

# Hyperelasticity based Mesh-Deformation

Malte Schuh

Januar 9th, 2023

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- 2 Link to solid mechanics
- 3 Brief excursion to solid mechanics
- 4 Choice of energy
- 5 Solver
- 6 Results

Mesh-deformation is useful for

- complex geometries
- multi-phase flow
- FSI
- smoothening a mesh from a mesh-generator
- ...

Focus today: Outer boundary do not move

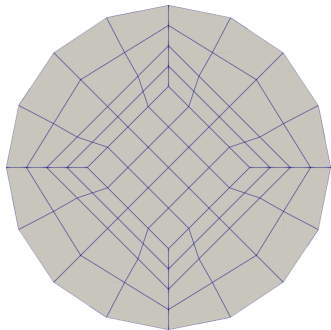


Figure: initial mesh

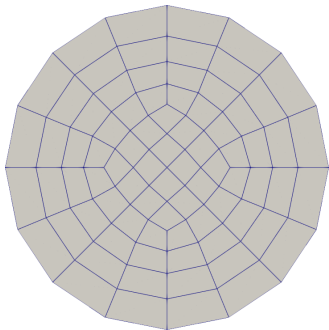


Figure: desired mesh

In solid mechanics

- engineers take an elastic material, for example a beam
- apply some load to it
- calculate the resulting stresses
- calculate the resulting strains
- calculate the deformed state
- and then calculate other quantities of interest

Sounds familiar!

- Each material has an energy that models the material behaviour
- The internal energy of a material must not depend on the position in space
- All systems seek a state that minimizes the energy in the system
- There exist stable and unstable states that minimize the energy in the system

Unfortunately, the model cannot be linear!

Let  $\gamma(X)$  be the mapping between the undeformed and deformed state. It can be proven that a model that is objective must depend on  $\mathbf{C} := (\nabla\gamma)^T(\nabla\gamma)$ .

Definition: A material model is called Neo-Hooke-Model if it only depends linear on  $\text{Tr}(\mathbf{C})$ , not on  $\frac{1}{2}((\text{Tr}(\mathbf{C}))^2 - \text{Tr}(\mathbf{C}^2))$  and in some way on  $\det(\mathbf{C})$ .

Let  $\Psi$  be the energy functional.

- Growth condition:  $\Psi(\nabla\gamma) \rightarrow \infty$  for  $\det(\nabla\gamma) \rightarrow 0$
- Growth condition:  $\Psi(\nabla\gamma) \rightarrow \infty$  for  $\{\|\nabla\gamma\| + \|\text{cof}(\nabla\gamma)\| + \det(\nabla\gamma)\} \rightarrow \infty$

The growth conditions rule out convexity.

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Neo-Hookean-Type model:

$$\tilde{\Psi}(\gamma) = \frac{1}{2}\lambda(\log(\sqrt{\det(\mathbf{C})}))^2 + \frac{1}{2}\mu(\text{Tr}(\mathbf{C}) - d - 2\log(\sqrt{\det(\mathbf{C})}))$$

with  $\lambda$  and  $\mu$  material parameters (Lamé-Parameters) and  $d$  the spatial dimension

Measure how much energy is required to deform an optimal cell into a cell of the mesh. Define  $\gamma : \hat{T} \rightarrow T$

Sum up all local contributions to the energy:

$$\begin{aligned}\Psi(\gamma) = & \int \left\{ \frac{1}{2} \lambda (\log(\sqrt{\det(\mathbf{C})}))^2 \right. \\ & \left. + \frac{1}{2} \mu (\text{Tr}(\mathbf{C}) - d - 2 \log(\sqrt{\det(\mathbf{C})})) \right\}\end{aligned}$$

This is the term we need to minimize  $\rightarrow$  Optimization in Banach spaces

## General Descent Algorithm for functions

given:  $F(x)$ ,  $x_0$

---

### General Descent Algorithm

---

find searchdirection  $s_k$

find stepsize  $\sigma_k$  with  $F(x_k + \sigma_k s_k) < F(x_k)$

$x_{k+1} = x_k + \sigma_k s_k$

---

For nonlinear optimization:

- Gradient Method:  $s_k = -\nabla F(x_k)$

- Newton:  $F''(x_k)s_k = -\nabla F(x_k)$

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Based on [1]

## Theorem

Let  $\Omega$  be a domain in  $\mathbb{R}^3$  and  $\hat{W} : \Omega \times \mathbb{M}_+^3 \rightarrow \mathbb{R}$  be a stored energy function with the following properties

- 1 Polyconvexity:** For almost all  $x \in \Omega$  there exists a convex function  $\mathbb{W}(x, \cdot) : \mathbb{M}^3 \times (0, +\infty) \rightarrow \mathbb{R}$  such that  $\mathbb{W}(x, F, \det(F)) = \hat{W}(x, F) \forall F \in \mathbb{M}_+^3$
- 2**  $\lim_{\det F \rightarrow 0^+} \hat{W}(x, \det(F)) = +\infty$
- 3 Coerciveness:** There exist  $\alpha, \beta, p, q, r$  such that  $\alpha > 0, p \geq 2, q \geq \frac{p}{p-1}, r > 1: \hat{W}(x, F) \geq \alpha(\|F\|^p + (\det(F))^r) + \beta$  and  $\Phi := \{\Psi \in W^{1,p}, \text{cof } \nabla \Psi \in L^q, \det(\nabla \Psi) \in L^r\}$  is not empty.

Then there exists at least one function  $\varphi$  such that  $\varphi \in \Phi$  and  $\int_{\Omega} \hat{W}(x, \nabla \varphi) = \inf_{\psi \in \Phi} \int_{\Omega} \hat{W}(x, \nabla \psi)$



Our energy is not polyconvex and not coercive!

Convex only as long as  $\det \nabla \gamma < \exp\left(\frac{\mu}{\lambda} + 1\right)$  Therefore: the energy is modified:

$$\begin{aligned} \tilde{\Psi}(\gamma) &= \frac{1}{2} \lambda (\log(\sqrt{\det(\mathbf{C})}))^2 \\ &+ \frac{1}{2} \mu (\text{Tr}(\mathbf{C}) - d - 2 \log(\sqrt{\det(\mathbf{C})})) \\ &+ \kappa \left( \left( \sqrt{\det(\mathbf{C})} - \exp\left(\frac{\mu}{\lambda} + 1\right) \right)_+ \right)^2 \end{aligned}$$

But: In practice, the last term should always be zero, so we ignore it from here on.

We want to use Newton:

$$F''(\gamma)[s_k, \psi] = F'(\gamma)\psi$$

$$F'(\gamma)\varphi = \int [\lambda \log(\det(\nabla\gamma))(\nabla\gamma)^{-T} - \mu(\nabla\gamma)^{-T} + \mu\nabla\gamma] : \nabla\varphi \, dx$$

$$\begin{aligned} F''(\gamma)[\varphi, \psi] &= \int \lambda [(\nabla\gamma)^{-T} : \nabla\psi][(\nabla\gamma)^{-T} : \nabla\varphi] \\ &\quad + \lambda \log(\det(\nabla\gamma))(-(\nabla\gamma)^{-T}(\nabla\psi)^T(\nabla\gamma)^{-T}) : \nabla\varphi \\ &\quad - \mu(-(\nabla\gamma)^{-T}(\nabla\psi)^T(\nabla\gamma)^{-T}) : \nabla\varphi \\ &\quad + \mu\nabla\psi : \nabla\varphi \, dx \end{aligned}$$

Problem:  $F''(\gamma)[s_k, \psi]$  is not positive definite.

$$\begin{aligned} H(\gamma, \alpha)[\varphi, \psi] &= \int \lambda [(\nabla\gamma)^{-T} : \nabla\psi][(\nabla\gamma)^{-T} : \nabla\varphi] \\ &\quad + \alpha\lambda \log(\det(\nabla\gamma)) (-(\nabla\gamma)^{-T} (\nabla\psi)^T (\nabla\gamma)^{-T}) : \nabla\varphi \\ &\quad - \alpha\mu (-(\nabla\gamma)^{-T} (\nabla\psi)^T (\nabla\gamma)^{-T}) : \nabla\varphi \\ &\quad + \mu \nabla\psi : \nabla\varphi dx \end{aligned}$$

Dennis-Moré-Condition:

$$\frac{\|(H_k - F''(\gamma^*))s_k\|}{\|s_k\|} \rightarrow 0$$

is necessary and sufficient for superlinear convergence. Therefore, we can use any heuristic for  $\alpha$  that guarantees  $\alpha_k \rightarrow 1$  for  $k \rightarrow \infty$ .

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 &\quad + \mu \nabla \psi : \nabla \varphi dx
 \end{aligned}$$

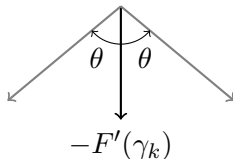
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The (Quasi-)Newton-direction might be bad, so we check the angle-condition:

$$\frac{(-F'(\gamma_k), s_k)}{\|F'(\gamma_k)\| \|s_k\|} \geq \beta$$
$$\beta = |\cos(\theta)|$$



If this does not hold: Use antigradient as searchdirection.

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## Armijo-Scheme

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given:  $x$ , searchdirection  $s$

choose  $\beta \in (0, 1)$ ,  $\gamma \in (0, 1)$ ,  $\sigma_0 > 0$ ,  $k = 0$

**while**  $f(x) - f(x + \sigma_k s) < -\gamma \sigma_k (\nabla f(x), s)$  **do**

$$\sigma_{k+1} = \beta \sigma_k$$

$$k = k + 1$$

**end while**

---

Typical values are:  $\sigma_0 = 1$ ,  $\beta = 0.5$ ,  $\gamma = 10^{-2}$

**Problem:** We need  $F'(\gamma_k)$  but we only have  $F'(\gamma_k)\varphi$ .

**Solution:** Riesz-Representative:  $s$  is the Riesz-Representative of  $F'(\gamma_k)$  if

$$(s, \varphi) = F'(\gamma_k)\varphi \quad \forall \varphi$$

$\Rightarrow$  We have to decide on a function space for our problem and a suitable dot-product.

For the following tests and results we choose  $H_0^1(\Omega)$  with

$$(\varphi, \psi) = \int_{\Omega} \nabla \varphi : \nabla \psi \, dx$$

so it is only solving a Poisson problem.

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Initial mesh: Take  $[0, 1]^2$ , refine it one time, then move the midpoint to  $(0.26, 0.26)$ , then refine again 5 times.  $\mu = 10$ ,  $\lambda = 1$ .

Optimal cell: A square with the volume  $\frac{\#cells}{vol(\Omega)}$ . Solver for both PDEs: PCG

Known optimal mesh: Refined unit-square.

Iter	Armojo-Steps	Newton-defect	$\ s_k\ $	funcvalue	angle	$\alpha$	Iter Solver $s_k$	defect $s_k$	Iter Solver Antigrad	defect Antigrad
1	6	7.08E+00	1.39E+02	1.13E+00	1	0.3	-	-	92	6.94E-04
2	4	1.48E+00	8.26E+01	6.45E-02	1	0.3	-	-	93	1.45E-04
3	4	5.81E-01	9.72E+00	5.75E-03	1	0.3	-	-	98	5.19E-05
4	4	1.84E-01	2.98E+00	6.11E-04	1	0.3	-	-	97	1.64E-05
5	4	5.59E-02	8.70E-01	7.15E-05	1	0.3	-	-	98	4.90E-06
6	0	1.93E-02	2.26E-02	4.44E-06	0.979	0.422	1	1.26E-06	98	1.69E-06
7	0	4.90E-03	5.36E-03	2.71E-07	1.000	0.583	1	3.16E-07	99	4.29E-07
8	0	1.20E-03	1.15E-03	1.97E-09	1.000	0.835	1	7.96E-08	99	1.05E-07
9	0	1.02E-04	9.02E-05	1.18E-16	1.000	1.000	1	6.95E-09	99	8.96E-09
10	0	7.15E-09	6.36E-09	9.94E-17	0.964	1.000	1	5.05E-13	98	6.05E-13

Video

When to stop the Newton-Scheme? Not the focus of this work.

Initial mesh: Take  $[0, 1]^2$ , refine it one time, then move the midpoint to  $(0.26, 0.26)$ , then refine again 5 times.  $\mu = 10$ ,  $\lambda = 1$ .  
 Optimal cell: A square with the volume  $\frac{\#cells}{vol(\Omega)}$ . Solver for both PDEs: PCG

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3	4	1.26E+01	9.09E+00	8.42E+00	1	0.3	0	-	9	4.33E-04
4	4	1.12E+01	8.19E+00	8.05E+00	1	0.3	0	-	9	2.52E-04
5	5	1.05E+01	7.52E+00	7.15E+00	1	0.3	0	-	9	2.96E-04
6	0	1.41E+00	5.47E-02	7.14E+00	0.993	0.311	1	2.14E-05	9	6.42E-05
7	0	9.95E-01	2.73E-02	7.13E+00	0.995	0.463	1	2.28E-05	9	4.47E-05
8	0	4.40E-01	1.04E-02	7.13E+00	0.996	0.546	1	6.76E-07	9	1.56E-05
9	0	1.69E-01	3.11E-03	7.13E+00	0.996	0.728	1	1.77E-06	9	5.73E-06
10	0	3.26E-02	4.77E-04	7.13E+00	0.996	0.993	1	5.80E-07	9	1.17E-06
11	0	1.61E-04	2.28E-06	7.13E+00	0.995	1	1	4.67E-09	9	5.49E-09
12	0	4.81E-09	1.13E-10	7.13E+00	0.922	1	1	1.70E-14	9	1.14E-13

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9	0	1.69E-01	3.11E-03	7.13E+00	0.996	0.728	1	1.77E-06	9	5.73E-06
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12	0	4.81E-09	1.13E-10	7.13E+00	0.922	1	1	1.70E-14	9	1.14E-13

Video

Another application: Adapt the mesh to inner boundaries.

Idea: Choose optimal cell size according to distance to the inner boundary. Do a few steps. Update the optimal cell size and calculate again. Repeat.

Initial mesh: unit square, Level 7.  $\mu = 100$ ,  $\lambda = 1$ , linear solver: PCG

Video

Total: 14 cycles, 140 Newton-Iterations, 514 Armijo-Steps, 470 Iterations to solve  $s_k$ , 14463 Iterations to solve for the Antigradient  
Visually, after 5 cycles / 50 Newton-Iterations not much is happening

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Another application: Adapt the mesh to inner boundaries.

Idea: Choose optimal cell size according to distance to the inner boundary. Do a few steps. Update the optimal cell size and calculate again. Repeat.

Initial mesh: unit square, Level 7.  $\mu = 100$ ,  $\lambda = 1$ , linear solver: PCG

Video

Total: 14 cycles, 140 Newton-Iterations, 514 Armijo-Steps, 470 Iterations to solve  $s_k$ , 14463 Iterations to solve for the Antigradient  
Visually, after 5 cycles / 50 Newton-Iterations not much is happening

**Thank you for your attention!**



P. G. CIARLET, Mathematical Elasticity, no. v. 20, 27, 29 in Studies in Mathematics and Its Applications, North-Holland ; Sole distributors for the U.S.A. and Canada, Elsevier Science Pub. Co, Amsterdam ; New York : New York, N.Y., U.S.A, 1988.