Adaptive Threshold and Principal Component Analysis for Features Extraction of Electrocardiogram Signals

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Abstract— **This paper presents a novel approach for QRS complex detection and extraction of electrocardiogram signals for different types of arrhythmias. Firstly, the ECG signal is filtered by a band pass filter, and then it is differentiated. After that, the Hilbert transform and the adaptive threshold technique are applied for QRS detection. Finally, the Principal Component Analysis is implemented to extract features from the ECG signal. Nineteen different records from the MIT-BIH arrhythmia database have been used to test the proposed method. A 96.28% of sensitivity and a 99.71% of positive predictivity are reported in this testing for QRS complexity detection, being a positive result in comparison with recent researches.**

Keywords-Adaptive threshold; Hilbert transform; Principal Component Analysis; electrocardiogram signals

I. INTRODUCTION

QRS is the most important wave in an electrocardiogram (ECG) signal, making this important to analyze its morphology, amplitude, and duration for detecting cardiac arrhythmias. Computer-based ECG analysis requires an accurate detection of QRS complex, in particular, an accurate detection of the R wave. Nevertheless, this is a non-easy task since real electrocardiogram signal usually faces muscular noise, motion artifacts, and baseline drifts changes [1]. Other components of an ECG, such as P and T waves are also found to be high in some cases, and these waves must be differentiated from the QRS waves. This increases the complexity of QRS detection [1][2]. False R-wave detection or the failure to detect R-waves may lead to undesired results in computer-based ECG analysis [1][2]. In addition, the number of false detections significantly increases in the presence of ECG signals of patients with pathologies or poor signal-to-noise ratios (SNR) [2].

Several QRS detection researches have been developed during decades; these researches have been mainly attained to three categories: time domain detection techniques, transform domain detection techniques, and other methods that include morphologic filtering techniques and template matching [3]. These techniques have been utilized into different applications like heart rate variability analysis, arrhythmia classification, heart rate calculation, feature extraction, ECG compression, R-R interval analysis, and P, S, and T wave detection [3].

Methods based on Hilbert transform have the ability to discriminate the dominant peaks from other peaks. These methods have been capable to improve the results of R-wave detection. However, they tend to fail in diseases that cause low-amplitude wave, and ischemic cases [4]. Normally, a threshold is needed for the detection of the R-wave in an electrocardiogram signal; a fixed threshold for detecting R-waves can be efficient and simple for ECG signals with normal beat morphology [5]. However, several researchers have reported that electrocardiogram signal waveforms may vary drastically from each other, due to movement of patients, and severe baseline drifting. Accordingly to this, there is a high probability that QRS complexes may be missed. Otherwise, adaptive thresholding has been proven to reduce the probability of missing QRS complex detection [4][5][6].

Usually, adaptive thresholding uses many thresholds empirically. In [7], authors presented an algorithm based on wavelet transform for detecting QRS complex, and P and T waves; a constant threshold was used, which was determined empirically. In [8], authors used a constant threshold for QRS detection; the threshold was also empirically determined. Their algorithm is based on wavelet transform too. In [3] and [9] , authors have shown that adaptive thresholding provides interesting results for R wave peak detection. In their case, the thresholds have been detected automatically.

This paper is focused on the analysis of ECG signals by means of applying the Hilbert transform and the adaptive threshold technique to detect the real R-peaks from an ECG signal. In addition, the application of Principal Component Analysis (PCA) to extract features of the electrocardiogram signals is presented. Feature extraction is applied to three types of heartbeats (normal heartbeats, premature ventricular contraction, and atrial premature contraction). Obtained results show that the performance of the proposed method reported a sensitivity

978-1-4799-5277-9/14 $31.00 © 2014 IEEE
DOI 10.1109/IS3C.2014.324

of 99.94% and a 99.73% of accuracy in QRS complex detection.

The rest of the paper is organized as follows: Section 2 presents a brief description of the methodology used for detecting the QRS complex from an ECG, including: the band pass filter, the first derivative differentiation, Hilbert transform, and adaptive threshold technique for detecting the QRS complex from an ECG. Section 3 discusses Principal Component Analysis for extracting the feature vector. Section 4 shows the obtained results after applying the proposed methodology. Finally, Section 5 presents conclusions and future work.

