

# L16: Deformation

Hao Su

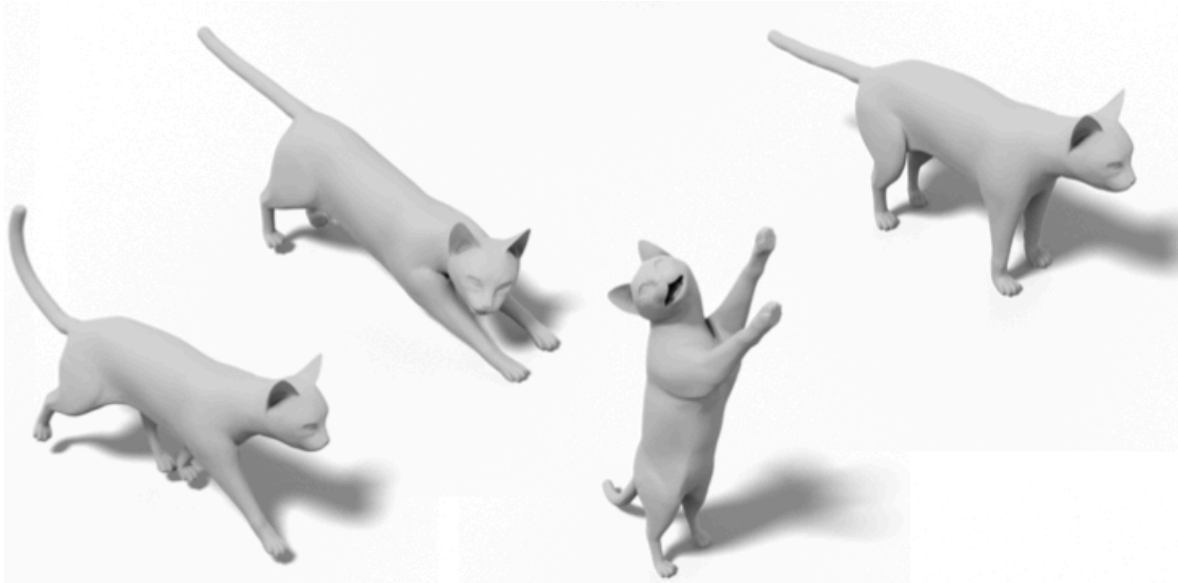
Ack: Yuzhe Qin and Fanbo Xiang for helping to prepare slides

# Agenda

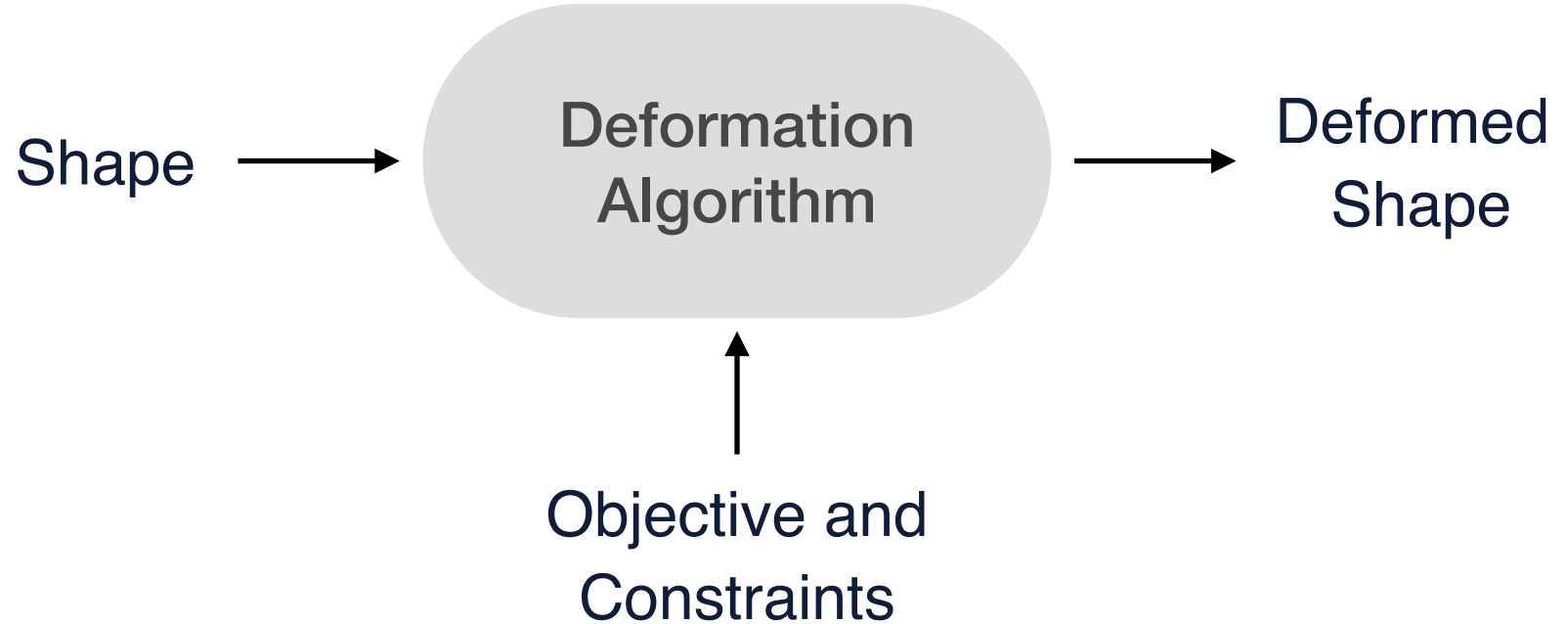
- Introduction
- Surface Deformation
- Space Deformation
- Skeleton Skinning

# Shape Deformation

- Generate new shape by deforming an existing one
  - e.g., to create animate character motion



