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Ground-Truth Free Meta-Learning for Deep Compressive Sampling

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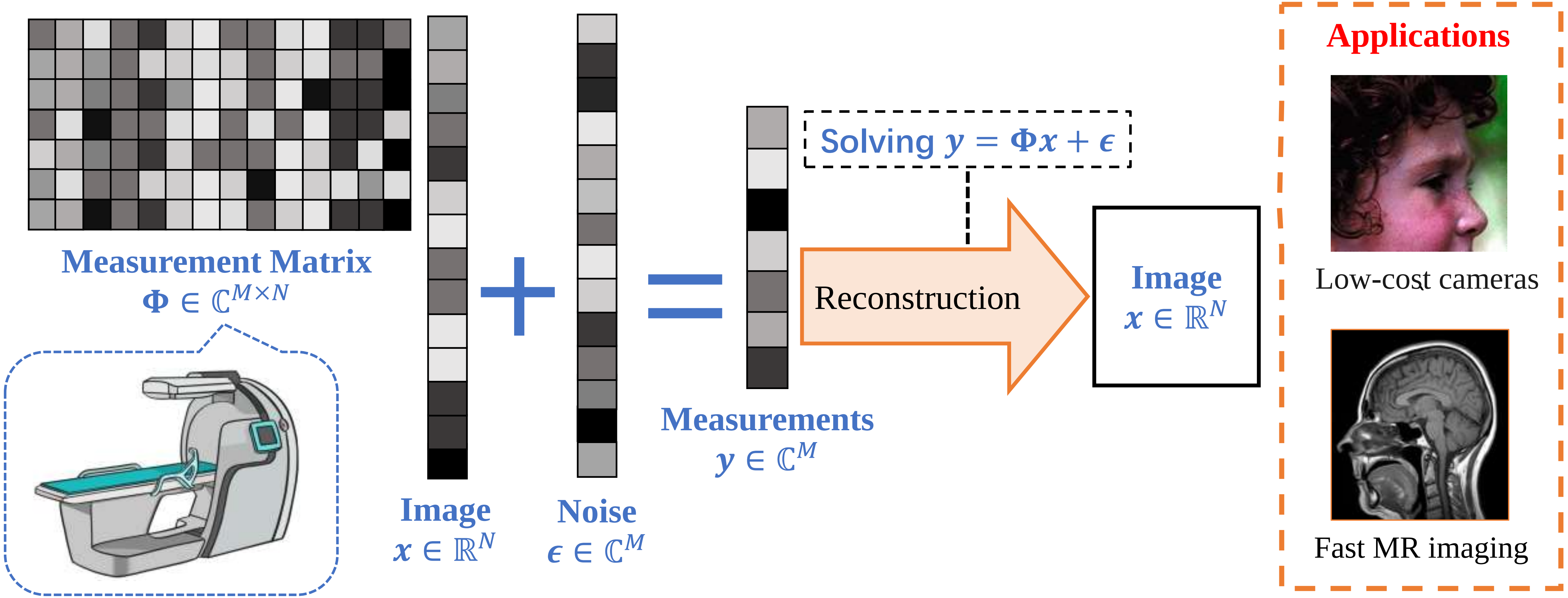
Compressive Sampling (CS) in Imaging



Motivation

Unsupervised External Learning (End2End DNNs)

(+) Exploiting large datasets

(+) Fast inference

(-) Non-adaptivity to test samples

Test-Time Internal Learning (Untrained DNNs)

(+) Sample-specific learning

(+) No dataset bias and OOD issues

(-) High-cost sample-wise fitting

Unsupervised (GT-Free) Meta-Learning for CS-Based Image Reconstruction

Framework

External

Training data $\mathbb{D} \coloneqq \{\boldsymbol{y}_j, \boldsymbol{\Phi}\}_j$

Model: $\mathcal{F}_{\boldsymbol{\omega}}$ (initial para. $\boldsymbol{\omega}$)

$\mathcal{F}_{\boldsymbol{\omega}} \xrightarrow{\textit{Meta Learning}} \mathcal{F}_{\widetilde{\boldsymbol{\omega}}}$

Internal

Test Sample $\boldsymbol{y}^*$

Meta-trained model: $\mathcal{F}_{\widetilde{\boldsymbol{\omega}}}$

$\xrightarrow{\textit{Model Adaption}} \mathcal{F}_{\boldsymbol{\omega}^*}$

Keys

Range-nullspace decommission $\mathbb{C}^N = \mathrm{Range}(\boldsymbol{\Phi}^{\mathrm{H}}) \oplus \mathrm{Null}(\boldsymbol{\Phi})$

- How to suppress measurement noise on $\mathrm{Range}(\boldsymbol{\Phi}^{\mathrm{H}})$ during training/adaption?
- How to learn reconstruction *w.r.t.* $\mathrm{Null}(\boldsymbol{\Phi})$?

