An Efficient Parallel Block Compressive Sensing Scheme for Medical Signals and Image Compression

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Abstract

Compressive Sensing or Compressed sensing (CS) is a latest technique used for compression of medical signals and medical images which benefits both the speed and accuracy. The performance of CS based compression is mostly dependent on decoding methods rather than the CS encoding methods used in practice. It has been found in literature that CS encoding algorithms have got least importance than decoding algorithms. In this paper an efficient CS encoding scheme based on modified parallel block processing has been suggested for biomedical signal and image compression. The input signals and images are acquired and preprocessed with suitable filtering techniques and then the same have been divided into number of cells and blocks. Each block is then processed in parallel to enable faster computation. Three performance indices, i.e., the peak signal to noise ratio (PSNR), reconstruction time (RT) and structural similarity index (SSIM) have been analyzed with respect to the compression ratio. A comparative study has been carried out between the standard CS based compression and the suggested technique. The results showed that proposed algorithm provides better performance than standard CS based compression. More specifically, the parallel block CS reported the best results than standard CS with respect to less reconstruction time and satisfactory PSNR and SSIM. The suggested technique offers SSIM improvement approximately by 8% and reduction in RT by 99% than the standard CS based compression for CT scan image compression. In case of brain signal compression, the suggested technique offers SSIM improvement approximately by 25%, PSNR improvement by around 2% and reduction in RT by 75% than the standard CS.

Keywords Compressed sensing · Parallel processing · Data compression · Peak signal to noise ratio · Image reconstruction · Image quality
1 Introduction

Compressive Sensing or Compressed Sensing (CS) is a signal processing technique used in almost all the field of communication engineering in recent years. CS can be used as a data reduction tool for efficient acquisition and reconstruction of a signal. In CS based reconstruction, underdetermined linear systems [1] are solved using linear programming and by finding solutions to the underdetermined system, perfect recovery of the signal is done. In [2], it is explained very well how the CS theory can be used to recover signals from very few number of samples (measurements) than traditional and conventional methods.

In this proposed paper, we have considered medical computerized tomography (CT) scan and X-ray images as input sample images [3, 4]. The input images are preprocessed and then splitted into numbers of cells and all the cells are again divided into number of blocks which are compressed simultaneously using CS. At the first step, the input images are filtered using averaging filter to obtain noise free input whereas the 16 channels sample brain signal (EEG) [5] is filtered using a band-pass filter to get frequencies between 0.1 and 40 Hz and the sampling frequency used is 250 Hz.

Both kind of biomedical signal and images are compressed and reconstructed from the compressed version and the relative performance parameters are calculated. The suggested technique is also compared with standard CS and the results obtained using suggested method is found to be promising one compared to standard CS based compression.

2 Related Work

A novel joint watermarking compression scheme by combining lossless compression and JPEG compression is proposed for ultrasound images in [6]. The proposed scheme introduced an acceptable distortion in images, however the complexity of the suggested method is very high compared to CS based compression. A new strategy for the compression of 3D images based on region of interest is presented in [7] for wireless communication. The proposed method is quite efficient in transmission time reduction but reconstruction time is not analyzed in this work.

Wavelet Based ECG Data Compression technique with different encoding has been suggested in [8]. Cosine modulated filter banks (CMFBs) are designed for Electrocardiogram (ECG) data compression in [9]. The maximum compression ratio and PSNR achieved is around 30% and 38 dB which is not very high compared to CS based compression.

[10] addresses the H.264 medical video compression for telemedicine. However for biomedical signal compression, the same techniques is not been tested.

Medical Image Analysis for Computer Aided Diagnosis is discussed in [11]. In [12], Empirical mode decomposition and wavelet transform is used for ECG signal compression. The paper [13] discusses about wavelet-based hybrid electrocardiogram (ECG) data compression. [14–16] discusses about most promising algorithms to be used for ECG compression. However the similar techniques are not discussed with respect to biomedical image compression.

In [17], medical image transmission over Wireless Multimedia Sensor Networks is described. The EZW algorithm has been discussed with Haar wavelet transform for
medical image compression in [18]. Wavelet and DCT based satellite image compression is discussed in [19, 20]. However medical signal transmission using the similar compression techniques are not been highlighted.

In [21], JPEG and JPEG2000 based compression is been provided for WSN transmission but the medical images are not used for analysis. Using features of wavelet and curvelet transforms is proposed for image compression in [22].

KLT-based compression algorithm for multispectral images have been discussed in [23] for multispectral images, however the medical image compression is not addressed here.

From the above related works reported it is clear that the methods used for compression are either suitable for image compression or suitable for signal compression but none of the compression technique used in literature are suitable for both kind of 1D and 2D signal compression with good quality of reconstruction and less reconstruction time. Hence in this paper we have suggested a novel compression technique suitable for 1D and 2D medical signal compression. Our suggested technique is capable of providing solutions to the problems faced by previously mentioned work.

