

An introduction to shape and topology optimization

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Part V

Density-based topology optimization techniques

- 1 From homogenization to density-based optimization
- 2 Density-based topology optimization problems
- 3 Numerical Aspects

A short reminder: homogenization-based topology optimization (I)

- Let us consider the following shape optimization problem, in the two-phase **conductivity setting**:

$$\min_{\Omega \subset D} J(\Omega), \text{ where } J(\Omega) := \int_D j(u_\Omega) dx, \quad (\text{SO})$$

and $j : \mathbb{R} \rightarrow \mathbb{R}$ is a given, smooth function.

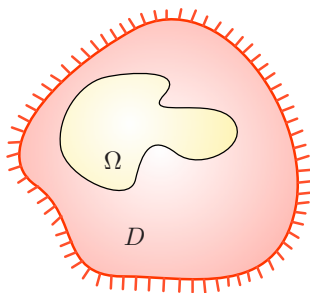
- Here, the **temperature** $u_\Omega \in H_0^1(D)$ is the solution to:

$$\begin{cases} -\operatorname{div}(\gamma_\Omega \nabla u_\Omega) & = f & \text{in } D, \\ u_\Omega & = 0 & \text{on } \partial D, \end{cases}$$

where the conductivity γ_Ω is of the form:

$$\gamma_\Omega(x) = \alpha + \chi_\Omega(x)(\beta - \alpha), \quad x \in D.$$

- This problem does not have a solution in general: minimizing sequences tend to create **"microstructures"**.



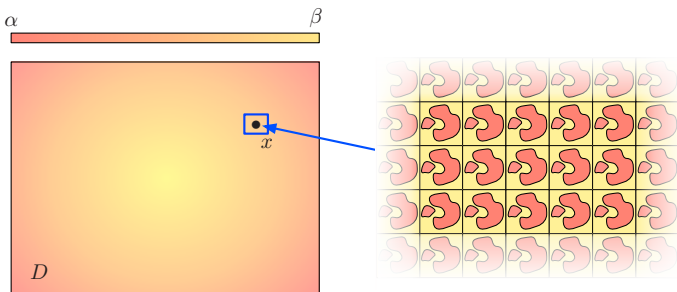
A short reminder: homogenization-based topology optimization (II)

The **homogenized formulation** of the problem extends the set of designs to **composite structures**:

$$(\theta, A) \in \mathcal{CD} := \{ \theta \in L^\infty(D, [0, 1]), A(x) \in G_{\theta(x)} \text{ a.e. } x \in D \},$$

where:

- $\theta(x) \in [0, 1]$ is the **local density** of material β around $x \in D$;
- $A(x) \in \mathbb{R}^{d \times d}$ is the **microstructure tensor**, in the set $G_{\theta(x)}$ of all the tensors obtained by homogenizing materials α, β in proportions $(1 - \theta(x))$ and $\theta(x)$.



A short reminder: homogenization-based topology optimization (III)

The **relaxed** version of the original problem is:

$$\min_{(\theta, A) \in \mathcal{CD}} J(\theta, A) := \int_D j(u_{\theta, A}) \, dx, \quad (\text{H})$$

where the **temperature** $u_{\theta, A}$ induced by the composite structure (θ, A) satisfies:

$$\begin{cases} -\operatorname{div}(A \nabla u_{\theta, A}) = f & \text{in } D, \\ u_{\theta, A} = 0 & \text{on } \partial D. \end{cases}$$

Under suitable hypotheses, the following facts hold true:

- The problem (H) has at least one **global minimizer** (θ^*, A^*) .
- Every such global minimizer is the **limit**, in the sense of homogenization, of a sequence of “classical designs” $\Omega^n \subset D$.
- Every minimizing sequence Ω^n of the original problem (SO) converges in the sense of homogenization to a global minimizer of the relaxed problem (H).

