MVA

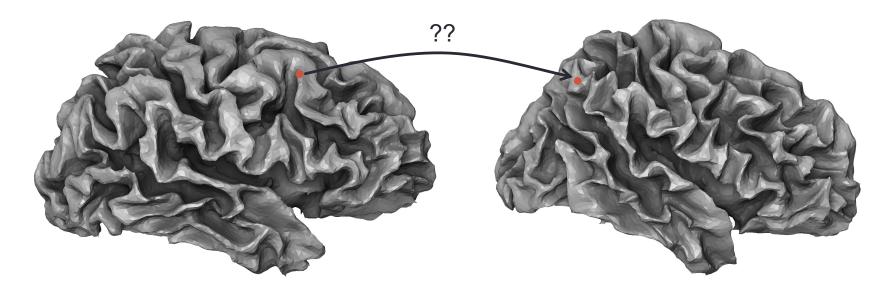
Geometry Processing and Geometric Deep Learning

Today

- Last week: geometric characterization of surfaces
- Optimization of geometric energies for shape matching
 - The matching problem
 - Topology
 - Surface parametrization
 - Surface deformation

Surface Correspondence Problem

Which points on one object correspond to points on another?

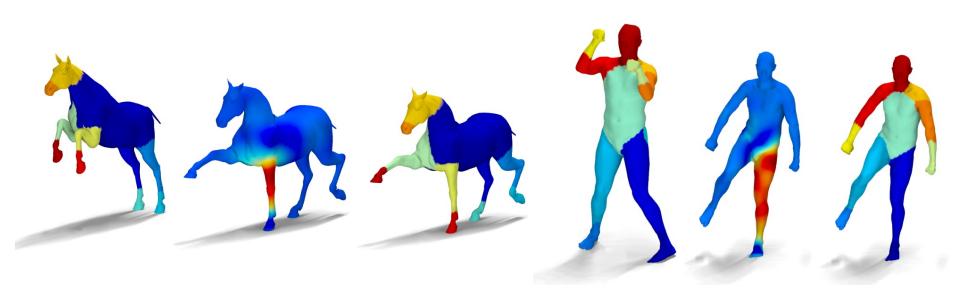


- Two approaches:
 - 1. Look for shared geometric structure
 - 2. Seek best alignment

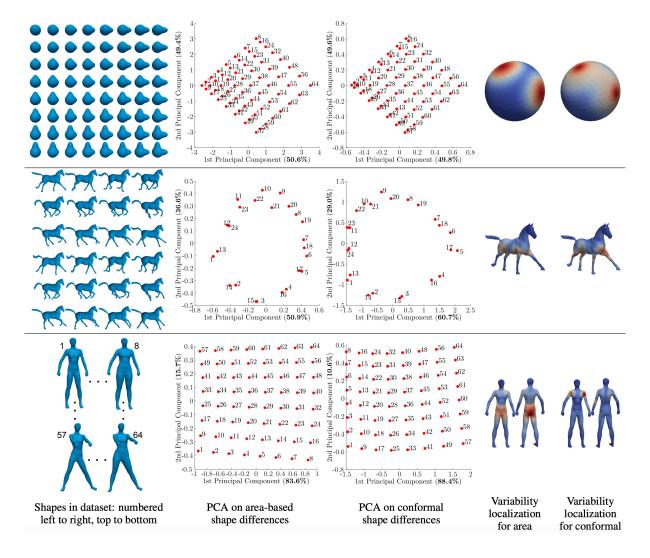
Deformation Transfer



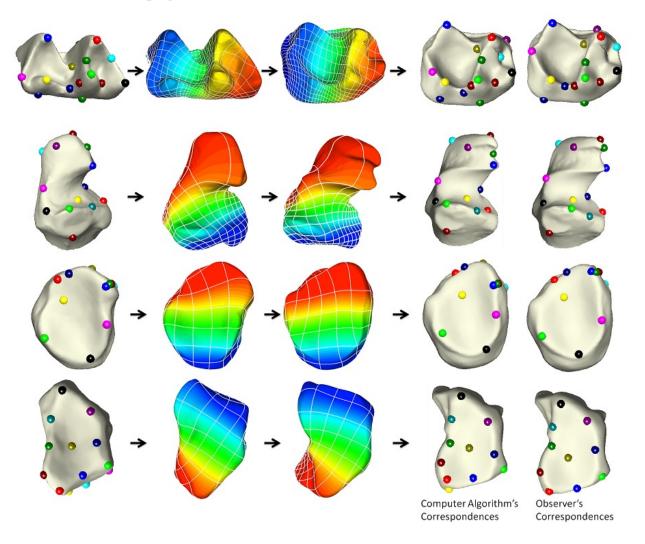
Segmentation Transfer



Statistical Shape Analysis

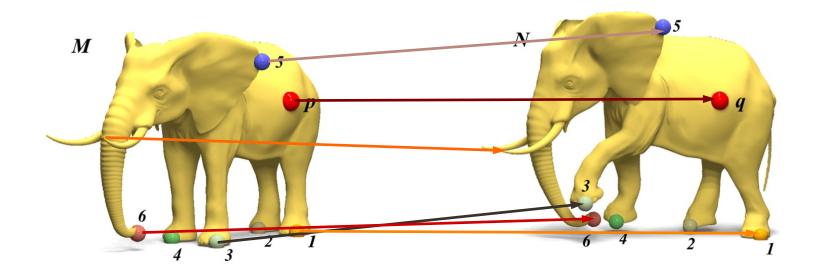


Paleontology



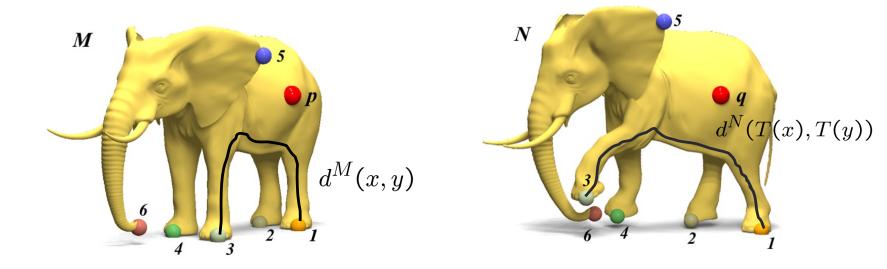
Mapping Problem

- Given a pair of shapes, find corresponding points
- An ideal map:
 - Preserves important features
 - Is fast to compute



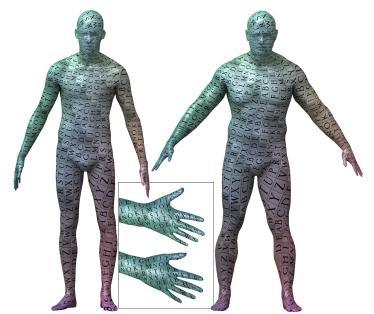
Mapping Problem

- Given a pair of shapes, find corresponding points
- An ideal map:
 - Preserves important features
 - Is fast to compute
 - Has low distortion (preserves geodesic distances)

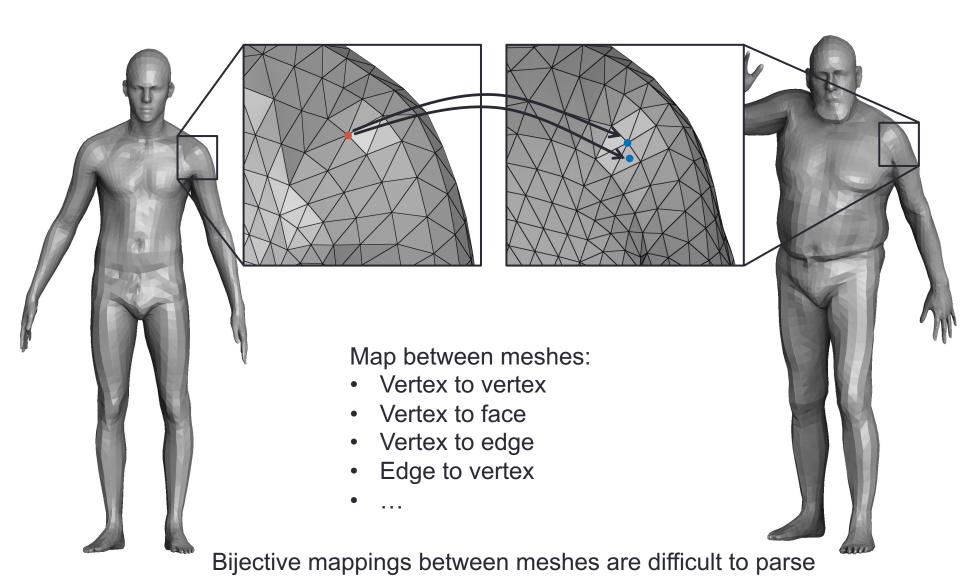


Mapping Problem

- Given a pair of shapes, find corresponding points
- An ideal map:
 - Preserves important features
 - Is fast to compute
 - Has low distortion (preserves geodesic distances)
 - Is continuous and bijective

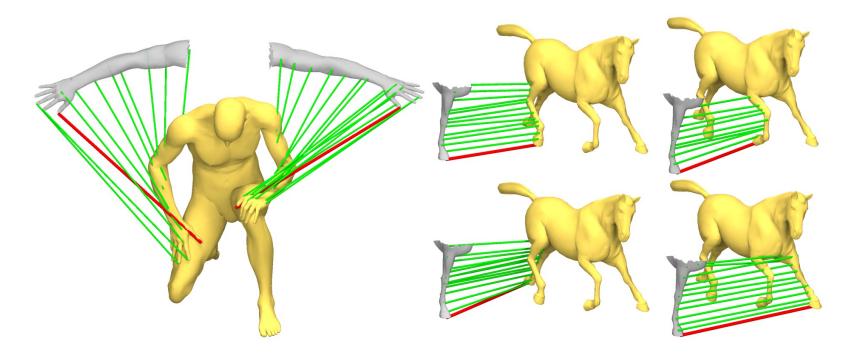


Surface to Surface Map On Meshes



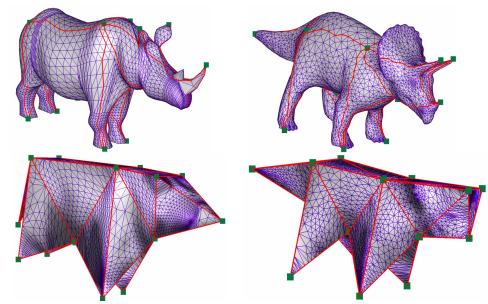
Vertex-To-Vertex Map

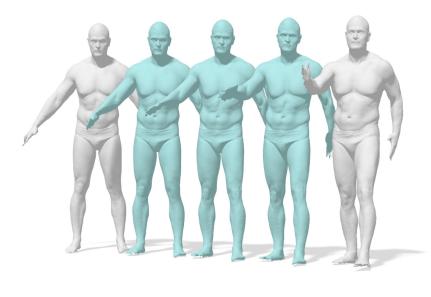
- Nearest neighbors on HKS and heat diffusion
 - Partial matching
 - No topological matching
 - Low cost
 - No continuity



Common Methods For Computing Maps

- Spectral methods: Laplacian eigenfunctions
 - Fast and very flexible but no guaranties
- Cross parametrization: find correspondences in a common domain
 - Slow but bijective and continuous
- **Deformations**: non-rigid alignment of surfaces
 - Slow but does not guaranty continuity

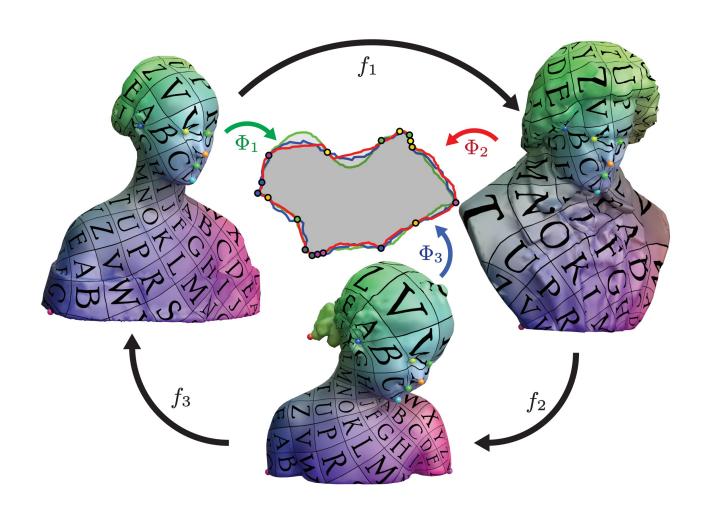




Cross-Parameterization and Compatible Remeshing of 3D Models

Divergence-Free Shape Interpolation and Correspondence

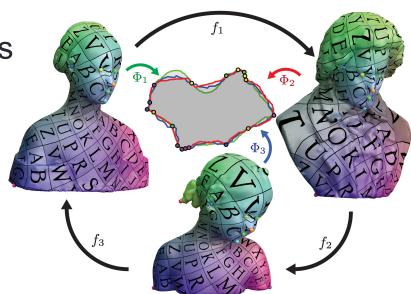
Parameterization for Matching



Cross Parameterization for **Continuous**Maps

- Topological obstruction to the computation of maps
- Triangle mesh parametrization
 - Tutte embedding
 - Conformal mappings
 - And more...

