15th European Signal Processing Conference (EUSIPCO 2007), Poznan, Poland, September 3-7, 2007, copyright by EURASIP

OPTIMUM WAVELET TRANSFORM-BASED ECG COMPRESSION AND DISSIMILARITY MEASURE BASED NOISE PERFORMANCE ANALYSIS

Mustafa NAMDAR, Lütfiye DURAK

Department of Electronics and Communication Engineering, Yildiz Technical University
34349, Yildiz-Istanbul, Turkey
phone: +(90) 212 259 70 70/2886, fax: +(90) 212 259 49 67, email: mustafa_namdar@yahoo.com, lutfiye@ieee.org

ABSTRACT

In this study, an optimum wavelet transform-based ECG compression technique is proposed and its noise performance analysis is investigated. The major addressed issue is guaranteeing an error limit as small as possible measured by the percent root mean square difference (PRD) for the reconstructed ECG signal at every segment while keeping the compression ratio (CR) as large as possible with reasonable implementation complexity. For this purpose, an optimum wavelet transform-based compression algorithm is developed. Noise effects on the normal and the arrhythmia signal is analyzed based on the compression ratio (CR) and the reconstruction distortion. The similarity measurement is used as a criterion to analyze how much the original signal is similar or closer to the reconstructed one. Two numerical metrics PRD and CR are used as the major performance evaluation parameters to analyze the results of the implemented method quantitatively. Using the developed technique, different types of orthonormal wavelets are compared.

1. INTRODUCTION

The aim of electrocardiogram (ECG) data compression is to reduce the amount of digitized ECG data as much as possible, so that reasonable implementation complexity is kept while maintaining clinically acceptable signal quality. In recent years, many schemes for ECG compression have been proposed, which can be grouped into two categories: Direct methods and transform methods [1-5]. In direct methods, the compression is performed directly on the ECG samples, i.e., AZTEC (Amplitude Zone Time Epoch Coding), TP (Turning Point), CORTES (Coordinate Reduction Time Encoding System), SAPA (Scan-Along Polygonal Approximation), PP (Peak-Picking), CC (Cycle-to-Cycle) are the examples of the direct methods. In transform methods, the original samples are transformed to another domain with the hope of achieving better compression performance. Some examples of transform methods include Fourier descriptors, Walsh transform, Karhunen-Loeve transform, and recently developed Wavelet transform [2]. In most cases, direct methods are superior to transform methods with respect to two reasons: System complexity and error control mechanism. However, transform methods usually achieve higher compression ratios (CR).

The major issue addressed in this paper is to guarantee an error limit measured by the percent root mean square difference (PRD) of the reconstructed ECG signal to be controlled at every signal segment, while keeping the CR as large as possible.

In this study, at first, a discrete orthonormal wavelet transform based ECG coding system is proposed. In order to achieve the goal, an optimum wavelet selection method is introduced. Optimum wavelets are selected based on the energy included in the approximation part of the wavelet coefficients in the first level. The proposed method is supported by the results of high CR and low PRD values.

Moreover, a composite noise model is simulated and noise is added to normal ECG and arrhythmia signals. The performance analysis based on CR and PRD parameters are investigated in detail. The relationship between the signal to noise ratio value (SNR) and the reconstruction distortion is determined.

In the first part of the algorithm, decomposition, uniform quantization, and entropy coding are applied to compress the digital ECG signal, successively. In the second part, i.e., the decoder part, entropy decoding, and inverse transformation are applied to reconstruct the original signal with minimum error.

Optimum wavelet search for ECG data compression among orthogonal wavelet families is one of the distinguishing aspects of this study. In the simulations, more than 25 wavelet functions are taken into account. The evaluation parameters, namely PRD and CR are used to compare the performance of the method implemented. Two different ECG signals, normal and arrhythmia signals are analyzed, and the results are reported.

