Generalized Video Deblurring for Dynamic Scenes

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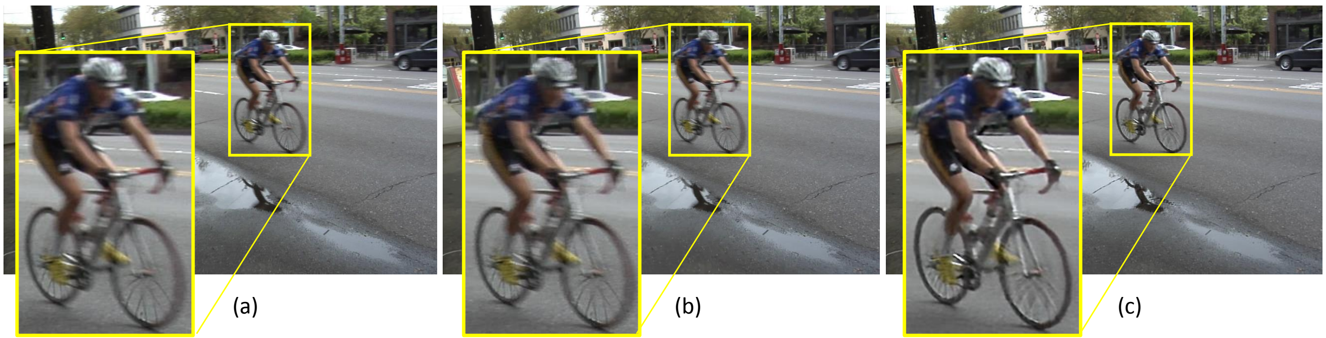

Figure 1: (a) Blurry frame of the bicycle sequence. (b) Deblurring result of Cho et al.[1]. (c) Our result.

Introduction

Several state-of-the-art video deblurring methods are based on a strong assumption that the captured scenes are static. These methods fail to deblur blurry videos in dynamic scenes. We propose a video deblurring method to deal with general blurs inherent in dynamic scenes, contrary to other methods. To handle locally varying and general blurs caused by various sources, such as camera shake, moving objects, and depth variation in a scene, we approximate pixel-wise kernel with bidirectional optical flows. Therefore, we propose a single energy model and efficient solver that simultaneously estimates optical flows and latent frames to solve our deblurring problem.

Key Idea

In conventional works, the motion blurs of each frame are approximated using parametric models such as homographies and affine models [1, 3]. However, blur kernels in dynamic scenes cannot be parameterized using global or segment-wise parameterization. Therefore, pixel-wise kernel estimation is necessary to cope with general blurs and we approximate the pixel-wise blur kernel using bidirectional optical flows. Our piece-wise linear kernel at frame i using bidirectional optical flows $\mathbf{u}_{i\to i-1}$ and $\mathbf{u}_{i\to i+1}$, and camera duty cycle τ_i is illustrated in Fig. 2. Using this pixel-wise kernel approximation, we can easily manage multiple different blurs in a frame unlike conventional methods. The superiority of our kernel model is shown in Fig. 3. Our kernel model fits blurs from differently moving objects and camera shake much better than the conventional homography-based model.

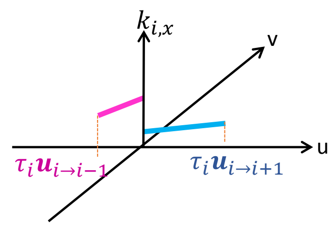

Figure 2: Piece-wise linear blur kernel at pixel location $\mathbf{x}$ using bidirectional optical flows.

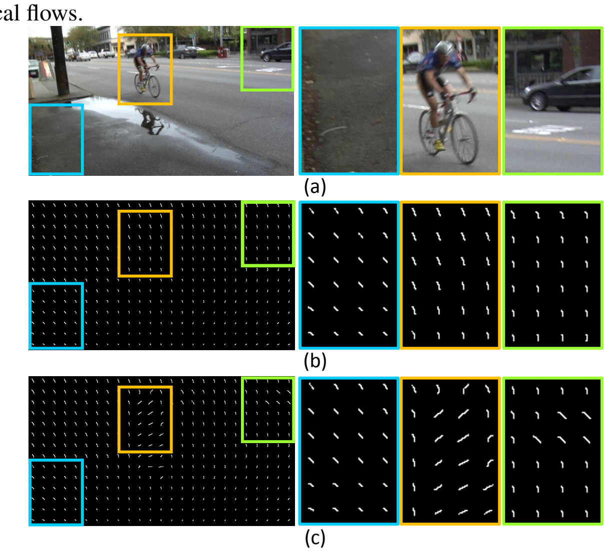

Figure 3: (a) Blurry frame of a video in dynamic scene. (b) Locally varying kernel using homography. (c) Our pixel-wise varying kernel using bidirectional optical flows.

Energy Model

We cast pixel-wise kernel estimation problem as an optical flows estimation problem and our final objective function for video deblurring is expressed as follows:

$$\begin{aligned}\min_{\mathbf{L},\mathbf{u}} \; & \lambda \sum_i \sum_{\partial_*} \|\partial_* \mathbf{K}_i(\tau_i, \mathbf{u}_{i\to i+1}, \mathbf{u}_{i\to i-1})\mathbf{L}_i - \partial_* \mathbf{B}_i\|^2 + \sum_i |\nabla \mathbf{L}_i| + \\ & \sum_i \sum_{n=-N}^{N} g_i(\mathbf{x})|\nabla \mathbf{u}_{i\to i+n}| + \sum_i \sum_{n=-N}^{N} \mu_n |\mathbf{L}_i(\mathbf{x}) - \mathbf{L}_{i+n}(\mathbf{x}+\mathbf{u}_{i\to i+n})|,\end{aligned} \tag{1}$$

where $\mathbf{L}$ and $\mathbf{u}$ denote the set of unknown latent frames and optical flows. Linear operator ∂_* denotes the partial derivative filters and $\mathbf{B}_i$ is blurry frame at i. Parameters λ and μ_n control the weight of each term and n denotes the index of neighboring frames at i. In (1), the first term denotes data term. Notably, kernel matrix $\mathbf{K}_i$ is a function of optical flows. Similar to [2], the second and third term denote edge-map, g_i, coupled spatial regularization terms. The last term denotes temporal regularization. To minimize, we divide the original problem into sub-problems and use conventional alternating optimization techniques used in [2].

Experiments

By minimizing the objective function in (1), we achieve significant improvements in numerous real challenging videos that other methods fail to do, as shown in Fig.1. Furthermore, we estimate more accurate optical flows compared with the state-of-the-art flow estimation method, that handles blurry images. The performances are demonstrated in our extensive experiments.

References

[1] Sunghyun Cho, Jue Wang, and Seungyong Lee. Video deblurring for hand-held cameras using patch-based synthesis. *ACM Transactions on Graphics*, 31(4): 64:1–64:9, 2012.

[2] Tae Hyun Kim and Kyoung Mu Lee. Segmentation-free dynamic scene deblurring. In *CVPR*, 2014.

[3] Jonas Wulff and Michael J. Black. Modeling blurred video with layers. In *ECCV*, 2014.

This is an extended abstract. The full paper is available at the Computer Vision Foundation webpage.