Compressed Sensing Joint Image Reconstruction Based on Multiple Measurement Vectors

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Abstract. In order to improve the quality of the reconstructed image for compressed sensing, a novel compressed sensing joint image reconstruction method based on multiple measurement vectors is put forward in this paper. Firstly, the original image is processed under the multiple measurement vectors (MWV) mode and random measured by two compressive imaging cameras, in vertical direction and horizontal direction, separately. Secondly, the vertical sampling image and horizontal sampling image are reconstructed with the multiple measurement vectors. Finally, the mean image is used to capture the correlation between these two similar images, and the original image is reconstructed. The experiment result showed that the visual effect and peak signal to noise ratio (PSNR) of the joint reconstructed image by this method is much better than the independent reconstructed images. So, it is an effective compressed sensing joint image reconstruction method.

Keywords: Compressed sensing · Image reconstruction · Joint reconstruction · Single measurement vector (SMV) · Multiple measurement vectors (MMV)

1 Introduction

Over the past few years, there have been increased interests in the study of compressed sensing—a new framework for simultaneous sampling and compression of signals [1]. Compressed sensing exploits the sparsity of an unknown signal to recover the signal from much fewer linear measurements than required by the Nyquist-Shannon sampling [2]. The fact that compressed sensing requires very few measurements makes it very useful to reduce sensing cost in a variety of applications.

Signal reconstruction algorithm is the key to compressed sensing theory. Presently, various reconstruction algorithms have been proposed, such as the orthogonal matching pursuit (OMP) algorithm [3], the basis pursuit (BP) algorithm [4], the hybrid simulated annealing thresholding algorithm [5], and the orthogonal super greedy algorithm 错误!未找到引用源。. However, all these reconstruction algorithms for compressed sensing are based on the sparsity of original signal, which can be described as the internal signal correlation. In order to make full use of the correlation between different image signals,

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some researchers have investigated the multi-view correlation and presented the relevant reconstruction methods. However, these methods either require estimating the relative camera positions or do not perform the reconstructions simultaneously. To date, how to improve the accuracy of reconstruction image via using the correlation between different image signals remains a critical problem [6].

In this paper, we assume that the original image is processed under the multiple measurement vectors (MWV) mode and random measured by two compressive imaging cameras, in vertical direction and horizontal direction, separately. The correlation between these two different sampling direction images is captured by the mean of these two visual similar images. In this way, the original image is joint reconstructed and the accuracy is improved. Firstly, each column and each row of the original image signal is individual treated as one-dimensional signal, and then linear measured via MWV framework separately [7]. Secondly, all one-dimensional signals are recovered and composed of two sampling direction reconstruction images. Finally, the original image is joint reconstructed by the mean of these two images.

2 The Basic Principle of Compressed Sensing

Compressed sensing, also known as compressed sampling or sparse sampling, is a technique for finding sparse solutions to underdetermined linear systems. Compressed sensing is applied in electronic engineering, especially signal processing, to obtain and reconstruct sparse or compressible signals. This method takes advantage of the sparse nature of the signal and is able to reconstruct the entire desired signal from fewer measurements than Nyquist's theory. The basic idea of compressed sensing is that any sparse or compressible signal can be projected from high dimension space into low dimensional space via linear measurement processing [8]. And then the original signal can be reconstructed by solving an optimization problem. Premise condition of compressed sensing is that the signal is sparse or compressible [9], but the actual signal usually can't meet this condition. To solve this problem [10], the orthogonal transformation processing can be performed [11]. For such signals without sparse properties, the processing process of compressed sensing is shown in Fig. 1 below:

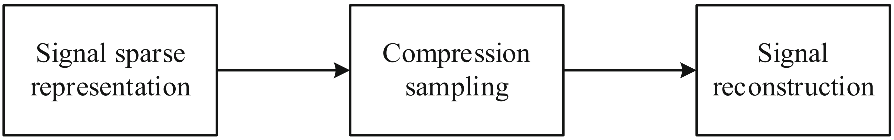


Fig. 1. The processing of compressed sensing

Compressed sensing, also known as compressed sampling, looks more intuitive. Compressed sensing is a signal sampling technology, it through some means, to achieve "compression sampling", to be precise, in the sampling process to complete the data compression process. Compressed sensing is to solve the problem of how to restore the signal perfectly under the condition of under-sampling. The classical signal processing system is built on the basis of classical linear algebra and statistics, so the number of equations is less than the number of unknowns to deal with this kind of under-sampled reconstruction problem. According to the theory of classical signal processing, this kind of problem has infinitely many solutions (can't uniquely and definitively recover the target image perfectly). We call this kind of problem an ill-posed problem, and Compressed Sensing is used to solve ill-posed inverse problems.

Consider a real-valued, finite-length, one-dimensional, discrete-time signal x, with the length of N. The signal x can be expressed as (1):

$$x = \sum_{i=1}^{N} \psi_i \alpha_i = \Psi \alpha, \tag{1}$$

where $\Psi = \{\psi_i\}_{i=1}^{N}$ is an orthogonal base matrix of $N \times N$ and α is a coefficient vector of $N \times 1$. If there are only $K < < N$ non-zero coefficients in vector α, the signal x can be seen as a sparse signal in the Ψ domain and the sparse degree is K.

Compressed sensing samples signal by directly acquiring a compressed signal representation without going through the intermediate stage of acquiring N samples. Consider a general linear measurement process that computes $M < N$ inner products between x a collection of vectors $\Phi = \left\{\varphi_j\right\}_{j=1}^{M}$, the measurement process can be expressed as (2):

$$y = \Phi x = \Phi \Psi \alpha, \tag{2}$$

where y is a measurement vector of $M \times 1$, and Φ is a measurement matrix of $M \times N$.

A necessary and sufficient condition for measurement matrix Φ to reconstruct the length-N signal x from $M < N$ measurements is that Φ must satisfy restricted isometry property (RIP) criterion [12]. The RIP criterion requires the matrix $\Theta = \Phi\Psi$ must satisfy the expression (3):

$$1 - \varepsilon \le \frac{||\Theta \alpha||_2}{||\alpha||_2} \le 1 + \varepsilon, \tag{3}$$

where $\varepsilon \in (0, 1)$ is a constant. The equivalent condition of RIP criterion is that measurement matrix Φ is incoherent with the basis Ψ.

Since $M < N$, the Eq. (2) appears ill-conditioned. However, α is a K sparse vector which means that there is only K non-zero coefficients, and then the problem can be solved provided $M \ge K$. The most direct way to reconstruct α is by solving optimization problem under l_0 norm:

$$\widehat{\alpha} = \arg\min ||\alpha||_0 \quad s.t. \;\; y = \Phi \Psi \alpha, \tag{4}$$

where $||\alpha||_0$ is the l_0 norm of vector α, i.e. the number of its non-zero coefficients. Finally, the signal x can be reconstructed by (1). The schematic diagram of compressed sensing is shown in Fig. 2.

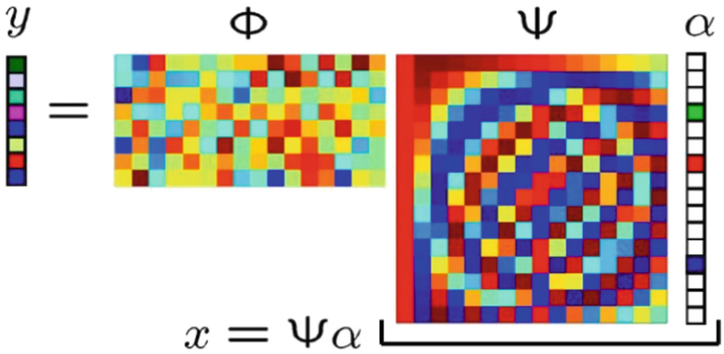


Fig. 2. The schematic diagram of compressed sensing

3 Compressive Imaging Based on Multiple Measurement Vectors

3.1 Random Measurement in Vertical and Horizontal Direction

According to the theory of compressed sensing introduced in the last section, any natural image signal X of $N \times P$ can be orthogonal transformed as (5), and the transposed matrix X^T of $P \times N$ can be also orthogonal transformed as (6):

$$X = \Psi_H S, \tag{5}$$

$$X^T = \Psi_L D, \tag{6}$$

where Ψ_H is an orthogonal base matrix of $N \times N$ and S is a sparse coefficient matrix of $N \times P$; Ψ_L is an orthogonal base matrix of $P \times P$ and D is a sparse coefficient matrix of $P \times N$.