The organization of the paper is as follows. In Section 2 discrete orthonormal wavelet transform (DOWT) scheme is given. In Section 3, optimum wavelet selection algorithm is introduced and Section 4 is about the noise modeling.

Dissimilarity model is presented in Section 5 and Experimental results are submitted in Section 6. Finally, Section 7 concludes the paper.

2. DISCRETE ORTHONORMAL WAVELET TRANSFORM METHOD

The ECG data compression method is based on optimum wavelet transform strategy. DOWT based coding

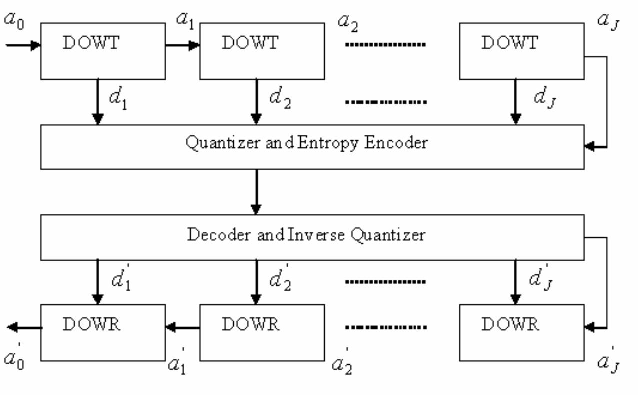

Figure 1 - DOWT based coding system

system is shown in Figure 1. The input discrete signal, a_0 is decomposed into a set of subsignals successively, where a_J is a smoothed version of a_0 where J represents the decomposition level. The differential subsignals, d_j, $1 \le j \le J$ are evaluated between the original signal and its smoothed versions at different resolutions [2].

The decomposed subsignals are then quantized and entropy-encoded in order to be transmitted to a receiver. If the transmission is error-free, the quantized subsignals of a_J' and d_j', $1 \le j \le J$ are used to reconstruct the original signal progressively by the discrete orthonormal wavelet reconstruction (DOWR) transform [2].

When the decomposed subsignals of $\{a_J, (d_j)\}$, $1 \le j \le J$ are quantized, reconstruction error between the original signal a_0 and the reconstructed signal a_0' occurs.

Let ε_j^d and ε_J denote the mean square errors (MSE) occurred in the quantization of dj and a_J, respectively, then the reconstruction MSE (RMSE) γ between the original signal a_0 and its reconstructed signal a_0' is given by,

$$\gamma = \varepsilon_j + \sum_{j=1}^{J} \varepsilon_j^d \tag{1}$$

The expected quantization MSE's of ε_j^d and ε_J can be approximated as in the Equation (2).

$$\varepsilon_J = \frac{1}{2^J}\gamma \ , \ \varepsilon_j^d = \frac{1}{2^j}\gamma \tag{2}$$

The reference wavelet model is as follows. The first stage of decomposition results in $CA1$ and $CD1$. This process is repeated to get the successive approximation and detail coefficients. Based on the decomposition level, i.e., for $J = 5$, $CA5$ in the 5th level and CDi's $(i = 1:5)$ are produced. Uniform quantization is applied for the approximation and detail coefficients. Therefore, the quantization step size, Δ, is different from one another. Due to the coefficients decomposed in different levels, each sample is represented by 8 bits. The quantization bin size is defined as:

$$\Delta = (2.A_{\max})/(2^n) \tag{3}$$

For the approximation and detail coefficients Δ is calculated as,

$$a_j \rightarrow \Delta = (2.\max(|CA5|)/(2^n))$$

$$d_j \rightarrow \Delta = (2.\max(|CDi|)/(2^n)) \tag{4}$$

In Equation (3) and (4), $n = 8$ bits and $A_{\max}$ is changing for all coefficients at different layers [4-7]. In case of $J = 5$, $A_{\max}$ is the maximum value of $CA5$, and CDi, $(i = 1:5)$, respectively.

