A METHOD OF IMAGE RESOLUTION ENHANCEMENT BASED ON THE MATCHING TECHNIQUE

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KEY WORDS: Photogrammetry, Image, Processing, Resolution, Software, Matching.

ABSTRACT:

In the field of digital photogrammetry, it is very important to enhance the image resolution. By enhancement, a clearer image with higher resolution is produced. So far, the enhancement technique is widely applied in various photogrammetric images. However, because of the restriction of the CCD sensor itself, the number of pixels on the sensor isn't much enough in some case. The image quality is affected and restricted. To solve this problem, the enhancement techniques are expended mainly in two categories: One is hardware solution; the other is software solution. In this paper, we propose a software algorithm for the enhancement of the image resolution considering inaccurate sub-pixel matching. In the proposed algorithm, the shifts, the gray values of the low-resolution images and the enhancement ratio are used to calculate the gray values of the higher- resolution image iteratively. Thus, the new image has higher resolution, so that it has higher definition. Experimental results indicate that the proposed algorithm has more universal applications.

1. INTRODUCTION

In digital photogrammetry imaging application, images with high spatial resolution are desired. Generally, high-resolution images are obtained depends on hardware solution, that it to say they are obtained directly from high precision optics and charge coupled devices (CCDs). However, the cost for high-precision optics and sensors is not inappropriate for general-purpose commercial applications, and the technology of CCDs and high precision optics cannot keep up with the demand for high-resolution images due to technical limits of sensor dimensions, shot noise etc. As a result, many software algorithms have been designed to obtain a high-resolution image.

Recently, it has been one of the most active research areas to enhance a high-resolution image from a number of low-resolution frames of the same scene. The topic of it has received considerable attention in research community. Early research on it dates back to the work by Huang and Tsai in 1984 (Tsai, 1984). They solved the problem in the frequency domain. Since then, researchers, primarily within the engineering community, have worked out many kinds of algorithms, such as non-uniform interpolation approach (Clark, 1985), projection onto convex sets (POCS) approach (Stark, 1989; Tekalp, 1992), stochastic approach (MAP estimate approach (Schulz, 1996) and ML estimate approach (Tom, 1995)), iterative back-projection (IBP) approach (Irani, 1991), adaptive filtering approach (Elad, 1999) etc.

In 2001, Fryer John and Kerry McIntosh presented a rigorous geometric (RG) algorithm to enhance a higher resolution image from several overlapping, and slightly offset, images of low resolution based on image matching technique (Fryer, 2001). This algorithm may be utilized for applications successfully where a higher resolution is desired than has been achieved previously. However, the algorithm is sensitive to noise in the input images, and the matching error wasn't considered. To overcome the limitations, this paper proposed a matching-error-considered extension of Fryer RG algorithm.

This paper is organized as follows: in section II, the rigorous geometric algorithm of Fryer is overviewed; in section III, the influence of the matching error on the enhancement process is analyzed; in section IV, the extended algorithm is proposed. Experimental results are shown in section V, and we conclude in section VI.

2. TRIGOROUS GEOMETRIC(RG) ALGORITHM

The steps of RG algorithm can be expressed as follows(Fryer, 2001):

1. Collect several low-resolution images, and select an enhancement ratio (range 1.1 to 1.9).
2. Select an image as reference arbitrarily, and determine pixel offsets of each other image from the reference image.
3. Form sets of equations using the offsets as coefficients, the enhancement ratio, and the grey values of the low-resolution images as observations.
4. Solve the sets of equations for higher resolution pixels using least squares.
5. Display the resultant higher resolution image.

The most important step of this algorithm is how to form the sets of equations in step 3. In the equations formation, the geometric relationships between coarse and fine pixels must be used. To develop the relationships, each pixel in the coarse images must be "mapped" onto the fine pixels coordinate system, thus determining which fine or unknown pixels are affected by each individual coarse pixel. For example in Fig. 1, the coarse pixel C2 covers the area bound by from (0.5, 2) to (2, 3.5) in the fine pixel coordinate system.

