

Continuous and Orientation-preserving Correspondences via Functional Maps

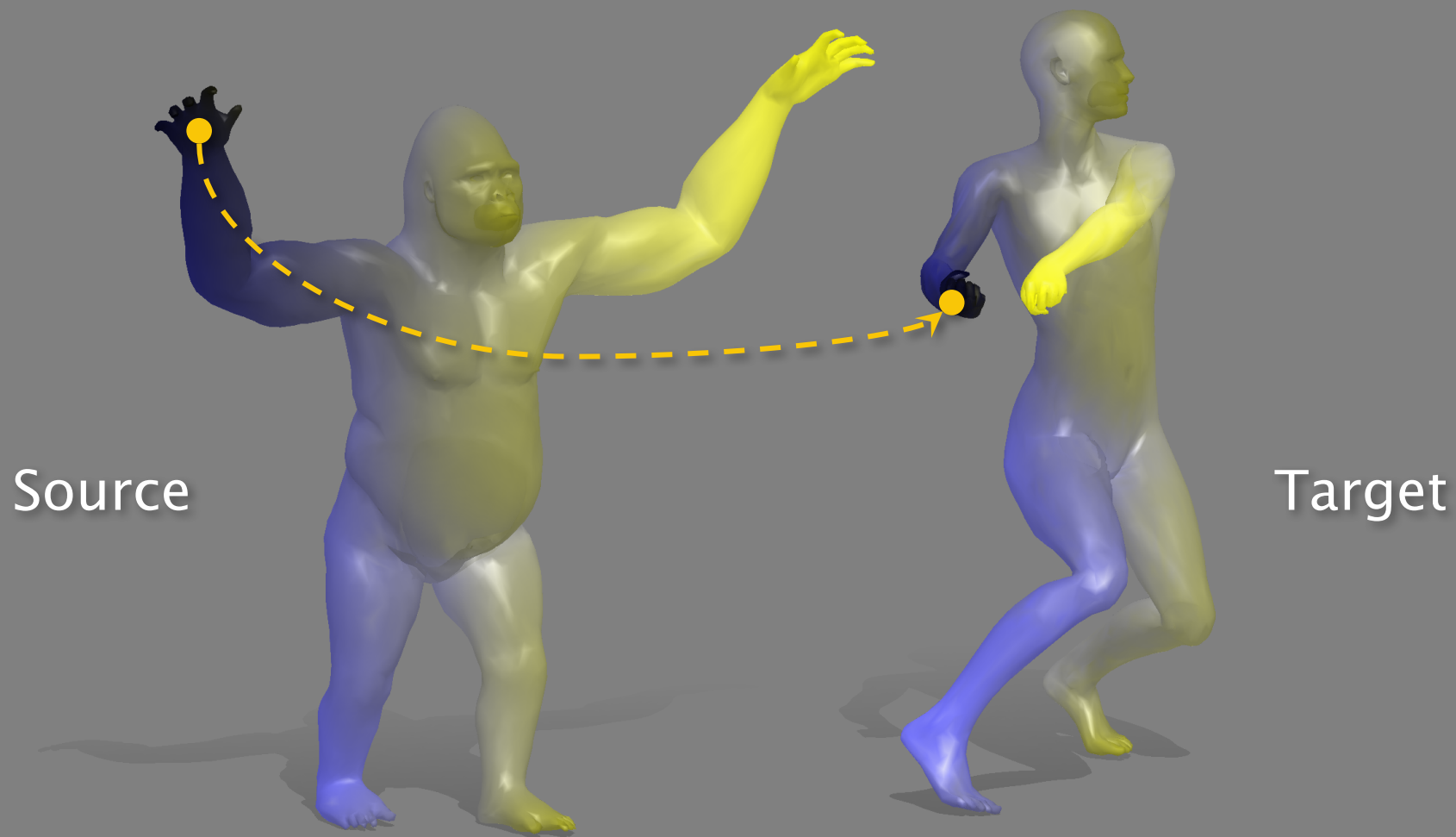
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Shape matching



Corresponding descriptors

Gaussian curvatures



Joint segmentation

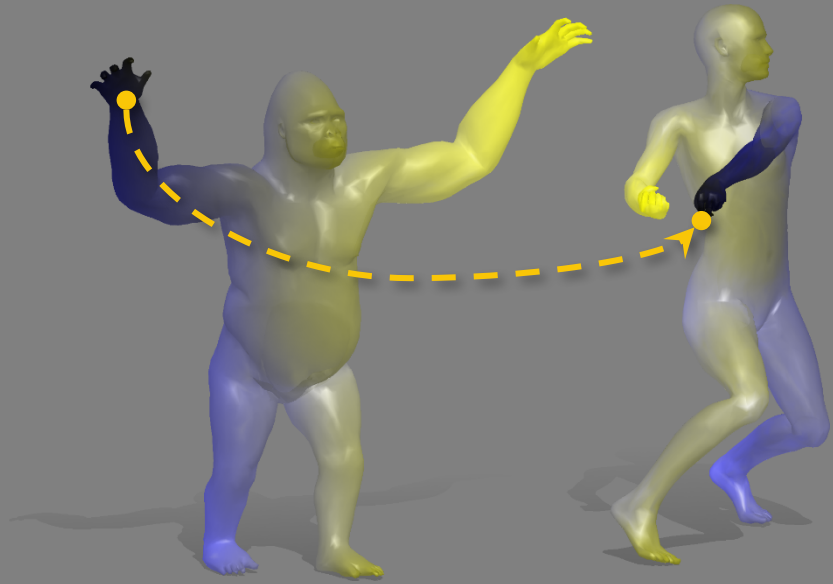


Wave kernel signature

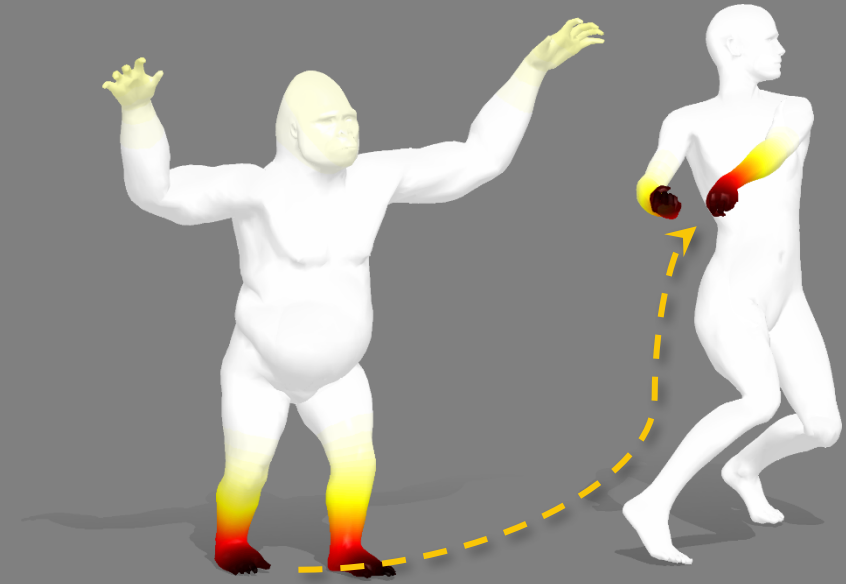


Problems

Left-right ambiguity



Leg-arm ambiguity



How to break the **symmetry** ambiguity?

Our **solution**: define **orientation-preserving** operators in the **functional map** framework.

Q1: what is the standard **functional map pipeline** to solve the shape matching problem?

Q2: how to define the **orientation-preserving** operator? Why does it work?

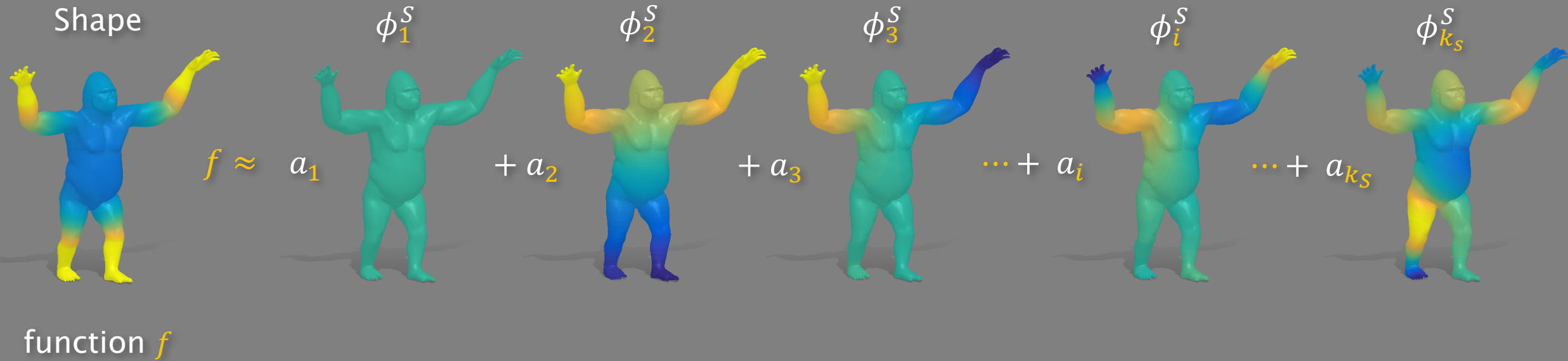
Q1: Functional map pipeline

Laplacian–Beltrami operator



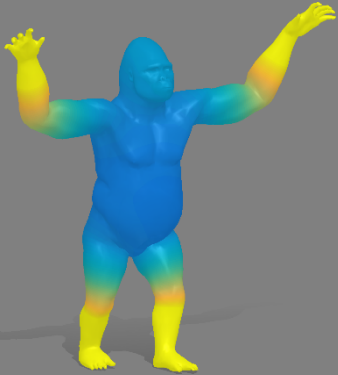
Q1: Functional map pipeline

Laplacian–Beltrami operator

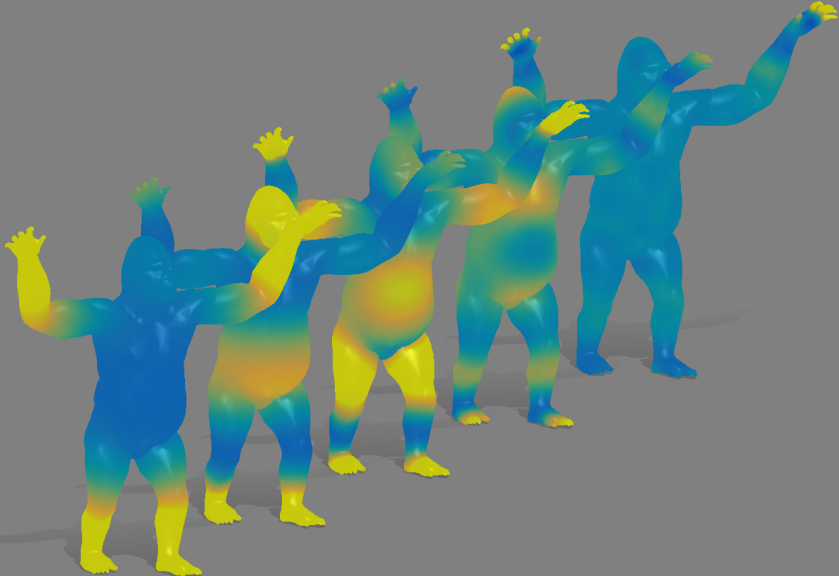


Q1: Functional map pipeline

Source



$$f \approx \Phi^S a$$

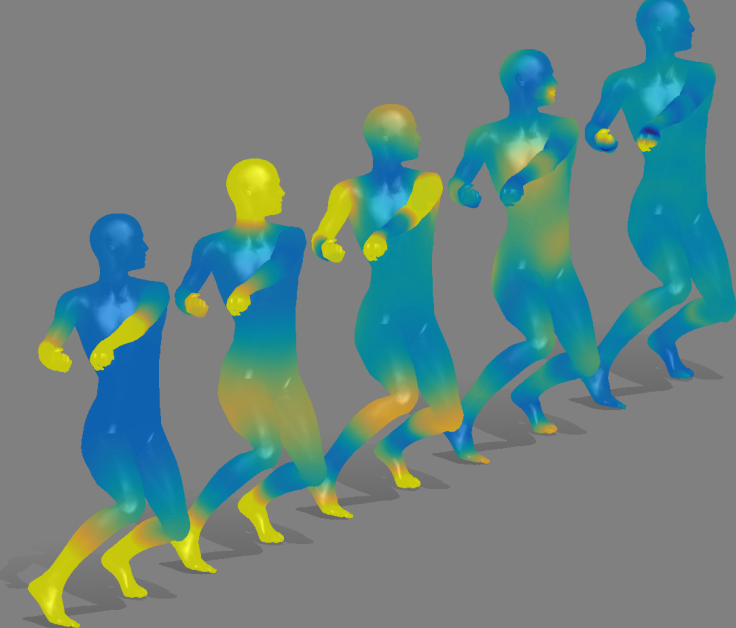


$$\{f_i\}_{i=1}^k \xrightarrow{\Phi^S} \{a_i\}_{i=1}^k$$

Target



$$g \approx \Phi^T b$$



$$\{g_i\}_{i=1}^k \xrightarrow{\Phi^T} \{b_i\}_{i=1}^k$$

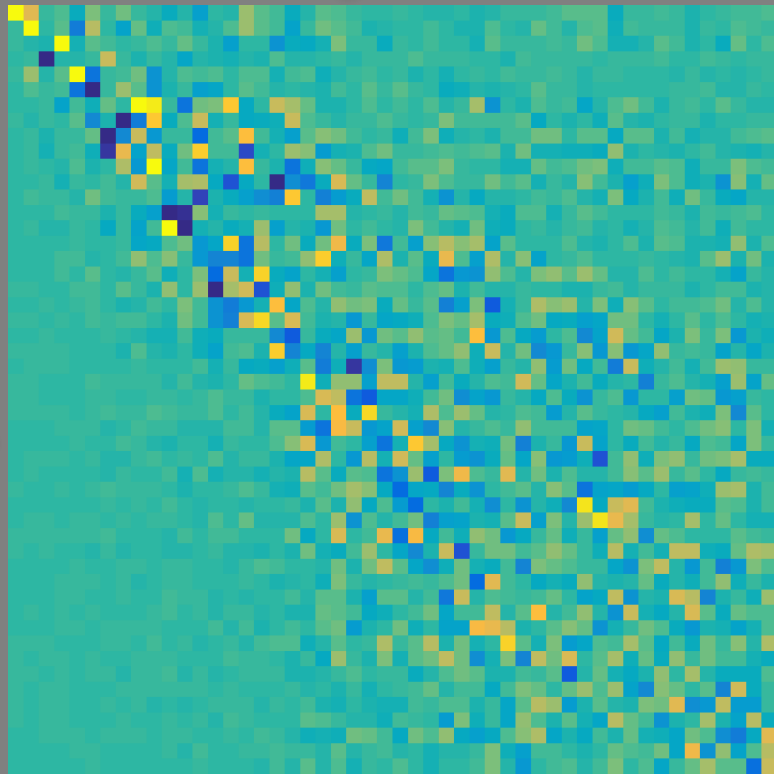
$$C a_i = b_i$$
$$\forall i = 1, \dots, k$$