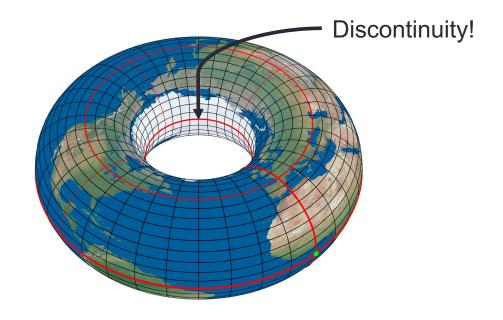
Computing correspondences



Topological Obstruction

• There is no **continuous bijective** map between these two shapes

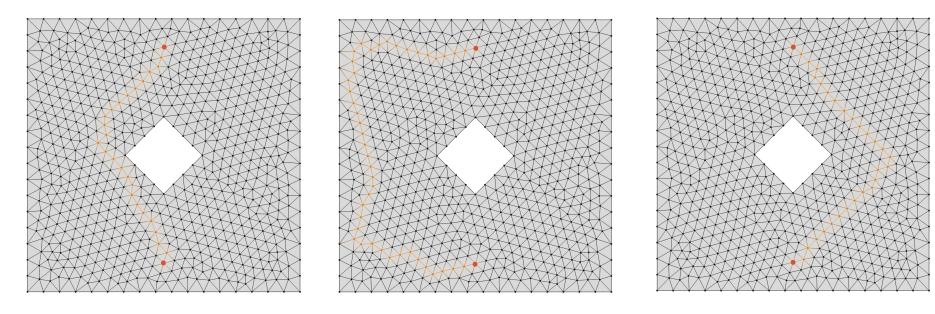




- Local geometry fully determines a surface (cf. first lecture)
- Topology studies **global** characteristics

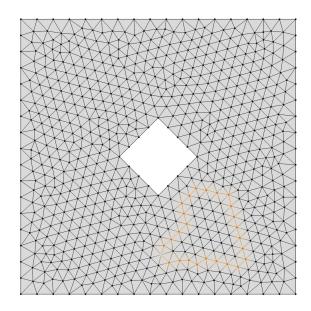


- Equivalent paths: equal up to a continuous deformation.
- Two paths are **independent** if they are not related by a continuously deformation

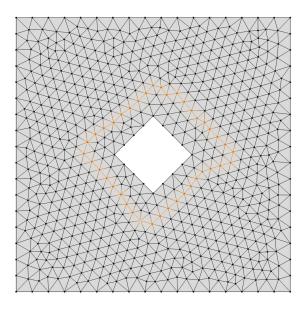


Independent

- Contractible loop: closed path that can be continuously contracted to a point.
- Otherwise, **non-contractible** loops.

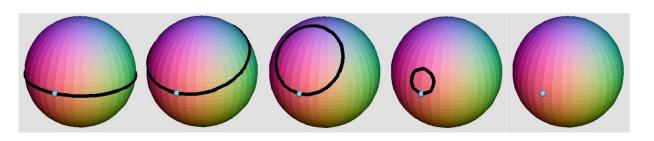


Contractible

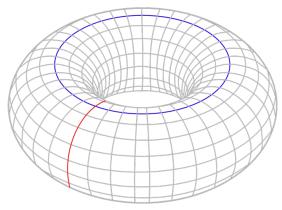


Non-contractible

- Contractible loop: closed path that can be contracted to a single vertex.
- Otherwise, **non-contractible** loops.



All loops are contractible

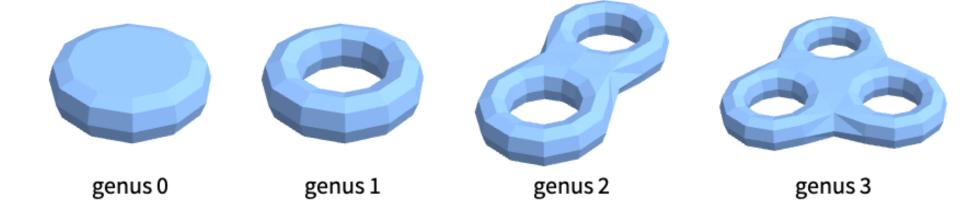


Some loops are non-contractible

- Contractible loop: closed path that can be contracted to a single vertex.
- Otherwise, **non-contractible** loops.



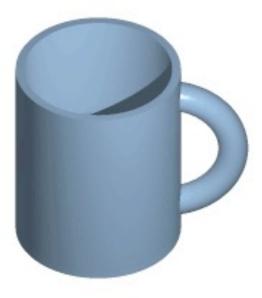
• **Genus**: number of independent loops divided by 2 ("number of holes")



Topology and Continuous Deformation

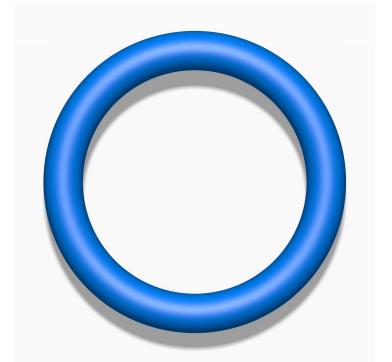
• There exists a continuous and bijective **map** between any two surfaces with same genus

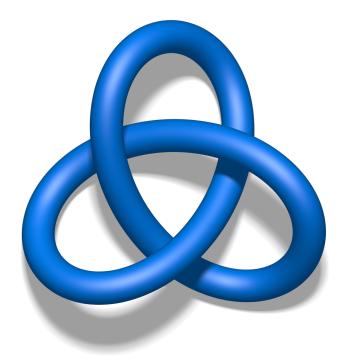




Topology and Continuous Deformation

- There exists a continuous and bijective **map** between any two surfaces with same genus
- It does not mean that there exits a bijective and continuous deformation



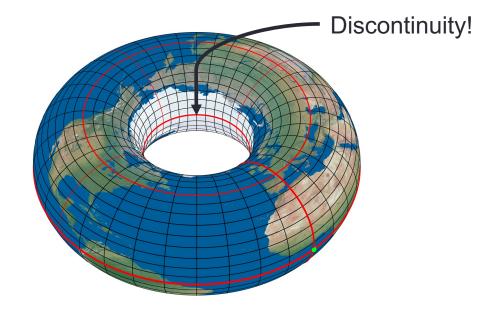


Topology and Continuous Deformation

• There is no **continuous bijective** map between these two shapes



Genus 0



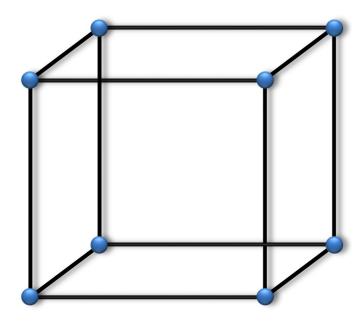
Genus 1

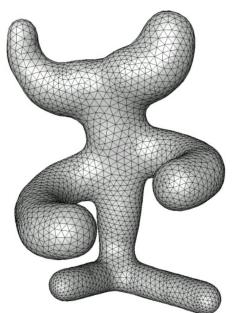
Manifold Meshes without Boundaries

edges

genus

• Euler-Poincaré formula F-E+V=2-2g # faces # vertices





20 proofs

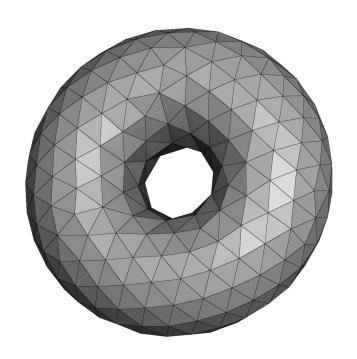
$$F = 7776$$

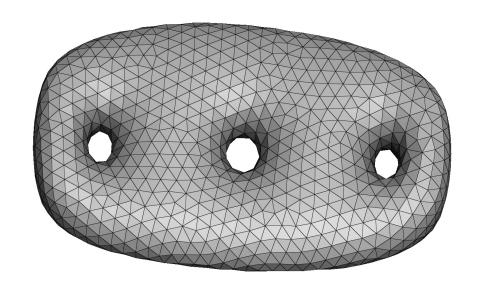
 $E = 11664$
 $V = 3890$
 $g = 0$

Manifold Meshes without Boundaries

• Euler-Poincaré formula F - E + V = 2 - 2g

20 proofs





$$F = 600$$

 $E = 900$
 $V = 300$
 $g = 1$

Topological Conclusion

- The genus is a global invariant of a surface
- The genus is easily computed with Euler-Poincaré formula
- Surfaces with same genus can continuously mapped into each

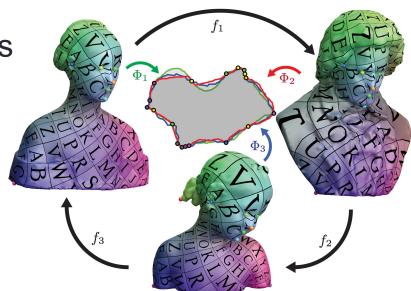
other



Cross **Parameterization** for Continuous Maps

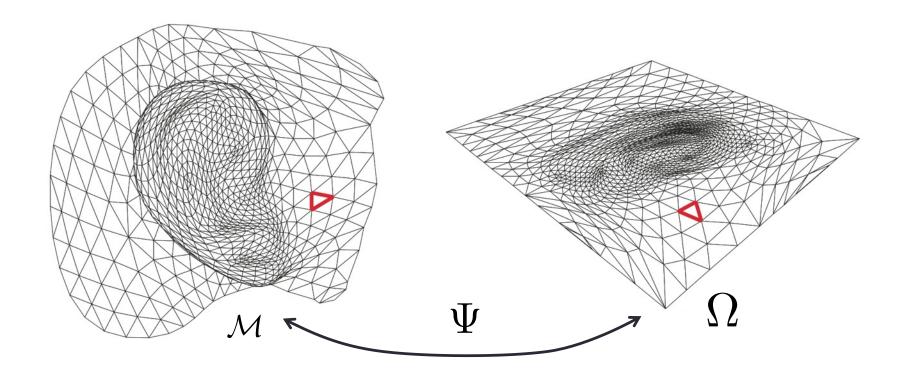
- Topological obstruction to the computation of maps
- Triangle mesh parametrization
 - Tutte embedding
 - Conformal mappings
 - And more...

Computing correspondences



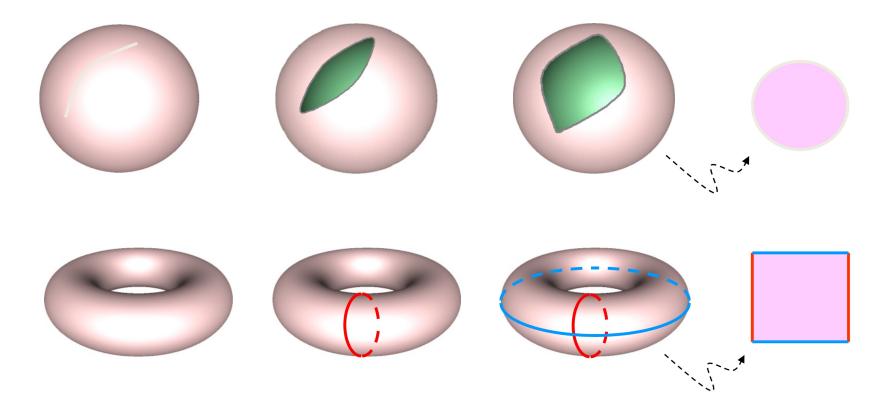
Parameterization Problem

Given a surface (mesh) \mathcal{M} in \mathbb{R}^3 and a planar domain Ω : Find a bijective map $\Psi: \Omega \longleftrightarrow \mathcal{M}$.

