Normal and Murmur Heart Sound Classification Using Linear Predictive Coding and k-Nearest Neighbor Methods

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***Abstract*— Heart rate sounds have a special pattern that is in accordance with a person's heart condition. An abnormal heart will cause a distinctive sound called a murmur. Murmurs caused by various things that indicate a person's condition. Through a Phonocardiogram (PCG), it can be seen a person's heart rate signal wave. Normal heartbeat and murmurs have a distinctive pattern, so that through this pattern it can be detected a person's heart defects. This study will make a classification program that will sense normal heart sounds and murmurs. This program uses feature extraction methods using LPC (Linear Predictive Coding) and classification using k-NN (k-Nearest Neighbor) to identify these 2 heart conditions. The data that will be used as a database consists of samples of normal heart rate sounds and murmurs, and also data obtained from the heart rate detection device in the .wav, mono format. The system for detecting heart abnormalities consists of three main parts, namely: recording heart rate sounds, feature extraction using LPC with order 10, and feature lines using k-NN with 3 types of distances and variations of k. From the results of testing with these types of distance, the obtained average accuracy value of Chebyshev, City Block, and Euclidean are 96.67, 91.67, and 93.33 percent, respectively. In addition, the value of k equal 3 is the most optimal value of k with an average level of 96.67 percent.**

***Keywords*— heart abnormalities, linear predictive coding, k-nearest neighbour.**

I. Introduction

Heart attack still in the first rank that causes of death in many countries of the world. Symptoms of heart abnormalities (murmurs) often come suddenly, therefore early recognition of heart abnormalities can help to avoid a heart attack. Until now doctors are still using heart sound cues to monitor heart performance by using a stethoscope whose produces weak sounds. Therefore, sensitivity of diagnosis and experience to identify the heart sound are needed. In addition, physical limitations also greatly affect the results of interpretation until the diagnosis results are strongly influenced by the physician's subjectivity.

The heart has an important role in supplying oxygen to the whole body and cleaning the body of metabolic products (carbon dioxide). This organ carries out its function by collecting oxygen-deprived blood from the whole body and impelling it into the lungs, where the blood will take up O_2 and remove CO_2. Next, the heart brings together the blood contain O_2 from the lungs to the entire human body tissues.

In order to find out the electrical activity of the heart muscle, it is necessary to record the heart rate from the surface of the body. Recording heart rate sounds can be done electronically using a phonocardiography tool. The recording results of this tool are called phonocardiogram (PCG). Patients who are affected by a heart disease, their PCGs can indicate the disease with a beating sound that is different from the sound of a normal heartbeat. Heart sound has a special pattern that is in accordance with the condition of one's heart health. An abnormal heart will produce additional sounds called murmurs.

This paper has the following structure; first in Section I we introduce the heart sound and its feature extraction, second in Section II, we indicate this topic relation with some same field researches. Then the accompanied methodology is described in Section III. The research results and its discussion are termed in Section IV. Finally, the conclusions based on the research results are provided.

II. Related Works

There are many researches in heart sound field such as in S1 and S2 detection until discrimination of normal heart sound. In [1] the authors have contribution in heart disease detection based on heart sound using S1 and S2 segmentation algorithm, after their participating in PASCAL Classifying HS Challenge. In order to obtain the clear heart sound, the author of [2] proposed a prototype which consists of transducer to obtain heart acoustic sensitively. Acoustic recognition of the sounds produced by blood flowing through partly obstructed coronary arteries cultivates a potential mechanism for non-contact sensing of this main disease process.

Furthermore, classification of heart sound research has been conducted by many authors, such as in [3-6]. In [3], the authors proposed a feature to sense abnormal heart sound using wavelet decomposition. The wavelet was utilized to remove the noise so that the heart sound can be classified properly. In [4], the authors also utilized wavelet in order to segment the heart sound. The utilized component which is the Empirical Wavelet Transform (EWT) based PCG signal analysis for characteristic heart sound from heart murmur and disturbing surroundings noise. In [5], the authors offered an effective HMM-based (Hidden Markov Model) grouping method to discriminate between the normal and abnormal heart sounds. In [6], the authors present a statistical parameter standard deviation as heart sound feature and then do performance comparison between three classification methods (k-Nearest Neighbors, Naïve Bayes, and Support Vector Machine).

