

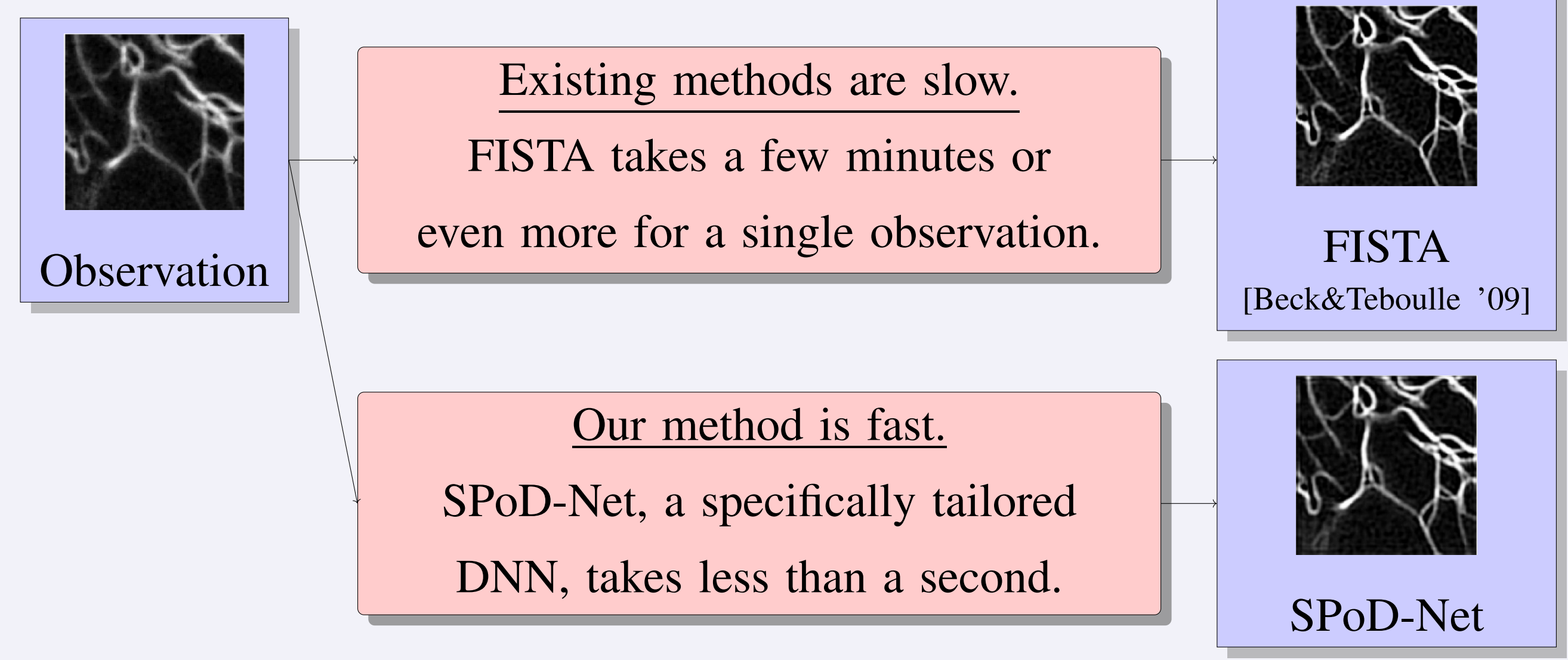
SPoD-Net: Fast Recovery of Microscopic Images Using Learned ISTA

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Research Overview

Fast Recovery of High-quality Microscopic Images



SPoD Microscope & Data

SPoD [Hafi+ '14; Wazawa+ '18]

