Blind image restoration:
from equations to applications

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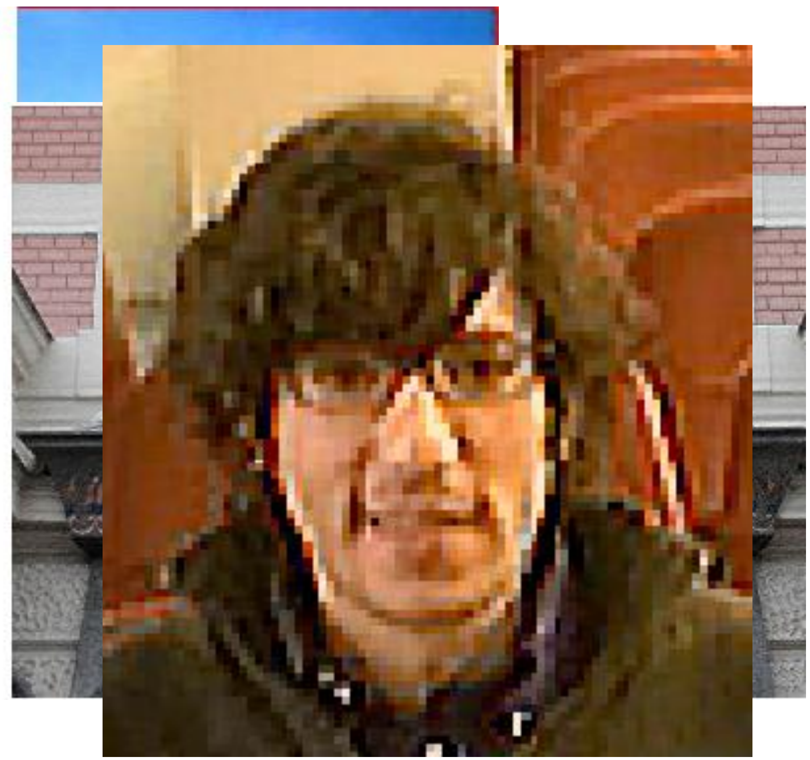
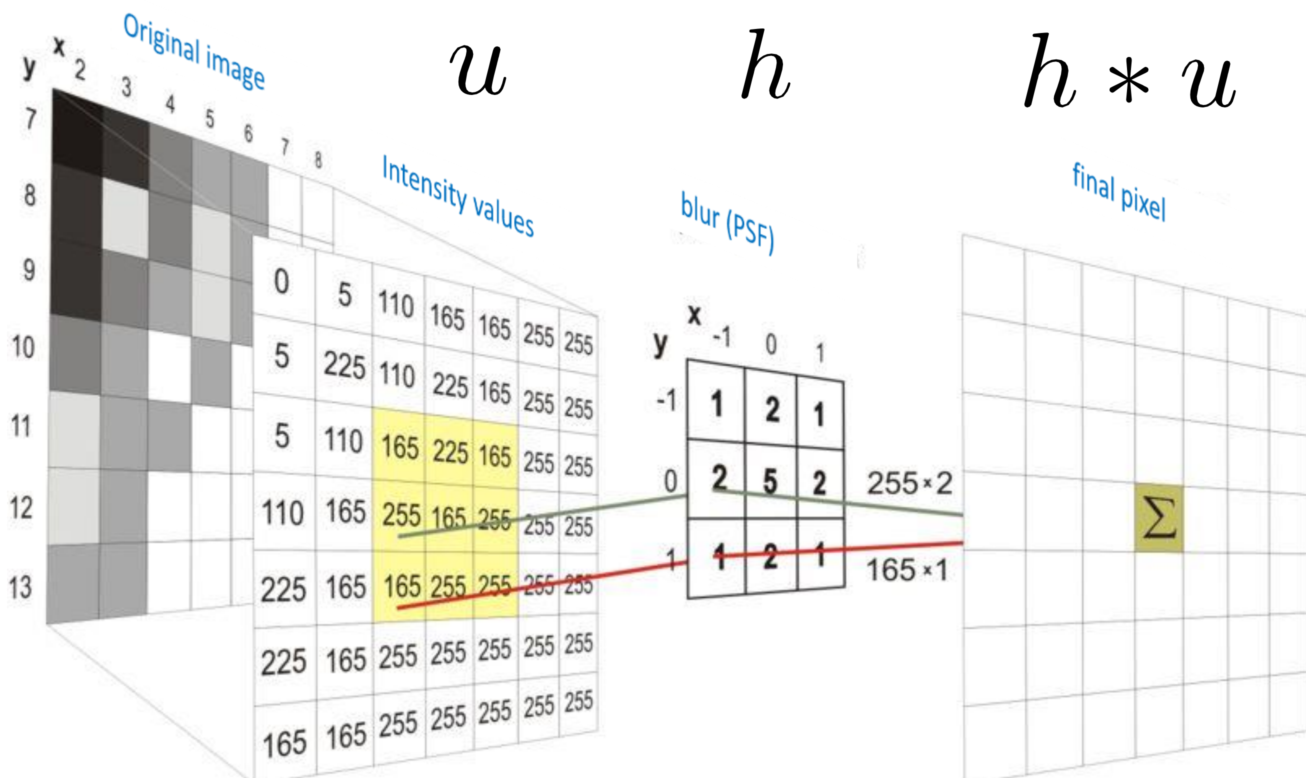
Image Restoration

- Denoising
- Deblurring (deconvolution)
- Super



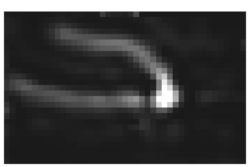
2D Convolution

$$h * u = \int u(x-s, y-t)h(s,t)dsdt$$



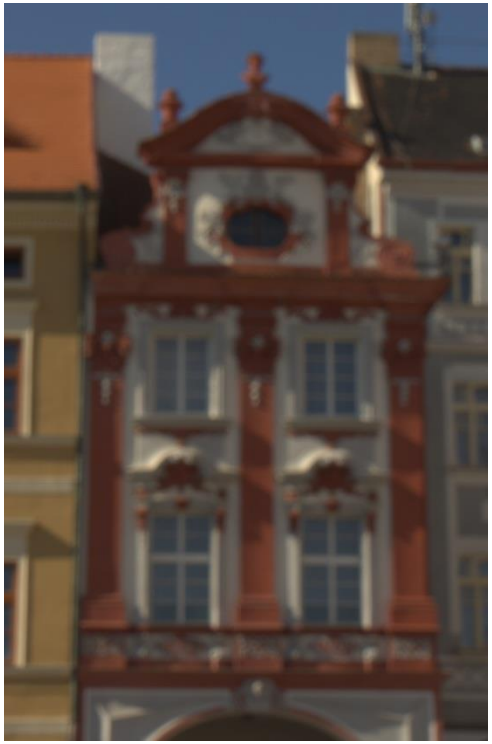
Motion Blur

=



*

Out-of-focus Blur



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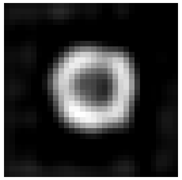

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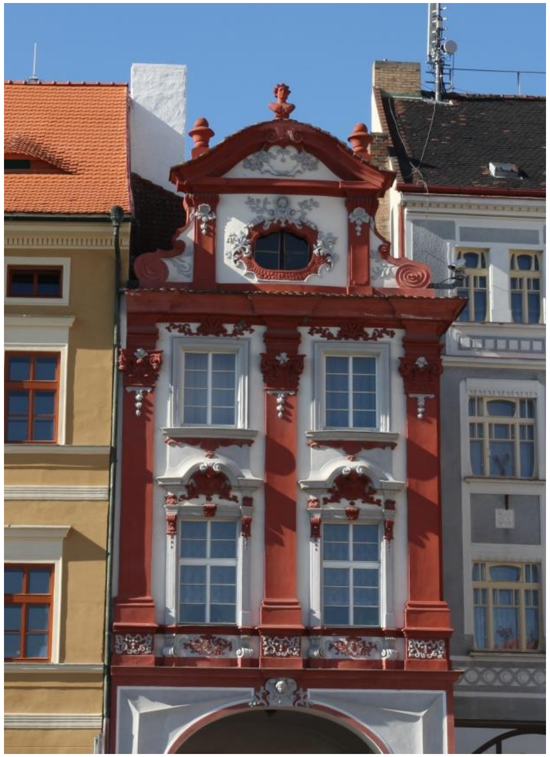
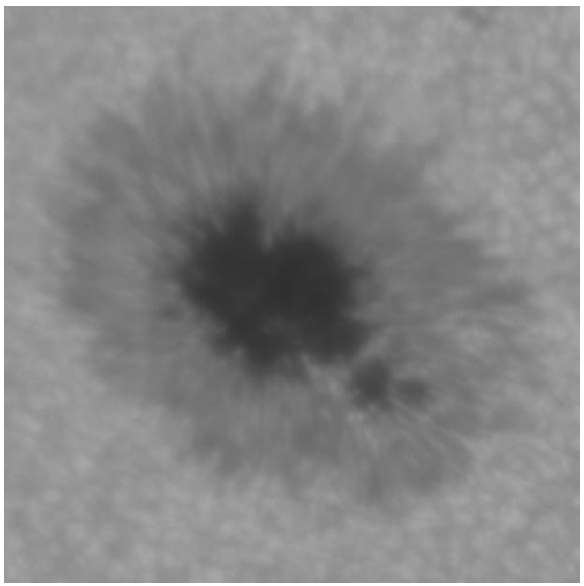


Atmospheric Turbulence



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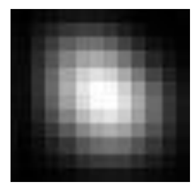

