G-MSM: Unsupervised Multi-Shape Matching with Graph-based Affinity Priors

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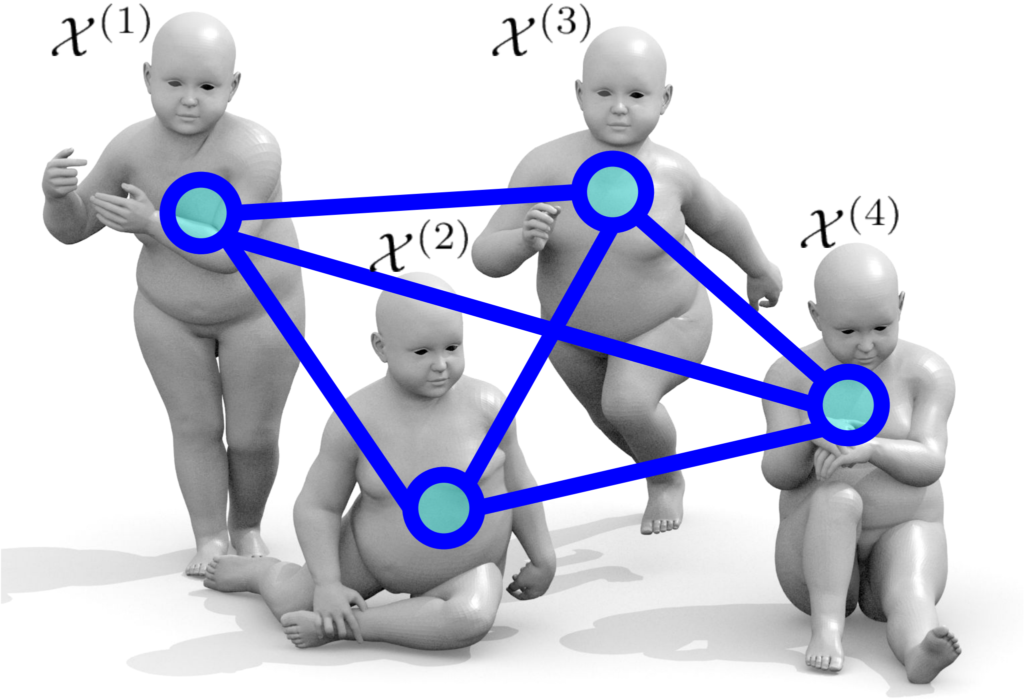
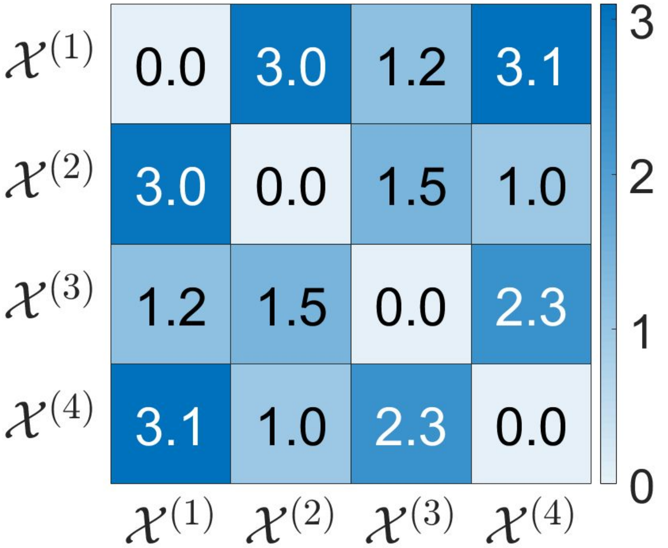
Poster ID: THU-PM-206

