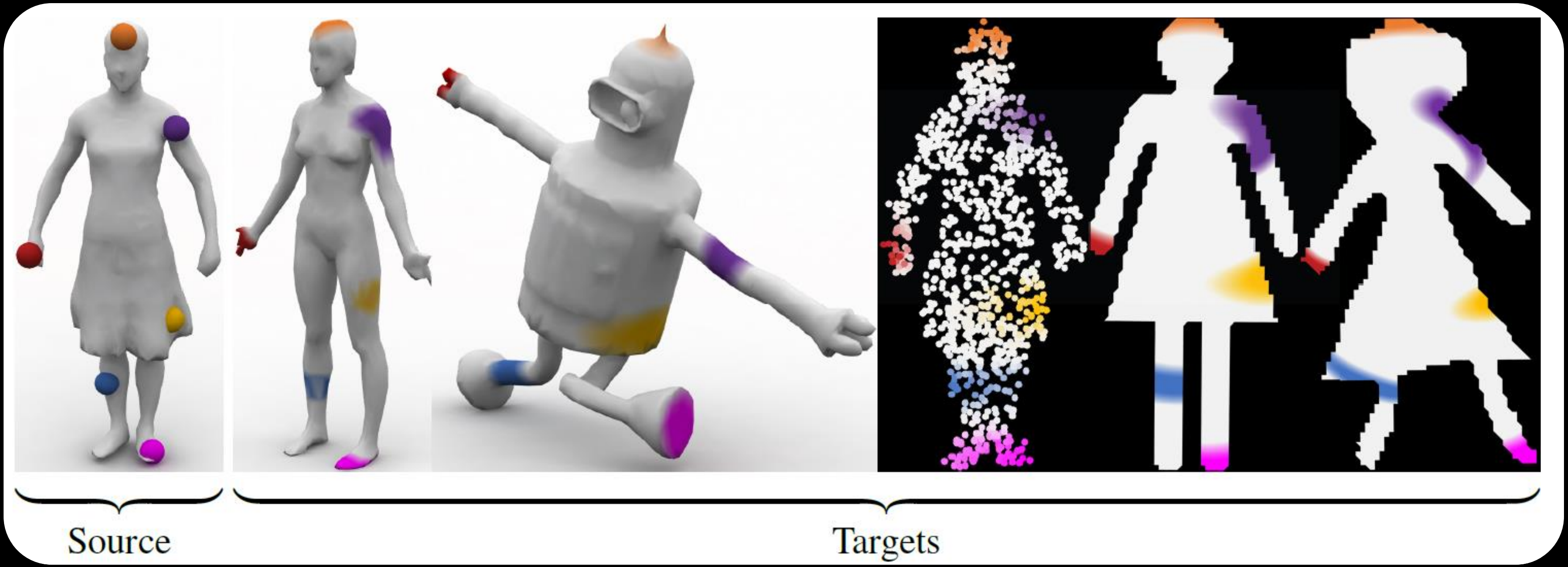
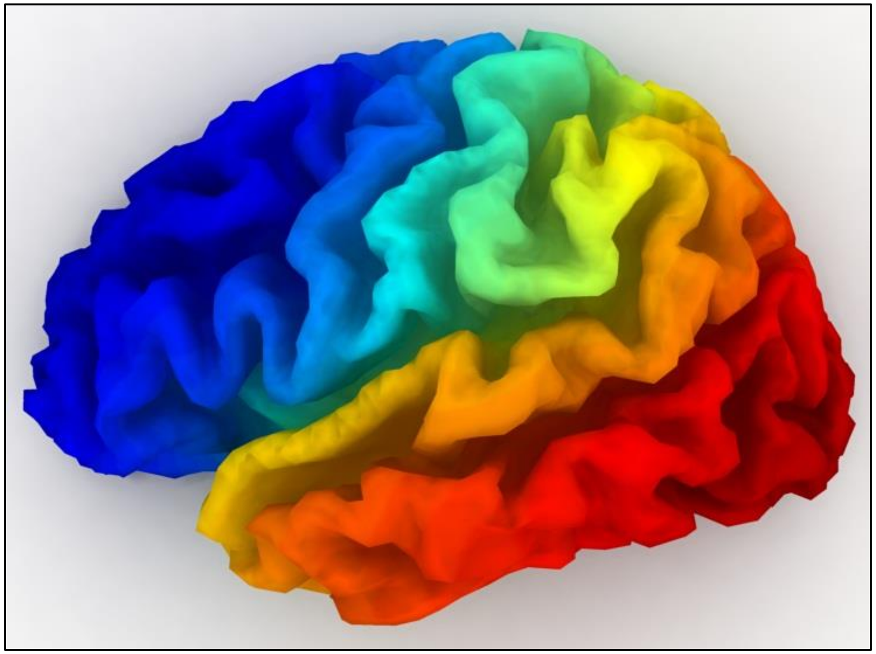
Image from "Entropic Metric Alignment for Correspondence Problems." Solomon et al., SIGGRAPH 2016.

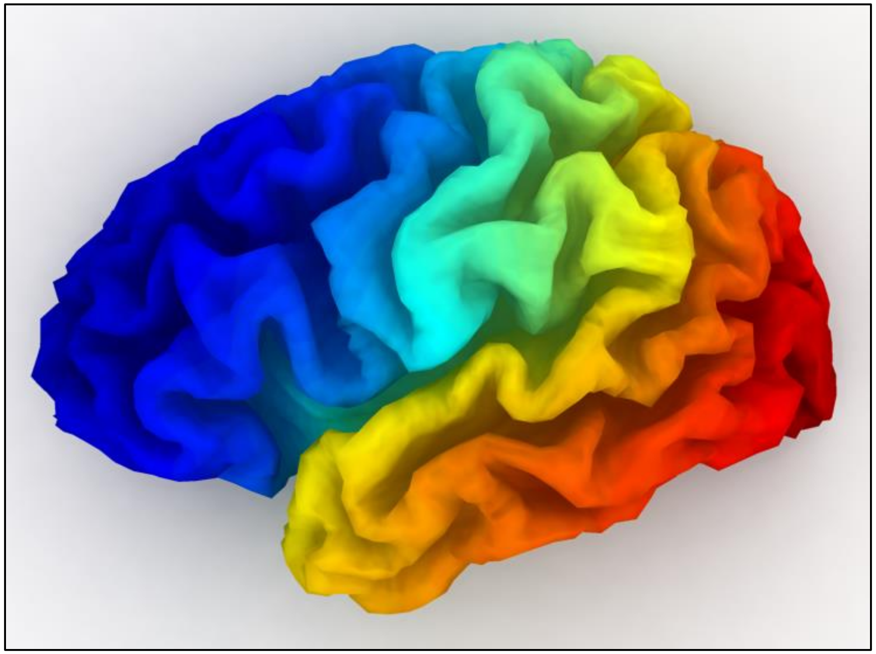


Surface Correspondence

Justin Solomon
MIT, Spring 2017

Correspondence Problems





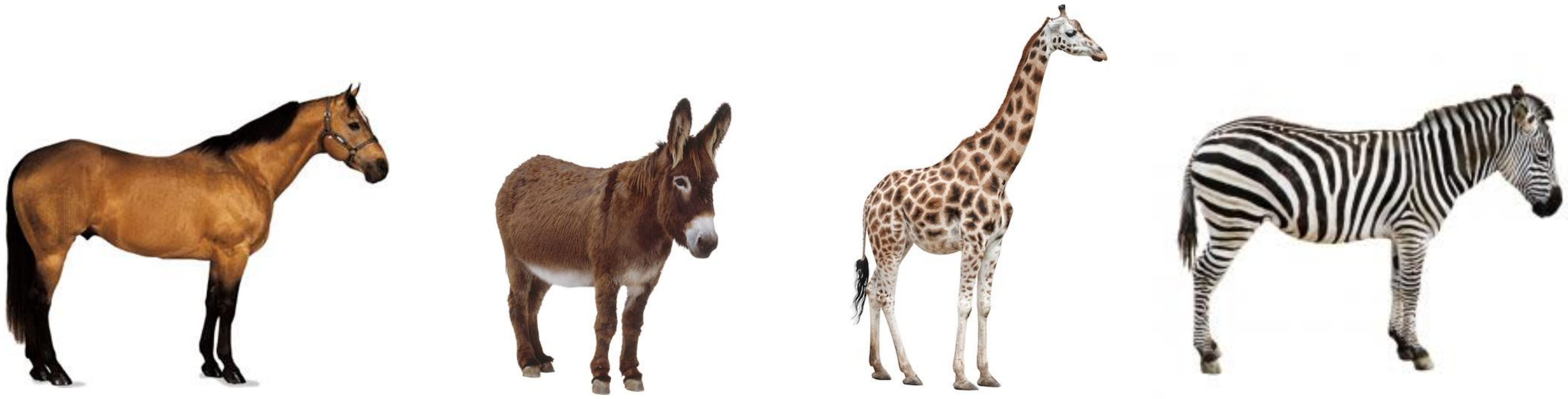
Which points on one object correspond to points on another?

Q:

How is this different from registration?

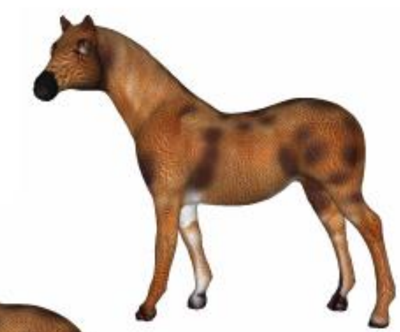
Typical Distinction

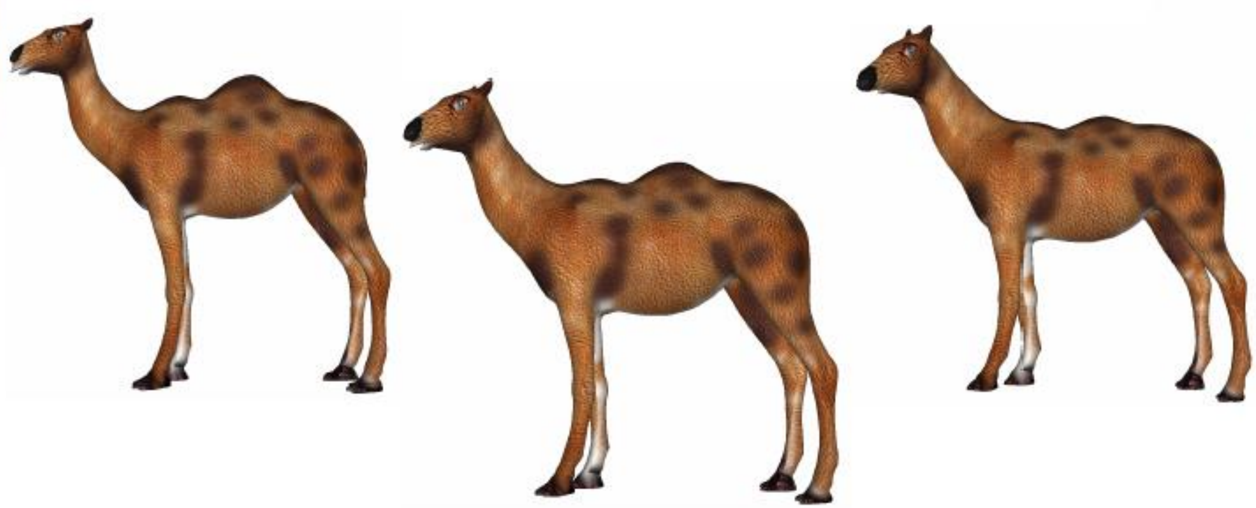
Seek shared structure instead of alignment



