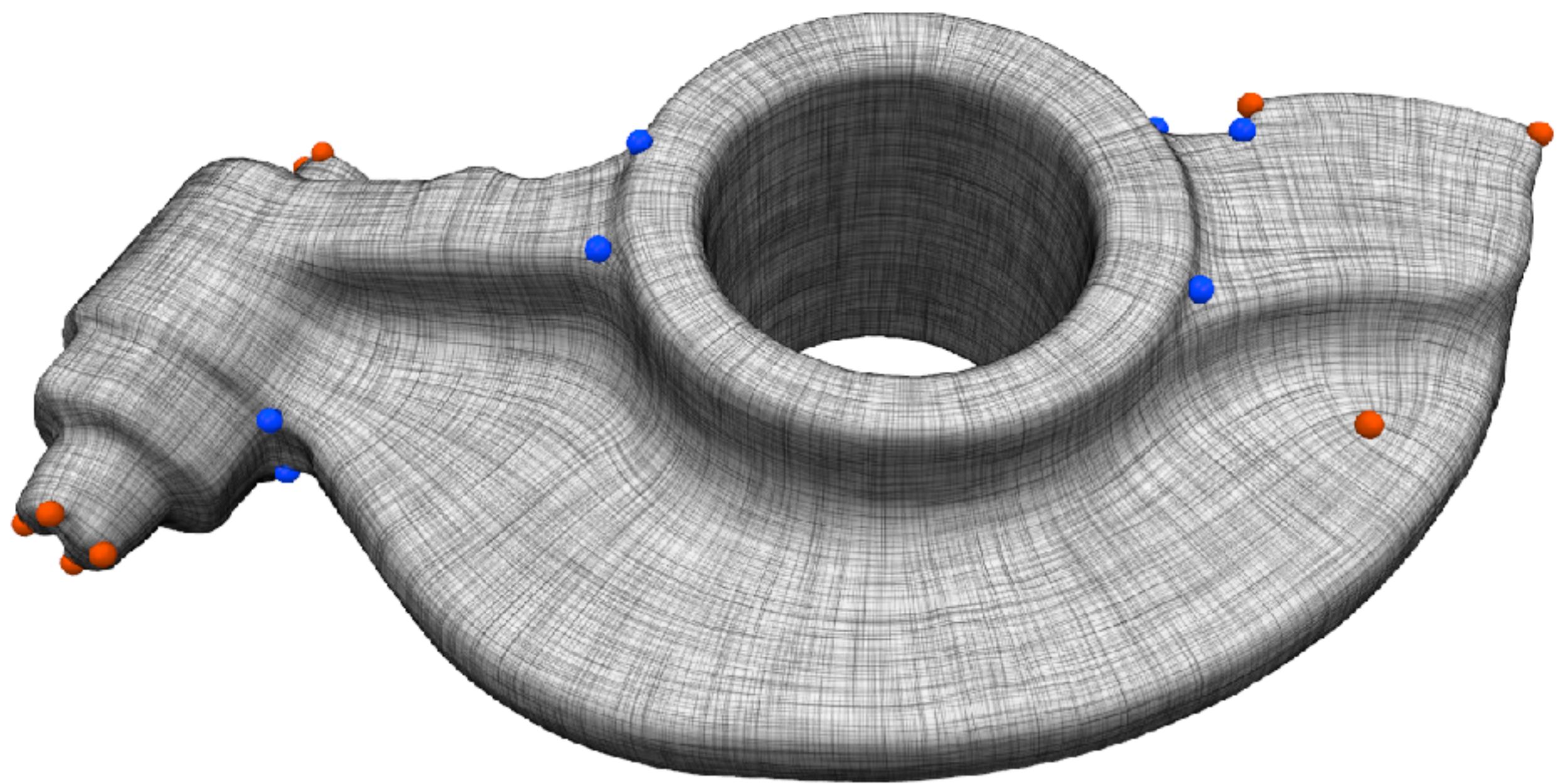


# Directional Fields

Extended version: [github.com/avaxman/DirectionalFieldSynthesis](https://github.com/avaxman/DirectionalFieldSynthesis)  
CSC 486B/586B - Geometric Modeling - Teseo Schneider

# Directional Fields

- Directional information per point of a domain
- Various types
  - vector vs. direction (with or without magnitude)
  - one or  $N$  per point
  - symmetric vs. non-symmetric



# Directional Fields in Nature



Photo Copyright: Richard Wheeler, Keenan Crane,  
Trisha Shears, and André Karwath

# Directional Fields

- We are here **not** concerned with measuring or analyzing them
- We are interested in the ***synthesis*** of directional fields
  - reproduction/simulation/modeling of natural phenomena
  - abstract mathematical tool for diverse applications
    - meshing
    - deformation
    - fabrication
    - data analysis
    - ...

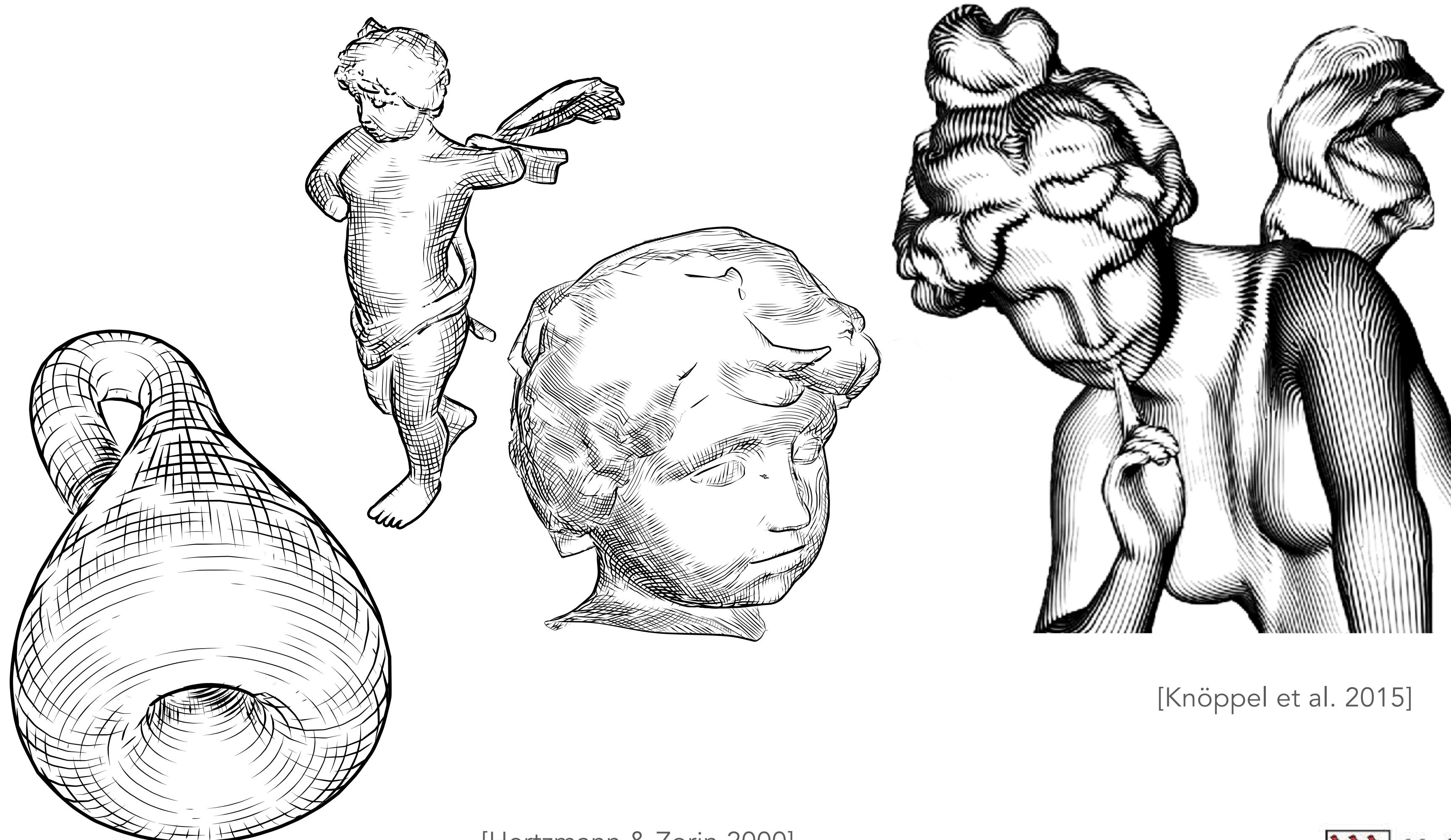


# Directional Field Synthesis

- This area of research has undergone significant development in past 10 years
  - technical novelties introduced in ~50 papers
- Numerous competing approaches for
  - representation
  - discretization
  - optimization
  - formulation of objectives
  - constraining

I will give a high-level overview,  
then focus on a specific case that happens often  
in geometry processing

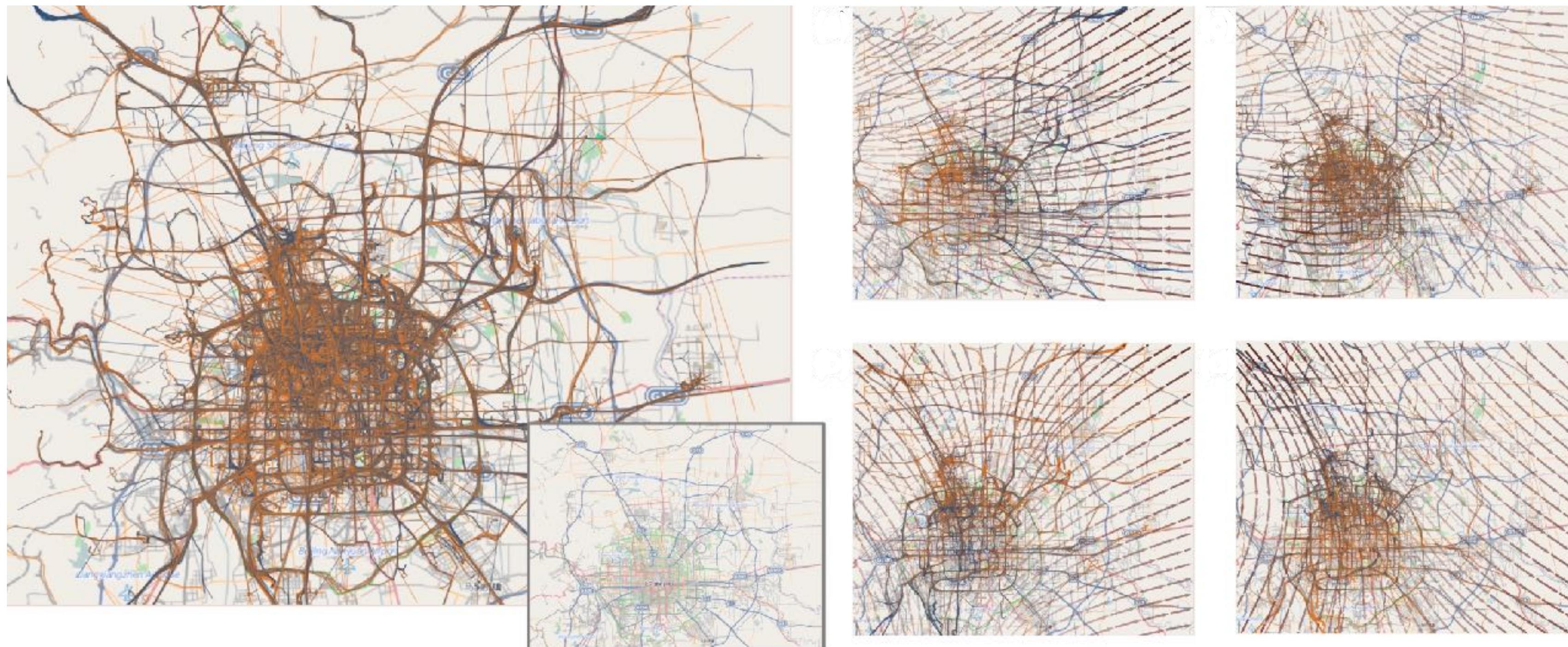
# Non-Photorealistic Rendering



[Knöppel et al. 2015]

[Hertzmann & Zorin 2000]

# Data Analysis



[Ferreira et al., 2013]

