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Modified Block Sparse Bayesian Learning-Based Compressive Sensing Scheme For EEG Signals

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***Abstract*—Advancement in medical technology creates some issues related to data transmission as well as storage. In real-time processing, it is too tedious to limit the flow of data as it may reduce the meaningful information too. So, an efficient technique is required to compress the data. This problem arises in Magnetic Resonance Imaging (MRI), Electrocardiogram (ECG), Electroencephalogram (EEG), and other medical signal processing domains. In this paper, we demonstrate Block Sparse Bayesian Learning (BSBL) based compressive sensing technique on an Electroencephalogram (EEG) signal. The efficiency of the algorithm is described using the Mean Square Error (MSE) and Structural Similarity Index Measure (SSIM) value. Apart from this analysis we also use different combinations of sensing matrices too, to demonstrate the effect of sensing matrices on MSE and SSIM value. And here we got that the exponential and chi-square random matrices as a sensing matrix are showing a significant change in the value of MSE and SSIM. So, in real-time body sensor networks, this scheme will contribute a significant reduction in power requirement due to its data compression ability as well as it will reduce the cost and the size of the device used for real-time monitoring.**

***Keywords*—Compressive Sensing (CS), Mean Square Error (MSE), Structural Similarity Index Measure (SSIM), EEG (Electroencephalogram), Digital Signal Processing (DSP), Block Sparse Bayesian Learning (BSBL)**

I. Introduction

IN today's world, it is so much typical to be healthy as the stress level is increasing day by day so as a resultant the human body is showing various types of adverse symptoms related to the degradation of body health. Due to the lack of time every person is not able to go for a routine check-up for the body. So, what is the solution in this domain? advancement in technology and connectivity provides many solutions to this problem. Real-time body vital parameters monitoring with the help of a body sensor network can provide a solution for this. This type of setup has opted for various hospitals in many countries, they can track the patients in the real-time domain. But a question arises here is it economical for a patient so he or she can opt for this, or it is easy to carry such type of equipment the whole day with you.

Some constraints are also there when we are designing this type of system. Three major constraints are:

a) Power Consumption (Energy Efficient) Structure.

b) High-level Compression of the real-time physiological signals.

c) Hardware Cost.

We have to follow all these constraints then only we can create an effective wireless body sensor network that can significantly measure the body vital parameters and then transmit it to the patient care center or hospital. Power consumption is directly associated with battery life, so our prime objective is to reduce energy consumption. This will reduce the size of the battery as well as increases the duration of the operation. Another constraint is the high-level compression of the EEG signals, but the compression does not affect the important information in the signal. That's why a specific approach should be kept into consideration. When we consider the first two constraints it will automatically reduce the cost of the device which is our third constraint.

So, the effectiveness of such type of systems only maintained if somehow we can reduce the data which we are analyzing through a body. But if we are reducing the data set then the real-time tracking has no use, so we are shifting toward the compression of data. Yes, data compression is a key technique that can reduce the size of data for storage and transmission without neglecting the important parameters of the data. Traditional data compression has lots of issues like the Nyquist sampling rate, which can enhance the power consumption as well as the unnecessary measurement of data which have no use. So our interest is shifting toward the Compressive Sensing theory. Although the Electroencephalogram data is not sparse in any domain or transform, Block Sparse Bayesian Learning (BSBL) sort out this problem related to EEG- Compressive Sensing. In the next section, we are moving toward compressive sensing and how to use it for Electroencephalogram. Section III is based on our experiments on the EEG signals, Section 4 is based on our findings and discussion. Section 5 is the conclusion of this work.

II. Compressive Sensing Framework For EEG Signal

In this paper, the author discusses the multichannel EEG signal based compressive sensing approach. To improve the performance of the compressive sensing approach for EEG signal Fourier transform and the non-convex optimization-based algorithm is used. Normalized Mean square error is calculated for the recovered EEG signal [1]. Another work in

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this domain is proposed by Muhammad Tayyib et. al., in their work reconstruction is done by Double Temporal sparsity-based reconstruction (DTSR) algorithm [2]. As a result, they conclude the results based on simulation and comparison with the work done by other researchers in the same domain. Normalized mean square error (NMSE) & signal to noise distortion ratio (SNDR) values are also mentioned by the author in their work. Seda Senay and Luis F. Chaparro et. al. in their paper proposed a method in which compressive sensing is used with random filtering by using the Slepian basis for EEG signals. As per the result shown by the authors' reconstruction using compressive sensing with a random filter method with sparse signals is less noisy than smooth signals [3]. Dharmendra Gurve et. al. in their work describes the reconstruction algorithms, various Basis, and sensing matrices that can be used for the EEG signals. The suggestion provided by the author shows that the selection of a sparse basis will affect the compressive sensing strategy for EEG signals [4]. In another paper by Nadia Mammone et. al. considered patients affected by Alzheimer's disease, mild cognitive impairment, and healthy control, then the high-density EEG signals for these patients are processed using the compressive sensing approach [5].

