



Original Article

A hybrid particle swarm optimization-SVM classification for automatic cardiac auscultation

Prasertsak Charoen^{1*}, Waree Kongprawechnon¹, and Kanokvate Tungpimolrut²

¹ *Sirindhorn International Institute of Technology,
Thammasat University, Khlong Luang, Pathum Thani, 12121 Thailand*

² *National Electronics and Computer Technology Center,
Thailand Science Park, Khlong Luang, Pathum Thani, 12120 Thailand*

Received: 10 November 2015; Revised: 29 March 2016; Accepted: 8 May 2016

Abstract

Cardiac auscultation is a method for a doctor to listen to heart sounds, using a stethoscope, for examining the condition of the heart. Automatic cardiac auscultation with machine learning is a promising technique to classify heart conditions without need of doctors or expertise. In this paper, we develop a classification model based on support vector machine (SVM) and particle swarm optimization (PSO) for an automatic cardiac auscultation system. The model consists of two parts: heart sound signal processing part and a proposed PSO for weighted SVM (WSVM) classifier part. In this method, the PSO takes into account the degree of importance for each feature extracted from wavelet packet (WP) decomposition. Then, by using principle component analysis (PCA), the features can be selected. The PSO technique is used to assign diverse weights to different features for the WSVM classifier. Experimental results show that both continuous and binary PSO-WSVM models achieve better classification accuracy on the heart sound samples, by reducing system false negatives (FNs), compared to traditional SVM and genetic algorithm (GA) based SVM.

Keywords: support vector machines, cardiac auscultation, particle swarm optimization, machine learning

1. Introduction

In recent years, surveys have shown an increasing trend for cardiovascular disease, which is the leading cause of death for people around the world (Lloyd *et al.*, 2007; Sekar *et al.*, 2011). However, the percentage of death caused by heart disease can be reduced, if we can detect the condition and properly treat the patients in an early state before the disease becomes fatal (World Health Organization [WHO], 2008). The mechanical operation of the heart and cardiovascular system, including pathology and physiology information, can be analyzed from the heart sound itself using the

auscultation technique. By using this technique, we can efficiently detect cardiac disorder with low cost. Unfortunately, traditional heart auscultation required experienced physicians and dependent on their ear sensitivity. Also, the availability of such an expert is limited, especially in local clinics in suburban areas (Clark, 2012).

Nowadays, artificial intelligence research in the biomedical field has become increasingly popular due to its capabilities in dealing with real world medical problems. Yuenyong (2009) had proposed automatic heart sound analysis using pattern recognition neural network (NN). In his work, electrocardiography (ECG) signal is used as a reference signal for segmentation of heart sounds. However, it is difficult to identify and segment some of abnormal heard sounds, where the signals become severely corrupted. To avoid segmentation of the heart sound, Yuenyong (2011) presented a

* Corresponding author.

Email address: prasertsak@siit.tu.ac.th

framework for automatic heart sound analysis based on auto-correlation of envelope signal to find length of cardiac cycle. He used multi-layer feedforward NN with back propagation (FFBP) to classify abnormal heart sounds from normal one. Phatiwuttipat (2011) extended the work by introduction of support vector machine (SVM) and replacing NN for cardiac auscultation classification. It was concluded that SVM with radial basis function (RBF) had better performance in term of accuracy and computational time than FFBP used in Yuenyong (2011).

By substitution of NN with SVM (Phatiwuttipat, 2011), each heart sound feature is treated as equal quality, as seen by the SVM classification. However, some of the heart sound features create more impact than others, which relate to the performance of the classifier. In this paper, we developed a weighted SVM classification system for heart auscultation using optimization techniques to achieve an optimum set of weighted features. Then, the weighted features will be used for training the SVM classifier, in which a higher accuracy can be obtained. The aim of the proposed method is to reduced time and difficulty for patients in rural areas where no major hospital is easily accessible.

This paper is organized as follows. In Section II, overview of methodology and the proposed method are presented. The experimental results, obtained with actual heart sound signals and discussion are given in Section III. Finally, conclusion and future work are drawn in Section IV.

