IGARSS 2021 - 2021 IEEE International Geoscience and Remote Sensing Symposium | 978-1-6654-0369-6/21/$31.00 ©2021 IEEE | DOI: 10.1109/IGARSS47720.2021.9553830

AN IMPROVED HYPERSPECTRAL IMAGE SUPER RESOLUTION RESTORATION ALGORITHM BASED ON POCS

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ABSTRACT

Super-resolution reconstruction is a rapidly growing research area in hyperspectral data processing. However, there exist some problems, such as edge blur, burr in the smooth area, subjective design of iteration times, et al. This paper analyzes the causes of blur and burr, and puts forward some countermeasures according to these problems. Firstly, gradient interpolation is used instead of the traditional nearest neighbor interpolation, which alleviates the edge blur to a certain extent problem, the projection operator calculated from the gradient map is introduced into the projection formula to solve the burr phenomenon in the smooth area. Then, the mean square error of the reconstructed image of adjacent iterations is used to measure the similarity of the reconstructed image between two adjacent iterations, which is used as the stopping criterion of iterations, avoiding the subjectivity of setting the iteration times artificially. Finally, the proposed algorithm is applied to every band of hyperspectral image. Experimental results show that the proposed algorithm has better performance than the traditional POCS algorithm in visual effect and quantitative criteria.

Index Terms— POCS, super resolution reconstruction, gradient interpolation, relaxation operator, adaptive iteration

1. INTRODUCTION

Compared with the traditional image, the spectral resolution of hyperspectral image (HSI) is high, while the spatial resolution is low, which limits its application. Therefore, it is necessary to use super-resolution reconstruction algorithm to improve the spatial resolution of HSI.

At present, the mainstream of hyperspectral super-resolution reconstruction is to process high resolution reconstruction directly in the spatial domain (band by band), in which projection onto convex sets (POCS) algorithm has been widely applied. POCS method was first proposed by Stark and Oskoui in 1989 [1], and has made good achievements in the field of super-resolution reconstruction in traditional optical imagery. Many scholars made improvement based on this algorithm. X. Xiao used gradient interpolation instead of traditional interpolation, which optimized the initial value of POCS and improved the edge quality of the reconstructed image [2]. H. Li adjusted the image point diffusion Point Spread Function (PSF), and applied different improved PSF to the horizontal and vertical edge pixels to improve the edge blur effect of the image. J. Chen proposed a new method to optimize the BM3D filtering by mean pre-screening of image blocks and limiting the number of image blocks, and then combined the optimized BM3D filtering with POCS restoration to enhance the anti-noise ability of the image edge [4]. An improved POCS based reconstruction algorithm is presented in [5], where local gradient consistency constraint is adopted to reduce the estimation error of traditional results computed with gray value consistency.

In this paper, an improved POCS algorithm is proposed to solve the problems of blurred edge, burr in smooth area and avoid subjective iterations in the traditional POCS reconstruction method. It is then applied to hyperspectral remote sensing image. The simulation experiments are carried out on the open hyperspectral data set. Finally, the mean square error (MSE), peak signal-to-noise ratio (PSNR) and structure similarity (SSIM) are used to compare the proposed algorithm with traditional POCS algorithm, and it is proved that the proposed algorithm can achieve better reconstruction effect.

2. ALGORITHM PROPOSED

2.1. POCS algorithm principle

POCS super-resolution reconstruction algorithm mainly uses multiple prior information of the image, each prior information constitutes a closed convex set, and the intersection of each closed convex set is the solution space of POCS super-resolution reconstruction.

For m priori knowledge, there will be m corresponding closed convex sets $C_i, i = 1, 2, \cdots m$ and $f \in C_0 = \cap_{i=1}^{m} C_i P_i . C_0$ is a nonempty closed convex set. For a given constraint set C_i, The corresponding projection operator is P_i. Then the iterative sequence can be expressed as follows:

$$f_{k+1} = T_m T_{m-1} \cdots T_1 f_k k = 1,2 \cdots\cdots \quad (1)$$

where $T_i = (1-\lambda_i) I + \lambda_i P_j, 0 < \lambda_i < 2$ is a relaxed projection operator, When the intersection C_0 of the constraint set converges weakly, it can be solved. Any element in intersection C_0 satisfies all prior knowledge or constraints, that is, it is a feasible solution of the problem, so the feasible solution obtained by POCS method is not unique.

