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

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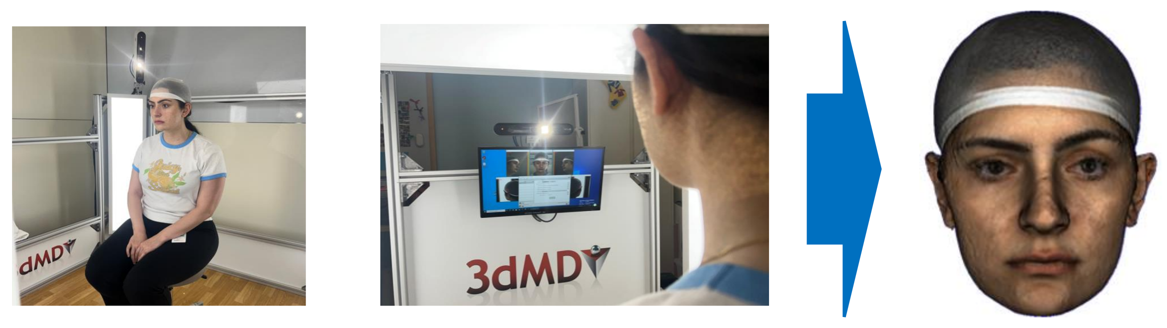
Background

3D photogrammetry



Cost efficient | Non-invasive | Accurate | Fast

State-of-the-art challenges

- ❑ High spatial resolutions with large number of vertices
- ❑ Variable number or vertices between patients
- ❑ Require sampling and/or interpolation
- ❑ Disregard local mesh structure information

Motivation

3D photogram registration is necessary to enable:

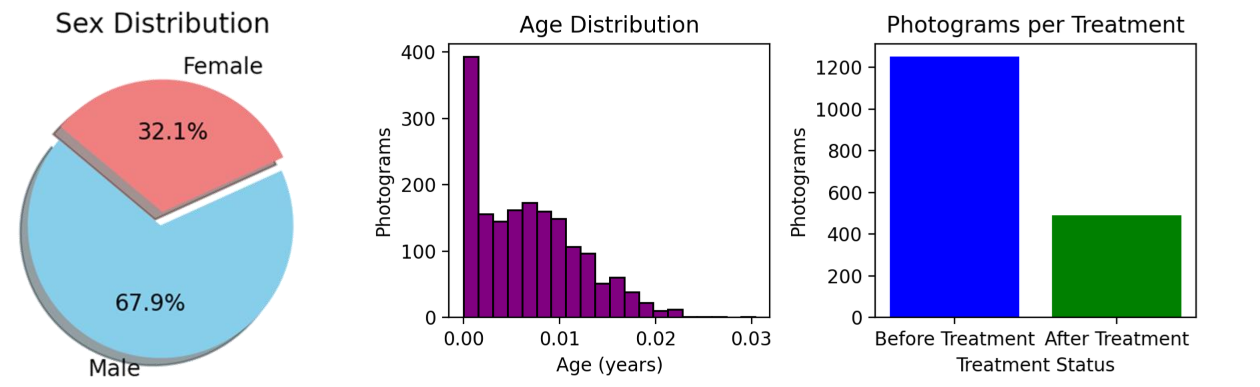
- ❑ Quantitative population studies (e.g., anatomical modeling)
- ❑ Longitudinal pediatric evaluation

Goal

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

Data

- ❑ ModelNet40 dataset [1]
  - 12,311 3D point clouds with 1024 points
  - 40 object categories
  - Uniformly sampled from original meshes
- ❑ 3D photograms dataset [2]
  - 1,744 3D photograms of children with craniosynostosis
  - Average age: 2.16 ± 2.32 years (range birth -18 years)
  - Average number of nodes: 23,686±915



