

Shape Modeling and Geometry Processing

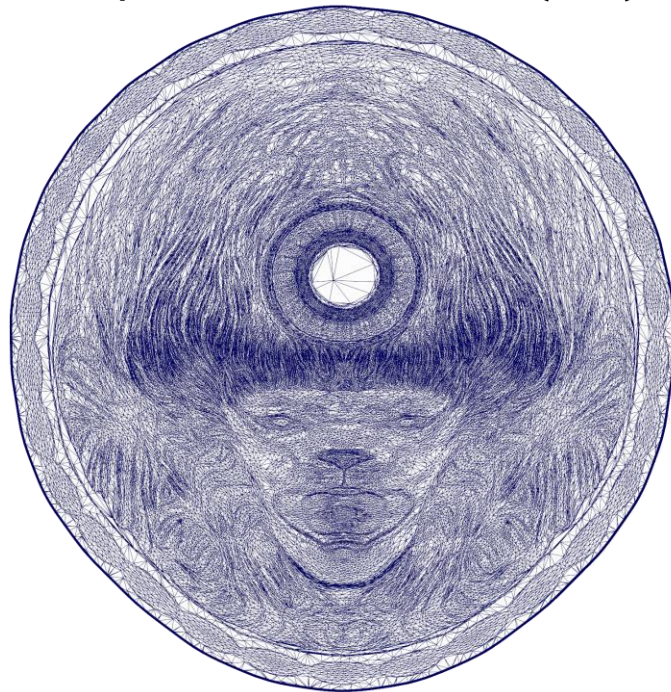
Assignment 4 - Mesh Parameterization

What is mesh parameterization

3D space (x, y, z)



2D parameter domain (u, v)



$$S(u, v) = \begin{pmatrix} x(u, v) \\ y(u, v) \\ z(u, v) \end{pmatrix}$$

What is mesh parameterization

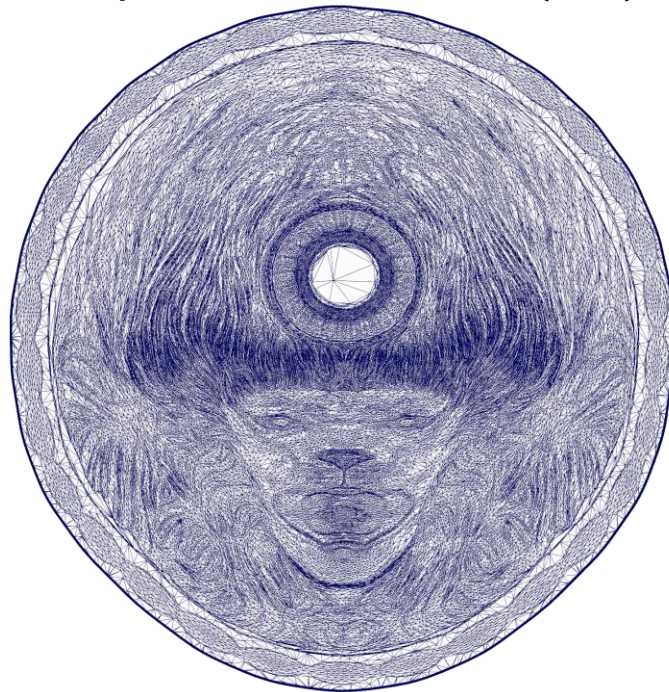
3D space (x, y, z)



$$f(x_i, y_i, z_i) = (u_i, v_i)$$



2D parameter domain (u, v)



What is mesh parameterization

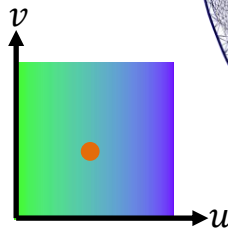


What is mesh parameterization

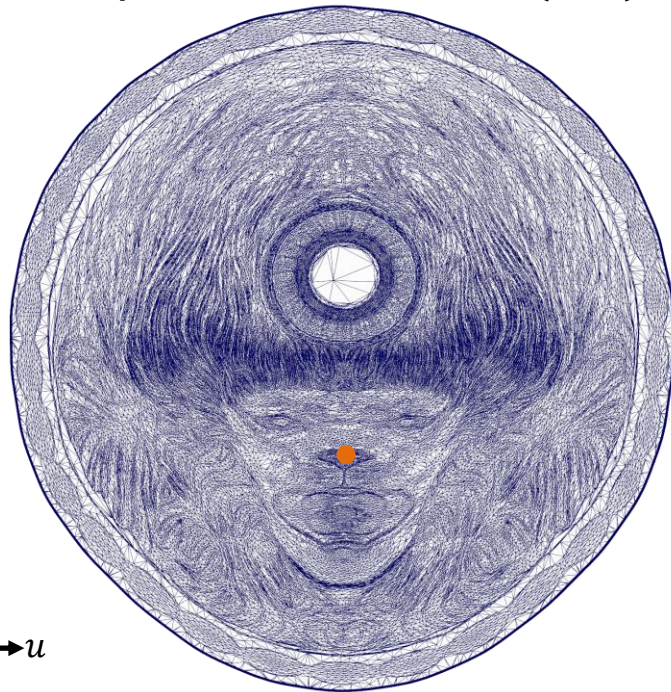
3D space (x, y, z)



$$f(x_i, y_i, z_i) = (u_i, v_i)$$



2D parameter domain (u, v)

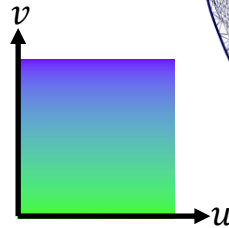


What is mesh parameterization

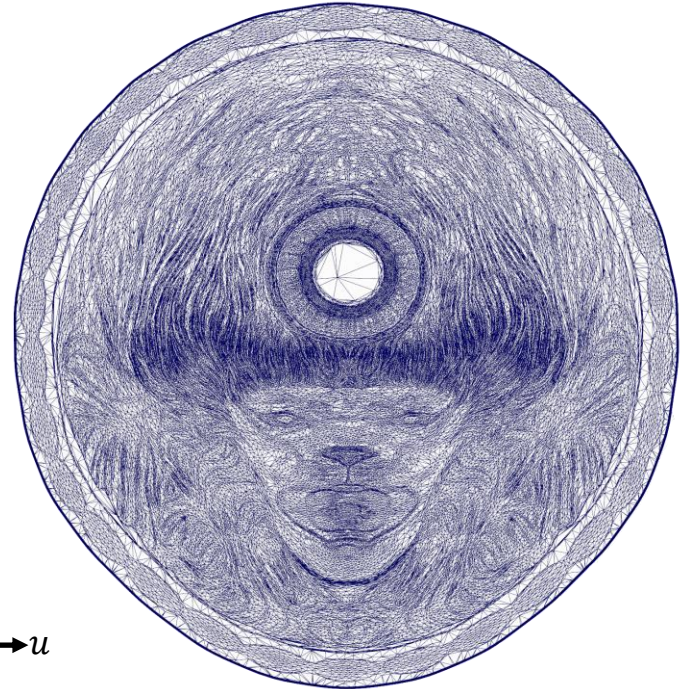
3D space (x, y, z)