Loss Functions | **Meta-Learning Scheme** | **NN Design**

Approach

Improved SURE (iSURE) loss for meta-learning and adaption

iSURE-based GT-free model-agnostic meta-learning (MAML)

Nullspace-consistent model adaptation

Unrolling CNN with bias-tuning

The iSure Loss

iSURE is a noisy form of SURE to provide robust estimation in $\mathrm{Range}(\boldsymbol{\Phi}^{\mathbf{H}})$.

$$\ell^{\mathrm{SURE}}(\boldsymbol{\omega}; \boldsymbol{y}, \boldsymbol{\Phi}) := \|\boldsymbol{\Phi}\mathcal{F}_{\boldsymbol{\omega}}(\boldsymbol{y}, \boldsymbol{\Phi}) - \boldsymbol{y}\|_2^2 + 2\sigma \mathrm{tr}(\boldsymbol{\Phi}^+(\partial \mathcal{F}_{\boldsymbol{\omega}}(\boldsymbol{y}), \boldsymbol{\Phi})/\partial \boldsymbol{y}))$$

$$\ell^{\mathrm{iSURE}}(\boldsymbol{\omega}; \boldsymbol{y}, \boldsymbol{\Phi}, \boldsymbol{\epsilon}') := \|\boldsymbol{\Phi}\mathcal{F}_{\boldsymbol{\omega}}(\boldsymbol{y} + \boldsymbol{\epsilon}', \boldsymbol{\Phi}) - \boldsymbol{y}\|_2^2 + 2\sigma \mathrm{tr}(\boldsymbol{\Phi}^+(\partial \mathcal{F}_{\boldsymbol{\omega}}(\boldsymbol{y} + \boldsymbol{\epsilon}'), \boldsymbol{\Phi})/\partial \boldsymbol{y}))$$

- Noise injection mitigates overfitting in GT-free meta-learning and model adaption, as well as allows ensemble in learning and inference.
- iSURE allows efficient gradient update, without using MCMC.

Theorem 1

Let $\boldsymbol{J}_{\boldsymbol{\omega}}$ be the Jacobian matrix w.r.t. $\boldsymbol{\omega}$, *i.e.* $\boldsymbol{J}_{\boldsymbol{\omega}}\boldsymbol{\mathcal{F}}_{\boldsymbol{\omega}} = \partial \boldsymbol{\mathcal{F}}_{\boldsymbol{\omega}}/\boldsymbol{\partial\omega}$ and $\boldsymbol{y} = \boldsymbol{\Phi}\mathbf{x} + \boldsymbol{\epsilon}$. Assume $\boldsymbol{\epsilon}, \boldsymbol{\epsilon}' \backsim \mathcal{N}(\mathbf{0}, \boldsymbol{\sigma}^2\boldsymbol{I})$ are independent. Then, we have:

$$\nabla_{\boldsymbol{\omega}} \mathbb{E}_{\boldsymbol{y},\boldsymbol{\epsilon}'} \ell^{\mathrm{iSURE}}(\boldsymbol{\omega}; \boldsymbol{y}, \boldsymbol{\Phi}, \boldsymbol{\epsilon}') = 2\mathbb{E}_{\boldsymbol{y},\boldsymbol{\epsilon}'}[\boldsymbol{J}_{\boldsymbol{\omega}}(\mathcal{F}_{\boldsymbol{\omega}}(\boldsymbol{y} + \boldsymbol{\epsilon}', \boldsymbol{\Phi})\boldsymbol{\Phi}^+(\boldsymbol{\Phi}\mathcal{F}_{\boldsymbol{\omega}}(\boldsymbol{y} + \boldsymbol{\epsilon}', \boldsymbol{\Phi}) - \boldsymbol{y} + \boldsymbol{\epsilon}')].$$

