Spectral Shape Analysis for 3D matching

Prof. Umberto Castellani, Simone Melzi and Riccardo Marin

UNIVERSITÀ di VERONA

SAPIENZA UNIVERSITÀ DI ROMA

Advanced Techniques for functional map

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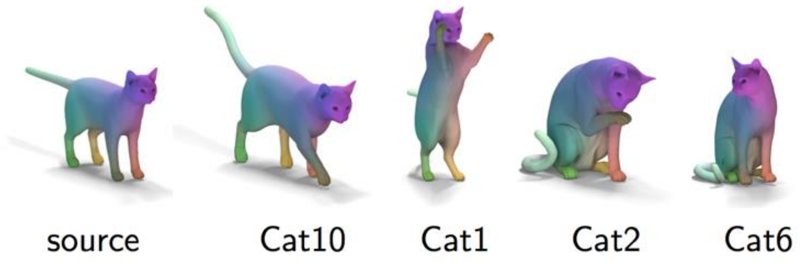
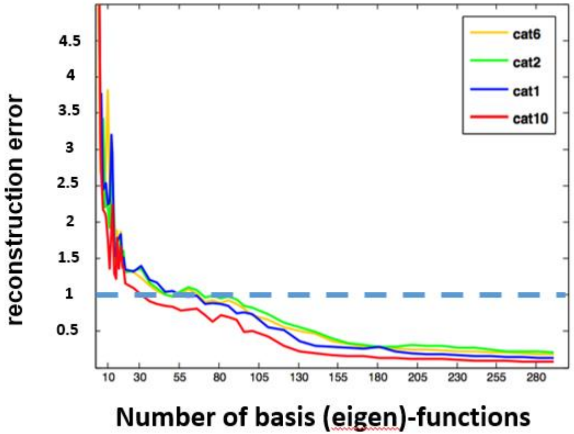
Functional map and the size of the basis

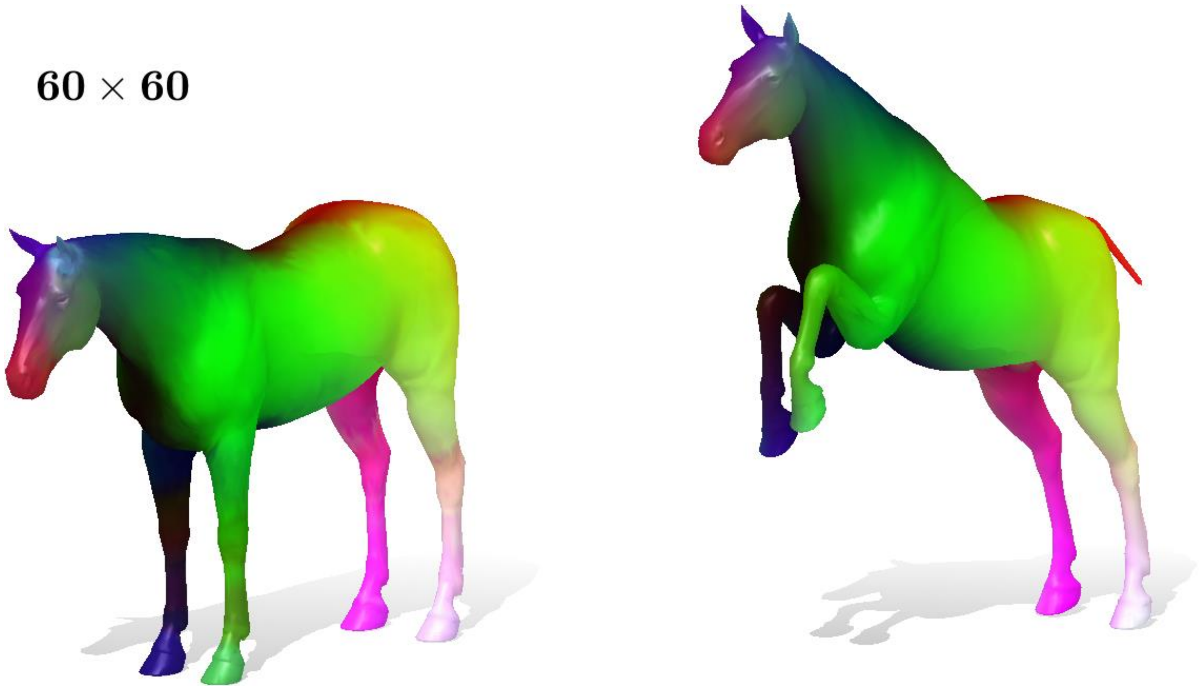
Slide credit M. *Ovsjanikov*





Functional maps: a flexible representation of maps between shapes, *Ovsjanikov, Ben-Chen, Solomon, Butscher, Guibas*, SIGGRAPH 2012

Fmaps and the low-pass filter

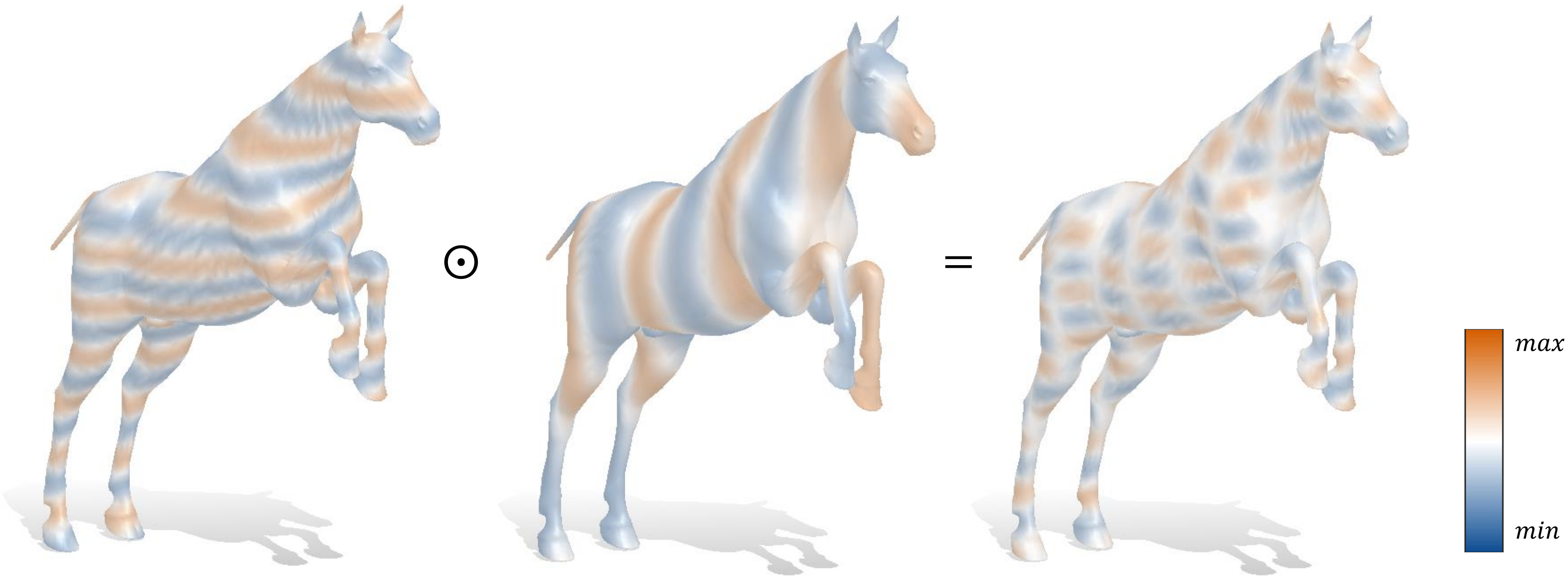


The trade-off

	+	–
Low-pass	Easy to optimize (fewer probe functions needed)	Low-pass representation (poor functional transfer)
High-frequencies	Better representation of details (good functional Transfer)	Hard to optimize (more probe functions needed)

Proposed solutions

Exploiting the Algebra of functions



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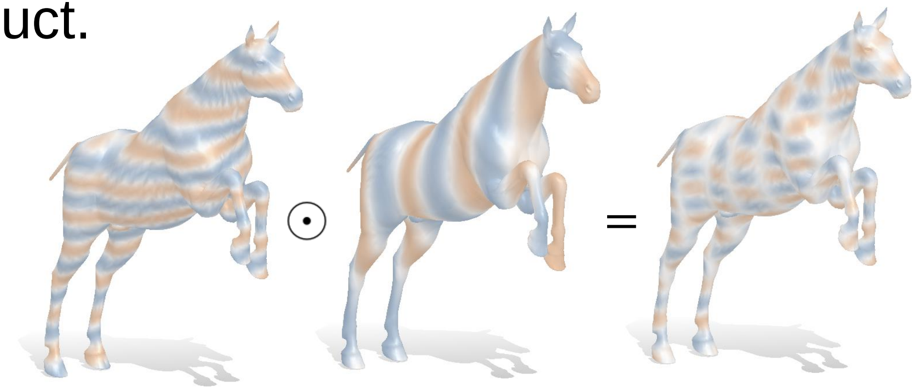
Pointwise Products

Theorem: A FMap that comes from a point-to-point map should preserves the pointwise products of functions.

$$T_F(f_1 \odot f_2) = T_F(f_1) \odot T_F(f_2)$$

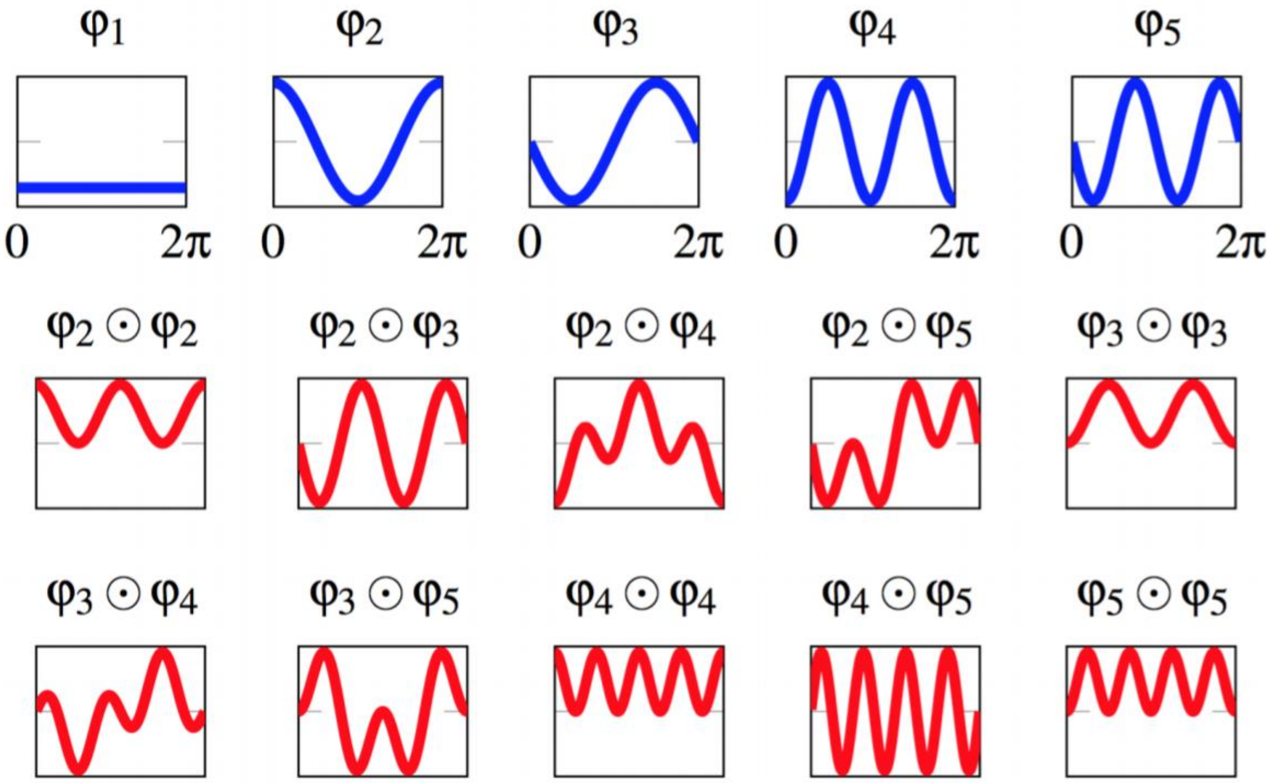
where $\odot$ is the pointwise product.

This Theorem tell us that these products are strictly related to the functional maps!

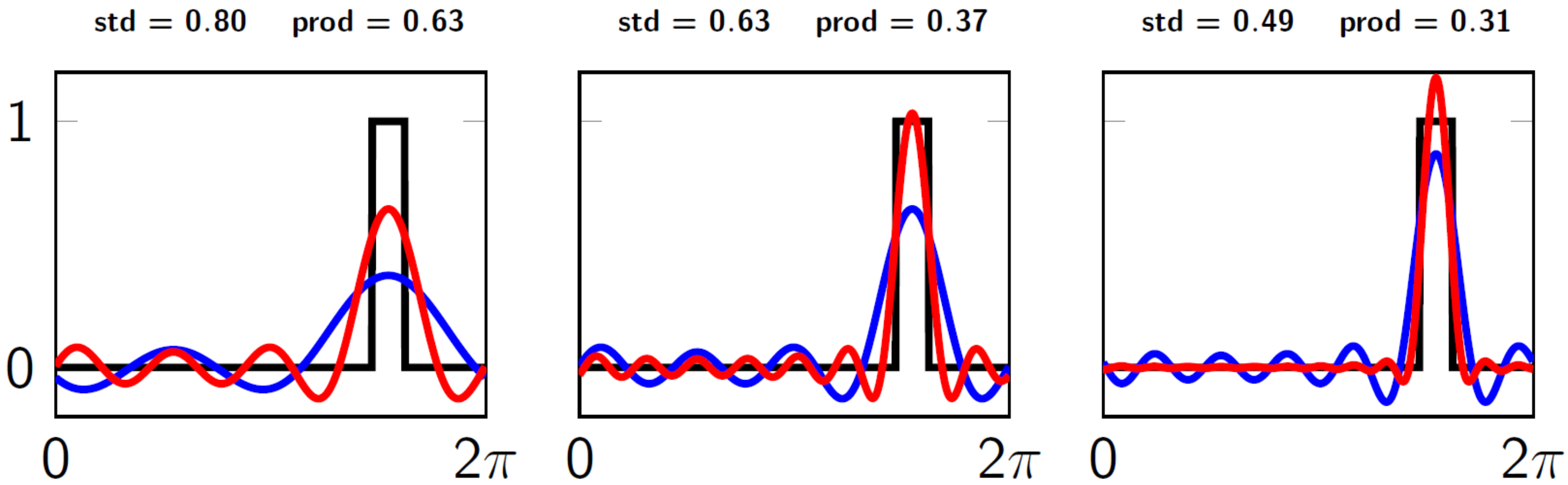


Composition operators on function spaces, *Singh, Manhas*, Elsevier 1993

Pointwise Products in 1D



Pointwise Products and high frequencies



$k = 4$ $k = 8$ $k = 12$

FMaps for pointwise products

$$\widetilde{\boldsymbol{C}}(\boldsymbol{C}) = \begin{bmatrix} \boldsymbol{C} & \mathcal{R}(\boldsymbol{C}) \\ 0 & \boldsymbol{C}(2:k,2:k) \otimes \boldsymbol{C}(2:k,2:k) \end{bmatrix}$$

$\widetilde{C}$ is a function of C and ϕ_1
NO FURTHER OPTIMIZATION REQUIRED

where $\otimes$ is the Kronecker product and

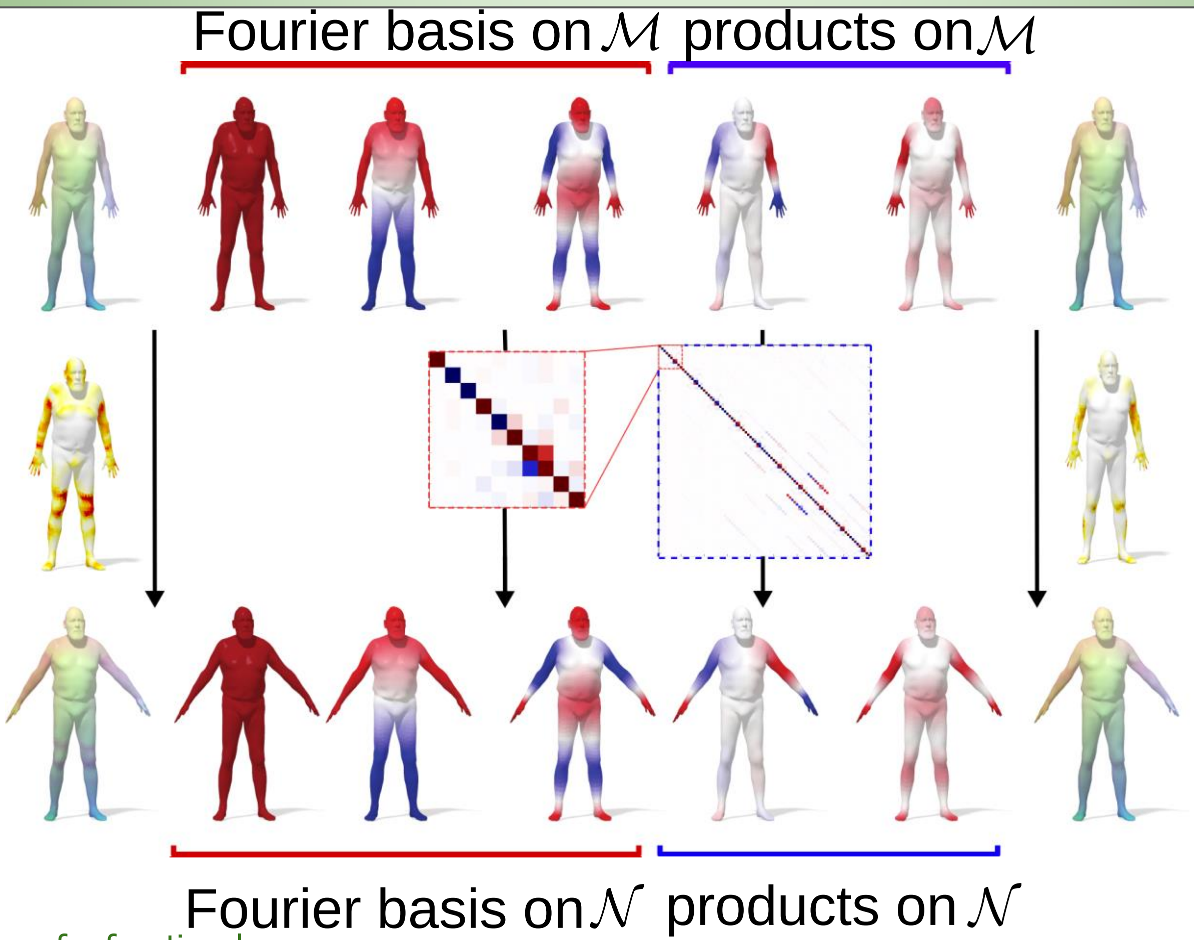
$$\mathcal{R}(\boldsymbol{C}) = \left[\phi_1 \boldsymbol{C}(1,2:k) \otimes \boldsymbol{C}(1:k,2:k) + \phi_1 \begin{bmatrix} 0 \ldots 0 \\ \boldsymbol{C}(2:k,2:k) \end{bmatrix} \otimes \boldsymbol{C}(1,2:k) \right]$$

$$\phi_1 = \phi_1(1,1)$$

$\boldsymbol{C}(1,2:k)$ is the row 1 of $\boldsymbol{C}$ columns from 2 to k

Improved functional mappings via product preservation, *Nogneng*, *Melzi*, *Rodolà*, *Castellani*, *M. Bronstein*, *Ovsjanikov*, CGF 2018

A visualization



Improved functional mappings via product preservation, *Nogneng*, *Melzi*, *Rodolà*, *Castellani*, *M. Bronstein*, *Ovsjanikov*, CGF 2018

Pointwise Products

Given $\mathcal{M}$ and $\mathcal{N}$ and their truncated Fourier bases:
$\Phi_{\mathcal{M}} = \{\phi_1, \dots, \phi_k\}$ and $\Psi_{\mathcal{N}} = \{\psi_1, \dots, \psi_k\}$

We consider the following dictionaries on $\mathcal{M}$ and $\mathcal{N}$:

$$\widetilde{\Phi} = \{\phi_1, \phi_2 \dots, \phi_k, \phi_2 \odot \phi_2, \phi_2 \odot \phi_3, \dots, \phi_{k-1} \odot \phi_k, \phi_k \odot \phi_k\}$$

$$\widetilde{\Psi} = \{\psi_1, \psi_2 \dots, \psi_k, \psi_2 \odot \psi_2, \psi_2 \odot \psi_3, \dots, \psi_{k-1} \odot \psi_k, \psi_k \odot \psi_k\}$$

The functions in the dictionaries $\widetilde{\Phi}$ and $\widetilde{\Psi}$ are not linear independent.