2. Materials and Methods

Auscultation consists of two parts: heart sound acquisition and heart sound analysis. In heart sound acquisition, a stethoscope is placed on the appropriate location on a patient's chest. The right amount of force is carefully applied to capture the heart sound. The second part, heart sound analysis, is used to identify whether the acquired heart sound is a healthy or diseased heart condition. Healthy adult heart sounds consist of mainly two events: the first heart sound (S1) and the second heart sound (S2), which are referred to as fundamental heart sound (FHS). The interval between the beginning of S1 and the beginning of the next S1 is a complete cardiac cycle of a single heartbeat, where systole is the interval between the ends of S1 and the commencement of the same cycles S2, and diastole is the interval between the ends of S2 and the commencement of the next cycles S1 (Yuenyong, 2011). However, in an abnormal heart, the cardiac cycle will present extra components that are not in the FHS. Those extra components can be classified into two types: extra heart sounds and murmur sounds. The second type, murmur heart sound, occurs when turbulent blood flows through a blocked (stenosis) valve, or backward through a leaking (regurgitation) valve. Those murmur events distort the FHS waveform, where the sounds can be heard in both systole and diastole. As a result, the FHS cannot be precisely determined. Overall block diagram of the proposed system is shown in Figure 1, which consists of data collection,

preprocessing, feature extraction, feature selection, classification, and weighting factor optimization.

2.1 Data collection and preprocessing

The input heart sound consists of digitized heart sound, acquired from Texas heart institute (Robert & Wilson, 2006). Heart sounds are labeled according to their conditions: normal heart or abnormal heart. In the preprocessing phase, the period of each heart cycle will be equalized and resampled at a rate of 4 kHz. Noise cancellation is performed using 5-level discrete wavelet transform (DWT) via soft threshold with Daubechies-6 wavelet family as suggested by (Phatiwuttipat, 2011). Finally, each heart sound x is normalized to have zero mean and unity variance using Equation (1):

$$\hat{x} = \frac{(x-\mu)}{\sigma}$$

where \hat{x} is the final preprocessed heart sound signal.

2.2 Feature extraction

In this work, we adapt feature extraction based on the wavelet packet (WP) technique since heart sounds are non-stationary signals, which are not well suited for a traditional Fourier based technique. The WP-based technique can retain most of the time-frequency information in the signal for multi-resolution decomposition, It yield superior performance at characterizing local time and a segregated piecewise

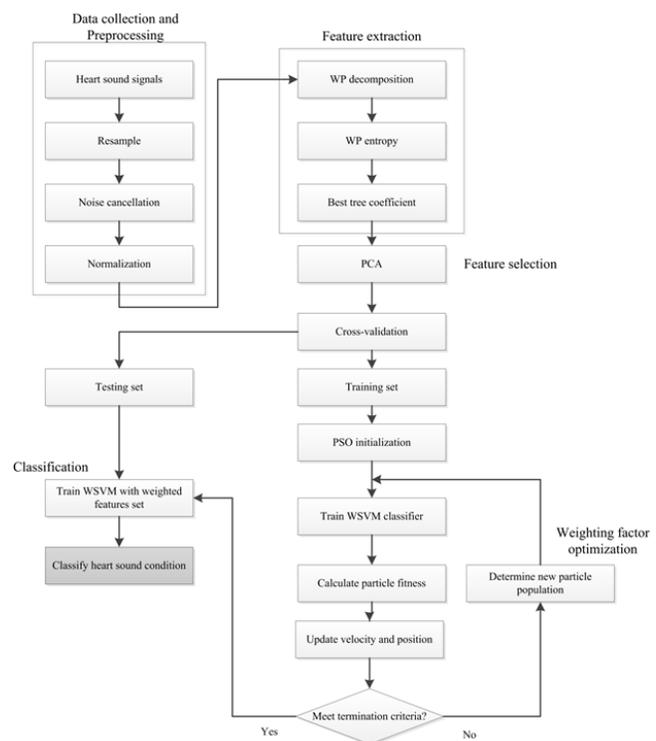


Figure 1. Overall block diagram of the proposed system.

