

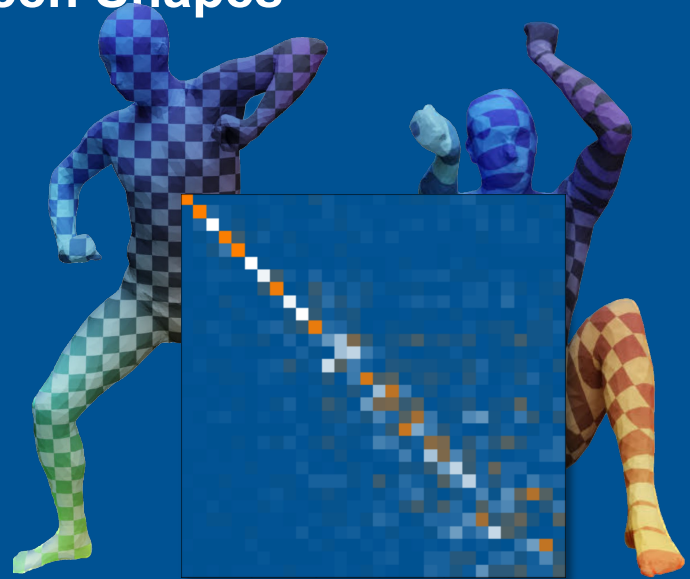
Functional Maps

A Flexible Representation of Maps Between Shapes

Seminar: 3D Shape Matching and Applications in Computer Vision

Yizheng Xie

Organisers: Viktoria Ehm, Maolin Gao



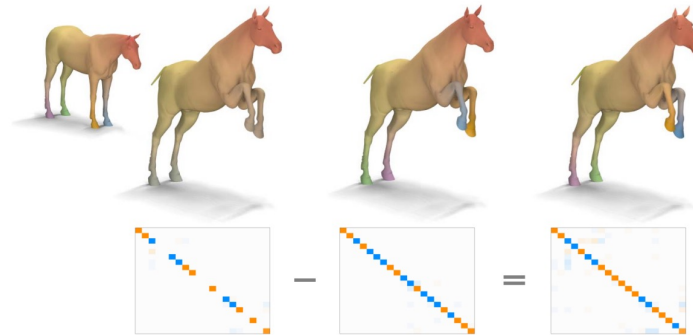
Ovsjanikov, M., Ben-Chen, M., Solomon, J., Butscher, A., & Guibas, L. (2012). Functional maps: a flexible representation of maps between shapes. *ACM Transactions on Graphics (TOG)*, 31(4), 1-11.

Sharp, N., Attaiki, S., Crane, K., & Ovsjanikov, M. (2022). Diffusionnet: Discretization agnostic learning on surfaces. *ACM Transactions on Graphics (TOG)*, 41(3), 1-16.

- 1 Intuition**
- 2 Functional Map Fundamentals**
- 3 Historical Background**
- 4 Applications**
- 5 Conclusions & Future Work**

Functional Maps: A Flexible Representation of Maps Between Shapes

Maks Ovsjanikov[†] Mirela Ben-Chen[‡] Justin Solomon[‡] Adrian Butscher[‡] Leonidas Guibas[‡]
[†] LIX, École Polytechnique [‡] Stanford University



Small

Accurate

Efficient

Flexible

Introduced in 2012

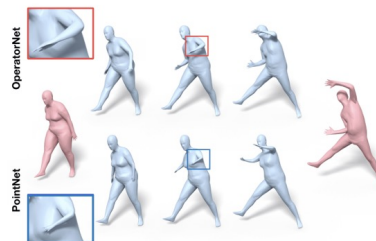
Extensively studied for the past decade



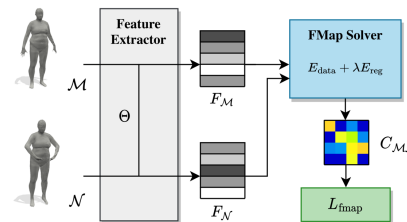
[Rodolà et al. 2017]



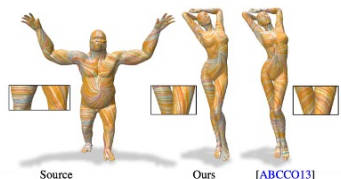
[Rustamov et al., 2013]



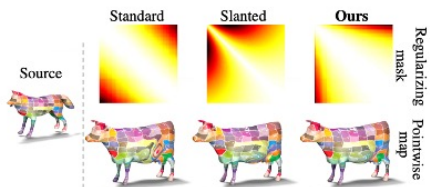
[Huang et al. 2019]



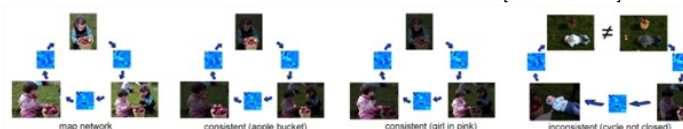
[Cao et al. 2023]



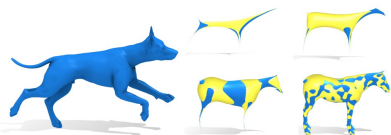
[Donati et al. 2022]



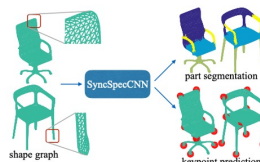
[Ren et al. 2019]



[Wang et al. 2013]



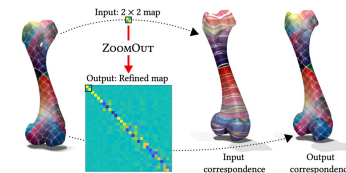
[Eisenberger et al. 2020]



[Yi et al. 2017]



Donati et al. 2020



[Melzi et al. 2019]

... and more

2023 Test-of-Time Award



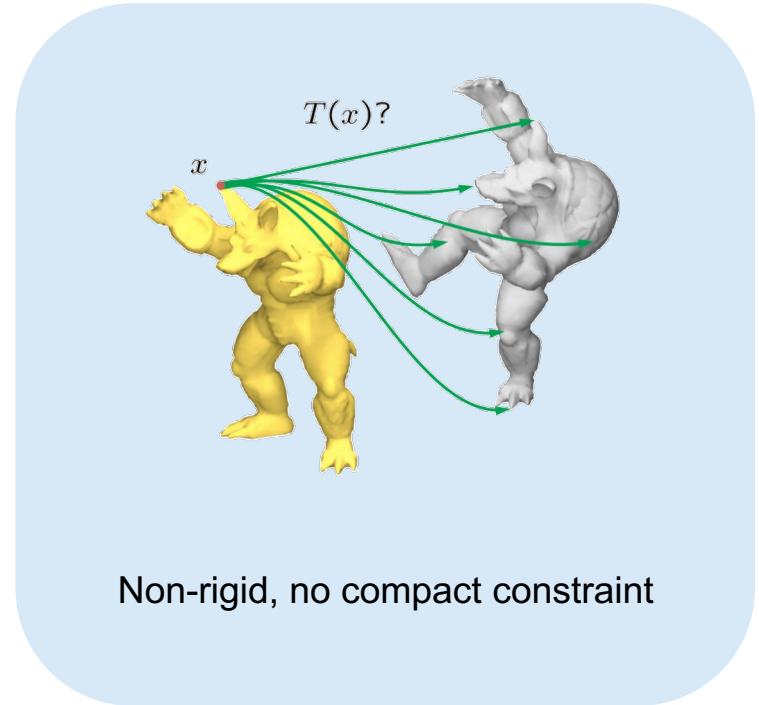
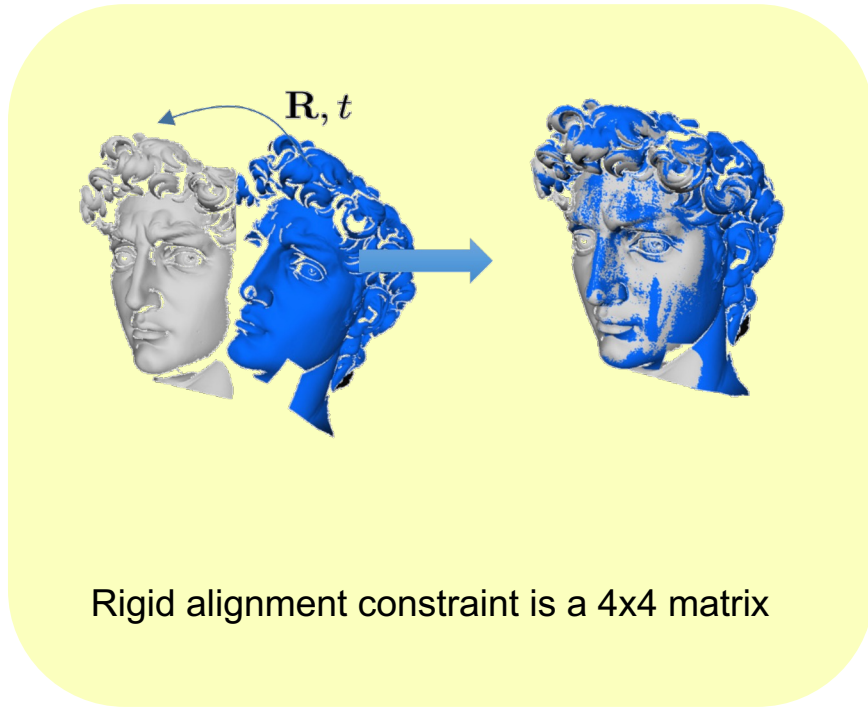
Aug. 2023

<https://blog.siggraph.org/2023/07/siggraph-2023-technical-papers-awards-best-papers-honorable-mentions-and-test-of-time.html/>

<https://twitter.com/AdamWHarley/status/1688661551744798721>

1 Intuition

Background

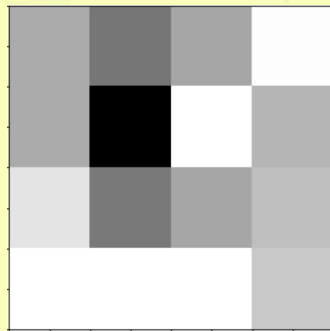


Solution Space

Rigid
 $4 \times 4 R_t$



aligns
xyz
coordinates



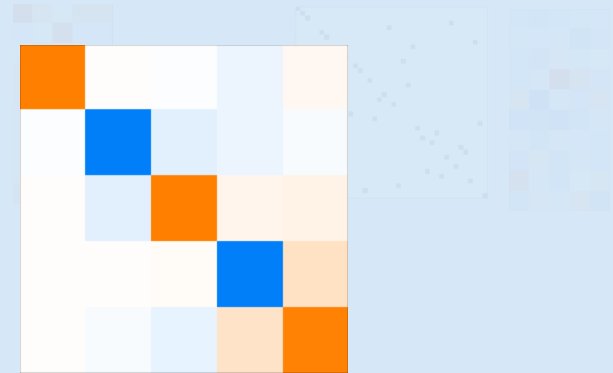
Alignment to
correspondences

Search for
Nearest Neighbor
in xyz
coordinates

Non-rigid
 $k \times k C$



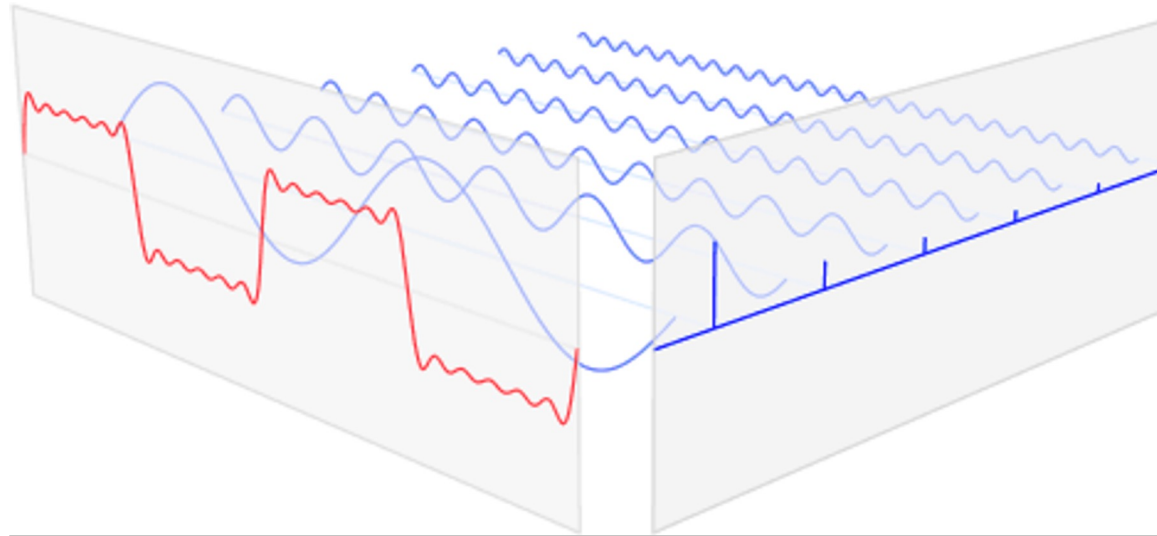
aligns
spectral
embeddings



Alignment to
correspondences

Search for
Nearest Neighbor
in spectral
embeddings

1D Continuous Fourier Analysis



$$F = a_0 * \phi_0 + a_1 * \phi_1 + \dots$$

Fourier Image analysis:
Discretized 2D Grid / Image



Fully encodes image information into **frequency coefficients**

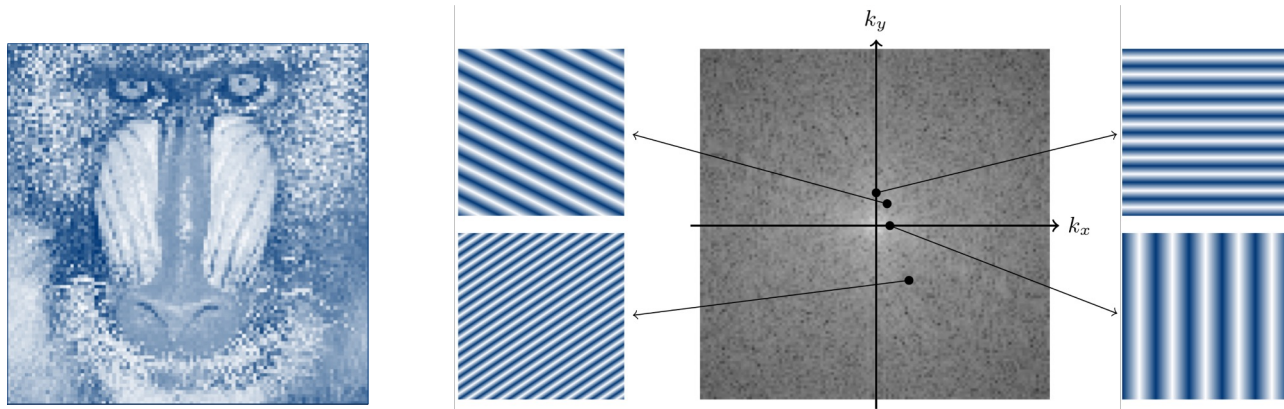
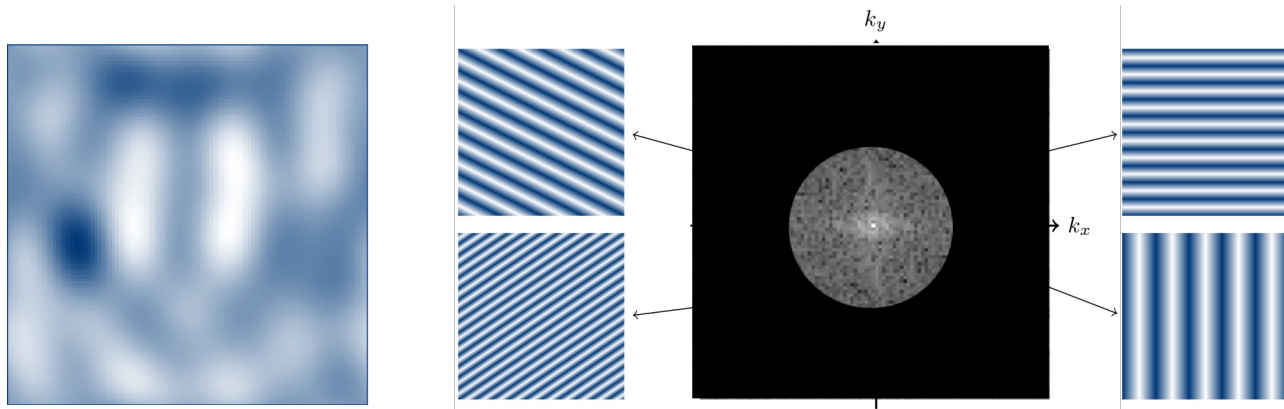
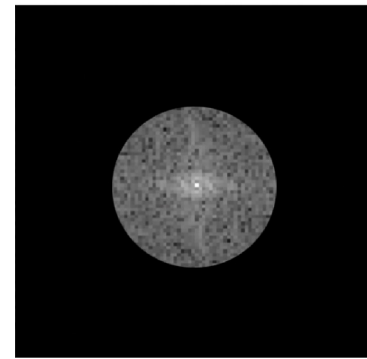
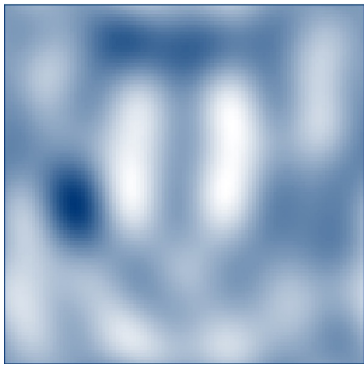
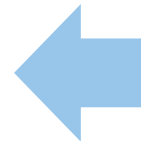
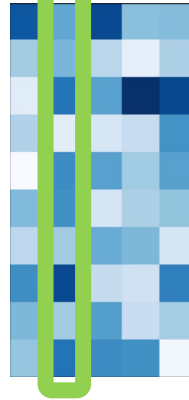
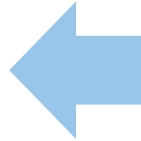


Image compression:

Truncated coefficients to only low frequency

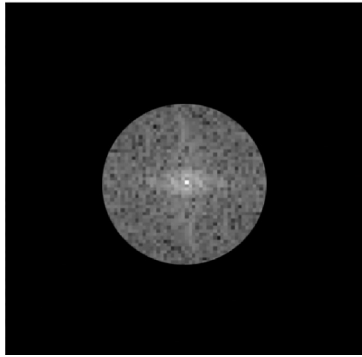



 f
 $=$
 Φ
 \cdot
 a


Each column vector represents an entire image

Fourier Basis Functions are **orthogonal**

From coefficients to reconstructed image

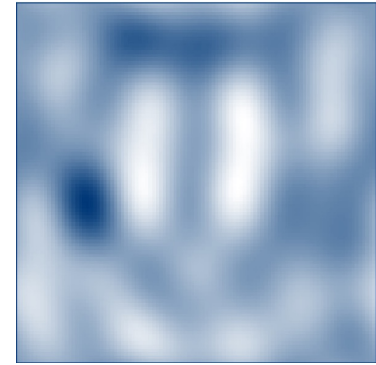


a

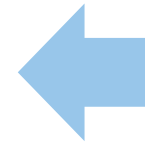
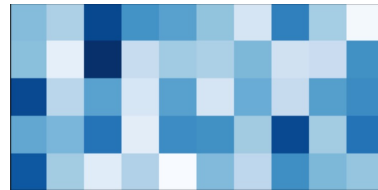
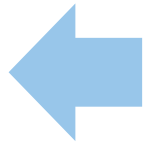


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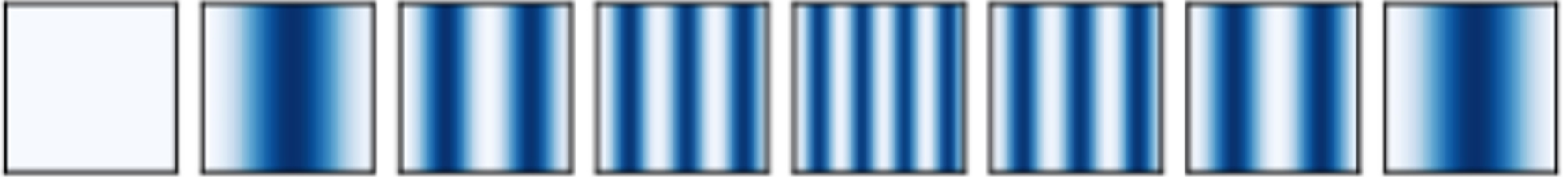
Φ^{-1}



f

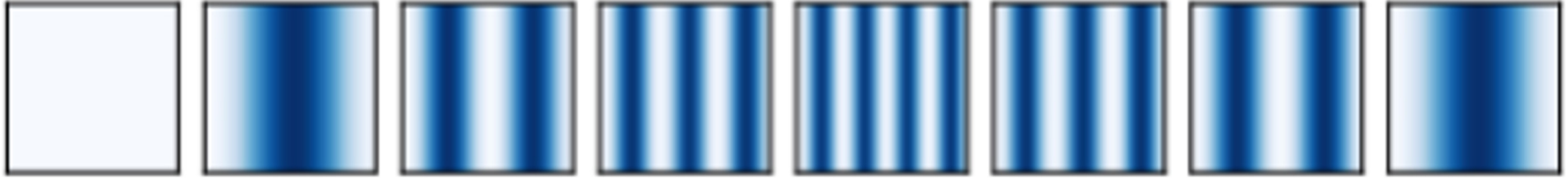


From an image, project to spectral coefficients

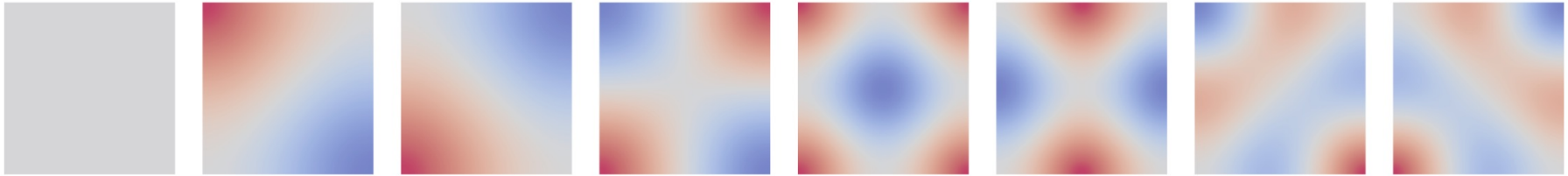


Same idea to 3d shape correspondence?

