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Kernel Estimation of Videodeblurringalgorithm and Motion Compensation of Residual Deconvolution

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ABSTRACT
This paper presents a videodeblurring algorithm utilizing the high resolution information of adjacent unblurredframes.First, two motion-compensated predictors of a blurred frame are derived from its neighboring unblurred frames via bidirectional motion compensation. Then, an accurate blur kernel, which is difficult to directly obtain from the blurred frame itself, is computed between the predictors and the blurred frame. Next, a residual deconvolution is employed to reduce the ringing artifacts inherently caused by conventional deconvolution. The blur kernel estimation and deconvolution processes are iteratively performed for the deblurred frame. Experimental results show that the proposed algorithm provides sharper details and smaller artifacts than the state-of-the-art algorithms.
Index Terms— deblurring, unblurred frames, blur kernel, bidirectional motion compensation.

I. INTRODUCTION

A motion blur is a common artifact that causes visually annoying blurry images due to inevitable information loss. This is due to the nature of imaging sensors, which accumulate incoming light for a certain amount of time to produce an image. During exposure time, if image sensors move, motion blurred images will be obtained. Especially, such a motion blur phenomenon often occurs in a dim lighting environment where a long exposure time is required. If the motion blur is shift-invariant, it can be modeled as the convolution of a latent image I with a motion blur kernel K, i.e., a point spread function (PSF), in which the kernel describes the trace of the image sensor.

$$B = I \otimes K, \qquad (1)$$

where B is an input blurred image and $\otimes$is the convolution operator. The main goal of deblurring is to reconstruct the latent image I from the input blurred image B. In general, image deblurring can be categorized into two types: single-imagedeblurring and multi-image deblurring. In the single image deblurring, unknown blur kernel and latent image are estimated and reconstructed from a single blur image [1-5, 13-15]. For example, Xu and Jia proposed a two-phase kernel estimation algorithm to separate computationally expensive non-convex optimization from quick kernel initialization [4]. However, their motion deblurring scheme may fail if considerably strong and complex textures exist in the latent image. Some have used the fact that deblurring can benefit from consecutive multiple images [6-9]. For instance, Yuan et al. presented an accurate kernel estimation using two images, of which one is noisy but has sharp edges, and the other is motion blurred; they also proposed a residual deconvolution to reduce ringing artifacts inherent in image deconvolution [8]. The above-mentioned multi-image deblurringalgorithms assumed that there was no motion between the multiple images. So, they are not suitable for reconstructing blurred frame(s) that may occur in general video sequences.

In order to overcome this problem, several video deblurring algorithms have been developed recently [10-11]. The authors proposed a video deblurring algorithm using motioncompensation between adjacent blurred/unblurred image pair and residual deconvolution [11]. Our previous work provides outstanding deblurring performance, but is still weak against non-translational motion which may often exist between neighboring images.

Thus, we present an improved video deblurringalgorithm that utilizes more accurate motion compensation (MC) based on the neighborhood of unblurred frames. First,an initial blur kernel of an input blurred frame is estimated. Second, the temporally previous/next unblurred frames nearest to the blurred frame are selected. Next, the selected frames are deliberately blurred using the initially estimated kernel. Between those two frames and the current frame, the bidirectional MC is performed. Then, the blur kernel is reestimatedusing the input blurred frame and its motioncompensatedpredictors, and deconvolution based on the reestimatedblur kernel is finally applied to the blurred frame. This entire process is iterated until the acceptable visual quality is obtained. The experimental results show that the proposed algorithm provides significantly better visualquality, and it also shows higher ISNR (the increase in signal to noise ratio) than the state-of-the-art deblurring algorithms.

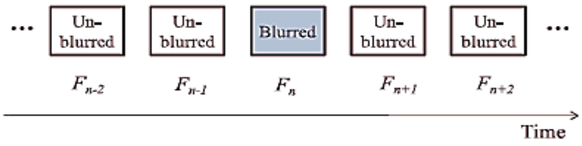


Fig. 1. Example of a blurred frame in a video sequence.