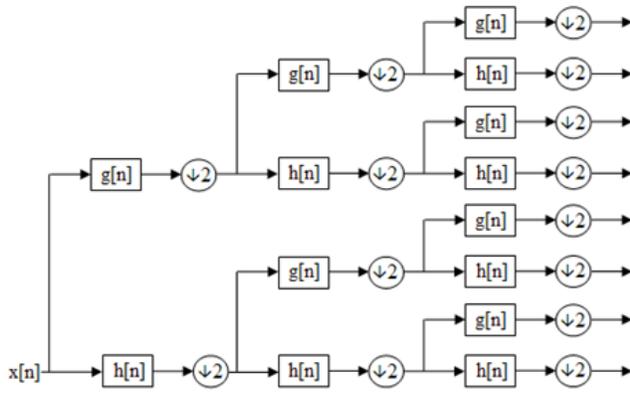


Figure 2. Wavelet packet decomposition structure.

frequency representation for each decomposition level, to improve frequency resolution, the higher-order Daubechies family wavelet is applied to extract features from the heart sound signal. In Figure 2, WP decomposition is shown such that the results of high pass $g[n]$ and low pass $h[n]$ filter with a factor 2 decimation are achieved for signal approximation and detail coefficients.

A non-normalized Shannon’s entropy criterion is used to evaluate each sub-band energy after WP decomposition as follows:

$$E(t) = -\left| \hat{x}(t) \right| \cdot \log \left| \hat{x}(t) \right| \quad (2)$$

where $\hat{x}(t)$ is the preprocessed heart sound signal and $E(t)$ is the Shannon’s entropy representation. Noise and disturbance are attenuated by the logarithmic term while allowing greater entropy weight for the signal intensity. We select 6-level decomposition on Daubechies-3 mother wavelet function to use with the heart sound signal as verified in Brechet (2007). Energy retention (99%) is selected to obtain the best-basis feature of 96% of compression rate, approaching hierarchically on the decomposition indices. Total feature outputs from the 2-channel filter banks can be found as in Equation (3):

$$k = \sum_{i=1}^n 2^i, n = 6 \quad (3)$$

where k is the total feature output after WP decomposition. As a result, 126 final output features are acquired from the piecewise components on the time-frequency plane.

2.3 Feature selection

In this work, we use the linear transformation method, principle component analysis (PCA), to eliminate insignificant feature sets. By using an orthogonal transformation to convert a set of possibly correlated features into a set of values of linearly uncorrelated features, only highly relevant

features are selected and thus, the dimension feature space is reduced, to be put into the classification. To describe the PCA feature selection method, we define the training set such that the magnitude of their eigenvalues are arranged in descending order from top to bottom as follows:

$$Z = \frac{1}{k-1} \sum_{i=1}^k (a_i - \bar{a})(a_i - \bar{a})^T \quad (4)$$

where k is the number of feature vectors, a_i are the raw feature vectors, and \bar{a} is the mean vector. The following equation is used to select relevant features:

$$A = QB \quad (5)$$

where A and B are matrices whose columns are feature vectors and Q is a matrix whose rows are eigenvectors of the covariance matrix of the training set Z . We select features from the matrix Q that make up 90% of the sum of all eigenvalues. After performing PCA feature selection, 12 features are obtained from the original 126 heart sound feature sets.

2.4 Support vector machine

Let us consider a supervised support vector machine

(SVM) classifier with a training dataset $\{x_i, y_i\}_{i=1}^N$, where x is the input sample and $y \in \{+1, -1\}$ is the label of classes. An SVM classifier is constructed by using an optimal hyperplane with far enough distance to isolate two classes of the training dataset. This hyperplane is defined as $w \cdot x - b = 0$, where x is a testing data point on the hyperplane, w determines the orientation of the hyperplane, and b is the bias value with respect to the origin. A margin is used to form the decision surface and is represented by the distance d between two supporting hyperplanes as $d = \frac{2}{w}$. The larger the margin d , the better the classifier can separate the dataset. To find the optimum hyperplane, we must minimized w^2 with the constraint $y_i (w \cdot x_i - b) \geq 1, i = 1, 2, \dots, n$. Thus, the optimization problem for finding the optimum hyperplane is given by

$$\begin{aligned} &\text{minimize}_w \quad \frac{1}{2} w^2 \\ &\text{subject to} \quad y_i (w \cdot x_i - b) \geq 1, i = 1, 2, \dots, n \end{aligned} \quad (6)$$

