Ultrasound Imaging based on the Variance of a Diffusion Restoration Model

EUSIPCO - Advances in Computational Ultrasound Imaging

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Presenter: Yuxin Zhang

27 - Aug – 2024

ROAD MAP

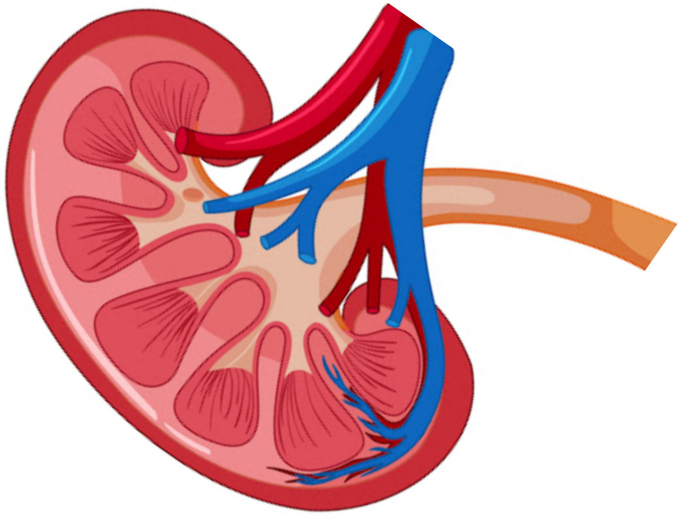
1. Introduction — Ultrasound Imaging, Despeckling, and SOTA

2. Method — Diffusion Models and the Application on Ultrasound

3. Results — Quantitative & Qualitative Comparison

4. Conclusion — Take-home Message

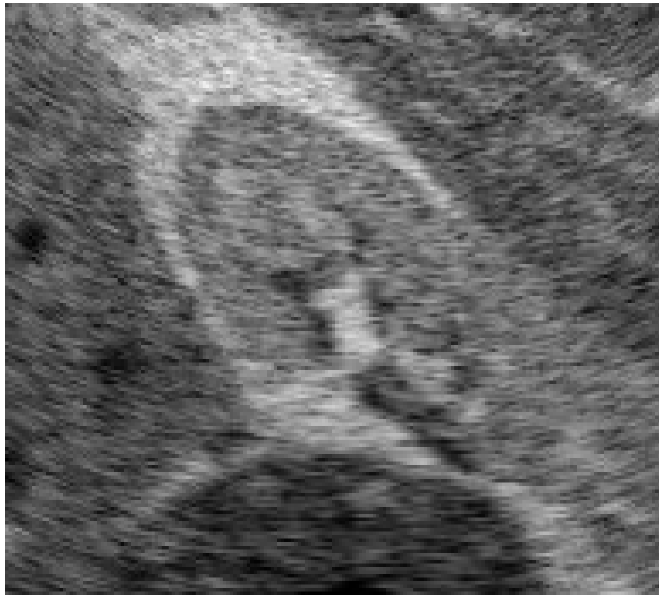
Why Ultrasound Despeckling



Echogenicity map

(average property of the tissue)

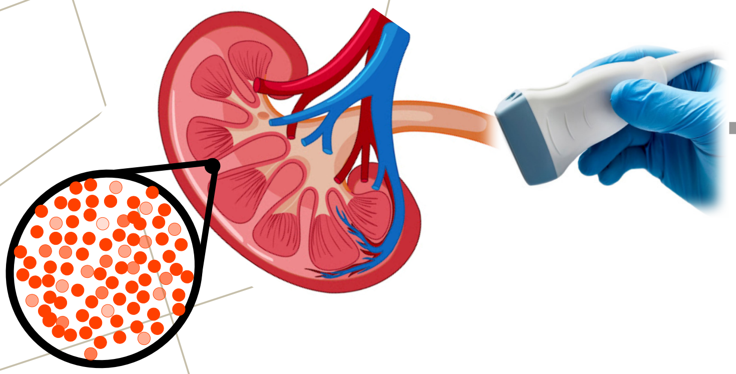
Observation



Ultrasound Despeckling enhances organ and tumor Classification and Segmentation.

https://field-ii.dk/?examples/kidney_example/kidney_example.html
https://fr.vecteezy.com/art-vectoriel/7637674-organe-interne-humain-avec-rein

Approximation of the Ultrasound Imaging Process



Electronic noise

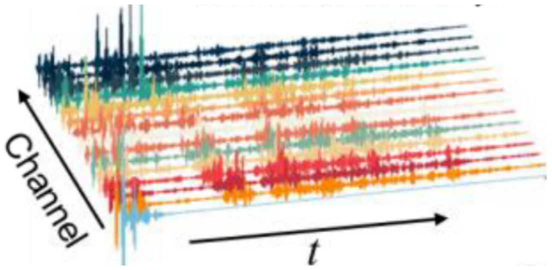
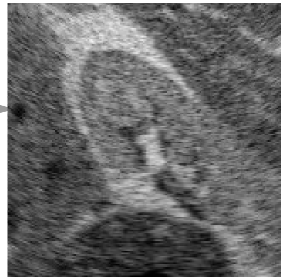


Image Reconstruction Algorithm

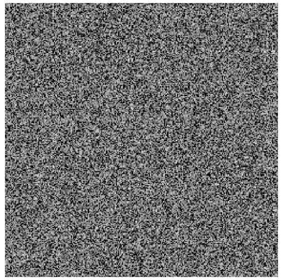
RF image



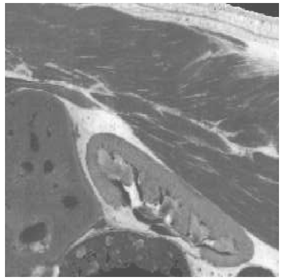
$\mathbf{m} \odot \mathbf{p}$ —— $\mathbf{H}$ forward operator ——> $\mathbf{y}$ measurements —— $\mathbf{B}$ backward operator ——> $\mathbf{By}$

DAS-type Reconstruction

$\tilde{\mathbf{n}}$ —— $\oplus$



Random field $\sim \mathcal{N}(\mathbf{0}, \boldsymbol{I})$

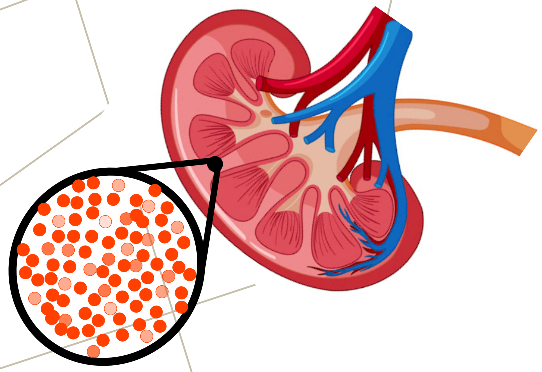


Echogenicity map

$$\mathbf{By} = \mathbf{BH}(\mathbf{m} \odot \mathbf{p}) + \mathbf{B}\tilde{\mathbf{n}}$$

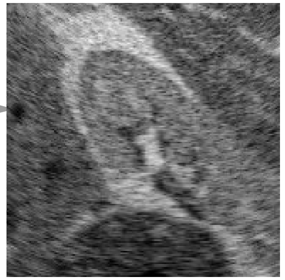
Approximation of the Ultrasound Imaging Process

Additive noise



Measuring

RF image

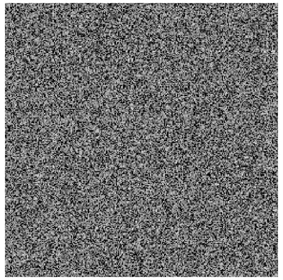


PSF

$\mathbf{A}$

$\mathbf{m} \odot \mathbf{p}$ → $\mathbf{f}$

$\mathbf{n}$ — $\oplus$



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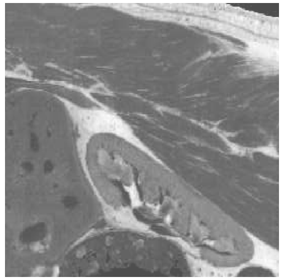

Echogenicity map

$$\mathbf{f} = \mathbf{A}\left(\mathbf{m} \odot \mathbf{p}\right) + \mathbf{n}$$

$$\mathbf{By} = \mathbf{BH}\left(\mathbf{m} \odot \mathbf{p}\right) + \mathbf{B}\tilde{\mathbf{n}}$$

State-of-the-Art of Ultrasound Despeckling

Model 1

$$\underbrace{\mathbf{f}}_{\text{RF image}} = \underbrace{\mathbf{A}}_{\text{PSF}} \left(\underbrace{\mathbf{m}}_{\sim\mathcal{N}(\mathbf{0},\mathbf{I})} \odot \mathbf{p} \right) + \underbrace{\mathbf{n}}_{\sim\mathcal{N}(\mathbf{0},\sigma\mathbf{I})}$$

[James Ng, IEEE TUFFC, 2007] (Wavelet)

State-of-the-Art of Ultrasound Despeckling

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$$\underbrace{\mathbf{f}}_{\text{RF image}} = \underbrace{\mathbf{A}}_{\text{PSF}}\big(\underbrace{\mathbf{m}}_{\sim\mathcal{N}(\mathbf{0},\mathbf{I})} \odot \mathbf{p}\big) + \underbrace{\mathbf{n}}_{\sim\mathcal{N}(\mathbf{0},\sigma\mathbf{I})}$$

[James Ng, IEEE TUFFC, 2007] (Wavelet)

Model 2

$$\underbrace{\mathbf{f}'}_{\text{Env}|\text{RF image}|} = \underbrace{\mathbf{m}'}_{\sim\text{Rayleigh Distr.}} \odot \mathbf{p} + \underbrace{\mathbf{n}'}_{\text{neglected}}$$

- [S. Aja-Fernandez, IEEE TIP, 2006, K. Krissian, TIP, 2007, G. Ramos-Llordén, TIP 2015, J. Xu, Signal Process.2016] Anisotropic Diffusion
- [S. Balocco, Ultrasound Med. Biol., 2010] Bilateral Filter
- [Y. Yue IEEE TMI 2006] Wavelet
- **[D. Mishra, ICPR, 2018, C.-C. Shen, Sensors, 2020] ML**

Model 3

$$\underbrace{\log(\mathbf{f}')}_{\log(\text{Env}|\text{RF image}|)} = \log(\mathbf{p}) + \log(\mathbf{m}')$$

[S. Gupta, IEEE Vision, Image and Signal Processing, 2005, M. I. H. Bhuiyan, Int. Symp. Circuits and Systems, 2007, S. Esakkirajan, Ultrasound Med. Biol, 2013] Wavelet

Model 4

$$\underbrace{\log(\mathbf{f}')}_{\log(\text{Env}|\text{RF image}|)} = \log(\mathbf{p}) + \log(\mathbf{p})^{0.5}\underbrace{\log(\mathbf{m}')}_{\sim\mathcal{N}(\mathbf{0},\sigma'\mathbf{I})}$$

- [F. Argenti, J. Adv. Signal Process. 2003, Y. Yue TMI 2006] Wavelet
- [P. Coupe, IEEE TIP, 2009] NonLocal Means
- [K. Krissian, CVPR, 2005] Anisotropic Diffusion

State-of-the-Art of Ultrasound Despeckling

Model 1

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[James Ng, IEEE TUFFC, 2007] (Wavelet)

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Model 4

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[F. Argenti, J. Adv. Signal Process. 2003, Y. Yue TMI 2006] Wavelet

[P. Coupe, IEEE TIP, 2009] NonLocal Means

[K. Krissian, CVPR, 2005] Anisotropic Diffusion

We adapt the most realistic model, estimating p by solving an Inverse Problem.