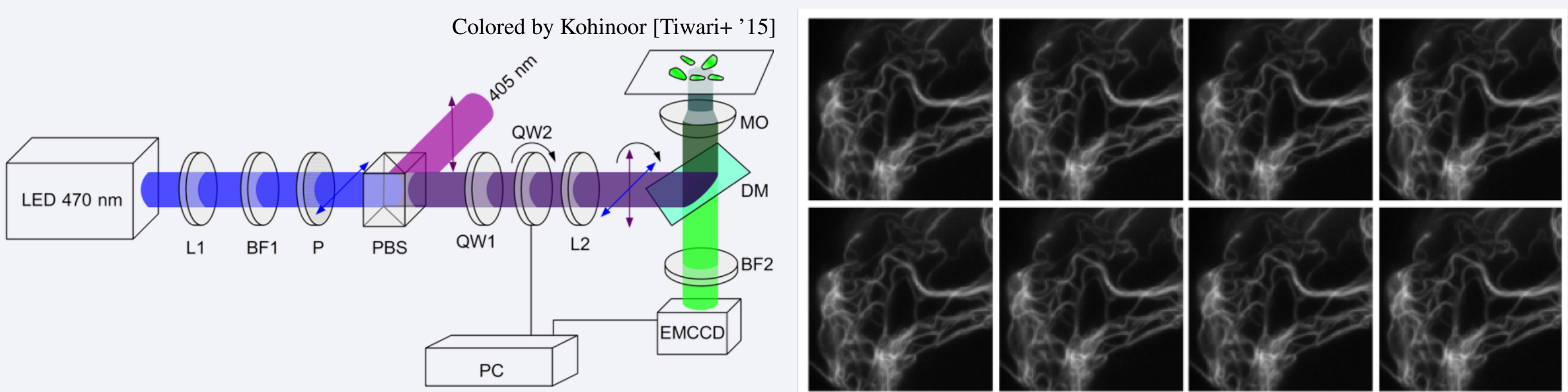


Figure 1: SPoD observes cells by controlling the polarization of the illumination.

Figure 2: A set of images observed under different illumination polarizations.

Physical Model of Observation

SPoD Observation Y : a series of *blurred* images $Y = \{y_1, y_2, \dots, y_c\}$.

$$y_t = a_t * X + \epsilon \quad (1)$$

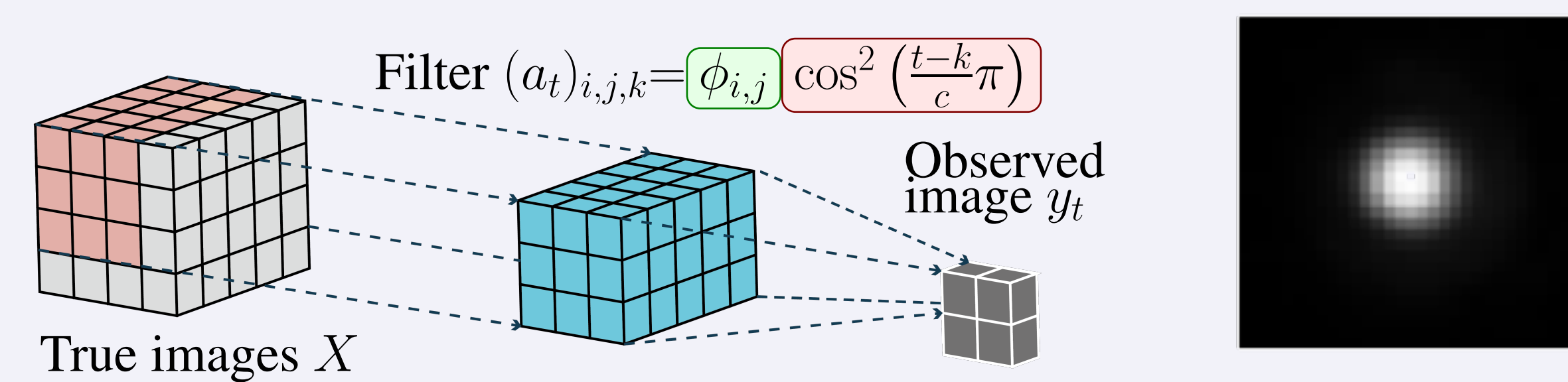


Figure 3: Graphical description of Eq.(1)

