# Improving Classification Accuracy of Heart Sound Recordings by Wavelet Filter and Multiple Features

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## Abstract

*This study aimed to improve the accuracy for normal/abnormal classification of heart sound recordings from PhysioNet/Computing in Cardiology Challenge 2016. In order to get the main elements of the first heart sound (S1) and the second heart sound (S2) for segmentation, the Butterworth filter with a pass-band of 25-400 Hz was replaced by the wavelet filter with the pass-band of 31.25-250 Hz. The pre-process in the example entry was modified to improve the accuracy of heart sound segmentation. The re-sampled heart sound was segmented into S1, systole, S2 and diastolic using a duration dependant logistic regression-based hidden semi-Markov model (HSMM). Then, twenty basic time domain features were calculated. Based on the above twenty features, four frequency domain features, four entropy features and two time domain features were added to improve the classification accuracy. Using the logistic regression method, the heart sound recordings were classified into normal and abnormal ones based on the obtained features. To evaluate the modified program, the sensitivity (Se) and specificity (Sp) of the classification results were presented. When performing on the hidden test set, we got the best results as Se of 71.6%, Sp of 78.2%, and the overall score of 74.9%.*

## 1. Introduction

The detailed description for the background of the competition could be found in [1][2]. This study aimed to improve the accuracy for normal/abnormal classification of heart sound recordings by changing the pass-band of the filter in the pre-processing and adding the frequency domain features and the entropy features which were helpful for classification.

## 2. Methods

### 2.1. Database

Detailed description about the challenge data please refer to [1].

### 2.2. Algorithm description

Figure 1 showed the algorithm flow chart. The proposed algorithm for the classification of heart sound recordings consisted of four steps. Step 1: Signal pre-processing; Step 2: Segmentation; Step 3: Features extraction and Step 4: Classification. Each step consisted of several sub-steps.

In Step 1, the heart sound recordings were re-sampled as 1000 Hz, as well as the baseline was filtered. Then, In order to get the main elements of S1 and S2 for segmentation, the Butterworth filter with the pass-band of 25-400 Hz used in the example entry [1] was replaced by the wavelet filter with the pass-band of 31.25-250 Hz. The heart sound was decomposed into 4 levels using the db6 mother wavelet. The data for segmentation was built with the reconstructed wavelet coefficients in the second, third, and forth levels.

In Step 2, the heart rate was derived based on analysis of the autocorrelation function and the positions of the peaks [3]. After all recordings were down-sampled to 1,000 Hz, four envelopes, i.e., homomorphic envelogram, Hilbert envelope, wavelet envelope and power spectral density (PSD) envelope, were calculated. Then, the re-sampled heart sound signal was segmented into S1, systole, S2 and diastolic using a duration dependant logistic regression-based HSMM [4].

In Step 3, the used features were extracted. In the example entry, twenty basic time domain features were extracted. There were always components of high frequency components in the heart sound recording while the heart sound was abnormal. So, four frequency domain features, four entropy features and two another time domain features were added to the twenty basic features for classification. Detailed description for the twenty basic features could be also found in [1].

1) Definition of the four frequency domain features

Frequency spectrum of the heart sound signal was computed using Fast Fourier Transformation (FFT). Then the definition for the four frequency domain features were presented as follows:

m_HFAll_Dia was the mean of the ratio between the sum of frequency spectrum higher than 250 Hz in the duration of diastolic and the sum of all the frequency

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spectrum in the duration of diastolic;

m_HFAll_Sys was the mean of the ratio between the sum of frequency spectrum higher than 250 Hz in the duration of systole and the sum of all the frequency spectrum in the duration of systole;

m_LFAll_Dia was the mean of the ratio between the sum of frequency spectrum lower than 50 Hz in the duration of diastolic and the sum of all the frequency spectrum in the duration of diastolic;

m_LFAll_Sys was the mean of the ratio between the sum of frequency spectrum lower than 50 Hz in the duration of systole and the sum of all the frequency spectrum in the duration of systole.

