

ZoomOut: Spectral Upsampling for Efficient Shape Correspondence

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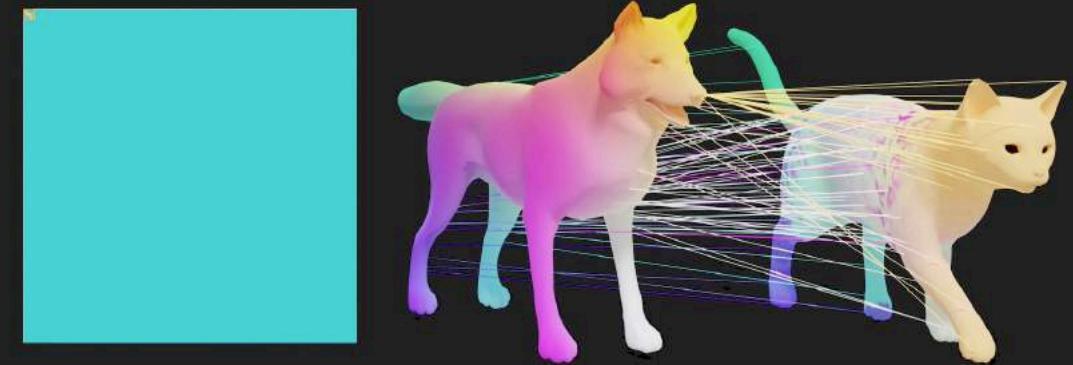
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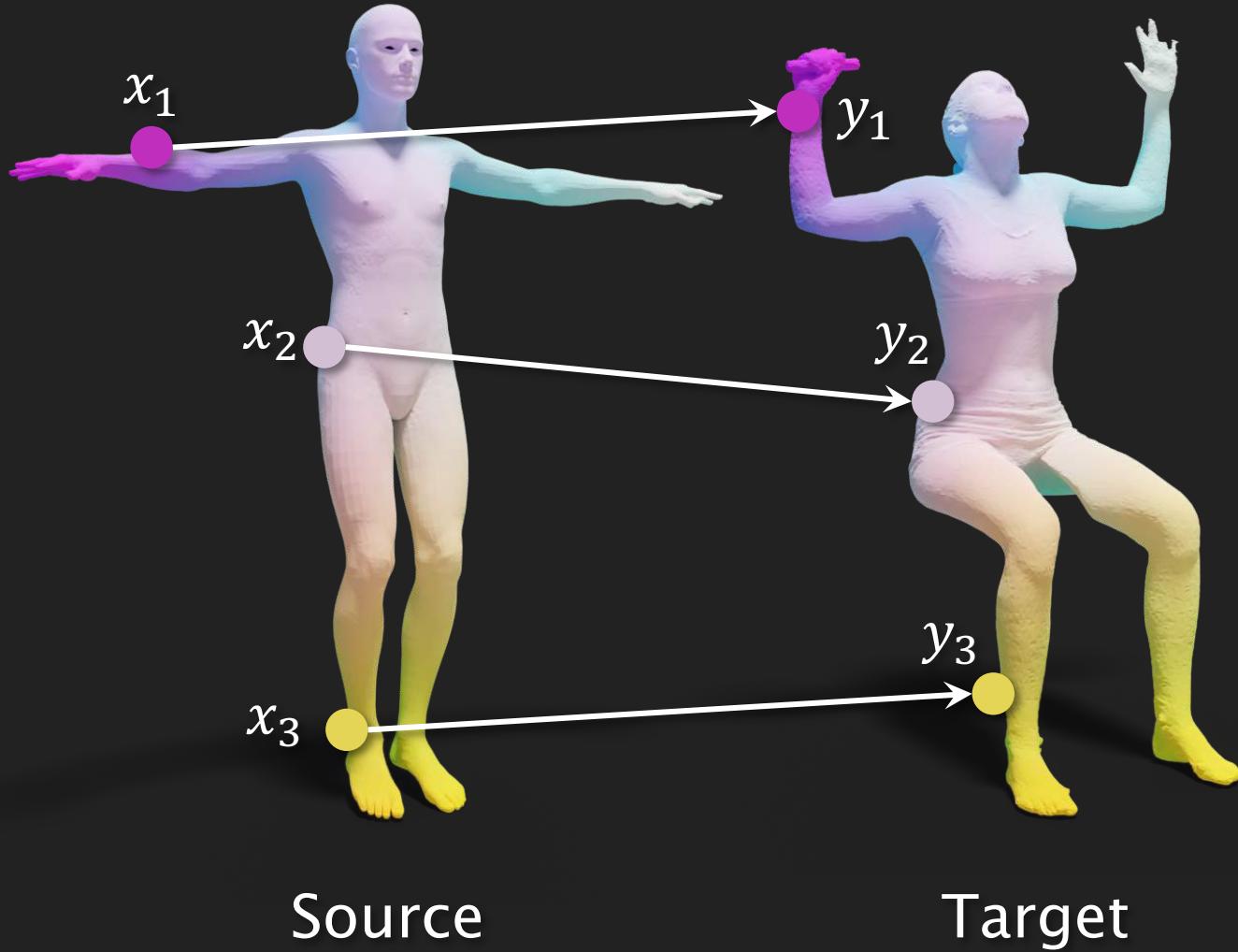
Peter Wonka, KAUST

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(*equal contribution; Presenter: Jing Ren)