In previous research of compressive imaging, most scholars will convert the two-dimensional image signal into one-dimensional signal when process image signal. For example, all columns of an image of $N \times P$ are linked end-to-end to compose a column vector of $N \cdot P \times 1$, which means that a long one-dimensional signal is processed under the single measurement vector (SMV) mode. But in this way, the scale of the measurement matrix would be very big, which will significantly increase the amount of calculation and storage space, and lead to a very long processing time.

In order to reduce the scale of the measurement matrix and improve the accuracy of reconstruction, each column of the image signal can be individual treated as one-dimensional signal of $N \times 1$. And P measurement vectors of $M \times 1$ can be obtained by the same measurement matrix, which means that the two-dimensional image signal is processed under the multiple measurement vectors (MWV) mode [13].

We assume that the original image X of $N \times P$ is processed under MWV mode and random measured by two compressive imaging cameras, in vertical and horizontal direction separately. In vertical direction, each column of the image signal is individual treated as one-dimensional signal of $N \times 1$, and then random liner measured by a random matrix Φ_H of $M \times N$. This linear measurement process can be described as (7):

$$y_i = \Phi_H X_i = \Phi_H \Psi_H S_i \quad (i = 1, 2 \cdots P), \tag{7}$$

where $y_i \quad (i = 1, 2 \cdots P)$ is observation vector of $M \times 1$, $X_i \quad (i = 1, 2 \cdots P)$ is the i column vector of original image signal X, and $S_i \quad (i = 1, 2 \cdots P)$ is the i column vector of sparse coefficient matrix S.

In horizontal direction, each row of the image signal is individual treated as one-dimensional signal of $1 \times P$, and then random liner measured by a random matrix Φ_L of $M \times P$. This linear measurement process can be described as (8):

$$z_j = \Phi_L X_j^T = \Phi_L \Psi_L D_j \quad (j = 1, 2 \cdots N), \tag{8}$$

where $z_j \quad (j = 1, 2 \cdots N)$ is observation vector of $M \times 1$, $X_j^T \quad (j = 1, 2 \cdots N)$ is the j row vector of original image signal X, and $D_i \quad (j = 1, 2 \cdots N)$ is the j column vector of sparse coefficient matrix D.

3.2 Image Joint Reconstruction

To reconstruct the original image X of $N \times P$ with the measurement vectors $y_i \quad (i = 1, 2 \cdots P)$ and $z_j \quad (j = 1, 2 \cdots N)$ [14], the most direct way is by solving two optimization problems under l_0 norm as (8) and (9) separately:

$$\widehat{S}_i = \arg\min ||S_i||_0 \quad s.t. \;\; y_i = \Phi_H \Psi_H S_i \;\; (i = 1, 2 \cdots P), \tag{9}$$

$$\widehat{D}_j = \arg\min ||D_j||_0 \quad s.t. \;\; z_j = \Phi_L \Psi_L D_j \quad (j = 1, 2 \cdots N), \tag{10}$$

where $||S_i||_0$ is the l_0 norm of vector S_i, i.e. the number of its non-zero coefficients; $||D_j||_0$ is the l_0 norm of vector D_j, i.e. the number of its non-zero coefficients. Signal reconstruction algorithm of compressed sensing, such as orthogonal matching pursuit (OMP) algorithm and basis pursuit (BP) algorithm, can be used to solve (9) and (10). So, we can get $\widehat{S} = \left\{\widehat{S}_i\right\}_{i=1}^{P}$ and $\widehat{D} = \left\{\widehat{D}_j\right\}_{j=1}^{N}$.

