



中国科学技术大学

University of Science and Technology of China

GAMES 301: 第3讲

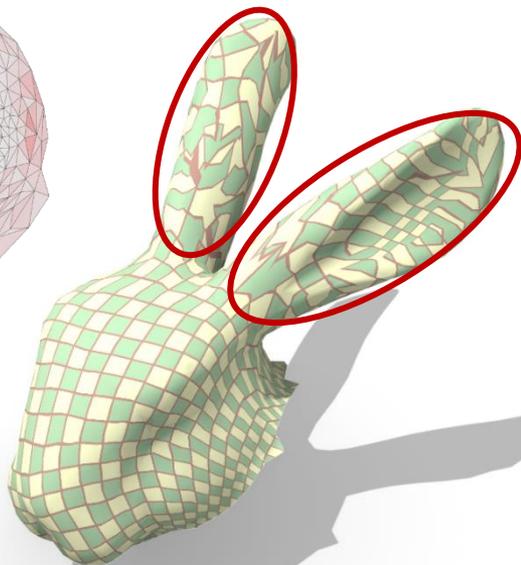
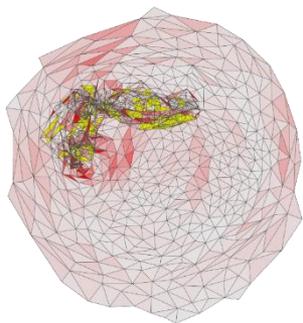
无翻转参数化方法 初始存在翻转

傅孝明

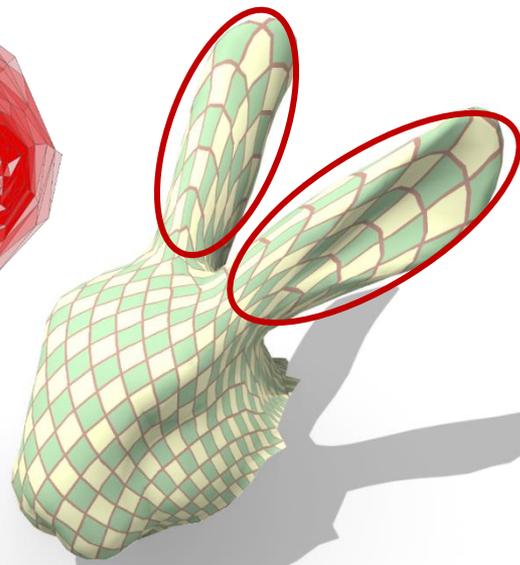
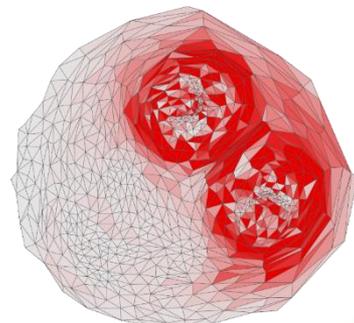
中国科学技术大学

Computing flip-free mappings
with flipped initializations

Problem definition



ARAP, Flipped



Flip-free

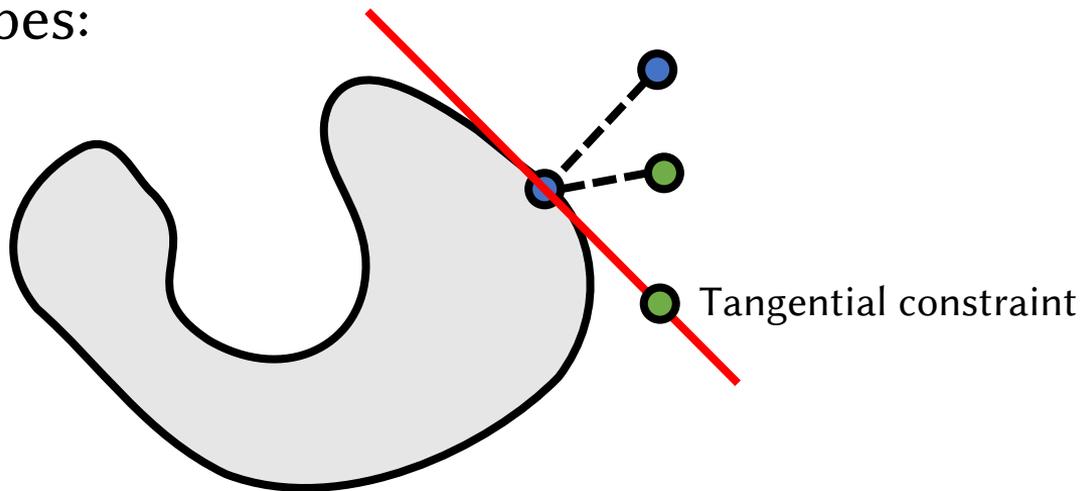


Projection

Key idea



- Project the flipped elements into the flip-free mapping space.
- An alternating algorithm
 - Local step: project each element onto the constraint set (flip-free space)
 - Global step: minimize the distance to the projected elements
- Common projection types:
 - Closest point projection
 - Tangential projection



Preliminaries



- Signed singular value decomposition: $J_i(\mathbf{u}) = U_i S_i V_i^T$
 - U_i and V_i are two rotation matrices
 - $S_i = \text{diag}(\sigma_{i,1}, \sigma_{i,2}, \sigma_{i,3}), \sigma_{i,1} \geq \sigma_{i,2} \geq |\sigma_{i,3}|$
- Foldover-free constraints
 - $\det J_i(\mathbf{u}) > 0, i = 1, \dots, N \Leftrightarrow \sigma_{i,3} > 0$
- Conformal distortion
 - $\tau(J_i(\mathbf{u})) = \sigma_{i,1}/\sigma_{i,3}$
- Bounded conformal distortion constraints
 - $1 \leq \tau(J_i(\mathbf{u})) \leq K$

Constraints



Flip-free
constraints

$$\det J_i(\mathbf{u}) > 0$$

$$\sigma_{i,3} > 0, \tau(J_i) = \sigma_{i,1}/\sigma_{i,3}$$

$$\sigma_{i,1} \geq \sigma_{i,2} \geq |\sigma_{i,3}|$$

$$K = \max_{i=1,\dots,N} \tau(J_i)$$

Bounded conformal
distortion constraints

$$1 \leq \tau(J_i(\mathbf{u}))$$

$$\tau(J_i(\mathbf{u})) \leq K$$

$$\tau(J_i) \geq 1, \sigma_{i,3} > 0, \sigma_{i,3} > 0$$

Formulation



$$\min_{\mathbf{u}} E_d = \sum_{i=1, \dots, N} \|J_i(\mathbf{u}) - H_i\|_F^2,$$

$$s. t. \quad H_i \in \mathcal{H}_i, i = 1, \dots, N,$$

$$A\mathbf{u} = b.$$

$\mathcal{H}_i = \{H_i | 1 \leq \tau(H_i) \leq K\}$: bounded conformal distortion space.

