Lossless ECG Signal Compression Using Non-linear Predictor and ASCII Character Encoding

Thivaagar Thamil Selvan[1], Kannan Ramakrishnan[1](✉), Vijayakumar Vengadasalam[1], and Rathimala Kannan[2]

[1] Multimedia University, Cyberjaya, Malaysia
kannan.ramakrishnan@mmu.edu.my
[2] Information Technology Department, Multimedia University, Cyberjaya, Malaysia

Abstract. Electrocardiogram is a method of recording the heartbeat of a patient electronically. Storing or transmitting enormous amount of ECG signals to another device or via online is an unendurable process without compressing the signals. The purpose of this paper is to develop an efficient Electrocardiogram (ECG) compression technique using non-linear predictor and ASCII character encoding. The digitized ECG signal values are applied to Multi-layer Perceptron (MLP) neural network algorithm for non-liner prediction and the residues of the signal are passed through ASCII character encoding for further compression. It is shown that a compression ratio of 2.3726 can be achieved through this technique without any loss of information for MIT-BIH arrhythmia database records.

Keywords: Biomedical · ECG signal · ASCII character · Lossless · Multilayer perceptron · Encoding · Decoding

1 Introduction

Compression of ECG signals is necessary to reduce the storage requirement of large biomedical databases in the hospitals, to satisfy the requirement of long-term storage of multi-channel biomedical data, to reduce the bandwidth requirement in telemedicine applications, and to reduce storage and bandwidth requirements in a home tele-healthcare system [1, 2].

Though several signal compression methods have been reported, they lack in satisfying the conflicting requirements of greater compression ratio and better signal fidelity. Hence there exists an acute need to develop an efficient biomedical signal compression method, which can achieve higher compression ratio without any significant degradation in the quality of the diagnostically important portions of their reconstructed signal.

Direct ECG data compression techniques such as combination of differential pulse code modulation (DPCM) and entropy encoding scheme, scan-along polygonal approximation (SAPA), amplitude zone time epoch coding (AZTEC), coordinate reduction time encoding system (CORTES), and turning point (TP) technique are discussed in [1].

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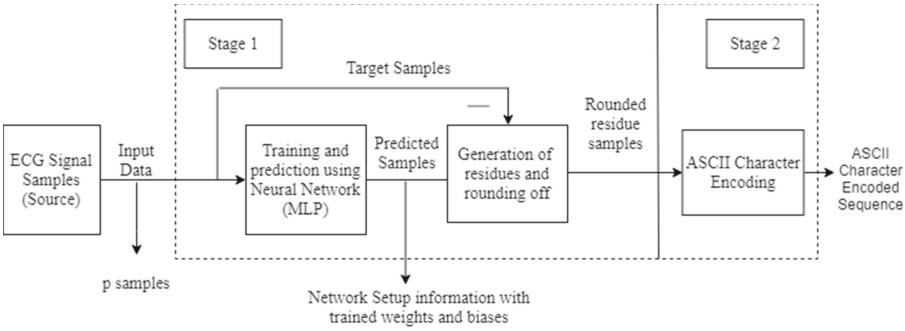

Fig. 1. Transmitting End

Transformation methods such as Fourier, Walsh, and K-L transforms are also discussed in [1] along with the framework for comparison of ECG compression techniques.

Non-linear prediction and encoding based lossless compression schemes for ECG signals are discussed in [2] and it was shown that compression schemes using neural network-based predictors are able to achieve 11% improvement in compression efficiency compared to linear predictor-based schemes with the same arrangement.

Hybrid lossy compression technique using linear predictive coding along with modified Huffman encoding is discussed in [3] and it was shown to achieve a compression ratio (CR) of 6.7 with percent of root- mean-square difference (PRD) value of 0.5.

Multi-channel ECG signal compression technique using adaptive linear prediction and Golomb-Rice encoding is proposed in [4] and it is shown that the proposed technique can be implemented in lost cost development board for telemedicine application.

