IMAGE SEQUENCE RESTORATION FOR REMOVING SPACE-VARIANT MOTION BLUR

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ABSTRACT

An image restoration algorithm for removing motion blur, which occurs in an image sequence or moving pictures, is proposed. More specifically, the proposed iterative restoration algorithm adaptively reduces nonuniform motion blur by using motion vector information from consecutive image fields. Motion vectors are estimated based on the well known block matching algorithm, and the corresponding blur model is embodied into the point spread function, which is used to implement the iterative image restoration algorithm.

A blur model modification method is also proposed to reduce artifacts on the boundary area between objects with different blur patterns

1 INTRODUCTION

Motion blur is one of the major degradation factors in images due to the nonideal function of a camera shutter. In this respect, motion blur differs from out-of-focus blur which caused by the depth in an image [1]. And its characteristics are also different. In general, motion blur is nonuniform or space-variant because objects in an image have different motions, and the motions become more complicated when combined with camera shift.

The blurred image is modeled as the output of a noncausal and space-variant system, which is characterized by a finite duration impulse response, called the point spread function (PSF) [2, 3]. Researches on identifying the PSF include frequency domain spectrum analysis, cepstrum analysis, statistical estimation, and so on [4]. In this paper, motion vector information is used for identifying the motion blur in the observed image sequences.

After identification of motion blur, an iterative restoration algorithm is applied to remove the blur. The proposed restoration algorithm can be adaptively implemented based on either pixels or blocks according to the pattern of irregularity of degradation. And the artifacts in boundaries of blocks in the restored image are alleviated by appropriately modifying the blur model.

The model of motion blur and iterative restoration process are explained in Sec. 2. In Sec. 3, the proposed algorithm is presented. Experimental results are shown in Sec. 4, and Sec. 5 concludes the paper.

2 BACKGROUND

In this section we analyze the motion blur process and briefly summarize the iterative restoration algorithm.

2.1 Motion Blur

The continuous model of motion blur can be described by the following

$$y(u,v) = \frac{1}{T}\int_{t=-T/2}^{T/2} x(u-u_l(t), v-v_l(t))dt, \qquad (1)$$

where y and x are an observed and the original images, respectively. And $u_l(t)$ and $v_l(t)$ respectively represent the trace of the blur in horizontal and vertical each directions while the shutter is opened during T seconds. Eq. (1) can be transformed into the frequency domain, such as

$$Y(\omega_u,\omega_v) = X(\omega_u,\omega_v)H_l(\omega_u,\omega_v), \qquad (2)$$

where

$$H_l(\omega_u,\omega_v) = \frac{1}{T}\int_{t=-T/2}^{T/2} \exp(-j\omega_u u_l(t)) \cdot \exp(-j\omega_v v_l(t))dt. \qquad (3)$$

The corresponding PSF can approximately identified by estimating the motion vector with proper scaling.

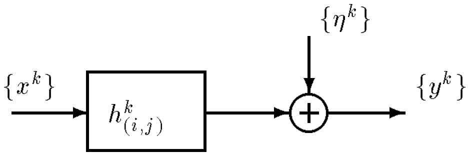

Figure 1: The image sequence degradation model

In other words, blur estimation may be simplified under the assumption that the image has only translational motion, and that the length of estimated motion is uniformly proportional to the real blur. In that case, the image formation process of (1) can be simplifed into (4).

$$y(u,v) = \frac{1}{T}\int_{t=-T/2}^{T/2} x(u-\alpha t, v-\beta t)dt, \qquad (4)$$

where α and β are constants.

2.2 Iterative Restoration

The discrete version of motion blur model (4) can be represented as the following matrix-vector form.

$$y = Hx + \eta, \qquad (5)$$

where y, H, x, and η are the observed image, PSF of the imaging system, the original image, and additive noise, respectively. If we consider an image sequence x^k as the input of the degradation model in (5), the image sequence degradation model is shown in Fig. 1, where the superscript k represents the time index of the image sequence, and the subscript (i,j) in h the (i,j)-th position in the image. In this paper, a regularized adaptive iterative restoration algorithm is used based on the degradation model in Fig. 1. Advantages of the interative algirithm are that there is no need to directly compute the inverse matrix, and that *a priori* knowledge can easily be incorporated [6].