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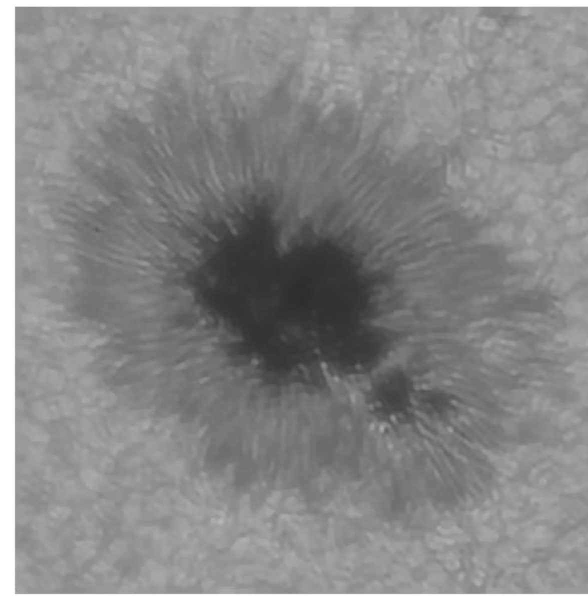
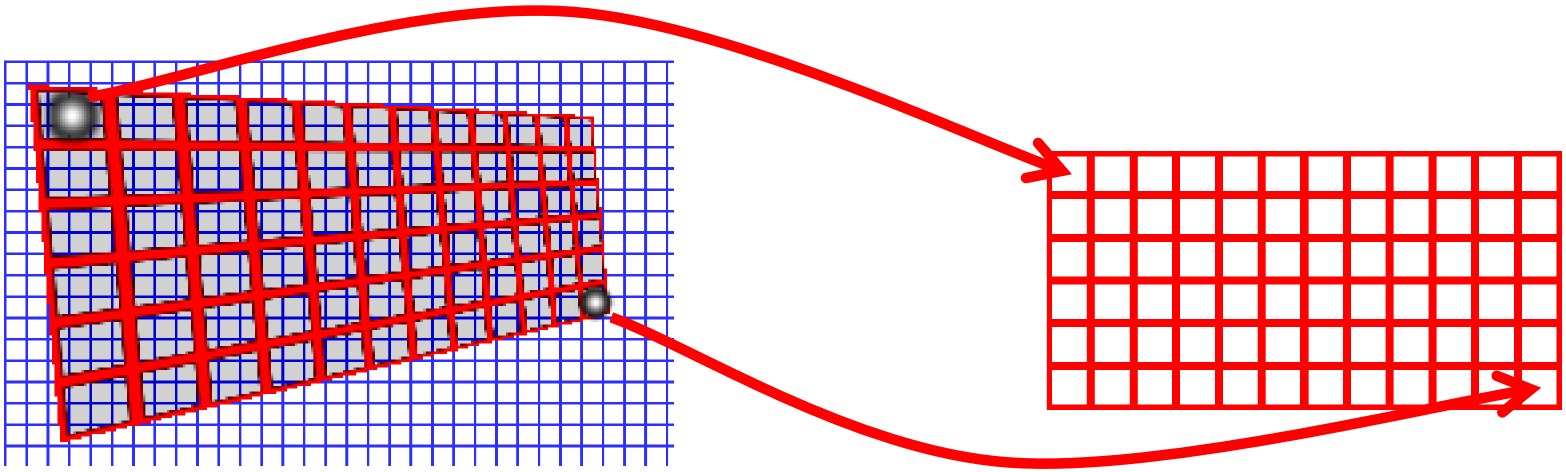


Downsampling operator D

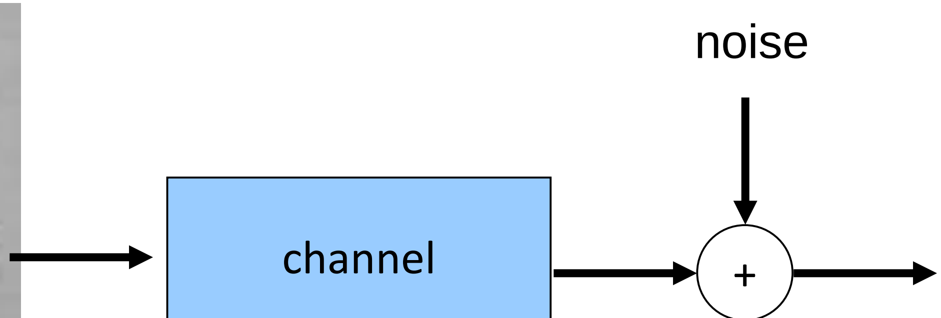
original HR image **recorded LR image**

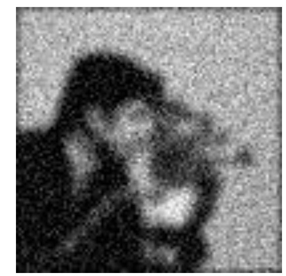


Beyond Camera Resolution

Acquisition Model

original image





acquired image

$$D[\underbrace{H\ \ u}_{h * u}](x) \quad + \quad n(x) \quad = \quad z(x)$$

$$N(x|0, \lambda^{-1})$$

Blind Image Restoration

$$D(h * u) + n = z$$

- Our problem lacks a stable solution
- Inverse linear problem

$$\mathbf{A}\mathbf{x} = \mathbf{b}$$

Degradation matrix Unknown!
Only the structure is known

Latent image Unknown!

Acquired Image (+ noise)

Bayesian Paradigm

$$\boxed{p(u,h|z)} = \frac{\boxed{p(z|u,h)}\boxed{p(u)p(h)}}{p(z)}$$

a posteriori **distribution**
unknown

likelihood
given by our problem

a priori **distribution**
our prior knowledge

- Maximum a posteriori (MAP): max p(u,h|z)
- Maximum likelihood (MLE): max p(z|u,h)

Blind deconvolution - MAP

- max *a posteriori* probability $p(u,h|z)$

  ==> min $-\ln p(u,h|z)$

$$-\ln p(u,h|z) = \boxed{-\ln p(z|u,h)}\boxed{-\ln p(u) - \ln p(h)} + C$$

- Exponential family

$$E(u,h) = \frac{\lambda}{2}\|u * h - z\|^2 + Q(u) + R(h)$$

Maximum Likelihood

$$\min_{u,h} \frac{\lambda}{2} \|u * h - z\|^2$$

- Infinite number of solutions

Alternating Min of MAP

$$\min_{u,h} E(u,h) = \min_{u,h} \frac{\lambda}{2}\|u * h - z\|^2 + Q(u) + R(h)$$

- Alternating Minimization

  1. *u-step:* $\hat{u} = \arg\min_u E(u, \hat{h})$

  2. *h-step:* $\hat{h} = \arg\min_h E(\hat{u}, h)$

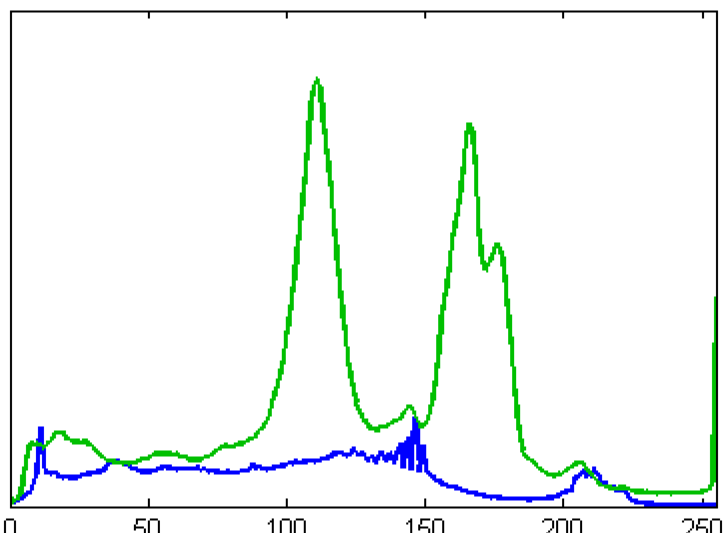
  3. *repeat 1 and 2.*

- ADMM (ALM+variable splitting), split-Bregman, FISTA

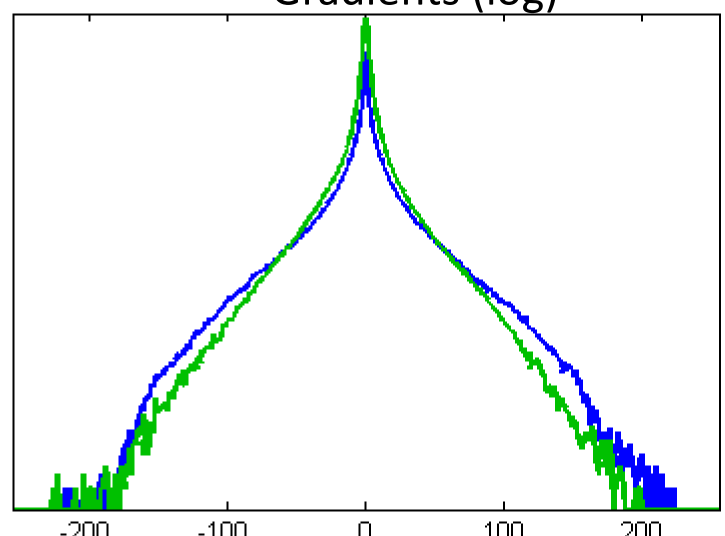
Quest for Priors

Gradient-based regularization

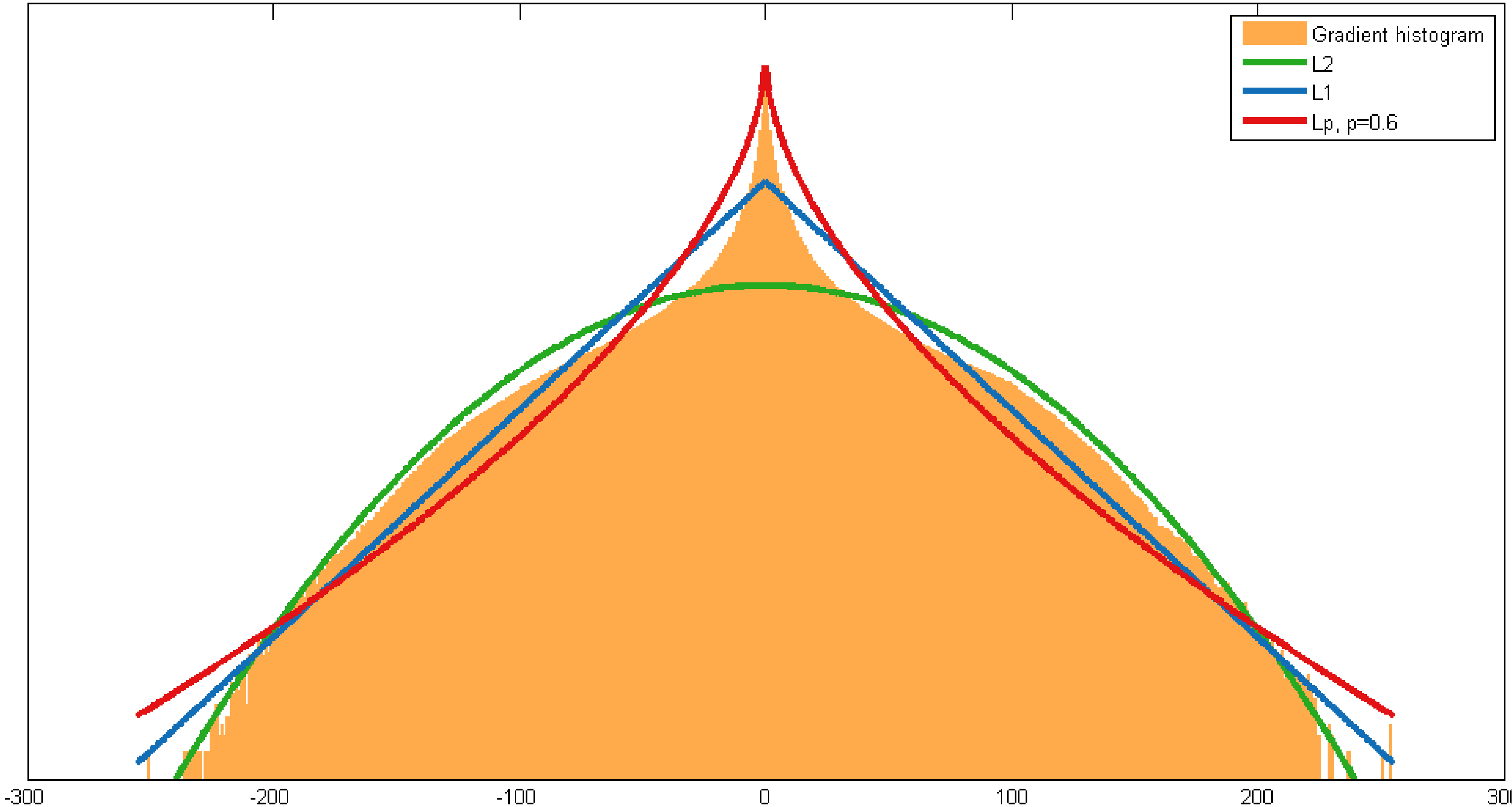
Intensities



Gradients (log)



