

ECG Compression Algorithm Based on Empirical Mode Decomposition

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Abstract

A compression algorithm based on Empirical Mode Decomposition (EMD) is described in order to investigate the performance of EMD in biomedical signals, and especially in the case of electrocardiogram (ECG). The proposed algorithm is computationally simple to treat non-stationary and nonlinear data without pre- or post-processing. In order to evaluate the performance of the proposed compression algorithm, MIT-BIH arrhythmia database is applied, and the compress ratio (CR), percent root mean square difference (PRD), percent root mean square difference normalized (PRDN), root mean square (RMS), signal to noise ratio (SNR), and quality score (QS) values are obtained. When compared, good fidelity parameters are yielded with high CR as compared to wavelet transform (WT).

Keywords: *Empirical Mode Decomposition (EMD), electrocardiogram (ECG), compression algorithm, MIT-BIH, wavelet decomposition*

1. Introduction

An electrocardiogram (ECG) is the graphical representation of electrical impulses due to ionic activity in the cardiac muscles of human heart. It is an important physiological signal which is exploited to diagnose heart diseases because every arrhythmia in ECG signals can be relevant to a heart disease [1]. ECG signals are recorded from patients for both monitoring and diagnostic purposes. Therefore, the storage of computerized is become necessary [2]. The effective use of wired or wireless communications resources is required a real-time data compression and transmission method in the case of a real-time ECG monitor or multichannel bio-signal acquirement devices. But ECG signal is usually bulky, so how to make it stored and transmission quantity decrease to improve on real-time process has become a widely deserves attention. Therefore, efficiently ECG data compression is necessary.

In early stage of research, several methods such as amplitude zone time epoch coding(AZTEC) [3-4] and coordinate reduction time encoding system(CORTES) [5], which are developed based on direct scheme in which compression is achieved by eliminating redundancy between different ECG samples in the time domain. Another example is turning point (TP) [6], which involved simple signal processing and yield minimum distortion with good compression.

In the past, researches have made in the many transformation methods. Examples include Karhunen–Loeve transform (KLT) [7], Fourier transforms [8], the Walsh transforms, the discrete cosine transform (DCT) [9], and the wavelet transforms (WT) [10]. By transforming original signal into another domain to compact much of the signal energy into a small number of transform coefficients, compression is achieved. In this

way, many small transform coefficients can be discarded in the hope of achieving better compression.

Recently, K. Khaldi and A.O. Boudraa proposed three coding frameworks: extrema coding, envelope coding and IA, IP and IF coding [11], which introduced new signals coding frameworks based on IMF. But methods are not perfect and experiments are not in detail. In this paper, we proposed an algorithm based on extrema coding.

The introduction to the compression method used by the proposed algorithm is provides in Section 1. To survey the algorithm's performance, we apply recordings of MIT-BIH arrhythmia database and compare proposed algorithm and other algorithms like WT in Section 3. The experimental results are reported in Section 4.

2. Material and Methods

2.1. Overview of the Proposed Algorithm

The proposed algorithm for ECG signal compression and reconstruction is summarized in Figure 1. As shown in this figure, it is composed of four compressing procedures and three reconstruction procedures. For compression, the first procedure is to obtain the EMD of the ECG signal. The second procedure is to detect the peak of each IMF and RES. The third procedure is to select threshold by using the wavelet soft threshold denoising. The final procedure is to apply the Huffman coding algorithm. The data transmitted to a server or a base station from e-health devices are the data block coming out of the last compression procedure.

Figure 1 also shows the reconstruction procedure that is the reverse order of the compression procedure. The first reconstruction procedure applies the inverse Huffman coding algorithm to the compressed data. The second procedure reconstructs each IMF and RES using the cubic spline algorithm. The third procedure obtains the sum of IMFs and RES, which is the reconstruction ECG signal.

