Computational Design of Metamaterials

Pengbin Tang





SGP 2025 Graduate School

Outline Today

- Introduction to Computational Design of Metamaterials
- Computational Models
 - Rigid Body, Finite Element Method, Discrete Elastic Rods
- Numerical Homogenization
- Case Study1: Mechanical Characterization
 - Discrete Interlocking Materials
- Numerical Methods in Inverse Design
- Case Study2: Metamaterials Design with Desired Behaviors
 - Inverse Design of Structured Surfaces and Discrete Interlocking Materials

Outline Today

- Introduction to Computational Design of Metamaterials
- Computational Models
 - Rigid Body, Finite Element Method, Discrete Elastic Rods
- Numerical Homogenization
- Case Study1: Mechanical Characterization
 - Discrete Interlocking Materials
- Numerical Methods in Inverse Design
- Case Study2: Metamaterials Design with Desired Behaviors
 - Inverse Design of Structured Surfaces and Discrete Interlocking Materials

Nature materials





Venation pattern of dragonfly wing



Scale skin of Pangolin

Trabecular structure of bone

What is metamaterials?

• Materials with tailored small-scale structures are metamaterials.



Mechanical Metamaterials

- Carefully designed microstructures allow for various macroscopic material properties with a single material
 - High stiffness-to-weight ratio
 - High durability
 - High energy absorption
 - Negative Poisson's ratio ...



[Schumacher et al. 2028]



[Xue et al. 2025]

Application - Soft Robotics



[Pascali et al. 2022]

[Jeong et al. 2018]

Application - Wearables



[Tang et al. 2023]

[Luo et al. 2022]

[Deng et al. 2022]

Design Challenges

• Forward prediction and characterization.



Large deformation/ Nonlinearity



Strong anisotropy



Contact

- Inverse design.
 - Nonlinear effect
 - High-dimensional design space

Outline Today

- Introduction to Computational Design of Metamaterials
- Computational Models
 - Rigid Body, Finite Element Method, Discrete Elastic Rods
- Numerical Homogenization
- Case Study1: Mechanical Characterization
 - Discrete Interlocking Materials
- Numerical Methods in Inverse Design
- Case Study2: Metamaterials Design with Desired Behaviors
 - Inverse Design of Structured Surfaces and Discrete Interlocking Materials

Computational Model

• Material characterization under static equilibrium.



Rigid elements

Rigid body



Continuum media

Finite Element Method



Elastic rods network

Discrete elastic rods

Compute static equilibrium state of rigid bodies with contact by an unconstrained minimization problem

$$\arg\min_{\mathbf{q}} E = E_{\text{Ext}}(\mathbf{q}) + E_{\text{Coll}}(\mathbf{q})$$





Vertex position of a rigid body

 $\mathbf{x} = \mathbf{T}_i + \mathbf{R}(\boldsymbol{\omega}_i)\mathbf{V}$

• The rotation matrix is computed by the Rodrigues' Rotation Formula

$$R(\omega) = \mathbf{I} + \operatorname{sinc}(\|\boldsymbol{\omega}\|)[\boldsymbol{\omega}] + 2\operatorname{sinc}^2\left(\frac{\|\boldsymbol{\omega}\|}{2}\right)[\boldsymbol{\omega}]^2$$





We use incremental potential contact (IPC) [Li et al. 2020] to compute contact energy

$$E_{Coll} = \kappa \sum_{k \in C} b(d_k(\mathbf{x}), \hat{d})$$

• *b* is the barrier potential

$$b(d,\hat{d}) = \begin{cases} -(d-\hat{d})^2 \ln(d/\hat{d}) & 0 < d \\ 0 & d \ge \hat{d} \end{cases}$$



Solve the unconstrained minimization problem via Newton's method

$$\arg\min_{\mathbf{q}} E = E_{\text{Ext}}(\mathbf{q}) + E_{\text{Coll}}(\mathbf{q})$$

Newton's method:

- Start from initial guess **q**₀
- For each iteration (until convergence)
 - Compute gradient $\nabla_{\mathbf{q}_i} \mathbf{E}$, Hessian $\nabla_{\mathbf{q}_i}^2 \mathbf{E}$
 - Compute search direction $\Delta \mathbf{q}_i = (\nabla_{\mathbf{q}_i}^2 \mathbf{E})^{-1} \nabla_{\mathbf{q}_i} \mathbf{E}$
 - Compute largest intersection-free step size α_m via Continuous Collision Detection (CCD)
 - \circ Back tracking line search α with maximum step size α_m
 - $\circ \quad \mathbf{q}_{i+1} = \mathbf{q}_i + \boldsymbol{\alpha} \cdot \Delta \mathbf{q}_i$

- For a deformable body, identify the
 - Undeformed state $\overline{\Omega} \subset \mathbf{R}^3$ describe by positions $\overline{\mathbf{x}}$
 - Deformed state $\Omega \subset \mathbf{R}^3$ describe by positions x
- Displacement filed **u** describe Ω in terms of $\overline{\Omega}$:

 $\mathbf{u}(\bar{\mathbf{x}}):\overline{\Omega} \to \Omega$ $\mathbf{x}(\bar{\mathbf{x}}) = \bar{\mathbf{x}} + \mathbf{u}(\bar{\mathbf{x}})$



