ANALYSIS AND METHODS TO TEST CLASSIFICATION OF NORMAL AND PATHOLOGICAL HEART SOUND SIGNALS

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ABSTRACT

An acute shortage of cardiologists and many rural clinics were run by nurses in Indonesia. We proposed to develop of a screening technique based on artificial intelligence that classifies of normal and pathological heart sound signals of human subjects due to signs important and symptoms for heart diagnosis based on knowledge of auscultation experts. Heart sound signal analysis system consisted of three stages. Firstly, preprocessing. Secondly, feature extraction with respect to the cardiac cycle based on wavelet analysis to differentiate normal and pathological heart sounds. Feature reduction using PCA was also carried out to reduce the dimension of the heart sound feature vectors for classification. Thirdly, three classifiers: ANN MLP-BP, FCM clustering and HCM clustering to classify normal, systolic murmur, diastolic murmur, and continuous murmur, respectively. The performance of each classifier was evaluated with statistical validation method. From our experimental results, the three classifiers that showed significant potential in their use as an alternative diagnostic tool were compared. The ANN achieved the best performance as an automated classifier rather than FCM and HCM methods. Its performance was 100% for sensitivity, specificity, and accuracy, respectively, of input 20,000 features. Furthermore, for input 300 features, the performance was 98.90%, 99.37%, and 99.03% for sensitivity, specificity, and accuracy, respectively. The heart sound signal analysis system was suitable to classify of normal and pathological cases. The proposed method was considered very important for objective screening and very useful as an alternative diagnostic tool that complies with the requirements for rural clinics. We hoped that the method would be beneficial in study of auscultatory technique for medical students. Surrogate data modeling of pathological heart sounds signals as an alternative tool of the heart sound simulator and for classification purpose was further study.

Keywords: *Wavelet Analysis, Principal Component Analysis (PCA), Artificial Neural Network Multilayer Perceptron Back Propagation (ANN MLP-BP), Fuzzy C-Means (FCM) Clustering, Hard C-Means (HCM) Clustering*

1. INTRODUCTION

Cardiac disease is the second most mortality disease after cerebrovascular accident in the world [1], [2] and has long been the leading cause of death in developed countries, particularly in Indonesia [3]. A preliminary, non-invasive identification of the cardiac diseases, with particular manners and follow-up treatments can avoid increasing of deadly hazards of the heart assaults [4]-[7]. One of the manners for early identification of cardiac disease can be performed thru detection of heart sounds [1], [8].

Heart sounds are low-frequency transient signals produced by vibration after opening and closing of cardiac valves, and/or by vibration of whole myocardium and connected structures during

a cardiac cycle. The cardiac cycle is divided into two periods; systole when the ventricles contract and ejects blood from the heart, and diastole, when the ventricles are relaxed and the heart is filled with blood. A normal functioning heart contains of two basic heart sounds, i.e., a first heart sound (S_1) and a second heart sound (S_2) [9]. The S_1 and S_2 produced by the closing of the atrioventricular valves (mitral valve and tricuspid valve) and semilunar valves (aortic valve and pulmonary valve), respectively. If closure of heart valve is not perfect and resulted in backflow of blood (regurgitation) or opening of heart valve is not perfect and ensued force blood thru a narrow opening (stenosis), then will be caused additional sound. An Abnormal heart sound appears as a result of turbulence flow of blood that passes by means of narrow openings is named murmur [9].

One of the valuable methods of heart valve diagnostic can be carried out by auscultation [1], [8]. The auscultation is conducted by listening to the heart sounds utilizing a stethoscope. Its auscultation is an imperative tool in the diagnosis of cardiac disease, non-invasive, and low-cost screening method. It can provide precious and modest diagnostic tool for detecting cardiac dysfunction, because of its ability to offer valuable evidence concerning the integrity and function of the heart valves and hemodynamics of the heart [10], [11]. Furthermore, electrocardiogram (ECG), Doppler, and ultrasound imaging techniques as new diagnostic modalities, although can afford more direct evidence but these diagnostic tests do not assure all valvular diseases. Additionally, auscultation remains the principal tool for screening and diagnosis in major health care, due in part to higher cost and limitedness existence the equipment, and to the special expertise necessary to manage and analyze the results of these new diagnostic modalities. In developing countries, particularly in Indonesia rural clinics, auscultation may be the only means available.

The heart sounds analysis by auscultatory technique is a very special expertise. Accurateness of the examination relies highly on the skill and practical learning of a listener that takes years to gain and fix [12]. Because this expertise is greatly difficult to be taught in a structured way, so that hearing of a cardiologist with another one who cannot be duplicated, although this technique has been learned both in educational and clinical aspects by means of basic literatures [9], [13]. Hence, the above cases and subjectivity of a cardiologist become deteriorations of auscultatory technique. Limitations of the auscultatory technique have stimulated us to utilize digital signal processing based method for identification and classification of normal and pathological heart sound signals. Mechanical events of the heart sound signals relating to a given normal and murmur were conceived in a single interval of cardiac cycle. Therefore, it was very essential to identify the single cycle for analysis of normal and murmur. For implementation of heart sound signal analysis system, it was necessary to detect the single cycle, extract feature from the single cycle, and then classify the signal due to signs important and symptoms for heart diagnosis based on knowledge of auscultation experts.

Feature extraction was one of the most important steps for implementation of the heart sound signal analysis system, since even the best classifier would perform poorly if the features were not chosen well. In our previous research, extensive characterization method wavelet-based analysis has revealed ability to outgrow problems of traditional auscultation to clarify objectively mechanisms of heart valves functions [2]. Furthermore, the method was more precisely to extract the heart sound characteristics rather than Short Time Fourier Transform (STFT) [14] and Fast Fourier Transform (FFT) [15] methods. Spectrogram STFT could not perfectly detect both S_1 components (mitral and tricuspid) and both S_2 components (aortic and pulmonary). The problem was caused by a trade-off between time and frequency resolutions along with preference of a time window length [14]. Furthermore, the FFT did not consider about time, so it could not reveal which of two valves of S_1 and S_2 components, respectively, were closed firstly [15]. In this study, the wavelet analysis would be performed to extract characteristics of the heart sounds. It was a method to acquire simultaneous high-resolution time and frequency explanation about a signal. The method used a flexible window modulation. Hence, it could provide detailed information of the heart sound during the cardiac cycle. The calculation results of feature extraction would be input for classification of the heart sound signals.

