Non-uniform Deblurring for Shaken Images

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LETTRES SCIENCES
ECOLE NORMALE SUPERIEURE

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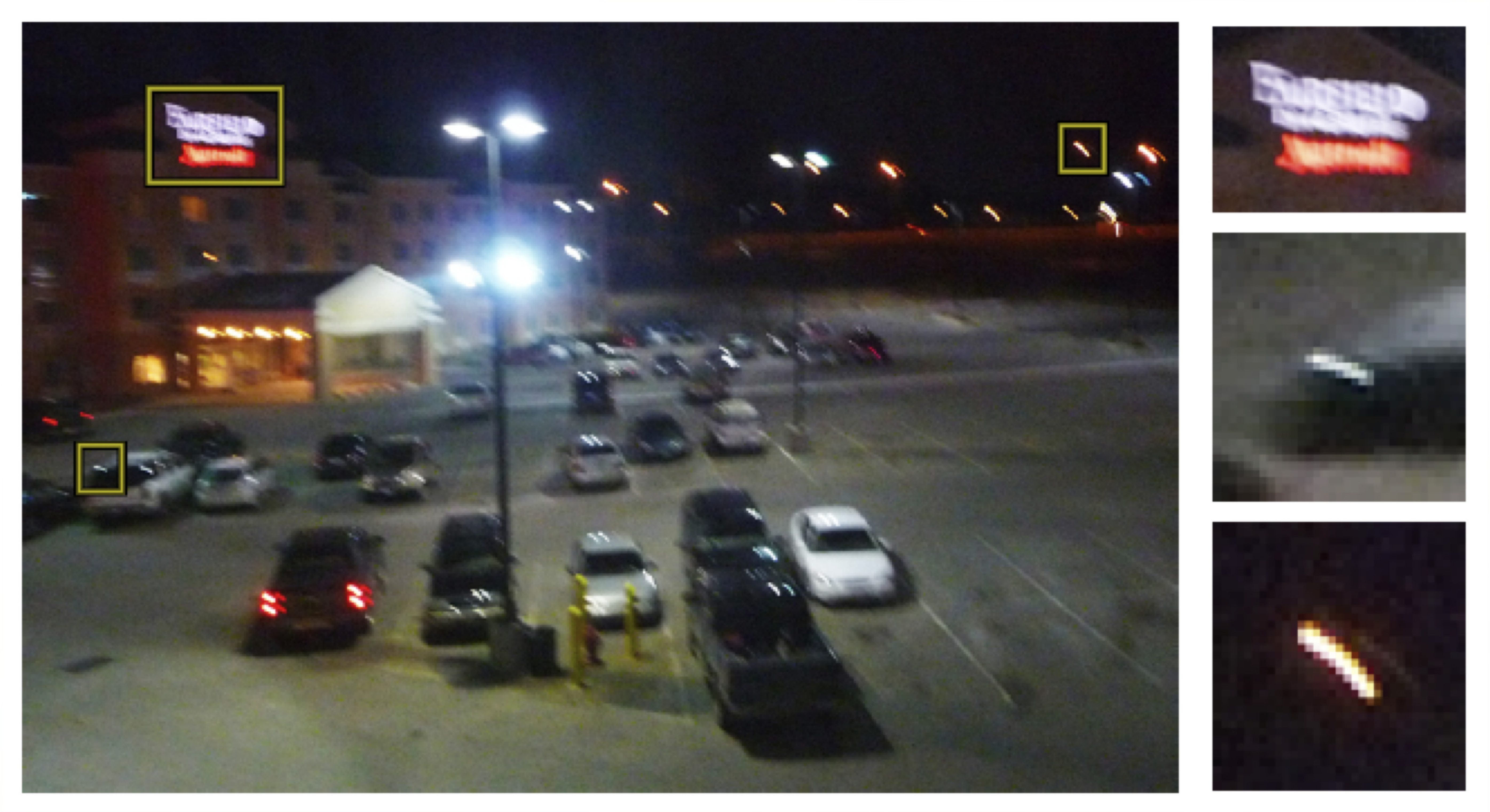
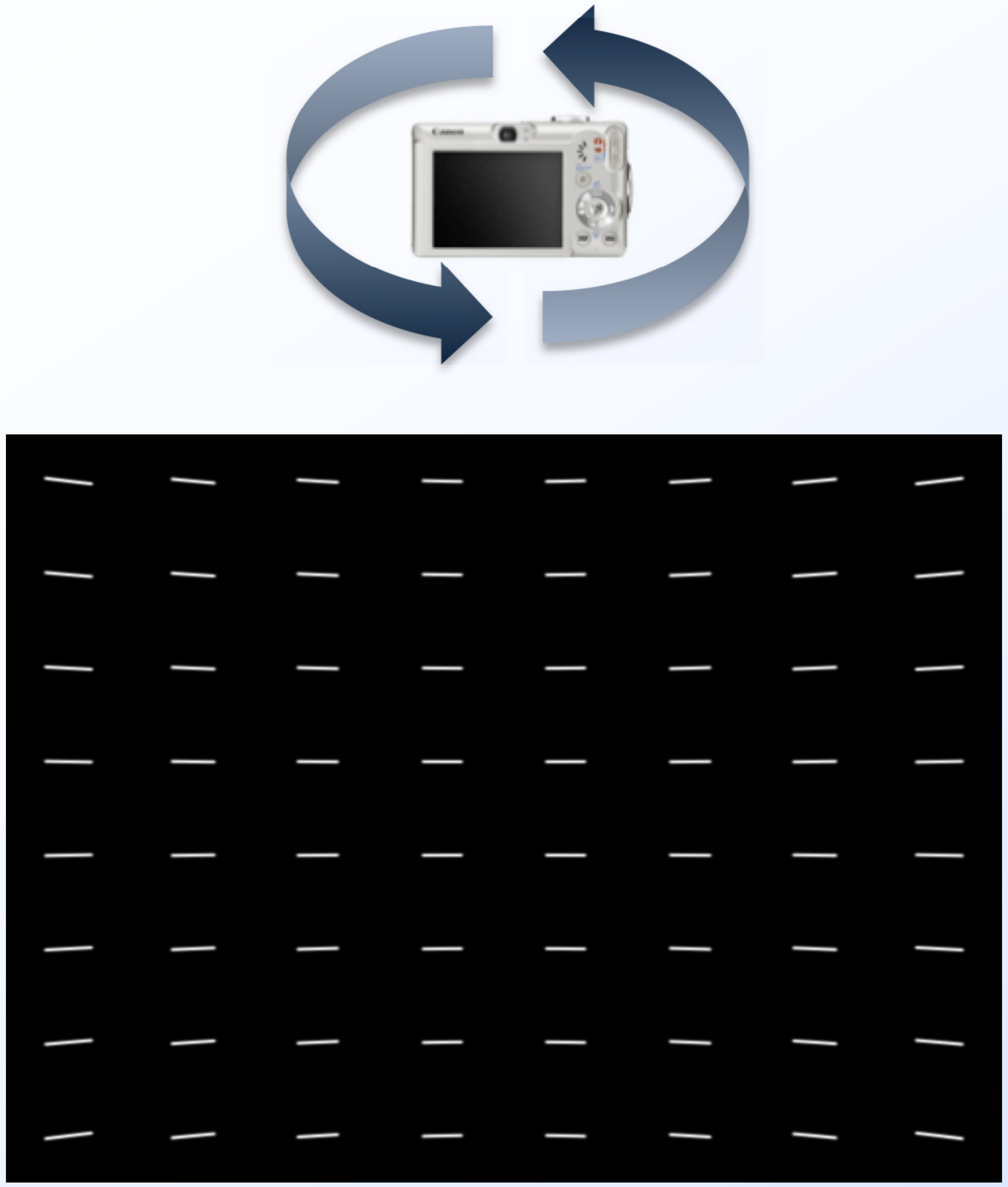
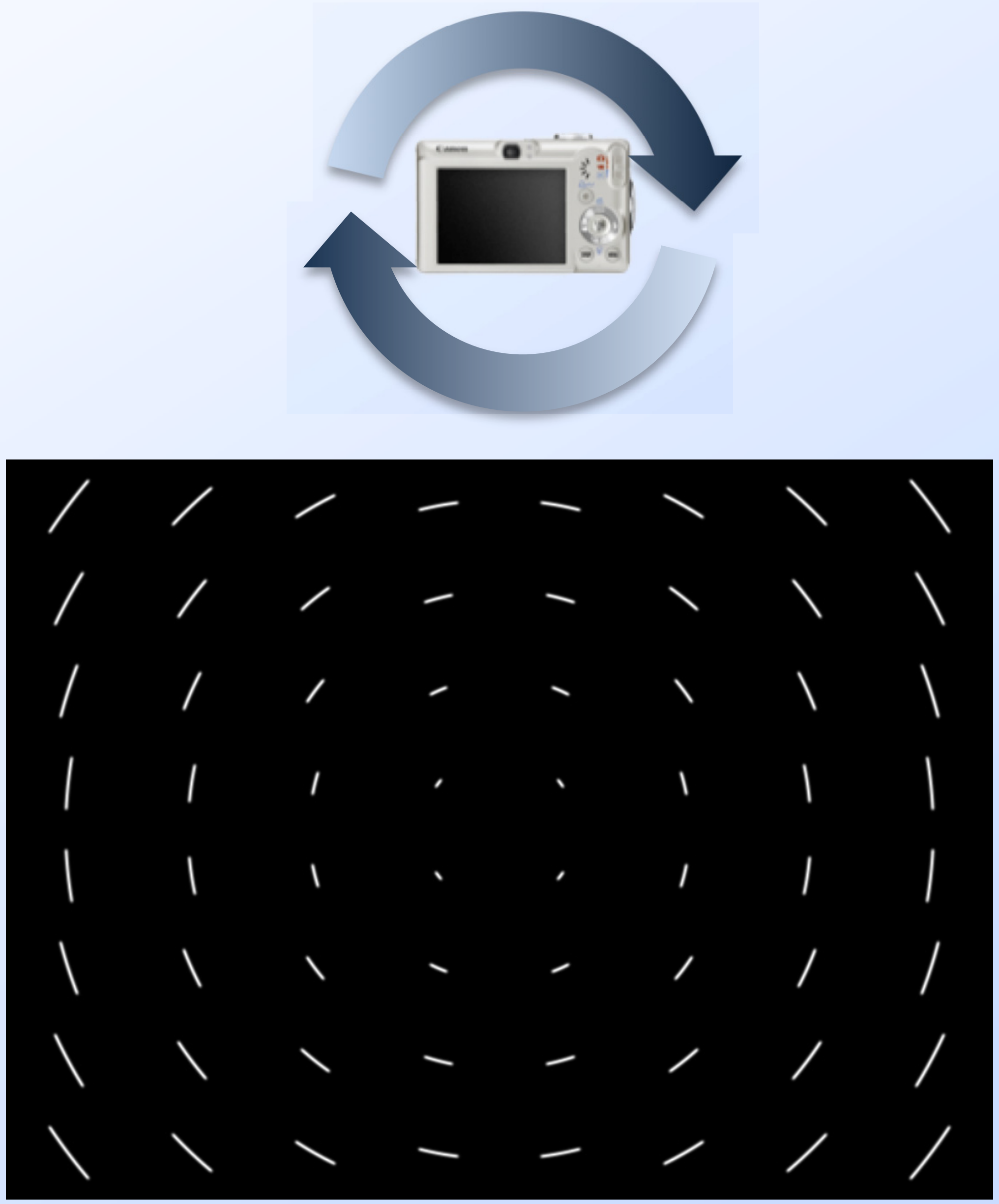
Non-uniform blur due to camera shake