Overview of the Proposed Method

Model 1

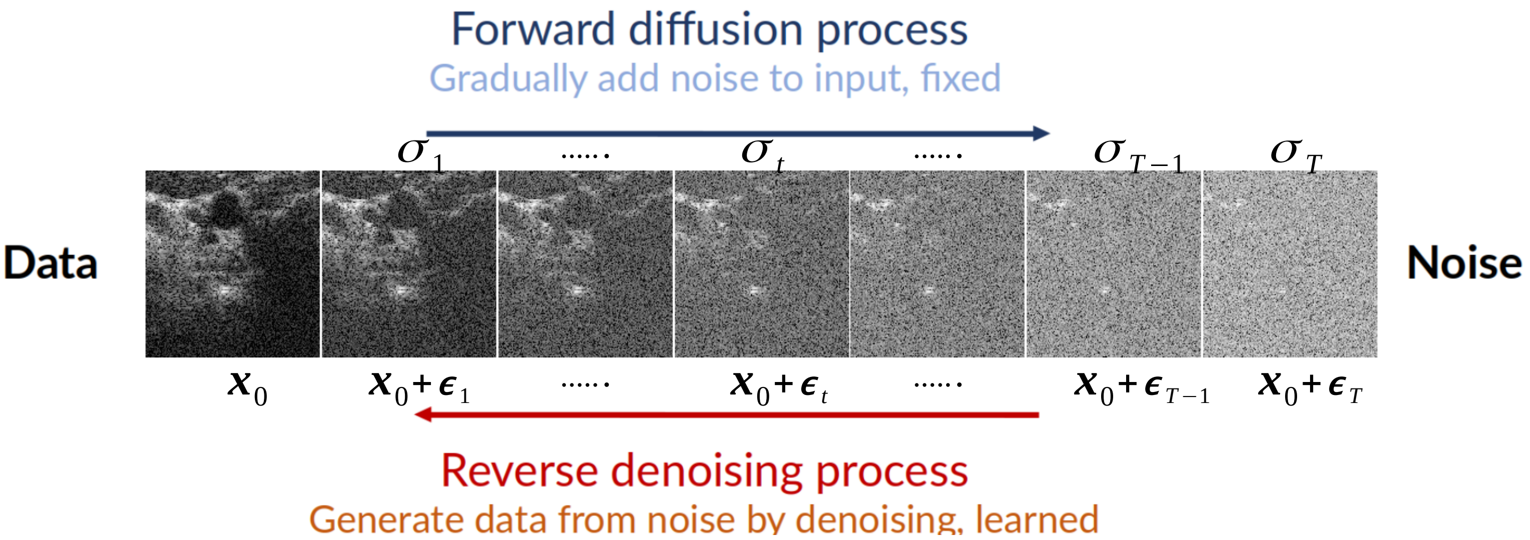
$$\underbrace{\mathbf{f}}_{\text{RF image}} = \underbrace{\mathbf{A}}_{\text{SIR}(\text{PSF})} \left(\underbrace{\mathbf{m}}_{\sim\mathcal{N}(\mathbf{0},\mathbf{I})} \odot \mathbf{p} \right) + \underbrace{\mathbf{n}}_{\sim\mathcal{N}(\mathbf{0},\sigma\mathbf{I})}$$

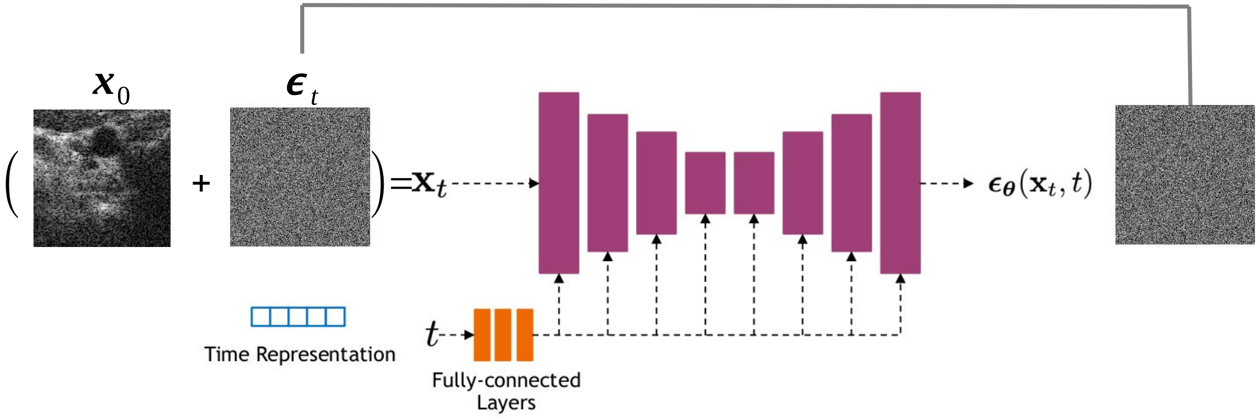
!!! Not the Anisotropic Diffusion But a Generative Model !!!

STEP 1 **Estimate $\mathbf{m} \odot \mathbf{p}$ via a Diffusion Inverse Problem Solver**

STEP 2 **Estimate $\mathbf{p}$ by leveraging the stochasticity of the generative sampling**

Denoising Diffusion Generative Models

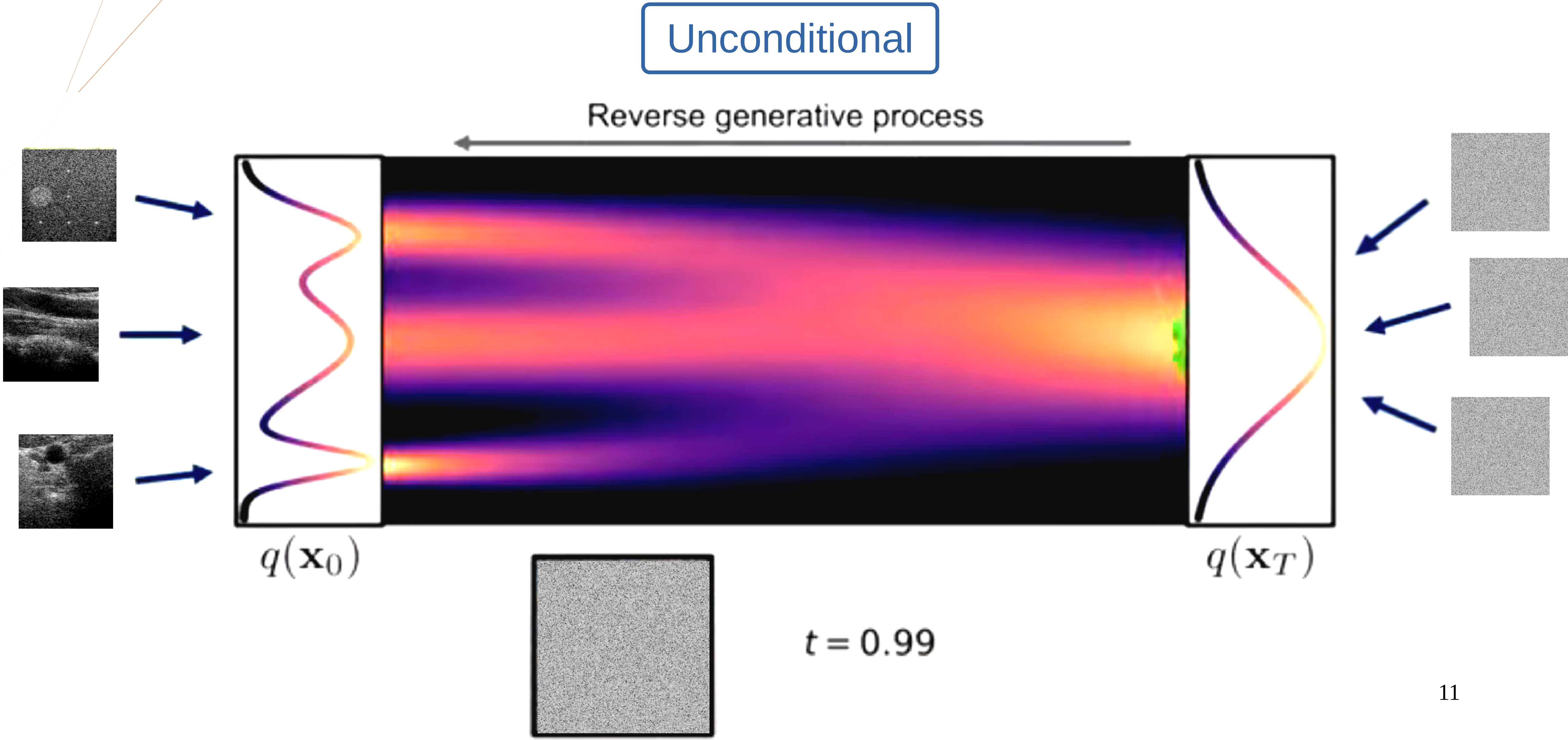




$$simpleLoss = \mathbb{E}_{\boldsymbol{x}_0 \sim p_{\text{data}}} \mathbb{E}_{\boldsymbol{\epsilon}_t \sim \mathcal{N}(\mathbf{0}, \sigma_t \boldsymbol{I})} \| \epsilon_\theta(x_t, t) - \epsilon_t \|_2^2$$

