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ECG compression by Discrete Cosine associated Wavelet 2-D Transforms

SPIHT statistical method and pic detector

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Abstract—**Biological signal compression and especially ECG has an important role in the survival analysis of heart diseases. The development of the signal compression algorithms is having compressive progress. These algorithms are continuously improved by new tools and aim to reduce, the number of bits necessary to the signal representation by means of minimizing the reconstruction error. In this paper we present a new compression scheme for biomedical signals, especially adapted to the complexity of ECG signals. Discrete Wavelets Transform (DWT) and SPIHT coding (set partitioning in hierarchical trees) efficiency has already been proved, we propose to adapt this transform by associating Discrete Cosine Transform (DCT), so to minimize losses and to improve compression efficiency using 2-D. The signal is converted into 2D and cut into blocks of pixels. Each block is decorrelated either by DCT or DWT according to statistical parameters of 1 or 2 orders. SPIHT encoder is finally applied after this process. After evaluation of proposed method, the results obtained are significant and offer many perspectives.**

Keywords-Compression; ECG; DWT; DCT; statistical parameters

I. INTRODUCTION (HEADING 1)

The growing amount of data generated in many hospitals or ambulatory and in medical imaging centers, now need us to use compression software to solve the problem of storage [1, 2, 3]. Those data will easily be transmitted on telecommunication way if their size is optimally reduced. The problem we want to solve in this paper is to optimize both storage and data transmission of biomedical signals. Compression is an alternative to solve this problem. The challenge is to have the highest compression ratio while providing an accurate reconstruction, and avoid any degradation that could lead to a fatal diagnostic error [1].

Several compression methods are presented in the literature. They can be grouped into two categories: direct methods and methods by transformed [4]. For direct methods, signal is converted into domains where parts without important information for reconstruction are eliminated. Method by transformed [5, 6] help to void duplication errors, and to approach the smallest element [7]. For the ECG compression, we have other methods founded on the principle of extraction of characteristic. Several well known transformations, such as the KLT [8, 9, 10, 11, 12, and 13], DCT [14, 15, 16, 17, 18, 19, and 20] are used for the compression of ECG signal. Take the signal from 1D to 2D allows better handling of parameters in image mode. In fact, many image compression techniques or standards can be applied on the constructed 2D data arrays. For example, in [21], it is proposed an ECG compression method that utilizes the interbeat correlation using the well known JPEG 2000 image compression standard. Readers can refer to [14, 15, 16, and 22] for more information where transform based 2D compression have been proposed. Thus, in this paper, we propose a new method for biomedical signal compression by exploiting signal path 1D to 2D. The image newly formed is processed by bloc using DCT or DWT according to statistical parameters. The result is submitted to SPIHT coder [23], which has been slightly modified to be used with DCT coefficients [24]. Signal to noise ratio, PRD and subjective test allows us to evaluate the performance of this technique. This paper is organized as follows, in Section 2, we present ECG signal; in section 3 we present the compression method, in Section 4, details on the conversion of ECG signal in 2D, and use of statistical parameters. The results are presented in Section 5 followed by a conclusion.

II. ELECTROCARDIOGRAPHIC SIGNALS

In the [25] Electrocardiogram (ECG) was introduced into clinical practice more than 100 years ago by Einthoven. It provides representation of the electrical activity of the heart over time and is probably the single-most useful indicator of cardiac function. It is widely accepted that the ECG waveforms reflect most heart parameters closely related to the mechanical pumping of the heart and can be used to infer cardiac health. The ECG waveform is recorded from the body surface using surface and an ECG monitoring system. Figure 1 illustrates the surface ECG X_100.

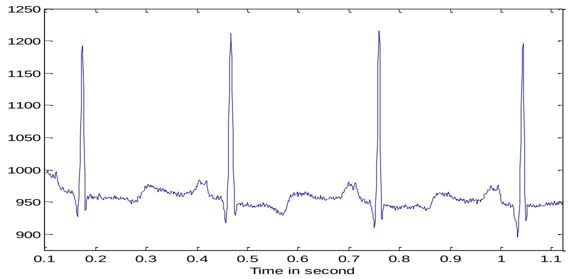


Figure 1. ECG signal

III. PRESENTATION OF THE COMPRESSION METHOD

Transform method, converts the time domain signal to the frequency or other domains and analyzes the energy distribution. Transformation methods involve processing of the input signal by a linear orthogonal transformation and encoding of the output using an appropriate error criterion. Two transforms chose: Discrete wavelets Transform (DWT) and Discrete Cosine Transform (DCT). DCT was used for ECG signal compression and wavelet transform has emerges as an efficient technique of the signals compression. But, the association of DCT and DWT was not exploited yet for ECG compression.

