An image super-resolution method considering edge character

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Abstract. Maximum A Posteriori (MAP) estimation is an important image super-resolution method. However, a clear edge is difficult to maintain. To address this problem, we analyze the causes of poor edge stability. We also present a method for reducing the smoothness of the edge, maintaining the smoothness of the soft regional area, and reducing pseudo noise to improve connected edge retention. The improved method fixes the iteration number and smoothing factor of the MAP estimation by using Gauss-Laplacian image edge extraction. Finally, the validity of this method is verified by its application to feature information recognition in remote sensing images.

1. Introduction

People typically desire to obtain useful information from an image in the image information extraction process. However, the result is often below expectation because of low image resolution; thus, improving image resolution is important. Two image resolution improvement methods have been developed: one involves the development of camera devices to improve resolution; the other involves the reconstruction of one or more high-resolution images by using low-resolution images. This method is known as image super-resolution method. Super-resolution reconstruction method is more economical, practical, and has more long-term significance than hardware technology improvement method. At present, the image super-resolution method is widely used in satellite remote sensing, military surveillance, medicine, banks, and traffic surveillance.

The image super-resolution method can be divided into two types: spatial domain method and frequency domain method. Tsai presented the image super-resolution concept in 1984 by using a kind of frequency domain method. However, frequency domain method is still not widely used because the premise of the theory is too idealistic and merging it with existing spatial domain theory knowledge is difficult. Spatial domain method can process complex motion models with corresponding interpolation, filtering, and resampling. This method is more advantageous than the frequency domain method because the former is in line with the image complexity degradation process. The common spatial domain methods include non-uniform interpolation method [1], backprojection iterative method [2], projection on convex sets (POCS) method [3-5], maximum a posteriori (MAP) estimation [6-7], MAP/POCS hybrid method [8], and adaptive filtering method [9]. The most typical and widely used

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methods are POCS method and MAP estimation. The computing speed of MAP estimation is faster than that of POCS, and MAP's algorithm is also more stable. Moreover, the MAP solution is unique.

The prior model is important in MAP because it dictates the application of prior knowledge in the algorithm. The commonly used prior probability models include Markov random field, generalized Gaussian, Gauss-Markov random field, and hidden Markov tree models. These models display good results with respect to the smooth region of the image; however, ineffective results are obtained with respect to image edge. This phenomenon is caused by the same smoothing coefficient, which matches the contribution degree of the pixels around the edge of the image to that of the edge pixels. Consequently, the edge of the resultant image is blurred by over-smoothing. Therefore, we use the Huber-Markov prior model, enhance and determine the edges using the Gauss-Laplacian algorithm, and set appropriately different smooth constraint coefficients according to the different gray level in the edge pixels to obtain an improved edge effect.

2. MAP model principle

The first step in the super-resolution reconstruction method is to determine the observation model. The general image observation model is shown as follows:

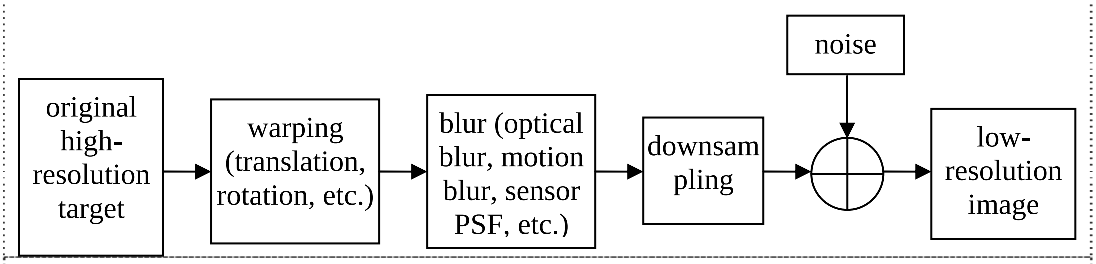

Figure 1. General image observation model

The observation model presents the relationship between the original high-resolution image and the low-resolution images. This relationship can be described by the following mathematical expression:

$$Y_i = D_i B_i W \times X + N_i \tag{1}$$

where X is the original high-resolution image, W is the downsampling matrix, B is the blur matrix, D is the geometrical movement matrix, N is noise (i.e., zero-mean-value Gaussian white noise). The expression can be simplified as $Y = H * X + N$.

