Comparison of our algorithm to Joshi CVPR 2008

Taeg Sang Cho
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Joshi *et al*. CVPR2008 minimize the following energy function to find the blur kernel:

$$\hat{k} = \arg\min_k \frac{\|M(B - k \otimes I)\|^2}{2\eta^2} + \lambda\|\nabla k\|^2 \tag{1}$$

where B is an input blurry photograph, k is a blur kernel, I is an image with predicted location of sharp edges, and M is a function to mask predicted edges and their neighborhood. We can distinguish our algorithm from theirs on two fronts: (i) using only perpendicular slices of blurred edges and (ii) using centroid constraints to align blurred edges to enable multi-modal blur estimation.

Our algorithm minimizes

$$\hat{k} = \mathrm{argmin}_k \left\{ \frac{\sum_{i \in E} \|\phi_{\theta_i} - R_{\theta_i} k\|^2}{2\eta^2} + \lambda_1 \|k\|^{\gamma_1} + \lambda_2 \|\nabla k\|^{\gamma_2} \right\} \tag{2}$$

where E is a set of edge samples, R_{θ_i} is a projection operator along the orientation of the i^{th} edge sample, and ϕ_{θ_i} is the blur kernel projection estimated from the i^{th} edge sample. The likelihood term $\frac{\sum_{i \in E} \|\phi_{\theta_i} - R_{\theta_i} k\|^2}{2\eta^2}$ ensures that when we explicitly project the restored blur kernel we recover projections similar to those estimated from the blurred image B. We could rewrite this likelihood term as follows:

$$\frac{\sum_{i \in E} \|\phi_{\theta_i} - R_{\theta_i} k\|^2}{2\eta^2} = \sum_{i \in E} S_{\theta_i} \left(\frac{\left(M(B) - M(k \otimes I)\right)^2}{2\eta^2} \right) \tag{3}$$

where S_{θ_i} is a "slicing" operator that returns a slice of the argument along the perpendicular orientation of the edge i. From this, we observe that our algorithm essentially reduces the dimensionality of the data. Joshi *et al*. in effect establish slicing constraints in virtually all possible orientations using the observation constraint $B - k \otimes I$. Instead of using slicing constraints from virtually all possible orientations, we use only the relevant information (i.e. perpendicular slices) for blur estimation, which improves the computational efficiency. This computational efficiency comes at a price of using just straight edges, as opposed to using curved edges. Because Joshi *et al*. use an observation constraint, they can use curved step edges in addition to straight edges.

Despite this drawback, using only the perpendicular slices actually has an added benefit that it can handle multi-modal blur kernels, as opposed to only uni-modal kernels as in Joshi *et al*. Joshi *et al*. predict the location of the sharp edge by propagating the flat region into the blurred edge. If the predicted location of the sharp edge is inaccurate, it will cause error in the latent image estimation (i.e. I), which would lead to blur kernel estimation error. This problem is more pronounced when the algorithm considers multi-modal blur because the sharp edge location prediction becomes more challenging. The error in the sharp edge location in the context of Joshi's work is equivalent to the misalignment of blur kernel projections in the context of our work. We can address this issue by aligning the blur kernel projections through aligning the centroids (see Section 2.2.2 in my thesis.). This algorithm is able to address multi-modal blur kernels as well. Cho *et al*. SIGGAsia 2009 extends the idea from Joshi *et al*. in a multi-scale manner to deal with complex kernels. Therefore, quantitative comparisons between Cho *et al*. and our work, presented in radon_blur.pdf, would hold for comparisons between Joshi *et al*. and our work.