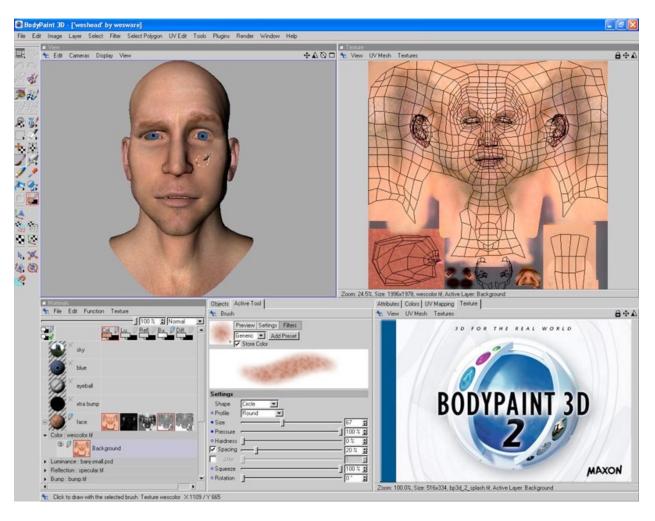


Cutting To a Disk

- For non-disk topology: need to creates artificial boundaries
- For high genus, the cut graph is constructed from non-contractible loops



Parameterization for Texture Mapping



Mesh simplification:

Approximate the geometry using few triangles

Idea:

Decouple geometry from appearance



~600k triangles

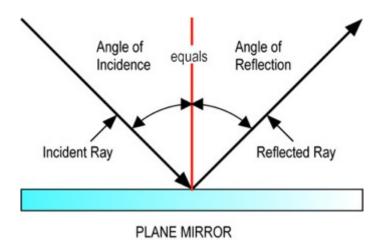
~600 triangles

Mesh simplification:

Approximate the geometry using few triangles

Idea:

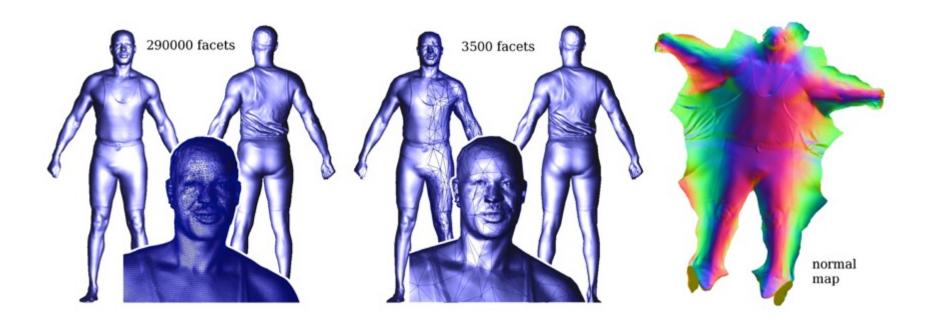
Decouple geometry from appearance



Observation: appearance (light reflection) depends on the geometry + normal directions.

Normal Mapping with parameterization:

Store normal field as an RGB texture.



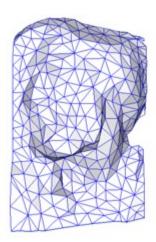
Normal Mapping

Idea:

- Decouple geometry from appearance
- Encode a normal field inside each triangle



original mesh 4M triangles



simplified mesh 500 triangles

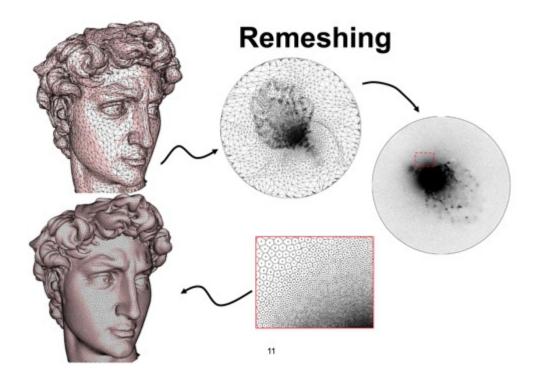


simplified mesh and normal mapping 500 triangles

Cohen et al., '98 Cignoni et al. '98

Parameterization – Applications

General Idea: Things become easier in a canonical domain (e.g. on a plane).



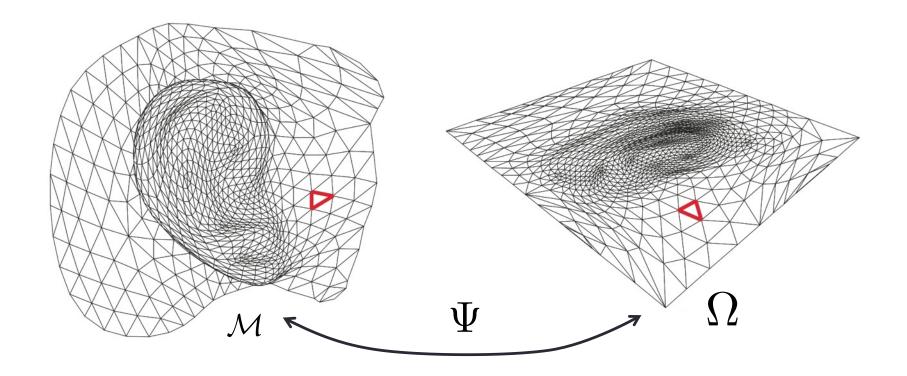
Other Applications:

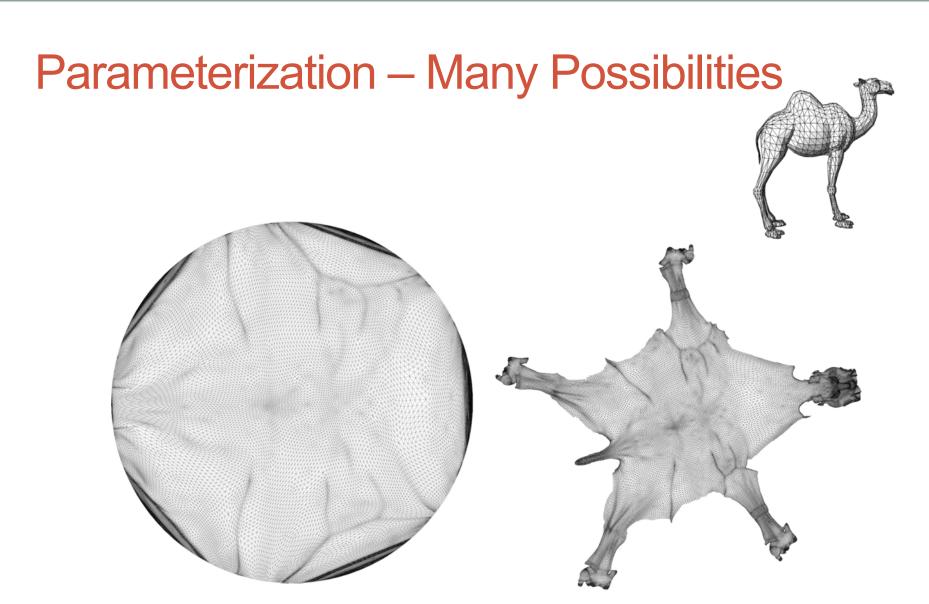
- Surface Fitting
- Editing
- Mesh Completion
- Mesh Interpolation
- Morphing and Transfer
- Shape Matching
- Visualization
- Feature Learning

. . .

Parameterization Problem

Given a surface (mesh) \mathcal{M} in \mathbb{R}^3 and a planar domain Ω : Find a bijective map $\Psi: \Omega \longleftrightarrow \mathcal{M}$.



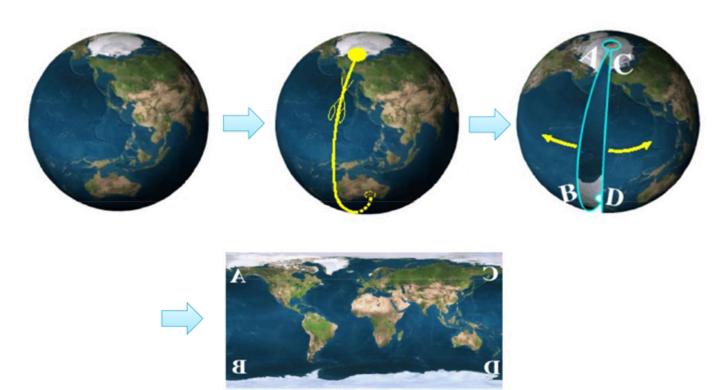


We need to quantify the distortion induced by the map

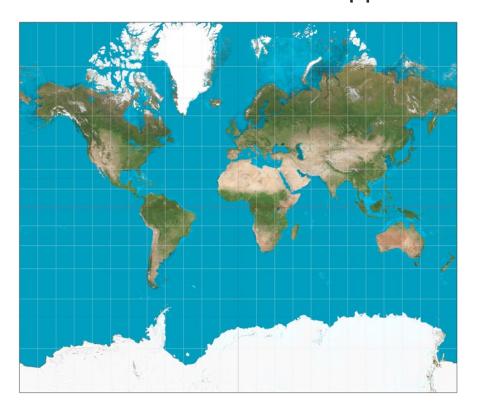
Parameterization onto the plane

Recall a related problem.

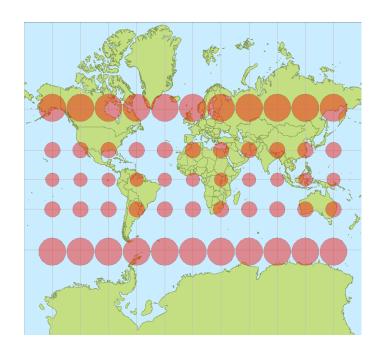
Mapping the Earth: find a parameterization of a 3d object onto a plane.