MAP method estimates an unknown image by maximizing the conditional probability density function $P\ (X/Y)$, which uses a series of observed images Y to determine the ideal image X. This method is based on Bayesian theory, and its mathematical representation can be written as follows:

$$\hat{X} = \arg\max_X P(X \mid Y) = \arg\max_X \left[\frac{P(Y \mid X) \bullet P(X)}{P(Y)} \right] \tag{2}$$

$P(Y)$ is negligible because it is unrelated to X; thus, the expression can be rewritten as follows:

$$\hat{X} = \arg\min_X \left[-\lg P(Y \mid X) - \lg P(X) \right] \tag{3}$$

The conditional likelihood probability density model is $P(Y|X)=P(N) = P(Y-HX)$. The probability density function can be rewritten as the expression shown below because of the zero-mean Gaussian white noise value. σ^2 is the image noise variance in this function.

$$P(Y \mid X) = P(N) = \frac{1}{(2\pi)^{\frac{M_1 M_2}{2}} \sigma^{M_1 M_2}} \exp\left\{-\frac{1}{2\sigma^2} N^T N\right\} \quad (4)$$

The Huber-Markov model, which has an effective edge maintenance capability, is used in the prior probability density function:

$$P(X) = A \exp\left\{-\frac{1}{2\lambda} \sum_{c \in C} \rho(d_c^t X)\right\} \quad (5)$$

where A is a constant, λ represents normalized parameters, c is the point cluster, C is cluster aggregation, d_c^t is the coefficient vector of cluster c, and $\rho(*)$ is the Huber function. $\rho(*)$ must satisfy the following condition, wherein T is the threshold of the Huber function.

$$\rho(x) = \begin{cases} x^2 & |x| \le T \\ T^2 + 2T(|x| - T) & |x| > T \end{cases} \quad (6)$$

The MAP super-resolution reconstruction equation can be written as follows:

$$\hat{X} = \arg\min_X (N^T N + \frac{\sigma^2}{\lambda} \sum_{i=1}^{M_1 M_2} (\sum_{j=1}^{M_1 M_2} d_{i,j} x)^2 + \frac{\sigma^2}{\lambda} \sum_{i=1}^{M_1 M_2} (T^2 + 2T(|d_i^t x| - T))) \quad (7)$$

In this paper, we argue that the threshold T is infinite; thus, Expression (7) can be simplified as follows:

$$\hat{X} = \arg\min_X ((Y - HX)^T (Y - HX) + \frac{\sigma^2}{\lambda} \sum_{i=1}^{M_1 M_2} (\sum_{j=1}^{M_1 M_2} d_{i,j} x)^2) \quad (8)$$

3. Improvement of MAP

The second half of the expression above represents a smoothing factor, whose coefficient is constant. That is, the direction of each pixel smoothing coefficient is the same. The value of $(\sum_{j=1}^{M_1 M_2} d_{i,j} x)^2$ at the edge of the image is large because the gradient change is great. The image becomes blurred at the edge because this area of the image is first smoothed to calculate the minimum $(\sum_{j=1}^{M_1 M_2} d_{i,j} x)^2$ value. The value of $(\sum_{j=1}^{M_1 M_2} d_{i,j} x)^2$ in the smooth region of the image is small because the change in gradient is minimal. That is, pixels in this area have little influence on the objective function and are sharpened in function iteration procedures, thus resulting in noise.

To address this problem, we set a different smoothing coefficient measure *Ei* in consideration of whether the pixel is located at the edge or not and to consider the various edge pixel gradient direction changes. Thus, Expression (8) is modified to:

$$\hat{X} = \arg\min_X ((Y - HX)^T (Y - HX) + \frac{\sigma^2}{\lambda} \sum_{i=1}^{M_1 M_2} \sum_{j=1}^{M_1 M_2} (\sum_{k=1}^{4} E_k d_{i,j,k} x)^2) \quad (9)$$

The directional smoothing measure of pixel $x_{i,j}$ is defined as follows:

$$\begin{aligned}
d_{i,j,1}x &= x_{i,j-1} - 2x_{i,j} + x_{i,j+1} \\
d_{i,j,2}x &= \frac{1}{\sqrt{2}}(x_{i-1,j-1} - 2x_{i,j} + x_{i+1,j+1}) \\
d_{i,j,3}x &= x_{i-1,j} - 2x_{i,j} + x_{i+1,j} \\
d_{i,j,4}x &= \frac{1}{\sqrt{2}}(x_{i-1,j+1} - 2x_{i,j} + x_{i+1,j-1})
\end{aligned} \tag{10}$$

The specific method of operation is provided as follows:

First, image edge extraction for low-resolution images is performed using a 3 × 3 Gauss-Laplace template. The edge pixels are determined to form matrix *Ai (I = 1, 2,..., k)*.

