LINN: **L**ifting **I**nspired **I**nvertible **N**eural **N**etwork for Image Denoising

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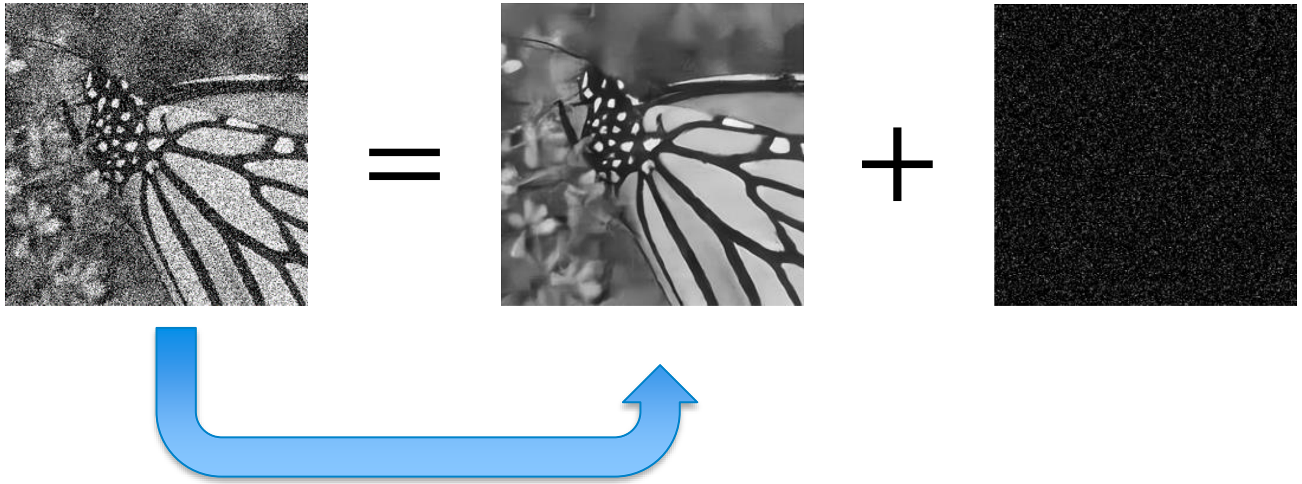
Background — Image Denoising

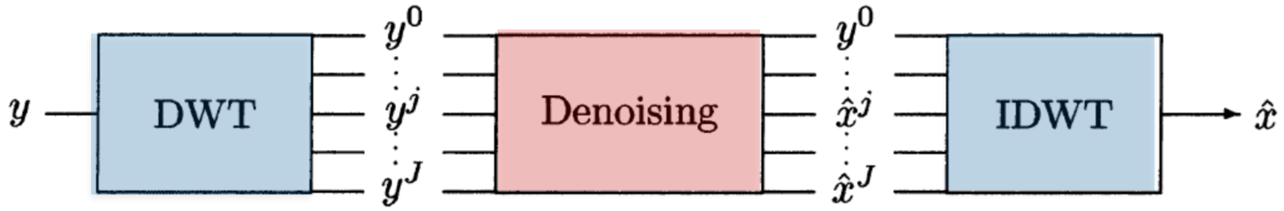
- The objective is to recover a clean image from the observed noisy image:



Background — Image Denoising

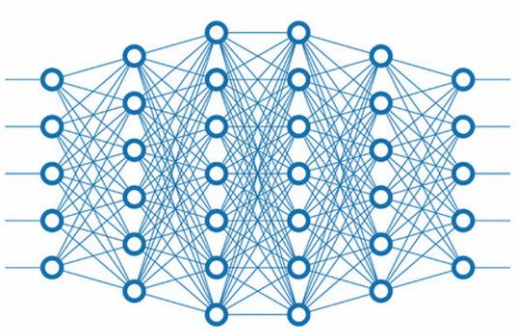
Model-based methods

- Based on well-defined image priors or noise statistics
- White-box systems with good interpretability and strong generalization ability



Learning-based methods

- Learning from noisy-clean image pairs
- Black-box system and restricted generalization ability



Motivation and Idea

- ***Motivation***: whether it is possible to learn **a non-linear wavelet transform** for image denoising and other image restoration tasks?

- ***Idea***: propose an **image denoising invertible neural network** based on the principle of transform-based denoising
  - ✓ A lifting inspired invertible neural network
  - ✓ Sparsity-driven denoising network