Figure 4: Point spread function ϕ

vertical and horizontal directions temporal direction

Existing Image Recovery Methods

Recovery through optimization (Loss function)

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

ISTA

- Initialize: $x \leftarrow 0$
 - Repeat until x converges:

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

$$x \leftarrow R_{\frac{\lambda}{B\eta}}(x) = \max\{0, x - \frac{\lambda}{B\eta}\}$$
- Time-consuming:** Thousands of iterations can take several tens of minutes

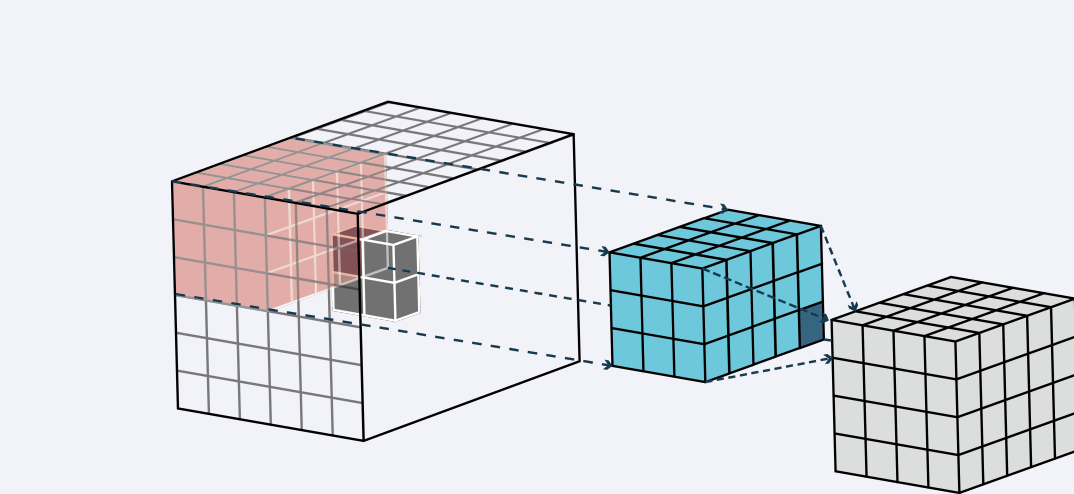


Figure 5: $\bar{*}$ denotes Transposed Convolution

LISTA (Learned ISTA)

[Gregor&LeCun '10; Kavukcuoglu+ '10]

Express ISTA as **convolutional neural network (CNN)**.

- Unroll the entire process of ISTA

$$x = R_{\theta}(\eta \sum_{k=1}^c p_t \bar{*} y_t)$$

$$\rightarrow x = R_{\theta}(x - \eta \sum_{k=1}^c p_t \bar{*} (p_t * x - y))$$

$$\rightarrow x = R_{\theta}(x - \eta \sum_{k=1}^c p_t \bar{*} (p_t * x - y))$$

Computationally efficient: A well-trained CNN with a few layers can recover images well.

