Ultrasound Image Reconstruction with Denoising Diffusion Restoration Models

DGM4MICCAI - 2023

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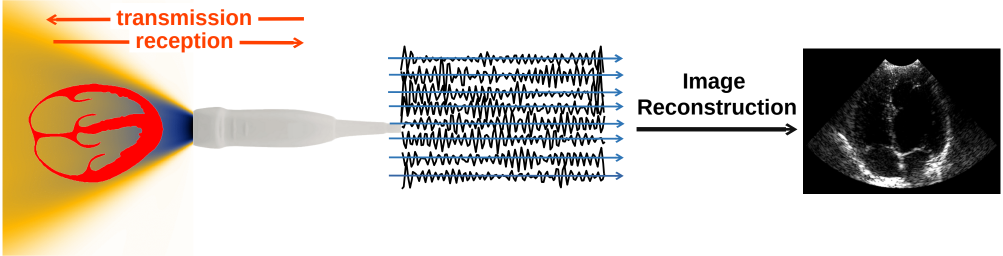
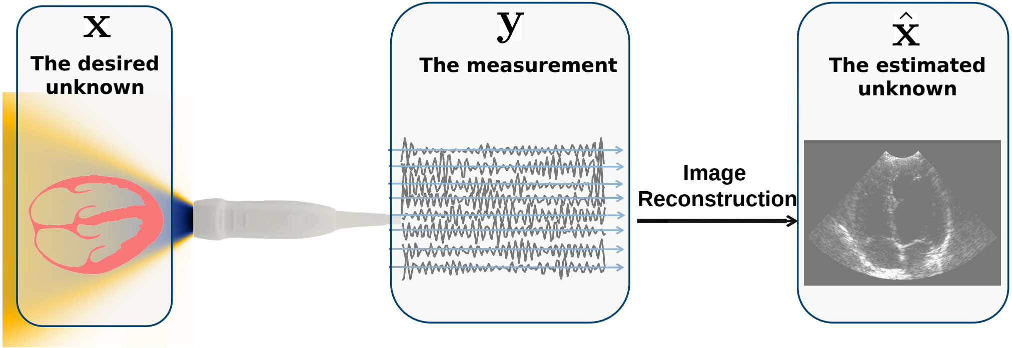


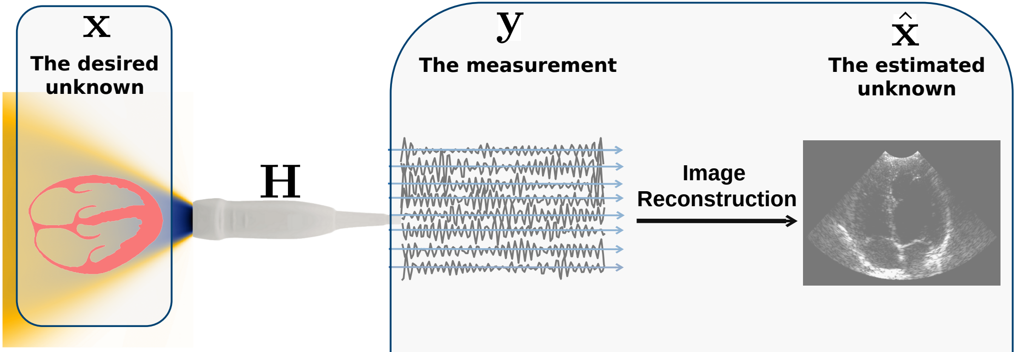
Source : https://www.biomecardio.com/files/Tracking_motions_in_the_body.pdf

Ultrasound Imaging



Source : https://www.biomecardio.com/files/Tracking_motions_in_the_body.pdf

Image Reconstruction → an Inverse Problem



By solving an Inverse Problem:

$$\mathbf{y} = \mathbf{H}\mathbf{x} + \mathbf{n}$$

Source : https://www.biomecardio.com/files/Tracking_motions_in_the_body.pdf

Model-based

$$\hat{\mathbf{x}} = \arg\min_{\mathbf{x}} \frac{1}{2}\|\mathbf{y} - \mathbf{H}\mathbf{x}\|_2^2 + \phi_{\text{reg}}$$

Ozkan et al. IEEE Trans. Ultrason. Ferroelectr. Freq. Control. 2018
Goudarzi et al. IEEE Trans. Ultrason. Ferroelectr. Freq. Control. 2022

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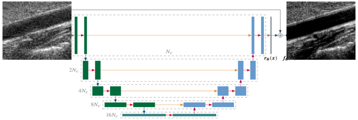
Learning-based



Perdios et al. IEEE Trans. Ultrason. Ferroelectr. Freq. Control. (accepted)

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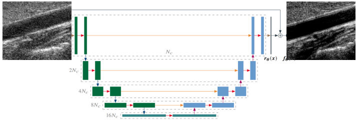
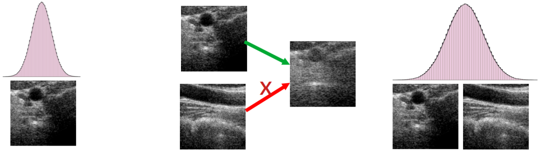
Learning-based



