A super-resolution technique with motion estimation considering atmospheric turbulence

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ABSTRACT

Image registration is a crucial part of the success of the super-resolution algorithms. In real applications, atmospheric turbulence is an important factor that brings further degradation to the low-resolution image sequence (video frames), besides other degradations such as global motion due to movement of the optical device, blurring due to the point spread function of the lens, and blurring due to the finite size of the detector array. In this paper, the degradation of the atmospheric turbulence to the low-resolution images is modeled as per-pixel motion in the high-resolution plane and is assumed to be spatially local and temporally quasi-periodic. The registration is a two-stage process: first, the global motion between frames is estimated using the phase-correlation method to remove "jitter" and stabilize the sequence; then, an optical flow method with quasi-periodic constraint is used to estimate the per-pixel motion. A threshold is used to separate the relatively larger object movement from per-pixel atmospheric turbulence. After registration, the shift map of each frame is obtained, along with a prototype of the high-resolution image. A maximum a posteriori (MAP) based super-resolution algorithm is therefore applied to reconstruct the high-resolution image. Experiments using synthetic images are conducted to verify the validity of the proposed method. Finally, conclusions are drawn.

1. INTRODUCTION

The goal of super-resolution is to estimate a high-resolution image from a sequence of low-resolution images while also compensating for blurring due to the point spread function of the camera lens and the effect of the finite size of the photo-detectors, as well as additive noise introduced by the capturing process. Super-resolution using multiple frames is possible when there exists subpixel motion between the captured frames. Thus, each of the frames provides a unique look into the scene. The problem of super-resolution is an active research area (Refs. 1–7). However, in most of the previous work, only three kinds of degradation were modeled in the acquisition process: subpixel motion, blurring, and subsampling. In real applications, there is one more cause of degradation that needs to be taken into consideration: atmospheric turbulence.

Atmospheric turbulence occurs when the air temperature in one region is different from others. It is an important factor that blurs the imagery data when it happens to exist between the objects and the optical scene. For example, a camera on a flying aircraft may experience difficulty in getting a clear snapshot of the remote objects on the ground due to the atmospheric turbulence. This is more critical in astronomy because longer exposure time of the film is needed to get a picture of remote stars. The atmospheric turbulence will reflect the light path and super-impose an object's image quasi-periodically around the location without reflection. The effect of long-time exposure will make the image less detailed around edges. In other words, the image is blurred due to atmospheric turbulence.

Depending on the modeling and treatment of atmospheric turbulence, previous research can be classified into the following two groups: the first group models the effect of atmospheric turbulence to each image as spatially local and temporally quasi-periodic motion (Refs. 8, 9); the second group models the effect of atmospheric turbulence as point spread funtion (PSF) blur (Refs. 10, 11). In the first group, registration is needed for each frame and a prototype (reference) image is important to the reconstruction. Once the prototype image is obtained, the residual blur deconvolution can be processed. To obtain a good registration, an adaptive control grid interpolation is used in Ref. 8 to suppress the atmospheric turbulence; while a windowed phase correlation method is developed in Ref. 9. In the second group, the estimation of the overall PSF function is

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crucial. Restoration of images degraded by atmospheric turbulence has been studied in Ref. 10 through the use of Wiener-type filters. The statistics of the overall PSF is included as the maximum a posteriori (MAP) formulation in Ref. 11 and a multiframe blind deconvolution algorithm is developed.

In this paper, we model the effect of atmospheric turbulence as quasi-periodically motion. This motion is the terms that remain after the rounding of the motion vectors to integers on the high-resolution grid. An optical flow equation with consideration of the quasi-periodical property of this motion is developed for better reconstruction.

The rest of the paper is organized as follows. In section 2, we provide the observation model used in this paper. Based on this model, a new procedure is developed in section 3 to generate a reconstructed high-resolution image with atmospheric turbulence included in the acquisition process. Experimental results are provided in section 4. Finally, conclusions are drawn in section 5.