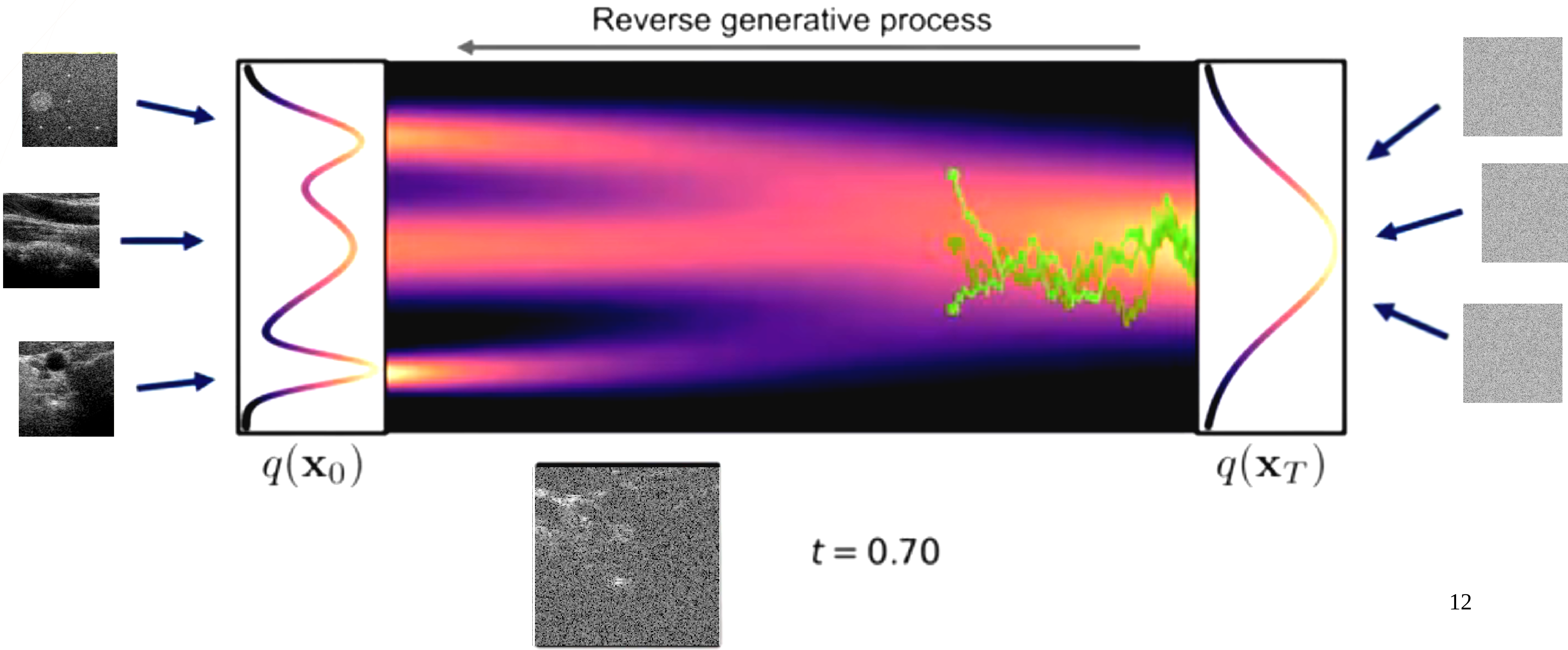
P. Dhariwal and A. Nichol, Diffusion models beat GANs on image synthesis, NeurIPS, 2021
A. Q. Nichol and P. Dhariwal, Improved Denoising Diffusion Probabilistic Models, ICML, 2021

