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Research

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RESEARCH

A Novel Intelligent System Based on Adjustable Classifier Models for Diagnosing Heart Sounds

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Abstract

Background: As an efficient method, heart sounds (HSs) analysis by classifying the features extracted from the four-stage sequence consisting of the first heart sound (S_1), second heart sound (S_2), duration from S_1 to S_2 and duration from S_2 to S_1 , has been widely used to diagnose heart disease and evaluate heart functions. However, the feature is difficult to be extracted with high accuracy due to the four stages segmented from HSs with low accuracy; the fixed classifiers achieved by training the features from the old samples cannot better fit the features from the new ones because they are not adjusted with the incremental features. Thus, a novel intelligent diagnostic system, the innovations of which are primarily reflected in the automatic feature extraction and adjustable classifier models, is proposed to realize the diagnosis of heart diseases with higher accuracy.

Methods: The three stages of the proposed system are summarized as follows. In stage 1, the short time modified Hilbert transform (STMHT)-based curve is used to segment and extract the first complex sound (CS_1) and second complex sound (CS_2). In stage 2, the envelopes CS_{1FE} and CS_{2FE} for periods CS_1 and CS_2 are obtained via a novel method, and the frequency features are automatically extracted from CS_{1FE} and CS_{2FE} by setting different threshold value (Thv) lines. Finally, the principal component analysis (PCA)-based first three principal components γ_1 , γ_2 , and γ_3 are determined as the diagnostic features. In stage 3, a Gaussian mixture model (GMM)-based objective function $f_{et}(\mathbf{x})$ is generated. Then, the χ^2 distribution for component k is determined by calculating the Mahalanobis distance from $\mathbf{x}$ to the class mean μ_k for component k , and the confidence region of component k is determined by adjusting the optimal confidence level β_k and used as the criterion to diagnose HSs.

Results: The performance evaluation was validated by sounds from online HS databases and clinical heart databases. The accuracy of the proposed method was compared to the accuracies of other well-known classifiers, and the highest classification accuracies of 99.43%, 98.93%, 99.13%, 99.85%, 98.62%, 99.67% and 99.91% in the detection of MR, MS, ASD, NM, AS, AR and VSD sounds were achieved by setting $\beta_k (k = 1, 2, \dots, 7)$ to 0.87, 0.65, 0.67, 0.65, 0.67, 0.79 and 0.87, respectively.

Conclusions: This proposed intelligent diagnosis system provides an efficient way to diagnose seven types of heart diseases. In addition, methods to manage the sounds (such as some ASD sounds) when CS_1 and CS_2 cannot be segmented and extracted via the STMHT method will be explored in the future to characterize the physical meanings of the frequency components and to build a model of the secondary curve in the frequency domain.

Keywords: Heart sound; Short time modified Transform (STMHT); PCA; GMM; Mahalanobis Distance; Chi-squared distribution (χ^2).

Background

As an efficient method, using heart sound (**HS**) analysis is often used to evaluate heart function; this approach has been widely used to diagnose heart disease and evaluate heart functions, such as congenital heart disease classification [1], ventricular septal defect detection [2], blood pressure estimation [3] and congenital heart disease screening [4], for children and adults. A normal **HS** is primarily composed of two basic sounds: the first sound (S_1) which is generated by the closing of aortic valves and the vibrations associated with tensing of the chordae tendineae and the ventricular walls, the second sound (S_2) is produced by the closure of the aortic and pulmonic valves at the beginning of is volumetric ventricular relaxation. However, **HSs** with unitary murmurs generally occur between S_1 and S_2 with different noise patterns [5]. Therefore, analyses of S_1 , S_2 , and the period between S_1 and S_2 play important roles in characterizing **HS** features with different types of information. Detailed information for S_1 , S_2 , and the sounds between S_1 and S_2 can be used to accurately classify **HS**. Additionally, to avoid analyzing the sounds between S_1 and S_2 , which are generally segmented from **HSs** with low accuracy, S_1 and part of the period between S_1 and S_2 are integrated to obtain CS_1 , and S_2 and the part of the period between S_1 and S_2 are integrated to form CS_2 . Then, the features are efficiently extracted from CS_1 and CS_2 . Finally, a classification method is established to diagnose heart diseases.

The studies regarding **HS** segmentation can be summarized into two branches: one branch includes studies that segment each cardiac cycle into a sequence of four heart stages: $S_1 \rightarrow \text{Systole period} \rightarrow S_2 \rightarrow \text{Diastole period}$ [6, 7]. As a result, the four fundamental stages to be segmented are different due to the nonstationary nature of an abnormal **HSs** signal and the effect of background noise. The other branch includes studies that segment a periodic **HSs** into a sequence of two heart stages, which are expressed as $\overbrace{\text{One part of Diastole} \rightarrow S_1 \rightarrow \text{One part of Systole}}^{CS_1} \rightarrow \overbrace{\text{The other of Diastole} \rightarrow S_2 \rightarrow \text{The other of Systole}}^{CS_2}$ based on the **STMHT** algorithm; this approach was reported to be successfully applied in diagnosing heart diseases, such as in ventricular septal defect (**VSD**) diagnosis [8] and several kinds of heart disease diagnosis [9]. Moreover, study [9] noted that the use of frequency features was more efficient in distinguishing normal from abnormal sounds than was the use of time features. Therefore, an efficient frequency feature extraction method should be developed.

As an important component of efficient feature extraction, the frequency width of the envelope over a given threshold value (Thv) has been verified to be useful for detecting heart diseases [8, 9, 10, 11]. However, for many types of **HSs**, it is difficult to extract frequency widths with an unsuitable Thv due to the existence of a non-smooth envelope. To extract the frequency widths for a smooth envelope without setting different Thv values, the smooth envelope can be treated as a secondary envelopes, as proposed in [9], and used to automatically extract the frequency feature matrix based on the **STMHT** technique; this method was successfully applied to detect different types of heart diseases. However, for mitral stenosis and mitral regurgitation noises, the feature matrix was not easily extracted because the second frequency component was missing. Therefore, to improve the classification accuracy

for diagnosing different types of heart disease and simplify the complexity of the diagnostic method, the smooth envelopes for CS_1 and CS_2 extraction in the frequency domain must be considered; additionally, more frequency widths corresponding to different Thv values should be used, and dimensionality reduction should be employed to reduce the number of features considered. Such a classification method could be applied in the efficient extraction of features for diagnosing heart diseases.

