Mesh registration via geometric feature homogenization and offset cross-attention: application to 3D photogrammetry

Inés A. Cruz-Guerrero[1], Connor Elkhill[1], Jiawei Liu[1], Phuong Nguyen[2], Brooke French[2], and Antonio R. Porras[1, 2, 3, 4]

[1] Department of Biostatistics and Informatics, Colorado School of Public Health, University of Colorado Anschutz Medical Campus
[2] Department of Pediatric Plastic and Reconstructive Surgery, Children's Hospital Colorado
[3] Department of Pediatric Neurosurgery, Children's Hospital Colorado, Aurora, CO
[4] Departments of Pediatrics, Surgery and Biomedical Informatics, School of Medicine, University of Colorado Anschutz Medical Campus, Aurora, CO

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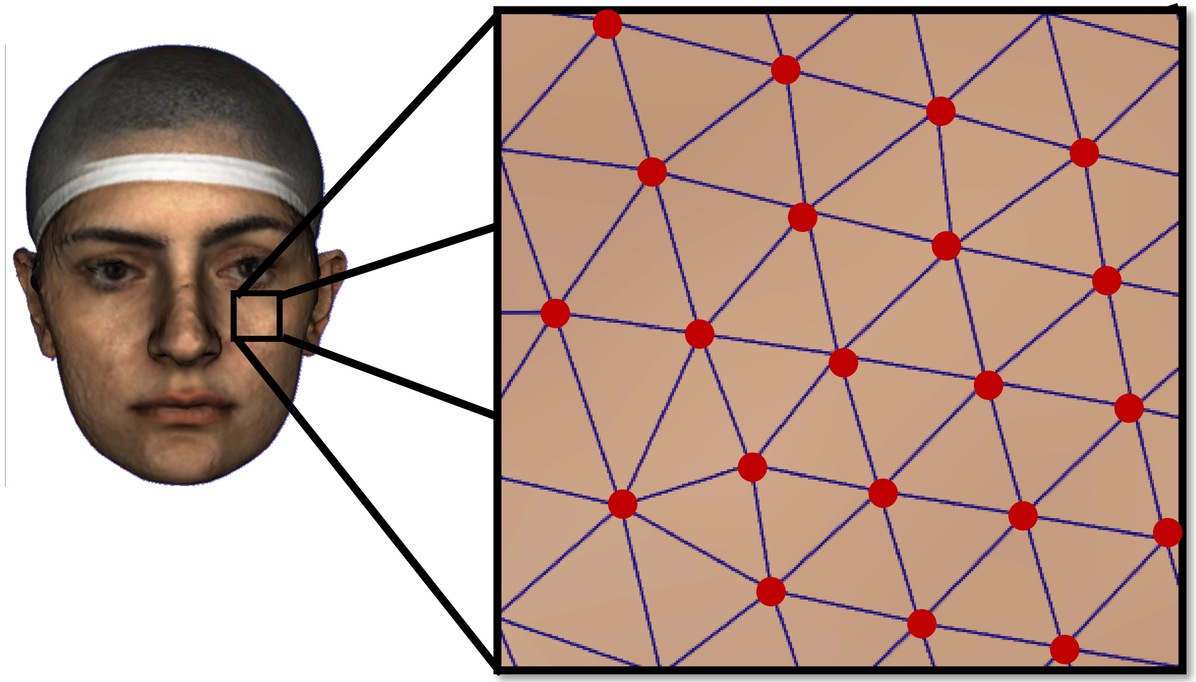
Introduction

3D photogrammetry



Cost efficient

Fast

Non-invasive

Radiation Free

Challenges of automated analysis of 3D photograms

Unstructured data representations

Variable spatial resolutions

Variable patient pose

Lack anatomical correspondences

State-of-the-art

- Point cloud-based methods: DCP[1], PointnetLK[2], DeepGMR[3], and PCRnet[4]
- Difficulties to process large numbers of nodes and require resampling to perform registration
- Do not consider local structure information (nodes connectivity)
- Inter-patient registration is often limited to selecting nodes with similar characteristics

Goal

To build an efficient and automated method for 3D photogram registration

[1] Wang & Solomon, 2019, Deep Closest Point.
[2] Aoki et al., 2019, Proceedings of the IEEE CVPR.
[3] Yuan et al., 2019, DeepGMR.
[4] Sarode et al., 2019, PCRNet.

