# Geometric Detection Algorithm Design for ECG Data Analysis Using Wavelet

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***Abstract***

*The need for clear ECG signals is increasing to reduce the probability of misdiagnosis regarding heart diseases. An algorithm was designed to diagnose patients with heart diseases using ECG signal analysis so that it can help physicians in the decision-making process. Before analyzing the ECG signal, noise of the low and high frequency components was removed through preprocessing. After preprocessing, pattern analysis detected important features on which diagnosis will be given. Then, the analysis was applied on the pure ECG signal to detect the patient's heart diseases. All feature points were extracted by using the proposed algorithm, called 'Geometric Detection (GD)'. Results showed that performance was superior to others in standard error of the sample mean and variance. Data from CSE (Common Standards for Electrocardiography) database were used to test each algorithm except for GD, because patients' ECG data was used to test the GD algorithm. Detection rate of the GD algorithm (se(%)) was 99.1% and we confirmed that the proposed algorithm is superior to the other algorithm in terms of stability and standard error of the sample mean. The result of the performance evaluation showed that the proposed algorithm produced higher accuracy and stability than the other algorithms.*

***Keywords****: Wavelet, ECG characteristic, Geometric Detection Algorithm*

## 1. Introduction

Today, due to the in aging population and the degradation of childbirth, Korean society has already entered the aging society. Also, due to the westernization of eating habits and lifestyle, hypertension, diabetes, chronic and incurable diseases like cancer increased. Not only that, the types of major diseases changed from acute diseases to chronic diseases.

Especially, cardiac disorders highly account for the cause of death. In addition, medical expenses to solve chronic disease are increasing and thus threatening national finances [1]. Diseases like myocardial infarction and stricture of the heart are also increasing rapidly in Korea [2]. In order to distinguish the prevalence of the heart diseases, clinical doctors diagnose patients by observing their ECG signal.

ECG is a signal from the heart measured by the potential difference between the ECG leads attached to the user [3]. Usually, there are 3 standard leads, a pre-cordial or cheat leads, and 3 augmented leads [4]. These ECG leads record traces from 12 different directions of the ECG signal which will be used to search for specific features (*ex.* Morphological characteristics of ECG waveform) by physicians to diagnose a patient. Therefore, the quality of the ECG signal recorded from patients influences the diagnosis significantly. The problem is the bio-signal recorded from a patient is often times contaminated by noises. This is because the baseline is comprised of a waveform, and

thus it is not an easy task to realize feature points. Therefore, several new approaches have been attempted to precisely extract these specific feature points, and significant researches are being reported internationally [5].

Currently, cardiologists' diagnosis is made subjectively by the combination of ECG signal visual inspection and observed symptoms from a patient. Therefore, diagnosis for a patient might be different depending on physicians. Sometimes, non-cardiologists use ECG signals frequently to diagnosis a patient about heart disease. For a non-cardiologist, diagnosis is mostly determined by the result of the automatic diagnosis ECG equipment [6]. As shown in Figure 1, key characteristic points of this waveform are P-wave, QRS-complex and T-wave. In a typical normal ECG, the U-wave does not show up clearly [7].

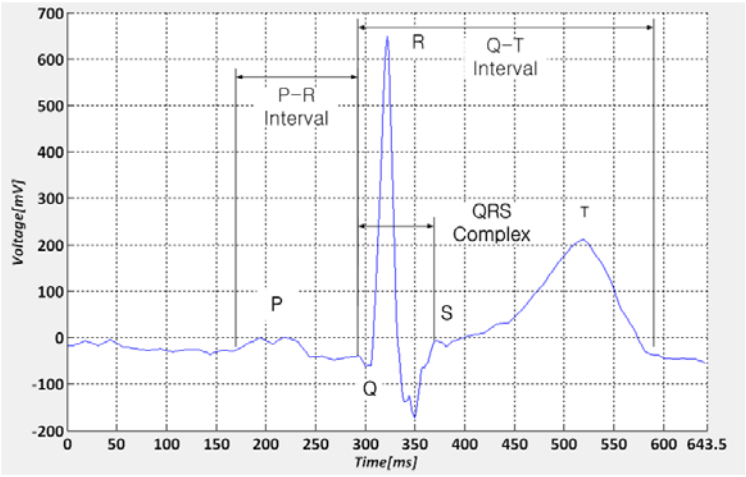



**Figure 1. Typical ECG Signal of a Normal Person**

In order to analyze an ECG signal, we took 2 steps including the pre-processing step and pattern recognition step. In pre-processing, baseline is corrected and noise is removed in the raw ECG signal. Next, in the pattern recognition step, verification and feature point search on the pre-processed ECG signal is included. Baseline in the raw ECG signal was corrected by the least square method [8] and noise was removed by using wavelet transform sequentially. Feature points were detected by the sliding window method and the proposed GD algorithm was used for verification and recognition.