Q1: Functional map pipeline

$$a = (\Phi^S)^\dagger f$$



$k_S = 50$



Functional Map C



a

$=$



b

$$\hat{g} \triangleq \Phi^T b$$



\hat{g}

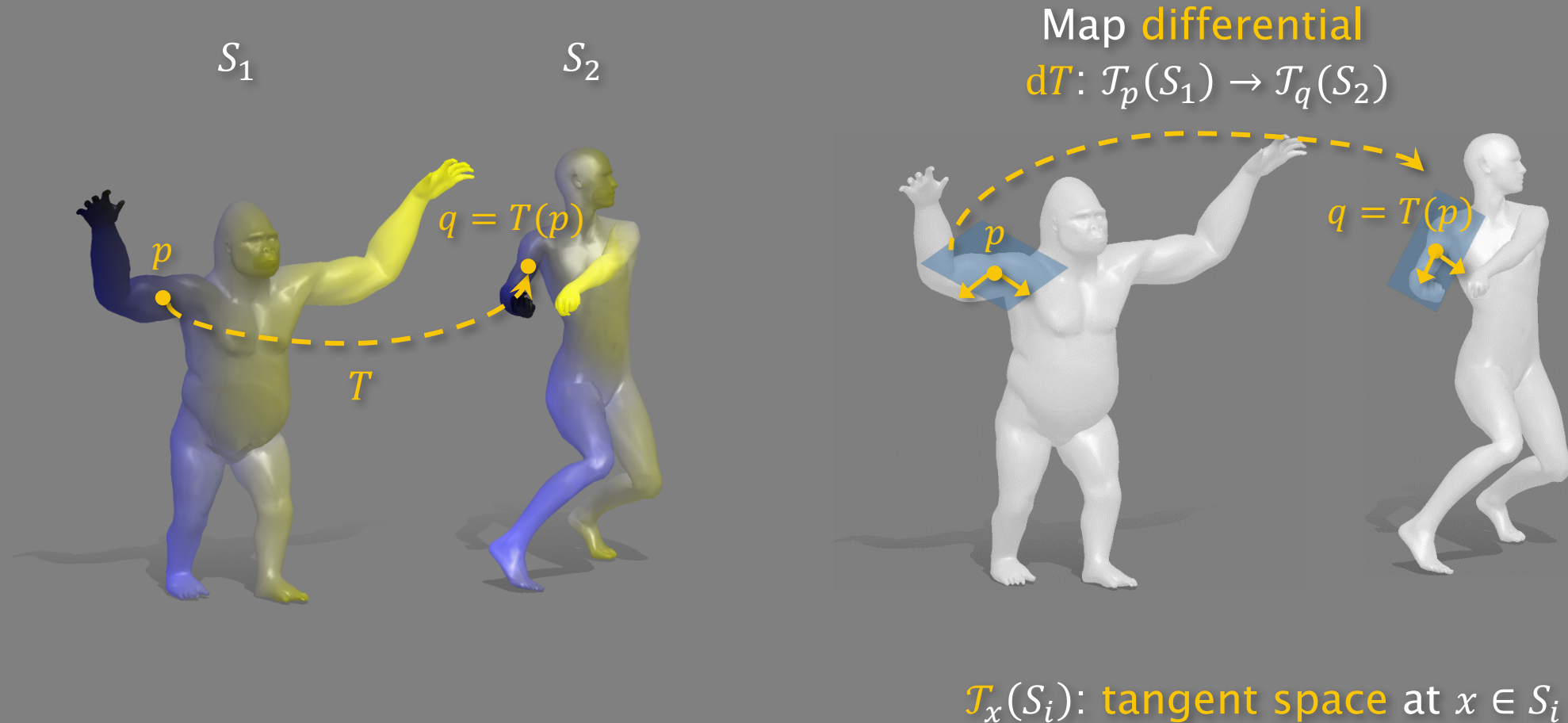
Q1: Functional map pipeline

How to find C ?

Given a pair of shapes S_1, S_2 , with Laplacian operators $\Delta_{S_1}, \Delta_{S_2}$

- Compute the **functional bases** on the two shapes. Store them in matrices Φ^{S_1}, Φ^{S_2}
- Project the corresponding **descriptors** $\{f_i, g_i\}_{i=1}^k$ into the functional space. Store the **coefficients** in matrices $A = [a_1 \cdots a_k], B = [b_1 \cdots b_k]$
- Solve $C^* = \underset{C \in \mathbb{R}^{k_T \times k_S}}{\operatorname{argmin}} E(C) = \|CA - B\|^2 + \|C\Delta_{S_1} - \Delta_{S_2}C\|^2$
- **Orientation-preservation term** $\sum_{i=1}^k \|C\Omega_{f_i} - \Omega_{g_i}C\|^2$

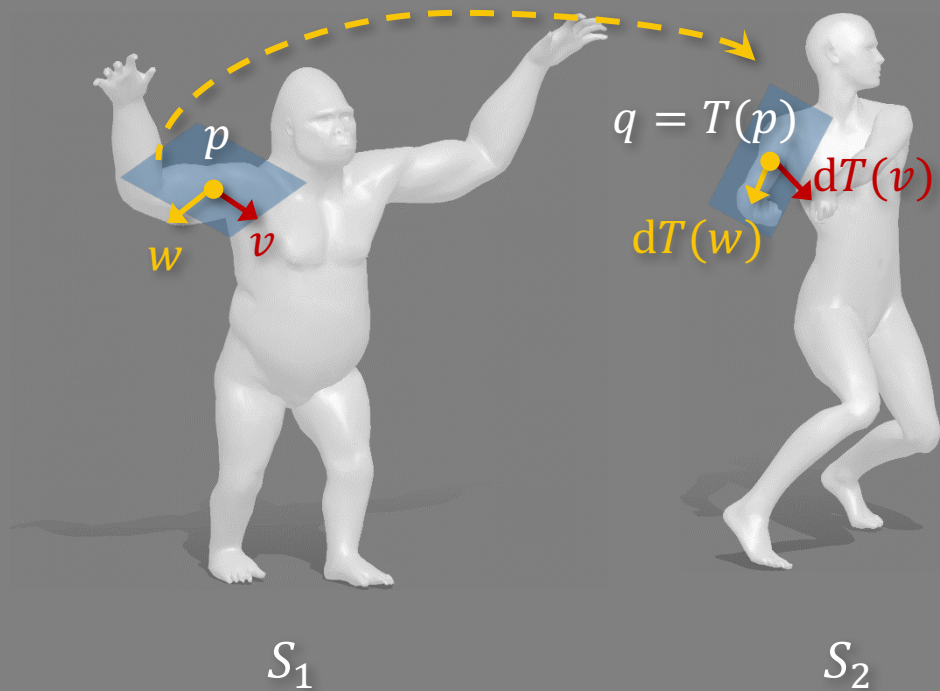
Q2: Orientation-preserving operators



A smooth map T is orientation preserving if and only if dT is orientation preserving

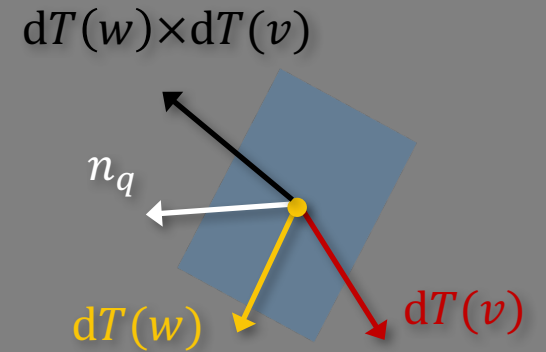
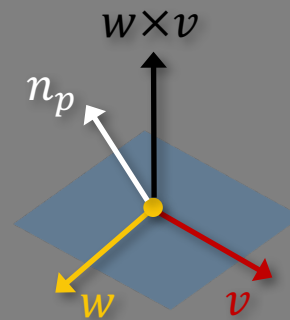
Q2: Orientation-preserving operators

Map differential
 $dT: \mathcal{T}_p(S_1) \rightarrow \mathcal{T}_q(S_2)$



Frame at p : (w, v, n_p)

Frame at $q = T(p)$: $(dT(w), dT(v), n_{T(p)})$



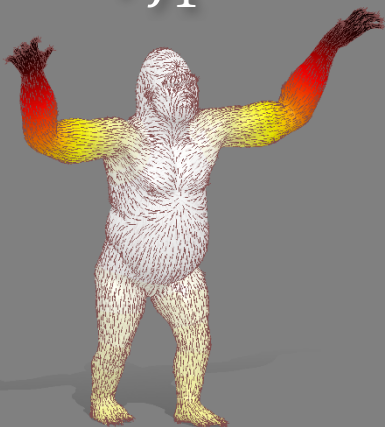
$(w \times v)^T n_p$ should have the **same** sign as $(dT(w) \times dT(v))^T n_{T(p)}$

