



Jeffrey A. Fessler

EECS Department, BME Department, Dept. of Radiology
University of Michigan

<http://web.eecs.umich.edu/~fessler>

[IMSI Workshop on Computational Imaging](#)
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Acknowledgments:

Jason Hu, Bowen Song, Xiaojian Xu, Liyue Shen

[arXiv 2406.02462](#)

Introduction

- Inverse problems

- Generative models

- Score matching / diffusion models

Patch-based models

- Non-overlapping patch model

- Patch Diffusion Inverse Solver (PaDIS)

- CT reconstruction results

- Summary

Book

Bibliography

- ▶ Applications: compressed sensing MRI, sparse-view CT, in-painting, ...

$$\mathbf{y} = \mathbf{A}\mathbf{x} + \varepsilon$$

\mathbf{y} : data

\mathbf{A} : wide system matrix (known)

\mathbf{x} : latent image (or image series in dynamic problems)

ε : noise with known distribution provides likelihood $p(\mathbf{y}|\mathbf{x})$

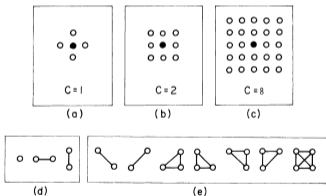
Maximum-likelihood estimation non-unique $\arg \max_{\mathbf{x}} \log p(\mathbf{y}|\mathbf{x})$

- ▶ Options

- hand-crafted regularizers $\arg \min_{\mathbf{x}} -\log p(\mathbf{y}|\mathbf{x}) + R(\mathbf{x})$
- black-box data-driven methods: $\mathbf{A}^+ \mathbf{y} \rightarrow \boxed{\text{NN}} \rightarrow \hat{\mathbf{x}}$
- unrolled deep learning methods (PNP, RED, MoDL, ...)
- Bayesian methods (e.g., MAP) based on a **prior** $p(\mathbf{x})$, lately (?) relabeled as **generative models**

Markov random field models

(e.g.) Geman & Geman 1984 [1]



Mostly for inference?

GEMAN AND GEMAN: STOCHASTIC RELAXATION, GIBBS DISTRIBUTIONS, AND BAYESIAN RESTORATION

737

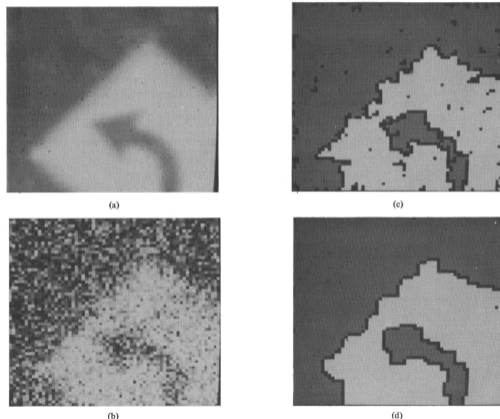


Fig. 7. (a) Blurred image (roadside scene). (b) Degraded image: Additive noise. (c) Restoration including line process; 100 iterations. (d) Restoration including line process; 1000 iterations.

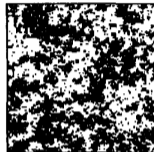
MRF as generators?

[2] T-PAMI 1994

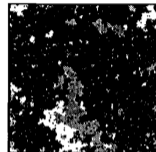
An Empirical Study of the Simulation of Various Models Used for Images

A. J. Gray, J. W. Kay, and D. M. Titterington

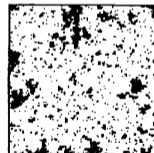
Abstract— Markov random fields are typically used as priors in Bayesian image restoration methods to represent spatial information in the image. Commonly used Markov random fields are **not** in fact capable of representing the moderate-to-large scale clustering present in naturally occurring images and can also be time consuming to simulate,



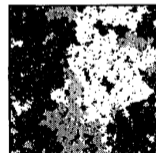
(b)



(f)



(c)



(g)

Gray, Kay, Titterington [2] T-PAMI 1994

... the local properties of spatial Markov models are undoubtedly plausible descriptors of the local associations typical of many images, which is the way in which the models are often used. Nevertheless, it would be reassuring if models used as priors did in fact provide a realistic representation of our prior assumptions and if their (empirical) properties were more widely known.

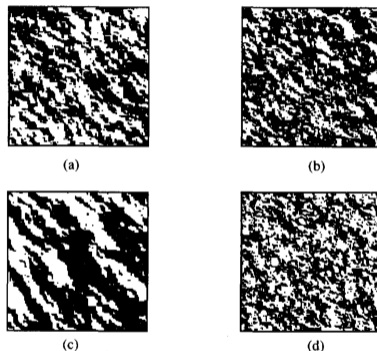
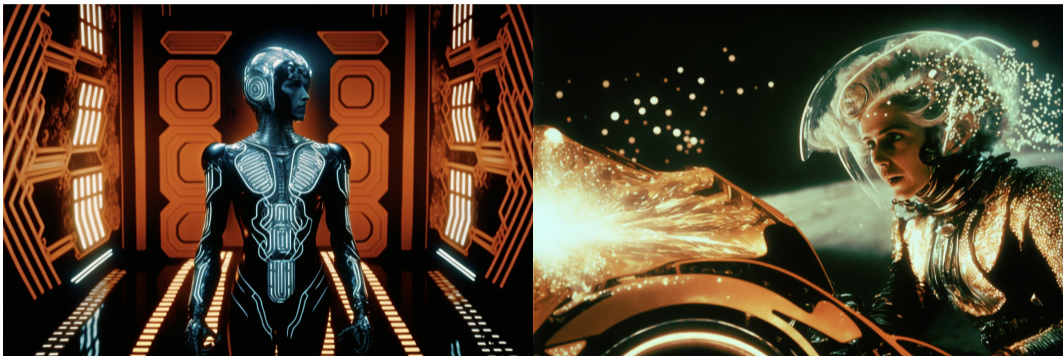


Fig. 4. Realizations of two-dimensional, one-parameter, autologistic Markov Mesh models: (a) binary, second-order model with $\beta = \log 5$; (b) three-color second-order model with $\beta = \log 5$; (c) binary second-order model with $\beta = \log 10$; (d) binary second-order model with $\beta = \log 3$.



