www.ijecs.in
International Journal Of Engineering And Computer Science ISSN: 2319-7242
Volume 5 Issue 5 May 2016, Page No. 16704-16707

Block Based Compressed Sensing Algorithm for Medical Image Compression

S.Spurthi, Parnasree Chakraborty
Department of electronics and communication B.S Abdur Rahman University Chennai, India
spurthisingha@gmail.com

Department of electronics and communication B.S Abdur Rahman University Chennai, India
prernasree@bsauniv.ac.in

Abstract— Block Compressive sensing technique has been proposed to exploit the sparse nature of medical images in a transform domain to reduce the storage space. Block based compressive sensing is applied to dicom image, where original dicom image is divided in terms of blocks and each block is processed separately. The main advantage of block compressive sensing is that each block is processed independently and combined with parallel processing to reduce the amount of time required for processing. Compressed sensing exploits the sparse nature of images to reduce the volume of the data required for storage purpose. Inspired by this, we propose a new algorithm for image compression that combines compressed sensing with different transforms. Different sparse basis like discrete cosine transform, discrete wavelet transform and contourlet are used to compress the original input image. Among these transforms, Dct transform has block artifacts problem [14]. Wavelet transform can overcome the block artifacts introduced in the reconstructed image. Contourlet transform effectively captures smooth contours[4] and hence Contourlet transform provides better reconstruction quality image. In order to reconstruct original image, different techniques such as basis pursuit, orthogonal matching pursuit etc. are used at the decoder.

Keywords—PSNR, SSIM, DCT, DWT, CT

Introduction

Compressive sensing (CS) is a technique used to compress and reconstruct the original signal [1] having a sparse representation in some basis. CS can be applied effectively to the sparse signals. To get sparse representation basis such as DCT or DWT or CT .Equation (1) describes generation of the sparse signal s measurement matrix (A).dct basis is based on cosine functions and transformation kernel is generated .wavelet basis is based on filter bank structure contourlet transform basis is based on direction filter bank structure .after applying to basis function Then the sparse signal further compressed as y with a suitable measurement matrix (M).

I. BASIS OF DIFFERENT TRANSFORMATION

A. DISCRETE COSINE TRANSFORM:

DCT transformation most popularly used transform and it is based on cosine functions[3] .DCT plays very important role for energy compaction property which is most important for image compression The 2D discrete cosine transform (2D DCT) can be expressed by

$$D(i,j) = \frac{1}{\sqrt{2N}} C(i)C(j) \sum_{x=0}^{N-1}\sum_{y=0}^{N-1} P(x,y) cos\left[\frac{(2x+1)i\pi}{2N}\right] cos\left[\frac{(2y+1)j\pi}{2N}\right] \quad (3)$$

$$c(u) = \begin{cases} \frac{1}{\sqrt{N}} & if\ u = 0 \\ 1 & if\ u = 1 \end{cases} \quad (4)$$

Where p(x, y) is the element of the image represented by matrix p N is the size of image. i, j represents the transformed image from pixel matrix dct transform leads to block artifact problem .These artifacts involes as a regular pattern of visible block boundaries.

S=psi*x (1) Where, x, is the input signal, psi is obtained by basis function. T is the Transform matrix or kernel and s is the sparse representation of the input data. After sparse generation, equation (1) expresses the generation of compressed sparse signal with the help of a randomly generated matrix A. The compressed sparse output y is given in Equation (2)

y=A*S (2) The input signal x is converted into sparse signal s by applying suitable transform matrix DCT/CT/DWT -[T]. Then the sparse signal further compressed as y with a suitable

B. DISCRETE WAVELET TRANSFORM

Discrete Wavelet Transform (DWT) of a signal x (n) is obtained by by using Filter banks for wavelet transform. [5] First the data are passed through a low pass filter and has impulse response g (n) giving particular coefficients. Signal decomposition by using a high pass filter h (n), giving the more no of coefficients. The low pass filter gives approximate coefficients

$$y_{low}[k] = \sum_{n} x[n] . g[2k-n] \quad (5)$$

$$y_{high}[k] = \sum_{n} x[n] . h[2k-n] \quad (6)$$

LL	LH
HL	HH

Fig 1. Wavelet Decomposition Using Four Sub Bands

wavelet transform decomposes an image in to four sub bands

DOI: 10.18535/ijecs/v5i5.62

.low-low frequency is represented as LL.low-high frequency is represented as LH.high-low frequency is represented as HL.high-high frequency is represented as HH.For this first layer, an image is decomposed into 4 sub bands LL1, HL1, LH1 and HH1 .This concept is also applied to the second and third levels of decompositions based on the principle of multi resolution analysis..