Q2: Orientation-preserving operators

f_1



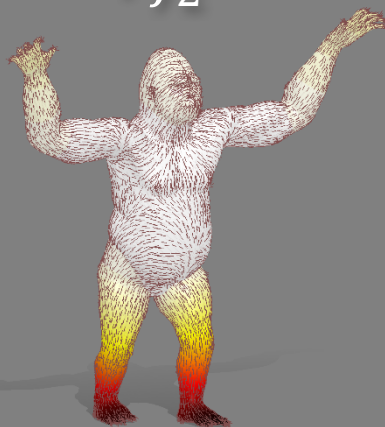
∇f_1



f_2



∇f_2



g_1



∇g_1



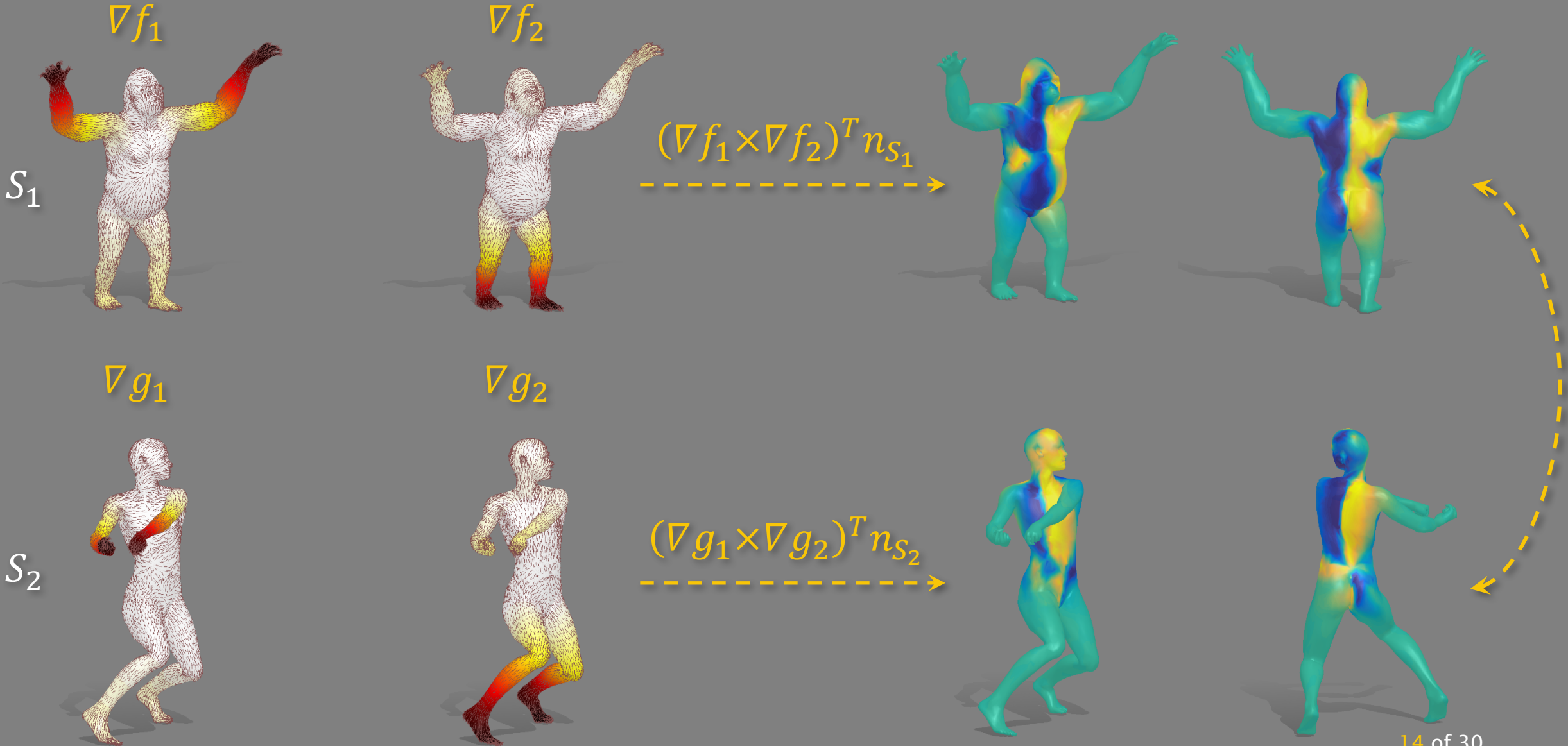
g_2



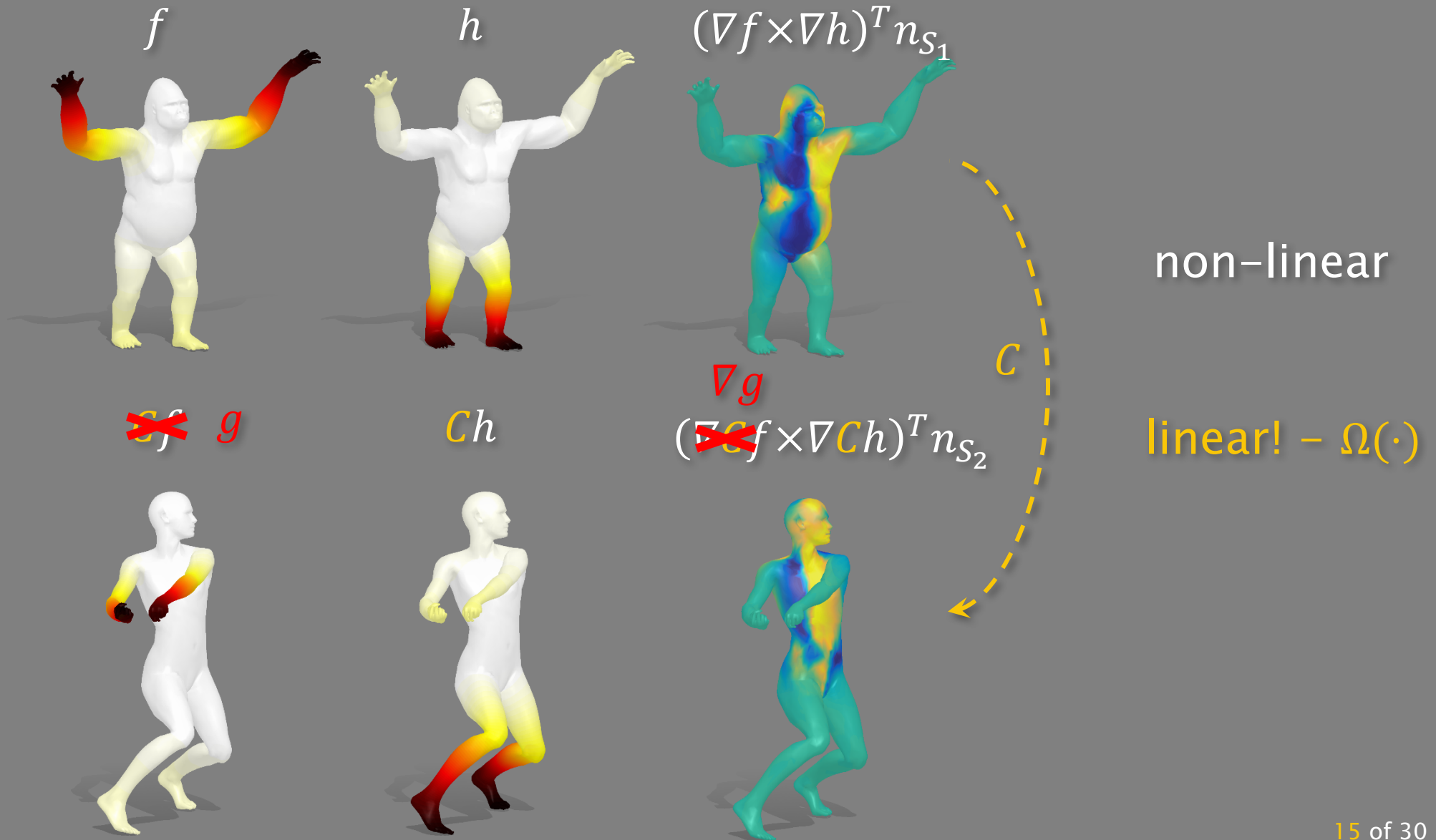
∇g_2



Q2: Orientation-preserving operators



Q2: Orientation-preserving operators



Q2: Orientation-preserving operators

Shape



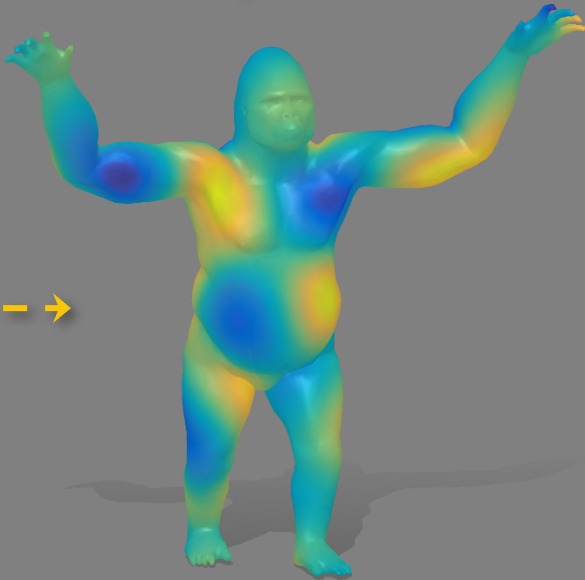
A descriptor function f
With symmetry ambiguity



$\Omega(\cdot)$

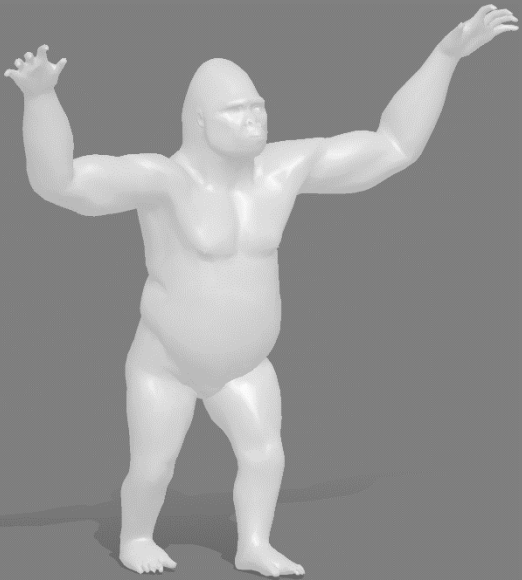


$\Omega(f)$
antisymmetric



Q2: Orientation-preserving operators

Shape



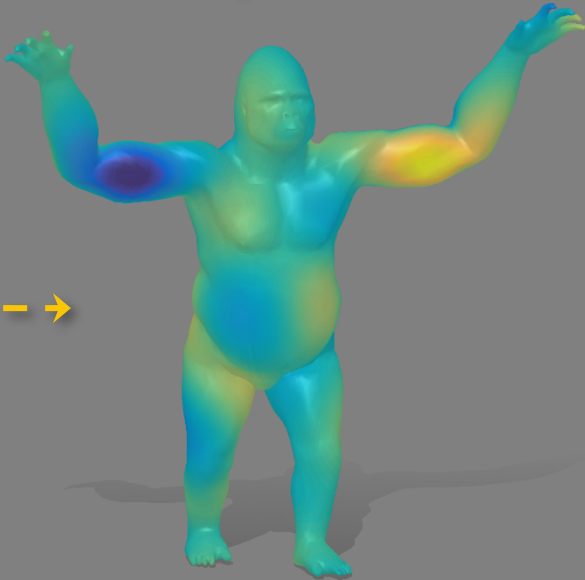
A descriptor function f
With symmetry ambiguity



$\Omega(\cdot)$



$\Omega(f)$
antisymmetric



Q2: Orientation-preserving operators

Shape



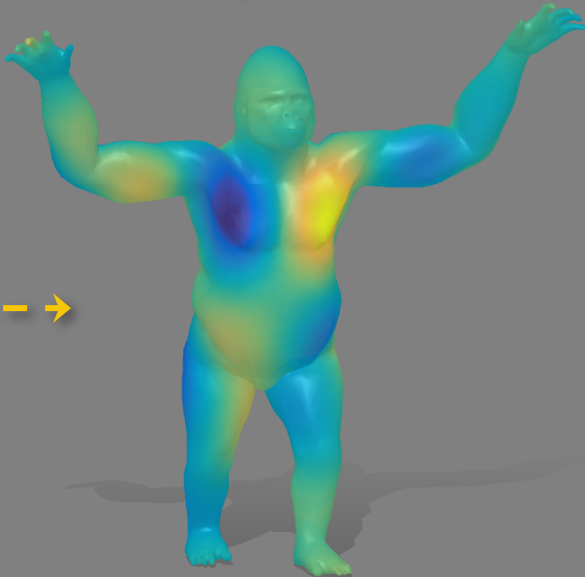
A descriptor function f
With symmetry ambiguity



$\Omega(\cdot)$



$\Omega(f)$
antisymmetric



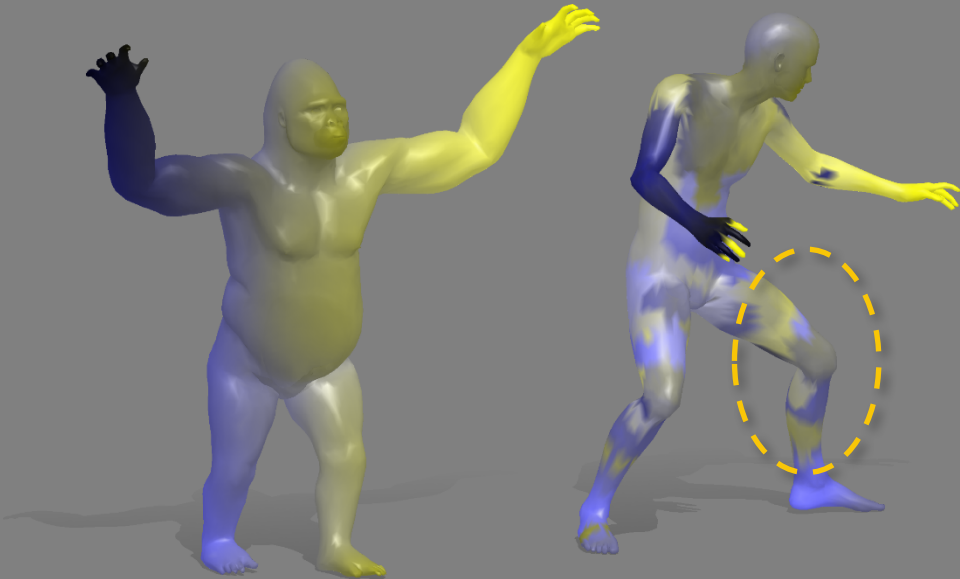
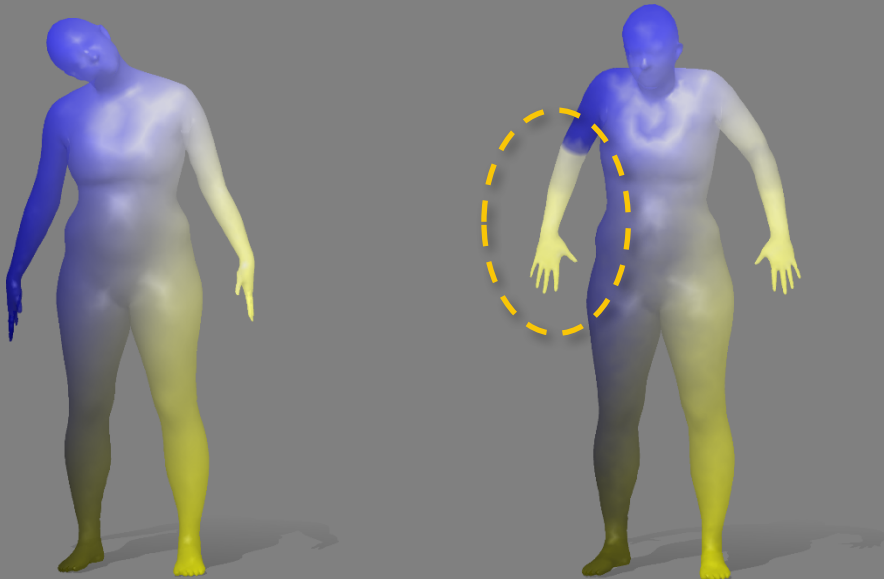
Orientation-preserving operators – defects

Source

Target

Source

Target



Intrinsic – no guarantee

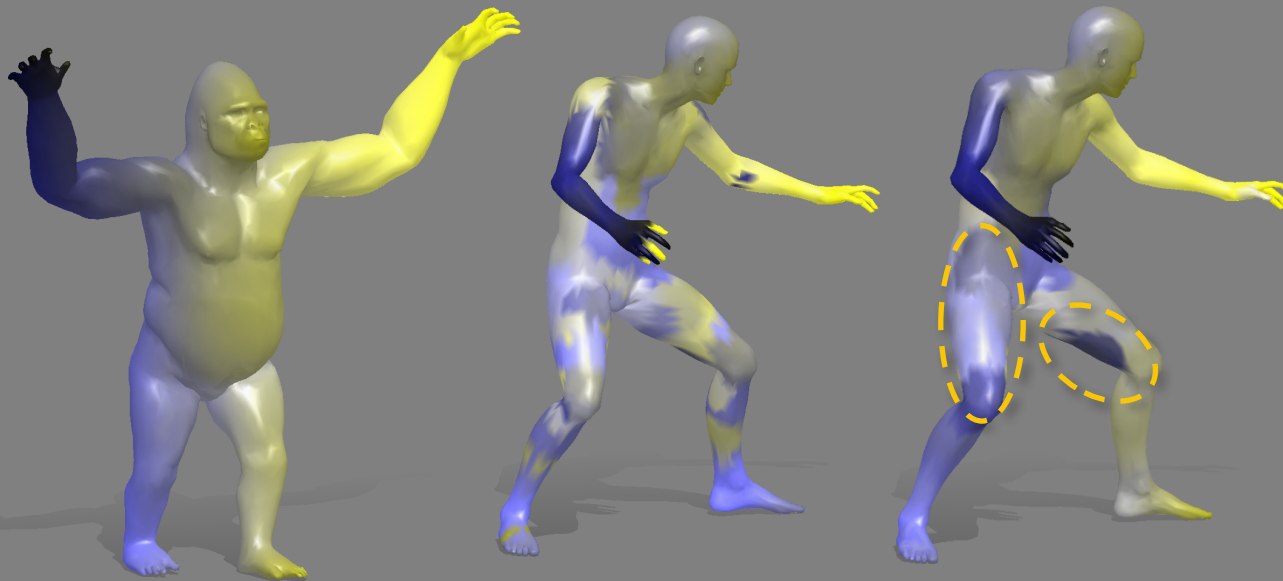
Induced – depends on the descriptors

Refinement! – iterative closest point (ICP)?