Geometric model

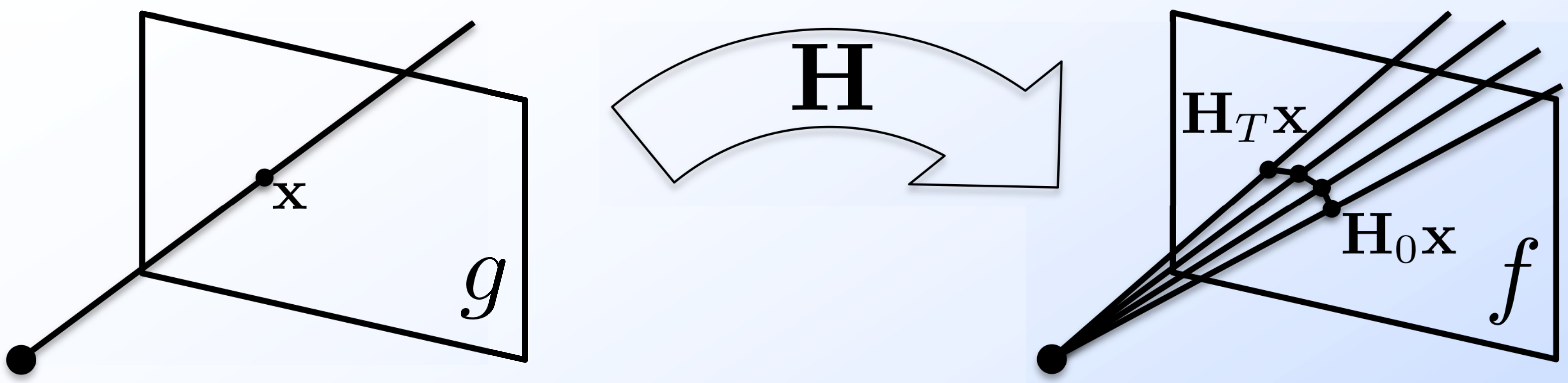
- Camera shake caused by 3D rotation of camera
- Camera rotations induce homographies:





Blur model

Blurry image is a sum of many projectively-transformed versions of (latent) sharp image.



Pixel in blurry image

Sequence of pixels in sharp image

$$g(\mathbf{x}) = \int_0^T f(\mathbf{H}_t\mathbf{x})\, dt + \varepsilon$$

blurry image

sharp image

homography at time instant t

noise

Blur model – continuous

- Blurry image has no temporal information
- Replace temporal integral with a weighted integral over all camera orientations

$$g(\mathbf{x}) = \int f(\mathbf{H}_{\boldsymbol{\theta}}\mathbf{x}) w(\boldsymbol{\theta}) \ d\boldsymbol{\theta} + \varepsilon$$

homography induced at camera orientation $\boldsymbol{\theta}$

weight function (inversely proportional to rotational velocity)

integrate over camera orientations

Blur model – discrete

- Continuous:

$$g(\mathbf{x}) = \int f(\mathbf{H}_{\boldsymbol{\theta}}\mathbf{x}) w(\boldsymbol{\theta})\ d\boldsymbol{\theta} + \varepsilon$$

- Discrete:

$$g_i = \sum_k \underbrace{\left(\sum_j C_{ijk} f_j \right)}_{} w_k + \varepsilon$$

blurry pixel with homogeneous coordinate vector $\mathbf{x}_i$

interpolation of the point $\mathbf{H}_k \mathbf{x}_i$ in the sharp image

weight for the k^{th} homography

Blur model – comparison

Convolution

(uniform)

$$g_i = \sum_{u,v} f_{x_i - u, y_i - v} w_{u,v} + \varepsilon$$

Weighted sum of **translated** copies of sharp image

Our model

(non-uniform)

$$g_i = \sum_k \Big(\sum_j C_{ijk} f_j \Big) w_k + \varepsilon$$

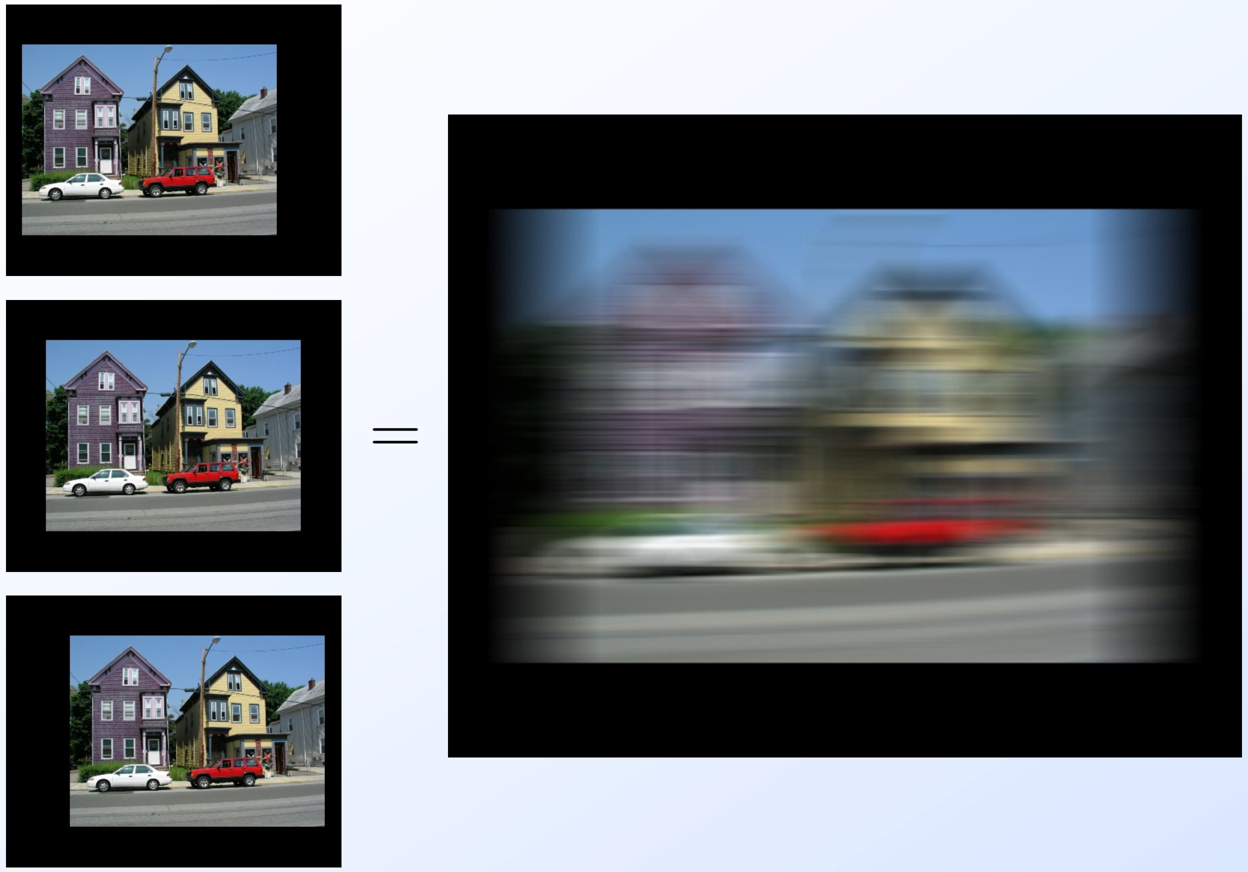
Weighted sum of **transformed** copies of sharp image

