Blur estimation and restoration of remote sensing images using a reference image

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Abstract: Remote sensing images are sometimes corrupted by blur and noise. To solve this problem, a novel blur estimation and restoration approach is presented in this paper. The approach uses a high quality image of the same scene as a reference. Such a reference image is usually available, given the increasing popularity of remote sensing applications. With the reference image, the point spread function (PSF) of another more blurry image can be less difficultly and more accurately estimated in the Bayesian framework. Once the PSF is known, many deconvolution approaches can be employed such as the total variation minimization method, which was used in this paper. Experiments with real remote sensing images show that the proposed method can effectively estimate the PSF and restore the blurred image.

Key words: blur estimation, image restoration, reference image, Bayesian estimation

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1 INTRODUCTION

Remote sensing images are inevitably degraded to some extent by noises and blurs in the acquisition stage. The blurs can be caused by out-of-focus, relative movement between an image sensor and the scene, atmospheric turbulence and so on. Image restoration theory and techniques build mathematical model for the degradation in the acquisition stage and reconstruct the original un-degraded image. A pure restoration problem assumes the point spread function (PSF) is already known and has a variety of algorithms to achieve satisfactory results (Starck & Pantin, 2002). However, the PSF is difficult to obtain and need to be estimated either in advance or in the meantime of the restoration process (Kundur & Hatzinakos, 1996), which is still a difficult task.

With the technological advances in remote sensing and its expanding use, it is usually effortless to obtain a series of images of the same scene, probably, with blurs of varied degree. Such images may come from the same sensor and be blurred differently due to well or ill focusing and/or diverse atmospheric circumstances among other reasons. They may also be acquired by different sensors and differ from each other in blur level because of the intrinsic performance of the sensors.

Two images of the same scene, one assumed without noise and the other with no blur, were used to estimate the PSF with Tikhonov regularization and Landweber method and reconstruct the original scene with R-L (Richard-Lucy) algorithm (Yuan, 2007). The inspiring approach, which is designed for consumer cameras, has two shortcomings when being applied to remote sensing images. For one thing, the need of an image without noise can be hardly satisfied. For another, the iterative algorithms are too complex for images of large size.

In this paper, we propose an approach to estimate the PSF and restore the original scene for a blurred image with the aid of another blur free image of the same scene. The PSF estimation is performed in Bayes framework and the restoration is done with total variation minimization method (Rudin *et al*., 1992). No assumption about noise is needed, nor the iterative algorithms.

2 METHOD

2.1 Using reference image

The degradation model of 2-dimensional images is shown in Fig. 1, where x is the undistorted image of a certain scene, h denotes the degradation function, y stands for the observed noisy and blurred image of the same scene, n is assumed to be Gaussian white noise of zero mean， and (m, n) is the 2-dimensional coordinates.

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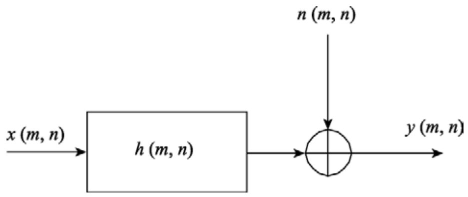

Fig. 1 Degradation model in image acquisition

From the model, we can get the degradation equation

$$y = x \otimes h + n_1, \tag{1}$$

where $\otimes$ denotes the convolution operation and n_1 is used instead of n only for the convenience of later use.

Now let $\tilde{x}$ be a blur free image of the same scene, i.e., $h_0 \approx 1$, then the following equation holds.

$$\tilde{x} = x \otimes h_0 + n_2 \approx x + n_2, \tag{2}$$

where we also assume n_2 to be Gaussian white noise of zero mean.

We then obtain from Eq. (1) and Eq. (2) that

$$y = \tilde{x} \otimes h + n_3. \tag{3}$$

Note n_3 is Gaussian noise of zero mean, for Gaussian noise always remain Gaussian when it passes a linear system. But n_3 does not necessarily remain white, which fortunately has no effect on our following discussion.

We can see from Eq. (3) that the task of blind PSF estimation is converted to a deconvolution problem, thanks to a blur free image of the same scene (no requirement on noise), that is, the estimation of h, given y and $\tilde{x}$.

After the estimation of h is completed, the restoration of x becomes a similar deconvolution task, i.e., to estimate x, known y and h, according to Eq. (1).