In this section, we present the block diagram corresponding to compression of biomedical signals. An overview of discrete wavelet transforms and discrete cosine is presented.

A. Discrete Cosine Transform

Discrete Cosine Transform (DCT) is a linear transformation similar to discrete Fourier transform. It tends to concentrate information, and makes it so usable for image compression [26] as used by the old JPEG standard. DCT has several advantages: it is real and can be calculated using a fast algorithm (easy implementation), on the other hand, the coefficients are decorrelated in the transform domain and it has excellent concentration of energy for highly correlated data. DCT is often used in signal. In two dimensions, it is given by:

$$B_{pq} = \alpha_p \alpha_q \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} A_{mn} \cos\left(\frac{\pi p(2m+1)}{2M}\right) \cos\left(\frac{\pi q(2n+1)}{2N}\right) \qquad (1)$$

with $0 \le p \le M-1$ and $0 \le q \le N-1$

$$\alpha_p = \begin{cases} \dfrac{1}{\sqrt{M}} & p = 0 \\ \sqrt{\dfrac{2}{M}} & 1 \le p \le M-1 \end{cases} \; ; \; \alpha_q = \begin{cases} \dfrac{1}{\sqrt{N}} & q = 0 \\ \sqrt{\dfrac{2}{N}} & 1 \le q \le N-1 \end{cases}$$

where M x N represent image dimension.

B. Discrete Wavelet Transform

Wavelet transform analyzes signals in both time and frequency domain simultaneously. Therefore it is suitable for the analysis of time-varying non-stationary signals such as ECG.

DWT is one of the most powerful tools in digital signal processing. It is often used in compression methods because of its energy compaction ability. A signal can be represented by scaling and translating a short wave called wavelet. Discrete coefficients describing the scaling and translations are called wavelet coefficients. In the DWT decomposition algorithm, every coefficient at any scale is related with two other coefficients at the immediate lower scale. The DWT can be represented as a dyadic filter bank with level n. For most physical signals the signal energy is concentrated in the lower frequency bands, thus this representation gives energy compaction.

Discrete wavelet transform (DWT) is a multi-resolution / multi-frequency representation [5, 27]. It allows you to efficiency analyze signals that combine phenomena of quite different scales. Transforms steps are hierarchical filtering. This gives sub-bands image decomposition with different filters (low pass h and high pass g). This requires using a separable two-dimensional DWT (rows + columns). The input image is decomposed at each time in four sub-images (approximated image CA, DH horizontal detail, vertical detail and diagonal detail DV DD) with different low-pass and high pass filters.

The reconstruction is done using quadrature mirror filters, represented by their impulses responses (h and g) [28, 29]. This is illustrated in figure 2.

C. SPIHT coding

The Set Partitioning in hierarchical trees (SPIHT) algorithm is a generalization of the EZW algorithm proposed in [23]. The SPIHT algorithm uses a partitioning of the trees in a manner that tends to keep insignificant coefficients together in large subsets. The partitioning decisions are binary decisions that are transmitted to the decoder, providing a significance map encoding more efficient than the EZW. As in EZW, the significance mape encoding, or set partitioning, is followed by a refinement pass in which the representations of the significant coefficients are refined.

Coding plays an important role in compression. SPIHT coding [23, 26] we use, has been slightly modified with respect to the threshold value $S_k(X_i)$. In fact, using DCT in conjunction with DWT introduced a sizing bug during coding. The advantage of this encoder is that according to threshold value, each part of the image can be looked as a detail or not. In the following equation, k is the number of coefficients to encode and S_k the importance of pixel X_i in terms of approximation or detail:

$$S_k(X_i) = \begin{cases} 1 & if \quad |X_i| \geq \dfrac{2^k}{k!} \\ 0 & else \end{cases} \qquad (2)$$

with $k = \left[\log_2 \max_i |X_i|\right] \qquad 0 \leq i \leq k$

D. Compression scheme proposed

Proposed compression scheme is shown in figure 3. Our implementation require QRS detector. The original signal is transformed into a 2D signal to be treated as an image. Once this transformation is made, the resulting image is then divided into pixel block size M × N. Each block in conventional reading order of an image is receiving either decorrelation by DCT or DWT based on an evaluation criterion base on statistical parameters of both transformation coefficients. Transform with best statistical parameters, is adopted and stored for reconstruction. This operation will be performed on all blocks of the image. SPIHT coding slightly modified will be applied to all coefficients. Opposite diagram will be performed for signal reconstruction.