# Shape Deformation



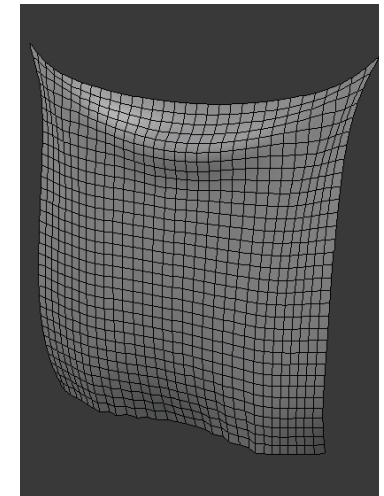
# Shape Deformation



Objective and Constraints

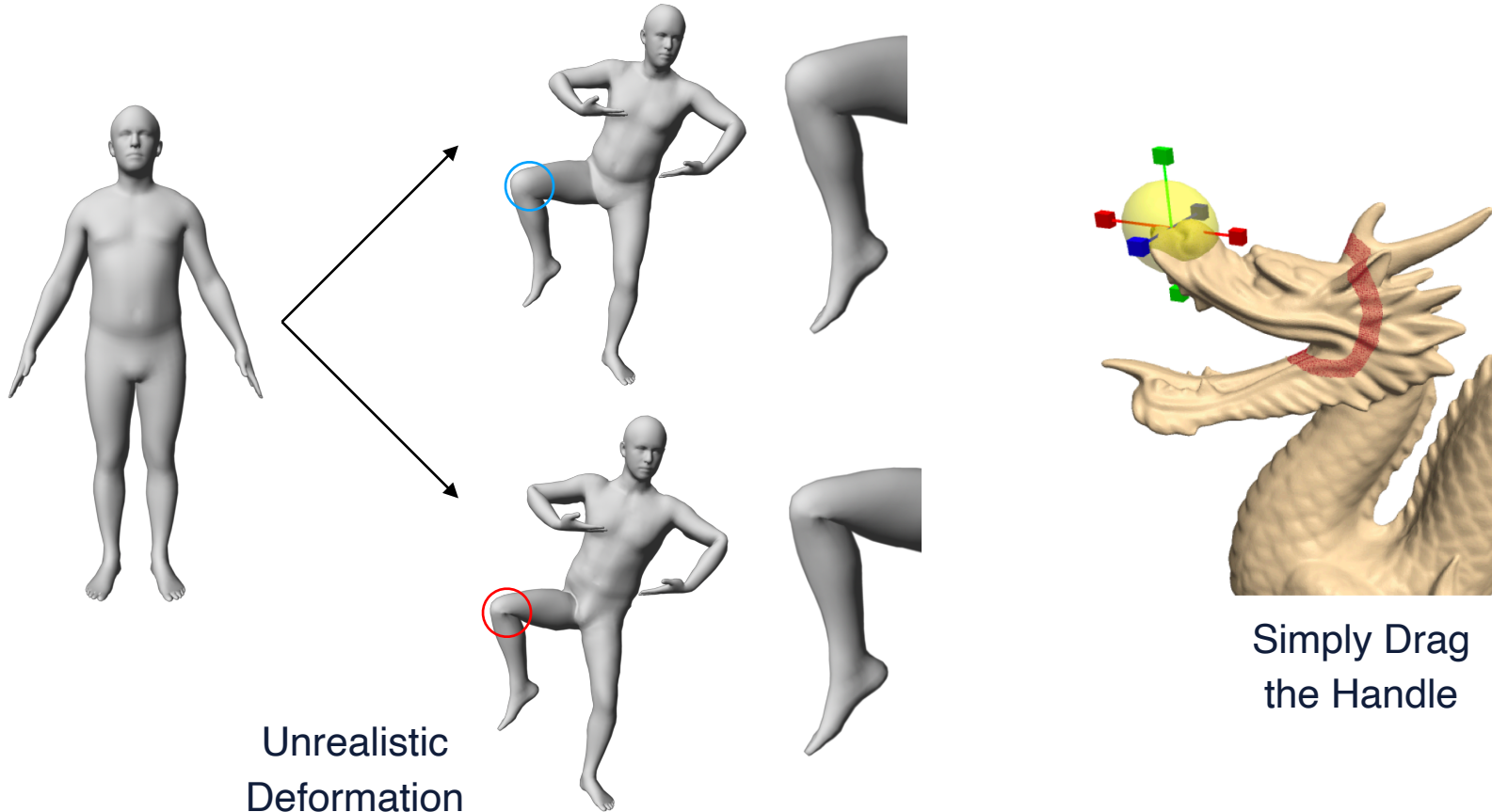
Objective:  
Modeler Input  
e.g., drag

Constraints:  
Geometry and Physics  
e.g., gravity



# Preferred Deformation Algorithm

- Deformation should be natural
- Modeler works less, algorithm does more



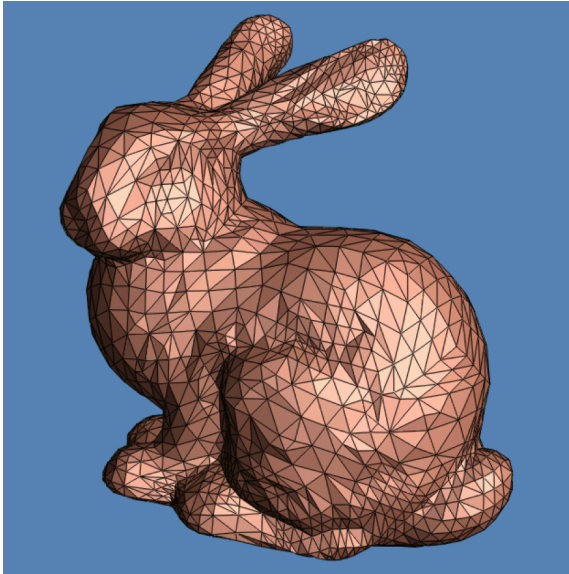
# Surface Deformation

Laplacian Surface Editing

As-Rigid-As-Possible Deformation

# Shape Surface Representation

- Recall Lecture 4:
  - Piece-wise Linear Surface Representation
  - E.g., triangular mesh



$$V = v_1, v_2, \dots, v_n \subset \mathbb{R}^3$$

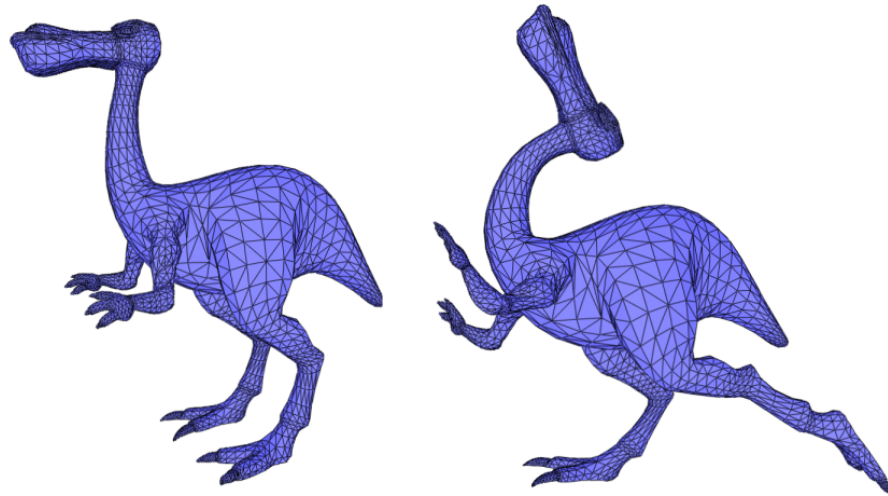
$$E = e_1, e_2, \dots, e_n \subseteq V \times V$$

$$F = f_1, f_2, \dots, f_n \subseteq V \times V \times V$$



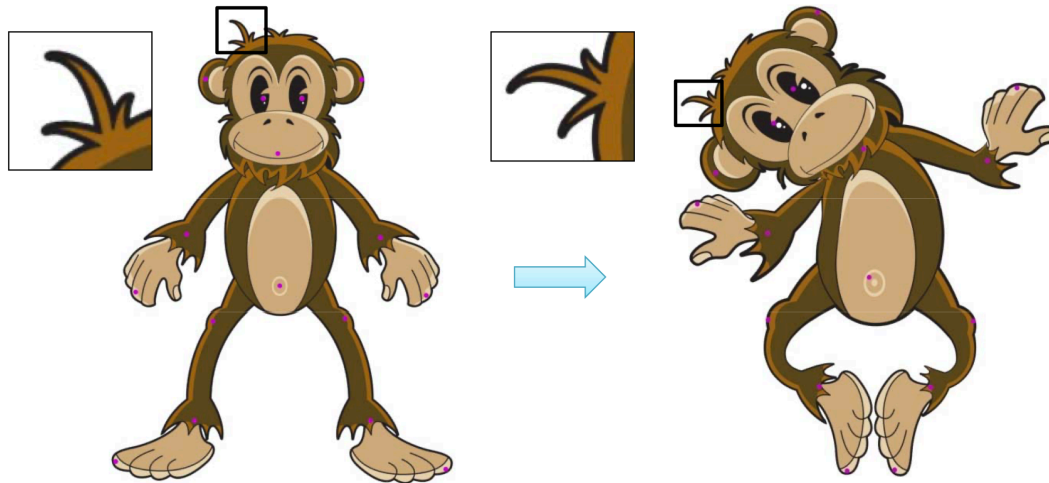
# Surface Deformation

- Deformation is only defined on the surface
- Surface deformation:  $d : V \rightarrow \mathbb{R}^3$
- $V$  is vertices of mesh



# Desired Surface Deformation

- Deformation is “natural”
  - It tries to preserve local geometry.



- Modelers do less, algorithms do more
  - E.g., given **vertex position objective** (new location of a few vertices), other points follow “naturally”.

# How to Preserve Local Geometry?

- Recall: Curvature completely determines local surface geometry
- We want to find a “natural” deformation that preserves curvature

# How to Preserve Curvature?

- Let us start with preserving mean curvature
- Recall: in HW2, Laplacian can be used to approximate mean curvatures

(b) The difference between a vertex  $x$  and the average position of its 1-ring neighborhood is a quantity that provides interesting geometric insight of the shape (see Figure 1). It can be shown that,

$$x - \frac{1}{|N(x)|} \sum_{y_i \in N(x)} y_i \approx H \vec{n} \Delta A \quad (2)$$

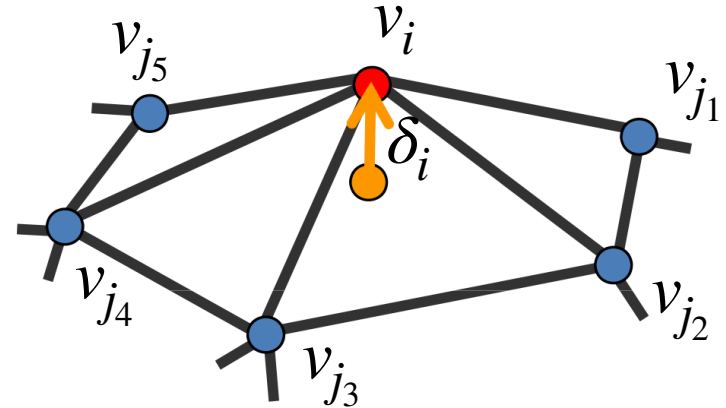
for a good mesh, where  $N(x)$  is the 1-ring neighborhood vertices of  $x$  by the mesh topology,  $H = \frac{1}{2}(\kappa_{min} + \kappa_{max})$  is the mean curvature at  $x$  (in the sense of the underlying continuous surface being approximated),  $\vec{n}$  is the surface normal vector at  $x$ , and  $\Delta A$  is a quantity proportional to the total area of the 1-ring fan (triangles formed by  $x$  and vertices along the 1-ring).

# Laplacian Coordinates

- Different from common mesh representation in global coordinates, we can represent a point relative to its neighbors

- $$\delta_i = v_i - \sum_{j \in N(v_i)} \frac{1}{d_i} v_j$$

- $d_i$ : degree of vertex  $i$



# Laplacian Coordinates

- Recall:

Laplacian matrix:  $L = D - A$

$D$  is degree matrix and  $A$  is adjacency matrix

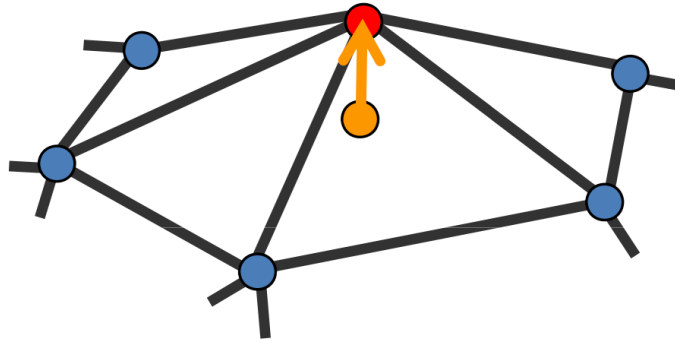
- Differential coordinates can be computed by a **normalized laplacian matrix**

$$\delta_i = v_i - \sum_{j \in N(i)} \frac{1}{d_i} v_j$$

$$\delta = (I - D^{-1}A)V = (D^{-1}L)V$$

- $V$  is a  $n \times 3$  matrix denotes vertices position

# Laplacian Coordinates Property



- Direction of  $\delta_i$  approximates the **normal direction**
- Size of the  $\delta_i$  approximates the **mean curvature**

$$\delta_i = v_i - \sum_{j \in N(i)} \frac{1}{d_i} v_j$$

- Note: mean curvature cannot fully determine local geometry. 2 numbers are needed