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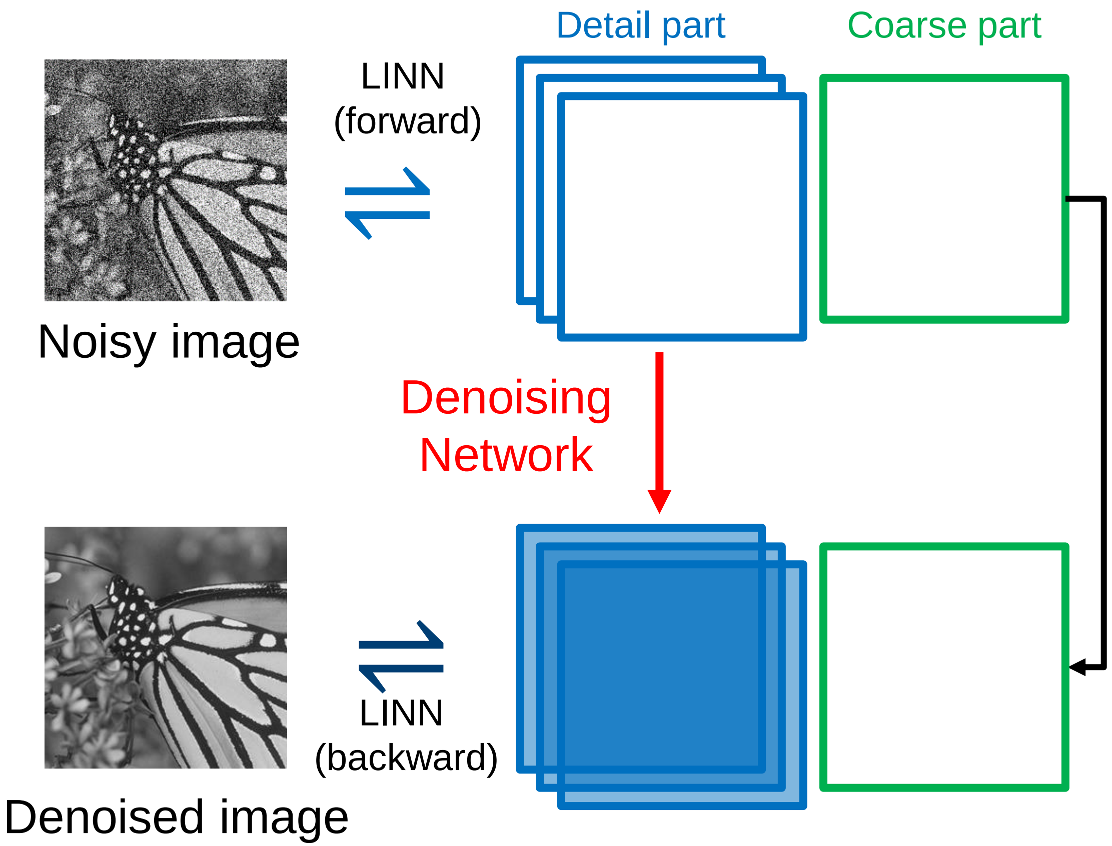
DnINN: Image Denoising Invertible Neural Network



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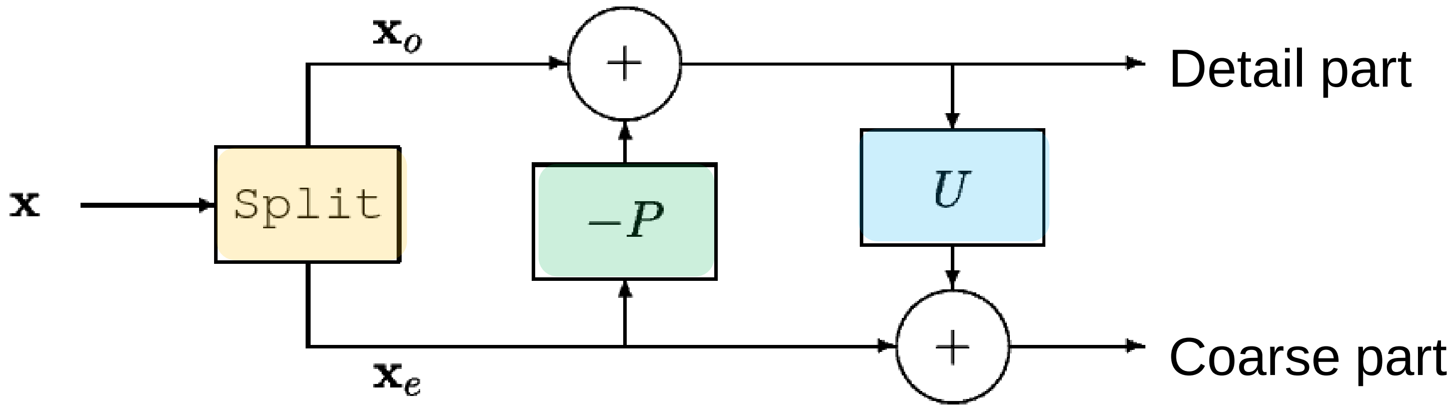
Lifting Scheme

Splitting and merging operator

- Split $\mathbf{x}$ into odd part $\mathbf{x}_o$ and even part $\mathbf{x}_e$
- Combine $\mathbf{x}_o$ and $\mathbf{x}_e$ into $\mathbf{x}$

