ACML'19@Nagoya, Japan

SPoD-Net: Fast Recovery of Microscopic Images Using Learned ISTA

Satoshi Hara[*], Wei Chih Chen[**],

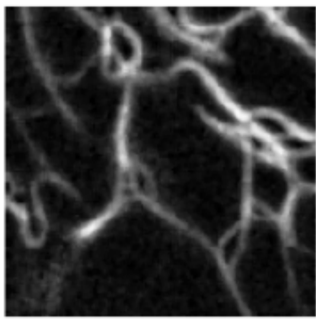
Takashi Washio[*], Tetsuichi Wazawa[*], Takeharu Nagai[*]

[*]Osaka University, [**]National Taiwan University

The Goal

- Fast image recovery for microscopy.

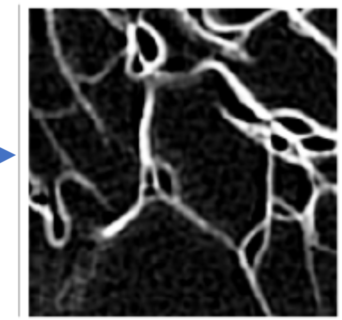
Observation



Current method takes around **an hour**.

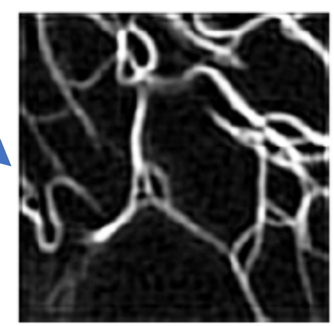
Recovered by FISTA

[Beck&Teboulle 09]



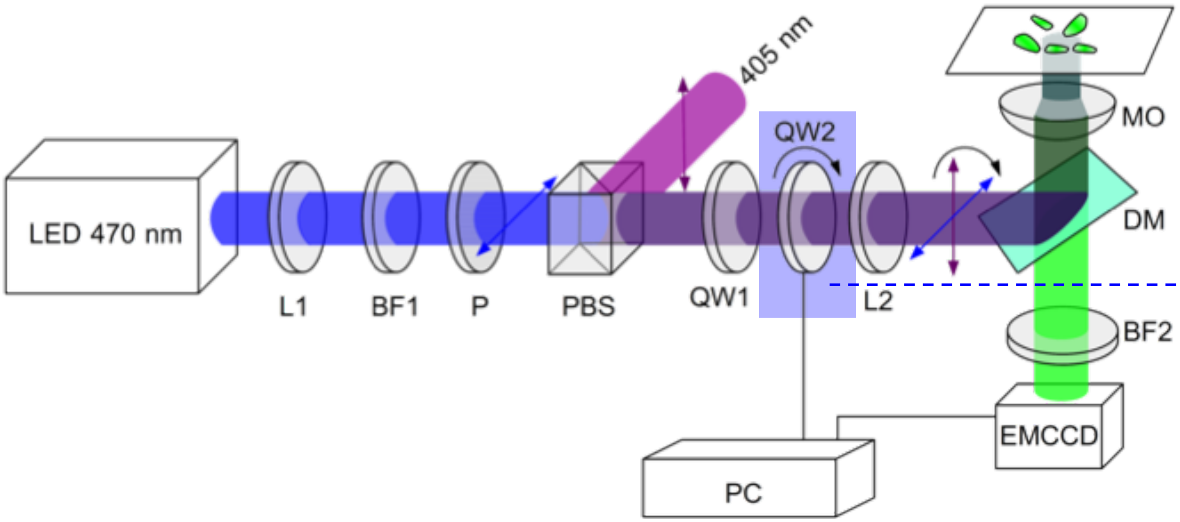
Takes **less than a second** by using the proposed method.