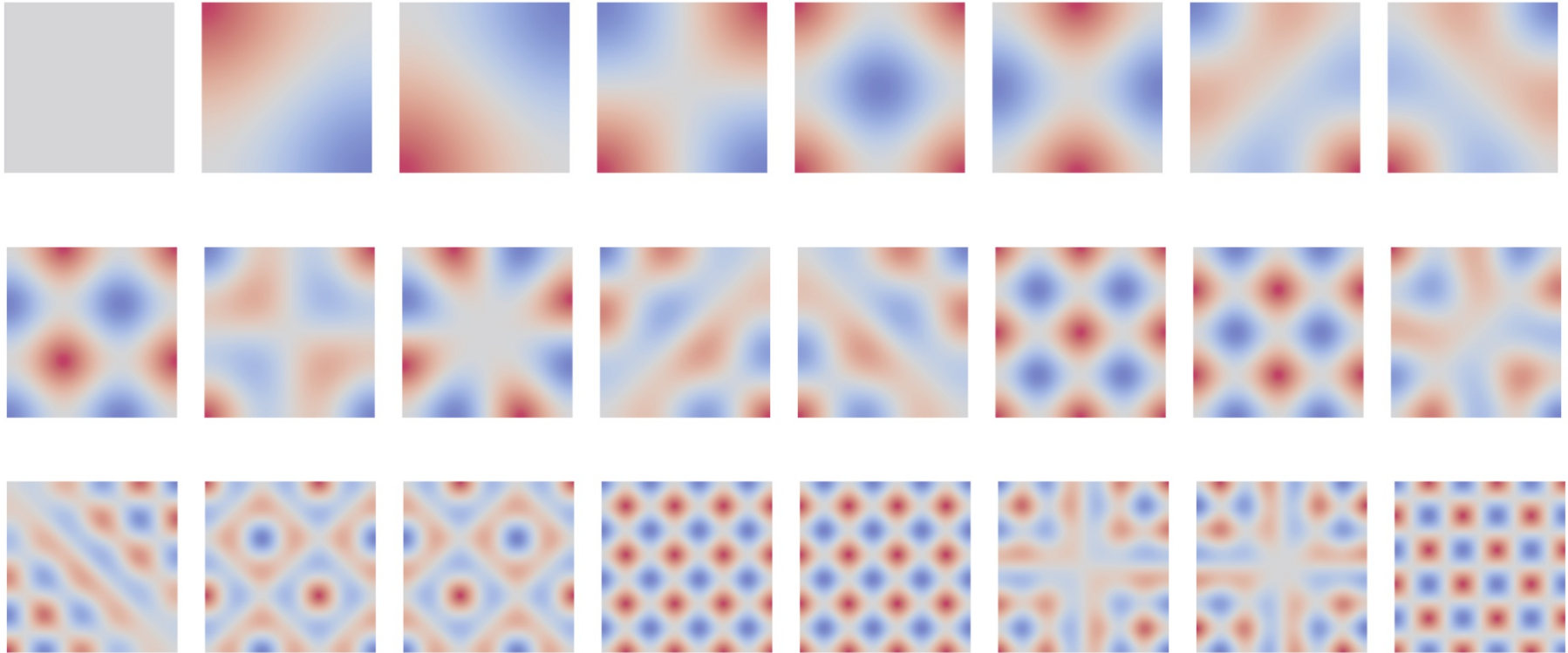




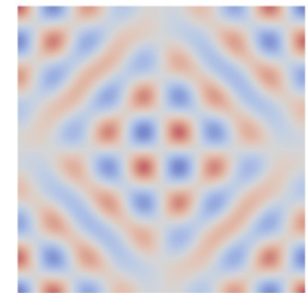
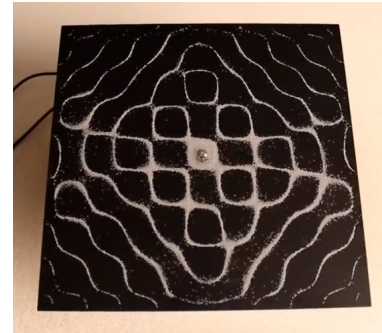
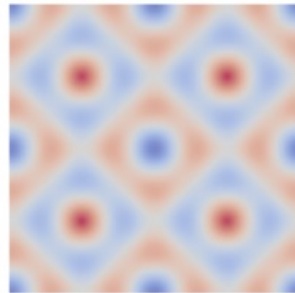
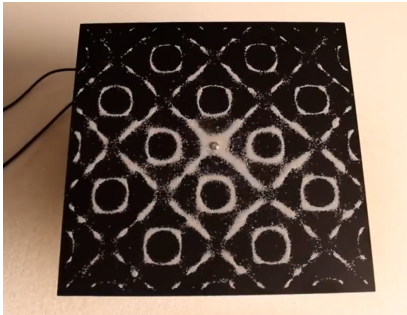
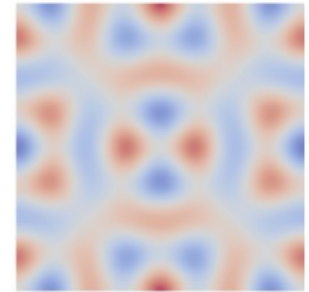
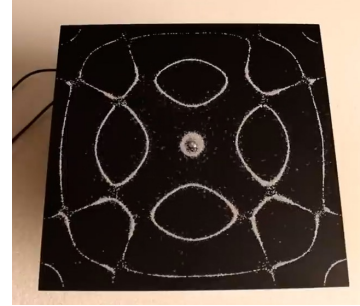
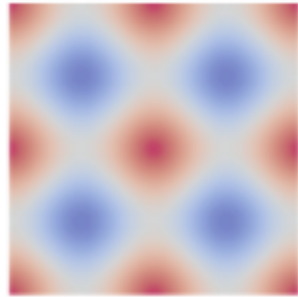
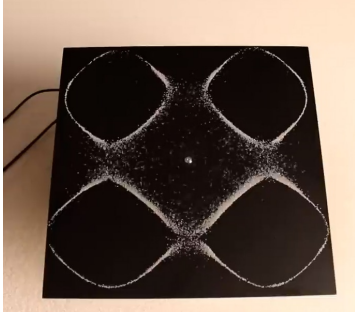
Eigenfunctions of the Laplace-Beltrami Operator



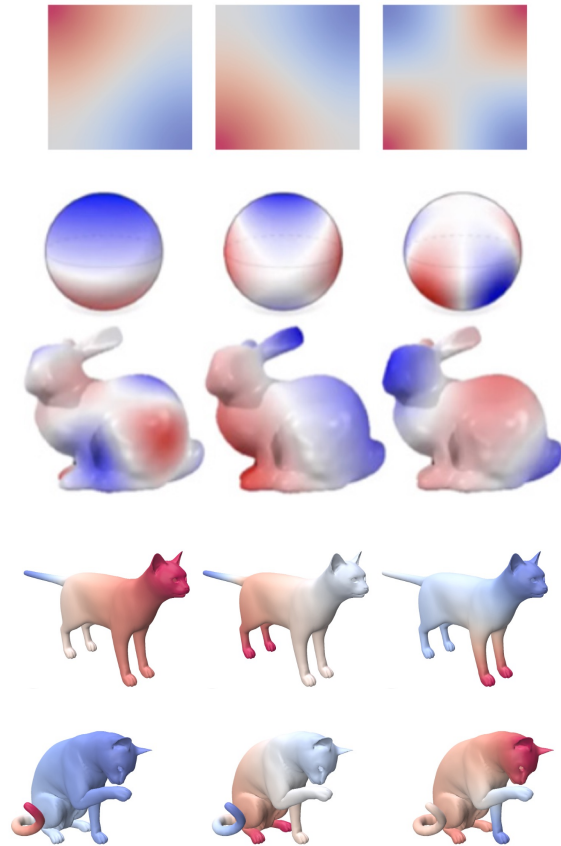
Eigenfunctions of the Laplace-Beltrami Operator



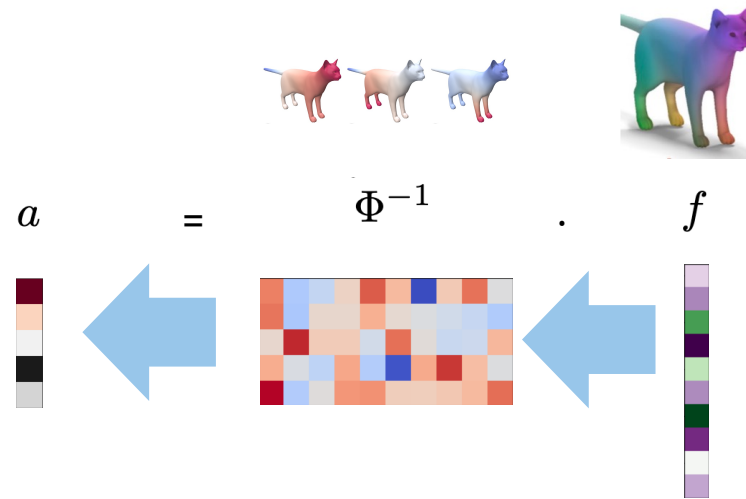
They are also **orthogonal**



Chladni plate patterns

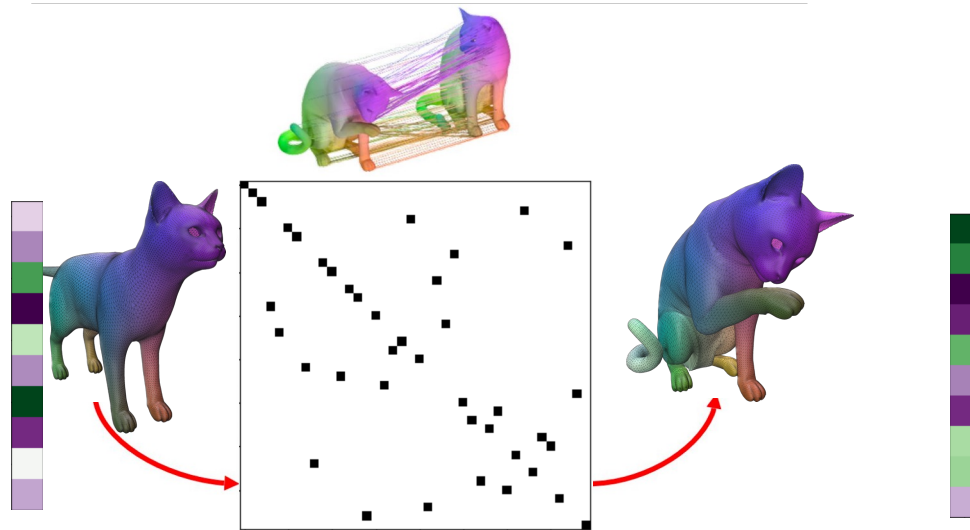


LBO Basis functions are defined for any shape surface



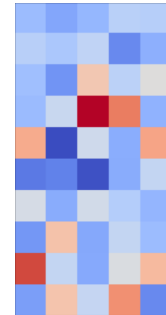
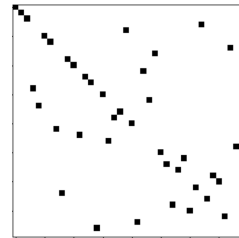
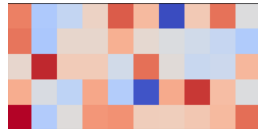
Goal:

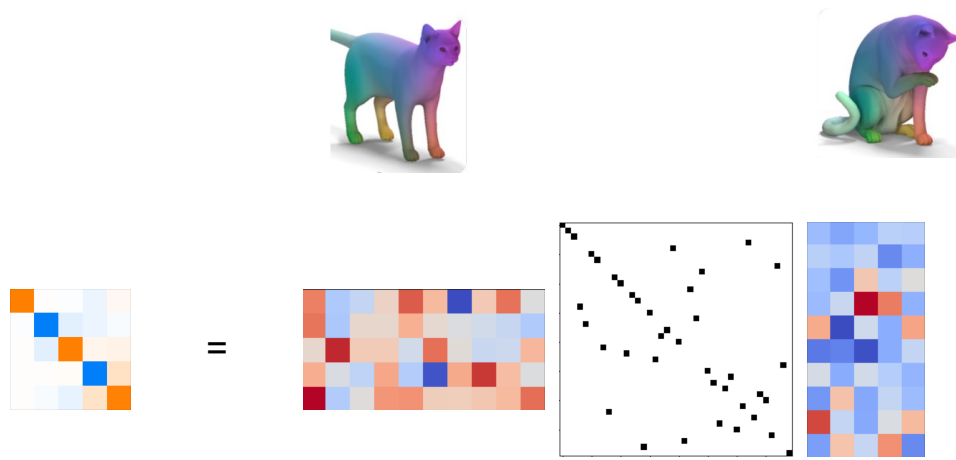
Given two shapes, encode **correspondence** into a small matrix accurately



Point map/ permutation matrix

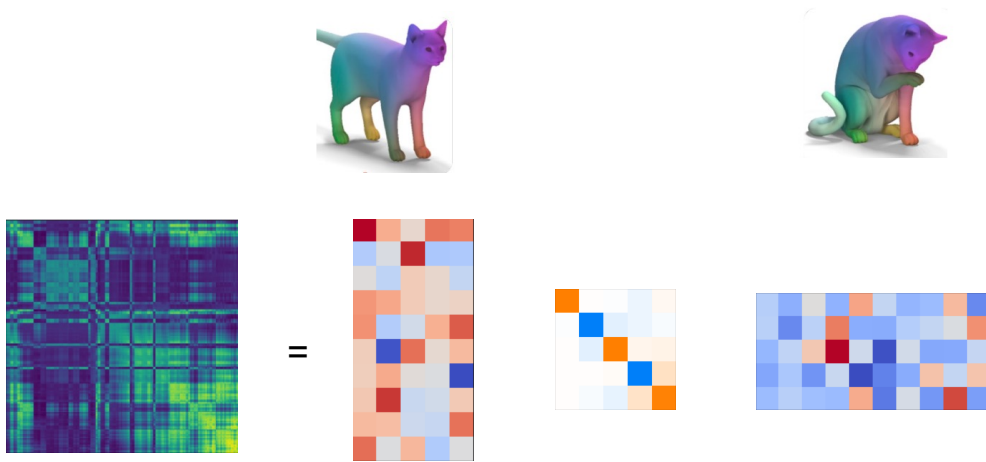
Can transfer/pull functions(colors/texture) from one shape to another





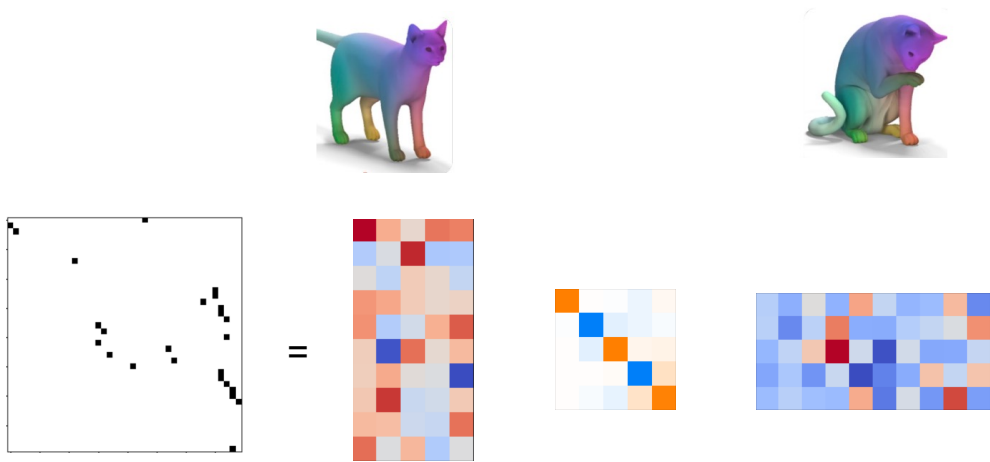
A functional map is a rank-k approximation of a point map

$$C = \Phi_1^\dagger \cdot P \cdot \Phi_2$$



$$P = \Phi_1 \cdot C \cdot \Phi_2^\dagger$$

A functional map is a rank-k approximation of a point map



$$P = \Phi_1 \cdot C \cdot \Phi_2^\dagger$$

**A functional map
is a rank-k
approximation of
a point map**

Texture transfer example

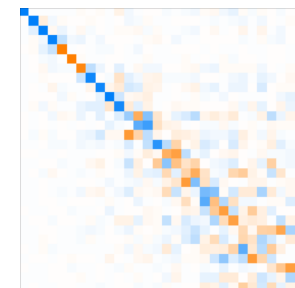
One is ground truth point map
One is functional map
Can you tell?



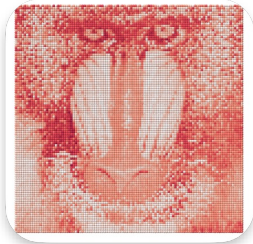
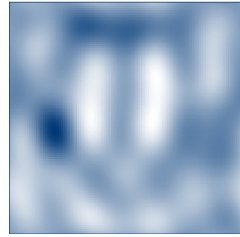
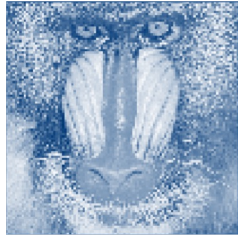
Source



Target

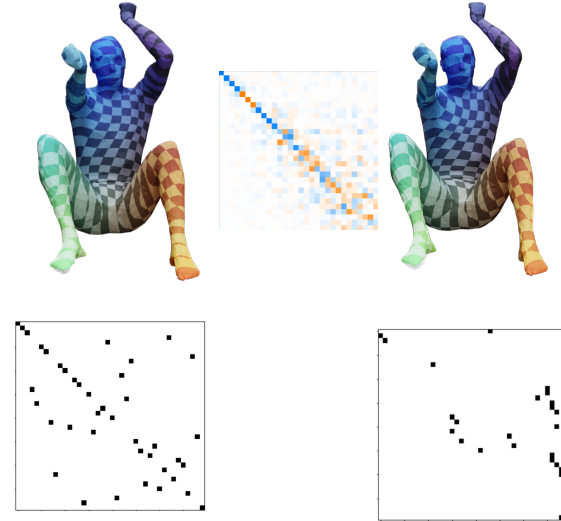


30x30
functional map



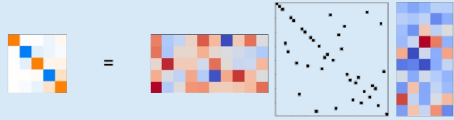
150
Basis coefficients

Does it make sense?