Mercator: meridians and latitudes are mapped to straight lines

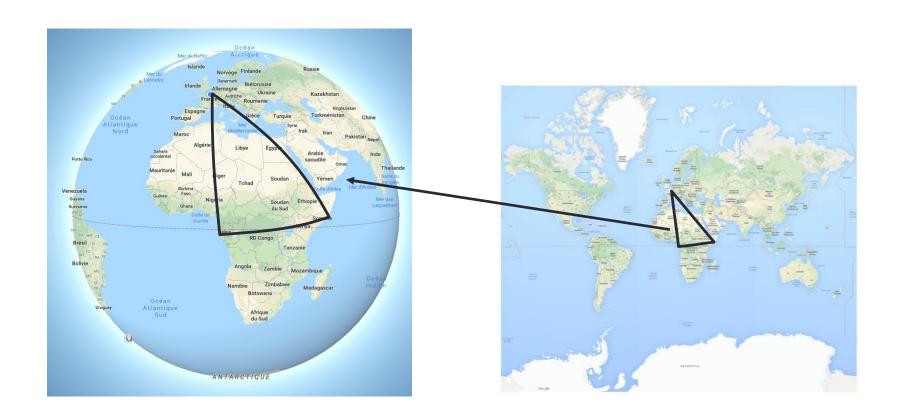


Mercator: undefined at poles, distorts areas

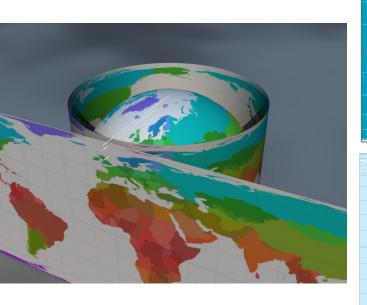


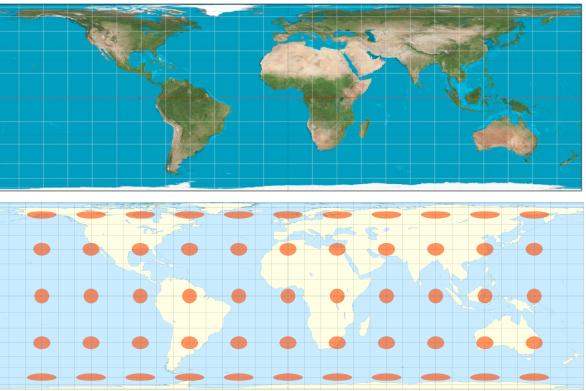


Mercator: undefined at poles, distorts areas, preserves angles

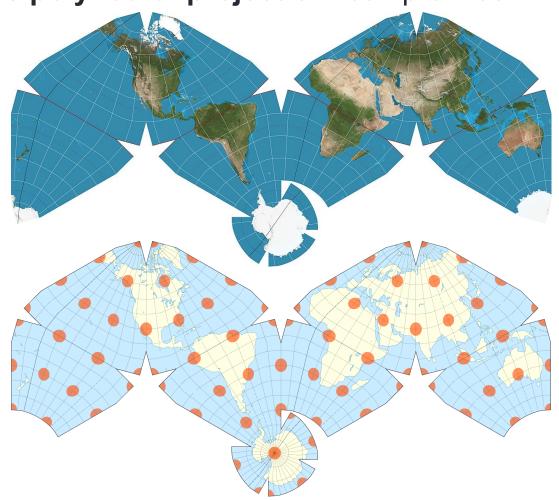


Lambert cylindrical projection: distorts angles, preserves areas





Cahill-Keyes polyhedral projection: compromise



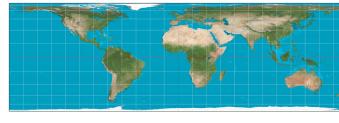
Different kinds of parameterization



Mercator conformal



Cahill-Keyes



LambertPreserves area

Different kinds of Parameterization

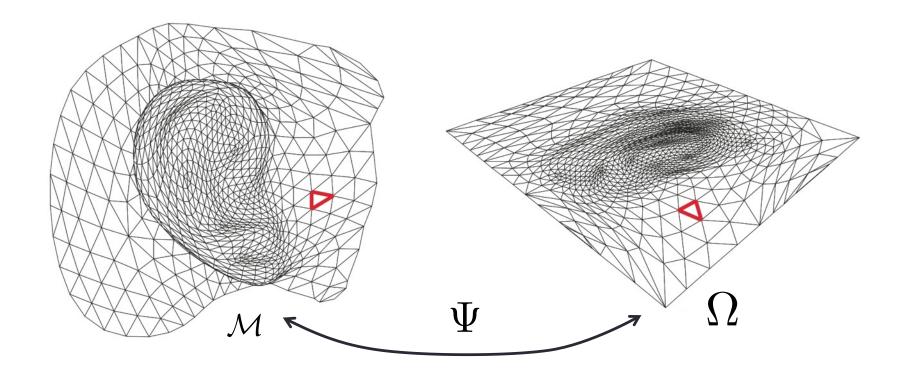
Various notions of distortion:

- 1. Equiareal: preserving areas
- 2. Conformal: preserving angles of intersections
- 3. Isometric: preserving geodesic distances

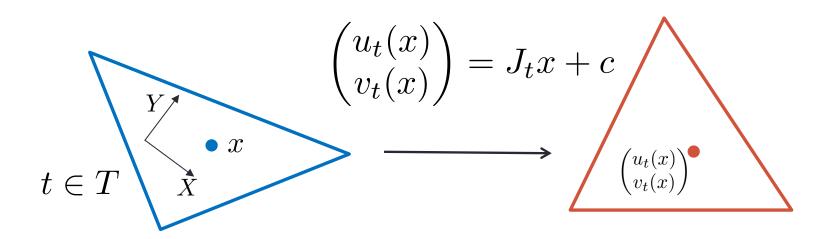
Theorem: Isometric = Conformal + Equiareal

Parameterization Problem

Given a surface (mesh) \mathcal{M} in \mathbb{R}^3 and a planar domain Ω : Find a bijective map $\Psi: \Omega \longleftrightarrow \mathcal{M}$.



Distortion of a Triangle



 J_t : Jacobian of the transformation

Distortion energy:
$$E(f) := \sum_{t \in F} \operatorname{distortion}(J_t)$$

Distortion Minimization

$$J_t$$
 : Jacobian of the transformation $\,x \mapsto \begin{pmatrix} u_t(x) \\ v_t(x) \end{pmatrix}$

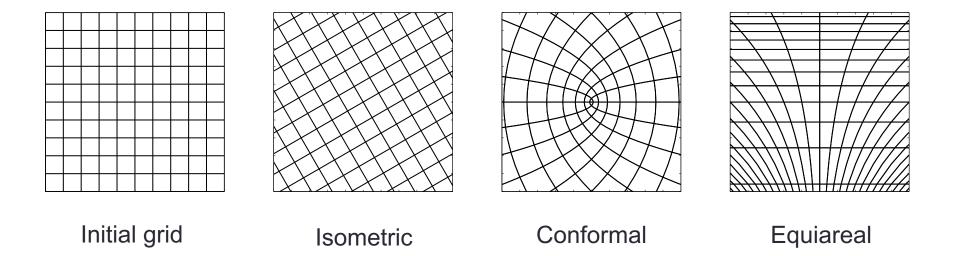
$$J_t = \begin{pmatrix} \frac{\partial u}{\partial X} & \frac{\partial v}{\partial X} \\ \frac{\partial u}{\partial Y} & \frac{\partial v}{\partial Y} \end{pmatrix} = \begin{pmatrix} \nabla u & \nabla v \end{pmatrix}$$

- 1. Isometric mapping: $J_t^ op J_t = I$
- 2. Conformal mapping: $\nabla v = n \times \nabla u$
- 3. Equiareal mapping: $\det J_t = 1$

Distortion energy can be non-linear and difficult to optimize for.

Distortion Minimization

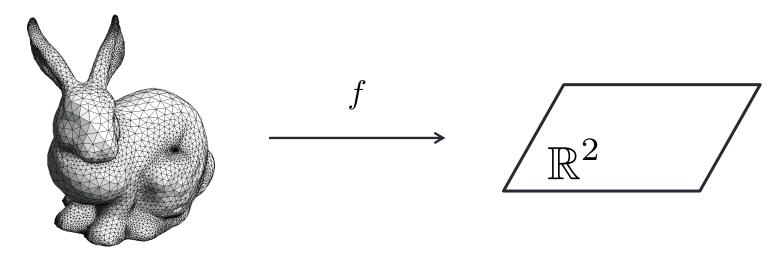
- 1. Isometric mapping: $J_t^{ op}J_t=I$ (local rotation)
- 2. Conformal mapping: $\nabla v = n imes \nabla u$ (local rotation + scaling)
- 3. Equiareal mapping: $\det J_t = 1$ (same local area)



Distortion energy can be non-linear and difficult to optimize for.

Formalizing Parametrization

How do you solve this problem numerically:



Define a measure of distortion:
$$E(f) := \sum_{t \in F} \operatorname{distortion}(J_t)$$

Define a parametrization as the minimum of energy:

$$(u_{\mathrm{opt}}, v_{\mathrm{opt}}) = \operatorname*{arg\,min}_{f=(u,v)} E(f)$$
 given boundary conditions

Parametrization with Fixed Boundary

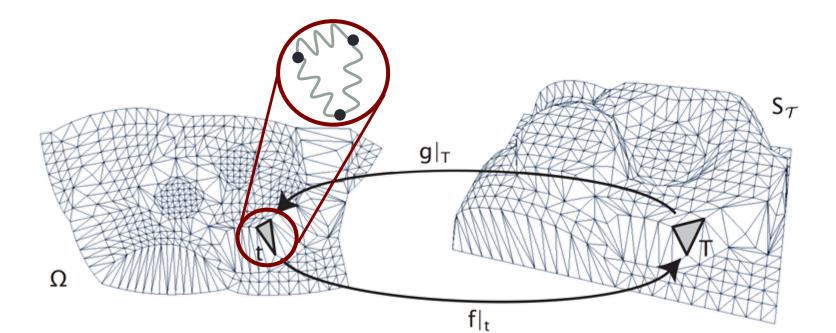
- Can we compute a parametrization by solving a linear system
- Assume we know exactly where the boundary must go



Spring Model for Parameterization

Given a mesh (T, P) in 3D find a bijective mapping $g(\mathbf{p}_i) = \mathbf{u}_i$ given constraints: $g(\mathbf{b}_j) = \mathbf{u}_j$ for some $\{\mathbf{b}_j\}$

Model: imagine a **spring** at each edge of the mesh. If the boundary is fixed, let the interior points find an **equilibrium**.

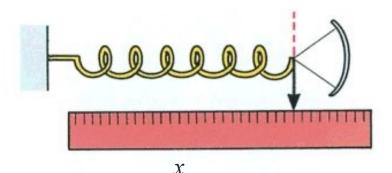


Spring Model for Parameterization

Recall: potential energy of a spring stretched by distance *x*:

$$E(x) = \frac{1}{2}kx^2$$

k: spring constant.



Spring Model for Parameterization

Given an embedding (parameterization) of a mesh, the potential energy of the whole system:

$$E = \sum_{e} \frac{1}{2} D_e \|\mathbf{u}_{e1} - \mathbf{u}_{e2}\|^2$$

$$= \frac{1}{2} \sum_{i=1}^{n} \sum_{j \in \mathcal{N}_i} \frac{1}{2} D_{ij} \|\mathbf{u}_i - \mathbf{u}_j\|^2 \quad , \ \mathcal{N}_i \text{ set of vertices adjacent to i}$$

Where $D_e = D_{ij}$ is the spring constant of edge e between i and j

Goal: find the coordinates $\{\mathbf{u}_i\}$ that would minimize E.

Note: the boundary vertices prevent the degenerate solution.

Finding the optimum of:

$$E = \frac{1}{2} \sum_{i=1}^{n} \sum_{j \in \mathcal{N}_i} \frac{1}{2} D_{ij} \|\mathbf{u}_i - \mathbf{u}_j\|^2$$

$$\frac{\partial E}{\partial \mathbf{u}_{i}} = 0 \Rightarrow \sum_{j \in \mathcal{N}_{i}} D_{ij} (\mathbf{u}_{i} - \mathbf{u}_{j}) = 0$$

$$\Rightarrow \mathbf{u}_{i} = \sum_{j \in \mathcal{N}_{i}} \lambda_{ij} \mathbf{u}_{j}, \text{ where } \lambda_{ij} = \frac{D_{ij}}{\sum_{j \in \mathcal{N}_{i}} D_{ij}}$$

I.e. each point u_i must be an **convex combination** of its neighbors.

Hence: barycentric coordinates.

To find a minimizer of E in practice:

- 1. Fix the boundary points $\mathbf{b}_i, i \in \mathcal{B}$
- 2. Form linear equations

$$\mathbf{u}_i = \mathbf{b}_i,$$
 if $i \in \mathcal{B}$

$$\mathbf{u}_i - \sum_{j \in \mathcal{N}_i} \lambda_{ij} \mathbf{u}_j = 0,$$
 if $i \notin \mathcal{B}$

3. Assemble into *two* linear systems (one for each coordinate):

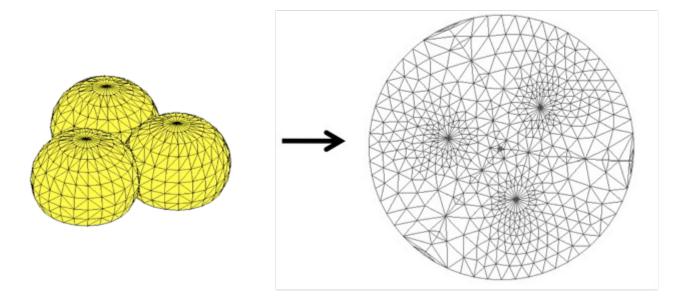
$$LU = \bar{U}, \quad LV = \bar{V}$$
 $L_{ij} = \begin{cases} 1 & \text{if } i = j \\ -\lambda_{ij} & \text{if } j \in \mathcal{N}_i, \ i \notin \mathcal{B} \\ 0 & \text{otherwise} \end{cases}$

4. Solution of the linear system gives the coordinates: $\mathbf{u}_i = (u_i, v_i)$ Note: system is very sparse, can solve efficiently.

Does this work?

Tutte's spring-embedding theorem:

Every **barycentric** drawing of a 3-connected planar graph (triangle mesh) is a valid embedding if its boundary is **convex**.



