

Study of Denoising Method to Detect Valvular Heart Disease Using Phonocardiogram (PCG)

Muhammad Yaumil Ihza ^{#1}, Satria Mandala ^{#2}, Miftah Pramudyo ^{#3}

School of Computing, Telkom University Jl. Telekomunikasi, Bandung, Jawa Barat, Indonesia

> ¹<u>ihzagobah@student.telkomuniversity.ac.id</u> ²<u>satriamandala@telkomuniversity.ac.id</u> ³miftah.pramudyo@gmail.com

Abstract

Heart sound is a very weak acoustic signal, very susceptible to external acoustic signals and electrical disturbances, especially friction caused by the subject's breathing or body movements. The heart sound signal will be recorded in a phonocardiogram (PCG) and produce heart sounds, noise, and extra sounds. The purpose of this work is to denoise the signal from the heart sounds recorded on the PCG and determine valvular heart disease (VHD). Several methods have been proposed for denoising heart sound signals, both in the time domain and in the frequency domain. Most of these methods still have problems for denoising results. In this paper, the techniques used to denoise the heart sound signal are Discrete Wavelet Transform (DWT), Short Term Fourier Transform (STFT), and Low-Pass filter.

Keywords: VHD, PCG, Denoising, DWT, STFT, Low-Pass Filter

Abstrak

Suara jantung adalah sinyal akustik yang sangat lemah, sangat rentan terhadap sinyal akustik eksternal dan gangguan listrik, terutama gesekan yang disebabkan oleh pernapasan atau gerakan tubuh subjek. Sinyal suara jantung akan direkam dalam fonokardiogram (PCG) dan menghasilkan suara jantung, kebisingan, dan suara tambahan. Tujuan dari pekerjaan ini adalah untuk menghilangkan sinyal dari suara jantung yang terekam pada PCG dan menentukan penyakit katup jantung (VHD). Beberapa metode telah diusulkan untuk menghilangkan sinyal suara jantung, baik dalam domain waktu maupun dalam domain frekuensi. Sebagian besar metode ini masih memiliki masalah untuk hasil denoising. Dalam makalah ini, teknik yang digunakan untuk mendenoise sinyal suara jantung adalah Discrete Wavelet Transform (DWT), Short Term Fourier Transform (STFT), dan Low-Pass filter.

Kata Kunci: VHD, PCG, Denoising, DWT, STFT, Low-Pass Filter

I. INTRODUCTION

The mortality rate for valvular heart disease (VHD) was high in the cardiovascular disorder group. The disease is caused by damage to the heart valves, which consist of the aortic, pulmonary, mitral, and tricuspid valves, which help prevent backflow of blood. Causes of VHD include blood clots, heart failure, stroke, and sudden cardiac death. Currently medical practitioners perform the initial procedure using a stethoscope [3].

A stethoscope is an acoustic device used to listen to the internal sounds of the human body and works on the principle of transmission from the chest piece through an air-filled tube to the ear. In an electronic stethoscope, the pressure waves generated from the diaphragm are transferred to a sound-sensing device, usually a microphone, which in turn generates a signal that is used to analyze the condition of the heart. However, this stethoscope has the disadvantage of inherent noise due to lung sounds and ambient sources, the presence of these sounds making diagnosis difficult [3].

Phonocardiogram (PCG) is a graphical representation of the mechanical activity of the heart, which provides valuable information for the diagnosis of VHD, congestive heart failure, and anatomic defects. The function of the PCG is the same as a stethoscope, the difference is that the results of the data from the PCG are in the form of signal data from heart sounds that can be processed so that the results of the diagnosis are more precise [5]. With the development of technology and utilizing the field of machine learning, the signal is processed in 3 stages, namely denoising, feature extraction, and classification. Denoising is the stage where this stage will process the obtained signal and then remove the noise in the signal and convert the signal data into discrete data. Feature extraction is the stage of extracting information or features that are used as parameters or input values to distinguish objects from one another at the classification stage. Classification is the stage for the final result in the form of accuracy for detection. In this paper we will focus on the denoising stage. For denoising the author will analyze several denoising methods including Discrete Wavelet Transform (DWT), Short Term Fourier Transform (STFT), and Low-Pass Filter.