Gaussian mixture models (**GMMs**) have been used in a wide variety of clustering applications [12, 13, 14, 15, 16, 17, 18] due to their powerful mathematical characteristics. Confidence regions are used to diagnose the detection data $\mathbf{x}$ in **GMMs**, and the optimal confidence regions is determined based on Mahalanobis distance following the Chi-square (χ^2) distribution. Thus, classifier models with adjustable sizes corresponding to the confidence bounds of the Chi-square (χ^2) distribution, which can be adjusted by changing the desired confidence level (denoted as β), are proposed. The χ^2 confidence bounds used as the classification criteria are employed to diagnose heart diseases.

In summary, this study proposes an innovative and intelligent system. The major contributions in this study are (1) the **STMHT**-based CS_1 and CS_2 are automatically located and extracted; (2) a novel method for obtaining the secondary curves of CS_1 and CS_2 are extracted in the frequency domain; (3) frequency features are automatically extracted over the given threshold value; (4) the diagnostic features γ_1 , γ_2 and γ_3 are determined based on **PCA**; and (5) the confidence region of the χ^2 distribution, which are adjusted based on the desired β , is determined and used as the classification criterion for diagnosing a given **HS**. The remainder of this paper is organized as follows. Section presents the approach for determining the diagnostic features $[\gamma_1, \gamma_2, \gamma_3]$, and a definition of the confidence region-based diagnostic method is given. In Section , the performance of the proposed method is compared with that of other efficient methods for diagnosing heart diseases. Finally, the conclusions are provided in Section .

Methodology

The flow chart of the proposed intelligent system, shown in Fig. 1, consists of three stages: the automatic location and extraction of CS_1 and CS_2 ; the automatic determination of frequency features γ_1 , γ_2 and γ_3 ; and the establishment of the Mahalanobis distance criterion-based diagnostic method. In stage 1, the **STMHT**-based curve (denoted as HS_{STMHT}), which is extracted for the HS_E envelope generated by the **HS**, is used to segment and extract CS_1 and CS_2 from the **HS** (Fig. 1A). In stage 2, the envelopes CS_{1FE} and CS_{2FE} for every period CS_1 and CS_2 are obtained via a novel method, and the frequency features are automatically extracted from CS_{1FE} and CS_{2FE} by setting different Thv lines. Finally, the first three principal components, γ_1 , γ_2 and γ_3 , which express 86.7% of the FF information, are determined and used as diagnostic features (Fig. 1B and C). In stage 3, the **GMM**-based mixed classification objective function $f_{et}(\mathbf{x})$ which combines component k with respect to the parameters π_k , μ_k , and Σ_k and the features $\mathbf{x} = [\gamma_1, \gamma_2, \gamma_3]$, is generated. Then, the χ^2 distribution for component k is determined by calculating the Mahalanobis distance from $\mathbf{x}$ to the class mean μ_k of component k , and the adjustable confidence bound (denoted as MDC_k shown in Fig. 1E) is determined to diagnose heart diseases.

$$HS_E[m] = \frac{1}{2W_m + 1} \sum_{k=m-W_m}^{m+W_m} (HS_T[k] - \overline{HS_T}[m])^2, m = W_m, W_m + 1, \dots, M - 1 - W_m, \quad (1)$$

Stage 1: Automatic location and extraction of CS_1 and CS_2

WD-based heart sound preprocessing

HSs are reported to be primarily dispersed in the frequency range of 20~700 Hz [9, 8, 2]. Therefore, according to the sampling frequency ($F_s = 44.1$ kHz), WD-based **HSs** are filtered to obtain the efficient frequency components (21.5 ~ 689 Hz). The Daubechies wavelet 10 (*dB10*) has been used to give the maximum signal-to-noise ratio and minimum root-mean-square error for **HSs** [19]. Therefore, *dB10* is selected for use as the mother wavelet for preprocessing **HSs**. A filtered and normalized sound, denoted as HS_T , is shown in Fig. 1A.

Extraction of the Viola integral-based heart sound envelope (HS_E)

The Viola integral-based envelope, denoted as HS_E , is extracted from the heart sound HS_T , as reported in studies [9, 8]; this envelope can effectively overcome amplitude variations and complex backgrounds and noise. This concept is described as follows. Consider a filtered sound $HS_T[m]$ for $m = 0, 1, \dots, M - 1$, where M denotes the number of **HSs**. In a W_m neighborhood of time m , called the width W_m time scale, the M -point envelope $HS_E[m]$ is obtained by Eq. (1): where

$$\overline{HS_T}[m] = \frac{1}{2W_m + 1} \sum_{k=m-W_m}^{m+W_m} HS_T[k], \quad (2)$$

$W_m = 2205$ if the duration of CS_1 or CS_2 greater than 0.13 s. Finally, normalization is performed by setting the maximum amplitude of HS_E to 1 (Fig. 1A).

STMHT extraction for **HSs** (denoted as HS_{STMHT})

Given an M -point **HS**, the **STMHT** for the **HSs**, HS_{STMHT} , is computed from Eq. (3) where $n = (N - 1)/2, \dots, M - 1 - (N - 1)/2$, and $W_N[l](l = -(N - 1)/2, \dots, (N - 1)/2)$ is a moving window of odd length N . According to studies [8, 2], the length N is set to 44101.

Automatic extraction of HS_{STMHT} -based CS_1 and CS_2

The characteristics of HS_{STMHT} considered in studies [8, 2], as shown in Fig. 2A and C, are as follows:

- 1) The negative-to-positive (**N2P**) points of HS_{STMHT} , denoted by $\blacktriangle$, correspond to the geometry center peaks of S_1 and S_2 .
- 2) The geometry center between S_1 and S_2 , denoted by $\blacktriangledown$ is determined by the positive-to-negative **P2N** points of HS_{STMHT} .

The interval from S_2 to S_1 is generally greater than that from S_1 to S_2 in one period of an **HS** [20, 21, 22]. Therefore, the **N2P** and **P2N**-based CS_1 and CS_2 features can be automatically segmented from one period of an **HS** and extracted by two procedures, as described in the following section.

Fig. 1. Flow chart of the proposed methodology.

$$HS_{STMHT}[n] = \sum_{m=n-\frac{N-1}{2}}^{n+\frac{N-1}{2}} HS_E[m] W_N[m-n] W_E[m-(n-\frac{N-1}{2})], \quad (3)$$

$$W_E[i] = \begin{cases} \frac{\cos(\frac{N-1-2i}{2N}\pi) - \cos(\frac{N-1-2i}{2}\pi)}{N \sin(\frac{N-1-2i}{2N}\pi)} & \text{for } i = 0, 1, \dots, N-1 \\ 0 & \text{for } i = \frac{N-1}{2} \end{cases} \quad (4)$$

$$DS_{HS_{STMHT}}[i] = S_{HS_{STMHT}}[i+1] - S_{HS_{STMHT}}[i], i = 1, 2, \dots, n. \quad (6)$$

$$D_{N2P}[i] = N2P[i+1] - N2P[i], i = 1, 2, \dots, n. \quad (8)$$

(a) N2P and P2N location

The algorithm for detecting N2P and P2N is detailed as follows.

