# Analysis of Noise Sensitivity of Different ECG Detection Algorithms

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| Article Info | ABSTRACT |
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This paper presents an analysis of noise sensitivities of different detection algorithms for electrocardiogram (ECG) taken from MIT-BIH arrhythmia database. Seven methods used in this paper are based on derivatives, digital filters (DF), neural network (NN) and wavelet transform (WT). The raw ECG is corrupted with 5 different types of synthesized noise, namely, power line interference, base line drift due to respiration, abrupt baseline shift, electromyogram (EMG) interference and a composite noise made from other types. A total of 315 data sets are constructed from 15 raw data sets for each type of noise adding 0%, 25%, 50%, 75% and 100% noise levels. The application of the methods to detect QRS complexes of a total of 33,774 beats of ECG shows that none of the algorithms are able to detect all QRS complexes without any false positives for all of the noise types at the highest noise level. Algorithms based on NN and WT show better performance considering all noise types and the two algorithms perform similarly. The result of this study will help to develop a more robust ECG detector and this will make ECG interpretation system more effective.

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## 1.    INTRODUCTION

Electrocardiogram (ECG)   is the graphical representation of the bioelectric potential generated by the muscles of the heart. ECG consists of characteristic P wave, QRS complex and T wave. Physicians always look for the amplitudes and duration of the waves as well as the inter-wave duration to take decision about the condition of cardiac and associated physiological systems. Computer based automatic recognition of ECG characteristic points are necessary to help physicians for quick, easy and accurate diagnosis of cardiac conditions. Computerized electrocardiography is now a well-established clinical practice. Because of its specific shape, the QRS complex serves as an entry point for almost all automated ECG detection algorithms.

Since QRS portion is usually easy to distinguish due to its relatively high amplitude and sharp peak, simple slope criteria [1], second order derivatives [2], [3] were the major consideration for many ECG beat detection algorithms for the last few decades. The ECG may be masked by many types of noise and interference such as electromyographic (EMG) interference, power line interference, base line drift, abrupt shift in the base line, electrosurgical noise, instrumental noise, electrode contact noise, etc. If an ECG wave is sufficiently corrupted by any of these or other unknown noise types, the signal features may not be readily comprehensible by the visual systems of a human observer. To avoid power line noise and to reduce the influence of the muscle artifact and base line shift, digital filters are used [4]. Filter banks are also used for

QRS detection [5], [6] via signal decomposition in separate frequency bands. Several efforts have been made to apply artificial neural networks (NN) for the purpose of ECG beat detection [7]-[9]. Wavelet transform (WT) techniques are more recently having many applications in ECG analysis especially for QRS detection [10]-[13]. Other approaches reported in the literature for QRS detection include artificial intelligence using hidden Markov models [14], genetic algorithm [15], fuzzy hybrid neural network [16], mixture of experts approach [17], etc.

Noise sensitivities for QRS detection algorithms based on slope and simple digital filters were tested by Friesen et al. [18] in their pioneer work in this domain. The paper shows that none of the nine algorithms tested was able to perform better than others in all situations. However, in most of the cases, digital filter (both FIR and IIR) based algorithms were more robust in detecting QRS complexes of ECG corrupted by noise of different levels. But that work was carried out on normal ECG data of only 32 second duration corrupted with different types of synthesized noise. Also, a lot of algorithms, specially based on NN and WT, have been reported in the literature since that work. Despite large variety of existing QRS detection algorithms, large diversity of the QRS complex waveforms and the noise & artifacts accompanying the ECG signals make no single algorithm universally acceptable. Also, most recent techniques such as NN and WT based algorithms are not extensively tested for noise corrupted ECG signal. Furthermore, many of the presented algorithms were not tested against a standard database or any database at all. This makes the result difficult to compare and to evaluate. With respect to the problems left in the QRS detection, in particular the algorithmic behavior in case of noisy signals, only a comparable and reproducible evaluation on a standard database may show the progress achieved by a novel method. The overall goal of this paper is to quantify the relative noise susceptibility of different recent and formerly proposed QRS detection schemes tested against a standard database and different types of noise contaminated ECG signal at different noise levels. Another objective of this paper is to test QRS detection algorithms of abnormal ECG corrupted by noise.

