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Identification of Normal ECG Signal Using Wavelet Detection

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***Abstract*-In this paper, the wavelet method used for detecting an electrocardiogram signal is the detection of a new wavelet. Wavelet detection method is based on the modification of existing wavelet mother. Specific form of the electrocardiogram signal which gives angle, amplitude, phase and certain frequency is used as the basis of new wavelet formation. Algorithm DeGeNorm is a new algorithm to detect normal wave electrocardiogram signal. The advantage of using this algorithm DeGeNorm is reducing the sensitivity to noise compared to other techniques, with the determination of each component of P, Q, R, S, T wave of the electrocardiogram accurately and quickly. The originality of this study was applied to normal electrocardiogram wave, with varying leads and it is analyzed for each component of its electrocardiogram signal.The results show the effectiveness of wavelet DeGeNorm algorithm utility to detect normal electrocardiogram wave for 6 lead electrocardiogram. With the value of auc=0.998 by using Receiver Operating Charactheristic (ROC) curve.**

Keywords :Electrordiogram, Wavelet Detection, QRS Detection.

1. INTRODUCTION

Heart disease is an important public health problem because of its high morbidity and mortality. In terms of financing as a result of the treatment time and cost of treating for heart disease as well as supporting examination. Not to mention the success of treatment relies heavily on the speed of treatment disease. Therefore, prevention of heart disease is very useful because it is definitely cheaper and more effective.

Computerized techniques in the identification of the electrocardiogram itself has been made since the last four decades. Several algorithms have been used in its development.The purpose of these algorithms are the same, namely to improve the accuracy and makes identification of these have the same ability as a cardiologist. These techniques rely on computing paradigm that is used, can be categorized as a rule-based system identification, fuzzy, artificial neural networks, statistical methods to the analysis of basic components.

Research on the electrocardiogram signal and its classification is mostly just detect the QRS complex, these techniques have drawbacks for some of the electrocardiogram to detect, especially in detecting ischemia (PVC and ST segment) as well as natural changes in the electrocardiogram signal. One model that is used to identify abnormalities in the electrocardiogram signal with Wavelet detection (wavelet). Wavelet is a wave in smaller and shorter size when compared with sinusoidal signals in general, where the energy is concentrated at certain time intervals which are used as a tool for analyzing transient, non-stationarity, and time variant phenomena. Methods for analyzing signal wave that being localized may use a wavelet detection. Wavelet detection, giving techniques at the electrocardiogram signal processing, divides electrocardiogram signal into several scales, making it easier to analyze signals at specific frequencies.

2. FUNDAMENTALTHEORY

2.1. Electrocardiogram

The electrocardiogram is a recording of electrical activity in the body resulting from the heart. Current flows through the tissue around the heart causing the emergence of an electrocardiogram signal. Electrocardiogram consists of several valleys and mountains, called P, Q, R, S, T, U as shown in Figure 1.

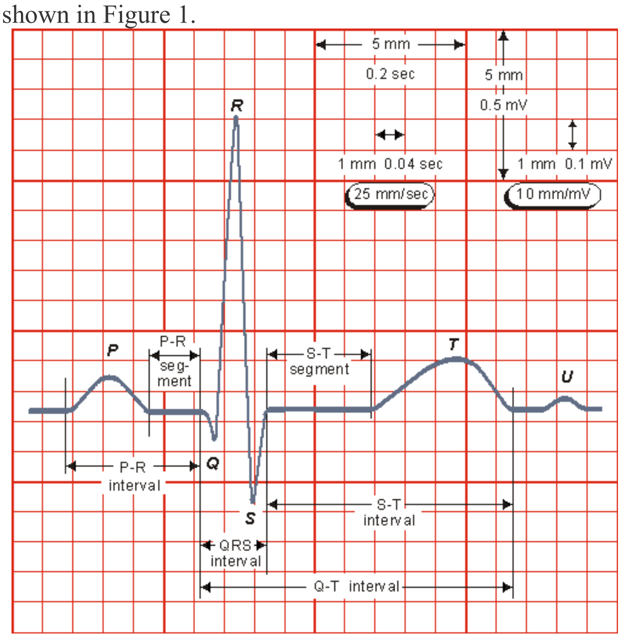

Figure 1. Normal electrocardiogram wave (Gabriel, 2003)