II. Detection of the QRS Complex

Electrocardiogram signal is one of the most important biological signals used to diagnose heart diseases. ECG signals allow the representation of the cyclical contraction and relaxation of human heart muscles. Heart muscle activity is controlled by electrical pulses which are transmitted through a nerve network; such electrical pulses are strong enough to be sensed by electrodes placed on the human skin [10][11]. In general, the ECG signal of a single cardiac cycle lies in the P, T, and QRS complex waves as depicted in Fig. 1. Sometimes a U-wave may also be present after the T-wave [12].

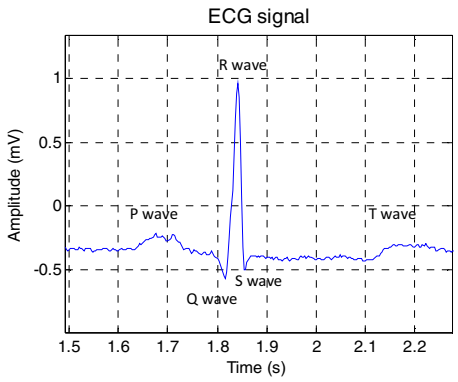

Figure 1. ECG for a single cardiac cycle; record 103 in MIT-BIH database [13].

The QRS complex represents the depolarization of the heart ventricles which have greater muscle mass and hence the consumption of electrical activity is higher. The detection of R waves is easier than other ECG signal wave detection due to its high amplitude and its structural form.

There are some difficulties in QRS complex detection. These difficulties can be summarized as follows: a) presence of non-stationarity, *i.e.*, the ECG statistical properties change over the time, b) presence of low QRS amplitudes, c) ventricular ectopics could arise, d) low SNR, *i.e.*, noisy ECG signals, e) presence of negative QRS polarities. Fig. 2 shows an R-peak with negative polarity. This can happen due to some extrasystoles lead to a sudden polarity change.

However, an algorithm for detecting QRS with R-peaks of both positive and negative polarity is desired. Fig. 3 shows an R-peak with low amplitude.

Therefore, ECG signals may vary drastically from one heartbeat to the next due to the movement of the patients and to severe baseline drifting, as seen in Fig. 4. Accordingly, it can also be noticed that a big fixed threshold can lead to missing detections. Moreover, a small fixed threshold can easily lead to inaccurate detections. The fixed threshold might also affect the detection of P and T waves. In another case, an adaptive threshold algorithm mainly implements multiple thresholds empirically, decreasing the possibility of missing QRS complexes.

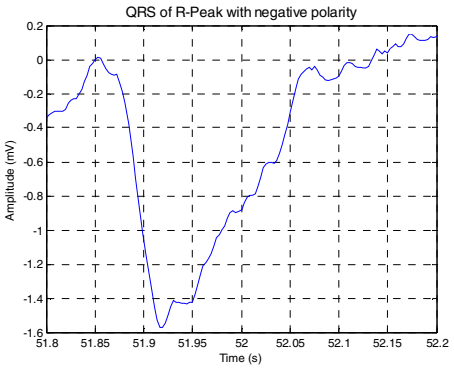

Figure 2. QRS of R-peak with negative polarity in the MIT-BIH arrythmia data base [13], record #228.

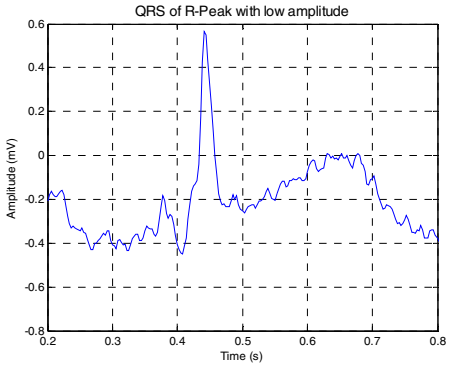

Figure 3. QRS of R-peak with low amplitude in the MIT-BIH arrythmia data base [13], record #228.

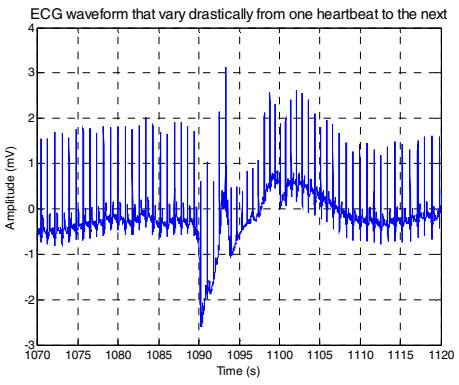

Figure 4. ECG signal with wave forms that vary drastically from one heartbeat to the next; record 103 in MIT-BIH database [13].