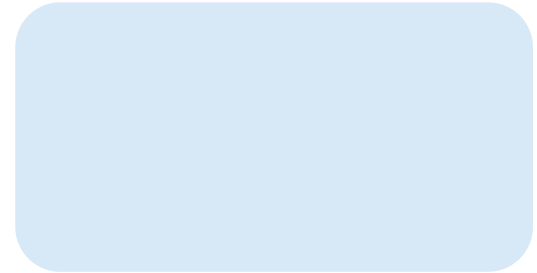
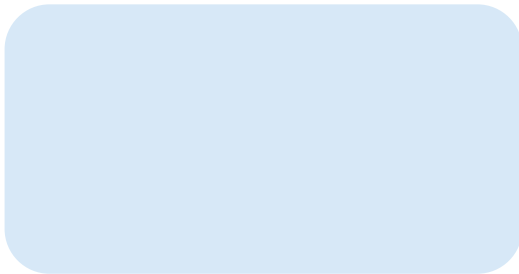
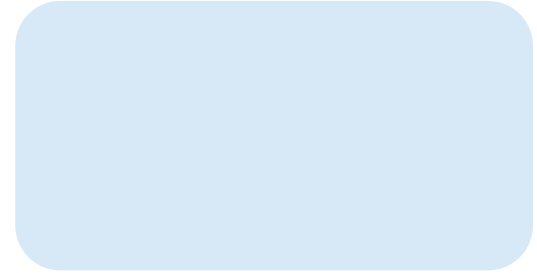
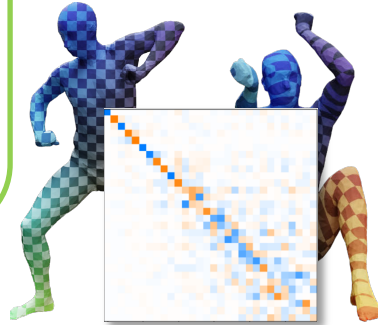
30x30
functional map

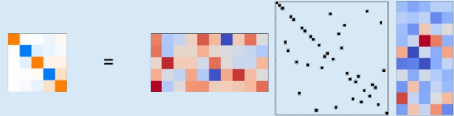
2 Functional map Fundamentals



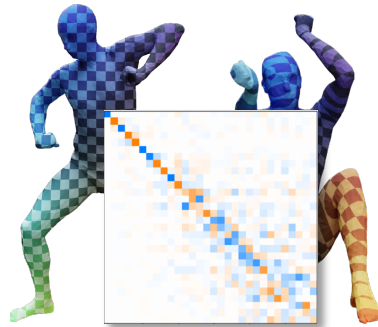
$$C = \Phi_1^\dagger \cdot P \cdot \Phi_2$$

Approximation
of Point Map




$$C = \Phi_1^\dagger \cdot P \cdot \Phi_2$$

Approximation
of Point Map

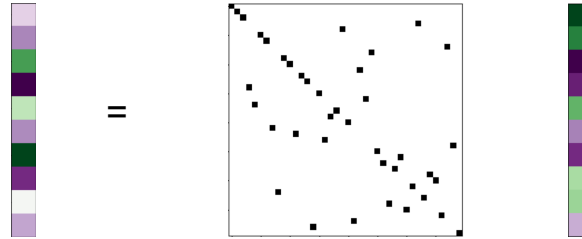


Focus on the input and
output of the matrix

Focus on the elements of
the matrix



Focus on the **input** and **output** of the matrix

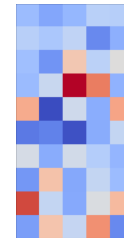
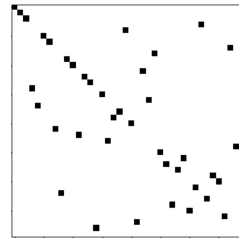
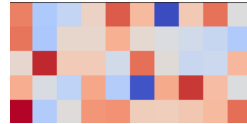
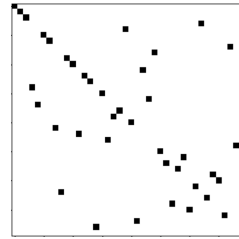


**A point map transfer functions between
two shapes**

Focus on the **input** and **output** of the matrix



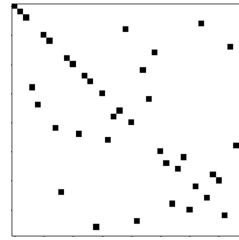
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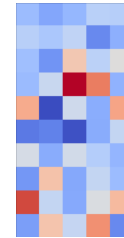
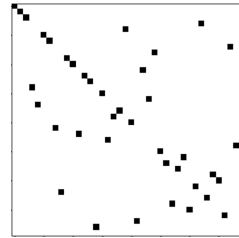
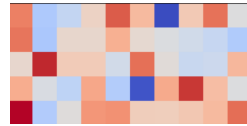
Focus on the **input** and **output** of the matrix



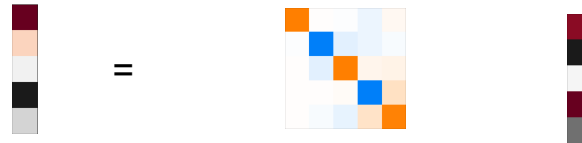
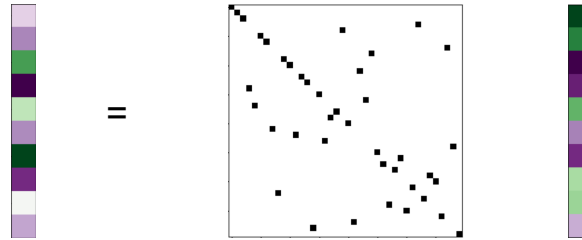
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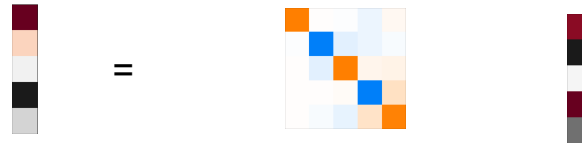
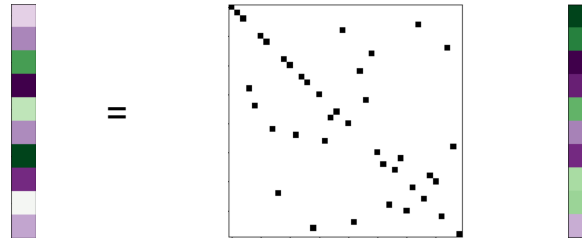
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Focus on the **input** and **output** of the matrix

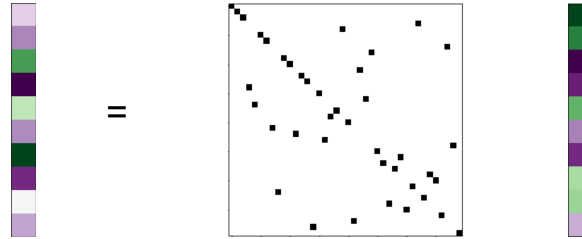


Focus on the **input** and **output** of the matrix



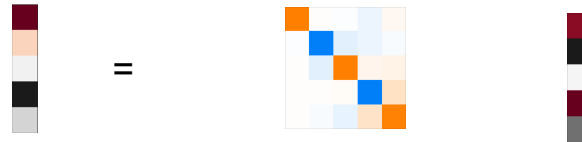
A functional map translates coefficients of functions between two shapes

Focus on the **input** and **output** of the matrix



Spatial domain

A point map transfer functions between two shapes



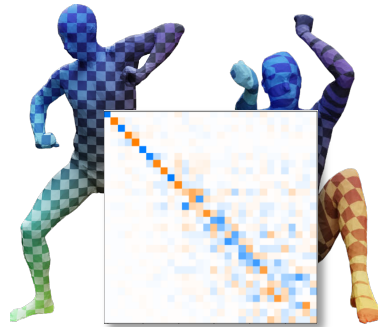
Spectral domain

A functional map translates coefficients of functions between two shapes

$$\mathbf{b} = \mathbf{C} \cdot \mathbf{a}$$

$$C = \Phi_1^\dagger \cdot P \cdot \Phi_2$$

Approximation
of Point Map



$$b = C \cdot a$$

Translates coefficients

$$C = \Phi_1^\dagger \cdot \Phi_2 a$$

Focus on the elements of
the matrix

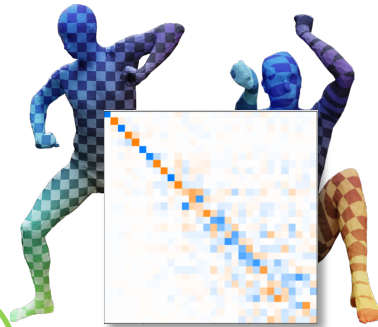
Columns are coefficients of target basis

$$\Phi_1 \cdot C = \Phi_2 a$$

Aligns Bases

$$C = \Phi_1^\dagger \cdot P \cdot \Phi_2$$

Approximation
of Point Map



$$b = C \cdot a$$

Translates coefficients

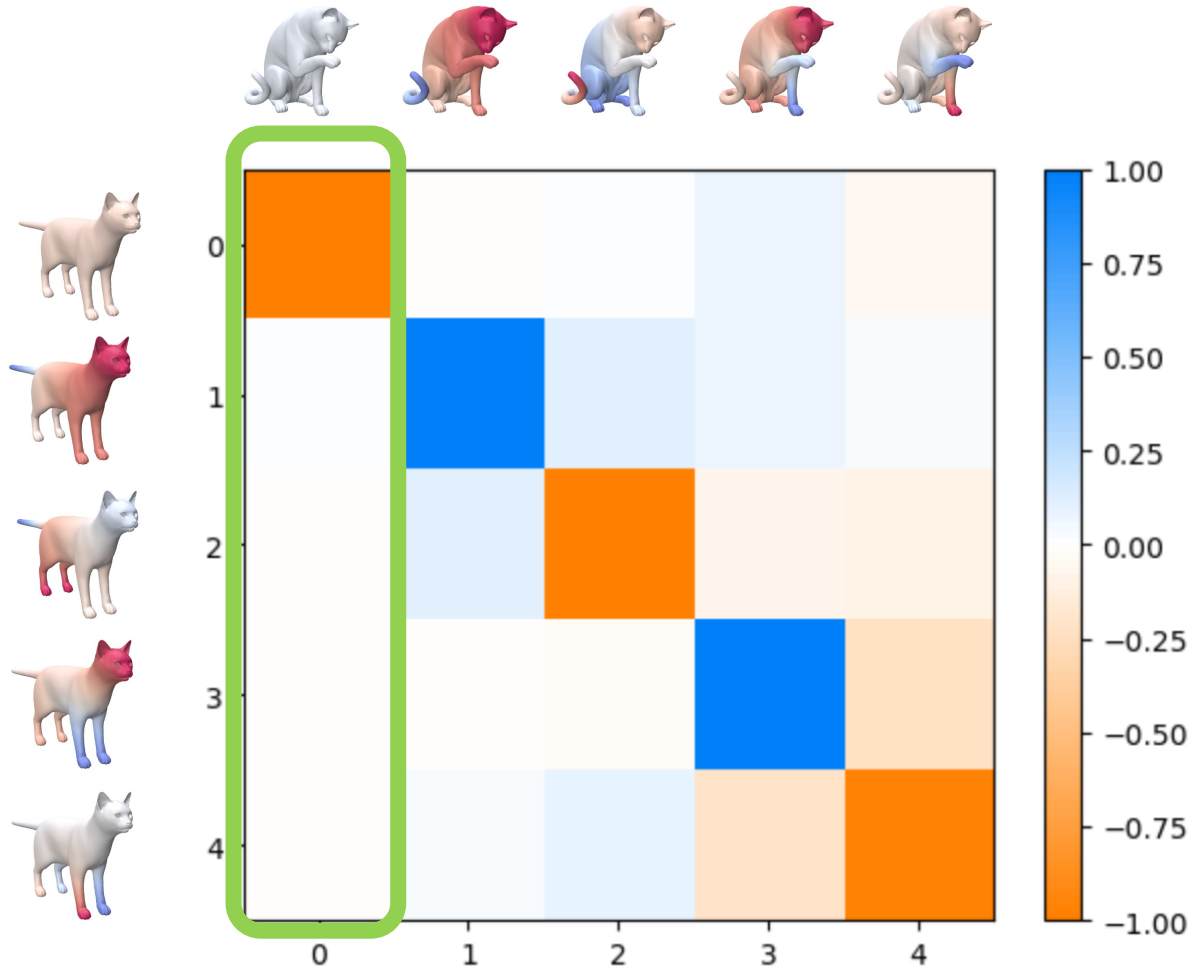
Focus on the elements of
the matrix

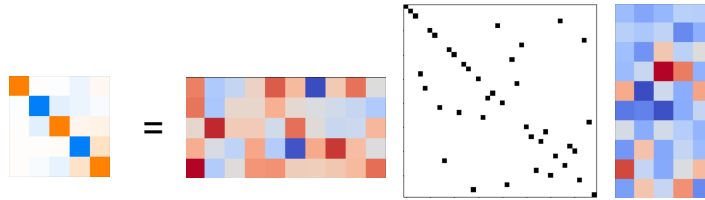
$$C = \Phi_1^\dagger \cdot \Phi_2 a$$

Columns are coefficients of target basis

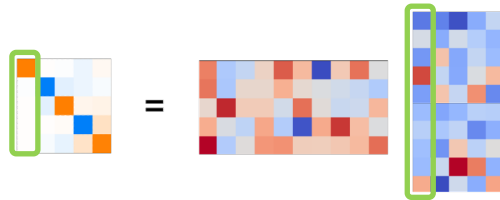
$$\Phi_1 \cdot C = \Phi_2 a$$

Aligns Bases

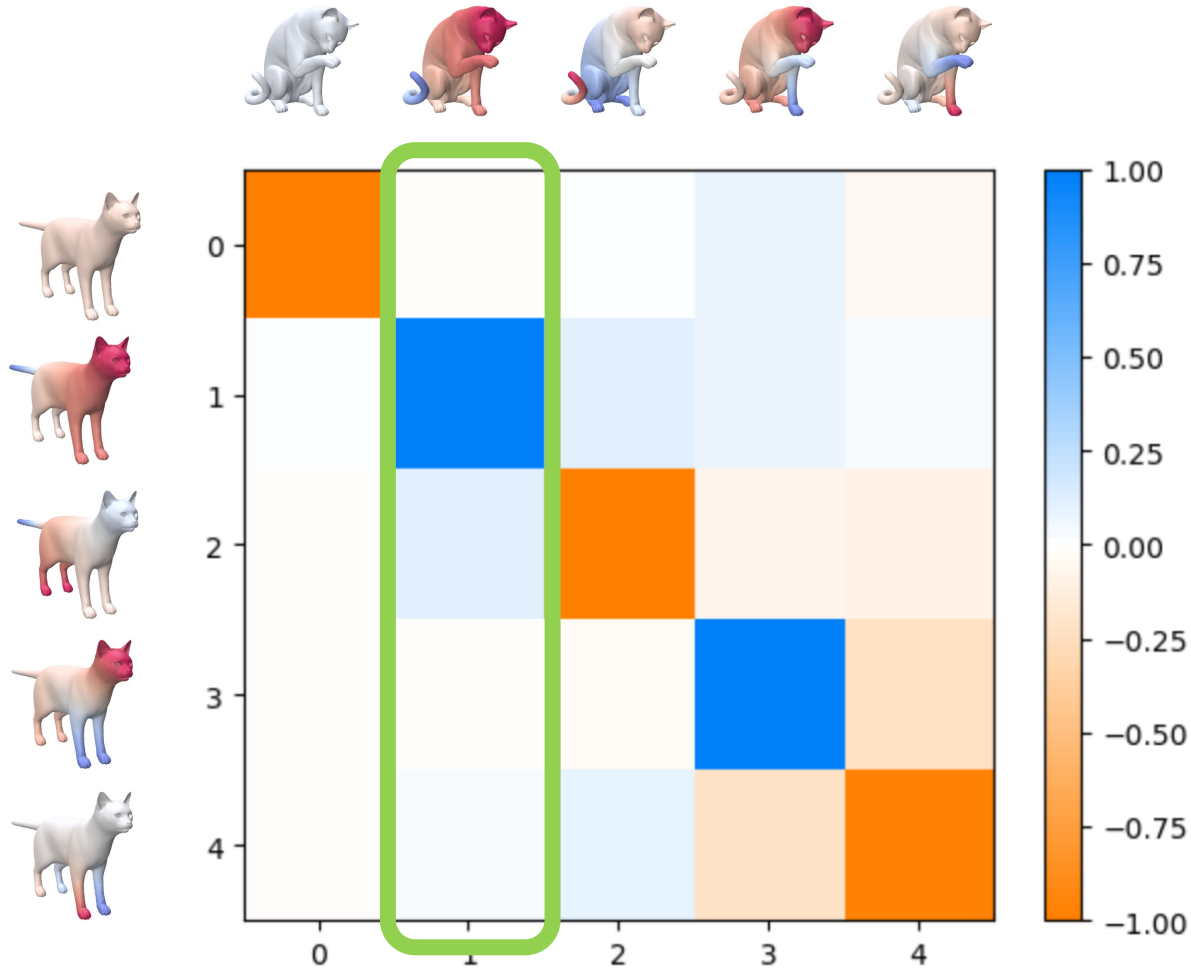




$$C = \Phi_1^\dagger \cdot P \cdot \Phi_2$$



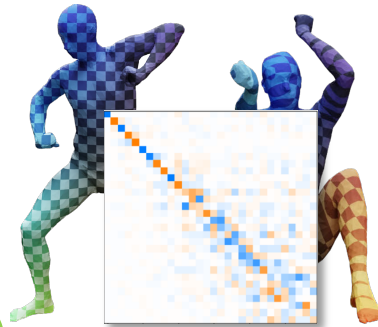
$$C = \Phi_1^\dagger \cdot \Phi_{2a}$$



Each column is a coefficient of the target basis function

$$C = \Phi_1^\dagger \cdot P \cdot \Phi_2$$

Approximation
of Point Map



$$b = C \cdot a$$

Translates coefficients

$$C = \Phi_1^\dagger \cdot \Phi_{2a}$$

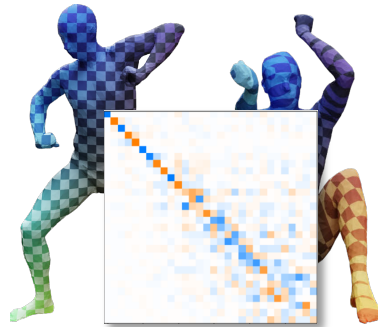
Columns are **coefficients** of target basis

$$\Phi_1 \cdot C = \Phi_{2a}$$

Aligns Bases

$$C = \Phi_1^\dagger \cdot P \cdot \Phi_2$$

Approximation
of Point Map



$$b = C \cdot a$$

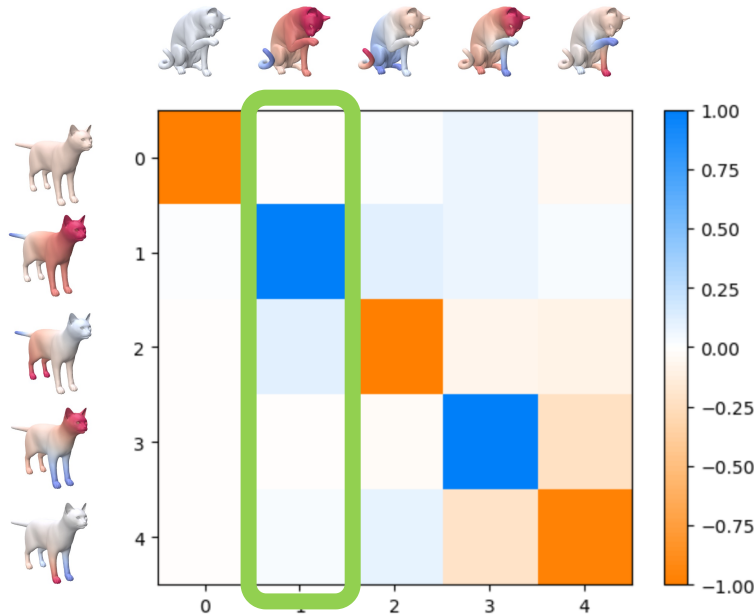
Translates coefficients

$$C = \Phi_1^\dagger \cdot \Phi_{2a}$$

Columns are **coefficients** of target basis

$$\Phi_1 \cdot C = \Phi_{2a}$$

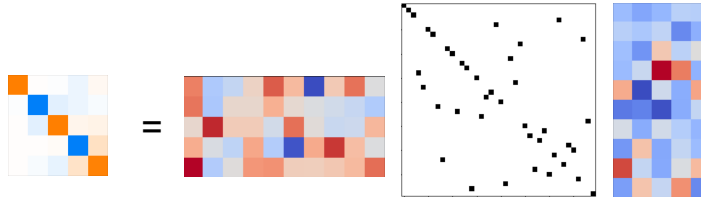
Aligns Bases



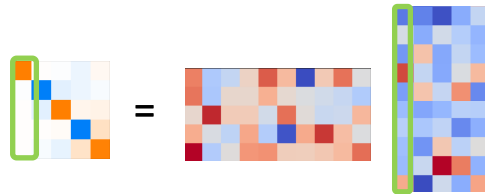
Each **column** is the **coeffieint** that combines into the target basis function