An ECG signal compression technique based on ASCII character encoding is discussed in [5–8]. These schemes applied ASCII character encoding on the difference array generated directly from ECG signals by performing the operations of multiplication, grouping, sign bit generation, conversion to ASCII characters at the transmitting end and reverse process at the receiving end.

In [9], a high ratio lossless compression scheme with low computational complexity is proposed whereas [10] proposed the scheme using stacked auto-encoder for mobile health application. Hybrid Electroencephalography (EEG) compression scheme involving three main units of preprocessing, compression and reconstruction is proposed in [11] with the usage of discrete cosine transform, discrete wavelet transform for lossy compression along with arithmetic coding and run length coding for lossless compression.

Combination of linear prediction with delta encoding is proposed in [12] for implementing low complexity lossless ECG compression algorithm for active implants. A heterogeneous Central Processing Unit (CPU)-Graphics Processing Unit (GPU) architecture with Compute Unified Device Architecture (CUDA) is proposed in [13] to implement lossless ECG data compression algorithm using ASCII character encoding.

In this paper, an efficient biomedical signal compression scheme is developed based on hybrid scheme of using non-liner predictor and ASCII character encoding in the two stages respectively. Optimal model is obtained by tuning various parameters to achieve

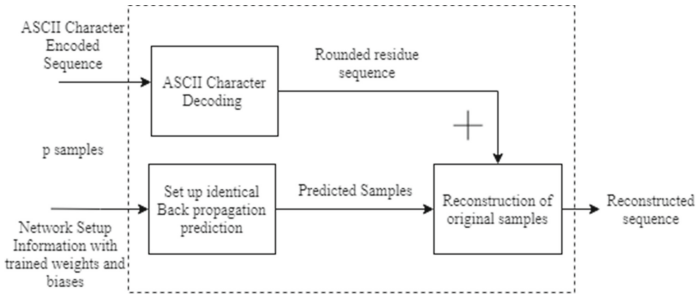

Fig. 2. Receiving End

higher compression ratio without distortion. Optimal scheme obtained can form a basis for applying compression in other domains also.

For the first stage, multilayer perceptron trained using backpropagation algorithm is used as nonlinear predictor to predict ECG signals and residues are obtained. In the second stage, modified ASCII character encoding scheme along with two flag bits for indicating the range of residues is used to compress the residues further. To the best of our knowledge, hybrid scheme involving non-liner predictor and modified ASCII character encoding for ECG compression has not been explored.

In Sect. 2, proposed method using MLP in the first stage as nonlinear predictor and ASCII character encoding in the second stage as decorrelator is discussed at both transmitting and receiving ends. In Sect. 3, experimental setup is discussed. In Sect. 4, experimental results, discussion, and dashboard are discussed, followed by conclusion in Sect. 5.

2 Proposed Method

2.1 Compression Through Neural Network Predictor

The proposed two stage lossless compression method at the transmitting end is given in Fig. 1 along with the way of reconstructing original ECG samples at the receiving end in Fig. 2 [2].

In the first stage, samples from ECG signal are used to train the neural network and tuning of parameters are done until the optimal model is identified [14]. For building the similar model at the receiving end, we need to send the trained weights and biases along with the overhead header such as network architectural and training information [2]. The first few samples are also sent based on the identification of optimal prediction order.

Optimal neural network model setup at the sending and receiving ends are used to generate predicted samples. Predicted sample values are subtracted from the original ECG sample values to generate residues at the sending end. Residues are further encoded with ASCII character encoding in the subsequent stage.

The ASCII encoded residue sequence is sent to the receiving end along with neural network parameters. Lossless decoding is done as a first step. Residues generated

9	0	-1	5	1	3	-2	6
re[0]	re[1]	re[2]	re[3]	re[4]	re[5]	re[6]	re[7]

Fig. 3. Sample of residue array after prediction

9	0	1	5	1	3	2	6
re[0]	re[1]	re[2]	re[3]	re[4]	re[5]	re[6]	re[7]

Fig. 4. Sample of residue array after conversion to positive integers

Sign Bit	Grouped Integers				Flag1	Flag2
34	90	15	13	26	0	0
gr[0]	gr[1]	gr[2]	gr[3]	gr[4]	gr[5]	gr[6]

Fig. 5. Sample of grouping array

from ASCII decoder is added to the predicted ECG samples and original samples are reconstructed without any distortion.