Laplace Operator

Laplace operator in Euclidean space:

Given a function $f: \mathbb{R}^n \to \mathbb{R}^n$

$$\nabla \cdot (\nabla f) = \Delta f = \sum_{i=1}^{n} \frac{\partial^2}{\partial x_i^2} f$$

$$\Delta f = Lf$$

Laplacian Matrix

Our system of equations (forgetting about boundary):

$$\mathbf{u}_i = \sum_{j \in \mathcal{N}_i} \lambda_{ij} \mathbf{u}_j$$
, where $\lambda_{ij} = \frac{D_{ij}}{\sum_{j \in \mathcal{N}_i} D_{ij}}$

$$LU = 0$$
 $L_{ij} = \begin{cases} 1 & \text{if } i = j \\ -\lambda_{ij} & \text{if } j \in \mathcal{N}_i \\ 0 & \text{otherwise} \end{cases}$ L is not symmetric

Alternatively, if we write it as:

$$\mathbf{u}_i \sum_{j \in \mathcal{N}_i} D_{ij} = \sum_{j \in \mathcal{N}_i} D_{ij} \mathbf{u}_j$$

We get:

$$LU = 0 L_{ij} = \begin{cases} \sum_{k \in \mathcal{N}_i} D_{ij} & \text{if } i = j \\ -D_{ij} & \text{if } j \in \mathcal{N}_i \\ 0 & \text{otherwise} \end{cases}$$

L is symmetric

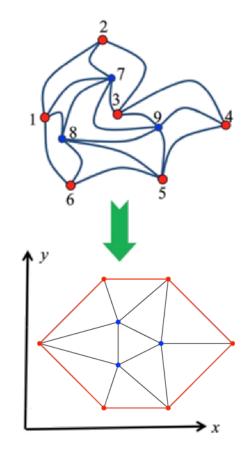
Example:

Uniform weights:

$$D_{ij} = 1$$

Laplacian Matrix

$$W = \begin{pmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 1 & 1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 1 & 1 & 0 & 0 & 0 \\ \end{pmatrix} \qquad b_{x} = \begin{pmatrix} 1 \\ 2 \\ 3 \\ 4 \\ 3 \\ 2 \\ 0 \\ 0 \\ 0 \end{pmatrix}$$

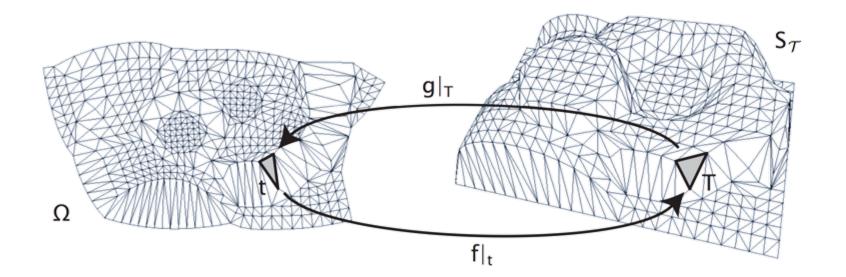


Linear Reproduction:

 If the mesh is already planar we want to recover the original coordinates.

Problem:

- Uniform weights do not achieve linear reproduction
- Same for weights proportional to distances.



Linear Reproduction:

 If the mesh is already planar we want to recover the original coordinates.

Problem:

- Uniform weights do not achieve linear reproduction
- Same for weights proportional to distances.

Solution:

• If the weights are **barycentric** with respect to **original points**:

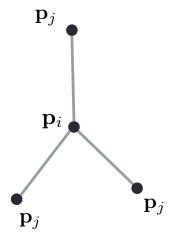
$$\mathbf{p}_i = \sum_{j \in \mathcal{N}_i} \lambda_{ij} \mathbf{p}_j, \quad \sum_{j \in \mathcal{N}_i} \lambda_{ij} = 1$$

The resulting system will recover the planar coordinates.

Solution:

Barycentric coordinates with respect to original points:

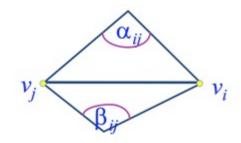
$$\mathbf{p}_i = \sum_{j \in \mathcal{N}_i} \lambda_{ij} \mathbf{p}_j, \quad \sum_{j \in \mathcal{N}_i} \lambda_{ij} = 1$$



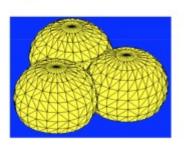
- If a point p_i has 3 neighbors, then the barycentric coordinates are **unique**.
- For more than 3 neighbors, many possible choices exist.

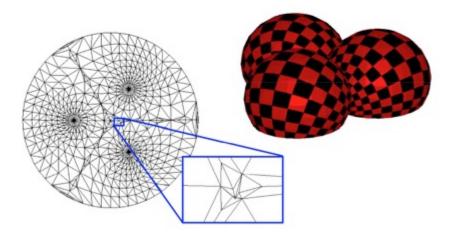
Barycentric (cotangent) weights

$$D_{ij} = \frac{\cot(\alpha_{ij}) + \cot(\beta_{ij})}{2}$$



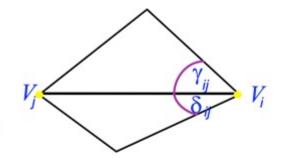
- Weights can be negative not always valid
- · Weights depend only on angles close to conformal
- 2D reproducible





Barycentric (mean value) weights

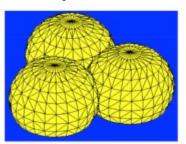
$$D_{ij} = \frac{\tan(\gamma_{ij} / 2) + \tan(\delta_{ij} / 2)}{2 \mid\mid V_i - V_j \mid\mid}$$

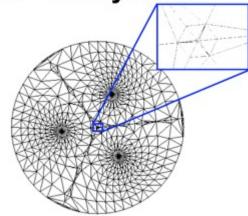


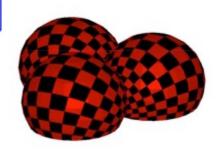
· Result visually similar to harmonic

No negative weights – always valid

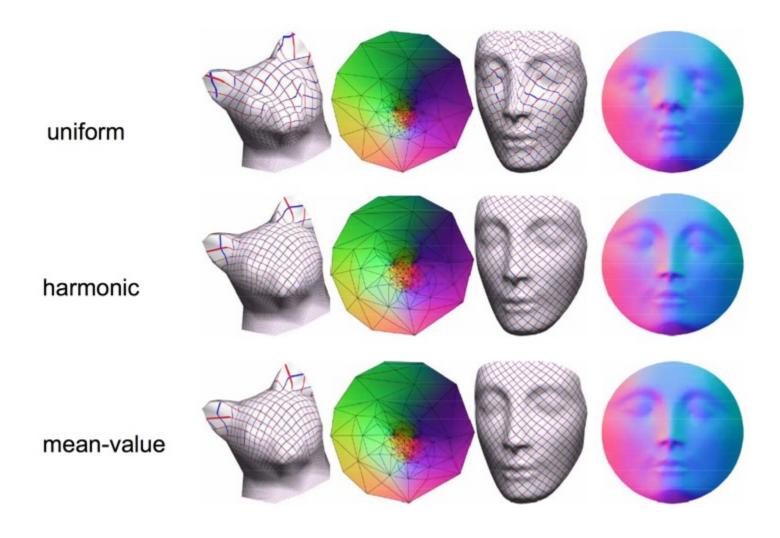
· 2D reproducible



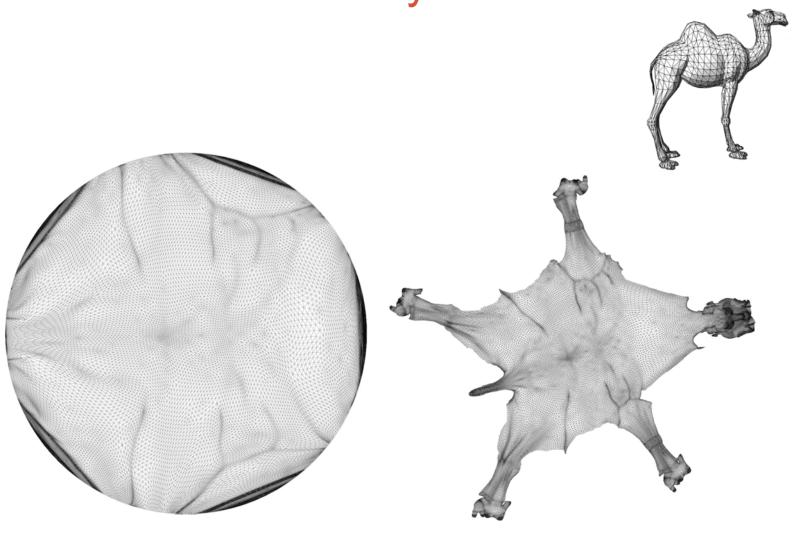




Barycentric Coordinates



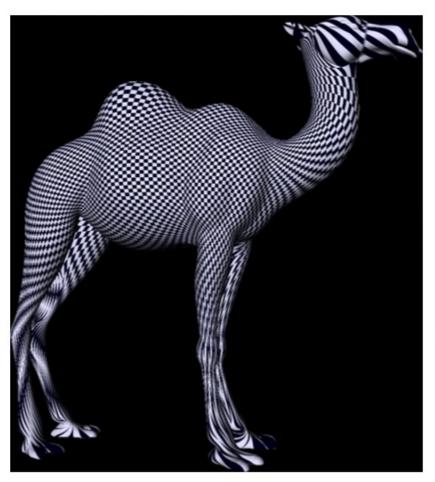
Fixed vs Free boundary

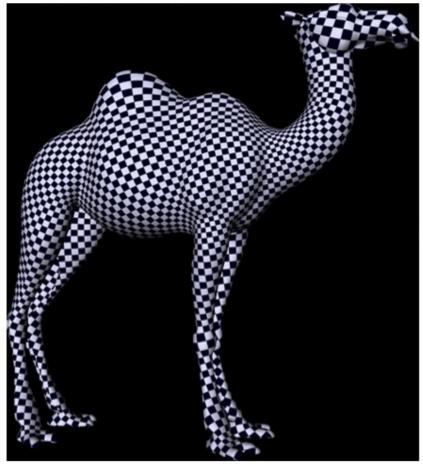


Tutte embedding

images by Mirela Ben-Chen

Fixed vs Free boundary





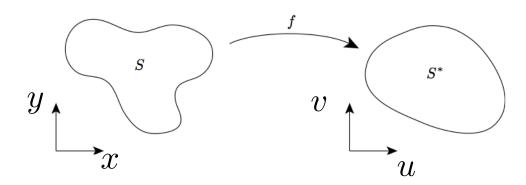
Conformal Mappings

$$J_t$$
 : Jacobian of the transformation $x \mapsto egin{pmatrix} u_t(x) \\ v_t(x) \end{pmatrix}$

Conformal mapping: $\nabla v = n \times \nabla u$

Riemann Mapping Theorem:

Any surface topologically equivalent to a disk, **can be** conformally mapped to a unit disk.



Conformal Mappings

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Riemann Mapping Theorem:

Any surface topologically equivalent to a disk, **can be** conformally mapped to a unit disk.

$$\Delta v = \operatorname{div} \nabla v \\
= \operatorname{div}(n \times \nabla u) \\
= \operatorname{curl} \nabla u \\
= 0$$

Conformal Mappings

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Riemann Mapping Theorem:

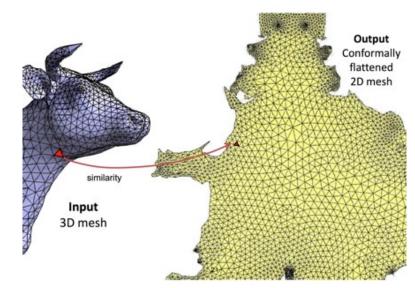
Any surface topologically equivalent to a disk, **can be** conformally mapped to a unit disk.

If a map $S \rightarrow (u,v)$ is conformal then both u and v are harmonic:

$$\Delta_S u = 0 \ \Delta_S v = 0$$

 Δ_S : Laplacian on S .

Like Tutte embeddings: each point must be an **convex combination** of its neighbors.



