Comparative Performance of Various Wavelet Transformation for the Detection of Normal and Arrhithmia ECG Signal

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***Abstract*— Cardiac Activity forms a signal of electrical potential waves in the heart that can be recorded using an Electrocardiogram (ECG). The results of the ECG signal can determine the conditions and abnormalities experienced by the heart, such as arrhythmias. Medical personnel diagnoses normal and arrhythmia heart conditions by looking at R peaks and R-R interval features. Normal conditions have regular R peaks and R-R intervals, whereas arrhythmias are irregular. The challenges in diagnosing ECG signals are that sometimes the signal has some noises that need reducing noise (denoising) are not required in the signal so it can be easier to detect abnormalities. This paper is a brief study of the comparison of the best performance in detecting ECG signals using various wavelet transforms and optimal threshold values based on empirical methods to obtain R peaks and R-R interval features. Wavelet transform describes the signals that can compress the ECG signal and reduce noise without losing important clinical information that can be achieved by medical personnel. The wavelet transform is suitable for approaching data with a discontinuity signal, so the frequency component will increase if noise or anomalies occur in the ECG signal. The various wavelet transforms used Daubechies (db4), Symlets (sym4), Coiflets (coif4), and Biorthogonal (bior3.7) with four types of Detail and Approximate levels; they are Level 1, 2, 3, and 4. The comparison result for the best performance of the various wavelet transforms is using Daubechies wavelet, and biorthogonal wavelet with an accuracy percentage of 100% at level 2 for diagnosing arrhythmia and 93.1% at level 1 for normal diagnosis from 31 data for arrhythmia and 18 for Normal sourced of the MIT-BIH Database. Hence, the total accuracy results obtained from all the data tested is 96.55%.**

Keywords—ECG signal, Arrhythmia Detection, Wavelet Transform Family, R-Peaks wave, Filter Noise

I. INTRODUCTION

An electrocardiograph is a graph signal to record the potential electrical activity[1] of the heart that is applied to the body's surface so that the signal is used to determine normal and abnormal heart conditions such as arrhythmias. Arrhythmia is a rhythm disturbance in heterogeneous conditions in which there is abnormal electrical activity of the heart, which refers to disturbances in the frequency, regularity, location of origin, or conduction of the heart's electrical impulses[2]. One way for medical personnel to determine arrhythmias and normal conditions in the EKG signal is to look at the R peak and R-R interval, where normal conditions have regular R waves and R-R intervals while arrhythmias are irregular[3]. The challenge in diagnosing ECG signals is that the signals obtained can have noise, so medical personnel has difficulty determining the results of the patient's condition on the ECG signal. The main source of noise in ECG signal measurement is obtained from the sensitivity of the device sensor, power line disturbances, muscle activity, and body movement [4], so it is necessary to reduce the noise from the signal so that it is easier to detect abnormalities that occur.

Algorithms for detecting normal and arrhythmias in ECG signals have been extensively researched and developed, such as deep learning algorithms, Fuzzy Wavelet Learning Vectors, Grammatical Evolution, Neural Networks, Genetic Algorithms, and decision trees, including using wavelets. Therefore, this paper focuses on the comparative performance of various wavelet transforms best for detecting ECG signals with normal and arrhythmic conditions and reducing noise from the signal (signal denoising). The ECG signal features used are R-Peak and R-R interval to detect normal conditions with regular R peaks and R-R intervals, while arrhythmias are irregular. The wavelet transform is very suitable for approaching data with sharp discontinuities, so the frequency component will increase if noise or anomalies occur. The compression feature of wavelets, especially in representing the wavelet domain of a signal, is based on the concept that regular signal components can be approximated accurately using elements such as approximation coefficients (at a properly selected level) and some detail coefficients. Thresholding[6] is used in wavelet domain to smooth out or to remove some coefficients of wavelet transform subsignals of the measured signal. The original ECG signal, which has noise, needs to be processed to result in the denoising signal through detail compression and approximate coefficient using various wavelet transforms. The threshold is used to obtain R peaks and R-R interval features with empirical methods to detect the location of the R peak to obtain the interval of each R-peak (R-R interval) on the ECG signal for diagnosing normal and arrhythmias conditions.

In this paper, the determination of the various wavelet transform and value of thresholding parameters are presented to extract the features of the R peaks and R-R interval of the ECG signal. These methods are used performance of various wavelet transforms sym4, db4, coif4, and bior3.7 with 4 type levels of Approximate and Detail coefficient are 1, 2, 3, and 4 levels. The threshold was performed empirically based on the optimal threshold function to find R peak and R-R interval detection for the ECG signal. The optimal threshold value and the suitable decomposition level can accurately detect the R peak and R-R interval and can classify normal and arrhythmia

How to cite: Gusnam, M., Kusuma, H., & Sardjono, T.A. (2023). Comparative Performance Various Wavelet Transformation for Detection Normal and Arrhithmia ECG Signal. *JAREE (Journal on Advanced Research in Electrical Engineering), 7(1).*

conditions from the ECG signal. System design for the detection of normal and arrhythmias conditions from ECG signals original and result of denoising signal then carried out to compare the best performance of the various wavelets transform with the accuracy level obtained as a second opinion on the diagnosis of medical personnel. The data being tested is sourced from the MIT-BIH database in the website Physionet, which has ECG signal data for arrhythmia classification, which will be displayed on the GUI Interface using Matlab. The database used is 31 data for arrhythmic conditions and 18 for normal conditions in the form of normal conditions and arrhythmias, which have been compared with the diagnoses carried out by medical personnel and other researchers who research ECG signals using other methods.

