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Noise-Immune ECG Classifier Using Wavelet Transform and Neural Networks

Anwar Al-Shrouf

Abstract- ***This paper proposes a novel algorithm for automatic classification of electrocardiogram (ECG) beats recorded by Holter systems. The algorithm is based on a combination of neural network and discrete wavelet transform. Discrete wavelet transform coefficients are used as an input of the neural network to perform the classification task. The proposed classifier wastested by both real ECG signals andartificially generated signals. Five Hermite functionswereused in generating the ECG artificial testing signals. Different levels of noise were added to the signals to examine the noise immunity of the classifier. The main advantage of the proposed classifier is that it is noise immune and accurate. The testing results on the proposed classier show that it is capable of recognising 40 beats, and it works properly in the classification of the ECG signal with a classification ratio of 100% for an SNR of more than 6 dB.***

Keywords- ***Wavelet transform, neural networks, ECG beat classification, arrhythmia, white noise, Hermite functions.***

I. INTRODUCTION

Electrocardiogram (ECG) signal is one of the most important bioelectrical signals. Since its invention in1887, analysis of ECG signal has become widely used for the diagnosis of several heart disorders. Several heart disturbances cannot be detected by performing a short-time routine recording of the ECG. So there is a real need for a long-term (e.g.,24 hours) recording of the ECG while the patient is performing his daily activities. This type of recording is known as Holter monitoring. In this long-term test, huge data with a huge number of heartbeats will be recorded, so it is difficult for physicians to decipher hidden information from these hugedata. Therefore, using computer algorithms is crucial in processing such huge data to help physicians in their diagnosis. As well, it can play a major role in managing cardiovascular diseases[1],[2].However, for the diagnosis of arrhythmia the most important step is the classification of heartbeats. The ECG signal rhythm can be ascertained by knowing the classification of successive heartbeats in the recorded signal [3]. The ECG signal processing procedure consists of denoising, baseline correction, feature extraction and arrhythmia detection. A typical ECG waveform consists of five basic waves—P, Q, R, S and T waves—and occasionally U waves. An ECG waveform is divided to intervals and segments[4],[5],[6]. A typical ECG waveform with an R-R interval and basic waves is shown in fig.1.

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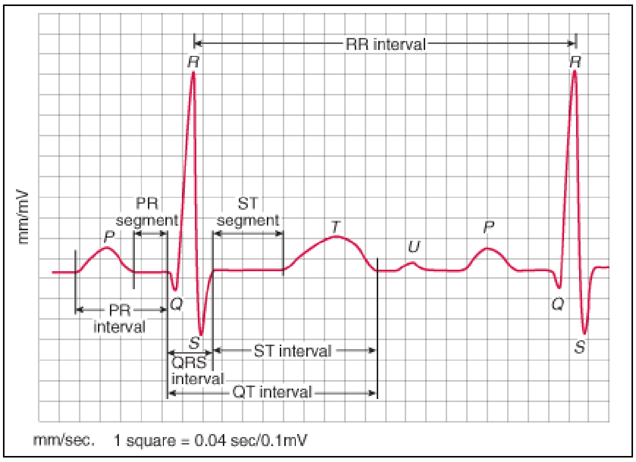

Fig.1. Typical ECG signal

The interpretation of ECG components could be found in several references such as[5],[7]: From the classification point of view the QRScomplex is the most important component of the ECG signal. QRS complex corresponds to the period of ventricular contraction or depolarisation. The normal duration of the QRS complex is 60–100ms.An ideal QRS complex may take one of the shapes in fig. 2.