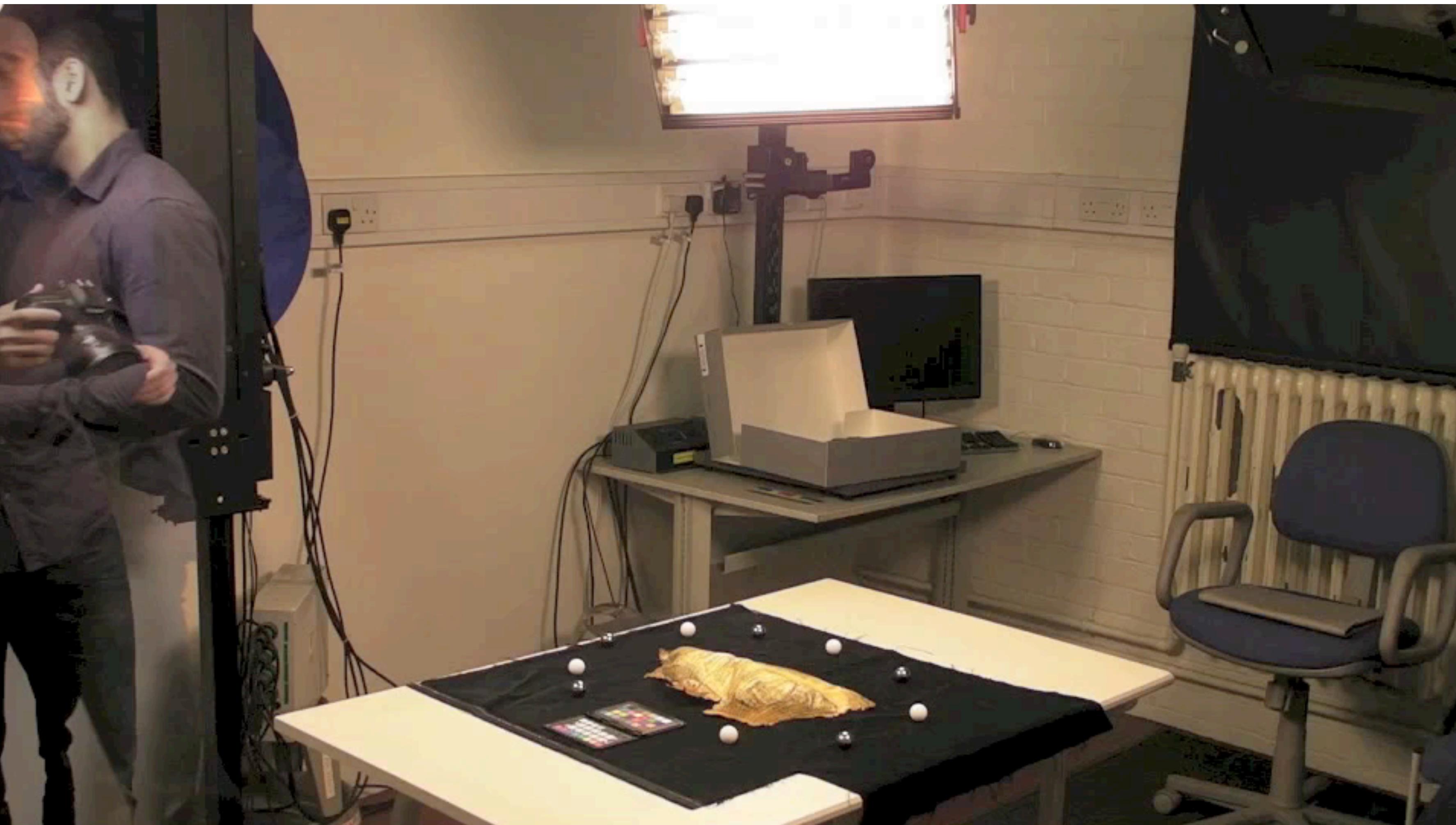


Computer Science

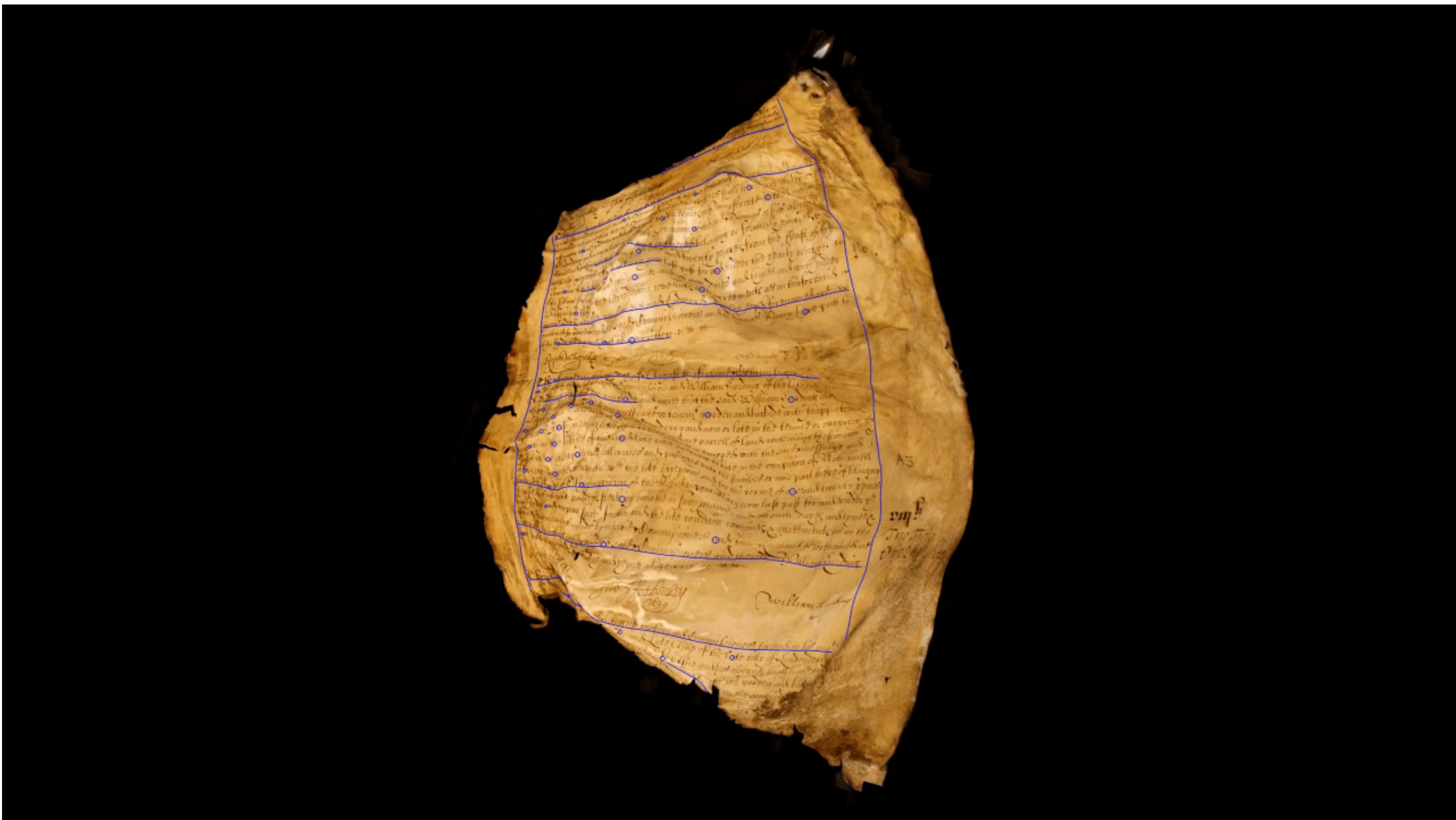
# Cultural heritage



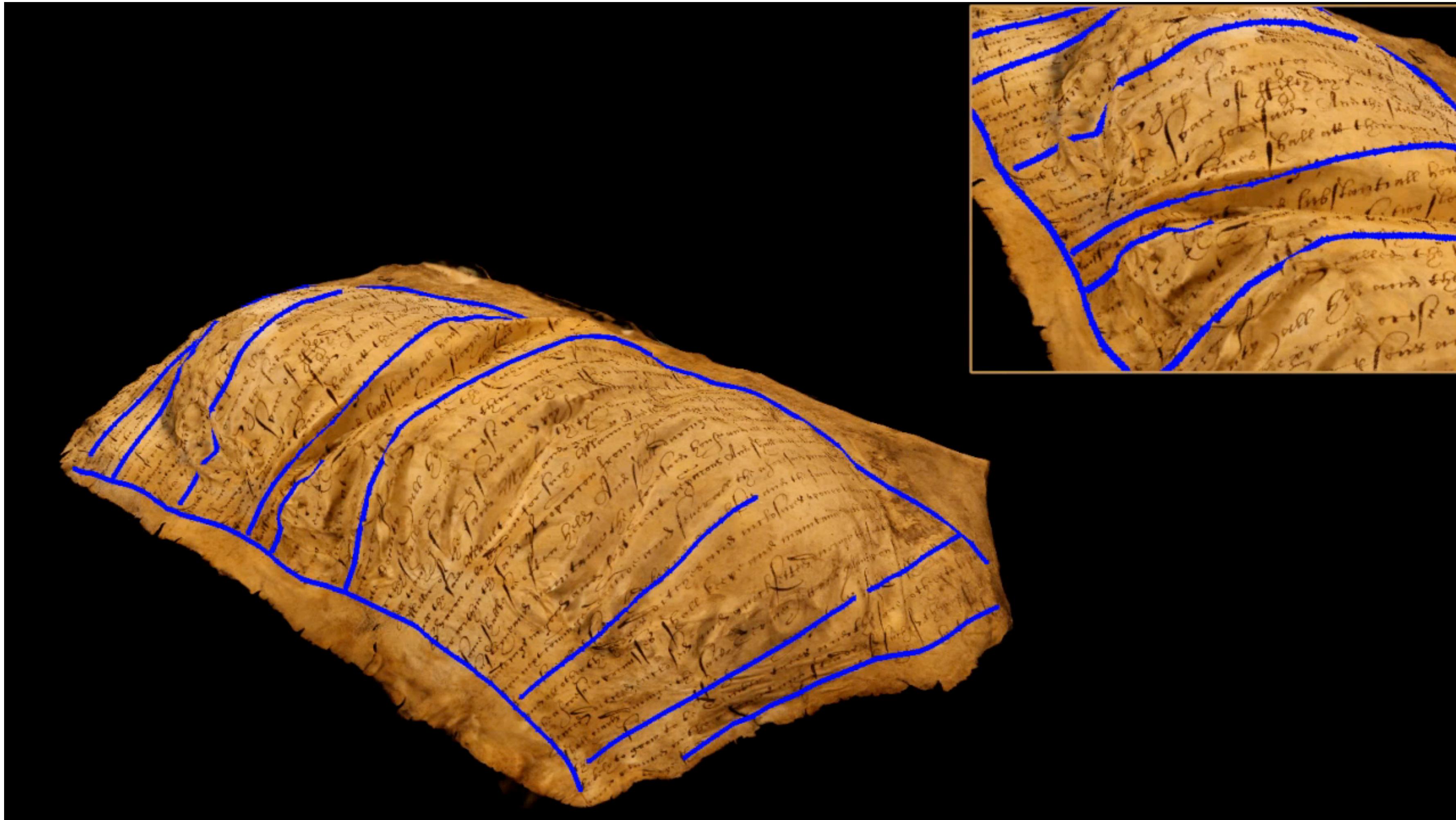
# Cultural heritage



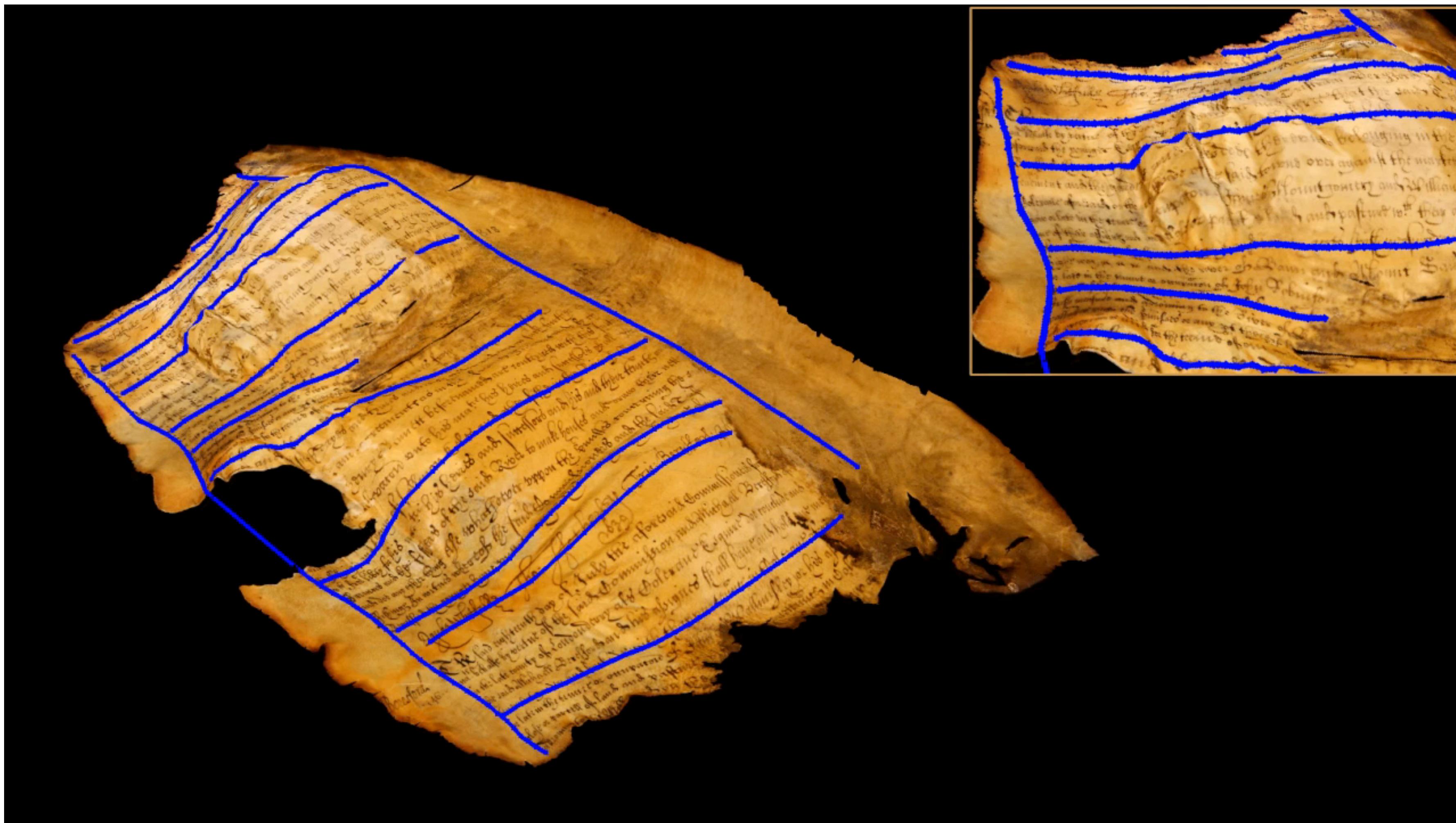
# Cultural heritage



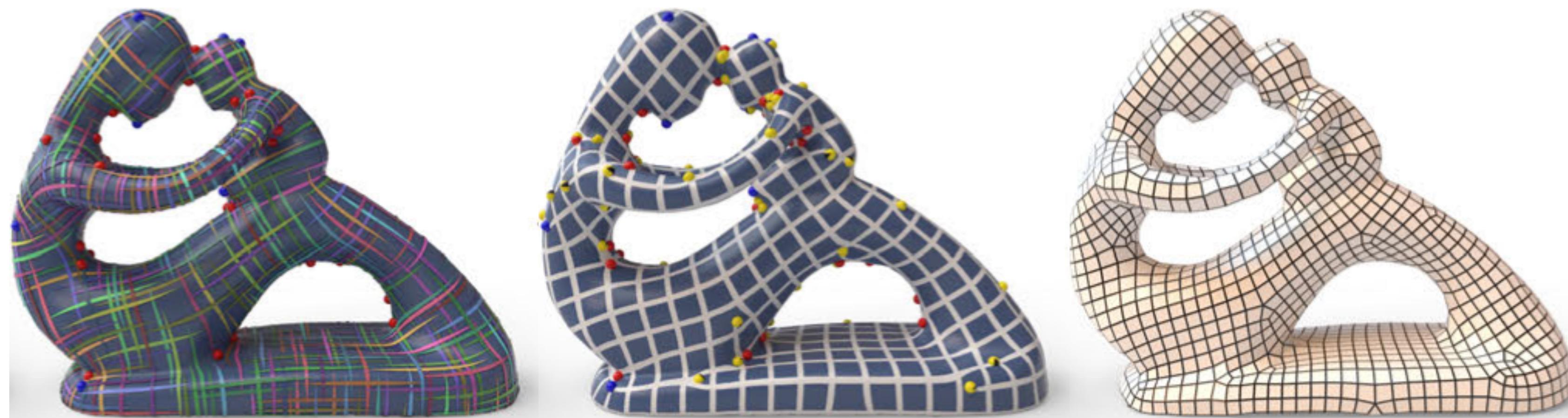
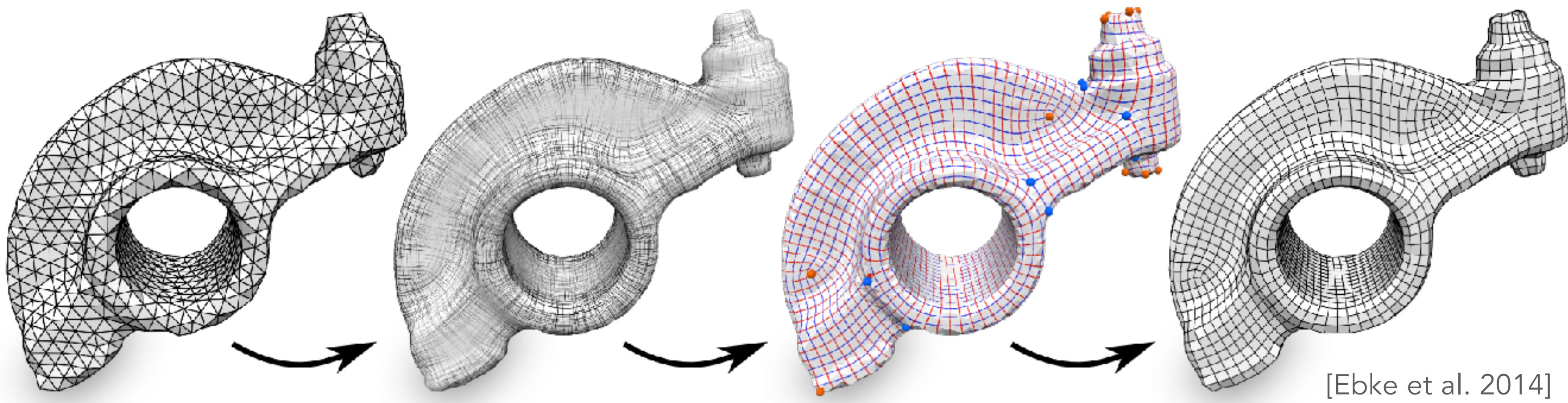
# Cultural heritage



# Cultural heritage



# Meshing



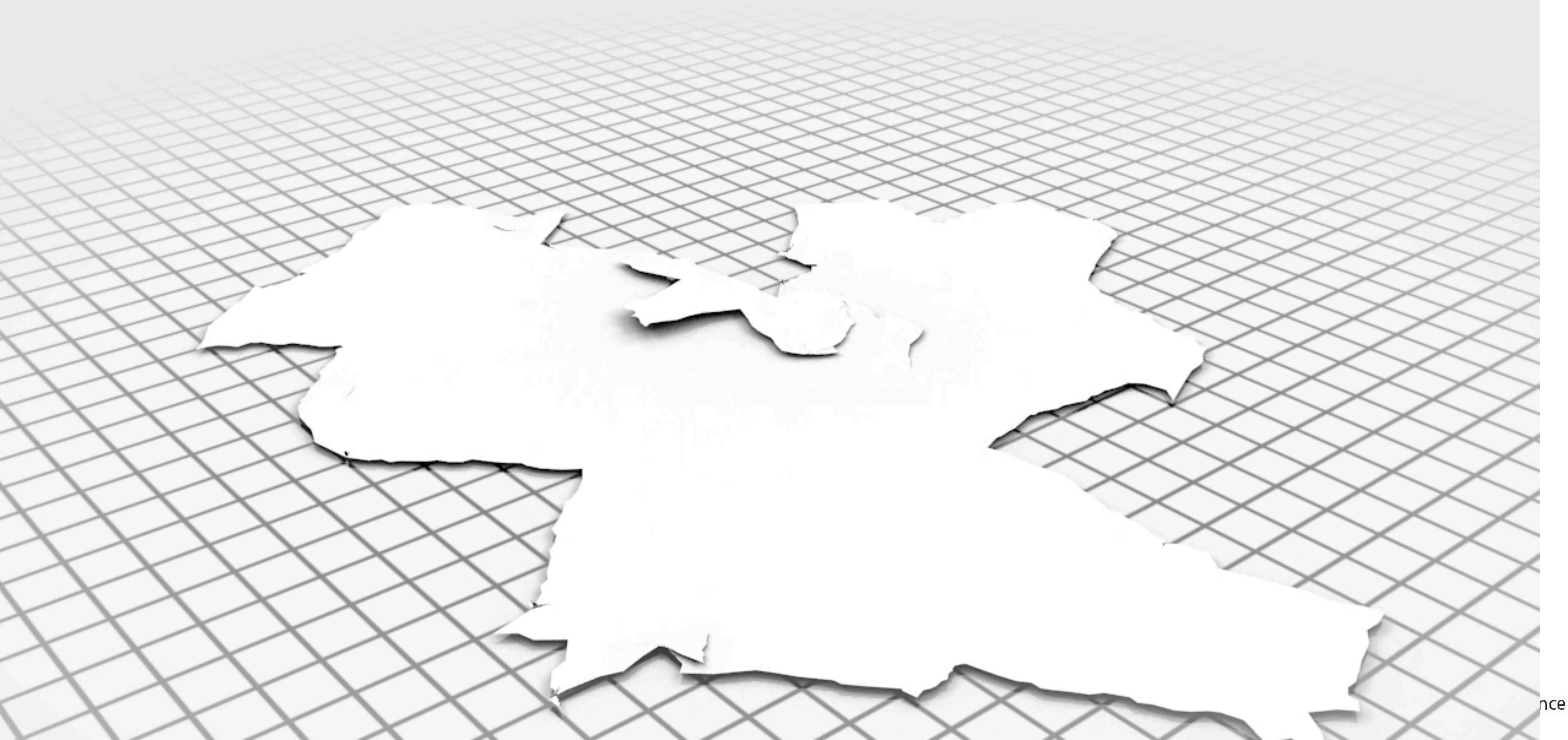
[courtesy of Hans-Christian Ebke]



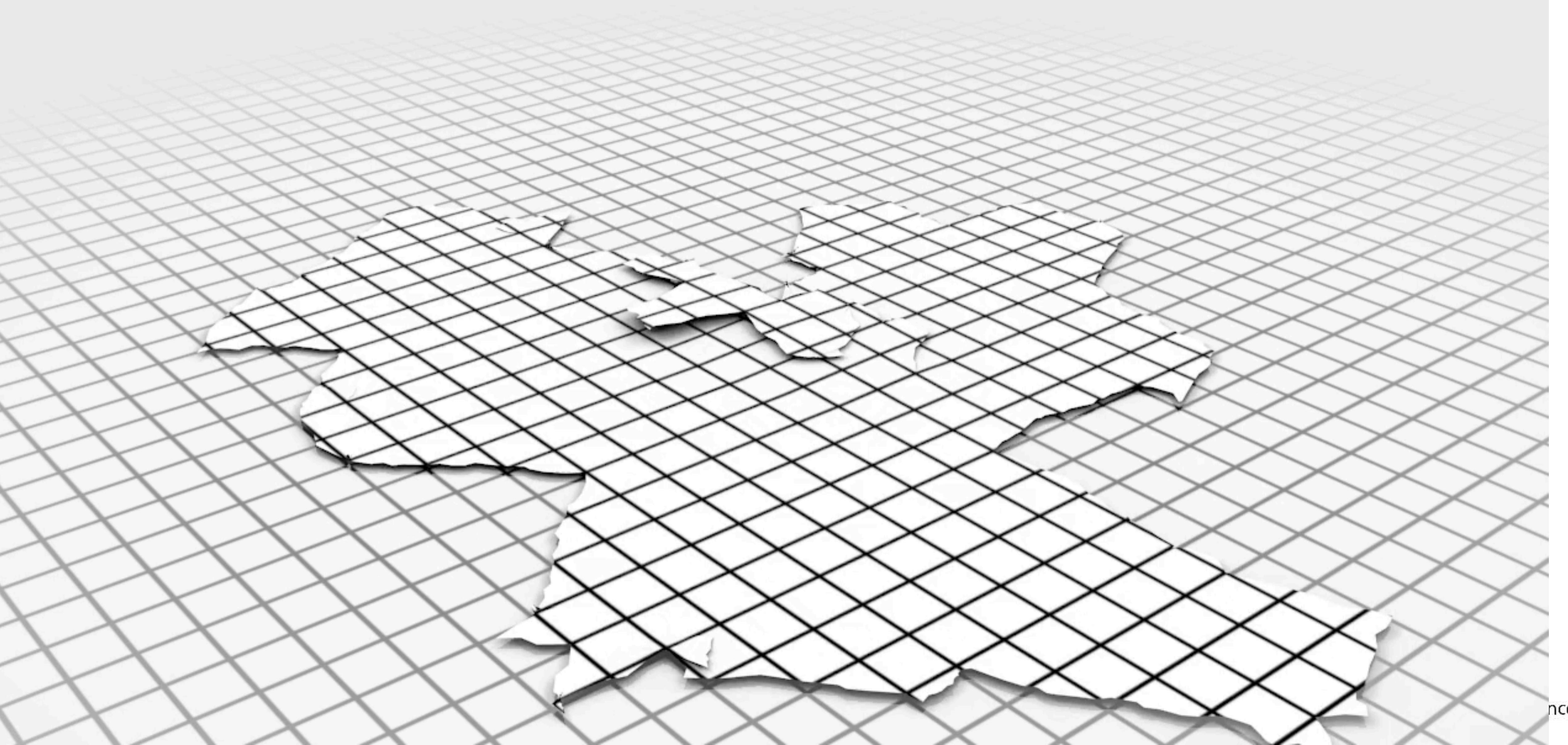
[courtesy of Hans-Christian Ebke]



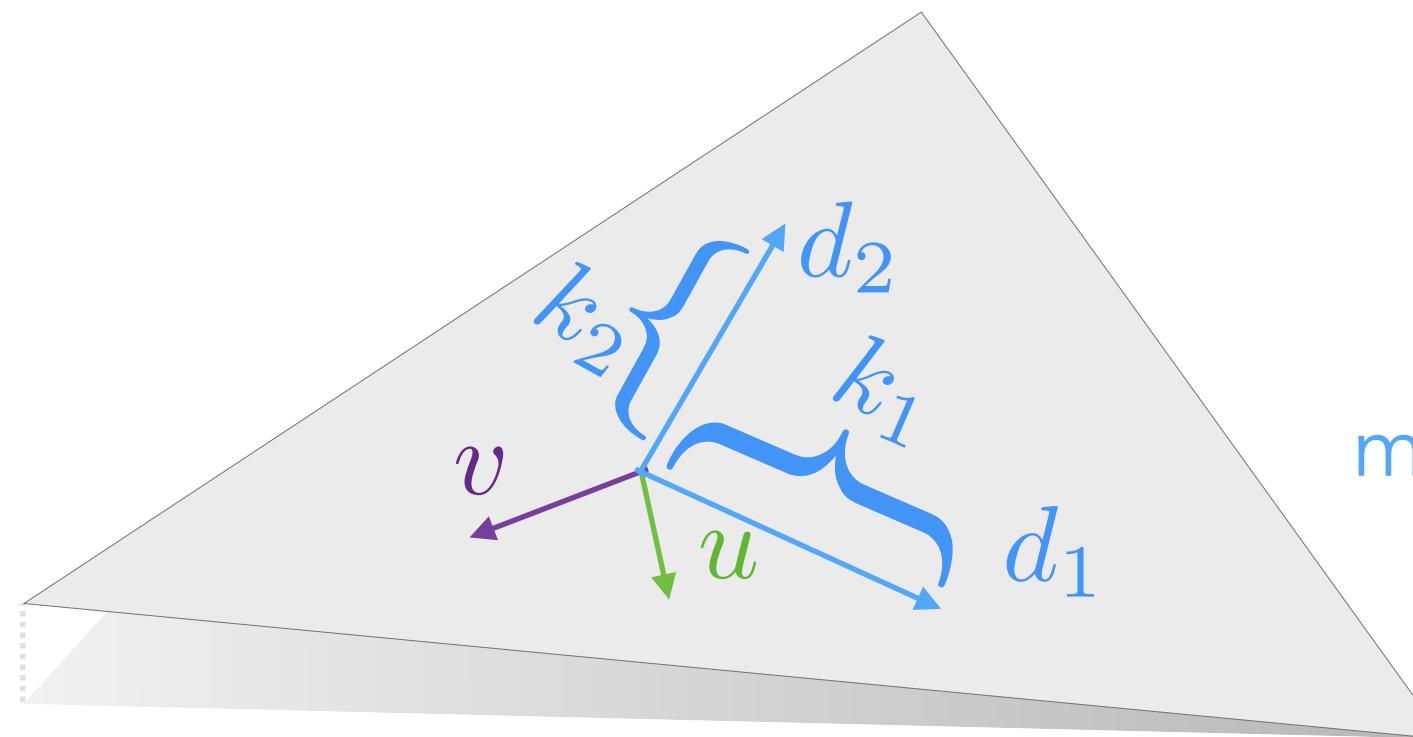
[courtesy of Hans-Christian Ebke]



[courtesy of Hans-Christian Ebke]

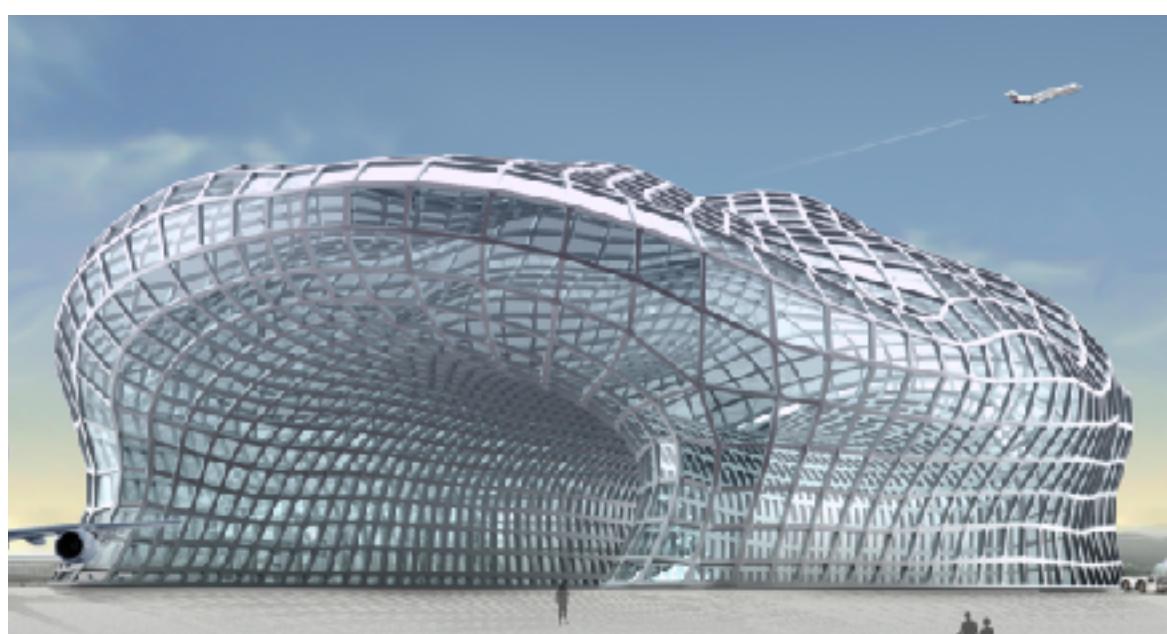


# Conjugate Direction Fields - Planar Meshing

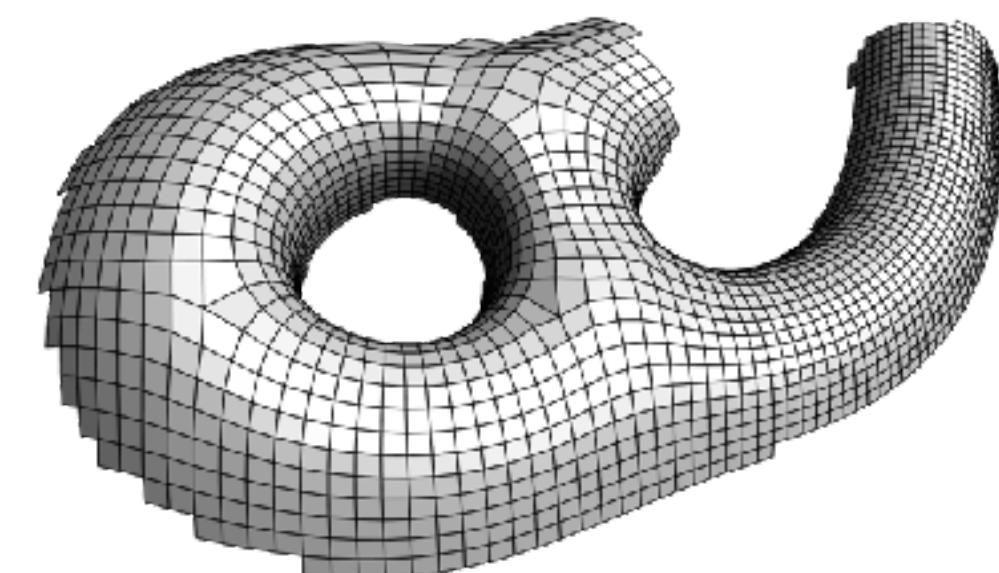


$$\kappa_1(u^T d_1)(v^T d_1) + \kappa_2(u^T d_2)(v^T d_2) = 0$$

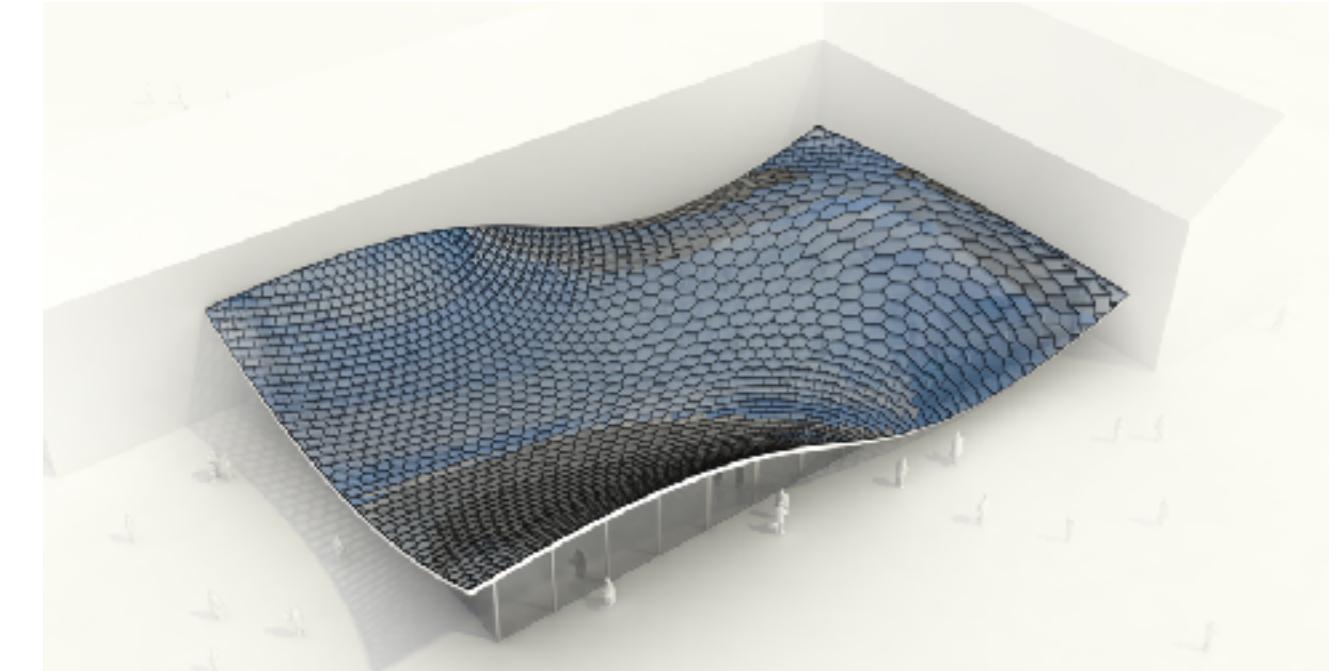
min/max curvatures      principal directions



[Liu et al. 2011]

