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An improved POCS super-resolution infrared image reconstruction algorithm based on visual mechanism

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ABSTRACT

The traditional projection onto convex sets (POCS) super-resolution (SR) reconstruction algorithm can only get reconstructed images with poor contrast, low signal-to-noise ratio and blurring edges. In order to solve the above disadvantages, an improved POCS SR infrared image reconstruction algorithm based on visual mechanism is proposed, which introduces data consistency constraint with variable correction thresholds to highlight the target edges and filter out background noises; further, the algorithm introduces contrast constraint considering the resolving ability of human eyes into the traditional algorithm, enhancing the contrast of the image reconstructed adaptively. The experimental results show that the improved POCS algorithm can acquire high quality infrared images whose contrast, average gradient and peak signal to noise ratio are improved many times compared with traditional algorithm.

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1. Introduction

For the advantages like strong adaptability to environment, long detection distance and good invisibility property, infrared imaging technology is widely applied to military and civil fields. The current fabrication technique of infrared focal-plane arrays is limited, while the low density of detector units is still lower than that of visible-light image sensor, resulting in the low resolution of infrared images. However, the SR reconstruction algorithm can restore the original scene image from multiple frames of low-resolution (LR) image, which effectively improves the spatial resolution of infrared images. Therefore, the research on SR infrared image reconstruction is of great significance.

SR image reconstruction refers to a signal processing method that uses the complementary information of LR images from the same scene to remove the degradation factors and restore a high-resolution (HR) image. The researches of SR image reconstruction have experienced three stages: frequency reconstruction method, spatial reconstruction method, and learning method.

In the 1980s, Tsai and Huang [1] proposed the frequency approximation method which relies on Fourier transform and Fourier inversion to reconstruct the high frequency information and image detail information by eliminating the spectrum aliasing. Though the frequency-based reconstruction method is easy on the theory and practice, it only considers the influence of movements

without other factors like noises, thus the development and application of this method is limited greatly.

Spatial reconstruction methods are represented by Iterative Back-projection (IBP) algorithm, Bayes algorithm and POCS algorithm. In 1991, Irani and Peleg [2] obtained the required HR image by use of the residuals between the estimated LR images and the real LR images, which is called IBP algorithm. In the mid-1970s, Richardson and Lucy introduced Bayes analysis method into the field of image reconstruction, opening the door for Maximum Likelihood (ML) algorithm and Maximum A Posteriori (MAP) algorithm, making Total Variation (TV) regularization and Bilateral Total Variation (BTV) regularization become possible [3]. In 1989, Stark and Oskoui [4] proposed POCS algorithm and applied it to multi-frame image SR reconstruction, improving the image resolution effectively.

Since the 21st century, SR image reconstruction algorithms based on learning method have become hot research area. In 2002, Freeman [5] proposed a reconstruction algorithm based on examples, which establishes the connection between the HR image blocks and LR ones through the Markov Network. In 2006, Donoho [6] put forward the concept of sparse representation, providing a new way of signal representation. On this basis, Yang [7] introduced an image restoration algorithm based on sparse representation. Although learning-based method can achieve better image visual effect, the large amount of calculation limits its application.

After analyzing all of the above algorithms, we find that POCS algorithm is superior in many respects, including calculation amount, real-time property and effectiveness. Especially that, as

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an important signal reconstruction method, the POCS reconstruction method can use a large amount of prior information, becoming one of the most popular methods in signal processing field. In this paper, the improved SR infrared image reconstruction algorithm is based on POCS reconstruction method. It is a kind of set theory method, and the constraint conditions, such as positive definiteness, boundedness of energy and smoothness, are defined as corresponding convex sets, and the intersection of these convex sets can be considered as the required solution space.

In recent years, various improvements based on traditional POCS algorithm have been proposed and widely used. In 2005, Liu [8] proposed a SR image reconstruction of POCS with edge preserving. In the same year, Wang [9] introduced an SR reconstruction algorithm combining POCS and Curvelet to reconstruct 3D digital cores. However, the existing POCS reconstruction algorithms still have the following two shortcomings: ① the correction threshold of data consistency constraint is constant, ignoring the differences between objects and background noises, resulting in blurring edges and low signal-to-noise ratios of obtained images; and ② the small number of used constraints limits the reconstruction results seriously, and adding new constraint convex sets is the key to improve the quality of the image. Further, as the evaluation organ of image quality is human visual system, new algorithms must consider visual mechanism.

2. Traditional POCS SR algorithm

POCS algorithm is an iterative process from one point in the imaging space to the points satisfying all the constraint convex sets. If we define the convex sets as projection operators $\mathbf{P}_1, \mathbf{P}_2, \dots, \mathbf{P}_{m-1}, \mathbf{P}_m$, HR image can be obtained according to formula (1).

$$\hat{z}^{n+1} = \mathbf{P}_m \mathbf{P}_{m-1} \dots \mathbf{P}_2 \mathbf{P}_1 \hat{z}^n \quad (1)$$

where $\hat{z}^{n+1}$ is the HR image from the $(n+1)$ th iterative computation, and $\hat{z}^n$ is the HR image from the n th iterative computation.

