

Isospectralization

or how to hear shape, style and correspondence

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CAN ONE HEAR THE SHAPE OF A DRUM?

MARK KAC, The Rockefeller University, New York

To George Eugene Uhlenbeck on the occasion of his sixty-fifth birthday

“La Physique ne nous donne pas seulement
l’occasion de résoudre des problèmes . . . , elle nous
fait présentir la solution.” H. POINCARÉ.

Wave equation



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$$\frac{\partial^2 u(x, y; t)}{\partial t^2} = \Delta u(x, y; t)$$

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$$\Delta \phi_i = \lambda_i \phi_i$$

$$u(x, y; t) = \sum_j d_j \phi_j(x, y) \left(\cos(\sqrt{\lambda_j} t) + i \sin(\sqrt{\lambda_j} t) \right)$$

λ = vibration frequencies

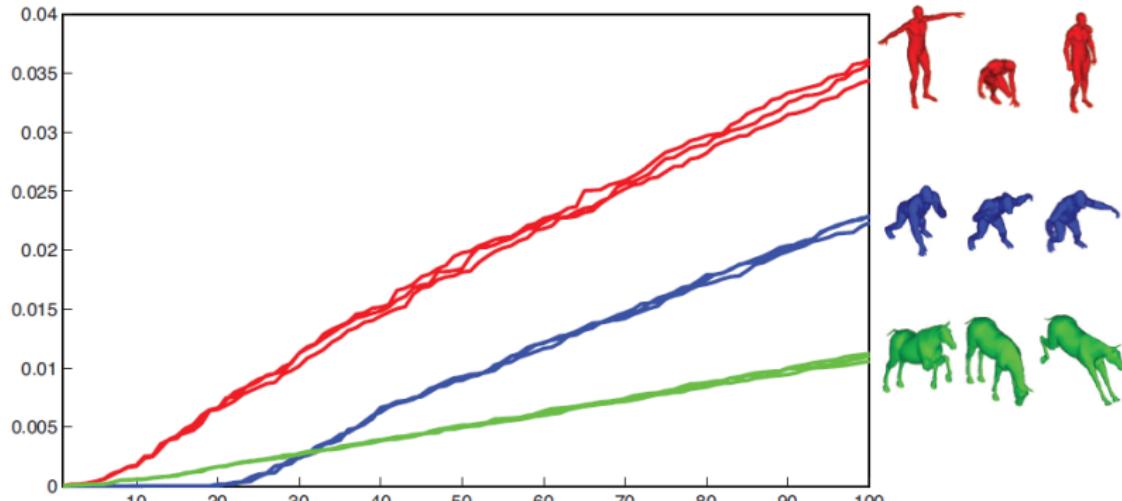
λ = vibration frequencies

ϕ = vibration modes

isometric \implies **isospectral**

isometric $\xrightleftharpoons{?}$ **isospectral**

Shape DNA



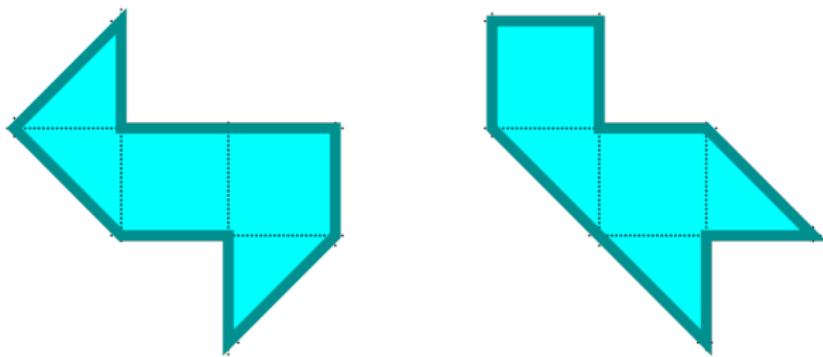
Laplacian spectrum used as deformation-invariant shape descriptor

Can we reconstruct the shape
from the sequence (λ_i) ?

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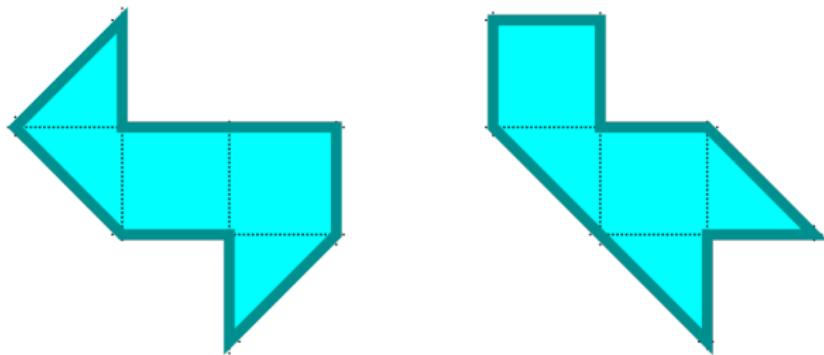
$$\int_{\mathcal{M}} \|\nabla \phi_i(x)\|^2 dx = \lambda_i$$

Not technically...



“One cannot hear the shape of the drum”, Gordon et al., 1991

Not technically...

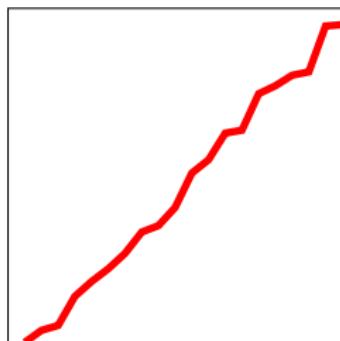


Claim: Isospectral non-isometric shapes are rare

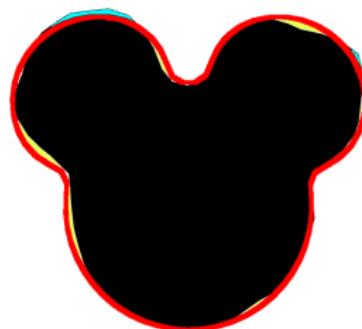
“One cannot hear the shape of the drum”, Gordon et al., 1991

Mickey-from-spectrum

In practice, it seems we can!

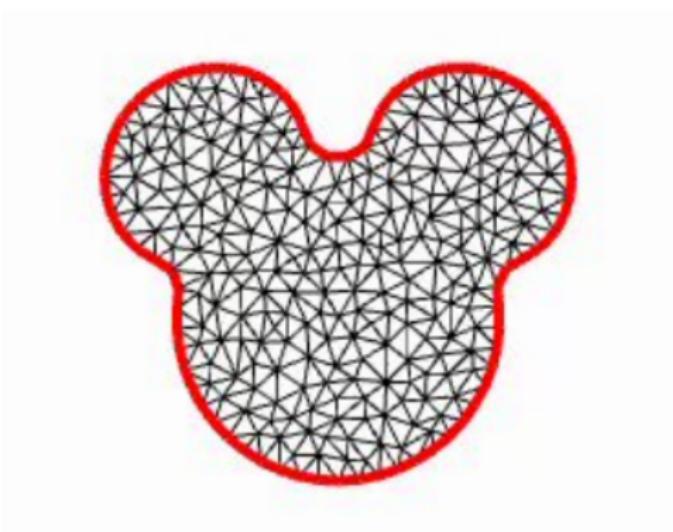


Input



Output

Discretization: shapes



Discretization: Laplace-Beltrami operator

1st order FEM discretization yields:

$$\mathbf{L} = \mathbf{A}^{-1} \mathbf{S}$$

where $\mathbf{S} = (s_{ij})$ is the **stiffness matrix** and $\mathbf{A} = (a_{ij})$ is the **mass matrix**.