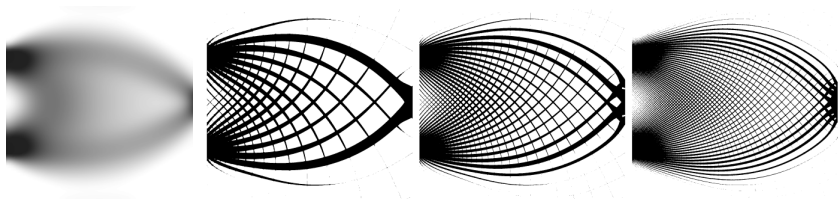
A short reminder: homogenization-based topology optimization (IV)

- From the optimal **composite design** $(\theta^*, A^*) \in \mathcal{CD}$, a true, “black-and-white” shape Ω is easily recovered by thresholding:

$$\Omega := \{x \in D, \theta^*(x) > c\},$$

where $c \in [0, 1]$ is chosen so that, e.g. Ω satisfies a desired volume constraint.

- More elaborate strategies are available, which do use the optimal microstructure tensor A^* to generate minimizing sequences Ω^n for $J(\Omega)$; see for instance the **deshomogenization method** from [PanTra, GroSig].



The “deshomogenization” method allows to infer minimizing sequences for the shape functional $J(\Omega)$ from the datum of the optimal composite design (θ, A^*) (picture from [AllGeoPan]).

From homogenization to density-based methods (I)

- A pattern $\omega \subset Y := (0,1)^d$ induces a **periodic distribution** of the two conductive phases α and β at any scale ε within D :

$$A_\omega^\varepsilon(x) = A_\omega\left(\frac{x}{\varepsilon}\right), \quad x \in D,$$

where for $y \in Y$,

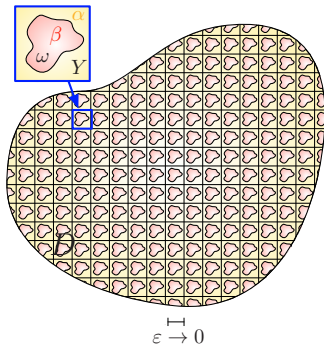
$$A_\omega(y) := \begin{cases} \beta & \text{if } x \in \omega, \\ \alpha & \text{if } x \notin \omega. \end{cases}$$

- The **effective conductivity** inside D as $\varepsilon \rightarrow 0$ is the matrix A_ω^* with entries:

$$(A_\omega^*)_{i,j} = \int_Y A_\omega(y) (e_i + \nabla w_i(y)) \cdot (e_j + \nabla w_j(y)) \, dy,$$

where the $w_i \in H_{\#}^1(Y)$ are the **cell functions**:

$$\begin{cases} -\operatorname{div}(A_\omega(y)(e_i + \nabla w_i)) = 0 & \text{in } Y, \\ y \mapsto w_i(y) & \text{is } Y\text{-periodic.} \end{cases}$$



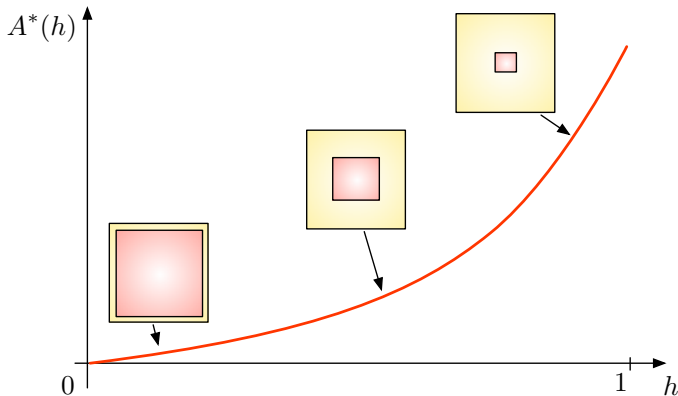
From homogenization to density-based methods (II)

- The set G_θ is made of all the effective conductivities A_ω^* of **periodic arrangements** of the phases α and β induced by patterns $\omega \subset Y$ with volume fraction $|\omega| = \theta$.
- This set can be characterized explicitly in the present two-phase conductivity setting, but this characterization is difficult to handle in practice.
- In general, only **bounds** are known about G_θ : the **Hashin-Shtrikman** bounds.

