Journal of Theoretical and Applied Information Technology
15 August 2012. Vol. 42 No.1

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

# A RECONSTRUCTION ALGORITHM WITH ADAPTIVE WEIGHTED FUSION IN COMPRESSED SENSING

[1, 2] YANJUN HU, [2]ZHONGYU LIU, [2]JIE XIANG, [2]XINDE CAO, [1, 2]ENJIE DING

[1] IoT Perception Mine Research Center, China University of Mining & Technology, Xuzhou 221008, China

[2] School of Information and Electrical Engineering, China University of Mining & Technology, Xuzhou,221008 , China

## ABSTRACT

An efficient energy-saving method is proposed by taking the advantages of lightweight encoder and high compression efficiency of Compressed Sensing, which is extremely suitable for image nodes in Wireless Multi-media Sensor Networks. However, the Orthogonal Matching Pursuit (OMP) reconstruction algorithms in CS can not balance the reconstruction image quality and processing time. A novel reconstruction algorithm is proposed in this paper. This algorithm fuses images which reconstructed by OMP according to the row vectors column vectors and diagonal vectors of sample data. And the fusion weights are adjusted by calculating the PSNR values among RIRV (Reconstructed Image by Row Vectors), RICV (Reconstructed Image by Column Vectors) and RIDV (Reconstructed Image by Diagonal Vectors). Experiments show this algorithm is workable, and it reduces the stripe noise. Also, it has a better performance of balancing the reconstruction image quality and processing time than traditional OMP and CoSamp algorithms.

**Keywords:** *Compressed Sensing, Image Fusion, Orthogonal Matching Pursuit, Adaptive Weighted Fusion*

## 1. INTRODUCTION

The lower energy consumption of the image node in Wireless Multimedia Sensor Networks (WMSN) under coalmine has been a hot topic in recent years [1]. Most researchers make use of the traditional data compression algorithm with high compression ratio to reduce the transmission energy consumption of the nodes [2, 3]. However, the traditional data compression algorithm is complicated generally. It means that the image nodes must spend significant amount of energy on compression processing to reduce transmission data. In other words, it pays processing energy consumption to save the transmission energy consumption. Thus, it is not an efficient energy-saving method by using traditional data compression algorithm to the image node in WMSN.

Recently, the Compressed Sensing (CS) which is also named Compressed Sample theory is put forward and provides a new way to implement the lower energy consumption nodes in WMSN[4-6]. In CS theory, the sampling process is just a matrix multiplication, and the reconstruction process is $l_0$ norm optimization problem. It means that the characteristics of the CS theory are the lightweight encoder and complexity decoder. The image nodes in WMSN take this advantage can consume minor image processing energy and reduce significant amount of transmission data by making use of this advantage. Therefore, an emergency image monitoring WMSN in coalmine could be implemented, whose nodes is low energy consumption based on CS theory. There is still a problem to be solved that how to reconstruction the image with best quality while spend minor processing time.

A classic CS reconstruction algorithm is matching pursuit (MP) algorithm[7] which needs one redundancy dictionary to approximate the true signal. Based on MP algorithm an Orthogonal Matching Pursuit (OMP) algorithm[8] is proposed, which reconstructs the true signal according to column vectors of sample data. This OMP algorithm can reconstruct the image with smoothness between row vectors and stripe noise between the columns. An algorithm[9] reconstructs the image by the column and diagonal vectors of sample data. However, the stripe noise still exists in the reconstructed image. To improve the reconstruction process speed with the expense of quality, the CoSamp algorithm[10] is proposed. To

Journal of Theoretical and Applied Information Technology
15 August 2012. Vol. 42 No.1

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

overcome disadvantages of those algorithms, a reconstruction algorithm is proposed. This algorithm can fuse the RIRV, RICV and RIDV according to the self-adaptive weights and balance the reconstruction process time and reconstructed image quality.

The rest of this paper is organized as follows. In Section II, the theoretical framework of compressed sensing is introduced. In Section III, the details of the proposed algorithm are demonstrated. In section IV, experiments are done. And the discussion and comparison of reconstructed quality and time consumption with other algorithms are presented. The conclusion is given in section V.

## 2. THE INTRODUCTION OF COMPRESSED SENSING

The theory of compressed sensing (CS) shows that if a signal is sufficiently sparse with respect to some basis or frame, it can be faithfully reconstructed from a small set of linear, non-adaptive measurements.

Let $x \in R^{N\times 1}$ be a signal and $\psi \in R^{N\times N}$ be a property basis.

$$x = \psi s = \sum_{i=1}^{N} s_i \psi_i \qquad (1)$$

where $s = [s_1, s_2 \ldots s_N]$ is a vector with $K$-sparse [1] which is defined as $\|s\|_0 = K << N$.

