

# Partial functional correspondence

Michael Bronstein



University of Lugano

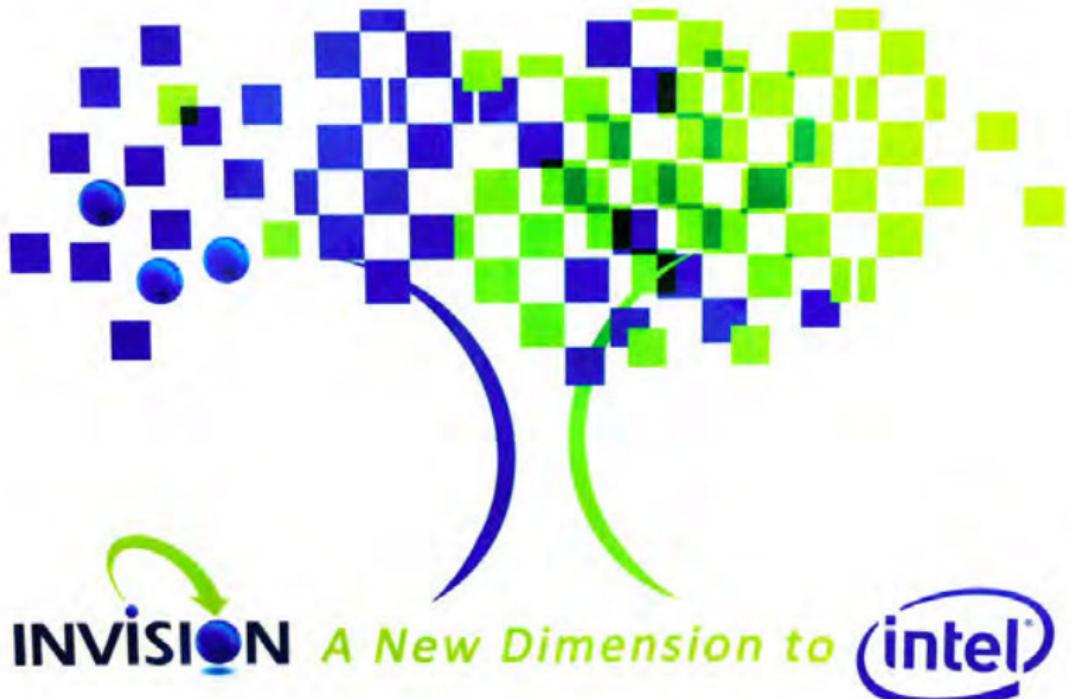


Intel Corporation

Lyon, 7 July 2016



Microsoft Kinect 2010



(Acquired by Intel in 2012)



intel REALSENSE™  
TECHNOLOGY



Different form factor computers featuring Intel RealSense 3D camera

# Deluge of geometric data



KINECT  
for XBOX 360  
 SoftKinetic

 REALSENSE

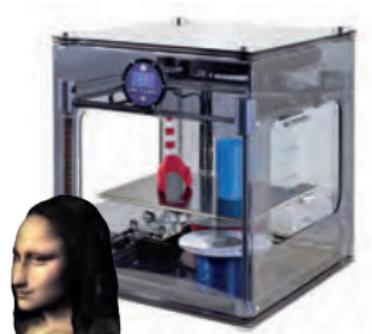
3D sensors



Google 3D warehouse

 shapeways

Repositories

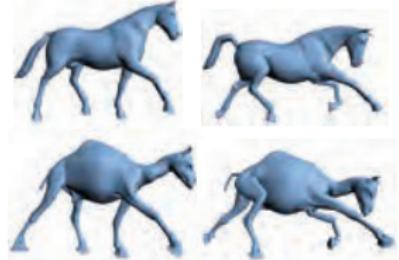


3D printers

# Applications



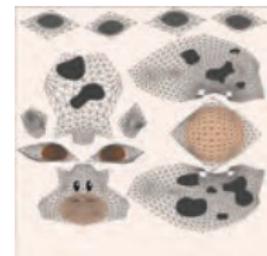
Deformable fusion



Motion transfer



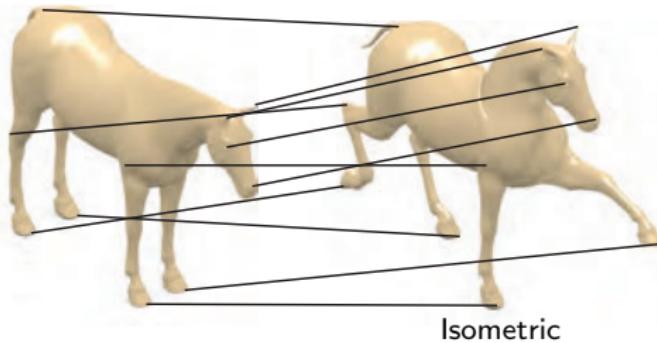
Motion capture



Texture mapping

Dou et al. 2015; Sumner, Popović 2004; Faceshift; Cow image: Moore 2014

# Shape correspondence problem



## Shape correspondence problem



Isometric



Partial

## Shape correspondence problem



Isometric

Partial



Different representation

# Shape correspondence problem



Isometric

Partial



Different representation

Non-isometric

## Partial Functional Correspondence

E. Rodolà<sup>1</sup>, L. Cosmi<sup>2</sup>, M. M. Bronstein<sup>3</sup>, A. Tosello<sup>2</sup>, D. Cremers<sup>2</sup>

<sup>1</sup>TU Munich, Germany <sup>2</sup>University of Venice, Italy <sup>3</sup>University of Lugano, Switzerland



**Figure 1:** Partial functional correspondence between two pairs of shapes with large missing parts. For each pair we show the matrix  $C$  representing the functional map in the spectral domain, and the action of the map by transferring colors from one shape to the other. The special slanted-diagonal structure of  $C$ , induced by the partiality transformation, is first estimated from spectral properties of the two shapes, and then exploited to drive the matching process.

### Abstract

In this paper, we propose a method for computing partial functional correspondence between non-rigid shapes. We use perturbation analysis to show how removal of shape parts changes the Laplace-Beltrami eigenfunctions, and exploit it as a prior on the spectral representation of the correspondence. Corresponding parts are optimization variables in our problem and are used to weight the functional correspondence; we are looking for the largest and most regular (in the Manifold-Shell sense) parts that minimize correspondence distortion. We show that our approach can cope with very challenging correspondence settings.

**Categories and Subject Descriptors** (according to ACM CCS): I.3.5 [Computer Graphics]: Computational Geometry and Object Modeling—Shape Analysis.

## Non-Rigid Puzzles

D. Lipman<sup>1,2</sup>, E. Rodolà<sup>2</sup>, A. M. Bronstein<sup>3,4</sup>, M. M. Bronstein<sup>3,4</sup>, D. Cremers<sup>2</sup>

<sup>1</sup>SRI-Air University, Israel <sup>2</sup>University of Ljubljana, Slovenia <sup>3</sup>Tel Aviv University, Israel <sup>4</sup>Soft Perception Computing, Israel <sup>5</sup>TU Munich, Germany



**Figure 1:** Example of the non-rigid puzzle problem considered in this paper: given a model human shape (leftmost, first column) and three query shapes (two deformed parts of the human and one unrelated "cat" head), the goal is to find a segmentation of the model shape (second column, shown in yellow and green, while extraneous parts without correspondence) into parts corresponding to subsets of the query shapes. Third column shows the complete correspondence between the parts corresponding parts as indicated in similar colors.

### Abstract

Shape correspondence is a fundamental problem in computer graphics and vision, with applications in various problem domains: shading approximation, texture mapping, volume vision, mesh of imaging, etc. Vision where the shapes are not rigid is a challenging problem, especially when the shapes have many holes or very irregular boundaries. In this work, we present a novel non-rigid shape matching algorithm. We assume to be given a reference shape and its multiple parts undergoing a non-rigid deformation. Each of these query parts can be additionally contaminated by clutter: may overlap with other parts, and there might be missing parts or redundant ones. Our method simultaneously solves for the segmentation of the reference model, and for a dense correspondence (or cohomology) of the parts. Experimental results on synthetic as well as real scenes demonstrate the effectiveness of our method in dealing with this challenging matching scenario.

**Categories and Subject Descriptors** (according to ACM CCS): I.3.5 [Computer Graphics]: Computational Geometry and Object Modeling—Shape Analysis.

Computer Graphics Forum  
SGP 2016

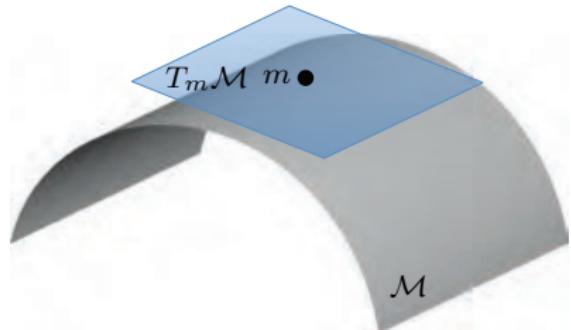
Computer Graphics Forum  
SGP 2016 **Best paper award**

# Outline

- **Background: Spectral analysis on manifolds**
- Functional correspondence
- Partial functional correspondence
- Non-rigid puzzles

# Riemannian geometry in one minute

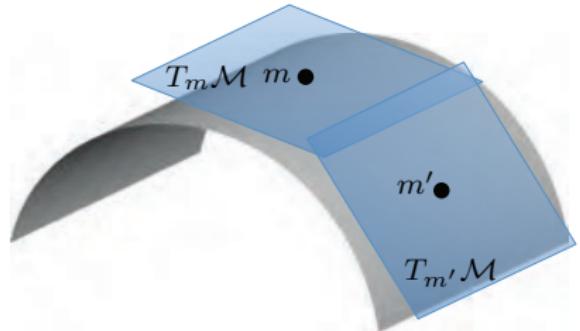
- Tangent plane  $T_m\mathcal{M}$  = local Euclidean representation of manifold (surface)  $\mathcal{M}$  around  $m$



# Riemannian geometry in one minute

- **Tangent plane**  $T_m \mathcal{M}$  = local Euclidean representation of manifold (surface)  $\mathcal{M}$  around  $m$
- **Riemannian metric**

$\langle \cdot, \cdot \rangle_{T_m \mathcal{M}} : T_m \mathcal{M} \times T_m \mathcal{M} \rightarrow \mathbb{R}$   
depending smoothly on  $m$



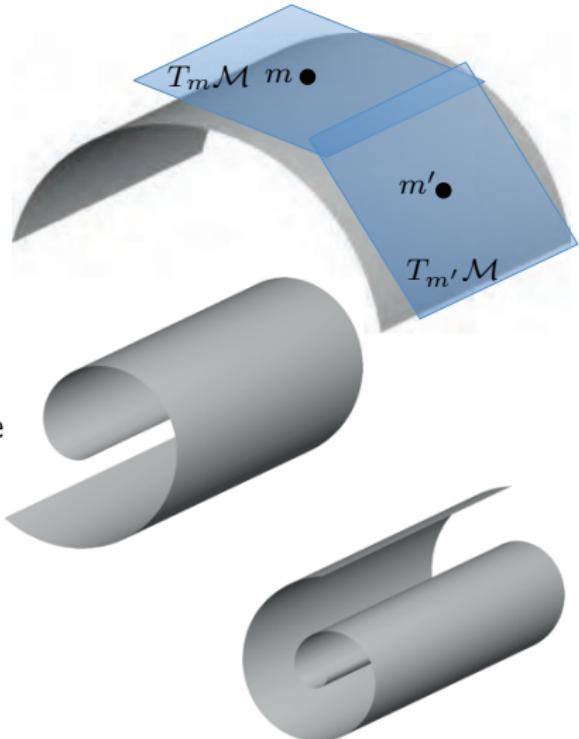
# Riemannian geometry in one minute

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**Isometry** = metric-preserving shape deformation



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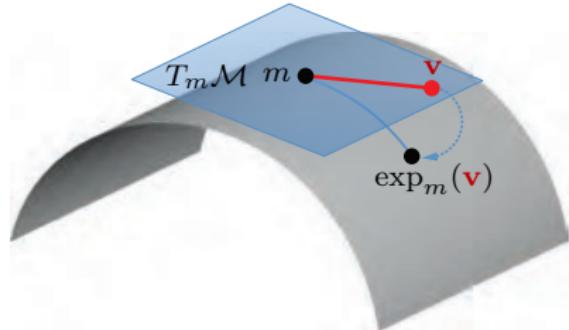
depending smoothly on  $m$

**Isometry** = metric-preserving shape deformation

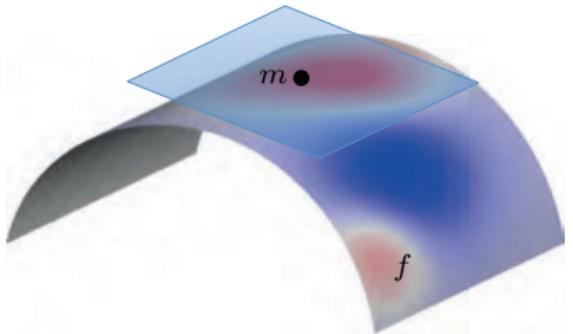
- **Exponential map**

$$\exp_m : T_m\mathcal{M} \rightarrow \mathcal{M}$$

'unit step along geodesic'

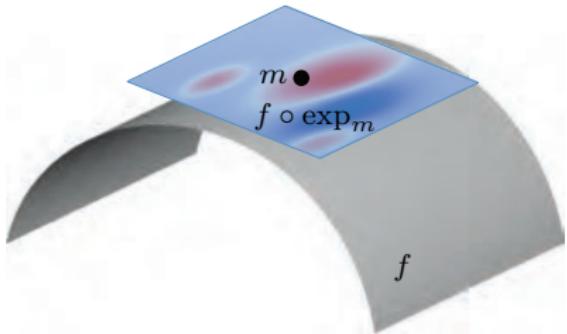


# Laplace-Beltrami operator



Smooth field  $f : \mathcal{M} \rightarrow \mathbb{R}$

# Laplace-Beltrami operator



Smooth field  $f \circ \exp_m : T_m \mathcal{M} \rightarrow \mathbb{R}$

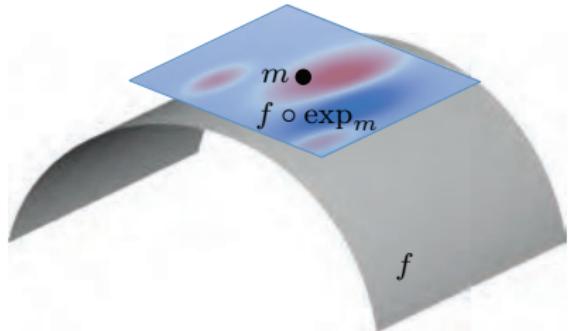
# Laplace-Beltrami operator

- Intrinsic gradient

$$\nabla_{\mathcal{M}} f(m) = \nabla(f \circ \exp_m)(\mathbf{0})$$

Taylor expansion

$$(f \circ \exp_m)(\mathbf{v}) \approx f(m) + \langle \nabla_{\mathcal{M}} f(m), \mathbf{v} \rangle_{T_m \mathcal{M}}$$