Here we can get two image-by-image reconstruction images as $\widehat{X}_H = \Psi_H \widehat{S}$ and $\widehat{X}_L = (\Psi_L \widehat{D})^T$. Reconstruction images $\widehat{X}_H$ and $\widehat{X}_L$ would be the same in the case of exact reconstruction. But the error would be introduced in actual measurement and calculation, which would lead to certain differences between $\widehat{X}_H$ and $\widehat{X}_L$. In order to improve the quality of the reconstruction image, we advocate the mean of these two-view image signals to capture the correlation between them. So, the joint reconstruction image is calculated as (11):

$$\widehat{X} = (\Psi_H \widehat{S} + \widehat{D}^T \Psi_L^T)/2, \tag{11}$$

3.3 Process of This Method

The specific steps of multi-view compressive imaging based on multiple measurement vectors can be concluded as follows:

Step 1: Initialization. It is assumed that the size of the original image signal X is $N \times P$, where N is the number of the rows of the figure and P is the number of lines of the figure. Measurement matrix Φ_H is a random matrix with the size of $M \times N$; and Measurement matrix Φ_L is a random matrix with the size of $M \times P$.

Step 2: Linear measurement. The original image is random measured by two compressive imaging cameras, in vertical and horizontal direction separately. In vertical direction, each column of the image signal X is individual treated as one-dimensional signal of $N \times 1$, and then linear measured by (7). In horizontal direction, each row of the image signal X is individual treated as one-dimensional signal of $1 \times P$, and then linear measured by (8).

Step 3: One-dimensional signal reconstruction. Sparse signal $\widehat{S}_i \quad (i = 1, 2 \cdots P)$ and $\widehat{D}_j \quad (j = 1, 2 \cdots N)$ can be recovered by solving the optimization problems in (9) and (10). In this paper, the classical greed iterative algorithm, i.e. orthogonal matching pursuit algorithm (OMP) [15], is used to solve these optimization problems. Then the sparse coefficient matrixes can be calculated as $\widehat{S} = \left\{\widehat{S}_i\right\}_{i=1}^{P}$ and $\widehat{D} = \left\{\widehat{D}_j\right\}_{j=1}^{N}$.

Step 4: Joint image reconstruction. Two image-by-image reconstruction images can be reconstructed as $\widehat{X}_H = \Psi_H S$ and $\widehat{X}_L = (\Psi_L D)^T$, and the final reconstructed image signal can be calculated as (11).

4 The Simulation Experiment Results

In order to verify the compressed sensing joint image reconstruction method presented in this paper, simulation experiments are carried out to four standard test images with the size of 256×256. These tests imaged are image "Lenna", "Cameraman", "Fruits" and "Peppers". In the experiments, the image signal is sparse represented with wavelet base matrix [16–18]; the measurement matrix is Gaussian random matrix; the vertical sampling rate and horizontal sampling rate are the same. Considering the fast calculation and high accuracy of OMP algorithm in compressed sensing signal reconstruction, the comparison experiments were conducted with single measurement vector OMP (SMV-OMP) algorithm in, multiple measurement vectors OMP (MMV-OMP) algorithm in [19], and the method in this paper. Classic compressed sensing problems can be summarized as: with a known single observation vector to solve the unknown single observation vector, namely the SMV problem. In the actual application of a variety of scenarios, however, there are multiple measurement vector valued known conditions, the sparse vector to recover at the same time, different from the SMV model said it to multiple measurements (MMV) model, that is, multiple sparse vector at the same time refactoring (recovery K sparse matrix x) at the same time, the vector matrix form. Multiple measurement vector model in terms of a single measurement vector model, can further use the signal and the signal correlation in between, with the same multiple of sparse vector for recovery at the same time, can improve the reconstruction accuracy. The simulation experimental conditions are as follows: Windows 7 SP1, Intel(R) Core (TM) i5-3210M CPU @ 2.50 GHz, 3.88 GB memory, and the tool is MATLAB R2012b.