In POCS super-resolution reconstruction, an image acquisition model of the original high-resolution image and the low-resolution observation sequence should be established. The low-resolution image can be regarded as the degradation of the original high-resolution image. The first convex set constraint is the support domain boundedness constraint:

$$C_S = \{ f : f(i_1, i_2) = 0, (i_1, i_2) \notin A \} \quad (2)$$

POCS is a super-resolution reconstruction method of sequence images. Firstly, one image is randomly selected from the sequence of low-resolution images, and then the remaining low-resolution images are used to guide its correction. Here is the second convex set constraint, that is, the data consistency constraint:

$$C_l = \{ f : f_1 \cap f_2 \cap f_3 \cap \cdots \} \quad (3)$$

In the actual imaging process, it is inevitable to be interfered by noise, so the influence of noise is introduced to connect the statistical characteristics of noise with prior boundary δ_0, In each iteration, the absolute value of the residuals should be limited to the preset boundary δ_0. Suppose the additive noise is Gaussian distribution and its variance is σ_v, then δ_0 should be equal to $c\sigma_v (c \geq 0)$. The third constraint is noise constraint:

$$C_{m_1 m_2} = \{ f(i_1, i_2) : r^{(y)}(m_1, m_2) \leq c\sigma_v \} \quad (4)$$

In addition, prior constraints such as amplitude can be used to improve the reconstruction results. The fourth constraint is the amplitude limit, which can be expressed as:

$$C_A = \{ f(i_1, i_2) : 0 \leq f(i_1, i_2) \leq 255 \} \quad (5)$$

All kinds of prior knowledge can be defined as restricted sets in a similar way. By adding these restricted sets to the iteration operation of equation (1), the reconstructed image can meet the requirements of prior knowledge.

2.2. Improved POCS

It is the first step of POCS algorithm to construct the initial high-resolution reference frame with interpolation method. Constructing the initial high-resolution reference frame is to use the existing low resolution image to obtain an initial estimation with the same resolution of the target high-resolution image by interpolation method. The higher the quality of the initial frame, the better the effect of the final reconstructed image. In the traditional POCS algorithm, the construction of the initial reference frame is generally based on the nearest neighbor interpolation method. This interpolation method has simple calculation principle, but the edge will appear sawtooth phenomenon, and the interpolation effect is poor. Therefore, in the improved POCS method, gradient interpolation is used to replace the nearest neighbor interpolation method.

Hypothesis $a_{11}, a_{12}, a_{21}, a_{22}$ corresponds to four adjacent pixels on the low resolution image respectively. $b_{ij} (0 \leq i \leq 4, 0 \leq j \leq 4)$ represents the pixel block corresponding to the interpolated high-resolution image. Firstly, the points on the original image are mapped to the points of the enlarged image $b_{11} = a_{11}, b_{13} = a_{12}, b_{31} = a_{21}, b_{32} = a_{22}$. Then, the values of the right, the lower right and the lower three adjacent pixels of the corresponding pixels on the enlarged image are calculated. First, b_{12} and b_{21} interpolation calculation, because the interpolation time also needs to find the absolute value of the gradient between a_{11} and a_{12}, a_{11} and a_{12}. In order to keep the edge of the image after interpolation, the interpolation should be close to the place with small gray value. In the horizontal interpolation, the gradient information in the horizontal direction is mainly used, while in the vertical interpolation, the gradient information in the vertical direction is mainly used. The method of interpolation in the region with small gray value close to the pixel is used. For the value of pixel b_{22}, the gradient in the diagonal direction of the low resolution image is used for similar calculation. The gradient based interpolation algorithm analyzes the characteristics of gray value change in the edge pixel region, and uses the gradient information of adjacent pixels to minimize the influence of interpolation points on the change rate of image edge gray value, making the image edge more obvious.

Before super-resolution reconstruction of image sequence, motion parameters must be estimated. The motion estimation of image sequence refers to solving the displacement difference of the same object between two images. There are many methods. This paper adopts the method based on block matching. In this method, each frame of the current low resolution image sequence is divided into several blocks. In the search window of the target high-resolution reference frame, the image block with the best matching result is searched. The minimum mean square error criterion is used in the matching. It is the most commonly used matching criterion with intuitive definition and relatively simple calculation.