Recovered by SPoD-Net



Microscopy with SPoD [Hafi+, 14; Wazawa+ 18]

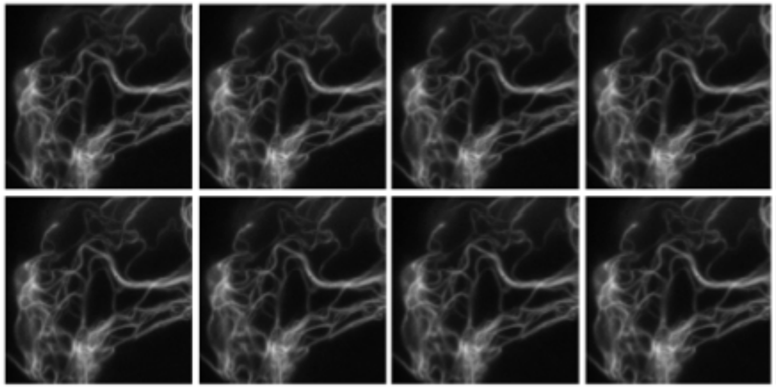
- SPoD (Super-resolution by Polarization Demodulation)
  - Observe cells by varying the polarization of the illumination.



Polarization of the illumination is controlled.

- <u>SPoD data</u>

  One observation $Y = \{y_1, y_2, \ldots, y_c\}$
  - **a set of images** observed under different illumination polarizations



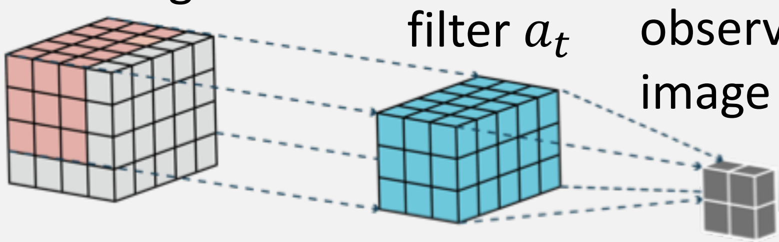
The Image Recovery Problem for SPoD

- What we do not know:
  - True images $X = \{x_1, x_2, \dots, x_c\}$ ← what we want to recover

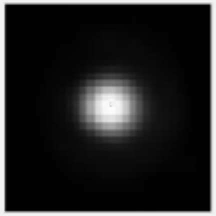
- What we do know:
  - Observed images $Y = \{y_1, y_2, \dots, y_c\}$ ← what we observe
  - The true image x_t is sparse, i.e. mostly zeros (= black).
  - Physical model of observation.

$$y_t = a_t * x + \epsilon, \qquad (a_t)_{i,j,k} = \phi_{i,j}\cos^2\left(\frac{t-k}{c}\pi\right)$$

Convolution



Point Spread Function (PSF)



The Image Recovery Problem for SPoD

- Image Recovery Problem for SPoD

$L(Y, x)$

$$\hat{x} = \underset{x \geq 0}{\operatorname{argmin}} \frac{1}{2A} \sum_{k=1}^{c} \|y_t - a_t * x\|^2 + \frac{\lambda}{B} \|x\|_1$$

The recovered image should be **non-negative.**

The recovered image should **reconstruct the observation**.

The recovered image should be sufficiently **sparse (i.e. black)**.

- Image recovery methods
  - Current Method: FISTA
    - Solves the problem **exactly**, but **slow**.
  - Proposed Method: SPoD-Net
    - Solves the problem **approximately**, but **fast**.

Image Recovery by ISTA

- Recovery through optimization

$$\hat{x} = \underset{x \geq 0}{\operatorname{argmin}} \frac{1}{2A} \sum_{k=1}^{c} \|y_t - a_t * x\|^2 + \frac{\lambda}{B} \|x\|_1$$

- <u>ISTA</u>
  - Initialize: $x \leftarrow 0$
  - Repeat until x converges:
    - Update x to minimize the first term.

$$x \leftarrow x - \frac{\eta}{A} \sum_{k=1}^{c} a_t \,\bar{*}\, (a_t * x - y)$$

$\bar{*}$: transposed convolution

    - Shrink x towards zeros.

$$x \leftarrow R_{\lambda/B\eta}(x) = \max\{0, x - \lambda/B\eta\}$$

<u>Time Consuming</u> Thousands of iterations are needed.
→ Takes several tens of minutes for recovery.

