



Optimality Criteria Method for Optimal Design Problems

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Stationary diffusion equation

Let $\Omega \subseteq \mathbf{R}^d$ be open and bounded, $\mathbf{A} \in L^\infty(\Omega; \text{Sym}_d)$ satisfying

$$\mathbf{A}\xi \cdot \xi \geq \alpha|\xi|^2, \quad \mathbf{A}^{-1}\xi \cdot \xi \geq \frac{1}{\beta}|\xi|^2, \quad \xi \in \mathbf{R}^d$$

and $f \in H^{-1}(\Omega)$. Stationary diffusion equation with homogenous Dirichlet boundary condition:

$$\begin{cases} -\operatorname{div}(\mathbf{A}\nabla u) = f \\ u \in H_0^1(\Omega) \end{cases}$$

Ω - mixture of two isotropic materials with conductivities $0 < \alpha < \beta$:

$$\mathbf{A} = \chi\alpha\mathbf{I} + (1-\chi)\beta\mathbf{I},$$

where $\chi \in L^\infty(\Omega; \{0, 1\})$.

Introduction

Multiple state optimal design problems
Optimality criteria method
Elasticity setting

Stationary diffusion equation



Stationary diffusion equation

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Multiple state optimal design problem

$$\left\{ \begin{array}{l} J(\chi) = \int_{\Omega} [\chi(\mathbf{x})g_{\alpha}(\mathbf{x}, \mathbf{u}(\mathbf{x})) + (1 - \chi(\mathbf{x}))g_{\beta}(\mathbf{x}, \mathbf{u}(\mathbf{x}))] d\mathbf{x} \longrightarrow \min, \\ \chi \in L^{\infty}(\Omega; \{0, 1\}), \int_{\Omega} \chi d\mathbf{x} = q_{\alpha}, \end{array} \right.$$

$0 < q_{\alpha} < |\Omega|$, and g_{α}, g_{β} Caratheodory functions which satisfy growth condition

$$g_j(x, \mathbf{u}) \leq a|\mathbf{u}|^s + b(x), \quad j = \alpha, \beta,$$

for some $a > 0, b \in L^1(\Omega)$ and $1 \leq s < \frac{2d}{d-2}$,

and $\mathbf{u} = (u_1, \dots, u_m)$, $m \geq 2$, where u_i is the solution of

$$\left\{ \begin{array}{l} -\operatorname{div}(\mathbf{A} \nabla u_i) = f_i, \\ u_i \in H_0^1(\Omega) \end{array} \right., \quad i = 1, \dots, m$$

where $f_i \in H^{-1}(\Omega)$, $\mathbf{A} = \chi \alpha \mathbf{I} + (1 - \chi) \beta \mathbf{I}$, $0 < \alpha < \beta$.



Definition (Composite material)

If a sequence of characteristic functions $\chi_n \in L^\infty(\Omega; \{0, 1\})$ and conductivities $\mathbf{A}^n(x) = \chi_n(x)\alpha\mathbf{I} + (1 - \chi_n(x))\beta\mathbf{I}$ satisfy

$$\begin{aligned}\chi_n &\xrightarrow{*} \theta \\ \mathbf{A}^n &\xrightarrow{H} \mathbf{A},\end{aligned}$$

then it is said that \mathbf{A} is homogenised tensor of two-phase composite material with proportions θ of first material and microstructure defined by the sequence (χ_n) .

Definition (H-convergence)

A sequence of matrix functions \mathbf{A}^n is said to H-converge to \mathbf{A} if for every f the sequence of solutions of

$$\begin{cases} -\operatorname{div}(\mathbf{A}^n \nabla u_n) = f \\ u_n \in H_0^1(\Omega) \end{cases}$$

satisfies $u_n \rightharpoonup u$ in $H_0^1(\Omega)$, $\mathbf{A}^n \nabla u_n \rightharpoonup \mathbf{A} \nabla u$ in $L^2(\Omega; \mathbf{R}^d)$, where u is the solution of the homogenised equation

$$\begin{cases} -\operatorname{div}(\mathbf{A} \nabla u) = f \\ u \in H_0^1(\Omega). \end{cases}$$

