Fractal dimension to classify the heart sound recordings with KNN and fuzzy c-mean clustering methods

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Abstract. The heart abnormalities can be detected from heart sound. A heart sound can be heard directly with a stethoscope or indirectly by a phonocardiograph, a machine of the heart sound recording. This paper presents the implementation of fractal dimension theory to make a classification of phonocardiograms into a normal heart sound, a murmur, or an extrasystole. The main algorithm used to calculate the fractal dimension was Higuchi’s Algorithm. There were two steps to make a classification of phonocardiograms, feature extraction, and classification. For feature extraction, we used Discrete Wavelet Transform to decompose the signal of heart sound into several sub-bands depending on the selected level. After the decomposition process, the signal was processed using Fast Fourier Transform (FFT) to determine the spectral frequency. The fractal dimension of the FFT output was calculated using Higuchi Algorithm. The classification of fractal dimension of all phonocardiograms was done with KNN and Fuzzy c-mean clustering methods. Based on the research results, the best accuracy obtained was 86.17%, the feature extraction by DWT decomposition level 3 with the value of kmax 50, using 5-fold cross validation and the number of neighbors was 5 at K-NN algorithm. Meanwhile, for fuzzy c-mean clustering, the accuracy was 78.56%.

1. Introduction

According to the ministry of health, the cardiovascular disease is the most deadly disease, until now in Indonesia. Many efforts have been made to solve this problem. One of them is early detection of abnormalities of the cardiovascular system. The abnormalities of heart can be detected from heart sound. A heart sound can be heard directly with a stethoscope or indirectly by a phonocardiograph, a machine of the heart sound recording. Phonocardiogram is a graphic representation of heart sounds made by a phonocardiograph. Phonocardiogram is very important in diagnosing murmurs that basically inaudible to the human ear because of the effects of fatigue on the ears from loud noise before. Thus the use of phonocardiogram is important in diagnosing certain conditions of the valve and congenital heart disease [1]. Besides through direct listening, early detection can be done by indirect method, where in this research the classification is based from the fractal dimension of phonocardiogram.

1.1. Abnormal Heart Sound

In healthy adults, there are two normal heart sounds often described as a lub and a dub, that occur in sequence with each heartbeat. These are the first heart sound (S1) and second heart sound (S2), produced
by the closing of the atrioventricular valves and semilunar valves, respectively. A normal heart sound has a frequency range of 20-100 Hz, while a murmur sound has a frequency range up to 1000 Hz. The first heart sound (S1) consists of energy in the frequency range 30-45 Hz, most of which is beneath the threshold of human hearing. The second heart sound (S2) usually has a higher pitch with the maximum energy in the range 50-70 Hz. One type that causes regurgitation murmur in the frequency range 100-600 Hz and even certain types of murmurs to 1000 Hz [2].

The abnormal heart sound is a noise or an additional heart sound. In this study, the abnormal heart sound examined were heart murmur and extrasystole. A heart murmur is an extra or unusual sound heard during a heartbeat. Murmurs range from very faint to very loud. Sometimes it sounds like a whooshing or swishing noise. The murmur caused by blood flow turbulence. Sometimes, this sound can not be heard and undetectable for most of cardiac dysfunction and disease. The following, a PCG showing the complex S1 and S2 with the murmur [3].

![Figure 1](image1.png)

**Figure 1.** (a) Normal Heart Sound        (b) Murmur Heart Sound

Extrasystole is a premature contraction of the heart that is independent of the normal rhythm of the heart and that arises in response to an impulse in some part of the heart other than the normal impulse from the sinoatrial node. The extrasystole is followed by a pause, as the heart electrical system "resets" itself and the contraction following the pause is usually more forceful than normal. An extrasystole can be caused by the presence of heart disease. If the disease is detected early, then treatment may be more effective. Here, an example of an PCG indicating extrasystole [4].

