

Denoising of the ECG Signal using Kohonen Neural Network

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Abstract: Noisy Electrocardiogram (ECG) signal can mask some of the important features of the original ECG signal. Therefore, it is necessary to remove the noise for proper analysis of the ECG signal. In this paper, the use of Kohonen Neural Network (KNN) for automatically identifying the cutoff frequency of ECG signal for low-pass filtering is presented. ECG signal having noise and baseline wandering is extracted from two classes: arrhythmia and supraventricular. Baseline wander is removed using the empirical mode decomposition method. Frequency spectrum of the baseline wandering removed ECG signal is used to train the KNN. The performance of the KNN with various parameters is investigated. The cutoff frequency identified using the KNN is applied to the low pass Finite Impulse Response filter and the resulting signal is compared with the conventional filtered ECG signal. The result show that the KNN based approach successfully denoised the ECG signals more effectively than the conventional method.

Keywords: Baseline Wandering (BW), Empirical Mode Decomposition (EMD), Kohonen Neural Network (KNN), Finite Impulse Response (FIR) filter, Electrocardiogram (ECG), Signal to Noise Ratio (SNR).

I. Introduction

Electrocardiogram (ECG) signal is used to measure the electrical activity of the heart muscle. A typical ECG tracing of the cardiac cycle (heartbeat) consists of a P wave, a QRS complex, a T wave, and a U wave, which is normally invisible in 50 to 75% of ECGs because it is hidden by the T wave and upcoming new P wave [14]. The frequency spectrum range of normal ECG signal is 0.01Hz to 100Hz. 90% of the Spectral energy of the signal focus on 0.25 Hz to 35 Hz. ECG measures electrical potentials on the body surface via contact electrodes. ECG signal often suffers from various types of noises. Conditions such as movement of the patient, breathing, and interaction between the electrodes and skin cause baseline wandering [1] of the ECG signal. Other sources of noise include Electrical power frequency interference caused by the electric power system (has the frequency of 50Hz) and electromyography generated by the activity muscle tension and has the frequency range of 0.01 Hz – 10 KHz [2]. The produced noise consists of low-frequency components that cause Baseline Wandering (BW), and high-frequency components due to power-line interference.

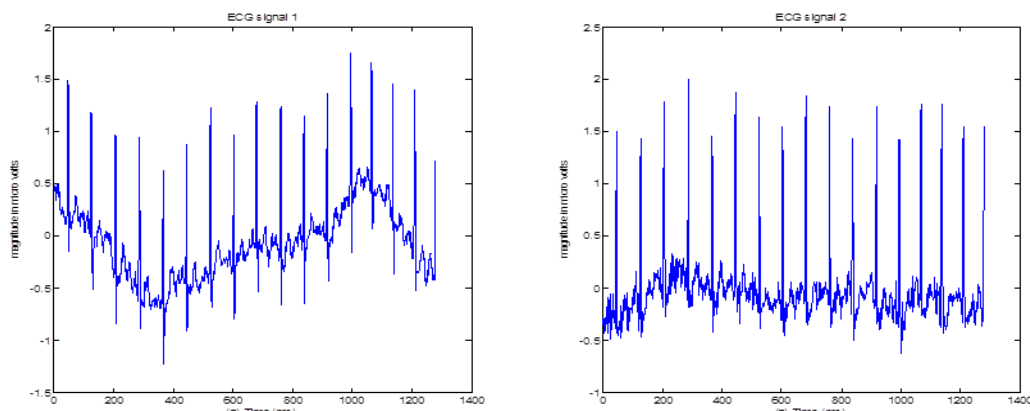


Figure 1: ECG Signals with Baseline Drift and high frequency noise components

ECG noise removal is complicated due to the time varying nature of ECG signals. Although there are many noise removal methods, but the intelligent methods that are applied commonly are evolutionary algorithms, artificial neural networks (ANN), higher order filters, swarm intelligence (SI) etc. The next section provides a review of some of the recently used noise removal methods.

II. Background

There are several methods, discussed in many research papers, of noise removal from the ECG signal. Mateo et al. (2007) proposed an adaptive approach to remove the noise frequencies from ECG recordings using

MADALINE Neural Network [20]. In this method, Widrow-Hoff Delta algorithm was used that offers much lower computational cost than the traditional back propagation algorithm. Caminal *et al.* (1992) presented an Adaptive Impulse Correlated Filter (AICF) to remove the noise from the event-related signals (such as ECG or evoked potentials), that are time-locked to a stimulus, by estimating the deterministic component of the signal and removes the noise uncorrelated with the stimulus [8].