Example – simple laminates: if χ_ε depend only on x_1 , then

$$\mathbf{A} = \operatorname{diag}(\lambda_\theta^-, \lambda_\theta^+, \lambda_\theta^+, \dots, \lambda_\theta^+),$$

where $\lambda_\theta^+ = \theta\alpha + (1 - \theta)\beta$,

$$\frac{1}{\lambda_\theta^-} = \frac{\theta}{\alpha} + \frac{1 - \theta}{\beta}.$$



Set of all composites:

$$\mathcal{A} := \{(\theta, \mathbf{A}) \in L^\infty(\Omega; [0, 1] \times \text{Sym}_d) : \mathbf{A} \in \mathcal{K}(\theta) \text{ a.e. on } \Omega\}$$

2D:

G-closure problem: for given θ find all possible homogenised (effective) tensors \mathbf{A}

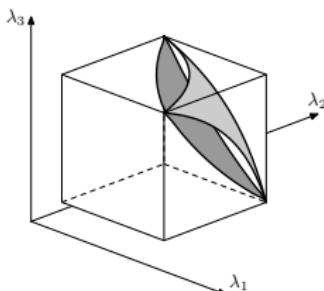
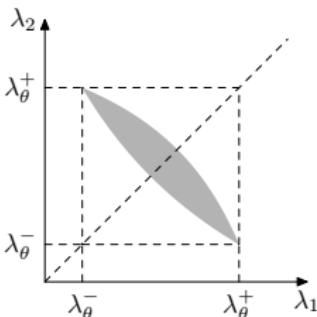
$\mathcal{K}(\theta)$ is given in terms of eigenvalues (Murat & Tartar; Lurie & Cherkaev):

$$\lambda_\theta^- \leq \lambda_j \leq \lambda_\theta^+ \quad j = 1, \dots, d$$

3D:

$$\sum_{j=1}^d \frac{1}{\lambda_j - \alpha} \leq \frac{1}{\lambda_\theta^- - \alpha} + \frac{d-1}{\lambda_\theta^+ - \alpha}$$

$$\sum_{j=1}^d \frac{1}{\beta - \lambda_j} \leq \frac{1}{\beta - \lambda_\theta^-} + \frac{d-1}{\beta - \lambda_\theta^+},$$





Original problem:

$$\begin{cases} J(\chi) = \int_{\Omega} [\chi(\mathbf{x})g_{\alpha}(\mathbf{x}, \mathbf{u}) + (1 - \chi(\mathbf{x}))g_{\beta}(\mathbf{x}, \mathbf{u})] d\mathbf{x} \rightarrow \min, \\ \chi \in L^{\infty}(\Omega; \{0, 1\}), \int_{\Omega} \chi d\mathbf{x} = q_{\alpha}. \end{cases}$$

Generalized objective function is

$$J(\theta, \mathbf{A}) = \int_{\Omega} [\theta(\mathbf{x})g_{\alpha}(\mathbf{x}, \mathbf{u}(\mathbf{x})) + (1 - \theta)(\mathbf{x})g_{\beta}(\mathbf{x}, \mathbf{u}(\mathbf{x}))] d\mathbf{x} + l \int_{\Omega} \theta(\mathbf{x}) d\mathbf{x}$$

where $\mathbf{u} = (u_1, \dots, u_m)$ and u_i is the solution of the state equation

$$\begin{cases} -\operatorname{div}(\mathbf{A} \nabla u_i) = f_i & , \\ u_i \in H_0^1(\Omega) & \end{cases} \quad i = 1, \dots, m.$$

Relaxed problem:

$$\begin{cases} J(\theta, \mathbf{A}) \rightarrow \min, \\ (\theta, \mathbf{A}) \in \{(\theta, \mathbf{A}) \in L^{\infty}(\Omega; [0, 1] \times \operatorname{Sym}_d) : \mathbf{A} \in \mathcal{K}(\theta) \text{ a.e. on } \Omega\}. \end{cases} \quad (1)$$



Optimality criteria method

-  G. Allaire, *Shape optimization by the homogenization method*, Springer-Verlag, 2002.
-  F. Murat, L. Tartar, *Calcul des Variations et Homogénéisation, in Les Méthodes de l'Homogenisation Théorie et Applications en Physique* (Bréau-sans-Nappe, 1983), Coll. Dir. Etudes et Recherches EDF, 57:319–369, Eyrolles, Paris 1985.
-  M. Vrdoljak, *On Hashin-Shtrikman bounds for mixtures of two isotropic materials*, Nonlinear Anal. Real World Appl., 11:4597–4606, 2010.