2.2 ASCII Character Encoding and Decoding

In the second stage, the residue is encoded into ASCII characters. This involves the following stages [5–8].

2.2.1 Sign Bit Generation at the Sending End

The first stage in encoding involves sign bit generation. A sample array consists of first 8 values of residues generated after prediction is given in Fig. 3.

Sign of each element of the array re[] is inspected and each positive value is set as '0' and negative value is set as '1'. After that, as an example for the elements from array re[] given in Fig. 3, a string of "00100010" is generated. The obtained string is equivalent to 34 in decimal. This is considered as the integer representing sign of the first eight residues [5]. This decimal value is converted to ASCII character. Absolute values are taken for all elements in the array, which is shown in Fig. 4, for further processing.

2.2.2 Grouping at the Sending End

The second stage in encoding process involves grouping. Every number in position re[i] will be multiplied by 10 and then added to the number in re[i + 1] position. Integers formed using this grouping are converted to ASCII characters, as shown in Fig. 5. Initial value of the counter is set as zero and this will be added by two for each iteration [6].

The proposed ASCII character encoding scheme is modified to include two-flag bits for indicating the residue range. (Flag1, Flag2) as (0,0) indicates the ECG signal residues in the range of (−9 to 9), (0, 1) indicates (−19 to 19), (1, 0) indicates (−29 to 29) and (1, 1) indicates (−39 to 39). Since our maximum error range is between (−39 to 39), we only consider two bits. Every set of grouped values is converted to their corresponding ASCII characters along with the sign bit information.

9	0	1	5	1	3	2	6
re[0]	re[1]	re[2]	re[3]	re[4]	re[5]	re[6]	re[7]

Fig. 6. Sample of residue array during reconstruction after ungrouping

9	0	1	-5	1	3	2	-6
re[0]	re[1]	re[2]	re[3]	re[4]	re[5]	re[6]	re[7]

Fig. 7. Sample of residue array during reconstruction after sign bit regeneration

2.2.3 Ungrouping at the Receiving End

First of all, in decompression, grouped integers of gr[] array is ungrouped using reverse logic [6]. The ungrouped data is kept for instance in array re[]. The grouped value in gr[] array will be divided by 10. After that, the quotient is kept in the first position and the remainder is kept in the following position of the re[] array as shown in Fig. 6. The Flag1 and Flag2 values are used to determine the range of error values. If the flag bits are in combination of (0, 0) then the quotient and reminder are stored as same values. If the flag bits are in combination of (0, 1), then the quotient is subtracted by 1 and the remainder is added with the value 10. If the flag bits are in combination of (1, 0), then the quotient is subtracted by 2 and the remainder is added with the value 20. If the flag bits are in combination of (1, 1), then the quotient is subtracted by 3 and the remainder is added with 30. After ungrouping the sample array is as shown in Fig. 6.

2.2.4 Sign Bit Regeneration at the Receiving End

In the next step, the integer representing sign byte, '34' is converted into binary "00100010" and the corresponding bit is inspected. If the sign bit shows 1, then the value is converted to negative number as shown in Fig. 7.

Reconstructed residues regenerated in a lossless manner are added to the predicted ECG signal values. These signal values are obtained using the optimal MLP model built using the received parameters from the transmitting end.

3 Datasets for Testing

Selected records from the standard MIT-BIH arrhythmia database [15] that were obtained by the Boston's Beth Israel Hospital Arrhythmia Laboratory are used to test the proposed compression method. Records such as 100, 101, 102, 103, 104, 105, 200, 201, 202, 203, 205 and 207 are chosen based on different arrhythmia conditions. This consists of 360 samples per second with a resolution of 11 bits/sample. The MIT-BIH arrhythmia database contains 48 two-channel records with around 30 min length for each signal [15]. In most records, the upper signal is a modified limb lead II (MLII), obtained by placing the electrodes on the chest. The lower signal is usually a modified lead V1 (occasionally V2 or V5, and in one instance V4); as for the upper signal, the electrodes are also placed on the chest [15].