Applications

Praun et al. 2001

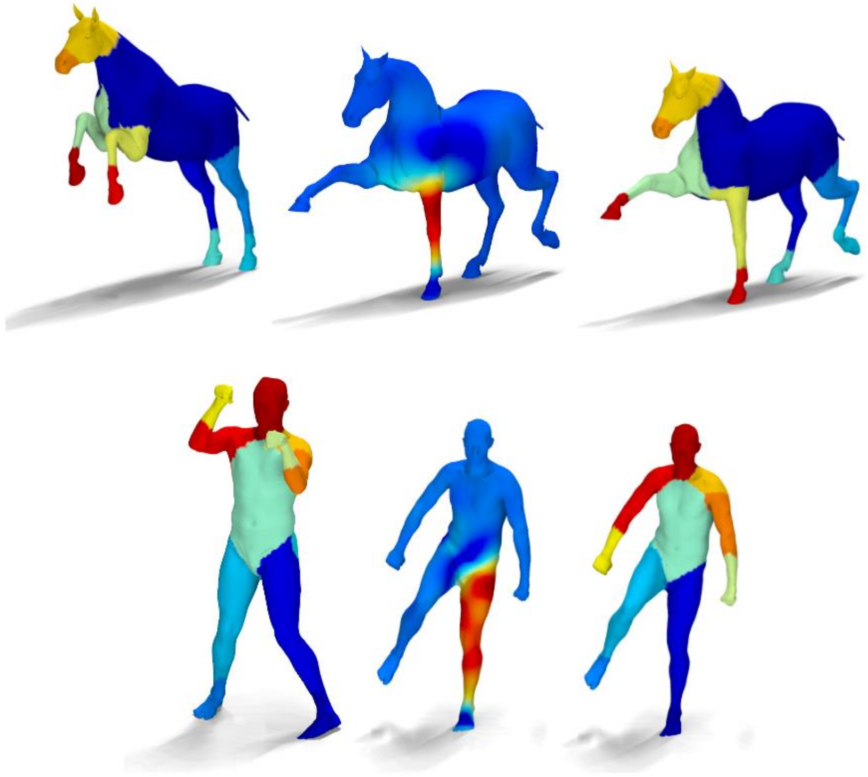




Kraevoy and Sheffer 2004

Texture transfer

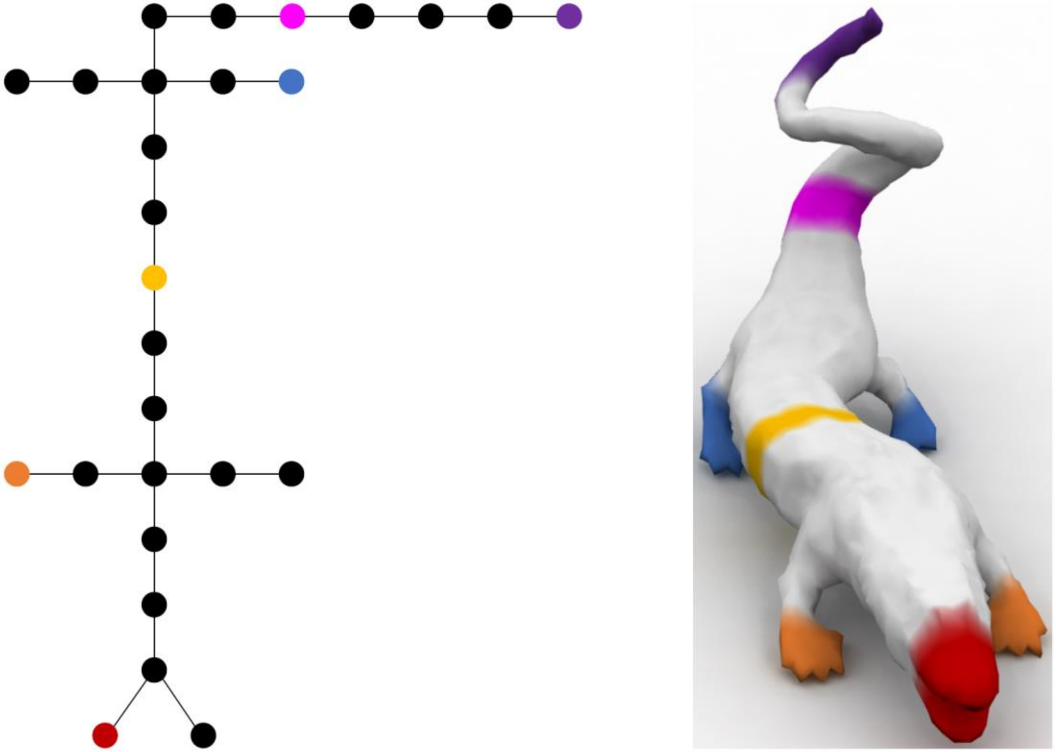
Applications



Ovsjanikov et al. 2012

Segmentation transfer

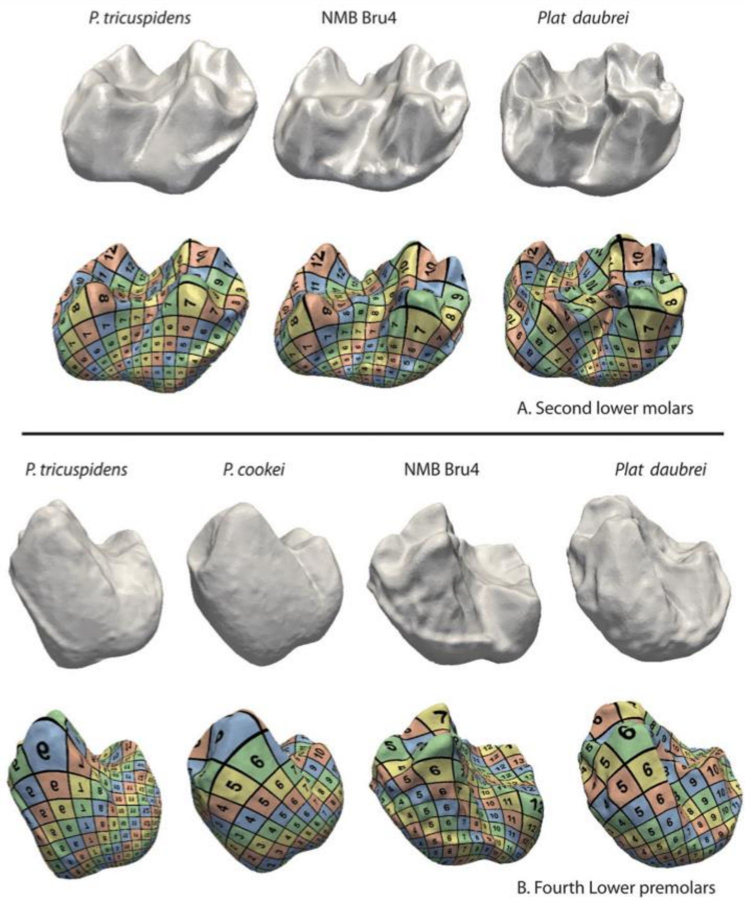
Applications



Solomon et al. 2016

Layout

Applications



Boyer, Costeur, and Lipman 2012

Paleontology

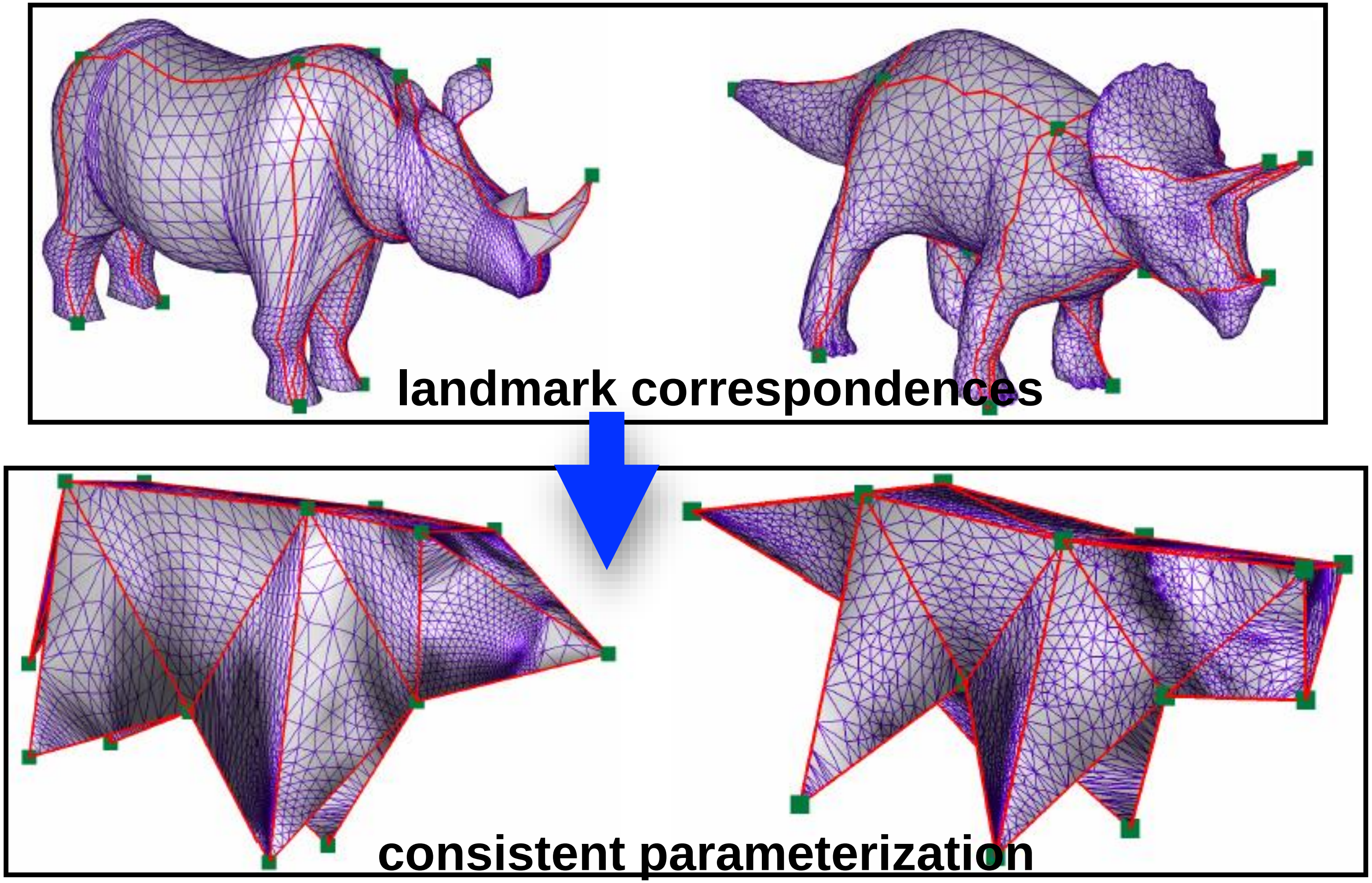
Desirable Properties

Given two (or more) shapes
Find a map f, that is:

- **Automatic**
- **Fast to compute**
- **Bijective**
  (if we expect global correspondence)
- **Low-distortion**

Adapted from slides by Q. Huang, V. Kim

Example: Consistent Remeshing

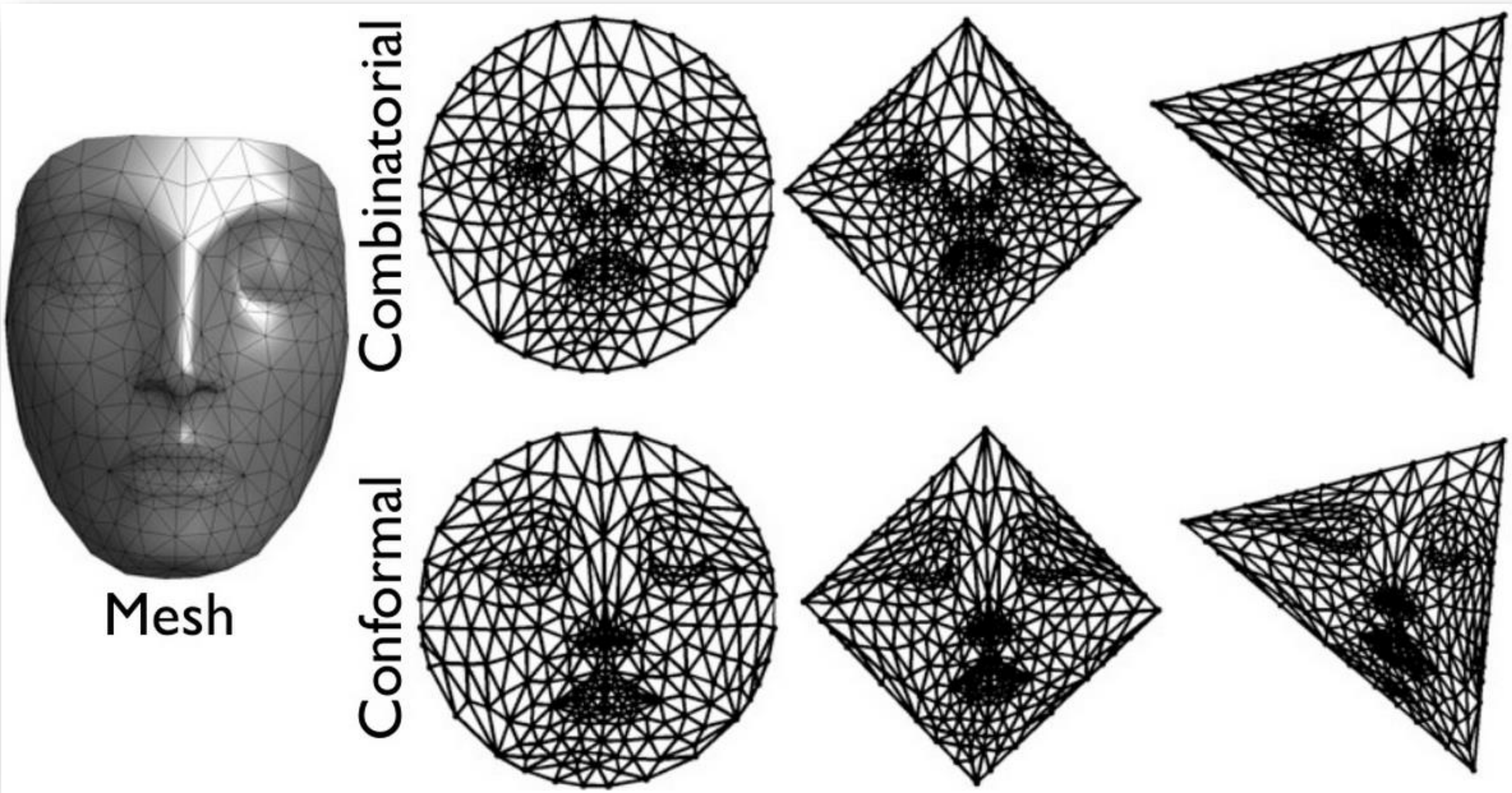


Kraevoy 2004

Adapted from slides by Q. Huang, V. Kim

Recall:

Example: Mesh Embedding



G. Peyré, mesh processing course slides

Recall:

Linear Solve for Embedding

$$\begin{aligned} \min_{x_1,\ldots,x_{|V|}} \quad & \sum_{(i,j)\in E} w_{ij}\|x_i - x_j\|_2^2 \\ \text{s.t.} \quad & x_v \text{ fixed } \forall v \in V_0 \end{aligned}$$

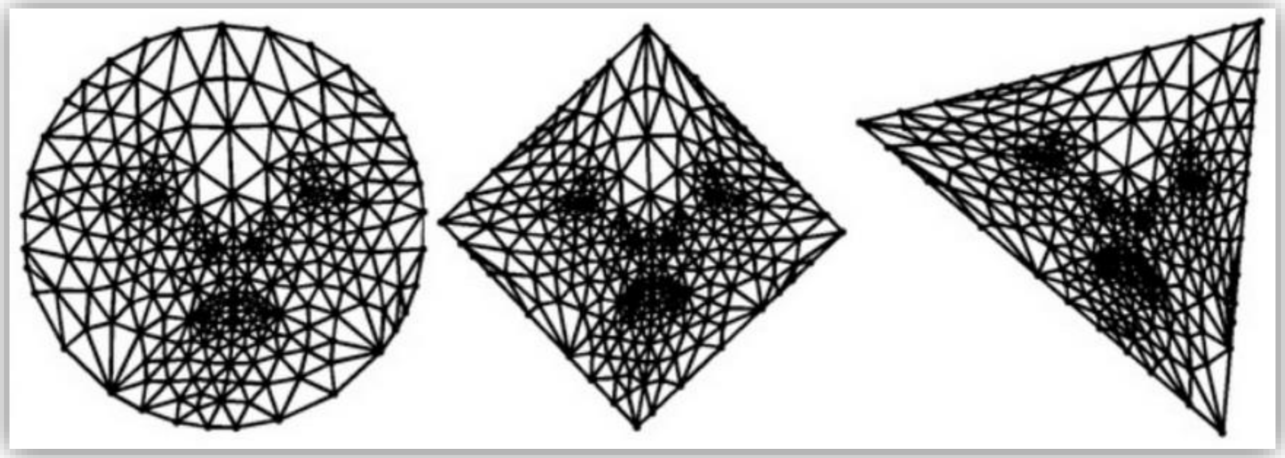
- $w_{ij} \equiv 1$**:** Tutte embedding
- w_{ij} **from mesh:** Harmonic embedding

Assumption: w **symmetric.**

Tutte Embedding Theorem

$$\begin{aligned} \min_{x_1,\ldots,x_{|V|}} \quad & \sum_{(i,j)\in E} w_{ij} \|x_i - x_j\|_2^2 \\ \text{s.t.} \quad & x_v \text{ fixed } \forall v \in V_0 \end{aligned}$$

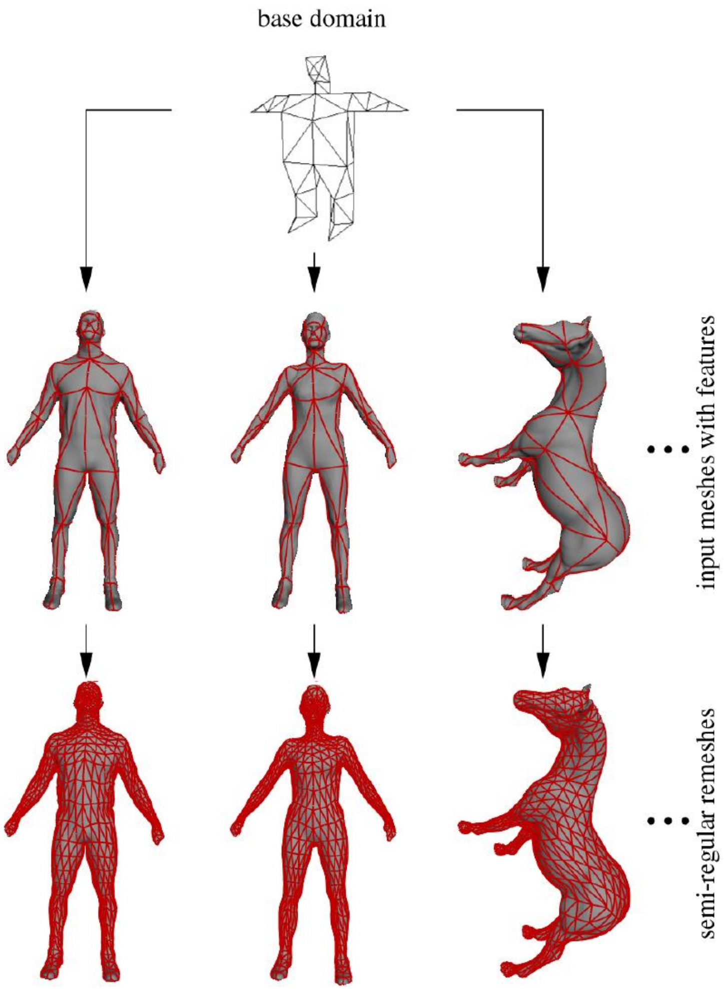
Tutte embedding bijective if *w* nonnegative and boundary mapped to a convex polygon.



"How to draw a graph" (Proc. London Mathematical Society; Tutte, 1963)

Tradeoff: Consistent Remeshing

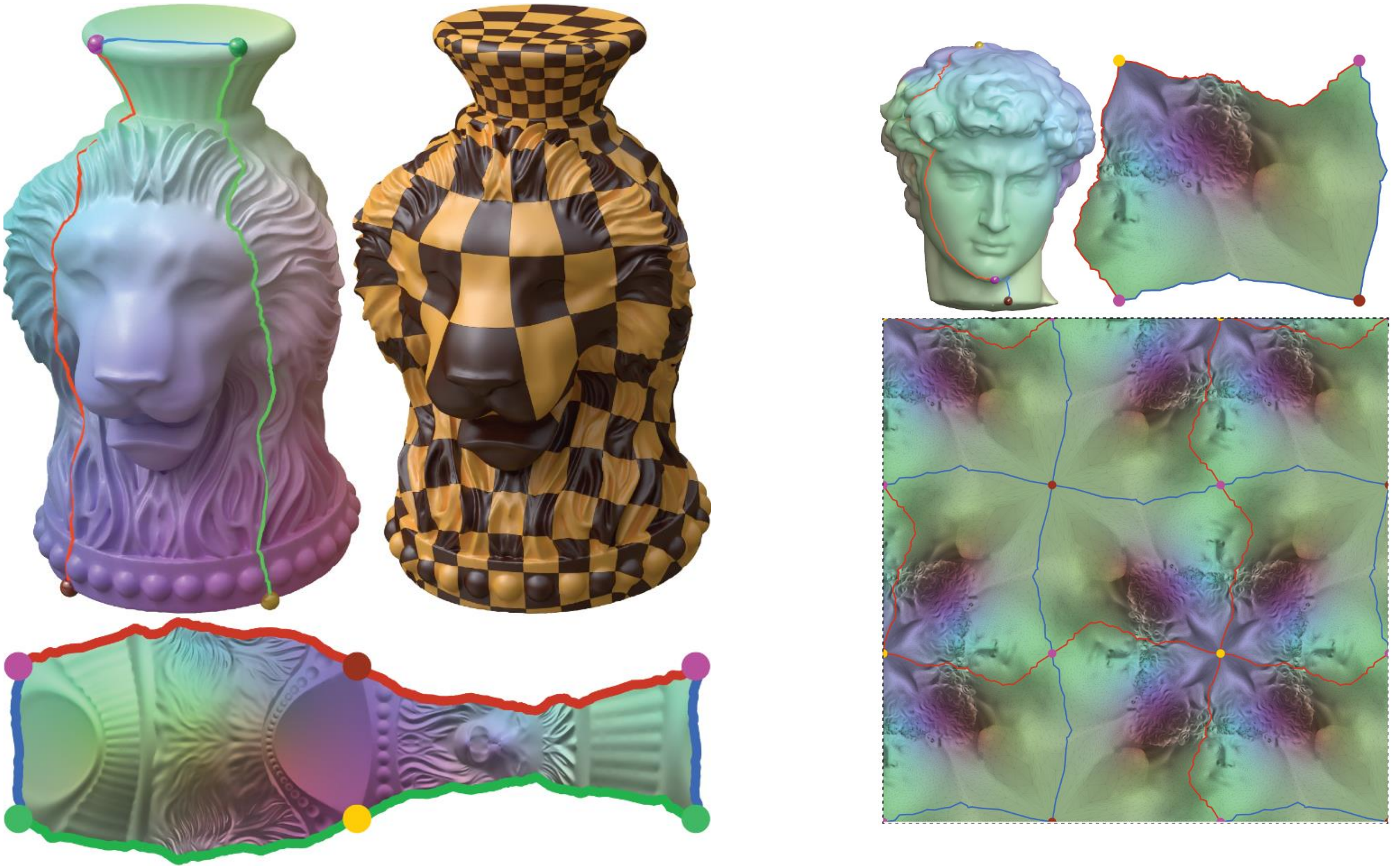
- **Pros:**
  - Easy
  - Straightforward applications
- **Cons:**
  - Need manual landmarks
  - Hard to minimize distortion



Praun et al. 2001

Adapted from slides by Q. Huang, V. Kim

Recently Revisited

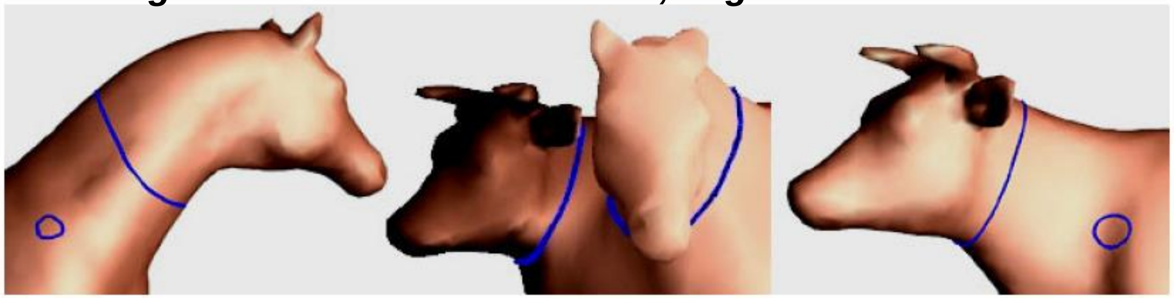


"Orbifold Tutte Embeddings" (Aigerman and Lipman, SIGGRAPH Asia 2015)

Automatic Landmarks

- Simple algorithm:
  - Set landmarks
  - Measure energy
  - Repeat
- Possible metrics
  - Conformality
  - Area preservation
  - Stretch

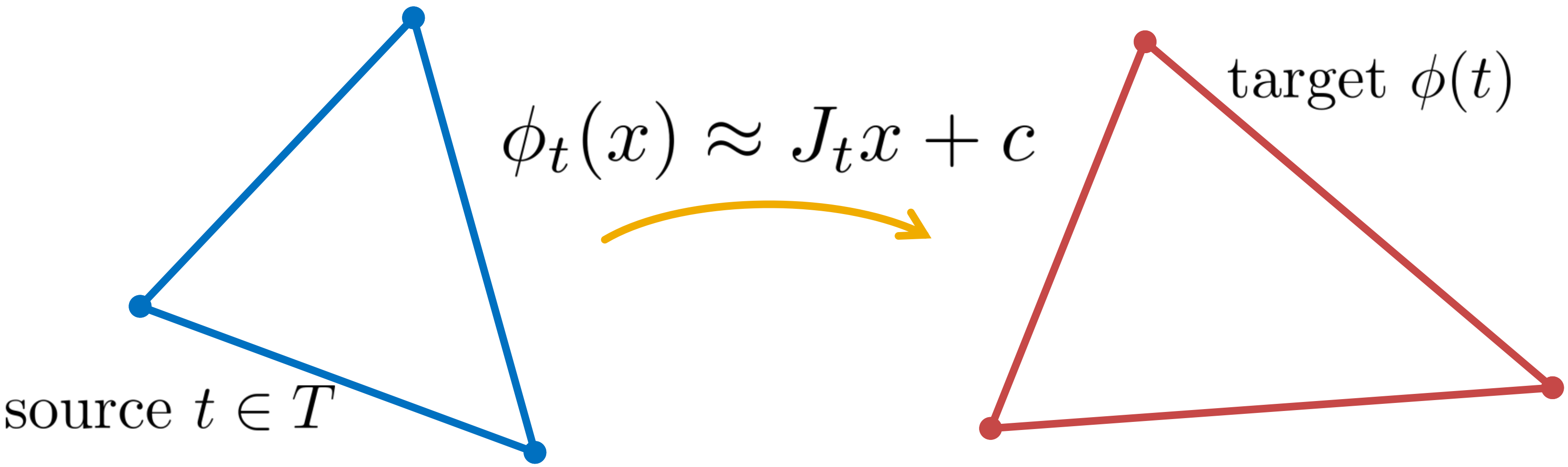
E.g. small conformal distortion, large area distortion:



Schreiner et al. 2004

Adapted from slides by Q. Huang, V. Kim

Local Distortion Measure



$$\text{Distortion} := \sum_{t \in T} A_t \mathcal{D}(J_t)$$

Triangle distortion measure

Notation from Rabinovich et al. 2017

Q:

How do you measure distortion of a triangle?