Source

Target

ICP



Problems of ICP:

- discontinuous
- Only in the spectral domain – no spatial info

A better refinement to improve the quality?

Without ground-truth correspondences, how do we measure the quality of a map?

Refinement! – improve smoothness

Source



Target: map 01



Target: map 02



smoother – better!

Refinement! – remove outliers

Source



Target: map 01



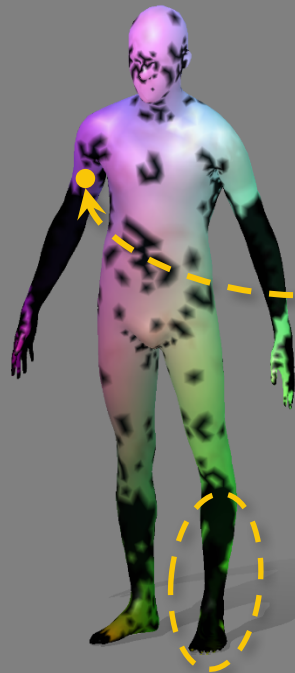
Target: map 02



smoother (no outliers)
– better!

Refinement! – improve coverage

Source



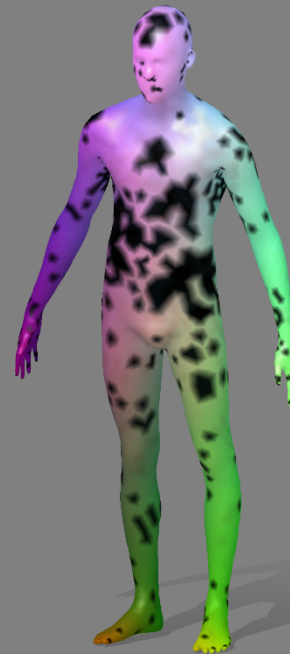
Target: map 01



Black region: not covered
(no correspondence)

Coverage: 48.9%

Source



Target: map 02

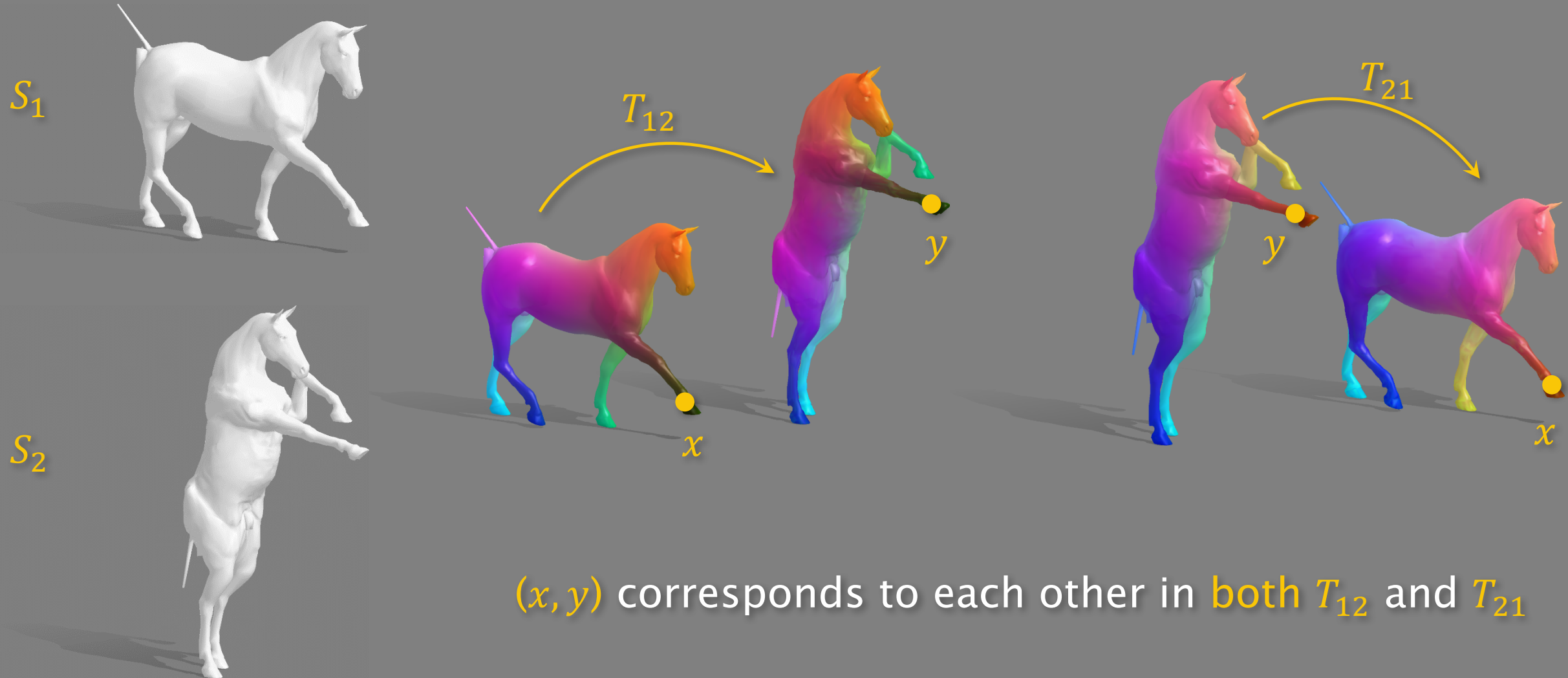


Coverage: 81.4%

Coverage: #vertex (or surface area) %
covered by the map

More vertices **covered**
– better!

Refinement! – improve **bijection**



Bijjective and Continuous ICP (BCICP)

- **Bijjectivity**

- Soft constraints: $T_{21} \circ T_{12}$ and $T_{12} \circ T_{21}$ are close to **identity**

- **Continuity**

- Smooth the **displacement vector field**

- **Coverage**

- Find the **nearest** neighbor with the **largest** preimage size

- **Outliers**

- Detected by **edge distortion** and fixed by the **nearest neighbor** classified as an **inlier**

code

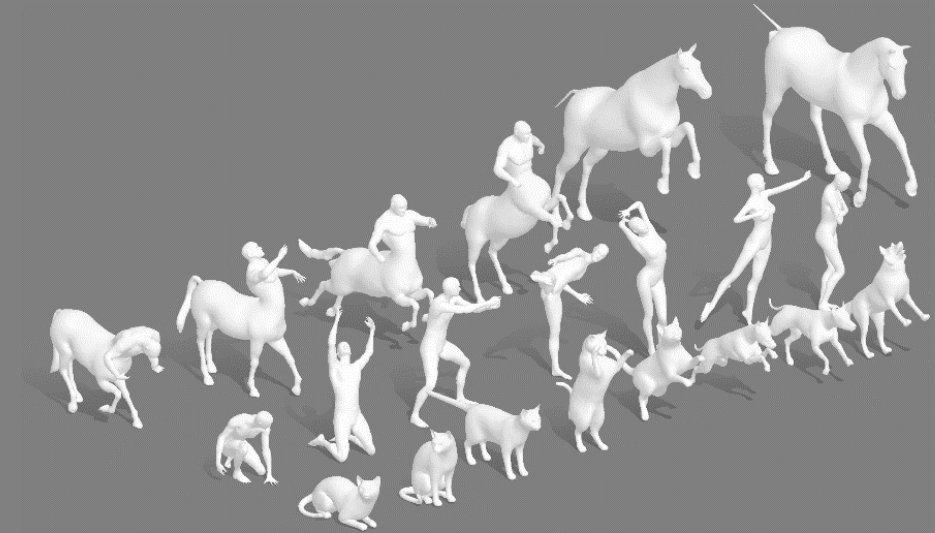


Benchmark datasets



FAUST dataset [Bogo et al. 2014]

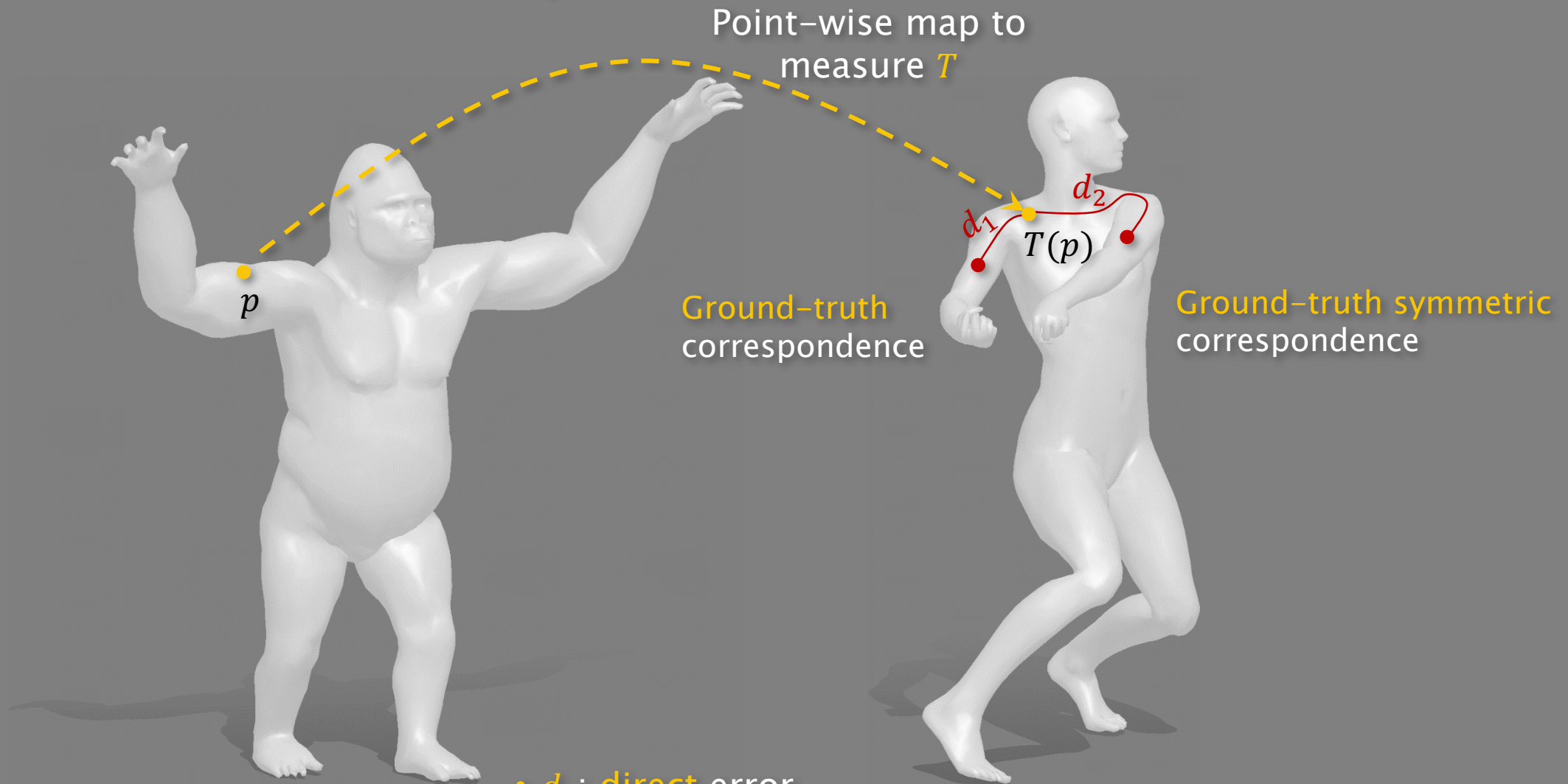
- 10 different humans in 10 different poses
- We tested on
 - 200 isometric pairs
 - 400 non-isometric pairs



TOSCA dataset [Bronstein et al 2008]

- 80 different humans and animals in 9 categories
- We tested on
 - 568 isometric pairs
 - 190 non-isometric pairs

