Electrocardiogram Compression by Linear Prediction and Wavelet Sub-Band Coding Techniques

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Abstract

Linear Predictive coding (LPC) is extensively used for analysis and compression of speech signal whereas the Discrete Wavelet Transform is widely preferred for electrocardiogram (ECG) compression. In this paper, we present LPC and wavelet based method to encode ECG signals. The compression algorithm has been evaluated with the MIT-BIH Arrhythmia Database, MIT-BIH Compression database and University of Glasgow noisy and normal database. The performance is quantified by computing distortion measures. The percentage root mean square difference (PRD) is found to be below 8% and wavelet-based weighted PRD (WWPRD) below 0.25. The upper quartile value of Wavelet energy based diagnostic distortion (WEDD) is less than 0.3 even for noisy data. It is observed that, a combination of LPC and wavelet subband coding offers fixed compression of 84.09%. Classification before decompression is achieved with accuracy of 97%.

1. Introduction

The electrocardiogram (ECG) is a graphical representation of heart's functionality and is an important tool used for diagnosis of cardiac abnormalities. A patient monitoring system acquires huge amount of ECG data which is either to be stored or to be transmitted in telemedicine applications. This necessitates compression of this data while preserving significant clinical content. Compression can be either lossless or lossy. In the lossless methods, data is compressed in such a way that the original data is exactly restored upon reconstruction (decompression). In the lossy methods, a tolerable data distortion is present between the original and reconstructed data. Most ECG compression techniques are of the second category, or a combination of the two categories. Recently, wavelet-based ECG compression is predominantly proposed because of its simplicity and high compression performance [1-3].

The technique composes of three main stages at encoding: linear prediction, wavelet transformation and removal of high frequency wavelet coefficients. Whereas at decoding, reconstruction is obtained by: wavelet reconstruction, inverse LPC filter. The brief theory of LPC and Discrete wavelet transform (DWT) is explained. Fuzzy c means clustering and feature extraction is described and finally the results of our experimentation are demonstrated. The performance of our method is validated by computing distortion measures.

2. Methods

2.1. Linear prediction coding

Linear prediction coding (LPC) is a method in which a particular value is predicted by linear function of past values of signal [4]. In our proposed ECG compressor, one step forward linear predictor is used, which is a FIR filter of order *p*. The predicted value is computed from the equation 1 as

$$\hat{x}(n) = -\sum_{k=1}^{p} a(k)x(n-k) \qquad (1)$$

where $\hat{x}(n)$ is predicted value, $x(n\text{-}1)$, $x(n\text{-}2)$, $x(n\text{-}3)$, ... $x(n\text{-}p)$ are past values of signal $x(n)$ and $a(1)$, $a(2)$, ... $a(p)$ are filter coefficients. The order *p* of LPC decides the accuracy of prediction. The good prediction can be achieved with optimal determination of the filter coefficients. In order to design filter coefficients coder attempts to minimise mean square error. The error of prediction is expressed as

$$e(n) = x(n) - \hat{x}(n) = \sum_{k=0}^{p} a(k)x(n-k) \qquad (2)$$

where $a(0) = 1$. The mean-square value of the error (MSE) is given by equation 3 as

$$MSE = E[e^2(n)] = E[(\sum_{k=0}^{p} a(k)x(n-k))^2] \qquad (3)$$

where $E[\cdot]$ denotes the mean value operator. The derivative of MSE with respect to each coefficient (a (k)) is equated to zero. This generates *p* equations from which coefficients are estimated by autocorrelation or autocovariance method.

2.2. Discrete wavelet transform

Wavelet transform is well accepted in the analysis of ECG signals detection, classification and compression. Discrete wavelet transform (DWT) is decomposition of the signal when concurrently passed through half bands high-pass filter (HPF) and low-pass filter (LPF). The impulse response of HPF represents wavelet function $\psi(t)$ and its output is denoted by detail cD. The impulse response of LPF, which is the quadrature mirror of the previous one (QMF), represents scaling function $\phi(t)$ and its output is known as approximation cA.