Typical Distortion Measures

Name	$\mathcal{D}(\mathbf{J})$	$\mathcal{D}(\sigma)$
Symmetric Dirichlet	$\\|\mathbf{J}\\|_F^2 + \\|\mathbf{J}^{-1}\\|_F^2$	$\sum_{i=1}^n (\sigma_i^2 + \sigma_i^{-2})$
Exponential Symmetric Dirichlet	$\exp(s(\\|\mathbf{J}\\|_F^2 + \\|\mathbf{J}^{-1}\\|_F^2))$	$\exp(s\sum_{i=1}^n (\sigma_i^2 + \sigma_i^{-2}))$
Hencky strain	$\left\\|\log \mathbf{J}^\top \mathbf{J}\right\\|_F^2$	$\sum_{i=1}^n (log^2 \sigma_i)$
AMIPS	$\exp(s \cdot \frac{1}{2}(\frac{\mathrm{tr}(\mathbf{J}^\top \mathbf{J})}{\det(\mathbf{J})} + \frac{1}{2}(\det(\mathbf{J}) + \det(\mathbf{J}^{-1})))$	$\exp(s(\frac{1}{2}(\frac{\sigma_1}{\sigma_2} + \frac{\sigma_2}{\sigma_1}) + \frac{1}{4}(\sigma_1\sigma_2 + \frac{1}{\sigma_1\sigma_2}))$
Conformal AMIPS 2D	$\frac{\mathrm{tr}(\mathbf{J}^\top \mathbf{J})}{\det(\mathbf{J})}$	$\frac{\sigma_1^2+\sigma_2^2}{\sigma_1\sigma_2}$
Conformal AMIPS 3D	$\frac{\mathrm{tr}(\mathbf{J}^\top \mathbf{J})}{\det(\mathbf{J})^{\frac{2}{3}}}$	$\frac{\sigma_1^2+\sigma_2^2+\sigma_3^2}{(\sigma_1\sigma_2\sigma_3)^{\frac{2}{3}}}$

Open challenge:
Optimize directly

Table from "Scalable Locally Injective Mappings" (Rabinovich et al., 2017)

Related Problem

Mapping specifically into the plane

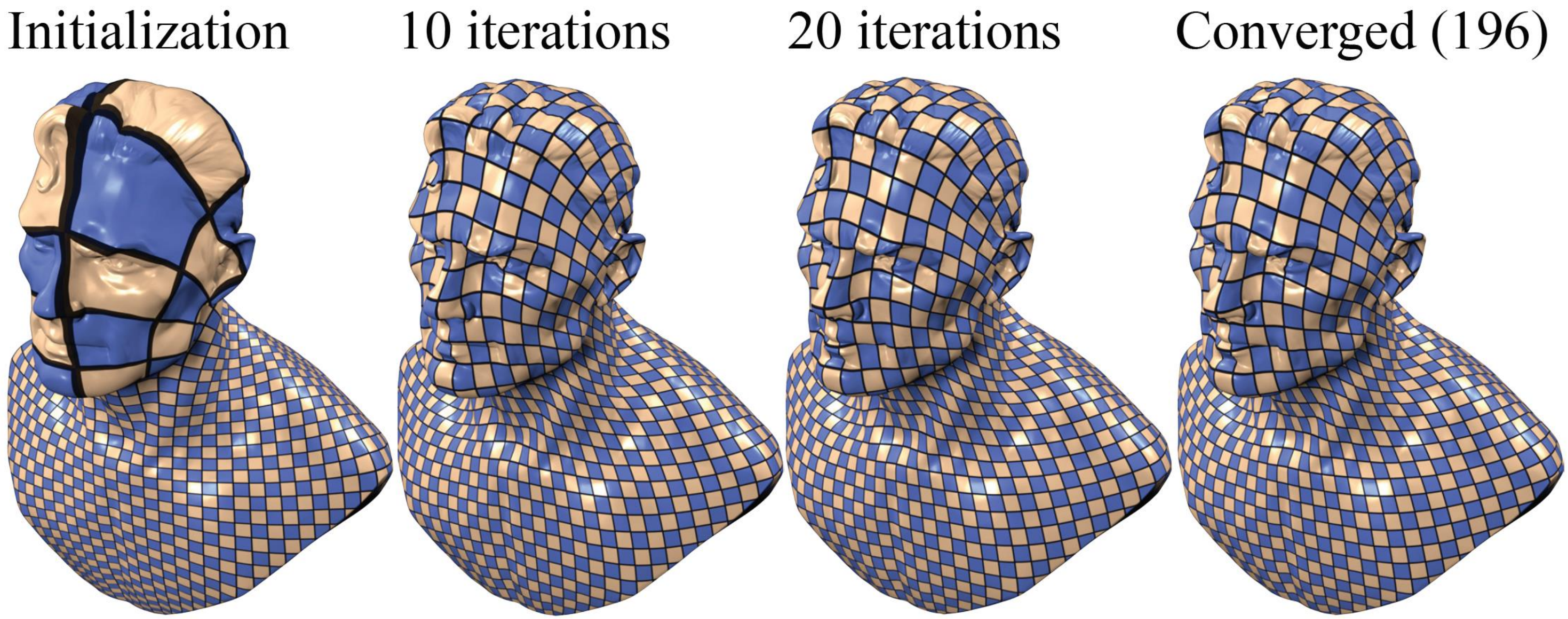


Image from "Scalable Locally Injective Mappings" (Rabinovich et al., 2017)

Parameterization

New Idea

Not all calculations have to be at the triangle level!

Long-distance interactions

can stabilize geometric computations.

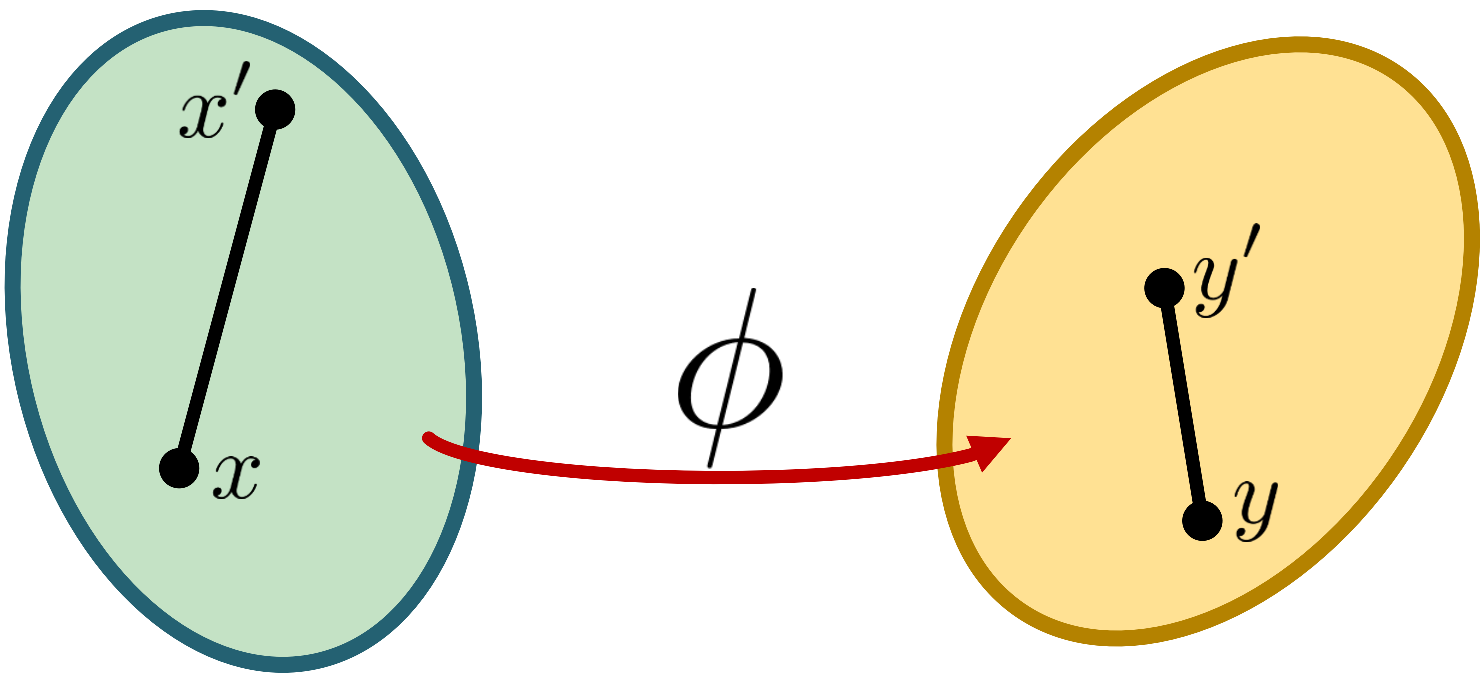
Gromov-Hausdorff Distance

Distance between metric spaces X, Y

$$d_{\mathrm{GH}}(X,Y) := \inf_{\phi: X\to Y} \sup_{x,x'\in X} |d_X(x,x') - d_Y(\phi(x),\phi(x'))|$$

Best map

Worst distortion



Recall:

Classical Multidimensional Scaling

1. Double centering: $B := -\frac{1}{2}JDJ$
   Centering matrix $J := I - \frac{1}{n}\mathbf{1}\mathbf{1}^\top$

2. Find m largest eigenvalues/eigenvectors

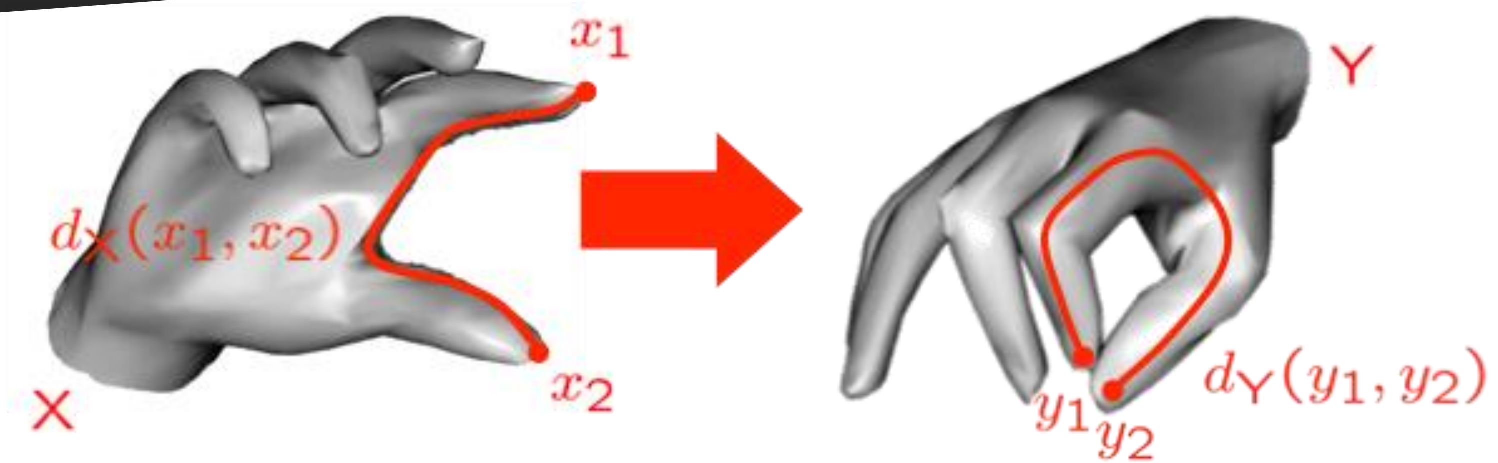
3. $X = E_m \Lambda_m^{1/2}$

"MDS"

Torgerson, Warren S. (1958). *Theory & Methods of Scaling*.

Generalized MDS

Search for a permutation!



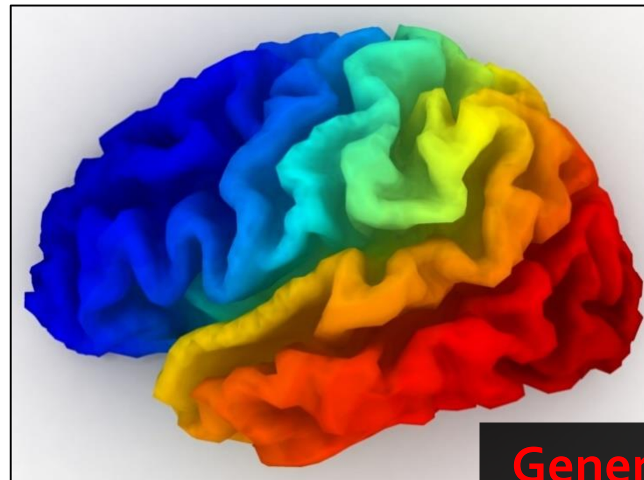
$$d_{\text{int}}(X,Y) := \min_{\{y_1,\ldots,y_n\}\subset Y} \|d_X(x_i,x_j) - d_Y(y_i,y_j)\|$$

Bronstein, Bronstein, and Kimmel; PNAS 2006

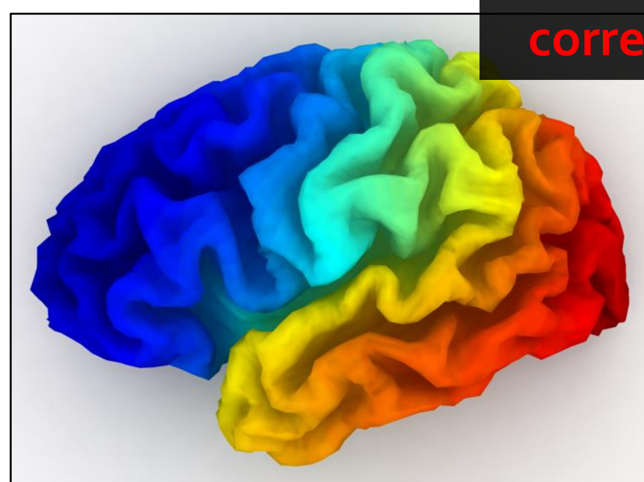
Problem: Quadratic Assignment

$$
\begin{aligned}
\min_T \quad & \langle M_0 T, T M_1 \rangle \\
\text{s.t.} \quad & T \in \{0,1\}^{n \times n} \\
& T\mathbf{1} = p_0 \\
& T^\top \mathbf{1} = p_1
\end{aligned}
$$

<u>Nonconvex</u> quadratic program!
NP-hard!

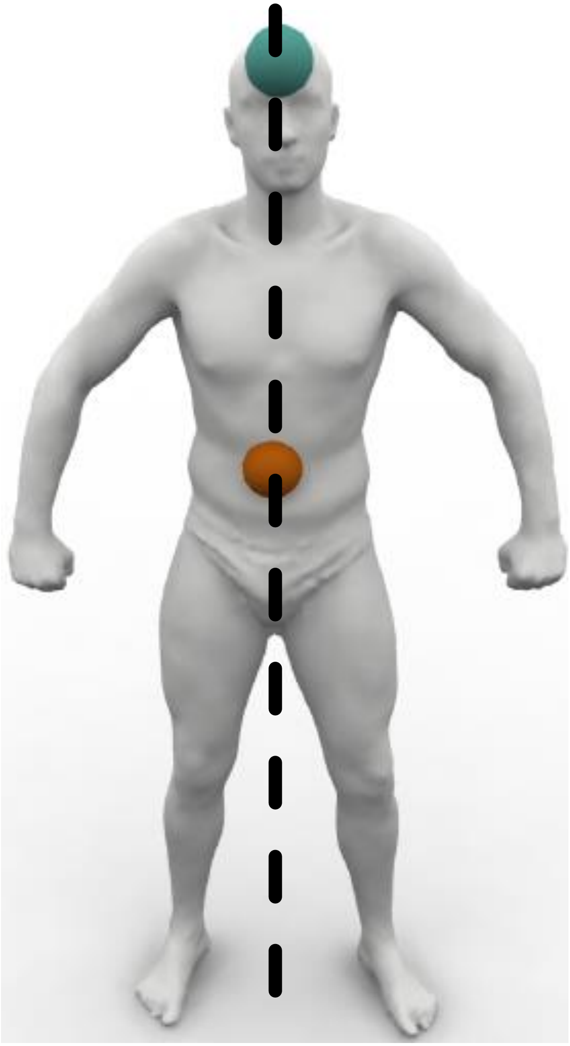


General notion of correspondence



What's Wrong?