The solution of the regularized iterative restoration method minimizes the following functional

$$f(x) = \frac{1}{2}x^T Tx - b^T x, \qquad (6)$$

where $T = H^T H + \lambda C^T C$, $b = H^T y$, λ represents a regularizaiton parameter, and C the matrix form of a highpass filter. In the nonadaptive version of the iterative algorithm, matrix T in (6) has block circulant structure, which represents the uniform motion blur over the entire image. In the adaptive version of the iterative algorithm, however, matrix T does not have block circulant structure any more.

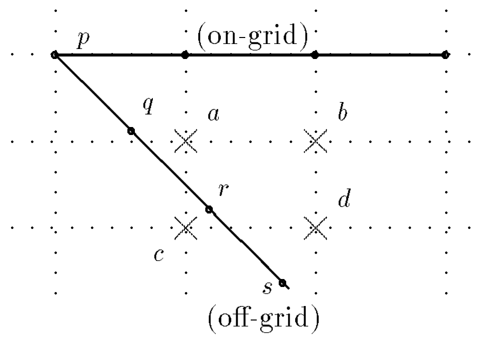

Figure 2: Generation of PSF in 2D discreite space

3 PROPOSED ALGORITHM

The proposed adaptive iterative restoration algorithm for reducing space-variant motion blur is presented in this section.

3.1 Blur Identification

Motion vector estimation is performed to identify the direction and the length of motion blur. The length of motion blur is usually smaller than the length of the corresponding motion vector because the motion vector is estimated between two temporally adjacent image fields, while the actual motion blur occurs during the shutter time which is,in general, shorter than the interval between the two image fields. The block matching algorithm is widely used for estimating motion of blocks in motion-compensated block coding applications. It is also possible to estimate the motion vector for each pixel, but the reliability decreases as the block size becomes samller. Therefore, we propose to use block-based motion estimation with image segmentation to localize similar motion vectors.

3.2 PSF Generation

At each pixel or block, two-dimensional (2D) PSF should be constructed to realize the proposed restoration algorithm which minimizes (6). But the problem is that some of the estimated motion vectors are "on-grid", but others are "off-grid" as shown in Fig. 2.

To solve the above mentioned problem, we first determine the number of samples in the PSF along the motion trajectory, such as

$$N = \lfloor \sqrt{m_x^2 + m_y^2} \rfloor, \qquad (7)$$

where (m_x, m_y) represent the horizontal and vertical motion blur length. Then, N samples are located on equispaced positions on the motion trajectory. For

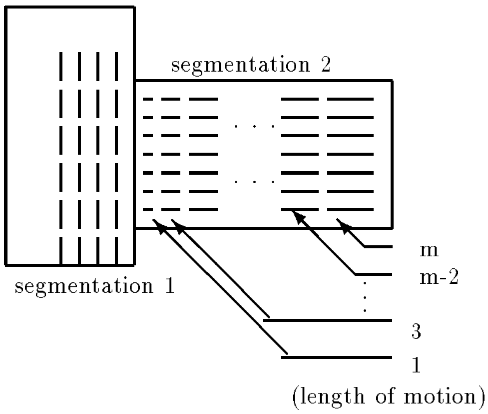

Figure 3: Modification of motion length in the boundary part of local region

example, p, q, r, and s represent the four equispaced samples along the off-grid motion trajectory in Fig. 2. Each equispaced sample has the value $1/N$, which is distributed to four neighboring grids. For example, the value $1/N$ corresponding to the sample r in Fig. 2 is appropriately distributed to a, b, c, and d. And the overlapped values from the neighboring samples are acummulated.

3.3 Boundary Artifacts Reduction

In the vicinity of boundary which discriminate segments that have different motion blur, undesired artifacts occur in the restored image. It is due to the fact that the restoration is performed over the range that is blurred by different motion. So it is necessary for the restoration process to be limited in the area which suffers from the same motion. In order to restrict the restoration area, we make the blur length decreased as it comes closer to the boundary to other segments which has different motion as shown in Fig. 3.