II. Methods

In this study, it was approved by medical personnel working at Dr. Cipto Mangunkusumo Hospital, Jakarta-Indonesia. We first described of system design followed by ECG signal analysis. ECG signal original from MIT-BIH database to the processing system for detecting normal and arrhythmias conditions using MATLAB and Simulink, which has some function of wavelet transform family for reduce noise. The Determain of the optimal threshold value for detecting R peaks and R-R regular features can diagnose normal and arrhythmia conditions from ECG signals. The result can compare the best performance of the various wavelets. The design flowchart system of this study is shown in Fig. 1.

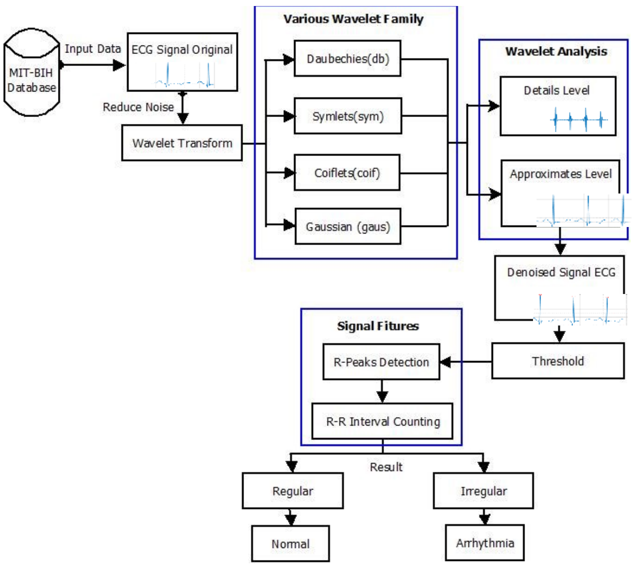


Fig. 1. Design flowchart system

The methodology from design flowchart system consists of following sections:

A. MIT-BIH Database ECG Signal

In this study, we used ECG signals from MIT-BIH Physionet arrhythmia and normal sinus recordings of subjects referred to the Arrhythmia Laboratory at Boston's Beth Israel Hospital. This paper uses the database to obtain 18 data normal and 31 data arrhythmia of ECG signal. Several records in the MIT-BIH Arrhythmia Database were selected because they contain complex combinations of rhythm, morphologic variation, and noise that can be expected to provide multiple challenges for automated arrhythmia analyzers[13]. The database sources from MIT-BIH Arrhythmia Database recordings were digitized at 360 samples per second per channel with 11-bit resolution over a 10 mV range with a signal length of 10 seconds[14,16]. For normal sinus, the sources of the database from MIT-BIH Normal Sinus Rhythm Database recordings were digitized with 128 Hz of Sampling frequency and had 2 rows of signals and 1280 columns (samples/signal) with the length of the signal being 10 seconds. The Normal database includes 18 long-term ECG recordings of subjects included in this database who were found to have had no significant arrhythmias; they include 5 men, aged 26 to 45, and 13 women, aged 20 to 50[15,16].

B. Arrhythmia and Normal ECG

The morphology of electrocardiogram contains several peaks named as P, Q, R, S, T and U and those are shown in Fig. 2 is an ideal waveform of ECG. P wave depicts atrial depolarization and ventricular depolarization is depicted by QRS complex. Where T wave depicts ventricular repolarization. Clinically U wave is very small in magnitude not an important one and interestingly it is inconspicuous of 70% people[8].

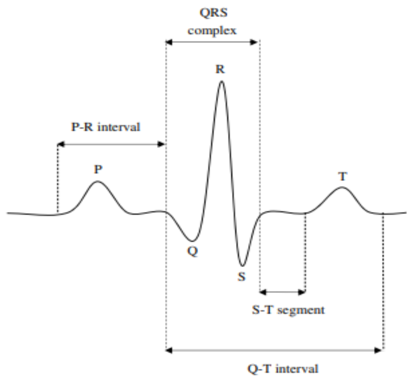
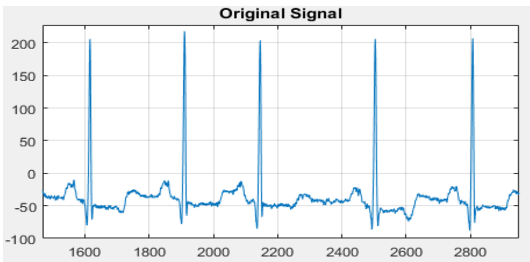
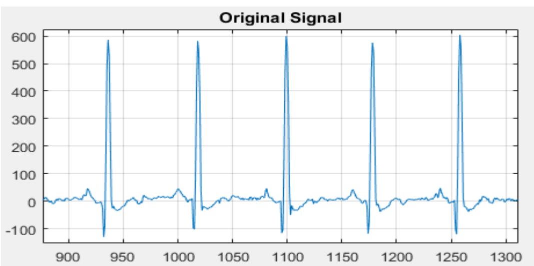


Fig. 2. The morphological of ECG [9]

Medical personnel diagnoses normal and arrhythmia heart conditions by looking at the R wave and the R-R interval, shown in Fig. 3. Normal conditions have regular R peaks and R-R intervals, while arrhythmias are irregular.



(a) Arrhythmia signal original



(b) Normal signal original

Fig. 3. Design flowchart system

C. Wavelet Transform Family

The wavelet transform process enables the detection of important points in the signal in the time and frequency domain. The mother wavelet is selected by matching its shape with the approximate shape of the frequency change in the signal using the defined Wavelet transform formula as[17]:

$$\mathrm{x(a,b)} = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{\infty} x(t) \Psi^{*} \left(\frac{t-b}{a}\right) dt \qquad (1)$$

The symbol Ψ is a function of the mother wavelet, * is denoted for the conjugated version, while a and b respectively represent dilation and translation parameters on a scale of $a > 0$ and $x(t)$ are signals. The basic concept of the wavelet transform is to choose the scale of the wavelet and draw it along the signal iterating through each sample in the signal. Each point in the signal is multiplied by a wavelet resulting in a convolution between the wavelet and the signal[17].