II. PROPOSED ALGORITHM

This paper assumes that the blur kernel is shift-invariant, andthat the blur phenomenon sparsely happens in a video sequence. In general, a sparsely occurring blurred frame in a video sequence may be recorded by digital camcorder under a dim lighting environment. Our goal is to reconstruct a high quality version of the blurred frame in the video sequence. Let B, R1 and R2 denote the target blurred frame and itsnearest unblurred frames, respectively. Note that the temporally previous and next unblurred frames are selected so that they are nearest to the input blurred frame. Fig. 1 shows the overview of the proposed algorithm. The main contribution of this paper in comparison with our previouswork [11] is to significantly improve deblurring performance by employing bidirectional motion compensation between B, R1, and R2 and to adopt optical flow instead of conventional MC such as block-matching algorithm (BMA). The mfollowing subsections describe the key components of the proposed algorithm in detail.

2.1. Initial kernel estimation and registration betweenblurred and unblurred frames:

This step is to generate a sharp reference image that ismotion-compensated from R1 (or R2) from the motion vector(MV) field between B and R1 (or R2). In general, it is veryhard to find an accurate MV field between blurred andunblurred frames. So, we estimate an initial blur kernel for Band artificially blur R1 and R2 by using the estimated blurkernel Ki. For the kernel estimation, we employed a fastkernel estimation algorithm proposed in [3].Next, bidirectional MC is applied between B and theartificially blurred R1 and R2, i.e., Ib1 and Ib2. In order tominimize the motion-compensated error and artifacts, weadopted well-known optical flow estimation presented in[12]. By applying the optical flow algorithm to Ib1 and Ib2,we can obtain two motion-compensated predictors. Then, wechoose the best matched block having smaller MC errorbetween two predictors on an L×L block basis, and extract the central M×M region of the selected predictor block. Inthis paper, L and M were empirically determined to 16 and 4, respectively and sum of absolute differences (SAD) were employed as a measure of MC error. Finally, we can obtain a sharp reference frame Im for the deblurring of B.

2.2. Kernel re-estimation:

Now, we re-estimate the blur kernel by using Im and B .Note that as m I is closer to the original latent frame, the reestimatedkernel may be more similar to its original kernel.mEq. (1) can be represented in matrix form as follows:

$$\mathbf{b} = \mathbf{A}\mathbf{k}\,, \qquad (2)$$

where b , A , and k denote matrix forms of B, I, and K, respectively. Let K' be the re-estimated kernel. We can derive the best K' via a minimization process of Eq. (3)

$$\mathbf{k}' = \min_{\mathbf{k}} \|\mathbf{A}\mathbf{k}-\mathbf{b}\|^2 + \lambda\|\mathbf{k}\|^2 \qquad (3)$$

In Eq. (3), Tikhonov regularization is employed to find a stable solution, and λ is empirically set to 5. In order to solve Eq. (3), we use the popular conjugate gradient (CG) method. Then, the gradient of the cost is defined by

$$\frac{\partial}{\partial \mathbf{k}}\left[\|\mathbf{A}\mathbf{k}-\mathbf{b}\|^2 + \lambda\|\mathbf{k}\|^2\right] = 2\mathbf{A}^T\mathbf{A}\mathbf{k} + 2\lambda\mathbf{k} - 2\mathbf{A}^T\mathbf{b} \qquad (4)$$

Eq. (4) should be evaluated many times in the minimization process. So, this direct computation of matrix operations requires heavy computational and storage overhead. Fortunately, since A Ak T and A b T correspond to convolution, we can accelerate the computation by fast Fourier transforms (FFTs), as in Eq. (5).