Improved functional mappings via product preservation, *Nogneng*, *Melzi*, *Rodolà*, *Castellani*, *M. Bronstein*, *Ovsjanikov*, CGF 2018

The proposed solutions

Given a function $f \in F(\mathcal{M})$ we would represent it as:

$$f \approx \widetilde{\Phi}\boldsymbol{\alpha} = \sum_{\boldsymbol{i=1}}^{\boldsymbol{k}} \alpha_i \phi_i + \sum_{\boldsymbol{i,j=2}}^{\boldsymbol{k}} a_{i,j} \phi_i \odot \phi_j$$

- **Approach A:** $\boldsymbol{\alpha} = \underset{\boldsymbol{\alpha}}{\operatorname{argm}in} \left\| \widetilde{\Phi}\boldsymbol{\alpha} - f \right\|_2 + \varepsilon \|\boldsymbol{\alpha}\|_p$ for $p = 1$ or $p = 2$

- **Approach B:** $\boldsymbol{\alpha} = V\Sigma^{\dagger}U^{\intercal}\sqrt{A_{\mathcal{M}}}f$ where $\mathrm{U}\Sigma V^{\intercal} = \sqrt{A_{\mathcal{M}}}\widetilde{\Phi}$

Improved functional mappings via product preservation, *Nogneng*, *Melzi*, *Rodolà*, *Castellani*, *M. Bronstein*, *Ovsjanikov*, CGF 2018

Qualitative results

original function

standard approx

product approx

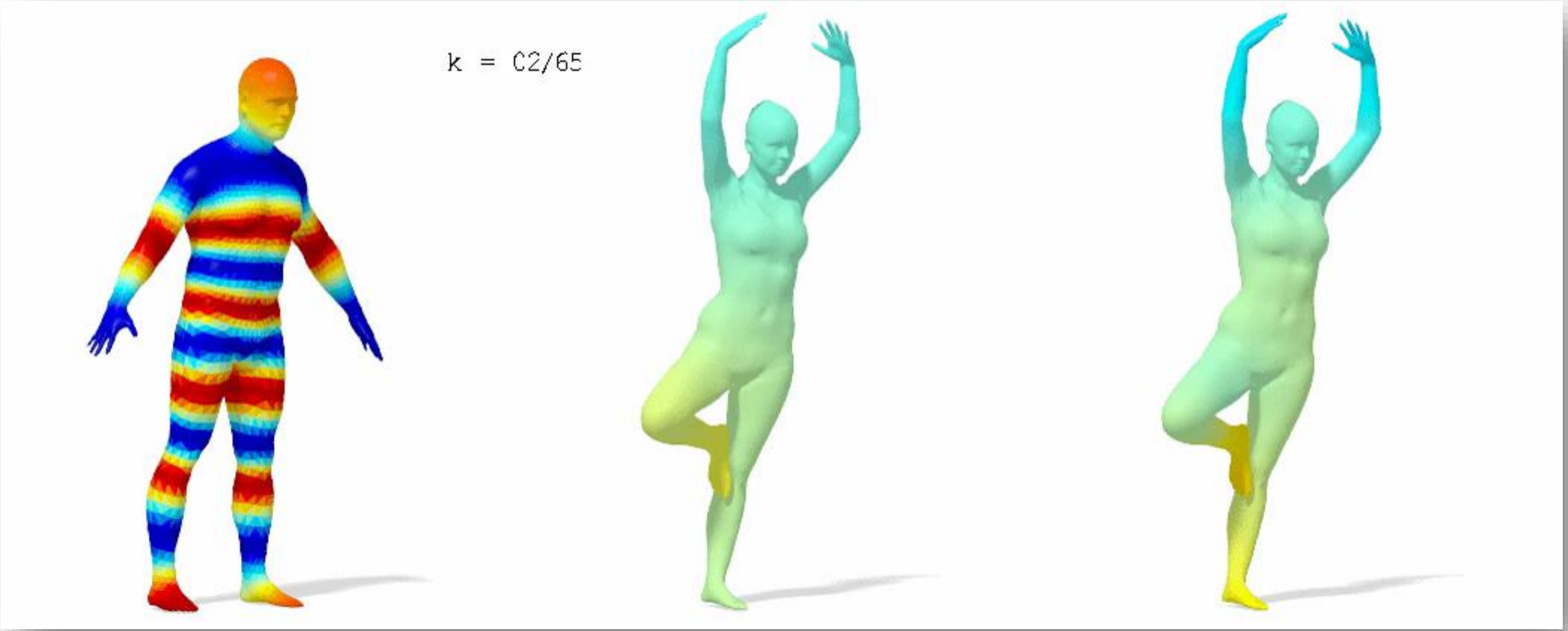
standard transfer

product transfer

Improved functional mappings via product preservation, *Nogneng*, *Melzi*, *Rodolà*, *Castellani*, *M. Bronstein*, *Ovsjanikov*, CGF 2018

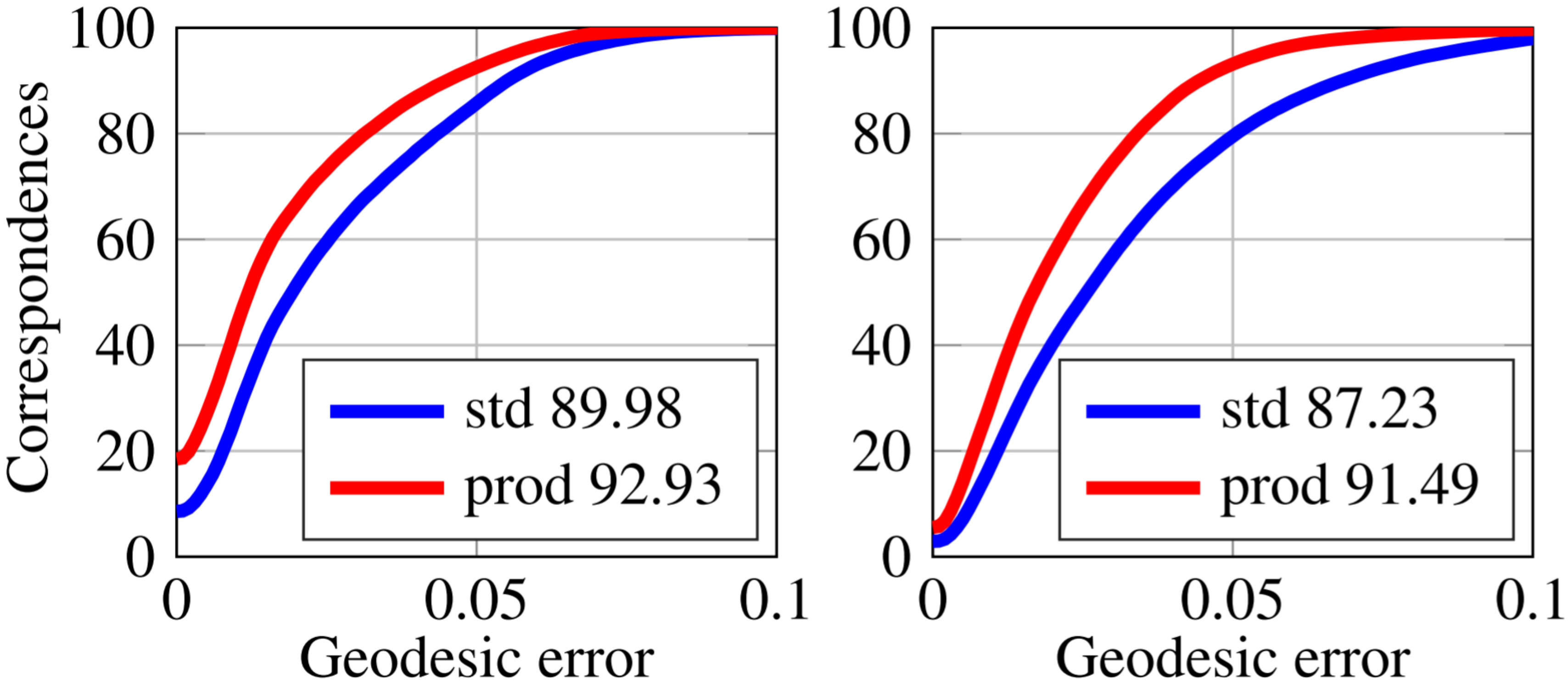
Comparison adding frequencies

original function standard transfer product transfer



Improved functional mappings via product preservation, *Nogneng*, *Melzi*, *Rodolà*, *Castellani*, *M. Bronstein*, *Ovsjanikov*, CGF 2018

Quantitative results

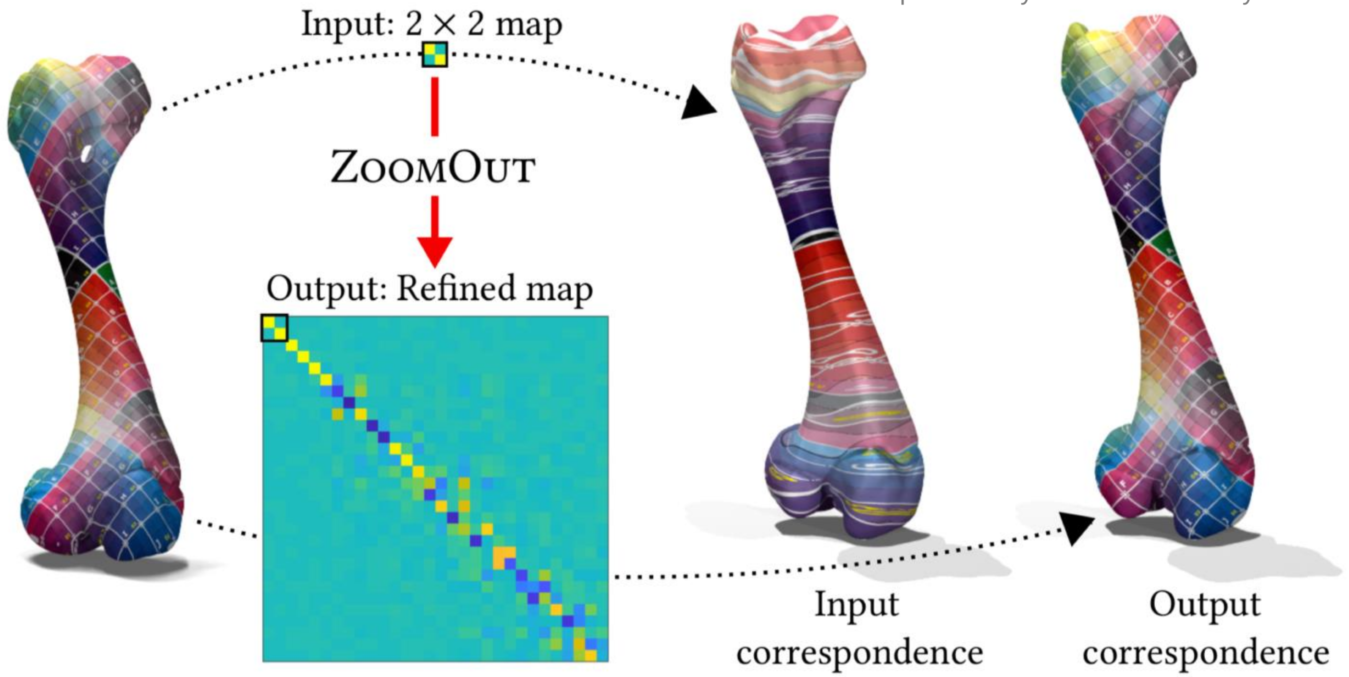


Improved functional mappings via product preservation, *Nogneng*, *Melzi*, *Rodolà*, *Castellani*, *M. Bronstein*, *Ovsjanikov*, CGF 2018

Exploiting the connection with point-to-point-map

Slide credit M. *Ovsjanikov*

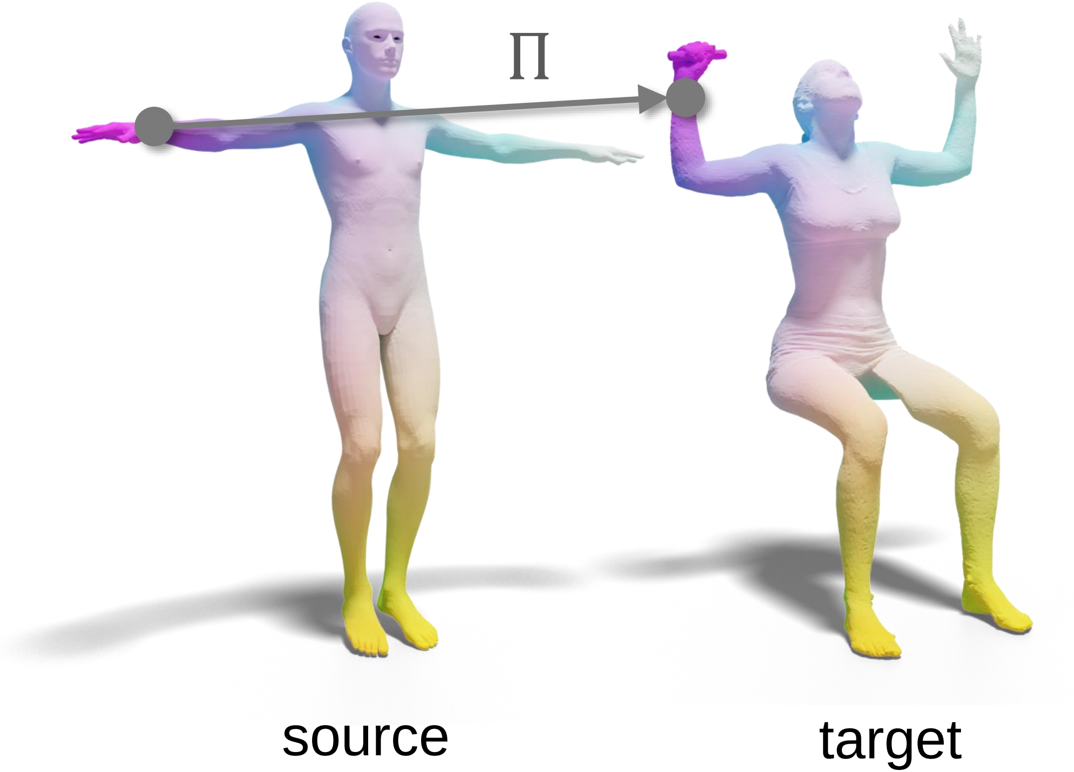
Dataset provided by the Natural History Museum in Paris



ZoomOut: Spectral Upsampling for Efficient Shape Correspondence, *Melzi*, *Ren*, *Sharma*, *Rodolà*, *Wonka*, *Ovsjanikov*, SIGGRAPH Asia 2019

Pointwise correspondence Π

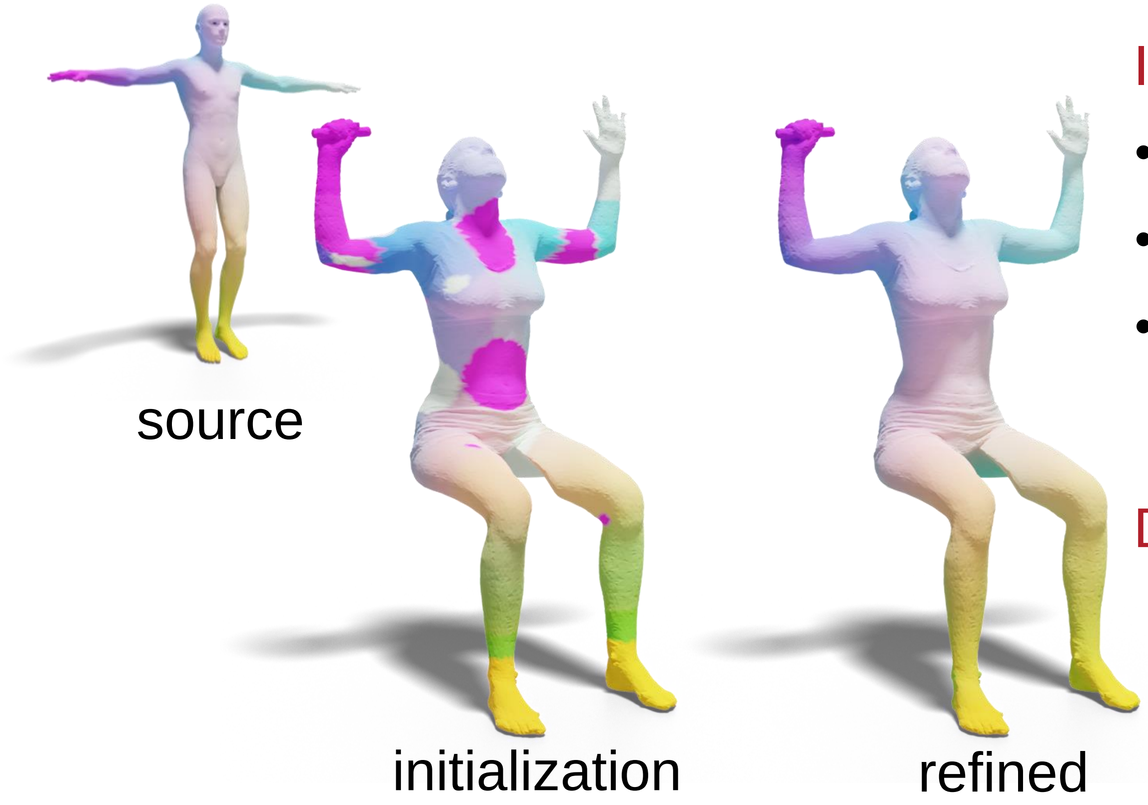
Slide credit J. *Ren*



The idea is to refine Π to obtain a more accurate map

Map refinement

Slide credit J. *Ren*



ICP-based

- Spatial (Besl, McKay 1992)
- Spectral (Ovsjanikov et al. 2012)
- Spatial & Spectral (Ren et al. 2018)