2.2 PSF estimation

If we estimate PSF with regularization method, we have to deal with an iterative optimization procedure, owing to the restrictions on h such as non-negative, normalized and finite supported (Yuan *et al.*, 2007). That is what we try to avoid, considering the large data size of remote sensing images. Non-iterative estimation can be done in Bayesian framework. Taking h and σ, the standard deviation of noise n_3, as parameters to be estimated, their estimates should maximize the joint probability density of y and $\tilde{x}$, which are supposed to be known. See the following equation.

$$\{\hat{h}, \hat{\sigma}\} = \arg\max_{h,\sigma} \ln p(y, \tilde{x}; h, \sigma). \tag{4}$$

By Bayes' formula, the joint probability density can be expressed as

$$p(y, \tilde{x}; h, \sigma) = p(y \mid \tilde{x}; h, \sigma) p(\tilde{x}). \tag{5}$$

Because the original image is irrelevant to blur and noise, the pdf of $\tilde{x}$ is independent on h and σ. Thus, to solve Eq. (4), we only need to solve the equation below

$$\{\hat{h}, \hat{\sigma}\} = \arg\max_{h,\sigma} \ln p(y \mid \tilde{x}; h, \sigma). \tag{6}$$

We can obtain from Eq. (3) that $p(y| \tilde{x}; h, \sigma) = p(n_3)$, where n_3 is zero-mean Gaussian noise, so we have

$$p(y \mid \tilde{x}; h, \sigma) \sim N(n_3 \mid 0, \sigma), \tag{7}$$

or

$$p(y \mid \tilde{x}; h, \sigma) = \frac{1}{\sqrt{2\pi \left|\sigma^2 I\right|}} \cdot \exp\left(-\frac{(y - H\tilde{x})^T (y - H\tilde{x})}{2\sigma^2} \right), \tag{8}$$

where H is the degradation function in the form of circular matrix. Take logarithm operation to both sides of the above equation, and we have

$$\ln p(y \mid \tilde{x}; h, \sigma) = -\frac{1}{2\sigma^2} (y - H\tilde{x})^{\mathrm{T}} \cdot (y - H\tilde{x}) - \frac{M}{2} \ln \sigma^2 + C, \tag{9}$$

where M is the image size and C is a constant. We can get another estimation expression by substitute Eq. (6) to Eq. (9), i.e.,

$$\{\hat{h}, \hat{\sigma}\} = \arg\min_{h,\sigma} \left\{ \frac{1}{2\sigma^2} (y - H\tilde{x})^{\mathrm{T}} \cdot (y - H\tilde{x}) + \frac{M}{2} \ln \sigma^2 \right\}. \tag{10}$$

The equation above can be induced to a linear system about h_i and σ, whose solution is unique, on the condition that the degradation function is symmetric and $h_i \geqslant 0$, $\Sigma_i h_i = 1$ and h has finite support (Zou, 2001).

2.3 Restoration

After having finished the PSF estimation, we can use the Total Variation (TV) regularization method (Zou, 2001) to restore the original image. This method can better preserve the detail information on the image and suppress the noise. The cost function is

$$J(f) = \frac{1}{2} \|g - Kf\|^2 + \frac{\alpha}{2} \int \sqrt{|\nabla f|^2 + \beta}, \tag{11}$$

where f and g are the functional of the undistorted image and the observed noisy and blurred image, respectively, K is the blur operator, ∇ is the gradient operator, $\alpha > 0$ is the regularization constant, the integral item is the TV of f and β is the small positive integer to avoid non-differentiability of the TV of f at zero.

The minimization of Eq. (11) with variational method is equivalent to solve the following Euler-Lagrange equation with Neumann condition

$$K^*(Kf - g) + \alpha \nabla \cdot \frac{\nabla f}{\sqrt{|\nabla f|^2 + \beta}} = 0, \tag{12}$$

where K^* is the adjoint operator of K.

As the equation is non-linear, we linearize it with a fixed-point iterative method (Vogal & Oman, 1998). From an initial f_0, we solve the fixed-point iterative equation below for every iterative step

$$\left(K^* K + \alpha \nabla \cdot \frac{\nabla}{\sqrt{\left|\nabla f^{(m)}\right|^2 + \beta}} \right) f^{(m+1)} = K^* g. \tag{13}$$

Discrete the iterative equation and we get the following equation in vector form

$$(H^{\mathrm{T}}H+\alpha D^{\mathrm{T}}Q_m^{-1}D)x^{(m+1)}=H^{\mathrm{T}}y, \tag{14}$$

where H is the non-periodic convolution kernel matrix formed by the degradation function, x and y are the vector expression of the undistorted image and the observed noisy and blurred image, respectively, and $D^{\mathrm{T}}Q_m^{-1}D$ is the discrete form of the partial differential operator $\nabla\cdot\dfrac{\nabla}{\sqrt{\left|\nabla f^{(m)}\right|^2+\beta}}$ (Zou, 2001). The matrix Eq. (14) can be solved with conventional numerical methods.