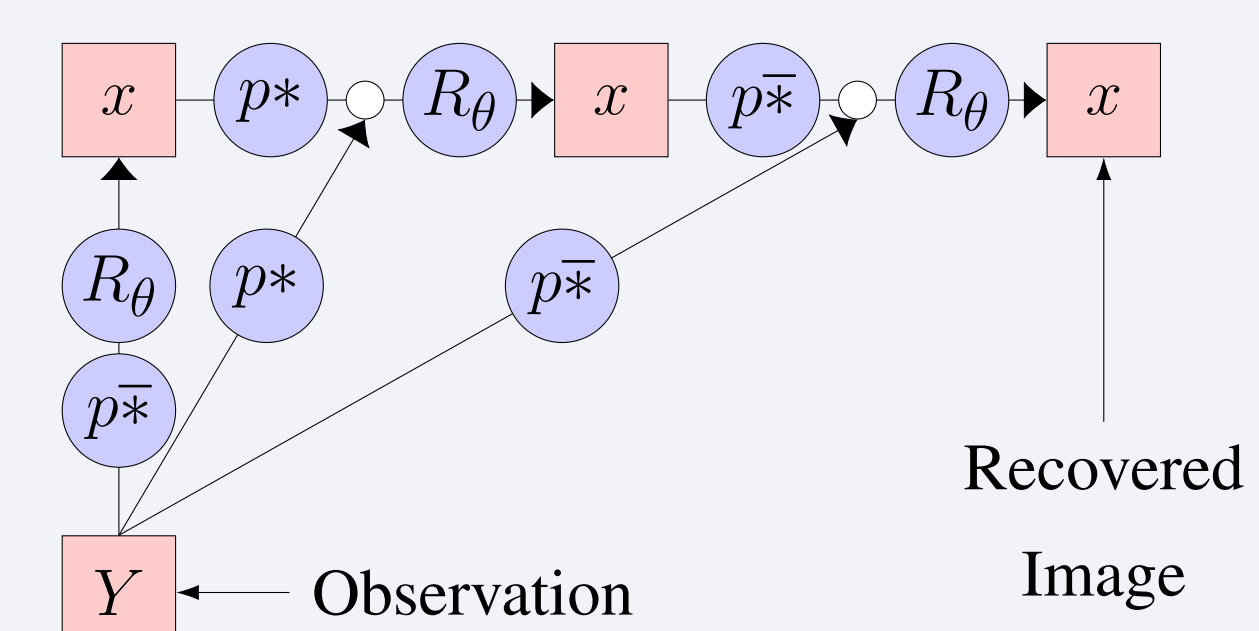


Figure 6: **LISTA:** Express ISTA as CNN. Optimize the CNN parameters p , η , and θ so that CNN can recover good images.

Procedure of LISTA

Training Phase

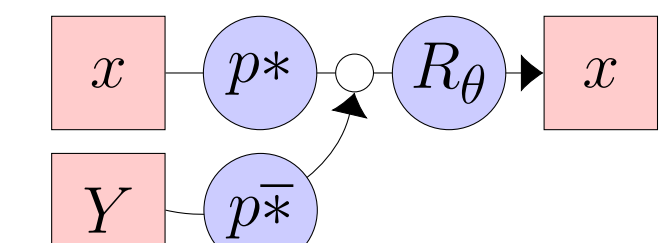
- Prepare many observations $\{Y_n\}_{n=1}^N$.
 - Prepare CNN $x = f(y; p, \eta, \theta)$ with a small number of layers.
 - Train CNN to minimize the loss (3).
- $$\min_{p, \eta, \theta} \frac{1}{N} \sum_{n=1}^N L(Y_n, f(Y_n; p, \eta, \theta)) \quad (3)$$
- $$L(Y, x) := \frac{1}{2A} \sum_{k=1}^c \|y_t - a_t * x\|^2 + \frac{\lambda}{B} \|x\|_1$$

Recovery Phase

- Compute $x = f(y; p, \eta, \theta)$ using the trained CNN.

Our Improvements: SPoD-Net

- Use a specific filter for p .
- Use leaky soft-thresholding for R_{θ} .



1. A Specific Filter for CNN

Decompose 3D filter \rightarrow (2D vertical and horizontal) and (1D temporal) directions.

Proposed Filter for SPoD-Net	Filter from observation
$(p_t)_{i,j,k} = \phi_{i,j} \bar{h}_{t-k}$	$(a_t)_{i,j,k} = \phi_{i,j} \cos^2\left(\frac{t-k}{c}\pi\right)$

The # of parameters is reduced to $h \times w + c \ll (h \times w \times c) \times c$.

The new filter can be trained with less data, and can avoid overfitting.

2. Leaky Soft-Thresholding

Stabilize the training by using an “easy-to-train” thresholding.

