INTERFRAME MOTION DEBLURRING USING SPATIO-TEMPORAL REGULARIZATION

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ABSTRACT

A motion deblurring method with spatio-temporal regularization is presented. In conventional motion deblurring, the best image for each frame is restored individually. The aim of proposed method is that the all frames achieve the same level of smoothness, and an extended total variation is introduced to the deconvolution approach. Our method can be applied to a video clip acquired by handheld camera with camera shakes. Experimental results show that the strongly blurred images are deblurred sufficiently and the temporal change is suppressed.

Index Terms— Image restoration, Video signal processing, Motion deblurring

1. INTRODUCTION

Various motion deblurring approaches have been studied to improve image sharpness[1],[2]. Motion estimation is commonly performed first, and then point spread functions (PSFs) of motion blur are estimated from the motion vectors and perform deconvolution. In [2], we have used nonlinear regularization approach and have suppressed ringing artifacts. These motion deblurring methods are considered a kind of intraframe approach, and the best image for each frame is restored individually.

In many video clips, motion vectors are space-variant and time-variant. Then motion blur is space-varying and time-varying in the strength and direction. The time-varying blur is conspicuous, and can be perceived as flicker. For example, video clips acquired by handheld cameras often include oscillatory motions caused by undesirable camera shakes. Such video clips are also degraded by oscillatory motion blur over the image. Alternate blurred frames and sharp frames are included.

In this paper, we propose an interframe motion deblurring approach which aims that all frames achieve the same level of smoothness. The total variation is extended to spatio-temporal domain, and introduced into the deconvolution approach to smooth the temporal change of blur.

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2. MOTION DEBLURRING WITH SPATIO-TEMPORAL REGULARIZATION

The degradation process is defined in spatio-temporal domain as

$$\begin{aligned} I_{x,y,t} &= \varphi^{(x,y,t)} \circ f_{x,y,t} + n_{x,y,t} \\ &= \sum_{(k,l)\in\Phi} \varphi^{(x,y,t)}_{k,l} \cdot f_{x+k,y+l,t} + n_{x,y,t}, \end{aligned} \tag{1}$$

where f, I are the original and degraded video images, and n is random additive noise. (x, y) is the coordinate of the image, and t is the frame numbers. φ is the PSF of motion blur at pixel (x, y), and Φ is the support of the PSFs. We assume that motion blur operator is linear, but not spatially invariant. This means that the motion is linear and constant during an integration time at each frame. Them, the discrete PSF of motion blur φ can be defined as the line integral along the motion vector at each pixel, and estimated by taking a spatial aperture of pixels into account. We also assume that the time varying of intensity I is mainly caused by the time varying of motion blur and noises. Therefore, $f_{x,y,t}$ is required not to have any motion. It can be obtained by digital video stabilization, which aligns all frames. In addition, $f_{x,y,t}$ is also assumed not to have moving object regions.

Solving this equation is an ill-posed problem and a regularization term R is commonly introduced. The problem is then to find a restored image f which minimizes the energy function E,

$$\hat{f} = \arg\min_{f} \{E[f]\}, \quad E[f] = F + R, \tag{2}$$

$$F = \sum_{x,y,t} \left[\frac{\lambda}{2} \left(\varphi^{(x,y,t)} \circ f_{x,y,t} - I_{x,y,t} \right)^2 \right], \tag{3}$$

where F is the data fidelity term commonly defined by the square function to indicate the degree of error and deviation from the model. λ is a positive parameter to balance the contributions from two terms.

For the regularization term R, we introduce an extended total variation norm with the spatio-temporal gradient. The total variation in image processing is introduced by Rudin, Osher, Fatemi for image denoising[3], and then applied to regularization of image restoration[4]. The conventional total variation is defined as

$$R = \sum_{x,y} \|\nabla f_{x,y}\|, \quad \nabla f_{x,y} = \left(\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}\right), \tag{4}$$

and it has effects to smooth only small oscillation and preserve image edges. We define an extended spatio-temporal total variation as follows.

$$R = \sum_{x,y,t} \|\nabla f_{x,y,t}\|, \quad \nabla f_{x,y,t} = \left(\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}, \frac{\partial f}{\partial t}\right). \tag{5}$$

It is extended to have a temporal smoothing effect with preserving temporal edges. Eq.(5) has been applied to deinterlacing in [5].

