Application of an improved regularized super resolution reconstruction method in infrared detection system

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Abstract. Super resolution reconstruction is a feasible technique to improve the image resolution without changing the existing infrared detection equipment. The original image usually contains noise, the traditional regularized super resolution method has the contradiction between restraining noise diffusion and protecting image details in the process of image reconstruction. In order to reduce the loss of reconstructed image information caused by noise suppression in the reconstruction process, this paper studied the reason of noise diffusion in original sequence image through image reconstruction model, proposed a method based on Lee’s regularized method using Huber Markov random field as prior model in image reconstruction process, Experiment results show that the proposed method improved the images obtained by the infrared detection system, is superior to traditional method and Lee method in subjective visual and objective indicators, can meet the practical detection requirements.

1. Introduction

In the battlefield environment, atmospheric attenuation, system noise and other factors will reduce the detection range of military imaging equipment, often affecting the performance of weapons and equipment. The super resolution reconstruction technology can process the original image sequence with sub-pixel displacement by the existing imaging equipment, and reconstruct the required high-resolution image [1]. This technology is more flexible and economical in many cases, in recent years, it has been widely used in satellite remote sensing, industrial flaw detection and medical imaging.

Super resolution reconstruction is an ill-posedness problem [2] in Hardmard sense, it should use a regularization method that the prior information of the solution is used to constrain a stable solution. The traditional regularization method uses Laplacian prior model to obtain the smooth solution by applying smoothing constraint on the high frequency part of the solution, there is a contradiction between suppressing noise diffusion and preserving details in the reconstructed image. In this paper, the influence of error factors in the process of super-resolution reconstruction is analyzed, in order to overcome the shortcomings of traditional methods, proposed a method based on Lee’s method [3] using Huber Markov random field as prior model that to constrain the reconstruction process, the local statistical characteristics of the image can be better described by Huber Markov random field, experimental results show that the proposed method improves the quality of reconstructed images.
2. Super resolution reconstruction model and error factor analysis

2.1. Super resolution reconstruction model

To reconstruct the high quality image by super resolution method, the first step is to establish the conversion model between the original high resolution image and the degraded low resolution image. Assuming low resolution image sequence \( \{y_k, k \in [1, N]\} \) contain \( N \) frame images, the size of low resolution image is \( M \times N \), the size of high resolution image is \( Mp \times Nq \), the degeneration progress from \( x \) to \( y \) can be expressed as:

\[
y_k = DB_k M_k x + n_k \quad k \in [1, N]
\]  

(1)

\( D \) is the decimation matrix, \( B_k \) is the blurring matrix caused by PSF(point spread function) or diffraction limit, \( M_k \) is the geometric warp matrix caused by motion deformation, \( n_k \) is the distributed additive noise. It can be seen from the image quality reduction model that due to the influence of sampling reduction, blurring, motion deformation and noise, the quality of high-resolution image is reduced to low resolution. And the super resolution progress is actually based on the low-resolution image sequence information.

2.2. The influence of error factors on reconstructed image quality

From the above analysis, it can be seen that the super-resolution reconstruction is the inverse process of image quality reduction, this process can be expressed as:

\[
\hat{x} = (DB_k M_k)^{-1} y_k
\]  

(2)

Substitute equation (1) into equation (2), and can get:

\[
\hat{x} = x + (DB_k M_k)^{-1} n_k
\]  

(3)

According to the reduction model, the quality of the super-resolution reconstructed image is based on the accurate estimation of the blurring matrix and the deformation matrix, as well as the noise suppression in the low-resolution image sequence. In the actual operation, the estimated values of \( \hat{B}_k \) and \( \hat{M}_k \) inevitably have errors, and the estimated values of \( B_k \) and \( M_k \) can be expressed as

\[
\hat{B}_k = B_k + \Delta B_k
\]

(4)

\[
\hat{M}_k = M_k + \Delta M_k
\]

(5)

\( B_k \) and \( M_k \) represent the exact values of the blurring matrix and the deformation matrix in the original high-resolution image quality reduction process, \( \Delta B_k \) and \( \Delta M_k \) represent the deviation between the estimate value and the exact value. Substitute equation (4), (5) into equation (3), and can get:

\[
\hat{x} = x + (DB_k \hat{M}_k)^{-1} n_k
\]  

\[
= x + [D(B_k + \Delta B_k)(M_k + \Delta M_k)]^{-1} n_k
\]

\[
= x + (DB_k M_k)^{-1} n_k + H_k^{-1} (\Delta B_k, \Delta M_k) n_k
\]  

(6)
In equation (4), \( H_k^{-1}(\Delta B_k, \Delta M_k) \) represent the effect of estimation error on the quality of super resolution reconstruction. It can be seen from equation (4) that in the case of no distributed additive noise interference (i.e., \( n_k = 0 \)), the reconstructed image \( \hat{x} \) is the same as the original high resolution image \( x \). However, due to the existence of noise \( n_k \) and estimation deviation \( \Delta B_k \) & \( \Delta M_k \) in practice, the noise in low-resolution image sequence will diffuse in the reconstructed image and cause the generation of false information such as edge oscillation and false texture [4, 5], resulting in the degradation of reconstructed image quality.

3. The improved regularized super resolution reconstruction method

The traditional regularized super resolution method use the Laplace priori model to smooth constraint on the high frequency part of the reconstructed image, While reducing the impact of noise on the reconstructed image, the details of the image are also blurred, and the regularized parameter in traditional regularized super resolution method is a global parameter, and its equilibrium point is difficult to set.

the deformation matrix error is not considered in traditional regularization method, Lee proposed to treat the deformation matrix error as gaussian noise[3] and modified the traditional regularization equation as:

\[
F(x) = \sum_{k=1}^{N} \{ \lambda_k \| y_k - DB_k M_k x \|^2 + \| C x \|^2 \} 
\]

(7)

Compared with the traditional method, the method proposed by Lee improves the quality of reconstructed images. However, since it still use Laplacian prior model to smooth and constrain the image noise, the details of reconstructed images will still be blurred.