Regularization based on natural image distribution



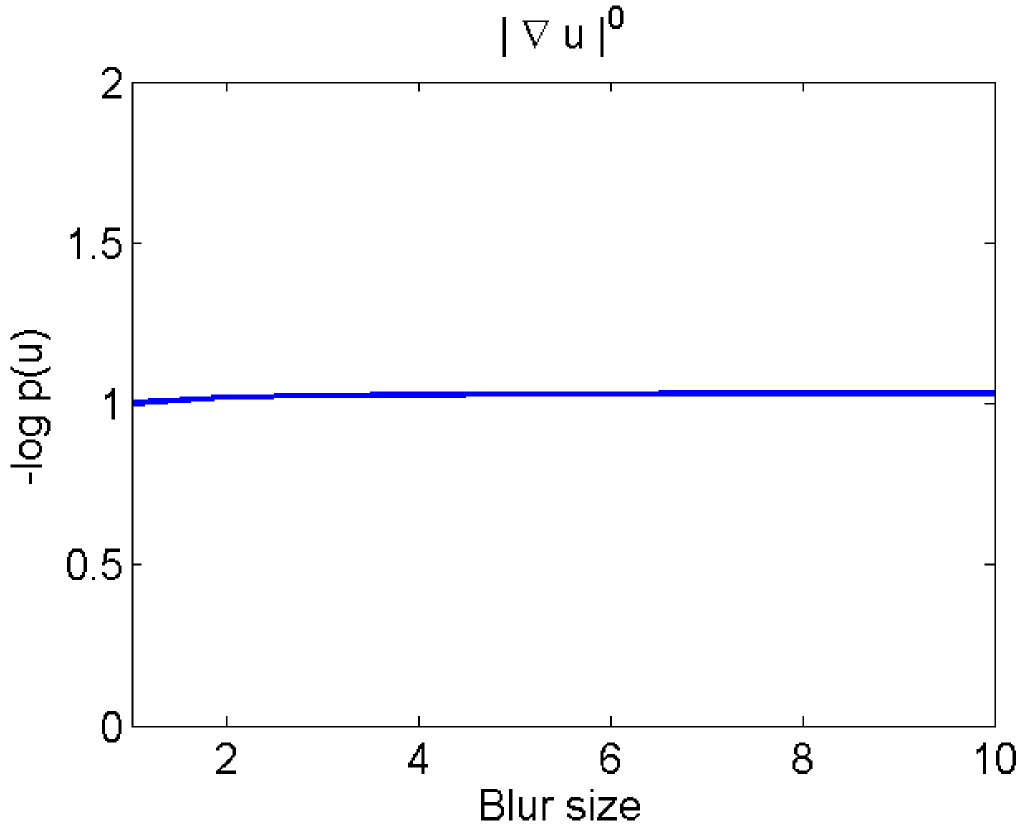
$$Q(u) = \sum_i \left([\partial_x u]_i^2 + [\partial_y u]_i^2 \right)^{\frac{p}{2}} = \sum_i |\nabla u_i|^p, \quad 0 < p \leq 1$$

“No-Blur” Solution

- The solution with the highest probability is

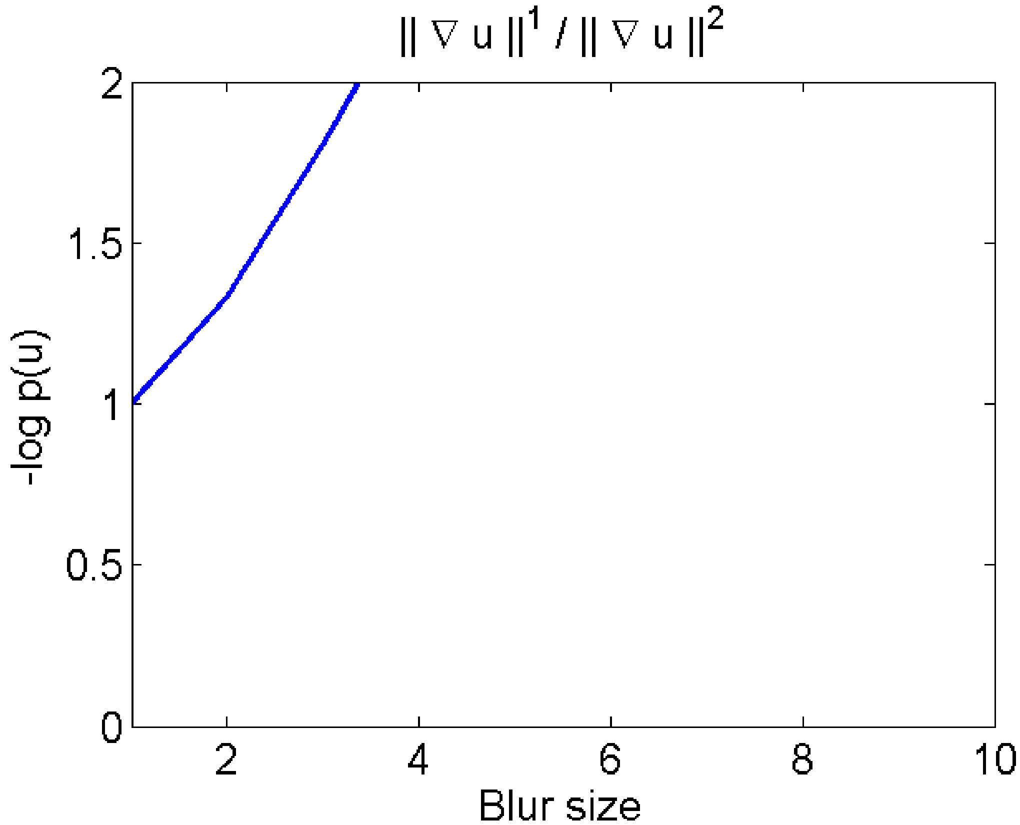
$$\hat{u} = z, \quad \hat{h} = \delta(x)$$