Unsupervised Multi-Shape Matching

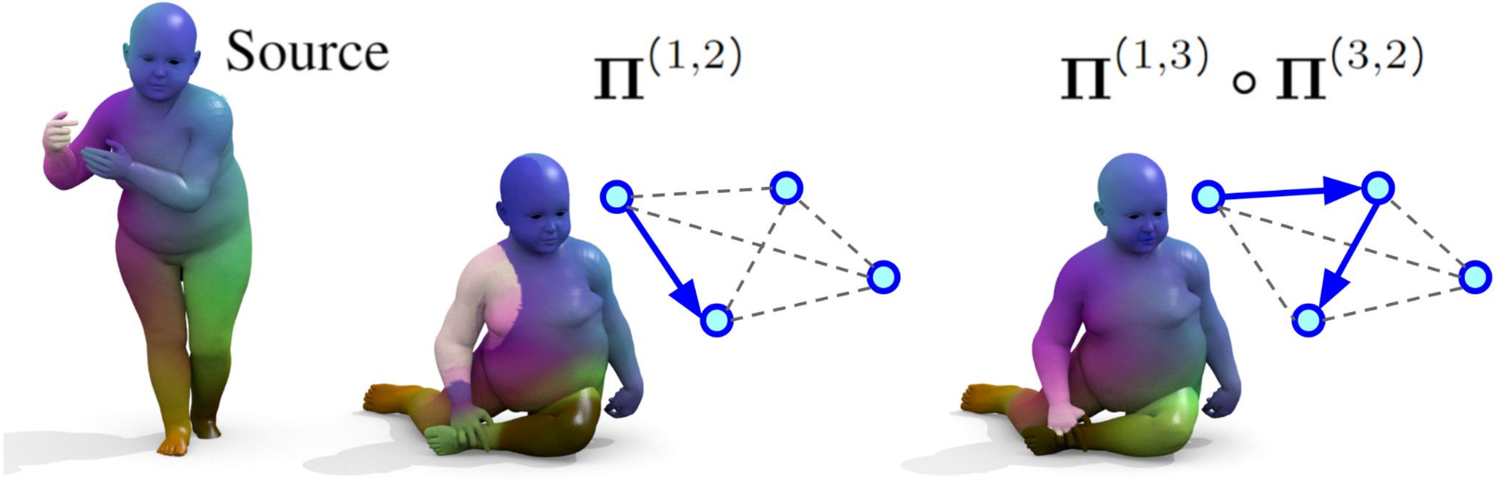




Approach – Summary

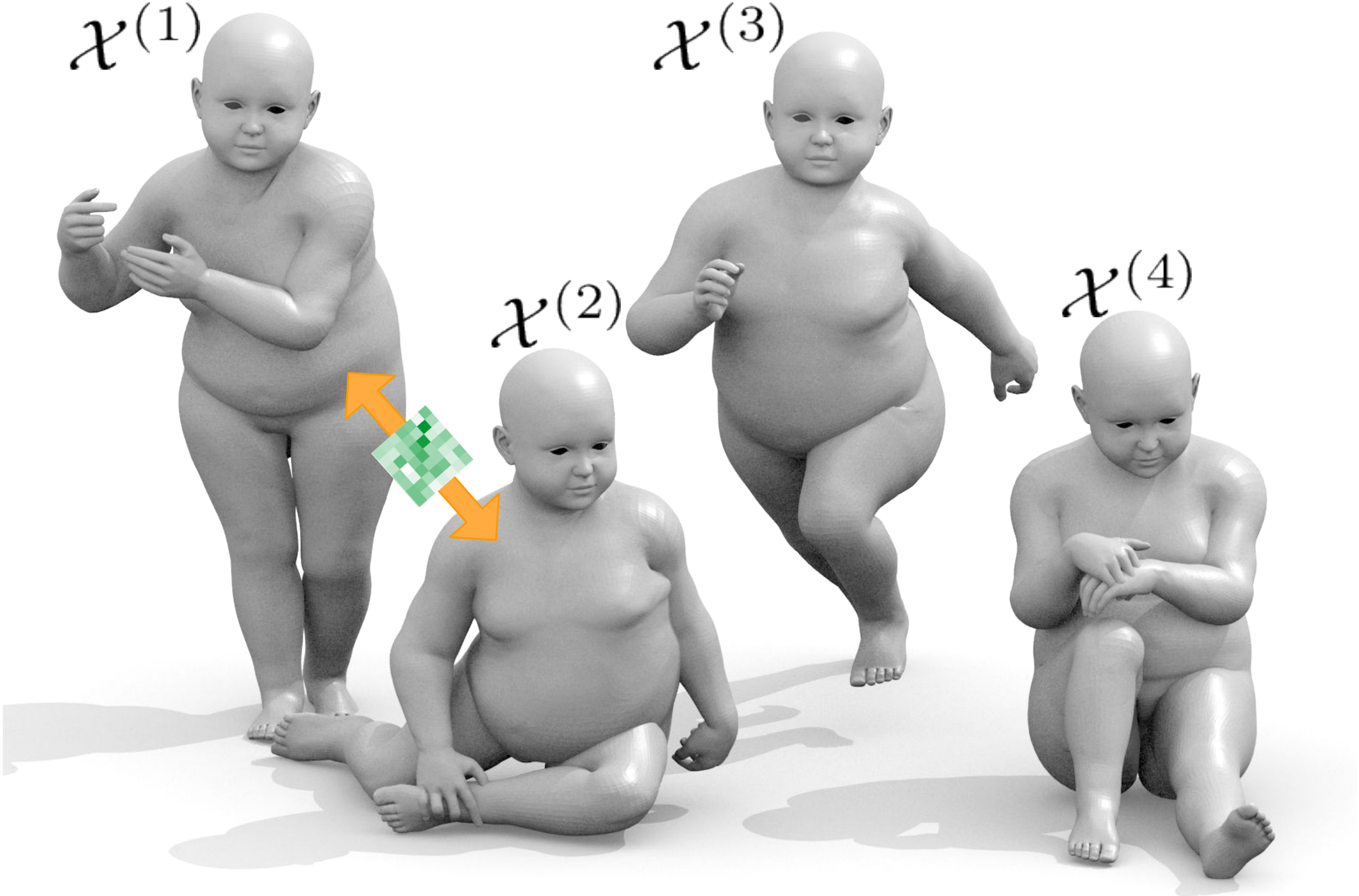
For a given collection of shapes $\mathscr{X}^{(i)}$:

1. Predict putative, pairwise matches.
2. Define self-supervised affinity scores $w^{(i,j)}$.
3. Extract multi-shape correspondences $\mathbf{\Pi}^{(i,j)}$.

