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QRS Complex Detection on Heart Rate Variability Reading Using Discrete Wavelet Transform

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ABSTRACT Heart Rate Variability or heart rate in humans is used to monitor the function of the human heart. This research designed a tool to compare the results of heart rate readings using the discrete wavelet transform method to facilitate the detection of R peak. This can be obtained by evaluating and studying each decomposition result from level 1 to level 4 on Discrete Wavelet Transform processing using Haar mother wavelets. This study further used a raspberry pi 3B as the microcontroller of the data processor obtained from the ECG module. Based on the results obtained in this study, it can be concluded that in heart rate readings, level 2 decomposition details coefficient had the best value as data processing that helps the heart rate readings with an error value of 0.531% compared to HRV readings that obtained 0.005 using phantom tools and a standard deviation of 0.039. Furthermore, the advantage obtained from this tool is a good precision value in HRV and BPM readings. In reading the HRV of the respondent, it was found that each initial condition of the patient's HRV would be high due to the respondent's unstable condition. The disadvantage of this tool is a delay in running the program and no display in the form of a signal in real time.

INDEX TERMS Heart Rate Variability, Discrete Wavelet Tranform, Decomposition.

I. INTRODUCTION

Heart is a vital organ that functions to circulate blood throughout the body. Information about the heart is very important to know the condition of a person's body. In addition, heart disease is the leading cause of sudden death in the world due to heart attacks. This further makes information about a person's heart health important [1]. The formation of a heart signal is caused by contraction of the atrial and ventricular muscles that occurs due to a pacemaker impulse so that a signal is formed in the form of P, Q, R, S and T signal [2][3]. The heart signal represents the condition of a person's body. In this case, one of the conditions that can be seen from the heart signal is the condition of the autonomic nervous system. In maintaining non-stationary balance, the heart will produce fluctuations, which will then affect the heart rate interval that is commonly referred to as HRV or Heart Rate Variability. Changes in heart rate over time provide morphological information for normal, ectopic, pacing, and artifact heartbeats. In such condition, measurements are generally carried out by mathematical analysis and the respondent is in a sinus rhythmic heart signal condition so that measurements can be carried out optimally [4].

HRV measurement can be done through time domain and frequency domain. In this case, the measurements using the frequency domain are carried out when analyzing short-term records, while the time domain was used when analyzing long-term records. Furthermore, short-term recordings have the disadvantage of failing to detect a very low-frequency oscillations, while long-term recordings are susceptible to external factors [5]. One tool that can display information about the heart in the form of signal is ECG. ECG is a non-invasive and most widely used technique for the diagnosis of heart disease. ECG intercepts the heart's electrical signals and is displayed in the form of signal. From the heart signal, the doctor can diagnose the respondent's condition (baseline correction). The basic parameter in ECG diagnosis is heart rate, but one of the parameters as a quantitative marker in ECG signal diagnosis is heart rate variability (HRV). HRV is used to analyze the interval between peaks R in ms units using a QRS signal detector [6]. Due to the importance of these HRV parameters, the development of ECG tools is currently advancing to support accurate diagnostic results. Therefore, several studies have been carried out on the detection of complex QRS to assist the peak R signal reading. In this case, several algorithms are used to make it easier to detect complex QRS.