Feature homogenization module

Based on Chebyshev polynomials[3]

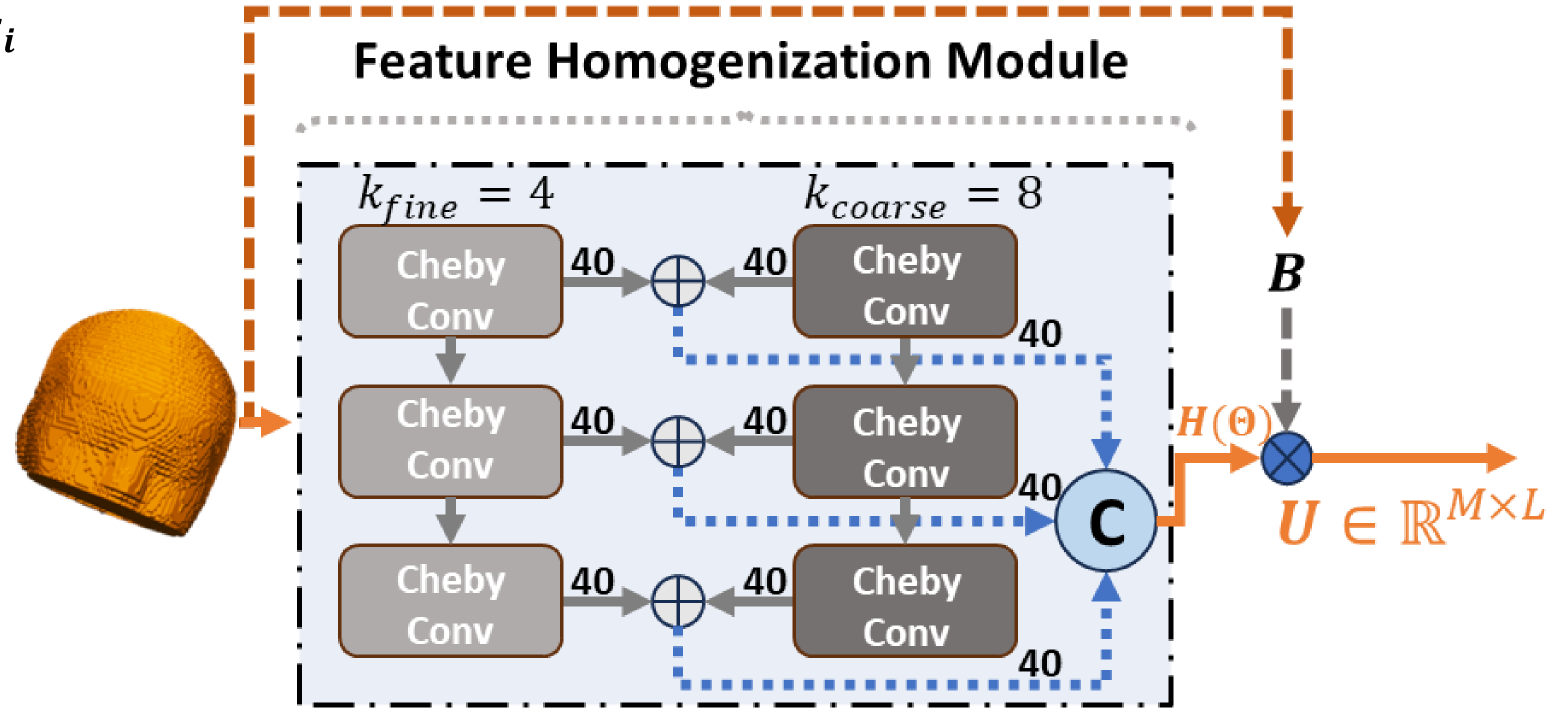
$$x_{i+1}(K;\theta^i) = \sum_{k=0}^{K-1} \theta_k^i T_k(\tilde{L}) x_i$$

x_i: input feature vector
K: Polynomials order [4,8]
θ^i: trainable coefficients
$\tilde{L}$: normalized graph Laplacian

Dimensionality reduction by:

$$U(B,\Theta) = B^T H(\Theta)$$

$U(B,\Theta)$: uniform output features
$H(\Theta)$: learned feature transformation
Θ: trainable coefficients
B: variable dimensionality input data



[3] Defferrard et al., 2016, Advances in Neural Information Processing Systems.