The minimization of the energy functional E is derived from the Euler-Lagrange equation.

$$\lambda \left\{\varphi^* \circ (\varphi \circ f - I)\right\}_{(x,y,t)} - \mathrm{div}\left\{\frac{\nabla f}{\|\nabla f\|}\right\}_{(x,y,t)} = 0. \tag{6}$$

Based on the gradient decent method, an iterative scheme is derived as follows,

$$\begin{cases} f^{(\tau+1)}_{(x,y,t)} = f^{(\tau)}_{(x,y,t)} \\ \qquad - \varepsilon[\lambda \left\{\varphi^* \circ (\varphi \circ f^{(\tau)} - I)\right\}_{(x,y,t)} \\ \qquad\qquad - \mathrm{div}\left\{\frac{\nabla f^{(\tau)}}{\|\nabla f^{(\tau)}\|}\right\}_{(x,y,t)}], \\ f^{(0)}_{(x,y,t)} = I_{(x,y,t)}, \end{cases} \tag{7}$$

where φ^* is an adjoint operator of φ, and τ is the iteration number. All frames are iterated simultaneously, and RGB colors are iterated independently.

Since the method adopts the spatially variant blur model, the minimization problem cannot be solved in a closed non-iterative way, and it leads to an iterative restoration algorithm. The forward difference is used as discretization of the partial derivative of f.

$$\begin{cases} \frac{\partial f}{\partial x} = f_{x+1,y,t} - f_{x,y,t} \\ \frac{\partial f}{\partial y} = f_{x,y+1,t} - f_{x,y,t} \\ \frac{\partial f}{\partial t} = w(f_{x,y,t+1} - f_{x,y,t}) \\ \mathrm{div}[z] \equiv \\ \quad (z_{x,y,t} - z_{x-1,y,t}) + (z_{x,y,t} - z_{x,y-1,t}) + w^2(z_{x,y,t} - z_{x,y,t-1}), \end{cases} \tag{8}$$

where w is a positive constant which means the ratio of the discretization interval of temporal to spatial directions.

3. EXPERIMENTAL RESULTS

First, we tested the deblurring method on a test video clip in four frames containing artificial motion blur. Fig.1 shows the generated video clip. (a) is the original image cropped from a ISO standard image data, and the image size is 300×300 pixels. (b)-(e) are the blurry images generated on the assumption that the camera is rotating. The rotation velocities θ [deg/frame] are also shown in Fig.1. (e) is strongly blurred, and (b) is relatively softly blurred. (b)-(e) are just motion blurred not moving, and random Gaussian noise with zero mean and standard deviation of 10 are added. Fig.2 shows the deblurred results of Fig.1. Only the upper half of the frame#1 and #4 are shown. The result of the conventional intraframe deblurring is shown for comparison. (g) is sharper than (e), and ringing artifacts are not produced in each deblurred image.

Fig.3 (a) shows the PSNR between the original and deblurred images. The improvement of frame#4 by interframe deblurring is much higher than conventional intraframe deblurring. The PSNR of interframe result is almost constant in all frames, and the temporal change in the strength of blur is considered to be suppressed. Fig.3 (b) shows the universal image quality index between the original and deblurred images. The universal image quality index is introduced in [7] to quantify the similarity. The similarity of interframe result is higher than intraframe result, and almost constant in all frames.

Secondly, we used a short time video clip acquired by a handheld video camera with camera shake. Motion estimation is performed by block matching algorithm, and then video stabilization is performed based on projective transformation [6]. After stabilization, each frame is cropped to 720*480 pixels and the length is 30 frames. The parameters are determined through experiments as follows, $\lambda = 3, \varepsilon = 0.03, w = 10$, and the number of iteration is fixed to 50.

Fig.4 (a) shows a sample frame of the input stabilized video clip. The yellow borders are generated by stabilization. (b) is the enlarged part of (a), and (c) is the next frame of (b). (c) is more blurry and noisy than (b). (f) and (g) are deblurred images by the interframe approach. (e) is still blurry, but (g) looks as sharp as (f).

Fig.5 (a) shows the universal image quality index at each frame compared to the first frame of the input video clip. The similarity of interframe result is higher than intraframe result. Fig.5 (b) shows the blurriness measure at each frame to quantify the deblurring performance defined by

$$B_t = \left[\sum_{x,y}\left\{(f_{x+1,y,t} - f_{x,y,t})^2 + (f_{x,y+1,t} - f_{x,y,t})^2\right\}\right]^{-1}. \tag{9}$$

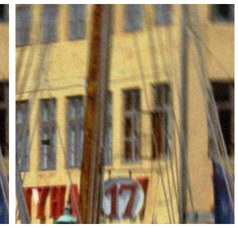
The blurriness of input images changes significantly. The result of the interframe deblurring has only small changes. The

(a) Original

(b) Frame#1, θ=0.5

(c) Frame#2, θ=1

(d) Frame#3, θ=1.5



(e) Frame#4, θ=2

Fig. 1. Test video clip.