Implementation of the coding algorithm consists of two parts, namely encoder and decoder parts. The first part comprises the following items [8]:

1. Segmenting input samples,
2. Wavelet decomposition,
3. Uniform quantization,
4. Entropy coding (LZW encoder is used).

The second part is the decoder part:

1. Entropy decoding (LZW decoder used),
2. Wavelet reconstruction.

In order to make the results quantitatively comparable, the most widely used numerical indexes, namely PRD and CR will be employed in this paper.

The CR is used to measure the compression efficiency, which is defined by the ratio of the bits of the original data to those of the compressed data.

$$CR = \frac{\text{original data bits size}}{\text{compressed data bits size}} \tag{5}$$

PRD is taken as a reference indicating the performance of the compression algorithm and formulized in Equation (6). PRD also gives the information of the distortion rate of the reconstructed signal waveform and how the reproduced signal is compatible with the original one [5].

$$PRD = \sqrt{\frac{\sum_{n=1}^{N}(x(n)-\tilde{x}(n))^2}{\sum_{n=1}^{N}x^2(n)}}\% \tag{6}$$

In the equation above, the definitions of the parameters are as follows.

$x(n)$: Samples of the original signals,
$\tilde{x}(n)$: Samples of the reproduced signal,
N: Length of the analyzed signal segment.

The rest of the paper makes use of the PRD and CR parameters. In the following section, optimum wavelet selection algorithm is explained. Then, the noise model is examined in detail.

3. OPTIMUM WAVELET SELECTION

While selecting an optimal wavelet function, the objective is to minimize the reconstructed error variance and maximize the signal to noise ratio (SNR) simultaneously. In general, optimum wavelets can be selected based on the energy content of the approximation part of the wavelet coefficients [9]. Signal energy in the k^{th} level based on approximation and detail coefficients are as follows.

$$E_a = \sum_{i=1}^{N_k}(CA_i)^2$$
$$E_d = \sum_{i=1}^{N_k}(CD_i)^2 \tag{7}$$

where, N_k is the number of the samples in the k^{th} level.

As a result, the signal with *N* discrete samples could store most of its energy in *N/2* approximation coefficients by employing optimum wavelets. The optimum wavelet search will be achieved by including noise. Section 4 describes the noise model in detail.

4. NOISE MODELING

The sources of noise in ECG data recordings may be modeled by following alternatives [10]. Electromyographic interference may be simulated by adding uniformly distributed random noise. The power line interference is another artifact where 60 Hz component is considered as an interferer, which can be generated by using a sinus function. Respiration effects can also be taken into account as a noise component. Besides all of these, electrode motion artifact may be simulated by adding a DC component and assumed to be another noise source. The overall noise model that has been focused in this study is the composite noise, which has been constructed by combining all of the noise types described above.

The composite noise is added to a normal ECG at four different levels: 25%, 50%, 75%, 100% of the maximum amplitude.

When noise is added to the original signal, distortion criteria for the performance evaluation is the parameter of SNR which is expressed as in the following equation [11-13].

$$SNR = 40 - 20.\log_{10}(PRD) \tag{8}$$

In the simulations, normal ECG and the arrhythmia ECG signals are taken from the MIT-BIH database [14]. Dissimilarity measure model is presented in the next section.

5. DISSIMILARITY MODEL

In this study, the similarity measurement is used as a criterion to analyze how much the original signal is similar or closer to the reconstructed one.

For this purpose, using the Gaussian Density function (GD) based on KLD distance (Kullback-Leibler Distance, KLD) gives the information about the similarity between the original ECG signal and the reconstructed version of it, the performance of the compression method and how successful the reproduced signal is obtained.

In the calculation of dissimilarity measurement, wavelet subband coefficient histogram of the normal ECG signal is modeled by Gaussian function and defined as in the following equation.

$$p(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-(x-\eta)^2/(2\sigma^2)} \tag{9}$$

In Equation (9), σ represents the variance and η is the mean value.

