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Wavelet and PCA Based ECG Compression

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***Abstract* - ECG is the most important biological signal for the diagnosis of cardiac diseases. In many cases, ECG monitoring devices generate a huge amount of data. Therefore, compression of ECG signal is an important objective of ECG signal processing for the purpose of efficient storage and transmission. In this paper, a wavelet PCA based ECG compression technique is proposed. Two statistical parameters Percent Root Mean Square Difference (PRD) and Compression Ratio (CR) are calculated to evaluate the performance of the proposed method. The database used for testing purpose is taken from MIT-BIH. The results show that the proposed compression technique provide good performance for different ECG signals considered from clinical point of view.**

Index Terms – ECG, Compression, 2-D Wavelet, PCA.

I. INTRODUCTION

ECG is considered as the most efficient tool for the diagnosis of the heart diseases. It is the graphical recording of hearts electrical activity. ECG is generated by two processes called depolarization and repolarization of cells. In the normal state, cardiac cells are electrically polarized. A flow of electric current is generated by the depolarization process. ECG signal mainly contains five peaks and valleys namely P, Q, R, S and T. It has some specific time interval as shown in the Fig.1. P-wave represents atrial depolarization. QRS-complex is obtained by ventricular depolarization. T-wave is generated by repolarization of ventricles [1].

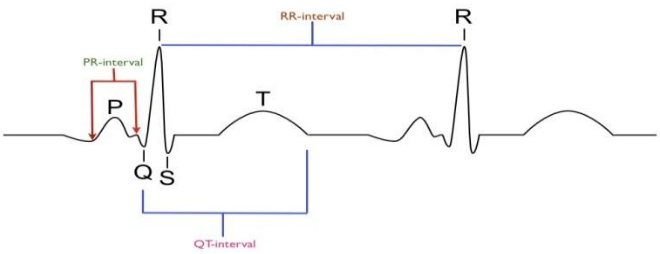

Fig.1: Components of ECG

In many cases, ECG monitoring devices have to monitor the heart condition of a patient for a long duration of time. In such cases, a huge amount of storage capacity is required to store the recorded data. For transmission purpose also, it is not possible to transmit such huge amount of data through network. Storage requirement is further increased with the increase of sampling rate, sample resolution and number of leads. Therefore, ECG compression is an essential operation and consequently represents an important objective of ECG signal processing [2-15].

Generally, compression techniques can be divided into two classes: lossless and lossy compression. In lossless compression method, the original signal can be reconstructed without any loss of information. But, in lossy compression, approximated version of the original signal can be reconstructed with a certain amount of distortion in the reconstructed signal. But in compression of ECG signals, it is important that decompressed signal contains all the clinically important information. Otherwise, the decompressed signal becomes misleading for the diagnosis of heart condition of a patient. Furthermore, ECG compression techniques can be classified into direct data compression techniques, transformation approaches and parameter extraction techniques.

Principal component analysis (PCA) is a statistical methodology whereby the main linear factors underlying the movement of a given multivariate data series are extracted as distinct vectors. It is a method of dimensionality reduction without sacrificing the accuracy much. PCA aims to summarize data with many independent variables to a smaller set of derived variables in such a way that first component has maximum variance, followed by second, followed by third and so on. Therefore, the first few principal components represent the information of the data. Hence, the original data can be reconstructed very well even if last few components are lost.

The organization of this work is as follows: in section II a brief review of literature is presented. Proposed compression method is explained in section III. Section IV presents the experimental results. Finally, conclusions are given in section V.

II. LITERATURE REVIEW

In ECG data compression algorithms, the main objective is to achieve a low information rate, while preserving the relevant diagnostic information in the reconstructed signal. In recent years, lots of ECG data compression methods have been proposed. In [2], a multichannel ECG compression technique based on Multiscale PCA in wavelet domain is proposed. Here a new PC selection method based on average fractional energy contribution of eigenvalues in a data matrix is also proposed. In this method, compression is achieved by uniform quantizer and entropy coding of PCA coefficients. For the evaluation of the compression result, two statistical parameters PRD of each lead and wavelet energy-based diagnostic distortion (WEDD) are calculated. The reconstructed signal quality was found to be very good containing the diagnostic information.