Offset cross-attention (OCA) module

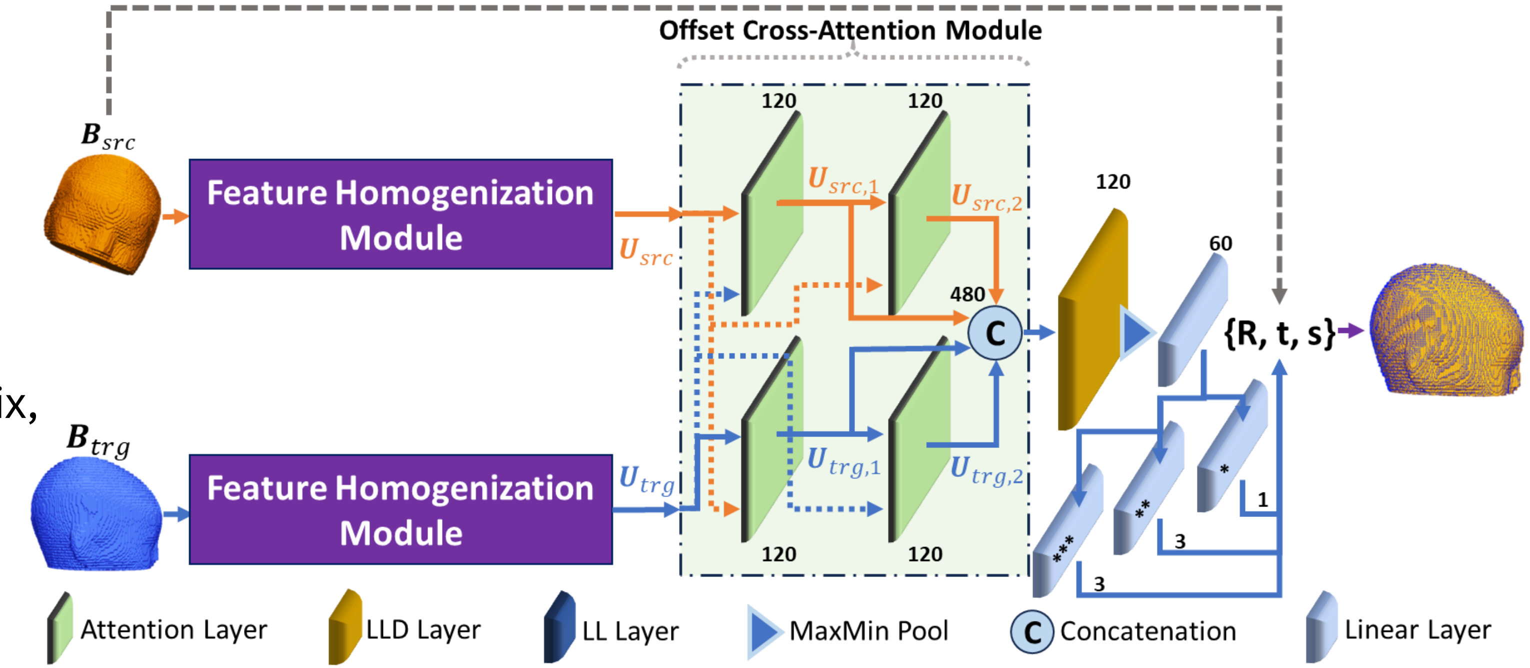
Offset Cross-Attention layers[4]

$$OCA(\boldsymbol{Z}_1, \boldsymbol{Z}_2) = LBL(\boldsymbol{Z}_1 - softmax(\boldsymbol{Q}\boldsymbol{K}^{\top})\boldsymbol{V}) + \boldsymbol{Z}_1$$

Four offset cross-attention layers

$$\boldsymbol{X}_{src,1} = OCA(\boldsymbol{U}_{src}, \boldsymbol{U}_{trg})$$
$$\boldsymbol{X}_{trg,1} = OCA(\boldsymbol{U}_{trg}, \boldsymbol{U}_{src})$$
$$\boldsymbol{X}_{src,2} = OCA(\boldsymbol{X}_{src,1}, \boldsymbol{U}_{src})$$
$$\boldsymbol{X}_{trg,2} = OCA(\boldsymbol{X}_{trg,1}, \boldsymbol{U}_{trg})$$

Three specialized final layers: rotation matrix, translation vector and scaler factor.