Ζ

- Consider material points \bar{x}_1 and \bar{x}_2 and $\bar{d} = \bar{x}_2 \bar{x}_1$ such that $|\bar{d}|$ is infinitesimal
 - The deformed vector Deformation $\begin{aligned} \mathbf{d} &= \mathbf{x}_2 - \mathbf{x}_1 = \bar{\mathbf{x}}_2 + \mathbf{u}(\bar{\mathbf{x}}_2) - \bar{\mathbf{x}}_1 - \mathbf{u}(\bar{\mathbf{x}}_1) \\ &= \mathbf{d} + \mathbf{u}\big(\bar{\mathbf{x}}_1 + \bar{\mathbf{d}}\big) - \mathbf{u}(\bar{\mathbf{x}}_1) \end{aligned}$ gradient F $\approx \bar{d} + \mathbf{u}(\bar{\mathbf{x}}_1) + \nabla \mathbf{u} \, \bar{d} - \mathbf{u}(\bar{\mathbf{x}}_1) = (\mathbf{I} + \nabla \mathbf{u}) \bar{d}$ y Ω Ω $\overline{\mathbf{X}}_{2}$ $\overline{\mathbf{X}}_{1}$ $\mathbf{X_1}$

х

- Deformation gradient $F=I+\nabla u$ maps undeformed vectors to deformed vectors as $d=F\bar{d}$
- Alternatively, we can write

$$\mathbf{F} = \frac{\partial \mathbf{x}}{\partial \bar{\mathbf{x}}} = \frac{\partial}{\partial \bar{\mathbf{x}}} (\bar{\mathbf{x}} + \mathbf{u}(\bar{\mathbf{x}})) = \mathbf{I} + \nabla \mathbf{u}$$

- Measure change in length squared in arbitrary directions, $\mathbf{d}^T \mathbf{d} - \mathbf{d}^T \mathbf{d} = \mathbf{d}^T (\mathbf{F}^T \mathbf{F} - \mathbf{I}) \mathbf{d}$
- Green strain

$$\mathbf{E} = \frac{1}{2} \left(\mathbf{F}^{\mathrm{T}} \mathbf{F} - \mathbf{I} \right) = \frac{1}{2} \left(\nabla \boldsymbol{u} + \nabla \boldsymbol{u} + \nabla \boldsymbol{u}^{\mathrm{T}} \nabla \boldsymbol{u} \right)$$

Neglecting quadratic terms leads to the linear Cauchy strain

$$\varepsilon = \frac{1}{2} (\nabla u + \nabla u) = \frac{1}{2} (\mathbf{F} + \mathbf{F}^{\mathrm{T}}) - \mathbf{I}$$

• Divide input solid model into elements



- 4-node tetrahedron has 4 linear basis functions
- Basis function are linear

 $N_i(\bar{x}, \bar{y}, \bar{z}) = a_i \bar{x} + b_i \bar{y} + c_i \bar{z} + d_i$

• From $N_i(\bar{\mathbf{x}}_j) = \delta_{ij}$, we obtain coefficient by solving

$$\begin{pmatrix} \bar{x}_{1} & \bar{y}_{1} & \bar{z}_{1} & 1 \\ \bar{x}_{2} & \bar{y}_{2} & \bar{z}_{2} & 1 \\ \bar{x}_{3} & \bar{y}_{3} & \bar{z}_{3} & 1 \\ \bar{x}_{4} & \bar{y}_{4} & \bar{z}_{4} & 1 \end{pmatrix} \begin{pmatrix} a_{i} \\ b_{i} \\ c_{i} \\ d_{i} \end{pmatrix} = \begin{pmatrix} \delta_{1i} \\ \delta_{2i} \\ \delta_{3i} \\ \delta_{4i} \end{pmatrix}$$



• Solve for coefficients of N_1

$$\begin{bmatrix} 0 & 0 & 0 & 1 \\ 1 & 0 & 0 & 1 \\ 0 & 1 & 0 & 1 \\ 0 & 0 & 1 & 1 \end{bmatrix} \begin{bmatrix} a_1 \\ b_1 \\ c_1 \\ d_1 \end{bmatrix} = \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

- $N_1(\bar{x}, \bar{y}, \bar{z}) = -\bar{x} \bar{y} \bar{z} + 1$
- $N_2(\bar{x}, \bar{y}, \bar{z}) = \bar{x}$
- $N_3(\bar{x}, \bar{y}, \bar{z}) = \bar{y}$
- $N_4(\bar{x}, \bar{y}, \bar{z}) = \bar{z}$



• Interpolate using basis functions

$$\bar{\mathbf{x}}(\bar{x},\bar{y},\bar{z}) = \sum_{i=1}^{n_e} N_i(\bar{x},\bar{y},\bar{z})\bar{\mathbf{x}}_i \qquad \mathbf{x}(\bar{x},\bar{y},\bar{z}) = \sum_{i=1}^{n_e} N_i(\bar{x},\bar{y},\bar{z})\mathbf{x}_i \qquad \overline{x}_2$$

• Deformation gradient

$$\mathbf{F} = \frac{\partial \mathbf{x}(\bar{\mathbf{x}})}{\partial \bar{\mathbf{x}}} = \sum_{i=0}^{4} \mathbf{x}_{i} \left(\frac{\partial N_{i}}{\partial \bar{\mathbf{x}}}\right)^{\mathrm{T}}$$