Let $\Phi$ be a CS measurement matrix which can be satisfied with restricted isometric property, then the sampling data $y \in R^{M\times 1}$ could be obtained

$$y = \Phi x \ . \qquad (2)$$

The reconstruction problem of $s$ is equivalent to find sparse vector through the convex optimization program.

$$\hat{s} = \arg\min \|s\|_1 \ \text{s.t.} \ y = \Theta s \qquad (3)$$

where $\Theta = \Phi\Psi$ .If we know $\hat{s}$ ,we could recover $x^*$ from the following ways.

$$x^* = \psi \hat{s} \qquad (4)$$

## 3. ALGORITHM DESCRIPTION

Let $Y \in R^{M\times N}$ be an image transmitted to receiver, $A$ is the sample matrix. The goal is to reconstruct the original image from $Y$ .

[1] A $K$-sparse vector has no more than $K$ nonzero components.

Step1 Initialize the parameters. Set iteration $n = 0$ , the residual $R^n = (r_c^n, r_r^n, r_d^n) = (Y, Y^T, diag(Y))$ , index set $Z^n = (Z_c^n, Z_r^n, Z_d^n) = \varnothing$ , the reconstructed signal $X^n = (X_c^n, X_r^n, X_d^n)$ and a temporary matrix $P^n = \varnothing$ .

Step 2 Reconstruct the RIRV (Reconstructed Image by Row vectors), RICV (Reconstructed Image by Column vectors), RIDV (Reconstructed Image by Diagonal vectors), $X^* = (X_c, X_r, X_d)$ .

Calculate the inner product $A$ and $R^n$ ;

$$G^n = (g_r^n, g_c^n, g_d^n) = A^T R^n \qquad (5)$$

(2) Get the large element of $G^n$

$$D^n = \left(\arg\max_{i\in\{1,2,\ldots,N\}} g_r^n[i], \arg\max_{i\in\{1,2,\ldots,N\}} g_c^n[i], \arg\max_{i\in\{1,2,\ldots,N\}} g_d^n[i]\right) \qquad (6)$$

(3) Update the index set $Z^n = Z^{n-1} \cup D^n$ .

(4) Update the temporary matrix $P^n = P^{n-1} \cup A_{D^n}$

(5) Estimate signal using least-squares algorithm;

$$X^n = P^{n\dagger} Y_d = ((P^n)^T P^n)^{-} P^n Y_d \qquad (7)$$

(6) Update the residual $R^n = X - P^n X^n$ and iteration value $n = n+1$ .

(7) If $\sum r_i^n > \varepsilon$ go to (1), else end the process.

Step 3 Calculate the PSNR values $PSNR(x_c, x_r)$ , $PSNR(x_r, x_d)$ , $PSNR(x_c, x_d)$ among $X^*$.

Step 4 Fuse the $X^* = (X_c, X_r, X_d)$ and reconstructed image $X$ is obtained.

$$\text{Fuse}(X^*) = \omega_c X_c + \omega_r X_r + \omega_d X_d \qquad (8)$$

where Fuse(*) denote an abstract fusion function. In this algorithm the function is defined as

$$\text{Fuse}(X^*) = \omega_c X_c + \omega_r X_r + \omega_d X_d \qquad (9)$$

where

Journal of Theoretical and Applied Information Technology
15 August 2012. Vol. 42 No.1

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

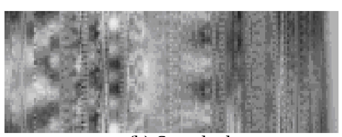
$$\begin{cases} \omega_c = \dfrac{PSNR(x_c, x_r)}{PSNR(x_c, x_r) + PSNR(x_c, x_d) + PSNR(x_r, x_d)} \\ \omega_r = \dfrac{PSNR(x_r, x_d)}{PSNR(x_c, x_r) + PSNR(x_c, x_d) + PSNR(x_r, x_d)} \\ \omega_d = \dfrac{PSNR(x_c, x_d)}{PSNR(x_c, x_r) + PSNR(x_c, x_d) + PSNR(x_r, x_d)} \end{cases}$$

## 4. EXPERIMENTS AND DISCUSSION

### 4.1. Experiments of the Algorithm

The Figure.1 shows the experiment result on a coalmine workface image. The sampling rate is 20%, Gaussian random matrix is adopted as measurement matrix $A$, and the DCT basis is used as the transform basis in reconstruction process.