## 2.    METHODOLOGY
### 2.1. Simulation of noises

A number of raw (noise free) ECG input signal provided from an MIT–BIH arrhythmia database was used as the source raw data [19]. It contains 48 half hour, two channel recordings of annotated ECG with sampling rate of 360 Hz and 11-bit resolution over a 10 mV range. The database contains both normal and abnormal beats. The abnormal beats mainly consist of different types of atrial premature contraction (APC), premature ventricular contraction (PVC), paced, bundle branch block (BBB), junctional abnormality, etc.

Since the purpose of this study was to evaluate the noise rejection properties of different QRS detection algorithms, the different representative noise sources [20] used for simulation are:
1. EMG interference because of its random properties and high frequency content,
2. Power line interference because it is ubiquitous,
3. Base line drift due to respiration because of its low frequency properties,
4. Abrupt shift in the base line due to its large first derivative, and
5. A composite of all of the above noises.

Electrosurgical and instrumental noise behaves similarly as random model for EMG hence these were not specifically modeled. Each noise type was varied in intensity in a step of 25%, i.e, 0%, 25%, 50%, 75% and 100%. The important characteristics and the procedures for simulation of the above-mentioned noises are detailed in [18], [20], and are briefly described here.

For the generation of power line noise, a 50Hz sine wave was generated having the max peak-to-peak amplitude of 0.333 mV. The EMG noise was simulated using the scaled input of a random number generator to the ECG signal, so that its amplitude would show random deviations in amplitude from the clean signal. Array of random numbers was created consisting of values of ±0.5. Then these random numbers were multiplied by the maximum of ECG amplitude and scaled by the percent noise that is to be added. Baseline drift noise was simulated by adding a 0.333 Hz and 1 mV sinusoid to the ECG signal. It is then scaled further by the percent noise to be added. For abrupt shift noise random numbers (within ±0.5 mV) were generated, but the same random number was taken for 500 ms duration cycle and then another random number was generated for next cycle and so on. Composite noise most accurately replicates an actual ECG signal by incorporating all four aforementioned types of noises into one. In this case, the maximum noise level was constructed by reducing the maximum noise levels for each of the previous described noise types to 50% of maximum and then summing them. Each type of noise was simulated following the above scheme and it was then added with the raw ECG. The noise corrupted ECG patterns are provided in Figure 1-2.
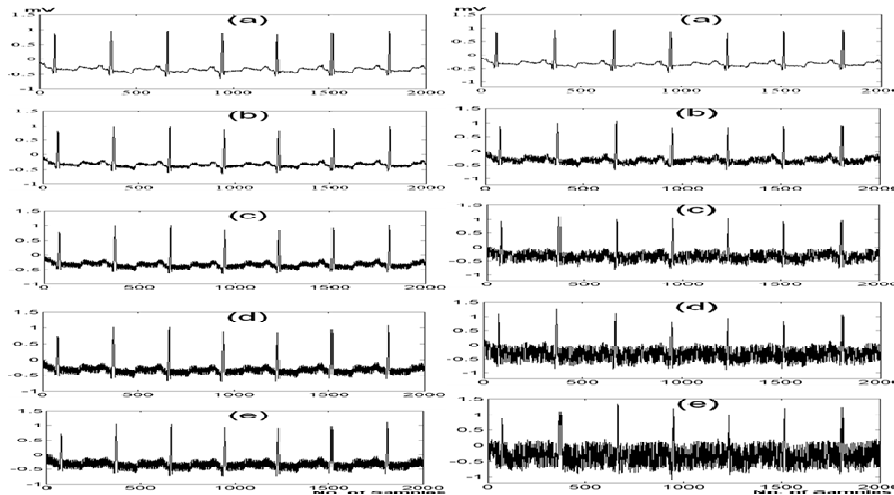
Figure 1. ECG corrupted by power line noise (left) and EMG noise (right). Each noise type was varied in intensity in a step of a) none, (b) 25%, (c) 50%, (d) 75%, and (e) 100%.
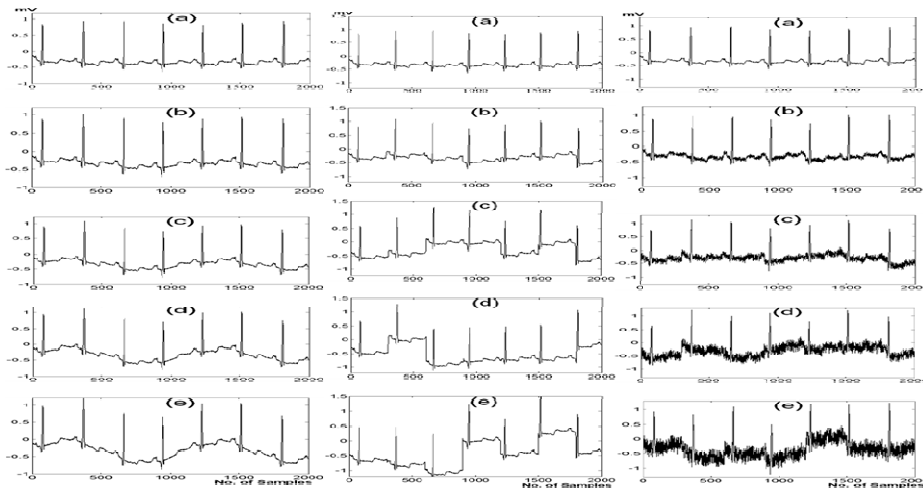