Conformal Free Boundary Method

$$J_t$$
 : Jacobian of the transformation $x \mapsto \begin{pmatrix} u_t(x) \\ v_t(x) \end{pmatrix}$

Conformal mapping: $\nabla v = n \times \nabla u$

Solve in a least-squares sense:

$$E_C(u,v) = \sum_{t \in T} A_t \|\nabla v - n \times \nabla u\|_t^2$$
 , A_t area of triangle t
$$= u^\top W u + v^\top W v - \sum_{ij \text{ at bnd}} (u_i v_j - u_j v_i)$$

W Cotangent matrix

Conformal Free Boundary Method

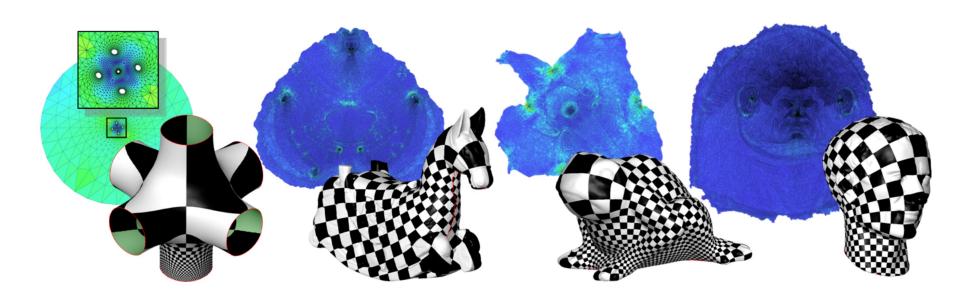
$$\min_{u,v} E_C(u,v) = \begin{pmatrix} u \\ v \end{pmatrix}^\top \begin{pmatrix} W & M \\ M^\top & W \end{pmatrix} \begin{pmatrix} u \\ v \end{pmatrix} \quad \text{Subject to:} \quad \|u\|^2 + \|v\|^2 = 1$$

Equivalent to the eigenvalue problem:

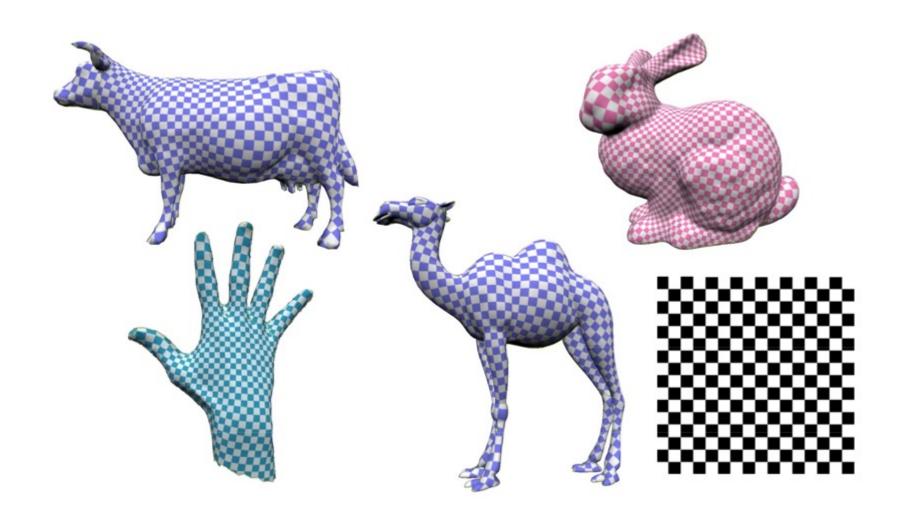
$$\begin{pmatrix} W & M \\ M^\top & W \end{pmatrix} \begin{pmatrix} u \\ v \end{pmatrix} = \lambda \begin{pmatrix} A & 0 \\ 0 & A \end{pmatrix} \begin{pmatrix} u \\ v \end{pmatrix} \quad \text{with A the area matrix}$$

Optimal solution: eigenfunction associated to the **third** smallest eigenvalue The first eigenfunctions are constant

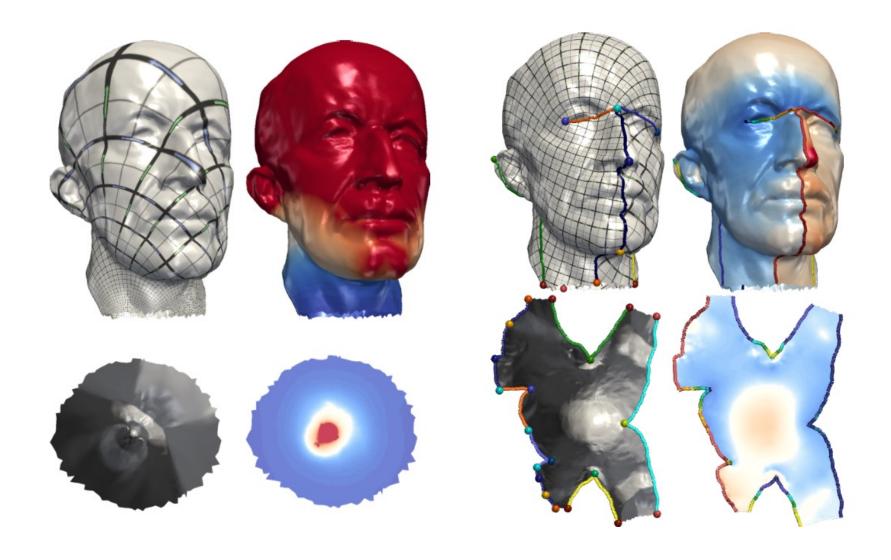
Conformal Free Boundary Method



Conformal Mappings



Reducing Distortion - More Cuts



Going Further: Curvature Prescription

- Parametrization: find a deformation to a surface with zero Gaussian curvature
- Gather Gaussian curvature into "cone points"
 - Target curvature is not 0 everywhere
- Cuts must pass through cone points
- Position of the cuts has no impact on the distortion

Going Further: Curvature Prescription



Adding more and more cone singularities...

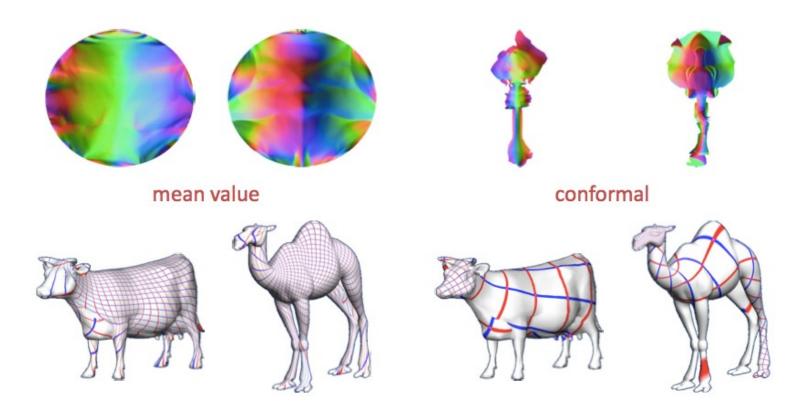
(Texture courtesy NASA Earth Observatory), from Soliman et al. 2018

Free boundary methods ...

- Solve for the (u,v) coordinates
 - MIPS [Hormann et al., 2000]
 - Stretch optimization [Sander et al., 2001]
 - LSCM (conformal, linear) [Levy et al., 2002]
 - DCP (conformal, linear) [Desbrun et al., 2002]
- Solve for the angles of the map (conformal)
 - ABF [Sheffer et al., 2001], ABF++ [Sheffer et al., 2004]
 - LinABF (linear) [Zayer et al., 2007]
- Solve for the edge lengths of the map by prescribing curvature
 - Circle patterns [Kharevych et al., 2006]
 - CPMS (linear) [Ben-Chen et al., 2008]
 - CETM [Springborn et al., 2008]
- Balance area/conformality
 - ARAP [Liu et al., 2008]
- More...

Some results

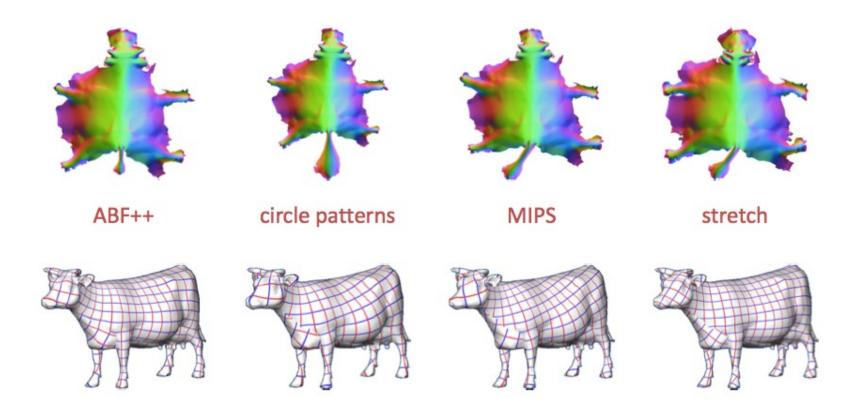
Linear Methods:



Purely linear methods can cause a very significant distortion.

Some results

Non-linear Methods:



Conclusions

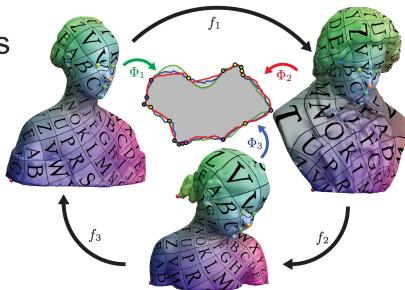
Surface parameterization:

- No perfect mapping method
- A very large number of techniques exists
- Conformal model:
 - Nice theoretical properties
 - Leads to a simple (linear) system of equations
 - Closely related to the Poisson equation and Laplacian operator
- More general methods
 - Can get smaller distortion using non-linear optimization
 - Very difficult to guarantee bijectivity in general

Cross Parameterization for Continuous Maps

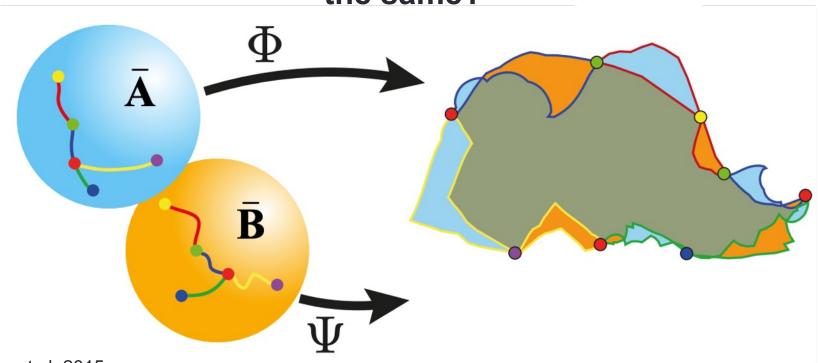
- Topological obstruction to the computation of maps
- Triangle mesh parametrization
 - Tutte embedding
 - Conformal mappings
 - And more...

Computing correspondences



Input: a set constrained points and cut graph

Where to cut so that the parametrization of A and B are the same?