Computer (“AI”) generated stills from hypothetical movie: Chilean director Alejandro Jodorowsky’s 1976 version of “Tron” using midjourney.com as reported in 2023-01-13 NY Times article “This film does not exist” by director Frank Pavich.

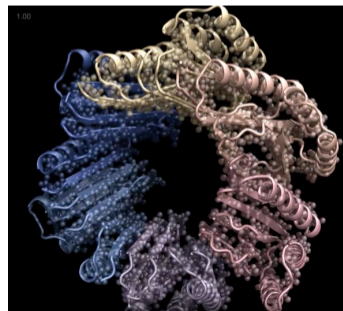
- ▶ 2020-11-21 NY Times “Designed to Deceive: Do These People Look Real to You?”
Article about generated (aka fake) faces.
- ▶ 2022-10-21 NY Times “A Coming-Out Party for Generative A.I., Silicon Valley’s New Craze”
(about “Stable Diffusion” image generator)
<https://nyti.ms/3SjsN0k>
- ▶ 2023-01-09 NY Times “A.I. Turns Its Artistry to Creating New Human Proteins”
<https://nyti.ms/3IzY66m>



Gender



Race and Ethnicity



Théâtre d'Opéra Spatial

https://en.wikipedia.org/wiki/Theatre_d'Opera_Spatial

Image created by the generative artificial intelligence platform Midjourney, using a prompt by Jason M. Allen. [1] The painting became a news story when it won the 2022 Colorado State Fair's annual fine art competition 2022-09-05.

Wikimedia: This file is in the public domain because it is the work of a computer algorithm or artificial intelligence and does not contain sufficient human authorship to support a copyright claim.

https://en.wikipedia.org/wiki/Generative_artificial_intelligence

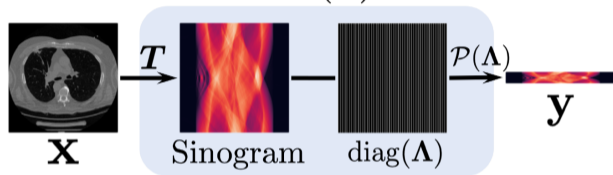
Zhao, Ye, Bresler: Jan. 2023 IEEE SpMag survey paper [3]

- ▶ Generative adversarial network (GAN) models
- ▶ Variation auto-encoder (VAE) models [4]
- ▶ Normalizing flows [5, 6]
- ▶ Score-based diffusion models
 - Zaccharie Ramzi et al., NeurIPS Workshop 2020 [7]
 - Yang Song & Liyue Shen et al., NeurIPS Workshop 2021, ICLR 2022 [8, 9]
 - Ajil Jalal et al. ... Jon Tamir, NeurIPS 2021 [10]
 - Hyungjin Chung & Jong Chul Ye, MIA, Aug. 2022 [11]
 - Luo et al., MRM, 2023 [12]
 - ...
- ▶ Kazerouni et al. [13] have github catalog, including >20 (!) survey papers
- ▶ ... (hopelessly incomplete lists)

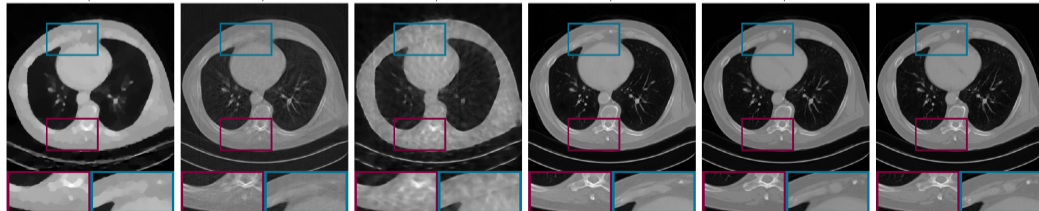
From Song & Shen et al., ICLR 2022 [9].

Trained with 47K 2D images; 23 projection views

$$\mathbf{A} = \mathcal{P}(\Lambda)\mathbf{T}$$



PSNR: 20.30, SSIM: 0.778 PSNR: 22.94, SSIM: 0.552 PSNR: 22.78, SSIM: 0.603 PSNR: 31.76, SSIM: 0.882 PSNR: 35.23, SSIM: 0.912



(a) FISTA-TV

(b) cGAN

(c) Neumann

(d) SIN-4c-PRN

(e) Ours

(f) Ground truth

- ▶ Bayesian inference methods use the posterior:

$$p(\mathbf{x}|\mathbf{y}) = \frac{p(\mathbf{y}|\mathbf{x}) p(\mathbf{x})}{p(\mathbf{y})}$$

- ▶ Here the prior $p(\mathbf{x})$ is for quantifying (prior) probability, not necessarily for generation.
- ▶ A model for the posterior $p(\mathbf{x}|\mathbf{y})$ opens many doors:
 - ▶ Maximizing $p(\mathbf{x}|\mathbf{y})$ is maximum a posteriori (MAP) estimation
 - ▶ The conditional mean $E[\mathbf{x}|\mathbf{y}] = \int \mathbf{x}p(\mathbf{x}|\mathbf{y}) d\mathbf{x}$ is the MMSE estimator
 - ▶ Sampling from the posterior $p(\mathbf{x}|\mathbf{y})$ facilitates uncertainty quantification in inference
- ▶ All of these require the prior $p(\mathbf{x})$, *i.e.*, a prior model $p(\mathbf{x}; \boldsymbol{\theta})$.
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- ▶ Or do they?