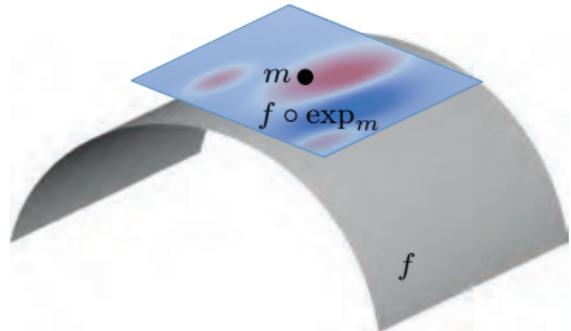
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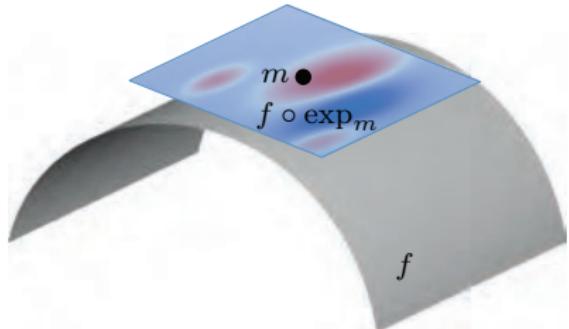
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- Intrinsic (expressed solely in terms of the Riemannian metric)

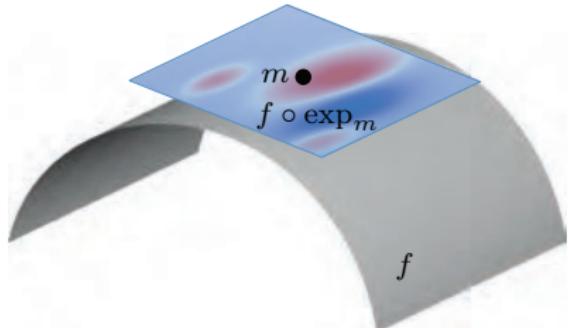
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$$\Delta_{\mathcal{M}} f(m) = \Delta(f \circ \exp_m)(\mathbf{0})$$

- Intrinsic (expressed solely in terms of the Riemannian metric)
- Isometry-invariant

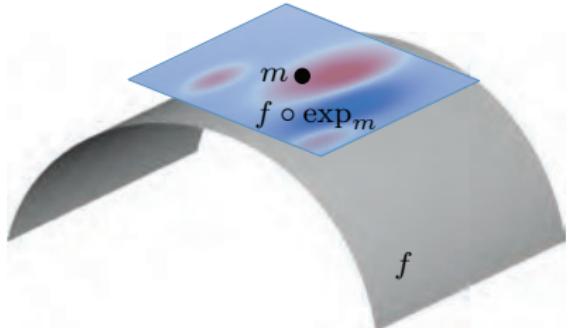
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- Laplace-Beltrami operator

$$\Delta_{\mathcal{M}} f(m) = \Delta(f \circ \exp_m)(\mathbf{0})$$

- Intrinsic (expressed solely in terms of the Riemannian metric)
- Isometry-invariant
- Self-adjoint  $\langle \Delta_{\mathcal{M}} f, g \rangle_{L^2(\mathcal{M})} = \langle f, \Delta_{\mathcal{M}} g \rangle_{L^2(\mathcal{M})}$

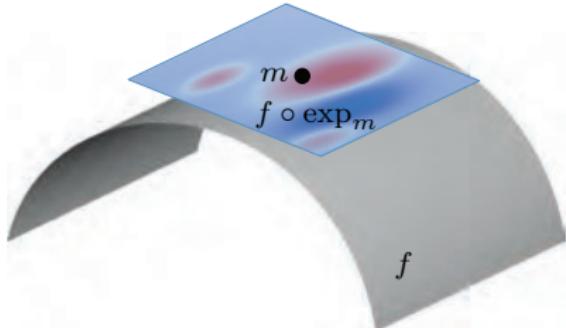
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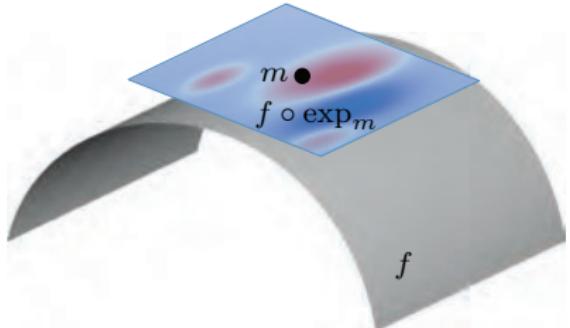
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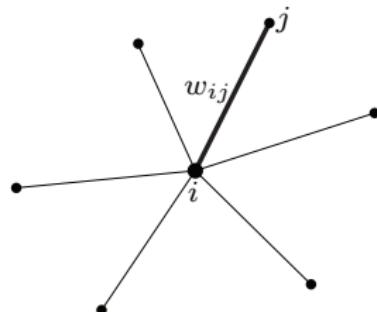


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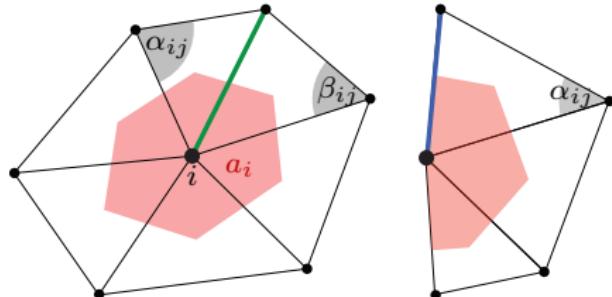
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- Positive semidefinite  $\Rightarrow$  non-negative eigenvalues

# Discrete Laplacian



**Undirected graph**  $(V, E)$

$$(\Delta f)_i \approx \sum_{(i,j) \in E} w_{ij} (f_i - f_j)$$



**Triangular mesh**  $(V, E, F)$

$$(\Delta f)_i \approx \frac{1}{a_i} \sum_{(i,j) \in E} w_{ij} (f_i - f_j)$$

$$w_{ij} = \begin{cases} \frac{\cot \alpha_{ij} + \cot \beta_{ij}}{2} & (i, j) \in E_i \\ \frac{1}{2} \cot \alpha_{ij} & (i, j) \in E_b \\ -\sum_{k \neq i} w_{ik} & i = j \\ 0 & \text{else} \end{cases}$$

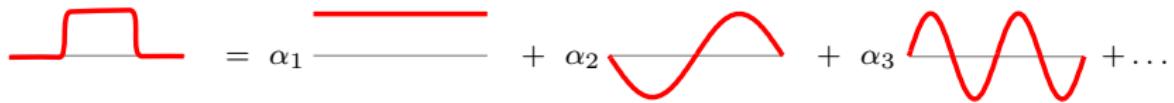
$a_i$  = local area element

Tutte 1963; MacNeal 1949; Duffin 1959; Pinkall, Polthier 1993

# Fourier analysis (Euclidean spaces)

A function  $f : [-\pi, \pi] \rightarrow \mathbb{R}$  can be written as Fourier series

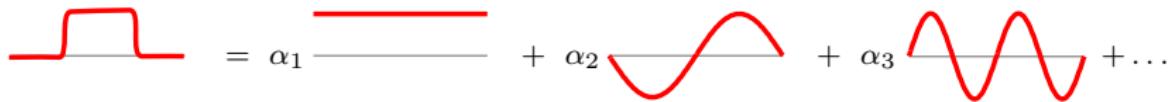
$$f(x) = \sum_{\omega} \frac{1}{2\pi} \int_{-\pi}^{\pi} f(\xi) e^{i\omega\xi} d\xi \quad e^{-i\omega x}$$



# Fourier analysis (Euclidean spaces)

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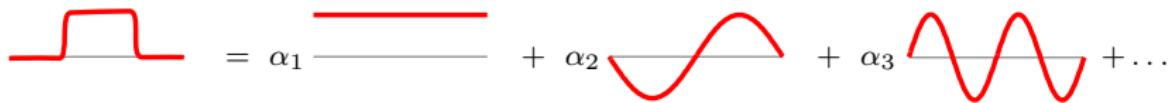
$$f(x) = \sum_{\omega} \underbrace{\frac{1}{2\pi} \int_{-\pi}^{\pi} f(\xi) e^{i\omega\xi} d\xi}_{\hat{f}(\omega) = \langle f, e^{-i\omega x} \rangle_{L^2([-\pi, \pi])}} e^{-i\omega x}$$



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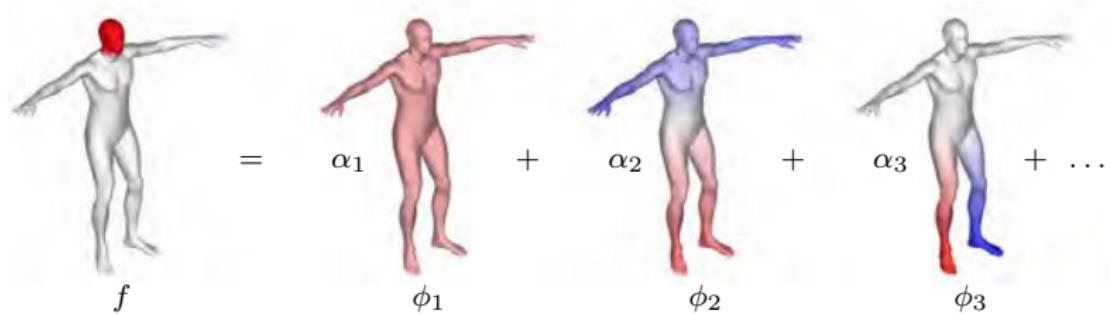


Fourier basis = Laplacian eigenfunctions:  $\Delta e^{-i\omega x} = \omega^2 e^{-i\omega x}$

# Fourier analysis (non-Euclidean spaces)

A function  $f : \mathcal{M} \rightarrow \mathbb{R}$  can be written as Fourier series

$$f(m) = \sum_{k \geq 1} \underbrace{\int_{\mathcal{M}} f(\xi) \phi_k(\xi) d\xi}_{\hat{f}_k = \langle f, \phi_k \rangle_{L^2(\mathcal{M})}} \phi_k(m)$$

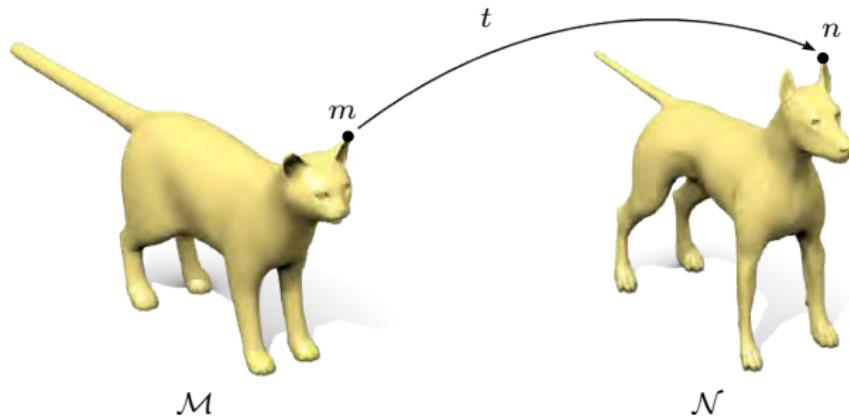


Fourier basis = Laplacian eigenfunctions:  $\Delta_{\mathcal{M}} \phi_k = \lambda_k \phi_k$

# Outline

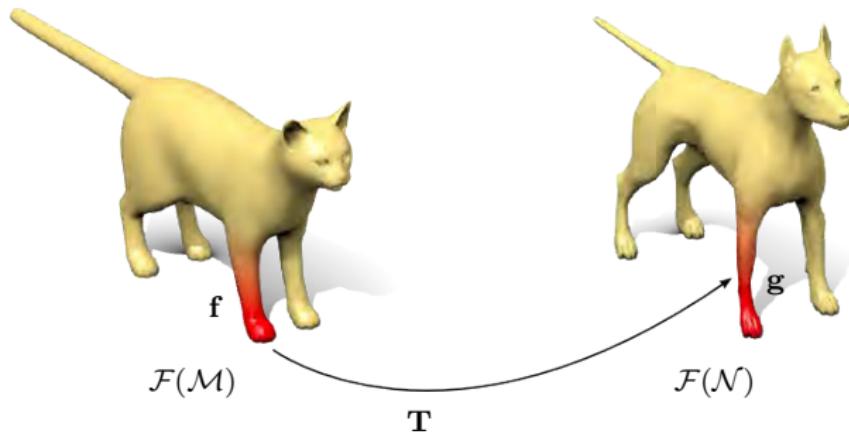
- Background: Spectral analysis on manifolds
- **Functional correspondence**
- Partial functional correspondence
- Non-rigid puzzles

## Point-wise correspondence



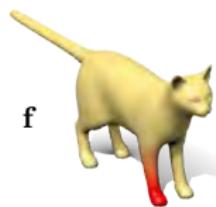
**Point-wise** maps  $t: \mathcal{M} \rightarrow \mathcal{N}$

