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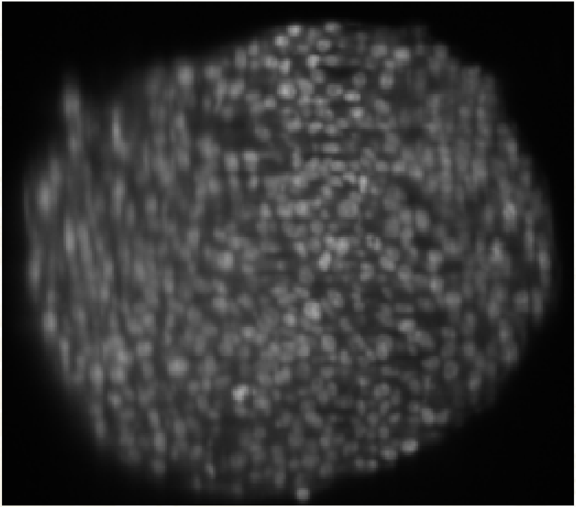
Deep-Blur: Blind Identification and Deblurring with CNN

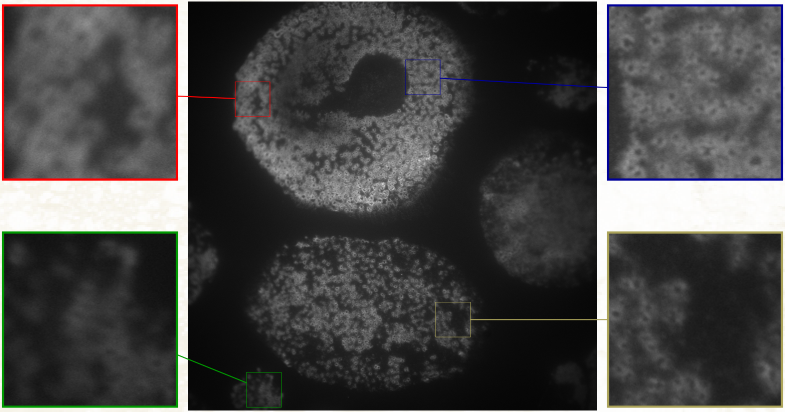
Valentin Debarnot & Pierre Weiss

December 7th, 2022, Paris,
Mathematical Models for Plug-and-play Image Restoration



Typical slice of a SPIM image. Here a spheroid (V. Lobjois, C. Lorenzo)

Motivation - Wide field microscopy

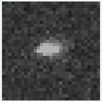


Wide field microscope: podosome, 2048×2048 pixels field of view, $200\mu m$ (T. Mangeat)

Two possible approaches

i) Calibration

Single bead ⟶



PSF

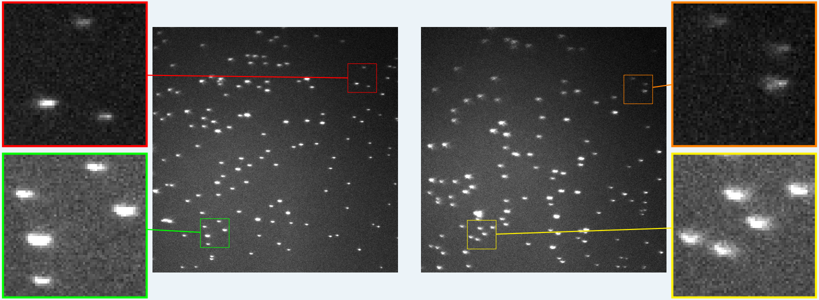
→ Simple

→ Accuracy

→ Time consuming

<u>Definition</u>: blur impulse response = point spread function = PSF

Time variation

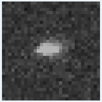


Wide field microscopy, image of beads at few minutes interval (S. Cantaloube).

Two possible approaches

i) Calibration

Single bead ⟶



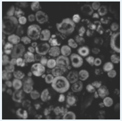
PSF

→ Simple

→ Accuracy

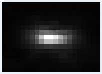
→ Time consuming

ii) Blind identification



Blurry obs.