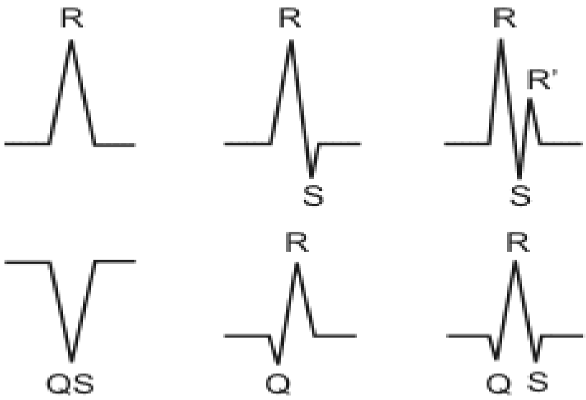

Fig.2. Ideal QRS complex shapes

The shape of the QRS complex in fig.2 is ideal. In fact, the shape depends on which lead is chosen to record the signal. For the same person the ECG signal may vary such that signals differ from each other and simultaneously similar for different types of heartbeats [8]. Classification of ECG waveform is essential for diagnosing various heart abnormalities. Automated classification of heartbeats has been done by using different techniques in both time and frequency domain. Examples of these techniques are wavelet coefficients[2],neural networks[9],[6], self-organising map [10] and linear prediction [11].

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Furthermore, in[3] heartbeat interval features are used for classification. Also, in [12] neural network based on a mixture of experts and a negatively correlated learning techniquehave been used for classifying the ECG. This paper aimed to build and test sensitive and noise immune ECG classifier using wavelets and neural networks.

II. Theoretical Basis of Wavelet Transform

In past two decades, wavelet transform and wavelet decomposition were widely used as powerful tools for ECG signal analysis and compression. The wavelet transform theory is discussed in several references such as [13],[14],[15] ,[16],[17] The wavelet transform is a powerful tool used for analysing signals of a nonstationary nature such as ECG signal. A mother wavelet $\psi(t)$is a function of zero average[14]:

$$\int_{-\infty}^{\infty} \Psi(t)dt = 0 \tag{1}$$

A wavelet family is generated from the mother wavelet $\psi(t)$ by two operations: dilation and translationas follows

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

where a and b are dilation and translation parameters, respectively. Both are real positive numbers. The continuous wavelet transform (CWT) of a function $f(t)$, $Wf(a,b)$, at scale a and position b is computed by correlating $f(t)$ with the translated and dilated wavelet function.

$$Wf(a,b) = \int_{-\infty}^{\infty} f(t)\, a^{-1/2}\,\Psi^{*}\left(\frac{t-b}{a}\right)dt \tag{3}$$

From the equation nr. 3, it can be noticed that the wavelet transform allows exceptional localisation both in the time domain via translations of the mother wavelet and in the scale (frequency) domain via dilations. The translation and dilation operations applied to the mother wavelet are performed to calculate the wavelet coefficients, which represent the correlation between the wavelet and a localised section of the signal. For analysis of digital signals, the discretewavelet transform (DWT)is used.DWT is defined as follows:

$$f(n) = \sum_{i} w_i\, a_i^{-1/2}\,\Psi\left(\frac{n-b_i}{a_i}\right) \tag{4}$$

The discretisation involves determining the parameters w_i, a_i and b_i in the equation nr. 4, based on a data sample.The dilation function of the discrete wavelet transform can be presented as a tree of low and high pass filters.This transform performsfor each step of the output of the low-pass filter. Fig. 3 shows the wavelet decomposition tree, where The original signal is successively decomposed into components of lower resolution, while the high-frequency components are not analysed any further. At each step of the DWT algorithm, there are two outputs: first,the scaling coefficients,$c^{j+1}(m)$, and second, the wavelet coefficients,$d^{j+1}(m)$.These coefficients are given, respectively, by

$$c^{j+1}(n) = \sum_{i=1}^{2n} h(2n-i)\,c^{j}(n) \tag{5.a}$$

and

$$d^{j+1}(n) = \sum_{i=1}^{2n} g(2n-i)\,c^{j}(n) \tag{5.b}$$

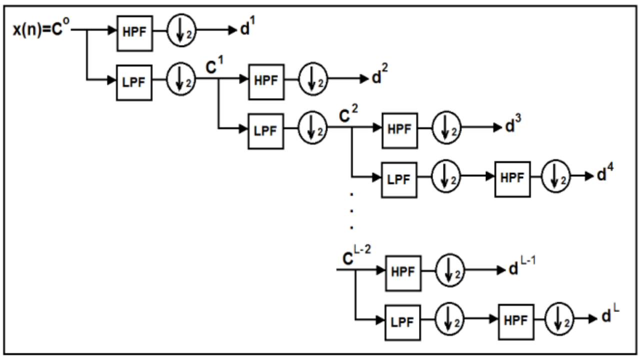

Fig.3. Sub-band decomposition of discrete wavelet transform implementation

where the inputsignal $x(n)$ is represented by c^0, andd^l(l=1,2,…,L) are the discrete wavelet transform coefficients [13].

