Heart Murmur Detection using Ensemble Empirical Mode Decomposition and Derivations of the Mel-Frequency Cepstral Coefficients on 4-Area Phonocardiographic Signals

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Abstract

This paper presents an automatic detection system for the classification of phonocardiographic (PCG) signals using 4 standard auscultation areas (one of each cardiac valve) for heart murmur diagnosis. The database of 4-area PCG records belongs to the National University of Colombia. A set of 50 individuals were labeled as normal, while 98 were labeled as exhibiting cardiac murmurs, caused by valve disorders. With the help of medical experts, 400 representative beats were chosen, 200 normal and 200 with evidence of cardiac murmur from 4 different areas of auscultation. First, the PCG signals were preprocessed; next, four different derivations of Mel Frequency Cepstral Coefficients (MFCC) were extracted. Additionally, statistical moments of Hilbert Huang Transform (HHT) were estimated using different combinations of the signal components by means of Empirical Mode Decomposition (EMD), Ensemble EMD (EEMD) and Complete EEMD with Adaptative Noise (CEEMDAN), independently, where the computational complexity were compared. Finally, stochastic analysis of the feature space was carried out by an ergodic-HMM and the global classification result was around 98% with acceptable sensitivity and specificity scores, using a 30-fold cross-validation procedure (70/30 split).

1. Introduction

The phonocardiographic (PCG) signals provide information about cardiac valve function, from the sound caused by blood flow between the atrium and ventricle, for detecting heart failures [1]. Commonly, this analysis is carried out using only one Standard Auscultation Area (SAA). However, in [2] and [3], it was demonstrated that the use of the four SAA allows to detect invisible murmurs for systems based only on one SAA.

Initially, taking advantage of the morphological changes in the PCG caused by heart murmurs, different approaches based on energy and temporal features were proposed [4][5]. However, cardiac murmurs have a nonstationary nature and exhibit sudden frequency changes and transients [6][7]. Other studies have considered the nonlinear nature of physiological signals in order to improve the training and classification stages [5][8], but 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, other decomposition methods such as the adaptive method Empirical Mode Decomposition (EMD), introduced to analyze nonstationary signals [10], and Hilbert-Huang Transform (HHT), express the signal as an expansion of basis functions which are signal-dependent [11]. These techniques have been frequently applied for extraction of foetal heart sounds from a recorded single channel abdominal PCG [12]. However, EMD has problems, as the presence of inappropriate oscillations [10], which is attenuated adding Gauss White Noise (WGN) to ensemble the signal by a method named Ensemble Empirical Mode Decomposition (EEMD) [13]. Nevertheless, EEMD has problems with the residual noise and the different number of modes. In this sense, different algorithms have been proposed in order to overcome these problems, such as: Complete Ensamble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) [14]. Another interesting area is related to the acoustical disturbances caused by heart murmurs, which can be analyzed using the Mel-Frequency Cepstral Coefficients (MFCC) [15] [16], but these procedures are very sensitive to artifacts or noises frequently involved in the acquisition stage [6]. Due to this, the combination of MFCC and statistical moments of HHT with appropriate EEMD components would be suitable. Likewise, the inclusion of stochastic models, such as Hidden Markov Models (HMM), have successfully complemented procedures for cardiac murmur detection [17].

In this work, a comparison among EMD, EEMD and CEEMDAN techniques was carried out for a decomposition of PCG signals, which were used to extract features using MFCC, HHT and statistic moments.

A reduced feature set was achieved using a Fuzzy Rough Set (FRS) algorithm and was used as input for a HMM classifier in order to provide an objective and accurate mechanism to improve the reliability of heart murmur detection.

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. From each patient, 8 recordings were recorded according to the four 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 (WelchAllynr Meditron model). Finally, 400 individual beats were chosen, 200 normal and 200 with evidence of cardiac murmur according to a visual and audible inspection by cardiologists.

2.2. Theoretical background

A. Empirical Mode Decomposition (EMD): This method, reported in [18], adaptively decomposes a multicomponent signal $x(t)$ into a number L of Intrinsic Mode Functions (IMFs), $h^{(i)}(t),\ 1 \le i \le L$,

$$x(t) = \sum h^{(i)}(t) + d(t) \qquad (1)$$

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.

B. Ensemble Empirical Mode Decomposition (EEMD): In this method, reported in [13], the IMF components are obtained applying EMD to ensembles by adding different realizations of WGN with finite variance to the original signal $x[n]$. EEMD algorithm is described in [10], as follow:

1) $x^i[n] = x[n] + \beta\omega^i[n]$, where $\omega^i[n]$ (*i=1,2,…,I*) are different realizations of zero mean unit variance WGN.
2) EMD is applied to each $x^i[n]$ (*i=1,2,…,I*) for obtaining their modes IMF_k^i[n], where *k=1…K* indicates the modes.
3) Assign IMF_k as the *k*th mode of $x[n]$, obtained as the average of the corresponding IMFs: $IMF_k[n] = \frac{1}{I}\sum_{i=1}^{I} IMF_k^i\,[n]$.

Each $x^i[n]$ is descomposed independly from other realizations and so for each one a residue $r_k^i[n] = r_{k-1}^i[n] -= IMF_k^i[n]$ is obtained.

C. Mel-Frequency Cepstral Coefficient (MFCC): In order to obtain relevant features for PCG signals, four different derivations of MFCC are calculated [19]:

S_MFCC. This coefficient is obtained from the MFCC on the signal $S_x(t)$ by

$$S_x(t) = X(t) - T_r(t) \qquad (2)$$

Where, $T_r(t) = \sum_i IMF$ and *i* is *i*th IMF.