- **Hard to optimize**
- **Multiple optima**



Tradeoff: GMDS

- Pros:
  - Good distance for non-isometric metric spaces
- Cons:
  - Non-convex
  - HUGE search space (i.e. permutations)

Adapted from slides by Q. Huang, V. Kim

GMDS in Practice

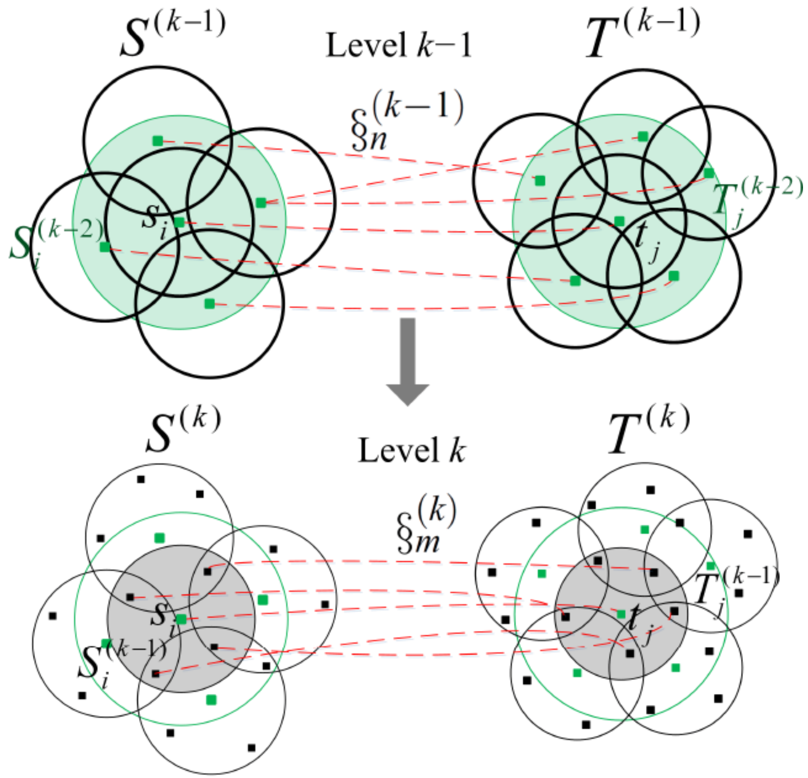
- Heuristics to explore the permutations
  - Solve at a very coarse scale and interpolate
  - Coarse-to-fine
  - Partial matching

Bronstein'08

Adapted from slides by Q. Huang, V. Kim

GMDS in Practice

- Heuristics to explore the permutations
  - Solve at a very coarse scale and interpolate
  - Coarse-to-fine
  - Partial matching

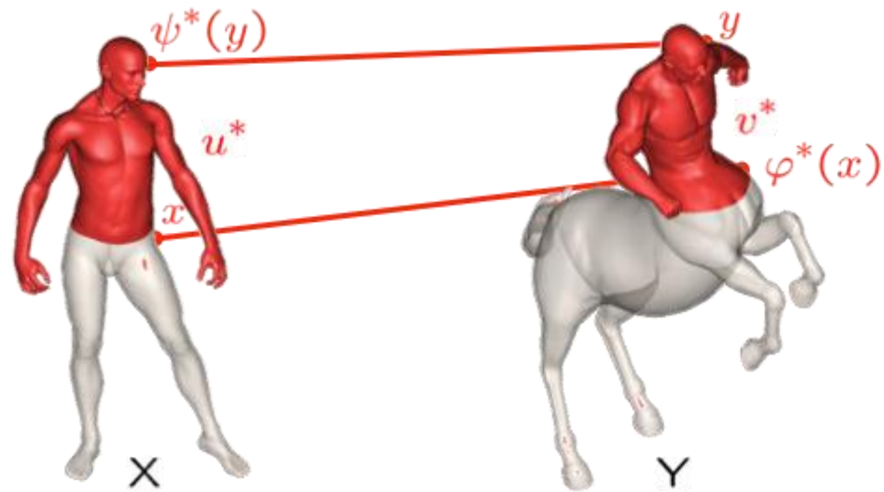


Sahillioglu'12

Adapted from slides by Q. Huang, V. Kim

GMDS in Practice

- Heuristics to explore the permutations
  - Solve at a very coarse scale and interpolate
  - Coarse-to-fine
  - Partial matching



- Find correspondence φ^*, ψ^* minimizing distortion between current parts u^*, v^*
- Select parts u^*, v^* minimizing the distortion with current correspondence φ^*, ψ^* subject to $\lambda(u^*, v^*) \leq \lambda_0$

Adapted from slides by Q. Huang, V. Kim

A. Bronstein, M. Bronstein, A. Bruckstein, R. Kimmel, *IJCV* 2008

Returning to Desirable Properties

Given two (or more) shapes
Find a map f, that is:

- Automatic
- ~~Fast to compute~~
- ~~Bijective~~
  (if we expect global correspondence)
- Low-distortion

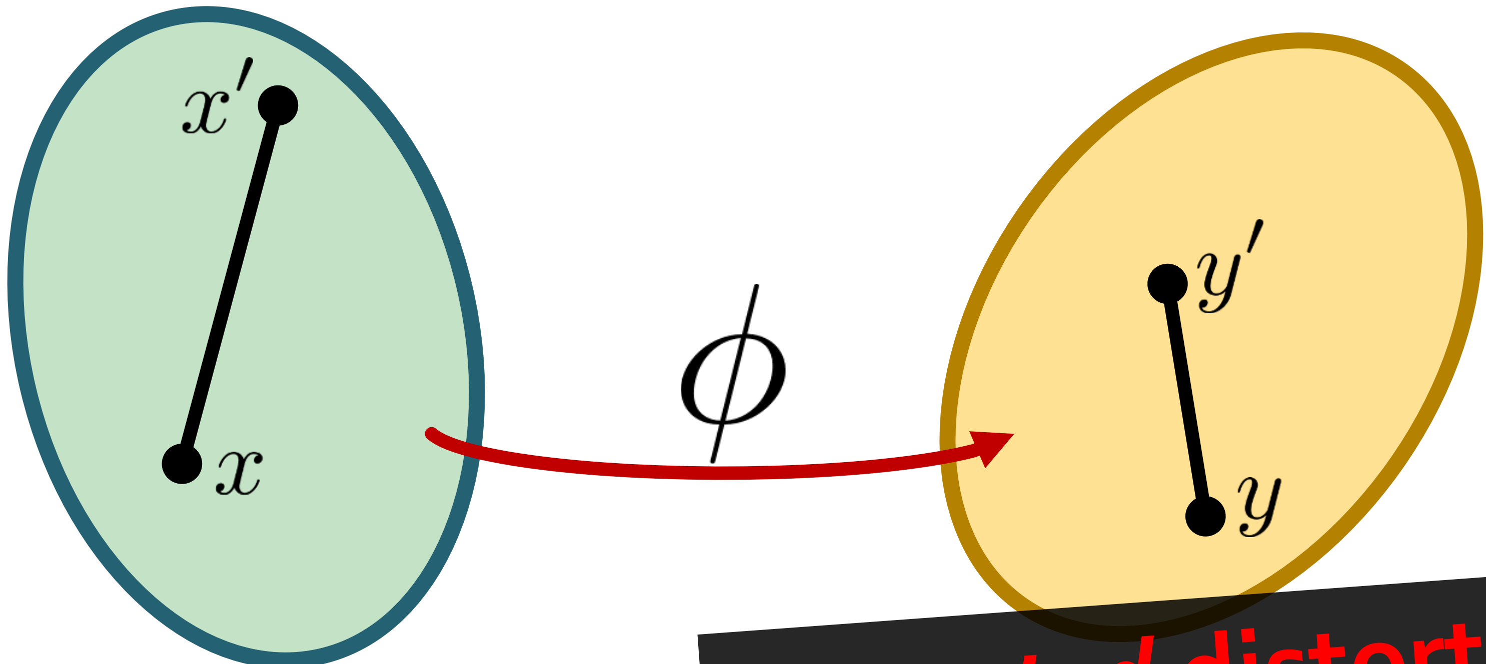
(unless local optimum is bad)

Adapted from slides by Q. Huang, V. Kim

Recent idea:

Gromov-Wasserstein Distance

[Mémoli 2007]



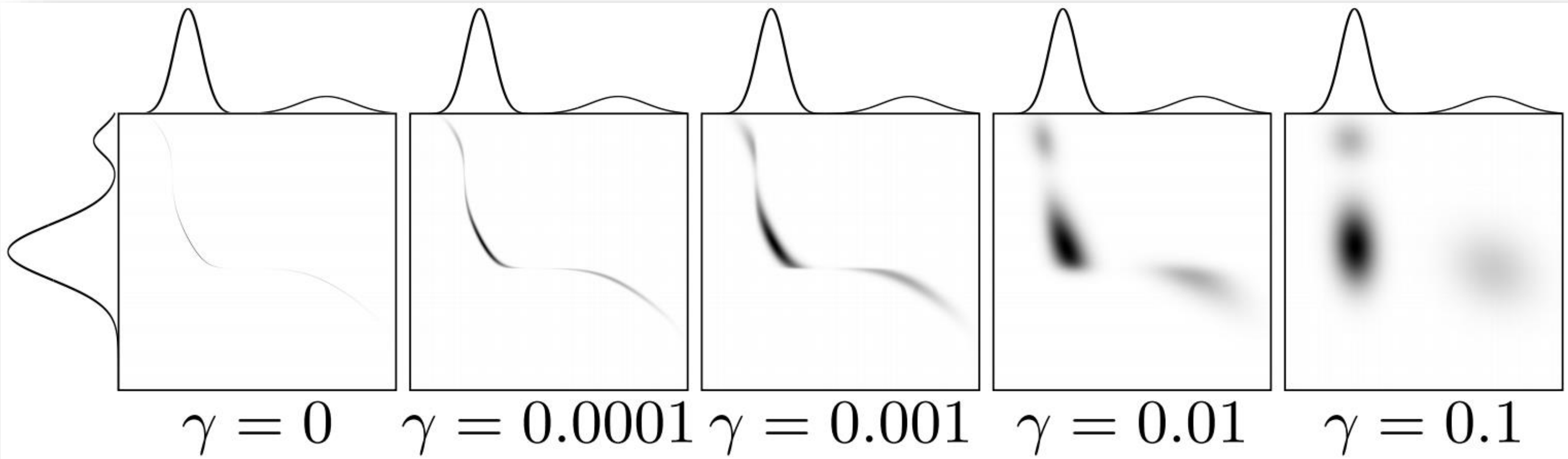
Expected distortion

$$\mathrm{GW}_2^2((\mu_0, d_0), (\mu, d)) :=$$

$$\min_{\gamma \in \mathcal{M}(\mu_0, \mu)} \iint_{\Sigma_0 \times \Sigma} [d_0(x, x') - d(y, y')]^2 \, d\gamma(x, y) \, d\gamma(x', y')$$

Recall:

Entropic Regularization



$$\begin{aligned} \min_T \quad & \textstyle\sum_{ij} T_{ij} d(x_i, x_j) - \gamma H(T) \\ \text{s.t.} \quad & \textstyle\sum_j T_{ij} = p_i \\ & \textstyle\sum_i T_{ij} = q_j \\ & T \geq 0 \end{aligned}$$

$$H(T) := -\sum_{ij} T_{ij} \log T_{ij}$$

Cuturi. "Sinkhorn distances: Lightspeed computation of optimal transport" (NIPS 2013)

Gromov-Wasserstein Plus Entropy

Entropic Metric Alignment for Correspondence Problems

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Gabriel Peyré CNRS & Univ. Paris-Dauphine
Vladimir G. Kim Adobe Research
Suvrit Sra MIT

Abstract

Many shape and image processing tools rely on computation of correspondences between geometric domains. Efficient methods that stably extract "soft" matches in the presence of diverse geometric structures have proven to be valuable for shape retrieval and transfer of labels or semantic information. With these applications in mind, we present an algorithm for probabilistic correspondence that optimizes an entropy-regularized Gromov-Wasserstein (GW) objective. Built upon recent developments in numerical optimal transportation, our algorithm is compact, provably convergent, and applicable to any geometric domain expressible as a metric measure matrix. We provide comprehensive experiments illustrating the convergence and applicability of our algorithm to a variety of graphics tasks. Furthermore, we expand entropic GW correspondence to a framework for other matching problems, incorporating partial distance matrices, user guidance, shape exploration, symmetry detection, and joint analysis of more than two domains. These applications expand the scope of entropic GW correspondence to major shape analysis problems and are stable to distortion and noise.

Keywords: Gromov-Wasserstein, matching, entropy

Concepts: •**Computing methodologies** → **Shape analysis;**

1 Introduction

A basic component of the geometry processing toolbox is a tool for *mapping* or *correspondence*, the problem of finding which points on a target domain correspond to points on a source. Many variations of this problem have been considered in the graphics literature, e.g.

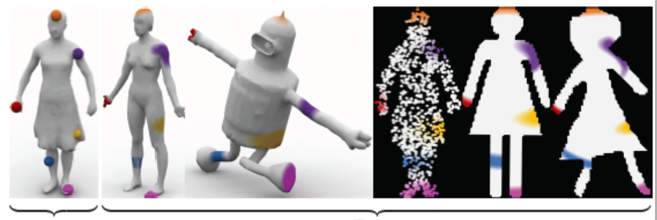


Figure 1: *Entropic GW can find correspo… surface (left) and a surface with similar… shared semantic structure, a noisy 3D po… hand drawing. Each fuzzy map was comp…*

are violated these algorithms suffer from… local elastic terms into a single global ma…

In this paper, we propose a new corres… minimizes distortion of long- and short-r… study an entropically-regularized version o… (GW) mapping objective function from [… the distortion of geodesic distances. The o… matching expressed as a "fuzzy" correspo… of [Kim et al. 2012; Solomon et al. 2012]… the correspondence via the weight of an e…

Although [Mémoli 2011] and subsequent… bility of using GW distances for geometric… tional challenges hampered their practical… these challenges, we build upon recent m… timal transportation introduced in [Benam… et al. 2015]. While optimal transportation… ent optimization problem from regularized GW computation (linear

function GROMOV-WASSERSTEIN$(\boldsymbol{\mu}_0, \mathbf{D}_0, \boldsymbol{\mu}, \mathbf{D}, \alpha, \eta)$
  // Computes a local minimizer $\boldsymbol{\Gamma}$ *of* (6)
  $\boldsymbol{\Gamma} \leftarrow \text{ONES}(n_0 \times n)$
  for $i = 1, 2, 3, \ldots$
    $\mathbf{K} \leftarrow \exp(\mathbf{D}_0[\![\boldsymbol{\mu}_0]\!]\boldsymbol{\Gamma}[\![\boldsymbol{\mu}]\!]\mathbf{D}^\top/\alpha)$
    $\boldsymbol{\Gamma} \leftarrow \text{SINKHORN-PROJECTION}(\mathbf{K}^{\wedge\eta} \otimes \boldsymbol{\Gamma}^{\wedge(1-\eta)}; \boldsymbol{\mu}_0, \boldsymbol{\mu})$
  return $\boldsymbol{\Gamma}$

function SINKHORN-PROJECTION$(\mathbf{K}; \boldsymbol{\mu}_0, \boldsymbol{\mu})$
  // Finds $\boldsymbol{\Gamma}$ *minimizing* $\mathrm{KL}(\boldsymbol{\Gamma}|\mathbf{K})$ *subject to* $\boldsymbol{\Gamma} \in \overline{\mathcal{M}}(\boldsymbol{\mu}_0, \boldsymbol{\mu})$
  $\mathbf{v}, \mathbf{w} \leftarrow \mathbf{1}$
  for $j = 1, 2, 3, \ldots$
    $\mathbf{v} \leftarrow \mathbf{1} \oslash \mathbf{K}(\mathbf{w} \otimes \boldsymbol{\mu})$
    $\mathbf{w} \leftarrow \mathbf{1} \oslash \mathbf{K}^\top(\mathbf{v} \otimes \boldsymbol{\mu}_0)$
  return $[\![\mathbf{v}]\!]\mathbf{K}[\![\mathbf{w}]\!]$

Algorithm 1: *Iteration for finding regularized Gromov-Wasserstein distances.* $\otimes, \oslash$ *denote elementwise multiplication and division.*

Convex Relaxation

Tight Relaxation of Quadratic Matching

Itay Kezurer[†] Shahar Z. Kovalsky[†] Ronen Basri Yaron Lipman

Weizmann Institute of Science

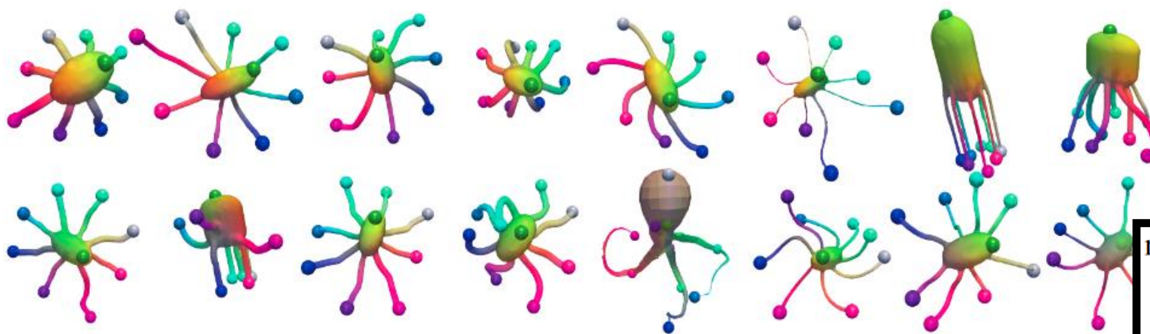


Figure 1: Consistent Collection Matching. Results of the proposed one-stage procedure for finding consistent corres
between shapes in a collection showing strong variability and non-rigid deformations.

Abstract

Establishing point correspondences between shapes is extremely challenging as it involves both finding se semantically persistent feature points, as well as their combinatorial matching. We focus on the latter and cons the Quadratic Assignment Matching (QAM) model. We suggest a novel convex relaxation for this NP-hard pro that builds upon a rank-one reformulation of the problem in a higher dimension, followed by relaxation in semidefinite program (SDP). Our method is shown to be a certain hybrid of the popular spectral and do stochastic relaxations of QAM and in particular we prove that it is tighter than both.

