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Image Analysis of 12 Lead Electrocardiogram Using Wavelet Transformation

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ABSTRACT: The heart is one of the most important human organs. One of instruments to detect cardiac abnormalities is the electrocardiogram (ECG). This research tries to analyze ECG image in normal heart condition from ECG machine. The previous research related to the pre-processing process is the same, only at the feature extraction process look for peaks P, Q, R, S, T, heart rate, and Deviation-ST. While this research is the characteristic extraction process using wavelet transformation. The image of lead ECG 12 is processed using discrete wavelet transforms with decomposition up to ten levels, by searching for mean square error (MSE). The type of mother wavelet and the wavelet order used are Daubechies (db) with 1 (db1 (Haar)). The smallest MSE value decomposition results are obtained at the level 5, which are lead I, II, III, aVR, aVF, V4 and V5, lead V1 & V2 on level 4, for aVL (level 9), V3 (level 7) and V4 (level 6). It is expected that such research can be followed up to the identification model of cardiac abnormalities using wavelets.

KEYWORDS: Electrocardiogram, wavelet, daubechies, mean square error

I. INTRODUCTION

The heart is a very important part of our body. Based on data from the World Health Organization (WHO) year 2019 shows 17,9 millions of people worldwide died from cardiovascular disease (heart) or representing 32% all global deaths[1]. The American Heart Association mentioned that almost every one of three people died is caused by cardiovascular disease. Therefore, we must maintain the condition of our bodies, especially the heart. Early heart detection can be performed by checking the heart condition with aids such as: electrocardiogram (ECG), blood test, nuclear heart scanning, cardiac catheterization, cardiac test, echocardiography and coronary angiography [2].

A instrument that is frequently used to check for heart abnormality is electrocardiogram (Figure 1). Electrocardiogram is a tool to determine the electrical activity of the heart in patients [3]. Where the results are used by the medical team to diagnose heart conditions [4]. Detection of cardiac abnormalities uses a simple ECG. An ECG device consists of 12 leads which is installed on several body parts, then records and prints out the result in the form of an ECG graph paper. From such graph paper it can be analyzed whether the patient's heart are in normal condition or have abnormalities. Based on the above review, this study also uses 12 lead ECG images according to the ECG device used by several hospitals. Image of lead 12 printed on ECG paper then scanned.

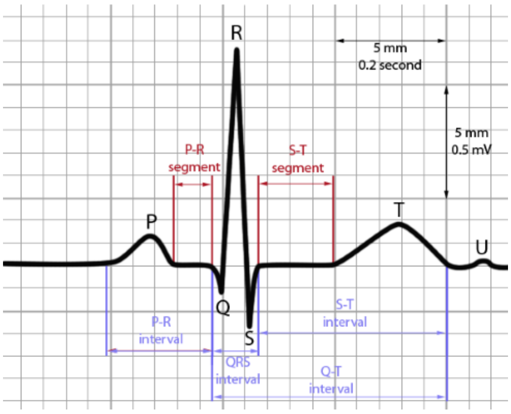


Fig 1. Electrocardiogram Example

The scanning results of each lead will be used as input in the pre-processing process. The pre-processing process uses several methods, including segmentation (changing color images to grayscale, then from grayscale to binary images), morphology (using dilation and erosion processes), and the latter transforming into spatial regions. The pre-processing results will then be made as input at the feature extraction process. Feature extraction applied wavelet transform decomposition, using mother wavelet of daubechies order one (Haar).The feature extraction result is the smallest MSE value of all 12 lead ECG.

II. RELATED WORK

Some studies that use the image are among others; pre-processing by converting RGB to Grayscale, feature extraction using Prewit edge detection and classification using artificial neural network of Resilient Propagation with testing accuracy 84,21% [5]. Pre-processing converts from RGB to grayscale by feature extraction using the Welch method, and the classification of ANN of Backpropagation obtains its accuracy 72,5% [6]. Performing binary pre-processing, noise and thinning removal, while feature extraction with Discrete Wavelet Transformation and PCA (Principal Component Analysis) [7].

Pre-processing is done by: Segmentation (gray scale and binary), Morphology (Dilation and Erosion), as well as changes to ECG graphic image, while feature extraction is to find the peaks of PQRST, Heart Rate (HR) and ST-Deviation [8]. Conducted the study by implementing a one-dimensional analysis approach (duration of the heart cycle) of heart rate variability to multidimensional analysis (shape parameters and peak location of the heart cycle) analysis of heart parameters [9]. Conducted an ECG signal study with a wavelet, where the threshold function is improved, and resulted in the best SNR improvement using the MIT-BIH arrhythmia database [10].