⟶



PSF

→ Mathematically challenging
Solution: deep learning

Definition: blur impulse response = point spread function = PSF

Hand-crafted methods

We developed 10 methods

All were failures

We tested 30 methods (some critically acclaimed)

All were failures

Our conclusion

Handcrafted = efficient in well controlled settings only

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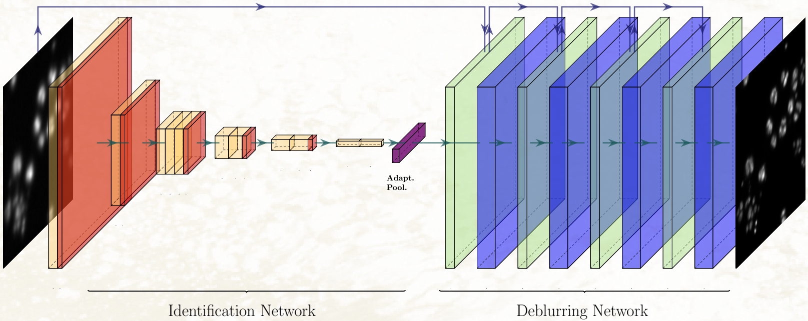
Handcrafted = efficient in well controlled settings only



The general architecture

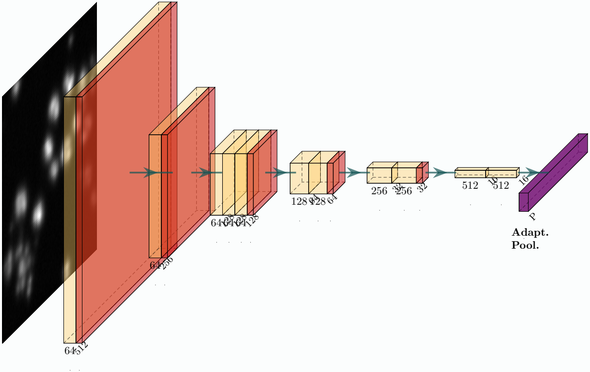
The identification network

Assumption

The blur is parametrized by P coefficients.

Deep-Blur

ResNet18 neural network, 11×10^6 parameters



Deep-Blur: from obs. image to operator coefficients

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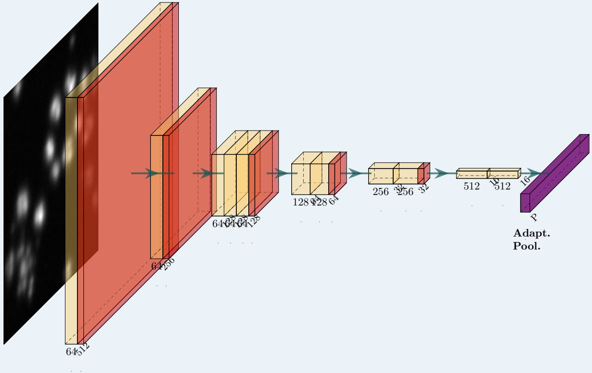
The blur is parametrized by P coefficients.

Deep-Blur

ResNet18 neural network, 11×10^6 parameters

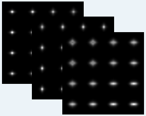


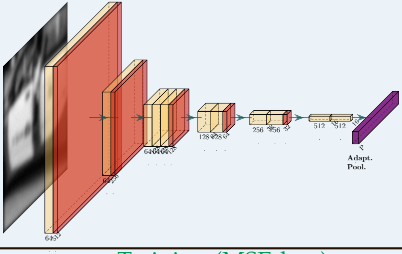
Deep-Blur: from obs. image to operator coefficients