The number of coefficients produced at the ouptut of both filter are doubled. Therefore downsampling by factor 2 is performed on both output signals. Procedure can be repeated and j^{th} level approximation coefficients cA_j are decomposed to obtain cA_{j+1} and cD_{j+1} coefficients. The number of iterations represents level (j) of decomposition. The initial signal is transformed to a set of coefficients containing the lowest approximation and j details. Original signal can be reconstructed by up-sampling and passing through the modified LPF and HPFs. For perfect reconstruction same filter coefficients with reverse order are used.

2.3. ECG compression algorithm

The ECG compressor (coder) used in the present work has *analysis by synthesis* structure. The long ECG record is first divided into excerpts, each of length N (1024 samples), then each excerpt is denoised for better accuracy [5]. Denoised signal is the input of compressor shown in Fig. 1. The difference of input and output of LPC filter results error signal. If the predicted signal $\hat{x}(n)$ follows the applied original signal $x(n)$ then error is minimum and clearly number of bits required for the representation of this error (residue) signal are less that of the original signal. This fact lays a foundation for our compression method.

Wavelet transformation of error signal using 'db4'.and up to second level generates cA_2, cD_2, and cD_1 coefficients. The approximation coefficients cA_2 defines output of encoder which is one fourth of the length of original signal and thus enhances compression.

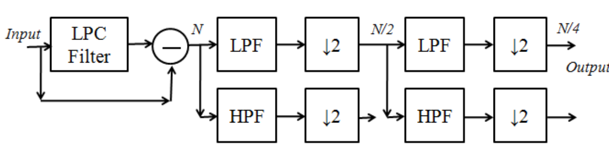

Figure 1. Compression scheme (Analysis section).

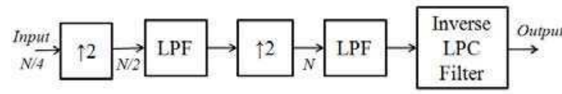

Figure 2. Decompression scheme (Synthesis section).

The decoder (decompressor), shown in Fig. 2, works exactly reverse way that of encoder process. The signal runs through two inverse wavelet sections followed by inverse LPC filter to regenerate the original signal.

2.4. Classification of beats

2.4.1. Feature extraction

Cardiac arrhythmia is a heart disease where heart beats indicate change in rhythm. Three cases are considered in our study: Normal, LBBB (Left Bundle Branch Block) and RBBB (Right Bundle Branch Block) which are provided at MIT-BIH database along with annotations [6]. The compact representation of signal pattern is called as feature vector. The method proposes a feature vector containing four temporal features extracted from coded ECG segment before decompression. Temporal features consist of average of absolute values of cA_2, minimum, maximum and standard deviation of cA_2 of each ECG excerpt. The feature vectors belonging to different classes are applied as inputs to Fuzzy c-means clustering (explained in next section).

2.4.2. Fuzzy c-means clustering

Clustering is collection of objects into different groups belonging to certain pattern. Fuzzy clustering allows each feature vector to belong to more than one cluster with different membership degrees (between 0 and 1) and vague or fuzzy boundaries between clusters [7]. This algorithm is based upon iterative optimization of the objective function, with update of membership and cluster centers. Objective function is weighted within groups' sum of squared errors J_m given by

$$J_m = \sum_{i=1}^{N}\sum_{j=1}^{C} u_{ij}^{\;m} \|x_i - c_j\|^2, 1 < m < \infty \tag{4}$$

where m is any real number greater than 1, u_{ij} is the degree of membership of x_i in the cluster j, x_i is the i th d-dimensional measured data, c_j is the d-dimension center of the cluster, and $\|\cdot\|$ is any norm expressing the similarity between any measured data and the center. Firstly u_{ij} are initialised, then centers are calculated by equation 5.and then memberships u_{ij} are updated by equation 6.

$$c_j = \left(\sum_{i=1}^{N} u_{ij}^{\;m} x_i\right) \Big/ \left(\sum_{i=1}^{N} u_{ij}^{\;m}\right) \tag{5}$$

$$u_{ij} = 1 \Bigg/ \sum_{k=1}^{C} \left(\frac{\| x_i - c_j \|}{\| x_i - c_j \|} \right)^{\frac{2}{(m-1)}} \qquad (6)$$

This iteration process stops when $\max\{| u_{ij}^{(k+1)} - u_{ij}^{k} |\} < \varepsilon$ where $0 < \varepsilon < 1$.