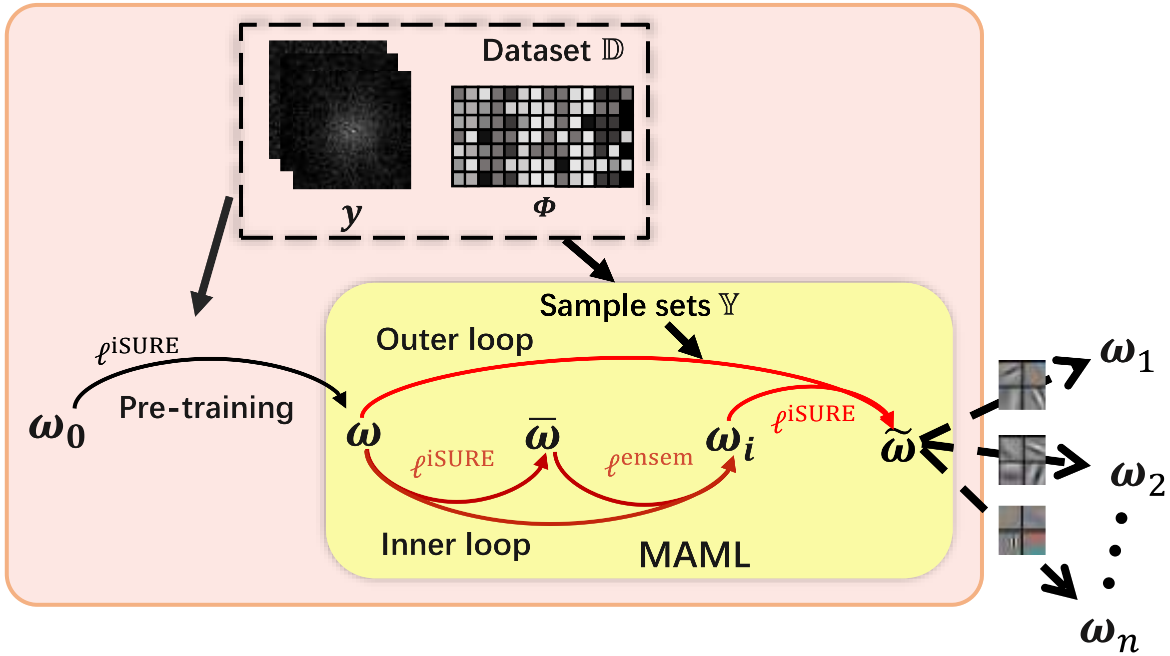
Unsupervised MAML with Improvement

Algorithm 1: GT-Free Meta-Learning for CSR

Input: Measurement dataset $\mathbb{D}$; Initial ω

Required: Learn_Rates α, β, γ; Inner_Iter_Num Q

```
Pre-training: update ω with an iSURE-based loss
while not done do                                        Outer
    Sample sets of measurements {𝕐_j}_j from 𝔻
    for each 𝕐_j do                                      Inner
        Initialize ω̄ with ω
        for q = 1, ··· , Q
            ω̄ ← ω̄ − γ∇_ω̄ L^iSURE_{𝕐_j}(ω̄)
        end
        ω_j = ω − α∇_ω L^ensem_{𝕐_j}(ω; ω̄)
    end
    Update ω ← ω − β∇_ω Σ_j L^iSURE_{𝕐_j}(ω_j)
end
```



$$\mathcal{L}_{\mathbb{Y}}^{\text{iSURE}}(\boldsymbol{\omega}) \coloneqq \mathbb{E}_{\boldsymbol{y}\in\mathbb{Y},\boldsymbol{\epsilon}'\sim\mathcal{N}(0,\sigma^2 I)}\,\ell^{\text{iSURE}}(\boldsymbol{\omega};\boldsymbol{y},\boldsymbol{\Phi},\boldsymbol{\epsilon}')$$

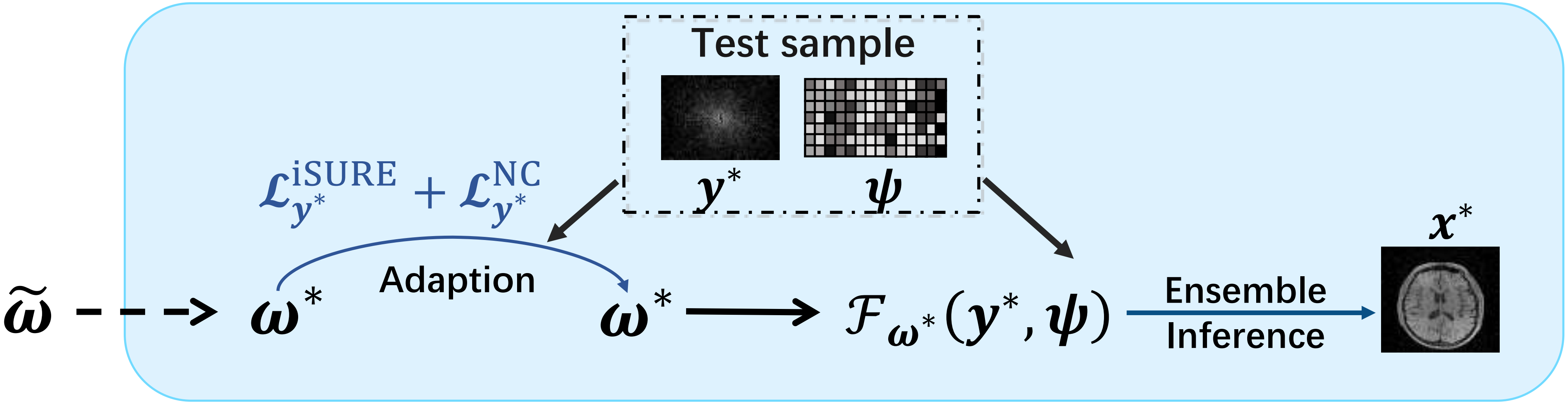
$$\mathcal{L}_{\mathbb{Y}}^{\text{ensem}}(\boldsymbol{\omega}) \coloneqq \mathbb{E}_{\boldsymbol{y}\in\mathbb{Y}}\left\|\mathcal{F}_{\boldsymbol{\omega}}(\boldsymbol{y},\boldsymbol{\Phi}) - 2\mathbb{E}_{\boldsymbol{\epsilon}''\sim\mathcal{N}(0,\sigma^2 I)}\mathcal{F}_{\boldsymbol{\omega}}(\boldsymbol{y}+\boldsymbol{\epsilon}'',\boldsymbol{\Phi})\right\|_2^2$$

- Incorporate iSURE into MAML.
- iSURE only measures errors on range space for learning.
- Inner loop with $\mathcal{L}_{\mathbb{Y}}^{\text{ensem}}$ for better addressing the ambiguity on $\text{Null}(\boldsymbol{\Phi})$.