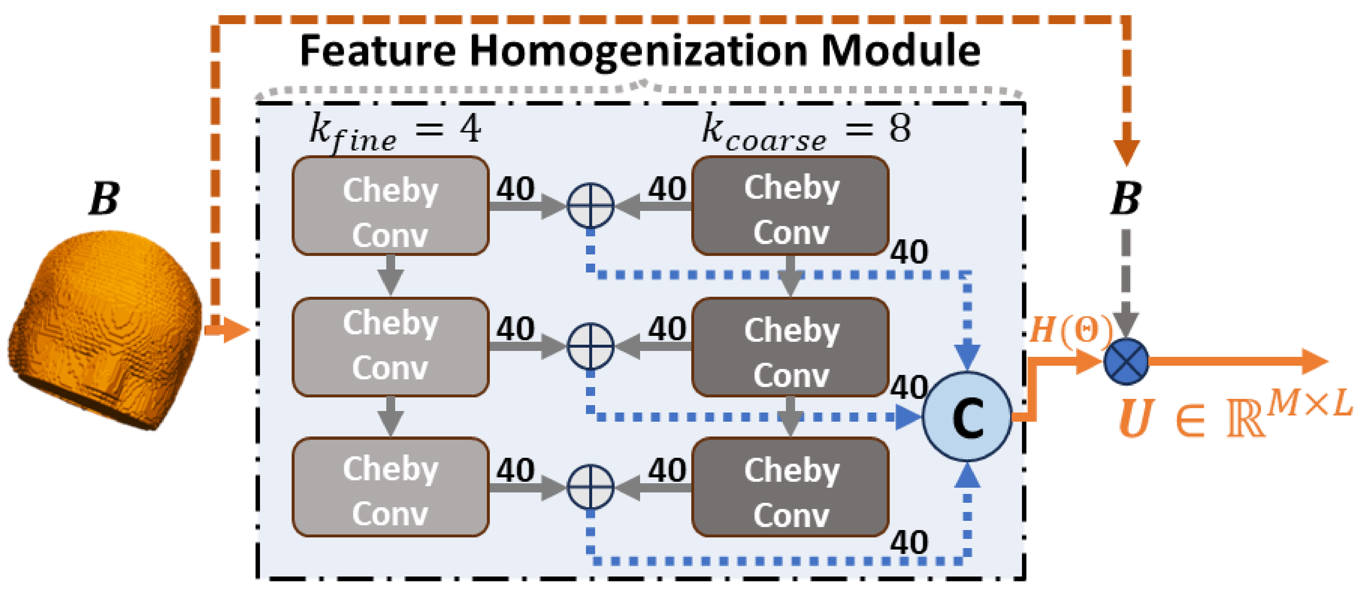
Methods

Feature homogenization network

Dimensionality reduction via feature homogenization:

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

$\boldsymbol{B} \in \mathbb{R}^{NxM}$: variable dimensionality input data
$\boldsymbol{H}(\boldsymbol{\Theta}) \in \mathbb{R}^{NxL}$: learned feature transformation
$\boldsymbol{U}(\boldsymbol{B},\boldsymbol{\Theta}) \in \mathbb{R}^{MxL}$: uniform dimensionality output features
$\boldsymbol{\Theta}$: trainable coefficients



