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Classification of Normal and Abnormal Heart Sounds Using Empirical Mode Decomposition and First Order Statistic

Hilman Fauzi[1], Achmad Rizal[2], Alvin Oktarianto[2], Mazaya 'Aqila[1], and Ziani Said[3]

[1] Biomedical Engineering Telkom University, Jalan Telekomunikasi Bandung West Java 40286, Indonesia
[2] Electrical Engineering, Jalan Telekomunikasi Bandung West Java 40286, Indonesia
[3] Health Technologies Engineering Department, Research Group in Biomedical Engineering and Pharmaceutical Sciences, ENSAM, Mohammed V University, Agdal, Morocco

Corresponding author: Hilman Fauzi (e-mail: hilmanfauzitsp@telkomuniversity.ac.id)

ABSTRACT Analysis of heart sound signals for automatic segmentation and classification has revealed in recent decades that it has the potential to detect pathology accurately in clinical applications. Various audio signal processing techniques have been used to reduce the subjectivity of heart sound analysis. In this study, the normal and abnormal classifications of heart sounds were carried out by a simple feature extraction method using statistical calculations. The feature extraction process was optimized by empirical mode decomposition (EMD) and calculated using five first-order statistical parameters: mean, variance, kurtosis, skewness, and entropy. The classification system is optimized with a mutual information algorithm to select traits that can significantly improve system performance. In addition, the selection of the optimal system configuration also includes the k-fold cross-validation and kNN methods with k values and the proper distance type. Based on the test results, the highest accuracy of 98.2% was obtained when the value of k = 1 and the type of cosine distance on kNN with a five-fold cross-validation system evaluation model. Based on these results, it can be concluded that the first-order statistical feature extraction method on heart sound signals will be optimal in detecting heart sound abnormalities with EMD optimization.

INDEX TERMS Heart Sound, Normal, Abnormal, EMD, First Order Statistic, Mutual Information, kNN, k-Fold Cross Validation

I. INTRODUCTION

During the cardiac cycle, the heart undergoes electrical activation that forms mechanical activity in the form of atrial and ventricular contraction. At the same time, blood movement in the heart chambers and throughout the body can impact the opening and closing of the heart valves [1]. The mechanical activity, the rapid initiation, and the cessation of fast blood flow in the heart caused an increase in the vibration of the entire cardiac system. The vibrations can be heard in the chest wall [2]. Listening to these specific sounds may help to determine whether a healthy heart or not. Since heart sounds are assessed based on the expertise and experience of doctors, various computer-based heart sound analysis methods have been developed by researchers [3], [4]. This method was developed based on the characteristics of the heart sound, which can be quantified using computer programming [5]. The simplest method for heart sound analysis is to calculate the statistical parameters of heart sounds, such as mean, variance, entropy, skewness, and kurtosis [6]. This parameter is calculated on the signal in the time domain. Meanwhile, several researchers explored the heart sound characteristics from the frequency domain [7]. The features used are peak frequency, total harmonic distortion (THD), and Q-factor. Another method quite popular for heart sound analysis is wavelet or time-frequency domain analysis [8]. The abnormal heart sound signals were learned and classified using hybrid signal processing method [9]. Meanwhile, Zhang et al. used a scaled spectrogram [8] to distinguish normal and abnormal heart sounds.

Because biological signals are suspected of having multi-scale properties, many methods involve decomposition processes before analyzing heart sounds or multi-scale methods. Safara et al. used wavelet decomposition to classify murmurs in heart sounds [10]. Meanwhile, Thomas et al. utilized fractal decomposition [11]. Multi-scale dispersion entropy was proposed for heart sound analysis as a biometric [12]. Another method is empirical mode decomposition (EMD) and its derivatives, which decompose the signal into an intrinsic mode function (IMF) consisting of the signal's main frequency components. With EMF, the local oscillation of the signal is eliminated. In previous studies, EMD was often used for signal component detection or denoising heart sound signals [13] [14]. Based on several previous studies regarding the classification of heart sounds, EMD is not used for the feature extraction process. In addition, the feature extraction method using first-order statistical methods is considered not good enough to produce exclusive features in large amounts of data. This study proposes classifying heart sounds using Empirical Mode Decomposition (EMD) [15] and first-order statistical parameters. The heart sound signal is decomposed into 10 Intrinsic Mode Functions (IMF), and then five statistical parameters are calculated as signal characteristics. The K-nearest neighbour is used for the classification process with several distance measurements and K-values. The contributions of this paper include: 1. Combining the EMD method and statistical features for feature extraction of heart sounds, 2. They are providing recommendations for a sufficient number of IMFs to be used in feature extraction of heart sounds. The proposed method is expected to produce high accuracy for heart sound classification and become an alternative feature extraction method for the classification of heart sounds.