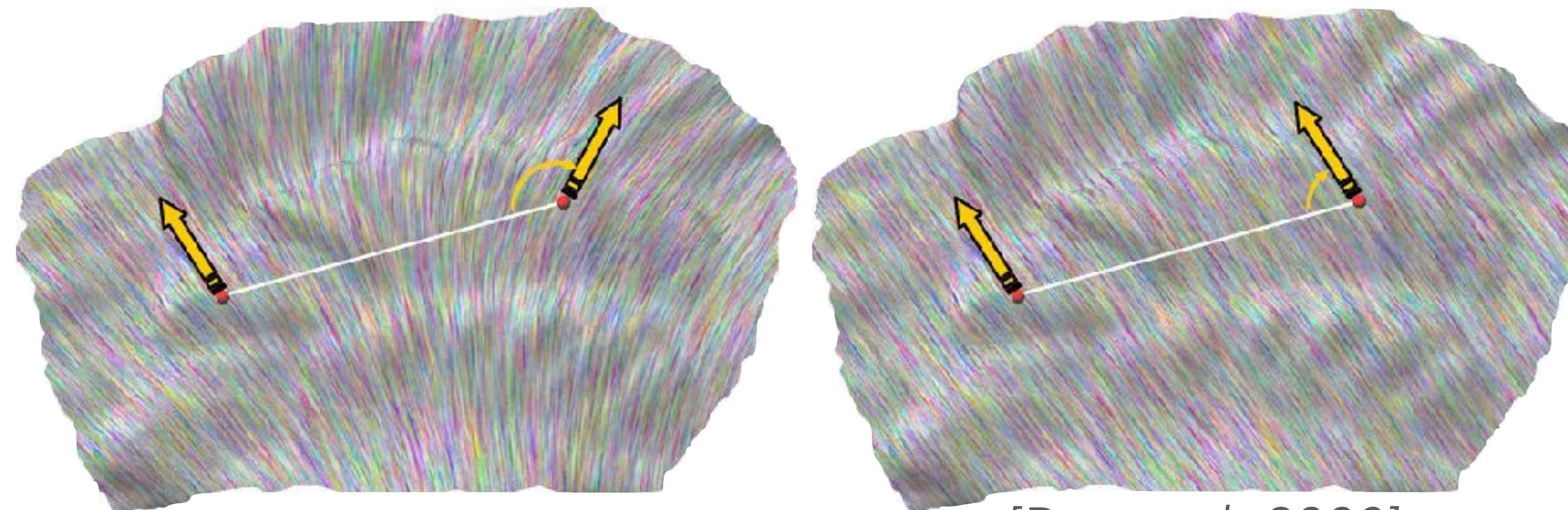


[Diamanti et al. 2015]



[Vaxman et al. 2015]

# Vector Field Design



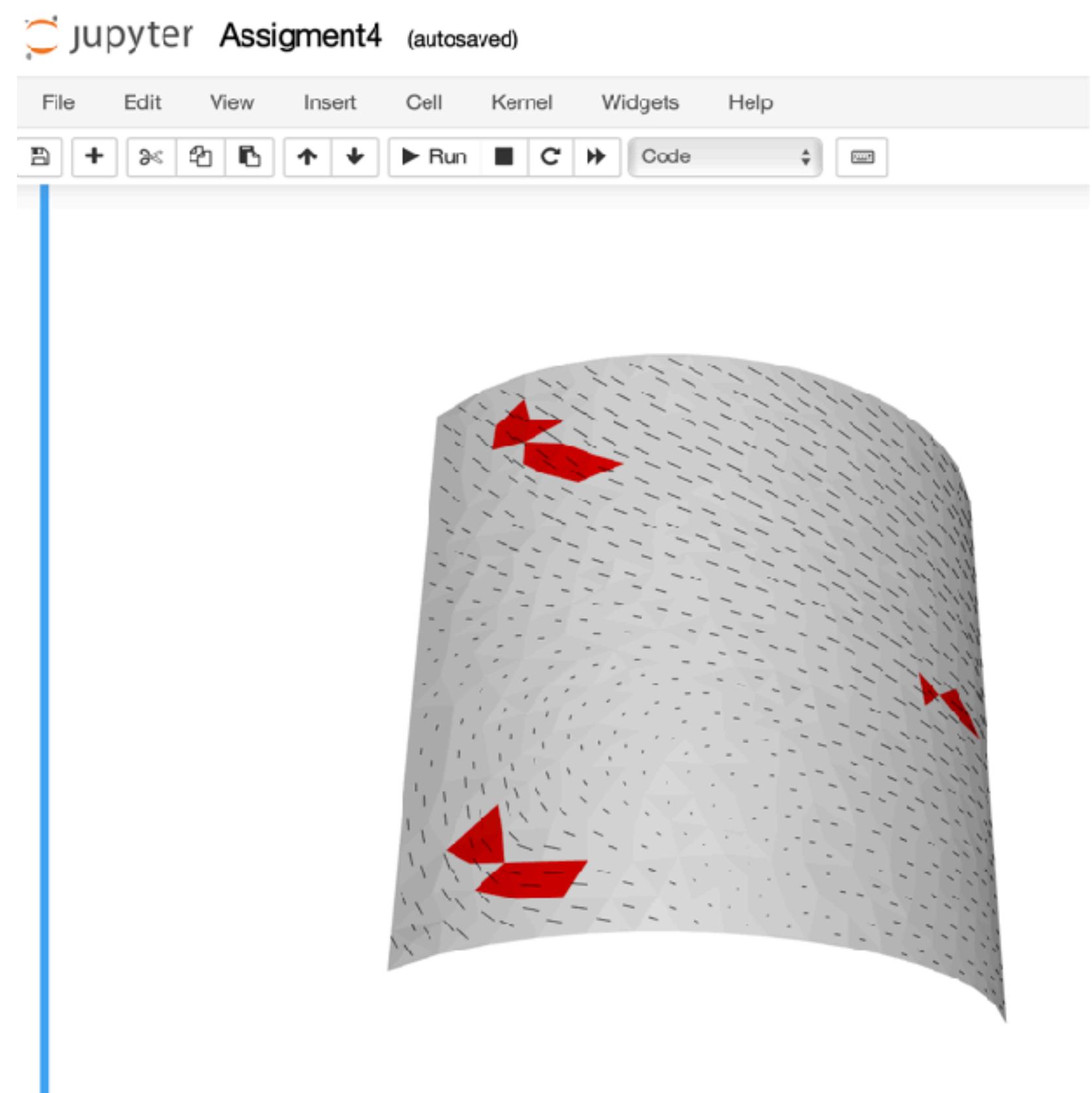
[Ray et al. 2008]

# Vector Field Design

- We will code a complete implementation of a simple algorithm to design **vector field**
- We will implement a method based on [Knöppel et al. 2013] and [Diamanti et. al. 2014]
  - The field will be discretized on **faces**
  - The topology will be **free**
  - The objective will be **smoothness (i.e. as-constant-as-possible)**
  - We will support **soft alignment constraints**

# Framework

- The reference implementation is provided as part of Assignment 4
- Self-contained
- Constraints are specified programmatically, you might want to write a simple UI to experiment more freely, using <https://ipywidgets.readthedocs.io/en/latest/examples/Using%20Interact.html>

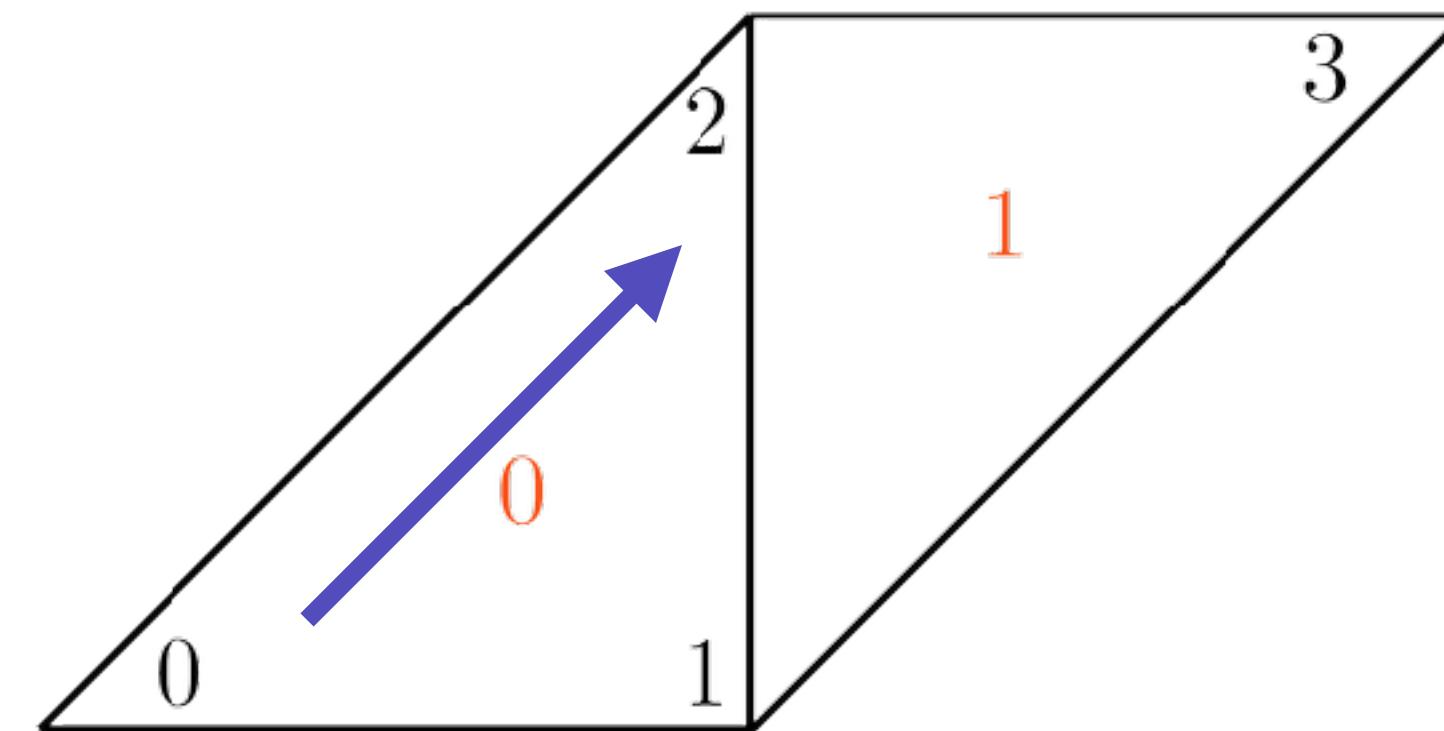


# Input/Output

- Mesh V, F

$$V = \begin{pmatrix} x & y & z \\ 0 & 0 & 0 \\ 1 & 0 & 0 \\ 1 & 1 & 1 \\ 2 & 1 & 0 \end{pmatrix}$$

$$F = \begin{pmatrix} 0 & 1 & 2 \\ 1 & 3 & 2 \end{pmatrix}$$



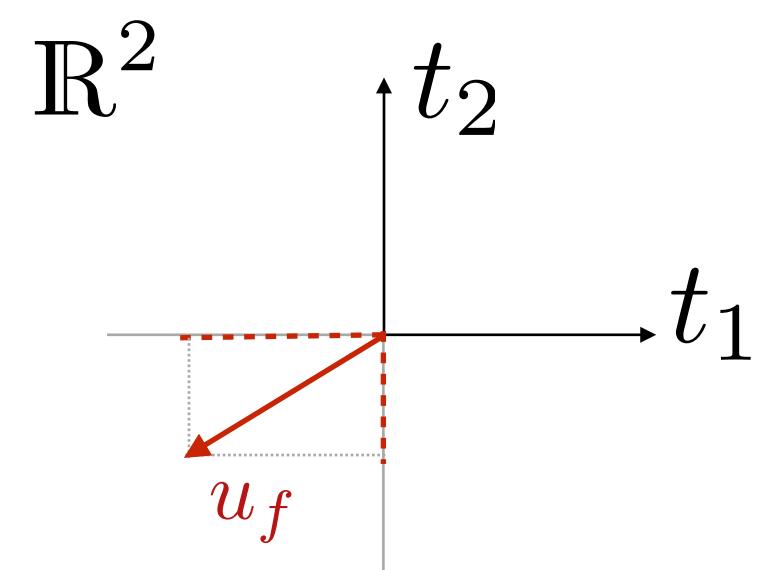
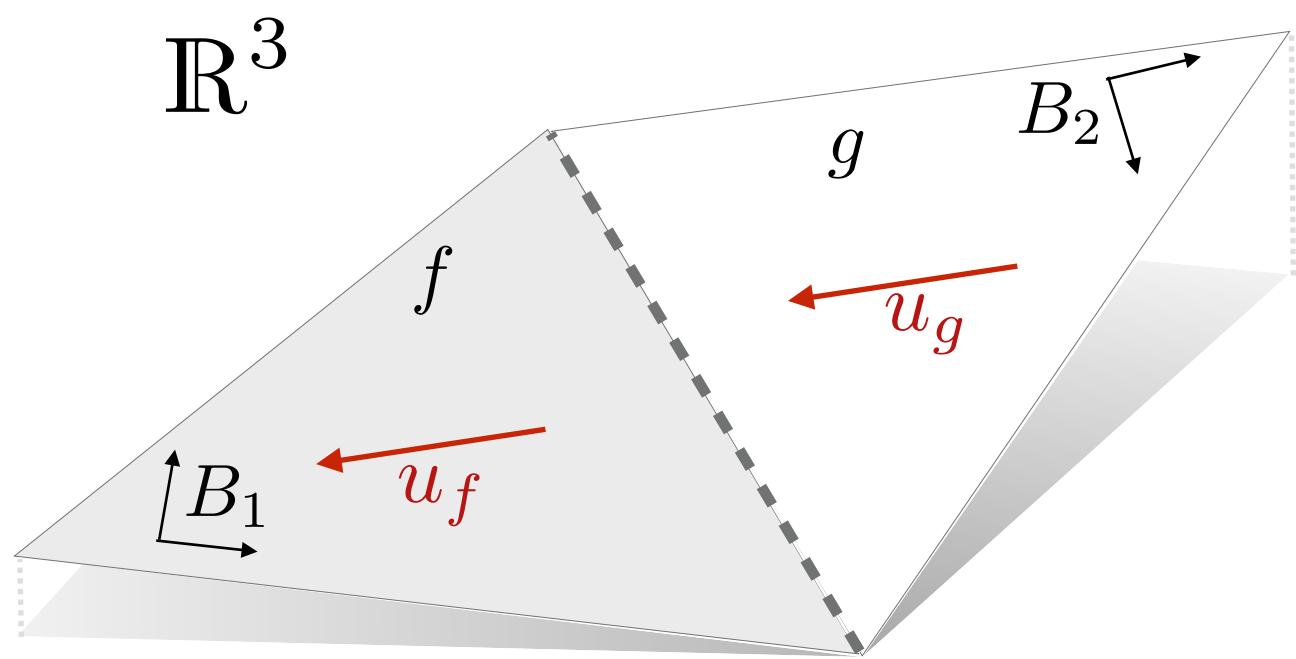
$$TT = \begin{pmatrix} -1 & 1 & -1 \\ -1 & -1 & 0 \end{pmatrix}$$

- Adjacency TT

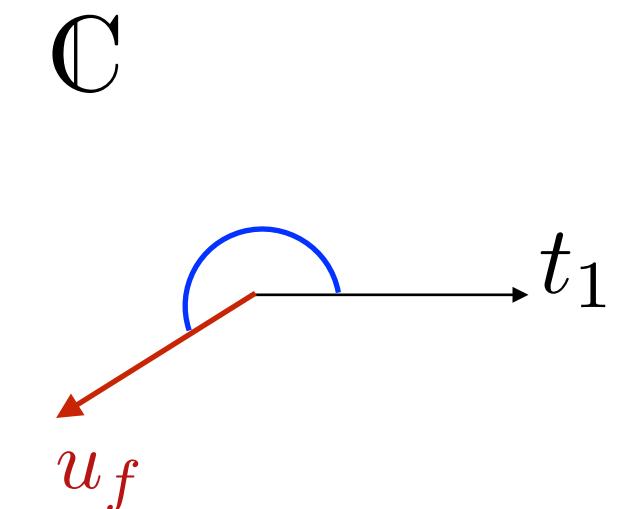
*soft\_id = 0, soft\_value = (1 1 0)*

- Constrained face ids *soft\_id* and directions *soft\_value*

# Discretization and Representation

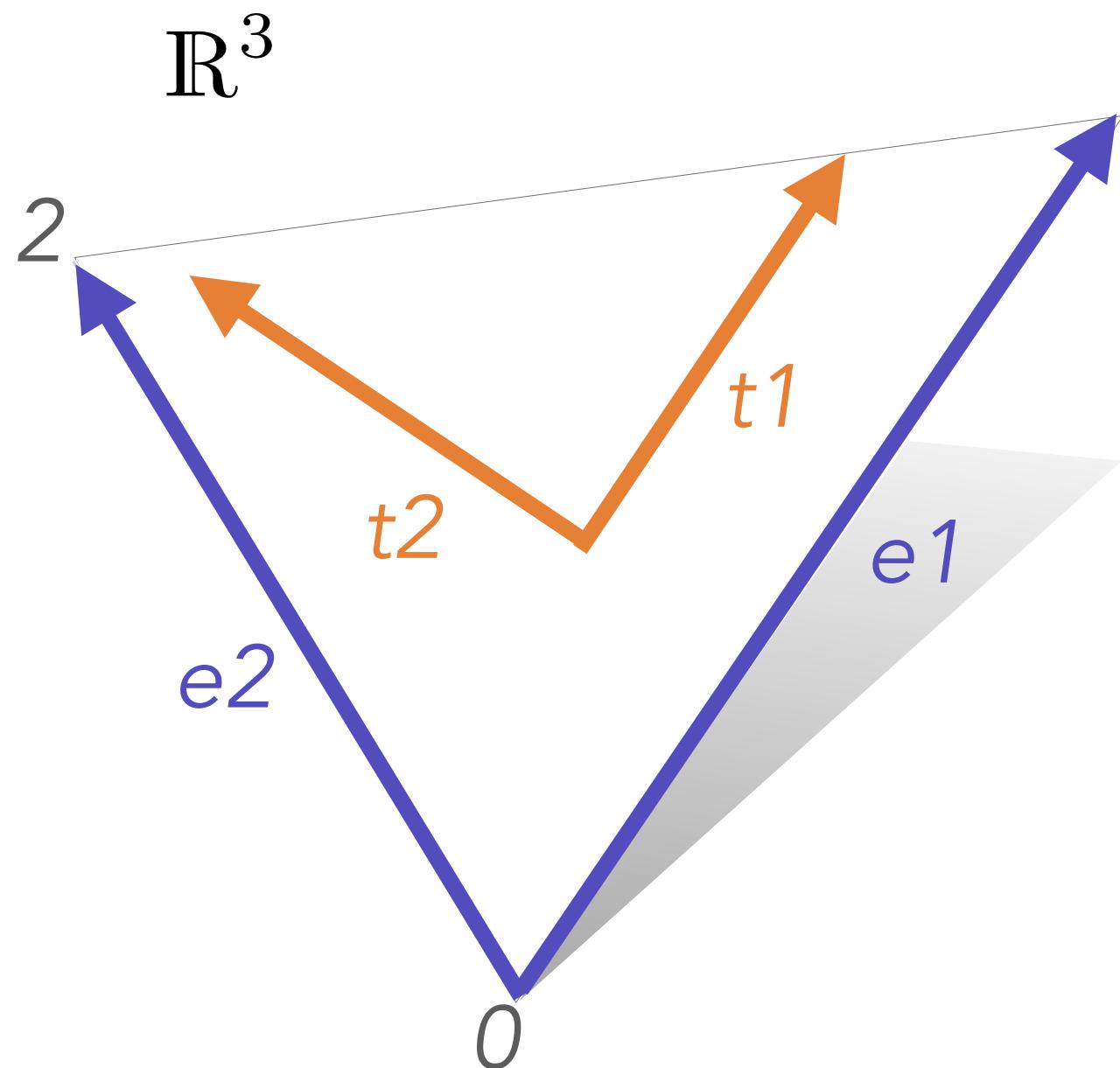


$$u_f = (u_f^x, u_f^y) \in \mathbb{R}^2$$



$$u_f = u_f^x + iu_f^y \in \mathbb{C}$$

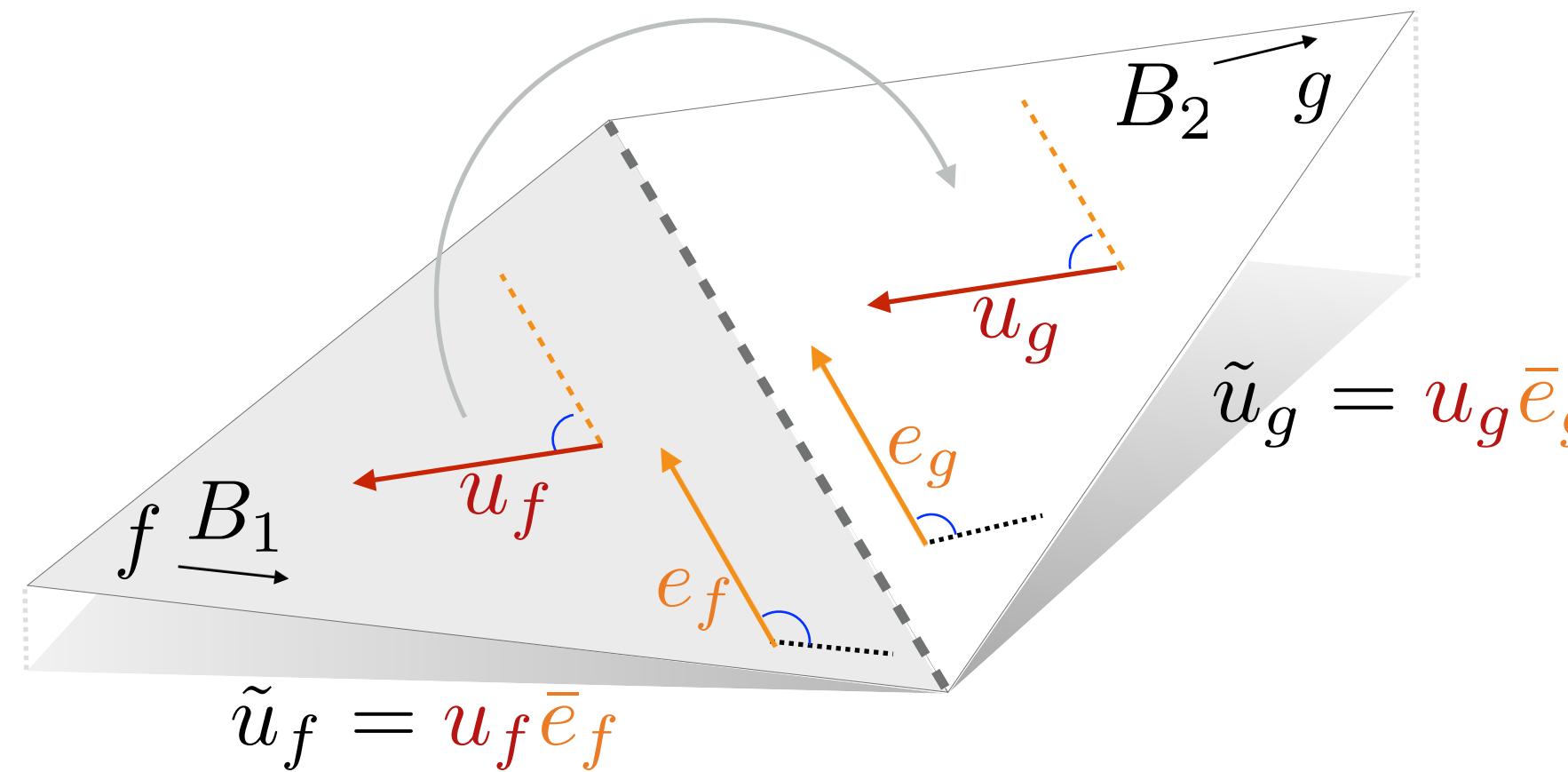
# Constructing Local Bases



```
# Edges
e1 = V[F[:, 1], :] - V[F[:, 0], :]
e2 = V[F[:, 2], :] - V[F[:, 0], :]

# Compute the local reference systems for each face, T1, T2
T1 = e1 / np.linalg.norm(e1, axis=1)[:,None]
T2 = np.cross(T1, np.cross(T1, e2))
T2 /= np.linalg.norm(T2, axis=1)[:,None]
```

# Discrete Transport



Constant field (over an edge)

$$u_f \bar{e}_f = u_g \bar{e}_g$$

```
# Compute the complex representation of the common edge
e = V[F[f, (ei+1)%3], :] - V[F[f, ei], :]

vef = np.array([np.dot(e, T1[f, :]), np.dot(e, T2[f, :])])
vef /= np.linalg.norm(vef)
ef = (vef[0] + vef[1]*1j).conjugate()

veg = np.array([np.dot(e, T1[g, :]), np.dot(e, T2[g, :])])
veg /= np.linalg.norm(veg)
eg = (veg[0] + veg[1]*1j).conjugate()
```

# Energy Formulation

- An ideally constant field satisfies (for each edge):

$$(u_f \bar{e}_f - u_g \bar{e}_g)$$

- We want to find the field that is as-constant-as-possible:

$$f(\mathbf{u}) = \sum_{f,g \in \mathcal{E}} \|u_f \bar{e}_f - u_g \bar{e}_g\|^2 + \lambda \sum_{f \in \mathcal{C}} \|u_f - c_f\|^2$$