- 1) First, the signum function of HS_{STMHT} , denoted as $S_{HS_{STMHT}}$, is calculated by

$$S_{HS_{STMHT}} = \begin{cases} -1 & \text{if } HS_{STMHT} < 0, \\ 0 & \text{if } HS_{STMHT} = 0, \\ +1 & \text{if } HS_{STMHT} > 0. \end{cases} \quad (5)$$

- 2) Then, the variation in $S_{HS_{STMHT}}$ ($DS_{HS_{STMHT}}$) is determined from Eq. (6)
- 3) Finally, **N2P** and **P2N** are determined by

$$\begin{cases} N2P = i/F_S & \text{if } DS_{HS_{STMHT}}[i] = +2 \\ P2N = i/F_S & \text{if } DS_{HS_{STMHT}}[i] = -2 \end{cases} \quad (7)$$

(b) Automatic extraction of CS_1 and CS_2

- 1) Calculate the difference between two adjacent **N2Ps**, denoted as D_{N2P} , with Eq. (8)
- 2) Determine the points CS_{12} and CS_{21} that are used for segmentation from CS_1 to CS_2 and from CS_2 to CS_1 , respectively, by using Eq. (9).
- 3) Extract CS_1 (denoted as CS_{1i}) and CS_2 (denoted as CS_{2i}) for the i th period of an **HS** as follows

$$\begin{cases} CS_{1i} = HS_T[CS_{21i} : CS_{12i}] \\ CS_{2i} = HS_T[CS_{12i} : CS_{21i+1}] \end{cases} \quad (10)$$

The automatic extraction procedures for CS_1 and CS_2 are illustrated in Fig. 2. Fig. 2(A and B) show a typical **AR** sound, and the typical **NM** sound is shown in Fig. 2(C and D).

Stage 2: Automatic feature generation

Secondary envelopes for CS_1 and CS_2 definition

Given an M -point **HS**, the secondary envelope in the frequency-domain, denoted as HS_F , can be calculated from Eq. (11): where l_1 , l_2 and $HS_F[k]$ are defined by Eq. (12): $|\cdot|$ is the absolute value sign, $2L_1 + 1$ is the first window width, and $2L_2 + 1$ is the second window width. According to studies [9, 25], L_1 and L_2 are set to 9 and 17, respectively. Moreover, HS_{F_E} is also normalized by setting the maximum amplitude of HS_{F_E} to 1.

$$\begin{cases} CS_{21}[i] = P2N[i], CS_{12}[i] = P2N[i+1], & \text{if } D_{N2P}[i] < D_{N2P}[i+1] \\ CS_{21}[i] = P2N[i+1], CS_{12}[i] = P2N[i+2], & \text{Otherwise} \end{cases} \quad (9)$$

Fig. 2. The automatic extraction procedures for CS_1 and CS_2 . **A-B** show the procedure for an example of a typical **AR** from the database in [23]. **C-D** show the procedure for an example of a typical normal sound from [24].

$$HS_{FE}[k] = \frac{\sum_{l_1} (L_1 + L_2 + 1 - |l_1|) HS_F[k + l_1] - \sum_{l_2} HS_F[k + l_2]}{(2L_1 + 1)(2L_2 + 1)}, \quad (11)$$

The secondary envelopes for CS_1 and CS_2 , denoted as CS_{1FE} and CS_{2FE} respectively, are illustrated by using an example of a normal sound in Fig. 3. CS_1 (colored yellow) and CS_2 (colored cyan), which are first automatically extracted based on the **STMHT** algorithm, are shown in Fig. 3A. Then, the frequency components of CS_1 and CS_2 are calculated with Eq. (12) and plotted in Fig. 3(B and C). Finally, the secondary envelopes for CS_1 and CS_2 , denoted as CS_{1FE} and CS_{2FE} respectively, are extracted from Eq. (11), and the results are shown in Fig. 3(B and C). In the following subsection, the frequency features for CS_1 and CS_2 are defined and automatically extracted by using the threshold line method.

Definition and automatic extraction of secondary envelope-based frequency features

The frequency features are illustrated in Fig. 3(B and C), and their gravities are calculated by

$$\begin{cases} CS_{1G} = \frac{\sum_{k=0}^{M-1} k \times CS_{1FE}[k]}{\sum_{k=0}^{M-1} CS_{1FE}[k]} \\ CS_{2G} = \frac{\sum_{k=0}^{M-1} k \times CS_{2FE}[k]}{\sum_{k=0}^{M-1} CS_{2FE}[k]} \end{cases}, \quad (13)$$

The frequency widths over a given threshold value are defined and calculated by

$$\begin{cases} CS_{1FWi} = R_{p_i} - L_{p_i} \\ CS_{2FWi} = R_{p_i} - L_{p_i} \end{cases}, \quad i = 1, 2, 3. \quad (14)$$

where L_{p_i} and R_{p_i} are the i^{th} left and right intersections, respectively, of CS_{1FE} and CS_{2FE} over the Thv lines ($Thv=0.3, 0.5$ and 0.8). Moreover, the frequency features are expressed based on Eq. (15).

$$\begin{cases} l_1 = -(L_1 + L_2), -(L_1 + L_2) + 1, \dots, (L_1 + L_2) \\ l_2 = -(L_1 - L_2 - 1), -(L_1 - L_2 - 1) + 1, \dots, (L_1 - L_2 - 1) \\ HS_F[k] = \left| \sum_{m=0}^{M-1} HS_T[m+1] e^{-j \frac{2\pi k l}{M}} \right|, \quad k = 0, 1, 2, \dots, M-1 \end{cases}, \quad (12)$$

Fig. 3. Example of feature definition and automatic extraction.