In previous researches, Chebil et al. [16] and Gupta et al. [17] have efficiently used the Artificial Neural Network (ANN) for detecting and classifying the heart sounds. However, satisfactory performance was not reported. Therefore, increment the classification performances of heart sounds should be managed into a more sensitive and could be more rigorous in analyzing abnormalities that appear in characteristics of the heart sounds for heart diagnosis.

We proposed to develop of a screening technique based on artificial intelligence to overcome limitations of the auscultatory technique for the heart diagnosis. The screening technique classifies of normal and pathological heart sound signals of human subjects, i.e., normal, systolic murmur, diastolic murmur, and continuous murmur, respectively, due to signs important and symptoms based on knowledge of auscultation experts. Three potential classifiers would be compared: Artificial Neural Network Multilayer Perceptron Back Propagation (ANN MLP-BP),

Fuzzy C-Means (FCM) clustering and Hard C-Means (HCM) clustering. The proposed method would be very important for objective screening and very useful as an alternative diagnostic tool that complies with the requirements for rural clinics. Additionally, the method promises a prominent role in study of auscultatory technique for medical students.

2. METHODS

The procedures used in analysis and methods to test classification of the normal and pathological heart sound signals are illustrated in Fig. 1. Discussion follows in the illustrated order.

2.1 Data Collection

Recording of the heart sounds was composed of three sets of 70 human subjects. The first set was collected from an acoustic transducer of ALOKA ProSound II SSD-6500 SV and the heart sounds were digitized with 1 kHz sampling frequency of two normal subjects. The second set was from an electronic stethoscope (3M Litmann Model 4100) and the sounds were digitized with 8 kHz sampling frequency of one mitral valve regurgitation (MR) subject with pathologic systolic murmur. The first and second parts of the subjects were participated in this research. Aim of an experiment was clarified to each subject and subject's consent was attained.
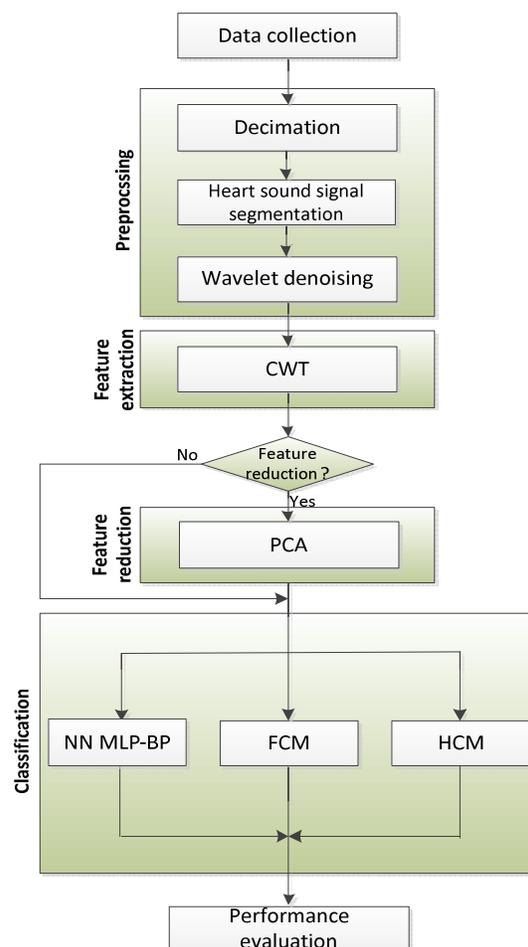

Figure 1: Block Diagram Of Heart Sound Signal Analysis System

The third set was collected from a cassette of literature [13] containing a selection of seven conditions of normal and pathological heart sounds, i.e., 5 normal, 5 MR, 10 atrial septal defect (ASD), 20 stenosis aorta (SA), 10 ventricular septal defect (VSD), 9 mitral stenosis (MS), and 8 persistent ductus arterious (PDA) subjects, respectively. The heart sounds of literature [13] were digitized with 11 kHz sampling frequency and they recorded for educational purpose. In this study, the pathological heart sounds consisted of systolic murmur (e.g. MR, ASD, SA, VSD), diastolic murmur (e.g. MS), and continuous murmur (e.g. PDA).

2.2 Heart Sound Signal Analysis

Heart sound signal analysis system for developing of a screening technique consisted of three stages (Fig. 1). The first stage presented three preprocessing units, i.e., decimation, segmentation with regard to the cardiac cycle, wavelet denoising

for augmenting quality of the signal. The second stage was feature extraction based on wavelet analysis (CWT, i.e., Continuous Wavelet Transform) to distinguish normal and pathological heart sounds. This feature extraction results would be input for classification purpose. Reduction of the feature using Principal Component Analysis (PCA) was also carried out in this stage to decrease the dimension of the heart sound feature vectors for classification. The third stage was the classification. Three classifiers, i.e., NN MLP-BP, FCM, and HCM were conducted to make their classification decisions of a heart sound's class based on signs important and symptoms for heart diagnosis in knowledge of auscultation experts. Hence, each classifier as an artificial knowledge based system could classify four classes, i.e., normal, systolic murmur, diastolic murmur, and continuous murmur, respectively. Furthermore, the classification performance of each classifier was evaluated with statistical validation method. Evaluation of the performance would be derived from classifier vector input of the wavelet analysis results as well as the feature reduction results. In this paper, Pascal programming language for the heart sound signal analysis was performed.

2.2.1 Preprocessing

Two filtering steps of the signal to reduce disturbance by background noise were conducted. First step, an eighth-order Butterworth bandpass IIR filter with cutoff at 20 Hz and 330 Hz was used from native signal of 1 kHz and 8 kHz sampling frequency, respectively, also with cutoff at 20 Hz and 1100 Hz from native signal of 11 kHz sampling frequency. Furthermore, the native signal of 8 kHz and 11 kHz sampling frequency was decimated by factor 4 and factor 5, respectively. Determination of bandwidth filtering was appropriate with Stein et al. [13]. The signal was afterward segmented that would be clarified later. Second step, algorithm implementation of the fixed threshold wavelet denoising that explained in Hall et al. [18] was performed for augmenting quality of the segmenting signal. A Daubechies wavelet of order 4 (Db4) with a decomposition level of 5 was picked.