From homogenization to density-based methods (III)

One early simplification proposition [BenKik]:

- Only **one** microstructure pattern (e.g. a square inclusion) is retained for a given value $h \in [0, 1]$ of the volume fraction, or **density**.
- The homogenization tensor $A^*(h)$ is completely parametrized by h .



From homogenization to density-based methods (III)

- In numerical practice, a continuous expression $h \mapsto A^*(h)$ is constructed by:
 - Calculating $A^*(h_i)$ from the homogenization formulas, using the finite element method on the unit cell Y , for sample values $0 \leq h_1 < \dots < h_N \leq 1$.
 - Interpolating the quantities $A^*(h_i)$ using e.g. polynomial functions (splines).
- The **density-based** version of the problem reads:

$$\min_{h \in L^\infty(D, [0,1])} J(h), \quad J(h) = \int_D j(u_h) \, dx,$$

where $u_h \in H_0^1(D)$ is the solution to:

$$\begin{cases} -\operatorname{div}(A^*(h)\nabla u_h) = f & \text{in } D, \\ u_h = 0 & \text{on } \partial D. \end{cases}$$

The problem falls in the setting of **parametric optimization**.

- One step further in this direction consists in dropping completely the requirement that the material law $h \mapsto A^*(h)$ be “physical”...

Part V

Topology optimization

- 1 From homogenization to density-based optimization
- 2 **Density-based topology optimization problems**
 - General features
 - Extensions to linear elasticity and fluid mechanics
- 3 Numerical Aspects

Density-based topology optimization (I)

- We take again the two-phase **conductivity setting**:

$$\min_{\Omega \subset D} J(\Omega), \text{ where } J(\Omega) = \int_D j(u_\Omega) dx. \quad (\text{SO})$$

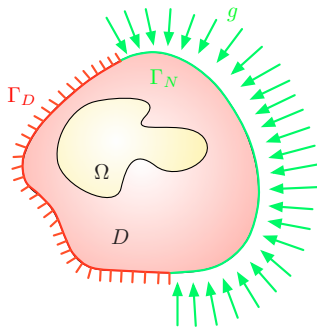
- In here, the temperature u_Ω is the solution to:

$$\begin{cases} -\operatorname{div}(\gamma_\Omega \nabla u_\Omega) & = f & \text{in } D, \\ u_\Omega & = 0 & \text{on } \Gamma_D, \\ \gamma_\Omega \frac{\partial u_\Omega}{\partial n} & = g & \text{on } \Gamma_N, \end{cases}$$

where the conductivity γ_Ω reads:

$$\gamma_\Omega = \alpha + \chi_\Omega(\beta - \alpha).$$

- The ideas that we now present extend to the contexts of linearized elasticity and fluid mechanics.



Density-based topology optimization (II)

- The (sought) “black-and-white” characteristic function $\chi_\Omega : D \rightarrow \{0, 1\}$ of the shape Ω , is replaced by a “grayscale” **density function** $h : D \rightarrow [0, 1]$.
- The properties (diffusion) of a region with **intermediate density** $h(x) \in (0, 1)$ are described via an empirical isotropic **interpolation law** $\zeta(h)$ between α and β :

$$\zeta(0) = \alpha, \text{ and } \zeta(1) = \beta.$$

- The problem rewrites:

$$\min_{h \in \mathcal{U}_{\text{ad}}} J(h), \text{ where } \mathcal{U}_{\text{ad}} = L^\infty(D, [0, 1]), \quad J(h) = \int_D j(u_h) \, dx,$$

and $u_h \in H^1(D)$ is the solution to:

$$\begin{cases} -\operatorname{div}(\zeta(h)\nabla u_h) = f & \text{in } D, \\ u_h = 0 & \text{on } \Gamma_D, \\ \zeta(h)\frac{\partial u_h}{\partial n} = g & \text{on } \Gamma_N. \end{cases}$$

- It is a heuristic simplification of the homogenized problem (H), where the microstructure tensor A^* is omitted.