The authors in [3], proposed a 2-D Discrete Wavelet Transform (DWT) based ECG compression technique. In the pre-processing stage, QRS-complex is detected. Then, a 2-D matrix is formed by storing each period as a row in the matrix. This 2-D matrix is wavelet transformed and the obtained wavelet coefficients are segmented into groups and thresholded. Finally, the thresholded coefficients are coded using coding technique. This method gives high compression ratio with relatively low distortion.

In [4], a 2-D wavelet based ECG compression method is proposed. Firstly, the 1-D ECG signal is segmented and aligned to form a 2-D data array. Then 2-D wavelet transform is applied to the constructed 2-D data array. Here, a modified vector quantization (VQ) is applied to the obtained wavelet coefficients. The experimental results provide higher compression ratio with clinical features well preserved.

In [5], an ECG compression method is presented based on beta wavelet using lossless encoding. In this method, run-length encoding is used. This method uses a modified thresholding. Here, the compression of the signal is improved by the wavelet filters based on beta function and its derivative. The results show the superiority of this technique in terms of compression ratio and signal quality.

The authors in [6], proposed target distortion level (TDL) and target data rate (TDR) wavelet based ECG compression algorithms for real time applications. Two statistical parameters PRD and Root Mean Square Difference (RMSE) are calculated as a quality measures. Here, different conditions of different ECG signals are considered for the evaluation of data rate variability and reconstructed signal quality. The experiment results show that the TDR algorithm provide high data rate for real-time application in communication.

In this paper, a single lead ECG compression method based on wavelet and PCA is proposed. In the proposed method, a new PC selection technique is proposed based on the variance of the original signal and the level of wavelet decomposition.

III. PROPOSED METHOD

The present work presents single lead ECG data compression using PCA. This method is based on 2D DWT. Here, a 2D matrix is formed from the original signal where each column of the matrix contains approximately one heart beat. Then PCA is applied to each 2D coefficient matrix obtained from 2D DWT of the generated 2D matrix. The block diagram for the proposed method is shown in Figure 2.

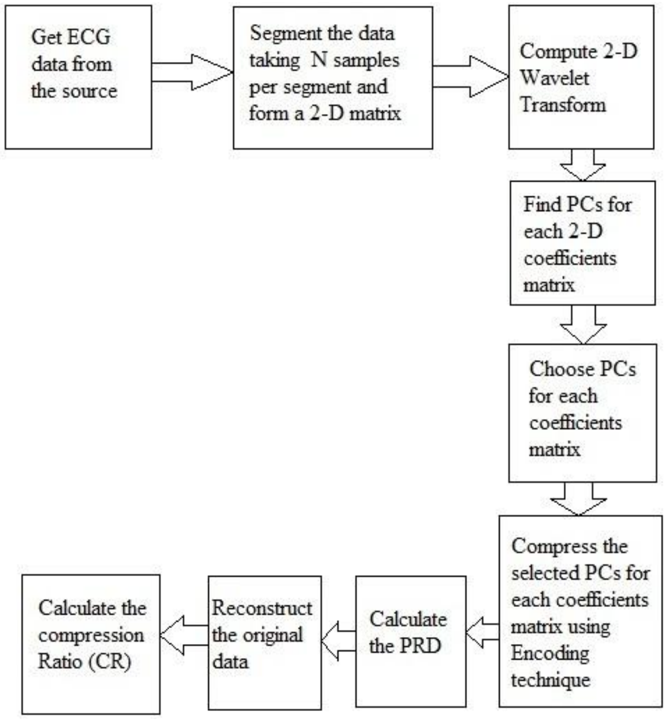

Figure 2: Block diagram for proposed method

A. *Pre-processing*

In pre-processing stage, denoising of ECG signal is performed. There are different types of noises that are present in an ECG signal during acquisition. The major ones are high frequency noise; power line interference and baseline wander noise. High frequency noise caused due to muscle activity and outer environment. Power line interference occurred due to improper grounding of power line. Baseline wander is a low frequency noise caused due to offset voltages in the electrodes, respiration and body movement. Thus noise removal becomes an essential part for proper analysis [16]. The outcome of ECG compression process is influenced by the noise level present in the signal. Accordingly, if the noise present in the signal is more, then the compression ratio will decrease. Here, probability based ECG denoising technique is used for noise removal [17]. In this process, at first the acquired ECG signal is decomposed using wavelet transform. Then, probability of wavelet coefficients are determined at different levels. The noisy coefficients are thresholded based on different probability based threshold for different levels. Finally, the pre-processed ECG signal is obtained by inverse wavelet transform (IWT) of the thresholded coefficients.