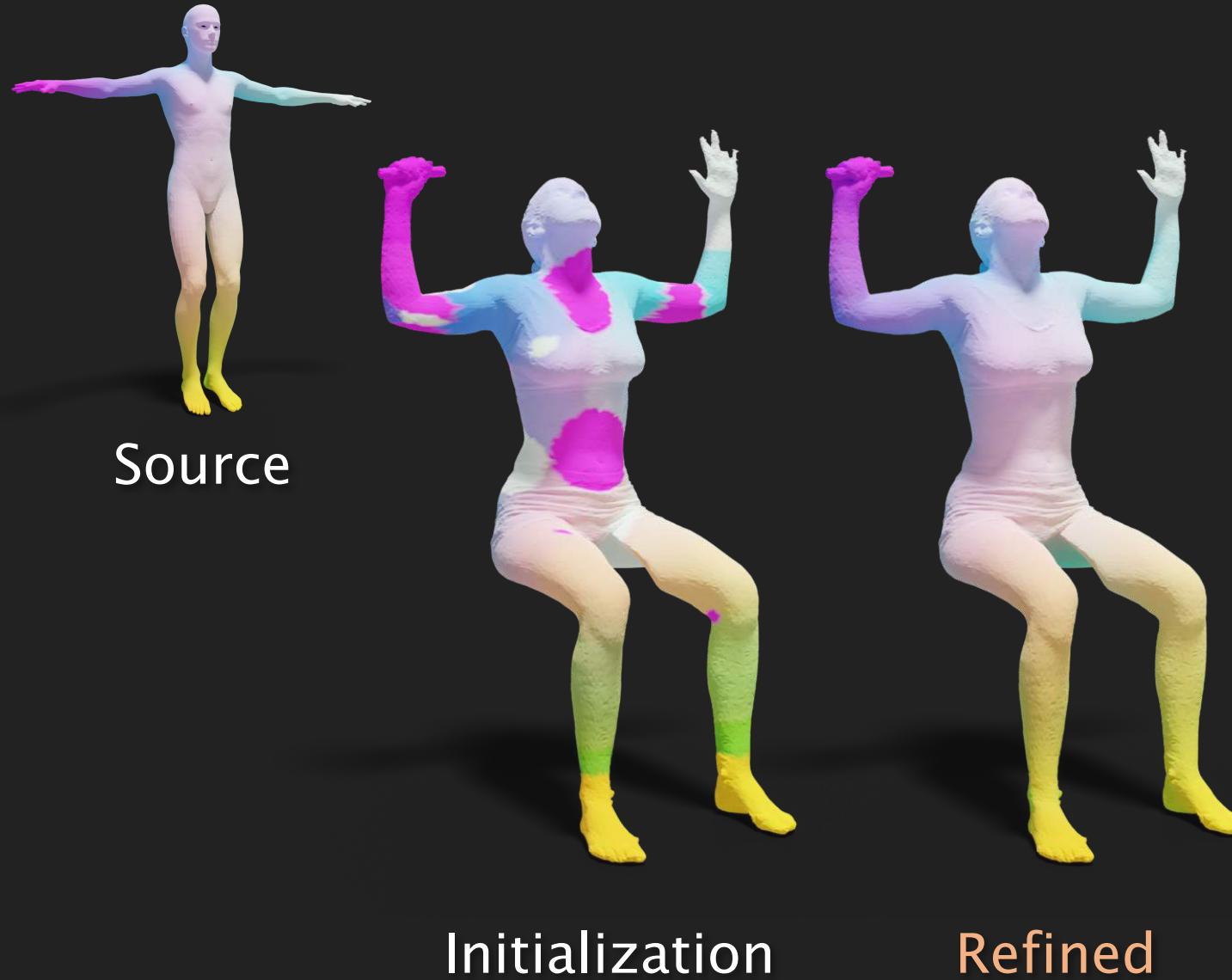


Shape Matching



- Point-based methods
 - [Bronstein et al. 2006],
 - [Huang et al. 2008]...
- Parametrization-based methods
 - [Lipman and Funkhouser 2009]
 - [Aigerman et al. 2017]...
- Optimal transport
 - [Solomon et al. 2016]
 - [Mandad et al. 2017]...
- Functional maps
 - [Ovsjanikov et al. 2012]
 - [Ezuz and Ben-Chen 2017]...
-

Map Refinement

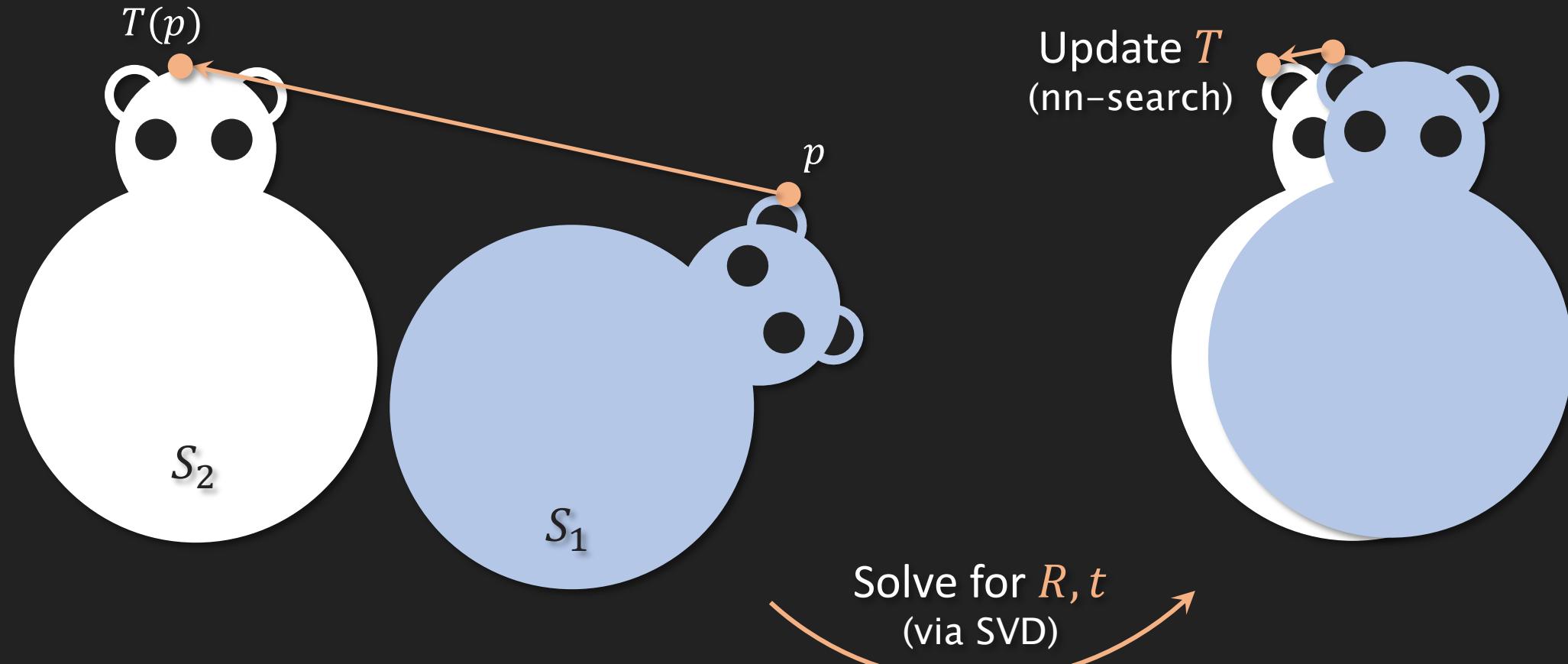


- ICP-based
 - [Besl and McKay 1992] (Spatial)
 - [Ovsjanikov et al. 2012] (Spectral)
 - [Ren et al. 2018] (Spatial & Spectral)
- Reversible Harmonic Maps
 - [Ezuz et al. 2019]
- Product Manifold Filter
 - [Vestner et al. 2017ab]
- Deblurring and Denoising
 - [Ezuz and Ben-Chen 2017]
-

Iterative Closest Point (ICP)

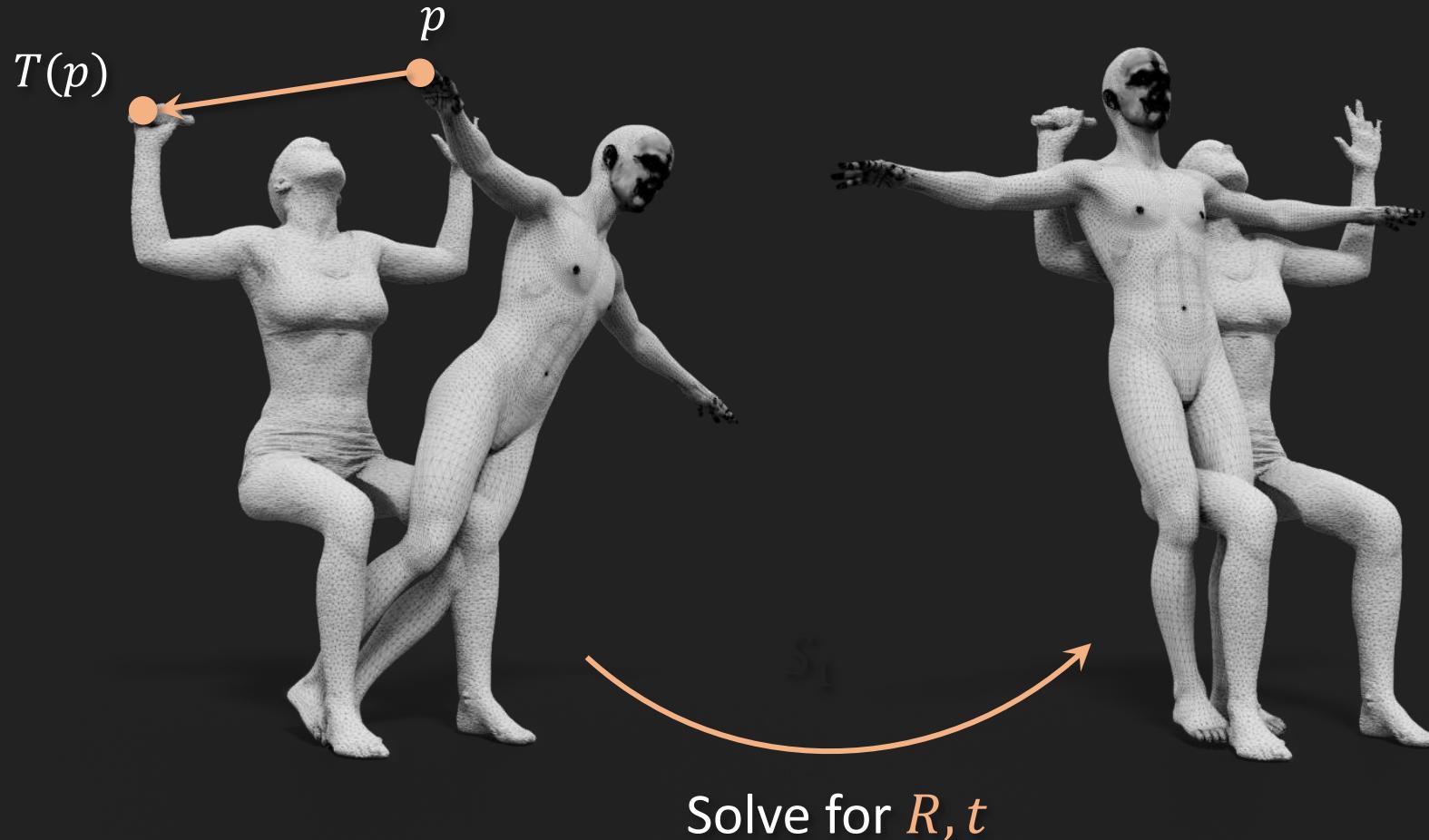
[Besl and McKay 1992]