II. LITERATURE REVIEW

Singh and Sunkaria [1] In his article, proposes a new method using empirical wavelet transform to correct for fundamental aberrations and reduce the influence of power lines on electrocardiogram (ECG) signals. Performance as a filter is compared with standard linear filters and empirical mode decomposition. The findings show that EWT provides the best performance. Srivastava, Anderson and Freed [2] A new method for eliminating 1D experimental signals using a wavelet transform applied to an electron spin resonance circuit is presented and found to increase the signal-to-noise ratio (SNR) by more than 32 dB without signal distortion. In addition, the calculation time is reduced by more than 6 times. When applied to a broad spectrum of cw-ESR, the new method was found to consistently and accurately reconstruct the original signal. Jain and Tiwari [3] For PCG signal denoising, Discrete Wavelet Transform (DWT) algorithm has shown good performance because it removes in-band noise in addition to out-of-band noise. In this paper, propose an adaptive method based on the statistical parameters of a given PCG signal to estimate the threshold. Statistical parameters have proven to be very effective for this purpose. In addition, this study proposes a new threshold function, a nonlinear mean function, to overcome the problem of SNR and transients in existing soft and hard threshold functions. The operation of the proposed method was also evaluated with the PCG signal and the signal with noise recorded in the actual noise scenario. The results obtained indicate that the proposed method is far superior to competing algorithms. Ali, El-Dahshan and Yahia [4] This study focuses on the removal of cardiac phonocardiogram (PCG) signals using different families of discrete wavelet transforms, threshold types and methods, and signal resolution levels. In particular, this study discusses the effect of the selected wavelet function and the degree of wavelet decomposition on the efficiency of the denoising algorithm. The denoising signal is compared with the original PCG signal to determine the best parameters for the denoising process (wavelet family, decomposition rate, and threshold type). The results show that the decomposition rate and

threshold type are the most important parameters affecting the performance of the denoising algorithm. Rouis, Ouafi and Sbaa [5] This work proposes a new approach to find the optimal decomposition rate and optimal parent wavelet for removing PCG signals. This approach consists of two algorithms designed to solve the problems of noise and variability due to PCG acquisition in real clinical settings for different categories of patients. The results obtained were evaluated by testing the coherence analysis (Corr) of the simulated PCG noise signal, the mean square error (MSE), and the correlation coefficient (Coh) of the signal-to-noise ratio (SNR). The experimental results show that the proposed method can effectively reduce the noise level. Chowdhury, Poudel and Hu [6] This paper presents an intelligent algorithm for heart sound analysis using multiresolution analysis based on discrete wavelet transform (DWT) and an efficient data compression algorithm based on DWT, energy packaging efficiency (EPE) and compressible run-length coding (RLE) to be served. About 93.70% of the signal without loss of pathological information. Chowdhury, Poudel and Hu [7] In this article, denoising using discrete wavelet transform (DWT), compression and clustering using scalable power spectrogram and cepstral frequency factor (MFCC), and various signal processing and deep processing for classification using 5-layer feed-forward deep neural networks (DNN). and the overall test accuracy is around 97.10%. Parchami, Zhu, Champagne and Plourde [8] This article provides an overview of the topic of shorttime Fourier transform noise reduction (STFT) with a focus on spectral reduction methods, Wiener filter methods, speech amplitude estimation, and STFT coefficient complex estimation. Yusoff, Isa, Hamid, Adzman, Rohani, Chai and Avop [9] In this article, we present the reduction of PD signal noise using three different methods. The results showed that ANN was the best noise reduction method because the maximum signal-tonoise ratio calculated using ANN, FFT, and DWT was 0.635938, followed by the FFT method having a signalto-noise ratio of 0.452903 followed by the lowest DWT is -0.154054. Ashwin and Manoharan [10] This article implements an audio noise reduction method based on the short-time Fourier transform (STFT). The proposed architecture uses a novel approach for adaptive estimation of environmental noise in speech and derives the values of signal-to-noise ratio (SNR) and peak signal-to-noise ratio (PSNR) for noise and denoising signals. Pham, Meignen, Dia, Fontecave-Jallon and Rivet [11] This study presents a new cardiac signal denoising (PCG) technique based on non-negative matrix factorization (NMF) and short-time Fourier transform (STFT) adaptive contour representation computational (ACRC) of spectrograms, and numerical experiments performed on real databases of Noisy PCG signal (SiSEC2016) illustrates the advantages of the proposed method over advanced techniques. Bhaskar and Uplane [12] This article describes the implementation of an efficient finite impulse response (FIR) filter using an FPGA-based distributed arithmetic (DA) architecture using Xilinx System Generator software. The results show that the high-frequency EMG noise from the ECG is effectively removed by using a FIR low pass filter. Sharma and Suji [13] In this article, an FIR low pass filter is implemented using a 50 Hz window technique to remove noise artifacts from the ECG signal. Comparison of electrocardiogram (ECG) signals before and after filtering was carried out based on two physical parameters, namely signal-tonoise ratio (SNR) and power spectral density (PSD). Results were calculated using Kaiser and Bartlett windows based on FIR filters. Velayudhan and Peter [14] In this study, various noises such as power line noise, line noise, baseline deviation, electromyographic (EMG) noise, electrode contact noise, and motion artifacts were analyzed. This article also describes several techniques for noise reduction in ECG signals. One of them is Low pass filter. Son, Kwon et al [15] This study created a database of five categories of heart sounds (PCG) from various sources, including one normal category and four abnormal categories, and this study proposes an improvement in the automatic heart disease classification algorithm using heart sound signals for classification using the Support Vector Machine (SVM), Deep Neural Network (DNN), and centroid displacement based on k-nearest neighbors (KNN).

