

# A brief overview of shape and topology optimization, with a few applications in electromagnetism

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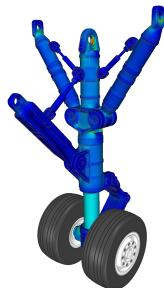
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## Foreword: Shape and topology optimization

- **Shape optimization** aims to **minimize** a function of the **domain**.
- Such problems can be traced back to the early human history...
- ... The needs to realize energy savings and get free from fossile fuels have aroused much enthusiasm for the discipline.
- It heralds promising applications in varied physical contexts.
- This presentation broaches a few of its specific issues:
  - Modeling: Choice of **adequate design variables**, of a **relevant physical model**.
  - Theory: Calculation of **derivatives with respect to the design**.
  - Numerical implementation: Efficient **design updates** (remeshing), **large scale solution** of physical equations.



*Hooke's principle: "As hangs the flexible chain, so but inverted stands the rigid arch"*



*Optimized design of a landing gear (courtesy of Ansys)*



## Disclaimer



### Disclaimer

- This presentation is by no means exhaustive, and it is strongly biased by the knowledge and experience of the author.
- See the [References](#) for more elaborate discussions.

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## A general panorama

A **shape and topology optimization problem** reads:

$$\min_{h \in \mathcal{U}_{\text{ad}}} J(h) \text{ s.t. } G(h) = 0. \quad (\mathcal{P})$$

In this formulation:

- The **design variable**  $h$  is sought within a set  $\mathcal{U}_{\text{ad}}$  of **admissible designs**.
- $J(h)$  is an **objective function**.
- $G(h) = (G_1(h), \dots, G_p(h))$  is a collection of  $p$  (equality) **constraints**.
- $J(h)$  or some of the  $G_i(h)$  depend on  $h$  via a **state**  $u_h$ , solution in a functional space  $V$  to a physical **boundary value problem**:

$$\text{Search for } u_h \in V \text{ s.t. } \mathcal{F}(h, u_h) = 0. \quad (BVP)$$

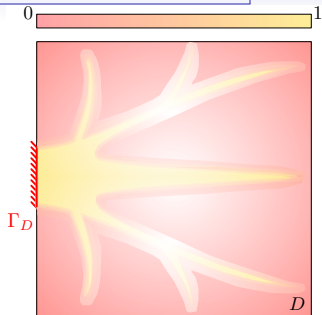
This generic formulation encompasses multiple frameworks.

## A parametric optimal design problem in thermal mechanics...

Let  $D \subset \mathbb{R}^d$  be a **thermal cavity**;

- The temperature is fixed to 0 on  $\Gamma_D \subset \partial D$ .
- The remaining boundary  $\partial D \setminus \overline{\Gamma_D}$  is insulated.
- A **source**  $f : D \rightarrow \mathbb{R}$  is acting in the medium.
- The **design variable**  $h : D \rightarrow [0, 1]$  is related to the distribution of conducting material inside  $D$ :

$$\gamma_h(x) = \alpha + (\beta - \alpha)h(x), \text{ for some } 0 < \alpha \leq \beta.$$



The **temperature**  $u_h : D \rightarrow \mathbb{R}$  is the solution to the **conductivity equation**:

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

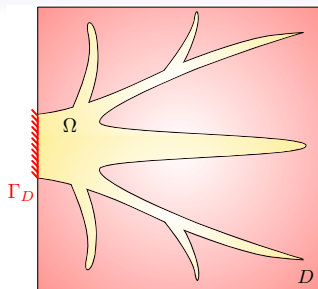
We minimize the **mean temperature** in  $D$  for a given amount  $V_T$  of material:

$$J(h) = \frac{1}{|D|} \int_D u_h \, dx, \text{ and } G(h) = \int_D h \, dx - V_T.$$

## ... and its shape optimization counterpart

- Concrete manufacturing processes cannot assemble arbitrary conductivities  $\gamma_h$ .
- Realistic patterns include distributions of **two materials** with conductivities  $\alpha, \beta$  within  $D$ .
- The **design variable**  $h$  is now the **shape**  $\Omega \subset D$  of the phase  $\beta$ , and the induced conductivity is:

$$\forall x \in D, \quad \gamma_{\Omega}(x) = \begin{cases} \beta & \text{if } x \in \Omega, \\ \alpha & \text{otherwise.} \end{cases}$$



The **temperature**  $u_{\Omega}$  inside  $D$  is the solution to the **two-phase conductivity equation**:

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

The considered objective and constraint functions read:

$$J(\Omega) = \frac{1}{|D|} \int_D u_{\Omega} \, dx, \quad \text{and} \quad G(\Omega) = \operatorname{Vol}(\Omega) - V_T, \quad \operatorname{Vol}(\Omega) := \int_{\Omega} dx.$$

## A shape and topology optimization problem in structure mechanics (I)

In structure mechanics, the **shape** is a bounded domain  $\Omega \subset \mathbb{R}^d$ , which is:

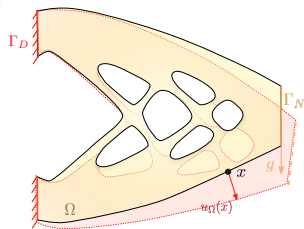
- **Fixed** on a part  $\Gamma_D$  of its boundary,
- Submitted to **surface loads**  $g$ , applied on another region  $\Gamma_N \subset \partial\Omega$ ,  $\Gamma_D \cap \Gamma_N = \emptyset$ .

