COMPRESSION AND DECOMPRESSION OF BIOMEDICAL SIGNALS

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ABSTRACT

In this work, a novel ECG data compression method is presented which employs set partitioning in hierarchical trees algorithm(SPIHT) on two dimensional electrocardiogram(2D-ECG).The 2D ECG is a two dimensioned array, in which each row of this array indicates one or more period and amplitude[7] normalized ECG beats. When SPIHT algorithm is used to compress one or two-dimensional signals separately it is observed that they achieve precise rate control, progressive quality, high compression ratio and low root mean square[7] difference(PRD).Better results are attained because of the wavelet transform eliminating effect[7] on redundancies between adjacent samples. It is also eliminated in one- dimensional ECG-and between adjacent beats by applying 2D wavelet transform. The SPIHT algorithm has achieved prominent success in signal compression. Experiments on selected records of ECG from MIT-BIH arrhythmia database revealed that the proposed algorithm is significantly more efficient for compression.

KEYWORDS

SPIHTAlgorithm, 2Dwavelet decomposition, encoding

1. INTRODUCTION

An ECG is a physiological signal for cardiac disease diagnostics. As the sampling rate, sample resolution, observation time and number of leads increase, the amount of ECG data also increases and so large storage capacity is required. Specially, when data transmission is required, the amount of transmission time also increases and it needs more bandwidth for compensation. With all of these limitations, ECG data compression has been the most active research areas in biomedical engineering and signal processing. Techniques for ECG compression can be classified into three categories:

1) Direct time-domain methods (AZTEC, CM, TP, CORTES, and SAPA, FAN)
2) Transform methods (Fourier, KLT, DCT, Wavelet) and
3) Parametric techniques (linear prediction, long-term prediction).

In technical literature, a number of time–frequency methods are available for the high resolution signal decomposition. This includes the short time Fourier transform(STFT),Wigner–Ville transform(WVT),Choi–Williams distribution (CWD) and the WT.DWT is the appropriate tool for the analysis of ECG signals as it removes the main shortcomings of the STFT[4]; it uses a single analysis window which is of fixed length in both time and frequency domains. This is a major

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drawback[2]of the STFT, since what we really needed are a window of short length(in time domain) for high frequency content of a signal and a window of longer length for low frequency content of the signal. The WT is more better compared to STFT, it is because it is possible to vary the window length depending on the frequency range of analysis. This is obtained by scaling (contractions and dilations)as well as shifting the basis wavelet. The continuous wavelet transform (CWT)transforms a continuous signal into a highly redundant signal of two continuous variables—translation and scale. The resulting transformed signal is easy to interpret and for time-frequency analysis.

An ECG is a pseudo periodic signal, means that not periodic in the strict mathematical sense and not completely a random signal. By looking at the time of evolution of the signal, a concatenation of similar events which almost never reproduce themselves identically is observed. Based on these, several compression methods have been developed. These methods are average beat subtraction with residual[6] differencing, long-term prediction and vector quantization (VQ). Most of these methods are using correlation between adjacent samples in a single cycle(intra-beat dependencies) and not using correlation between adjacent beats across cycles (inter-beat dependencies).Some works have been done to utilize inter-beat dependencies. In this project a new method of ECG compression, using set partitioning in hierarchical trees algorithm (SPIHT) in wavelet domain is presented and it is applied to 2D-ECG.Simulation results, based on data from MIT/BIH arrhythmia database is provided to show the effectiveness of this approach. All ECG data used here are sampled at 360 Hz, 11 bits/sample.

The ECG signal is composed from five waves labeled using five capital letters from the alphabet : P,Q,R,S and T (Fig.1).Compressing the ECG signal while preserving the original shape of the reconstructed signal and especially the amplitudes of Q,R and S peaks, without introducing distortions in the low amplitude ST segment, P and T waves are the main objectives of our project.

