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IMPROVED MEASURE ALGORITHM BASED ON CoSaMP FOR IMAGE RECOVERY

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Abstract- In order to improve the quality of the reconstruction image which using Compressive sensing(CS) algorithm. Based on improved measurement matrix combined with CS Matching Pursuit(CoSaMP)algorithm, this paper presents a kind of Fourier Ring Compressive Sampling Matching Pursuit (FR-CoSaMP) algorithm. The algorithm superimposed deterministic ring measurement matrix to optimize measurement process on the basis of Fourier measurement matrix. And solve the iterative inverse operation by using FFT fast Fourier calculation method, which can make the measurement information more complete, and speed up the signal reconstruction. Then introduces the mathematical framework and algorithmic processes of the FR-CoSaMP algorithm in details. Finally, compare these types of traditional algorithms and the improved algorithm by analysis and simulation. The results show that, under the same image sparsity and measurement scale, the improved FR-CoSaMP algorithm has better performance in terms of the image reconstruction.

Index terms: Compressed sensing, Measurement Matrix, Fourier Ring, Orthogonal Matching.

I. INTRODUCTION

The traditional image signal collecting is based on the Shannon-Nyquist sampling theory. After the high-speed sampling of the image signal and compression coding. The capturing device needs to collect large amounts of complete data . Most of this data is redundant if the signal or image is sparse, It will remove from the process of compression encoding. Therefore, according some characteristics of the signal to research on how to achieve collection, which less than the Shannon sampling frequency, to reduce the amount of data collected is of great significance. Attracted the attention of many scientists, who carried out extensive research.

In recent years, by D.Donoho, E.Cands and J.Romberg who proposed a new signal sampling theory, the Compressive sensing (CS[1,2,3])theory, which break the bottleneck of traditional Shannon sampling theory, the theory is based on the theory which image signal showing sparsity in the dictionary library. Measurement matrix projected sparse signal onto another low-dimensional space, the random linear projection retains most useful information of the original signal, to make an accurate reconstruction of the original signal by various of nonlinear algorithm. That is the M low-dimensional measurement vector reconstruct $N(N>M)$ high-dimensional signal. The greatest advantage of Compressive sensing theory is that, the randomness of measuring projector ensure the robust of random coding. To cut down the workload of the front sensor, by reducing the work of signal acquisition. and which can reduce the number of acquisition and the acquisition time of the original signal effectively, but increases the complexity of the reconstruction. Also, due to the sparse dictionary, measurement matrix, and select unreasonable reconstruction algorithm, will result corresponding error in the reconstructed signal. Therefore, signal reconstruction algorithm is one of the research focuses on Compressive sensing technology. There are two types of reconstruction techniques currently: the Greedy algorithm and the Convex Optimization algorithms[4]. Greedy algorithm is done by selecting the appropriate atom, and after a series of escalating way, to achieve approximation signal vector, development of such algorithms include Matching Tracking algorithm, Orthogonal Matching Pursuit algorithm and Fill Space Matching Pursuit algorithm, and so on. The convex optimization algorithm, is the 0-norm relaxed to 1-norm by solving linear programming, the algorithm developed include Gradient Projection algorithm[5], Based Tracking algorithm, and the Minimum Angle Regression algorithm. The Convex Optimization algorithm asking more accurate solution than the Greedy algorithm, but at the same time, requires higher computational complexity than the latter.

In this paper, based on Compressive Sensing, after analyzing the advantages of several Greedy algorithms, since the image reconstruction algorithm based on Fourier measurement, the weakness is that, can not guaranteed to select useful information at selected measuring value. This paper proposes a new Fourier Ring Compressive Sampling Matching Pursuit(FR-CoSaMP) algorithm, which increase isometric ring measurement vector to get image information, in addition to the Fourier angle measurement. The improved algorithm makes information gathering more secure, some of the original data which may preserved, can involve the reconstruction algorithm. So that the quality of the image reconstructed has been greatly improved.

II. THEORETICAL FRAMEWORK OF COMPRESSIVE SENSING

The first condition to use Compressive sensing techniques is the signal sparse, therefore, how to ensure signal thinning is becoming a prerequisite for the CS application. According to observation, most of the existing signals, especially image signal in a some sparse basis (the dictionary) projection, the approximate absolute sparse emerged, which result the application and development of CS theory has provided a broad space.