In this paper, we propose heart sound classification using LPC and k-NN for feature extraction and pattern classification, respectively. Moreover, we consider Chebyshev, City Block, and Euclidean as distance type for k-NN pattern classification.

III. METHODOLOGY

The conducted methodology consists of three main steps, which are preparing heart sound, providing feature extraction of heart sound using LPC (Linear Predictive Coding), and classifying of hear sound utilizing k-NN. The detail of the methodology is shown in Fig. 1. Furthermore, the accuracy testing is performed by using Confusion Matrix. In this section we describe these steps in detail as follows.

A. Heart Sound Signal Preparation

The first step of our research methodology is preparing the heart sound. We collect many heart sounds which are obtained from recorded file [7]. The recording consists of Records A and B training. The Record A consists of data collection from the general public through the iStethoscope Pro iPhone application. The record contains 5 normal heart sound and 5 murmur heart sound. The Record B consists of 15 normal and 15 murmur heart sound from clinical trials in a hospital using a DigiScope digital stethoscope. This research uses 60 data records, which are split to 40 and 20 data as training and testing data, respectively. From the testing data, 10 data were obtained from records using a heart sound acquisition device that was connected to the application with a normal diagnosis and 10 data are from the murmur dataset.

The heart sound audio files are in digital *.wav format and it must be sampled digitally for next LPC process. They are varying in length between 1 second and 30 second (some durations have been cut to reduce excessive noise and provide prominent fragments of sound). Most of the information of heart sounds contain low frequency components, with noise in higher frequency. The training process of this study does not use heart sound data with noise conditions so the system output will only recognize Normal and Murmur conditions in accordance with the training data pattern. The digital sample results of the normal and murmur heart sounds are given away in Fig. 2.

B. Heart Sound Feature Extraction

The feature extraction stage is a very important stage in the process of processing heart sound signals. The feature extraction can describe the characteristics or patterns between one group of heart sounds with another group. In this study, feature extraction of heart sound signals is obtained by predicting the LPC coefficients.

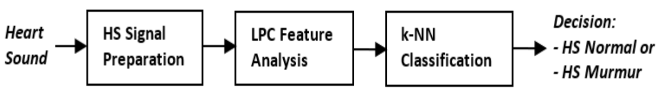

Fig. 1. The diagram block of heart sound classification system.

Furthermore, analysis of the predicted value with LPC coefficients are obtained by the following stages.

- *Pre-Emphasis.* This stage is used to flatten the spectral signal and to increase the signal authenticity in the next signal processing. The equation for the calculation in the pre-emphasis process is as follows.

$$h'(n) = h(n) - \beta h(n-1) \tag{1}$$

where $h'(n)$ is pre-emphasis function, $h(n)$ denotes n^{th} data signal, $h(n-1)$ represents $(n-1)^{\text{th}}$ data signal, and β is a pre-emphasis coefficient and has range value $0.9 \leq \beta \leq 1.0$.

- *Frame blocking and windowing.* This stage groups the signal results of the pre-emphasis process into frames with a size equal to the data entered. After the frame blocking process is carried out, the next process is the windowing process. The purpose of windowing is smoothing per frame signal. This process uses the Hamming equation, which is written as follows [8].

$$w(n) = 0.54 - 0.46cos(\frac{2\pi n}{N} - 1) \tag{2}$$

where $w(n)$ is Hamming function and N is number of signal block sample. Then the windowed signal x(n) is as follows

$$x(n) = w(n)\, h'(n) \tag{3}$$

- *Autocorrelation*. The autocorrelation function is the correlation of a waveform with itself. After windowing process, per frame signal x(n) will be autocorrelated each other. Then the autocorrelated signal c(m) is expressed in the following formula.