$$FF = [CS_{1FW1}, CS_{1FW2}, CS_{1FW3}, CS_{1G}, CS_{2FW1}, CS_{2FW2}, CS_{2FW3}, CS_{2G}] \quad (15)$$

Experimental results for several typical types of heart disease

The features FF of six typical and normal sounds are illustrated in Fig. 4. From Fig. 4, CS_1 and CS_2 are first automatically located and extracted, as shown in Fig. 4A; then, the envelopes for every CS_1 and CS_2 are extracted by Eq. (11), as shown in Fig. 4B and Fig. 4C, respectively. Finally, the features defined by Eq. (15) for CS_1 and CS_2 in the frequency domain are automatically extracted with Eqs. (13–14). The experimental sounds are 665-period **AR** sounds (3M database [26], medical sound library [27], heart auscultation sounds [28], auscultation sound [29], continuing medical implementation [23], sounds Database of the University of Dundee [24], and patients only with **AR** disease from the Nanyang First People's Hospital), 381-period **AS** sounds (continuing medical implementation [23], sounds database of the University of Dundee [24], 3M database [26], medical sound library [27], auscultation sound [29], and patients only with **AS** disease from the Nanyang first People's Hospital, and heart auscultation sounds [28]), 315-period **ASD** sounds (Medical sound library [27], heart auscultation sounds [28], 3M database [26], patients only with **ASD** disease from the Nanyang First People's Hospital, and medical sound library [27]), 769-period **MR** sounds (3M database [26], sounds database of the University of Dundee [24], heart auscultation sounds [28], medical sound library [27], and auscultation sound [29]), 439-period **MS** sounds (3M database [26], auscultation sound [29], medical sound library [27], and continuing medical implementation [23]), and 1056-period **NM** sounds (3M database [26], Michigan database [30], medical sound library [27], ThinkLabs database [31], and healthy undergraduates from Nanyang Institute of Technology, China) (whom I thank for the data used in this study)). Moreover, the boxplots for the features are plotted in Fig. 5, where Fig. 5A shows the features extracted from CS_1 and Fig. 5B shows the features from CS_2 for each type of heart disease. The scatter plots of features in Fig. 5 illustrate the

discrimination ability of the model in distinguishing among different heart diseases and highlighting the following findings:

- ✦ The **MS** and **VSD** sounds are easy to distinguish from the other sounds by using CS_{1FW1} (Fig. 5A).
- ✦ By using the CS_{2FW1} (Fig. 5B), the **VSD** sound is easy to distinguish from the other sounds.
- ✦ The **MS** sound is easy to distinguish from the other sounds based on CS_{1FW2} (Fig. 5A).
- ✦ By using the CS_{2FW2} (Fig. 5B), the **AR** and **VSD** sounds are distinguished from other sounds.
- ✦ The **NM** sound is easy to distinguish from other sounds using CS_{1FW3} (Fig. 5A).
- ✦ The **AR** and **VSD** sounds are easy to distinguish from the other sounds using CS_{2FW3} , as shown in Fig. 5B.
- ✦ Fig. 5A indicates that CS_{1G} can be used to easily distinguish **MR** from other sounds and the **AS** and **ASD** sounds from other sounds.
- ✦ Fig. 5B shows that the distribution of CS_{2G} from **AS** sounds is different from that for other sounds, except **NM** sounds. Moreover, CS_{2G} can be used to easily distinguish different sounds.

The analysis results discussed above indicate that different combinations of several features defined by Eq. (15) can be used to distinguish among various types of heart disease. Therefore, to simplify features and develop a diagnostic method that is simple and effective, dimension reduction is used to determine new features; this process is described in detail as follows.

Diagnostic feature determination

To simplify the computation when using features to diagnose heart diseases, **PCA**, a linear dimensionality reduction technique for finding principal components and replacing high-dimension data, is employed. **PCA** has been used in studies of heart arrhythmias classification [32], heart disease classification [33, 2], emotion recognition [34], respiratory rate extraction [35], electrocardiogram heart disease diagnosis [36], and real-time magnetoencephalography neurofeedback [37]. A few major principal components are used to characterize **HS** features and diagnose heart diseases. The flow chart corresponding to the new features that are generated via **PCA** for FF is shown in Fig. 6. The eigenvector ξ_i , which corresponds to the eigenvalue λ_i and is calculated for the matrix Z in step 2, as shown in Table 2, is the actual weighted coefficient for the i th principal component γ_i . Table 2 shows that the largest absolute coefficients in the first principal component γ_1 are CS_{1FW1} , CS_{2FW2} and CS_{1FW2} ; the second principal component γ_2 is mainly weighted based on CS_{1G} , CS_{2FW2} , CS_{1FW1} and CS_{2FW3} ; and the third component γ_3 is mainly weighted based on CS_{1FW2} , CS_{1FW3} and CS_{2FW3} (Table 2). To determine the smallest number of principal components m should be considered, the Pareto chart is used; this chart provides a tool for visualizing the Pareto principle, which states that observing a small set of variables that influence a common outcome is more common than detecting many variables that influence the same outcome. This approach has been used to determine the percent variability explained by each principal component

Fig. 4. Examples of a typical normal sound and six types of typical heart disease sounds.

Fig. 5. Box plot representation of FF for each type of heart disease. **A** shows the box plots for features from CS_1 . In addition, **B** represents the features from CS_2 .

Fig. 6. The flow chart corresponding to the efficient feature generation procedure.

Table 1. Mean (μ_{FF}) and standard deviation (σ_{FF}) of the features.

Statistics	Frequency features ($\mu_{FF} + \sigma_{FF}$)							
	Features from CS_1				Features from CS_2			
	CS_{1FW1}	CS_{1FW2}	CS_{1FW3}	CS_{1G}	CS_{2FW1}	CS_{2FW2}	CS_{2FW3}	CS_{2G}
$\mu_{FF} \pm \sigma_{FF}$	45.3 ± 11.8	33.1 ± 5.8	18.8 ± 3.6	80.6 ± 21.7	44.1 ± 23.1	32.2 ± 9.1	18.4 ± 6.5	79.8 ± 18.9

Table 2. Eigenvector ξ_i and eigenvalue λ_i ($i = 1, \dots, 8$) for Σ in descending order of eigenvalues

Features	Eigenvector (eigenvalue) in descending order of eigenvalues							
	$\xi_1(\lambda_1 = 3.6423)$	$\xi_2(\lambda_2 = 1.7643)$	$\xi_3(\lambda_3 = 1.5316)$	$\xi_4(\lambda_4 = 0.4671)$	$\xi_5(\lambda_5 = 0.3226)$	$\xi_6(\lambda_6 = 0.1748)$	$\xi_7(\lambda_7 = 0.0606)$	$\xi_8(\lambda_8 = 0.0368)$
$S1_{FW1}$	0.4309	-0.2169	0.0818	-0.2179	0.8062	-0.2394	-0.0499	0.0616
$S1_{FW2}$	0.3716	-0.0757	0.5303	0.0431	-0.0306	0.6778	0.2873	-0.1735
$S1_{FW3}$	0.3411	-0.0983	0.5431	0.0444	-0.4364	-0.6126	-0.1001	-0.0375
$S1_G$	0.2385	0.6501	-0.0157	-0.2122	0.0212	0.0986	-0.5500	-0.4031
$S2_{FW1}$	0.3313	0.0487	-0.2471	0.8958	0.0977	-0.0299	-0.0699	-0.0944
$S2_{FW2}$	0.4475	-0.2390	-0.2924	-0.1628	-0.3044	0.2633	-0.3928	0.5607
$S2_{FW3}$	0.3517	-0.2191	-0.5142	-0.2650	-0.2357	-0.1047	0.3750	-0.5353
$S2_G$	0.2632	0.1026	-0.0768	-0.0662	-0.0207	-0.1308	0.5506	0.4386

