Image Compressed Sensing Algorithm Based on Contourlet Sparse Representation

Peng Jing[1], Jia Junxia[1], Liu Tao[2]

1: Department of Electronic and information, Lanzhou Jiaotong University, LanZhou, 730070, China
2: Faculty of Geomatics ,Lanzhou Jiaotong University, LanZhou, 730070, China

Corresponding author is Peng Jing

Abstract
In order to improve the performance of sparse representation of compressed sensing image, we put forward an image compressed sensing algorithm based on contourlet transform and directional sub bands sparse representation. First, By using discrete contourlet transform achieved that the multi-scale decomposed into multiple high frequency sub bands according to the characteristics of direction orthogonal to rebuild. Secondly, using the random Gauss matrix to measure the sub band after rebuilding respectively, then according to the orthogonal matching pursuit to solve accurate estimation of the direction sub band coefficient, rebuilding the coefficients of every sub band, restoring the sub band recombination, taking Contourlet transform on the low frequency sub-band, finally according to the directional sub bands of Contourlet transform to rebuild the original image. The experimental results showing that, in the same sampling rate, the algorithm of image reconstruction of this paper is superior to other algorithms in the subjective visual effect and the reconstruction speed, in the different sampling rate conditions, the peak signal to noise of the algorithm of this paper is higher than the comparison algorithm.
Keywords: IMAGE COMPRESSED, COMPRESSED SENSING, CONTOURLET SPARSE REPRESENTATION, IMAGE, SUB BAND, TRANSFORM.

1. Introduction

The super resolution reconstruction algorithm of image processes the single and multiple low resolution image to obtain the image with relative higher resolution. The cost of this technology is very low and it can process the existing low resolution images, having great application value in military, medical imaging, remote sensing, high-definition television and other fields. In 1984, Tsai and Huang first proposed the ideas of using the complementary information of the low resolution image sequences in the same scene to improve the image resolution. However, the inaccuracy of registration will make the image quality decrease sharply, and in some special conditions we can only obtain a single low resolution image, so the research of the method of single frame image super-resolution having more practical value.

Super resolution image reconstruction methods can be divided into two main categories: frequency domain method and spatial domain method. Frequency domain method refers to the method by eliminating spectral aliasing in the frequency domain to improve the spatial resolution of the image. The image super resolution reconstruction technique of early are concentrated in the frequency domain method. The spatial domain method refers to the method of using image pixels constraints to improve image quality in the image pixel scale. The spatial domain method in-

cludes interpolation method, iterative back projection method, projection onto convex sets, maximum likelihood estimation and maximum a posteriori estimation. The spatial domain method can make full use of the prior knowledge of the image, for example, in recent years the super resolution image reconstruction based on compressing sensing that got extensive attention. The basic idea is to using the natural images that has the sparse prior knowledge in a transform domain. The literature applies the newer two step iterative algorithm and (TwIST) and regularization function with a good edge preserving of total variation (TV) into super resolution reconstruction, can be better to reconstruct the original edge information. Super resolution reconstruction method based on wavelet transform has become a very active research field in recent years, wavelet transform helping the algorithm to focus on the high frequency information of the image, having great application value in the field of super resolution reconstruction. The literature low resolution image as the low frequency sub band of image with high resolution, then through the high frequency zero padding operation to take the inverse wavelet transform to get the initial estimate of high-resolution image, and finally using the Cycle-spinning technology to take afterprocessing to improve the sawtooth effect of reconstruction image processing edge. The literature proposed DASR algorithm in this paper, the basic idea is to take interpolation processing on the low resolution image and high frequency sub bands, and taking them as every sub band of reconstructing high resolution image. The method has good accuracy, but because the high-frequency part of the image having a direction that will lead the reconstruction image to produce shadow, local being unsmooth and un natural.