C. CONTOURLET TRANSFORM

Contourlet transform consists of two blocks, a Laplacian pyramid and a directional filter bank (DFB). Laplacian pyramid and directional filter bank posses dual filter bank structure [4]. This dual filter bank structure is called as a pyramidal directional filterbank (PDFB) where the Laplacian pyramid is first used to capture the point discontinuities, then followed by a directional filter bank which provides directionality .PDFB allows to approximate a smooth contour at multiple resolutions. In the frequency domain representation, the contourlet transform provides a multiscale and directional decomposition. Contourlet transform uses a double filter bank structure to get the smooth contours of images. In LP stage it uses “9/7” filters. Similarly, in directional decomposition stage, the ladder structure PKVA filters are used. PKVA filters are PKVA filters are effective in localizing edge direction and it reduces inter direction mutual information of PDFB coefficients.

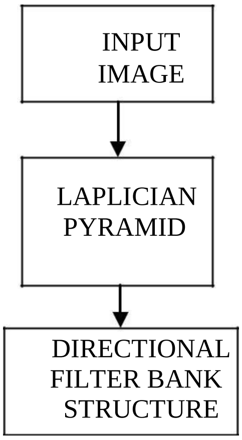

Fig 2 Block Diagram of PDFB

In LP stage it uses “9/7” filters. Similarly, in directional decomposition stage, the ladder structure PKVA filters are used. PKVA filters are effective in localizing edge direction and it reduces inter direction mutual information of PDFB coefficients.

II. RECOVERY ALGORITHM

A nonlinear algorithm is used in CS [9] at receiver end to reconstruct original signal. This algorithm requires knowledge of a basis representation (original or transform) in which the signal is exact sparse (exact recovery) or approximate sparse (approximate recovery).

A. BASIS PURSUIT

In compressive sensing the original signal is restored from fewer samples or measurements if it satisfies two important conditions called sparsity and incoherence [8]. The sparsity shows that it has more number of zero valued components except very few. These sparse signals are spreaded over and decomposed into various bass in the measurement or sensing matrix called dictionary. In dictionary bases must have high incoherence to each other. So, finding the exact solution for recovery of original signal by picking up the exact basis from the dictionary is called Basis Pursuit using l1 norm.

B. l1 –MINIMIZATION

We define a compressed image y=A*S, if there is an approximation s∗ , the original sparse signal S can easily be recovered S∗ , this approximation should produce more sparse to a same set of samples than the original signal S, We define a compressed image y=A*S, if there is an approximation s∗ , the original sparse signal S can easily be recovered S∗ , this approximation should produce more sparse to a same set of samples than the original signal S,and if we minimize l 0 norm of s, the sparsity constraint can be satisfied.this sparsity constraint leads to NP-hard algorithms, whose realistic values of N makes complex and it is difficult to solve the problem of l0 -minimization, Donoho [8]developed the relaxation of the constraint on l 0 by requiring that the l1 norm of reconstructed signals. l1 -minimization promotes sparsity and l1 minimization is also known as Basis Pursuit [10]. The purpose of Basis Pursuit is to have easier optimization problems where by replacing the hard problem sparse. The definition of the sparse problem is given as follows: min k=0 where Ax = b. The difficultly with the sparse definition problem is the l0 norm. Basis Pursuit replaces the l0 norm with the l1 to make the problem easier to work with, The definition of Basis Pursuit is given as : minkxk1 where Ax = b. for evaluting the performance of three bases reconstruction algorithm used is l1 -Dantzig selector [10],which is implemented in l1 -Magic[11] Toolbox

C. NORM: l0, l1 AND l2 NORM

The name refers to the normed vector space pronounced “little ell one.space or matrices. For simplicity, we can say the higher the norm is, bigger the value in matrix or vector is.