Predictor and updater

- A predictor is used to predict $\mathbf{x}_o$ from $\mathbf{x}_e$
- The updater adjusts $\mathbf{x}_e$ based on the prediction error of $\mathbf{x}_o$



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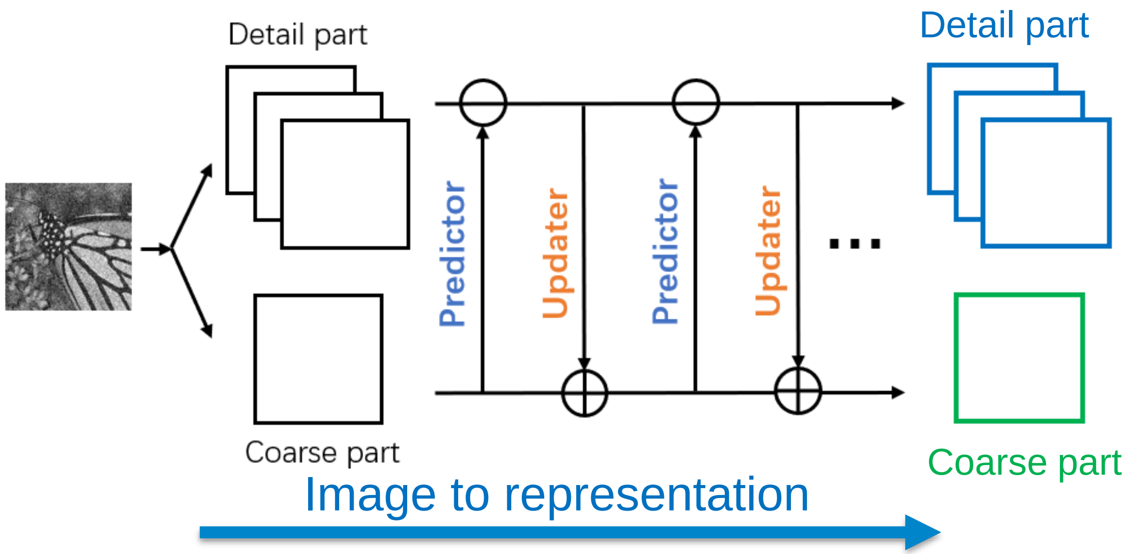
Lifting inspired Invertible Neural Network

- Forward pass



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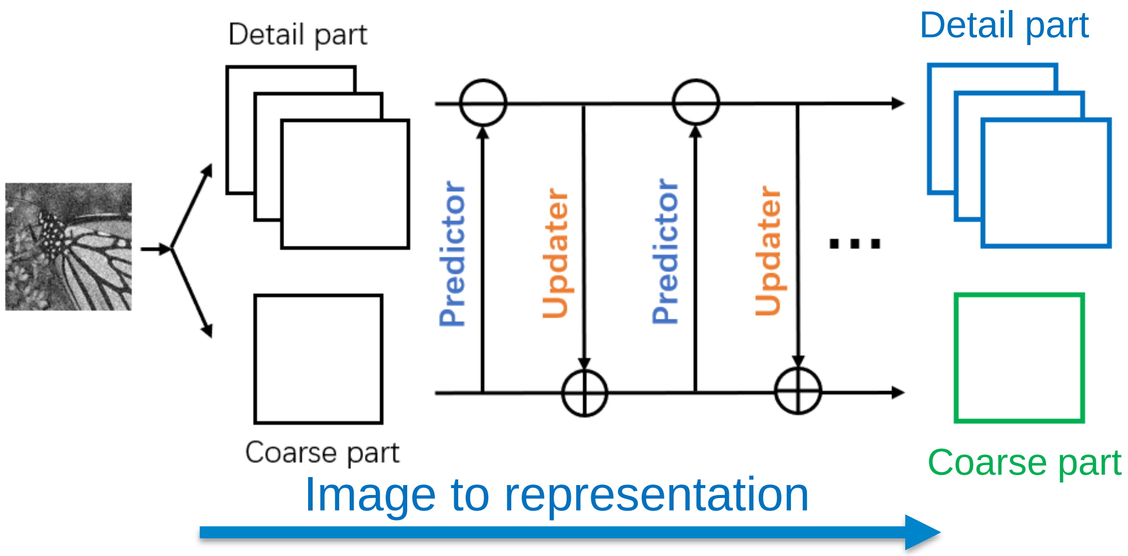
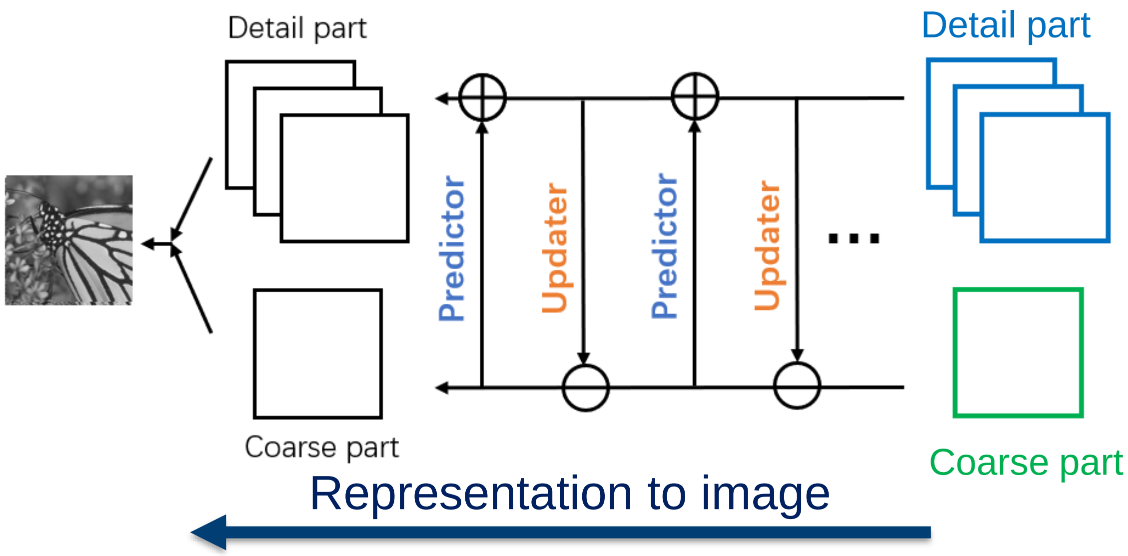
Lifting inspired Invertible Neural Network