The **displacement**  $u_\Omega : \Omega \rightarrow \mathbb{R}^d$  is the vector field governed by the **linear elasticity system**:

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

where  $e(u) = \frac{1}{2}(\nabla u^T + \nabla u)$  is the **strain tensor**, and  $A$  is the **Hooke's law** of the material:

$$\forall e \in S_d(\mathbb{R}), \quad Ae = 2\mu e + \lambda \operatorname{tr}(e)I.$$



The linear elasticity model



Optimized design of a pylon

## A shape and topology optimization problem in structure mechanics (II)

In this context, the objective function  $J(\Omega)$  could be:

- The work of the external loads  $g$  or **compliance**  $C(\Omega)$  of  $\Omega$ :

$$C(\Omega) = \int_{\Omega} A e(u_{\Omega}) : e(u_{\Omega}) \, dx = \int_{\Gamma_N} g \cdot u_{\Omega} \, ds$$

- A **least-square error** between  $u_{\Omega}$  and a target displacement  $u_T \in H^1(\Omega)^d$  (useful when designing micro-mechanisms):

$$D(\Omega) = \left( \int_{\Omega} k(x) |u_{\Omega} - u_T|^{\alpha} \, dx \right)^{\frac{1}{\alpha}},$$

where  $\alpha$  is a fixed parameter, and  $k(x)$  is a weight factor.

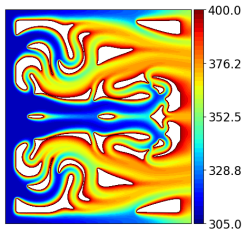
Such problems usually features a constraint on the **volume** ( $\approx$  mass) of the shape:

$$G(\Omega) = \text{Vol}(\Omega) - V_T, \text{ where } V_T \text{ is a target.}$$

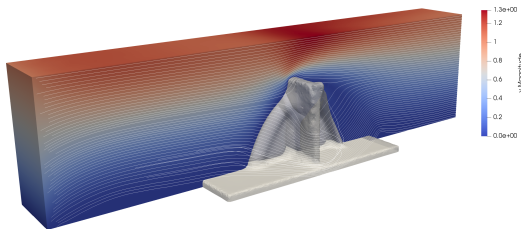
## A wide variety of applications beyond

Optimal design has recently aroused burning issues in such diverse fields as:

- **Fluid mechanics:** external aerodynamics, fluid transport, mixing devices, etc.

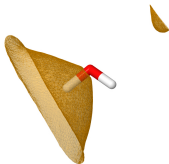


Optimized 2d section of a heat exchanger.

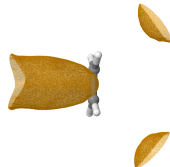


Optimized shape of a solid obstacle to a fluid flow.

- **Quantum chemistry,** with the theory of **Maximum Probability Domains:**



Maximum probability domain for the H<sub>2</sub>O molecule.



Maximum probability domain for the C<sub>2</sub>H<sub>4</sub> molecule.

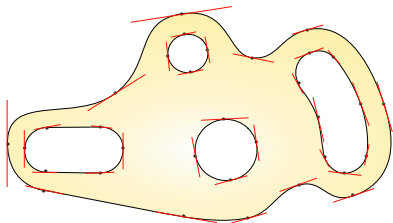
- **Electromagnetism:** electric machines, current sensors, photonic crystals, etc.



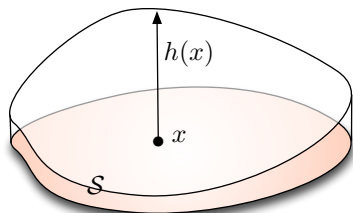
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## Parametric optimization (I)

The considered designs  $h$  are described by a collection of **parameters**  $\{p_i\}_{i=1,\dots,N}$ , typically thicknesses, curvature radii, etc...



Description of a mechanical part via the control points of a CAD model.



Parametrization of a plate with cross-section  $S$  via the thickness function  $h : S \rightarrow \mathbb{R}$ .

## Parametric optimization (II)

- The parameters describing shapes are the **design variables**, and the shape optimization problem rewrites:

$$\min_{\{p_i\} \in \mathcal{P}_{\text{ad}}} J(p_1, \dots, p_N) \text{ s.t. } G(p_1, \dots, p_N) = 0,$$

where  $\mathcal{P}_{\text{ad}}$  is a set of **admissible parameters**.

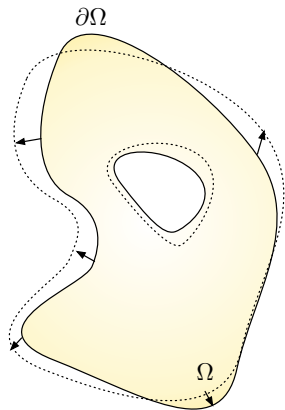
- In this framework, it is straightforward to account for **variations** of a shape  $\{p_i\}_{i=1, \dots, N}$ :

$$\{p_i\}_{i=1, \dots, N} \rightarrow \{p_i + \delta p_i\}_{i=1, \dots, N}.$$

- However, the variety of possible designs is severely restricted, and the use of such methods relies on an **a priori knowledge** about the sought optimized design.

## Geometric optimization

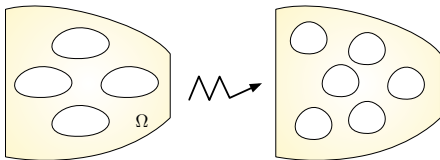
- The **topology** of shapes (i.e. their number of holes in 2d) is fixed.
- The whole **boundary**  $\partial\Omega$  of shapes  $\Omega$  is the optimization variable.
- This setting allows for greater freedom, since no a priori knowledge about the relevant features of the optimized shape is required.