$$\sum = \| \| \qquad (7)$$

Above equation tells the condition for x in l1 norm, in signal processing, infinity is reduced to a large finite number N, and shown that, l1magic [10] boils down to a problem in LP. The basic idea is to minimize an l1 norm, || x ||1 =Σ | xi |, subject to agreement with an appropriately random set of measurements. Under very general conditions simplex method is about as good solution. In effect, l1 is a happy medium between the least-squares norm l2, which sums the squares of the coefficients, and the combinatorial metric, l0 which simply counts the number of nonzero coefficients. The stunning
“magic” of l1 is that it combines l0 and the computational efficiency of l2. The sparse representation means data with a small number of nonzero coefficients for a given basis (and no noise) can (with high probability) be reconstructed exactly via l1-minimization.

III PERFORMANCE PARAMETERS

To measure the performance of the reconstructed images certain parameters are evaluted in terms of MSE, PSNR and SSIM [6]

A .MSE

The MSE measures the quality change between the original image Io and reconstructed image Ir.The average of the squared error measure is given by

$$MSE = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}\|I0(i,j) - Ir(i,j)\|^2 \qquad (8)$$

DOI: 10.18535/ijecs/v5i5.62

B. **PSNR**

Peak signal to noise ratio measures via MSW which is given by the equation d is the maximum value of the pixel

$$PSNR = 10log_{10}\left(\frac{d2}{MSE}\right) \quad (9)$$

C. **SSIM**

The structural similarity (SSIM) index is method used for measuring the similarity between original and reconstructed images. SSIM is developed to improve the PSNR and MSE. Which is insensitive to human eye.

$$ssim(x,y) = \frac{(2\mu_x 2\mu_y + c_1)(2cov_{xy} + c_2)}{(\mu x^2 + \mu y^2 + c_1)(\sigma x^2 + \sigma y^2 + c_2)} \quad (10)$$

μ x is the average of x; μy is the average of y; σ1is thevariance of x; σ2 the variance y; covxy is the covariance of x and y;

c1 = (l1 L)^2 ,c2 = (l2 L)^2 two variables to stabilize the division with weak denominator; L is the dynamic range of the pixel-values; and l1 = 0.01 and l2 = 0.03 is constant by default

IV EXPERIMENTAL SETUP

Fig 3. below shows the steps followed in this work . An original image in dicom format of size 1722X1422 is considered as input .The input image is then divided into blocks of size 64X64. CS algorithm is applied to all the blocks parellely. CS reconstruction is performed and performance parameters mentioned in the previous section are evaluated.

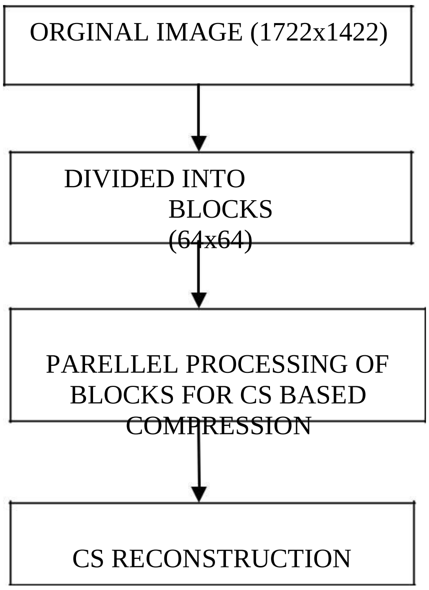

Fig 3 .Flow Diagram Of Block Based Cs

V EXPERIMENTAL RESULTS

Compressed Sensing Algorithm is performed using MATLAB. Compressed sensing algorithm is used to achieve 50% compression ratio. Different basis functions such as discrete cosine transform, discrete wavelet and contourlet transform is applied to generate sparse signal and then compression is performed. Reconstruction is performed using basis pursuit method.

Fig 4.below shows original image of size 1722X1423.Fig 5. Shows reconstructed image using dct basis.Fig 6. Shows reconstructed image using dwt basis and Fig 7. shows reconstructed image using contourlet basis.