$$\mathbf{A}^T\mathbf{A}\mathbf{k} = \mathcal{F}^{-1}\left[\overline{\mathcal{F}(I)} \circ \mathcal{F}(I) \circ \mathcal{F}(K)\right], \quad \mathbf{A}^T\mathbf{b} = \mathcal{F}^{-1}\left[\overline{\mathcal{F}(I)} \circ \mathcal{F}(B)\right]. \qquad (5)$$

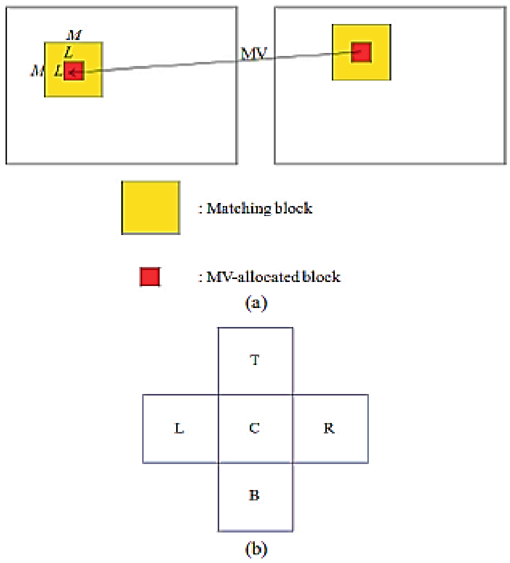


Fig.5(a)Motion Estimation (b)Four neighbor Blocks for OBMC

$$\underset{W^C}{\begin{bmatrix} 4 & 5 & 5 & 4 \\ 5 & 6 & 6 & 5 \\ 5 & 6 & 6 & 5 \\ 4 & 5 & 5 & 4 \end{bmatrix}} \quad \underset{W^T}{\begin{bmatrix} 2 & 2 & 2 & 2 \\ 1 & 1 & 1 & 1 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}} \quad \underset{W^B}{\begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 1 & 1 & 1 & 1 \\ 2 & 2 & 2 & 2 \end{bmatrix}} \quad \underset{W^L}{\begin{bmatrix} 2 & 1 & 0 & 0 \\ 2 & 1 & 0 & 0 \\ 2 & 1 & 0 & 0 \\ 2 & 1 & 0 & 0 \end{bmatrix}} \quad \underset{W^R}{\begin{bmatrix} 0 & 0 & 1 & 2 \\ 0 & 0 & 1 & 2 \\ 0 & 0 & 1 & 2 \\ 0 & 0 & 1 & 2 \end{bmatrix}}$$

Fig.6 Weight matrices for Matrices

$$\begin{aligned} I_m(i,j) = {} & W^C(i,j)\cdot R^C(i,j) + W^T(i,j)\cdot R^T(i,j) \\ & + W^B(i,j)\cdot R^B(i,j) + W^L(i,j)\cdot R^L(i,j) \\ & + W^R(i,j)\cdot R^R(i,j) \end{aligned} \tag{6}$$

Here, F(X) and F(X) indicate the FFTs of a matrix Xand its complex conjugate, respectively. Also, o stands for pixel-wise multiplication. Finally, the re-estimated kernel K' is normalized for energy preservation.

2.3. Residual de-convolution:

Given the re-estimated blur kernel K', the deblurred frame I'can be reconstructed from m I and B, as shown in Fig. 2. In this paper, we employ the concept of the residual deconvolution proposed by Yuan et al. in [8]. Instead of doing the deconvolution directly on B, Yuan et al. applied to deconvolution to the residual blurred image so as to reduce ringing artifacts. However, if there is a shift between the neighboring frame pairs, such a deconvolutionrarely works for video sequences. So, we apply the deconvolution to B and Im which is motion-compensated from the unblurredframes. Thus, we perform deconvolution on the residual blurred frame _B ≡ _I ⊗ K′ to recover the motioncompensatedresidual frame _I . _B is derived from the following equation:

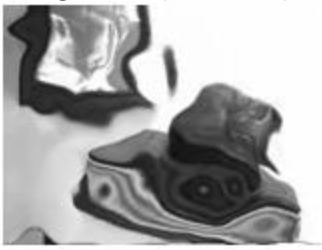
$$\Delta B = B - (I_m \otimes K') \tag{7}$$

