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Study and Analysis of Medical Image Compression Using Compressive Sampling

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Abstract —Nowadays in medical science, patience are examined by various medical images. The acquisition of these types of images is very expensive and time lengthy process. Also storage of medical images is one of the problems by considering the number of patience increase day by day. So overcome to problem related to size of storage and lengthy process time, in this paper new acquisition process for medical images is proposed using compressive sampling. The compressive sampling is a new signal processing theory which is sampled and compressed data simultaneously. The compressive sampling process is applied on medical image such as CT, MRI and Ultrasound image. In this paper, compressive sampling process is applied on CT image and the results show that this process reduces the acquisition time and storage size without affecting the quality of the CT image.

Keywords- Compressive Sampling, DWT, Medical Image, PSNR, RMSE, SSIM, SVD

I. INTRODUCTION

In medical science and treatment of patients is done by using various medical images. The many diseases in the human body are identified by using various images such as CT, MRI and Ultrasound images. The acquisition of these images has required more time and more storage capacity for storing these type images [1, 3]. The block diagram of conventional medical image compression is given in Figure 1. In this approach, the data are first taken and then sampling is performed on acquiring data. Finally transformed is applied on sampled data. Then transformed coefficients of data are analysed and coded by using some conventional image compression standard such as JPEG and then an image is stored in compressed format [2]. The main limitation of this approach is that it is using whole data and then removed many transformed coefficients of data; time length process and wastes of storage size.

Figure 1. Conventional Medical Image Compression

To overcome to limitation of acquisition and compression of medical image, compressive sampling is one of the solutions. Compressive sampling is mostly applied to MRI image to reduce the scan time of image acquisition [1-3]. M. Lustig and its research team first introduced the application of compressive sampling for MRI image acquisition and how this theory has reduced the scan time of MRI image acquisition [1, 2]. M. Sevak and its research team discussed sparsity property of various wavelets with compressive sampling for CT image compression [3]. In these existing methods, researchers are exploring sparsity property of wavelet transform and generate sparse coefficients of medical image.

In this paper, sparsity property of wavelet transforms and singular value decomposition (SVD) is used for generation hybrid sparse coefficients of data. Then various sizes of measurements of data have taken for medical image compression. The quality measure such as PSNR, RMSE and SSIM is used for quality checked of compressed medical image. The rest of paper organized such as section 2 given information about Singular Value Decomposition (SVD). Section 3 given information about compressive sampling. Section 4 given step of medical image compression using compressive sampling, section 4 given results and finally conclusion of the paper is given.

II. SINGULAR VALUE DECOMPOSITION (SVD)

Any image with size M×N can be represented using Singular Value Decomposition (SVD) into three different matrices which denote below equation 1. Singular Value decomposition (SVD) decomposed image into three matrices such as a singular value matrix with size of M×N and two unitary matrices U with size of M×M and V with size of N×N. The properties of these three matrices [12, 13] are given below.

$$[U, S, V] = SVD(I) \tag{1}$$

1. It can be represented as I=U*S*V^T.
2. U is called an M×M real or complex unitary matrix and V^T (the conjugate transpose of V) is called an N×N real or complex unitary matrix.
3. S is an M×N rectangular diagonal matrix with nonnegative real numbers on the diagonal. This matrix is also called as singular matrix.
4. Brightness and geometric characteristics of the image can be represented by this singular matrix vector.
5. This Singular matrix is also important for compressive sensing and watermarking because this matrix values are arranged diagonally and in ascending order.
6. This singular matrix values are produced sparse coefficients of any image.

(a) U Matrix *(b) S Matrix* *(c) V Matrix*

Figure 2. Example of Singular Value Decomposition (SVD)

When SVD is applied on any image and it decomposed into three different matrices which are shown in Figure 1. The singular matrix is provided sparse property compared to other two matrices. In singular matrix, black portion is shown zero values and white portion is shown non negative real values. So that singular matrix values are used as sparse coefficients of an image. The sparsity of singular matrix values is shown in Figure 2 where many singular values are near zero.