Sampling from a *prior* $p(\mathbf{x}; \boldsymbol{\theta})$ just needs its **score function** $\nabla_{\mathbf{x}} \log p(\mathbf{x}; \boldsymbol{\theta})$, using Langevin dynamics, aka stochastic gradient ascent of log-prior:

$$\mathbf{x}_t = \mathbf{x}_{t-1} + \alpha_t \underbrace{\nabla \log p(\mathbf{x}_{t-1}; \boldsymbol{\theta})}_{\text{score function}} + \beta_t \mathcal{N}(\mathbf{0}, \mathbf{I}), \quad t = 1, \dots, T.$$

- Draws samples from $p(\mathbf{x}; \boldsymbol{\theta})$ for suitable choices of $\{\alpha_t\}$, $\{\beta_t\}$, and (large) T [14].
- If $\alpha_t = 0$ and $\beta_t = \beta$, then akin to (isotropic) diffusion or Brownian motion

- ▶ Typical distribution models: $p(\mathbf{x}; \boldsymbol{\theta}) = \frac{1}{Z(\boldsymbol{\theta})} e^{-U(\mathbf{x}; \boldsymbol{\theta})}$.

Goal: learn $\boldsymbol{\theta}$ from training data $\mathbf{x}_1, \dots, \mathbf{x}_T$

- ▶ For IID samples $\{\mathbf{x}_t\}$, one could try to learn $\boldsymbol{\theta}$ by ML estimation:

$$\begin{aligned}\hat{\boldsymbol{\theta}} &= \arg \max_{\boldsymbol{\theta}} p(\mathbf{x}_1, \dots, \mathbf{x}_T; \boldsymbol{\theta}) = \arg \max_{\boldsymbol{\theta}} \sum_{t=1}^T \log(p(\mathbf{x}_t; \boldsymbol{\theta})) \\ &= \arg \max_{\boldsymbol{\theta}} \left(-T Z(\boldsymbol{\theta}) + \sum_{t=1}^T -U(\mathbf{x}_t; \boldsymbol{\theta}) \right).\end{aligned}$$

Typically intractable due to the partition function $Z(\boldsymbol{\theta})$.



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Typically intractable due to the partition function $Z(\boldsymbol{\theta})$.

- ▶ In contrast, the **score function** is easier to handle:

$$\mathbf{s}(\mathbf{x}; \boldsymbol{\theta}) \triangleq \nabla_{\mathbf{x}} \log p(\mathbf{x}; \boldsymbol{\theta}) = \nabla_{\mathbf{x}} (-\log Z(\boldsymbol{\theta}) - U(\mathbf{x}; \boldsymbol{\theta})) = -\nabla_{\mathbf{x}} U(\mathbf{x}; \boldsymbol{\theta}).$$

- ▶ Given training data $\mathbf{x}_1, \dots, \mathbf{x}_T$, learn score function $\mathbf{s}(\mathbf{x}; \boldsymbol{\theta}) \stackrel{?}{=} \nabla_{\mathbf{x}} \log p(\mathbf{x}; \boldsymbol{\theta})$
- ▶

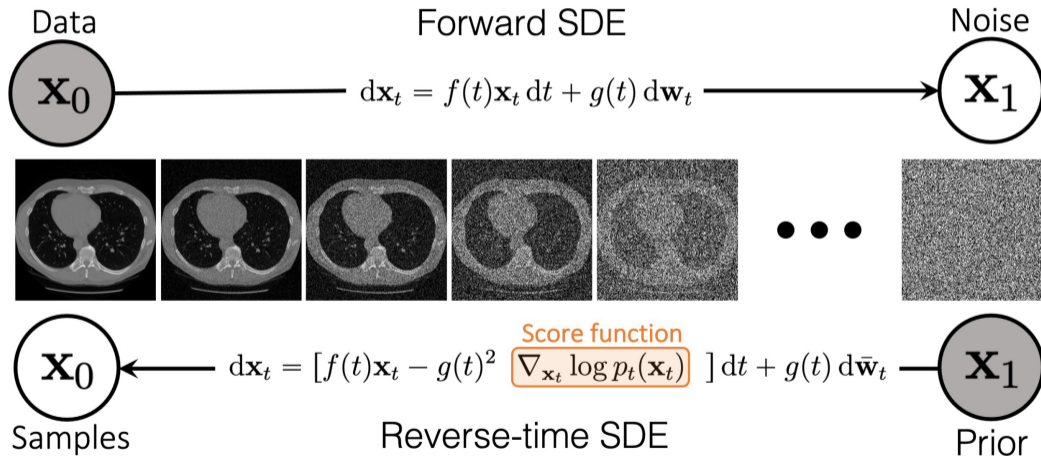
- ▶ Given training data $\mathbf{x}_1, \dots, \mathbf{x}_T$, learn score function $\mathbf{s}(\mathbf{x}; \boldsymbol{\theta}) \stackrel{?}{=} \nabla_{\mathbf{x}} \log p(\mathbf{x}; \boldsymbol{\theta})$
- ▶ Explicit score matching (ESM) (Hyvärinen, 2005 [15])
- ▶ Implicit score matching (ISM)
- ▶ Denoising score matching (DSM) (Vincent, 2011 [16])
- ▶ Noise-conditional score matching (NCSM) (Song, 2019 [17, eqn. (5)]):