- N_i are linear on elements, $\mathbf{F} \in \mathbf{R}^{3 \times 3}$ is constant within a linear tetrahedral element.
- Hence, element energy $E = \int_{\overline{\Omega}_e} \Psi \, dV = \Psi(\mathbf{F}) \cdot \overline{V}_e$

 \bar{x}_4

- Material model links strain to energy (and stress)
- Linear isotropic material (generalized Hooke's law)
- Energy density $\Psi = \frac{1}{2}\lambda tr(\varepsilon)^2 + \mu tr(\varepsilon^2)$
- Cauchy stress $\sigma = \frac{\partial \Psi}{\partial \varepsilon} = \lambda tr(\varepsilon) \mathbf{I} + 2\mu \varepsilon$
- λ and μ are Lame parameters.
- Nonlinear elasticity, replace Cauchy strain with Green strain
- St. Venant-Kirchhoff material (StVK)
- Energy density $\Psi = \frac{1}{2}\lambda tr(\mathbf{E})^2 + \mu tr(\mathbf{E}^2)$

Discrete Elastic Rods

- Discrete Kirchhoff elastic rods
- Stretching energy
- Bending energy
- Twisting energy

 $E_{elastic} = E_s + E_b + E_t$





[Bergou et al. 2008]

Discrete Elastic Rods - Stretching

• Elastic stretching energy

$$E_s = \frac{1}{2} \sum_{j=0}^n k_s^j \left(\varepsilon^j\right)^2 L^j$$

with axial strain
$$\varepsilon^{j} = \frac{l^{j}-L}{L^{j}}$$



Discrete Elastic Rods - Bending

• Elastic Bending energy

$$E_b = \frac{1}{2} \sum_{i=1}^n \frac{1}{\overline{l}} (\kappa_i - \overline{\kappa}_i)^T B_i (\kappa_i - \overline{\kappa}_i)$$



Discrete Elastic Rods - Twisting



• Parallel transport is a minimum rotation that aligns two vectors.

$$\mathbf{P}_{\mathbf{r}_1}^{\mathbf{r}_2} = \mathbf{R}\left(\frac{\mathbf{r}_1 \times \mathbf{r}_2}{|\mathbf{r}_1 \times \mathbf{r}_2|}, \angle(\mathbf{r}_1, \mathbf{r}_2)\right)$$

Discrete Elastic Rods - Twisting

- Measure difference between frames
 - Parallel transport frames by $\mathbf{P}_{\mathbf{t}_{i-1}}^{\mathbf{t}_i}$
 - Measure angle difference $\Delta \theta$
- Twist

 $m_i = \theta^i - \theta^{i-1} + \Delta \theta$

• Elastic twisting energy

$$E_t = \frac{1}{2} \sum_{i=1}^n \frac{\beta_i (m_i - \overline{m}_i)^2}{\overline{l}_i}$$



Outline Today

- Introduction to Computational Design of Metamaterials
- Computational Models
 - Rigid Body, Finite Element Method, Discrete Elastic Rods
- Numerical Homogenization
- Case Study1: Mechanical Characterization
 - Discrete Interlocking Materials
- Numerical Methods in Inverse Design
- Case Study2: Metamaterials Design with Desired Behaviors
 - Inverse Design of Structured Surfaces and Discrete Interlocking Materials

Numerical Homogenization

• Design tileable metamaterial based on *unit cells.*



Numerical Homogenization

• Target: Macroscopic material properties from microscopic geometry



2D

3D

Macromechanical model

Anisotropic Kirchhoff plates

• Strain energy density

$$W(\boldsymbol{\epsilon}, \boldsymbol{\kappa}) = W_M + W_B = \frac{1}{2}\boldsymbol{\epsilon}: \mathbb{C}: \boldsymbol{\epsilon} + \frac{1}{2}\boldsymbol{\kappa}: \mathbb{B}: \boldsymbol{\kappa}$$

• Membrane and bending stress

$$\sigma = \mathbb{C} : \epsilon$$
 $M = \mathbb{B} : \kappa$



Numerical Homogenization

Problems:

- Regular simulation does not consider tiling
- How to apply directional deformations?
- Fix the positions of vertices will artificially stiffen the structure



In-plane Periodic Boundary Conditions

• In-plane periodic boundary conditions



Macroscopic In-plane Deformation

• Apply biaxial deformation

$$\mathbf{d}_{ij} = \varepsilon_p(\bar{\mathbf{d}}_{ij}^{\mathrm{T}}\mathbf{d}_p)\mathbf{d}_p + \varepsilon_o(\bar{\mathbf{d}}_{ij}^{\mathrm{T}}\mathbf{d}_o)\mathbf{d}_o$$

Macroscopic deformation gradient

$$\mathbf{F}_{\text{macro}} = \varepsilon_p \mathbf{d}_p \mathbf{d}_p^{\text{T}} + \varepsilon_o \mathbf{d}_o \mathbf{d}_o^{\text{T}}$$

or
$$\mathbf{F}_{\text{macro}} = \begin{bmatrix} \mathbf{x}_i - \mathbf{x}_j & \mathbf{x}_k - \mathbf{x}_l \end{bmatrix} \begin{bmatrix} \mathbf{X}_i - \mathbf{X}_j & \mathbf{X}_k - \mathbf{X}_l \end{bmatrix}^{-1}$$