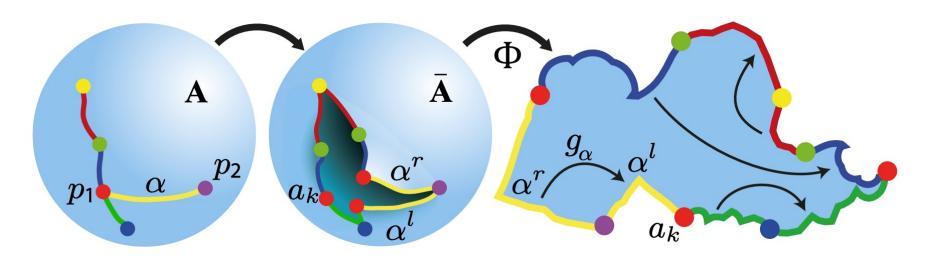
Aigerman et al. 2015

Seamless parametrization: set constrained points and cut graph, add global linear constraints on duplicated edges

Affine transition functions:

$$g: \mathbb{R}^2 \to \mathbb{R}^2$$

$$x \mapsto \begin{pmatrix} a & b \\ -b & a \end{pmatrix} x + \tau$$

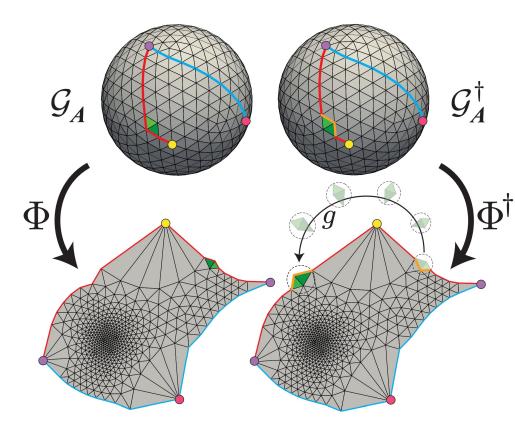


Seamless parametrization: set constrained points and cut graph, add global linear constraints on duplicated edges

Affine transition functions:

$$g: \mathbb{R}^2 \to \mathbb{R}^2$$

$$x \mapsto \begin{pmatrix} a & b \\ -b & a \end{pmatrix} x + \tau \quad \Phi$$



In practice:

- 1. Find the duplicated boundary vertices $i_r, i_l \in \mathcal{B}$
- 2. Fix the constrained points $\mathbf{b}_i, i \in \mathcal{C}$
- 3. Solve the linear system of equations:

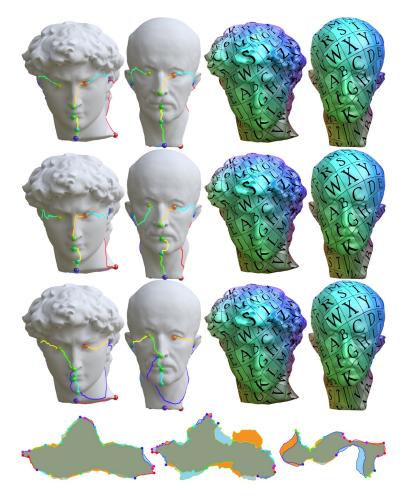
$$\mathbf{u}_{i} = \mathbf{b}_{i}, \qquad \text{if } i \in \mathcal{C}$$

$$\mathbf{u}_{i_{r}} - \mathbf{u}_{j_{r}} = g_{\alpha}(\mathbf{u}_{i_{l}} - \mathbf{u}_{j_{l}}), \qquad \text{if } i, j \in \mathcal{B}$$

$$\mathbf{u}_{i} - \sum_{j \in \mathcal{N}_{i}} \lambda_{ij} \mathbf{u}_{j} = 0, \qquad \text{if } i \notin \mathcal{B}$$

4. Solution of the linear system gives the coordinates: $\mathbf{u}_i = (u_i, v_i)$

Same cut graphs, same mapping.

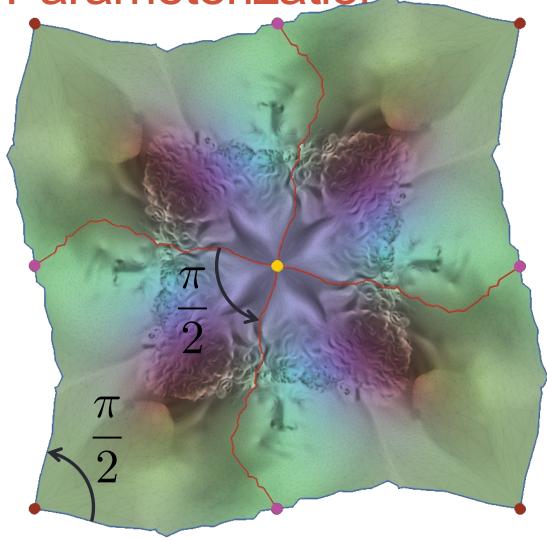


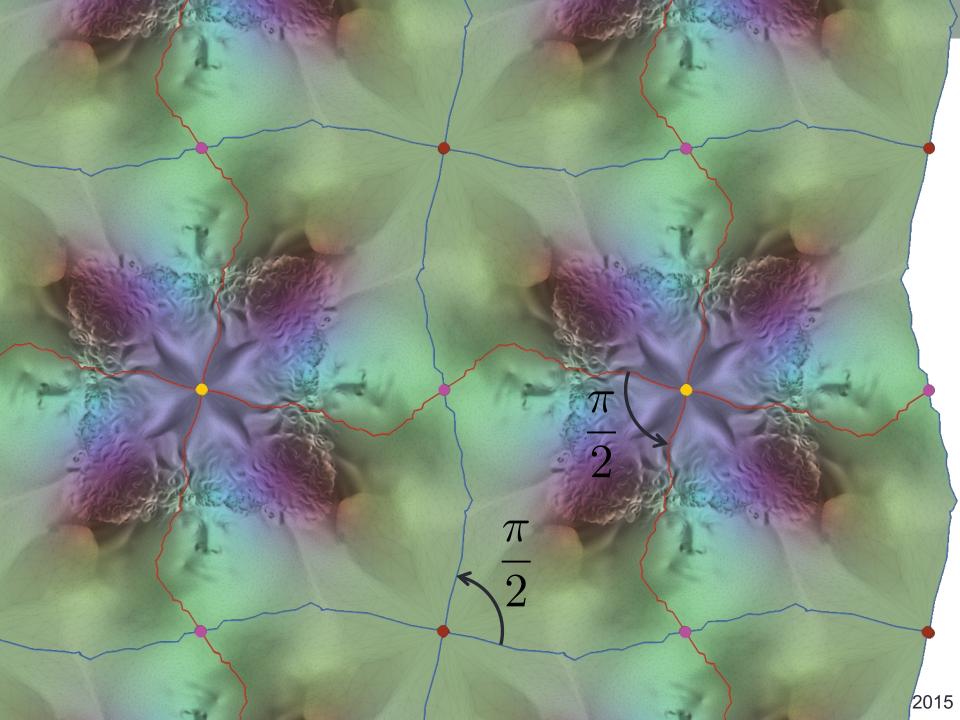
Parametrization domain lack structure!

Toric Seamless Parameterization

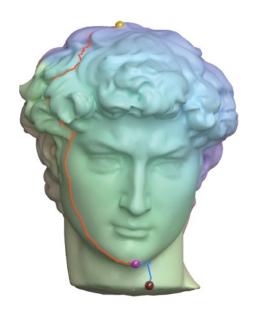
- Three point cuts
- Rotation constraints on cuts
- Spring distortion
- Tiles the entire space

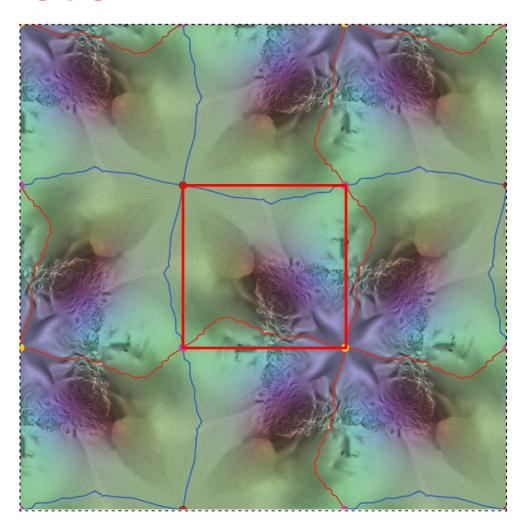






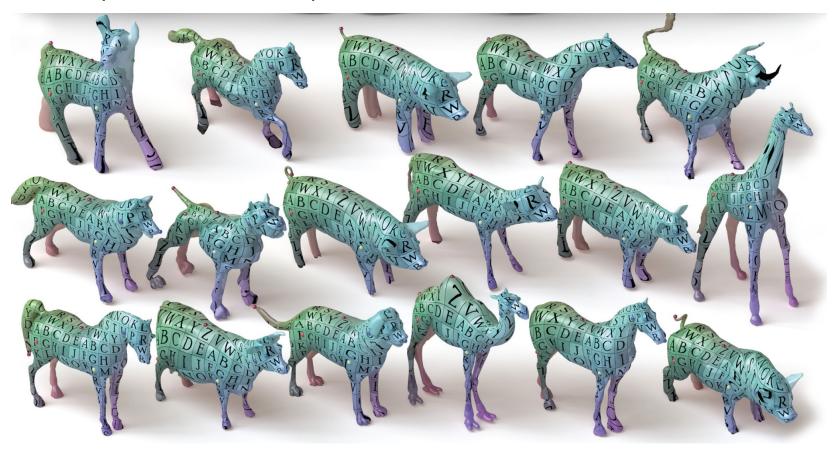
- Three point cuts
- Rotation constraints on cuts
- Spring or LSCM distortion
- Tiles the entire space



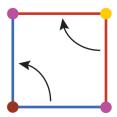


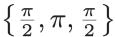
Cuts are invisible!

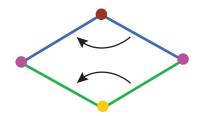
Compute continuous maps between surfaces from few constraints



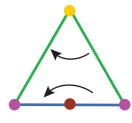
- Different space tiling
- Different parametric spaces



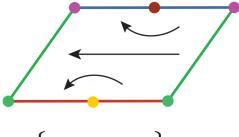




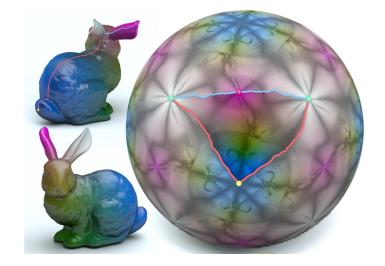
$$\left\{\frac{\pi}{2}, \pi, \frac{\pi}{2}\right\} \qquad \left\{\frac{2\pi}{3}, \frac{2\pi}{3}, \frac{2\pi}{3}\right\} \qquad \left\{\pi, \frac{2\pi}{3}, \frac{2\pi}{6}\right\} \qquad \left\{\pi, \pi, \pi, \pi\right\}$$



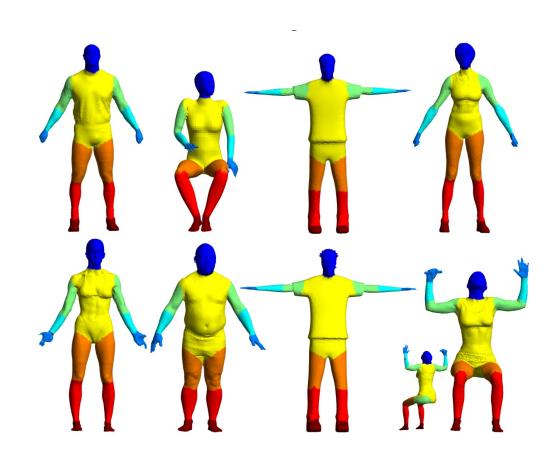
$$\left\{\pi, \frac{2\pi}{3}, \frac{2\pi}{6}\right\}$$



$$\{\pi,\pi,\pi,\pi\}$$



Use image CNN on parametrization for segmentation



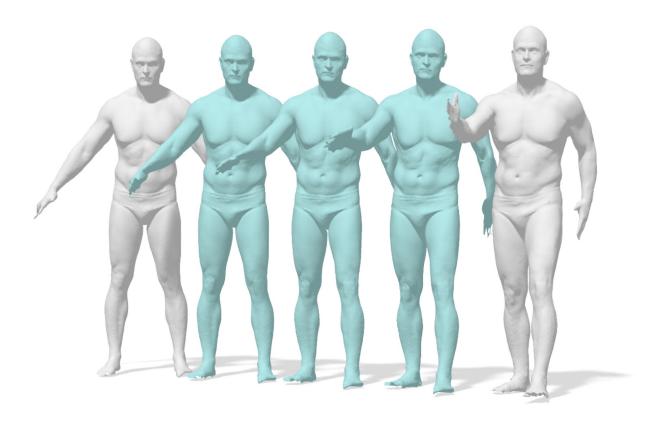
Conclusion

Toric parametrization

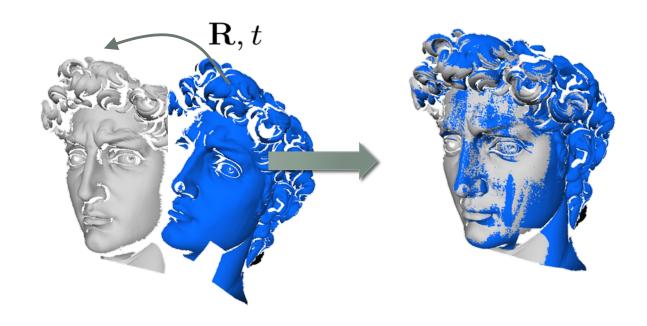
- Compute bijective maps from a small set of landmarks
- Very efficients
- Little control over the distortion

Surface Non-Rigid Alignment

Compute a deformation for aligning shapes



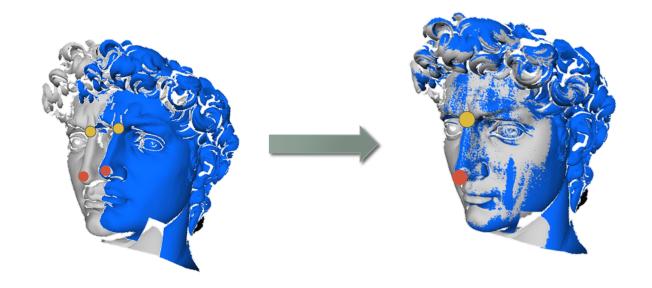
Simpler problem: Rigid Alignment



- Given a pair of shapes, find the optimal *Rigid Alignment* between them.
- The unknowns are the rotation/translation parameters of the source onto the target shape.