Testing Priors



Testing Priors

normalized prior

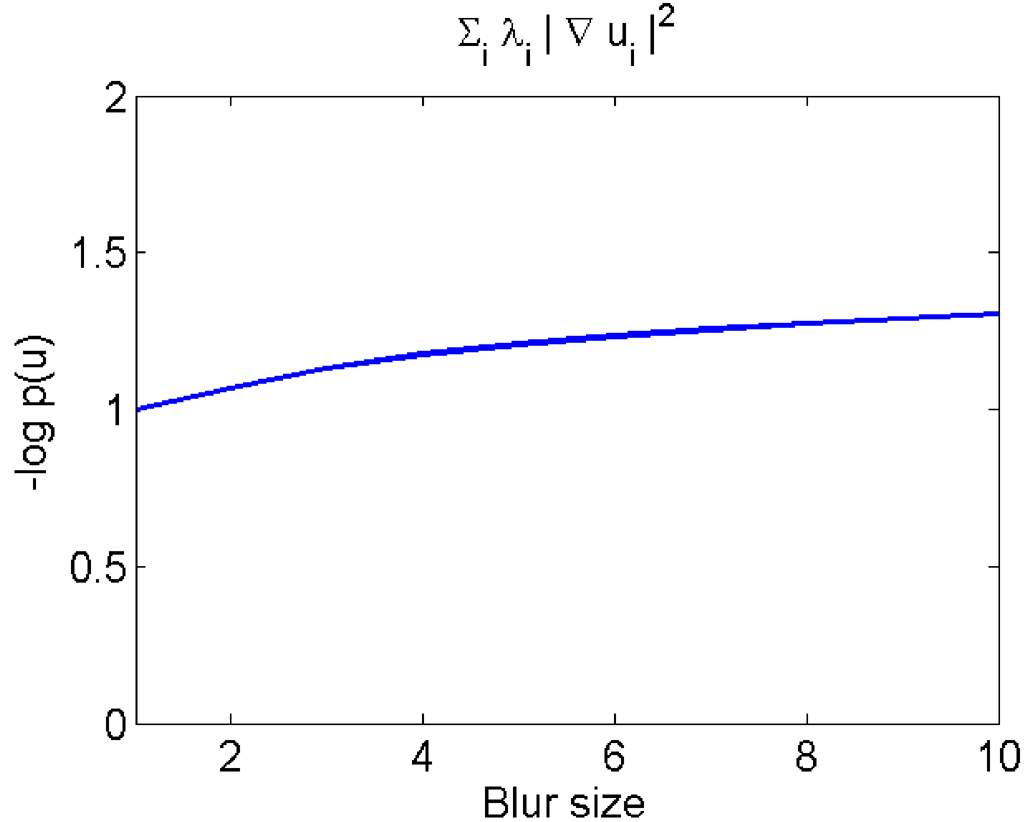


D.Krishnan et al., CVPR2011

Testing Priors

Automatic Relevance Determination

- leads to Student's-t distribution

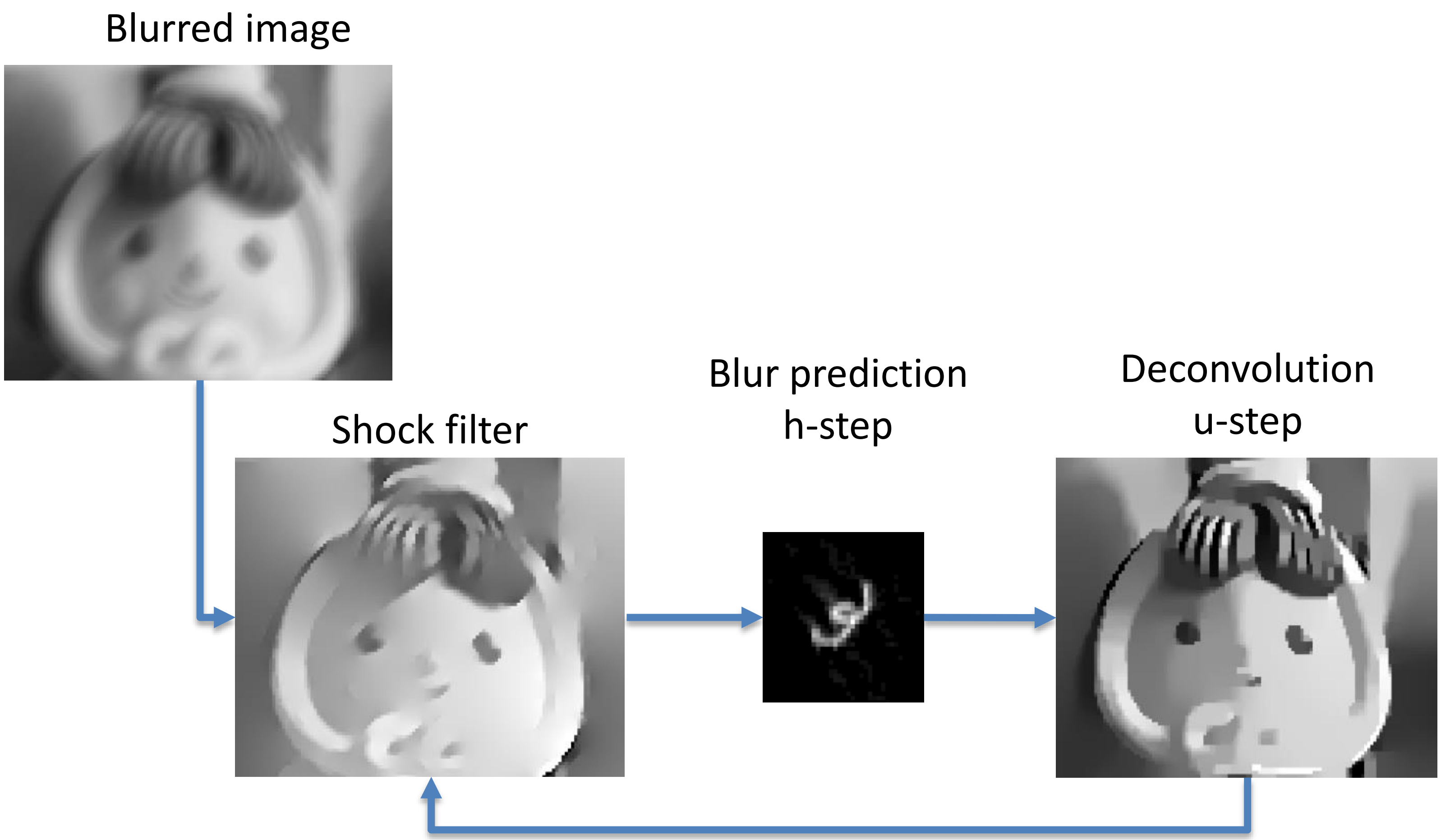


D. Tzikas et al., TIP 2009

We need tricks!

- To avoid “no-blur” solution:
  - Artificial sharpening (Shan et al. SigGraph 2008, Cho et al., SigGraph 2009)
  - Remove spikes (Xu et al., ECCV 2010)
  - Adjusting priors on the fly (Almeida et al., TIP 2010)
  - Hierarchical approach (everybody)

Artificial Sharpening

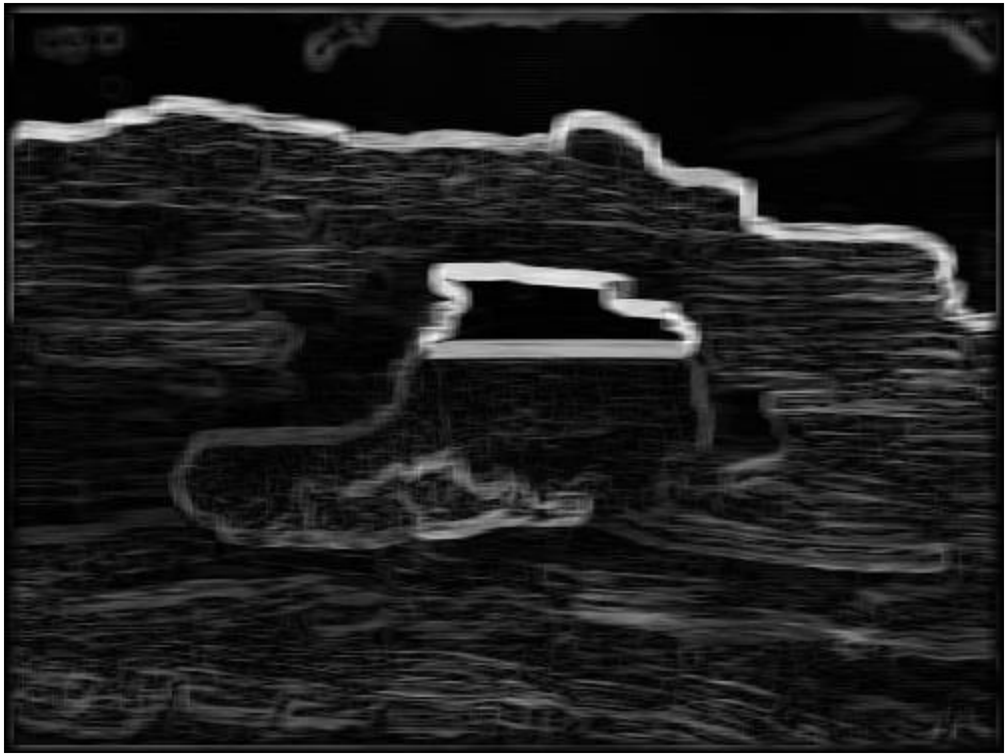


Cho et al., SIGGRAPH 2009

Remove Spiky Objects

Xu et al., ECCV 2010

Remove Spiky Objects



Mask out small objects

Xu et al., ECCV 2010

Remove Spiky Objects

Reconstructed image with
small objects removed

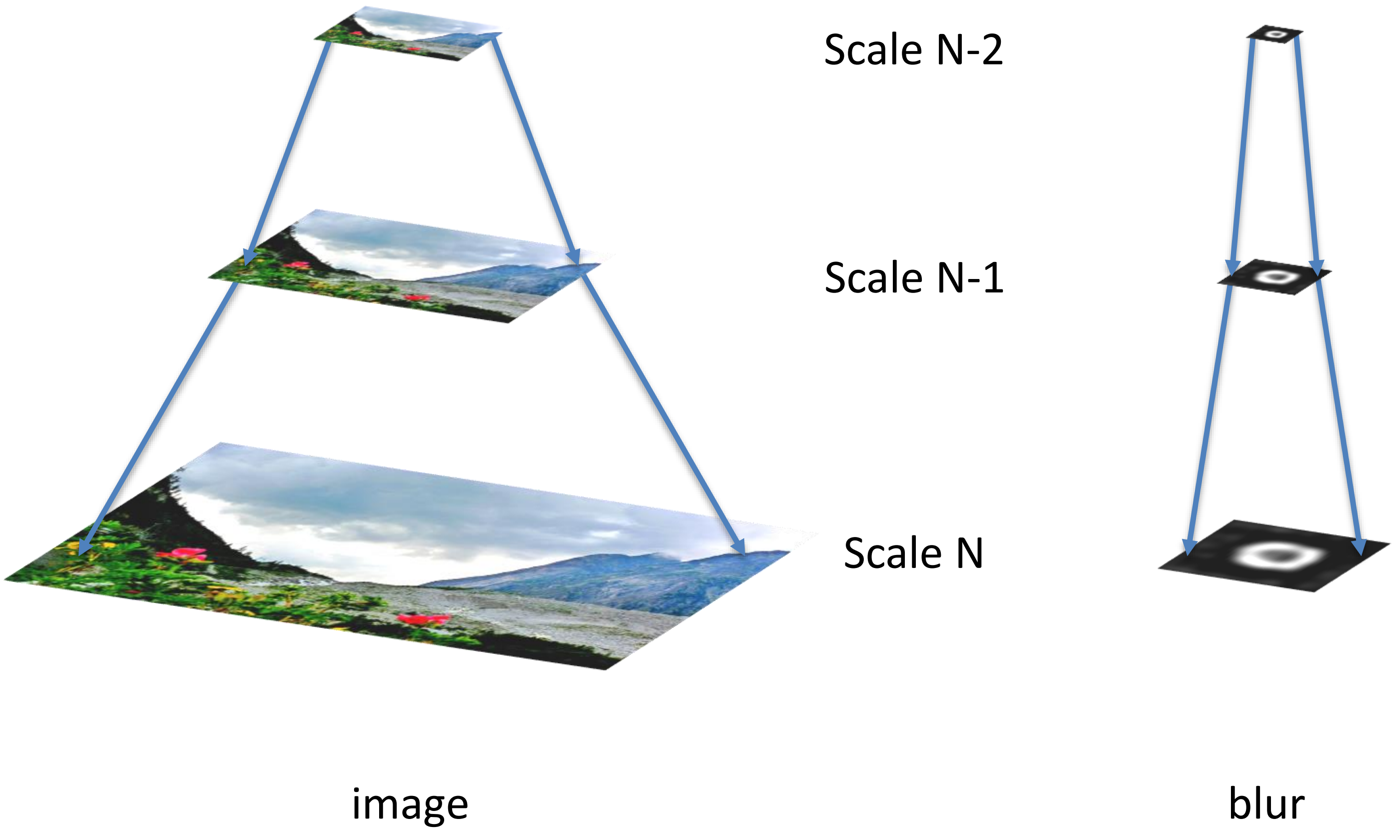
Xu et al., ECCV 2010

Adjusting priors

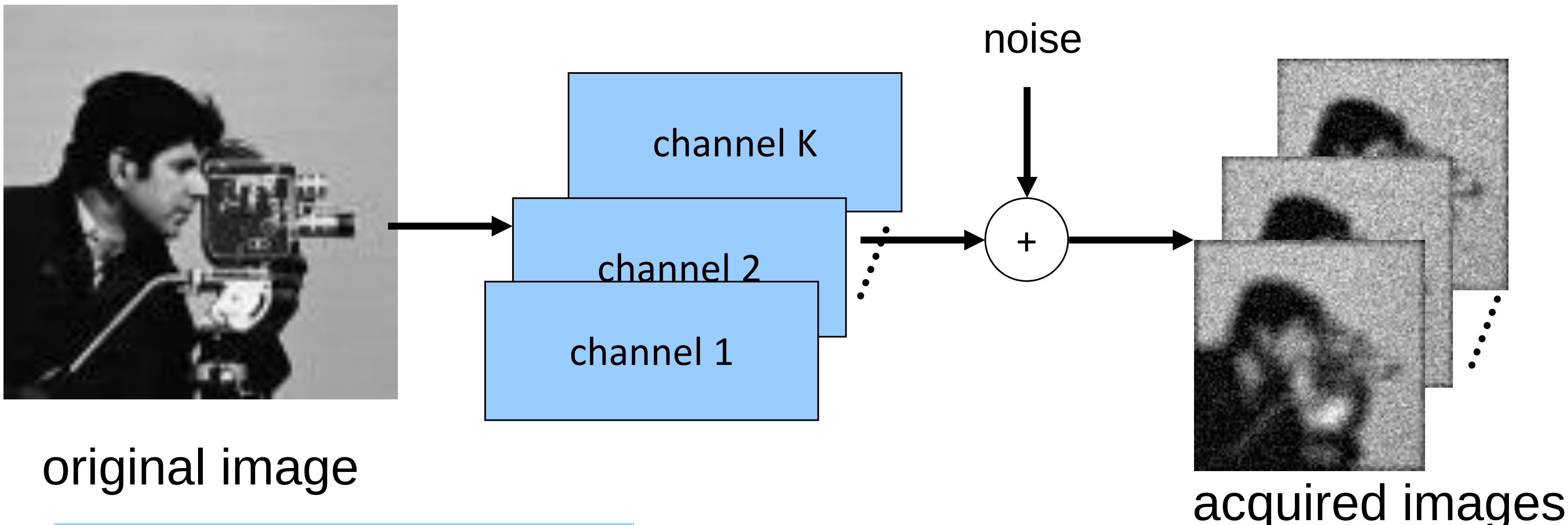
u $\quad Q(u) = \sum_i |\nabla u_i|^2 \quad \sum_i |\nabla u_i|^1 \quad \sum_i |\nabla u_i|^{0.5}$

- Start with an overestimated noise level and slowly decrease it to the correct level.
- Start with p<<1 and slowly increase it to p=1.