Macroscopic In-plane Deformation

- Anisotropic Kirchhoff plates membrane stress $\sigma = \mathbb{C} : \epsilon$
- Macroscopic Cauchy strain tensor

$$\boldsymbol{\epsilon}_{\text{macro}} = \frac{1}{2} (\mathbf{F}_{\text{macro}} + \mathbf{F}_{\text{macro}}^{\text{T}}) - \mathbf{I}$$

Macroscopic Cauchy stress tensor

$$\boldsymbol{\sigma}_{\text{macro}} = [\mathbf{f}_0 \quad \mathbf{f}_1][\mathbf{n}_0 \quad \mathbf{n}_1]^{-1}$$


Characterizing In-plane Mechanical Properties

• Fit the homogenized compliance tensor $S = C^{-1}$ by solving

$$\mathbb{S}^{\mathrm{H}} = \operatorname*{argmin}_{\mathbb{S}} \sum_{i=1}^{N} \frac{1}{||\boldsymbol{\epsilon}_{\mathbf{i}}||_{F}^{2}} ||\mathbb{S}: \boldsymbol{\sigma}_{i} - \boldsymbol{\epsilon}_{i}||_{F}^{2}$$

• Directional Young's modulus

$$E(\mathbf{d}) = \frac{1}{(\mathbf{d}\mathbf{d}^{\mathrm{T}}):\mathbb{S}:(\mathbf{d}\mathbf{d}^{\mathrm{T}})}$$

• Directional Poisson's ratio

$$\nu(\mathbf{d}) = -\frac{(\mathbf{d}\mathbf{d}^{\mathrm{T}}):\mathbb{S}:(\mathbf{n}\mathbf{n}^{\mathrm{T}})}{(\mathbf{d}\mathbf{d}^{\mathrm{T}}):\mathbb{S}:(\mathbf{d}\mathbf{d}^{\mathrm{T}})}$$





Bending Periodic Boundary Conditions

• Bending with single bending curvature κ_c with direction **v**

 $\mathbf{x}_j = \mathbf{R}_{ij}\mathbf{x}_i + \mathbf{d}_{ij}$



Characterizing Bending Mechanical Properties

• Fit the homogenized bending stiffness by solving

$$\mathbb{B}^{H} = \arg\min_{\mathbb{B}} \sum_{i=0}^{M} \left(\frac{1}{2} \, \mathbf{\kappa}_{i} : \mathbb{B} : \mathbf{\kappa}_{i} - W_{i} \right)^{2}$$

• Directional bending stiffness

$$b(\mathbf{d}) = (\mathbf{d}\mathbf{d}^{\mathrm{T}}) : \mathbb{B} : (\mathbf{d}\mathbf{d}^{\mathrm{T}})$$





Outline Today

- Introduction to Computational Design of Metamaterials
- Computational Models
 - Rigid Body, Finite Element Method, Discrete Elastic Rods
- Numerical Homogenization
- Case Study1: Mechanical Characterization
 - Discrete Interlocking Materials
- Numerical Methods in Inverse Design
- Case Study2: Metamaterials Design with Desired Behaviors
 - Inverse Design of Structured Surfaces and Discrete Interlocking Materials



P. Tang, S. Coros, B. Thomaszewski. Beyond Chainmail: Computational Modeling of Discrete Interlocking Materials. ACM SIGGRAPH 2023



Discrete Interlocking Materials



Discrete Interlocking Materials



Macromechanical Properties

Discrete Interlocking Materials



A new computational framework for modeling and characterizing DIM composed of quasi-rigid elements.

Overview



Native-Scale Model

• We simulate static equilibrium states of DIM as rigid bodies with contact by an unconstrained minimization problem

 $\min_{\mathbf{q}} E_{\text{Ext}}(\mathbf{q}) + E_{\text{Coll}}(\mathbf{q})$



Macro-Scale Deformations – In-plane

Periodicity:

$$\mathbf{T}_j = \mathbf{T}_i + \mathbf{t}_{ij}$$

 $\boldsymbol{\omega}_j = \boldsymbol{\omega}_i$



Macro-Scale Deformations – Out-of-plane

 Single curvature states with periodic boundary conditions can be conveniently modeled.



• However, one cannot, in Euclidean geometry, define a finite-sized, doublecurvature patch that tiles with itself [Sausset and Tarjus 2007].