The KLD distance defines the similarity between the original signal and the reconstructed one uses the Gaussian model and calculated as follows [15].

$$D(p(.;\sigma_1)\,\|\,q(.;\sigma_2)) = \frac{(\sigma_2-\sigma_1)^2}{\sigma_2.\sigma_1} \tag{10}$$

The σ_2 and σ_1 parameters mentioned in Equation (10) are the variances of the histogram, belongs to the reconstructed signal and the original one, respectively. In general, if the distance D, is close to 1 or equal to 1, means that the original signal is not similar to the reconstructed one. If D is smaller then 1, both signals are approximately similar to one another. In case of normal ECG signal compression, the distance D, in other word dissimilarity parameter is calculated as 0.00035. The result is so important in terms of supporting the experimental results.

Experimental results are presented in Section 6.

6. EXPERIMENTAL RESULTS

In this paper, an optimum wavelet transform-based ECG compression is determined by employing different wavelet families. The original and the reconstructed ECG signal provided after the synthesis process is shown in Figure 2-(a) and (b), respectively. The compression performance, namely the CR value is obtained as 12.91. A widely used quantitative distortion measure for ECG coding is the PRD and is calculated as 2.38% [16].

At the end of the synthesis process, it is observed that the distortion in the original signal seems to happen along the P and T waves. The error between the original signal and the reconstructed one is displayed in Figure 2-(c).

In the simulations, we observe that the reconstruction distortion measure for the arrhythmia ECG signal is higher than the result obtained from the normal ECG signal. CR value is calculated as 16.28, whereas PRD is 43.01%. The compression process for the arrhythmia signal causes loss of information for the diagnosis purposes. When the

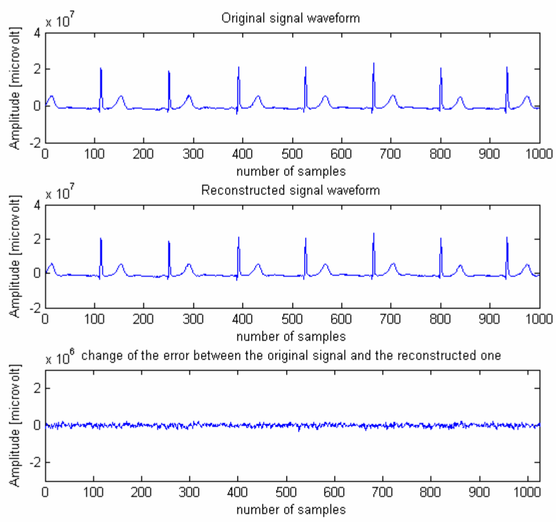

Figure 2 - (a) The original ECG signal, (b) the reconstructed signal, and (c) error between the original and the reconstructed one is presented. In optimum wavelet transform based ECG signal compression, CR and PRD values are calculated as 12.91 and 2.38%, respectively

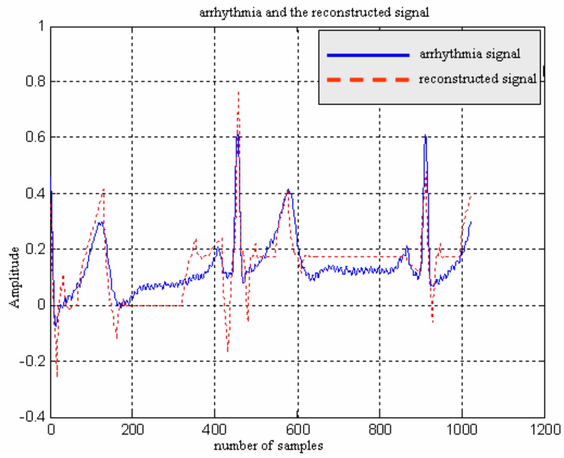

Figure 3 - Optimum wavelet transform based arrhythmia ECG signal compression concluded with the CR value of 16.28 and PRD value of 43.01%

optimal wavelet transform based compression algorithm is applied to the arrhythmia signal the reconstructed waveform is shown in Figure 3 [17]

