Research and Improvement of Remote Sensing Image Restoration Algorithm Based on Wiener Filter

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Abstract. On the condition of spatial imaging, remote-sensing images are always blurred by many elements. Wiener filter method is broadly used in semi-blind image restoration field. To avoid complex operations of power spectrum ratio in traditional Wiener filter, a new semi-blind remote sensing image recovery method on the basis of improved Wiener filter and comprehensive evaluation factor was presented. The method adopts improved Wiener filter to restore the blurred remote sensing data. And the degraded function factor is appraised via linear motion model. The power spectrum specific value of acquired remote sensing image is evaluated through multiple iterative calculation. Iterative stopping condition is stipulated by an integrated evaluation parameter, which is comprised of three no-reference quality parameters, GMG, IE and CF. Simulations and experiments indicate that the improved Wiener filter method acquires relatively approving restoration results and time overhead. And the proposed algorithm could be applied in restoring the remote sensing images blurred by linear motions and Gaussian noise.

Keywords: Remote sensing restoration · Comprehensive evaluation factor · Improved wiener filter method · Power spectrum

1 Introduction

Image's restoration plays a significant role in remote sensing processing field [1, 2], which aims to restore a blurred remote sensing image to a better state [3, 4].

In order to keep more target's details and reduce more noise of the image [5, 6], many inverse filtering algorithms were proposed, such as total variation method, regularization method, and EM method [7, 8]. On the other hand, many image restoration algorithms are on the basis of point spread function, such as Richardson-Lucy method, Winner filter method, and least-squares constrained solutions [9, 10].

With the increase of computing capability, using neural network model to restore degraded images has attracted more research [11–13]. However, neural network methods are not conducive in space-based processing.

Classic Wiener filter is an another popular method in image reconstruction [14]. The main problem when implementing Wiener filter is the complex calculation of the original and blurred image's power spectrum [15].

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Based on classic Wiener, this paper proposes an improved Wiener filter remote sensing restoration method on the basis of comprehensive evaluation factor. Before image restoration, the point spread function is appraised by a linear motion model. Then the image's power spectrum ratio is estimated via iterative calculation. The iterative stopping condition is fixed via a comprehensive evaluation parameter, which integrates three no-reference quality factors. Experimentations demonstrate that the improved Wiener filter method could obtain relatively approving restoration results and time cost.

2 Remote Sensing Image Restoration Model

Figure 1 is the remote sensing image's degradation and restoration model, $p(x, y)$ is original remote sensing image, $q(x, y)$ is the blurred image function, and $d(x,y)$ is degradation function. $g(x, y)$ is the noise (Gaussian function).

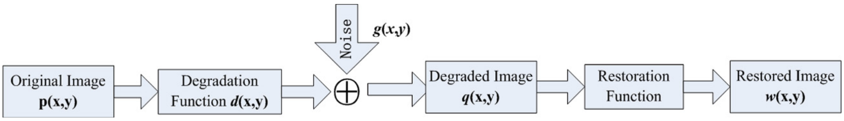

Fig. 1. Image degradation and restoration process

Suppose $d(x, y)$ is a space-changeless linear function. So the Fourier transform of degradation process could be described as

$$Q(u, v) = P(u, v)D(u, v) + G(u, v) \tag{1}$$

Assume $w(x, y)$ is the restored image function. So the restoration process's goal is to make the processed image be close to the original one.

$$W(u, v) = P(u, v) \tag{2}$$

3 Improved Wiener Filter Algorithm

3.1 Wiener Filter Method

After Fourier transformation, Wiener filter could be described as

$$H_{wiener}(u, v) = \frac{1}{D(u, v)} \frac{|D(u, v)|^2}{|D(u, v)|^2 + R_g(u, v)/R_p(u, v)} \tag{3}$$

Here $D(u, v)$ is the degradation function, and $R_g(u, v) = |G(u, v)|^2$ represents the noise's power spectrum. $R_f(u, v) = |P(u, v)|^2$ represents the original image's power spectrum. Actually, $R_g(u, v)$ and $R_f(u, v)$ are both hard to calculate, so does the power spectrum ratio $R_g(u, v)/R_f(u, v)$. In this paper, the value of $R_g(u, v)/R_f(u, v)$ is simplified as a constant C. The expression of Wiener filter could be obtained by

$$H_{wiener}(u,v) = \frac{1}{D(u,v)} \frac{|D(u,v)|^2}{|D(u,v)|^2 + C} \tag{4}$$

So the value of C is the new power spectrum ratio.