A functional map are **coefficients** that aligns two sets of basis functions together

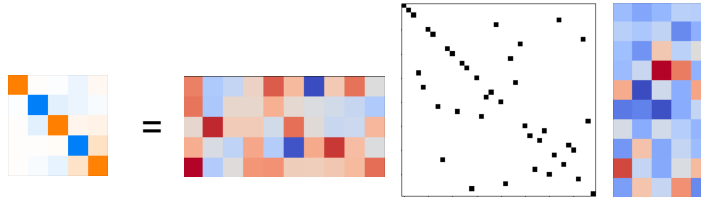
Functional map **aligns** basis functions



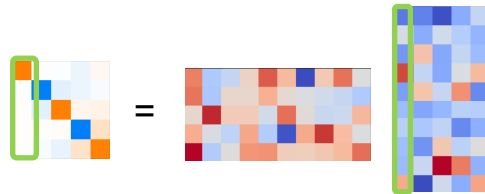
$$C = \Phi_1^\dagger \cdot P \cdot \Phi_2$$



$$C = \Phi_1^\dagger \cdot \Phi_{2a}$$



$$C = \Phi_1^\dagger \cdot P \cdot \Phi_2$$

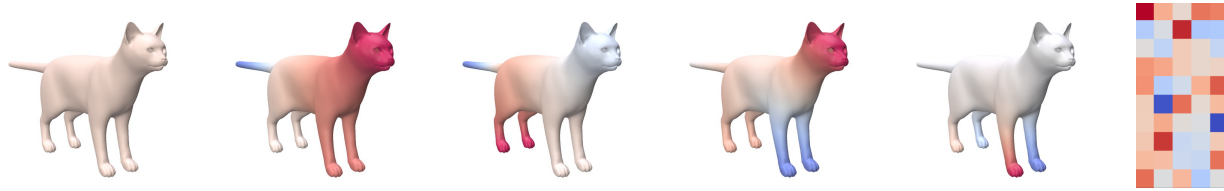


$$C = \Phi_1^\dagger \cdot \Phi_{2a}$$

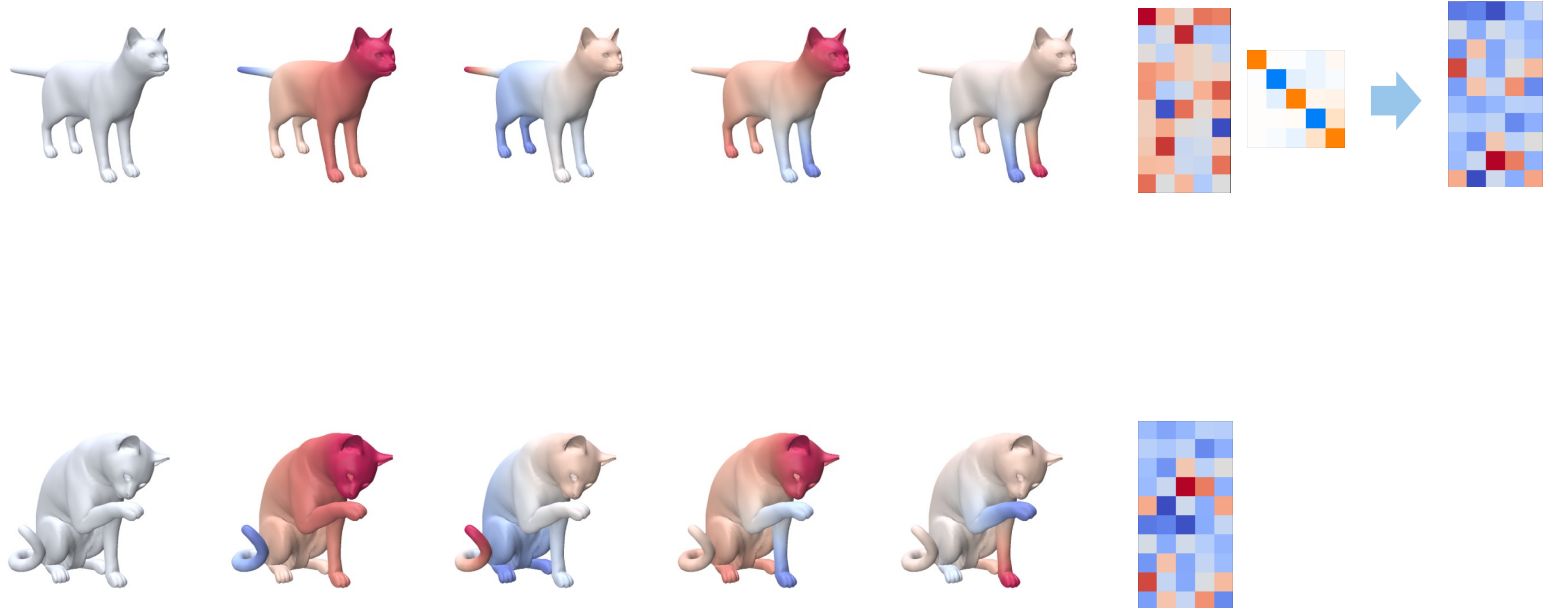


$$\Phi_1 \cdot C = \Phi_{2a}$$

Functional map **aligns** basis functions

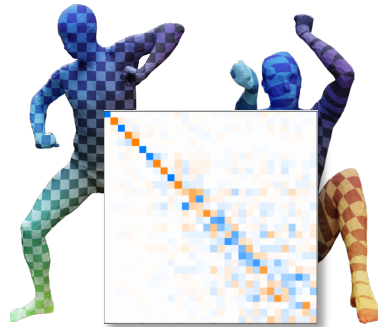


Functional map **aligns** basis functions



$$C = \Phi_1^\dagger \cdot P \cdot \Phi_2$$

Approximation
of Point Map



$$b = C \cdot a$$

Translates coefficients

$$C = \Phi_1^\dagger \cdot \Phi_{2a}$$

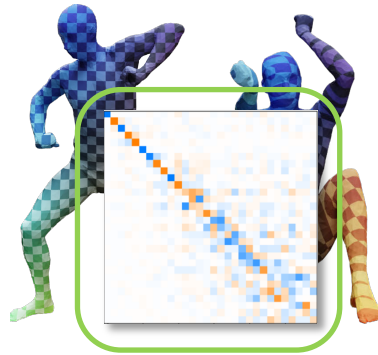
Columns are **coefficients** of target basis

$$\Phi_1 \cdot C = \Phi_{2a}$$

Aligns Bases

$$C = \Phi_1^\dagger \cdot P \cdot \Phi_2$$

Approximation
of Point Map



$$b = C \cdot a$$

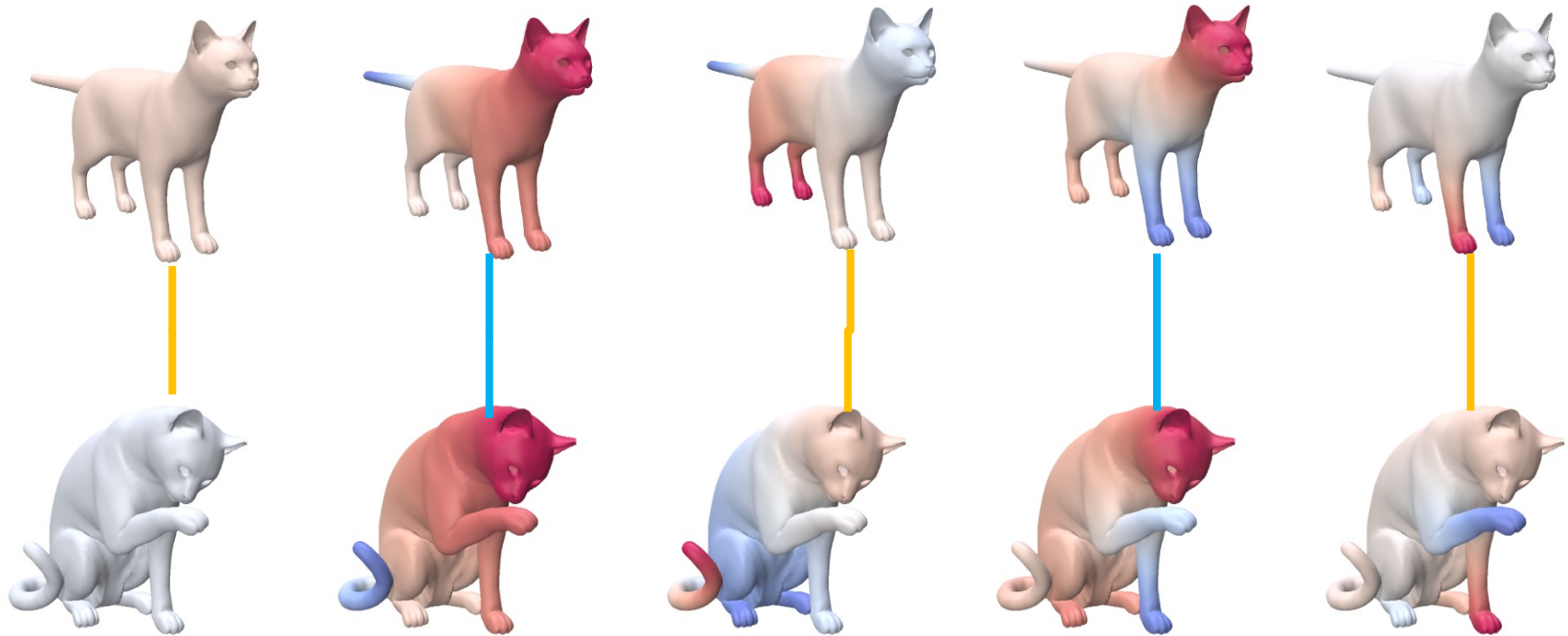
Translates coefficients

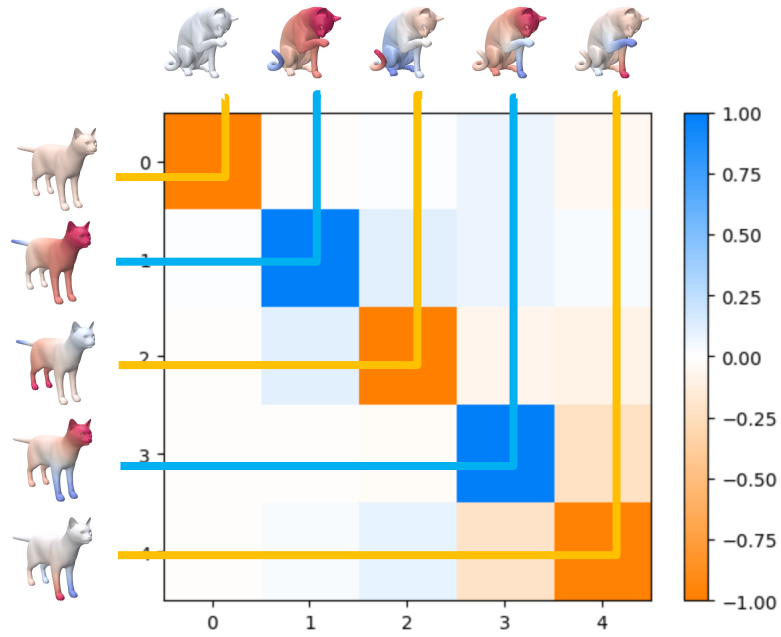
$$C = \Phi_1^\dagger \cdot \Phi_{2a}$$

Columns are **coefficients** of target basis

$$\Phi_1 \cdot C = \Phi_{2a}$$

Aligns Bases





Properties of the eigenfunctions of the LBO

$$\Delta\phi_i = \lambda_i\phi_i \quad \Delta(f) = -\operatorname{div}\nabla(f)$$

Unstable under perturbations:

- Sign flipping
- Eigenfunction order changes

But:

- Space spanned by the top basis functions
are **stable** under near-isometries



$\lambda_0 = 0$ $\lambda_1 = 2.6$ $\lambda_2 = 3.4$ $\lambda_3 = 5.1$ $\lambda_4 = 7.6$

Definition of the Functional Map matrix

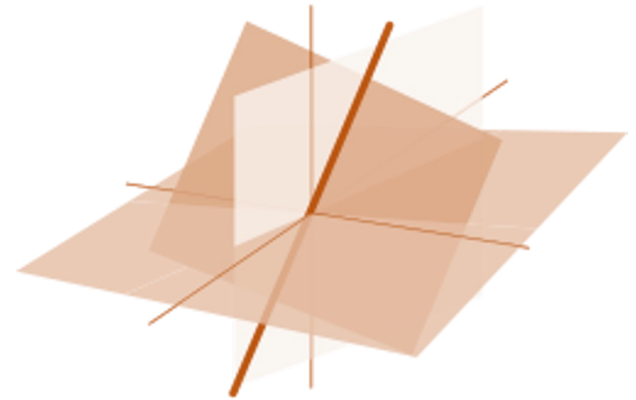
Definition:

For a fixed choice of basis functions $\{\phi^{\mathcal{M}}\}$, $\{\phi^{\mathcal{N}}\}$, and a linear transformation T_F between functions, a functional map is a matrix C , s.t. for any $f = \sum_i a_i \phi_i^{\mathcal{M}}$ if $T(f) = \sum_i b_i \phi_i^{\mathcal{N}}$, then:

$$\mathbf{b} = C\mathbf{a}$$

C_{ij} : coefficient of $T_F(\phi_j^{\mathcal{M}})$ in the basis of $\phi_i^{\mathcal{N}}$.

In an orthonormal basis: $C_{ij} = \int_{\mathcal{N}} T_F(\phi_j^{\mathcal{M}}) \phi_i^{\mathcal{N}} d\mu$



Definition of the Functional Map matrix

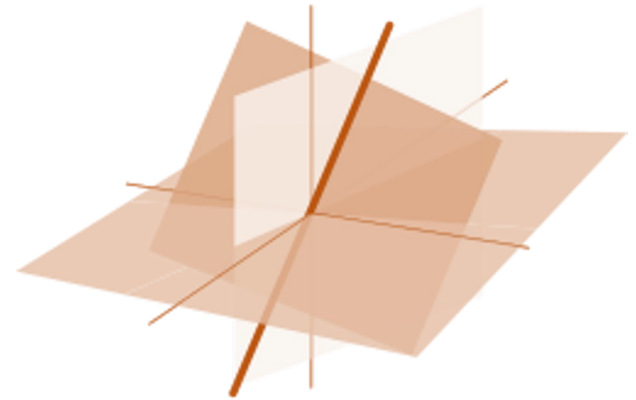
Definition:

For a fixed choice of basis functions $\{\phi^M\}$, $\{\phi^N\}$, and a linear transformation T between functions, a functional map is a matrix C s.t. for any $\sum_i a_i \phi_i^M$ if $T(f) = \sum_i b_i \phi_i^N$ then:

$$\mathbf{b} = \mathbf{C} \cdot \mathbf{a}$$

- Functional Map translates function coefficients from one space to another

In an orthonormal basis: $C_{ij} = \int_{\mathcal{X}^N} T(\phi_j^M) \phi_i^N d\mu$



Definition of the Functional Map matrix

Given two shapes with $n_{\mathcal{M}}, n_{\mathcal{N}}$ points and a map: $T : \mathcal{N} \rightarrow \mathcal{M}$

$\mathbf{T} : n_{\mathcal{N}} \times n_{\mathcal{M}}$ matrix encoding the map T ,
one 1 per column with zeros everywhere else.

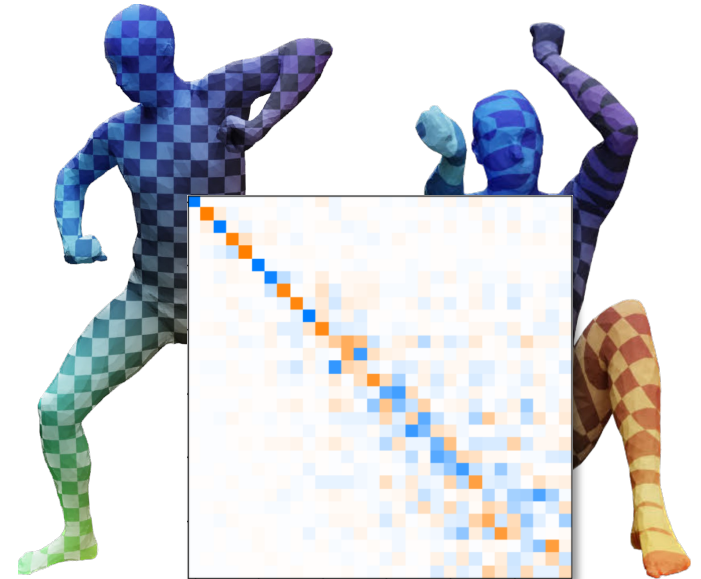
If functions are represented in the reduced basis:

$\Phi_{\mathcal{M}} : n_{\mathcal{M}} \times k_{\mathcal{M}}$ matrix of the first $k_{\mathcal{M}}$ eigenfunctions of $\Delta_{\mathcal{M}}$ as columns.

$\Phi_{\mathcal{N}} : n_{\mathcal{N}} \times k_{\mathcal{N}}$ matrix of the first $k_{\mathcal{N}}$ eigenfunctions of $\Delta_{\mathcal{N}}$ as columns.

The functional map matrix:

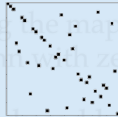
$$C = \Phi_{\mathcal{N}}^+ \mathbf{T}^T \Phi_{\mathcal{M}} \quad + : \text{left pseudo-inverse.}$$



Definition of the Functional Map matrix

Given two shapes with n_M, n_N points and a map: $T : \mathcal{N} \rightarrow \mathcal{M}$

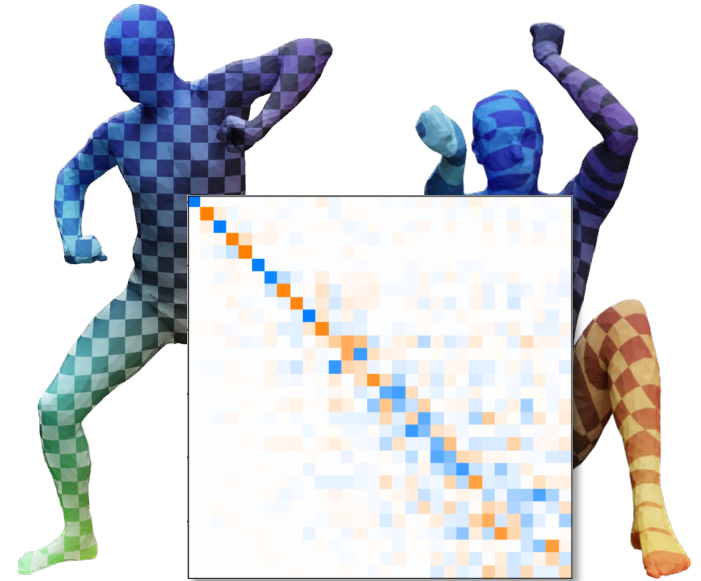
$T : n_N \times n_M$ matrix encoding $T(x) = z$ or 1 if $x = z$ everywhere else.