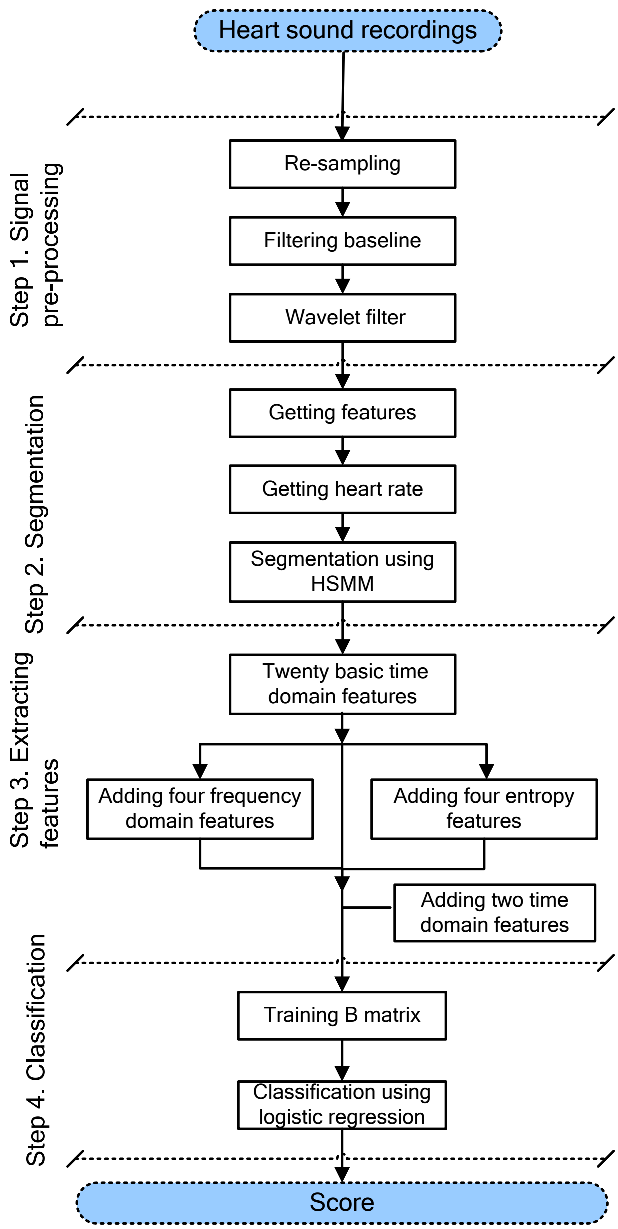


Figure 1. Algorithm flow chart

2) Definition of the four entropy features

Sample entropy (SampEn) presented by Richman [5] showed a set of measures of time series complexity and based on the approximate entropy (ApEn). The larger the SampEn was, the more complex the series were.

The fast algorithm of SampEn was used to compute the entropy features, which was improved based on the fast algorithm of ApEn [6]. The usual parameter choices of the SampEn in this literature were: $m = 2, r = 0.1 \times SD$ ($m$ was the sequence length to be compared, $r$ was tolerance for accepting matches, $SD$ was standard deviation of the heart sound signal).

The detailed description of the fast algorithm [7] was as follows:

(a) For a time series of N points, the $N \times N$ distance matrix $D$ was calculated using the following equation:

$$d_{ij} = \begin{cases} 1 & |x(i)-x(j)| < r \\ 0 & |x(i)-x(j)| \geq r \end{cases} \tag{1}$$

where $d_{ij}$ was the element in row $i$ and column $j$, $1 \leq i, j \leq N$;

(b) $B_i^2(r)$ and $B_i^3(r)$ were computed using the following equations:

$$B_i^2(r) = \sum_{j=1}^{N-1} d_{ij} \cdot d_{(i+1)(j+1)} \tag{2}$$

$$B_i^3(r) = \sum_{j=1}^{N-2} d_{ij} \cdot d_{(i+1)(j+1)} \cdot d_{(i+2)(j+2)} \tag{3}$$

(c) The mean of all the $B_i^m(r)$ was calculated as $B^m(r)$ using the following equation:

$$B^m(r) = \frac{1}{N-m+1} \sum_{i=1}^{N-m+1} B_i^m(r) \tag{4}$$

(d) Then we could get $B^2(r)$ and $B^3(r)$;

(e) $\mathrm{SampEn}(m,r,N)$ was calculated using the following equation:

$$\mathrm{SampEn}(m,r,N) = -\ln\left[ B^{m+1}(r) / B^m(r) \right] \tag{5}$$

Then four entropy features, i.e., m_SaEn_Sys, sd_SaEn_Sys, m_SaEn_Dia and sd_SaEn_Dia, were calculated referred to as the mean of SampEn of heart sound recordings in systole, the standard deviation (SD) of SampEn of heart sound recordings in systole, the mean of SampEn of heart sound recordings in diastolic and the standard deviation of SampEn of heart sound recordings in diastolic respectively.

3) Definition of the two time domain features

m_Ratio_S1S2 was mean of the ratio of S1 intervals and S2 intervals in each heart beat;

sd_Ratio_S1S2 was SD of the ratio of S1 intervals and S2 intervals in each heart beat.