3. Results

The proposed method has been tested on ECG data obtained from MIT-BIH arrhythmia database (360 samples/s, 11-bit resolution) and University of Glasgow database (500 samples/s, 12-bit resolution). The ECG signal excerpt was applied to LPC of encoder. The optimum order of LPC was selected as 4 on the basis of minimum RMS error shown in Fig. 3. The different wavelets adopted in this algorithm were Daubechies4, Daubechies2, bior4.4, bior5.5, bior6.8 which are good for ECG [8].

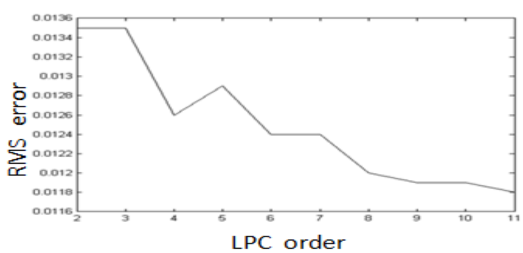

Figure 3. RMS error between original and reconstructed signals versus LPC order.

Compression performances on records from MIT-BIH compression database proved that 'Db4' is better choice. Results of record 08730_01 are shown in Table 1.

Table 1: Compression performances

Wavelet	*RMSE*[a]	*SNR*[b]
Db 2	6.2	48.06
Db 4	5.9	48.74
Bior 4.4	5.7	49.64
Bior 5.5	5.8	49.10
Bior 6.8	4.8	53.07

([a]RMSE = RMS error, [b]SNR = Signal to Noise ratio)

The root mean square error (RMSE) and signal to noise ratio (SNR) is given by equation 7 and 8.

$$RMSE = \sqrt{\frac{1}{N} \sum_{n=1}^{N} (x(n) - \tilde{x}(n))^2} \qquad (7)$$

$$SNR = 10 \log \left(\frac{\sum_{n=1}^{N} (x(n) - \overline{x}(n))^2}{\sum_{n=1}^{N} (x(n) - \tilde{x}(n))^2} \right) \qquad (8)$$

where N = number of samples in the signal, $x(n)$ = original ECG signal, $\overline{x}(n)$ = mean of $x(n)$, $\tilde{x}(n)$ = reconstructed (decompressed signal) signal.

The actual signal, output of LPC (predicted signal) and the difference (error) signal is shown in Fig. 4 for ECG record '*NOISY_29018.01*' from University of Glasgow database.

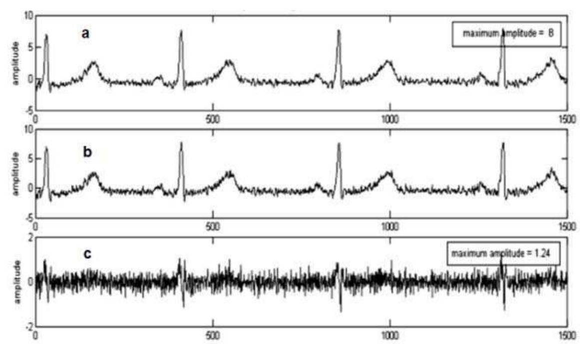

Figure 4. (a) Typical original ECG signal from noisy database, (b) Predicted Signal, (c) Error Signal.

It can be clearly seen from Fig. 4(c) that amplitudes of the resulting error samples are much smaller than the original. Thus 7 bits are required for representation of error signal with same resolution instead of 11 bits. Finally, after two level wavelet decomposition and truncation, the signal is represented with 256×7 bits instead of 1024×11 bits and offers a fixed compression ratio of 84.09 %.