Since the baseline corrected ECG signal is still mixed with noises, it would be difficult to extract critical information for diagnosis such as the presence and types of heart diseases. Wavelet transform is well known as a useful tool for removing noises and detecting feature points despite the baseline change during respiration and the muscular twitching [9]. Therefore in this paper, wavelet transform was used to remove noises and detecting feature points [10, 11].

The first aim of this research is to determine the presence of disease using the proposed algorithm, which would provide more information than typical similarity computation of the ECG data. The second aim of this research is to help physicians diagnose the heart diseases by providing results from the proposed algorithm. To achieve our aims, the automatic algorithm was studied for ECG signal analysis and the results were verified through an experiment. All feature points were detected by the proposed algorithm of which results were superior to the WD (Wavelet-based Detector), TD (Threshold-based Detector), and the MMD (Multi-scale Morphological Derivative transform-based detector) according to the standard error of the sample mean and variance (see Table 3). Detailed analysis of feature points of the ECG presented in this paper would provide new possibilities in effective ECG signal analysis for further research. Overall, the proposal of this research is the application of a classical method of signal processing to ECG signals.

Our motivation is to enable clinical doctors to use this as a method to build a clinical database about the ECG signal, so that ultimately it will enhance clinical decisions.

Following the introduction, in Section II, materials and methods used in this paper will be explained including ECG signal recognition methods, baseline adjustment method, wavelet transform and feature point detection. In Section III, our outstanding results compared to MMD, TD, WD and CSE will be shown, and lastly, overall assessment and future research will be discussed in Section IV.

## 2. Materials and Methods

### 2.1. ECG Signal Recognition Methods

ECG signals recorded from electrodes include noises that blur the pure cardiac signal. There are two kinds of noises in the ECG signal. One is the baseline fluctuation and the other is high frequency components, which require an additional filtering process. Generally, the raw ECG signal can be represented by summation S(i), which is defined as the following computation in which $S_O$ is the pure ECG signal, $S_H$ is high frequency and $S_L$ is low frequency components.

$$S(i) = S_O(i) + S_H(i) + S_L(i) \quad \text{----------(1)}$$

In the pre-processing, it is required to remove the low and high frequency noise component before analyzing ECG data [12]. This process includes the wavelet filtering to extract the pure ECG signal $S_O(i)$ by removing high ($S_H(i)$) and low ($S_L(i)$) frequency components.

The pattern process step is performed after the preprocessing process is completed. The pattern process consists of pattern recognition and validation. Results of these processes will provide important data which is used to predict the presence of heart disease.

Figure 2 schematically shows the process step of the ECG signal.

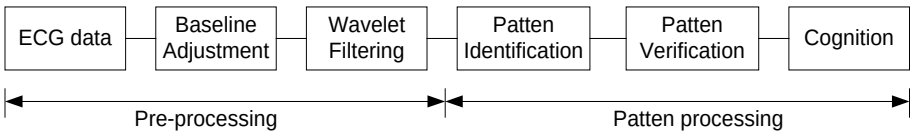



**Figure 2 Block Diagram of the ECG Signal Analysis**

### 2.2. Baseline Adjustment

The raw ECG signal is contaminated by baseline fluctuation, which requires high-pass filtering to remove time-varying baseline fluctuation [13]. Baseline was determined by the equation (f(x)-g(x)), in which f(x) is the recorded ECG, and g(x) is the 8'th order regression model. The regression model was computed by polynomial interpolation [14] which is known to estimate the trend of a signal using consecutive multiple points. For the regression model, least square method (LSM) was used as shown in equation (2).

$$\text{Min}\sum \varepsilon_i^2 = \text{Min}\sum (Y_i - \hat{Y}_i)^2 = \text{Min}\sum (Y_i - a - bx_i)^2 \quad \text{----------(2)}$$

Figure 3 shows the process diagram to obtain baseline-corrected ECG from recorded ECG. The baseline, estimated from the difference between the polynomial regression model and the recorded ECG, was subtracted from the recorded ECG as described in the diagram.