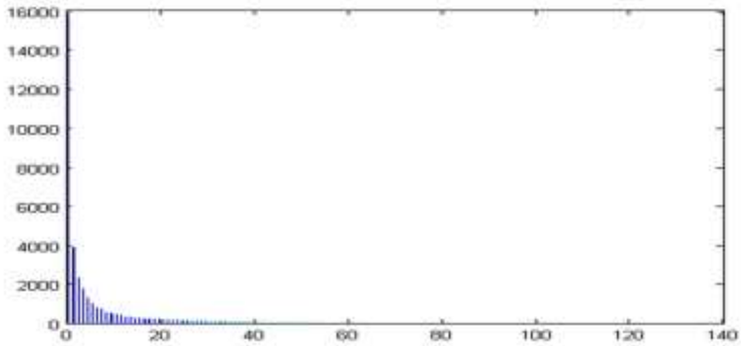


Figure 3. Sparsity Property of Singular Matrix

III. INFORMATION ABOUT COMPRESSIVE SAMPLING

Using Image acquisition is a basic part of any image processing technique. The digital image is taken sampling and quantization process. The first sampling theory is introduced by Shannon – Nyquist sampling theory. The limitation of the Shannon – Nyquist sampling theory is that it is required twice sampling rate for signal reconstructions from its samples. The limitation of the Shannon – Nyquist sampling theory is overcome by introducing the new signal sampling theory which is known as compressive sensing or sampling theory. This theory is described by D. Donoho and E. Candès around 2006 [4, 5, and 6]. They are proving that original signal or image can be exactly reconstructed from its few transform coefficients. Compressive sampling is divided into two parts such as CS theory acquisition process and CS theory recovery process.

In CS theory acquisition process, image or signal is converted in its sparse measurements using sparsity properties of various transform and measurement matrix. The sparse measurements of image or signal can be generated using compressing sensing theory acquisition process is given by equation 2, 3. The size of measurement matrix is decided compression ratio for image or signal.

$$y = A \times x \tag{2}$$

$$x = \psi \times f \quad (3)$$

Where, y = sparse measurements of image or signal, A = measurement matrix, x = sparse coefficients of image or signal, Ψ = image transform, f = image or signal.

The CS theory recovery techniques recovered image or signal from its sparse measurements which having very less information for reconstruction of image or signal. There are so many researchers are proposed and described CS recovery algorithms which is based on optimization techniques in the last few years [5]. The CS theory recovery techniques are divided into two types such as linear optimization based techniques and greedy techniques. L norm minimization technique [5, 6] is based on linear optimization and provides good stability for signal or image reconstruction. But this technique is taken more computation time for image or signal reconstruction. When greedy techniques such as orthogonal matching pursuit (OMP), compressive sampling matching pursuit (COSAMP), basis pursuit (BP), and subspace pursuit (SP) and Iterative Hard Thresholding (IHT) [7, 8, 9, 10] are based on an iteration calculation for approximation coefficients of the image until a convergence criterion is fulfilled.

IV. MEDICAL IMAGE COMPRESSION USING COMPRESSIVE SAMPLING

The block diagram of medical image compression using compressive sampling is shown in Figure 4. In this approach, sparsity property of discrete wavelet transform and singular value decomposition is explored for the generation of sparse coefficients of image data. The steps of medical image compression are given below.

