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ECG Signal Compression using Improvised Error Back Propagation Neural Network with GDAL

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ABSTRACT: Electrocardiogram (ECG) data is bulky in size and needs to compress through suitable compression techniques for reducing storage requirement s and to transfer ECG signal over low bandwidth channel in less time over the network. In this paper we have applied a novel approach of improvised Error Back Propagation Neural Network with Gradient Descent Learning rate for network to learn with in an adaptive manner. In our experiments we have found that an average compression ratio of 9 and Percentage Mean square Error (PRD) between 2 to 7 is achieved with this method. In addition to that the network learns faster than the tradition neural network after implementing Gradient Learning mechanism.

KEYWORDS: Electrocardiogram, Gradient descent learning, Compression Ratio, Percentage Mean Root Square Difference

I. INTRODUCTION

ECG signal depicts the exact picture of the activities associated with the functioning of the heart. After examining an ECG signal various heart diseases can be diagnosed. Furthermore, ECG signal needs to be compressed for reducing its size for rapid transmission and economical storage.

Even though the processor speed, bandwidth and storage capacity has been increased tremendously the demand for ECG compression has been still in picture. The main objective of ECG compression is to reduce redundancy presented in the ECG signal without loss of clinical information and the reconstructed signal must contain all the clinical features intact for diagnosis purpose.

1.1 Types of Compression Techniques:

The compression algorithms can be broadly classified [1, 2] into two categories:

(A) Lossless Compression:

In this type of compression the reconstructedsignal is exact replica of the original signal and there is no loss of information in that reconstructed signal at all. The reconstructed signal is identical to the original signal. This type of compression comes under the category of lossless signal compression.

(B) Lossy Compression:

In lossless compression there is some loss of information and reconstructed signal is not exactly same as the original signal but the quality of reconstructed signal should not be compromised [3]. In lossless compression techniques the higher compression ratio is achieved as compared to lossy compression technique. Almost all the signal compression tools prefers lossless compression technique to achieve higher compression rates [4, 5].

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1.2PERFORMANCEEVALUATION

The effectiveness of ECG compression techniques is described in terms of Compression Ratio[6] (CR) and Percentage Mean Square Difference (PRD)[6].The quality of reconstructed ECG signal can be examined with these criteria.

1.2.1 Compression Ratio (CR)

It is defined as the ratio of original data to compressed data without considering factors such as bandwidth, sampling rate, word length, reconstruction error, noise level etc. The CR is the ratio of the original file size to the compressed file size, given as follows:

$$CR = \frac{\text{Original File Size}}{\text{Compressed File Size}} \quad (1.1)$$

Larger the CR better is the compression.

1.2.2 Percentage Root Mean Square Difference (PRD)

PRD is measurement of percentage error. This factor evaluates the distortion regarding the difference between the original and the reconstructed signal. The factor can be represented by the following formula. The definition of the PRD is given by following equation:

$$PRD = \sqrt{\frac{\sum_{n=1}^{N}\left(x[n] - \hat{x}[n]^2\right)}{\sum_{n=1}^{N}\left(x[n]^2\right)}}\ X\ 100 \quad (1.2)$$

where $x[n]$ and $\hat{x}[n]$ are the original and reconstructed signals, respectively; and N its length. For better reconstruction of the original signal, the values of the PRD should be very low.Thus collectively we require large CR and smaller PRD for better compression.

1.3 Types of Artificial Neural Networks

Artificial Neural Network topologies are classified intotwo categories [7,8]:

1. **Feed Forward ANN**

In this type of neural network information flow is unidirectional. This network has no feedback (loops) i.e. the output of one layer has no effect on other layer. Feed-forward ANNs tend to be straight forward networks that associate inputs with outputs .They are used in pattern generation/recognition/classification[7, 8]. They have fixed inputs and outputs.

2. **Feed Back ANN**

The signals can travel in both the directions in Feedback networks byimplementing loops in the network Feedback networks are dynamic; their 'state' is changing continuously until they reach an saturation point.

1.4 Working of ANNs

Each connection between two nodes has some weight, a real number that carries the information. Their weights are adjusted until the desired output is obtained.