Macro-Scale Deformations – Out-of-plane

• Circular finite patches of paraboloid surfaces

 $z = Ax^2 + By^2 + Cxy$



Native-Scale Simulations



Stretching





Compression

Bending

Strain-Space Representation



Macro-Scale Model



Macro-Scale Model



Threefold Symmetric Chainmail



Threefold Symmetric Chainmail





Threefold Symmetric Chainmail



Strain Space Boundary (Stretching)







Torus Knot Material



Torus Knot Material



Strain Space Boundary (Stretching)







Strain Space Boundary (Bending)



Scale Mail







Scale Mail



Scale Mail

Bending Under Gravity - Side 1









Outline Today

- Introduction to Computational Design of Metamaterials
- Computational Models
 - Rigid Body, Finite Element Method, Discrete Elastic Rods
- Numerical Homogenization
- Case Study1: Mechanical Characterization
 - Discrete Interlocking Materials
- Numerical Methods in Inverse Design
- Case Study2: Metamaterials Design with Desired Behaviors
 - Inverse Design of Structured Surfaces and Discrete Interlocking Materials

Forward Problem

• Consider a 2D elastic bar



• Forward problem: given design parameter p and external force \mathbf{f}_{ext} , compute equilibrium configuration x by solving

$$\mathbf{f}(\mathbf{x},\mathbf{p}) = \mathbf{f}_{\text{ext}} + \mathbf{f}_{\text{int}}(\mathbf{x},\mathbf{p}) = \mathbf{0}$$

Forward Problem

• Change the undeformed state **p** changes the equilibrium state **x**



• How can we determine **p** that leads to a desired equilibrium state?



Inverse Design Objective

• Introduce objective that quantifies distance to target

$$T(\mathbf{x}) = \frac{1}{2} \|\mathbf{x} - \mathbf{x}_{\text{tar}}\|^2$$





- Constraint: x has to be an equilibrium state for p, i.e., f(x,p)=0



Target shape x_{tar}

- Objective: find **x** and **p** such that **x** minimizes *T*
- Constraint: x has to be an equilibrium state for p, i.e., f(x, p) = 0

Inverse Problem

• Formulation



• Interpretation:

From all possible equilibrium states x, i.e., those x for which there exists p such that f(x, p) = 0, find the one that minimizes T(x).

Constrained Optimization

Generic optimization problem

 $\min_{\mathbf{x}} f(\mathbf{x}) \quad \text{s.t.} \quad \mathbf{C}(\mathbf{x}) = \mathbf{0}$

- Unknowns $\mathbf{x} \in \mathbf{R}^n$
- Objective function $f(\mathbf{x}): \mathbf{R}^n \to \mathbf{R}$
- Constraints $C(x): \mathbb{R}^n \to \mathbb{R}^m$

How can we solve this optimization problem?

Numerical Methods in Inverse Design

- Sequential Quadratic Programming (SQP)
- Sensitivity Analysis
- Interior Point Methods
- Augmented Lagrangian Method
- ...

SQP for Inverse Problems

- Lagrangian $L(\mathbf{x}, \mathbf{p}, \boldsymbol{\lambda}) = T(\mathbf{x}) + \mathbf{f}(\mathbf{x}, \mathbf{p})^{\mathrm{T}} \boldsymbol{\lambda}$
- x deformed positions
- **p** undeformed positions

$$\mathbf{s} = (\mathbf{x}, \mathbf{p}, \boldsymbol{\lambda})^{\mathrm{T}} \in \mathbf{R}^{3 \cdot D \cdot n}$$

• First order optimality conditions: $\nabla_s L = \mathbf{0}$

$$\nabla_{\mathbf{x}} L = \nabla_{\mathbf{x}} T(\mathbf{x}) + \nabla_{\mathbf{x}} \mathbf{f}(\mathbf{x}, \mathbf{p})^{\mathrm{T}} \boldsymbol{\lambda} = 0$$

$$\nabla_{\mathbf{p}} L = \nabla_{\mathbf{p}} T(\mathbf{x}) + \nabla_{\mathbf{p}} \mathbf{f}(\mathbf{x}, \mathbf{p})^{\mathrm{T}} \boldsymbol{\lambda} = 0$$

$$\nabla_{\boldsymbol{\lambda}} L = \mathbf{f}(\mathbf{x}, \mathbf{p}) = 0$$

SQP for Inverse Problems

• Given s, find Δs such that

$$\nabla_{\mathbf{s}} L(\mathbf{s} + \Delta \mathbf{s}) = \mathbf{0} \quad \rightarrow \quad \nabla_{\mathbf{ss}} L \cdot \Delta \mathbf{s} = -\nabla_{\mathbf{s}} L$$

$$\begin{bmatrix} \nabla_{\mathbf{x}\mathbf{x}}T + \nabla_{\mathbf{x}\mathbf{x}}\mathbf{f}^{\mathrm{T}}\boldsymbol{\lambda} & \nabla_{\mathbf{x}\mathbf{p}}\mathbf{f}^{\mathrm{T}}\boldsymbol{\lambda} & \nabla_{\mathbf{x}}\mathbf{f}^{\mathrm{T}} \\ \boldsymbol{\lambda}^{\mathrm{T}}\nabla_{\mathbf{x}\mathbf{p}}\mathbf{f} & \nabla_{\mathbf{p}\mathbf{p}}\mathbf{f}^{\mathrm{T}}\boldsymbol{\lambda} & \nabla_{\mathbf{p}}\mathbf{f}^{\mathrm{T}} \\ \nabla_{\mathbf{x}}\mathbf{f} & \nabla_{\mathbf{p}}\mathbf{f} & \mathbf{0} \end{bmatrix} \cdot \begin{bmatrix} \Delta \mathbf{x} \\ \Delta \mathbf{p} \\ \Delta \boldsymbol{\lambda} \end{bmatrix} = -\begin{bmatrix} \nabla_{\mathbf{x}}L \\ \nabla_{\mathbf{p}}L \\ \nabla_{\boldsymbol{\lambda}}L \end{bmatrix}$$

