Ultrasound Image Reconstruction with Deep Learning

ED seminar - 2023

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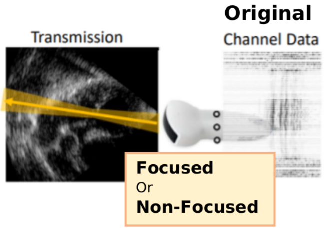
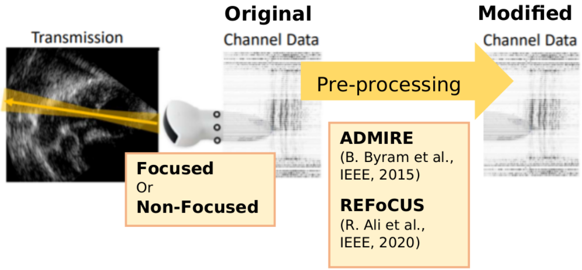
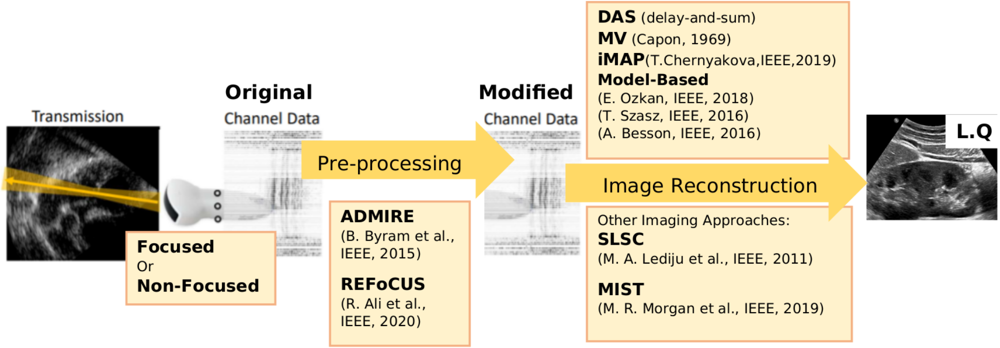
Medical Ultrasound Image Reconstruction Workflow



Medical Ultrasound Image Reconstruction Workflow



Medical Ultrasound Image Reconstruction Workflow



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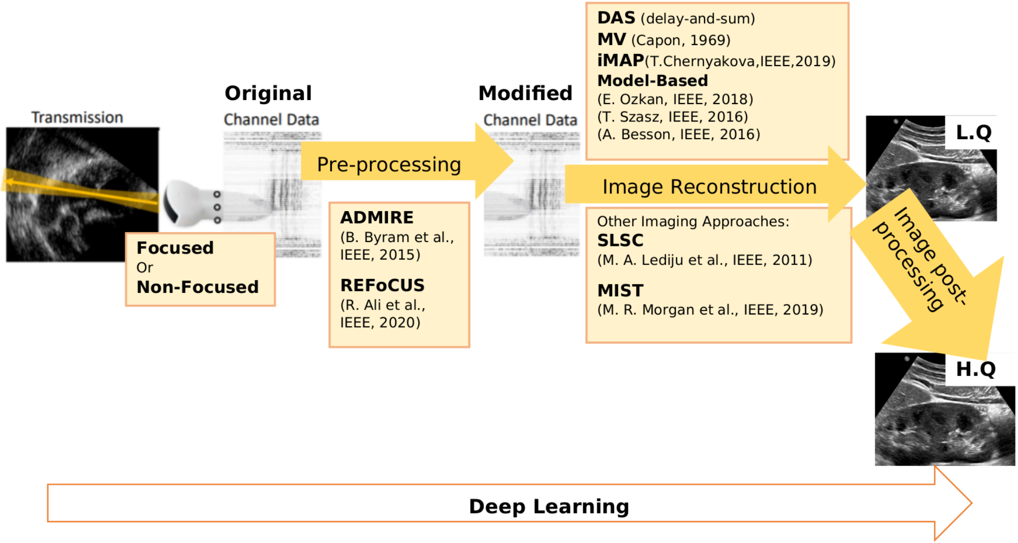
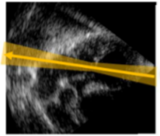


$$\mathbf{y} = \mathbf{H}\mathbf{x} + \mathbf{n}$$

x : reflectivity map



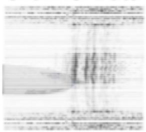
H : model matrix

with the info. of

-time delay

-pulse-echo response

y : channel data



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

State-of-the-art : ϕ_{reg} based on the prior assumptions [1-4] / data-adaptive [5]

