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Heart sound signal classification using fast independent component analysis

Yücel KOÇYİĞİT*
Department of Electrical and Electronics Engineering, Engineering Faculty, Celal Bayar University, Manisa, Turkey

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Abstract: The analysis of heart sound signals is a basic method for heart examination. It may indicate the presence of heart disorders and provide clinical information in the diagnostic process. In this study, a novel feature dimension reduction method based on independent component analysis (ICA) has been proposed for the classification of fourteen different heart sound types; the method was compared with principal component analysis. The feature vectors are classified by support vector machines, linear discriminant analysis, and naive Bayes (NB) classifiers using 10-fold cross validation. The ICA combined with NB achieves the highest average performance with a sensitivity of 98.53%, specificity of 99.89%, g-means of 99.21%, and accuracy of 99.79%.

Key words: Heart sound classification, wavelet transform, principal component analysis, independent component analysis, support vector machines, linear discriminant analysis, naive Bayes

1. Introduction

The heart sound is produced by the mechanical function of the heart, blood flow, and valve movements during heart contraction and relaxation. The heart sound signals provide vital clinical information in the diagnostic process of heart disorders. Traditionally, heart auscultation was a screening method for the early diagnosis of heart diseases, but it was limited to human hearing. Thus, skilled physicians were required to diagnose the heart sounds more accurately. Phonocardiography was developed to record the heart sound signals with a conventional sound sensor on the chest that can supply more information about the heart condition by recording and analyzing heart sound signal. Numerous methods of automatic analysis and diagnosis based on heart sounds can be employed with the fast development of signal processing and machine learning technologies.

In recent years, a lot of researchers have attempted to automate the heart sound diagnosis, which is regarded as a promising topic. Some researchers have focused on studies of feature extraction and classification of heart sounds. A number of attempts to extract features from heart sounds by using time-frequency methods have been reported in the literature [1–10].

Ölmez and Dokur [2] classified heart sound signals into seven types using the grow and learn (GAL) network with a total performance of 99%. Andrisevic et al. [3] extracted the features from two types of heart sound signals by using wavelet transform (WT) and principal component analysis (PCA) and classified them by a neural network with a specificity of 70.5% and a sensitivity of 64.7%. Gupta et al. [4] obtained the features by using WT. Classification of three types of heart sound signals was achieved using GAL and Multilayer perceptron/back-propagation neural networks with a total performance of 96.52 and 97.02% respectively. Uguz

*Correspondence: yucel.kocyigit@cbu.edu.tr

et al. [5] obtained the features from two types of heart sound signals by using short-time Fourier transform and WT and classified them by a hidden Markov model with a specificity of 92% and a sensitivity of 97%. Dokur and Ölmez [6] determined the features by using discrete WT (DWT) and performed the classification by using an incremental self-organizing map (ISOM). Classification performance of the ISOM for fourteen different heart sound signals was obtained as 95%. Saracoğlu [7] determined the features from two types of heart sound signals by using discrete Fourier transform. After reducing the dimension of the features by using PCA, classification of heart sound signals was performed by a discrete hidden Markov model with a specificity of 93.3% and a sensitivity of 70.3%. Uğuz [8] determined the features from three types of heart sound signals by using DWT. In order to reduce the dimension of the features, Shannon entropy was performed and heart sound signals were classified by an adaptive neuro fuzzy inference system (ANFIS) with a specificity of 95.24% and a sensitivity of 100%. Safara et al. [9] employed wavelet packet transform for heart sound analysis. After calculating the entropy for deriving feature vectors, the classification was performed for five types of heart sounds by Bayes net with an accuracy of 96.94%. Patidar and Pachori [10] determined the features by using the constrained tunable-Q WT (TQWT), time-domain representation, and Fourier–Bessel expansion of heart sound signals. The adaptively selected features for 21 heart sound types, classified by the least squares support vector machine (SVM) classifier together with the radial basis kernel function, provided significant classification accuracy of 94.01%.