The resulting density-based problem is within the realm of **parametric optimization!**

Theorem 1.

The objective function

$$J(h) = \int_D j(u_h) \, dx$$

is Fréchet differentiable at any $h \in \mathcal{U}_{\text{ad}}$, and its derivative reads

$$\forall \hat{h} \in L^\infty(D), \quad J'(h)(\hat{h}) = \int_D \zeta'(h)(\nabla u_h \cdot \nabla p_h) \hat{h} \, dx,$$

where the **adjoint state** $p_h \in H^1(D)$ is the unique solution to the system:

$$\begin{cases} -\operatorname{div}(\zeta(h)\nabla p_h) = -j'(u_h) & \text{in } D, \\ p_h = 0 & \text{on } \Gamma_D, \\ \zeta(h)\frac{\partial p_h}{\partial n} = 0 & \text{on } \Gamma_N. \end{cases}$$

The interpolation profile

- The interpolation profile $\zeta(h)$ prescribes **material properties** (diffusion, etc.) to regions with (fictitious) intermediate densities.
- In the practice of the **Solid Isotropic Method with Penalization** (SIMP), a power law of the form

$$\zeta(h) = \alpha + h^p(\beta - \alpha)$$

is used (often, $p = 3$).

- This has the effect to **penalize** the presence of “grayscale” intermediate regions, and to steer the optimized density towards a “black-and white” function.
- This interpolation law is **empirical**: there is no guarantee that a material with such properties does exist!
- In the article [Am2], other choices for $\zeta(h)$ are discussed, which are more consistent from the physical viewpoint.

Part V

Topology optimization

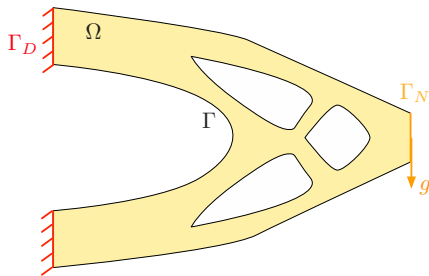
- 1 From homogenization to density-based optimization
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The linearized elasticity setting (I)

- We consider the optimal design problem:

$$\min_{\Omega} J(\Omega), \text{ where } J(\Omega) = \int_{\Omega} j(u_{\Omega}) \, dx,$$

and $j : \mathbb{R}^d \rightarrow \mathbb{R}$ is a smooth function.



- The displacement u_{Ω} is the unique solution to the linearized elasticity system:

$$\begin{cases} -\operatorname{div}(Ae(u_{\Omega})) = 0 & \text{in } \Omega, \\ u_{\Omega} = 0 & \text{on } \Gamma_D, \\ Ae(u_{\Omega})n = g & \text{on } \Gamma_N, \\ Ae(u_{\Omega})n = 0 & \text{on } \Gamma, \end{cases} \quad (\text{E})$$

where the optimized boundary Γ is traction-free.

The linearized elasticity setting (II)

The state equation for u_Ω is approximated by the **Ersatz material method**:

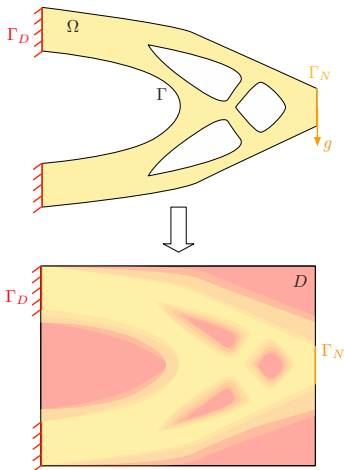
- A large computational box D is considered.
- The void $D \setminus \bar{\Omega}$ is filled with a very **soft material**, with Hooke's tensor εA , $\varepsilon \ll 1$.
- The solution u_Ω to (E) is replaced by that u_ε to:

$$\begin{cases} -\operatorname{div}(A_\Omega e(u_\varepsilon)) = 0 & \text{in } D, \\ u_\varepsilon = 0 & \text{on } \Gamma_D, \\ A_\Omega e(u_\varepsilon)n = g & \text{on } \Gamma_N, \\ A_\Omega e(u_\Omega)n = 0 & \text{on } \partial D \setminus (\bar{\Gamma}_D \cup \bar{\Gamma}_N), \end{cases}$$

with:

$$A_\Omega = \varepsilon A + \chi_\Omega(1 - \varepsilon)A.$$

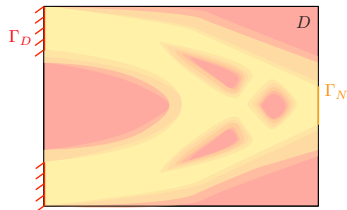
- This is only possible because the boundary Γ in contact with void is **traction-free**.



The linearized elasticity setting (III)

- The **density-based** version of the problem is:

$$\min_h J(h), \text{ where } J(h) = \int_D j(u_h) dx.$$



- The approximate displacement u_h is the solution to:

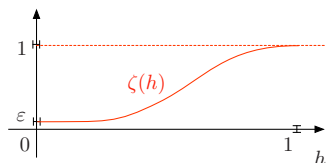
$$\begin{cases} -\operatorname{div}(\zeta(h)Ae(u_h)) = 0 & \text{in } D, \\ u_h = 0 & \text{on } \Gamma_D, \\ \zeta(h)Ae(u_h)n = g & \text{on } \Gamma_N, \\ \zeta(h)Ae(u_h)n = 0 & \text{on } \partial D \setminus (\overline{\Gamma_D} \cup \overline{\Gamma_N}). \end{cases}$$

- The transition between the soft and bulk materials is realized by a smooth **interpolation profile**:

$$\zeta : [0, 1] \rightarrow [0, 1], \quad \zeta(0) = \varepsilon, \text{ and } \zeta(1) = 1.$$

For instance:

$$\zeta(h) = \varepsilon + h^3(1 - \varepsilon).$$

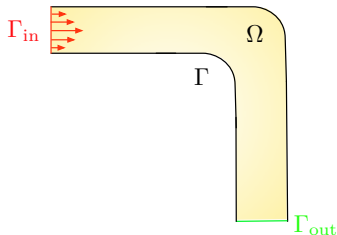


Treatment of fluid mechanics by the artificial porosity method (I)

- We consider the optimal design problem:

$$\min_{\Omega} J(\Omega), \text{ where } J(\Omega) = \int_{\Omega} j(u_{\Omega}) \, dx,$$

and $j : \mathbb{R}^d \rightarrow \mathbb{R}$ is a smooth function.



- The **velocity** and **pressure** $u_{\Omega} : \Omega \rightarrow \mathbb{R}^d$, $p_{\Omega} : \Omega \rightarrow \mathbb{R}$ are solutions to the incompressible Stokes equations:

$$\left\{ \begin{array}{ll} -2\nu \operatorname{div}(D(u_{\Omega})) + \nabla p_{\Omega} = 0 & \text{in } \Omega, \\ \operatorname{div}(u_{\Omega}) = 0 & \text{in } \Omega, \\ u_{\Omega} = u_{\text{in}} & \text{on } \Gamma_{\text{in}}, \\ \sigma(u_{\Omega}, p_{\Omega})n = -p_{\text{out}}n & \text{on } \Gamma_{\text{out}}, \\ u_{\Omega} = 0 & \text{on } \Gamma, \end{array} \right. \quad (S)$$

where **no-slip boundary conditions** are imposed on the optimized boundary Γ .