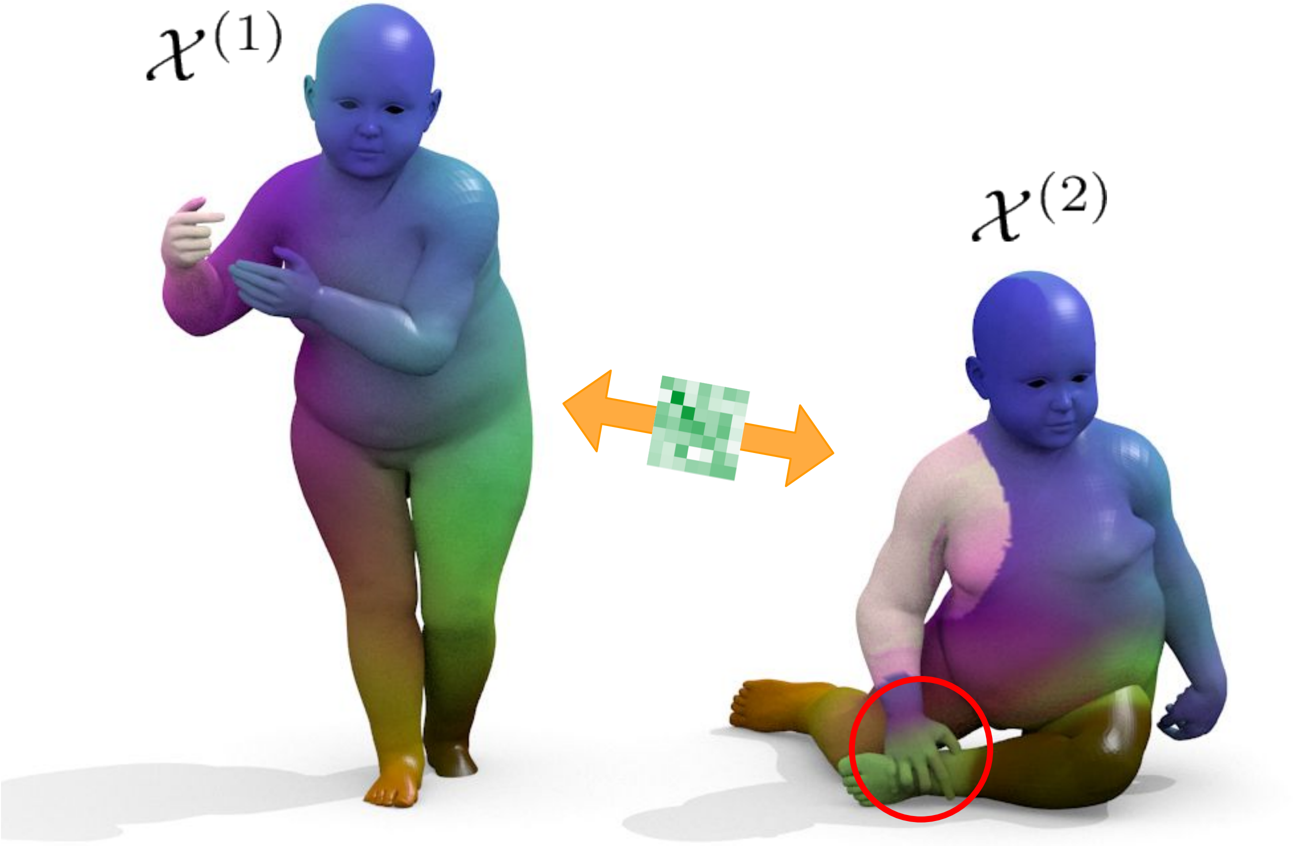


Code

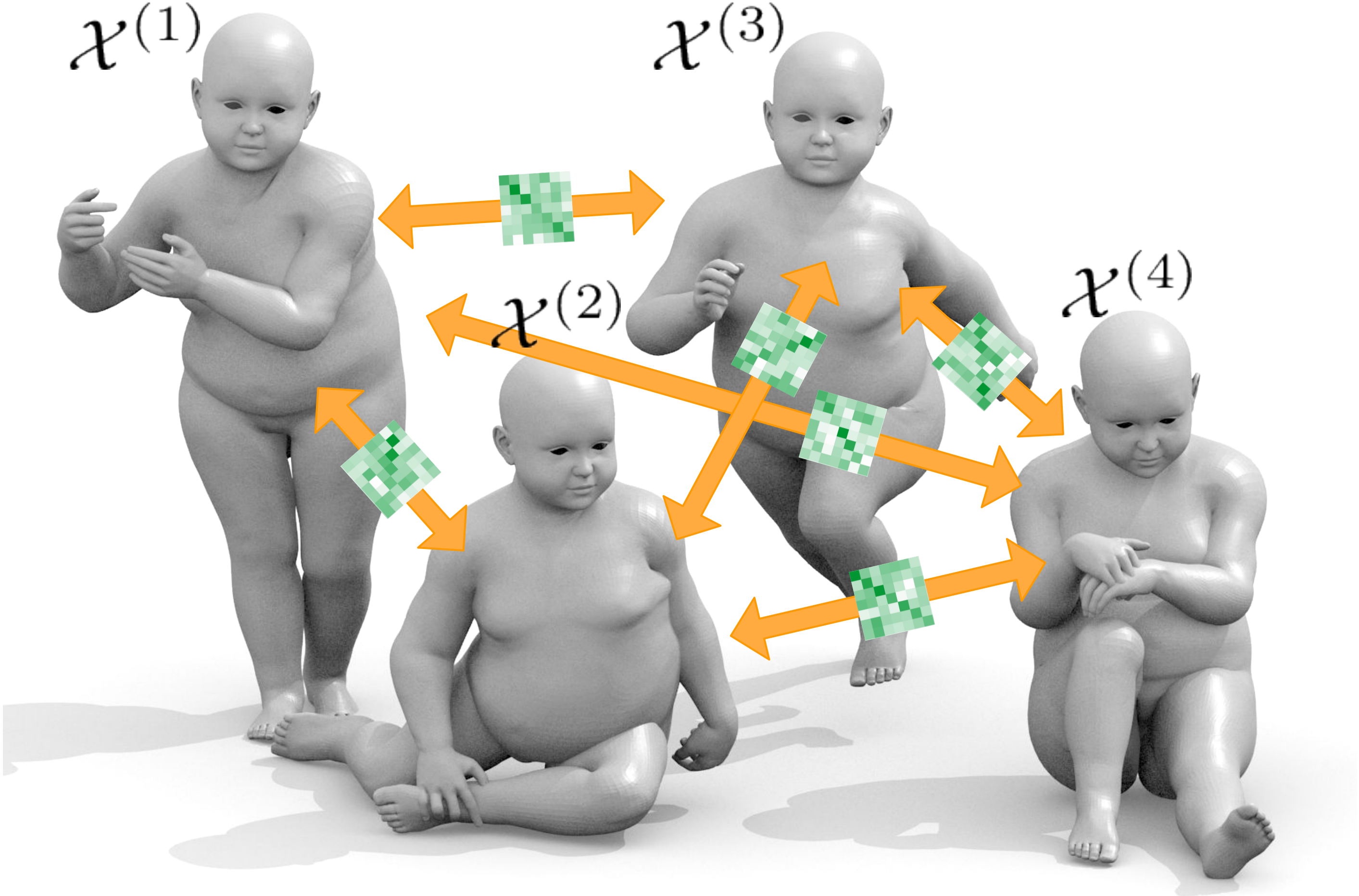
Multi-Shape Matching



Multi-Shape Matching



Multi-Shape Matching



Approach

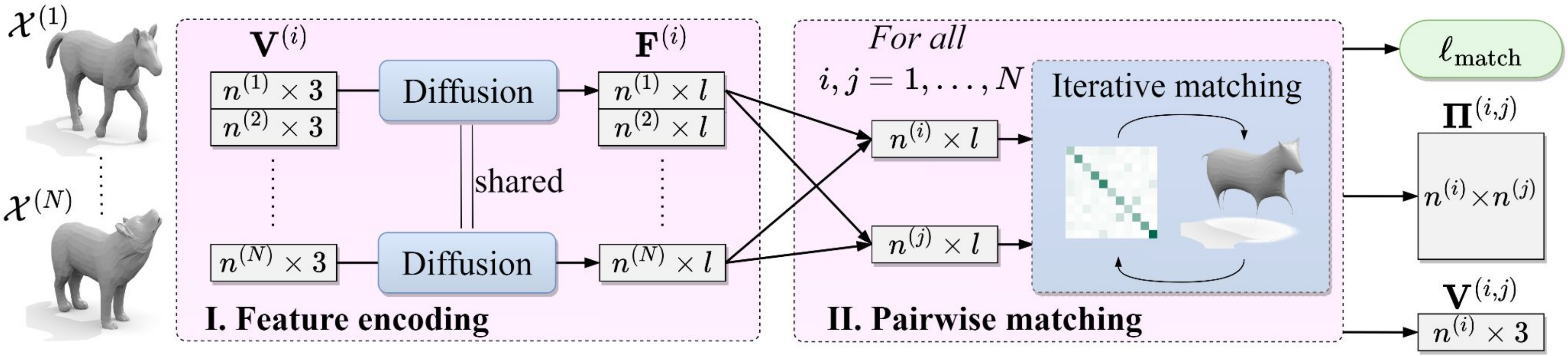
For a given collection of shapes:

1. Predict putative, pairwise matches.

2. Define self-supervised affinity scores.

3. Extract multi-shape correspondences.