Figure 2. ECG corrupted by base line drift (left), abrupt baseline shift noise (middle) and composite noise (right). Each noise type was varied in intensity in a step of a) none, (b) 25%, (c) 50%, (d) 75%, and (e) 100%.

## 2.2. Description of algorithms

A great deal of study was used to determine which of the available QRS detection algorithms were to be used. Each algorithm used in this study is based on fundamental concept presented in the literature. There are seven basic types of algorithms included in this study employed one or more preset constants, either as multipliers or as thresholds. In some cases these constants were not given in the literature, while in others they were not compatible with the data format that used in this study. A tuning procedure was carried out in order to determine the value for these constants, which would give the best results for the composite noise corrupted data. Since most of the current QRS detector can be divided into two stages: a preprocessor filtering stage to emphasize the QRS complex and a decision stage to threshold the QRS enhanced signal, to provide similar platform for comparison simple threshold used in all algorithms.

### 2.2.1. Algorithm based on amplitude and first derivative (AFD)

The concept of this QRS complex detector was derived from the algorithm developed by Mahoudeaux *et al.* [21]. Let $x(n) = x(1), x(2),\ldots\ldots x(k)$, where $k$ is the number of samples for analysis, represent a one dimensional array of sample points of the synthesized digitized ECG. An amplitude threshold is calculated as a fraction of the largest positive valued element of that array as $0.3\max[x(n)];\quad 1 < n < k$

The first derivative, $y(n)$, is calculated at each point of $x(n)$ from the difference equation,

$$y(n) = x(n+1) - x(n-1); \quad 2 < n < k-1 \tag{1}$$

A QRS candidate occurs when,

$$y(i), y(i+1), y(i+2) > 0.1 \tag{2}$$

And,

$$y(j), y(j+1) < -0.1 \tag{3}$$

Where $(i+2) < j < (i+25)$ and $x(i), x(i+1), \ldots, x(j+1) \geq$ are Amplitude threshold.

### 2.2.2. Algorithm based on first derivative (FD)
This algorithm was adapted from one developed by Menard [22]. The first derivative is similar to a five point parabolic smoothing filter:

$$y(n) = -2x(n-2) - x(n-1) + x(n+1) + 2x(n+2); \quad 3 < n < k-2 \tag{4}$$

The slope threshold is calculated as $0.25\max[y(n)]; \quad 3 < n < k-2$

The first derivative array was searched for points which exceed the slope threshold and taken as the QRS candidate: $y(i) >$ slope threshold.