Simpler problem: Rigid Alignment

What does it mean for an alignment to be good?



Intuition: want corresponding points to be close after transformation.

Problems

- 1. We don't know what points correspond.
- 2. We don't know the optimal alignment.

Iterative Closest Point (ICP)

 Approach: iterate between finding correspondences and finding the transformation:

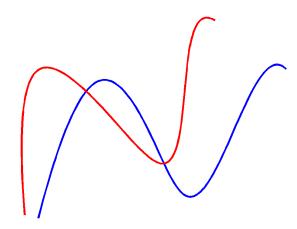


- 1. For each $x_i \in X$ find **nearest** neighbor $y_i \in Y$.
- 2. Find deformation \mathbf{R} , t minimizing:

$$\sum_{i=1}^{N} \|\mathbf{R}x_i + t - y_i\|_2^2$$

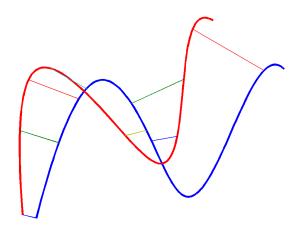
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 Approach: iterate between finding correspondences and finding the transformation:



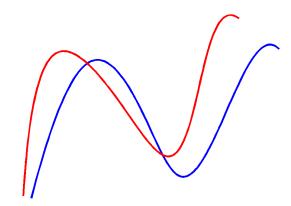
- 1. For each $x_i \in X$ find **nearest** neighbor $y_i \in Y$.
- 2. Find deformation \mathbf{R} , t minimizing: $\sum_{i=1}^{n} ||\mathbf{R}x_i + t y_i||_2^2$

 Approach: iterate between finding correspondences and finding the transformation:



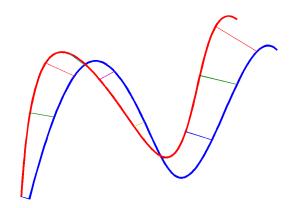
- 1. For each $x_i \in X$ find **nearest** neighbor $y_i \in Y$.
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 Approach: iterate between finding correspondences and finding the transformation:



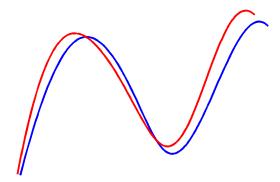
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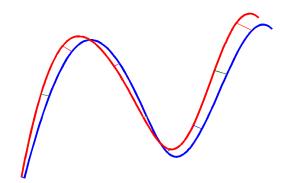
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 Approach: iterate between finding correspondences and finding the transformation:



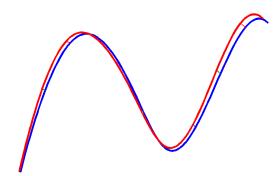
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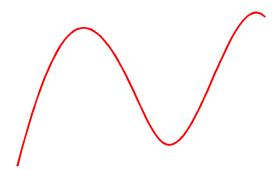
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- 1. For each $x_i \in X$ find **nearest** neighbor $y_i \in Y$.
- 2. Find deformation \mathbf{R} , t minimizing: $\sum_{i=1}^{\infty} \|\mathbf{R}x_i + t y_i\|_2^2$

Iterative Closest Point

 Approach: iterate between finding correspondences and finding the transformation:



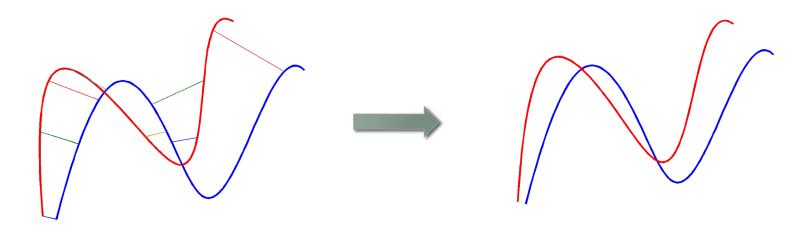
Given a pair of shapes, X and Y, iterate:

- 1. For each $x_i \in X$ find **nearest** neighbor $y_i \in Y$.
- 2. Find deformation \mathbf{R} , t minimizing: $\sum_{i=1}^{\infty} \|\mathbf{R}x_i + t y_i\|_2^2$

Iterative Closest Point

Requires two main computations:

- 1. Computing nearest neighbors.
- 2. Computing the optimal transformation



Non-Rigid Alignment Problem

- Compute a deformation for aligning shapes
 - Non-rigid deformation!



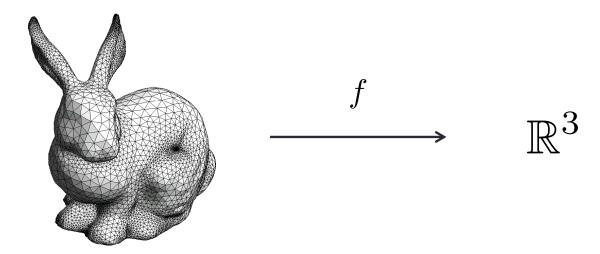
Compute a deformation for aligning shapes





Formalizing Deformation

How do you solve this problem numerically:



Define a measure of distortion:
$$E(f) := \sum_{t \in F} \operatorname{distortion}(J_t)$$

Define the **deformation** as the minimum of energy:

$$(u_{\mathrm{opt}}, v_{\mathrm{opt}}, w_{\mathrm{opt}}) = \mathop{\arg\min}_{f=(u,v,w)} E(f)$$
 Possibly given handle conditions

• Deformation of vertex neighborhood \mathcal{N}_i limited to a rotation R_i :

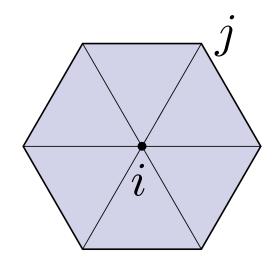
$$\mathbf{u}_i - \mathbf{u}_j = R_i(\mathbf{x}_i - \mathbf{x}_j)$$

• Energy for edges incident to i:

$$\sum_{j \in \mathcal{N}_i} w_{ij} \|\mathbf{u}_i - \mathbf{u}_j - R_i(\mathbf{x}_i - \mathbf{x}_j)\|^2$$

Energy on all vertices:

$$E(\mathbf{u}, R) = \sum_{i=1}^{n} \sum_{j \in \mathcal{N}_i} w_{ij} \|\mathbf{u}_i - \mathbf{u}_j - R_i(\mathbf{x}_i - \mathbf{x}_j)\|^2$$
$$w_{ij} = \frac{1}{2} (\cot \alpha_{ij} + \cot \beta_{ij})$$



Solving the optimization problem:

$$\min_{\mathbf{u},R} E(\mathbf{u},R) = \sum_{i=1}^{n} \sum_{j \in \mathcal{N}_i} w_{ij} \|\mathbf{u}_i - \mathbf{u}_j - R_i(\mathbf{x}_i - \mathbf{x}_j)\|^2$$

- Iterates between:
 - Minimization for **u** (solve three linear systems of size nxn)
 - Minimization for each rotation R_i (compute SVD at each vertex)

Finding the optimum for the variable **u**:

$$E(\mathbf{u}, R) = \sum_{i=1}^{n} \sum_{j \in \mathcal{N}_i} w_{ij} \|\mathbf{u}_i - \mathbf{u}_j - R_i(\mathbf{x}_i - \mathbf{x}_j)\|^2$$

$$\frac{\partial E}{\partial \mathbf{u}_i} = 0 \Rightarrow \sum_{j \in \mathcal{N}_i} w_{ij} ((\mathbf{u}_i - \mathbf{u}_j) - \frac{1}{2} (R_i + R_j) (\mathbf{x}_i - \mathbf{x}_j)) = 0$$

$$\Rightarrow (W\mathbf{u})_i = \sum_{j \in \mathcal{N}_i} \frac{w_{ij}}{2} (R_i + R_j) (\mathbf{x}_i - \mathbf{x}_j))$$

Cotangent matrix

Finding the optimum for the variable R_i :

$$E(\mathbf{u}, R) = \sum_{i=1}^{n} \sum_{j \in \mathcal{N}_i} w_{ij} \|\mathbf{u}_i - \mathbf{u}_j - R_i(\mathbf{x}_i - \mathbf{x}_j)\|^2$$

Under the constraint: $R_i^{\top} R_i = I$, $\det R_i = 1$

Equivalent to solving:

$$\max_{R_i} \langle R_i, B_i \rangle_F, \text{ with } B_i = \sum_{j \in \mathcal{N}_i} w_{ij} (\mathbf{u}_i - \mathbf{u}_j) (\mathbf{x}_i - \mathbf{x}_j)^\top$$

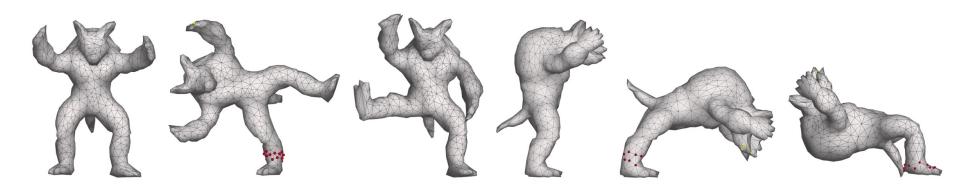
Orthogonal Procrustes problem: there exists a closed form solution using the SVD

$$B_i = U \Sigma V^ op$$
 with U, V orthogonal matrix $R_i = U egin{pmatrix} 1 & 0 & 0 \ 0 & 1 & 0 \ 0 & 0 & \det(U V^ op) \end{pmatrix} V^ op$

Solving the optimization problem:

$$\min_{\mathbf{u},R} E(\mathbf{u},R) = \sum_{i=1}^{n} \sum_{j \in \mathcal{N}_i} w_{ij} \|\mathbf{u}_i - \mathbf{u}_j - R_i(\mathbf{x}_i - \mathbf{x}_j)\|^2$$

- Iterates between:
 - Minimization for (solve three linear systems of size nxn)
 - Minimization for each rotation (compute SVD at each vertex)

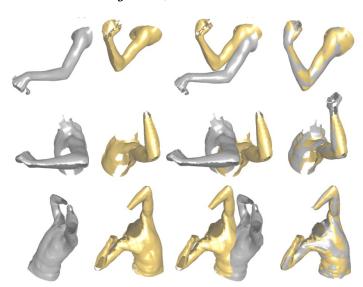


Non-Rigid Surface Alignment

Given a pair of shapes, X and Y, iterate:

- 1. For each $x_i \in X$ find **nearest** neighbor $y_i \in Y$.
- 2. Find the deformation of X minimizing the

distance:
$$E(\mathbf{u}, R) = \sum_{i=1}^{n} \sum_{j \in \mathcal{N}_i} w_{ij} \|\mathbf{u}_i - \mathbf{u}_j - R_i(y_i - y_j)\|^2$$



Non-Rigid Surface Alignment

Pros:

- Need to find a good deformation model
- Strong regularization of the deformation (volume preservation, basis of deformation)
- Lots of research and good theoretical understanding

Cons:

- Approximative matching (no continuity, no bijectivity)
- Computationally slow
- Often limited to small deformations