The original image, simulation experiment results of SMV-OMP algorithm, MMV-OMP algorithm and the method in this paper are illustrated in Fig. 3, 4, 5 and 6 [20]. From these simulation experiment results it can be seen that the accuracy and visual effect of the joint reconstruction images by this method are much better than the reconstruction results by the other two algorithms. Form the reconstruction results of image "Lenna", "Cameraman", "Fruits" and "Peppers" we can see that the image acuity and visual effect of the proposed joint reconstructed image is much better than that of the SMV-OMP reconstructed image and MMV-OMP reconstructed image, which verify the effectiveness of the proposed method.

In order to quantitatively evaluate the performance of these algorithms, peak signal to noise ratio (PSNR) is used as evaluation index of the image reconstruction algorithm. Peak signal-to-noise ratio (PSNR) [21], an objective criterion for image evaluation, has been applied in many scenarios. It is local, PSNR is the abbreviation of Peak Signal to Noise Ratio. Peak means peak in Chinese. PSNR is generally used for an engineering project between the maximum signal and the background noise. Usually after image compression, usually the output image will be different from the original image in some way. In order to measure the image quality after processing, we usually refer to the PSNR value to measure whether a process is satisfactory or not. The PSNR shows the difference degree between the reconstructed image and the original image, and it can be calculated as (12):

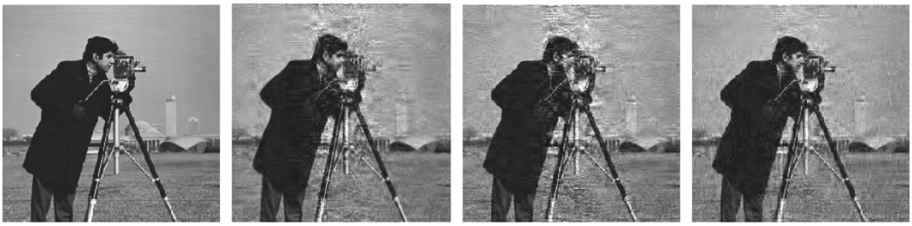
$$PSNR \triangleq 10\log_{10}\left[\frac{255 \times 255}{\frac{1}{N \times P}\sum_{i=1}^{N}\sum_{j=1}^{P}|X(i,j) - \widehat{X}(i,j)|^2}\right], \tag{12}$$

where $N \times P$ is the size of original image signal X, and $\widehat{X}$ is the reconstruction image.

(a) (b) (c) (d)

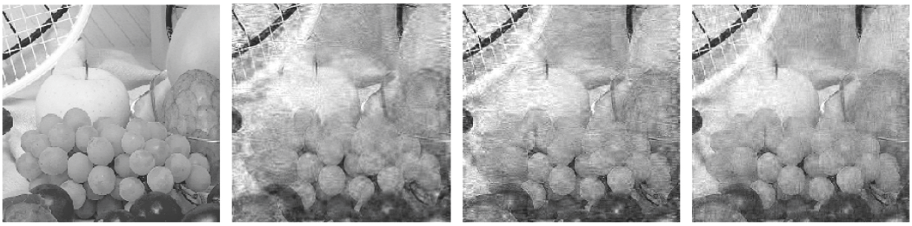
Fig. 3. Reconstruction results of image Lena, sampling rate is 40%. (a) Original image; (b) SMV-OMP reconstructed image; (c) MMV-OMP reconstructed image; (d) Joint reconstructed image

Table 1 shows PSNR of the simulation experiment results with the sampling rate of 0.3, 0.4 and 0.5. From Table 1, it can be seen that, the reconstructions quality of all algorithms is improved with the increase of sampling rate. And we can conclude that under the same simulation conditions, the joint reconstruction images in this method provide higher PSNR than the images reconstructed by SMV-OMP algorithm and MMV-OMP algorithm.