Solver



- Local-global solver

Local step

Fix \mathbf{u} and J_i , solve H_i

$$\min_{\mathbf{u}} E_d = \sum_{i=1, \dots, N} \|J_i(\mathbf{u}) - H_i\|_F^2,$$

$$s. t. H_i \in \mathcal{H}_i, i = 1, \dots, N,$$

Global step

Fix H_i , solve \mathbf{u}

$$\min_{\mathbf{u}} E_d = \sum_{i=1, \dots, N} \|J_i(\mathbf{u}) - H_i\|_F^2,$$

$$s. t. A\mathbf{u} = b$$

Very slow convergence...

Anderson acceleration



- Fixed-point iteration

$$G = \phi \circ P$$

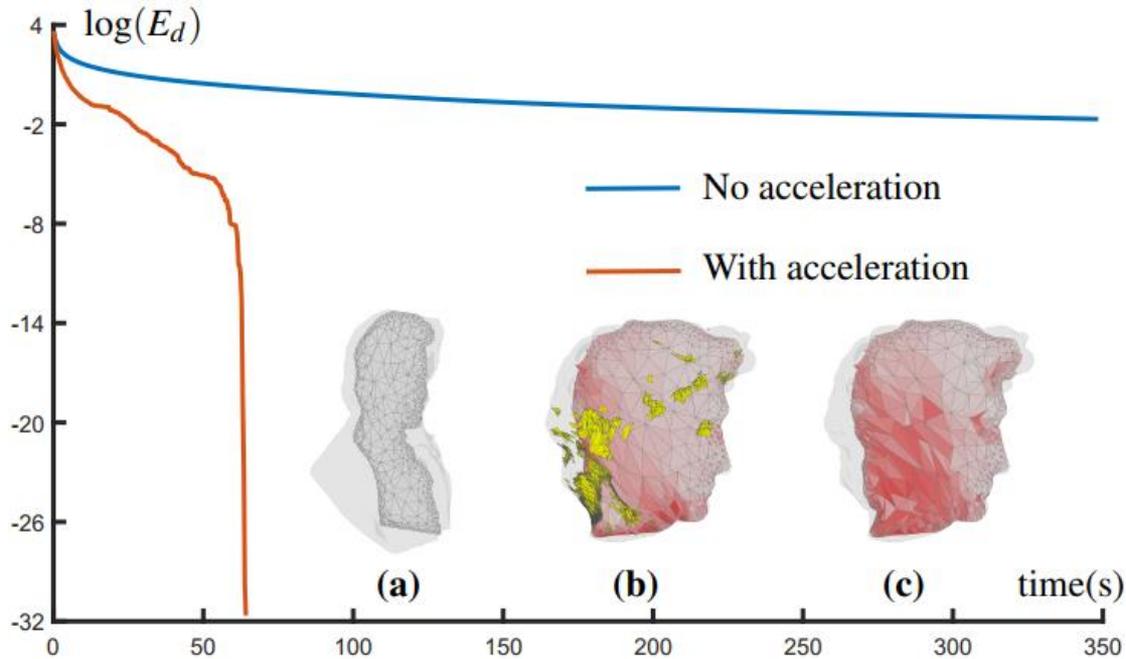
- Accelerated iteration $\mathbf{x}^{k+1} = G(\mathbf{x}^k)$

$$\mathbf{x}_{AA}^{k+1} = G(\mathbf{x}^k) - \sum_{j=1}^m \theta_j^* (G(\mathbf{x}^{k-j+1}) - G(\mathbf{x}^{k-j}))$$

where $(\theta_1^*, \dots, \theta_m^*)$ is the solution to a linear least-squares problem:

$$\min_{(\theta_1, \dots, \theta_m)} \left\| F^k - \sum_{j=1}^m \theta_j (F^{k-j+1} - F^{k-j}) \right\|^2, F^k = G(\mathbf{x}^k) - \mathbf{x}^k$$

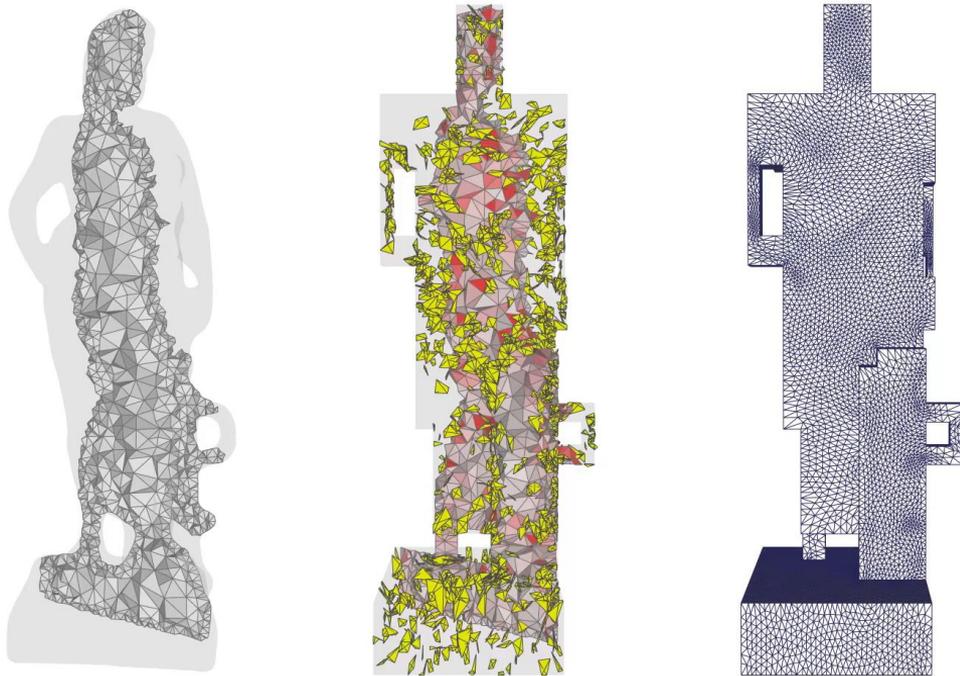
Anderson acceleration



Update bound K



- Projection cannot eliminate all foldovers



round:1 iter:0 foldovers:3274

- $K^{new} = \beta K$
 - $\beta = 2$
 - initialize $K = 4$

Recap of the algorithm



Elimination Process :

alternates in each round:

- generate conformal distortion bound
- try to project the mapping into the bounded distortion space

Tangential projection

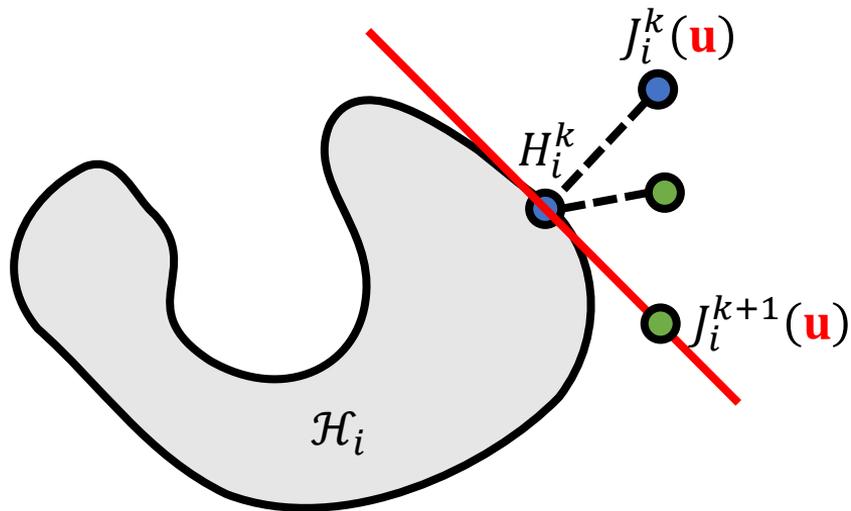


- Global step: fix H_i , solve \mathbf{u}

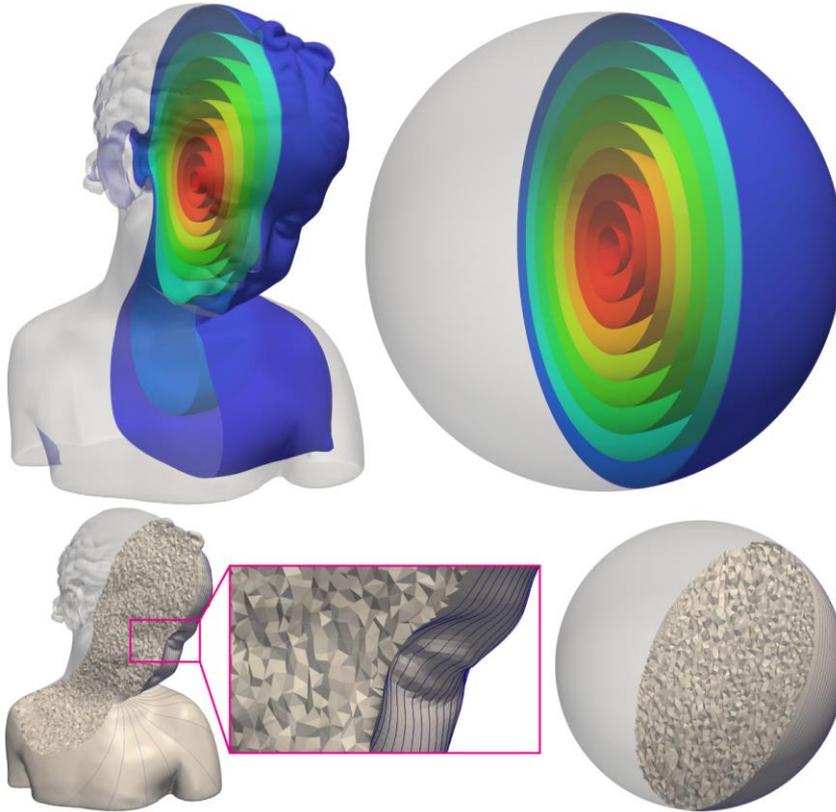
$$\min_{\mathbf{u}} E_d = \sum_{i=1, \dots, N} \|J_i(\mathbf{u}) - H_i\|_F^2,$$