Optimization of  $\Omega$  via “free” perturbations of the boundary  $\partial\Omega$ .

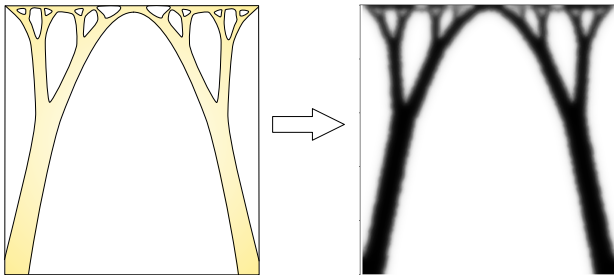
## Topology optimization

- The **topology** of the shape is often unknown, and also subject to optimization.



- It is often preferred not to represent the boundaries of shapes, but to employ different descriptions, allowing for a more natural account of **topological changes**.

**Example** The shape  $\Omega$  is replaced by a **density function**  $h : D \rightarrow [0, 1]$ .



An optimal design framework is the combination of:

- A **model** (a boundary value problem) for the physical situation, which is
  - Sufficiently elaborate to be physically relevant, ...
  - ... yet simple enough to be tractable for optimization.
- A **mathematical description** of designs:  $h =$  a set of parameters, a “true” shape, ...?
- An efficient **numerical representation** of  $h$ : by a mesh, a density function, ...?
- Numerical **algorithms** dedicated to
  - *Geometric computations*: e.g. the normal vector, the curvature of the shape;
  - *Mechanical computations*: solution of boundary value problems characterizing the physical performance of the shape;
  - *Algorithmic operations*: update (deformation) of the shape throughout the iterations of the process.

All these choices are **intimately related!**

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## Differentiation with respect to the design

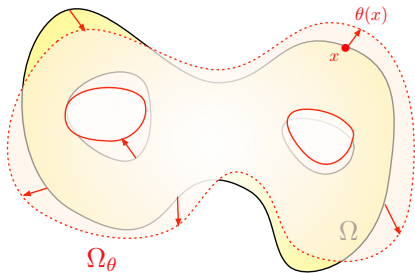
- The solution of the optimal design problem ( $\mathcal{P}$ ) often hinges on the **derivatives** of the functions  $J(h)$  and  $G(h)$ .
- When the design  $h$  belongs to a **vector space**  $H$  (e.g. in parametric optimization), the **sensitivity** of a function  $J(h)$  is encoded in the **derivative**  $H \ni \hat{h} \mapsto J'(h)(\hat{h})$ .
- The knowledge of  $J'(h)$  allows to identify a **descent direction**  $\hat{h} \in H$  for  $J(h)$ :  
$$J'(h)(\hat{h}) < 0 \Rightarrow \text{For "small" } \tau > 0, \quad J(h + \tau\hat{h}) \approx J(h) + \tau J'(h)(\hat{h}) < J(h),$$
and the new design  $h + \tau\hat{h}$  is **better** than  $h$  with respect to  $J(h)$ .
- Most **constrained optimization methods** use descent directions for  $J(h)$  and  $G(h)$ .
- Differentiation w.r.t. the design is more subtle when the latter is a **shape**  $\Omega \subset \mathbb{R}^d$ .



**Hadamard's boundary variation method** features variations of a reference, Lipschitz domain  $\Omega$  of the form:

$$\Omega_\theta := (\text{Id} + \theta)(\Omega),$$

for "small"  $\theta \in W^{1,\infty}(\mathbb{R}^d, \mathbb{R}^d)$ .



## Lemma 1.

For all  $\theta \in W^{1,\infty}(\mathbb{R}^d, \mathbb{R}^d)$  with norm  $\|\theta\|_{W^{1,\infty}(\mathbb{R}^d, \mathbb{R}^d)} < 1$ ,  $(\text{Id} + \theta)$  is a Lipschitz diffeomorphism of  $\mathbb{R}^d$ , with Lipschitz inverse.

## Definition 1.

Let  $\Omega \subset \mathbb{R}^d$  be a smooth domain. A function  $\Omega \mapsto J(\Omega)$  is *shape differentiable* at  $\Omega$  if the mapping

$$W^{1,\infty}(\mathbb{R}^d, \mathbb{R}^d) \ni \theta \mapsto J(\Omega_\theta)$$

is Fréchet-differentiable at 0, i.e. the following expansion holds:

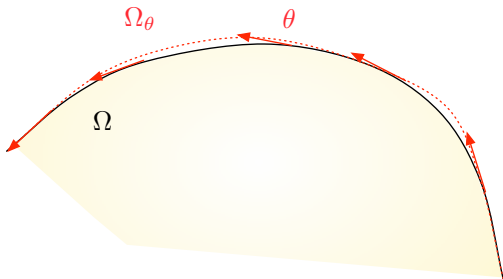
$$J(\Omega_\theta) = J(\Omega) + J'(\Omega)(\theta) + o(\|\theta\|_{W^{1,\infty}(\mathbb{R}^d, \mathbb{R}^d)}), \text{ where } \frac{o(\theta)}{\|\theta\|_{W^{1,\infty}(\mathbb{R}^d, \mathbb{R}^d)}} \xrightarrow{\theta \rightarrow 0} 0.$$

The mapping  $\theta \mapsto J'(\Omega)(\theta)$  is the *shape derivative* of  $J(\Omega)$  at  $\Omega$ .