Nullspace-Consistent (NC) Adaptation

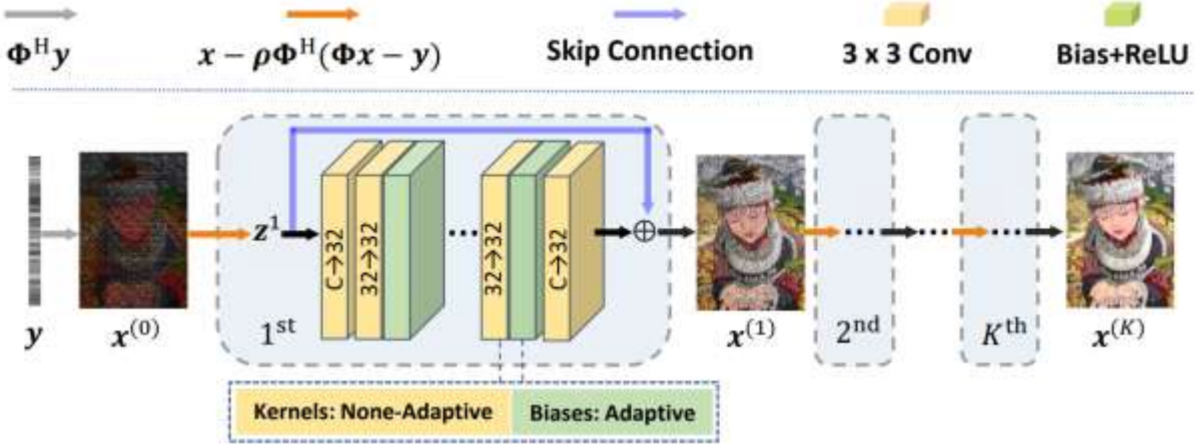
- Given a test sample $(\boldsymbol{y}^*, \boldsymbol{\psi})$, iSURE only considers reconstruction on $\mathrm{Range}(\boldsymbol{\psi}^{\mathrm{H}})$ and may bring negative effects to prediction on $\mathrm{Null}(\boldsymbol{\psi})$.
- NC adaptation mitigates negative effects in $\mathrm{Null}(\boldsymbol{\psi})$ by pulling the prediction on $\mathrm{Null}(\boldsymbol{\psi})$ back, done by the NC loss:

$$\mathcal{L}_{\boldsymbol{y}^*}^{\mathrm{NC}}(\boldsymbol{\omega}; \boldsymbol{\psi}, \boldsymbol{\omega}^*) := \left\|(\mathbf{I} - \boldsymbol{\psi}\boldsymbol{\psi}^{\dagger})(\mathcal{F}_{\boldsymbol{\omega}}(\boldsymbol{y}^*, \boldsymbol{\psi}) - \mathcal{F}_{\widetilde{\boldsymbol{\omega}}}(\boldsymbol{y}^*, \boldsymbol{\psi}))\right\|_2^2.$$



Unrolling CNN with Bias-Tuning

- Unroll $\boldsymbol{x}^{(k)} = \mathrm{Prox}_{\boldsymbol{\psi}}\left(\boldsymbol{x}^{(k-1)} - \rho\boldsymbol{\Phi}^{\mathrm{H}}(\boldsymbol{\Phi}\boldsymbol{x}^{(k-1)} - \boldsymbol{y})\right)$ and replace the proximal operator $\mathrm{Prox}_{\boldsymbol{\psi}}$ replaced by a sub-CNN.

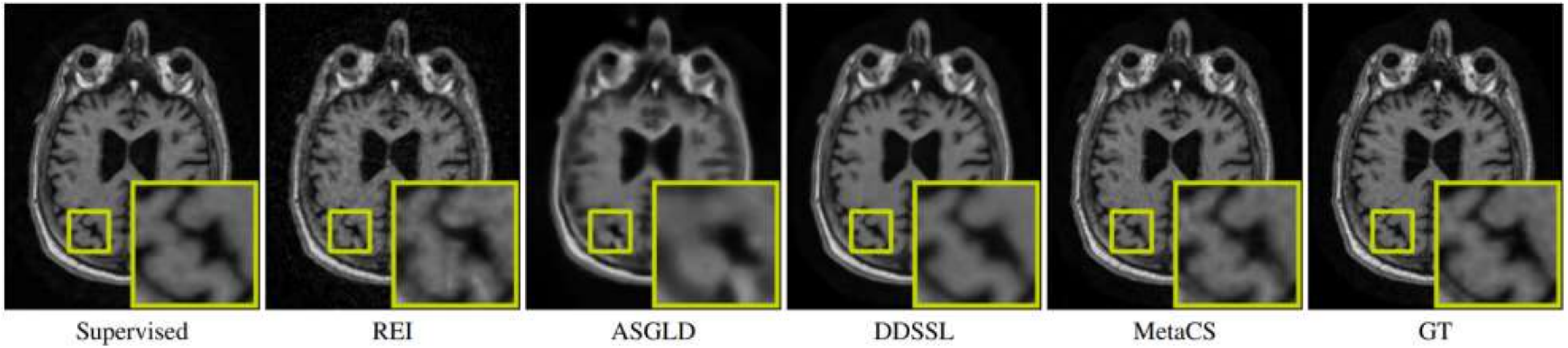


- An unrolling CNN acts as an iterative shrinkage process. The biases play a similar role to the thresholds of shrinkage, which are critical.
- **Bias-Tuning**: Only adjusting the bias parameters during adaption.