$$\ell(\boldsymbol{\theta}; \sigma) \triangleq \frac{1}{2} \mathbb{E}_{q_0(\mathbf{x})} \left[\mathbb{E}_{g_\sigma(\mathbf{z})} \left[\left\| \mathbf{s}(\mathbf{x} + \mathbf{z}; \boldsymbol{\theta}, \sigma) + \frac{\mathbf{z}}{\sigma^2} \right\|_2^2 \right] \right], \quad \mathcal{L}(\boldsymbol{\theta}; \{\sigma_l\}) = \frac{1}{L} \sum_{l=1}^L \sigma_l^2 \ell(\boldsymbol{\theta}; \sigma_l),$$

where $\mathbf{s}(\mathbf{x}; \boldsymbol{\theta}, \sigma)$ denotes a *noise-conditional score network* (NCSN).

- ▶ $\mathbf{d}(\mathbf{x}; \boldsymbol{\theta}) \triangleq \mathbf{x} + \sigma^2 \mathbf{s}(\mathbf{x}; \boldsymbol{\theta}, \sigma)$: equivalent image denoiser by Tweedie's formula [18]
- ▶ Recommended choice [19]: $\mathbf{s}(\mathbf{x}; \boldsymbol{\theta}, \sigma) \triangleq \tilde{\mathbf{s}}(\mathbf{x}; \boldsymbol{\theta})/\sigma$, where $\tilde{\mathbf{s}}$ is unitless

Shen & Song et al., NeurIPS 2021 [8]



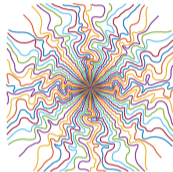


- ▶ No adversarial training needed
- ▶ High quality sample generation (if enough training data)
- ▶

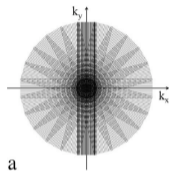
- ▶ No adversarial training needed
- ▶ High quality sample generation (if enough training data)
- ▶ Expensive sample generation (vs GAN models)
 - Distillation methods [20]
 - Consistency models [21]
 - Geometric decomposition [22]
 - Multi-scale [23, 24] and pyramidal [25] and coarse-to-fine [26] models
 - Faster ODE solvers [27]
 - Warm starts [28]
 - Latent diffusion models: use VAE and diffuse in latent space [29–31].
Used in Stable Diffusion by start-up Stability AI
 - 3D image reconstruction using 2D models [32, 33]
- ▶ Learning 3D (or 3D+T) whole-image generative models is challenging (training data, GPU memory, ...)

Jan. 2023 survey paper on generative models [3] does not mention “patch” once!?

MRI k-space sampling:

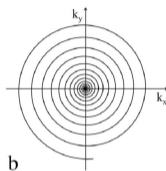


[34]

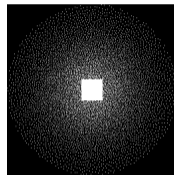


a

[35]



b



[36]

Patch-based models have long history in inverse problems, e.g.,

- patch GAN [37–39]
- patch dictionary models [40, 41]
- non-local means, BM3D
- Wasserstein patch prior [42, 43] ...

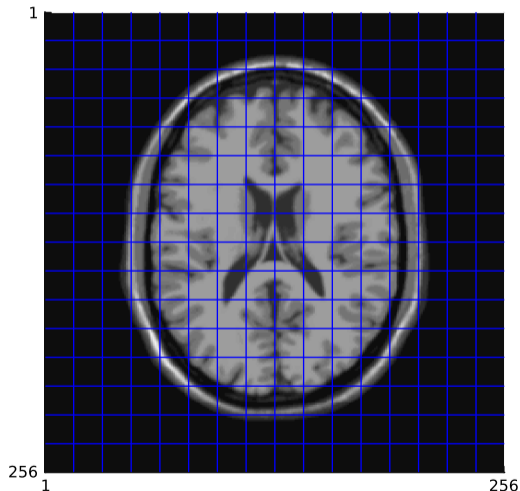
- ▶ Could patch-based generative models provide better robustness to distribution shifts, perhaps at the cost of reduced in-distribution performance?
- ▶ Especially in applications with very limited training data?
e.g., dynamic MRI
- ▶ Can we use the “latest” generative models, namely score-based models, for patches?

Warm up:

simple, but less effective, approach:

- Fixed patch size
- Fixed patch grid
- No position information

(Fessler, Hu, Xu, BASP 2023 [44])



- ▶ Start with MRF formulation, aka *fields of experts* model [49–51] for image \mathbf{x} :

$$p(\mathbf{x}; \boldsymbol{\theta}) = \frac{1}{Z(\boldsymbol{\theta})} e^{-\sum_c V_c(\mathbf{x}; \boldsymbol{\theta})} = \frac{1}{Z(\boldsymbol{\theta})} \prod_c e^{-V_c(\mathbf{x}; \boldsymbol{\theta})}.$$

- $\boldsymbol{\theta}$: parameter vector that describes the prior
 - V_c : *clique potential* for the c th image *patch*
 - $Z(\boldsymbol{\theta})$: (intractable) partition function
- ▶ Assume (temporarily) statistical spatial stationarity (image shift invariance):

$$V_c(\mathbf{x}; \boldsymbol{\theta}) = V(\mathbf{G}_c \mathbf{x}; \boldsymbol{\theta})$$