Learning framework

Natural images

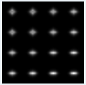
Sampled blur: $\gamma \in \mathbb{R}^P$





Est. blur

$\hat{\gamma} \in \mathbb{R}^P$

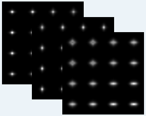


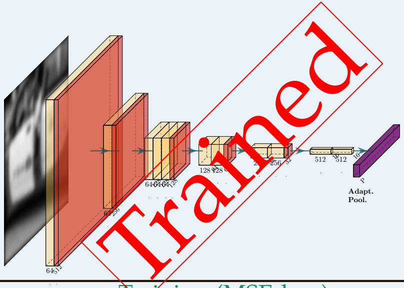
Training (MSE loss)

Learning framework

Natural images

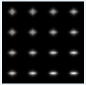
Sampled blur: $\gamma \in \mathbb{R}^P$





Est. blur

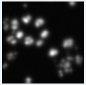
$\hat{\gamma} \in \mathbb{R}^P$

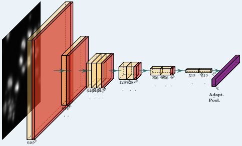


Training (MSE loss)

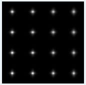
Estimation framework

Blurry obs.





Est. blur



The deblurring network

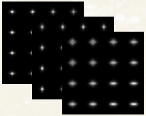
A FISTA unrolled architecture

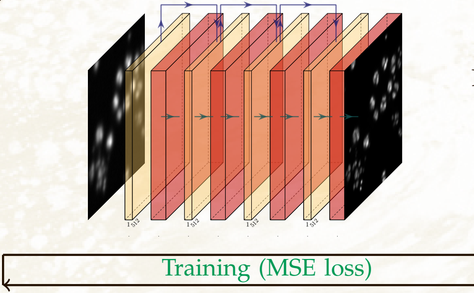
The deblurring network is:

1. FISTA algorithm with 15 iterations
2. The proximal operator is replaced by a simple trainable CNNs
3. Training independent of identification

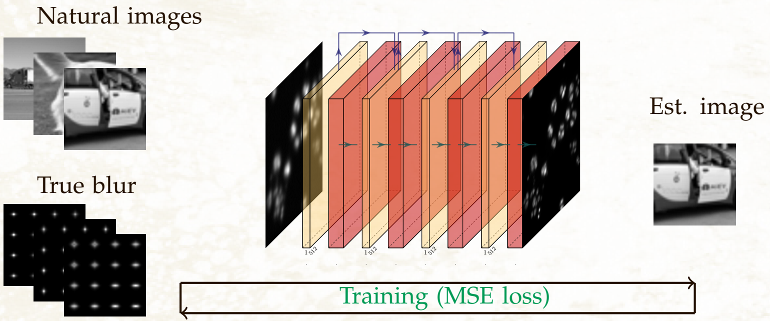
Natural images

True blur





Est. image



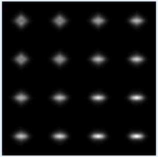
Deep-Blur: intermediate step between Plug and Play and Unrolled network:

	Deep-Blur	Unrolled network	Plug and Play
Family of operator	✓	×	✓
Task specific	✓	✓	×

The blur model

Blur model

1. Spatially varying (no convolution): product-convolution



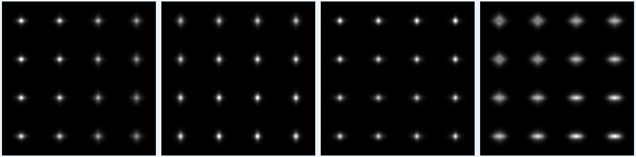
Reference

Escande, P., & Weiss, P. (2020). Approximation of integral operators using product-convolution expansions, JMIV.