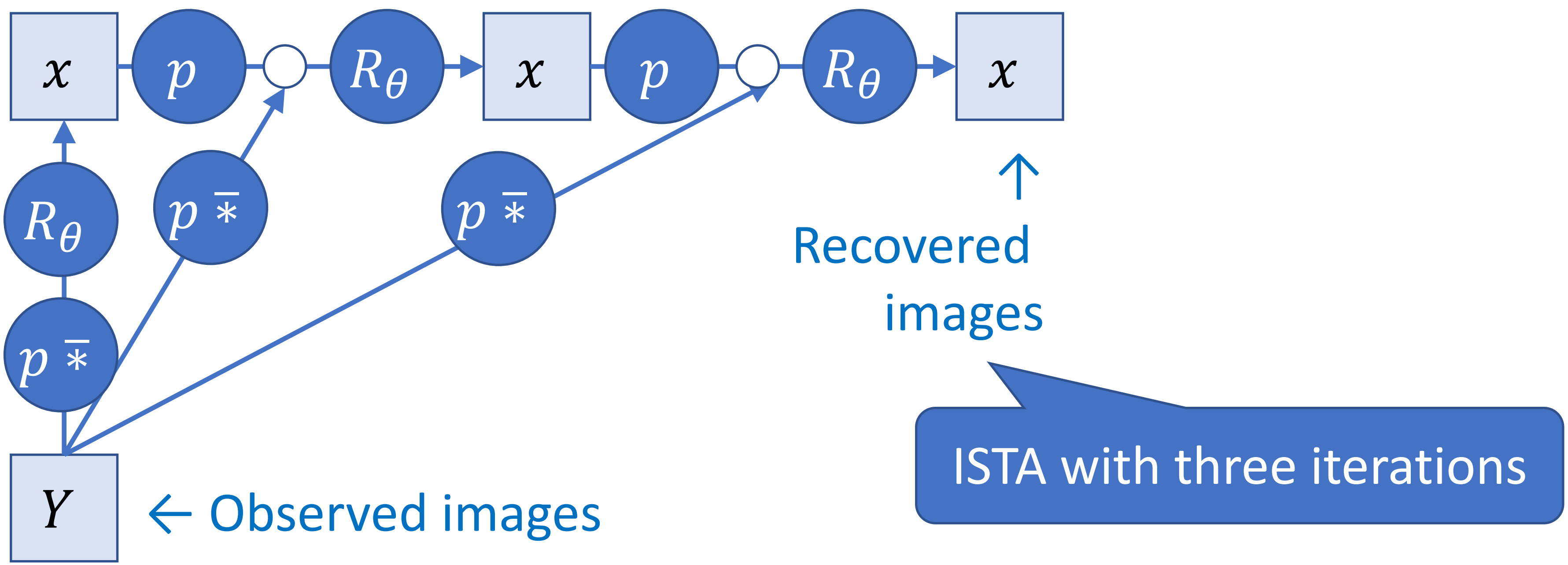
Learning to Recover: Learned ISTA

[Gregor and LeCun, ICML'10]

- One step of ISTA is **Conv-ConvTranspose-ReLU**.

$$x = R_\theta\left(x - \eta \sum_{k=1}^{c} p_t \,\overline{*}\, (p_t * x - y)\right)$$