In our work, we are describing a model that how we can use the EEG compressive sensing approach nowadays to deploy it with real-time monitoring of a patient by using the Internet of Things (IoT) and other communication strategies. The data which we gather by applying the EEG process on a subject further processed using compressive sensing, first we compress it then recover it using few samples. Then this data which is recovered using a few samples can be transmitted or stored using various connectivity protocols according to the requirement as shown in Figure (1). But in the majority of cases, we use smartphones as an intermediatory model for primary storage or transmission towards the IoT cloud or Health care units.

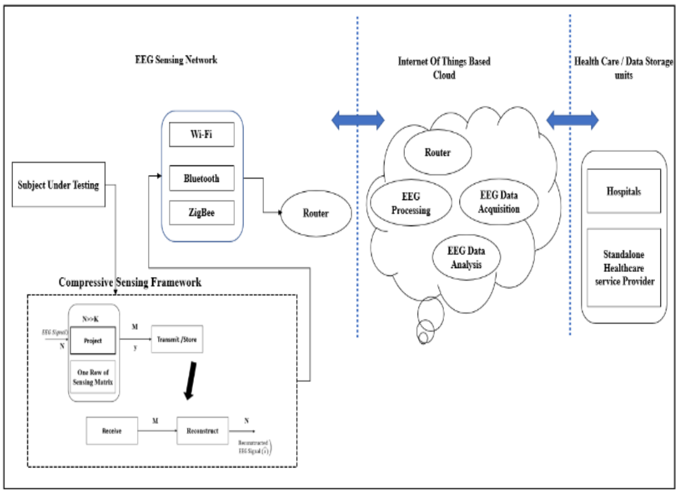


Figure 1. Compressive Sensing Framework with remote Health Care Unit & Patient for EEG Signals

When we talked about the data which is complex and too large then there is the only single option of computation which is known as compression. Compression is the way that provides a dense representation of the signal with very low distortion & fine target level. Transform coding is the theory which is widely used for compression. The main aim of transform coding is to search the basis which provides a sparse representation of a signal [6, 7, 8]. Sparse representation is the theory by which a signal which has length n can be showed easily by k coefficients & k<<n non zero components. This is well known as compressive sensing. The signals which are compressible & sparse can easily be represented with high fidelity & high preserving values with very few numbers of coefficients.

Compression & decompression is a key idea of transform coding, but compressive sensing is a new groundwork which is used for data acquisition & designing of a sensor. Compressive sensing is the way that is used to reduce the data which is potentially very large for sampling & has a high cost of storage, but the data have a sparse representation. As per the statement given by Nyquist- Shannon, a minimum number of samples are required for the proper reconstruction of the signal [9]. We represent the signal with the sparse coefficients to reduce the number of measurements to an exceedingly great extent that needs to be stored. As per the results we got after the proper reconstruction, we can easily say that the reconstruction which is done using the sparse signals is much better than the classical results. So much precisely the CS is the process in which the traditional way of compression is not followed in which first we have to do sampling at a very high rate then the compression is done for the sampled data rather than we can directly observe data in compressed form at very below to the Nyquist Rate. This valuable theory is developed by famous researchers Candes, Tao, Romberg, and Donoho. The theory which is given by them shows that the data which is finite with the additional property of sparsity can easily be reconstructed by using a small set of linear and non-adaptive measurements [10, 11, 12-14, 15, 16]. The challenge nowadays is to practically implement this type of theory and then get the productive result from this CS theory.