Offset cross-attention (OCA) network

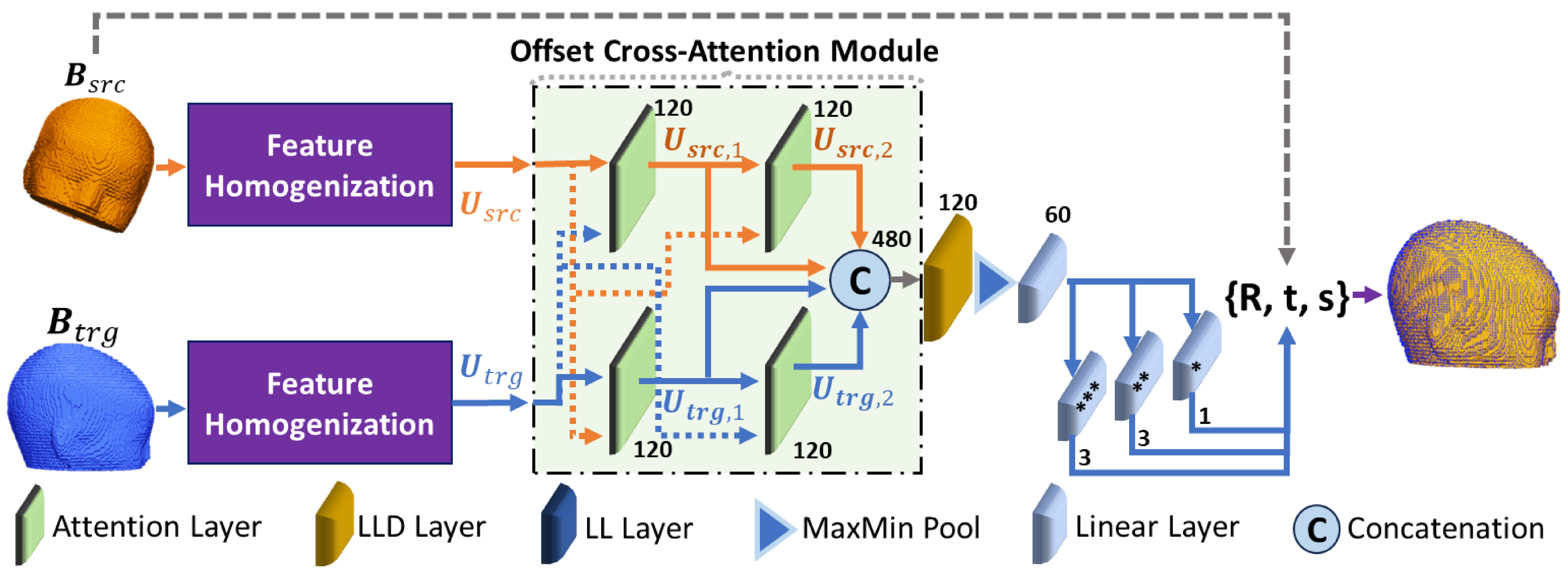
Efficient comparisons between latent feature representations:

- ❑ Offset Cross-Attention operation

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

- ❑ Four OCA layers

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



Optimization

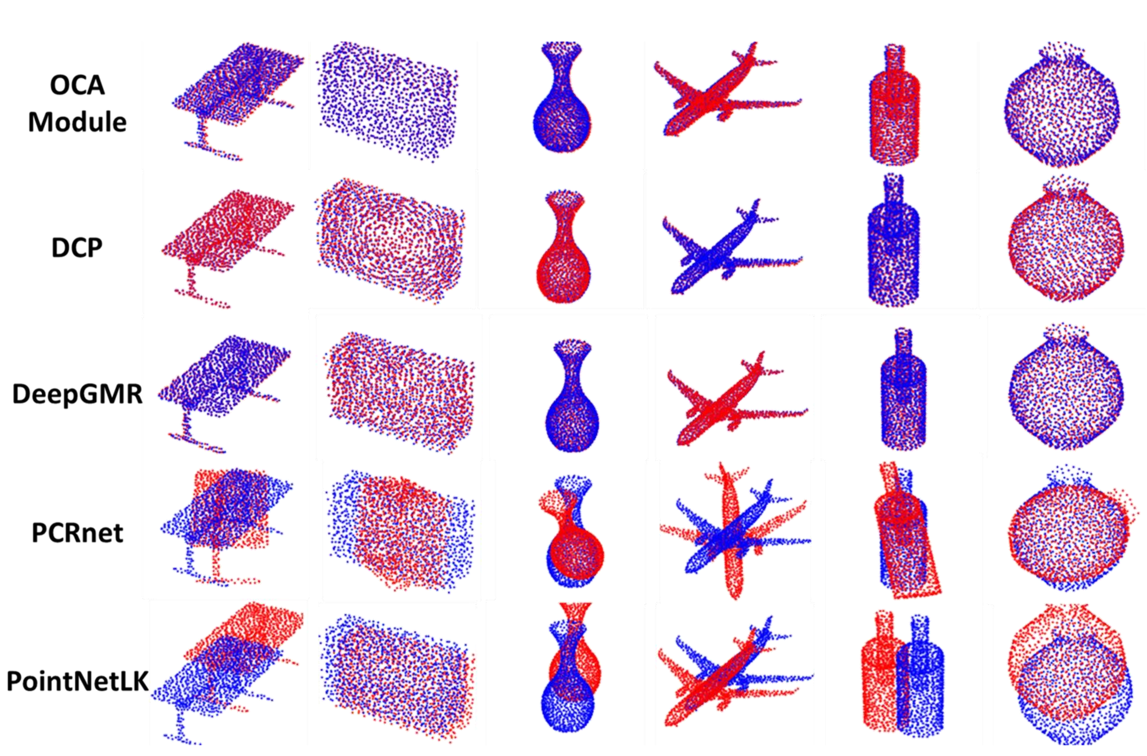
$$\mathcal{L} = \left\|R(\alpha,\beta,\gamma)^{T}R(\hat{\alpha},\hat{\beta},\hat{\gamma}) - I\right\|_F$$
$$+\|t-\hat{t}\|^2 + \|s-\hat{s}\|^2$$