2. The Theory of Compressed Sensing

Assuming $x \in R^N$ is the dimensional column vector of N* 1, if x was K- sparse(only having $K(K<<N)$ nonvanishing element) signal, using an observation matrix $\mathbf{\Phi} \in R^{M\times N}$ $(M<<N)$ to measure signal x, getting the observation vector $y \in R^M$:

$$y = \mathbf{\Phi} x \tag{1}$$

We can see that, compressed sensing subdue the signal x from N dimension to the observed signal y with M dimension to achieve the data compression. The actual image signal is not sparse, but through an orthogonal basis or tight frame $\mathbf{\Psi} \in R^{M\times N}$ transform can get the sparse representation of the image,

$$\text{i.e.: } x = \mathbf{\Psi} s \tag{2}$$

In which, $\mathbf{\Psi}$ being sparse signal, s expressing the sparse coefficient of signal in the transform domain $\mathbf{\Psi}$, meeting the K-sparse conditions, through the transform condition we can know $s = \mathbf{\Psi}^T x$, so ,we can amend the formula (1) to:

$$y = \mathbf{\Phi} s = \mathbf{\Phi} \mathbf{I}^T x = \mathbf{A}^x \tag{3}$$

In which, $\mathbf{A}$ known as the measurement matrix, $(\mathbf{A}_{M\times N} = \mathbf{\Phi}_{M\times N} \mathbf{\Psi}_{N\times N}{}^T)$. Because the observation dimension M is far less than the dimension of signal N, so it can't directly solve the signal x from M observations of y. The essence of the CS reconstruction problem is that in the known condition of the low dimensional observation signal y and observation matrix $\mathbf{\Phi}$, how to quickly and accurately reconstruct the original high dimensional signal x according to the optimization algorithm. Candes E J, Romberg J, Tao T proposed the use of solving optimization problems in the norm of l_1 to solve the exact or approximate of x i.e.

$$\min \left\| \mathbf{\Psi}^T x \right\|_1 \text{ s.t. } \mathbf{\Phi}\mathbf{\Psi}^T x = y \tag{4}$$

In here, $\mathbf{\Phi}$ and $\mathbf{\Psi}$ are required to meet the requirements of incoherence, namely that when selected the measurement matrix $\mathbf{\Phi}$ should be orthogonal design as far as possible with $\mathbf{\Psi}$, can achieve the accurate reconstruction of the original signal x. The most commonly used methods of solving of formula (4) are the basis pursuit (BP, Basis, Pursuit), Matching Pursuit tracking method (MP, Matching Pursuit tracking method) and orthogonal matching pursuit (OMP Matching, Orthogonal Pursuit) and so on. In practice, we can firstly solve the sparse coefficient estimation $\hat{s}$ of the signal, then according to the formula (2) to do the inverse transform, getting signal $\hat{x}$ after reconstruction.

Contourlet transform is a multi-resolution, multi direction, localized representation of image. The support interval of Contourlet transform matrix is the strip structure that the ratio of length to width changes with the scale, having directionality and anisotropy, making the Contourlet coefficients expressing the image edge be more concentrated, which is available for using a small coefficient to express the smooth contour of image. Therefore, compared to the wavelet transform, Contourlet transform can be sparser to represent the image.

Continuous Contourlet transform will decompose the square integrable space L2 (R2) into a series of mutually orthogonal subspace with multi-scale and multi direction.

$$L^2(R^2) = V_{j0} \oplus \left(\bigoplus_{j\le \dot{p}} W_j \right) = V_{j0} \oplus \left(\bigoplus_{j\le \dot{p}} \left(\bigoplus_{k=0}^{2^{l_j}-1} W_{j,k}^{(l_j)} \right) \right) \tag{5}$$

3. The Reconstruction of Super Resolution Image Based on Compressive Sensing

How to choose the acquisition of the needed high and low frequency sub bands $\widetilde{LL}$, $\widetilde{LH}$, $\widetilde{HL}$, $\widetilde{HH}$ of reconstructing high resolution image is the focus of this paper. Simple interpolation method can realize the amplification of each sub band image, but due to the high frequency part of the image having directionality, high frequency coefficients estimated by interpolation through the inverse wavelet transform can lead the reconstruction image produce artifacts. In this paper used the algorithm with higher reconstruction precision to compensate for quality loss in reconstruction. Super-resolution reconstruction algorithm based on compressed sensing using the newest theory of the field of compressed sensing to apply the two step iterative shrinkage and total variation of sparse representation to super resolution reconstruction, we can get the reconstructed image with smoother and more natural edge and , more realistic visual image. Applied it in the framework of wavelet transform, we can focus on information of each high frequency sub-band and take separate algorithm parameters and threshold setting, realizing further optimization of the reconstruction of the edge information.