III. Sparsity Based Modelling Of Signal

U is a real, finite length, discrete-time signal. To represent the input signal in the form of a vector in RN vector space as the Nx1 column vectors like U [0], U[1],.......U[N]. This vector property used by Basis vector in which any high dimension signal in vector space RN can be represented in terms of basis vectors is the columns of complete basis matrix of order NxN [10].

$$U = \sum_{j=1}^{N} S_j \Psi_j \quad \text{Or} \quad U = \Psi S \tag{1}$$

Here S j, j=1, 2…. N are the column component of S matrix of order Nx1. S j can be computed by

$$S = \langle U, \Psi_j \rangle = \Psi^T U \tag{2}$$

Signal U is a representation in time domain or space domain while the signal is presented in the form of basis matrix ψ domain by S for sparse representation of signal A. For the proper representation of the sparse signal, it is required that it hold some (K) large magnitude components and discarded (N-K) small magnitude coefficients. Most of the energy and important information of the signal is condensed in the large magnitude coefficients (which represents K-sparse) which are used to recover the original structure of the signal. These K-sparse signals are encoded for the transmission.

In the beginning, the BSBL model only used for the reconstruction of a signal consists of a block arrangement. According to this theory, the signal splits into various non-overlapping blocks, with some non-zero blocks [17]. In some findings the partition of blocks is decided by the user, it will further applicable to regularize the covariance of the signal. But in this work, we have observed that even no block structure is followed by the signal but the BSBL model can be applied for effective recovery of signal. Due to this reason here, it is considered for the Compressive sensing approach. In our work, we used a bound optimization-based algorithm (BSBL-BO), with the gaussian sensing matrix we also used Poisson, Exponential, Rayleigh, Chi-Square random matrices. This change is incorporated in the algorithm used for the compression and recovery of the signal. In the next section, we are going to define the experimental results and observations. In some cases, we found the BSBL-BO with our modified approach representing a significant change in the reconstruction of the original signal.

IV. Result And Analysis

The EEG signal that is considered for the computation process is “eeglab_data.set” which is extracted from EEGLab [18]. The dataset consists of an EEG signal for 32 channels, each channel consists of 80 epochs and these 80 epochs contain 384 points each. Muscle movement artifacts are also considered in the signal. Matlab 2020a, computer with Processor (i5-1.80 GHz), and 8.00 GB ram is utilized for the computation purpose.

A. *Mean Square Error (MSE)*

Mean Square Error is a parameter for quality evaluation of the EEG signal. The main objective of MSE is to find out the distortion level between the actual and reconstructed signal. The relation for MSE between actual & reconstructed signal is given below [19].

$$MSE(Q,S) = \frac{1}{n}\sum_{1}^{n}((Q_i - S_i)^2) \qquad (3)$$

Where Q = EEG Test signal, S = Reconstructed EEG signal, n = Number of iterations.

B. *Compression Ratio Per Frame*

The Compression Ratio is a very crucial parameter in audio signal processing. It depicts the number of measurements that are used for the reconstruction divided by the whole number of measurements.

$$CR = K / N \qquad (4)$$

Here, K= Reconstruction measurements, N= Total number of measurements.

C. *Structural Similarity Index Measure (SSIM)*

Structural Similarity Index Measure is the method that defines the quality measure between the original signal & the reconstructed signal. SSIM is based on contrast, luminance, structure, or correlation between two signals. Multiplication of these aspects provides the value of SSIM [20]. Here j is contrast, k is luminance and p represent the structural index values.

$$SSIM(g,h) = [j(g,h)]^{\alpha} \cdot [k(g,h)]^{\beta} \cdot [p(g,h)]^{\gamma} \qquad (5)$$

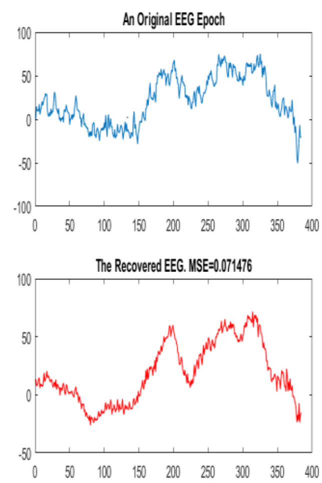
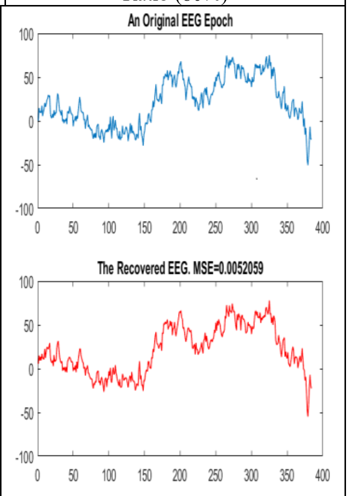
$$SSIM(g,h) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_x\sigma_y + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \qquad (6)$$