Hierarchical Deconvolution



Multichannel Model



$$\boxed{D[\,H_k[\,u\,]\,](x)} \quad + \quad n_k(x) \quad = \quad z_k(x)$$

$$N(0, \lambda^{-1})$$

PSF multichannel "prior"

$$u$$

$$z_1 = u * h_1 \qquad h_2 * u = z_2$$

$$\boxed{z_1 * h_2} = u * h_1 * h_2 \qquad h_1 * h_2 * u = \boxed{h_1 * z_2}$$

$$\boxed{z_1 * h_2} - \boxed{h_1 * z_2} = 0$$

$$R(\{h_i\}) = \frac{1}{2} \sum_{1 \le i,j \le K} \|z_i * h_j - z_j * h_i\|^2$$

Bayesian Paradigm revisited

- Marginalize the posterior

$$p(h|z) = \int p(u, h|z) du$$

- Maximize the marginalized prob.

$$\hat{h} = \arg\max_h p(h|z)$$

- and then maximize the posterior

$$\hat{u} = \arg\max_u p(u, \hat{h}|z)$$

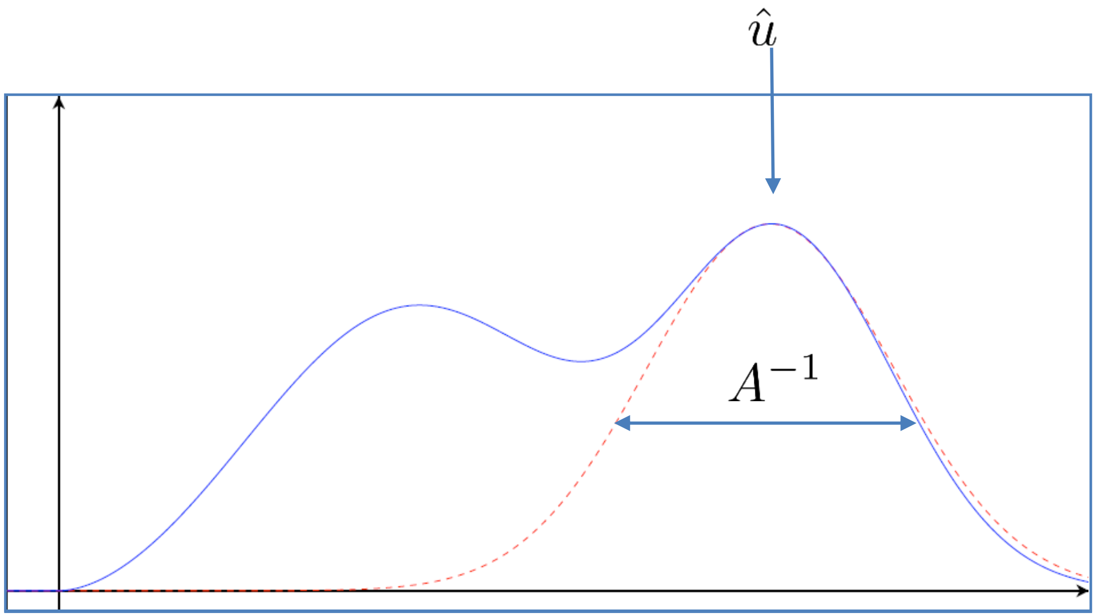
How to marginalize?

$$p(h|z) = \int p(u, h|z)du$$

- If Gaussian distributions => Gaussian marginalized distribution
- If not (our case) => approximation

Approximate Posterior

- Laplace approximation
  - Taylor expansion of the exponent=> Gaussian distribution



$$\hat{u} = \arg\max_u p(u, h|z)$$

$$A = -\nabla_u \nabla_u \ln p(u, h|z)|_{\hat{u}}$$

$$p(h|z) \approx \det(A)^{-1/2} p(\hat{u}, h|z)$$

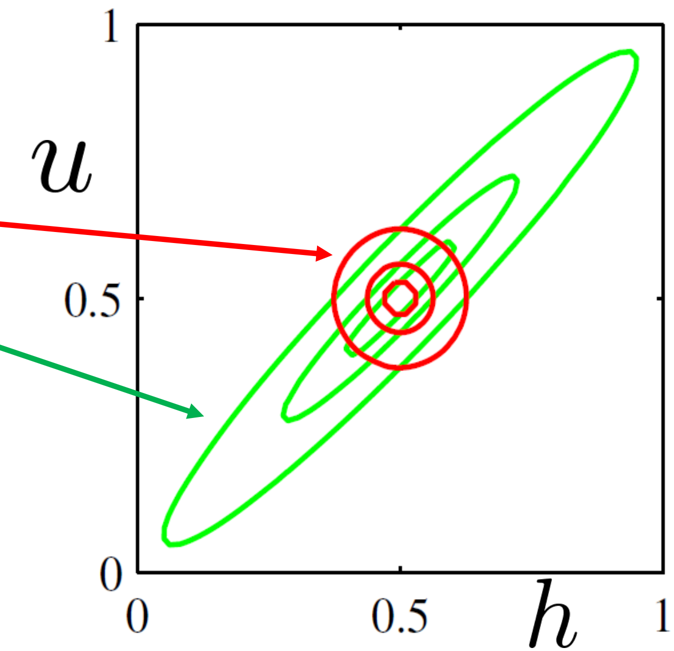
N.Galatsanos et al., TIP 2000

Approximate Posterior

- Variational Bayesian inference
  - Factorization of the posterior

$$\underbrace{p(u,h|z)} \approx \underbrace{q(u)q(h)}$$

  - then marginalization is trivial.

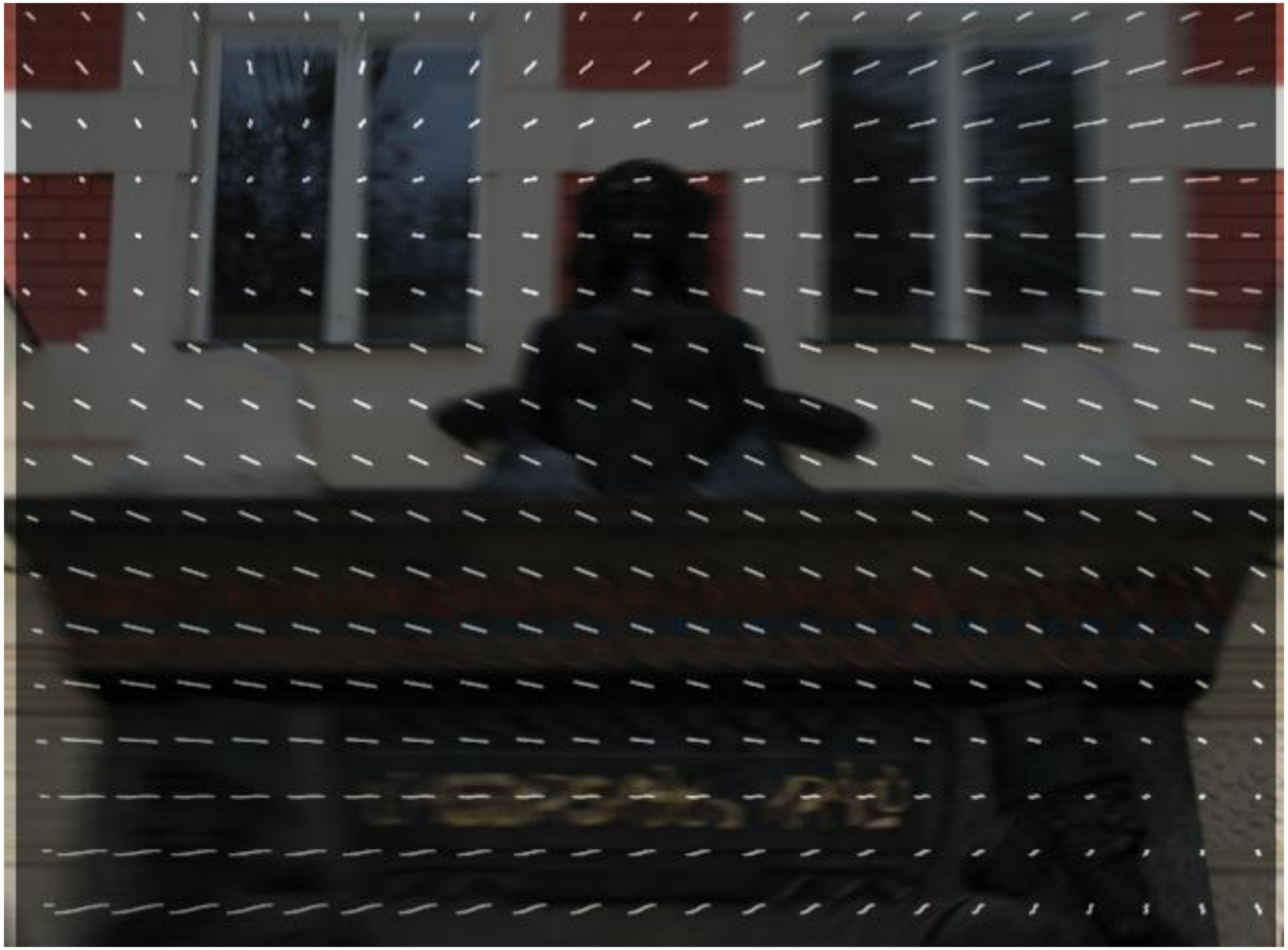


Every factor q depends on moments of other variables => must be solved iteratively.