Furthermore, for a practical classification problem, the data sample may not always be linearly separable. The positive slack variable ξ_i is introduced for a nonlinear decision surface by substitution into the optimization problem. This allows an error term in the SVM classifier as a soft-margin classification. The new optimization problem is shown as in Equation (7):

$$\text{minimize}_w \quad \frac{1}{2} w^2 + C \sum_{i=1}^N \xi_i$$

$$\begin{aligned} \text{subject to } & y_i (w \cdot x_i - b) \geq 1 - \xi_i, \\ & i = 1, 2, \dots, n \\ & \xi_i \geq 0 \end{aligned} \tag{7}$$

where C is a non-negative cost parameter which controls the tradeoff between maximizing margin and minimizing error. Finally, the classification decision function becomes:

$$f(x) = \text{sing} \left(\sum_{i=1}^N L_i y_i K(x_i, x_j) - b \right) \tag{8}$$

where L_i are Lagrange multipliers, and $(x_i, x_j) = \varphi(x)$. For a nonlinear classifier, a kernel function $\varphi(x)$ is used to map the nonlinear data into a higher dimensional space. In this work, we select the RBF kernel function for the SVM classifier as suggested by Phatiwuttipat (2011). The RBF kernel is calculated by using $K(x_i, x_j) = \exp(-\gamma \|x_i - x_j\|^2)$ where $x_i = [x_{i1}, x_{i2}, \dots, x_{id}]^T$ and $x_j = [x_{j1}, x_{j2}, \dots, x_{jd}]^T$ are two sample data sets and $\gamma > 0$ is the width of the Gaussian.

2.5 Weighted support vector machine

In traditional SVM (Phatiwuttipat, 2011), each feature of a sample data set is assumed to have equal contribution to the classification results. However, the quality of features may have a different impact on the performance of a learning algorithm. Thus, if we assign a different weight for each feature, the performance of a learning algorithm can be improved.

Given the training dataset $\{x_i, y_i\}_{i=1}^N$ and weighted vector $\alpha \in \mathfrak{R}^d$, defined as $\sum_{i=1}^d \alpha_i = 1$ for $\alpha_i \geq 0$, the optimization problem can be modified as follows:

$$\begin{aligned} \underset{w}{\text{minimize}} \quad & \frac{1}{2} w^2 \\ \text{subject to } & y_i (w \cdot \text{diag}(\alpha) \cdot x_i - b) \geq 1, i = 1, 2, \dots, n \end{aligned} \tag{9}$$

where $\text{diag}(\alpha)$ is a diagonal matrix with diagonal entries α . A new optimization problem can be formulated by substituting Equation (9) into Equation (7) as:

$$\begin{aligned} \underset{w}{\text{minimize}} \quad & \frac{1}{2} w^2 + C \sum_{i=1}^N \xi_i \\ \text{subject to } & y_i (w \cdot \text{diag}(\alpha) \cdot x_i - b) \geq 1 - \xi_i \\ & i = 1, 2, \dots, n \\ & \xi_i \geq 0 \end{aligned} \tag{10}$$

$$\begin{aligned} \sum_{i=1}^d \alpha_i &= 1 \\ \alpha_i &\geq 0 \end{aligned}$$

Similar to traditional SVM, the final classification decision function becomes:

$$f(x) = \text{sing} \left(\sum_{i=1}^N L_i y_i K'(x_i, x_j) - b \right) \tag{11}$$

where the weighted RBF kernel is

$$K'(x_i, x_j) = \exp \left(-\gamma \sqrt{\sum_{k=1}^d \alpha_k (x_{ik} - x_{jk})^2} \right)$$

2.6 Particle swarm optimization

Particle swarm optimization (PSO) is a stochastic optimization and one of the evolutionary computational techniques proposed by Kennedy and Eberhart (Kennedy & Eberhart, 1995, 2001). Inspired by the social behavior of fish schooling and bird flocking, PSO is a population-based search method, similar to other evolutionary computation algorithms such as genetic algorithms (GA) (Whitley, 1994) that exploit sharing social information. The main idea of the PSO can be viewed as follows; during solution searching process in the d -dimension space, each individual or candidate solution, called a particle, will adjust its velocity and position based on its previous experience and also those of the other companion particles in the population, called a swarm. Thus, each particle of a given population can benefit from the previous experiences of all other individuals in the same swarm.