	Non-negative soft-thresholding	Proposed: Leaky soft-thresholding
Pros	Zeroes out signals. Helpful for recovering sparse images.	Does not zero out gradients. Helpful for stabilizing the training.
Cons	Can zero out gradients, and halt the training.	The images can be negative (post-thresholding helps: $x \leftarrow \max(0, x)$).

Results

Experiment1. Evaluation of the Two Improvements

Evaluate the effectiveness of the two improvements (Specific filter vs. Generic filter / Leaky soft-thresholding vs. Non-negative soft-thresholding).

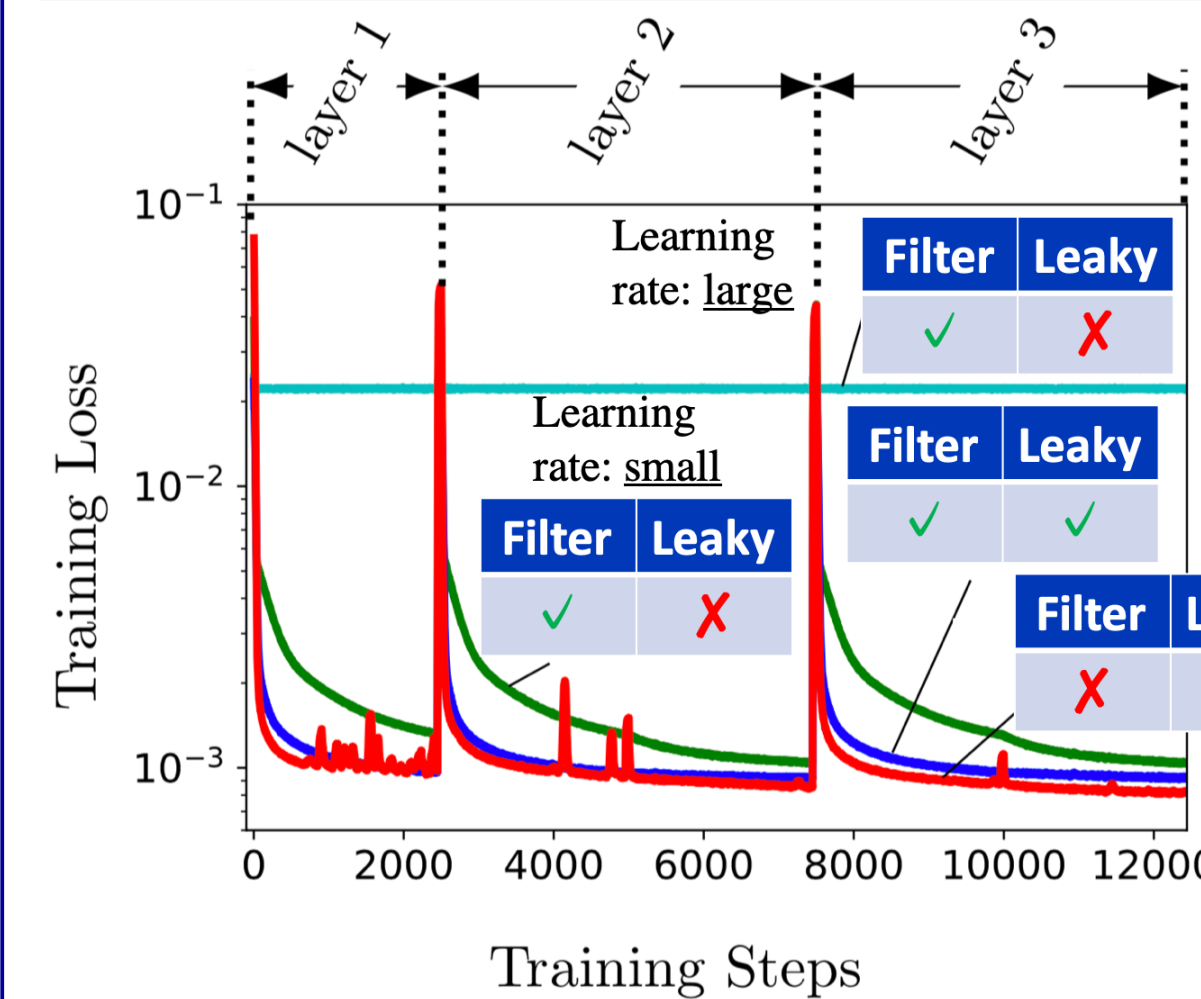


Figure 7: Learning curves

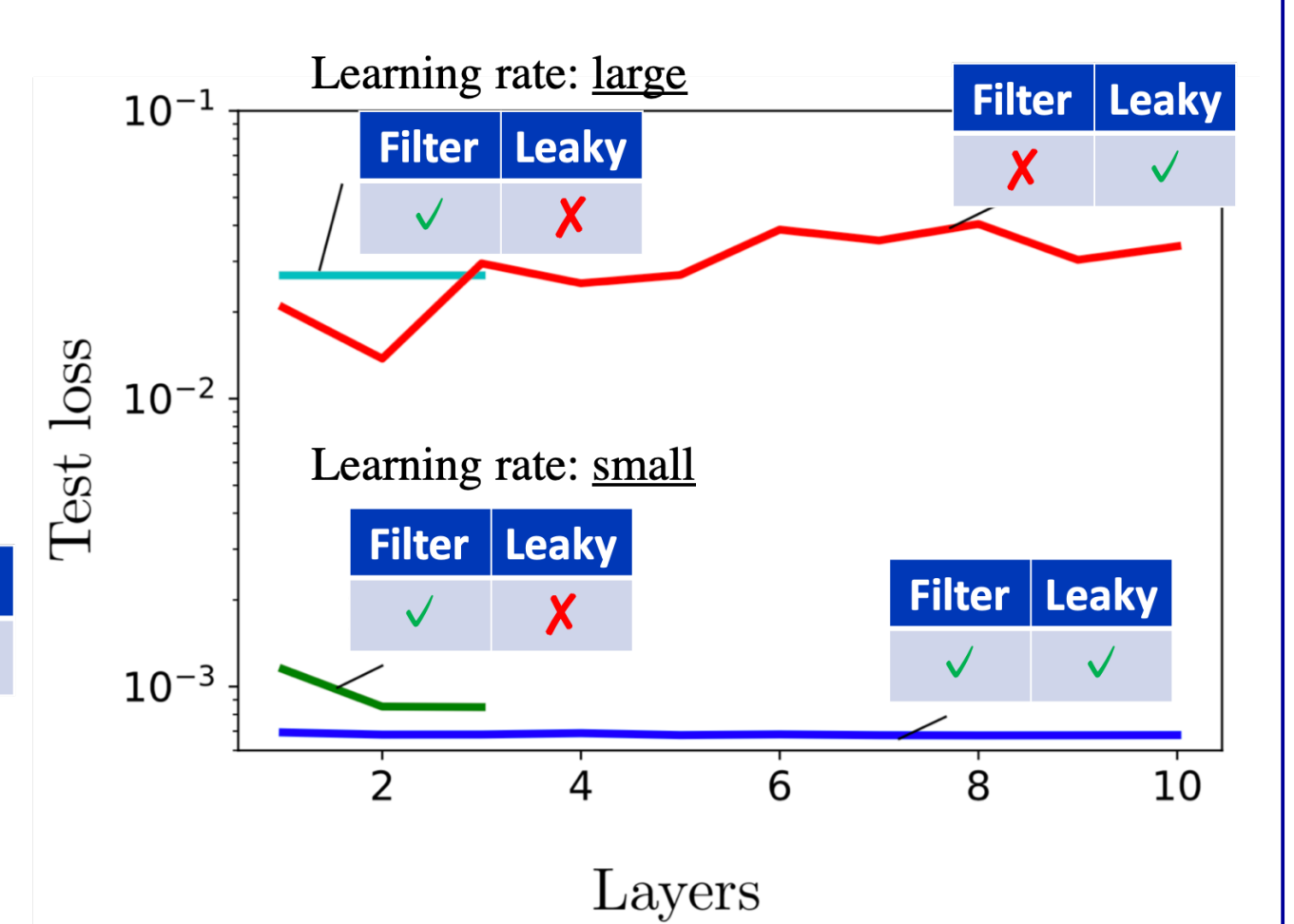


Figure 8: Test losses

Experiment2. Comparison with FISTA

Compare FISTA and SPoD-Net (Specific filter & Leaky soft-thresholding).

