

Optimal Selection of Wavelet Coefficients for Electrocardiograph Compression

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ABSTRACT—This paper presents a simple method to implement a complete on-line portable wireless holter including an electrocardiogram (ECG) monitoring, processing, and communication protocol. The proposed algorithm significantly reduces the hardware resources of threshold estimation for ECG compression, using the standard deviation updated with each new input signal sample. The new method achieves superior performance in terms of hardware complexity, channel occupation and memory requirements, while keeping the ECG quality at a clinically acceptable level.

Keywords—ECG holter, thresholding, telemedicine, wavelet compression, low voltage implementation.

I. Introduction

New trends in telemedicine take advantage of wireless mobile networks. Applications focusing on portable devices for 24-hour on-line heart monitoring are in increasing demand. However, serious difficulties are encountered in attempting to reduce the channel costs and electronic resources. Several attempts have been made which partly solve the problem using compression algorithms [1], [2].

Nowadays, continuous electrocardiogram (ECG) signal acquisition requires performance improvements of the conventional compression algorithms. The main goal is an optimized compression which can minimize the number of samples needed to transmit the ECG signal without losing the remarkable information of the original signal in order to achieve a correct clinical diagnostic. Wavelet transform

techniques are among the most extended methods for data compression. Most coder wavelet compression techniques require a large number of zero samples (non-correlated elements) to be codified. In wavelet noise reduction thresholding methods, the increase of the compression ratio is achieved by setting zeros at some parts of the signal [1]-[3]. A balance is established between setting a maximum threshold to remove the non-relevant information and optimizing it to increase the zero values in the wavelet coefficients vector.

The acquired ECG signals are extremely redundant in terms of information and are contaminated by noise from different sources. Denoising the signal by choosing an optimum noise reduction increases both the quality recovery and the compression ratio (CR). Since denoising methods are an important and widely studied topic in processing ECG signals, a large number of threshold definitions and techniques can be found in technical literature [4]. Unfortunately, in portable wireless devices, where the noise variance of an instantaneous signal is *a priori* unknown, the main problem is the assumption of a fixed threshold before the signal is acquired. Previously reported wavelet noise thresholding methods use noise threshold estimation based on the median. The median implies a high amount of memory resources to reorder stored samples, and it slows down the continuous signal transmission process in wireless networks. This is a disadvantage in real-time low-voltage electronic implementations [5].

This letter presents an efficient solution for hardware simplification with a minimum of transmission delay. Our method uses a threshold estimation based on the standard deviation and minimizes the amount of data needed to calculate noise thresholds according to the best channel latency. The proposed procedure combines linear and non-linear thresholding techniques, and is therefore named the hybrid linear non-linear thresholding method (HLNTM).

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II. Hybrid Linear Non-linear Thresholding Method

Linear thresholding methods assume that noise is found at lower wavelet decomposition levels while the upper levels store richer frequency information. Therefore, noise estimation is independent of the size of the coefficients vector. Linear methods are good in signal smoothing and have no signal end effects. The HLNTM vector coefficients are eliminated under a reference level which is chosen by evaluating the discarded signal energy using this value.

Non-linear thresholding methods are based on the assumption that the noise is continuously distributed along all levels. Using time location properties of the wavelet transform, noise in every coefficient can be independently estimated. Moreover, a hard-thresholding to zero in the coefficients is better than a soft-thresholding. But it implies high arithmetic complexity, speed reduction, and a high computation load, so it is not suitable for real-time applications. The proposed HLNTM algorithm is executed in four main steps:

- Step 1.** Decomposition of an ECG signal by the pyramidal digital wavelet transforms
- Step 2.** Linear method: a scale thresholding of the detail coefficients up to the chosen decomposition level
- Step 3.** Non-linear method: hard-thresholding of the remaining coefficient vector by applying the estimated threshold
- Step 4.** Variable run-length coding

1. Wavelet Decomposition

Let X be an ECG signal of N samples which is decomposed according to the pyramidal digital wavelet transform (DWT) using the bior3.9 wavelet up to the level $L=4$ [1]. Let WC be a vector defined as

$$WC = (CA4, CD4, CD3, CD2, CD1),$$

where $CA4$ is the approximation coefficient vector and the detail coefficient vectors are named $CD4$ to $CD1$.

2. Hybrid Linear Thresholding Method

Let S be the scale threshold. The scale threshold value (S) is calculated considering the influence of the approximation and detail coefficients in the target energy of the ECG signal, as will be shown in section III. Therefore, the thresholding vector WC^{LT} is

$$WC^{LT} = (WC(i)=0) \text{ for } i \leq S.$$

3. Non-linear Thresholding Method

After linear thresholding, a threshold calculated using the standard deviation is employed. This threshold is a global (applied to the entire vector) modified threshold based on the

universal Donoho method [4]. Donoho solved the denoising problem of noise contaminated signal, following a normal law $N(0, \hat{\sigma})$ where $\hat{\sigma}$ is the noise variance estimated using the median parameter. Notice that in HLNTM, $\hat{\sigma}$ is calculated instantaneously using the standard deviation parameter. This avoids storing the previous data and it simplifies the memory requirements. The defined threshold can be applied to the wavelet coefficients after a decomposition process as

$$TH = \frac{\hat{\sigma} \sqrt{2 \cdot \ln N}}{\sqrt{N}},$$

where TH is the threshold, and N is the coefficient length. Applying the previous threshold to the whole vector, the hard-thresholding vector WC^{NLT} is obtained as

$$WC^{NLT} = (CA4^{NLT}, CD4^{NLT}, CD3^{NLT}, CD2^{NLT}, CD1^{NLT}).$$

The proposed threshold is optimal to increase the number of vector null elements with good arithmetical efficiency. Both the detail and approximation coefficients are used to estimate the noise threshold. All the coefficients are denoised.

