

Ultrasound Image Reconstruction with Denoising Diffusion Restoration Models

DGM4MICCAI - 2023

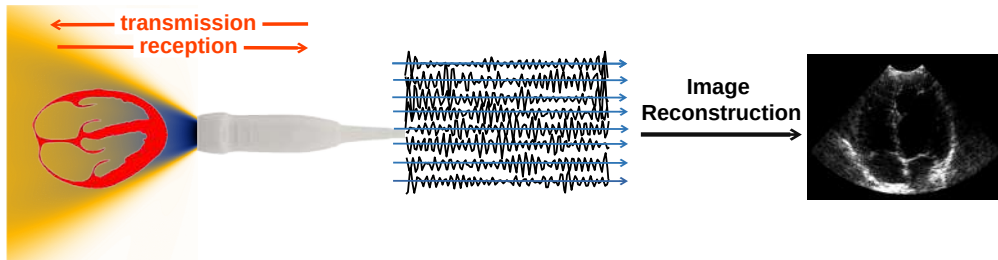
Yuxin Zhang

Supervisors : Clément Huneau, Jérôme Idier, Diana Mateus

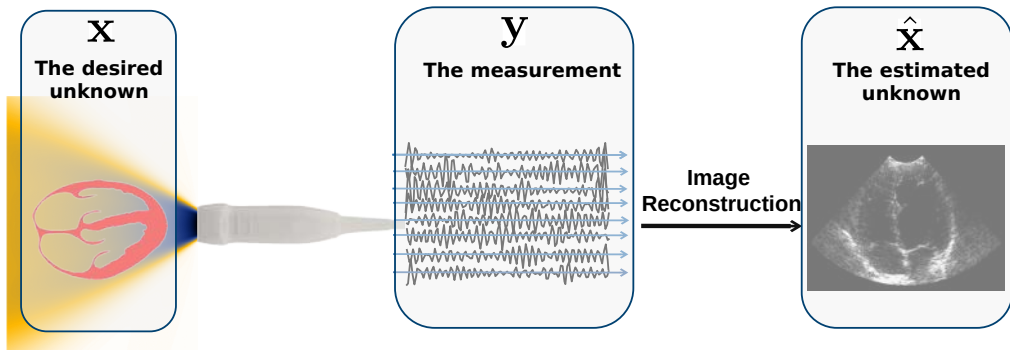
Nantes Université, École Centrale Nantes, LS2N,
CNRS, UMR 6004, F-44000 Nantes, France

8 - October - 2023



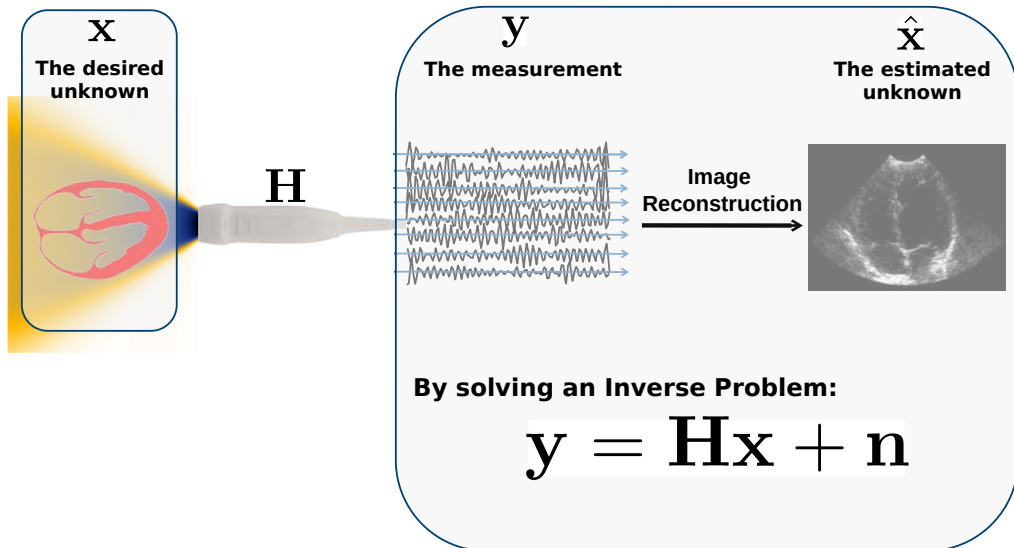


Source : https://www.biomecardio.com/files/Tracking_motions_in_the_body.pdf



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

Image Reconstruction → an Inverse Problem



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)



Model-based

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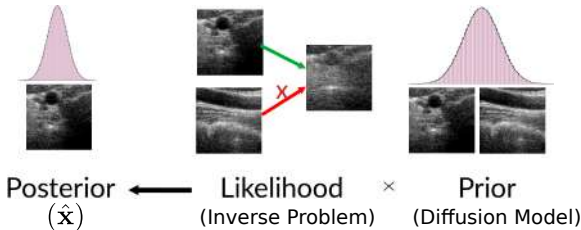
Learning-based



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



Hybrid



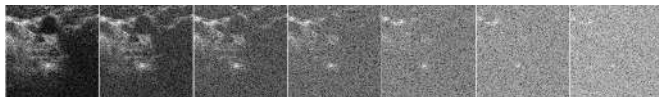
$$\mathbf{y} = \mathbf{H}\mathbf{x} + \mathbf{n}$$

- 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
- Kavar B et al. Denoising diffusion restoration models. NeurIPS. 2022 (**DDRM**)