Many studies focused on removing baseline wandering from the ECG signal. Laguna *et al.* (1992) worked on a two stage cascaded adaptive filter for removing the baseline wander preserving the low frequency components of the ECG [7]. Park *et al.* (1998) presented a Wavelet Adaptive Filter (WAF) to remove BW from the ECG signal by first decomposing the signal into seven frequency bands using wavelet and then applying adaptive filter over the seventh lowest-frequency band signal as primary input and a constant as reference input [13].

Apart from the excellent response shown by the Artificial Neural Network (ANN) techniques to remove the noise from the ECG signal, many optimization algorithms such as genetic algorithm, particle swarm optimization, ant colony optimization etc. are used nowadays to optimize the filter coefficients for denoising the ECG signal. But insufficient research work has been done in automatically determining the cut off frequencies.

This paper presents the application of Kohonen method in training the ANN to find the automatic cut off frequency for the removal of high frequency noise in ECG signals using an FIR filter. FIR filter is preferred over IIR filter because FIR filters are less complex and are computationally more efficient.

III. Proposed Methodology

Figure 2 shows the sequence of the proposed methodology. Different stages of the methodology are described below:

A. Collection of ECG Data

Several ECG signals are present at the official website of MIT-BIH database for research purposes. A total 12 ECG signals were collected using physiobank ATM from the MIT-BIH Supraventricular Arrhythmia database and the MIT-BIH Atrial Fibrillation database [15]. Out of these 12 signals, two signals were selected as shown in fig. 1 that contains baseline wandering and high frequency noise. The sampling frequency of both these signals was found to be 125 Hz.

B. Removal of Baseline Wandering

Baseline wandering is the low frequency noise present in the ECG signal which masks certain features of the ECG signal and makes it difficult to analyse. Removing the baseline wandering is usually the pre-processing step to enhance the signal characteristics for diagnosis. BW arises due to the patient movement, skin resistance, skin-electrodes improper interference etc. The frequency range of the BW is usually 0.5Hz, which is similar to the frequency range of ST segments, and hence makes the assessment of ST segment difficult in ECG signal [2]. Compared with the removal of high frequency noise, it seems to be more difficult to correct the baseline wander in the nonlinear and non-stationary ECG signals, since baseline wanders are the low frequency components overlapping the ST segment in ECG. So removal of BW is necessary before analysing the ECG signal.

There are several techniques to remove BW [3-4]. In this paper the most recent method, Empirical Mode Decomposition (EMD), is presented to remove BW. In EMD, the signal is first decomposed into a sum of intrinsic mode functions (IMFs) with a final residue signal [9-12]. IMFs are the narrowband oscillatory components arranged in a column matrix from high to low frequency. After decomposition, low frequencies IMFs are subtracted from the ECG signal to remove BW.

Figure 3 & 4 shows that the BW is eliminated successfully using EMD method. The results of the EMD method were compared with the results of wavelet based method shown in figures 3 & 4. SNR of both the methods were compared which shows that EMD method is more efficient than Wavelet method as it has higher SNR.

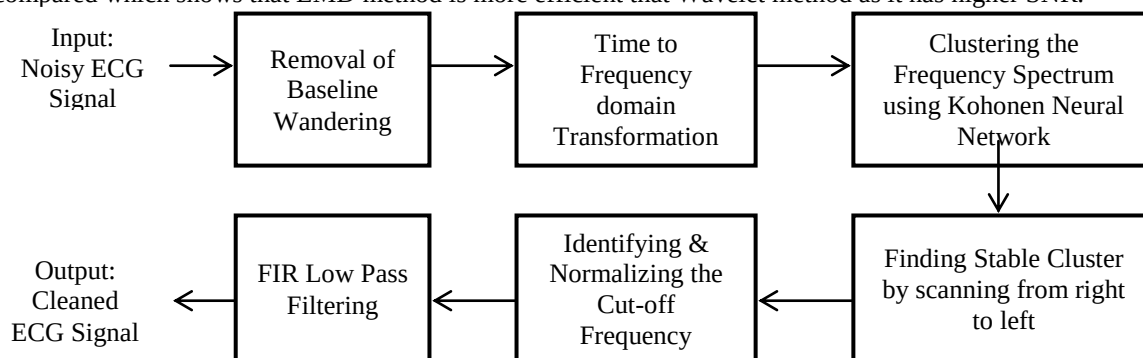


Figure 2: Flowchart describing the Proposed Methodology

C. Time to Frequency domain Transform

After the removal of BW, next step is to remove the high frequency noise components present in the ECG signal by the electromyography interference. For this purpose, the ECG signal in time domain is converted into frequency domain using Fast Fourier Transform (FFT) [6]. Transformation in frequency domain increases processing efficiency, and the formula of FFT for the transformation process is given by the following equation:

$$X_p = \sum_{q=0}^{N-1} x_q e^{-i2\pi p \frac{q}{N}} \quad (1)$$

for $p = 0, \dots, N-1$, $0 \leq q \leq N$

where $X_p, \dots, X_{N-1}$ are complex numbers, N is the number of samples, x_q is the sample q in the time domain and X_p is the corresponding sample in the frequency domain.

On applying FFT on the ECG signals obtained after the removal of BW as shown in fig. 3(b) & 4(b), the length of the frequency spectrum was found to be 640 for both the signals, which means we get 640 frequency coefficients for each signal. The next step is to apply Kohonen Neural Network (KNN) technique on these frequency coefficients to automatically identify the cut off frequency of the noise which is to be filtered out.

D. Applying Kohonen Neural Network

KNN (also called Self Organizing Map (SOM)) comes under the category of unsupervised learning. It clusters the frequency coefficients according to their amplitude values from high to low. KNN is a two layer Neural Network: the first layer is input layer and the second layer is the competitive layer [18]. Each node of the input layer is attached with every node of the competitive layer. There is a weight vector which is assigned to each node in both the layers. The frequency coefficients are applied to the input layer as a vector of size 4×1 in turn. Initially, the weight vector (which is a matrix of size 4×4) is assigned values randomly. During each training cycle, Euclidean distance is calculated between the input vector x_v and every weight vector w_i for determining the winning node according to the following equation:

$$\|x_v - w_i\| = \min \|x_v - w_i\| \quad (2)$$

where $\| \cdot \|$ indicates Euclidean distance, and x_v indicates the input vector [16-17]. After determining the winning node, the corresponding weight vector of the weight matrix is updated by the following equation:

$$\Delta w_i = \alpha (x_v - w_i^{old}) \quad (3)$$

where $i \in N_p$, α is the learning coefficient and has exponential decaying nature with increasing number of iterations, w_i^{old} is the weight vector to be updated, and N_p is the collection of all the nodes in the neighborhood of radial distance p from the input layer. This training cycle is repeated for a maximum of 200 iterations and a trained weight matrix is obtained. This trained weight matrix is used to cluster the frequency coefficients into four clusters [19] according to their amplitude values as shown in the fig. 5(c). Next step is to scan the clusters from right to left to identify the stable sample in the cluster. As the lowest cluster contains the low amplitude values which are actually noise amplitudes and is therefore discarded and the sample at which the cluster value changes from 1st cluster to 2nd cluster is considered. A sample is considered stable in a cluster if there exist atleast four consecutive samples and left neighborhood border (δ). According to the empirical results, the value of δ was found to be 7. So the cutoff frequency is where there are atleast four consecutive samples and where $\delta=7$ in the 2nd cluster.

E. FIR Low Pass Filtering

FIR low pass filtering is done to attenuate the high frequency noise present in the ECG signal shown in fig. 1(a). FIR filter implementation requires three parameters: cutoff frequency (ω_c), filter order (D) and the window type [5-6]. The cutoff frequency obtained using KNN is normalized using the following equation:

$$\omega = \frac{\omega_c}{f_s} \quad (4)$$

where f_s is the sampling frequency and its value was found to be 125 Hz for the signals shown in fig. 1. The default window is the Hamming window of size $D+1$. The FIR filter is represented by equation (5):

$$w_n = 0.54 - 0.46 \cos\left(2\pi \frac{n}{D}\right) \quad (5)$$

for $0 \leq n \leq D$

Transition bandwidth is determined by the filter order. Higher the filter order, lesser is the transition width and sharper is the cutoff frequency response. The filter order used was 43. Next section provides the test results of the automatic identification of cutoff frequency using KNN and experiments of FIR filter in denoising the ECG signal.