As-constant-as-possible



Soft-constraints

- We can rewrite this expression in matrix form:

$$f(\mathbf{u}) = \|\mathbf{Lu}\|^2 + \lambda \|\mathbf{Cu} - \mathbf{d}\|^2$$



As-constant-as-possible

Soft-constraints

# Energy Formulation

$$f(\mathbf{u}) = \|\mathbf{Lu}\|^2 + \lambda \|\mathbf{Cu} - \mathbf{d}\|^2$$

- We can rearrange the expression in a single norm
- which can be minimized solving a complex linear system

# Energy Formulation

$$f(\mathbf{u}) = \|\mathbf{Lu}\|^2 + \lambda \|\mathbf{Cu} - \mathbf{d}\|^2$$

- We can rearrange the expression in a single norm

$$\left\| \begin{bmatrix} \mathbf{L} & \mathbf{u} \end{bmatrix} \right\|^2 + \lambda \left\| \begin{bmatrix} \mathbf{C} & \mathbf{u} \\ \mathbf{u} & \mathbf{d} \end{bmatrix} \right\|^2$$

$$\lambda \left\| \begin{bmatrix} \mathbf{L} & \mathbf{u} \\ \mathbf{C} & \mathbf{u} - \mathbf{d} \end{bmatrix} \right\|^2$$

- which can be minimized solving a complex linear system

# Energy Formulation

$$f(\mathbf{u}) = \|\mathbf{Lu}\|^2 + \lambda \|\mathbf{Cu} - \mathbf{d}\|^2$$

- We can rearrange the expression in a single norm

$$f(\mathbf{u}) = \left\| \begin{pmatrix} \mathbf{Lu} \\ \sqrt{\lambda} \mathbf{Cu} - \sqrt{\lambda} \mathbf{d} \end{pmatrix} \right\|^2 = \|\mathbf{Au} - \mathbf{b}\|^2$$
$$\mathbf{A} = \begin{pmatrix} \mathbf{L} \\ \sqrt{\lambda} \mathbf{C} \end{pmatrix}$$
$$\mathbf{b} = \begin{pmatrix} \mathbf{0} \\ \sqrt{\lambda} \mathbf{d} \end{pmatrix}$$

- which can be minimized solving a complex linear system

$$\nabla f(\mathbf{u}) = \mathbf{A}^* \mathbf{A} \mathbf{u} - \mathbf{A}^* \mathbf{b} = 0$$

█

Optimized Field

# System Assembly - Smoothness

- For each edge we want one row in  $\mathbf{A}$   $\|u_f \bar{e}_f - u_g \bar{e}_g\|^2 / \|\mathbf{L}\mathbf{u}\|^2$

```
index = 0
for f in range(F.shape[0]):
    for ei in range(3): # Loop over the edges

        # Look up the opposite face
        g = TT[f, ei]

        # If it is a boundary edge, it does not contribute to the energy
        # or avoid to count every edge twice
        if g == -1 or f > g:
            continue

        # Compute the complex representation of the common edge
        e = V[F[f, (ei+1)%3], :] - V[F[f, ei], :]

        vef = np.array([np.dot(e, T1[f, :]), np.dot(e, T2[f, :])])
        vef /= np.linalg.norm(vef)
        ef = (vef[0] + vef[1]*1j).conjugate()

        veg = np.array([np.dot(e, T1[g, :]), np.dot(e, T2[g, :])])
        veg /= np.linalg.norm(veg)
        eg = (veg[0] + veg[1]*1j).conjugate()

        # Add the term conj(f)^n*ui - conj(g)^n*uj to the energy matrix
        data.append(ef); ii.append(index); jj.append(f)
        data.append(-eg); ii.append(index); jj.append(g)

    index += 1
```

# System Assembly - Soft Constraints

- Similarly, we add a row to  $\mathbf{A}$  for each constrained face
- Note that the corresponding entry of  $\mathbf{b}$  is not zero

$$\lambda \sum_{f \in \mathcal{C}} \|u_f - c_f\|^2 \quad \|\sqrt{\lambda} \mathbf{Cu} - \sqrt{\lambda} \mathbf{d}\|^2$$

```
b = np.zeros(index + soft_id.shape[0], dtype=complex)

for ci in range(soft_id.shape[0]):
    f = soft_id[ci]
    v = soft_value[ci, :]

    # Project on the local frame
    c = np.dot(v, T1[f, :]) + np.dot(v, T2[f, :])*1j

    data.append(sqrtl); ii.append(index); jj.append(f)
    b[index] = c * sqrtl

    index += 1
```



# Solving the Linear System

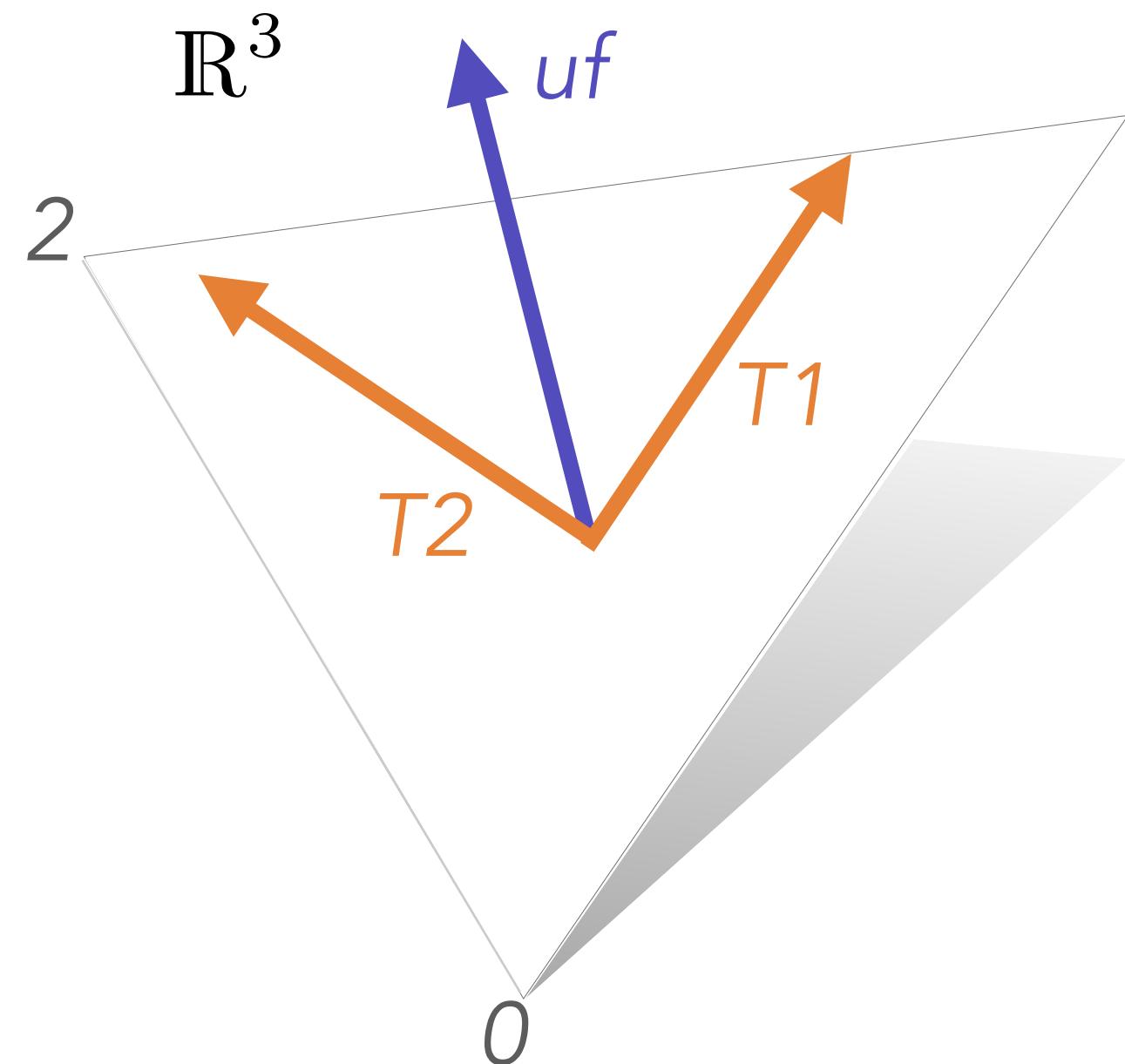
- The linear system is solved using a sparse direct solver.

$$\| \mathbf{A}\mathbf{u} - \mathbf{b} \|^2$$

$$\nabla f(\mathbf{u}) = \mathbf{A}^* \mathbf{A}\mathbf{u} - \mathbf{A}^* \mathbf{b} = 0$$

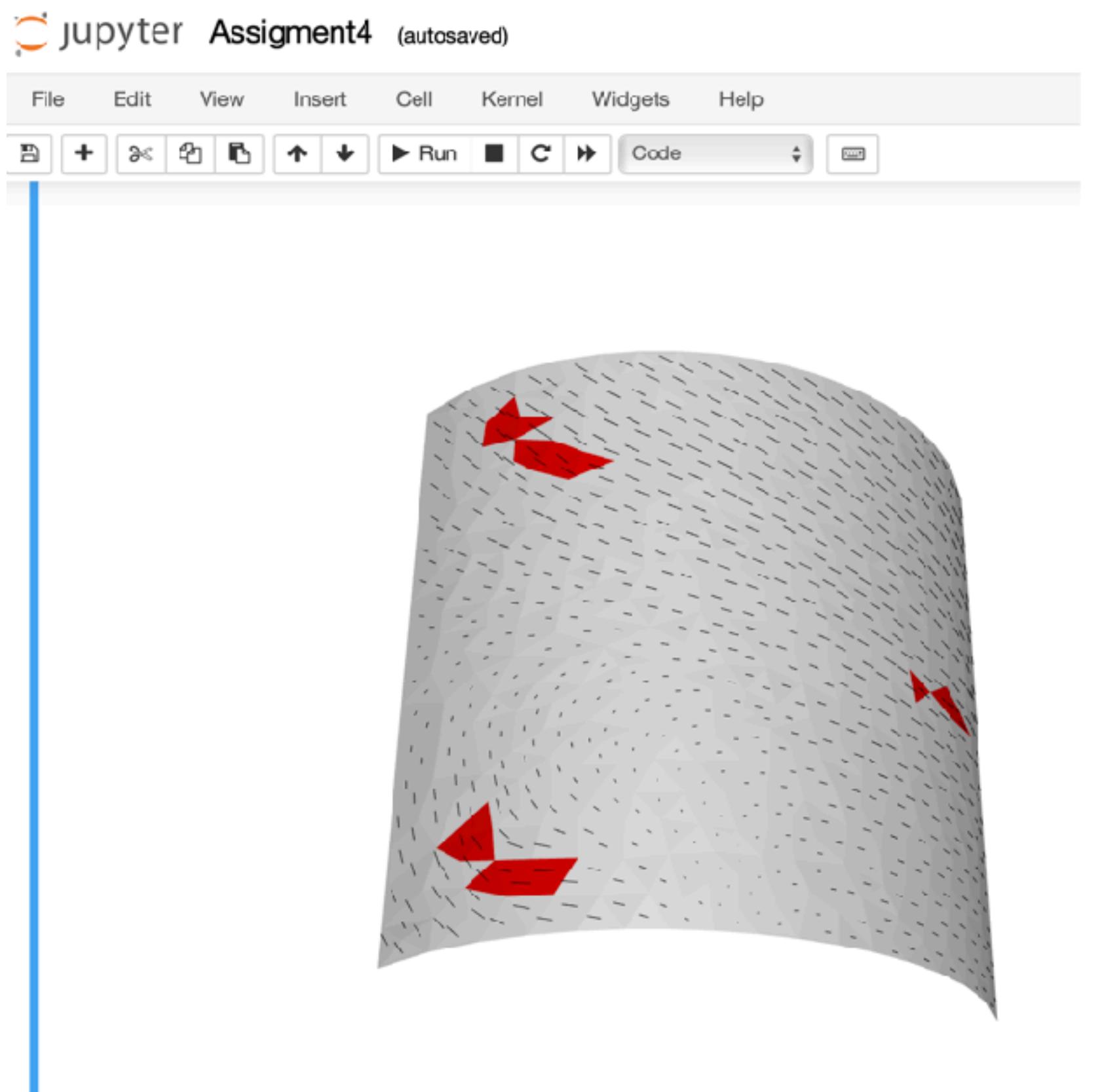
```
# Solve the linear system
A = sp.coo_matrix((data, (ii, jj)), shape=(index, F.shape[0])).asformat("csr")
u = sp.linalg.spsolve(A.H @ A, A.H @ b)
```

# Extraction of the Interpolated Field



```
R = T1 * u.real[:,None] + T2 * u.imag[:,None]
```

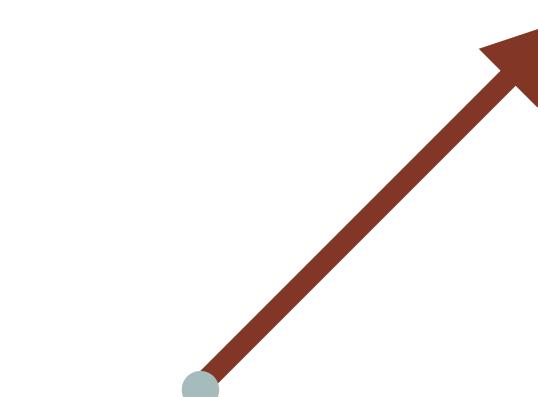
# Demo



# Taxonomy for general directional fields

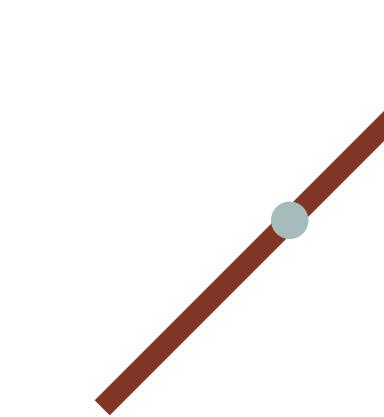
# Taxonomy

1-vector



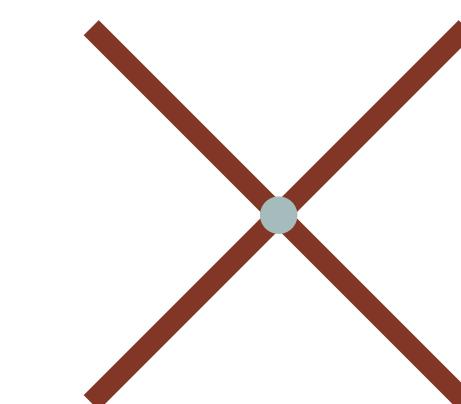
"classical vector"

2-direction



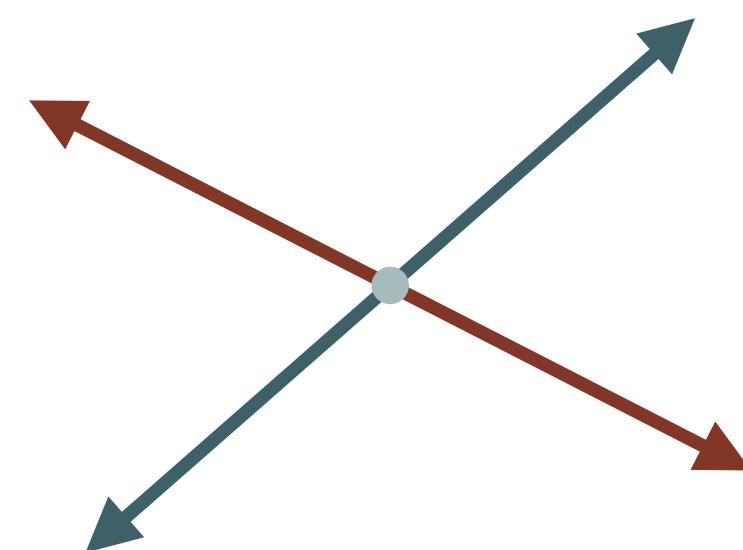
"line", "2-RoSy"

4-direction



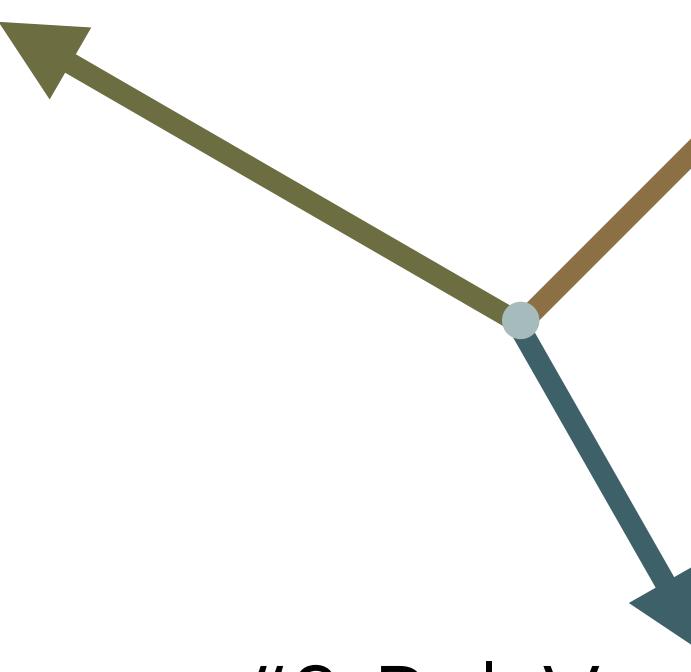
"unit cross", "4-RoSy"

$2^2$ -vector



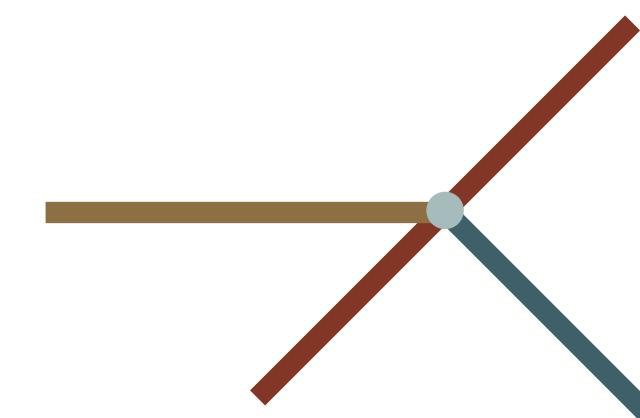
"Frame field"

$1^3$ -vector



"3-PolyVector"

$(1^2, 2)$ -direction



"4-PolyDirection  
including a line"