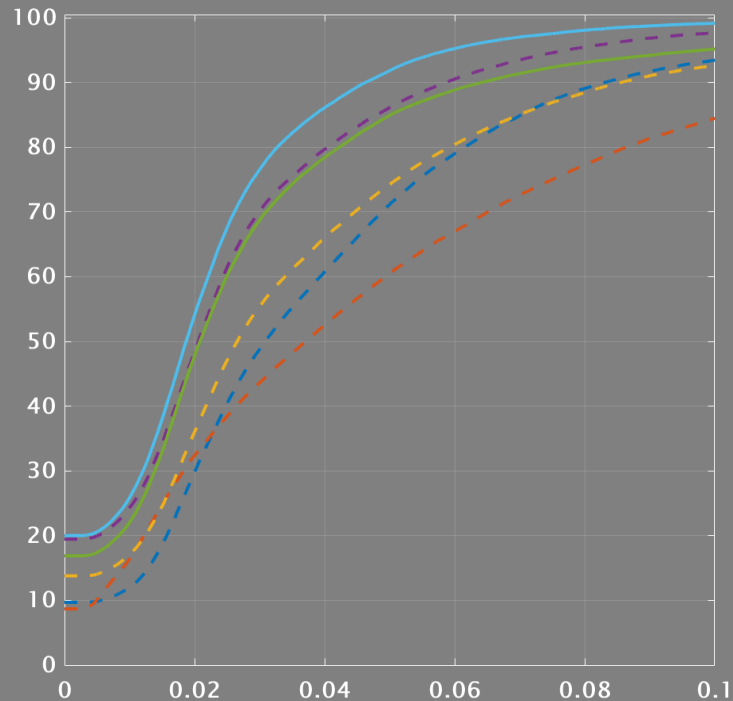
Measurement – Accuracy



- d_1 : direct error
- d_2 : symmetric error
- $\min(d_1, d_2)$: per-vertex error

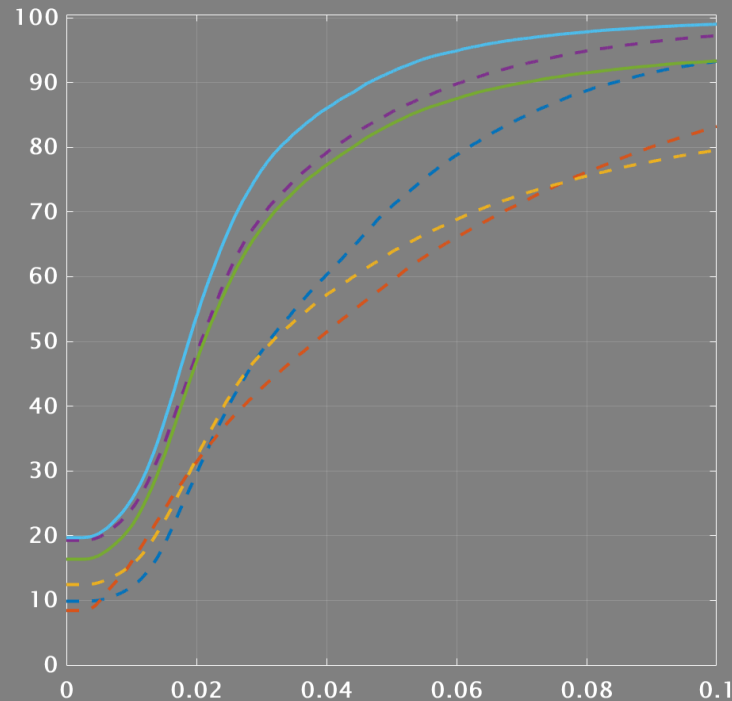
Results – FAUST Isometric dataset (200 pairs)

per-vertex error



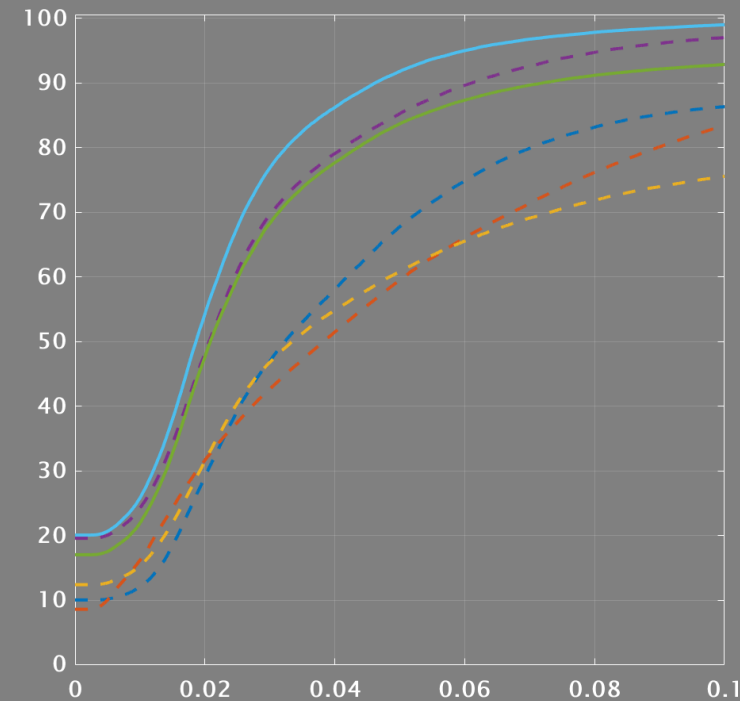
Geodesic Error

per-map error



Geodesic Error

direct error



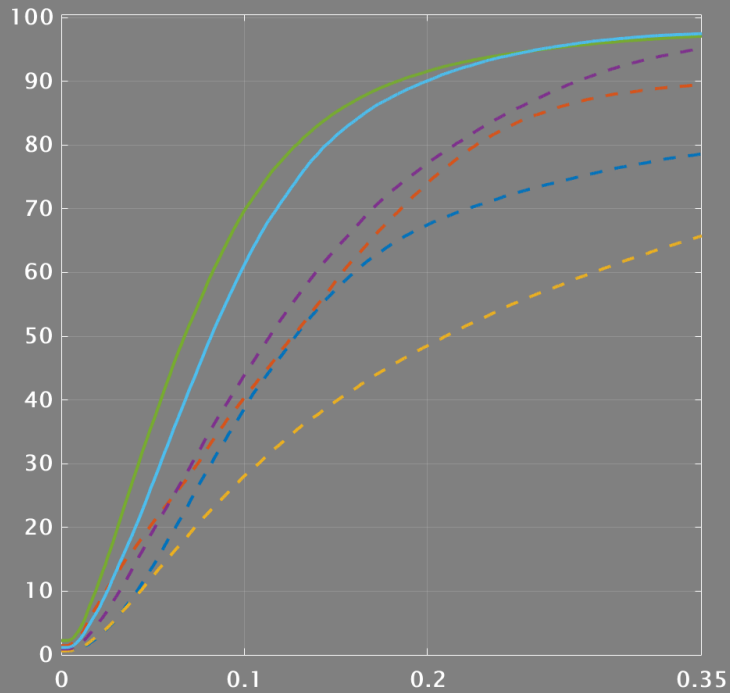
Geodesic Error

Solid lines: our methods (with different descriptors)

Dashed lines: state-of-the-art methods

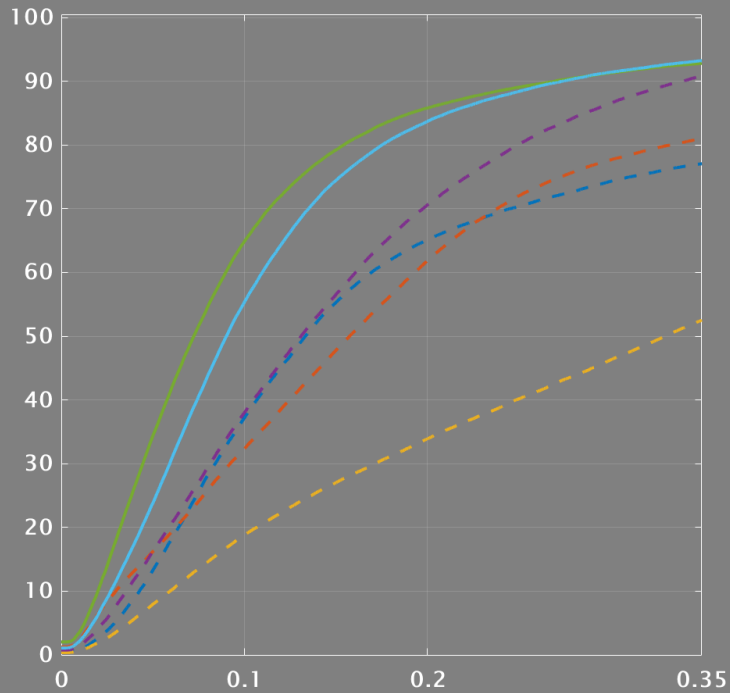
Results – TOSCA non-Isometric dataset (190 pairs)

per-vertex error



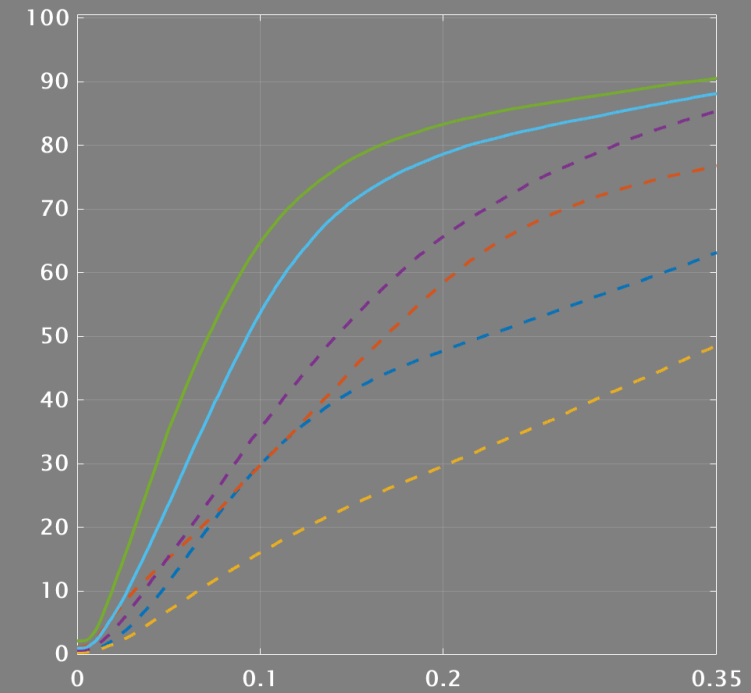
Geodesic Error

per-map error



Geodesic Error

direct error



Geodesic Error

Solid lines: our methods (with different descriptors)

Dashed lines: state-of-the-art methods

Summary

- Introduce **orientation-preserving operator** into functional map framework
- Propose a refinement technique, **BCICP**, which improves the **bijectionity**, **continuity**, and **coverage**
- Verify the **usefulness** of the orientation-preserving operator and the BCICP refinement on **large** datasets, w.r.t. **different measurements**

Thanks for your attention 😊

Continuous and Orientation-preserving Correspondences via Functional Maps

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Supplementary

Problems

Source



Outliers



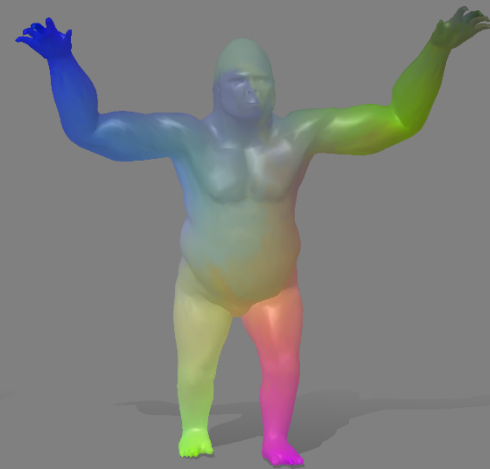
Back-to-front



Left-to-right



Leg-to-arm



Ours



Results – Summary

Measurement \ Dataset (#pairs)	FAUST		TOSCA	
	Isometric 200	Non-isometric 400	Isometric 586	Non-isometric 190
Per-vertex	17.8%	24.1%	31.4%	38.3%
Per-map	17.5%	18.4%	14.6%	37.1%
Direct	17.5%	18.4%	38.8%	43.5%

Relative improvement of our method (**directOp + BCICP**)
over the **best** baseline methods
w.r.t. the **average error** of three measurements

Q2: Orientation-preserving operators

Encode into **functional map** framework:

- Given a functional map C maps function on S_1 to function on S_2
- For every pair of corresponding **descriptor** (f, g) , $f \in \mathcal{F}(S_1)$, $g \in \mathcal{F}(S_2)$
- We can add the orientation-preserving constrain $C \left((\nabla f \times \nabla h)^T n_{S_1} \right) = (\nabla g \times \nabla C(h))^T n_{S_2}$
 - $\nabla f, \nabla g$: vector field on the source and target mesh resp.
 - $h, C(h)$: functions defined on the source and target resp.
 - $\nabla h, \nabla C(h)$: vector field
 - $(\nabla f \times \nabla h)^T n_{S_1}$ defines a function on the source
 - $(\nabla g \times \nabla C(h))^T n_{S_2}$ defines a function on the target
 - they should correspond to each other! – use functional map to transport the function
- $C \left((\nabla f \times \nabla h)^T n_{S_1} \right) = (\nabla g \times \nabla C(h))^T n_{S_2}$
- **OrientationPreserving**(C) for every pair of corresponding descriptors (f, g)