Learning in ANNs

ANNs has learning capability and they are trained. There [9, 10] are several learning mechanism as follows

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- **Supervised Learning** − this is also known as Associative learning. In this matching output pattern is also presented to the network along with the input. Input patterns learn and they are tuned and classified to the matching input patterns.
- **Unsupervised Learning** − Here the network learns from provided input patterns .It creates a class itself without external help and tuned accordingly. It learns from its own classes and different types of patterns presented in it.

1.5 Error Back Propagation Neural Network-

The Back propagation [11] was invented by Bryson and Ho in 1969 which is a method for learning in multi-layer network. The Back propagation algorithm is a sensible approach for dividing the contribution of each weight.

There are two differences for the updating rule:
1) The activation of the hidden unit is used instead of activation of the input value.
2) The rule contains a term for the gradient of the activation function.

II. RELATED WORK

2.1 Literature Review of ECG Signal Compression Techniques

ECG signal compression is required for efficient storage and fast transmission of ECG signal over a low bandwidth channel. Several algorithms have been developed for compression of ECG signal in a way such that the clinical contents will remain intact after reconstruction for diagnostic purpose. For above mentioned objective a literature review on previous work on different ECG compression techniques has been carried out for lossless and lossy data compression techniques.

First time arithmetic coding technique [12] was used to compress ECG signal. It was implemented on real time microprocessor based instrument because of its computation efficiency. It was done in two stage process. In the stage one compression is done via adaptive sampling through Turning point and FAN/Scan-Along Polygonal Approximation (SAPA) algorithm and in second stage adaptive arithmetic coding was applied. It is a lossless method so compression ratio below 4 is achieved and with a very good reconstructed signal quality.JPEG2000 is a new technique and is particularly used for the compression of still images and videos. This technique was used to compress ECG signals [13] by eliminating intra-beat and inter-beat redundancy presented in ECG signal. The desirable characteristics of the JPEG2000 codec, such as precise rate control and progressive quality, are retained in the presented scheme. In the year 1982, new algorithms for ECG signal compression using local extreme extraction, adaptive hysteretic filtering and Lempel-Ziv-Welch (LZW) coding was presented [14]. In this method essential features of ECG signals are extracted using local extreme extraction and noise is removed using adaptive hysteretic filters .Thereafter the signal compressed using delta coding and Lempel-Ziv-Welch (LZW) coding. Eight of the most frequent normal and pathological types of cardiac beats ECG signals from the MIT-BIH database used to test this algorithm. This algorithm was also validated using neural networks that was trained with original heartbeat patterns including Principal Component Analysis (PCA) and tested with the reconstructed signals. Compression ratio of 12.74 is achieved with the Percentage root mean square Difference of 0.61. In another work [15] researchers had reported that one of the direct data compression method turning point (TP) algorithm suffers from a limitation that the data compression is independent from the morphology of the ECG signal . Therefore the reconstruction is not reliable. In another work [16] Amplitude Zone Time Epoch Coding algorithm (AZTEC) was applied for data compression .This method gave very high compression ratio around 10 but the reconstructed signal was sometimes not clinically acceptable due to a complete loss of P wave, widening of QRS complex and a decrease in its amplitude ,loss of PR and ST segment durations etc.Berti introduced a new ECG data reduction method based on a double logarithmic quantization of the ECG Walsh spectrum [17]. This solution was theoretically justified by the decay characteristics of the spectrum energy content at high spectral index and was proved to be fast and efficient method.Karhunen-Loeve transform technique [18] for ECG data compression has been applied in two ways in this research work. It was applied on the entire beat signal as well as to independent windows (P wave, QRS complex and ST-T complex) for the MIT-BIH Arrhythmia database. For the entire beat a mean compression ratio of 12.1 with a mean MSE of 0.3% and for independent windows a mean compression ratio of 17.21 with a mean value of MSE of 0.44% was achieved.

