I J C T A, 9(15), 2016, pp. 7283-7290

Energy efficient Daubechies Wavelet transform based CS for WSN

R. Monika*

ABSTRACT

Lifetime of the sensor nodes can be enhanced by using a technique which minimizes the energy consumption. Compressed Sensing (CS) is one such technique which helps achieving image compression and energy efficiency. However it adopts random projection of signal components, which reduces the quality of the reconstructed image. In order to achieve better image quality, adaptive projection of signal components is required. Coefficient Permuted Energy based Re-weighted Sampling (CPERWS) is used to adaptively extract high energy frequency components of the image. Hence Block CS (BCS) with Daubechies Wavelet Transform (Daub WT) based CPERWS technique is proposed to distinctly sample components based on their information content. Analysis confirms that proposed method outperforms conventional CS and the reconstructed image quality is greatly enhanced even for lesser number of measurements. Experimental analysis is done using Atmega128 of Mica2 mote. Execution time and energy consumed are computed in the hardware platform. DaubWT based CPERWS has approximately 33% lesser energy consumption than DCT based BCS techniques.

Keywords: Atmega128, CPERWS, OMP, Daubechies Wavelet transform, Sparse Binary Random Matrix

1. INTRODUCTION

WSNs are resource constrained and have high band width demand. It is essential to reduce the energy consumption involved in image transmission to increase the lifetime of nodes [3]. In order to achieve this, data transmitted within the nodes should be compressed. Conventional compression techniques are not efficient in achieving compression of data for WSN.

CS technique is used for reconstruction of the image from relatively fewer measurement values. However it follows non adaptive random projection of signal components. Signal components are chosen in a random manner irrespective of their energy contribution to the image. This significantly degrades the quality of the reconstructed image. In order to overcome this, Block compressed sensing (BCS) techniques are adopted. BCS [9] follows adaptive projection of signal components i.e., projection of vectors is along the direction of signal components with higher energy. Moreover same measurement matrix is applied to all the blocks which reduces storage space and computation complexity.

2. RELATED WORKS

D.L.Donoho [11] explains about the basic concepts of CS. He claims that certain signals and images can be recovered from fewer samples or measurements. In [9] Lu Gan discussed about block compressed sensing of natural images. Image acquisition is conducted in block by block manner thereby capturing the complicated geometric structures of the natural images

Zhirong Gao, Chengyi Xiong, Lixin Ding, Cheng Zhou[4], investigated a method called CRP which is effective in balancing the sparsity of sampled vectors in DCT domain. As a result performance gain will be high.

* Assistant Professor, ECE department SRM University INDIA, *Email: moni.rajendran@gmail.com*

Yi Yang, Oscar C. Au, Lu Fang, Xing Wen and Weiran Tang [7] introduced a weighting scheme into conventional CS framework. Weight values are determined based on statistics of image and a weight matrix is designed. This matrix extracts signal components with larger magnitude thereby enhancing quality of reconstructed image. Alternatively Energy matrix is designed in [2]. Energy values are determined based on the energy distribution of the image. The quality of the reconstructed image was found to be better than all other existing methods.

In this paper, coefficient permuted energy based reweighted sampling in DCT and DaubWT domain are investigated. This technique is extension of one proposed in [2]. This technique involves balancing the sparsity of the blocks and acquiring the frequency components of the image which has very high energy. Hence poorly sparse blocks are reconstructed well and higher energy components which contribute for reconstruction of image with better psnr is effectively extracted. The measurements are taken using daub DWT, which reduces the energy consumption effectively.

The performance of DCT, DWT and wavelets like Haar Wavelet and Daubechies Wavelet for still image compression system is discussed in [5]. Daub WT is used in this paper. This technique is capable of reducing the calculation work and run time. Summing and difference coefficients are obtained faster than other techniques.

The rest of the paper is organized as follows: overview of CS is provided in Section III, Section IV discusses about the CPERWS, Section V discusses about DaubWT based CPERWS, experimental results are provided in Section VI and Section VII concludes the paper.