ECG research to detect Arrhythmias by comparing CSVM and SVM standards, resulting in a better CSVM accuracy rate when compared to SVM which is 98.25% [11]. Conducts a literature review by reviewing advanced machines and deep learning-based CAAC (computer-aided arrhythmia classification) expert systems for surprising introduction of ECG signals, discussing their strengths, advantages, and disadvantages [12]. There are many studies using ECG signals and wavelets such as [13], [14], [15], [16], [17], [18], [19], [2], [21], [22], [23], [24], [25], [26], [27], [28], [29], [30], [31], [32], [33], [34], [35], [36], [37], [38], [39], [40], [41], [42], [43], [44], [45], [46], [47], [48], [49], [50], and [51].

Research conducted by [8], detects PQRST peak search, heart rate and ST deviation, in which ECG image data is captured by scan. The computational results show upward and downward deflection of the isoelectric P, Q, R, S respectively and T waves represent clinical EKG calculations. Research [8] allows to be expanded to a broader extent to extract its features, resulting in more accurate results of ECG information.

This study proposes to find the smallest MSE value of wavelet decomposition using Daubechies order 1 (db1(Haar)) using image data of ECG 12 lead. Pre-processing is done with several steps including: Segmentation (grayscale and binary), Morphology (Dilation and Erosion), as well as changes to ECG graphic image [8]. The feature extraction step for finding the best decomposition of the Daubechies wavelet with 10 levels is seen from the smallest MSE values of 12 lead ECG

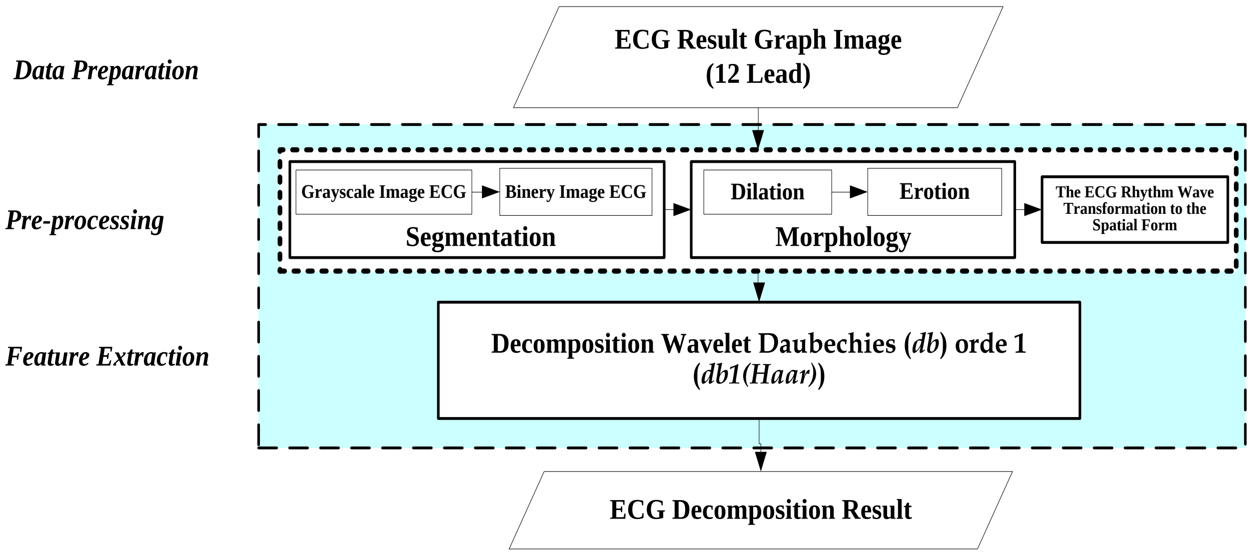


Fig 2. Methodology Proposed

III.

IV. METHODOLOGY

The models developed in this research include the steps, like: data preparation, pre-processing and feature extraction shown in the Figure 2. ECG graphic image data is obtained from the scanning data of ECG recordings. The process of data preparation and pre-processing is similar to that done by [8].

A. Feature Extraction

The feature extraction stage uses Wavelet Transform Decomposition with the mother wavelet Daubechies on the order 1 (db1(Haar)). Wavelet is a method of processing a signal in which a signal is split into several parts. Wavelet is a set of functions generated by a single function ψ with dilation and translation process [52].

$$\Psi_{a,b}(t) = |a|^{-1/2}\psi\left(\frac{t-b}{a}\right) \qquad (1)$$

With ψ (t) as the mother wavelet function, a is the parameter of dilation a, and B is the translation parameter. This research used wavelet transform decomposition, the drawing of a time scale of digital signal which is obtained by using digital filtering technique. A signal must be passed in two filters, namely the highpass filter and the lowpass filter to allow the frequency of the signal to be analyzed.This decomposition process can be through one or more levels. Example of a one-level signal decomposition is Figure 3.