Our method for QRS complex detection is based on combining both Hilbert transform and the adaptive threshold technique. The steps of this method are explained next.

A. ECG filtering

The first stage of our proposed method is the ECG filtering. Firstly, the band pass filter is applied to maximize the QRS complex, and to remove muscular noise from the ECG signal. A 6th order band-pass Butterworth filter was applied. The band stop frequencies were set from 5 to 15 hz. The 5 hz is the starting frequency and 15 is the stopping frequency. This allows removing high frequencies and baseline wander [14]. It also suppresses the P and T waves, and maximizes the QRS complex.

B. Differentiation

The first derivative is applied to indicate the minimum slope of the ECG signal (*i.e.*, the falling of signal from R to S). Also, the first derivative indicates the high slope points (*i.e.*, the rising of signal from Q to R). The first derivative differentiation using 2-point central difference is calculated using (1).

$$\mathbf{y}(k) = \frac{1}{2\Delta t}(\mathbf{y}(k+1) - \mathbf{y}(k-1)), \quad k = 0,1,2,\ldots,N-1 \tag{1}$$

where Δt is the sampling frequency and N is the total number of samples. Initial conditions are set to minimize the error at the boundaries, *i.e.*, initial condition is specified for $k = 0$, and $k = N-1$. The derivative output of the filtered ECG signal allows removing baseline drifts and motion artifacts.

C. Hilbert transform

For a discrete time series $\mathbf{y}(k)$, the Hilbert transform is defined as

$$H(k) = \mathbf{y}_H(k) = FFT^{-1}(\mathbf{f}(k) * \mathbf{h}(i)) \tag{2}$$

where the vector $\mathbf{h}$ is created as shown in (3). The vector $\mathbf{f}$ stores the Fast Fourier Transform (FFT) of the $\mathbf{y}(k)$ signal, and the FFT^{-1} is the Inverse Fast Fourier Transform.

$$\begin{aligned} &0 \quad \text{for} \quad i = (N/2)+2,\ldots,N \\ &2 \quad \text{for} \quad i = 2,3,\ldots,(N/2) \\ &1 \quad \text{for} \quad i = 1,(N/2)+1 \end{aligned} \tag{3}$$

Therefore, the analytic signal $\mathbf{z}(k)$ is given in (4). It is also considered as the pre-envelope of the original signal $\mathbf{y}(k)$.

$$\mathbf{z}(k) = \mathbf{y}(k) + j\mathbf{y}_H(k) \tag{4}$$

The envelope $\mathbf{a}(k)$ of $\mathbf{z}(k)$ is described in (5). It is also considered as the instantaneous magnitude of $\mathbf{z}(k)$.

$$\mathbf{a}(k) = \sqrt{\mathbf{y}^2(k) + \mathbf{y}_H{}^2(k)} \tag{5}$$

and the instantaneous phase angle in the complex plane is defined in (6).

$$\theta(k) = \arctan\left(\frac{\mathbf{y}_H(k)}{\mathbf{y}(k)}\right) \tag{6}$$

D. Adaptive threshold for QRS detection

Adaptive threshold is a technique carried out for detecting the R wave peak. This technique is performed by using a pair of threshold limits called upper limited threshold (u_{th}) and lower limited threshold (l_{th}). The upper threshold is defined by (7), where α is the maximum value attained $\mathbf{y}(k)$ on the point $k = 1,\ldots,N$.

$$u_{th} = 0.5 \times \alpha \tag{7}$$

The lower threshold is defined by (8)

$$l_{th} = 0.10 \times \alpha \tag{8}$$

The threshold values are updated in iteration time, where the number of detected peaks above the l_{th} threshold is obtained, and also, the number of detected peaks above u_{th} is calculated. Thus, Nl_{th} is the number of QRS complexes detected by l_{th}, and Nu_{th} is the number of QRS complexes detected by u_{th}. The thresholds are updated during each iteration, meanwhile the number of detected peaks by the up and down limits is different. The value of u_{th} is updated using (9).

$$u_{th}(k+1) = u_{th}(k) - w\Delta \tag{9}$$

Where the error weight $w = 0.125$, and $\Delta = u_{th} - l_{th}$ is the difference between the defined two limits. The value of l_{th} is updated by using (10). We assume w and Δ as the same as defined in (9).

$$l_{th}(k+1) = l_{th}(k) + w\Delta \tag{10}$$

Accordingly to the previous definitions, $w\Delta = 0.05 \times \alpha$. Then the lower threshold limit is increased by $w\Delta$ and the upper threshold limit is decreased by $w\Delta$ as well. This process continues until the same QRS number (*i.e.*, $Nl_{th} = Nu_{th}$) is obtained.