- Forward pass



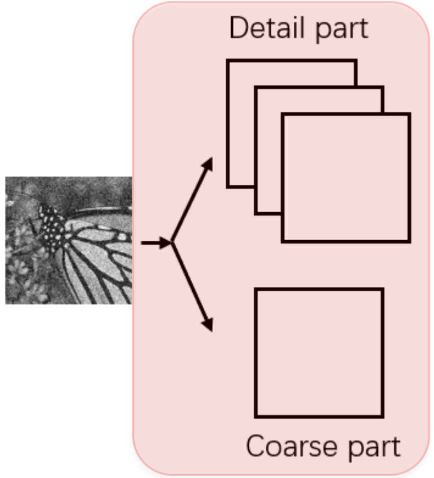
- Backward pass



When no operation is applied on the representation, perfect reconstruction can be achieved using the backward pass.

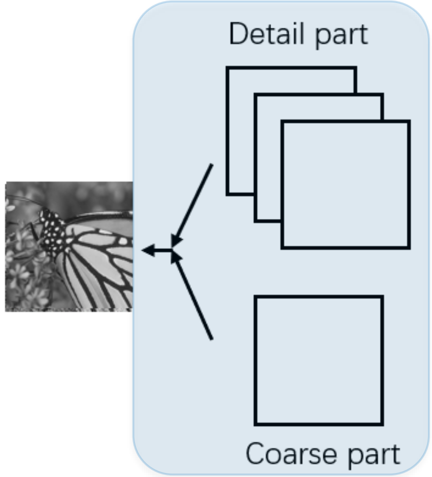
LINN — Splitting/Merging Operator

- Forward pass



The splitting operator is the **Undecimated** Haar Wavelet Transform

- Backward pass



The merging operator is the Inverse **Undecimated** Haar Wavelet Transform

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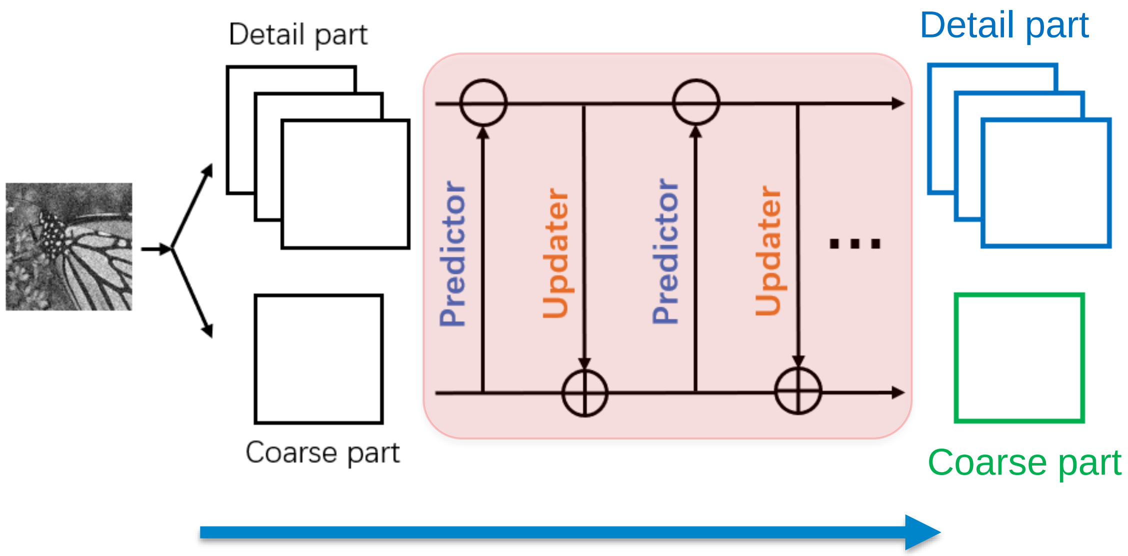
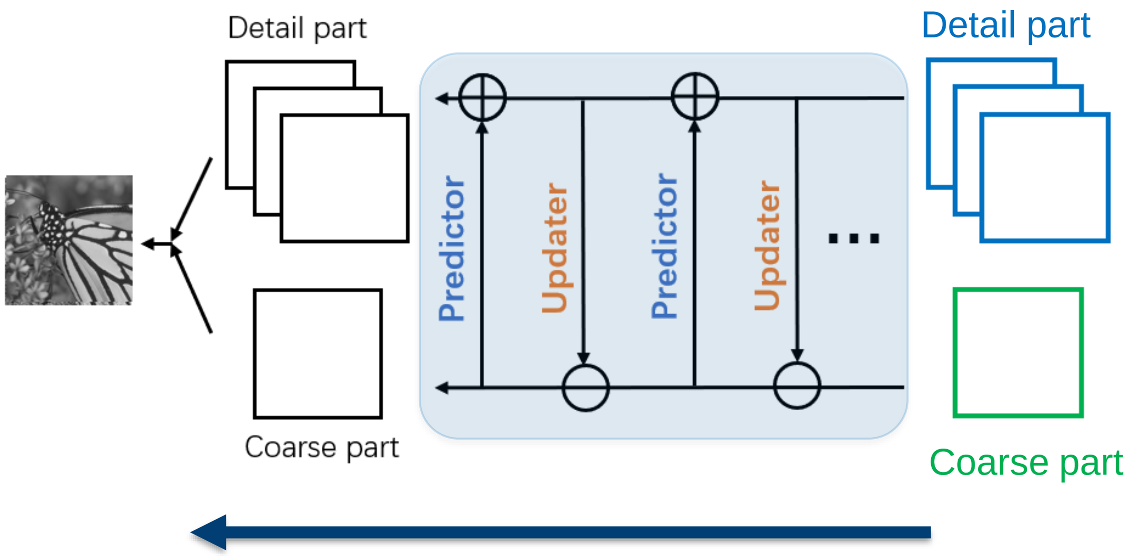
LINN — Predictor/Updater Networks

- Forward pass



- Backward pass



LINN — Predictor/Updater Networks