Essentially, CS is a non-adaptive, non-linear, information transform domain available signal reconstruction algorithm. Here, we specify the original signal is N-dimensional $x(x\in \boldsymbol{R}^{N\times 1})$in a group of sparse basis has k-sparse description $\mathbf{s}=\mathbf{\Psi}\times x(\mathbf{\Psi}=[\Psi_1,\Psi_2,...\Psi_N], x=[x_1,x_2,... x_N]^T)$, that is:

$$\sum\nolimits_s := \left\{ x \in \boldsymbol{R}^N : \|x\|_0 \le s \right\} \quad (1)$$

The measurement matrix abstracted as a matrix $\mathbf{\Phi}(M\times N)$, which $\mathbf{\Phi} = \left\{ \phi_1^T, \phi_2^T, \ldots, \phi_M^T \right\}$ $(k<M<<N)$,obtained the measurement value y of thinning signal matrix s by matrix $\mathbf{\Phi}$. Which is given by:

$$y=\mathbf{\Phi}\boldsymbol{s}=\mathbf{\Phi\Psi}x \quad (2)$$

General call $\mathbf{\Theta}=\mathbf{\Phi\Psi}$ as sensing matrix, which $\mathbf{\Theta}\in\mathbf{R}^{M\times N}$, the matrix need to meet some certain parameters conditions such as Restricted isometry property (RIP[6,7,8]). The measurement process of CS explained by Figure 1 directly:

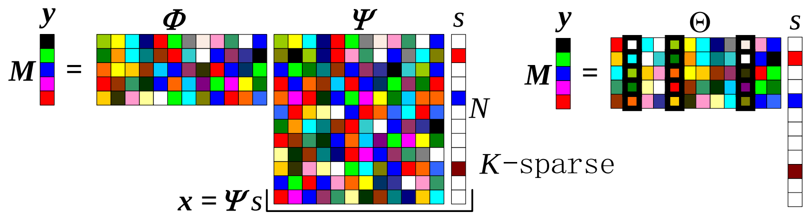

Figure 1. CS linear measurement process

According to k<M<<N we know, the CS measurement process[9], from a mathematical sense, the signal reconstruction problem based on the theory of Compressive sensing is actually solving a underdetermined equations problem of optimal solutions, its essence is an NP-problem to solve the smallest l_0 norm, therefore, the issues are usually constructed model of solving l_0 as:

$$\min\|\Psi x\|_0 \ (x \in R^{N\times 1}) \quad s.t. \quad y = \Phi\Psi x \tag{3}$$

$\|\Psi x\|_0$ representation the 0-norm of $\boldsymbol{s}=\Psi x$ mentioned above, which is the number of non-zero elements after a sparse conversion signal. The solving of this problem can also be transformed into a l_p optimization problem of $\|\boldsymbol{s}\|_p$, which $0<p<<1$,define the p norm of $\boldsymbol{s}$ and given by:

$$\|\boldsymbol{s}\|_p = \left(\sum_{i=1}^{\infty} |s_i|^p\right)^{1/p} \tag{4}$$

when p=1, by solving the zero-norm problem in equation (3) equivalent as solving the l_1-norm of linear programming problem. Then:

$$\min\|\Psi x\|_1 \ (x \in R^{N\times 1}) \quad s.t. \quad y = \Phi\Psi x = \Phi\mathbf{s} \tag{5}$$

By the analysis above, construct rational and effective measurement matrix Φ, it has a significant role to measured value acquisition and original signal reconstruction, measurement matrix Φ not only meet unrelated with sparse basis, but also need to satisfy the RIP. There are many measurement matrix which satisfying the above conditions, including Gauss random matrix, Fourier measurement matrix[10], Bernoulli random matrix[11], Part Hadamard matrix, Sparse and non-sparse projection matrix etc. For easy achieved, this article selected wavelet basis[12]and Gauss random matrix as sparse basis and measurement matrix of the greedy reconstruction algorithm.

Greedy algorithm is the earliest and most classic CS reconstruction algorithm in many of the existing reconstruction algorithm. After several years of research, Compressive sensing reconstruction algorithm achieved many new breakthroughs and development, but the core of the CS theory: By observing sparse signal which far less than the original signal, then get the corresponding observed values *y*, after inverse calculation to the available data by reconstruction algorithm can reproduce the original signal perfectly, the framework of CS theory will not change.