3.1. The Vasic Principles

Assuming discrete one-dimensional real signal $x \in R^m$, taking sparse transform $x = \Psi\tilde{x}$, in which, Ψ expressing matrix of transformation base, $\tilde{x}$ being the equivalent representation of $\mathbf{x}$ in sparse domain. Then taking the random projection on it $y = Ax$, $y \in \mathbb{R}^n$, $n = m$, in which, $\mathbf{A} \in \mathbb{R}^{n\times m}$ representing the random projection matrix, $\mathbf{A}$ and Ψ need to meet the independence of each other. On the surface, the problem is underdetermined, existing multiple solutions. But the theory of compressed sensing using the prior knowledge of original signal can be sparse represented in transform domain to obtain optimal solution.

Seeing the x of here as high resolution image to be reconstructed of super-resolution problems, $\mathbf{y}$ as the low resolution input image, then we can use the existing algorithms of compressed sensing to solve the problem of super resolution. The medium distance sampling matrix $\mathbf{A}$ of super resolution problem has high correlation with transformation matrix Ψ, so before sampling we should add a low pass filter $\mathbf{G}$ to reduce the correlation between them. Namely:

$$y = AG\Psi\tilde{x} \tag{6}$$

The so-called super resolution reconstruction of compressed sensing is to obtain the sparsest representation of signal when meet the observation conditions, namely:

$$\min_{\tilde{x}} \|\tilde{x}\|_0 \; s.t. \quad y = AG\Psi\tilde{x} \tag{7}$$

But the optimization problem (2) is a NP-hard problem, so we usually transform it into the optimization problem of equivalent ℓ_1:

$$\min \|\tilde{x}\|_1 \; s.t. \quad y = AG\Psi\tilde{x} \tag{8}$$

Assuming the objective function $f(x)$ in the process of solving:

$$f(x) = \frac{1}{2}\left\|y - AG\Psi\tilde{x}\right\|^2 + \lambda\Phi(x) \tag{9}$$

In (9) formula the first term represents the fidelity of the observing data, the second $\Phi(x)$ being regular function.

3.2 The Total Variation Regularization Method

The regular function of formula (9) usually chooses ℓ_p or total variation function. This paper selects the total variation regularization to maintain the contrast and sharpness of the boundary, the effect of the reconstruction of the edge is smoother and more natural:

$$\Phi_{TV}(x) = \sum_i \sqrt{\left(\Delta_i^h x\right)^2 + \left(\Delta_i^v x\right)^2} \tag{10}$$

In which, Δ_i^h and Δ_1^v respectively express first difference operator of the horizontal and vertical directions of two-dimensional plane.

3.3 The Two Iterative Shrinkage Algorithm

Two step iterative shrinkage was first applied in the field of blur image restoration. For linear system $y = Hx + \upsilon$, in which υ expresses Gauss noise, $\mathbf{H}$ expressing blurring operator. We can see that the above formula has a certain equivalence property with formula(10), so using TwIST algorithm to realize image restoration and super-resolution reconstruction of the compressed sensing is feasible. The core of the algorithm is to use the first estimated value to update the current value, the literature giving the update process of the algorithm:

$$x_1 = \Gamma_\lambda(x_0) \tag{11}$$

$$x_t = (1-\alpha)\cdot x_{t\text{-}2} + (\alpha-\beta)\cdot x_{t\text{-}1} + \beta\cdot\Gamma_\lambda(x_{t\text{-}1}) \tag{12}$$

