

Removing Camera Shake from a Single Photograph

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This is a problem...



...this is how standard software solves it...



...and this is how we will solve it



Assumptions

- ▶ No significant parallax
- ▶ Any image-plane rotation of camera is small
- ▶ No parts of the scene are moving relative to one another

Image model

$$\mathbf{B} = \mathbf{K} \otimes \mathbf{L} + \mathbf{N} \quad (1)$$

$$\mathbf{N} \sim \mathcal{N}(0, \sigma^2) \quad (2)$$

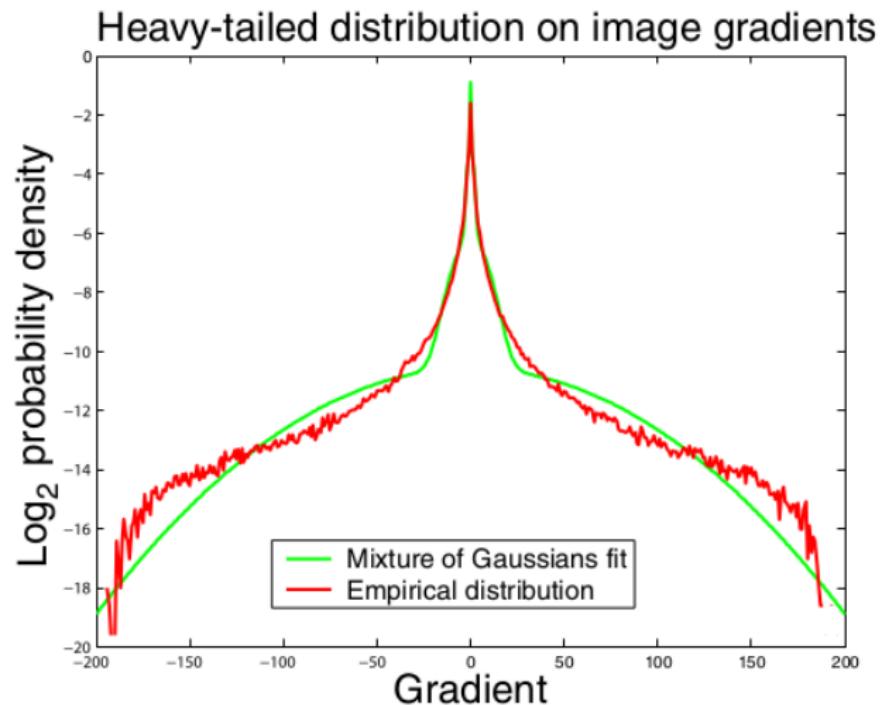
B is a blurred input image

K - blur kernel

L - true image

N - noise

Distribution of gradients of natural, non-blurred images



A priori assumptions about images

- ▶ Prior $p(\nabla P)$ is a mixture of C zero-mean Gaussians (with variance ν_c and weight π_c)
- ▶ Prior $p(K)$ is a mixture of D exponential distributions (with scale factors λ_d and weights π_d). It encourages zero values in the kernel, and requires all entries to be positive.

Algorithm

User supplies:

- ▶ Blurred image \mathbf{B}
- ▶ A rectangular patch \mathbf{P} within the \mathbf{B}
- ▶ An upper bound on the size of \mathbf{K}
- ▶ Initial guess on the orientation of \mathbf{K}

We convert \mathbf{P} to linear color space and grayscale.

Estimating blur kernel

Given the grayscale blurred patch \mathbf{P} , we estimate \mathbf{K} and the latent patch image $\mathbf{L}_\mathbf{p}$ by finding the values with highest probability, guided by a prior on the statistics of \mathbf{L} .

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So posterior distribution will be:

$$\begin{aligned} p(\mathbf{K}, \nabla \mathbf{L}_p | \nabla \mathbf{P}) &\propto p(\nabla \mathbf{P} | \mathbf{K}, \nabla \mathbf{L}_p) p(\mathbf{K}) p(\nabla \mathbf{L}_p) \\ &= \prod_i \mathcal{N}(\mathbf{P}(i) | (\mathbf{K} \otimes \nabla \mathbf{L}_p(i)), \sigma^2) \\ &\quad \prod_i \sum_{c=1}^C \pi_c \mathcal{N}(\nabla \mathbf{L}_p(i) | 0, v_c) \\ &\quad \prod_j \sum_{d=1}^D \pi_d \exp(\mathbf{K}_j | \lambda_d) \end{aligned}$$

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- ▶ MAP objective function attempts to minimize all gradients (even large ones)
- ▶ Whereas we expect natural images to have some large gradients.
- ▶ The algorithm yields a two-tone image (virtually all gradients are zero)
- ▶ When we reduce the noise variance then we have no deblurring

Solution #2

Approximate the full posterior distribution $p(\mathbf{K}, \nabla \mathbf{L}_p | \nabla \mathbf{P})$, then compute the kernel \mathbf{K} with **maximum marginal probability**. This method selects a kernel that is most likely with respect to the distribution of possible latent images, thus avoiding the overfitting that can occur when selecting a single "best" estimate of the image. I won't show here details of the algorithm.

Multi-scale approach

- ▶ Previous section is subject to local minima, particularly for large blur kernels
- ▶ Hence, we perform estimation in a coarse-to-fine manner, starting with a 3x3 kernel.
- ▶ Initial kernel is picked by user from 2 possibilities: vertical or horizontal line.
- ▶ Initial estimate for the $\nabla \mathbf{L}_p$ is produced by running the inference scheme, while holding K fixed
- ▶ Then we work back up, upsampling \mathbf{K} and $\nabla \mathbf{L}_p$ from previous pass to use as initialization for inference at current scale.

Image reconstruction

- ▶ Standard non-blind deconvolution methods produce unacceptable levels of artifacts.
- ▶ Inferring whole \mathbf{B} , while holding \mathbf{K} fixed and then using Poisson image reconstruction was no better than previous attempt
- ▶ In the end Richardson-Lucy deconvolution algorithm gave best results

Results