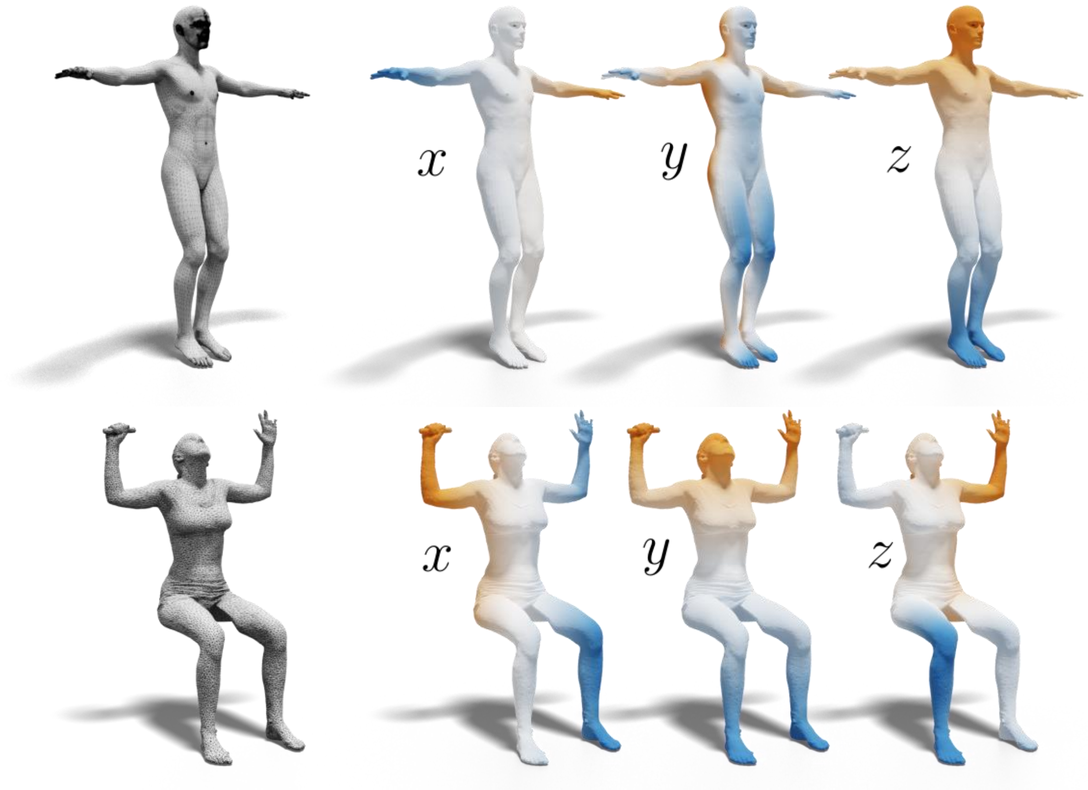
⋮

Deblurring and Denoising

(Ezuz and Ben-Chen 2017)

ICP in the spatial domain

Slide credit J. *Ren*



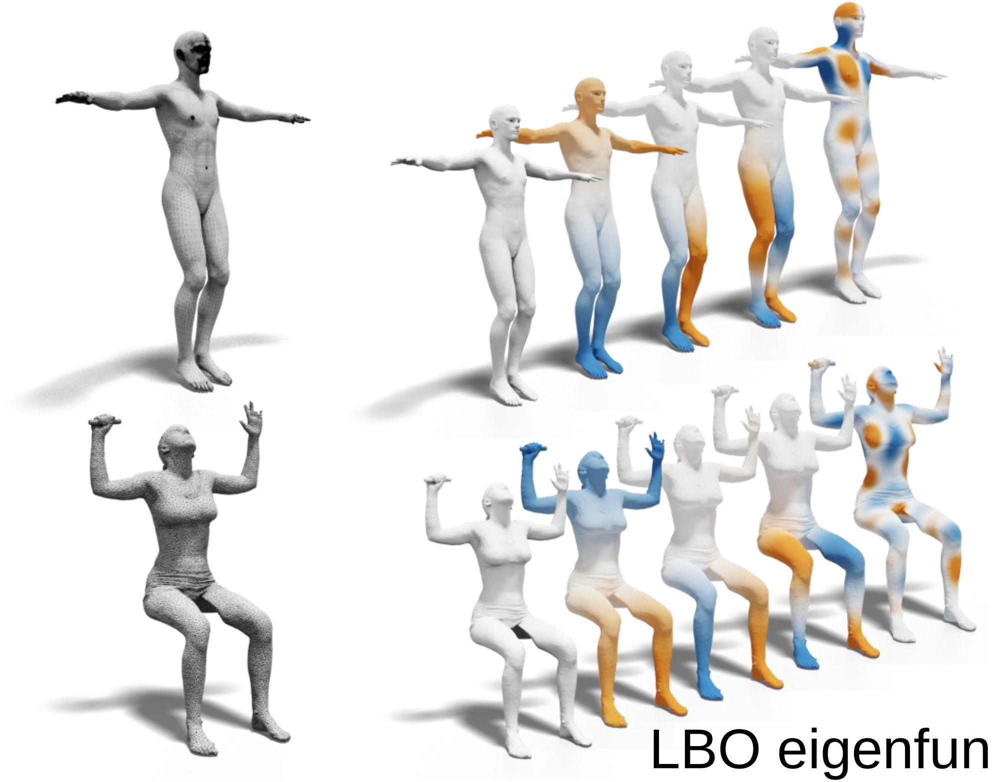
A method for registration of 3-D shapes, *Besl, McKay*, IEEE PAMI 1992

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

Optimize for a 3D rotation to align the vertex coordinates

ICP in the spectral domain

Slide credit J. *Ren*



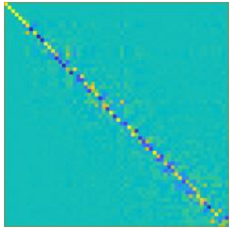
LBO eigenfunctions

$$\min_{\substack{C,\Pi \\ C^T C = I}} \|\Phi_1 C - \Phi_2(\Pi,:)\|_F^2$$

Optimize for C as a rotation in the spectral domain.

Iteratively solve for C and Π

(C with fixed size = k)



Functional maps: a flexible representation of maps between shapes, *Ovsjanikov, Ben-Chen, Solomon, Butscher, Guibas*, SIGGRAPH 2012

ICP and precise maps

ICP: $\min_{\substack{C,\Pi \\ C^T C = I}} \|\Phi_1 C - \Phi_2(\Pi,:)\|_F^2$

$$\min_{C,\Pi} \left\|\Phi_1^\dagger \Phi_1 C - \Phi_1^\dagger \Phi_2(\Pi,:)\right\|_F^2$$

$$\min_{C,\Pi} \left\|C - \Phi_1^\dagger \Phi_2(\Pi,:)\right\|_F^2$$

$$\min_{C,P} \left\|C - \Phi_1^\dagger P_{12} \Phi_2\right\|_F^2$$

$$\begin{array}{ll} \underset{P_{12}}{\text{minimize}} & R(P_{12}) + \|C_{12} - \Phi_1^\dagger P_{12} \Phi_2\|_F^2 \\ \text{subject to} & P_{12} \in \mathcal{P}_{12} \end{array}$$

The functional maps must correspond to vertex-to-point maps

Deblurring and Denoising of Maps between Shapes, *Ezuz, Ben-Chen*, SGP 2017

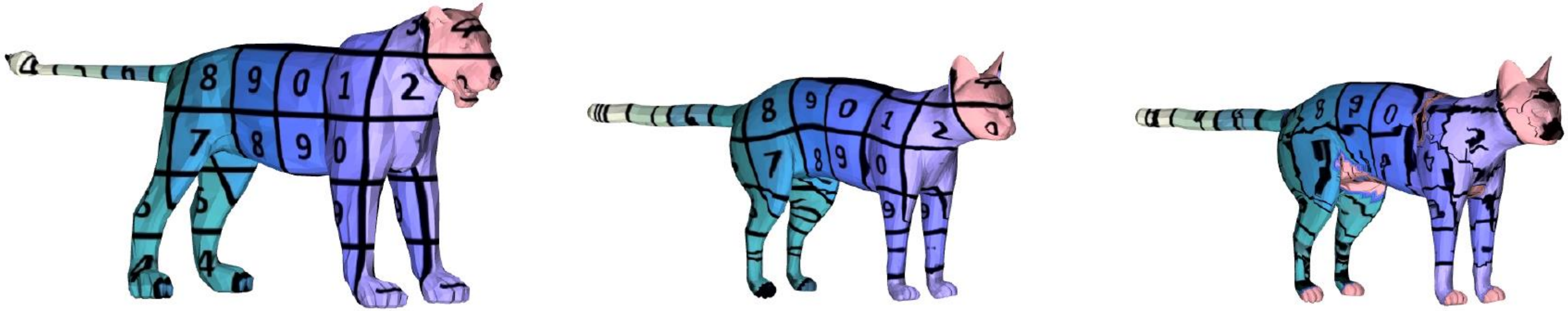
Functional maps deblurring

The functional maps must correspond to vertex-to-point maps

$$R(P_{12}) = \|(Id - \Phi_1 \Phi_1^{\dagger}) P_{12} \Phi_2\|_{M_1}^2$$

$$P_{12}\Phi_2 \in \operatorname{span}(\Phi_1)$$

$$\begin{aligned} \underset{P_{12}}{\text{minimize}} \quad & R(P_{12}) + \|C_{12} - \Phi_1^{\dagger} P_{12} \Phi_2\|_F^2 \\ \text{subject to} \quad & P_{12} \in \mathcal{P}_{12} \end{aligned}$$



Deblurring and Denoising of Maps between Shapes, *Ezuz, Ben-Chen*, SGP 2017

ZoomOut Idea

Slide credit J. *Ren*

Progressively registering the eigenfunctions
Exploiting the connection between functional and point-to-point map

ZoomOut

- 5 lines of code
- Similar complexity to ICP

```
function [C,P]=ZoomOut(M,N,C, k_final)

for k=size(C,1):k_final-1
  x = knnsearch(N.Phi(:,1:k)*C',M.Phi(:,1:k));
  P = sparse(1:M.n,x,1,M.n,N.n);
  C = M.Phi(:,1:k+1)'*M.A*P*N.Phi(:,1:k+1);
end
```

ZoomOut: Spectral Upsampling for Efficient Shape Correspondence, *Melzi*, *Ren*, *Sharma*, *Rodolà*, *Wonka*, *Ovsjanikov*, SIGGRAPH Asia 2019

ZoomOut Algorithm

Slide credit J. *Ren*

$$\boxed{\min_{C,\Pi} \|\Phi_1 C - \Phi_2(\Pi,:)\|_F^2}$$

Algorithm

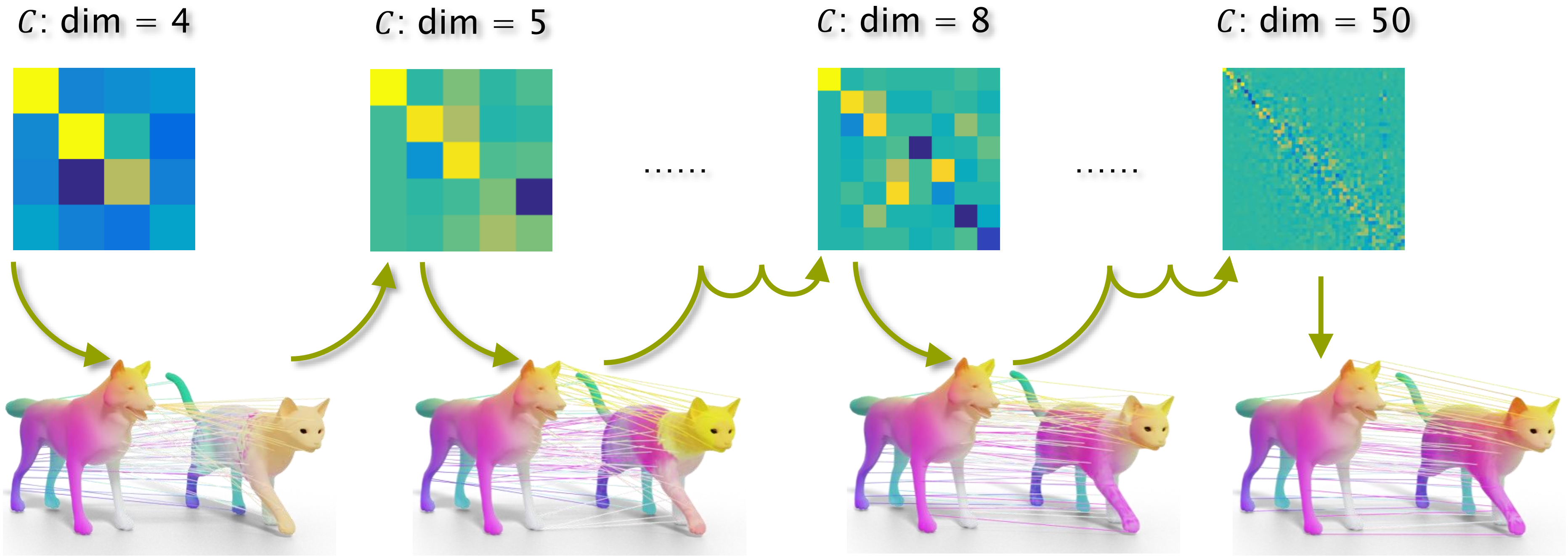
1. Input: an initial map Π and an integer k
2. Solve $C^k = \underset{C}{\operatorname{argmin}} \left\|\Phi_1^k C - \Phi_2^k(\Pi,:)\right\|_F^2$
3. Update $\Pi = \underset{\Pi}{\operatorname{argmin}} \left\|\Phi_1^k C^k - \Phi_2^k(\Pi,:)\right\|_F^2$
4. Update $k = k + 1$
5. Return to step 2.

Φ_i^k are the first k eigenfunctions of S_i

ZoomOut: Spectral Upsampling for Efficient Shape Correspondence, *Melzi*, *Ren*, *Sharma*, *Rodolà*, *Wonka*, *Ovsjanikov*, SIGGRAPH Asia 2019

ZoomOut: a visualization

Slide credit J. *Ren*

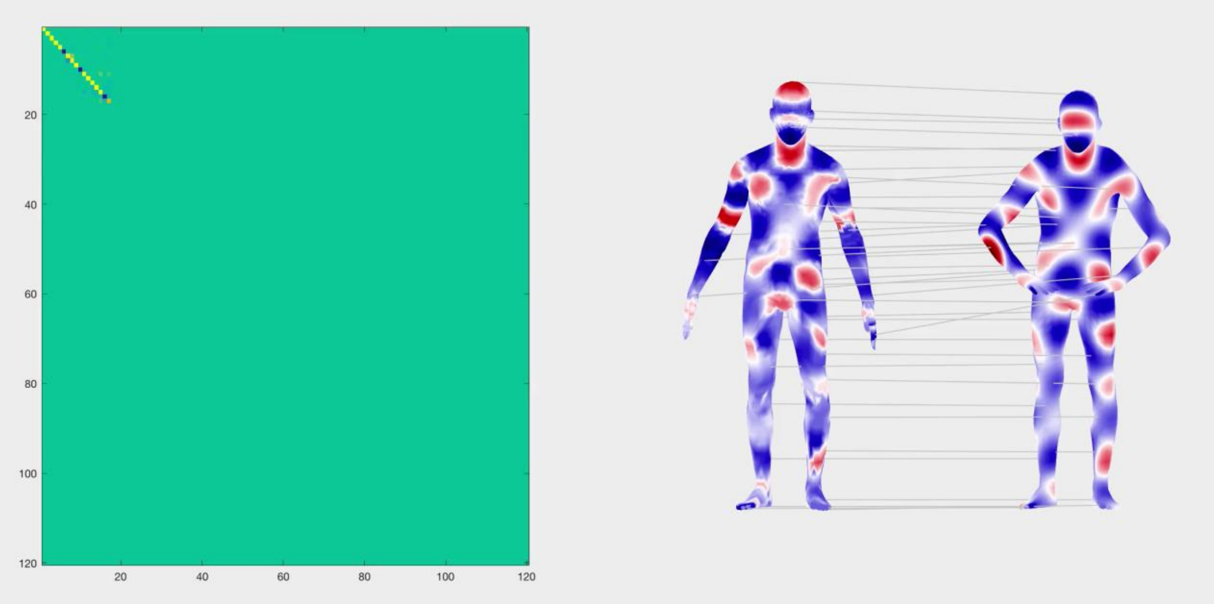


ZoomOut: Spectral Upsampling for Efficient Shape Correspondence, *Melzi*, *Ren*, *Sharma*, *Rodolà*, *Wonka*, *Ovsjanikov*, SIGGRAPH Asia 2019

Increasing the size of the functional map

Slide credit M. *Ovsjanikov*

From 20x20 to 120x120

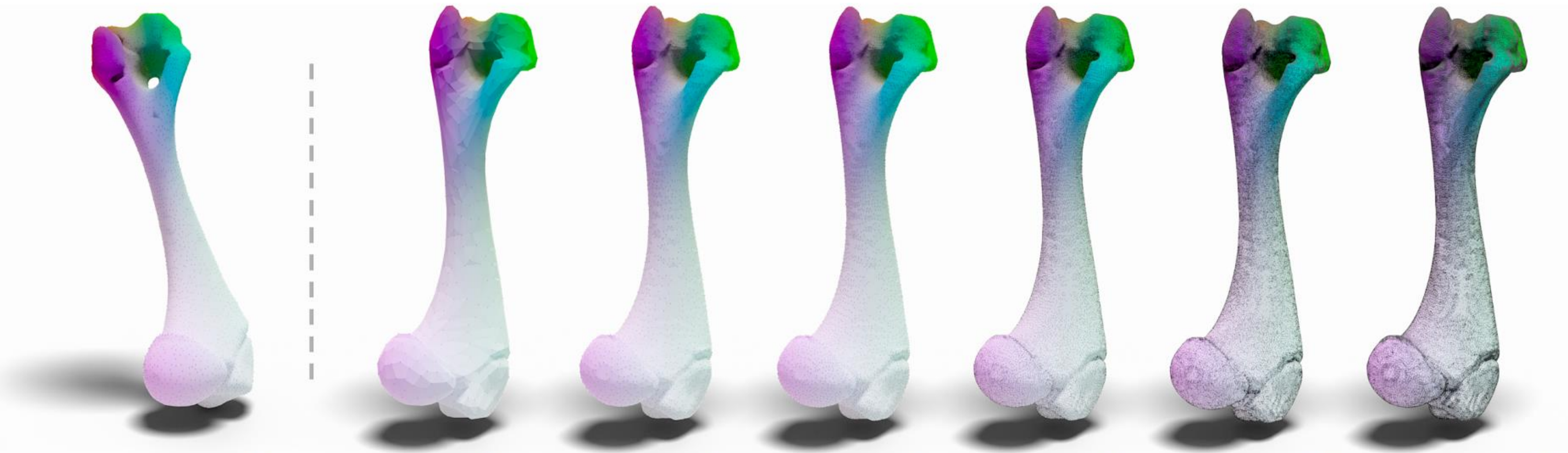


ZoomOut: Spectral Upsampling for Efficient Shape Correspondence, *Melzi*, *Ren*, *Sharma*, *Rodolà*, *Wonka*, *Ovsjanikov*, SIGGRAPH Asia 2019

Scalability

Slide credit J. *Ren*

Computation time dominated by:
eigenfunctions computation and nearest-neighbor search