- \mathbf{G}_c : wide binary matrix that grabs pixels of the c th patch from image \mathbf{x}
- $V(\mathbf{v}; \boldsymbol{\theta})$: common patch clique function

- ▶ Resulting log-prior:

$$\log p(\mathbf{x}; \boldsymbol{\theta}) = -\log Z(\boldsymbol{\theta}) - \sum_c V(\mathbf{G}_c \mathbf{x}; \boldsymbol{\theta})$$

- ▶ Corresponding overall *image score function* arises from *patch score function*:

$$\mathbf{s}(\mathbf{x}; \boldsymbol{\theta}) \triangleq \nabla_{\mathbf{x}} \log p(\mathbf{x}; \boldsymbol{\theta}) = \sum_c \mathbf{G}'_c \mathbf{s}_V(\mathbf{G}_c \mathbf{x}; \boldsymbol{\theta}), \quad \mathbf{s}_V(\mathbf{v}; \boldsymbol{\theta}) \triangleq -\nabla_{\mathbf{v}} V(\mathbf{v}; \boldsymbol{\theta}).$$

- ▶ All we must learn is the patch score function $\mathbf{s}_V(\mathbf{v}; \boldsymbol{\theta}) : \mathbb{R}^n \mapsto \mathbb{R}^n$, e.g., a UNet.
- ▶ For non-overlapping patches:

$$\underbrace{\left\| \mathbf{s}(\mathbf{x} + \mathbf{z}; \boldsymbol{\theta}) + \mathbf{z}/\sigma^2 \right\|_2^2}_{\text{image "denoise"}} = \left\| \sum_c \mathbf{G}'_c \mathbf{s}_V(\mathbf{G}_c(\mathbf{x} + \mathbf{z}); \boldsymbol{\theta}) + \mathbf{z}/\sigma^2 \right\|_2^2$$

$$= \sum_c \underbrace{\left\| \mathbf{s}_V(\mathbf{x}_c + \mathbf{z}_c); \boldsymbol{\theta} \right\|_2^2}_{\text{patch "denoise"}}, \quad \mathbf{z}_c \triangleq \mathbf{G}_c \mathbf{z}$$



- ▶ For training image patches $\{\mathbf{v}_1, \dots, \mathbf{v}_T\}$, apply *denoising score matching* (DSM) of Vincent, 2011 [16], typically for a range of noise variances σ^2 [14]:

$$\hat{\boldsymbol{\theta}} = \arg \min_{\boldsymbol{\theta}} \frac{1}{T} \sum_{t=1}^T \mathbb{E}_{\sigma \sim p(\sigma)} \left[\sigma^2 \mathbb{E}_{\mathbf{z} \sim \mathcal{N}(0, \sigma^2 \mathbf{I}_n)} \left[\frac{1}{2} \left\| \mathbf{s}_V(\mathbf{v}_t + \mathbf{z}; \boldsymbol{\theta}, \sigma) + \frac{\mathbf{z}}{\sigma^2} \right\|_2^2 \right] \right].$$

- ▶ Final patch score model is $\mathbf{s}_V(\mathbf{v}; \hat{\boldsymbol{\theta}}, \sigma_{\min})$.
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- ▶ Network input is just image patches, never the entire image
 \implies scales to large 2D images, 3D, 4D, etc.
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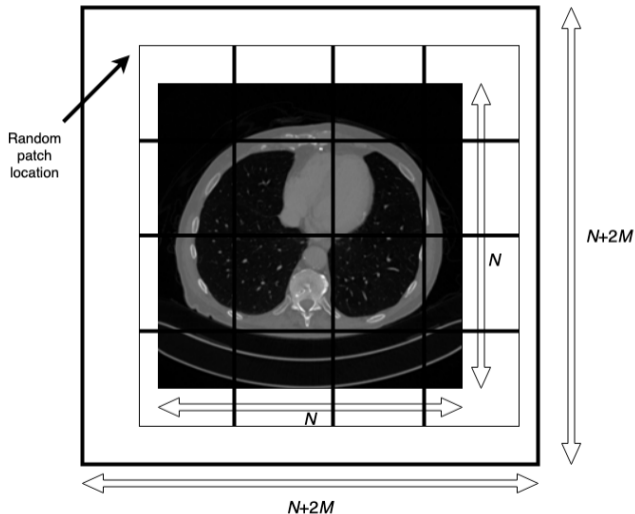
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- ▶ Final patch score model is $\mathbf{s}_V(\mathbf{v}; \hat{\boldsymbol{\theta}}, \sigma_{\min})$.
- ▶ Network input is just image patches, never the entire image
 \implies scales to large 2D images, 3D, 4D, etc.
- ▶ Drawbacks:
 - Visible patch boundaries
 - Fixed patch size slows learning
 - Suboptimal stationarity assumption (*cf.* vertebrae)

- ▶ zero-pad image x
- ▶ use multiple grid locations

Inspirations:

- Wavelet “cycle spinning” [45, 52–55]
- Wang, NeurIPS 2023 [56]



- ▶ $N_1 \times N_2$: original image size
- ▶ $P_1 \times P_2$: patch size
- ▶ $K_i \triangleq 1 + \lfloor N_i/P_i \rfloor$, $i = 1, 2$: # non-overlapping patches for original image
- ▶ $(N_1 + 2M_1) \times (N_2 + 2M_2)$: padded image size; $M_i \triangleq K_i P_i - N_i$
- ▶ Product probability model:

$$p(\mathbf{x}) \triangleq \frac{1}{Z} \underbrace{\prod_{m=1}^{M_1 M_2}}_{\text{grid shifts}} \left(\underbrace{p_{m,B}(\mathbf{x}_{m,B})}_{\text{border region}} \underbrace{\prod_{k=1}^{K_1 K_2} p_{m,k}(\mathbf{x}_{m,k})}_{\text{patches}} \right) = \frac{1}{Z} \prod_{m=1}^{M_1 M_2} \prod_{k=1}^{K_1 K_2} \underbrace{e^{-V(\mathbf{x}_{m,k}; m, k)}}_{\text{position encoding}}$$