In this study, the authors present an update in the form of research by improving performance and analyzing three denoising algorithms (Discrete Wavelet Transform (DWT), Short Term Fourier Transform (STFT), and Low-Pass filter) to detect heart valve abnormalities that have not been found in previous studies.

III. RESEARCH METHOD

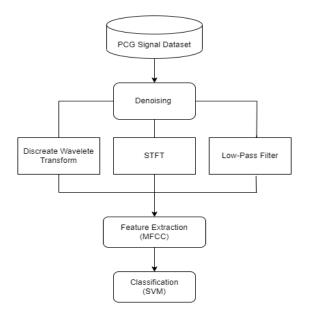


Fig 1. Flowchart System of Denoising Study to Detect Valvular Heart Disease

A. Dataset

The PCG dataset was retrieved from the GitHub database Son, Kwon et al [15] consisting of 1000 audio files from PCG recordings. The data is divided into 5 categories of heart sound signals (PCG signals) from various sources consisting of 1 normal category and 4 abnormal categories. The data size for one record is 1000 data samples, all of which are in the .wav format.

B. Denoising

Denoising is the initial stage of data processing where the signal will be cleaned first of the existing noises. For the denoising method, there are 3 ways in this research including:

1. Discreate Wavelet Transform

Discrete Wavelet Transform is one method that is often used. This method analyzes a signal with different scales and presents it in a time scale and in stages starting from determining the type of wavelet with the reason that the wavelet function varies and is grouped according to each function. Then the wavelet decomposition which breaks the signal into components that have a lower resolution. And finally determine the thresholding method which is a filtering method using signal estimation techniques by exploiting signal denoising.

Let us suppose that s[n] is the original signal, spanning the frequency band from 0 to π rad/s. The DWT of a time-domain signal s[n] is defined as:

$$W_{\chi}(a,b) = \sum_{n} \frac{1}{\sqrt{a}} s[n] \psi^*\left(\frac{n-b}{a}\right) \tag{1}$$

where a and b take only discrete values in the DWT. The index a, commonly chosen as 2 j with $j = 0, 1, 2 \dots$, log2 (N), is called the octave of transformation. When the scale index j increases by one, the discrete mother wavelet function is stretched in the time domain and compressed in the frequency domain by a factor of two. Thus, the frequency resolution doubles with each such scale increase.

2. Short Term Fourier Transform (STFT)

STFT is a Fourier-related transformation to determine the sinusoidal frequency and phase content of the local part of a signal. The longer time signal is split into shorter segments when calculating STFT in practice and then calculating the Fourier transform individually on each shorter segment [10].

3. Low-Pass Filter

The low pass digital filter helps limiting the noise artifacts for routine heart rhythm monitoring. As the PCG signal is low frequency signal, a FIR filter is less complex and easy to design so, it is the right choice to remove the noise Artifacts [13].

C. Feature Extraction

In this feature extraction stage, it is used to represent the potential behavior of the input signal along with the characteristics of the source. Features are extracted from PCG audio signals in time, frequency, and time frequency domains and the algorithm used in this research is the MFCC algorithm [15].

D. Classification

At this stage, the data classification process that has been denoised and extracted is carried out previously. And the classification algorithm used and analyzed is the SVM algorithm [15].

E. Evaluation Methodology

The performance of the proposed denoising algorithm is calculated using Signal-to-Noise Ratio (SNR), Peak Signal-to-Noise Ratio (PSNR), and Root Mean Squared Error (RMSE) [4]. Meanwhile, the performance of the classification algorithm will be calculated using accuracy, specificity, and sensitivity, as follows:

Accuracy
$$= \frac{TP+TN}{TP+FP+FN+TN}$$
 (2)

Specificity
$$=\frac{FP}{FP+TN}$$
 (3)

Sensitivity
$$=\frac{TP}{TP+FN}$$
 (4)

where

- True Positive (TP): the condition is abnormal, and the algorithm detects it.
- True Negative (TN): the condition is normal, and the algorithm declared that
- False Positive (FP): the condition is a normal state, but the algorithm does not generate it.