These coordinates show the upper, lower, left and right bounds of the coarse pixel. Using these bounds, the proportion of the coarse pixel which affects each fine pixel can be found, such that in terms of grey-scale values:

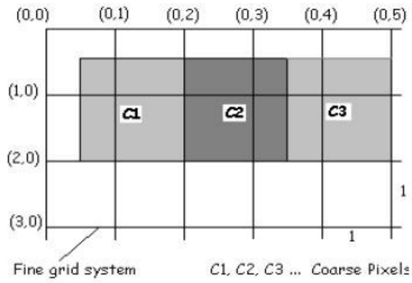

Figure 1. Coarse data mapped on the enhancement grid

$$C2 = [F(2,3) + 0.5 * F(1,3) + 0.5 * F(2,4) + 0.25 * F(1,4)] * \rho^{-2} \qquad (1)$$

Where p is the enhancement ratio , which in this case is 1.5 as deduced form Figure 1 .

The observation model may be represented as

$$y = Ax + n \qquad (2)$$

where y contains the grey values of the low resolution image pixels, x are the required high resolution image pixels, A is the matrix of the coefficients, n represents the additive noise matrix.

Based on the least squares theory, the solution of (2) results from the minimization of

$$F(x) = \| n \|^2 = \| y - Ax \|^2 \qquad (3)$$

So the solution is

$$x = [A^T A]^{-1} * A^T y \qquad (4)$$

3. IMAGE MATCHING ERROR ANALYSIS

Image matching is a very important step to the success of the resolution enhancement. Therefore, accurate matching methods, based on robust motion models should be needed (Park, 2003). However, subpixel matching is not accurate enough due to many reasons in practice. So the matching error should be considered in the resolution enhancement.

In (2), A is the matrix of the coefficients containing the sub-pixel motion information of the low-resolution images, it can be written as

$$A = \bar{A} + \Delta A \qquad (5)$$

where A is the accurate contribution of the high-resolution image to the low-resolution image. $\bar{A}$ is the matrix of the weights containing the estimated matching parameters. ΔA is the uncertainty caused by inaccurate matching. As the matching error increases, the difference between $\bar{A}$ and ΔA increases. The difference distorts the reconstructed high-resolution image[11]. Equations (2) and (5) can be written as

$$y = (\bar{A} + \Delta A)x + n \;\; = A + (\Delta \bar{A}x + n) = \bar{A}x + \bar{n} \qquad (6)$$

where $\bar{n} = \Delta Ax + n$, includes the intrinsic additive noise and the matching error noise. In Lee's paper (Lee, 2003), it is empirically proved that the matching error noise has a Gaussian type, and that its standard deviation is proportional to the degree of the matching error. Therefore, $\bar{n}$ may be regarded as Gaussian type noise in the enhancement process.

4. PROPOSED ALGORITHM

The problem of estimating a high-resolution image from some low-resolution images is ill-posed, since many solutions satisfy the constrains of the observation. In RG Algorithm, the least squares solution is advisable if there is not any noise or the noise is small enough to neglect. In many cases, however, perfect matching is practically impossible to realize. That is to say, there may be considerable matching error noise in the enhancement process. In this case, the solution of (4) cannot satisfy the enhancement demand.

To solve this problem, solution for high-resolution image is constructed by applying regularization technique that involves a functional $\| Cx \|^2$ and a regularization parameter α to the minimization problem. The solution results from the minimization of

$$F(\alpha, x) = \| y - Ax \|^2 + \alpha \| Cx \|^2 \qquad (7)$$

where α is the regularization parameter controlling the terms $\| y - Ax \|^2$ and $\| Cx \|^2$, C is a high-pass operator. We select 2-D Laplacian for C.

The necessary condition for the minimum is that the derivative of $F(\alpha, x)$ with respect to x is equal to zero, which is

$$\frac{\partial F(\alpha, x)}{\partial x} = 2A^T Ax - 2A^T y + 2\alpha\alpha^T Cx = 0 \qquad (8)$$

The solution is

$$x = [A^T A + \alpha C^T C]^{-1} * A^T y \qquad (9)$$

Regularization parameter α controls the balance between fidelity to the data and smoothness of the solution (Lee, 2003). If it is too large, the resolution will be too smooth and loss fidelity; if it is too small, the noise problem will not be solved effectively. To solve this problem, we employ an iterative algorithm to estimate the regularization parameter at the same time with the enhanced image.

