM

Table 1. HMM with MFCC-HHT-EMD features

	8-MFCC IMF-C1	8-MFCC IMF-C2	12-MFCC IMF-C1	12-MFCC IMF-C2
Accuracy (%)	95±2.1	96±2	93.1±3.7	<b>98.7±1.2</b>

classification performance for MFCC-HHT features over EMD components IMF-C2, considering each auscultation area. Finally, this classification approach is compared with

Table 2. Statistical performance by auscultation area

Area	Accuracy (%)	Sensitivity (%)	Specificity (%)
Aortic	98.8±1.2	99.2±0.5	98.3±1.5
Pulmonic	97.5±1.7	98.3±0.3	96.7±1.4
Mitral	99.2±0.8	100±0.0	98.3±0.9
Tricuspid	99.2±0.8	99.2±0.7	99.1±0.9
Mean	98.7	99.2	98.1

other HMM-based classifiers trained with features of single auscultation signals (see Table 3), where a greater performance is evidenced.

Table 3. Comparison with other approaches

Approach	Accuracy (%)
DHMM [19]	96.3
HMM-MFCC [14]	95.4
CHMM-Wavelets [18]	94.3
HMM-MFCC-HHT-EMD (this work)	<b>98.7</b>

## 4. Conclusion

An objective and accurate mechanism of 4-SAA PCG signal classification for a more reliable cardiac murmur detection, in terms of sensitivity and specificity, was obtained. The representation capability of the EMD technique applied to 4-SAA PCG signals and stochastic analysis performed by an ergodic HMM of acoustic features derived from MFCC and statistical moments of HHT offered a high performance in the detection of heart murmurs. Although this stochastic classifier was demonstrated to be highly dependent on the signal representation and parameter initialization for the model optimization. The combination of different EMD components enhances the acoustical content associated with cardiac murmurs and reduces the acoustical components related to the normal heart sounds or noises included in the acquisition stage.

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