$$f(x_i, y_i, z_i) = (u_i, v_i)$$



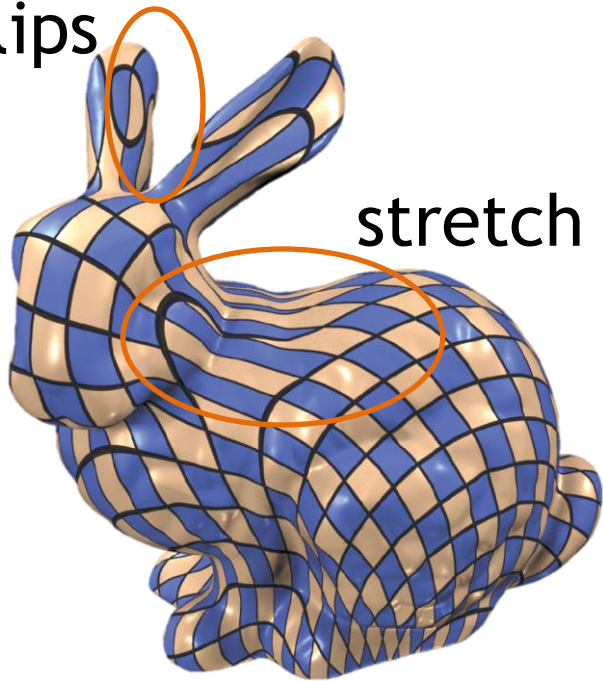
2D parameter domain (u, v)



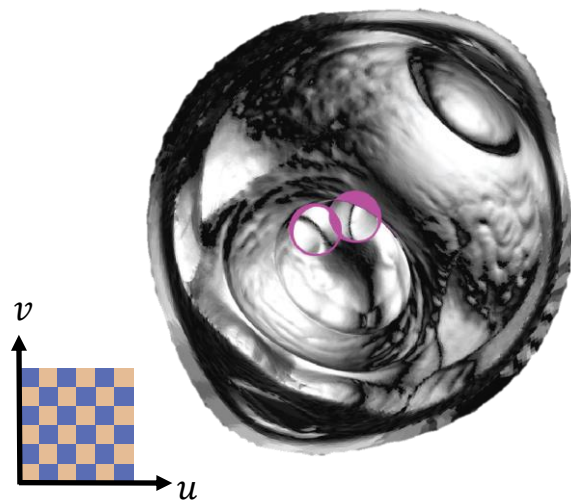
What is a **good** parameterization

flips

stretch

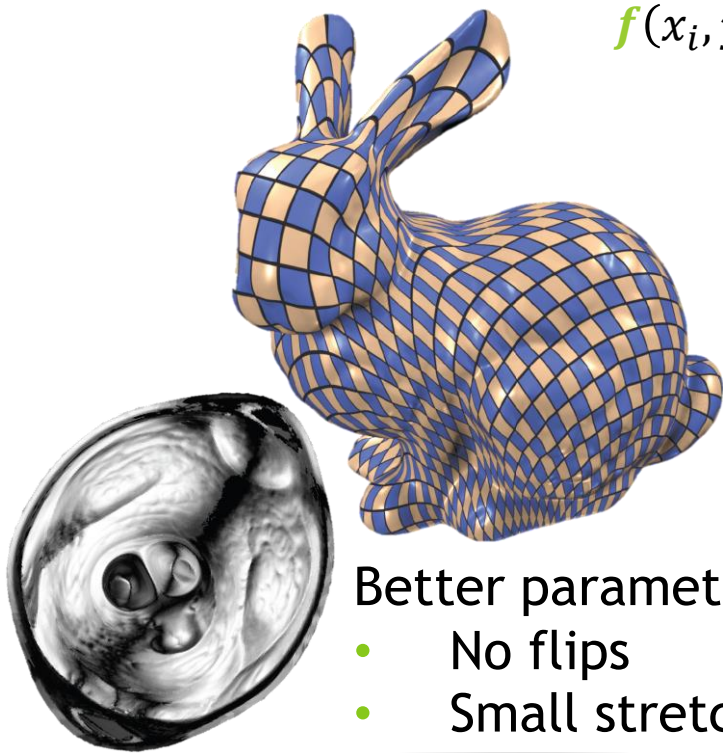
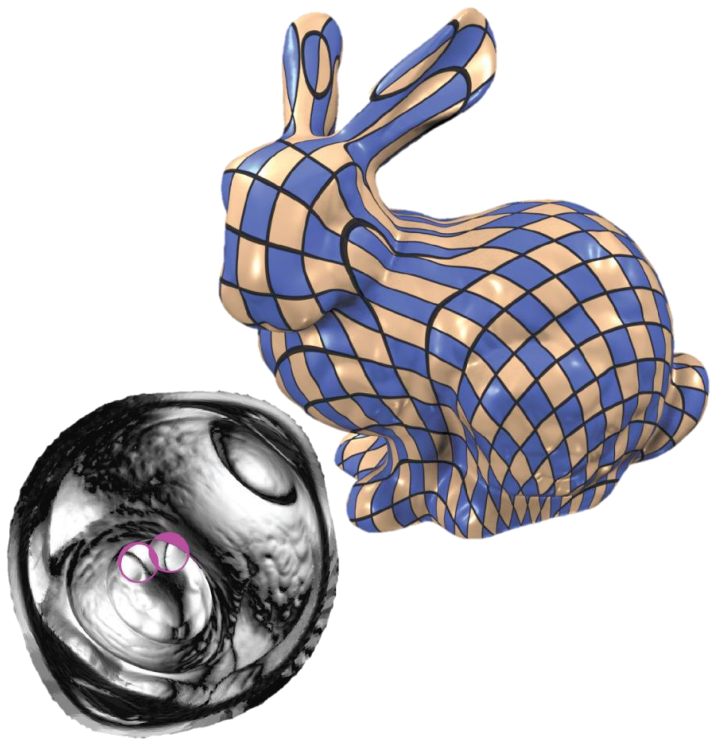


$$f(x_i, y_i, z_i) = (u_i, v_i)$$



What is a **good** parameterization

$$f(x_i, y_i, z_i) = (u_i, v_i)$$



Better parameterization

- No flips
- Small stretch/distortion

How to find a parameterization

- Goal: find parameterization

$$f(x_i, y_i, z_i) = (u_i, v_i)$$

- i.e., for each vertex, find 2D coordinates
- Such that some distortion is minimized
- How to measure distortions?

The Jacobian

- A mapping $f(x, y): \mathbb{R}^2 \rightarrow \mathbb{R}^2$ is defined by two functions $u(x, y), v(x, y)$:

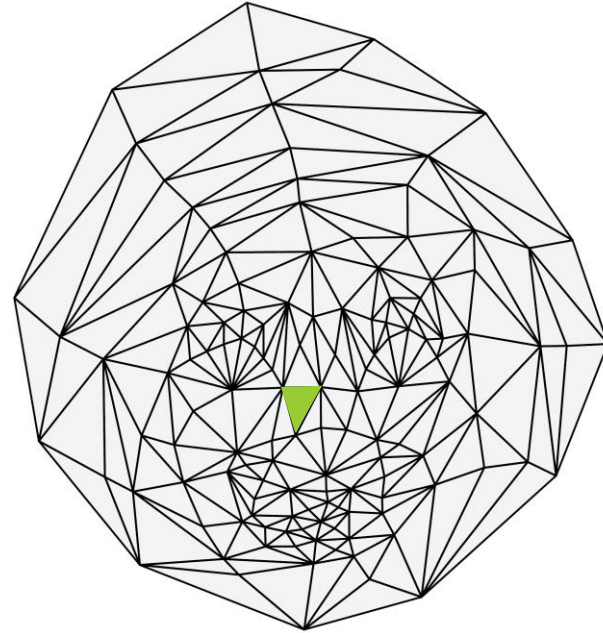
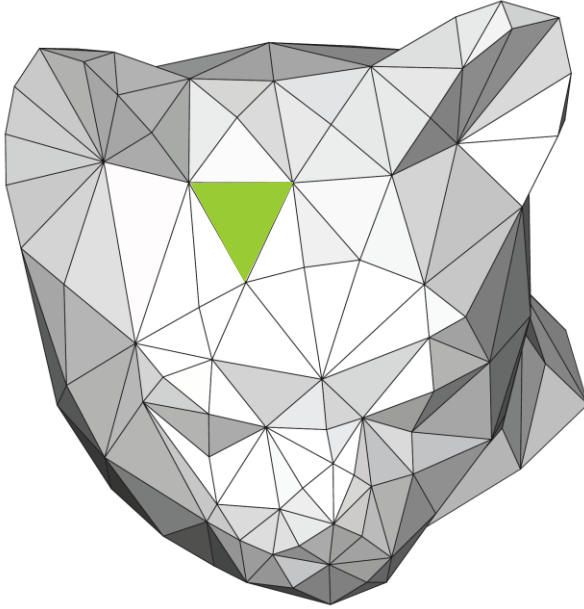
$$f(x, y) = (u(x, y), v(x, y))$$

- The Jacobian J is defined by:

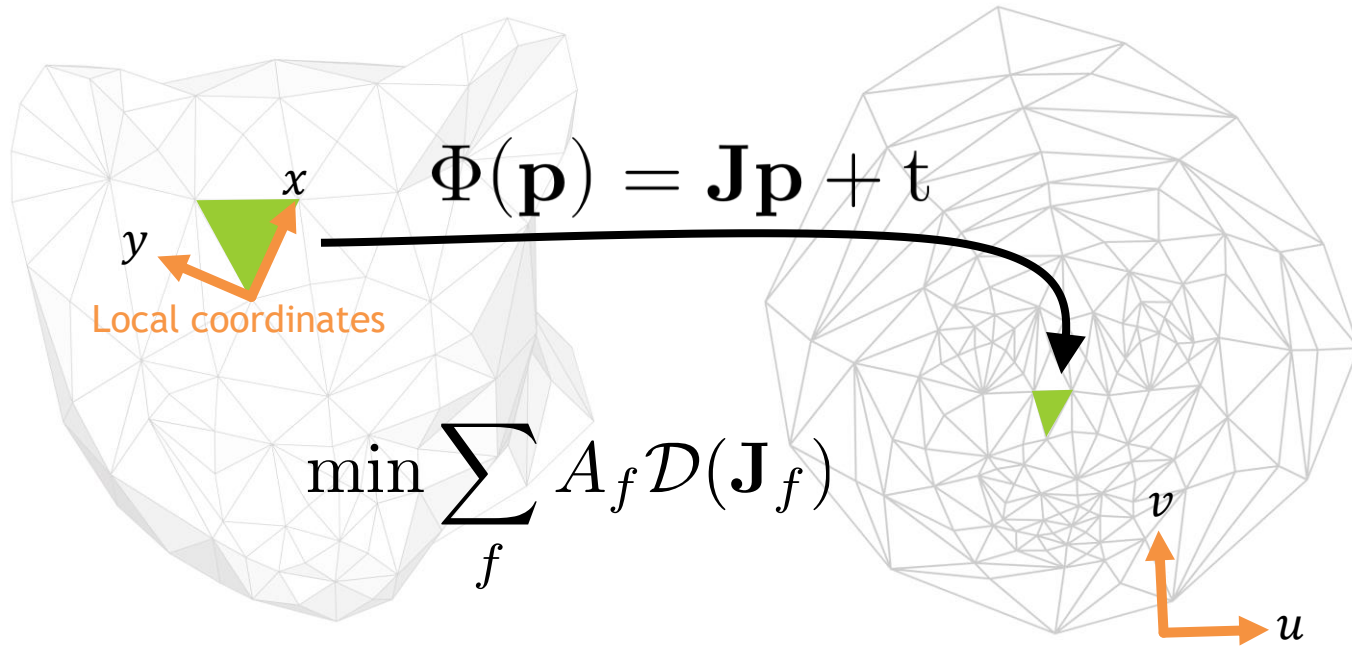
$$J = \begin{pmatrix} \nabla_x u & \nabla_y u \\ \nabla_x v & \nabla_y v \end{pmatrix} = \begin{pmatrix} \nabla u \\ \nabla v \end{pmatrix}$$

→ The Jacobian demonstrates the distortion

Distortion Measure



Distortion Measure



Distortion Types

- Conformal - angle preserving

$$\mathcal{D}(J) = \|J + J^T - \text{tr}(J)I\|_F^2$$

- Isometric - length preserving

$$\mathcal{D}(J) = \min_{R \in SO_2} \|J - R\|_F^2$$

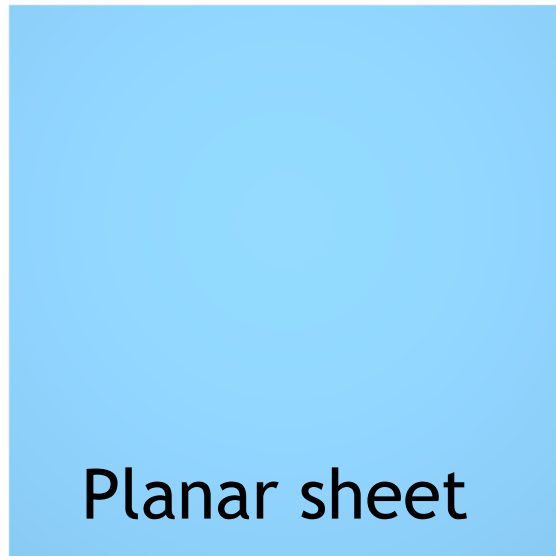
- Authalic - area preserving

$$\mathcal{D}(J) = (\det J - 1)^2$$

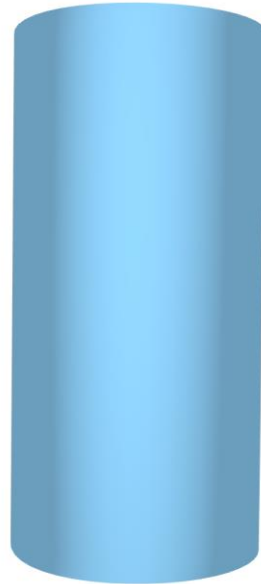
...and many more!