Main steps of compression algorithm are presented in figure 3. Note that **(A)** of figure 3 is given by:

$$(A) = \begin{cases} \text{DCT} & \textit{if statistcis parameters better than those of the DWT} \\ \text{DWT} & \text{else} \end{cases} \qquad (3)$$

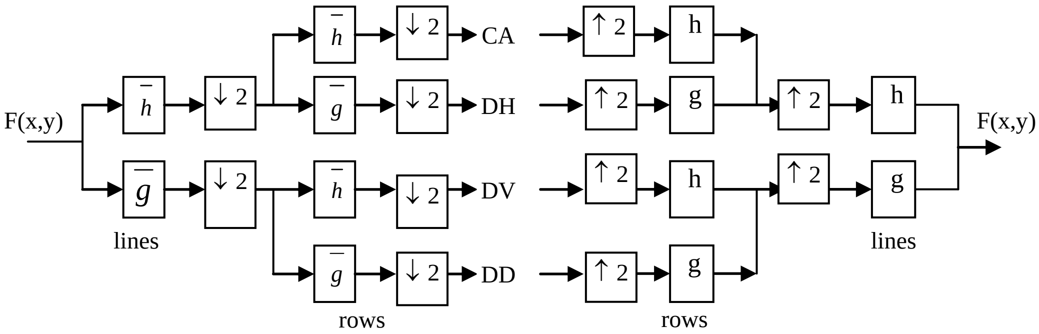


Figure 2. Relation between wavelet coefficients at different scale

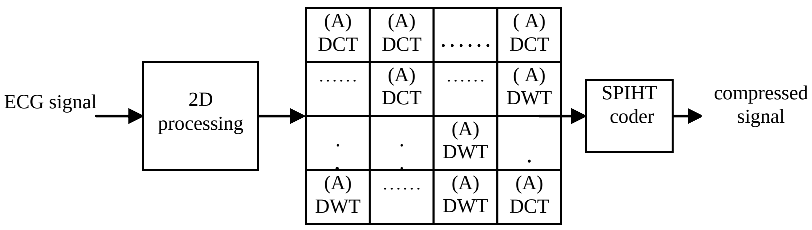


Figure 3. Compression diagram.

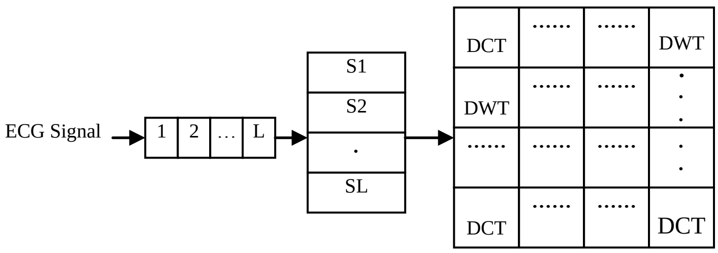


Figure 4. 2D processing diagram

IV. 2D PROCESSING AND COMPARISON MODULE

ECG is a complex signal which has specific features. The presence or not of the QRS complex is essential for diagnosis, hence the importance of a faithful reconstruction. To qualify as an image, the 2D array must have a very good inter dependence between pixels (correlation). The following algorithm optimally performs ECG signal into 2D:

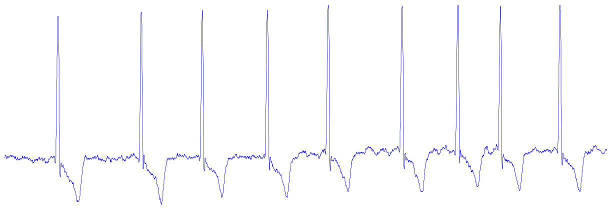
- a maximum detector is used to list all QRS of the signal;

- then a program will be responsible for aligning QRS on after other;
- distance between two consecutive QRS (peak) is N (N columns). However, this distance is not always the same. To standardize their length, an appropriate number of zero is added for each sequence, and we get a new value of N. The number of zero to complete is given by: $Z = 2^{[Log_2(\max(N_i))]}$, *i = 1, 2, ...M.*

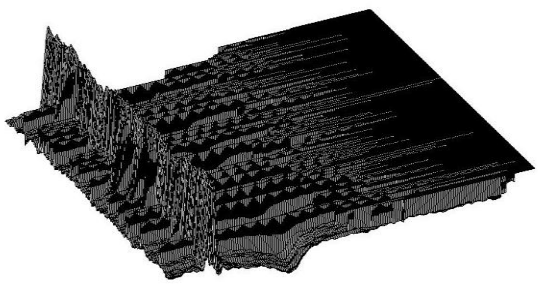
Where N_i represents the length of each heartbeat that forms the matrix.