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III. METHODOLOGY

The neural network for Error Back Propagation is designed Gradient Descent with Adaptive Learning Rate Back propagation mechanism with MATLAB Tool box. A proper learning rate must be chosen for proper learning at efficient convergence [19]. In Gradient Descent Adaptive learning rate mechanism first the initial network and error are calculated and at every epoch new weights and biases are calculated using the current learning rate. The network adopts the new learning rates and new outputs and errors are again calculated for adaptive learning[20,21]. This algorithm shows the steps for this procedure.

Algorithm

1. Initialize network with random weights
2. For all training cases (called examples):
a. Present training inputs to network and calculate output
b. For all layers (starting with output layer, back to input layer):
i. Compare network output with correct output (error function)
ii. Adapt weights in current layer
3. Method for learning weights in feed-forward (FF) nets
4. Use gradient descent to minimize the error
    - Propagate deltas to adjust for errors backward from outputs to hidden layers to inputs
5. After training the compressed file contains compressed signal.
6. Compressed file is used to reconstured signal.
7. Compression Ratio, Root Mean Square Difference is calculated to identify the quality of reconstructed signal.

Figure 1 shows architecture of the Error Back Propagation Neural Network with hidden layer[22].

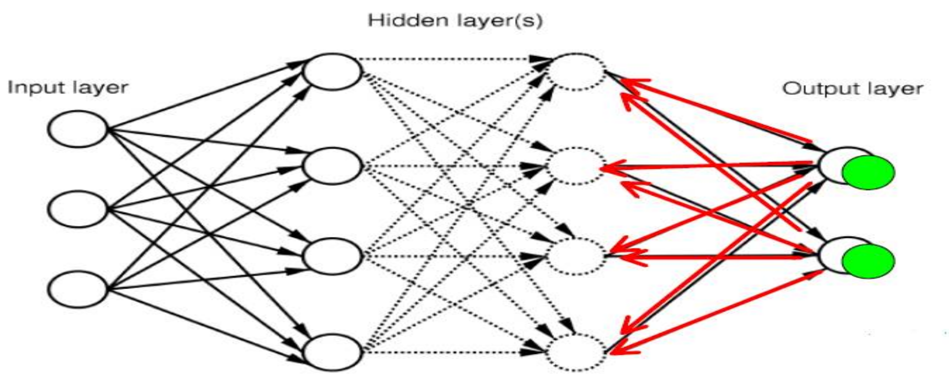

Figure 1: Architecture of Error BackPropagation Algorithm with hidden layer

IV. EXPERIMENTAL RESULTS

4.1 Experimental Results

Error Back propagation neural network with gradient descent learning has been applied on both the leads of 15 patients out of 48 patients taken from MIT-BIH Arrthymia database. The process and the results of this experiment is explained in this section. Each lead is consisting of 628404 numbers of samples. This experiment is done on raw ECG data.

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4.1.1 Performance Evaluation

To authenticate the reconstruction of the original data from this algorithm, a performance criterion is needed. For this, we have taken percentage root mean-square difference (PRD) [9] and Compression Ratio (CR) [9] as performance measure which has already been explained in previous section. Both the leads of 15 patients are reconstructed using this method. Table 1 shows the CR and PRD of both leads of 15 patients after reconstruction. This table also shows the original file size along with the size of compressed file.

Table 1: CR and PRD of Lead I and Lead II of 15 Patients

Patient No.	Lead I				Lead II			
	Original size(Kb)	Compressed file(Kb)	CR	PRD	Original size (Kb)	Compressed file (Kb)	CR	PRD
100	3093	322	9.8999	3.6	3178	328	9.5456	5.2
101	3137	334	9.3123	3.8	3587	380	9.5651	6.23
102	3149	324	9.7345	7.1	3524	356	9.6457	4.22
103	3171	342	9.3455	4.2	3584	362	9.8004	5.23
104	3197	375	8.9845	3.3	3621	402	9.5201	2.33
105	3237	380	8.4045	4.22	3597	389	9.2785	3.56
106	3237	380	8.2345	6.32	3630	394	9.2789	3.42
107	3303	416	7.9843	4.52	3552	420	8.4578	3.52
108	3218	366	8.8383	3.56	3557	388	9.1457	4.32
109	3244	360	9.0123	4.25	3605	394	9.1497	4.22
112	3079	332	9.2436	3.50	3071	313	9.7895	5.22
113	3240	359	9.0565	7.1	3641	375	9.7854	6.33
114	3299	349	9.3345	3.2	3573	368	9.7895	4.56
115	3109	320	9.8394	3.12	3207	321	9.4571	4.12
117	3073	336	9.2939	4.23	3123	319	9.8978	5.23