4 EXPERIMENTAL RESULTS

Fig. 4 shows a part of the 16th odd field in the football image sequence with 240×240 size and 256 gray level. As shown in the figure, there exists nonuniform motion blur. In the experiment, block matching algorithm was applied to obtain the motion of each 8×8 block in the image.

The motion vector, estimated from the observed image sequenc, is segmented as shown in Fig. 5. Fig. 6 depicts the segmented area and shows the motion vectors in each segment. The observed image is restored by using the segmented motion vector information. The upper part of the resotred result is shown in Fig. 7. As shown in the figure, there exist artifacts between blocks which have different motions. And such boundary artifacts are efficiently suppressed by applying proposed blur model modification technique as shown in Fig. 8.

5 CONCLUSIONS

An adaptive image restoration algorithm for reducing space-variant motion blur in image sequences has been proposed.

As the motion estimation procedure, a block-based motion vector estimation is performed using two consecutive image fields followed by motion-based segmentation. Based on the estimated motion blur parameters, the proposed adaptive iterative image restoration can efficiently reduce the nonuniform motion blur without boundary artifacts.

For efficient restoration of an image which is degraded by motion blur, both blur identification and restoration should be performed coincidently. In other words, althout one of the two functions very well, overall performance will not be satisfactory if the other doesn't work well. So, the robust connection between blur identification and restoration are crucial.

In this paper block based motion estimation algorithm is used for reliability and computational efficiency. But the motion-based segmentation may not characterize each motion correctly, which makes the restoration results suboptimal. For the optimal restoration results, blur parameters for each pixel are required. For that purpose more accurate and efficient motion vector estimation algorithm should be developed first.

Second, the restoration algorithm should be improved by using more sophiscated adaptation. The adaptive iterative algorithm requires optimal regularization parameter for each local region, and its convergence should be guranteed.

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Figure 4: 240×240, 256 gray level original football image

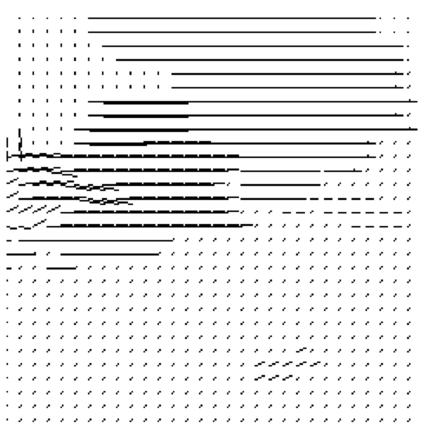

Figure 5: Segmentation results based on motion vectors

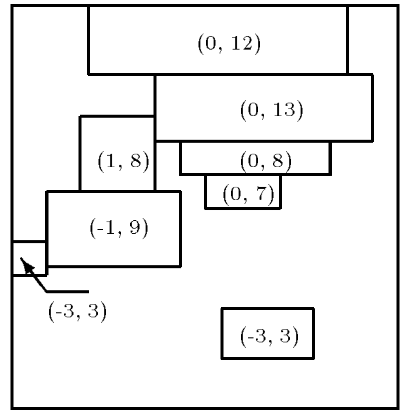

Figure 6: Segmented area and motion vector for each segment

Figure 7: Restored image without considering the boundary problem

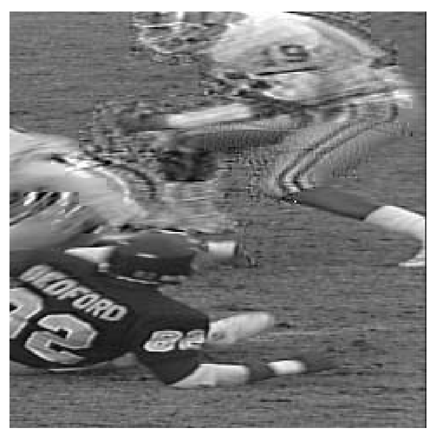

Figure 8: Restored image by using proposed methods