3 Review of Standard CS Encoding and Decoding Algorithm

3.1 CS Encoding

Conventional sampling theorem need not be followed in CS based compression. To make this possible, CS relies on two principles: one is Sparsity and the other principle is incoherence. Sparsity [1], depends on the density of the signal and incoherence, which depends on the sensing modality. Both the principles are discussed in detail as follows.

3.1.1 Sparsity

A sparse matrix is a matrix or a sparse array is an array in which few elements are non-zero and most of the elements are zero. On the other hand, most of the elements are nonzero in a dense matrix. The parameter sparsity can be found by finding the number of zero-value elements divided by the total number of elements in a matrix or array. The sparsity can also be found by subtracting the density of the matrix from unity. In general many signals are sparse or compressible by nature. This behaviour of signal is exploited by CS theory. The meaning is, the signals have sparser representations when they are expressed in the proper basis $\Psi$. Mathematically if we have a vector ‘$x$’ of length ‘$N$’ (i.e. $x \in \mathbb{R}^N$), then the vector ‘$x$’ can be expanded using an orthonormal basis $\Psi = [\Psi_1, \Psi_2, \Psi_3, \ldots \Psi_N]$ using the Eq. (1).

$$s = \sum_{i=1}^{N} x_i \Psi_i$$  (1)

where sparse representation of input signal ‘$x$’ is denoted by ‘$s$’. The number of non-zero components in the vector ‘$s$’ are much lesser than the non-zero components in vector ‘$x$’ if the spreading basis is sparse. From Eq. (1) it is clear that when a signal has a sparse representation, small coefficients can be discarded without much perceptual loss.
3.1.2 Incoherence

Incoherence principle is extended by the duality between time and frequency. It expresses the idea that objects having a sparse representation in a basis \( \Psi \) must be spread out in the domain in which they are acquired. The concept of incoherence can be made much clear with the help of a spike signal or impulse signal. In the time domain a Dirac or a spike signal is concentrated to one particular time instant whereas when the same signal is represented in frequency domain, it spreads out in the frequency domain. Similar concept can be used in CS based sparse representation of the signal. Suppose given a pair of \((\Phi, \Psi)\) orthobases of dimension \( \mathbb{R}^n \) each. For explanation of incoherence let ‘\( \Phi \)’ basis is used for sensing the signal ‘\( x \)’ and the other basis is used to represent ‘\( x \)’ in sparse domain. The relation between these two bases decides the reconstruction quality in CS recovery and hence it is essential to determine the degree of correlation between the pair of orthobases. The mutual coherence of a pair of orthobases \((\Phi, \Psi)\) is the measure of highest similarity factor between any two columns of \( \Psi \) and ‘\( \Phi \)’. If ‘\( \Phi \)’ and ‘\( \Psi \)’ contain correlated elements, the coherence is large, otherwise the mutual coherence value is small.

The mutual coherence between the sensing basis ‘\( \Phi \)’ and the representation basis ‘\( \Psi \)’ is given by the Eq. (2).

\[
\mu(\Phi, \Psi) = \sqrt{n} \cdot \max \left( \Phi_k \Psi_j \right)
\]  

(2)

where \( 1 \leq k, j \leq n \).

In CS based reconstruction, small mutual coherence value is desirable as it provides better recovery of the signal.

The CS algorithm can be better explained with the help of mathematical expressions given in this section. Conversion of the acquired medical signals or images into a sparse signal is done by the use of sparsifying kernel in CS. Sparse signals are the signals which are very few in number and has complete structure and meaningful information which are essential to reconstruct the original signal or image. The generation of the sparse signal (s) in matrix form is given in Eq. (3).

\[
s = \Psi \cdot x
\]

(3)

In Eq. 3, the input signal is denoted by ‘\( x \)’ and ‘\( s \)’ is the sparse representation of the input data and ‘\( \Psi \)’ is the transform matrix or kernel. After sparse generation, measurement matrix ‘\( A \)’ is used for compression of the sparse signal or image. The output ‘\( y \)’ which is the compressed version of input ‘\( x \)’ is given in Eq. (4),

\[
y = A \cdot s
\]

(4)

where ‘\( A \)’ is called the measurement or sensing matrix, ‘\( s \)’ is the sparse representation and ‘\( y \)’ is the compressed output.

3.2 CS Decoding

CS involves a variety of methods for representation of a signal on the basis of a limited number of samples. CS based recovery of signals involve reconstruction of signal from these reduced number of samples. The major issue in CS recovery [24] is how to effectively reconstruct the original signal from the compressed data without the loss of generality. Currently, there are
varieties of reconstruction algorithms available in literatures which are defined either based on the framework of convex optimization, or greedy approaches. These are namely: Convex Relaxation, Non Convex Minimization Algorithms, Greedy Iterative Algorithm, Combinatorial/Sublinear Algorithms, Iterative Thresholding Algorithms, Bregman Iterative Algorithms.