As the most important constraint, data consistency constraint describes the relationship between LR images and HR image, shown in formula (2).

$$\mathbf{g}_k = H_k \mathbf{z} + \mathbf{n}_k \quad (2)$$

where $\mathbf{g}_k$ is the k th LR image; H_k is the point spread function (PSF); $\mathbf{z}$ is the required HR image; $\mathbf{n}_k$ is the additive noise.

The corresponding convex set about data consistency constraint is as follow:

$$C(m_1, m_2) = \{\hat{z}^k(i_1, i_2) : |r_k(m_1, m_2)| \leq \delta\} \quad (3)$$

where $\hat{z}^k(i_1, i_2)$ represents the estimated HR image; $r_k(m_1, m_2)$ represents the residual error between $\hat{z}^k(i_1, i_2)$ and the required HR image, shown in formula (4).

$$r_k(m_1, m_2) = \mathbf{g}_k(m_1, m_2) - \sum_{i_1=0}^{M_1-1} \sum_{i_2=0}^{M_2-1} \hat{z}^k(i_1, i_2) H_k(m_1, m_2; i_1, i_2) \quad (4)$$

$$\delta = c\sigma (c > 0) \quad (5)$$

In formula (5), δ is the allowable maximal error, called the correction threshold of data consistency constraint, which is in direct proportion to σ (the variance of the noise).

The PSF $H_k(m_1, m_2; i_1, i_2)$ links a certain pixel point in a LR image with the points in a certain area of the HR image, and the size of the area is $M_1 \times M_2$. In Eqs. (3) and (4), (m_1, m_2) represents the position of the current LR pixel point; (i_1, i_2) is the corresponding position of the related HR point, which need traverse all the points in the $M_1 \times M_2$ block.

Then the projection operator describing data consistency constraint can be shown as follow:

$$\mathbf{P}[\hat{z}^k(i_1, i_2)] = \hat{z}^k(i_1, i_2) + \begin{cases} \frac{|r_k(m_1, m_2) - \delta| H_k(m_1, m_2; i_1, i_2)}{\sum_{x_1} \sum_{x_2} H_k^2(m_1, m_2; x_1, x_2)}, & \text{if } r_k(m_1, m_2) > \delta \\ 0, & \text{if } |r_k(m_1, m_2)| \leq \delta \\ \frac{|r_k(m_1, m_2) + \delta| H_k(m_1, m_2; i_1, i_2)}{\sum_{x_1} \sum_{x_2} H_k^2(m_1, m_2; x_1, x_2)}, & \text{if } r_k(m_1, m_2) < -\delta \end{cases} \quad (6)$$

Afterwards scholars have introduced some other constraints [10,11], such as boundedness of energy, amplitude, and phase. One of the most common ones is amplitude constraint, defined in formula (7).

$$C_A = \{\hat{z}^k(i_1, i_2) : B_1 \leq \hat{z}^k(i_1, i_2) \leq B_2\} \quad (7)$$

For 8-bit grayscale images, $B_1 = 0$, and $B_2 = 255$. The projection operator $\mathbf{P}_A$ of amplitude constraint is here:

$$\mathbf{P}_A[\hat{z}^k(i_1, i_2)] = \begin{cases} 0, & \hat{z}^k(i_1, i_2) < 0 \\ \hat{z}^k(i_1, i_2), & 0 \leq \hat{z}^k(i_1, i_2) \leq 255 \\ 255, & \hat{z}^k(i_1, i_2) > 255 \end{cases} \quad (8)$$

Like this, the principle of POCS algorithm is simple. It can take advantage of almost all of the required apriori constraints. If we set the number of iterations or iterative stopping criteria, the required HR image can be get.

3. The improved POCS SR infrared image reconstruction algorithm

3.1. The improved POCS algorithm based on data consistency constraint with variable correction thresholds

Theoretically, if $r_k(m_1, m_2)$ equals zero, the current estimated HR image is identical with the real HR one. However, the situation is impossible. We can make the estimated HR image approximate the real one as far as possible by adjusting the value of δ .

Generally, bigger δ means fewer pixel points to be corrected, leading to the fact that some points with large errors are ignored and not corrected. Oppositely, smaller δ means more pixel points to be corrected, which may bring about extra noises. Thus δ is the most important factor in POCS algorithm, directly related to the quality and visual effect of the image reconstructed.

In existing POCS algorithms, δ is constant, ignoring the differences between objects and background noises, giving the same processing mode to all the pixel points, resulting in blurring edges and low signal-to-noise ratios of obtained images.

In 1739, Jurin discovered the eye micro-movements (EMms) phenomenon of human eyes. Namely, when observing a stationary object, human eyeballs move in tiny amplitudes and high frequencies [12,13]. In 2002, Greschner [14] indicated the influence of EMms on luminance information perception by comparing the different experimental results with or without EMms. In 2004 Martinez-Conde [15] and in 2009 Hafed [16] both pointed out that EMms are some kinds of microscanning controlled by epithalamia nerves. The latest research finds that EMms makes the image of interested objects always locate in the central fovea where the density of photoreceptor cells is the biggest, while the image of uninterested background is located in other retinal areas where the number of photoreceptor cells is fewer. It can be seen that the human visual system can give different observation degrees to objects and background. The mechanism inspires us to propose an improved POCS algorithm with variable correction thresholds, and the algorithm can give different correction degrees to different pixel areas, achieving the aim of enhancing the edges and filtering the noises adaptively.

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