If functions are represented in the reduced basis:

$$C = \Phi_1^\dagger \cdot P \cdot \Phi_2$$

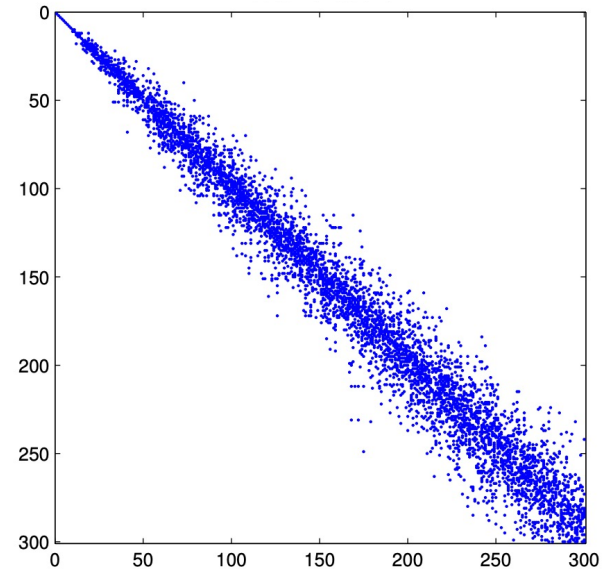
- Functional Map are rank-k approximations of a Point Map under two basis functions



Structure of the Functional Map matrix

Sparsity Pattern:

- Over 94% of the values are below 0.1
- Diagonally funnel-shaped



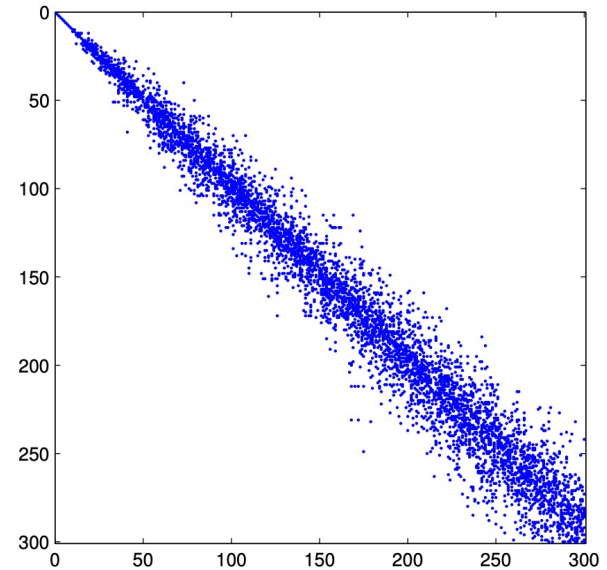
Structure of the Functional Map matrix

High-frequency perturbations:

- Due to high-frequency eigenfunction swaps

But:

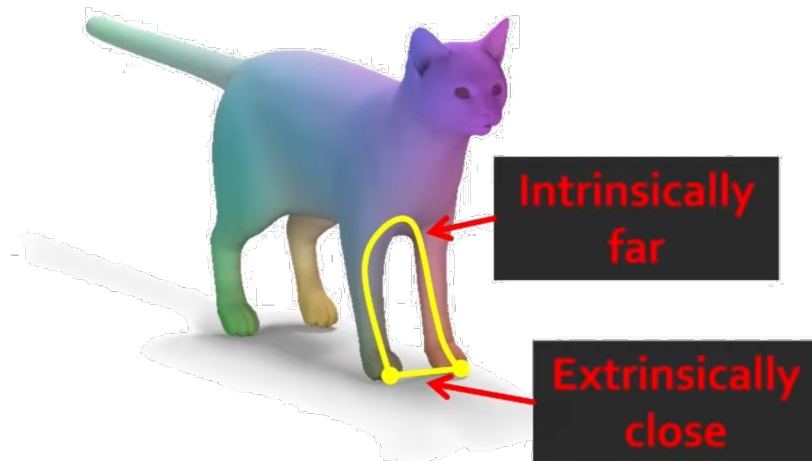
- Space spanned by the eigenfunctions are **stable**
- the functional representation naturally encodes such changes



Accuracy of the Functional Map

Geodesic Distance:

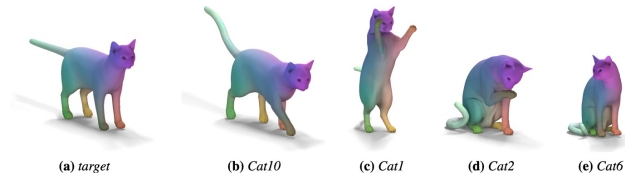
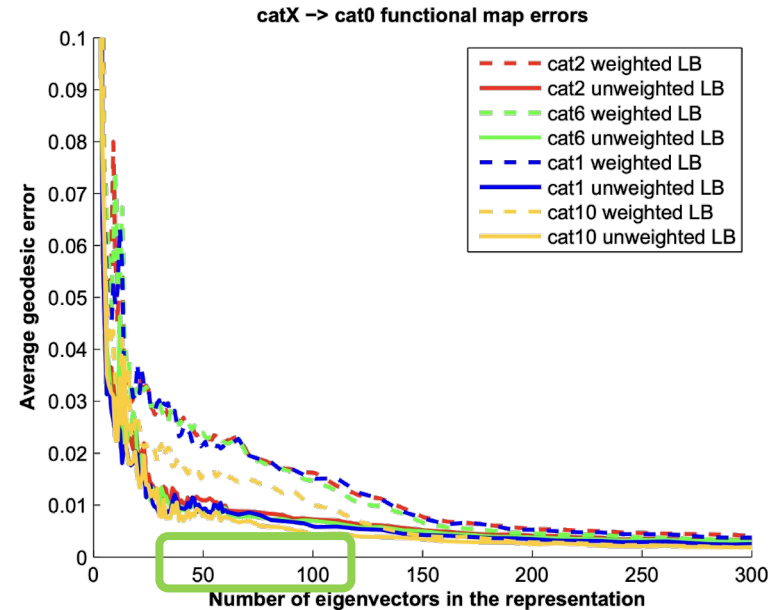
Length of the shortest path, constrained not to leave the manifold.



Accuracy of the Functional Map

Average mapping error vs. number of basis used

- In practice, somewhere between 20 to 100 basis are sufficient



Properties of Functional Maps

Lemma 1:

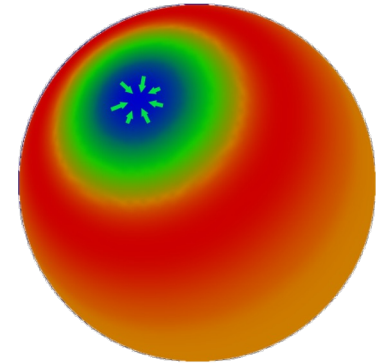
The mapping is *isometric*, if and only if the functional map matrix commutes with the Laplacian:

$$C\Delta_{\mathcal{M}} = \Delta_{\mathcal{N}}C$$

Implies that isometries result in diagonal functional maps.

Lemma 2:

The mapping is *locally volume preserving*, if and only if the functional map matrix is *orthonormal*.



Properties of Functional Maps

Lemma 1:

The mapping is *isometric*, if and only if the functional map matrix commutes with the Laplacian:

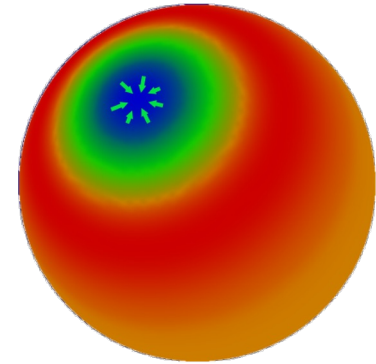
- Good Functional Maps are **diagonal**

$$C\Delta_M = \Delta_N C$$

Implies that isometries result in diagonal functional maps.

Lemma 2:

- The mapping is *orthonormal*, if and only if the functional map matrix is *orthonormal*.

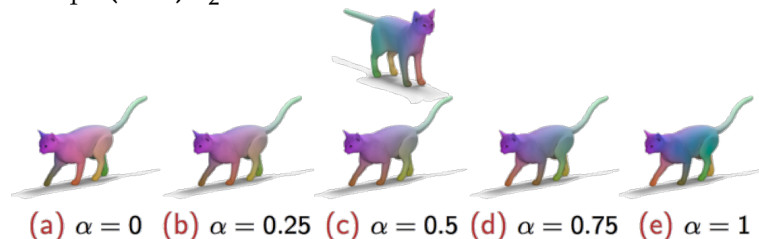


Functional Map algebra

1. Map composition becomes matrix multiplication.
2. Map inversion is matrix inversion (in fact, transpose).
3. Algebraic operations on functional maps are possible.

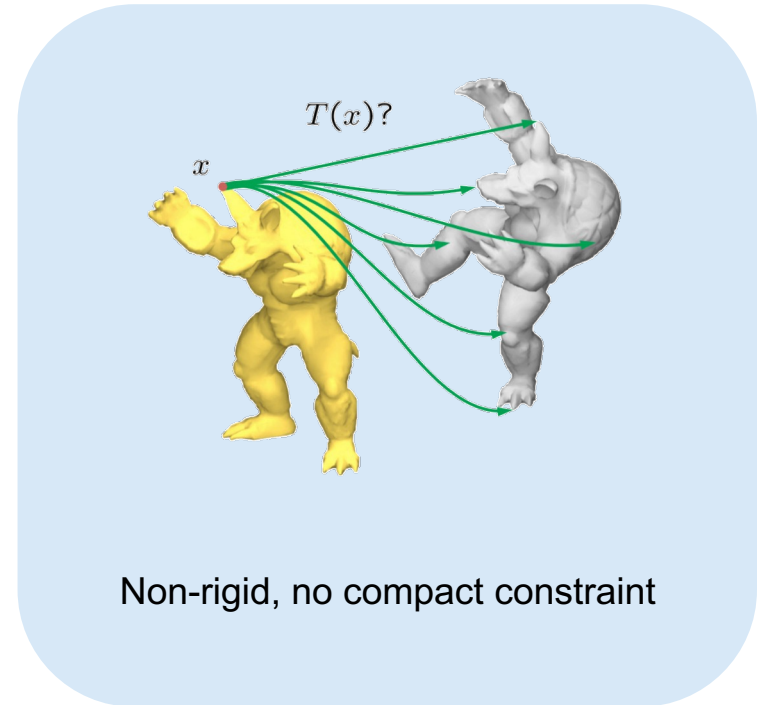
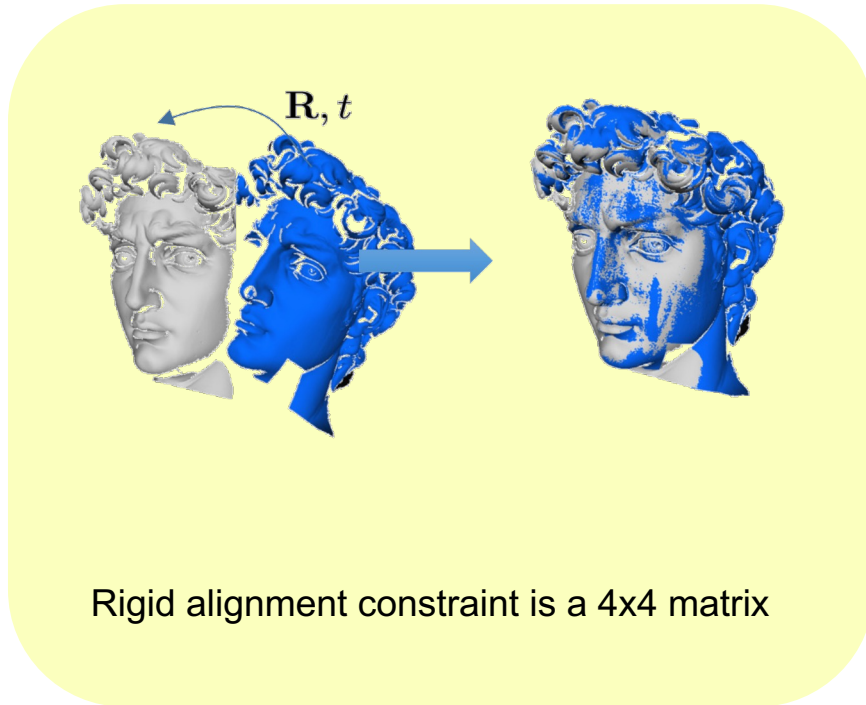
E.g. interpolating between two maps with

$$C = \alpha C_1 + (1-\alpha)C_2.$$

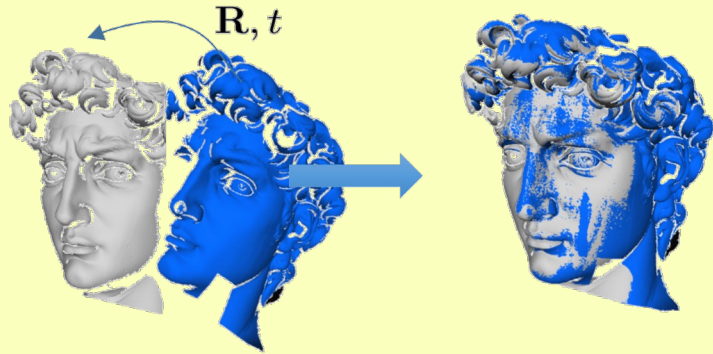


3 Historical Background

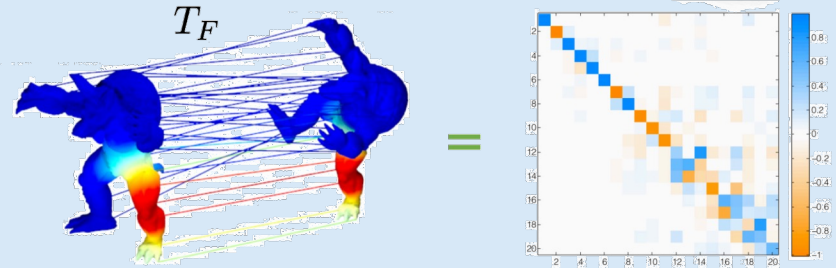
Background



Spectral Rigid Alignment



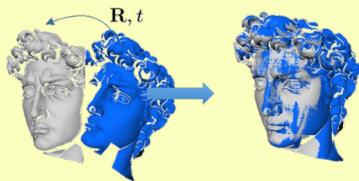
Rigid alignment constraint is a 4x4 matrix