3 EXPERIMENTS

We used two high-resolution Quickbird-2 images taken at different time (See Fig. 2) to verify the proposed approach. Fig. 2(a) is an image of Haihe river mouth, Tianjin, China, shot on Jan. 9, 2008 and (b) is an image of same scene acquired on Feb. 20, 2009. (e) and (f) are the local zooms of (a) and (b), respectively. It can be seen from (e) and (f) that where is a noticeable degree of blur on the image shown as Fig. 2(a), while on image (b) there is not. Therefore, we could estimate the PSF of image (a) and make the restoration using image (b) as a blur free reference.

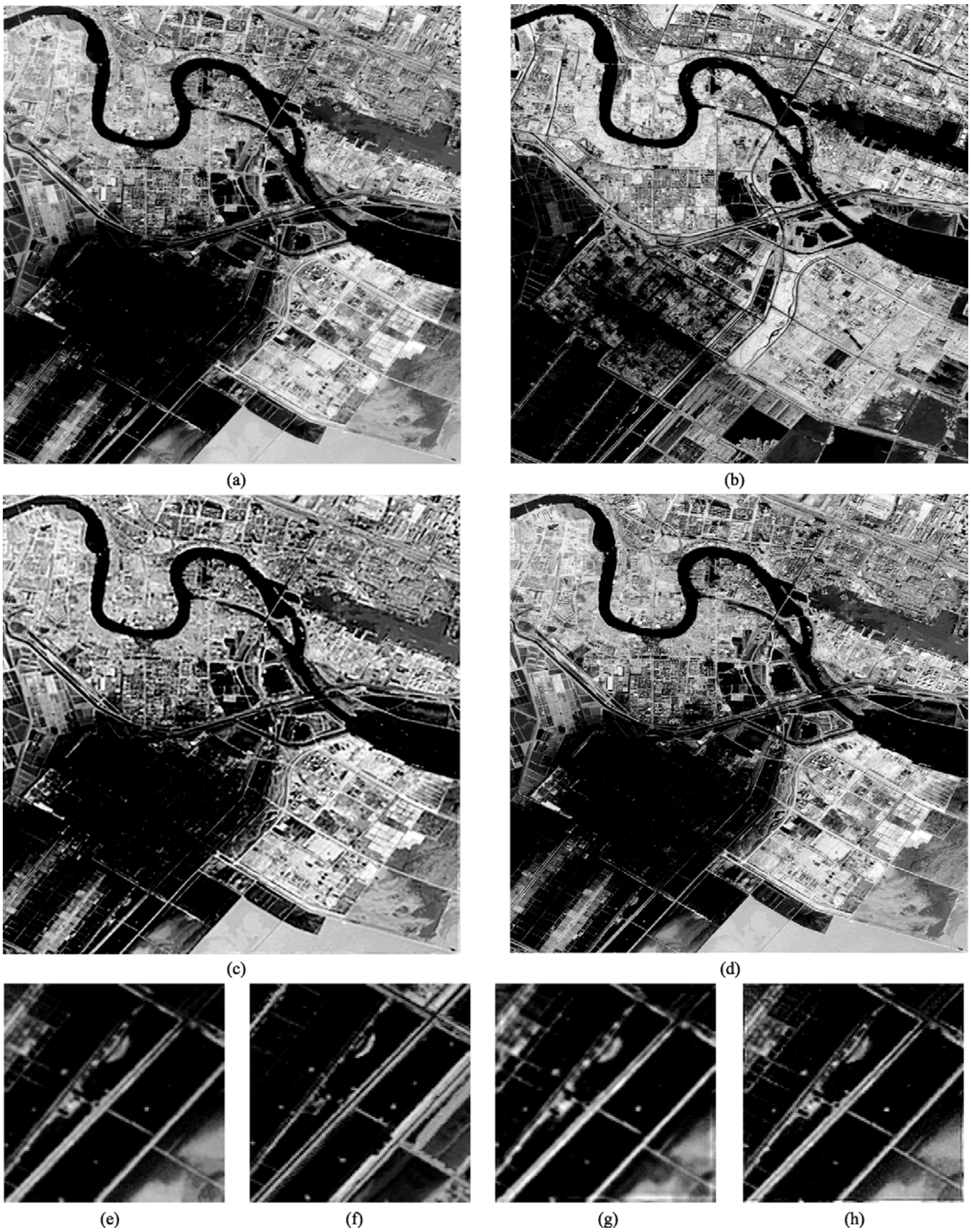

Fig. 2 Restoration Results (Source: ©DigitalGlobe)