$$s. t. \quad A\mathbf{u} = b$$

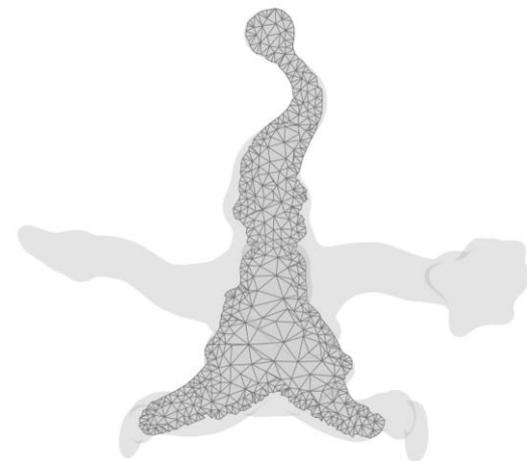
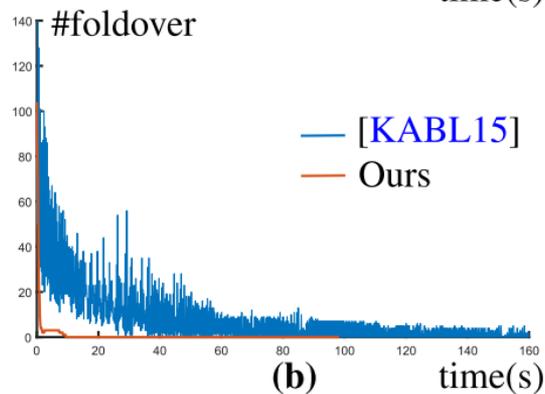
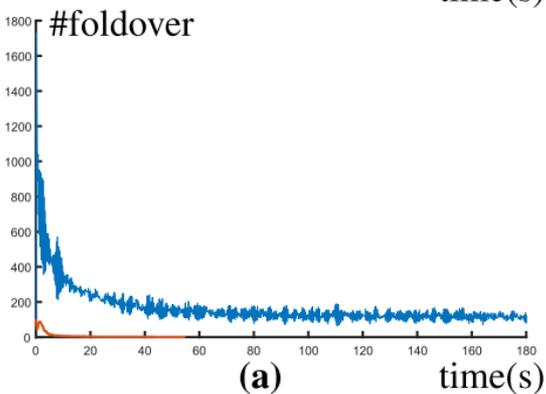
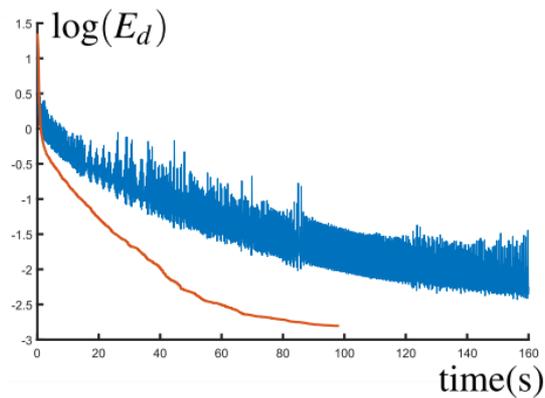
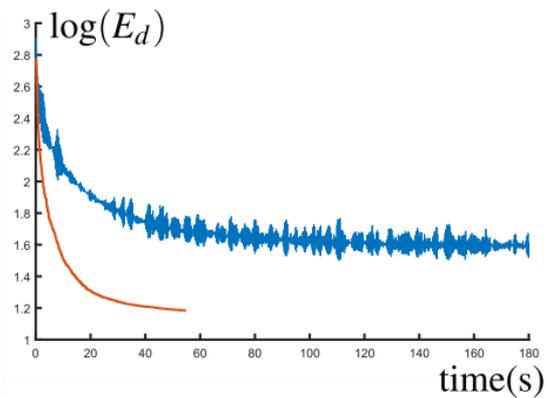
$$(J_i^k(\mathbf{u}) - H_i^k) \perp (J_i^{k+1}(\mathbf{u}) - H_i^k)$$



Results



Comparison



Penalty

Overview



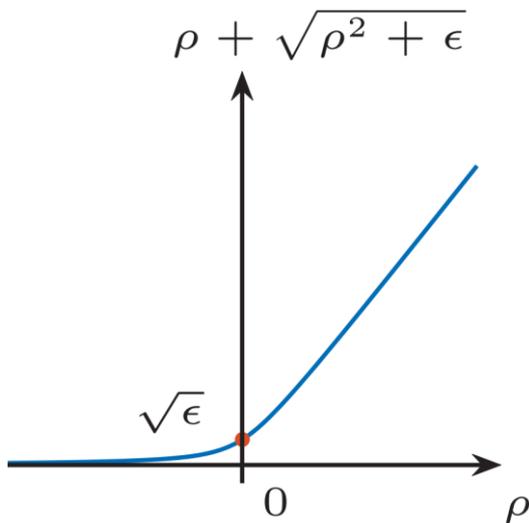
- Key idea: penalize the flipped elements via penalty functions
- Main properties:
 - it is very large to penalize flipped Jacobian matrices;
 - it is very small to accept flip-free Jacobian matrices.
- Solvers are then the challenges
 - Non-linear and non-convex

Common penalty functions



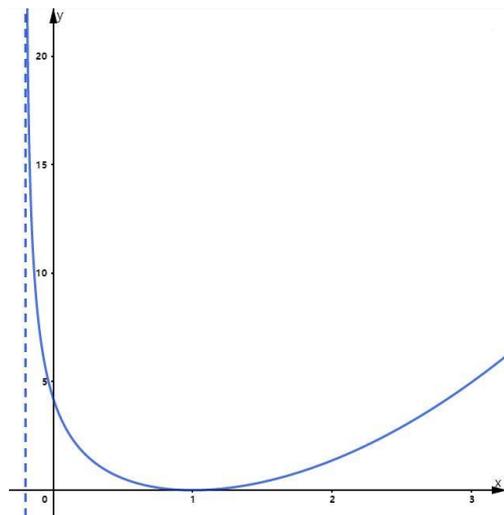
$$\sum_i \frac{\|J_i\|_F^d}{\det J_i + \sqrt{(\det J_i)^2 + \varepsilon}}$$

Key: the small positive ε



$$\sum_i (\det J_i - 1)^2 + \left(\log \frac{x - \varepsilon}{1 - \varepsilon} \right)^2$$

Key: parameter ε



Parameter ε



the regularization parameter ε^k . Starting from $\varepsilon^0 := 1$, we define the sequence as follows:

$$\varepsilon^{k+1} := \begin{cases} \left(1 - \frac{\sigma^k \sqrt{(D_-^{k+1})^2 + (\varepsilon^k)^2}}{|D_-^{k+1}| + \sqrt{(D_-^{k+1})^2 + (\varepsilon^k)^2}} \right) \varepsilon^k, & \text{if } D_-^{k+1} < 0, \\ (1 - \sigma^k) \varepsilon^k, & \text{if } D_-^{k+1} \geq 0, \end{cases}$$

where $D_-^{k+1} := \min_{t \in 1 \dots \#T} \det J_t^{k+1}$ is the minimum value of the Jacobian determinant over all cells of the mesh at the iteration $k + 1$, and $\sigma^k := \max \left(\frac{1}{10}, 1 - \frac{F(U^{k+1}, \varepsilon^k)}{F(U^k, \varepsilon^k)} \right)$.