### 2.2.3. Algorithm based on first and second derivative (FSD)
This algorithm was adapted from the QRS detector scheme developed by Ahlstrom and Tompkins [2]. The rectified first derivative is calculated from ECG:

$$y_0(n) = \text{abs}[x(n+1) - x(n-1)]; \quad 2 < n < k-1 \tag{5}$$

The rectified first derivative is then smoothed. Smoothing is done by a three point moving average filter:

$$y_1(n) = [y_0(n-1) + 2y_0(n) + y_0(n+1)]/4; \quad 2 < n < k-1 \tag{6}$$

The rectified second derivative is calculated:

$$y_2(n) = \text{abs}[x(n+2) - 2x(n) + x(n-2)]; \quad 3 < n < k-2 \tag{7}$$

The rectified and smoothed first derivative is added to the rectified second derivative:

$$y_3(n) = y_1(n) + y_2(n); \quad 3 < n < k-2 \tag{8}$$

The maximum value of this array is determined and scaled to serve as primary and secondary thresholds:

Primary threshold = $0.4\max[y_3(n)]; \quad 3 < n < k-2$

Secondary threshold = $0.05\max[y_3(n)]; \quad 3 < n < k-2$

The array of the summed first and second derivatives is searched for QRS candidate in this way:
$y_3(i) \geq$ Primary threshold and $y_3(i+1), y_3(i+2), \ldots, y_3(i+6) >$ Secondary threshold.

### 2.2. 4. Algorithm based on FIR digital filter (DFF)
This algorithm is an adaptation of Okada's QRS detection algorithm [1], [4]. The first stage smoothes the ECG using a three point moving average filter:

$$y_0(n) = [x(n-1) + 2x(n) + x(n+1)]/4; \quad 2 < n < k-1 \tag{9}$$

The output of the moving average filter is passed through another moving average low pass filter:

$$y_1(n) = \frac{1}{2m+1} \sum_{l=n-m}^{n+m} y_0(l); \quad m < n < k - m \tag{10}$$

The difference between the input and output of the low pass filter, which acts as a band-pass filter is then squared:

$$y_2(n) = (y_0(n) - y_1(n))^2; \quad m < n < k - m \tag{11}$$

The squared difference is filtered to enhance the QRS complex:

$$y_3(n) = y_2(n) \left\{ \sum_{l=n-m}^{n+m} y_2(l) \right\}^2; \quad m < n < k - m \tag{12}$$

A fourth array is formed to discard peaks due to abrupt baseline shift, using the following formula:

$$y_4(n) = y_3(n) \quad \text{if } [y_0(n) - y_0(n-m)][y_0(n) - y_0(n+m)] > 0 \tag{13}$$

The maximum value of this array is determined and scaled to form the threshold: Threshold = 0.125 max[$y_4(n)$]; $m<n<k-m$. A QRS candidate occurs when a point in $y_4(n)$ exceeds the threshold: y4(n) > threshold. The value of $m$ was set to six in order to give good performance while keeping the computational requirements at a reasonable level.

### 2.2.5. Algorithm based on IIR digital filter (DFI)

This algorithm uses the QRS detection method developed by Pan and Tompkins [6]. The digitized ECG signal is passed through a band pass filter composed of cascaded high-pass filter and low pass integer filter, differentiation, squaring and moving average filter. Difference equation for the second order low pass filter is:

$$y_1(n) = 2y_1(n-1) - y_1(n-2) + x(n) + 2x(n-6) + x(n-12) \tag{14}$$

And the difference equation for the high pass filter is:

$$y_2(n) = -y_2(n-1) - y_1(n) + 32y_1(n-16) + y_1(n-32) \tag{15}$$

After the signal has been filtered, it is then differentiated through a five point differentiator:

$$y_3(n) = (2y_2(n+1) + y_2(n+2) - 2y_2(n-1) - y_2(n-2))/8 \tag{16}$$

Squaring operation makes all data positive; it emphasizes the higher frequency component nonlinearly:

$$y_4(n) = y_3(n)^2 \tag{17}$$

A moving average filter is now employed as a smoother and performs a moving window integrator over 150ms:

$$y_5(n) = (y_4(n-(N-1)) + y_4(n-(N-2)) + \ldots\ldots\ldots + y_4(n))/N \tag{18}$$

Thresholds are set up to detect QRS complexes in the output of the moving average filter. This algorithm uses a dual threshold technique and a search back for missed beats.