Consider a swarm of size S , each particle P_i , where $i = 1, 2, \dots, S$ in the swarm is characterized by its current position $p_i(t) \in \mathfrak{R}^d$ at iteration T . This is a candidate solution of the optimization problem, its velocity $v_i(t) \in \mathfrak{R}^d$, and the best position from its past trajectories $p_{bi}(t) \in \mathfrak{R}^d$. Define $p_g(t) \in \mathfrak{R}^d$ as the best global position from all trajectories visited by the particles in the swarm. The fitness function, defined in relation to the considered optimization problem, is used to measure position optimality. The particles update their velocities according to the following equation during the searching process:

$$\begin{aligned} v_i(t+1) &= w_0 v_i(t) + c_1 r_1(t) (p_{bi}(t) - p_i(t)) \\ &\quad + c_2 r_2(t) (p_g(t) - p_i(t)) \end{aligned} \tag{12}$$

where c_1 and c_2 are acceleration constants adjusting the relative velocities, with respect to the best global position and local position, respectively, $r_1(\cdot)$ and $r_2(\cdot)$ are random variables in the range of $[0, 1]$, which will provide a stochastic weighting for each particle velocity term, and w_0 is the inertia

weight that can be predefined by the user. Finally, the new position of each particle can be updated as in Equation (13):

$$p_i(t+1) = p_i(t) + v_i(t+1) \quad (13)$$

In general, the parameters of PSO are considered as scaling factors to determine the relationship between the global best position and the best position of each particle, referred to as the cognitive and social rates, respectively. The parameters influence how much a particle updates its position for each iteration. A tradeoff between the global and local exploration capabilities of the swarm is determined by the inertia weight w_0 , where a large weight allows better global exploration, and a small weight leads to a fine search in the solution space. In (12), the velocity at iteration $T+1$ is updated for each particle in the swarm. The equation linearly combines particle current velocity (at iteration T) with the distances that separates the current particle position from its previous best position and the best global position. Stopping criteria are when the best value of the fitness function is a certain value or the iteration has reached a predefined maximum number of iterations.

2.7 Proposed PSO-WSVM classification

In this section, we describe the proposed PSO-WSVM classification method for cardiac auscultation. The aim of this system is to optimize a set of weighting factors for the feature set, such that the highest accuracy of the classifier can be achieved. The system is derived from an optimization framework based on PSO. In order to classify heart sound signal into two categories, normal and abnormal, the proposed system used SVM with RBF kernel, which proved to be superior method to cardiac signals (Phatiwuttipat, 2011). We further defined PSO-WSVM into two types: continuous and binary. In continuous case, the weighting factor could be valued ranged from 0 to 1. In binary case, the weighing factor only takes a value of 0 or 1. The position $p_i(t)$ of each particle P_i in the swarm is viewed as a feature weighting factor. Let $f(i)$ be the fitness function value associated with the i^{th} particle. The procedure describing the proposed PSO-WSVM classification system for the heart auscultation is as follows:

1. Initialization
 - 1.1 Randomly generate an initial swarm of size S .
 - 1.2 Set the velocity vectors $v_i (i = 1, 2, \dots, S)$ for each particle in the swarm with a value of zero.
 - 1.3 Train an SVM classifier and compute the corresponding fitness function $f(i)$ (i.e. the accuracy) of each position $p_i(t)$ for each $P_i(t)$ in the swarm.
 - 1.4 Select the best position from each particle with its initial position as in (14):

$$p_{bi} = p_i, (i = 1, 2, \dots, S) \quad (14)$$

2. Optimization process
 - 2.1 Determine the best global position p_g from particles in the swarm by the fitness function over all

explored trajectories.

2.2 Update the velocity of each particle using Equation (12).

2.3 Update the position of each particle using Equation (13).

2.4 Train an SVM classifier and compute the corresponding fitness function $f(i)$ for each candidate particle $p_i (i = 1, 2, \dots, S)$.

2.5 Update the best position p_{bi} of each particle, if the corresponding position has a smaller fitness function value.