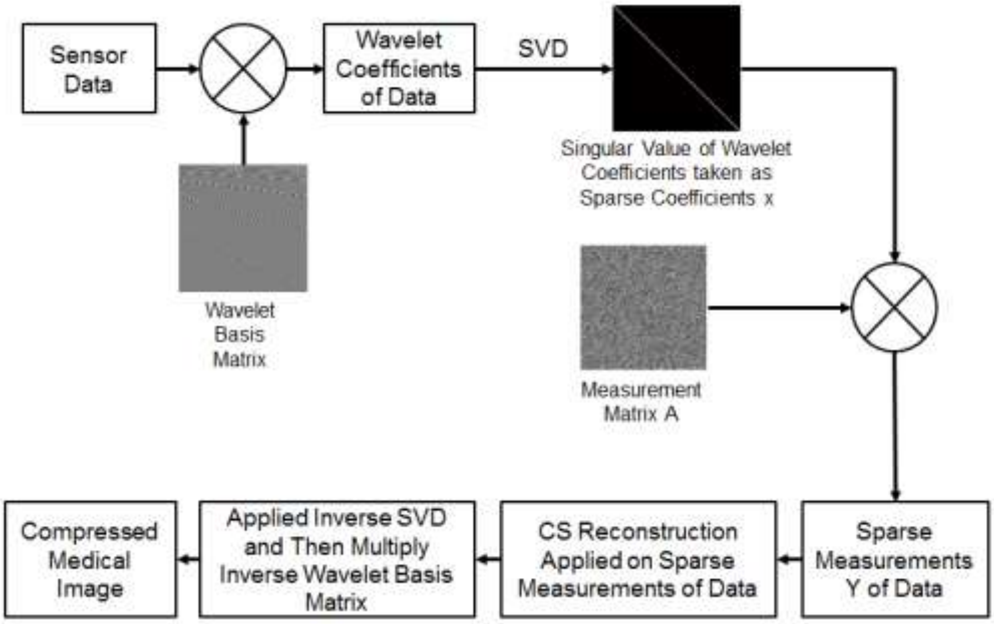


Figure 4. Medical Image Compression Using Compressive Sampling

- Take a sensor data with size of N×N. Then calculate the size of data.
- Generate discrete wavelet transform basis matrix with equal size of sensor data.
- Then sensor data converted into its wavelet coefficients by multiplying DWT basis matrix with original sensor data.
  $$W = \Psi \times I \quad (4)$$
  Where W = Wavelet Coefficients of Sensor Data, Ψ = DWT Basis Matrix, I = Original Sensor Data.
- Then apply Singular Value Decomposition (SVD) on wavelet coefficients of a sensor data and decomposed into singular value S, unitary matrix U & V. Then the singular value of wavelet coefficients is chosen as sparse coefficients *x*. The reason behind choosing a singular value as sparse coefficients is that it is sparser than wavelet coefficients.
  $$[U, S, V] = svd(W) \quad (5)$$
- Generate measurement matrix A with size of M×N using normal distribution with mean =0 and variance = 1. This measurement matrix A is same for embedder and decoder side. The value of M is decided the compression ratio of image.
- Generate sparse measurements of a sensor data by multiplication of the measurement matrix with sparse coefficients of a sensor data.
  $$y = A \times S \quad (6)$$

Where y = Sparse Measurements of Sensor Data, A = Measurement Matrix, S = Singular Value of Wavelet Coefficients of Sensor Data.

- Then apply the CS recovery algorithm on sparse measurements of the sensor data along with measurement matrix. The output of the CS recovery algorithm is a singular value of wavelet coefficients of a sensor data.

$$S' = OMP(y,A,M) \tag{7}$$

Where S' = Extracted Singular Value of Wavelet Coefficients of a Sensor Data, y = Sparse Measurements of a Sensor Data, OMP = Orthogonal Matching Pursuit, A = Measurement Matrix, M = Row Size of a Sensor Data.

- Then apply inverse Singular Value Decomposition (SVD) on extracted sparse coefficients of sensor data with original unitary matrix U & V to get extracted sparse coefficients of a sensor data.

$$x_{Extracted} = U * S' * V^T \tag{8}$$

Where S' = Extracted Singular Value of Wavelet Coefficients of a Sensor Data, U & V = Original Unitary Matrices, $x_{Extracted}$ = Extracted Wavelet Coefficients of a Sensor Data.

- Finally, the inverse DWT basis matrix is multiplied with extracted wavelet coefficients of a sensor data to get compressed medical image.

$$I_{Compressed} = \Psi' \times x'_{Extracted} \tag{9}$$

Where $I_{Compressed}$ = Compressed Medical Image, $x_{Extracted}$ = Extracted Sparse Coefficients of a Sensor Data,Ψ' = Inverse DWT Basis Matrix.

V. RESULTS

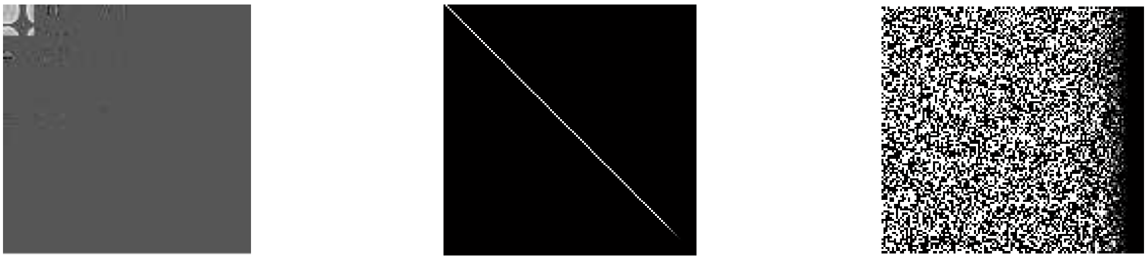
In this paper, wavelet transform such as Daubechies and singular value decomposition is used to create sparse coefficients of medical image which is necessary required of compressive sampling. For testing of proposed approach, CT medical image with size of 128×128 pixels is taken and which is shown in Figure 5.

Figure 5. Test CT Images

The orthogonal measurement matrix A is generated using a standard normal distribution with various sizes of M×N. The M is compression factor which is required for compression of medical image is decided first and then generate measurement matrix. Then this matrix is multiplied with the sparse coefficients of medical image to get sparse measurements using compressive sampling. Then OMP algorithm [8] is used for image reconstruction. The CT medical image can be compressed using compressive sampling using below procedure.

First generate Discrete Wavelet Transform (DWT) basis matrix with size of 128×128 using Daubechies (db2) wavelet. Then multiply DWT basis matrix with the original CT image to get wavelet coefficients of a CT image with size of 128×128. Apply SVD on wavelet coefficients of a CT image to get the singular value of wavelet coefficients of CT image with size of 128×128. This singular value of wavelet coefficients of a CT image is taken as sparse coefficients. Then generate a measurement matrix with size of 115×128 using a standard normal distribution with mean = 0 and variance =1. The sparse measurements of standard normal distribution with size of 115×128 are generated using $y_{115\times128} = A_{115\times128} \times x_{128\times128}$. These sparse measurements are fed to the OMP algorithm with correct measurement matrix to get compressed CT image with compression ratio of 0.9. Figure 6 shows the original CT Image, Compressed CT Image, Wavelet coefficients of CT Image, Singular value of wavelet coefficients and sparse measurements of CT Image respectively.

(a) Original CT Image *(b) Compressed CT Image with CR = 0.9*



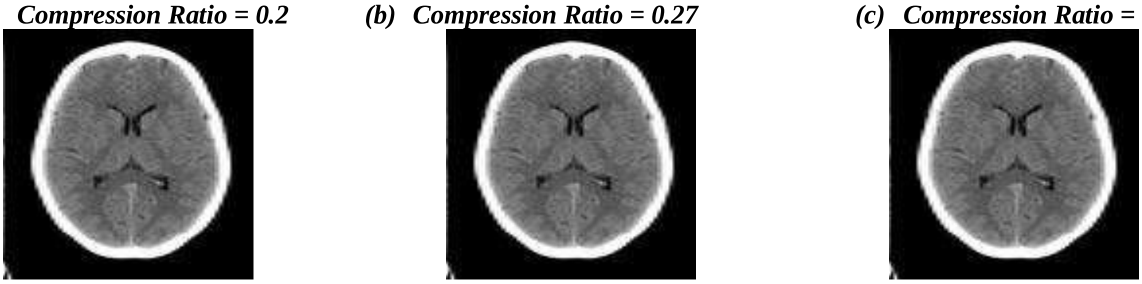
(c) Wavelet Coefficients *(d) Singular Value of Wavelet Coefficients* *(e) Sparse Measurements of CT Image*

Figure 6. Results of Compressed CT Image Using Compressive Sampling

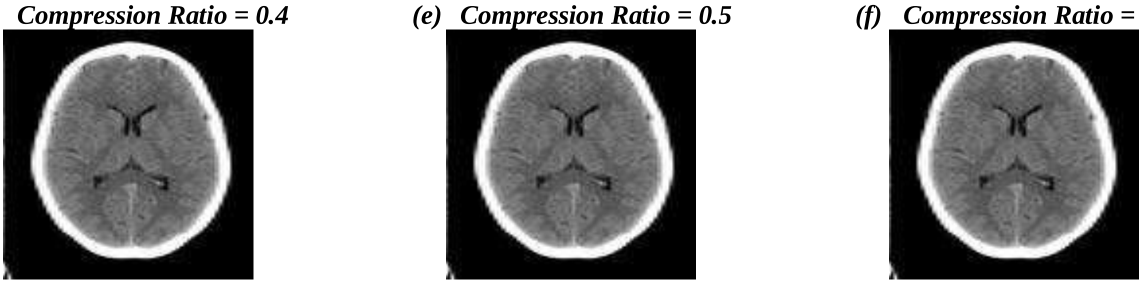
The quality measure such as Peak Signal to Noise Ratio (PSNR), Root Mean Square Error (RMSE), and Normalized Cross Correlation (NCC) are used for quality checked of compressed medical image [3, 11]. The compression ratio for medical image is calculated using below equation 10. The various sizes of sparse measurements have been generated and medical image is compressed using these measurements. The resultant compressed CT medical image is shown in Figure 7. The values of quality measures are calculated for these sparse measurements and summarized in Table 1.

$$Compression\_Ratio = \frac{Size\_of\_Sparse\_Measurements}{Size\_of\_Original\_Image} \quad (10)$$

(a) Compression Ratio = 0.2 *(b) Compression Ratio = 0.27* *(c) Compression Ratio = 0.3*



(d) Compression Ratio = 0.4 *(e) Compression Ratio = 0.5* *(f) Compression Ratio = 0.6*