Non-rigid, spectral rigid alignment constraint is a $k \times k$ matrix

Spectral Rigid Alignment

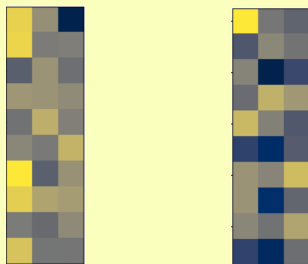
Rigid



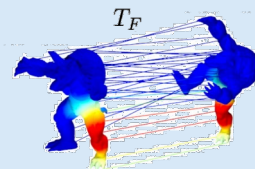
4x4 Rt



aligns
xyz
coordinates



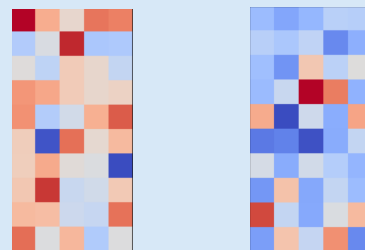
Non-rigid



$k \times k$ C

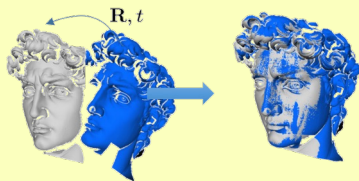


aligns
spectral
embeddings



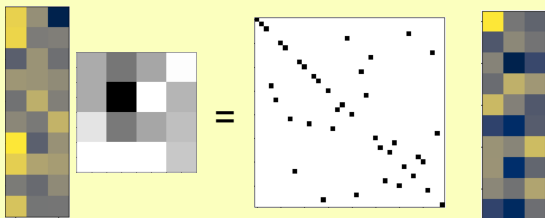
Spectral Rigid Alignment

Rigid

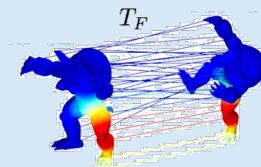


4x4 Rt

aligns
xyz
coordinates

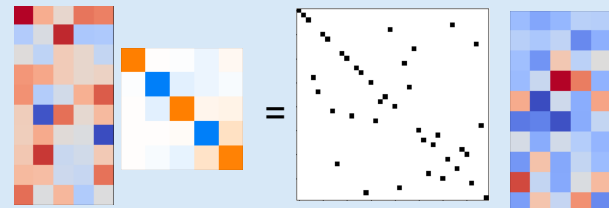


Non-rigid



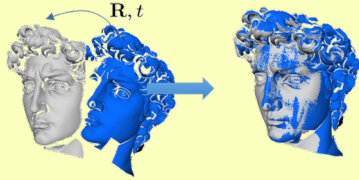
$k \times k$ C

aligns
spectral
embeddings



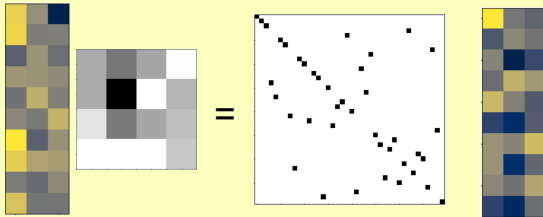
Spectral Rigid Alignment

Rigid



4x4 R_t

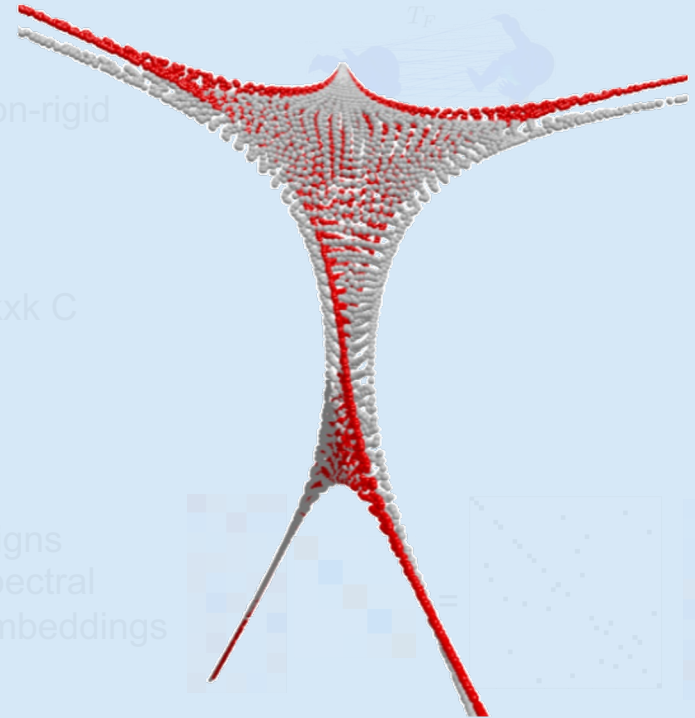
aligns
xyz
coordinates



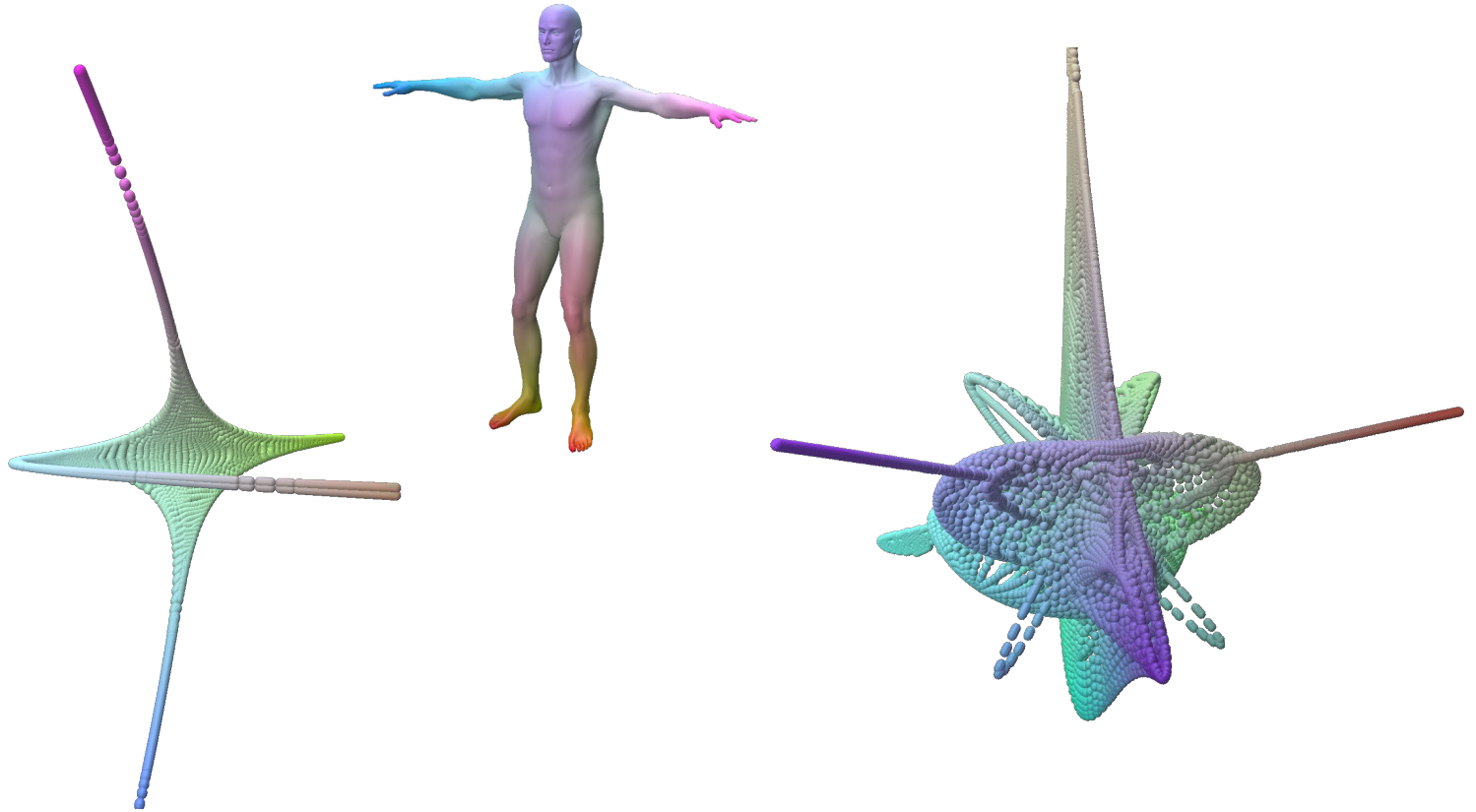
Non-rigid

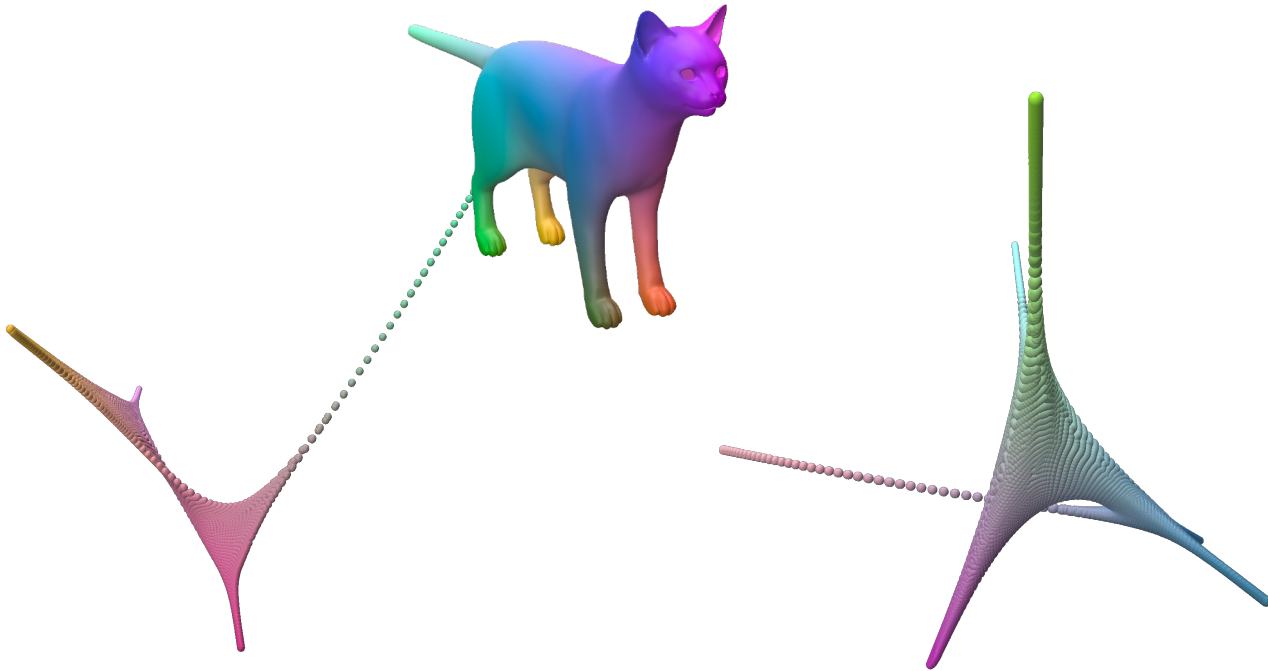
$k \times k$ C

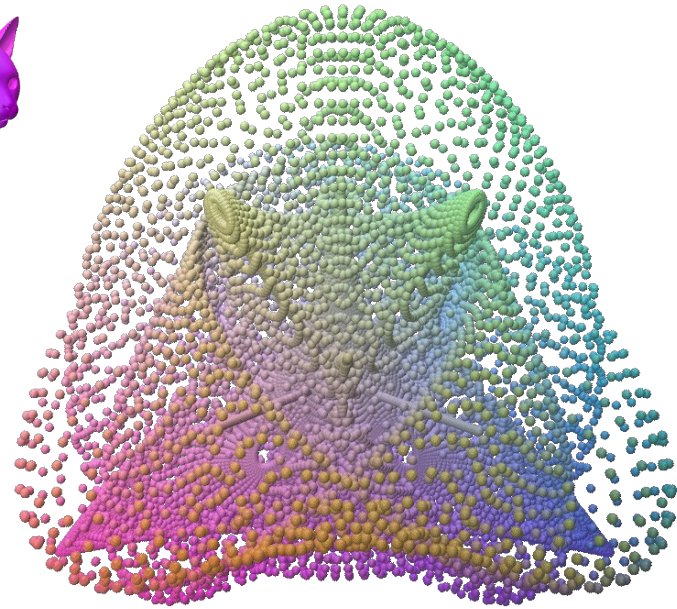
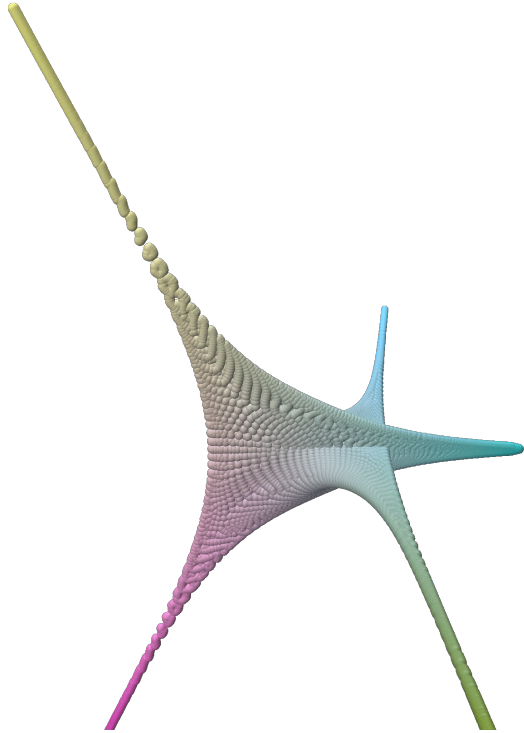
aligns
spectral
embeddings









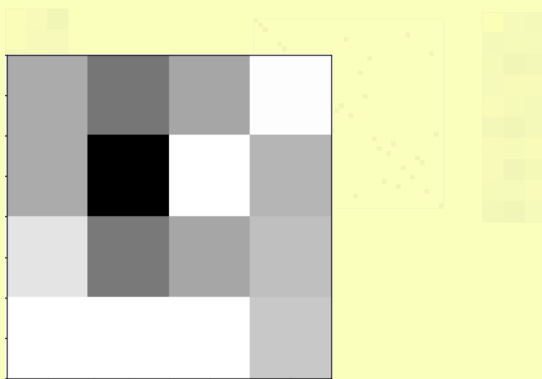


Solution Space

Rigid
4x4 Rt



aligns
xyz
coordinates



Alignment to
correspondences

Search for
Nearest Neighbor
in xyz
coordinates

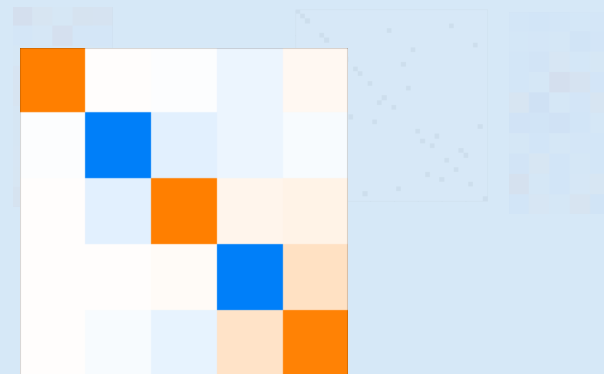


$\lambda_0 = 0$ $\lambda_1 = 2.6$ $\lambda_2 = 3.4$ $\lambda_3 = 5.1$ $\lambda_4 = 7.6$

Non-rigid
kxk C



aligns
spectral
embeddings



Alignment to
correspondences

Search for
Nearest Neighbor
in spectral
embeddings

4 Applications

Introduced in 2012

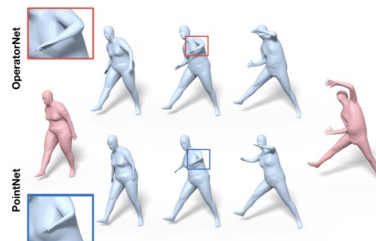
Extensively studied for the past decade



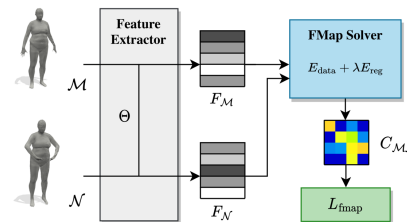
[Rodolà et al. 2017]



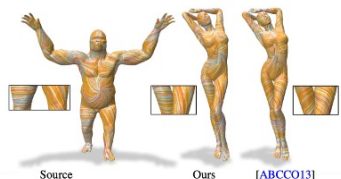
[Rustamov et al., 2013]



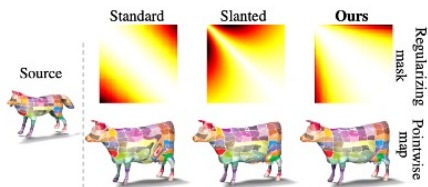
[Huang et al. 2019]



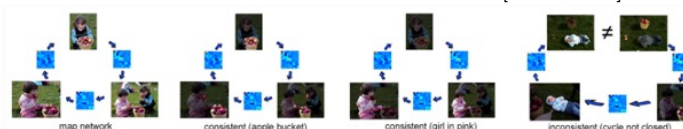
[Cao et al. 2023]



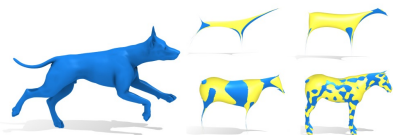
[Donati et al. 2022]



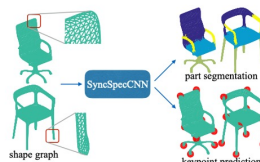
[Ren et al. 2019]



[Wang et al. 2013]



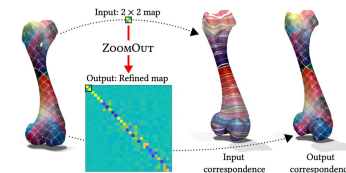
[Eisenberger et al. 2020]



[Yi et al. 2017]



Donati et al. 2020



[Melzi et al. 2019]

... and more

Applications



Map Refinement

2012

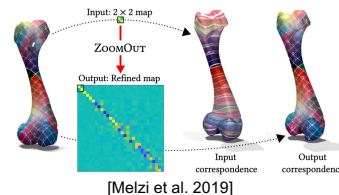


FAUST [Bogo et al. '14]

TOSCA [Bronstein et al. '08]

SCAPE [Angelov et al. '05]

Shape Matching



2018

2020

2019



Donati et al. 2020

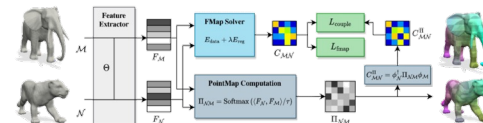
2017

2023



[Litany et al. 2017]

2020



[Cao et al. 2023]

Deep Functional Maps

Map Refinement: ICP

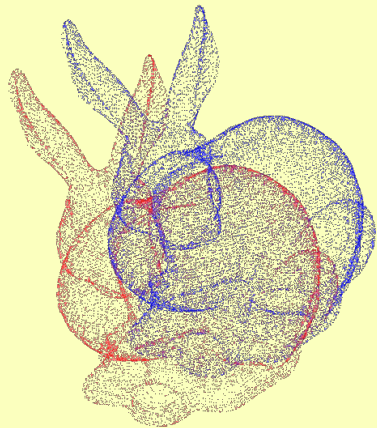


Map Refinement



2012

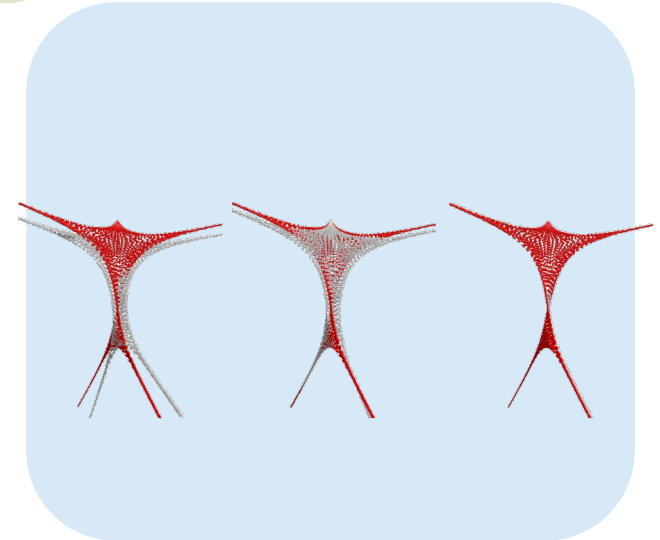
Iteration 0



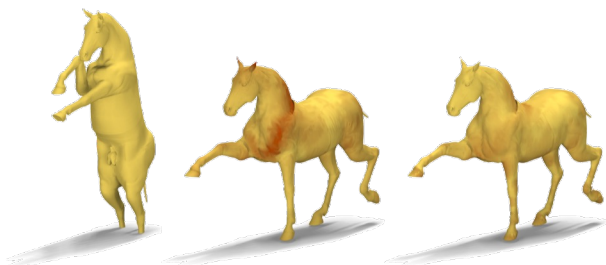
Initial Map:



1. **Correspondence**
(Point Map)
2. **Rigid Alignment**
(Functional Map)

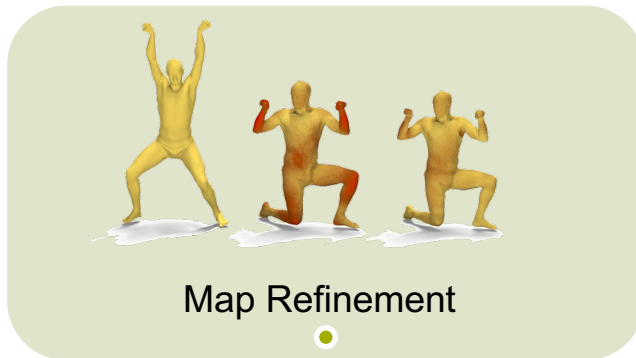


Map Refinement: ICP



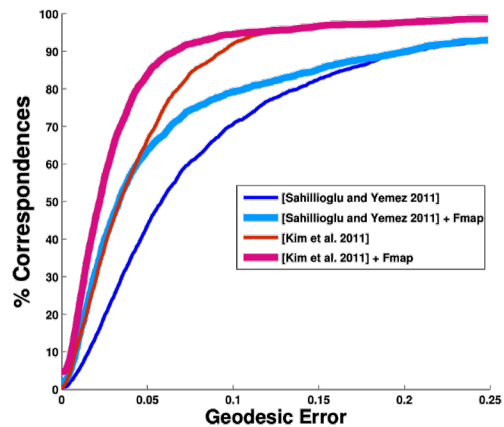
Source Baseline After

Color Error Visualization

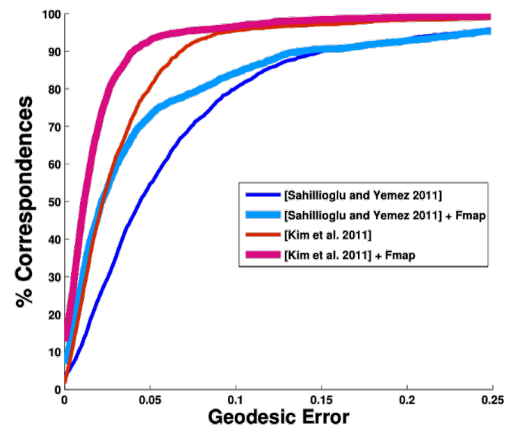


Map Refinement

2012



(a) *SCAPE*



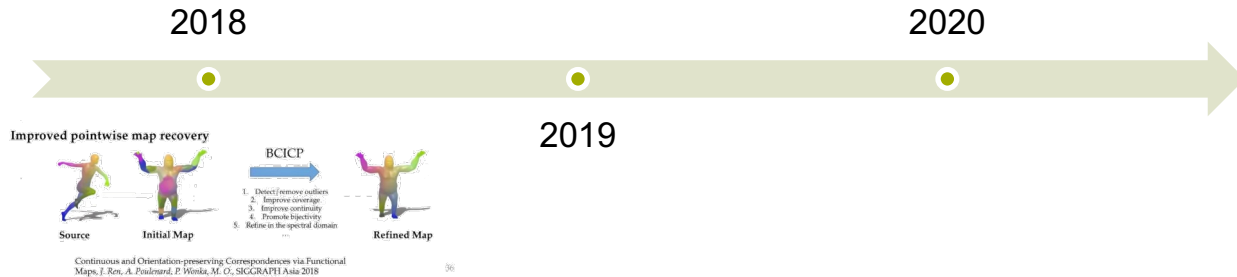
(b) *TOSCA*

Map Refinement



Map Refinement

2012



2018



Map Refinement

Improved pointwise map recovery



Source



Initial Map

BCICP



1. Detect/remove outliers
2. Improve coverage
3. Improve continuity
4. Promote bijectivity
5. Refine in the spectral domain



Refined Map

Continuous and Orientation-preserving Correspondences via Functional Maps, *J. Ren, A. Poulernard, P. Wonka, M. O.*, SIGGRAPH Asia 2018

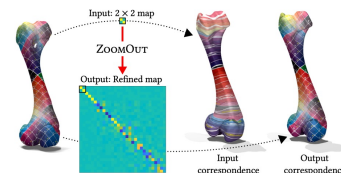
Advanced, but **complicated**

Map Refinement



Map Refinement

2012



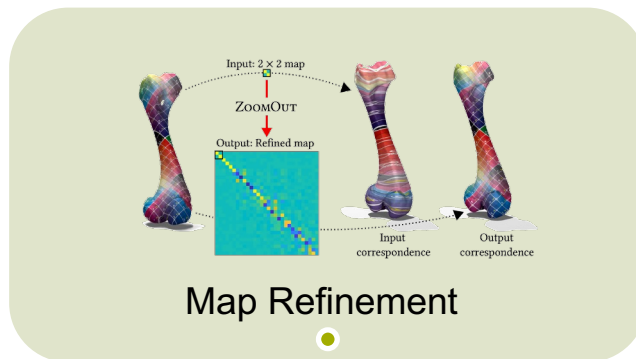
2018

2019

2020

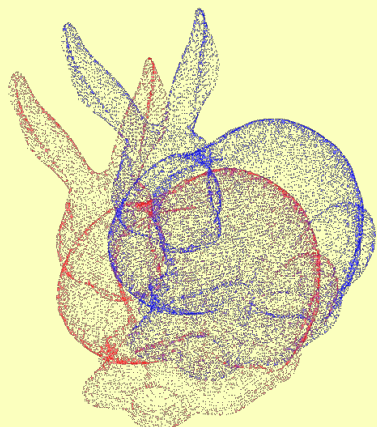
Simple, effective

Map Refinement: ZoomOut



2019

Iteration 0



Initial Map:



while spectrally upsampling

1. **Correspondence**
(Point Map)
2. **Rigid Alignment**
(Functional Map)

Source
 $n = 4.3K$



Ini: 4×4



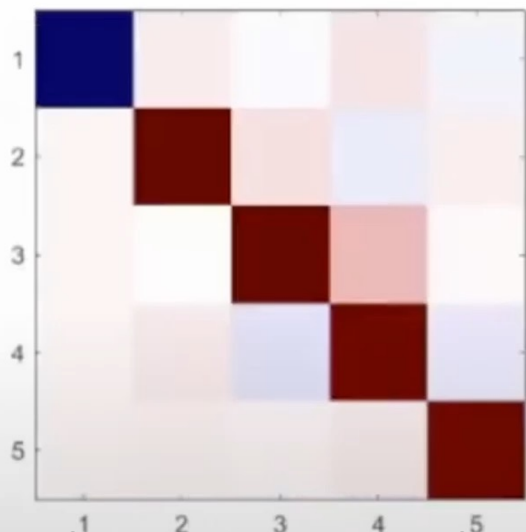
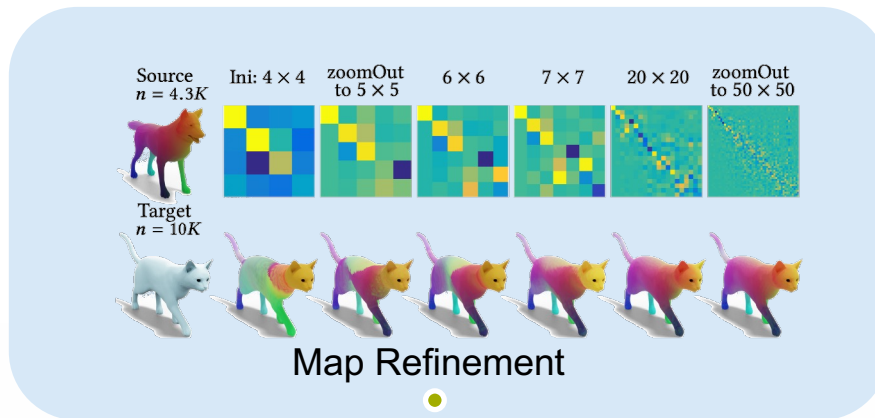
zoomOut
to 5×5