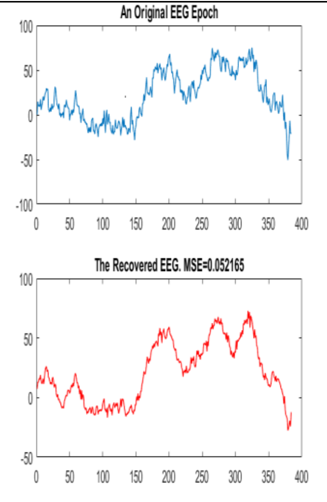
Here μ_x and μ_y are the local means, σ_x and σ_y are the standard deviations and σ_{xy} is the cross-covariance for the original and reconstructed signal. If $\alpha=\beta=\gamma=1$

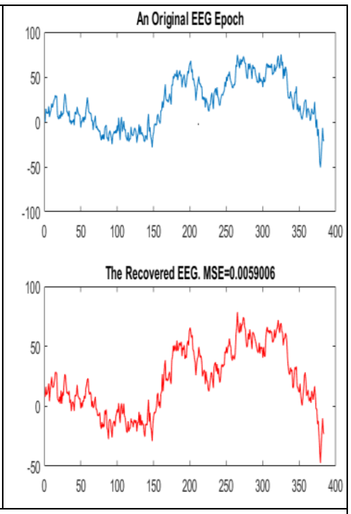
Table I is representing the original EEG Epoch and Reconstructed EEG Epoch. The experiment conducts on seven compression levels i.e. from 20% compression ratio to 80% compression ratio. In the table, 5 combinations are considered for Basis and Sensing matrices. Two parameters which are representing the quality level of reconstruction given in the table below, one is Mean Square Error (MSE) and another is the Structural Similarity Index Measure (SSIM). Execution time for the algorithm is also calculated using the Matlab in seconds.

For the compression purpose we use a 192 x 384 dimension-based (i.e 50% compression level) sensing matrix and for reconstruction purpose we 192 x 384 dimension-based basis matrix. We have done the computation for each epoch contain by this EEG frame. We compare our proposed work with the previously mentioned work, the comparison is based on the mean square error value and the structural similarity index measure values. In our proposed work we use the DCT basis matrix with Gaussian, Exponential, Poisson, Rayleigh, and Chi-square random matrices as sensing matrices. In table I we provide the pictorial representation for original and reconstructed EEG signal only for two levels of compression, one is least i.e. 20% and another is 80% compression level. The value of MSE for the recovered EEG signal window is given above the reconstructed signal. So here we can check that the value of MSE is very less so the signal approaching the best quality with very few samples used for the recovery purpose.

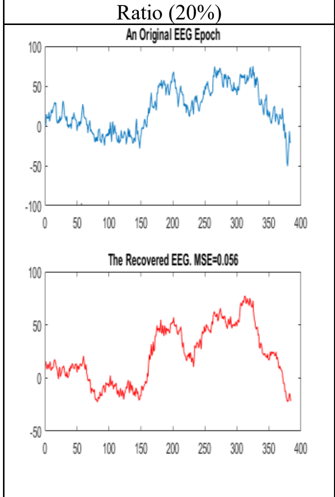
Table I
Reconstructed and Original Signal with Mentioned Sensing and Basis Matrices

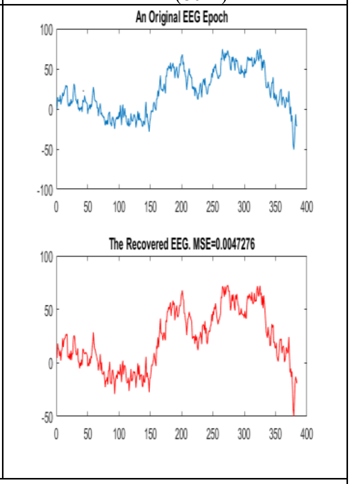
Basis Matrix: DCT	
Sensing Matrix: Gaussian	
Original V/s Reconstructed EEG Signal for Least Compression Ratio (20%)	Original V/s Reconstructed EEG Signal for Higher Compression Ratio (80%)
	
Sensing Matrix: Poisson	
Original V/s Reconstructed EEG Signal for Least Compression Ratio (20%)	Original V/s Reconstructed EEG Signal for Higher Compression Ratio (80%)