- Both are bilinear in blur kernel and sharp image
- We can use our model with existing algorithms

Blur model – comparison

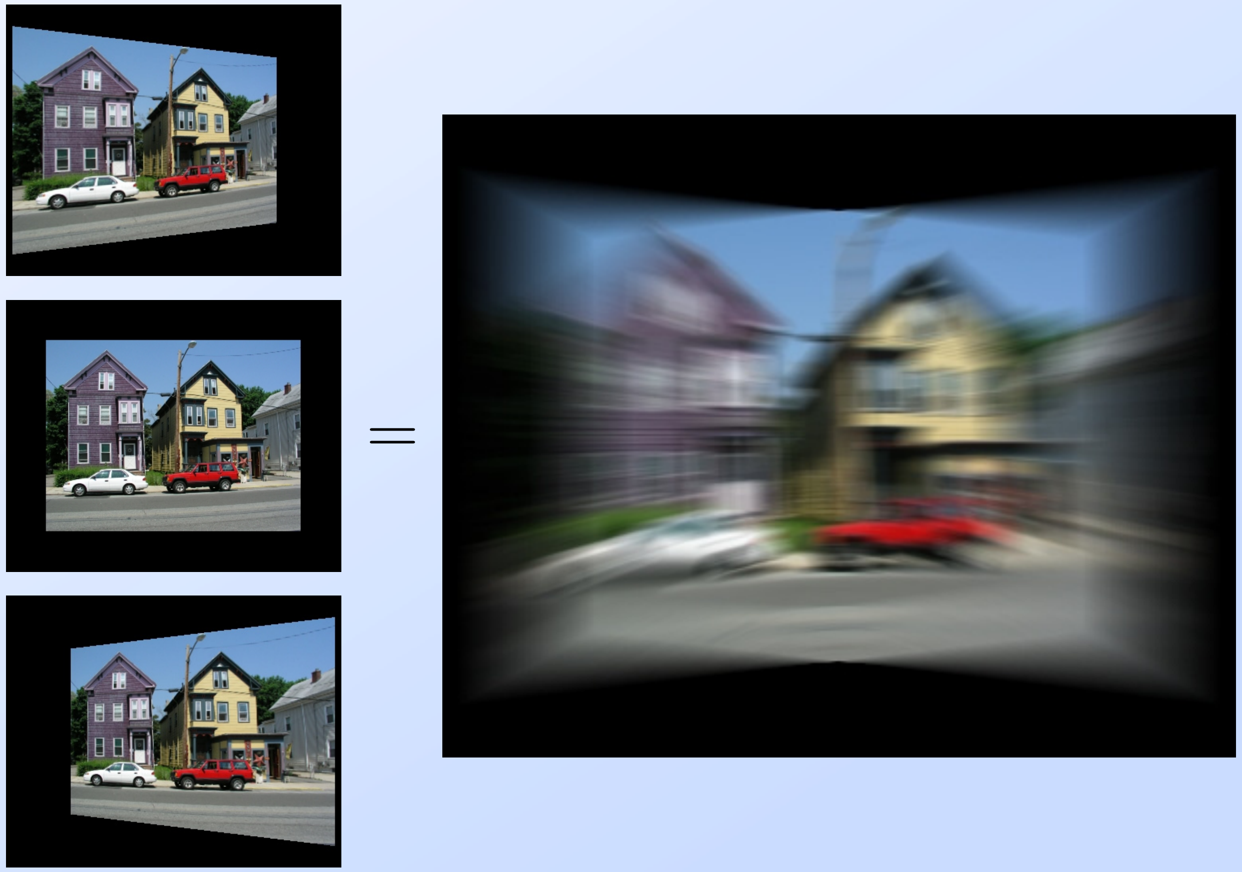
Convolution
(uniform)

$$g_i = \sum_{u,v} f_{x_i - u, y_i - v} w_{u,v} + \varepsilon$$



Our model
(non-uniform)

$$g_i = \sum_k \left(\sum_j C_{ijk} f_j \right) w_k + \varepsilon$$



Application I: Blind deblurring

- Estimate sharp image and kernel from a single blurry image

$$g_i = \sum_k \Big(\sum_j C_{ijk} f_j \Big) w_k + \varepsilon$$

observed

latent variables we want to recover

- Ill-posed problem – requires priors / regularisation on $\mathbf{f}$ & $\mathbf{w}$
- We apply our non-uniform model in the algorithm of Fergus *et al.,* SIGGRAPH '06

Blind deblurring (Fergus *et al., 2006*)

- Approximate posterior with a simpler factorised distribution (Miskin & MacKay, 2000)

$$p(\mathbf{f}, \mathbf{w}|\mathbf{g}) \propto p(\mathbf{g}|\mathbf{f}, \mathbf{w})p(\mathbf{f})p(\mathbf{w})$$

- $p(\mathbf{g}|\mathbf{f}, \mathbf{w})$: blur model + Gaussian noise model
- $p(\mathbf{f})$: sparse gradients (mixture of Gaussians)
- $p(\mathbf{w})$: sparse kernel (mixture of Laplacians)

Blind deblurring (Fergus *et al., 2006*)

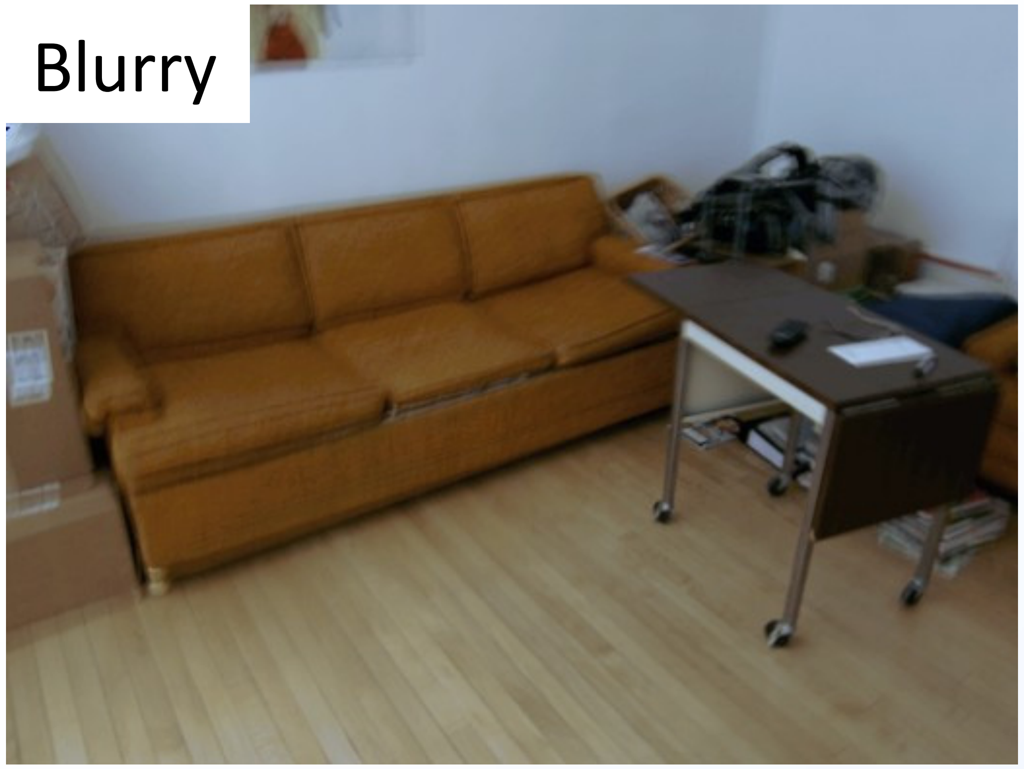
- Approximate posterior with a simpler factorised distribution (Miskin & MacKay, 2000)

$$p(\mathbf{f}, \mathbf{w} | \mathbf{g}) \approx \prod_j q(f_j) \prod_k q(w_k)$$

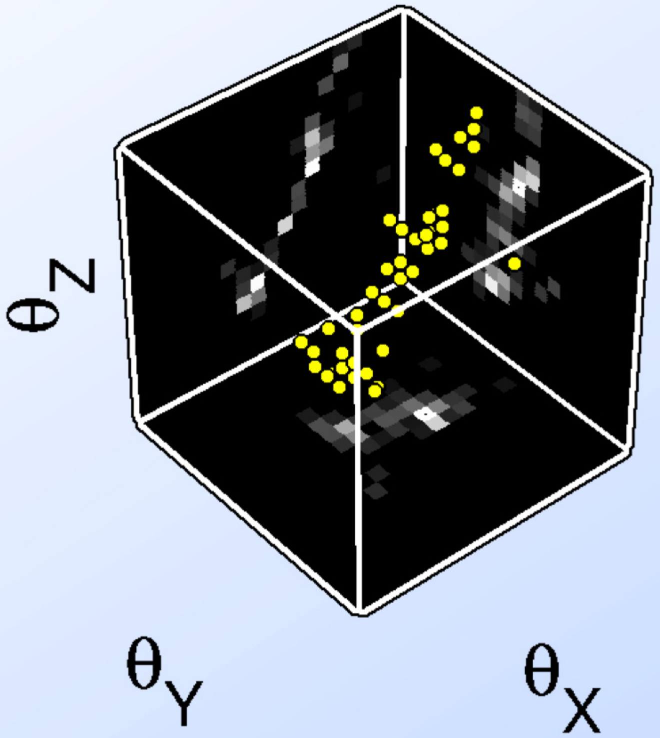
- Learn parameters of q distributions by minimising KL divergence with true posterior
- Estimate $\mathbf{w}$ by (trivial) marginalisation
- Deblur with Richardson-Lucy algorithm