- Indefinite matrix
 - Quadratic programming solver (MOSEK, GUROBI...)
- Apply Newton's method to solve the problem.
 - Merit function, e.g., l_1 merit function $\phi(\mathbf{s}) = T(\mathbf{s}) + \mu \sum_i |c_i(\mathbf{s})|$
SQP Discussion

- SQP is a powerful optimization method, and it can be very fast
- Hessian of Lagrangian involves higher-order derivatives
 - Difficult and expensive to compute
 - can introduce indefiniteness
 - Alternative: use Quasi-newton methods to approximate Hessian
- SQP leads to large number of variables
 - One variable per DoF
 - One variable per parameter
 - One Lagrange multiplier per constraint

Sensitivity Analysis



- In this problem, the design parameters **p** are effective DoFs.
- **x** = simulation(**p**)
- For design, we need derivatives

$$\frac{dT}{d\mathbf{p}} = \frac{\partial T}{\partial \mathbf{x}} \frac{d\mathbf{x}}{d\mathbf{p}} + \frac{\partial T}{\partial \mathbf{p}}$$

• How to compute?

$$\frac{d\mathbf{x}}{d\mathbf{p}} = \frac{d \text{ simulation}}{d\mathbf{p}}$$

Sensitivity Analysis

• Simulation map: **x** = simulation(**p**)

f(x, p) = 0 has to hold always

• Any change in design parameters p should lead to corresponding change in state x such that f(x, p) = 0 is still satisfied.

$$\frac{d\mathbf{f}}{d\mathbf{p}} = 0 \quad \rightarrow \quad \frac{\partial \mathbf{f}}{\partial \mathbf{x}} \frac{d\mathbf{x}}{d\mathbf{p}} + \frac{\partial \mathbf{f}}{\partial \mathbf{p}} = 0$$

Sensitivity Matrix $\frac{d\mathbf{a}}{d\mathbf{p}} = -\left(\frac{d\mathbf{a}}{\partial \mathbf{x}}\right) \frac{d\mathbf{a}}{\partial \mathbf{p}}$	Sensitivity Matrix	$\frac{d\mathbf{x}}{d\mathbf{p}} = -$	$-\left(\frac{\partial \mathbf{f}}{\partial \mathbf{x}}\right)^{-}$	$\frac{1}{\partial \mathbf{f}}$	
--	--------------------	---------------------------------------	---	---------------------------------	--

Sensitivity Analysis

• Design objective gradient

$$\nabla_{\mathbf{p}}T = \frac{\partial T}{\partial \mathbf{x}}\frac{d\mathbf{x}}{d\mathbf{p}} + \frac{\partial T}{\partial \mathbf{p}}$$

• Solve the problem by using Gradient Descent or LBSGS

```
Gradient Descent

Until Convergence:

Compute search direction \Delta \mathbf{p} = -\nabla_{\mathbf{p}}T

\alpha = 1

Line search Loop:

\mathbf{p}_{L+1} = \mathbf{p} + \alpha \Delta \mathbf{p}

\mathbf{x}_{L+1} = \text{Simulation}(\mathbf{p}_{L+1})

\alpha = \alpha/2

Until T_{L+1} < T_L

End
```

Adjoint Method

• Design objective gradient

$$\nabla_{\mathbf{p}}T = \frac{\partial T}{\partial \mathbf{x}}\frac{\partial \mathbf{x}}{\partial \mathbf{p}} + \frac{\partial T}{\partial \mathbf{p}} = -\frac{\partial T}{\partial \mathbf{x}}\left(\frac{\partial \mathbf{f}}{\partial \mathbf{x}}\right)^{-1}\frac{\partial \mathbf{f}}{\partial \mathbf{p}} + \frac{\partial T}{\partial \mathbf{p}}$$

- The expensive part here is computing $\frac{d\mathbf{x}}{d\mathbf{p}} = -\left(\frac{\partial \mathbf{f}}{\partial \mathbf{x}}\right)^{-1} \frac{\partial \mathbf{f}}{\partial \mathbf{p}}$
 - \circ if number of state variables x is large
 - \circ $\$ If number of design parameters p is large
- Avoid computing $\frac{d\mathbf{x}}{d\mathbf{p}}$ explicitly, defining adjoint vector $\mathbf{\lambda} \in \mathbf{R}^n$ as

$$\frac{\partial \mathbf{f}}{\partial \mathbf{x}}^{\mathrm{T}} \boldsymbol{\lambda} = \frac{\partial T}{\partial \mathbf{x}}^{\mathrm{T}}$$

• Design objective gradient

$$\nabla_{\mathbf{p}}T = -\boldsymbol{\lambda}^{\mathrm{T}}\frac{\partial \mathbf{f}}{\partial \mathbf{p}} + \frac{\partial T}{\partial \mathbf{p}}$$

Inverse Design of Metamaterials

• Forward problem, given design parameter **p**, compute equilibrium configuration **x** by solving

$$\mathbf{f}(\mathbf{x}, \mathbf{p}) = \mathbf{f}_{ext} + \mathbf{f}_{int}(\mathbf{x}, \mathbf{p}) = \mathbf{0}$$