The electrical flow of the heart is started from rest / resting phase, the duration of time when the heart refuses electrical activity.The second phase of the heart's electrical flow is depolarization which indicate that heart pacemaker cells located in the superior vena this cava. This cell collectively formSinoatriuml Node (SA). Electrical impulses spread through the specialized cells and heart cells (through muscle tissue). Although the electrical signal spreads rapidly through certain nerve tissue than in muscle tissue (Gabriel, 2003)

2.2. Wavelet

Wavelet is a mathematical function that divides the data into several components of different frequencies and analyze each component with a resolution corresponding to the scale. Short waves have the advantage when compared to Fourier style shift methods in analyzing a non-stationary signals. A wave is normally defined as an oscilation function of time such as sinusoidal waves. Fourier analysis is a wave analysis where this analysis expands signals or function of a sinusoidal wave having a periodic phenomenon, not changing time (time invariant), and stationary.

In the short wave range over used term translation and scale, because the term of time and frequency is already used in the Fourier style shift. Translation is the location of the modulation window when it is slide along the the signal, associated with timing information. Scale is related with frequency, high scale (low frequency) associated with the global information of a signal, while the low scale (high frequency) associated with the detail information. Continuous Wavelet Transform (CWT):

$$\gamma(s,\tau) = \int f(t)\psi^{*}_{s,\tau}(t)\,dt \qquad (1)$$

<u>Explanation:</u>

$\gamma(s,\tau)$: Signal Function adalah fungsi sinyal setelah transformasi,

s : Scale

τ :(translastion) as new dimension.

$f(t)$: Input Signal.

$\psi^{*}_{s,\tau}(t)$: Basic Function Wavelet,

* :Complex Conjugate.

3. NEW FORM WAVELET DETECTION

In this study testing a new Wavelet detection by performing cross-correlation between Normal electrocardiogram signal with a new type of wavelet that has been obtained under the appropriate signal pattern of normal electrocardiogram signal.

The equation used for the cross-correlation is as follows :

$$R_{yx}(m) = \frac{1}{N}\sum_{n=1}^{N-m+1} y(n)x(n+m-1) \quad \ldots\ldots (2)$$

Where m=1,2,3,…,N+1

<u>Explanation:</u>

R_{yx} : Correlation result

N : Amount of Sample.

$y(n)$: New Wavelet Function, Length n

$x(n+m-1)$:Normal ECG Signal

If the value R_{yx} (m) = 0 then it can be said that the two signals x (n) and y (n) are not correlated or statistically independent otherwise, assumed with zero average value.

This new wavelet include Wavelet for normal electrocardiogram. Electrocardiogram signal corresponding to the type of the new wavelet will give a higher correlation score than other electrocardiogram signal. The new wavelet is determined by calculating the highest correlation values that appear in each of the electrocardiogram signal Normal

Seen from the group, function that obtained by shifting and making the scale of the parent GS (mother wavelet)

Ψ (t) $\in L_2(R)$,

$$\Psi_{a,b}(t) = \frac{1}{\sqrt{|a|}}\Psi\left(\frac{t-b}{a}\right), \ldots\ldots\ldots\ldots (3)$$

With $a, b \in R$ ($a \neq 0$)and normalization is performed in order to make norm

$\|\Psi_{a,b}(t)\| = \|\Psi(t)\|$

(For now assumed a can be positive or negative). Furthermore, it is assumed that this wavelet is able to fulfill acceptance requirement (admissibility condition).

$$C_\Psi \int_{-\infty}^{\infty} \frac{|\Psi(\omega)|^2}{|\omega|}\,d\omega(\infty \qquad (4)$$

where $\Psi(\omega) = \int_{-\infty}^{\infty} \Psi(t)e^{j\omega t}\,dt$

With Ψ (ω) is the FT function of Ψ (t). In practice, Ψ (ω) will always decrease (decay), in order to make acceptance decrease and fulfill Ψ (0)=0:

$$\int_{-\infty}^{\infty} \Psi(t)\,dt = \Psi(0) = 0$$

Because the FT is zero at the beginning and spectrum decreases at higher frequencies, Wavelet shows field-escape behavior (band-pass). This Wavelet further normalized so it has energy unit, or

$$\|\Psi(t)\|^2 = \int_{-\infty}^{\infty} |\Psi(t)|^2\,dt = \frac{1}{2\pi}\int_{-\infty}^{\infty} |\Psi(\omega)|^2\,d\omega = 1$$

4.EXPERIMENTALRESULTS

4.1 Basis Wavelet DeGeNorm$_1$

Researchers create the first equation, named Wavelet DeGeNorm1 as written in the following equation 5:

$$\psi_{DeGeNorm_1} = e^{-x^2/2}[(cos2x) * (cos2x)] \qquad (5)$$

Now we know the equation of the Wavelet DeGeNorm$_1$ that will be simulated by taylor tools into equation 6 as follows

exp(-x^2/2)*(cos(2*x)*cos(2*x)) (6)

As shown in Figure 2 Wavelet DeGeNorm$_1$ it is expected to have high enough correlation value to be able to determine the shape of a normal electrocardiogram signal. Left peak and right peak are created in equal amplitude.

