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Blind Multi-image Super-resolution Reconstruction with Motion Blur Estimation

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Abstract: Blind image super-resolution reconstruction is a hot and difficult problem in image processing. A framework of blind multi-image super-resolution reconstruction is proposed. In the low-resolution imaging model, the processes of movement and motion blur are considered. The horizontal shift and vertical shift between the low resolution images are estimated with sub-pixel precision. The parameter of motion blur is estimated through an error-parameter analysis method. Using Wiener filtering image restoration algorithm, an error-parameter curve at different motion distance is generated. By setting threshold, the motion distance of the motion blur can be estimated automatically. The super-resolution image is reconstructed through the Iterative Back Projection (IBP) algorithm. The experimental results show that the motion blur is estimated with high accuracy and that motion blur estimation plays an important part in improving the quality of the SR reconstructed image.

Key words: Multi-image, super-resolution, motion blur, iterative back projection, error-parameter analysis

INTRODUCTION

High resolution image has always been required in many signal processing applications, such as video surveillance, remote sensing, medical imaging, etc. Super-resolution (SR) refers to the techniques achieving High-resolution (HR) enlargements of Low-resolution (LR) image. Basically, according to the amount of LR images utilized, there are two kinds of SR, namely, multi-image SR and single-image SR.

Multi-image SR refers to reconstructing a HR image from several LR images of the same scene to be aligned in sub-pixel accurately. Garcia *et al*. (2013) proposed a multiview-image super resolution method using depth information. Zhang *et al*. (2011) proposed a multiframe image super-resolution algorithm adapted with local spatial information. Giannoula (2011) proposed a classification-based adaptive filtering for multiframe blind image restoration.

Single-image SR generates a HR image from a single LR image. In recent years, single-image super-resolution reconstruction is researched via learned geometric dictionaries and clusters sparse coding (Yang *et al*., 2012), using sparse regression and natural image prior (Kim and Kwon, 2010), using self-examples and texture synthesis (Chris, 2011), using overcomplete dictionaries (Rueda *et al*., 2013).

In many practical applications, the image restoration problem is always blind which means that the blur function of the imaging system is most likely unknown or is known only to within a set of parameters (Zou, 2004). However, in most of the current algorithms, the blur is assumed to be a known Point Spread Function (PSF) with given parameters, or the blur is not considered at all which does not meet the real imaging model of optical devices. Thus, blind image SR reconstruction has become one of the advanced issues and challenges in image restoration (He *et al*., 2009). Gaussian PSF is often considered in most blind image SR reconstruction algorithms, but the motion blur existing in many cases is seldom discussed.

In this study, a framework of blind multi-image SR reconstruction algorithm is proposed. In the LR imaging model, the processes of movement and motion blur are considered. The movement parameters are estimated from coarseness to fine. The parameter of motion Point Spread Function (PSF) is estimated through an error-parameter analysis method. Utilizing the estimated movement and motion PSF, the SR image is reconstructed through an Iterative Back Projection (IBP) algorithm (Qin *et al*., 2009), in which the LR imaging model is estimated approximately. The experimental results show that motion blur estimation plays an important role on the quality of the SR image.

FRAMEWORK OF MULTI-IMAGE SR RECONSTRUCTION

Low resolution imaging model: In most multi-image SR reconstruction algorithm, only the down-sampling process is considered in the low resolution imaging model which limited the application area. In this study, the low resolution imaging model mainly includes three processes as shown in Fig. 1, namely, motion blur, down-sampling, as well as noise.