# Functional correspondence



**Functional maps**  $\mathbf{T}: \mathcal{F}(\mathcal{M}) \rightarrow \mathcal{F}(\mathcal{N})$

# Functional correspondence



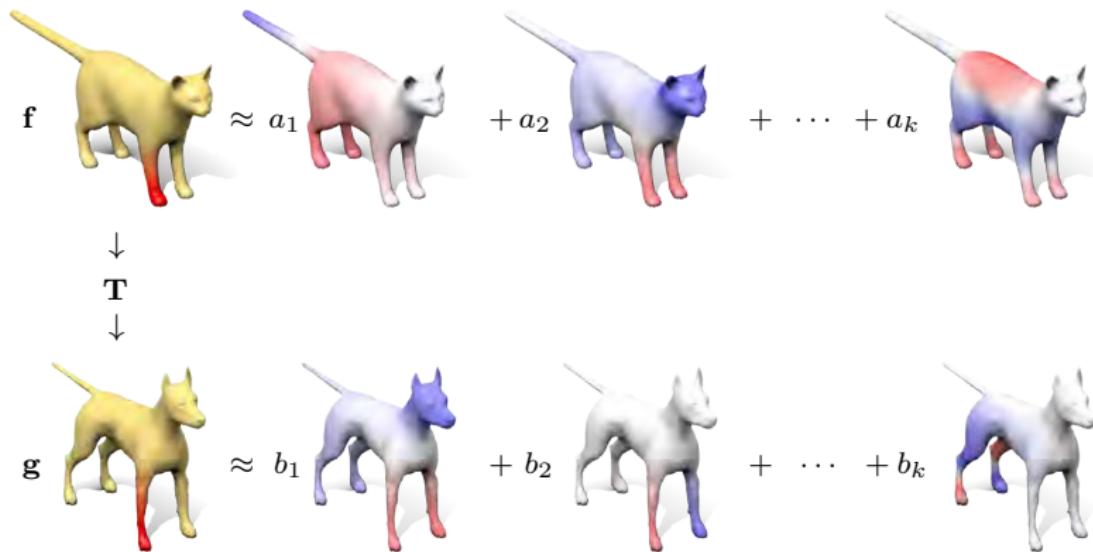
**f**

↓  
**T**  
↓

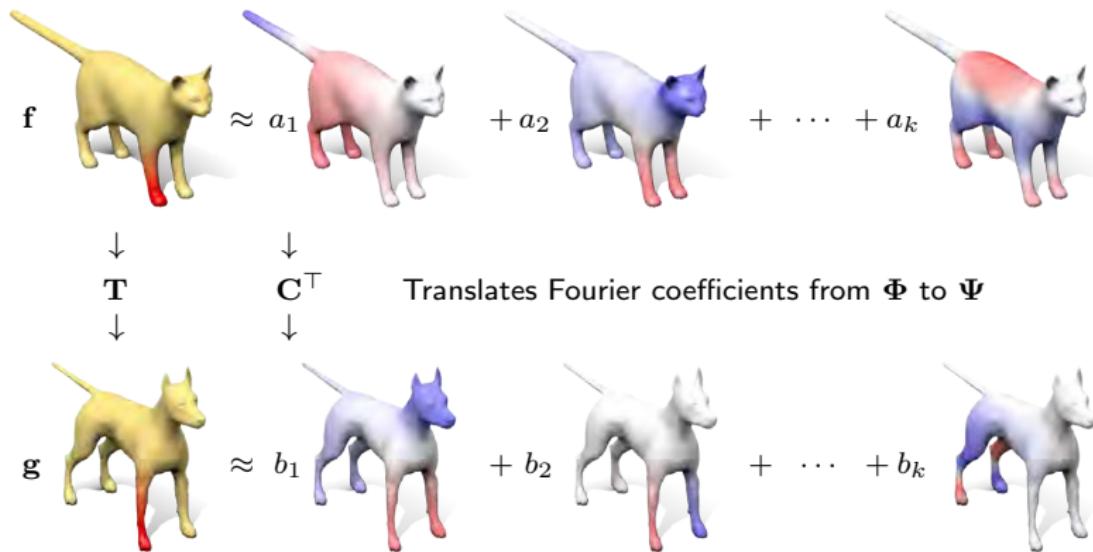


**g**

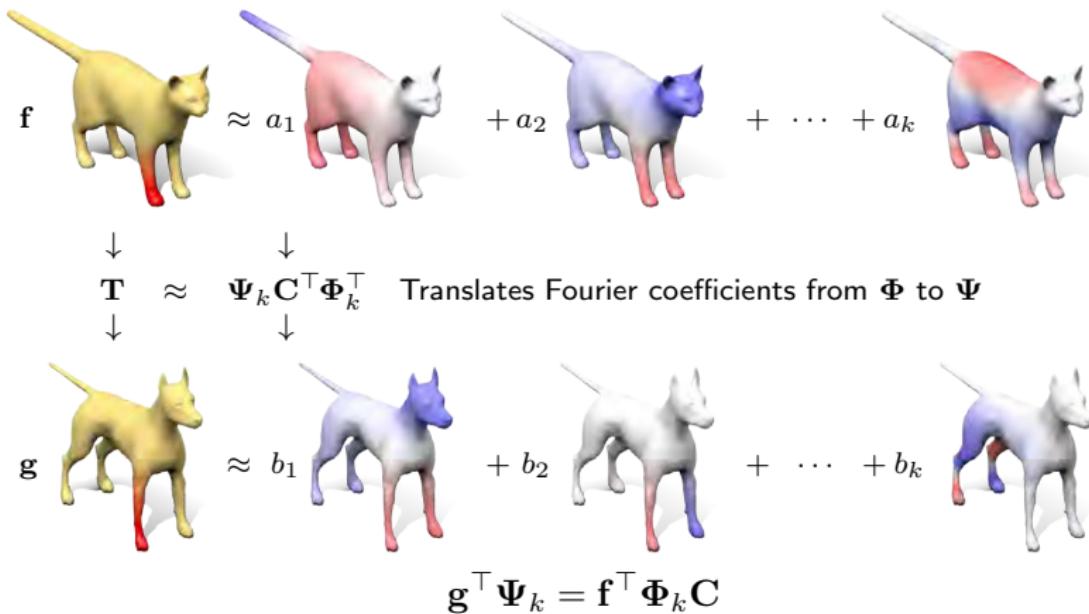
# Functional correspondence



# Functional correspondence

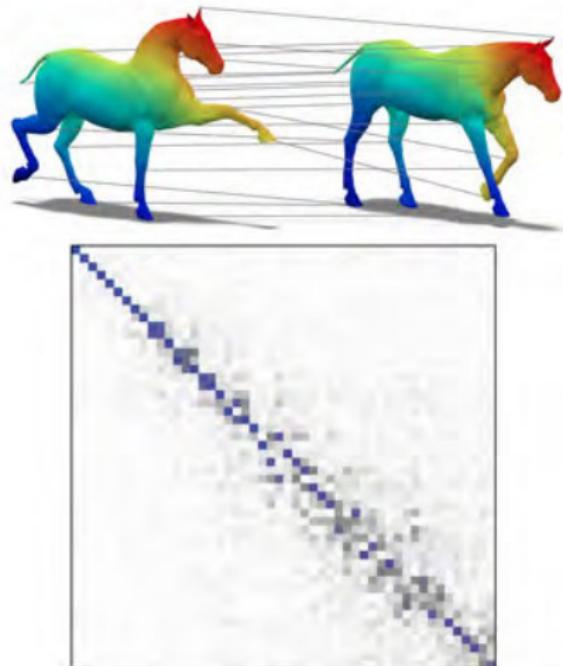


# Functional correspondence



where  $\Phi_k = (\phi_1, \dots, \phi_k)$ ,  $\Psi_k = (\psi_1, \dots, \psi_k)$  are truncated Laplace-Beltrami eigenbases

## Functional correspondence in Laplacian eigenbases

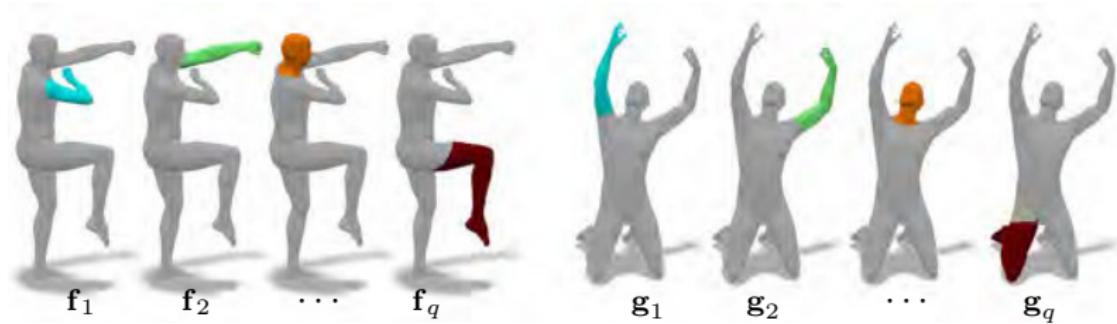


For **isometric simple spectrum** shapes  $\mathbf{C}$  is diagonal since  $\psi_i = \pm \mathbf{T}\phi_i$

# Computing functional correspondence

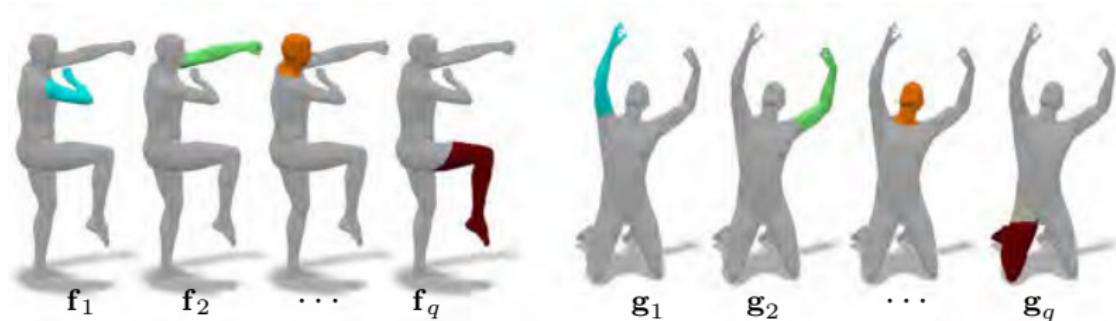


# Computing functional correspondence



- Given **ordered** set of functions  $f_1, \dots, f_q$  on  $\mathcal{M}$  and corresponding functions  $g_1, \dots, g_q$  on  $\mathcal{N}$  ( $g_i \approx \mathbf{T}f_i$ )

# Computing functional correspondence



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- C** found by solving a system of  $qk$  equations with  $k^2$  variables

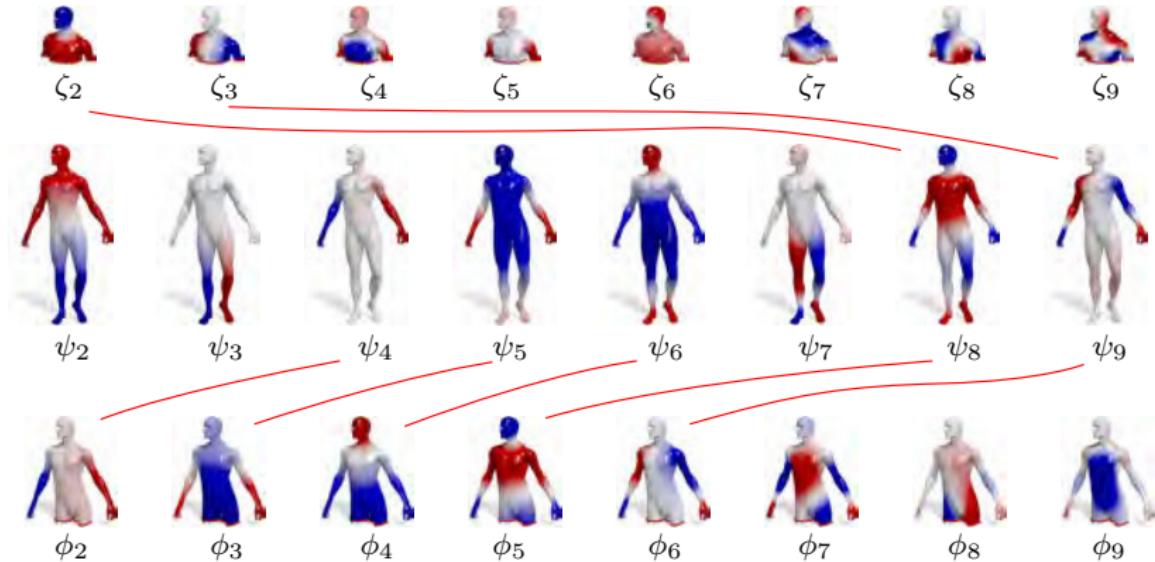
$$\mathbf{G}^\top \boldsymbol{\Psi}_k = \mathbf{F}^\top \boldsymbol{\Phi}_k \mathbf{C}$$

where  $\mathbf{F} = (f_1, \dots, f_q)$  and  $\mathbf{G} = (g_1, \dots, g_q)$  are  $n \times q$  and  $m \times q$  matrices

## Key issues

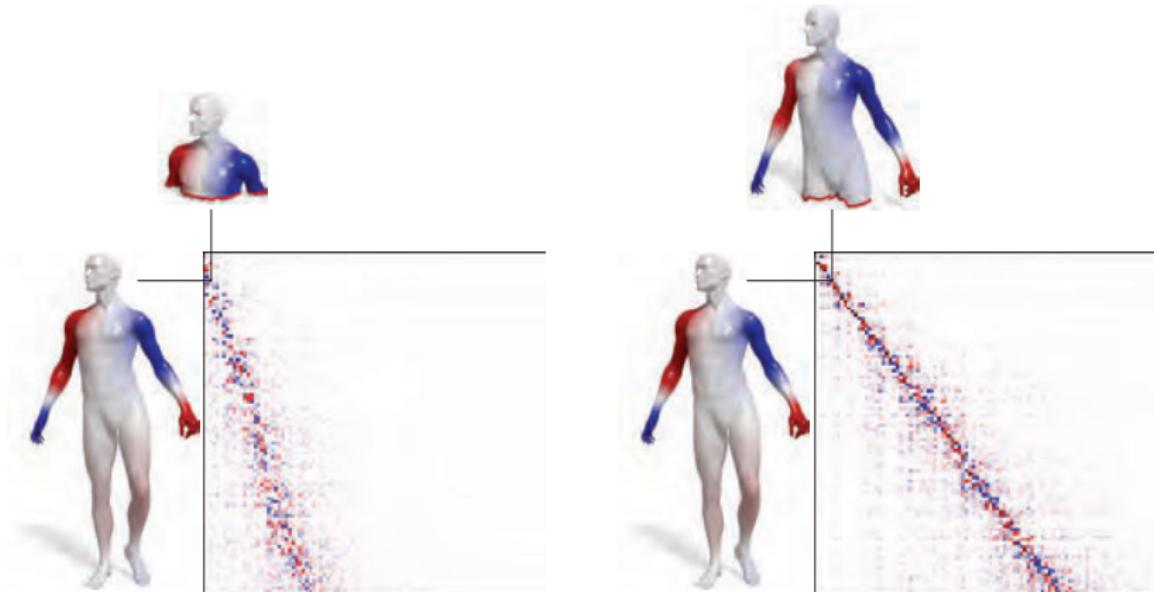
- How to recover point-wise correspondence with some guarantees (e.g. bijectivity)?
- How to automatically find corresponding functions  $\mathbf{F}$ ,  $\mathbf{G}$ ?
- Near isometric shapes: easy (a lot of structure!)
- Non-isometric shapes: hard
- Does not work well in case of **missing parts** and topological noise

# Partial Laplacian eigenvectors



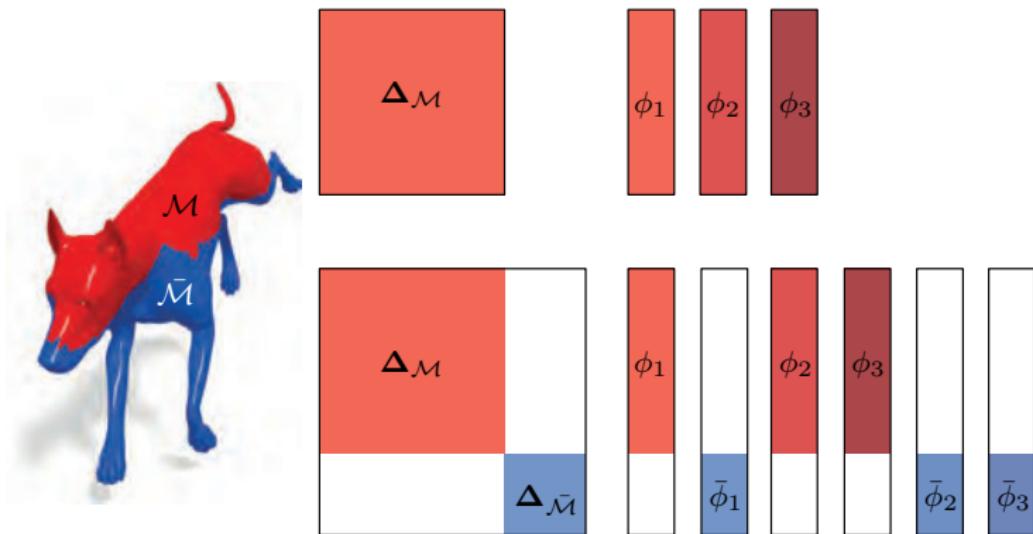
Laplacian eigenvectors of a shape with missing parts  
(Neumann boundary conditions)