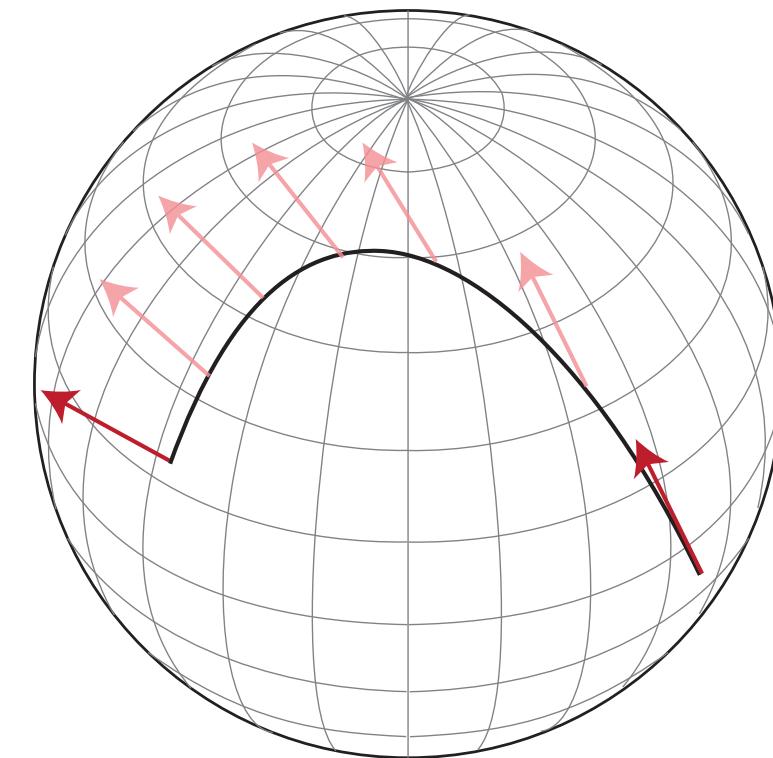


University  
of Victoria

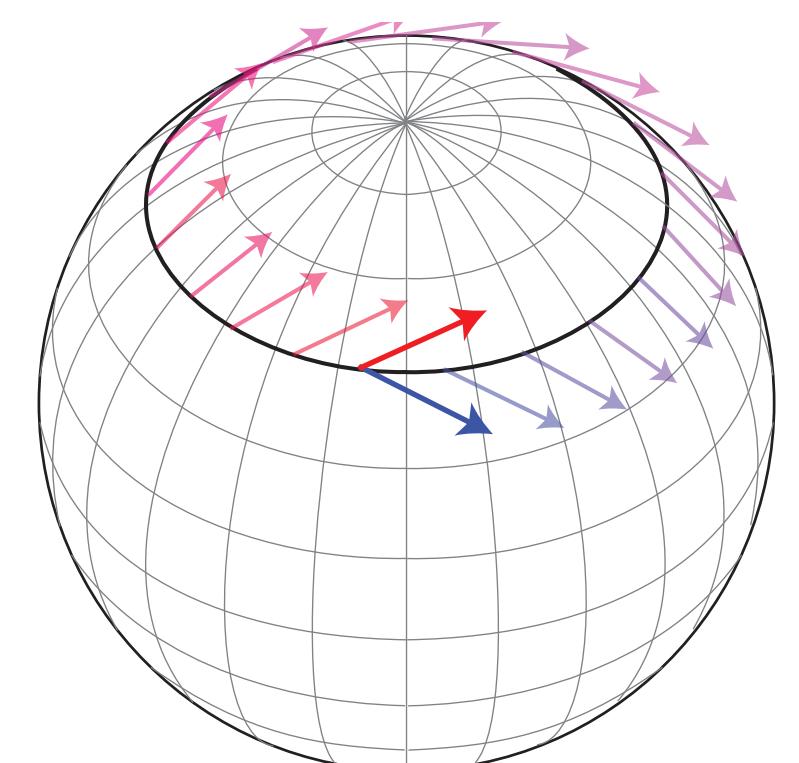
Computer Science

# Discretization

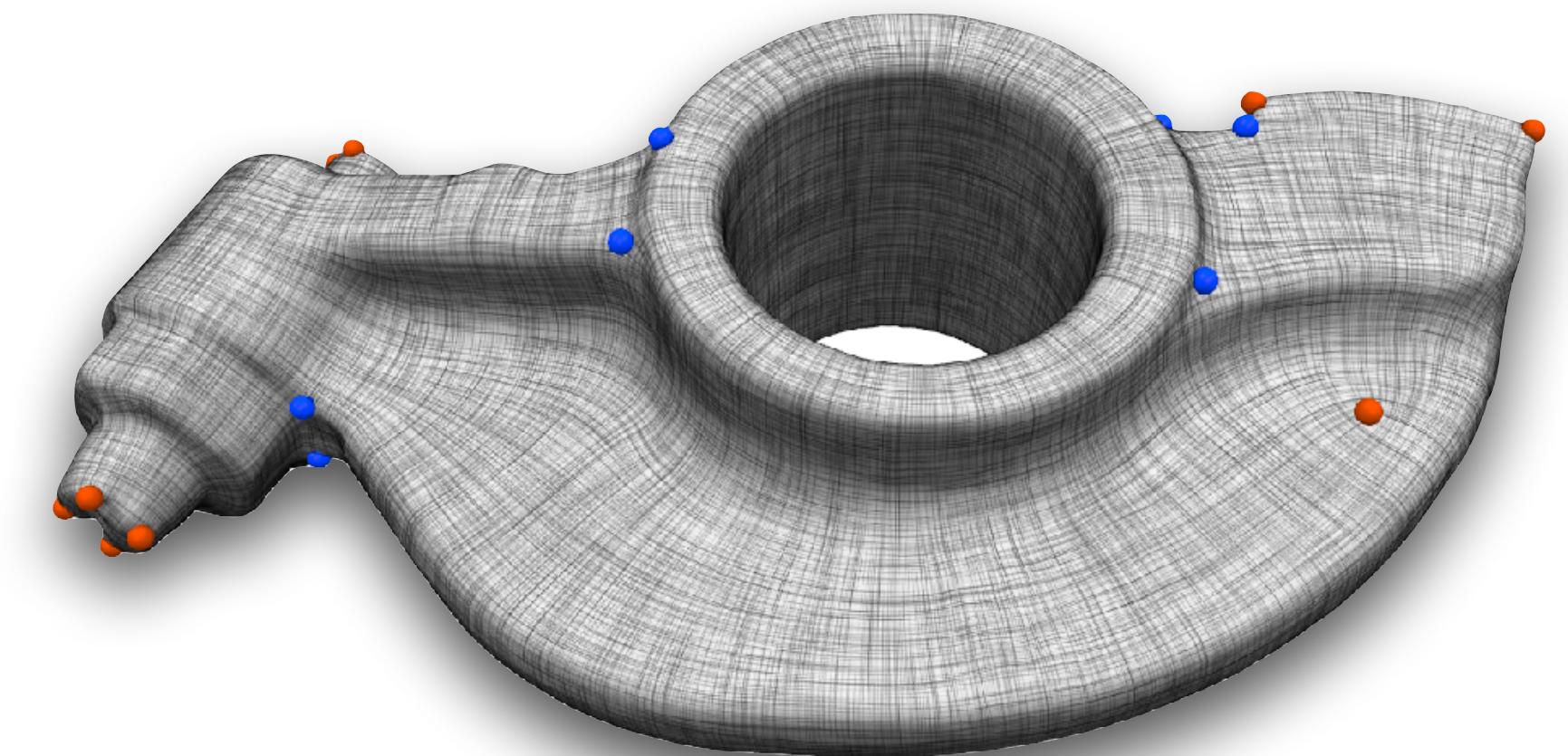
# Well Studied in the Continuum



Parallel Transport

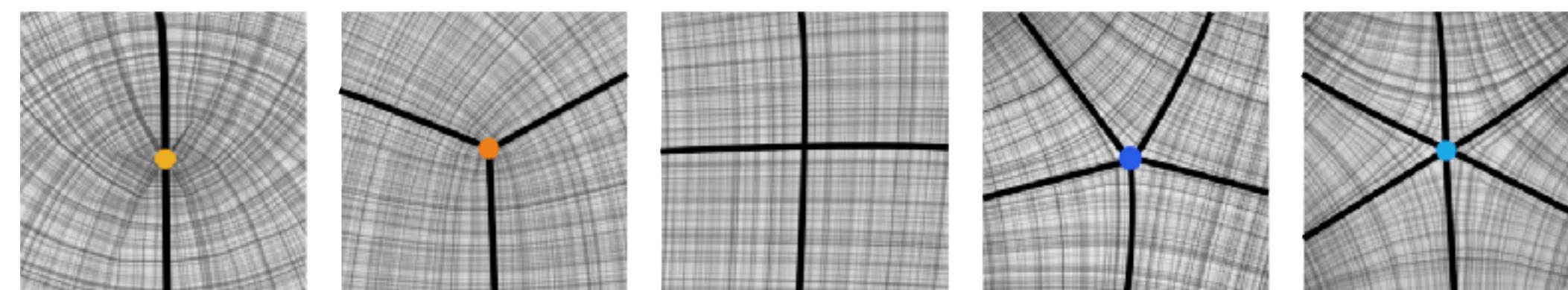


Holonomy



Poincare-Hopf Theorem

Singularities

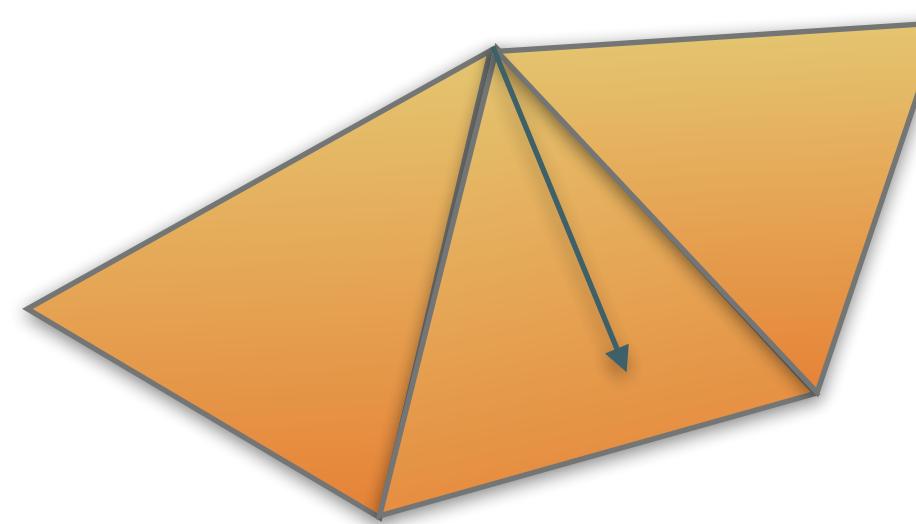


University  
of Victoria

Computer Science

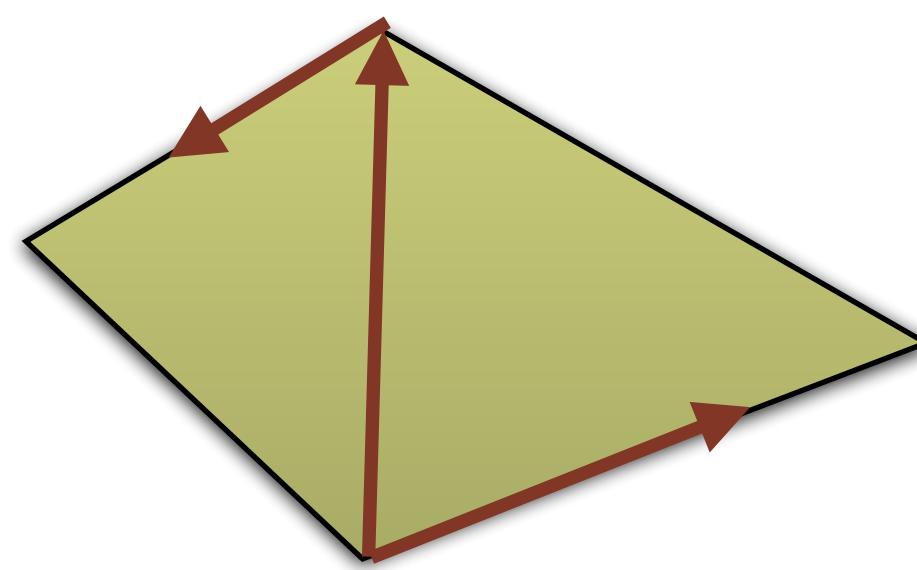
# Discretizations

Vertex based



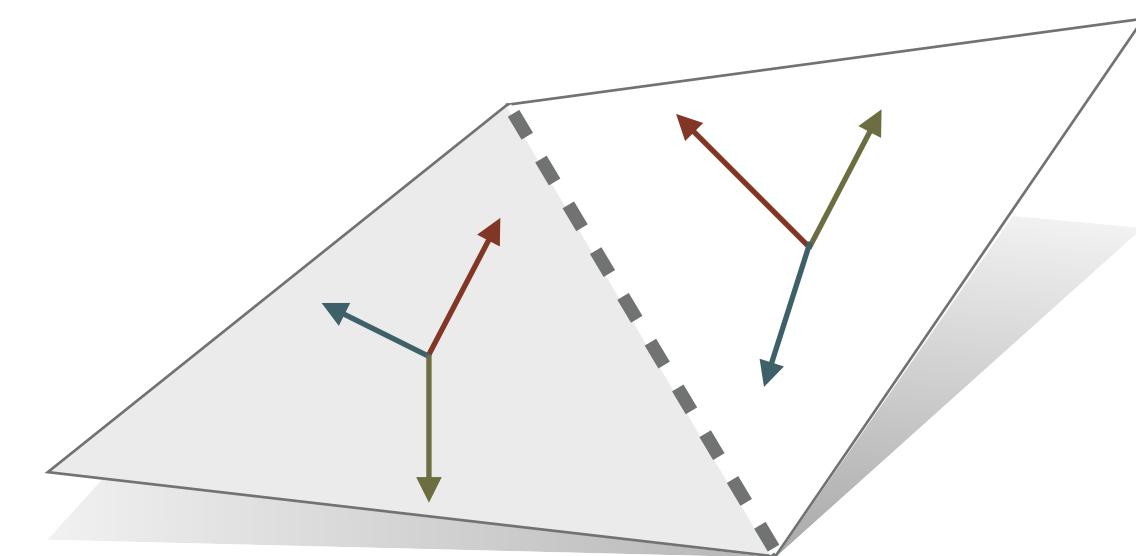
[Polthier and Schmies 98]  
[Zhang et al. 2006]  
[Knöppel et al. 2013]

Edge based



[Desbrun et al. 2005]  
[Fisher et al. 2007]  
[Ben-Chen et al. 2010]

Face based

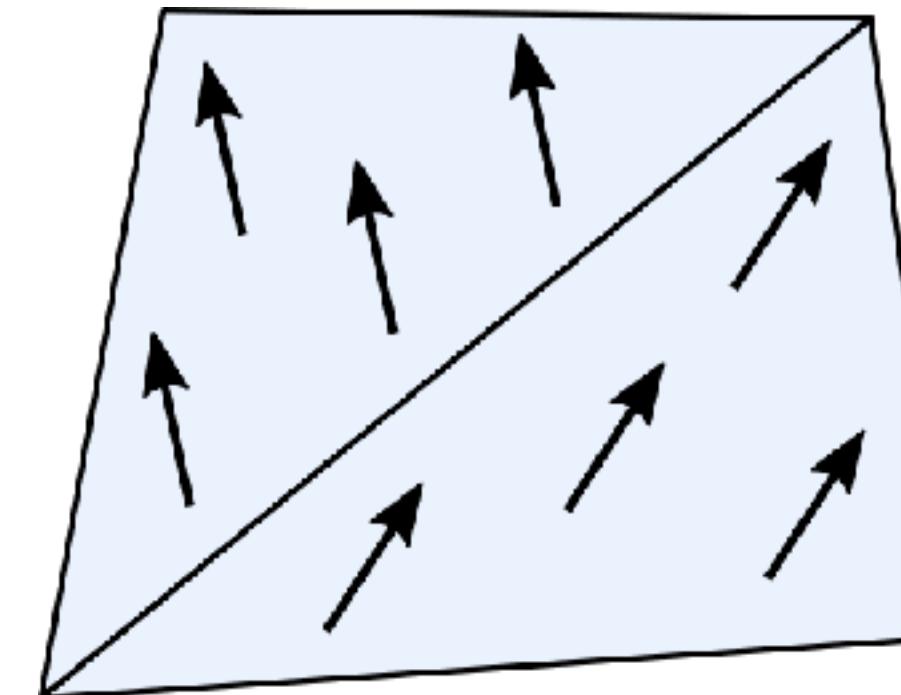


[Bommes et al. 2009]  
[Crane et al. 2010]  
[Diamanti et al. 2014]

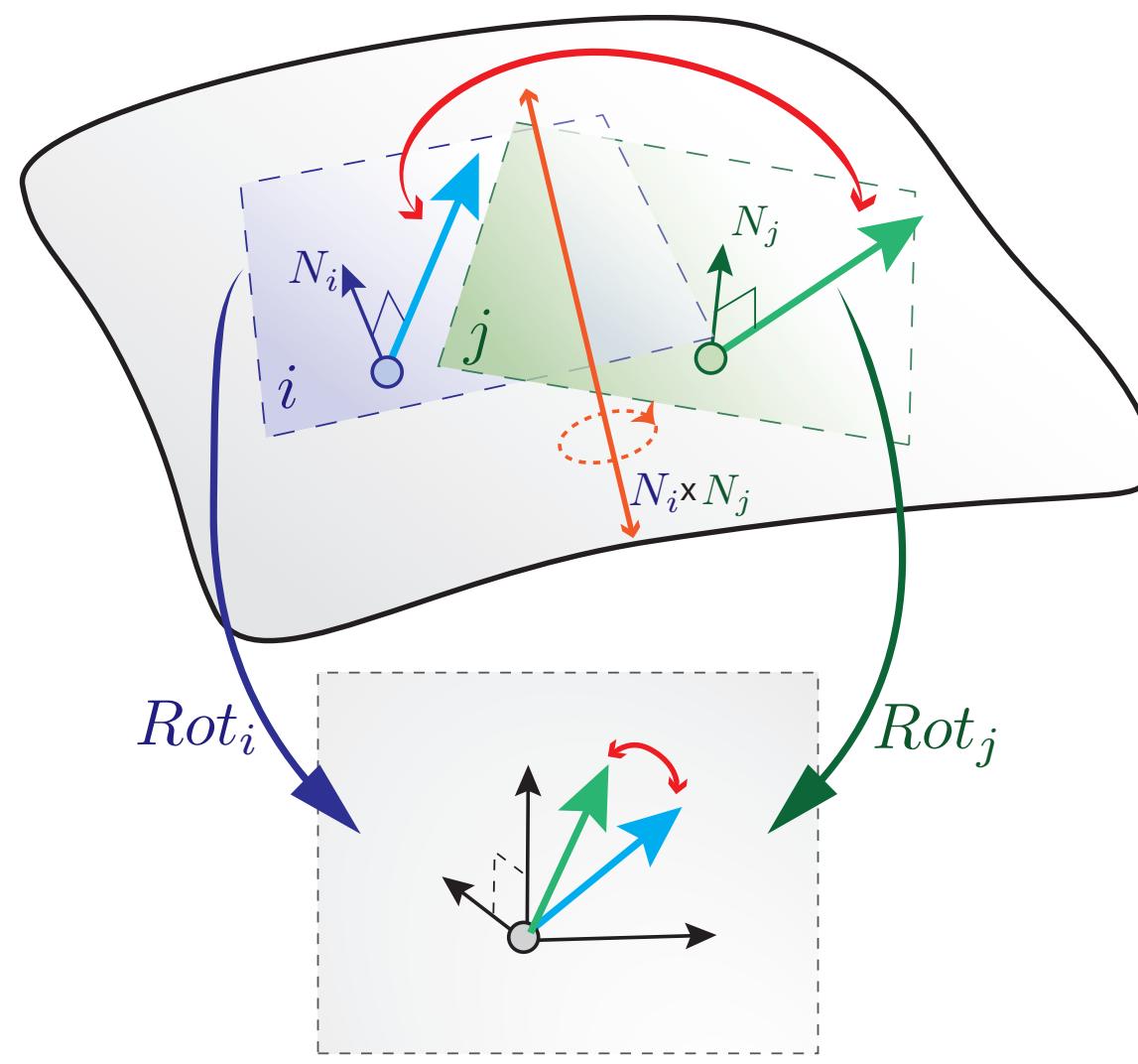
*Choice of tangent space and differential implications: see [deGoes et al. 2016].*