3. OVERVIEW OF CS

Consider a signal X of length N. suppose if we can choose n measurements (n << N) from X then CS process is defined as follows

$$Y = \Phi X \tag{1}$$

Where Y represents $n \times 1$ sampled vector and Φ is n×N measurement matrix. If a signal is sparsely represented in certain domain Ψ then X can be represented as

$$X = \Psi S \tag{2}$$

Where S denotes sparse representation of discrete signal X.

The sampling process can be expressed in general form as

$$Y = \Phi \Psi S \tag{3}$$

When Φ and Ψ are incoherent and if their product satisfies RIP [4] then K-Sparse (Non zero values) can be well reconstructed from $n \geq cK \log(N/K)$ where c is a constant.

Sparse binary random matrix is used as measurement matrix. This has performance similar to gaussian random matrix. This matrix uses only binary digits 0's and 1's. Hence it simplifies computation complexity. Sparse binary random matrix will have RIP with high probability irrespective of the choice of transform basis [4]. Orthogonal matching pursuit(OMP) [10] is used as reconstruction algorithm.

4. PROPOSED METHOD CPERWS

CS uses a fixed measurement matrix, which identically samples all signal components irrespective of their information content. As a result reconstructed image quality is poor. In order to achieve efficiency low frequency components which occupy larger part of energy are to be extracted. In [2] adaptive measurement matrix is designed based on the energy distribution of the image. However sparsity of the sampled blocks

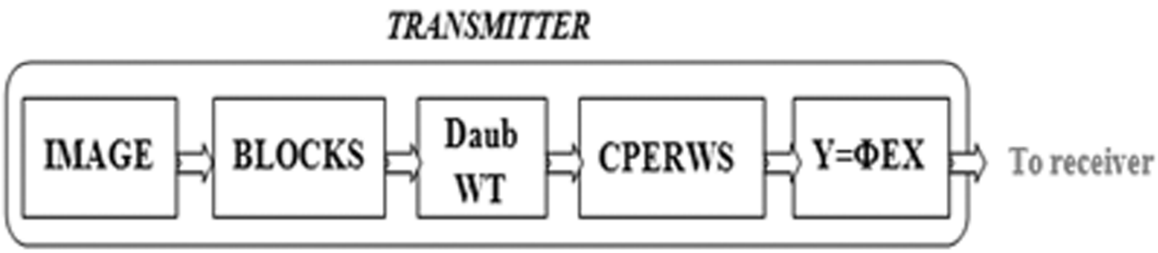

Figure 1: Transmitter section

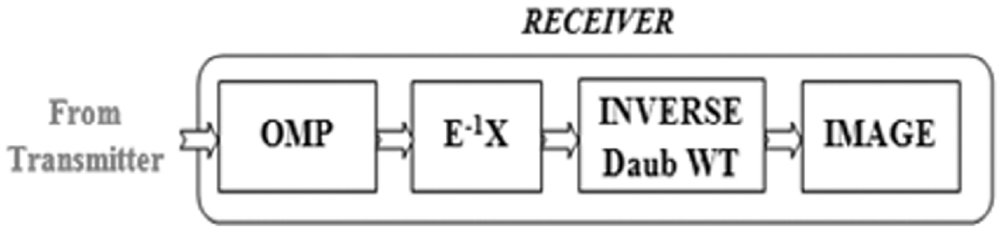

Figure 2: Receiver section

are not balanced which reduces the sampling efficiency. In CPERWS, the coefficients are permuted to achieve balance in sparsity and Energy matrix is designed to extract the high energy components of the image.

Fig. 1. shows the transmitter section. High energy components of the image are chosen by multiplying the image vector with energy matrix. These high energy components are then passed on to the receiver section. The block diagram of the receiver section is shown below in Fig. 2. OMP reconstruction algorithm is used for fast reconstruction. Energy inverse matrix is multiplied at the receiver side to recover the coefficients. Recovered coefficient are grouped together to form image.