II. MATERIALS AND METHODS

FIGURE 1 shows the procces stages in the proposed method. The stages explain the process of processing heart sounds so that they can be classified as normal and abnormal heart sounds.

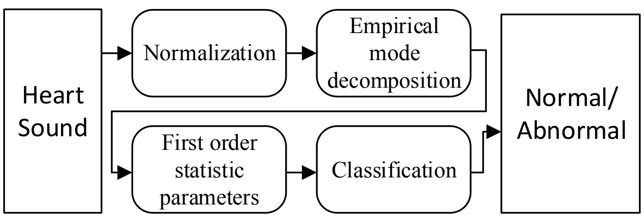

FIGURE 1. Proposed method

A. HEART SOUND DATASET

We used the heart sound dataset used in the PhysioNet/Computing in Cardiology Challenge 2016 [16]. The dataset is available at Physionet, one of today's most complete physiology signal dataset and tool providers [17]. The heart sound recordings were taken from various locations on the body. The four typical locations are the aortic area, the pulmonic area, the tricuspid area, and the mitral area, but they could be any of nine different locations. Heart sound recordings were divided into two types in both the training and test sets: normal and abnormal heart sound recordings. The normal recordings came from healthy people, while the abnormal ones came from people who had a confirmed cardiac diagnosis. The patients have a variety of illnesses (which we do not provide on an individual basis), but they are typically heart valve defects and coronary artery disease patients. Mitral valves prolapse, mitral regurgitation, aortic stenosis, and valvular surgery are all examples of heart valve defects. All data is in short recording (10-60s) from a single precordial location and was resampled to 2000 Hz and in wav file. In this paper we only used dataset A from all datasets provided with 409 number of data (subjects) [16].

For each data, the normalization process includes DC removal and amplitude normalization as in equations (1) and (2).

$$y(n) = x(n) - \frac{1}{N}\sum_{i=1}^{N} x(n) \tag{1}$$

$$y(n) = \frac{x(n)}{max|x|} \tag{2}$$

where x(n) is the input signal, N is the length of the signal, and y(n) is the output signal. By equations (1) and (2), the input signal will have an average value of 0 and a range of -1 to +1.

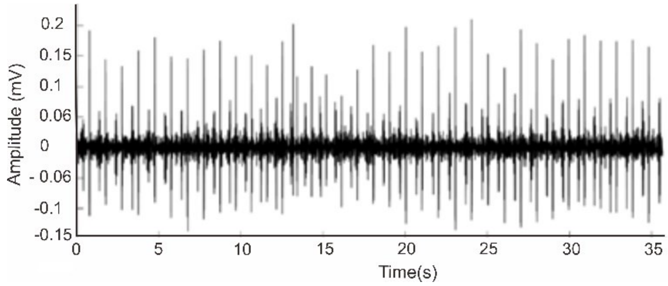

FIGURE 2. Sample of Normalized Data Signal

B. EMPIRICAL MODE DECOMPOSITION

Huang et al. developed empirical mode decomposition (EMD), a non-stationary signal analysis technique. [18]. By removing local oscillations from the signal, EMD decomposes it into several intrinsic mode functions (IMF) and residuals [19]. EMD is the first part of the Hilbert-Huang Transform (HHT) used to calculate a signal's instantaneous frequency (IF). [20]. EMD is widely used for lung sound analysis [21]–[23] for different applications such as noise, Velcro, or Crackle identification.