### 2.2.6. Algorithm based on neural network (NN)

A Time Lagged Feed forward Network (TLFN) was applied as an adaptive filter [8], [23]. The TLFN is a supervised network, which acts like a one-step predictor of the current sample using the immediately preceding samples. The over-all behavior of the network is primarily to predict lower frequencies contained in the ECG. The occurrence of a QRS complex, which is associated with higher frequency content, implies that the prediction error will suddenly increase, and, accordingly, indicate the presence of a QRS. The TLFN consists of a forward and a backward pass. In the forward pass, the stimulus (input) propagates rightwards through the entire network in order to produce a prediction. The error between such a prediction and the desired response is then propagated backwards in order to update the synaptic weights. This procedure is referred to as the training of the network. The growing network was tested against the noisy signal and it was seen that a 6-5-1 configuration gives satisfactory result, where a hyperbolic tangent function is used in hidden layer neurons and linear function for output layer neuron. The multiplayer perceptron (MLP) configuration was trained with different sets of 200,000 samples of noisy signal by Levenberge-Marquardt algorithm using an adaptive scalar constant (μ) which is initially 0.001 with a increasing factor of 10 and a decreasing factor of 0.1. The training is generally stopped when the change in error flattens off and becomes asymptotic. For this study the training was stopped at 500 iterations with a mean squared error (MSE) of 0.0206. This TLFN was used for simulation process. After smoothing the output of TLFN, a matched filter was applied to improve the SNR. It is well-known that the impulse response $h(n)$, of the matched filter is a time-reversed replica of the event to be detected, i.e., the QRS complex. The template of the matched filter was updated after detecting each beat. The output of the matched filter is then propagated further to the adaptive threshold function to detect the QRS complex. Such a threshold function uses 60% of peak amplitude of the previous detected QRS complex in order to adapt the threshold.

### 2.2.7. Algorithm based on first derivative (FD)

The WT decomposes the signal into different scales with different levels of resolution by dilating a mother wavelet. Wavelet has a zero net area, suggesting that the transformation kernel of WT is a compactly support function, thereby offering the potential to capture the QRS spikes which normally occur in a short period of time. For discrete time signals, discrete wavelet transform (DWT) is equivalent to an octave filter bank [24]. This multiresolution analysis (MRA) decomposes a signal into scales with different time and frequency resolution. We can discriminate the QRS spikes from other portions of signal through the decomposition of MRA into different levels. Almost all wavelet based QRS detection methods are based on local maxima of the wavelet coefficients. Most of the energy of the QRS complex lie between 5 to 30 Hz. Selection of maximum decomposition levels depends on this frequency band. Twenty independent noisy signals were used to evaluate the performance of the applied denoising methods when considering the compactly supported orthogonal wavelet families, the Coiflet wavelet basis was found most suitable. The Coiflet wavelet of order 2 (*Coif*2) was used which had lowest denoising error among Coiflet functions with soft thresholding and a fixed threshold of $\sigma[2\ln(n)]^{0.5}$, where $n$ is the number of samples and $\sigma$ is the variance. A five level wavelet decomposition of the noisy signal using *Coif*2 wavelet was analyzed for denoising. The energy for motion artifacts and baseline wander (i.e. noise) increased for scales greater than five. The wavelet used for QRS detection was Biorthogonal spline (*bior*6.8) for which symmetry and exact reconstruction are possible. The QRS complex detection was accomplished by using the modulus maxima pair of the WT coefficients. The transitions in the input denoised ECG signal corresponded to local maxima in the decomposition modulus at different scales. The frequency content of the ECG characteristic waves is different, so they are distinguished at different decomposition scales. The energy of the QRS complex usually is covered by scale 1 and 2 (scale a=$2^1$ and $2^2$ the dyadic sampling grid). Abrupt shift in base line causes isolated peaks in wavelet transformed signal. After rejecting all isolated and redundant peaks, the modulus maxima pair of the wavelet transformed signal is searched for local maxima by peak detection logic with threshold value. When a local peak exceeds the threshold, it is stored as a QRS candidate and successive search in vicinity is performed for higher peaks, which could replace the previous QRS candidate. Highest QRS between two levels are taken as exact QRS.