# Partial Laplacian eigenvectors



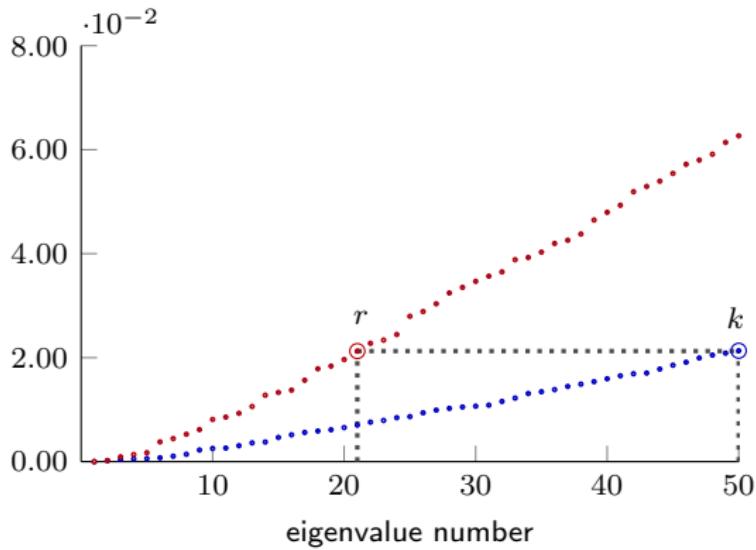
Functional correspondence matrix  $\mathbf{C}$

# Perturbation analysis: intuition



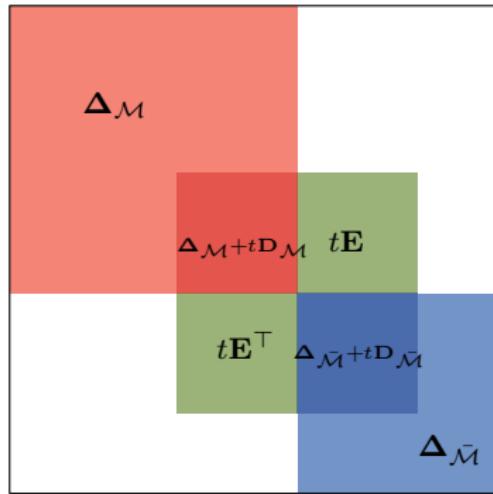
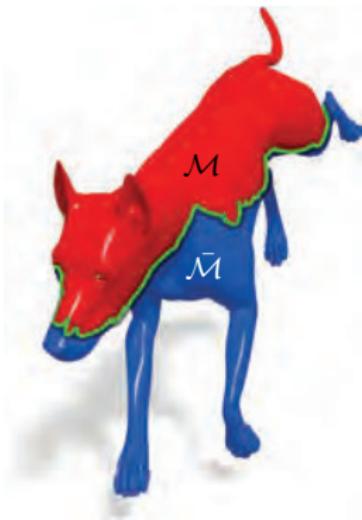
- Ignoring boundary interaction: disjoint parts (block-diagonal matrix)
- Eigenvectors = Mixture of eigenvectors of the parts

# Perturbation analysis: eigenvalues

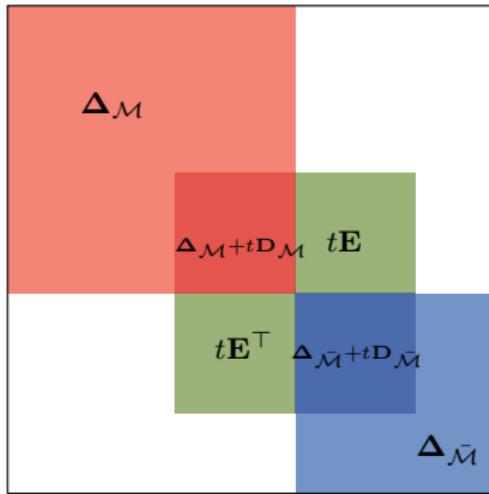
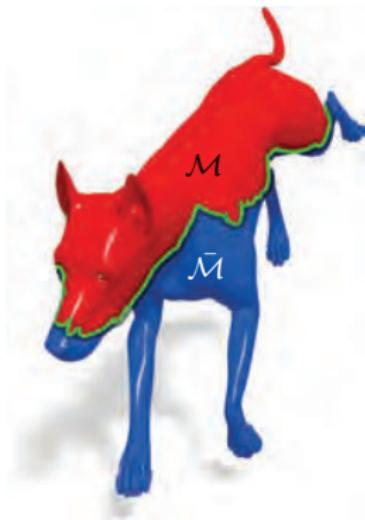


- Slope  $\frac{r}{k} \approx \frac{|\mathcal{M}|}{|\mathcal{N}|}$  (depends on the area of the cut)
- Consistent with Weil's law

## Perturbation analysis: details

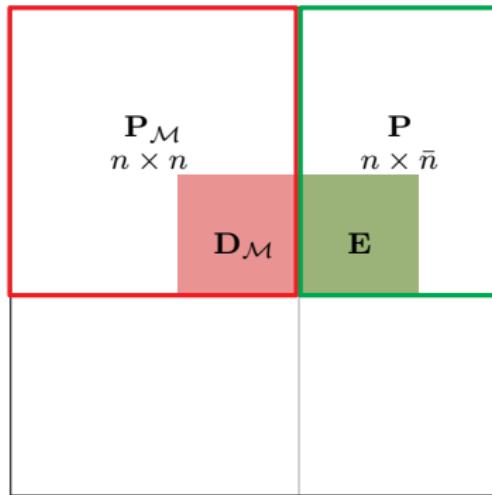
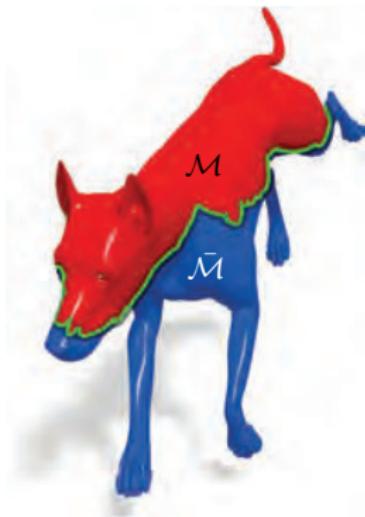


## Perturbation analysis: details



**“How would the Laplacian eigenvalues and eigenvectors of the red part change if we attached a blue part to it?”**

## Perturbation analysis: details



**“How would the Laplacian eigenvalues and eigenvectors of the red part change if we attached a blue part to it?”**

## Perturbation analysis: details

Denote  $\Delta_{\mathcal{M}} + t\mathbf{P}_{\mathcal{M}} = \Phi(t)\Lambda(t)\Phi(t)^\top$ ,  $\Delta_{\bar{\mathcal{M}}} = \bar{\Phi}\bar{\Lambda}\bar{\Phi}^\top$ ,  $\Phi = \Phi(0)$ , and  $\Lambda = \Lambda(0)$ .

**Theorem 1 (eigenvalues)** The derivative of the non-trivial eigenvalues is given by

$$\frac{d}{dt} \lambda_i = \phi_i^\top \mathbf{P}_{\mathcal{M}} \phi_i \quad \mathbf{P}_{\mathcal{M}} = \begin{pmatrix} \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{D}_{\mathcal{M}} \end{pmatrix}$$

## Perturbation analysis: details

Denote  $\Delta_{\mathcal{M}} + t\mathbf{P}_{\mathcal{M}} = \Phi(t)\Lambda(t)\Phi(t)^\top$ ,  $\Delta_{\bar{\mathcal{M}}} = \bar{\Phi}\bar{\Lambda}\bar{\Phi}^\top$ ,  $\Phi = \Phi(0)$ , and  $\Lambda = \Lambda(0)$ .

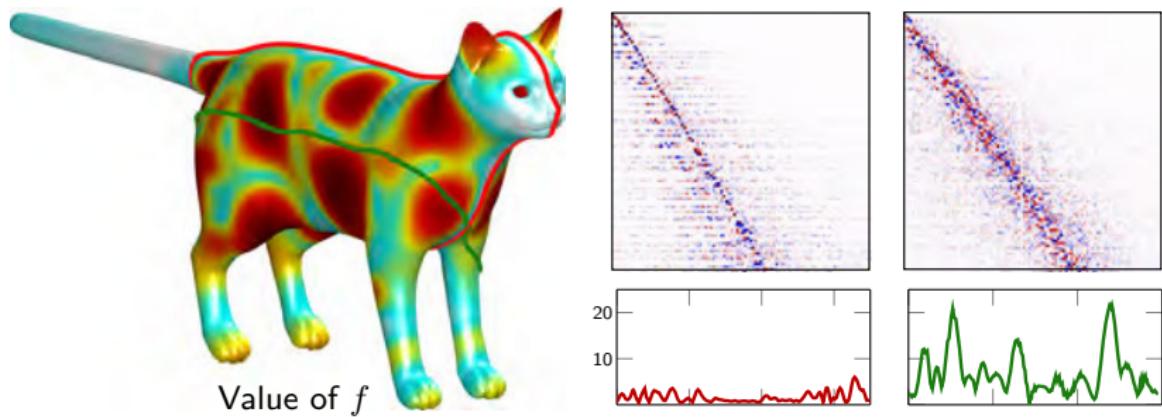
**Theorem 1 (eigenvalues)** The derivative of the non-trivial eigenvalues is given by

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**Theorem 2 (eigenvectors)** Assuming  $\lambda_i \neq \lambda_j$  for  $i \neq j$  and  $\lambda_i \neq \bar{\lambda}_j$  for all  $i, j$ , the derivative of the non-trivial eigenvectors is given by

$$\frac{d}{dt} \phi_i = \sum_{\substack{j=1 \\ j \neq i}}^n \frac{\phi_i^\top \mathbf{P}_{\mathcal{M}} \phi_j}{\lambda_i - \lambda_j} \phi_j + \sum_{j=1}^{\bar{n}} \frac{\phi_i^\top \mathbf{P} \bar{\phi}_j}{\lambda_i - \bar{\lambda}_j} \bar{\phi}_j \quad \mathbf{P} = \begin{pmatrix} \mathbf{0} & \mathbf{0} \\ \mathbf{E} & \mathbf{0} \end{pmatrix}$$

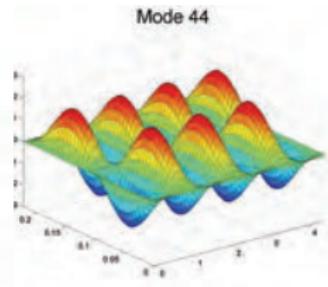
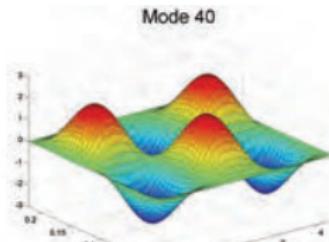
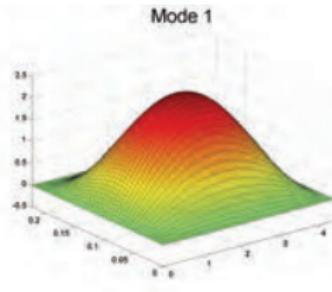
# Perturbation analysis: boundary interaction strength



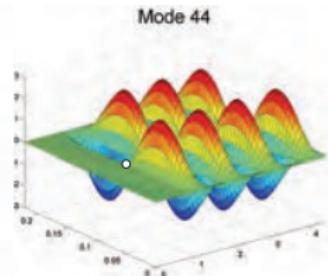
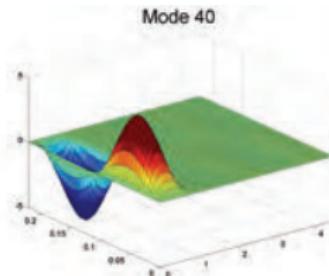
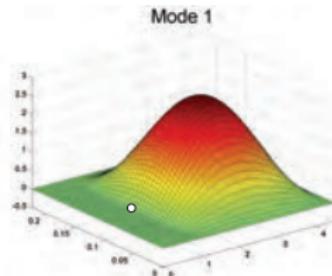
- Eigenvector perturbation depends on **length** and **position** of the boundary
- Perturbation strength  $\|\frac{d}{dt}\Phi\|_F \leq c \int_{\partial\mathcal{M}} f(m) dm$ , where

$$f(m) = \sum_{\substack{i,j=1 \\ j \neq i}}^n \left( \frac{\phi_i(m)\phi_j(m)}{\lambda_i - \lambda_j} \right)^2$$

# Laplacian perturbation: typical picture



Plate



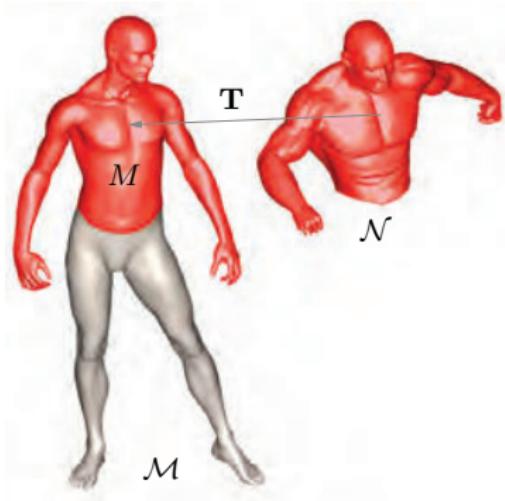
Punctured plate

Figure: Filoche, Mayboroda 2009

# Partial functional maps

- Model shape  $\mathcal{M}$
- Query shape  $\mathcal{N}$
- Part  $M \subseteq \mathcal{M} \approx$  isometric to  $\mathcal{N}$
- Data  $\mathbf{F}, \mathbf{G}$
- Partial functional map

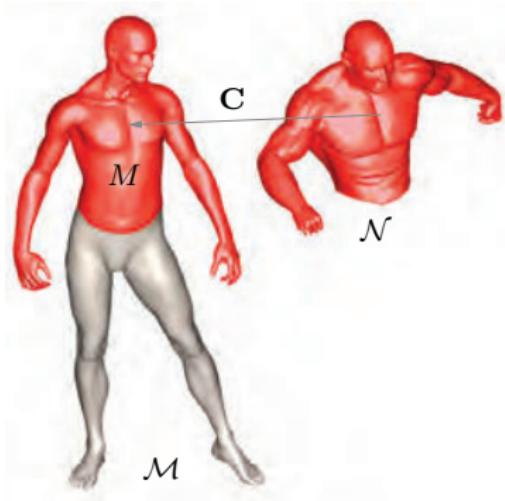
$$\mathbf{T}\mathbf{G} \approx \mathbf{F}(M)$$