$$c(m) = \sum_{n=0}^{N-1-m} x(n)x(n+m) \tag{4}$$

- *LPC Analysis.* In this stage we get the LPC parameters, which is known as LPC coefficients. We use Levinson-Durbin algorithm to find the LPC coefficients, which has recursive procedure as follows.

i) $E^{(0)} = c(0)$
ii) for $1 \leq i \leq p$

$$k_i = \frac{\left[c(i) - \sum_{j=1}^{i-1} \alpha_j^{(i-1)} c(i-j)\right]}{E^{(i-1)}}$$

iii) $\alpha^{(i)} = k_i$
iv) for $1 \leq j \leq i\text{-}1$ $\alpha_j^{(i)} = \alpha_j^{(i-1)} - k_i\, \alpha_{i-j}^{(i-1)}$
v) $E^{(i)} = (1 - k_i^2)\, E^{(i-1)}$
vi) Final solution $\theta_j = \alpha_j^{(p)}$ with $1 \leq j \leq p$

The value of p indicates the LPC order, this notation also presents the number of LPC coefficients. The increase of p value shows the decrease of error, if we turn back the LPC coefficients to its original signal.

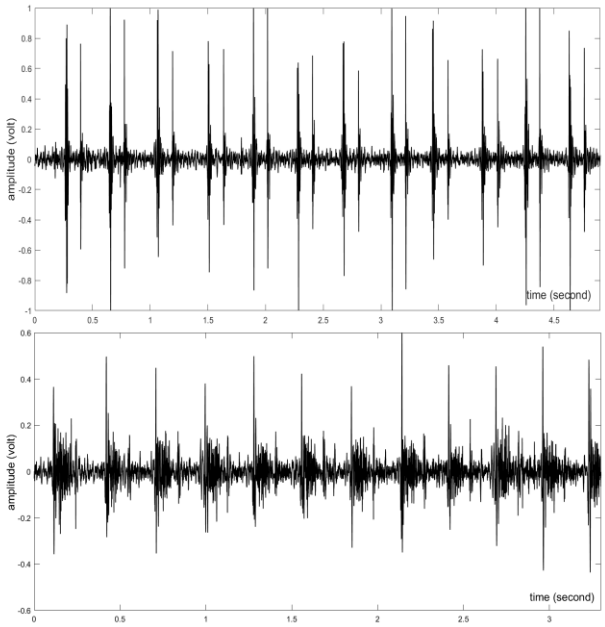

Fig. 2 The example of HS wave form, normal (upper) and murmur (lower).

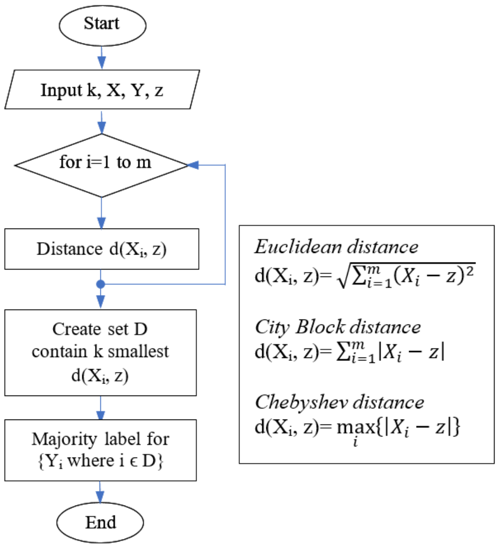

Fig. 3. The flow chart of pattern classification using k-NN..

TABLE I. CONFUSION MATRIX

Classification		Predicted Class	
		Class N	Class M
Observed Class	Class N	True Positive (TP)	False Negative (FN)
	Class M	False Positive (FP)	True Negative (TN)

C. *Pattern Classification*

The coefficient value, which is produced by feature extraction, represents the feature of heart sound. Different heart sound has different LPC coefficient value. The collection of features is being grouped as training data. Furthermore, the data will be used as the input k-NN classification which will indicate whether the heart sound belongs to normal or murmur. In addition, k-NN classification process applies 3 distance methods, namely Chebyshev, City block, and Euclidean with different k variations. In the k-NN we use different values of k, which are 3, 5, and 10. Flowchart of pattern classification using k-NN is shown in Fig. 3.

