Fast Removal of Non-Uniform Camera Shake

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Joint work with ...





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What is Camera Shake? What problem do we want to solve?





Outline

- Related Work
- Past Forward Model
- o Algorithm for Single Image Blind Deblurring
- 4 Results
- Limitations
- Conclusions

• Fergus et al. (SIGGRAPH'06): Removing camera shake from a single image

Blurry Photo





 $y \approx F x$

Point Spread Function (PSF):

A fully describes the optical system. System response to a light point.

• Fergus et al. (SIGGRAPH'06): Removing camera shake from a single image



Point Spread Function (PSF):

A fully describes the optical system. System response to a light point. Common assumption:

$$F \neq F(s,t) \Rightarrow y = Fx = f * x$$

• Fergus et al. (SIGGRAPH'06): Removing camera shake from a single image

 Blurry Photo
 PSF
 Sharp Image

 Image
 Image
 Image

 Image
 Image
 Image

 $y \approx f *$

Task of Blind Deconvolution:

Given blurry image y recover x without knowing f.

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• Fergus et al. (SIGGRAPH'06): Removing camera shake from a single image



- Cho and Lee (SIGGRAPH ASIA'09): Fast Motion Deblurring
- Xu and Jia (ECCV 2010): Two-Phase Kernel Estimation for Robust Motion Deblurring
- Levin et al. (CVPR 2009): Understanding and Evaluating Blind Deconvolution Algorithms

What is Camera Shake? Let's have a closer look...





• Hirsch et al. (CVPR 2010): Efficient Filter Flow Framework



$$y = Z_y^{\mathsf{T}} \sum_{r=0}^{p-1} C_r^{\mathsf{T}} F^{\mathsf{H}} \operatorname{Diag}(FZ_a a^{(r)}) F \operatorname{Diag}(w^{(r)}) C_r x,$$



• Hirsch et al. (CVPR 2010): Efficient Filter Flow Framework



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• Hirsch et al. (CVPR 2010): Efficient Filter Flow Framework



$$\mathbf{y} = \mathbf{Z}_{\mathbf{y}}^{\mathsf{T}} \sum_{r=0}^{p-1} \mathbf{C}_{r}^{\mathsf{T}} F^{\mathsf{H}} \operatorname{Diag}(F \mathbf{Z}_{a} a^{(r)}) F \operatorname{Diag}(w^{(r)}) \mathbf{C}_{r} \mathbf{x}$$

• Harmeling et al. (NIPS'10): Space-Variant Single-Image Blind Deconvolution for Removing Camera Shake



• Hirsch et al. (CVPR 2010): Efficient Filter Flow Framework



$$\mathbf{y} = \mathbf{Z}_{\mathbf{y}}^{\mathsf{T}} \sum_{r=0}^{p-1} \mathbf{C}_{r}^{\mathsf{T}} F^{\mathsf{H}} \operatorname{Diag}(F \mathbf{Z}_{a} a^{(r)}) F \operatorname{Diag}(w^{(r)}) \mathbf{C}_{r} \mathbf{x}_{a}$$

• Harmeling et al. (NIPS'10): Space-Variant Single-Image Blind Deconvolution for Removing Camera Shake



Blurred Image

Cho and Lee

Harmeling et al.

What is Camera Shake really?



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- Tai et al. (Tech Report'09): Richardson-Lucy Deblurring for Scenes under Projective Motion Path
- Whyte et al. (CVPR'10): Non-uniform Deblurring for Shaken Images
- Gupta et al. (ECCV'10): Single Image Deblurring using Motion Density Functions



Modified from Oliver Whyte's CVPR 2010 talk slides.

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Modified from Oliver Whyte's CVPR 2010 talk slides.

• Oliver Whyte et al. (CVPR 2010): Non-uniform Deblurring for Shaken Images

Restrict allowed motion to rotations only and take a discrete set of camera orientations. Inference is performed on the weighting vector.



Modified from Oliver Whyte's CVPR 2010 talk slides using plot_nonuni_kernel.m. Pros:

 Camera motion constraint is inherent in the imaging model, i.e. only physically plausible camera motions are allowed.

Cons:

- Computationally expensive, e.g. 1200x1600 pixels \approx 180s.
- For comparison: our space-varying filtering \approx 1.5s @CPU, 0.01s @GPU.

Question

How can we combine both approaches in a unified framework?

Forward Model

Camera Motion Constraint Efficient Filter Flow

Inception - How the idea was born...

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Inception - How the idea was born...

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Inception - How the idea was born...


Looking how a Point Grid Transforms



For EFF we need to know the PSF. As the PSF is the system's response to a point source, let's see how a grid of dots transforms.