When the camera is imaging, the image always degenerates, which is caused by the PSF of the imaging system. In the implementation of POCS algorithm, each pixel of the low resolution image is mapped to the high resolution imaging grid one by one, and the scope of PSF is found out. Then, the estimated value of the current pixel corresponding to the low resolution image is calculated by using PSF and image degradation model, and the residual is made with the actual value of the low resolution image, and the reference frame is corrected according to the residual.

In the implementation of POCS algorithm, the image PSF is determined by the specific imaging system, $h(x,y)$ represents the common Gaussian model, which can be expressed as:

$$h(x,y)=e^{-\frac{(x-x_0)^2+(y-y_0)^2}{2}},(x,y)\in S_h \tag{6}$$

Where x_0 and y_0 represents the center point coordinates of the point spread function, x and y represent the abscissa and ordinate of the target image pixel, S_h is the support region of the point spread function. The size of the support region is generally 3 × 3 or 5 × 5.

Image gradient is a common image information measurement method, which represents the difference between the current pixel and the surrounding pixels. The larger the gradient is, the greater the difference between the current pixel and the surrounding pixels is; on the contrary, the smaller the difference is.

Gaussian gradient map is introduced to measure the importance of pixels. If the size of the original image $F=\left[f\left(m_1,m_2\right)\right]_{M_1\times M_2}$ is $M_1\times M_2$, the weighted gradient of the image can be defined according to the neighborhood distribution of the current pixel, as shown in equation (7).

$$g=\frac{g_1+g_2+g_3+g_4}{4} \tag{7}$$

Where: g_1,g_2,g_3,g_4 are shown in formula (8), formula (9), formula (10) and formula (11), respectively.

$$g_1=\left\|\begin{matrix}f\left(m_1,m_2-1\right)-f\left(m_1,m_2+1\right)+\\ \frac{1}{2}\left[f\left(m_1,m_2-2\right)-f\left(m_1,m_2+2\right)\right]\end{matrix}\right\| \tag{8}$$

$$g_2=\left\|\begin{matrix}f\left(m_1-1,m_2\right)-f\left(m_1+1,m_2\right)+\\ \frac{1}{2}\left[f\left(m_1-2,m_2\right)-f\left(m_1+2,m_2\right)\right]\end{matrix}\right\| \tag{9}$$

$$g_3=\left\|\begin{matrix}f\left(m_1-1,m_2-1\right)-f\left(m_1+1,m_2+1\right)+\\ \frac{1}{2}\left[f\left(m_1-2,m_2-2\right)-f\left(m_1+2,m_2+2\right)\right]\end{matrix}\right\| \tag{10}$$

$$g_4=\left\|\begin{matrix}f\left(m_1-1,m_2+1\right)-f\left(m_1+1,m_2-1\right)+\\ \frac{1}{2}\left[f\left(m_1-2,m_2+2\right)-f\left(m_1+2,m_2-2\right)\right]\end{matrix}\right\| \tag{11}$$

Where: g_1,g_2,g_3,g_4 is the weighted gradient value of the current pixel in each direction. The weighted gradient value is used to reduce the influence of noise. At the same time, the distance gradient takes a smaller weight, and also adds the idea of local mean.

After getting the gradient map, a Gaussian filter is used to filter out the noise, and the remaining points with larger gradient can be determined to be pixels near the edge. The traditional POCS method corrects the initial reference frame indifferently, and does not distinguish the smooth area and the edge area in the image. The gray value change of the smooth area is smaller than that of the edge area, but the correction degree of the smooth area is the same as that of the edge area, so the reconstructed image will appear burr in the smooth area.

Gaussian gradient graph can represent the different amount of information contained in the neighborhood of a pixel. Near the strong edge, the gradient value is large, and near the weak edge, the gradient value is small. The relaxation operator used to define the method also has this property. The relaxation operator is shown in equation (12).

$$\lambda\left(m_1,m_2\right)=\ln\left(\frac{g\left(m_1,m_2\right)}{\max(g)+\epsilon}+1\right) \tag{12}$$

Where: $\max(g)$ is the maximum value of the gradient graph, ε is a positive integer, avoiding the denominator to be zero.

If the relaxation operator is added to the projection formula, the projection formula will become as shown in equation (13).

According to equation (13), the image can be modified adaptively according to the change characteristics of the gray level of the image. In the smooth area, the degree of each correction is small, and the burr is suppressed; in the edge area, the degree of each correction is large, and the convergence speed is accelerated.