III. ECG Classifier System

In this paper, the beat classification is based on a combination of cascade neural networks and discrete wavelet transforms. Fig. 4 shows the proposed automated classification systems. The first system uses artificially generated signal and noise aimed to test the noise immunity of the classifier. The second system uses the classification of a real ECG signal.

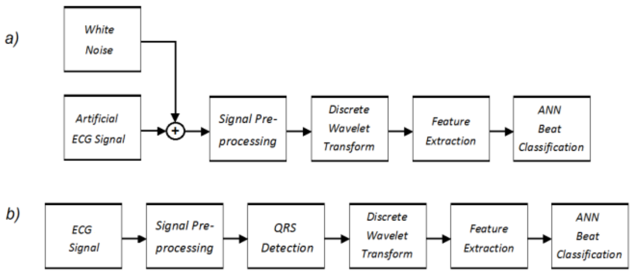

Fig.4. Proposed classification system

3.1 Generating Artificial ECG Signal

In many situations, such as a stress test and the Holter system, the recorded ECG is usually corrupted by one or more of six kinds of noise or artefacts: power-line interference, baseline drift, flat line (missing lead), low-amplitude signal, steep slope (spike noise) and electromyogram (EMG) noise due to motion artefacts and muscle contraction [18],[19],[20].

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EMG noise is the one that most severely affects the worth of the ECG signal, especially when computer-aided algorithms are utilised. Because EMG noise possesses characteristics similar to those of white noise, it is characterised by a frequency range of 5 to 100 Hz. EMG noise covers the frequency range of the ECG signal, making it difficult to eliminate [19]. Fig. 5 shows an example of EMG noise. This ECG signal is taken from the American Heart Association (AHA) database record (N11.dat). The figure shows that the last three beats are accumulated by a noise with low dB levels, but unfortunately, these levels could not be measured.

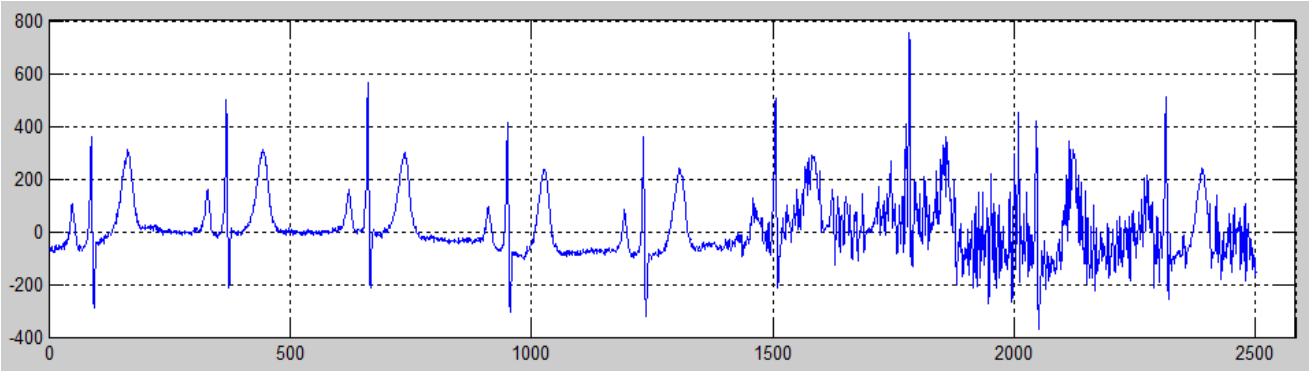

Fig.5. ECG with different noise levels

Generally, noise causes false detection of QRS or false classification of this complex. Therefore, there is a real need to test the immunity of any proposed classifier on different levels of noise. Classifier testing should be done first on 'clean', noiseless signals. Second, testing should be done on noisy signals. For this purpose, a noise with a known signal-to-noise ratio (SNR) has been added to the noiseless signal in order to determineon which dB level the classifier is working properly. In this paper, artificial ECG signals have been generated using a linear combination of the first five Hermite functions $H_n(t)$ as the following:

where

$$ecg(t)=\begin{cases}\frac{N-2j}{N}\Phi_0(t,\sigma)+\frac{2j}{N}\Phi_1(t,\sigma) & 0\le j<10\\ \frac{N-j}{N}\Phi_0(t,\sigma)+\frac{2N-2j}{N}\Phi_1(t,\sigma) & 10\le j<20\\ \frac{N-2j}{N}\Phi_0(t,\sigma)+\frac{2j}{N}\Phi_1(t,\sigma)+\frac{j}{N}\Phi_2(t,\sigma)+\frac{1.2(N-j)}{N}\Phi_3(t,\sigma)+\frac{0.4(N-j)}{N}\Phi_4(t,\sigma) & 20\le j<30\\ \frac{N-2j}{N}\Phi_0(t,\sigma)+\frac{2j}{N}\Phi_1(t,\sigma)+\frac{j}{N}\Phi_2(t,\sigma)+\frac{0.4(N-j)}{N}\Phi_3(t,\sigma)+\frac{1.2(N-j)}{N}\Phi_4(t,\sigma) & 30\le j<40\end{cases} \tag{6}$$

$$\Phi_n(t,\sigma)=\frac{1}{\sqrt{\sigma 2^n n!\sqrt{\pi}}}\exp(-\frac{t^2}{2\sigma^2})H_n(\frac{t}{\sigma}) \tag{7}$$

Hermitepolynomials $H_n(t)$ can be computed recursively as

$H_n(t) = 2tH_{n-1}(t) - 2(n-1)H_{n-2}(t)$, where $H_0(t)=1$ and $H_1(t)=2t$. (8)

These functions are generated for $t\geq 0$. For $t<0$: $H_n(-t)= H_n(t)$ when n is even and $H_n(-t)= -H_n(t)$ when n is odd. The σ parameter controls the width of the polynomial,thismeans it determines the width of QRS complex[21],[22]. In this work, σ parameter has been chosen to match the frequency of generated QRS to the standard frequency of the real normal QRS, which is around 15–17 Hz. The first five Hermitefunctions are shown in fig.6.

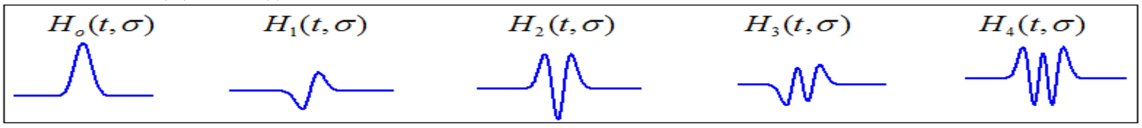

Fig.6. First five Hermitefunctions

3.2 White Noise Generating

As mentioned above, EMG noise is the noise most severely affecting the worth of ECG signal because EMG noise possesses characteristics similar to those of white noise.It covers the frequency range of the ECG signal, making it difficult to eliminate. For this reason,in this work only white noise is added to the artificial ECG signalin order to simulate the EMG noise. White noise has been generated using aMATLABprogram.

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For this purpose, a memoryless transformation of a uniformly distributed random variable is used to generate a set of uncorrelated noise samples. The range of the generated samples is determined, and its power is calculated. Before adding the noise to the signal, noise samples are scaled by a factor to achieve the desired SNR. The SNR is calculated as follows:

$$SNR = 10\log\left(\frac{P_S}{P_N}\right) \qquad (9)$$

where P_S: power of the ECG signal P_N: power of the added noise

Fig. 7 shows artificially generated signal, where (7.a) represents a noiseless generated signal, and (7.b), (7.c), (7.d), (7.e) and (7.f) represent the signal after adding white noise with SNR 20 dB, 15 dB, 10 dB, 5 dB and 0 dB, respectively.