III. IMPROVED FR-CoSaMP ALGORITHM

a. Compressive sampling matching pursuit algorithm

The advantage of the Compressive Sampling Matching Pursuit (CoSaMP[13]) algorithm is that leading into "Backtracking" idea, here the "Backtracking" idea refers to keep those atoms which satisfy optimal choice condition and pass through the condition check in previous iteration, otherwise it will be removed as the next candidate, maximum ensure the selected atoms global optimal. The CoSaMP algorithm through calculate the current optimal solution set of corresponding support with the previous approximate solution support as a new candidate set in each iteration, then using least square method to calculate the coefficient estimates on the new candidate set.

When the measurement matrix $\mathbf{\Phi}(M\times N)$ satisfy a certain limitations such as permit conditions(RIP), CoSaMP algorithm is a high probability to reconstruct the original signal. Assuming that x is a sparse signal under sparse basis , $u=\mathbf{\Phi}x+e$ is a measured signals vector by noise pollution, when given an arbitrary precision parameter η, the algorithm is able to reconstruct the approximation signal vector $\boldsymbol{a}$ to satisfy the following equation:

$$\|x-a\|_2 \le C\cdot\max\left\{\eta, \frac{1}{\sqrt{s}}\left\|x-x_{s/2}\right\|_1+\|e\|_2\right\} \tag{6}$$

in the above equation(6), s as sparse coefficient of the signal x,where $x_{s/2}$ is the s-sparse approximation of x. When assuming that the number of samples m=O($s\log^{\alpha} N$), many types of random sampling matrices satisfy the RIP characteristics. Therefore, the above assumptions applies to a wide class of sampling schemes when the number of samples is proportional to the target sparsity and logarithmic in the ambient dimension of the signal space.

That is, the CoSaMP algorithm has linear convergence, the total runtime is roughly proportional to the reconstruction signal-to-noise ratio.

$$R-SNR=10\log_{10}\left(\frac{\|x\|_2}{\|x-a\|_2}\right)\text{dB} \tag{7}$$

The above equation R-SNR[14] is calculated in decibels, assume that x is s-sparse. For each $k \geq 0$, the signal approximation a^k is s-sparse, and

$$\left\| x - a^{k+1} \right\|_2 \leq 0.5 \left\| x - a^k \right\|_2 + 10\nu \tag{8}$$

$$\left\| x - a^{k+1} \right\|_2 \leq 2^{-k} \left\| x \right\|_2 + 20\nu \tag{9}$$

in the above equation(8)and(9)implies that, after k iterations, the reconstruction R-SNR satisfies the following inequality:

$$R - SNR \geq \min\left\{3k, SNR - 13\right\} - 3 \tag{10}$$

and each iteration increases the reconstruction R-SNR by about 3 decibels until the error nears the noise floor. To reduce the error to its minimal value, the number of iterations is proportional to the R-SNR.

Let x be an s-sparse signal with noisy samples $u=\mathbf{\Phi}x+e$. Let a^{k-1} be the signal approximation at the end of the (k−1)th iteration, and let T be the set of components identified by the support merger. Then:

$$\left\| a^{k-1} - \mathbf{\Phi}_T^{+} \right\|_2 \leq 2.112 \left\| x - a^{k-1} \right\|_2 + 1.06 \left\| e \right\|_2 \tag{11}$$

By construction of T, the approximation a^{k-1} is supported inside T, so we can conclude:

$$\mu(\mathbf{\Psi}, \boldsymbol{F}^R) = \sqrt{n} \max_{1 \leq i, j \leq n} \left| \langle \psi_i, F_j^R \rangle \right| \tag{12}$$

According to $b|_T=\mathbf{\Phi}^{+}{}_T u$, $b|_{T^c}=0$, and $u=\mathbf{\Phi}x+e$, then:

$$\left\| x - b \right\|_2 \leq 1.112 \left\| x |_{T^e} \right\|_2 + 1.06 \left\| e \right\|_2 \tag{13}$$

From equation(13)lemma, we may calculate how far a^{k-1} lies from the solution to the least-squares problem.