Theorem

Let (θ^*, \mathbf{A}^*) be a local minimizer for relaxation problem (1) with corresponding states u_i^* and adjoint states p_i^* , solutions of

$$\begin{cases} -\operatorname{div}(\mathbf{A}^* \nabla p_i^*) = \theta \frac{\partial g_\alpha}{\partial u_i}(\cdot, \mathbf{u}) + (1 - \theta) \frac{\partial g_\beta}{\partial u_i}(\cdot, \mathbf{u}) & i = 1, \dots, m. \\ p_i^* \in H_0^1(\Omega) \end{cases}$$

We introduce symmetric matrix $\mathbf{N}^* = \operatorname{Sym} \sum_{i=1}^m \sigma_i^* \otimes \tau_i^*$, for $\sigma_i^* = \mathbf{A}^* \nabla u_i^*$, $\tau_i^* = \mathbf{A}^* \nabla p_i^*$ and define function $g(\theta, \mathbf{N}^*) = \min_{\mathbf{A} \in \mathcal{K}(\theta)} (\mathbf{A}^{-1} : \mathbf{N}^*)$. Then

$$(\mathbf{A}^*)^{-1}(\mathbf{x}) : \mathbf{N}^*(\mathbf{x}) = g(\theta^*(\mathbf{x}), \mathbf{N}^*(\mathbf{x})), \quad \text{a.e. } x \in \Omega.$$

Moreover, if we define function

$$R^*(\mathbf{x}) = g_\alpha(\mathbf{x}, \mathbf{u}^*) - g_\beta(\mathbf{x}, \mathbf{u}^*) + l + \frac{\partial g}{\partial \theta}(\theta^*(\mathbf{x}), \mathbf{N}^*(\mathbf{x}))$$

the optimal θ^* satisfies (a. e. on Ω)

$$\begin{aligned} \theta^*(\mathbf{x}) &= 0 && \text{if } R^*(\mathbf{x}) > 0 \\ \theta^*(\mathbf{x}) &= 1 && \text{if } R^*(\mathbf{x}) < 0 \\ 0 \leq \theta^*(\mathbf{x}) &\leq 1 && \text{if } R^*(\mathbf{x}) = 0. \end{aligned}$$



Algorithm

Take some initial θ^0 and \mathbf{A}^0 . For k from 0 to N:

- ① Calculate u_i^k , $i = 1, \dots, m$, the solution of

$$\begin{cases} -\operatorname{div}(\mathbf{A}^k \nabla u_i^k) = f_i \\ u_i^k \in H_0^1(\Omega). \end{cases}$$

- ② Calculate p_i^k , $i = 1, \dots, m$, the solution of

$$\begin{cases} -\operatorname{div}(\mathbf{A}^k \nabla p_i^k) = \theta^k \frac{\partial g_\alpha}{\partial u_i}(\cdot, \mathbf{u}^k) + (1 - \theta^k) \frac{\partial g_\beta}{\partial u_i}(\cdot, \mathbf{u}^k) \\ p_i^k \in H_0^1(\Omega), \mathbf{u}^k = (u_1^k, \dots, u_m^k) \end{cases}$$

and define $\sigma_i^k := \mathbf{A}^k \nabla u_i^k$, $\tau_i^k := \mathbf{A}^k \nabla p_i^k$ and $\mathbf{N}^k := \operatorname{Sym} \sum_{i=1}^m (\sigma_i^k \otimes \tau_i^k)$.

- ③ For $\mathbf{x} \in \Omega$, let $\theta^{k+1}(\mathbf{x})$ be the zero of function

$$\theta \mapsto g_\alpha(\mathbf{x}, \mathbf{u}^k(\mathbf{x})) - g_\alpha(\mathbf{x}, \mathbf{u}^k(\mathbf{x})) + l + \frac{\partial g}{\partial \theta}(\theta, \mathbf{N}^k(\mathbf{x})),$$

and if a zero doesn't exist, take 0 (or 1) in case when this function is positive (or negative) on $(0, 1)$.

- ④ Let $(\mathbf{A}^{k+1})^{-1}(\mathbf{x})$ be the minimizer in the definition of $g(\theta^{k+1}(\mathbf{x}), \mathbf{N}^k(\mathbf{x}))$.



Theorem (d=2)

If dimension $d = 2$, then for given $\theta \in [0, 1]$ and matrix \mathbf{N} with eigenvalues $\eta_1 \geq \eta_2$ we have

- A. If $\eta_2 > 0$ and $\theta^A := \left(\alpha \frac{\sqrt{\eta_1}}{\sqrt{\eta_2}} - \beta \right) \frac{1}{\alpha - \beta}$, then

$$\frac{\partial g}{\partial \theta}(\theta, \mathbf{N}) = \begin{cases} \frac{1}{\beta} (\beta^2 - \alpha^2) \left(\frac{\sqrt{\eta_1} + \sqrt{\eta_2}}{(\theta(\alpha - \beta) + \beta + \alpha)} \right)^2, & \theta < \theta^A \\ \frac{(\beta - \alpha) \eta_1}{(\theta(\alpha - \beta) + \beta)^2} + \eta_2 \left(\frac{1}{\alpha} - \frac{1}{\beta} \right), & \theta \geq \theta^A \end{cases}.$$

- B. If $\eta_1 < 0$ and $\theta^B := \left(\frac{\sqrt{-\eta_1}}{\sqrt{-\eta_2}} - 1 \right) \frac{\beta}{\alpha - \beta}$, then

$$\frac{\partial g}{\partial \theta}(\theta, \mathbf{N}) = \begin{cases} -\frac{1}{\alpha} (\beta^2 - \alpha^2) \left(\frac{\sqrt{-\eta_1} + \sqrt{-\eta_2}}{\theta(\alpha - \beta) + 2\beta} \right)^2, & \theta > \theta^B \\ \frac{(\beta - \alpha) \eta_1}{(\theta(\alpha - \beta) + \beta)^2} + \eta_2 \left(\frac{1}{\alpha} - \frac{1}{\beta} \right), & \theta \leq \theta^B \end{cases}.$$

- C. If $\eta_1 \geq 0$ and $\eta_2 \leq 0$, then

$$\frac{\partial g}{\partial \theta}(\theta, \mathbf{N}) = \frac{(\beta - \alpha) \eta_1}{(\theta(\alpha - \beta) + \beta)^2} + \eta_2 \left(\frac{1}{\alpha} - \frac{1}{\beta} \right).$$



Theorem (d=3)

For $d = 3$, given $\theta \in [0, 1]$ and matrix \mathbf{N} with eigenvalues $\eta_1 \geq \eta_2 \geq \eta_3$ we have

A. If $\eta_3 = 0$ then $\frac{\partial g}{\partial \theta}(\theta, \mathbf{N}) = \frac{\beta - \alpha}{(\theta\alpha + (1-\theta)\beta)^2}(\eta_1 + \eta_2)$.

B. If $\eta_3 > 0$ and additionally $\sqrt{\eta_2} + \sqrt{\eta_3} - \sqrt{\eta_1} > 0$, it holds

$$\frac{\partial g}{\partial \theta}(\theta, \mathbf{N}) = \begin{cases} \beta^{-1}(\beta - \alpha)(\alpha + 2\beta) \left(\frac{\sqrt{\eta_1} + \sqrt{\eta_2} + \sqrt{\eta_3}}{2\theta(\alpha - \beta) + \alpha + 2\beta} \right)^2, & \theta < \theta_1^B, \\ \beta^{-1}(\beta^2 - \alpha^2) \left(\frac{\sqrt{\eta_2} + \sqrt{\eta_3}}{\theta(\alpha - \beta) + \alpha + \beta} \right)^2 + (\beta - \alpha) \frac{\eta_1}{(\theta\alpha + (1-\theta)\beta)^2}, & \theta_1^B \leq \theta < \theta_2^B, \\ \eta_3(\alpha^{-1} - \beta^{-1}) + \frac{\beta - \alpha}{(\theta\alpha + (1-\theta)\beta)^2}(\eta_1 + \eta_2), & \theta \geq \theta_2^B, \end{cases}$$

where $\theta_1^B = 1 - \frac{\alpha(\sqrt{\eta_2} + \sqrt{\eta_3} - 2\sqrt{\eta_1})}{(\alpha - \beta)(\sqrt{\eta_2} + \sqrt{\eta_3} - \sqrt{\eta_1})}$ and $\theta_2^B = 1 - \frac{\alpha(\sqrt{\eta_3} - \sqrt{\eta_2})}{(\alpha - \beta)\sqrt{\eta_3}}$.

If $\sqrt{\eta_2} + \sqrt{\eta_3} - \sqrt{\eta_1} \leq 0$ then we omit the first case in the above formula.

C. If $\eta_3 < 0$ then, if η_2 and η_1 are negative as well then

$$\frac{\partial g}{\partial \theta}(\theta, \mathbf{N}) = \begin{cases} -\alpha^{-1}(\beta - \alpha)(2\alpha + \beta) \left(\frac{\sqrt{-\eta_1} + \sqrt{-\eta_2} + \sqrt{-\eta_3}}{2\theta(\alpha - \beta) + 3\beta} \right)^2, & \theta > \theta_1^C, \\ -\alpha^{-1}(\beta^2 - \alpha^2) \left(\frac{\sqrt{-\eta_2} + \sqrt{-\eta_3}}{\theta(\alpha - \beta) + 2\beta} \right)^2 + \eta_1 \frac{\beta - \alpha}{(\theta\alpha + (1-\theta)\beta)^2}, & \theta_2^C < \theta \leq \theta_1^C, \\ (\alpha^{-1} - \beta^{-1})\eta_3 + \frac{\beta - \alpha}{(\theta\alpha + (1-\theta)\beta)^2}(\eta_1 + \eta_2), & \theta \leq \theta_2^C, \end{cases}$$

where $\theta_1^C = \frac{\beta(\sqrt{-\eta_2} + \sqrt{-\eta_3} - 2\sqrt{-\eta_1})}{(\beta - \alpha)(\sqrt{-\eta_2} + \sqrt{-\eta_3} - \sqrt{-\eta_1})}$ and $\theta_2^C = \frac{\beta(\sqrt{-\eta_3} - \sqrt{-\eta_2})}{(\beta - \alpha)\sqrt{-\eta_3}}$.

If $\eta_2 < 0$ and $\eta_1 \geq 0$ then θ_1^C is not defined and we can express $\frac{\partial g}{\partial \theta}(\theta, \mathbf{N})$ by the second and third term in the formula above, omitting the assumption $\theta \leq \theta_1^C$ in the second case.

If $\eta_2 \geq 0$ then both θ_1^C and θ_2^C are not defined and $\frac{\partial g}{\partial \theta}$ is given by formula in the third case above, for any $\theta \in [0, 1]$.



Example 1.

We consider two dimensional problem of weighted energy minimization

$$J(\theta, \mathbf{A}) = 2 \int_{\Omega} f_1 u_1 \, d\mathbf{x} + \int_{\Omega} f_2 u_2 \, d\mathbf{x} \longrightarrow \min,$$

where $\Omega \subseteq \mathbf{R}^2$ is a ball $B(\mathbf{0}, 2)$, $\alpha = 1$, $\beta = 2$, while u_1 and u_2 are state functions for

$$\begin{cases} -\operatorname{div}(\mathbf{A} \nabla u_i) = f_i \\ u_i \in H_0^1(\Omega) \end{cases}, \quad i = 1, 2,$$

where we take $f_1 = \chi_{B(\mathbf{0}, 1)}$ and $f_2 \equiv 1$ for right-hand sides.

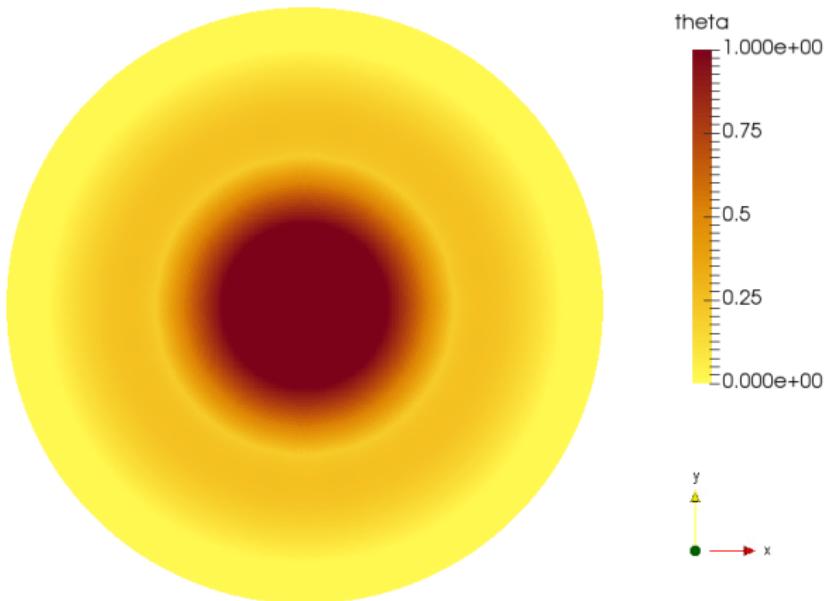


Figure: Optimal distribution of materials in circle with volume constraint 25% of the first material.

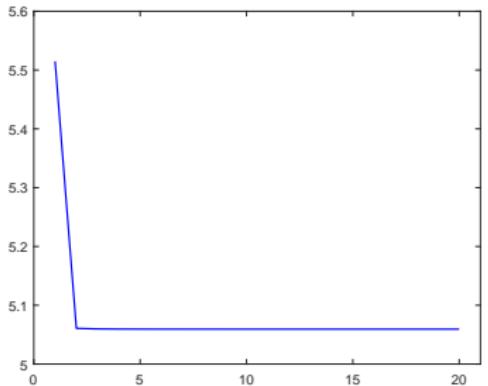
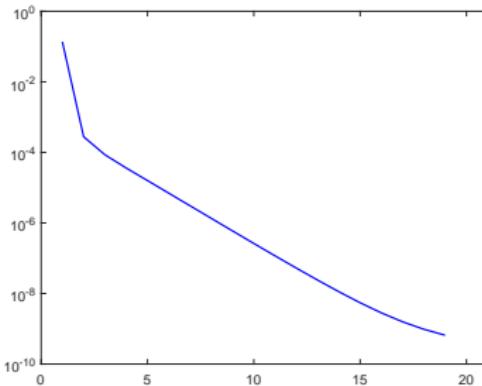
(a) Cost functional J .(b) $\| \theta^k - \theta^{k+1} \|_{L^2}$ in terms of the iteration number k .

Figure: Convergence history for energy minimization in circle.



Comparison between numerical and exact solution

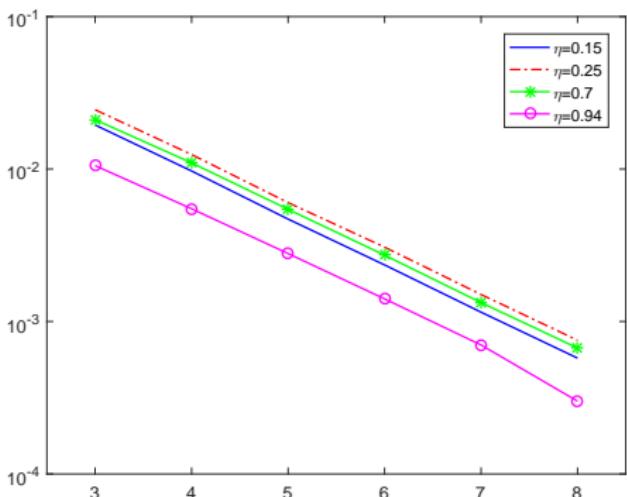


Figure: L^1 norm of difference between numerical and exact solution with respect to mesh refinement (each refinement introduces four times finer mesh) for various choices of volume fractions η of the first phase.



Example 2.

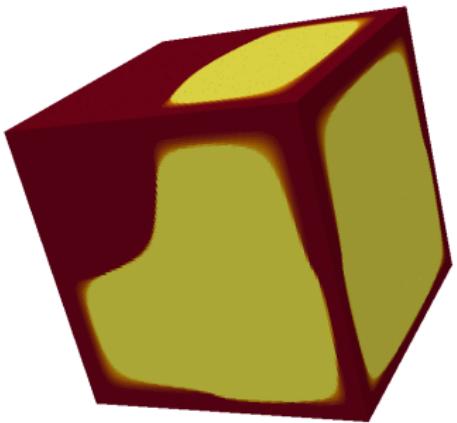
Second example is three dimensional energy minimization problem

$$J(\theta, \mathbf{A}) = \int_{\Omega} (f_1 u_1 + f_2 u_2) d\mathbf{x} \longrightarrow \min,$$

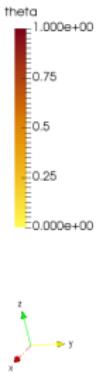
with $\alpha = 1$, $\beta = 2$ and two state equations

$$\begin{cases} -\operatorname{div}(\mathbf{A} \nabla u_i) = f_i \\ u_i \in H_0^1(\Omega) \end{cases}, \quad i = 1, 2.$$

We take cube $\Omega = [-1, 1]^3$ as domain and set function f_1 to be zero on the upper half ($z > 0$) and 10 on the lower half of the cube, while function f_2 to be zero on the left half ($y < 0$) and 10 on the right half of the cube.