False Negative (FN): the condition is abnormal, but the algorithm does not detect it.

IV. RESULTS AND DISCUSSION

A. Experimental Setup

This section describes the installation environment used in this study. We use python programming language, because python is generally used for machine learning and the system we use is google collab with available libraries for the three denoising methods, namely Discrete Wavelet Transform (DWT), Short Term Fourier Transform (STFT), and Low-Pass Filter.

1. Denoising

The denoising process starts with processing all the raw or original signals, which amount to 1000 data and are divided into five categories. There are three denosing methods, first, namely Discrete Wavelet Transform (DWT) in this method the first step is that all raw signals are added first with a noise signal, the signal we use as a noise signal is Additive White Gaussian Noise (AWGN) with SNR = 10 dB, then after all the data is mixed with noise, the DWT method is applied in the denoising process by applying a wavelet family algorithm, namely db8, decomposition level = 3 and using a hard thresholding wavelet type. The second method is Short Term Fourier Transform (STFT), the initial steps are the same, namely adding a noise signal (AWGN) with SNR = 10 dB to the raw signal and denoising with the STFT algorithm and setting parameters including $n_{grad_freq} = 1$, $n_{grad_time} = 2$, win_length = 2048, hop_length = 512, n_std_thresh = 1.5, prop_decrease = 0, as well as other parameters involved in the form of raw signal, noise signal, verbose, and visual. The third method is the Low-Pass Filter, in this method it does not use a noise signal but by removing the signal with a specified frequency. For this algorithm we use low_cutoff_freq = 2000 which will filter the signal and remove the noise signal. There are also parameters in this algorithm in the form of a hamming window with settings eq 1 = 0.54 and coeff = 0.46. Then we look for the results of the performance test using three test metrics, namely the SNR obtained from the result of 10 multiplied by the log value of the comparison between the maximum signal value after denoise with the maximum noise value, while for RMSE it is obtained from the square root of the MSE value, and for PSNR it is obtained from the result of 20 is multiplied by log 10 and multiplied again by the ratio between the maximum value of the original signal and the RMSE. All the results of the denoising test metrics are presented in table 1.

2. Feature Extraction

After denoising, data was extracted using MelFrequency Cepstral Factor (MFCC). It also removes data from unnecessary label-based columns and groups, then normalizes them after encoding them to integers based on those groups. The data is then divided into training and test data with the settings test size = 0.2 and random state = 127, so we have 80 training data, 20 test data, and are ready to classify the data.

3. Classification

The data in the sample is then classified using the SVM classification algorithm. Using the following SVM settings: C = [0.1, 3.5] Gamma = [0.01, 0.001, 0.0001], Kernel = ['rbf', 'linear']. For the classification, the performance results will also be tested using the three test metrics that have been described previously and the results are in table 1.

B. Result

The results of the application of the method used in this study, especially in the denoising process that applies the Discrete Wavelet Transform, Short Term Fourier Transform and Low Pass Filter algorithms. The denoised data was then extracted and classified by SVM. The results of this study obtained performance results in the form of SNR, PSNR, RMSE values from denoising, while for classification in the form of accuracy, sensitivity, and specificity. All the results of the test metric values can be seen in table 1.

| | Denoising | | | Klasifikasi (SVM) | | |
|-----------------|-----------|-------|------|-------------------|-------------|-------------|
| | SNR | PSNR | RMSE | Accuracy | Specificity | Sensitivity |
| DWT | 15.02 | 34.45 | 0.02 | 0.95 | 1.0 | 0.96 |
| STFT | 15.83 | 19.61 | 0.10 | 0.98 | 0.97 | 1.0 |
| Low-Pass Filter | - | 9.19 | 0.35 | 0.99 | 1.0 | 1.0 |

TABLE I PERFORMANCE METHODOLOGY

V. CONCLUSION

In this paper, for the process of denoising heart sound audio using three methods or algorithms, namely Discrete Wavelet Transform, Short Term Fourier Transform and Low-Pass Filter. From the three algorithms, the values of SNR, PSNR, and RMSE were obtained, and the best results were obtained through the DWT algorithm with values of SNR = 15.02, PSNR = 34.45, and RMSE = 0.02. While the best SVM classification results are obtained when using the Low-Pass Filter denoising algorithm with 99% accuracy, 100% sensitivity, and 100% specificity. The results of this study can help detect heart valve abnormalities based on 5 types of categories, 4 abnormal (AS, MR, MS, MVP) and one normal (N). In the future, the study of this could be further enhanced for other machine learning models for VHD and on a larger scale and in more innovative ways.

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