(a) Original image



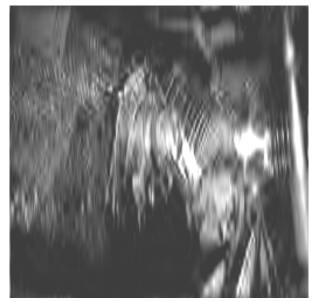
(b) Sample date

(c)Reconstructed image

Figure 1: the simulation of the algorithm (sample rate is 20%)

Figure 2 shows the reconstructed images named RIR, RIC and RIC which is reconstructed according to the row vector, column vector or diagonal vector of sample date.

(a)RIRV (Reconstructed Image by Row Vectors of sample data)



(b)RIRC (Reconstructed Image by Column Vectors of sample data)

(c) RIDV(Reconstructed Image by Diagonal Vectors of sample data)

Figure 2: the OMP algorithm based on different directions vector (sample rate is 20%)

Figure 2(a), Figure 2(b) and Figure 2(c) show that the stripe noise exists in each image. Compared with Fig1(c), the image re- constructed by proposed algorithm removes the stripe noise.

It means that the proposed algorithm is workable and has a better reconstruction performance.

### 4.2. Comparison of Fusion Models on Reconstructed Image Quality

Eq.8 shows other fusion algorithms can be used in the reconstruction process. Typically, there are four types of fusion algorithms.

(a) Fusion algorithm of pixels inserted into column vectors, and it is defined as

$$\text{Fuse}(X^*) = \begin{cases} X_c(i,j), & j \bmod 3 = 2 \\ X_r(i,j), & j \bmod 3 = 1 \\ X_d(i,j), & j \bmod 3 = 0 \end{cases} \qquad (10)$$

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

(b) Fusion algorithm of pixels inserted into row vector, and it is defined as

$$\text{Fuse}(X^*) = \begin{cases} X_c(i,j), & i \bmod 3 = 2 \\ X_r(i,j), & i \bmod 3 = 1 \\ X_d(i,j), & i \bmod 3 = 0 \end{cases} \quad (11)$$

(c) Fusion algorithm of largest pixel gray value adopted, and it is defined as

$$\text{Fuse}(X^*) = \max\{X_c(i,j), X_r(i,j), X_d(i,j)\} \quad (12)$$

**TABLE 1**
**THE COMPARISON OF THE PSNR VALUE OF DIFFERENT FUSION ALGORITHMS**

| Different fusion algorithm | The different PSNR value at different sample rate (M:N) | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 |
| The algorithm in the paper | 18.01 | 20.90 | 23.39 | 25.49 | 27.28 | 28.91 | 30.39 | 31.66 | 32.97 |
| fusion algorithm a | 15.57 | 17.77 | 19.89 | 22.04 | 23.66 | 25.36 | 26.67 | 27.92 | 29.36 |
| fusion algorithm b | 15.51 | 17.74 | 19.89 | 22.08 | 23.70 | 25.32 | 26.77 | 27.92 | 29.26 |
| fusion algorithm c | 14.69 | 16.78 | 18.85 | 20.99 | 22.55 | 24.32 | 25.69 | 26.84 | 28.16 |
| fusion algorithm d | 14.81 | 16.83 | 18.99 | 21.11 | 22.65 | 24.32 | 25.70 | 26.76 | 28.23 |

(d) Fusion algorithm of minimum pixel gray value adopted, and it is defined as

$$\text{Fuse}(X^*) = \min\{X_c(i,j), X_r(i,j), X_d(i,j)\} \quad (13)$$

Experiments using different fusion algorithms are done. Table 1 shows the results. From Table 1, it shows that the proposed algorithm is better than the other four fusion algorithms, as the algorithm makes use of all the information including the sensitive information and non-sensitive information in images of RIR, RIC and RID . The proposed algorithm can display all the details in all the directions of the image very well. It means that the fusion method used in the proposed algorithm is the best.

### 4.3. COMPARISON OF RECONSTRUCTED PROCESS TIME AND RECONSTRUCTED IMAGE QUALITY AMONG DIFFERENT ALGORITHMS

To show the reconstructed image quality of the proposed algorithm, the CoSamp algorithm and traditional OMP algorithm are considered. Figure 4 shows the comparison of the PSNR.