$\{\alpha,\beta,\gamma\}$: rotation angles
t : translation vector
s: scaler factor

Experiments and results

1 OCA Evaluation with ModelNet40 dataset [1]

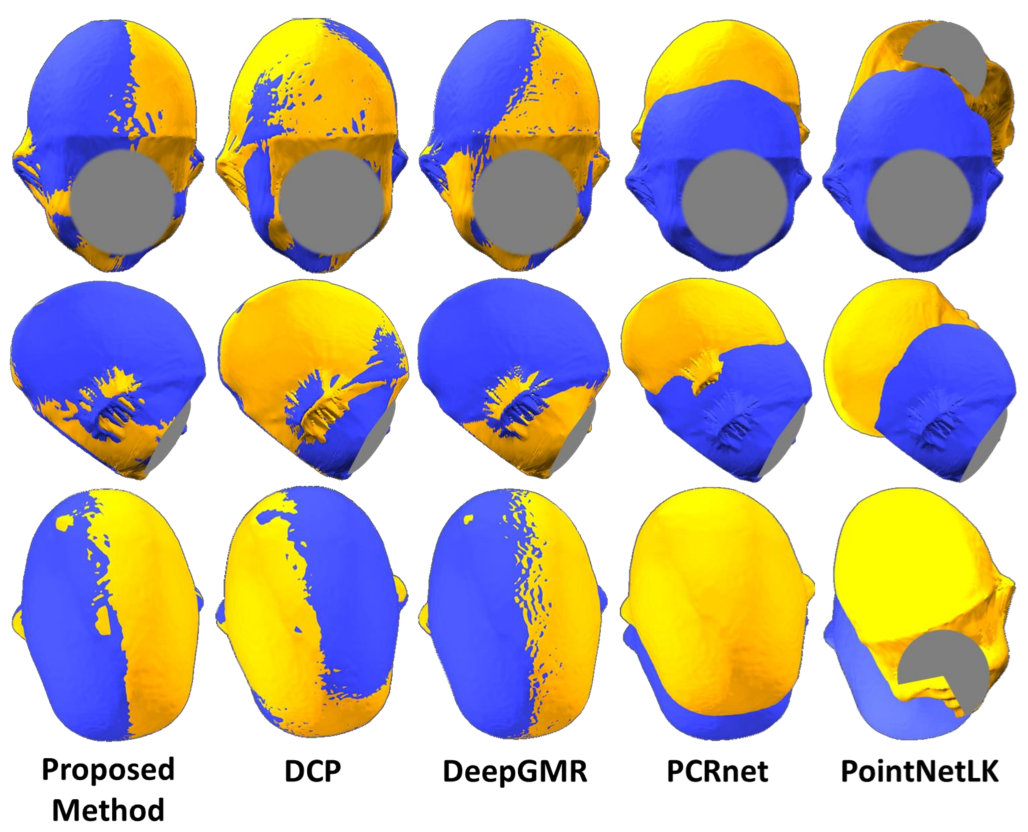
- ❑ Training size: 9,846
- ❑ Testing size: 2,468
- ❑ Rotation: ±45º
- ❑ Translation: ±0.5