B. *Wavelet PCA based Compression*

In this scheme, compression is achieved by applying entropy coding to the selected principal components of each 2-D coefficients array obtained from 2-D DWT of ECG signal. The selection of PC is based on variance of the original signal and the level of wavelet decomposition. This compression technique has five major steps. First, the signal is segmented to form a 2-D array such that each segment contains approximately one heart beat. In the second step, 2-D DWT is applied up to 4 decomposition level to the constructed 2-D array in the first step. In the third step, principal components (PCs) are extracted for each 2-D coefficients array. In the next step, PCs are selected for each 2-D coefficients matrix. Finally, selected PCs are compressed by using entropy coding.

Each of the steps is discussed in detail in the following subsections.

1. Generating data matrix:

The signal segment of a heart beat is represented by the column vector as-

$$y = \begin{bmatrix} x(1) \\ x(2) \\ . \\ . \\ . \\ x(N) \end{bmatrix}$$

where N is the number of samples of the segment. If M number of heart beats are considered, then the entire ensemble is compactly represented by the $N \times M$ data matrix,

$$X = [y_1 \quad y_2 ....y_M]$$

Thus X is the data matrix.

2. Wavelet decomposition:

The 2-D data matrix X of size $N \times M$ is decomposed by applying 2-D DWT. The `L' level wavelet decomposition results in `L' th approximation 2-D coefficients array cA_L and ` $j$ 'th detail 2-D coefficients array in three orientations (horizontal, vertical and diagonal) as $cH_j$, $cV_j$ and $cD_j$ where $j = 1, 2, ....., L$. This results in `3L+1' number of 2-D coefficients matrices and arranged as $[cA_L, (cH_L, cV_L, cD_L), ..., (cH_1, cV_1, cD_1)]$.

3. Applying PCA on coefficient matrix:

After taking 2-D DWT, the PCA of each 2-D coefficients matrix is performed. This gives number of eigenvalues and eigenvectors and they will be in pairs. Eigenvalues and their corresponding eigenvectors are arranged in descending order. The principal components are selected based on the eigenvectors with corresponding higher eigenvalues. The number of eigenvalues chosen determines the reduction of dimension. Ordered eigenvalues in approximation (A) and detail coefficients matrices (H, V, D) are:

$$\lambda_{A_1}, \lambda_{A_2}, \lambda_{A_3}, ..., \lambda_{A_n}$$

$$\lambda_{H_{j1}}, \lambda_{H_{j2}}, \lambda_{H_{j3}}, ..., \lambda_{H_{jn}}$$

$$\lambda_{V_{j1}}, \lambda_{V_{j2}}, \lambda_{V_{j3}}, ..., \lambda_{V_{jn}}$$

$$\lambda_{D_{j1}}, \lambda_{D_{j2}}, \lambda_{D_{j3}}, ..., \lambda_{D_{jn}}$$

where, ` $j$ ' is the wavelet scale and `n' is the total number of eigenvalues for that particular 2-D coefficients array.

4. PC selection method:

Here, a new PC selection scheme based on the variance of the original ECG signal is proposed. The PC selection process is performed by deriving different threshold for different coefficients matrices. These thresholds depend on the variance (σ) of the original ECG signal. Because, if variance is less, then the value of these thresholds will be more and less number of PCs will be selected, that resulting more compression. Conversely, if variance is more, then the value of these thresholds will be less and more number of PCs will be selected, that resulting less compression. These PC selection thresholds can be defined as:

$$T_A = \frac{\sum_{i=1}^{n} \lambda_{A_i}}{\sigma L} \qquad (1)$$

$$T_{H_j} = \frac{\sum_{i=1}^{n} \lambda_{H_{ji}}}{\sigma L} \qquad (2)$$

$$T_{V_j} = \frac{\sum_{i=1}^{n} \lambda_{V_{ji}}}{\sigma L} \qquad (3)$$

$$T_{D_j} = \frac{\sum_{i=1}^{n} \lambda_{D_{ji}}}{\sigma L} \qquad (4)$$

Where, T_A is the threshold for Approximation coefficients matrix. T_{H_j}, T_{V_j} and T_{D_j} are thresholds for horizontal, vertical and diagonal detail matrices at ` j 'th decomposition level. Those eigenvalues which are greater than threshold are selected from each coefficient matrix (A, H_j, V_j, D_j), that decide the number of PCs.