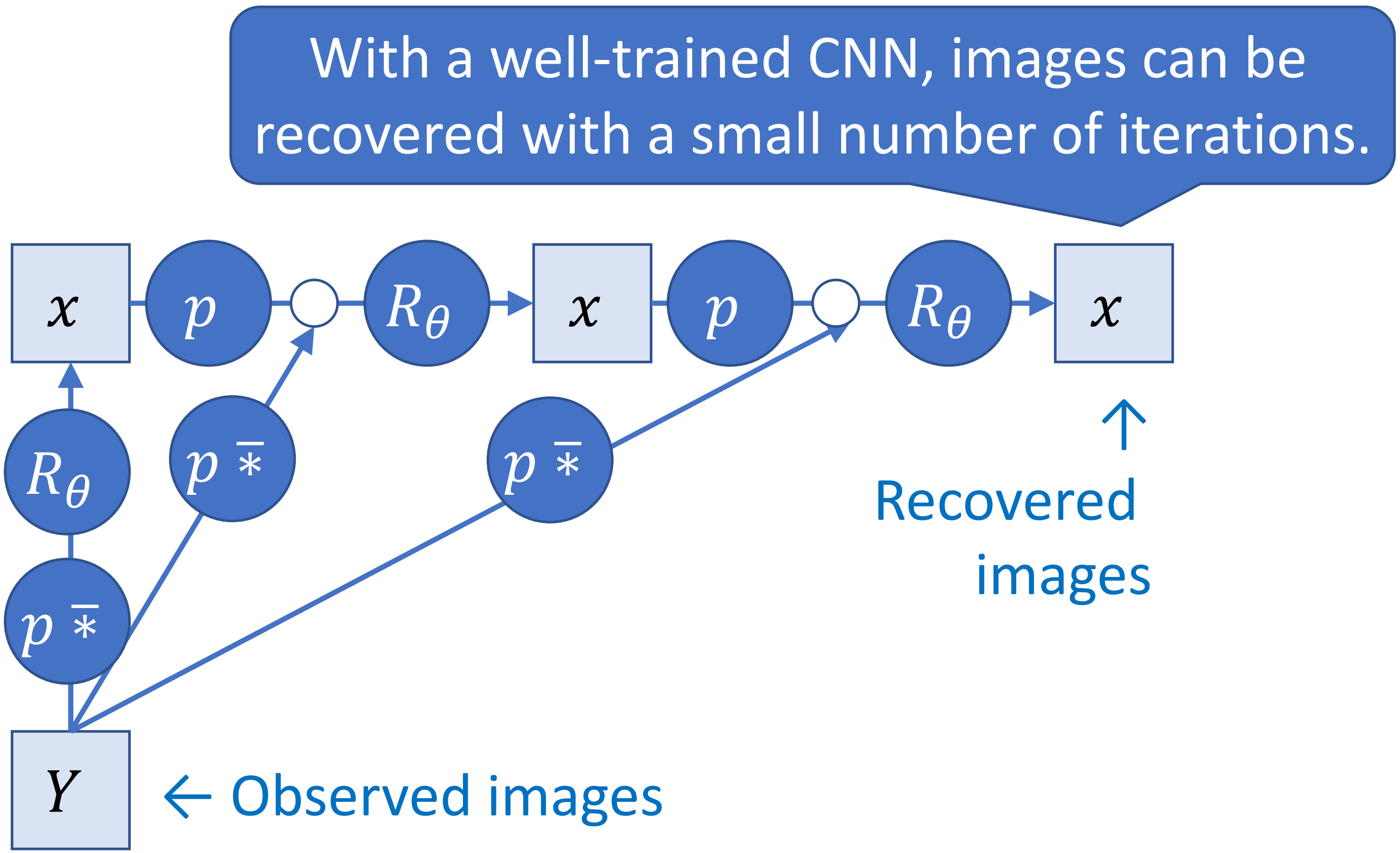
- Iteration of ISTA = **Convolutional Neural Networks (CNNs)**



Learning to Recover: Learned ISTA

[Gregor and LeCun, ICML'10]

- Train CNN so that it can recover images.
  - CNN: $x = f(y; p, \eta, \theta)$
    - Train $p\ \eta, \theta$ so that CNN can recover images well.



Learning to Recover: Learned ISTA

[Kavukcuoglu et al., NIPS'10; Sreter and Giryes, arXiv'17]

Training Phase

- Prepare **many observed images** $\{Y_n\}_{n=1}^{N}$.
- Prepare CNN $x = f(y; p, \eta, \theta)$ **with a small number of iterations (layers)**.
- Train CNN to minimize the following loss function.

$$\min_{p,\eta,\theta} \frac{1}{N} \sum_{n=1}^{N} L(Y_n, f(Y_n; p, \eta, \theta))$$

$$L(Y, x) := \frac{1}{2A} \sum_{k=1}^{c} \|y_t - a_t * x\|^2 + \frac{\lambda}{B} \|x\|_1$$

Recovery Phase

- Compute $x = f(Y; p, \eta, \theta)$ using the trained CNN.
  - The recovery is fast: the number of iterations is small.