By using Equation (7), the energy of the original signal and the 1^{st} level approximation and detail coefficients is calculated as shown in Table 1. Table 1 summarizes the energy contributions of the approximation and detail coefficients. *Db20* wavelet function is shown that it includes the highest energy in the first level approximation part, therefore decided as the "optimum wavelet". In order to find the optimum one, orthogonal wavelet families including *DbN*, *coifN*, and *symN* is tested. [18]

The effect of the additive noise to the reconstructed signal at the end of the synthesis process is depicted in Figure 4. In the compression procedure, optimum *Db20* wavelet is employed.

Using the similarity measure model, how the original signal is similar to the reconstructed one is calculated with KLD distance defined in Equation (10) and found as 0.00035.

7. CONCLUSIONS AND DISCUSSIONS

In this paper, optimum wavelet transform-based ECG signal compression is investigated by searching the performances among different orthogonal wavelet families. Normal and arrhythmia ECG signals are both taken into account. Based on the energy inclusion properties in the approximation part of the wavelet coefficients in the first level decomposition, *Db20* is determined as the optimum wavelet. The parameters of PRD, CR and SNR are used to compare the performance of the method implemented. The algorithm is noticeably successful for normal ECG signals.

TABLE 1 - Signal energy distribution

wavelet family (orthogonal wavelets... dbN, symN, coifN)	Ea (1 st level approximation coefficients energy) [e+4]v^2	Ed (1st level detail coefficients energy) [e+3]v^2	Ea contribution to the signal energy [%]	Ed contribution to the signal energy [%]
db2	8.23	4.39	94.95	5.06
db4	8.42	2.58	97.05	2.97
db6	8.49	1.87	97.91	2.16
db8	8.49	1.95	97.94	2.25
db10	8.52	1.83	98.20	2.11
db12	8.56	1.43	98.70	1.64
db20	8.58	1.22	98.91	1.40
haar (=db1)	7.96	7.12	91.79	8.21
sym1	7.96	7.12	91.79	8.21
sym2	8.23	4.39	94.95	5.06
sym4	8.43	2.45	97.21	2.82
sym6	8.48	1.94	97.81	2.24
sym8	8.51	1.69	98.12	1.95
db1	7.96	7.12	91.79	8.21
db3	8.34	3.31	96.19	3.82
db5	8.47	2.09	97.63	2.41
db7	8.50	1.88	97.96	2.16
db9	8.50	1.95	98.00	2.25
sym3	8.34	3.31	96.19	3.82
sym5	8.44	2.40	97.27	2.77
sym7	8.47	2.09	97.65	2.41
coif1	8.29	3.82	95.61	4.40
coif2	8.45	2.31	97.39	2.66
coif3	8.50	1.82	98.04	210
coif4	8.54	1.59	98.46	1.83
coif5	8.56	1.45	98.71	1.67

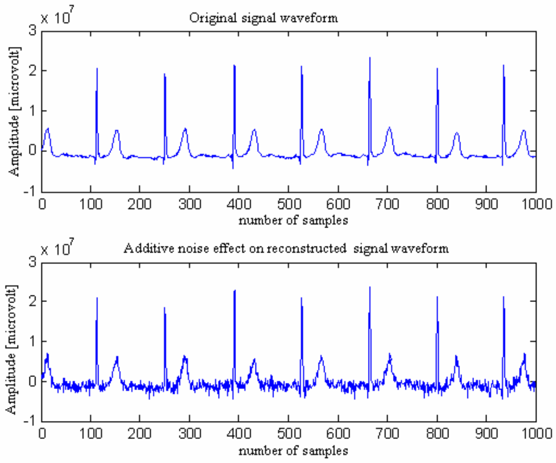

Figure 4 - Reconstructed signal is depicted when the realistic noise is added to the original ECG signal

REFERENCES

[1] Jalaleddine S., Hutchens C., Strattan R., Cobberly W., "*ECG data compression tecniques-A unified approach*", IEEE Trans. Biomed. Eng. vol. 37, pp. 329-343, Apr. 1990.