# Challenges in the Discrete Setting

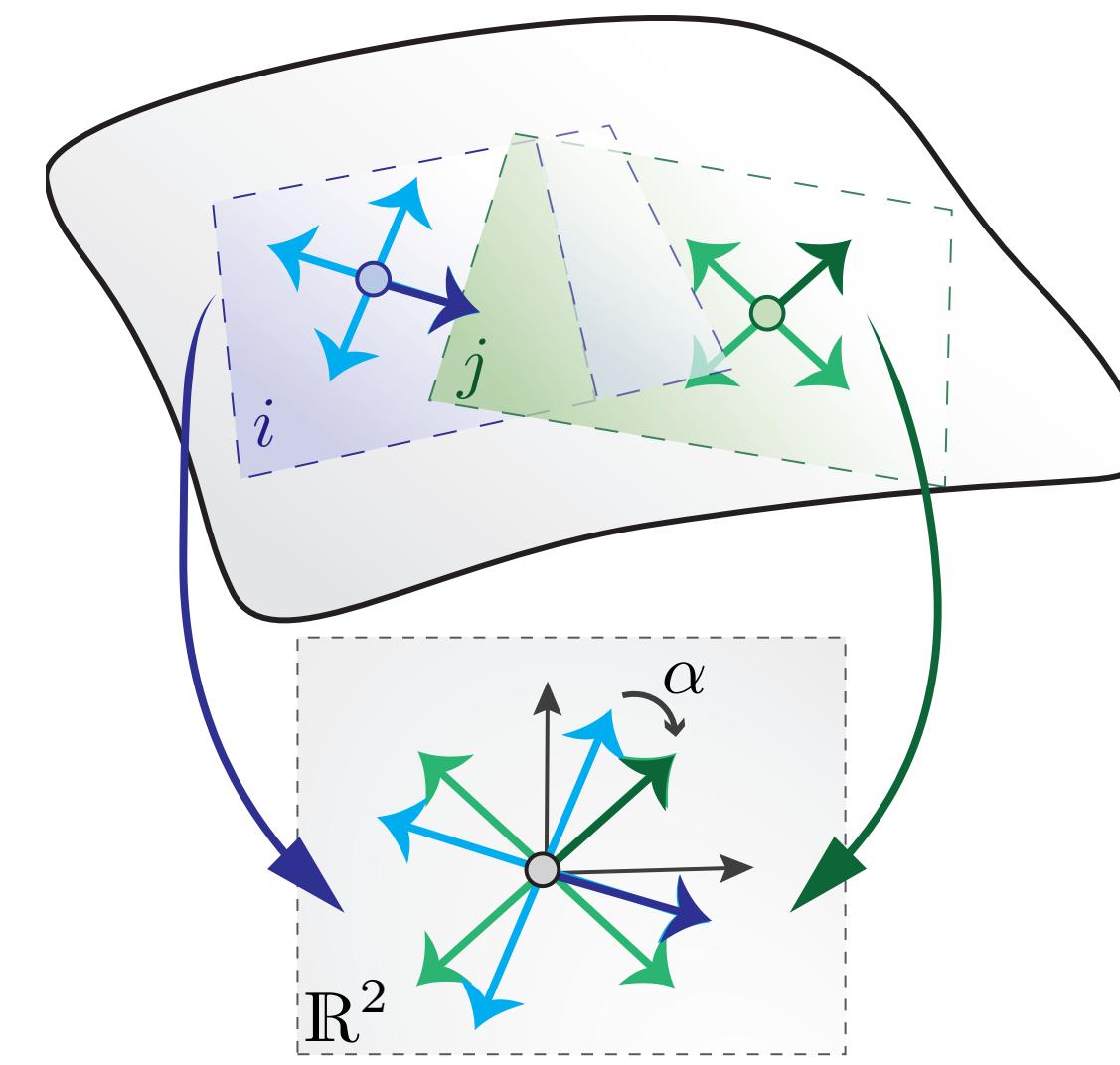
Discontinuity



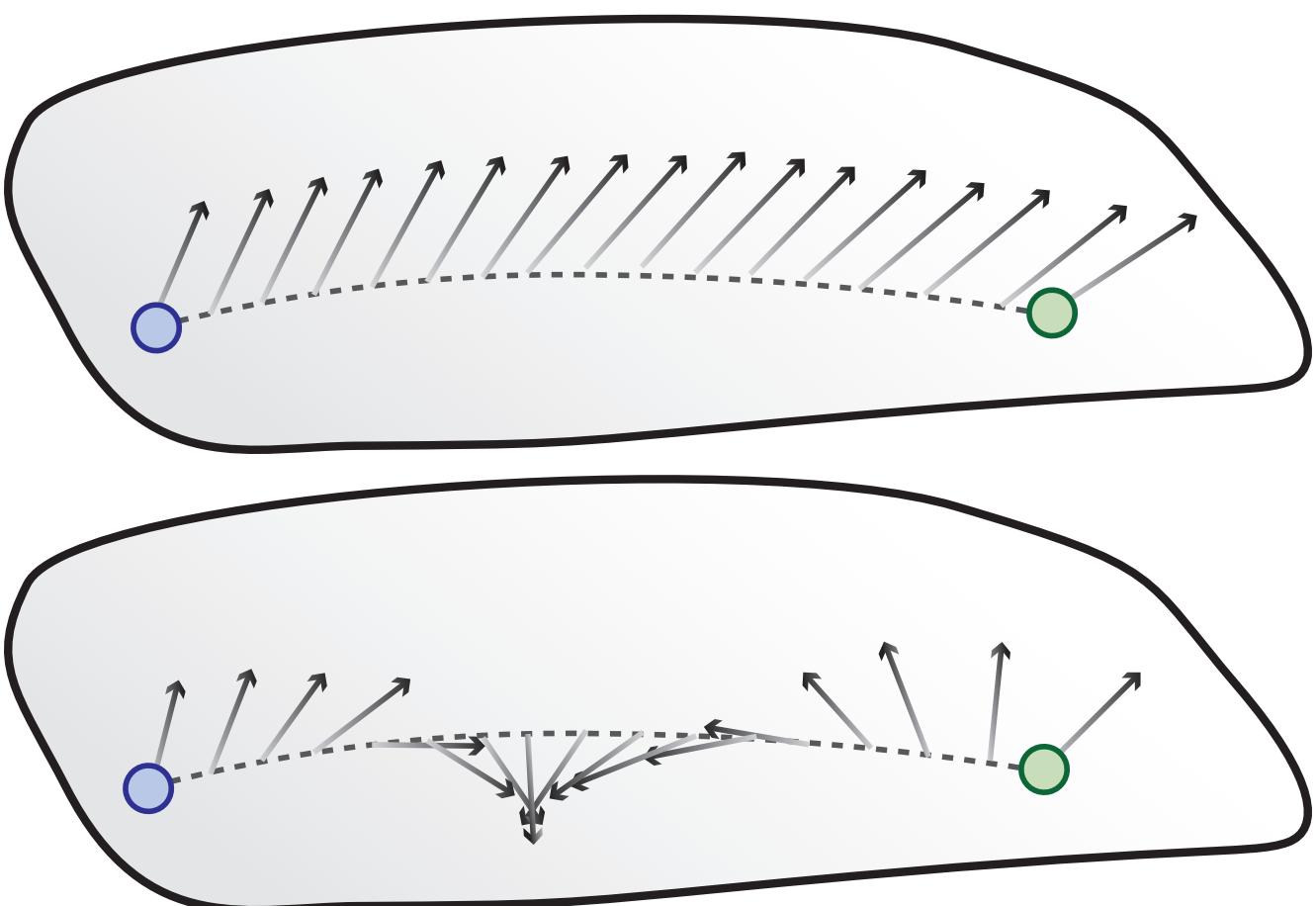
Connection



Matching



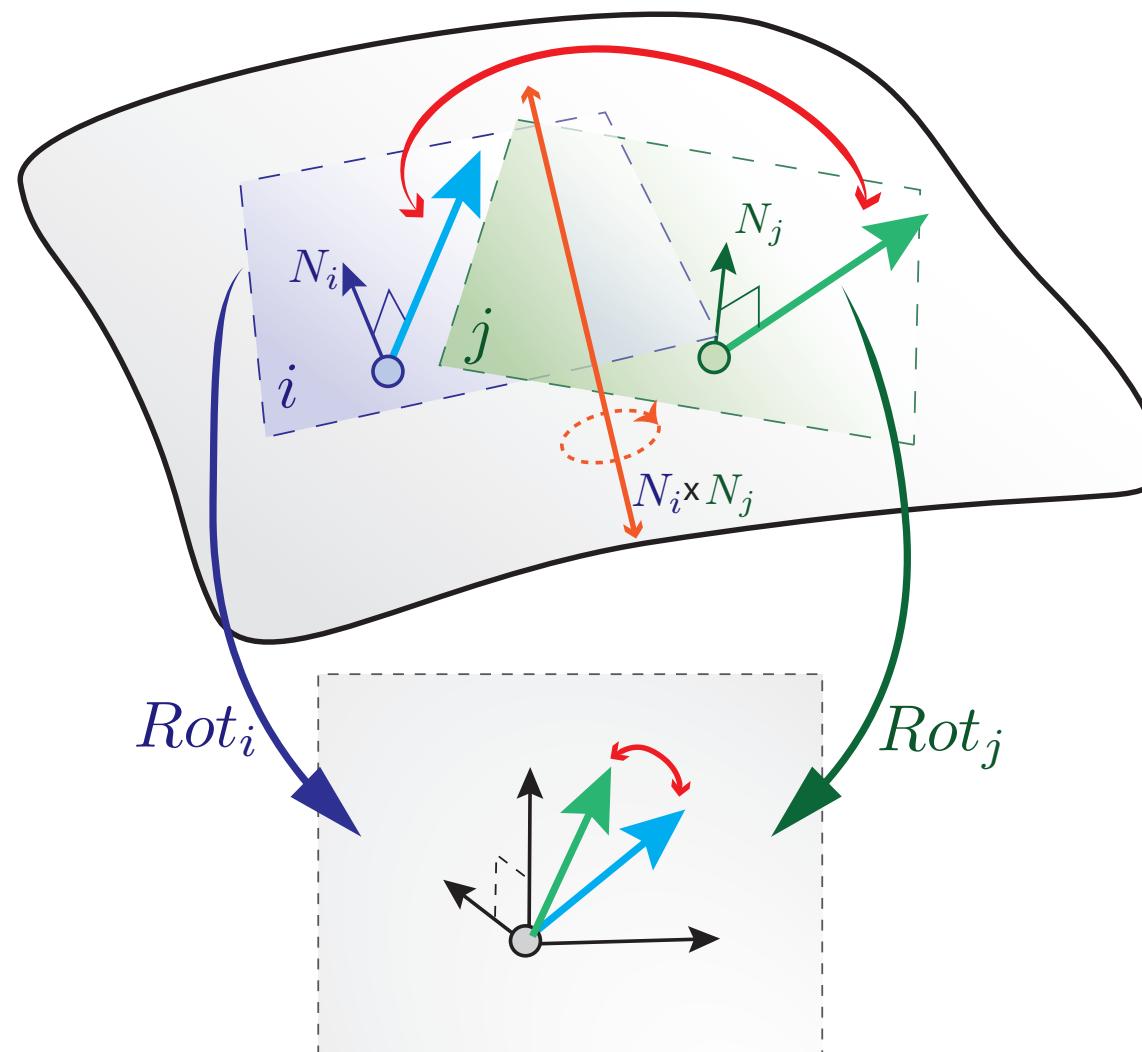
Interpolation



# Discrete Connection

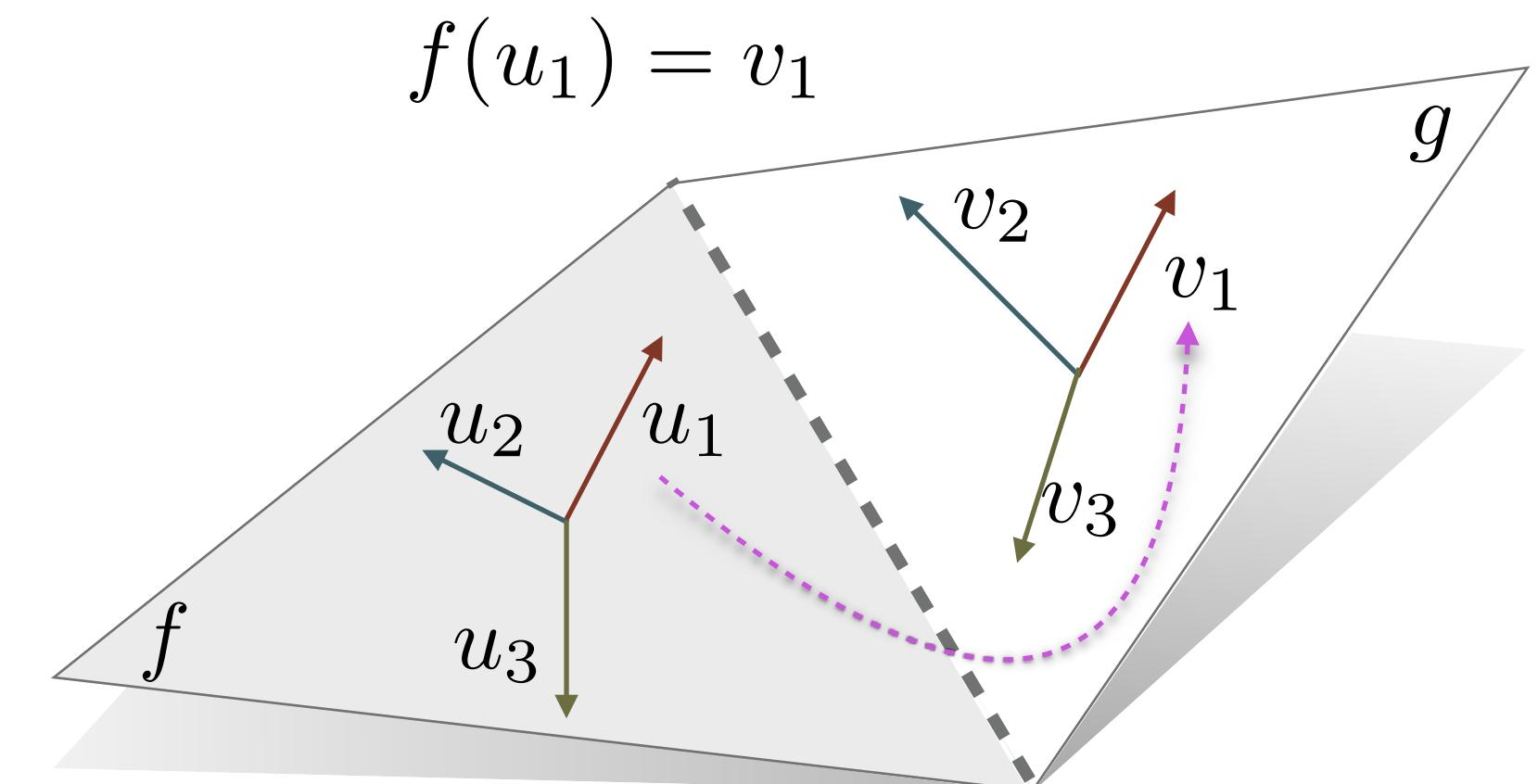
- Bijective linear map between adjacent tangent spaces.
- Popular choice: flattening

[Ray et al. 2008]  
[Crane et al. 2010]  
[Knöppel and Pinkall 2015]



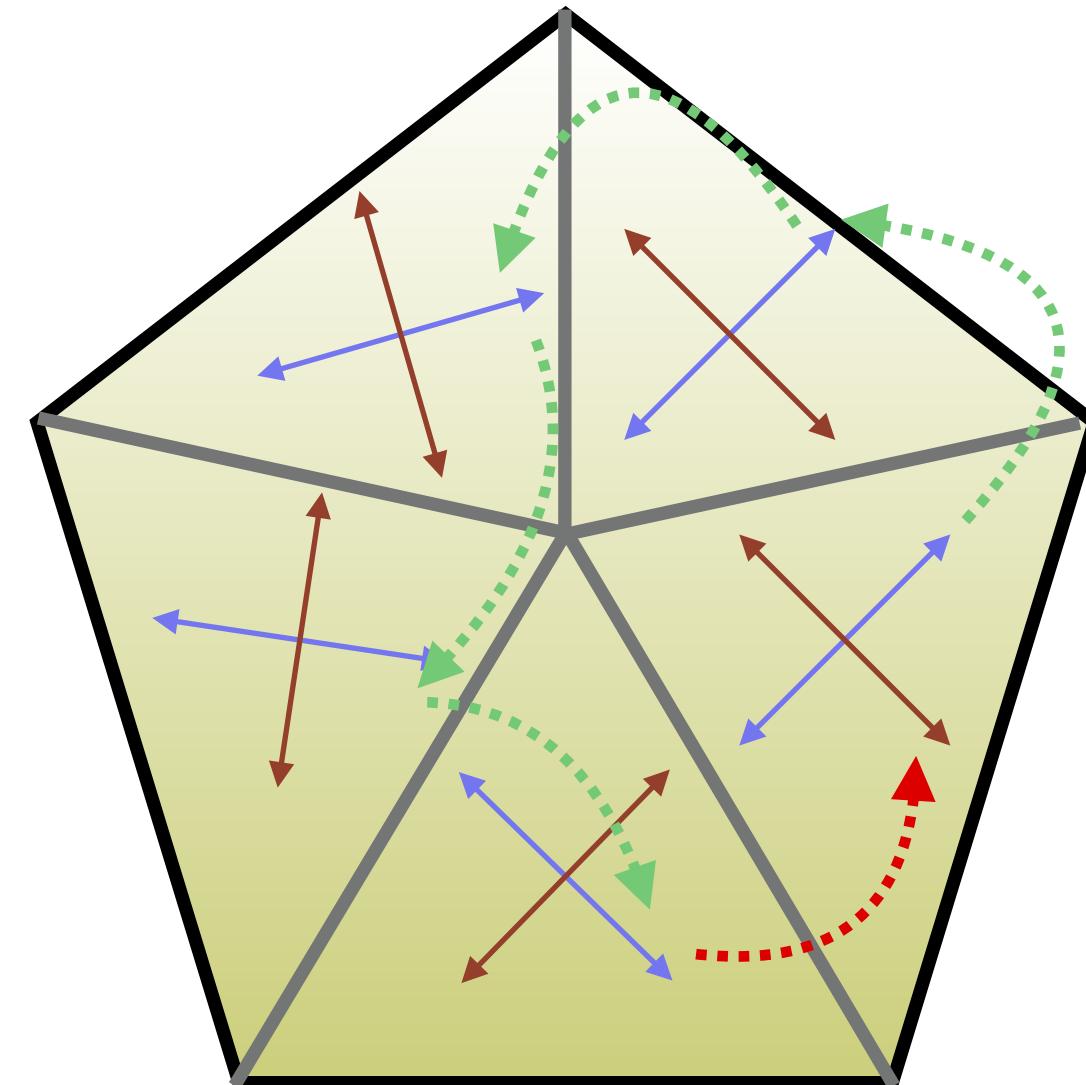
# Discrete Matching

- Which direction to which other?
- $N$ -directional:  $N$  possible choices.
  - How best to choose?



# Singularities

- Around a matching cycle, directional returns to itself.
  - Up to a different matching!



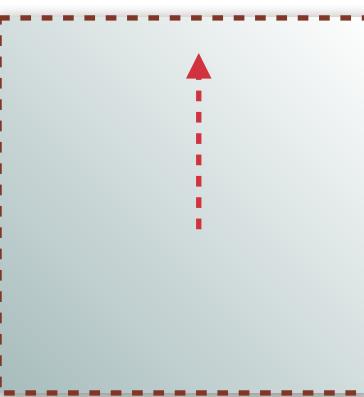
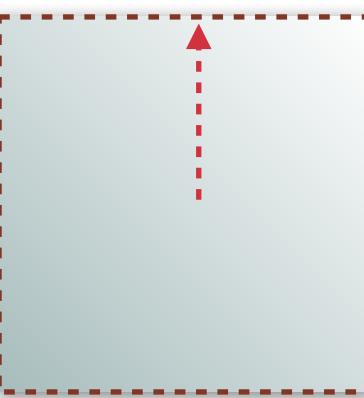
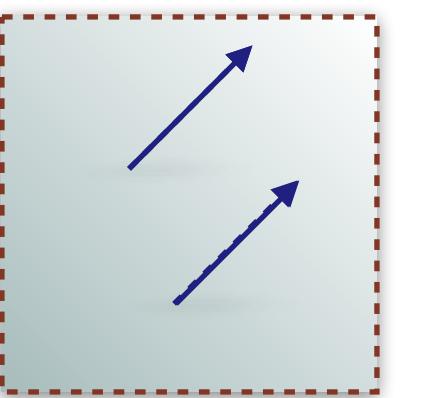
Index of singularity:  $\frac{1}{k}$

# Discrete Interpolation

- What happens in between?
  - Valid **rotation** choices:

$$\delta_{ij} = \frac{\pi}{4} + 2\pi k, k \in \mathbb{Z}$$

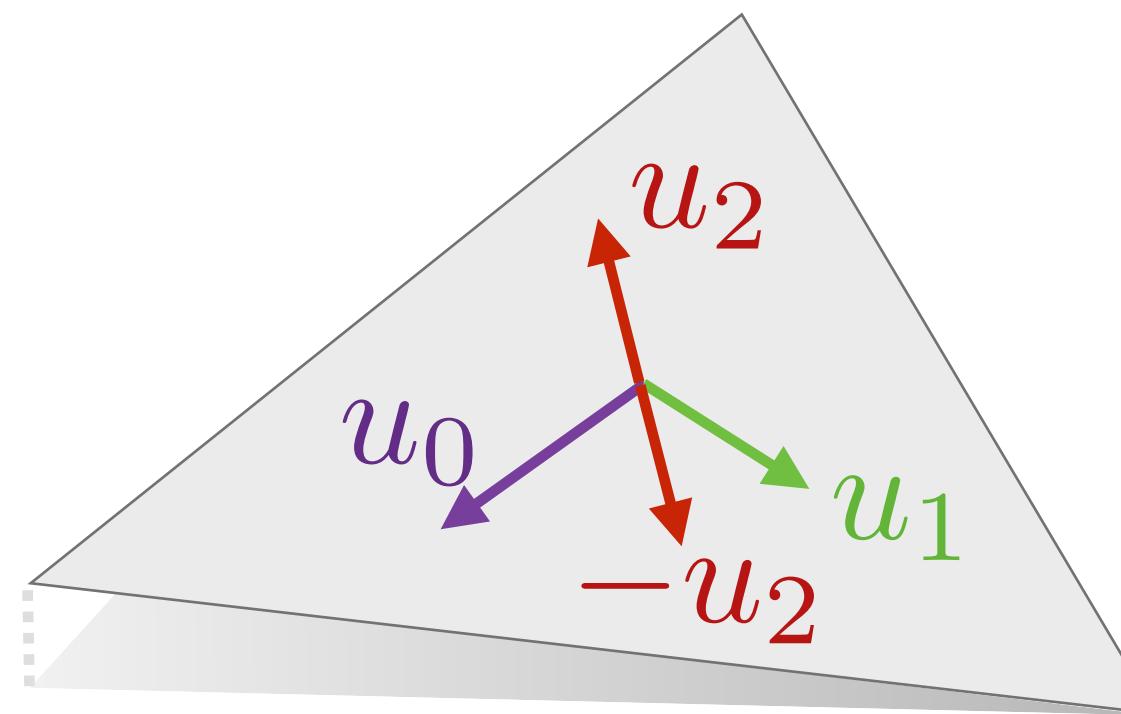
*Principal Rotation*      *Period Jump*  
[Li et al. 2006]



- Implicit: can only assume principal.
- Explicit: period given.

# Polyvector Representation

# N-PolyVectors



$$P(z) = (z - u_0)(z - u_1)(z^2 - u_2^2)$$

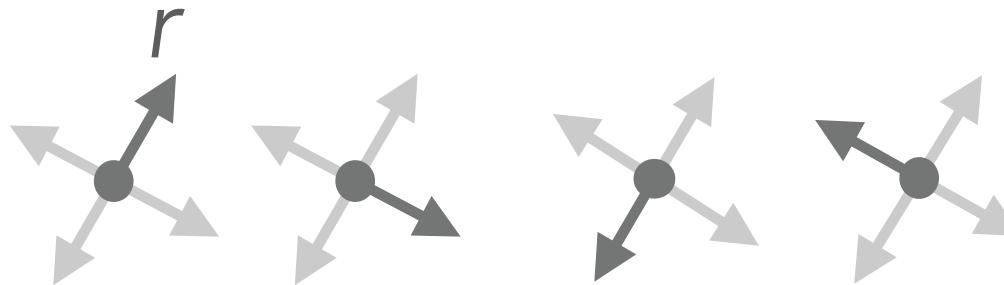
$$P(z) = z^4 - (u_0 + u_1)z^3 + (u_0 u_1 - u_2^2)z^2 + u_2^2(u_0 + u_1)z - u_0 u_1 u_2^2$$

order: 1                    order: 2                    order: 3                    order: 4

# N-vector fields

- Instead of representing the field with a 2D vector (complex number) we use a complex polynomial to represent a n-vector field.

$$p(z) = z^n - r^n$$



- Our new variable to interpolate is
- The transport slightly changes in
- The constraints need to be converted with
- To extract the field, we need to find the roots of  $p$

$$u = r^n$$

$$(u_f(\bar{e}_f)^n - u_g(\bar{e}_g)^n)^2$$

$$u = r^n$$

# Roots of a complex polynomial - companion matrix

- The roots of a polynomial in the form

$$p(t) = c_0 + c_1 t + \cdots + c_{n-1} t^{n-1} + t^n$$

- are the eigenvalues of the corresponding companion matrix

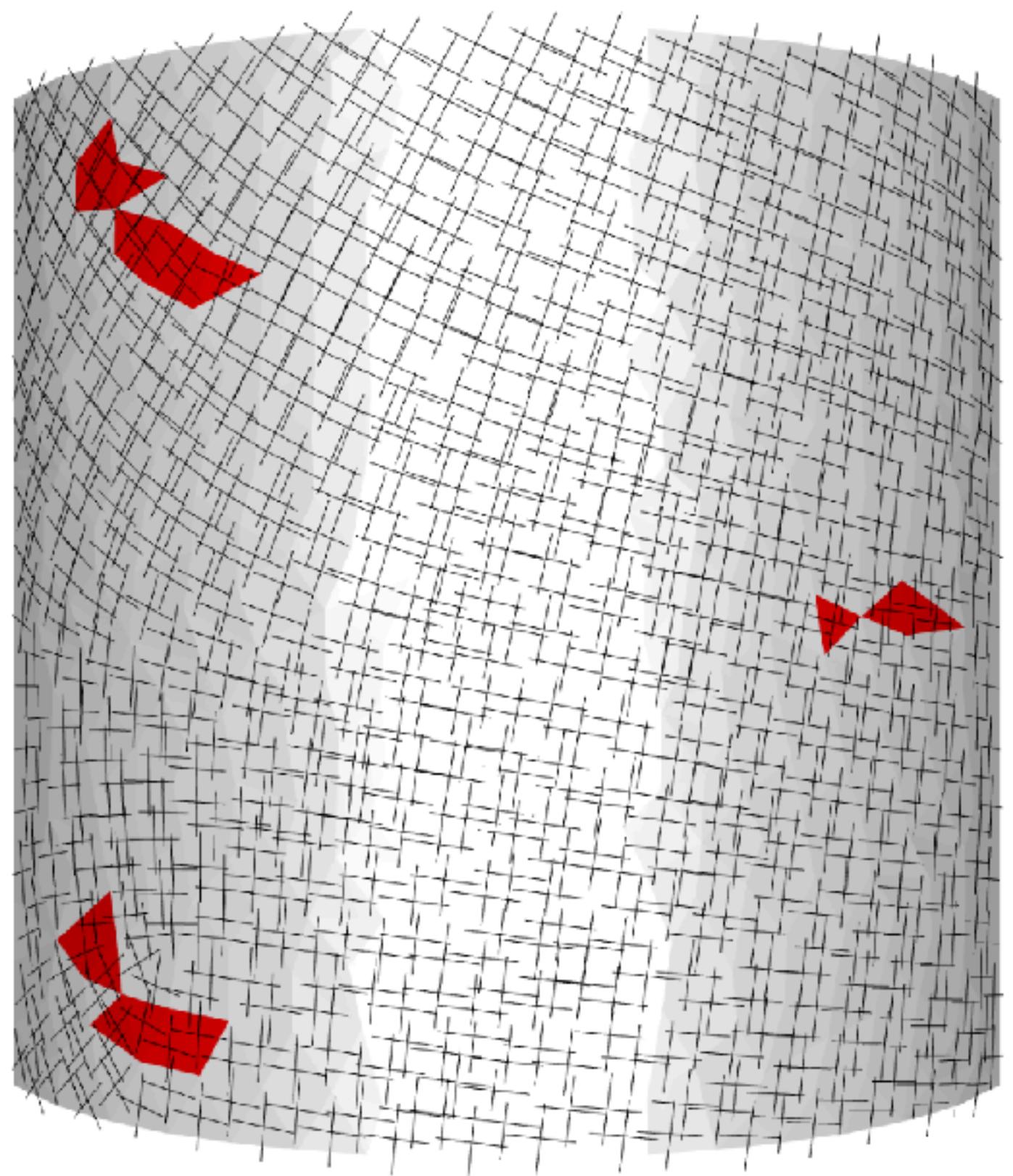
$$C(p) = \begin{bmatrix} 0 & 0 & \dots & 0 & -c_0 \\ 1 & 0 & \dots & 0 & -c_1 \\ 0 & 1 & \dots & 0 & -c_2 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \dots & 1 & -c_{n-1} \end{bmatrix}.$$

```
def find_root(c0,n):
    M = np.zeros((n,n),dtype=complex)
    for i in range(1,n):
        M[i,i-1] = 1.0
    M[0,n-1] = c0
    w, v = np.linalg.eig(M)
    return w[0]
```

- For more information: [https://en.wikipedia.org/wiki/Companion\\_matrix](https://en.wikipedia.org/wiki/Companion_matrix)

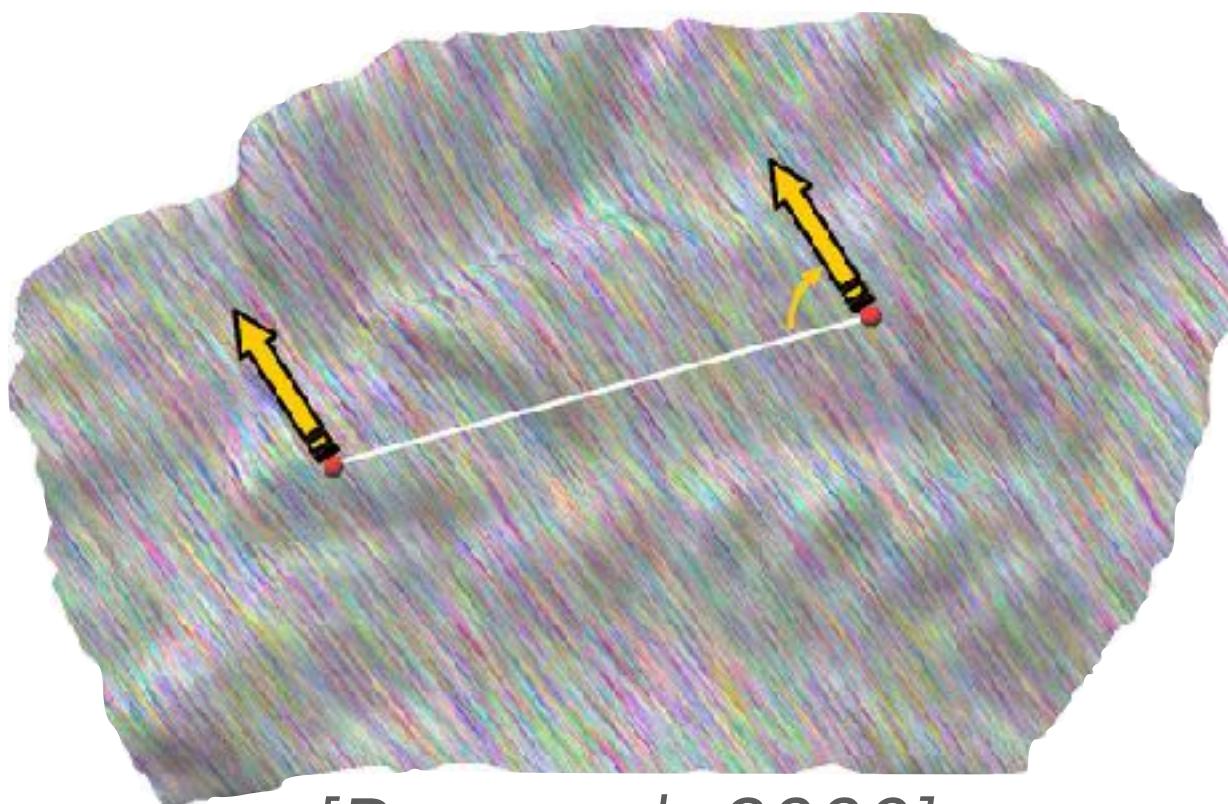
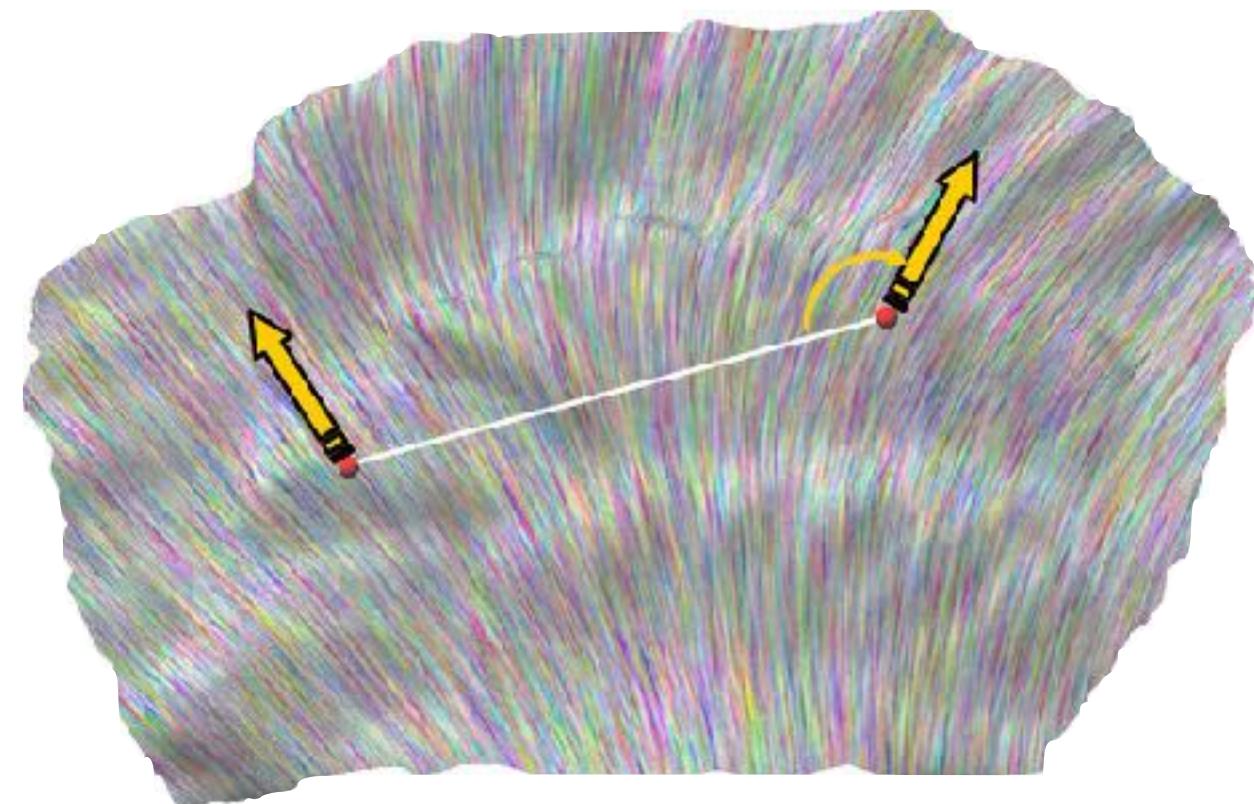
# Polyvector Demo

```
In [6]: R = align_field(v, f, tt, cf, c, 1e6, 4)
plot_mesh_field(v, f, R, cf, 4)
```

