Our approach

Fast Forward Model

Problem

Goal is to model and deblur images degraded by real camera shake causing non-uniform blur, i.e. the PSF varies spatially across the image planes, such as shown in the example images below.

Photo blurred by camera shake
Illustration of PSF variation
Device for PSF sampling

Algorithm for Single Image Blind Deconvolution

(i) Blur parameter update step: Initializing $m$ with the blurry image $g$, the estimation of the camera shake blur parameters $m_{\text{ba}}$ is performed by iterating over the following three steps:

- Predict true image:
  - remove noise in flat regions of $g$ by edge-preserving bilateral filtering
  - overemphasize edges by shock filtering
  - compute gradient selection mask via map approach of Xu et al. (2010) to use only informative edges for estimation. In particular, it neglects structures that are smaller in size than the local filters, which could be misleading for the blur parameter estimation.

- Estimate blur parameters:
  - update the blur parameters given the blurry image $g$ and the current estimate of the predicted / obtained by bilateral and shock filtering.
  - for a preconditioning effect use only the gradient images of $s$
  - enforce smoothness of camera trajectory
  \[
  \frac{|\partial g - m_{\text{ba}} \odot \partial f|^2}{\partial f} + \lambda |\partial f|^2 + \gamma |\partial g|^2, 
  \]

where $m_{\text{ba}}$ is a mask (computed by map approach), that weights gradients according to their information content (see previous step). The regularization constants $\lambda$ and $\gamma$ balance the likelihood against the prior terms. The above optimization problem is efficiently solved by gradient-based optimization techniques (e.g. lbfgsb or Barzilai-Borwein).

- Latent image update step:
  - update the current deblurred image $f$ by solving a least-squares cost function using a smoothness prior on the gradient image via direct deconvolution (see Direct Deconvolution section below)

\[
|g - x_{\text{ba}}| + \lambda |\partial g|^2 
\]

(ii) Non-blind deblurring (following Krishnan and Fergus, 2009): given the EFF parameterized by $x$, yield the final image estimate by alternating between the following two steps:

- Latent variable estimation: estimate latent variables regularized with a sparsity prior that approximate the gradient of $f$. This can be efficiently solved with look up tables as well as analytically. see ‘x sub-problem’ of Krishnan and Fergus (2009) for details.

- Image estimation step: update the current deblurred image $f$ by directly solving a least-squares cost function while penalizing the Euclidean norm of the gradient image to the latent variables of the previous step, see ‘x sub-problem’ of Krishnan and Fergus (2009) for details and Direct Deconvolution section below.

Direct Deconvolution

The optimization problem Eq. (5) can be solved directly via an approximate inverse

\[
\frac{|g - x_{\text{ba}}| + \lambda |\partial g|^2}{|\partial f|} 
\]

Deblurring Results and Comparison

Comparison with state-of-the-art stationary and non-stationary deblurring algorithms on real-world data. Only qualitative comparisons were made. Run-time of our GPU implementation with PyCuda is about 30 seconds on Nvidia C2050 for a 2M pixel image.

Table

Limitations

Saturated pixels
Out-of-focus blur
Objects in motion
Severe blur

References

http://webdav.is.mpg.de/pixel/fast_removal_of_camera_shake