Diffusion Generative Process



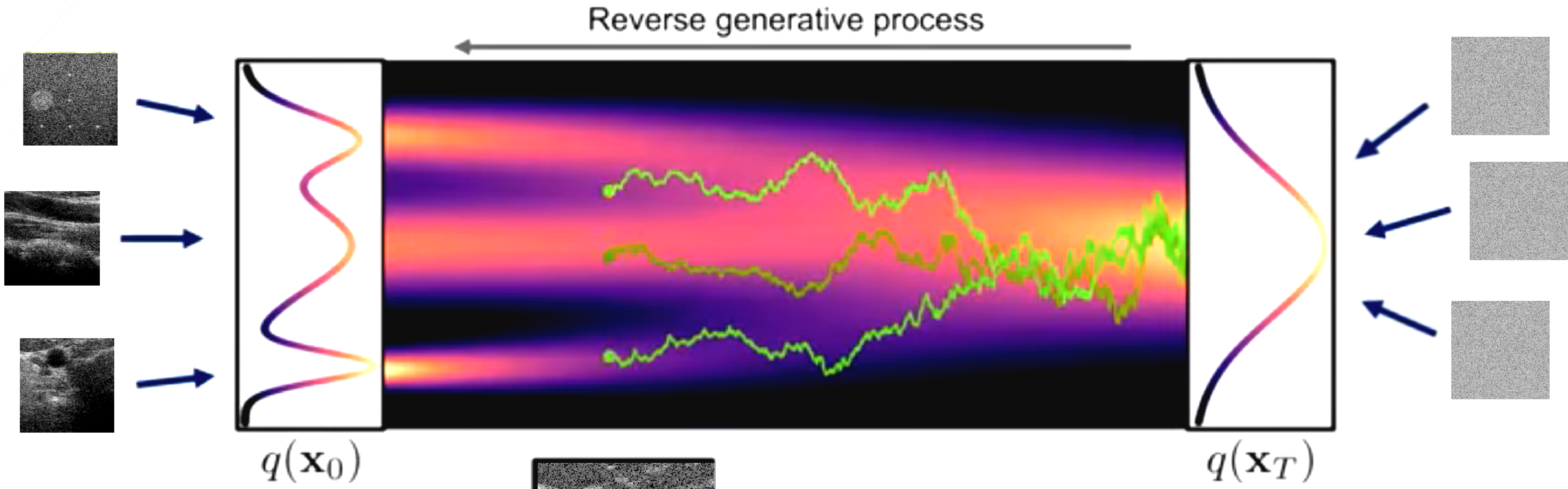
Diffusion Generative Process

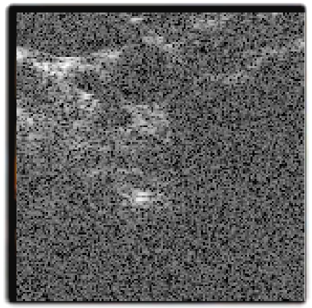
Unconditional



Diffusion Generative Process

Unconditional

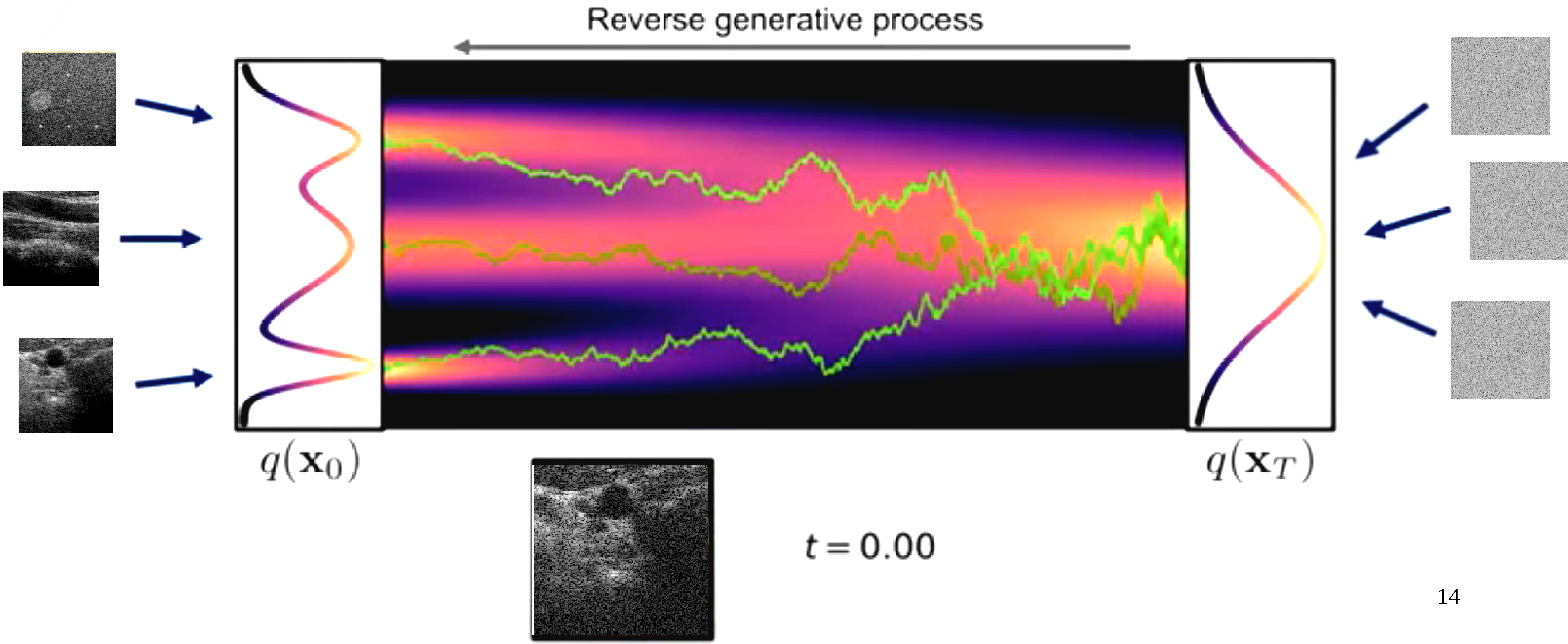




$t = 0.28$

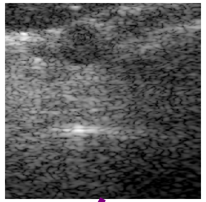
Diffusion Generative Process

Unconditional



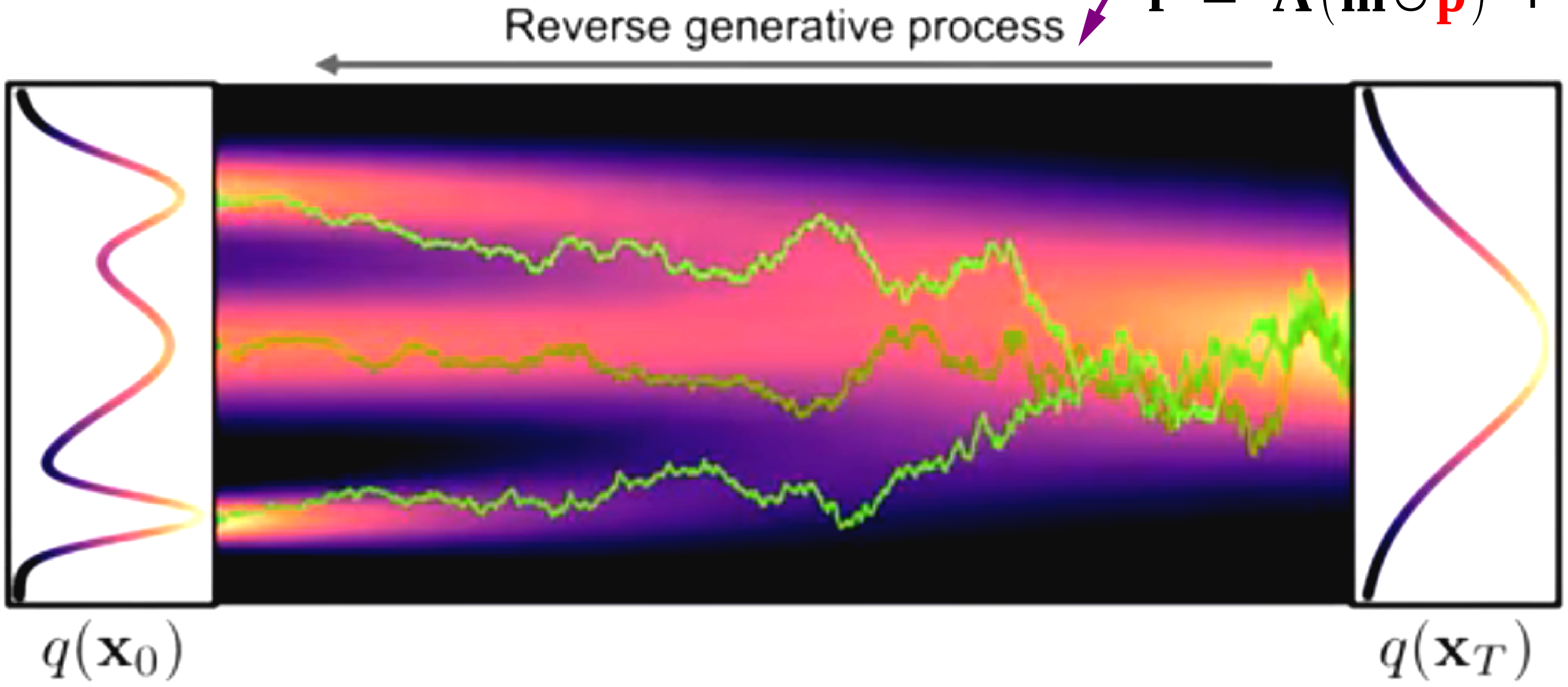
Diffusion Reconstruction of Ultrasound Images

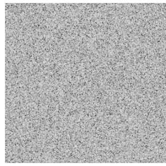
Conditional



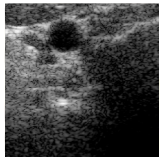
$\mathbf{f}$ (RF image)

$\mathbf{f} = \mathbf{A}(\mathbf{m} \odot \mathbf{p}) + \mathbf{n}$





$\widehat{(\mathbf{m} \odot \mathbf{p})}$



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Overview of the Proposed Method

Model 1

$$\underbrace{\mathbf{f}}_{\text{RF image}} = \underbrace{\mathbf{A}}_{\text{SIR(PSF)}} \left(\underbrace{\mathbf{m}}_{\sim\mathcal{N}(\mathbf{0},\mathbf{I})} \odot \mathbf{p} \right) + \underbrace{\mathbf{n}}_{\sim\mathcal{N}(\mathbf{0},\sigma\mathbf{I})}$$

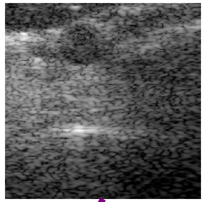
Y. Zhang et al., Ultrasound image reconstruction with denoising diffusion restoration models. MICCAI, 2023

STEP 1 **Estimate $\mathbf{m} \odot \mathbf{p}$ via a Diffusion Inverse Problem Solver**

STEP 2 **Estimate $\mathbf{p}$ by leveraging the stochasticity of the generative sampling**

Stochasticity of the Diffusion Generative Process

Conditional

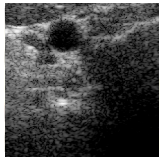


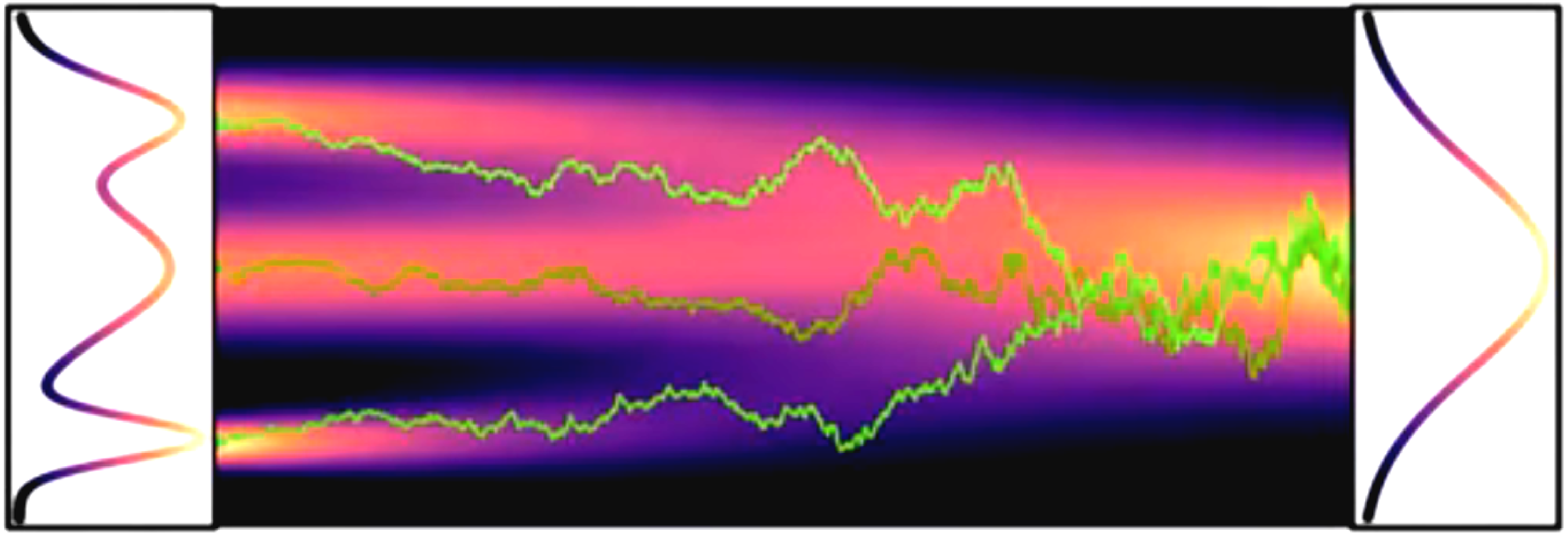
$\mathbf{f}$ (RF image)

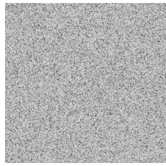
$$\mathbf{f} = \mathbf{A}(\mathbf{m}\odot\mathbf{p}) + \mathbf{n}$$