Treatment of fluid mechanics by the artificial porosity method (II)

The state equation on a shape Ω is approximated by the **artificial porosity method**:

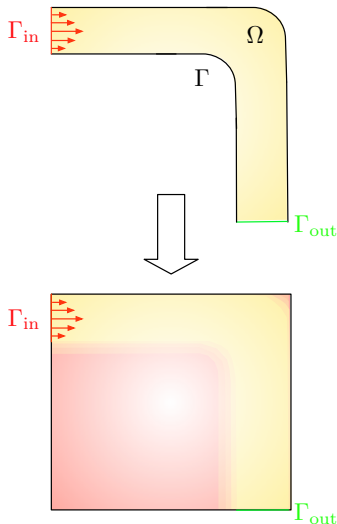
- A large computational box D is considered.
- The void $D \setminus \bar{\Omega}$ is filled with a **solid material with very small porosity $\varepsilon \ll 1$** .
- The velocity u_Ω and pressure p_Ω are approximated by the solutions $u_\varepsilon, p_\varepsilon$ to the **Brinkman** equation:

$$\begin{cases} -2\nu \operatorname{div}(D(u_\varepsilon)) + \nabla p_\varepsilon + \alpha_\Omega u_\varepsilon = 0 & \text{in } D, \\ \operatorname{div}(u_\varepsilon) = 0 & \text{in } \Omega, \\ u_\varepsilon = u_{\text{in}} & \text{on } \Gamma_{\text{in}}, \\ \sigma(u_\varepsilon, p_\varepsilon)n = -p_{\text{out}}n & \text{on } \Gamma_{\text{out}}, \\ u_\varepsilon = 0 & \text{on } \partial D \setminus (\bar{\Gamma}_D \cup \bar{\Gamma}_N), \end{cases}$$

where α_Ω takes very large values in the “void”:

$$\alpha_\Omega := \frac{1}{\varepsilon}(1 - \chi_\Omega).$$

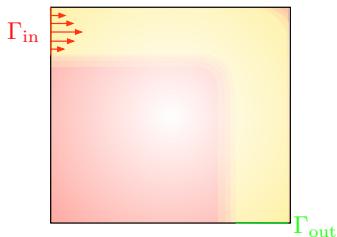
- This approximation is only possible because the boundary Γ bears **no slip boundary conditions**.



Treatment of fluid mechanics by the artificial porosity method (III)

- The density-based version of this problem reads:

$$\min_h J(h), \text{ where } J(h) = \int_D j(u_h) dx.$$



- The velocity u_h and pressure p_h are the solutions to the **Brinkman equations**:

$$\left\{ \begin{array}{ll} -2\nu \operatorname{div}(D(u_h)) + \nabla p_h + \alpha(h)u_h = 0 & \text{in } D, \\ \operatorname{div}(u_h) = 0 & \text{in } D, \\ u_h = u_{\text{in}} & \text{on } \Gamma_{\text{in}}, \\ \sigma(u_h)n = -p_{\text{out}}n & \text{on } \Gamma_{\text{out}}, \\ u_h = 0 & \text{on } \partial D \setminus (\overline{\Gamma_{\text{in}}} \cup \overline{\Gamma_{\text{out}}}). \end{array} \right.$$

- The **artificial porosity coefficient** $\alpha(h)$ is of the form:

$$\alpha(h) = \alpha_{\max} + (\alpha_{\min} - \alpha_{\max})h \frac{1+q}{h+q},$$

where q is a parameter (e.g. $q = 3$), α_{\max} is typically 10^6 and $\alpha_{\min} \approx 0$.