In the iteration steps, the choice of α utilizes the information available at each iteration step in the enhancement process of the high-resolution image. It satisfies the following properties:

- $\alpha(x)$ is proportional to $\| y - Ax \|^2$
- $\alpha(x)$ is inversely proportional to $\| Cx \|^2$
- $\alpha(x)$ is larger than zero

To satisfy these conditions, the proposed regularization functional is designed as follows:

$$\alpha_{k+1} = \ln(\lambda * \frac{\| y - Ax_k \|^2}{\| Cx_k \|^2 + r} + 1) \qquad (10)$$

where r is the control parameter prevents the dominator from becoming zero, λ is the modified factor of α , which ranges from 0.01 to 0.3.

The high-resolution image is solved by employing the successive iterations:

$$\mathrm{x}_{\mathrm{k+1}} = \mathrm{x}_{\mathrm{k}} + [\mathrm{A}^{\mathrm{T}}\mathrm{y} - (\mathrm{A}^{\mathrm{T}}\mathrm{A} + \alpha_{\mathrm{k+1}}\mathrm{C}^{\mathrm{T}}\mathrm{C})\mathrm{x}_{\mathrm{k}}] \qquad (11)$$

The criterion that is used to terminate the iteration is

$$\| x^{k+1} - x^k \|^2 / \| x^n \|^2 \leq d \qquad (12)$$

The iterative steps can be expressed as :

1. Select a initial value for α and solve the initial image using equation (9).
2. Using the equation (10) calculate the α of the next iterative step.
3. Solve the iterative image.
4. If the two successive iterative images don't satisfy the terminating condition (12), goto the step 2; if the condition is satisfied, the last iterative image is the solution.

5. EXPERIMENTAL RESULTS

In this section, we illustrate the effectiveness of our proposed algorithm for matching errors in solving high-resolution image reconstruction problems.

In the experiments, we constructed high-resolution images from four low-resolution images. The low-resolution images which were simulated from a original Lena image by translating and downsampling a factor of 2 in each dimension as{ (0.0,0.0), (0.0,0.5), (0.5,0.0), (0.5,0.5)}, is shown in Figure 2.The stopping criterion of this proposed algorithm is $\| x^{k+1} - x^k \|^2 / \| x^n \|^2 \leq 10^{-6}$ and λ was set to 0.15.

Firstly, RG algorithm was used to enhance a high-resolution image using the known sub-pixel shifts. The result is shown in figure 3(a). In order to demonstrate the performance of the proposed matching-error-considered algorithm, it is assumed that the estimation of the sub-pixel shifts is incorrect as { (0.0,0.0), (0.15,0.35), (0.35,0.15), (0.35,0.35)}, and the RG algorithm and the proposed algorithm are used to solve the solution respectively. The results are shown in Figure 3(b) and Figure 3(c). The results visually show that our proposed algorithm yields better performance. Figure 3(b) has more artifacts because the matching error isn't considered. However, Figure 3(c) has little difference from Figure 3(a), which enhanced using correct sub- pixel shifts. So the proposed algorithm can lower the effect of the matching error effectively.

Figure 2. Four simulated Lena low-resolution images

(a) (b) (c)

Figure 3 (a) enhanced image of RG algorithm using known correct shifts, (b) enhanced image of RG algorithm using incorrect shifts, (c)enhanced image of proposed algorithm using incorrect shifts.

6. CONCLUSIONS

A new algorithm to estimate a high-resolution image from a set of undersampled low-resolution images considering the matching error noise has been proposed. The proposed algorithm has been validated experimentally with Lena image frames. It has shown that the result of the proposed algorithm has little difference from that is enhanced using correct sub-pixel shifts. So the algorithm can lower the effect of the matching error effectively and has good robustness.

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