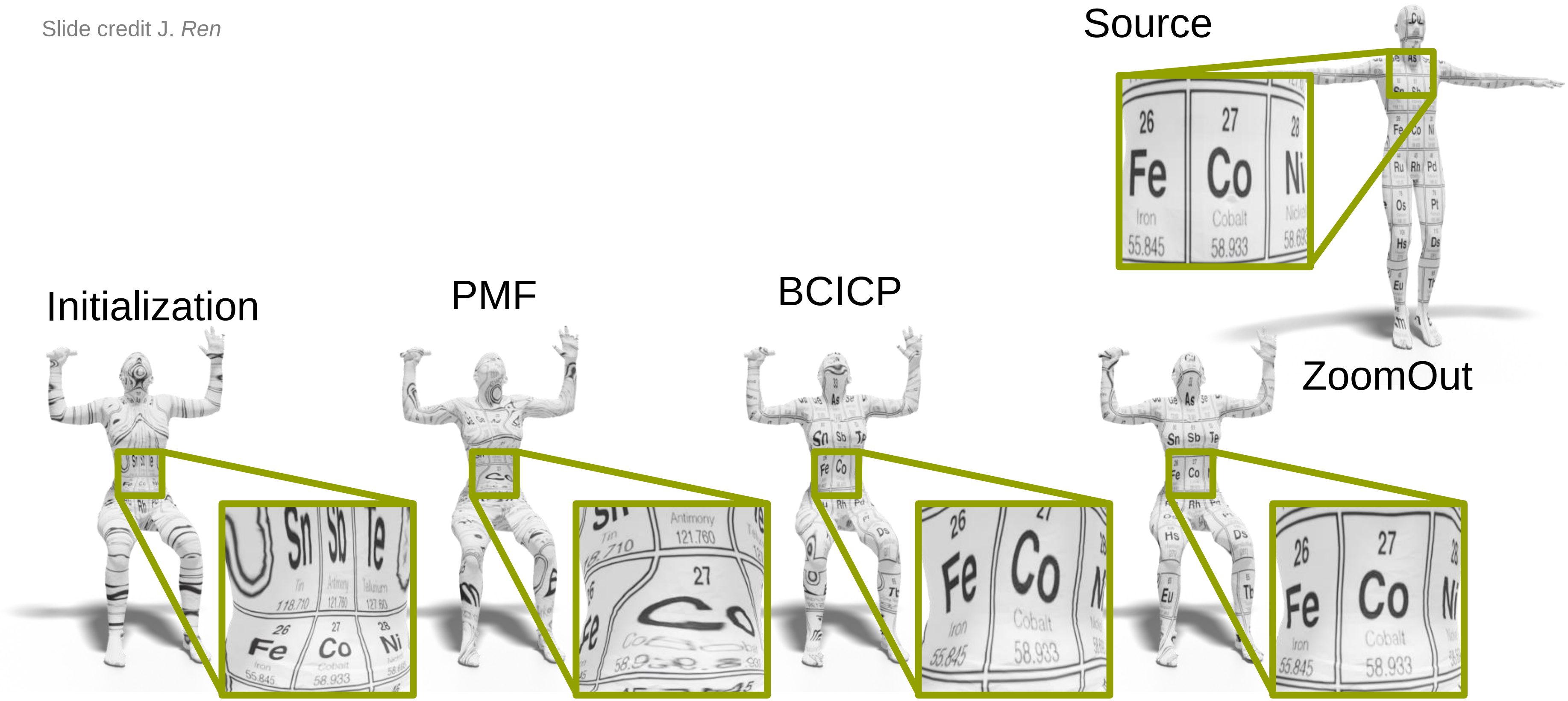


Source: $n = 5K$	$n = 1K$	$n = 5K$	$n = 10K$	$n = 50K$	$n = 100K$	$n = 150K$
	$t = 1.2$	$t = 5.7$	$t = 11$	$t = 55$	$t = 110$	$t = 169$

ZoomOut: Spectral Upsampling for Efficient Shape Correspondence, *Melzi*, *Ren*, *Sharma*, *Rodolà*, *Wonka*, *Ovsjanikov*, SIGGRAPH Asia 2019

Qualitative results

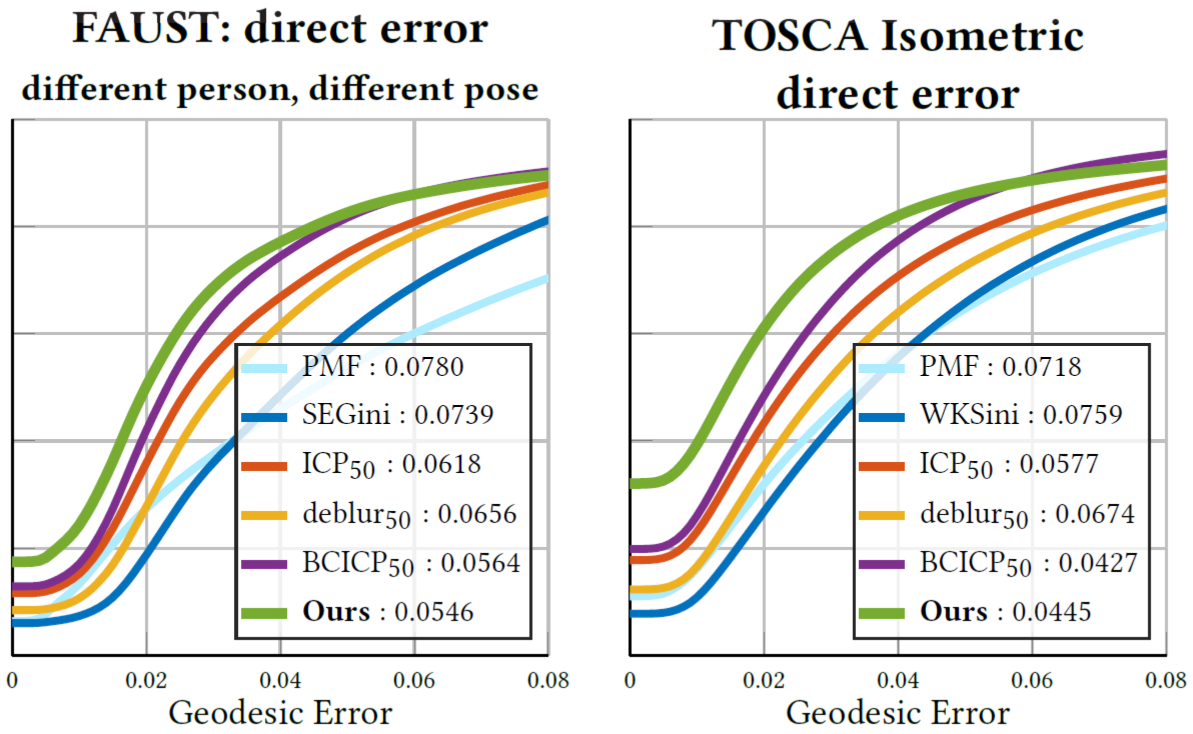
Slide credit J. *Ren*



ZoomOut: Spectral Upsampling for Efficient Shape Correspondence, *Melzi*, *Ren*, *Sharma*, *Rodolà*, *Wonka*, *Ovsjanikov*, SIGGRAPH Asia 2019

Quantitative results

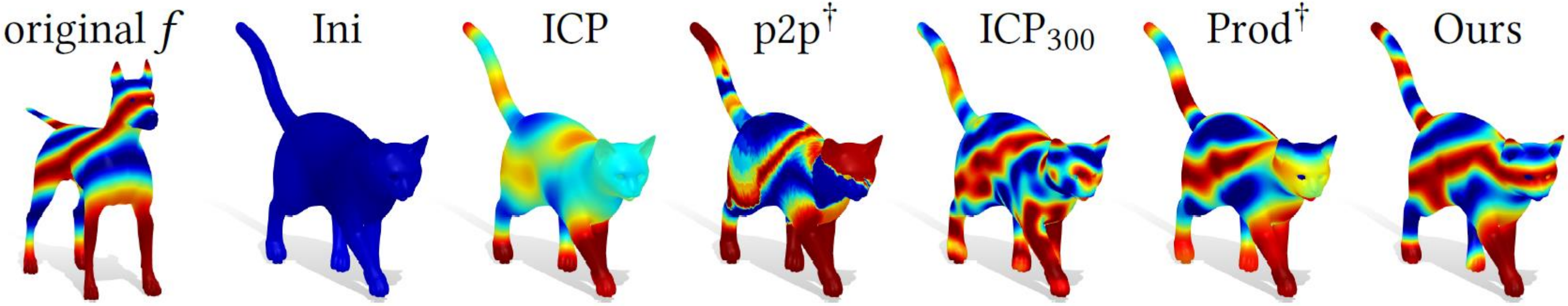
Slide credit J. *Ren*



ZoomOut: Spectral Upsampling for Efficient Shape Correspondence, *Melzi*, *Ren*, *Sharma*, *Rodolà*, *Wonka*, *Ovsjanikov*, SIGGRAPH Asia 2019

Information transfer results

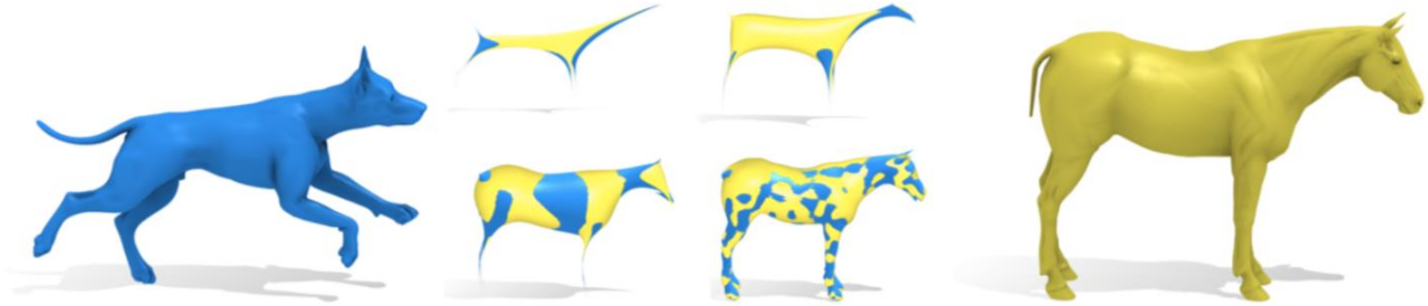
Slide credit J. *Ren*



ZoomOut: Spectral Upsampling for Efficient Shape Correspondence, *Melzi*, *Ren*, *Sharma*, *Rodolà*, *Wonka*, *Ovsjanikov*, SIGGRAPH Asia 2019

Smooth Shells

A fully automatic initialization is proposed
A deformation and extrinsic registration energy are involved
Additional extrinsic information (coordinatess and normals)



Smooth Shells: Multi-Scale Shape Registration with Functional Maps, *Eisenberger, Lahner, Cremers*, CVPR 2020

Smooth Shells: iterative scheme

Correspondence is calculated by nearest neighbors between:

$$\bar{Y}_K = (\Psi_K, Y_K, n_K^Y) \quad \in \mathbb{R}^{M\times(K+6)}$$

Laplace-Beltrami Eigenfunctions

K-th Shell Coordinates

K-th Shell Normals

$$\bar{X}_K^* = (\Phi_K C^\top, X_K + \Phi_k \tau, n_K^*) \quad \in \mathbb{R}^{N\times(K+6)}$$

Smooth Shells: Multi-Scale Shape Registration with Functional Maps, *Eisenberger, Lahner, Cremers*, CVPR 2020

Open problems

Why not and why yes to high-frequencies

NOT: Avoid to make the functional map estimation more difficult

NOT: The alignment of high-frequencies is not easy (too unstable for different shapes)

YES: the point to point maps contain high-frequencies

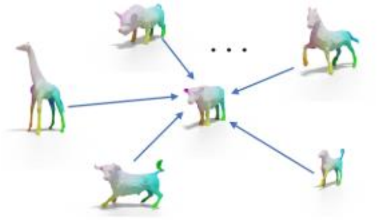
YES: high-frequencies are necessary for real application (information transfer)

How to recover high frequencies

1. The **algebra structure** of the functional space is useful
2. More information can be recovered from the fact that the functional map encodes a **point-to-point map**
3. Define **New basis** for the functional space

ZoomOut is a trend in shape matching

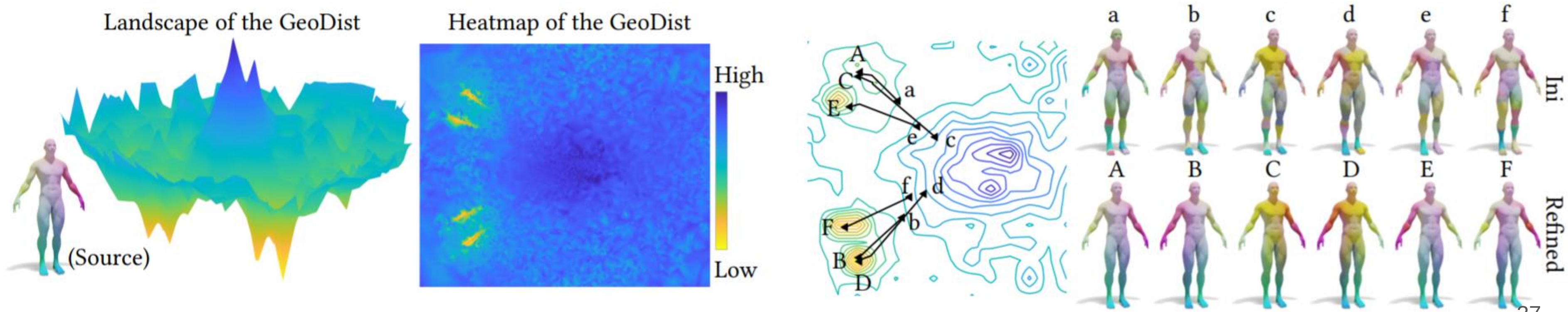
Consistent ZoomOut proposed at SGP 2020 one month ago:



[Consistent ZoomOut: Efficient Spectral Map Synchronization]

We have a recently accepted at SIGGRAPH ASIA (yesterday) paper based on ZoomOut:

[MapTree: Recovering Multiple Solutions in the Space of Maps]



Data-driven approaches for functional maps

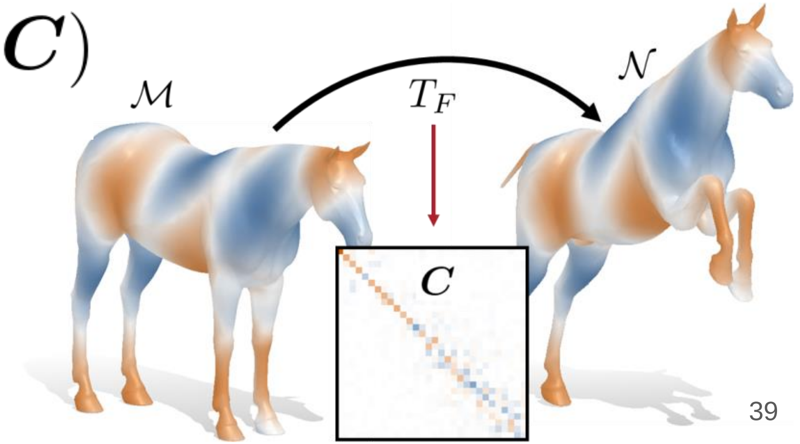
FMAP pipeline again

1. Compute the first *k* (~30-100) eigenfunctions of the LBO.
   Store them in matrices: $\Phi_{\mathcal{M}}, \Phi_{\mathcal{N}}$

2. Compute probe functions (e.g., landmarks or descriptors) on $\mathcal{M}, \mathcal{N}$. Express them in $\Phi_{\mathcal{M}}, \Phi_{\mathcal{N}}$, as columns of $\boldsymbol{A}$ and $\boldsymbol{B}$

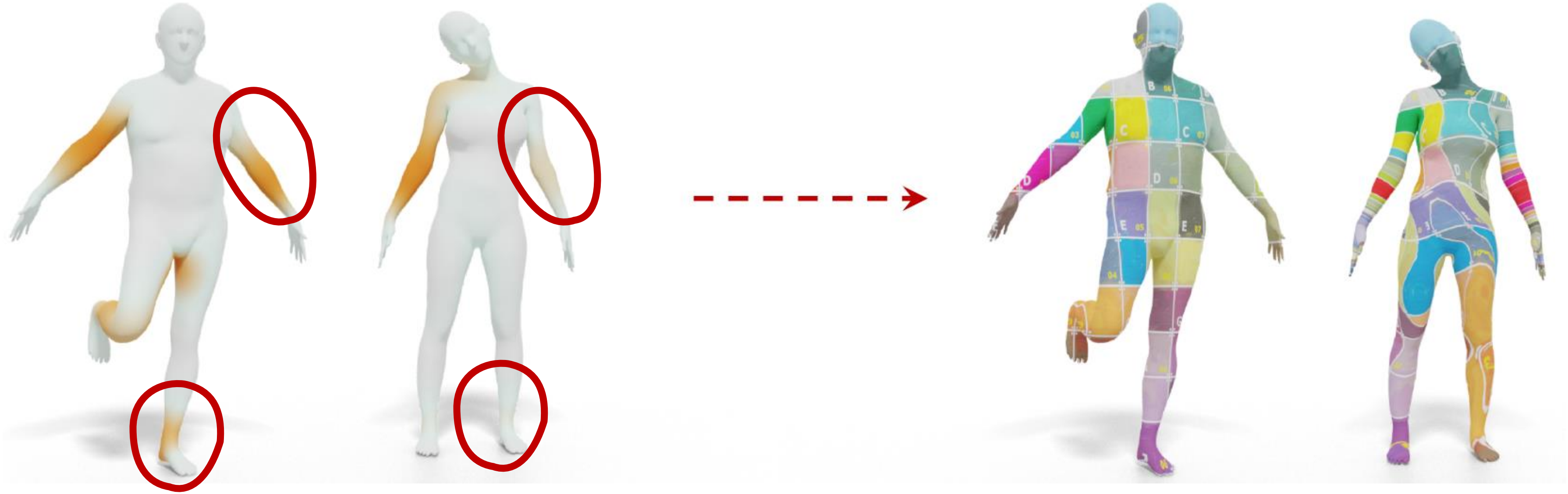
3. Solve $\underset{\boldsymbol{C}}{argmin} \|\boldsymbol{C}\boldsymbol{a} - \boldsymbol{b}\|_F^2 + \mathcal{R}(\boldsymbol{C})$