1. Pairwise Matching



[1] Sharp, Nicholas, et al. "Diffusionnet: Discretization agnostic learning on surfaces." ACM Transactions on Graphics (2022).
[2] Eisenberger, Marvin, et al. "Deep shells: Unsupervised shape correspondence with optimal transport." NeurIPS (2020).

2. Affinity Weights

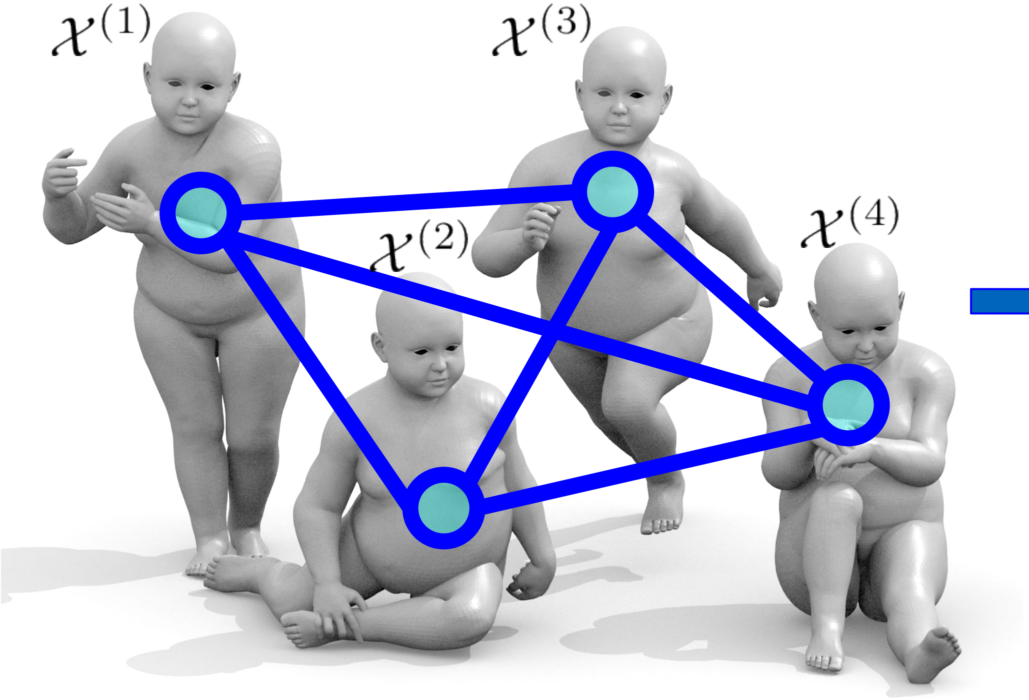
➔ We use the optimal transport matching distance:

$$E_{\text{match}}(\mathbf{F}, \mathbf{G}; \mathbf{\Pi}) := \sum_{i'=1}^{m} \sum_{j'=1}^{n} \mathbf{\Pi}_{i',j'} \left\| \mathbf{F}_{i'} - \mathbf{G}_{j'} \right\|_2^2$$

➔ For each pair of shapes, define an affinity score:

$$w(\mathcal{X}^{(i)}, \mathcal{X}^{(j)}) := \min\left\{ E_{\text{match}}(\mathbf{\Pi}^{(i,j)}), E_{\text{match}}(\mathbf{\Pi}^{(j,i)}) \right\}.$$

2. Affinity Weights



	$\mathcal{X}^{(1)}$	$\mathcal{X}^{(2)}$	$\mathcal{X}^{(3)}$	$\mathcal{X}^{(4)}$
$\mathcal{X}^{(1)}$	0.0	3.0	1.2	3.1
$\mathcal{X}^{(2)}$	3.0	0.0	1.5	1.0
$\mathcal{X}^{(3)}$	1.2	1.5	0.0	2.3
$\mathcal{X}^{(4)}$	3.1	1.0	2.3	0.0

3. Multi-Matching

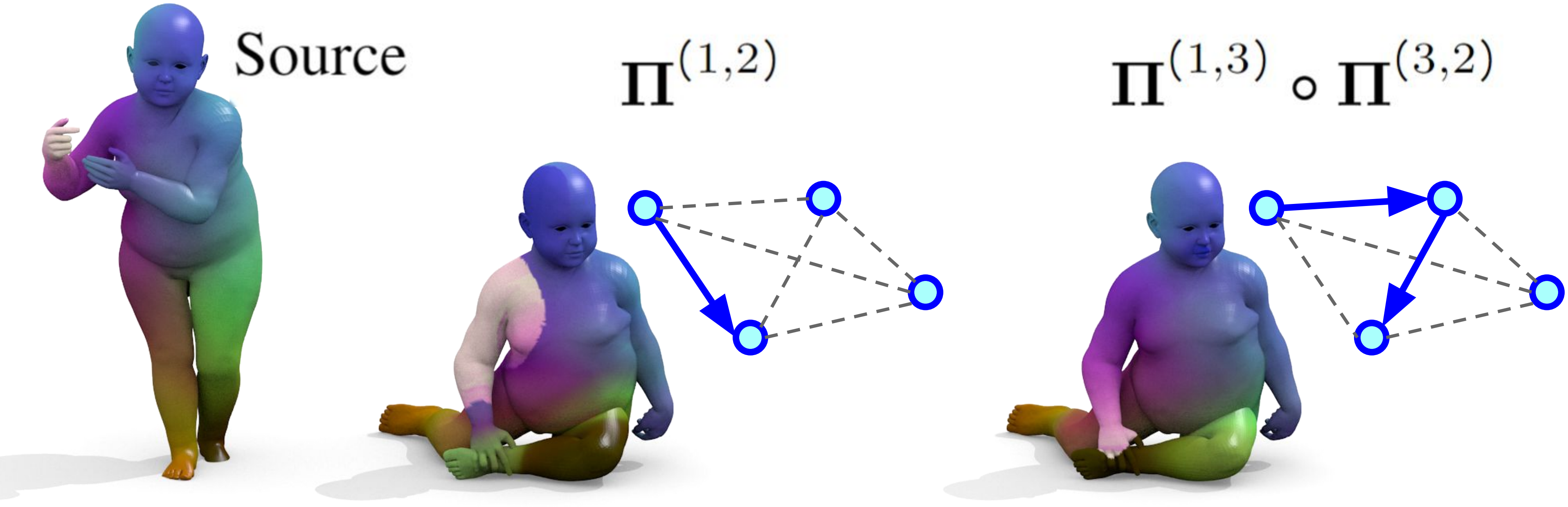
➔ Concatenate maps along shortest paths in the shape graph:

$$\left(i, s_1, \ldots, s_{M-1}, j\right) \;:=\; \mathrm{Dijkstra}\left(\mathcal{X}^{(i)}, \mathcal{X}^{(j)}; \mathcal{G}\right)$$