### 3.    PERFORMANCE ANALYSIS

The accuracy of different algorithms tested against different types of noisy and noiseless signal were measured in terms of percentage detection error rate. This error rate (ER), the rate to obtain an incorrect decision, is given by:

$$ER \quad = \frac{FP \ + \ FN}{TP} \times 100$$

Where, *TP* denotes number of true QRS complexes, and *FP* is the number of false positives that correspondences to detecting a QRS complex when there is none and *FN* is the number of false positives that correspondences to not detecting a QRS complex when there is one.

Out of 47 data sets of MIT-BIH database, lead II ECG of a total of 15 data sets namely 100, 103, 105, 107, 109, 115, 118, 124, 202, 209, 212, 220 228, 231 and 234 were taken for QRS detection. These data sets contain a total of 33,774 beats of which 21,061 are normal ones. Out of the rest 12,713 beats, there are APC (650), blocked APC (10), aberrated APC (19), PVC (589), fusion PVC (8), blocked PVC (2), Paced (2078), left BBB (2492), right BBB (6776), junctional premature (79), junctional escape (5) and unclassifiable (5) beats. The detection error rates of the seven algorithms applied to five types of noise of different levels (25%, 50%, 75% and 100%) along with the raw signal (0% noise) are provided in Table 1.

### 3.1. Analysis for power line noise corrupted ECG signal

The results for the 50 Hz power line interference show that the algorithms based on DFs, NN and WT give approximately constant error rate, which indicates that these algorithms are relatively insensitive to power line noise. Algorithms based on derivatives show that the error rate increases with the noise level. The error rate for algorithms based on first and second derivative is higher than that of first derivative for different noise level. It is due to the fact that the amplitude of the differentiated signal depends on the frequency of the signal. The DFs use band pass step that attenuates power frequency signal. Since different decomposition level of wavelet transformed signal consist different frequency band, levels that contain power line signal are discarded from analysis.

### 3.2. Analysis for baseline drift corrupted ECG signal

Baseline drift due to respiration presents a lesser challenge to all of the algorithms. All the algorithms give good performance. Low frequency noise (<0.5 Hz) of this type is apparently ignored by all the algorithms. Derivative based algorithms attenuate this low frequency signal. The band-pass step of the DF rejects base line wander. The output of the TLFN predictor gives less error for low frequency variation of the input signal. During detection process of wavelet transformed signal, low frequency approximate signal is discarded.

### 3.3. Analysis for abrupt baseline shift corrupted ECG signal

FSD gives the worst result as the noise level increases. Abrupt shifts produce spikes in the derivatives; in the case of FSD these spikes are almost like QRS complex with small width and may be detected as QRS. In the first derivative signal the QRS complex gives both negative and positive slope but the spikes for abrupt shifts have only positive slope. As FD does not use this concept, it shows a significant error rate. AFD uses this concept and shows relatively small increase of error as the noise level increases. Algorithms based on DF show better performance than derivative based algorithms FD and FSD, because they use isolated peak pruning techniques. For this step FIR based DF (DFF) considers elements of QRS complex each symmetric on the time axis whereas the spikes due to abrupt shift are not and IIR based DF (DFI) considers the width of the QRS complex. DFI shows slightly better performance than DFF. WT gives the best performance against this noise among the algorithms. QRS complex represents maxima-minima pair in the transformed signal whereas shifts in the baseline represent only one maxima which are ignored. NN also performs well but exhibits slightly poor performance than WT.