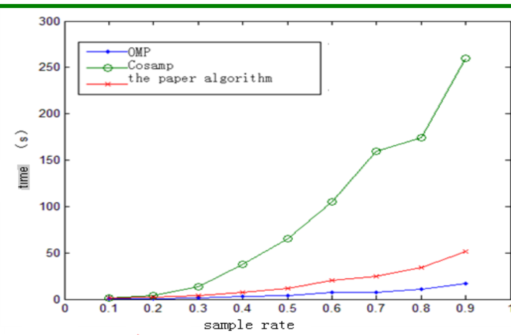


*Figure 4: The Comparison of reconstruction calculation time*

According to the comparison between the reconstructed quality of Figure 5 and the reconstruction time of Figure 4 , the reconstructed quality of the CoSamp algorithm is the worst and the reconstruction time of CoSamp algorithm is the

longest when the sampling rate is(namely compression ratio) between 0.1 and 0.6. Compared with them, the quality of image reconstructed by traditional OMP algorithm is between the two algorithms with shortest reconstruction time. When the sampling rate (namely compression ratio) is between 0.6 and 0.9, the reconstructed quality of CoSamp algorithm is between the two algorithms, the reconstruction time of algorithm is the longest. The reconstructed effect of Standard OMP

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

algorithm is the worst, and the reconstruction time of algorithm is the shortest. This algorithm is with the best reconstructed effect, and the reconstruction time of the algorithm is between them. Therefore, the algorithm in this paper makes on a compromise in reconstruction quality and reconstruction time.

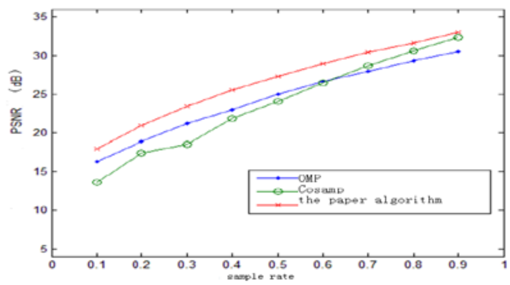



*Figure 5: The Comparison Of Reconstruction Quality*

## 5. CONCLUSION

In this paper, a compressed sensing reconstruction algorithm has been proposed. The algorithm fuses images which are reconstructed by OMP according to row, column and diagonal vectors of sample date. The essence of the algorithm is self-adaptive fusion weight by calculating the PSNR values among RIR, RIC and RID. This algorithm reduces the stripe noise in reconstructed process image. Also, this algorithm needs lower reconstruction time. Experiments show the algorithm balances the reconstructed image quality and reconstruction process time compared with traditional OMP algorithm and CoSamp algorithm.

## ACKNOWLEDGEMENTS

The project is supported by the National Natural Science Foundation of China (Grant No. 60972059).

## REFRENCES:

[1] Alippi. C, "Detecting External Disturbances on the Camera Lens in Wireless Multimedia Sensor Networks, Instrumentation and Measurement", *IEEE Transactions on Information Forensics and Security*, Vol.59, No.1, 2011, pp.2982-2990.

[2] Tsang. P, "Near-computation-free image encoding scheme based on adaptive decimation", IET *Image Processing*, Vol. 4, No. 2, 2008, pp. 175-184.

[3] Lin W.S., Tjoa S. K., Zhao H.V et al., "Digital image source coder forensics via intrinsic fingerprints", IEEE Transactions on Information Forensics and Security, Vol. 3, No. 4, 2009, pp. 460-475.

[4] J. Tropp and A. Gilbert, "Signal recovery from random measurements via orthogonal matching pursuit", *IEEE Transactions on Information Theory*, Vol. 53, No. 12, 2008, pp. 4655-4666.

[5] E Candes, J Romberg, T Tao, "Robust uncertainty principles: exact signal reconstruction from highly incomplete frequency information", *IEEE Transactions on Information Theory*, Vol. 52, No. 2, 2006, pp. 489-509.

[6] E Candes, T Tao, "Near optimal signal recovery from random projections: Universal encoding strategies", *IEEE Transactions on Information Theory*, Vol. 52, No. 12, 2006, pp. 5406-5425.

[7] T Do Thong, Lu Gan, et al., "Sparsity adaptive matching pursuit algorithm for practical compressed sensing", *Asilomar Conference on Signals, Systems, and Computers*, 2008, pp.581-587.

[8] L Rebollo-Neira, D Lowe, "Optimized Orthogonal Matching Pursuit Approach", IEEE Signal Processing Letters, Vol. 9, No. 6, 2002, pp. 137-140.

[9] Joel A. Tropp, Anna C. Gilbert, "Signal Recovery From Random Measurements Via Orthogonal Matching Pursuit", *IEEE Transactions on Information Theory*, Vol. 53, No. 12, 2007, pp. 4655-4666.

[10] D. Needell and J. Tropp, "COSAMP: Iterative Signal Recovery from Incomplete and Inaccurate Samples", *IEEE Information Theory and Applications*, Vol. 26, No. 2, 2009, pp. 301-321.