![Figure 2](image2.png)

**Figure 2.** a PCG of Extrasystole

2. **Classification process of heart sound recording**

2.1. **Feature Extraction**

Researches on analysis of bio signal, particular heart sound signals have been done by various researchers. Among them, the research conducted by Mukherjee, et al.,[5] detected heart murmurs using fractal analysis of signals phonocardiograph using feature extraction Continuous Wavelet Transform (CWT), Higuchi algorithm for calculating the fractal dimension, and classification process with Neural Network. Roy, et al.,[3], made a distinction between a normal phonocardiograph sound (PCG) and a sound with murmurs using Kant algorithm and statistical analysis to fractal dimension of PCG signal. Often, important information hidden within the signal frequency. In this study, we characterized the signal in terms of its various frequency components. Discrete Wavelet Transformation was used to reduce the representation set of features. The wavelet transform superior to Fourier transformation because it is able to represent not only the information signal frequency in the frequency space, but also
being capable of demonstrating change its frequency respect to time [6]. Discrete Wavelet Transform (DWT) analyzes a signal at different scales and represents it on a time scale using a filtering technique, which uses different filters of cut-off frequency. DWT is defined as follows:

$$DWT(j, k) = \sum_{t=-\infty}^{\infty} x(t) \frac{1}{\sqrt{2^j}} \varphi \left( \frac{t - 2^j k}{2^j} \right)$$

(1)

2.2. Higuchi Fractal Dimension

A fractal dimension is an index for characterizing fractal patterns or sets by quantifying their complexity as a ratio of the change in detail to the change in scale [7]. Different from topological dimension, the fractal dimension can take non-integer values. For instance, a curve with fractal dimension very near to 1, it look like an ordinary line, but a curve with fractal dimension near to 2 has a shape like a string of threads that fill the surface [8]. Several types of fractal dimension can be measured empirically and theoretically. By calculating the fractal dimension of tofu, tissues or soil will be known how dense the tofu, tissues or the soil. Fractal dimensions are used to characterize a broad spectrum of objects, including turbulence, river networks, human physiology such as eye fundus [9], and market trends. Higuchi Algorithm is one of the algorithms to calculate fractal dimension in form of time series data. In many cases, the usage of the Higuchi’s fractal dimension is more appropriate than the spectral exponent to analyze an irregular time series.

Given a one-dimensional time series $X = x[1], x[2], ..., x[N]$. The algorithm for calculating Higuchi fractal dimension described as follows [11].

1. Set a new time series of $k$, $X^k$ defined as follows:

$$X^k = \left\{ x[m], x[m + k], x[m + 2k], ..., x[m + \text{int}\left(\frac{N-m}{k}\right)k] \right\}$$

(2)

Where $k$ and $m$ are integers, $k$ indicates discrete time intervals, while $m = 1, 2, ..., k$ indicates the value of the initial time.

2. The length of each new time series can be defined as follows:

$$L(m, k) = \frac{\left\{ \text{int}\left(\frac{N-m}{k}\right) \right\} \sum_{i=1}^{\text{int}\left(\frac{N-m}{k}\right)} |x[m+ik] - x[m + (i-1)k]|}{k}$$

(3)

Where $N$ is the length of the original time series $X$, and $|x[m+ik] - x[m + (i-1)k]| = h_i$. Thus, $L(m, k)$ is the normalized number of segment length $h^i$ indicate different distance values on the coordinate pair of points as far as $k$, starting on samples to $m$, $x[m]$ with $m = 1, 2, ..., k$. Figure 3 below, is an example of the determination $h^i$ when $k = 3$ and $m = 2$.

![Figure 3. Example Sequence Determination of $h^i$ on a curve when $k = 3$ and $m = 2)](image-url)
The length of the curve for the time interval $k$ obtained by dividing all subseries $L(m,k)$ with $k$.
For $m=1,2,...,k$

$$L(k) = \frac{\sum_{i=1}^{m} L(m,k)}{k}$$

(4)

3. Thus, Higuchi Fractal Dimension is defined as the slope of the line in accordance with the $[\ln(L(k)), \ln(1/k)]$ is estimated using a linear quadratic most suitable. And the result is the fractal dimension Higuchi.

2.3. Classification
Classification is a process of dividing things into groups according to their type. In this study, we classified the fractal dimension values into groups based on normal, murmur or extrasystole heart sound.

KNN method
K-Nearest Neighbors (KNN) algorithm is a method to classify objects into $K$ groups in a training data based on the closest distances, in this research, the distance used was Euclidean distance.