# Deform by Laplacian Coordinates

- Input: vertex (control point) position objective
- Consider a simple objective of moving several vertices towards the new location:  $v'_i = u_i$ , where  $v'$  is vertex after deformation.
- Energy function:

$\mathcal{L}(v'_i)$  is laplacian coordinates of  $v'_i$

$$E(V') = \sum_{i=1}^n \|\delta_i - \mathcal{L}(v'_i)\|^2 + \sum_{i=m}^n \|v'_i - u_i\|^2$$

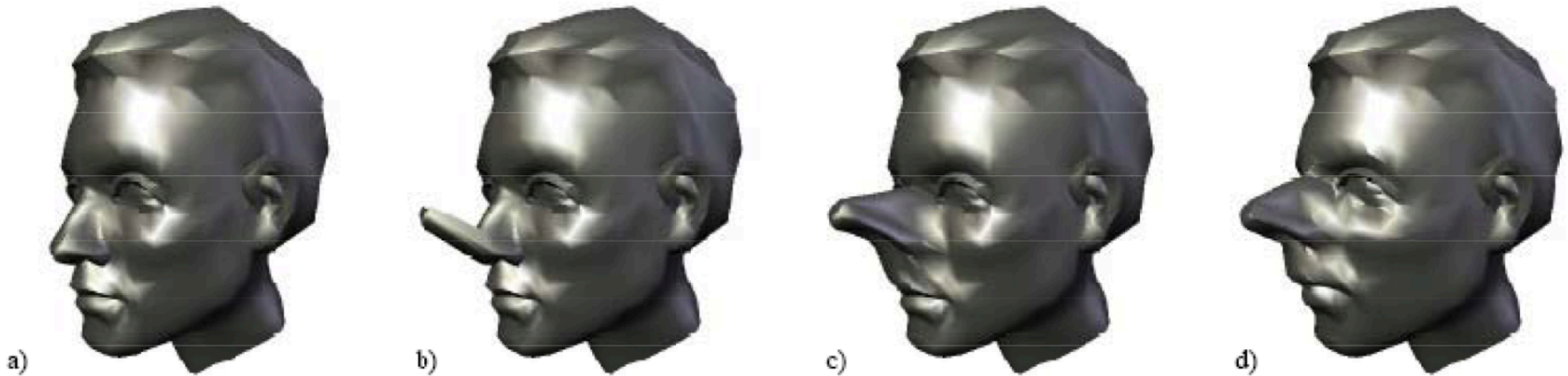
Laplacian Coordinate of Original Mesh      Laplacian Coordinate of Deformed Mesh      Objective: Control Point



# Deform by Laplacian Coordinates

- Deformed shape can be solved by minimizing  $E(V')$

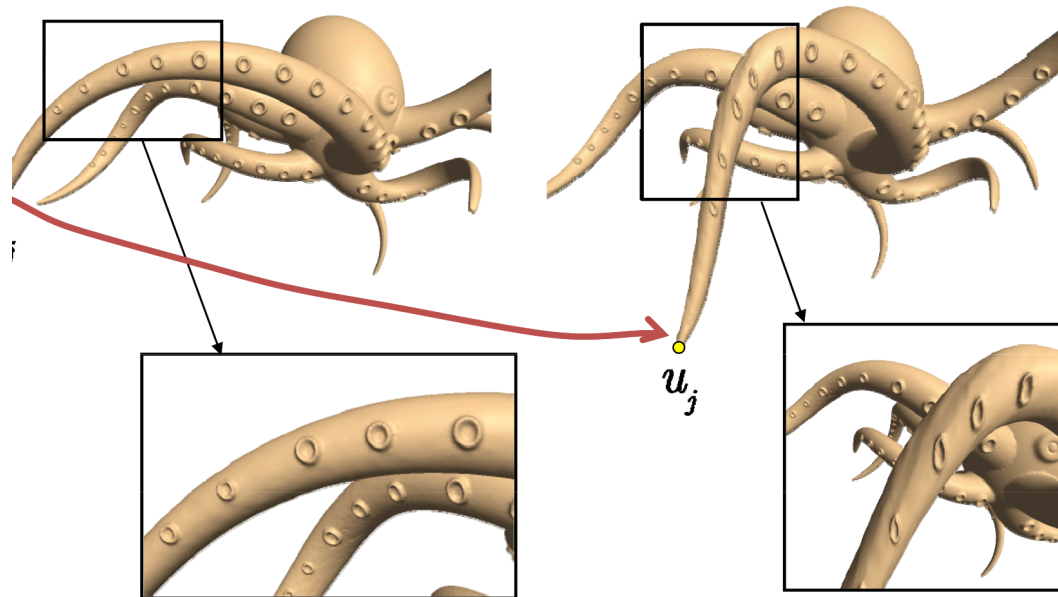
$$E(V') = \sum_{i=1}^n \|\delta_i - \mathcal{L}(v'_i)\|^2 + \sum_{i=m}^n \|v'_i - u_i\|^2$$



$E(V')$  decreases by iterations

# Issues?

- Other than preserving the mean curvature,  $\sum_{i=1}^n \|\delta_i - \mathcal{L}(v'_i)\|^2$  also have tried to preserve normal.
- However, normal preservation is undesired
- How can we cancel the effect of normal preservation?



# Laplacian Coordinates Under Transformation

- Normals are invariant under translation, so

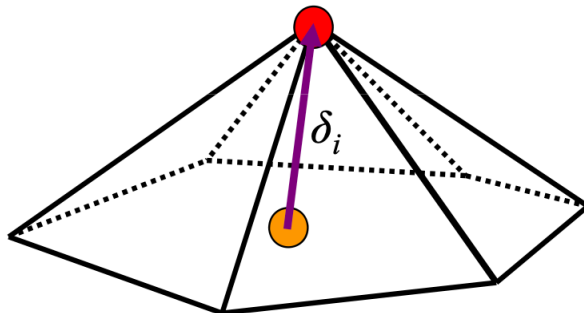
$$\mathcal{L}(v_i) = \mathcal{L}(v_i + t)$$

# Laplacian Coordinates Under Transformation

- Normals are invariant under translation, so

$$\mathcal{L}(v_i) = \mathcal{L}(v_i + t)$$

- However, normal changes under rotation, so Laplacian coordinates change under rotation

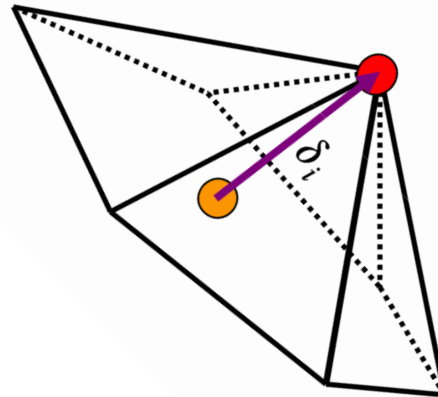


# Laplacian Coordinates Under Transformation

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$$\mathcal{L}(v_i) = \mathcal{L}(v_i + t)$$

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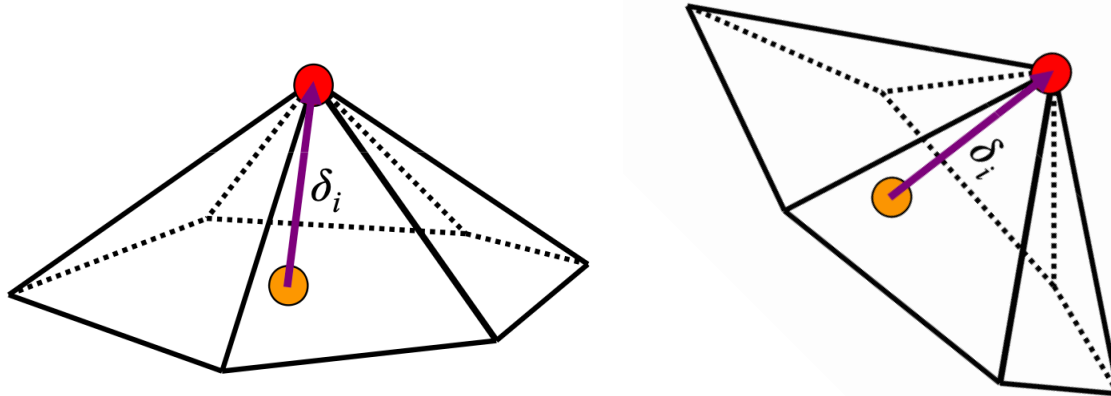
# Laplacian Coordinates Under Transformation

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$$\mathcal{L}(v_i) = \mathcal{L}(v_i + t)$$

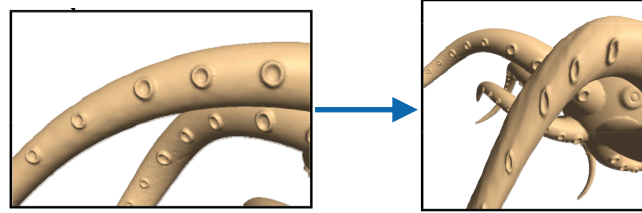
- However, normal changes under rotation, so Laplacian coordinates change under rotation

$$R\mathcal{L}(v_i) = \mathcal{L}(Rv_i)$$



# Solution

- After deformation, assuming that the local region of the surface will rotate



- Original optimization target:

$$E(V') = \sum_{i=1}^n \|\delta_i - \mathcal{L}(v'_i)\|^2 + \sum_{i=m}^n \|v'_i - u_i\|^2$$