Optimization

$$L = \left\| R(\alpha, \beta, \gamma)^T R(\hat{\alpha}, \hat{\beta}, \hat{\gamma}) - I \right\|_F + \|t - \hat{t}\|^2 + \|s - \hat{s}\|^2$$

$\{\alpha, \beta, \gamma\}$: rotation angle in $\{X, Y, Z\}$, t : translation vector, and s: scaler factor

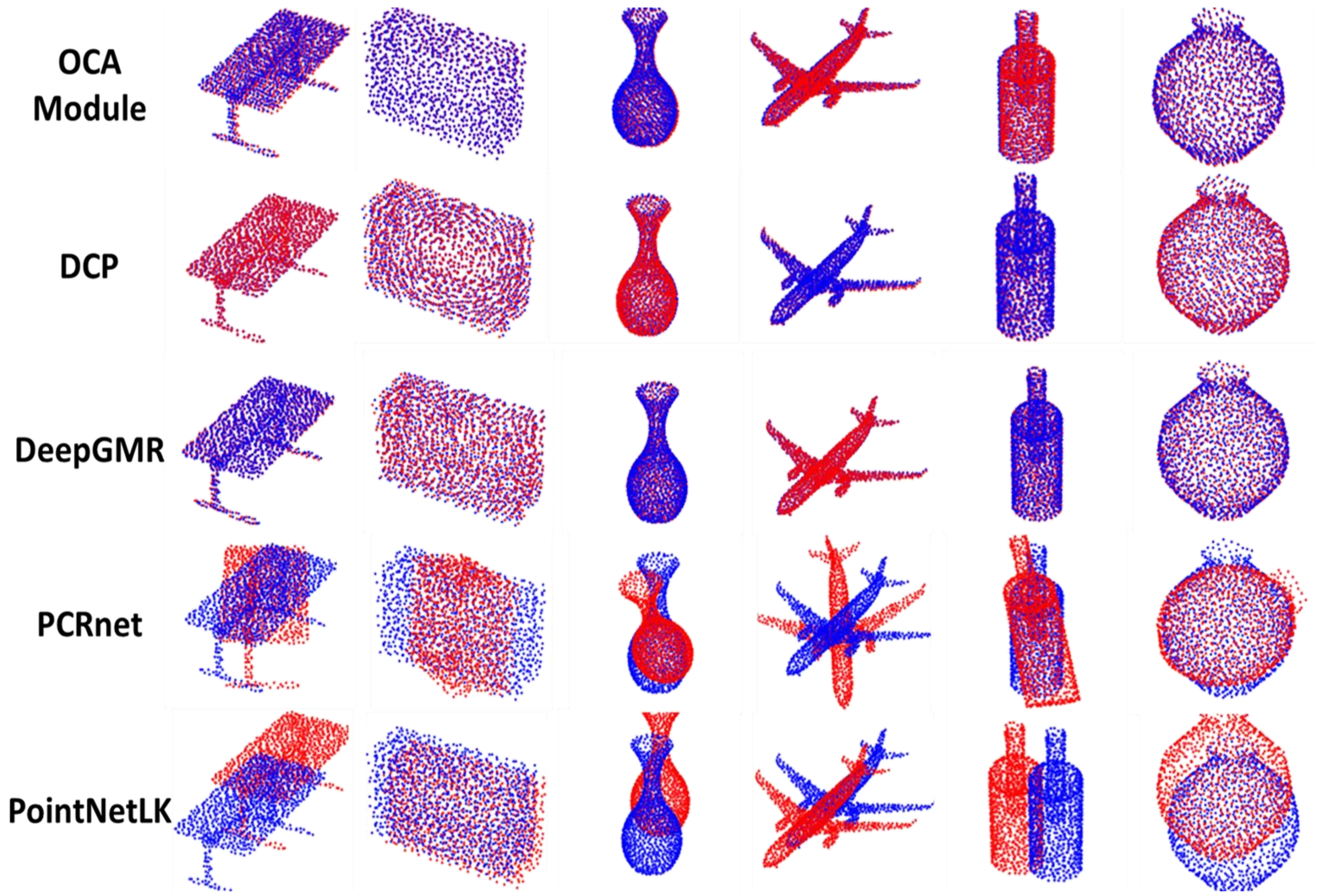
[4] Guo et al., 2021, Computational Visual Media.