## Differentiation with respect to the domain: Hadamard's method (III)

- The shape derivative of “most” functions of the domain has the **surface form**:

$$J'(\Omega)(\theta) = \int_{\partial\Omega} v_\Omega \theta \cdot n \, ds, \text{ for some scalar field } v_\Omega : \partial\Omega \rightarrow \mathbb{R}.$$



A **tangential** vector field  $\theta$ , (i.e.  $\theta \cdot n = 0$ ) only accounts for a **convection** of the shape  $\Omega$  and  $J'(\Omega)(\theta) = 0$ .

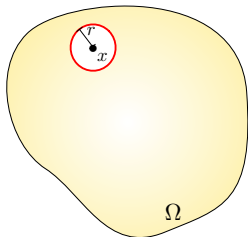
- A **descent direction** for  $J(\Omega)$  is readily revealed from this expression:

$$\theta = -v_\Omega n \Rightarrow J'(\Omega)(\theta) < 0.$$

The notion of **topological derivative** features variations of a shape  $\Omega \subset \mathbb{R}^d$  of the form

$$\Omega_{x,\varepsilon} := \Omega \setminus \overline{B(x,\varepsilon)},$$

where  $x \in \Omega$ , and  $\varepsilon \ll 1$ .



## Definition 2.

The function  $J(\Omega)$  has a **topological derivative** at  $\Omega$  and at the point  $x \in \Omega$  if there exists  $dJ_T(\Omega)(x) \in \mathbb{R}$  such that:

$$J(\Omega_{x,\varepsilon}) = J(\Omega) + \varepsilon^d dJ_T(\Omega)(x) + o(\varepsilon^d).$$

Intuition: If  $dJ_T(\Omega)(x) < 0$ , it is beneficial to **drill a tiny hole** around  $x$ .

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## The adjoint method in an abstract framework (I)

- “Many” useful functionals in shape and topology optimization are of the form:

$$J(h) = j(u_h),$$

where


- The **design**  $h$  belongs to a **Hilbert space**  $(H, \langle \cdot, \cdot \rangle_H)$ .
- The **state**  $u_h$  belongs to another Hilbert space  $(V, \langle \cdot, \cdot \rangle_V)$ .
- It is the solution to a **boundary value problem**

$$\text{Search for } u_h \in V \text{ s.t. } \mathcal{F}(h, u_h) = 0, \quad (\text{BVP})$$

where  $\mathcal{F} : H \times V \rightarrow V$  is a suitable operator.

- The **observable**  $j : V \rightarrow \mathbb{R}$  is smooth enough.
- We aim to calculate the derivative  $J'(h)(\hat{h})$  and to find a **descent direction** for  $J(h)$ .
- We present the **adjoint method** in an abstract setting, agnostic of the nature of  $h$ .

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 **R.-E. Plessix**, *A review of the adjoint-state method for computing the gradient of a functional with geophysical applications*, Geophysical Journal International, 167 (2006), pp. 495–503.

## The adjoint method in an abstract framework (II)

- The **implicit function theorem** ensures that the mapping  $h \mapsto u_h$  is differentiable.
- Differentiation in (BVP) yields a characterization of the **derivative**  $u'_h(\hat{h}) \in V$ :

$$\left[ \frac{\partial \mathcal{F}}{\partial h}(h, u_h) \right] (\hat{h}) + \left[ \frac{\partial \mathcal{F}}{\partial u}(h, u_h) \right] u'_h(\hat{h}) = 0.$$

- Likewise, by applying the chain rule, we calculate the derivative of  $J(h)$ :

$$J'(h)(\hat{h}) = \left\langle j'(u_h), u'_h(\hat{h}) \right\rangle_V.$$

- This expression does not lend itself to identification of a **descent direction**.

$\Rightarrow$  One would have to try multiple  $\hat{h} \in H$ , calculate  $u'_h(\hat{h})$ , ... until finding one such that  $J'(h)(\hat{h}) < 0$ .

## The adjoint method in an abstract framework (III)

- To overcome this issue, we introduce the **adjoint state**  $p_h \in V$  as the solution to:

$$\left[ \frac{\partial \mathcal{F}}{\partial u}(h, u_h) \right]^* p_h = -j'(u_h).$$

- An elementary calculation yields:

$$\begin{aligned} J'(h)(\hat{h}) &= \left\langle j'(u_h), u'_h(\hat{h}) \right\rangle_V \\ &= - \left\langle \left[ \frac{\partial \mathcal{F}}{\partial u}(h, u_h) \right]^* p_h, u'_h(\hat{h}) \right\rangle_V \\ &= - \left\langle \left[ \frac{\partial \mathcal{F}}{\partial u}(h, u_h) \right] u'_h(\hat{h}), p_h \right\rangle_V \end{aligned}$$

where we have used the definitions of  $p_h$  and of the adjoint operator  $\left[ \frac{\partial \mathcal{F}}{\partial u}(h, u_h) \right]^*$ .