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$$s_{ij} = \begin{cases} \frac{-\ell_{ij}^2 + \ell_{jk}^2 + \ell_{ki}^2}{8A_{ijk}} + \frac{-\ell_{ij}^2 + \ell_{jh}^2 + \ell_{hi}^2}{8A_{ijh}} & \text{if } e_{ij} \in E_i \\ \frac{-\ell_{ij}^2 + \ell_{jh}^2 + \ell_{hi}^2}{8A_{ijh}} & \text{if } e_{ij} \in E_b \\ -\sum_{k \neq i} s_{ik} & \text{if } i = j \end{cases}$$

$$a_{ij} = \begin{cases} \frac{1}{3} \sum_{lk:ilk \in F} A_{ilk} & \text{if } i = j \\ 0 & \text{if } i \neq j \end{cases}$$

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$$\ell_{ij}(\mathbf{X}) = \|\mathbf{X}^i - \mathbf{X}^j\|_2$$

Optimization

$$\min_{\mathbf{X} \in \mathbb{R}^{n \times d}} \|\boldsymbol{\lambda}(\Delta_X(\mathbf{X})) - \boldsymbol{\mu}\|_\omega + \rho_X(\mathbf{X})$$

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A screenshot of a Google search results page. The search bar contains the query "isospectralization". Below the search bar, the "All" tab is selected, followed by "Maps", "Videos", "Images", "Shopping", and "More". To the right of the search bar are a microphone icon and a magnifying glass icon. Below the search bar, the text "Your search - **isospectralization** - did not match any documents." is displayed. Underneath this, the heading "Suggestions:" is shown, followed by a bulleted list of three items.

Your search - **isospectralization** - did not match any documents.

Suggestions:

- Make sure that all words are spelled correctly.
- Try different keywords.
- Try more general keywords.

Optimization

$$\min_{\mathbf{X} \in \mathbb{R}^{n \times d}} \|\boldsymbol{\lambda}(\Delta_X(\mathbf{X})) - \boldsymbol{\mu}\|_\omega + \rho_X(\mathbf{X})$$

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A screenshot of a Google search results page. The search bar at the top contains the query "isospectralization". Below the search bar, there are several navigation links: "All" (which is underlined in blue), "Maps", "Videos", "Images", "Shopping", and "More". To the right of these are "Settings" and "Tools". The main search results section starts with the text "About 255 results (0.29 seconds)". Below this, a result is listed: "Isospectralization, or how to hear shape, style, and correspondence" by L Cosmo - 2018. The URL is <https://arxiv.org>.

About 255 results (0.29 seconds)

Isospectralization, or how to hear shape, style, and correspondence

<https://arxiv.org> > cs ▾

by L Cosmo - 2018

Nov 28, 2018 - In this paper, we introduce a numerical procedure called {item **isospectralization**}, consisting of deforming one shape to make its Laplacian ...

Implementation details

- **Data term:** weighted norm (higher frequencies attenuated)

$$\|\boldsymbol{\lambda} - \boldsymbol{\mu}\|_{\omega}^2 = \sum_{i=1}^k \frac{1}{\mu_i^2} (\lambda_i - \mu_i)^2$$

Implementation details

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$$\rho_1(\mathbf{X}) = \sum_{ij \in \mathcal{E}_b} \ell_{ij}^2(\mathbf{X})$$

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$$\rho_1(\mathbf{X}) = \sum_{ij \in \mathcal{E}_b} \ell_{ij}^2(\mathbf{X})$$

- Avoid triangle flips:

$$\rho_2(\mathbf{X}) = \max \left\{ \sum_{ijk \in \mathcal{F}} (\mathbf{R}_{\frac{\pi}{2}}(\mathbf{x}_j - \mathbf{x}_i))^{\top} (\mathbf{x}_k - \mathbf{x}_i), 0 \right\}$$

Implementation

- Few eigenvalues ($k \leq 30$)

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Implementation

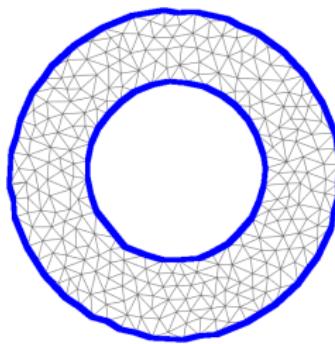
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- Re-sampling step once every 200 iterations

Implementation

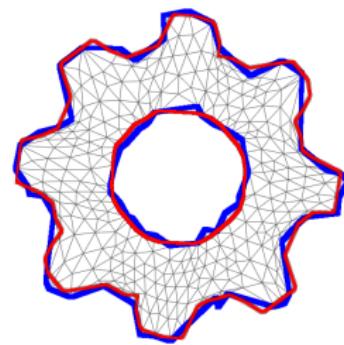
- Few eigenvalues ($k \leq 30$)
- Alternate optimization over boundary and interior points
- Re-sampling step once every 200 iterations
- Adam optimizer with auto-differentiation

Cosmo, Panine, Rampini, Ovsjanikov, Bronstein, Rodolà (CVPR 2019); Kingma and Ba, 2014

Topology

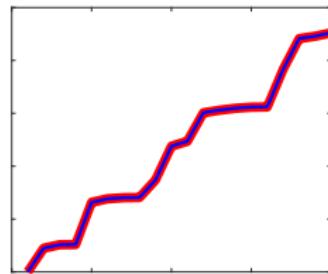
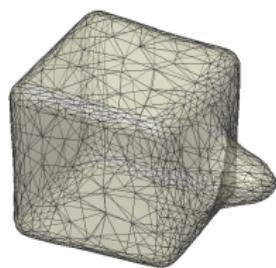
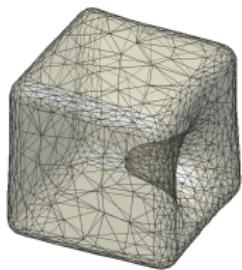


Initialization

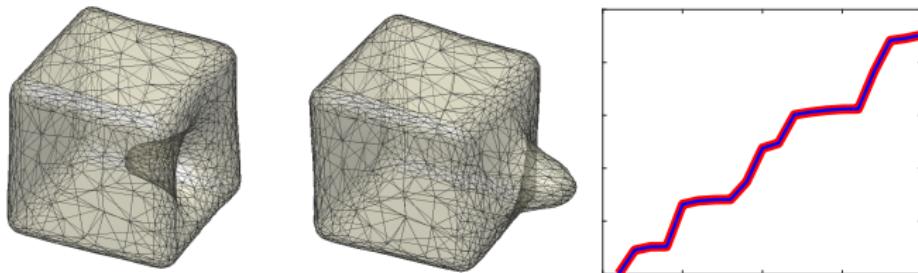


Reconstruction

Reconstruction of surfaces



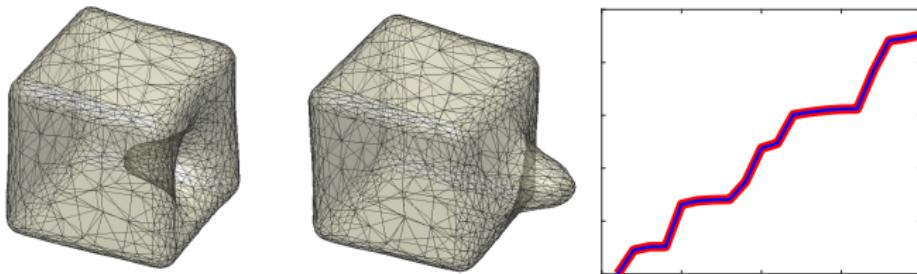
Reconstruction of surfaces



- Smoothness-promoting regularizer:

$$\rho_1(\mathbf{X}) = \|\mathbf{L}\mathbf{X}\|_F^2$$

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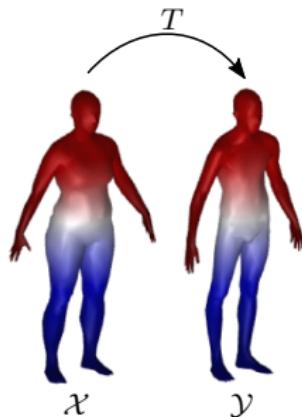
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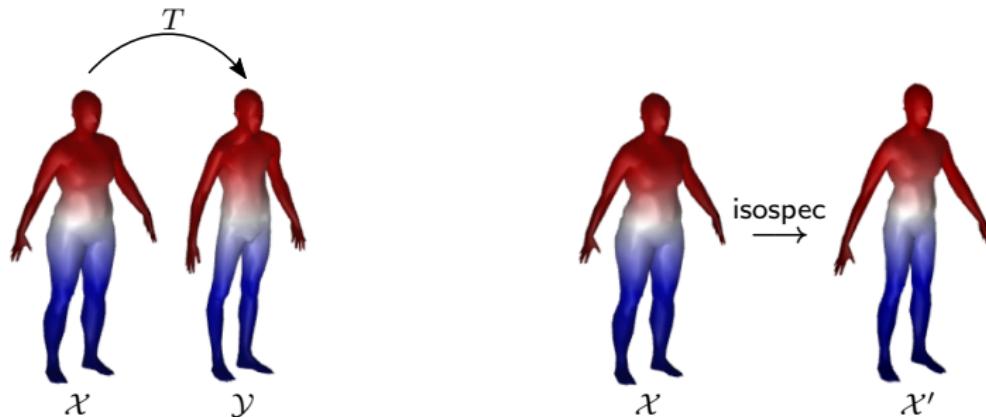
- Volume expansion regularizer to avoid isometric ambiguities:

$$\rho_2(\mathbf{X}) = \left(\begin{smallmatrix} 1 & \\ & 1 & \\ & & 1 \end{smallmatrix}\right)^\top \sum_{ijk \in F} ((\mathbf{X}^j - \mathbf{X}^i) \times (\mathbf{X}^k - \mathbf{X}^j))(\mathbf{X}^i + \mathbf{X}^j + \mathbf{X}^k)$$

Application: non-isometric correspondence

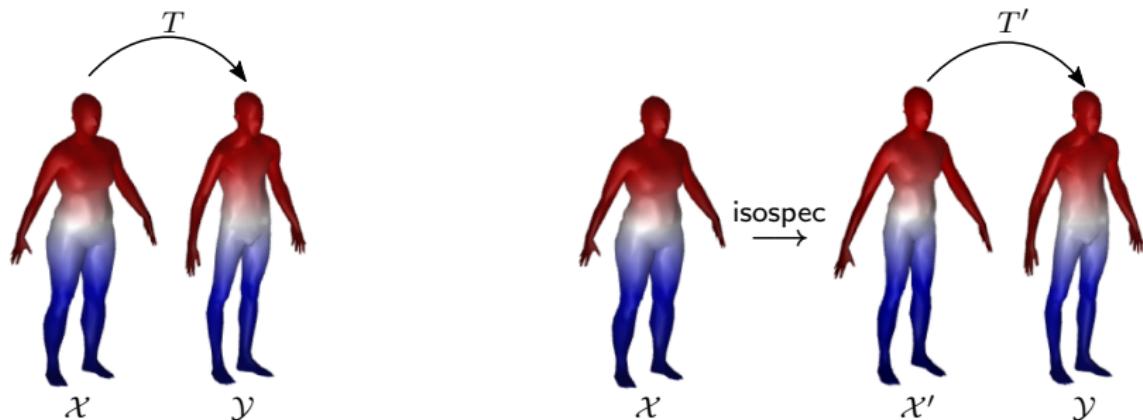


Application: non-isometric correspondence



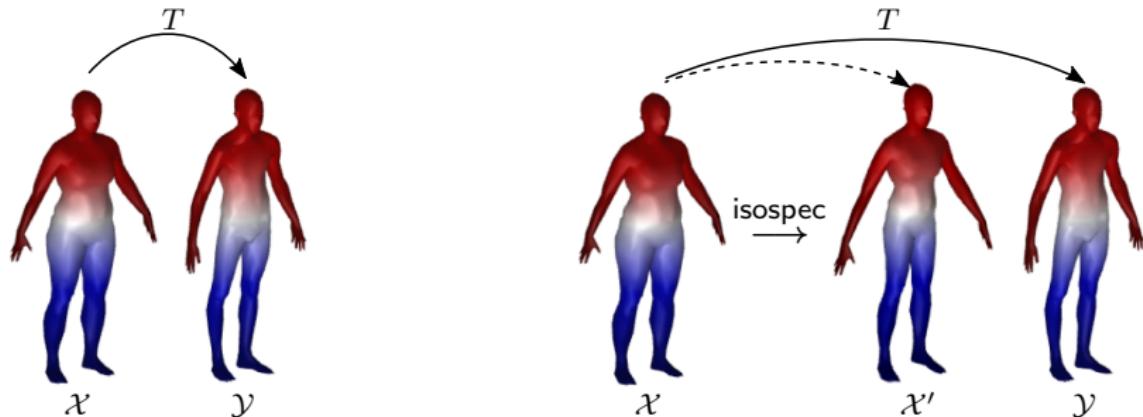
- ① **Isospectralization:** deform \mathcal{X} into \mathcal{X}' whose spectrum $\lambda_{\mathcal{X}'}$ is aligned with $\lambda_{\mathcal{Y}}$