$$\begin{aligned} \left\| a^{k-1} - \mathbf{\Phi}_T^{+} u \right\|_2 &\leq \left\| x - a^{k-1} \right\|_2 + \left\| X - \mathbf{\Phi}_T^{+} u \right\|_2 \\ &\leq \left\| x - a^{k-1} \right\|_2 + 1.112 \left\| x |_{T^\varepsilon} \right\|_2 + 1.06 \left\| e \right\|_2 \\ &\leq 2.112 \left\| x - a^{k-1} \right\|_2 + 1.06 \left\| e \right\|_2 \end{aligned} \tag{14}$$

Make margin $r=x-a^{k-1}$, then:

$$\begin{aligned} \left\| x - a^k \right\|_2 &\leq 2 \left\| x - b \right\|_2 \\ &\leq 2 \cdot \left(1.112 \left\| x |_{T^\varepsilon} \right\| + 0.0022 \left\| r \right\|_2 + 1.062 \left\| e \right\|_2 \right) \\ &\leq 2.224 \left\| r |_{\Omega^\varepsilon} \right\|_2 + 0.0044 \left\| r \right\|_2 + 2.124 \left\| e \right\|_2 \end{aligned}$$

$$< 0.5\|r\|_2 + 7.5\|e\|_2$$

$$= 0.5\|x - a^{k-1}\|_2 + 7.5\|e\|_2 \quad (15)$$

The iterations number of least squares method, is based on its approximate value meets or not performance requirements, which the CoSaMP algorithm determined. When the termination condition is satisfied(margin r), then output $a=a^{k-1}$. If not satisfied, then make $k=k+1$ to continue iterating until satisfied.

In the measurement matrix satisfy RIP limit conditions, CoSaMP algorithm is given to reconstruction of guarantee under the measuring signal of noise pollution, the use of multi-atomic selection (excluded) mode to increase the speed of image reconstruction in ensuring under higher accuracy conditions.

b. Improved measurement FR-CoSaMP algorithm

CoSaMP algorithm can achieve more accurate reconstruction under any noise measurement when satisfy the condition of certain RIP, its image reconstruction speed is well, but the reconstruction results are unsatisfactory. Based on the lack of the above algorithm, this paper describes an improved Fourier Ring measurement combined CoSaMP reconstruction algorithm, propose a new algorithm of Fourier Ring Compressive Sampling Matching Pursuit(FR-CoSaMP), which can improve the quality of image reconstruction effectively, detailed algorithm process is given below.

Fourier-Ring measurement matrix is based on image sparse signal Fourier transform, then use the normalization process to get an $N\times N$ orthogonal matrix $\boldsymbol{F}$, overlay the $N\times N$ Ring matrix $\boldsymbol{R}$ after the normalization, selected in M row randomly in the overlay measurement matrix, then unit on each row to generate measurement matrix $\boldsymbol{F}^R$. By using the method of FFT[15] fast calculation and overlay measurement matrix makes information gathering more complete and accurate, achieve improved image signal reconstruction effects and ensuring the calculation speed at the same time. The Fourier-Ring overlay matrix measurement as follows:

$$\boldsymbol{F}_{ij} = (w^{ij})_{i,j=0,1,\dots,N} \Big/ \sqrt{N} \quad (16)$$

$$\boldsymbol{R}_{ij} = \sqrt{(a_{i,j} - r_i)^2 + (b_{i,j} - r_i)^2} \,/\, \sqrt{N} \quad (17)$$

$$\boldsymbol{F}^R_{M\times N} = (\exp(-2\pi i / N)^{ij} + \sqrt{(a_{ij} - r_i)^2 + (b_{ij} - r_i)^2}) \,/\, \sqrt{N} \quad \text{(selected } M \text{ rows randomly)} \quad (18)$$

Among *i,j=1,2,...N*, exp(*-2πi/N*) is the main value of the 1's *N*-th root, which is to be selected. (*a*, *b*) is the coordinates of the center of the measurement matrix, $1/\sqrt{N}$ is the normalization factor. r_i is the radius of the Ring, Fourier Ring measurement matrix composed by the Fourier measurement matrix and Ring measurement matrix.