After selection of PCs, they are quantized and Huffman encoded. Here different quantization levels such as 4-bits to 8-bits are used for different PCs. The compressed data is obtained after Huffman coding the quantized PCs. Then the compression ratio (CR) is calculated as:

$$CR = \frac{Original\ File\ Size}{Compressed\ File\ Size} \qquad (5)$$

To reconstruct the original signal, Huffman decoding, de-quantization and PCA reconstruction is performed. The wavelet coefficients are passed through the same wavelet reconstruction filter. Finally PRD is calculated between reconstructed and original ECG signal using equation (6).

$$PRD = \sqrt{\frac{\sum_{n=1}^{N}(x[n]-\hat{x}[n])^2}{\sum_{n=1}^{N}(x[n])^2}} \times 100 \qquad (6)$$

Where, $x[n]$ is the original signal and $\hat{x}[n]$ is decompressed signal.

IV. EXPERIMENTAL RESULTS

In this paper, a new 2-D DWT and PCA based ECG compression technique is proposed with minimum loss of clinical information in the reconstructed signal. This section presents the experimental results obtained from the proposed compression algorithm. The database is taken from MIT-BIH [18] for the evaluation of the proposed compression method. Each file in the database consists of two lead recordings sampled at 360 Hz with 11 bits per sample resolution. From each record first 3000 samples of first lead are considered for experimental purpose. Wavelet decomposition using Daubechies 7/9 biorthogonal wavelet filters are used and same has been applied for reconstruction filters also. Here, original ECG signal is segmented to form a 2-D data matrix where each segment contains approximately one heart beat. Then 2-D DWT is applied on this 2-D data matrix. In this work, wavelet decomposition up to 4 levels is used. As a result, 13 coefficients matrices are found. PCA is then applied on each of these coefficients matrices.

Table 1: PC selection for each coefficients matrix of 105 Arrhythmia database

2-D coefficients matrix	Total extracted PCs	Selected PCs
cA_4	16	4
cH_1	14	9
cH_2	15	7
cH_3	16	5
cH_4	16	4
cV_1	14	8
cV_2	15	7
cV_3	16	6
cV_4	16	5
cD_1	14	8
cD_2	15	7
cD_3	16	6
cD_4	16	5

The efficiency of the proposed compression technique can be measured based on two parameters. The compression ratio (CR) is the first measurement that reflects the ratio between the original to the compressed ECG file size. The second one is PRD, used for distortion measurement between the original ECG signal and the reconstructed ECG signal.

Fig. 3(a) shows original ECG signal from record 105 from MIT-BIH Arrhythmia database and (b) shows the decompressed signal. Some circled areas are shown in Fig. 3(b). These are distortions observed in the decompressed signal. Here, distortions are mainly observed in the areas where diagnostic information is less. Table 1 presents principal components obtained for each of the coefficients matrices for 105 Arrhythmia database. Here, the first column presents different coefficients matrices obtained from 2D DWT, the second column shows total number of PCs extracted for each coefficients matrix and the last column indicates the number of selected PCs by the proposed PC selection procedure.

Table 2: Average PRD and CR values for the proposed compression method

Database Type	Record no.	Without denoising		With denoising	
		PRD	CR	PRD	CR
Arrhythmia	100-124, 200-207	0.617	8.192	0.527	10.305
PTB Diagnostic	S0010 ,s0014-s0017, s0021	1.612	8.152	1.690	9.149
Noise Stress	118e00, 118e06, 119e00	2.035	8.060	2.022	9.297
Non-Invasive Fetal ECG	Ecgca102, ecgca192, ecgca252	3.743	8.401	3.568	8.898
Sudden Cardiac death holter	30-32	2.983	7.202	2.382	9.113
Average		2.198	8.001	2.037	9.352