4.1. CPERWS Sampling scheme

1. The input image of size M × N is divided into blocks of size m×n and then sparsified by using 2D DWT.
2. Vectorize the DWT coefficients of each block into 1D sequence.
3. Coefficients belonging to same frequency from all blocks are grouped and randomly permuted to achieve balanced sparsity.
4. Blocks are rebuilt from the permuted vectors.
5. Energy values corresponding to each frequency component is then calculated and assigned as $\{E_1, E_2, \ldots E_{m\times n}\}$.
6. Energy values are calculated by using the formula

$$E = |\mu_i|^2 + \sigma_i \tag{4}$$

Where

μ_i denotes the mean of components with same frequency. σ_i

ρ_i denotes the variance of components with same frequency.

$$i = 1, 2\ldots m \times n.$$

7. Energy values are placed along the leading diagonal of the matrix with other elements as zeroes. Energy matrix is represented as

$$E = \begin{bmatrix} E_1 & 0 & . & 0 \\ 0 & E_2 & . & 0 \\ . & . & . & 0 \\ 0 & 0 & 0. & E_{m\times n} \end{bmatrix} \tag{5}$$

8. CPERWS is performed for each rebuilt vector and is described as follows

$$Y = \Phi E S_{cp} \tag{6}$$

Where S_{cp} denotes sparse representation of coefficient permuted discrete signal X.

9. The recovered coefficients are regrouped.
10. Inverse permutation is performed for recovered frequency components.
11. Coefficients are rebuilt for each recovered image block.
12. At the receiver side energy inverse matrix is multiplied.
13. IDWT is taken for all blocks.

5. DAUB WT BASED CPERWS

DCT is floating point transform. Coefficients are calculated using multiplications and additions. Floating point implementations are slow in hardware. As a result it occupies more space and power. Conventional DWT [1] involves convolution procedure which makes them more complicated. Hence simpler and faster DWT, Daub WT is used in this paper.

The Daub WT decomposes a discrete signal into two sub signals of half its original length. One sub signal is running average and other one is the running difference. They use overlapping windows which easily reflects all high frequency changes [5]. Hence reconstructed image is of high quality and are more suitable for image compression applications. Daubechies 4tap wavelet has been chosen for implementation. Daub WT is conceptually simple and fast. It is memory efficient. Hence Daub WT based CPERWS is more advantageous than DCT based CPERWS.

6. EXPERIMENTAL RESULTS

Simulation and energy analysis is done for the proposed method. Mica2 platform with Atmel Atmega128L processor is used for energy analysis. Computation is performed using WinAVR with ‘-O3’ optimization for 8 × 8 image blocks. The test image [Cameraman (256 × 256)] is taken from image database [16,17].

Table 1
PSNR Comparison for Various Techniques

No of measurements	Cameraman (256 × 256), Block size = 8 × 8 *TECHNIQUES*			
	DCT		DWT	
	RWS [7]	CPERWS	RWS [7]	CPERWS
10	21.3802	24.8632	23.3002	25.3432
8	18.8479	23.3004	23.1547	25.0452
6	17.3005	22.0002	23.0012	24.8246
4	15.4388	20.5064	22.7892	24.0024

Sparse binary random matrix is used as measurement matrix. PSNR comparison for DCT and DWT based RWS and CPERWS is tabulated in table 1.

It is evident from Table 1 that DWT based CPERWS is more efficient than DCT based CPERWS. However they involve convolution procedures which increase the CPU cycles when implemented in hardware platform. Hence simplest and fastest DWT calculation procedure, Daub WT is chosen for the energy efficiency of Sensor nodes. Also CPERWS is more efficient than RWS [7] in improving the PSNR values. Therefore reconstructed image is of better quality

From Table II it is clear that Daub WT based CPERWS has achieved better PSNR values than DCT and conventional DWT based CPERWS. Although there is only slight improvement in the PSNR values, when implemented in hardware platform they show significant improvement in reducing the CPU cycles. As a result energy consumption is also reduced to great extend.

Fig. 3. shows graphical representation of PSNR value comparison for DCT, DWT and Daub WT based CPERWS techniques. It is evident that proposed method is very efficient in increasing the PSNR for lesser number of measurements.

In hardware platform DCT based CPERWS consumes more time and energy because of the complexity involved in the calculation procedure. It involves floating point multiplications and additions. As a result CPU cycles, execution time and energy consumed is more. Conventional DWT is also not so efficient because it involves convolution procedures thereby increasing the complexity.

In order to reduce the execution time and energy consumed, faster DWT calculation procedure – Daub WT is used. It involves averaging and differencing the coefficients which consumes less energy.