(a) Image to be restored; (b) High quality reference image; (c) Image Restored by IBD; (d) Image restored by the proposed method; (e)—(h) are the zoomed version of part of (a)—(d), respectively

First of all, relative radiometric calibration was conducted to gain a better result. In fact, image (a) had already been calibrated with histogram matching method. The method behaves well for images from the same sensor and taken at different time (Yang & Lo, 2000).

We also restored image (a) with iterative blind deconvolution (IBD) method to compare the results. The restored image and its local zoom are shown in Fig. 2(c) and (g). The IBD method highly depends on the initiative value of PSF, improper choice of which frequently make the method end up with apparent ringing effect. If we made a proper estimation of PSF first, the restoration result could be greatly improved.

The restoration result using the proposed approach and the local zoom are shown in Fig. 2(d) and (h), respectively. It can be seen by comparing (h) with the original (e) that the edges between the ground objects became clearer and the blur was reduced.

We also applied objective assessment to the comparison of the images. As we known, the mean of DN values of an image indicates the overall brightness and the average gradient implies the sharpness of the details on the image such as edges and textures. So the two values can be used to evaluate the restoration results (Li & Zhu, 2005). We listed the means and average gradients in Table 1. The means show that there was no noticeable loss in brightness after the restoration process with the proposed method, and the average gradient values indicate that the sharpness was increased, both of which are in accord with the visualized judgments.

Table 1 Assessment of restoration results

Image	Mean	Average gradient
Observed	122.7761	0.0138
Reference	123.1693	0.0553
IBD restored	122.6815	0.0148
Restored with the proposed approach	122.7673	0.0467

4 CONCLUSION

We proposed in this paper a PSF estimation and image restoration approach based on a relatively blur free reference image of the same scene. The approach does not need iterative process and therefore reduces the calculation complexity, which is desirable in remote sensing applications. Experiments with genuine remote sensing images showed that we can gain satisfactory restoration results using the proposed approach.

Restoration methods based on IBD greatly depend on the choice of initiative value of PSF (Zou *et al.*, 1996). If we made a proper estimation of PSF first using the proposed method, the following IBD restoration could avoid apparent ringing effect caused by an improper choice of PSF initiative values.

Compared with PSF estimation methods based on sharp edges, the proposed approach does not need to choose edges interactively and therefore has potential applications in automatic restoration process. For example, in automatic spatial change detection based on multitemporal remote sensing images of the same scene, the proposed approach can be used as a preprocess step to improve the detection accuracy.

REFERENCES

Helstrom C W. 1967. Image restoration by the method of least squares. *Opt. Soc. Amer.*, **57**(3): 297—303

Kundur D and Hatzinakos D. 1996. Blind image deconvolution. *IEEE Signal Processing Mag.*, **13**(3): 43—64

Li S and Zhu C. 2005. DMC satellite image MTF analysis and restoration method research. *Journal of remote sensing*, **9**(4): 475—479

Rudin L, Osher S and Fatemi E. 1992. Nonlinear total variation based noise removal algorithms. *Physica D*, **60**: 259—268

Starck J L, Pantin E and Murtagh F. 2002. Deconvolution in astronomy: a review. *Publications of the Astronomical Society of the Pacific*, **114**(800): 1051—1069

Vogal C R, Oman M E. 1998. Fast robust total variation-based reconstruction of noisy blurred images. *IEEE Trans. Image Proc.*, **7**(6): 813—824

Yang X J and Lo C P. 2000. Relative radiometric normalization performance for change detection from multi-date satellite images. *Photogrammetric Engineering and Remote Sensing*, **66**(8): 967—980

Yuan L, Sun J, Quan L and Shum H Y. 2007. Image deblurring with blurred/noisy image pairs. *ACM Transactions on Graphics*, **26**(3): 1—10

Zou Y and Unbehauen R. 1996. An iterative method of blur identification and image restoration. IEEE Proceedings of International Conference on Image Processing, Lausanne, Switzerland