In 2008, Desmond B. Keenan conducted a study on the analysis of detecting and correcting ectopic beats for HRV using Discrete wavelet transform (DWT). The experiment was carried out using an algorithm to detect ectopic beats by analyzing the coefficients of the Discrete wavelet transform. There were two techniques used for filtering and replacing ectopic beats, namely using wavelet hard thresholding and linear interpolation to replace ectopic cycles. Data collection was carried out for 24 hours to detect PVC and eliminate noise and leakage generated by the ectopic cycle. The advantage of this research is that DWT processing can read ectopic beats using a db4 mother wavelet. However, this study had a drawback in the forms of the lack of explaining the results of the RR interval and HRV and the absence of results when using other mother wavelets [7]. In 2012, Desai K.D. conducted a study on the development of realtime fetal ECG using extraction features and Discrete wavelet transform to determine fetal heart rate. This study performed a Fetal ECG extraction feature of maternal abdominal ECG signals. The QRS complex detection in this study used discrete wavelet transform. This research had an advantage in the forms of high accuracy of 99.5% where the results are greater than previous studies. Meanwhile, the drawback of this study is that there was no explanation regarding the mother wavelet used [8]. In 2017, Iben H. Bruun et al conducted a study on automatic detection of atrial fibrillation by combining atrial activity and heart rate variability to screen respondents. In the peak detection section, the researcher used the Pan and Tompskins and DWT algorithms. Tests were carried out on 48 data records from MITDB using three mother wavelets, namely Daubechies 4 (DB4), Daubechies 5 (DB5), and Symlet 4 (Sym4) to detect the DWT peaks. [9]. In 2013, Ibtihel Nouira et al conducted a study on the use of a strong R peak detection algorithm using wavelet transform for studying the heart rate variability. The use of a bandpass filter with a range of 1.5 Hz to 50 Hz was useful for reducing noise in the ECG signal with a sampling rate of 256 Hz. This research also used Discrete wavelet transform as filter and decomposition function. Tests were carried out with several mother wavelets to find the best results [10]. Furthermore, in 2014, Vikram C.M. et al conducted research on wavelet-based entropy features and Support Vector Machine (SVM) for classifying the heart rate variability. The experiment was carried out using the MIT-BIH ECG signal database and DWT decomposition 3 to reduce noise in the ECG signal [11]. In addition, another research project was also conducted in 2014 by Zultan German-Sallo in comparing the method of feature extraction of heart rate variability between Wavelet Packet Transform (WPT) and Fourier transformed. In 2012, Gaurav Jaswal et al conducted a study comparing the DWT and "Sho and Chan" methods in detecting QRS complexes [12]. In 2014, Rachid Hadadi conducted a study to detect QRS complexes from ECG signals. DWT was used to eliminate baseline wander in the ECG signal. The test was carried out using Daubechies (Db4) of order 1-8 as the mother wavelet [13]. Furthermore, Mohamed Elgendi (2013) carried out a study on rapid QRS detection using a knowledge-based method that was optimized by evaluating11 standard ECG databases where the method used showed high robustness and an almost negligible error rate. The method used achieved a very high detection rate. The researchers developed a numerically efficient algorithm to accommodate battery-powered ECG devices and to analyze signals with long-term recordings using time-efficient methods. The QRS detection method used by the author was a two moving average. The proposed method could be easily implemented in digital filter design. The author's device did a different recording with a sampling rate between 128Hz – 1KHz and interference. In addition, lead I was used on every record without exception. Appropriate reference R markers were provided in the data set for reference [14]. John Malik, et al in 2020 further also conducted a study on the use of an adaptive QRS detection algorithm for long-term ECG recording and intermittent deformations in signal quality that occur due to subject movement, noise, and incorrect placement of the ECG electrodes. The author's aim was to propose a QRS detection algorithm that overcome these challenges. The proposed method was applied based on two further modifications, namely the first modification by implementing local signal amplitude estimation. The second modification was conducted on the mechanism by which the algorithm became adaptive to changes in heart rate. The authors proposed a state-of-the-art algorithm using short-term ECG recordings from 11 annotated databases on the Physionet application, as well as visualized 14-day long-term ECG recordings. In the database algorithm proposed by the author, the sensitivity results were 99.90%, while the positive predictive value was 99.73%. Meanwhile, the latest QRS detection algorithm achieved a sensitivity of 99.30% and a positive predictive value of 99.68% in the same database. In this case, samples were taken at 200Hz [15]. Szi Wen Chen, et al. in 2006 also conducted a research on real-time QRS detection method based on moving average and wavelet denoising. In this study, they proposed a simple moving average method to detect QRS in real time. In addition, to obtain the signal, the authors incorporated a wavelet-based denoising procedure to effectively reduce the rate of rise of the ECG data. The overall structure of the algorithm proposed by the authors allows QRS detection to be carried out and implemented in real time with time efficiency. Algorithm performance was carried out against the MIT-BIH arrhythmia database. The results showed that the algorithm achieved a detection rate of about 99.5% for standard databases, and can also work with and even under conditions of poor signal quality in the measured ECG data [16]. In addition, Sami Torbey, et al in 2012 conducted a study on QRS Multi-lead detection using windows pairs. The authors designed a new approach for multi-lead QRS detection. The algorithm used equations with two different window widths to generate signal features and detection thresholds. This made it possible to adapt to a wide range of QRS changes and noise levels. The result further obtained an error detection rate of 0.29% in the MIT-BIH Arrhythmia database. This algorithm was also computationally efficient and able to resolve differences between multiple leads [17]. Another study was done by Shweta Jain et al in 2016 on QRS detection using adaptive filters. In this case, the ECG signal monitoring was done through QRS detection. In this paper, an improved QRS detection algorithm based on the principle of adaptive filtering was designed. The calculation of the effectiveness of various LMS variants used in the QRS detection algorithm based on adaptive filtering had been carried out using fidelity parameters such as sensitivity, positive predictiveness, and processing time of 99.68%, 99.84%, and 0.45 seconds, respectively. Reported results were tested with the MIT/BIH arrhythmia database. The presented study also concluded that the performance of most variants was affected due to low SNR but Leaky LMS performed better even in high noise conditions [18]. In 2015, Jenkal Wissam et al conducted a study to improve the complex QRS detection algorithm using discrete wavelet transform. The research used Sym7 as the mother wavelet with a level 2 decomposition, where the first one was used as high frequency noise and the second one was used as baseline wandering. The data employed were data from Physionet, namely MIT-BIH Arrhythmia data with a sampling frequency of 360 Hz. In this paper, thresholding was performed twice, in which the first was to allow reading complex QRS with small amplitudes and the second was to remove incorrect QRS locations. After the thresholding, it was done to ascertain the maximum peak of the QRS complex with 160ms windows. Simulations were carried out using MATLAB R2014a. The results of this study obtained positive productiveness (Pp) of 99.84% and sensitivity (Se) of 99.71% [19].