- New optimization target by introducing a variable to cancel the rotation:

$$E(V') = \min_{\{R_i\}} \sum_{i=1}^n \|R_i \delta_i - \mathcal{L}(v'_i)\|^2 + \sum_{i=m}^n \|v'_i - u_i\|^2$$

# Alternating Optimization

We optimize vertex  $V$  and rotation  $R$  iteratively

1. Estimate rotation  $R$  from the deformed shape

$$\min_{V'} E(V') = \sum_{i=1}^n \|R_i \delta_i - \mathcal{L}(v'_i)\|^2 + \sum_{i=m}^n \|v'_i - u_i\|^2$$

2. Estimate shape  $V'$  given rotation

$$\min_{R_i} (\|R_i \delta_i - \mathcal{L}(v'_i)\|^2 + \sum_{j \in N(v_i)} \|R_i v_j - v'_j\|^2)$$



# Numerical Method

- Known  $\{R_i\}$  to get  $V'$ : Quadratic optimization with a closed-form solution

$$\min_{V'} E(V') = \sum_{i=1}^n \|R_i \delta_i - \mathcal{L}(v'_i)\|^2 + \sum_{i=m}^n \|v'_i - u_i\|^2$$

- Known  $V'$  to get  $\{R_i\}$ : Quadratic optimization with a constraint on  $R$  in  $SO(3)$

$$\min_{R_i} \|R_i v_i - v'_i\|^2 + \sum_{j \in N(v_i)} \|R_i v_j - v'_j\|^2$$

$$R_i R_i^T = I, \det(R) = 1$$

- Recall: Orthogonal Procrustes Problem in Lecture 11!

# Other Issues?

- Only mean curvature is considered
  - Full curvature (2 numbers) is required to fully determine the local geometry.
- Solution to the issue
  - Deformation energy should consider both mean curvature and Gaussian curvature (geodesic distance preservation)

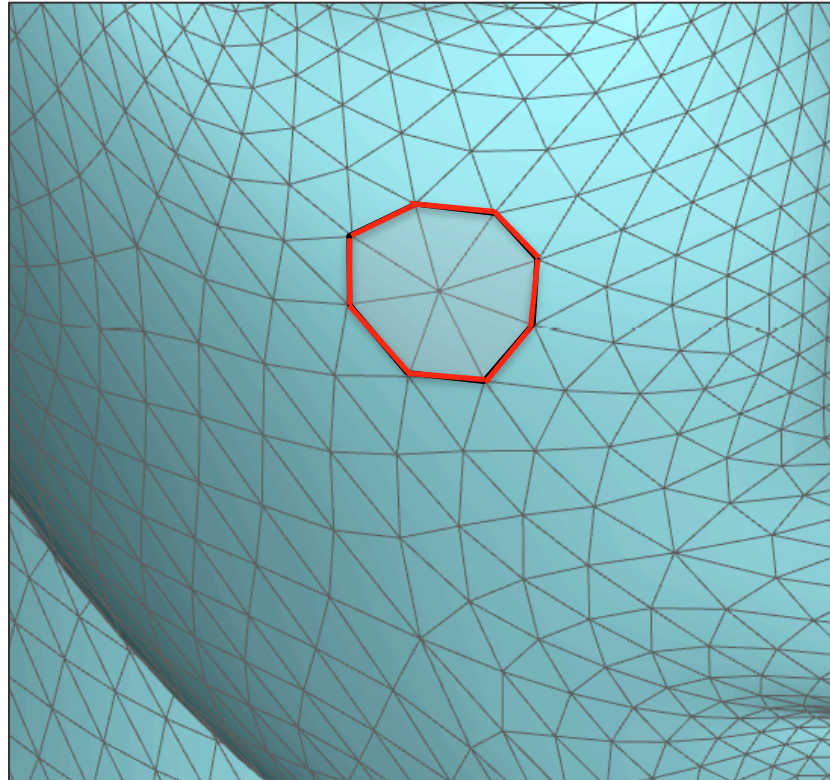
# Surface Deformation

Laplacian Surface Editing

As-Rigid-As-Possible Deformation

# Local Deformation

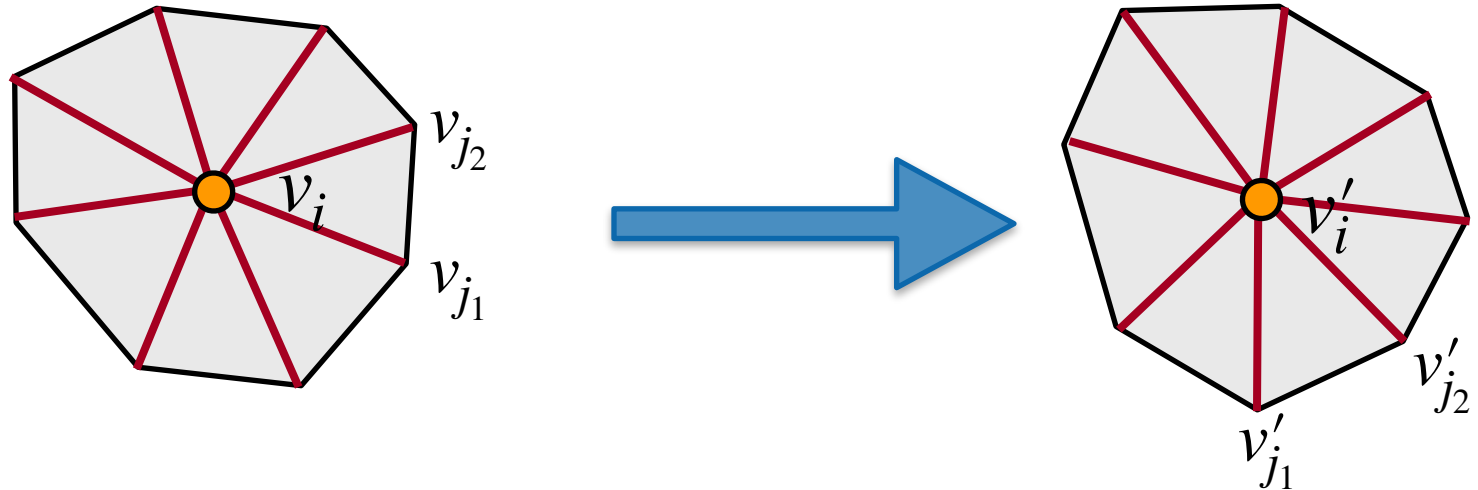
- Let's look at a local region centered at a vertex (called a cell).



How do we define a better deformation energy of this cell?

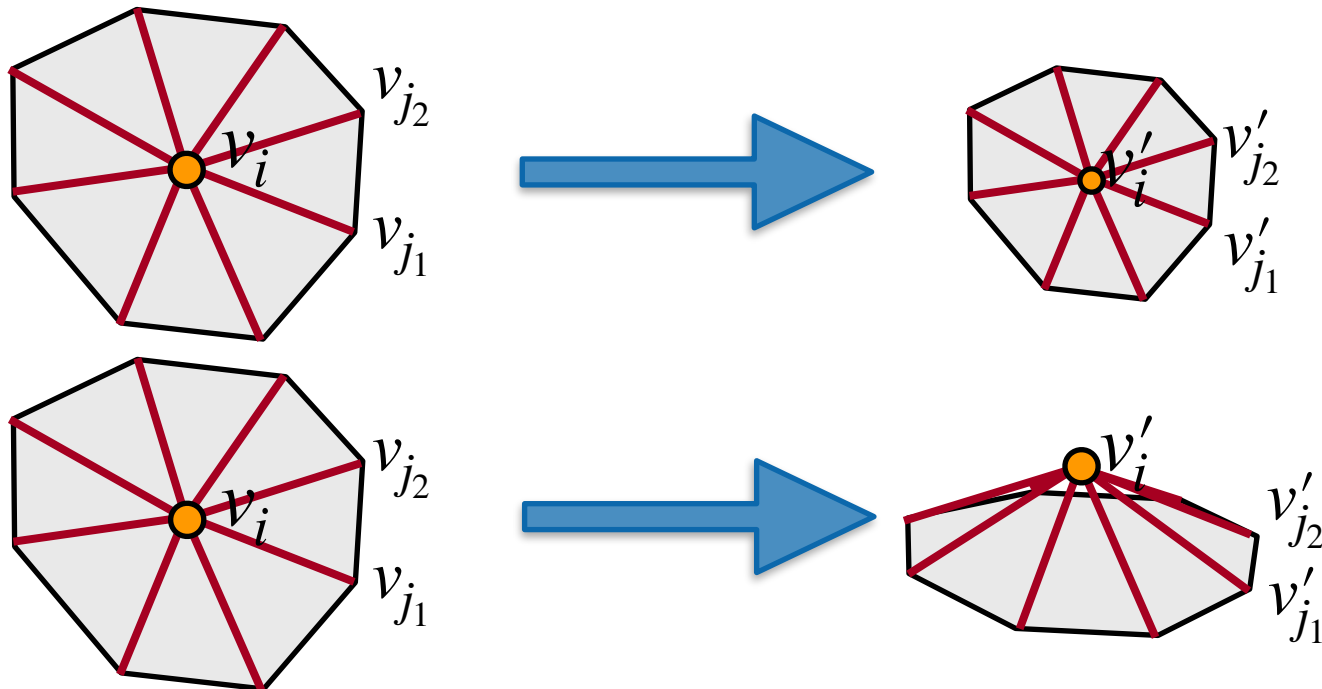
# Desired Property for Deformation Energy

- Translation and rotation should not change the deformation energy.



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- Translation and rotation should not change the deformation energy.
- **Stretching** (length change) and **bending** (angle change) increase deformation energy.