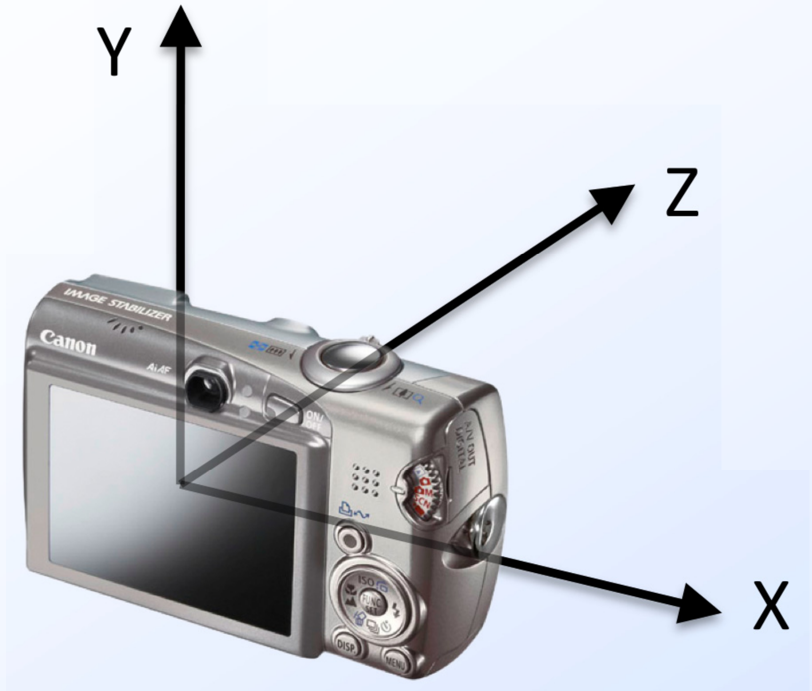
Blind deblurring – results

Blurry

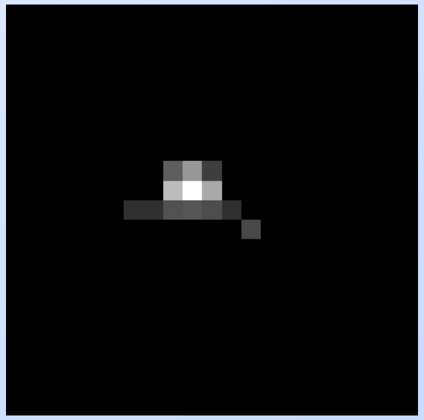


Our result





Fergus *et al.*



Blind deblurring – blurry image

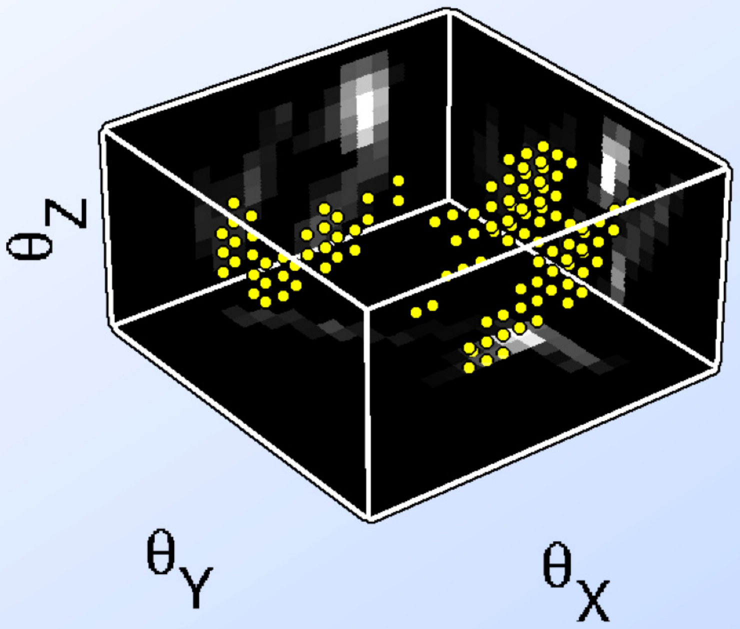
Blind deblurring – Fergus *et al.*

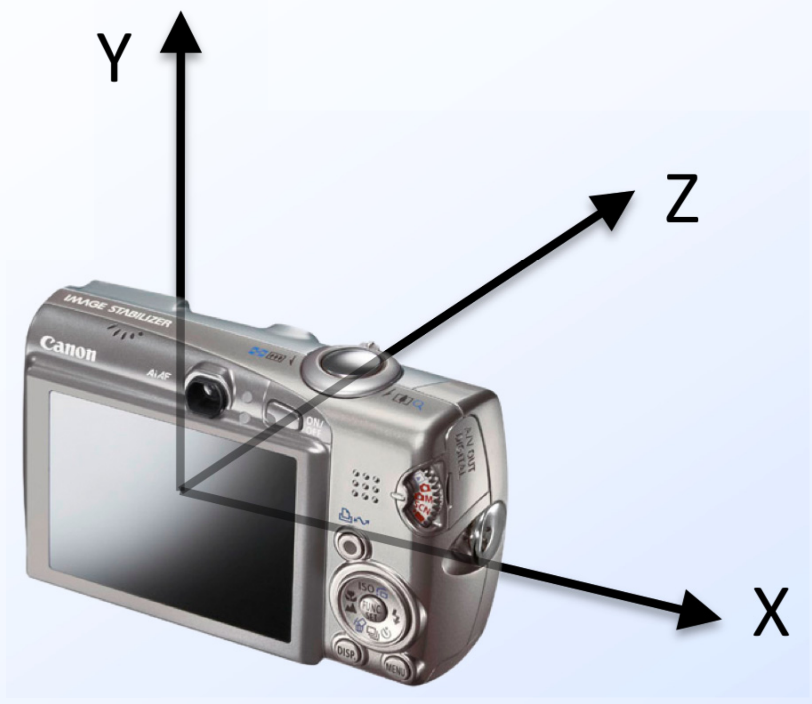
Blind deblurring – our result

Blind deblurring – results

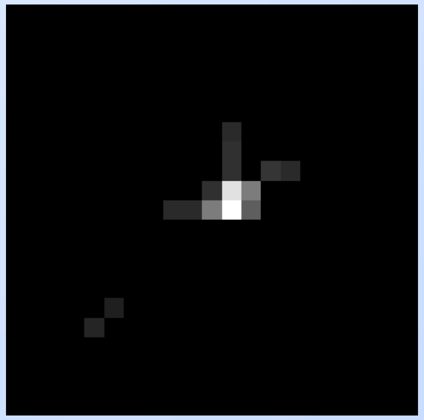
Blurry

Our result

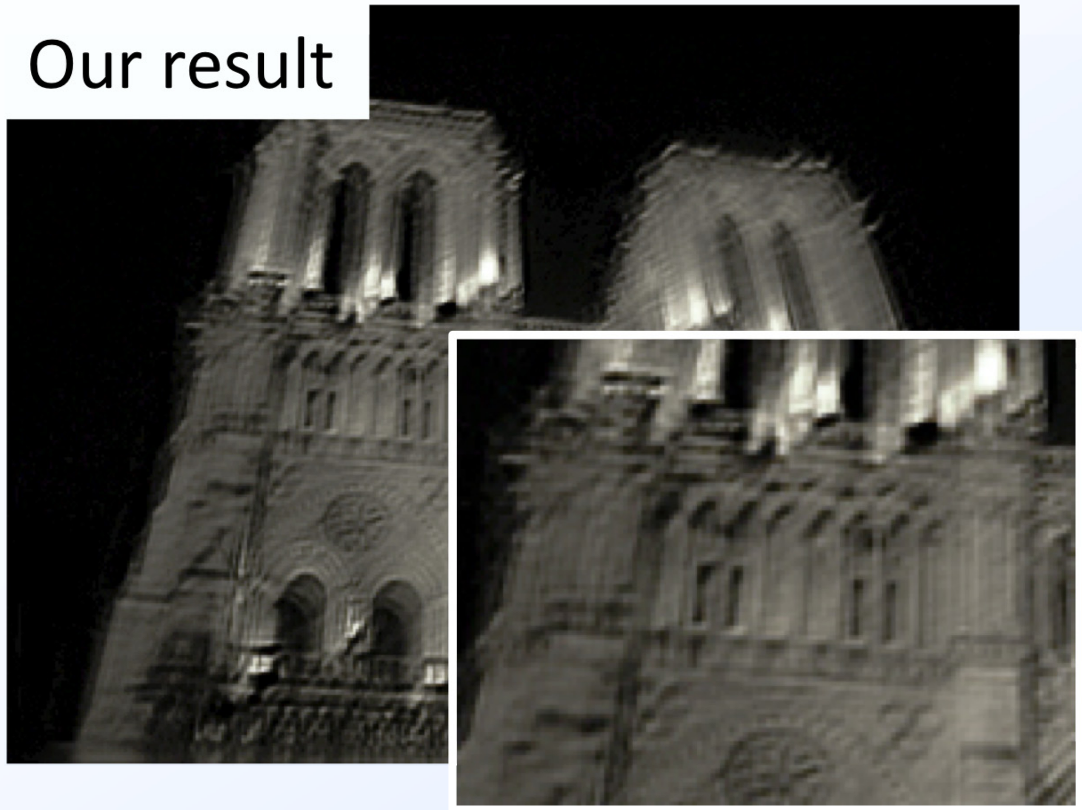


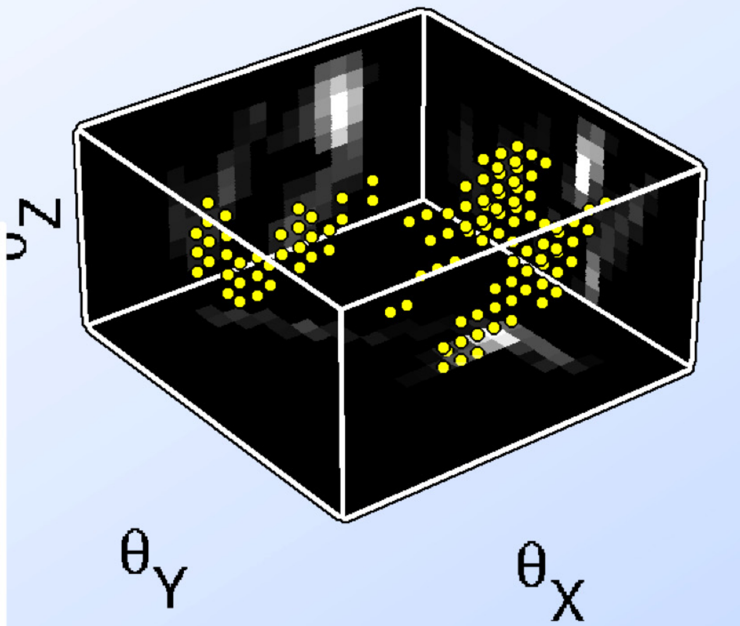


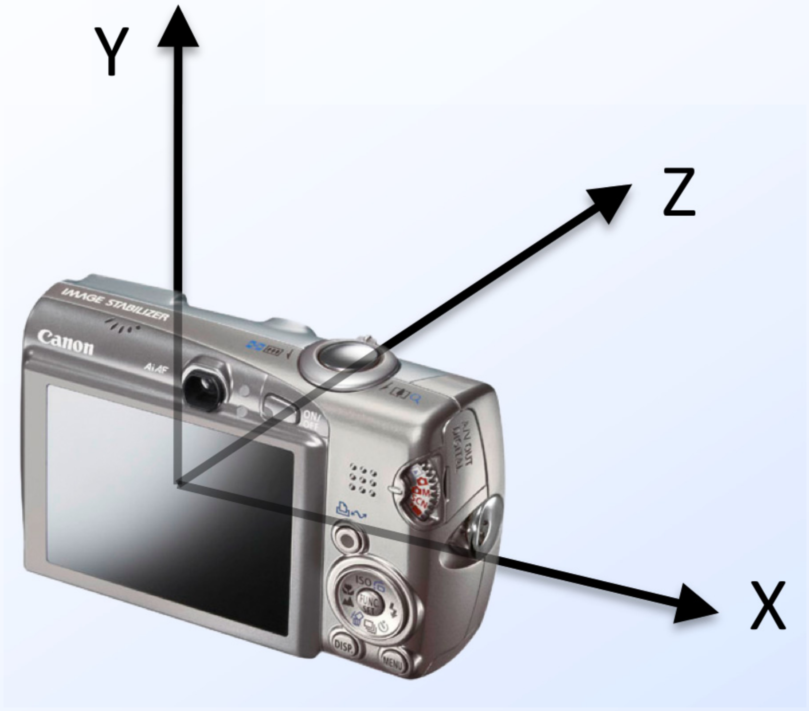
Fergus *et al.*

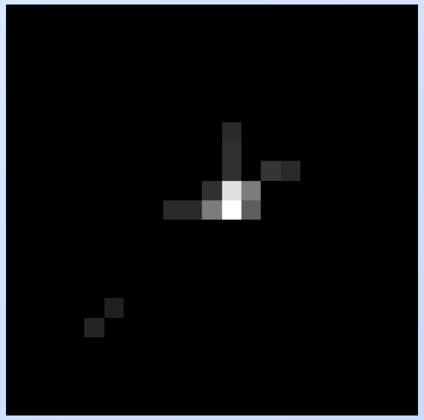