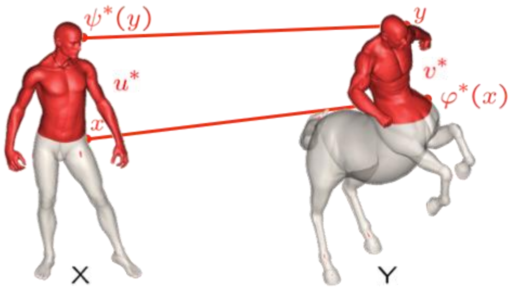
Experimental evaluation shows that the proposed relaxation is extremely tight: in the majority of our experim it achieved the certified global optimum solution for the problem, while other relaxations tend to produce optimal solutions. This, however, comes at the price of solving an SDP in a higher dimension.

$$
\begin{aligned}
\max_{Y} \quad & \operatorname{tr}(WY) \\
\text{s.t.} \quad & Y \succeq [X][X]^T \\
& X \in \operatorname{conv} \Pi_n^k \\
& \operatorname{tr} Y = k \\
& Y \geq 0 \\
& \sum_{qrst} Y_{qrst} = k^2 \\
& Y_{qrst} \leq \begin{cases} 0, & \text{if } q = s,\ r \neq t \\ 0, & \text{if } r = t,\ q \neq s \\ \min\{X_{qr}, X_{st}\}, & \text{otherwise} \end{cases}
\end{aligned}
$$

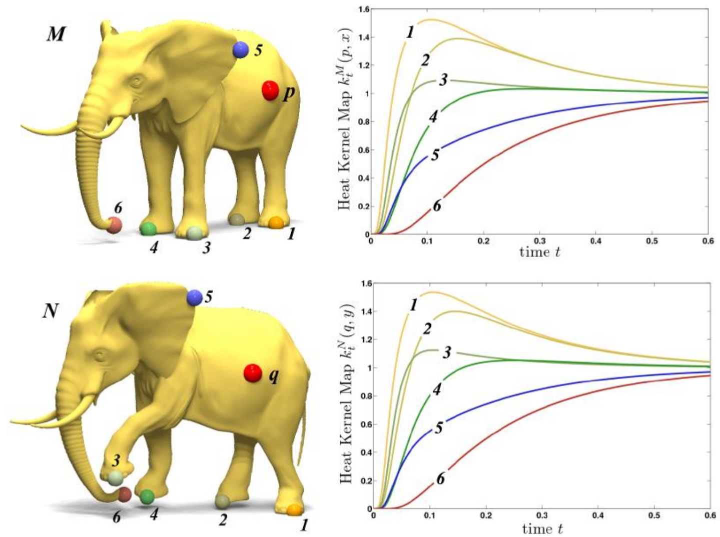
Continuum

Weak assumptions

Strong assumptions



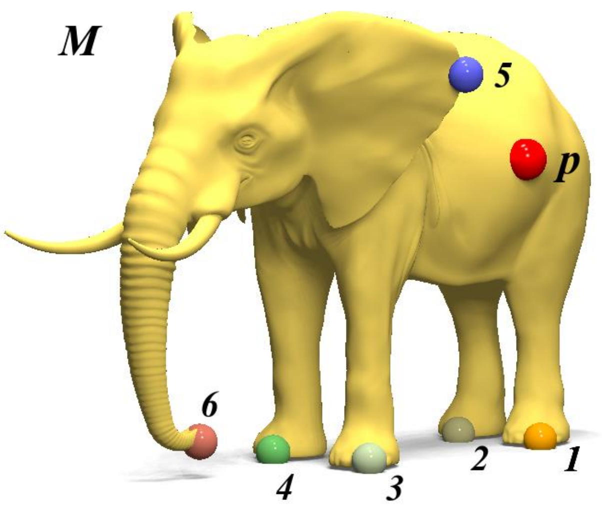
Low-distortion

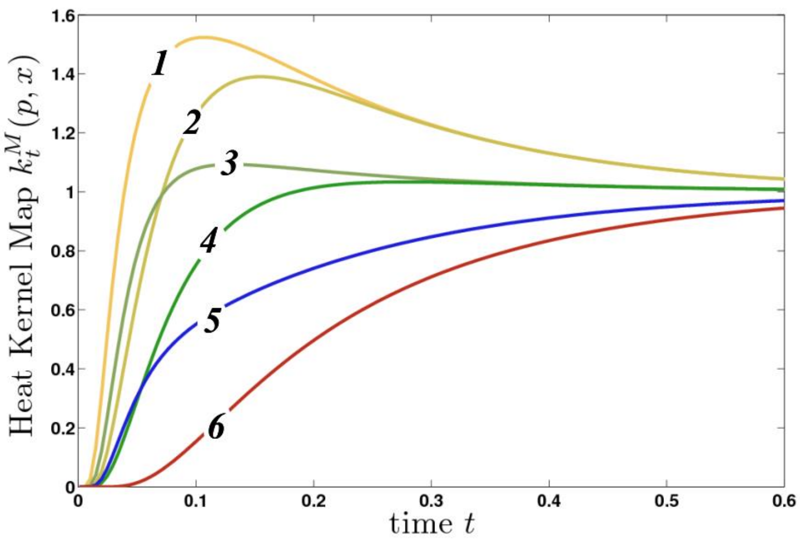


Isometry

Recall:

Heat Kernel Map





$$\mathrm{HKM}_p(x,t) := k_t(p,x)$$

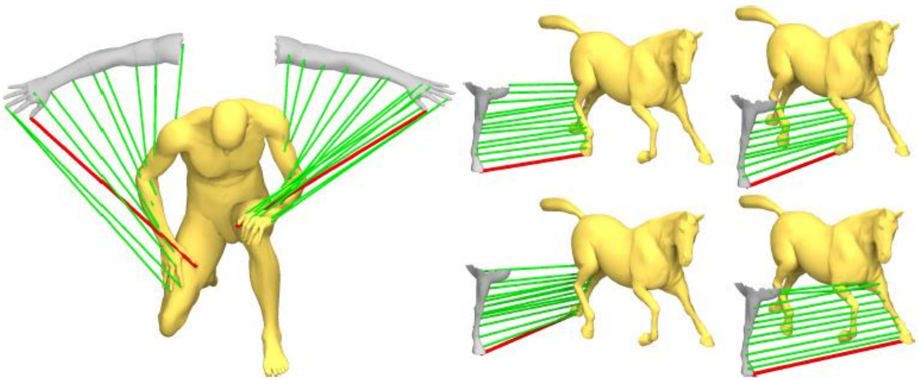
Theorem: Only have to match one point!

KNN

One Point Isometric Matching with the Heat Kernel

Ovsjanikov et al. 2010

Tradeoff: Heat Kernel Map



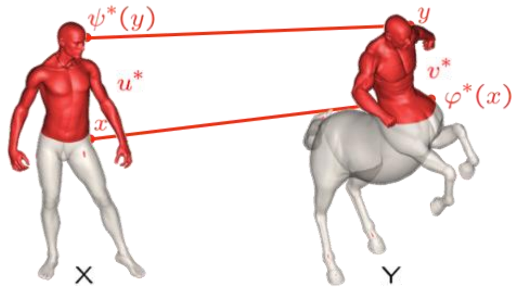
- Pros:
  - Tiny search space
  - Some extension to partial matching
- Cons:
  - (Extremely) sensitive to deviation from isometry

Adapted from slides by Q. Huang, V. Kim

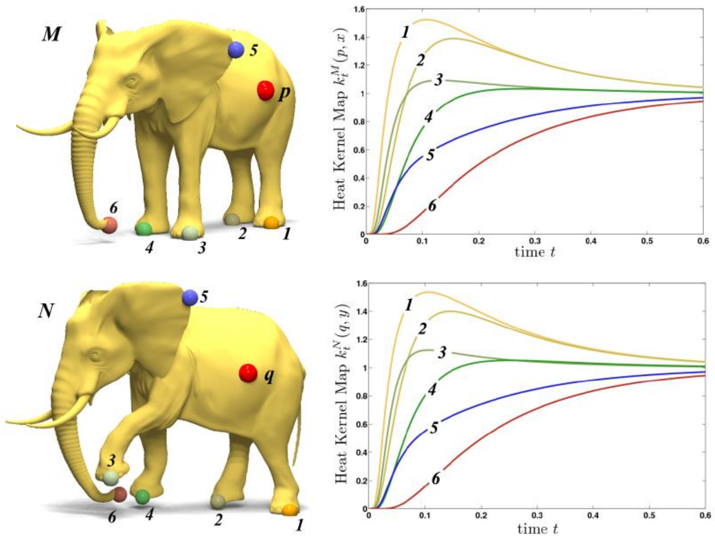
Continuum

????

Weak assumptions — Strong assumptions



Low-distortion



Isometry

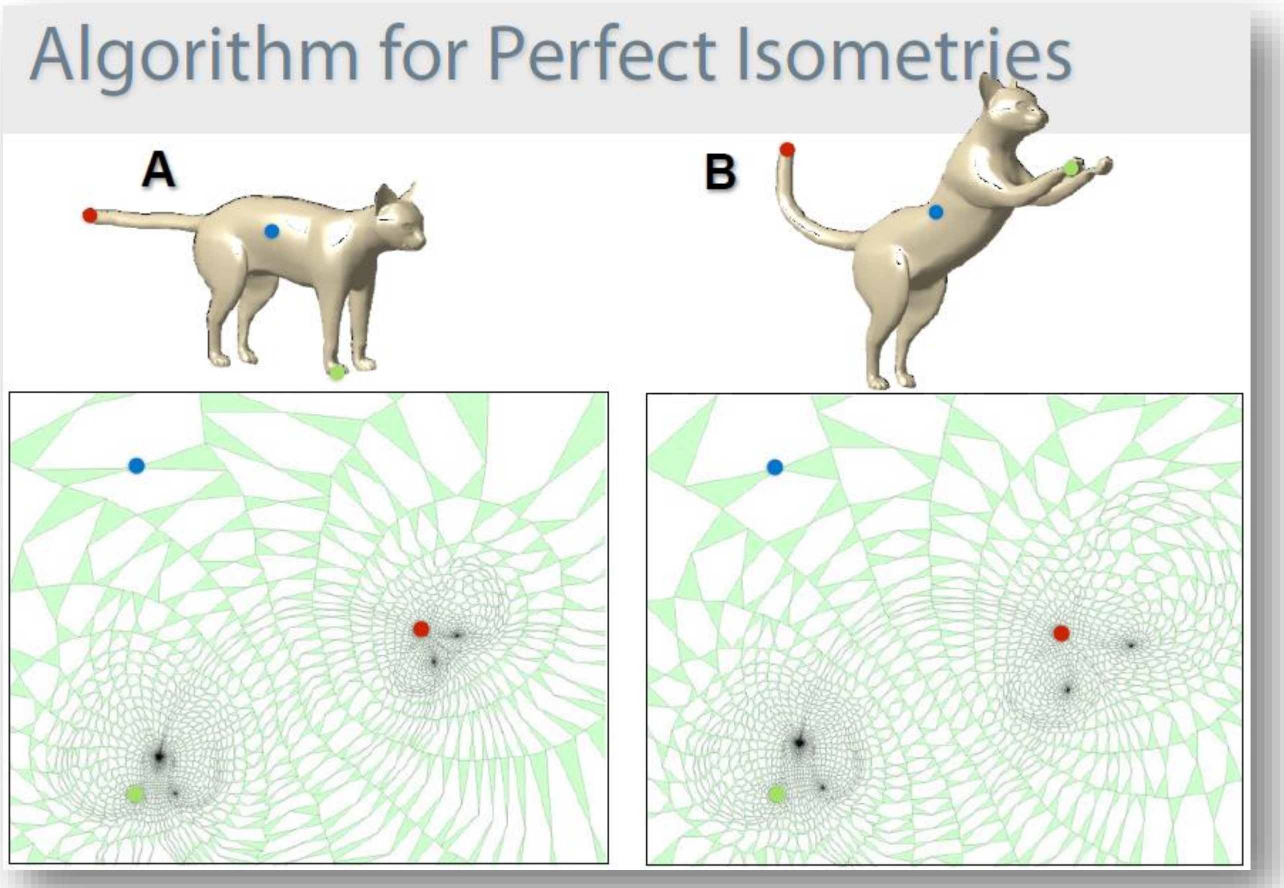
Observation About Mapping

Angle and area preserving *Angle preserving*

$$\text{isometries} \subseteq \text{conformal maps}$$

Hard! **Easier**

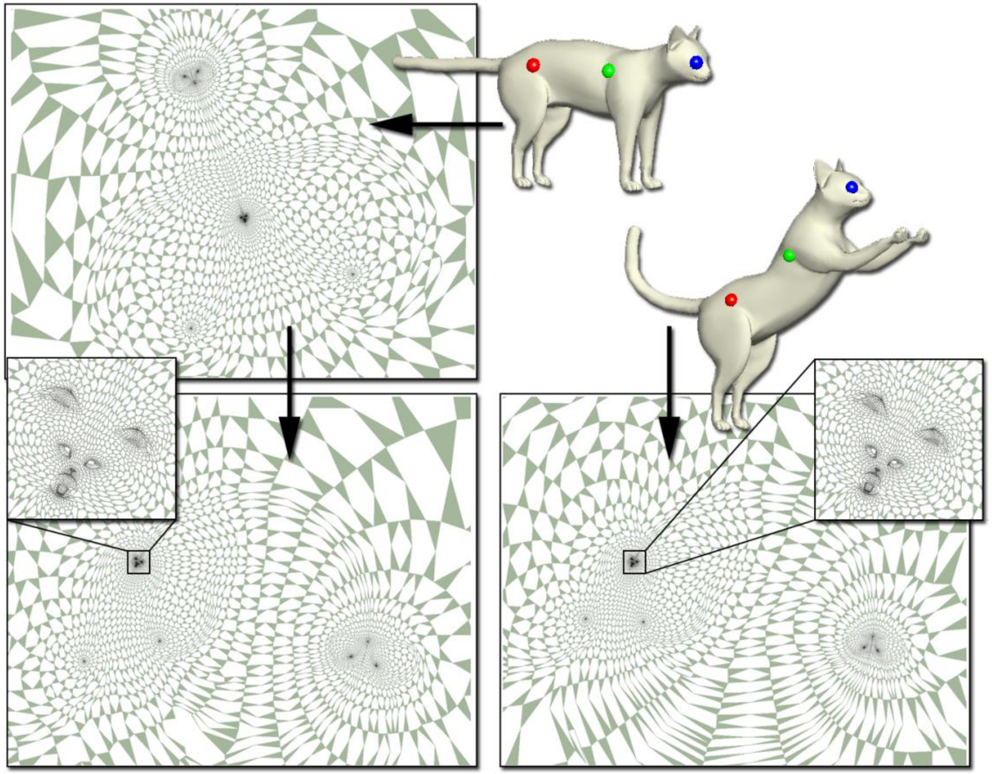
$O(n^3)$ Algorithm for Perfect Isometry



http://www.mpi-inf.mpg.de/resources/deformableShapeMatching/EG2011_Tutorial/slides/4.3%20SymmetryApplications.pdf

Map triplets of points

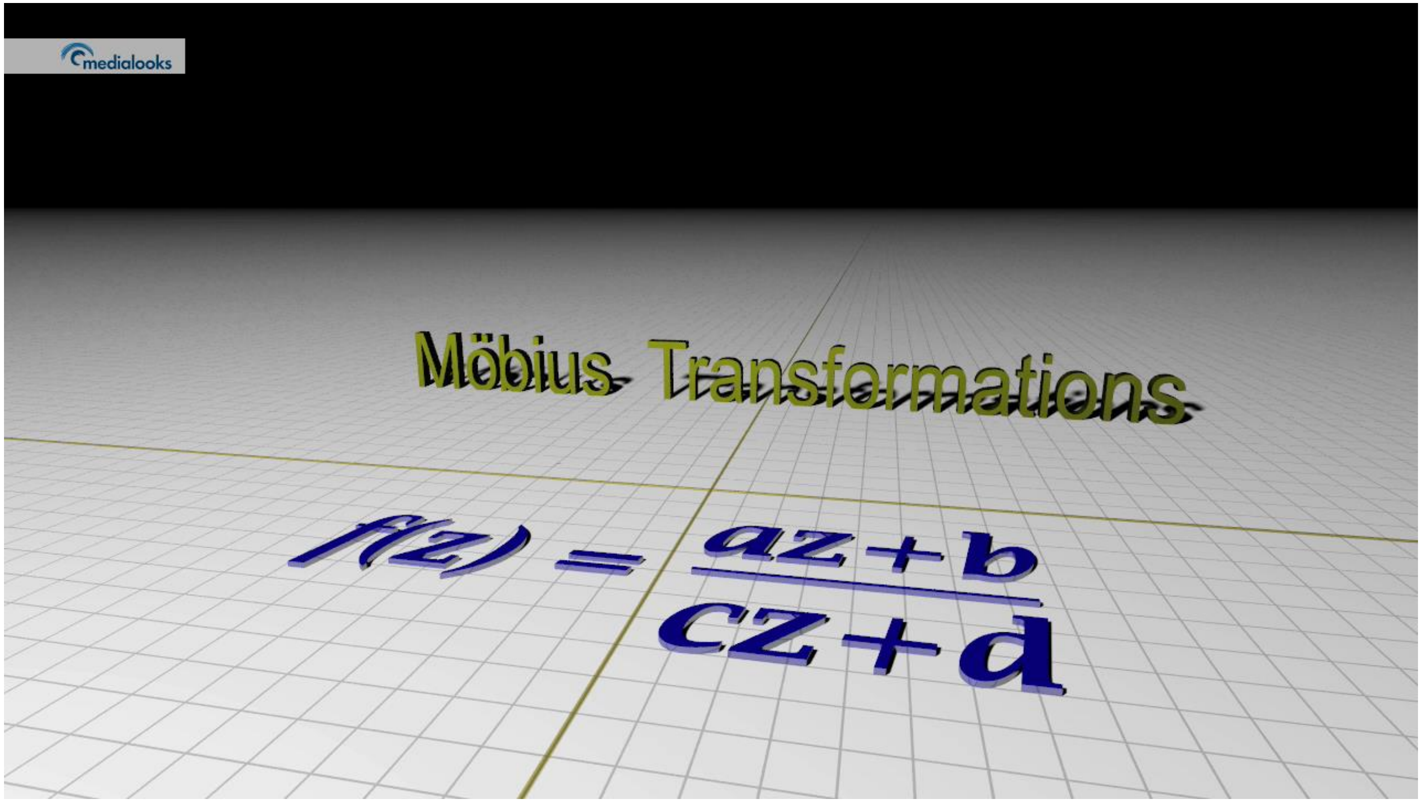
Möbius Voting



1. Map surfaces to complex plane
2. Select three points
3. Map plane to itself matching these points
4. Vote for pairings using distortion metric to weight
5. Return to 2