3.2 Degradation Estimating

Uniform motion blurred images are given priority in this paper. The point spread function of degraded system satisfy the following expression.

$$d(x) = \frac{1}{s}, \quad 0 \leq x \leq s-1 \tag{5}$$

Where s is the blurred dimension. To calculate the value of s, autocorrelation function is introduced. The specific process are as follows.

(1) Carry out differential operation on vertical direction of the degrading blurred $q(x, y)$.

$$q_y(i,j) = q(i,j) - q(i,j-1) \tag{6}$$

(2) Carry out differential operation on horizontal direction.

$$q_{yx}(i,j) = q_y(i,j) - q_y(i-1,j) \tag{7}$$

(3) List the degrading image's autocorrelation function of every row. Assume the row j has l pixels, then the autocorrelation function is given by

$$r(k) = \sum_{i=l}^{M-k-l} \sum_{m=-l}^{l} f(i+k+m,j) f(i+m,j) \quad k \in [-1, 1] \tag{8}$$

Where M represents the image height.

(4) Count the autocorrelation function's mean values. Based on these values, draw autocorrelation function graphs. By scanning the minimum value of this graphs, the blurred dimension is estimated easily.

3.3 Estimation of Power Spectrum Ratio

There is always no corresponding vivid image in remote sensing restoration. So three widely used assessment factors are adopted in this algorithm.

(1) Grayscale Mean Gradient (GMG). In a sense, the value of GMG reflects the image's texture features and contrast.

$$GMG = \frac{1}{(M-1)(N-1)} = \sum_{i=1}^{M} \sum_{j=1}^{N} \sqrt{\frac{[f(i,j+1) - f(i,j)]^2 + [f(i+1,j) - f(i,j)]^2}{2}} \tag{9}$$

(2) Information Entropy (IE). IE characterizes the fullness level of merged image. The larger value of IE is, the larger the image's average information is.

$$IE = -\sum_{i=0}^{L-1} p_i \log p_i \quad p_i = \frac{N_i}{N_t}, \quad 1 \le i \le L-1 \tag{10}$$

Where IE is the value of information entropy of image, L is the value of total grey order, N_i is number of pixel which grey value equals i, and N_t is the total number of image's pixels.

(3) Spatial Frequency (SF). SF represents the dynamic level of the image in spatial-domain. The bigger the SF's value is, the more ideal the process results are. The definition of SF could be given as

$$SF = \sqrt{CF^2 + RF^2} \tag{11}$$

CF and RF the image's column frequency and row frequency, respectively. For a remote sensing image of $M \times N$ size, the calculating method of RF and CF could be given as

$$RF = \sqrt{\frac{1}{MN} \sum_{i=0}^{M-2} \sum_{j=0}^{N-2} [f(i,j+1) - f(i,j)]^2} \quad CF = \sqrt{\frac{1}{MN} \sum_{i=0}^{M-2} \sum_{j=0}^{N-2} [f(i+1,j) - f(i,j)]^2} \tag{12}$$

A comprehensive assessing parameter Q_c is adopted to make a synthesis evaluation of restoration quality. Q_c could be expressed via IE, GMG and SF.

$$Q_c = w_1 \times \frac{GMG_r - GMG_g}{GMG_g} + w_2 \times \frac{IE_r - IE_g}{IE_g} + w_3 \times \frac{SF_r - SF_g}{SF_g} \tag{13}$$

Where w_1, w_2 and w_3 are the weight parameters. GMG_r, IE_r and SF_r are the evaluation indexes of restored image, GMG_g, IE_g and SF_g are evaluation indexes of degraded image.

To obtain remote sensing restored images with high quality, the synthetically evaluation parameter Q_c must be as large as possible by acquiring an optimal value of C.