Steps to calculate the K-Nearest Neighbor algorithm:
1. Determine the parameters $K$ (Number of closest distance neighbors)
2. Calculate the Euclidean distance between the data to be evaluated and all of training data.
3. Sort the distance and determine nearest neighbors based on k-th minimum distance.
4. Gather the corresponding class.
5. Find the number of classes from the nearest neighbors and assign the majority class as a class data to be evaluated.

Fuzzy c-mean clustering
In fuzzy clustering, data points can potentially belong to multiple clusters with a membership degree of a point in each cluster that shows the quality measurement of the point is in a cluster. Given a finite set of data, $X$, the problem of fuzzy clustering is to find a fuzzy c-partition and the associated cluster centers by which the structure of the data is represented as best as possible [12]. Let $X = \{x_1, x_2, ... , x_n\}$ be a set of given data. A fuzzy c-partition of $X$ is a family of fuzzy subsets of $X$, denoted by $P=\{A_1, A_2, ..., A_c\}$, which satisfies:

$$\sum_{i=1}^{c} A_i(x_k) = 1 \quad \text{and} \quad 0 < \sum_{k=1}^{n} A_i(x_k) < n, \forall i$$

(5)

for every partition $A_i$, the center is calculated by:

$$v_i = \frac{\sum_{k=1}^{n} [A_i(x_k)]^m x_k}{\sum_{k=1}^{n} [A_i(x_k)]^m}$$

(6)

Fuzzy c-mean algorithm is given below [9],
Step 1. Select a value $c$ indicate the number of clusters, a real number $m>1$, a small enough real positif number $\varepsilon$.
Step 2. Select an initial fuzzy c-partition $P_0$.
Step 3. Calculate the cluster center $v_i(t), v_2(t), ..., v_c(t)$ for every c partition of $P_t$.
Step 4. Find the $P_{t+1}$ with following procedure: For each $x_k \in X$, if $\|x_k - v_i(t)\|^2 > 0$, $\forall i$ then define:

$$A_i^{(t+1)}(x_k) = \left[ \sum_{j=1}^{c} \left( \frac{\|x_k - v_j(t)\|^2}{\|x_k - v_j(t)\|^2} \right) \right]^{-1}$$

(7)

If $\|x_k - v_i(t)\|^2 = 0$, for some $i \not\in I$, then define $A_i^{(t+1)}(x_k)$ by any non negatif real number such that the sum of it on I equal 1, and define $A_i^{(t+1)}(x_k) = 0$, for $i \in N_c-I$.
Step 5. If $\|P_{t+1} - P_t\| < \varepsilon$ then stop, otherwise return to step 3.
Cross Validation
Cross validation is a method to evaluate the performance of a classifier. This method divides the data into two subsets of data with the same size, one used as training data set and others for testing data set. Training set and testing set must revolve respectively so that each data has a chance to be a testing set. One method of cross-validation is k-fold cross validation. In k-fold cross-validation, the data is randomly partitioned into k equal-sized subsets. From the k subsets, one subset is chosen as the testing data for testing the model, and the remaining k−1 subsets are used as training data. The cross-validation process is then repeated k times (the folds), with each of the k subsets used exactly once as the testing data.

3. Methodology
In this study, the recording data of heart sound used were the database obtained from the internet: (http://www.peterjbentley.com/heartchallenge/index.html). The data used were 120, contained 40 data of normal heart sound, 40 data of extrasystole, and 40 data of murmurs. The data obtained from a clinic trial in hospitals using the digital stethoscope DigiScope. The data was in wav format and the bit rate was 64 kbps. The procedure to classify the heart sound recording can be seen in the following flow chart.

The data: The input data in this study was the data recording of heart sound with *.wav format. This data was processed by using software MATLAB R2009a with the sampling frequency of 4000 Hz, bitrate 64 kbps and 16-bit quantization. The cutting process of signal was done to have the same duration signal and regarding on a cycle signal (lub-dub-lub).