Experiment 1

OCA Evaluation

ModelNet40 Dataset	Applied Transformations
Training set: 9,846	Rotation range: $\pm 45^{\circ}$
Test set: 2,468	Translation range: ± 0.5

Method	MSE		MAE		MSE	Chamfer
	$\{\alpha, \beta, \gamma\}$	**t**	$\{\alpha, \beta, \gamma\}$	**t**	(src,trg)	(src,trg)
DCP	5.43	**4E-4**	1.45	**0.01**	**4E-4**	0.46
PointNetLK	80.30	0.08	1.52	0.24	0.09	0.23
DeepGMR	32.67	1E-3	2.45	0.02	2E-3	**0.02**
PCRnet	683.18	0.08	22.63	0.24	0.05	0.13
OCA module	**3.42**	1E-3	**1.29**	0.02	1E-3	0.07



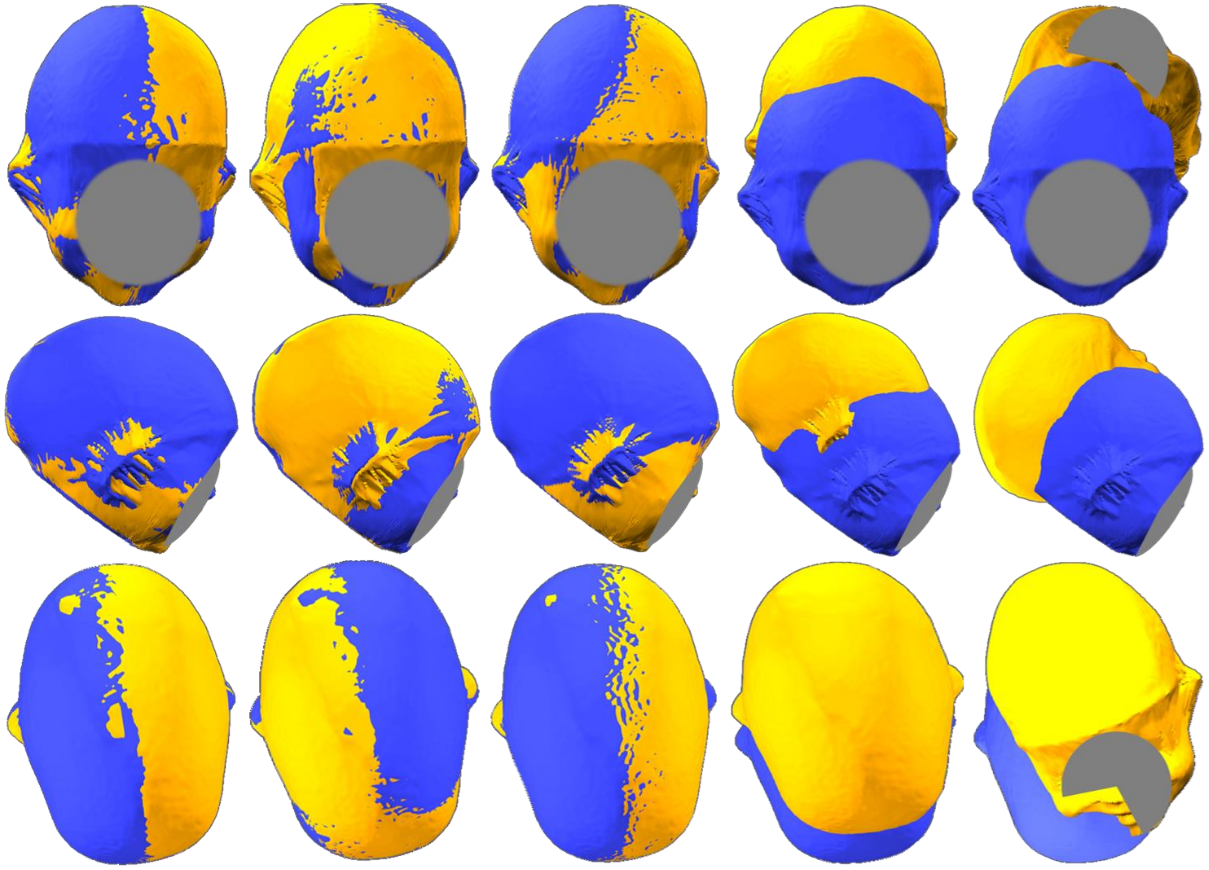
[5] Wu et al., 2015, Proceedings of the IEEE CVPR.