R.Fergus et al., SIGGRAPH 2006

Space-variant Blurs

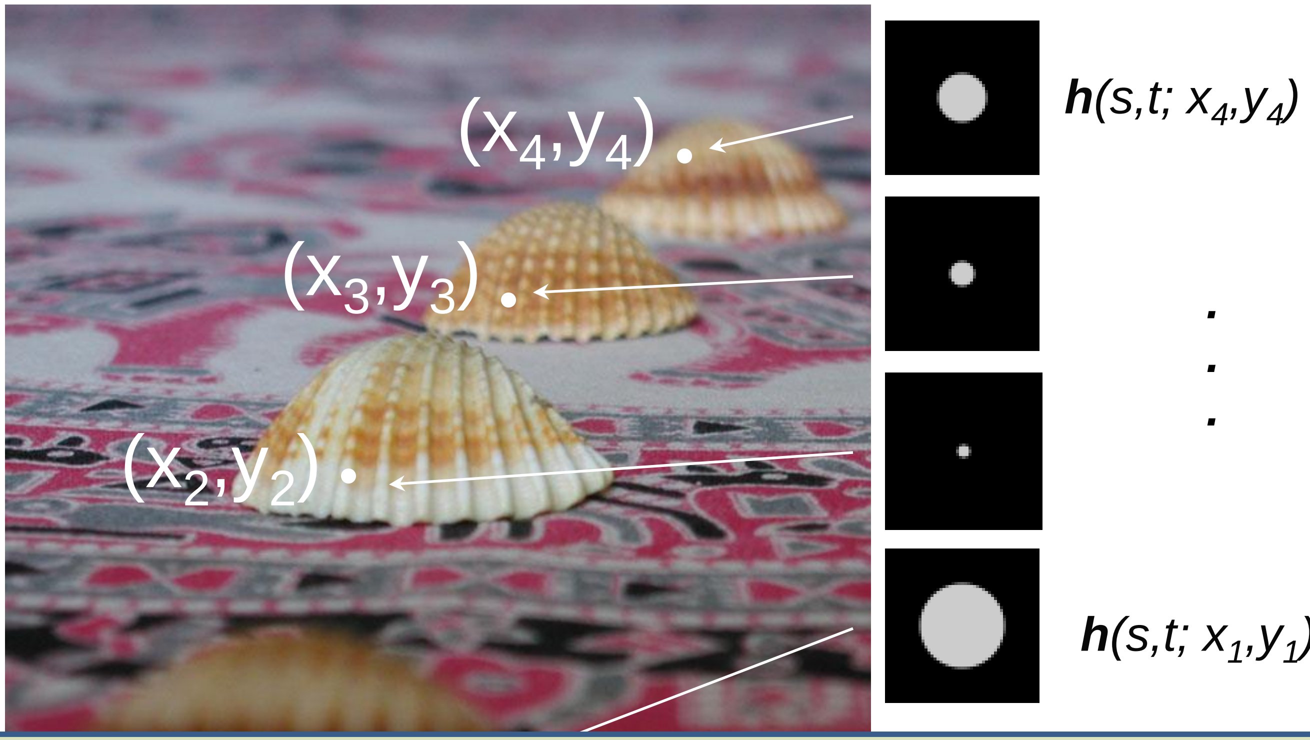
Space-variant Motion Blur due to Camera Motion



Space-variant Motion Blur due to Object Motion

Lens aberration

Space-variant Out-of-focus Blur



$$[Hu](x,y) = \int u(x-s, y-t)h(s,t,x-s,y-t)dsdt$$

Approximation of SV Blur

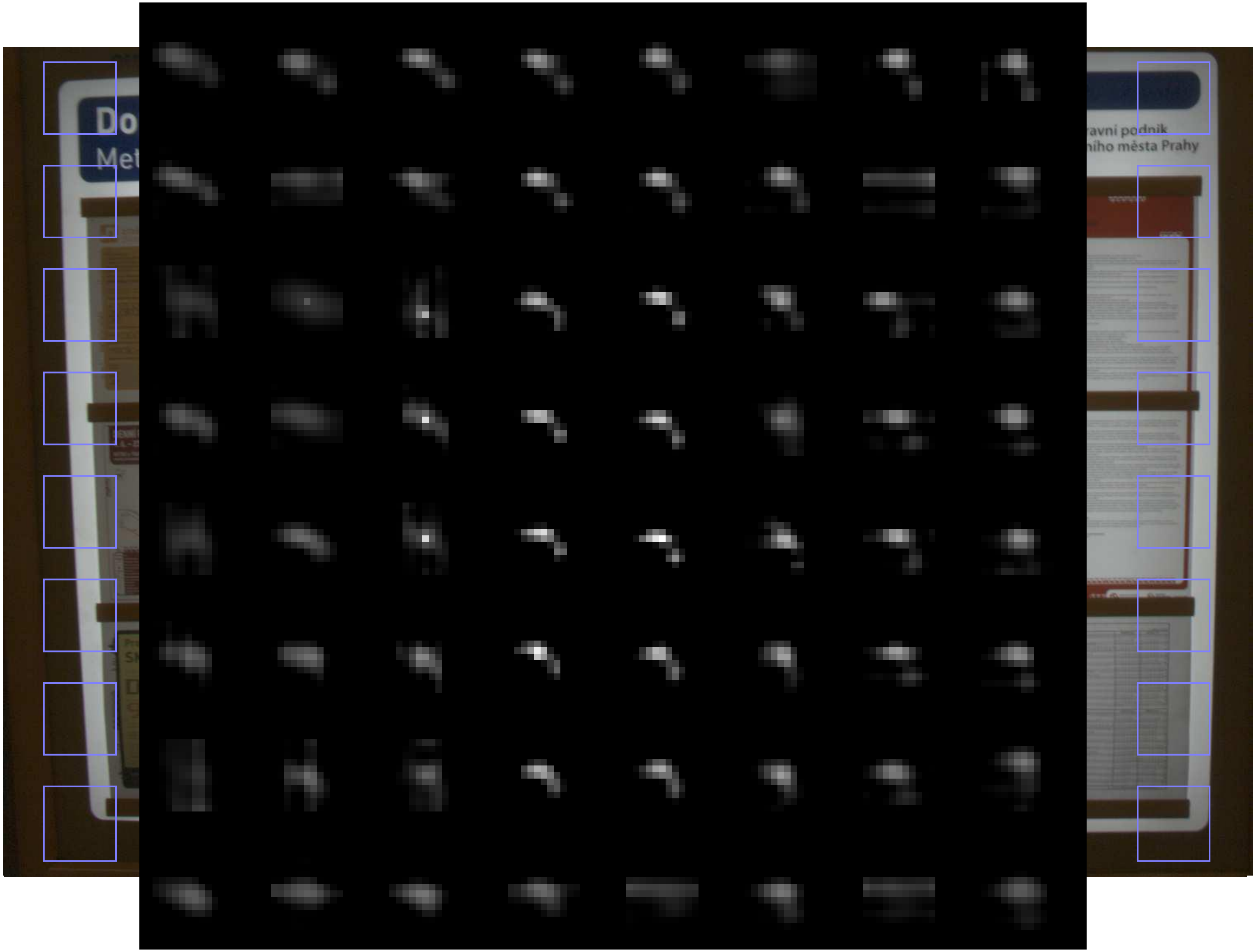
- Patch-wise convolution
  - General SV PSF
  - Localy convolution may not hold
- Parametric model (Blur Basis)
  - More accurate
  - Model may not hold
- Masking
  - Local Object motion
  - Does not remove degradation