IV. Results and Experiments

The results of baseline wandering and the automatic identification of the cutoff frequency using KNN for low pass filtering are shown in figures 3, 4 & 5 respectively. In the BW removal, the results of EMD method are compared with that of wavelet method as shown in figures 3 & 4. SNR using EMD method is found to be 4.5958dB and that using wavelet method is 4.2974dB for the input signal shown in figure 3(a). Both these methods were also implemented on another signal shown in figure 4(a) and similar results were obtained which shows that EMD method is more efficient and effective in removing the BW from ECG signal.

Normalized cutoff frequency founded automatically using KNN method is 0.38 which is much less than that found using conventional method (0.64) for the signal shown in figure 5(a) and hence removes more noise component from ECG signal by low pass filtering. SNR using KNN is found to be 0.6537dB and that using conventional method is 0.2935dB. The default window used is Hamming window. Experiments are also carried out using Hanning and Blackman window as shown in the figures 5(e) & 5(f). Blackman window shows better results of ECG denoising as it has higher SNR than the SNRs of other windows used.

V. Conclusion and Future Scope

This paper has shown that the KNN method is effective and reliable solution for automatically identifying the cutoff frequency. The results show that EMD method is better able to remove BW than wavelet method and has higher SNR. The limitations of EMD method are that it is computationally more demanding and slightly attenuates the amplitude, but the results obtained using it overshadowed its limitations. Also, results show that KNN is better able to denoise the ECG signal than the conventional method and hence medical experts can promisingly use this methodology for diagnosing heart disorders using ECG.

In the future work, this thesis work can be extended by employing different Metaheuristic Algorithms such as Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Genetic Algorithm (GA), Firefly Algorithm (FA), Cuckoo Search (CS) algorithm to automatically determine the cutoff frequency and also to optimize the filter coefficients so that the filter response becomes very close to the ideal filter response and hence can give better results.

