# Analysis of Three-Dimensional Shapes

(IN2238, TU München, Summer 2015)

Shape Analysis @TUM (29.06.2015)

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# Partial matching



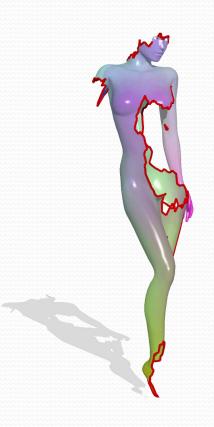
# Partial matching

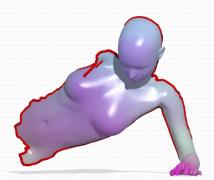
We only considered the "simple" case in which on of the two shapes is full (i.e. it can be seen as a template).



What happens **if both of them are incomplete**? In this case, we wouldn't even know how much they overlap!

# Partial matching



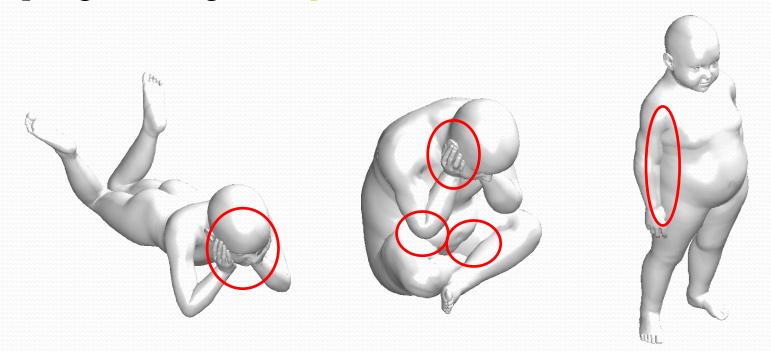


- Unknown overlap
- Topological changes?
- Non-isometric deformations?
- Clutter?

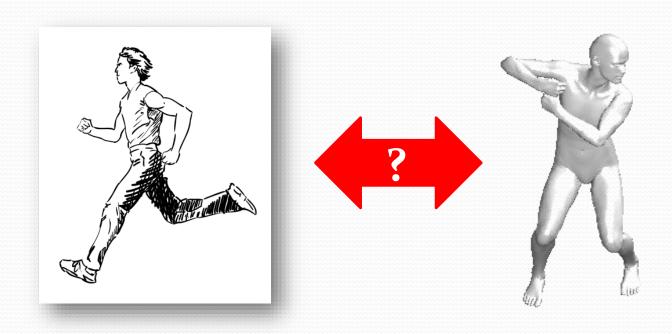


# Topological changes

We published a dataset for **deformable shape matching under topological changes**. ( <a href="http://vision.in.tum.de/data/datasets/kids">http://vision.in.tum.de/data/datasets/kids</a>)

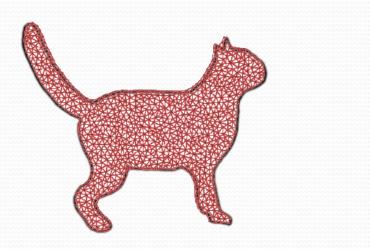


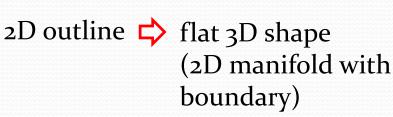
The matching problem in this case is very challenging and there is limited research in this direction. Can we make the change?



- Are they **similar**?
- Can we find a **point-to-point correspondence**?
- Can we find a **functional correspondence**?
- Can we **transfer the deformation** from one shape to the other?

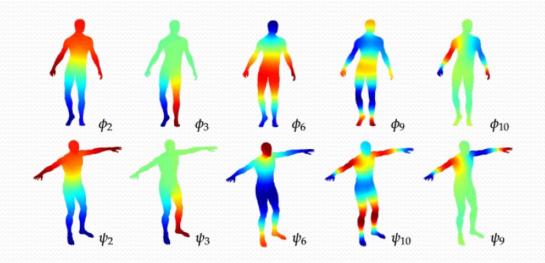
It turns out that we can indeed establish a functional correspondence between the drawing and the 3D model, if we take some simplifying assumptions.





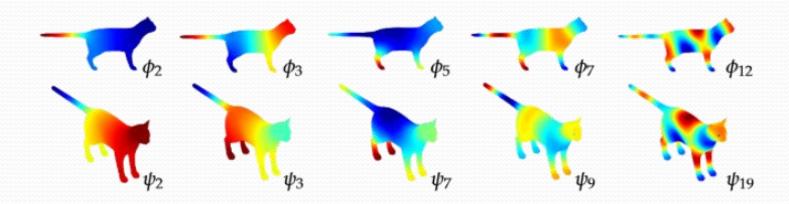


full 3D shape



Surprisingly, we observed a similar behavior to the 3D-to-3D partial matching case!