It can be seen from this table highest CR of **9.8999**is achieved for Lead I of patient 100. Similarly the lowest CR of **7.9843**is obtained for Lead I of patient 107.PRD obtained for both the leads of all the patients varies in the range of 2 to 7 .This implies that very negligible loss of information is there. This method has a limitation that CR up to a certain limit can be achieved with this method. An average CR of 9 is achieved with this method.

4.2 Comparison of Original and Reconstructed ECG signal

The Original and reconstructed signal of the lead I of patient 101 is shown in figure 2.It can be seen in this figure that the original signal is same as reconstructed signal.

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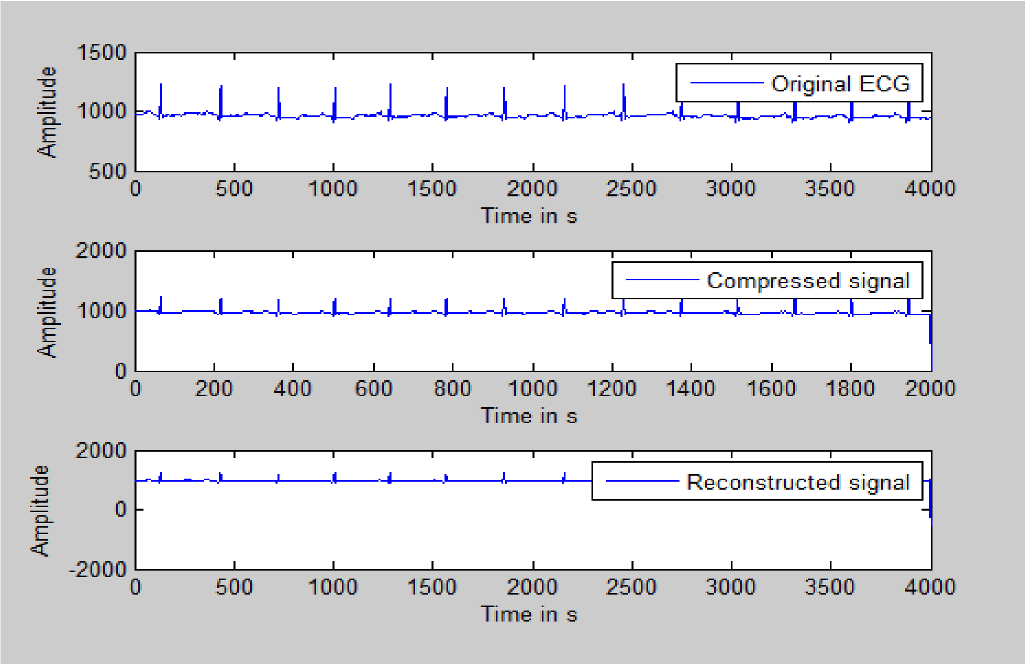

Figure 2: Original and Reconstructed signal of Patient 101 with first 4000 samples (Lead I)

To prove that the reconstructed signal is almost same as originalsignal, these are placed in sub plotted form. The compressed signal is also shown with the original signal and reconstructed signal. It can be seen from this figure the signal is reconstructed properly and with very low loss of information.