(1) Smoothness in frequency domain

$\frac{1}{2}\|\mathbf{W}_f\mathbf{D}_1\mathrm{abs}(\mathbf{F}\mathbf{x})\|_2^2 + \frac{1}{2}\|\mathbf{W}_f\mathbf{D}_2\mathrm{abs}(\mathbf{F}\mathbf{x})\|_2^2$, where $\mathbf{F} =$ DCT (Ozkan et al. [2018])

(2) Smoothness in spatial domain

$\|\mathbf{D}_1\mathrm{Env}(\mathbf{x})\|_1 + \|\mathbf{D}_2\mathrm{Env}(\mathbf{x})\|_1$ (Zhang et al. [2021])
$\|\nabla\mathbf{x}\|_2^2$ (Bodnariuc et al. [2016])

(3) Sparsity in wavelet domain

$\left\|\psi^\dagger\mathbf{x}\right\|_1$, where $\psi = \frac{1}{\sqrt{8}}[\psi_1, \psi_2, ..., \psi_8]$ (Zhang et al. [2021]/Carrillo et al. [2015]/Carrillo et al. [2013])

(4) Sparsity in spatial domain

Tikhonov – $\|\mathbf{x}\|_1$ and $\|\mathbf{x}\|_2^2$ (Szasz et al. [2016])
use envelope – $\|Env(\mathbf{x})\|_1$ (Zhang et al. [2021])

(5) Data-adaptive

$\frac{1}{2}\mathbf{x}^T(\mathbf{x} - Denoi(\mathbf{x}))$ [Regularization by Denoising (RED)] under the Plug-and-Play (PnP) framework (Goudarzi et al. [2022])

Solving the Inverse Problem of Ultrasound Image Reconstruction

$$\text{Solving} \quad \mathbf{y} = \mathbf{H}\mathbf{x} + \mathbf{n} \quad \text{by} \quad \hat{\mathbf{x}} = \arg\min_{\hat{\mathbf{x}}} \tfrac{1}{2}||\mathbf{y} - \mathbf{H}\mathbf{x}||_2^2 + \phi_{reg}$$

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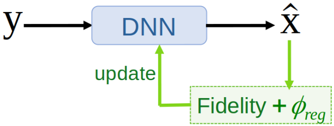
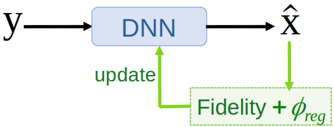
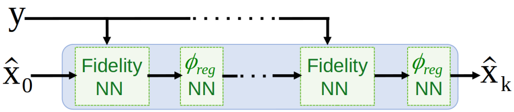
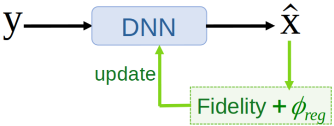
Solve with Deep Neural Networks ?

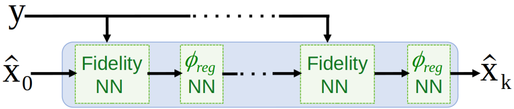

y
DNN
$\hat{x}$
update
Fidelity + ϕ_{reg}

Solving the Inverse Problem of Ultrasound Image Reconstruction









- **Self-Supervised** (Zhang et al. [2021])

  Fidelity$[H\hat{x}, y]$ $\boxed{\phi_{reg} \text{ based on the prior assumptions}}$

  inaccurate prior knowledge

- **Fully Supervised** (Perdios et al. [2022])

  $\boxed{\text{Fidelity}[\hat{x}, x]}$ *Not leverage* ϕ_{reg}

  requires a lot of $[L.Q, H.Q]$ data pairs

- **Supervised Unrolling** (Luijten et al. [2023])

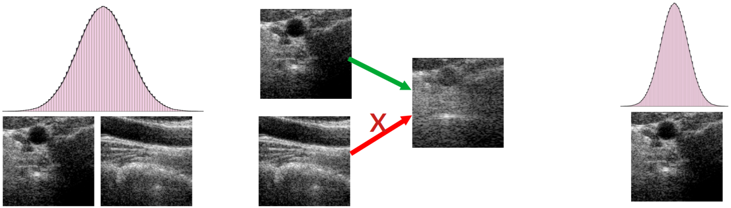
  $\boxed{\text{Fidelity}[\hat{x}, x]}$ Learned ϕ_{reg}

  requires a lot of $[L.Q, H.Q]$ data pairs

Common drawback :
1 Trained DNN <—> 1 Inverse Problem Model

[Med Image Anal] Ultrasound Image Reconstruction from Plane Wave Radio-Frequency Data by Self-Supervised Deep Neural Network (Zhang et al. [2021])
[IEEE TUFFC] CNN-based Image Reconstruction Method for Ultrafast Ultrasound Imaging (Perdios et al. [2022])
[IEEE ICASSP] Neural Maximum-a-Posteriori Beamforming for Ultrasound Imaging (Luijten et al. [2023])