Fig 4. orginal image(1722X1422)

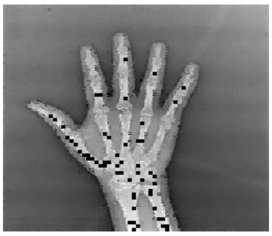

Fig 5. Reconstructed image using dct basis

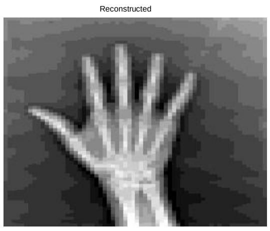

Fig 6. Reconstructed image using dwt basis

Fig 7. Reconstructed image using contourlet basis

Table 1. Comparison of Different Basis of Transformation

PARAMETERS	DCT	DWT	CONTOURLET
MSE	0.41	0.38	0.31
PSNR	51.3	52.6	53.4
SSIM	0.5880	0.6029	0.7088

VI CONCLUSION

Compressed sensing algorithm is used to compress and reconstruct the orginal image. Different transforms are used as sparse basis to generate compressed image. Different parameters like MSE, PSNR and SSIM are measured after performing reconstruction. Comparison of dct, dwt and contourlet is obtained which is shown in Table 1. Dct provides poor reconstruction compared to dwt and contourlet dwt cannot able to resolve smooth contours .contourlet overcomes the disadvantage of dwt .and provides better reconstruction.

REFERENCES

[1] E. J. Cande`s, J. Romberg, and T. Tao, "Robust uncertainty principles Exact signal reconstruction from highly incomplete frequency information,"Information Theory, IEEE Transactions on, vol. 52, no. 2, *pp.489–509*, 2006

[2] D. L. Donoho, "Compressed sensing," Information Theory, IEEE Transactions on, vol. 52, no. 4, pp. 1289–1306, 2006

[3] G.Richard, Baraniuk, .E. Candes, Robert Nowak, Compressive sampling, I*EEE signal processing magazine*,2008.3,12-13

[4] Minh N. Do, *Member*, *IEEE*, and Martin Vetterli An Efficient Directional Multi resolution Image Representation, *IEEE*

[5] Zhenghua Zou ; Dept. of Comput. Sci., Tsinghua Univ., Shenzhen, China ; Xinji Liu ; Shu-Tao Xia A comparative study of wavelets and adaptively learned dictionary in compressive image sensing Signal Processing (ICSP), 2012IEEE11th International Conference on(Volume:2)

[6] M. Blanco-Velasco, F. Cruz-Roldan, F. Lopez-Ferreras, and P. Martin-Martin, "Comparison of wavelet packets with cosine-modulated pseudo-QMF bank for ECG compression," in proceedings of 23. Annual International
Conference of the IEEE Engineering in Medicine and Biology Society, Instambul Turkey, 2001.

[7] M. Blanco-Velasco, F. Cruz-Roldan, F. Lopez-Ferreras, and P. Martin-Martin, "Comparison of wavelet packets with cosine-modulated pseudo-QMF bank for ECG compression," in proceedings of 23. Annual International
Conference of the IEEE Engineering in Medicine and Biology Society, Instambul Turkey, 2001.

[8] E. Cande`s and J. Romberg, "l1-magic," www. l1-magic. org, 2007.Transactions on, vol. 53, no. 12, pp. 4655– 4666, 2007.

[9] S. Chen and D. Donoho, "Basis pursuit," in Signals,
Systems and Computers, 1994. 1994 Conference Record of the Twenty-Eighth Asilomar Conference on, vol. 1. IEEE, 1994, pp. 41–44.

[10] E. Candes and T. Tao, "The dantzig selector: Statistical estimation when p is much larger than n," The Annals of
Statistics, pp. 2313–2351, 2007

[11] J. A. Tropp and A. C. Gilbert, "Signal recovery from random measurements via orthogonal matching pursuit,"
Information Theory, IEEE Transactions on, vol. 53, no. 12, pp. 4655–4666, 2007.

[12] Y. Nesterov, "Gradient methods for minimizing composite objective function," CORE discussion paper, no. 76, University of Catholic Louvain, Belgium, Sept. 2007

[13] Parnasree Chakraborty and C. Tharini, " Analysis of suitable modulation scheme for compressive sensing algorithm in wireless sensor network© Emerald Group Publishing Limited [ISSN 0260-2288] [DOI 10.1108/SR-06-2014-666]

Ying luo and rabab k. ward, removing the blocking artifacts of block-based dct compressed imagesieee transactions on image processing, vol. 12, no. 7, july 2003