Möbius Voting for Surface Correspondence
Lipman and Funkhouser 2009

Möbius Transformations

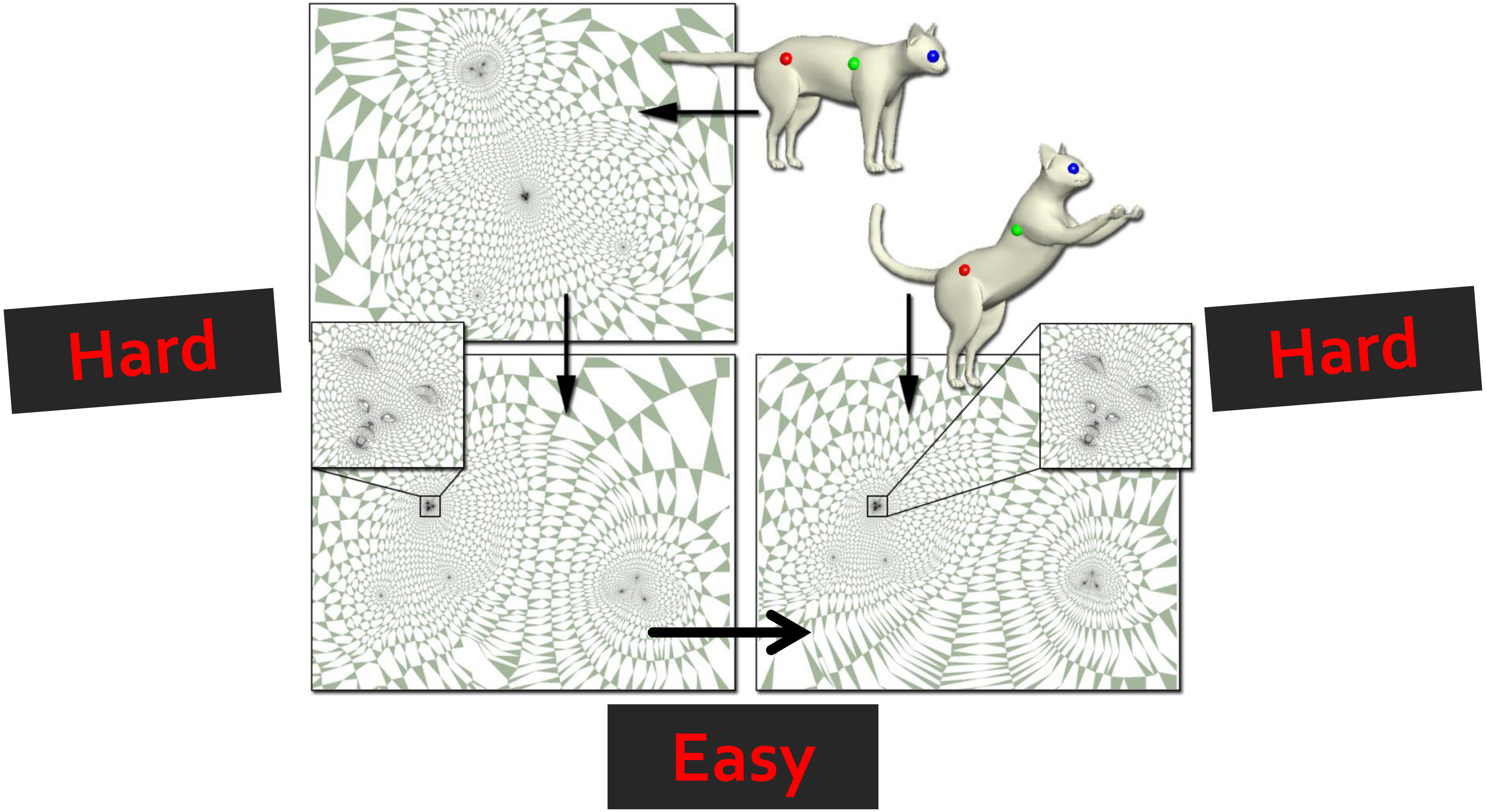


$$\frac{az+b}{cz+d}$$

http://www.ima.umn.edu/~arnold//moebius

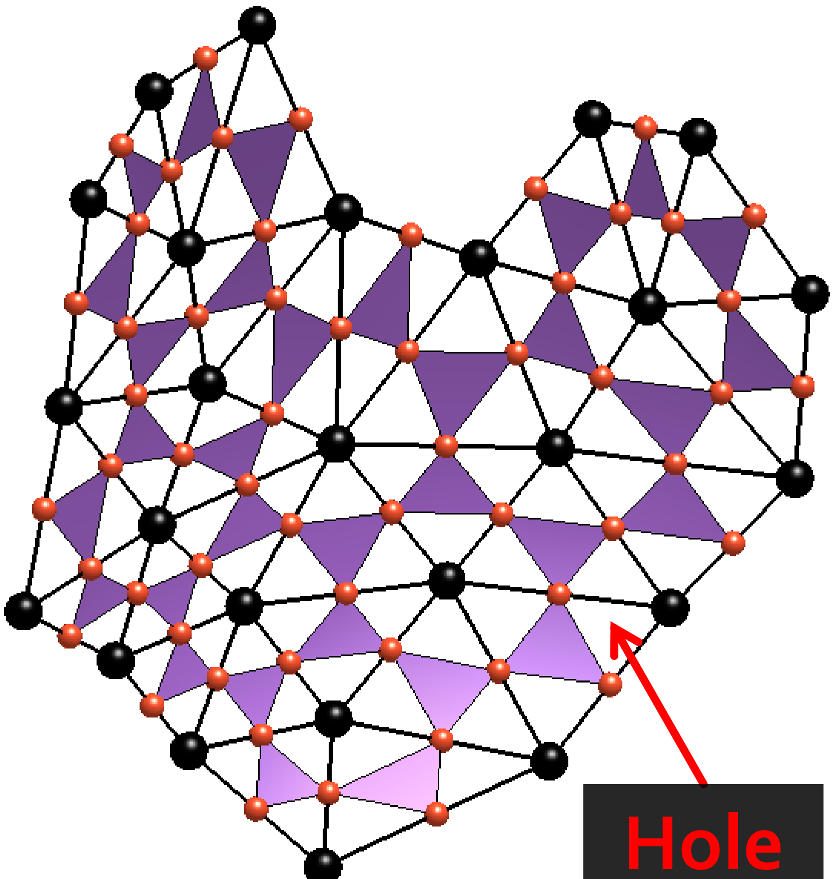
Bijective conformal maps of the extended complex plane

Observation



Hard work is per-surface, not per-map

Mid-Edge Flattening



$$\Phi(v) = u(v) + iu^*(v)$$

PL, continuous

$$\Delta u = 0$$

PL, continuous at midpoints

Rotate gradient of *u* 90°

Cannot scale triangles to flatten

Voting Algorithm

Input: points $\Sigma_1 = \{z_k\}$ and $\Sigma_2 = \{w_\ell\}$
number of iterations I
minimal subset size K
Output: correspondence matrix $C = (C_{k,\ell})$.

```
/* Möbius voting */
```

while *number of iterations* $< I$ **do**

Random $z_1, z_2, z_3 \in \Sigma_1$.

Random $w_1, w_2, w_3 \in \Sigma_2$.

Find the Möbius transformations m_1, m_2 s.t.

$m_1(z_j) = y_j,\ m_2(w_j) = y_j,\ j = 1, 2, 3.$

Apply m_1 on Σ_1 to get $\bar{z}_k = m_1(z_k)$.

Apply m_2 on Σ_2 to get $\bar{w}_\ell = m_2(w_\ell)$.

Find mutually nearest-neighbors $(\bar{z}_k, \bar{w}_\ell)$ to formulate candidate correspondence c.

if *number of mutually closest pairs* $\geq K$ **then**

Calculate the deformation energy $\mathbf{E}(c)$

```
/* Vote in correspondence matrix */
```

foreach $(\bar{z}_k, \bar{w}_\ell)$ *mutually nearest-neighbors* **do**

$C_{k,\ell} \leftarrow C_{k,\ell} + \frac{1}{\varepsilon + \mathbf{E}(c)/n}$.

end

end

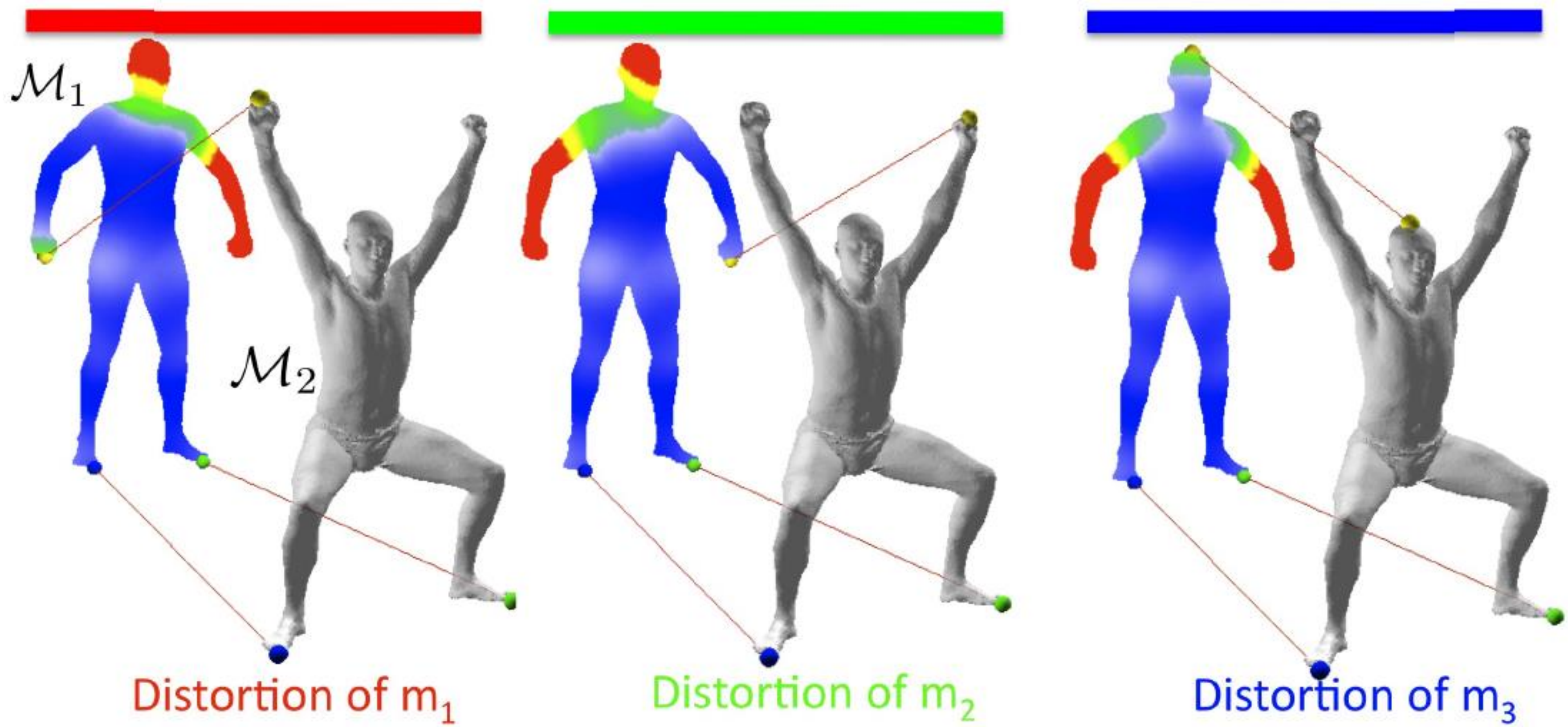
end

Tradeoff: Möbius Voting

- **Pros:**
  - Efficient
  - Voting procedure handles some non-isometry
- **Cons:**
  - Does not provide smooth/continuous map
  - Does not optimize global distortion
  - Only for genus 0

Adapted from slides by Q. Huang, V. Kim

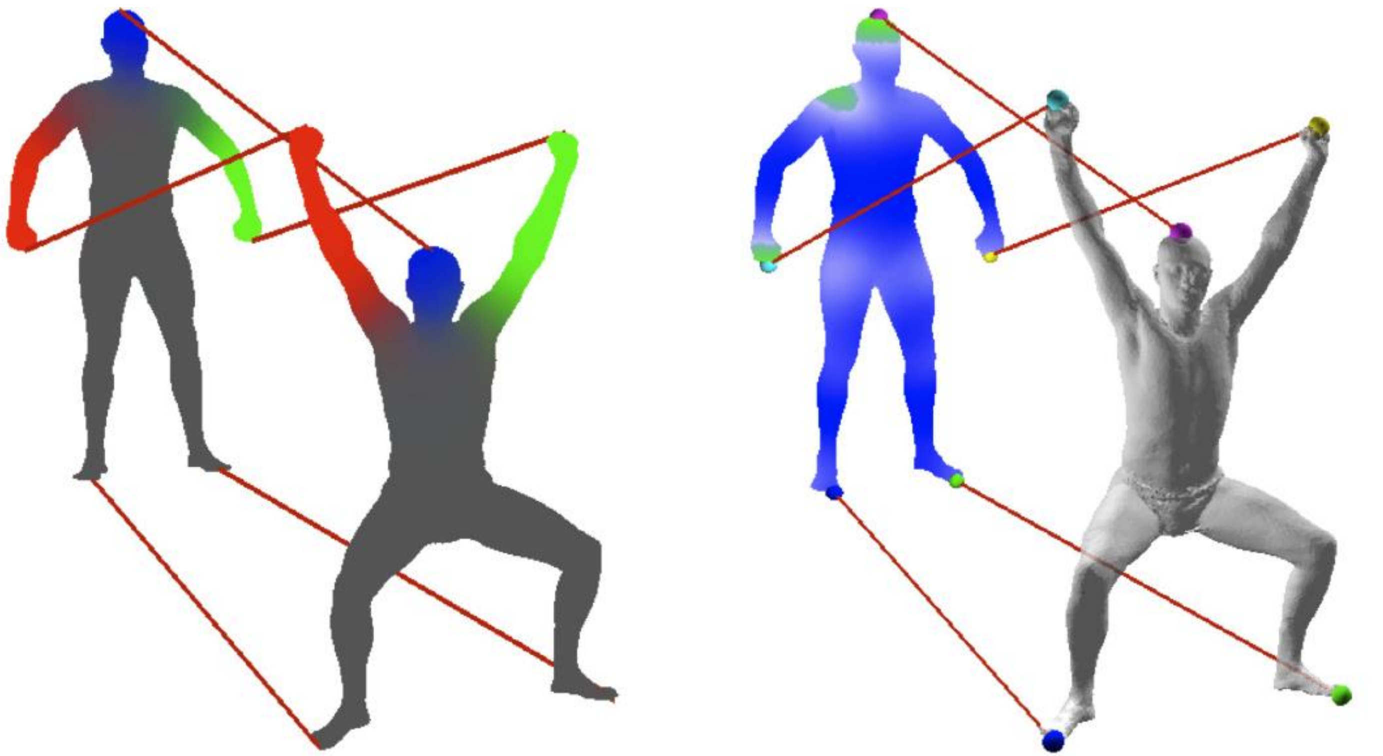
Blended Intrinsic Maps



Different conformal maps distorted in different places.

Blended Intrinsic Maps
Kim, Lipman, and Funkhouser 2011

Use for Dense Mapping



Blending Weights for m_1, m_2, and m_3 Distortion of the Blended Map

Combine good parts of different maps!

Blended Intrinsic Maps
Kim, Lipman, and Funkhouser 2011

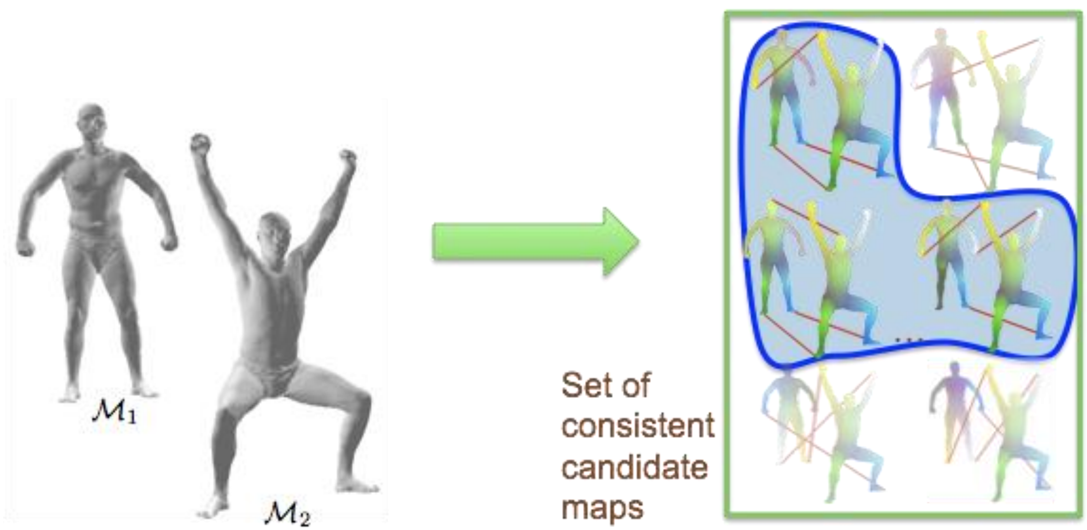
Blended Intrinsic Maps

- **Algorithm:**
  - **Generate consistent maps**
  - **Find blending weights per-point on each map**
  - **Blend maps**

Kim'11

Blended Intrinsic Maps

- Algorithm:
  - Generate consistent maps
  - Find blending weights per-point on each map
  - Blend maps



Adapted from slides by Q. Huang, V. Kim

Kim'11

Blended Intrinsic Maps

- **Algorithm:**
  - **Generate consistent maps**
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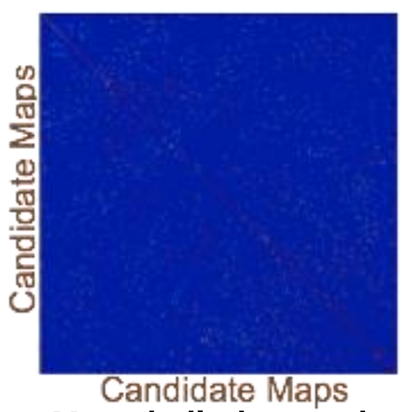


Map similarity matrix

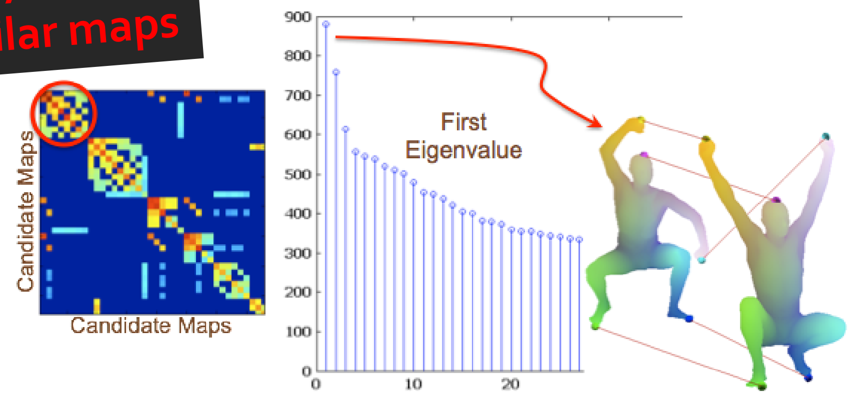
Adapted from slides by Q. Huang, V. Kim

Kim'11

Blended Intrinsic Maps

- Algorithm:
  - Generate consistent maps
  - Find blending weights per-point on each map
  - Blend maps

Eigen-analysis:
“Block” of similar maps

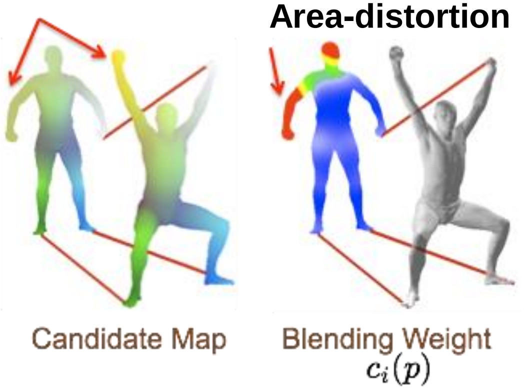


Adapted from slides by Q. Huang, V. Kim

Kim’11

Blended Intrinsic Maps

- Algorithm:
  - Generate consistent maps
  - Find blending weights per-point on each map
  - Blend maps



Adapted from slides by Q. Huang, V. Kim

Kim'11

Blended Intrinsic Maps

- **Algorithm:**
  - **Generate consistent maps**
  - **Find blending weights per-point on each map**
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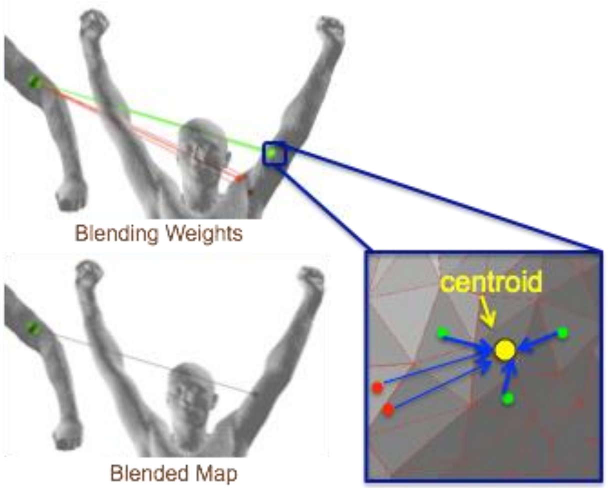