Target
 $n = 10K$



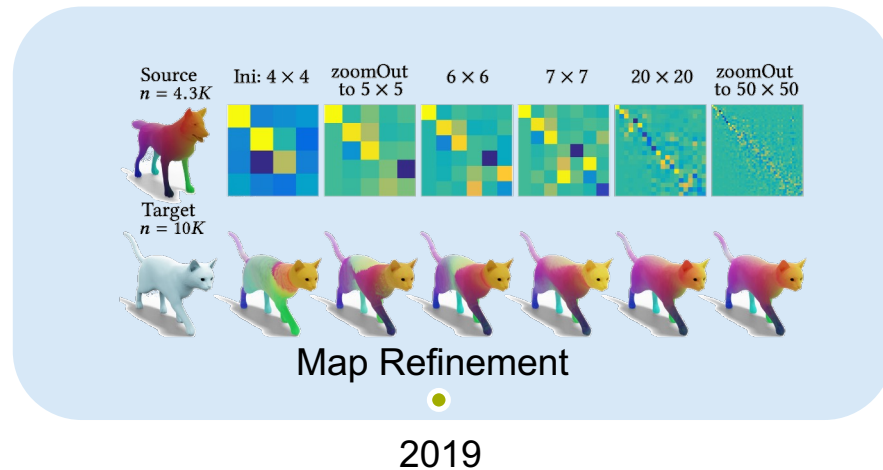
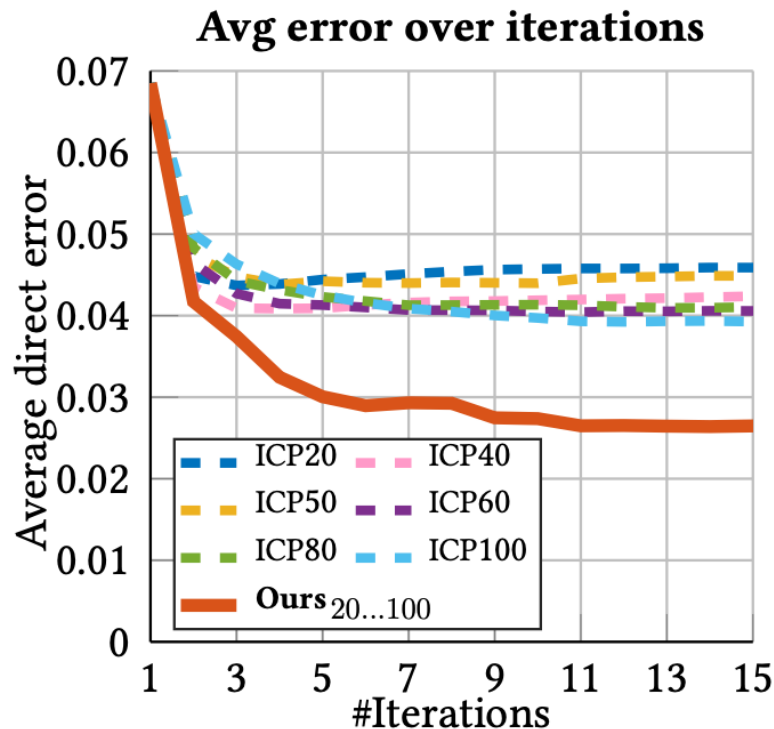
Map Refinement: ZoomOut



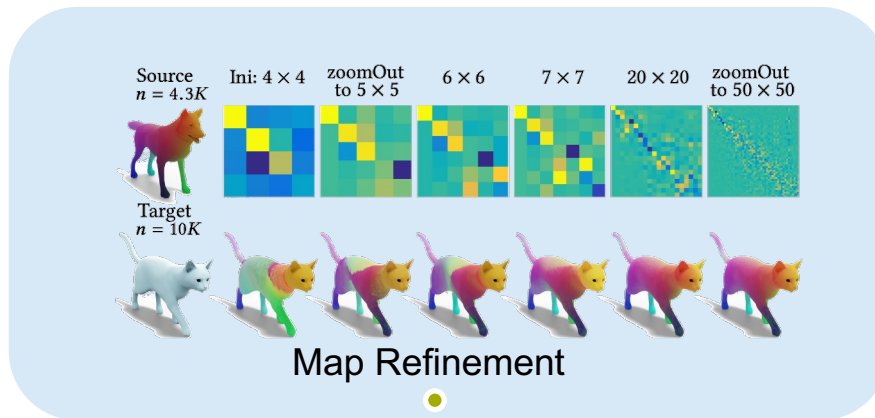
2019



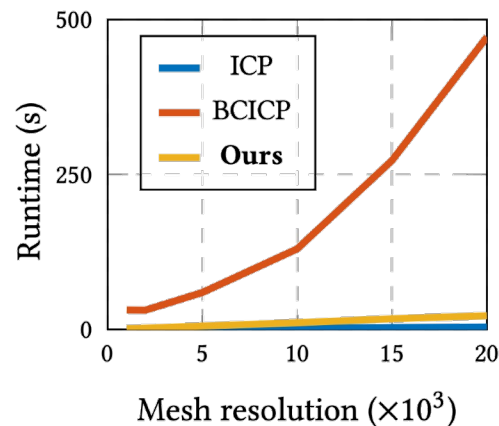
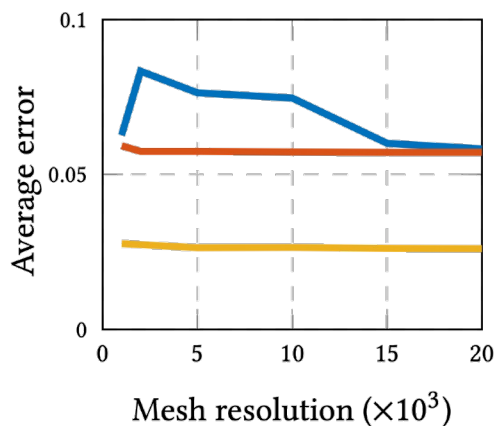
Map Refinement: ZoomOut



Map Refinement: ZoomOut



2019



Applications



Map Refinement

2012

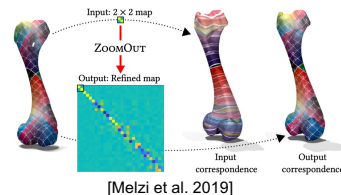


FAUST [Bogo et al. '14]

TOSCA [Bronstein et al. '08]

SCAPE [Angelov et al. '05]

Shape Matching



2018

2020

2019



Donati et al. 2020

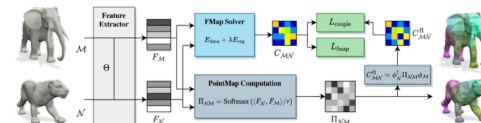
2017

2023



[Litany et al. 2017]

2020



[Cao et al. 2023]

Deep Functional Maps

2012

FAUST [Bogo et al. '14] TOSCA [Bronstein et al. '08] SCAPE [Angelov et al. '05]

Shape Matching

The diagram shows three examples of shape matching. Each example consists of two 3D point cloud models of a human figure. The first model is rendered in a single color (e.g., green), and the second is rendered in a multi-color gradient (e.g., purple to yellow). A dense network of thin, colored lines connects corresponding points between the two models, illustrating the mapping process. A small blue dot is positioned above the TOSCA example.

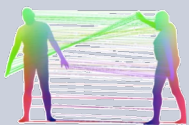
$$b = C \cdot a$$

The diagram illustrates the equation $b = C \cdot a$. On the left, a vertical column of five colored squares (red, white, black, white, grey) represents the vector b . To its right is an equals sign. Further right is a 5x5 grid of colored squares (blue, orange, white, blue, orange) representing the matrix C . To the right of the matrix is another vertical column of five colored squares (red, white, black, white, grey) representing the vector a .

Translates coefficients

Given two shapes, find a map

2012



FAUST [Bogo et al. '14]



TOSCA [Bronstein et al. '08]



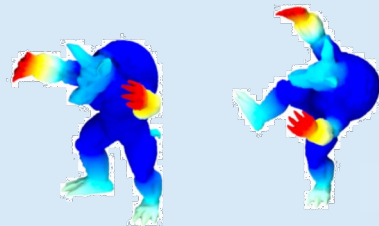
SCAPE [Anguelov et al. '05]

Shape Matching

Given two shapes, find a map

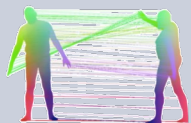
Given a pair of shapes \mathcal{M}, \mathcal{N} :

1. Compute the first k ($\sim 80-100$) eigenfunctions of the Laplace-Beltrami operator. Store them in matrices: $\Phi_{\mathcal{M}}, \Phi_{\mathcal{N}}$
2. Compute descriptor functions (e.g., Wave Kernel Signature) on \mathcal{M}, \mathcal{N} . Express them in $\Phi_{\mathcal{M}}, \Phi_{\mathcal{N}}$, as columns of: \mathbf{A}, \mathbf{B}
3. Solve $C_{\text{opt}} = \arg \min_C \|C\mathbf{A} - \mathbf{B}\|^2 + \|C\Delta_{\mathcal{M}} - \Delta_{\mathcal{N}}C\|^2$
 $\Delta_{\mathcal{M}}, \Delta_{\mathcal{N}}$: diagonal matrices of eigenvalues of LB operator
4. Convert the functional map C_{opt} to a point to point map T .



Shape Matching

2012



FAUST [Bogo et al. '14]



TOSCA [Bronstein et al. '08]



SCAPE [Anguelov et al. '05]

Shape Matching

Given two shapes, find a map



3. Solve

$$\begin{bmatrix} \text{purple} \\ \text{orange} \\ \text{black} \end{bmatrix} = \begin{bmatrix} \text{white} & \text{blue} & \text{white} \\ \text{white} & \text{white} & \text{white} \\ \text{white} & \text{white} & \text{white} \end{bmatrix} \begin{bmatrix} \text{purple} \\ \text{orange} \\ \text{black} \end{bmatrix}$$

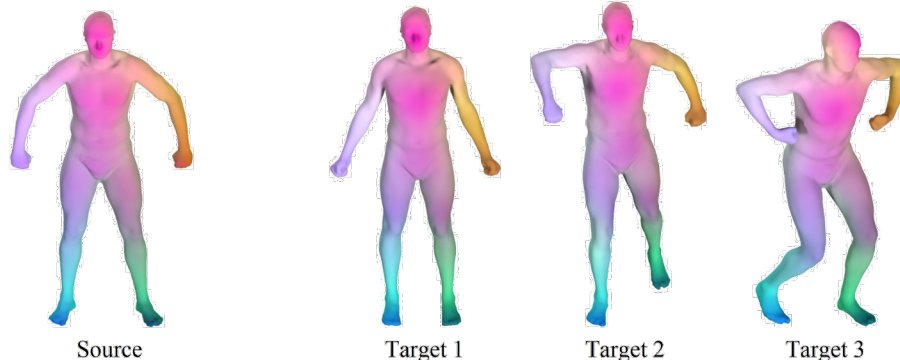


and some regularization

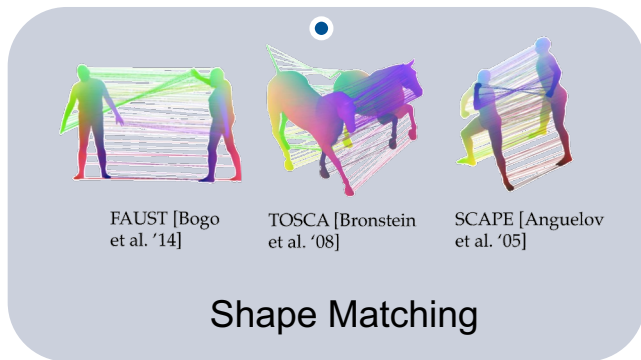
1. Feature Descriptors

2. Feature coefficients

Shape Matching



2012



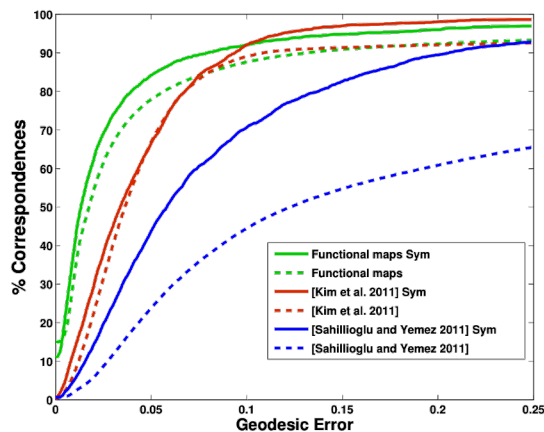
FAUST [Bogo et al. '14]

TOSCA [Bronstein et al. '08]

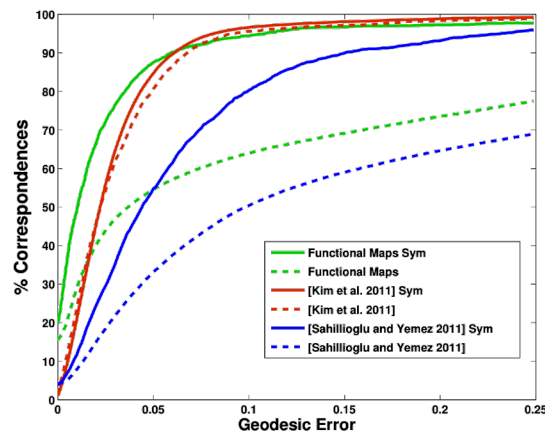
SCAPE [Angelov et al. '05]

Shape Matching

- Functional maps Sym
- - - Functional maps
- [Kim et al. 2011] Sym
- - - [Kim et al. 2011]
- [Sahillioglu and Yemez 2011] Sym
- - - [Sahillioglu and Yemez 2011]



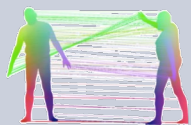
(a) SCAPE



(b) TOSCA

Shape Matching

2012



FAUST [Bogo et al. '14]



TOSCA [Bronstein et al. '08]



SCAPE [Angelov et al. '05]

Shape Matching

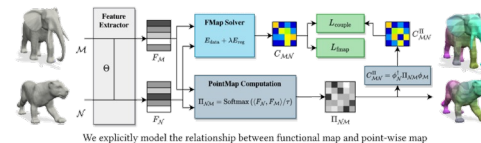
2017



2020



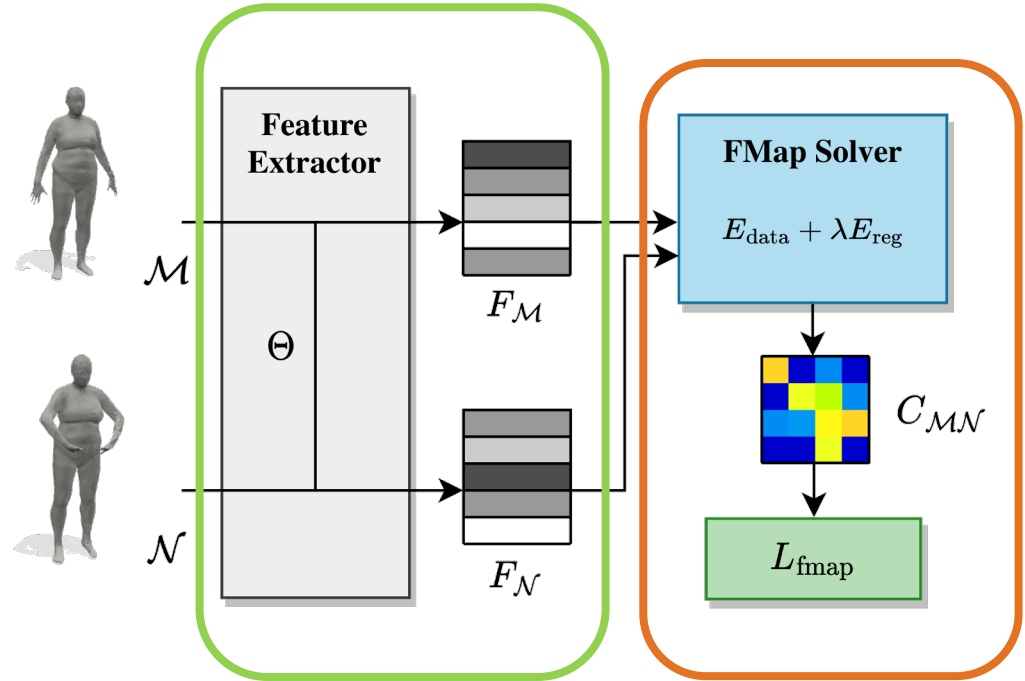
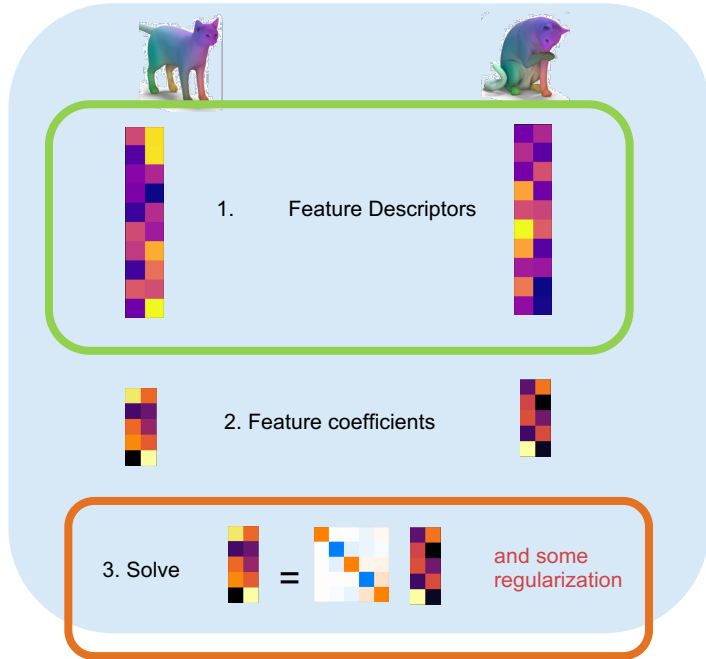
2023



Deep Functional Maps

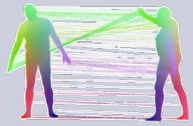
Given two shapes, find a map

Shape Matching



Unsupervised Learning of Robust Spectral Shape Matching

2023



FAUST [Bogo et al. '14]

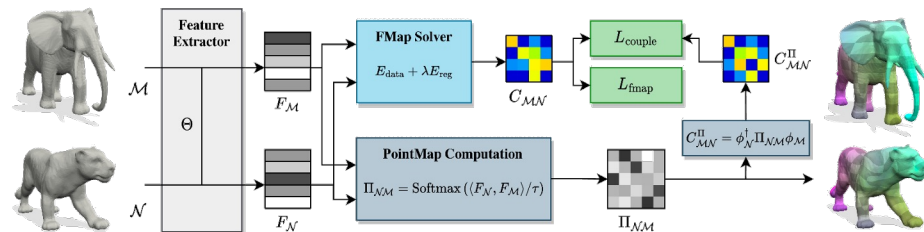
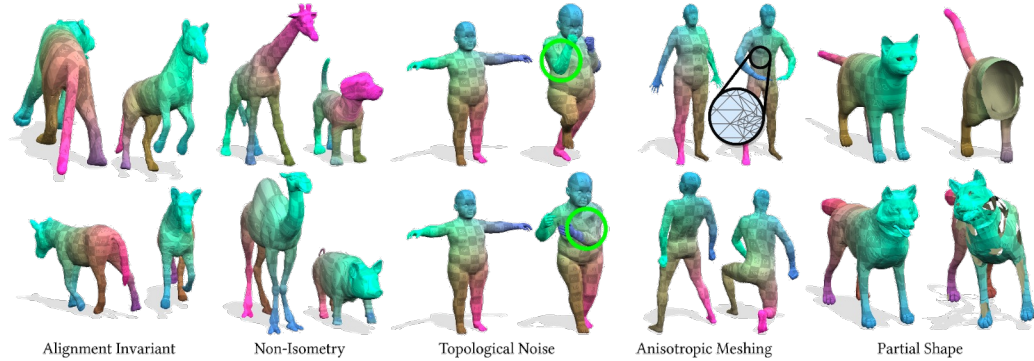


TOSCA [Bronstein et al. '08]



SCAPE [Anguelov et al. '05]

Shape Matching



We explicitly model the relationship between functional map and point-wise map

Table 3. **Near-isometric shape matching and cross-dataset generalisation on FAUST, SCAPE and SHREC’19**. The numbers in parentheses show refined results using the indicated post-processing technique. The **best** results in each column are highlighted. Our method outperforms previous axiomatic, supervised and unsupervised methods in most settings without any post-processing techniques and demonstrates better cross-dataset generalisation ability (see columns in which *Train* and *Test* are different).