Based on several studies that have been carried out previously, the comparison of results from the use of different levels of decomposition has not been carried out. The use of different levels of DWT decomposition using Haar mother wavelets on complex QRS readings has not been carried out yet.

Related to all previous studied described above, current research was conducted because previous studies did not explain the effect of the level of decomposition of discrete wavelet transforms, especially the use of mother wavelet Haar in reading HRV. Hence, this research was carried out with the level of influence of the decomposition of discrete wavelet transform with mother wavelet transform to read HRV. In this study, the level of decomposition used was the level of decomposition of one to the level of decomposition of four.

II. MATERIALS AND METHODS

A. *DATA COLLECTION*

In this study, data collection was carried out using a module that had been created. In this case, the data collection was carried out on Phantom (Fluke MPS450) as a comparison tool and data collection on respondents. Data collection on Phantom was carried out at BPM 30, 60, 90, 120 and 180, while data collection on respondents was carried out on 10 male respondents. In this case, the respondents involved were asked to sit and relax during the data collection. Experiments to collect data on phantom and respondents were carried out 3 times, where each experiment was carried out for 10 minutes. ECG signal data collection on patients and phantoms was carried out using the ECG module as shown in FIGURE 1. In this study, the design of this ECG module used IC AD620 as a basic instrumentation for tapping the ECG signal followed by a series of filters in the form of low pass filters and high pass filters along with amplification circuits [20][21]. The filter range used passed a frequency of 5-40 Hz, while the frequencies outside this range was muted. The use of raspberry pi 3B as a microcontroller for data processing using discrete wavelet transform. From the design of the module circuit, data in the form of an ECG signal were obtained and then data processing was carried out using a discrete wavelet transform with decomposition level experiments of 1 to 4 [22]. In the results of the decomposition, measurement values were obtained in the form of BPM, R-R interval, and HRV value. In this case, a comparison was made on each coefficient to get the best results among the three parameters.