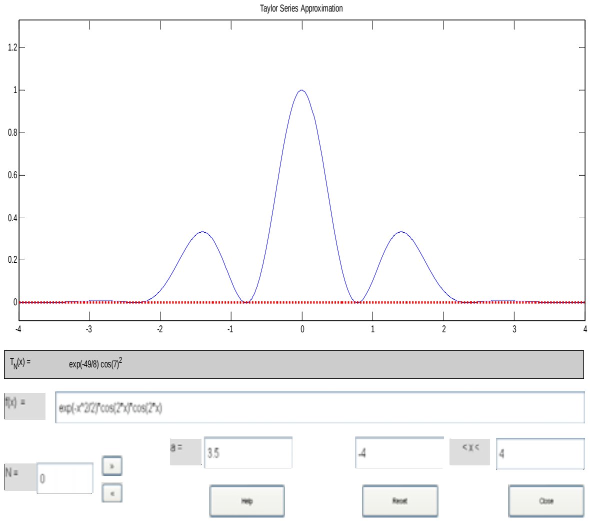

Figure 2. Wavelet DeGeNorm$_1$ are simulated in the Taylor series

The test phase is done by not sifting electrocardiogram signal noise, so that the input signal of its electrocardiogram still hs electrocardiogram signal noise as shown in figure 3.

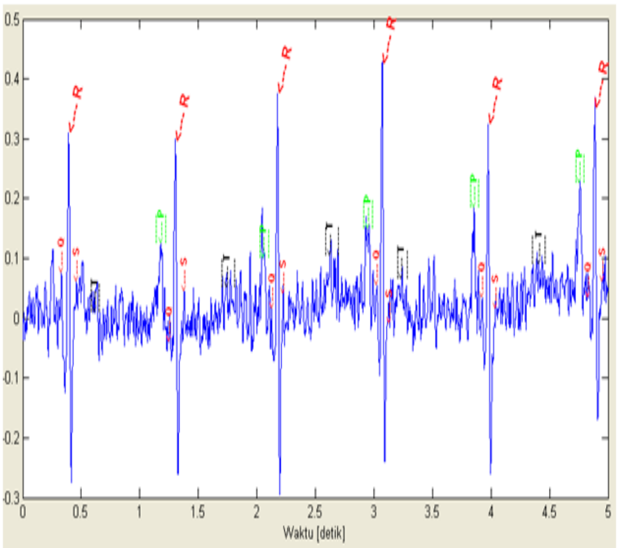

Figure 3. Wavelet DeGeNorm1 testing onSecond Lead with noise

Table 1. The sensitivity result of detection of the QRS component with DeGeNorm$_1$

Pasien 1	**Lead 1**	**Lead 2**	**Lead 3**	**avr**	**avl**	**avf**
Total komponen QRS	86	86	86	86	86	86
QRS Terdeteksi	85	85	84	80	78	82
PositifBenar(PB)	85	85	84	80	78	82
NegatifSemu(NS)	1	1	2	6	8	4
PositifSemu (PS)	0	0	0	0	0	0
Sensitivitas (%)	98	98	97	93	90	95

From the result of table 1 above it appears that the average program sensitivity is 95% to be able to detect the R peak with detection of DeGeNorm$_1$ Wavelet

4.2Basis Wavelet DeGeNorm$_2$

Researchers make the second equation, named Wavelet DeGeNorm$_2$ as written in the following equation 7:

$$\psi_{DeGeNorm_2} = e^{-x^2/2} * \left\{\left[\cos\left(2x - \frac{7\pi}{4}\right)\right] * [\cos(2x)]\right\} \quad (7)$$

Now we know the equation of the Wavelet DeGeNorm$_2$ which will be simulated by taylor tools into equation 8 as follows.

exp(-x^2/2)*(cos(2*x-(7*pi/4))*cos(2*x)) (8)

As shown in Figure 4, this Wavelet DeGeNorm$_2$ has a different equation than the Wavelet DeGeNorm$_1$ that is at the top right hand has higher amplitude than the amplitude at the top left.