- Using now the problem satisfied by  $u'_h(\hat{h})$ , we obtain:

$$J'(h)(\hat{h}) = \left\langle \left[ \frac{\partial \mathcal{F}}{\partial h}(h, u(h)) \right] \hat{h}, p_h \right\rangle_V.$$



## The adjoint method in an abstract framework (IV)

- Introducing the adjoint  $\left[\frac{\partial \mathcal{F}}{\partial h}(h, u_h)\right]^* : V \rightarrow H$  of  $\left[\frac{\partial \mathcal{F}}{\partial h}(h, u_h)\right] : H \rightarrow V$ , we end up with:

$$J'(h)(\hat{h}) = \left\langle \left[\frac{\partial \mathcal{F}}{\partial h}(h, u_h)\right]^* p_h, \hat{h} \right\rangle_H.$$

- Now, a **descent direction**  $\hat{h}$  for  $J(h)$  is immediately revealed:

$$\hat{h} = - \left[\frac{\partial \mathcal{F}}{\partial h}(h, u_h)\right]^* p_h \Rightarrow J'(h)(\hat{h}) = - \left\| \left[\frac{\partial \mathcal{F}}{\partial h}(h, u_h)\right]^* p_h \right\|_H^2.$$

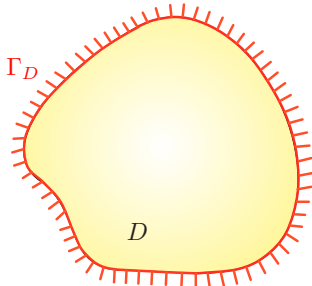
- The evaluation of  $\hat{h}$  demands:
  - The calculation of  $u_h$  (finite element solution);
  - The calculation of  $p_h$  (finite element solution);
  - The calculation of the operator  $\left[\frac{\partial \mathcal{F}}{\partial h}(h, u_h)\right]^*$  (derivative of the explicit dependence of the boundary value problem w.r.t the design).

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## The adjoint method: worked example (I)

- Let  $D \subset \mathbb{R}^d$  be a fixed domain.
- The temperature is set to 0 on  $\partial D$ .
- A source  $f : D \rightarrow \mathbb{R}$  is acting in the medium.
- The considered designs are **conductivity coefficients**:

$$h \in \mathcal{U}_{\text{ad}} := L^\infty(D, [0, 1]).$$



- We consider the functional:

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

where  $u_h$  is the **temperature**.

- It is the solution in  $H_0^1(D)$  to:

$$\begin{cases} -\operatorname{div}(\gamma_h \nabla u_h) & = f & \text{in } D, \\ u_h & = 0 & \text{on } \partial D, \end{cases} \quad \text{where } \gamma_h(x) := \alpha + h(x)(\beta - \alpha).$$

## The adjoint method: worked example (II)

For a fixed design  $h \in \mathcal{U}_{\text{ad}}$ ,

- The **variational formulation** characterizing  $u_h$  reads:

$$\text{Search for } u_h \in H_0^1(D) \text{ s.t. } \forall v \in H_0^1(D), \quad \int_D \gamma_h \nabla u_h \cdot \nabla v \, dx = \int_D f v \, dx.$$

- This problem has a unique solution  $u_h \in H_0^1(D)$ , which satisfies:

$$\|u_h\|_{H_0^1(D)} \leq C \|f\|_{L^2(D)},$$

for some constant  $C > 0$ , owing to the **Lax-Milgram theorem**.

## Theorem 2.

The objective function

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

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

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

where the **adjoint state**  $p_h \in H_0^1(D)$  is the solution to the boundary value problem:

$$\begin{cases} -\operatorname{div}(\gamma_h \nabla p_h) = -j'(u_h) & \text{in } D, \\ p_h = 0 & \text{on } \partial D. \end{cases}$$

## The adjoint method: worked example (IV)

Proof: The proof is divided into three steps:

- 1 We use the **implicit function theorem** to prove that the state mapping

$$\mathcal{U}_{\text{ad}} \ni h \mapsto u_h \in H_0^1(D)$$

is **Fréchet differentiable**, with derivative  $\hat{h} \mapsto u'_h(\hat{h})$ .

- 2 We calculate the derivative of  $J(h)$  by using the **chain rule**.
- 3 We give a more convenient structure to this derivative, by introducing an **adjoint state**  $p_h$  to eliminate the occurrence of  $u'_h(\hat{h})$ .

Step 1: *Differentiability of  $h \mapsto u_h$ :*

For any  $h \in \mathcal{U}_{\text{ad}}$ ,  $u_h$  is the unique solution in  $H_0^1(D)$  to the variational problem:

$$\forall v \in H_0^1(D), \quad \int_D \gamma_h \nabla u_h \cdot \nabla v \, dx = \int_D f v \, dx.$$

## The adjoint method: worked example (V)

Let

$$\mathcal{F} : \mathcal{U}_{\text{ad}} \times H_0^1(D) \rightarrow H^{-1}(D)$$

be the mapping defined by:

$$\mathcal{F}(h, u) : v \mapsto \int_D \gamma_h \nabla u \cdot \nabla v \, dx - \int_D f v \, dx.$$

One verifies that

- $\mathcal{F}$  is a mapping of class  $\mathcal{C}^1$ .
- For given  $h \in \mathcal{U}_{\text{ad}}$ ,  $u_h$  is the unique solution  $u$  to the equation

$$\mathcal{F}(h, u) = 0.$$

- The derivative of the partial mapping  $u \mapsto \mathcal{F}(h, u)$  reads:

$$H_0^1(D) \ni \hat{u} \mapsto \left[ v \mapsto \int_D \gamma_h \nabla \hat{u} \cdot \nabla v \, dx \right] \in H^{-1}(D).$$

It is an isomorphism, owing to the **Lax-Milgram theorem**:

For all  $g \in H^{-1}(D)$ , there exists a unique  $u \in H_0^1(D)$  s.t.

$$\forall v \in H_0^1(D), \int_D \gamma_h \nabla u \cdot \nabla v \, dx = \langle g, v \rangle_{H^{-1}(D), H_0^1(D)}.$$

## The adjoint method: worked example (VI)

The **implicit function theorem** guarantees that the mapping  $h \mapsto u_h$  is of class  $\mathcal{C}^1$ .