(a) Optimal distribution of materials in a cube.



(b) Intersection of the cube with $x=0$ plane.

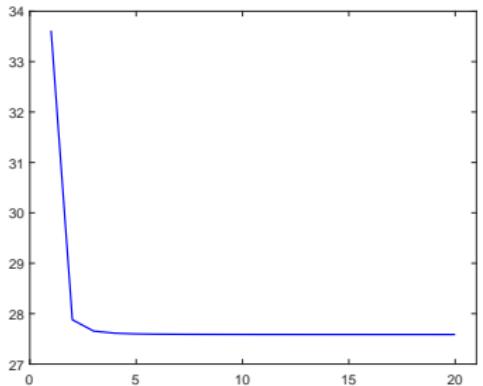
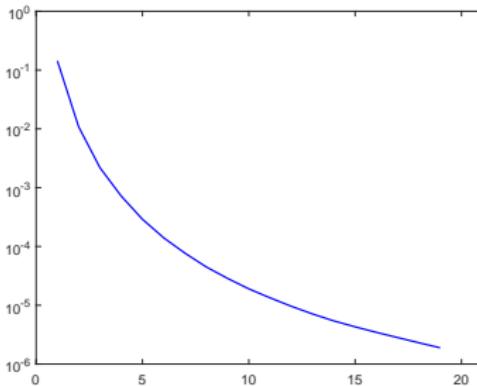
(c) Cost functional J .(d) $\|\theta^k - \theta^{k+1}\|_{L^2}$ in terms of the iteration number k .

Figure: Convergence history for energy minimization.



Convergence of the optimality criteria method

- single-state problems, case of a self-adjoint optimization problem

$$J(\theta, \mathbf{A}) = \pm \int_{\Omega} f u \, d\mathbf{x} + l \int_{\Omega} \theta \, d\mathbf{x}$$

- G. Allaire, *Shape optimization by the homogenization method*, Springer-Verlag, 2002.

- multiple-state problems, case of minimization of the conic sum of energies

$$J(\theta, \mathbf{A}) = \sum_{i=1}^m \mu_i \int_{\Omega} f_i u_i \, d\mathbf{x} + l \int_{\Omega} \theta \, d\mathbf{x}, \quad \mu_i > 0, i = 1, \dots, m.$$



Theorem

If $m < d$, then, in every step of the algorithm, \mathbf{A}^{k+1} is a simple laminate with the lamination direction orthogonal to σ_i^k , $i = 1, \dots, m$.

Theorem

If Ω is spherically symmetric, θ^k and f_i are radial functions for $i = 1, \dots, m$, and \mathbf{A}^k is a simple laminate with the lamination direction orthogonal to the radial vector, then θ^{k+1} is also a radial function, while \mathbf{A}^{k+1} is a simple laminate with the lamination direction orthogonal to σ_i^k , $i = 1, \dots, m$.



Linearized elasticity system

Let $\Omega \subseteq \mathbf{R}^d$ be open and bounded, $\mathbf{A} \in L^\infty(\Omega; \text{Sym}_d^4)$ defined as

$$\mathbf{A}(\mathbf{x}) = \chi(\mathbf{x})\mathbf{A} + (1 - \chi(\mathbf{x}))\mathbf{B},$$

where $\mathbf{A}, \mathbf{B} = 2\mu_{\mathbf{A}, \mathbf{B}}\mathbf{I}_4 + \left(\kappa_{\mathbf{A}, \mathbf{B}} - \frac{2\mu_{\mathbf{A}, \mathbf{B}}}{d}\right)\mathbf{I}_2 \otimes \mathbf{I}_2$, for $0 < \mu_{\mathbf{A}} \leq \mu_{\mathbf{B}}$ and $0 < \kappa_{\mathbf{A}} \leq \kappa_{\mathbf{B}}$. The state equation reads

$$\begin{cases} -\text{div}(\mathbf{A}e(\mathbf{u})) = \mathbf{f} \\ \mathbf{u} \in H_0^1(\Omega; \mathbf{R}^d) \end{cases}$$

where $e(\mathbf{u}) = \frac{1}{2}(\nabla \mathbf{u} + \nabla \mathbf{u}^\top)$ and $\mathbf{f} \in H^{-1}(\Omega; \mathbf{R}^d)$.