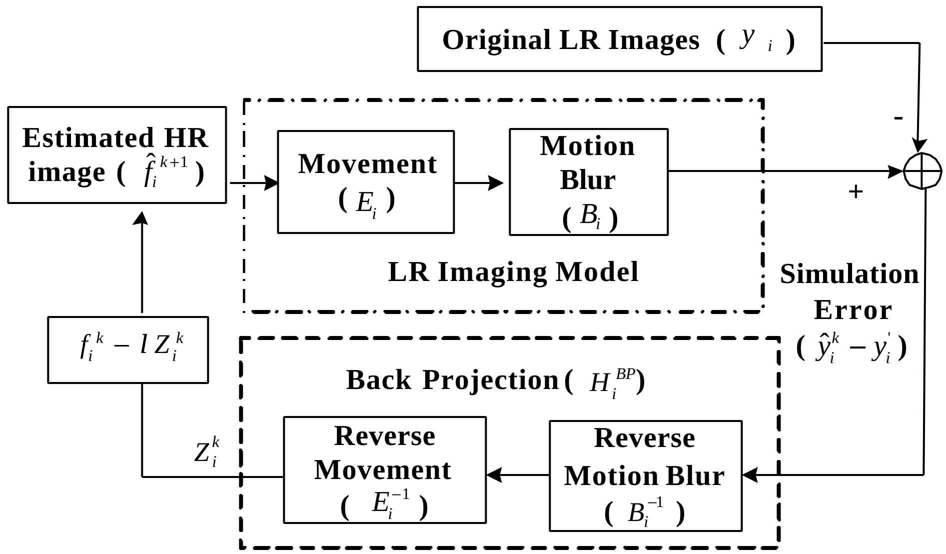

Fig. 1: Framework of IBP algorithm

The motion blur is seldom considered in current studys. Here, the blur caused by linear motion of camera or objects is considered. The factor of down-sampling is and integer number. The noise is assumed to be the white noise with zero means.

Iterative back projection method: If the reconstructed super-resolution image is close to the original high-resolution image, the simulated output low-resolution images gained by the reconstructed super-resolution image under the low-resolution observation model will be consistent with the input low-resolution image of the system. Projecting the error onto the high-resolution image grid, with the convergence of the error, we will ultimately get the corresponding super-resolution image. According to this idea, the process of the iterative back projection method may be shown in Fig. 1.

Where, k is the iteration number; $\hat{f}$ is the estimated HR image; y is the observed low-resolution image; $\hat{y}$ is the simulated low-resolution images of $\hat{f}$ under the low-resolution image observation model; B and D are the matrix forms of the motion blur and down-sampling respectively; B^{-1} and D^{-1} denote the inverse operation of B and D; n is the system noise; H^{BP} is the back projection operation which ensures the convergence of the iterative process and makes the reconstructed image be close to the original high-resolution image; $\hat{y}-y$ is the difference of simulated LR image and the practical low-resolution image; λ is the gradient step.

The mathematical description of the iterative back projection algorithm is expressed as:

$$\hat{f}_{k+1} = \hat{f}_k - \lambda H^{BP}(\hat{y}_k - y) \tag{1}$$

The above process is repeated until that the iteration number reaches the maximum iteration number, or that the relative error:

$$\left\|\hat{f}_{k+1} - \hat{f}_k\right\|^2 / \left\|\hat{f}_k\right\|^2$$

is below a given threshold value. After multiple iterations, with the convergence of the error, the estimated HR image, namely, the SR reconstructed image will ultimately be gained.

MOVEMENT ESTIMATION METHOD

Here, the globle movement with vertical shift and horizontal shift are considered. If the reference image is r(x', y') and the other image is s(x, y), a and b are the horizontal shift and vertical shift respectively, the rigid transformation model between the coordinates of these two images is denoted as:

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} x \\ y \end{bmatrix} + \begin{bmatrix} a \\ b \end{bmatrix} \tag{2}$$

The mathematical relationship of these two images can be expressed as follow:

$$s(x, y) = r(x', y') = r(x + a, y + b) \tag{3}$$

Two-dimensional series expansion at (x, y) is made to the right part of the preceding equation. Ignoring the high order terms, the following approximate expression will be get:

$$s(x,y) \approx r(x,y) + a\frac{\partial r}{\partial x} + b\frac{\partial r}{\partial y} \tag{4}$$

Thus, the object function can be written as:

$$E(a,b) = \sum\left[r(x,y) + a\frac{\partial r}{\partial x} + b\frac{\partial r}{\partial y} - s(x,y)\right] \tag{5}$$

where, Σ represents the summation to the overlapped part of r and s. Monimizing the object fuction. Performing partial derivatives about a and b respectively and letting them equal to zero, the optical estimated parameters will be obtained:

$$X = A^{-1}B \tag{6}$$

Where:

$$X = \begin{bmatrix}\hat{a}\\ \hat{b}\end{bmatrix},\ A = \left[\sum\frac{\partial r}{\partial x}\quad \sum\frac{\partial r}{\partial y}\right],\ B = \sum(s-r) \tag{7}$$

In order to improve the precision and to expand the applicable area of the above registration algorithm, the optimal movement parameters are estimated from coarseness to fine through an iterative way and three-level Gaussian pyramid image models (Qin *et al*., 2009).