$$\min_{\substack{R, t, T \\ R^T R = I}} \sum_{p \in S_1} \|RX_1(p) + t - X_2(T(p))\|_F^2$$



Iterative Closest Point (ICP)

$$\min_{\substack{R,t,T \\ R^T R = I}} \sum_{p \in S_1} \|RX_1(p) + t - X_2(T(p))\|_F^2$$



Problem:

- nn-search in spatial domain does not work
- Vertex positions (X_1, X_2) are **extrinsic** features

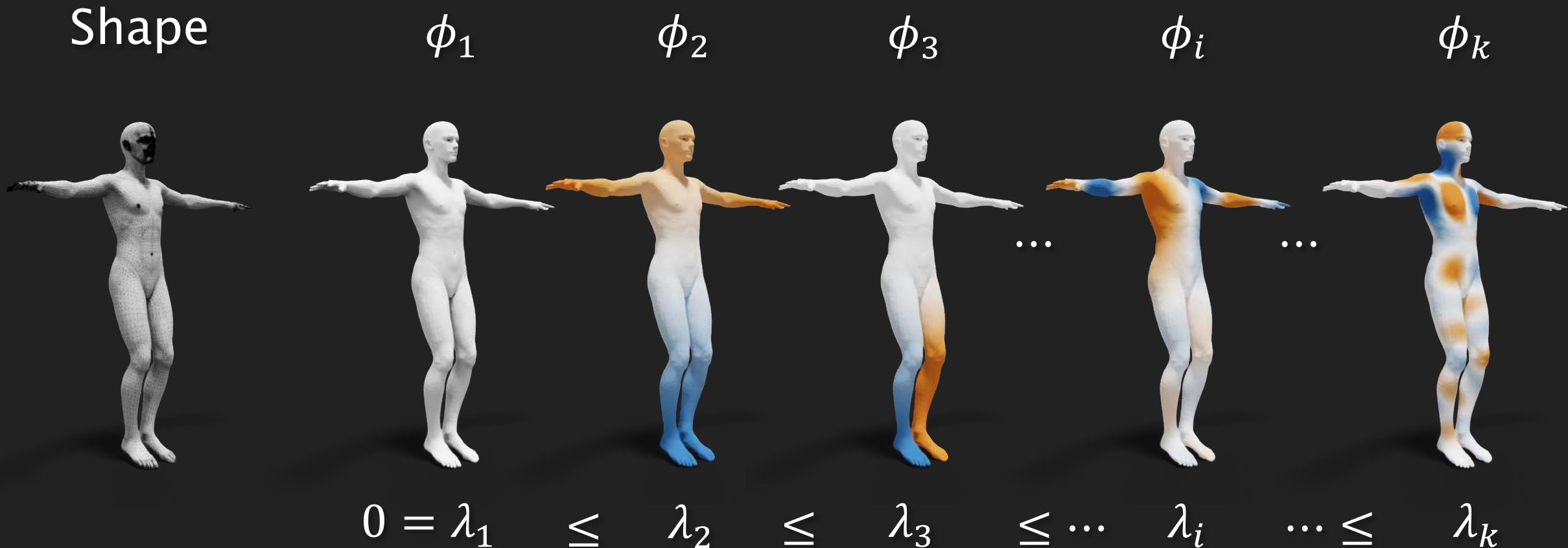
Solution:

- Align **intrinsic** features

Laplace–Beltrami Operator Δ

Eigenfunctions & Eigenvalues

Helmholtz equation
 $\Delta\phi_i = \lambda_i\phi_i$

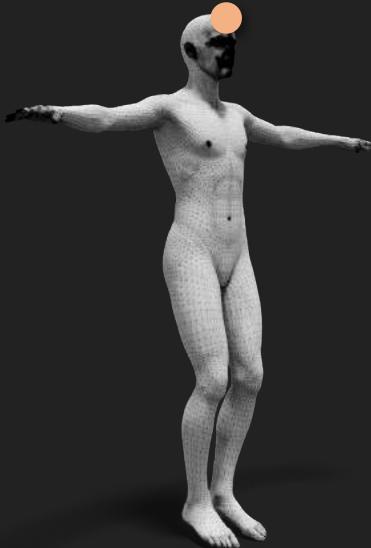


Intrinsic features

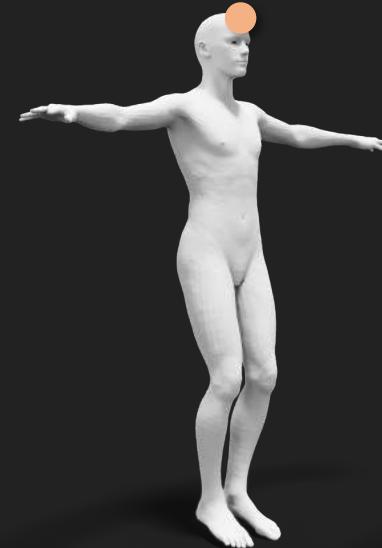
Eigenfunctions of Δ

$\Phi(p) = (0.1, 1, 0, \dots, 0.2, \dots, 1.5)$ intrinsic feature at p

p



$$\phi_1(p) = 0.1$$



$$\phi_2(p) = 1$$



$$\phi_3(p) = 0$$



$$\phi_i(p) = 0.2$$



$$\phi_k(p) = 1.5$$



...

...

ICP in the spectral domain

Spatial ICP [Besl and McKay 1992]

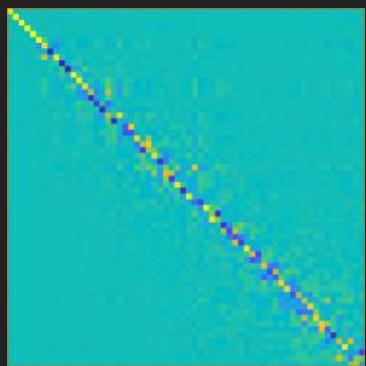
$$\min_{\substack{R,t,T \\ R^T R = I}} \sum_{p \in S_1} \|RX_1(p) + t - X_2(T(p))\|_F^2$$

$X_1(\cdot), X_2(\cdot)$: vertex positions

Spectral ICP [Ovsjanikov et al.2012]

$$\min_{\substack{C,T \\ C^T C = I}} \sum_{p \in S_1} \|\mathcal{C}\Phi_1(p) - \Phi_2(T(p))\|_F^2$$