# Partial functional maps

- Model shape  $\mathcal{M}$
- Query shape  $\mathcal{N}$
- Part  $M \subseteq \mathcal{M} \approx$  isometric to  $\mathcal{N}$
- Data  $\mathbf{F}, \mathbf{G}$
- Partial functional map

$$\mathbf{G}^\top \Psi \mathbf{C} \approx \mathbf{F}(M)^\top \Phi$$

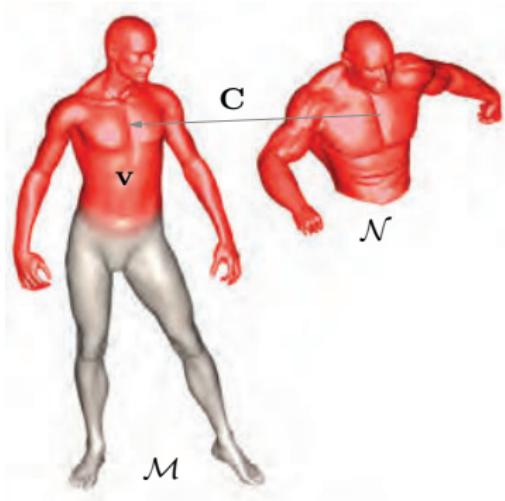


# Partial functional maps

- Model shape  $\mathcal{M}$
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- Part  $M \subseteq \mathcal{M} \approx$  isometric to  $\mathcal{N}$
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- Partial functional map

$$\mathbf{G}^\top \Psi \mathbf{C} \approx \mathbf{F}^\top \text{diag}(\mathbf{v}) \Phi$$

$\mathbf{v} \in \mathcal{F}(\mathcal{M})$  indicator function of  $M$



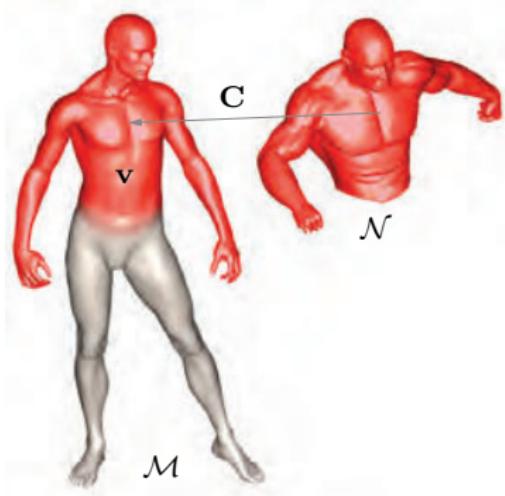
# Partial functional maps

- Model shape  $\mathcal{M}$
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- Partial functional map

$$\mathbf{G}^\top \Psi \mathbf{C} \approx \mathbf{F}^\top \text{diag}(\eta(\mathbf{v})) \Phi$$

$\mathbf{v} \in \mathcal{F}(\mathcal{M})$  indicator function of  $M$

$$\eta(t) = \frac{1}{2}(\tanh(2t - 1) + 1)$$



**Optimization problem w.r.t. correspondence  $\mathbf{C}$  and part  $\mathbf{v}$**

$$\min_{\mathbf{C}, \mathbf{v}} \|\mathbf{G}^\top \Psi \mathbf{C} - \mathbf{F}^\top \text{diag}(\eta(\mathbf{v})) \Phi\|_{2,1} + \rho_{\text{corr}}(\mathbf{C}) + \rho_{\text{part}}(\mathbf{v})$$

# Partial functional maps

$$\min_{\mathbf{C}, \mathbf{v}} \|\mathbf{G}^\top \Psi \mathbf{C} - \mathbf{F}^\top \text{diag}(\eta(\mathbf{v})) \Phi\|_{2,1} + \rho_{\text{corr}}(\mathbf{C}) + \rho_{\text{part}}(\mathbf{v})$$

# Partial functional maps

$$\min_{\mathbf{C}, \mathbf{v}} \|\mathbf{G}^\top \mathbf{\Psi} \mathbf{C} - \mathbf{F}^\top \text{diag}(\eta(\mathbf{v})) \mathbf{\Phi}\|_{2,1} + \rho_{\text{corr}}(\mathbf{C}) + \rho_{\text{part}}(\mathbf{v})$$

- **Part regularization**

$$\rho_{\text{part}}(\mathbf{v}) = \mu_1 \left( |\mathcal{N}| - \int_{\mathcal{M}} \eta(\mathbf{v}) dm \right)^2 + \mu_2 \int_{\mathcal{M}} \xi(\mathbf{v}) \|\nabla_{\mathcal{M}} \mathbf{v}\| dm$$

where  $\xi(t) \approx \delta\left(\eta(t) - \frac{1}{2}\right)$

# Partial functional maps

$$\min_{\mathbf{C}, \mathbf{v}} \|\mathbf{G}^\top \Psi \mathbf{C} - \mathbf{F}^\top \text{diag}(\eta(\mathbf{v})) \Phi\|_{2,1} + \rho_{\text{corr}}(\mathbf{C}) + \rho_{\text{part}}(\mathbf{v})$$

- **Part regularization**

$$\rho_{\text{part}}(\mathbf{v}) = \underbrace{\mu_1 \left( |\mathcal{N}| - \int_{\mathcal{M}} \eta(\mathbf{v}) dm \right)^2}_{\text{area preservation}} + \underbrace{\mu_2 \int_{\mathcal{M}} \xi(\mathbf{v}) \|\nabla_{\mathcal{M}} \mathbf{v}\| dm}_{\text{Mumford-Shah}}$$

where  $\xi(t) \approx \delta(\eta(t) - \frac{1}{2})$

# Partial functional maps

$$\min_{\mathbf{C}, \mathbf{v}} \|\mathbf{G}^\top \boldsymbol{\Psi} \mathbf{C} - \mathbf{F}^\top \text{diag}(\eta(\mathbf{v})) \boldsymbol{\Phi}\|_{2,1} + \rho_{\text{corr}}(\mathbf{C}) + \rho_{\text{part}}(\mathbf{v})$$

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where  $\xi(t) \approx \delta(\eta(t) - \frac{1}{2})$

- **Correspondence regularization**

$$\rho_{\text{corr}}(\mathbf{C}) = \mu_3 \|\mathbf{C} \circ \mathbf{W}\|_{\text{F}}^2 + \mu_4 \sum_{i \neq j} (\mathbf{C}^\top \mathbf{C})_{ij}^2 + \mu_5 \sum_i ((\mathbf{C}^\top \mathbf{C})_{ii} - d_i)^2$$

# Partial functional maps

$$\min_{\mathbf{C}, \mathbf{v}} \|\mathbf{G}^\top \boldsymbol{\Psi} \mathbf{C} - \mathbf{F}^\top \text{diag}(\eta(\mathbf{v})) \boldsymbol{\Phi}\|_{2,1} + \rho_{\text{corr}}(\mathbf{C}) + \rho_{\text{part}}(\mathbf{v})$$

- **Part regularization**

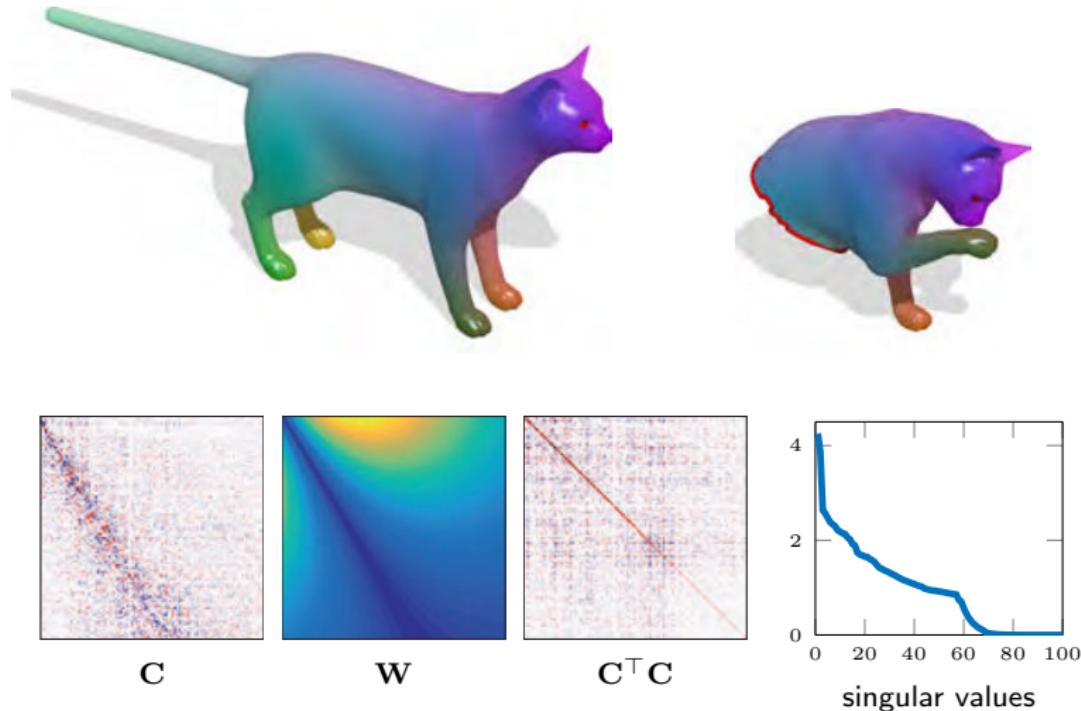
$$\rho_{\text{part}}(\mathbf{v}) = \underbrace{\mu_1 \left( |\mathcal{N}| - \int_{\mathcal{M}} \eta(\mathbf{v}) dm \right)^2}_{\text{area preservation}} + \underbrace{\mu_2 \int_{\mathcal{M}} \xi(\mathbf{v}) \|\nabla_{\mathcal{M}} \mathbf{v}\| dm}_{\text{Mumford-Shah}}$$

where  $\xi(t) \approx \delta(\eta(t) - \frac{1}{2})$

- **Correspondence regularization**

$$\rho_{\text{corr}}(\mathbf{C}) = \underbrace{\mu_3 \|\mathbf{C} \circ \mathbf{W}\|_{\text{F}}^2}_{\text{slant}} + \underbrace{\mu_4 \sum_{i \neq j} (\mathbf{C}^\top \mathbf{C})_{ij}^2}_{\approx \text{orthogonality}} + \underbrace{\mu_5 \sum_i ((\mathbf{C}^\top \mathbf{C})_{ii} - d_i)^2}_{\text{rank} \approx r}$$

# Structure of partial functional correspondence



# Alternating minimization

- **C-step:** fix  $\mathbf{v}^*$ , solve for correspondence  $\mathbf{C}$

$$\min_{\mathbf{C}} \|\mathbf{G}^\top \Psi \mathbf{C} - \mathbf{F}^\top \text{diag}(\eta(\mathbf{v}^*)) \Phi\|_{2,1} + \rho_{\text{corr}}(\mathbf{C})$$

- **v-step:** fix  $\mathbf{C}^*$ , solve for part  $\mathbf{v}$

$$\min_{\mathbf{v}} \|\mathbf{G}^\top \Psi \mathbf{C}^* - \mathbf{F}^\top \text{diag}(\eta(\mathbf{v})) \Phi\|_{2,1} + \rho_{\text{part}}(\mathbf{v})$$

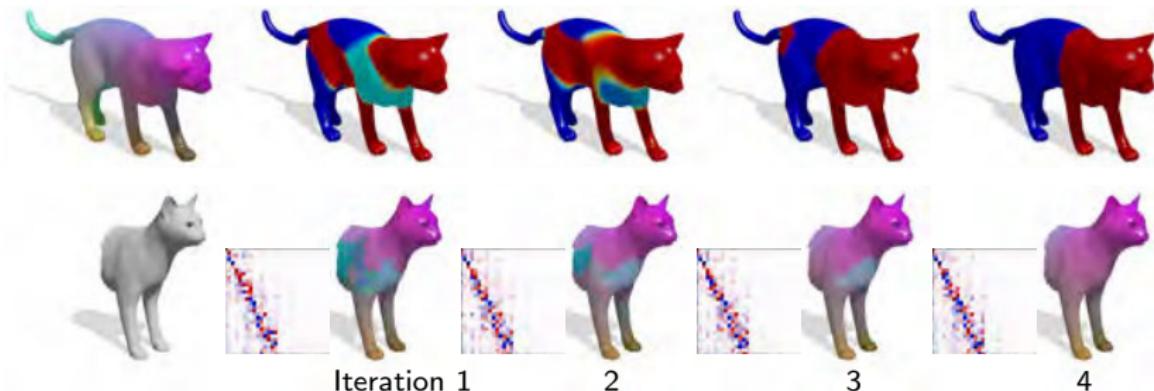
# Alternating minimization

- **C-step:** fix  $\mathbf{v}^*$ , solve for correspondence  $\mathbf{C}$

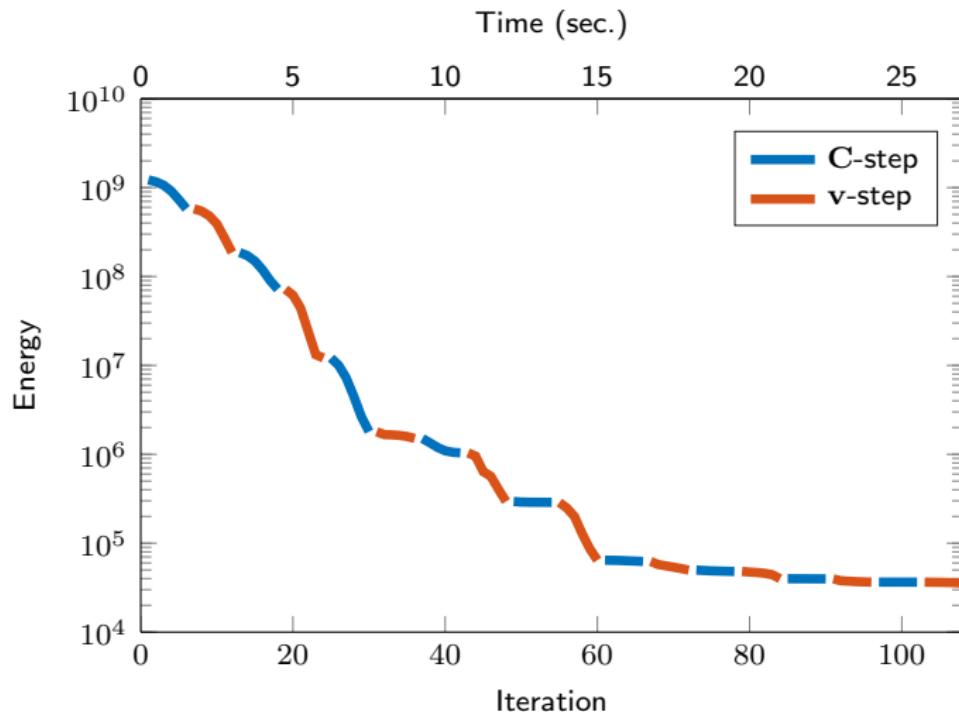
$$\min_{\mathbf{C}} \|\mathbf{G}^\top \Psi \mathbf{C} - \mathbf{F}^\top \text{diag}(\eta(\mathbf{v}^*)) \Phi\|_{2,1} + \rho_{\text{corr}}(\mathbf{C})$$

- **v-step:** fix  $\mathbf{C}^*$ , solve for part  $\mathbf{v}$

$$\min_{\mathbf{v}} \|\mathbf{G}^\top \Psi \mathbf{C}^* - \mathbf{F}^\top \text{diag}(\eta(\mathbf{v})) \Phi\|_{2,1} + \rho_{\text{part}}(\mathbf{v})$$