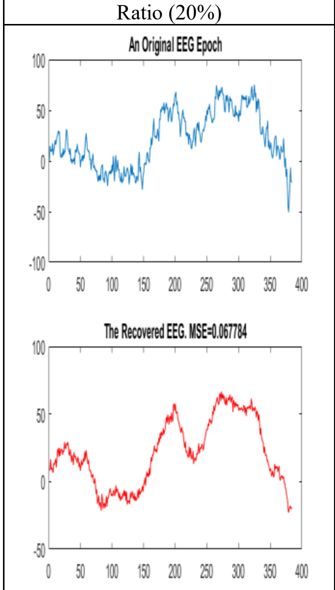


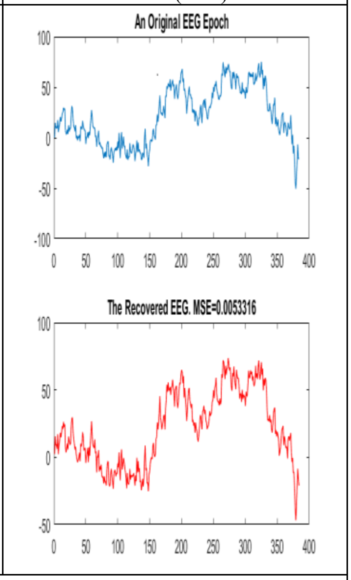
Sensing Matrix: Exponential	
Original V/s Reconstructed EEG Signal for Least Compression Ratio (20%)	Original V/s Reconstructed EEG Signal for Higher Compression Ratio (80%)



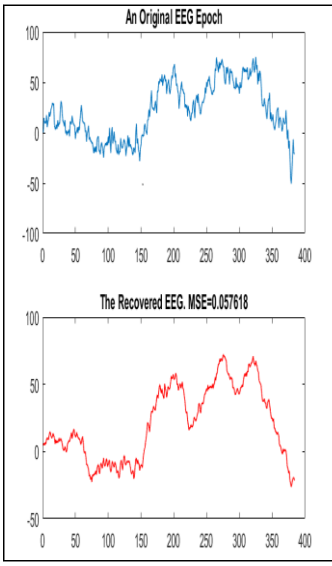


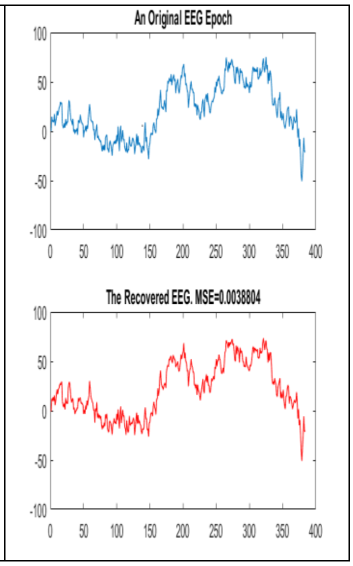
Sensing Matrix: Rayleigh	
Original V/s Reconstructed EEG Signal for Least Compression Ratio (20%)	Original V/s Reconstructed EEG Signal for Higher Compression Ratio (80%)





Sensing Matrix: Chi-Square	
Original V/s Reconstructed EEG Signal for Least Compression Ratio (20%)	Original V/s Reconstructed EEG Signal for Higher Compression Ratio (80%)





In table II the Mean Square error [21] values are shown with a different compression level of EEG signals. Here we can see that the Exponential and Chi-Square-based compressive sensing method shown the least values of the mean square error. It means that when we use these random matrices as sensing matrix, so the reconstructed EEG signal is much more accurate to the original signal level. To confirm the structural similarity of the recovered signal we are showing the SSIM values of the recovered EEG signals in the table below.

TABLE II
COMPRESSION RATIO (CR) V/S MSE FOR MENTIONED BASIS AND SENSING MATRICES

CR	Compression Ratio v/s MSE				
	Basis Matrix: DCT				
	Sensing Matrix				
	Gaussian	**Exponential**	**Rayleigh**	**Poisson**	**Chi-Square**
0.2	0.068896	0.056	0.067784	0.052165	0.057618
0.3	0.047534	0.036523	0.04367	0.039167	0.046049
0.4	0.026896	0.029765	0.025243	0.02551	0.028672
0.5	0.018577	0.021247	0.017421	0.018268	0.024927
0.6	0.012071	0.015307	0.012893	0.0099978	0.011403
0.7	0.0074953	0.007982	0.007396	0.0092991	0.008135
0.8	0.0052059	0.004727	0.005331	0.0059006	0.0038804