Adapted from slides by Q. Huang, V. Kim

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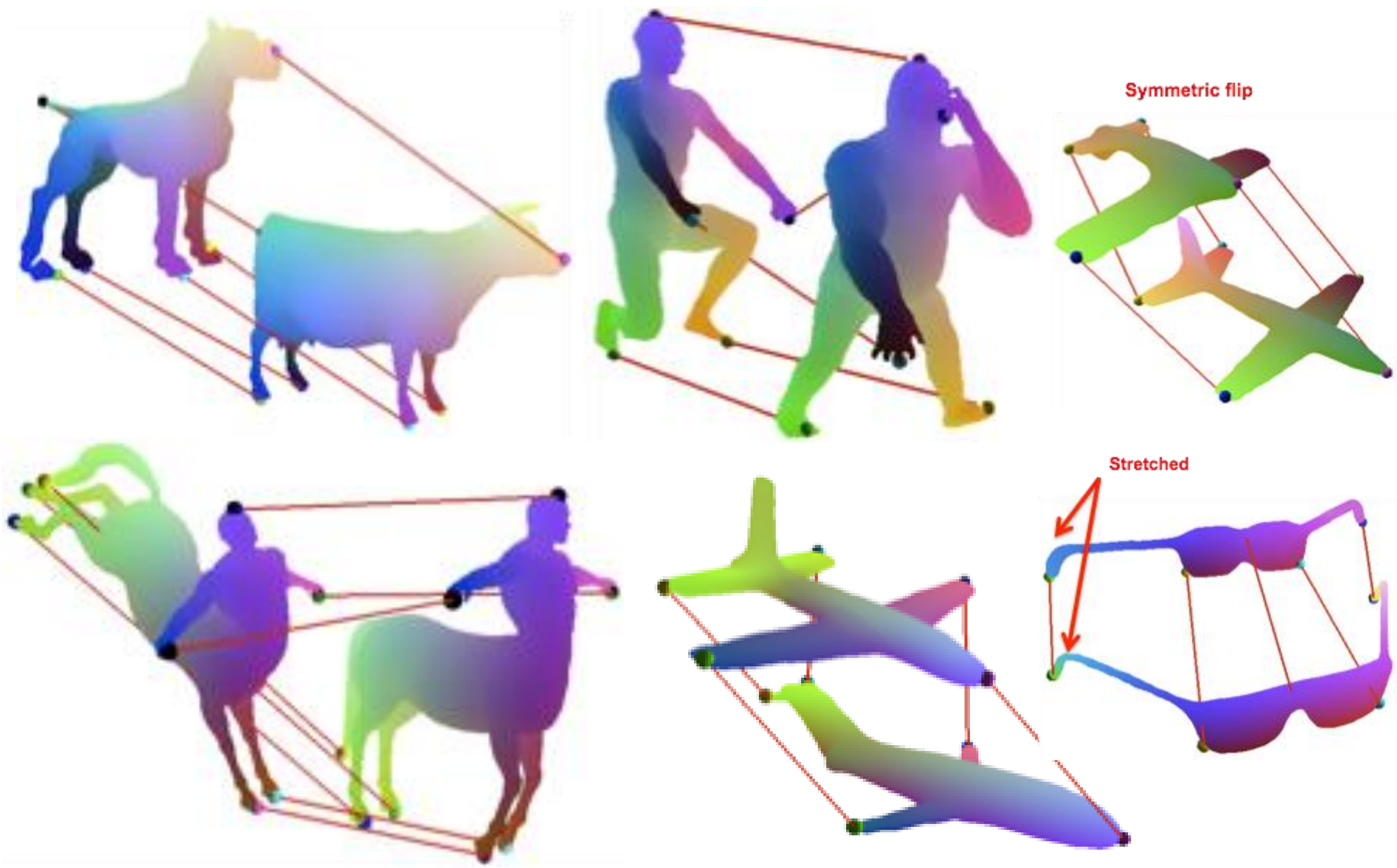
Some Examples



Adapted from slides by Q. Huang, V. Kim

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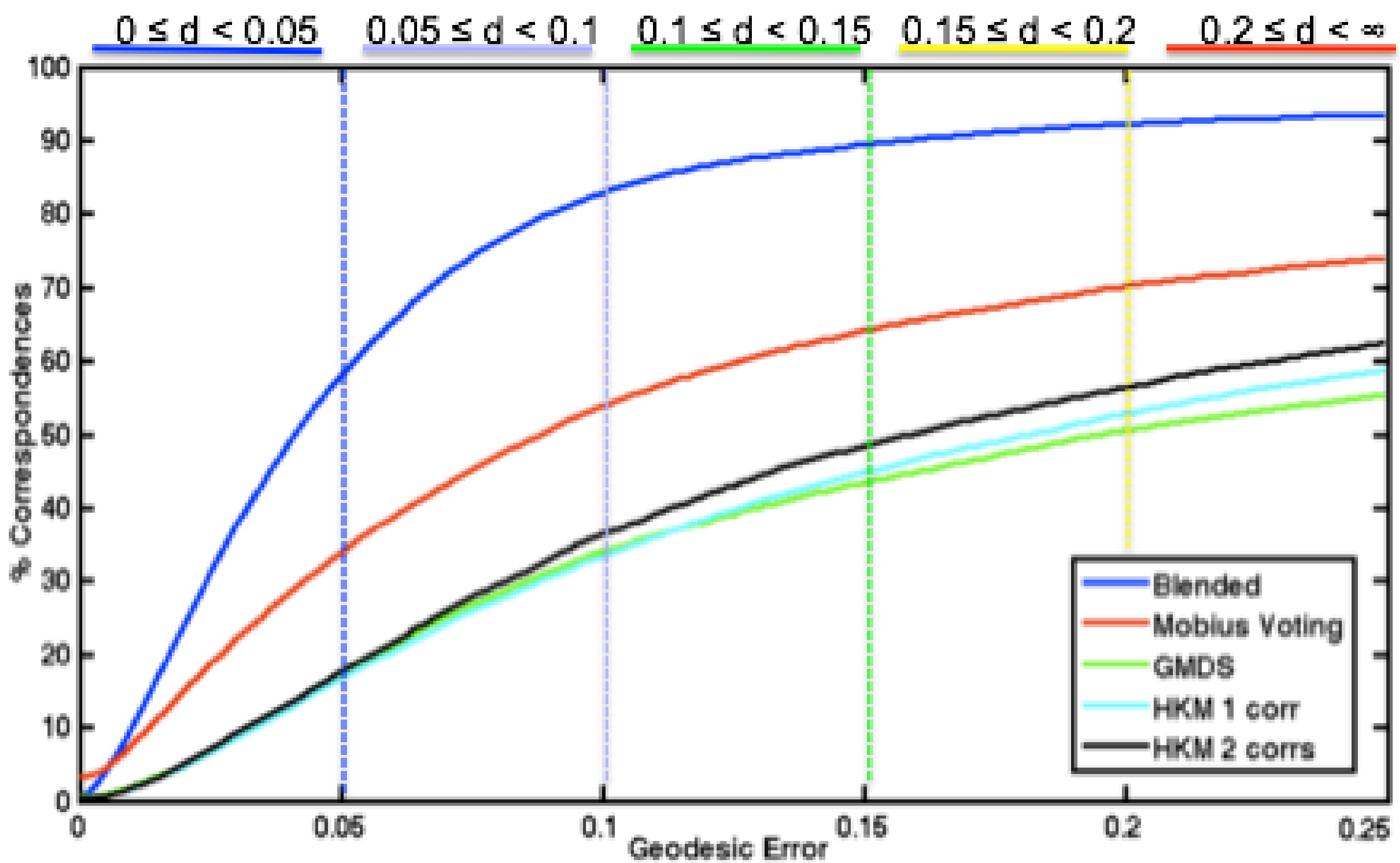
Evaluation



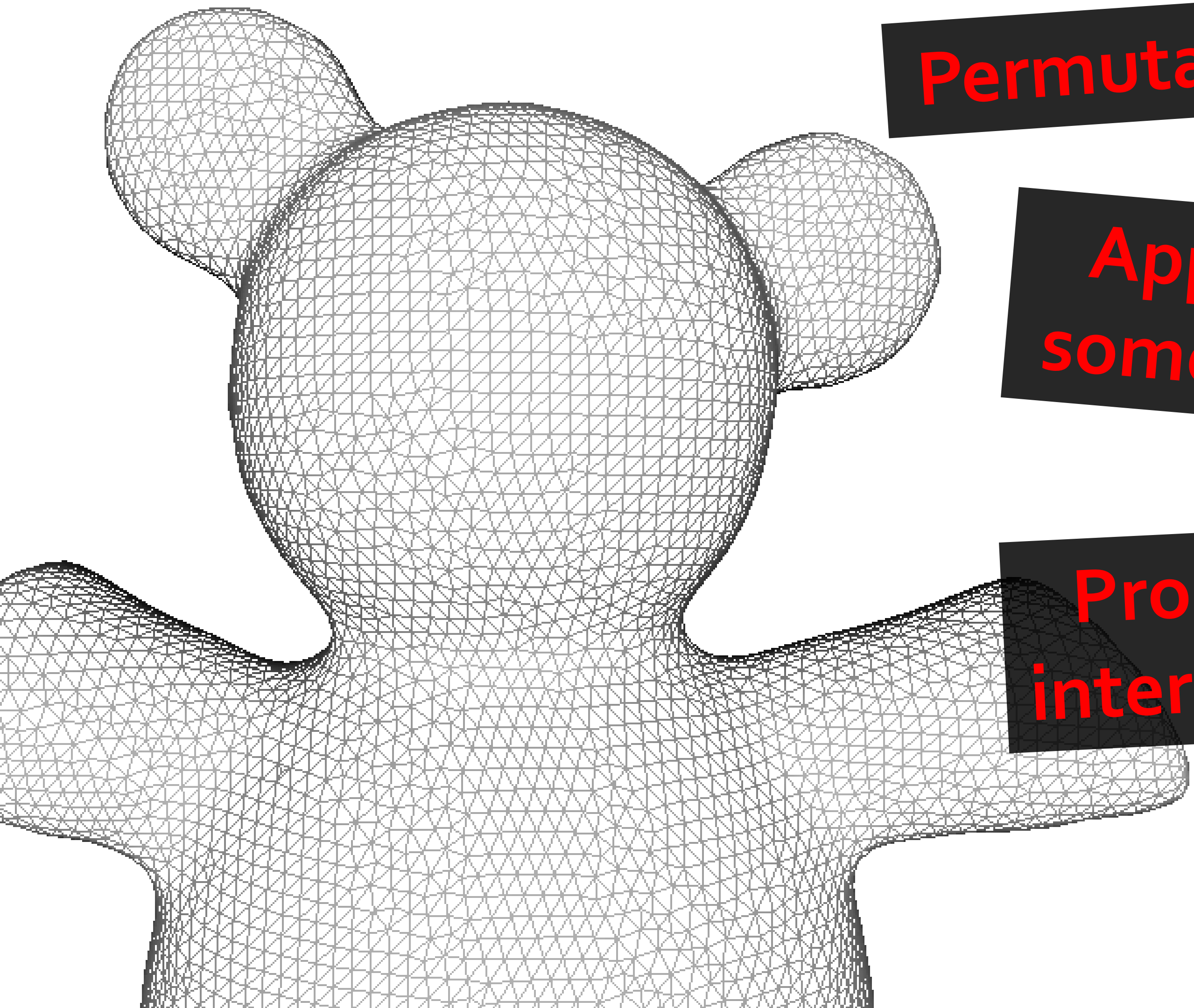
Kim'11

Tradeoff: Blended Intrinsic Maps

- **Pros:**
  - Can handle non-isometric shapes
  - Efficient
- **Cons:**
  - Lots of area distortion for some shapes
  - Genus 0 manifold surfaces

Adapted from slides by Q. Huang, V. Kim

Subtlety: Representation



Permutation?

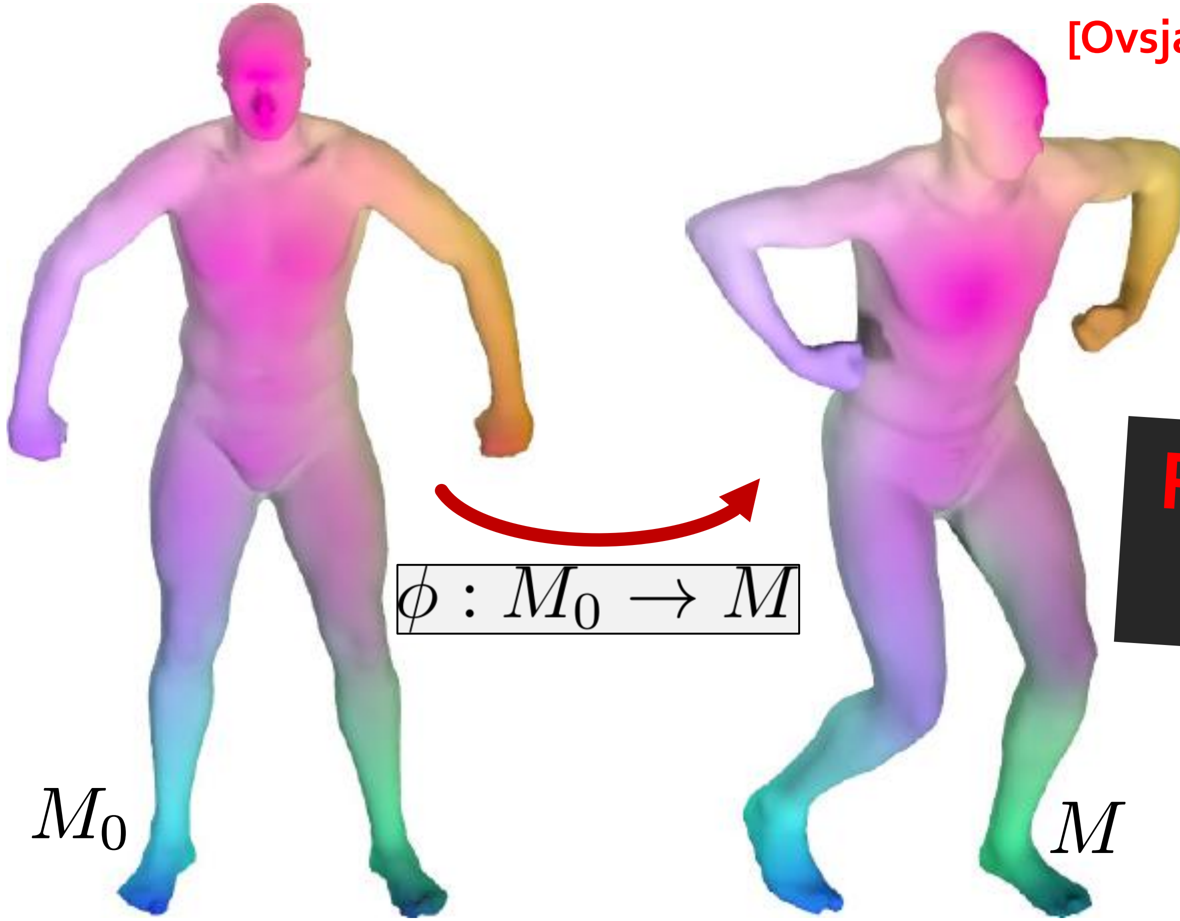
Approximation of something smooth?

Probabilistic interpretation?

Invertibility?

Functional Maps

[Ovsjanikov et al. 2012]

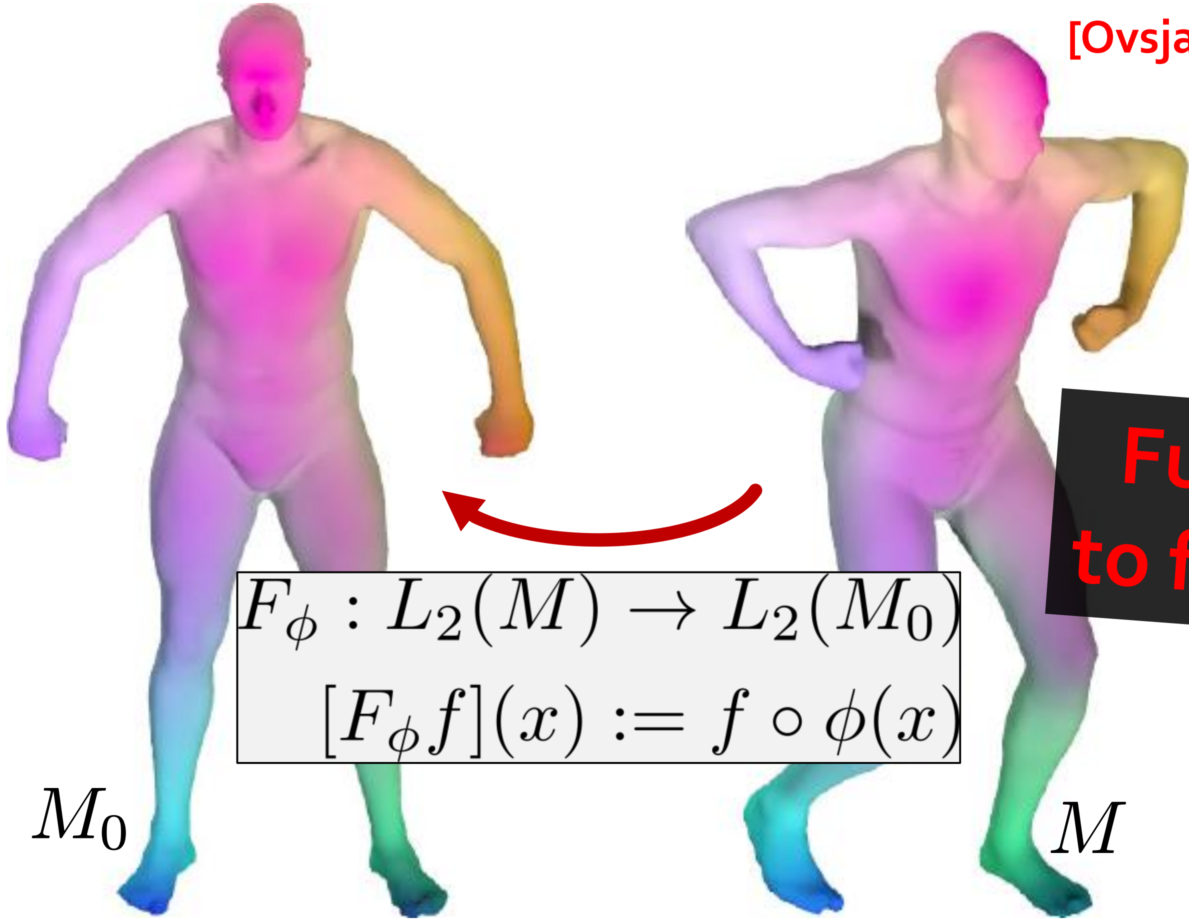


Points to points

Points on M_0 to points on M

Functional Maps

[Ovsjanikov et al. 2012]