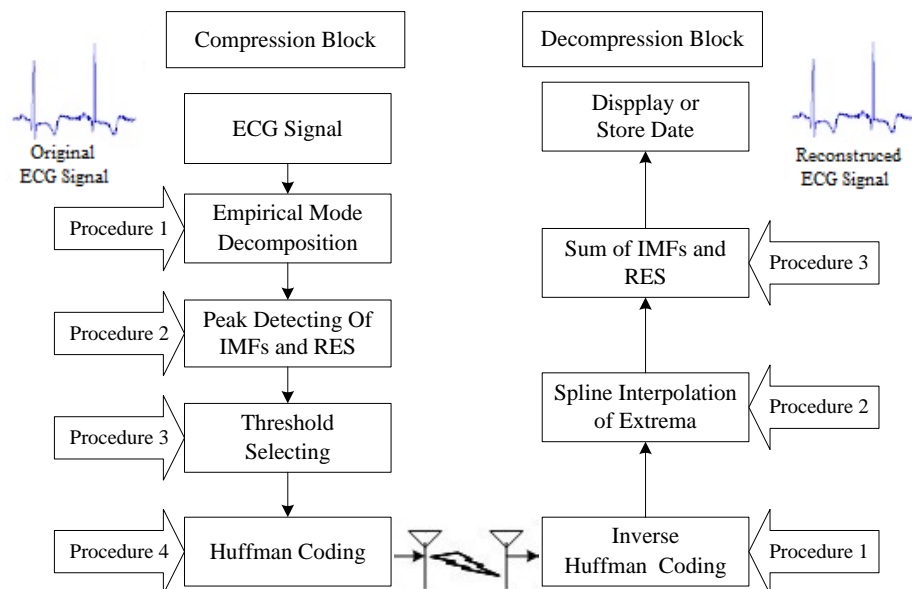


Figure 1. Block Diagram of Compression and Decompression Procedures

In this paper, we use mixed programming of MATLAB and LABVIEW for designing, implementation and analysis of the proposed algorithm by applying MIT-BIH arrhythmia datasets database, where the core algorithm is implemented by using MATLAB.

2.2. Empirical Mode Decomposition

EMD is intuitive and adaptive, with basic functions derived fully from the data. The computation of EMD does not require any previously known value of the signal [12]. The key task here is to identify the intrinsic oscillatory modes by their characteristic time scales in the signal empirically, and accordingly, decompose the signal into intrinsic mode functions (IMFs) [13]. It is considered to be an IMF that satisfies two conditions [14]: first, the number of zero-crossings of local extreme point must be equal or a difference of one at most in the whole data set. And second, the mean value of the envelope of the local maxima and minimum must be zero at any point.

The concrete steps of EMD decomposition are described as follows:

- i. Seek the local maxima X_{max} and minimum X_{min} of signal $X(t)$.
- ii. Original data $X(t)$ of the upper and lower envelope are determined according to X_{max} and X_{min} via cubic spline interpolation respectively.
- iii. The local mean $m_{1l}(t)$ of original data $X(t)$ is obtained according to the upper and lower envelope, the difference between original data and local extreme are defined as:

$$h_{1l} = X(t) - m_{1l}(t) \quad (1)$$

- iv. Replace h_{1l} with $X(t)$, then repeat step i-iii until standard deviation (SD) of two consecutive screening

$$SD = \sum_{t=0}^T \frac{|h_{k-1}(t) - h_k(t)|^2}{h_{k-1}^2(t)} \quad (2)$$

is smaller than standard setting (generally between 0.2 to 0.3), which is considered that h_{1k} is an IMF component. Then defined c_l , r_l and $X(t)$ as

$$c_l = h_{1k} \quad (3)$$

$$r_l = X(t) - c_l \quad (4)$$

$$X(t) = r_l \quad (5)$$

- v. Repeat step i-iv until r_n or c_n is smaller than a predetermined value, or $r_n(t)$ becomes a monotonic function, the EMD decomposition end. The results are obtained as

$$X(t) = \sum_{i=1}^n c_i + r_n \quad (6)$$

We select the record no.100 of MIT-BIH arrhythmia database as the ECG signal (time-period of signal is 4.158 seconds and sampling rate is 360Hz). Figure 2 shows the EMD of record no.100, which obtain 10 IMFs and RES.