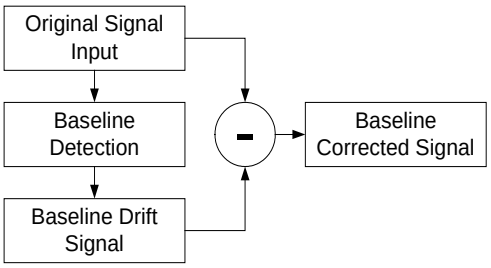



**Figure 3. Block Diagram for the Proposed ECG Signal Conditioning Algorithm**

To compute the baseline curve, LSM was used to estimate the regression curve as equation (3). Coefficients of polynomials were computed using the matrix product as described in equation (4).

$$p(x) = p_0 x^n + p_1 x^{n-1} + \cdots + p_{n-1} x + p_n \quad \text{----------(3)}$$

$$\begin{bmatrix} m & \sum x_i & \sum x_i^2 & \cdots & \sum x_i^n \\ \sum x_i & \sum x_i^2 & \sum x_i^3 & \cdots & \sum x_i^{n+1} \\ \sum x_i^2 & \sum x_i^3 & \sum x_i^4 & \cdots & \sum x_i^{n+2} \\ \vdots & \vdots & \vdots & & \vdots \\ \sum x_i^n & \sum x_i^{n+1} & \sum x_i^{n+2} & \cdots & \sum x_i^{2n} \end{bmatrix} \begin{bmatrix} p_n \\ p_{n-1} \\ p_{n-2} \\ \vdots \\ p_0 \end{bmatrix} = \begin{bmatrix} \sum p_i \\ \sum x_i p_i \\ \sum x_i^2 p_i \\ \vdots \\ \sum x_i^n p_i \end{bmatrix} \quad \text{--------(4)}$$

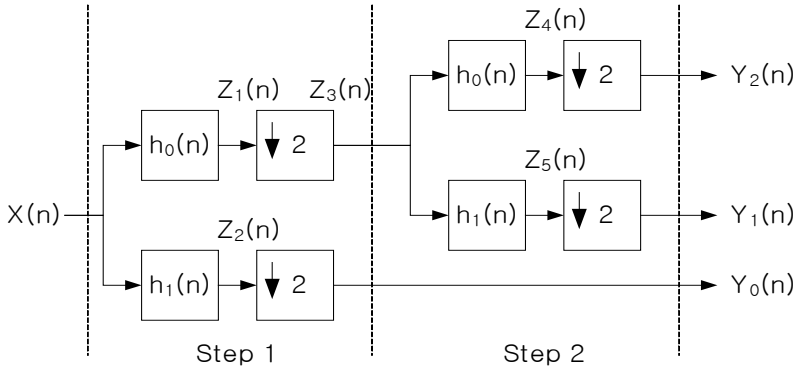
### 2.3. Wavelet Transform

The ECG signal can be treated as a linear combination of sinusoidal waves with different frequencies, instead of a time-dependent random signal. Therefore, the ECG signal can be analyzed either in the time-domain or frequency-domain. This is because analysis in the frequency-domain unveils certain characteristics which cannot be seen in time-domain analysis. This analysis is called 'Fourier Transform Analysis'. However, the Fourier transform analysis is limited by time and not appropriate to nonlinear and high frequency signals such as ECG [9]

Also, Fourier coefficients are not appropriate for time-variant signals [6]. In spite of all odds, limitations of Fourier transform analysis are overcome by Wavelet transform which analyze both the time and frequency domain of the ECG signals and reduce the contaminated noise.

Therefore, in this paper, Wavelet transform has been used to improve the quality of the signal containing high frequency and critical medical information. The Wavelet transform is widely used for feature extraction, filtering, data compression and transportation [9], [15-17]. Using the superiority of the Wavelet transform, this paper removed the high frequency components in the recorded ECG with a wide frequency range [18].

Figure 4 shows a schematic diagram for the Wavelet transform. The raw ECG is separated into a high (h1) and low (h0) frequency signal by Wavelet low-pass filtering. According to the sampling theory, sampling time is set to be the half of the maximum frequency component of the raw ECG [19]. Since the filtered signal still contains high and low frequency components, Wavelet filtering was repeatedly applied until an optimum signal was obtained. The final signal obtained from the Wavelet filtering was used to extract feature points and temporal characteristics of those feature points.