Pre-Processing
Before the feature extraction, the signal had been filtered and normalized. The low-pass filter used to remove high-frequency components that are not desirable, and the type of filter used is a digital IIR (Infinite Impulse Response) order-10 types Butterwort with a cut-off frequency of 1000 [13]. This process aimed to reduce noise in the signal of heart sound. The process of normalization was done with changed the amplitude to the interval from -1 to 1, to equalize the maximum amplitude of each sound signal so that the heart sound recognition process was not influenced by amplitude differences.

Feature Extraction Processes
Feature extraction process using DWT was done from the feature vector signal. The purpose of this process was to compress the signal by dividing the original signal into smaller parts (sub-band) and separating between high-frequency components and low-frequency components, where the components of the low-frequency is a feature vector of signals which was useful in the process of pattern recognition. With this decomposition process, the computing process became faster [14]. In this research, the decomposition process level was 3. The resulting signal of decomposition approximation level 1 (A1), level 2 (A2) and level 3 (A3) in the time domain and the frequency was converted to the frequency domain to see the frequency range with a Fast Fourier Transform [13].

Calculating Fractal Dimension
The fractal dimensions of Approximation signal decompositions level 1, level 2, and level 3, which has been transformed into the frequency domain by the FFT were calculated using Higuchi algorithms. The k-max value 16, 28, 32, 50, and 60 were compared in this study.
Classification
(1). After calculation of fractal dimension using Higuchi algorithm, then the data were partitioned using 5-fold Cross Validation, then the next step was the process of classification using K-Nearest Neighbor (K-NN) algorithms. The number used of neighbors (K) were 3, 5, and 7.
(2). The data of fractal dimension of heart sound recording were partitioned using fuzzy c-mean clustering with c=3 and m=2.

To know the accuracy of the classifier, the results of the classification process were compared with the classification on the database (http://www.peterjbentley.com/heartchallenge/index.html). The accuracy of the system was calculated by the following equation:

\[ \text{Accuracy} = \frac{\text{number of correct data}}{\text{number of overall data}} \times 100\% \]

The higher the accuracy the better of the performance of the classifier system means that the system can recognize the given input.

4. Result and Discussion

In this study, all heart sound signals data was cut on 1 phase of systolic and 1 phase of diastolic.

(a)  
(b)  

Figure 4. (a) Original Signal.  (b) Signal after cutting process.

Pre-processing: The filtering to reduce noise in the signal and the normalization to equalize the amplitude of the signal.

(a)  
(b)  

Figure 5. (a). Signal After Filtering Using IIR (b) Normalized Signal
Feature extraction by DWT: In the process of DWT, vector signal was reduced to a half of the original signal vector. Here is an example of signal decomposition part Approximation level 1, 2, and 3 as well as the frequency spectrum.

![Signal decomposition and frequency spectrum](image)

**Figure 6.** (a) Decomposition signals on level 1-3  (b) FFT of each level

Calculation of fractal dimension using Higuchi Algorithm.

The fractal dimension of all waveform of heart sound data was calculated and the mean of fractal dimension for every class was obtained. The table below described the mean of fractal dimension for every class of heart sound using decomposition level 3 with kmax 50.

| Class Of Heart Sound | Normal  | Extrasystole | Murmur  |
|----------------------|---------|--------------|---------|
| Mean of Fractal Dimension | 1.7377  | 1.7998  | 1.8396  |

From the table, it can be seen that the bigger of the fractal dimension, the higher of the level of voice disorders in someone's heart and higher the risk of people developing heart disease.

**Classification Using K-NN Nearest Neighbors.**

The fractal dimension of all data was classified using the K-NN algorithm, with K=1, 3, 5 and 7. The value of K selected were odd number to avoid the appearance of the same amount of distance in the process of classification. The performance of the classification was checked by 5-fold cross validation.