Method	MSE		MAE		MSE	Chamfer
	{α, β, γ}	**t**	{α, β, γ}	**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

2 Intra-subject registration of 3D photograms

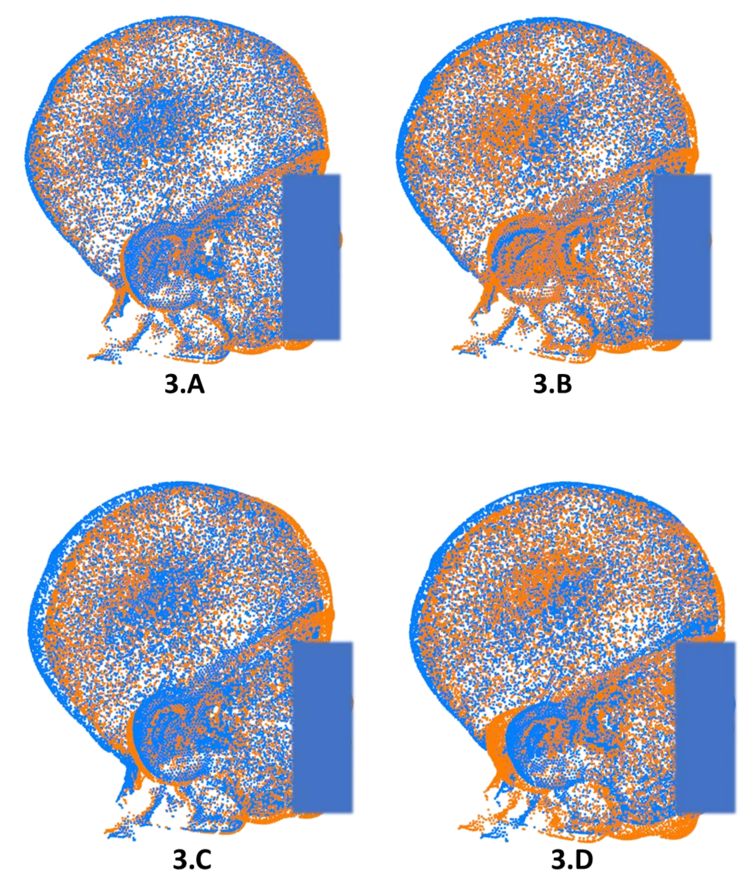
- ❑ Training size: 1,396
- ❑ Testing size: 174
- ❑ Rotation: ±45º
- ❑ Translation: ±0.5



Method	MSE		MAE		MSE	Chamfer
	{α, β, γ}	**t**	{α, β, γ}	**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**

3 Intra/Inter-subject registration of 3D photograms with scaling

- ❑ Training size: 13,952
- ❑ Testing size: 1,744
- ❑ Rotation: ±45º
- ❑ Scaling: $[-0.5, 0.5]$
- ❑ Translation: ±50%



Metric		MSE			MAE			MSE	Chamfer
Experiment		{α, β, γ}	***t***	s	{α, β, γ}	***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

Conclusions

- ❑ 3D surface registration method independent from the number of nodes and spatial resolution
- ❑ Feature homogenization module allows creating uniform representations independent from 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

References

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Github code and more information: