Conditional Cone Beam Neural Tomography —

Improving neural field-based cone beam CT reconstruction using a novel conditioning method

authors: S. Papa, D.M. Knigge, N. Moriakov, R. Valperga, M. Kofinas, J.J. Sonke, E. Gavves

0. *abstract —*

To **improve memory efficiency** and **reconstruction speed** of deep learning-based Cone Beam CT reconstruction (CBCT), we optimise a **neural field-based surrogate** of the CBCT **acquisition process** using projection data.

To **increase noise resistance** and **leverage anatomical consistencies**, we use **neural fields conditioned** through a **patient-specific** learned field of **modulations:** *neural modulation fields (NMF)*.

links —

affiliations —

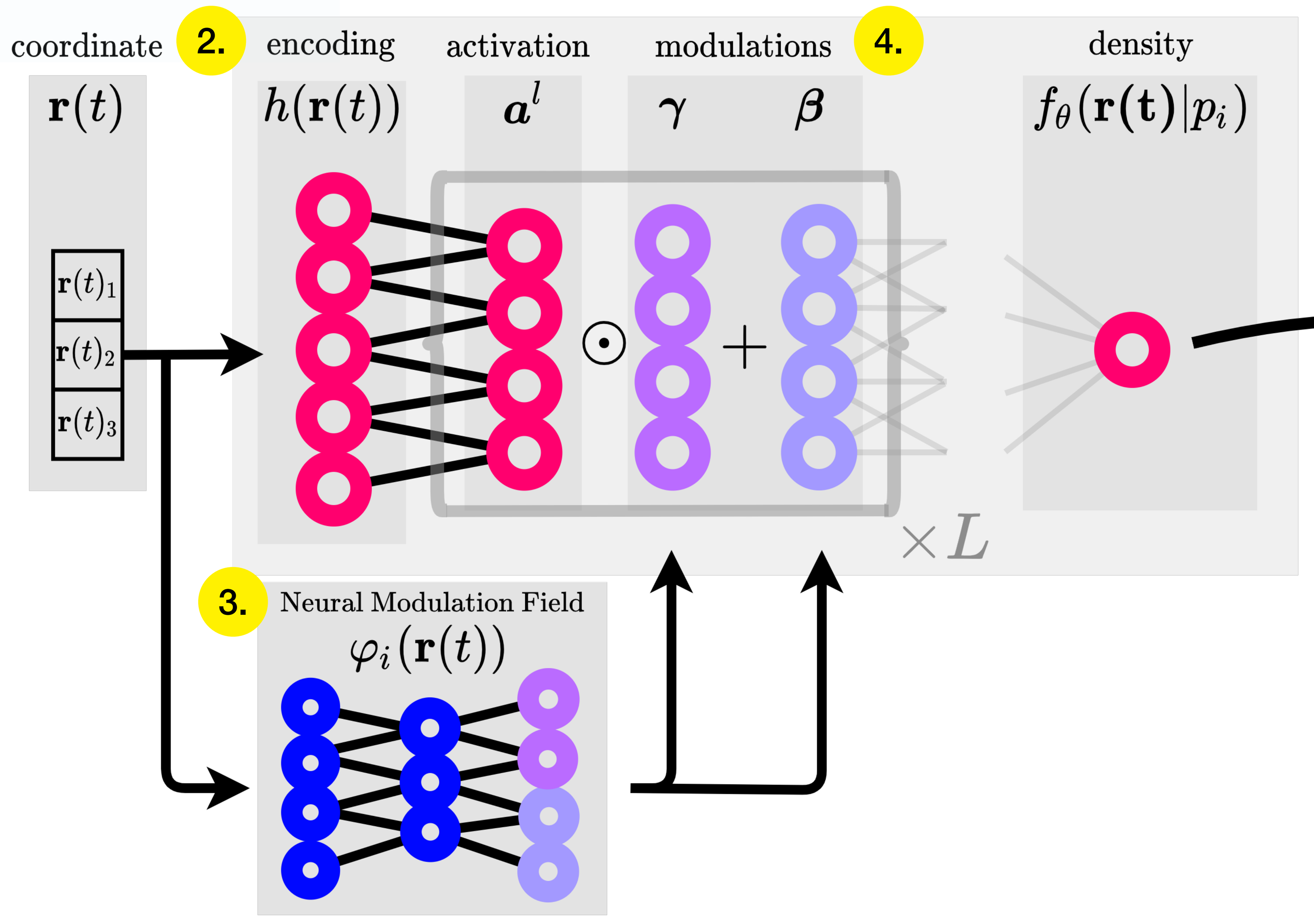
UNIVERSITY OF AMSTERDAM

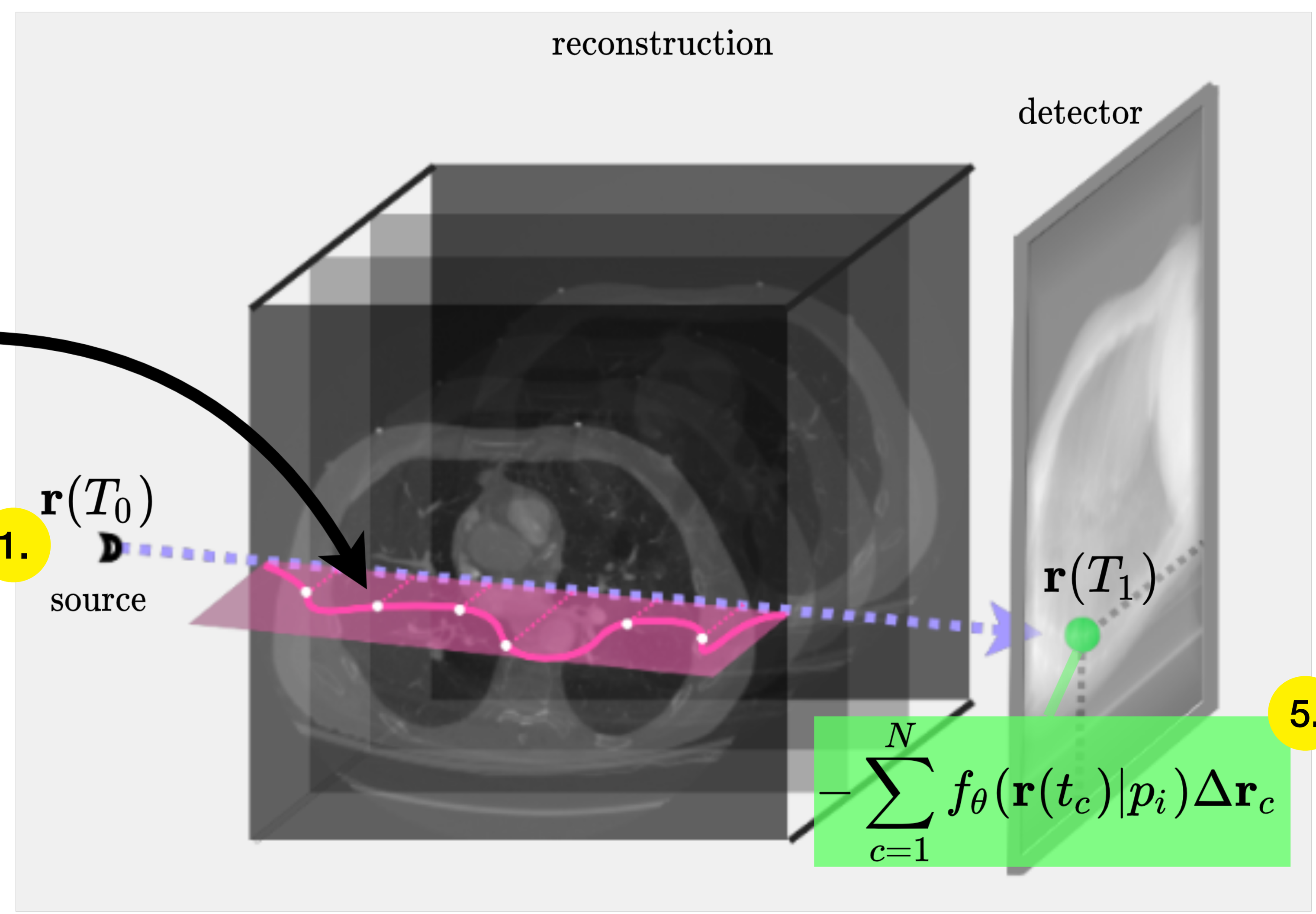
NETHERLANDS CANCER INSTITUTE ANTONI VAN LEEUWENHOEK

POP AART lab

Elekta

1. *method —*





density model:

1. Values for integral along a ray $\mathbf{r} : T \rightarrow \mathbb{R}^3$ from source to detector are modelled as neural field $f_\theta : \mathbb{R}^3 \rightarrow \mathbb{R}$.
2. Coordinates $\mathbf{r}(t)$ are embedded in multiresolution hash-encoding $h(\mathbf{r}(t))$, passed through L linear layers.

conditioning:

3. To leverage anatomical consistencies over patients, we model density for a patient p_i by modulating the activations $\boldsymbol{a}^l$ of a conditional shared neural field f_θ, by a patient-specific *Neural Modulation Field* (NMF) φ_i.
4. This conditioning function learns a field of $\boldsymbol{\gamma}, \boldsymbol{\beta}$ FiLM modulations over the input space $\mathbb{R}^3$ for a patient p_i.

optimisation:

5. The line integral $-\Sigma_{c=1}^{N} f_\theta(\mathbf{r}(t_c)\,|\,p_i)\Delta\mathbf{r}_c$ is supervised using the projection value observed at the corresponding detector pixel location.

2. *experiments —*

Tab. 1. Mean ± standard deviation of metrics over test set for FDK, Iterative, LIRE-L, NAF, and CondCBNT (ours). LIRE-L slightly outperforms CondCBNT but requires more GPU memory. **Our method excels with less memory and comparable runtime**.

		Noisy			Noise-free			
P.	Method	PSNR (↑)	SSIM (↑)	Time (s/vol)	PSNR (↑)	SSIM (↑)	Time (s/vol)	Mem. (MiB)
50	FDK	14.54 ± 2.90	.20 ± .07	0.8	16.09 ± 3.22	.43 ± .09	0.8	100
	Iterative	26.36 ± 2.11	.70 ± .08	7.7	27.13 ± 2.80	.71 ± .08	30.8	300
	LIRE-L	29.48 ± 2.07	.83 ± .05	3.9	-	-	-	2.1k
	NAF	22.83 ± 2.24	.58 ± .10	161	24.26 ± 2.52	.72 ± .08	582	18
	CondCBNT	28.31 ± 1.22	.80 ± .05	124	30.21 ± 1.42	.86 ± .05	647	96
400	FDK	16.43 ± 3.38	.45 ± .12	7	16.71 ± 3.47	.65 ± .09	7	100
	Iterative	28.38 ± 3.27	.78 ± .11	87.4	31.40 ± 6.22	.91 ± .07	174	600
	LIRE-L	30.70 ± 2.25	.88 ± .05	12.8	-	-	-	4k
	NAF	25.93 ± 2.45	.75 ± .08	275	25.04 ± 2.91	.77 ± .08	580	205
	CondCBNT	29.89 ± 1.39	.86 ± .05	763	30.63 ± 1.43	.88 ± .04	595	96