Blind deblurring – results



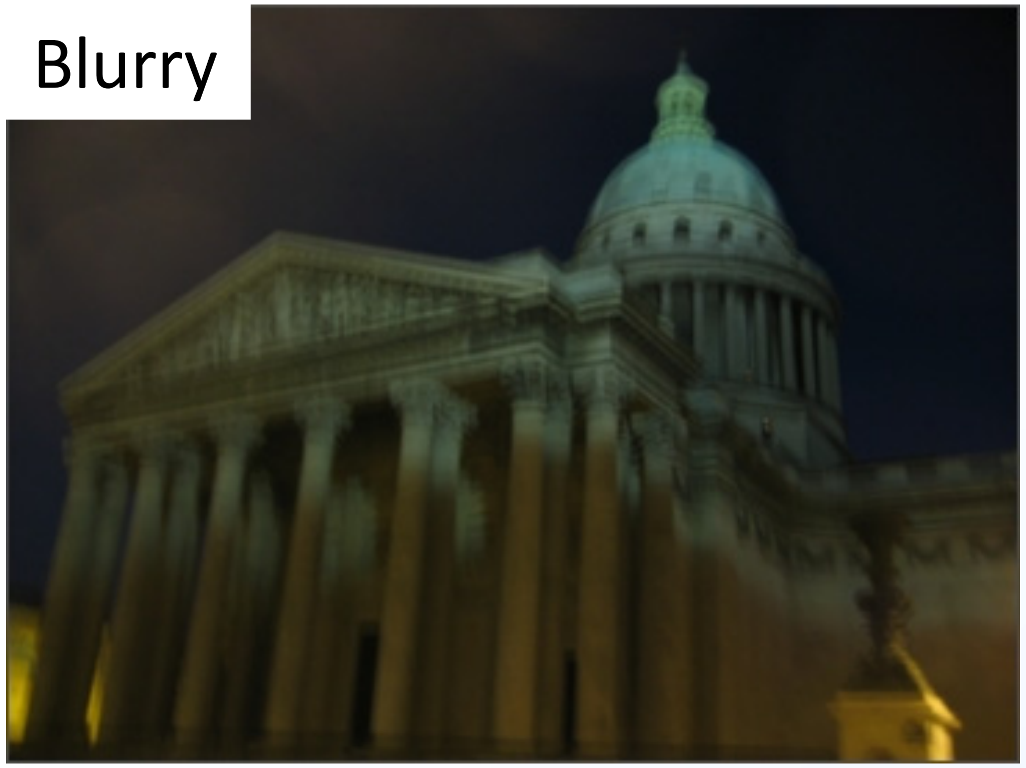




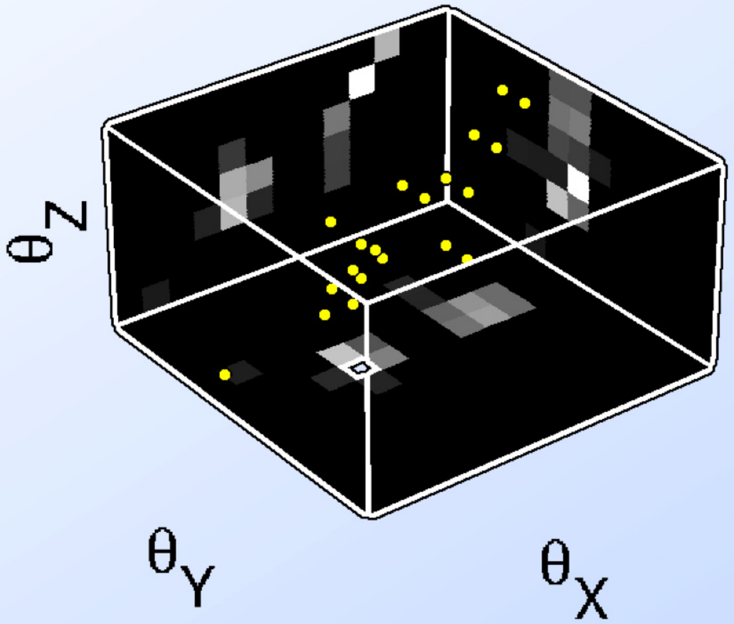


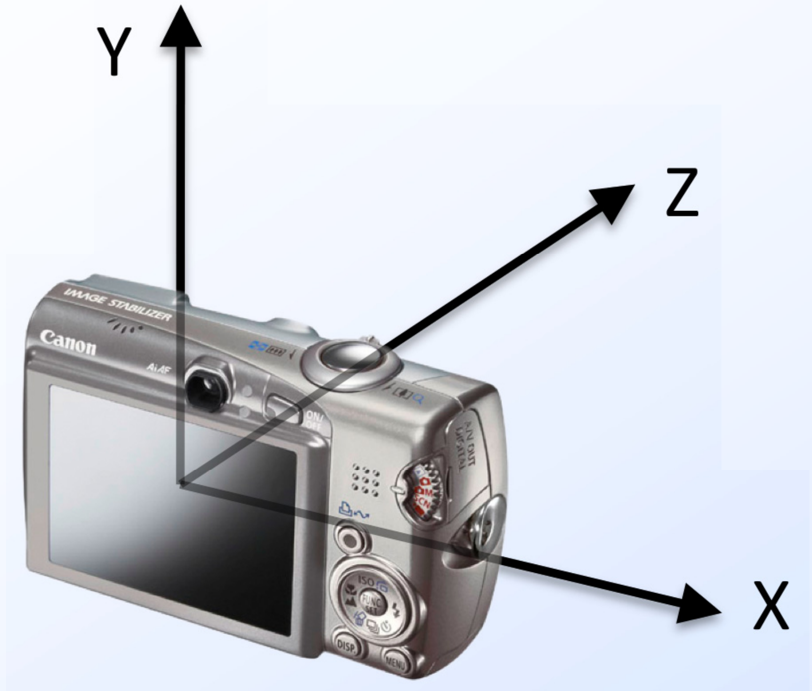
Blind deblurring – results

Blurry

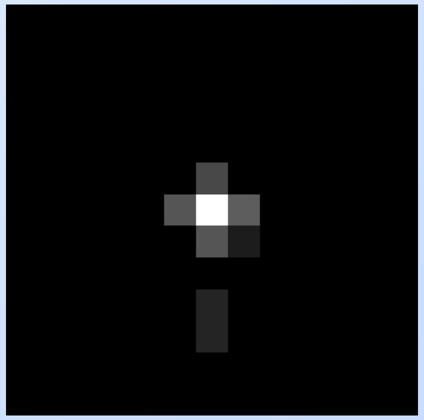


Our result

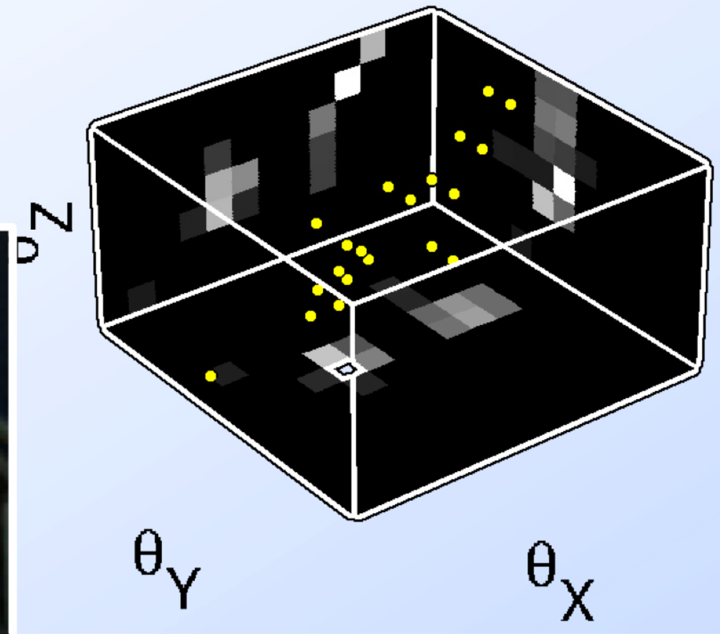


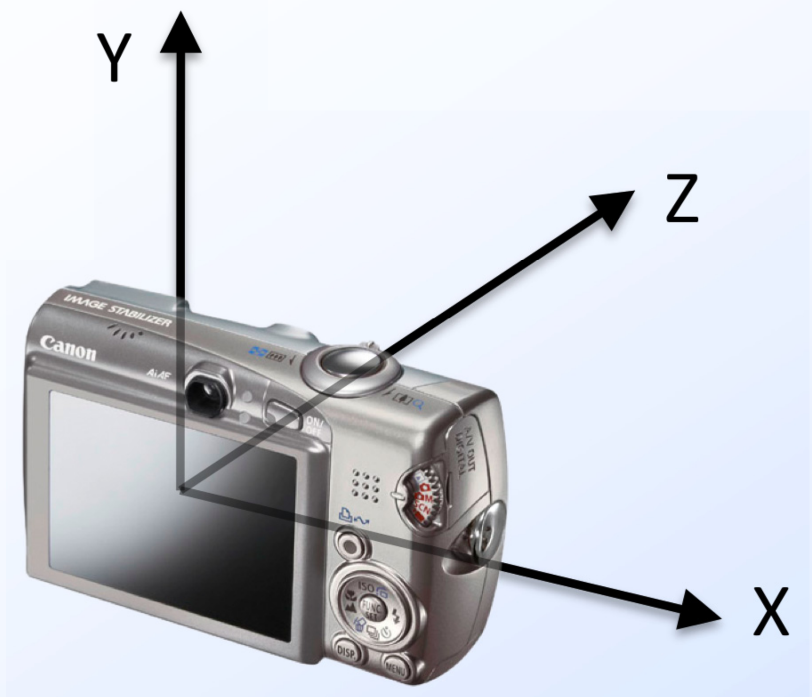


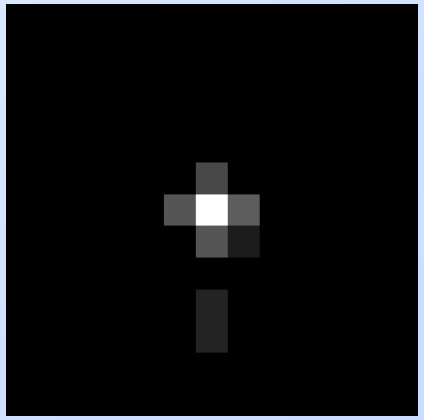
Fergus *et al.*



Blind deblurring – results





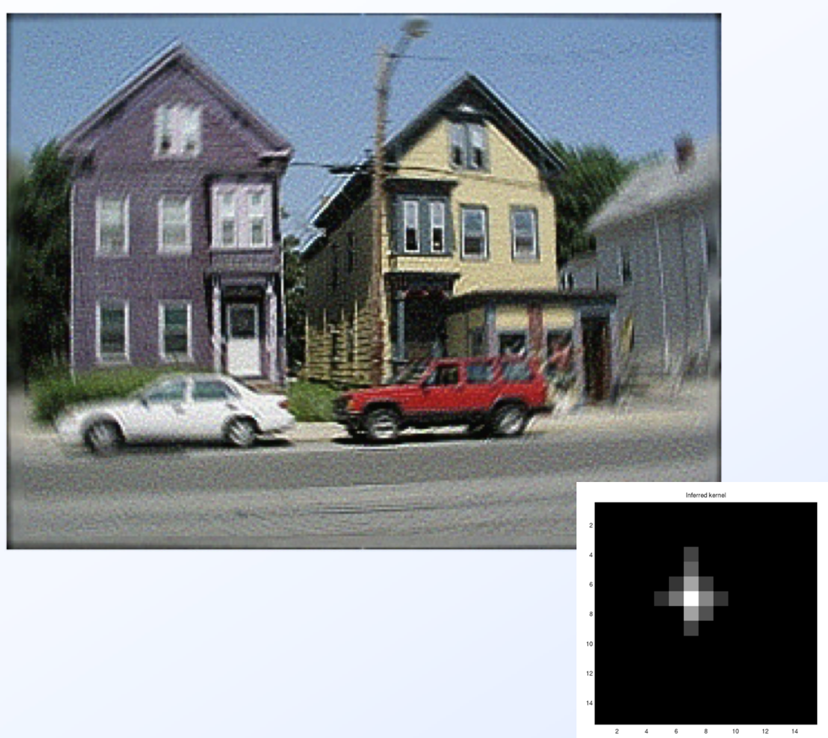


Blind deblurring – synthetic

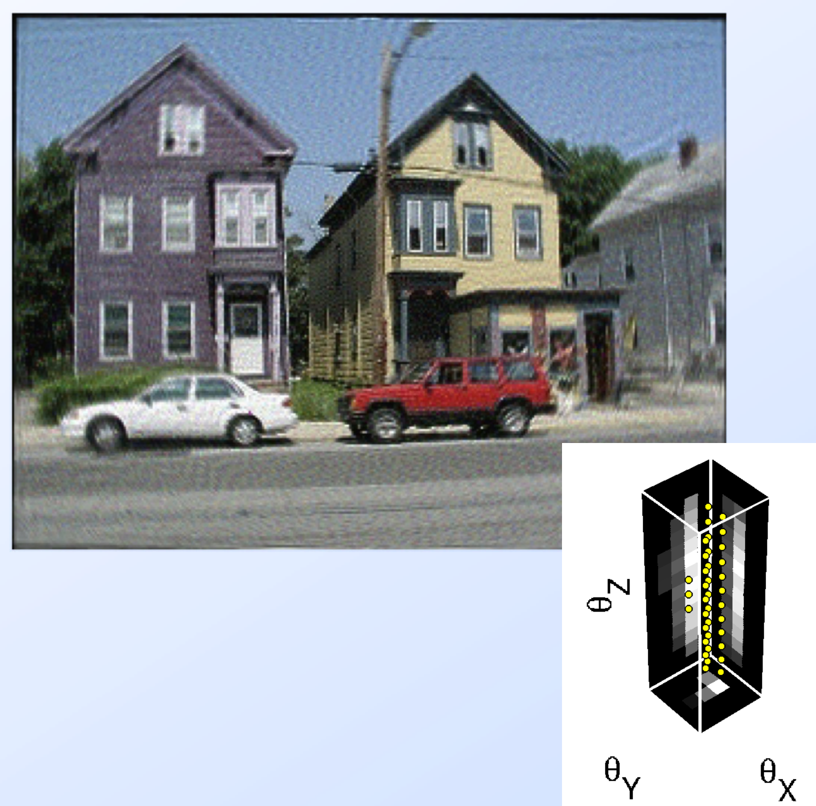
Sharp image

Blurry image

Fergus *et al.*



Our result

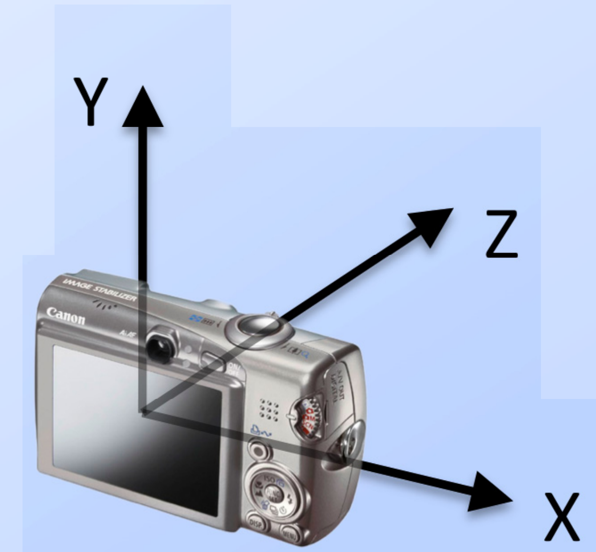


