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Super – Resolution Image Reconstruction Based on an Improved Maximum a Posteriori Algorithm

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Abstract: A maximum a posteriori (MAP) algorithm is proposed to improve the accuracy of super resolution (SR) reconstruction in traditional methods. The algorithm applies both joints image registration and SR reconstruction in the framework, but separates them in the process of iteratiion. Firstly, we estimate the shifting parameters through two low resolution (LR) images and use the parameters to reconstruct initial HR images. Then, we update the shifting parameters using HR images. The aforementioned steps are repeated until the ideal HR images are obtained. The metrics such as PSNR and SSIM are used to fully evaluate the quality of the reconstructed image. Experimental results indicate that the proposed method can enhance image resolution efficiently.

Key words: super-resolution (SR); maximum a posteriori (MAP); peak signal to noise ratio; structure similarity

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Super-resolution (SR) image reconstruction produces high resolution imagesfrom low resolution images using image enhancement techniques[1]. With the focal plane array (FPA) technology approaching the best imaging limit, SR image reconstruction plays an important role in many applications, such as video surveillance[2], criminal investigation analysis[3-4], medical image processing[5] and satellite imaging[6].

SR image reconstruction is developing rapidly and a variety of algorithms have been proposed, such as the iterative back-projection (IBP) algorithm[7], projection onto convex sets (POCS) algorithm[8], maximum likelihood (ML) algorithm[9] and maximum a posteriori (MAP) algorithm[10]. The MAP algorithm has received much attention because of its advantages, such as complete theory framework, flexible spatial domain observation model, powerful inclusion of apriori-knowledge and producing superior results[11]. However, the traditional MAP algorithm cannot reconstruct a precise image due to the estimate of shifting.

In this paper, we introduce an improved MAP algorithm which applies image registration in the framework but separate it in process of iteration to minimize the influence of shifting estimate. Experimental results indicate that the proposed method can enhance image resolution efficiently.

1 Observation Model

The observation model describes the connection between a high resolution (HR) image and a LR image[12], it can help us to understand the theory of SR image reconstruction, as shown in Fig. 1.

The observation model can be denoted as

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$$y = DMBx + n \tag{1}$$

where y is the LR image, x is the unknown HR image, D is the down-sampling operator, M is the motion operator, B is the blurring function, and n is the additive noise.

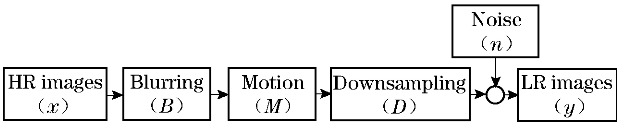

Fig. 1 Degradation process of imaging

2 MAP Algorithm

From the observation model, many image details are lost during degradation process; therefore, SR reconstruction is an ill-posed problem. MAP algorithm can provide a flexible and suitable way to model a priori knowledge to constrain the solution. What we should do is to maximize the posteriori probability $\Pr(x \mid y)$ and estimate $\hat{x}$ with the following equation as [13]

$$\hat{x} = \arg\max_{x}\{\Pr(x \mid y)\} \tag{2}$$

After apply the theorem of Bayesian, the estimate $\hat{x}$ can be expressed as

$$\hat{x} = \arg\max_{x}\left\{\frac{\Pr(y \mid x)\Pr(x)}{\Pr(y)}\right\} \tag{3}$$

Because the LR image y doesn't affect the reconstruction of the SR image in the framework of MAP, we can get the optimization problem by substituting the logarithmic function to the expressions

$$\hat{x} = \arg\max_{x}\{\lg \Pr(y \mid x) + \lg \Pr(x)\} \tag{4}$$

where $\Pr(y \mid x)$ is the conditional density model that can be defined as

$$\Pr(y \mid x) = \frac{1}{\sigma\sqrt{2\pi}}\exp\left\{-\frac{\| y - DMBx \|^2}{2\sigma^2}\right\} \tag{5}$$

and $\Pr(x)$ is the prior model that can be defined as

$$\Pr(x) = \exp\left\{-\left(\frac{\lambda}{2}\| U(x) \|^2\right)\right\} \tag{6}$$