$\Phi_1(\cdot), \Phi_2(\cdot)$: LB eigenfunctions

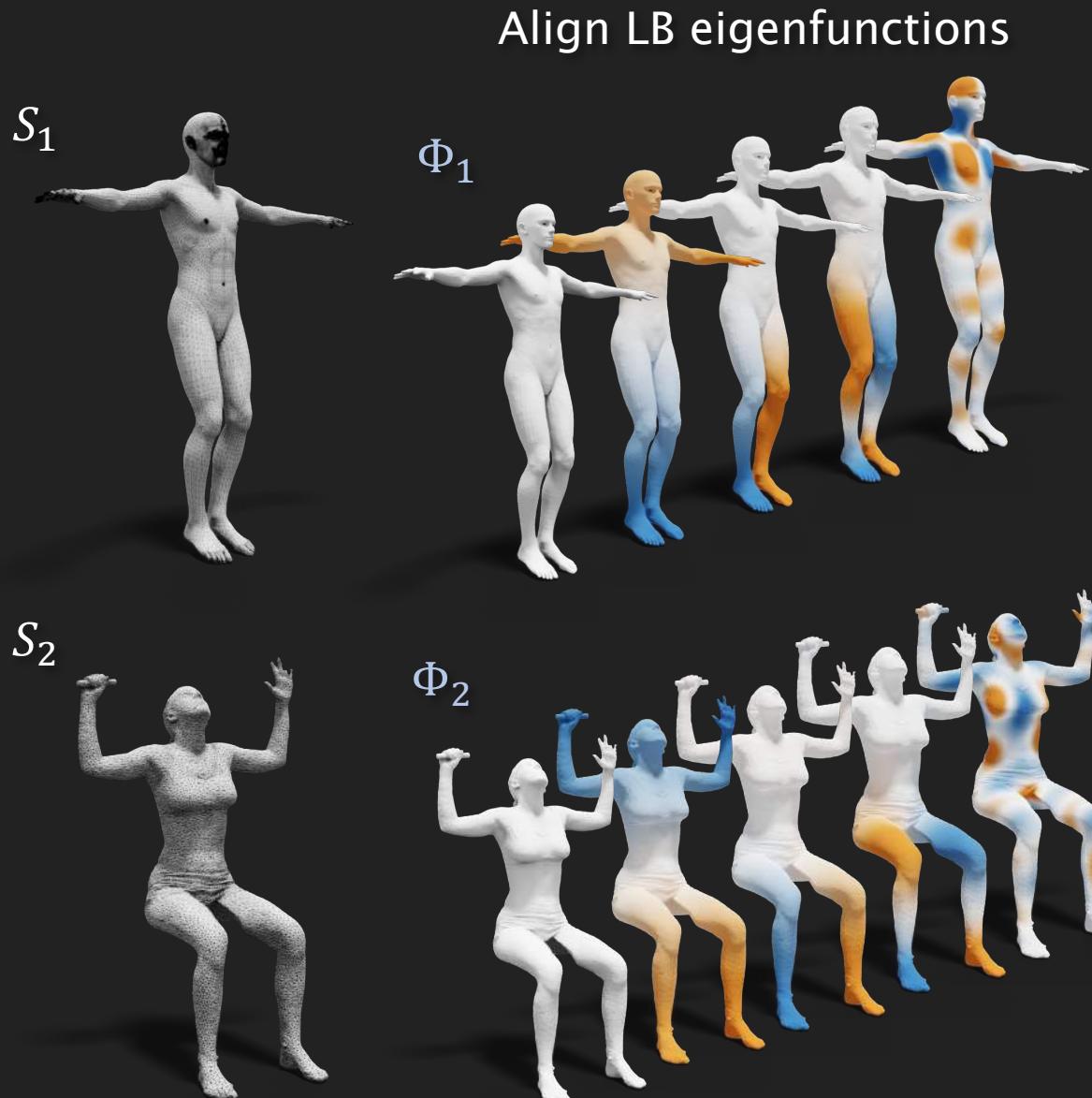


C : functional map

Optimize for a functional map

- [Ovsjanikov et al.2012]
- [Nogneng and Ovsjanikov 2017]
- [Ren et al. 2018]
-

ICP in the spectral domain



$$\min_{\mathcal{C}, \mathcal{T}} \sum_{p \in S_1} \left\| \mathcal{C} \Phi_1(p) - \Phi_2(\mathcal{T}(p)) \right\|_F^2$$

Observations

- Dimensionality of Φ_1, Φ_2 : 50~250
- Solve for $\mathcal{C} \in R^{250 \times 250}$:
 - might be under-determined
 - easy to get trapped in a local minimum

Our solution: ZoomOut

- progressively registering the feature space
- without assumption on \mathcal{C}

ZoomOut Algorithm

Some intuitions

Align the body



Align the head



Align the ear



Global structure → Local structure

ZoomOut Algorithm

Some intuitions



Low frequency → High frequency

ZoomOut Algorithm

Notation

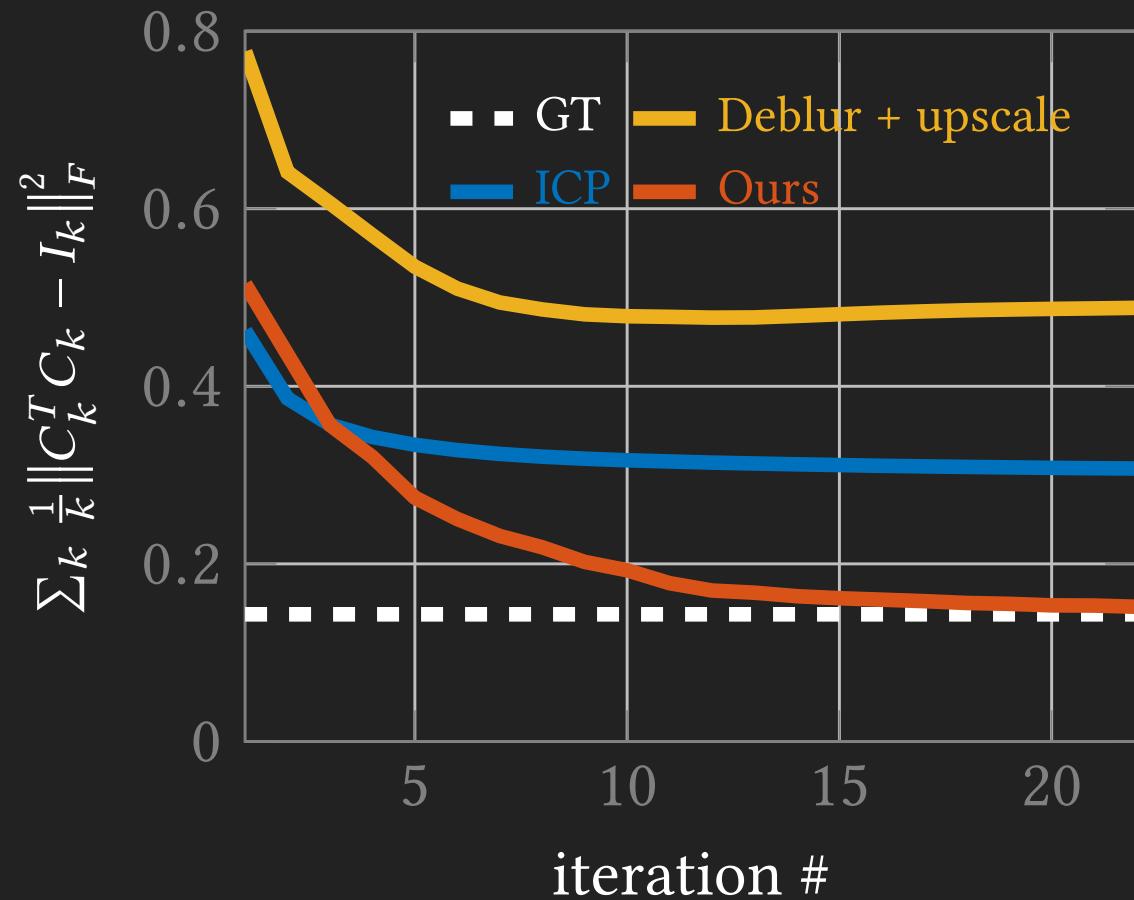
- Φ_i^k : stores the first k eigenfunctions of S_i