Part V

Topology optimization

- 1 From homogenization to density-based optimization
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- 3 **Numerical Aspects**
 - Generalities about the numerical practice of density methods
 - Filtering
 - Numerical examples

Density-based relaxation (I)

- The density-based formulation of our model problem reads:

$$\min_{h \in L^\infty(D, [0,1])} J(h), \text{ where } J(h) := \int_D j(u_h) \, dx$$

and $u_h \in H^1(D)$ is the solution to:

$$\begin{cases} -\operatorname{div}(\zeta(h)\nabla u_h) = f & \text{in } D, \\ u_h = 0 & \text{on } \Gamma_D, \\ \zeta(h)\frac{\partial u_h}{\partial n} = g & \text{on } \Gamma_N. \end{cases}$$

This boils down to a **parametric optimization** problem!

- As we have seen, the simple parametric setting allows for the use of basic **gradient algorithms**, but also more advanced optimization algorithms, such as:
 - The Method of Moving Asymptotes (MMA);
 - The quasi-Newton BFGS method;
 - Conjugate gradient algorithms.

Density-based relaxation (II)

- As the result of a density-based topology optimization process, a density function h is obtained, which may present **grayscale values**.
- However, in general, a real “**black-and-white**” design $\Omega \subset D$ is expected.
- Hence there is the need to **threshold** the density h , i.e. for an adequate value $c \in (0, 1)$, Ω is obtained as:

$$\Omega = \{x \in D, h(x) > c\}, \text{ that is,}$$

- Regions where $0 \leq h(x) \leq c$ are considered to be “void”;
- Regions where $c < h(x) \leq 1$ are considered to be “full of material”.
- Like in the homogenization setting, one simple method is to proceed by **dichotomy**, so that Ω satisfies a volume target.
- “Minimizing sequences” of shapes Ω^n , showing features at scales $\frac{1}{n} \rightarrow 0$ can also be obtained from h by a variant of the **deshomogenization** method [GroSig].

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Density filters (I)

- Often, desired properties of the density h (regularity, etc.) are enforced by **filtering**: h appears in the state (and adjoint) equations via the quantity Lh , where

$$L : L^\infty(D, [0, 1]) \rightarrow L^\infty(D, [0, 1])$$

is the **filter operator**.

- The problem rewrites:

$$\min_{h \in \mathcal{U}_{\text{ad}}} J(h), \text{ where } J(h) = \int_D j(u_h) dx,$$

and u_h is the solution to:

$$\begin{cases} -\operatorname{div}(\zeta(Lh)\nabla u_h) = f & \text{in } D, \\ u_h = 0 & \text{on } \Gamma_D, \\ (\zeta(Lh)\nabla u_h)n = g & \text{on } \Gamma_N. \end{cases}$$

- The calculation of the derivative of $J(h)$ now reads:

$$\begin{aligned} J'(h)(\hat{h}) &= \int_D \zeta'(h)(\nabla u_h \cdot \nabla p_h)(L\hat{h}) dx, \\ &= \int_D L^T (\zeta'(h)(\nabla u_h \cdot \nabla p_h)) \hat{h} dx. \end{aligned}$$

Density filters (II)

Here are some examples of **regularizing filters**:

- Convolution-based filter: For ε 'small' ($\varepsilon \approx$ mesh size), one defines:

$$L_\varepsilon h = h * \eta_\varepsilon,$$

where η_ε is a **mollifying kernel**; i.e. $\eta_\varepsilon(x) = \frac{1}{\varepsilon^d} \eta\left(\frac{x}{\varepsilon}\right)$,

$$\eta \in C_c^\infty(\mathbb{R}^d), \text{ supp}(\eta) \subset B(0, 1), \text{ and } \int_{\mathbb{R}^d} \eta \, dx = 1.$$

- PDE-based filter: For small ε ,

$$L_\varepsilon h = q,$$

where q is the unique solution in $H^1(D)$ to the problem:

$$\begin{cases} -\varepsilon^2 \Delta q + q = h & \text{in } D, \\ \frac{\partial q}{\partial n} = 0 & \text{on } \partial D. \end{cases}$$