X(n): ECG signal, $h_i(n)$: Transfer function
$Z_i(n)$: Wavelet transform signal
$Y_i(n)$: De-wavlet signal

**Figure 4. Wavelet Transform**

Step1 is for the Wavelet transform of ECG, and step 2 is the Wavelet transform on low-pass filtered ECG from step 1. In step 2, data was reconstructed by the inverse Wavelet transform of the combined signals from low-pass filtered signal y2(n), high-pass filtered y1(n) and y0(n). In other words, the ECG signal was low-pass filtered, then was reconstructed by reverse wavelet transform.

### 2.4. Feature Points Detection and Signal Analysis

After removing the noises from the raw ECG signal, we analyzed the pattern of this signal to detect feature points. Results obtained from this may provide important information for diagnosis. The following steps describe feature point detection processes.

1. Critical feature points were determined by the slope change point using the sliding window method.

2. If the detected feature points pass the significance test, voltage and time of the points are saved.

3. Using the data points from step 2, important parameters (ex. Interval between feature points) were computed for diagnosis.

#### 2.4.1. Sliding Window Method

Selecting proper window size is an open question, because a narrow window is too sensitive for trivial change of the signal and may detect more than needed feature points, which may not pass significance test. On the other hand, if a window is too wide, it may miss significant feature points, because it is not sensitive [20]. Therefore, we applied various window sizes to detect feature points on the ECG signal. In equation (5), f(x) represents a window with $x_m$ data points, and g(x) is the slope of f(x)

$$f_1(x) = \{x_0, x_1, x_2, \cdots x_i \cdots, x_m\}$$

$$g_1(x) = \{M_0, M_1, \cdots, M_{m-1}\}$$

$$M_0 = \frac{y_1 - y_0}{x_1 - x_0}, M_1 = \frac{y_2 - y_1}{x_2 - x_1}, \cdots, M_{m-1} = \frac{y_m - y_{m-1}}{x_m - x_{m-1}} \quad \text{--------(5)}$$

$$b(x) = \{C_0, C_1, C_2, \cdots, C_n\}$$

Group b(x) was made by comparing the sign change of the slop (positive, negative and 0) to slope group g(x) from the previous window. The group b(x) is described in equation (6).

$$b(x) \begin{cases} \text{initial value } C_0 = 0 \\ \text{skip, if sign(all g(x)) = sign of obtained value from previous window(b(x-1))} \\ f(x_0), \text{ if sign(all g(x)) } \neq \text{ sign of obtained value from previous window(b(x-1))} \end{cases} \text{---(6)}$$

The group b(x) is not updated when the signs of b(x-1) are the same as signs of b(x), which means that the signal is not changing, or consistently increasing, or consistently decreasing. This would not affect the group b(x), because these points are not significant feature points.

If all points in b(x) and b(x-1) were different, then it would mean that there were meaningful changes (sign change of first derivatives). For instance, from increment to decline or no-change, from decline to increment or no-change, and from no-change to increment or decline (a total of 6 possibilities). These characteristics are determined as feature points and the first element of the window is defined as the beginning point of change. The beginning point of change is stored in b(x). Once the analysis of the signal from a window is done, analysis moves on to the next window by applying the same principle as previously described(making group b(x) and finding feature points). Repeating analysis on the moving window creates a group of feature points. Equation (7) shows the second window f2(x) and slope g2(x), succeeding the process from equation (5).

$$f_2(x) = x_2, x_3, x_4, \cdots, x_{m+1}$$

$$g_2(x) = M_1, M_2, M_3, \cdots, M_m \text{ ---------- (7)}$$

Figure 5 presents the results of equation (6), which show the positive slope and negative slope through the sliding window method.