(Fig. 7A). Therefore, according to the smallest m value such that $\eta_\Sigma(m) > 80\%$ [38], combined with the scatter plot for the first m principal components, the smallest m is determined. The Pareto chart of the PCA results in Fig. 7A shows the explained variance and accumulated variance for each principal component γ_i , where $i = 1, 2, \dots, 8$. According to Fig. 7A, 67.58% of the total variance is captured by the first two components, γ_1 and γ_2 , and 86.73% of the total variance is captured by the first three components γ_1 , γ_2 and γ_3 . Therefore, the following conclusions can be obtained.

(a) γ_1 and γ_2 lead to a dimensionality reduction of 75% (from 8 to 2 variables) and only 32.42% information loss. The scatter diagram of γ_1 and γ_2 given in Fig. 7B indicates that although the distribution region corresponding to each type of heart disease is obviously different and the overlaps between MR and other diseases, AR and other diseases, and VSD and other diseases are small, the overlaps among MS, ASD, NM, and AS are relatively large; therefore, it is difficult to accurately distinguish among these four types of heart diseases.

(b) However, the scatter diagram of γ_1 , γ_2 and γ_3 , plotted in Fig. 7C, shows that there are different distribution regions for these types of heart diseases. In addition, $\eta_\Sigma(3) = 86.73\%$, as shown in Fig. 7A, based on feature number determination [38]. Thus, γ_1 , γ_2 and γ_3 lead to a dimensionality reduction of 62.5% (from 8 to 3 variables) with only 13.27% information loss. The scatter diagram of γ_1 , γ_2 and γ_3 in Fig. 7C is used to verify the different distribution regions corresponding to these types of heart diseases.

Therefore, m is set to 3, and the new 3-dimensional feature matrices consisting of γ_1 , γ_2 and γ_3 (see Fig. 7C) are used to diagnose heart diseases.

Stage 3: Classification based on the squared Mahalanobis distance criterion

Classifier determination

The squared Mahalanobis distance classification criterion-based diagnostic methodology, consisting of the five sequential steps as shown in the flow chart (Fig. 8A), is proposed to diagnose HSs and is described in the following 5 steps.

Step 1. GMM-based μ_k and Σ_k generation

In the design step of GMM, the estimated target function, $f_{et}(\mathbf{x})$, is a mixture of d -dimensional normal Gaussian distributions $p(\mathbf{x}|\mu_k, \Sigma_k)$ that reflect the training

Fig. 7. PCA results. **A** shows the Pareto chart of the variance by contribution of each principal component, **B** plots the scatter diagram of the first two components γ_1 and γ_2 , and **C** shows the scatter diagram of the first three components γ_1 , γ_2 and γ_3 .

pattern of each component; it is assumed that components can be modeled by mixtures of normal Gaussian distributions by

$$f_{et}(\mathbf{x}) = \sum_{k=1}^K \pi_k p(\mathbf{x}|\mu_k, \Sigma_k), \quad (16)$$

where

$$p(\mathbf{x}) = \frac{1}{\sqrt{(2\pi)^d |\Sigma_k|}} \exp\left(-\frac{1}{2}(\mathbf{x}-\mu_k)^T \Sigma_k^{-1} (\mathbf{x}-\mu_k)\right) \quad (17)$$

expresses the posterior probabilities corresponding to each component; K is the number of components; π_k corresponds to the mixed weights, such that $\sum_{k=1}^K \pi_k = 1$; and μ_k and Σ_k are the mean value and covariance matrix of the k^{th} component, respectively. Because the goal is to maximize the function $f_{et}(\mathbf{x})$, the parameters (π_k , μ_k , and Σ_k) are determined based on the **EM** algorithm [39] for a set of sample records. Based on the types of heart disease described in Subsection and the scatter diagram plotted in Fig. 7C, the number of Gaussian mixture components is set to $K = 7$, and the *fitgmdist* function in MATLAB 2018b is used to return a **GMM** with $K = 7$ components fitted to the features $[\gamma_1, \gamma_2, \gamma_3]$ established in Section using the **EM** algorithm by assigning a posterior probability to each component density with respect to each observation. Furthermore, the regularization value is set as 0.01 to avoid ill-conditioned covariance estimates, and the number of optimization iterations is set to 1000 based on experience. The Gaussian mixture parameter estimates for π_k , μ_k and Σ_k are obtained and shown in Table 3. To characterize the 3-dimensional interspace corresponding to each 3-dimensional Gaussian component for diagnosing heart diseases, the 3-dimensional interspaces can be used as 3-dimensional classifiers to diagnose heart diseases with high classification accuracy; the overlapping interspace between two random components is made as small

Table 3. The Gaussian mixture parameter estimates are achieved for the new features $[\gamma_1, \gamma_2, \gamma_3]$ by setting the number of Gaussian mixture components as 7.

Components	Component number	Gaussian mixture parameter estimates						
		π_k	μ_k			Σ_k		
MR Classifier	$k = 1$	0.1947	0.7056	2.7126	1.4950	0.0425	-0.0007	0.0013
						-0.0007	0.2343	-0.0126
						0.0013	-0.0126	0.2122
						0.3310	-0.0094	-0.0122
MS Classifier	$k = 2$	0.0827	3.2981	-2.6064	-3.7382	-0.0094	0.3906	-0.0210
						-0.0122	-0.0210	0.5386
						0.5373	-0.0172	-0.0039
						-0.0172	0.0608	-0.0053
ASD Classifier	$k = 3$	0.1130	2.3453	-0.3484	0.5773	-0.0039	-0.0053	0.1883
						0.1403	0.0107	0.0063
						0.0107	0.2549	0.0016
						0.0063	0.0016	0.1301
NM Classifier	$k = 4$	0.1683	2.7874	1.8620	-0.9829	0.0972	0.0077	-0.0161
						0.0077	0.0344	-0.0050
						-0.0161	-0.0050	0.2634
						0.3301	-0.0011	0.0025
AS Classifier	$k = 5$	0.0783	0.7511	0.3199	-0.5341	-0.0011	0.0230	0.0005
						0.0025	0.0005	0.3255
						0.1338	0.0048	-0.0155
						0.0048	0.1449	-0.0095
VSD Classifier	$k = 7$	0.0954	-0.1631	-1.1167	0.9454	-0.0155	-0.0095	0.1573

Fig. 8. Flow chart of the diagnostic determination and 3-dimensional surface classifier results.

as possible, and the independent 3-dimensional interspace corresponding to each component is considered.