Reverse generative process

$$\widehat{(\mathbf{m}\odot\mathbf{p})}$$





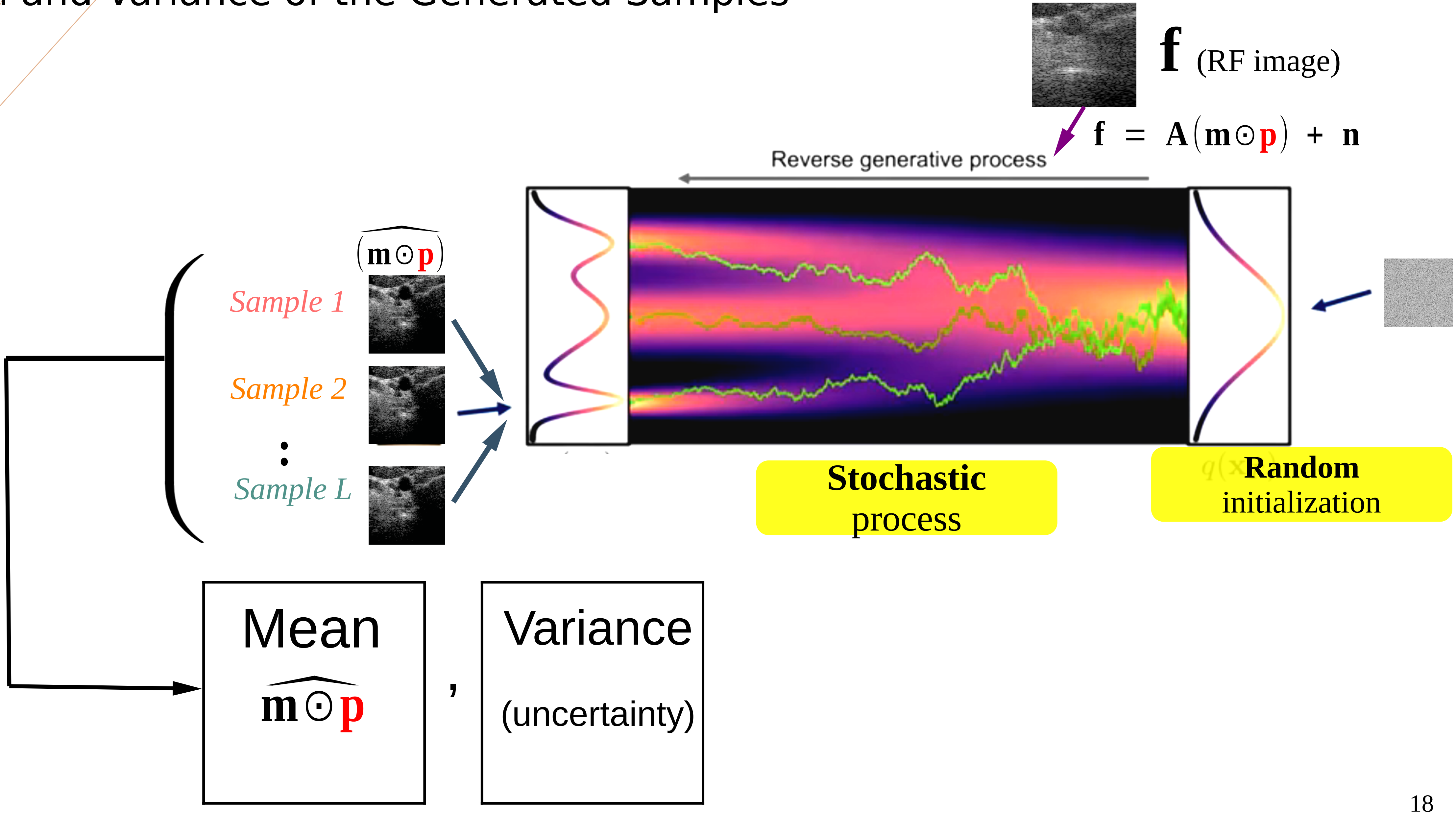


Stochastic process

Random initialization

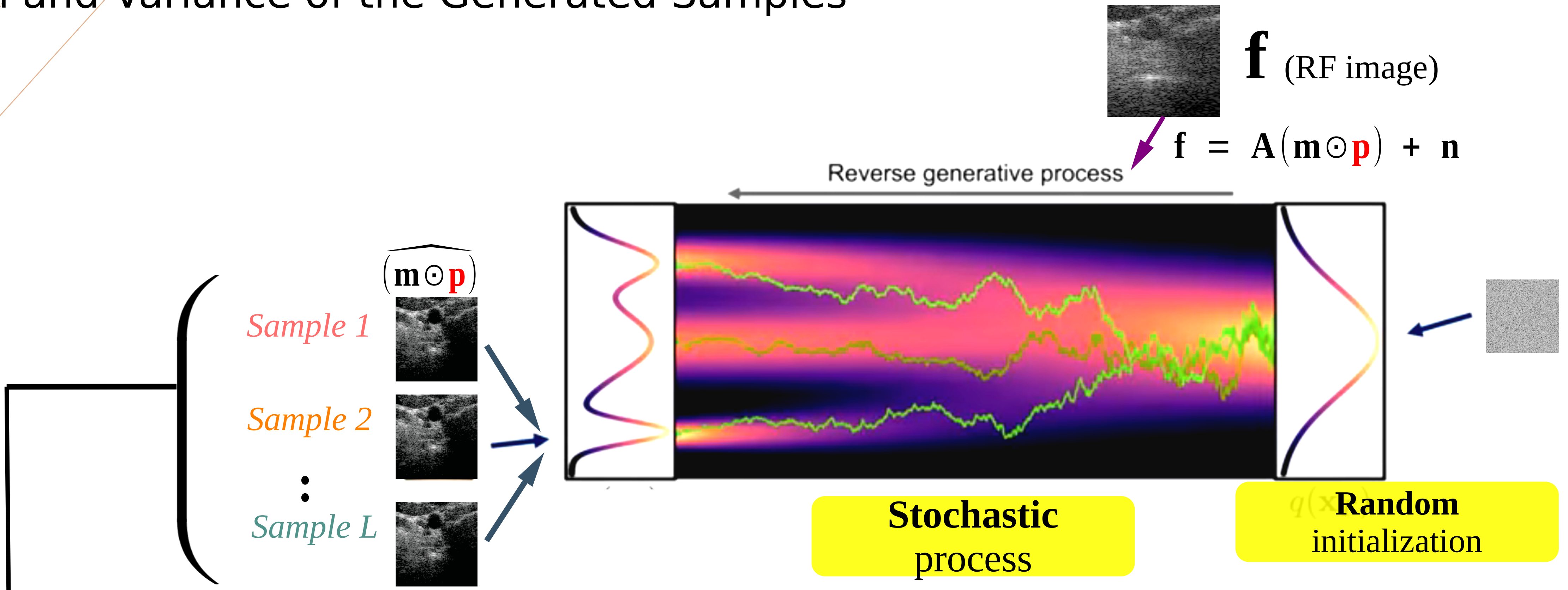
We can generate unlimited number of **different reconstructions** from a **single observation**

Mean and Variance of the Generated Samples



Chung, H. et al., Score-based diffusion models for accelerated MRI. Medical image analysis, 2022

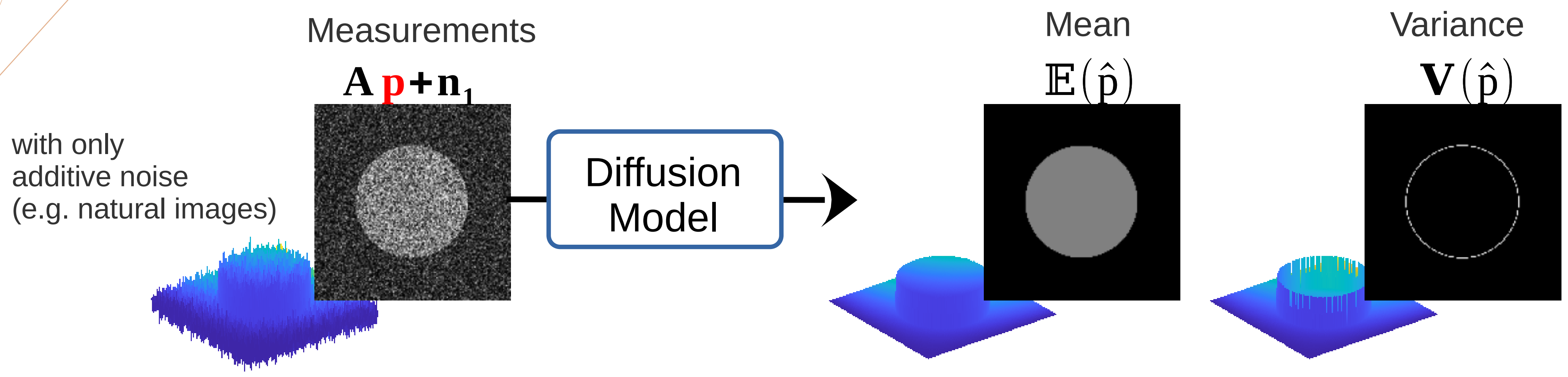
Mean and Variance of the Generated Samples



Mean $\widehat{\mathbf{m}\odot\mathbf{p}}$, **Variance**

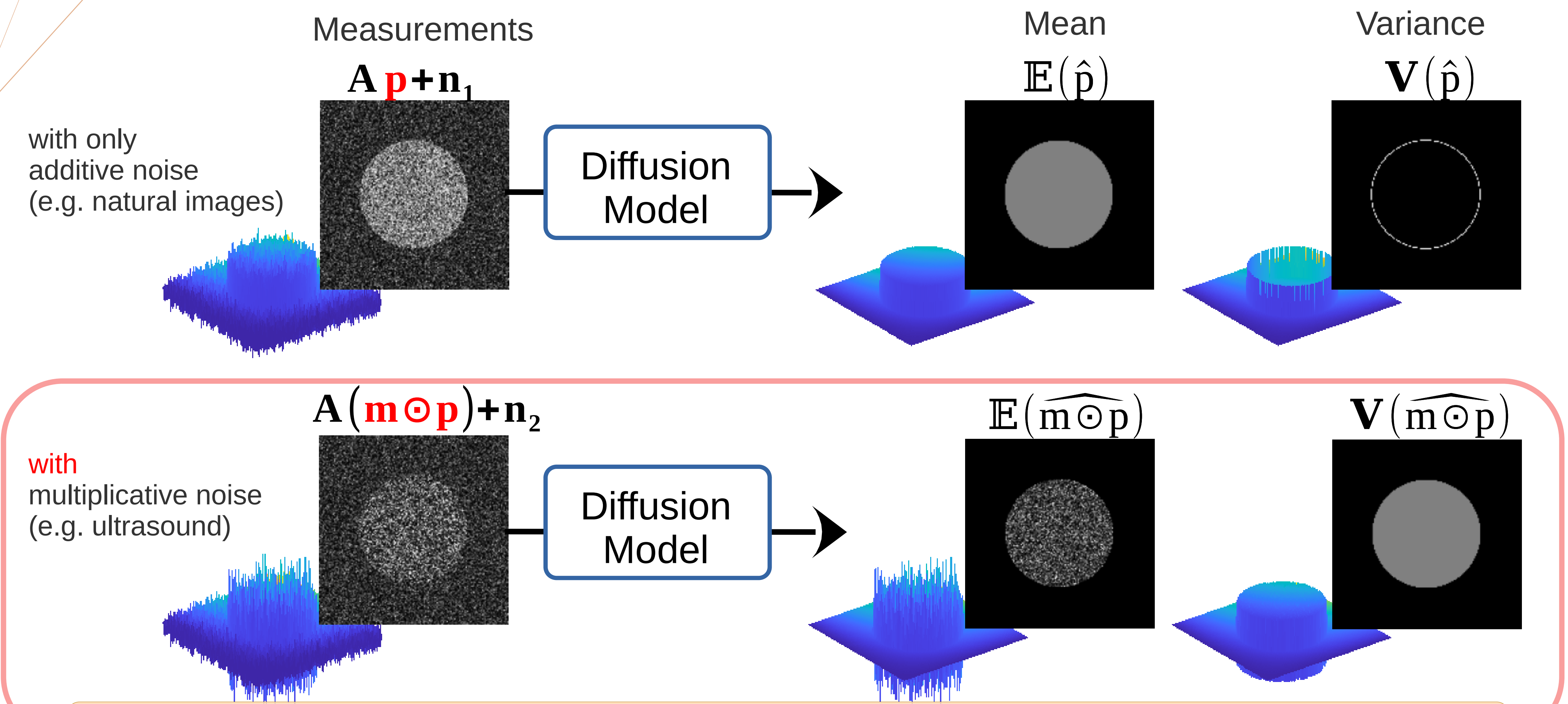
Diffusion Variance is proportional to the level of the multiplicative noise (p)

Diffusion Variance Behavior



Kawar, B. et al., SNIPS: Solving noisy inverse problems stochastically. NeurIPS, 2021