# Local Deformation Energy

- Translation and rotation should not change the deformation energy.
- **Stretching** (length change) and **bending** (angle change) increase deformation energy.

$$E(v_i) = \min_{R_i} \sum_{j \in N(i)} \|(v'_i - v'_j) - R_i(v_i - v_j)\|^2$$

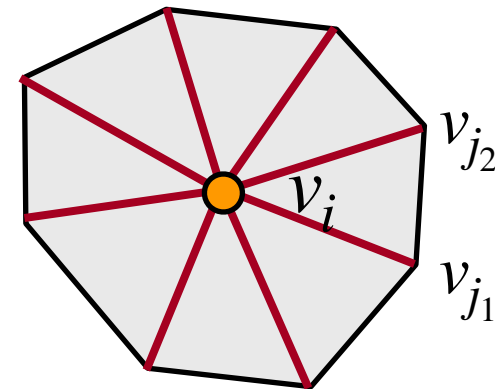
Local Deformation Energy

# Local Deformation Energy

- Translation and rotation should not change the deformation energy.
- **Stretching** (length change) and **bending** (angle change) increase deformation energy.

Minimum over all rotations, rotation-invariant

$$E(v_i) = \min_{R_i} \sum_{j \in N(i)} \|(v'_i - v'_j) - R_i(v_i - v_j)\|^2$$



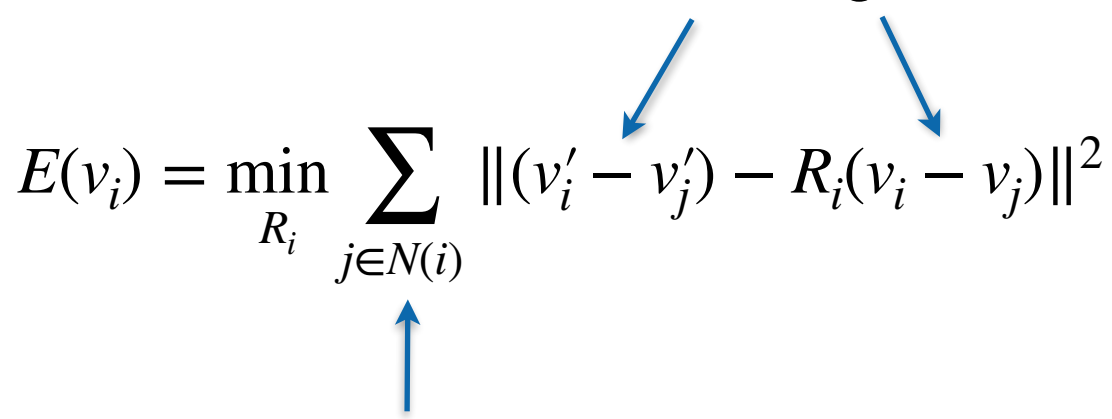
Relative to the cell center ( $v_i$  or  $v'_i$ ), translation-invariant



# Local Deformation Energy

- Translation and rotation should not change the deformation energy.
- **Stretching** (length change) and **bending** (angle change) increase deformation energy.

Penalize change of length

$$E(v_i) = \min_{R_i} \sum_{j \in N(i)} \|(v'_i - v'_j) - R_i(v_i - v_j)\|^2$$


$R_i$  is shared by the cell, penalize change of angle

# Local Deformation Energy

$$E(v_i) = \min_{R_i} \sum_{j \in N(i)} \|(v'_i - v'_j) - R_i(v_i - v_j)\|^2$$

- It is (again) an Orthogonal Procrustes Problem!

# Total Deformation Energy

- Sum up the local deformation energy over all vertices

$$E(V') = \min_{v'} \sum_{i=1}^n \min_{R_i} \sum_{j \in N(i)} \|(v'_i - v'_j) - R_i(v_i - v_j)\|^2$$

*s . t .*  $v'_j = c_j, j \in C$

$C$ : the set of control point indices

- Minimizing total deformation energy
  - As-Rigid-As-Possible deformation (ARAP deformation)

# Total Deformation Energy

- Alternating optimization
  - Given initial guess  $v'_0$ , find optimal rotations  $R_i$ .
    - This is a per-cell task! We already showed how to estimate  $R_i$  when  $v, v'$  are known
  - Given the  $R_i$  (fixed), minimize the energy by finding new  $v'$

$$E(V') = \min_{v'} \sum_{i=1}^n \sum_{j \in N(i)} \|(v'_i - v'_j) - R_i(v_i - v_j)\|^2$$

Linear Least Square

# Total Deformation Energy

- Alternating optimization
  - Given initial guess  $v'_0$ , find optimal rotations  $R_i$ .
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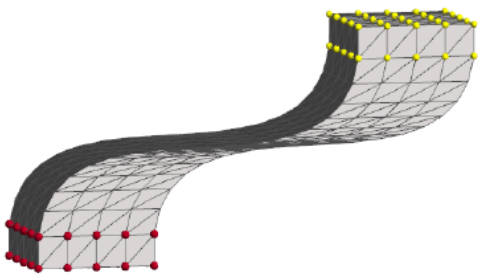
$$E(V') = \min_{v'} \sum_{i=1}^n \sum_{j \in N(i)} \|(v'_i - v'_j) - R_i(v_i - v_j)\|^2$$

↓ use Laplacian

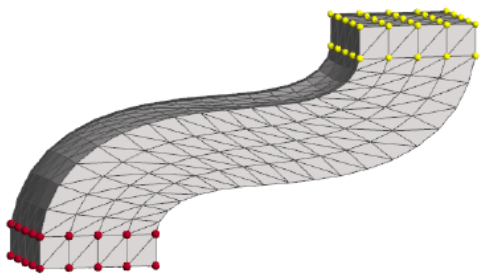
$$\min_{V'} \|\mathcal{L}V' - b\|^2$$

# Initialization

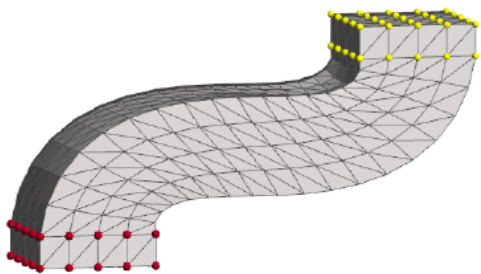
Start from naïve Laplacian editing as initial guess and iterate