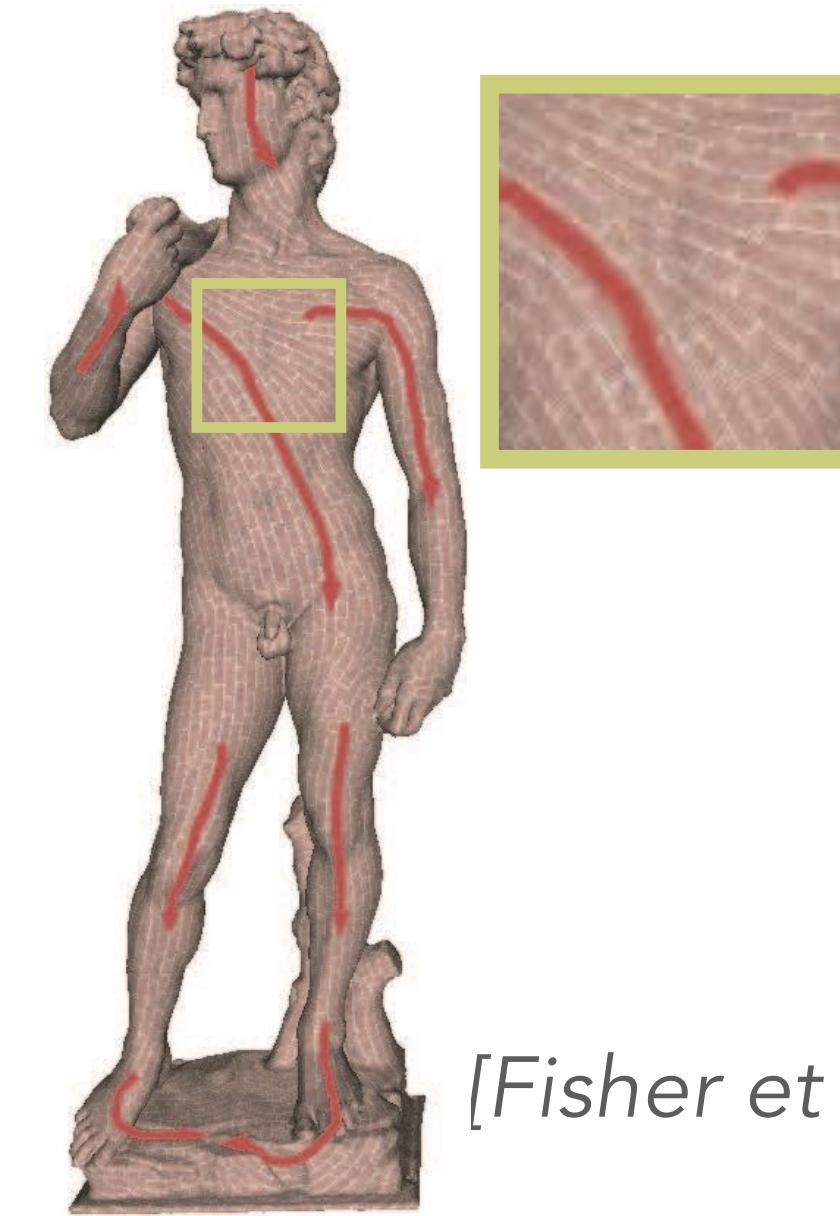


# Constraints

# Constraints - Alignment



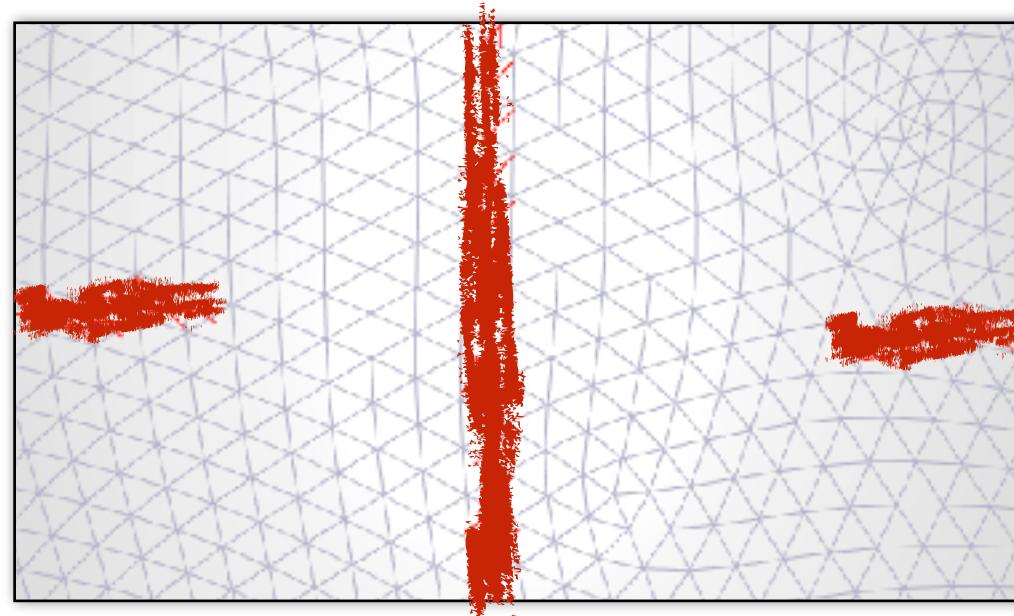
[Ray et al. 2008]



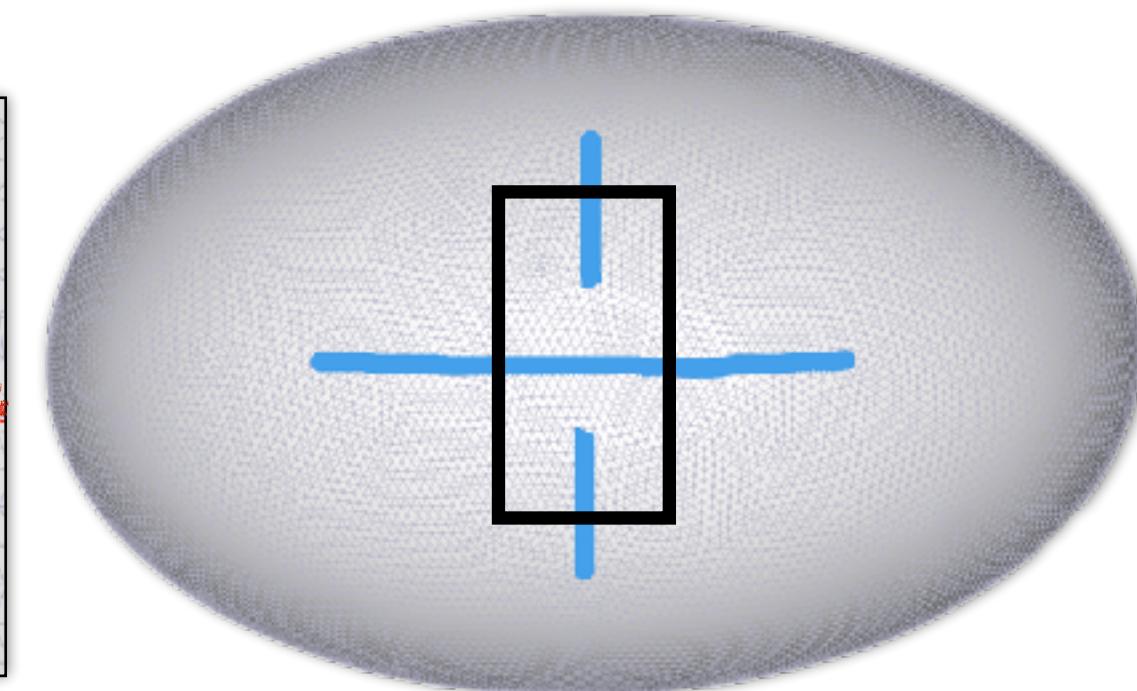
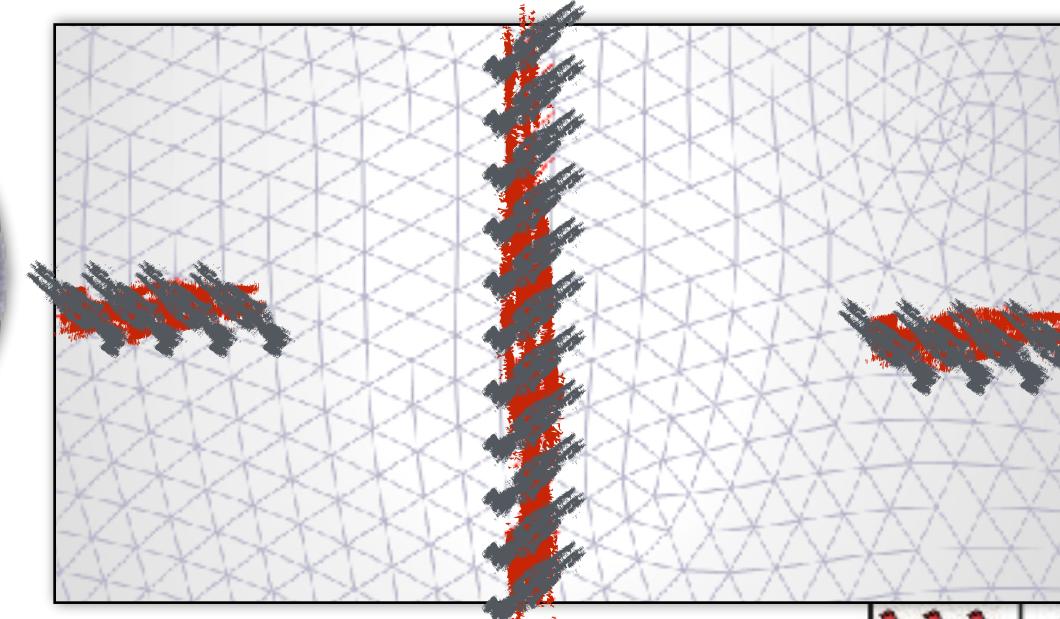
[Fisher et al. 2007]

- Complete or Partial

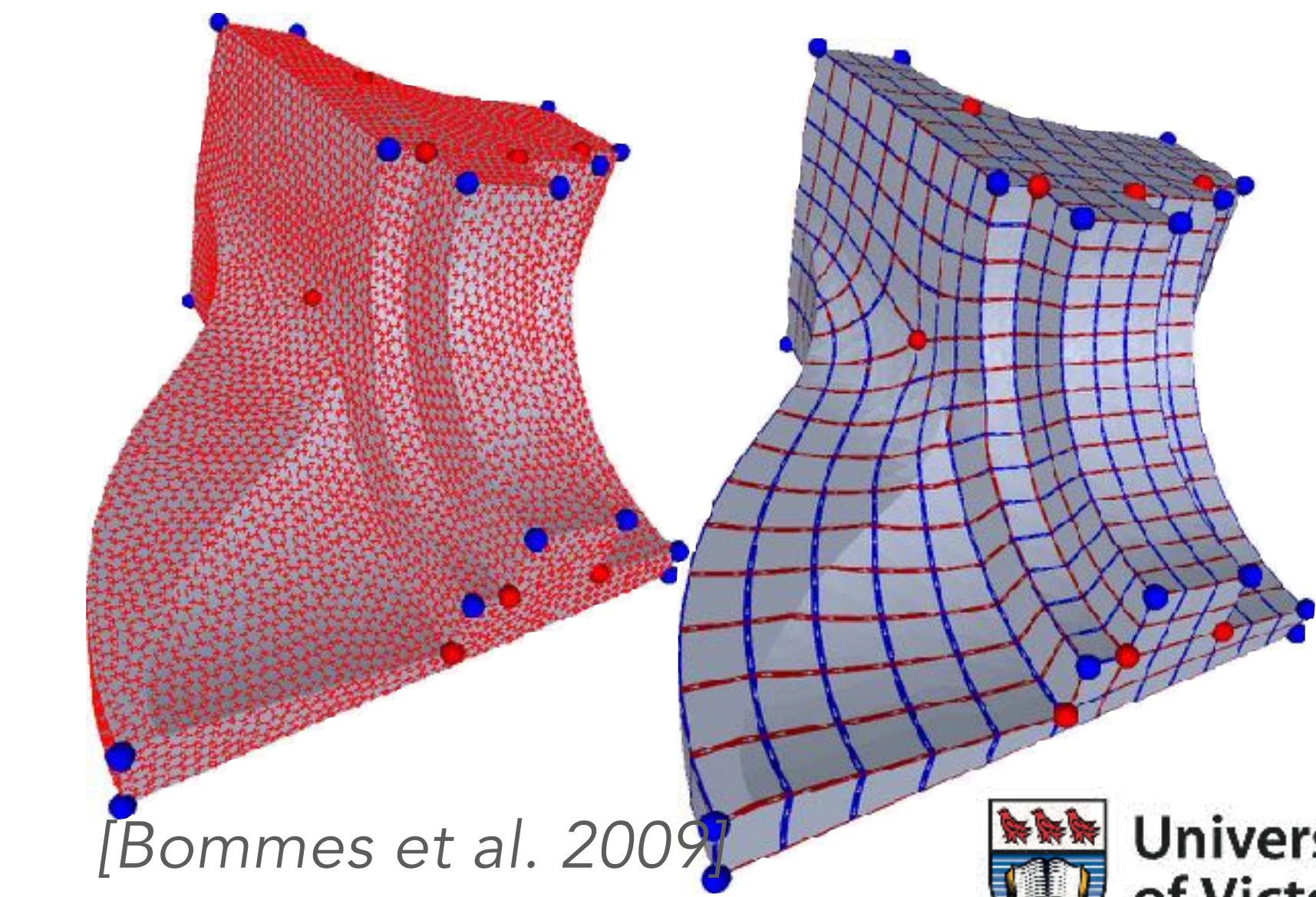
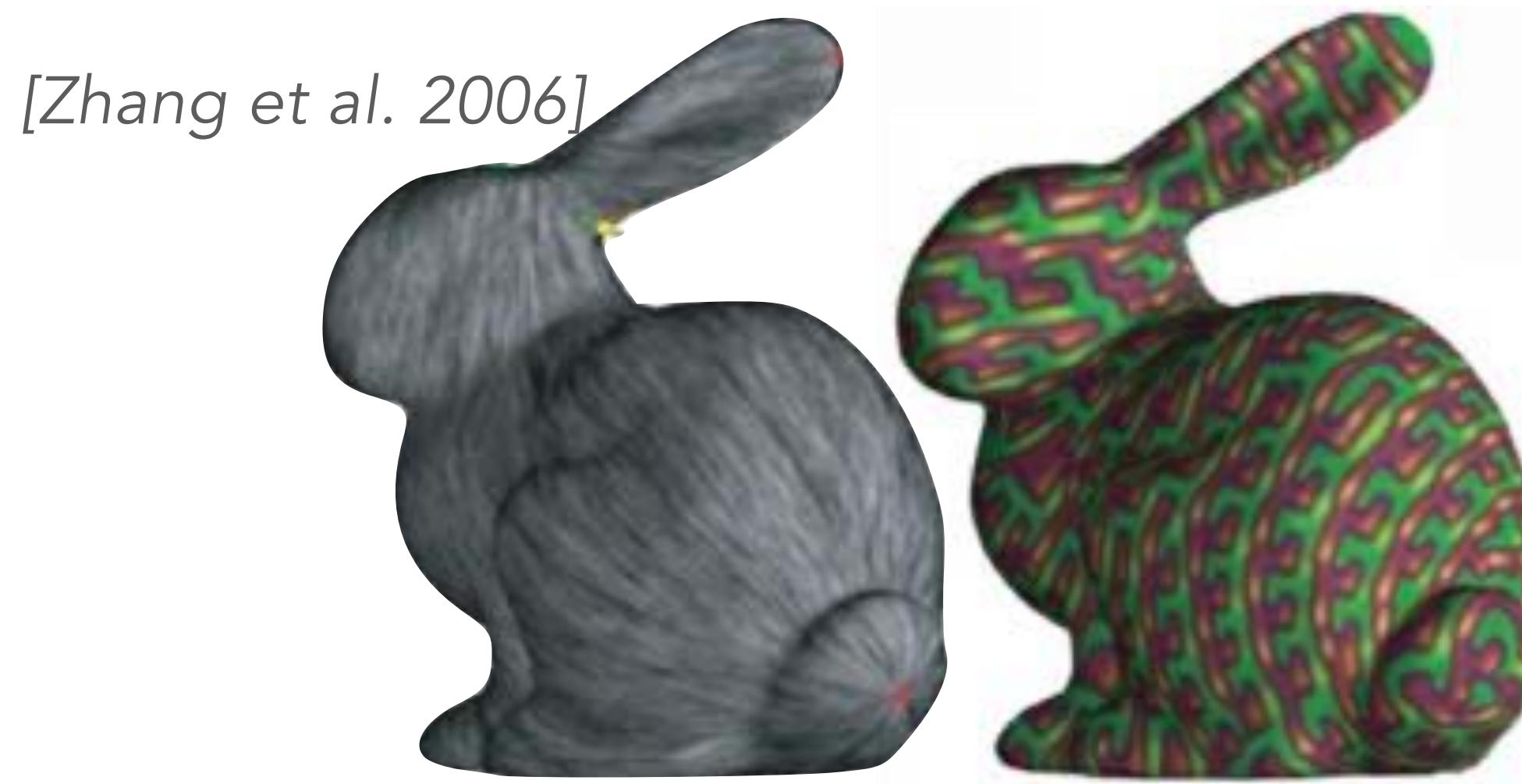
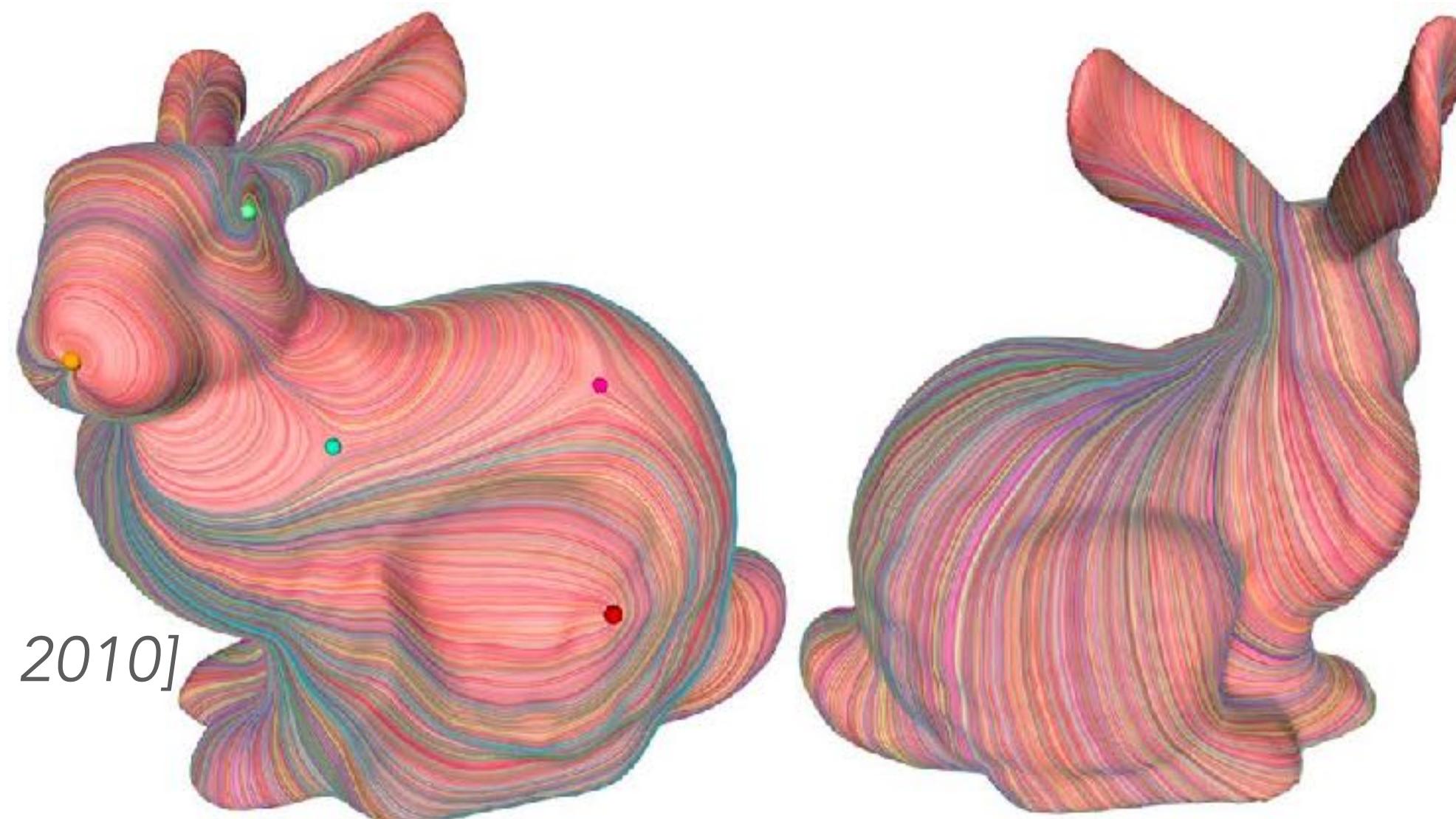
*partial constraints*



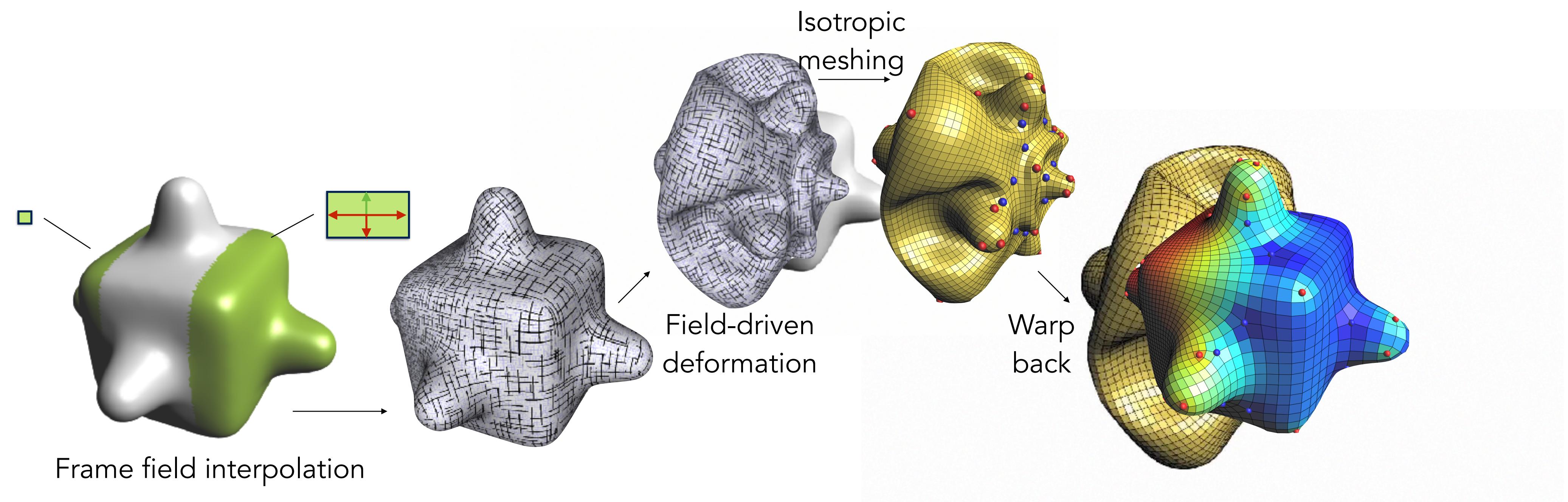
*full constraints*



# Constraints - Topology

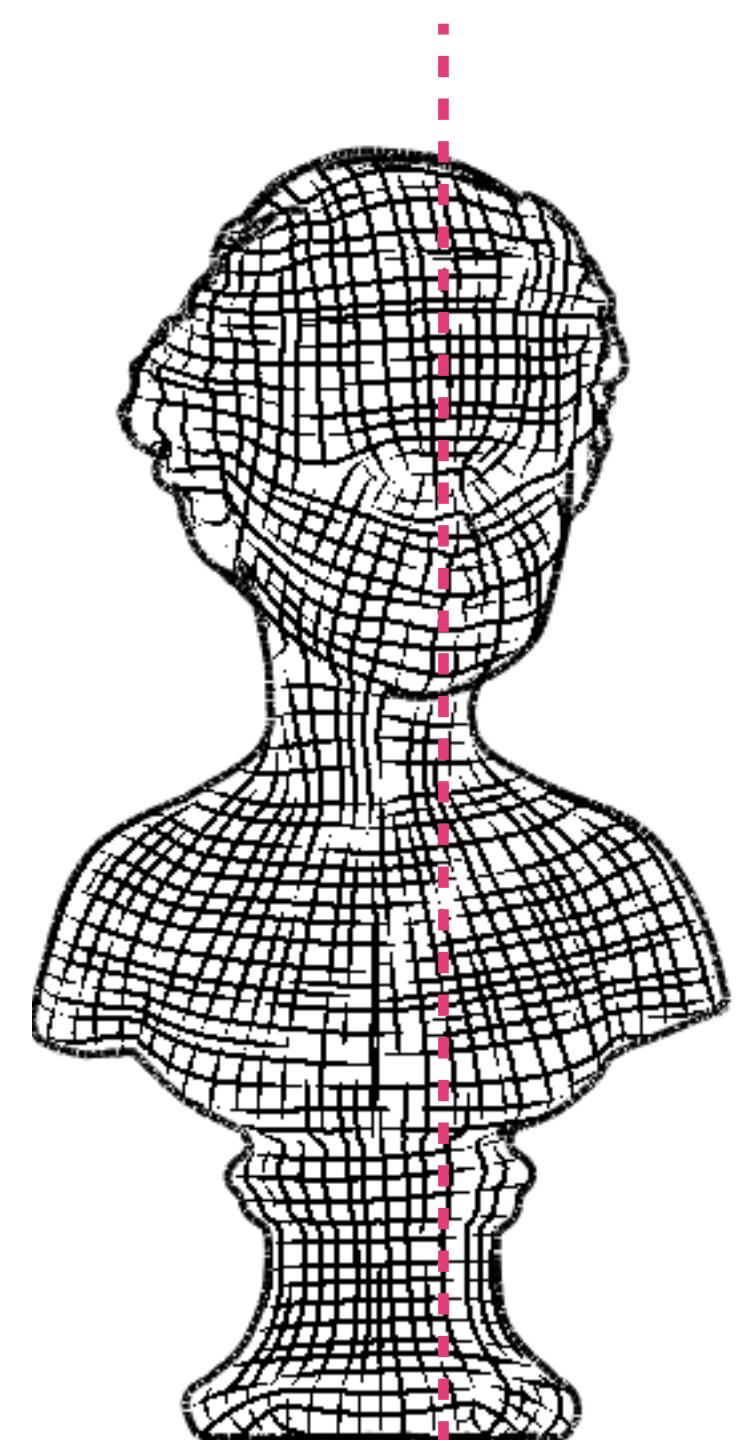


# Constraints - Scale



[Panozzo et al. 2014]