Sequences are arranged over and under, until an acceptable image matrix is obtained. Once this is done, obtained gray levels are divided into an M×N block. Each block can be transformed into discrete wavelet or discrete cosine based on their statistical parameters. The block diagram in figure 4 summarizes this stage of compression, where *S1, S2 ... SL* are different sequences.

Figure 5 shows an example ECG signal obtained in 2D.



(a)



(b)

(c)

Figure 5. 2D signal X_219: a) QRS peak detection, b) 3D alignment, c) obtained image

After this transformation, the resulting image is divided into pixel block size M × N (Figure 6). This block 32 x 32 produce less interband correlation.

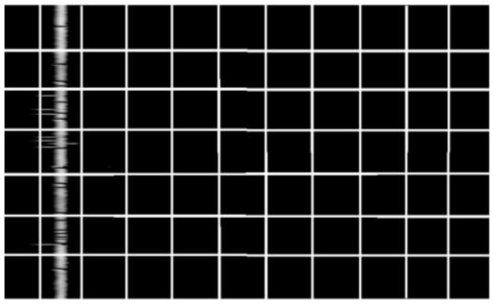


Figure 6. Cut areas undergoing DWT and DCT

Choosing appropriate transformed to each part of the image depends on statistical parameters. Our algorithm evaluates which of two transforms has best statistical parameters. It is necessary to minimize the entropy in order to increase compression ratio. However, it should choose the most sensitive parameter to the program. Because of their easy implementation, variance and entropy has been selected and approved. Variance of a signal depends on its medium and is defined by:

$$\sigma_X^2(n_1) = E\left[\left(X(n_1) - m_X(n_1)\right)^2\right] \quad (4)$$

with $m_X(n_1) = E\left\{X(n_1)\right\}$

and $E\left\{X^m(n_1)\right\} = \int_{-\infty}^{+\infty} x^n p_x(x, n_1)dx$

with $m = 1$, where $p_x(x, n_1)$ is probability density.

Variance helps to evaluate average distance between different samples. Entropy which measure disorder can be defined by its empirical formula:

$$H = -\sum p_i \log_2(p_i) \quad (5)$$

V. Results and Discussion

Reconstruction quality is measured using SNR, compression ratio (CR) and PRD (percent root mean square difference). These criteria are defined as follows: PRD is the most used in literature because of its high sensitivity. It is defined by [30]:

$$\mathrm{PRD} = \frac{\sqrt{\sum_i (x_{org}(n) - x_{rec}(n))^2}}{\sqrt{\sum_i (x_{org}(n))^2}} \times 100 \quad (6)$$

X_{org} represent the original signal and X_{rec} the reconstructed signal.

PRD is link to SNR by:

$$SNR = -20\log_{10}(0.01 * PRD) \tag{7}$$

Compression ratio (CR) is given by:

$$CR = \left(1 - \left(\frac{size\ of\ compressed\ signal}{size\ of\ original\ signal}\right)\right) * 100 \tag{8}$$

Our approach was tested on real ECG data from MIT-BIH arrhythmia database [31]. Bi-orthogonal wavelet 9 / 7 was chosen for DWT. The number of samples is 1024. Results were obtained on signals X_100, X_101,X_117 and X_219. Curves in figures 7 and 8 show variations of SNR and PRD as a function of compression ratio. These curves are decreasing. Indeed, when TC increases, SNR decreases thus, when compression ratio increases, PRD also increases. It shows that the relative error in energy is large at high compression rates. the layout of the PRD according to CR, shows that below CR = 92%, the PRD is included between 0 and 1. The optimal compression ratio is thus around 93%. Examples of original and reconstructed signals are shown in figures 9 and 10.

We note that beyond a compression ratio of 95 % or 97 %, ECG signals begin to degrade. However, this limit depends on used signal. Table 1 summarizes a comparison of results with those in literature for various signals used.