In this paper, Wavelet family used to denoise the signal, specified as one of the following are sym, bior, coif and db[17].

1) Daubechies: One of the brightest stars in the world of wavelet research, invented what are called compactly supported orthonormal wavelets.

2) Biorthogonal: This family of wavelets exhibits the property of linear phase, which is needed for signal and image reconstruction. By using two wavelets, one for decomposition and the other for reconstruction instead of the same single one, interesting properties are derived.

3) Coiflets: The wavelet function has 2*N* moments equal to 0 and the scaling function has 2*N*-1 moments equal to 0. The two functions have a support of length 6*N*-1.

4) Symlets: The properties of the two wavelet families are similar. Here are the wavelet functions psi.

Wavelets have a scale function that can describe stretching or shrinking which works exactly like a wavelet where the smaller the scale factor, the more compressed the wavelet, while the larger the scale, the wider the wavelet can shown in Fig. 4.

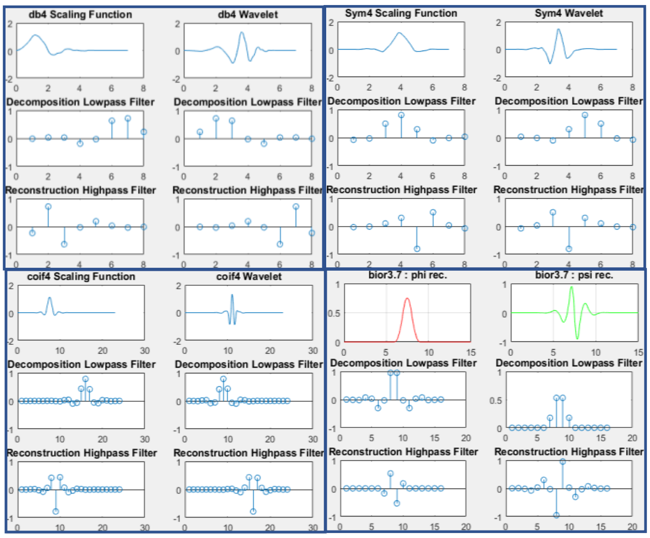


Fig. 4. Quadratic spine function wavelet

The relationship between the scale and the frequency used is that the wider the wavelet used, the longer the portion of the signal being compared and the coarser the signal features as measured by the wavelet coefficient. If a small scale is used, the wavelet will be compressed, and the detail coefficient can change quickly so that the frequency is high, whereas if it uses a long scale, the wavelet will be stretched wide so that it changes slowly, so the feature becomes coarse and the frequency is low.

The differences between the wavelet transforms of the wavelets sym4, db4, coif4, and bior3.7 shown in Fig. 5 representing the mother wavelet for each ECG signal. ECG signals that contain noise are decomposed using various wavelet transforms at the detail and approximate coefficient levels 1, 2, 3, and 4 by selecting the mother wavelet being tested. The selection of the right mother wavelet is adjusted to the ECG signal being tested to reduce noise.

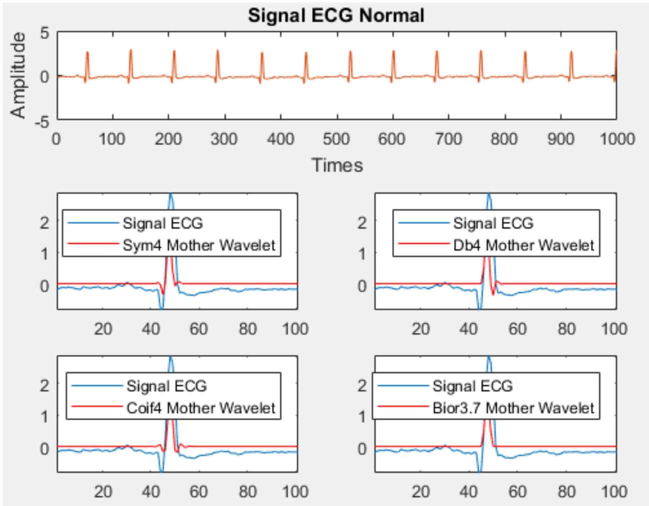


Fig. 5. Frequency mother wavelet

The Wavelet Transform is highly effective mathematical function that detects changes in signal frequency in the time domain. The Wavelet Transform is defined as[17]:

$$(W_n(s),\ n = 0, 1, 2, \ldots) \qquad (2)$$

$$W_{2n}(s) = 2^{\frac{1}{2}} \sum_{k=0}^{2N-1} h(k) W_n(2s-k) \qquad (3)$$

$$W_{2n+1}(s) = 2^{\frac{1}{2}} \sum_{k=0}^{2N-1} g(k) W_n(2s-k) \qquad (4)$$

where $W_0(s) = \varphi(s)$ is the scaling function and $W_1(s) = \psi(s)$ is the wavelet function. Wavelet decomposition filters, specified as a pair of even-length real-valued vectors. Level of decomposition, specified as a positive integer and wavedec does not enforce a maximum level restriction. The bookkeeping vector l is used to parse the coefficients in the wavelet decomposition vector by level. The vector contains the number of coefficients by level and the length of the original signal. The bookkeeping vector is used to parse the coefficients in the wavelet decomposition vector c by level. The decomposition vector and bookkeeping vector are organized as in this level 4 decomposition diagram shown in Fig. 6. Wavelet expansion coefficients of the data to be compressed or denoised, specified as a real-valued vector. If the data is one-dimensional, c is the output of wavedec. Size of wavelet expansion coefficients of the signal or image to be compressed or denoised, specified as a vector or matrix of positive integers. For signals, l is the output of wavedec[17].