3. Stopping Criteria

3.1 If not at maximum iteration, repeat the optimization process. Otherwise, continue step 4.

4. Classification

4.1 From the best global position p_g in the swarm, train a WSVM classifier with the subset of weighted features associated with p_g .

4.2 Classify the heart sound signals with the trained WSVM classifier.

For the binary case, a particle moves in a state space restricted to 0 and 1 on each dimension, where each v_i represents the probability of bit p_i taking the value 1. As suggested in Nezamabadi-pour (2008), a logistic function transformation $S(v_i)$ could be defined as in Equation (15):

$$S(v_i) = Sigmoid(v_i) = \frac{1}{1 + e^{-v_i}} \quad (15)$$

where $S(v_i)$ is a sigmoid limiting transformation. Instead of using Equation (13) in the case of continuous PSO, the position of each particle can be updated as in Equation (16):

$$\begin{aligned} \text{if } rand() < S(v_i(t+1)), \text{ then } x_i(t+1) = 1 \\ \text{else } x_i(t+1) = 0 \end{aligned} \quad (16)$$

where $rand()$ is a quasi-random number selected from a uniform distribution in $[0,1,1,0]$.

3. Results and Discussion

The proposed method was tested with 352 individual labeled heart sounds in digitized WAV file format with 16 bits resolution, mono sound and 8 kHz. The pathological heart sounds consist of 208 samples and comprised of aortic stenosis, aortic regurgitation, mitral stenosis, and mitral regurgitation. The numbers of heart sounds in each type are shown in Table 1. To evaluate the performance, ten-fold cross validation is used, where the data is divided into ten portions as follows:

$$Data = F_1 \cup F_2 \cup \dots \cup F_{10}, F_i \cap F_j = \emptyset; i \neq j \quad (17)$$

where F_i is the i^{th} portion of the data. Then, in each fold F_i , one portion is reserved for testing exactly once while the remaining folds L_i are used as a training set. The process continues until all portions are tested. Cross validation results

Table 1. Heart sound type in the training set.

Heart Sound Type	Number of samples
Normal	144
Aortic Stenosis	52
Aortic Regurgitation	52
Mitral Stenosis	52
Mitral Regurgitation	52

can be evaluated by four numbers: True positive (TP): the proportion of actual positives that are correctly identified; False positive (FP): the proportion of actual positives that are incorrectly identified; True negative (TN): the proportion of negatives that are correctly identified; False negative (FN): the proportion of negatives that are incorrectly identified.

In this experiment, positive means a heart with disease and negative means a healthy heart. Performance rate can be calculated by using sensitivity, specificity, positive predictive value (PPV), negative predictive value (NPV) and accuracy in a confusion matrix. Sensitivity defines how well the classifier can identify a diseased heart correctly, also called true positive rate. Specificity means the tests ability to exclude healthy heart from diseased heart correctly. The accuracy results show the proportion of correctly identified heart sound conditions. The performance indicators can be calculated as

$$Sensitivity = \frac{TP}{TP + FN} \tag{18}$$

$$Specificity = \frac{TN}{FP + TN} \tag{19}$$

$$Positive\ predictive\ value\ (PPV)\ or\ Precision = \frac{TP}{TP + FP} \tag{20}$$

$$Negative\ predictive\ value\ (NPV) = \frac{TN}{FP + TN} \tag{21}$$

$$Accuracy = \frac{\sum Correctly\ classified\ heart\ sounds}{\sum Heart\ sounds} \tag{22}$$

The four outcomes and performance indicators can be formulated in a confusion matrix as in Table 2. The results of the proposed methods were compared with FFBP classifier (Yuenyong, 2011), traditional SVM classifier (Phatiwuttipat, 2011), where all features are equally weighted, and GA based SVM classifier (Banpavichit, 2013). The PSO parameters are set up based on preliminary experiment as shown in the Table 3. The results of continuous PSO-WSVM and binary PSO-WSVM are shown in Table 4 and 5, respectively. Table 6 shows comparisons of the proposed method with other classification methods.

As shown from the experimental results, both PSO-based WSVM achieve higher classification accuracy than traditional SVM and FFBP. The results came from the fact

Table 2. Confusion matrix structure.