To calculate optimal value of power spectrum ratio, the automatic iterative method is adopted. The implementation steps are as follows.

Step 1: Initialize the values C_0, ΔC and C_t, where C_0 is initial power spectrum ratio, ΔC is the alternative step, C_t is the alternative times. Let $C = C_0$;
Step 2: Though the value of power spectrum ratio, implement the Winner filter process and calculate the comprehensive evaluation factor Q_c.
Step 3: Reset the value of C, $C = C_0 + \Delta C$. And the alterative times $t = t + 1$.
Step 4: Circulate implementing Step 2 and Step 3 until $t = C_t$. And a series of synthetically evaluation parameter values could be obtained.
Step 5: Based on the changing trend of Q_c, search for the optimal power spectrum ratio C_{opt}. If C_{opt} is not the first or last value, C_{opt} would be selected as the optimal parameter of proposed Winner filter. And the iteration process ends.
Step 6: If the initial value of C has the largest value of Q_c, reset ΔC, and $\Delta C = \Delta C/10$, repeat Step 2 to Step 5. If the last value of C has the largest value of Q_c, reset ΔC, and $\Delta C = \Delta C \times 10$, reiterate Step 2 to Step 5.

4 Experimental Verification and Analysis

4.1 Simulations

Figure 2(a) is the classical "Lena" image with the size of 512 × 512, which is chosen as the first test image. Figure 2(b) is the degraded image. The image is blurred by Gaussian noise and uniform motion point spread function. The blurred scale is set as 5. $C0 = 0$, $\Delta C = 0.0001$, $Ct = 100$. Three evaluation indexes' weight parameters are set as $w_1 = 0.4$, $w_2 = 0.4$ and $w_3 = 0.2$.

(a) Original "Lena" image (b)Blurred image

Fig. 2. Original and blurred "Lena" image

This paper choose conventional classic Wiener filter and inverse filtering are to compare to the proposed improved Wiener filter, as shown in Fig. 3.

Through observing with naked eyes, it is obvious that the improved Wiener filter's process effect is more excellent than the other two methods. Figure 3(b) shows the process results of classic Wiener filter. It seems that the image's quality is not better than Fig. 2(b). And new noises are introduced to the image.

Table 1 shows the evaluation indexes of the original image, degraded image and three methods' process results. It is evident that the proposed method is relatively

(a) Inverse filter (b) Classic Wiener filter (c) Improved Wiener filter

Fig. 3. Processing effects of three methods

effective at the condition of Gaussian noise and PSF. And the proposed algorithm could also get a relatively large PSNR (Peak Signal-Noise Ratio).

Table 1. Comparisons of processing results

	GMG	IE	SF	Q_c	PSNR
Original image	0.0226	0.0689	16.3	–	–
Degraded image	0.0185	0.0578	13.3	–	17.9
Inverse filter	**0.0872**	**0.0794**	13.9	0.15612	11.8
Conventional Wiener filter	0.008	0.0646	5.67	−1.52748	23.6
Improved Wiener filter	0.0214	0.0607	**15.5**	**0.44232**	**26.4**

4.2 Experimental Restoration Tests

To validate the effectiveness of proposed method, five blurred remote sensing images are chosen to implement restoration tests, as shown in Fig. 4. These images' size is 2000 × 2000. According to the simulation above, the original parameters are as follows. $C_0 = 0.003$, $\Delta C = 0.001$, $C_t = 100$. Three evaluation indexes' weight parameters are set as 0.35, 0.35 and 0.3, respectively.

After restoration, the images' details and contours seems more distinguishable, as shown in Fig. 5. The targets' features are more evident and seems more brightsome than degraded image. In terms of operation time, the mean consuming time of one remote sensing image is less than 5.7 s, which is relatively ideal.

After implementing the proposed improved Wiener filter, all remote sensing images' quality factors are improved to a certain extent, as shown in Table 2.

4.3 Analysis of Experimental Results

Statistically speaking, the Wiener filter could be the best way to realize image restoration to some extent. After integrating various parameters, the proposed improved Wiener contains more useful information. So, the method could obtain more gratifying remote sensing restored results.