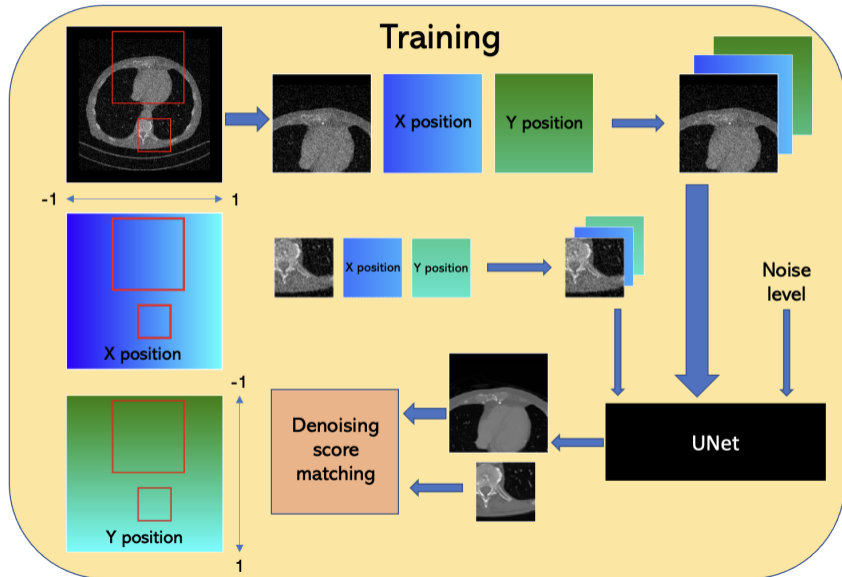
- $\mathbf{x}_{m,B}$: border pixels for m th shift (all zero)
- $\mathbf{x}_{m,k}$: k th patch for m th shift



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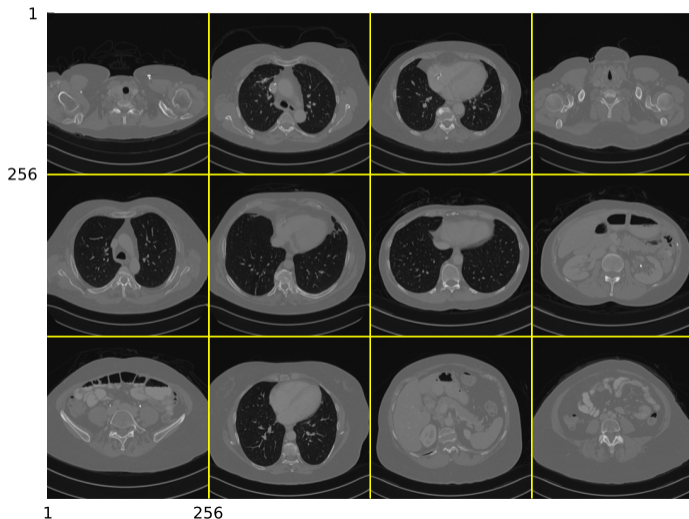
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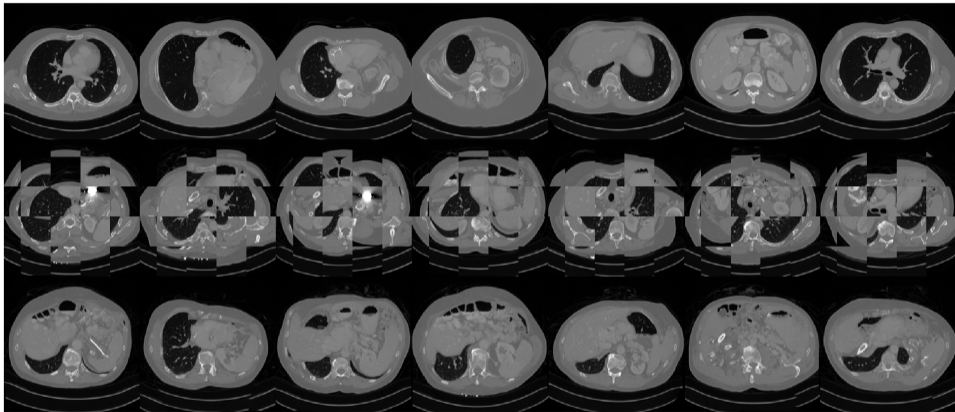
- $\mathbf{x}_{m,B}$: border pixels for m th shift (all zero)
- $\mathbf{x}_{m,k}$: k th patch for m th shift
- ▶ Learn position-dependent patch score function $\mathbf{s}(\mathbf{v}; \boldsymbol{\theta}, m, k) = -\nabla_{\mathbf{v}} V(\mathbf{v}; m, k)$



AAPM 2016 CT challenge data [58];
10 3D volumes,
rescaled to 256^3

Example slices:

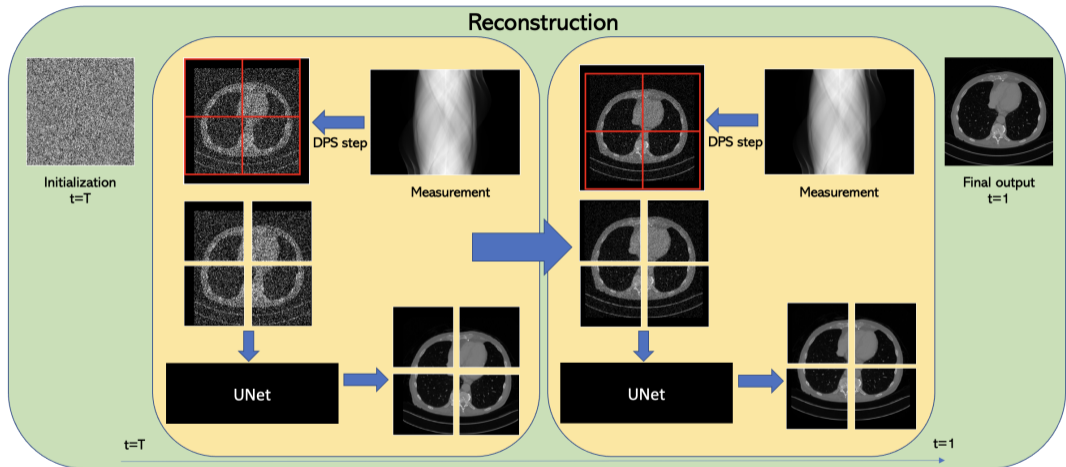




- Top: generation with a network trained on whole images (2D...)
- Middle: patch-only version of [56] (non-overlapping patches).
- Bottom: proposed PaDIS method.

2 A40 GPUs using PyTorch and ADAM

- ▶ whole image model: 24 – 36 hours
- ▶ patch-based model: \approx 12 hours



Diffusion posterior sampling (DPS) (Chung et al., ICLR 2023 [59]) with Langevin dynamics, modified to use patch score with random grid shifts.

Input: \mathbf{y} , \mathbf{A} , T , $\sigma_1 < \sigma_2 < \dots < \sigma_T$, $\epsilon > 0$, $\{\zeta_t > 0\}$, P_1, P_2, M_1, M_2 ,
trained noise-conditional, position-encoded patch denoiser $\mathbf{d}(\cdot; \theta_*, m, k, \sigma)$

Initialize random image $\mathbf{x} \sim \mathcal{N}(\mathbf{0}, \sigma_T^2 \mathbf{I})$

for $t = T : 1$ **do**

Randomly select grid integer $m \in \{1, \dots, M_1 M_2\}$

for $k = 1 : (K_1 K_2)$ **do** (parallelizable)

Extract patch $\mathbf{x}_{m,k}$

Denoise patch: $\mathbf{d}_{m,k} \triangleq \mathbf{d}(\mathbf{x}_{m,k}; \theta_*, m, k, \sigma_t)$

end for

Combine denoised patches to get denoised image \mathbf{d}

Compute image score function: $\mathbf{s} = (\mathbf{d} - \mathbf{x}) / \sigma_t^2$

Data term: $\mathbf{x} := \mathbf{x} - \zeta_t \nabla_{\mathbf{x}} \|\mathbf{A} \mathbf{d}(\mathbf{x}) - \mathbf{y}\|_2^2$

Sample $\mathbf{z} \sim \mathcal{N}(\mathbf{0}, \sigma_t^2 \mathbf{I})$

Step size $\alpha_t \triangleq \epsilon \sigma_t^2$

Langevin update: $\mathbf{x} := \mathbf{x} + \frac{\alpha_t}{2} \mathbf{s} + \sqrt{\alpha_t} \mathbf{z}$

end for

Default setup:

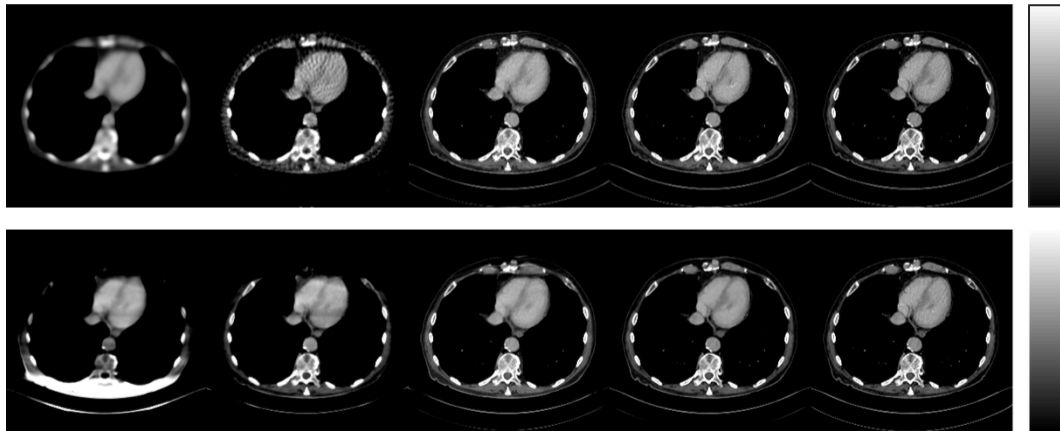
- 9 of 10 volumes for training \implies 2304 slices
- 25 slices of 10th volume for testing
- 512 element parallel-beam CT detector
- \mathbf{A} from Operator Discretization Library (ODL)
- 56×56 patch size
- U-Net of Karras 2022 [57]
- Step size $\zeta_t = \zeta / \|\mathbf{A}d(\mathbf{x}_t) - \mathbf{y}\|_2$
- 1000 neural function evaluations (NFEs) [57]