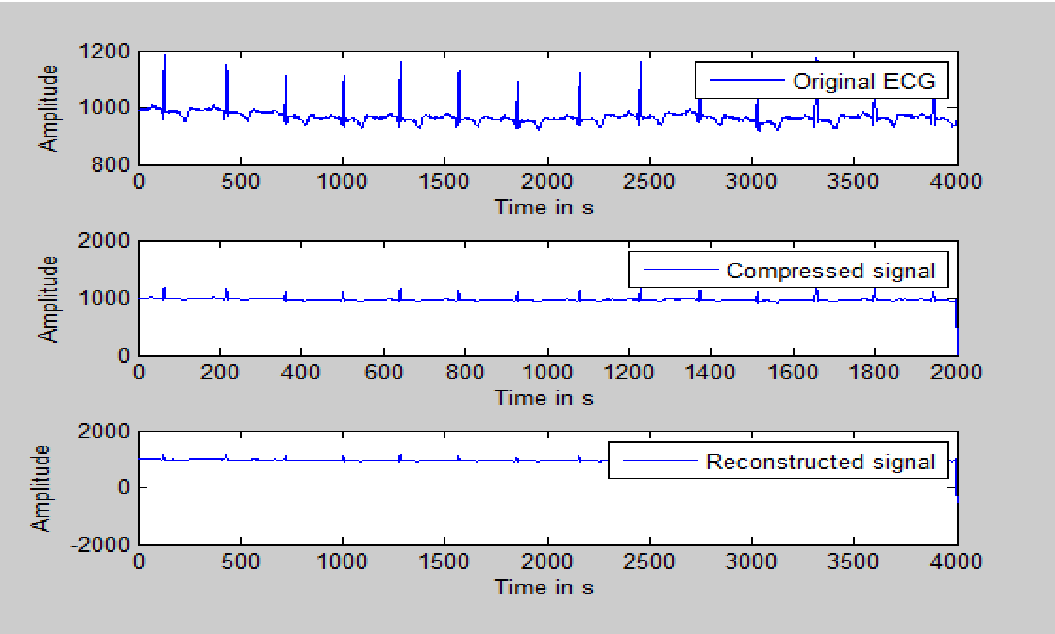

Figure 3: Original and Reconstructed signal of Patient 100 with first 4000 samples (Lead I)

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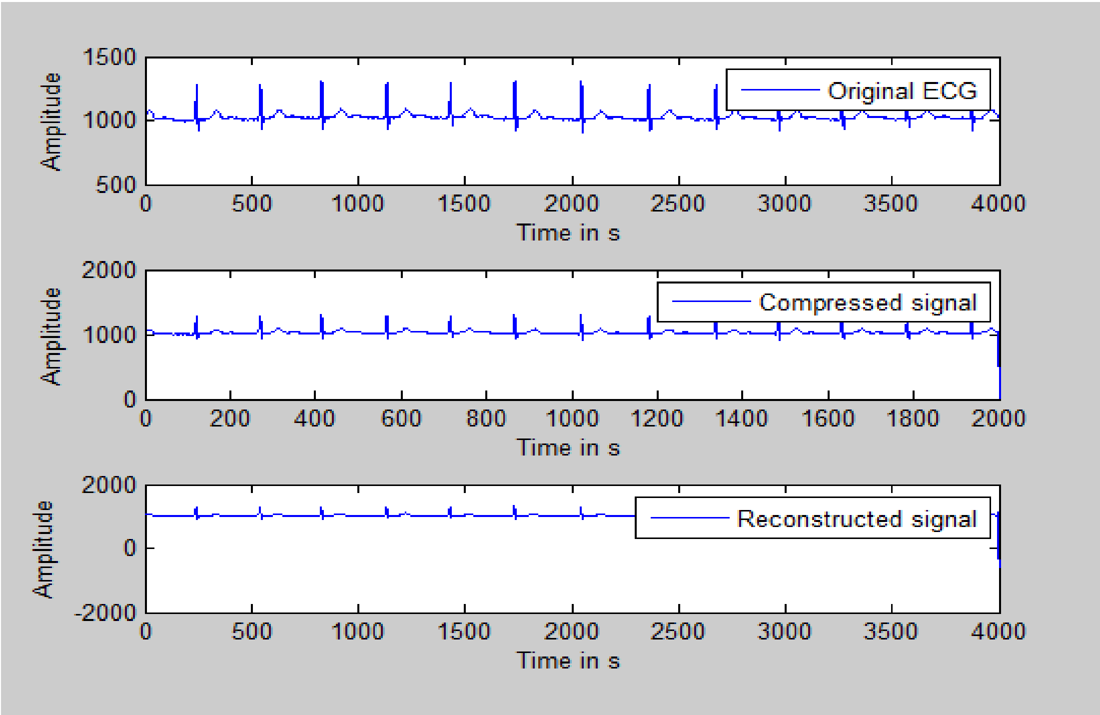

Figure 4: Original and Reconstructed signal of Patient 103 with first 4000 samples (Lead I)

Figure 3 and 4 show the same for the patient 100 and 103 and similar results can be seen for all the patients. Therefore, this method is very useful for compression and retains all the clinical properties of ECG signal after reconstruction.