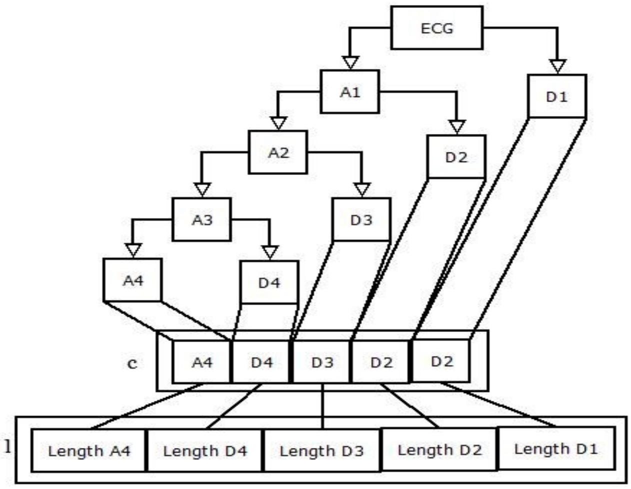


Fig. 6. Approximate and detail diagram

The wavelet transform provides a multiscale signal analysis to improve peak detection in ECG signals. Fig. 7 shows the process the original signal with noise before reduction to the denoised signal after reducing noise. The original ECG signal is extracted first using the detail and approximate coefficient level 1. The approximate coefficient is denoted by A, which indicates a lowpass filter followed by downsampling, and the detail coefficient is denoted by D, which indicates a highpass filter followed by downsampling. After getting the feature extraction results, the approximate coefficient results at level 1 are used again to extract the next feature, which produces detail and approximate coefficient level 2. After getting the approximate coefficient feature extraction results at level 2, the results are used again to extract features at level 3, which produces detail and approximate coefficient level 3. Then, the results of the approximate coefficient at level 3 are used to extract features at level 4, which produce detail and approximate coefficient level 4. Furthermore, the results of the approximate coefficient at level 4 are used to extract features at level 5, which produce detail and approximate coefficient level 5. The filtration results on the wavelet transform show that the denoised signal is much cleaner, and the noise is reduced compared to the original signal using detail and approximate coefficient levels 1, 2, 3, 4, and 5.

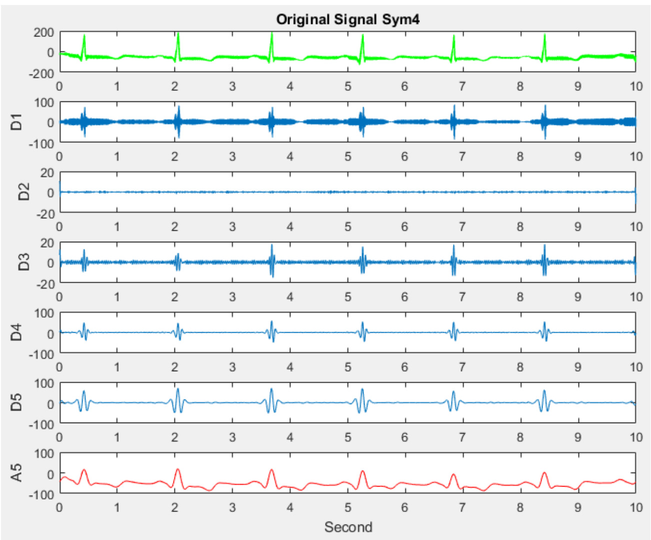


Fig. 7. Detail and approximate process

D. Threshold

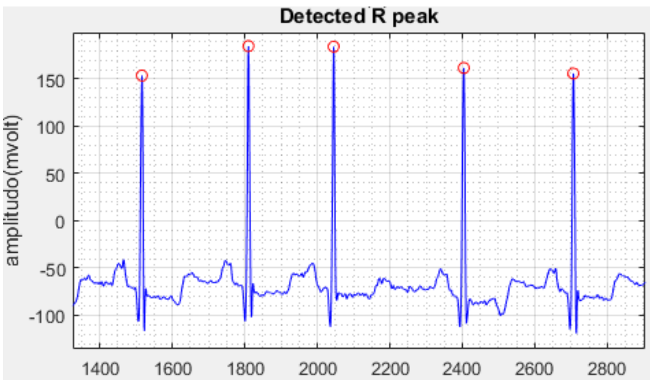
The threshold function is used to detect location R peaks and R-R interval features after denoising the ECG signal by acting on the detail and approximate coefficient wavelet. Variable R means the value of R peaks location refers to the resulting signal representing the wavelet coefficients and threshold value from the threshold function. The threshold value is the critical parameter affecting noise suppression quality. For the selected value, the denoised ECG signal could either retain some interferences or have some distortion and discontinuities, depending on whether the threshold value was too small or overly large. The common threshold values used in the literature are defined as follows:

Threshold1 = 0.6 * maximum R peak level 1
Threshold2 = 0.5 * maximum R peak level 2
Threshold3 = 0.3 * maximum R peak level 3
Threshold4 = 0.15 * maximum R peak level 4

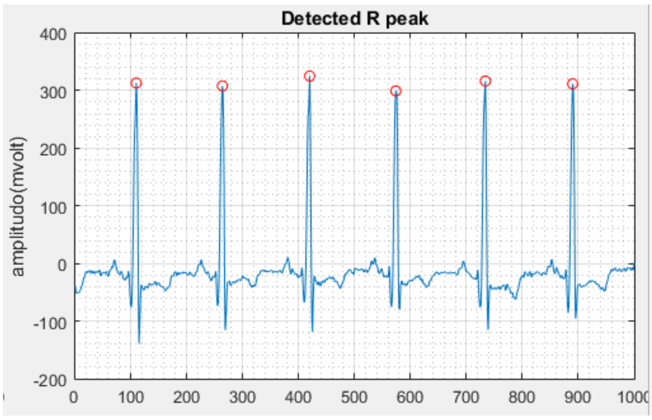
The threshold was performed empirically based on the optimal threshold function to find R peak and R-R interval detection for the ECG signal. The optimal threshold value and the suitable decomposition level can detect the R peak and R-R interval with high accuracy and classify normal and arrhythmia conditions from the ECG signal.