2.2.2 Segmentation

The segmentation regarding a cardiac cycle was a prominent stage in analyzing of the heart sounds. Identification the location and intervals of S_1 and S_2 could be very beneficial information about the mechanical event of the cardiac condition. The native signal would be declared in more modestly and effortlessly seen by exploiting of Shannon envelope based on the S_1 as well as S_2 [2].

The Shannon envelope or the normalized average Shannon energy was competent to diminish the effect of low noise and to create the low intensity sounds more effortless to be located [19]. The algorithm was described as follows.

First of all, normalization of a native heart sound was performed in the form Eq. (1).

$$x_{norm}(i) = \frac{x(i)}{\max(|x(\cdot)|)} \qquad (1)$$

where $\max|x(\cdot)|$ was absolute maximum of signal.

Second, as in Eq. (2),

$$E_x = -\frac{1}{N}\sum_{i=1}^{N} x_{norm}^2(i) \cdot \log x_{norm}^2(i) \qquad (2)$$

the average Shannon energy was computed where $x_{norm}(i)$ was the ith normalizing signal and N was amount of points within 0.02 sec. segment and 0.0165 sec. segment for normal and murmur subjects, respectively, which corresponds to a frame, for normal, i.e., $N = 20$, and for murmur, i.e., $N = 33$. Third, normalization of E_x thru all of the frames as in Eq. (3),

$$P(t) = \frac{E_x(t) - M(E_x(t))}{S(E_x(t))} \qquad (3)$$

where $M(E_x(t))$ and $S(E_x(t))$ were mean and standard deviation of average Shannon energy of frame t, so $P(t)$ as Shannon envelope [19]. Fourth, $P(t)$ was filtered reverse direction. The resulting sequence had precisely zero phase filter, thus therein no time delay.

Identification for the amplitude peaks of S_1, S_2, and S_1 of the following cycle from filtering of $P(t)$ was visual inspection based. The systole is shorter than the diastole as fundamental knowledge of the S_1 and S_2 peaks selection [20]. The peak adjacent to the systole was recognized as S_1. The peak adjacent to the diastole was recognized as S_2 [19]. Therefore, p_{max} as maximum among the three peaks was acquired. Additionally, p_{min} as minimum of interval that involved the three peaks was attained. Determination of a thresholding value, i.e., $p_{min} + c_{env} \times p_{max}$, where c_{env} was a thresholding coefficient of $P(t)$ was performed [2]. Picking of c_{env} was set manually and diverse ($0.00 < c_{env} < 0.74$). Its

picking based on onset until ending incidents of S_1 and S_2, respectively, as well S_1 onset of the following cycle.

Systolic is interval of time of S_1 onset until S_2 onset. Diastolic is interval of time of S_2 onset until S_1 onset of the next cycle. Furthermore, single cycle is interval of time of S_1 onset of a cycle and S_1 onset of the following cycle [2].

2.2.3   Feature extraction

CWT as a feature extractor is appropriate for analyzing of non-stationary signals especially heart sound signals. Because the wavelet may be stretched or suppressed, distinct features of the signal were extracted. While a dilated wavelet takes on the lower frequency constituents, a narrow wavelet extracts high-frequency constituents of the signal. CWT was calculated by relating the signal $x(t)$ with set of time frequency atoms $f(t)$; it produced a collection of coefficients $C(b,s)$ stated by Eq. (4),

$$C(b,s) = \frac{1}{\sqrt{s}} \int_{-\infty}^{\infty} x(t) f^* \left(\frac{t-b}{s} \right) dt \qquad (4)$$

where b was the time location, s was the scale factor and it was inversely proportionate to the frequency ($s > 0$), $f(t)$ was the mother wavelet, and symbol * indicates a complex conjugate.

The most important properties of the mother wavelet $f(t)$ consisted of integrability, square integrability, continuity, progressivity, also it has no d.c. component [21]. Moreover, $f(t)$ has to be focused in both time and frequency as much as possible. It is renowned that the smallest time bandwidth product is achieved by the Gaussian function [22]. Morlet wavelet as in Eq. (5),

$$f(t) = e^{-2i\pi f_0 t} e^{\frac{-t^2}{2}} \qquad (5)$$

was a complex exponential modulated Gaussian function, where f_0 was 0.849 Hz [23]. The most trustworthy wavelet for the time-frequency of the heart sound signals was the Morlet wavelet [24].

The result of CWT, in the matrix feature form, was a large amount of wavelet coefficients that was function of position and scale (or b and s, respectively: see Eq. (4)). In color spectrum, the coefficients were depicted as magnitude normalization value between 0.0 until 1.0, where red and purple indicated the highest and the lowest intensity, respectively. The feature extraction of wavelet coefficients was 200×100 (time $\times$ scale)

and scale factors as of 1.0×10^{-2} up to 1.0×10^{-1}. The feature extraction results would be an input at classification stage.

2.2.4   Feature reduction

Principal component analysis (PCA) was conducted to decrease the dimension of the heart sound feature vectors by picking only the vectors that had great variances. The aim of PCA was to replace a set of m variables $\mathbf{x_1}$, $\mathbf{x_2}$, …, $\mathbf{x_m}$, which may be correlated, by another set $\mathbf{f_1}$, $\mathbf{f_2}$, …, $\mathbf{f_m}$, called the principal components or principal factors. These factors were independent (uncorrelated) variables [25], [41].

The algorithm started with the correlation matrix $\mathbf{R}$ which was an $m \times m$ symmetric matrix such that r_{ij} was the correlation coefficient between variable $\mathbf{x_i}$ and variable $\mathbf{x_j}$. The correlation matrix $\mathbf{R}$ using Eq. (6):

$$\mathbf{R} = \frac{1}{n} \mathbf{X}\mathbf{X}^T \qquad (6)$$

where $\mathbf{X} = [\mathbf{x_1}, \mathbf{x_2}, …, \mathbf{x_m}]$ and $\mathbf{x_i}$ as the i-th column vector.

