Feature Extraction of Heart Signals using Fast Fourier Transform

Hindarto[1], Izza Anshory[2], Ade Efiyanti[1]
[1]Departement of Informatics, Universitas Muhammadiyah Sidoarjo, Indonesia
[2] Departement of Electrical, Universitas Muhammadiyah Sidoarjo, Indonesia
e-mail: hindarto@umsida.ac.id

Abstract— Heart disease is a disease that is very dangerous. Even today in Indonesia an estimated 20 million or approximately 10% of the population of the archipelago suffer from heart disease. Such conditions make cardiovascular disease the number one killer in Indonesia. Not only in Indonesia, the number of heart patients in the world very much, it is estimated there are at least one billion people. This study was designed with the aim to classify the heart signals, the data taken from Physiobank namely MIT-BIH Arrhythmia Database and MIT-BIH Normal Sinus Rhythm Database, the data is processed by taking the feature extraction methods Fast Fourier Transform. The results of the feature extraction method used will be selected prior to use for the classification process. Classification is using Backpropagation Neural Network. From the research found, the feature extraction method of Fast Fourier Transform by taking 64 point data after FFT process and backpropagation as classification of obtaining a classification accuracy rate of 87 %.

Keywords— Heart, FFT, Backpropagation.

INTRODUCTION

Heart sounds heard by cardiologists using a stethoscope is a low-frequency transient signals produced by the vibration after the closing and opening of the heart valves, and / or by the vibration of the entire myocardium and structures connected [1]. From the heart rate produced two different sounds that can be heard on the stethoscope, which is often expressed with lub-dub [2]. the Lub sound is caused by closing tricuspid and mitral valves (atrioventricular) allowing the flow of blood from the atria (auricle) to the ventricle (heart chamber) and to prevent backflow. Generally, this is called the first heart sound (S1), which occurred almost simultaneously with the onset of the QRS complex from Electrocardiography signal and occurs before the systole (the period of the heart to contract). the Dub sound is called the second heart sound (S2) and is caused by the closure of the semilunar valves (aortic and pulmonary) liberating blood into the circulatory system of the lungs and systemic. The valve is closed at the end of systole and before the atrioventricular valves reopen. The sound S2 occurred almost simultaneously with the end of the T wave of Electrocardiography signal [3]. Third heart sound (S3) in accordance with the cessation of the atrioventricular charging, while the fourth heart sound (S4) has a correlation with atrial contraction. The S4 sound sting has low amplitude and low frequency components [4].

The abnormal heart broadcast additional sound called a murmur [5]. The murmur caused by valve opening imperfect or stenosis (which forces the blood passes through narrow openings), or by regurgitation caused by imperfect closure of the valve and cause the backflow of blood. In each case the sound that arises is due to blood flow at high speed (turbulence) which passes through narrow openings. Other causes for the murmur is any leakage heart septum that separates the left and the right so that the blood flows from the left ventricle to the right ventricle thus distorting the systemic circulation.

ECG signal can be used to diagnose heart disease so much, but the ECG signal does not fully describe the character of the heart, because the heart is also influenced by opening and closing the valves of the heart is a factor in the voice of the heart. Besides, there is damage to the heart that are difficult to detect using ECG eg abnormality of structure naturally or opening and closing valves imperfect heart, as well as damage to the heart that cause heart murmurs or abnormal noise [6].

DATA STUDY

The scheme was designed from the algorithm in this research for classification Heart signals are shown in Figure 1. The first stage is the stage of data processing, the choice of sampling data, segmentation data, and feature extraction. The next stage is classification of heart signal, which is the main goal of this research.

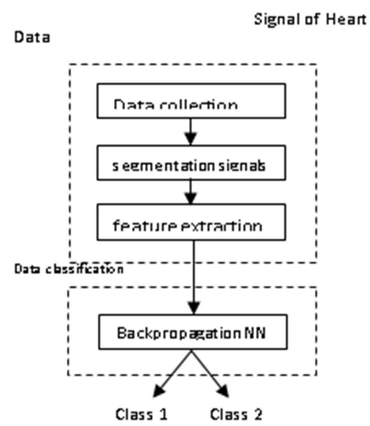
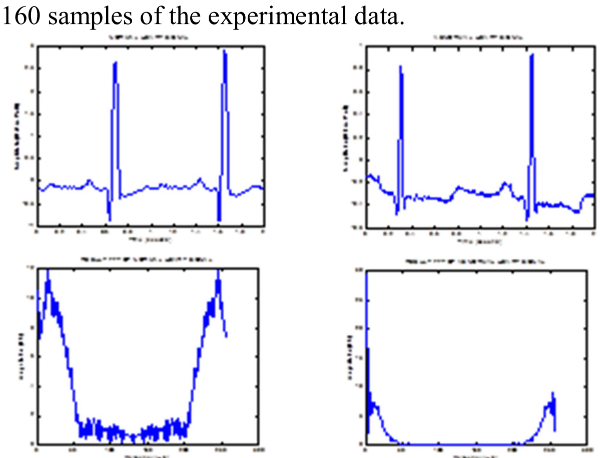


Fig 1. Block diagram of the system

This study uses data from Physiobank namely MIT-BIH Arrhythmia Database and MIT-BIH Normal Sinus Rhythm Database. There are 15 files with length of time of 1 minute and a sample frequency of 360 Hz, the normal pulse signal and a different type of pulse arrhythmia. All selected files take segmentation 2 seconds in order to get 160 samples of the experimental data.