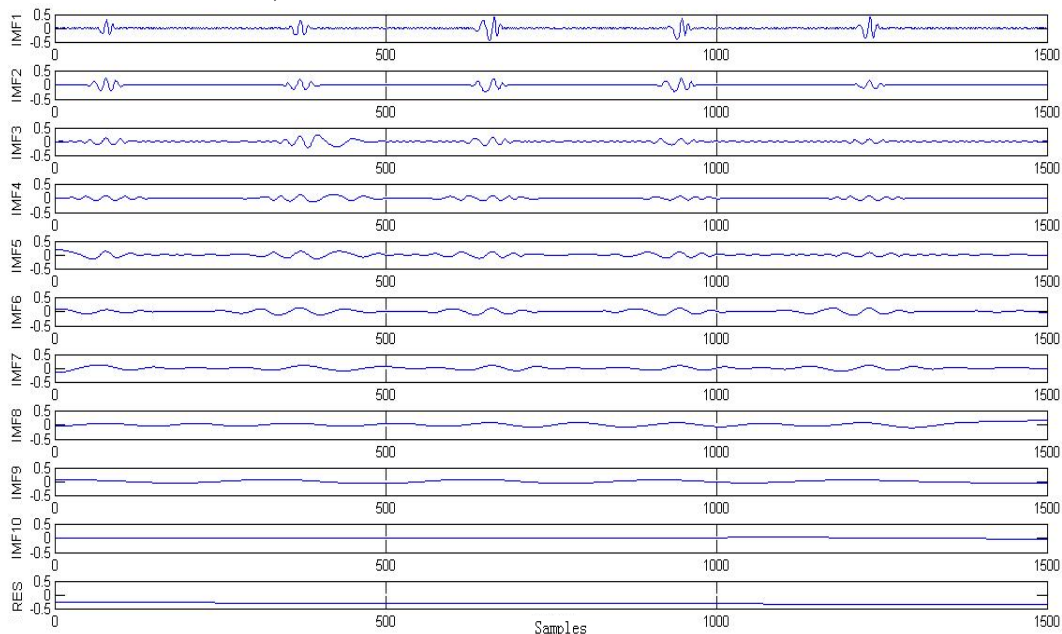


Figure 2. Decompression of Record no.100 by EMD

2.3. Peak Detecting of IMFs and Threshold Selecting

Threshold selecting is using the wavelet soft threshold denoising. Each IMF is threshold processed. The soft threshold function is represented as

$$\eta(y_i) = \begin{cases} 0, & |y_i| \leq t, \\ \text{sgn}(y_i) (|y_i| - t), & |y_i| \geq t \end{cases} \quad (7)$$

Where $\eta(y_i)$ is coefficients of IMF after selecting threshold, t is the value of threshold function y_i .

Optimal threshold can be defined by

$$t = \sigma \sqrt{2 \log(N)} \quad (8)$$

Where σ is non-essential information signal variance, N is the time-period of signal.

Extrema of IMFs of record no.100 is given in Figure 3. Where, by reconstruction, the number of extrema decreases from one IMF to the next one.

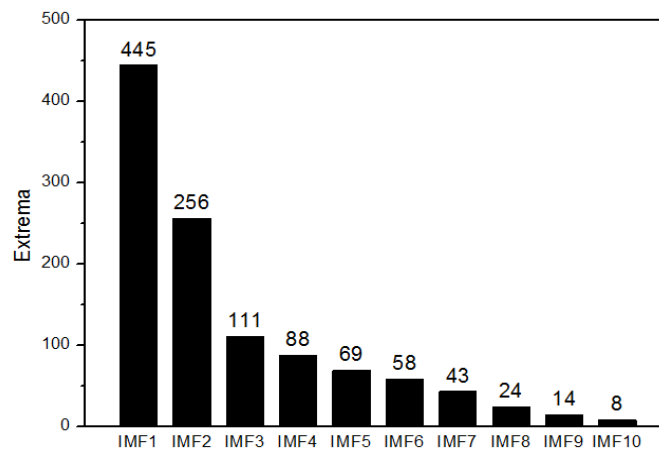


Figure 3. Number of Extrema per IMF of Record no. 100

Each IMF and RES can be represented by their extrema. Figure 4 shows an example of IMF4 and its approximate version by interpolation of its extrema with negligible reconstruction error. Where the solid line represents original IMF4, the dashed line represents reconstruction IMF4, the dotted line represents the error, which is near zero. This example illustrates the feasibility of encoding extrema. The number of extrema of each IMF and RES can be reduced using selecting threshold. Only extrema saved in the coding are those that extend above threshold. Both minima and maxima are encoded.