The complexity of the CS recovery algorithm and also the computational speed of the algorithms are very important as these factors influence the recovery of the signal in practical situations. In general, the convex relaxation method is used for CS reconstruction for its simplicity and computational speed. Convex relaxation [25] based recovery method has high computational speed compared to other reconstruction algorithms mentioned above. The convex relaxation reconstruction method is used in this work.

4 Proposed Algorithm and Methodology

In order to compress very large dimension medical image and long duration brain signal, proposed modified parallel CS is suggested in which the input signal/image is divided into number of cells and each cell is compressed simultaneously to perform compression.

The brain signal [5] compression using the proposed method undergoes the following steps. The multichannel EEG signal of size \((A \times B)\) is first acquired where ‘A’ is the number of samples in each channel and ‘B’ is the number of channels. The acquired signal is now divided into cells where each cell again divided into \((8 \times 8)\) blocks each. In order to make each block of size \((8 \times 8)\), necessary zero padding is performed. All the blocks are then considered and simultaneously the compression is performed on each block.

Medical 2D signal of size \((M \times N)\) is considered and taken from database [3]. The size of row ‘M’ and size of column ‘N’ are divided by 4 and cells are generated. Preferably the row and column size ‘M’ and ‘N’ must be of multiple of 4. If row and column size is not multiple of 4 then zero padding is done to make row and column size of image that to be compressed are of multiple of 4. Each cell is separately compressed using proposed algorithm [26]. The reconstruction result shows very good quality. The steps involved in suggested method for a signal of size \((M \times N)\) is shown in figure. Parallel Processing of each cells for CS based compression is performed and reconstruction of each cell is performed. At last step all the reconstructed cells are combined to get final reconstructed signal and image. The proposed encoding scheme is presented in Fig. 1.

Figure 1. shows the steps involved in proposed scheme. Both the signal and image is first acquired and filtered. The filtered signal/image is then divided into cells and subsequently into blocks. Each block is compressed in parallel to make the compression process faster. After the compression is being performed in each block, all the compressed version of the signals and images are joined together in sequential manner to form the overall compressed signal which can be used for transportation or for easy storage in medical signal processing. At the decoder, the reverse process is performed and the convex relaxation based CS reconstruction method is used to obtain the reconstructed signal and image.

5 Results and Discussions

Figures 2a, 3a and 4a shows the input sample medical image and brain signal of size \((M \times N)\) matrix. This image/signal is then compressed by both standard CS and by using proposed scheme. The compression ratio is maintained 2:1. From the compressed
Fig. 1 Efficient parallel block CS encoder

Fig. 2  
(a) Sample Image of size (64×64).  
(b) Reconstructed Image of size (64×64) using standard CS.  
(c) Reconstructed Image of size (64×64) using modified parallel block CS
pixel values, the data is reconstructed [27] and shown in figure below. Figure 2b shows
the image reconstructed using standard CS and Fig. 2c is the resultant image by pro-
posed technique reconstruction for CT scan sample image. Figure 3b shows the image
reconstructed using standard CS and Fig. 3c is the resultant image by proposed tech-
nique reconstruction for the sample X-ray image.

Each input image of size (64×64) is first filtered using averaging filter and then
divided into (16×16) size cells and each cell is further broken into (4×4) size blocks. Each block is then compressed using 50% compression rate in parallel manner to obtain
the desired compression. From the compressed pixel using the CS reconstruction, the
reconstructed images are obtained with good quality.

The brain signal is considered as next input to the suggested algorithm. The brain
signal dimension is used (5000×16). The raw signal is then filtered using the band pass
filter to band limit the signal between 0.1 and 40 Hz and the sampling frequency used
is 250 Hz. The filtered signal is then divided into two cells and each cell is then divided
into (8×8) blocks. Proposed encoding technique is then applied to all the blocks in par-
allel manner to compress. The reconstruction is then performed. The original & recon-
structed signals are shown in following Fig. 4a,b,c.