# Example of convergence



## Examples of partial functional maps



## Examples of partial functional maps

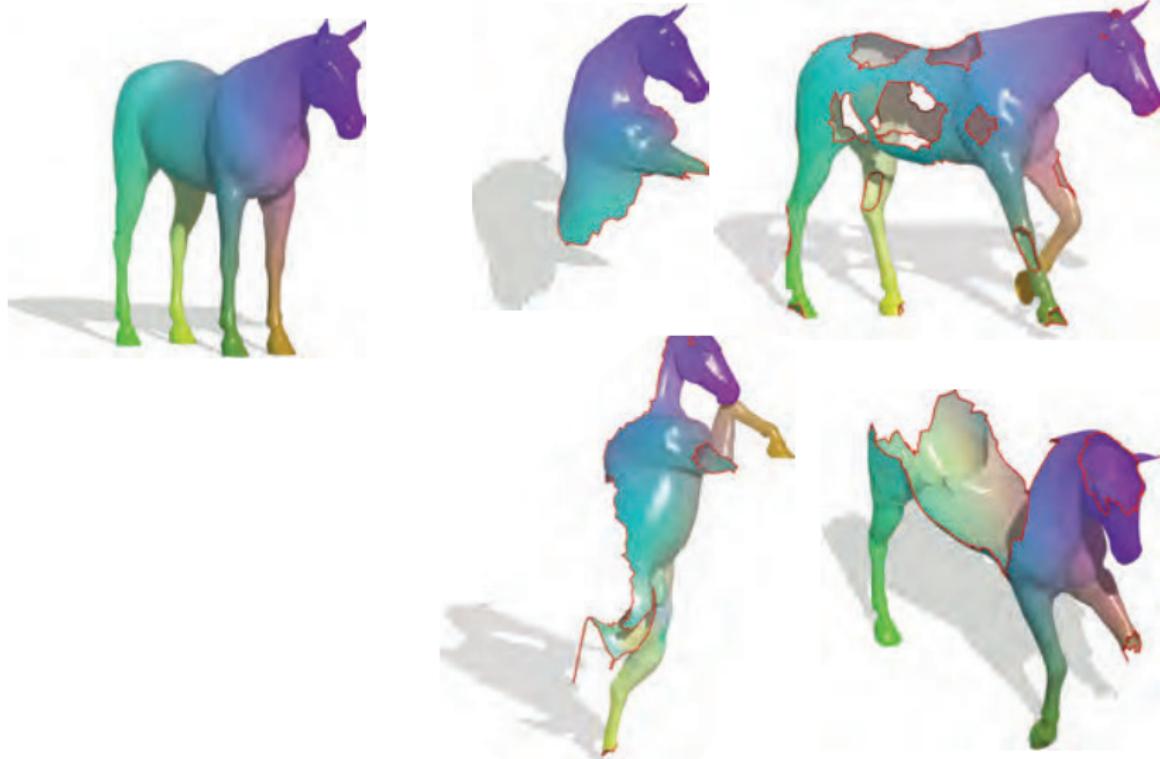


Rodolà, Cosmo, B, Torsello, Cremers 2016

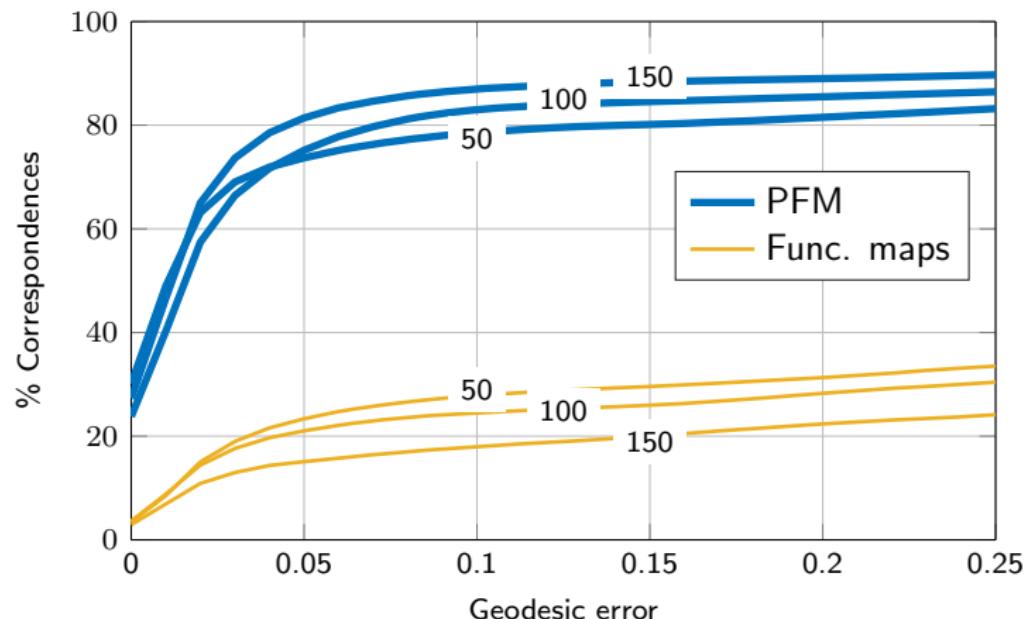
## Examples of partial functional maps



## Examples of partial functional maps

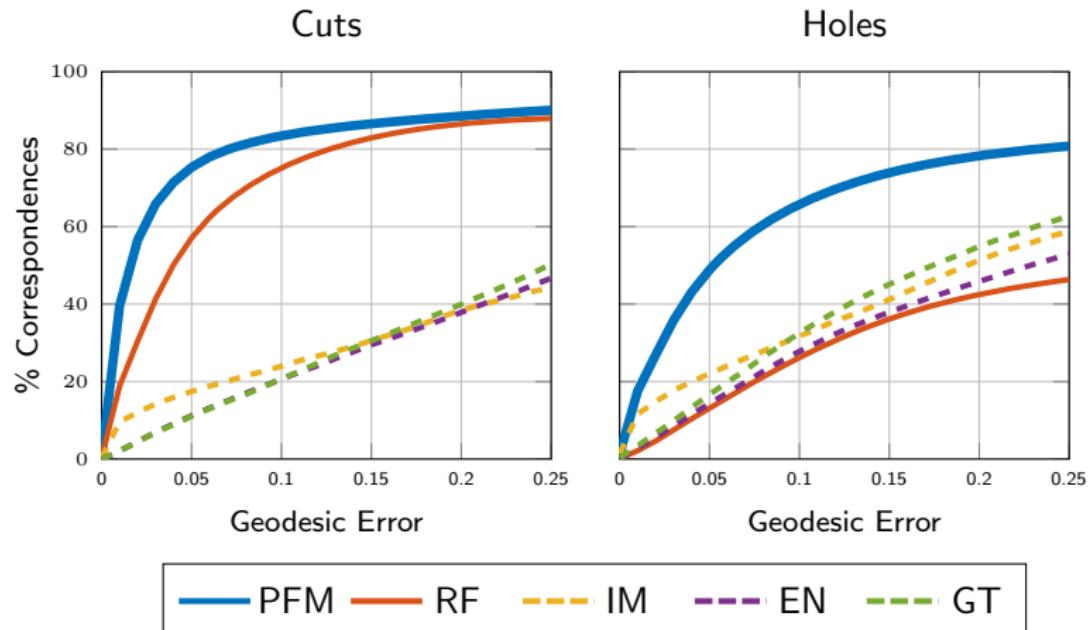


# Partial functional maps vs Functional maps



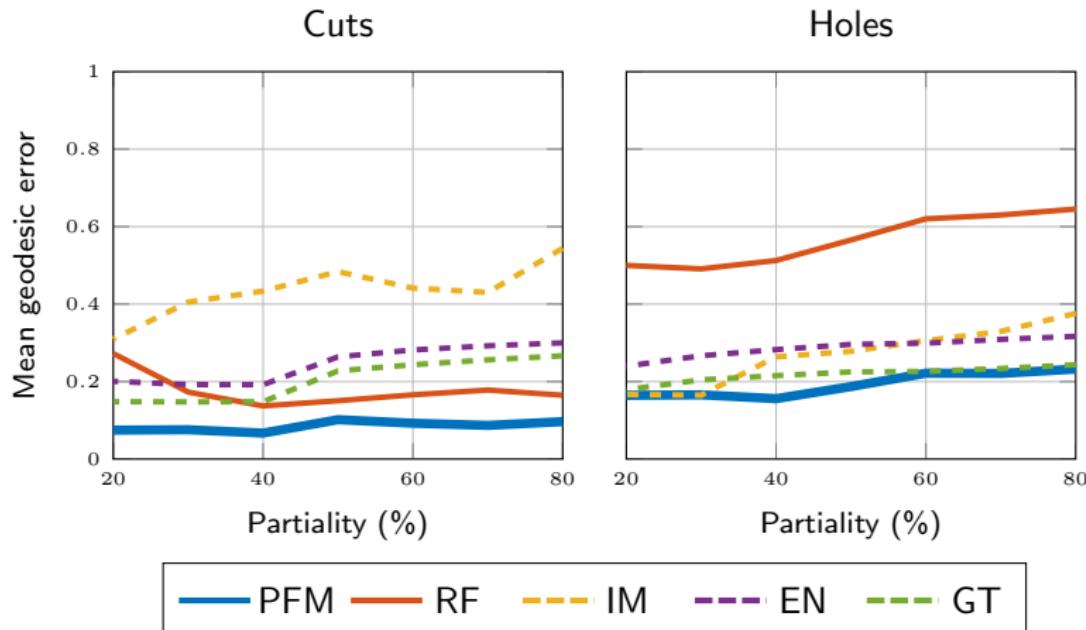
Correspondence performance for different rank values  $k$

# Partial correspondence performance



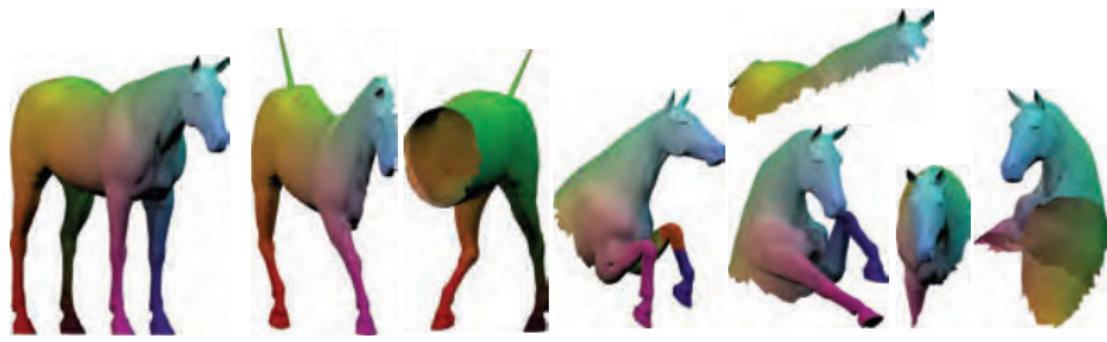
SHREC'16 Partial Matching benchmark Rodolà et al. 2016; Methods: Rodolà, Cosmo, B, Torsello, Cremers 2016 (PFM); Sahillioglu, Yemez 2012 (IM); Rodolà, Bronstein, Albarelli, Bergamasco, Torsello 2012 (GT); Rodolà et al. 2013 (EN); Rodolà et al. 2014 (RF)

# Partial correspondence performance



SHREC'16 Partial Matching benchmark Rodolà et al. 2016; Methods: Rodolà, Cosmo, B, Torsello, Cremers 2016 (PFM); Sahillioglu, Yemez 2012 (IM); Rodolà, Bronstein, Albarelli, Bergamasco, Torsello 2012 (GT); Rodolà et al. 2013 (EN); Rodolà et al. 2014 (RF)

# Deep learning + Partial functional maps



Correspondence



Correspondence error

# Deep learning + Partial functional maps



Correspondence



Correspondence error

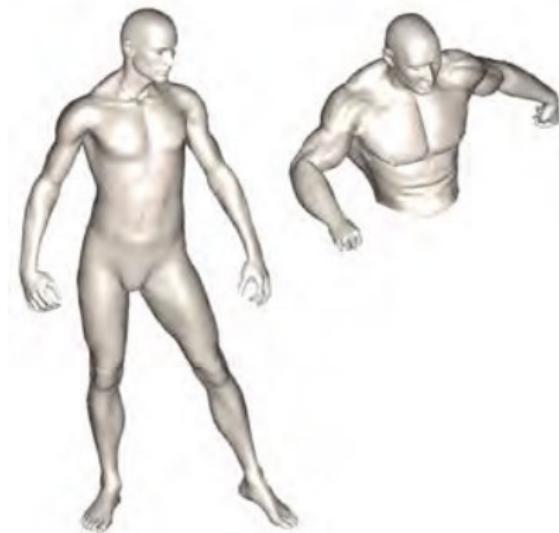
# Outline

- Background: Spectral analysis on manifolds
- Functional correspondence
- Partial functional correspondence
- **Non-rigid puzzles**