The k value of k-fold was selected randomly, with condition the amount of data used divided by k. In this research, the kmax value used were 16, 28, 32, 50, and 60. So, the total of experiments conducted as many as 60 times. The following table showed the results.
Table 2. Table of Experiment Result

| Accuracy | 5-fold |
|----------|--------|
|          | 1-NN   | 3-NN   | 5-NN   | 7-NN   |
| Kmax 60  |        |        |        |        |
| Lev 1    | 40.83% | 46.67% | 49.17% | 55.83% |
| Lev 2    | 50.00% | 54.17% | 51.67% | 59.17% |
| Lev 3    | 70.83% | 80.00% | 75.83% | 78.33% |
| Kmax 50  |        |        |        |        |
| Lev 1    | 46.67% | 48.33% | 39.17% | 44.17% |
| Lev 2    | 49.17% | 53.33% | 50.83% | 50.00% |
| Lev 3    | 82.50% | 86.66% | 86.67% | 85.83% |
| Kmax 32  |        |        |        |        |
| Lev 1    | 45.83% | 44.17% | 48.33% | 52.50% |
| Lev 2    | 47.50% | 50.00% | 49.17% | 50.00% |
| Lev 3    | 56.67% | 50.83% | 63.33% | 64.17% |
| Kmax 28  |        |        |        |        |
| Lev 1    | 42.50% | 48.33% | 50.00% | 50.83% |
| Lev 2    | 46.67% | 50.00% | 50.00% | 44.17% |
| Lev 3    | 50.83% | 54.17% | 48.33% | 55.00% |
| Kmax 16  |        |        |        |        |
| Lev 1    | 31.67% | 45.00% | 40.83% | 33.33% |
| Lev 2    | 40.00% | 45.83% | 41.67% | 43.33% |
| Lev 3    | 40.83% | 46.67% | 47.50% | 50.00% |

Based on the table, it can be seen that the best accuracy is 86.67% with the value kmax 50 on the decomposition of level 3 by 5-fold cross validation (data is divided into 5 partitions) and 5-NN (the number of nearest neighbors is 5). Based on the experiment, the most appropriate value of kmax was 50. Selection value of K in K-NN also affected the accuracy of the results. The value of K that produced the best accuracy was 5.

Classification using fuzzy c-mean clustering

For the data of fractal dimension of heart sound recording, the value of c=3 (there are 3 classes, normal, extrasystole and murmur), m=2 and ε=0.001.

For initial fuzzy 3-partition, we chose the degree membership for every dimension fractal in one partition was the same, that were $A_1(x_k)=0.532$, $A_2(x_k)=0.347$ dan $A_3(x_k)=0.121$, $\forall k$.

The algorithm of fuzzy c-mean clustering were stop after 7 cycles, and the last center were $v_1=1.705228181$ for $A_1$ (class of normal sound heart), $v_2=1.787594889$ for $A_2$ (class of extrasystole) and $v_3=1.845496764$ for $A_3$ (class of murmur). These centers are similar with the mean of dimension fractal for every class in table 1. To check the accuracy this partition, we calculated the number data that include in the correct partition. We called a datum was in the correct partition if the maximum membership degree of this datum is in the appropriate class, for example if $x_n$ is a dimension of a murmur sound heart recording and $A_3(x_n)$ greater than both $A_1(x_n)$ and $A_2(x_n)$, then we call $x_n$ is a member of the murmur class, so it was in the correct partition. The data was include in the correct partition was 78.56% of all data, so the accuracy of this pseudo partition was 78.56%.

5. Conclusion

Based on the experiments and the analysis of the classification of heart sounds recordings (phonocardiogram) with Higuchi algorithm for calculating fractal dimension and the classification method, it can be concluded that:

The heart sound signal characteristics extracted by using DWT level 3 to get the feature vector of the signal was better than the wavelet decomposition level 1 and 2. The kmax value of Higuchi’s algorithm that suits better for the signal length in this study was 50, compared to kmax 60, 32, 28, and 16. The K value of K-NN algorithms to have the best accuracy of classification was 5. The best accuracy of the classification of recording heart sounds (phonocardiogram) is 86.67% on the decomposition level 3 with kmax 50, partition data using 5-fold cross validation and the number of neighbors in the K-NN is 5. Meanwhile, for fuzzy c-mean clustering, the accuracy was 78.56%. This showed that the Higuchi’s
algorithm and K-NN can be used to classify the recordings of heart sound (phonocardiogram) into a normal heart sound, a murmur, or an extrasystole based on the analysis of fractal dimension of the waveform of heart sound recording and the KNN method as a classifier give the better performance than fuzzy c-mean clustering.

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