Solvers



- Block coordinate descent method
- Monotone preconditioned conjugate gradient method
- L-BFGS
- SGD
- Second-order methods

Bounded distortion spaces

Bounded distortion space



- Goal: explicitly bound the conformal distortion
- Constraints: $\delta_t^{con} = \frac{\sigma_{max}}{\sigma_{min}} < K, \det J_t > 0$
- Non-linear and non-convex

$$J_t = \begin{pmatrix} a_t + c_t & d_t - b_t \\ d_t + b_t & a_t - c_t \end{pmatrix}$$
$$\sigma_{max} = \sqrt{a_t^2 + b_t^2} + \sqrt{c_t^2 + d_t^2}$$
$$\sigma_{min} = \left| \sqrt{a_t^2 + b_t^2} - \sqrt{c_t^2 + d_t^2} \right|$$

Reformulation



$$J_t = \begin{pmatrix} a_t + c_t & d_t - b_t \\ d_t + b_t & a_t - c_t \end{pmatrix} \quad \begin{aligned} \sigma_{max} &= \sqrt{a_t^2 + b_t^2} + \sqrt{c_t^2 + d_t^2} \\ \sigma_{min} &= \left| \sqrt{a_t^2 + b_t^2} - \sqrt{c_t^2 + d_t^2} \right| \end{aligned}$$

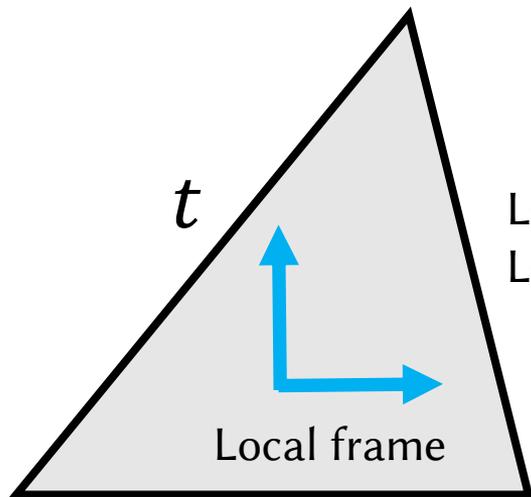
$$\delta_t^{con} < K, \det J_t > 0$$

$\det J_t > 0$	\longrightarrow	$\sqrt{c_t^2 + d_t^2} < \sqrt{a_t^2 + b_t^2}$		$r_t \leq \sqrt{a_t^2 + b_t^2}$	Non-convex
			}	$\sqrt{c_t^2 + d_t^2} \leq \frac{K-1}{K+1} r_t$	Convex
$\delta_t^{con} < K$	\longrightarrow	$\sqrt{c_t^2 + d_t^2} \leq \frac{K-1}{K+1} \sqrt{a_t^2 + b_t^2}$		$r_t > 0$	Convex

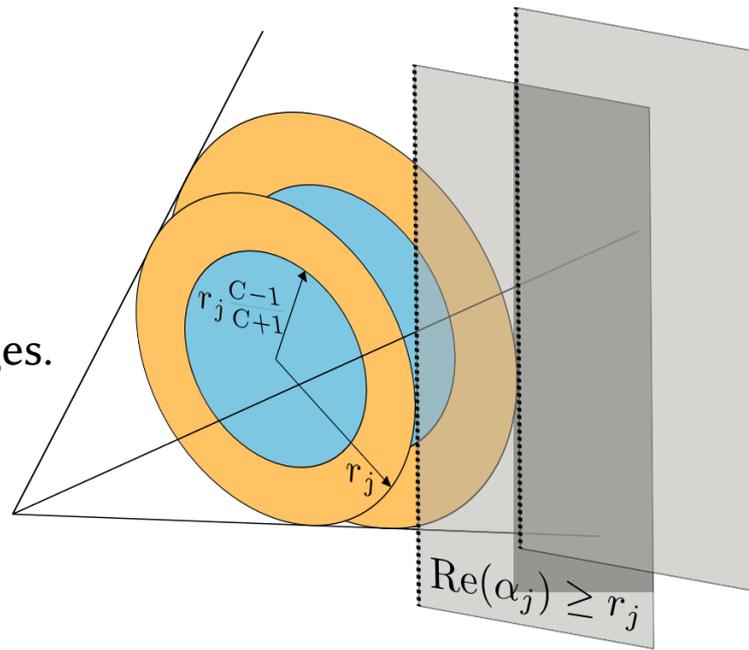
Maximum convex subset



$$r_t \leq \sqrt{a_t^2 + b_t^2} \longrightarrow r_t \leq a_t \quad \text{Convex}$$



Local frame changes, a_t changes.
Local frame is also a variable.



$$\alpha_j = a_j + i \cdot b_j$$

Optimization process



- Objective function:

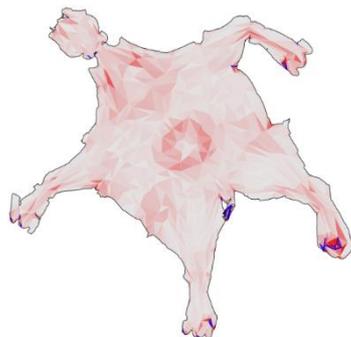
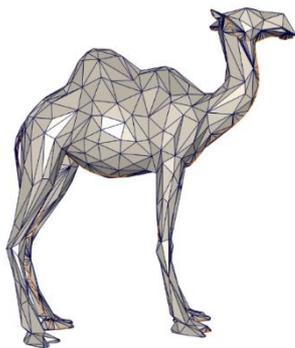
- LSCM: $E = \sum_t \text{Area}(t) \cdot (c_t^2 + d_t^2)$

- ARAP: $E = \sum_t \text{Area}(t) \cdot \left((a_t - 1)^2 + b_t^2 + c_t^2 + d_t^2 \right)$

$$J_t = \begin{pmatrix} a_t + c_t & d_t - b_t \\ d_t + b_t & a_t - c_t \end{pmatrix}$$

- Optimization:

- Fix the local frame on each triangle: Second-Order Cone Programming;
 - Update local frame to let $b_t = 0$.



$$\delta_{max}^{con} = 26.98$$

Time: 4.03s

1. How to choose K?
2. The speed is slow.

Known U and V



- Signed singular value decomposition:
 - $J_i = U_i S_i V_i^T$
 - U_i and V_i are two rotation matrices
 - $S_i = \text{diag}(\sigma_{i,1}, \sigma_{i,2}, \sigma_{i,3}), \sigma_{i,1} \geq \sigma_{i,2} \geq |\sigma_{i,3}|$
- Observation:
 - $S_i = U_i^T J_i V_i$
 - if U_i and V_i are known, S_i is a linear vector function w.r.t vertex positions.
 - Bounded conformal distortion constraint
 - $\tau(J_i) = \sigma_{i,1}/\sigma_{i,3} \leq K$ become linear inequality constraint.
- Problem: how to get U_i and V_i ?