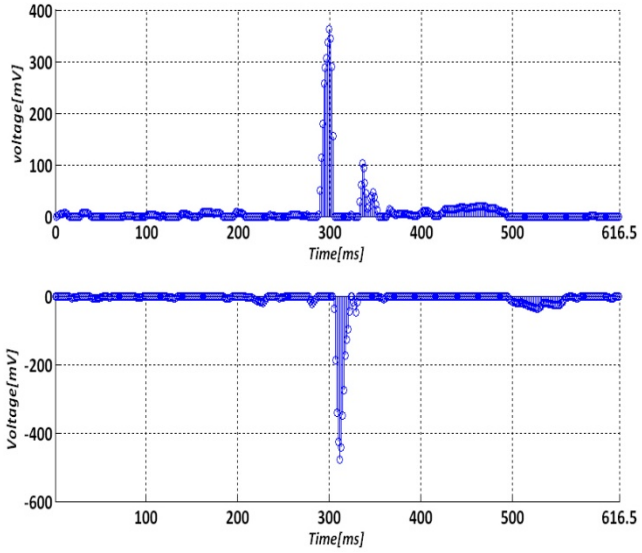



**Figure 5. (a) Positive Slope (b) Negative Slope through Sliding Window Method**

### 2.4.2. Feature Points Detection

#### 2.4.2.1. Detection Algorithm

In this paper, the time interval between feature points was mainly extracted to differentiate patients from the control group [21]. The extracted feature points were $P_1$(the starting point of P-wave), $P_2$(the peak of P-wave), $P_3$(the finishing point of P-wave), $Q_1$(the starting point of QRS-complex), $Q_2$(the finishing point of Q-wave), R, $S_1$(the starting point of S-wave), $S_2$(the finishing point of QRS-complex), $T_1$(the starting point of T-wave), $T_2$(the peak of T-wave), and $T_3$(the finishing point of T-wave).

Secondly, the duration of interval and waves identified were P-wave(the duration between $P_1$ and $P_3$), QRS-complex(the duration between $Q_1$ and $S_2$), PR-interval(the duration between $P_1$ and R), QT-interval(the duration between $Q_1$ and $T_3$), T-wave(the duration between $T_1$ and $T_3$), and ST-segment(the duration between $S_1$ and $T_3$).

The detection algorithm looks for the R-peak which is easy to detect using a peak-detection algorithm, because R-peak has the highest amplitude. Once R-peak is detected, feature points b(x) is searched within the time window (164 ms left and 246 ms right from the R-peak) by the sliding window method. A significance test to improve accuracy is applied first on feature points that are clearly distinguishable.

Based on the R point, P2, Q2, S1, T1 and T2 were searched within the predetermined time window. When one of those points is found, feature points b(x) are searched within the time window. For example, Q1 is searched from a certain location on the left side from Q2 and S2 is searched from a certain location on the right side of S1 within the time window (see Figure 6), to find feature points b(x).

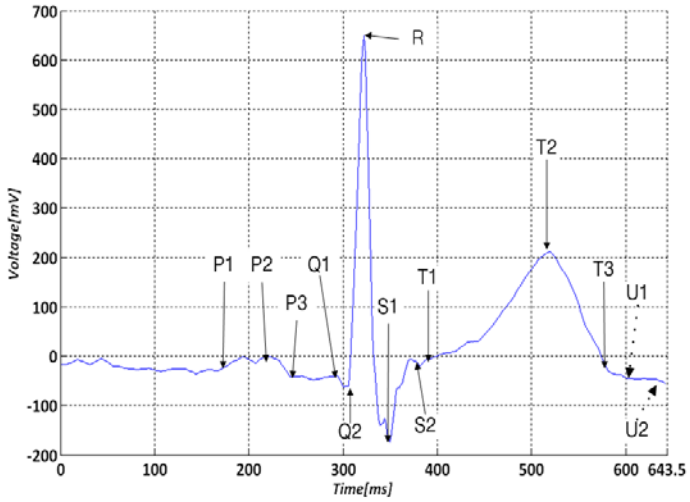



**Figure 6. ECG Characteristic Points**

#### 2.4.2.2. Example of Program

Figure 7 shows the algorithm and codes to detect a P(off) feature point. The P(off) point is defined as the point falling below the baseline when checking the slope of the signal within the time range for the expected occurrence of P(off).

```
// to find end point of P wave
// P2_priod = priod to find end point
// sig_slope = signal slope data
// slop_find() = to search slope data that is over threshold value
P2_pot = 0; end point
for i=P_pot : P_pot + P2_priod
    seg = sig_slope(i:i+P2_no_slope); // segment priod
    num_th = slop_find(seg); // search slope
    if num_th == n_th  // compare threshold
         P2_pot = i;  // find end point
    end
end
```

**Figure 7. Example of Program Code to Find Characteristic of P(off)**

## 3. Results

### 3.1. Pre-treatment Results

Pre-treatment is the process to remove the noises from the raw ECG signal before analyzing the signal. First, it removes the low frequency noises and then high frequency noises. Figure 8 is the result of removing the low frequency noises. Figure 8(a) shows the raw ECG signal and we can see the baseline wave. The dotted line in the figure is the regression curve using equations (3) and (4). Figure 8(b) shows the waveform which removed the low frequency noises and adjusted the baseline.