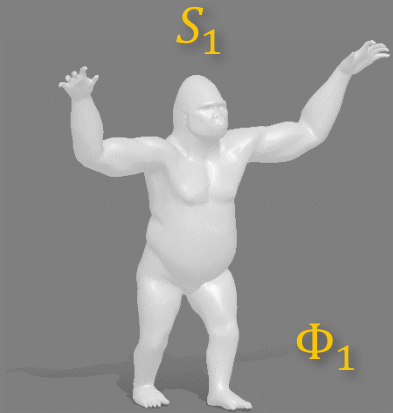
Q2: Orientation-preserving operators

- Define $\omega(w, v, n) = (w \times v, n)$
- If T is orientation preserving, we have $\text{sign}(\omega(w, v, n_p)) = \text{sign}(\omega(dT(w), dT(v), n_{T(p)}))$ for any pair of $w, v \in \mathcal{T}_p(S_1)$, and for any vertex p

Encode into **functional map** framework:

- Given a pair of corresponding **descriptor** (f, g) , $f \in \mathcal{F}(S_1)$, $g \in \mathcal{F}(S_2)$
- $\forall h \in \mathcal{F}(S_1)$, it is mapped to $C(h) \in \mathcal{F}(S_2)$ via a functional map C
- Orientation-preserving:
 - For any **point** $p \in S_1$ (corresponds to $q \in S_2$ via C)
 - $\omega(\nabla f(p), \nabla h(p), n_p) \approx \omega(\nabla g(q), \nabla(C(h))(q), n_q)$
 - Define a function $\Omega(\cdot, \cdot, \cdot) \in \mathcal{F}(S_1)$ such that $\Omega(p) = \omega(\cdot_p, \cdot_p, \cdot_p)$
 - $C(\Omega(\nabla f, \nabla h, n_{S_1})) = \Omega(\nabla g, \nabla C(h), n_{S_2})$
- **OrientationPreserving**(C) for every pair of corresponding descriptors (f, g)

BCICP refinement – improve **bijection**



Notation:

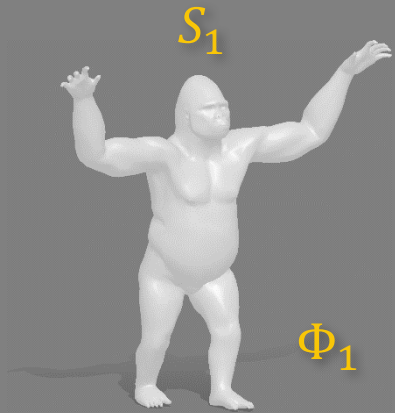
- Point-wise map (**vector!**) T_{12} : i -th vertex on S_1 is mapped to $T_{12}(i)$ -th vertex on S_2
- Shape S_i has Laplacian-Beltrami Basis Φ_i
- Functional map (**matrix!**) C_{12} : maps the functional space $\mathcal{F}(S_1|\Phi_1)$ to $\mathcal{F}(S_2|\Phi_2)$

Recall **ICP**:

- C_{12} is associated with T_{21}
 - Arbitrary function $f \in \mathcal{F}(S_1)$ can be transported to S_2 in two ways:
 - Using the point-wise map directly, i.e., $g = f(T_{21}) \in \mathcal{F}(S_2)$
 - Use the functional map, i.e., $g = \Phi_2 \left(C_{12}(\Phi_1^\dagger f) \right)$
- Two transportations should give **similar** result – for any f
- Minimize $\|\Phi_2 C_{12} - \Phi_1(T_{21}, :)\|^2$
 - ICP: alternatively solve for C_{12} and T_{21}



BCICP refinement – improve **bijection**



Bijection in the **spectral** domain:

- $\|\Phi_2 C_{12} - \Phi_1(T_{21}, :)\|^2 + \|\Phi_2 C_{21} - \Phi_1(T_{12}, :)\|^2$

Bijection in the **spatial** domain:

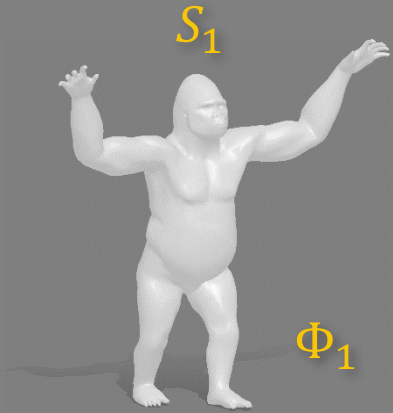
- $T_{21} \circ T_{12}$: maps S_1 to itself (S_1)
- We can add a similar term $\|\Phi_1 C_{11} - \Phi_1(T_{21} \circ T_{12}, :)\|^2$
 - where C_{11} is an **auxiliary** variable, maps the functional space $\mathcal{F}(S_1|\Phi_1)$ to itself
- We can similarly define the energy for $T_{12} \circ T_{21}$



New energy

$$\begin{aligned} & \lambda_1 \|\Phi_2 C_{12} - \Phi_1(T_{21}, :)\|^2 \\ & + \lambda_2 \|\Phi_2 C_{21} - \Phi_1(T_{12}, :)\|^2 \\ & + \lambda_3 \|\Phi_1 C_{11} - \Phi_1(T_{21} \circ T_{12}, :)\|^2 \\ & + \lambda_4 \|\Phi_2 C_{22} - \Phi_2(T_{12} \circ T_{21}, :)\|^2 \end{aligned}$$

BCICP refinement – improve **bijection**



ICP energy

$$\|\Phi_2 C_{12} - \Phi_1(T_{21}, :)\|^2$$



New energy

$$\begin{aligned} & \lambda_1 \|\Phi_2 C_{12} - \Phi_1(T_{21}, :)\|^2 \\ & + \lambda_2 \|\Phi_2 C_{21} - \Phi_1(T_{12}, :)\|^2 \\ & + \lambda_3 \|\Phi_1 C_{11} - \Phi_1(T_{21} \circ T_{12}, :)\|^2 \\ & + \lambda_4 \|\Phi_2 C_{22} - \Phi_2(T_{12} \circ T_{21}, :)\|^2 \end{aligned}$$

BCICP refinement – improve smoothness

Source

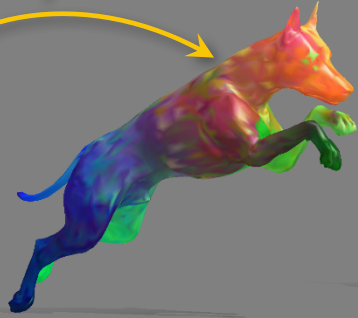
VtxPos X



T

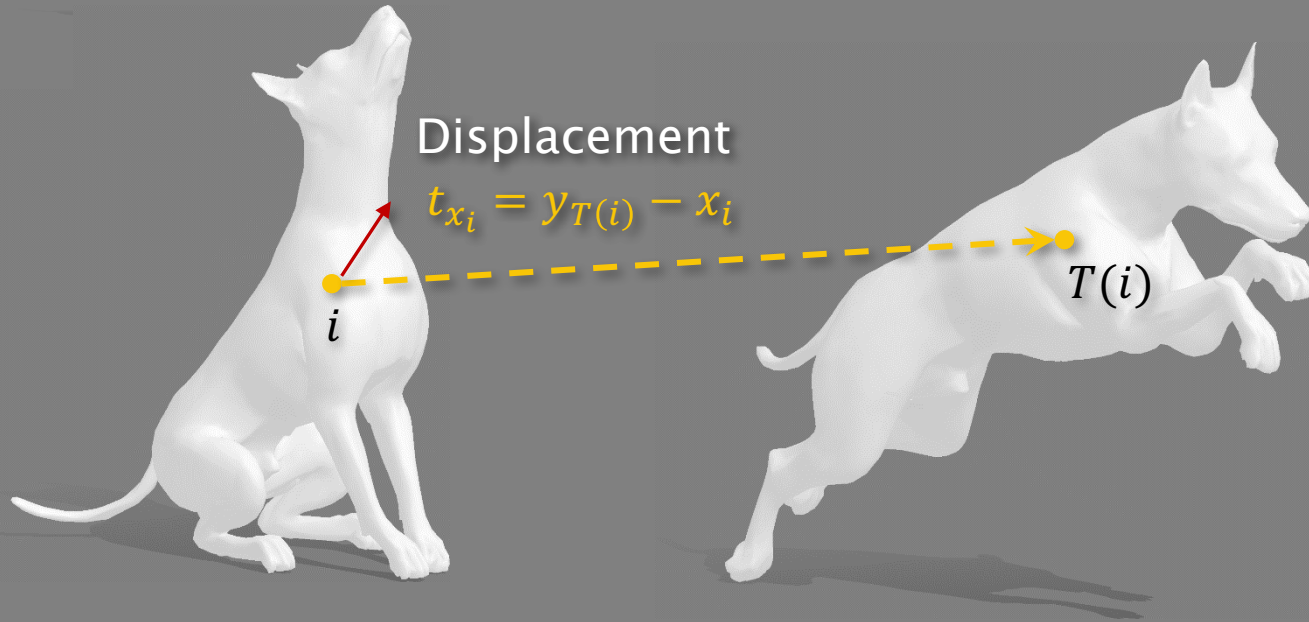
Target

VtxPos Y



Displacement

$$t_{x_i} = y_{T(i)} - x_i$$



BCICP refinement – improve smoothness

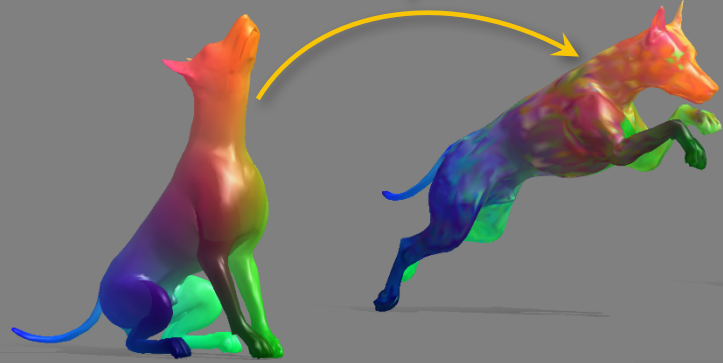
Source

VtxPos X

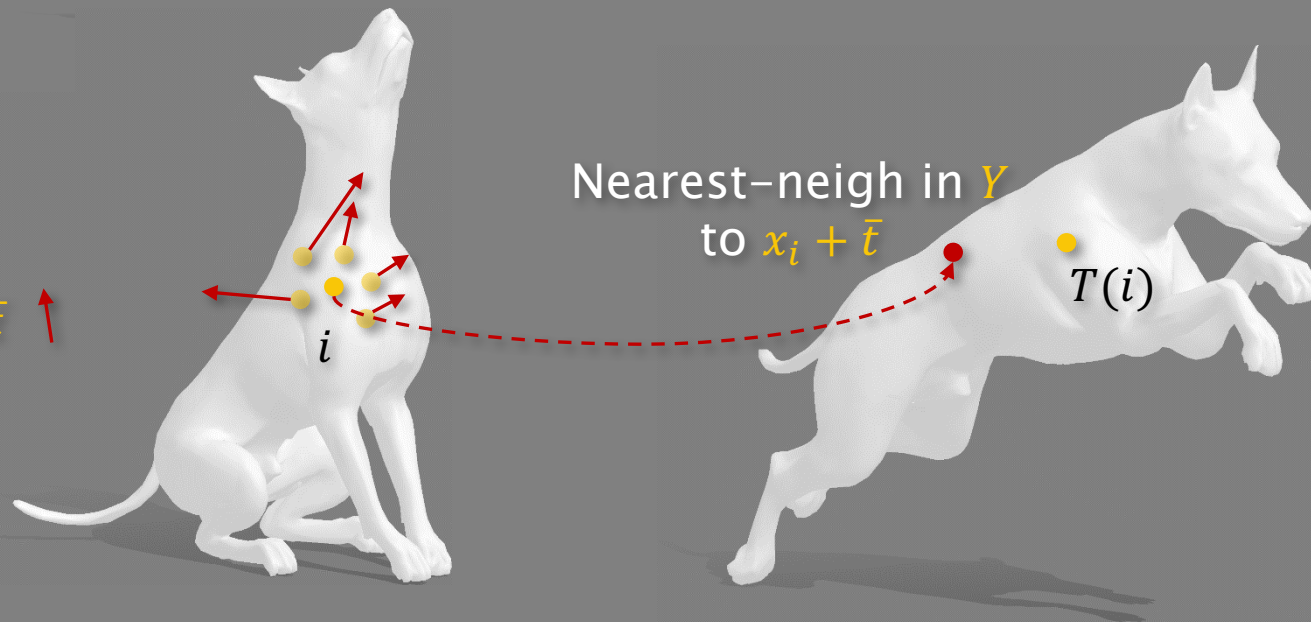
Target

VtxPos Y

T



Average displacement \bar{t} ↑



[Papazov and Burschka 2011]

BCICP refinement – improve smoothness

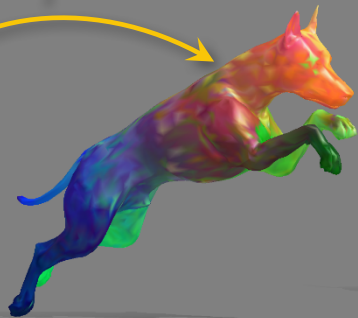
Source

VtxPos X



Target

VtxPos Y



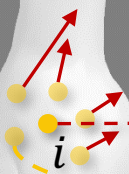
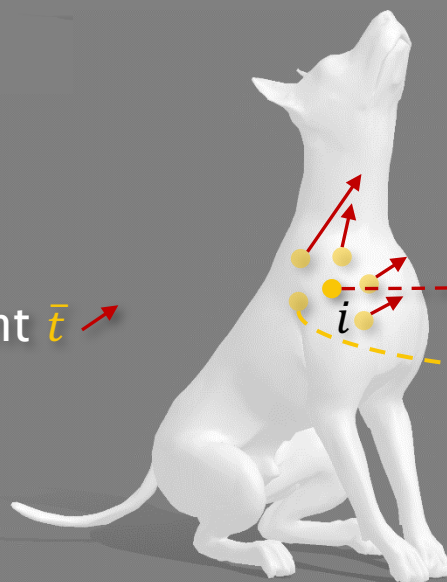
T



