Fast Non-uniform Deblurring using Constrained Camera Pose Subspace

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Introduction: Camera shake during exposure time often results in non-uniform blur across the entire image. Recent algorithms [1, 3] model the non-uniform blurry image B as a linear combination of images observed by the camera at discretized poses θ, and focus on estimating the time fraction w_θ positioned at each pose,

$$B = \sum_{\theta \in S} w_\theta (K_\theta L) + n, \tag{1}$$

where K_θ is the matrix that warps latent image L to the transformed copy at a sampled pose θ and S denotes the set of sampled camera poses. While these algorithms show promising results, they entail high computational cost as the high-dimensional camera motion space and the latent image have to be computed during the iterative optimization procedures.

In this paper, we propose a fast single-image deblurring algorithm to remove non-uniform blur. We first introduce an initialization method that facilitates convergence and avoid local minimums of the formulated optimization problem. We then propose a new camera motion estimation method which optimizes on a small set of pose weights of a constrained camera pose subspace at a time rather than using the entire space. We develop an iterative method to refine the camera motion estimation and introduce perturbation at each iteration to obtain robust solutions. Fig. 1 summarizes the main steps of our method.

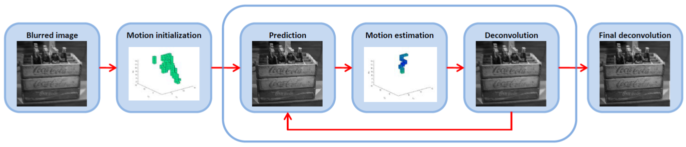

Figure 1: Algorithm overview

Initialization: Motivated by the backprojection techniques in image processing which are used to reconstruct the 2-D signal from its 1-D projections, we develop a method to reconstruct the camera motion from multiple blur kernels (the projection of the camera motion trajectory). From multiple estimated blur kernels of different regions, the direct approximation of the camera motion is to use the inverse transformation by duplicating the 2-D blur kernels across the camera motion space. That is, for each entry in blur kernel k_l, we determine the possible camera poses whose projection $p(\theta, l)$ at this site l is the interest entry and then duplicate the weight of this entry across all the possible camera poses. This procedure is called backprojection commonly used in image reconstruction and we denote $bp(k_l, l)$ as the backprojected value by

$$bp(k_l, l) = \sum_i \sum_{\{\theta | p(\theta, l) = i\}} k_l(i) \Gamma(\theta), \tag{2}$$

where $\Gamma(\theta)$ is an indicator function of camera poses with value 1 for pose θ and 0 for others. To obtain better results, we formulate the initialization estimation with an optimization problem and enforce sparse constraints of the weighs to get better reconstruction results due to the fact that the camera motion trajectory is sparse in the motion space. Moreover, we assign each backprojection function $bp(k_l, l)$ a confidence value $a(l)$ based on the distance of the site l to the optical center which can usually be assumed to be the center of the image. Thus, the initial estimation of weights W is formulated as,

$$\hat{W} = \arg\min_W ||W - \sum_l a(l) bp(k_l, l)||^2 + ||W||_1. \tag{3}$$

Weight Estimation on Constrained Pose Subspace: We formulate the weight estimation problem as

$$\min_W \sum_{\partial_*} \alpha_* || \sum_{\theta \in S} w_\theta \partial_* (K_\theta \widetilde{L}) - \partial_* B||^2 + \beta ||W||^2, \qquad \text{s.t.} \quad W \geq 0. \tag{4}$$

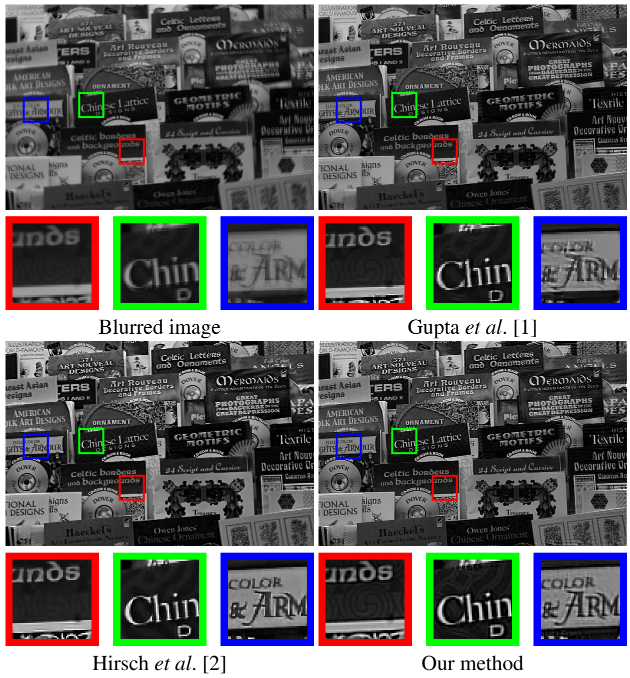

Figure 2: Comparison with state-of-the-art single image deblurring methods for spatially variant blur.

where $\partial^* \in \{\partial_x, \partial_y, \partial_{xx}, \partial_{xy}, \partial_{yy}\}$ denotes the partial derivative, and $\alpha_* \in \{\alpha_1, \alpha_2\}$ is the weight for partial derivative of different order. In this formulation, a direct optimization on the whole pose set S is computationally expensive. In this work, we propose to optimize Eqn. 4 only on a sparse subset of poses referred as an active set $A \subset S$. The active set represents the set of poses which are likely to lie on the motion trajectory.

We use the threshold strategy with a threshold ε to determine the active set at each iteration. Suppose $A^{(i)} = \{\theta_1, \ldots, \theta_{p+q}\}$ is the active set at iteration i, and the corresponding weights $W_A^{(i)} = \{w_1, \ldots, w_{p+q}\}$ is sorted in the descending order $w_1 \geq \ldots \geq w_p \geq \varepsilon \geq w_{p+1} \geq \ldots \geq w_{p+q}$. At iteration $i+1$, we set the new active set to be

$$A^{(i+1)} = \{\theta_1, \ldots, \theta_p, \hat{\theta}_{p+1}, \ldots, \hat{\theta}_{p+q}\}, \tag{5}$$

by deleting the smallest q weights $\{\theta_{p+1}, \ldots, \theta_{p+q}\}$ and adding new poses $\{\hat{\theta}_{p+1}, \ldots, \hat{\theta}_{p+q}\}$ as perturbation. We obtain the new poses by sampling based on the previous active set $A^{(i)}$ using a Gaussian distribution (with small variance). Once we determine the active set A, we assign the weights for the poses of the inactive set to be 0, and estimate the weights of poses in the active set by replacing S with A in Eqn. 4. Since the active set is already sparse with respect to the whole space, it is not necessary to introduce a sparse regularization term in the above optimization problem.

Experimental Results: We evaluate the proposed algorithm against several state-of-the-art single image deblurring methods for spatially variant blur (Fig. 2 as an example). Our MATLAB implementation is about 1.5 times faster than the MATLAB implementation of [2], the most efficient single-image non-uniform deblurring method to the best of our knowledge.

[1] A. Gupta, N. Joshi, L. Zitnick, M. Cohen, and B. Curless. Single image deblurring using motion density functions. In *ECCV*, pages 171–184, 2010.

[2] M. Hirsch, C. J. Schuler, S. Harmeling, and B. Scholkopf. Fast removal of non-uniform camera shake. In *ICCV*, pages 463–470, 2011.

[3] O. Whyte, J. Sivic, A. Zisserman, and J. Ponce. Non-uniform deblurring for shaken images. In *CVPR*, pages 491–498, 2010.