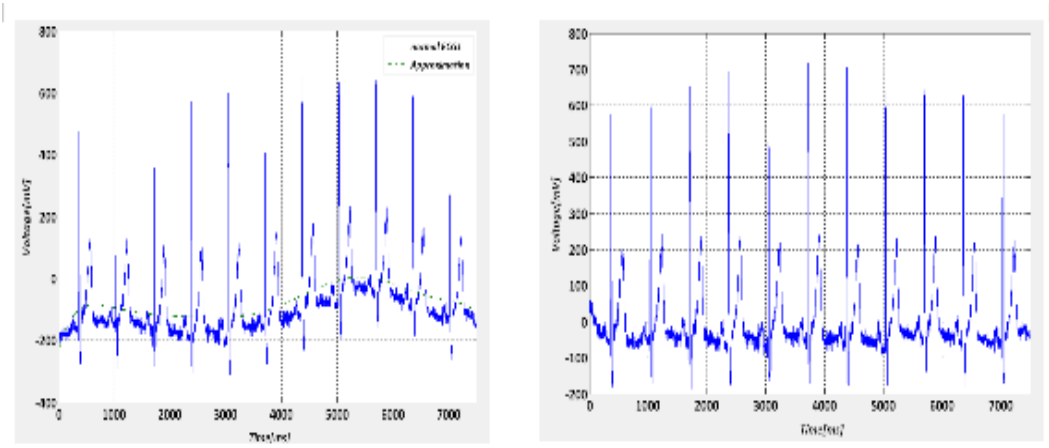


**Figure 8. Original ECG Signal (left), ECG Signal after Baseline Correction (right)**

After removing the low frequency noises, the high frequency noise was removed using wavelet transform. Figure 9(a) is the mixed raw ECG signal with a low and high frequency component and 9(b) shows that the high frequency component is distributed as the result of analyzing the frequency component of the raw ECG signal. Figure 9(d) is the result of analyzing the frequency component of Figure 9(c) and we can confirm that the noise in the high frequency band seen in Figure 9(b) is removed.