Step 2. χ_3^2 determination for the k^{th} component in 3-dimensional interspace

Since the squared Mahalanobis distances for each Gaussian component follow the Chi-square distribution (χ_3^2) in 3-dimensional interspace, to determine the decision region for classifying the test data $\mathbf{x}$ via the components estimated in the above step, the squared Mahalanobis distance in 3-dimensional interspace for the k^{th} component with mean μ_k and full covariance matrix Σ_k , $d_3^2(\mathbf{x}|\mu_k, \Sigma_k)$, is computed as follows:

$$d_3^2(\mathbf{x}|\mu_k, \Sigma_k) = (\mathbf{x} - \mu_k)^T \Sigma_k^{-1} (\mathbf{x} - \mu_k). \quad (18)$$

Therefore, χ_3^2 , which is constructed based on component k and denoted as $\chi_3^2(\mu_k, \Sigma_k)$, is determined by

$$d_3^2(\mathbf{x}|\mu_k, \Sigma_k) \sim \chi_3^2(\mu_k, \Sigma_k). \quad (19)$$

Therefore, the squared Mahalanobis distance $d_3^2(\mathbf{x}|\mu_k, \Sigma_k)$ specified based on the desired confidence level, denoted as β_k , can be used as the k^{th} classifier criterion for determining whether feature $\mathbf{x}$ belongs to the k^{th} class.

Step 3. The k^{th} confidence level (β_k) determination

Actually, the k^{th} confidence region, as specified by the k^{th} desired confidence level β_k , is surrounded by the k^{th} ellipsoid, and this relation is expressed as

$$d_3^2(\mathbf{x}|\mu_k, \Sigma_k) \leq \text{MDC}_k = \chi_{3, \beta_k}^2, \quad (20)$$

where χ_{3, β_k}^2 is the inverse of χ_3^2 for a given confidence level β_k , and MDC_k represents the classification criterion for component k and satisfies the following equation

$$\chi^2(d_3^2(\mathbf{x}|\mu_k, \Sigma_k) = \text{MDC}_k | \mu_k, \Sigma_k) = \beta_k \quad (21)$$

For the χ_3^2 distribution, although the confidence regions corresponding to the confidence levels of 68.3%, 95%, and 97.5% are widely used classification criteria in many studies [40, 41, 42, 43, 2], the optional β_k is identified by setting $\beta_k \in [63 : 2 : 97]\%$ combined with the following rules: 1) each ellipsoid should be as large as possible; 2) each common region should be as small as possible; and 3) the classification accuracy defined in Eq. (22) should be as high as possible. The classification accuracies for classifying sound data summarized in subsection are plotted in Fig. 9, and Fig. 9 shows the following results.

✂ **For VSD sounds**, high accuracy can be achieved by setting the desired confidence level β to each value within the interval of $(0.71 < \beta < 0.89)$, as shown in Fig. 9(VSD).

✂ **For AR and MR sounds**, by setting the desired confidence level β based on $\beta \in [0.69, 0.81]$, high classification accuracy could be achieved (Fig. 9(MR and AR));

Fig. 9. The achieved accuracies corresponding to classifying the heart sounds described in subsection by setting β from 0.63 to 0.97 with a step of 0.02.

✂ **For MS, AS and NM sounds:** To achieve the accurate classification of **HSs**, the interval of the desired confidence level β should be set as $[0.63, 0.65]$ (Fig. 9).

✂ **For ASD sounds:** Fig. 9(ASD) shows that the highest classification accuracy is achieved by setting the desired confidence level to $\beta \in [0.63, 0.69]$.

Furthermore, the desired confidence level β can be adjusted to improve the classification accuracy and fit new datasets without reperforming the computations for the objective function, especially for **VSD** sounds and **MR** sounds (Fig. 9(VSD and MR)). In this study, according to the rules described above combined with the accuracy analysis results plotted in Fig. 9, the $\beta_k (k = 1, \dots, 7)$ values are set as 0.87, 0.65, 0.67, 0.65, 0.67, 0.79 and 0.87, respectively.

Step 4. MDC_k determination corresponding to β_k

Based on the k^{th} confidence level achieved for β_k in the above step, by using the function 'chi2inv' in MATLAB 2018b, the inverse of χ^2_{3, β_k} , denoted as $MDC_k = \chi^2_{3, \beta_k}$, is determined. The analysis results for the k^{th} confidence region in the 3-dimensional interspace, which is surrounded by the k^{th} ellipsoid corresponding to the k^{th} desired confidence level β_k , are determined and shown in Fig. 8B. Furthermore, Fig. 8B shows that the common regions between two random ellipsoids are almost zero; thus, a faulty decision process is avoided because the input will not fall into two or more categories.

Step 5. MDC_k -based diagnostic result determination

According to the confidence region shown in Fig. 8B, MDC_k -based diagnostic results for a test feature $\mathbf{x} = [\gamma_1, \gamma_2, \gamma_3]$ are determined by

$$\begin{cases} \text{Class } k, d_3^2(\mathbf{x}|\mu_k, \Sigma_k) \leq MDC_k \\ \text{Unknown class,} & \text{otherwise} \end{cases}, \quad (22)$$

where class k corresponding to the type of heart disease is detailed in Table 3, and MDC_k (1, 2, ..., 7) is 5.6489, 3.2831, 3.4297, 3.2831, 3.4297, 4.5258 and 5.6489. Moreover, to evaluate the performance of these ellipsoids in 3-dimensional space, the classification accuracy (CA), sensitivity (Se) and specificity (Sp) values are calculated by

$$\begin{cases} CA(\%) &= \frac{TP+TN}{TP+FP+FN+TN} \times 100 \\ Se(\%) &= \frac{TP}{TP+FN} \times 100 \\ Sp(\%) &= \frac{TN}{FP+TN} \times 100 \end{cases}, \quad (23)$$

where TP, FP, TN and FN are the numbers of true positives, false positives, true negatives and false negatives, respectively. To evaluate the performance of this diagnostic system, the classification method based on the ellipsoids shown in Fig. 8 is applied.

Definition of the diagnosis results

Based on the ellipsoid surfaces, the diagnosis method is described as follows.