To calculate the derivative  $\hat{h} \mapsto u'_h(\hat{h})$ , we return to the variational formulation for  $u_h$ :

$$\forall v \in H_0^1(D), \quad \int_D \gamma_h \nabla u_h \cdot \nabla v \, dx = \int_D f v \, dx.$$

Taking derivatives with respect to  $h$  in a direction  $\hat{h} \in L^\infty(D)$  yields:

$$(\beta - \alpha) \int_D \hat{h} \nabla u_h \cdot \nabla v \, dx + \int_D h \nabla u'_h(\hat{h}) \cdot \nabla v \, dx = 0,$$

and so, for all  $\hat{h} \in L^\infty(D)$ ,  $u'_h(\hat{h})$  is the unique solution in  $H_0^1(D)$  to:

$$\forall v \in H_0^1(D), \quad \int_D h \nabla u'_h(\hat{h}) \cdot \nabla v \, dx = -(\beta - \alpha) \int_D \hat{h} \nabla u_h \cdot \nabla v \, dx.$$



## The adjoint method: worked example (VII)

### Step 2: Calculation of the derivative of $J(h)$ :

Since  $h \mapsto u_h$  is of class  $C^1$ , the **chain rule** yields immediately:

$$\forall \hat{h} \in L^\infty(D), \quad J'(h)(\hat{h}) = \int_D j'(u_h) u'_h(\hat{h}) \, dx.$$

- This expression is **awkward**: the dependence  $\hat{h} \mapsto J'(h)(\hat{h})$  is not explicit and it is difficult to find a **descent direction**, i.e. a  $\hat{h} \in L^\infty(D)$  such that:

$$J'(h)(\hat{h}) < 0.$$

- Fortunately, the expression of  $J'(h)$  can be simplified thanks to the introduction of the **adjoint state**  $p_h$ .

## The adjoint method: worked example (VIII)

**Step 3:** Reformulation of  $J'(h)$  using an adjoint state:

The **adjoint state**  $p_h$  is the unique solution in  $H_0^1(D)$  to the variational problem:

$$\forall v \in H_0^1(D), \quad \int_D \gamma_h \nabla p_h \cdot \nabla v \, dx = - \int_D j'(u_h) v \, dx,$$

to be compared with the variational formulation for  $u'_h(\hat{h}) \in H_0^1(D)$ :

$$\forall v \in H_0^1(D), \quad \int_D \gamma_h \nabla u'_h(\hat{h}) \cdot \nabla v \, dx = -(\beta - \alpha) \int_D \hat{h} \nabla u_h \cdot \nabla v \, dx.$$

Then, we calculate:

$$\begin{aligned} J'(h)(\hat{h}) &= \int_D j'(u_h) u'_h(\hat{h}) \, dx, \\ &= - \int_D \gamma_h \nabla p_h \cdot \nabla u'_h(\hat{h}) \, dx, \\ &= - \int_D \gamma_h \nabla u'_h(\hat{h}) \cdot \nabla p_h \, dx, \\ &= (\beta - \alpha) \int_D \hat{h} \nabla u_h \cdot \nabla p_h \, dx. \end{aligned}$$

where the last line uses the variational formulation of  $u'_h(\hat{h})$  with  $p_h$  as test function.

## The adjoint method: final comments

- The adjoint state  $p_h$  can be interpreted as the **Lagrange multiplier** associated to the PDE constraint if we formulate the minimization problem of  $J(h)$  as:

$$\min_{(h,u)} \int_D j(u) \, dx \text{ s.t. } \begin{cases} -\operatorname{div}(h\nabla u) = f & \text{in } D, \\ u = 0 & \text{on } \partial D. \end{cases}$$

- This general methodology allows to deal with
  - Different physical situations,
  - Other optimal design frameworks, including “true” **geometric optimization**.
- Another (formal and sometimes dangerous) method allows to calculate shape derivatives: **Céa's method**.

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## A generic numerical algorithm

The numerical solution of  $(\mathcal{P})$  hinges on a **constrained optimization algorithm**:

**Initialization:** Start from an initial design  $h^0$ ,

**For  $n = 0, \dots$  convergence:**

- 1 Calculate the **derivatives**  $J'(h^n)$  and  $G'(h^n)$  of  $J(h)$  and  $G(h)$  at  $h = h^n$ ;
- 2 Identify **descent directions**  $\hat{h}_J^n$  and  $\hat{h}_G^n$  for  $J(h)$  and  $G(h)$  from  $h^n$ ;
- 3 Infer a descent direction  $\hat{h}^n$  for the optimization problem  $(\mathcal{P})$ ;
- 4 Select an appropriate **time step**  $\tau^n > 0$ ;
- 5 Update the design as:

$$h^{n+1} = h^n - \tau^n \hat{h}^n.$$

The main difficulty is to find a **numerical discretization** of shapes which lends itself to:

- Step ②: Finite element solutions;
- Step ⑤: Deformation of the shape.