Inverse Design of Metamaterials

• Target: Microscopic geometry from macroscopic material properties



Microscopic structure



Inverse Design Objective

• Introduce design objective that quantifies the distance to target

$$T(\mathbf{x}) = \frac{1}{2n} \sum_{i}^{n} \left(\frac{E_H(\mathbf{d}_i)}{E_{tar}} - 1 \right)^2$$



Outline Today

- Introduction to Computational Design of Metamaterials
- Computational Models
 - Rigid Body, Finite Element Method, Discrete Elastic Rods
- Numerical Homogenization
- Case Study1: Mechanical Characterization
 - Discrete Interlocking Materials
- Numerical Methods in Inverse Design
- Case Study2: Metamaterials Design with Desired Behaviors
 - Inverse Design of Discrete Interlocking Materials and Structured Surfaces



P. Tang, B. Thomaszewski, S. Coros, B. Bickel. Inverse Design of Discrete Interlocking Materials with Desired Mechanical Behavior. ACM SIGGRAPH 2025

Challenge

• How to inverse design Discrete Interlocking Materials with desired kinematic deformation limits?



• Designing with explicit triangle meshes is computational expensive.

Challenge



[Du et al. 2024]

Implicit Contact Model

Represent by parametric torus

> $V_x(u, v) = (R + r_{c0}\cos(v))\cos(u)$ $V_{v}(u, v) = (R + r_{c0}\cos(v))\sin(u)$ $V_z(u, v) = r_{c1} \sin(v)$



• Contact potential between tori
$$b(d, \hat{d}) = \begin{cases} -(d - \hat{d})^2 \ln(d/\hat{d}) & 0 < d \\ 0 & d \ge \hat{d} \end{cases}$$

Minimum squared distance

$$\min_{\mathbf{c}_{ij}} d(\mathbf{c}_{ij}, \mathbf{q}_{ij}) = \left\| \mathbf{V}_i^t - \mathbf{V}_j^t \right\|^2$$



Singularity



Implicit Contact Model

- Revised contact potential $E_{Coll} = \kappa \sum_{k \in C} \mathbf{s}(\mathbf{c}, \mathbf{q}) \cdot b(\mathbf{c}, \mathbf{q}, \hat{d})$
- Compute static equilibrium states by solving

 $\min_{\mathbf{q}} E_{\text{Ext}}(\mathbf{q}) + E_{\text{Coll}}(\mathbf{q})$

• CCD to find maximum intersection-free step size α_t

$$\min_{\alpha_t} d$$
s.t. $d(\alpha_t) = \min_{\mathbf{c}_{ij}} d(\mathbf{c}_{ij}, \mathbf{q}_{ij} + \alpha_t \Delta \mathbf{q}_{ij})$

$$0 \le \alpha_t \le \alpha_{hi}$$
o If $d < d_{th}$, we shrink α_{hi} by 0.9 until $d > d_{th}$.

Inverse Design of Deformation Limits

• In-plane objective function

$$\min_{\mathbf{p}} T = \sum_{i} \frac{1}{2} (\boldsymbol{\epsilon}(\mathbf{p}, \theta_{i}) - \boldsymbol{\epsilon}_{t}(\theta_{i}))^{2}$$

s.t. $\mathbf{f}_{\text{planar}}(\mathbf{y}(\mathbf{p}), \mathbf{p}, \theta_{i}) = 0, \forall i$
 $\mathbf{C}_{ij}(\mathbf{p}) > \epsilon_{c}, \forall (i, j) \in \mathbf{N}$
 $\epsilon_{l} < \mathbf{p} < \epsilon_{h}$

Out-of-plane objective function

$$\min_{\mathbf{p}} T = \sum_{i} \frac{1}{2} (\mathbf{\kappa}(\mathbf{p}, \theta_{i}) - \mathbf{\kappa}_{t}(\theta_{i}))^{2}$$

s.t. $\mathbf{f}_{\text{bending}}(\mathbf{y}(\mathbf{p}), \mathbf{p}, \theta_{i}) = 0, \forall i$
 $\mathbf{C}_{ij}(\mathbf{p}) > \epsilon_{c}, \forall (i, j) \in \mathbf{N}$
 $\epsilon_{l} < \mathbf{p} < \epsilon_{h}$



In-plane Deformation Limits



In-plane Deformation Limits



Out-of-plane Deformation Limits



Out-of-plane Deformation Limits



Fourfold Symmetric Material



4-in-1 Chainmail





J. Montes, Y. Du, R. Hinchet, S. Coros, B. Thomaszewski. Differentiable Stripe Patterns for Inverse Design of Structured Surfaces. ACM SIGGRAPH 2023

Motivation



[Knöppel et al. 2015]

Motivation



Motivation



Goal



 $\frac{\partial v}{\partial p} \qquad \qquad \frac{\partial (x, \hat{x}_i)}{\partial v}$ Stripes eigenvector sensitivities Simulation sensitivities