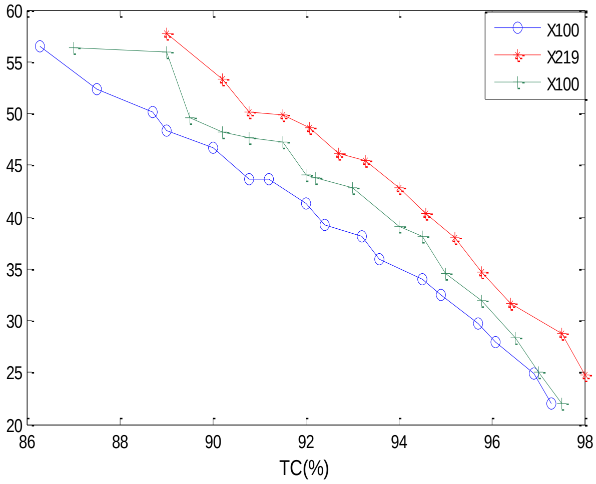


Figure 7. SNR variation as function of CR

TABLE I. COMPARISON OF DIFFERENTS RESULTS

Methods	Signals	CR (%)	PRD (%)
Our algorithm	X_100	90	0.46
	X_117	85	0.92
Sana ktata [32]	X_117	45	1.31
Istepanian [1]	X_100	8	0.57

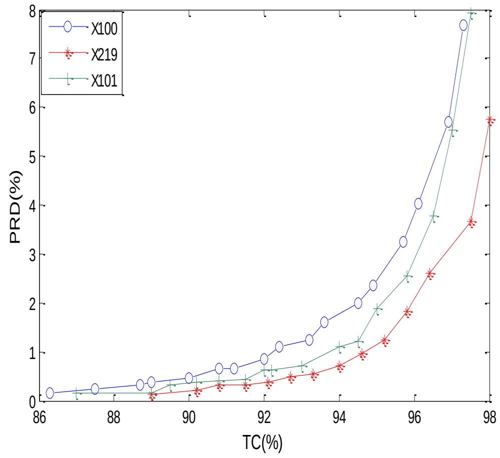


Figure 8. PRD variation as function of CR

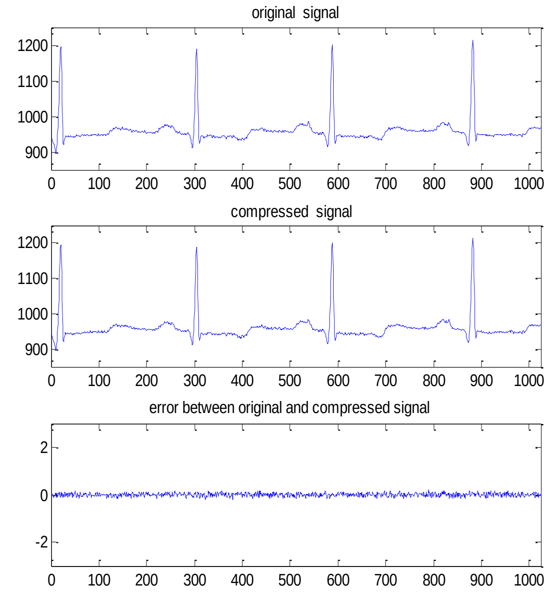


Figure 9. Original and reconstructed ECG X_100; CR=92.5%, PRD=1.23%

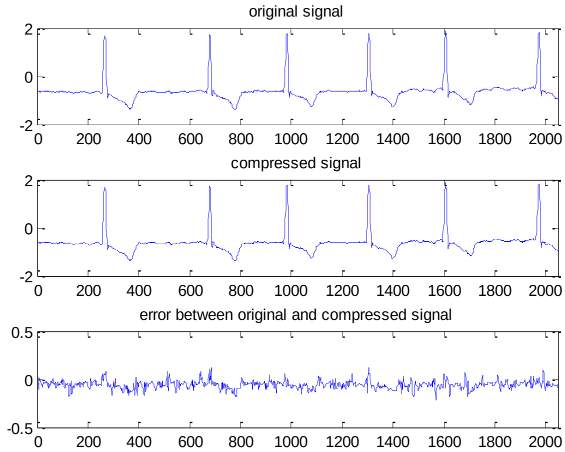


Figure 10. Original and reconstructed ECG X_219; CR=89%, PRD=0.21%

VI. CONCLUSION

In this paper, we have shown that it is possible to compress ECG signals using a compression technique which combined DWT and DCT in dimension 2 according to their respective statistical parameters. The method applied to different signals, developed a pretty good tolerance to high levels of compression. For compression ratios above 96 % (PRD between 1.5 and 3 %), the signal is distorted. Distortion due in part to factors ignored by SPIHT coding and error introduced by the difference between coefficients of DWT and DCT. A brief comparison with other methods has shown an amelioration bring out by our technique. Looking ahead, it will be necessary to extend decorrelation to more than two transformations and see how it is possible to find a better way of combining different statistical parameters. Moreover, it is necessary to see how to select optimal block size M x N. Assessment could prove to be better, but program implementation could be very difficult.

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