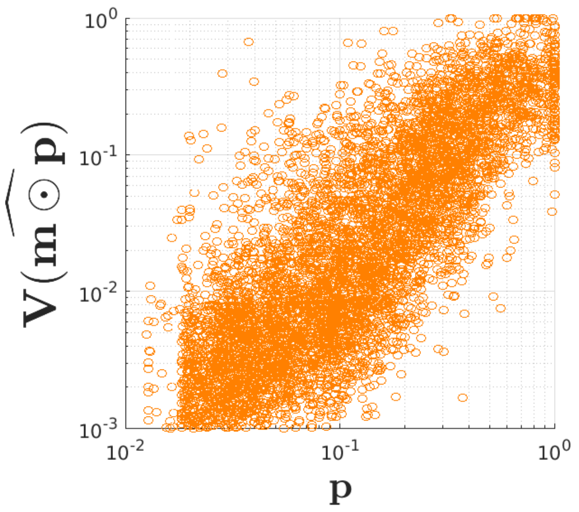
Diffusion Variance Behavior

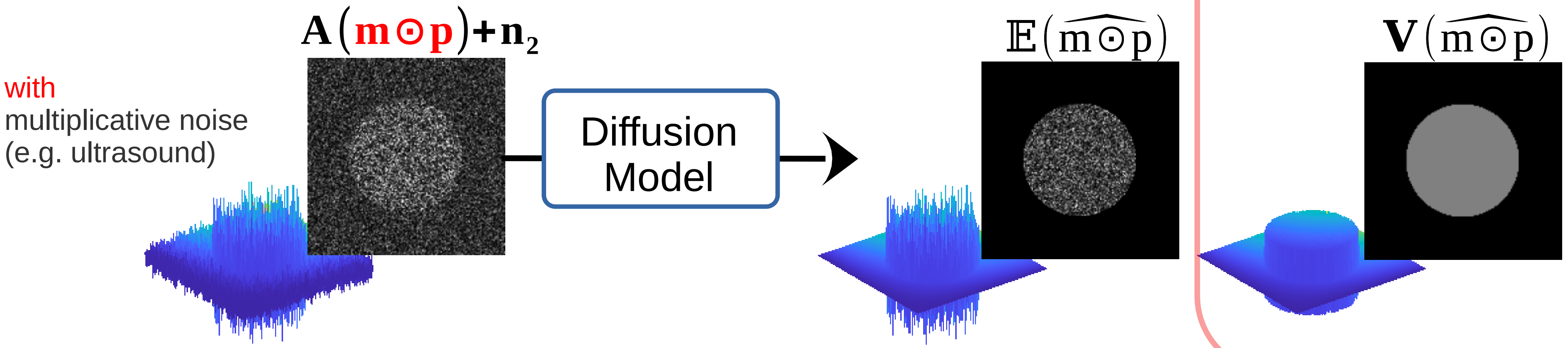


Variance of diffusion samples inform the level of the multiplicative noise

Diffusion Variance Behavior

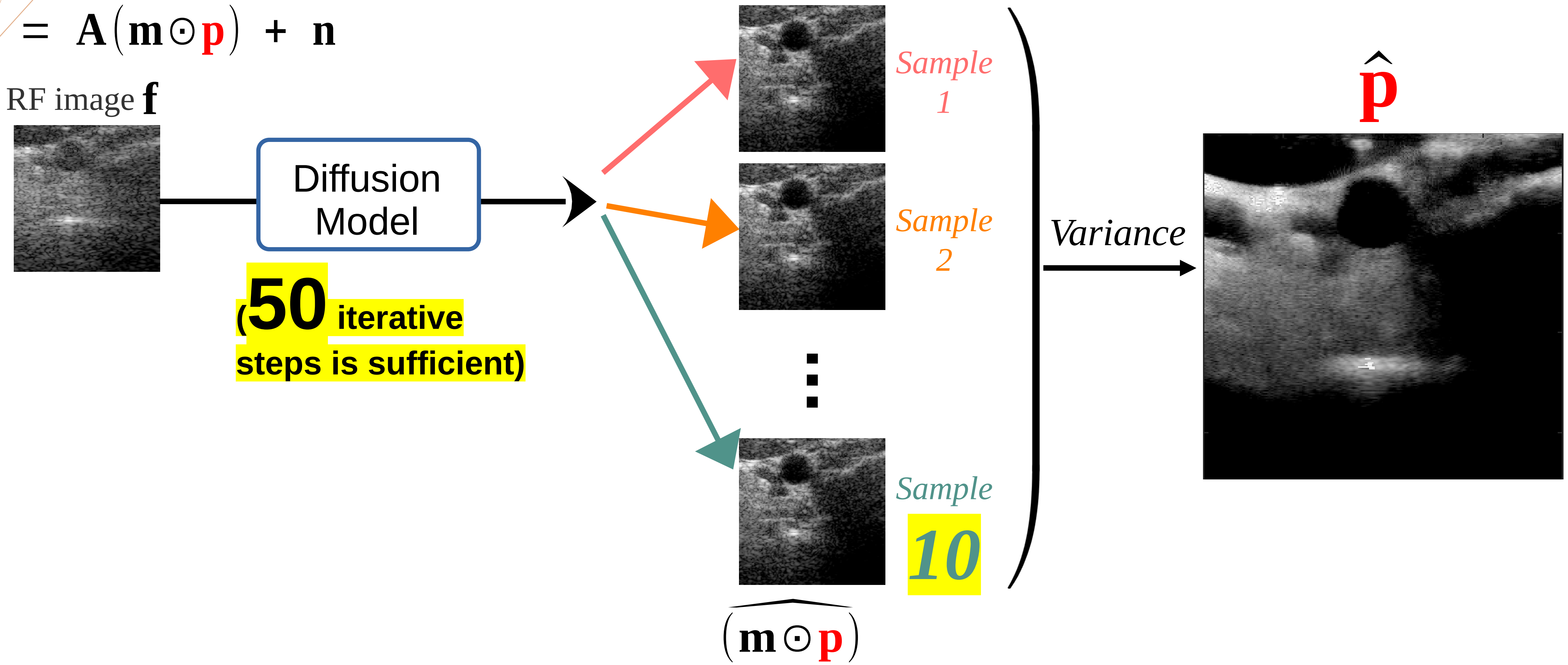
Variance of diffusion samples inform the level of the multiplicative noise



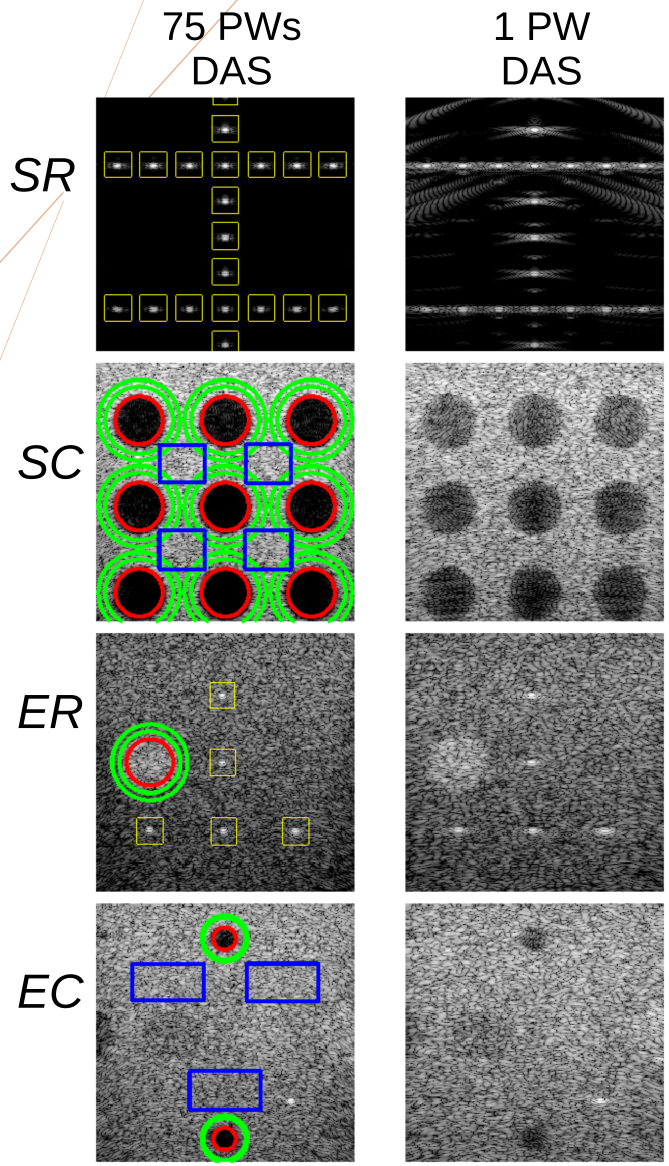


Workflow

$$\mathbf{f} = \mathbf{A}(\mathbf{m} \odot \mathbf{p}) + \mathbf{n}$$



On Simulated & Experimental Datasets



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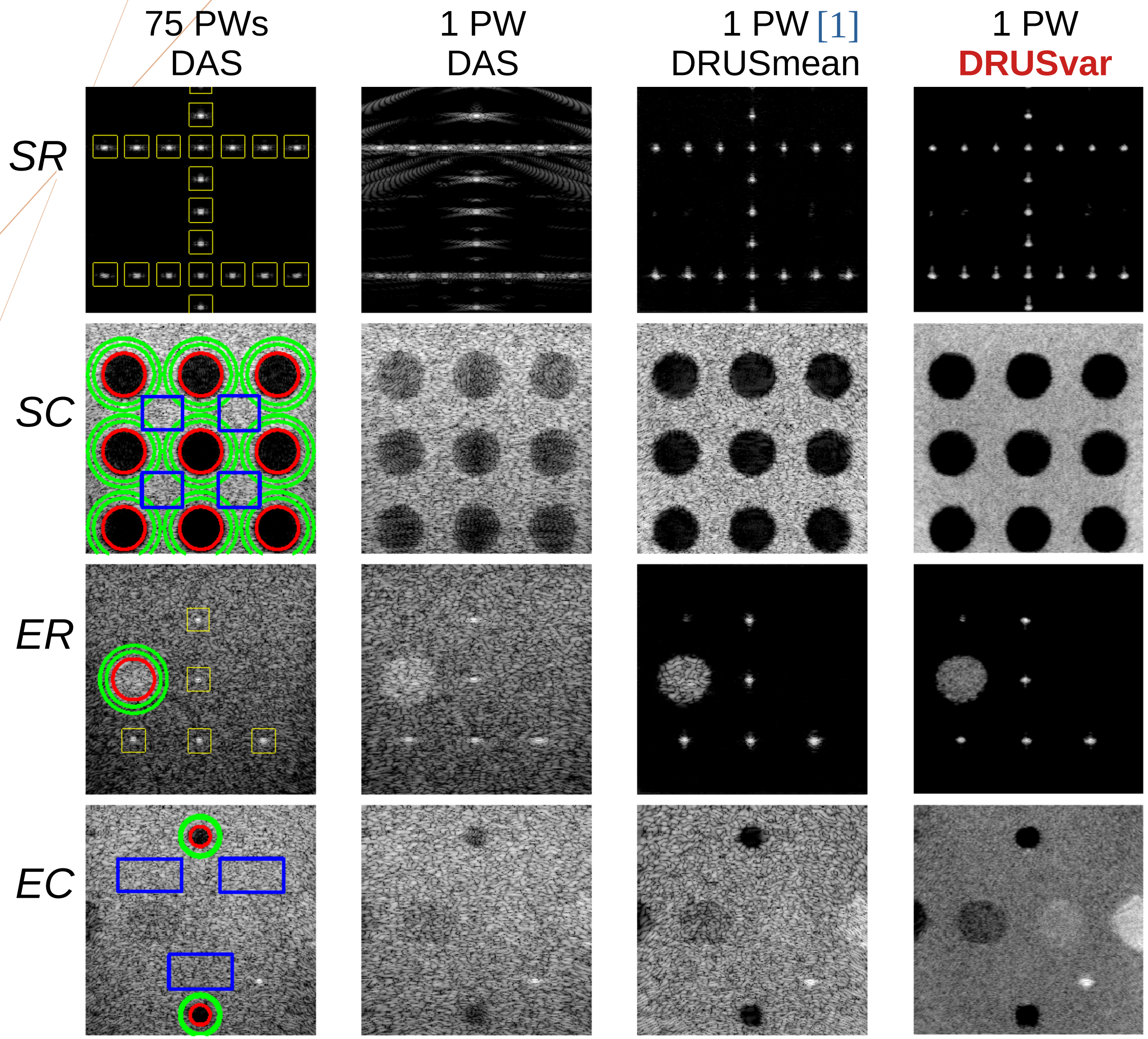
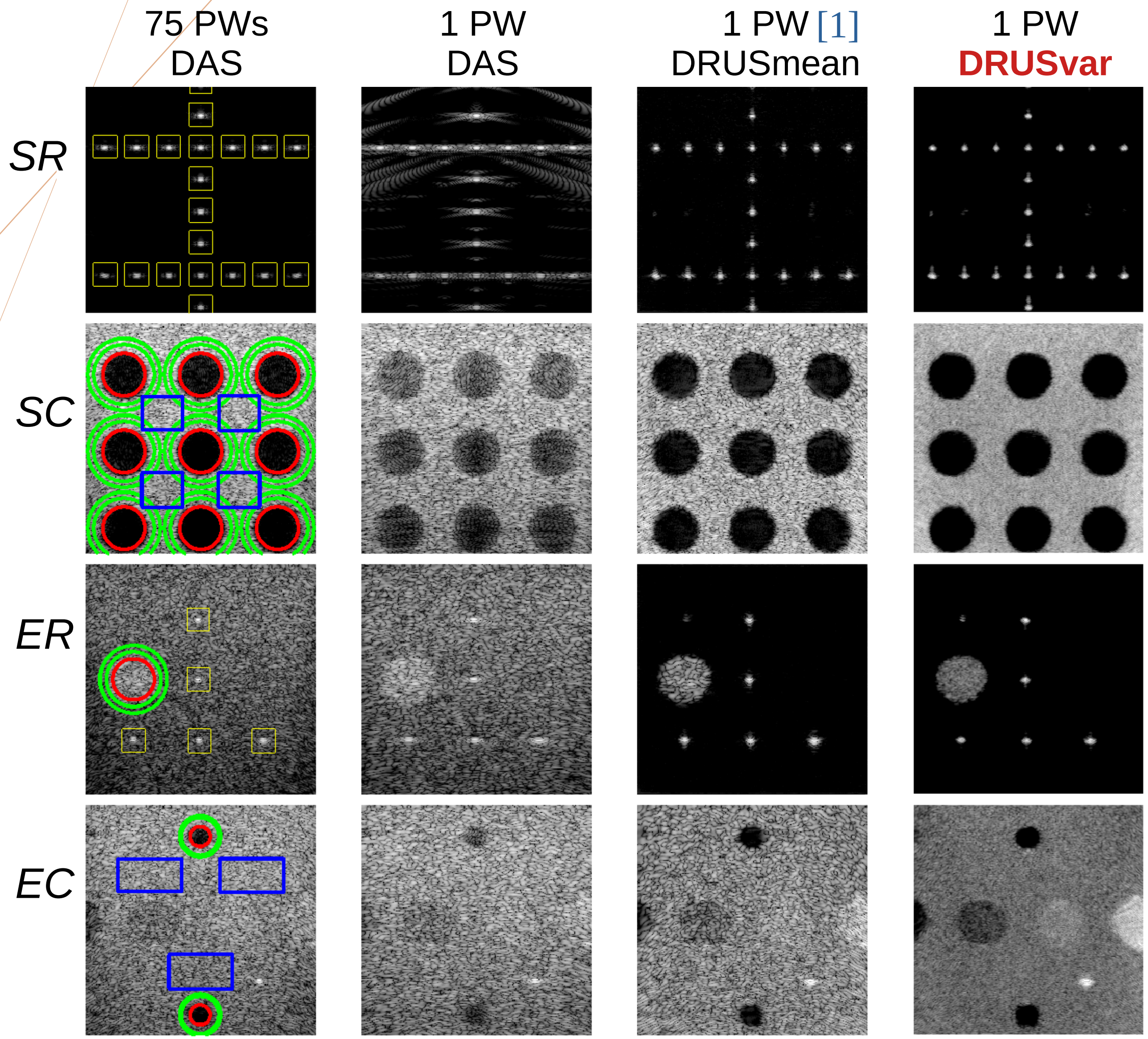