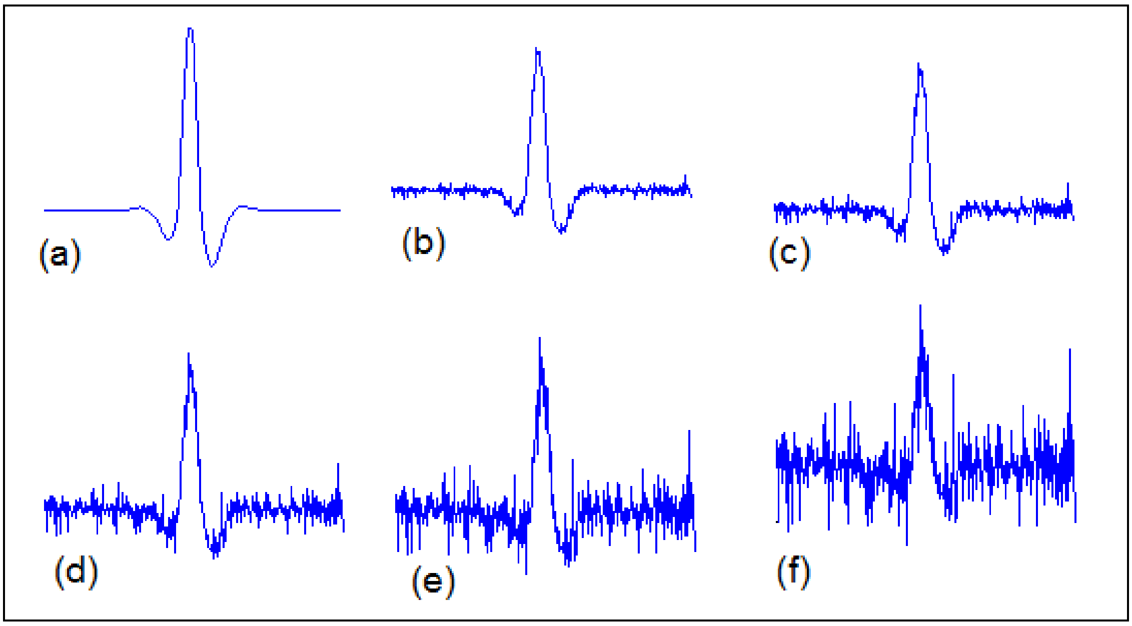

Fig.7 Generated ECG signal with different SNR levels

1.3 Feature Extraction and Classification

After the processing stage,which consists of noise elimination and QRS detection, the next stage was feature extraction. This stageis considered the most important step in signal classification and pattern recognition. In this paper, thediscrete wavelet transform coefficients for the QRS complex are chosen to be the extractedfeatures. The reason for using this small interval instead of the complete ECG beat is to minimise the neuron numbers in a hidden layer.The next stageafter the feature extraction isbuilding theneural networkwhose output is the ternary vector that carries information aboutthe class of the ECG beat. So as mentioned above, the wavelet transform coefficient of the QRS complex under classification is used as a blueprint for the ECG signal instead of the original signal. This blueprint is fed to a self-organising map neural network (SOMNN) proposed by Kohonen[23]. This type of networks has the ability to force adjacent neurons in thefeature map (network) to respond to similar feature inputs.

IV. Tests and Results

As mentioned above, Hermitefunctions are used to model QRS complexes. In fact, this model does not reflect an optimum modelling of a real-life ECG, but it offers excellent testing signals before a move toward real ECG is made. Based on observations on this artificial model, the learningcapabilities andsensitivity ofthe proposedclassifier have been studied. Aseriesof40QRSshapes are generatedusinglinearcombinationsofthefirstfiveHermitefunctions $\Phi_0,\Phi_1,\ldots, \Phi_5$. The 40 generated QRS are shown in fig.8.Those 40 templates guarantee a fluent change of morphology from monophasic to five-phasic templates.

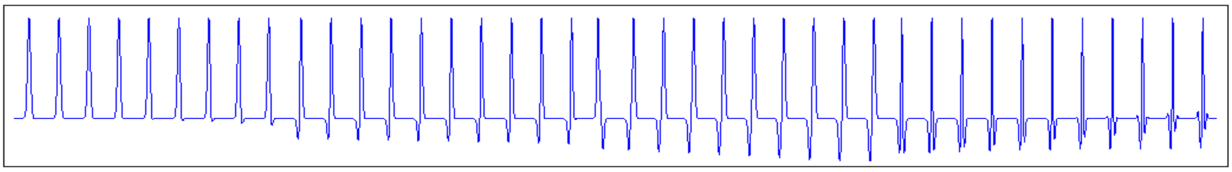

Fig.8.Artificial generated signal

The first step of testing the proposed classifier was done by adding white noise to the artificial ECG signal. The classifier was tested with different values of SNR from 20 dB down to 0 dB.