Zou Y. 2001. Deconvolution and Signal Recovery. Beijing: Defense Industry Press

利用参考图像的遥感图像模糊估计与恢复

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摘 要: 提出一种新的利用参考图像的模糊估计与恢复方法。同一场景不同时相的图像, 由于拍摄条件的不同, 清晰化程度也往往不同, 将高质量的图像作为参考, 为模糊估计和恢复提供先验知识, 在 Bayes 统一的框架内进行快速 PSF 估计, 然后使用总变分最小化方法进行恢复。通过真实遥感图像实验, 结果表明所提出的方法可以有效地估计退化模糊、恢复未失真图像。

关键词: 模糊估计, 图像恢复, 参考图像, Bayes 估计

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1 引 言

遥感图像在获取过程中, 由于散焦、景物与相机之间的相对运动、大气扰动等因素的影响, 不可避免地产生一定的模糊。图像复原技术建立图像获取过程中质量下降的退化模型, 重建未失真图像, 改善图像质量。对于单纯的复原问题, 假设点扩展函数(point spread function, PSF)准确已知, 很多方法可以达到满意的复原效果(Starck & Pantin, 2002)。但是通常情况下, PSF 很难直接获得, 需要首先估计 PSF, 然后再实施复原, 或者同时估计 PSF 和未失真图像(Kundur & Hatzinakos, 1996), 这样的盲复原问题目前仍然是比较困难的。

随着遥感技术应用的日益发展, 通常能够获取同一场景的一系列图像, 其清晰程度也不同。同一遥感器, 由于调焦或不同的大气状况等因素, 在不同时间得到质量很好和模糊严重的同场景图像; 不同遥感器, 由于自身性能的差异, 分别获得高质量和退化严重的同场景不同时相图像等。

在消费数码领域, 已有研究利用无噪声和无模糊同场景两幅图像, 使用 Tikhonov 规整化和 Landweber 迭代算法估计 PSF, 使用 R-L(Richard-Lucy)去卷积方法重建图像(Yuan, 2007)。但该方法对参考图像要求严格, 必须无噪声, 不易满足, 而且应用了迭代方法估计 PSF, 计算复杂度比较高。

本文提出一种不同时相遥感图像恢复的方法, 利用高质量图像提供先验信息, 在 Bayes 框架内快速进行非迭代的模糊估计, 并利用总变分最小化方法进行复原(Rudin 等, 1992), 恢复相同场景遥感图像。

2 方 法

2.1 利用参考图像

二维图像的退化模型如图 1, 其中 x 为某一场景对应的未失真图像, h 为退化函数, y 为观测到的退化模糊图像, n 为零均值高斯白噪声, (m, n)为二维位置坐标。

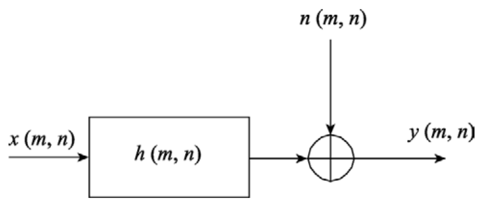

图 1 图像获取过程中的退化模型

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为行文方便，我们此处用 n_1 表示噪声，则退化模型的数学表达式为

$$y = x \otimes h + n_1 \tag{1}$$

式中，⊗表示卷积运算。

另有同一场景不同时相的清晰化程度很高的图像 $\tilde{x}$，满足 $h_0 \approx 1$，则 $\tilde{x}$ 可以表示为

$$\tilde{x} = x \otimes h_0 + n_2 \approx x + n_2 \tag{2}$$

其中 n_2 也是零均值高斯白噪声。

由式(1)和式(2)可知

$$y = \tilde{x} \otimes h + n_3 \tag{3}$$

由于高斯噪声通过线性系统仍然是高斯的，n_3 是零均值高斯噪声，不再是白噪声，但并不影响问题的讨论。

从式(3)可以看出，借助于同一场景的高质量的清晰化图像(噪声不要求)，可以把 PSF 的盲估计转化为去卷积问题，即已知 y 和 $\tilde{x}$，估计 h。

h 估计完成后，由式(1)，复原未失真图像也是一个类似的去卷积问题，即已知 y 和 h，估计 x(图 1)。

2.2 PSF 估计

使用规整化方法估计 PSF 时，由于 h 满足非负、归一化、有限支撑等约束条件，导致一个迭代的优化过程(Yuan 等, 2007)。由于遥感图像数据量大，有必要避免复杂的迭代计算过程。将 h 与噪声 n_3 和标准差 σ 作为参数，可以在 Bayes 框架内进行无需迭代的参数估计。因为 y 和 $\tilde{x}$ 已知，h 与 σ 的估计值应使 y 和 $\tilde{x}$ 的联合概率密度达到最大，即

$$\{\hat{h}, \hat{\sigma}\} = \arg\max_{h,\sigma} \ln p(y, \tilde{x}; h, \sigma) \tag{4}$$