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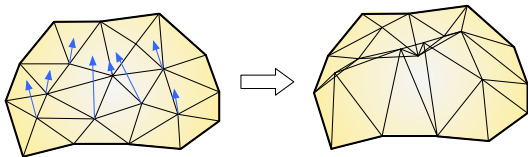
## “Lagrangian” approaches

- Each shape  $\Omega^n$  is represented by a (triangular) **mesh**  $\mathcal{T}^n$ .
- The **Finite Element method** is applied on  $\mathcal{T}^n$  for computing  $u_{\Omega^n}$  (and  $p_{\Omega^n}$ ).
- The descent direction  $\theta^n$  is obtained from the **surface form** of the shape derivative:

$$J'(\Omega)(\theta) = \int_{\partial\Omega} v_{\Omega} \theta \cdot n \, ds \quad \Rightarrow \quad \theta^n = -v_{\Omega^n} n \text{ on } \partial\Omega^n.$$

- The **shape advection** step  $\Omega^n \xrightarrow{(\text{Id} + \tau^n \theta^n)} \Omega^{n+1}$  is performed by **pushing the nodes** of  $\mathcal{T}^n$  along  $\tau^n \theta^n$ , to obtain the new mesh  $\mathcal{T}^{n+1}$ :

$$\forall \text{ vertex } x \in \mathcal{T}^n, \quad x \mapsto x + \tau^n \theta^n(x).$$



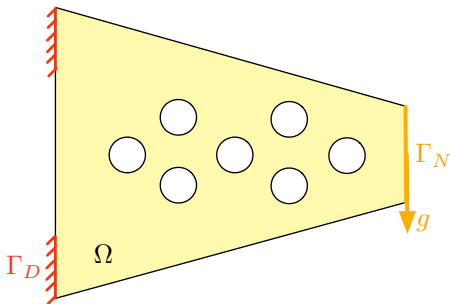
*Pushing nodes according to the velocity field may result in an invalid configuration.*

## “Lagrangian” approaches: example

- In the context of **linear elasticity**, one aims at minimizing the **compliance**  $C(\Omega)$  of a cantilever beam:

$$C(\Omega) = \int_{\Omega} A e(u_{\Omega}) : e(u_{\Omega}) dx.$$

- A **volume constraint** is imposed:  $G(\Omega) = \text{Vol}(\Omega) - V_T$ .

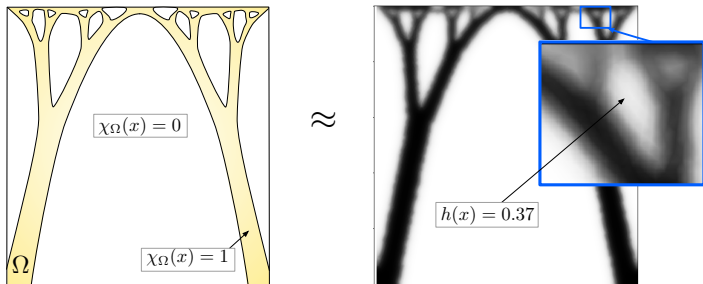




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## Density-based topology optimization (I)

- The design variable  $h$  is a **density function**  $h : D \rightarrow [0, 1]$  defined on a fixed hold-all domain  $D$ .
- $h \approx$  **relaxed version** of the characteristic function  $\chi_\Omega : D \rightarrow \{0, 1\}$  of a shape  $\Omega$ .



- The cornerstone of these methods is to **endow intermediate regions**  $h(x) \in (0, 1)$  **with a physical meaning**.
- We present this methodology in the context of the conductivity equation.
- It can be adapted to multiple physical contexts beyond.

## Density-based topology optimization (II)

- We consider an unconstrained shape optimization problem in the two-phase **conductivity setting**:

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

- In here, the **temperature**  $u_\Omega$  is the solution to:

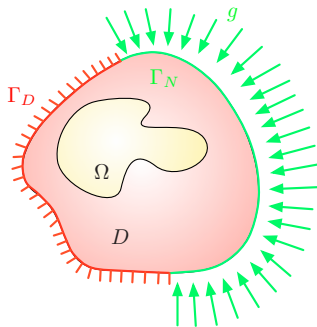
$$\begin{cases} -\operatorname{div}(\gamma_\Omega \nabla u_\Omega) & = f & \text{in } D, \\ u_\Omega & = 0 & \text{on } \Gamma_D, \\ \gamma_\Omega \frac{\partial u_\Omega}{\partial n} & = g & \text{on } \Gamma_N, \end{cases}$$

where the conductivity  $\gamma_\Omega$  reads:

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

and  $\chi_\Omega$  is the **characteristic function** of  $\Omega$ :

$$\forall x \in D, \quad \chi_\Omega(x) = \begin{cases} 1 & \text{if } x \in \Omega, \\ 0 & \text{otherwise.} \end{cases}$$



## Density-based topology optimization (III)

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

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

- The problem rewrites:

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

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

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

- The problem (TO) falls in the realm of **parametric optimization!**

## The interpolation profile

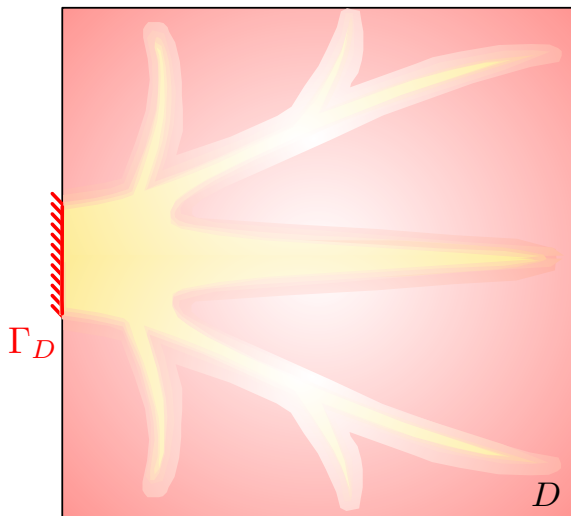
- The interpolation profile  $\zeta(h)$  prescribes **material properties** (diffusion, etc.) to regions with (fictitious) intermediate densities.
- In the practice of the **Solid Isotropic Method with Penalization** (SIMP), a power law of the form

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

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!