- Forward pass
  - There are I pairs of P-Net and U-Net to sequentially update the detail and the coarse part

$$\begin{cases} z_d^{(i)} = z_d^{(i-1)} - P_i\left(z_c^{(i-1)}\right) \\ z_c^{(i)} = z_c^{(i-1)} + U_i\left(z_d^{(i)}\right) \end{cases} \longrightarrow$$

- Backward pass
  - The same I pairs of P-Net and U-Net are used for reconstruction

$$\longleftarrow \begin{cases} z_c^{(i-1)} = z_c^{(i)} - U_i\left(z_d^{(i)}\right) \\ z_d^{(i-1)} = z_d^{(i)} + P_i\left(z_c^{(i-1)}\right) \end{cases}$$

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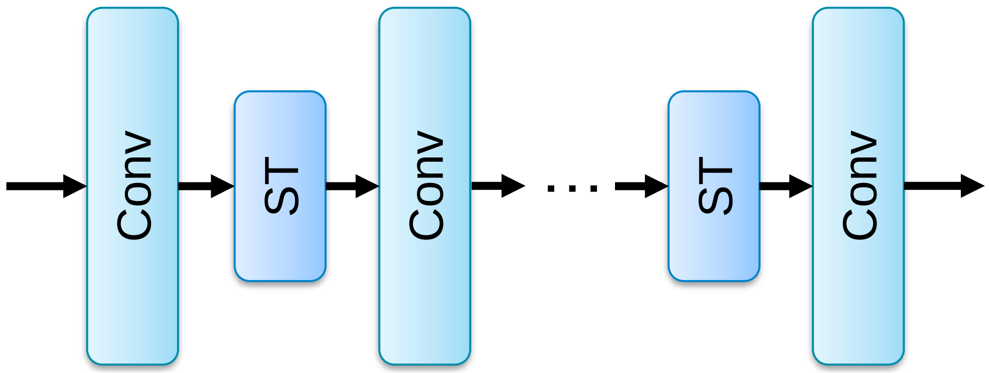
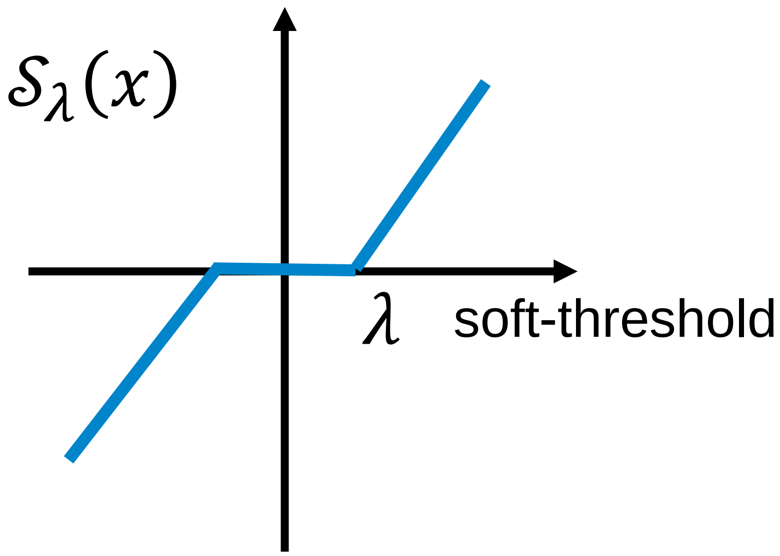
LINN — Predictor/Updater Networks