Experiment 2

Intra-subject registration of 3D photograms

3D Photogram Dataset	Applied Transformations
Training set: 1,396 Test set: 174 Validation set: 174	Rotation range: $\pm 45^{o}$ Translation range: ± 0.5

Method	MSE		MAE		MSE	Chamfer
	$\{\alpha, \beta, \gamma\}$	**t**	$\{\alpha, \beta, \gamma\}$	**t**	(src,trg)	(src,trg)
DCP	60.09	0.01	5.01	0.06	0.03	4.81
PointNetLK	278.43	0.10	5.87	0.25	0.13	0.30
DeepGMR	31.53	0.01	**3.14**	0.06	0.02	0.189
PCRnet	494.64	0.01	15.12	0.25	0.08	0.19
Proposed method	**27.761**	**1E-3**	3.66	**0.03**	**0.01**	**0.02**



Proposed Method **DCP** **DeepGMR** **PCRnet** **PointNetLK**

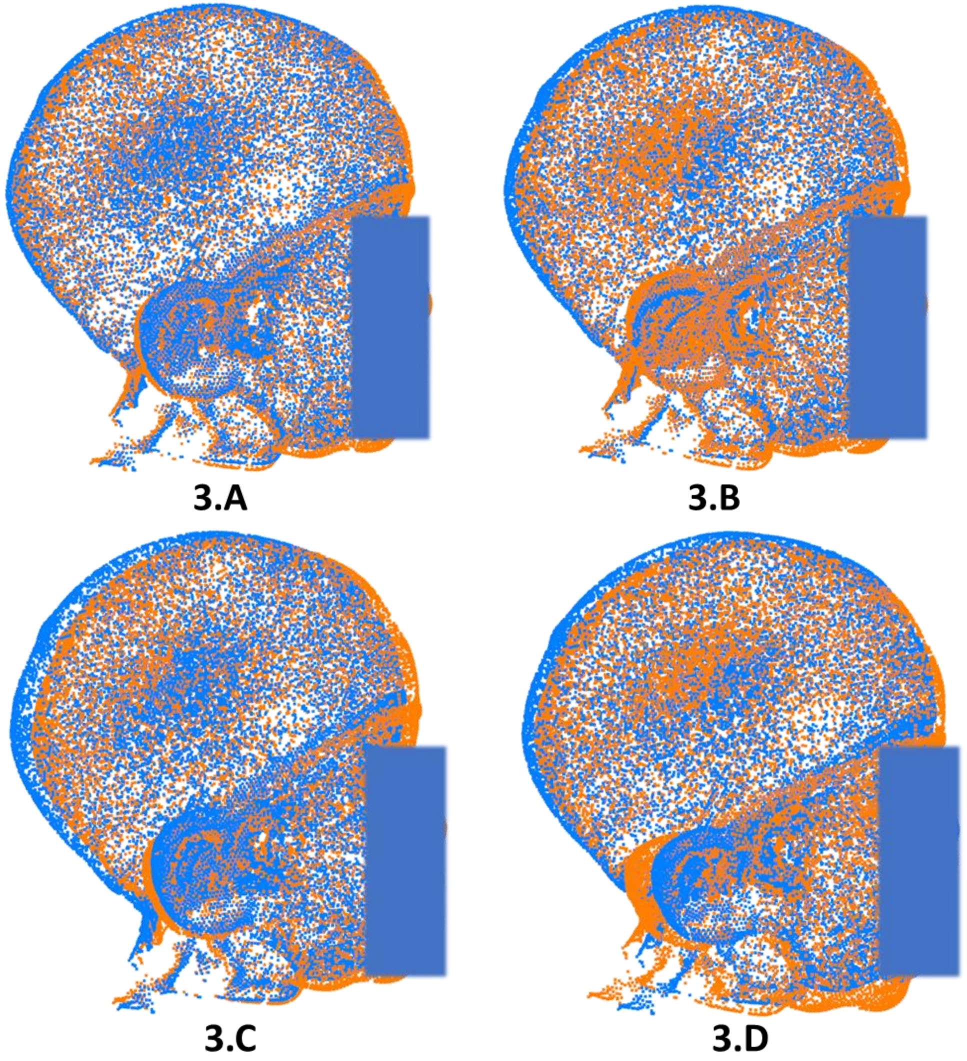
[6] Elkhill et al., 2023, Computer Methods and Programs in Biomedicine.