2. OBSERVATION MODEL

The image degradation process is modeled by motion, linear blur, subsampling by pixel averaging and an additive Gaussian noise process (Refs. 1–5). All vectors are ordered lexicographically. Assume that p low-resolution frames are observed, each of size $N_1 \times N_2$. The desired high-resolution image $\mathbf{z}$ is of size $N = L_1N_1 \times L_2N_2$ where L_1 and L_2 represent the down-sampling factors in the horizontal and vertical directions, respectively. Thus, the observed low-resolution images are related to the high resolution image through motion shift, blurring and subsampling. Let the kth low-resolution frame be denoted as $\mathbf{y}_k = [y_{k,1}, y_{k,2}, \dots, y_{k,M}]^T$ for $k = 1, 2, \dots, p$ where $M = N_1N_2$. The full set of p observed low-resolution images can be denoted as

$$\mathbf{y} = [\mathbf{y}_1^T, \mathbf{y}_2^T, \dots, \mathbf{y}_p^T]^T = [y_1, y_2, \dots, y_{pM}]^T. \tag{1}$$

The observed low resolution frames are related to the high-resolution image through the following model:

$$y_{k,m} = \sum_{r=1}^{N} w_{k,m,r}(\mathbf{s}_k)z_r + \eta_{k,m}, \tag{2}$$

for $m = 1, 2, \dots, M$ and $k = 1, 2, \dots, p$. The weight $w_{k,m,r}(\mathbf{s}_k)$ represents the "contribution" of the rth high-resolution pixel to the mth low resolution observed pixel of the kth frame. The vector $\mathbf{s}_k = [s_{k,1}, s_{k,2}, \dots, s_{k,K}]^T$, is the K registration parameters for frame k, measured in reference to a fixed high resolution grid. The term $\eta_{k,m}$ represents additive noise samples that are assumed to be independent and identically distributed (i.i.d.) Gaussian noise samples with variance σ_η^2. The system can be modeled in matrix notation as

$$\mathbf{y} = \mathbf{W_z z} + \mathbf{n}. \tag{3}$$

In equation (3), the degradation matrix

$$\mathbf{W_z} = [\mathbf{W_{z,1}}, \mathbf{W_{z,2}}, \cdots, \mathbf{W}_{\mathbf{z},p}]^T \tag{4}$$

performs the operation of motion, blur and subsampling. Therefore $\mathbf{W_z}$ for frame k can be written as:

$$\mathbf{W}_{\mathbf{z},k} = \mathbf{S}\mathbf{B}_k\mathbf{M}_k, \tag{5}$$

where $\mathbf{S}$ is the $N_1N_2 \times N$ subsampling matrix, $\mathbf{B}_k$ is the $N \times N$ blurring matrix, and $\mathbf{M}_k$ is the motion matrix.

In this paper, unlike previous studies that assumed global translational motion, we model the motion into two parts: a pixel-level motion due to the "shaking" of the optical device or object movement within the scene, and a local subpixel motion due to atmospheric turbulence. The first part, translational motion between frames or blocks can be estimated using the phase-correlation method[12] to remove "jitter" and stabilize the sequence; then an optical flow method with quasi-periodic constraint is used to estimate the per-pixel motion.

A threshold can be applied to separate the relatively larger object movement from per-pixel atmospheric turbulence. The simplest thresholds can be set to a multiple of the low-resolution precisions, i.e., the motion vectors are rounded to the nearest multiple of $\frac{1}{L_1}$ and $\frac{1}{L_2}$ on the two axes, respectively. The integer part of this rounding is the translational pixel-level motion, while the reminder of the rounding is the subpixel-level atmospheric turbulence motion.

3. A PROCEDURE TO RECONSTRUCT THE HIGH-RESOLUTION IMAGE WITH ATMOSPHERIC TURBULENCE MOTION IN THE ACQUIRED LOW-RESOLUTION IMAGES

In most previous work in super-resolution, the first low-resolution frame is selected as the "reference" frame. The motion of all frames is estimated with respect to the reference frame. In the case when atmospheric turbulence exists, the first frame has the same chance as any other frame to be distored by atmospheric turbulence, making it unsuitable to be the "reference" frame. Instead, we obtain and update a reference frame in the high-resolution grid using following method:

(i) We perform bilinear interpolation of the low-resolution images to the high-resolution grid. This procedure is necessary for the following optical flow estimation.

(ii) We average the available frames/blocks to get the "averaged" frame/blocks. Ideally, this "averaged" frame/block can be used as the "reference" frame/block if the low-resolution sequence is exactly temporally quasi-periodic, but usually this is not the case.