Perdios et al. IEEE Trans. Ultrason. Ferroelectr. Freq. Control. (accepted)

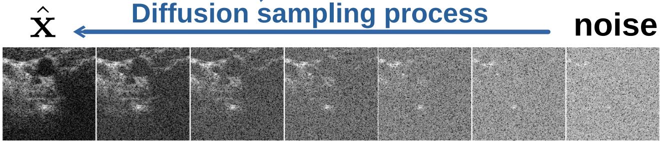
Hybrid



Posterior $(\hat{\mathbf{x}})$ ← Likelihood (Inverse Problem) × Prior (Diffusion Model)

$$\mathbf{y} = \mathbf{H}\mathbf{x} + \mathbf{n}$$

- Song Y et al. Solving inverse problems in medical imaging with score-based generative models. ICLR, 2022
- Song J et al. Pseudoinverse-guided diffusion models for inverse problems. ICLR, 2023
- Chung H et al. Score-based diffusion models for accelerated MRI. Med Image Anal. 2022
- Chung H et al. Diffusion posterior sampling for general noisy inverse problems. ICLR, 2023
- Kawar B et al. Denoising diffusion restoration models. NeurIPS. 2022 **(DDRM)**

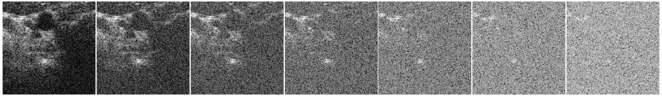


$$\mathbf{y} = \mathbf{H}\mathbf{x} + \mathbf{n}$$

$$\boldsymbol{\Sigma}^{\dagger}\mathbf{U}^{T}\mathbf{y} = \mathbf{V}^{T}\mathbf{x} + \boldsymbol{\Sigma}^{\dagger}\mathbf{U}^{T}\mathbf{n}$$

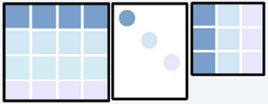
$$\bar{\mathbf{y}} = \bar{\mathbf{x}} + \bar{\mathbf{n}}$$

$\hat{\mathbf{x}}$ ← **Diffusion sampling process** — **noise**



DDRM runs "denoising and/or inpainting" in the space transformed by Singular Value Decomposition

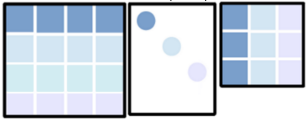
$$\mathbf{H} = \mathbf{U} \; \boldsymbol{\Sigma} \; \mathbf{V}^{T}$$



DDRM (Kawar et al. NeurIPS 2022) initially for **natual images**

Data Compressing & Noise Whitening

$\mathrm{SVD}(\mathbf{H})$

$\mathbf{y} =$  $\mathbf{x} +$ white $\mathbf{n}$

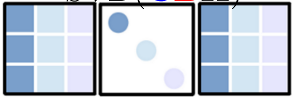
data compressing

$\mathrm{SVD}(\mathbf{BH})$

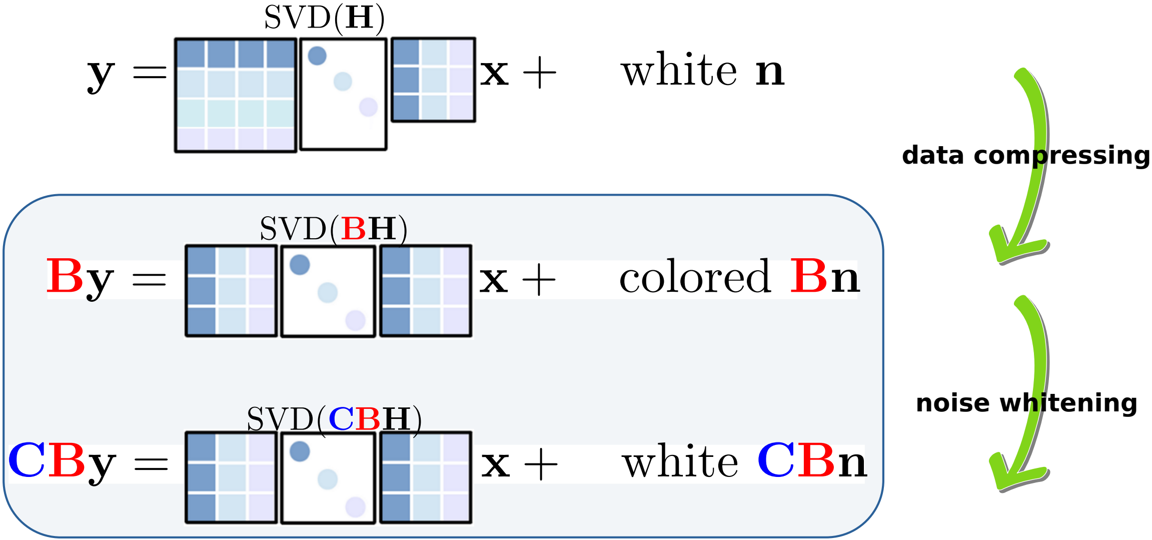
$\mathbf{By} =$  $\mathbf{x} +$ colored $\mathbf{Bn}$

noise whitening

$\mathrm{SVD}(\mathbf{CBH})$

$\mathbf{CBy} =$  $\mathbf{x} +$ white $\mathbf{CBn}$

Data Compressing & Noise Whitening



Datasets

Natural Images **VS** Ultrasound Images (SIGNED)

Pre-trained on :

Figure – the ImageNet dataset (1,281,167 images) (?)