The k-NN is then tested using patterns of LPC extraction data values that have been trained with new data. This recognition process is based on the pattern of the heart rate LPC sound extraction value data. If the classification program runs and the value of k with a predetermined distance approaches the majorities of normal training data values, the classification result will display NORMAL value. Conversely, if the value of k with a predetermined distance approaches the majorities of the murmur training data values, then the classification yields MURMUR value.

D. *Accuracy, Specificity, and Sensitivity Testing*

The accuracy, specificity, and ssensitivity testing are performed in order to show performance of the k-NN algorithm that applies to data set. Confusion matrix is a calculation that compares the dataset with the results of the classification in accordance with actual data with the total amount of data. The result of matrix is the level of accuracy with units of percent (%). This level of accuracy will be utilized as a reference, which is related to the performance of the classification algorithm. Confusion Matrix is an evaluation of a data mining classification, which is represented as a Table I.

TABLE II. PERFORMANCE METRIC OF K-NN WITH K=3

Distance	k=3				Acc (%)	Spe (%)	Sen (%)
	TP	TN	FN	FP			
Euclidean	10	9	1	0	95	100	91
City Block	10	9	1	0	95	100	91
Chebyshev	10	10	0	0	100	100	100

TABLE III. PERFORMANCE METRIC OF K-NN WITH K=5

Distance	k=5				Acc (%)	Spe (%)	Sen (%)
	TP	TN	FN	FP			
Euclidean	10	10	0	0	100	100	100
City Block	9	8	2	1	85	89	82
Chebyshev	10	10	0	0	100	100	100

TABLE IV. PERFORMANCE METRIC OF K-NN WITH K=10

Distance	k=10				Acc (%)	Spe (%)	Sen (%)
	TP	TN	FN	FP			
Euclidean	8	9	1	2	85	82	89
City Block	10	9	1	0	95	100	91
Chebyshev	9	9	1	1	90	90	90

TABLE V. AVERAGE OF ALL PERFORMANCE METRICS

Distance	Acc Average (%)	Spe Average (%)	Sen Average (%)
Euclidean	93.33	93.94	93.27
City Block	91.67	96.30	87.88
Chebyshev	96.67	96.67	96.67

The matrix contains information, which compares the label classification results with the actual label [9]. Table I illustrates confusion matrix with two labels, namely Normal (N) and Murmur (M). where TP means positive classification results with actual positive class, FN means negative classification results with actual positive class. FP mean the results of the positive classification with the actual negative class, TN means the results of the negative classification with the actual negative class.

The two remain performance metrics, the specificity is the ability of classifier (k-NN) correctly indicate the normal heart sound which it is normal in reality and the sensitivity is the ability of k-NN indicate the murmur heart sound which it is murmur in reality.

Furthermore, the performance metrics accuracy, specificity, and sensitivity of k-NN algorithm is calculated by utilizing the following equation.

$$\text{Accuracy} = \frac{TP+TN}{TP+FN+FP+TN} \text{ x100\%} \quad (5)$$

$$\text{Specificity} = \frac{TN}{FP+TN} \text{ x100\%} \quad (6)$$

$$\text{Sensitivity} = \frac{TP}{TP+FN} \text{ x100\%} \quad (7)$$

IV. Results and Discussion

System evaluation is performed by recording heart sounds using a heartbeat detection device (electronic stethoscope) that is connected by cable and Bluetooth to the application. We also record heart sounds of 10 people who have been declared normal by medical institution. The 10 data consists of 5 samples, which obtained by using cable connection and 5 samples, which are attained by utilizing Bluetooth connection. The time required for recording is 2 seconds, which will then be sampled for detection. Moreover, we use 10 murmur sound samples of heart patients, which are obtained from the dataset and does not include data for k-NN training. This test is carried out with variations type of distance, namely Euclidean, City block and Chebyshev, with the k values are 3, 5 and 10 for each distance. Accuracy testing is conducted by confusion matrix calculation with the results of the average of each test.