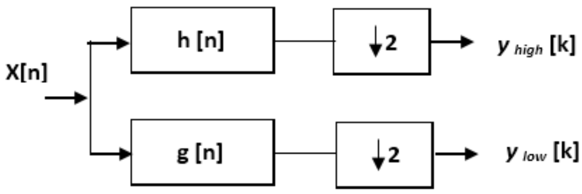


Fig. 3. Example of signal decomposition

In figure 3, the result of the highpass filter, *yhigh* [k] is called the detailed signal and the result of the lowpass filter, the *ylow* [k] is called the approximation signal, x[n] is the original signal. The decomposition of a single-level signal is written with mathematical expressions of the equations 2 and 3 [52].

$$y_{high}[k] = \sum_n [n]h[2k-n] \qquad (2)$$

$$y_{low}[k] = \sum_n [n]g[2k-n] \qquad (3)$$

yhigh [k] and *ylow* [k] is the result of highpass filter and lowpass filter, h[n] is highpass filter and g[n] is lowpass filter, n and k are integer variables. This inner signal serves as the main signal or mother wavelet. When the decomposition process is executed, the approximation coefficient signal will be the mother wavelet and it is decomposed based on the high pass and low pass filter, and so on according to the level we want. In wavelet decomposition the signal is divided into components of approximation and detail (Figure 4). The approximation component is then subdivided into the approximate and detailed components, and so on up to the desired level [53].

Mathematically the decomposition of wavelet 3 level can be written [53].

$$\begin{aligned} X &= cA_1 + cD_1 \\ &= cA_2 + cD_2 + cD_1 \\ &= cA_3 + cD_3 + cD_2 + cD_1 \qquad (4) \end{aligned}$$

Where X the decomposition of a signal, with A is called the approximate coefficient of level i, and D is called the detail coefficient at level i.

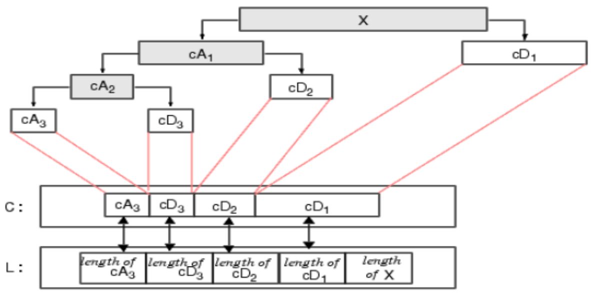


Fig. 4. Wavelet Decomposition

B. Mean Square Error

The performance of this research was analyzedusing Mean Square Error (MSE).The greater the error value, the less good the results obtained. Likewise the smaller the error value the better the results. The equation used to find the MSE is in the equation 5 [54].

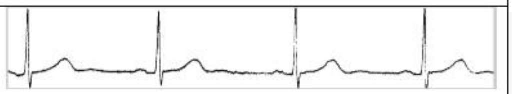
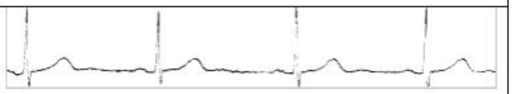
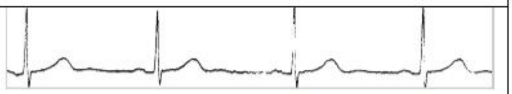
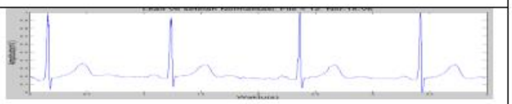
$$\text{MSE} = 1/(M.N)\sum_{x=0}^{M-1}\sum_{y=0}^{N-1}(f(x,y)-g(x,y))^2 \qquad (5)$$

Where $f(x,y)$ is the input value of the image and $g(x,y)$ the mean value of the image, M is the number of input image rows and N the number of input image columns, for x,y which contains 0.1,2, ... , n.

V. RESULT

The experimental material is a data of heartcondition image of the 12 lead ECG that have been scanned and transformed from the time zone to the spatial region. The pre-procesing steps are the same as those done by [8] (Table 1).

Table 1. The Pre-Processing Steps [8]

Method	Output
ECG Image	
Grayscale	
Binary	
Dilation	
Erosion	
Graphic	

Results from the pre-processing stage as in Table 2.