In the above formula, $t \geq 2$, $\mathbf{x_0}$ represents the initial value, parameter α and β are convergence rate to decide algorithm. $\Gamma_\lambda(x)$ is the noise reduction function, being the new estimated value obtained by taking threshold processing on the transform coefficients of estimated value, and then taking inverse transform:

$$\Gamma_\lambda(x_t) = \Psi_\lambda\left(x_t + H^T(y - Hx_t)\right) \tag{13}$$

Ψ_λ expresses the noise reduction operator, this paper using TV regularization method to com-

plete the calculation of denoising operator. Let $g = x_t + H^T(y - Hx_t)$, so $\Psi_\lambda(g)$ can be expressed as:

$$\hat{u} = \arg\min\left(\frac{\|u-g\|_2^2}{2\lambda} + \sum_{1\le i,j\le n}(\nabla u)_{i,j}\right) \quad (14)$$

3.4 The Procedure of Algorithm

Setting the termination conditions of iterated algorithm as:

$$C(x_t, x_{t\text{-}1}) = \frac{|f(x_t) - f(x_{t\text{-}1})|}{f(x_{t\text{-}1})} \quad (15)$$

When $C(x_t, x_{t\text{-}1}) < \varepsilon$, iteration is over, in which ε is the setting stop value. Data initialization: $x_0 = 0$, iterations $t = 1$, setting the stop value ε:

according to the formula (4) to calculate the objective function value $f(x_0)$;

taking noise reduction processing on $\mathbf{x_0}$:

$$x_1 = \Gamma_\lambda(x_0) = \Psi_\lambda\left(x_0 + \frac{H^T(y - Hx_0)}{s}\right) \quad (16)$$

In which, s representing step length, the initial value is set to 1: calculating the corresponding objective function $f(\mathbf{x_1})$, comparing the size of $f(\mathbf{x_1})$ and $f(\mathbf{x_0})$, if $f(\mathbf{x_1}) > f(\mathbf{x_0})$, after s multiplied by 2 repeating step 3; otherwise continue, $t = t + 1$;

On the basis of calculating the first two estimated value, using formula (7) to estimate the new $\mathbf{x_t}$, calculating $f(\mathbf{x_t})$ and comparing the size of it with the size of $f(\mathbf{x_{t\text{-}1}})$, if $f(\mathbf{x_t}) > f(\mathbf{x_{t\text{-}1}})$, $\mathbf{x_0} = \mathbf{x_{t\text{-}1}}$, returning to step (3), otherwise continue;

According to equation (10) to determine whether the termination condition is satisfied, if $C(\mathbf{x_t}, \mathbf{x_{t\text{-}1}}) > \varepsilon$ so $t = t + 1$, returning to step (4) to continue iteration, otherwise stopping the iteration.

4. Experimental Results

Algorithm using wavelet transform to decompose the input image, using super resolution algorithm based on compressed sensing to improve the resolution on the high frequency sub-band, the input image itself is largely preserved, directly being as the low frequency sub bands of the inverse wavelet transform. We use the MATLAB to test the algorithm and other compared algorithms proposed by this paper, evaluating the algorithm through comparing the visual effect of image reconstruction and the reconstruction error evaluation index of every algorithm.

4.1. The Test and Comparison of Effect of Reconstruction Algorithm

Experiment 1 Select the size of 512pixel*512 pixel gray image Childface as the original high-resolution image, selecting the CDF97 as the tool of decomposition of the image of wavelet, after two consecutive times wavelet decomposition getting the size of 128 pixel *128 pixel the input image (low frequency sub bands), comparing the 4 times reconstruction effect of the following methods:

The classical interpolation methods: spatial domain bilinear interpolation.

DASR method: DASR method using traditional bilinear interpolation method to get each sub band image of reconstructed high resolution image.

Using the WZP algorithm to obtain the initial estimation of reconstructed image, then make use of Cycle-spinning to take after treatment, in the experiment, moving 2 units of all directions of images.

TwIST algorithm: TwIST algorithm can be directly applied to super resolution reconstruction of space domain.

Every algorithm uses unified CDF97 wavelet to test the condition that the parameters and the threshold meet the optimal reconstruction effect. The quality of image reconstruction measured by using the peak signal to noise ratio (PSNR) and structural similarity (SSIM) index. Among them, PSNR is the most common, the most widely used objective method to evaluate image quality; SSIM is a measure that based on structural information to measure the image quality, it can be better to reflect the human visual characteristics, the bigger the SSIM value, representing the better the quality of reconstruction, the biggest value is 1. Fig. 1 shows the image reconstruction effect, local amplification effect and reconstruction of PSNR and SSIM of five algorithms to compare.

