# Conditioning 3D Diffusion Models with 2D Images:

Towards Standardized OCT Volumes through En Face-Informed Super-Resolution

Coen de Vente<sup>1,2,3</sup>, Mohammad Mohaiminul Islam<sup>1,2</sup>, Philippe Valmaggia<sup>4,5</sup>, Carel Hoyng<sup>6</sup>, Adnan Tufail<sup>7</sup>, Clara I. Sánchez<sup>1,2</sup> on behalf of the MACUSTAR consortium

<sup>1</sup>qurAl Group, Informatics Institute, University of Amsterdam, The Netherlands; <sup>2</sup>Amsterdam UMC location University of Amsterdam, Biomedical Engineering and Physics, The Netherlands; <sup>3</sup>DIAG, Department of Radiology and Nuclear Medicine, Radboudumc, The Netherlands; <sup>4</sup>Department of Biomedical Engineering, Universität Basel, Switzerland; <sup>5</sup>Department of Ophthalmology, University Hospital Basel, Switzerland; <sup>6</sup>Department of Ophthalmology, Radboudumc, Nijmegen, The Netherlands; <sup>7</sup>Moorfields Eye Hospital NHS Foundation Trust, London, United Kingdom.

# Motivation

- -Volumetric medical images commonly suffer from **high anisotropy** (*i.e.*, having different resolutions in different directions). For example, in optical coherence tomography (OCT), **slice spacing varies substantially**.
- This can result in inaccuracies in shape measurements or quantifications of biological objects of interest:



## **Experiments**

- -Dataset: MACUSTAR, a European multicenter study.
- -Training: Patch size of 128 × 128 × 16.
- -Sampling: Patch size of 496 × 496 × 16, using DDIM & RePaint<sup>[1]</sup>, upsampling volumes from 30 to 240 slices.

	Tricubic	DDIM	DDIM <sub>ef</sub> (no CFG)	DDIM <sub>ef</sub>
MSE ↓	<b>0.006</b> ± 0.002	<b>0.006</b> ± 0.003	<b>0.006</b> ± 0.003	<b>0.006</b> ± 0.003
SSIM ↑	<b>0.451</b> ± 0.116	<b>0.444</b> ± 0.107	<b>0.447</b> ± 0.107	<b>0.447</b> ± 0.107
PSNR (dB)↓	<b>22.472</b> ± 1.418	<b>22.401</b> ± 1.644	<b>22.495</b> ± 1.673	<b>22.450</b> ± 1.683
$\textbf{LPIPS}_{\textbf{axi}} \downarrow$	<b>0.120</b> ± 0.027	<b>0.138</b> ± 0.030	<b>0.138</b> ± 0.030	<b>0.141</b> ± 0.031
$\textbf{LPIPS}_{\textbf{cor}} \downarrow$	0.548 ± 0.103	<b>0.158</b> ± 0.047	<b>0.158</b> ± 0.048	<b>0.162</b> ± 0.050
$\textbf{LPIPS}_{\textbf{sag}} \downarrow$	0.540 ± 0.088	<b>0.144</b> ± 0.049	<b>0.144</b> ± 0.049	<b>0.147</b> ± 0.050
LPIPS <sub>2.5D</sub> ↓	0.403 ± 0.072	<b>0.147</b> ± 0.041	<b>0.147</b> ± 0.042	<b>0.150</b> ± 0.043
$\textbf{LPIPS}_{_{\textbf{efproj}}}\downarrow$	0.231 ± 0.055	0.063 ± 0.039	<b>0.060</b> ± 0.039	<b>0.064</b> ± 0.039

 Segmented volume
 64.0 nL
 49.1 nL (-23.2%)

-Aim: Artifically upsample #slices in volumetric data.

### **Methods**



**Table I:** Classical image similarity metrics (MSE, SSIM, and PSNR) and perceptual metrics (all LPIPS variants). Results show mean ± std. dev.



reference  $\tilde{v}_{\theta}(\mathbf{x}_{t}, t, \mathbf{x}_{LR}, \mathbf{x}_{enface}) = (1 - w)v_{\theta}(\mathbf{x}_{t}, t, \mathbf{x}_{LR}) + wv_{\theta}(\mathbf{x}_{t}, t, \mathbf{x}_{LR}, \mathbf{x}_{enface})$ 



Fig. 3: Effect of classifier-free guidance (CFG).

# Conclusion

- Conditioning 3D diffusion models with **complementary**, **readily available 2D imaging** data results in **improved super-resolution**, especially in terms of perceptual metrics and image sharpness.
- This could be an important step **towards standardized and high quality medical imaging**.



c.w.devente@uva.nl coendevente.com

#### References

[1] Lugmayr, A., Danelljan, M., Romero, A., Yu, F., Timofte, R., & Van Gool, L. (2022). Repaint: Inpainting using denoising diffusion probabilistic models. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition* (pp. 11461–11471).