[1] Y. Zhang et al., Ultrasound image reconstruction with denoising diffusion restoration models. MICCAI, 2023

On Simulated & Experimental Datasets

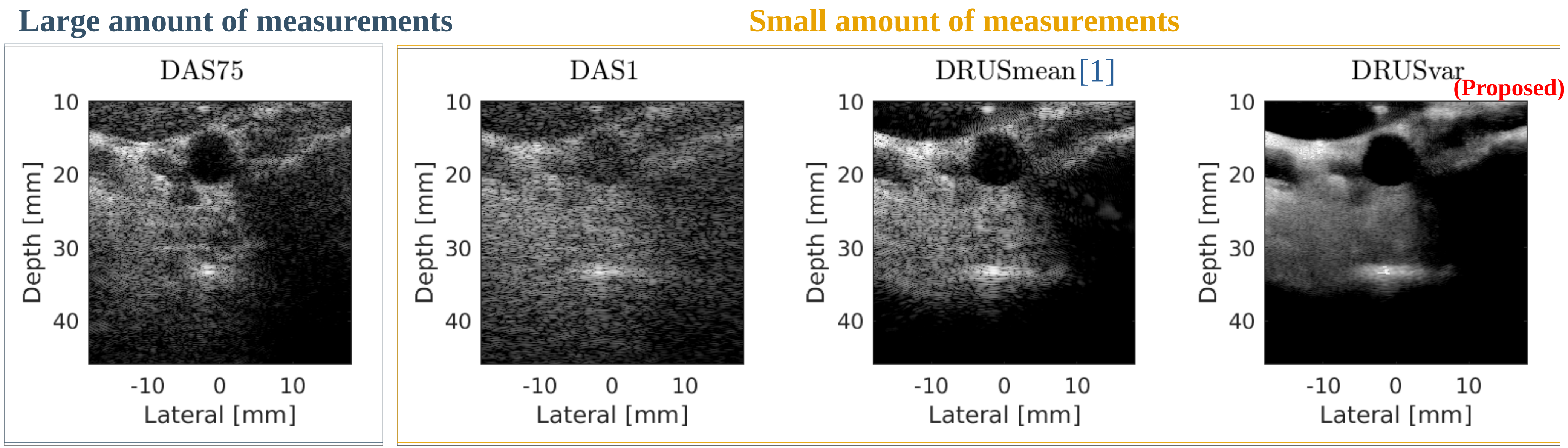


			75PWs DAS	1PW DAS	1PW DRUSmean[1]	1PW DRUSvar
SR	FWHM [mm]	A↓	0.38	0.38	0.32	**0.29**
		L↓	0.56	0.81	0.40	**0.32**
SC	CNR[dB]↑		15.89	10.41	15.55	**17.59**
	gCNR↑		**1.00**	0.91	0.99	**1.00**
	SNR↑		1.68	1.72	2.03	**3.28**
ER	FWHM [mm]	A↓	0.54	0.56	**0.25**	0.34
		L↓	0.56	0.87	0.55	**0.32**
	CNR[dB]↑		6.70	5.60	9.50	**18.40**
	gCNR↑		0.77	0.69	0.91	**1.00**
EC	CNR[dB]↑		12.00	7.85	10.90	**14.30**
	gCNR↑		0.95	0.87	0.96	**0.98**
	SNR↑		1.92	1.97	1.93	**3.03**

[1] Y. Zhang et al., Ultrasound image reconstruction with denoising diffusion restoration models. MICCAI, 2023

On an *In-Vivo* Dataset

Carotid Cross

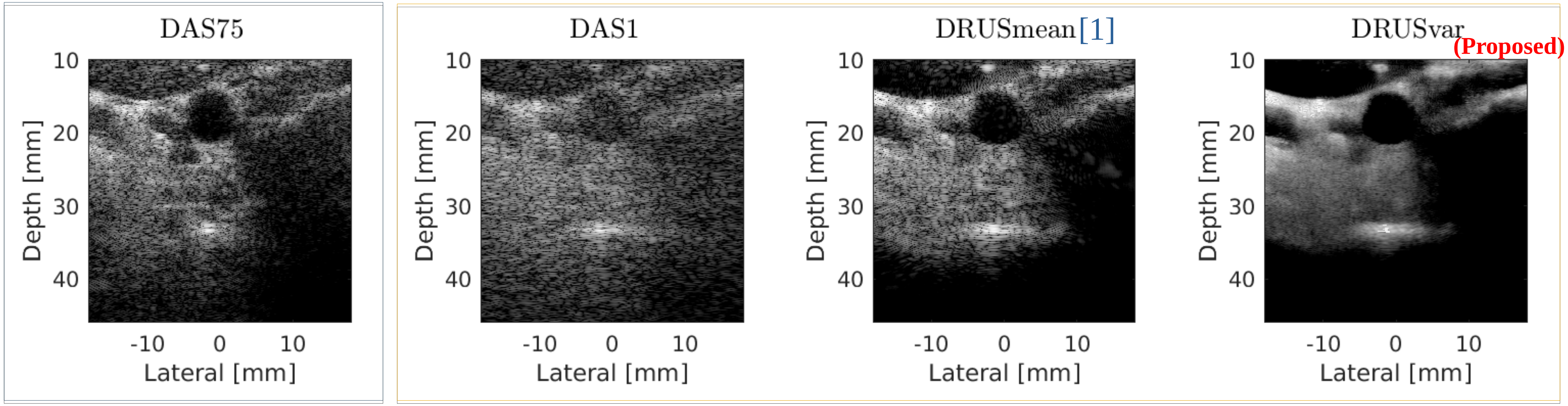


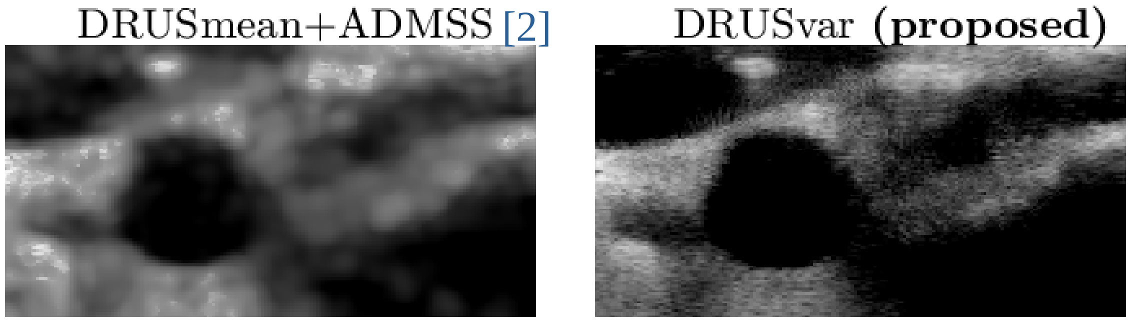
[1] Y. Zhang et al., Ultrasound image reconstruction with denoising diffusion restoration models. MICCAI, 2023