As can be seen from Fig. 1, in the subjective visual effect of reconstruction, the method of this paper is better than other methods obviously: the color of the reconstructed image by the bilinear interpolation method is nonuniform and having particles, the details of the reconstructed image on the edge and irregular structure region being vague, the sawtooth effect being obvious; DASR algorithm to enlarge the high-frequency sub band images by interpolation, and the high-frequency part of the image having a direction, causing reconstructed image produces artifacts, local being not smooth and unnatural; although the WZP-CS method has higher reconstruction accuracy, the edge of reconstructed image is fuzzy; the effect of reconstruction of TWIST algorithm is better than the former methods but the reconstructed image with little cartoon effect; the method of this paper, the boundary is smooth and natural, transition being uniform, awtooth effect basically eliminated, edge

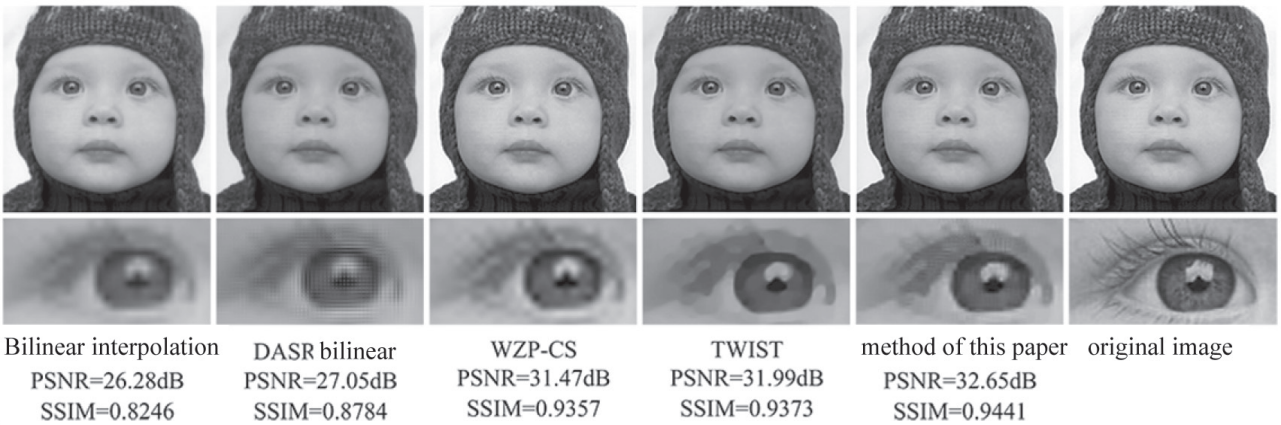

Figure 1. The comparison of 4 times super resolution reconstruction effect chart and the PSNR and SSIM between the method of this paper and other methods

visual effect being improved significantly. From the texture of hat and eyes to see the effect of reconstruction, the method of this paper has better accuracy, being more close to the original image in the visual HR. From the evaluation index, the method of this paper reconstructing PSNR and SSIM is higher than other methods.

4.2. Comparison of DASR Algorithm and the Method of this Paper

Experiment 2 we test the 512pixl*512pixl gray image Baboon, Elaine, Pirate and text image, using the uniform CDF97 wavelet to take 4 times sampling to get low resolution image, and then reconstruct the original image by using DASR algorithm and the method of this paper, the selection and use of parameters being similar to the above algorithm. The visual effect of reconstruction of the method of the paper is more close to the original picture, especially having a very excellent performance on the reconstruction of edge texture and image detail. Such as Baboon image, the detail of bear is clear; the figure Elaine can show more detailed local reconstruction effect of eyes; the edge, hair and feathers of pirate graph is more exquisite and lifelike; the reconstruction effect of the edge of font is smooth, eliminating the aliasing effect. We can see from Table 1 and Table 2 that the comparison of the method with the DASR algorithm the evaluation index PSNR and SSIM of reconstruction error also reflected the superiority.

