Blur Kernel Estimation using Normalized Color-Line Priors

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This paper proposes a single-image blur kernel estimation algorithm that utilizes the normalized color-line prior to restore sharp edges without altering edge structures or enhancing noise. The proposed prior is derived from the color-line model [4], a local statistical model which claims that pixel colors $\mathbf{x}$ within a local image patch can be well represented by linear combinations of two color centroids:

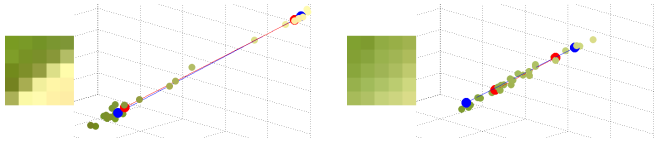
$$\mathbf{x} = \alpha \mathbf{c}_1 + (1-\alpha)\mathbf{c}_2, \tag{1}$$

where $\mathbf{c}_1$ and $\mathbf{c}_2$ are centers of two color clusters, and α is the linear mixing parameter. Joshi *et al*. [2] adopted the color-line model to non-blind deconvolution. They used the k-means algorithm to find two color centers for every image patch and built a prior for image reconstruction. Different from their approach, we propose to use *the normalized color-line prior* for *blur kernel estimation* based on two observations. First, the k-means centers are not effective enough for blind deconvolution because the blur process would have shrunk the distance between two centers of an image patch. Second, the color-line prior is more effective for blur kernel estimation than image reconstruction.

As for the first observation, Figure 1 visualizes the color-line distribution of a sharp patch and its blurred version in the RGB space. As seen from this figure, the centers found by the k-mean algorithm from the blur patch are too close and not effective for restoring contrast of the patch. To address the problem, we design the normalized color-line prior for a patch P:

$$\rho(P) = \frac{\sum_{j\in P}\sum_{k=1}^{2} r_{jk}\left\|\mathbf{x}_j - \mathbf{c}_k\right\|^2}{\left\|\mathbf{c}_1 - \mathbf{c}_2\right\|^2}, \tag{2}$$

where $r_{jk} = 1$ if $\mathbf{x}_j$ is assigned to the k-th cluster, and $r_{jk} = 0$ otherwise. By minimizing Equation (2), pixel colors are pulled close to $\mathbf{c}_1$ and $\mathbf{c}_2$ while the distance between $\mathbf{c}_1$ and $\mathbf{c}_2$ is stretched. Thus, the contrast is enhanced and the patch becomes sharper.



(a) Sharp patch (b) Blurred patch

Figure 1: The color-line distribution of a sharp patch and its blurred version. The red dots are k-means centers, and the blue dots are centers found by our model. The blur process shrinks the distance between two color clusters and brings close two clusters. Thus, the k-mean centers found from the blurred patch is less effective for deblurring than the ones found by our model.

Our second observation is that the color-line prior is more effective for patches around salient image structures such as edges than other regions such as flat regions, texture regions and noisy patches. Thus, it is more appropriate to apply it on salient structures only for kernel estimation rather than relying on it for reconstructing the whole image. Our approach is a MAP-based framework that iteratively solves the latent image x and the blur kernel k for the input blur image y using a coarse-to-fine scheme.

1. x**-step**. Given the current estimation of the blur kernel k, we minimize the following objective function to obtain an intermediate image $\hat{x}$:

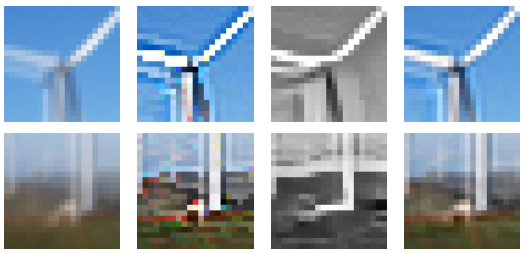
$$E_x(\hat{\mathbf{x}}) = \|\mathbf{M}\mathbf{y} - \mathbf{M}\mathbf{K}\hat{\mathbf{x}}\|_2^2 + \lambda \sum_{*\in\{h,v\}} \|\mathbf{M}\nabla_*\hat{\mathbf{x}}\|_2^2 + \frac{\beta}{|M|}\sum_{i\in M}\rho(\mathbf{P}_i\hat{\mathbf{x}}). \tag{3}$$

Here, $\mathbf{M}$ encodes the edge mask M, a binary mask indicating pixel locations that we want to apply our color priors; $\hat{\mathbf{x}}$ and $\mathbf{y}$ are vector forms of $\hat{x}$ and y; and $\mathbf{K}$ is the convolution matrix corresponding to k. ∇_h and ∇_v are the matrix forms of the partial derivative operators in horizontal and vertical directions respectively. $\mathbf{P}_i$ is a binary extraction operator that extracts the patch centering at i. Since $\rho(\mathbf{P}_i\hat{\mathbf{x}})$ is non-linear, we iterate between updating $\mathbf{c}_1$ and $\mathbf{c}_2$ and updating $\hat{\mathbf{x}}$ to solve Equation (3).

2. k**-step**. Given the current intermediate image $\hat{x}$, we minimize the following objective function for obtaining the blur kernel k:

$$E_k(k) = \sum_{*\in\{h,v\}} \|\nabla_* y - k\otimes(M\odot\nabla_*\hat{x})\|_2^2 + \gamma\|k\|_1, \tag{4}$$

where $\odot$ is the component-wise multiply operator.



(a) Input (b) Shock filter (c) Patch prior (d) Our prior

Figure 2: The intermediate patches constructed using the shock filter [1], the patch prior [5], and our normalized color-line prior.

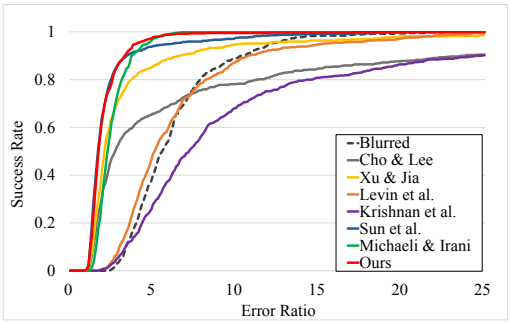


Figure 3: The cumulative distributions of error ratios with different methods. Our method is slightly better than Sun *et al*. [5] and Michaeli and Irani [3], but significantly outperforms the other state-of-the-art methods.

Figure 2 compares the intermediate patches recovered by our method and two other edge-based methods. Our color-line prior restores sharp edges without enhancing noise or altering structures. After estimating blur kernels, we apply the non-blind deconvolution method of Zoran and Weiss [6] to recover the whole latent images. We evaluate our method on Sun *et al*. [5]'s dataset and compare to the state-of-the-art algorithms. Experiments show that our algorithm produces accurate and stable blur kernels, and outperforms the state-of-the-art methods on this large benchmark for image deblurring as shown in Figure 3.

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