III. FEATURE EXTRACTION

A. Principal Component Analysis

The Principal Component Analysis is a technique for linear dimensionality reduction that provides projection of the data in the direction of the highest variance [15]. This technique is carried out to extract relevant features from

the ECG data set. The signal segment of a heartbeat is represented by $\mathbf{y}(k)$, as in (11).

$$\mathbf{y}(k) = \begin{bmatrix} y(1) \\ y(2) \\ \vdots \\ y(M) \end{bmatrix} \tag{11}$$

Where M is the number of samples of the heartbeat. Thus, the heartbeats $\mathbf{y}_1, \mathbf{y}_2, \ldots, \mathbf{y}_N$ are N observations of heartbeats (as in (12)). The entire ensemble of heartbeats is represented by the $M \times N$ matrix.

$$\mathbf{Y} = \left[\mathbf{y}_1\ \mathbf{y}_2 \ldots \mathbf{y}_N\right] \tag{12}$$

The Principal Component Analysis consists of the following steps:

1) Calculate the mean vector. The mean vector of each heartbeat is calculated as in (13).

$$\bar{\mathbf{y}} = \frac{1}{M}\sum_{i=1}^{M}\mathbf{y}_i \tag{13}$$

2) Compute the mean adjusted data (see (14) and (15)) as follows

$$\mathbf{yadj}_i = \mathbf{y}_i - \bar{\mathbf{y}} \tag{14}$$

$$\mathbf{Yadj} = \left[\mathbf{yadj}_1\ \ \mathbf{yadj}_2\ \ \cdots \mathbf{yadj}_N\right] \tag{15}$$

3) Compute the covariance matrix, as shown in (16).

$$\mathbf{C} = \frac{1}{M-1}\sum_{i=1}^{M}(\mathbf{y}_i - \bar{\mathbf{y}})^T(\mathbf{y}_i - \bar{\mathbf{y}}) \tag{16}$$

4) Calculate the eigenvectors and eigenvalues of the covariance matrix. The eigenvalues λ_i and eigenvectors e_i, correspond to (17).

$$\mathbf{C} \cdot e_i = \lambda_i \cdot e_i, \quad i = 1, \ldots N \tag{17}$$

5) Choosing components and forming a feature vector. The eigenvector with the highest value is the principal component. Then, the eigenvectors are ordered by eigenvalues from highest to lowest, which returns the components in order of significance. Subsecuently, the dimensionality is reduced by selecting K -principal components that retain the physiological information. Thus, the percentage of variance, $\mathbf{r_K}$, of each eigenvalue is obtained by applying (18).

$$\mathbf{r_K} = \frac{\sum_{i=1}^{K}\lambda_i}{\sum_{i=1}^{N}\lambda_i} \tag{18}$$

Furthermore, we select the Principal Components whose percentage of variance is higher than the percentage threshold, th, that is 0.9 or 0.95 as shown in (19).

$$\hat{\mathbf{r}}_\mathbf{K} = (\mathbf{r_K} \geq th) \tag{19}$$

6) Deriving the new data set. The final dataset is obtained by (20).

$$\mathbf{Ypca}(k) = \hat{\mathbf{r}}_\mathbf{K}{}^T\ \mathbf{Yadj}^T \tag{20}$$

IV. Results and Discussion

The QRS automatic detection and extraction methods have been validated using the MIT-BIH arrhythmia database [13][16]. The MIT-BIH arrhythmia database contains records sampled at 360 Hz, with 11-bit resolution over 5 mV range. Each record contains a duration of 30 minutes and 5.556 seconds. For QRS detection, only the first channel of each record has been considered. A total of 19 records have been considered. These records contain inverted QRS polarity and low amplitude QRS, ventricular ectopic beats with low SNR, premature ventricular beats, and premature atrial beats. The performance of the proposed algorithm has been essentially evaluated by two parameters: Sensitivity (Se), and positive predictivity ($+P$), given them by (21) and (22).