The images/signal reconstructed with 50% pixels using cell compressed sensing is
shown in Figures above. The quality of both the original and reconstructed image can
be best measured by calculating the Peak Signal-to-Noise Ratio (PSNR), reconstruction
time (RT) and structural similarity index (SSIM) which are shown in tables.
Fig. 4  a Sample brain signal of size (5000 × 16).  b Reconstructed brain signal of size (5000 × 16) using standard CS.  c Reconstructed brain signal of size (5000 × 16) using Modified parallel block CS
PSNR values of input and reconstructed image/signal indicate that both the images/signal are of equal quality and hence CS can be used for compression of large medical images [28, 29]. The PSNR and SSIM values are calculated using Eqs. (5) and (6).

\[
\text{Peak signal to noise ratio (PSNR)} = 10 \times \log_{10} \left( \frac{\text{peak signal level}^2}{\text{MSE}} \right) \quad (5)
\]

\[
\text{SSIM} = \frac{\left(2\mu_s\mu_{sr} + C_1\right)\left(2\sigma_{ssr} + C_2\right)}{\left(\mu_s^2 + \mu_{sr}^2 + C_1\right)\left(\sigma_s^2 + \sigma_{sr}^2 + C_2\right)} \quad (6)
\]

The reconstruction time (RT) is the time taken for compression and reconstruction from original signal/image to reconstructed signal/image. In order to obtain RT, we have used the same simulation environment.

In Eq. (5), The MSE represents the cumulative squared error between the compressed and the original signal/image. In Eq. (6), \( \mu \) and \( \sigma \) are the local mean and standard deviation of the two signals/images (input and output), \( C_1 \) and \( C_2 \) are constants used to stabilize the equation in the presence of weak denominators, and \( \sigma_{ssr} \) is the sample cross correlation (zero mean). Conventionally \( C_1 = (k_1 L)^2 \) and \( C_2 = (k_2 L)^2 \) where \( k_1 = 0.01 \), \( k_2 = 0.03 \), and \( L \) is the dynamic range of the pixel values.

Table 1 shows the PSNR, RT and SSIM values of CT scan sample image. It is clear from the above table that the suggested modified parallel block CS scheme performs better than the standard CS as there are improvements in PSNR and SSIM values and very less reconstruction time in case of suggested method.

Table 2 shows the PSNR, RT and SSIM values of X-Ray sample image. Here also there is an improvement in each performance parameters for suggested technique.

Table 3 shows the PSNR, RT and SSIM values of brain signal. In this kind of signal too, the suggested method outperforms than standard CS.

### Table 1

| Types of compression technique | Sampling ratio | PSNR in dB | RT in seconds | SSIM |
|-------------------------------|----------------|------------|---------------|------|
| Standard CS                   | 2:1            | 31.348     | 124.150       | 0.6188 |
| Modified parallel block CS    | 2:1            | 31.092     | 1.0285        | 0.6916 |

The above table shows the measured PSNR values in dB

### Table 2

| Types of compression technique | Sampling ratio | PSNR in dB | RT in seconds | SSIM |
|-------------------------------|----------------|------------|---------------|------|
| Standard CS                   | 2:1            | 30.012     | 124.752       | 0.795 |
| Modified parallel block CS    | 2:1            | 31.383     | 1.134         | 0.815 |

### Table 3

| Types of compression technique | Sampling ratio | PSNR in dB | RT in seconds | SSIM |
|-------------------------------|----------------|------------|---------------|------|
| Standard CS                   | 2:1            | 36.968     | 62.399        | 0.652 |
| Modified parallel block CS    | 2:1            | 38.785     | 15.785        | 0.911 |
From all the above Tables 1, 2, 3, it is clear that the suggested method is very powerful in reducing the reconstruction time than standard CS. The SSIM values also have significant improvement where as there is very minor improvement in PSNR values. The results obtained here with block size (4×4) in case of image and (8×8) in case of EEG signal compression. The similar analysis is performed with varied block size but in that case, the result does not show any improvement. If the block size is considered large then the computational complexity of the algorithm increases and which in turn requires large RT. If the block size is considered too small the sparse nature of the signal gets disturbed and hence CS does not perform well which results poor quality reconstruction.

6 Conclusion

The proposed efficient CS scheme based on modified parallel block compression technique for biomedical signal and image have been analyzed and the performance measuring metrics have been computed. Results of this work show that with 50% samples of original signal and 50% pixels of original image, the reconstruction quality is much better than standard CS based compression. Performance measuring parameters like PSNR, SSIM and RT are computed for proposed and existing standard CS compression method. Among all the three parameter, the reconstruction time (RT) shows tremendous reduction in proposed method. Due to less reconstruction time, the suggested method may be much suitable in real time signal and image compression. The suggested method enables the compression process to take place in parallel manner for all the divided blocks of input signal and image which in turn reduces the overall time taken by the process. The calculated SSIM and PSNR values are also very high in suggested method and hence the proposed compression scheme is much suitable in medical data and image compression.

Future works may also involve to implement the suggested algorithm in hardware for real time medical signal and image compression.

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Data Availability The data set that support the findings of this work are available in [https://www.kaggle.com/kmader/siim-medical-images, https://www.kaggle.com/paultimothymooney/chest-xray-pneumonia, https://physionet.org/physiobank/database/noneeg].

Declarations

Conflict of interest The authors declare that there is no conflict of interest.

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