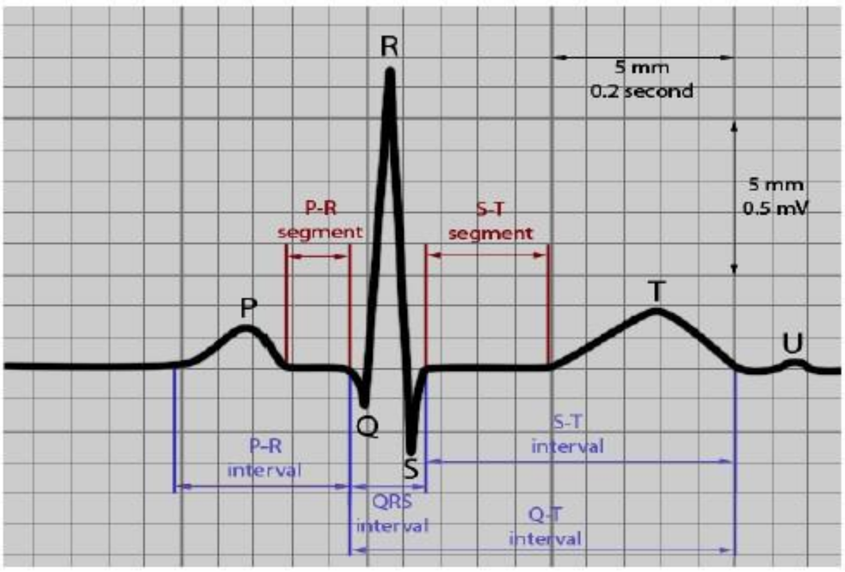

Figure1. Schematic Representation of ECG Signal in Time Domain

2. SYSTEM DESIGN

The project is based on the following block diagram. The first stepis to procure an ECG signal from an existing ECG database over the World Wide Web.A signal cannot be compressed as such and certain pre-processing is needed that is coefficients have to be extracted from the signal.Different types of transforms can beused for this purpose.But,wavelet transform is opted because of its advantages over other transformation methods in this specific compression method.Once the coefficients are obtained,SPIHT compression technique is applied and we obtain the compressed form of the ECG signal as the input.

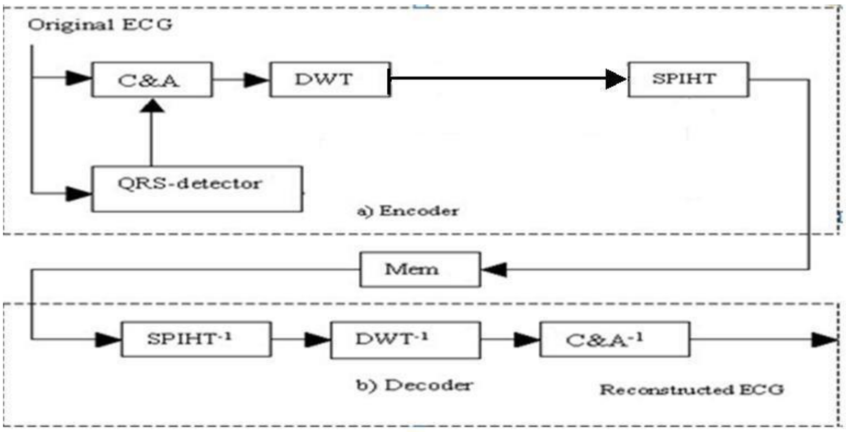

Figure2.Blockdiagram

According to the intra beat correlation and the inter beat correlation of ECG signals, a[5]2-DECG signal compression algorithm is proposed. The proposed algorithm is generally implemented in the following steps.

- QRS detection of the 1-DECGsignal.
- 2-DECGdata array construction.
- 2-D wavelet decomposition.
- Coefficients encoding.
- Reconstruction.

2.1 QRS complex detection of the 1-d ECG signal

In order to fully utilize the inter beat correlation, the input1-DECGsignalhastobefirstQRS complex detected and the original 1-Dsignalcanbe segmented and aligned according to the results of QRS detection. By comparing ever altypical QRS detection algorithms, it is found that the QRS detection scheme is based on wavelet transform, and it has robust noise performance.Itemploysthemulti-resolutionanalysisandbearsflexibilityinanalyzingthe time-varying morphology of ECG data.

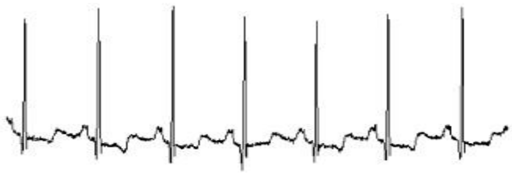

Figure 3.ECG signal

2.2 2-D ECG Data array Detection

Construction of a cut and aligned 2-D ECG data array after the QRS detection is shown in Fig3.Segment the1-D ECG signal according to the heart beat period(namely the R–R interval).A number of zeros are padded to the end of each heart beat data sequence, so that the length of each segment becomes uniform .Because the length of each heartbeat is coded, the number of padded zeros need not be preserved for decoding process. In order to improve the coding efficiency further, estimate the mean heart beat period from some initial cycles of the ECG data and preserve or send it to the decoder. The difference between the mean heart beat period and each heart beat period is coded.