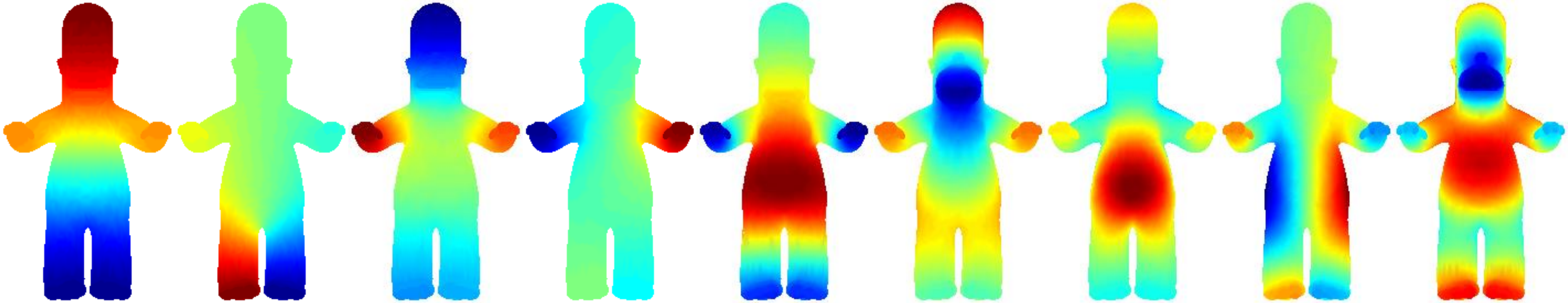
$$\boxed{\begin{aligned} F_\phi : L_2(M) &\to L_2(M_0) \\ [F_\phi f](x) &:= f \circ \phi(x) \end{aligned}}$$

Functions to functions

Functions on *M* to functions on *M*$_0$

Functional Maps

[Ovsjanikov et al. 2012]

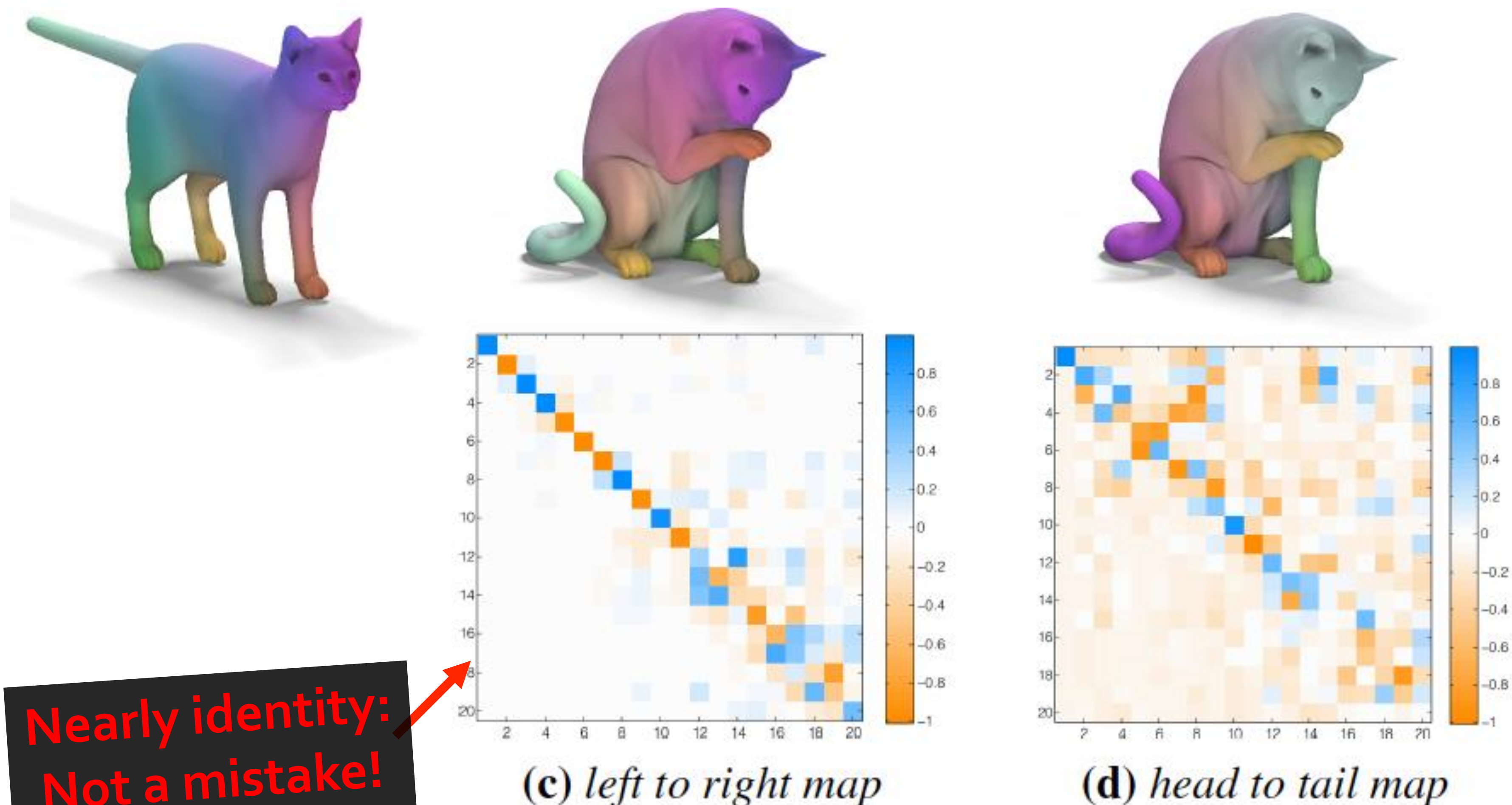


$$f(x) = \sum_i a_i \psi_i(x)$$

Functional map:

Matrix taking Laplace-Beltrami (Fourier) coefficients on *M* to coefficients on M_0

Example Maps



Nearly identity:
Not a mistake!

Adapted from slides by Q. Huang, V. Kim

Functional Maps

- Simple Algorithm
  - Compute some geometric functions to be preserved: A, B
  - Solve in least-squares sense for C: B = C A
- Additional Considerations
  - Favor commutativity
  - Favor orthonormality (if shapes are isometric)
  - Efficiently getting point-to-point correspondences

Adapted from slides by Q. Huang, V. Kim

Ovsjanikov'12

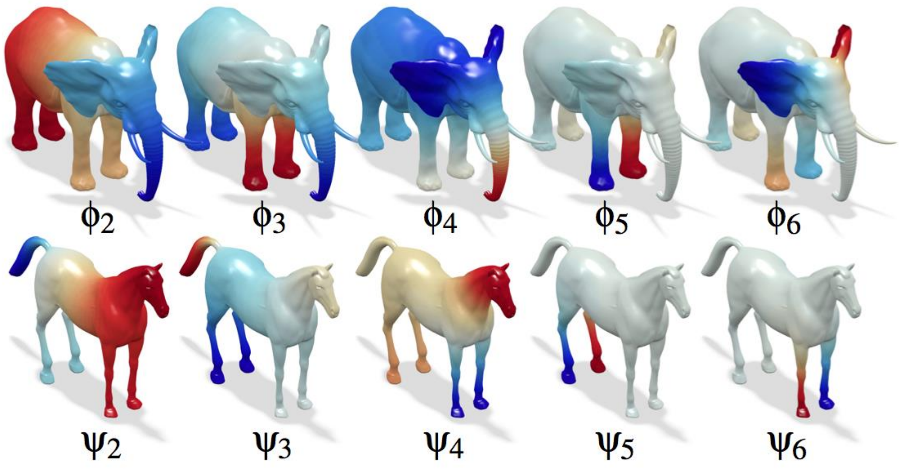
Tradeoff: Functional Maps

- **Pros:**
  - **Condensed representation**
  - **Linear**
  - **Alternative perspective on mapping**
  - **Many recent papers with variations**
- **Cons:**
  - **Hard to handle non-isometry**
    Some progress in last few years!

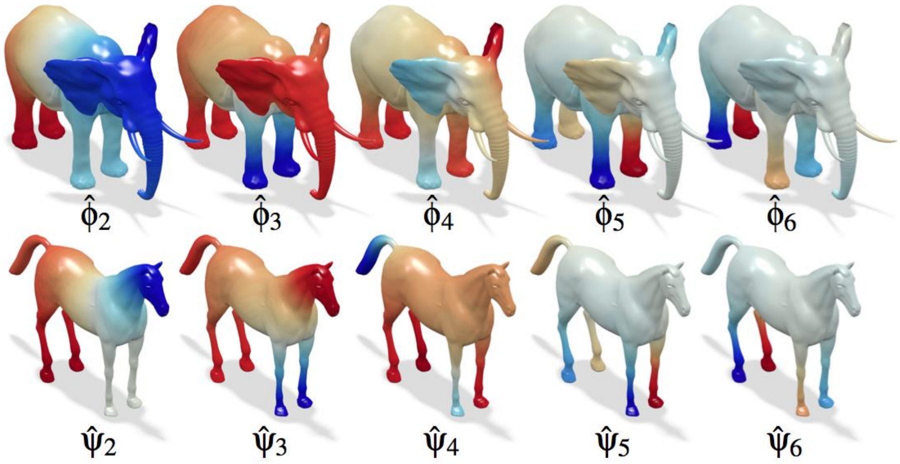
Adapted from slides by Q. Huang, V. Kim

Example extension:

Coupled Quasi-Harmonic Basis



Laplacian eigenbases

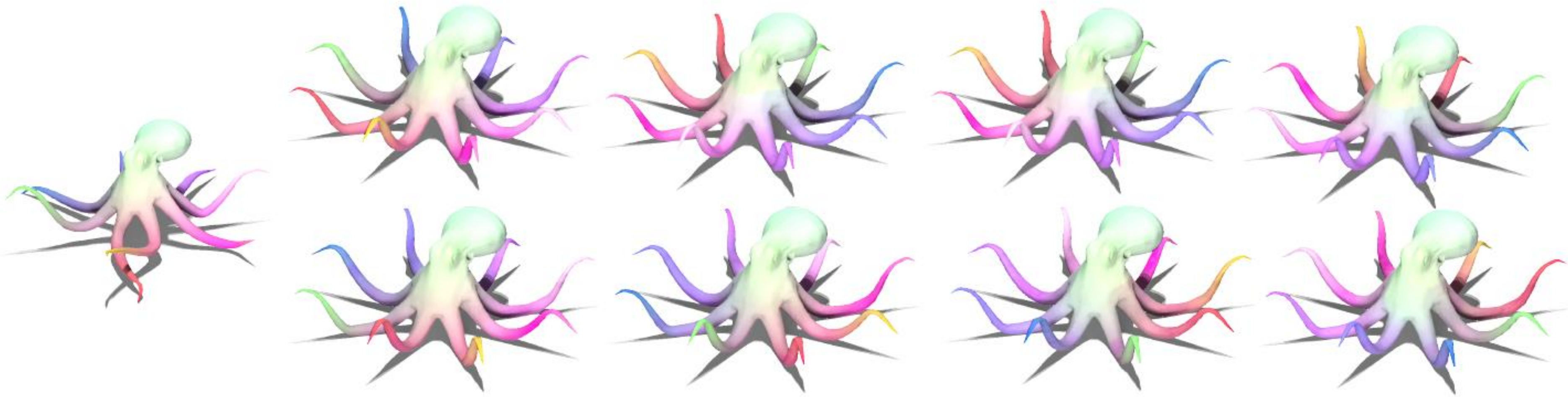


Coupled quasi-harmonic bases

Bronstein'12

Example extension:

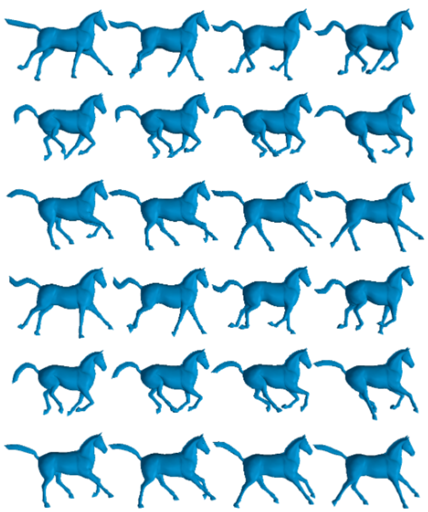
Leverage Symmetry

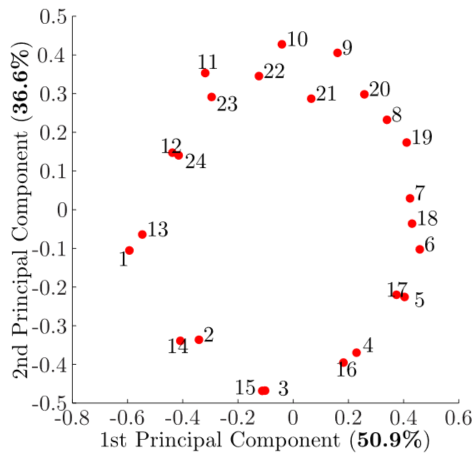


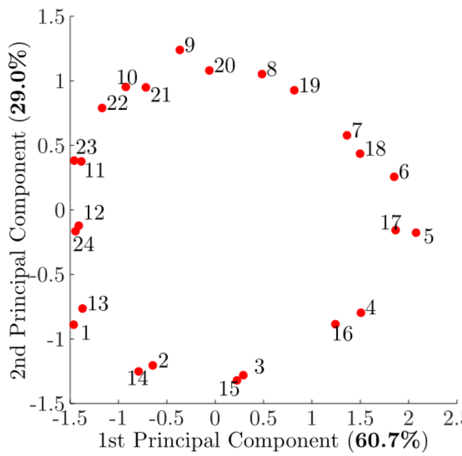
Ovsjanikov’13

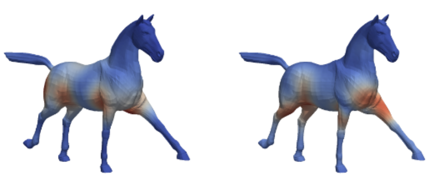
Example extension:

Analyze Deformation





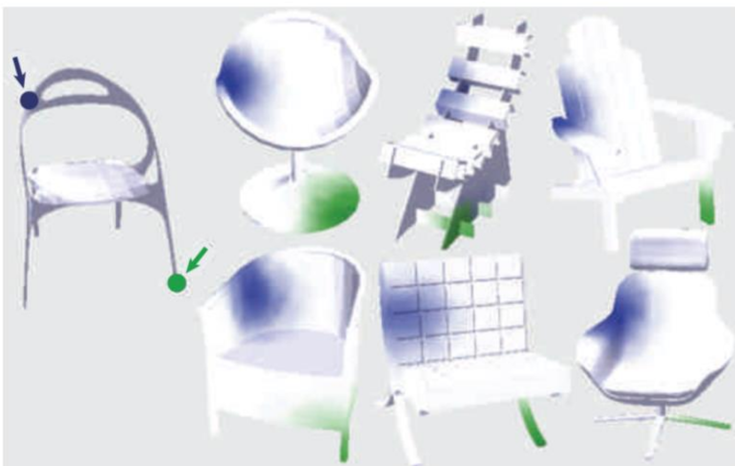


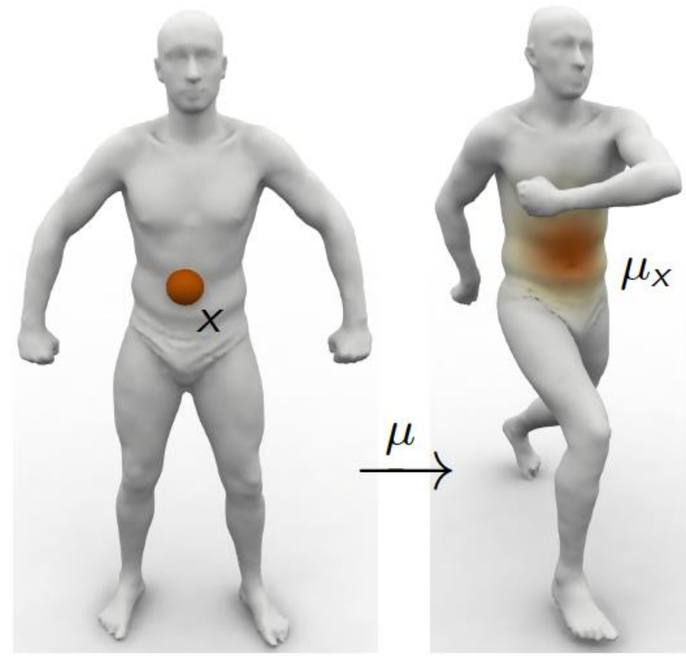


Rustamov '13

Related method:

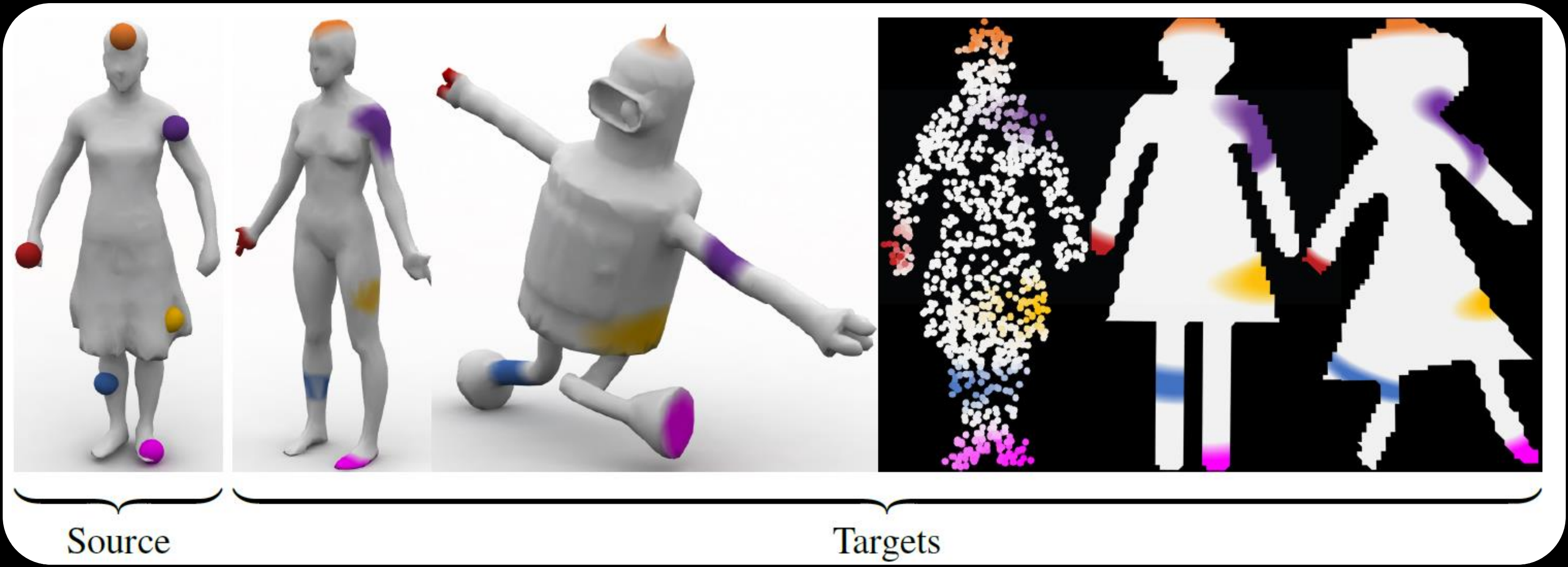
Soft/Fuzzy Maps





Kim'12, Solomon'12, Solomon'13

Image from "Entropic Metric Alignment for Correspondence Problems." Solomon et al., SIGGRAPH 2016.



Surface Correspondence

Justin Solomon

MIT, Spring 2017