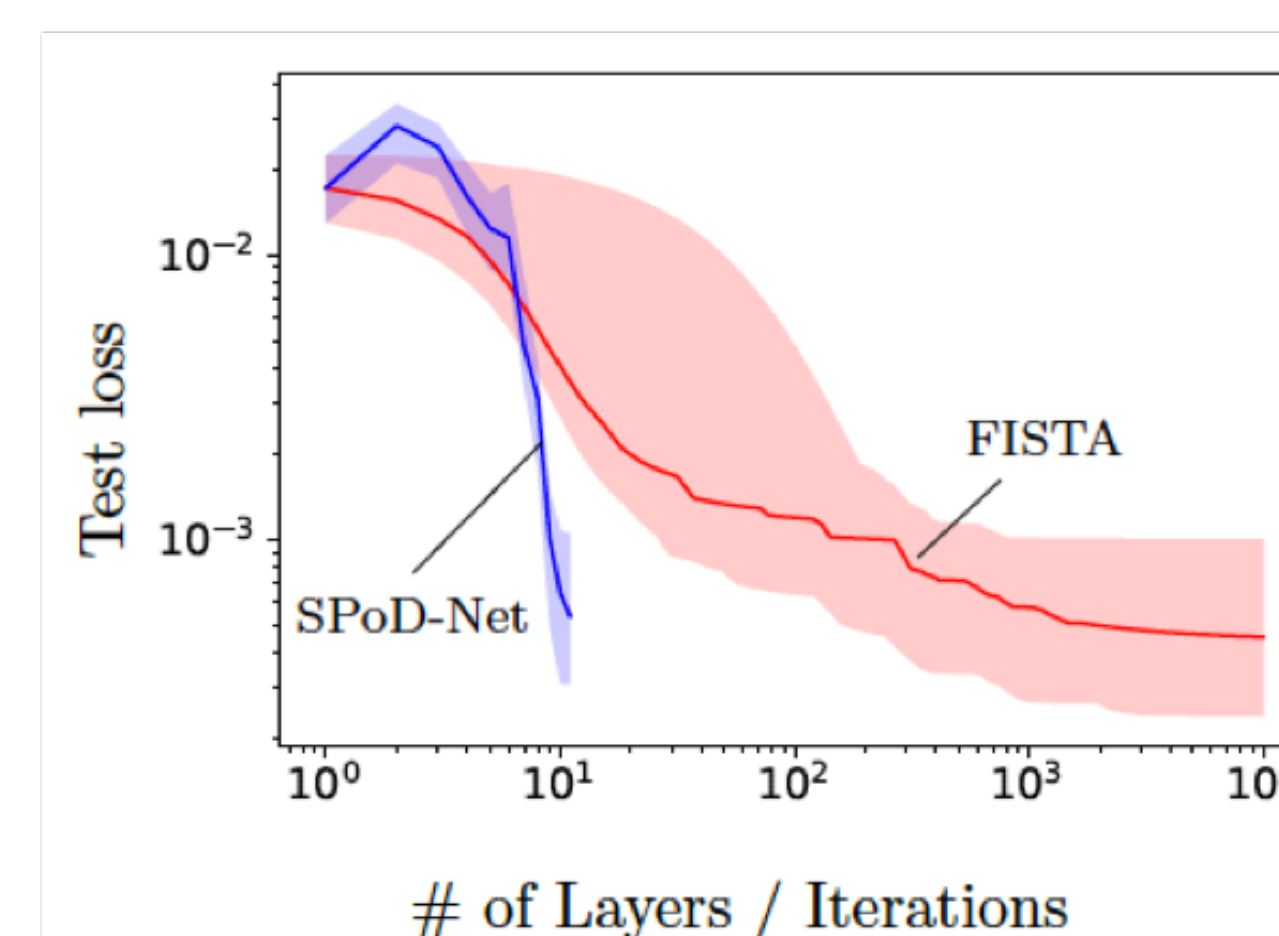


Figure 9: Convergence speeds