Application: non-isometric correspondence



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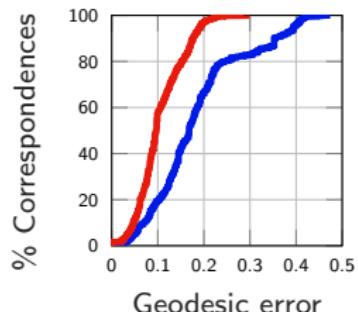
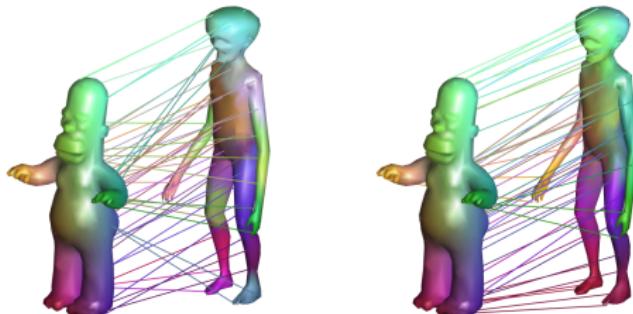
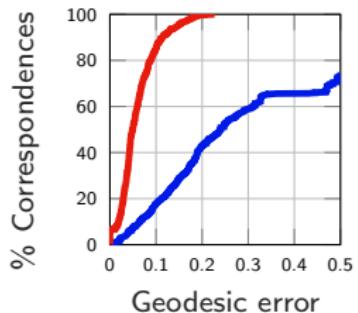
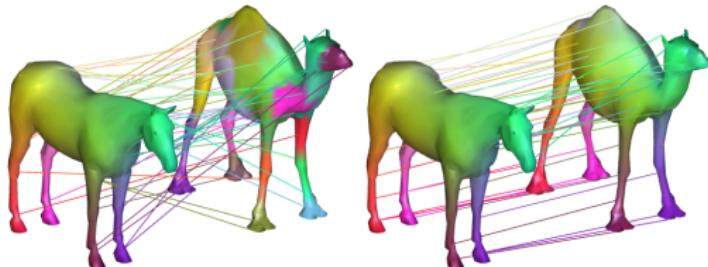
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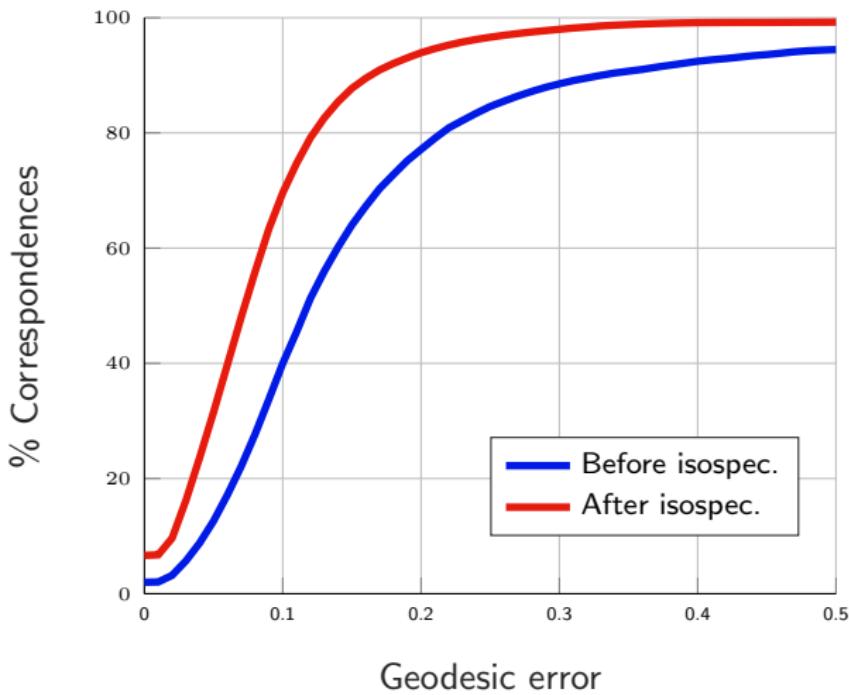
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- ➋ Compute the correspondence $T' : \mathcal{X}' \rightarrow \mathcal{Y}$ using an existing **isometric** matching algorithm
- ➌ Convert T' to $T : \mathcal{X} \rightarrow \mathcal{Y}$ using the identity map between \mathcal{X} and \mathcal{X}' .

Correspondence examples

Before isospectralization **After** isospectralization



Results: average geodesic error



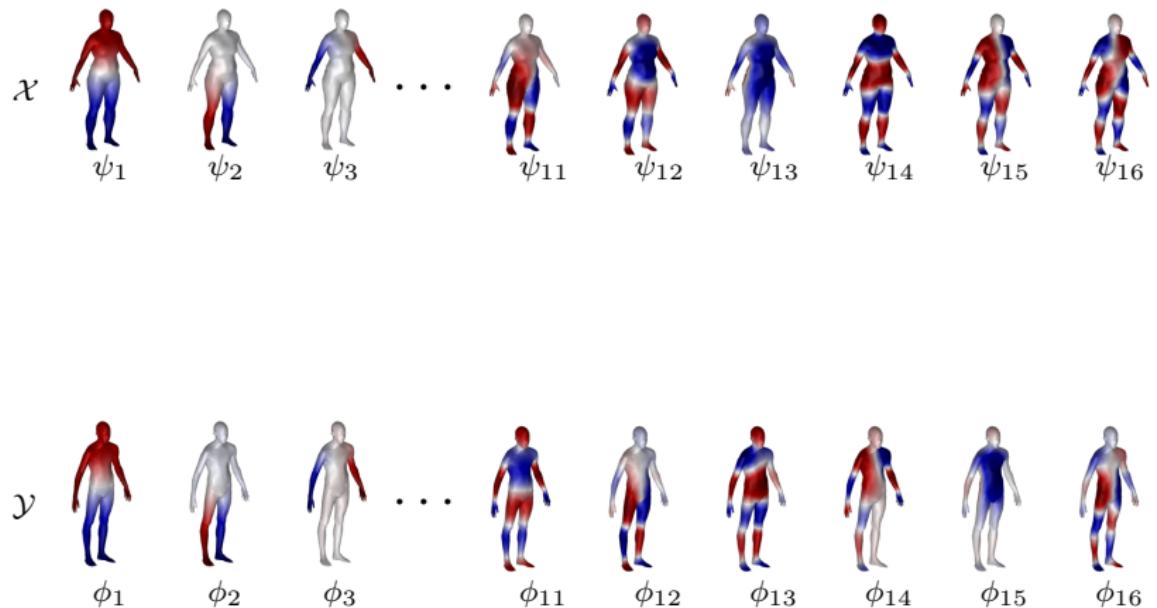
Correspondence examples



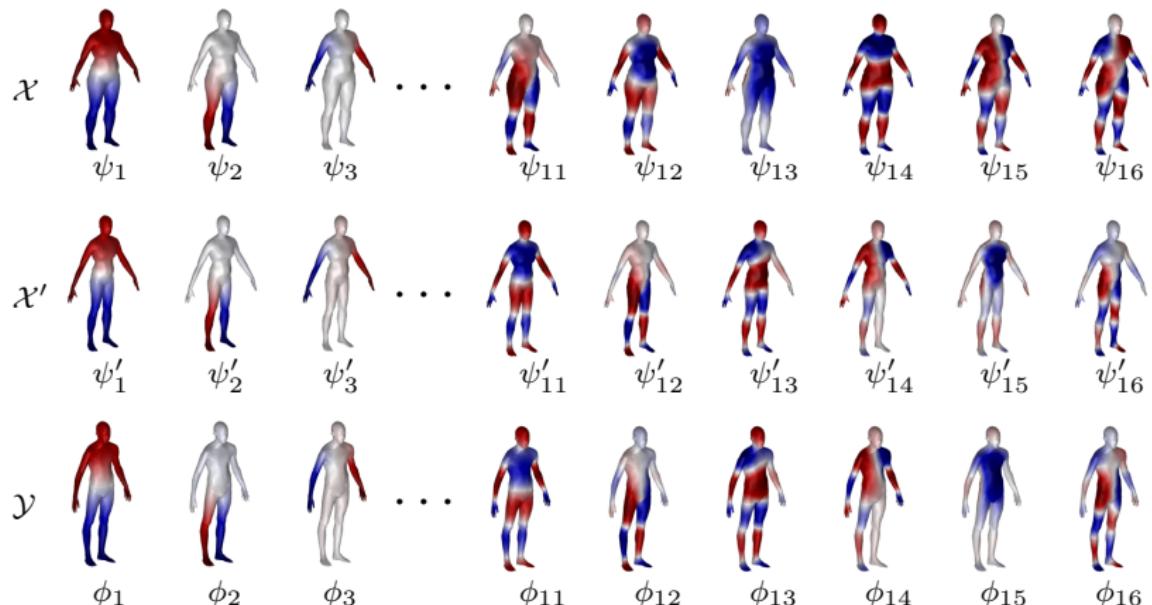
Correspondence examples



Why it works



Why it works



Isospectralization aligns the eigenspaces!