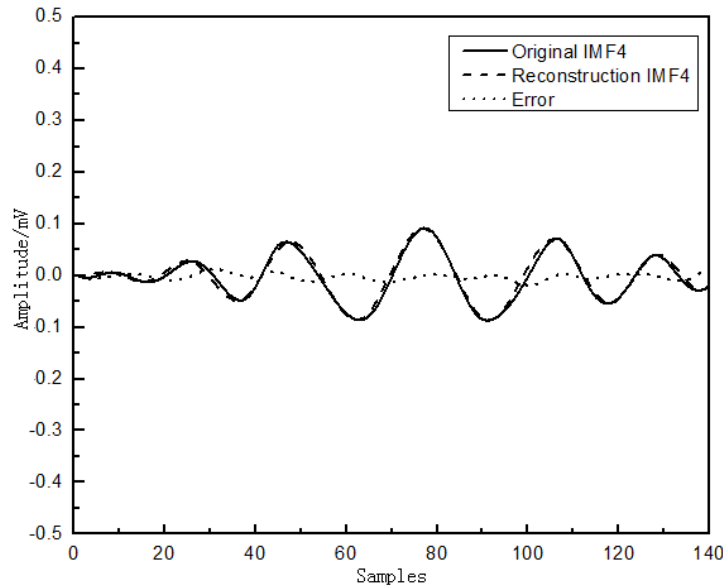


Figure 4. Reconstruction of IMFs by Spline Interpolation

The average error of per reconstruction IMF is showed in Table 1.

Table 1. Average Error of per Reconstruction IMF of ECG Signal

IMF	1	2	3	4	5	6	7	8	9	10
error	0.0015	0.0019	0.0036	0.0010	0.0032	0.0002	0.0007	0.0093	0.0033	0.0019

2.4. Huffman Coding

The Huffman coding algorithm, which allocates frequently occurring data in a low-bit format while allocating less occurring data in a relatively high bit format, is used as the final procedure of the compression. The coding dictionary of Huffman encode per IMF and RES, which complete the second data compression after threshold selecting.

2.5. Reconstruction of the Compressed ECG Data

The reconstruction of the compressed data is accomplished by following the compression procedures in the backward direction as shown on the right side of Figure 1. The first procedure for reconstruction is to apply the inverse Huffman coding. The second procedure is reconstructing IMFs and RES using spline interpolation of extrema after selecting. The third procedure is to calculate the sum of IMFs and RES, which is the reconstruction ECG signal. It can be described as

$$s(t) = \sum_{k=1}^{K-1} IMF_k(t) + RES(t) \quad (9)$$

Where $s(t)$ is reconstruction ECG signal, $RES(t)$ is the residual, K is the number of IMFs and RES.

3. Results and Discussion

Numerous researchers have presented various compression techniques for ECG signals. In general, an evaluation of data compression algorithms uses the six parameters that are CR, PRD, PRDN, RMS, SNR and QS, more detailed definitions can be found in references [15].

We have chosen MIT-BIH arrhythmia datasets as test signals. The algorithm was programmed using MATLAB 2012a and LABVIEW 8.20 based on mixed programming

language. Each procedure of the algorithm was written as a subroutine module. After the implementation of the algorithm, the average CR, PRD, PRDN, RMS, SNR, and QS values were obtained and evaluated. To estimate the algorithm performance fairly, we compare the results to the performance of other compression algorithms like WT, which is showed in Figure 5. The proposed algorithm yields higher CR, SNR, QS and lower PRD, PRDN values as compared to WT (db8), which we chose record no.100 from MIT-BIH arrhythmia datasets as test signals. With the threshold increasing, CR, PRD, PRDN and RMS increase, which shows a positive correlation, while the SNR decreases, which shows a negative correlation. At first, QS increases, and then decreases basically, which exists a maximum. When the threshold exceeds appropriate range, SNR becomes negative value, which means the reconstructed signal has been distorted. Figure 6 shows the results of the algorithm at different threshold for 100 data instance. We can clearly determine the data distortion with threshold greater than 6×10^{-3} from the original signal.