Density filters (III)

Morphological filters are often useful to express the idea of **geometric robustness**:

- The dilation filter

$$D_\delta h(x) = \frac{1}{\beta} \log \left(\frac{1}{|B(x, \delta)|} \int_{B(x, \delta)} e^{\beta h(z)} dz \right)$$

interpolates between the average and the maximum of h on $B(x, \delta)$:

$$D_\delta h(x) \xrightarrow{\beta \rightarrow 0} \frac{1}{|B(x, \delta)|} \int_{B(x, \delta)} h(z) dz, \text{ and } D_\delta h(x) \xrightarrow{\beta \rightarrow \infty} \max_{z \in B(x, \delta)} h(z).$$

- The erosion filter

$$E_\delta h(x) = 1 - \frac{1}{\beta} \log \left(\frac{1}{|B(x, \delta)|} \int_{B(x, \delta)} e^{\beta(1-h(z))} dz \right)$$

interpolates between the average and the minimum of h on $B(x, \delta)$:

$$E_\delta h(x) \xrightarrow{\beta \rightarrow 0} \frac{1}{|B(x, \delta)|} \int_{B(x, \delta)} h(z) dz, \text{ and } E_\delta h(x) \xrightarrow{\beta \rightarrow \infty} \min_{z \in B(x, \delta)} h(z).$$

Density filters (III)

The **Heaviside filter** allows to steer the optimized density towards values 0 and 1 during the optimization:

$$\widetilde{H}_{\beta,\eta}h = \frac{\tanh(\beta\eta) + \tanh(\beta(h - \eta))}{\tanh(\beta\eta) + \tanh(\beta(1 - \eta))},$$

where β and η are user-defined parameters which may be updated in the course of the process.

- All these filters can be combined (i.e. composed), up to some tuning.
- See for instance [WanSig] for other examples of filters.

Sensitivity filters

- As in the parametric optimization context, the expression of the derivative

$$\forall \hat{h} \in L^\infty(D), J'(h)(\hat{h}) = \int_D \zeta'(h)(\nabla u_h \cdot \nabla p_h) \hat{h} \, dx$$

lends itself to a straightforward choice of a descent direction:

$$\hat{h} = -\zeta'(h)(\nabla u_h \cdot \nabla p_h),$$

that is, \hat{h} is the (negative) $L^2(D)$ gradient of $J'(h)$.

- Other choices are possible (and often more adequate) by **changing inner products**:

$$\hat{h} = -V,$$

where V solves:

$$\forall w \in \mathcal{H}, \langle V, w \rangle_{\mathcal{H}} = J'(h)(w),$$

for an adapted choice of Hilbert space and inner product \mathcal{H} and $\langle \cdot, \cdot \rangle_{\mathcal{H}}$.

- This stage is often called **sensitivity filtering** in density-based methods.

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Example: the cantilever benchmark

- In the context of **linearized elasticity**, the **compliance** of a cantilever beam is minimized:

$$C(h) = \int_D \zeta(h) A e(u_h) : e(u_h) dx.$$

- A constraint on the **volume** $\text{Vol}(h) = \int_D h dx$ of the structure is added.

Example: the pipe benchmark

- In the context of **fluid mechanics**, the **viscous dissipation** within a pipe is minimized:

$$C(h) = \int_D \zeta(h) A e(u_h) : e(u_h) dx.$$

- A constraint on the **volume** $\text{Vol}(h) = \int_D h dx$ of the pipe is added.

A brief summary

Assets of density-based methods






- Simplicity of the mathematical analysis (calculation of derivatives, etc).
- They allow for the use of efficient mathematical programming routines.
- Robustness of the implementation: everything takes place on a fixed mesh, no mesh deformation is required.

Drawbacks






- Need to reformulate and approximate the physical equations.
- The geometry of shapes is lost, which may make it difficult to formulate, e.g. geometric constraints.

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