Ground-truth

Blind deblurring – synthetic

	10px		20px		30px	
Y-axis	R	U	R	U	R	U
$\sigma = 0$	**23.1** (1.4)	23.2 (1.4)	**27.2** (1.1)	58.1 (2.4)	**32.2** (1.1)	129.3 (4.4)
$\sigma = 5$	**24.9** (1.3)	25.8 (1.3)	**29.0** (1.1)	56.8 (2.2)	**33.4** (1.1)	62.9 (2.1)
$\sigma = 10$	**27.0** (1.2)	30.1 (1.3)	**30.7** (1.1)	48.7 (1.8)	**41.9** (1.3)	57.8 (1.8)
Z-axis	R	U	R	U	R	U
$\sigma = 0$	**14.4** (1.3)	21.8 (2.0)	**18.1** (1.0)	26.1 (1.6)	**25.4** (1.2)	57.6 (2.7)
$\sigma = 5$	**17.4** (1.2)	24.8 (1.7)	**23.2** (1.2)	54.5 (2.8)	**30.6** (1.3)	58.6 (2.5)
$\sigma = 10$	**22.0** (1.1)	50.9 (2.7)	**26.5** (1.1)	55.8 (2.4)	**30.0** (1.2)	57.5 (2.2)

RMS errors for deblurred results



(R) our rotational model, compared to (U) Fergus *et al.*

In parentheses, the ratio to the RMS error achieved using the ground-truth kernel.

Our model gives lower errors, particularly as the blur's non-uniformity increases

Blind deblurring – uniform blur

Sharp image

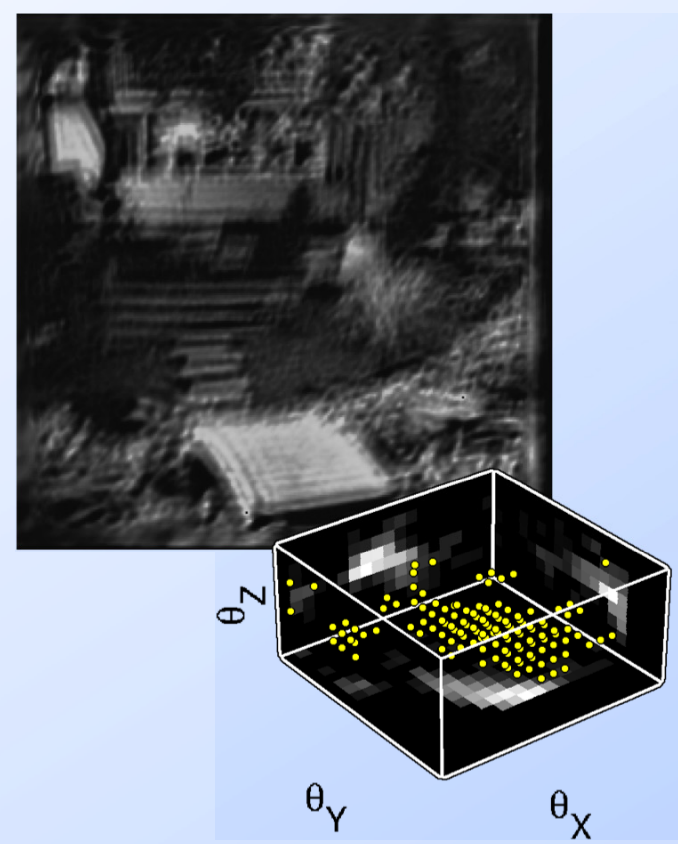
Blurry image

From Levin *et al.* CVPR ‘09

Fergus *et al.*

Ours $\theta_Z = 0$

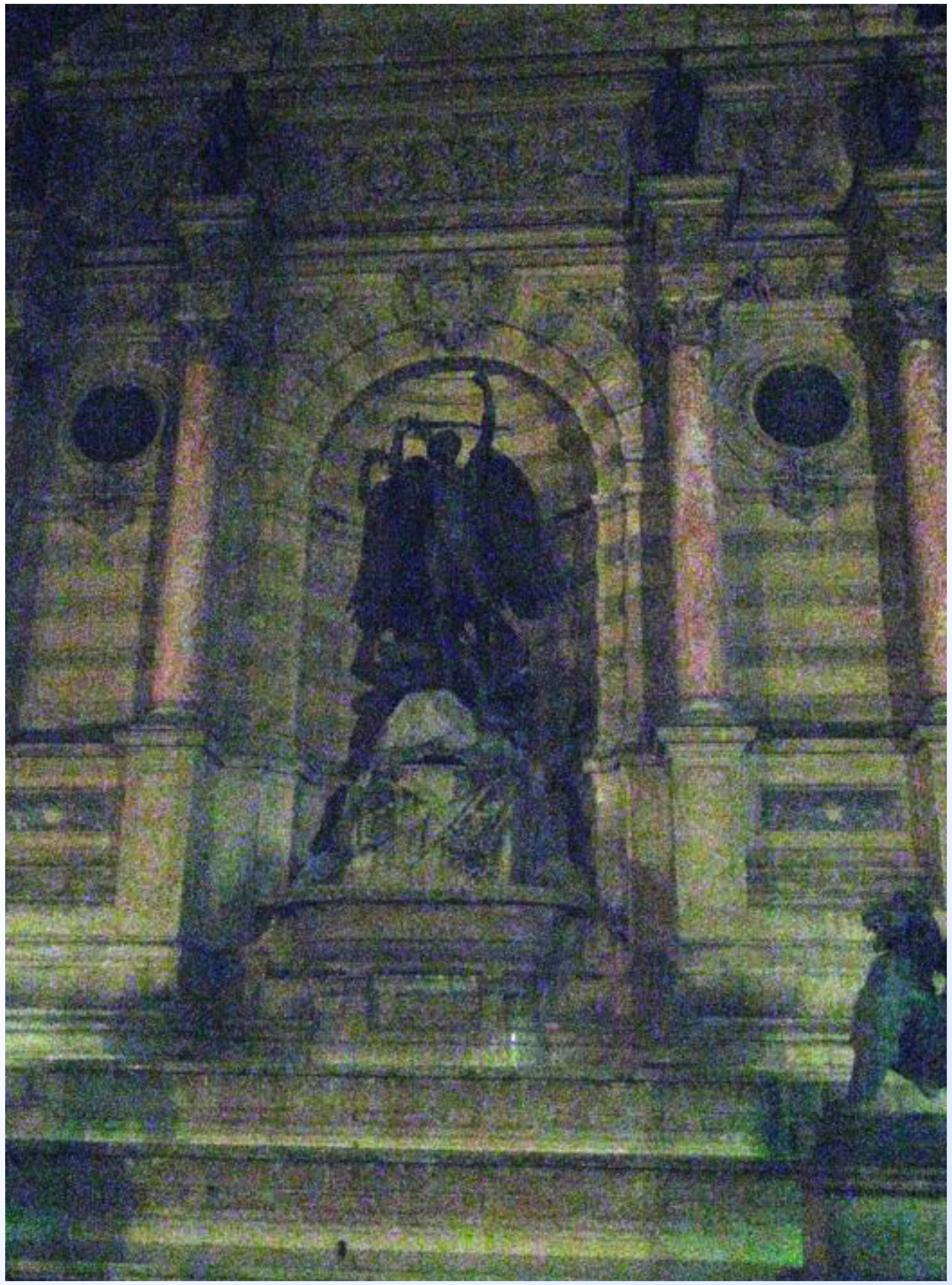
Ours



Ground-truth

Application II: Noisy / blurry images

Noisy



Blurry

Noisy / blurry image pairs (Yuan *et al., 2007*)