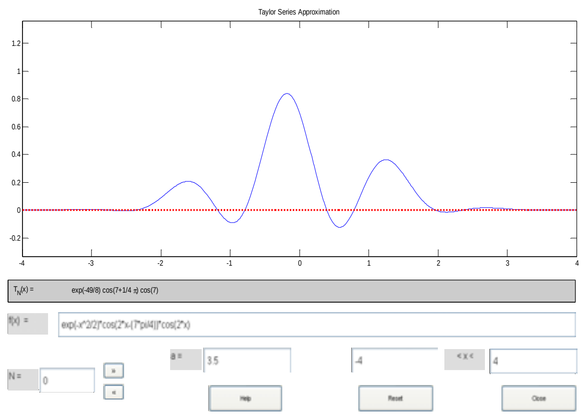

Figure 4. Wavelet DeGeNorm$_2$ are simulated in the Taylor series

DeGeNorm2 short waves are used to detect the normal electrocardiogram as shown in Figure 5 which shows detection that experience error detection. The first error is the detection of R peak which is not positioned at the crest of a wave, the second error is the false detection of the R component exceeds a peak current of normal conditions, this can be seen the identification of a component of T.

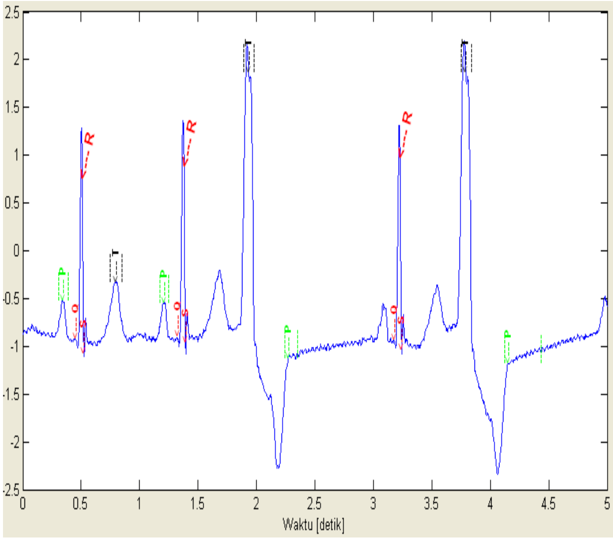

Figure 5. *Wavelet Test DeGeNorm$_2$*

Testing for Wavelet DeGeNorm2 detection can be seen in Table 2 below.

Table 2. Sensitivity result of detection of the QRS component with DeGeNorm2

Pasien 1	**Lead 1**	**Lead 2**	**Lead 3**	**avr**	**avl**	**avf**
Total Komponen QRS	86	86	86	86	86	86
QRS Terdeteksi	80	70	65	78	60	58
PositifBenar(PB)	80	70	65	78	60	58
NegatifSemu(NS)	6	16	21	8	26	28
PositifSemu (PS)	0	0	0	0	0	0
Sensitivitas (%)	93	81	75	90	69	67

From the above results it appears that average program sensitivity is 79% to be able to detect the components of the QRS with Wavelet detection DeGeNorm$_2$.

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4.3 Basis Wavelet DeGeNorm$_3$

Researchers made the third equation, named Wavelet DeGeNorm$_3$ as written in the following equation 9

$$\Psi_{DeGeNorm_3} = e^{-x^2/2} * \left\{\left[\cos\left(2x - \frac{1\pi}{4}\right)\right] * [\cos(2x)]\right\} \quad (9)$$

Now we know the equation of the Wavelet DeGeNorm$_3$ will be simulated by taylor tools into equation 10 as follows

exp(-(out2.^2)/2).*(cos(2*out2-(1*pi/4))).*cos(2*out2) .(10)

As shown in Figure 6, Wavelet DeGeNorm$_3$ has a different equation than the Wavelet One is its top right hand has a higher amplitude than the amplitude at the top left.