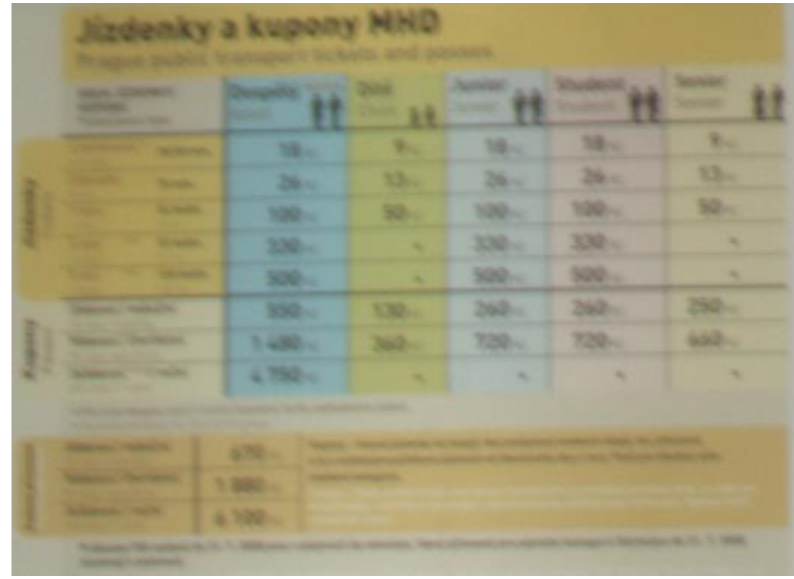
Sorel ICIP2009

Whyte CVPR2010
Gupta ECCV2010

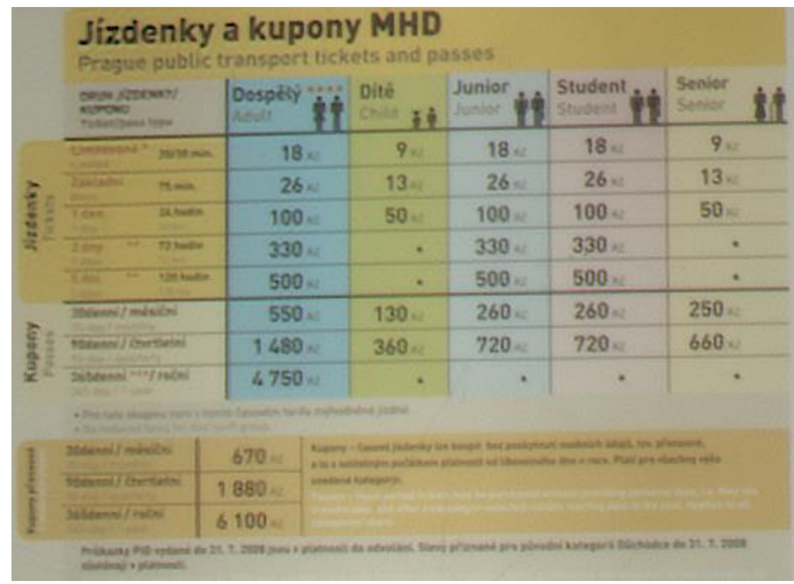
Sroubek ICPR2009

Patch-wise restoration

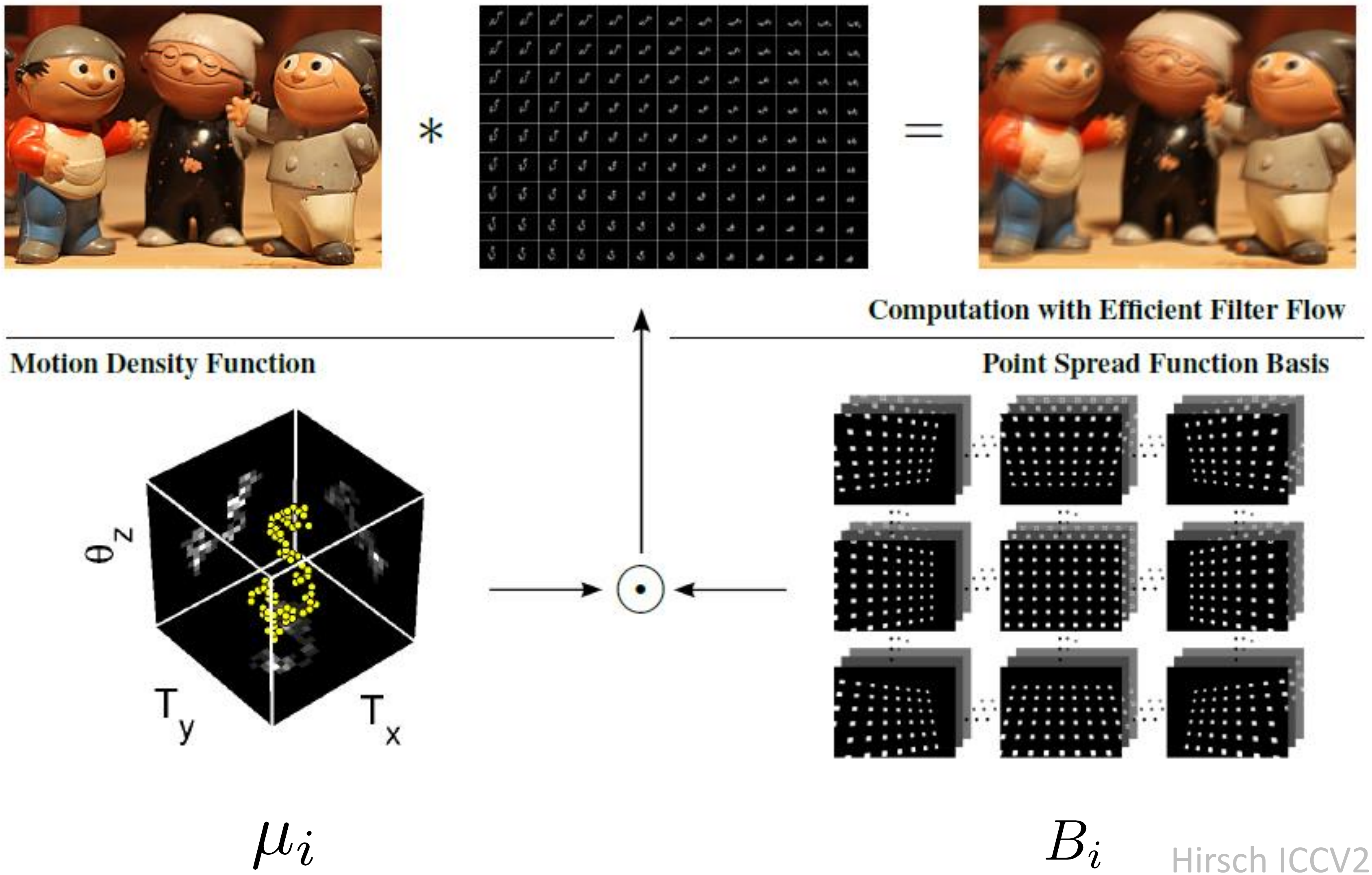



Jízdenky a kupony MHD


Dopravní podnik
hlavního města Prahy


Jízdenky a kupony MHD
Prague public transport tickets and passes
Dospělý
Dítě
Junior
Student
Senior
Jízdenky
Kupony
18 9 18 18 9
26 13 26 26 13
100 50 100 100 50
330 • 330 330 •
500 • 500 500 •
30denní / měsíční 550 130 260 260 250
90denní / čtvrtletní 1 480 360 720 720 660
365denní / roční 4 750 • • • •
30denní / měsíční 670
90denní / čtvrtletní 1 880
365denní / roční 6 100

Parametric Model (Blur Basis)