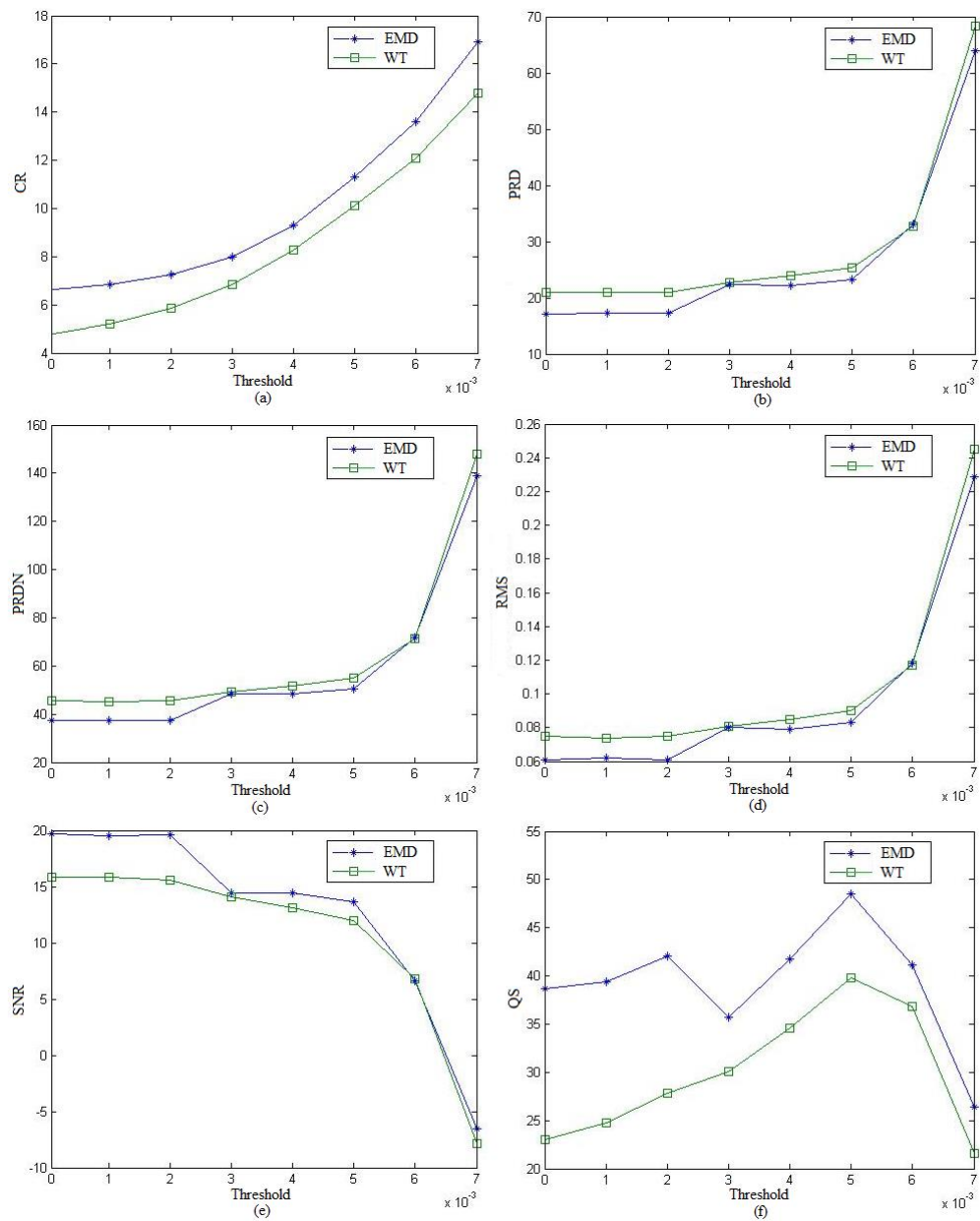


Figure 5. Curves of Six Comparative Evaluation Parameters

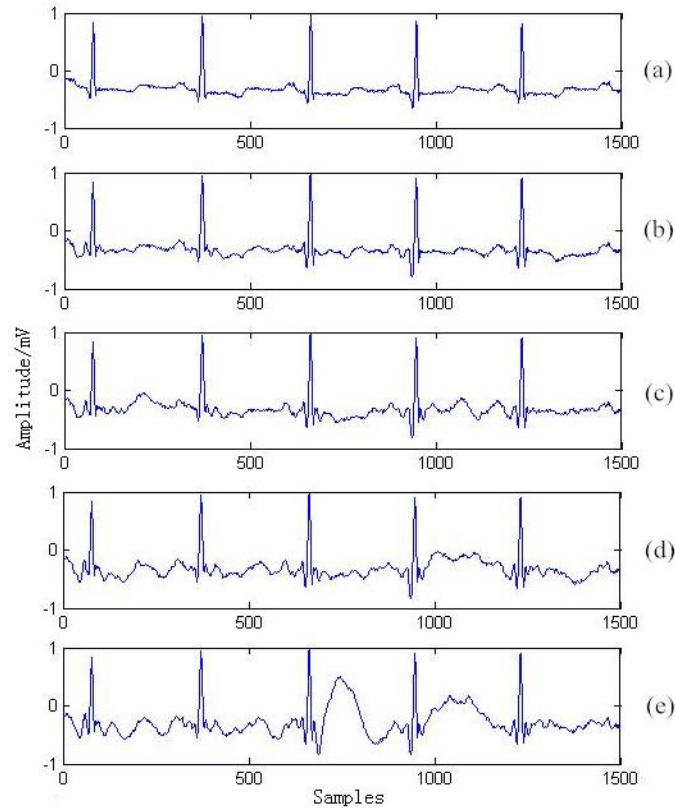


Figure 6. Difference between Original and Reconstructed Signal of Record no.100 at Different Threshold