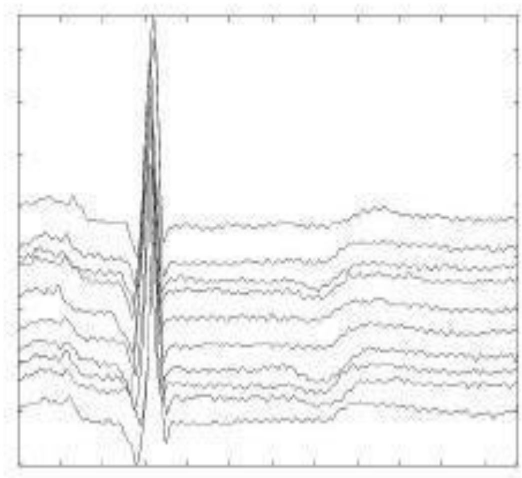

Figure 4. 2-DECGdata array after cutting, padding and aligning

Amplitude normalization brings further similarity between the ECG data. Each sample of a heart beat is divided by the magnitude of the largest sample of that beat. This makes the highest amplitude sample of each beat equal to one. Thus, the variations between the magnitudes of different segments are decreased. To improve the coding efficiency, estimate the mean R-peak value from some initial values of R peaks and preserve or send it to the decoder. The difference between the mean R-peak value and the value of each R peak is noted.

2.3 Iterpolation and decemation

The process of increasing the sampling rate is called interpolation. Interpolation is up sampling followed by filtering. The process of decreasing the sampling rate is called decimation. Decimation is down sampling with appropriate filtering. Interpolation involves inserting new samples between existing samples of a sequence with values derived from the values of the existing samples. Interpolation is up sampling followed by appropriate filtering. so y(n)obtained by interpolating x(n),is generally represented as:

$$y(n)=x(n/L)$$

The simplest method to interpolate by a factor of L is to add L-1 zeros in between the samples, multiply the amplitude by L and filter the generated signal, with aanti-imaging low pass filter at the high sampling frequency.

Decimation is the exact opposite of interpolation. To decimate or down sample a signal x(n) by a factor of M implies collecting every Mth value of x(n)to a new signal. This is given by:

$$y(n)=x(Mn)$$

Down sampling by an integer factor M indicates retaining one sample and discarding the remaining M-1 samples and this is done forever yM samples.ie,It involves the deleting of samples of a sequence with the values derived from values of existing neighbours.Instead of adding signals like in interpolation, signals carrying information about neighbours are deleted, once it is ensured that all the existing samples is enough to reconstruct the signal.

2.4 D wavelet Decomposition

In technical literature, a number of time frequency methods are available for the high resolution signal decomposition. This includes the short time Fourier transform (STFT),Wigner–Ville transform (WVT),Choi–Williams distribution (CWD) and the WT. Out of these, the wavelet transform is the most favored tool by researchers as it does not contain the cross terms in herent in the WVT and CWD methods while possessing frequency-dependent windowing which allows for arbitrarily high resolution of the high frequency signal components.DWT is the appropriate tool for the analysis of ECG signals as it removes the main shortcomings of the STFT; it uses a single analysis window which is of fixed length in both time and frequency domains. This is a major drawback of the STFT, since what are really required area window of short length(in time domain) for the high frequency content[1]of a signal and a window of longer length for the low frequency content of the signal. The WT improves upon STFT by varying the window length depending on the frequency range of analysis. This effect is obtained by scaling as well as shifting the basis wavelet. The continuous wavelet transform (CWT) transforms a continuous[3] signal into a highly redundant signal of two continuous variables translation and scale. The resulting signal is easy to interpret and valuable for time-frequency analysis. In this step we will use wavelet transform.