$$Se(\%) = \frac{TP}{TP + FN} \times 100 \tag{21}$$

$$+P(\%) = \frac{TP}{TP + FP} \times 100 \tag{22}$$

where TP (True Positive) is the number of heartbeats properly detected (*i.e.*, QRS complexes properly detected), FN (False Negative) indicates the number of heartbeats that were not detected by the method (*i.e.*, QRS complexes that were not detected), and FP (False Positive) indicates the false heartbeats detected (*i.e.*, QRS complexes detected by the method when no QRS complexes are present).

The Sensitivity parameter (Se) indicates the percentage of heartbeats that were correctly detected by the algorithm. The positive predictivity ($+P$) indicates the percentage of heartbeats detections which were real true heartbeats.

A beat is considered as detected within a window of ± 13 samples around the true temporal beat detection. Table I presents the results of the adaptive threshold method applied to the nineteen records extracted from the MIT-BIH arrhythmia database. The algorithm detects the R-wave that is even very close to the end of the record, *e.g.*, record 100. The method achieved fairly good results also for very noisy records, *e.g.*, record 108 (see Fig. 5). In

addition, the method detected precise results for record 117 which has a low amplitude R-peaks and low SNR (see Fig. 6).

TABLE I. PERFORMANCE OF ADAPTIVE THRESHOLD METHOD ON MIT-BIH ARRHYTHMIA DATABASE.

Record	No of beats	*TP*	*FP*	*FN*	*Se*	*+P*
100	2273	2273	0	0	100.00	100.00
101	1865	1863	9	1	99.94	99.51
103	2084	2082	0	1	99.95	100.00
108	1774	1494	1	60	96.13	99.93
112	2539	2539	4	0	100.00	99.84
116	2412	2359	5	28	98.82	99.78
117	1535	1535	1	0	100.00	99.93
121	1863	1859	1	2	99.89	99.94
200	2601	2593	5	4	99.84	99.80
202	2136	2094	1	21	99.00	99.95
205	2656	2646	14	5	99.81	99.47
209	3005	3005	11	0	100.00	99.63
213	3251	3244	85	3	99.90	97.44
215	3363	3269	0	47	98.58	100.00
220	2048	2048	0	0	100.00	100.00
223	2605	2552	0	26	98.99	100.00
228	2053	428	2	672	38.90	99.53
231	1573	1569	1	2	99.87	99.93
233	3079	3066	2	7	99.77	99.93
Total	**44715**	**42518**	**142**	**879**	**96.28**	**99.71**

The results of our method to detect QRS complexes are significantly precise. Our method scored *Se*=96.28% and *+P*=99.71 over 44715 heartbeats, as shown in Table I. It is necessary to mention that our method achieved not so good sensitivity rate for record 228 which presents negative QRS polarities and ventricular ectopics (see Fig. 7); this can explain the high number of false negative (FN) beats, as can be seen in Table I.

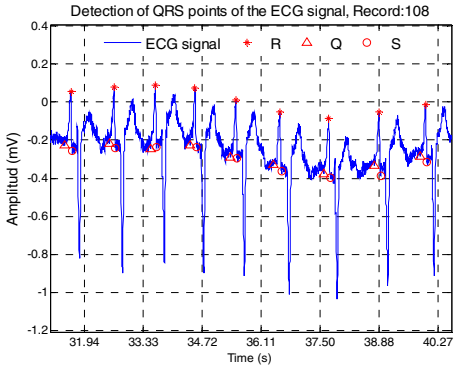

Figure 5. Detection of QRS in noisy record 108; from MIT-BIH arrythmia database [13].

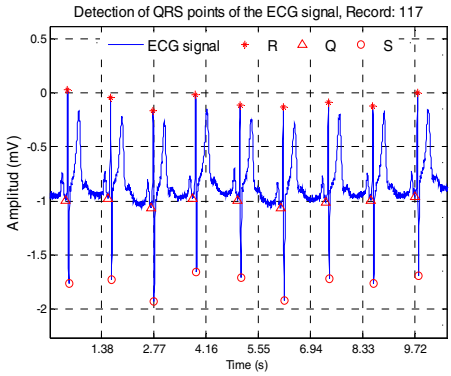

Figure 6. Detection of the QRS with low amplitud and low SNR, record 117, in MIT-BIH arrhythmia database [13].