In order to protect the details of the reconstructed image while suppressing the noise, the prior model should not only apply the smoothness constraint to the high frequency part of the image, but also should consider the inherent relevance and regularity of the image to improve the reconstruction effect.

On the basis of Lee's method, this paper selects HMRF (Huber Markov random field) as prior model [6, 7], which is more consistent with image characteristics, to constrain the image. This prior model believes that the image is segmented smooth, and the segmented changing regularization parameter is used to replace the global regularization parameter. The regularization term of this prior model can be expressed as:

\[
\varphi(x) = \sum_{c \in C} V_c(x) 
\]

(8)

\[
V_c(x) = \sum_{m=1}^{4} \rho(d_m^c(x)) 
\]

(9)

In the above formula, \( c \) represents the cluster, that is, the domain system of a pixel in the image, \( C \) is the set of the neighborhood system. \( V_c(x) \) Is the corresponding potential function to \( c \); \( d_m^c(x) \) is the smoothness measure of the image in \( c \); \( \rho(\cdot) \) is the function of smoothing measure \( d_m^c(x) \), in HMR (Huber Markov random field) prior model, \( \rho(i) = i^2 \); \( d_1^c(x), d_2^c(x), d_3^c(x) \) and \( d_4^c(x) \) represent the horizontal, vertical, diagonal and anti-diagonal changes of the image respectively.

The super resolution regularization framework of this paper can be expressed as:
\[
\hat{x} = \arg \min_{k=1}^{N} \left\{ \sum_{m=1}^{4} \rho(d_{c}^{m}(x)) \right\}
\]

The formula of the regularization parameter is:

\[
\lambda_{k}^{n}(x) = \sqrt{\frac{\sum_{m=1}^{4} \rho(d_{c}^{m}(x))}{\| y_{k} - DB_{k}M_{k}x \|^2 + \delta_{k}}}
\]

It can be seen from the above formula that the HMRF (Huber Markov random field) prior model is used in the regularization framework to constrain the reconstructed image, instead of smoothing the high frequency part as a whole part. It can effectively describe the local characteristics of the image to suppress the generation of false information in reconstruction; The regularization parameters can be adjusted adaptively according to the characteristics of the image to protect the image details and improve the image reconstruction effect.

The improved regularization framework (10) can be iteratively solved by the SD (steepest descent) method as below, that is, the actual image sequence can be iteratively updated until the set conditions are met:

\[
\hat{x}^{n+1} = \hat{x}^{n} - \beta \left\{ \sum_{k=1}^{N} M_{k}^{T} B_{k}^{T} D_{k} \phi(\lambda_{k} \| y_{k} - DB_{k}M_{k}x \|^2) + \phi(\sum_{m=1}^{4} \rho(d_{c}^{m}(\hat{x}^{n}))) \right\}
\]

4. The Experimental results and analysis

To illustrate advantages and effective of the proposed method in practical application, a building image sequence with size of 160 × 120 taken by a certain type of infrared imaging system during translational motion was selected as the experimental object. Nine of the infrared images were selected for super resolution reconstruction by the traditional regularized super resolution method, the Lee method and the improved method, Gaussian blur is set as the PSF of the imaging system, and the optical flow method [8, 9] is set for motion estimation.

Because there is no original reference image in the infrared image taken, the average gradient of the image is selected as the objective evaluation index of the reconstructed image, which is defined as:

\[
\overline{G} = \frac{1}{M \times N} \sum_{i=1}^{M} \sum_{j=1}^{N} \left\{ \left( \frac{\partial f_{i,j}}{\partial x_{i}} \right)^2 + \left( \frac{\partial f_{i,j}}{\partial y_{j}} \right)^2 \right\}^{1/2}
\]

\( \overline{G} \) represents the average gradient of the image, \( M \times N \) represents the size of the reconstructed image, \( f_{i,j} \) and is the gray value of the image pixel \((i,j)\). The average gradient value can reflect the changes of image edge and texture, the larger the value is, the better the quality of reconstructed image will be.

(a) Original LR image   (b) Traditional method   (c) Lee method   (d) Improved method

Figure 1. Super-resolution results of infrared building image sequence
Table 1. Reconstruction gradient of infrared building image sequence

| Method          | Traditional method | Lee method | Improved method |
|-----------------|--------------------|------------|-----------------|
| \( G \)         | 5.367              | 5.759      | 6.042           |

It can be seen from the super-resolution reconstruction results of infrared images that the visual effect of the improved method is better than the traditional method and Lee method, and the pseudo-information of the image is reduced in the reconstructed images, especially at the edges and textures of the images. Objective indexes prove the effectiveness of the improved method proposed in this paper.

5. Conclusion

In this paper, based on Lee's method, Huber markov prior model is introduced into the regularized super resolution reconstruction framework to realize the suppression of pseudo-information generation in the reconstructed image while protecting the image details of the high-frequency part; Moreover, the regularization parameters can be combined with the local information of the image to adjust the relationship between the data approximation term and the regularization term in the regularization equation adaptively, so as to improve the visual effect of image details. The experimental results show that the improved method can effectively overcome the shortcomings of the traditional method and Lee method, and the reconstructed images by the improved method have better visual effects and objective indicators, It can make up the deficiency of the existing infrared image resolution and provide an effective method to improve the resolution of image obtained by the existing equipment.

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