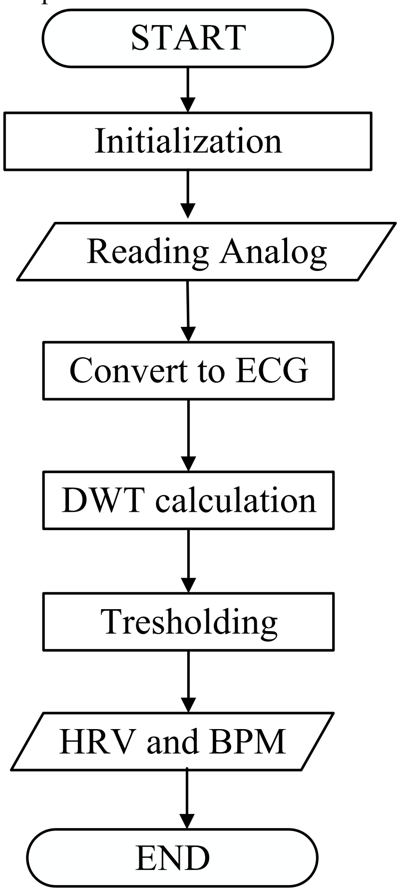


FIGURE 1. Flow chart of how the system works from the beginning to read the ADC value until it is processed and produces HRV and BPM values.

Furthermore, the data collection that was conducted on the male respondents also used the ECG Recorder Fukuda FX-

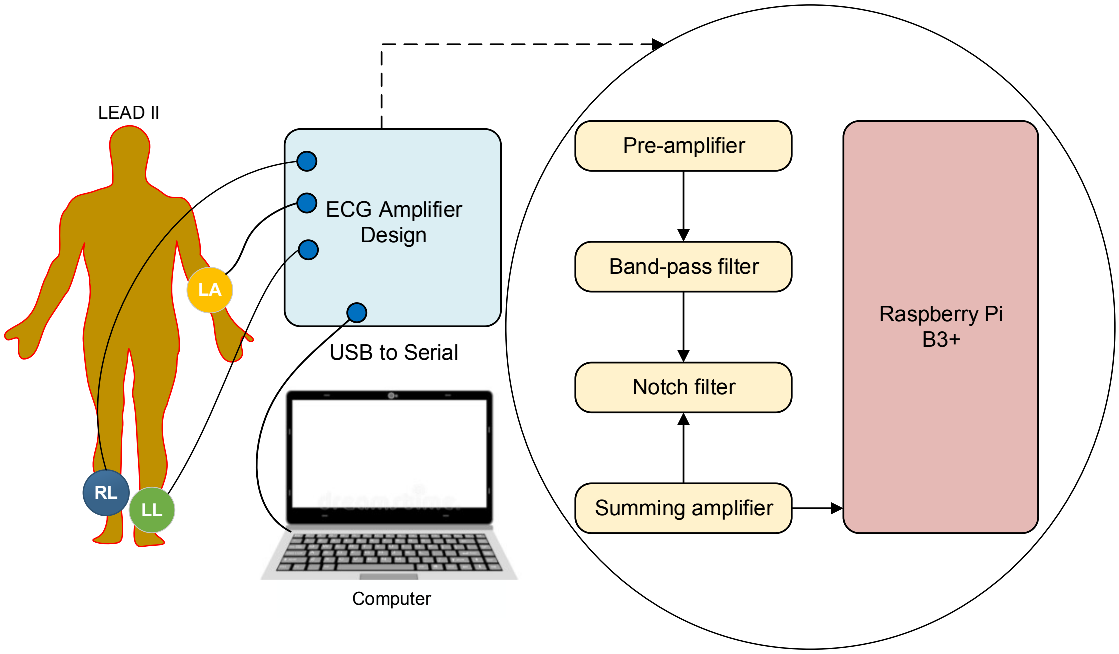


FIGURE 2. System Diagram Blocks. When the system is turned on, the voltage on the patient electrode will be tapped and processed on the ECG Module. The Raspberry microcontroller will process the ECG signal from the ECG Module. Then the data will be processed and displayed on the PC

8100. In this case, the data collection was carried out on all respondents involved. The patient was given the same treatment, namely sitting and relaxing, then the ECG signal data were printed on the ECG paper. From this paper, the BPM value for each patient and the HRV value for each patient were further calculated. These results were further compared to the ECG Module that has been made in this study. The design was then calibrated using ECG Recorder using Fukuda type FX-8100 with three channels that further used for data retrieval.