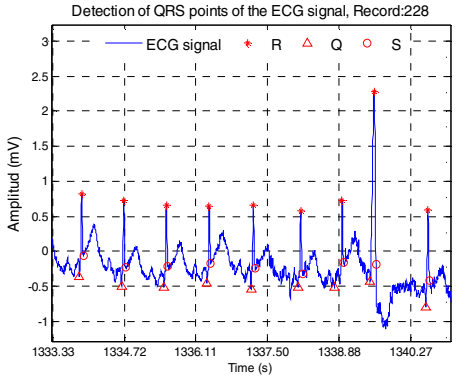

Figure 7. Detection of the QRS with ventricular ectopics, record 228, in MIT-BIH arrhythmia database [13].

After the QRS detection, 90 samples were selected from the left side of R-peak and 90 samples after the R-peak point. Then, the PCA technique presented in section III has been applied to select useful features which can be used for further ECG recognition.

The heartbeats in $\mathbf{Y}(k)$ (see (12)) are the normal beats, premature ventricular contraction, and atrial premature contraction. The total number of heartbeats is $N = 36$. Every heartbeat has been chosen with $M = 180$ samples. The linear dimensionality reduction of the input patterns $\mathbf{Y}(k)$ is obtained by the PCA technique. This technique provides projection of $\mathbf{Y}(k)$ in the direction of highest variance. Fig. 8 shows the fraction of total variance in the data as explained by each principal component. As it can be seen the first four principal components account for around 99% of the variance.

Accordingly to the cumulative variance proportion, $K = 4$ principal components of the input patterns were extracted, with $M = 180$ components corresponding to the dimensionality of the input pattern, as shown in (12). Therefore, the number of input patterns in $\mathbf{Ypca}(k)$ is $K < N$. The selected components contribute about 90% ($th >= 0.90$, as shown in (19)) of the total energy of the signal. These K principal components are used in the next step of the classification as inputs to the neural network.

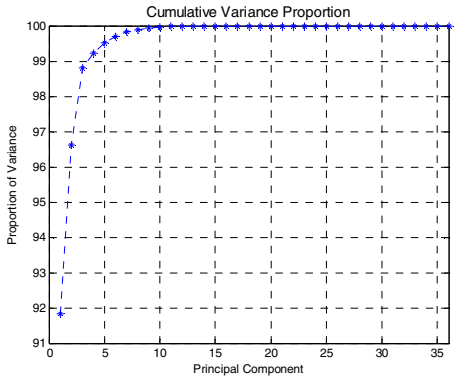

Figure 8. Cumulative variance proportions by each principal component.

V. CONCLUSIONS

This paper has presented a novel approach for QRS detection of electrocardiogram signals by applying the Hilbert transform and the adaptive threshold technique. In addition, Principal Component Analysis is implemented for feature extraction of QRS complex.

Our approach for QRS complexes detection introduces an adaptive threshold technique to improve the accuracy of QRS complexes detection in records with ventricular ectopics, negative QRS polarities, low signal-to-noise ratio, and low amplitude R-peaks. Our experiments showed that our proposed approach achieves precise detection rates with an overall positive predictivity of 99.71 % and a sensitivity of 96.28%.

As future work we propose to automate the classification of cardiac arrhythmias using multilayer perceptron neural network with a backpropagation learning technique.

ACKNOWLEDGMENT

R. R. would like to thank his previous Ph.D. supervisor-specialist Doc. Ivo Bukovsky for his valuable suggestions. R. R., also would like to thank Prof. Noriyasu Homma and Kei Ichiji from Cyberscience Center, Tohoku University for their suggestions and support.

This work was supported by PROMEP, grant No. PROMEP/103.5/13/9045, and by Technological University of Ciudad Juarez.

REFERENCES

[1] D. Benitez, P. Gaydecki, A. Zaidi, A. Fitzpatrick, “The use of the Hilbert transform in ECG signal analysis,” Computers in Biology and Medicine, vol. 31, issue 5, September 2001, pp. 399–406, doi: 10.1016/S0010-4825(01)00009-9.

[2] B. U. Kohler, C. Hennig, and R. Orglmeister, “QRS detection using zero crossing counts,” Progress in Biomedical Research, vol. 8, No. 3, September 2003, pp.138-145.