Jacobi iterative method was a procedure for numerical determination of eigenvalues and eigenvectors of correlation matrix $\mathbf{R}$. The method looked for an orthogonal matrix $\mathbf{\Phi}$ such that as in Eq. (7),

$$\mathbf{\Phi^T} \, \mathbf{R} \, \mathbf{\Phi} = \mathbf{\Lambda} \qquad (7)$$

yielded a diagonal matrix $\mathbf{\Lambda}$, where $\mathbf{\Lambda} = \text{diag}[\lambda_1, \lambda_2, …, \lambda_m]$ and $\mathbf{\Phi} = [\boldsymbol{\phi_1}, \boldsymbol{\phi_2}, …, \boldsymbol{\phi_m}]$ were eigenvalues and eigenvectors, respectively. The method was based on a series of rotations (called Jacobi or Givens rotations) which were chosen to eliminate off-diagonal elements while preserving the eigenvalues. A Givens rotation was represented by a matrix of the form

$$\mathbf{\Phi}(i, j, \alpha) = \begin{pmatrix} 1 & & & & & & & & \\ & \ddots & & & & & & & \\ & & b & & v & & & & \\ & & & 1 & & & & & \\ & & & & \ddots & & & & \\ & & -v & & b & & & & \\ & & & & & & 1 & & \\ & & & & & & & \ddots & \\ & & & & & & & & 1 \end{pmatrix}$$

where all diagonal elements were unity from two elements b in rows i and j, and all off-diagonal

elements were zero apart from the elements v and $-v$ (in rows and columns i and j). thus, if ϕ_i and ϕ_j were the i-th and j-th vectors of an orthonormal basis and if $b = \cos\alpha$ and $v = \sin\alpha$ then Φ represented a rotation of angle α in the (oriented) (ϕ_i, ϕ_j)-plane, which leaves all other basis vector unchanged.

The procedure started with correlation matrix $\mathbf{R}_0 = \mathbf{R}$, and produced a sequence of matrices $\mathbf{R}_k = \Phi_k^T \mathbf{R}_{k-1} \Phi_k$, where at the k-th step Φ_k was a plane rotation constructed to annihilate the maximal off-diagonal entry in $\mathbf{R}_{k-1}$. In particular, if r_{ij} was the entry of maximal magnitude in $\mathbf{R}_{k-1}$, then Φ_k was the rotator in the (ϕ_i, ϕ_j)-plane define by setting

$$v = \frac{1}{\sqrt{1+\beta^2}} \text{ and } b = \frac{\beta}{\sqrt{1+\beta^2}} \text{, where } \beta = \frac{(\phi_{ii} - \phi_{jj})}{2\phi_{ij}}$$

For $m > 2$, as in Eq. (8),

$$\left\| \mathbf{R}_k^{'} \right\|_F^2 \leq \left(1 - \frac{2}{m^2 - m}\right)^k \left\| \mathbf{R}_k^{'} \right\|_F^2 \to 0 \text{ as } k \to \infty \quad (8)$$

where $\left\| \mathbf{R}_k^{'} \right\|_F^2$ was the Frobenius matrix norm. Therefore, if $\Phi^{(k)}$ was the orthogonal matrix defined by $\Phi^{(k)} = \Phi_1 \Phi_2 \cdots \Phi_k$, then in the form Eq. (9),

$$\lim_{\mathbf{k} \to \infty} \Phi^{(k)^T} \mathbf{R} \Phi^{(k)} = \lim_{\mathbf{k} \to \infty} \mathbf{R}_k = \Lambda \quad (9)$$

was a diagonal matrix.
The eigenvalues were ordered ($\lambda_1 > \lambda_2 > \ldots > \lambda_m$) and were the variances of the principal factors (eigenvectors). Their sum $\sum_{i=1}^{m} \lambda_i$ was equal to m. Therefore, the percentage of variance associated with the i-th factor was equal to $\frac{\lambda_i}{m}$.

If Φ was the matrix of eigenvectors of $\mathbf{R}$, the correlation coefficient between variable $\mathbf{x_i}$ and factor $\mathbf{f_j}$ (sometimes called *loading*) was calculated using Eq. (10):

$$R_{\phi_{ij}} = \phi_{ij} \sqrt{\lambda_j} \quad (10)$$

The coordinates of the principal components (sometimes called *scores*) were specified in Eq. (11):

$$\mathbf{F} = \mathbf{Z}\Phi \quad (11)$$

where $\mathbf{F} = [\mathbf{f_1}, \mathbf{f_2}, \ldots, \mathbf{f_m}]$, $\mathbf{f_i}$ as the i-th column vector, and $\mathbf{Z}$ denoted the matrix of scaled original variables of the form Eq. (12):

$$Z_{ij} = \frac{X_{ij} - a_j}{s_j} \quad (12)$$

where a_i and s_i were the mean and standard deviation of the i-th variable.
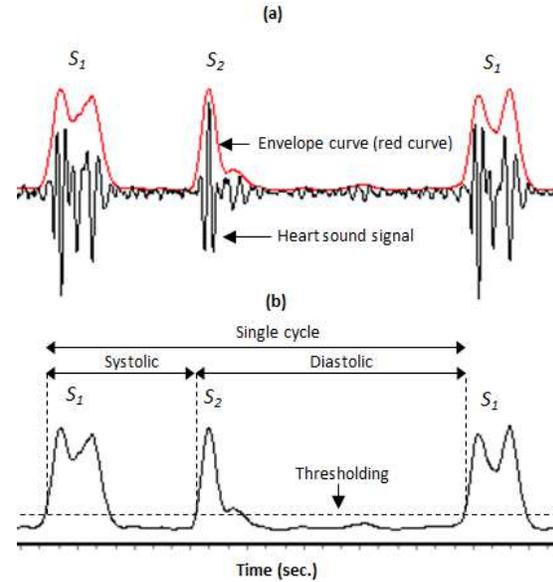
Figure 2: An example of segmentation. (a) A heart sound signal of normal subject and its Shannon envelope (red curve). (b) Single cycle, systolic, and diastolic were obtained from the segmentation result

Assuming that i-th principal component $\mathbf{f_i}$, and the ordering of all the principal components of interest was such that the first principal component was associated with the largest variance in the input data, the second principal component was associated with the second-largest variance in the input data, and so on. Furthermore, discard any components that only account for a small proportion of the variation in the data.

In this study, the $n \times m$ matrix $\mathbf{X}$ was a collection of wavelet coefficients (matrix feature form) as shown in Eq. (4), where $m = 200$ was amount of time location (variables) and $n = 100$ was amount of scale factor (samples). A set of variables $\mathbf{x_1}$, $\mathbf{x_2}$, …, $\mathbf{x_{200}}$, which may be correlated. From Eq. (11), principal components $\mathbf{f_1}$, $\mathbf{f_2}$, …, $\mathbf{f_{200}}$ were obtained. These variables were uncorrelated. Using PCA as an orthogonal linear transformation that transform the collection of wavelet coefficients to a new coordinate system such that the greatest

eigenvalue by any projection of the collection of wavelet coefficients comes to lie on the first coordinate, the second greatest eigenvalue on the second coordinate, and so on. Furthermore, discard any components that only had small percentage of variance, i.e., $\frac{\lambda_i}{200}$ associated with the i-th component $\mathbf{f_i}$. Hence, feature vectors that had great variances would be input to classifier network.