If given a signal x(t), the EMD algorithm is simple as follows [24]:

1. Identify the extrema of the x(t) signal. Connect the local maxima and local minima using interpolation to form the upper and lower envelopes.
2. Calculate the average $m_1(t)$ value of the upper and lower envelopes. The difference between the signals x(t) and $m_1(t)$ is expressed by $h_1(t) = x(t)-m_1(t)$.
3. If $h_1(t)$ is not IMF, then the process in steps (1) and (2) is repeated and calculated $h_{12}(t)=h_{11}(t)-m_{11}(t)$.
4. After the k-th iteration, $h_{1k}(t)$ will become IMF if $h_{1(k-1)}(t)-m_{1k}(t)=h_{1k}(t)$. When $m_{1k}(t)$ approaches 0, $h_{1k}(t)$ is called $c_1(t)$.
5. Calculate the first residue $res_1(t)=x_1(t)-c_1(t)$. This residue will be the data for the next IMF calculation. This process will continue until the average envelope value becomes monotonic.

Thus, the signal x(t) can be expressed as follows:

$$x(t)=c1(t)+c2(t)+\cdots+ck(t)+res(t) \tag{3}$$

where $c_1(t)$, $c_2(t)$,…,$c_e(t)$ is the IMF while res(t) is the residual.

In this study, lung sounds were performed by EMD until the 10th IMF. The selection is up to the 10th IMF. It is because most of the data used for lung ballots have an IMF of up to 13. In the 13rd IMF, the signal becomes relatively monotonous so that it cannot be distinguished from one class of data to another.

C. FIRST ORDER STATISTIC

The method used to extract the characteristics of the heart sound signal in this study is to use first-order statistics. The statistical parameters include the mean, standard deviation, skewness, kurtosis, and entropy.

1) MEAN

Mean is measuring the central tendency of the data. It implies one number that best summarizes the entire set of measurements. In addition, several studies said that the Mean-Variance has a general purpose because of its excellent structural properties [25]–[29]. Thus, the mean result can be used to estimate or represents the value of the whole data set. The formula of the mean is shown in equation (4).

$$Mean\ (\bar{Y}) = \frac{\sum_{i=1}^{N} Y_i}{N} \tag{4}$$

where Yi is the data point, and N is the number of data.

2) STANDARD DEVIATION

Standard deviation is calculating the square root of the variance to measure the dispersion of the dataset relative to its mean. One study said that standard deviation could better evaluate and prioritize classification because significant differences were found in the final values [30]. Variance (VAR) is stated in equation (5), and standard deviation (s) is formulated in equation (6)

$$VAR = \frac{1}{N-1}\sum_{i=1}^{N} Y_i^{\,2} \tag{5}$$

$$s = \sqrt{VAR} \tag{6}$$

3) SKEWNESS AND KURTOSIS

Skewness is a measure of the skewness of the distribution of data. By the skewness method, a data set can be known as a symmetrical data set. The data distribution can be called symmetry if the distribution has the same section between the left and right of the center point. If the skewness is different from 0, the distribution appears to deviate from symmetry [31]. The skewness formula is shown in equation (7).

$$Skewness = \frac{\sum_{i=1}^{N}(Y_i-\bar{Y})^3/N}{s^3} \tag{7}$$

Generally, kurtosis is associated with the distribution of the tail, shoulder, and peakedness [32]. Kurtosis is a measure of the sharpness of the distribution of data. Kurtosis can be used to show whether the data are heavy-tailed or light-tailed in comparison to a normal distribution. The heavy-tailed one has data set with high kurtosis, and the light-tailed one has data set with low kurtosis. If the kurtosis differs from 0, the distribution appears to deviate from normality at the Tai mass [33]. The formula of kurtosis is shown in equation (8).

$$Kurtosis = \frac{\sum_{i=1}^{N}(Y_i-\bar{Y})^4/N}{s^4} \tag{8}$$

As skewness increases, kurtosis must increase because of a relationship where kurtosis≥ skewness2 – 2 [34]. Scheffe, in his study, said that kurtosis and skewness are the essential indicators where abnormality affects, which is usually made in the analysis of variance [35].

4) ENTROPY

Entropy is used for estimating information contained in random data. The probability density function (pdf) can determine the estimated entropy value. The entropy (H) is expressed in equation (9).

$$H = -\sum_{i=1}^{N} pdf(x)\log\left(pdf(x)\right) \tag{9}$$

Pdf is the probability of the x value in the heart sound.