FIGURE 1. shows a flow chart tool where the voltage value from the patient's lead point was converted into ADC data and processed using an ECG circuit. Then, the data entered the microcontroller which were then processed using discrete wavelet transform to produce HRV and BPM. FIGURE 2. is a system block where the initial process from the patient's Lead II electrode tapping point was processed using a discrete wavelet transform and then thresholding was carried out so that it can produce output in the form of BPM and HRV.

In the next stage, the ECG signal has been tapped using Lead II and obtained from the ECG module [23]. The data were then processed using discrete wavelet transform using mother wavelet Haar to facilitate the detection of complex QRS [24]. In this case, the decomposition level that was tested in this research is the decomposition level 1 to 4. Meanwhile, the coefficients to be tested were the details coefficient 1, details coefficient 2, details coefficient 3, and details coefficient 4.

$$yhigh[k] = \sum_{n} x[n] \cdot g[2k-n] \qquad (1)$$

$$ylow[k] = \sum_{n} x[n] \cdot h[2k-n] \qquad (2)$$

Where x[n] is the original signal that passed through a halfband highpass filter g[n] and a lowpass filter h[n]. In addition, yhigh[k] and ylow [k] are the output of the HPF and LPF after subsampling by a factor of 2. Mathematically, each coefficient in the discrete wavelet transform was obtained from the above equation. ECG data that has been taken will be processed using a low pass filter on a discrete wavelet transform which produced an approximation coefficient. Meanwhile, the high pass filter produced details coefficient [25]. The concept of decomposition level can be seen on FIGURE 3.

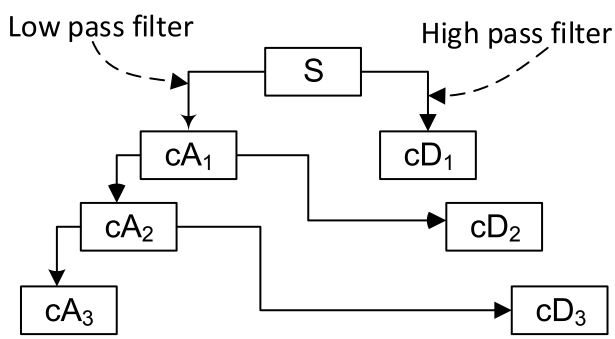


FIGURE 3. Details Coefficient and Aproximation Coefficient from Discrete Wavelet Transform Decomposition

Based on the results of the processing, a QRS complex detection was carried out in order to obtain parameters in the form of RR interval, BPM, and HRV which were further discussed in this study.

B. *DATA ANALYSIS*

Measurements on each parameter such as BPM, R-R interval, and HRV were carried out 3 times with a duration of 10 minutes for each experiment. For each parameter, data analysis was carried out in the form of mean value using the following equation (3):

$$X = \frac{X1 + X2 + \cdots + Xn}{n} \quad (3)$$

X is the result of the mean value on the k3-n measurement. X1 represents the first measurement and X2 represents the second measurement, and so on.

In measuring HRV results, data analysis was carried out in the form of RMSSD calculations to get HRV results for each patient, the RMSSD equation can be seen in equation (4):

$$\text{RMSSD} = \sqrt{\frac{(RR_2 - RR_1)^2 + (RR_3 - RR_2)^2 + \cdots + (RR_n - RR_{n-1})^2}{n}} \quad (4)$$

RMSSD is the mean difference in each RR Interval (HRV). RR2 is the second R-R interval with the first R-R interval, while n is the number of data to be averaged.

The %error shows the error of the system. The lower error value is the difference between the mean of each data. The error can show the deviation between the standard and the design or model. The error formula is shown in equation (5).