Table 1. The comparison of 4 times reconstruction PSNR of the DASR algorithm and the method of this paper (dB)

	Baboon	Elaine	Pirate	word
DASR	19.21	26.93	22.44	15.91
the method of this paper	20.65	31.43	26.20	22.86

Table 2. The comparison of 4 times reconstruction SSIM of the DASR algorithm and the method of this paper (dB)

	Baboon	Elaine	Pirate	character
DASR	0.6003	0.8919	0.7722	0.8544
the method of this paper	0.7305	0.9421	0.8857	0.9805

4.3. Comparison of the Quality of Reconstruction of Several Methods and the Method of this Paper

Experiment 3 In order to compare reconstruction quality of the method, using a variety of single frame image super-resolution method to take 4 times experiments on multiple image, the PSNR of reconstructed image being listed in Table 3.

Table 3. Comparison of 4 times reconstructed PSNR of several algorithms (dB)

	Lena	Elaine	Peppers	Barbara
The nearest neighbor interpolation	21.43	23.84	20.59	18.84
Bilinear interpolation	23.19	25.58	22.18	20.30
bicubic interpolation	22.77	25.19	21.83	19.77
WZP_CS(CDF97)	28.21	30.36	27.75	22.86
DASR(Haar)	23.20	24.76	21.78	20.36
DASR(CDF97)	24.25	26.93	24.11	21.56
TwIST	28.63	30.84	28.78	22.86
Haar+TwIST	28.60	31.20	29.62	23.24
Method of this paper	28.94	31.43	29.80	23.32

The first three methods of Table 3 and Table 4 are respectively the traditional interpolation methods, brackets expressing the selected wavelet, TwIST saying the two iterative shrinkage algorithm of spatial domain, Haar+TwIST method and the method of this paper having the same design ideas, the difference is

that it used the Haar wavelet to decompose the image, through analysis we can draw the following conclusions:

Table 4. Comparison of 4 times reconstructed SSIM of several algorithms

	Lena	Elaine	Peppers	Barbara
The nearest neighbor interpolation	0.7089	0.7013	0.7439	0.6021
Bilinear interpolation	0.7841	0.8232	0.8264	0.6794
bicubic interpolation	0.7728	0.7985	0.8111	0.6610
WZP_CS(CDF97)	0.9285	0.9402	0.9460	0.8217
DASR(Haar)	0.8012	0.8288	0.8365	0.6935
DASR(CDF97)	0.8525	0.8919	0.8896	0.7598
TwIST	0.9256	0.9372	0.9503	0.8201
Haar+TwIST	0.9266	0.9391	0.9525	0.8289
Method of this paper	0.9307	0.9421	0.9535	0.8307

Compared with other methods, this method has higher PSNR and SSIM on the 4 times reconstructed image, the reconstruction error being less. Just as Lena, compared with DASR (CDF97) method, PSNR of this method tower above 4.69dB, SSIM tower above 0.0782.

On the aspect of choosing the wavelet, using CDF97 wavelet is always having higher PSNR and SSIM than Haar wavelet, showing that CDF97 has better performance in the wavelet super resolution method. Just as Lena, compared with Haar wavelet, PSNR of the CDF97 wavelet of the method of this paper used town above 0.34dB, the SSIM tower above 0.0041.

This method compared with the spatial domain, it's directly using TwIST combined with total variation regularization method has better reconstruction effect. Just as Lena, compared with TwIST reconstruction algorithm, the PSNR of the method of this paper tower above 0.31dB, the SSIM tower above 0.0051, indicates that the introduction of wavelet do indeed help to restore the high frequency information of image.

Conclusion

This paper proposed a new image super resolution reconstruction method, using the CDF97 wavelet to separate the low frequency sub bands and high frequency sub bands of inputting low resolution image, and then using the image reconstruction method based on two iterative shrinkage algorithm and the total variation sparse representation to enlarge the low resolution image and the high frequency sub-band image respectively, getting the reconstructed image by inverse wavelet transform. Simulation results show that this method not only has better visual effect, reconstructed image evaluation index of PSNR and SSIM having physical advantages, it can be better to reconstruct the original image detail and edge information.

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