From Eq. (6), _I ' can be derived via deconvolution. Here, we employed a simple deconvolution algorithm using a Gaussian prior. Finally, the deblurred frame is obtained by

I IIm ′ = + _ ′ . Note that as MC becomes more accurate, _B has less energy. Therefore, while preserving sharp edges thanks to m I , the residual deconvolution can predict _I ′with noticeably suppressed ringing artifacts. For more accurate deblurring, the above-mentioned processes are iterated as shown in Fig. 1. Note that at the 1st iteration, MC is applied to Ib1, Ib2 and B, but from the next iterations it is performed directly between R1, R2 and I' to find accurate MVs. We were able to observe that thedeblurring results converge at about the 10th iteration, so we fixed the number of iterations at 10 in this paper.

III. EXPERIMENTAL RESULTS

For performance evaluation of the proposed algorithm, weused well-known 1280 720 video sequences, i.e., City and Jets. Due to the computational burden, the central 640360 of each frame in the sequences was cropped and used for the following experiments. We compared the proposed algorithm with two state-of-the-art algorithms: Xu's [4], and Lee's algorithms [11] in terms of subjective visual quality as well as objective visual quality. For quantitative evaluation in terms of objective visual quality, we employed the socalled ISNR (the increase in signal to noise ratio) proposed by Almeida [5]. To calculate ISNR values, we artificially blurred the test video sequences with two different blur kernels (see Fig. 3 (a) and Fig. 4 (a)). The blur kernels whose sizes are 21·21 and 25·25, respectively were illustrated at the upper-left corners of Fig. 3 (a) and Fig. 4 (a). Fig. 3 clearly shows that the proposed algorithm outperforms the other algorithms. Note that because the proposed algorithm employs more accurate motion compensation than our previous work [11], it successfully reconstructs straight edges of the building in comparison with the other methods. Also, we can find from Fig. 4 that the proposed algorithm produces sharper characters than the others. In addition, we showed the computed ISNR values in Fig. 3 and Fig. 4 for quantitative comparison. Even from the perspective of ISNR values, the proposed algorithm is superior to several state-of-the-art algorithms (see Table I).



Detected Blur Image from Video

Input

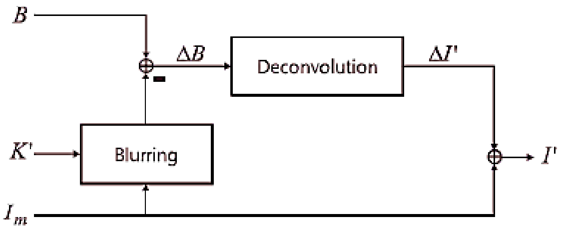
output

TABLE I
ISNR comparison results for several video sequences [dB].

		Fergus's	Shan's	Cho's	Xu's	Prop
City	Mean	4.65	3.43	4.85	6.62	9.64
	Variance	1.34	0.16	0.72	0.05	0.38
Jets	Mean	2.54	5.30	3.21	5.18	7.90
	Variance	3.38	2.79	0.06	0.03	0.05

IV. CONCLUSION

This paper presents an iterative video deblurring algorithm utilizing a neighborhood of unblurred frames. First, the sharp predictor of a blurred frame is derived from its neighboring unblurred frames using bidirectional motion compensation. Second, an accurate blur kernel is reestimated using the predictors and the blurred frame. Third, again using both of those frames, a residual deconvolution is proposed to significantly reduce the ringing artifacts inherent in conventional deconvolution. From the experimental results we proved that the proposed algorithm reconstructs details better than conventional algorithms do, with fewer ringing artifacts. In this paper, we assume that the blur kernel is uniform. As for further work, we plan to extend our approach to non-uniform blur kernels.



V. ACKNOWLEDGEMENT

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