Method	CT, 20 Views		CT, 8 Views		Deblurring		Superresolution	
	PSNR \uparrow	SSIM \uparrow	PSNR \uparrow	SSIM \uparrow	PSNR \uparrow	SSIM \uparrow	PSNR \uparrow	SSIM \uparrow
Baseline	24.93	0.595	21.39	0.415	24.54	0.688	25.86	0.739
ADMM-TV	26.82	0.724	23.09	0.555	28.22	0.792	25.66	0.745
PnP-ADMM [60]	26.86	0.607	22.39	0.489	28.82	0.818	26.61	0.785
PnP-RED [61]	27.99	0.622	23.08	0.441	29.91	0.867	26.36	0.766
Whole image diffusion	32.84	0.835	25.74	0.706	30.19	0.853	29.17	0.827
Langevin dynamics [17]	33.03	0.846	27.03	0.689	30.60	0.867	26.83	0.744
Predictor-corrector [11]	32.35	0.820	23.65	0.546	28.42	0.724	26.97	0.685
VE-DDNM [62]	31.98	0.861	27.71	0.759	-	-	26.01	0.727
Patch Averaging [48]	33.35	0.850	28.43	0.765	29.41	0.847	27.67	0.802
Patch Stitching	32.87	0.837	26.71	0.710	29.69	0.849	27.50	0.780
PaDIS (Ours)	33.57	0.854	29.48	0.767	30.80	0.870	29.47	0.846

(Averages across all test images.)

Method	CT, 60 Views		CT, Fan Beam		Heavy Deblurring	
	PSNR \uparrow	SSIM \uparrow	PSNR \uparrow	SSIM \uparrow	PSNR \uparrow	SSIM \uparrow
Baseline	25.89	0.746	20.07	0.521	21.14	0.569
ADMM-TV	30.93	0.833	25.78	0.719	26.03	0.724
Whole image diffusion	35.83	0.894	26.89	0.835	28.35	0.808
PaDIS (Ours)	39.28	0.941	29.91	0.932	28.91	0.818

baseline FBP ADMM-TV whole image diffusion PaDIS ground truth



Top: 60 view CT

Bottom: fan-beam CT

≈ 400 HU window width

Patchsize

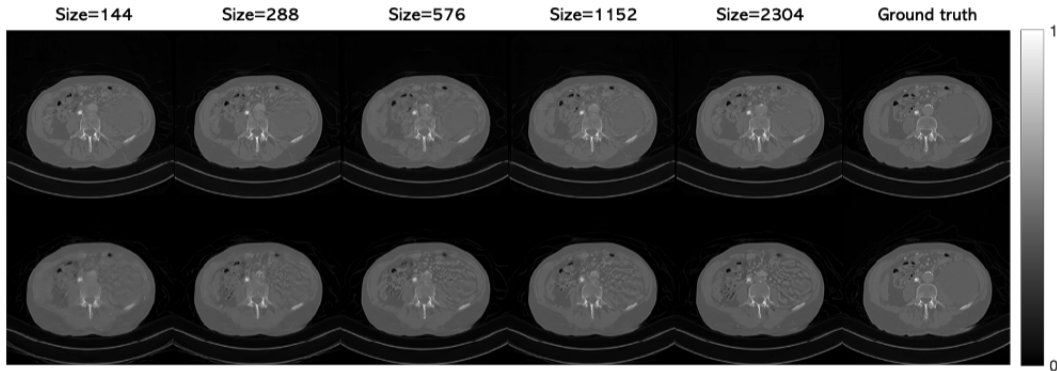
P	PSNR \uparrow	SSIM \uparrow
8	32.57	0.844
16	32.57	0.829
32	32.72	0.853
56	33.57	0.854
96	33.36	0.854
256	32.84	0.835

Positional encoding

	PSNR \uparrow	SSIM \uparrow
no position enc.	23.25	0.459
no position+init	24.51	0.518
with position	33.57	0.854



Dataset size	Patches 56×56		Whole image 256×256	
	PSNR \uparrow	SSIM \uparrow	PSNR \uparrow	SSIM \uparrow
144	32.28	0.841	29.12	0.804
288	32.43	0.837	31.09	0.829
576	33.03	0.846	31.81	0.835
1152	33.01	0.849	31.36	0.834
2304	33.57	0.854	32.84	0.835

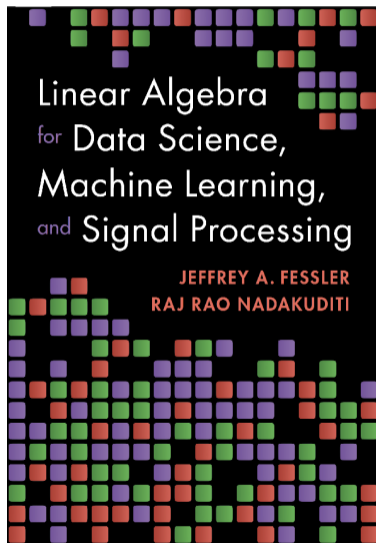


Top : PaDIS

Bottom : whole image diffusion model

- ▶ Learning patch score models is feasible with denoising score matching
- ▶ For limited training data, patch-models can outperform whole-image models
- ▶ Integrate invariances: amplitude scale / rotation / flip / DC offset ...
- ▶ Explore trade-offs between generalizability and in-distribution performance
- ▶ Extend to 3D, 3D+Time, 3D+Multicontrast

Tutorial Julia code: <https://github.com/JeffFessler/ScoreMatching.jl>



- Online demos:
<https://github.com/JeffFessler/book-la-demo>
- Topics include: low-rank matrix approximation, robust PCA, photometric stereo, video foreground/background separation, spectral clustering, matrix completion, ...
- Available from Cambridge Univ. Press

Talk and code available online at
<http://web.eecs.umich.edu/~fessler>



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