Disclaimer: Isometric Maps

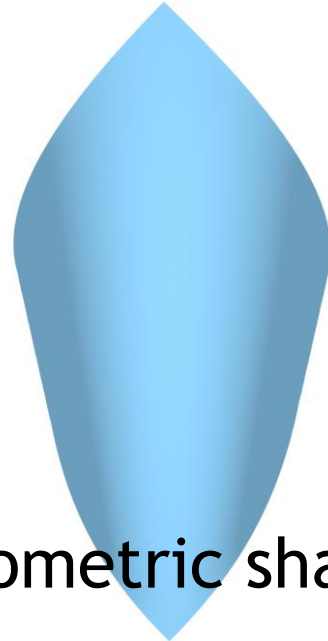
- Isometries preserves Gaussian curvature



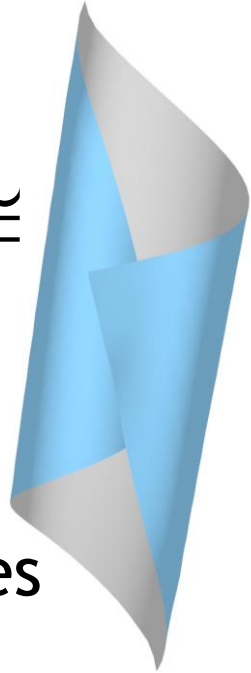
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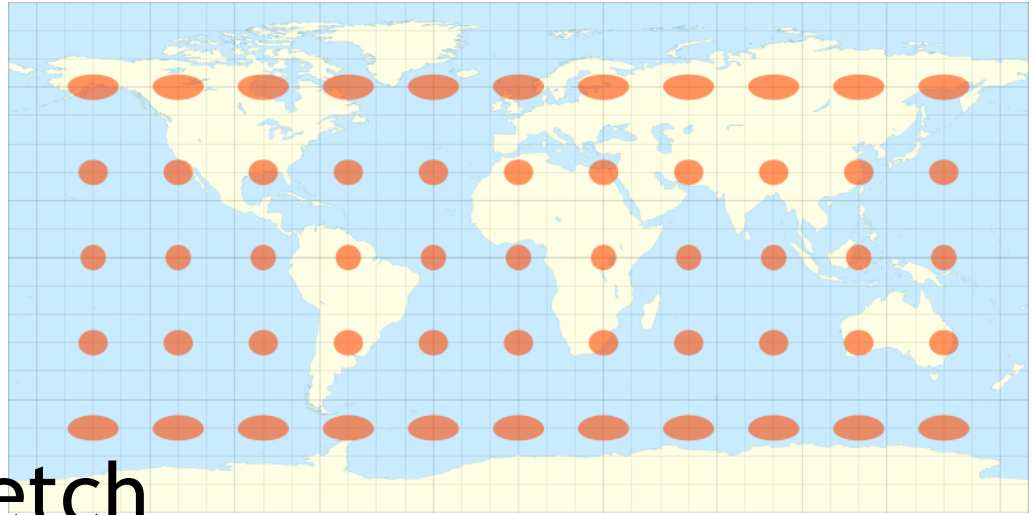
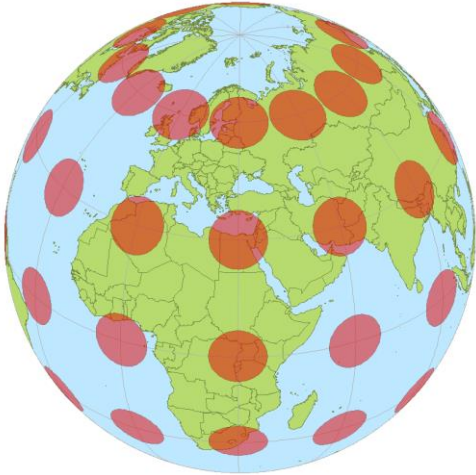
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Isometric shapes

Disclaimer: Isometric Maps

- No isometric map to the plane if non-zero Gaussian curvature !

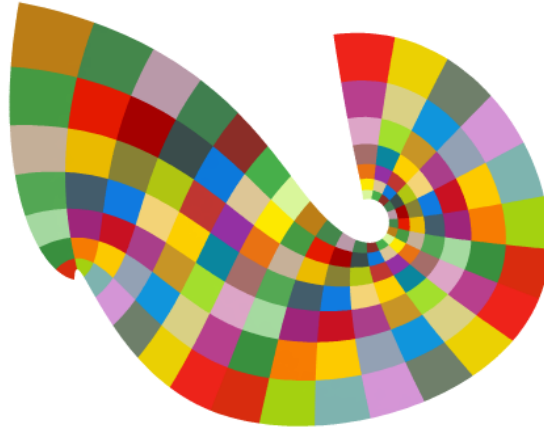


Stretch

Distortion Types



Conformal



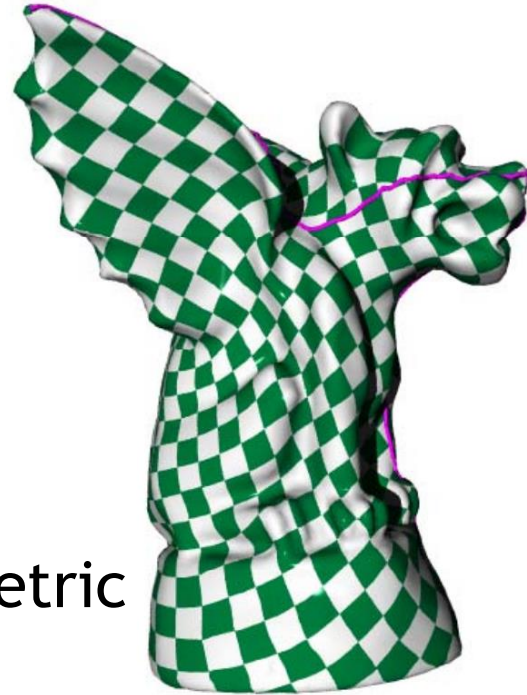
Isometric



Distortion Types



Conformal



Isometric

Parameterization

- **Goal:** We want to solve for the parameterization u, v by minimizing energies defined on $J = \begin{pmatrix} \nabla_x u & \nabla_y u \\ \nabla_x v & \nabla_y v \end{pmatrix}$
- **Solution:** rewrite the gradient operator ∇ as a linear transformation i.e., $\nabla_x f = D_x f$, $\nabla_y f = D_y f$
- We then reformulate the problem as a least-square problem

$$\min_{u,v} \left\| \mathcal{A} \begin{pmatrix} u \\ v \end{pmatrix} - b \right\|^2$$

- where \mathcal{A} is constructed from the gradient operator (matrix) D_x, D_y

Example: Dirichlet Energy

Example: Dirichlet Energy

- Goal: $\min_{u,v} \sum_f A_f \|J_f\|_F^2$
- Assume we know the matrices D_x and D_y (defined per-face)

Check libigl 204!

$$J_f = \begin{pmatrix} D_x u & D_y u \\ D_x v & D_y v \end{pmatrix}$$

- $\sum_f A_f \|J_f\|_F^2 = \|A^{0.5}(D_x u, D_y u, D_x v, D_y v)\|_F^2$
- $A = \text{diag}(A_1, \dots, A_{n_f})$

Example: Dirichlet Energy

$$\begin{aligned}\sum_f A_f \|J_f\|_F^2 &= \|A^{0.5}(D_x u, D_y u, D_x v, D_y v)\|_F^2 \\ &= \left\| \begin{pmatrix} A^{0.5} D_x & 0 \\ A^{0.5} D_y & 0 \\ 0 & A^{0.5} D_x \\ 0 & A^{0.5} D_y \end{pmatrix} \begin{pmatrix} u \\ v \end{pmatrix} \right\|^2 = \|\mathcal{A} \begin{pmatrix} u \\ v \end{pmatrix}\|^2\end{aligned}$$

Example: Dirichlet Energy

$$\min_{u,v} \left\| \mathcal{A} \begin{pmatrix} u \\ v \end{pmatrix} \right\|^2 \rightarrow \text{solve } \mathcal{A}^T \mathcal{A} \begin{pmatrix} u \\ v \end{pmatrix} = 0$$

$$\mathcal{A}^T \mathcal{A} = \begin{pmatrix} D_x^T A D_x + D_y^T A D_y & 0 \\ 0 & D_x^T A D_x + D_y^T A D_y \end{pmatrix}$$