(iii) When we obtain the remaining subpixel motion using optical flow method, we apply the quasi-periodic constraint to it. To do this, we first get the averaged motion vector for each block. If this "averaged motion vector" is the zero vector, the quasi-periodic property has been satisfied. Otherwise, we find the closest motion vector of this block among the bilinear-interpolated low-resolution frames. In this work, we use Euler distance, to evaluate the diversity. The Euler distance is defined as the distance between each motion vector compared to its averaged motion counterpart, i.e., $\sqrt{(sx_{k,l} - \bar{sx}_{k,l})^2 + (sy_{k,l} - \bar{sy}_{k,l})^2}$ for frame $k = 1, \cdots, p$ and $l = 1, \cdots, K$ under translational motion case $\mathbf{s}_{k,l} = [sx_{k,l}, sy_{k,l}]$. The $\bar{sx}$ and $\bar{sy}$ are the averaged motion components. The idea behind this is to make the averaged motion vector smaller when it is recalculated in the iteration process. The corresponding block with the smallest Euler distance is removed from the averaging process in step i.

(iv) Steps ii and iii are repeated until a good "gathering" of the quasi-periodic frames/blocks is reached. The last "gathering" is selected to be the "reference" frame. A threshold of the Euler distance may be used to limit the number of iteration.

After the above procedure, a reference frame in the HR grid is obtained. The remaining task for super-resolution is to remove PSF blur and noise filtering. In this work, a MAP based super-resolution algorithm[4] with observation model as in section 2 is adapted to reconstruct the high-resolution image, because it shows a good trade-off between blur deconvolution and noise filtering. We should notice here that the reference frame is also "blurred" due to the down-sampling/upsampling. Therefore, an additional "box-car" (uniform) de-blurring procedure can be used to get a more enhanced image.

4. EXPERIMENTAL RESULTS

A number of experiments were conducted, some of which are presented here. To test the performance of our algorithms, we use the 256×256 "Cameraman" test image for a synthetic test. Down-sampling ratios are $L_1 = L_2 = 2$. To obtain the synthetic data, we include the spatially local and temporally quasi-periodic property (Ref. 8) and blocked technique as in Ref. 9. Each of the low-resolution images is generated using the following procedure: (1) Partition the original 256×256 high-resolution image into blocks. In this work, we use 16×16 blocks; (2) Assign block motion to each block, where the motion vector is randomly selected from the Cartesian product set $\{1 - L_1, 2 - L_1, \ldots, 0, 1, \ldots, L_1 - 1\} \times \{1 - L_2, 2 - L_2, \ldots, 0, 1, \ldots, L_2 - 1\}$; We can see that the absolute value of each component of the generated motion vector is less than L_1 and L_2, respectively. This means that the motion is per-pixel when the frame is down-sampled to the low-resolution size. (3) Interpolate the blank regions that are left by the block motion; This procedure is used to avoid black gaps between blocks. This procedure can be omitted for the special case where the motion of all blocks is the same within any given frame (global translational motion for the low-resolution sequence). But, in the case of atmospheric turbulence effects, this should not be case. So, this procedure is usually necessary. (4) Point spread function (PSF) blurring of the block-motion operated image; the PSF blur is assumed to be Gaussian type with support size 15×15 and standard deviation $\sigma = 0.7$. (5) Down-sampling via pixel averaging for each $L_1 \times L_2$ block; (6) Additive Gaussian noise with SNR=30 dB.

Figure 1. Original Cameraman image.

Without loss of generality, we don't use over-pixel motion in this synthetic test. We can see that there are totally $(2L_1 - 1) \times (2L_2 - 1)$ possible combinations of the motion vectors for each block. To have a good effect of atmospheric turbulence with quasi-periodic property, usually $K \times (2L_1 - 1) \times (2L_2 - 1)$ low-resolution frames are needed in synthesis, where K is a positive integer number to favor the randomness generator. The larger the K, a better chance for a randomly distributed motion vectors. An ideal case is $K = 1$ where different motion vectors are selected by the blocks in different frames. But, this is usually not the case in real applications. Thus in this work, we choose $K = 2$ as a trade-off between computational cost and random distribution. In this example, $L_1 = L_2 = 2$, when $K = 2$, totally 18 frames are used in the test with the procedure in section 3.

The original high-resolution image, one of the low-resolution frame, the average of the LR frames, the reference frame with one repeating of "gathering", and the reconstructed image are shown in Figs. 1-5. The optical flow motion of a low-resolution frame is also shown in Fig. 6. The PSNR values of the bilinear interpolation of the low-resolution frame, the reference HR frame and the reconstructed HR frame are 23.42, 23.59, and 24.87 dB. We can see that the final reconstructed high-resolution image has good image quality.