Applications: style transfer

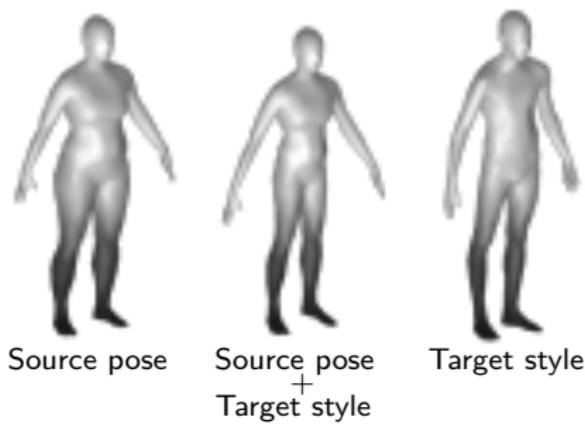


Source pose



Target style

Applications: style transfer



Embedding-free formulation

$$\underbrace{(\Delta + \rho)}_{\text{Hamiltonian } H}$$

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$$\underbrace{(\Delta + \rho)}_{\text{Hamiltonian } H} f(x) = \Delta f(x) + \rho(x)f(x)$$

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$\rho : \mathcal{X} \rightarrow \mathbb{R}_+$ is the **characteristic function** of a region $\mathcal{R} \subset \mathcal{X}$



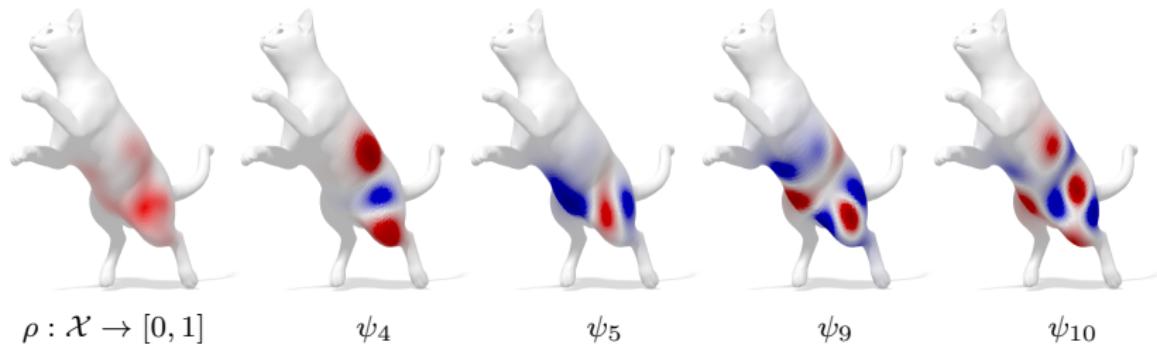
$$\rho : \mathcal{X} \rightarrow [0, 1]$$

Embedding-free formulation

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$$H\psi = \lambda\psi$$



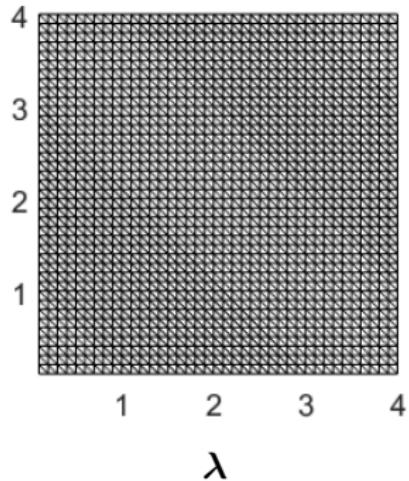
Melzi, Rodolà, Castellani, Bronstein (CGF 2018); Choukroun et al 2017

Embedding-free formulation

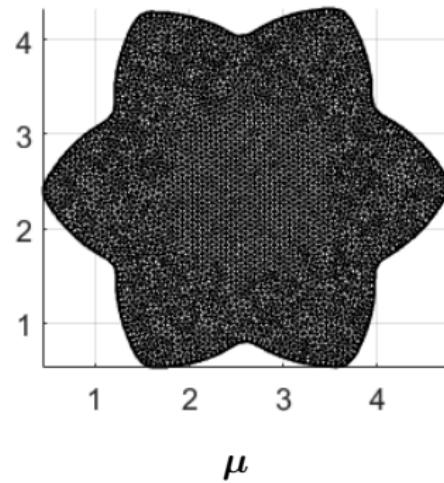
$$\min_{\rho \in [0,1]^{w \times h}} \|\lambda(\Delta + \rho) - \mu\|_w$$

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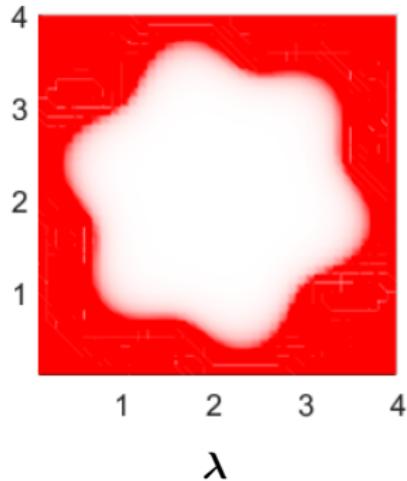
Eigenvalues of the Hamiltonian $\Delta + \rho$



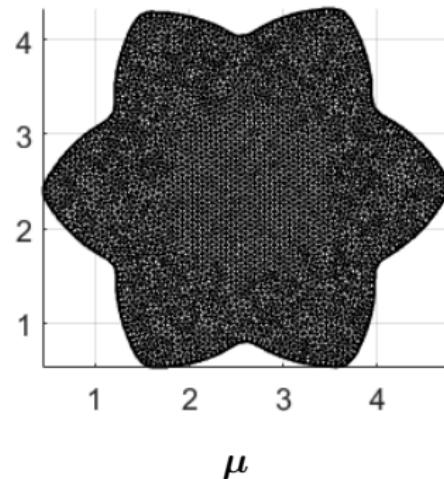
Dirichlet eigenvalues of the Laplacian

Embedding-free formulation

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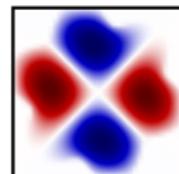
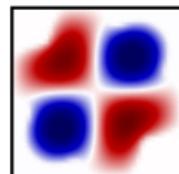
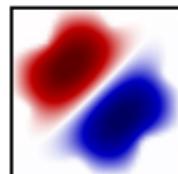
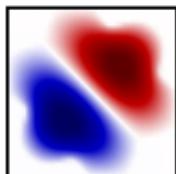
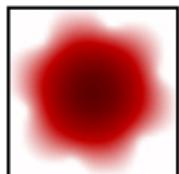
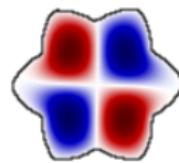
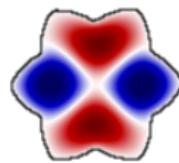
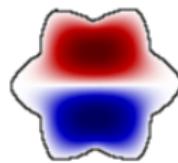
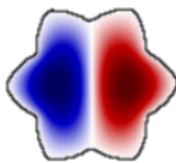
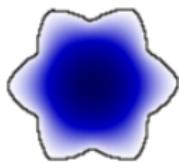
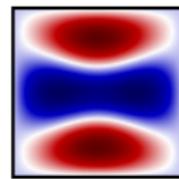
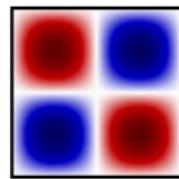
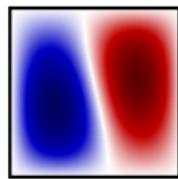
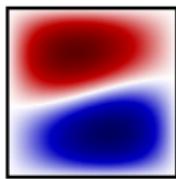
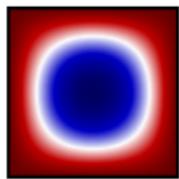