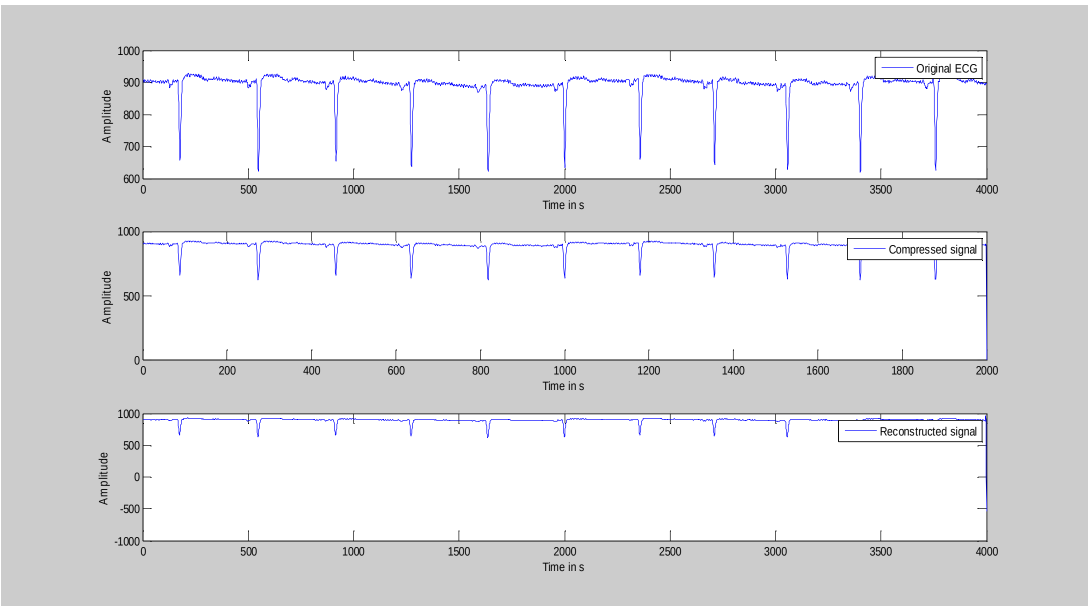

Figure 5: Original and Reconstructed signal of Patient 101 with first 4000 samples (Lead II)