5. CONCLUSION

In this paper, the degradation of the atmospheric turbulence to the low-resolution images is modeled as per-pixel motion in the high-resolution plane, with property as spatially local and temporally quasi-periodic. The registration is a two-stage process: first, global motion between frames are estimated using the phase-correlation

Figure 2. One of the low-resolution frames.

Figure 3. The average of the low-resolution frames.

Figure 4. The reference frame.

Figure 5. The reconstructed high-resolution image.

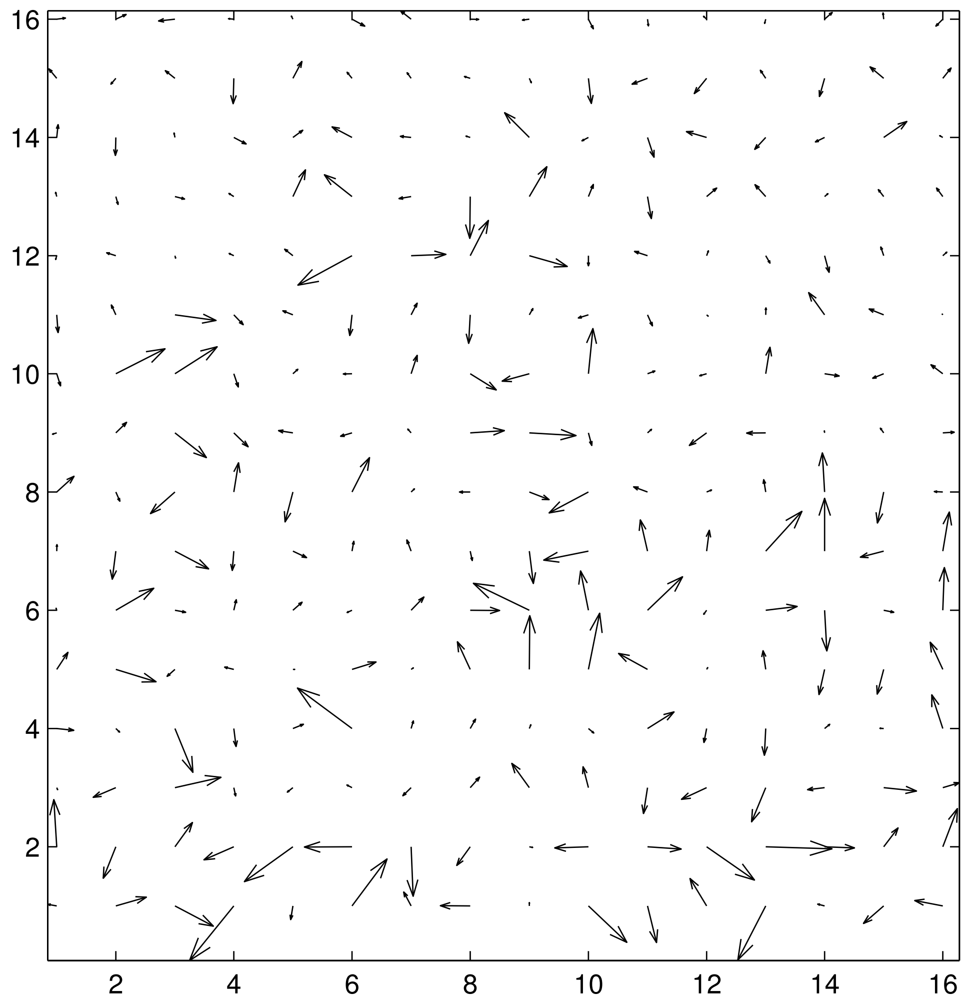

Figure 6. The optical flow motion of one of the low-resolution frames.

method to remove "jitter" and stabilize the sequence; then, an optical flow method with quasi-periodic constraint is used to estimate the per-pixel motion. A threshold is used to separate the relatively larger object movement from per-pixel atmospheric turbulence. After registration, the shift map of each frame is obtained, along with a prototype of the high-resolution image. A MAP based super-resolution algorithm is therefore applied to reconstruct the high-resolution image. Experiments using synthetic images are conducted to verify the validity of the proposed method.

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