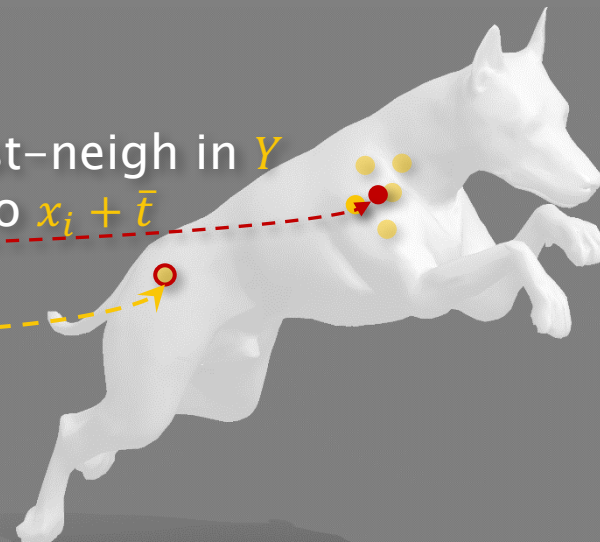
Smoothed map



Average displacement \bar{t}



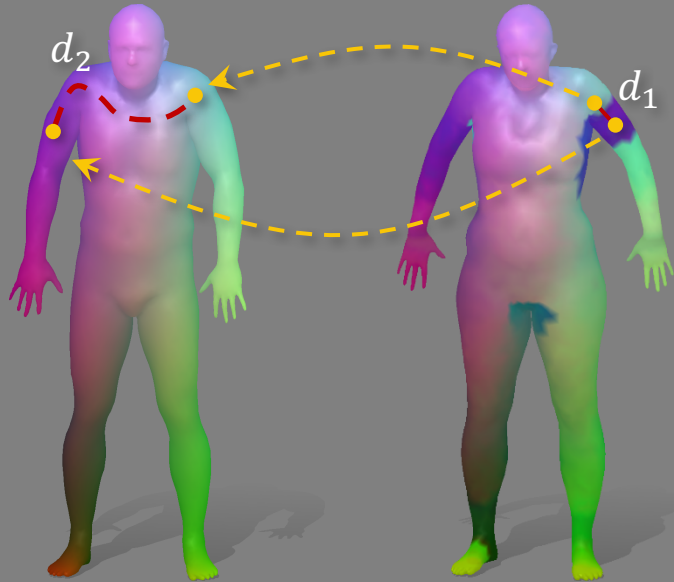
Nearest-neighbor in Y
to $x_i + \bar{t}$