- (a) Original data. (b) Threshold $=4 \times 10^{-3}$. (c) Threshold $=5 \times 10^{-3}$. (d) Threshold $=6 \times 10^{-3}$.
(e) Threshold $=7 \times 10^{-3}$

Figure 7 shows the original ECG signal (record no.100) and reconstructed ECG signal based on EMD and WT. The proposed algorithm retains the main message of the original ECG signal and yields good fidelity parameters as compared to WT.

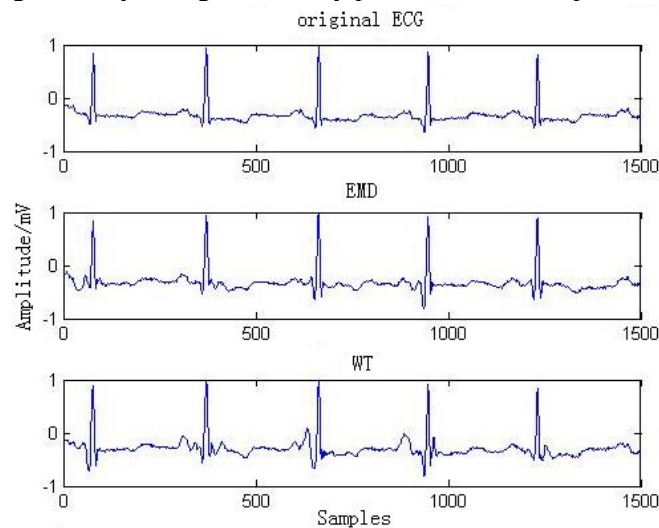


Figure 7. Reconstructed ECG Signal

In Table 2, we chose all 48 MIT-BIH arrhythmia datasets as test signals, whose time-period of signal is 4.158 seconds and sampling rate is 360 Hz, to testify validity of this arithmetic with an appropriate threshold. It can be chosen appropriate compression strategy based on Table 2 for different ECG signal characteristics.