The Proposed Model: SPoD-Net

1. Use a specific filter for CNN.

- $(p_t)_{i,j,k} = g_{i,j}\, h_{t-k}$

# of params $= h \times w + c$

$g_{i,j}$: horizontal and vertical directions

h_{t-k}: temporal direction

Physical Filter

$$(a_t)_{i,j,k} = \phi_{i,j} \cos^2\left(\frac{t-k}{c}\pi\right)$$

- Small number of parameters to be optimized.
  → SPoD-Net can be **trained efficiently**.
  - Less training data is required for training.

The Proposed Model: SPoD-Net

1. Use a specific filter for CNN.

- $(p_t)_{i,j,k} = g_{i,j}\, h_{t-k}$

# of params $= h \times w + c$

h_{t-k}: temporal direction

$g_{i,j}$: vertical and horizontal directions

Physical Filter

$$(a_t)_{i,j,k} = \phi_{i,j} \cos^2\left(\frac{t-k}{c}\pi\right)$$

- Small number of parameters to be optimized.
  → SPoD-Net can be **trained efficiently**.
  - Less training data is required for training.

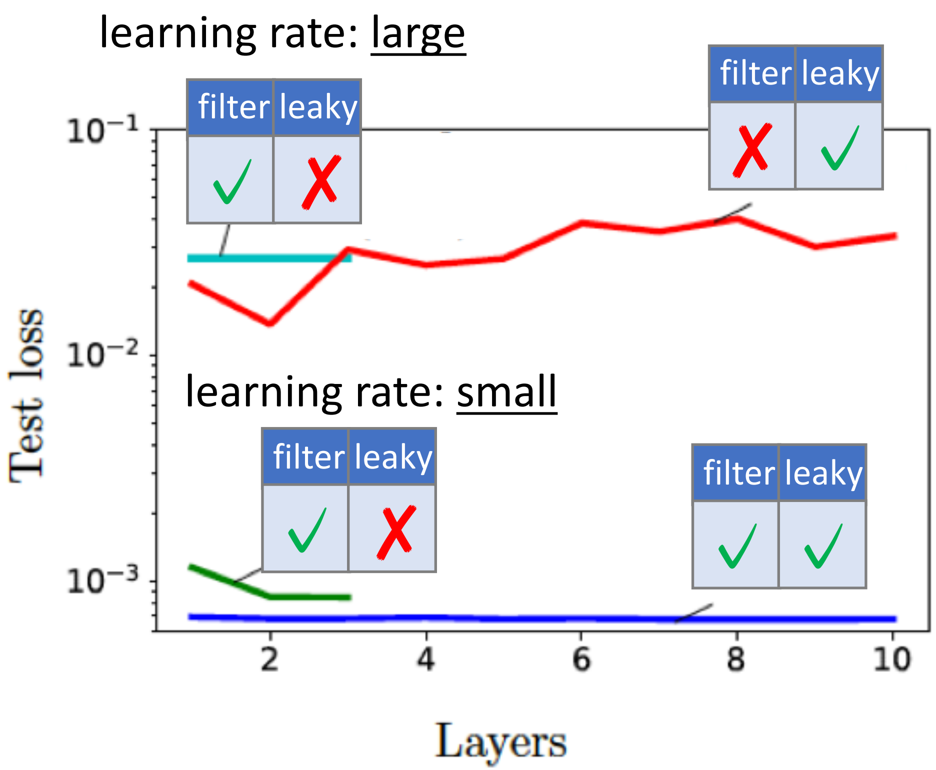
2. Use Leaky-ReLU instead of ReLU.

- Leaky-ReLU is **helpful for stabilizing the training**.
- ReLU can make the training of Learned ISTA unstable.