What information is the **boundary** giving us?



We applied a similar approach to the one we used for partial matching:

$$\min_{C} \|CA - B\|_F^2 + \mu \rho(C)$$

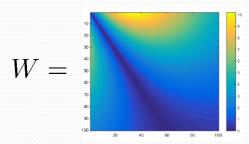
where we considered the following **convex** regularizers  $\rho(C)$ :

$$||W \circ C||_F^2$$

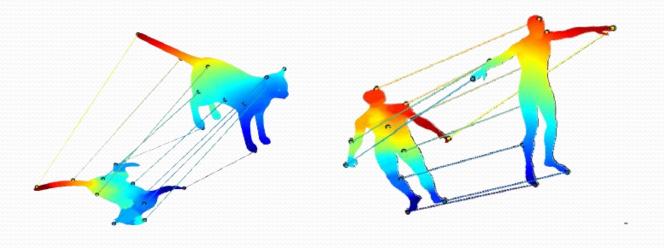
$$||W \circ C||_1$$

$$||C||_*$$

slanted-diagonal mask



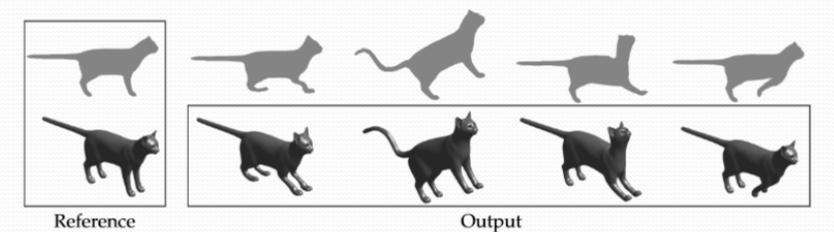
low-rank functional map (due to partiality)



#### Master's Thesis:

#### **Aneta Stevanovic**

"Dense 2D-to-3D Shape Matching via Low-Rank Functional Correspondence"



## From functional to point-to-point

We have seen how to convert a given functional map  $C \in \mathbb{R}^{k \times k}$  back to a point-to-point map  $T: M \to N$  .

The approach boils down to a nearest-neighbor search in  $\mathbb{R}^k$ . For each point  $y \in N$ , we look for the point  $x \in M$  minimizing:

$$\min_{x \in M} \|C\Phi^T \delta_x - \Psi^T \delta_y\|_2$$

However, the resulting point-to-point map can (and will) be **one-to-many**.

In addition, if the two shapes are only **approximately** isometric, the *L*<sub>2</sub> distance might not be the best choice!

## From functional to point-to-point

Let us take another look at the conversion process from point-to-point to functional:

$$C = \Psi^T P \Phi$$

We said that we can regard the functional map representation as simply a change of basis (from standard basis to Laplacian eigenbasis).

However, the moment we **truncate the basis** from n = 10,000 to k = 50 basis functions, there is a huge loss of information!

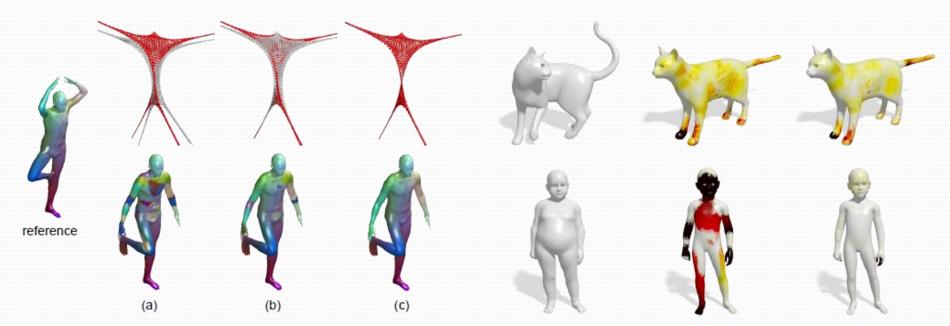
$$C = \Psi^T P \Phi$$
 rank at most 10,000

## From functional to point-to-point

Thus, the inverse conversion is **ill-posed and highly underdetermined**:

$$P = \Psi C \Phi^T$$

We proposed to rephrase the point-to-point map recovery problem in a probabilistic setting. Simply put, we perform a non-rigid alignment in  $\mathbb{R}^k$ :

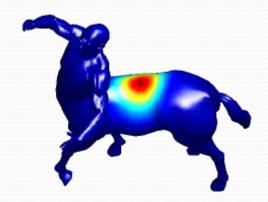


We defined the Laplacian on a manifold as the linear operator:

$$\Delta f = \operatorname{div}(\nabla f)$$

From the Laplacian we derived several interesting quantities such as the **heat kernel**, diffusion distance, GPS, and functional maps.