- (a) The 3-dimensional diagnostic features $[\gamma_1, \gamma_2, \gamma_3]$ are first transformed from the features FF (denoted as FF_s) of the testing sample and calculated with the following equation

$$\gamma_i = \frac{FF_s - \mu_{FF}}{\sigma_{FF}} \times \xi_i, i = 1, 2, 3 \quad (24)$$

where μ_{FF} and σ_{FF} are shown in Table 1.

- (b) Then, according to the confidence region shown in Fig. 8B, the MDC_k -based diagnostic result for a test features $\mathbf{x} = [\gamma_1, \gamma_2, \gamma_3]$ is determined by Eq. (22).

System performance evaluation

The performance of the proposed methodology is evaluated by comparison with the efficient methods summarized in Table 4. The comparison of the results of sound diagnosis is summarized in Table 5, and results are shown in Table 6. The following results are given in Table 6.

✂ **Method #1.** The highest classification accuracies were obtained based on the rules described in a previous study [8].

✂ **Method #2.** The highest CA results were obtained based on the following rules.

Rule 1: If the 8th value of Lyapunov exponent ($LPE_8 \geq 0.79$ and $(LPE_9) \leq 0.38$ then the heart is normal.

Rule 2: If $LPE_2 \leq 0.17$ and $(LPE_8) \leq 0.79$, then the heart disease is **VSD**.

Rule 3: If $LPE_4 \geq 0.17$, $LPE_6 \leq 0.39$, and $LPE_3 \leq 0.56$, then the heart disease is **MR**.

Rule 4: If $LPE_5 \geq 0.17$, $LPE_4 \geq 0.67$, and $LPE_3 \geq 0.37$, then the heart disease is **MS**.

Rule 5: If $LPE_7 \geq 0.54$, $LPE_3 \geq 0.29$, and $LPE_5 \geq 0.49$, then the heart disease is **AR**.

Rule 6: If $LPE_8 \geq 0.39$, $LPE_5 \geq 0.72$, and $LPE_2 \leq 0.68$, then the heart disease is **ASD**.

Table 4.

Efficient methods successfully used in diagnosing normal sounds from other common heart diseases

Method	Refs	Performance evaluation
# 1	[8]	The higher CA, achieved in this study, was 95.5%, 92.1%, 96.2% and 99.0% for diagnosing small ventricular septal defect (VSD), moderate VSD , large VSD and normal sounds, respectively.
# 2	[44]	A rule-based classification tree method proposed by this study achieved very high CA: 95.45% for diagnosing VSD , 100% for diagnosing normal, 100% for diagnosing aortic stenosis and 95.45% for diagnosing aortic insufficiency.
# 3	[45]	Artificial neural networks (ANNs) was reported to achieve the second-best score compared to the other methods in classifying the phonocardiogram recordings provided by the CinC Challenge.
# 4	[46]	Random forest, a meta-learning approach that uses multiple random decision trees as base learners and aggregates them to compute the final ensemble prediction, was successfully used in sound classification such as studies.
# 5	[47]	Tunable-Q wavelet transform approach proposed by this study, which yielded more successful diagnosing results for distinguishing septal defect from NM with an accuracy of 100% at the tenth level of decomposition for $Q = 6$.
# 6	[48]	the multi-level basis selection (MLBS) method proposed in this study, which achieved a higher specificity of 98.31% for diagnosing MR than other selection methods
# 7	[49]	The PCA-DHMM approach proposed in this study yielded more successful diagnosing results for detecting PS with an accuracy of 98.3% than other studies [50, 51]
# 8	[11]	The multi-support vector machine (M-SVM) method achieved very high classification accuracies: 96.88% for diagnosing AF, 93.94% for diagnosing MR, and 99.8% for diagnosing NM.

Table 5. Experimental sounds used to evaluate the performance

Data source	Period numbers of every type of heart disease/Patients						
	MR	MS	ASD	NM	AS	AR	VSD
sounds in subsection	769/10	439/5	315/7	1056/45	381/10	665/15	327/10
New sounds	156/3	132/2	82/2	183/8	126/3	153/4	70/3
Total sounds	925/13	571/7	397/9	1239/53	507/13	818/19	397/13

Rule 7: If $LPE_9 \geq 0.64$, $LPE_3 \geq 0.39$, and $LPE_7 \geq 0.21$, then the heart disease is **AS**.

Rule 8: If none of these conditions are met, the **HS** is undefined.

✠ **Method #3.** The most accurate results were obtained by the structure consisting of one input layer with 60 neurons, one hidden layer with 11 neurons and one output layer with five neurons.

✠ **Method #4.** The most accurate results were obtained by setting the number of features at each node, the number of trees and the maximum depth of trees to 1, 108, and 36, respectively.

✠ **Method #5.** The most accurate results were obtained by setting $Q = 3, 2, 5, 6, 2, 5$ and 3.

✠ **Method #6.** The most accurate results were obtained by setting the sample parameters to the values given in [10].

✠ **Method #7.** The highest **CA** was obtained by using the Euclidean metric in the distance calculation for the **KNN** classifier.

✠ **Method #8.** The accuracy of the results obtained with the **PCA-DHMM** method was the highest for the detection of **MR**, **MS**, **ASD**, **NM**, **AS**, **AR** and **VSD** by setting the p parameters to 3, 5, 8, 3, 7, 8 and 8 respectively.

✠ **Method #9.** The most accurate results were obtained for the diagnosis of **MR**, **MS**, **ASD**, **NM**, **AS**, **AR** and **VSD** at $Thv = 0.4, 0.3, 0.2, 0.2, 0.4, 0.1$ and 0.2, respectively.

The results in Table 6 support the following conclusions.

Table 6. Comparative analysis of eight different methods for the diagnosis of heart diseases summarized in Table 5