Generation of Stripe Patterns



Generation of Stripe Patterns



Generalized eigenvalue problem

 $[\boldsymbol{A}(\boldsymbol{p}) - \lambda \boldsymbol{B}]\boldsymbol{v} = 0$

 $\pmb{\phi}(\pmb{v})$

Multiplicity Two Eigenspace



Constraining the eigenspace

$$v_{k} = (a_{k}, b_{k})$$

$$\min_{v} E_{\psi} = \frac{1}{2} v^{T} A(p) v - \frac{1}{2} \lambda v^{T} B v - \mu b_{k}$$

$$b_{k} = 0$$

$$b_{k} = 0$$

$$v_{i} = (a_{i}, b_{i})$$

$$v_{i}^{\perp} = (-b_{i}, a_{i})$$

$$v^{\theta} = \cos(\theta) v + \sin(\theta) v^{\perp}$$

Constraining the eigenspace

$$\min_{\boldsymbol{v}} E_{\boldsymbol{\psi}} = \frac{1}{2} \boldsymbol{v}^T \boldsymbol{A}(\boldsymbol{p}) \boldsymbol{v} - \frac{1}{2} \lambda \boldsymbol{v}^T \boldsymbol{B} \boldsymbol{v} - \boldsymbol{\mu} \boldsymbol{b}_k$$



$$\begin{pmatrix} \boldsymbol{A}(p) - \lambda \boldsymbol{v} & -\boldsymbol{B}\boldsymbol{v} & \boldsymbol{e}_{b_k} \\ (-\boldsymbol{B}\boldsymbol{v})^T & 0 & 0 \\ \boldsymbol{e}_{b_k}^t & 0 & 0 \end{pmatrix} \begin{pmatrix} \frac{\partial \boldsymbol{v}}{\partial p} \\ \frac{\partial \boldsymbol{v}}{\partial \lambda} \\ 0 \end{pmatrix} = \begin{pmatrix} -\frac{\partial^2 E}{\partial \boldsymbol{v} \partial p} \\ 0 \\ 0 \end{pmatrix}$$

Simulation and X-Fem



Simulation (Solid SHells)



Solid shells and X-Fem



Macro-Mechanical Modulation


Variable Stiffness Materials



Compliant Gripper



Soft Pneumatic Actuator



Structural Optimization of Thin Shells



Unoptimized

Optimized

Outline Today

- Introduction to Computational Design of Metamaterials
- Computational Models
 - Rigid Body, Finite Element Method, Discrete Elastic Rods
- Numerical Homogenization
- Case Study1: Mechanical Characterization
 - Discrete Interlocking Materials
- Numerical Methods in Inverse Design
- Case Study2: Metamaterials Design with Desired Behaviors
 - Inverse Design of Structured Surfaces and Discrete Interlocking Materials

Outlook

• Neural metamaterial design.



[Li et al. 2023]

Outlook

• Generative AI for metamaterial design.



[Xue et al. 2025]

Acknowledgement



Prof. Bernd Bickel

Prof. Bernhard Thomaszewski

Prof. Stelian Coros

References

- [Schumacher et al. 2018] "Mechanical characterization of structured sheet materials." *ACM Transactions on Graphics (TOG)* 37.4 (2018).
- [Xue et al. 2025] Xue et al. "MIND: Microstructure INverse Design with Generative Hybrid Neural Representation." arXiv preprint arXiv:2502.02607 (2025).
 - [Pascali et al. 2022] Pascali et al. "3D-printed biomimetic artificial muscles using soft actuators that contract and elongate." *Science Robotics* 7.68 (2022): eabn4155.
- [Jeong et al.]Jeong et al. "Design and analysis of an origami-based three-finger manipulator." Robotica 36.2 (2018): 261-274.
- [Gao et al. 2023] Gao et al. "Programmable and Variable-Stiffness Robotic Skins for Pneumatic Actuation." Advanced Intelligent Systems 5.12 (2023): 2300285.
- [Tang et al. 2023] Tang et al. "Beyond Chainmail: Computational Modeling of Discrete Interlocking Materials." ACM Transactions on Graphics (TOG) 42.4 (2023).
- [Luo et al.] Luo et al. "Digital fabrication of pneumatic actuators with integrated sensing by machine knitting." Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems. 2022.
- [Deng et al.] Deng et al. "Inverse design of mechanical metamaterials with target nonlinear response via a neural accelerated evolution strategy." Advanced Materials 34.41 (2022): 2206238.
- [Tang et al. 2023] Tang et al. "Beyond Chainmail: Computational Modeling of Discrete Interlocking Materials." ACM Transactions on Graphics (TOG) 42.4 (2023): 1-12.
- [Bergou et al. 2008] Bergou et al. "Discrete elastic rods." ACM SIGGRAPH 2008 papers. 2008
- [Montes Maestre et al. 2023] Montes Maestre et al. Differentiable Stripe Patterns for Inverse Design of Structured Surfaces. ACM SIGGRAPH 2023
- [Knöppel et al. 2015]"Stripe patterns on surfaces." ACM Transactions on Graphics (TOG) 34.4 (2015).
- [Tang et al. 2025] Tang et al. Inverse Design of Discrete Interlocking Materials with Desired Mechanical Behavior. ACM SIGGRAPH 2025.
- [Li et al. 2023] Li et al. "Neural metamaterial networks for nonlinear material design." ACM Transactions on Graphics (TOG) 42.6 (2023).
- Nocedal, Jorge, and Stephen J. Wright, eds. Numerical optimization. New York, NY: Springer New York, 1999.

Thank you!