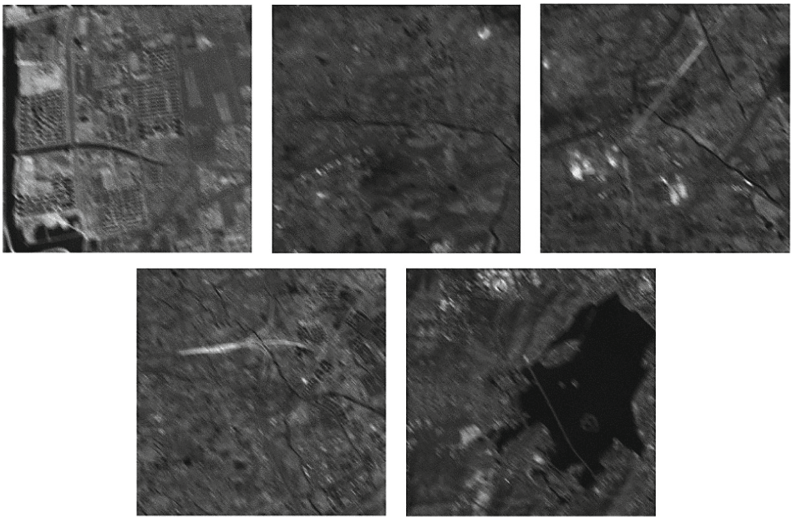

Fig. 4. Original remote sensing images, No.1–No. 5

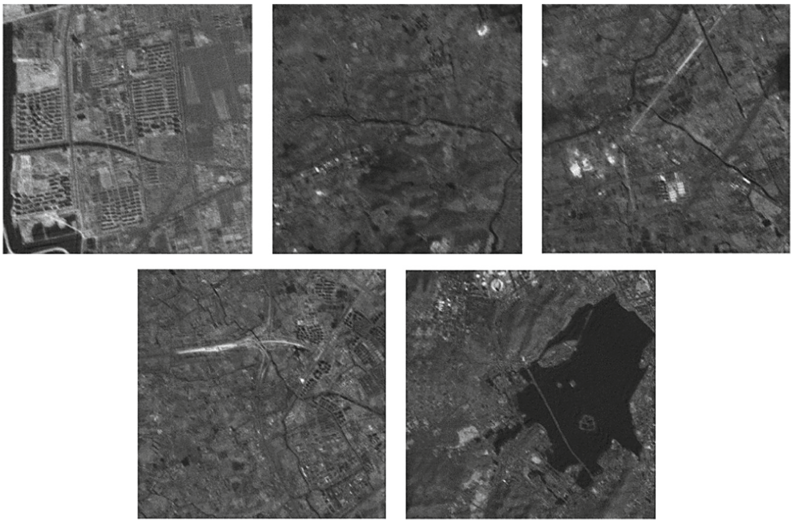

Fig. 5. Restored results of proposed improved Winner filter method

Table 2. Three methods' process results

Image No.	GMG		IE		SF		Q_c
	Before	After	Before	After	Before	After	
1	0.064	**0.072**	0.091	**0.104**	13.5	**15.2**	0.52
2	0.056	**0.070**	0.082	**0.131**	12.1	**14.9**	0.86
3	0.062	**0.081**	0.103	**0.121**	13.7	**15.8**	0.64
4	0.047	**0.068**	0.079	**0.096**	10.2	**13.6**	1.03
5	0.037	**0.045**	0.110	**0.170**	10.5	**12.7**	0.68

5 Conclusions

The paper proposes a new semi-blind remote sensing restoration algorithm on the basis of improved Wiener filter and synthetical evaluation parameter. Compared with traditional filtering methods, the proposed algorithm has two major advantages: (a) Automatic iteration method based on synthetical evaluation parameter could obtain more exact values of power spectrum ratio. And this value is important when implementing image restoration. (b) The proposed semi-blind restoration method integrates three no-reference quality parameters, which represents the non-degraded image's property to some extent. Experiments show that the improved Wiener filter method acquires relatively approving restoration results and time overhead. So the proposed restoration algorithm could be applied in restoring the remote sensing images blurred by uniform motion and Gaussian noise.

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