Looking how a Point Grid Transforms



Transformed point grid depicts the response of the optical system to point sources, i.e. it encapsulates the space-varying PSF at abitrary positions.

Looking how a Point Grid Transforms



Transformed point grid depicts the response of the optical system to point sources, i.e. it encapsulates the space-varying PSF at abitrary positions.







Camera Motion Constraint Efficient Filter Flow



Flow Filter Efficient amera Motion Constraint



Voxel intensity (density) corresponds to time spen in certain camera pose during exposure





Motion Constraint Efficient Filter Flow amera

PSF Basis **Precomputed by Homographica** Transformations on Point Grid and Stored as Sparse Matrices









Camera Motion Constraint Efficient Filter Flow





Efficient Filter Flow

Motion Density Function Efficient computation of Spatially-varying convolution via Efficient Filter Flow T, T,



Discussion

Computation Time



Accuracy



Expressivity



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Vertical motion

X





























































Rotational motion

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Rotational motion

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Rotational motion

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Rotational motion

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Single Image Blind Deblurring Algorithm

Overview of Single Image Blind Deblurring Algorithm

(i) Step 1: Motion Blur Estimation: We are iterating over four steps:

- Prediction Step: Apply shock and bilateral filtering to counter noise and emphasize edges (Cho and Lee (SIGGRAPH 2009))
- Gradient Selection: Select informative edges via gradient confidence map (rmap approach of Xu and Jia ECCV 2010)
- Blur Parameter Estimation: Update blur parameter by minimizing:

$$\min_{\mu} \left\| \partial g - m_{S} \odot \partial(\mu \diamond \tilde{f}) \right\|_{2}^{2} + \kappa \left\| \mu \right\|_{2}^{2} + \lambda \left\| \partial \mu \right\|_{2}^{2}, \tag{1}$$

• Latent Image Estimation: Update latent image by minimizing:

$$\min_{f} \left\| g - \mu \diamond f \right\|_{2}^{2} + \nu \left\| \partial f \right\|_{2}^{2}$$
(2)

(ii) Step 2: Latent Image Estimation:

Given the motion blur estimate we estimate the final deblurred image following Krishnan and Fergus (NIPS 2009):

$$\min_{f} \|g - \mu \diamond f\|_{2}^{2} + \eta \|f\|_{2/3}^{2/3}$$
(3)

Step 1: Motion Blur Estimation



Blurred Image

Input





Blurred Image

SCALE 1 / ITERATION 1

Blurred Image

SCALE 1 / ITERATION 1

PSF Basis

Rmap



Predicted Image

Blurred Image

SCALE 1 / ITERATION 1

PSF Basis










































STEP 1: Blur Motion Estimation



STEP 1: Blur Motion Estimation







Latent Image



PSF Basis













Latent Image





STEP 1: Blur Motion Estimation

Latent Image





STEP 1: Blur Motion Estimation





















STEP 1: Blur Motion Estimation



Step 2: Latent Image Estimation

STEP 2: Latent Image Estimation



Predicted Image

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Motion Blur

STEP 2: Latent Image Estimation



Predicted Image

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Motion Blur



Latent Image

RUNTIME: 0.132s

STEP 2: Latent Image Estimation



Predicted Image

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Motion Blur



Latent Image

TOTAL RUNTIME: 8.454s

Comparison

Comparison with [Harmeling et al. 2010 NIPS]

[Harmeling et al. 2010 NIPS] estimates the motion blur locally and doesn't enforce global consistency. This leads to unintentional local distortions as most noticeable in the elephant example. Harmeling et al. also provide ground truth data for the captured PSF. A comparison with our estimated PSF shows very close agreement and serves as an additional validation of our approach. We also show their results for [Cho and Lee 2009 Siggraph] who assume uniform blur.

Elephant

Image Size	441x611
PSF Size	19x19
Kernel Estimation	8.316 sec
Final deconvolution	0.132 sec
Total processing time	8.454 sec



Blurred image



[Cho and Lee 2009 Siggraph]



[Harmeling et al. 2010 NIPS]



Our approach



Blurred image
Comparison with [Whyte et al. 2010 CVPR]

For comparison, we also show their results of the method of [Fergus et al. 2006 Siggraph] which assume uniform blur.

Pantheon

Image Size	366x274x2
PSF Size	15x15
Kernel Estimation	5.078 sec
Final deconvolution	0.07 sec
Total processing time	5.156 sec





[Fergus et al. 2006 Siggraph]



[Whyte et al. 2010 CVPR]



Our approach



Comparison with [Gupta et al. 2010 ECCV]

We also show results for a state-of-the-art single image blind deblurring method which assumes uniform blur [Xu and Jia 2010 ECCV].