4 Performance Evaluation

The performance of ECG compression schemes is measured by distortion and compression efficiency measures.

4.1 Distortion Measure

The Percent of root-mean-square difference (PRD) is the measure of the distortion between the original and the reconstructed signals. PRD is used to compare the original and reconstructed signal values to measure the quality of compression. PRD is defined in Eq. (1) [1], where x_0 indicates the original data, x_r indicates the reconstructed data, and N represents the number of samples.

$$PRD = \sqrt{\left[\frac{\sum_{n=0}^{N-1}[x_0(n) - x_r(n)]^2}{\sum_{n=0}^{N-1}\left[x_0^2(n)\right]}\right] \times 100\%} \tag{1}$$

4.2 Compression Efficiency Measure

The compression ratio (CR) is used to determine how much compression can be achieved with the compressed signal compared to original ECG signal using the proposed method and shown as Eq. (2) [1].

$$CR = \frac{Bits\ required\ for\ original\ ECG\ signal}{Bits\ required\ for\ compressed\ ECG\ signal} \tag{2}$$

Compression efficiency results obtained using single stage and two stages are listed in Tables 1 and 2 respectively.

For a single stage ECG compression, only MLP predictor is used in both transmitting and receiving ends. Residues (original signal—predicted signal) obtained in the transmitting end are sent directly to the receiving end for reconstruction. Since the reconstructed signal values are same as original signal values, PRD value calculated is zero for all the signals.

For two stage ECG compression, the ASCII character encoding is used to encode the residues, before sending to the receiving end. By using this method, higher compression ratio can be achieved. However, the compression ratio for all the signals will be the same since the bit rate is fixed for each residue transmitted to the receiving end in the form of ASCII character. The result is shown in Table 2.

Table 3 shows the performance comparison of the proposed method with similar methods in the literature. Even though compression efficiency achieved by the proposed method is lower compared to other methods in the literature, signals are reconstructed exactly same as the original signals in the proposed method compared to distortion introduced in ECG signals for other methods during compression. In our proposed method, by reconstructing the exact ECG signal, we will not be missing any diagnostically important information, and this will be useful for accurate diagnosis using the reconstructed ECG signals.

Table 1. Compression efficiency using single stage (MLP as predictor)

Dataset		**CR**
100	MLII	1.6363
	V5	1.6455
101	MLII	1.6181
	V1	1.6432
102	V5	1.6301
	V2	1.6022
103	MLII	1.6353
	V2	1.6273
104	V5	1.6181
	V2	1.6204
105	MLII	1.6252
	V1	1.6442
200	MLII	1.6062
	V1	1.6147
201	MLII	1.6577
	V1	1.6356
202	MLII	1.6240
	V1	1.6296
203	MLII	1.4485
	V1	1.5596
205	MLII	1.6608
	V1	1.6557
207	MLII	1.6199
	V1	1.5958
Average		**1.6189**

Table 2. Compression efficiency using two stages (MLP as predictor, ASCII character encoding)

Dataset	**CR**
100 MLII,V5, 101 MLII,V1, 102 V5,V2, 103 MLII,V2, 104 V5,V2, 105 MLII,V1, 200 MLII,V1, 201 MLII,V1, 202 MLII, V1, 203 MLII,V1, 205 MLII,V1, 207 MLII,V1	2.3736

Figure 8 shows the original, predicted signal and residues obtained at the transmitting end for a sample 100 MLII record.