[2] Chen J., Itoh S., "*A Wavelet Transform-Based ECG Compression Method Guaranteeing Desired Signal Quality*", IEEE Trans. Biomedical Engineering, vol. 45, no. 12, pp. 1414-1419, Dec. 1998.

[3] Ahmed N., Milne P. J., Harris S. G., "*Electrocardiographic data compression via orthogonal transform*", IEEE Trans. Biomed. Eng., vol. 22, pp. 484-498, Jun. 1975.

[4] Thakor N., Sun Y., Rix H., Caminal P., "*Multiwave: A wavelet-based ECG data compression algorithm*", IEICE Trans. Inform. Syst., vol. E76-D, no.12, pp. 1462-1469, 1993.

[5] Hilton M., "*Wavelet and wavelet packet compression of electrocardiograms*", IEEE Trans. Biomed. Eng., vol. 44, pp. 394-402, May 1997.

[6] Hammil S.C., O'Keefe J.H., Freed M., *The Complete Guide to ECG*, Physicians' Press, Minnesota, 2001.

[7] Jayant N. S., Noll P., *Digital Coding of Waveforms: Principles and Applications of Speech and Video*, Englewood Cliffs, NJ: Printice-Hall, 1984.

[8] Ziv J., Lempel A., "*Compression of individual sequences via variable-rate coding*", IEEE Trans. Information Theory, vol. 24, pp. 530-536, 1978.

[9] Mawla A., M.A. Najih, A. R. Ramli, V. Prakash, "*Speech Compression Using Discrete Wavelet Transform*", 4th National Conference on Telecommunication Technology Proceedings, pp. 1-4, Jan. 2003.

[10] Gutierez A., P.R. Hernandez, M. Lara, S.J. Perez, "*A QRS Detection Algorithm Based on Haar Wavelet*", Computers in Cardiology, pp. 353-356, 1998.

[11] Amjed S., A. Fahoum, "*Quality Assesment of ECG Compression Techniques Using a Wavelet Based Diagnostic Measure*", IEEE Trans. Information Technology in Biomedicine, vol. 10, no. 1, pp. 182-191, Jan. 2006.

[12] Coifman R.R., Wickerhauser M.V., "*Entropy-Based Algorithms for Best Basis Selection*", IEEE Trans. Information Theory, vol.38, no.2, pp. 713-718, Mar. 1992.

[13] Proakis J.G., *Digital Communications*, McGraw-Hill, 2001.

[14] http://ecg.mit.edu/

[15] Do M.N., Vetterli M., "*Wavelet-Based Texture Retrieval Using Generalized Gaussian Density and Kullback-Leibler Distance*", IEEE Transactions on Image Pocessing, vol. 11, no.2, pp.146-158, February 2002.

[16] Istepanion, R.S., A.A. Petrosian, "*Optimal Zonal Wavelet-Based ECG Data Compression for a Mobile Telecardiology System*", IEEE Transactions on Information Technology in Biomedicine, vol. 4, no. 3, pp. 200-211, September 2000.

[17] Alesanco A., S. Olmos, R. Istepanion, J. Garcia, "*A novel Real-Time Multilead ECG Compression and De-Noising Method based on the Wavelet Transform*", IEEE Computers in Cardiology, vol. 30, pp. 593-596, 2003.

[18] Zhou X., C. Zhou, I.J. Kemp, "*An Improved Methodology for Application of Wavelet Transform to Partial Discharge Measurement Denoising*", IEEE Transactions on Dielectrics and Electrical Insulation, vol. 12, no. 3, pp. 586-594, June 2005.