- Convolutional networks with soft-thresholding non-linearity





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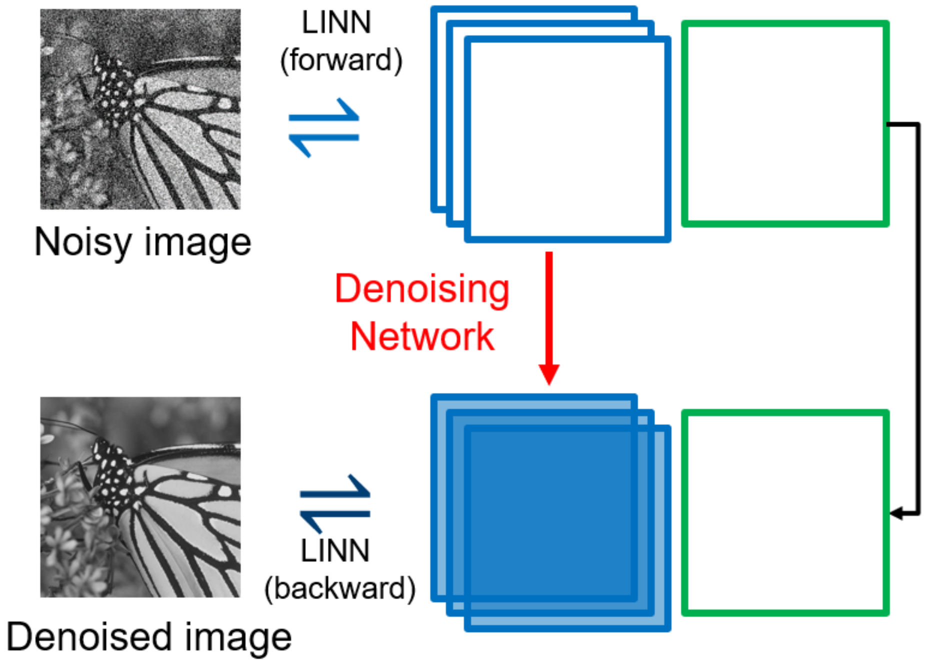
Denoising Network

- Non-invertible component
- The denoising network enforces the detail part to be sparse
- A well-understood denoising network can lead to enhanced interpretability



Denoising Network

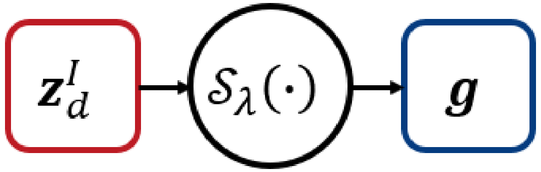
- l_1-norm minimization problem:

$$g = \underset{g}{\operatorname{argmin}} \frac{1}{2\sigma^2} \| z_d^I - g \|_2^2 + \lambda \| g \|_1$$

  – Closed-form solution:

$$g = \mathcal{S}_{\sigma^2 \lambda}\left(z_d^I\right)$$

Noise adaptive soft-threshold



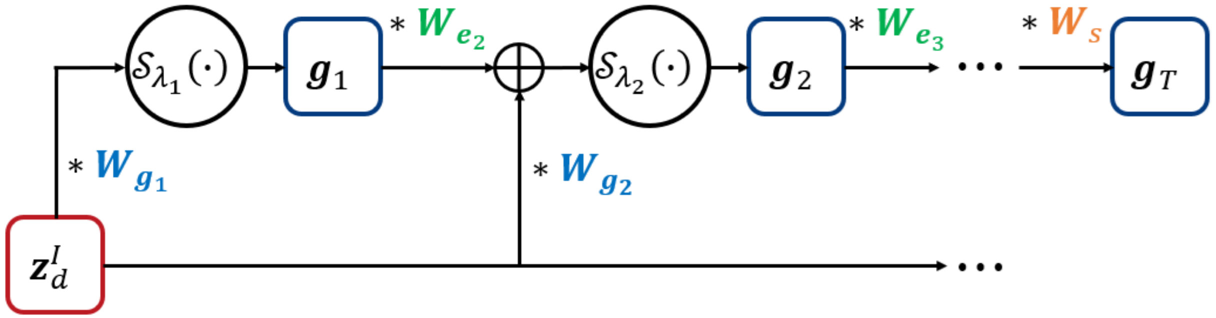
Denoising Network

- Over-parameterized l_1-norm minimization problem:

$$g = \underset{g}{\operatorname{argmin}} \frac{1}{2\sigma^2} \left\| z_d^I - D * g \right\|_2^2 + \lambda \|g\|_1$$

  - Learned Iterative Shrinkage Thresholding Algorithm (ISTA):

$$g_{t+1} = \mathcal{S}_{\lambda/\mu}\left(\left(I - \frac{1}{\mu} D^{\mathrm{T}} * D\right) * g_t + \frac{1}{\mu} D^{\mathrm{T}} * z_d^I\right)$$



Simulation Results

- Training loss:
  - Mean squared error between restored image and clean image
- Optimizer:
  - ADAM with learning rate 1×10^{-3}
- Training data:
  - BSD dataset: 400 images of size 180×180

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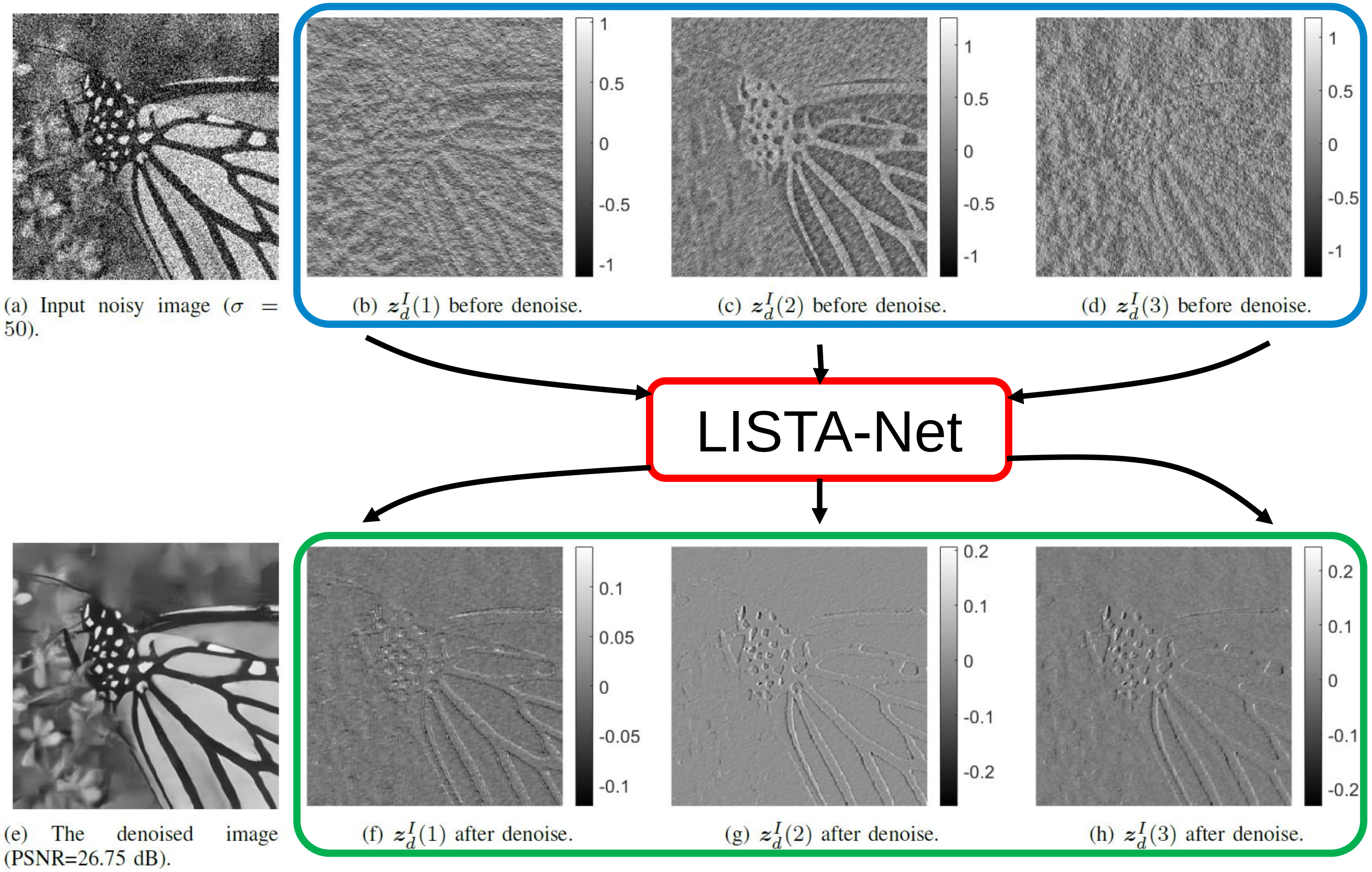
Simulation Results