E. R-Peak and R-R Interval Detection

In Fig. 8. (a) to detect R-peak for arrhythmia conditions and Fig. 8.(b) to detect R-peak for normal conditions.



(a) Detection arrhythmia R peaks and R-R interval



(a) Detection arrhythmia R peaks and R-R interval

Fig. 8. R Peak and R-R Interval from ECG Signal

The detection of the R peak feature is obtained from the original signal ECG using various wavelet transforms into the denoised signal with the appropriate optimal threshold to detect normal or arrhythmias conditions. After the location of the R peaks feature has been obtained, the distance between each detected R-peaks is calculated. The difference in the distance between R peaks is called the R-R interval, which can be determined by measuring the distance between locations from the first R peaks into second R peaks, second R peaks into third R peaks, and so on up to 10 seconds.

The standard deviation calculates the R-R interval obtained from the detected R peak to detect normal or arrhythmic conditions from the ECG signal. After the R peaks and R-R intervals are obtained, the standard deviation is calculated to determine regular and irregular R peaks. R peaks regular for detecting normal conditions obtained a smaller standard deviation while for detecting arrhythmic conditions with a larger standard deviation.

1) Standard Deviation (STD:) Formula for detection of regular or irregular ECG signal using calculation root of a variant from the signal.

$$\text{Standard Deviation (STD)} = \sqrt{\frac{\sum_{locs=1,2,3\ldots n}^{N}(x_{locs}-\bar{x})^2}{N}} \quad (5)$$

x_{locs} is the difference of each R-R interval obtained from the location of R peaks on the ECG signal, N is the number of detected R-R intervals, and $\bar{x}$ is the mean of the calculated R-R interval obtained from the difference between R peaks locations.

2) Accuracy (%): Formula for calculation by percentage of total detected R peaks minus error R peaks among total number of peaks.

$$\text{Accuracy (A)} = \frac{Total\ Peaks - Error\ R\ Peaks}{Total\ R\ Peaks} \times 100\% \quad (6)$$

III. Results and Discussion

The result of reducing noise from the original signal into denoising signal ECG is shown in Fig.9 and 10. First plots of the original signal for reducing noise using various wavelets into denoising ECG signal. The feature signal has been obtained, so the detection process is carried out into a normal or arrhythmic ECG signal using the detection peak location. After the R peak and R-R interval are obtained, the standard deviation is calculated to determine the regular and irregular R peaks. Regular R peak for detecting normal conditions obtained a smaller standard deviation, while for detecting arrhythmia conditions with a larger standard deviation.

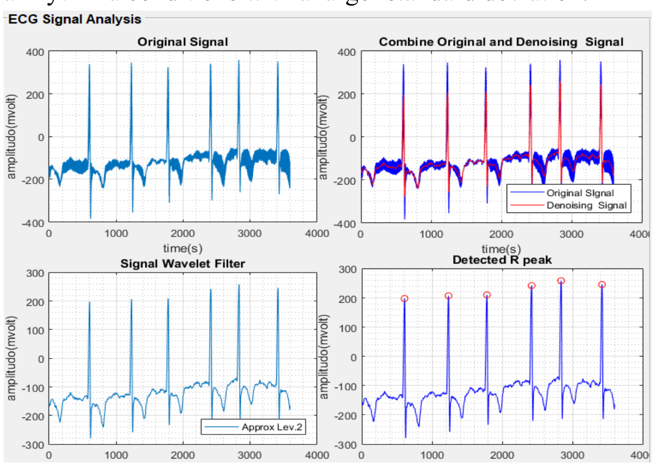


Fig. 9. Denoising signal ECG for arrhythmia

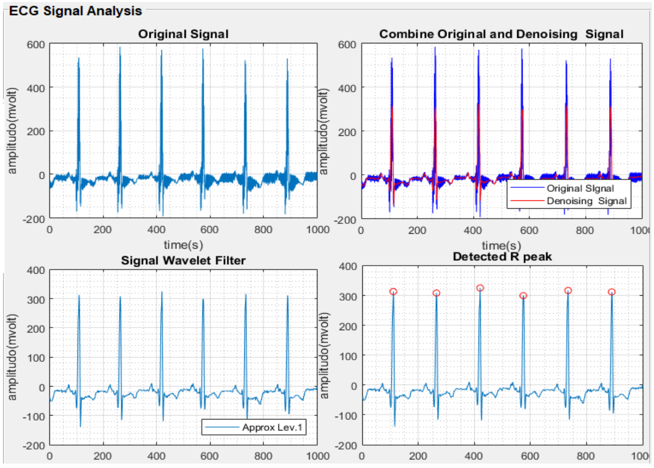
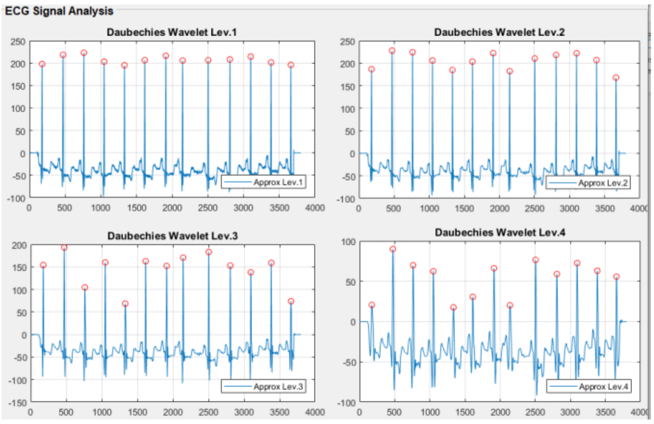
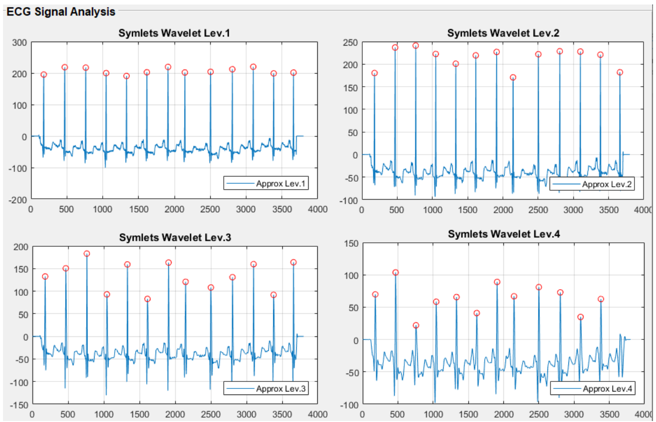