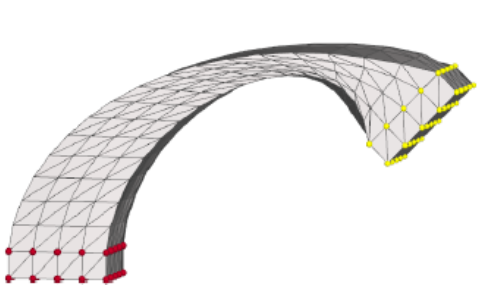
initial guess



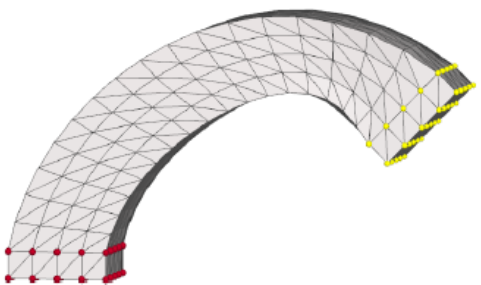
1 iteration



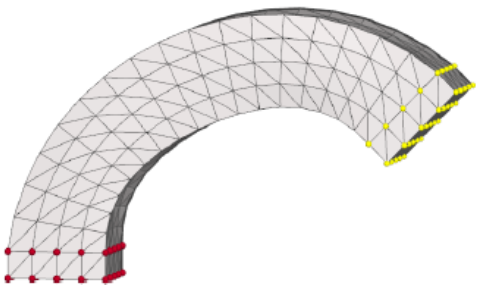
2 iterations



initial guess

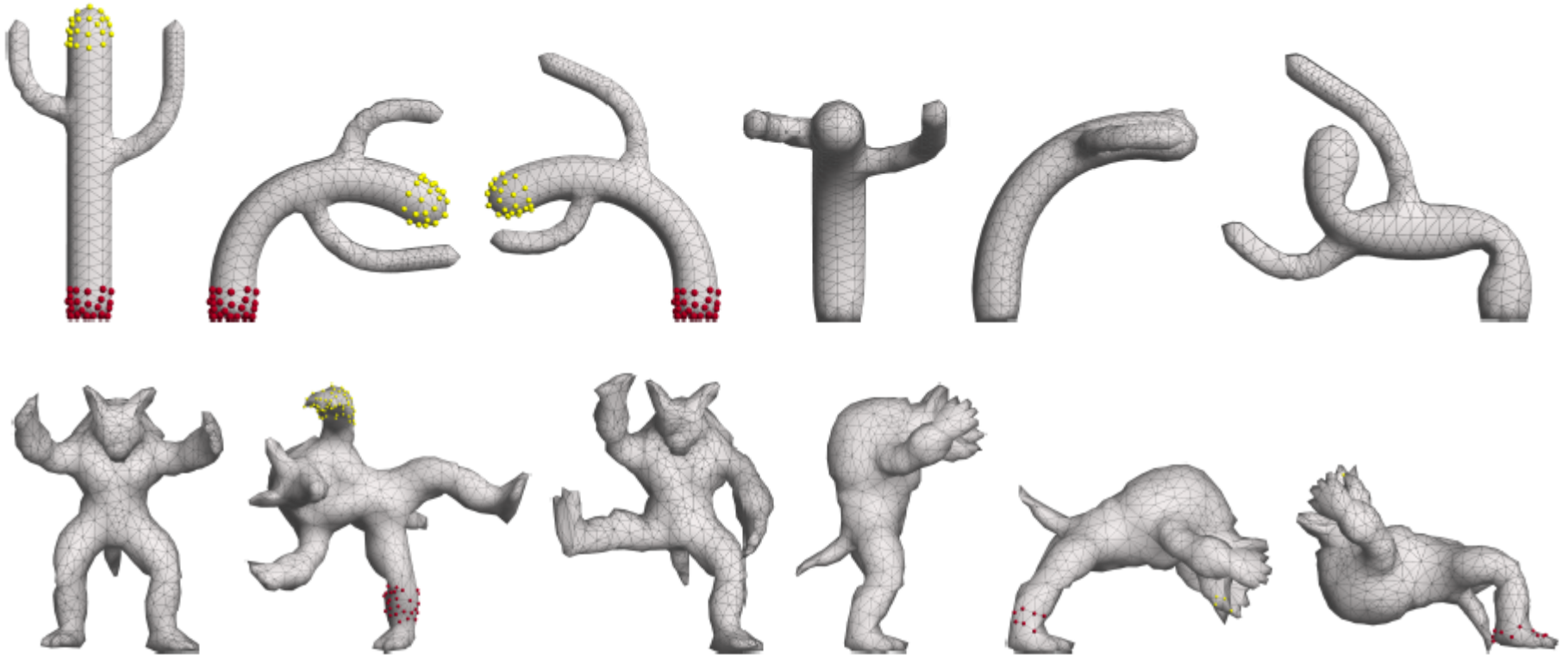


1 iterations



4 iterations

# Examples



# Summary

- As-rigid-as-possible deformation iteratively minimize the deformation energy.
- The deformation energy penalizes both mean curvature change and length change.



# Further Comments

- Iterative algorithm, slow on large meshes.
- Guaranteed to converge (energy is bounded and monotonically decreasing for each iteration)
- The idea can generalize to other energy definition or 3D volume deformation (real physical deformation)

# **Space Deformation**

a.k.a. Free-Form Deformation

# Surface vs Space Deformation

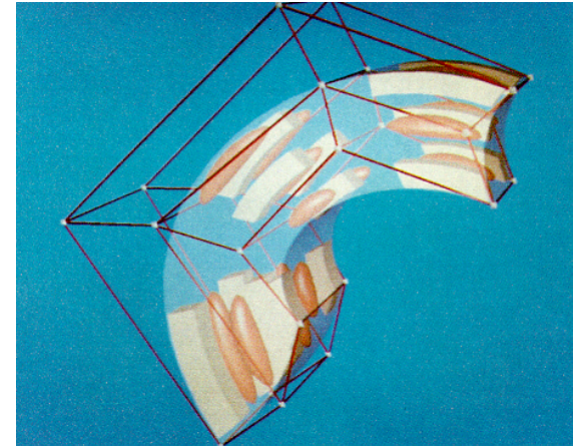
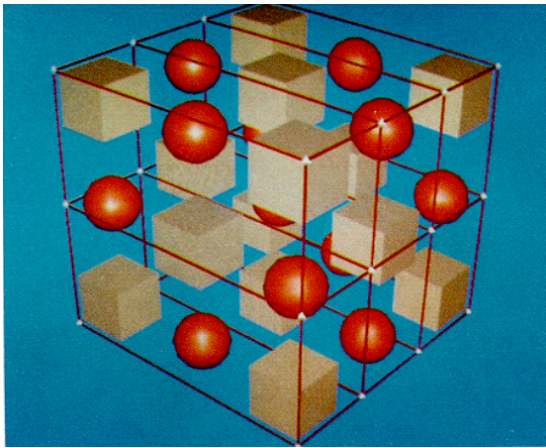
- Previously: surface deformation
  - Move vertices of the mesh
- Space deformation
  - Define a function that warps the  $\mathbb{R}^3$  space.

$$f : \mathbb{R}^3 \rightarrow \mathbb{R}^3$$

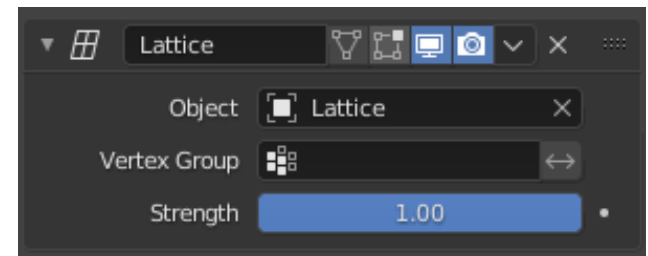
- Evaluate the space deformation on mesh vertices to deform the mesh.

# Free-Form Deformation

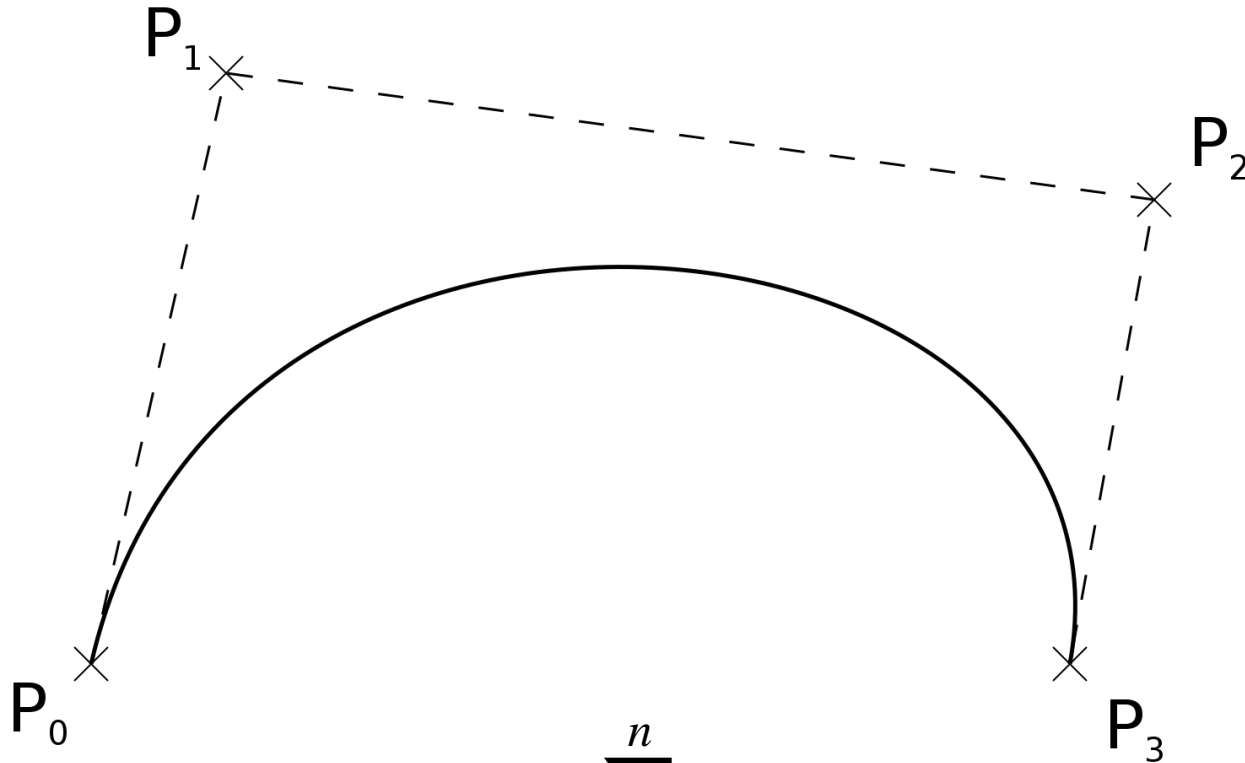
- Free-Form Deformation (Sederberg & Parry, 1986)



- Still widely used today
  - e.g. Blender Lattice modifier



# Recall: Bezier Curve from Lecture 1



$$s(t) = \sum_{i=0}^n p_i B_i^n(t)$$

# 3D Free-Form Deformation

- Control points: 3D lattice
- Modelers drag the vertices of the lattice to define displacements  $d_i$ .
- Displacements of points in space are computed by interpolating  $d_i$  with interpolating weights  $B_i$

$$d(x) = \sum_i B_i(x) d_i$$

# 3D Free-Form Deformation

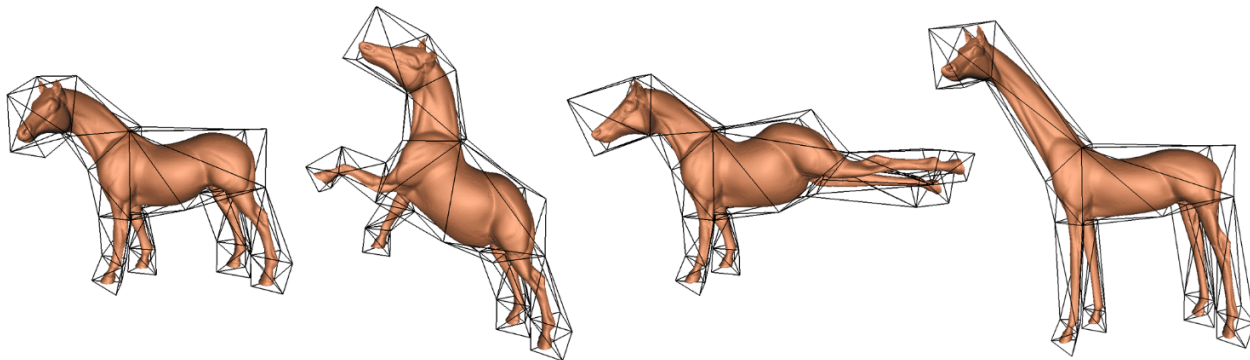
$$d(x) = \sum_i B_i(x) d_i$$

- Compute the Bezier parameters in each dimension and apply **tricubic** interpolation.