Solving the Inverse Problem of Ultrasound Image Reconstruction



Prior × Likelihood ⟶ Posterior

- **Leverage the Generative Priors**

  + One Trained Generative model <—> ~~One~~ Unlimited Inverse Problem Models

  + ~~assumed~~ learned prior

  + ~~[LQ, HQ]~~ HQ required for training

The solving methods can be adapted to other inverse problems

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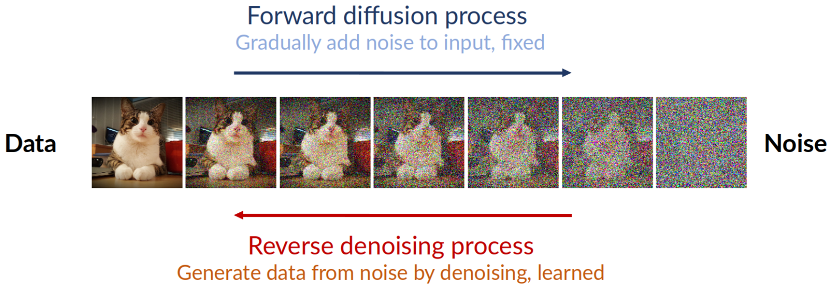
* Generative Models : **Diffusion Models**



Unconditional sampling :

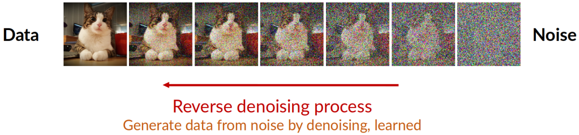


Figure – Unconditional CIFAR10 progressive generation (Ho et al. [2020]).

Unconditional sampling :

Data

Noise

Reverse denoising process

Generate data from noise by denoising, learned

Figure – Unconditional CIFAR10 progressive generation (Ho et al. [2020]).

Conditional sampling :

Data

Noise

Reverse denoising process

Generate data from noise by denoising, learned

$$y_d = H_d x_d + n_d$$

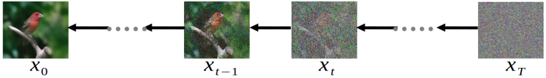
Figure – Generation process of a conditioned generator.

Start with a simple case :

[Diagonal]

$$y_d = H_d x_d + n_d$$

[Noisy observation] [Noise, i.i.d Gaussian, known variance]



[NeurIPS] Denoising Diffusion Restoration Models (Kawar et al. [2022])

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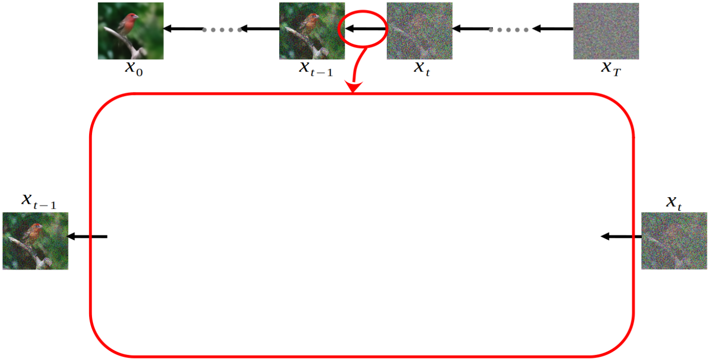

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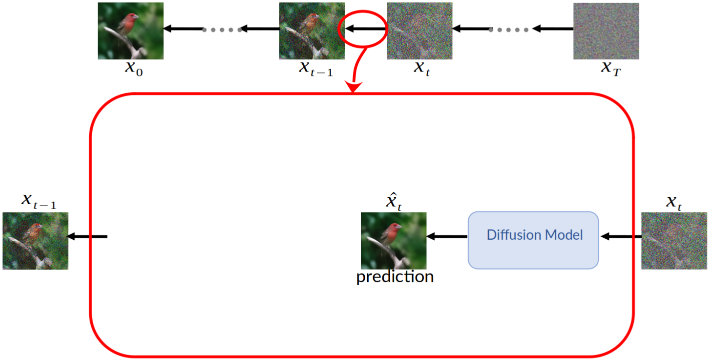