2.2.5 Classifiers

Each of three methods utilized a unique signal processing technique to analyze a certain characteristic of the heart sounds for classification purposes.

The FCM was a clustering algorithm that proposed by Bezdek as one of the greatest used methods in fuzzy clustering [26]. The objective of FCM was to locate cluster centers (centroids) that minimize an error function. The FCM utilized fuzzy partitioning such that a data point could be permissible belongs to all groups with distinct membership values between 0.0 and 1.0. FCM was a recurrent algorithm. For instance, the FCM algorithm minimized the least-squares function that was specified by a generalized among groups sum of square errors function where n was amount of individuals to be clustered, c was amount of clusters, u_{ik} was the degree of membership of individual k in cluster i, x_k was the vector of h characteristics for individual k, v_i was the vector of the cluster means of the h characteristics for cluster i, and w was the weighting for exponent. The sum of squared errors was calculated using Eq. (13):

$$\sum_{k=1}^{n}\sum_{i=1}^{c}(u_{ik})^w \left(\|x_k - v_i\|^2 \right) \qquad (13)$$

and FCMs objective was to minimize Eq. (13).

The HCM was one of the simplest unsupervised learning algorithms to solve the clustering problem [26]. The method followed a plain and easy manner to classify a given data set thru a certain number of clusters fixed a priori. The main idea was to define k centroids, one for each cluster. Each point belonging to the given data set was related to the nearest centroid. When no point was pending, the first step was completed and an early group was done. At this point, to recalculate k new centroids as centers of the clusters resulting from the previous step was required. After these k new centroids have been acquired, a new binding has to be finished between the nearest new centroid and the same data set points. A loop has been

yielded. To inspect that the k centroids changed their location step by step until no more changes are done.

In this study, clustering criterion was the sum of the squared Euclidean distances between the centroid and each data point, as in Eq. (14):

$$E(m_1, m_2, ..., m_M) = \sum_{i=1}^{N}\sum_{k=1}^{M} \|x_i - m_k\|^2 \qquad (14)$$

where $X = \{x_1, x_2, \ldots, x_N\}$, $x_N \in \Re^d$, M was the cluster numbers, $\{m_1, m_2, \ldots, m_M\}$ was the centroids. The criterion was termed clustering error and depended on the centroids.

The MLP-BP was a supervised learning algorithm. The algorithm uses feed-forward networks which utilizes of target values or teacher signals [27]. The algorithm was principally a gradient descent method and its purpose was to minimize the mean squared error between the actual output of the network and the target values. The MLP-BP algorithm mainly involved two stages. Firstly, the forward propagation stage was no learning and the network would certainly yield an erroneous value at its output before learning. Secondly, the backward propagation stage was learning network. The value of the actual output was then compared to a target value and the error yielded was then back propagated thru the layers of the network. The whole process was then iterated as far as the requisite convergence or when the error limit was achieved. In this study, the algorithm was utilized to classify the features into normal, systolic murmur, diastolic murmur, as well as continuous murmur. Each feature vector was classified using a three layer neural network. The input layer consisted of 20.000 neurons and 300 neurons, respectively, one hidden layer that contained 50 hidden neurons, whereas the output layer was specified to 4 neurons for the four classes. The target output for the trained pattern of the four classes was of Boolean type where [1, 0, 0, 0] representing normal class, [0, 1, 0, 0] as systolic murmur class, [0, 0, 1, 0] as diastolic murmur class, and [0, 0, 0, 1] as continuous murmur class, respectively. Bipolar sigmoid activation function was conducted. Training was performed as far as the mean error falls below 0.001 and learning rate was 0.5.

2.3 Performance Evaluation of Classification Methods

Evaluation methods to measure the performance of the classification results were

utilized. The methods were sensitivity, specificity, and accuracy measurements [28]. If the system tried to classify subjects to see if they had a certain disease, there were four possible outcomes. Subjects with the disease could be classified to have the disease (true positives) or they could be classified not to have the disease (false positives). Subjects who did not have the disease could be classified to either had the disease (false negative) or not (true negative). Thus, amount of true positives (*TP*), true negatives (*TN*), false positives (*FP*) and false negatives (*FN*) covered the whole set.

Furthermore, the sensitivity was a measure of percentage of unhealthy subjects (who had the disease) that were recognized as unhealthy, of the form Eq. (15),

$$Sensitivity = \frac{TP}{TP + FN}\% \qquad (15)$$

The specificity was a measure of percentage of healthy subjects (who had no the disease) that were recognize healthy, as in Eq. (16),

$$Specificity = \frac{TN}{TN + FP}\% \qquad (16)$$

Additionally, the accuracy was a measure of ratio percentage of amount of samples correctly classified to the total amount of samples (*N*), as in Eq. (17),

$$Accuracy = \frac{TP + TN}{N}\% \qquad (17)$$

3. RESULTS

Figure 2 describes an example of heart sound normal from segmentation result that associated with the cardiac cycle by utilizing Shannon envelope. Determination of a thresholding value (dotted horizontal line on Fig. 2(b)) based on onset until ending incidents of S_1 and S_2, respectively, as well S_1 onset of the following cycle, so that the single cycle, systolic, and diastolic were acquired. From the segmentation results, 269 signals of the normal and murmur subjects for single cycle, systolic period, and also diastolic period were obtained, respectively. In this study, the single cycles of 70 subjects were allocated into two groups. First group consisted of 44 subjects or 214 single cycles (87 N, 92 systolic murmurs, 17 diastolic murmurs, and 18 continuous murmurs) and was utilized for classification training of MLP-BP network. Second group was conducted for

classification testing (MLP-BP, FCM, and HCM networks) and contained 26 subjects or 155 single cycles (66 N, 68 systolic murmurs, 11 diastolic murmurs, and 10 continuous murmurs).