Exp1. Evaluation of the two improvements

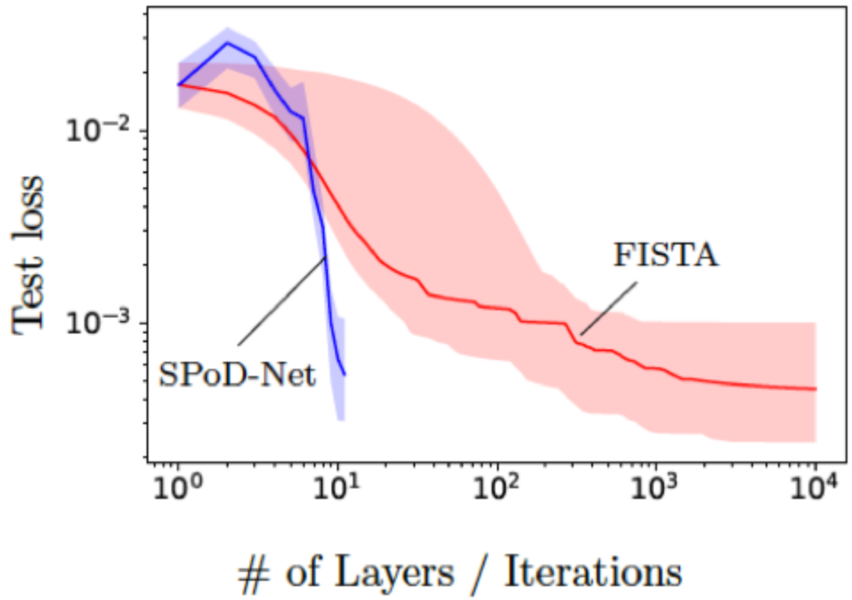
- 10-layer SPoD-Net
  - Using both of the improvements performed well.
  - Using only one of them were not effective.

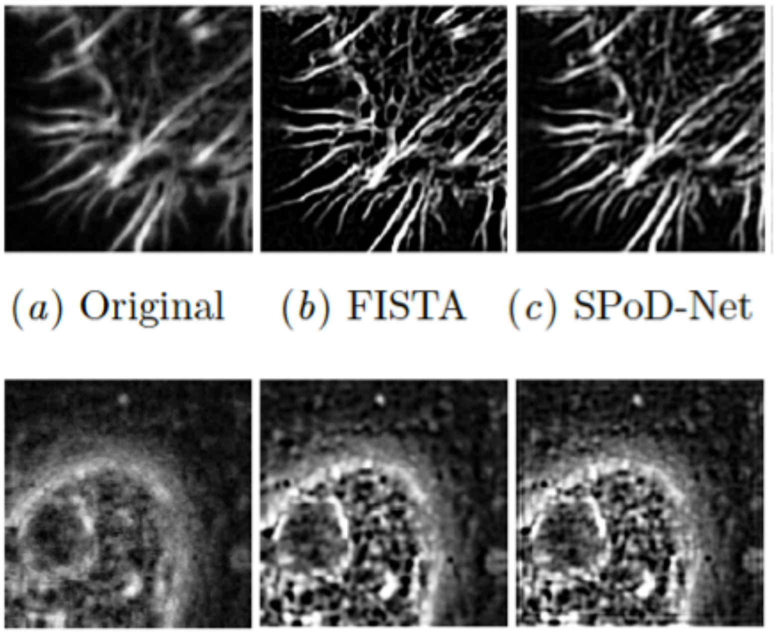
Test Loss = $\frac{1}{N}\sum_{n=1}^{N} L(Y_n, \hat{x}_n)$



Exp2. Comparison with FISTA

- SPoD-Net was significantly faster than FISTA.
  - SPoD-Net: less than 1sec.
  - FISTA: more than 5 minutes for 1000 iterations.





(a) Original (b) FISTA (c) SPoD-Net

(d) Original (e) FISTA (f) SPoD-Net

The recovered images by SPoD-Net were comparably well as FISTA.

Summary

- Goal
  - Fast image recovery for SPoD data.

- SPoD-Net
  - A variant of Learned ISTA that “trains” ISTA.
  - Two key improvements
    - Use a specifically designed filter.
    - Use Leaky-ReLU.

- SPoD-Net was significantly faster than FISTA.
  - SPoD-Net: less than 1sec.
  - FISTA: more than 5 minutes for 1000 iterations.