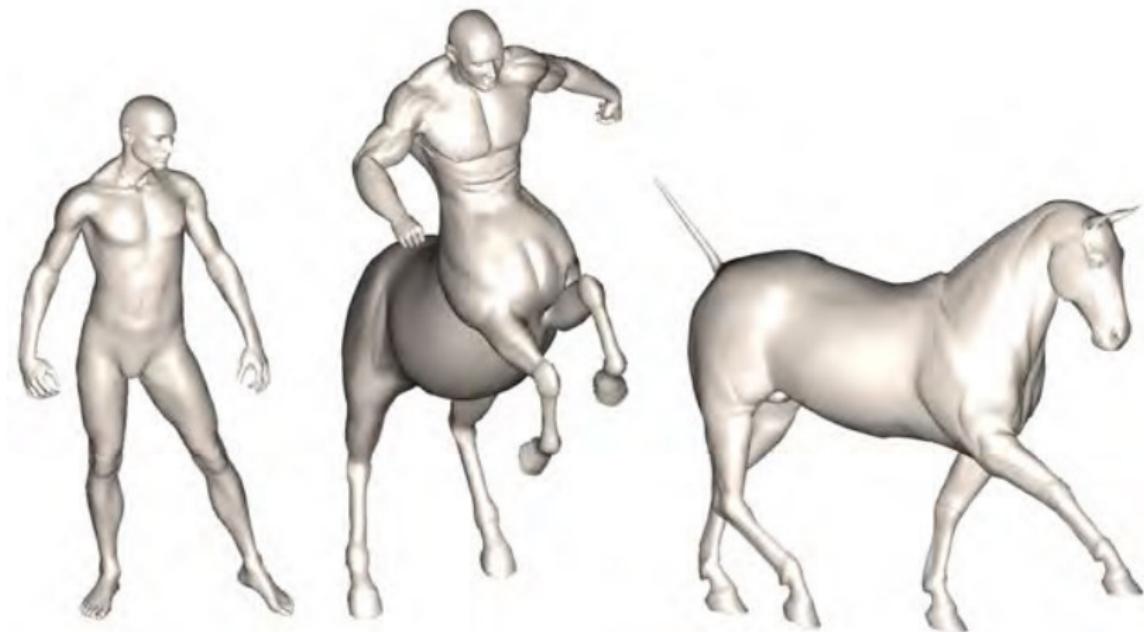


Litani, BB 2012

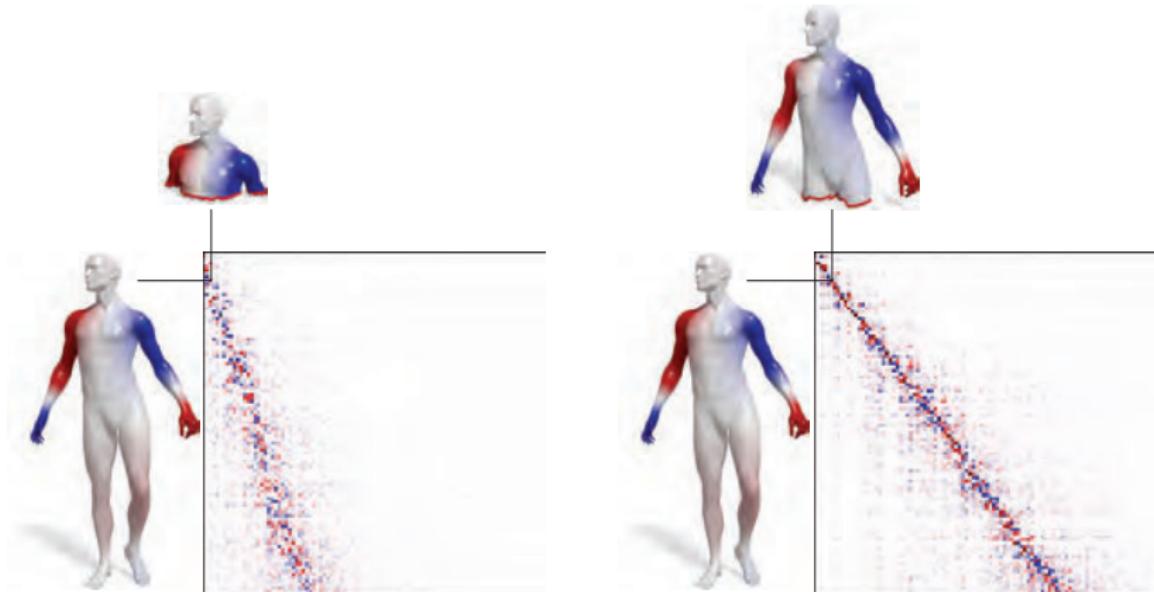
## Partial correspondence



## Non-rigid puzzle

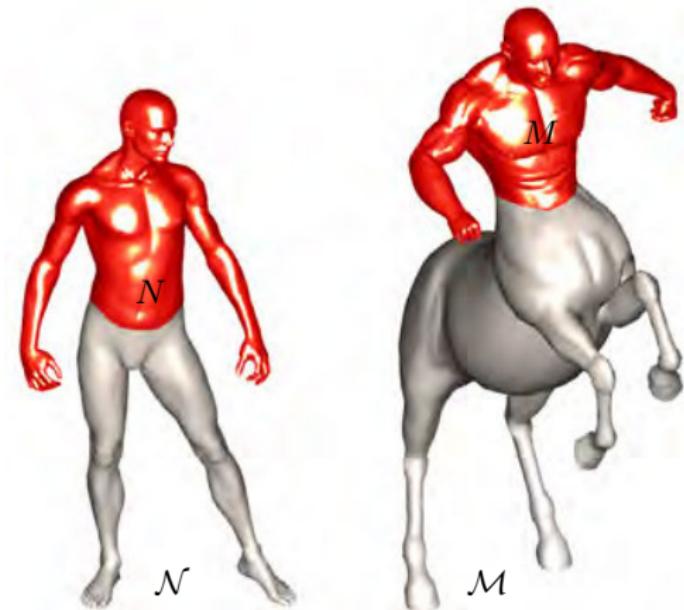


# Partial Laplacian eigenvectors



Functional correspondence matrix  $\mathbf{C}$

## Key observation



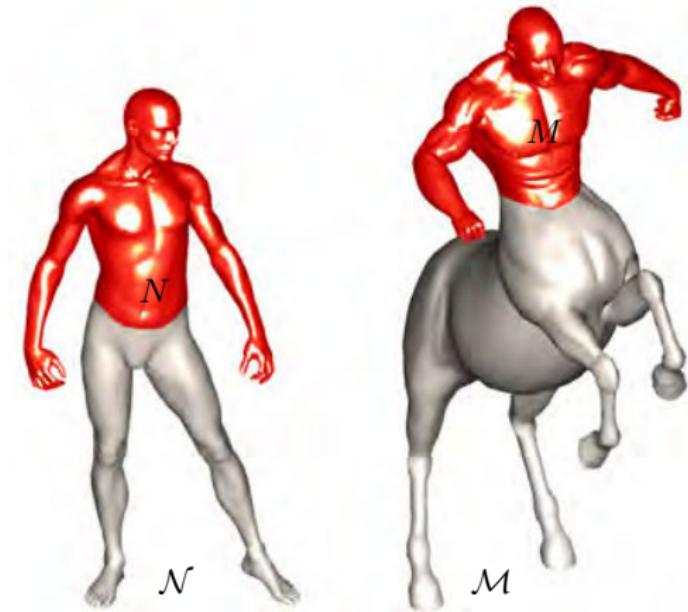
$\mathbf{C}_{NN}$

$\mathbf{C}_{MM}$

$$\text{slant} \propto \frac{|N|}{|\mathcal{N}|}$$

$$\text{slant} \propto \frac{|M|}{|\mathcal{M}|}$$

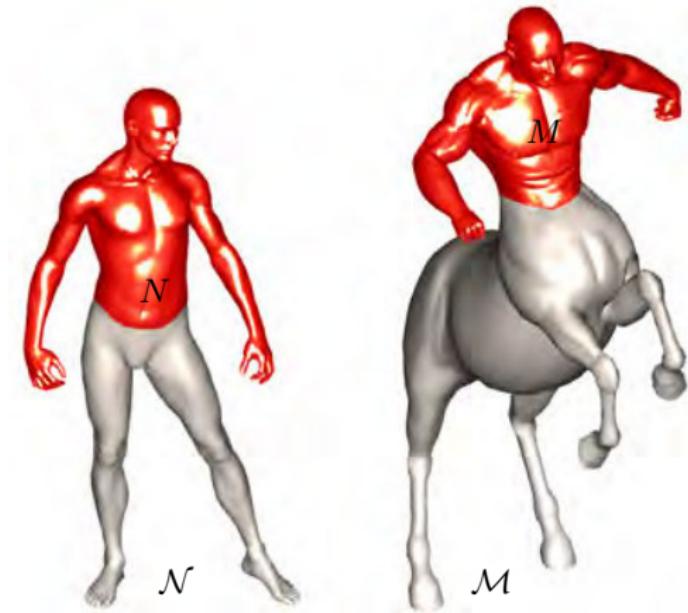
## Key observation



$$\mathbf{C}_{NM} = \mathbf{C}_{NN}\mathbf{C}_{NM}\mathbf{C}_{MM}$$

$$\text{slant} \propto \frac{|N|}{|N|} \frac{|M|}{|M|}$$

## Key observation



$$\mathbf{C}_{NM} = \mathbf{C}_{NN}\mathbf{C}_{NM}\mathbf{C}_{MM}$$

$$\text{slant} \propto \frac{|N|}{|N|} \frac{|M|}{|M|} = \frac{|N|}{|M|}$$

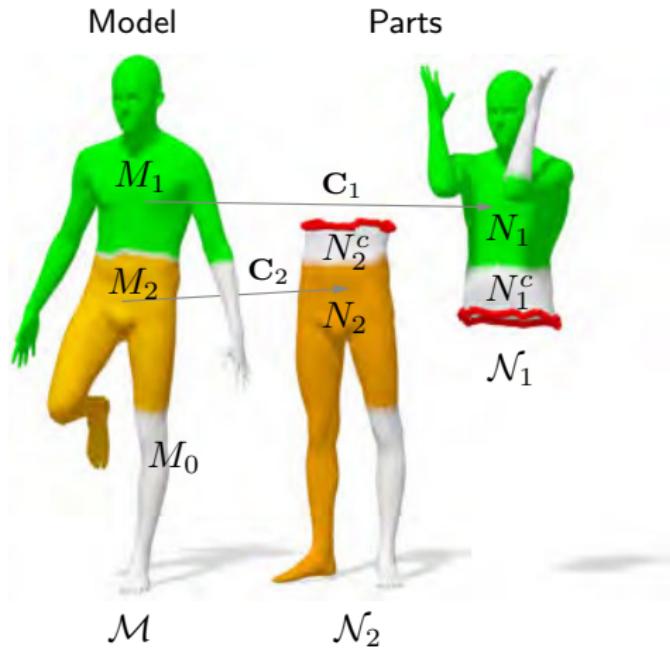
# Non-rigid puzzles problem formulation

## Input

- Model  $\mathcal{M}$
- Parts  $\mathcal{N}_1, \dots, \mathcal{N}_p$

## Output

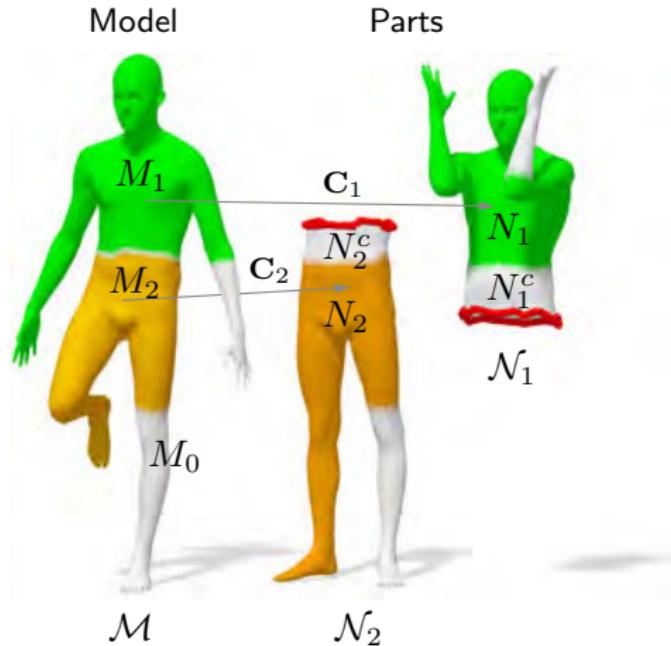
- Segmentation  $M_i \subseteq \mathcal{M}$
- Located parts  $N_i \subseteq \mathcal{N}_i$
- Correspondences  $\mathbf{C}_i$
- Clutter  $N_i^c$
- Missing parts  $M_0$



# Non-rigid puzzles problem formulation

- Data  $\mathbf{F}_i, \mathbf{G}_i$
- Model basis  $\Phi, \Phi(M_i)$
- Part bases  $\Psi_i, \Psi_i(N_i)$
- Data term

$$\mathbf{F}_i^\top \Phi(M_i) \approx \mathbf{G}_i^\top \Psi_i(N_i) \mathbf{C}_i$$



# Non-rigid puzzles problem formulation

$$\begin{aligned} \min_{\substack{\mathbf{C}_i \\ M_i \subseteq \mathcal{M}, N_i \subseteq \mathcal{N}_i}} \quad & \sum_{i=1}^p \|\mathbf{G}_i^\top \boldsymbol{\Psi}_i(N_i) \mathbf{C}_i - \mathbf{F}_i^\top \boldsymbol{\Phi}(M_i)\|_{2,1} \\ & + \lambda_{\mathcal{M}} \sum_{i=0}^p \rho_{\text{part}}(M_i) + \lambda_{\mathcal{N}} \sum_{i=1}^p \rho_{\text{part}}(N_i) \\ & + \lambda_{\text{corr}} \sum_{i=1}^p \rho_{\text{corr}}(\mathbf{C}_i) \\ \text{s.t.} \quad & M_i \cap M_j = \emptyset \quad \forall i \neq j \\ & M_0 \cup M_1 \cup \dots \cup M_p = \mathcal{M} \\ & |M_i| = |N_i| \geq \alpha |\mathcal{N}_i|, \end{aligned}$$

# Non-rigid puzzles problem formulation

$$\begin{aligned} \min_{\substack{\mathbf{C}_i \\ \mathbf{u}_i, \mathbf{v}_i}} \quad & \sum_{i=1}^p \|\mathbf{G}_i^\top \text{diag}(\eta(\mathbf{u}_i)) \boldsymbol{\Psi}_i \mathbf{C}_i - \mathbf{F}_i^\top \text{diag}(\eta(\mathbf{v}_i)) \boldsymbol{\Phi}\|_{2,1} \\ & + \lambda_{\mathcal{M}} \sum_{i=0}^p \rho_{\text{part}}(\eta(\mathbf{v}_i)) + \lambda_{\mathcal{N}} \sum_{i=1}^p \rho_{\text{part}}(\eta(\mathbf{u}_i)) \\ & + \lambda_{\text{corr}} \sum_{i=1}^p \rho_{\text{corr}}(\mathbf{C}_i) \\ \text{s.t.} \quad & \sum_{i=1}^p \eta(\mathbf{u}_i) = 1 \\ & \mathbf{a}_{\mathcal{M}}^\top \mathbf{u}_i = \mathbf{a}_{\mathcal{N}}^\top \mathbf{v}_i \geq \alpha \mathbf{a}_{\mathcal{N}_i}^\top \mathbf{1} \end{aligned}$$