[3] R. Burte, and R. Ghongade, “Advances in QRS detection: Modified Wavelet energy gradient method,” International Journal of Emerging Trends in Signal Processing, vol 1, issue 1, November 2012, pp. 23-29.

[4] H. Rabbani, M.P. Mahjoob, E.Farahabadi, and A. Farahabadi, “R. Peak Detection in Electrocardiogram Signal Based on an Optimal Combination of Wavelet Transform, Hilbert Transform, and Adaptive Thresholding, ” Journal of Medical Signals and Sensors, vol.1, issue 2, May-Aug 2011, pp. 91-98.

[5] M. Elgendi, B. Eskofier, S. Dokos, D. Abbott, “Revisiting QRS Detection Methologies for Portable, Wearable, Battery-Operated, and Wireless ECG Systems,” PLoS ONE, Vol. 9, Issue 1, January 2014, doi:10.1371/journal.pone.0084018.

[6] J.P. Madeiro, P.C. Cortez, F.I. Oliveira, and R.S. Siqueira, “A new approach to QRS segmentation based on wavelet bases and threshold technique,” Medical Engineering and Physics, vol. 29, issue 1, January 2007, pp. 26-37, doi:10.1016/j.medengphy.2006.01.008.

[7] C. Li, C. Zheng, and C. Tai, “Detection of ECG Characteristic Points Using Wavelet Transforms,” IEEE Transactions on Biomedical Engineering, vol. 42, issue 1, January 1995, pp. 21-28, doi: 10.1109/10.362922.

[8] S. Kadambe, R. Murray, and G.F. Boudreaux-Bartels, “Wavelet Transform-Based QRS Complex Detector,” IEEE Transactions on Biomedical Engineering, vol. 46, issue 7, July 1999, pp. 838-848, doi: 10.1109/10.771194.

[9] X. Xu, and Y. Liu, “Adaptive threshold for QRS Complex Detection Based on Wavelet Transform,” Proc. IEEE 27th Annual International Conference of the Engineering in Medicine and Biology Society (IEEE -EMBS 2005), Shanghai, China, September 2005, pp. 7281-7284, DOI:10.1109/IEMBS.2005.1616192.

[10] V.S. Asirvadam, K. S. Pisal, L. I. Izhar, N. A. A. M Khuzi, “ECG Viewed Using Grayscale Patterns,” Proc. of the International Conference on Man-Machine Systems (ICoMMS 2009), Penang, Malaysia, 2009, pp. 1C2 1 - 1C2 5.

[11] M. Kotas, “Projective filtering of time-aligned ECG beats for repolarization duration measurement,“ Computer Methods and Programs in Biomedicine”, vol. 85, issue 2, February 2007, pp. 115-123, 10.1016/j.cmpb.2006.10.001.

[12] M. Elgendi, M. Jonkman, and F. De Boer,“Improved QRS Detection Algorithm using Dynamic Thresholds,” International Journal of Hybrid Information Technology, vol. 2, issue 1, January 2009, pp. 65-80.

[13] A.L. Goldberger, L.A.N. Amaral, L. Glass, J.M. Hausdorff, P.C. Ivanov, R.G. Mark, J.E. Mietus, G.B. Moody, C.-K. Peng, H.E. Stanley, “PhysioBank, PhysioToolkit, and PhysioNet: Components of a New Research Resource for Complex Physiologic Signals,” Circulation, vol. 101, issue 23, June 2000, pp. e215-e220,doi:10.1161/01.CIR.101.23.e215.

[14] H.C. Chen and S.W. Chen, “A moving average based filtering system with its application to real-time QRS detection,” Proc. IEEE Computers in Cardiology, Sept. 2003,pp. 585-588, doi: 10.1109/CIC.2003.1291223.

[15] V. Monasterio, P. Laguna, J. P. Martinez, “Multilead Analysis of T-Wave Alternants in the ECG using Principal Component Analysis,” IEEE Transactions on Biomedical Engineering, vol. 56, issue 7, July 2009, pp.1880-1890, doi: 10.1109/TBME.2009.2015935.

[16] G.B. Moody and R.G. Mark,”The impact of the MIT-BIH Arrhithmia Database,” IEEE Engineering in Medicine and Biology, vol. 20, issue 3, May-June 2001, pp. 45-50, 10.1109/51.932724.