Algorithm

1. With initial T & k (use existing methods)
2. Solve $C^k = \underset{C}{\operatorname{argmin}} \sum_p \|C\Phi_1^k(p) - \Phi_2^k(T(p))\|_F^2$ (align the first k features)
3. Update $T = \underset{T}{\operatorname{argmin}} \sum_p \|C^k\Phi_1^k(p) - \Phi_2^k(T(p))\|_F^2$ (nn-search after alignment)
4. $k \leftarrow k + 1$ (increase the feature space to register)
5. Go to step 2 (with the first k dim well-aligned, align the $k + 1$ features)



ZoomOut: Theoretical Analysis



ZoomOut Energy

$$\min_{C \in \mathbb{P}} \sum_k \frac{1}{k} \|C_k^T C_k - I_k\|_F^2$$

Notation

- C_k : principal sub-matrix of C
- I_k : $k \times k$ identity matrix
- \mathbb{P} : set of fMaps arising from pointwise maps

Theorem:

- Global minimum: isometry

Comparison to state-of-the-art

	ICP [Ovsjanikov et al. 2012]	PMF [Vestner et al. 2017]	BCICP [Ren et al. 2018]	RHM [Ezuz et al. 2019]	Ours
fast?					
easy to implement?					
accuracy					
scalability					
point cloud?					

Property: easy to implement

Our method:

- 5 lines of code
- Similar complexity to ICP

```

1 function [C,P]=ZoomOut(M,N,C,k_final)
2
3 for k=size(C,1):k_final-1
4     x = knnsearch(N.Phi(:,1:k)*C',M.Phi(:,1:k));
5     P = sparse(1:M.n,x,1,M.n,N.n);
6     C = M.Phi(:,1:k+1)'*M.A*P*N.Phi(:,1:k+1);
7 end

```

Other baselines

- PMF: kernel construction & linear assignment solver
- RHM: sophisticated energy function & optimization
- BCICP: ICP in both spatial & spectral domain with a lot of heuristics



Property: scalability

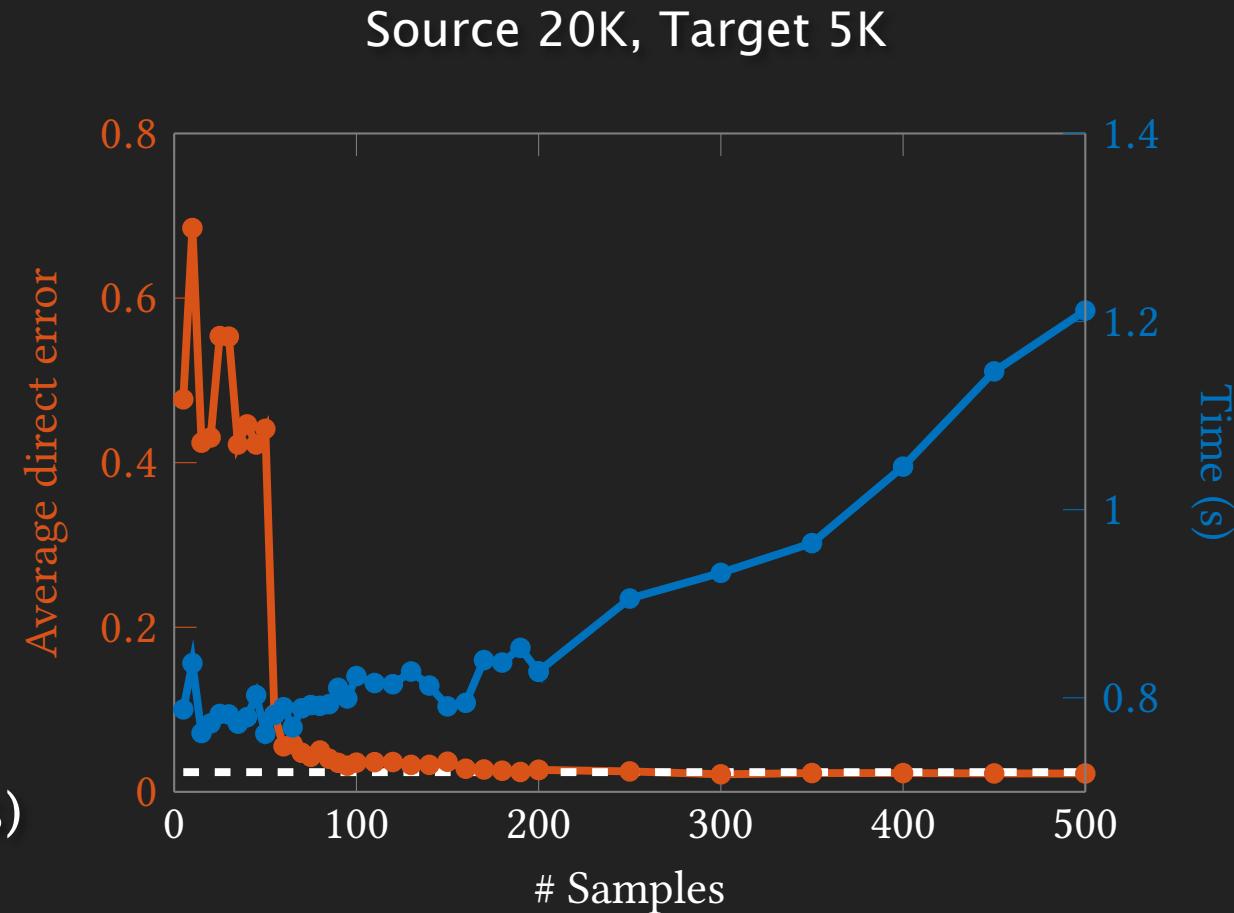
Speed-up by sampling

Recall:

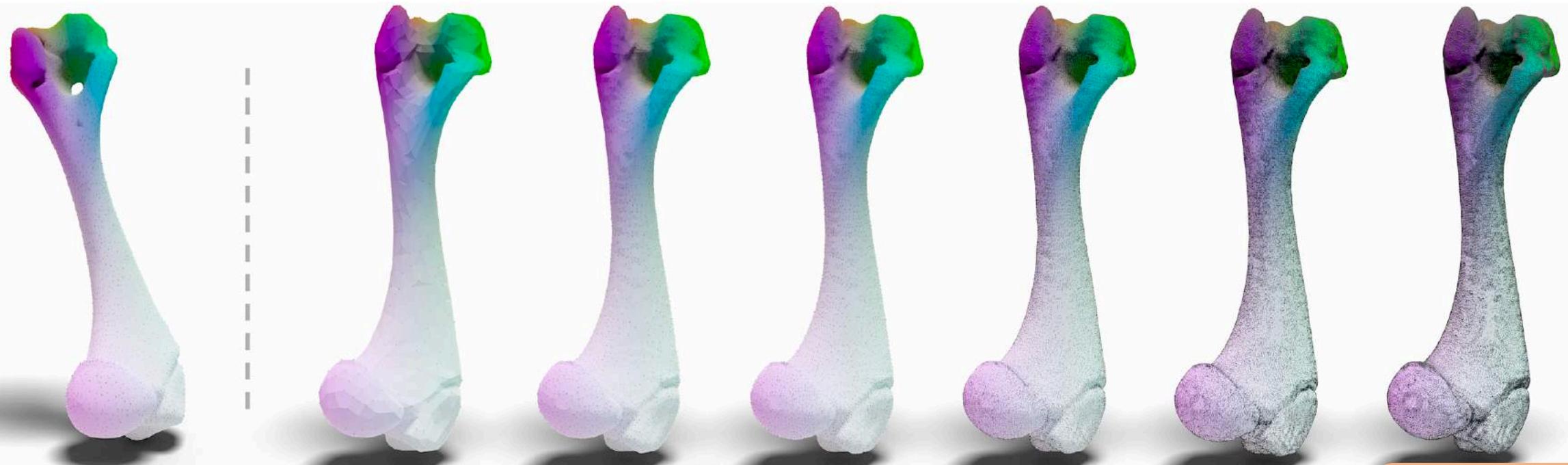
- 1...
2. Solve $C^k = \operatorname{argmin}_C \sum_p \|C\Phi_1^k(p) - \Phi_2^k(T(p))\|_F^2$
- 3...