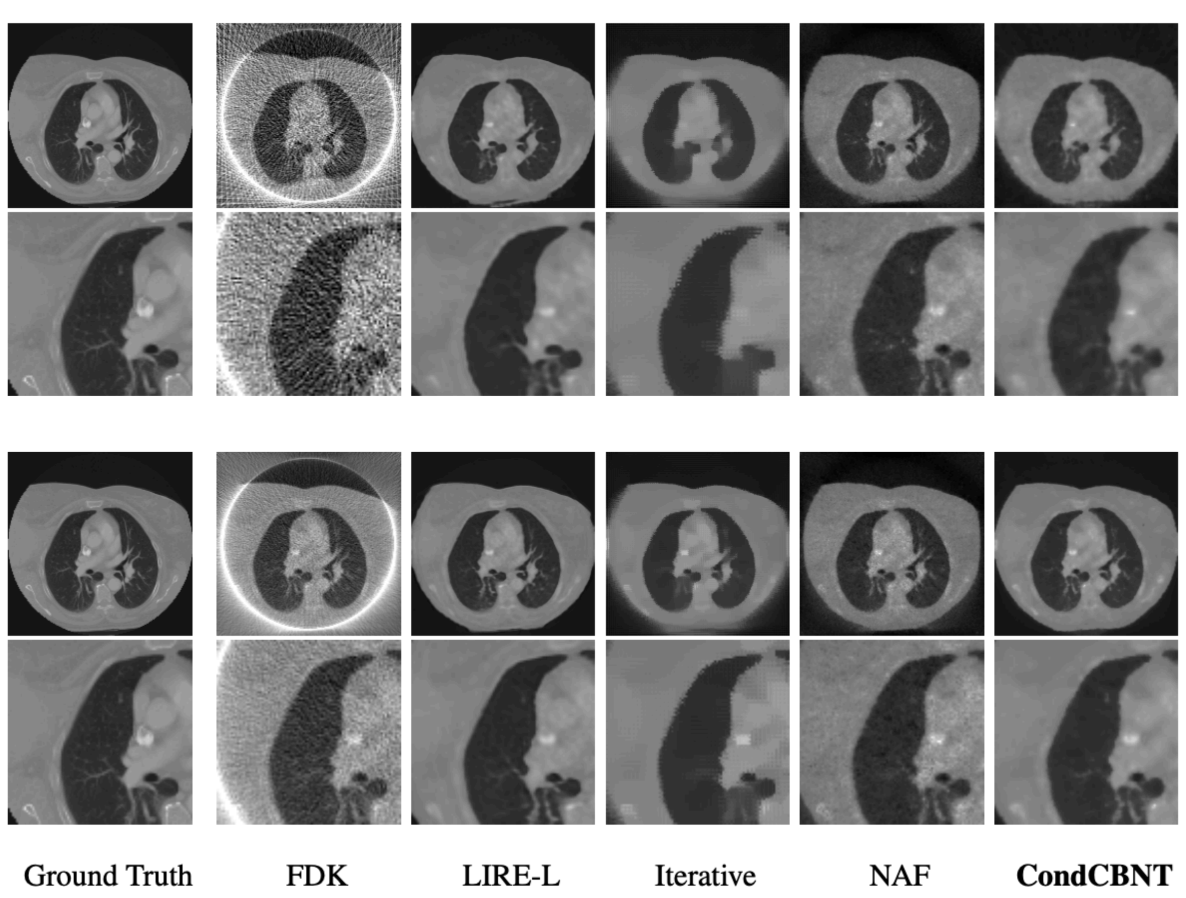


Fig. 3. Ground truth and reconstructions using all the methods applied to noisy projections. Top 50, bottom 400 projections. Grayscale with density in $[0 - 0.04]$. **Our method does not overfit the noise and maintains contrast**.

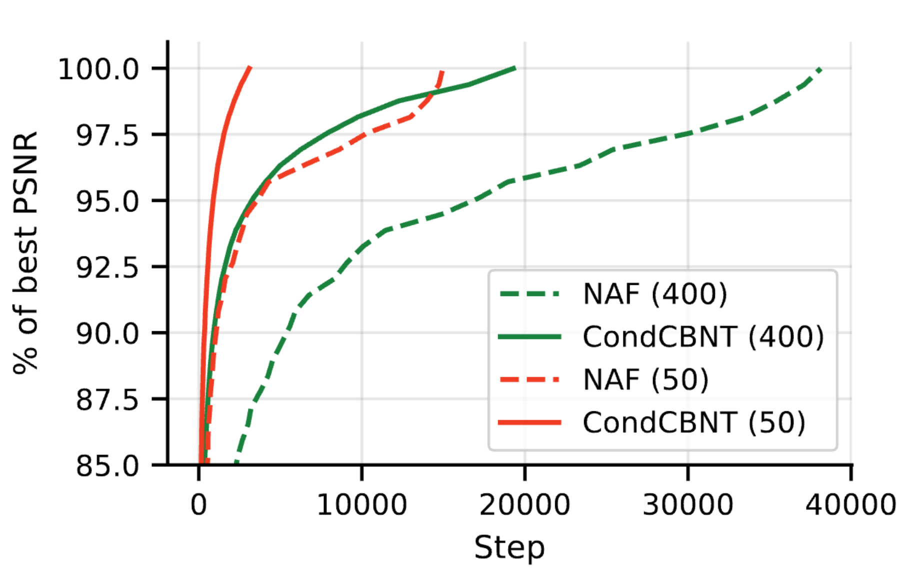


Fig. 2. Using noisy projections, the percentage of the best PSNR ↑ that a model can reach over the number of steps required to achieve it. **CondCBNT converges significantly faster**.

3. *conclusion —*

- We **improve noise resistance** of CBCT reconstruction methods by **sharing a conditional neural field over scans from different patient**.
- We propose learning a **continuous, local conditioning function** through sample-specific ***Neural Modulation Field***, which **modulates activations** in the conditional neural field to **express volume-specific details**.
- CondCBNT represents an efficient **improvement** over previous approaches in **memory scalability and quality**.