Example: Dirichlet Energy

$$\begin{aligned}\mathcal{A}^T \mathcal{A} &= \begin{pmatrix} D_x^T A D_x + D_y^T A D_y & 0 \\ 0 & D_x^T A D_x + D_y^T A D_y \end{pmatrix} \\ &= \begin{pmatrix} L & 0 \\ 0 & L \end{pmatrix}\end{aligned}$$

Boundary Conditions

Boundary Conditions

- In the assignment you are asked to fix the **boundary** of the parameterization to **a disc**, or to only a **few fixed vertices**. These constraints can be specified by a sparse linear system

$$C \begin{pmatrix} u \\ v \end{pmatrix} = d$$

Boundary Conditions

$$\begin{aligned} \min_{u,v} \quad & \left\| \mathcal{A} \begin{pmatrix} u \\ v \end{pmatrix} - b \right\|^2 \\ \text{s.t.} \quad & \mathcal{C} \begin{pmatrix} u \\ v \end{pmatrix} = d \end{aligned}$$

Boundary Conditions

$$\min_{u,v} \left\| \mathcal{A} \begin{pmatrix} u \\ v \end{pmatrix} - b \right\|^2$$

$$\text{s.t. } \mathcal{C} \begin{pmatrix} u \\ v \end{pmatrix} = d$$

Lagrange
Multiplier Method



$$\min_{u,v,\lambda} \left\| \mathcal{A} \begin{pmatrix} u \\ v \end{pmatrix} - b \right\|^2 + \lambda^T \left(\mathcal{C} \begin{pmatrix} u \\ v \end{pmatrix} - d \right)$$

Boundary Conditions

$$\min_{u,v,\lambda} \left\| \mathcal{A} \begin{pmatrix} u \\ v \end{pmatrix} - b \right\|^2 + \lambda^T \left(\mathcal{C} \begin{pmatrix} u \\ v \end{pmatrix} - d \right)$$

Compute gradient
w.r.t u, v, λ , and
set to zero

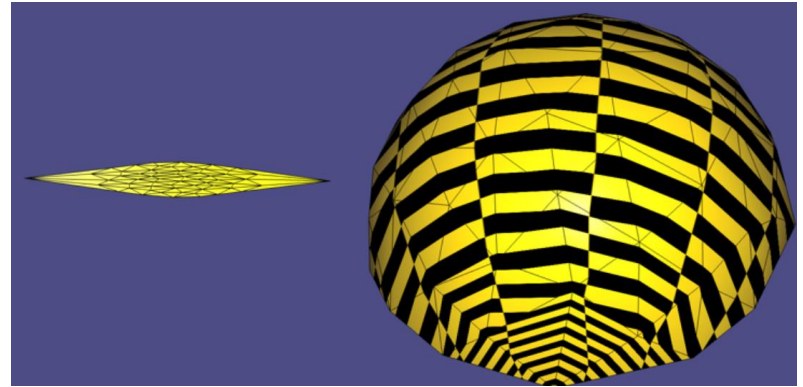
$$\begin{pmatrix} \mathcal{A}^T \mathcal{A} & \mathcal{C}^T \\ \mathcal{C} & 0 \end{pmatrix} \begin{pmatrix} u \\ v \\ \lambda \end{pmatrix} = \begin{pmatrix} \mathcal{A}^T b \\ d \end{pmatrix}$$

Boundary conditions

- Which points to select?
- For LSCM - far away points
 - More uniform distortion distribution
 - Less chance for flips

Boundary conditions

- For ARAP
 - Points for which a reasonable guess can be made
 - Hint: remember that ARAP tries to preserve lengths on the mesh
 - Example for a bad guess:



Boundary conditions

- Does that mean fixing two points might be too strict?
- Task 1.2: you should think about how many DoF you really need to fix for LSCM and ARAP
- It can help to think about when the matrix gets full rank and/or how many DoF you need in each case to fix translation, rotation as well as scale

Distortion Types

- Conformal - angle preserving

$$\mathcal{D}(J) = \|J + J^T - \text{tr}(J)I\|_F^2$$

- Isometric - length preserving

$$\mathcal{D}(J) = \min_{R \in SO_2} \|J - R\|_F^2$$

- Authalic - area preserving (not in assignment)

$$\mathcal{D}(J) = (\det J - 1)^2$$

LSCM Parameterization

- $\mathcal{D}(J) = \|J + J^T - \text{tr}(J)I\|_F^2$
- Recall the lecture notes, it is equivalent to $\mathcal{D}(J) = (J_{11} - J_{22})^2 + (J_{12} + J_{21})^2$ where

$$J = \begin{pmatrix} D_x u & D_y u \\ D_x v & D_y v \end{pmatrix}$$

- ... now you can write out the least-square system

ARAP Parameterization

- $\mathcal{D}(J) = \min_{R \in SO_2} \|J - R\|_F^2$
- R is the closest rotation matrix to J
- Non-linear relationship via SVD:

$$J = U\Sigma V^T \rightarrow R_J = U \begin{pmatrix} 1 & 0 \\ 0 & \det(UV^T) \end{pmatrix} V^T$$

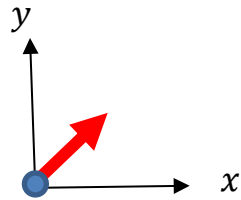
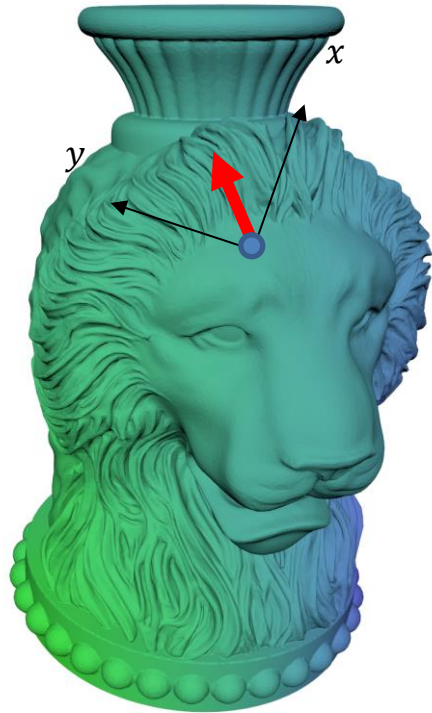
ARAP Parameterization

1. Initialize (e.g., using LSCM)
2. Compute Jacobians and closest rotations
3. Minimize $\mathcal{D}(J) = \|J - R\|_F^2$ via linear system with rotations found in (2) fixed
4. If not converged, go to 2

you don't need to implement this yourselves, we provide the code
in the template 😊

Gradient on Mesh

Gradients on surfaces



Like Euclidean gradient
arrow pointing in
steepest direction

Arrows are tangent to the
surface

described in *local frames*

How to compute gradient on mesh?