(g) Compression Ratio = 0.7 *(h) Compression Ratio = 0.8* *(i) Compression Ratio = 0.9*

Figure 7. Compressed CT Image Using Various Compression Ratio

Table 1. Quality Measures for CT Image Compression Using Compressive Sampling

Size of Sparse Measurements, $y = A \times S$	Compression Ratio (CR)	RMSE	PSNR (dB)	NCC
3328	0.20	53.68	22.56	0.994
4352	0.27	47.77	28.49	0.994
4864	0.30	45.19	31.84	0.994
6528	0.40	38.63	43.57	0.994
8192	0.50	34.82	53.63	0.994
9856	0.60	31.54	65.36	0.994
11520	0.70	29.36	75.42	0.994
13056	0.80	27.31	87.14	0.994
14720	0.90	25.86	97.20	0.994

This approach is compared with existing approach available in the literature with various parameters are summarized in Table 2. The existing approach in the literature used sparsity property of wavelet transform while in this proposed approach sparsity property of singular value decomposition is used. The PSNR value shows that proposed approach is outperformed compared to existing approach available in the literature.

Table 2. Comparison of Proposed Approach with Existing Approach in the Literature

Features	Sevak Technique (2014) et al. [3]	Proposed Approach
Type of Image	CT Image	CT Image
Used Image Transform for Sparse Measurement Generation	Discrete Wavelet Transform (DWT)	Discrete Wavelet Transform (DWT) + Singular Value Decomposition (SVD)
PSNR value Rage	30 to 60 dB	20 to 98 dB

VI. CONCLUSION

Compressive sampling is a new signal acquisition technique which takes a signal in compressed format. The technique is overcome the limitation of Nyquist criteria and conventional sampling theory. This technique gives better compression of medical image as well as acquisition simultaneously. In this paper, sparsity property of SVD is combined with DWT coefficients of CT image is explored. The compressive sampling approach is applied along with these hybrid coefficients of CT image to generate compressed CT image using various compression ratios. The results show that this hybrid approach gives better result compared to single transform coefficients approach.

REFERENCES

[1] M. Lustig, D. Donoho, J. Santos and J. Pauly, "Compressed Sensing MRI", IEEE Signal Processing Magazine, pp. 72–82, March 2008.
[2] M. Lusting, "Sparse MRI", A Ph.D. Thesis, Stanford University, September 2008.
[3] M. Sevak, D. Dalwadi, A. Choksi and R. Patel, "Compressive Sensing for CT Images: A Performance Analysis of Various Wavelets", International Journal of Graphics & Image Processing, vol. 4, issue 1, pp. 21–24, February 2014.
[4] D. Donoho, "Compressed Sensing", IEEE Transaction on Information Theory, vol. 52, issue 4, pp. 1289–1306, April 2006.
[5] E. Candes and J. Romberg, "L1-Magic: Recovery of Sparse Signals via Convex Programming, October 2005.
[6] R. Baraniuk, "Compressive Sensing", IEEE Signal Processing Magazine, vol. 24, issue 4, pp. 118–124, July 2007.
[7] A. Gilbert, M. Strauss, J. Tropp and R. Vershynin, "One Sketch for all: Fast Algorithms for Compressed Sensing", 39th ACM Symposium on Theory of Computing (STOC), San Diego, California, USA, June 2007.
[8] J. Tropp and A. Gilbert, "Signal Recovery from Random Measurements via Orthogonal Matching Pursuit", IEEE Transactions on Information Theory, vol. 53, issue 12, pp. 4655–4666, December 2007.
[9] J. Laska, M. Davenport and R. Baraniuk, "Exact Signal Recovery from Sparsely Corrupted Measurements through the Pursuit of Justice", Asilomar Conference on Signals, Systems and Computers, Pacific Grove, California, USA, November 2009.
[10] W. Dai and O. Milenkovic, "Subspace Pursuit for Compressive Sensing Signal Reconstruction", 2009.
[11] M. Mrak, S. Grgic and M. Grgic, "Picture Quality Measures in Image Compression Systems", IN EUROCON 2003, Computer as a Tool, The IEEE Region 8, vol. 1, pp. 233 – 236, September 2003.
[12] A. Kothari and V. Dwivedi, "Design, Implementation and Performance Analysis of Digital Watermarking for Video", Ph.D. Thesis, JJTU, November 2013.
[13] A. Sreedhanya and K. Soman, "Ensuring Security to the Compressed Sensing Data Using a Steganographic Approach", Bonfring International Journal of Advances in Image Processing, vol. 3, no. 1, pp. 1–7, March 2013.