Pipeline



Algorithm 1: Projection on \mathcal{F}_K

Input: Tetrahedral mesh $\mathbf{M} = (\mathbf{T}, \mathbf{V})$
Source map $\Phi \in \mathcal{F}$ to project
Distortion bound $K \geq 1$

Output: K -bounded-distortion map $\text{Pr}(\Phi) \in \mathcal{F}_K$

$\Psi^0 = \Phi;$

while $\text{Dist}(\Psi^{n+1}, \Psi^n) > \varepsilon$ **do**

 Compute SSVD $B_j^n = U_j \Sigma_j V_j^T$ for all $t_j \in \mathbf{T};$

 Update:

$\Psi^{n+1} = \text{argmin} \text{Dist}(\Psi \mathbf{w}, \Psi^n)$

 s.t.

$\mathbf{w} \in \mathbb{R}^{3 \times n}$

 and for every $t_j \in \mathbf{T},$

 the diagonal $\mathbf{x} = (x_1, x_2, x_3)$ of $U_j^T B_j(\mathbf{w}) V_j$

 satisfies $x_k \leq K x_\ell, 1 \leq k, \ell \leq 3$

Return $\text{Pr}(\Phi) = \Psi^{n+1};$

Results



- A small number of iterations
 - < 10 iterations
- Quadratic programming is time-consuming
- Set K ?

Area-based methods

Total unsigned area



- Signed area S_t of a triangle t
- Unsigned area U_t of a triangle t

- Facts for any 2D triangulation or 3D tetrahedron \mathcal{T} :
 - Total signed area $\sum_t S_t = \text{Area}(\mathcal{T})$
 - Total unsigned area $\sum_t U_t \geq \text{Area}(\mathcal{T})$
 - \mathcal{T} is flip-free iff $\sum_t U_t = \text{Area}(\mathcal{T})$

- Optimizing total unsigned area for achieving flip-free mappings.

Failure reasons



- It is not smooth, considered as a function of the embedding
 - TUA exhibits a C^1 discontinuity as a vertex moves across the supporting line of its opposite edge in a triangle.
- While any injective embedding achieves the global minimum of TUA, the inverse is not true
 - the triangulation containing degenerate elements is a global minimum of TUA but a non-injective embedding
- TUA has zero gradients with respect to any vertex surrounded by a ring of consistently oriented triangles.

Total lifted content



$$\sum_t \frac{1}{d!} \sqrt{\det(X^T X + \alpha \tilde{X}^T \tilde{X})}$$

- X : a $d \times d$ matrix whose column vectors are the edge vectors from one vertex to the other d vertices.
- Thus, $\sqrt{\det(X^T X)} = U_t$.
- \tilde{X} : similar to X , but from an auxiliary simplex, such as an equilateral triangles or tetrahedra of the same size as the input.
- TLC becomes TUA when $\alpha = 0$.

Properties of TLC



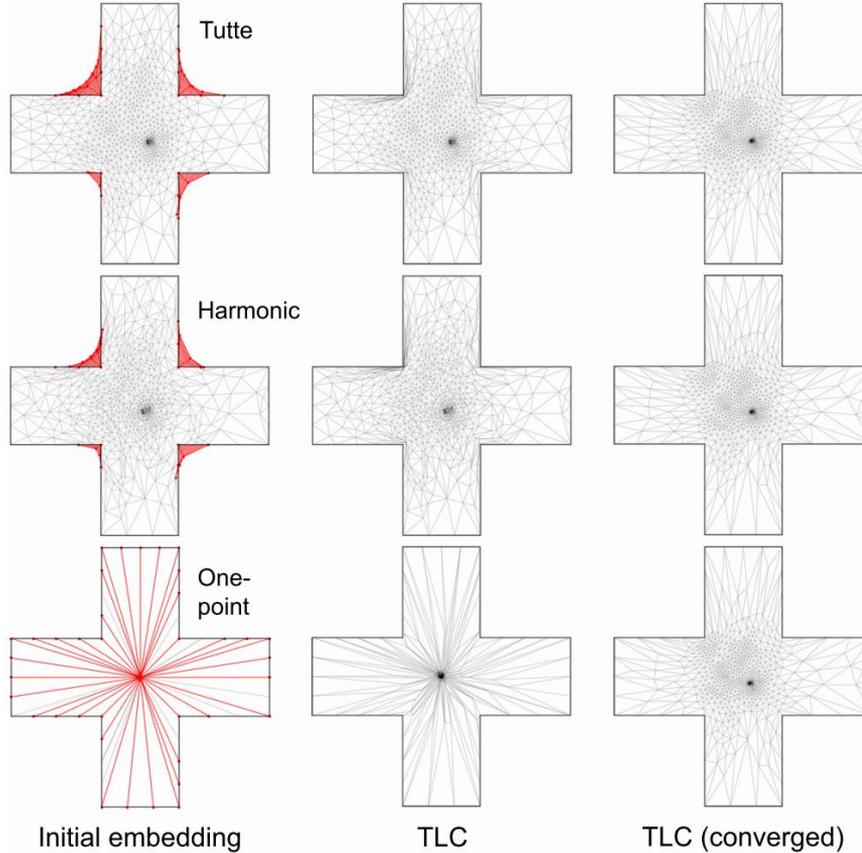
- TLC is smooth over the entire space

COROLLARY 4.2. The Total Lifted Content, $E_{\tilde{T}, \alpha}(T)$, is strictly positive, greater than the total unsigned areas or volumes of T , and differentiable to any order over the embedding space of T , given any set of non-degenerate auxiliary simplices \tilde{T} and positive α .

- TLC has only an injective global minimum for sufficiently small values of α .

PROPOSITION 4.3. Let T_0 be some d -dimensional ($d = 2, 3$) injective embedding into the target boundary and \tilde{T} be a set of non-degenerate auxiliary simplices. Then there exists some $\beta > 0$ such that $E_{\tilde{T}, \alpha}(T) > E_{\tilde{T}, \alpha}(T_0)$ for any non-injective embedding T and $\alpha < \beta$.