由 Bayes 公式可知，式(4)的联合概率密度可以表示为

$$p(y, \tilde{x}; h, \sigma) = p(y \mid \tilde{x}; h, \sigma)\, p(\tilde{x}) \tag{5}$$

由于未失真图像应与退化和噪声无关，所以 $\tilde{x}$ 的概率密度函数与 h 和 σ 无关。因此求解式(4)转化为求解

$$\{\hat{h}, \hat{\sigma}\} = \arg\max_{h,\sigma} \ln p(y \mid \tilde{x}; h, \sigma) \tag{6}$$

由式(3)，$p(y \mid \tilde{x}; h, \sigma) = p(n_3)$，而 n_3=0 均值高斯噪声，所以有

$$p(y \mid \tilde{x}; h, \sigma) \sim N(n_3 \mid 0, \sigma) \tag{7}$$

或

$$p(y \mid \tilde{x}; h, \sigma) = \frac{1}{\sqrt{2\pi \left|\sigma^2 I\right|}} \cdot \exp\left(-\frac{(y - H\tilde{x})^T (y - H\tilde{x})}{2\sigma^2}\right) \tag{8}$$

式中，H 为以循环矩阵形式表示的退化函数。对上式取对数，有

$$\ln p(y \mid \tilde{x}; h, \sigma) = -\frac{1}{2\sigma^2}(y - H\tilde{x})^{\mathrm{T}} \cdot (y - H\tilde{x}) - \frac{M}{2}\ln\sigma^2 + C \tag{9}$$

式中，M 为图像尺寸，C 为常数。代入式(6)可得

$$\{\hat{h}, \hat{\sigma}\} = \arg\min_{h,\sigma}\{\frac{1}{2\sigma^2}(y - H\tilde{x})^{\mathrm{T}} \times (y - H\tilde{x}) + \frac{M}{2}\ln\sigma^2\} \tag{10}$$

上式在退化函数对称，且 $h_i \geqslant 0$，$\Sigma_i h_i=1$，h 具有有限支持域等约束条件下，可归结为求解一个关于 h_i 和 σ 线性方程组，并得到唯一解(邹炎谋, 2001)。

2.3 复原

PSF 估计完成后，由于总变分(total variation, TV)最小化规整化方法可以更好的保持图像细节信息，很好的抑制噪声，所以，本文采用总变分最小化方法(邹炎谋, 2001)对图像进行恢复。其代价泛函为

$$J(f) = \frac{1}{2}\|g - Kf\|^2 + \frac{\alpha}{2}\int\sqrt{\left|\nabla f\right|^2 + \beta} \tag{11}$$

式中，f 和 g 分别为表示未失真图像和观测图像的泛函，K 为模糊算子，∇ 为梯度算子，$\alpha>0$ 为规整化常数，积分项是 f 的总变分，β 为较小的正整数，防止总变分在零点不可微。

利用变分方法，最小化式(11)，等价于求解带有 Neumann 条件的 Euler-Lagrange 方程

$$K^*(Kf - g) + \alpha\nabla \cdot \frac{\nabla f}{\sqrt{\left|\nabla f\right|^2 + \beta}} = 0 \tag{12}$$

式中，K^* 为 K 的伴随算子。

由于该方程是非线性的，采用定点迭代方法(Vogal & Oman, 1998)使之线性化，即从初始值 f_0 起，每一步迭代解方程

$$\left(K^*K + \alpha\nabla \cdot \frac{\nabla}{\sqrt{\left|\nabla f^{(m)}\right|^2 + \beta}}\right) f^{(m+1)} = K^* g \tag{13}$$

将该定点迭代方程离散化，可以得到向量形式的方程

$$(H^{\mathrm{T}} H + \alpha D^{\mathrm{T}} Q_m^{-1} D) x^{(m+1)} = H^{\mathrm{T}} y \tag{14}$$