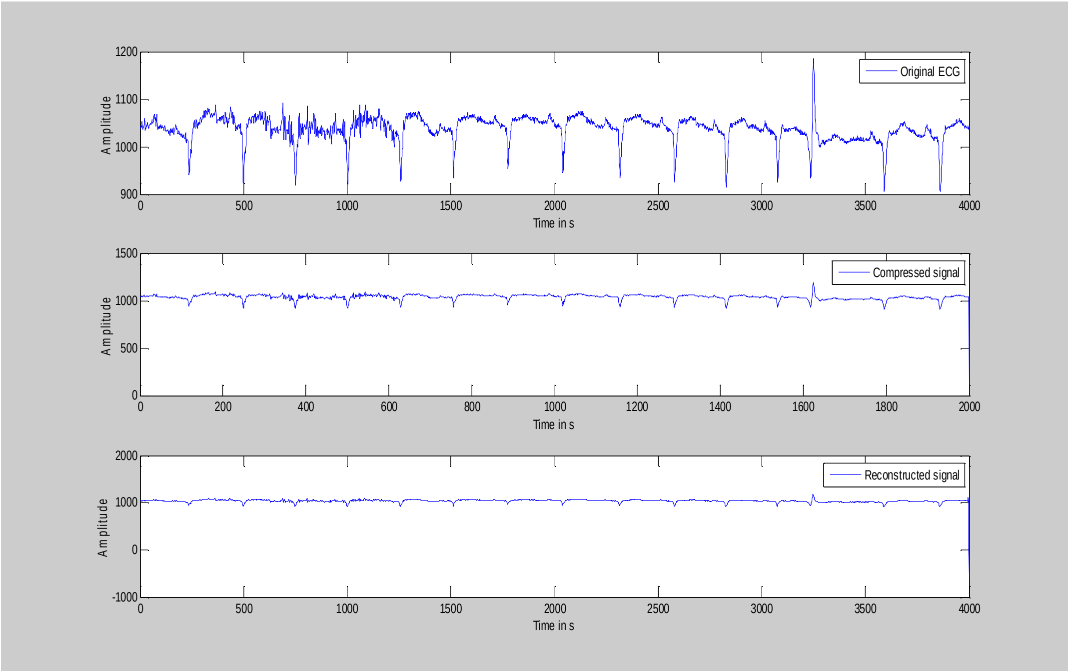

Figure 6: Original and Reconstructed signal of Patient 100 with first 4000 samples (Lead II)

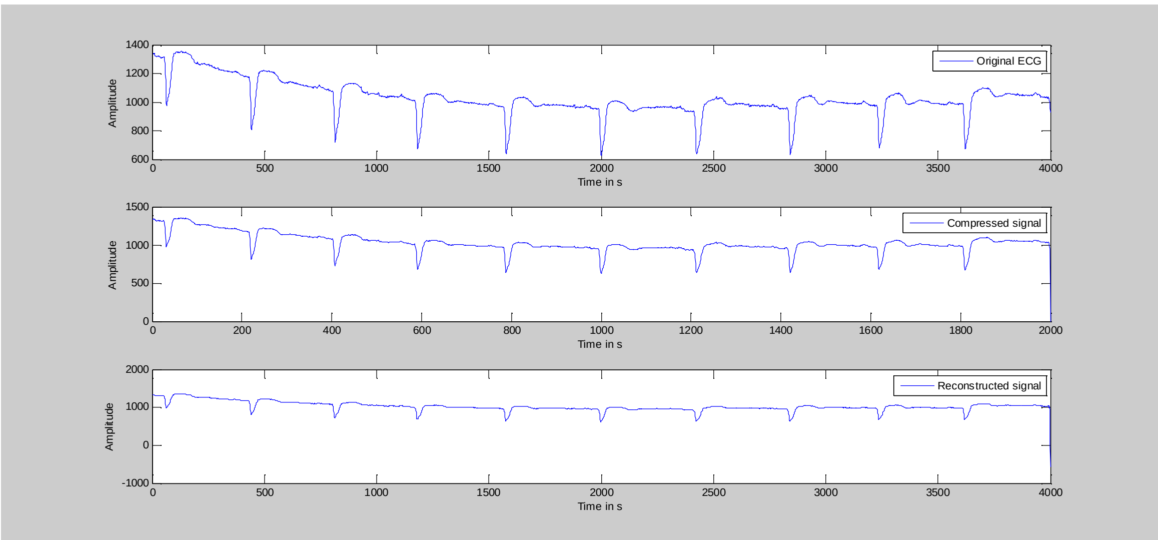

Figure 7: Original and Reconstructed signal of Patient 105 with first 4000 samples (Lead II)

Figure 5, 6 and 7 show second lead for the same for the patient 101,100 and 103 and similar results can be seen for all the patients. Both the leads of all the patients have been successfully reconstructed.

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V. CONCLUSION

This method has been applied on both the leads of 15 subjects from MIT-BIH Arrthymia database.An improvised BackPropagation algorithm has been used with Gradient Descent Adaptive learning mechanism in which the learning rate is adaptive in nature and it is changed dynamically for better convergence and learning. Original signal is compressed and reconstructed and afterwards, CR and PRD of both the leads of the 15 subjects iscalculated. A good compression ratio of average 9 is achieved with a very low error with a good recons trued signal quality.

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