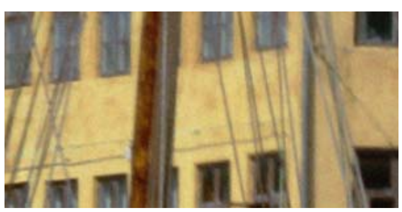
(a) Original image

(b) Input blurry image #1

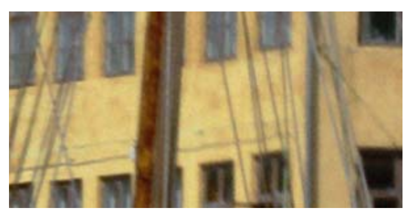
(c) Input blurry image #4

(d) Intraframe deblurring #1

(e) Intraframe deblurring #4

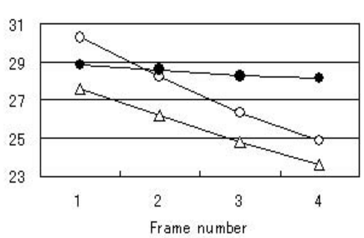


(f) Interframe deblurring #1

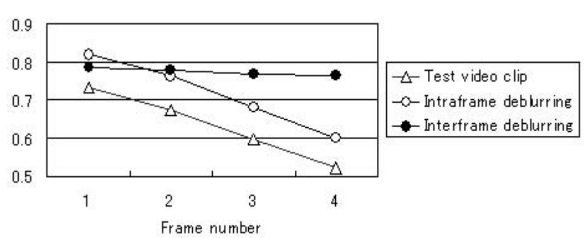


(g) Interframe deblurring #4

Fig. 2. Deblurred images.



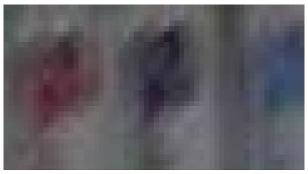
(a) PSNR.



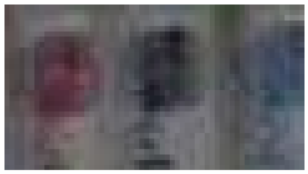
(b) Universal image quality index

Fig. 3. Experimental results.

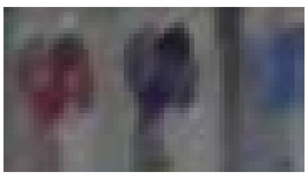
(a) Input image #23



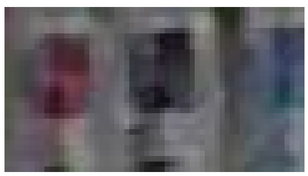
(b) Input image#23



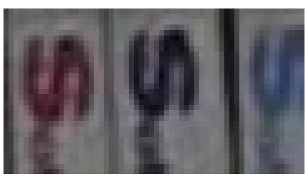
(c) Input image#24



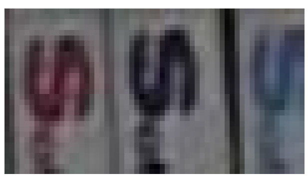
(d) Intraframe#23



(e) Intraframe#24



(f) Interframe#23



(g) Interframe#24

Fig. 4. Deblurred images.

temporal change of blurriness is considered to be suppressed by the interframe approach.

4. CONCLUSIONS

We have proposed the interframe motion deblurring method with the spatio-temporal regularization, and compared it with the conventional intraframe method. Experimental results show that the strongly blurred images are deblurred sufficiently and the temporal change of blur is suppressed by the interframe approach.

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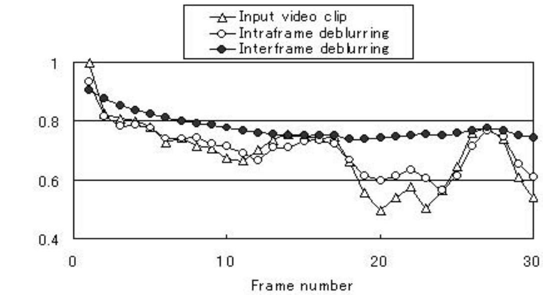
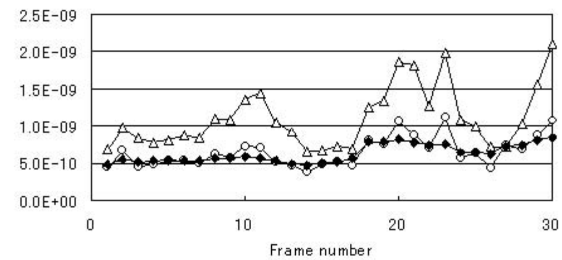


(a) Universal image quality index



(b) Blurriness measures

Fig. 5. Experimental results.

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