ST_MFCC. The MFCC technique is applied to the results of the energy operator on the frequency domain of S_x (FFT with sliding hamming window, 50% overlap), as follow:

$$\Psi\big(S_x(i)\big) = S_x^2(i) - S_x(i+1)S_x(i-1),$$
$$i = 1,2,\ldots\, ith\ window \qquad (3)$$

SW_MFCC. These coefficients capture the effects derived from the change of frequency bands of the spectral energy distribution, applying MFCC to the sliding hamming window (50% overlap) of the signal $W_x(t)$, reconstructed by:

$$W_x(t) = \sum_i WIMF, \text{ where } WIMF_i = C_i * IMF_i \quad (4)$$

And C_i are weights obtained by:

$$C_i = 1 + \frac{\left|1 - \frac{N+1}{2}\right|}{10},\ i = 1,2,\ldots,N \text{ and for } i\text{th odd.}$$

$$C_i = \begin{cases} 1 + \frac{i-1-\frac{N}{2}}{10},\ i = 1,2,\ldots N/2 \\ 1 + \frac{i-\frac{N}{2}}{10},\ i = \frac{N+1}{2},\ldots N \end{cases} \text{with } ith \text{ even}$$

SWT_MFCC. These coefficients are obtained from the combination of ST_MFCC and SW_MFCC, where the SW_MFCC is calculated applying MFCC to the power spectrum of $W_x(t)$.

D. Hidden Markov Models (HMM)

HMM is an extension of Markov chains [20]. This study has focused on training criteria based on the MLE criterion, given the good performance in previous studies [21]. Let $X = \{\varphi_r^{n\varphi_r} : r = 1,\ldots,R\}$ a training set of R samples, with categories $C = \{c_r^{n\varphi_r} : r = 1,\ldots,R\}$ for M

different classes, i.e., $c^r \in \{c_m : m = 1, \ldots, M\}$. The training based on MLE criterion is carried out with the following objective function to a probability P:

$$f_{MLE}(\Theta) = \sum_{r=1}^{R} \log(P(\varphi_r^{n\varphi_r} | c^r)) \quad (5)$$

The optimization of (5) is achieved by adjusting the parameters of each model separately, relying on the training observation data, so that expression (5) gets a maximum value. This procedure includes the Expectation Maximization (EM) algorithm which is a well-known method when the data are incomplete or have hidden parameters [22].

2.3. Proposed procedure

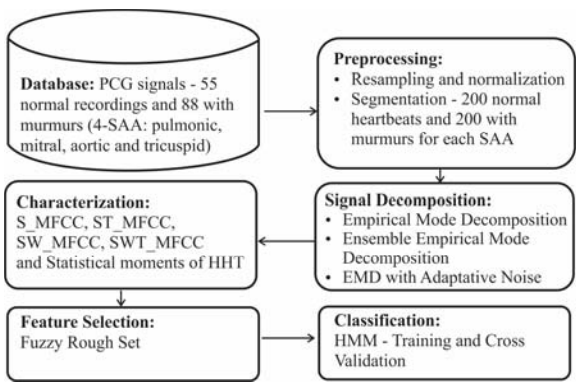

Figure 1. Proposed methodology.

According to Figure 1, PCG signals were resampling to 4410 *Hz* and normalized in [-1 1]. Later, in order to obtain a relevant feature set, a decomposition analysis was carried out using EMD, EEMD and Adaptive EEMD. Next, four different derivations of MFCC (S_MFCC, ST_MFCC, SW_MFCC and SWT_MFCC) were calculated from two constructed signals as result of adding to odd and even IMF. Additionally, nine statistical moments of HHT were calculated, and the feature selection was performed using the FRS algorithm. Finally, the stochastic analysis of the feature space, in order to recognize the beat samples, was carried out by a classifier type ergodic HMM. The training stage was developed using an EM algorithm in order to estimate the maximum likelihood parameters with a convergence at 10e-6. 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 computational cost of the PCG decomposition using EMD, EEMD and CEEMDAN, showing the EMD as the major performance in terms of the time processing, but the CEEMD demonstrated the lowest residual error. Table 2 shows the classification accuracy for the cardiac murmur detection system using 4-SAA PCG signals and HMM, where a set of 60 features were obtained from constructions based on IMFs. The first 10 statistical moments of HHT were included in this features set. These results show that the variants of MFCC provide relevant information about heart valve damages. Finally, this system is compared with the HMM-EMD-MFCC approach (Table 3) where a small increase in performance was evidenced.

Table 1. Performance EMD - EEMD and CEEMDAN.

Decomposition	Processing time (s)	Residual error (%)
EMD	0.159	4.54e-6
EEMD	10.59	7.54e-6
CEEMDAN	23.5	2.83e-6

Table 2. Accuracy HMM - decomposition techniques.

Decomposition	Accuracy (%)	Sensitivity(%)	Specificity(%)
HMM-EMD	96.7±1.4	98.6±2.1	94.±2.2
HMM-EEMD	95±1.5	97±2.1	93.3±2.3
HMM-CEEMDAN	98.9±0.7	99.2±1.1	98.5±1.1

Table 3. Comparison with other approaches.

Approach	Accuracy (%)
HMM-EMD-MFCC [2]	98.7
HMM-EMD-MFCC (this Work)	98.9

4. Conclusion

In this study, we compared EMD, EEMD and CEEMDAN, in combination with features based on different types of MFCC and statistics moments, and showed an increase in the accuracy, specificity and sensibility of the HMM classification system when CEEMDAN was used. Additionally, the different types of MFCC demonstrated high discrimination capacity for detecting cardiac murmurs. However, CEEMDAN implied a high computational cost for PCG signal decomposition compared to the EMD technique; which must be taken into account for a computer aided diagnostic system.

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