		Actual heart condition		
		Abnormal	Normal	
Classified heart condition	Abnormal	TP	FP	PPV
	Normal	FN	TN	NPV
		Sensitivity	Specificity	Accuracy

Table 3. PSO setting parameters.

Parameters	Values
Swarm size	50
The inertia weight w_0	0.9
Acceleration constants c_1 and c_2	2
Maximum number of iterations	70

Table 4. Classification results of the proposed continuous PSO-WSVM.

		Actual heart condition		
		Abnormal	Normal	
Classified heart condition	Abnormal	185	0	100.00%
	Normal	23	144	86.22%
		Sensitivity 88.94%	Specificity 100.00%	Accuracy 93.47%

Table 5. Classification results of the proposed binary PSO-WSVM.

		Actual heart condition		
		Abnormal	Normal	
Classified heart condition	Abnormal	189	0	100.00%
	Normal	19	144	88.34%
	Sensitivity	95.19%	Specificity	100.00%
			Accuracy	94.60%

that the PSO algorithm can reduce the systems FNs, which prevent patients from not knowing they have the heart disease. Thus, this helps patient being treated in the early stage of the disease. From Table 6, the FN results of continuous and binary PSO-WSVM dramatically decreased by 14.81% and 29.63% from 27 in traditional SVM and FFBP to 23 and 19, respectively. The binary PSO-WSVM has the highest accuracy of 94.60%, which is improved by 2.27% compared to traditional SVM and FFBP classifiers. The continuous PSO-WSVM has also gained 1.14% in accuracy

from the previous methods. The lower weighting factors of the features mean weaker sensitivity for the system while the higher weighting factors mean stronger sensitivity for the system. The binary PSO-WSVM achieves the best classification accuracy over the other methods since noisy features with low impact on the classification can be omitted. Thus, only the dominant features, which are sensitive for training the classifier, are turned on.

Another indicator, which can be used to measure a test's performance, is F-measure value. The balanced F-measure or F_1 , which is the harmonic mean of precision and sensitivity, can be calculated as

$$F_1 = \frac{2TP}{2TP + FP + FN} \tag{23}$$

The F_1 values for continuous and binary PSO-WSVM are 94.15% and 95.22%, respectively, compared to 93.06% in FFBP and traditional SVM classifiers and 94.15% in GA-SVM classifier.

Table 7 shows computational time for each classifier based on tested system, equipped with 2.7 GHz Intel Core i5 processor and MATLAB R2014b version. Heuristic based SVM classifiers require longer computational time than FFBP and traditional SVM. This is due to reiterative run of SVM to update the weighting factor of the features. However, the proposed system is designed for offline. Hence, slower computational time has less impact on practical use.

Compared to the previous methods, reduction in FN of the proposed method shows an improvement of classification in the case of correctly classifies patients with abnormal heart. The feature weighting factors with PSO emphasized on the important characteristic of features in the heart sounds while suppressed features that irrelevant to the system. This led the system a better decision when classifying diseased

Table 6. Classification results comparison for FFBP-NN, traditional SVM, GA-SVM, continuous PSO-WSVM, and binary PSO-WSVM.

Method	TP	TN	FP	FN	Sensitivity	Specificity	Accuracy	F-measure
FFBP-NN	181	144	0	27	87.02%	100%	92.33%	93.06%
Traditional SVM	181	144	0	27	87.02%	100%	92.33%	93.06%
GA-SVM	185	144	0	23	88.94%	100%	93.47%	94.15%
Continuous PSO-WSVM	185	144	0	23	88.94%	100%	93.47%	94.15%
Binary PSO-WSVM	189	144	0	19	95.19%	100%	94.60%	95.22%

Table 7. Computational time for each type of classifier.

Type of Classifier	Computational time (sec)
FFBP-NN	430.1
Traditional SVM	30.1
GA-SVM	8404.2
Continuous PSO-WSVM	3521.1
Binary PSO-WSVM	5735.1

heart sounds as abnormal hearts. However, the system cannot perfectly classify all the heart sound conditions and wrong decision occurred when the diseased heart sounds are very similar to the normal heart sound as shown in the remaining FN. It could be concluded that the method proposed by this study obtains promising results for an automatic cardiac auscultation classification system.