MOTION BLUR ESTIMATION METHOD

PSF of motion blur: Motion blur is very common in many applications which is often caused by the motion of the camera or the moving objects. Generally, the Point Spread Function (PSF) of horizontal linear motion blur may be expressed as follows:

$$h(m,n) = \begin{cases}\frac{1}{L}, & 0 \le m \le L \text{ and } n = 0\\ 0, & \text{others}\end{cases} \tag{8}$$

where, L is the linear motion distance, namely, the parameter of the motion PSF to be estimated.

Wiener filtering image restoration algorithm: Wiener filter is a classic image restoration method which is used to generate the error-parameter curves of the observed low resolution image in this study. The estimation gained by Wiener filter is expressed as follows:

$$\hat{X}(\omega) = \frac{H^*(\omega)Y(\omega)}{|H(\omega)|^2 + S_{nn}(\omega)/S_{xx}(\omega)} \tag{9}$$

where, $\hat{X}$ is the DFT of the restoration image $(\hat{x})$; Y is the DFT of the observed image (y); H is the DFT of the point spread function; S_{xx} and S_{nn} are the power spectrum of the real image (x) and the noise (n) which are very difficult to estimate. Thus, the Wiener filter is often approximated as:

$$\hat{X} = \frac{H^*Y}{|H|^2 + \Gamma} \tag{10}$$

where, Γ is a positive constant. The best value of Γ is taken as the reciprocal of the SNR of the observed image.

Error-parameter analysis method: Error-Parameter Analysis Method may be utilized to estimate the parameter of PSF (Zou, 2004). Given a range of the motion distance, the parameter (L) changes from small to big. For each parameter, utilizing Wiener filtering image restoration method, a restored image may be gained and the corresponding restoration error may be calculated. In this way, an error-parameter curve is generated at different motion distance (L). In the case of different sizes of the Gaussian PSF, multiple curves will be generated. By analyzing the relationship between these curves, the real size and standard deviation can be estimated approximately. The motion blur estimation criterion is as follows: when the parameter (L) changes from big to small, the changes of the error-parameter curve decreases evidently around the true parameter, taking the medium of this flat range as the estimated motion distance. In this way, the parameter (L) and its corresponding motion PSF may be estimated approximately.

The description of this algorithm may be expressed as follows:

Step 1: Select a range of motion distance [L_{min}, L_{max}], a researching number S. So, $\Delta L = (L_{max}-L_{min})/S$

Step 2: for i = 1:S

- Calculate the current parameter: $L_i = L_{min}+(i-1)\Delta L$
- Calculate the current PSF: $h = 1/L_i$;
- Using Wiener filter, calculate the estimated image $\hat{x}_i$
- Calculate the estimation error: $E_i = \|y - \hat{x}_i * h_i\|$
- end

Step 3: Under different parameter (L), plot the error-parameter curve (E)

EXPERIMENTS

Simulate LR images: Experiments are performed on simulated LR image to test the algorithm objectively and subjectively. The HR image of size 256×256 is shown in Fig. 2.

Fig. 2: HR image

The HR image is passed through the LR imaging model as shown in Fig. 1. Firstly, the HR image is horizontally and vertically shifted by the parameters in Table 1. Secondly, the five moved images are convolved by a motion PSF with motion distance (L_0) of 2.3. The generated LR images are shown in Fig. 3. Take the first LR image as reference image.

Movement estimation: Relative to the reference de-noised LR image The estimated movement parameters are denoted as $\hat{a}_i$ and $\hat{b}_i$. The absolute estimation errors are defined as:

$$\Delta a_i = |\hat{a}_i - a_i|,\ \Delta b_i = |\hat{b}_i - b_i|$$

The estimated absolute estimation errors are shown in Table 2.

Table 1: Movement parameters

Sequence number (i)	Horizontal shift (a_i) (in pixel)	Vertical shift (b_i)(in pixel)
1	0.0000	0.0000
2	-2.5465	-2.7634
3	1.4547	-2.5671
4	-1.6452	2.2747
5	1.3456	-2.6857

Fig. 3(a-e): Simulated LR images

Motion blur estimation: When L_{min} = 1.1, L_{max} = 5, S = 50, using Wiener filtering image restoration algorithm, calculate the restoration err (E) at different motion distance (L). The error-parameter curve of the reference image as shown in Fig. 3a is shown in Fig. 4. From which the motion distance can be estimated approximately. According to the motion blur estimation criterion, when the parameter (L) changes from big to small, calculate the slop at each distance of motion blur. The threshold of slop is taken as 0.01. The estimated flat range is [1.9001, 2.8]. The estimated motion distance ($\hat{L}$) is taken as the medium of the flat range, namely $\hat{L}$ = 2.3501. The relative estimation error is $|\hat{L}-L_0|/L_0$ = 0.0218.