Table 2. Performance of Proposed Compression Algorithm

Record	Threshold	CR	PRD	PRDN	RMS	SNR	QS	Record	Threshold	CR	PRD	PRDN	RMS	SNR	QS
100	0.004	9.30	22.23%	48.27%	0.079	14.57	41.79	201	0.004	10.29	28.62%	35.44%	0.074	20.74	35.96
101	0.002	7.43	22.89%	41.66%	0.082	17.51	32.44	202	0.003	7.75	32.08%	32.88%	0.067	22.24	24.15
102	0.001	7.29	28.49%	43.41%	0.076	16.69	25.60	203	0.005	12.25	25.07%	27.81%	0.126	25.59	48.88
103	0.003	8.50	25.28%	32.55%	0.103	22.45	33.63	205	0.004	11.74	19.73%	49.54%	0.088	14.05	59.48
104	0.005	12.03	34.14%	41.86%	0.118	17.42	35.23	207	0.003	7.95	28.61%	33.63%	0.108	21.79	27.79
105	0.007	15.57	36.38%	47.60%	0.143	14.84	42.79	208	0.006	13.34	49.42%	52.23%	0.269	12.99	26.99
106	0.007	10.25	35.02%	38.11%	0.141	19.29	29.28	209	0.005	10.17	37.76%	46.92%	0.112	15.13	26.93
107	0.008	21.13	40.38%	41.68%	0.344	17.50	52.33	210	0.004	9.12	37.89%	47.09%	0.112	15.06	24.08
108	0.006	13.11	17.86%	39.55%	0.061	18.55	73.41	212	0.005	9.45	30.99%	33.56%	0.104	21.83	30.51
109	0.012	25.08	26.88%	47.78%	0.179	14.77	93.31	213	0.007	15.45	32.70%	40.01%	0.230	18.32	47.24
111	0.008	18.06	36.51%	47.74%	0.089	14.79	49.48	214	0.005	11.64	26.29%	27.41%	0.119	25.89	44.29
112	0.005	15.57	10.13%	50.52%	0.094	13.66	153.74	215	0.007	10.93	42.21%	48.07%	0.112	14.65	25.90
113	0.004	9.29	58.88%	63.45%	0.253	9.10	15.78	217	0.010	17.80	52.58%	52.85%	0.305	12.75	33.86
114	0.005	10.45	53.83%	54.29%	0.133	12.22	19.40	219	0.005	15.91	19.74%	33.13%	0.146	22.09	80.58
115	0.006	15.31	35.56%	71.81%	0.207	6.62	43.06	220	0.004	12.15	17.24%	39.72%	0.121	18.47	70.47
116	0.007	13.37	18.69%	35.16%	0.215	20.91	71.54	221	0.006	10.86	42.35%	45.80%	0.149	15.62	25.65
117	0.007	18.16	13.76%	51.32%	0.121	13.34	131.94	222	0.002	7.52	35.25%	42.49%	0.060	17.12	21.34
118	0.006	13.06	11.45%	35.18%	0.125	20.89	114.04	223	0.007	26.52	29.60%	53.39%	0.202	12.55	89.60
119	0.007	17.84	16.44%	32.83%	0.164	22.28	108.55	228	0.006	11.83	19.30%	32.80%	0.057	22.29	61.31
121	0.005	16.10	11.90%	48.14%	0.097	14.62	135.24	230	0.005	12.86	38.33%	50.83%	0.175	13.53	33.55
122	0.011	19.07	17.66%	42.25%	0.155	17.23	107.99	231	0.005	12.93	37.29%	41.23%	0.117	17.72	34.68
123	0.005	15.23	22.87%	73.79%	0.214	6.08	66.58	232	0.003	11.07	18.34%	33.01%	0.037	22.17	60.35
124	0.005	15.97	15.86%	41.96%	0.141	17.37	100.69	233	0.005	19.74	31.94%	34.35%	0.200	21.37	61.81
200	0.008	17.49	45.82%	48.31%	0.196	14.55	38.17	234	0.005	13.83	39.17%	39.19%	0.110	18.74	35.30

Figure 8 shows the distributions of appropriate thresholds. From the distributions, we can see that appropriate thresholds are relatively concentrated from 5 to 7×10^{-3} .

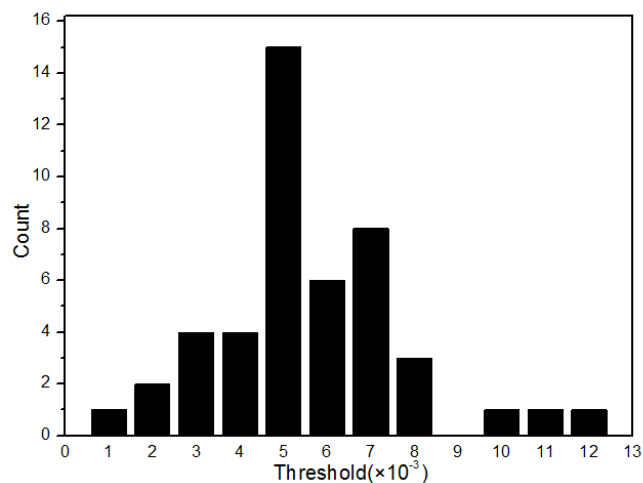


Figure 8. Distributions of Appropriate Thresholds

4. Conclusion

In this paper, an algorithm based on EMD is proposed. Based on IMF properties, the strategy is computationally simple to treat non-stationary and nonlinear data without pre- or post-processing. The algorithm consists of four steps: empirical mode decomposition, peak detecting of IMF and RES, threshold selecting, Huffman coding. When compared, the algorithm yields good fidelity parameters with higher CR, SNR, QS and lower PRD,

PRDN values as compared to CT via using appropriate thresholds. Appropriate thresholds are relatively concentrated from 5 to 7×10^{-3} . The framework is not limited to ECG signals, but also can be extended to large classes of signals such as EEG or EMG signals. As future work, it can be extend to images.

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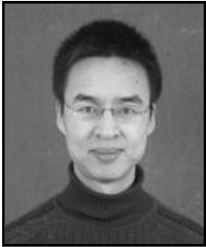
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