Suppose x_s be an arbitrary vector in $\mathbf{C}^N$, The sample vector can be expressed as $u=\boldsymbol{F}^R x_s + e^*$, e^* is the actual noise amount. where

$$\left\|e^*\right\|_2 \le 1.05\left[\left\|x-x_s\right\|_2+\frac{1}{\sqrt{s}}\left\|x-x_s\right\|_1\right]+\left\|e\right\|_2 \le \sqrt{1+\delta_s}\left[\left\|x-x_s\right\|_2+\frac{1}{\sqrt{s}}\left\|x-x_s\right\|_1\right]+\left\|e\right\|_2 \qquad (19)$$

According to $b|_T=\boldsymbol{F}^{R*}{}_T u$, $b|_{T^c}=0$, the sample vector $u=\boldsymbol{F}^R x_s + e^*$, margin $r_s=x_s-a^{k-1}$, then

$$\begin{aligned}\left\|x_s-a^{k+1}\right\|_2 &\le 0.5\left\|x_s-a^k\right\|_2+7.5\left\|e^*\right\|_2 \\ &\le 0.5\left\|x_s-a^k\right\|_2+7.5\left\|e^*\right\|_2+1.5\left\|x-x_s\right\|_2 \\ &\le 0.5\left\|x_s-a^k\right\|_2+10\nu \\ &\le \left\|x_s-b\right\|_2+10\nu \\ &\le 1.112\left\|x_s|_{T^e}\right\|_2+0.0022\left\|r_s\right\|_2+1.062\left\|e^*\right\|_2+10\nu < 0.25\left\|r_s\right\|_2+3.75\left\|e^*\right\|_2+10\nu \\ &= 0.25\left\|x_s-a^{k-1}\right\|_2+3.75\left\|e^*\right\|_2+10\nu\end{aligned} \qquad (20)$$

FR-CoSaMP algorithm continues CoSaMP algorithm, the least squares Iterative estimation, when the termination condition is satisfied (margin r_s), and output $a=a^k$, FR-CoSaMP algorithm using sparse wavelet basis **Ψ** and measurement matrix $\boldsymbol{F}^R$, its coherence can define as follows

$$\mu(\boldsymbol{\Psi},\boldsymbol{F}^R)=\sqrt{n}\max_{1\le i,j\le n}\left|\langle\psi_i,F_j^R\rangle\right| \qquad (\mu\in[1,\sqrt{N}]) \qquad (21)$$

References [16] is pointed out that the reconstruction of low coherent performance improved Greedy algorithm performance, Fourier-Ring measurement matrix as a Fourier superposition measurement matrix satisfy the requirements of coherent in the reconstruction experiment. The ideal state is each measured value contains information about the original signal in the compression process of the sampling, and different as far as possible.**Ψ**and $\boldsymbol{F}^R$ is completely orthogonal scilicet, the coherent μ is zero, the mathematical relationship between signal sparsity and incoherence is very strict, Don't go into detail here, you can refer to Reference[17] and[18].

c. FR-CoSaMP algorithm processes

To sum up, generalize the improved measurement FR-CoSaMP algorithm as follows:

1) Initialize $a_0=0$, initial residuals $r_{s0}=u$, iteration count k=1;

2) Read the original image signal x, Select the maximum value of the signal max(x),and normalized processing for it;
3) Build the Fourier Ring measurement matrix $\boldsymbol{F}^R$ as new measurement matrix, get follows:$y=\boldsymbol{F}^R\boldsymbol{s}=\boldsymbol{F}^R\boldsymbol{\Psi}x$;
4) Generate agent signal $c=\boldsymbol{F}^R r_{k-1}$ from the sampling residual signal;
5) Locate the position of the new largest agent signal component, and merge the last iteration support set: $\Omega=\text{supp}(c_{2s})$, $T=\Omega\cup\text{supp}(a^{k-1})$;
6) Least squares signal estimation:$b|_{\mathrm{T}}=\boldsymbol{F}^{R^*}{}_{\mathrm{T}}u$, $b|_{\mathrm{T}^c}=0$, to obtain a new approximation;
7) Retain maximum signal component obtained by the minimum mean square error criterion. Then updating residual;
8) When satisfy the end condition, output $a=a^k$, if not satisfied then go back to step 2, set $k=k+1$.