4. Convert the functional map to a point to point map *T*.



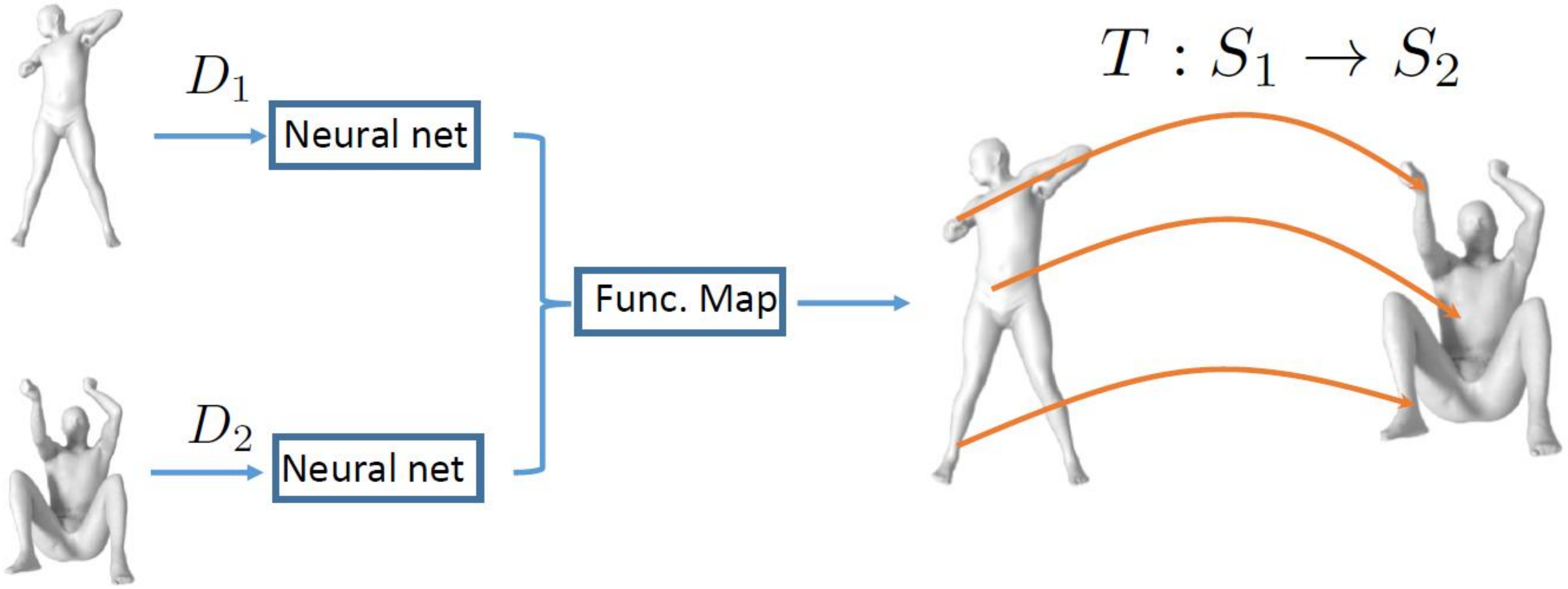
Bad descriptors

Slide credit M. *Ovsjanikov*



FMNET idea

Slide credit M. *Ovsjanikov*

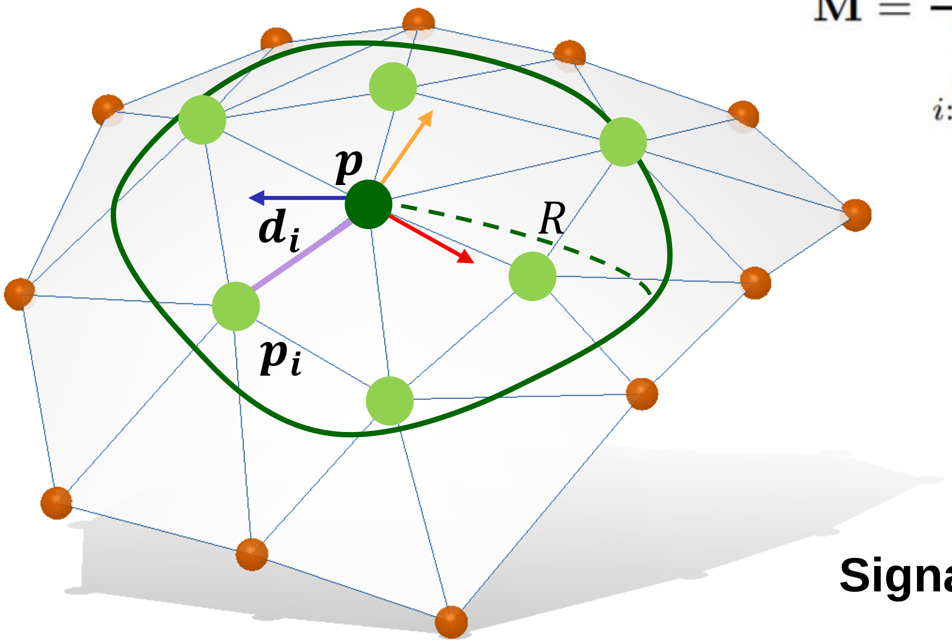


Deep functional maps: Structured prediction for dense shape correspondence, O. Litany, et al, ICCV (2017).

Do you remebrer SHOT?

For all $\boldsymbol{p}$ we define the covariance matrix:

$$\mathbf{M} = \frac{1}{\sum_{i:d_i \leq R} (R - d_i)} \sum_{i:d_i \leq R} (R - d_i)(\mathbf{p}_i - \mathbf{p})(\mathbf{p}_i - \mathbf{p})^T$$



From the eigenvetors of M we obtaine a LRF (x, y, z) that is then used to define:

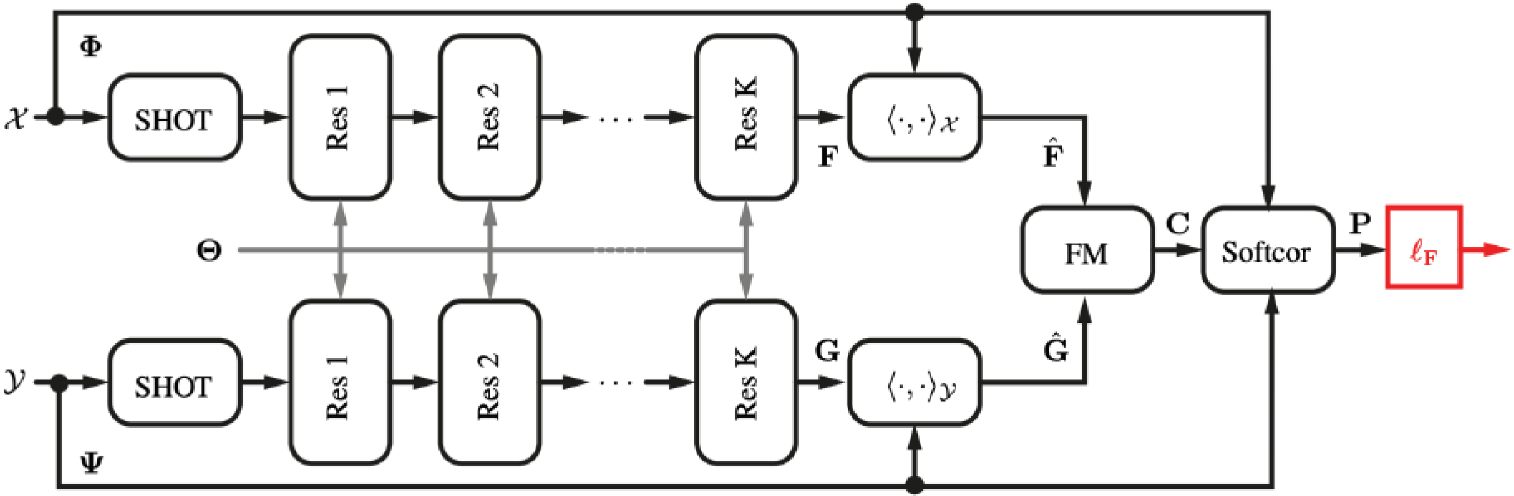
Signature of Histograms of OrienTations

Unique Signatures of Histograms for Local Surface Description, *Tombari et al.*, ECCV 2010

FMNET network

Slide credit M. *Ovsjanikov*

A learning-based strategy to compute correspondences

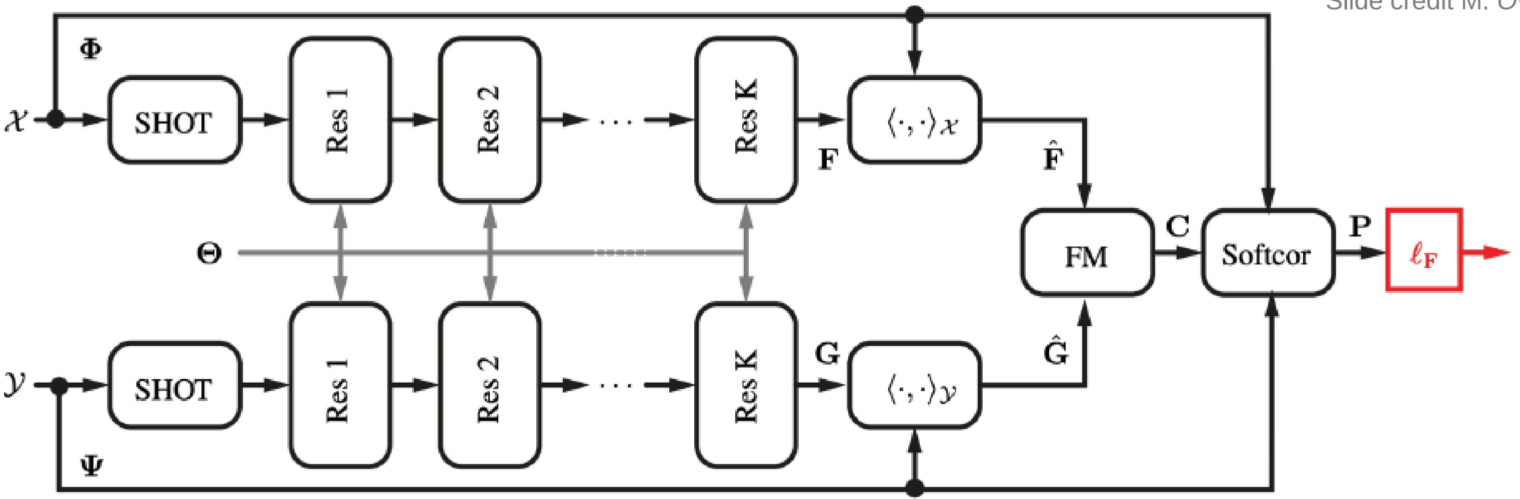


The FM layer corresponds to: $C = \underset{C}{argmin} ||C\hat{F} - \hat{G}||$

Deep functional maps: Structured prediction for dense shape correspondence, O. Litany, et al, ICCV (2017).

FMNET loss

Slide credit M. *Ovsjanikov*

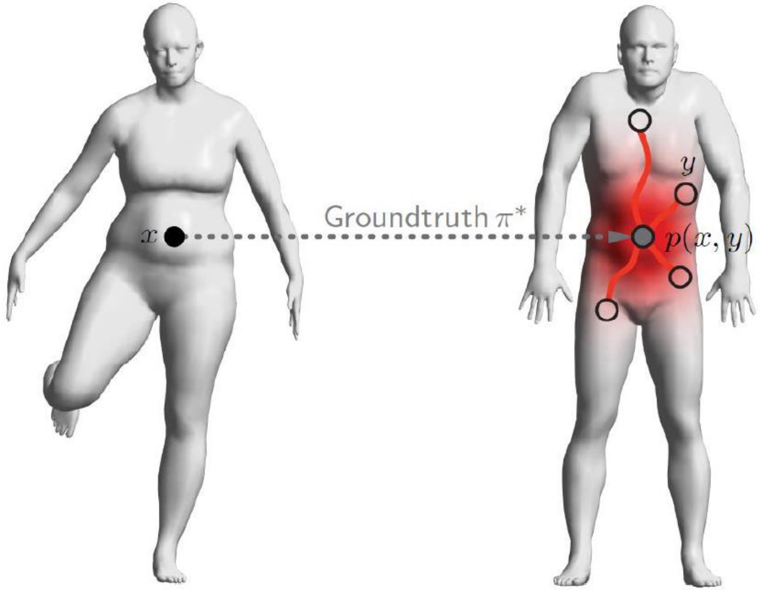


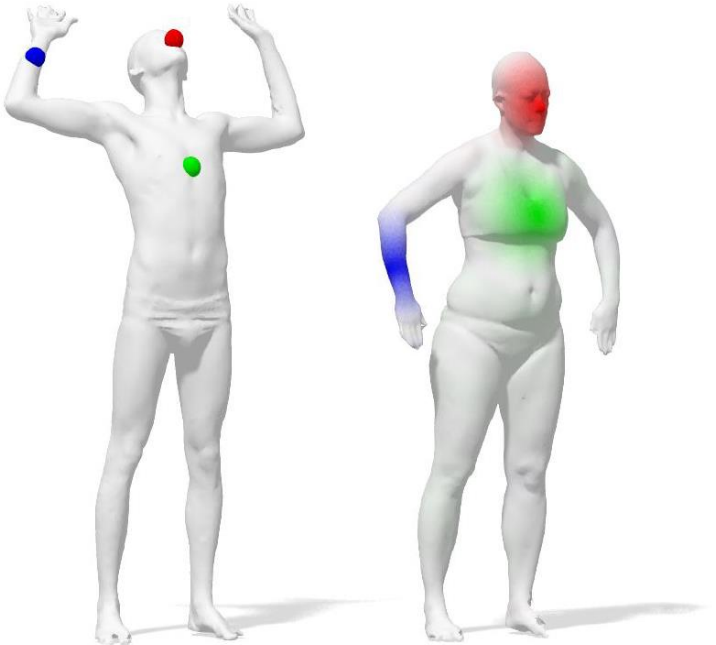
Training loss: $$\ell_{\mathrm{F}} = \sum_{(x,y)\in(\mathcal{X},\mathcal{Y})} P(x,y)d_{\mathcal{Y}}(y,\pi^*(x))$$

Deep functional maps: Structured prediction for dense shape correspondence, O. Litany, et al, ICCV (2017).

P = soft correspondence error

$$P = |\Psi C \Phi^\top \Omega_\mathcal{X}| \longrightarrow P(x,y) = |\Psi C \Phi^\top \Omega_\mathcal{X} \delta_x|_y$$

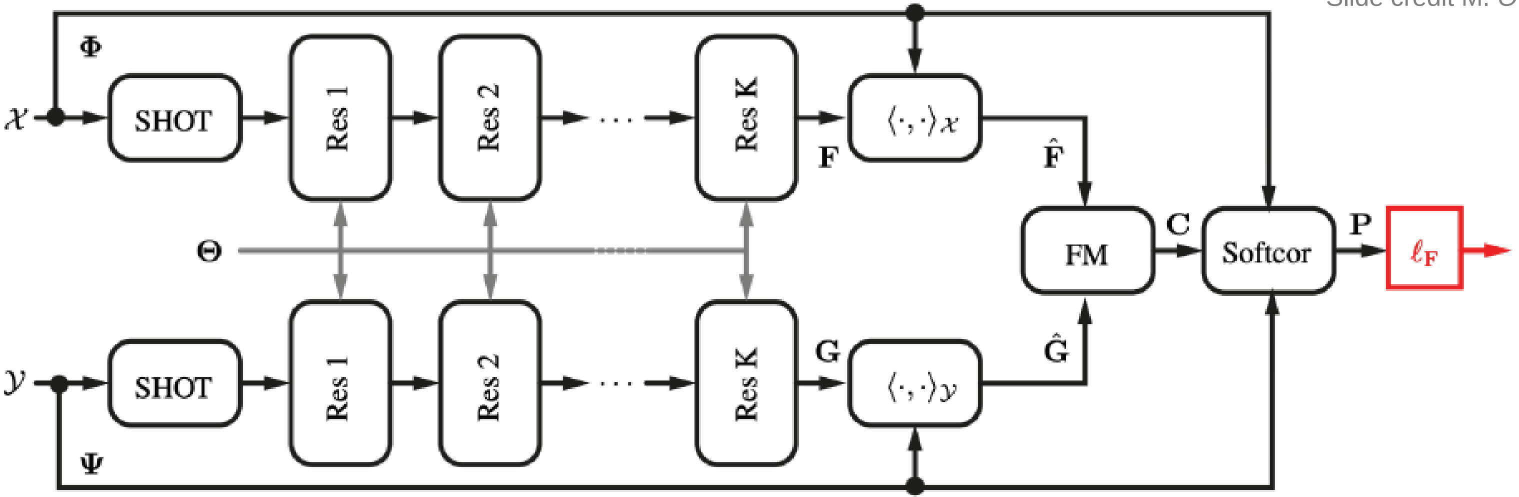




Deep functional maps: Structured prediction for dense shape correspondence, O. Litany, et al, ICCV (2017).

Positive aspect

Slide credit M. *Ovsjanikov*



Positive aspect: evaluating the fmaps representation all the correspondences are evaluated together

Deep functional maps: Structured prediction for dense shape correspondence, O. Litany, et al, ICCV (2017).

Negative aspect

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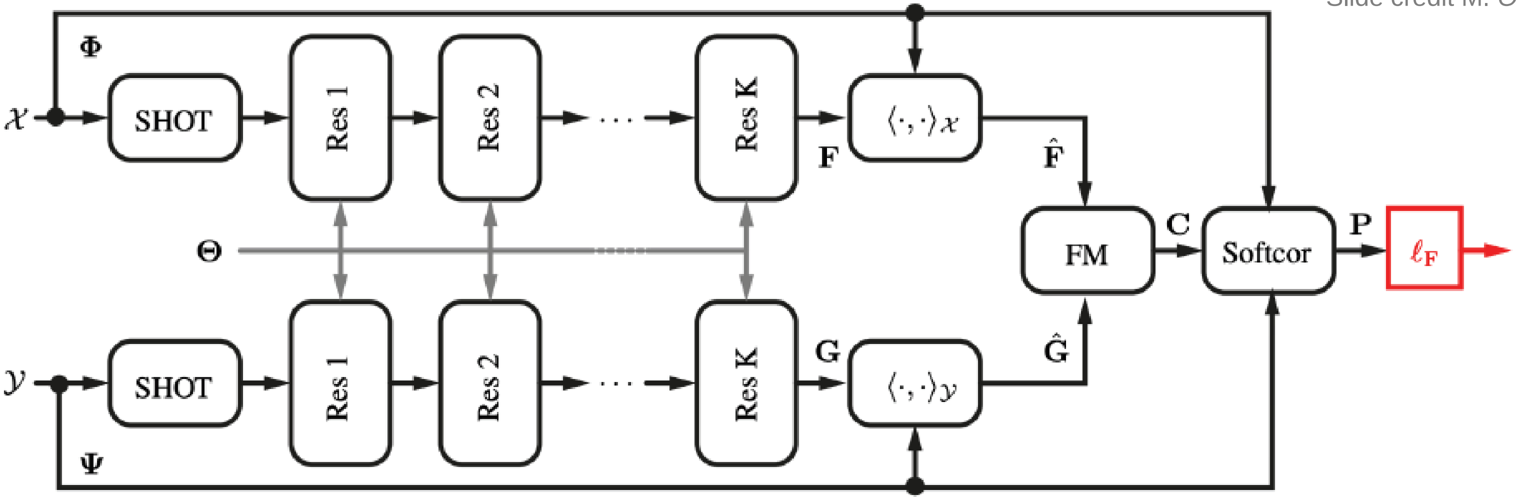

Negative aspect: **the ground-truth correspondences between training data are required**

Deep functional maps: Structured prediction for dense shape correspondence, O. Litany, et al, ICCV (2017).

State of the art results in 2017

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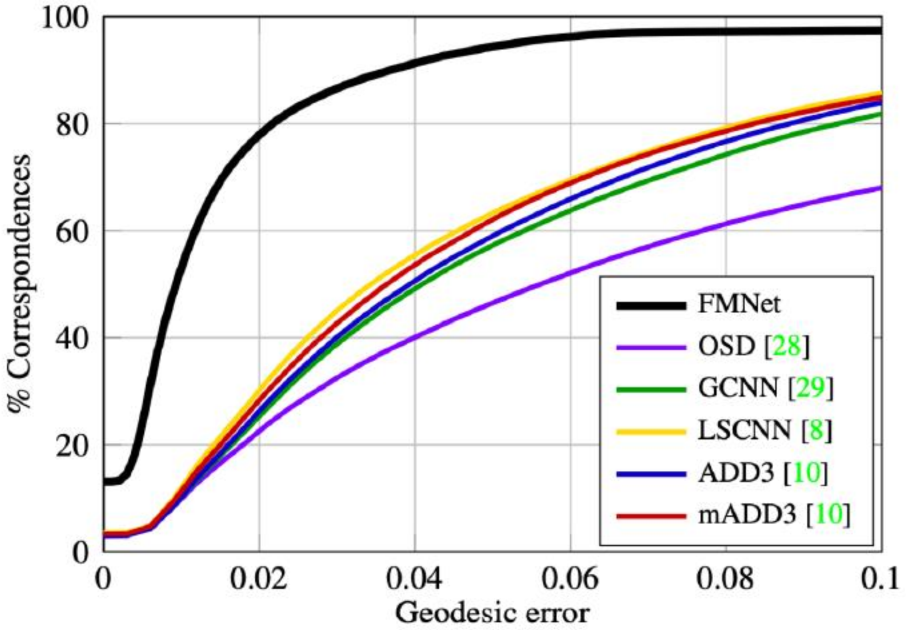

Deep functional maps: Structured prediction for dense shape correspondence, O. Litany, et al, ICCV (2017).