Fig. 10. Denoising signal ECG for normal

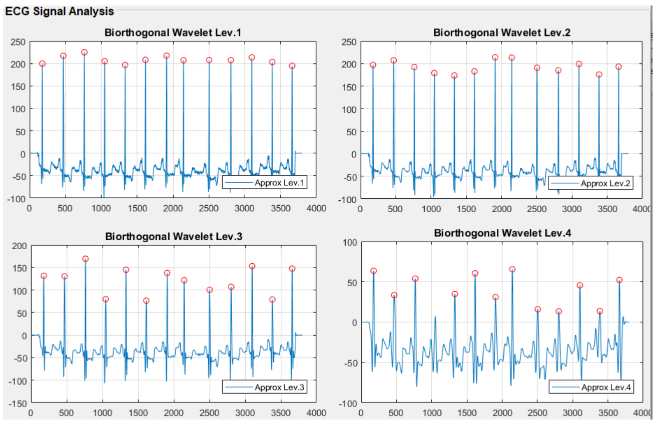
Comparing the performance of various wavelet transform for detecting normal and arrhythmias have shown in Fig. 11 and 12. The results are divided into 2 types for analysis and comparison for detecting normal and arrhythmias conditions from ECG signal. First, compare the performance of various wavelet transforms (db4, sym4, bior3.7, and coif4), and second, compare the performance detail and approximate coefficient per level (1, 2, 3, and 4). The threshold was performed empirically based on the optimal threshold function to find R peak and R-R interval detection for the ECG signal. The optimal threshold value and the suitable decomposition level can accurately detect the R peak and R-R interval for classifying normal and arrhythmia conditions from the ECG signal. The results of the various wavelet transform in Fig. 11 and 12 (a) using the Daubechies Wavelet version show that the R peaks obtained at levels 1,2,3, and 4 are suitable for detecting normal conditions and arrhythmias in the ECG signal. The results of the various wavelet transform in Fig. 11 and 12 (b) using the Symlet Wavelet version show that the R peaks obtained at levels 1,2,3 and 4 are suitable for detecting normal conditions, but in arrhythmic conditions, on the ECG signal, there are still errors at level 4. The results of the various wavelet transform in Fig. 11 and 12 (c) using the Biothogonal Wavelet version show that the R peaks obtained at levels 1,2,3, and 4 are suitable for detecting normal conditions and arrhythmias in the ECG signal. The results of the various wavelet transform in Fig. 11 and 12 (d) using the Coiflet Wavelet version show that the R peaks obtained at levels 1,2,3 and 4 are suitable for detecting normal conditions, but in arrhythmic conditions, on the ECG signal, there are still errors at the level 4. The occurrence of an error in the detection of the ECG signal is caused when the noise reduction at a certain level does not have noise but affects the reconstruction of the location of the R peak so that the R peak cannot be detected. We can be anticipated this by selecting the appropriate mother wavelet according to the ECG signal being tested to reduce noise. Therefore, the percentage of accuracy for each use of various wavelets and the level of detail and approximation obtained from the research results will have an impact; if the R peak detection is appropriate, then the accuracy obtained will be high, whereas if the R peak detection is appropriate, then the accuracy obtained will decrease. The overall results obtained from the research show that the best use of wavelets is Daubechies Biorthogonal wavelets.



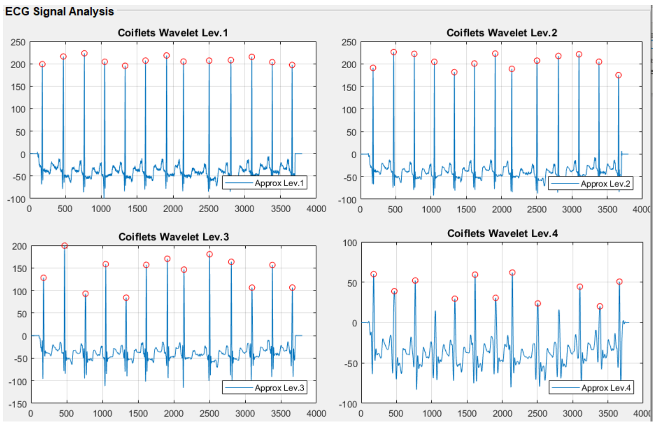
(a) Arrhythmia using db4 wavelets with level 1,2,3 and 4