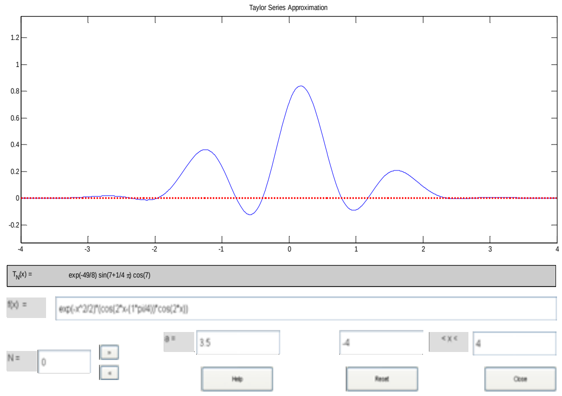

Figure 6. Wavelet DeGeNorm$_3$ are simulated in the Taylor series

The short wave detection results can be seen in Figure 7 where for the detection of P component works well but for the other components is moved. Highest peak is identified as Q component, thus R component experience changing identification.

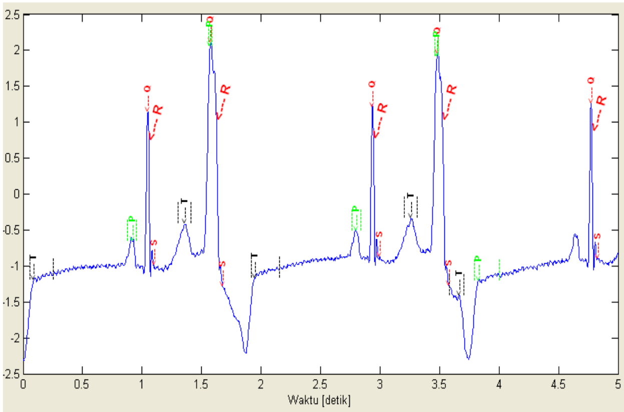

Figure 7. Wavelet testing DeGeNorm$_3$

Wavelet DeGeNorm$_3$ detection can be seen in Table 3 below. From the results it appears that the average program sensitivity is 73% to be able to detect the components of the QRS with Wavelet detection DeGeNorm$_3$.

Table 3. Sensitivity result of detection of the QRS component with DeGeNorm$_3$

Pasien 1	**Lead 1**	**Lead 2**	**Lead 3**	**avr**	**avl**	**avf**
Total Komponen QRS	86	86	86	86	86	86
QRS Terdeteksi	72	65	60	70	58	55
PositifBenar(PB)	72	65	60	70	58	55
NegatifSemu(NS)	14	21	26	16	28	31
PositifSemu (PS)	0	0	0	0	0	0
Sensitivitas (%)	83	75	69	81	67	63

Table 4. indicates that the value of Area Under the Curve $DeGeNorm_1$ = 0.998 has the highest value compared with the algorithms of DeGeNorm2 and DeGeNorm3.

Table.4 Comparison OfDeGeNorm ROC Curve

Comparison of ROC curves

Variable 1	DeGeNorm1
Variable 2	DeGeNorm2
Variable 3	DeGeNorm3
Classification variable	QRS

Sample size		36
Positive group :	QRS = 1	18
Negative group :	QRS = 0	18

	AUC	SE [a]	95% CI [b]
DeGeNorm1	0,998	0,00218	0,900 to 1,000
DeGeNorm2	0,838	0,0655	0,677 to 0,939
DeGeNorm3	0,730	0,0859	0,556 to 0,864

[a] DeLong et al., 1988
[b] Binomial exact

Pairwise comparison of ROC curves

DeGeNorm1 ~ DeGeNorm2	
Difference between areas	0,160
Standard Error[c]	0,0659
95% Confidence Interval	0,0313 to 0,290
z statistic	2,435
Significance level	P = 0,0149
DeGeNorm1 ~ DeGeNorm3	
Difference between areas	0,269
Standard Error[c]	0,0862
95% Confidence Interval	0,0996 to 0,437
z statistic	3,117
Significance level	P = 0,0018
DeGeNorm2 ~ DeGeNorm3	
Difference between areas	0,108
Standard Error[c]	0,0466
95% Confidence Interval	0,0168 to 0,199
z statistic	2,320
Significance level	P = 0,0203

[c] DeLong et al., 1988

5.CONCLUSIONS

In the study, Wavelet detection algorithm with a new form is used to detect a normal electrocardiogram signal. The highest correlation value is used to detect the electrocardiogram signal.

New Wavelet named Wavelet DeGeNorm is designed to detect normal electrocardiogram signal. Wavelet DeGeNorm1 Testing Results with P and T components result in Sensitivity = 95%. This value is the highest one compared to sensitivity of Wavelet $DeGeNorm_2$ with a higher component of T = 79%. Wavelet DeGeNorm3 sensitivity to the component P is higher than the components of T = 73%.

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