Learning and shape matching questions (1)

Problem: the need for ground-truth correspondences between pairs of shapes:

- Not always available
- Not available for all the classes or type of data
- Not easy to encode for different discretizations

1. Can we avoid ground-truth correspondences and compute a globally coherent correspondence efficiently?

Note: related concurrent paper: Unsupervised learning of dense shape correspondence. Halimi et al. , CVPR, 2019

Unsupervised learning

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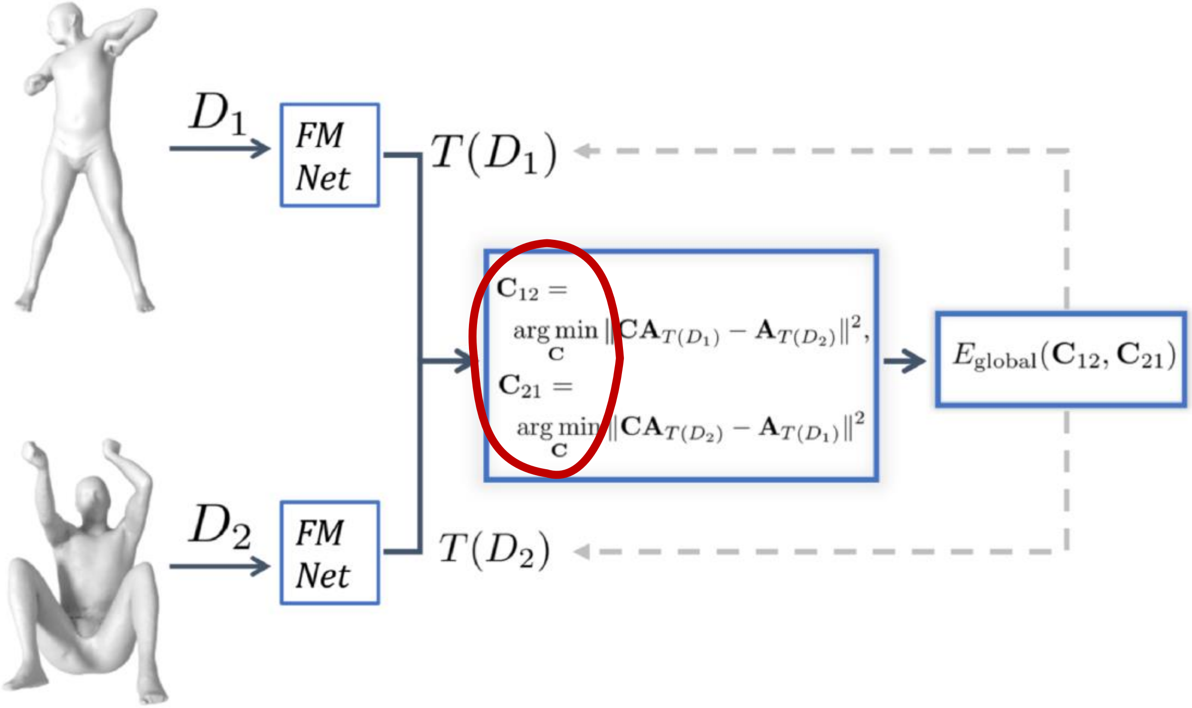
Replace supervised loss with **unsupervised** loss



Unsupervised Deep Learning for Structured Shape Matching, J.-M. Rouffosse et al., ICCV 2019

SURFMNet

Slide credit M. *Ovsjanikov*

$$loss_{unsupervised} = \sum_{i \in \text{penalties}} w_i E_i(C_{1\text{-}2}, C_{2\text{-}1})$$

$$\begin{cases} E_1(C_{12}, C_{21}) = \|C_{12}C_{21} - Id\|^2 \\ E_1(C_{12}, C_{21}) = \|C_{21}C_{12} - Id\|^2 \end{cases}$$ Bijectivity

$$E_2(C) = \|C^T C - Id\|^2$$ Area-preservation

$$E_3(C) = \|\Lambda_2 C - C\Lambda_1\|^2$$ Near-isometry

$$E_4(C) = \sum \|CX_{f_i} - Y_{g_i}C\|^2$$ Functional map close to pointwise one.

50 times faster than FMNET

All these penalties are represented in the reduced basis (50 Fourier basis)

Unsupervised Deep Learning for Structured Shape Matching, J.-M. Rouffosse et al., ICCV 2019

Training dataset

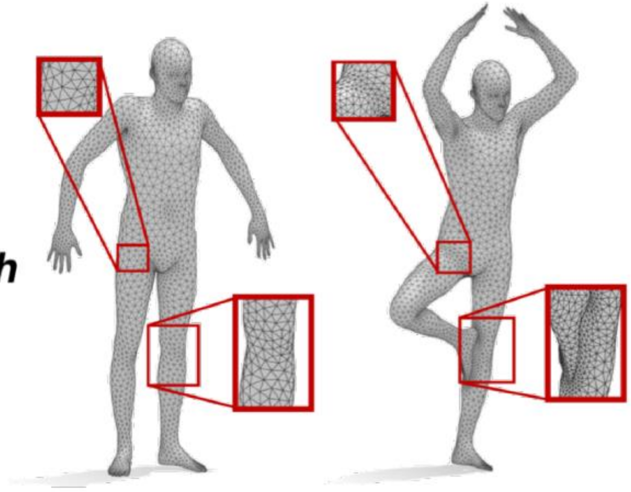
Slide credit M. *Ovsjanikov*

FAUST :

- Subset: train on 80 and test on 20
- Whole set : train on 100 shapes, ***without ground truth***

SCAPE :

- Subset: train on 50 and test on 10
- Whole set : train on 60 shapes, ***without ground truth***



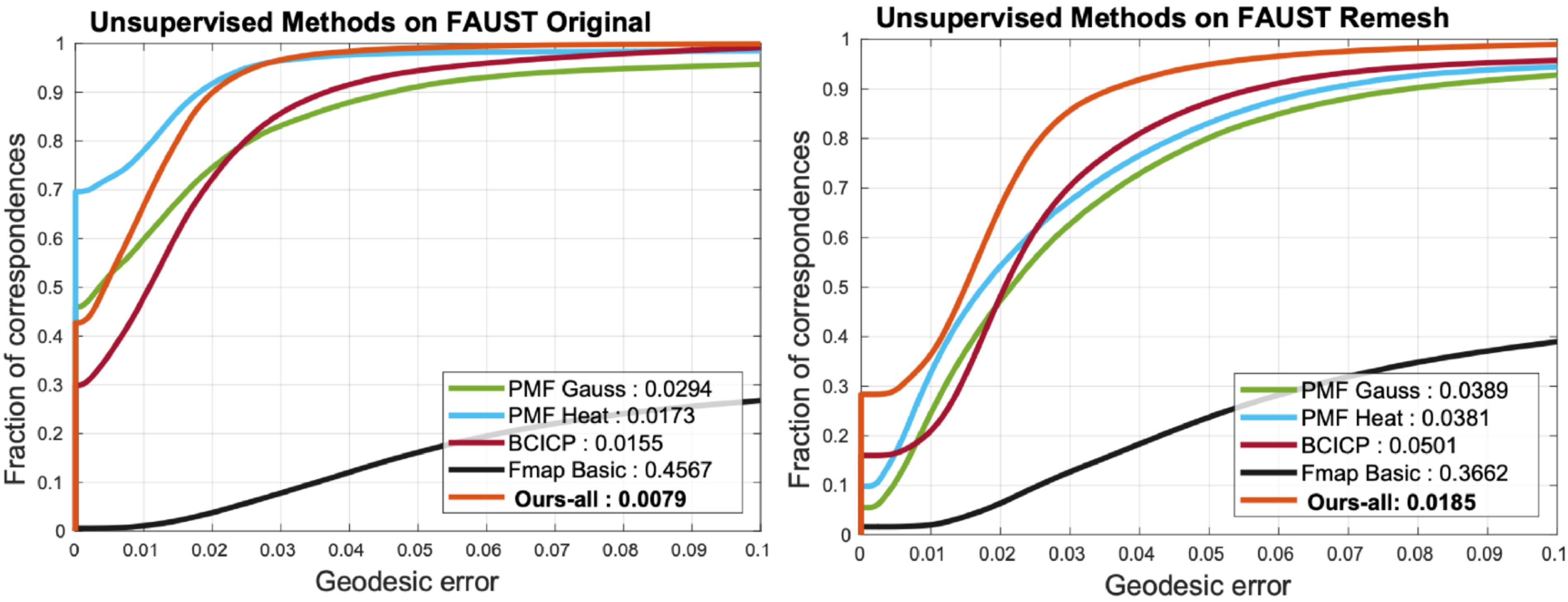
Remeshed FAUST - 5000 vertices

Datasets released as part of: *Continuous and Orientation-preserving Correspondences via Functional Maps*, J. Ren, A. Poulenard, P. Wonka, M. O, SIGGRAPH Asia 2018

Unsupervised Deep Learning for Structured Shape Matching, J.-M. Rouffosse et al., ICCV 2019

Comparison to unsupervised methods

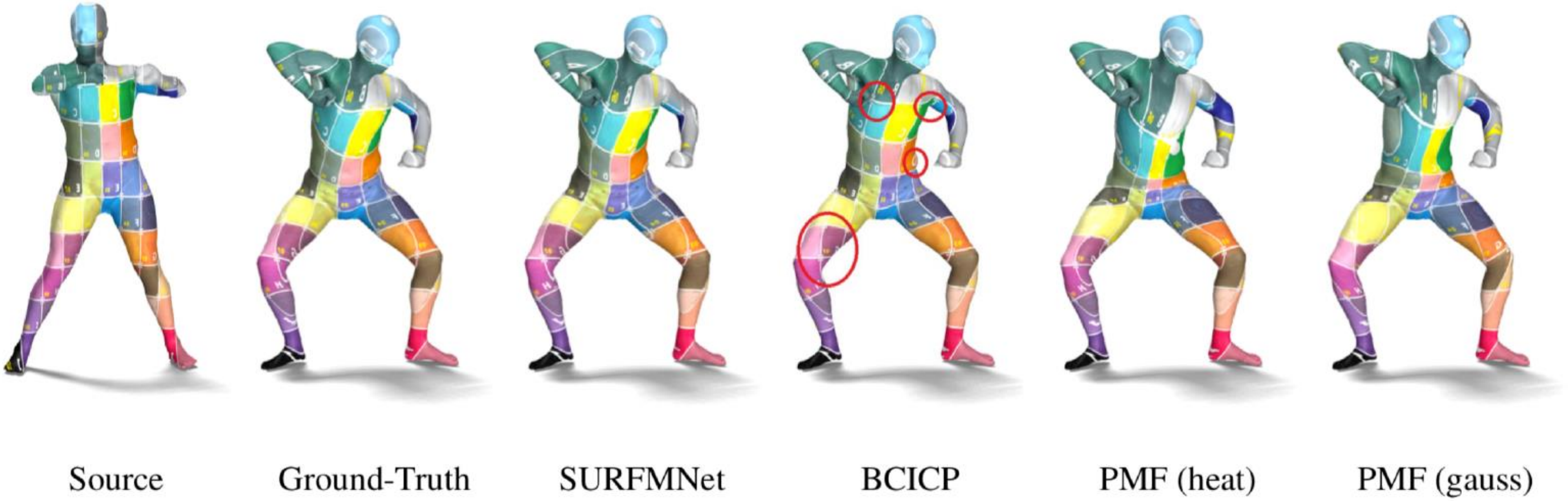
Slide credit M. *Ovsjanikov*



Unsupervised Deep Learning for Structured Shape Matching, J.-M. Rouffosse et al., ICCV 2019

Qualitative comparison

Slide credit M. *Ovsjanikov*

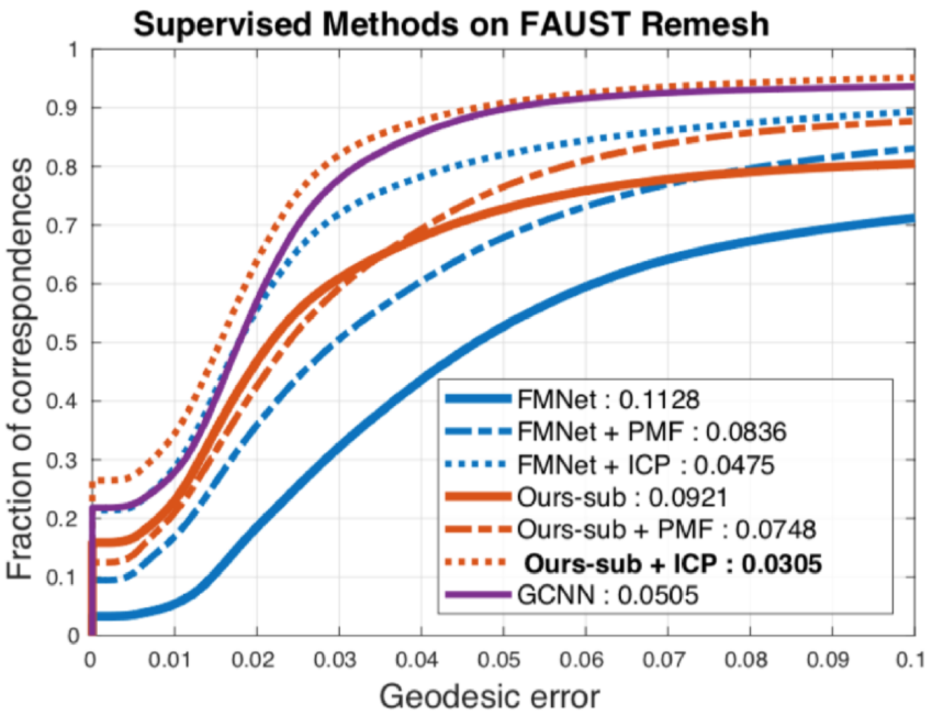


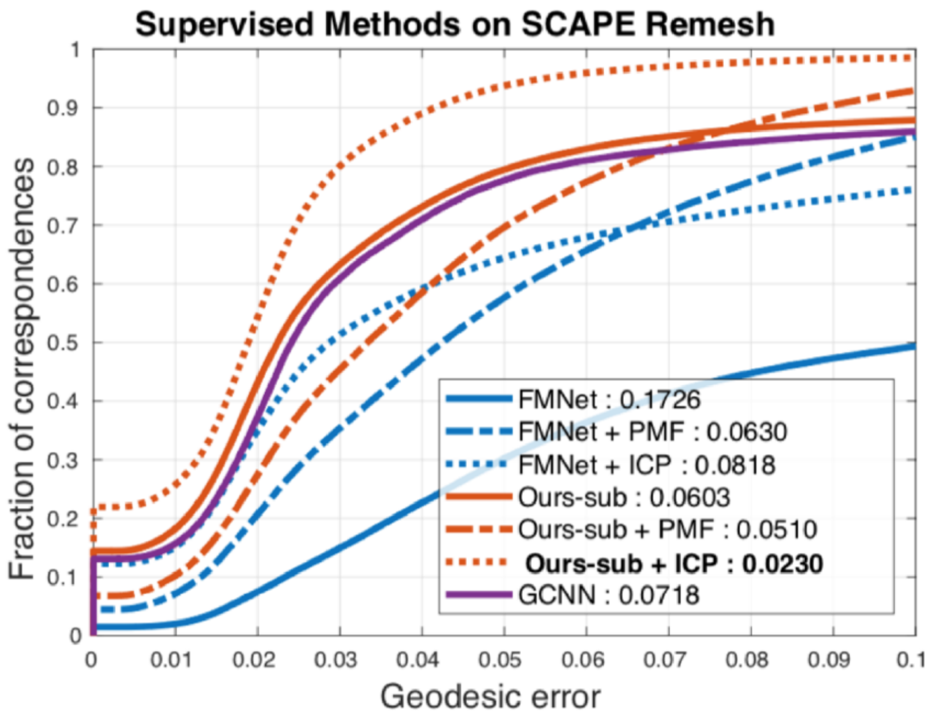
State-of-the-art for unsupervised methods

Unsupervised Deep Learning for Structured Shape Matching, J.-M. Rouffosse et al., ICCV 2019

Comparison to supervised methods

Slide credit M. *Ovsjanikov*

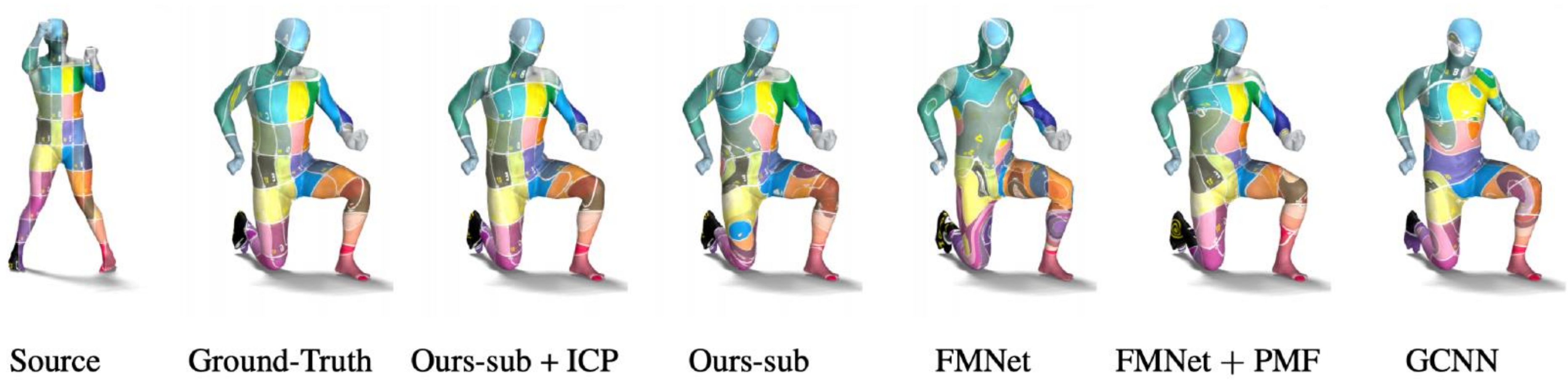




Unsupervised Deep Learning for Structured Shape Matching, J.-M. Rouffosse et al., ICCV 2019

Qualitative comparison to supervised methods

Slide credit M. *Ovsjanikov*



Comparable to supervised methods

Unsupervised Deep Learning for Structured Shape Matching, J.-M. Rouffosse et al., ICCV 2019