In order to represent more intuitive and clear information on the Fourier Ring measurement matrix, select the measurement angle Number as T(T=50) by using (0,1) binary image representation:

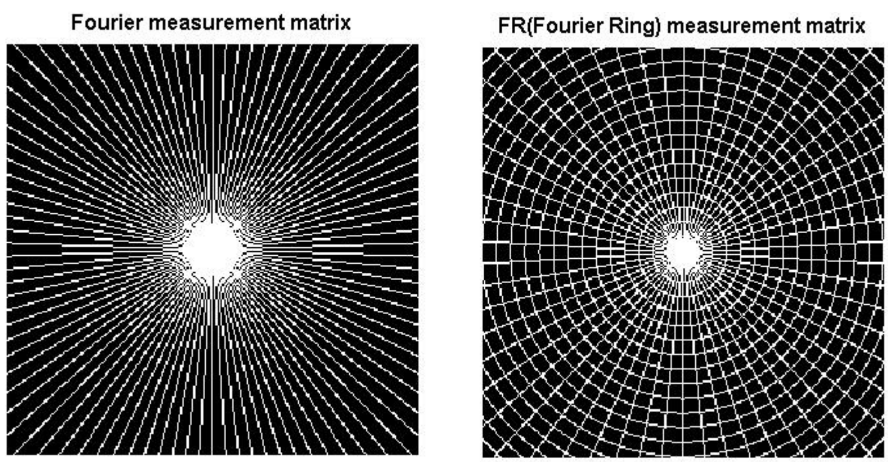

Figure 2. Fourier measurement and FR measurement 2D picture show

Through the contrast of the binary image, Fourier-Ring matrix have been greatly improved in terms of measurement range and randomness aspects, which ensure the image reconstruction accuracy and effectiveness strongly.

IV. ALGORITHM PERFORMANCE SIMULATION AND COMPARISON

Since the comparison of experimental results has a great influence according to different experimental platforms and devices, in order to ensure the objectivity of reconstruction algorithm performance comparison, the reconstruction experimental running at the Tsinghua Tongfang brand machine which CPU is Intel i3-2120 (dual-core 3.30GHz), memory is 3.00GB. And compare the performance between common reconstruction algorithm and the proposed improved algorithm in the one-dimensional signal. Select the sparse signal length N =256, sparsity of k=16, 50. choose Gaussian random matrix as measurement matrix. And select OMP,StOMP,CoSaMP and FR-CoSaMP algorithm as reconstruction algorithm for simulation comparison. The purpose of this experiment is to observe the relationship between exact reconstruction probability under different algorithms, and the signal measurement number M. Taking M={10,20,30,...,140,150} to experiment, also, in order to reduce the uncertainty of the Gaussian random matrix to affect the results, run 10 times for each M, and calculated average, the reconstruction results are as follows Figure3-Figure 4.

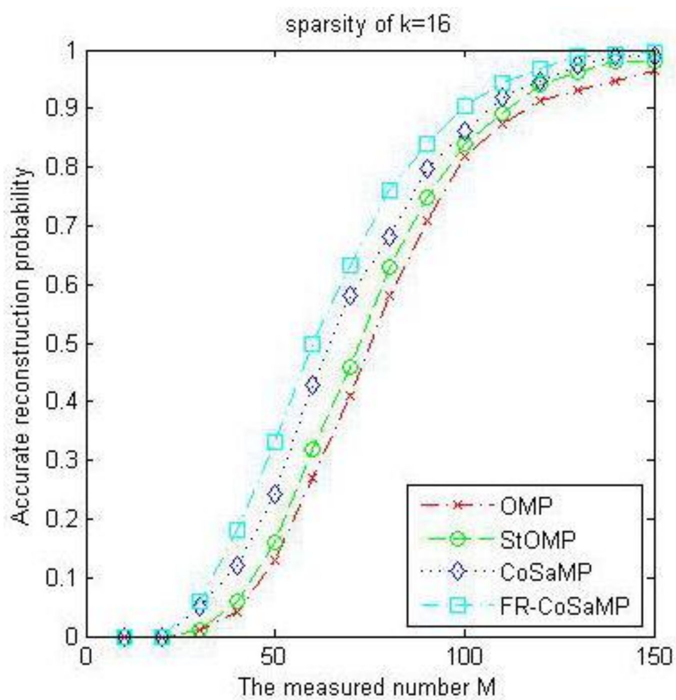

Figure 3. sparsity of k=16, M=10,20,30,...,140,150. Accurate reconstruction probability comparison of OMP,StOMP,CoSaMP and FR-CoSaMP algorithm