The heat kernel is an **intrinsic** quantity of the surface, and it is **isotropic**: the diffusion process does not depend on any particular direction, in other words **heat diffuses equally in all directions**.



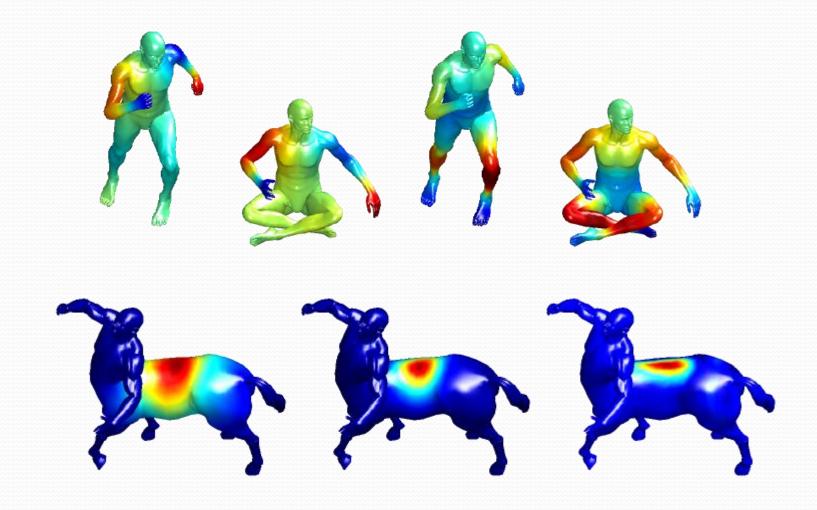
Can we diffuse heat **along a particular direction** of our choice?

We did so by considering the following operator, which we called **anisotropic Laplace-Beltrami operator**:

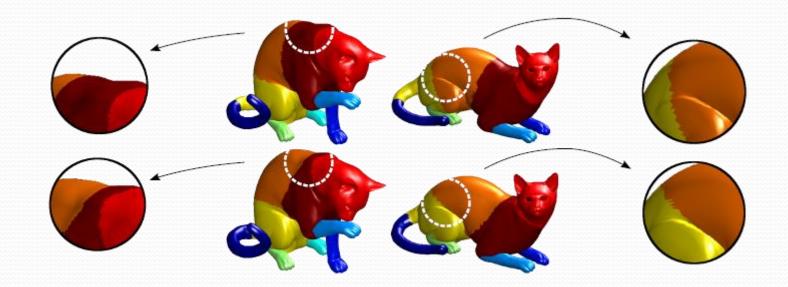
$$\Delta f = \operatorname{div}(D(\nabla f))$$

where D is a diagonal matrix promoting faster diffusion along the directions of principal curvature.

The resulting operator is still **linear**, and still admits an eigendecomposition with **real eigenvalues** and **orthonormal eigenfunctions**.



Shape segmentation can take advantage of the anisotropy:

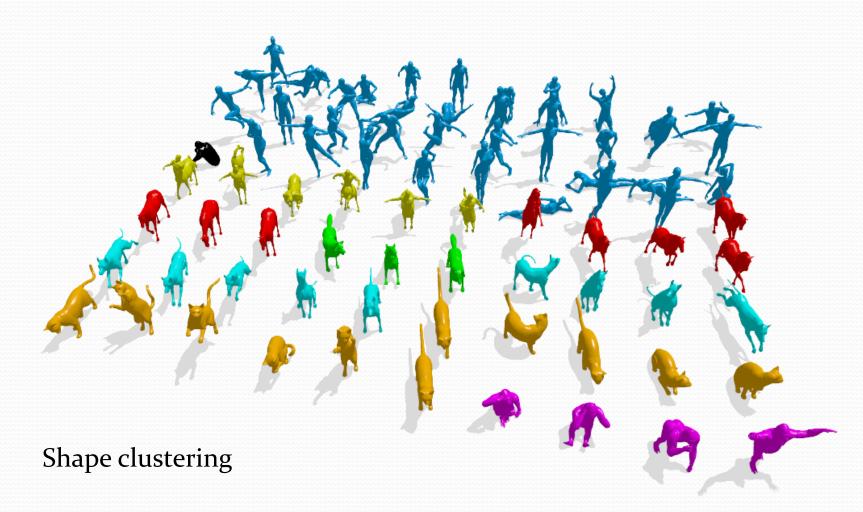


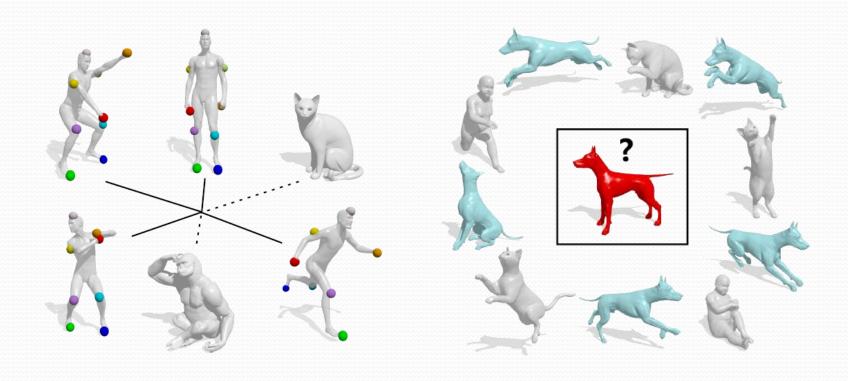
Open question: What else can we do with this operator?



As **3D shape collections** become increasingly available, there is a growing interest into analyzing them.

A good amount of research is being devoted to the problem of **jointly matching multiple shapes**.

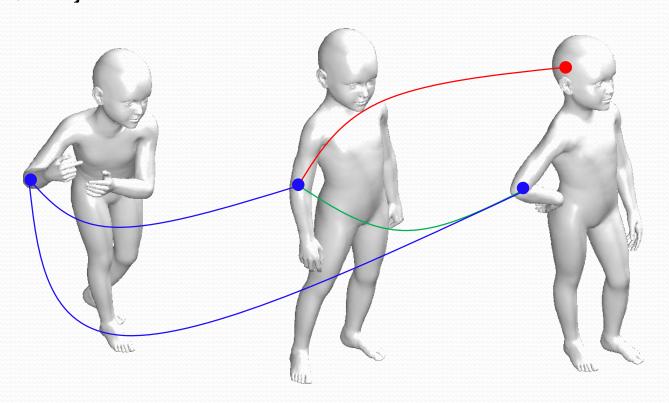




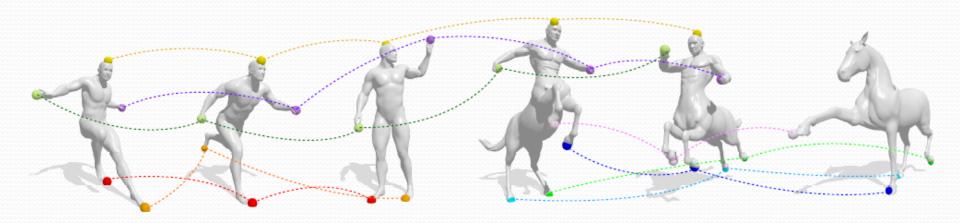
Point-to-point maps

Shape retrieval

One of the key requirements is that the extracted correspondence should be "transitive", or **cycle-consistent**:

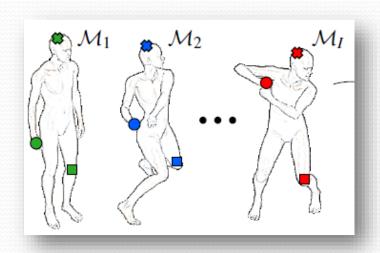


We extended the notion of **Gromov-Hausdorff distance** to multiple metric spaces, and provided an efficient algorithm to find **cycle-consistent** matches which are **robust to partiality and outliers**.

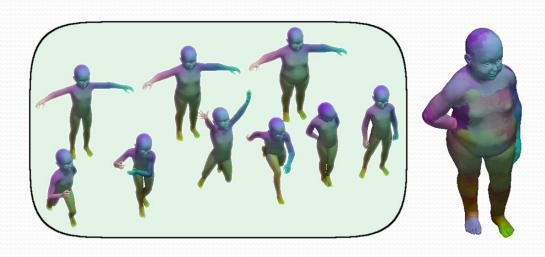


Open question: Can we make it dense?

#### Machine Learning and Shape Analysis



Optimal intrinsic descriptors



Example-based dense matching

What else?

# **BS/MS** Thesis

We offer theses for BS/MS students in Computer Science and Mathematics.

See: <a href="http://vision.in.tum.de/members/rodola/teaching">http://vision.in.tum.de/members/rodola/teaching</a>

The group is currently composed of **2 post-docs**, **2 PhD students**, and **2 Master's students**.

The coolest topics we are currently pursuing are kept secret to the human eye. If you want to find out more, come visit us!



#### References

- Partial Functional Correspondence. E. Rodolà et al. 2015. http://arxiv.org/abs/1506.05274
- Point-wise Map Recovery and Refinement from Functional Correspondence. E. Rodolà et al. 2015. <a href="http://arxiv.org/abs/1506.05603">http://arxiv.org/abs/1506.05603</a>
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- Consistent Partial Matching of Shape Collections via Sparse Modeling.
  L. Cosmo et al. 2015. (submitted to CGF)