Results



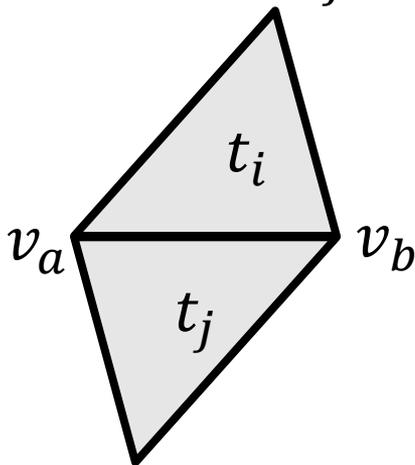
Different representations

Affine transformation



- Key observation: the parameter space is a 2D triangulation, uniquely defined by all the **AFFINE TRANSFORMATIONS** on the triangles.
- **Edge assembly constraints:**

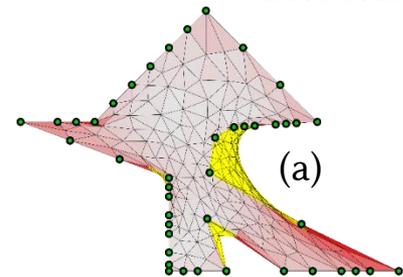
$$J_i(v_a - v_b) = J_j(v_a - v_b)$$



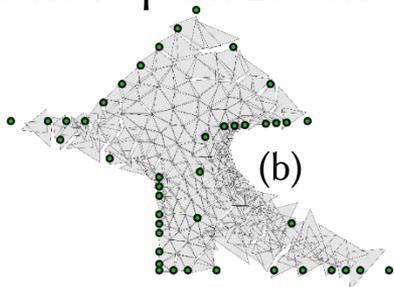
Key idea



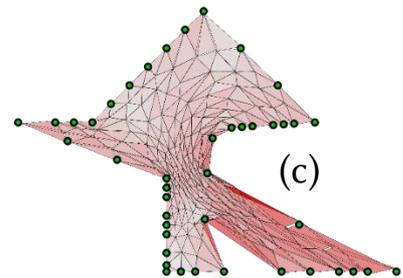
- Disassembly + Assembly
 - Treat affine transformation as variables
 - Unconstrained optimization



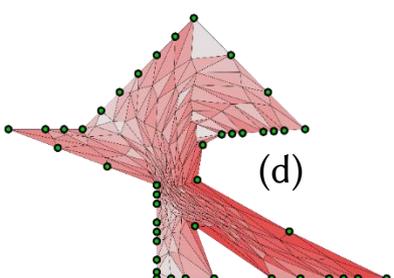
(a)



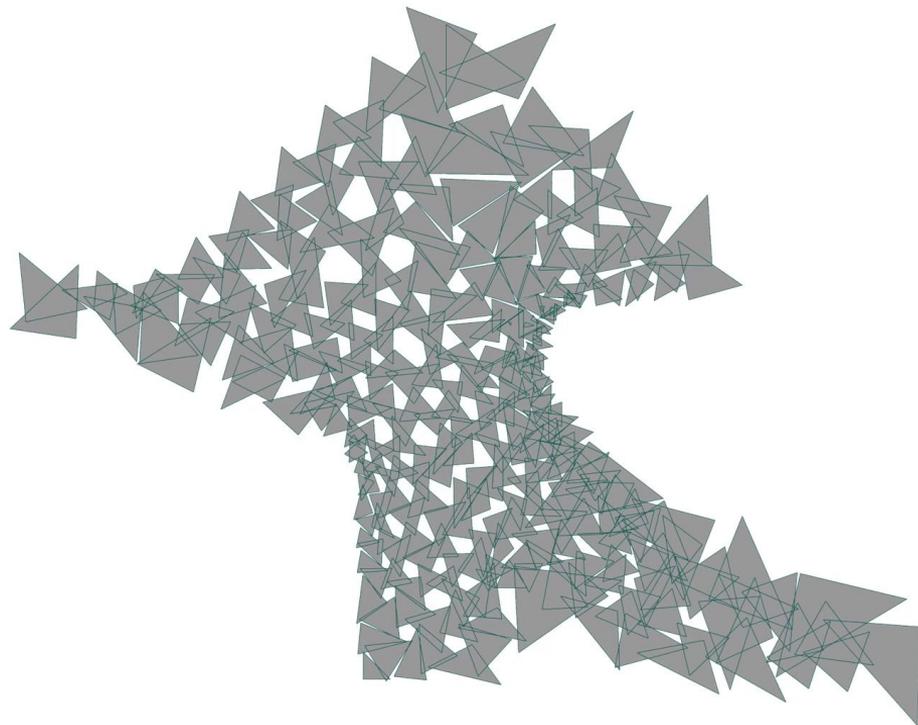
(b)



(c)



(d)



Unconstrained optimization problem

Disassembly: project initial A_i^0 into feasible space.

Assembly: unconstrained optimization.

$E_{assembly}$: summation of squares of edge, assembly constraints.