Second, the direction template at the edge is used to judge and record direction.

Third, the coefficient E_k is set. If the pixel is not an edge pixel, then $E_k = 1$. If the pixel is an edge pixel, then the smoothing coefficients in two diagonal directions are 1. The gray level differences of the edge pixel in the edge direction and the vertical edge direction in low-resolution images are computed. Assuming that the gray value of the pixel is x, the gray values of two adjacent points in the edge direction are x_1 and x_2, and the gray values of two adjacent points in the vertical edge direction are x_3 and x_4. To achieve the normalization effect, we assume that $t(|x_1 - x| + |x_2 - x| + |x_3 - x| + |x_4 - x|) = 4$. The smoothing coefficient at the edge direction of the pixel is then expressed as $t(|x_1 - x| + |x_2 - x|)/2$ and the smoothing coefficient in the vertical edge direction of the pixel is expressed as $t(|x_3 - x| + |x_4 - x|)/2$.

Setting a different smoothing measure coefficient according to the different edge pixel characteristics improves the margin status in super-resolution reconstruction.

4. Results and analysis

A remote sensing image of Taian shot in the summer of 2006 was used as the experimental image in this study. This image contains rich landmark information.

The original high-resolution image, which has a resolution of 380 × 380, is shown in Figure 2. A series of low-resolution images were obtained by downsampling, affine transformation, blurring, and noise addition. One of the low-resolution images, which has a resolution of 190 × 190, is shown in Figure 3.

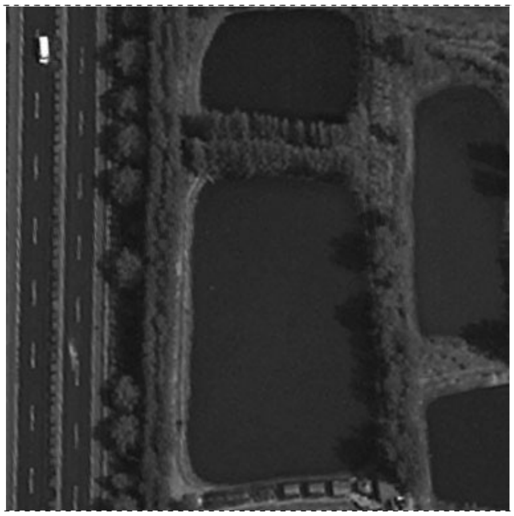

Figure 2. The original high-resolution image

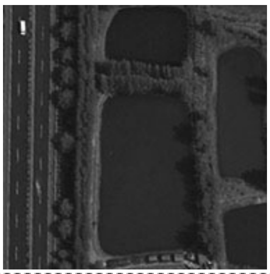

Figure 3. A low-resolution image

We applied interpolation method, traditional MAP super-resolution reconstruction method, and the method proposed in this study to our experiments. The experimental results are as follows:

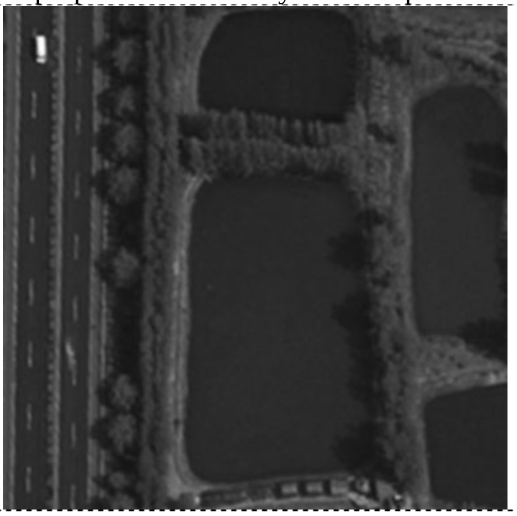

Figure 4. The resultant image from using interpolation method.

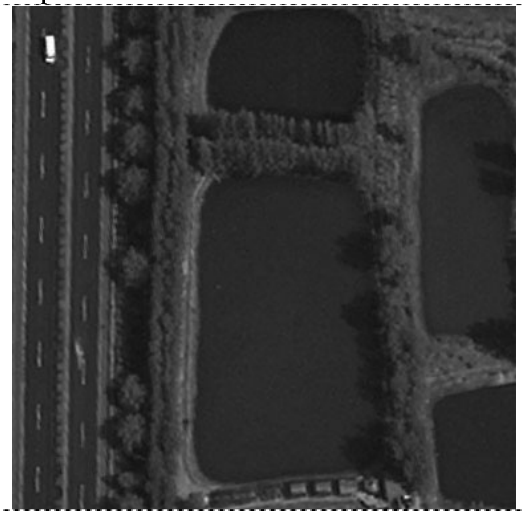

Figure 5. The resultant image from using traditional MAP method.