In our experimental results, each single cycle of the 269 cardiac cycles was extracted by utilizing CWT method. Figure 3(a) depicts an example of single cycle of the normal subject that consisted of systolic period (which comprises S_1) and diastolic period (which contains S_2). Furthermore, Figure 3(c) shows artifacts in systolic period which indicates the presence of systolic murmur at SA subject. The contours of the artifacts are depicted clearly in Fig. 3(d). Furthermore, Fig. 3(e) describes MS subject that contain murmur at diastolic period. The contours of the diastolic murmur are showed obviously in Fig. 3(f). Figure 3(g) depicts an example of continuous murmur of PDA subject that contain the artifacts in systolic period as well as diastolic period. The time-scale map of this murmur is depicted at Fig. 3(h). All of each feature extraction results (i.e., 100×200 matrix form), would be input for classification as 20,000 features in a vector feature form.

The PCA was used to reduce dimension of feature vectors of CWT coefficients by picking only the vectors that had great variances. In our experimental results, high correlations existed between the original variables (i.e. 200 variables), which were therefore not independent. According to eigenvalues (Eq. (9)), the last 197 of 200 principal factors might be neglected since they represented with average less than 12.55% of the total variance. The original variables depended mainly on the first three factors. The PCA reduced the 20,000 element feature vector into 300 element feature vector. Therefore, each single cycle in any the signal has 300 features as input to classifier network.

Three classifiers, i.e., NN MLP-BP, FCM, and HCM were conducted to make their classification decisions of a heart sound's class based on signs important and symptoms for heart diagnosis in knowledge of auscultation experts. Each classifier of the heart sounds was performed for classification of normal, systolic murmur, diastolic murmur, as well as continuous murmur. In our experimental results, the classification results of the three classifiers from input of 20,000 and 300 features are depicted in Table 1 and Table 2, respectively. From the diagnosis of auscultation experts in each class as many as 155 single cycles (26 subjects), the three classifier systems were calculated the input of the feature vector. The classification results were

number of testing for each class. For 20,000 features (Table 1), 2 normal and 3 normal of single cycles were classified incorrectly by FCM and HCM clustering, respectively. Furthermore, 1 continuous murmur of single cycle was classified incorrectly by HCM clustering. For 300 features (Table 2), 2 normal of single cycles were classified incorrectly by HCM clustering. Additionally, 3 systolic murmurs, 9 systolic murmurs, and 11 systolic murmurs of single cycles were classified incorrectly by NN MLP-BP, FCM, and HCM, respectively.

The classification performances of three classifiers were evaluated with statistical validation method. Table 3 shows classification performance results from 20,000 and 300 features, respectively. The ANN MLP-BP achieved the best performance (i.e. sensitivity, specificity, and accuracy) as an automated classifier rather than FCM and HCM methods. Moreover, the sensitivity, specificity, and accuracy values, respectively, of each classifier from 20,000 features were greater than 300 features. Moreover, decreased performance from reduction of the features is described in Table 3. The performances of three classifier systems were decreased due to the feature reduction of PCA.

4. DISCUSSIONS

Selecting the thresholding (Fig. 2(b)) would cut off the signal at certain points to acquire the beginning until the ending occurrences of S_1 and S_2, respectively, also onset of S_1 of the next cycle. Its thresholding be conditional on c_{env} value. Variation of c_{env} of normal and pathological subjects powerfully depended on the individual variation and measurement condition. Hence, we were arranged its c_{env} to have an appropriate thresholding for consistent yields manually. In our study, the pathological heart sound recordings were very complex and the phases of the heart sounds vary largely. Two of four times the recording on the MR subject were omitted. The sudden release for a short time of the stethoscope from the subject caused in imprecise detection. Additionally, the matters for taking out the peaks, i.e., many extra peaks and artifact that look like apparent peaks both in time interval and amplitude. Large intensity murmur overlapped with S_1 or S_2 would make the proper identification and segmentation improbable.

Feature extraction was one of the most important stages in classification, since even the best classifier would perform poorly if the features were not chosen well. In our previous study, signal processing and extensive characterization method wavelet-based analysis were considered precious to describe mechanisms of heart valves functions [2]. Time-scale maps yielded by CWT calculation were resolved using magnitude thresholding operation and center of gravity to confine time-scale of valvular events. Duration of S_1 and S_2, S_1-S_2 spaced time, events of closuring mitral and tricuspid valves during systole, closuring aortic and pulmonal valves during diastole, and physiological split time between valves activities in each cardiac sub-cycle could be characterized exactly. The method was capable to distinguish objectively and clearly between normal and pathological heart sounds. Therefore, in this study, the CWT method was performed to extract the heart sound essential characteristics. The mechanical events of the heart sounds relating to a given normal and murmur were conceived in a single cycle of the heart sound signal (e.g. Fig. 3(b), (d), (f), (h), respectively). Hence, the method could provide detailed information of the heart sound during the cardiac cycle. Furthermore, the calculation results of feature extraction would be input for classification.

In this study, PCA was conducted to reduce the dimension of the heart sound feature vectors by picking only the vectors that had great variances, i.e., the first three factors of 200 principal factors. Therefore, the PCA reduced the 20,000 element feature vector from coefficients of wavelet into 300 element feature vector. Using PCA could be easily calculated and had less computational load (i.e. input 300 features) that compared to before feature reduction (i.e. input 20,000 features) during classification process. However, input 300 features resulted in declining classification performance of the three classifiers as shown in Table 3. Moreover, each decreasing maximum for sensitivity, specificity, and accuracy, respectively, is 2.55% (FCM method), 1.77% (HCM method), and 2.90% (HCM method). This showed trade-off between computational load and classification performance. However, a decrease in the classification performance as a result of the feature reduction was not significant, because a very small percentage. Therefore, overall of the proposed method, input of 300 features for classification more potential as a screening for the heart diagnosis, because it had less computational load.

Sensitivity and specificity as shown in Eq. (15) and Eq. (16), respectively, are measurements of how good of a medical test result. In other words, both equations ((15) and (16)) state that if the subject's disease status is known, then sensitivity

means that "I know my subject has the disease. What is the chance that the test will show that my subject has it?" Furthermore, specificity means that "I know my subject doesn't have the disease. What is the chance that the test will show that my subject doesn't have it?" For the system performance, higher sensitivity decreases the number of subjects with an unhealthy heart that are told they are healthy. On the other side, higher specificity decreases the number of subjects with healthy heart that are told they are unhealthy. In our experimental results, both sensitivity and specificity of the MLP-BP, as well as FCM and HCM, were better than Vos et al. [29]. They experimental results were 90% and 96.5%, respectively, less than the values are shown in Table 3.