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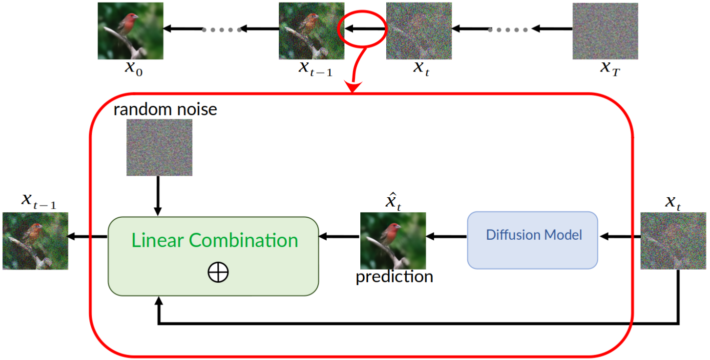

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Denoising Diffusion Restoration Models

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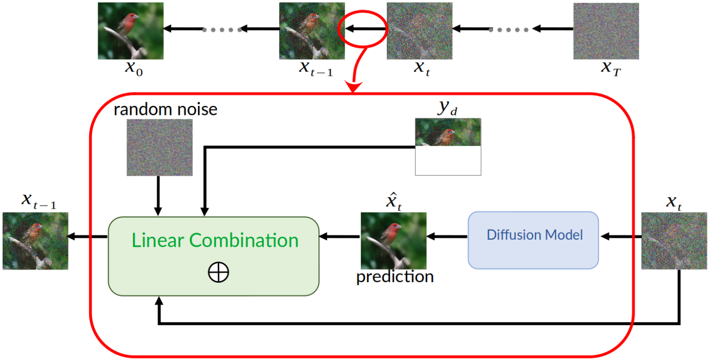
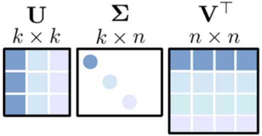


[NeurIPS] Denoising Diffusion Restoration Models (Kawar et al. [2022])

Denoising Diffusion Restoration Models

Most general case : **any linear inverse problem**

$$H_d = U \Sigma V^T$$



H is "diagonal" in transformed space from SVD

$$\Sigma^\dagger U^T y_d = V^T x_d + \Sigma^\dagger U^T n_d$$

$$\overline{y_d} = \overline{x_d} + \overline{n_d}$$

DDRM: run "denoising and/or inpainting", but in the space transformed by SVD

[NeurIPS] Denoising Diffusion Restoration Models (Kawar et al. [2022])

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From $\mathbf{y} = \mathbf{H}\mathbf{x} + \mathbf{n}$ to $\mathbf{B}\mathbf{y} = \mathbf{B}\mathbf{H}\mathbf{x} + \mathbf{B}\mathbf{n}$

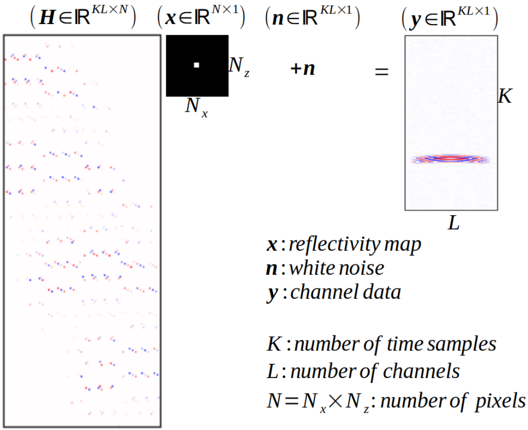


Figure – Forward model of ultrasound image reconstruction

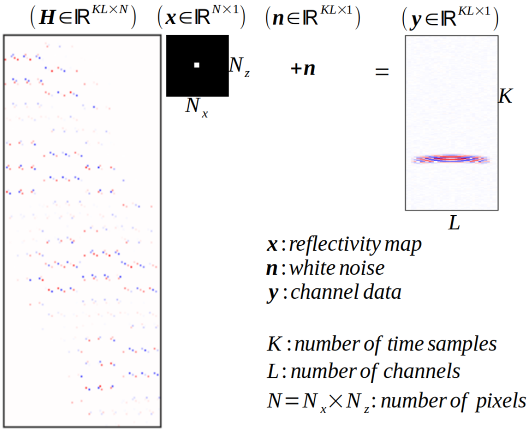


Figure – Forward model of ultrasound image reconstruction

Problem : TOO MUCH data to control !