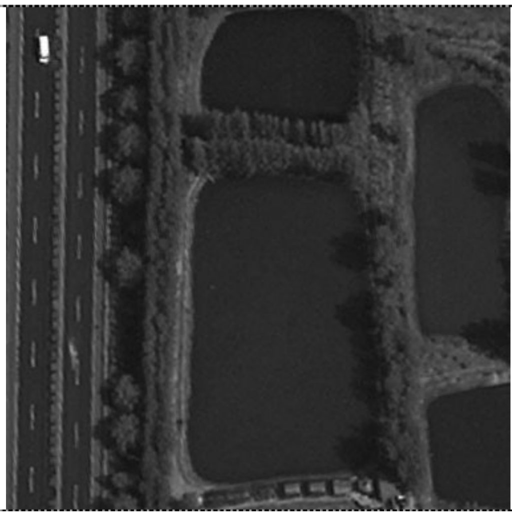

Figure 6. The resultant image from using the method proposed in this study.

Basing on the results of the experiment, we determined that traditional MAP method is better than interpolation method, and the method proposed in this study is better than traditional MAP method based on the result of the experiment. In traditional MAP method, the smoothing measure coefficient is fixed, thereby affecting edge information recovery. The proposed method displayed good effectiveness by setting different smoothing coefficients according to image information changes at the image edge, which contribute to image reconstruction in varying degrees.

5. Conclusions

In this paper, we presented a method based on traditional MAP method. In this method, different smoothing coefficients were set according to the information changes in edge pixels oriented in different directions. The proposed method reduces smoothness at the edge, maintains the smoothness of the soft regional area, and reduces pseudo noise. The experimental results show that the method significantly improves high-frequency information image reconstruction, especially the quality of the image edge.

References

[1] UR H and Gross D 1992 Improved resolution from sub-pixel shifted pictures *Graphical Models and Image Processing* **54(2)** 181

[2] Irani M and Peleg S 1991 Improving resolution by image registration *Graphical Models and Image Processing* **53(3)** 231

[3] Stark H and Oskoui P 1989 High-resolution image recovery from imageplane arrays,using convex projections *Journal of the Optical Society of America,A: Optics,Image Science and Vision* **6(11)** 1715

[4] Fan Chong, Zhu Jianjun and Gong Jianya 2006 POCS SuperresolutionSequence Image Reconstruction Based on ImprovementApproach of Keren Registration Method *IEEE Trans. on Computer Engineering and Applications* **8(6)** 28

[5] Yu Jing, Su Kaina, Xiao Chuangbai 2007 Edge Artifact Reduction for Super-resolution Image Reconstruction *ACTA AUTOMATICA SINICA* **33(6)** 577

[6] Schultz R R and Stevenson R L 1996 Extraction of High-resolution Frames from Video Sequences *IEEE Trans. on Image Processing* **5(6)** 996

[7] Zhang L, Zhang H and Shen H 2010 A super-resolution reconstructionalgorithm for surveillance images *Signal Processing* **90(3)** 848

[8] Elad M and Feuer A 1997 Restoration of a single superresolution imagefrom several blurred, noisy and undersampled measured images *IEEE Transactions on Image Processing* **6(12)** 1646

[9] Elad M and Feuer A 1999 Superresolution restoration of an image sequence:Adaptive filtering approach *IEEE Transactions onImage Processing* **8(3)** 387

[10] Zhang Lei, Yang Jianfeng, Xue Bin, Yan Xingtao 2011 Modified MAP Algorithm for Single Frame Super-Resolution Reconstruction *Laser & Optoelectronics Progress* **48** 11003

[11] Hou Yueqian, Tan Qingchang, Sun Qiucheng 2010 Self-adaptive Super-resolution Reconstruction Algorithm Based on Low-resolution Images *Computer Engineering* **36(16)** 0192

[12] Zhang Hongyan, Shen Huanfeng, Zhang Liangpei, Li Pingxiang, Yuan Qiangqiang 2011 Blind super-resolution reconstruction method based on maximum a posterior estimation *Journal of Computer Applications* **31(5)** 01209