POCS super-resolution reconstruction is a process of repeated iteration and correction. If the number of iterations is too small, the degree of correction is not enough and the effect is not good; if the number of iterations is too large, the time cost is too large, and even the result may deteriorate. Therefore, how to select an appropriate number of iterations becomes an urgent problem for POCS. Traditional POCS method is to artificially set an iteration number, which is too subjective to make the algorithm achieve approximate results on different data sets. To solve this problem, this paper proposes an adaptive iteration number algorithm, which takes the mean square error of two adjacent iterations as the judgment criterion. When the mean square error is lower than a certain threshold, it is considered that the two adjacent iterations are the best The results are approximate enough, the algorithm converges and exits the iteration.

Finally, the improved POCS algorithm is used to complete the super-resolution reconstruction of each band gray image of hyperspectral image.

$$P_{m_1,m_2}\left[x(i_1,i_2)\right] = x(i_1,i_2) + \begin{cases} \lambda(m_1,m_2)\dfrac{\left[r^{(y)}(m_1,m_2)-\delta_0\right]}{\sum\limits_{x_1}\sum\limits_{x_2} h_k^2(m_1,m_2;x_1y_1)} h(m_1,m_2;i_1,i_2) & r^{(y)}(m_1,m_2)>\delta_0 \\ 0 & \left|r^{(y)}(m_1,m_2)\right|<\delta_0 \\ \lambda(m_1,m_2)\dfrac{\left[r^{(y)}(m_1,m_2)+\delta_0\right]}{\sum\limits_{x_1}\sum\limits_{x_2} h_k^2(m_1,m_2;x_1y_1)} h(m_1,m_2;i_1,i_2) & r^{(y)}(m_1,m_2)<-\delta_0 \end{cases} \tag{13}$$

3. EXPERIMENTAL RESULTS

3.1. Dataset: Pavia scene

The hyperspectral data set of Pavia University was acquired by ROSIS sensor in the University of Pavia in northern Italy in 2001, shown in Fig.1. The spectral range is 0.43 ~ 0.86 μm, the spatial resolution is 1.3 m, and the image size is 610 * 340. After removing 12 noisy bands, there are 103 bands left.

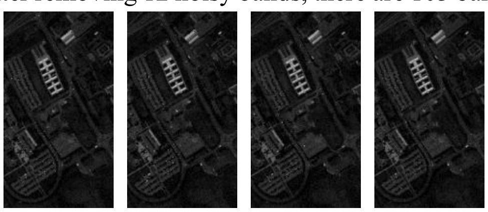

Fig. 1. Sequence of Low resolution images of PaviaU data set

In order to prove that the improved POCS algorithm is better than the traditional POCS algorithm, the simulation results of the improved algorithm and the traditional algorithm are compared. The comparison criteria were MSE, PSNR and SSIM shown in Table 1, supplemented by visual effects in Fig.2. The best result is with the lower MSE, the higher PSNR and the higher SSIM. Obviously, these results favor our approach much.

(a) POCS (b) IPOCS

Fig. 2. Super resolution results by POCS and IPOCS

Table 1. Quantitative comparison by three criteria

Algorithm	MSE	PSNR	SSIM
POCS	138.4454	26.7180	0.9051
IPOCS	**95.0828**	**28.3498**	**0.9471**

From the simulation results, we can see that the edge of the image reconstructed by the improved POCS method is sharper, and the burr in the smooth area is also suppressed; in terms of digital evaluation criteria, compared with the traditional POCS method, the improved POCS has lower MSE, higher PSNR and higher SSIM, and the three evaluation criteria are optimized.

4. CONCLUSION

In this paper, according to the defects of the traditional POCS super-resolution reconstruction algorithm, the corresponding improvement methods are proposed, which are: using gradient interpolation to replace the nearest interpolation to sharpen the edge of the image; adding the relaxation operator calculated according to the gradient image in the projection formula to modify the image adaptively to suppress the burr in the smooth area; using two adjacent iterations to reconstruct the image The square error is used as the criterion to adaptively adjust the number of iterations, which avoids the subjectivity of artificially setting the number of iterations. Finally, the simulation results show that the improved POCS algorithm is better than the traditional POCS algorithm.

5. ACKNOWLEDGEMENTS

This work is supported by the National Nature Science Foundation of China (61801075), China Postdoctoral Science Foundation (2020M670723, 2020M680925), Open Research Funds of State Key Laboratory of Integrated Services Networks, Xidian University (ISN20-15) and the Fundamental Research Funds for the Central Universities (3132019341).

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