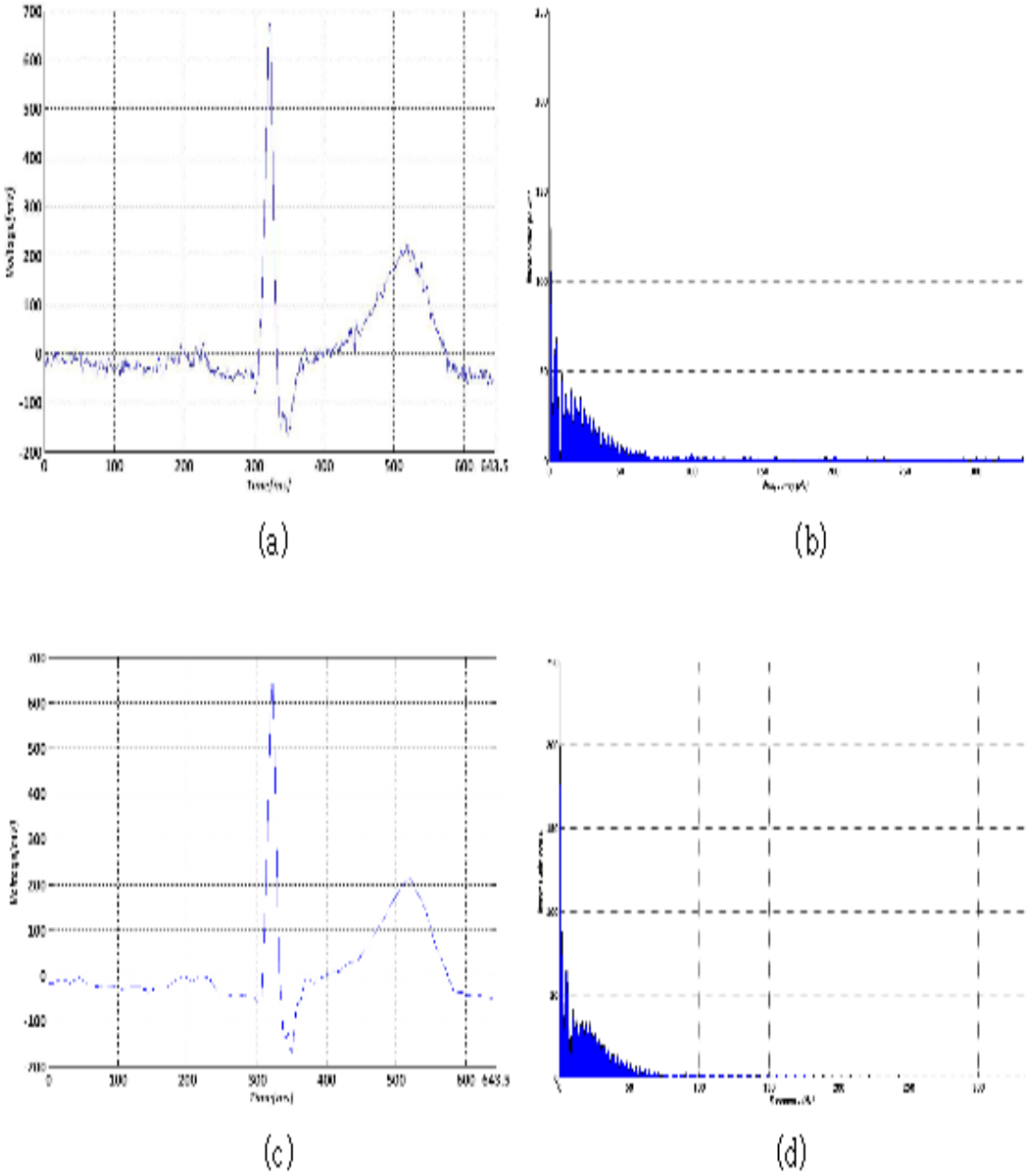



**Figure 9. (a) Original ECG Signal (b) Frequency Spectrum Analysis for Original Signal (c) De-noised Signal by Wavelet (d) Frequency Spectrum Analysis for de-noised Signal**

### 3.2. Signal Analysis Results

The typical data which is needed to diagnosis a patient with heart disease are the width of the P wave, QRS complex, the interval and the size of PR and QT, the size of T, and the size of the U wave. This data is gained easily from feature points detected. In other words, since these feature points include information about the value of the time axis(X axis) and the value of the voltage axis(Y axis), width, interval and size of each wave can be calculated. Table 1 shows the comparison between the time of the feature point and the average time of the feature point which was detected in the first cycle using the proposed algorithm.

**Table 1. Normal ECG 1 Channel 1-cycle Characteristic Points Time**

| Identifications | Time(ms) | | Differences |
|---|---|---|---|
| | Normal ECG lead I (1st Cycle) | ECG lead I (Mean values) | |
| P1 | 99ms | 94.09ms | 4.909 |
| P2 | 160.5ms | 143.31ms | 17.18 |
| P3 | 166.5ms | 170.86ms | -4.36 |
| Q1 | 216ms | 207.95ms | 8.04 |
| Q2 | 231ms | 227.18ms | 3.81 |
| R | 247.5ms | 247.5ms | 0 |
| S1 | 273ms | 272.31ms | 0.68 |
| S2 | 292.5ms | 291.81ms | 0.68 |
| T1 | 316.5ms | 323.31ms | -6.81 |
| T2 | 436.5ms | 440.59ms | -4.09 |
| T3 | 502.5ms | 503.18ms | -0.68 |

The duration (time) of each wave and interval can be calculated using the time of each feature point of the Table 1 for diagnosis, and the results were shown in Table 2.

**Table 2. Normal ECG 1 Channel 1-Cycle Characteristic Wave, Interval, Segment Time**

| Identification | Time(ms) |
|---|---|
| P-Wave | 45ms |
| QRS-Complex | 51ms |
| PR-Interval | 33ms |
| QT-Interval | 67ms |
| T-Wave | 124ms |
| ST-Segment | 16ms |

On the whole, the ECG signal is comprised of P-wave, QRS-complex, and T-wave. The PR-interval spreads from the onset of the P-wave to the onset of the Q-wave. The PR-Segment is the interval from the offset of the P-wave to the onset of the Q-wave. The ST-segment is the even baseline following the QRS and QT-interval spreads from the onset of the Q to the offset of the T-wave. Lastly, the QRS complex is the interval from the onset of the Q-wave to the onset of the ST-segment.