Observation

- do NOT need all p to compute $C^k \in R^{k \times k}$
- A small subset is enough! (e.g., 200 samples)



Property: scalability



Source: $n = 5K$

$n = 1K$

$t = 1.2$

$n = 5K$

$t = 5.7$

$n = 10K$

$t = 11$

$n = 50K$

$t = 55$

$n = 100K$

$t = 110$

$n = 150K$

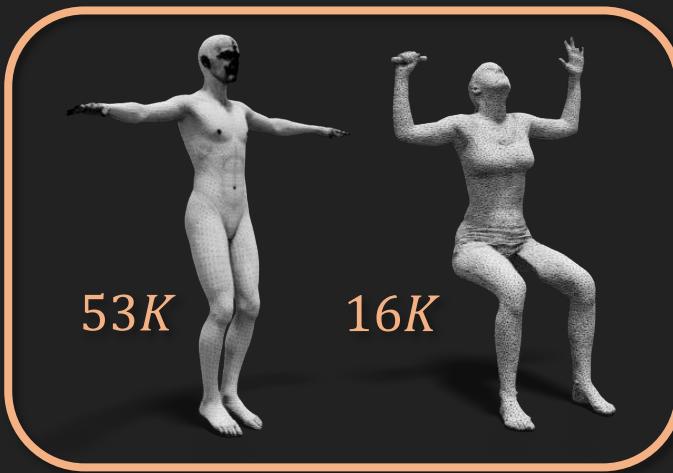
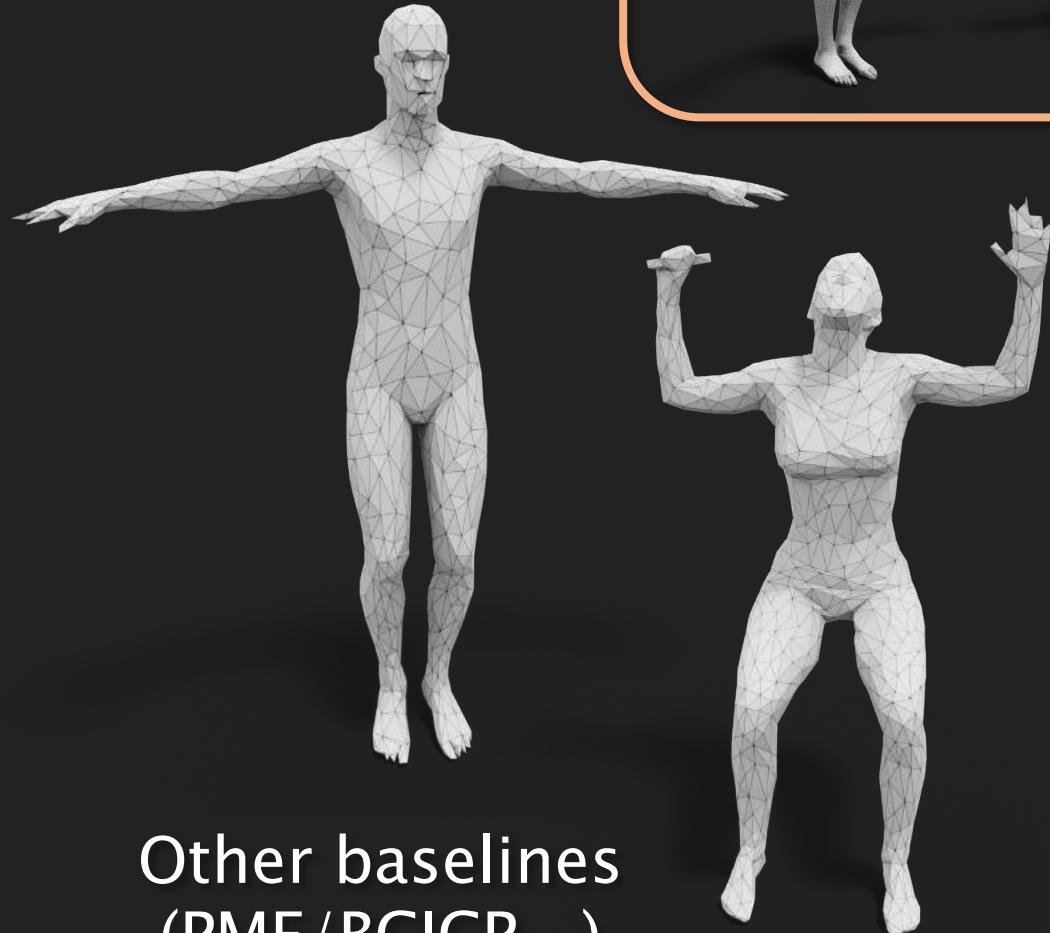
$t = 169$

Property: sample without remeshing



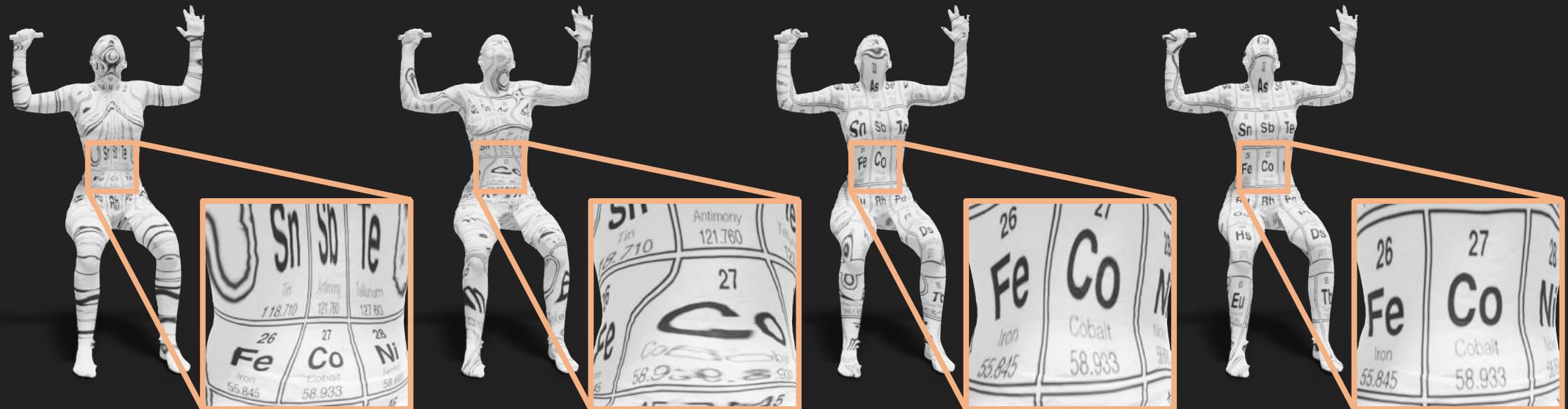
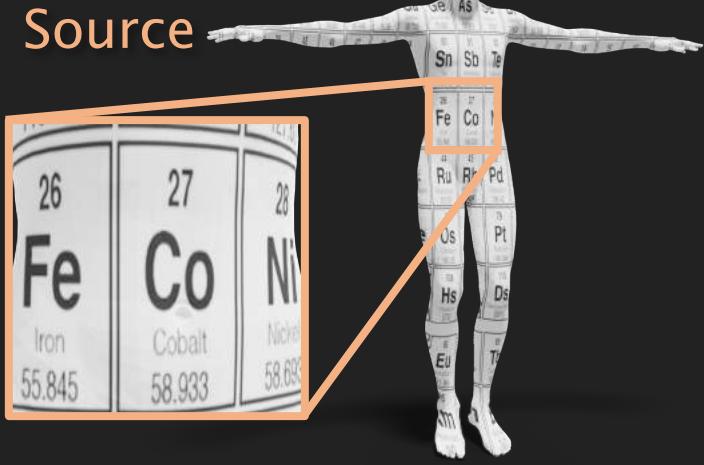
Ours

Other baselines
(PMF/BCICP...)