Table 2
PSNR Comparison for CPERWS using various Techniques

	Cameraman (256 × 256), Block size = 8 × 8 NUMBER OF MEASUREMENTS			
Techniques	10	8	6	4
DCT	24.8632	23.3004	22.0002	20.5064
DWT	25.3432	25.0452	24.8246	24.0024
Daub WT	25.6542	25.4941	25.4200	24.8542

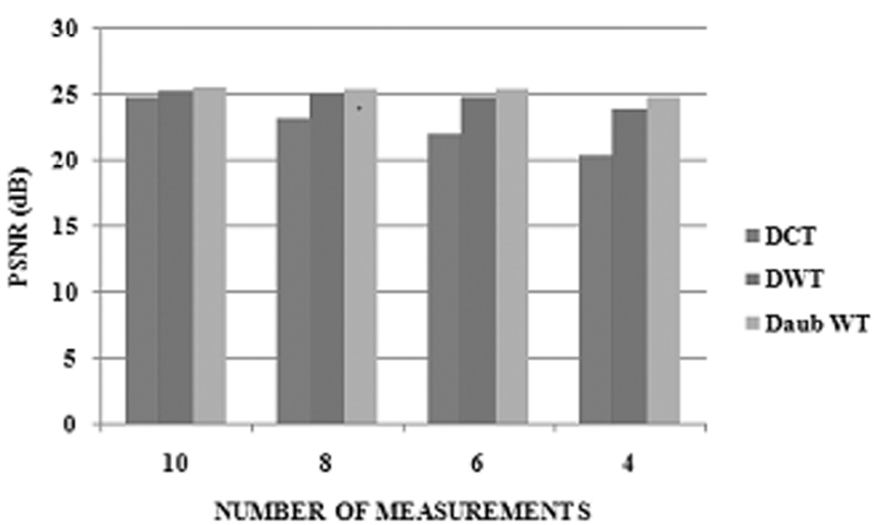

Figure 3: PSNR comparison

Table 3
Comparison of CPU Cycles for RWS and CPERWS

No. of measure-ments	Initiali-zation cycles	Coefficient permutation cycles	Transform cycles				Weight matrix design cycles			Total cycles			
			RWS		CPERWS					RWS		CPERWS	
			DCT	Daub WT	DCT	Daub WT	RWS	CPERWS	CS cycles	DCT	Daub WT	DCT	Daub WT
10	8607	77	3044368	2043278	3044368	2043278	7443	390	12	3060885	2059417	3053454	2052364
8	7455	65	3044368	2043278	3044368	2043278	7443	390	8	3059339	2058249	3052286	2051196
6	6303	53	3044368	2043278	3044368	2043278	7443	390	6	3058173	2057083	3051120	2050030
4	5151	41	3044368	2043278	3044368	2043278	7443	390	4	3057007	2055917	3049954	2048864

Table 4
Comparison of Execution time for DCT and Daub WT based CPERWS

Transform	*No. of measurements*	*Total cycles*	*Execution time (ms)*
DCT	10	3053454	382.7
	8	3052286	382.6
	6	3051120	382.5
	4	3049954	382.3
Daub WT	10	2052364	251.8
	8	2051196	251.6
	6	2050030	251.4
	4	2048864	251.2

Table 5
Comparison of Energy consumption for DCT and Daub WT based CPERWS

Transform	*No. of measurements*	*Total cycles*	*Energy consumed (mJ)*
DCT	10	3053454	8.3102
	8	3052286	8.3008
	6	3051120	8.2978
	4	3049954	8.2900
Daub WT	10	2052364	5.6320
	8	2051196	5.6228
	6	2050030	5.6200
	4	2048864	5.5980

From Table III, it is clear that number of cycles for RWS is more than that of CPERWS. Daub WT based RWS and CPERWS has less number of cycles than DCT based RWS and CPERWS. It is evident that Daub WT is efficient than DCT and CPERWS is efficient than RWS. Hence Daub WT based CPERWS is the most efficient one in reducing the CPU cycles.