Books

Image Size	768x512x3
PSF Size	17x17
Kernel Estimation	10.3 sec
Final deconvolution	0.172 sec
Total processing time	10.482 sec





[Xu and Jia 2010 ECCV]



[Gupta et al. 2010 ECCV]



Our approach



Comparison with [Joshi et al. 2010 Siggraph]

[Joshi et al. 2010 Siggraph] uses additional inertial measurement sensor data. In contrast, we use the blurry image only. We also show the result for a state-of-the-art single image blind deblurring method which assumes uniform blur [Xu and Jia 2010 ECCV].

Coke Cans

Image Size	1123x749x3			
PSF Size	21x21			
Kernel Estimation	12.776 sec			
Final deconvolution	0.27 sec			
Total processing time	13.07 sec			





[Xu and Jia 2010 ECCV]



[Joshi et al. 2010 Siggraph] (using sensor data)



Our approach



Limitations

Staturation

Our method suffers from saturated pixels regions as in these regions the linearity assumption of our forward model is violated. Although the PSF seems to be estimated correctly, the final deconvolution reveals severe artifacts.





Our approach

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Estimated PSF

Objects in Motion

Our method assumes a static scene. The case where objects in the scene are moving (left train) is not covered by our approach.



Superimposed camera and object motion

Severe Blur

For large camera motions our approach becomes instable and fails to find a meaningful PSF.



Severe camera motion blur

Summary

- We proposed a unified imaging model which combines the efficiency of the EFF and incorporates the global camera motion constraint of the Proejctive Motion Path Blur Model.
- Ideally suited for parallel computation (→ GPU) and hence very efficient and fast.
- Improved and robust sharpening algorithm for a single blurred image with spatially varying blur.
- Visit our poster tonight at poster stand 75
- Visit our webapge at http:

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

How to Visualize Camera Shake...



Experimental Setup of Harmeling et al. (NIPS 2010)





How to Visualize Camera Shake...



Experimental Setup of Harmeling et al. (NIPS 2010)

Elephant PSF comparison

While the local PSF estimation of [Harmeling et al. 2010 NIPS] faces difficulties in regions with little edge information (as e.g. sky), our camera motion constrained EFF framework is able to use the textural information within the entire image to infer a globally consistent PSF. The benefit is not only apparent in the elephant example but also in the subsequent example of the vintage car (bottom left).


Ground truth



[Cho and Lee 2009 Siggraph]



[Harmeling et al. 2010 NIPS]



Our approach



Ground truth

Butcher Shop

Image Size	601x401
PSF Size	25x25
Kernel Estimation	13.638 sec
Final deconvolution	0.036 sec
Total processing time	13.686 sec



Blurred image



[Cho and Lee 2009 Siggraph]



[Harmeling et al. 2010 NIPS]

Our approach



Blurred image



Ground truth



[Cho and Lee 2009 Siggraph]



[Harmeling et al. 2010 NIPS]



Our approach



Ground truth

Vintage Car PSF comparison



Blurred image



[Cho and Lee 2009 Siggraph]



[Harmeling et al. 2010 NIPS]



Our approach



Blurred image

Vintage Car

Image Size	621x441
PSF Size	19x19
Kernel Estimation	8.306 sec
Final deconvolution	0.038 sec
Total processing time	8.354 sec



Ground truth



[Cho and Lee 2009 Siggraph]



[Harmeling et al. 2010 NIPS]



Our approach



Ground truth

Petrol Station Example

This example image was reported to be challenging due to the great variation of depth in the scene. The slight shift in our restoration stems from the translational invariance of the deblurring problem, i.e. a shift in the restored image can be compensated by a shift in the opposite direction of the corresponding PSF.

Image Size	679x406x3
PSF Size	19x19
Kernel Estimation	8.194 sec
Final deconvolution	0.132 sec
Total processing time	8.338 sec



Blurred image



[Xu and Jia 2010 ECCV]



[Gupta et al. 2010 ECCV]



Our approach



Blurred image

Notre Dame

Image Size	354x265x3
PSF Size	21x21
Kernel Estimation	7.388 sec
Final deconvolution	0.082 sec
Total processing time	7.474 sec



Blurred image


[Fergus et al. 2006 Siggraph]



[Whyte et al. 2010 CVPR]



Our approach



Blurred image

Statue

[Whyte et al. 2010 CVPR] takes a noisy/blurry image pair for image restoration. In contrast, we use the blurry image only. We also show the result for a state-of-the-art single image blind deblurring method which assumes uniform blur [Cho and Lee 2009 Siggraph].

Image Size	523x710x3
PSF Size	21x21
Kernel Estimation	12.434 sec
Final deconvolution	0.174 sec
Total processing time	12.618 sec



Blurred image



[Cho and Lee 2009 Siggraph]



[Whyte et al. 2010 CVPR]



Our approach



Blurred image

References



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