Based on mathematical calculation at above then we can summarize the performance metrics results into Table II to Table V. The calculation results show that with the type of distance Chebyshev obtained an average accuracy value of Chebyshev 96.67% higher than City block 91.67%, and Euclidean 93.33%. Furthermore, the accuracy average of each k values of three distance types is shown in Fig. 4. The value of k = 3 is the most optimal K value with an average accuracy rate of the three types of distances of 96.67%.

The Chebyshev distance method also with the value k=3 shown the highest value for Specificity and Sensitivity, both have 96,67 %, which are exposed in Fig. 5 and Fig. 6.

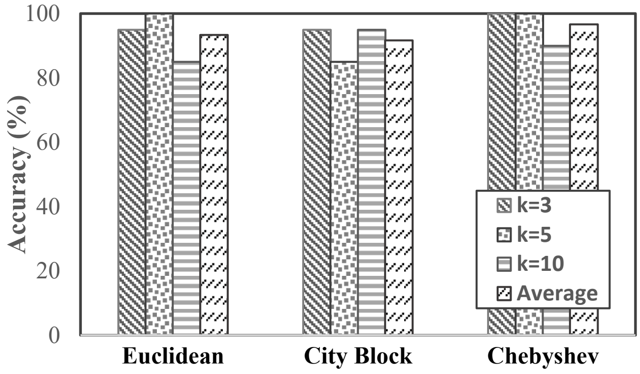

Fig. 4. Accuracy result of different k values of three k-NN distance types.

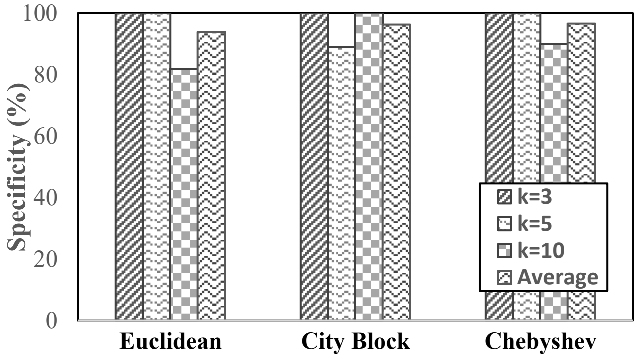

Fig. 5. Specificity result of different k values of three k-NN distance types.

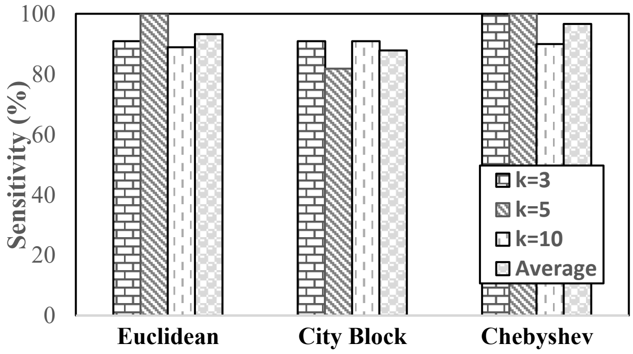

Fig. 6. Sensitivity result of different k values of three k-NN distance types.

V. Conclusion

Based on the results of our research that has been done it can be concluded that the heart sound classification application that has been made can record, store, play back sound recordings of heart and heart rate detection. And successfully implemented the K-Nearest Neighbor algorithm with the type of distance Euclidean, City Block and Chebyshev with different variations in the value of k. Through calculations with the confusion matrix shows that with the type of distance Chebyshev obtained an average value of Accuracy 96.67% higher than City Block distance 91.67%, and Euclidean distance 93.33%. Furthermore, the value of k = 3 is the most optimal k value, with an average accuracy rate of the three types of distances is 96.67%. Other performance metric specificity and sensitivity also indicate that Chebyshev distance method for k-NN classification has the highest value 96,67%.

ACKNOWLEDGMENT

This work was supported by Diponegoro University Research Council (LPPM) under International Publication Research (RPI) scheme, in 2018 funded year.

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