Eigenvalues of the Hamiltonian $\Delta + \rho$

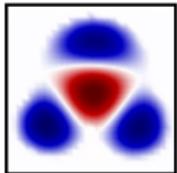
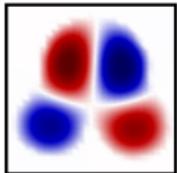
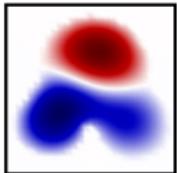
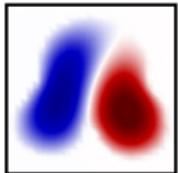
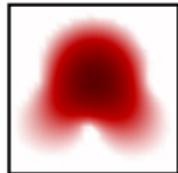
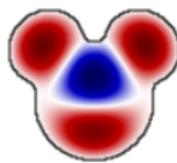
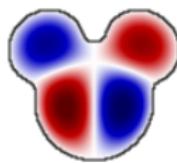
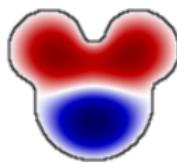
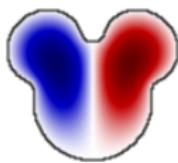
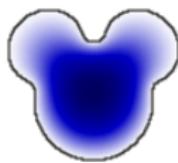
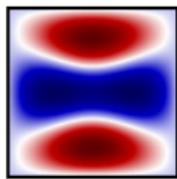
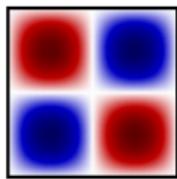
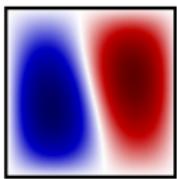
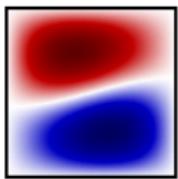
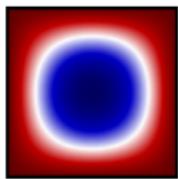


Dirichlet eigenvalues of the Laplacian

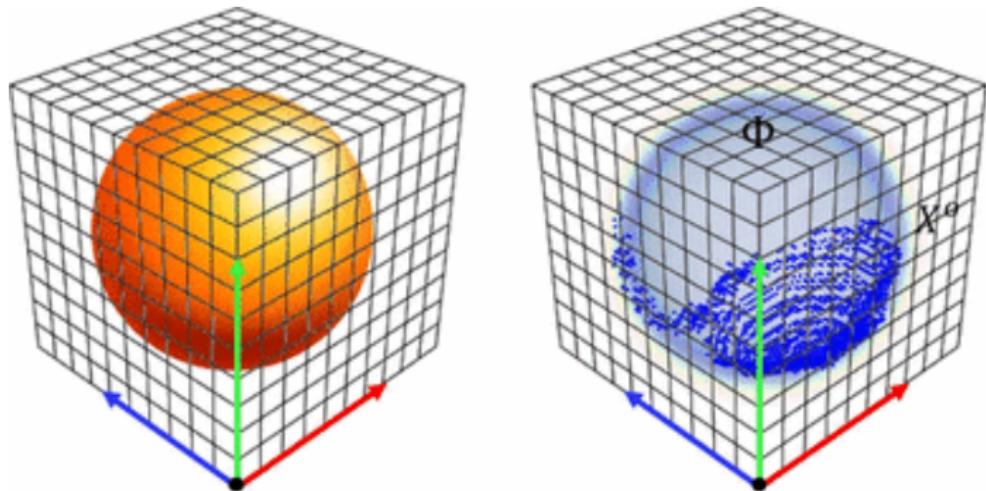
Examples



Examples



Recovering volumes



We may recover 3D shapes by modeling them as potentials in \mathbb{R}^3

Optimization

$$\min_{\rho \in [0,1]^{w \times h}} \|\lambda(\Delta + \rho) - \mu\|_w$$

Algorithm:

- Initialize $\rho = 1$
- Update $\rho^{(t)} = \rho^{(t-1)} - \alpha \nabla \|\lambda(\Delta + \rho^{(t-1)}) - \mu\|_w$

Optimization

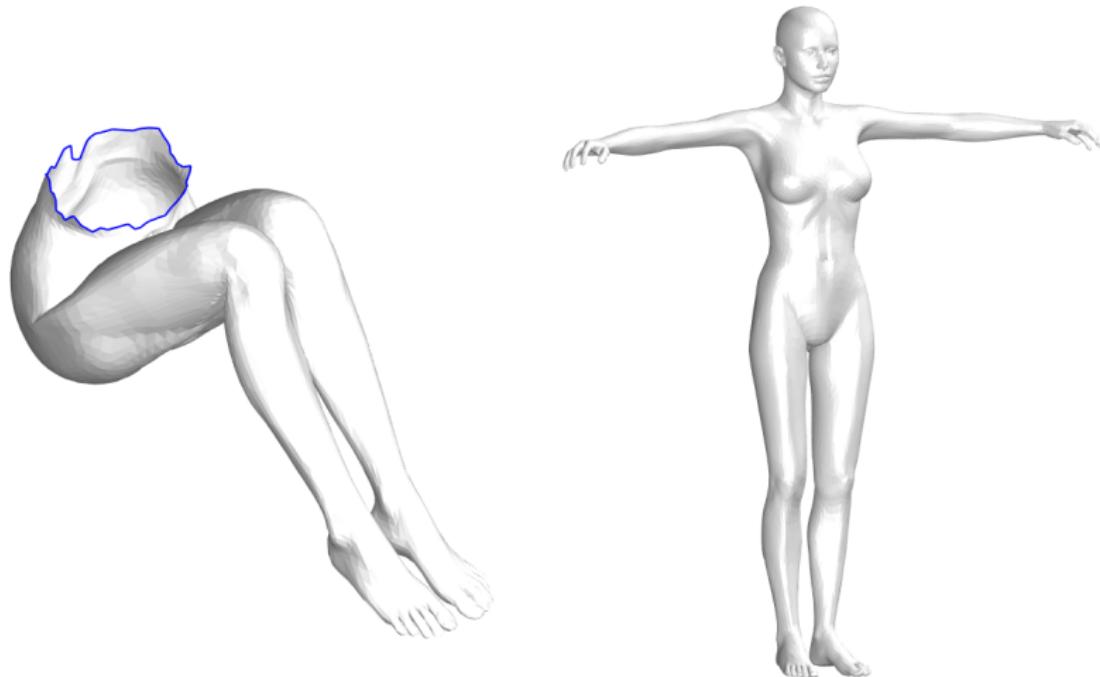
$$\min_{\rho \in [0,1]^{w \times h}} \|\lambda(\Delta + \rho) - \mu\|_w$$

Algorithm:

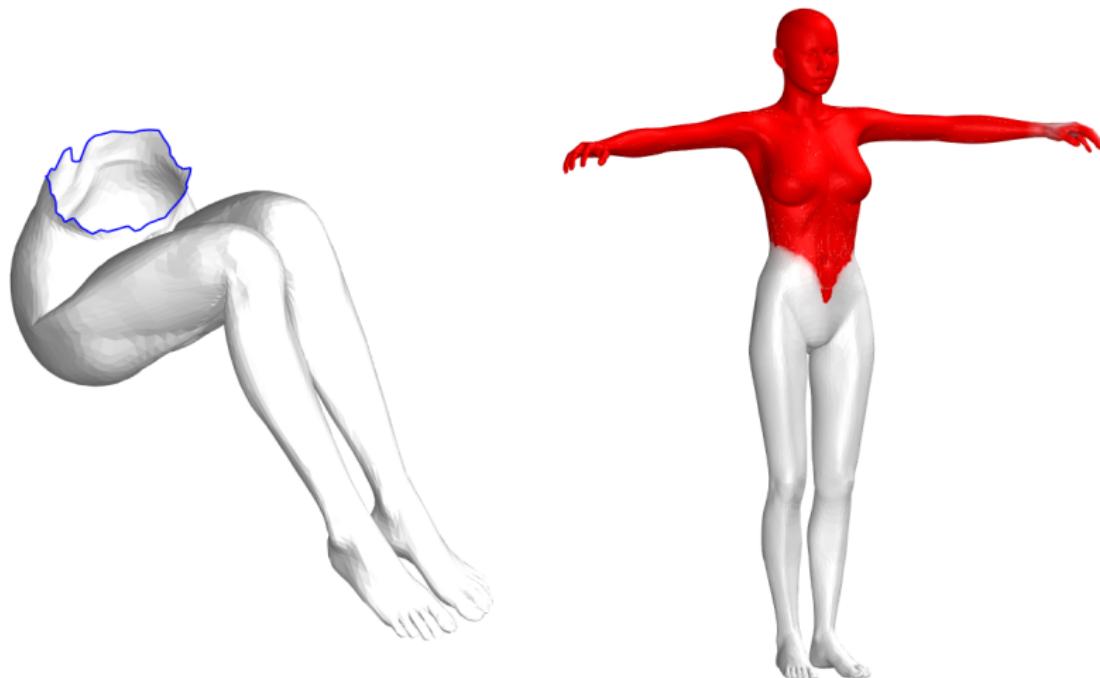
- Initialize $\rho = 1$
- Update $\rho^{(t)} = \rho^{(t-1)} - 2\alpha(\Phi^{(t-1)} \circ \Phi^{(t-1)}) \frac{\lambda^{(t-1)} - \mu}{\mu^2}$

Boils down to solving a sequence of eigenvalue problems

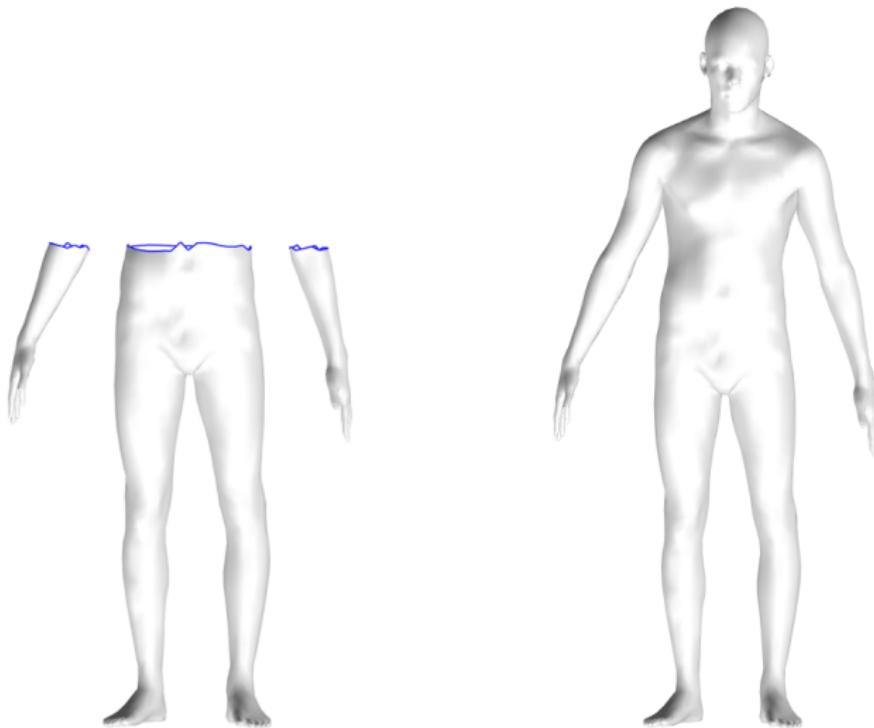
Application: Correspondence-free localization



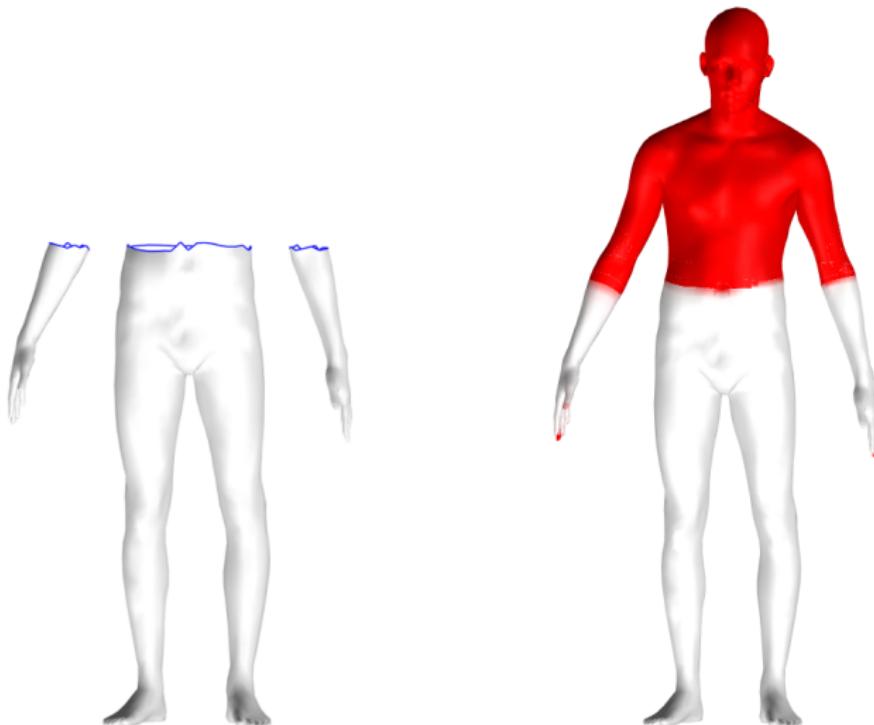
Application: Correspondence-free localization



Application: Correspondence-free localization



Application: Correspondence-free localization



Conclusions and perspectives

**Main value:
Get rid of correspondence**

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- One may hear the shape of the drum **in practice** by aligning Laplacian eigenvalues (**isospectralization**)

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- Applications in computer vision, graphics, learning?