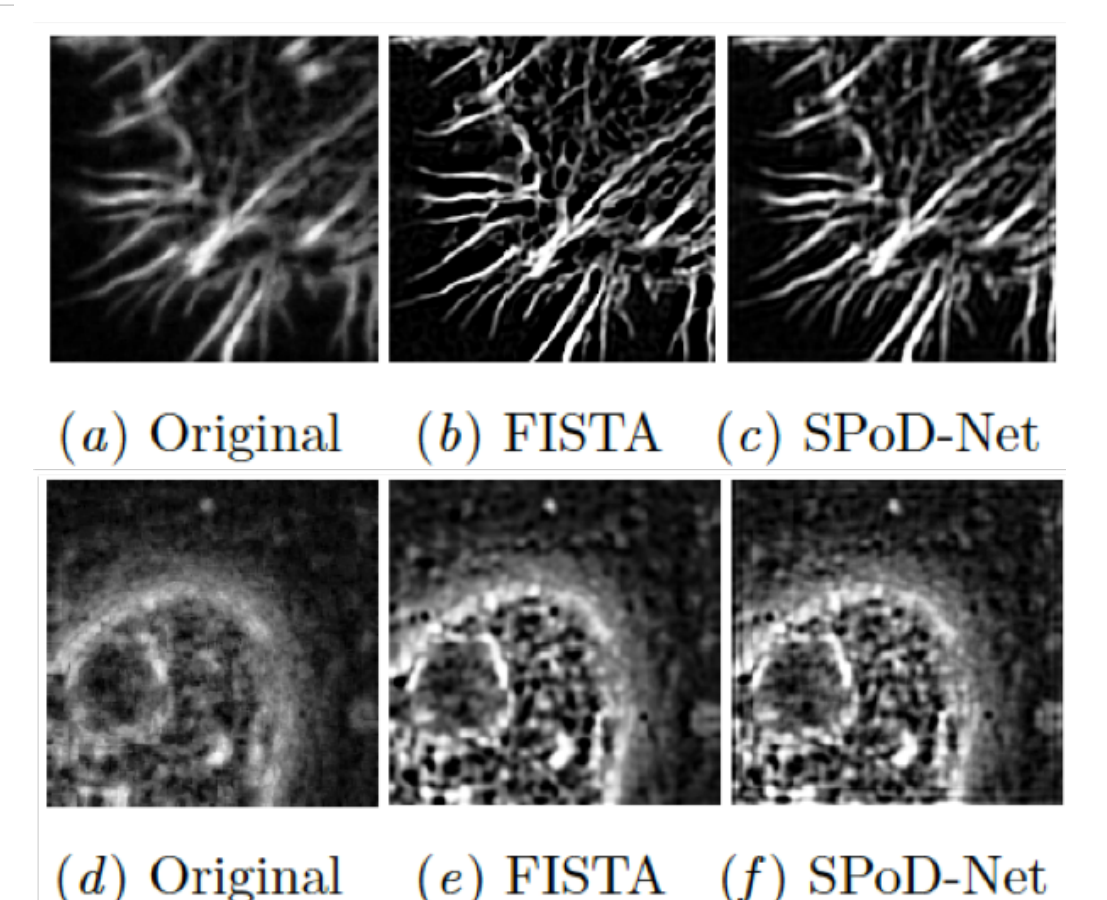


Figure 10: Recovered images