Table 3. Performance comparison with similar methods in the literature

Algorithm	CR	PRD
ASCII Character Encoding [7]	11.1225	0.0208
ASCII Character Encoding [6]	15.72	7.89
ASCII Character Encoding [5]	7.18	0.023
Nonlinear Predictor+Huffman encoder [2]	3.3104	0.0301
Linear Predictive Coding [3]	6.7	0.5
Proposed Method (Nonlinear predictor+ASCII character encoding)	2.3736	0

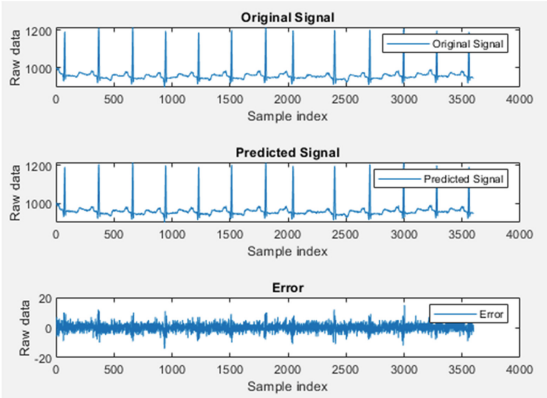

Fig. 8. Original, predicted, and residue signals at the sending end (MIT-BIH record 100MLII).

Figure 9 shows the visualization of how the signal is reconstructed at the receiving end without any error.

Figure 10 shows the histogram plot of residues after prediction for the record 100 MLII. It can be noted that most of the prediction residue values fall between −10 and + 10 with a concentration around zero. On the average, residue signal can be encoded with lower number of bits per sample using ASCII character encoding in the second stage.

4.3 Dashboard

A dashboard is created to facilitate the users to perform the ECG signal compression in an easy and convenient manner. In this application, the user loads the csv file of the ECG signal by using the 'Load Signal' button. After that, the compression of ECG signal can be done by using 'Compress ECG Signal' button. Prediction and encoding are done at the background and the input ECG signal is compressed and compression ratio is calculated. Receiving end can be simulated by using 'Reconstruct ECG signal' button.

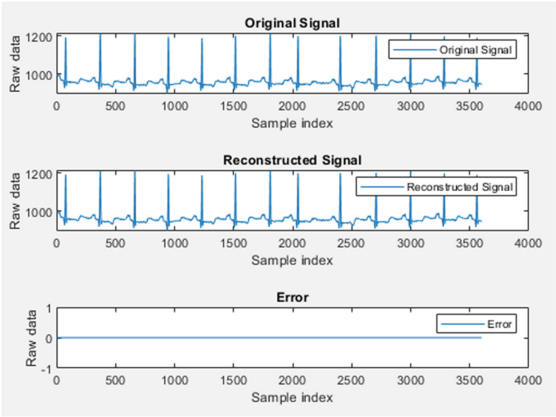

Fig. 9. Original, reconstructed, and error signals at the receiving end (MIT-BIH record 100MLII).

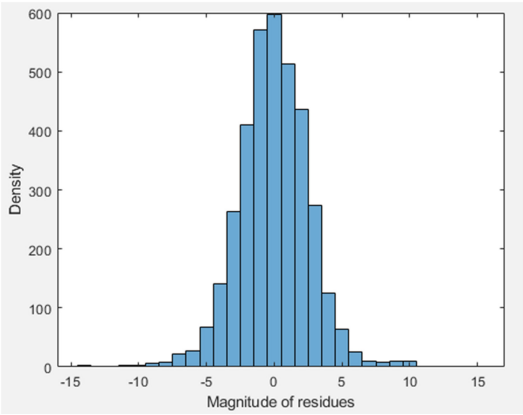

Fig. 10. Histogram plot of residues after prediction at the sending end (MIT-BIH record 100MLII).

Reconstructed signal is displayed after performing decoding, prediction, and addition of predicted signal values. PRD is calculated and the value is displayed.

5 Conclusion

This paper has proposed a lossless compression scheme using artificial neural network as a non-linear predictor followed by ASCII character encoding in two stages. Selected records from the standard MIT-BIH arrhythmia dataset are used to evaluate the compression efficiency of the proposed method. The results have indicated that two-stage method with a non-linear predictor and ASCII character encoding has improved the compression efficiency significantly compared to single-stage method involving only MLP as a predictor. The proposed method can be applied to the exact reconstruction of ECG signals at the receiving end (Fig. 11).

Fig. 11. ECG Signal Compression and Decompression GUI

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