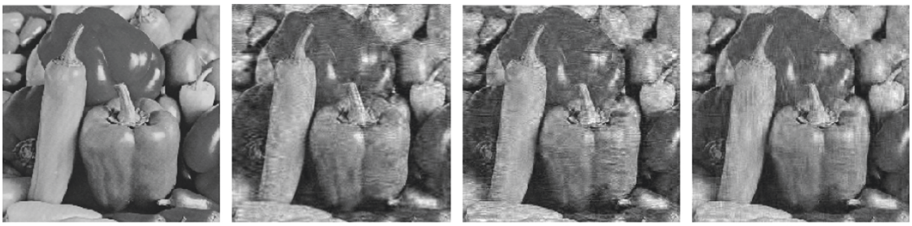
(a) (b) (c) (d)

Fig. 4. Reconstruction results of image Cameraman, sampling rate is 40%. (a) Original image; (b) SMV-OMP reconstructed image; (c) MMV-OMP reconstructed image; (d) Joint reconstructed image



(a) (b) (c) (d)

Fig. 5. Reconstruction results of image Fruits, sampling rate is 40%. (a) Original image; (b) SMV-OMP reconstructed image; (c) MMV-OMP reconstructed image; (d) Joint reconstructed image



(a) (b) (c) (d)

Fig. 6. Reconstruction results of image Peppers, sampling rate is 40%. (a) Original image; (b) SMV-OMP reconstructed image; (c) MMV-OMP reconstructed image; (d) Joint reconstructed image

Table 1. The PSNR of simulation results (dB).

Test images	Sampling rate = 30%			Sampling rate = 40%			Sampling rate = 50%		
	SMV OMP	MMV OMP	Joint result	SMV OMP	MMV OMP	Joint result	SMV OMP	MMV OMP	Joint result
Lena	18.94	21.51	**22.32**	23.56	24.28	**25.41**	26.46	27.19	**27.49**
Cameraman	14.79	19.82	**21.78**	21.74	22.10	**24.47**	24.01	24.44	**27.07**
Fruits	15.54	20.72	**22.94**	22.11	22.96	**25.55**	24.74	25.40	**28.06**
Peppers	15.86	20.04	**22.20**	22.16	22.83	**25.04**	25.21	25.32	**27.55**

For the range of sampling rate is large, the experiment also can verify the robustness of the method. Figure 7 shows the PSNR comparison chart of image Lena, under the condition of different sampling rate. From Fig. 5 it can be seen that the PSNR of the joint reconstruction images in this method provide higher PSNR than the images reconstructed by the other two algorithms, under the same sampling rate. And the performance of this method dose not appears large fluctuations. It maintains a good stability with the change of sampling rate. So it is an effective compressive imaging method [22, 23].

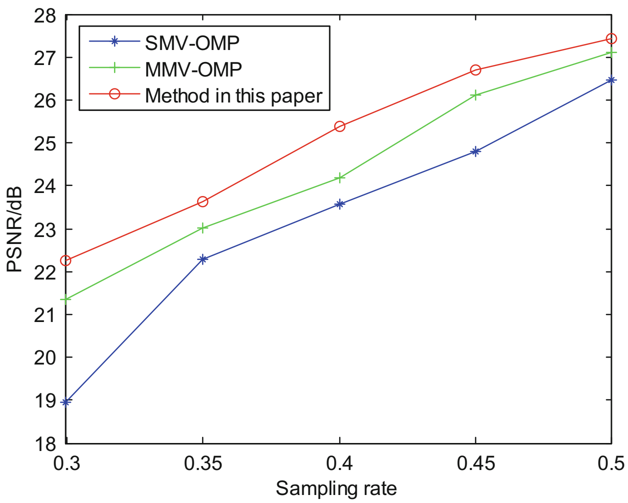


Fig. 7. The PSNR contrast diagram of image Lena under different sampling rate

5 Conclusions

A novel compressed sensing joint image reconstruction method based on multiple measurement vectors is put forward in this paper. We assume that the original image is processed under the multiple measurement vectors (MWV) mode and random measured by two compressive imaging cameras, in vertical direction and horizontal direction, separately. After these two different sampling direction images are reconstructed, the mean image is used to capture the correlation between them and the original image is joint reconstructed. The experiment results showed that the accuracy and visual effect of the joint reconstruction images by this method are much better than the reconstruction results by SMV-OMP algorithm and MMV-OMP algorithm. And the performance of this method dose not appears large fluctuations with the change of sampling rate. So, it is an effective compressed sensing joint image reconstruction method.

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