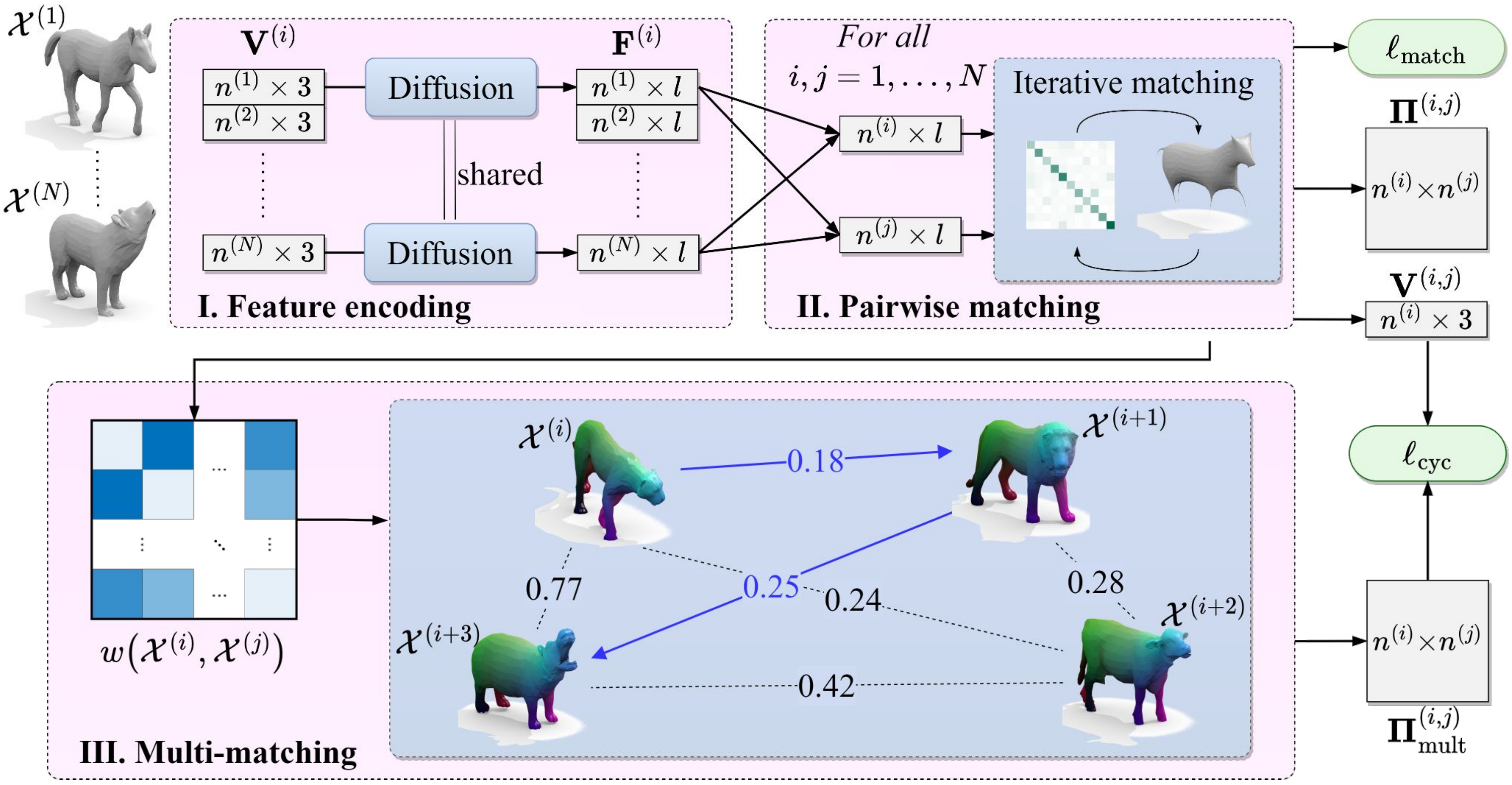
$$\mathbf{\Pi}_{\mathrm{mult}}^{(i,j)} := \mathbf{\Pi}^{(i,s_1)} \circ \mathbf{\Pi}^{(s_1,s_2)} \circ \cdots \circ \mathbf{\Pi}^{(s_{M-1},j)}.$$