Classical optimal design problem:

$$\begin{cases} J(\chi) = \int_{\Omega} [\chi(\mathbf{x})g_{\mathbf{A}}(\mathbf{x}, \mathbf{u}(\mathbf{x})) + (1 - \chi(\mathbf{x}))g_{\mathbf{B}}(\mathbf{x}, \mathbf{u}(\mathbf{x}))] d\mathbf{x} \longrightarrow \min, \\ \chi \in L^{\infty}(\Omega; \{0, 1\}), \quad \int_{\Omega} \chi d\mathbf{x} = q_{\alpha}. \end{cases}$$

Relaxed formulation:

$$\begin{cases} J(\theta, \mathbf{A}) = \int_{\Omega} [\theta(\mathbf{x})g_{\mathbf{A}}(\mathbf{x}, \mathbf{u}(\mathbf{x})) + (1 - \theta)(\mathbf{x})g_{\mathbf{B}}(\mathbf{x}, \mathbf{u}(\mathbf{x}))] d\mathbf{x} + \\ \quad + l \int_{\Omega} \theta(\mathbf{x}) d\mathbf{x} \longrightarrow \min, \\ (\theta, \mathbf{A}) \in \{(\theta, \mathbf{A}) \in L^{\infty}(\Omega; [0, 1] \times \text{Sym}_d^4) : \mathbf{A} \in G_{\theta} \text{ a.e. on } \Omega\}. \end{cases}$$



Compliance optimization

Theorem

If (θ^*, \mathbf{A}^*) is a minimizer of the objective function $J(\theta, \mathbf{A}) = \int_{\Omega} \mathbf{f}(\mathbf{x}) \cdot \mathbf{u}(\mathbf{x}) d\mathbf{x} + l \int_{\Omega} \theta(\mathbf{x}) d\mathbf{x}$ and if σ is the unique corresponding minimizer of

$$\min_{\substack{\tau \in L^2(\Omega; \text{Sym}_d) \\ -\text{div} \tau = \mathbf{f} \text{ in } \Omega}} \int_{\Omega} \mathbf{A}^{-1} \tau : \tau d\mathbf{x} + l \int_{\Omega} \theta d\mathbf{x},$$

then σ satisfies

$$\begin{cases} \sigma = \mathbf{A}^* \mathbf{e}(\mathbf{u}) & \text{in } \Omega \\ -\text{div} \sigma = \mathbf{f} & \text{in } \Omega \\ \mathbf{u} = 0 & \text{on } \partial\Omega, \end{cases}$$

with $\mathbf{u} \in H_0^1(\Omega, \mathbf{R}^d)$, and, almost everywhere in Ω

$$\mathbf{A}^{*-1} \sigma : \sigma = g(\theta^*, \sigma),$$

while θ^* is the unique minimizer of the convex optimization $\min_{0 \leq \theta \leq 1} (g(\theta, \sigma) + l\theta)$, where $g(\theta, \sigma)$ is the lower Hashin-Shtrikman bound on complementary energy defined by

$$\mathbf{A}^{*-1} \sigma : \sigma \geq \mathbf{B}^{-1} \sigma : \sigma + \theta \max_{\eta \in \text{Sym}_d} \left(2\sigma : \eta - (\mathbf{A}^{-1} - \mathbf{B}^{-1})^{-1} \eta : \eta - (1 - \theta)(\mathbf{B}\eta : \eta - h(\mathbf{B}\eta)) \right),$$

where $h(\eta) = \min_{\mathbf{e} \in S^{d-1}} \frac{1}{\mu_{\mathbf{B}}} (|\eta \mathbf{e}|^2 - (\eta \mathbf{e} \cdot \mathbf{e})^2) + \frac{1}{2\mu_{\mathbf{B}} + \lambda_{\mathbf{B}}} (\eta \mathbf{e} \cdot \mathbf{e})^2$.



Thank you for your attention!