Original vs learned descriptors

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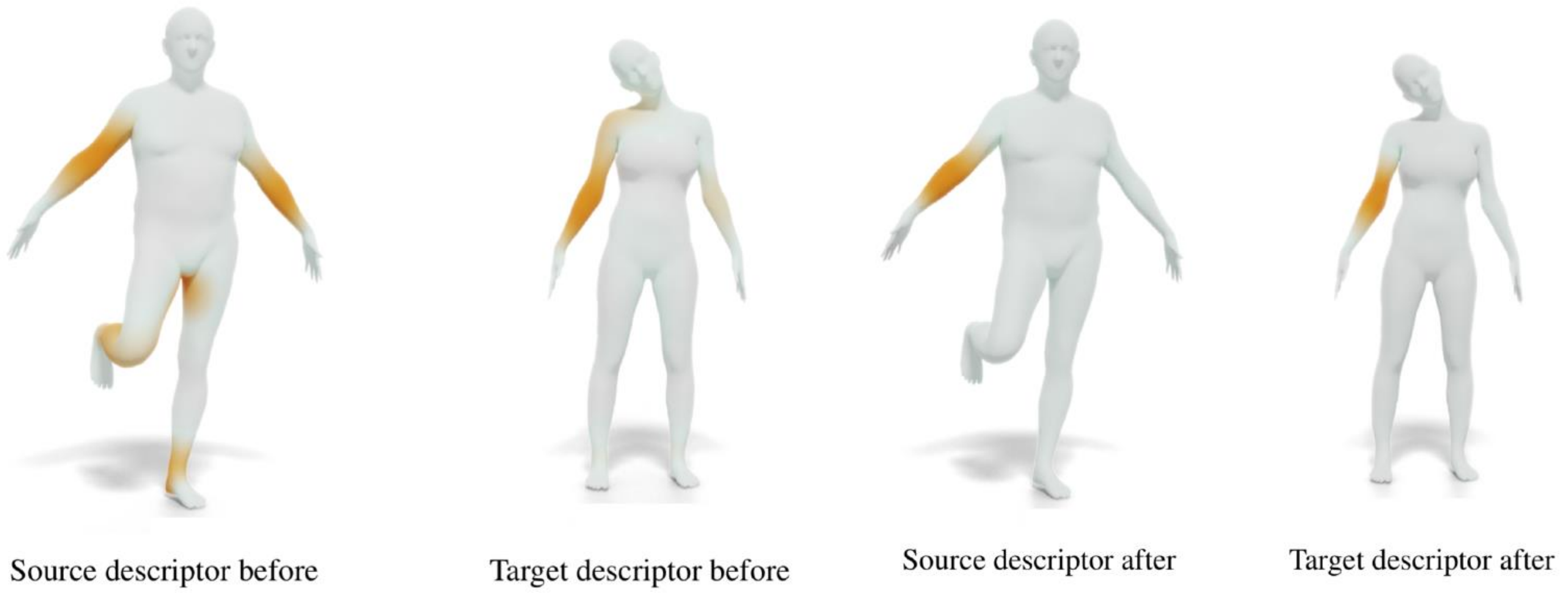
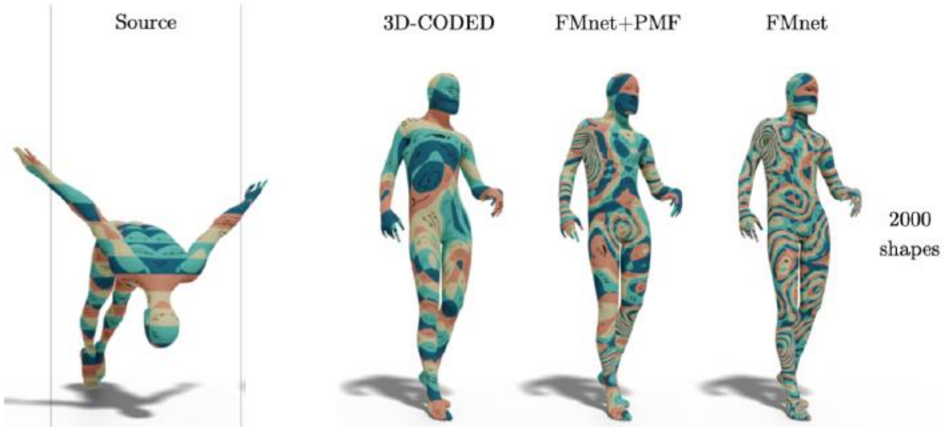


Unsupervised Deep Learning for Structured Shape Matching, J.-M. Rouffosse et al., ICCV 2019

Learning and shape matching questions (2)

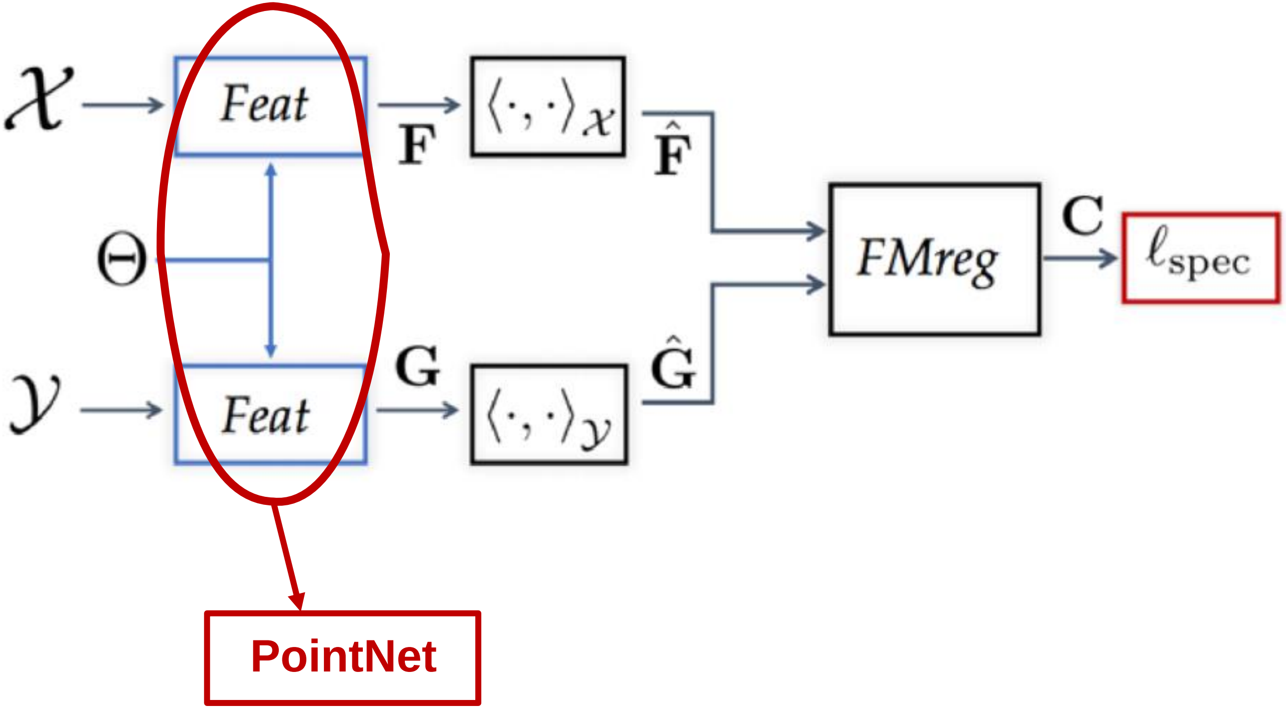
Slide credit M. *Ovsjanikov*

1. Can we directly learn the descriptors from raw data without using pre-computed descriptors like SHOT?
2. Can we be invariant to different connectivity or discrete representations?



Descriptors from raw geometry

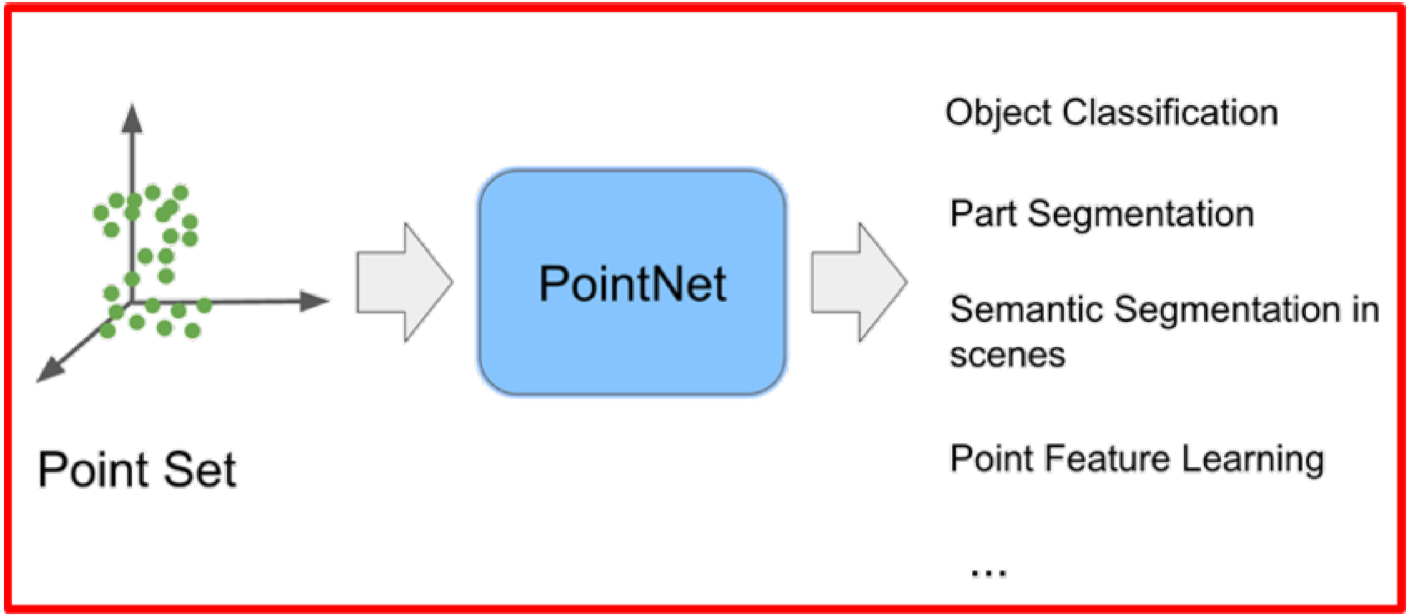
Slide credit M. *Ovsjanikov*



Deep Geometric Functional Maps: Robust Feature Learning for Shape Correspondence, Donati et al., CVPR 2020

PointNet

Slide credit M. *Ovsjanikov*



Pointnet: Deep learning on point sets for 3d classification and segmentation, Qi et al., CVPR 2017

PointNet applications

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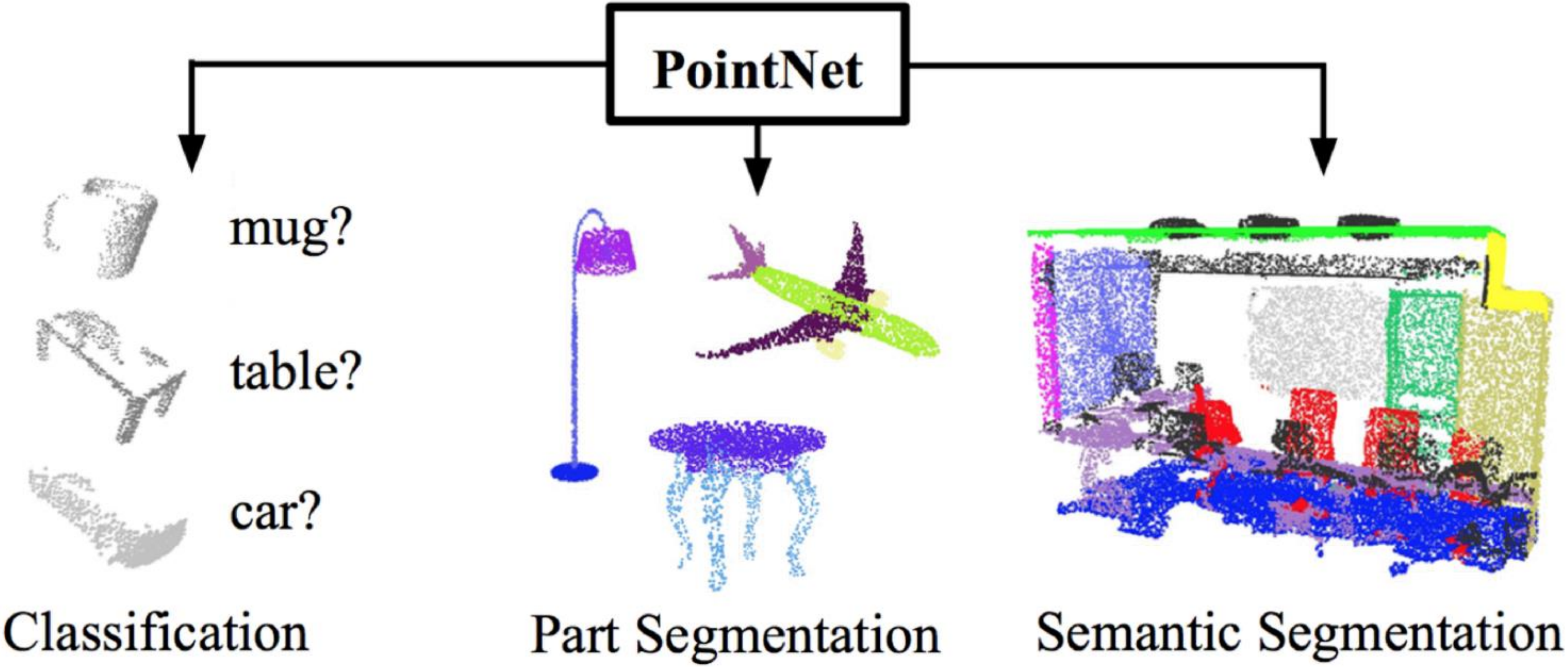

Pointnet: Deep learning on point sets for 3d classification and segmentation, Qi et al., CVPR 2017

PointNet-architecture (in brief)

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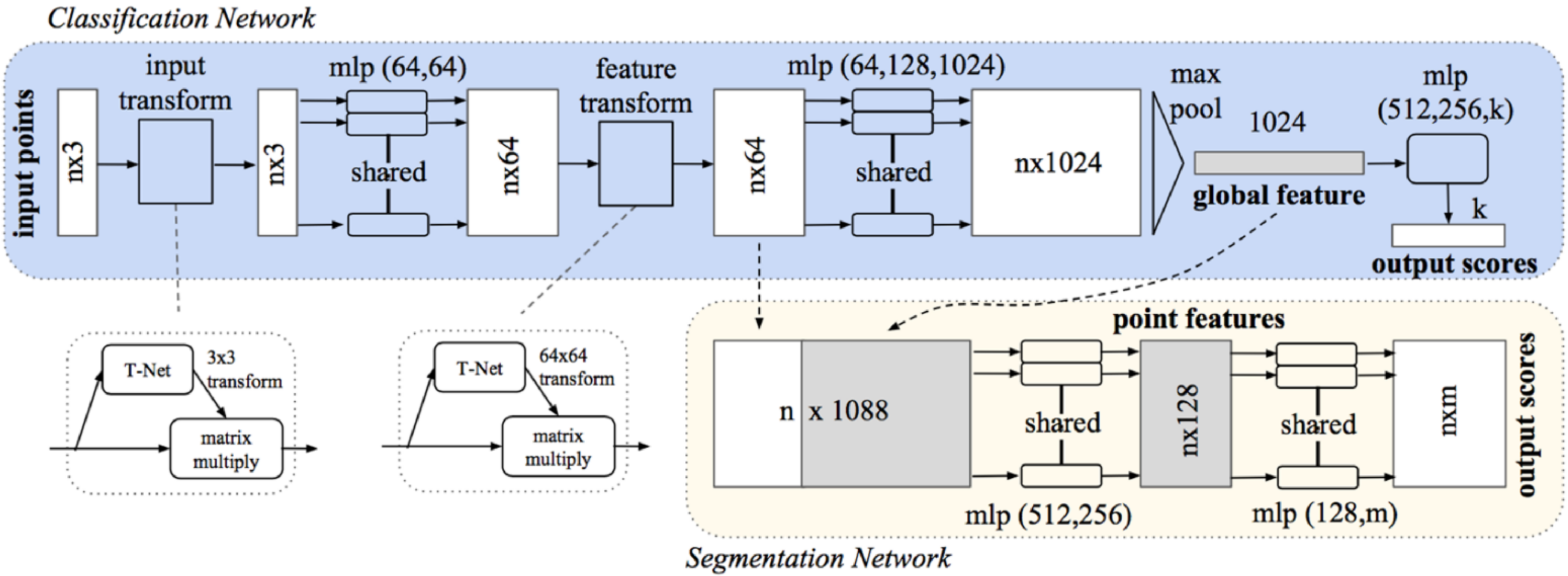
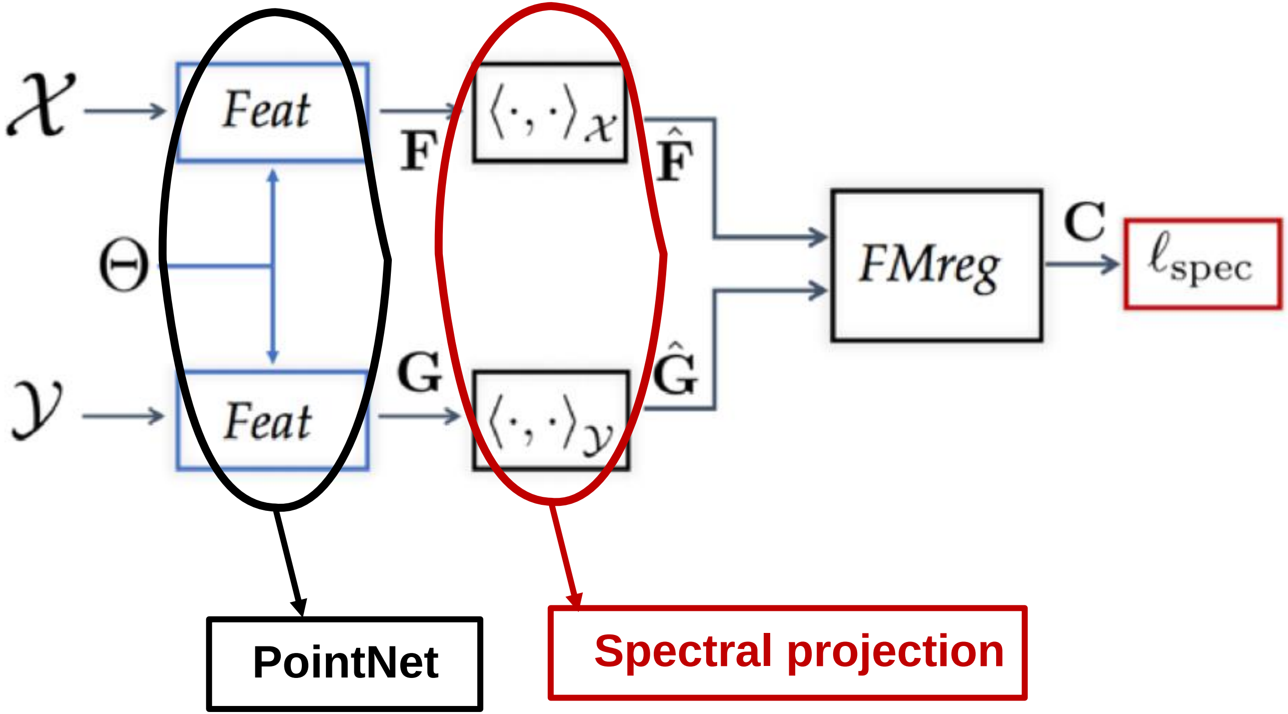