Solution :
COMPRESS the data by applying an operator $\mathbf{B} \approx \mathbf{H}^t$

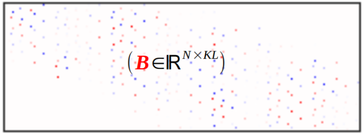
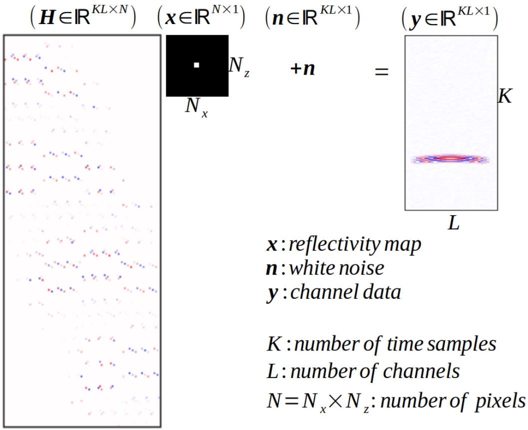


Figure – Matrix $\mathbf{B}$

From $\mathbf{y} = \mathbf{H}\mathbf{x} + \mathbf{n}$ to $\mathbf{B}\mathbf{y} = \mathbf{B}\mathbf{H}\mathbf{x} + \mathbf{B}\mathbf{n}$



$\boldsymbol{x}$: *reflectivity map*
$\boldsymbol{n}$: *white noise*
$\boldsymbol{y}$: *channel data*

K : *number of time samples*
L : *number of channels*
$N = N_x \times N_z$: *number of pixels*

Figure – Forward model of ultrasound image reconstruction

Then :

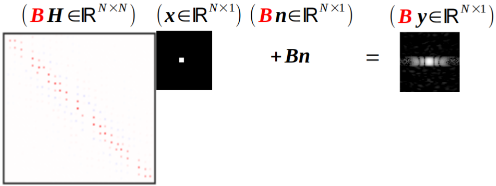


Figure – Data-compressed forward model

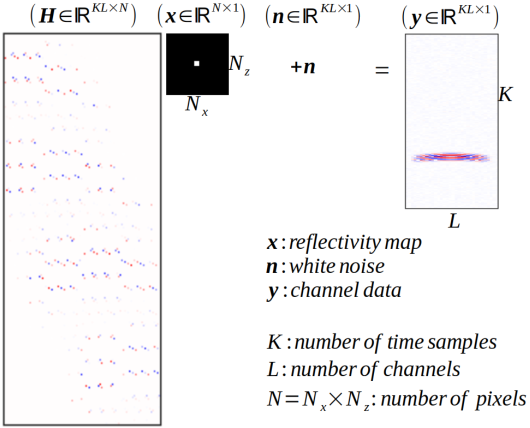


Figure – Forward model of ultrasound image reconstruction

Then :

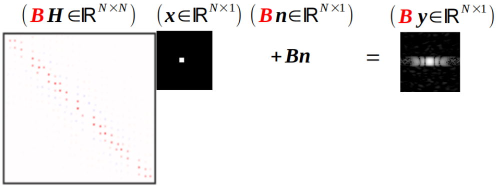
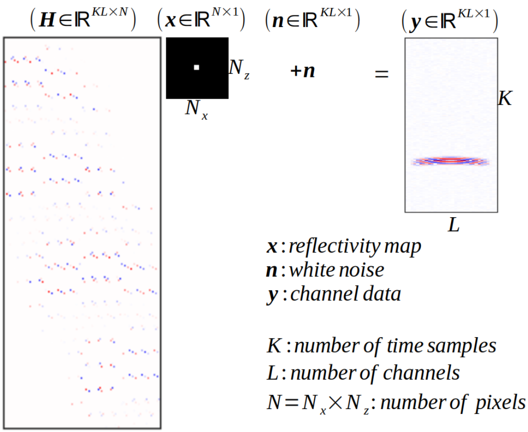


Figure – Data-compressed forward model

Conflict :
colored noise $\mathbf{Bn}$ does not meet the assumption of DDRM

Solution : Apply a whitening operator $\mathbf{C}$

From $\mathbf{By} = \mathbf{BHx} + \mathbf{Bn}$ to $\mathbf{CBy} = \mathbf{CBHx} + \mathbf{CBn}$