Blur model

1. Spatially varying (no convolution): product-convolution
2. Can capture an entire microscope:

$$A(\gamma)x = \sum_{p=1}^{P} \gamma_p A_p(x)$$



Reference

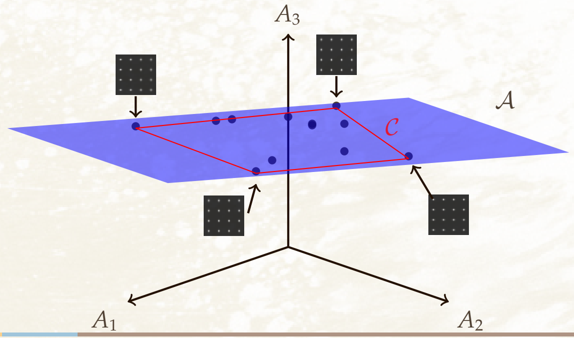
Debarnot, V., Mangeat, T., & Weiss, P. (2020). Learning low-dimensional models of microscopes, IEEE TCI.
Debarnot, V., Escande, P., & Weiss, P. (2019). A scalable estimator of sets of integral operators. Inverse Problems

Blur model

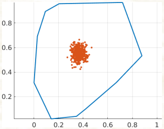
1. Spatially varying (no convolution): product-convolution
2. Can capture an entire microscope:

$$A(\gamma)x = \sum_{p=1}^{P} \gamma_p A_p(x)$$

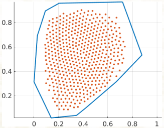
3. Can be reduced to a convex set: $\gamma \in \mathcal{C}$



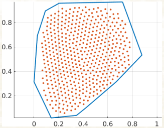
$\mathcal{C}$ convex set of admissible operators



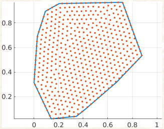
t=0



t=1,000



t=2,000



t=10,000

Problem

How to sample a convex set $\mathcal{C} \subset \mathbb{R}^P$?

Solve approximation of MaxiSumMin problem:

$$\sup_{\{\delta_1,\ldots,\delta_L\}\in\mathcal{C}^L} \sum_{l=1}^{L} \min_{\substack{l' \\ l\neq l'}} \|\delta_l - \delta_{l'}\|_2$$

Projected subgradient descent algorithm

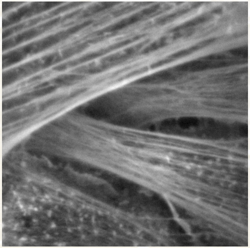
Main features

- Scalable: up to $P = 100$ and $L > 10,000$
- Single pass

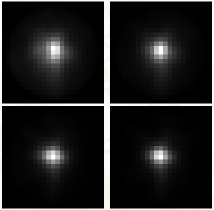
Experimental results

Identification network

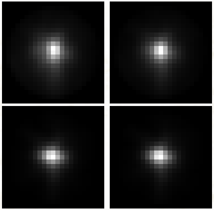
Product-convolution operator with $P = 16$
Training: 10^6 blurs randomly applied on $40k$ images from MS COCO
Evaluation: biological images



Observation



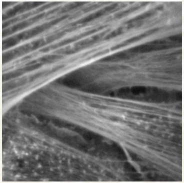
True



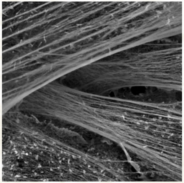
Estimated (22.5dB)

Ddeblurring network

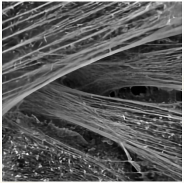
Product-convolution operator with $P = 16$
Training: 10^6 blurs applied on $40k$ images from MS COCO
Evaluation: biological images