BCICP refinement – remove outliers

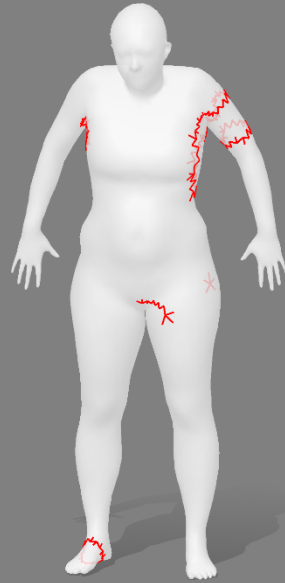
Source

Target



Compute the edge distortion $r = d_2/d_1$

Edges with large distortion



Remove these edges from the adjacency matrix of the mesh

Find the largest connected component

Trustworthy vertices



Find the outlier region

Outlier vertices

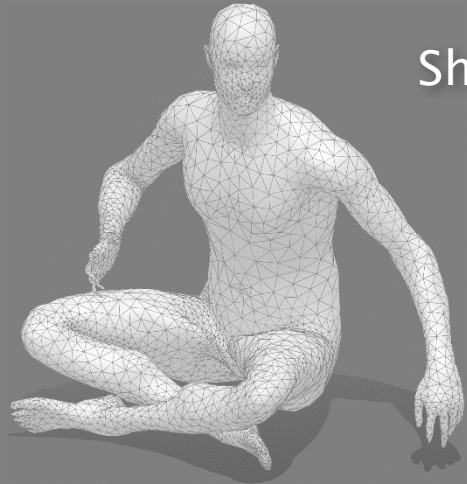


Outlier – find its NN in the “trustworthy” vertex set

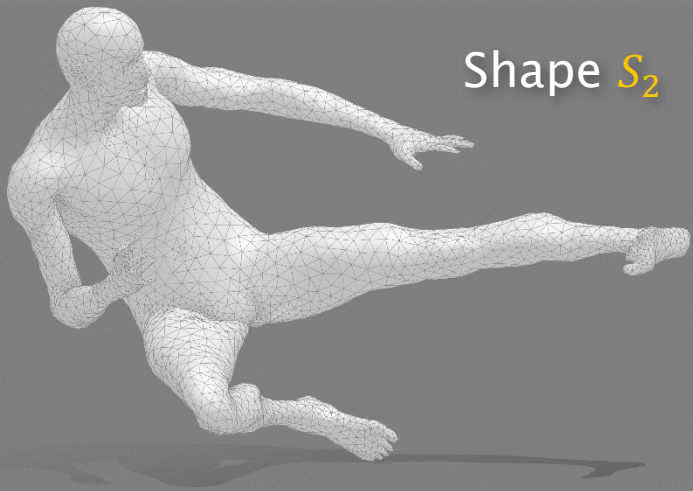
Final map



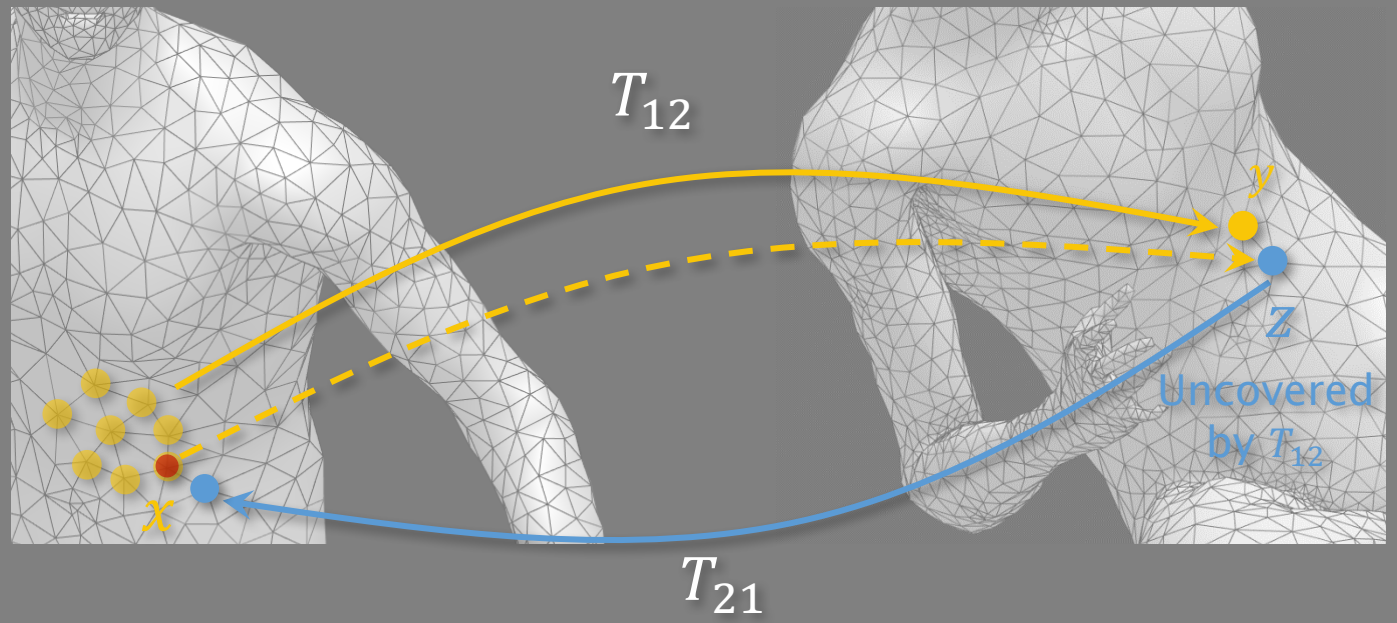
BCICP refinement – improve coverage



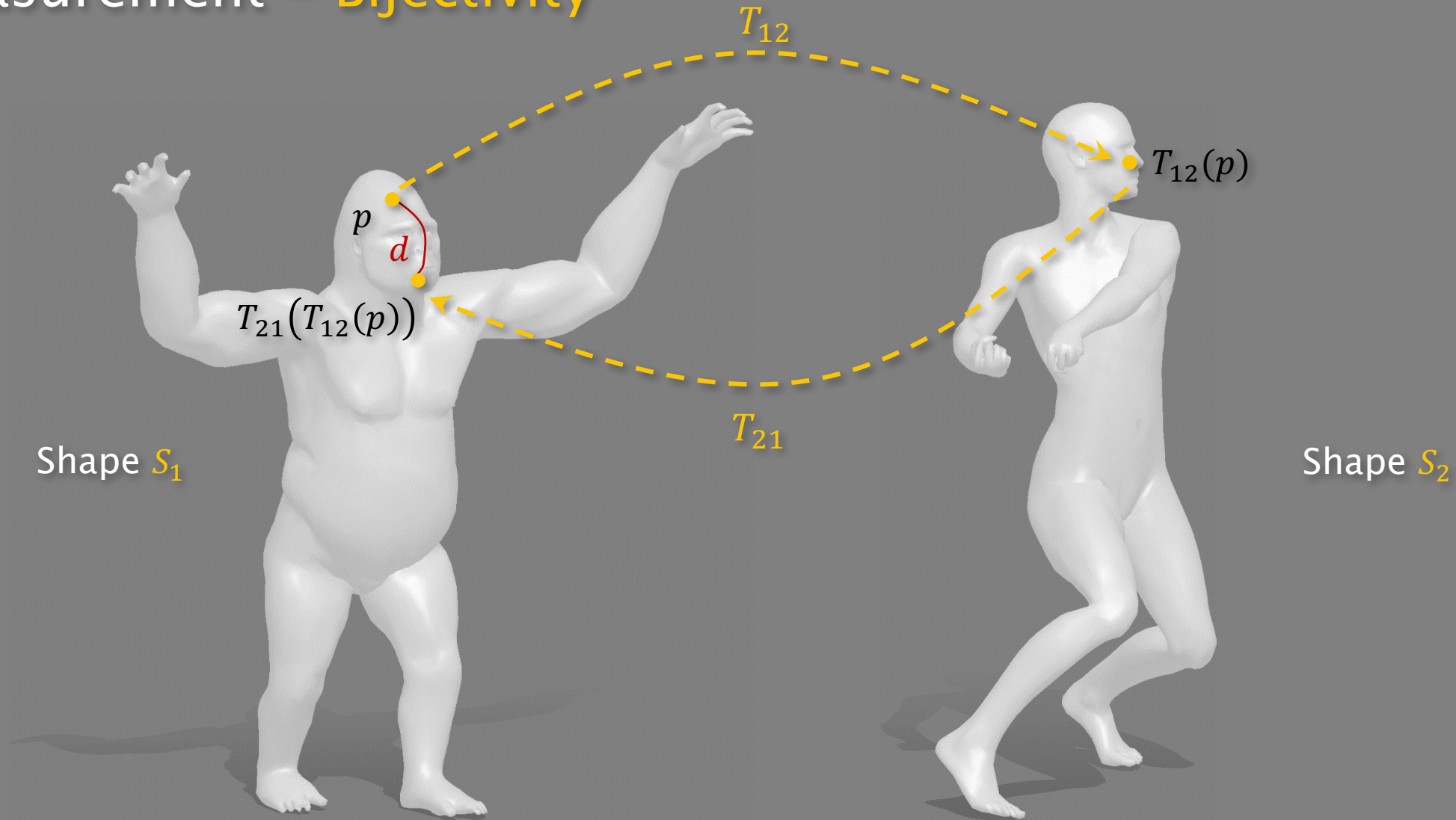
Shape S_1



Shape S_2

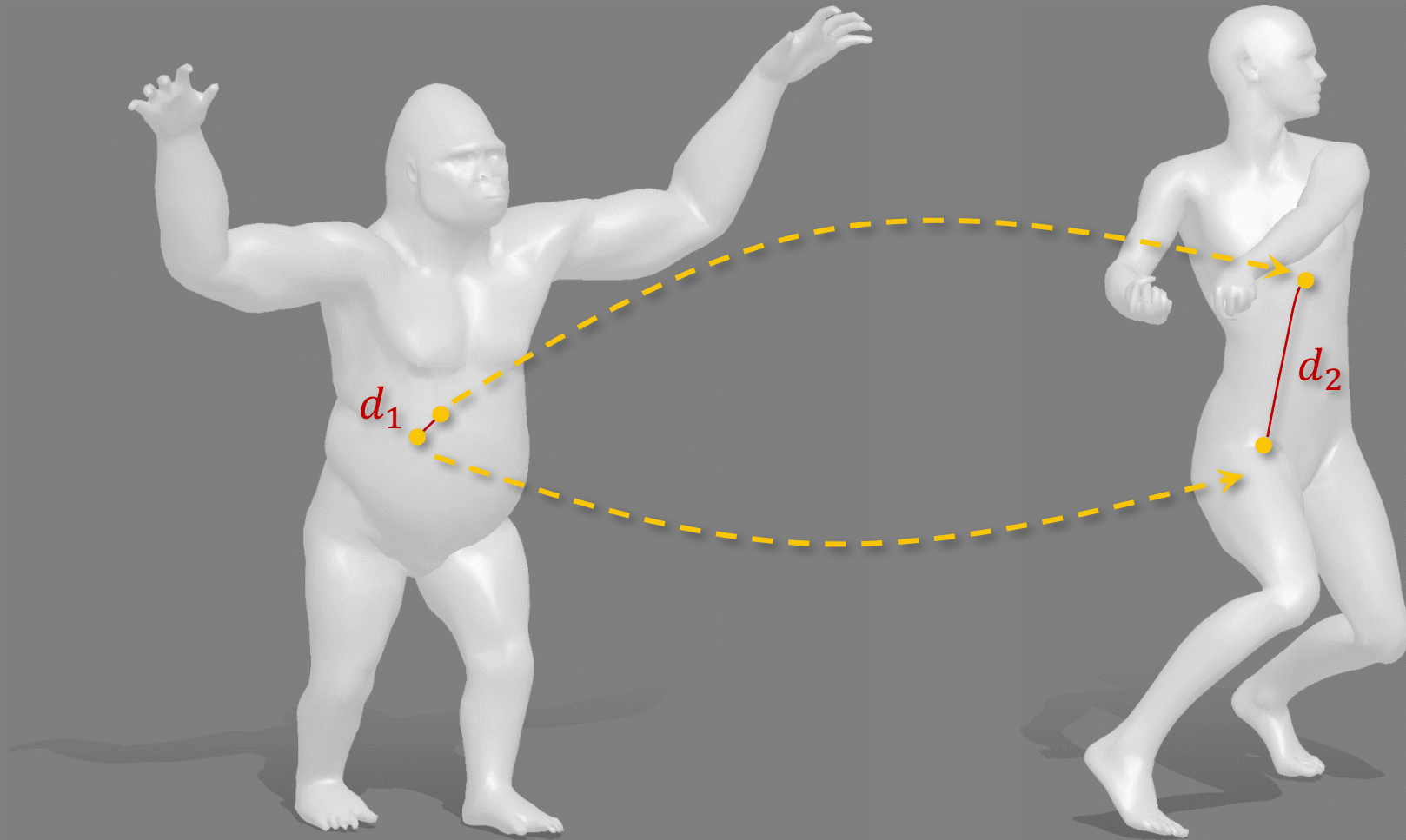


Measurement – Bijection



- d : geodesic distance between p and $T_{21}(T_{12}(p))$
- Measure the difference between $T_{21}(T_{12}(\cdot))$ and the identity map

Measurement – Smoothness



- $\frac{d_2}{d_1}$: edge distortion **ratio** to measure the smoothness

Refinement

Heuristic measurement

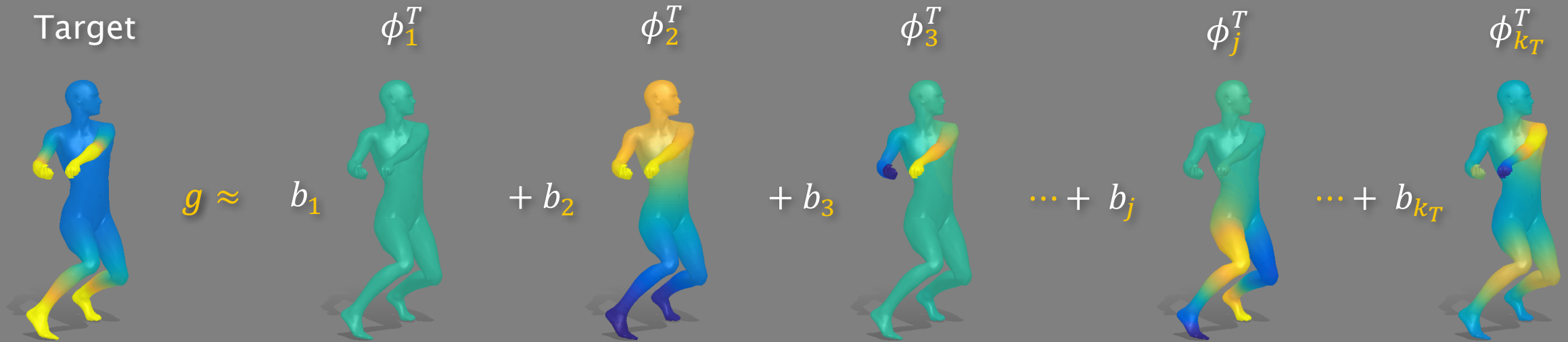
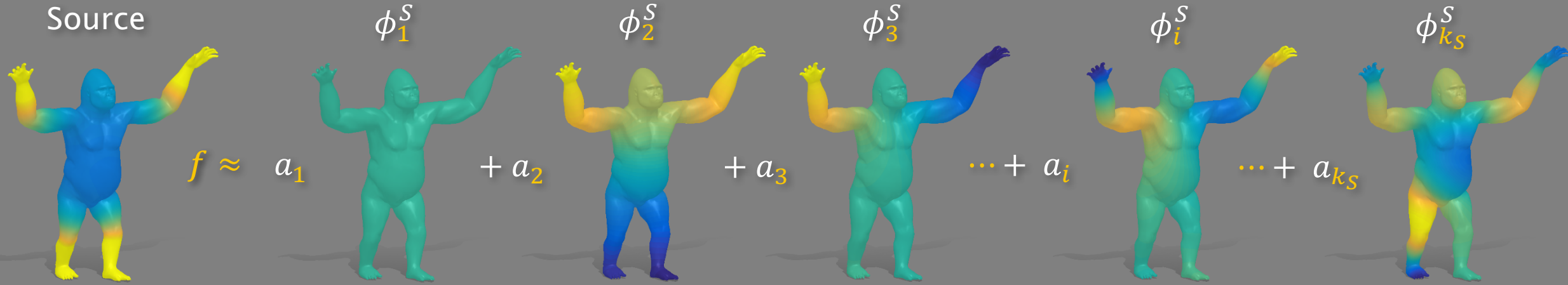
- High **bijection**
- High **smoothness**
 - No **outliers**
 - High **coverage**

Our solution – bijective and continuous ICP (**BCICP**)

- Refine the map simultaneously in the **spectral** and the **spatial** domain
- Improve the **bijection**, **continuity**, and **coverage**

Q1: Functional map pipeline

Descriptors f/g



Q1: Functional map pipeline

Laplacian–Beltrami basis

Source



ϕ_1^S



ϕ_2^S



ϕ_3^S



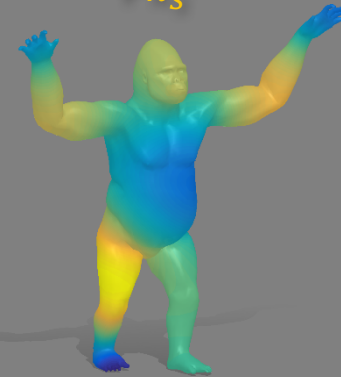
...

ϕ_i^S

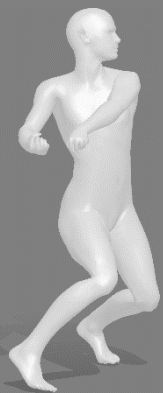


...

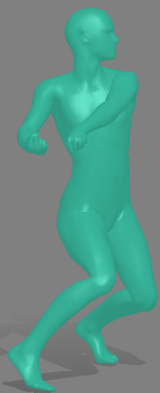
$\phi_{k_s}^S$



Target



ϕ_1^T



ϕ_2^T



ϕ_3^T



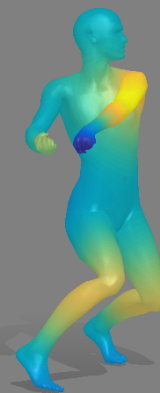
...

ϕ_j^T



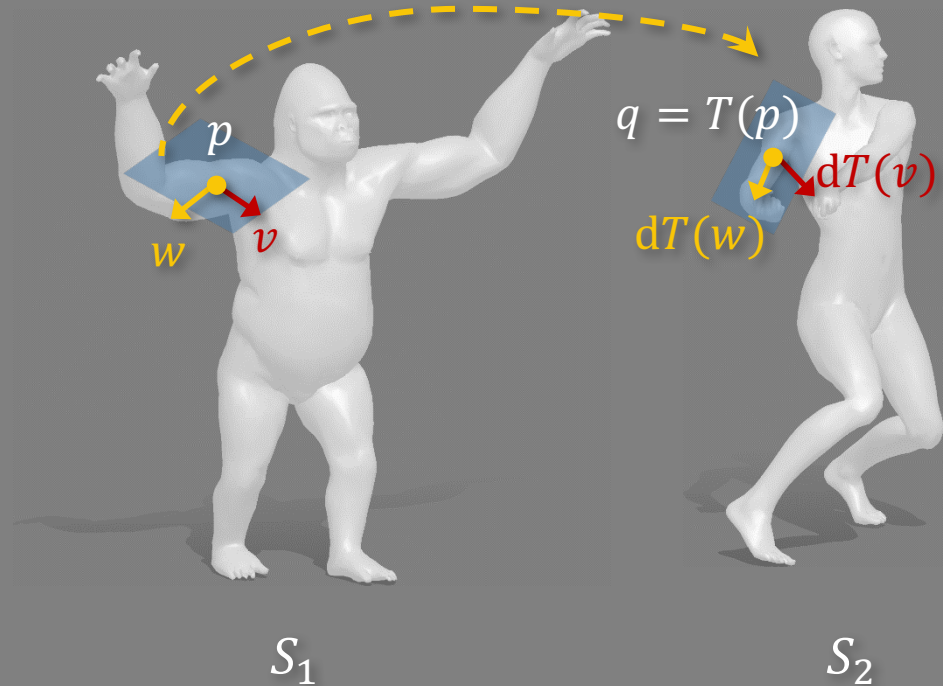
...

$\phi_{k_t}^T$



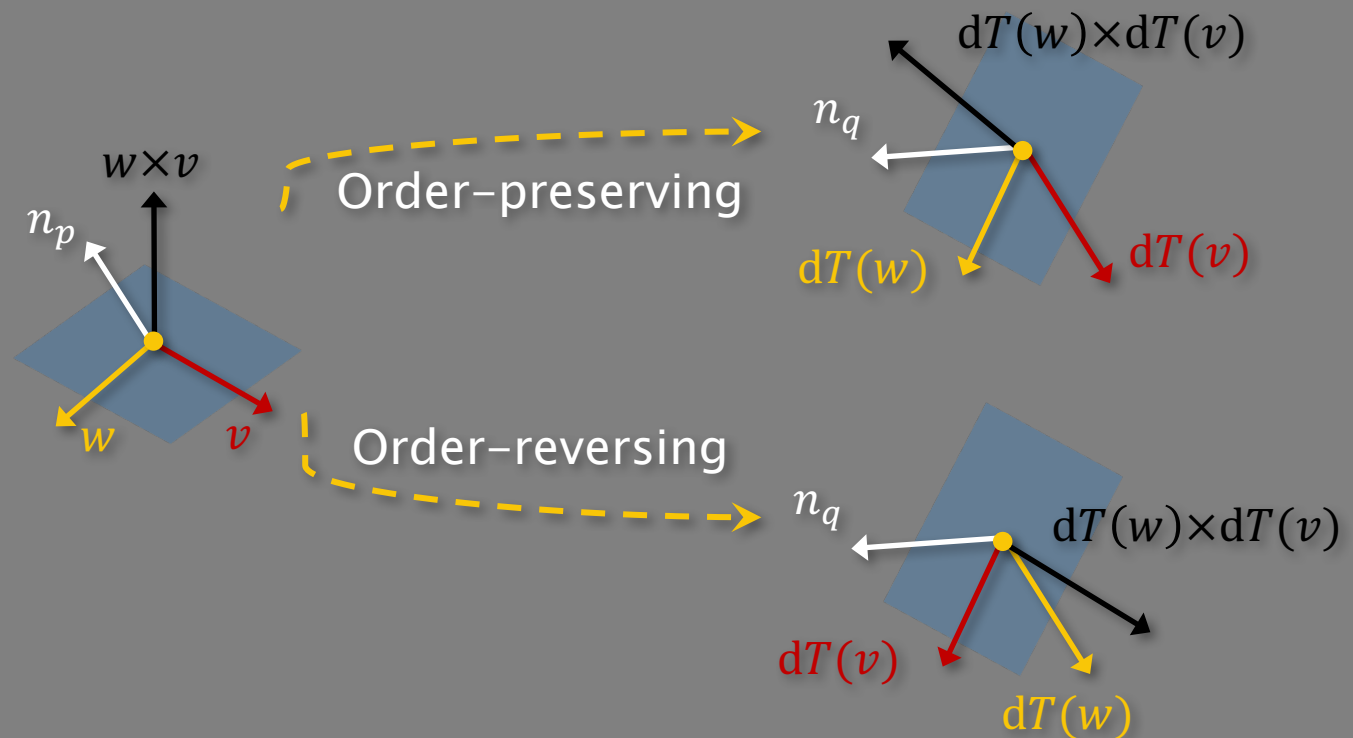
Q2: Orientation-preserving operators

Map differential
 $dT: \mathcal{T}_p(S_1) \rightarrow \mathcal{T}_q(S_2)$



Frame at p : (w, v, n_p)

Frame at $q = T(p)$: $(dT(w), dT(v), n_{T(p)})$



$(w \times v)^T n_p$ should have the **same** sign as $(dT(w) \times dT(v))^T n_{T(p)}$

Q1: Functional map pipeline

- First introduced by Ovsjanikov et al in 2012 : “*Functional Maps: A Flexible Representation of Maps between Shapes*”
- Map a **function** defined on the source shape to another **function** on the target
- The **functions** defined on the source/target shape are represented in a **compressed** form using the **Laplacian–Beltrami basis**