So the optimization problem can be expressed as

$$\hat{x} = \arg\min_{x}\{\| y - DBMx \|^2 + \lambda \| U(x) \|^2\} \tag{7}$$

When we find the solution of this minimization problem, we can get the estimate image $\hat{x}$. From the observation model of Fig. 1, the processes of SR image reconstruction include three steps: image registration, non-uniform interpolation and reconstruction. We can get the parameters of shifting and blurring with the traditional MAP algorithm. Then, we use the parameters to reconstruct the SR image. However, the estimation of shifting and blurring interacts with SR image reconstruction. We can't get a high precision solution of the shifting parameter if the HR image is unknown. Therefore, we propose an improved MAP algorithm which applies image registration in the framework but separates it in process of iteration to minimize the influence of shifting estimate. In other words, we update the shifting parameter in the process of SR image reconstruction constantly. The framework of the algorithm can be expressed as

$$\hat{x}, \hat{s} = \arg\max_{x,s}\{\lg \Pr(y \mid x, s) + \lg \Pr(x) + \lg \Pr(s)\} \tag{8}$$

where s is the shifting parameter. Based on Eq. (6), the optimization problem of the improved algorithm can be expressed as

$$\hat{x}, \hat{s} = \arg\min_{s}\{\| y - DBM(s)x \|^2 + \lambda \| U(x) \|^2\} \tag{9}$$

We first assume a coarse shifting parameter, and use Eq. (6) to find a $\hat{x}$. After getting the estimated $\hat{x}$, we can find a more precision solution of the shifting parameter by use the following formula as

$$\hat{s} = \arg\min_{s}\{\| y - DBM(s)x \|^2\} \tag{10}$$

When we get a more precision solution, a better estimation of $\hat{x}$ can be found by using this solution and the best image can be got by repeating the process.

3 Experimental Results and Analyses

In order to demonstrate the effects of the improved MAP image reconstruction algorithm, we compare the performance of our method with that of two other image reconstruction methods (i. e., bilinear interpolation and traditional MAP) by using two parallel experiments. The resolution of the LR images in the visible image experiment is 102 × 102 pixels and infrared image experiment is 64 × 51 pixels. The experimental results can be seen from Fig. 2 and Fig. 3.

(a) LR (b) Bi-interpolation (c) Traditional MAP (d) Improved MA

Fig. 2 Results of visible image by using different SR image reconstruction methods

(a) LR (b) Bi-interpolation (c) Traditional MAP (d) Improved MA

Fig. 3 Results of infrared image by using different SR image reconstruction methods

Fig. 2 and Fig. 3 illuminate the effects of different SR reconstruction methods for visible and infrared images. The resolutions of the reconstructed visible and infrared images are 204 × 204 pixels and 128 × 102pixels respectively. The effects of image reconstruction by different algorithms (Fig. 2 and Fig. 3) show that the proposed method can enhance image resolution efficiently. The edges and details of the reconstructed images are expressed faultlessly.

Furthermore, in order to fully evaluate the quality of reconstructed images, various quality metrics such as peak signal to noise ratio (PSNR) and structure similarity image measure (SSIM) would be used. PSNR evaluated gray similarity and SSIM evaluate structure similarity between two images. We can evaluate the algorithm efficiency by using PSNR and SSIM simultaneity.

From the data presented in Tab. 1 and Tab. 2, higher SSIM and FSIM values from the proposed approach indicate that the structure and features are recovered to a large extent. From Tab. 1, the PSNR of the improved algorithm increases 1. 39 dB for the visible image and 1. 52 dB for the infrared image compared with that of the traditional algorithm. From Tab. 2, the SSIM increases 0. 019 6 and 0. 026 1 respectively. The improved algorithm performed the best on the image reconstruction and can enhance image resolution efficiently.

Tab. 1 PSNR (dB) of different reconstructed methods in visible and infrared images

Algorithm	Bilinear interpolation	Traditional MAP	Improved MAP
Visible image	27. 01	27. 42	28. 81
Infrared image	26. 61	27. 16	28. 68

Tab. 2 SSIM of different reconstructed methods in visible and infrared images

Algorithm	Bilinear interpolation	Traditional MAP	Improved MAP
True image	0. 791 1	0. 845 8	0. 865 4
Infrared image	0. 699 1	0. 759 3	0. 775 4

4 Conclusion

In this paper, we present an improved MAP algorithm to reconstruct SR images. The algorithm takes full account of the relationship between image registration and reconstruction in the process of super resolution reconstruction. The method can minimize the influence of shifting estimate in the process of iteration to improve the performance of SR image reconstruction. Because the improved algorithm can replace the shifting parameter on time, the structure and features are recovered to a large extent in the reconstruction image. The improved performance of our algorithm is evident from the qualitative and analytical results. In addition, the computational cost of our algorithm is not increased compared with the traditional MAP algorithm.

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