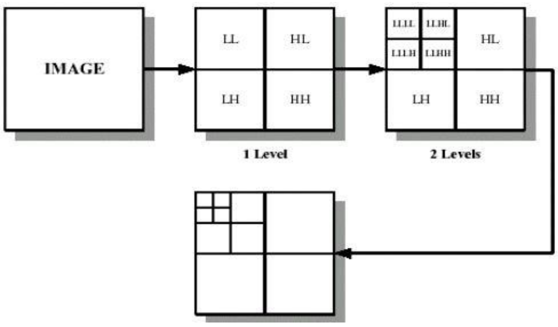

Figure 5.3level2-Ddecomposition

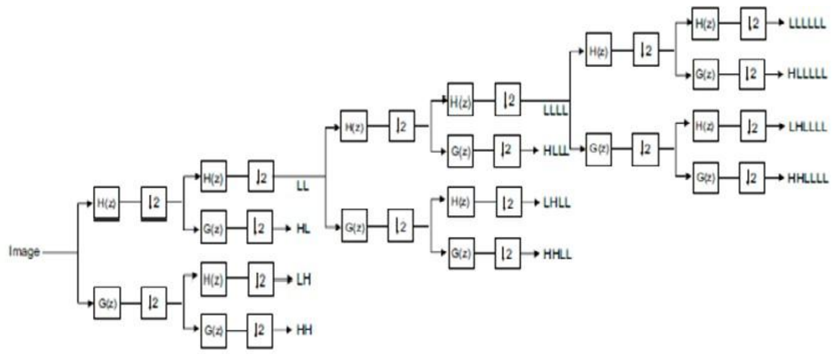

Figure 6.3 level 2-Ddecomposition

Here first, constructed 2-D ECG is decomposed by using 2D wavelet transform upto three levels.After that,the coefficients in each subband[3]of wavelet tree are thresholded. Thresholding does not create significant distortion in reconstructed signal because of the energy invariance property of orthogonal wavelet transforms.This decomposition is repeated to increase the frequency resolution and the approximation coefficients decomposed with high and low pass filters and then downsampled. This is represented as a binary tree with nodes representing a sub-space with a different time-frequency localization. The tree is known as a filter bank.

2.5 Compression algorithm-set partitioning in hierarchical trees

The SPIHT algorithm is a generalization of the EZW algorithm. The SPIHT algorithm was proposed by Amir Said and William Pearlman. In EZW we transmit a lot of information for little cost[1]when we declare an entire sub tree to be insignificant and represent all coefficients in it with a zero tree root label. The SPIHT algorithm uses a partitioning of the trees (which in SPIHT are called spatial orientation trees) in a manner that tends to keep in significant coefficients together in larger subsets. The partitioning decisions are binary decisions[1] are transmitted to the decoder, providing a significance map encoding that is more efficient than EZW.In fact, efficiency of the significance map encoding in SPIHT is such that arithmetic coding of binary decisions provides very little gain.

Thresholds used for checking significance are powers of two, so in essence the SPIHT algorithm sends the binary representation of the integer value of the wavelet coefficients. A sin EZW,the significance map encoding, or set partitioning and ordering step,is followed by a refinement step in which the representations[1]of the significant coefficients are refined.

– O(i,j):off spring of node (i,j)
– D(i,j):all descendants of node (i,j)
– L(i,j)=D(i,j)-O(i,j)
– H:tree roots

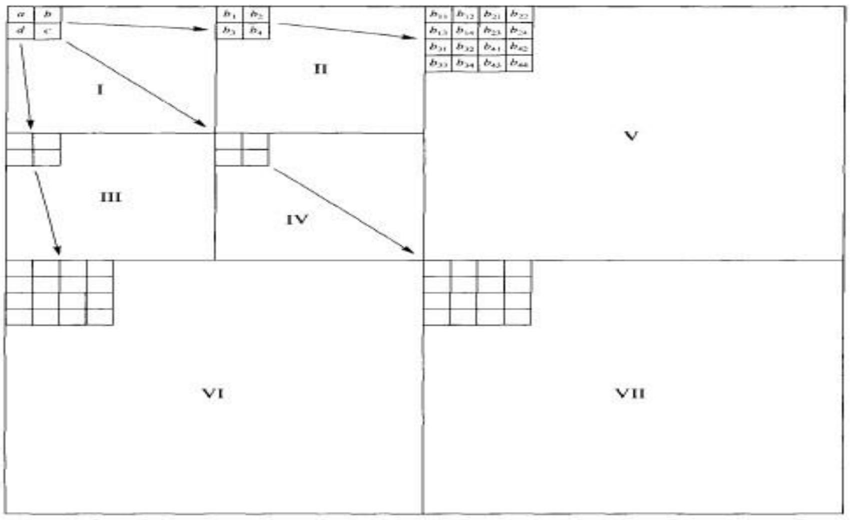

Figure 7.SPIHT wavelet transform example

The algorithm makes use of three different lists: the list of insignificant pixels(LIP),the list of significant pixels(LSP),and the list of insignificant sets(LIS).LSP and LIS lists will contain the coordinates of coefficients, while the LIS will contain the coordinates of the roots of sets of type D or L. We start by determining the initial value of the threshold. We do this by calculating

$$n = [\log 2\ C_{max}]$$

where C_{max} is the maximum magnitude of the coefficients to be encoded. The LIP list is initialized with the set H. Those elements of H that have descendants are also placed in LIS as type D entries. The LSP list is initially empty.