Conclusions and perspectives

Main value: Get rid of correspondence

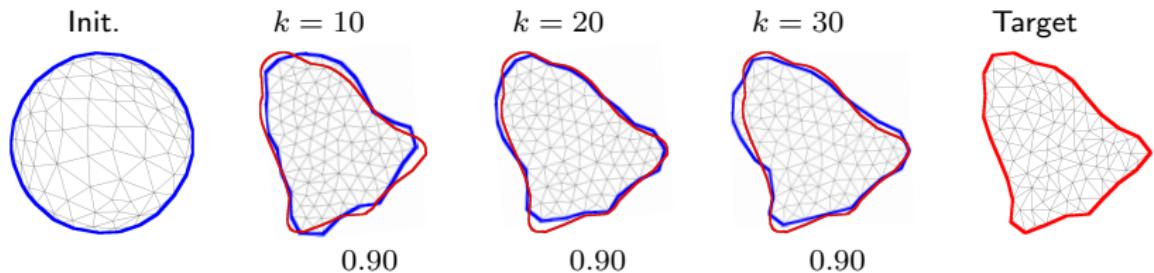
- One may hear the shape of the drum **in practice** by aligning Laplacian eigenvalues (**isospectralization**)
- Applications in computer vision, graphics, learning?
- May be useful for **generative models** and **shape optimization**

Thank you!

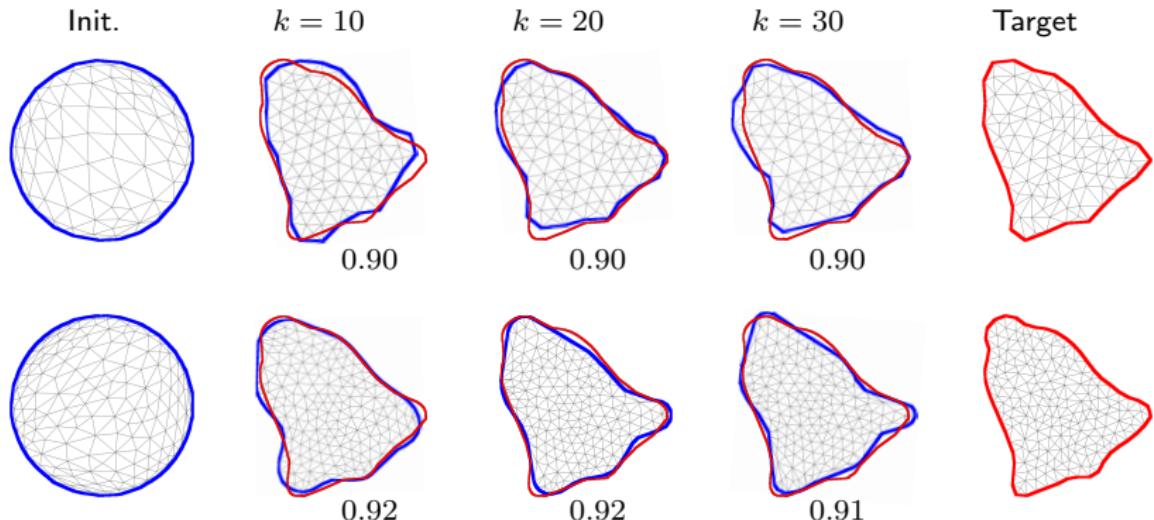


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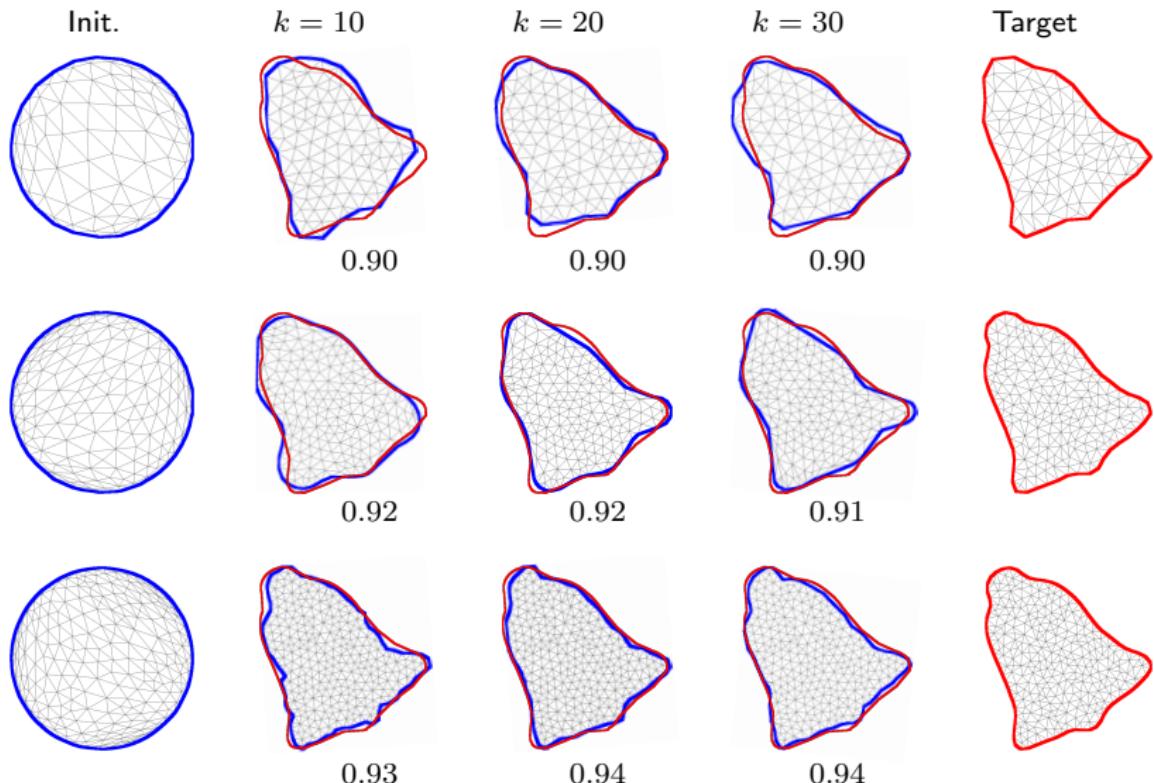
Bandwidth and mesh resolution



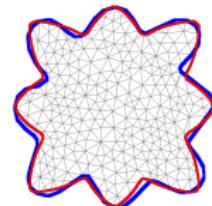
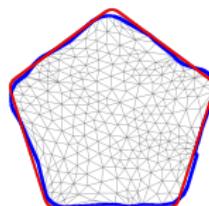
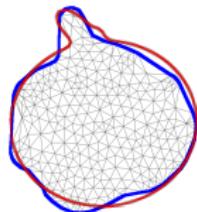
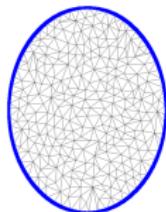
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Bandwidth and mesh resolution



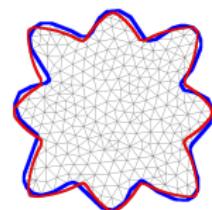
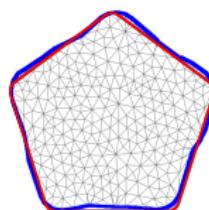
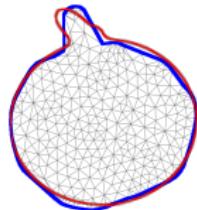
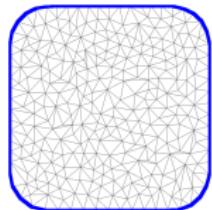
Initialization independence



0.92

0.95

0.93



0.93

0.95

0.93