Table 2. Image & Signal 12 Lead ECG

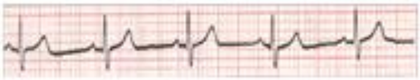
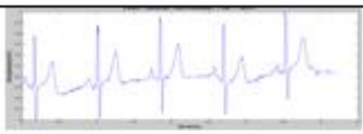
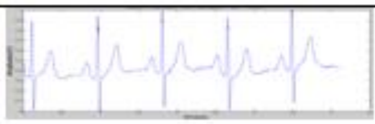
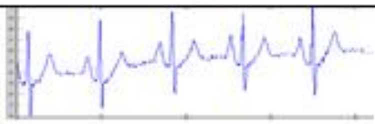
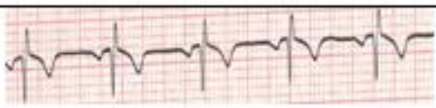
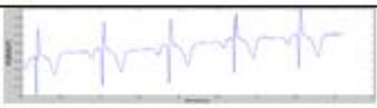
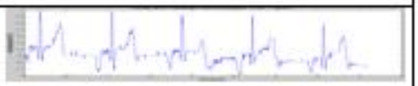
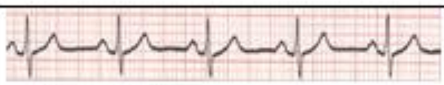
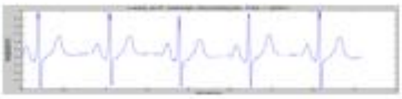
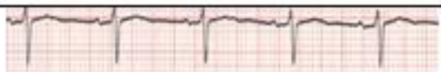
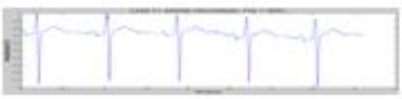
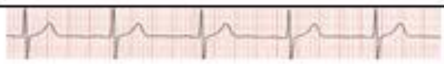
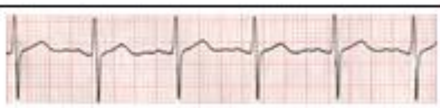
Lead	Image	Signal
I		
II		
III		
aVR		
aVL		
aVF		
V1		
V2		
V3		

Table 3. MSE Value of Mother Wavelet Deubicies with 10 Decompositions in Each Lead

No.	Lead											
	I	II	III	aVR	aVL	aVF	V1	V2	V3	V4	V5	V6
1	0.1854	0.2084	0.3078	0.3241	0.1277	0.2271	0.5382	0.2386	0.1838	0.3270	0.1372	0.1580
2	0.1852	0.2082	0.3077	0.3240	0.1275	0.2269	0.5380	0.2383	0.1839	0.3267	0.1366	0.1577
3	0.1847	0.2075	0.3076	0.3236	0.1268	0.2260	0.5374	0.2378	0.1835	0.3257	0.1361	0.1564
4	0.1840	0.2057	0.3069	0.3230	0.1262	0.2251	0.5349	0.2348	0.1823	0.3246	0.1354	0.1554
5	0.1819	0.2039	0.3066	0.3220	0.1238	0.2229	0.5357	0.2361	0.1832	0.3239	0.1349	0.1544
6	0.1835	0.2062	0.3069	0.3227	0.1242	0.2237	0.5367	0.2371	0.1816	0.3218	0.1356	0.1554
7	0.1838	0.2070	0.3071	0.3228	0.1254	0.2248	0.5376	0.2371	0.1813	0.3231	0.1358	0.1566
8	0.1842	0.2070	0.3070	0.3231	0.1266	0.2264	0.5373	0.2375	0.1826	0.3254	0.1370	0.1573
9	0.1829	0.2057	0.3076	0.3256	0.1182	0.2250	0.5384	0.2360	0.1825	0.3223	0.1351	0.1565
10	0.1848	0.2082	0.3076	0.3234	0.1277	0.2272	0.5381	0.2387	0.1849	0.3270	0.1371	0.1580

This experiment will look for what type of wavelet is most appropriate to the 12 lead ECG image pattern by finding the smallest mean square error (MSE). The 12 lead ECG image is processed using discrete wavelet transforms with decomposition up to ten levels, then each decomposition coefficient i.e., cA10, cD10, cD9, cD8, cD7, cD6, cD5, cD4, cD3, cD2 and cD1 is recalculated for reconstruction of the ECG signal (Equation 4). After obtaining the reconstructed signal results, the MSE value is sought (Equation 5). The result of feature extraction is shown in Table 3.

V. CONCLUSION

The decomposition result is viewed from the smallest MSE value from which it can be known that each lead obtained by the smallest mean value is obtained at the 5 level decomposition, i.e., lead I, II, III, aVR, aVF, V4 and V5, whereas for V1 & V2 is obtained at the 4 level, for aVL (level 9), V3 (level 7) and V4 (level 6). Future research is expected to be followed up to compare with other mother wavelets or to identify cardiac abnormalities based on ECG images.

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