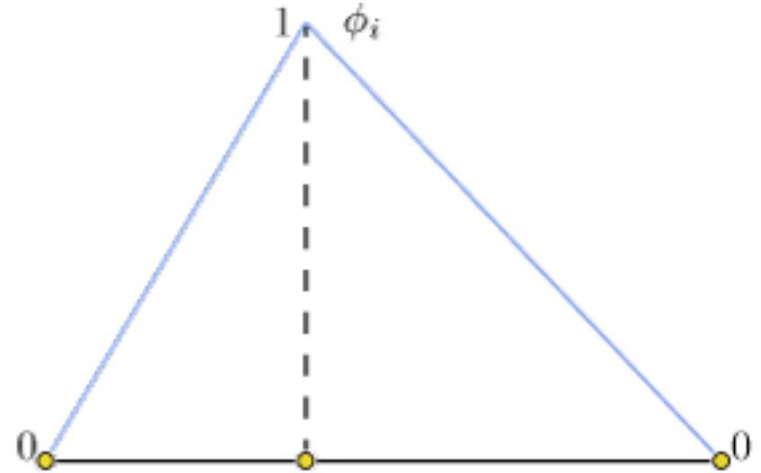
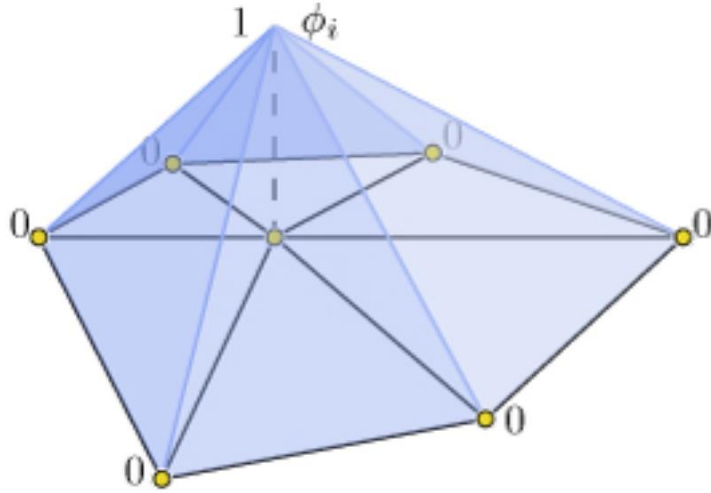
- A piecewise linear function defined on mesh $f: \mathcal{S} \rightarrow R$, where $f(v_i) = f_i$
 - Defined on each vertex
 - For a point inside a triangle: interpolation via Barycentric coordinate

How to compute gradient on mesh?

- Rewrite $f(\mathbf{x}) = \sum_{i=1}^{n_v} \Phi_i(\mathbf{x}) f_i$
 - \mathbf{x} is an arbitrary point on shape \mathcal{S}
 - $\Phi_i(\mathbf{x})$ is a hat function defined on vertex v_i :

$$\Phi_i(\mathbf{x}) = \begin{cases} 1, & \mathbf{x} = v_i \\ 0, & \mathbf{x} \neq v_i \end{cases}$$

Interpolation hat function



"Libigl Tutorial 204"

How to compute gradient on mesh?

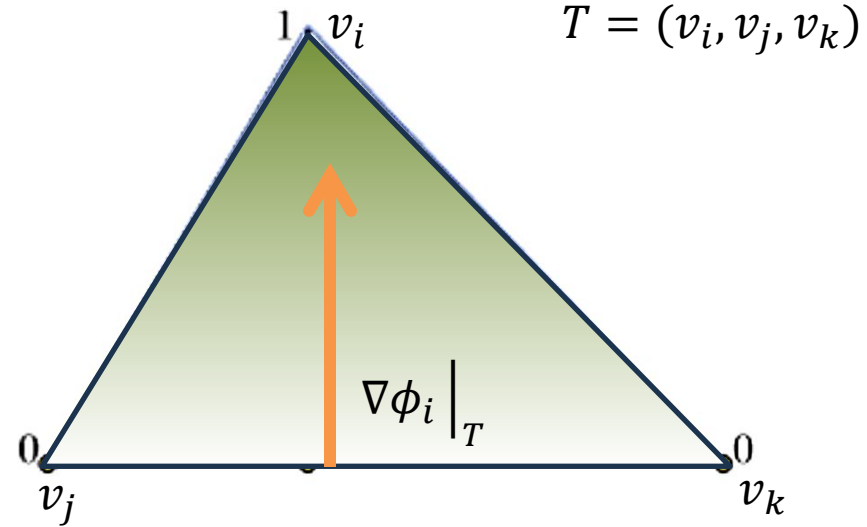
- Rewrite $f(\mathbf{x}) = \sum_{i=1}^{n_v} \phi_i(\mathbf{x}) f_i$
- Now, we can compute gradient of any f

$$\nabla f(\mathbf{x}) = \sum_{i=1}^{n_v} \nabla \phi_i(\mathbf{x}) f_i$$

- What is the gradient of a hat function?

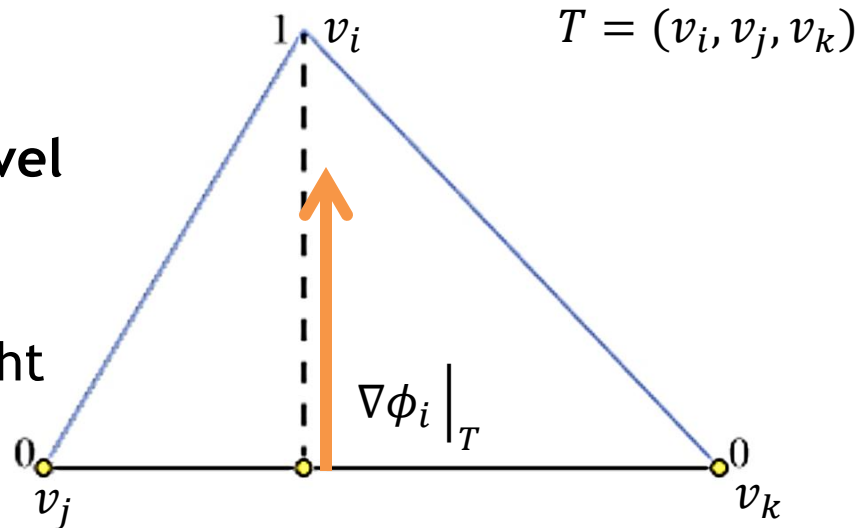
Gradient of a hat function

- ϕ_i is piecewise **linear**
- $\nabla\phi_i$ is **constant** in each triangle!
- Recall **gradient** is the **steepest ascent** direction.
- The steepest ascent direction of a triangle is its **height** direction



Gradient of a hat function

- Also recall in Assignment 2, you have proven that **gradient direction is parallel to the normal of the zero level set!**
- Here the zero level set is the edge $(v_j, v_k) \rightarrow$ it is in direction of the height as suspected before 😊

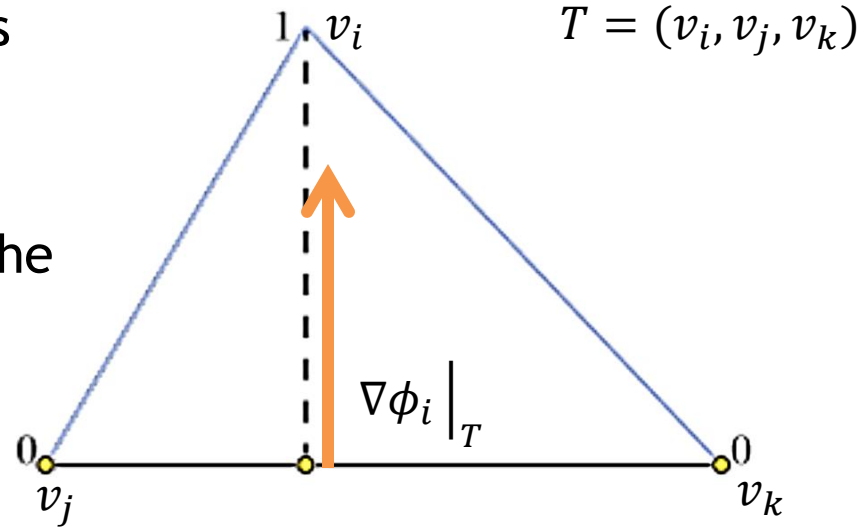


Gradient of a hat function

- We now know the gradient direction is orthogonal to the edge jk :

$$(v_j - v_k)^T \nabla \phi_i = 0$$

- How to compute the **scale/length** of the gradient?