Hirsch ICCV2011

input

SR

input

SR

t-2 t-1 t t+1 t+2

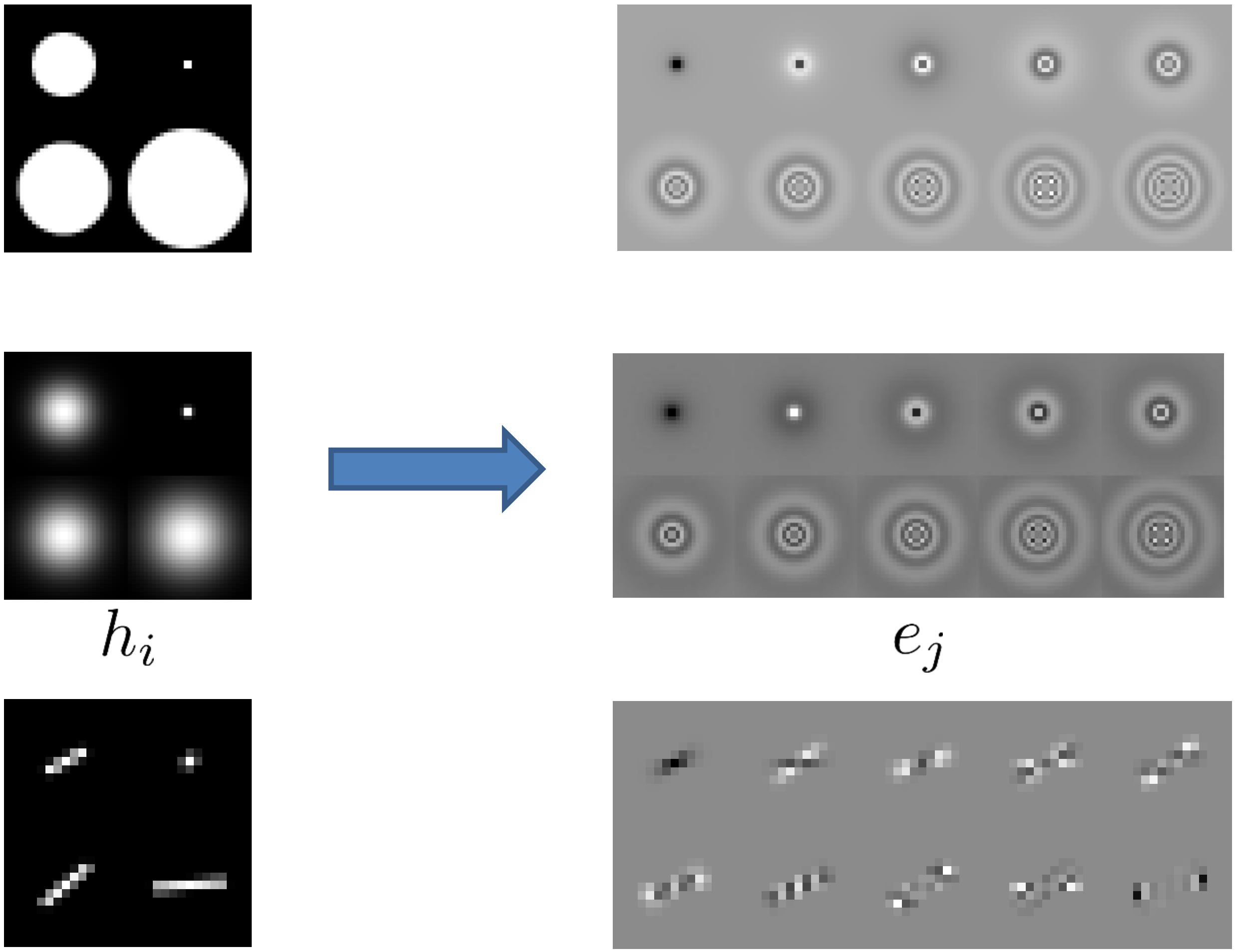
input

SR

SR + masking

t-2 t-1 t t+1 t+2

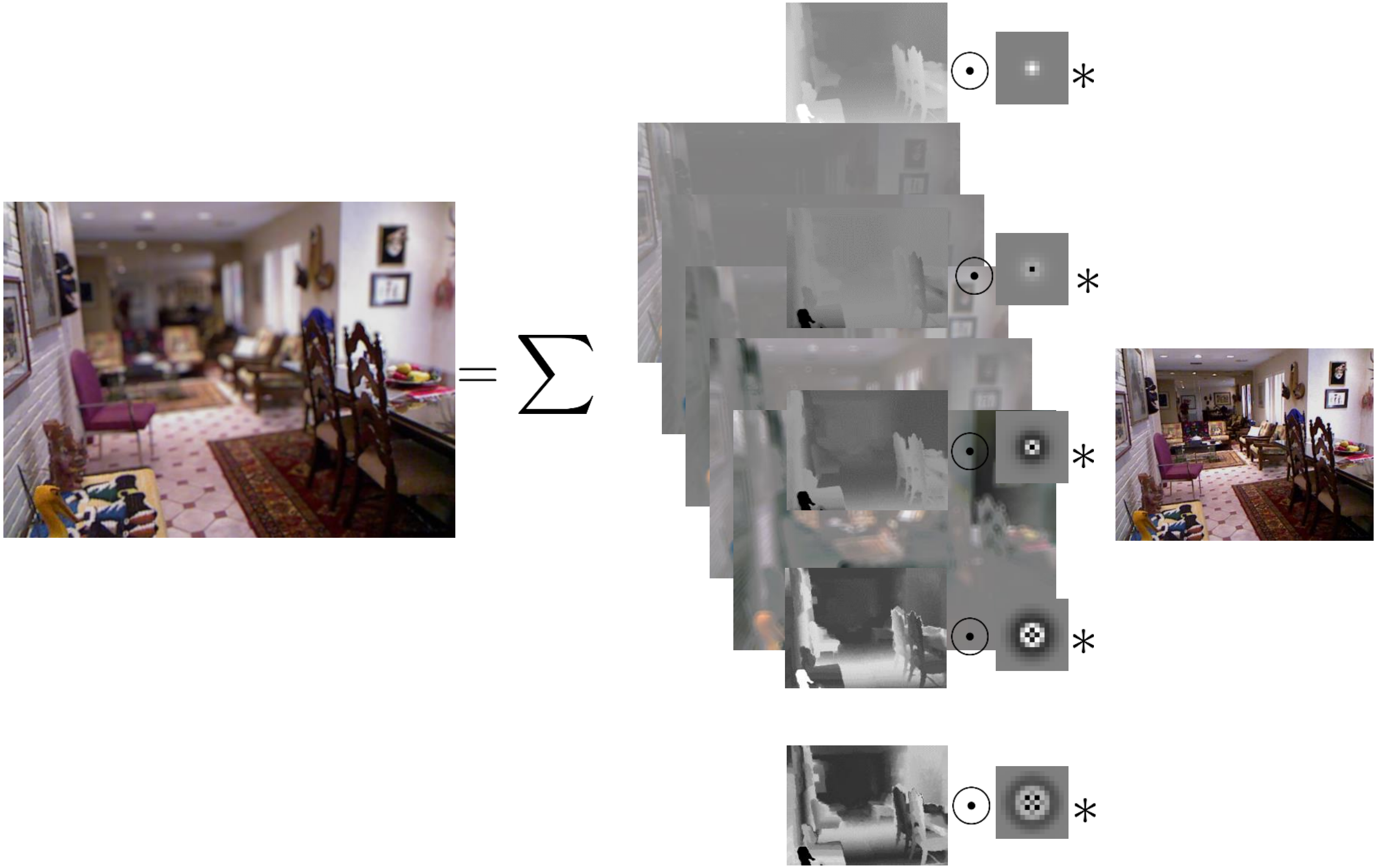
SV Blur decomposition



$$h_i = \sum_j \alpha_{ij} e_j$$

H. Deng et al., Int.J.Comp.Math. 2014

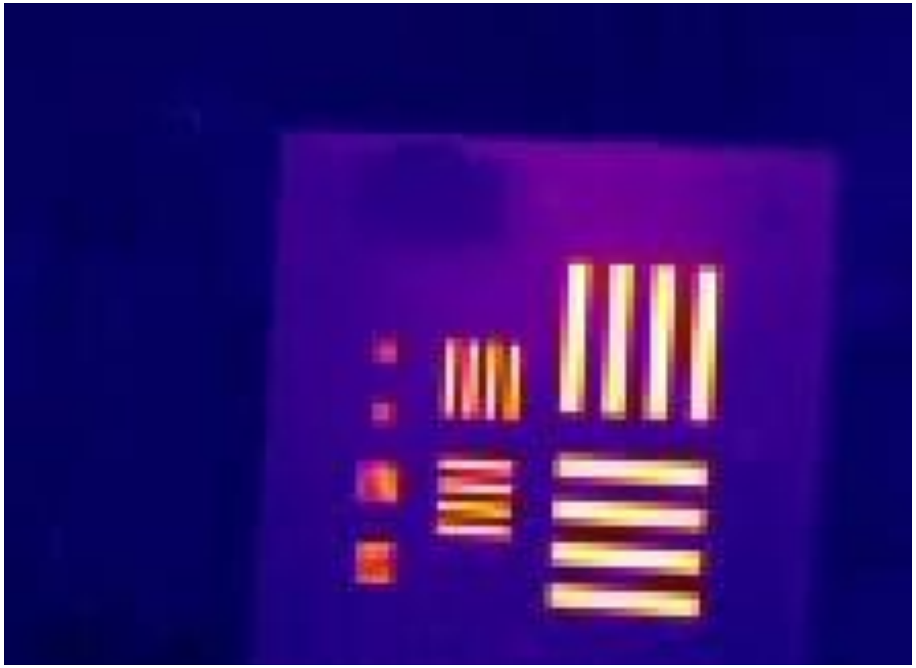
Decomposition of SV blurred image



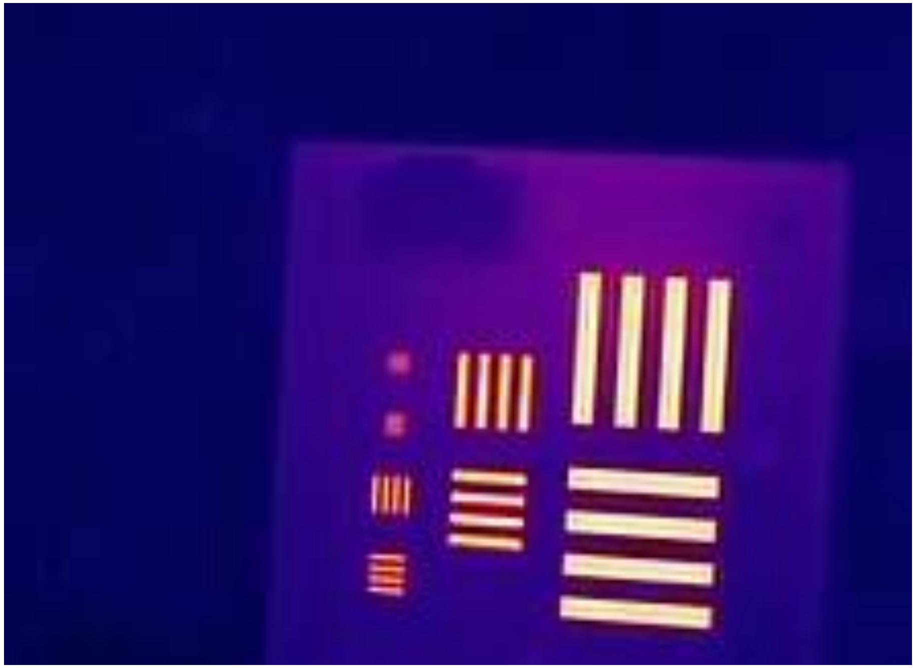
Infrared video restoration

- Handheld thermal camera (9-14µm)
  - 160 x 120, 9 fps

- Real-time super-resolution
  - with factor 2 (320 x 240)
  - computed directly inside the camera using DSP

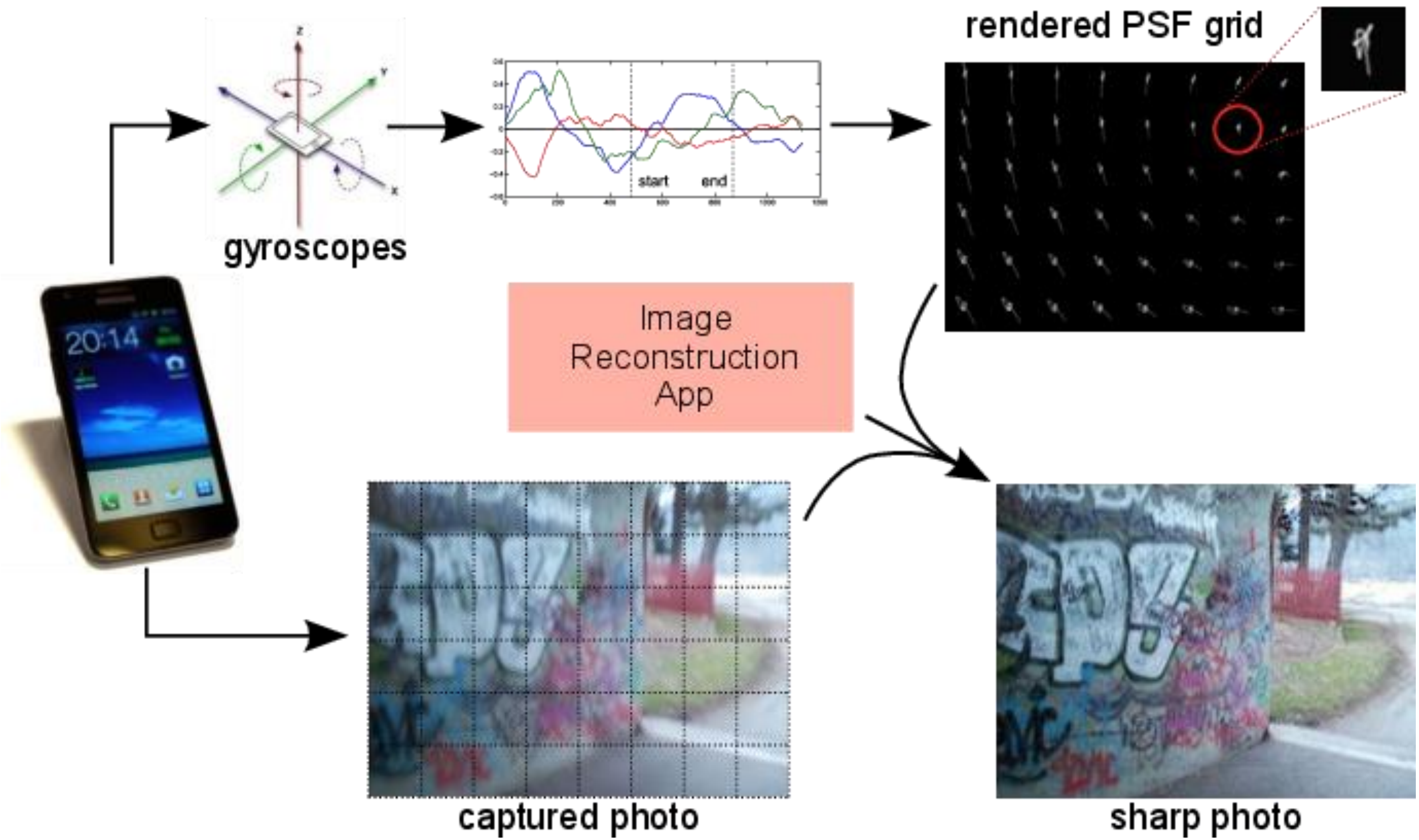


input



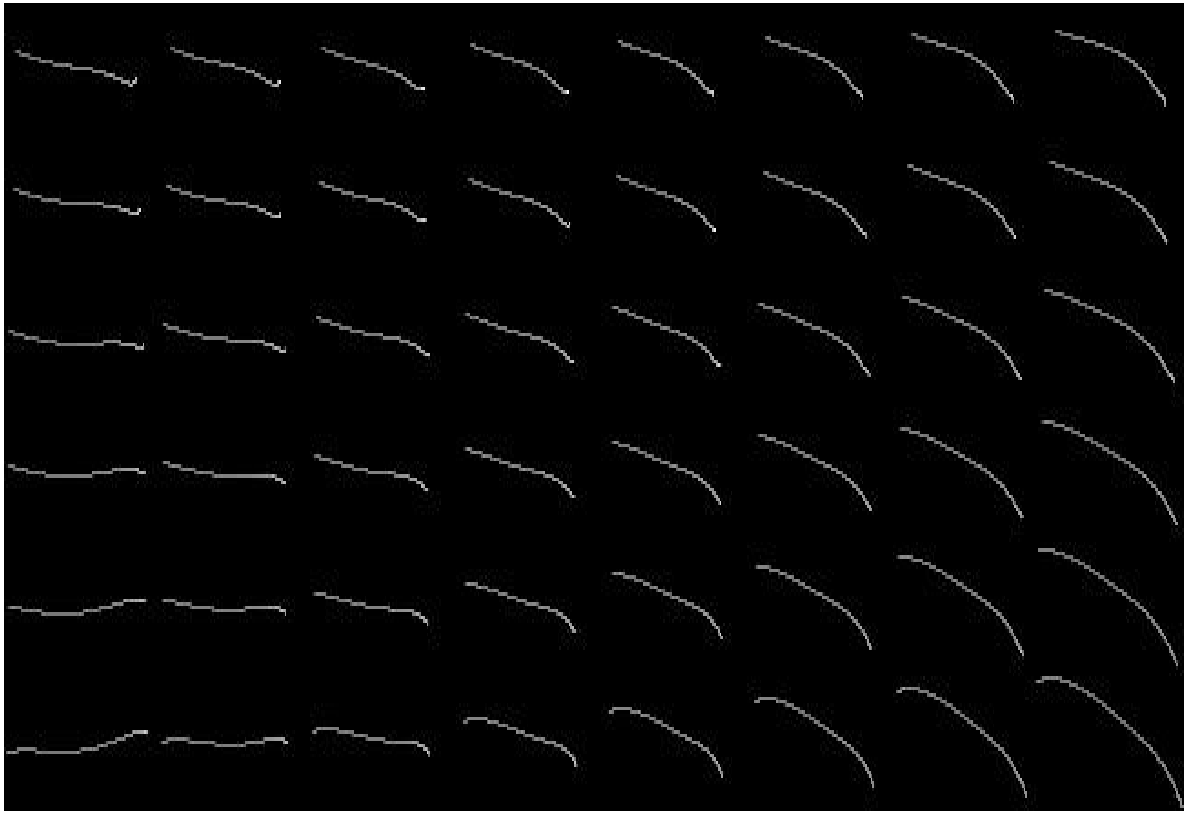
output

Smartphone Application



Acquired blurred image

Blur estimation



Patch-wise Deconvolution

Challenges

- Poor performance of blind deconvolution in practice
  - Avoid any camera postprocessing
  - Better image priors -> not i.i.d and dictionaries
  - Better blur priors -> e.g. for motion blurs
  - Robust noise models
- Space-variant blind deconvolution should be our next goal

Thank You…