Fine-tuned on :

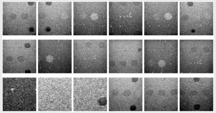


Figure – Examples of the self-acquired dataset (800 images)

Test set : PICMUS dataset (?) gives the observation $\mathbf{y}$.

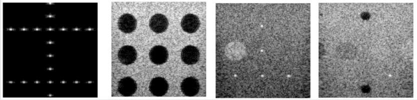
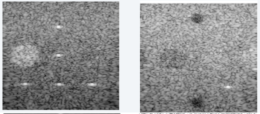
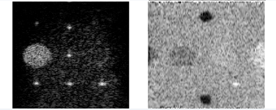


Figure – Examples of PICMUS reconstructed ultrasound images

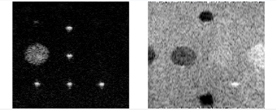
1 transmission (Fast acquisition)



Baseline (DAS1)

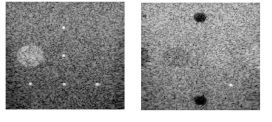


DRUS **(ours)**
$(\mathbf{By} = \mathbf{BHx} + \mathbf{Bn})$



WDRUS **(ours)**
$(\mathbf{CBy} = \mathbf{CBHx} + \mathbf{CBn})$

75 transmissions (Slow acquisition)



Golden standard (DAS75)

	Resolution (FWHM [mm]↓)		Contrast (CNR[dB] ↑)
	Axial	Lateral	
Baseline	0.51	1.21	8.15
DRUS	0.26	0.69	**12.9**
WDRUS	**0.25**	0.62	11.95
Golden standard	0.49	0.59	12.05

Diffusion Inverse Problem Solver

- **Model-based** ✓
- **Learning-based** ✓

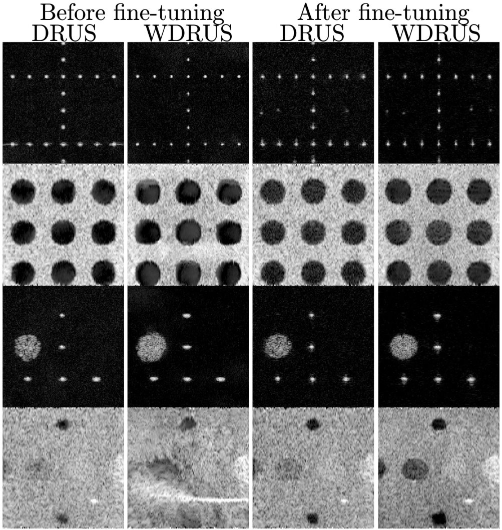
Ultrasound Inverse Problem Model

noise whitened ← **data compressed** ← **original**

Fine-Tuning from a Natural-Image Diffusion Model

Thank you !

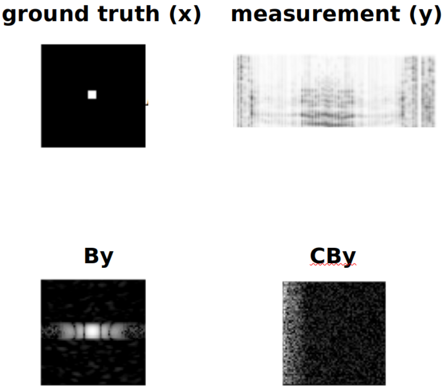
Fine-tuning



*$\mathbf{B} = \mathbf{H}^t$

*$\mathbf{C} = \mathbf{\Lambda}^{-\frac{1}{2}}\mathbf{V}^t$, where $\mathrm{eig}(\mathbf{B}\mathbf{B}^t) = \mathbf{V}\mathbf{\Lambda}\mathbf{V}^t$

$\mathrm{Cov}(\mathbf{CBn}) = \mathrm{E}\left[\mathbf{CBnn}^t\mathbf{B}^t\mathbf{C}^t\right] = \gamma^2\mathbf{CBB}^t\mathbf{C}^t = \gamma^2\mathbf{CV\Lambda V}^t\mathbf{C}^t = \gamma^2\mathbf{I}_M$



In summary

$\mathbf{y} = \mathbf{Hx} + \mathbf{n}$

|___$\mathbf{By} = \mathbf{BHx} + \mathbf{Bn}$ (DRUS)

|___$\mathbf{CBy} = \mathbf{CBHx} + \mathbf{CBn}$ (WDRUS)