The results of the reliability, mean error and standard deviation used to evaluate the proposed algorithm for detecting the feature points are shown in Table 3. As a parameter of reliability, se(%) is the standard error of the mean for detecting the feature points and the m(ms) is the mean value for detecting the feature points.

**Table 3. Normal ECG Characteristics Time Calculation [22]**

| | parameter | p(on) | p(off) | QRS(on) | QRS(off) | T(on) | T(off) |
|---|---|---|---|---|---|---|---|
| GD | se(%) | 97.4 | 98.7 | 100 | 100 | 99.2 | 99.8 |
| | m(ms) | 1.55 | 6.82 | 2.91 | 1.73 | 5.82 | 5.55 |
| | sd(ms) | 1.08 | 1.64 | 0.79 | 1.42 | 5.05 | 3.87 |
| MMD | se(%) | 97.2 | 94.8 | 100 | 100 | 99.8 | 99.6 |
| | m(ms) | 9 | 12.8 | 3.5 | 2.4 | 7.9 | 8.3 |
| | sd(ms) | 9.4 | 13.2 | 6.1 | 10.3 | 15.8 | 12.4 |
| TD | se(%) | 96.2 | 97 | 99.9 | 99.9 | 98.8 | 98.9 |
| | m(ms) | 10.3 | -5.7 | -7.3 | -3.6 | 23.3 | 18.7 |
| | sd(ms) | 14.1 | 13.6 | 10.9 | 10.7 | 28.3 | 29.8 |
| WD | se(%) | 89.9 | 89.9 | 100 | 100 | 99.1 | 99.2 |
| | m(ms) | 13 | 5.4 | 4.5 | 0.8 | -4.8 | -8.9 |
| | sd(ms) | 12.7 | 11.9 | 7.7 | 8.7 | 13.5 | 18.8 |

The se (%) shows the detection factor of the feature point as a parameter of reliability. The sd(ms) shows the stability of an algorithm through standard deviation. We found out all the feature points using the proposed detector as shown in Table 3 and the statistical results obtained by the proposed detector were compared with those obtained by the MMD, TD, and WD [22]. Overall, better performance by the proposed GD algorithm was observed.

## 4. Discussion

This study's aim is to propose an algorithm developed to check the presence of diseases by analyzing the ECG signal and to diagnose a patient of heart disease using accumulated ECG signals. The results of ECG signal analysis may act as a critical secondary data for clinical doctors to diagnose a patient. It is for this purpose that we developed and evaluated the algorithm. Results showed that the proposed algorithm was superior to the existing ECG analysis. As illustrated in Section 3, by using the baseline wave and wavelet transform, noises included in the raw ECG signal were effectually removed. The removed signal was geometrically analyzed and the significant feature points of the ECG signal was found perfectly.

Table 3 shows the results of comparison and analysis between the proposed and existing algorithms. GD (Geometric Detection) means the proposed algorithm. The results are to analyze the same data from the CSE (Common Standards for Electrocardiography) database using each algorithm except for GD and the result of GD is to analyze the recorded ECG data. Detection rate of the proposed algorithm(se(%)) was 99.1% and we confirmed that the proposed algorithm is superior to the other algorithm in the stability or standard error of the sample mean.

In the case of P(on), standard error of the sample mean is 1.55ms in the case of GD, which is superior compared to 9ms in the case of MMD. Also, standard deviation which means the stability of an algorithm, shows a high stability as 1.08ms in comparison with 9.4ms in MMD. In the case of P(off), standard error of the sample mean is 6.82ms but the standard deviation is 1.64ms which means the error is within an acceptable range.

The most challenging part in analyzing ECG feature points is point T(on), because the standard error is 5.82ms and the standard deviation is 5.05ms, making it more unstable than any other points. This is due to the ECG signal's characteristic of being lower in T(on) feature points geometrically. However, the proposed algorithm's results showed that it had a superior performance to the other algorithms in the way of stability and accuracy.

After this, we will evaluate the stability of the algorithm using various ECG signals and will determine the heart disease to compare and analyze the ECG signal of normal and abnormal patients. Furthermore, we will extend the study so that clinical doctors can use this as a secondary data to build a clinical database [23] about the ECG signal, so that ultimately it will enhance clinical decisions.

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