

# 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:

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

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

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

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



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## Multiple state optimal design problem

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

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

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

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

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

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  $\theta$  of first material and microstructure defined by the sequence  $(\chi_n)$ .

## 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  $\chi_\varepsilon$  depend only on  $x_1$ , then

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

where 
$$\lambda_\theta^+ = \theta\alpha + (1 - \theta)\beta, \quad \frac{1}{\lambda_\theta^-} = \frac{\theta}{\alpha} + \frac{1 - \theta}{\beta}.$$



Set of all composites:

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

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

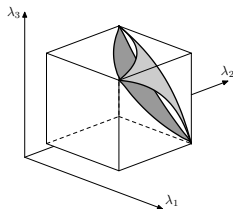
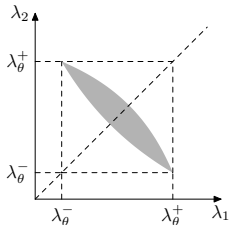
$\mathcal{K}(\theta)$  is given in terms of eigenvalues (Murat & Tartar; Lurie & Cherkhaev):

$$\lambda_\theta^- \leq \lambda_j \leq \lambda_\theta^+ \quad j = 1, \dots, d \quad \text{3D:}$$

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

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

2D:





Original problem:

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

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:

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







## Theorem

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

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

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  $\theta^*$  satisfies (a. e. on  $\Omega$ )

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



## Algorithm

Take some initial  $\theta^0$  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  $\langle 0, 1 \rangle$ .

- 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  $\eta_2$  and  $\eta_1$  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  $\theta_1^C$  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  $\theta_1^C$  and  $\theta_2^C$  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.

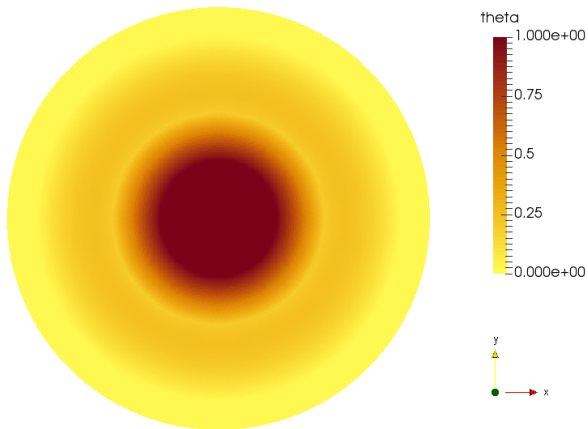
We consider two dimensional problem of weighted energy minimization

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

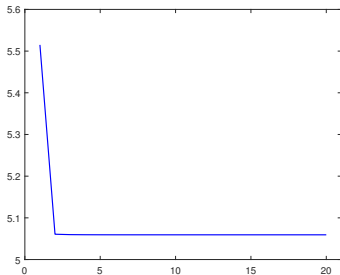
where  $\Omega \subseteq \mathbf{R}^2$  is a ball  $B(\mathbf{0}, 2)$ ,  $\alpha = 1$ ,  $\beta = 2$ , while  $u_1$  and  $u_2$  are state functions for

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

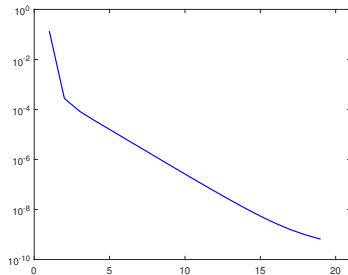
where we take  $f_1 = \chi_{B(\mathbf{0}, 1)}$  and  $f_2 \equiv 1$  for right-hand sides.



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



(a) Cost functional  $J$ .

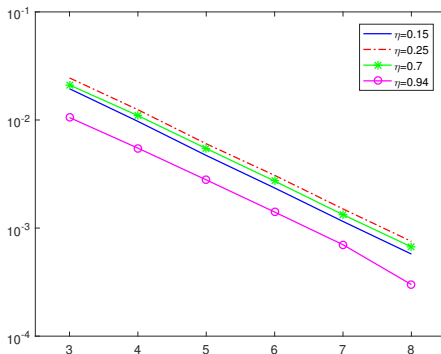


(b)  $\|\theta^k - \theta^{k+1}\|_{L^2}$  in terms of the iteration number  $k$ .

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  $\eta$  of the first phase.





## Example 2.

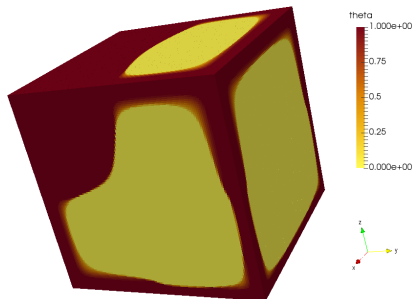
Second example is three dimensional energy minimization problem

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

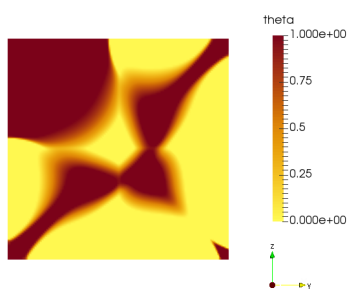
with  $\alpha = 1$ ,  $\beta = 2$  and two state equations

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

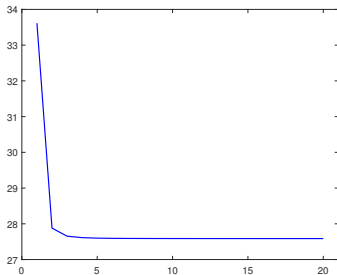
We take cube  $\Omega = [-1, 1]^3$  as domain and set function  $f_1$  to be zero on the upper half ( $z > 0$ ) and 10 on the lower half of the cube, while function  $f_2$  to be zero on the left half ( $y < 0$ ) and 10 on the right half of the cube.



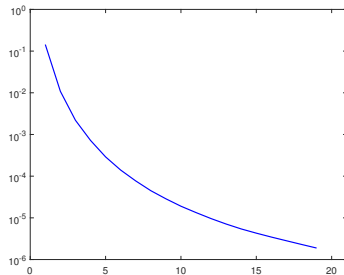
(a) Optimal distribution of materials in a cube.



(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

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



## 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  $\sigma_i^k$ ,  $i = 1, \dots, m$ .*

## Theorem

*If  $\Omega$  is spherically symmetric,  $\theta^k$  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  $\theta^{k+1}$  is also a radial function, while  $\mathbf{A}^{k+1}$  is a simple laminate with the lamination direction orthogonal to  $\sigma_i^k$ ,  $i = 1, \dots, m$ .*



## 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:

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

Relaxed formulation:

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



*Thank you for your attention!*