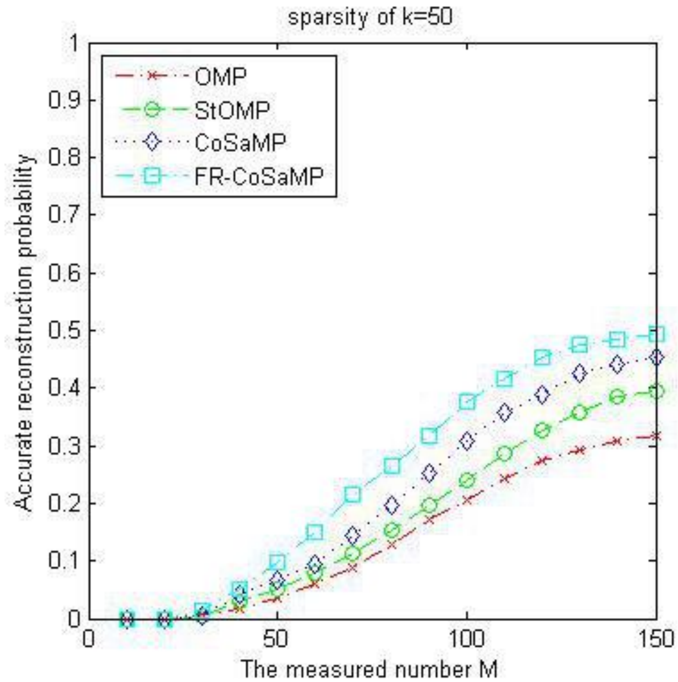

Figure 4. sparsity of k=50, M=10,20,30,...,140,150. Accurate reconstruction probability comparison of OMP,StOMP,CoSaMP and FR-CoSaMP algorithm

It can be seen from Figure 3-Figure 4: When the sparsity k fixed, choose the same measurement matrix, M is proportional to the probability of the accurate reconstruction of sparse signal, when the M reaches a certain number, signals can be 100% accurate reconstruction. For different sparsity k, the larger k requires larger M. Sparsity k and the measurement number M satisfy $M \geq ck \log\{N/k) \leq N$. Where c is a constant related to M/N. Also,select a different reconstruction algorithm will affect the probability of the sparse signal reconstruction, as we can seen, the improved FR-CoSaMP algorithm can achieve a higher probability of reconstruction than other algorithms, the sparsity k is greater, the effect is more obvious. Then followed CoSaMP algorithm, CoSaMP algorithm, the worst effect is OMP algorithm.

Then, compare the performance of these common reconstruction algorithm and improved FR-CoSaMP algorithm in two-dimensional image signal, using image Lena(512×512) as the original image, then respectively using OMP, StOMP, CoSaMP and improved measurement FR-CoSaMP algorithm on the image reconstruction experiments, comparative analysis according to various parameters of the experimental data ,and explain as follow.

Peak Signal-to-Noise Ratio(PSNR[19])as a kind of image quality evaluation standard, often used to measure the distortion between the processed output image and the original image. Image distortion is smaller when the PSNR value is greater, on the other hand shows that the greater the image distortion.

To description image reconstruction quality intuitively, this paper obtain comparison of the PSNR value by using above several reconstruction algorithm when the sampling rate *f* is 0.3-0.6, as shown in Figure 5. as follow.