Train	FAUST			SCAPE			FAUST + SCAPE		
	FAUST	SCAPE	SHREC’19	FAUST	SCAPE	SHREC’19	FAUST	SCAPE	SHREC’19
Axiomatic Methods									
BCICP	6.1	11.0	-	6.1	11.0	-	6.1	11.0	-
ZoomOut	6.1	7.5	-	6.1	7.5	-	6.1	7.5	-
Smooth Shells	2.5	4.7	-	2.5	4.7	-	2.5	4.7	-
DiscreteOp	5.6	13.1	-	5.6	13.1	-	5.6	13.1	-
Supervised Methods									
FMNet (+ <i>pmf</i>)	11.0 (5.9)	30.0 (11.0)	-	33.0 (14.0)	17.0 (6.3)	-	-	-	-
3D-CODED	2.5	31.0	-	33.0	31.0	-	-	-	-
HSN	3.3	25.4	-	16.7	3.5	-	-	-	-
ACSCNN	2.7	8.4	-	6.0	3.2	-	-	-	-
GeomFMaps (+ <i>zoomout</i>)	2.6 (1.9)	3.4 (2.4)	9.9 (7.9)	3.0 (1.9)	3.0 (2.4)	12.2 (9.8)	2.6 (1.9)	2.9 (2.4)	7.9 (7.5)
TransMatch	1.7	30.4	14.5	15.5	12.0	37.5	1.6	11.7	10.9
Unsupervised Methods									
SURFMNet (+ <i>icp</i>)	15.0 (7.4)	32.0 (19.0)	-	32.0 (23.0)	12.0 (6.1)	-	33.0 (23.0)	29.0 (17.0)	-
UnsupFMNet (+ <i>pmf</i>)	10.0 (5.7)	29.0 (12.0)	-	22.0 (9.3)	16.0 (10.0)	-	11.0 (6.7)	13.0 (8.3)	-
WSupFMNet (+ <i>zoomout</i>)	3.8 (1.9)	4.8 (2.7)	-	3.6 (1.9)	4.4 (2.6)	-	3.6 (1.9)	4.5 (2.6)	-
Deep Shells	1.7	5.4	27.4	2.7	2.5	23.4	1.6	2.4	21.1
NeuroMorph	8.5	28.5	26.3	18.2	29.9	27.6	9.1	27.3	25.3
ConsistFMaps	1.5	3.2	19.7	3.2	2.0	28.3	1.7	3.2	17.8
DUO-FMNet	2.5	4.2	6.4	2.7	2.6	8.4	2.5	4.3	6.4
AttentiveFMaps	1.9	2.6	6.4	2.2	2.2	9.9	1.9	2.3	5.8
AttentiveFMaps-Fast	1.9	2.6	5.8	1.9	2.1	8.1	1.9	2.3	6.3
Ours	1.6	2.2	5.7	1.6	1.9	6.7	1.6	2.1	4.6

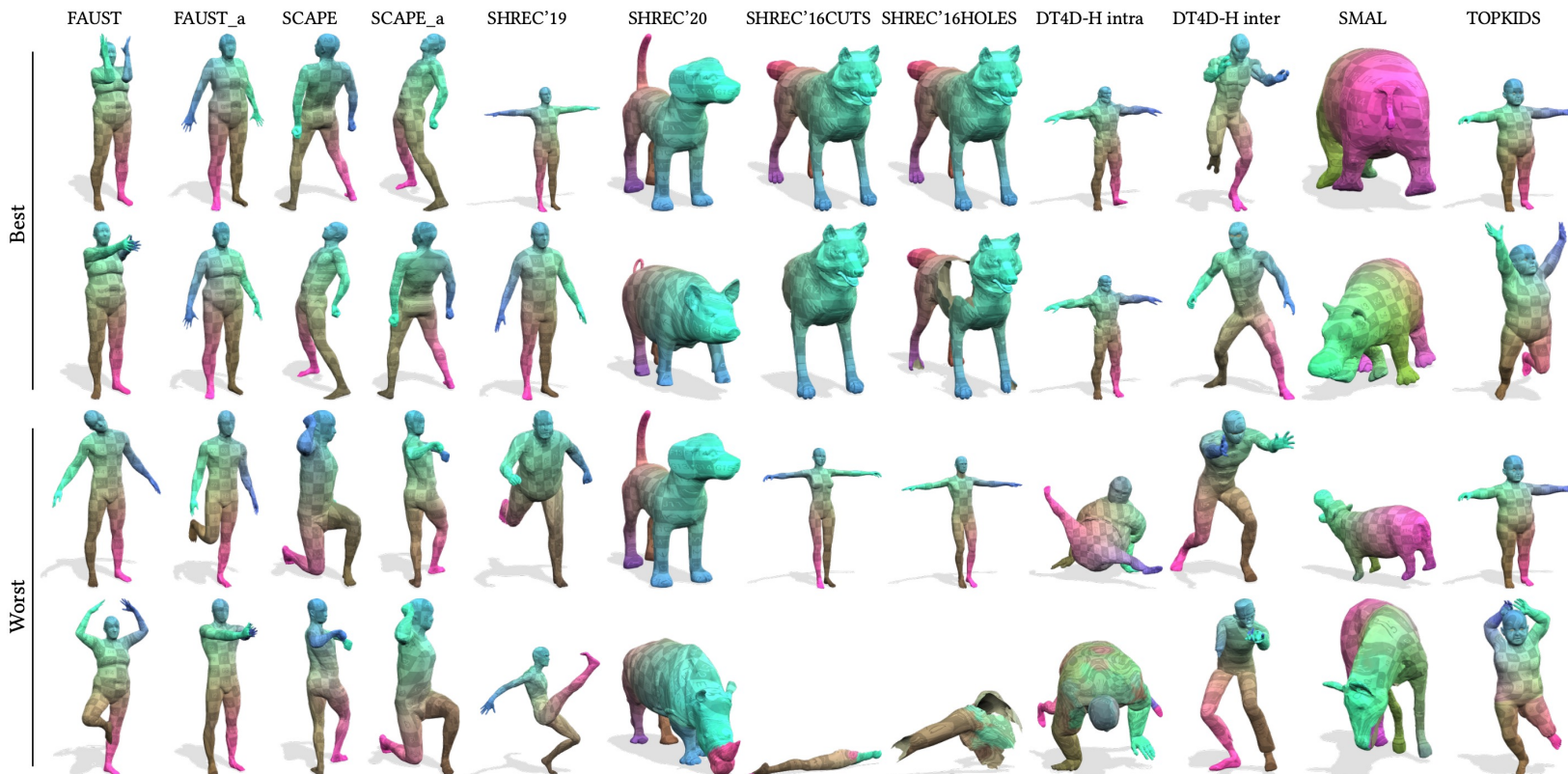
Table 5. **Topological noise on TOPKIDS.** Our method is more robust to topological noise compared to existing methods.

Geo. error ($\times 100$)	TOPKIDS	Fully intrinsic
Axiomatic Methods		
ZoomOut	33.7	✓
Smooth Shells	11.8	✗
DiscreteOp	35.5	✓
Unsupervised Methods		
UnsupFMNet	38.5	✓
SURFMNet	48.6	✓
WSupFMNet	47.9	✓
Deep Shells	13.7	✗
NeuroMorph	13.8	✗
ConsistFMaps	39.3	✓
AttentiveFMaps	23.4	✓
AttentiveFMaps-Fast	28.5	✓
Ours	9.2	✓

Table 6. **Non-isometric matching on SMAL and DT4D-H.** Our method sets to new state of the art on the SMAL dataset by a large margin. For DT4D-H inter-class matching, our method is the first unsupervised method that shows comparable performance to the state-of-the-art supervised method.

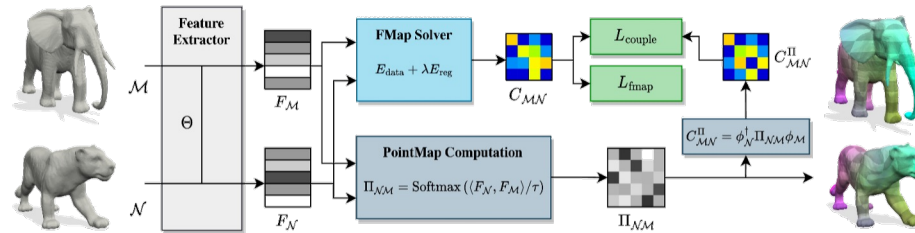
Geo. error ($\times 100$)	SMAL	DT4D-H	
		intra-class	inter-class
Axiomatic Methods			
ZoomOut	38.4	4.0	29.0
Smooth Shells	36.1	1.1	6.3
DiscreteOp	38.1	3.6	27.6
Supervised Methods			
FMNet	42.0	9.6	38.0
GeomFMaps	8.4	2.1	4.1
Unsupervised Methods			
WSupFMNet	7.6	3.3	22.6
Deep Shells	29.3	3.4	31.1
DUO-FMNet	6.7	2.6	15.8
AttentiveFMaps	5.4	1.7	11.6
AttentiveFMaps-Fast	5.8	1.2	14.6
Ours	3.9	0.9	4.1

Shape Matching



Near isometries are near perfect

Shape Matching



We explicitly model the relationship between functional map and point-wise map

1. 200 basis functions
2. Point Map + Functional Map
3. Unsupervised Test Time Adaptation
4. Extensive evaluations
5. ...

Very well
execution

Shape Matching



Failure Case



Partiality

Extreme Non-isometry

Topological Noise

5. Summary

Functional Maps: A Flexible Representation of Maps Between Shapes

Maks Ovsjanikov[†]

Mirela Ben-Chen[‡]

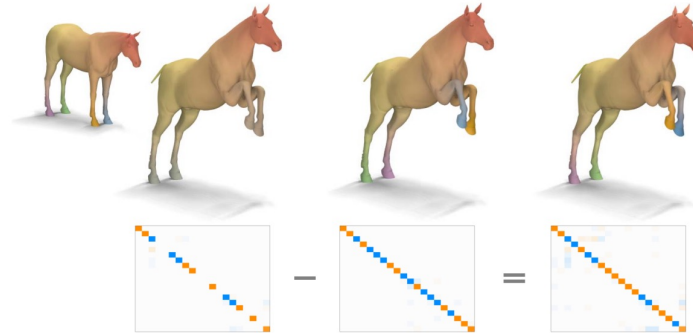
Justin Solomon[‡]

Adrian Butscher[‡]

Leonidas Guibas[‡]

[†] LIX, École Polytechnique

[‡] Stanford University



Small

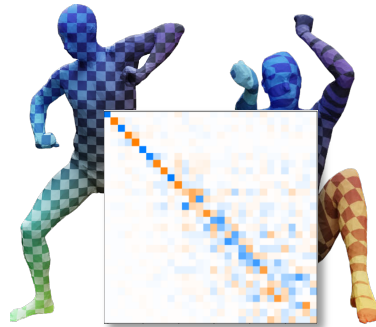
Accurate

Efficient

Flexible

$$C = \Phi_1^\dagger \cdot P \cdot \Phi_2$$

Approximation
of Point Map



linear, compact
and flexible

$$b = C \cdot a$$

Translates coefficients

$$C = \Phi_1^\dagger \cdot \Phi_{2a}$$

Columns are **coefficients** of target basis

$$\Phi_1 \cdot C = \Phi_{2a}$$

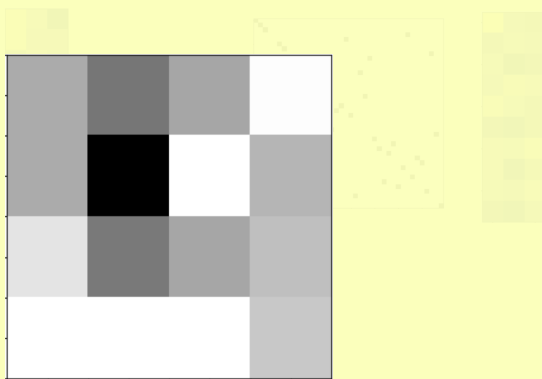
Aligns Bases

Solution Space

Rigid
 $4 \times 4 R, t$



aligns
xyz
coordinates



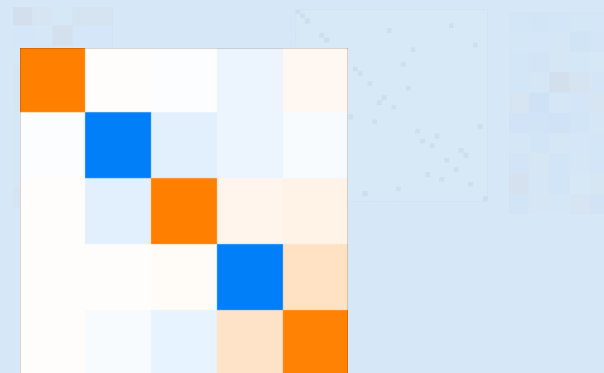
Alignment to
correspondences

Search for
Nearest Neighbor
in xyz
coordinates

Non-rigid
 $k \times k C$



aligns
spectral
embeddings



Alignment to
correspondences

Search for
Nearest Neighbor
in spectral
embeddings

Shape Matching



Failure Case



Partiality

Extreme Non-isometry

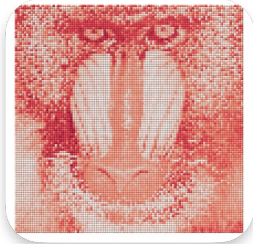
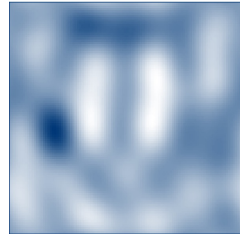
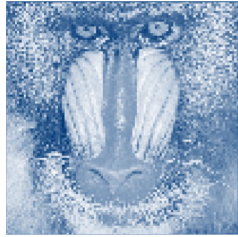
Topological Noise

- 1. Partiality, Non-isometry, Topological Noise**
- 2. Non-rigid Noisy Point Cloud**
- 3. Runtime (eigen problem 1~2 seconds)**
- 4. Unsupervised feature learning**
- 5. ...**

References

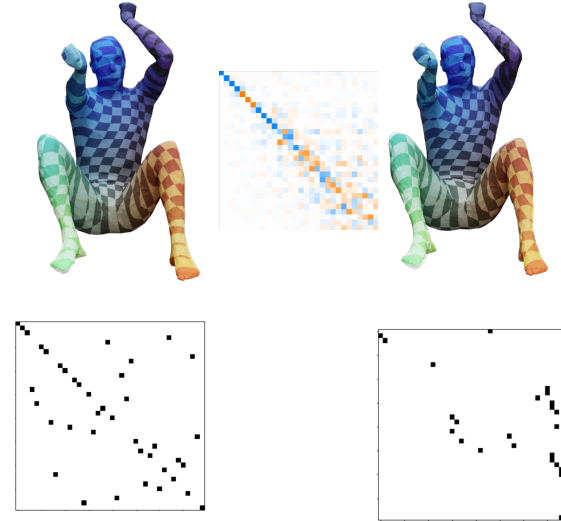


- [1] Ovsjanikov, M., Ben-Chen, M., Solomon, J., Butscher, A., & Guibas, L. (2012). Functional maps: a flexible representation of maps between shapes. *ACM Transactions on Graphics (ToG)*, 31(4), 1-11.
 - [2] Sharp, N., Attaiki, S., Crane, K., & Ovsjanikov, M. (2022). Diffusionnet: Discretization agnostic learning on surfaces. *ACM Transactions on Graphics (TOG)*, 41(3), 1-16.
 - [3] Ovsjanikov, M., Corman, E., Bronstein, M., Rodolà, E., Ben-Chen, M., Guibas, L., ... & Bronstein, A. (2016). Computing and processing correspondences with functional maps. In *SIGGRAPH ASIA 2016 Courses* (pp. 1-60).
 - [4] Rippel, O., Snoek, J., & Adams, R. P. (2015). Spectral representations for convolutional neural networks. *Advances in neural information processing systems*, 28.
 - [5] Melzi, S., Ren, J., Rodola, E., Sharma, A., Wonka, P., & Ovsjanikov, M. (2019). Zoomout: Spectral upsampling for efficient shape correspondence. *arXiv preprint arXiv:1904.07865*.
 - [6] Donati, N., Sharma, A., & Ovsjanikov, M. (2020). Deep geometric functional maps: Robust feature learning for shape correspondence. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition* (pp. 8592-8601).
 - [7] Litany, O., Remez, T., Rodola, E., Bronstein, A., & Bronstein, M. (2017). Deep functional maps: Structured prediction for dense shape correspondence. In *Proceedings of the IEEE international conference on computer vision* (pp. 5659-5667).
 - [8] Cao, D., Roetzer, P., & Bernard, F. (2023). Unsupervised Learning of Robust Spectral Shape Matching. *arXiv preprint arXiv:2304.14419*.
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- Additional resources:
- [10] Blog post on SIGGRAPH 2023 Technical Papers Awards: <https://blog.siggraph.org/2023/07/siggraph-2023-technical-papers-awards-best-papers-honorable-mentions-and-test-of-time.html>
 - [11] Tweet by Adam W. Harley: <https://twitter.com/AdamWHarley/status/1688661551744798721>
 - [12] Article on Fourier Transformation in Image Processing: <https://medium.com/crossml/fourier-transformation-in-image-processing-84142263d734>
 - [13] YouTube video on Chladni plate patterns: <https://youtu.be/wvJAgUBF4w>
 - [14] YouTube video on Iterative Closest Point: https://www.youtube.com/watch?v=uzOCS_gdZuM
 - [15] Lecture notes on the Laplace-Beltrami operator: <https://brickisland.net/DDGSpring2021/2021/04/20/lecture-18-the-laplace-beltrami-operator/>
 - [16] Wikipedia page on Linear Algebra: https://en.wikipedia.org/wiki/Linear_algebra
 - [17] MIT course webpage: https://groups.csail.mit.edu/gdpgroup/6838_spring_2021.html

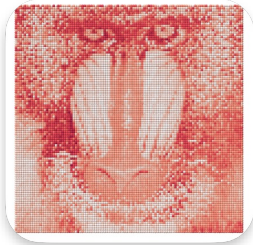
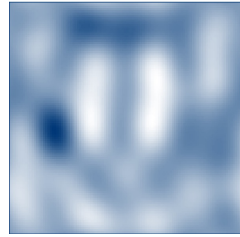
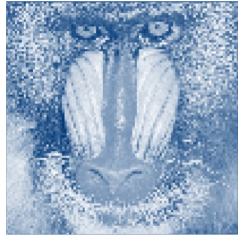


150
Basis coefficients

Does it make sense?

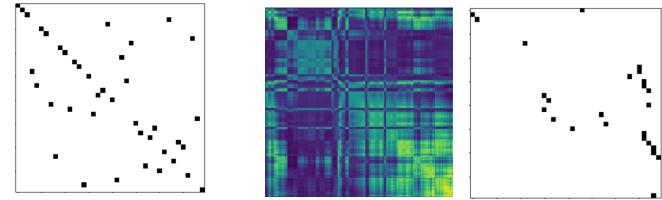
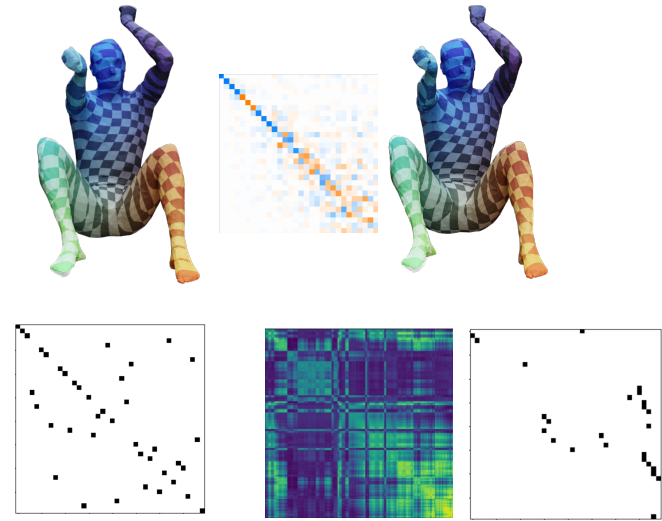


30x30
functional map

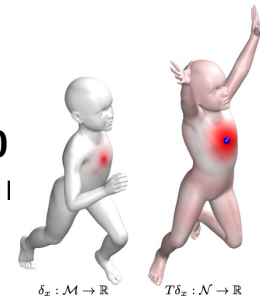


150
Basis coefficients

Does it make sense?



30x30
functional \downarrow



$\delta_x : \mathcal{M} \rightarrow \mathbb{R}$ $T\delta_x : \mathcal{N} \rightarrow \mathbb{R}$

Pixelized



Recovered

Hello from the other side

Original

Hello from the other side