D. CLASSIFIER

Classification is done using the k-Nearest Neighbors (k-NN) method with the help of distance metrics. The trick is to determine the number of k-neighbors, then calculate the distance using the distance metric between the k-neighbors.

After that, a sample of the nearest k-neighbors is taken, whose distance has been calculated using a distance metric. Among all those k-neighbors, count the number of data points by category. The final step is to enter a new data point into the category where the number of neighbors reaches the maximum. These new data points will be categorized by looking at the nearest k-neighbors. The distance metric calculation method is used to see the closest k points based on the number of k we want. In this study, there are normal and abnormal categories. If the new data point has the most k-NN in the normal category, then the data point is included in the normal category, and vice versa.

III. RESULT

In this study, several stages of testing were carried out using the Matlab R2022a application, starting with the process of Empirical Mode Decomposition (EMD), then extracting features of normal and abnormal heart sounds from a file that has been downloaded from Physionet Challenge 2016. The extraction results test the classification accuracy using the first-order statistical parameter method. The statistical parameter method used the classification learner with five-fold and 10-fold cross-validation limitations.

A. EMPIRICAL MODE DECOMPOSITION (EMD) RESULT

The results of PCG signal decomposition using the EMD method in the form of Intrinsic Mode Function (IMF) are signals that have eliminated local fluctuations. The decomposition results can be seen in FIGURE 3 and FIGURE 4.

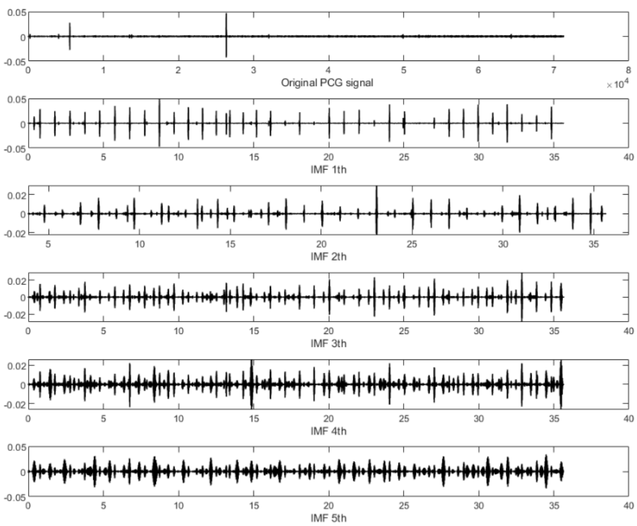

FIGURE 3. Normal PCG Signal and Decomposition Result at 5 IMF

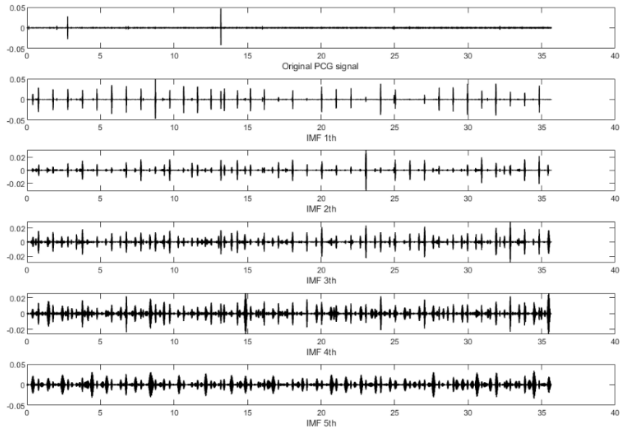

FIGURE 4. Abnormal PCG Signal and Decomposition Result at 5 IMF

B. OTHER RECOMMENDATIONS

The feature selection aims to determine which feature composition can significantly affect the system performance as measured by the accuracy calculation. The feature selection method used in this study is mutual information calculation. The calculation of mutual information will determine the information of any features; when the MI value is higher, the information will be higher. The value of mutual information is obtained from the five features: mean, variance, kurtosis, skewness, and entropy. The value of mutual information is obtained as shown in table 1. The mutual information value on the skewness and entropy features is much higher than the other three, with a value of more than 0.3. Determine whether the selected feature requires a MI threshold value. The method of determining the threshold is done by calculating the average MI value of all features and getting a value of 0.145. Thus, the selected features have an MI value higher than 0.145. The selected features that comply with these provisions are skewness and entropy. Furthermore, skewness and entropy are selected features that will be tested on the classification system and compared with a system that uses all features. The mutual information value can be seen in TABLE 1.