Methods	Model Size	$\sigma_N = 15$	$\sigma_N = 25$	$\sigma_N = 50$
BM3D [9]	-	31.07	28.57	25.63
WNNM [10]	-	31.37	28.83	25.87
EPLL [24]	-	31.21	28.68	25.67
TNRD [12]	26.6×10^3	31.42	28.92	25.97
DnCNN [13]	556.0×10^3	31.70	29.19	26.20
DnINN_{ST}	134.7×10^3	31.58	29.08	26.14
$\text{DnINN}_{\text{LISTA}}$	135.2×10^3	31.59	29.09	26.14
DnINN_{ST} (2-scale)	269.3×10^3	31.62	29.14	26.19
$\text{DnINN}_{\text{LISTA}}$ (2-scale)	270.3×10^3	31.63	29.14	26.20

TABLE I
THE MODEL SIZE AND PSNR (DB) RESULTS OF DIFFERENT METHODS ON BSD68 DATASET ON NOISE LEVEL $\sigma_N = 15, 25, 50$.

Simulation Results



Detail channels output from the lifting scheme neural network

Detail channels after denoising

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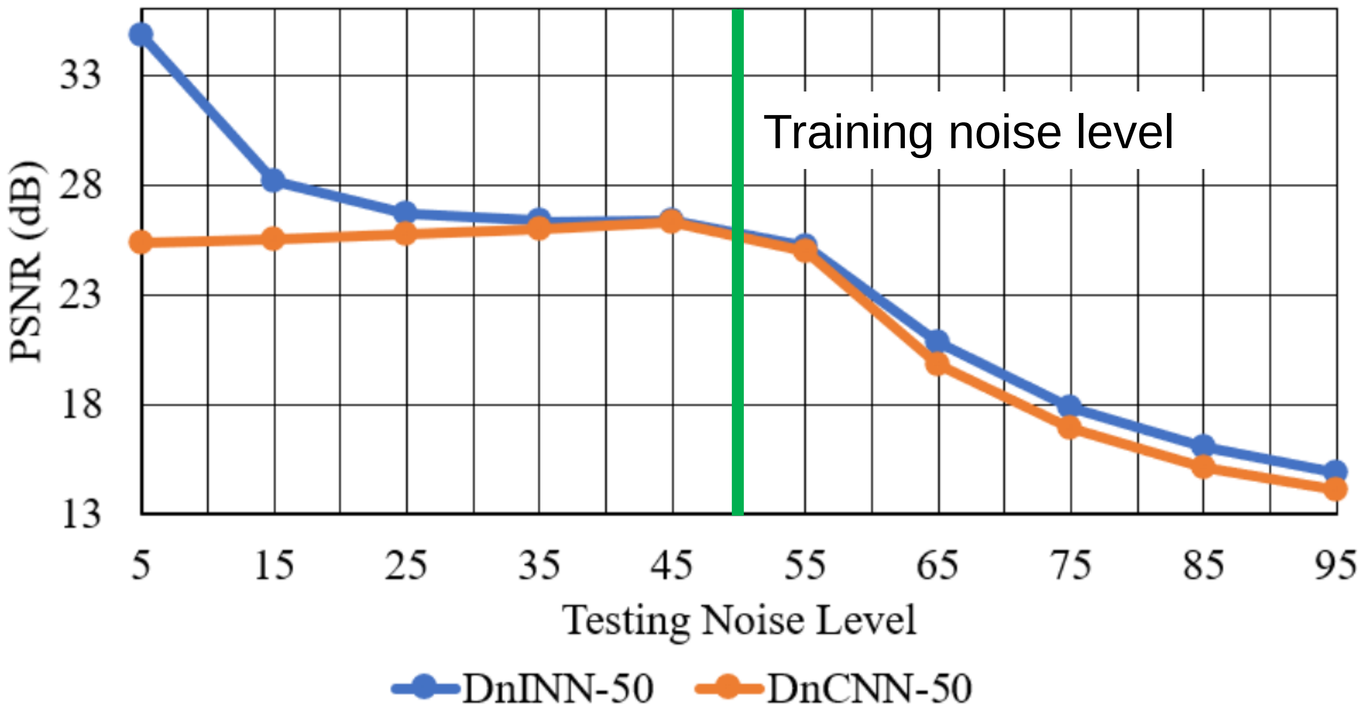
Simulation Results



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Conclusions

- We proposed a image denoising invertible neural network (**DnINN**) method based on the principles of transform-based denoising
  - LINN implements the non-linear transform with perfect reconstruction capability
  - Simple denoising networks can remove the noise in the transform coefficients

- Simulation results show that DnINN method achieves comparable results as the DnCNN method while using $^1/_4$ learnable parameters