•LIP-list of insignificant pixels

• LIS-list of tree roots (i,j)of insignificant descendant sets D(i,j)(TypeA) or insignificant descendant of offspring sets L(i,j)=D(i,j)-O(i,j)(Type B)

•LSP-list of significant pixels.

2.6 Reconstruction

In the decoder side, the same process is running. The only difference is that the significant/ insignificant decisions found in the encoder by comparing the coefficients to a threshold are input to the decoder. Since the lists are initialized identically, they are formed in the decoder exactly as in the encoder. In there finement pass,the threshold is added to the significant coefficients, instead of subtracted.(The addition or subtraction of threshold is equivalent to adding or removing a bit in a bit plane representation of the coefficient's magnitude.)

Note that the encoding and decoding are comprised of simple operations : comparison to threshold, movement of co-ordinates to lists, and bit manipulations. There are no complex calculations needed for modeling and training prior to coding. The only search is the single search for the initial threshold. The method is completely self-adaptive, always finding the most significant bits of the largest coefficients and sending them before those bits of smaller coefficients.The method is also extremely efficient, as it has the capability to locate large descendent sets with maximum magnitude smaller the final threshold and representing with a single

3. Experimental result

- Compression ratio(CR) : It is defined as the ratio of total number of bits used to represent the digital signal before and after the compression.

- Mean squared error(MSE) : It is defined as the mean squared error. Given a noise-free m×n monochrome image I and its noisy approximation K,MSE is defined as:

$$MSE = \frac{1}{m\,n}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[I(i,j) - K(i,j)]^2$$

- Peak signal to noise ratio(PSNR) : It is the ratio between maximum possible power of a signal and power of corresponding noise that affects the fidelity of its representation. It is usually represented in logarithmic decibel scale. The signal in this case is the original data and noise is the error introduced by compression.

$$\begin{aligned} PSNR &= 10 \cdot \log_{10}\left(\frac{MAX_I^2}{MSE}\right) \\ &= 20 \cdot \log_{10}\left(\frac{MAX_I}{\sqrt{MSE}}\right) \\ &= 20 \cdot \log_{10}(MAX_I) - 10 \cdot \log_{10}(MSE) \end{aligned}$$

Here, *MAXI* is the maximum possible pixel value of the image
Our simulation results are
MSE = 5.5342e-04
PSNR= 48.2475
CR= 1.7104

4. Conclusion

In literature,numerous ECG compression methods have been developed.They may be defined either as reversible methods(offering low compression ratios but guaranteeing an exactor near- lossless signal reconstruction), irreversible methods (designed for higher compression ratios at the cost of a quality loss that must be controlled and characterized),or scalable methods(fully adapted to data transmission purposes and enabling lossy reconstruction). Choosing one method mainly depends on the use of the ECG signal. In the case of the needs of a first diagnosis, a reversible compression would be most suitable. However, ifcompresseddatahastobestored on low-capacity data supports, an irreversible compression would be necessary. Finally, scalable techniques clearly suit data transmission.

In this project, an ECG signal is compressed effectively. It is a new hybrid electrocardiogram (ECG) data compression technique. Firstly, in order to fully utilize the two correlations of heart beat signals,1-DECG data are segmented and aligned to a 2-Ddata arrays. Secondly, 2-D wavelet transform is applied to the constructed 2-D data array. Thirdly, the set partitioning hierarchical trees (SPIHT) method is modified, according to the individual characteristic of different coefficient sub band and the similarity between the sub bands. Finally, a hybrid compression method of the modified SPIHT is employed to the wavelet coefficients. Records selected from the MIT/BIH arrhythmia database are tested.

SPIHT is a simple and efficient algorithm with many unique and desirable properties. One of the stand out features of the SPIHT algorithm is idempotency,that is,lossless recompression at the same bitrate. The algorithm is multiresolution scalable which highlights the ability of the encoder or the decoder to track resolution of bits automatically. The lack of complexity makes SPIHT a very convenient tool for compression ofsignals, especially ECG signals. The entire algorithm is based explicitly on 3 specificlists: List of significant and significant pixels and list of tree roots.Another important feature of the algorithm is there finement pass used.After the completion of the first pass, lossless compression is achieved. Low order bits are more efficiently coded by switching from bit plane transmission at some given highrate there by improving the overall efficiency over a constant value. Due to this, efficient reconstruction is also available which is managed by truncation of file.In other words it is scalable in fidelity. The color planes are coded together. Bits are not allocated in memory locations explicitly providing the algorithm flexibility. Due to this property, different bits will have different transforms suiting the irrequirement. Overall, the algorithm is robust and efficient than other algorithms used for compression of ECG signals.

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