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TABLE 1
Mutual information value

Features	Mean	Var	Kurt	Skew	Ent	Avg
MI Value	0	0.018	0	0.397	0.309	0.145

C. FIVE-FOLD CROSS VALIDATION RESULT

In measuring five-fold cross-validation with all features, all distance types of kNN show an increase in accuracy as the value of K increases by an average of 3.7%. However, the accuracy on euclidean and city block distance types decreased at K=7 with an average of 0.95%. In addition, the highest accuracy occurs at K=5 with a value of 71.6% for the euclidean distance type and 71.4% for the city block distance type. Meanwhile, the K value constantly increases on the cosine distance type until K = 7. Generally, the testing system uses five-fold cross-validation with all features; the highest accuracy value occurs at K=5 with 71.6% for the euclidean distance type. In comparison, the lowest accuracy value occurs at K=1 with a value of 62.6% for the same distance type. The test results can be seen in TABLE 2.

TABLE 2
Five-fold cross validation measurement using all features

Type of distance	K Value			
	1	3	5	7
Euclidean	62.6	68.2	*71.6*	70.4
City block	63.6	68.9	71.4	70.7
Cosine	64.3	68	68.2	69.7

In contrast to the performance in a testing system with all features on changes in the K value, change accuracy on a system with selected features experience a decreasing pattern as the K value increases or the pattern is inversely proportional. Patterns of change happened to all types of distances: Euclidean, city block, and cosine. The highest accuracy value occurs at k=1 on cosine distance type with an accuracy of 98.2%. In comparison, the lowest accuracy value occurs at k=7 on the Euclidean distance type with an accuracy of 83.3%. Compared with a system using all features, the system's accuracy with selected features has increased by 26.6%. The results of the testing system using 5-fold cross-validation with selected features can be seen in TABLE 3.

TABLE 3
Five-fold cross validation measurement using selected features

Type of distance	K Value			
	1	3	5	7
Euclidean	91.2%	86.8%	85.1%	83.3%
City block	88.6%	85.1%	85.1%	84.2%
Cosine	*98.2%*	94.7%	92.1%	87.7%

D. SIZING OF GRAPHICS

In measuring 10-fold cross-validation using all features, the average measurement of accuracy value is 67.88%. Measurements using the Euclidean distance type obtained an average accuracy value of 67.95%, City Block has an average accuracy value of 68.4%, and cosine has an average accuracy value of 67.3%. In this measure, the Euclidean and City Block distance type constantly increased until K=7, while the cosine distance type decreased at K=5 but increased back at K=7. The measurement with the highest accuracy value occurred in the Euclidean distance type and K=7 with 71.6%. In comparison, the measurement with the lowest accuracy value occurs in the cosine distance type and K=1 with 63.6%. The results of the testing system with 10-fold cross-validation can be seen in TABLE 4.

TABLE 4
10-fold cross validation measurement using all features

Type of distance	K-value			
	1	3	5	7
Euclidean	64.5	67	68.7	71.6
City block	64.8	67.7	69.7	71.4
Cosine	63.6	69.2	67	69.4

In the testing system with 10-fold cross-validation, the system's accuracy decreases as the value of K increases. It occurs at all types of distances. The highest accuracy is 97.4% with cosine distance type and K-value of 1. Whereas the lowest accuracy is 84.2% using the distance type of city block with K=7. Thus, there has been an increase in the system's accuracy by 25.8% compared to the system's accuracy using all features. The results of the testing system using 10-fold cross-validation measurements on selected features can be seen in TABLE 5.

TABLE 5
10-fold cross validation measurement using selected features

Type of distance	K Value			
	1	3	5	7
Euclidean	91.2%	86.8%	85.1%	83.3%
City block	88.6%	85.1%	85.1%	84.2%
Cosine	*98.2%*	94.7%	92.1%	87.7%

E. THE COMPARATION RESULT

Based on the testing system results, it was obtained that the optimal classification system occurs in 5-fold cross-validation with two features selected, such as skewness and entropy. Accuracy in the system with 5-fold cross-validation is 98.2% or 0.8% higher than the system with 10-fold cross-validation. The comparison of the accuracy system based on cross-validation is shown in FIGURE 5.