# Convergence example



Outer iteration 1

## Convergence example



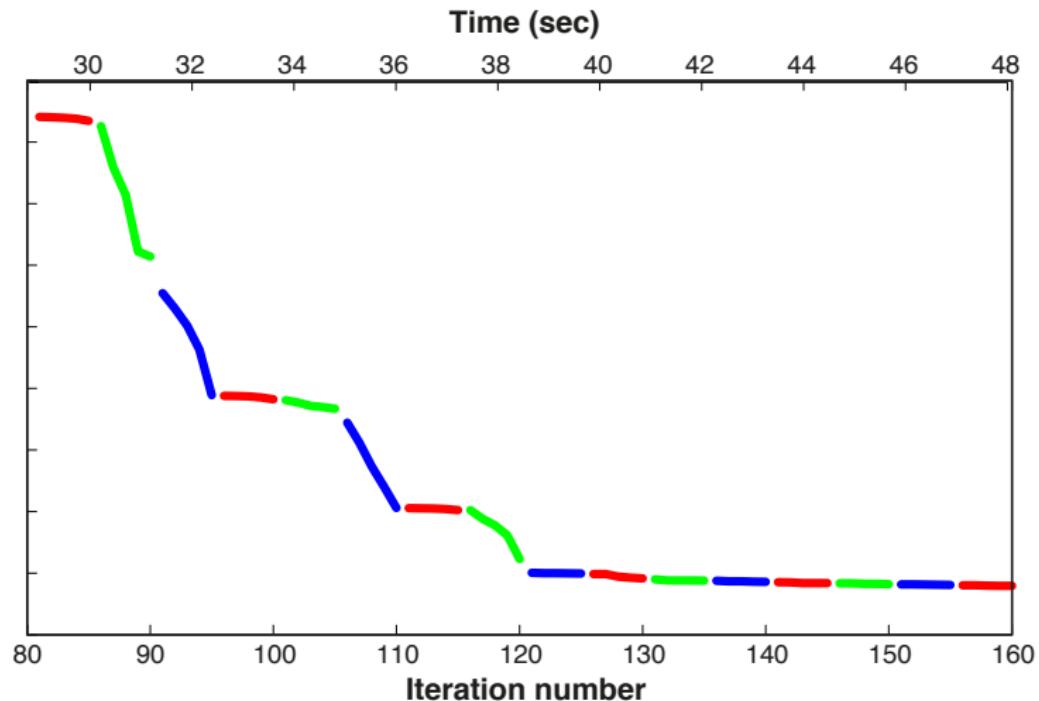
Outer iteration 2

## Convergence example



Outer iteration 3

## Convergence example



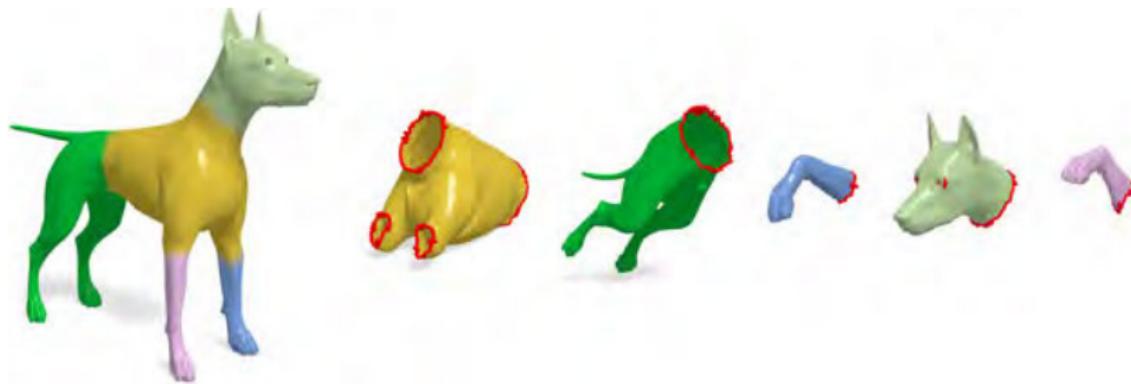
## “Perfect puzzle” example

Model/Part	Synthetic (TOSCA)
Transformation	Isometric
Clutter	No
Missing part	No
Data term	Dense (SHOT)



## “Perfect puzzle” example

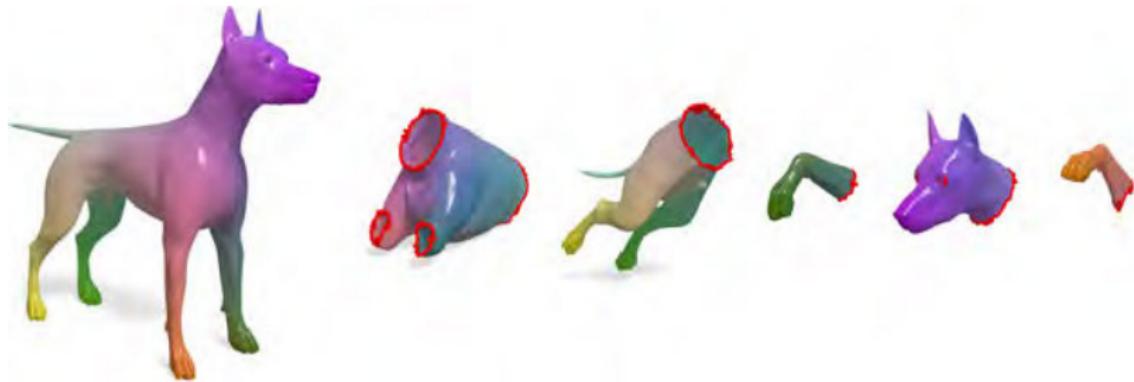
Model/Part	Synthetic (TOSCA)
Transformation	Isometric
Clutter	No
Missing part	No
Data term	Dense (SHOT)



Segmentation

## “Perfect puzzle” example

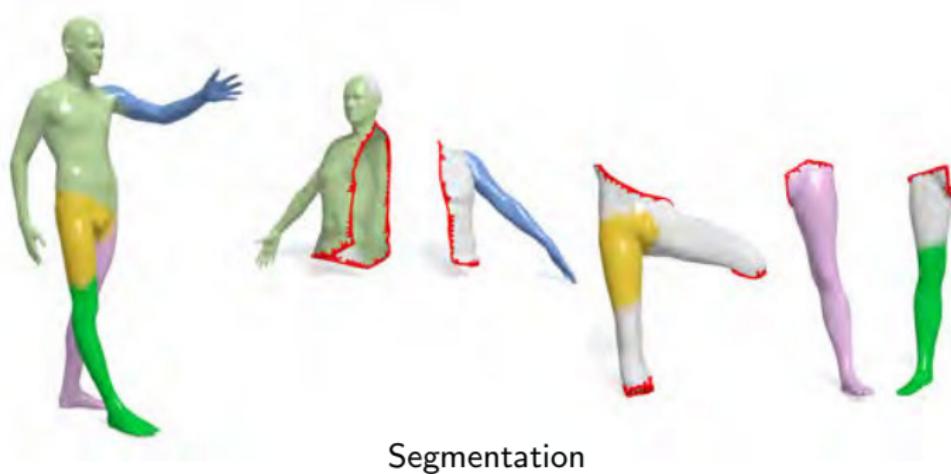
Model/Part	Synthetic (TOSCA)
Transformation	Isometric
Clutter	No
Missing part	No
Data term	Dense (SHOT)



Correspondence

# Overlapping parts example

Model/Part	Synthetic (FAUST)
Transformation	Near-isometric
Clutter	<b>Yes (overlap)</b>
Missing part	No
Data term	Dense (SHOT)



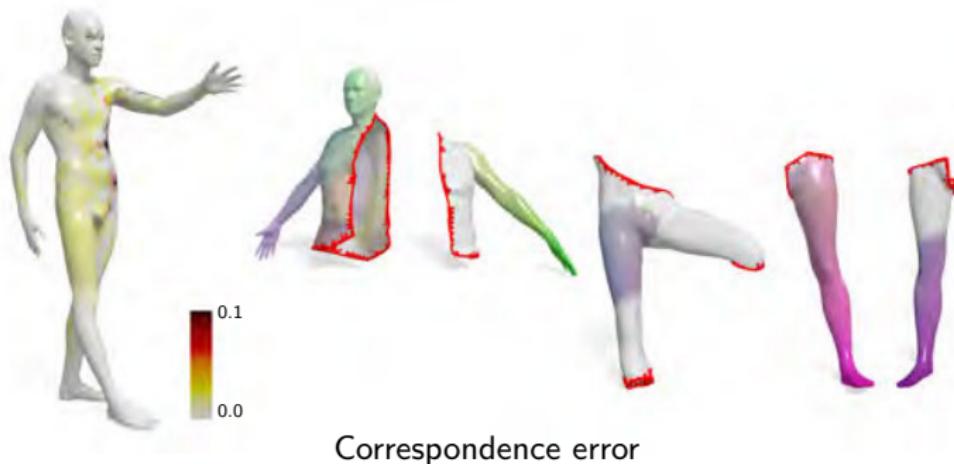
# Overlapping parts example

Model/Part	Synthetic (FAUST)
Transformation	Near-isometric
Clutter	<b>Yes (overlap)</b>
Missing part	No
Data term	Dense (SHOT)



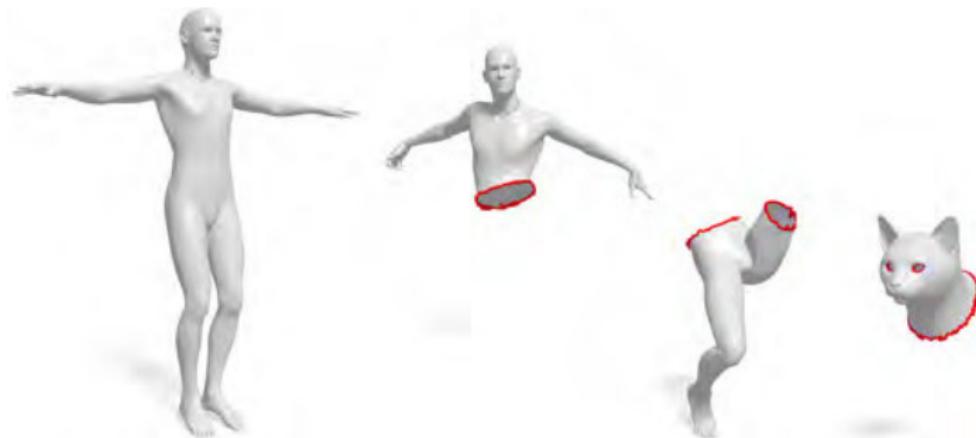
# Overlapping parts example

Model/Part	Synthetic (FAUST)
Transformation	Near-isometric
Clutter	<b>Yes (overlap)</b>
Missing part	No
Data term	Dense (SHOT)



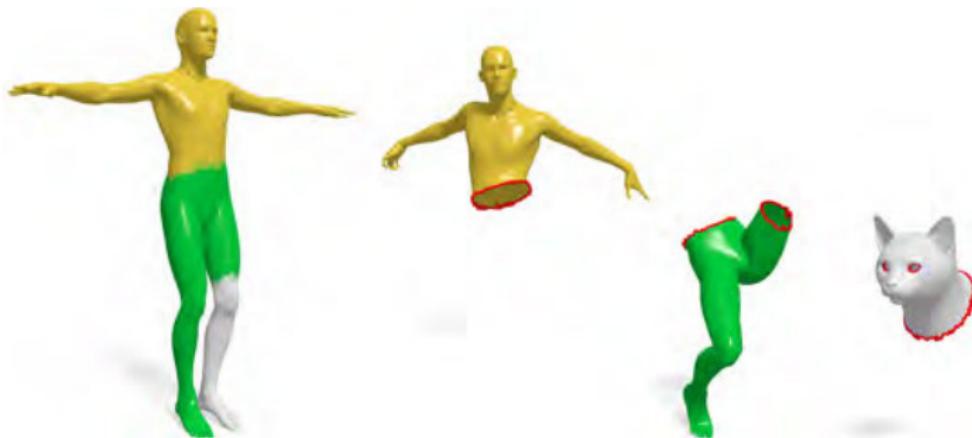
## Missing parts example

Model/Part	Synthetic (TOSCA)
Transformation	Isometric
Clutter	<b>Yes (extra part)</b>
Missing part	<b>Yes</b>
Data term	Dense (SHOT)



# Missing parts example

Model/Part	Synthetic (TOSCA)
Transformation	Isometric
Clutter	<b>Yes (extra part)</b>
Missing part	<b>Yes</b>
Data term	Dense (SHOT)



Segmentation

# Missing parts example

Model/Part	Synthetic (TOSCA)
Transformation	Isometric
Clutter	<b>Yes (extra part)</b>
Missing part	<b>Yes</b>
Data term	Dense (SHOT)



Correspondence

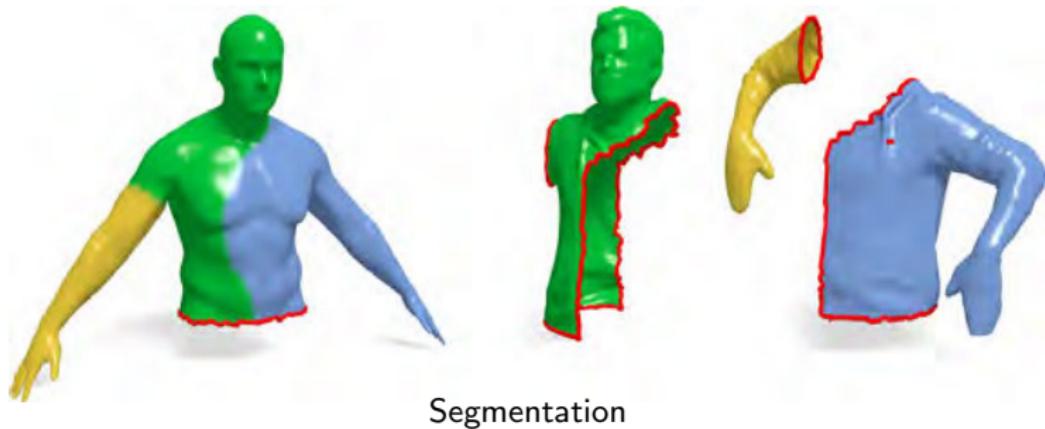
## Scanned data example

Model/Part	Synthetic (TOSCA) / Scan
Transformation	<b>Non-Isometric</b>
Clutter	No
Missing part	No
Data term	Sparse deltas

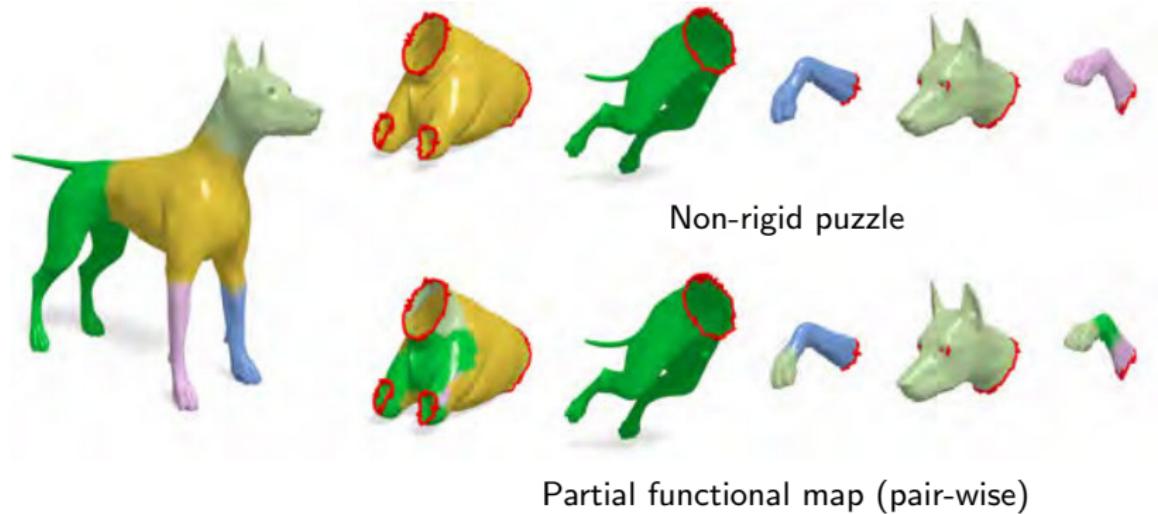


## Scanned data example

Model/Part	Synthetic (TOSCA) / Scan
Transformation	<b>Non-Isometric</b>
Clutter	No
Missing part	No
Data term	Sparse deltas

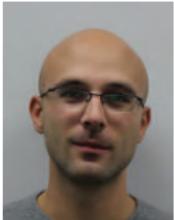


## Non-rigid puzzle vs Partial functional map



# Summary

- New insights about spectral properties of Laplacians
- Extension of functional correspondence framework to the partial setting
- Practically working methods for challenging shape correspondence settings
- Code available (SGP Reproducibility Stamp)
- Some over-engineering - can be done simpler! (stay tuned...)



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Thank you!