In previous studies, Chebil et al. [16] and Gupta et al. [17] have efficiently used the Artificial Neural Network (ANN) for detecting and classifying the heart sounds. From research of Chebil et al., 21 signals for training (i.e. 7N and 14 SA) and 61 signals for testing (1N, 32 systolic murmurs, and 28 diastolic murmurs) were used [16]. The study utilized discrete wavelet transform to identify S_1, S_2 and murmurs. Energy of the signal within the systole and the diastole was conducted. If the energy exceeds a specified threshold in each interval, then the heart sound signal was classified as having systolic murmur or diastolic murmur. Otherwise, the signal was classified as normal. However, the accuracy of the classification results was 92.3%. Its accuracy value was less than of our experimental results, as shown in Table 3. Furthermore, Gupta et al. have classified a three way for normal, systolic murmur, and diastolic murmur using MLP-BP [17]. The architecture of network consisted of 12 input nodes, 1 hidden layer with 12 nodes, 3 output nodes. Moreover, 41 subjects (340 single cycles) consisted of 135 cycles for training (45N, 45 systolic murmurs, and 45 diastolic murmurs) and 205 for testing (65N, 79 systolic murmurs, and 61 diastolic murmurs) were conducted. A classification accuracy of 94.5% was achieved [17]. However, in our study (Table 3), the accuracy was better than Gupta et al., i.e. 100% (from input 20,000 features) and 99.03% (from input 300 features). Therefore, increment of our classification performances achieved into a more sensitive and could be more rigorous in analyzing abnormalities that appear in essential characteristics of the heart sounds for heart diagnosis.

Cardiac auscultatory was regarded as a prominent tool for medical doctors in acquiring a precise cardiovascular evaluation and confirming a cost-effective approach in outpatient-based medicine. Several recent researches evaluating the performance of clinicians in training have shown unsatisfactory results for cardiac auscultatory [30-34]. Expert cardiologists had an auscultatory accuracy of roughly 80% [30]. Furthermore, the auscultatory accuracy of primary care doctors was 20% up to 69% [31-34]. In this study, all the three classifiers systems clearly had far better accuracy than the primary care doctors as depicted in Table 3. Our proposed method would improve the accuracy of auscultation by providing objective additional information and could be assistance for physicians to make their ultimate diagnoses.

Role of screening technique for the early detection of heart diseases was very important to prevent sudden cardiac death. Phonocardiogram screening of detection and classification of the systolic murmur using a neural network for elementary school children was performed in Japan [35], [36]. Furthermore, Yoshinaga has studied about school-based cardiovascular screening to children and adolescents who life-threatening cardiovascular diseases [37]. In the first of three stages of screening method, phonocardiography as the early detection and diagnosis of heart disease was performed. In this research, our proposed method was considered significant potential as a screening alternative technique. The proposed method could aid general doctors to arise with more accurate and trustworthy diagnosis at early stages for massive examination.

In previous study, Cholkraisuwat et al. have determined prevalence of unrecognized congenital heart disease among elementary school students and study the types and frequency of congenital heart disease in rural Thailand using trained nurses and other health care personnel [38]. Five hundred forty eight students were suspected to have heart diseases and 102 students were diagnosed as congenital heart disease. Simple acyanotic lesions (VSD, ASD, and pulmonary stenosis) were common in this study (32.35%, 16.67%, and 11.76%, respectively). Qualified nurses or health care workers could be useful for identifying patients with congenital heart disease. Therefore, the role of these personnel in the national heart screening program should be further clarified. In Indonesia, many rural clinics were run by nurses, because the limited availability of physicians. The nurses often work in communities where they were called on to perform duties usually done by physicians and auscultation may be the only means available. Our proposed method could be benefit

for computer-assisted diagnosis of cardiac disorders and very useful as an alternative diagnostic tool that complies with the requirements for rural clinics.

Investigation to clarify cardiac auscultatory expertise for 18 family practice residents thru a Cardionics CardioSim Digital Heart Sound Simulator® (Cardionics, Inc., Houston) in the study of auscultatory technique was performed [39]. The recording of simulated heart sounds was utilized in the educational intervention and evaluation, including SA (systolic murmur), MS (diastolic murmur), and PDA (continuous murmur) from 14 cardiac auscultation findings. The participants were encouraged to listen with their stethoscopes to each sound over the speaker of a standard commercial portable home stereo system. Although the participants in small-group discussion sessions and repetitive auscultation could improve resident's ability to identify heart sounds audiotaped, but study of Horiszny was only restricted in teaching auditory and undertaken a simulator [39]. Whereas, in our research, systolic murmur, diastolic murmur, and continuous murmur could be clarified more simply recognized visually (e.g. Fig. 3), in the usage of temporal-frequency related parameters (such as our previous studies [2], [11]), also auditory inspection. Additionally, in our previous research, surrogate data modeling of normal heart sounds was created to extract knowledge about characteristics and mechanisms of generation of the human heart sound signals. The model described more objectively how the normal heart sounds were reproduced by utilizing of random phases [40]. Furthermore, our exploration was addressed to modeling of surrogate pathological heart sound signals for further research in related to classification the signal and very useful for an alternative tool of the heart sound simulator. Thus, our study was considered beneficial to aid in the study of auscultatory method from the signal processing manner viewpoint.

Our proposed method was suitable to classify of normal and pathological heart sound signals of human subjects due to signs important and symptoms for heart diagnosis based on knowledge of auscultation experts. The wavelet analysis could provide detailed information of the heart sound during the cardiac cycle as input for classification. Although the heart sound data were collected partially from cassette of literature [13], the noise from the circumstance and wires could still affect the quality of recording. This could affect the classification of the signals. From the high of classification result, it was denoting that the

wavelet analysis was adequate for classifying into normal or pathological occurrences. Additionally, the three classifiers (ANN MLP-BP, FCM and HCM) that showed significant potential in their use as an alternative diagnostic tool were compared. The ANN achieved the best performance as an automated classifier rather than FCM and HCM methods. The proposed method was considered very important for objective screening and very useful as an alternative diagnostic tool that complies with the requirements for rural clinics. Moreover, the method would be helpful in study of auscultation technique for medical students. Surrogate data modeling of pathological heart sounds signals as an alternative tool of the heart sound simulator and for classification purpose was further study.