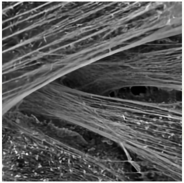
Observation – SSIM: 0.42



True

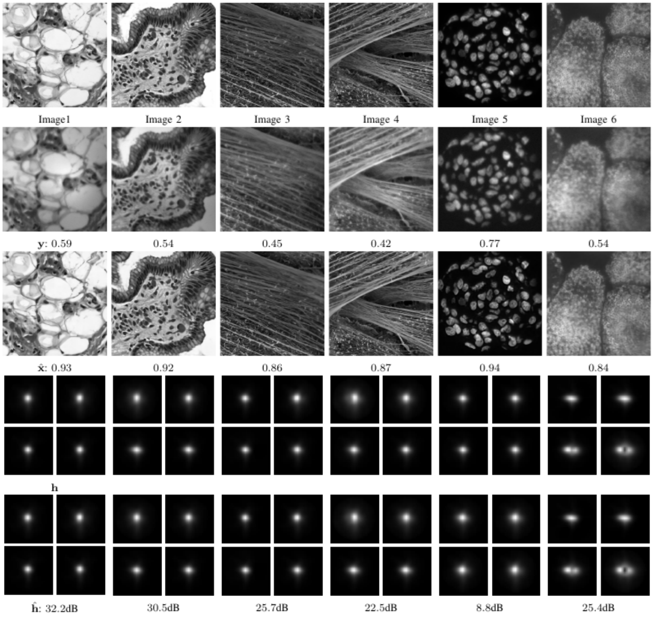


Est., trained with true op.– SSIM: 0.866



Est., trained with est. op. – SSIM: 0.868

Blur identification: spatially varying blur



Contributions

- New identification network
- New blind deblurring architecture
- Applicable to Fresnel approx., space varying and experimental operators

Key ideas

- Combine physics modelling and deep learning
- Train identification and deblurring net sequentially

Related paper

Debarnot, V. & Weiss, P. (2022). Deep-Blur: blind parameterized deblurring.
hal-03687822

Toolbox

- **Debarnot, V., Sage, D., Soubies, E., Mangeat, T., & Weiss, P.** (2021). Eigen-PSF extractor. ongoing

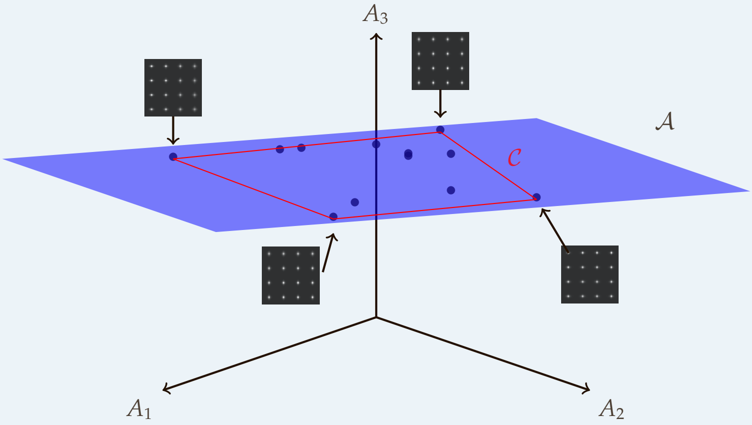
Methodology

- **Debarnot, V. & Weiss, P.** (2022). Deep-Blur: blind parameterized deblurring. hal-03687822
- **Debarnot, V., Mangeat, T., & Weiss, P.** (2020). Learning low-dimensional models of microscopes, IEEE TCI.

Foundations

- **Debarnot, V., & Weiss, P.** (2021). Blind deblurring and super-resolution with isolated spikes. Information & Inference
- **Debarnot, V., Escande, P., & Weiss, P.** (2019). A scalable estimator of sets of integral operators. Inverse Problems

Improve identifiability



$\mathcal{A}[\mathcal{C}] \stackrel{\text{def.}}{=} \left\{ \sum_{p=1}^{P} \gamma_p A_p, \gamma \in \mathcal{C} \subset \mathbb{R}^P \right\}$, $\mathcal{C}$ convex set of admissible operators

Zernike example

Zernike

$P = 7$ Zernike coefficents in $[-0.15, 0.15]$. 10^6 blurs randomly applied on $40k$ images from MS COCO dataset.


True


Blurry-Noisy


Deep-Blur


Goldstein Fattal


NAFNET

Blur identification: spatially varying blur