



School of Computing

Task Setting



(a) Objaverse

Our method registers multiple NeRF blocks. (a) One of the collected objects from the Objaverse dataset. We render the images from a predefined camera trajectory to construct our training data. (b) NeRF models are trained in different coordinate frames. (c) Our method aligns NeRF blocks into the same coordinate frame without accessing raw image data.

Training Data Rendered from 3D Objects





































DReg-NeRF: Deep Registration for Neural Radiance Fields Yu Chen Gim Hee Lee **National Unviersity of Singapore**

APPROACH

(b) NeRF models are trained in different coordinate frame

(c) DReg-NeRF aligns NeRF blocks into the same coordinate frame without accessing raw image data











Training Loss

✓ Surface Field Loss $\mathcal{L}_{sf} = \frac{1}{N} ||\mathbf{S}([\widehat{\mathbf{X}}_{src}, \widehat{\mathbf{X}}_{tgt}]) + \mathbf{S}([\widetilde{\mathbf{X}}_{src}, \widetilde{\mathbf{X}}_{tgt}])||_1$ **Definition:** The surface field is the differential probability of the ray hitting a surface at a given point **X**. ✓ Confidence Loss $\mathcal{L}_{conf} = BCE(\widehat{\mathbf{S}}_{src}, \widetilde{\mathbf{S}}_{src}) + BCE(\widehat{\mathbf{S}}_{tgt}, \widetilde{\mathbf{S}}_{tgt})$ ✓ Correspondence Loss $C_{corr} = \sum \rho(S ||T^*(\mathbf{x}_i) - \mathbf{y}_i||; \eta, \gamma)$ ✓ Final Loss $C_{\text{final}} = C_{\text{conf}} + \lambda_1 C_{\text{sf}} + \lambda_2 C_{\text{corr}} + \lambda_3 C_{\text{feat}}$

Network Architecture



) Extract the pairwise voxel grid and a binary mask from the source and target NeRF. 2) Feed the voxel grid and a binary mask into the 3D feature pyramid network to extract voxel features.

3) **Downsample** the extracted voxel grid features by their spherical neighborhood. 4) Strengthen the resulting source and target features features by a transformer, where a self-attention layer is used to enhance the intra-contextual relations, and a crossattention layer is used to learn the inter-contextual relations. 5) **Decode** the features into correspondences and their corresponding confidence scores by a single-head attention layer.

Quantitative Results

1		Food 5648	Chair 4b05 (Chair 4659	Chair 3f2	d Cone	37b5 Figu	rine 260d	Figurine 0a5b	Figurine 09	f0 Banana 3a0	7 Banana 2373	Banana 0a07
$\Delta \mathbf{R}$	FGR [45]	178.34	50.50	28.54	81.3	1 10	04.52	89.13	26.35	138.0	00 12.1	7 6.92	2.86
	REGTR [42]	169.07	150.38	92.80	98.6	7	62.50	111.80	106.12	176.4	48 136.0	2 178.36	173.96
	Oursdf	77.48	160.13	157.21	22.9	1 10	08.09	121.32	10.53	95.8	39 95.4	3 3.49	6.96
	Ours	6.01	6.53	17.74	18.8	8	18.79	2.11	7.62	8.2	25 15.5.	5 10.95	1.36
Δt	FGR [45]	17.44	2.27	7.10	8.6	5	30.49	19.25	10.93	35.2	22 8.5) 1.53	1.36
	REGTR [42]	30.72	15.41	24.97	60.5	3	84.20	62.07	35.48	42.1	10 10.7	5 50.40	13.17
	Ours _{df}	15.52	7.32	11.72	2.2	9	21.70	33.61	1.95	21.4	40 13.1-	4 4.28	0.50
	Ours	1.78	4.13	8.74	5.0	17	3.06	3.54	10.68	3.1	18 0.4	6 1.00	1.22
		Fireplug 06d	5 Fireplug 00	63 Fireplu	ng 0152 S	hoe 18c3	Shoe 1627	Shoe 0 bf9	Shoe 022c	Teddy 1b47	Elephant 183a	Elephant 1608	Elephant 1a39
$\Delta \mathbf{R}$	FGR [45]	6.1	9 20.	32	7.50	10.23	178.14	71.55	50.28	8.05	7.65	21.37	30.97
	REGTR [42]	156.9	2 99.	60	4.04	2.55	175.21	97.92	154.91	149.17	177.15	172.28	102.62
	Ours _{df}	156.1	7 45.	76	12.34	14.69	131.66	158.66	6.84	6.32	6.97	3.92	126.94
	Ours	7.9	6 17.	43	4.86	6.06	12.95	6.48	2.93	11.44	8.00	11.13	13.84
Δt	FGR [45]	5.8	3 0.	83	1.17	0.04	4.99	8.82	35.47	1.11	4.51	14.08	11.03
	REGTR [42]	68.7	1 38.	74	2.13	3.53	43.40	61.37	102.00	42.84	52.26	66.15	34.54
	Ours _{df}	10.5	4 5.	32	2.60	4.66	28.63	24.82	4.40	2.20	4.26	1.40	33.57

Qualitative Results



CHECK OUT OUR PROJECT PAGE FOR MORE DETAILS! https://aibluefisher.github.io/DReg-NeRF



PARIS