“Libigl Tutorial 204”

Gradient of a hat function

- ϕ_i is piecewise linear, thus can rewrite as

$$\phi_i(x) = \phi_i(v_i) + \nabla\phi_i(v_i)^T(x - v_i)$$

- Evaluate it at vertex v_j

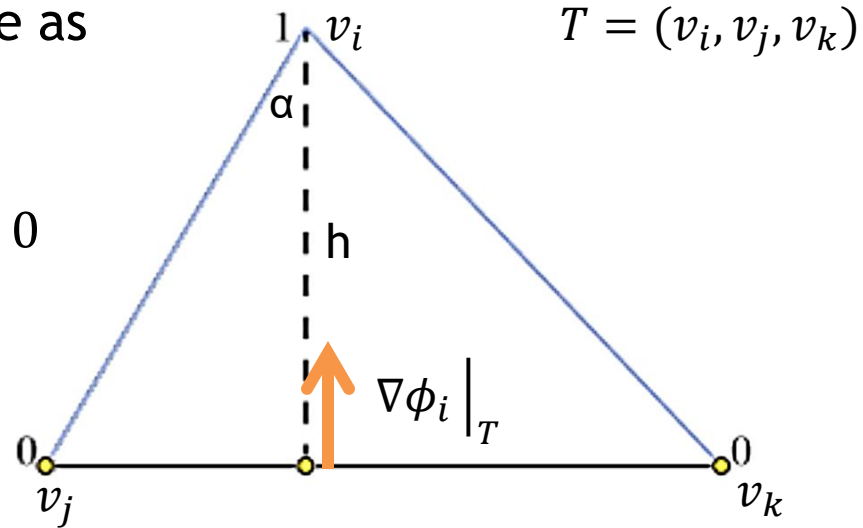
$$\phi_i(v_j) = \boxed{1} + \nabla\phi_i \bigcirc^T(v_j - v_i) = 0$$

- i.e., $\nabla\phi_i^T(v_i - v_j) = 1$

$$|\nabla\phi_i^T| |v_i - v_j| \cos \alpha = 1$$

$$|\nabla\phi_i^T| |v_i - v_j| \frac{|h|}{|v_i - v_j|} = 1$$

$$|\nabla\phi_i^T| |h| = 1 \rightarrow |\nabla\phi_i^T| = \frac{1}{|h|}$$



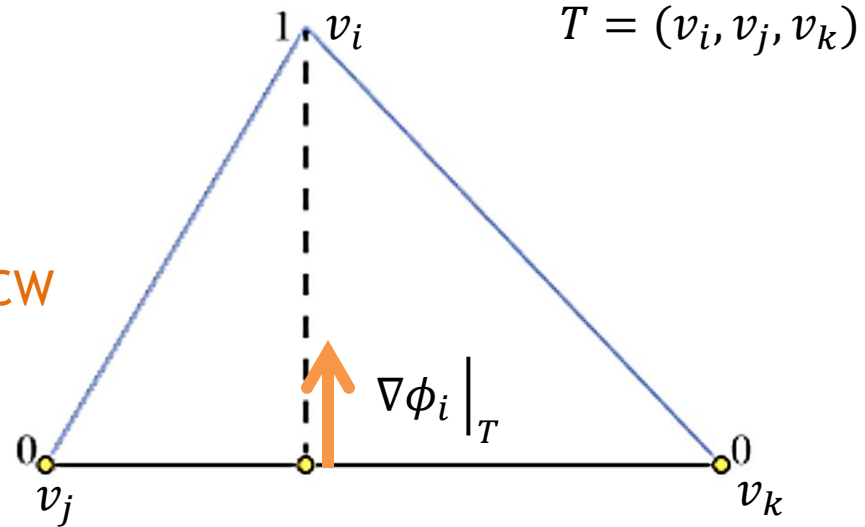
Gradient of a hat function

- Bringing together **scale** and **direction**:

- $$\nabla \phi_i = \frac{1}{|h|} \frac{e_{jk}^\perp}{|e_{jk}^\perp|}$$

$e_{jk}^\perp = n_T \times (v_k - v_j)$, rotate the edge 90° CCW

- $$\nabla \phi_i = \frac{e_{jk}^\perp}{2A_T}$$



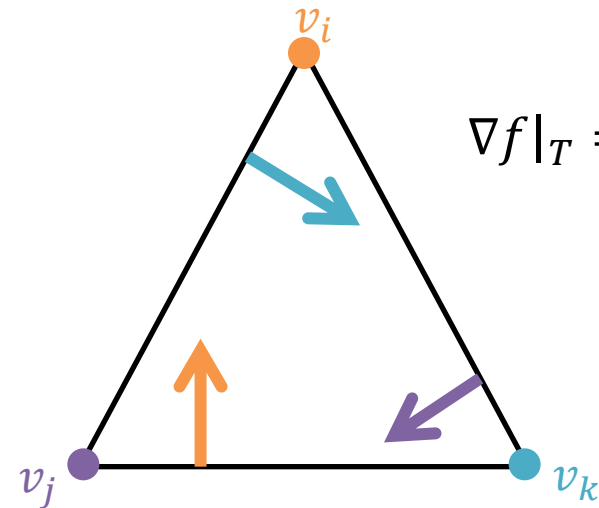
How to compute gradient on mesh?

- Rewrite $f(\mathbf{x}) = \sum_{i=1}^{n_v} \phi_i(\mathbf{x}) f_i$
- Now, we can compute gradient of any f

$$\nabla f(\mathbf{x}) = \sum_{i=1}^{n_v} \nabla \phi_i(\mathbf{x}) f_i$$

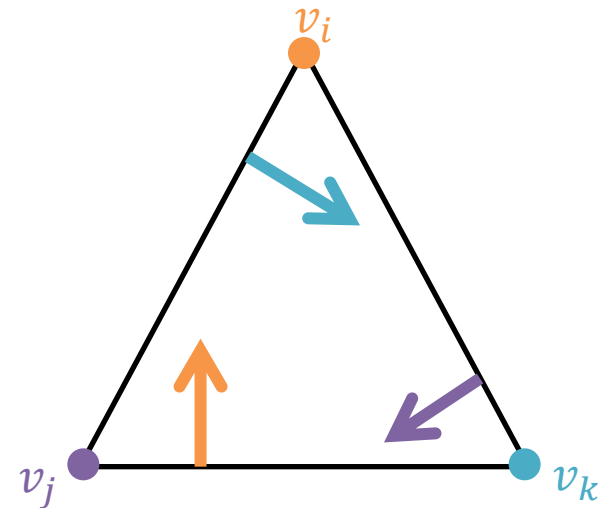
$$\nabla \phi_i \big|_{T=(v_i, v_j, v_k)} = \frac{e_{jk}^\perp}{2A_T}$$