4. Run-Length Coding

The run-length algorithm is used to code the HLNTM resulting vector to increase the compression ratio.

III. Results and Discussion

To test the efficiency of the proposed HLNTM, the two channels of the MIT-BIH Arrhythmia DB records and on-line records are used. The corresponding test dataset includes the following: 100, 101, 102, 104, 107, 117, 119, 201, 207, 208, 209, 212, 213, 214, and 232. Each record was sampled at a rate of 360 Hz using 11 bits/sample of resolution. Offset values have been added to achieve a zero-mean signal.

The energy contribution of each wavelet decomposition level to the whole decomposition vector has been analyzed measuring the energy packing efficiency (EPE). This energy figure has been defined in many different ways. In this case, the formula is applied to the vector WC before thresholding to study the energy contributed by the level coefficient with respect to the total vector energy:

$$EPE (\%) = \frac{\sum_{n=1}^{L_i} Wc_i^2[n]}{\sum_{n=1}^N Wc^2[n]} \times 100,$$

where L_i is the sample number of the c_i -th decomposition level and N is the number of elements of the complete wavelet vector. The performance of every coefficient level on a desired

EPE takes advantage of the total energy between adjacent levels. This property makes it possible to choose which coefficient levels can be suppressed, that is, which specific scale threshold S should be applied in linear thresholding.

The system is optimized using frames of only 512 samples (this is equivalent to an acquisition time of only 1.42 seconds) and is able to obtain the required channel throughput. All the calculated EPEs in the simulation results assure the best performance with a target EPE above 99.8% for a given signal. The best threshold behaviour is determined by analyzing error figures and medical inspection. As an example, Table 1 shows the EPE results for record 117 (first frame) where more than 99.9% of the signal energy is practically concentrated in a few coefficients from the three upper levels (CD3, CD4, and CA4). The threshold level $S=2$ implies that only the coefficients above level 3 are codified.

Observing the approximation and details of the vector histogram before and after thresholding, two results are obtained. The first one is that the detail coefficients are more deeply affected than approximation coefficients when thresholding is executed. The second conclusion is that the detail coefficients have influence on increasing the total null components to be codified later.

In the non-linear step, a global noise threshold has been used on the complete coefficient vector. The best quality performance is achieved using a global universal method, the standard deviation, and all the approximation coefficients to estimate the threshold TH. After that, all the coefficients with absolute value less or equal to TH are zeroed.

Common criteria for performance testing are the compression ratio CR and the percentage root-mean-square difference PRD1 (independent from the mean value), defined as in [2]. The values of PRD1 between 0% and 9% guarantee good reconstructed signals. The evolution of the EPE, PRD1, and the compression ratio of the proposed HLNTM according to the variation of the input size from 256 to 2048 is given in Table 2.

Table 1. Energy contributed by every level to the total energy.

	CD1	CD2	CD3	CD4	CA4
Vect. size	265	142	80	49	49
EPE (%)	0.017	0.060	0.407	25.117	74.396

Table 2. EPE, PRD1, and CR of the proposed HLNTM.

	Number of ECG samples				
	256	512	1024	2048	4192
EPE (%)	99.9	99.9	99.9	99.9	99.9
PRD1 (%)	8.9	5.4	5.5	4.4	4.2
CR	9.8	12.8	8.6	9.9	9.1

The simplicity of the electronic implementation of the proposed HLNTM, optimized for a lower number of samples (512 samples), makes it suitable for portable applications with low memory resources and channel occupancy. Table 3 shows the comparison between the proposed method and the best methods reported in the literature in terms of error figures and compression rates [2], [3] using the same number of samples. Both are very similar in CR versus PRD1. For the 119 record, the PRD1 and CR obtained are better than in [2] and [3]. For the other records, the results obtained are comparable.

Table 3. Comparison of HLNTM with other algorithms. Although HLNTM is optimized for less data, the performance is similar.

		e117	e119	e232	
Proposed HLNTM	PRD1 (%)	4.20	4.61	3.99	9.77
	PRD (%)	1.12	2.25	2.19	5.01
	CR	9.14	16.78	19.01	9.02
Blanco-Velasco [2]	PRD1 (%)	3.56	7.76	9.45	10.48
	PRD (%)	1.17	2.53	5.04	6.28
	CR	8.24	17.40	18.02	9.70
Chen [3]	PRD1 (%)	-	-	-	-
	PRD (%)	1.07	2.0	2.65	4.91
	CR	8.31	17.45	18.14	9.78

IV. Conclusion

The proposed HLNTM algorithm allows a reduction of hardware complexity, channel costs, and memory resources for a real-time embedded ECG holter. The results show that its compression performance is similar to that of other existing methods and preserves the signal quality for medical diagnosis.

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