Utilizing the estimated motion PSF, SR image is reconstructed through IBP algorithm proposed in this study. In order to verify the influence of the PSF estimation on the quality of the reconstructed image, SR reconstruction is carried out at different estimated motion distance and the corresponding PSNR of the SR image is shown in Fig. 5.

Some of the reconstructed images are shown in Fig. 6. We can see that the motion PSF estimation plays an important role in the quality of the SR reconstructed image. When the estimated motion distance is around the real value, as the imaging model can be estimated much

Table 2: Estimated absolute estimation errors

Sequence number (i)	Horizontal estimation error (Δa_i) (in pixel)	Vertical estimation error (Δb_i)(in pixel)
1	0.0000	0.0000
2	0.0107	0.0688
3	0.0135	0.0662
4	0.0077	0.0504
5	0.0139	0.0677

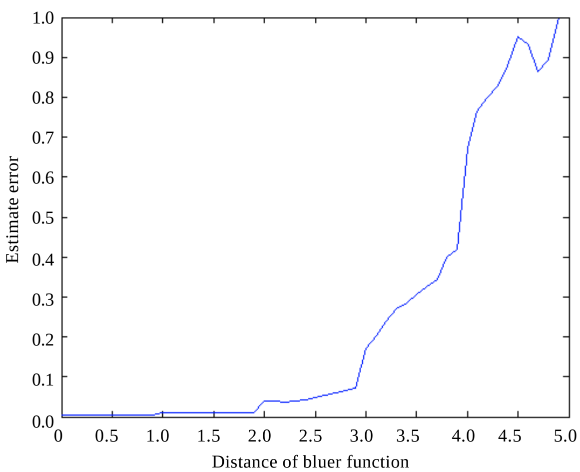

Fig. 4: Error-parameter curve of the reference LR image

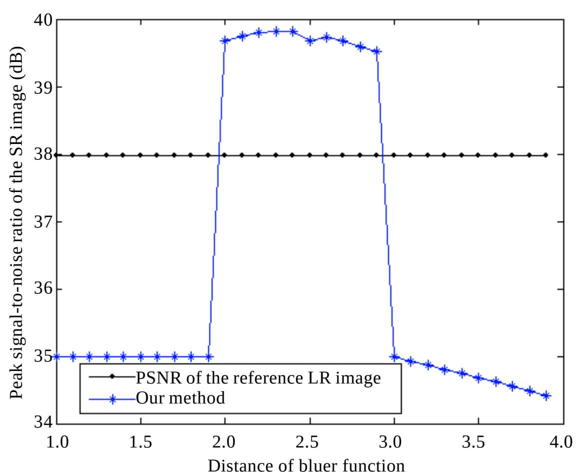

Fig. 5: PSNR of the reference LR image and the SR images reconstructed at different estimated motion distance

Fig. 6(a-d): Continue

Fig. 6(a-d): Reconstructed SR images at different estimated motion distance. (a) $\hat{L}$ = 1, PSNR = 34.9869dB, (b) $\hat{L}$ = 2.3501, PSNR = 39.8186dB, (c) $\hat{L}$ = 3, PSNR = 34.9968 dB and (d) $\hat{L}$ = 5, PSNR = 33.5561 dB

more accurately, the SR reconstructed image has higher PSNR and better visual effect as shown in Fig. 5 and Fig. 6b. When the motion distance is far away from the real value, the PSNR of the SR reconstructed image decreases or even below that of the LR image as shown in Fig. 5 and the SR reconstructed images are illegible and appears obvious ringing effect as shown in Fig. 5a-d.

CONCLUSION

Blind image restoration has always been one of the hot and challenging problems in signal processing. A framework of blind multi-image SR reconstruction method is proposed in this study. In the LR imaging model, the movement and linear motion blur are considered. The horizontal shift and vertical shift are estimated with sub-pixel precision. Utilizing Wiener filtering image restoration method, the estimation error at different motion distance is calculated. By analyzing the generated error-parameter curve, the motion distance can be estimated approximately. Utilizing the estimated movement and motion PSF, the SR image is reconstructed through IBP algorithm. The experimental results justify the fact that motion PSF estimation plays an important role on the SR reconstructed image. Around the real PSF, the SR reconstructed image has higher PSNR and better visual effect.

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