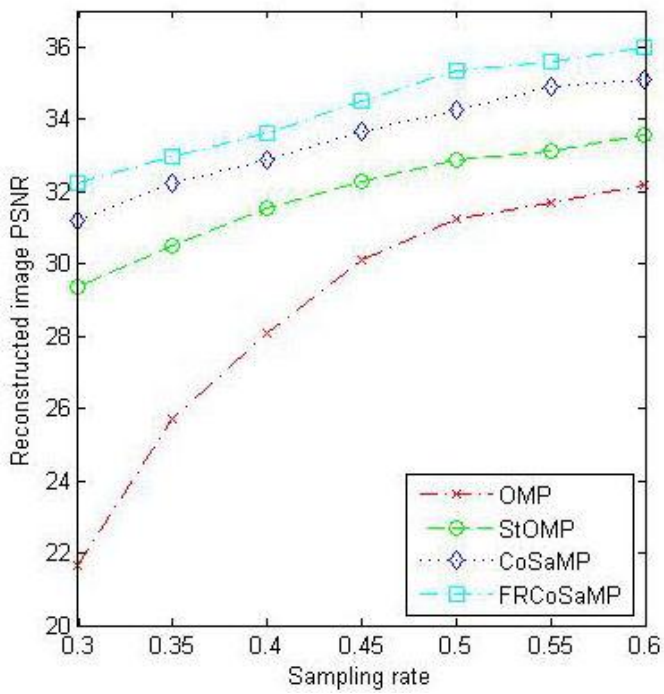

Figure 5. lena512×512,change the sampling rate as *f*(0.3-0.6), the obtained PSNR value comparison of OMP,StOMP,CoSaMP and FR-CoSaMP

The above data shows, the improved FR-CoSaMP algorithm of PSNR value is significantly higher than other several algorithms, under the condition of the same sample rate, the reconstruction quality is better than the original CoSaMP algorithm and the other two algorithms. This is because the Fourier-Based image reconstruction algorithm can not completely guarantee the selection of useful information when selecting measured value, however the improved measure in the original angle measurement based on Fourier, which increase the Equidistant Ring on image measure information, and make information gathering more completely, some of the original data could be discarded was retained to participate in the reconstruction. achieve the selecting useful information to be more completer, and the quality of reconstructed image will be higher, by iteration.

To further validate, the improved Fourier Ring measurement matrix impact on the quality of the reconstruct image. In this paper, using the same original image lena(512×512) for simulation experiments, in ensuring the same sampling rate f=0.3, apply the four algorithms to reconstruct the image lena, and shown below in Figure 6.

(a) (b)

(c) (d) (e)

Figure 6. lena512×512, sampling rate f =0.3, OMP,StOMP,CoSaMOP and FR-CoSaMP algorithm reconstruction comparison

(f) (g)

Figure 7. sampling rate f =0.3, CoSaMOP(f) and FR-CoSaMP(g) algorithm reconstruction image detail comparison

Compare and analysis the effect of four reconstruction algorithms, can be more intuitive to see, by Figure 6 and Figure 7. In the same condition, the sampling rate f = 0.3, addition to OMP algorithm, which is rather vague in reconstructed image. Other Compressive sensing algorithm, such as StOMP, CoSaMP and improved FR-CoSaMP algorithms are capable of a higher probability, to recover the original image signal. Among, the improved FR-CoSaMP algorithms have been greatly improved in the reconstruction quality, compared to the original CoSaMP algorithm and OMP, StOMP algorithm. Furthermore, these four kinds of algorithms, their reconstruction time (average of 10 times)comparison in Table1 below.

Table 1: f=0.3,0.5,0.7, image reconstruction time comparison

Sampling rate	Algorithm/time(in sec)			
	OMP	StOMP	CoSaMP	FR-CoSaMP
f=0.3	2.8245	0.32117	1.4015	0.7392
f=0.5	2.6269	0.31064	1.2827	0.6125
f=0.7	1.9892	0.29162	1.0123	0.4318

The comparison of the reconstruction time can be seen from Table 1, FR-CoSaMP compared with CoSaMP, the reconstruction speed is faster, this is because the improved measurement matrix can obtain more effective image information. Thus the calculated approximation can be more quickly approaching the true value of the image, in the iterative process of the algorithm, the iteration margin stop quickly when it meet the set criteria. FR-CoSaMP algorithm has been further improved in terms of image reconstruction performance .

V. CONCLUSIONS

This research mainly present a improved algorithm which based on the Compressive Sampling Matching Pursuit (CoSaMP) algorithm: FR-CoSaMP algorithm, the algorithm mainly ensure more complete, and accurate retention of the useful images information, by improving the measurement matrix of measurement range and structure in the selected dictionary basis and measurement matrix incoherence of the premise. By experiment, in several existing mature Compressive sensing reconstruction algorithm, the improved FR-CoSaMP algorithm need shorter reconstruction time and the quality of the reconstructed image is greatly improved, which is more important in the same conditions. The reconstruction performance is also ideal.

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