Experiment 3

Intra/Inter-subject registration of 3D photograms

3D Photogram Dataset	Applied Transformations
Training set: 13,952	Rotation range: $\pm 45^{o}$
Test set: 1,744	Translation range: ± 0.5
Validation set: 1,744	Scaler range: $\pm 50\%$

Metric		MSE			MAE			MSE	Chamfer
Experiment		$\{\alpha, \beta, \gamma\}$	$\boldsymbol{t}$	s	$\{\alpha, \beta, \gamma\}$	$\boldsymbol{t}$	s	(src,trg)	(src,trg)
3.A	Same subject	11.55	1E-3	-	2.03	0.02	-	0.01	0.02
3.B	Inter-subject	23.72	1E-3	-	3.51	0.02	-	0.01	0.02
3.C	Same subject	13.34	1E-3	4E-3	2.23	0.03	0.05	0.01	0.02
3.D	Inter-subject	30.42	1E-3	4E-3	3.94	0.03	0.05	0.01	0.02



[6] Elkhill et al., 2023, Computer Methods and Programs in Biomedicine.

Conclusions

- 3D surface registration method independent from the number of nodes and spatial resolution
- Feature homogenization module allows creating uniform representations independent from original data dimensionality
- Offset cross-attention module improves registration performance by learning common spatial patterns between meshes
- State-of-the-art accuracy without data pre-processing or spatial sampling

Thanks!

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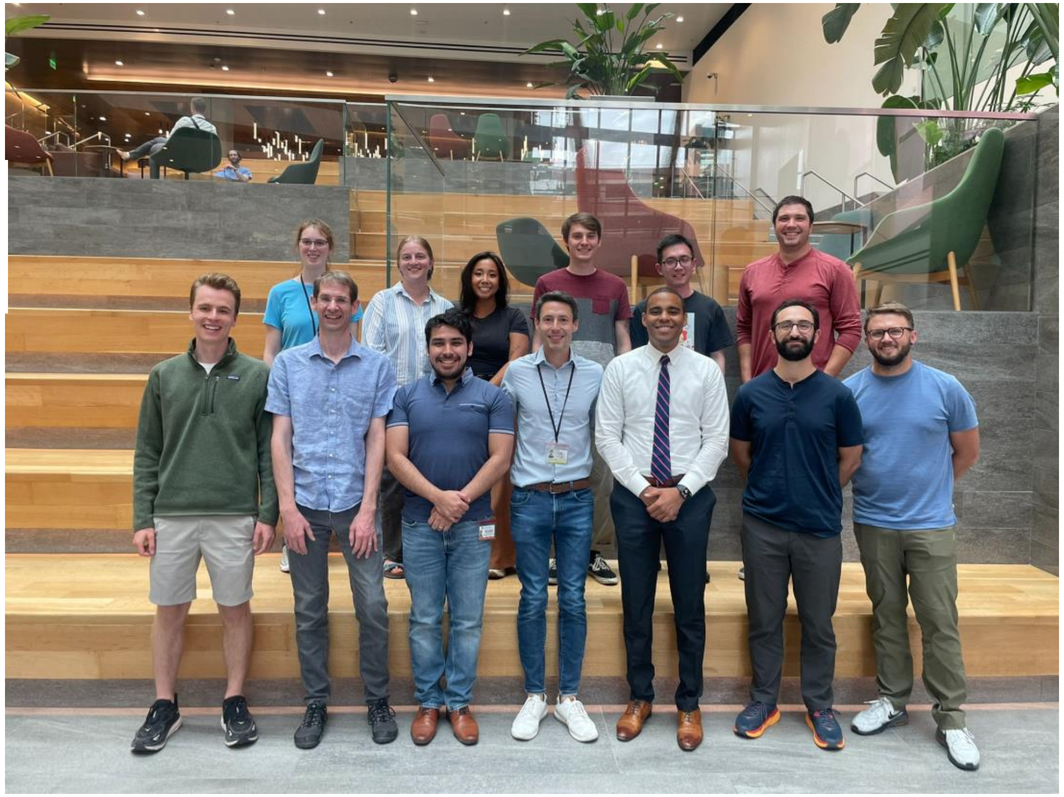

alejandro.cruzguerrero@cuanschutz.edu