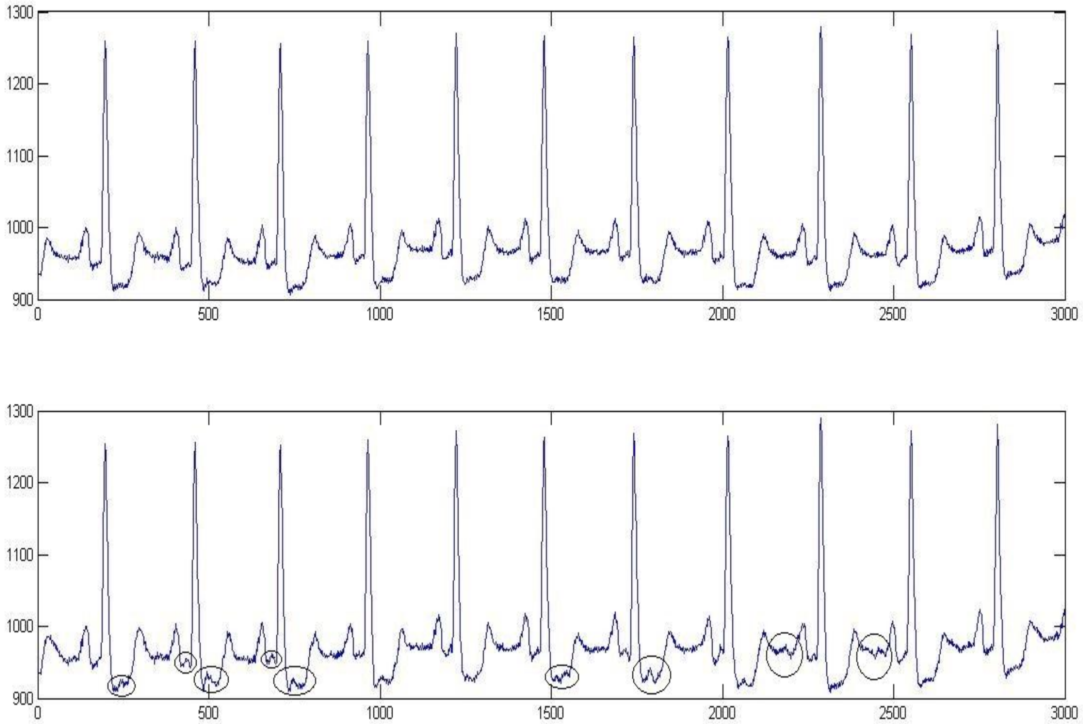

Figure 3: Reconstructed signal by proposed method: (a) Original Signal (b) Decompressed Signal (105 Arrhythmia database from MIT-BIH

The results obtained by the proposed method when applied on various databases are given in Table 2. The first and the second column in the table show different type of databases from MIT-BIH and the records that are used for testing purpose. Next two columns in the table provide results obtained by the proposed ECG compression technique without applying any denoising technique on the ECG signals. Last two columns give results obtained by the proposed method after applying denoising technique. It is seen from the results that the PRD value is improved when denoising technique is applied. Similarly, CR is also increased when denoising technique is used. The proposed compression method is compared with existing data compression methods in Table 3. The experimental results show that proposed method provides an average PRD of 2.037 and CR of 9.352. It is observed from Table 3 that, [3] and [6] provide more CR. But, PRD values are also increased. Therefore, the proposed method shows good CR with low PRD value. It is also observed that the clinical information is preserved to the significant level in reconstructed signals.

Table 3: PRD and CR comparison with existing methods

Methods	Database used	No. of channels	PRD	CR
Proposed method	MIT-BIH	1	2.037	9.352
L. N. Sharma et al.[2]	CSE Multilead Measurement library	12	2.090	5.980
M. Abo-Zahhad[3]	MIT-BIH	1	2.209	24.288
Manikandan et al.[6]	MIT-BIH, Creighton University	1	6.330	12.000

V. CONCLUSION

This paper presents single lead ECG data compression. In this proposed method, a 1-D ECG data is first segmented and aligned to form a 2-D data array and compression is achieved by entropy coding of selected principal components. This method is based on 2-D DWT of 2-d data array. It is observed that the proposed algorithm provides good compression ratio with good reconstruction signal quality in terms of clinical information present. Hence, the proposed method can be considered as a simple but effective ECG compression method. In some cases, clinical components are not preserved correctly. In future the algorithm can be improved by modifying the PC selection threshold for effective reconstruction of the signals. Later, it can be extended for multichannel ECG signal.

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