4. Conclusions

This paper presented a PSO based approach WSVM to construct a weighted feature set for SVM in classification of automatic heart sound analysis. The method is applicable to a wide range of heart sounds, from healthy hearts to those diseased hearts containing severe abnormal heart conditions. The main objective of this system is to act as a cheap and efficient screening system so that patients with potential heart disease can be identified. The proposed PSO-WSVM took into account the degree of importance of each heart sound feature and assigned diverse weights to the different features. Also, the proposed binary PSO-WSVM further omits noisy features and emphasizes dominant features with strong sensitivity to be trained with SVM. The results of the proposed method show that the accuracy of the system can be improved with weighted SVM. Further research could be to combine advantages of both PSO and GA optimization techniques. This hybrid PSO-GA approach could deliver more accurate search for the optimum weighting factor set. Furthermore, classification on individual type of heart diseases can be obtained using a multi-SVM classifier, to further identify types of heart disease after diagnosing patients with heart diseases. Also, in binary-PSO, we could examine other logistic function transformations that take the previous particles position into account for updating the position of each particle in the swarm. Finally, the project will be evaluated by a doctor from hospital to verify and compare the record with the proposed method.

References

- Banpavichit, S., Kongprawechnon, W. & Tungpimolrut, K. (2013). Cardiac auscultation with hybrid GA/SVM. *Proceeding of the 9th International Conference on Computing and Information Technology (IC2IT 2013)*, 185-194. doi:10.1007/978-3-642-37371-8_22
- Brechet, L., Lucas, M-F., Doncarli, C., & Farlina, D. (2007). Compression of biomedical signals with mother wavelet optimization and best-basis wavelet packet selection. *IEEE Transactions on Biomedical Engineering*, 54(12), 2186-2192.
- Clark III, D. (2012). An argument for reviving the disappearing skill of cardiac auscultation. Retrieved from <http://www.ccjm.org/content/79/8/536.full>
- Kennedy, J., & Eberhart, C. (1995). Particle swarm optimization. *Proceeding of IEEE International Conference on Neural Networks (ICNN)*, 1942-1948.
- Kennedy, J., & Eberhart, C. (2001). *Swarm intelligence*. San Francisco, CA: Morgan Kaufmann.
- Lloyd, S., Gavaghan, D., Simpson, A., Mascord, M., Seneurine, C., Williams, G.,...G. de Fabritiis. (2007). Integrative biology—the challenges of developing a collaborative research environment for heart and cancer modeling. *Future Generation Computer Systems*, 23, 457-465.
- Nezamabadi-pour, H., Rostami-shahrbabaki, M., & Farsangi, M.M. (2008). Binary particle swarm optimization: Challenges and new solutions. *The Journal of Computer Society of Iran (CSI) on Computer Science and Engineering*, 6(1-A), 21-32.
- Phatiwuttipat, P., Kongprawechnon, W., & Tungpimolrut, K. (2011). Cardiac auscultation analysis system with neural network and SVM technique. *Proceeding of 8th International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology (ECTI-CON)*, 1027-1030.
- Robert, J.H., & Wilson, J.M. (2006). *Auscultation: Heart murmurs CD-ROM*. Texas, TX: Texas Heart Institute
- Sekar, B.D., Dou, J.Y., Fu, B.B., Fei, X.L., Dong, M.C., & Ming, C. (2011). Complexity and similarity analysis of heart sound for cardiovascular disease detection. *Biotechnology*, 10(4), 316-322. doi:10.3923/biotech.2011.316.322
- Whitley, D. (1994). A genetic algorithm tutorial. *Statistics and Computing*, 4(2), 65-85.
- World Health Organization. (2008). *Prevention of cardiovascular disease pocket guidelines for assessment and management of cardiovascular risk*. Geneva, Switzerland: Author.
- Yuenyong, S., Kongprawechnon, W., Tungpimolrut, K., & Nishihara, A. (2009). Automatic heart sound analysis for tele-cardiac auscultation, *ICROS-SICE International Joint Conference*, 1599-1604.
- Yuenyong, S., Nishihara, A., Kongprawechnon, W., & Tungpimolrut, K. (2011). A framework for automatic heart sound analysis without segmentation. *Biomedical Engineering Online*, 10. doi:10.1186/1475-925X-10-13