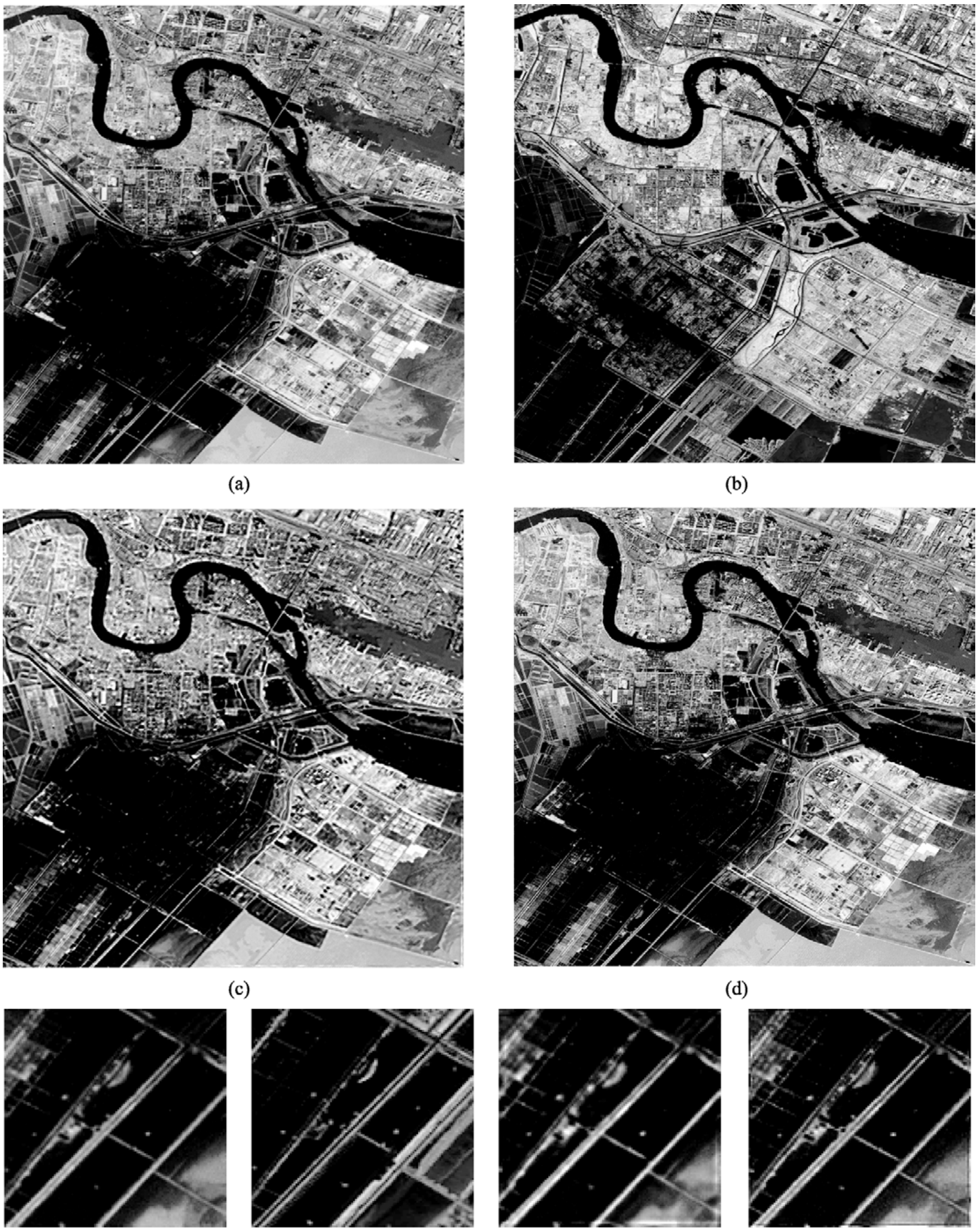
其中 H 为降晰函数形成的非周期卷积核矩阵，x 和 y 分别为未失真图像和观测图像的向量表达，$D^{\mathrm{T}} Q_m^{-1} D$ 为偏微分算子 $\nabla \cdot \frac{\nabla}{\sqrt{\left|\nabla f^{(m)}\right|^2 + \beta}}$ 的离散化形式(邹炎谋, 2001)。该矩阵方程可以用常规的数值方法来求解。

3 实 验

选取两幅不同时相的 Quickbird-2 高分辨率图像, 验证本文提出的方法。如图 2 所示, (a) 2008- 01-09 获取的天津市塘沽口的一幅图像; (b) 2009- 02-20 获取的同一场景图像。从相应的局部放大图(e)和(f)看, (a)存在一定的模糊, 而(b)质量较好, 可以把(b)作为参考图像, 估计(a)的退化函数并进行恢复。