From Table IV it can be seen that proposed method has less Execution time than DCT based CPERWS. From TableV it can be found that energy consumption is also significantly reduced for proposed method. Hence proposed technique is the most efficient one for wireless sensor networks.

Table 6
Percentage reduction in CPU cycles, Execution Time and Energy Consumed

Evaluation Parameters	*Percentage Reduction*
CPU Cycles	32.78 %
Execution time	34.29 %
Energy Consumed	32.5 %

7. CONCLUSION AND FUTURE WORK

Image representation using BCS in Daub WT for compression application is investigated in this paper. Proposed CPERWS is very efficient in extracting only high energy components of the image and also in balancing the sparsity of blocks. This technique has achieved a significant increase in PSNR value than other techniques. CPU cycles, energy consumption and execution time in hardware platform is very less. Daub WT based CPERWS takes 33% less CPU cycles than DCT based CPERWS. Hence Daub WT based

CPERWS is the most efficient method for WSN. Future work is to propose a technique which is less complex and more efficient in terms of memory.

REFERENCES

[1] D. Gupta and S. Choubey, “Discrete Wavelet Transform for Image Processing”, International Journal of Emerging Technology and Advanced Engineering, vol. 4, no. 3, 2015, pp. 598-602.

[2] R.Monika, R.Hemalatha, S.Radha, **“**Energy efficient weighted sampling matrix based CS technique for WSN”, sensors 2015, IEEE, pp. 1835-1838.

[3] Razzaque, Mohammad Abdur, and Simon Dobson, “Energy-efficient sensing in wireless sensor networks using compressed sensing”, Sensors 14, no. 2 ,2014, pp. 2822-2859.

[4] Z. Gao, C. Xiong, L. Ding and C. Zhou, “Image representation using block compressive sensing for compression applications”, Journal of Visual Communication and Image Representation, vol. 24, no. 7, 2013, pp. 885-894.

[5] S. Malik and V. Verma, “Comparative analysis of DCT, Haar and Daubechies Wavelet for Image Compression”, International Journal of Applied Engineering Research, vol. 7, no. 11, 2012.

[6] Gao, Z., Xiong, C., Zhou, C., & Wang, H. “Compressive sampling with coefficients random permutations for image compression,” In International Conference on Multimedia and Signal Processing (CMSP), May 2011 , Vol. 1, pp. 321-324.

[7] Y. Yang, O. C. Au, L. Fang, X. Wen and W. Tang, “Reweighted Compressive Sampling for image compression”, Proc. IEEE Picture Coding Symposium, 2009, pp. 1-4.

[8] E. J. Candes and M. B. Wakin, “An introduction to compressive sampling”, IEEE Signal Processing Magazine, vol. 25, no. 2, 2008, pp. 21-30.

[9] L. Gan, “Block compressed sensing of natural images”, Proc. IEEE 15th International Conference on Digital Signal Processing, 2007, pp. 403-406.

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

[11] D. L. Donoho, “Compressed sensing”, IEEE Transactions on Information Theory, vol. 52, no. 4, 2006, pp. 1289-1306.

[12] Lai, Zongying, Xiaobo Qu, Yunsong Liu, Di Guo, Jing Ye, Zhifang Zhan, and Zhong Chen. “Image reconstruction of compressed sensing MRI using graph-based redundant wavelet transform.” Medical image analysis 27, 2016, pp. 93-104

[13] Zhao, Hui, Hao Ye, and Ruyan Wang. “The construction of measurement matrices based on block weighing matrix in compressed sensing.” *Signal Processing* , 2016.

[14] Sanei, S., Phan, A. H., Lo, J. L., Abolghasemi, V., & Cichocki, A. “A compressive sensing approach for progressive transmission of images,” In 16th International Conference on Digital Signal Processing,, 2009, pp. 1-5.

[15] Bajwa, W. U., Haupt, J. D., Raz, G. M., Wright, S. J., & Nowak, R. D. “Toeplitz-structured compressed sensing matrices,” In IEEE/SP 14th Workshop on Statistical Signal Processing,, 2007, pp. 294-298.

[16] “The USC-SIPI Image Database”, University of Southern California, http://sipi.usc.edu/database/.

[17] “Image repository,” The University of Waterloo, http://links.uwaterloo.ca