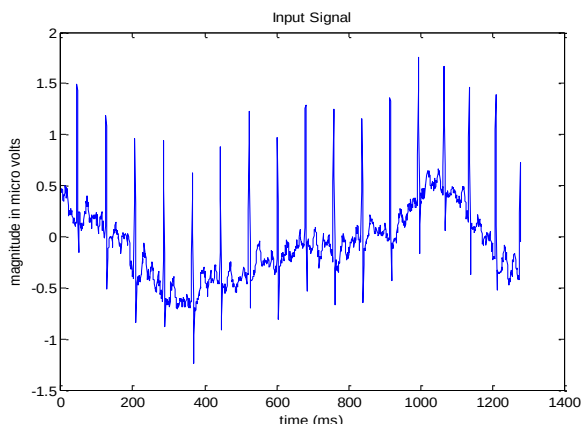


Figure 3(a) Input ECG Signal

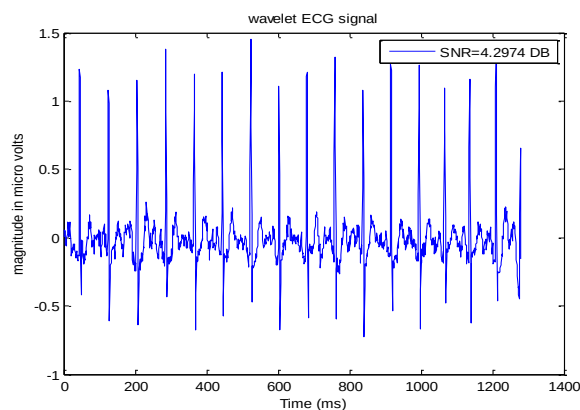


Figure 3(c) BW removed using Wavelet Method

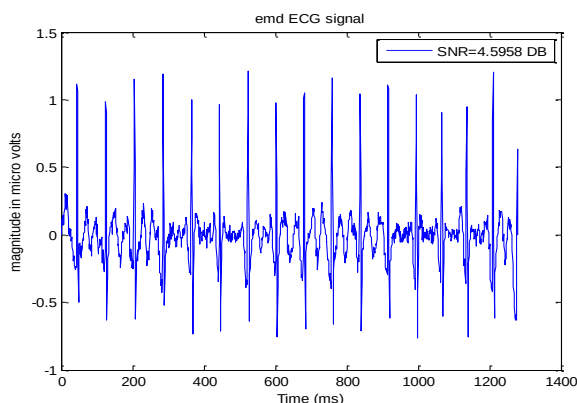


Figure 3(b) BW removed using EMD Method

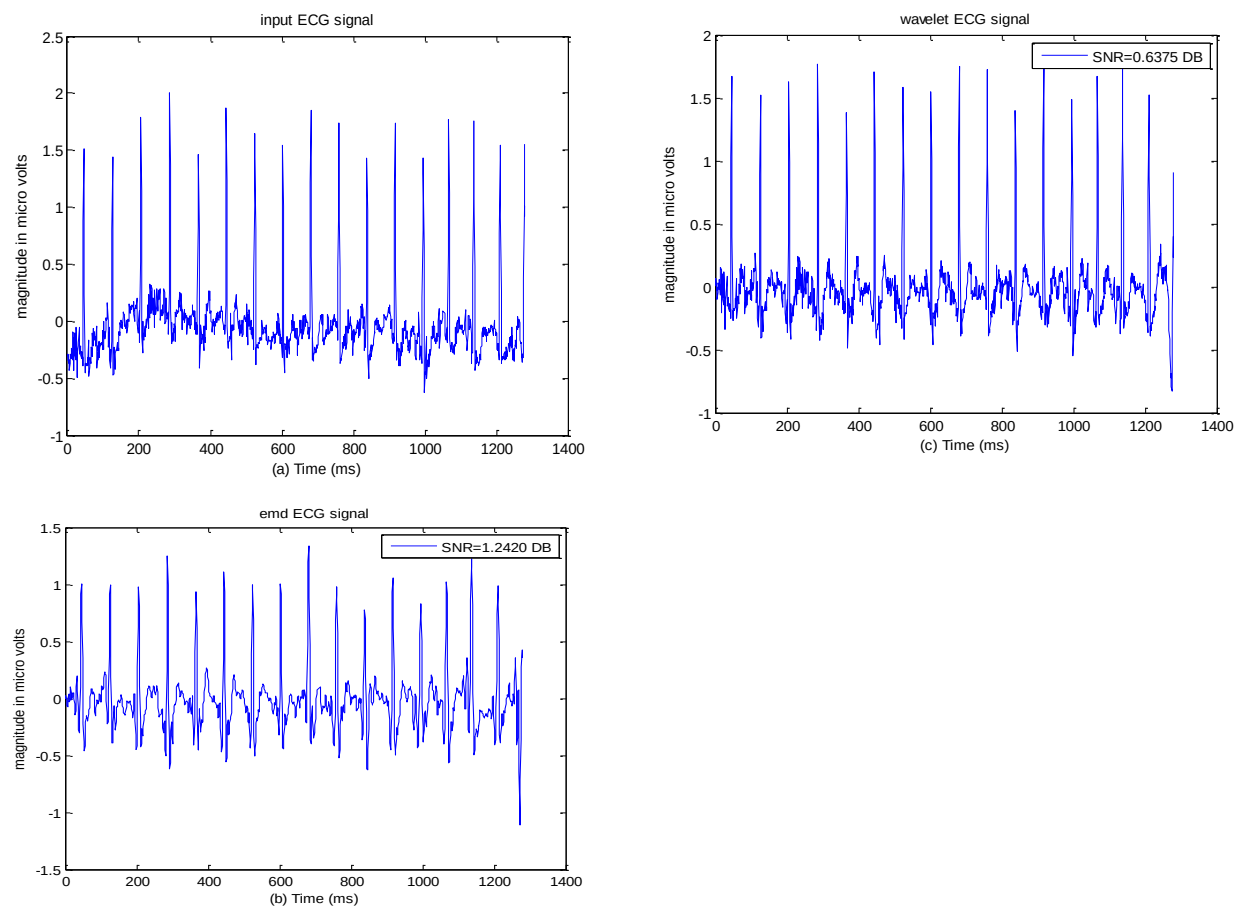


Figure 4. Testing EMD method of BW removal with the signal shown in fig. 1(b). (a) Supraventricular ECG signal. (b) BW removed using EMD method. (c) BW removed using Wavelet method.