How to compute gradient on mesh?



$$\begin{aligned}\nabla f|_T &= \sum_{l=1}^{n_v} \nabla \phi_l(\mathbf{x}) f_l = \nabla \phi_i(\mathbf{x}) f_i + \nabla \phi_j(\mathbf{x}) f_j + \nabla \phi_k(\mathbf{x}) f_k \\ &= \frac{1}{2A_T} (f_i e_{jk}^\perp + f_j e_{ki}^\perp + f_k e_{ij}^\perp)\end{aligned}$$

How to write gradient in matrix form

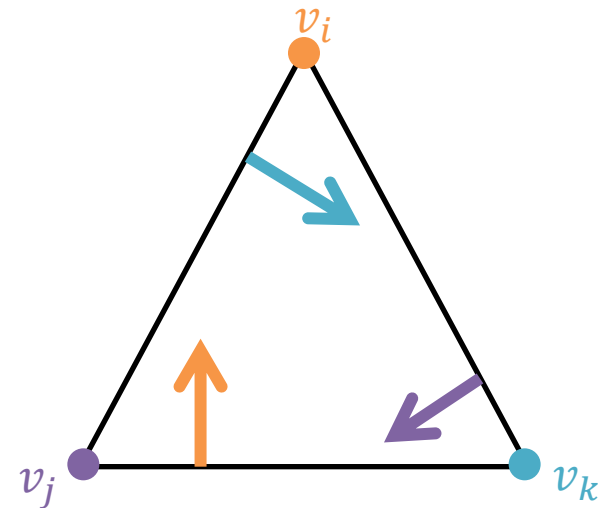


$$\nabla f \big|_T = \frac{1}{2A_T} (f_i e_{jk}^\perp + f_j e_{ki}^\perp + f_k e_{ij}^\perp)$$

- f is defined on **vertices**, i.e., $f \in R^{n_v \times 1}$
- ∇f assigns a constant vector to each **face**, i.e., $\nabla f \in R^{n_f \times 3}$, i -th row represent the gradient in the i -th face
- We can flatten ∇f to a vector, i.e., $\nabla f \in R^{3n_f \times 1}$
- Gradient operator is a **linear transformation** G :

$$\nabla f = Gf, \text{ where } G \in R^{3n_f \times n_v}$$

How to write gradient in matrix form

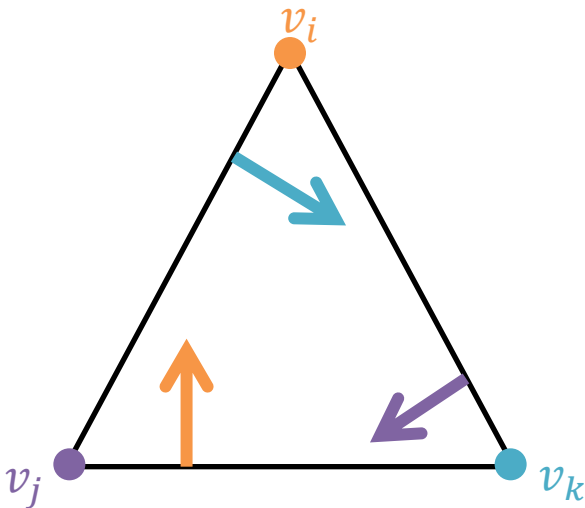


$$\nabla f \Big|_T = \frac{1}{2A_T} (f_i e_{jk}^\perp + f_j e_{ki}^\perp + f_k e_{ij}^\perp)$$

- $\nabla f = Gf$, where $G \in R^{3n_f \times n_v}$
- $G(t, i) = \frac{1}{2A_t} (e_{jk}^\perp)_1$
- $G(t + n_f, i) = \frac{1}{2A_t} (e_{jk}^\perp)_2$
- $G(t + 2n_f, i) = \frac{1}{2A_t} (e_{jk}^\perp)_3$

Flatten the three entries of the gradient vector
Similar for j, k

How to write gradient in matrix form



```
193 // create sparse gradient operator matrix
194 G.resize(dims*m,nv);
195 std::vector<Eigen::Triplet<typename DerivedV::Scalar> > Gijv;
196 Gijv.reserve(4*dims*m);
197 for(int f = 0;f<F.rows();f++)
198 {
199     for(int d = 0;d<dims;d++)
200     {
201         Gijv.emplace_back(f+d*m,F(f,1), eperp13(f,d));
202         Gijv.emplace_back(f+d*m,F(f,0), -eperp13(f,d));
203         Gijv.emplace_back(f+d*m,F(f,2), eperp21(f,d));
204         Gijv.emplace_back(f+d*m,F(f,0), -eperp21(f,d));
205     }
206 }
207 G.setFromTriplets(Gijv.begin(), Gijv.end());
208 }
209
210
```

"igl::grad"

A green box highlights the four `emplace_back` calls in the inner loop, with a green arrow pointing from the text *"igl::grad"* to it.

Why only used e_{13}^\perp and e_{21}^\perp ?

Hint: try to prove **by definition** $e_{13}^\perp + e_{32}^\perp + e_{21}^\perp = 0$

Gradient in local frame

```
76
77 "src/main.cpp"
78 static void computeSurfaceGradientMatrix(SparseMatrix<double> & D1, SparseMatrix<double> & D2)
79 {
80     MatrixXd F1, F2, F3;
81     SparseMatrix<double> DD, Dx, Dy, Dz;
82
83     igl::local_basis(V, F, F1, F2, F3);
84     igl::grad(V, F, DD);
85
86     Dx = DD.topLeftCorner(F.rows(), V.rows());
87     Dy = DD.block(F.rows(), 0, F.rows(), V.rows());
88     Dz = DD.bottomRightCorner(F.rows(), V.rows());
89
90     D1 = F1.col(0).asDiagonal()*Dx + F1.col(1).asDiagonal()*Dy + F1.col(2).asDiagonal()*Dz;
91     D2 = F2.col(0).asDiagonal()*Dx + F2.col(1).asDiagonal()*Dy + F2.col(2).asDiagonal()*Dz;
92 }
93
94
```

$G = DD = \begin{pmatrix} D_x \\ D_y \\ D_z \end{pmatrix} \in R^{3n_f \times n_v}$

$F_1, F_2 \in R^{n_f \times 3}$ local frames defined per face

Gradient in local frame

```
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78 static void computeSurfaceGradientMatrix(SparseMatrix<double> & D1, SparseMatrix<double> & D2)
79 {
80     MatrixXd F1, F2, F3;
81     SparseMatrix<double> DD, Dx, Dy, Dz;
82
83     igl::local_basis(V, F, F1, F2, F3);
84     igl::grad(V, F, DD);
85
86     Dx = DD.topLeftCorner(F.rows(), V.rows());
87     Dy = DD.block(F.rows(), 0, F.rows(), V.rows());
88     Dz = DD.bottomRightCorner(F.rows(), V.rows());
89
90     D1 = F1.col(0).asDiagonal()*Dx + F1.col(1).asDiagonal()*Dy + F1.col(2).asDiagonal()*Dz;
91     D2 = F2.col(0).asDiagonal()*Dx + F2.col(1).asDiagonal()*Dy + F2.col(2).asDiagonal()*Dz;
92 }
93
94
```

D_x, D_y, D_z gradient operator in R^3

$D_1, D_2 \in R^{n_f \times n_v}$ gradient operator along the two local axis

Thank You