➔ Enforce cycle-consistency during training

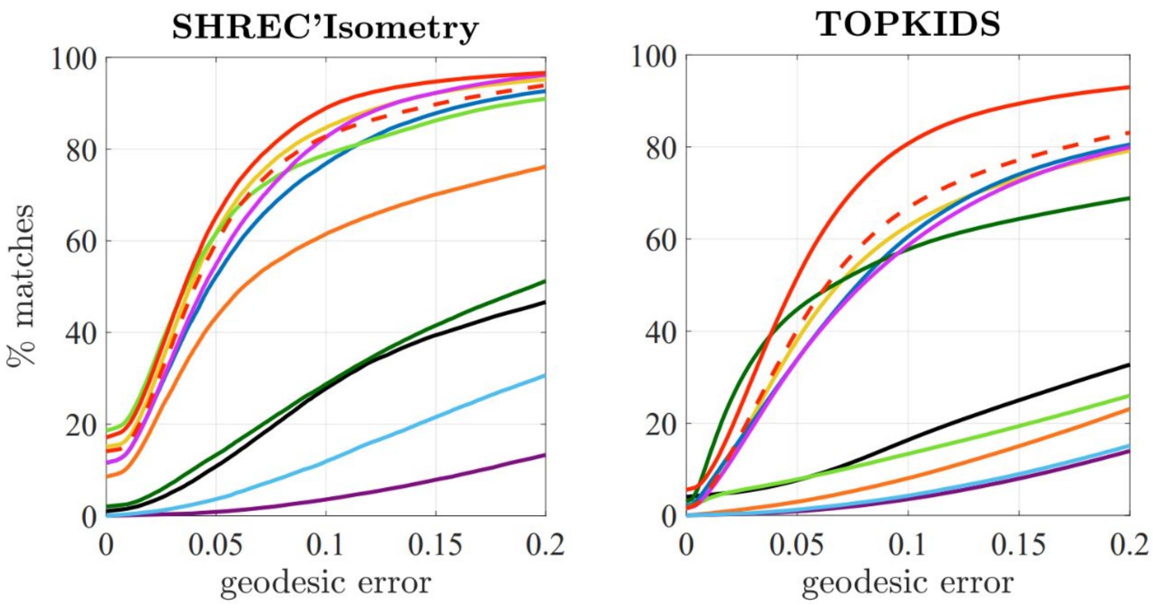
3. Multi-Matching



Architecture

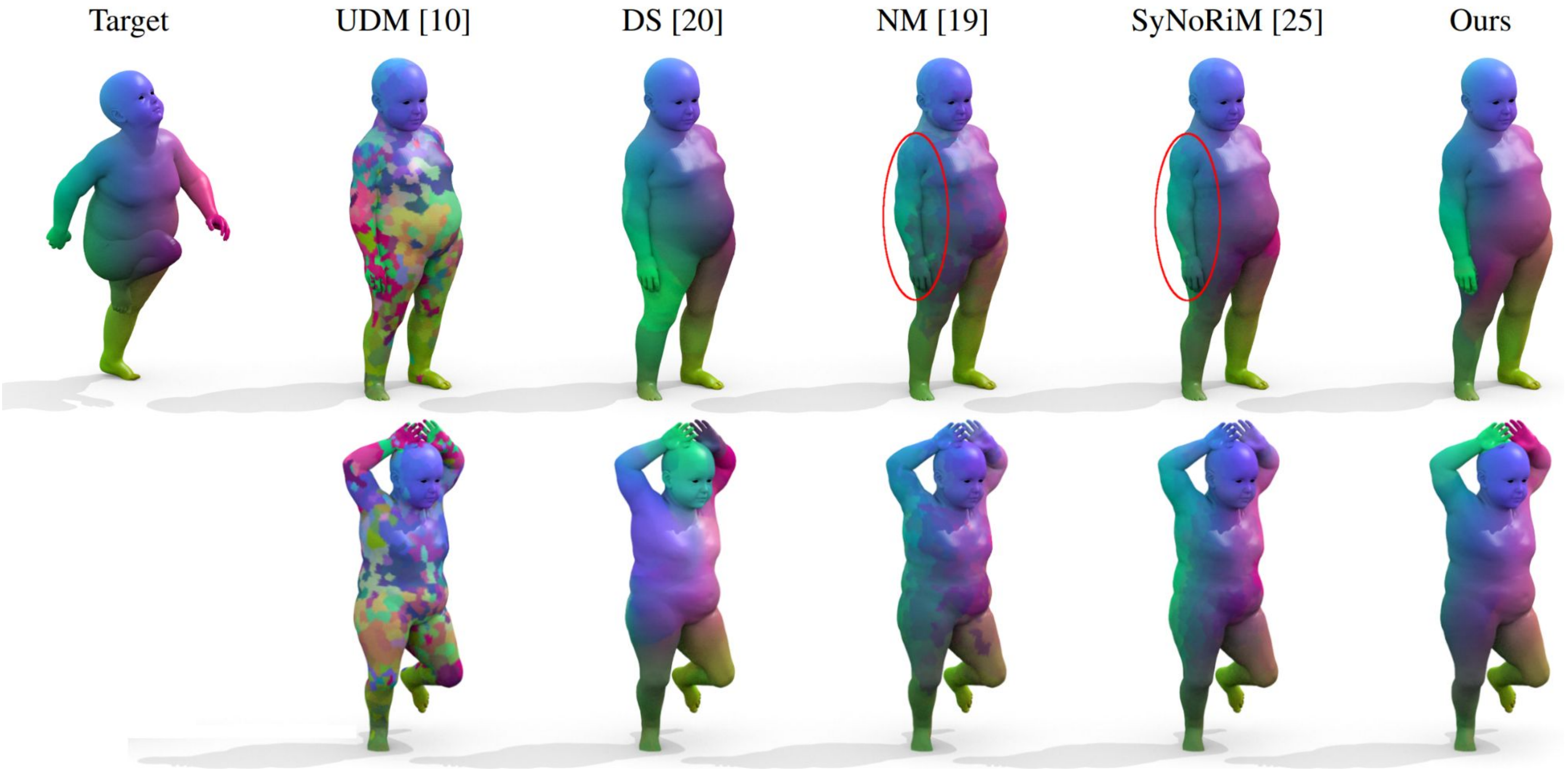


Results: Topological changes



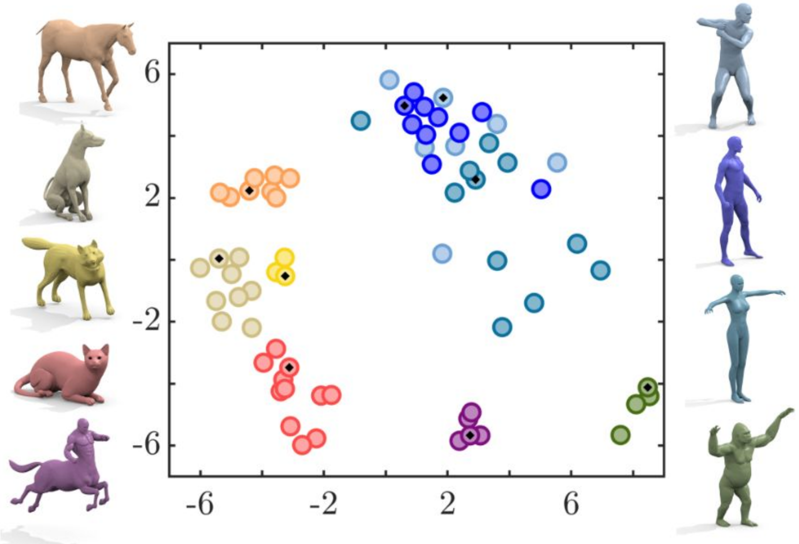
Method	SH'Iso	KIDS
UFM [23]	13.4	38.5
SURFM [50]	45.6	48.6
WFM [55]	38.0	47.9
DiffNet [56]	26.5	35.7
DS [20]	6.3	13.7
NM [19]	7.7	13.8
CZO [27]	7.6	39.3
UDM [10]	23.6	18.2
SyNoRiM [25]	6.2	13.8
Ours w/o **III**	6.3	12.0
Ours	**5.2**	**7.9**

Results: Topological changes



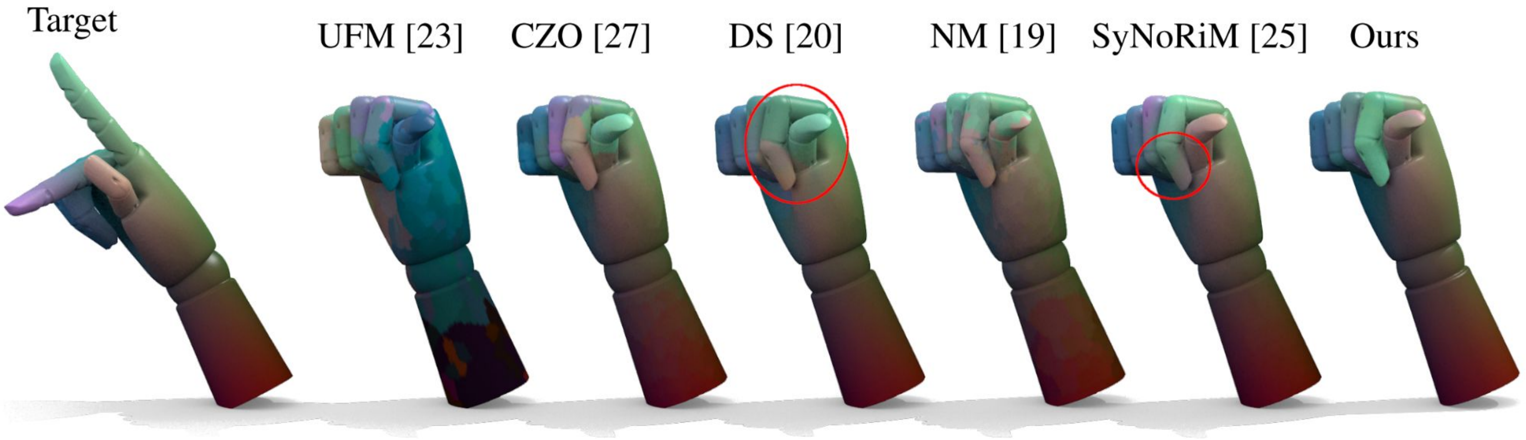
Results: Inter-class matching

		SH'20 on	SH'20 on TOSCA					
	SH'20	**SMAL**	Cat	Centaur	Dog	Horse	Human	Wolf
UFM [23]	39.8	32.9	39.4	39.2	37.5	34.1	49.6	4.4
SURFM [50]	53.4	37.7	54.0	57.7	57.9	57.0	65.8	55.3
WFM [55]	31.4	20.2	20.6	21.9	16.7	22.4	38.1	5.7
DiffNet [56]	40.5	18.2	14.2	8.3	13.6	9.1	24.5	2.6
DS [20]	35.0	10.8	7.6	9.1	5.5	2.5	10.1	2.1
NM [19]	**10.0**	9.9	16.8	12.7	14.6	11.2	29.7	1.5
CZO [27]	21.7	–	–	–	–	–	–	–
UDM [10]	52.6	25.5	40.7	34.3	43.6	43.0	45.8	34.3
SyNoRiM [25]	10.4	5.7	12.8	11.6	10.6	7.1	28.2	2.0
Ours w/o **III**	11.1	3.4	6.3	6.0	4.9	2.6	20.1	2.2
Ours	10.6	**2.6**	**5.2**	**2.0**	**3.0**	**2.2**	**8.3**	**1.4**



Conclusion

- ➔ Introduce shape graphs, self-supervised affinity weights.
- ➔ Predict multi-shape matches, enforce cycle consistency.
- ➔ SOTA performance on several non-isometric benchmarks.



Code

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