On an *In-Vivo* Dataset

Carotid Cross

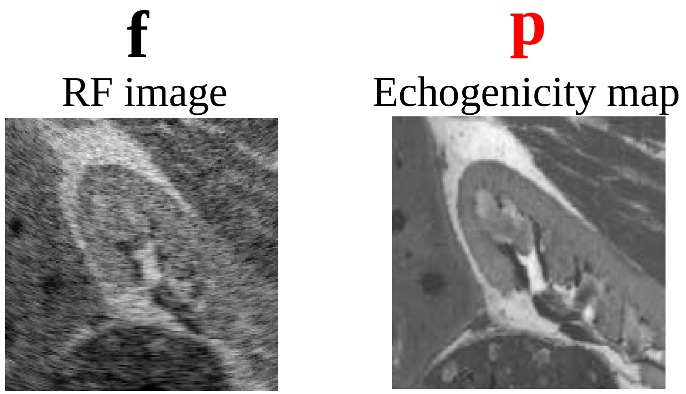
Large amount of measurements **Small amount of measurements**





[1] Y. Zhang et al., Ultrasound image reconstruction with denoising diffusion restoration models. MICCAI, 2023
[2] G Ramos-Llordén et al., Anisotropic Diffusion Filter With Memory Based on Speckle Statistics for Ultrasound Images, IEEE TIP 2015

Take-Home Message



Problem: Ultrasound Despeckling

Contribution:

Adapt the most Realistic Model, and solve an Inverse Problem

$$\mathbf{f} = \mathbf{A}(\mathbf{m} \odot \mathbf{p}) + \mathbf{n}$$

Reveal that Variance of diffusion samples ∝ level of the multiplicative noise

$$\mathrm{Var}(\widehat{\mathbf{m} \odot \mathbf{p}}) \rightarrow \hat{\mathbf{p}}$$

Current Challenges:

-- The requirement of the **SVD(A)**

-- **Non-real-time** reconstruction (1.25sec/iter --> 1min/sample)

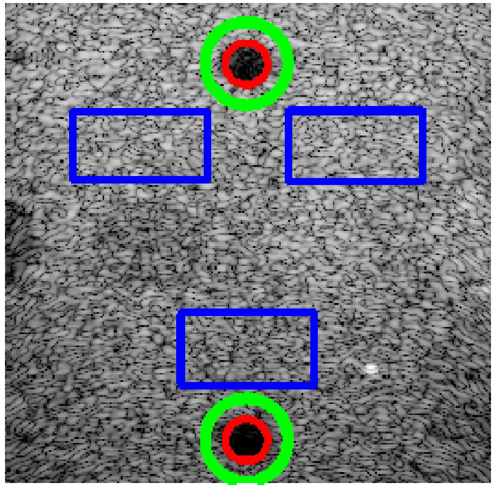
THANK YOU!

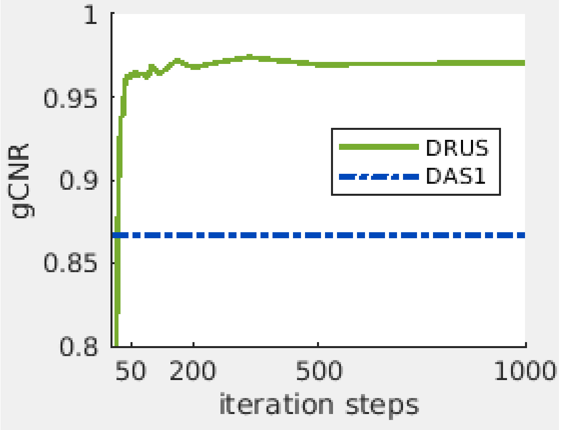
yuxin.zhang@ls2n.fr

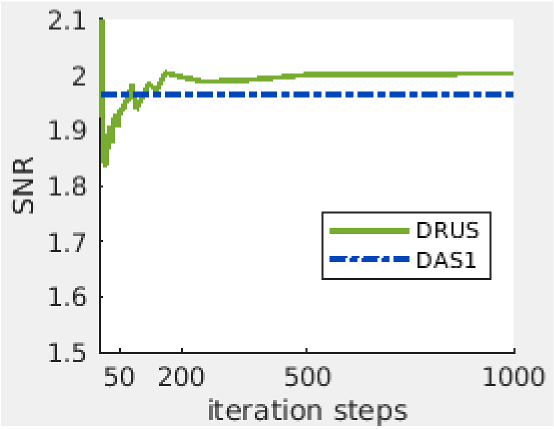
Github Code

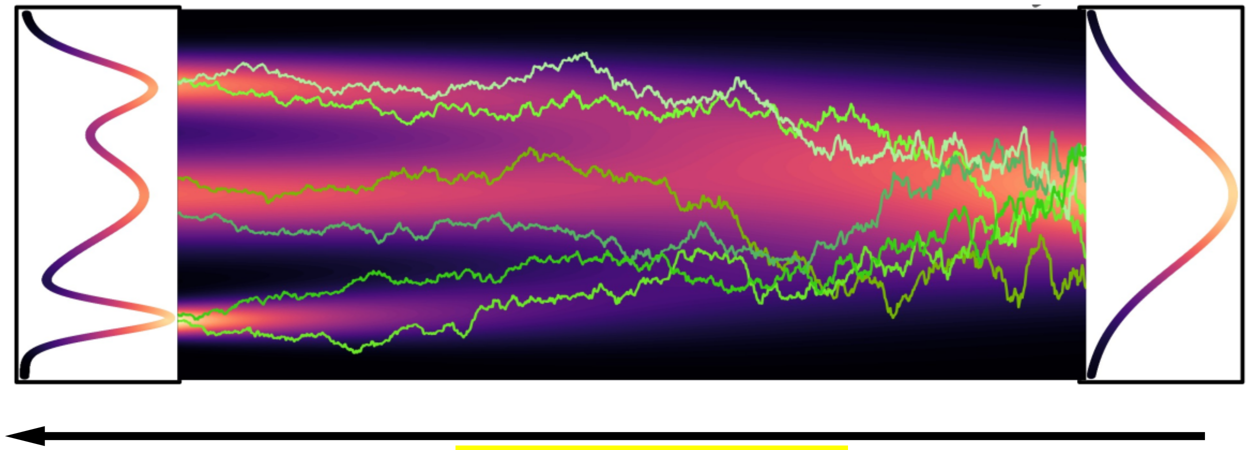
Paper

Sensitivity to the Number of Iterative Steps (for a single sample)



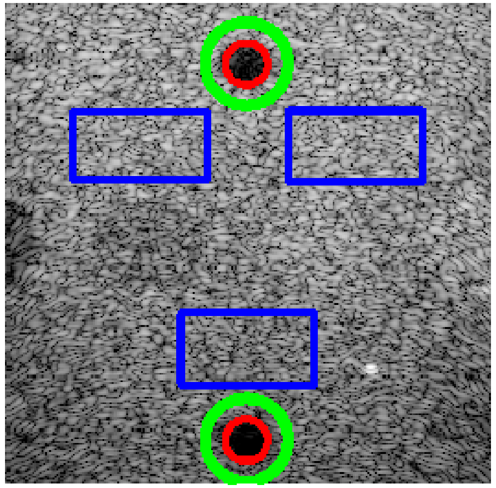


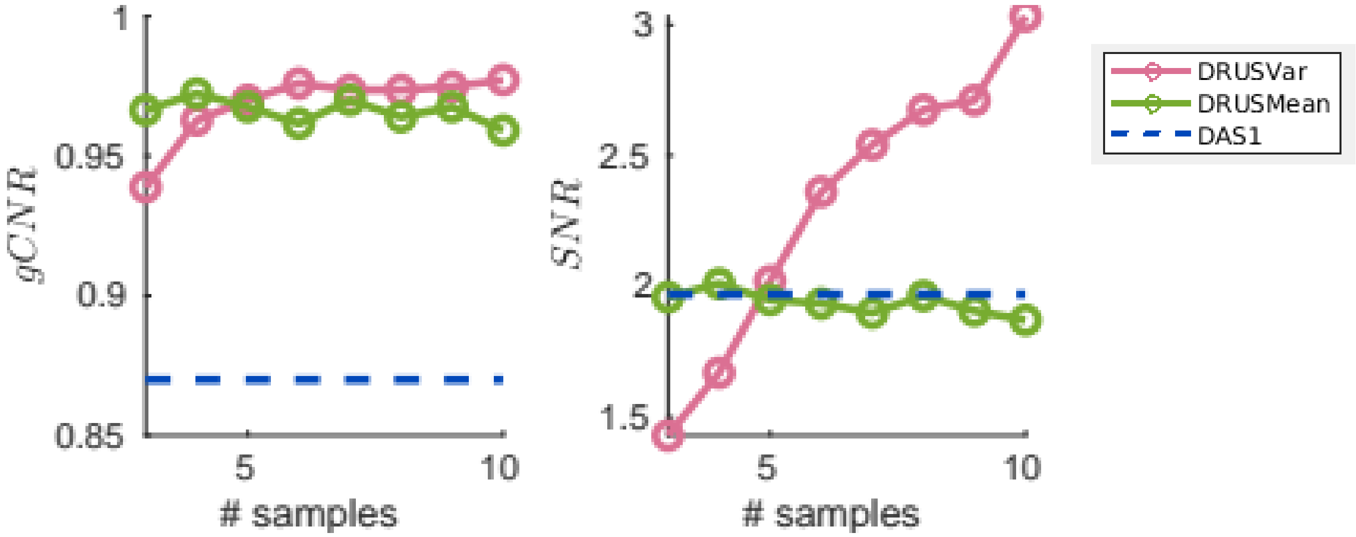


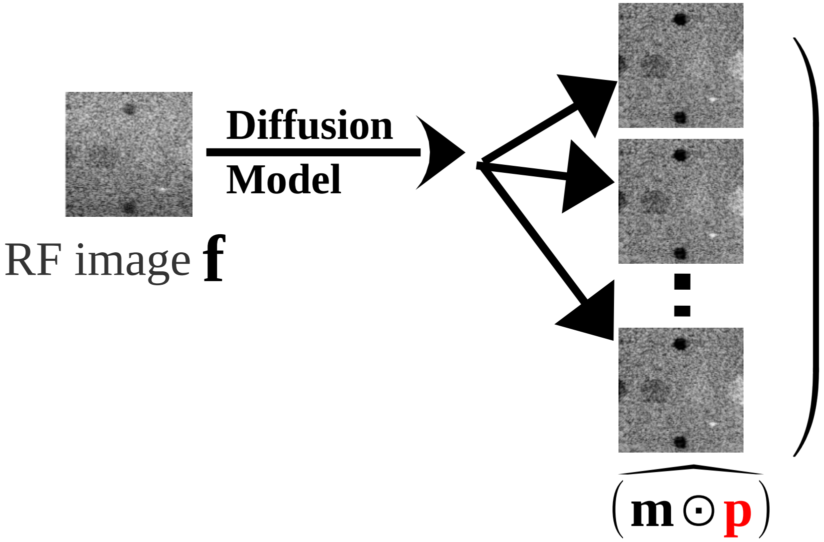


50 steps is good!

Sensitivity to the Number of Samples







10 samples is good!