# Constraints - SYMMETRY

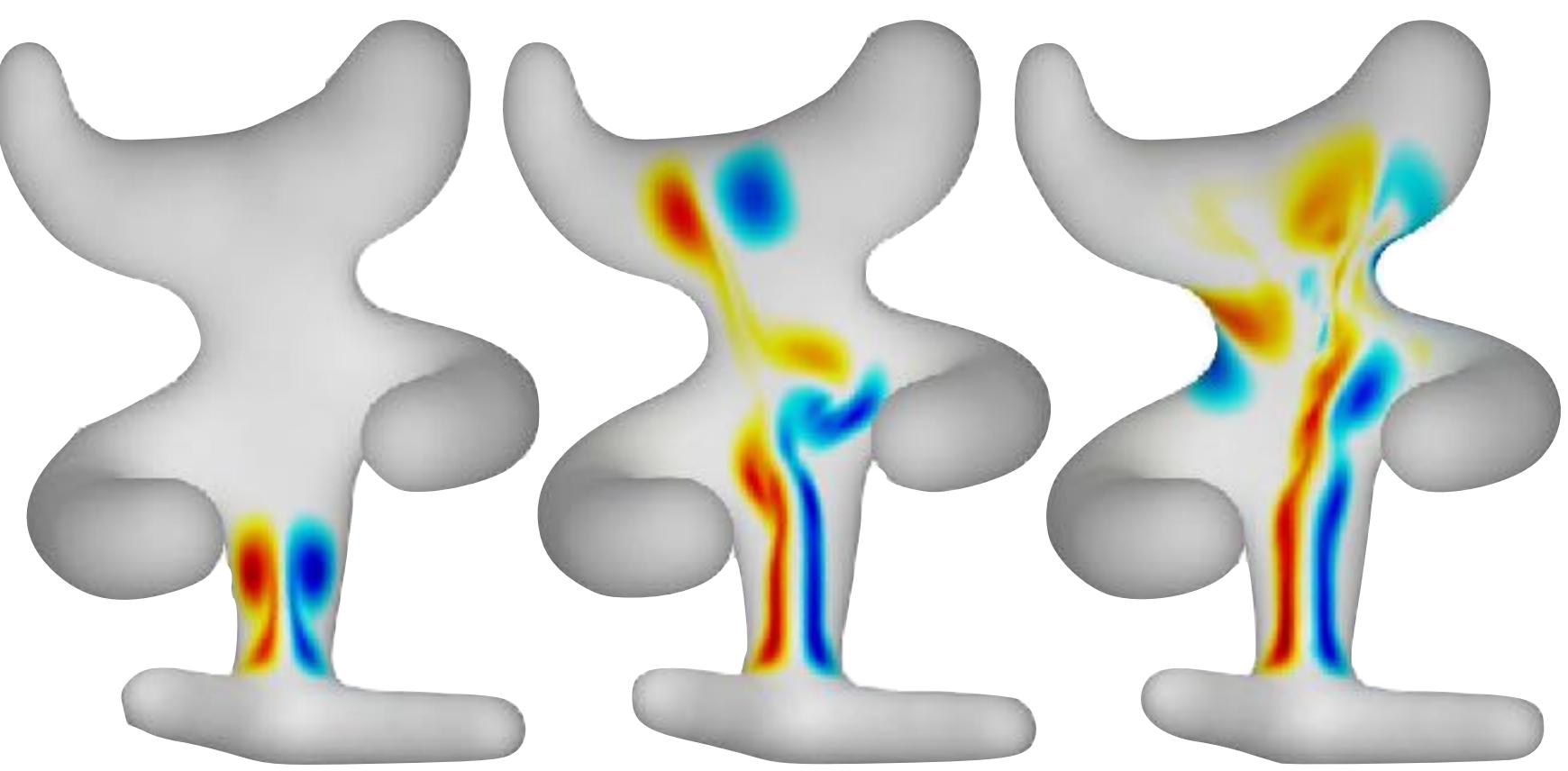
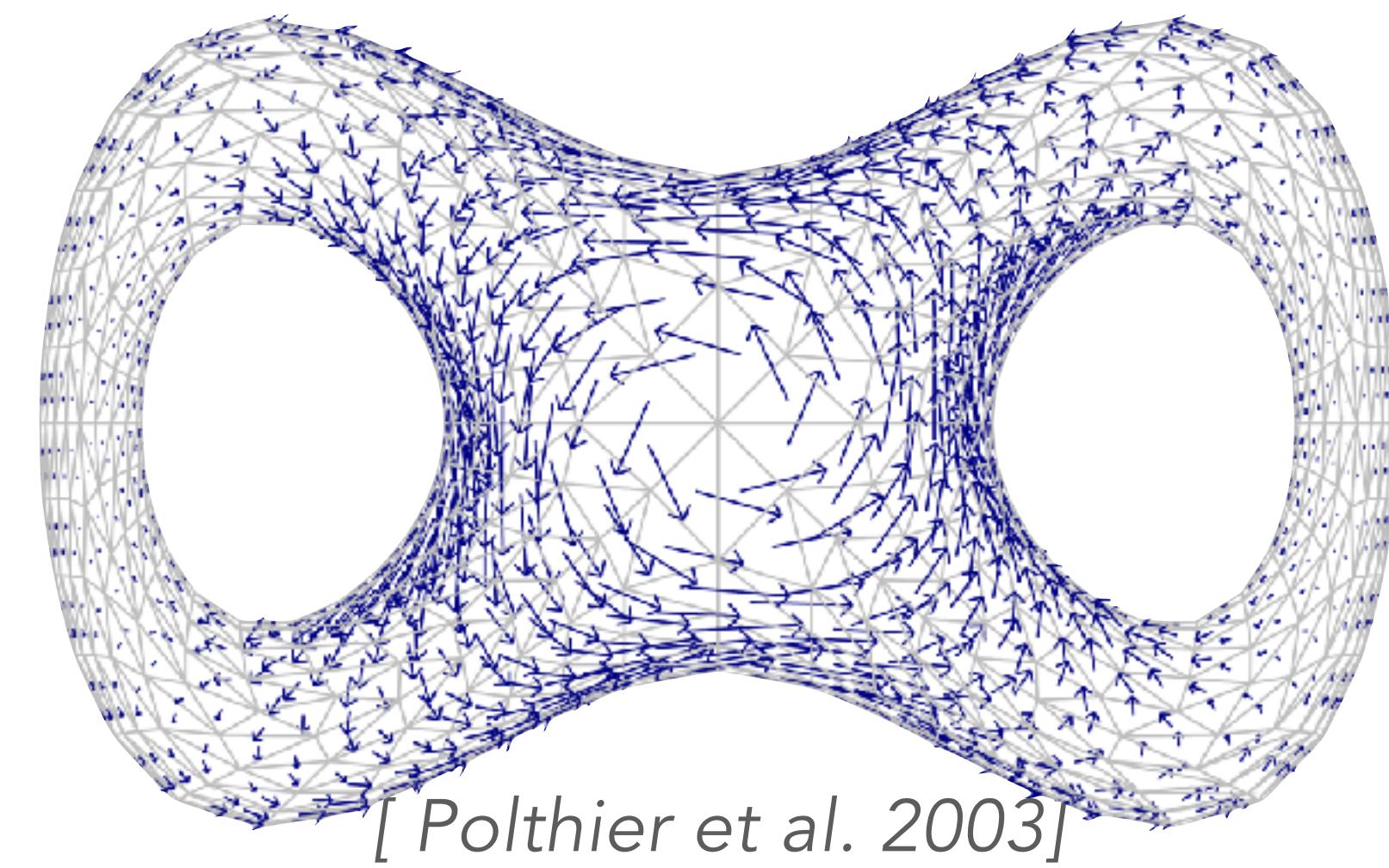
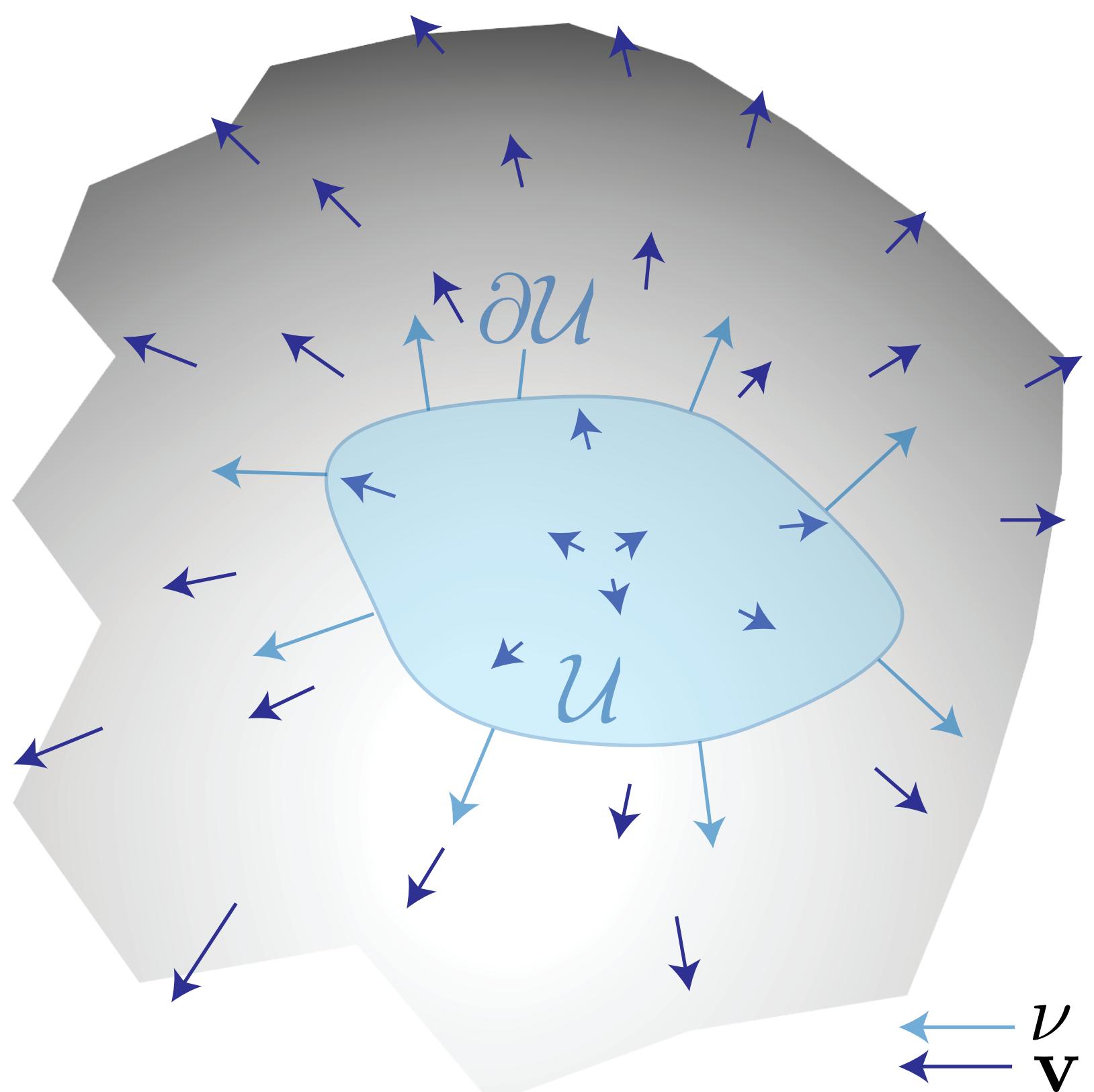


[ Panizzo et al. 2012]



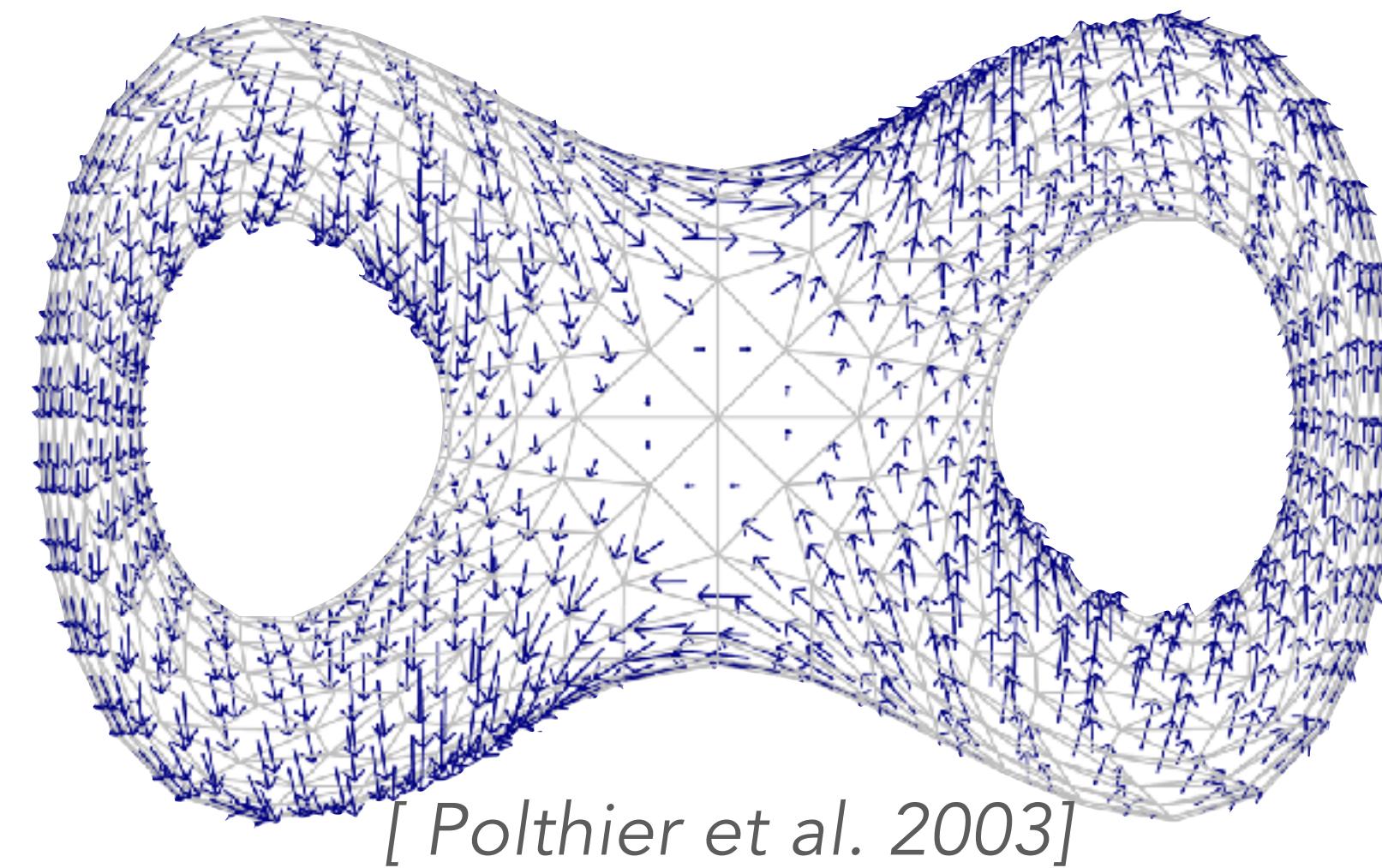
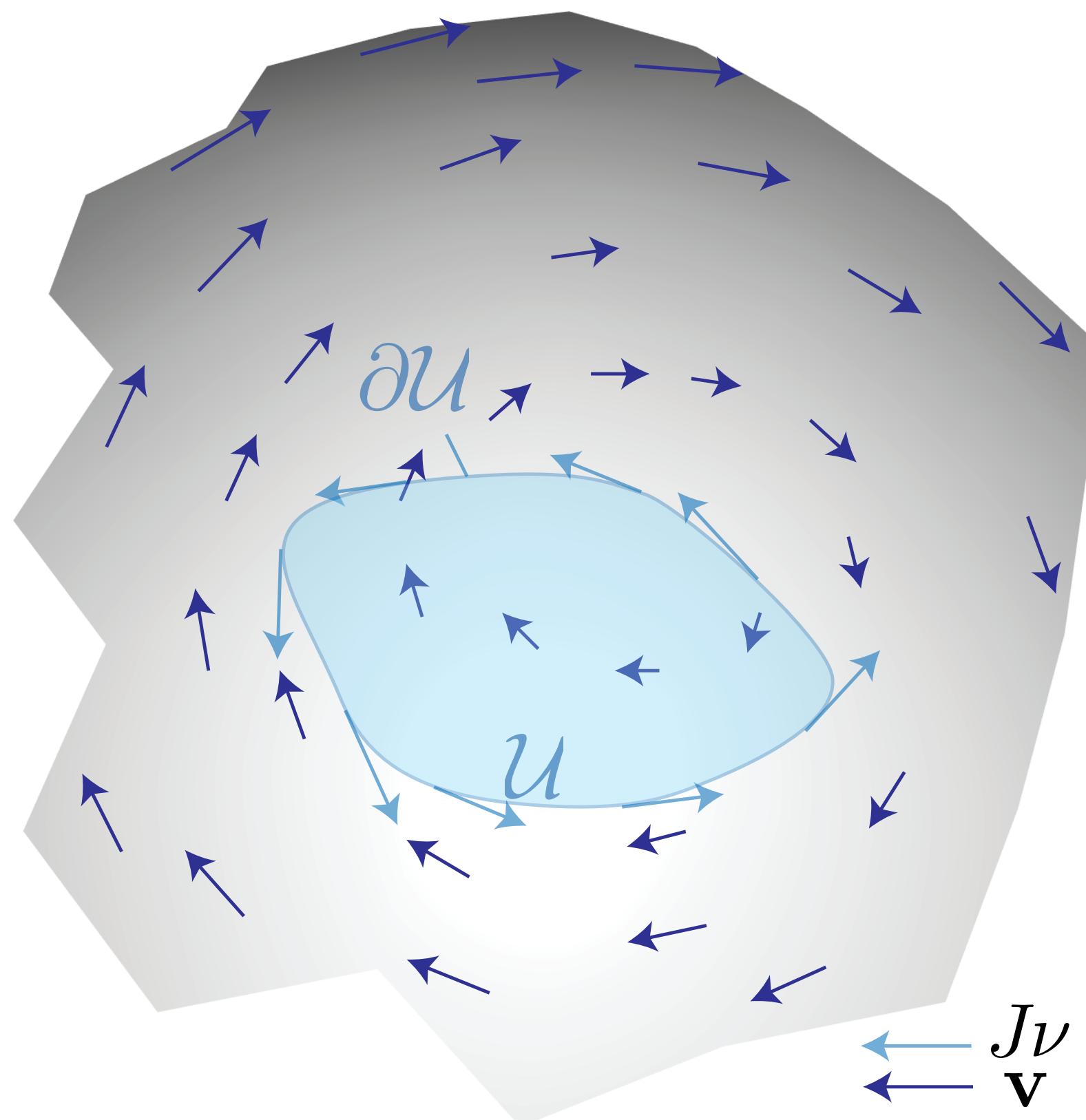
[ Azencot et al. 2013]

# Constraints - Differential - Divergence

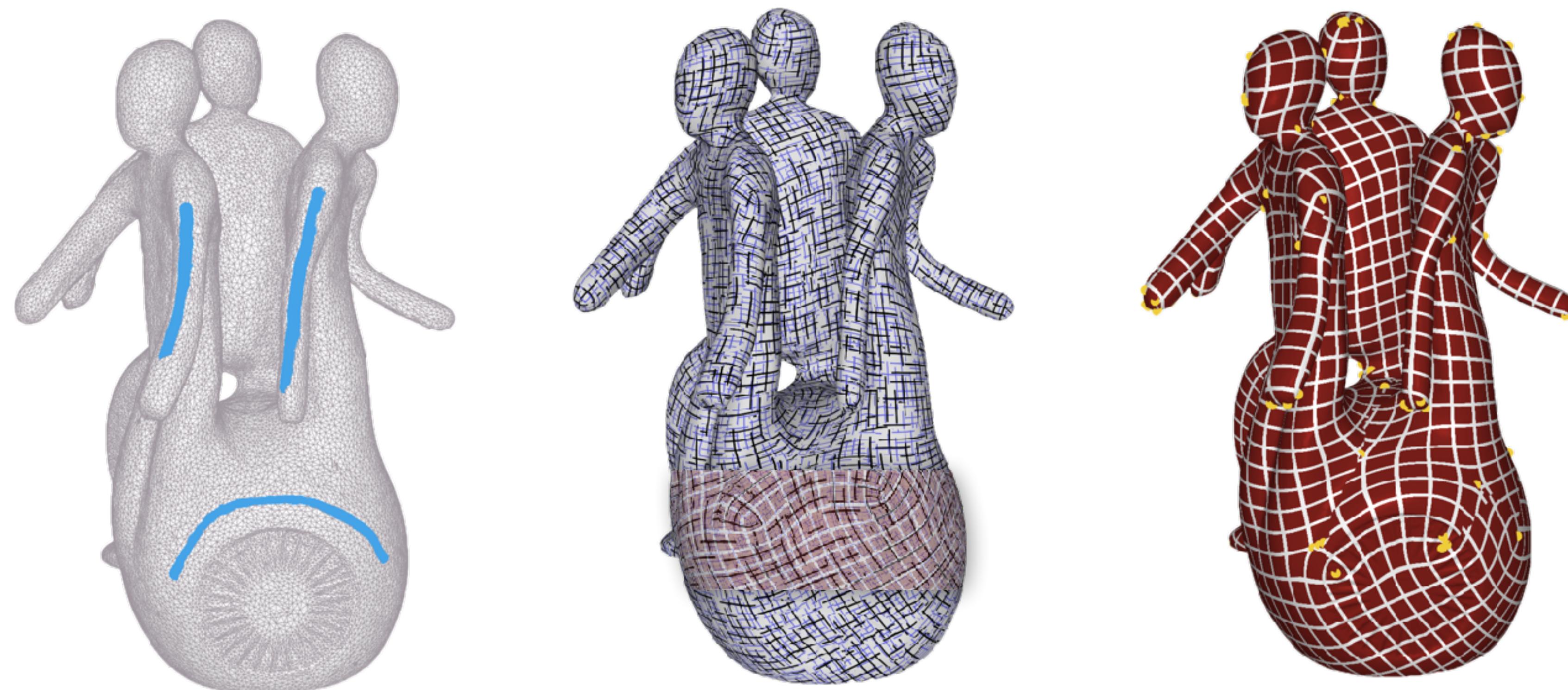


[Azencot et al. 2014]

# Constraints - Differential - curl



# Constraints - Differential - curl



[ Diamanti et al. 2015]

# Remarks

- We implemented a simple but powerful algorithm to design vector and polyvector fields
- You will need this algorithm for the next assignment. You can copy this code but you will have to implement hard constraints instead of soft ones
- A lot more information on this topic is available at:  
<https://github.com/avaxman/DirectionalFieldSynthesis>
- Takeaway: You now know how to process scalar and directional fields on surfaces!

# References

- [github.com/avaxman/DirectionalFieldSynthesis](https://github.com/avaxman/DirectionalFieldSynthesis)