Property: sample without remeshing

#samples = 5000



Initialization

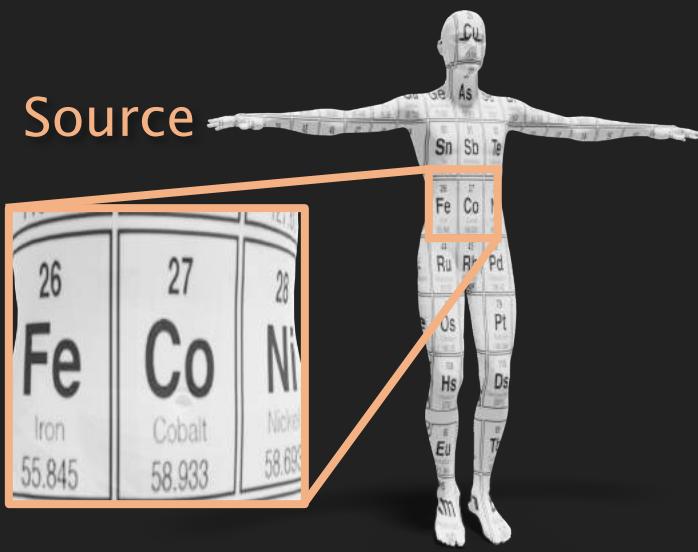
PMF

BCICP

Ours

Property: sample without remeshing

#samples = 500



Initialization

PMF

72.9s

BCICP

90.0s

Ours

1.5s

Property: state-of-the-art accuracy

Refinement for shape matching

Accuracy: 15% ~ 30% improvement, Runtime: 10 ~ 500× improvement

		Average Error ($\times 10^{-3}$)			Average Runtime (s)		
Method \ Dataset		Original	Remeshed	Resampled	Original	Remeshed	Resampled
Ini		67.3	44.0	46.5	-	-	-
ICP		54.0	36.3	29.3	10.2	10.1	5.32
Deblur		61.9	38.6	44.4	10.9	11.7	10.4
RHM		41.9	33.3	32	41.4	42.5	47.4
PMF		26.4	25.9	86.4	736.5	780.2	311.5
BCICP		21.6	19.5	26	183.7	117.8	364.2
Ours		15.8	13.3	21.7	9.60	9.64	6.49
Ours*		17.5	14.5	24.6	1.14	1.15	0.68
Improv.	Ours	26.9%	31.8%	16.5%	19×	12×	56×
	Ours*	19.0%	25.6%	5.4%	160×	100×	535×

Property: state-of-the-art accuracy

Refinement for shape matching

Source	Initial	ICP	PMF	RHM	BCICP	Ours	GT
Runtime	3s	312s	56s	301s	0.47s	0.028	0.024
Error	0.069	0.108	0.039	0.028	0.024		

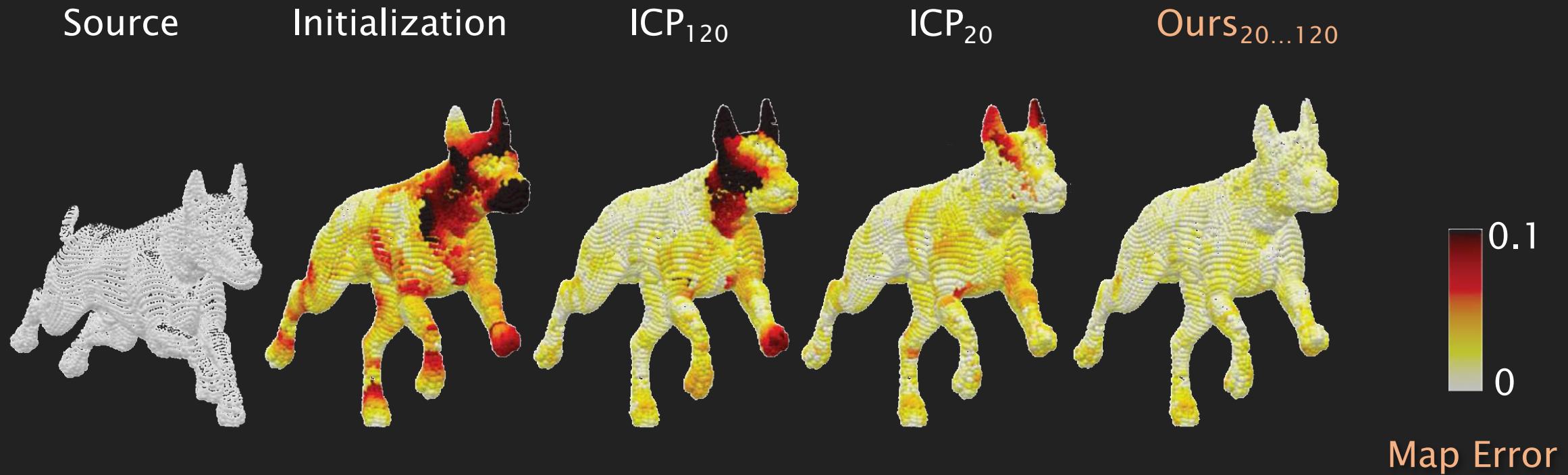
Property: state-of-the-art accuracy

Challenging cases: topological noise



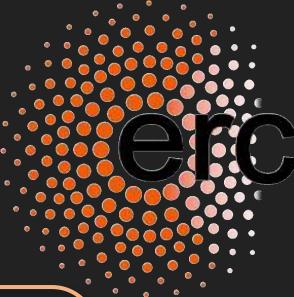
Property: applicable to point clouds

[Belkin et al. 2009]: estimation of Laplace Operator on point clouds



Summary

- Goal: refine given maps
- ZoomOut: progressively refine the correspondences in the spectral domain (no extra heuristics)
- Properties:
 - Simplicity: 5 lines of code
 - State-of-the-art accuracy
 - Efficiency: (compared to the best baseline)
 - Without sampling: $(4\sim 50)\times$ faster (with better accuracy)
 - With sampling: $(100\sim 500)\times$ faster (with comparable results!)
 - Scalability: works with a mesh of $150K+$ vertices
 - Applicable to point clouds directly
- Limitations:
 - Need initial correspondences