MR Image Reconstruction

Mean PSNR(dB)/SSIM of MR image reconstruction on MRI150 dataset.

CS Ratio	Noise Level	Regularized		Unsupervised	Internal		Unsupervised+Internel		Supervised	
		ZF [JMRI-01]	SparseMRI [MRM-07]	REI [CVPR-22]	BNN [ECCV-20]	ASGLD [CVPR-22]	DDSSL [ECCV-22]	MetaCS (Ours)	ADMMNet [TPAMI-19]	Supervised
20%	0	30.41/.72	35.46/.89	36.07/.90	35.54/.88	36.08/.90	36.73/.92	37.12/.93	37.17/.93	37.58/.94
	10	29.18/.64	29.74/.64	33.94/.89	35.54/.88	36.08/.90	33.79/.90	34.34/.91	34.04/.89	34.32/.90
30%	0	33.01/.80	37.72/.91	38.01/.92	37.14/.89	38.11/.93	38.47/.94	39.59/.95	39.84/.93	40.70/.94
	10	30.39/.67	30.55/.68	34.04/.89	31.86/.85	32.25/.87	34.51/.91	35.25/.92	34.82/.90	35.18/.91
40%	0	35.14/.85	38.51/.93	39.06/.95	38.63/.91	39.29/.95	41.00/.96	41.24/.97	41.56/.96	42.52/.98
	10	30.81/.68	31.24/.69	34.45/.90	33.32/.86	33.71/.87	34.83/.90	35.53/.91	35.31/.91	35.64/.91
50%	0	37.07/.89	39.93/.94	40.95/.95	40.24/.93	41.60/.95	42.53/.97	43.92/.98	43.00/.97	44.09/.98
	10	30.87/.66	31.54/.67	35.11/.91	34.39/.89	34.51/.89	35.35/.91	36.23/.93	35.71/.91	36.44/.93



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Mean PSNR(dB)/SSIM of natural image reconstruction on Set11 dataset.

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10%	0	22.45/0.38	25.00/.65	22.79/.64	27.49/.83	28.15/.83	27.48/.84	28.02/.84	26.94/.82	28.34/.84	25.02/.75
	10	21.02/0.54	23.31/.64	22.26/.66	25.23/.76	26.02/.76	26.10/.78	26.17/.78	25.03/.70	25.81/.78	24.48/.73
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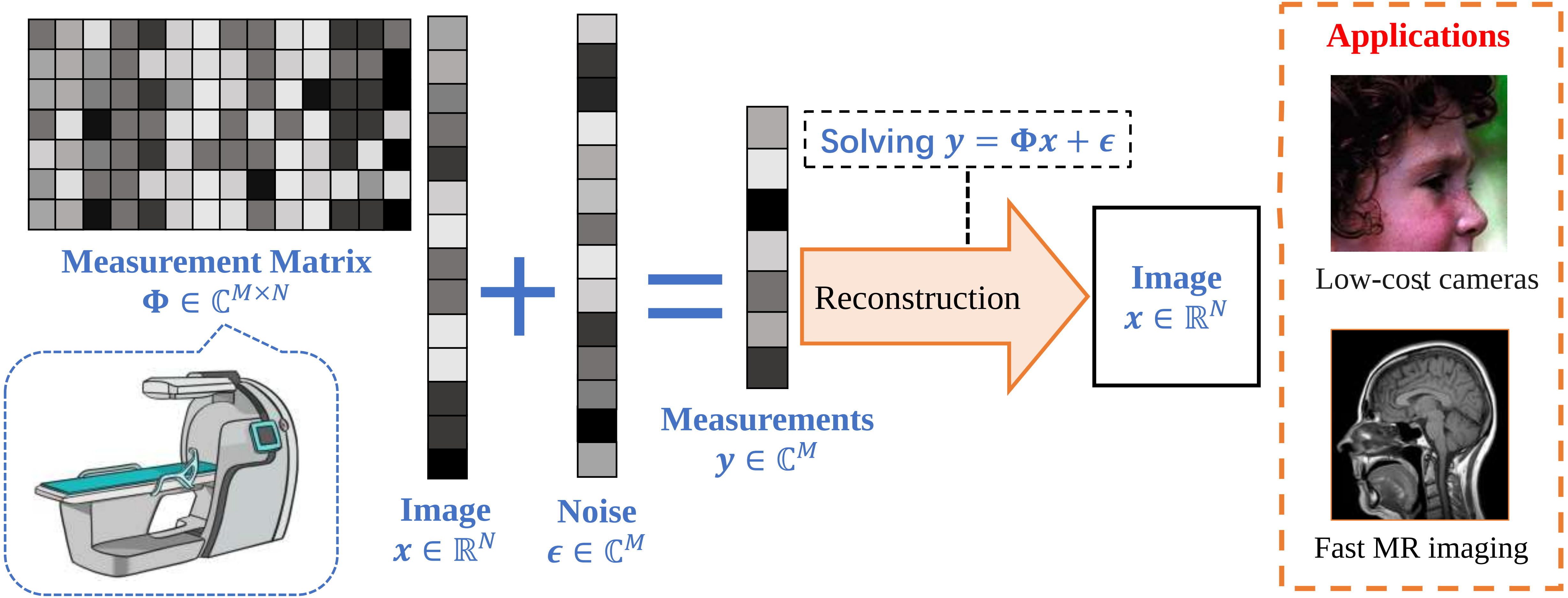
	10	26.66/0.72	28.73/.81	28.99/.81	30.39/.88	31.11/.90	31.58/.88	31.64/.88	31.14/.89	31.16/.89	30.58/.89

COAST REI ASGLD DDSSL MetaCS GT

Now, let's dive into the details...