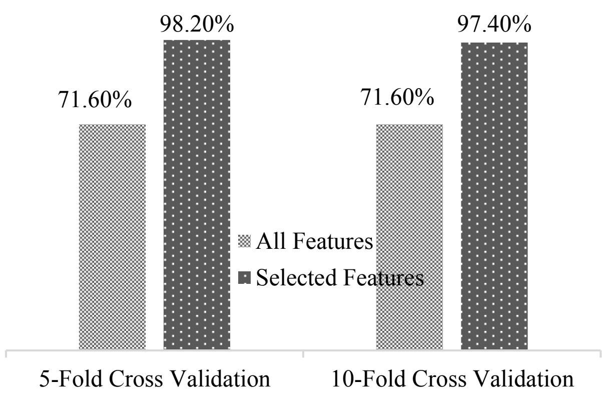

FIGURE 5. The comparison of the accuracy system

In a system with data processing of five first-order characteristics (mean, variance, skewness, kurtosis, and entropy), the highest accuracy is obtained with the distance type of Euclidean kNN. On average, the highest accuracy is obtained by distance type of city block with a value of

68.65% for 5-fold cross-validation and 68.4% for 10-fold cross-validation. It is a contrast to the system with selected features using mutual information. The optimal type of distance used in kNN is cosine, with an average accuracy of 96.3% of 5-fold cross-validation and 93.2% of 10-fold cross-validation.

IV. DISCUSSION

Based on the test findings, it was discovered that systems using only a few features outperformed systems using all features by more than 34%. It demonstrates that skewness and entropy are the only first-order statistical parameters pertinent to, compatible with, and exclusive to heart sound signals. The heart sound signal's characteristics should be as exclusive as possible to make it easy for the system to recognize the label or class.

There are difficulties with the first-order statistical feature extraction methods used in the heart sound categorization system. The feature extraction method used in this work is considered superior to other feature extraction methods used on comparable systems. It is since, in this investigation, using just two feature parameters and a straightforward first-order statistics computation procedure, the system accuracy that was produced attained high values of more than 98%. As a result, the value of the predictable system calculation time increases. However, the EMD optimization process must be completed before the high precision value produced by this method may be used. In order to achieve high heart sound classification results, the first-order statistical feature extraction method needs to be combined with an optimization procedure. The classification of normal and pathological heart sounds using a first-order statistical feature extraction method has been demonstrated in this work to be highly effective.

The weakness of the proposed method is the number of features still quite a lot. The highest accuracy of 98.2% is obtained when using 10 IMFs with five statistical features or 50 characteristics. Meanwhile, using one feature at 10 IMFs only resulted in the highest accuracy of 71.6%. This study has not conducted further tests on the optimal number of IMFs for feature extraction. Selection of the number of IMF = 10 based on previous studies on lung sounds [36]. In this research, the feature subset selection (FSS) process has not been carried out to select the best features to produce the highest accuracy.

Compared to previous research, the resulting accuracy is quite competitive. The number of datasets used in this study is more than the study by Komalasari et al. [37], which only used 50 normal heart sound data and 50 abnormal heart sound data. Meanwhile, Hamdi et al. [38] uses the complete PhysioNet/Computing in Cardiology Challenge 2016 dataset [16] with an accuracy of 92%. From the number of features used, the resulting features are still more than those used in (Ratna Komala) which only uses four features in the form of heart sound fractal dimensions. Of the three previous studies discussed as a comparison, this method produces higher accuracy with a sufficient number of data sets. Testing with larger datasets and the FSS process is interesting to do in future research.

V. CONCLUSION

In this study, the proposed feature extraction method for classifying heart sounds uses EMD and feature statistics. Heart sounds were decomposed using EMD to produce 10 IMFs, and then each IMD was calculated for its statistical characteristics. EMD decomposes the signal to obtain the fundamental heart sound frequency, which is considered the difference between normal and abnormal heart sounds. Classification using KNN and 5-fold CV produce the highest accuracy of 98%. Simple deception, the proposed method can produce a high accuracy compared to other methods. The next interesting research topic is the selection of the number of IMF combined with the use of more advanced machine learning.

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