(b) Arrhythmia using sym4 wavelets with level 1,2,3 and 4

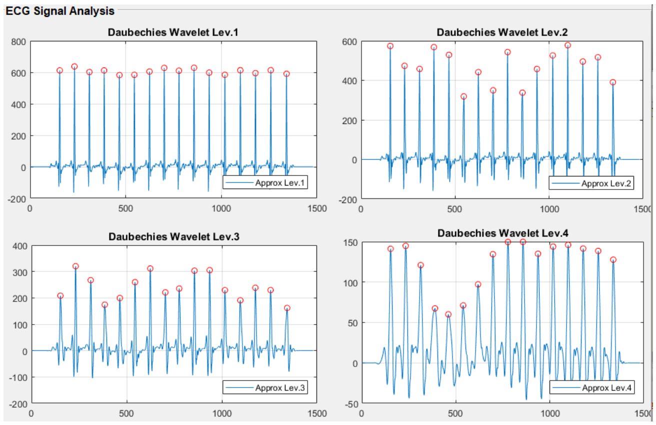


(c) Arrhythmia using bior3.7 wavelets with level 1,2,3 and 4

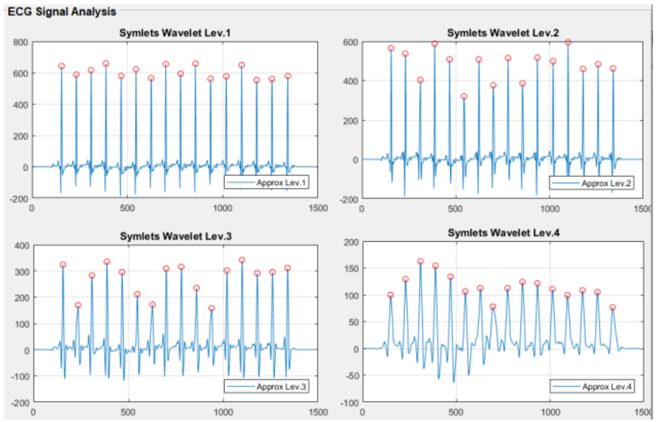


(d) Arrhythmia using coif4 wavelets with level 1,2,3 and 4

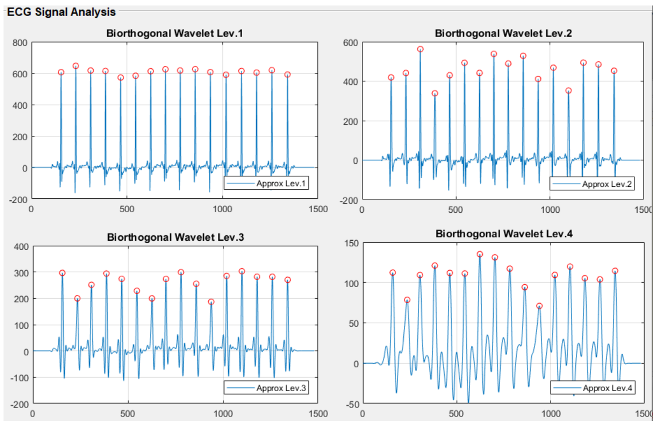
Fig. 11. Arrhythmia R peak and R-R interval using various wavelet



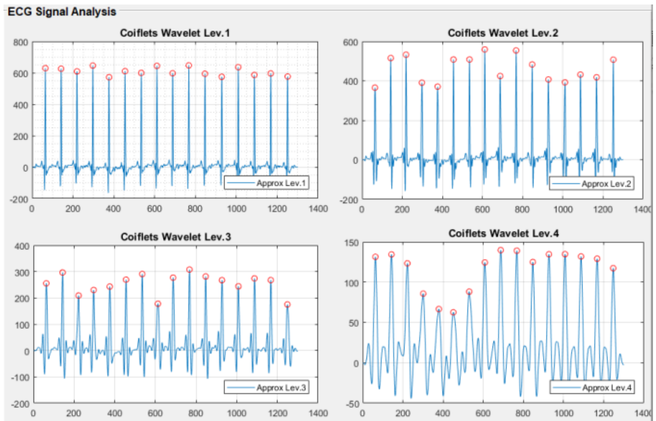
(a) Normal using db4 wavelets with level 1,2,3 and 4



(b) Normal using sym4 wavelets with level 1,2,3 and 4



(c) Normal using bior3.7 wavelets with level 1,2,3 and 4



(d) Normal using coif4 wavelets with level 1,2,3 and 4

Fig. 12. Normal R peak and R-R interval using various wavelet

The results of the standard deviation obtained after the R peak and the R-R interval are known to have shown in Table 1 and 2. It can show that if the standard deviation increases, the R peak condition and the R-R interval will be irregular so that it will detect arrhythmias. While the standard deviation has decreased, the R peak condition and the R-R interval will be regular to detect normal conditions.

TABLE I. APPROXIMATE LEVEL DATA NORMAL

100m	Approximate Level			
	Level 1	Level 2	Level 3	Level 4
Daubechies	1.87	2.09	3.09	2.43
Symlets	1.91	2.09	2.63	3.38
Biorthogonal	1.73	1.85	2.14	3.26
Coiflets	1.87	2.07	3.05	2.71

TABLE II. APPROXIMATE LEVEL DATA ARRHYTHMIA

16265m	Wavelet Transform			
	Symlets	Daubechies	Coiflets	Biorthogonals
Level 1	27.66	27.05	27.05	27.05
Level 2	27.91	27.10	27.10	27.41
Level 3	25.76	27.98	27.88	26.04
Level 4	25.63	31.08	27.80	85.73

In Fig. 13 is a research table for results to obtain for comparative performance using various wavelets. In determining the R peak and R-R interval by using various wavelet transform and determining the threshold with the empirical base method, it is found that to detect arrhythmias on the ecg signal using detail and approximation coefficient.