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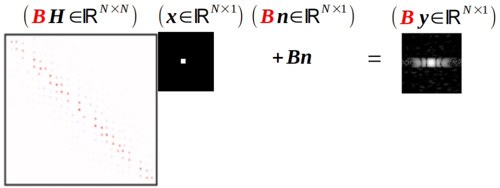


Figure – Data-compressed forward model

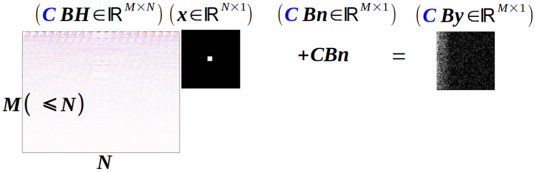


Figure – Noise-whitened and data-compressed forward model

Inverse Problem Models :

Use $\begin{cases} \mathbf{By} = \mathbf{BHx} + \mathbf{Bn} & \text{(DRUS)} \\ \mathbf{CBy} = \mathbf{CBHx} + \mathbf{CBn} & \text{(WDRUS)} \end{cases}$ to recover $\mathbf{x}$ with the given $\mathbf{y}$.

Test set : PICMUS dataset (Liebgott et al. [2016]) gives the observation $\mathbf{y}$.

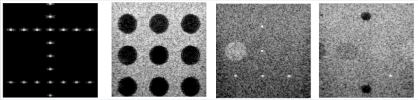
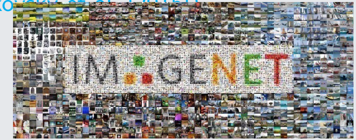


Figure – Examples of PICMUS reconstructed ultrasound images

Diffusion Model :

Fine-tune the public-available one which was trained on the ImageNet dataset (1,281,167 images) (Russakovsky et al. [2015])



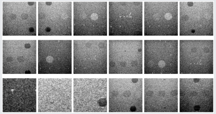
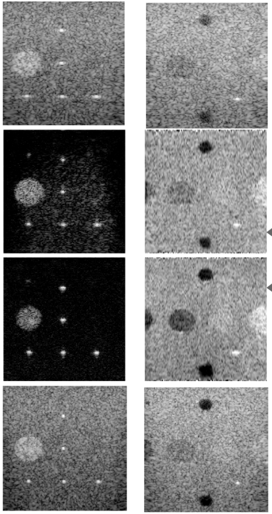


Figure – Examples of the fine-tune set (800 images)

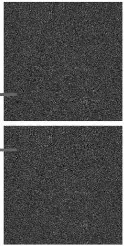


L.Q. (DAS1)

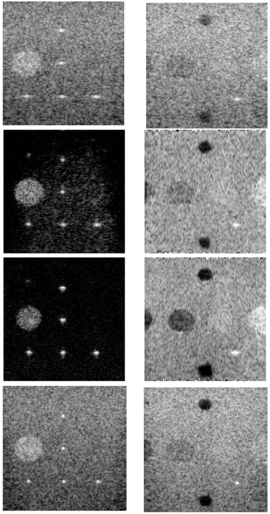
$$\mathbf{By} = \mathbf{BHx} + \mathbf{Bn} \qquad \text{(DRUS)}$$

Diffusion Model

$$\mathbf{CBy} = \mathbf{CBHx} + \mathbf{CBn} \quad \text{(WDRUS)}$$



Golden standard (DAS75)
(use more channel data)



L.Q. (DAS1)

DRUS

WDRUS

Golden standard (DAS75)

	Resolution (FWHM [mm]↓)		Contrast (CNR[dB] ↑)
	Axial	Lateral	
DAS1	0.51	1.21	8.15
DRUS	0.26	0.69	**12.9**
WDRUS	**0.25**	0.62	11.95
DAS75	0.49	0.59	12.05

Ultrasound Image Reconstruction with Denoising Diffusion Restoration Models

+ 1 pre-trained Diffusion Model $\rightarrow$ different Inverse Problem Models
+ ~~training from scratch~~ Fine-tuning with [~~LQ~~ , HQ] image ~~pairs~~

- Artifacts
- Requiring the SVD of the model matrix

DGM4MICCAI workshop at MICCAI 2023 (submit)

Future work :

- Enlarging the train/test dataset
- Removing the dependency on SVD

Thank you !

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