In Step 4, the heart sound recording were classified as normal or abnormal using the logistic regression model based on the feature extracted in Step 3 after the B matrix was re-trained [1]. The entries improved based on the example entry and the new features mentioned above in Step 3 were named as follows:

1) Entry_passband_improved, in which the Butterworth filter with the pass-band of 25-400 Hz was replaced by the wavelet filter with the pass-band of 31.25-250 Hz based on the example entry;

2) Entry_four_freq_added, in which four frequency domain features mentioned in Step 3 were added based on the example entry;

3) Entry_four_entropy_added, in which four sample entropy features mentioned in Step 3 were added based on the example entry;

4) Entry_mixed, in which four frequency domain features, four sample entropy features and two time domain features mentioned in Step 3 were added based on the example entry.

## 3. Results

Table 1 shows the results calculated using the example entry and the four entries mentioned above in Step 4 for the training set used in this challenge, where there were totally 3,153 heart sound recordings including 665 abnormal ones and 2,488 normal ones. The highest overall score was 69.9% made by the entry_passband_improved, where the number of right answers of normal and abnormal recordings was more than those made by example entry. Another three entries had bad performance on identifying the abnormal recordings correctly.

Table 2 shows the results calculated using the example entry and the four entries mentioned above in Step 4 for the validation set, where there were totally 301 heart sound recordings including 151 abnormal ones and 150 normal ones. The entry_four_entropy had the best performance with the overall score of 73.4%. Besides, compared the entry_four_freq_added with the entry_mixed, the number of the right answers of abnormal recordings had a big difference. The entry_four_freq_added had good sensitivity to the abnormal recordings. Maybe some features in the entry_mixed should be removed according to the classification method.

For the hidden test set in PhysioNet's scoring environment, the best results were got as Se of 71.6%, Sp of 78.2% and the overall score of 74.9% using the entry_passband_improved. And the results for the hidden test set using a part of entries mentioned above were shown in Table 3.

Table 1. Results of the example entry and the four improved entries for the training set.

| Entry using different features | The number of right answers | | | results | | | |
|---|---|---|---|---|---|---|---|
| | **Normal** | **Abnormal** | **total** | **Se(%)** | **Sp(%)** | **overall score(%)** | **Accuracy (%)** |
| example entry | 1902 | 403 | 2305 | 60.6 | 76.5 | 68.5 | 73.1 |
| entry_passband_improved, | 1911 | 419 | 2330 | 63.0 | 76.8 | 69.9 | 74 |
| entry_four_freq_added | 2305 | 191 | 2496 | 28.7 | 92.6 | 60.7 | 79.2 |
| entry_four_entropy_added | 2346 | 230 | 2576 | 34.6 | 94.3 | 64.4 | 81.7 |
| entry_mixed | 2324 | 267 | 2591 | 40.2 | 93.4 | 66.8 | 82.2 |

Table 2. Results of the example entry and the four improved entries for the validation set.

| Entry using different feature | The number of right answers | | | results | | | |
|---|---|---|---|---|---|---|---|
| | **Normal** | **Abnormal** | **total** | **Se(%)** | **Sp(%)** | **overall score(%)** | **Accuracy (%)** |
| example entry | 106 | 108 | 214 | 71.5 | 70.7 | 71.1 | 71.1 |
| entry_passband_improved, | 14 | 110 | 124 | 73.5 | 8.7 | 41.1 | 41.1 |
| entry_four_freq_added | 44 | 136 | 180 | 29.1 | 90.7 | 59.9 | 59.8 |
| entry_four_entropy_added | 115 | 106 | 221 | 70.2 | 76.7 | 73.4 | 73.4 |
| entry_mixed | 128 | 71 | 199 | 47.0 | 85.3 | 66.2 | 66.1 |

## 4. Conclusions

We have proposed a multi-feature method for classifying the normal or abnormal heart sound recordings. This method performed well for the training set used in this challenge. However, the method was poor in identifying the abnormal heart sound recordings comparatively. Further development by selecting the features presented in this study will facilitate to improve the performance of the present method.

Table 3. Results of a part of entries for the hidden test set.

| Entry using different features | results | | |
|---|---|---|---|
| | Se(%) | Sp(%) | overall score(%) |
| entry_passband_improved, | 71.6 | 78.2 | 74.9 |
| entry_four_freq_added | 31.4 | 96.7 | 64.0 |
| entry_mixed | 29.7 | 97.7 | 63.7 |


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