No	Data Name	MIT-BIH Classification	Medical Personnel Classification	Wavelets Classification	Level	Standard Deviation			
						Symlets	Daubechies	Coiflets	Biorthogonals
1	100m	Arrhythmia	Normal	Arrhythmia	Level 1	27.66	27.05	27.05	27.05
2	101m		Arrhythmia			11.33	11.33	11.33	11.30
3	102m					9.30	9.20	9.20	9.05
4	103m					10.54	10.38	10.38	10.38
5	105m					7.94	7.91	7.94	8.04
6	16265m	Normal	Normal	Normal		1.91	1.87	1.87	1.73
7	16272m					1.56	1.51	**29.42**	1.51
8	16273m					1.91	1.99	1.95	1.99
9	16420m					1.88	1.56	1.70	1.56
10	16483m					**31.18**	0.91	**21.21**	0.91
1	100m	Arrhythmia	Normal	Arrhythmia	Level 2	27.91	27.10	27.10	27.41
2	101m		Arrhythmia			11.60	11.29	11.30	11.30
3	102m					9.95	9.51	9.40	8.72
4	103m					10.42	10.50	10.23	10.50
5	105m					8.00	7.95	7.90	7.94
6	16265m	Normal	Normal	Normal		2.09	2.09	2.07	1.85
7	16272m					2.00	2.00	**27.24**	**60.39**
8	16273m					2.37	2.37	2.19	2.26
9	16420m					**54.13**	**22.58**	2.28	1.61
10	16483m					**55.50**	**35.75**	**13.06**	**29.60**
1	100m	Arrhythmia	Normal	Arrhythmia	Level 3	25.76	27.98	27.88	26.04
2	101m		Arrhythmia			11.18	11.11	10.94	11.45
3	102m					11.46	12.43	12.75	9.26
4	103m					11.80	10.38	10.96	10.86
5	105m					7.47	8.26	8.21	7.64
6	16265m	Normal	Normal	Normal		2.63	3.09	3.05	2.14
7	16272m					**28.21**	**29.73**	**28.27**	**27.86**
8	16273m					**27.88**	**25.62**	**26.24**	**27.03**
9	16420m					**38.86**	**29.60**	**29.02**	**29.24**
10	16483m					**22.42**	**22.82**	**25.00**	**16.11**
1	100m	Arrhythmia	Normal	Arrhythmia	Level 4	25.63	31.08	27.80	85.73
2	101m		Arrhythmia			**14.50**	**19.46**	**18.71**	**18.74**
3	102m					12.32	10.03	10.13	10.59
4	103m					**32.14**	**34.98**	**31.97**	**31.98**
5	105m					**28.46**	**25.84**	**24.38**	**24.65**
6	16265m	Normal	Normal	Normal		3.38	2.43	2.71	3.26
7	16272m					**30.00**	**27.97**	**25.68**	**26.33**
8	16273m					**28.54**	**25.96**	**13.46**	**19.85**
9	16420m					**39.38**	**30.06**	**28.10**	**32.72**
10	16483m					0.26	2.40	0.59	0.46

Fig. 13. Result table for performance various wavelet

The best performance using level 2 with an accuracy rate of 100% in research with a database from MIT-BIH. In the study, it was found that the approximate and detail at level 4 had experienced errors in determining the R-peak and R-R interval because the normal ECG signal experienced excessive signal denoise, so the R peak and R-R interval features had decreased performance. Level 3 is still possible, but less good than Level 2. Level 1 is almost as good as level 2, but the noise in the original ECG signal is still visible, which will interfere with determining the value of the ECG signal feature used. In comparing the best performance of various wavelets for detecting arrhythmias, Daubechies and Biorthogonals Wavelets with 100% accuracy are used. For symlet and coiflet can still be used with the empirical determination of the method to determine the threshold. The ECG signal under study has been approved by medical personnel so that it can be used as a second opinion to detect arrhythmias.

The author compares with a study entitled "The Continuous Wavelet Transform Using For Natural ECG Signal Arrhythmias Detection By Statistical Parameters" (Alharbey. et al., 2022). In that study, the method used is the wavelet transform together with entropy and statistical analysis in detecting arrhythmic conditions only. The process decomposes the ECG signal into a wavelet transformation (CWT or WPT) to obtain the appropriate frequency subband at a certain wavelet level. Then the level of the wavelet transform is investigated for the best performance where the wavelets used are only simple. Using entropy, standard deviation, and energy to model the pathological features present in the ECG signal can detect arrhythmic conditions. The results of this study show an accuracy and overall reach of 77%. The entropy and STD results are better than those obtained from the energy taken over by the WPT[18]. The author conducted research by developing a system to compare the best performance of various wavelet transforms in detecting normal and arrhythmia conditions on ECG signals. The use of wavelet transformation in system design serves to decompose data or signals into different components by performing filtration in compressing ECG signals and reducing noise without losing important clinical information that can be achieved. The wavelet transform is very suitable for approaching data with sharp discontinuities so that the frequency component will increase if noise or anomalies occur in the data. The best results in comparing performance per level are using level 1 with an accuracy of 93.06% for detecting normal conditions and level 2 with an accuracy of 100% for detecting arrhythmia conditions. Moreover, the best result comparing performance for various wavelet transform are using Wavelet Daubechies (db4) and Biorthogonal (bior3.7), with a percentage of 100% for detecting normal or arrhythmias conditions. Hence, the total accuracy results obtained from all the data tested is 96.55%.

IV. CONCLUSION

Wavelet transform is proven to reduce noise in ECG signals, and a threshold can detect R peaks and R-R Interval features. The ECG Signal consists of 31 data for Arrhythmias and 18 for Normal, sourced from MIT-BIH. The results are divided into 2 types for analysis and comparison for detecting normal and arrhythmias conditions from ECG signal. First, compare the performance of various wavelet transforms (db4, sym4, bior3.7, and coif4), and second, compare the performance detail and approximate coefficient per level (1, 2, 3, and 4). The best results in comparing performance per level are using level 1 with an accuracy of 93.06% for detecting normal conditions and level 2 with an accuracy of 100% for detecting arrhythmia conditions. Moreover, the best result comparing performance for various wavelet transform are using Wavelet Daubechies (db4) and Biorthogonal (bior3.7), with a percentage of 100% for detecting normal or arrhythmias conditions. Hence, the total accuracy results obtained from all the data tested is 96.55%.

ACKNOWLEDGMENT

In the work, In this work, we need to thank Dr. Ir. Hendra Kusuma, M.Eng.Sc.and Dr. Tri Arief Sardjono, S.T., M.T. because he provides some help in the paper. We should thank all reviewers and editors who propose valuable comments to improve the quality of the paper.

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