### 3.4. Analysis for emg noise corrupted ECG signal

This type noise was greatest noise for all the algorithms. This noise type has broadband frequency characteristics, which overlaps the frequency spectrum of the QRS complex. Derivative based algorithms have the worst performance among all. FD and FSD give false positives about four times that of QRS complex. EMG noise has first and second derivative characteristics that are similar to those of QRS complex. Though threshold of AFD was calculated from the raw signal, this algorithm did not perform satisfactorily for EMG noise because differentiator amplifies this type of noise. Since frequency spectrum of EMG noise overlaps that of QRS, algorithms based on DFs which use band pass filtering step, fails to attenuate EMG noise. As a result as the noise level increases the error rates also increase. NN and WT based algorithms show better performance among all algorithms. However NN exhibits slightly better performance than WT. The TLFN acts as an adaptive predictor and gives relatively small error in its output because the amplitude of the QRS complex is still considerably greater than the noise. Algorithm based on WT uses wavelet based denoising approach to remove random EMG noise. But denoising causes loss of low amplitude QRS complex because this technique uses thresholding concept where signal less than the threshold is discarded.

### 3.5. Analysis for composite noise corrupted ECG signal

Composite noise most accurately replicates an actual ECG signal which was simulated by summing different scaled down noisy signals. Although individual noise types are scaled down before they are combined to form composite noise, the results are generally worse than that of the individual noise except EMG noise. The performances of the algorithms for individual noise are reflected in the composite noise. The derivative based algorithms exhibit very poor performance for abrupt shift and EMG noise. As a consequence these algorithms show poor performance for composite noise also. Algorithms based on amplitude and first derivative and digital filter show better performance than derivative based algorithms but these results are also unsatisfactory. The NN and WT based algorithms show reasonable results. WT perform better than NN at 25% noise level but as the noise level increases NN shows better result than WT with small increase of error rate.

From the aforementioned noise sensitivity analysis of different QRS detection algorithm, it is clear that algorithms based on derivative are not suitable for noisy signal. Even algorithm based on amplitude and first derivative and digital filters show unsatisfactory results as the noise level increases. Algorithms based on NN and WT give reasonably good results and in most cases show similar performance, which demands for separate comparison between these two algorithms. Table 2 shows the mean value with standard deviation (SD) of percentage detection error for all the datasets (noisy and noiseless) that were tested in this study for NN and WT. Up to 100% of all noise types, a total of 315 datasets (15 raw and 75 each of 4 noise levels) are used to evaluate the performance. The slightly varying performance of each method depending on noise level made us to evaluate whether there was any difference in the detection ability of any method than other. Statistical analysis of variance (ANOVA) was applied using both one- and two-way classification [30] with 95% confidence level. A one-way ANOVA shows that there is no significant difference of error rates between the two methods for 0% noise (raw ECG). The application of two-way ANOVA in the other noise levels shows that the difference in error rate due to applied method is insignificant in all cases. However, the difference due to type of noise is significant for 50%, 75% and 100% noise levels. Also, the interaction between method and noise type is insignificant.

Table 1. Detection error rate (in %) of seven algorithms for 12,251 beats (normal 9962, abnormal 2289) of ECG of MIT-BIH database