$\hat{\mathbf{x}}$

Diffusion sampling process

noise



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

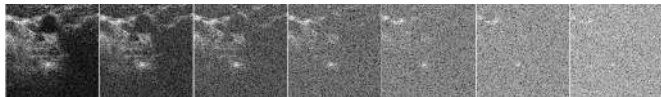
$$\Sigma^\dagger \mathbf{U}^T \mathbf{y} = \mathbf{V}^T \mathbf{x} + \Sigma^\dagger \mathbf{U}^T \mathbf{n}$$

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

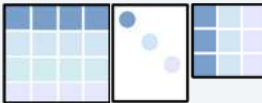
 $\hat{\mathbf{x}}$

Diffusion sampling process

noise



DDRM runs “denoising and/or inpainting” in the space transformed by **Singular Value Decomposition**

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


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

$$\mathbf{y} = \overset{\text{SVD}(\mathbf{H})}{\begin{bmatrix} \text{blue grid} & \text{white box with blue dots} & \text{blue grid} \end{bmatrix}} \mathbf{x} + \text{white } \mathbf{n}$$

$$\mathbf{B}\mathbf{y} = \overset{\text{SVD}(\mathbf{B}\mathbf{H})}{\begin{bmatrix} \text{blue grid} & \text{white box with blue dots} & \text{blue grid} \end{bmatrix}} \mathbf{x} + \text{colored } \mathbf{B}\mathbf{n}$$

$$\mathbf{C}\mathbf{B}\mathbf{y} = \overset{\text{SVD}(\mathbf{C}\mathbf{B}\mathbf{H})}{\begin{bmatrix} \text{blue grid} & \text{white box with blue dots} & \text{blue grid} \end{bmatrix}} \mathbf{x} + \text{white } \mathbf{C}\mathbf{B}\mathbf{n}$$

data compressing



noise whitening



$$\mathbf{y} = \text{SVD}(\mathbf{H}) \mathbf{x} + \text{white } \mathbf{n}$$

$$\mathbf{B}\mathbf{y} = \text{SVD}(\mathbf{B}\mathbf{H}) \mathbf{x} + \text{colored } \mathbf{B}\mathbf{n}$$

$$\mathbf{C}\mathbf{B}\mathbf{y} = \text{SVD}(\mathbf{C}\mathbf{B}\mathbf{H}) \mathbf{x} + \text{white } \mathbf{C}\mathbf{B}\mathbf{n}$$

data compressing

noise whitening

Natural Images

VS

Ultrasound Images (SIGNED)

Pre-trained on :



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

Fine-tuned on :

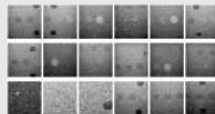


Figure – Examples of the self-acquired dataset (800 images)

Test set : PICMUS dataset (?) gives the observation y .

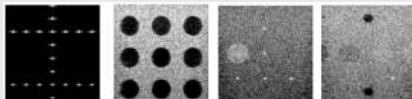
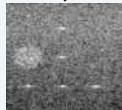
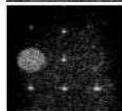


Figure – Examples of PICMUS reconstructed ultrasound images

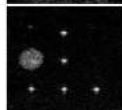
1 transmission (Fast acquisition)



Baseline (DAS1)

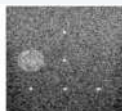


DRUS (**ours**)
($\mathbf{B}_y = \mathbf{B}_H \mathbf{x} + \mathbf{B}_n$)



WDRUS (**ours**)
($\mathbf{CB}_y = \mathbf{CB}_H \mathbf{x} + \mathbf{CB}_n$)

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 



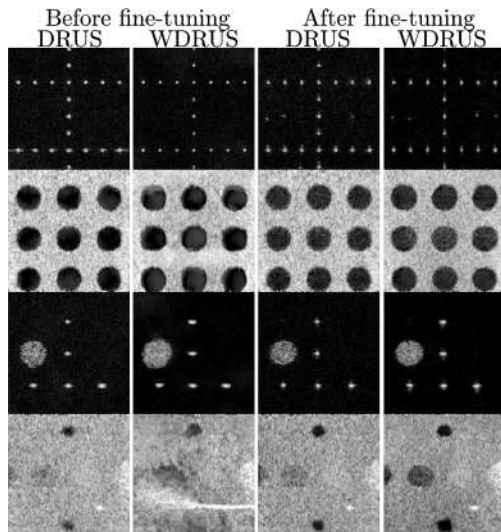
Ultrasound Inverse Problem Model

noise whitened
↖
data compressed
↖
original



Fine-Tuning from a Natural-Image Diffusion Model

Thank you !



B and C in a simple case

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

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

$$\text{Cov}(\mathbf{C}\mathbf{B}\mathbf{n}) = \mathbb{E} [\mathbf{C}\mathbf{B}\mathbf{n}\mathbf{n}^t\mathbf{B}^t\mathbf{C}^t] = \gamma^2 \mathbf{C}\mathbf{B}\mathbf{B}^t\mathbf{C}^t = \gamma^2 \mathbf{C}\mathbf{V}\mathbf{\Lambda}\mathbf{V}^t\mathbf{C}^t = \gamma^2 \mathbf{I}_M$$

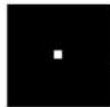
In summary

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

$$\text{---} \mathbf{B}\mathbf{y} = \mathbf{B}\mathbf{H}\mathbf{x} + \mathbf{B}\mathbf{n} \text{ (DRUS)}$$

$$\text{---} \mathbf{C}\mathbf{B}\mathbf{y} = \mathbf{C}\mathbf{B}\mathbf{H}\mathbf{x} + \mathbf{C}\mathbf{B}\mathbf{n} \text{ (WDRUS)}$$

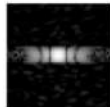
ground truth (x)



measurement (y)



$\mathbf{B}\mathbf{y}$



$\mathbf{C}\mathbf{B}\mathbf{y}$