5. CONCLUSIONS

We have developed a screening technique that suitable to classify of normal and pathological heart sound signals of human subjects due to signs important and symptoms for heart diagnosis based on knowledge of auscultation experts. Three computerized algorithm classifiers that showed significant potential in their use as an alternative diagnostic tool were compared. The ANN MLP-BP achieved the best performance as an automated classifier rather than FCM and HCM methods. The performance of ANN was 100% for sensitivity, specificity, and accuracy, respectively, of input 20,000 features. Furthermore, for input 300 features, the performance of ANN was 98.90%, 99.37%, and 99.03% for sensitivity, specificity, and accuracy, respectively. The proposed method was considered very important for objective screening and useful as an alternative diagnostic tool that complies with the requirements for rural clinics. We hoped that the method would be beneficial in study of auscultatory technique for medical students. Next topic of our study was modeled surrogate data of pathological heart sound signals as an alternative tool of the heart sound simulator.

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Table 1: Classification Percentage Of 155 Single Cycles (26 Subjects) Before Using PCA

Method	Diagnosis / Testing Class (%)			
	Normal	**Systolic murmur**	**Diastolic murmur**	**Continuous murmur**
NN MLP-BP	66 / 66 (100.00)	68 / 68 (100.00)	11 / 11 (100.00)	10 / 10 (100.00)
FCM	66 / 64 (96.97)	68 / 68 (100.00)	11 / 11 (100.00)	10 / 10 (100.00)
HCM	66 / 63 (95.45)	68 / 68 (100.00)	11 / 11 (100.00)	10 / 9 (90.00)

Table 2: Classification Percentage Of 155 Single Cycles (26 Subjects) After Using PCA

Method	Diagnosis / Testing Class (%)			
	Normal	**Systolic murmur**	**Diastolic murmur**	**Continuous murmur**
NN MLP-BP	66 / 66 (100.00)	68 / 65 (95.59)	11 / 11 (100.00)	10 / 10 (100.00)
FCM	66 / 66 (100.00)	68 / 59 (86.76)	11 / 11 (100.00)	10 / 10 (100.00)
HCM	66 / 64 (96.97)	68 / 57 (83.82)	11 / 11 (100.00)	10 / 10 (100.00)

Table 3: Classification Performance Of The Classifier Network

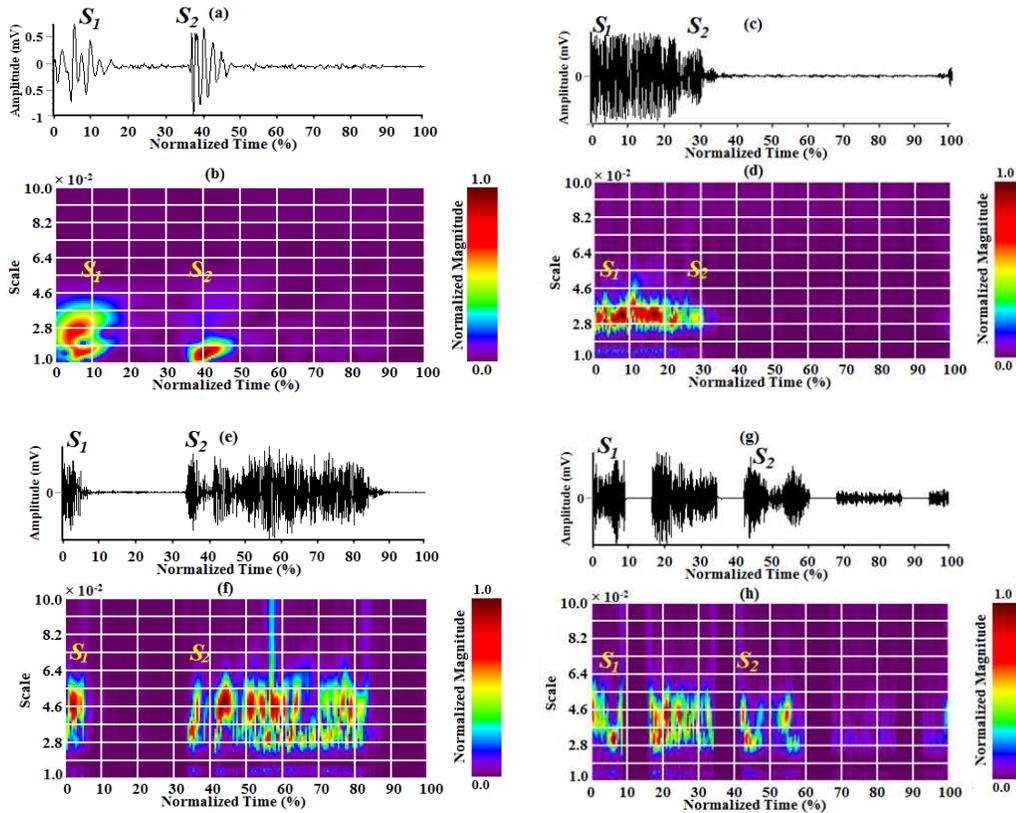| Method	20,000 features			300 features			Decreased performance from reduction of the features		
	Sensitivity (%)	**Specificity (%)**	**Accuracy (%)**	**Sensitivity (%)**	**Specificity (%)**	**Accuracy (%)**	**Sensitivity (%)**	**Specificity (%)**	**Accuracy (%)**
NN MLP-BP	100.00	100.00	100.00	98.90	99.37	99.03	1.10	0.63	0.97
FCM	99.24	99.54	99.35	96.69	98.12	97.10	2.55	1.42	2.26
HCM	96.36	99.20	98.71	95.20	97.43	95.81	1.17	1.77	2.90

Figure 3: (A), (C), (E), And (G) Example Of Single Cycle Of The Normal, Systolic Murmur (SA), Diastolic Murmur (MS), And Continuous Murmur (PDA) Subjects, Respectively. (B) Coefficients Of CWT For (A) In Color Spectrum. The Color Spectrum Is Magnitude Normalization Of Wavelet Coefficient Between 0.0 And 1.0, Where Purple And Red Represent The Lowest And The Highest Energy, Respectively. (D). Coefficients Of Wavelet For (C). A Format Alike With Fig. 3(B). (F) Coefficients Of Wavelet For (E), Where The Format Alike With Fig. 3(B). (H) Coefficients Of Wavelet For (G), Where The Format Alike With Fig. 3(B).