| Noise Type | Level % | AFD | FD | FSD | DFF | DFI | NN | WT |
|---|---|---|---|---|---|---|---|---|
| No noise | 0 | 0.48 | 0.85 | 1.64 | 1.04 | 0.94 | 1.63 | 1.14 |
| Power line | 25 | 0.54 | 1.01 | 2.39 | 0.86 | 0.94 | 1.64 | 1.13 |
|  | 50 | 0.86 | 1.51 | 6.03 | 0.79 | 0.94 | 1.64 | 1.14 |
|  | 75 | 1.95 | 21.00 | 4.94 | 0.79 | 0.94 | 1.63 | 1.16 |
|  | 100 | 3.63 | 20.82 | 8.02 | 0.80 | 0.94 | 1.63 | 1.16 |
| Base line drift | 25 | 0.48 | 0.85 | 1.64 | 1.04 | 0.94 | 1.63 | 1.14 |
|  | 50 | 0.51 | 0.85 | 1.64 | 1.04 | 0.94 | 1.60 | 1.14 |
|  | 75 | 0.51 | 0.85 | 1.64 | 1.04 | 0.94 | 1.61 | 1.16 |
|  | 100 | 0.51 | 0.85 | 1.64 | 1.04 | 0.94 | 1.69 | 1.15 |
| Abrupt base line shift | 25 | 5.51 | 4.60 | 2.86 | 3.10 | 2.92 | 1.90 | 1.28 |
|  | 50 | 5.72 | 6.77 | 8.33 | 3.58 | 3.43 | 2.21 | 1.34 |
|  | 75 | 6.27 | 8.03 | 15.10 | 5.41 | 4.51 | 2.05 | 1.55 |
|  | 100 | 7.39 | 9.64 | 23.29 | 8.26 | 5.77 | 2.55 | 1.89 |
| EMG | 25 | 92.07 | 91.59 | 139.7 | 8.66 | 6.90 | 2.01 | 1.51 |
|  | 50 | 89.32 | 183.8 | 215.3 | 22.34 | 38.77 | 6.85 | 11.03 |
|  | 75 | 81.56 | 228.3 | 272.9 | 25.64 | 41.52 | 9.30 | 10.43 |
|  | 100 | 74.50 | 269.6 | 304.6 | 38.25 | 51.93 | 17.53 | 16.08 |
| Composite | 25 | 7.32 | 17.98 | 53.27 | 5.63 | 4.66 | 2.08 | 1.53 |
|  | 50 | 10.57 | 70.98 | 136.1 | 8.26 | 7.88 | 2.37 | 3.23 |
|  | 75 | 14.23 | 132.3 | 195.0 | 10.98 | 13.11 | 2.58 | 4.27 |
|  | 100 | 18.78 | 182.2 | 237.1 | 16.47 | 21.35 | 4.28 | 5.74 |

Table 2. Comparison of detection error with NN and WT based algorithms

| Noise level (%) | NN (%) | WT (%) |
|---|---|---|
| 0 | 1.77 $\pm$ 1.88 | 1.29 $\pm$ 1.84 |
| 25 | 2.12 $\pm$ 2.72 | 1.73 $\pm$ 2.79 |
| 50 | 3.65 $\pm$ 6.56 | 6.55 $\pm$ 11.57 |
| 75 | 9.55 $\pm$ 17.83 | 9.84 $\pm$ 18.46 |
| 100 | 17.67 $\pm$ 27.29 | 14.70 $\pm$ 24.27 |

## 4. CONCLUSION

An analysis of the QRS detection algorithms for noisy ECG is presented. The results of derivative and filter based algorithms are consistent with that of the previously obtained by Friesen et al. [26]. However, they used the normal ECG of a short duration, only of 32 sec. The biodiversity, subject-to-subject variation of biological signal is well known. Hence it is difficult to exactly duplicate any experiment where living body is the subject. This paper tries to follow the methodology developed by Friesen et al. [26], specially for noise simulation and derivative and filter based algorithm development. However, this study includes a wide range of data of long duration of a popular database. Also, the test data includes both normal and abnormal ECG.

The results of this study show that no algorithm exhibits superior performance in all situations. Algorithms based on NN and WT show relatively robust noise performance. Despite its simplicity, differentiation should be avoided with noisy data. Digital filters are not suitable for noise whose frequency band overlaps the spectrum of QRS complex, such as EMG interference. Despite its computational burden the use of a NN for QRS detection (nonlinear prediction) is an interesting academic exercise. Wavelet transforms are fairly novel approaches for processing of non-stationary signals. As a single detection criterion always has its particular weaknesses, a combination of algorithms might perform better extracting the strength from each algorithm. The best choice of parameters for the composite noise may not yield the best results for other types of noise. The result for a given noise type can often be improved if the algorithm parameters are selected specifically for that noise type. The use of adaptive thresholding and adaptive peak pruning can improve the performance. This work can be extended to analyze the effect of noise on different abnormal beats and for noise sensitivity analysis of different ECG pattern classifiers to distinguish between normal and abnormal beat patterns as well as classify different abnormal beat morphologies under noisy environment.

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