(a) (b)

Fig 2. Signal heart in the time and the frequency domain (a) Normal heart signals (b) abnormal heart signals

METHOD OF FAST FOURIER TRANSFORM

One form of transformation that is commonly used to convert a signal from domain time to the frequency domain is the Fourier transform. A Fourier transform to a continuous time signal x (t) is mathematically written as:

$$X(\omega) = \int_{-\sim}^{\sim} x(t)e^{j\omega t}\, dt \qquad (1)$$

If X (ω) is known, it can be obtained value x (y) of the equation inverse Fourier transformation.

$$X(t) = \frac{1}{2\pi}\int_{-\sim}^{\sim} x(\omega)e^{j\omega t}\, d\omega \qquad (2)$$

For example, there is a sine signal with a frequency of 5 Hz and amplitude of 1 Volt. In time domain you will see like in the Figure below the top. While in the frequency domain will be obtained as at the bottom.

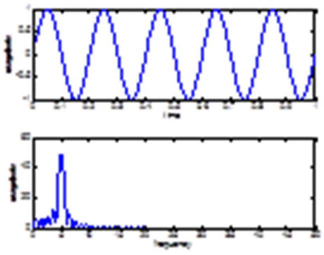


Fig 3. Signal heart in the time and the frequency domain

In this study, after the FFT process it would have taken some of the values of the FFT process by 64 point data. from the 64 point data of FFT then do the inverse FFT.

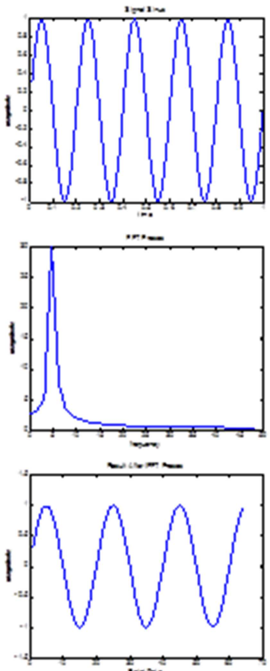


Fig 4. FFT process to IFFT process by taking 64 points data

RESULT AND DISCUSSCION

In this research, the Fast Fourier Transform is able to show the frequency characterization of normal and abnormal conditions / disorders of the heart. Normal heart signal and not normal in the time domain and the frequency can be seen in Figure 2. The results of the Fast Fourier Transform in vector form consisting of 64 elements of the FFT is ready to make input the classiffication of heart.

Classification of heart signals are processed using Back Propagation neural network as shown in Figure 5 final processing is done after the initial process is the search of feature.

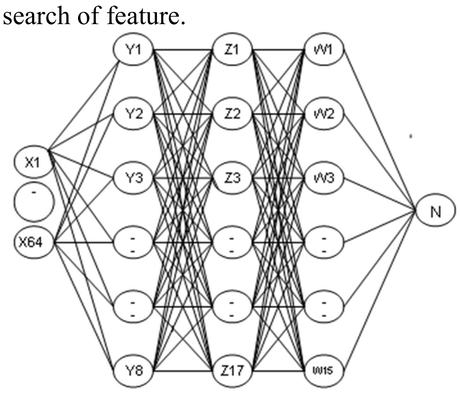


Fig 5. The back propagation network architecture 3 Hidden Layer

Note:

X1, x2, ..., x64	=	Input (Result of FFT)
Y1, Y2, Y3,…., Y8	=	Neuron-neuron hidden layer 1
Z1, Z2, Z3, …, Z17	=	Neuron-neuron hidden layer 2
W1, W2, W3, …, W15	=	Neuron-neuron hidden layer 3
N	=	Output

Extraction characteristic of 64 element of FFT are used for inputs to the neural network, this study using Back Propagation (64-8-17-15-1) is an input that comes from the characteristics of heart signals and 3 hidden layers, each of which contained 8 units, 17 units and 15 units as well as the 1 targets (heart normal and abnormal heart).

Data taken in this study were 150 heart signal file data. One file heart signal normally has 75 data points and the abnormal heart signal file has 75 data points. Results of FFT shown in figure 6 and figure 7 by taking two examples.