TABLE III
COMPRESSION RATIO (CR) V/S SSIM FOR MENTIONED BASIS AND SENSING MATRICES TABLE

CR	Compression Ratio v/s SSIM				
	Basis Matrix: DCT				
	Sensing Matrix				
	Gaussian	**Exponential**	**Rayleigh**	**Poisson**	**Chi-Square**
0.2	0.3008	0.3096	0.5726	0.3514	0.4124
0.3	0.5697	0.03721	0.689	0.585	0.6352
0.4	0.6653	0.7444	0.7802	0.709	0.7425
0.5	0.826	0.8358	0.7888	0.7225	0.8693
0.6	0.8382	0.873	0.8403	0.844	0.8711
0.7	0.8414	0.9226	0.8918	0.8937	0.8947
0.8	0.9354	0.927	0.9124	0.9291	0.9474

Table IV is showing the compression ratio v/s execution time for the proposed algorithm. Increment in the number of samples is showing a significant increase in the execution time of the algorithm. But the Rayleigh sensing matrix has the least value of execution time at 0.8 compression ratio than other sensing matrices as shown in table IV.

TABLE IV
COMPRESSION RATIO (CR) V/S EXECUTION TIME OF ALGORITHM FOR MENTIONED BASIS AND SENSING

CR	Compression Ratio v/s Execution Time for Algorithm				
	Basis Matrix: DCT				
	Sensing Matrix				
	Gaussian	Exponential	Rayleigh	Poisson	Chi-Square
0.2	0.042	0.043	0.046	0.046	0.042
0.3	0.047	0.053	0.051	0.047	0.054
0.4	0.054	0.048	0.061	0.056	0.057
0.5	0.062	0.099	0.065	0.059	0.063
0.6	0.072	0.073	0.068	0.07	0.069
0.7	0.07	0.082	0.079	0.083	0.081
0.8	0.091	0.086	0.084	0.09	0.094

TABLE V
COMPARATIVE VALUES OF MSE AND SSIM FOR PROPOSED AND EXISTING APPROACH (AT 50% COMPRESSION LEVEL)

S.No.	Name of Framework Used	MSE	SSIM
1	**Proposed Modified DCT Based BSBL_BO**	0.024927	0.8693
2	DCT Based BSBL-BO	0.078	0.85
3	BSBL- Without DCT	0.116	0.81
4	DCT-Based l_1	0.493	0.48
5	DCT-Based Block-CoSaMP	0.434	0.45

If we want to define the efficiency of the reconstruction algorithm, then here we have two parameters one is MSE and another is SSIM. Here in table 5, we compare these parameter values with previously measured values [22]. The least value of SSIM is observed for the Chi-Square sensing matrix, for the same matrix we have shown the value of MSE also.

V. CONCLUSION

BSBL-BO is an efficient algorithm based on a compressive sensing approach for EEG signals. But we still want to enhance the efficiency of the algorithm in a verified manner. So, in our proposed work, this enhancement is shown, we represent MSE, SSIM and the pictorial reconstructed EEG signal which is very much close to the actual signal. Some concluding remarks which are the key findings for our work are as follows.

- The value of the Compression Ratio directly affects the reconstruction process, but if we observe table 2, then we can find that this also depends on the type of sensing matrix. For the same compression Ratio (0.80), Gaussian (0.0052059), Exponential (0.0047276), Rayleigh (0.0053316), Poisson (0.0059006) Chi-square (0.0038804) sensing matrices are showing different MSE values as mentioned in brackets.
- SSIM values are mentioned in table 3, for the Chi-Square sensing matrix the value of SSIM is maximum for the proposed framework.
- One most important conclusion which we get from this analysis is, for the reconstruction of the EEG signal even if the value of MSE is minimum in some cases like Gaussian (0.0052059) and Exponential (0.0047276) but the value of SSIM is higher than the Exponential sensing matrix. So we can say even the reconstructed and original EEG signal has a minimum difference in the MSE values but their structural similarity has some variation.)
- As we increase the number of samples in the reconstruction process the value of execution time (in seconds) also increases. This execution time is also based on the complexity of the sensing matrices as we can see the Rayleigh sensing matrix-based reconstruction has the least value of the execution time.
- In table 5, which is the main comparison table of our work with previously stated work [22] we can observe that our proposed work at 50% compression level is showing a higher value of SSIM and least value for the MSE. The comparison is based on four different methods of EEG signal reconstruction.

So, we can say that the proposed framework is effective, and we can use it in the real-time EEG signal acquisition process. This approach can also enhance the lifetime of the battery and less power is required to sense the EEG signal as we can get the informative part even if we reduce the number of samples which we consider to reconstruct the EEG signal. The framework, which is mentioned in figure 1, is much effective with this proposed methodology.

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