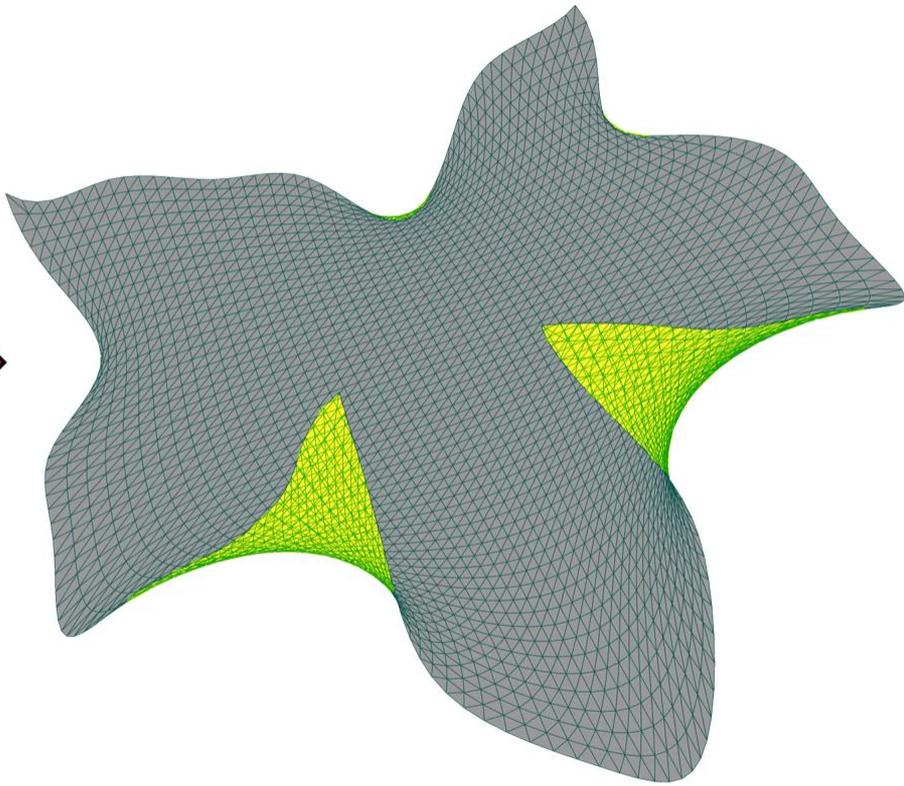
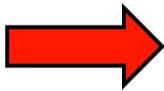
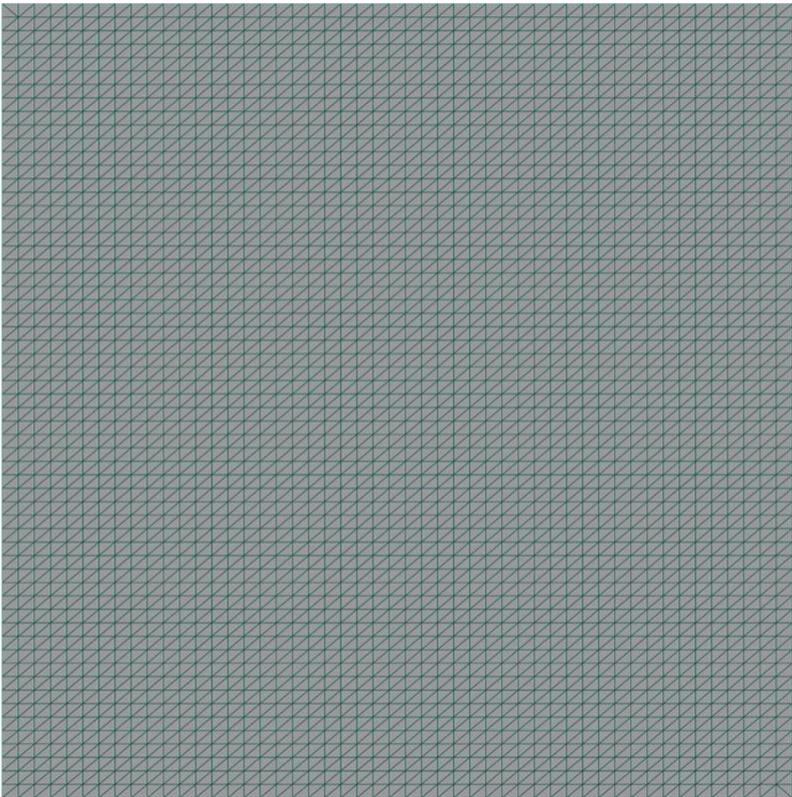
$$\min_{\substack{J_1, \dots, J_N \\ T_1, \dots, T_N}} \lambda E_{assembly} + E_C + \mu E_m$$

E_C : Barrier function on distortion

$$\lambda_{k+1} = \min \left(\lambda_{\min} \cdot \max \left(\frac{E_{C,k} + \mu E_{m,k}}{E_{assembly,k}}, 1 \right), \lambda_{\max} \right)$$

E_m : users' designed energy

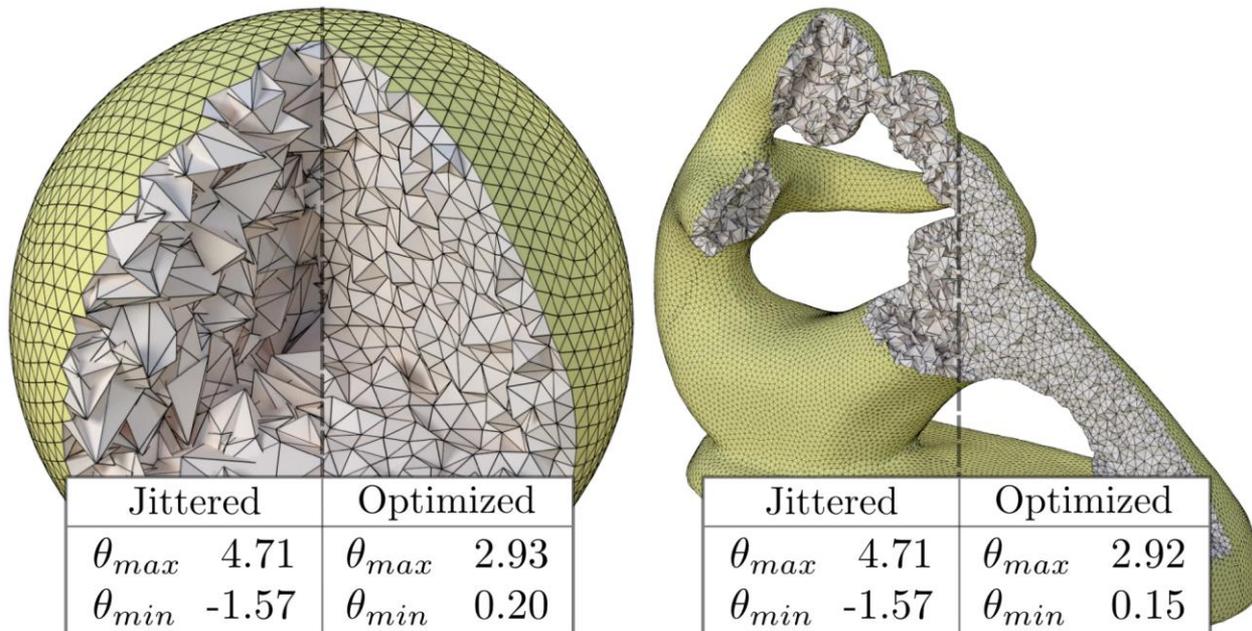
1. $E_{assembly}$ dominates the energy, approach zero;
2. λ_{\max} : avoid large distortion.



Angles



- 2D: Angle-based flattening
- 3D: Dihedral Angle-based Maps of Tetrahedral Meshes





中国科学技术大学

University of Science and Technology of China

谢谢！