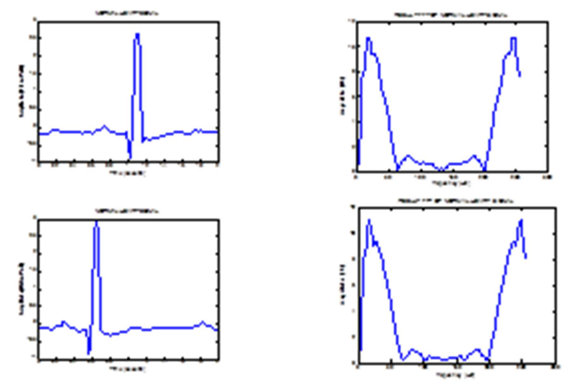


Fig 6. Normal heart Signal in the time and the frequency domain

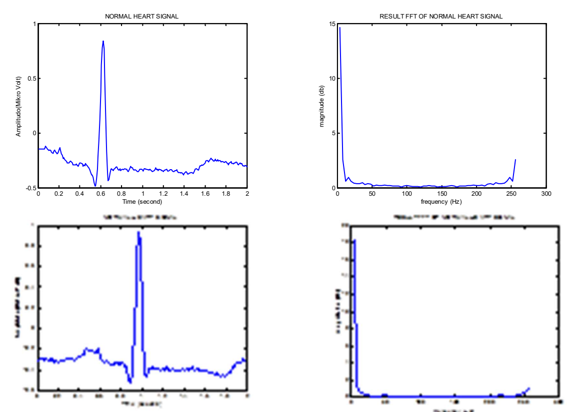


Fig 7. Signal abnormal heart Signal in the time and the frequency domain

Data input of FFT used for the classification process using back propagation neural network. There are two stages to the process of classification that pembelajarn processes and process mapping. The learning process using the learning rate parameter of 0.1 and error to be achieved 0.001. the starting price is determined random weights in the range of -1 to 1.

To search for the optimal parameter result best performance of the neural network is to make an assessment by size Mean squared error (MSE) and the optimal number of hidden units at the time of trainning. Performance results can be found in Figure 8.

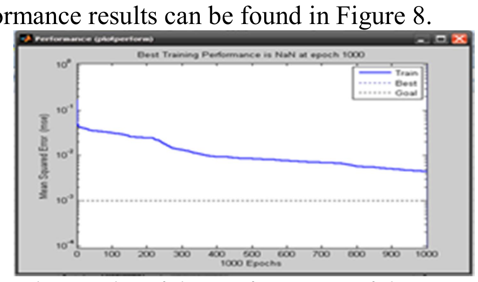


Fig 8. The results of the performance of the training process with a number of hidden layer 3

Based on the picture 8 with hidden layer 3, classification process has amount of MSE barely meet the target.

Table 1. The performance of the neural network to the number of different Hidden Layer

	MSE (1 Hidden Layer)	MSE (2 Hidden Layer)	MSE (3 Hidden Layer)
Time	32 second	60 second	65 second
Iteration	1000	1000	1000
MSE	0.148	0.028	0.008
Accuracy	79 %	%	87 %

CONCLUSION

In this study, researchers introduced a Fast Fourier Transform by taking 64 point data to extract features. Backpropagation neural network for classification. Data used 75 file data signals the heart to training later at the time of classification into two classes of data files heart signals plus 75 file data signals so as to 150 data files heart signals, the accuracy of the classification of propagation of 87% for the test data using three hidden layer. This study shows that the number of hidden layer on the propagation affect the amount of Mean squared error (MSE). Job future researchers, researching search techniques suitable for feature extraction and classification of cardiac signals, so that the level of accuracy for the classification will be better. The results obtained will be compared with the methods that have been studied.

REFERENCES

[1] Ranagayyan, "Biomedical Signal Analysis A Case-Study Approach," IEEE Press, John Wiley & Sons, INC, Canada, 2002.
[2] J.P. de Vos, and M.M. Blanckenberg, "Automated Pediatric Cardiac Auscultation," IEEE Trans. Biomed. Eng., vol. 54, pp. 244-252, 2007.
[3] R.J. Lehner, and R.M. Rangayyan, "A Three-Channel Microcomputer System for Segmentation and Characterization of the Phonocardiogram," IEEE Trans. Biomed. Eng., vol. BME-34, pp. 485-489, 1987.
[4] X. Zhang, L.-G. Durand, L. Senhadji, H.C. Lee, and J.-L. Coatrieux, "Time-Frequency Scaling Transformation of the Phonocardiogram Based of the Matching Pursuit Method," IEEE Trans. Biomed. Eng., vol. 45, pp. 972-979, 1998.
[5] M. Akay, J.L. Semmlow, W. Welkowitz, M.D. Bauer, and J.B. Kostis, " Detection of Coronary Occlusions Using Autoregressive Modeling of Diastolic Heart Sounds," IEEE Trans. Biomed. Eng., vol. 37, pp. 366-373, 1990.
[6] E.A. Suprayitno, R.Hendra, A. Arifin, "Analisa Sinyal *Electrocardiography* dan *Phonocardiography* Secara Simultan Menggunakan *Continuous Wavelet Transform,*" Proceedings of the The 6th – EECCIS Seminar 2012 at Brawijaya University, Malang, pp. B18-1 - B18-6, 2012.