The performance of algorithm was validated by calculation of the distortion measures such as PRD, Wavelet based weighted PRD (WWPRD) and Wavelet based energy diagnostic distortion (WEDD) [9]. PRD is given by

$$PRD = 100 \times \sqrt{\sum_{n=1}^{N} [x(n) - \tilde{x}(n)]^2 \Bigg/ \sum_{n=1}^{N} [x(n)]^2} \qquad (9)$$

For measuring *WWPRD* and *WEDD*, original signal and reconstructed signal were wavelet decomposed to fifth level using 'Db4'. *WWPRD* is expressed by equation 10.

$$WWPRD = \sum_{j=1}^{L} w_j WPRD_j \qquad (10)$$

where, L is the number of decomposition level, w_j the weight of the j^{th} subband and $WPRD_j$ is the PRD value of the j^{th} subband. In *WWPRD* measure, the weight of each subband is calculated as the ratio of sum of the absolute value of coefficients within that band and the sum of absolute value of Wavelet coefficients in all the bands [8]. *WWPRD* was found to be less than 0.25 as indicated in Fig. 5.

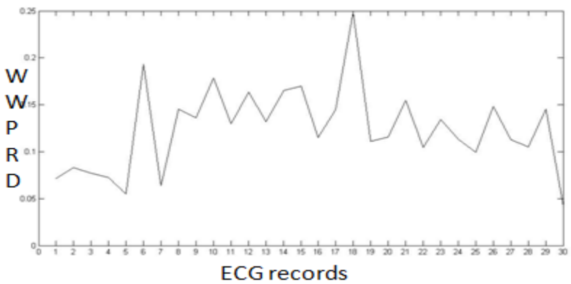

Figure 5. WWPRD for 30 records of MIT Compression.

WEDD is described by equation 11 and associated weights are obtained from percentile energy contribution defined by equation 12.

$$WEDD = \sum_{j=1}^{L+1} w_j WPRD_j \tag{11}$$

$$w_l = \left(\sum_{k=1}^{K_l} d_l^{\,2}(k) \right) \Bigg/ \left(\sum_{m=1}^{L+1} \sum_{k=1}^{K_l} d_m^{\,2}(k) \right) \tag{12}$$

WEDD was calculated for different databases. The box-plots are shown in Fig. 6.

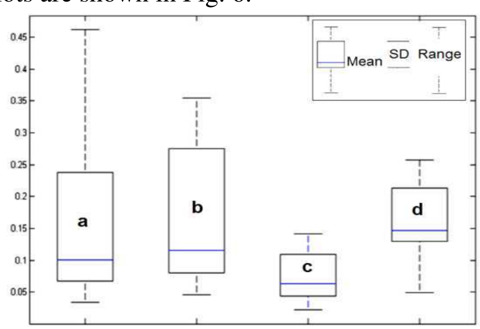

Figure 6. Boxplots of WEDD over different databases
(a) Glasgow ECG database, (b) Glasgow Noisy ECG database, (c) MIT-BIH ECG arrhythmia database,and
(d) MIT-BIH ECG compression database

The feature set was obtained from segments of three records selected pertaining to Normal (103.dat), LBBB (214.dat) and RBBB (124.dat), from MIT –BIH database. Modified lead II samples of above records were used to acquire the segments. The class of unknown segment was declared by calculating Euclidean distance of feature vector from cluster centers. Fuzzy c-Means clustering provided better classification accuracy of 97%. Cluster center of concerned class was updated after finding the class.

4. Conclusion

The proposed compression method of signal provides improved performance in terms of computational efficiency and compression rate where the clinically significant features ECG signal are preserved. The higher compression rate is unsafe in case of ECG because important information of patient under critical condition may be lost. For better accuracy fuzzy c means clustered data may be applied to neural network. This compressor can be easily implemented on FPGA platform.

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