Compressive Sampling (CS) in Imaging



Ground Truth (GT)-Free Learning Meets CS

- New trend: Training deep neural networks (DNNs) for CS-based reconstruction w/o using GT images.
- Two types of GT-free deep learning:

End2End unsupervised learning	Untrained DNNs on test samples
EI/REI [1,2]; DDSSL [3]	BNN [4], SURE(s) [5],
External learning	Internal Learning

[1] Equivariant imaging: Learning beyond the range space. ICCV 2021.
[2] Robust equivariant imaging: a fully unsupervised framework for learning to image from noisy and partial measurements. CVPR 2022.
[3] Dual-Domain Self-supervised Learning and Model Adaption for Deep Compressive Imaging. ECCV 2022.
[4] Self-supervised Bayesian deep learning for image recovery with applications to compressed sensing. ECCV 2020.
[5] Unsupervised learning with stein's unbiased risk estimator. arXivpreprint arXiv, 2018.

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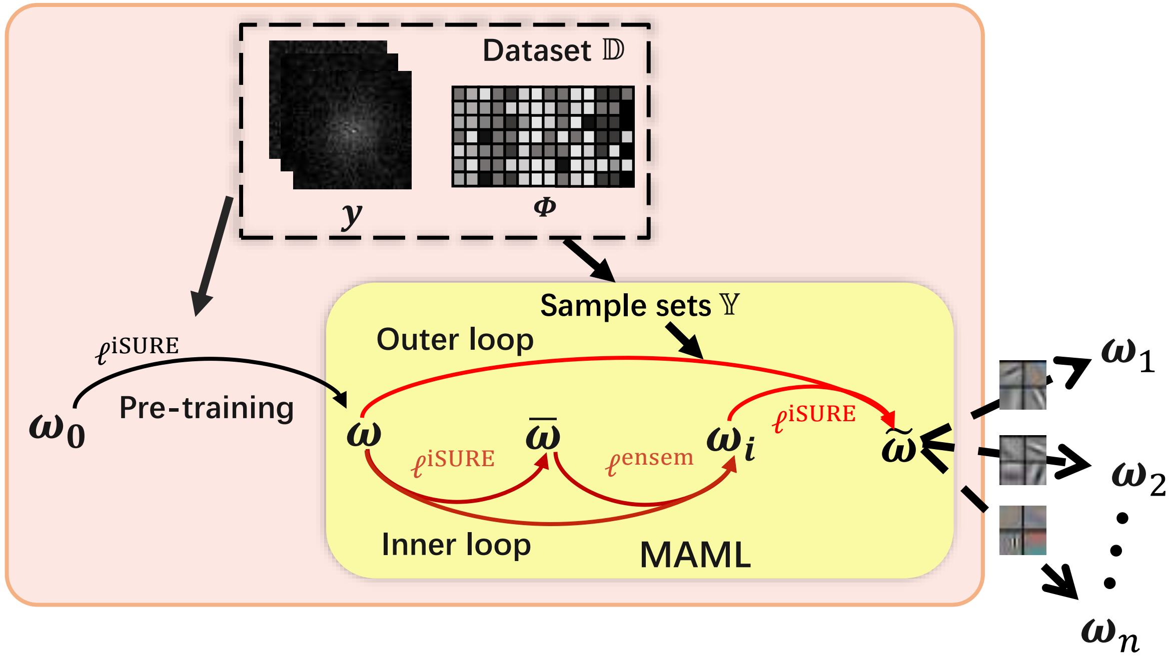
3. Sample sets of measurements $\{\mathbb{Y}_j\}_j$ from $\mathbb{D}$
4. **for each** $\mathbb{Y}_j$ **do** *Inner*
5. Initialize $\bar{\omega}$ with ω
6. **for** $q = 1, \cdots, Q$
7. $\bar{\omega} \leftarrow \bar{\omega} - \gamma \nabla_{\bar{\omega}} \mathcal{L}^{\text{iSURE}}_{\mathbb{Y}_j}(\bar{\omega})$
8. **end**
9. $\omega_j = \omega - \alpha \nabla_{\omega} \mathcal{L}^{\text{ensem}}_{\mathbb{Y}_j}(\omega; \bar{\omega})$
10. **end**
11. Update $\omega \leftarrow \omega - \beta \nabla_{\omega} \sum_j \mathcal{L}^{\text{iSURE}}_{\mathbb{Y}_j}(\omega_j)$
13. **end**



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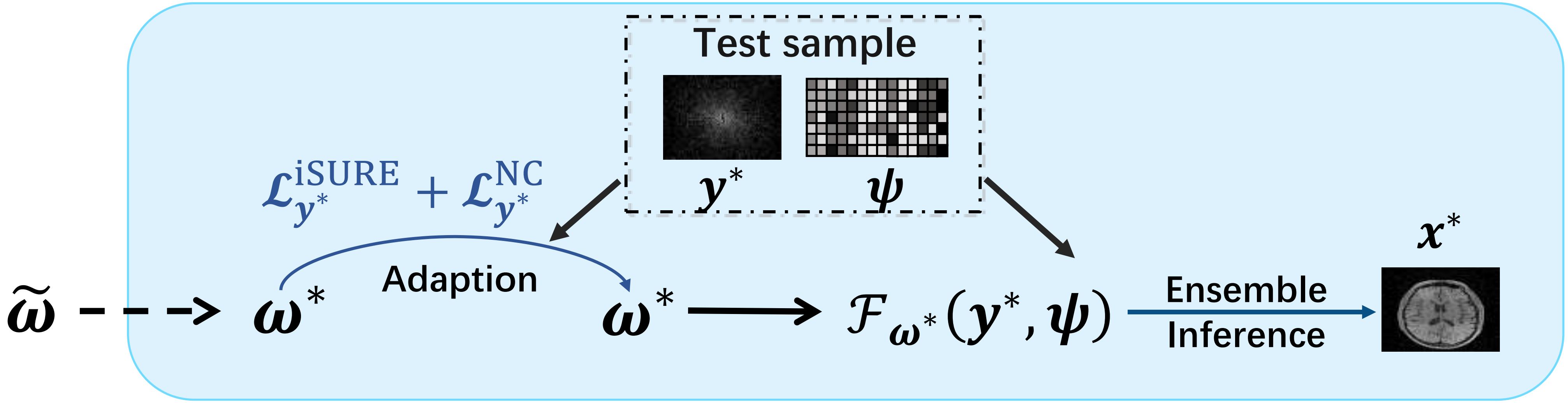

Unrolling CNN with Bias-Tuning

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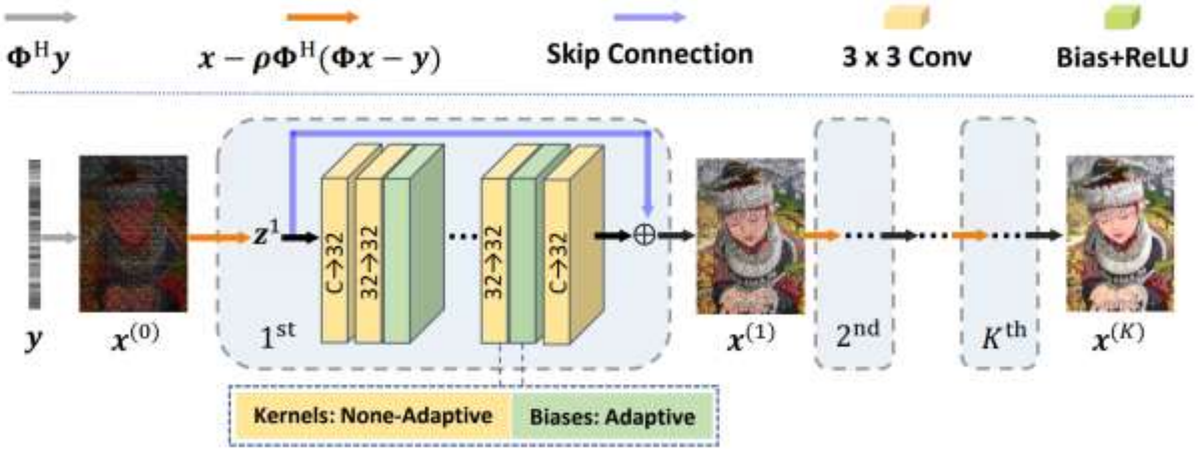

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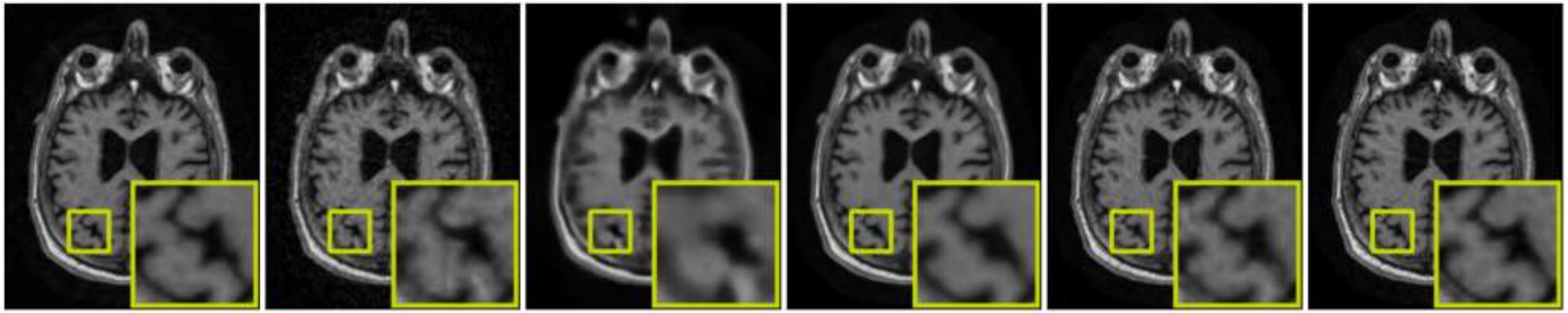