为取得较好的结果, 首先对两幅图像进行相对辐射校正。图 2(a)所示图像已经使用直方图匹配法进行了校正。对于同一遥感器不同时间获得的图像, 该方法有较好的相对校正效果(Yang & Lo, 2000)。

为了验证方法的有效性, 本文还对图 2(a)所示图像进行了迭代盲复原(IBD), 以对比复原效果, 结



(a) (b) (c) (d) (e) (f) (g) (h)

图 2 复原结果图(图像来源: ©DigitalGlobe)

(a) 待复原图像; (b) 高质量参考图像; (c) IBD 复原结果; (d) 本文方法复原结果; (e)—(h)依次为(a)—(d)的局部放大

果及其局部放大如图 2(c)和(g)所示。该方法模糊估计和复原的效果非常依赖于的 PSF 的初始值，不正确的初值常常导致大的振铃效应，而首先进行准确地 PSF 估计，就会取得较好恢复效果。

图 2(d)和(h)分别为本文提出方法的复原结果和其局部放大图。目视比较(h)和(e)可以看出，模糊状况有了很大的改善，地物边界线变得清晰，细节不再模糊。

由于均值反映图像整体亮度水平，平均梯度从整体上反映图像边缘、纹理细节等结构的清晰程度，可依据复原前后的图像均值和平均梯度(李盛阳 & 朱重光, 2005)客观地评价复原效果。见表 1，从图像均值可以看出，本文方法复原后，亮度没有明显的损失。从平均梯度可以看出，与观测图像相比，本文方法复原后图像锐度有了较大的提高。与目视比较的结果相一致。

表 1 复原结果评价

图像	均值	平均梯度
观测图像	122.7761	0.0138
参考图像	123.1693	0.0553
IBD 复原图像	122.6815	0.0148
本文方法复原图像	122.7673	0.0467

4 结 论

本文提出了一种基于不同时相的同场景参考图像的模糊估计与复原方法。估计复原过程无需执行复杂耗时的迭代，简化了计算复杂性，适合应用于遥感图像。通过对真实的遥感图像进行实验，表明该方法有较好的模糊估计和复原效果。

基于 IBD 等迭代复原方法(Zou 等, 1996)严重依赖于初始 PSF 的选择，事先应用本文提出的方法进行 PSF 估计，可以减小由于初值选择不当引起的大的振铃效应。

与基于刃边的 PSF 估计(李盛阳 & 朱重光, 2005)，然后再复原的方法相比，本方法不需要人工挑选刃边，只需要配准和相对辐射校正的前期工作，有自动化作业的应用前景。对于基于不同时相遥感图像进行空间变化检测等方面的应用，本方法可以作为一个预处理步骤，可提高变化检测和测量的精度。

REFERENCES

Helstrom C W. 1967. Image restoration by the method of least squares. *Opt. Soc. Amer.*, **57**(3): 297—303

Kundur D and Hatzinakos D. 1996. Blind image deconvolution. *IEEE Signal Processing Mag.*, **13**(3): 43－64

Li S Y and Zhu C G. 2005. DMC satellite image MTF analysis and restoration method research. *Journal of remote sensing*, **9**(4): 475—479

Rudin L, Osher S and Fatemi E. 1992. Nonlinear total variation based noise removal algorithms. *Physica D*, **60**: 259—268

Starck J L, Pantin E and Murtagh F. 2002. Deconvolution in astronomy: a review. *Publications of the Astronomical Society of the Pacific*, **114**(800): 1051—1069

Vogal C R, Oman M E. 1998. Fast robust total variation-based reconstruction of noisy blurred images. *IEEE Trans. Image Proc.*, **7**(6): 813—824

Yang X J and Lo C P. 2000. Relative radiometric normalization performance for change detection from multi-date satellite images. *Photogrammetric Engineering and Remote Sensing*, **66**(8): 967—980

Yuan L, Sun J, Quan L and Shum H Y. 2007. Image deblurring with blurred/noisy image pairs. *ACM Transactions on Graphics*, **26**(3): 1—10

Zou Y and Unbehauen R. 1996. An iterative method of blur identification and image restoration. IEEE Proceedings of International Conference on Image Processing, Lausanne, Switzerland

Zou Y M. 2001. Deconvolution and Signal Recovery. Beijing: Defense Industry Press

附中文参考文献

李盛阳，朱重光. 2005. DMC 卫星图像 MTF 分析及其复原方法研究. 遥感学报, **9**(4): 475—479

邹炎谋. 2001. 反卷积和信号复原. 国防工业出版社