In the present study, a novel feature dimension reduction method based on ICA was developed for the classification of fourteen different heart sound types with a feature extraction method based on wavelet coefficients. The study primarily consists of three stages: feature extraction, dimension reduction, and classification. The heart sound is considered a nonstationary signal. It is very difficult to analyze this signal in the time domain. Therefore, the obtained heart sound signal is decomposed into its subbands using DWT at the feature extraction stage. In order to keep the decision-making process simple and fast without sacrificing the performance, high-dimensional feature vectors are subjected to dimension reduction operations, namely PCA and ICA, to reduce the dimension of the feature vectors and to choose the most significant features obtained with DWT. At the last stage, classification of fourteen different heart sound types is performed by linear discriminant analysis (LDA), SVMs, and naive Bayes (NB) classifiers.

2. Methods

In this section, the methods used for feature extraction of heart sounds by DWT, dimension reduction of feature vectors, and classification stages are explained.

2.1. Feature extraction by DWT

Unlike the Fourier transform, the WT presents various resolutions by decomposing the signal into its frequency bands. The DWT supplies a compact representation of a signal in time and frequency that is obtained from the continuous WT. The DWT can be carried out using a fast and pyramidal algorithm related to filter banks [11]. Figure 1 shows the DWT decomposition using filter banks.

Each subband includes half of the number of samples of the previous upper frequency subband. In the pyramidal algorithm, the signal is analyzed by decomposing the signal into detail and approximation information at various frequency bands with various resolutions. In the next level, the approximation is again decomposed using the identical wavelet decomposition process.

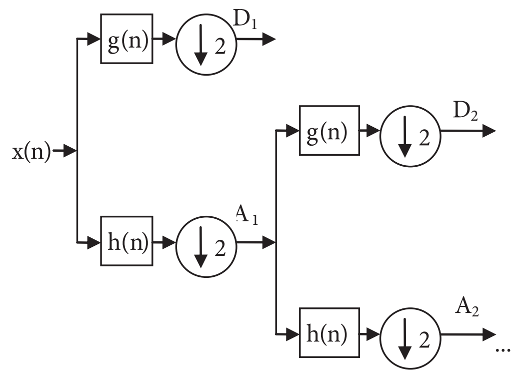

Figure 1. DWT decomposition using filter banks. D and A denote the detail and approximation coefficients, respectively. h and g are low-pass and high-pass filters.

This is performed by sequential low-pass and high-pass filtering of the time domain signal using the following equations:

$$y_{low}\left(k\right) = \sum_{n} x\left(n\right) h\left(2k - n\right) \tag{1}$$

$$y_{high}\left(k\right) = \sum_{n} x\left(n\right) g\left(2k - n\right) \tag{2}$$

where $y_{low}(k)$ and $y_{high}(k)$ are the outputs of the low-pass (h) and high-pass (g) filters, respectively, after subsampling by two. Because of the down-sampling, the total number of coefficients is precisely the same as the number of signal points.

While the approximation coefficients are presented by the outputs of the $h(n)$ filters, the detail coefficients are presented by the outputs of the $g(n)$ filters. For fourteen types of heart sound signals, the features were acquired by WT. After carrying out DWT, the 0–172 Hz frequency subband, which consists of 0–86 Hz for the approximation coefficients and 87–172 Hz for the detail coefficients, accounted for the features. Considering the 44100 Hz sampling frequency and using the eighteenth-order symlet mother wavelet [6], it was observed that the approximation and detail coefficients at the eighth decomposition level represent the heart sound signals better.

2.2. Dimension reduction

In the present study, two dimension reduction techniques were used: PCA and ICA. Based on the classification performance, the best dimension reduction method was identified.

2.2.1. PCA

PCA is the most widely used linear dimension reduction method that seeks to project the data into the directions of highest variability [12]. Principal components are the basis vectors of directions in decreasing order of variability. The first principal component is the direction of highest variability in the data. The second principal component is the next orthogonal (uncorrelated) direction of highest variability, and so on.

In order to compute the principal components, the eigenvalue problem $\mathrm{E}^T(\mathrm{XX}^T)\mathrm{E} = \Lambda$ is solved where X is a matrix whose columns consist of training samples, E is a matrix of eigenvectors, and Λ is the corresponding diagonal matrix of eigenvalues.

The transform of data, $\mathrm{P}_p = \mathrm{E}_p^T \mathrm{X}$, from the original n-dimensional space to p-dimensional subspace presented by p principal eigenvectors is optimal in the mean squared error sense. Therefore, the n dimension of data matrix X is reduced to the p dimension of the new data matrix P with minimum error.