$$d(x, y, z) = \sum_i \sum_j \sum_k B_i(x) B_j(y) B_k(z) \mathbf{d}_{ijk}$$

# Issues

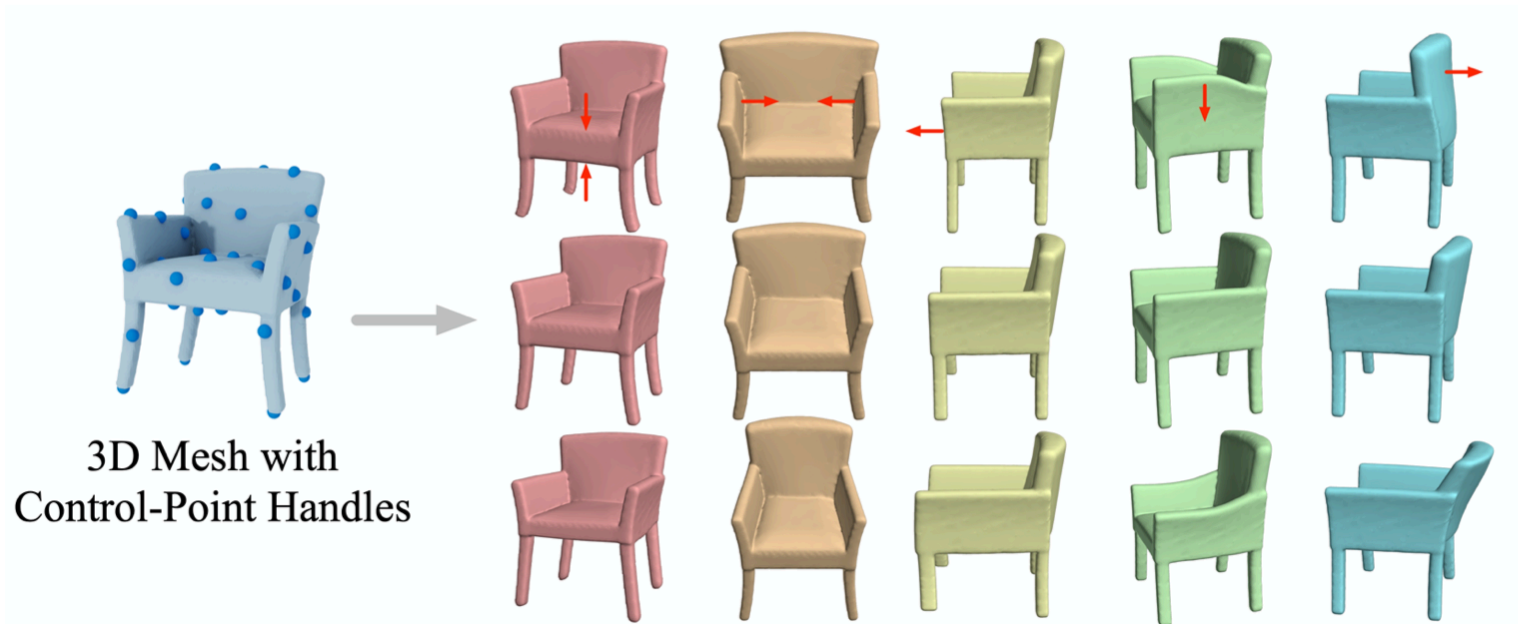
- Lattice can be large. Modelers do too much: move control points one by one by hand.
- Like Bezier curves, not easy to intuitively relate position of control points with the geometry.
- There are approaches using fewer point points, e.g., cage deformation, key-point based deformation





# Learning-based Deformation Field by Keypoints

- Use keypoints as control points
- Use network to learn a basis function from data!



# Summary

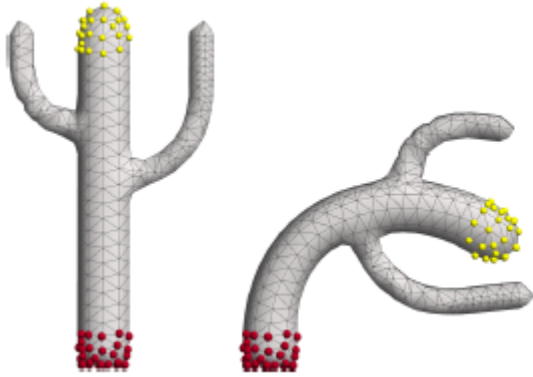
- Space deformation are typically very fast
- Run in real time
- Widely used in real-time animation

# **Skeleton Skinning**

Linear Blend Skinning

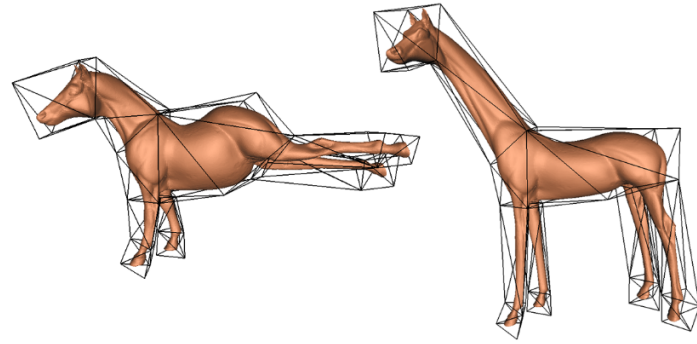
***Read yourself***

# Boneless Shape Editing



Surface Deformation

- Pro: Automatically preserve curvatures
- Con: Slow



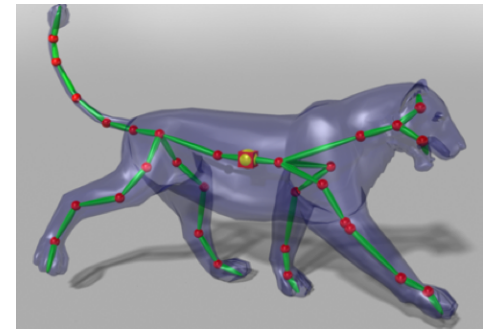
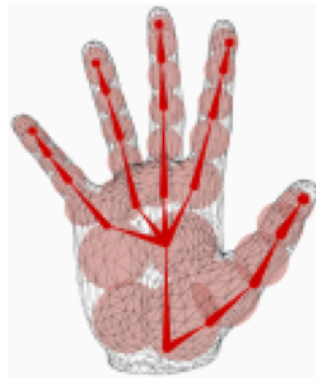
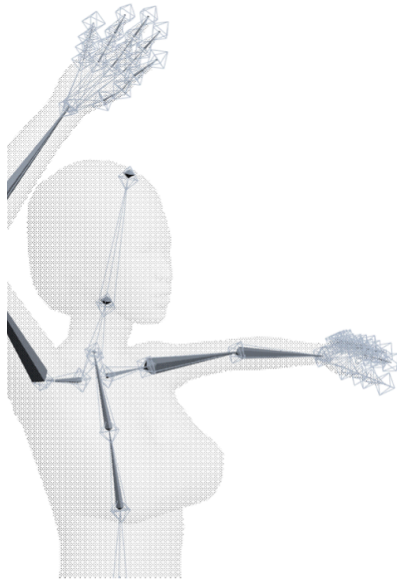
Space Deformation

- Pro: Fast
- Con: Need artists to tune control point movements to achieve curvature preservation

***Read yourself***

# Deformation for Objects with Bones

- Many objects have “bones” — deformation may be interpreted as
  - coarse-level bone transformation; and
  - fine-level skin transformation



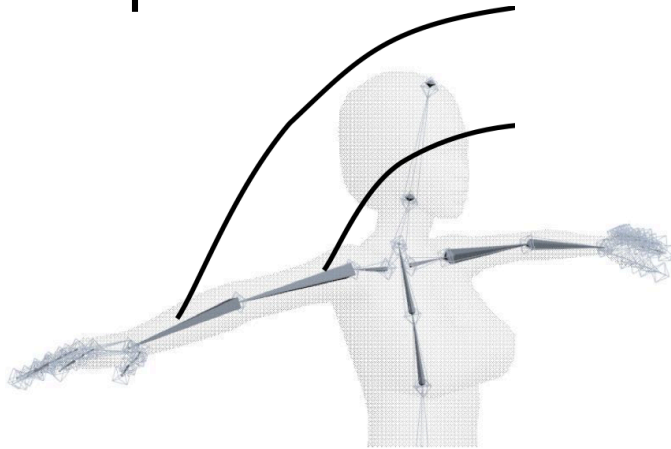
# Skeleton

- Skeleton: bones of body linked together
- The pose of bones can be represented using a set of matrices  $T_i \in SE(3)$  from current pose to rest pose