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	10	21.02/0.54	23.31/.64	22.26/.66	25.23/.76	26.02/.76	26.10/.78	26.17/.78	25.03/.70	25.81/.78	24.48/.73
25%	0	27.63/0.62	31.31/.90	31.11/.90	32.30/.92	33.06/.92	33.28/.94	33.38/.94	32.44/.92	33.85/.94	30.42/.89
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40%	0	31.21/0.75	33.30/95	35.63/.95	35.71/.95	35.87/.95	37.18/.96	37.25/.96	36.02/.96	36.94/.96	33.73/.93
	10	26.66/0.72	28.73/.81	28.99/.81	30.39/.88	31.11/.90	31.58/.88	31.64/.88	31.14/.89	31.16/.89	30.58/.89

COAST REI ASGLD DDSSL MetaCS GT

Comparison on Computational Complexity

Running time (minutes) of different methods on Set11, tested on a TITAN RTX GPU.

Method	LSURE	BNN	ASGLD	DDSSL	MetaCS
r=40%	0.45	282	178	5.72	0.89

Compared to the latest adaption method DDSSL, our MetaCS takes only around 1/7 time!

Comparison in number of model parameters (M).

COAST	SSLIP	LDAMP-SURE	ASGLD	DDSSL	MetaCS (whole)	MetaCS (bias-only)
1.12	0.67	0.38	2.19	0.67	0.3756	0.0013

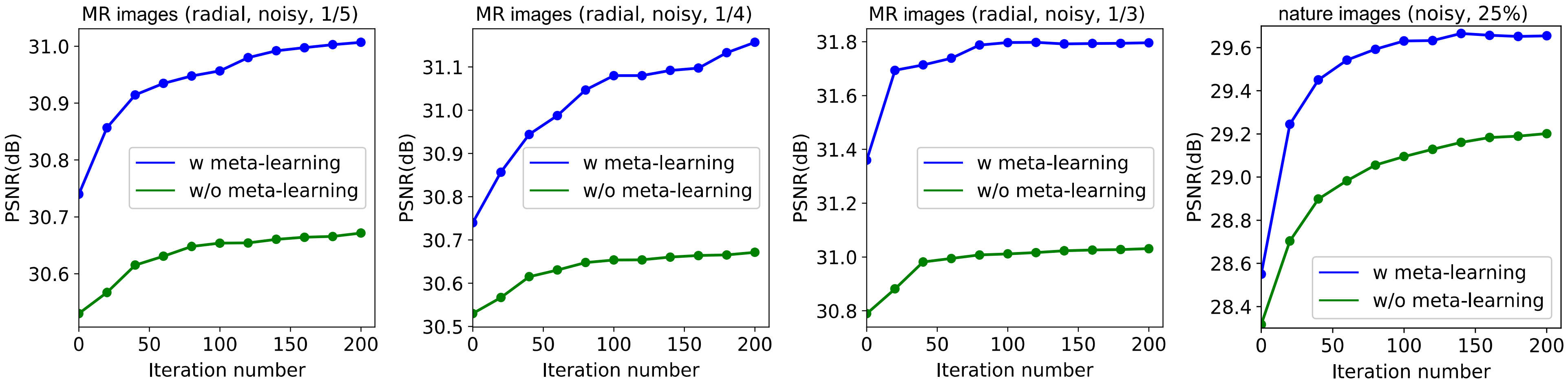
Our bias-tuning scheme significantly reduces the number of parameters being adapted.

Ablation Studies

Method	Noiseless MR Imaging			Noisy MR Imaging		
	r = 1/5	1/4	1/3	r = 1/5	1/4	1/3
iSure $\rightarrow$ gSURE	29.13	32.57	34.29	28.56	29.17	29.14
w/o Meta-Learn	32.93	33.97	35.68	29.52	30.03	30.34
Standard MAML	32.86	34.01	35.73	29.63	30.08	30.42
w/o Adaption	33.63	34.40	35.89	29.60	30.78	31.36
w/o NC	33.71	34.65	36.40	30.41	31.01	31.66
All weights	34.02	34.82	36.58	30.60	31.19	31.74
Gain-tuning	33.68	34.58	36.19	30.35	30.83	31.37
MetaCS	34.00	34.85	36.54	30.56	31.17	31.79

Each component of our approach has noticeable contribution to the performance.

Effectiveness of Meta-Learning & Adaption



Meta-learning leads to faster and more effective model adaptation.

Adaption for Unseen Measurement Matrices

Test Mask	Train=Test		Gauss, r=1/4	
	REI	MetaCS	REI	MetaCS
Gauss, r=1/3	36.72	37.87	36.38	37.8
Gauss, r=1/5	34.04	35.52	33.63	35.47
Radial, r=1/4	33.15	34.46	32.62	34.84

Thanks

See more at https://csyhquan.github.io