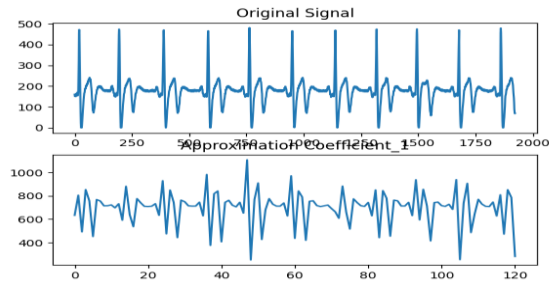
$$\%\,ERROR = \frac{(Xn - X)}{Xn}\, x\, 100\% \quad (5)$$

where Xn is the value measured from the calibrator machine, while the X is the value measured from the design.

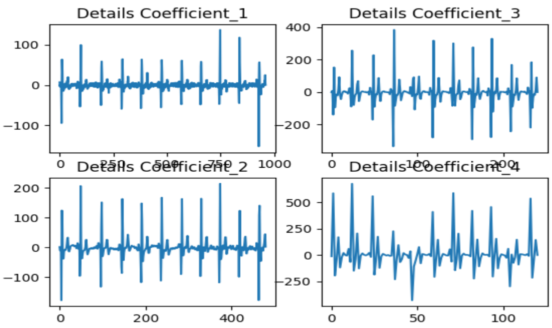
III. RESULT

Exploration on discrete wavelet transform was done using mother wavelet Haar with decomposition level 1 to 4. The exploration was done by looking at the signal results on each coefficient result. In each discrete wavelet transform processing results, data were obtained in the form of details coefficient 1, details coefficient 2, details coefficient 3, details coefficient 4, and approximation coefficient 4. The results of data processing on each coefficient can be seen in FIGURE 4.

(a)



(b)



(c)

FIGURE 4. (a) Results of the respondent's signal on the ECG paper. (b) The original signal on the module and the results of the approximation coefficient level 4. (c) The results of the details coefficient level 1 to 4.

FIGURE 4 shows the results of the patient's ECG signal data processing using a discrete wavelet transform in addition to the patient's signal results from the ECG Recorder.

The module testing on Phantom was carried out on each coefficient in order to find the best results which were further used to collect the respondent data. In this case, TABLE 1. describes the results of several coefficients in BPM and HRV readings on the Phantom device.

TABLE 1. Comparison of Measurement Results on Each Coefficient.

Decomposition	Average HRV Reading (s)	BPM Average Reading Error Value (%)	Standard Deviation
Coefficient Detail 1	0.012	0.370	0.259
Coefficient Detail 2	0.005	0.531	0.039
Coefficient Detail 3	0.054	1.403	1.297
Coefficient Detail 4	0.040	91.000	89.328

The retrieval of respondent data was carried out for three times. The number of respondents who were involved were 10 men in a relaxed sitting condition. In this case, the experiment was conducted in each respondent lasted for 10 minutes. Then, the data on the module were compared with the data on the ECG Recorder. These results can be seen in TABLE 2.

TABLE 2. Comparison of Measurement Results on Module and ECG Recorder.

No.	Heart Rate Variability on Reading Module(s)	Heart Rate Variability on ECG Recorder Measurements (s)	Difference in Measurement Results (s)
Respondent 1	0.0356	0.0387	0.0031
Respondent 2	0.0421	0.0388	0.0033
Respondent 3	0.1315	0.0440	0.0875
Respondent 4	0.0355	0.0734	0.0379
Respondent 5	0.0213	0.0404	0.0191
Respondent 6	0.0760	0.0437	0.0323
Respondent 7	0.0421	0.0141	0.0280
Respondent 8	0.0320	0.0437	0.0117
Respondent 9	0.0670	0.0225	0.0445
Respondent 10	0.0223	0.0367	0.0144

IV. DISCUSSION

At each increase in the level of decomposition, the amount of data were divided into 50%. The reduction in the sampling frequency caused some missing information such as a reduced peak R signal or a loss of peak R signal. This further interfered with reading the HRV value.