# Skeleton

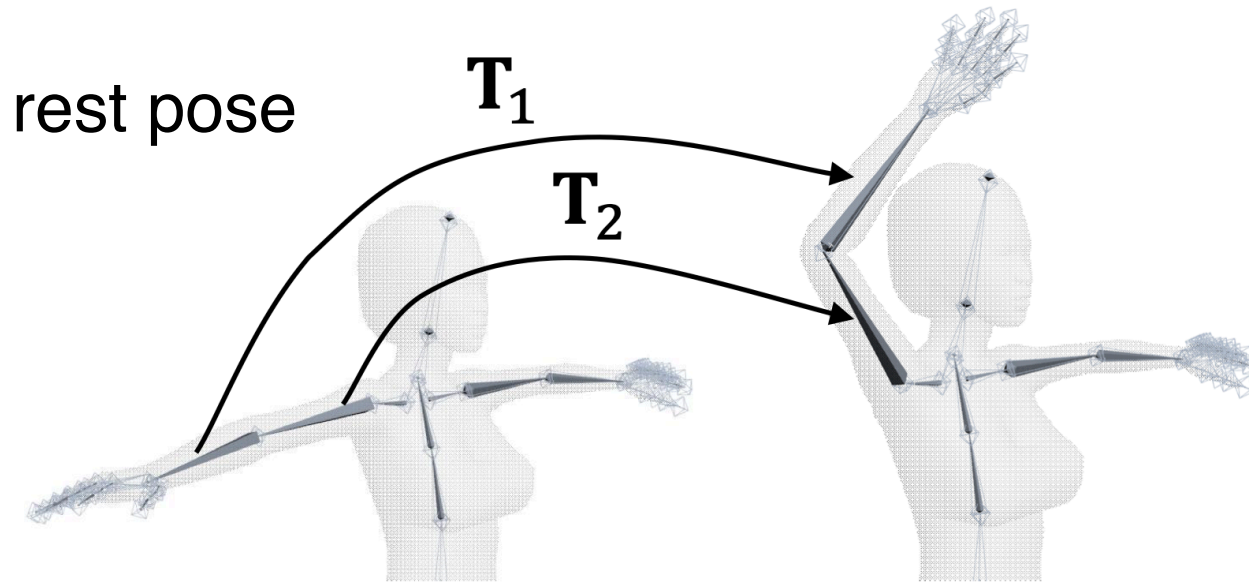
- Skeleton: bones of body linked together
- The pose of bones can be represented using a set of matrices  $T_i \in SE(3)$  from current pose to rest pose

rest pose



# Skeleton

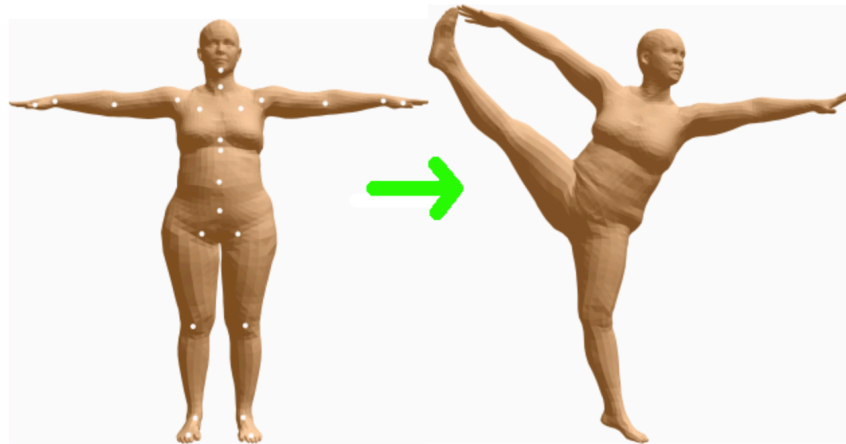
- Skeleton: bones of body linked together
- The pose of bones can be represented using a set of matrices  $T_i \in SE(3)$  from current pose to rest pose





# Skinning

- The surface of body **deforms** as the skeletons are transformed rigidly



# Linear Blend Skinning

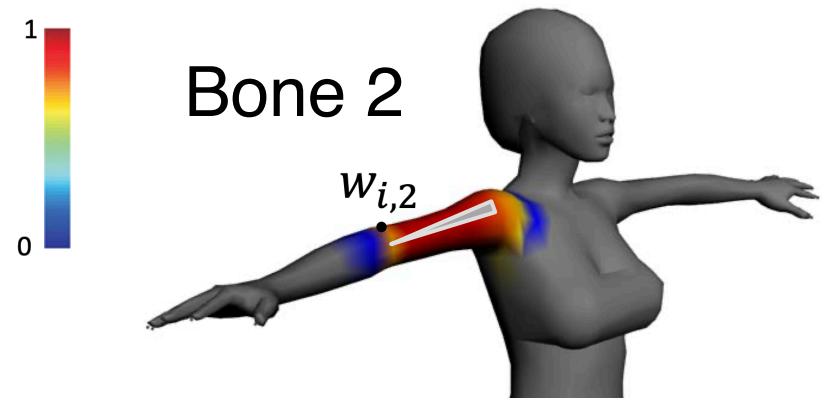
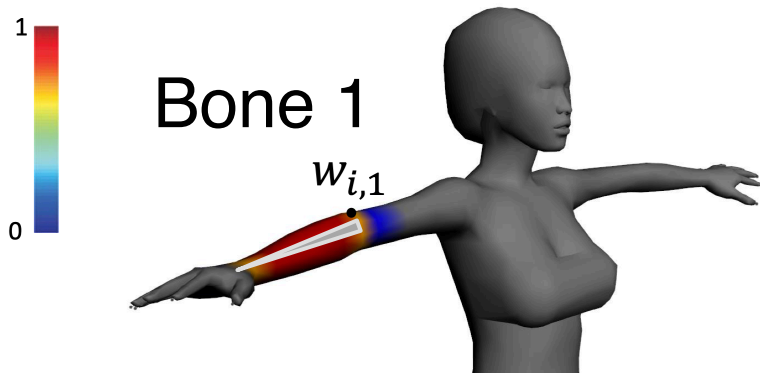
- Skin vertex move when pose of bone  $T_j$  change
  - If  $v_i$  on the  $j$ -th bone, then it will move to  $T_j v_i$
- Around joints there will be cracks. In practice, each vertex is governed by multiple bones,
  - e.g., averaged by a **linear** model (SMPL):

$$v'_i = \sum_{j=1}^m w_{i,j} T_j v_i = \left( \sum_{j=1}^m w_{i,j} T_j \right) v_i$$

- $w_{i,j}$ : skinning weights
  - Describes the amount of influence of bone  $j$  on vertex  $i$

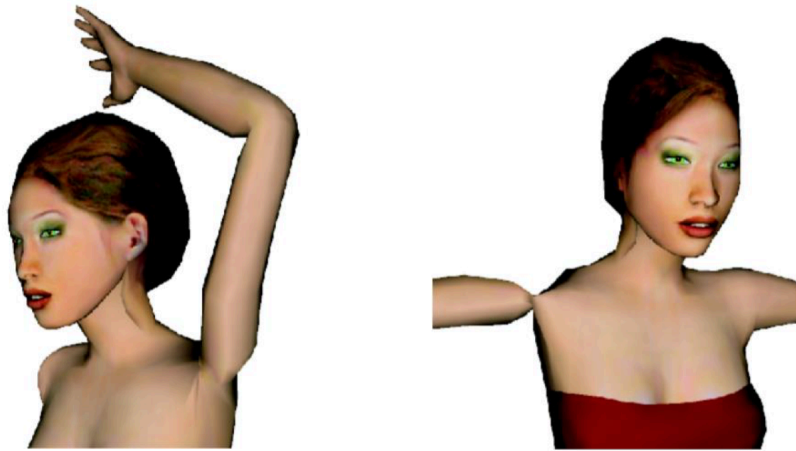
# Skinning Weights

- We commonly require  $w_{i,j} \geq 0$ ,  $\sum_{j=0}^m w_{i,j} = 1$



# Limitations I

- Linear combination of transformations is simple
- However, note that rotation matrices are not in a linear space



Candy-wrapper artifacts

# Limitations I

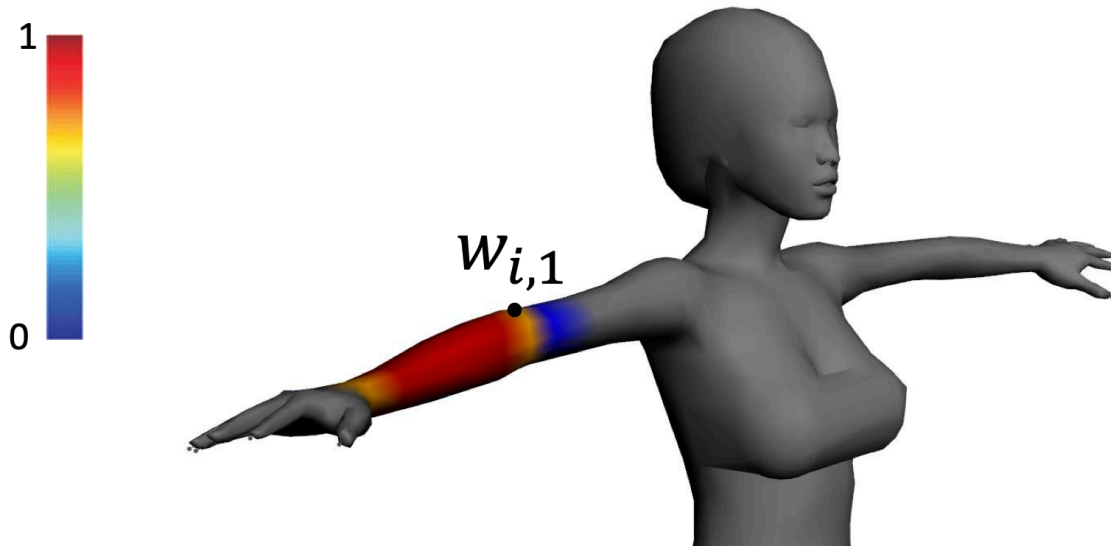
- Linear combination of transformations is simple
- However, note that rotation matrices are not in a linear space

## How to address the issue?

- Use quaternion and some tricks to achieve linear interpolation of rotations
- SLERP: **S**pherical **L**inear **I**nt**ER**Polation (<https://en.wikipedia.org/wiki/Slerp>)

# Limitations II

- Modelers do too much: Assigning skinning weights is cumbersome
- Can we learn weights from data? Next lecture!



# Summary

- Skeleton: linked bones
- Skinning: deform the surface along skeleton transformation
- Linear Blend Skinning:
  - Rest pose
  - Bone transformation
  - Skinning weight

# Deformation in Blender

- You can find these deformation algorithms in blender. Try it yourself!
- There are a lot more to play with!