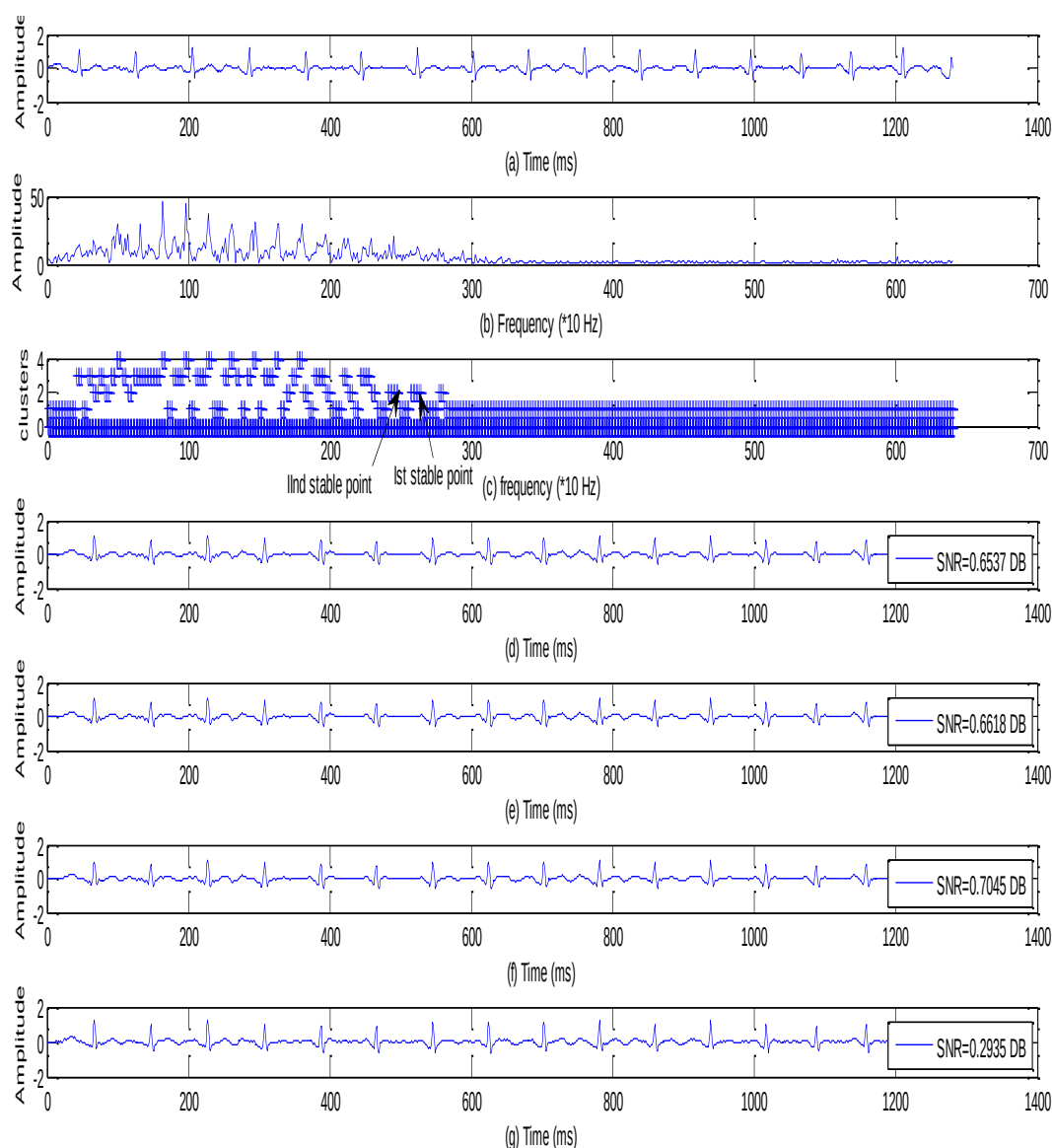


Figure 5. KNN Denoising results. (a) Noisy ECG signal as shown in the fig. 3(b) after removing BW. (b) Frequency Spectrum of the ECG signal. (c) Frequency spectrum clustered using KNN according to their amplitude values from high to low. After scanning from right to left 1st and 11nd stable points are marked. These points are actually the cutoff frequencies and can be obtained by dividing the value with 10. (d) ECG signal filtered using cut off frequency calculated from KNN method and using Hamming window. (e) ECG signal filtered using cut off frequency calculated from KNN method and using Hanning window. (f) ECG signal filtered using cut off frequency calculated from KNN method and using Blackman window. (g) ECG signal filtered using cut off frequency calculated from Conventional method and using Hamming window.

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