Method	MR			MS			ASD			NM			AS			AR			VSD		
	Se%	CA(%)	Sp(%)	Se%	CA(%)	Sp(%)	Se%	CA(%)	Sp(%)	Se%	CA(%)	Sp(%)	Se%	CA(%)	Sp(%)	Se%	CA(%)	Sp(%)	Se%	CA(%)	Sp(%)
#1	90.1	87.34	86.7	83.2	86.81	87.3	90.2	83.13	82.5	85.7	81.90	80.6	91.3	90.40	90.3	87.2	84.04	83.4	96.2	97.66	97.8
#2	88.6	85.93	85.3	86.1	89.72	90.2	79.8	82.10	82.3	96.1	98.93	99.9	98.3	91.95	96.2	85.1	86.97	83.6	87.5	87.19	82.1
#3	88.1	87.6	87.8	83.1	89.36	90.2	80.3	81.67	81.8	92.6	91.63	91.3	83.9	86.04	86.3	90.1	84.69	83.6	87.6	86.03	85.9
#4	89.7	91.64	92.1	85.2	83.52	83.3	86.3	87.49	87.6	93.7	91.61	90.9	90.1	87.05	86.7	85.2	82.21	81.6	90.8	91.63	91.7
#5	87.9	91.29	92.1	87.9	90.72	91.1	93.2	87.59	87.1	90.9	95.36	96.9	90.6	88.54	88.3	83.1	82.43	82.3	91.7	90.65	90.9
#6	93.6	95.30	95.7	88.1	83.78	83.2	83.6	84.79	84.9	90.2	86.77	85.6	87.3	86.31	86.2	87.2	82.29	81.3	89.3	85.90	85.6
#7	91.6	87.63	86.7	83.2	80.20	79.8	85.1	80.32	79.9	93.7	92.13	91.6	96.3	83.23	81.7	90.3	88.30	87.9	83.9	83.16	83.1
#8	83.1	86.75	87.6	89.3	87.18	86.9	86.1	85.17	85.1	90.1	90.91	91.2	85.9	89.66	90.1	83.1	80.93	80.5	83.7	81.39	81.2
This	100	99.43	99.3	99.2	98.93	98.9	99.6	99.13	99.1	100	99.85	99.8	98.8	98.62	98.6	100	99.67	99.6	100	99.91	99.9

(a) Although using method #2 to diagnose **NM** yielded a higher Sp than that of the proposed method, the CA was lower than that of the proposed method, partially due to the high Se achieved by the proposed method.

(b) For other sounds, the classification accuracies achieved the proposed method were all greater than those of the other methods listed in Table 6 .

Overall, the efficiency of the proposed method in diagnosing **MR**, **MS**, **ASD**, **NM**, **AS**, **AR** and **VSD** diseases was evaluated by comparison with the other efficient methods listed in Table 6.

Conclusion

A novel intelligent system was proposed for diagnosing heart diseases with high CA . The innovation of this approach is primarily reflected in: 1) the automatic extraction of secondary envelope-based frequency features; 2) the automatic determination of **PCA**-based diagnostic features γ_1 , γ_2 and γ_3 ; and 3) the determination of adjustable confidence regions corresponding to the χ^2 distribution. The confidence regions are obtained by calculating the Mahalanobis distance, which is adjusted by the desired confidence level β , and the results are used as the classification criteria for diagnosing heart diseases. The procedure for the implementation of the intelligent system involves three stages. Stage 1 describes the location and extraction of **STMHT**-based CS_1 and CS_2 . In stage 2, in the frequency domain, a novel method was first proposed to generate the envelopes CS_{1Fe} and CS_{2Fe} ; then, based on the Thv lines, FF is automatically extracted. Finally, based on **P-CA**, the first three principal components, γ_1 , γ_2 and γ_3 , which express 86.7% of the FF information, were determined and used as diagnostic features. In stage 3, the **GMM**-based objective function $f_{et}(\mathbf{x})$ with respect to the features $\mathbf{x} = [\gamma_1, \gamma_2, \gamma_3]$ and the parameters $[\pi_k, \mu_k, \Sigma_k]$, where $k = 1, 2, \dots, K$, was generated. Then, the χ^2 distribution for component k was determined by calculating the Mahalanobis distance from $\mathbf{x}$ to the class mean μ_k of component k , and the confidence region for component k was determined by adjusting the optimal confidence level β_k and used as the criterion (denoted as MDC_k) to diagnose a given **HS**. The performance evaluation was validated by sounds from online **HS** databases and clinical heart databases. The accuracy of the proposed method was compared to the accuracies of other well-known classifiers, and the highest classification accuracies of 99.43%, 98.93%, 99.13%, 99.85%, 98.62%, 99.67% and 99.91% in the detection of **MR**, **MS**, **ASD**, **NM**, **AS**, **AR** and **VSD** sounds were achieved by setting $\beta_k (k = 1, 2, \dots, 7)$ to 0.87, 0.65, 0.67, 0.65, 0.67, 0.79 and 0.87, respectively. Therefore, this proposed intelligent diagnosis system provides an efficient way to diagnose seven types of heart diseases. In addition, methods to manage the sounds (such as some **ASD** sounds)

when CS_1 and CS_2 cannot be segmented and extracted via the **STMHT** method will be explored in the future to characterize the physical meanings of the frequency components and to build a model of the secondary curve in the frequency domain.

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Abbreviations

HSs: Heart sounds; S_1 : First heart sound; S_2 : Second heart sound; **STMHT**: Short time modified Hilbert transform; (CS_1): First complex sound; (CS_2): Second complex sound; CS_{1FE} : Frequency envelope corresponding to (CS_1); CS_{2FE} : Frequency envelope corresponding to (CS_2); Thv : Threshold value; **PCA**: Principal component analysis; γ_1 : First principal component; γ_2 : Second principal component; γ_3 : Third principal component; **GMM**: Gaussian mixture model; $f_{et}(x)$: Objective function; χ^2 : Chi-squared distribution; μ_k : the k^{th} class mean; β_k : k^{th} confidence level;

Availability of data and materials

Not applicable

Ethics approval and consent to participate

This study protocol was approved by the local ethics committee of Nanyang Institute of Technology and the First peoples hospital of Nanyang, China. We followed data collection of WHO guidance on heart sound auscultation to perform this study.

Competing interests

The authors declare that they have no competing interests.

Consent for publication

Not applicable

Authors' contributions

Sun, Biqiang Zhang, He: collection, organizing, and review of the literature. Sun, Biqing Zhang and Huang: preparing the manuscript. Sun, Biqiang Zhang, Fan, Yan, Jiale Zhang and Chen: manuscript revision and modification. All authors read and approved the final manuscript.

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Figures

Figure 1

Flow chart of the proposed methodology.

Figure 2

The automatic extraction procedures for CS1 and CS2. A-B show the procedure for an example of a typical AR from the database in [23]. C-D show the procedure for an example of a typical normal sound from [24].

Figure 3

Example of feature definition and automatic extraction.

Figure 4

Examples of a typical normal sound and six types of typical heart disease sounds.

Figure 5

Box plot representation of FF for each type of heart disease. A shows the box plots for features from CS1. In addition, B represents the features from CS2.

Figure 6

The flow chart corresponding to the efficient feature generation procedure.

Figure 7

PCA results. A shows the Pareto chart of the variance by contribution of each principal component, B plots the scatter diagram of the first two components γ_1 and γ_2 , and C shows the scatter diagram of the first three components γ_1 , γ_2 and γ_3 .

Figure 8

Flow chart of the diagnostic determination and 3-dimensional surface classifier results.

Figure 9

The achieved accuracies corresponding to classifying the heart sounds described in subsection by setting β form 0.63 to 0.97 with a step of 0.02.