Thank you for your attention 😊

ZoomOut: Spectral Upsampling for Efficient Shape Correspondence

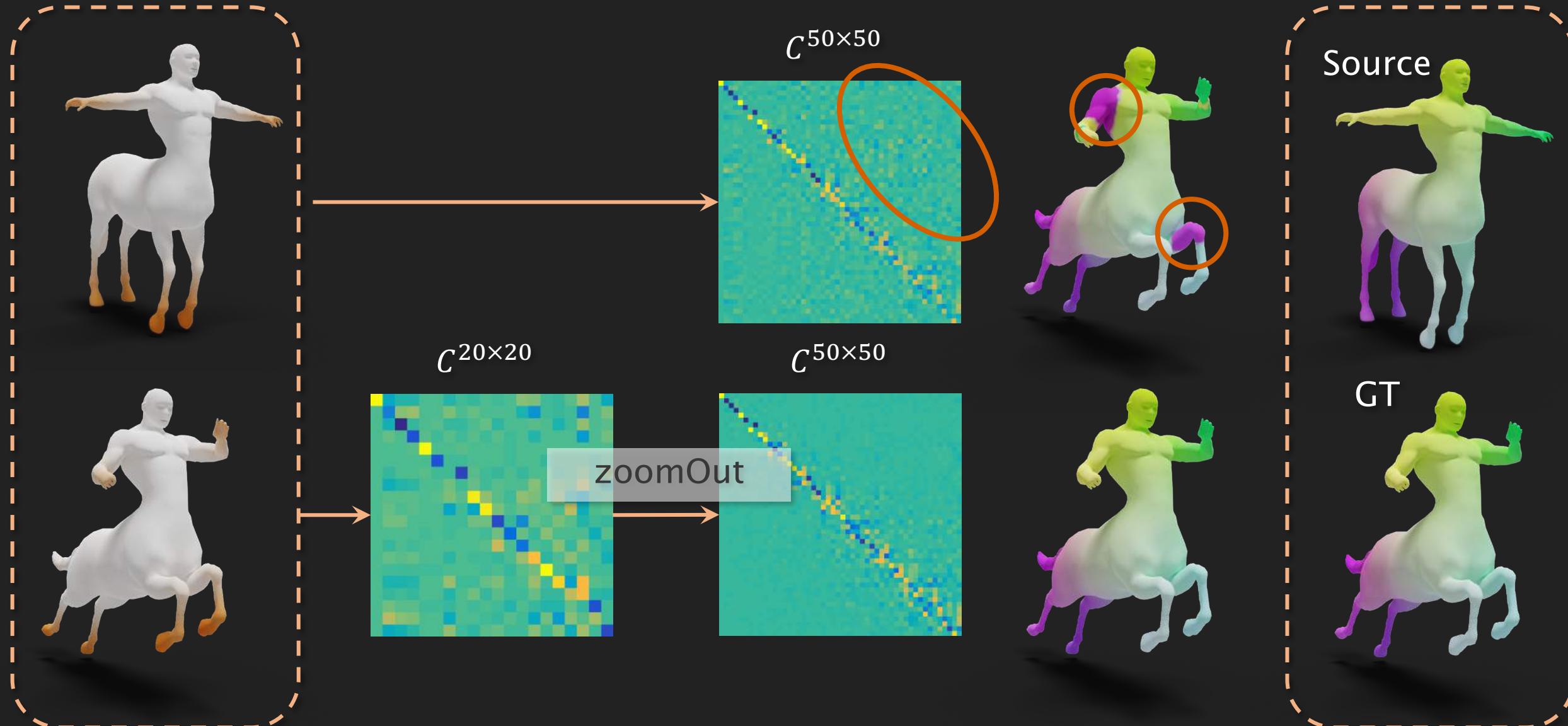
The authors wish to thank the anonymous reviewers for their valuable comments and helpful suggestions, and Danielle Ezuz and Riccardo Marin for providing source code for experimental comparisons. This work was supported by KAUST OSR Award No. CRG-2017-3426, a gift from the NVIDIA Corporation, the ERC Starting Grant StG-2017-758800 (EXPROTEA) and StG-2018-802554 (SPECGEO).



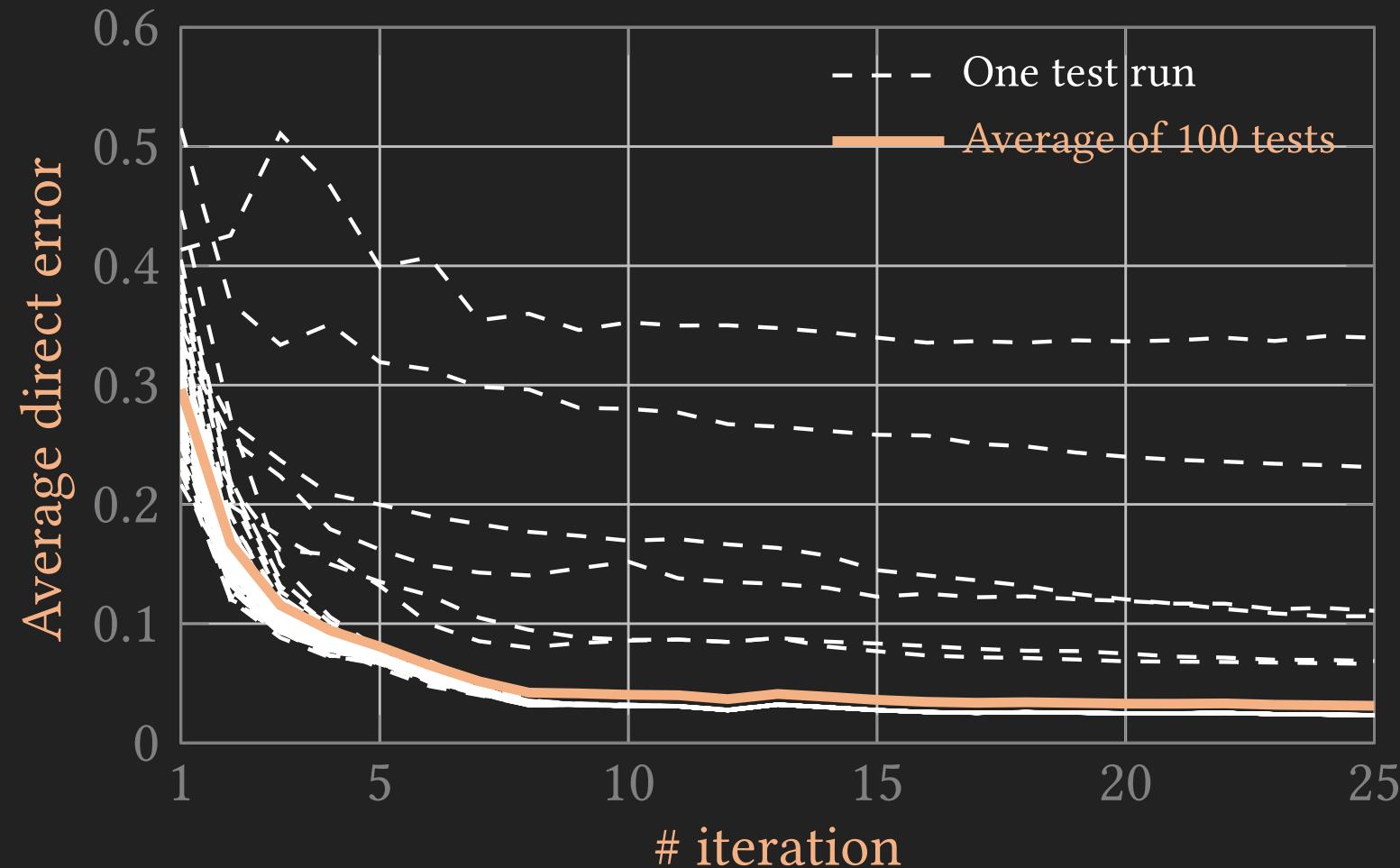
https://github.com/llorz/SGA19_zoomOut/

Additional materials

Property: robust to noise



Property: robust to noise



Adding white noise to initialization (4x4 functional map):
96 out of 100 converged to exactly the same solution

More Applications

Symmetry detection



Ground-
truth

BIM
[Kim et al.
2011]

GroupRep
[Wang and
Huang 2017]

IntSymm
[Nagar and
Raman 2018]

OrientRev
[Ren et al.
2018]

BCICP
[Ren et al.
2018]

Ours

More Applications

Symmetry detection

Measurement	Average Error ($\times 10^{-3}$)		Average Runtime (s)	
Method \ Dataset	FAUST	SCAPE	FAUST	SCAPE
BIM [Kim et al. 2011]	65.4	133	34.6	41.7
GroupRep [Wang and Huang 2017]	224	347	8.48	16.7
IntSymm [Nagar and Raman 2018]	33.9	60.3	1.35	1.81
OrientRev (Ini) [Ren et al. 2018]	68.0	110	0.59	1.07
Ini + BCICP [Ren et al. 2018]	29.2	49.7	195.1	525.6
Ini + Ours	16.1	46.2	22.6	62.7
Ini + Ours*	18.5	46.6	1.78	3.66
Improv. w.r.t state-of-the-art	Ini + Ours	44.9%	7.0%	8×
	Ini + Ours*	36.6%	6.2%	110×
				140×

More Applications

Function Transfer



Original

 f

Initialization

ICP

p2p[†]ICP₃₀₀Prod[†]

Ours

Challenging case

Partial Shape Matching



Failure case