2.2.2. ICA

ICA can be used as a feature extraction and dimension reduction method [13,14]. The ICA model assumes that the observed signals x, which are the DWT coefficients in a subband, consist of linearly mixed source signals [15,16]. The ICA model is given by:

$$x(t) = a_1 s_1 + a_2 s_2 + \ldots + a_N s_N = As(t) \tag{3}$$

where x is an observed M-dimensional vector $\left(x(t) = [x_1(t), x_2(t), \ldots, x_M(t)]^T\right)$, s is an N-dimensional source vector $\left(s(t) = [s_1(t), s_2(t), \ldots, s_N(t)]^T\right)$, and A denotes the weight matrix with components a_{ij}.

The aim of ICA is to discover the independent source vectors by estimating for the components of matrix A from the observed mixed vector x. This aim is the same as to discover a decomposing matrix W that satisfies the following:

$$\hat{s} = Wx \tag{4}$$

where $\hat{s}$ is the estimation of s and W is the inverse of A.

In ICA there are two rather standard preprocessing steps: centering and whitening [15]. First, in order to provide that the observed signals have zero means, the mean of the data is generally subtracted to center the data. In the second step, in order that the observed signals are uncorrelated and have unit variance, the data is whitened.

After the preprocessing steps, the ICA discovers a decomposing matrix W that minimizes the statistical dependencies between the estimated sources. Depending on the data to be analyzed, there are several independence criteria such as kurtosis maximization or minimization, maximization of non-Gaussianity, negentropy, and the FastICA algorithm. For the ICA in the study, the FastICA software package (FastICA MATLAB Package online at http://www.cis.hut.fi/projects/ica/fastica) for MATLAB was applied for the computation of independent components [17].

After applying the independence criteria, the output was calculated by multiplying with the whitened data, and then, this result was multiplied with the transpose of the input data.

2.3. Classification process

In the present study, the comparative performances of SVMs, LDA, and NB classifiers were examined for the classification of heart sounds.

2.3.1. SVMs

The SVM based classifier is one of the widely utilized classifiers in biomedical studies due to its learning and generalization ability for high-dimensional data sets. For the SVM classifier, a two-group data set can always be separated by a hyper-plane, provided that a suitable nonlinear mapping to a sufficiently high dimension is found [18,19]. Quadratics, polynomials, or other kernel functions may be used for achieving this. In addition, during the construction of SVMs, one of the major tasks is to find separating hyperplane(s) with the largest possible margin, thereby usually resulting in a classifier with better generalization ability. In the present study, to realize a soft margin, the quadratic kernel was used as a kernel function.

Due to the fact that SVM suits for only two-class classification, multi-SVM classifiers with one-against-all strategy by Cody Neuburger (Florida Atlantic University, http://www.mathworks.com/matlabcentral/fileexchange/39352-multi-class-svm) was chosen for the classification of heart sound signals. The one-against-all strategy consists of the construction of one SVM per class, which is trained to separate the samples of one class from the samples of all remaining classes. Generally, classification of an unknown pattern is carried out referring to the maximum output among all SVMs.

2.3.2. LDA

LDA attempts to discover one hyperplane in order to divide one group from another for a two-class classification problem [19]. The performance of LDA is affected by a variety of parameters, including the distance metric. For the present study, the Euclidean distance metric was selected because of its simplicity. Since the classes were more than two in this study, majority voting was used for decision making.

2.3.3. NB classifier

The NB classifier is an independent model that is a simple probabilistic classifier based on applying Bayes theorem with strong independence assumptions [20]. The classifier assumes that the presence or absence of a particular feature of a class is unrelated to the presence or absence of any other feature. Because of this fact, even if these features depend on each other, the classifier considers all the properties to independently contribute to the probability. NB is advantageous for small-size training samples to calculate the mean and variance of the feature vectors necessary for classification.

2.3.4. Performance evaluation of the classifiers

Ten-fold cross validation was used as performance evaluation. The data set was divided into ten subsets. Each time, one subset was utilized for testing and for the classifier performance evaluation while the remaining nine were utilized for training. As shown in Figure 2, the cross-validation results yielded a confusion matrix. There are four possible outcomes; if a positive sample is classified correctly, it is counted as a true positive (TP), otherwise a false negative (FN); if the negative sample is classified correctly, it is counted as a true negative (TN), otherwise a false positive (FP) [19].

		Predicted class	
		Predicted positives	Predicted negatives
Real class	Real positives	TP	FN
	Real negatives	FP	TN

Figure 2. Confusion matrix.

From the confusion matrix, four indicators of performance can be calculated by:

1) Sensitivity: an indicator of the classifier's ability to discover the true class.

   Sensitivity = TP/(TP+FN)

2) Specificity: an indicator of the classifier's ability to define other classes.

   Specificity = TN/(TN+FP)

3) G-means: an indicator of classification performance combining the sensitivity and specificity into a unique measure named the geometric mean.

   $\text{G means} = \sqrt{\text{sensitivity} * \text{specificity}}$

4) Accuracy: an indicator of success of the classification performance.

   $\text{Accuracy} = (\text{TP}+\text{TN}) \,/\, (\text{TP}+\text{TN}+\text{FP}+\text{FN})$

3. Results

In the study, the feature vectors were obtained by analyzing fourteen different heart sound signals: opening snap (OPS), aortic stenosis (AST), midsystolic click and late systolic murmur (MSC + LSM), normal FCG (NFC), third heart sound (S3), fourth heart sound (S4), ventricular septal defect (VSD), patent ductus arteriosus (PDA), atrial septal defect (ASD), mitral stenosis (MST), mitral regurgitation (MR), pulmonic stenosis (PS), hypertrophic cardiomyopathy (HCM), and pericardial friction rub (PFR). Figure 3 depicts fourteen different heart sound signals analyzed in the study. Simulations were performed using MATLAB.

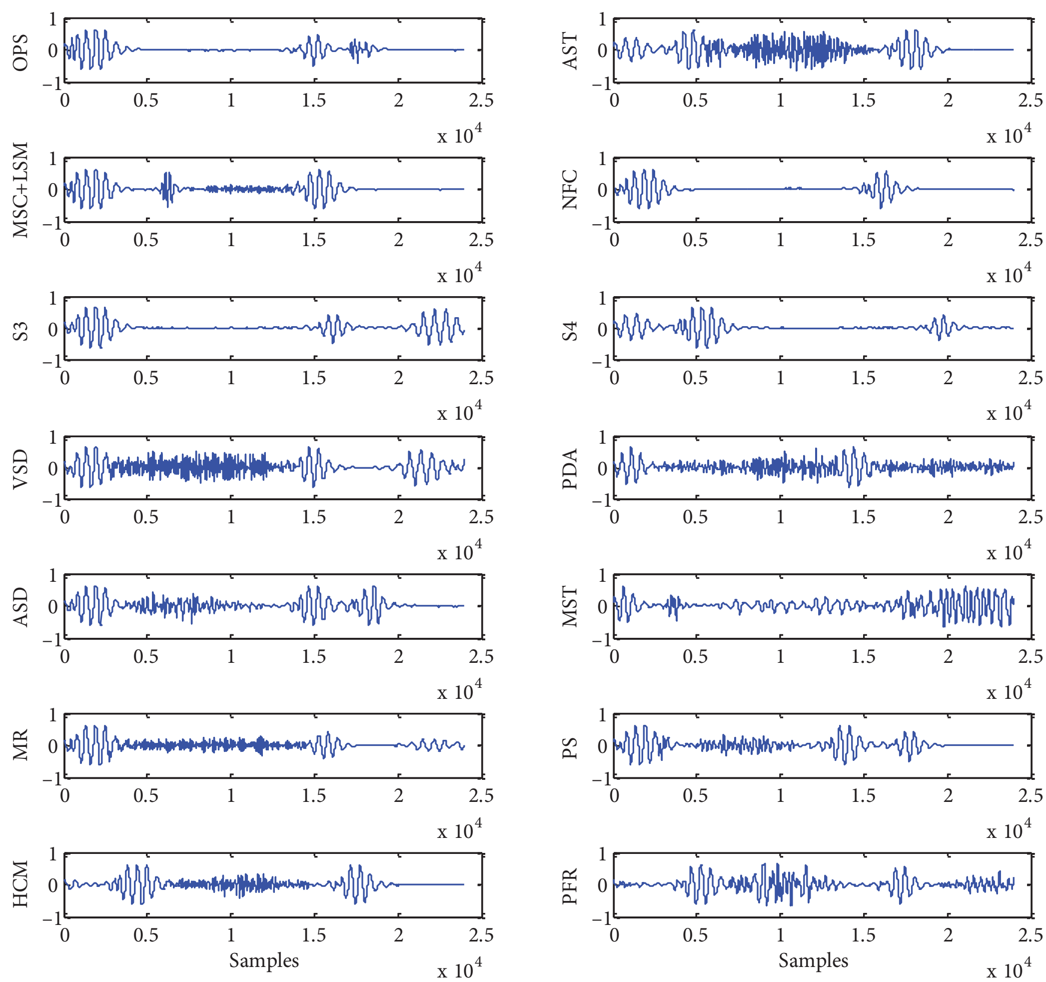

Figure 3. One period of fourteen different heart sound signals.

Heart sound signals were obtained from the students' training CD of the book [6,21,22], which were formed using an electronic stethoscope. They were sampled at 44,100 Hz frequency and analyzed within windows that contain 24,000 discrete data. Each heart sound type record included 17 periods of heart sounds. Since the quantities of the heart sound signals may be rather different, a normalization process is required to standardize all the signals to the same level. Thus, the mean value of the heart sound signal is set to zero and peak-to-peak magnitudes of the windowed heart sound signals are normalized to 1 Volt. The data set for the classification is formed by 238 heart sound periods of 14 different types.

In the present study, DWT was applied to extract features from the heart sound signals. In DWT, choosing an appropriate mother wavelet and defining the decomposition level number are very important to present the required frequencies of the signal for classification. Since the eighteenth-order symlet mother wavelet for feature extraction was suggested in [6], the DWT was computed on each of the heart sounds using that mother wavelet. In the DWT, determining the percentage of energy corresponding to the approximation and detail coefficients, and also defining the dominant frequency components of the heart sound signals, the eighth-level approximation and detail coefficients together were applied for dimension reduction and classification. The feature vectors consisted of 128 approximation coefficients and 128 detail coefficients (a total of 256 features) after carrying out the DWT. Figure 4 and Figure 5 show the eighth-level approximation and detail coefficients for the fourteen different heart sound signals, respectively.

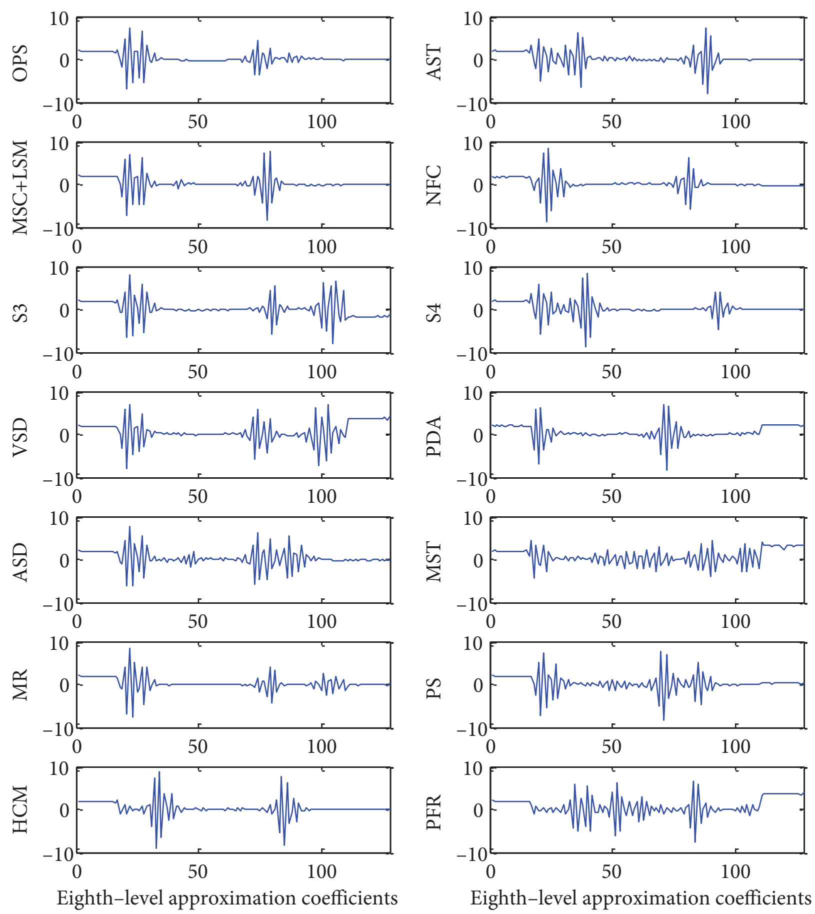

Figure 4. The eighth-level approximation coefficients for fourteen different heart sound signals following DWT.

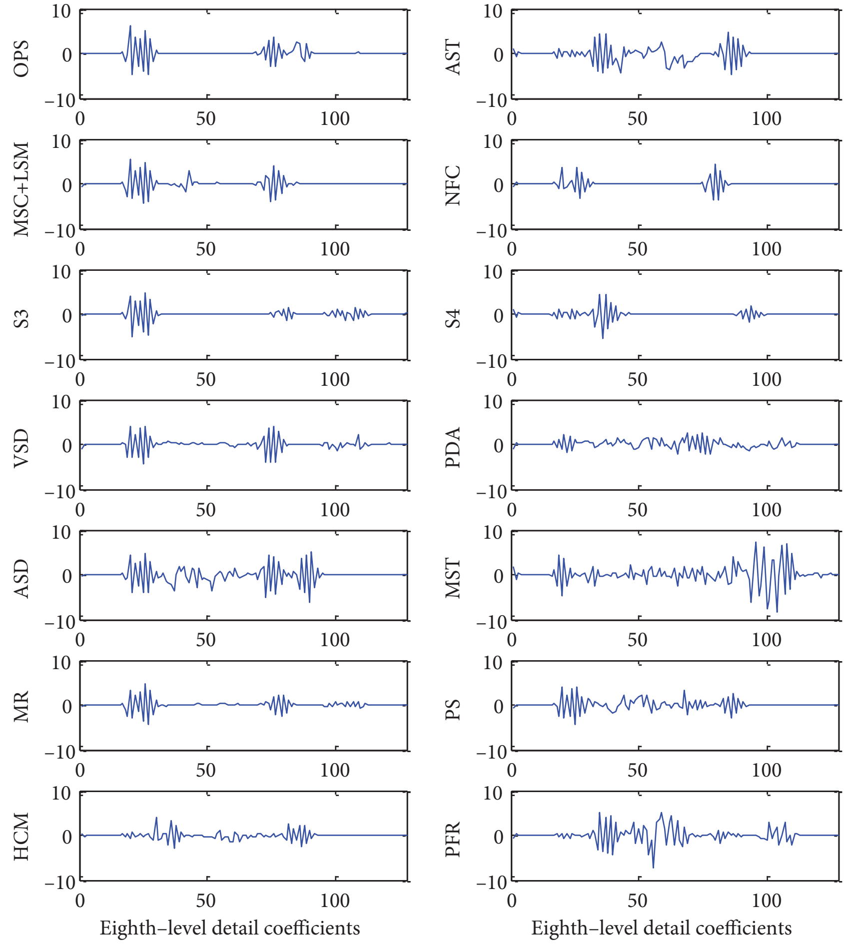

Figure 5. The eighth-level detail coefficients for fourteen different heart sound signals following DWT.

While DWT provides better representation of heart sound signals in the time-frequency domain and extracts vital parameters of heart sounds, ICA and PCA reduce the dimension of the feature vectors and choose the most significant features obtained with DWT [14,16,23]. For ICA and PCA, using the cumulative percent variance criterion, which is a measure of the percent variance captured by the first k components, the most appropriate k components can be selected from all of the components to represent the data. Since greater than 99% of the cumulative percent variance was selected, the number k of the independent and principal components was determined as 80.

The feature vectors with reduced dimension were subjected to classification by LDA, SVM, and NB using 10-fold cross validation. Ten-fold cross-validation enables to get unbiased training data in order to obtain stable classification results. Table 1 and Table 2 show the details of the classification results for the feature vectors extracted by DWT + ICA combination for one analysis. As seen in Table 1, there are 19 patterns classified as S3 when tested with NB. Out of that, only 17 patterns are TP. The remaining two patterns are wrongly classified as S3 or FP. These patterns are actually NFC. Out of 17 OPS true targets, there is one OPS pattern classified as PDA or FN. With NB, it is concluded that NFC and HCM, AST and S3 are the highest wrongly classified heart sound types for FN and FP, respectively, whereas the other heart sounds are the highest correctly classified types as TP (100%). We calculated the sensitivity, specificity, g-means, and accuracy of NB; the test results of each heart sound are summarized in Table 2 for one analysis. The accuracy of the classifier architecture with

ICA in detecting each heart sound is more than 99%, which suggests that the classifier architecture with ICA performs well.

Table 1. Classification results of the NB classifier for the feature vectors extracted by the DWT + ICA combination for one analysis.

	Target	Predicted results of naive Bayes for test data													
		OPS	AST	MSC+LSM	NFC	S3	S4	VSD	PDA	ASD	MST	MR	PS	HCM	PFR
Real heart sounds	OPS	16	0	0	0	0	0	0	1	0	0	0	0	0	0
	AST	0	17	0	0	0	0	0	0	0	0	0	0	0	0
	MSC+LSM	0	0	17	0	0	0	0	0	0	0	0	0	0	0
	NFC	0	0	0	15	2	0	0	0	0	0	0	0	0	0
	S3	0	0	0	0	17	0	0	0	0	0	0	0	0	0
	S4	0	0	0	0	0	17	0	0	0	0	0	0	0	0
	VSD	0	0	0	0	0	0	17	0	0	0	0	0	0	0
	PDA	0	0	0	0	0	0	0	17	0	0	0	0	0	0
	ASD	0	0	0	0	0	0	0	0	17	0	0	0	0	0
	MST	0	0	0	0	0	0	0	0	0	17	0	0	0	0
	MR	0	0	0	0	0	0	0	0	0	0	17	0	0	0
	PS	0	0	0	0	0	0	0	0	0	0	0	17	0	0
	HCM	0	2	0	0	0	0	0	0	0	0	0	0	15	0
	PFR	0	0	0	0	0	0	0	0	0	0	0	0	0	17

Table 2. Evaluation of test results of each heart sound by using the ICA + NB combination for one analysis.

	TP	FP	FN	TN	Sensitivity (%)	Specificity (%)	G-means (%)	Accuracy (%)
OPS	16	0	1	221	94.12	100	97.01	99.58
AST	17	2	0	219	100	99.10	99.55	99.16
MSC+LSM	17	0	0	221	100	100	100	100
NFC	15	0	2	221	88.24	100	93.93	99.16
S3	17	2	0	219	100	99.10	99.55	99.16
S4	17	0	0	221	100	100	100	100
VSD	17	0	0	221	100	100	100	100
PDA	17	1	0	220	100	99.55	99.77	99.58
ASD	17	0	0	221	100	100	100	100
MST	17	0	0	221	100	100	100	100
MR	17	0	0	221	100	100	100	100
PS	17	0	0	221	100	100	100	100
HCM	15	0	2	221	88.24	100	93.93	99.16
PFR	17	0	0	221	100	100	100	100

The performance of each classifier is obtained by taking the average of the 10-folds' performances for each analysis. In Table 3, the results for overall average accuracy and standard deviation evaluated over all ten analyses are presented.

Table 3. Overall average accuracy and standard deviation evaluated over all ten analyses.

		Sensitivity (%)	Specificity (%)	G-means (%)	Accuracy (%)
ICA	LDA	88.07 ± 1.05	99.08 ± 0.08	93.41 ± 0.29	98.30 ± 0.15
	SVM	86.93 ± 0.98	98.99 ± 0.08	92.77 ± 0.27	98.13 ± 0.14
	NB	98.53 ± 0.34	99.89 ± 0.03	99.21 ± 0.09	$\mathbf{99.79 \pm 0.05}$
PCA	LDA	86.93 ± 1.40	98.99 ± 0.11	92.77 ± 0.39	98.13 ± 0.20
	SVM	64.83 ± 0.80	97.29 ± 0.06	79.42 ± 0.22	94.98 ± 0.11
	NB	93.49 ± 0.57	99.50 ± 0.04	96.45 ± 0.16	99.07 ± 0.08

It can be seen from Table 3 that classification performances with the features determined by ICA result in higher sensitivity and accuracy than the sensitivity and accuracy obtained by PCA. ICA combined with NB achieved the highest average performance with a sensitivity of 98.53%, specificity of 99.89%, g-means of 99.21%, and accuracy of 99.79%. In addition, there was a tiny standard deviation, pointing to a more stable classifier performance by the classifier architecture with ICA.

4. Discussion and conclusions

The objective of the present study was to reveal the advantage of the ICA method with DWT for a novel feature extraction and reduction instead of using PCA for the classification of fourteen different heart sound types, which was supported by the results. Although the hidden complexities in the heart sound signals are apparent more noticeably in the frequency domain than in the conventional time domain, the DWT representation of the heart sound signal was scattered. Therefore, a few coefficients of DWT include more information [24]. When the dimension reduction method was applied on a scattered representation, the features would enclose a compact representation [16,23]. Therefore, classifying these features by automated classifiers would result in higher accuracy. The PCA and ICA methods, which are frequently used for dimension reduction in the literature, were used to reduce the dimension of feature vectors composed of DWT coefficients.

In the present study it was experimentally shown that both dimension reduction methods have generated high accuracies with the classifiers. For example, while the approach of PCA application yielded 99.07% accuracy using NB, the approach of ICA gave the highest performance with 99.79% accuracy using NB. However, according to Table 3, it should be noted that the sensitivity, specificity, and g-means of ICA with all the classifiers, in particular with the SVM, have higher performances than those of PCA.

"Since ICA aims to transform the original features into new features that are statistically independent of each other as much as possible, the ICA transformation is likely to fit well with the NB model and its independent assumption [25,26]". Thus, the developed approach demonstrates a more stable classifier performance and it can be employed in automatic auscultation equipment since it yields good classification accuracies for heart sound analysis.

It was expected that SVM with the quadratic kernel function would be more successful than LDA because

Table 4. Statistical performance values of various methods used to classify heart sounds.

Classifiers	# of HS types	Sensitivity (%)	Specificity (%)	Accuracy (%)
GAL Network [2]	7	-	-	99
WT-PCA-Neural Network [3]	2	64.7	70.5	-
WT-GAL/MLP-BP [4]	3	-	-	96.52/97.02
STFT/WT-Hidden Markov [5]	2	97	92	-
DWT-ISOM [6]	14	-	-	95
DFT-PCA-Hidden Markov [7]	2	70.3	93.3	-
DWT-Shannon Entropy-ANFIS [8]	3	100	95.24	-
WPT-Entropy-Bayes Net [9]	5	-	-	96.24
Tunable Q WT/Time Domain/ Fourier Bessel-Least Squares SVM [10]	21	-	-	94.01
Proposed Method	14	99.89	98.53	99.79

GAL: grow and learn, WT: wavelet transform, PCA: principal component analysis, MLP-BP: multilayer perceptron–back-propagation, STFT: short-time Fourier transform, DWT: discrete wavelet transform, ISOM: incremental self-organizing map, DFT: discrete Fourier transform, ANFIS: adaptive neuro fuzzy inference system, WPT: wavelet packet transform.

of the soft margin. However, the results were on the contrary for PCA and ICA. In the experiments the SVM performance was the worst.

On the other hand, the present study and others are not easily comparable because their aims are different (e.g., the types and number of heart sound signals) and the data sets used are not standard. Table 4 shows the statistical outcomes of several studies in this field. It can be observed that many studies have less than 5 types of heart sound signals for classification. Thus, it is argued that this study is more comprehensive. Moreover, the number of heart sound signals is relatively higher as is the total accuracy.

The study only focused on the classification of heart sound signals by using dimension reduction methods PCA and ICA. When the segmentation of each heart sound cycle is not correctly established, the features will be negatively affected and the classifiers will not give accurate results. Hence, employing WT for the feature extraction and segmentation of heart sounds enables better examination of the features by increasing the resolution in both time and frequency, and consequently supports good results by using ICA.

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