Pointnet: Deep learning on point sets for 3d classification and segmentation, Qi et al., CVPR 2017

Deep-Geometry FMaps

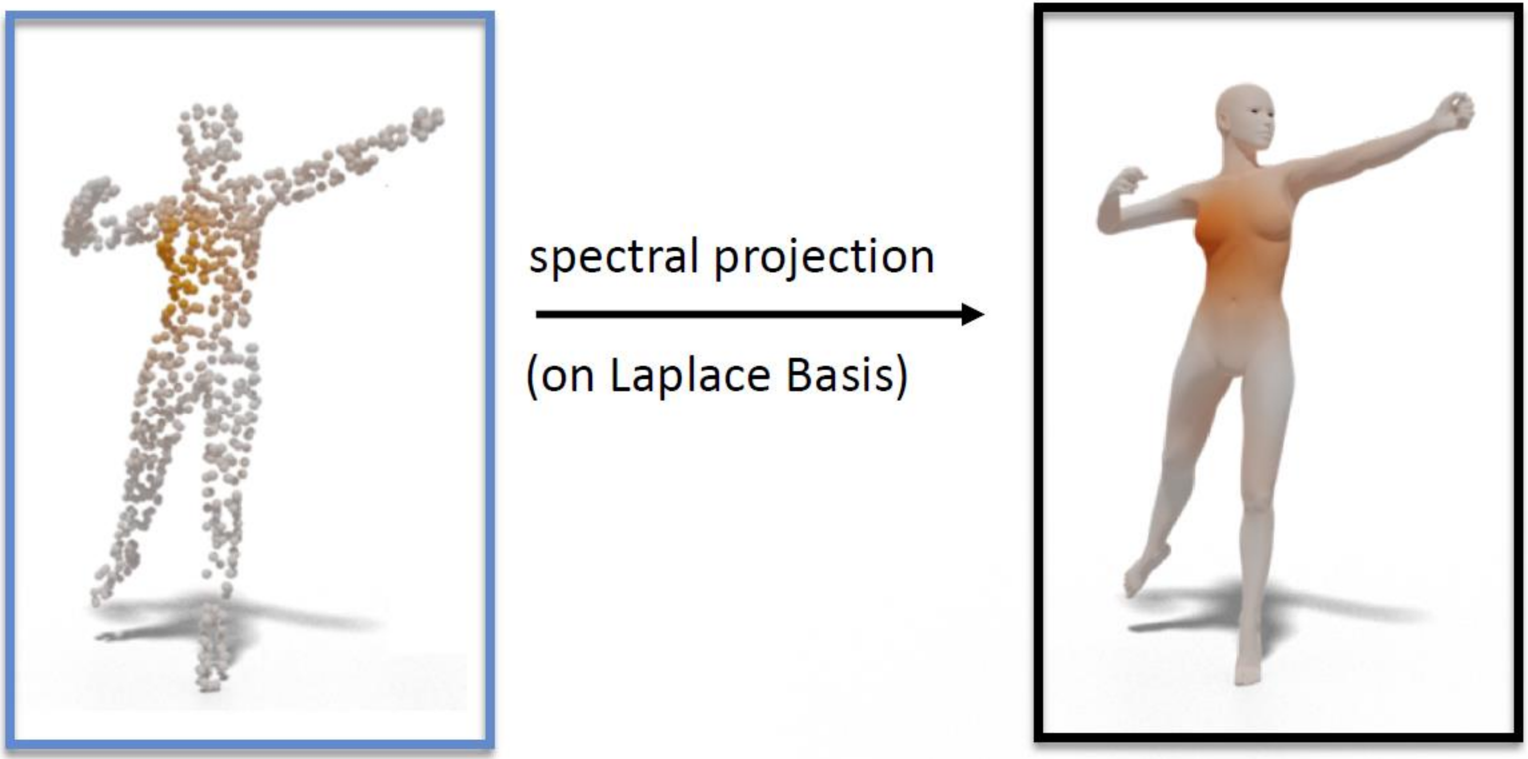
Slide credit M. *Ovsjanikov*



Deep Geometric Functional Maps: Robust Feature Learning for Shape Correspondence, Donati et al., CVPR 2020

Descriptors from raw geometry

Slide credit M. *Ovsjanikov*



Deep Geometric Functional Maps: Robust Feature Learning for Shape Correspondence, Donati et al., CVPR 2020

Additional constraint in the FM layer

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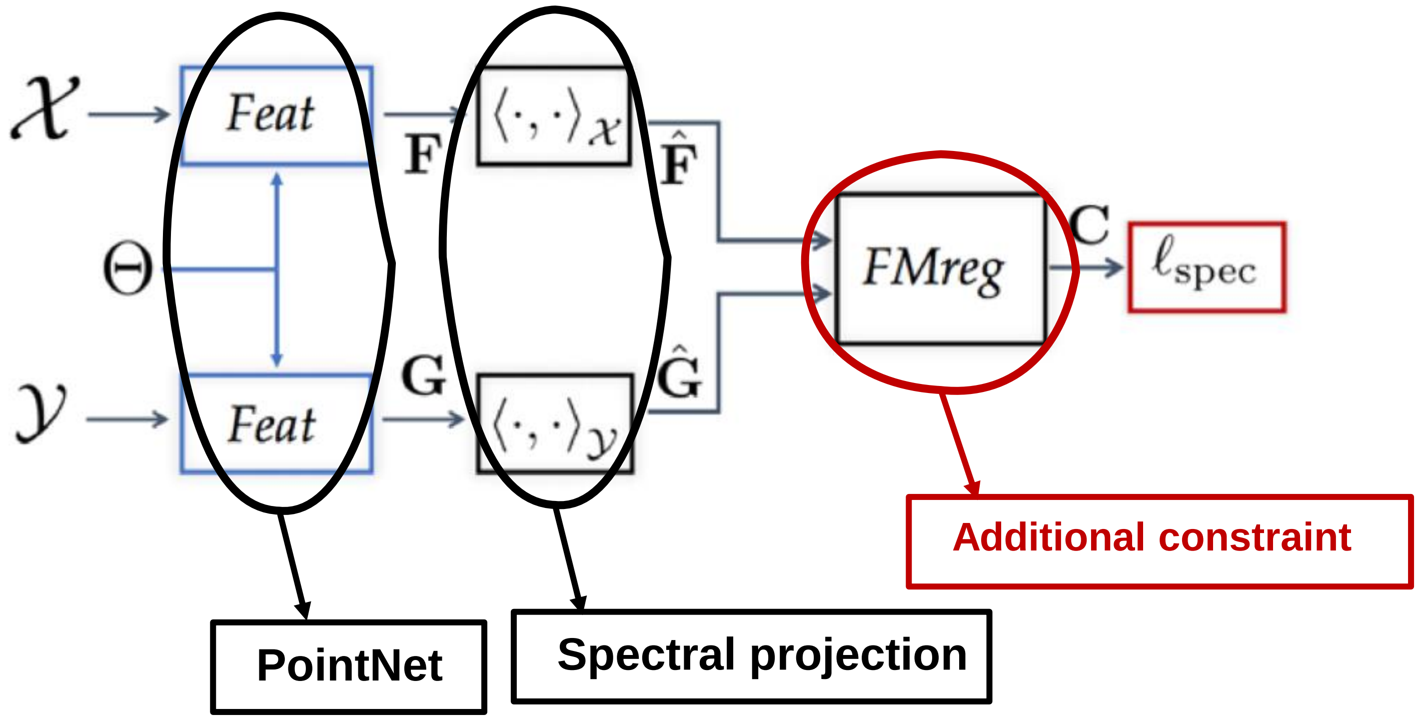

Deep Geometric Functional Maps: Robust Feature Learning for Shape Correspondence, Donati et al., CVPR 2020

Commutativity with the Laplacian

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$$\min_{\mathbf{C}} ||\mathbf{CA} - \mathbf{B}||^2 + \lambda ||\mathbf{C}\Delta_{\mathcal{M}} - \Delta_{\mathcal{N}}\mathbf{C}||^2$$

Linear system for every row in $\mathbf{C}$!

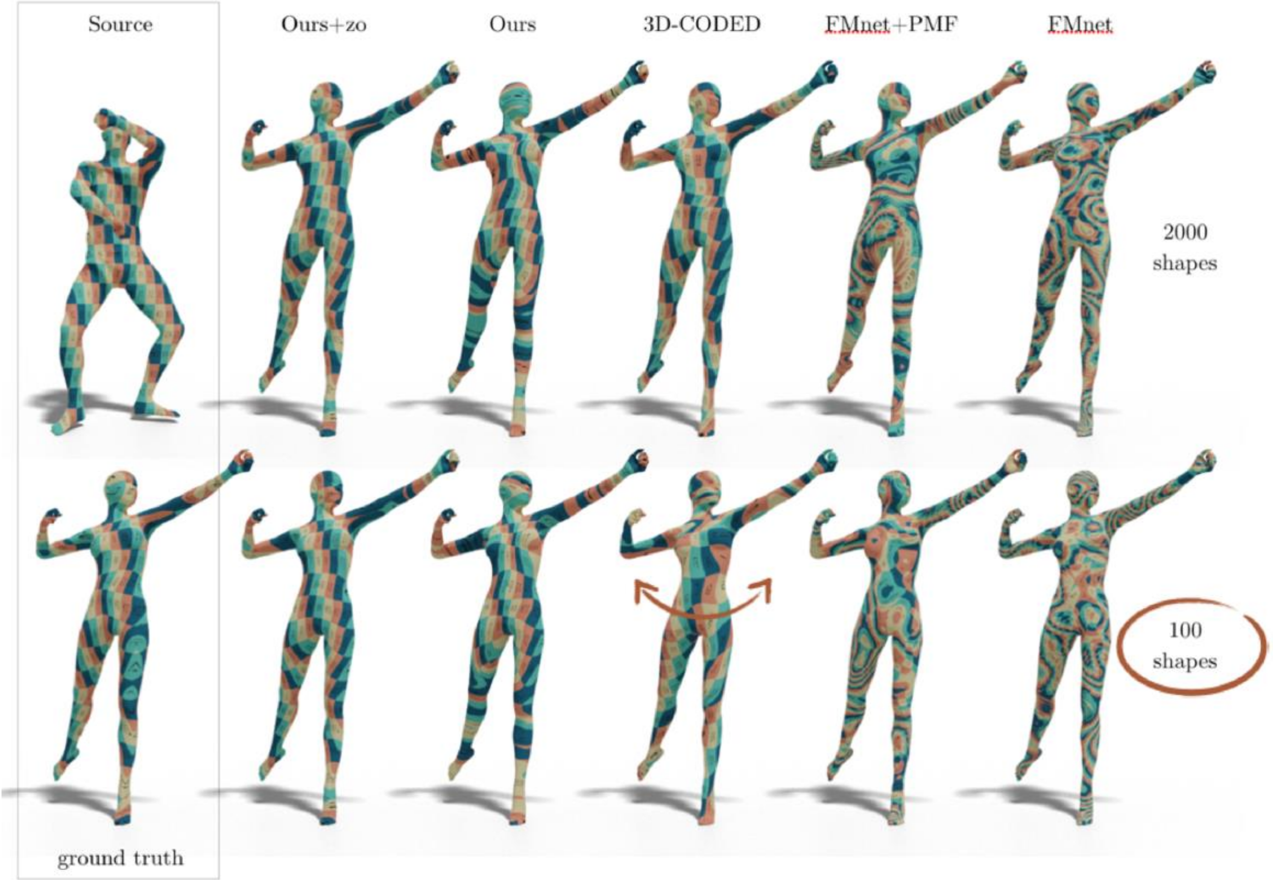
- Fully differentiable
- gives better maps

Already used for the standard FMAPS methods and for the first time adopted in a data-driven approach

Deep Geometric Functional Maps: Robust Feature Learning for Shape Correspondence, Donati et al., CVPR 2020

Qualitative comparison

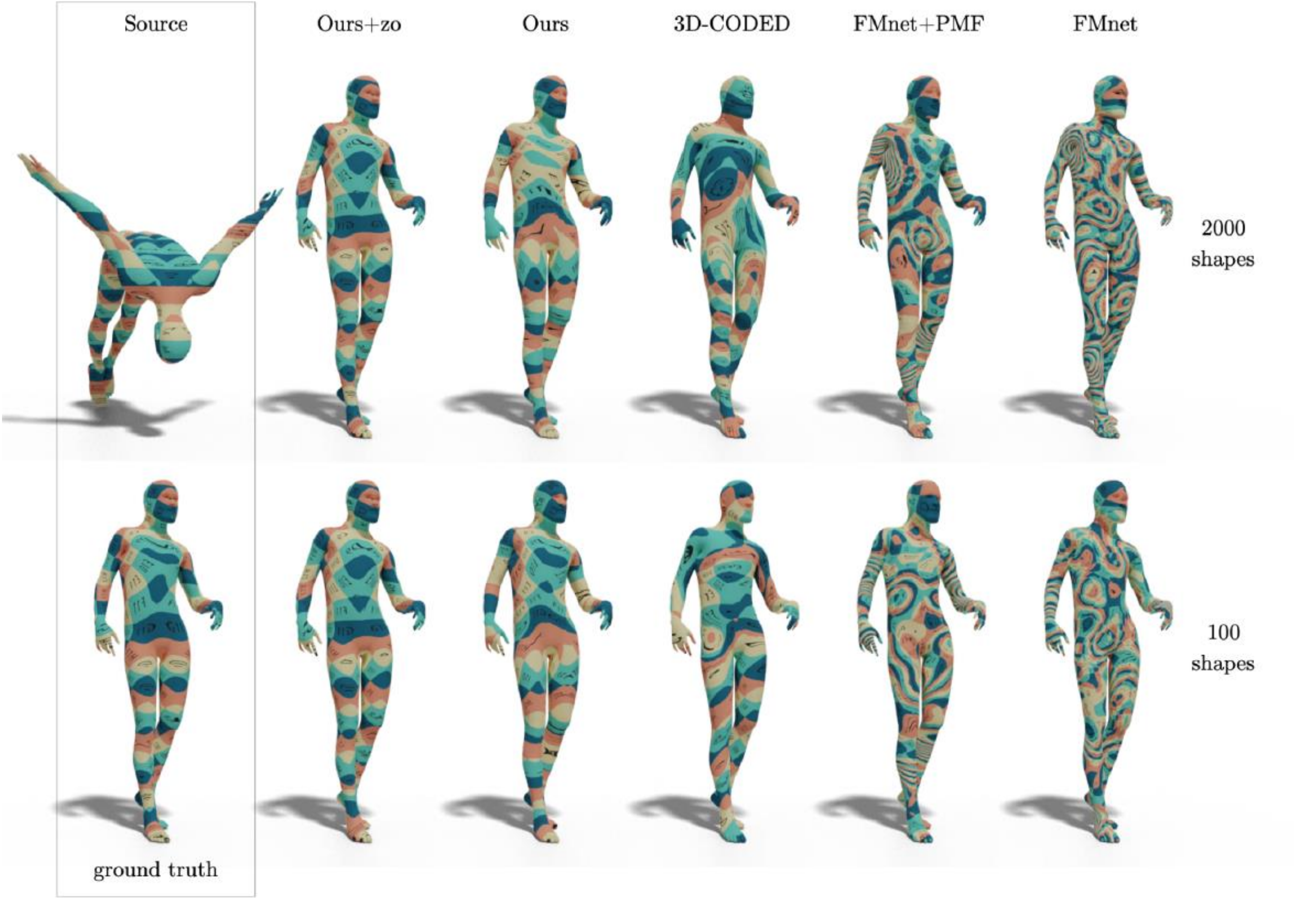
Slide credit M. *Ovsjanikov*



Deep Geometric Functional Maps: Robust Feature Learning for Shape Correspondence, Donati et al., CVPR 2020

Generalization across datasets

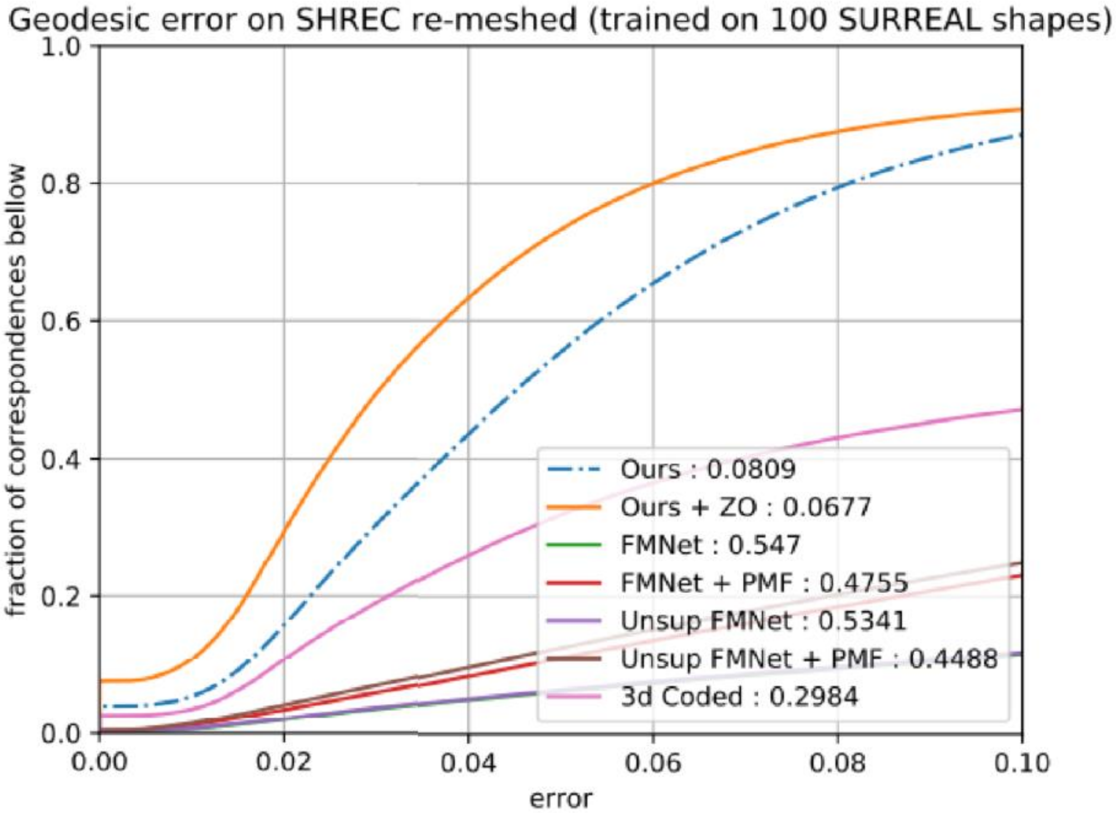
Slide credit M. *Ovsjanikov*



Deep Geometric Functional Maps: Robust Feature Learning for Shape Correspondence, Donati et al., CVPR 2020

Quantitative evaluation

Slide credit M. *Ovsjanikov*



Deep Geometric Functional Maps: Robust Feature Learning for Shape Correspondence, Donati et al., CVPR 2020

Conclusion on data-driven approaches

1. It is useful to compute better descriptors to generate constraints for FMAPs
2. In the conext of FMAPS different unsupervised constraints can be defined
3. The dimensionality of the learned variables and the problem are smaller
4. The descriptors can be learned directly from the raw geometry
5. Refinement techniques can be applied to the estimated correspondence

Possible future directions:

- Can we learn a new basis for FMAPS?
- Can we learn new constraints for FMAPS?
- Can we learn a refinement process for the estimated correspondences?

questions?

?