Details coefficient level 1 showed the average HRV reading with a value of 0.012. In terms of reading BPM, the error value on the coefficient level 1 had the best results with an error value of 0.379%. However, the standard deviation of the coefficient level 1 was 0.259. In this case, the coefficient level 1 was conducted the best value in reading the BPM value

Furthermore, Details Coefficient level 2 had an average error value in BPM readings of 0.531%. This value is lower than the reading of the BPM details coefficient level 1. Details coefficient level 2 showed the average HRV reading with a value of 0.005. This value is the best value than the other coefficients. Compared to the coefficient details level 1, the reading value of the BPM coefficient level 2 is not better than the coefficient level 1. However, the standard deviation of the coefficient level 2 has a better value than the coefficient level 1. In reading the HRV details coefficient level 2, it has a higher value. In addition, the standard deviation of coefficient value level 2 has a better value too. In this case, it can be concluded that the details coefficient level 2 has the best results in HRV readings, with a standard deviation of 0.039 and better precision than the level 1 details coefficient.

The BPM reading on the details coefficient level 3 had an average error value of 1.403%. This value is certainly not better than the lower details coefficient level. This is because, with every increase in the level of decomposition, the sampling frequency will decrease. The loss of some data information will affect the loss of the R peak signal so that it affects the detection of QRS complexes and makes the reading results worse.

Meanwhile, BPM readings on the details coefficient level 4 had an average error value of 91%. The BPM readings of 60, 90 and 120 have high error values. This is because a lot of information is missing.

The respondent's HRV reading on the ECG Recorder was done by manually measuring the distance between the R's on the ECG paper. In 10 respondents involved, the lowest HRV value was in respondent 7 with an HRV value of 0.0141. The smaller the HRV value, the more stable the patient's condition. One of the factors that can affect the HRV value is the respondent's state of mind. The average HRV reading on the ECG Recorder is 0.0396, with the smallest HRV value of 0.0141 and the largest HRV value of 0.0734.

The respondents' HRV readings using the module were carried out three times for data collection with each experiment lasting for 10 minutes. Each respondent had a different R-R interval and HRV value due to the different habits and conditions of the respondents. The average HRV reading of respondents in the module is 0.05, with the smallest HRV value of 0.0213 and the largest HRV value of 0.1315.

The results of the comparison between the HRV value on the module reading and the ECG Recorder. The smallest difference value is 0.0031, while the largest difference is 0.0875. The average result of the difference between the readings of the HRV module and the ECG Recorder is 0.0282. There are many factors that affect the result of the difference between the module readings and the ECG Recorder. Previously, this retrieval was carried out using discrete wavelet transform decomposition level 2 data processing, the best HRV reading was on the details coefficient level 2. The result of the difference between the HRV readings was due to the accuracy of the module itself. Meanwhile, another factor is the length of data collection and human error. When reading the R-R interval value on the ECG paper, reading errors may be unavoidable so that there is a slight difference from the actual value. From the discussion on these coefficients, it can be concluded that in reading HRV, the details coefficient level 2 had the best results.

V. CONCLUSION

This research is conducted because several previous studies have no explanation regarding the effect of the decomposition rate of discrete wavelet transforms, especially the use of mother wavelet haar in reading HRV. For this reason, this research is carried out with the level of influence of discrete wavelet transformation decomposition with mother wavelet transformation to read HRV. The best results are found on the coefficient of detail level 2 with an average HRV reading of 0.005, an error value of 0.531%, and a standard deviation of 0.039. These results indicate that the detail coefficient 2 has the best precision value. The advantage of this research is that the HRV value reading is more precise. Storage data is recorded and stored automatically. To some extent, reducing the sampling frequency has the effect of reducing signal noise. Furthermore, the disadvantages of this research are that the signal is not displayed in real time, the accuracy is not good, the program experiences delays at some decomposition levels, and some of the peak R information disappears. In the next development, it is recommended for further researchers to add a decomposition level, make changes to the microcontroller by processing data in real time, and display the processed signal in real time. Indeed, the completion of the program in HRV reading will be very useful in future research.

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