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Each artificial ECG template was generated 60 times for a specified level of noise to simulate one minute of ECG recording. So the total number of artificial beats (N_t) for a given noise level was 2400. In this paper, the quality of classification is measured by classification ratio (CR). Classification ratio is calculated as follows:

$$CR = \left(\frac{N_C}{N_t} \right) * 100\% \quad (10)$$

where Cr: classification ratio
N_C: number of correctly classified beats
N_t: total number of tested beats

The results of testing different levels of SNR are shown in table 1. Where, the The classifier performscorrect classification with a classification ratio (CR) of 100% with SNR down to 8 dB. Also the CR>98when the SNR is from 6 down to 4dB.While the CR is not satisfied when the SNR < 3 dB.

Table 1. Results for artificial signal with different noise levels

SNR [dB]	20	15	12	10	8	6	5	4	3	2	1	0
N_C	2400	2400	2400	2400	2400	2395	2389	2360	2275	2150	2113	1835
CR [%]	100.0	100.0	100.0	100.0	100.0	99.8	99.5	98.3	94.8	89.6	88.0	76.5

The second step of testing was done on a real ECG signal. In this work,selected intervals from real records of ECG signalwere used. The ECG signal was taken fromthe MIT-BIH arrhythmia database as well as the AHAdatabase.Results of testing for different records of both databases are shown in tables (2) and (3), respectively.

Table 2. Results for the MIT-BIH-selected records

Record number	100	102	105	106	107	201	203	208	209	210	215	total
Number of tested beats	75	223	76	71	137	199	202	146	169	149	243	1690
Number of correct classified beats	75	218	76	69	132	194	197	142	164	143	237	1647
CR [%]	100.0	97.8	100.0	97.2	96.4	97.5	97.5	97.3	97.0	96.0	97.5	97.5

Table 3. Results for the AHA-selected records

Record number	N11	N12	N13	N14	N18	V71	V72	V73	V74	V75	V76	total
Number of tested beats	9	14	12	16	14	17	12	16	21	17	18	166
Number of correct classifiedbeats	8	14	12	15	14	15	12	16	21	16	18	161
CR [%]	88.9	100.0	100.0	93.8	100.0	88.2	100.0	100.0	100.0	94.1	100.0	97.0

In their paper[24], M. K. Sarkaleh and A. Shahbahrami compared their obtained results with another proposed algorithm. In fact, to make a comparison between any classifiers, the test should be done on the same signals. However,M.K. Sarkaleh and A. Shahbahrami mentioned that the best CR=96.89%was achieved by E. D. Ubeyli (2008)[25]and their proposed algorithm,where they achieved CR=96.5%.In this paper,the achieved CR was 97.0% for data from AHA and 97.5% for data from MIT-BIH. Furthermore, when the total number of beats was taken into account from both databases, the CR=97.4%was achieved,which means that the proposed classification algorithm providesthe best performance.

V. CONCLUSIONS

This paper proposes a wavelet- and neural-network-based classifier system for automatic ECG classification. The proposed classifier system consists of three phases:preprocessing, discrete wavelet transform and neural network.To test the proposed system, both real and artificial ECG signalswere used.The artificial ECG signal was used to test the behaviour of the system on different levels of noise. The artificial signal was generated using a combination of the first five Hermite functions. The added noise was white noise. The result shows that the classifier works properly even in low dB levels of noise and is capable of recognising 40 artificial beats. The real ECG signal used for testing was taken from both well-recognised AHA and MIT-BIH databases. Eleven records from each database with a total number of beats of 1856 were used.

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The testing results from the proposed system on artificial signal shows that it could be used in the classification of the ECG signal with a classification ratio of 100% for SNR of more than 6 dB. However, the testing result fromthe real ECG signal demonstratesthat it could be used in the classification of the ECG signal with a classification ratio of 98.3%.

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