- Use a noisy image as a proxy for the sharp image, estimate kernel using least squares:

$$\min_{\mathbf{w}} \|\mathbf{g} - \hat{\mathbf{g}}(\mathbf{f}_N, \mathbf{w})\|_2^2 \qquad \text{s.t.} \quad \|\mathbf{w}\|_1 = 1$$

$$w_k \geq 0 \quad \forall k$$

"reconstruction" of blurry image using $\mathbf{f}_N$ & $\mathbf{w}$

noisy image

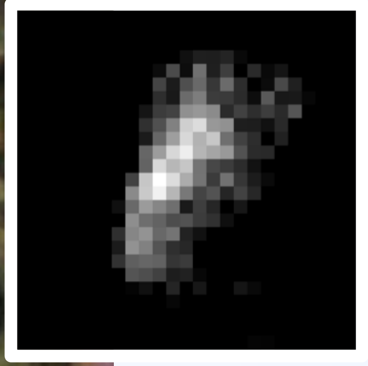
- Linear least squares thanks to bilinear model:

$$\hat{\mathbf{g}}(\mathbf{f}_N, \mathbf{w}) = \mathbf{B}_N \mathbf{w}$$

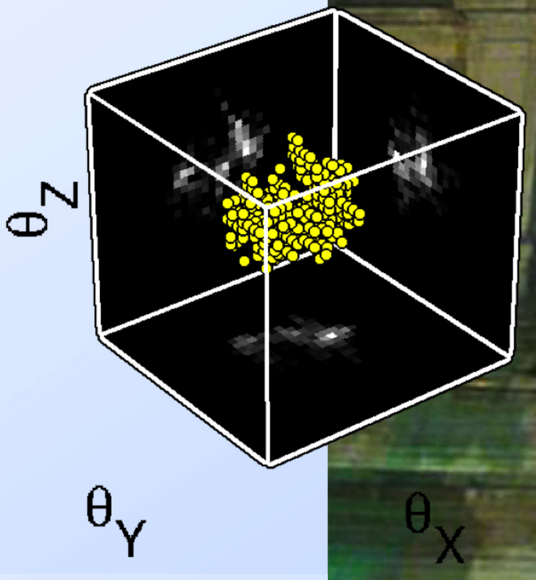
- Deblur with modified Richardson-Lucy algorithm

Noisy / blurry image pairs – results

Uniform result



Our result



Noisy / blurry image pairs – detail

Noisy Blurry Uniform result Our result

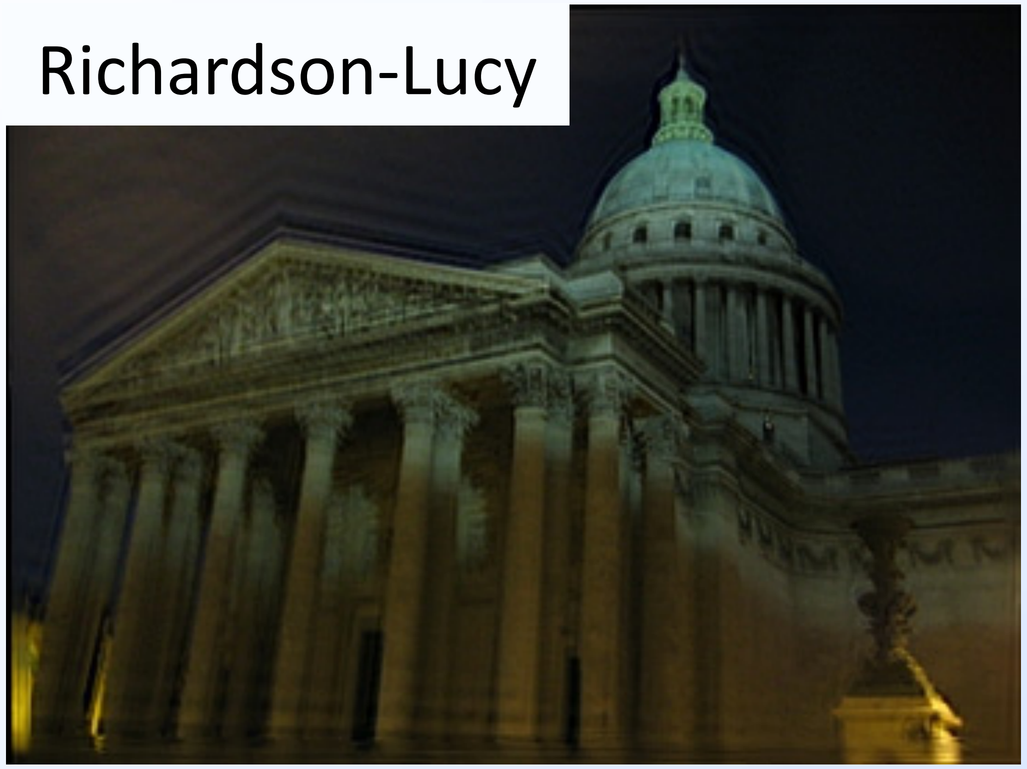
Conclusions

- A geometrically derived model for non-uniform blur due to camera-shake
- Bilinear computational form generalises typical convolution blur model
- Can plug our model into existing deblurring algorithms

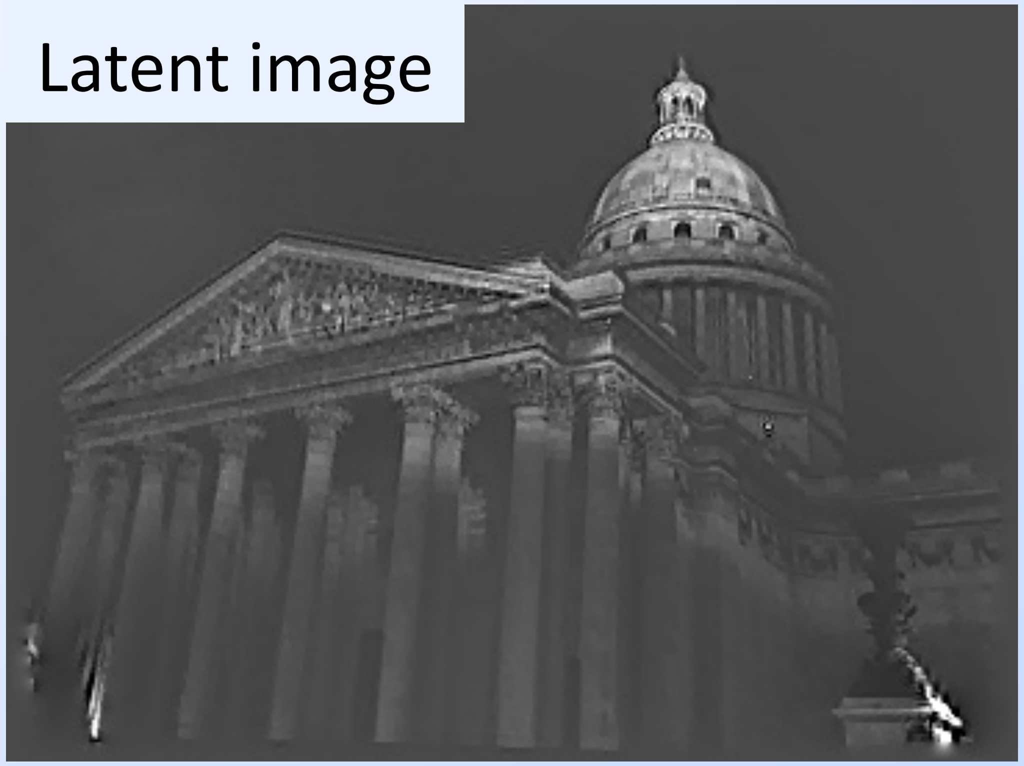
Future directions

- Problem of "ringing" in deblurred images, due to Richardson-Lucy algorithm
  - Possibility of using latent image directly from variational algorithm

Richardson-Lucy



Latent image



Future directions

- Problem of “ringing” in deblurred images, due to Richardson-Lucy algorithm
- Better algorithms for estimating and removing the blur
- Computational cost

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