# Density-based topology optimization of a heat diffuser



## Density-based topology optimization (IV)

### Assets of density-based methods

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

### Drawbacks

- A **reformulation** and **approximation** of the physical equations are necessary.
- The geometry of shapes is lost, which may make it difficult to formulate, e.g. geometric constraints.

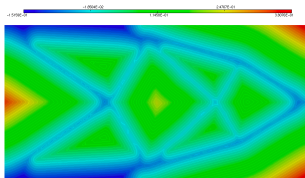
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# The level set method for geometric optimization (I)

- At the continuous level, the design variable  $h$  is a **domain**  $\Omega \subset \mathbb{R}^d$ , inside a fixed 'hold-all' domain  $D$ .
- The sensitivity of a function  $J(\Omega)$  is captured by the notion of **shape derivative**.
- At the discrete level,  $\Omega$  is represented by a "**level set**" function

$$\phi : D \rightarrow \mathbb{R}, \text{ on a fixed mesh } \mathcal{T} \text{ of } D.$$



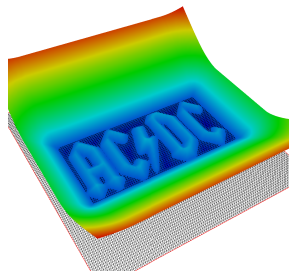
- The motion of  $\Omega$  along the **descent direction**  $\theta$  is translated by a **partial differential equation** for  $\phi$ .

## A short detour by the Level Set Method

**A paradigm:** [OSE] *the motion of an evolving domain is best described in an **implicit** way.*

One domain  $\Omega \subset \mathbb{R}^d$  is equivalently defined by a function  $\phi : \mathbb{R}^d \rightarrow \mathbb{R}$  such that:

$$\phi(x) < 0 \quad \text{if } x \in \Omega \quad ; \quad \phi(x) = 0 \quad \text{if } x \in \partial\Omega \quad ; \quad \phi(x) > 0 \quad \text{if } x \in \mathring{\Omega}$$



(Left) A bounded domain  $\Omega \subset \mathbb{R}^2$ ; (right) Graph of an associated level set function.

## Surface evolution equations in the level set framework

- Let  $\Omega(t) \subset \mathbb{R}^d$  be a domain moving according to a velocity field  $v(t, x) \in \mathbb{R}^d$ .
- Let  $\phi(t, x)$  be a level set function for  $\Omega(t)$ .
- The motion of  $\Omega(t)$  translates in terms of  $\phi$  as the **level set advection equation**:

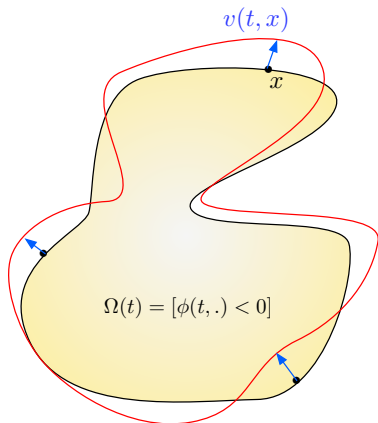
$$\frac{\partial \phi}{\partial t}(t, x) + v(t, x) \cdot \nabla \phi(t, x) = 0$$

- If  $v(t, x)$  is normal to the boundary  $\partial\Omega(t)$ , i.e.:

$$v(t, x) := V(t, x) \frac{\nabla \phi(t, x)}{|\nabla \phi(t, x)|},$$

this rewrites as a **Hamilton-Jacobi equation**:

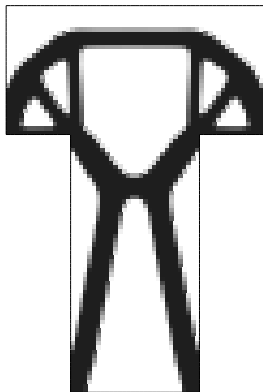
$$\frac{\partial \phi}{\partial t}(t, x) + V(t, x) |\nabla \phi(t, x)| = 0$$



$$\Omega(t + dt) = [\phi(t + dt, \cdot) < 0]$$

## The level set method of Allaire-Jouve-Toader [AlJouToa]

- The shapes  $\Omega^n$  are embedded in a working domain  $D$  equipped with a **fixed** mesh.
- The successive shapes  $\Omega^n$  are accounted for in the **level set** framework, i.e. via a function  $\phi^n : D \rightarrow \mathbb{R}$  which **implicitly** defines them.
- At each step  $n$ , the exact linear elasticity system for  $u_{\Omega^n}$ , posed on  $\Omega^n$ , is approximated by the **Er-satz material approach**: the void  $D \setminus \Omega^n$  is filled by a very “soft” material.  
  
⇒ **Approximate** system posed on  $D$ .
- This approach is very versatile and does not require a mesh of the shapes at each iteration.



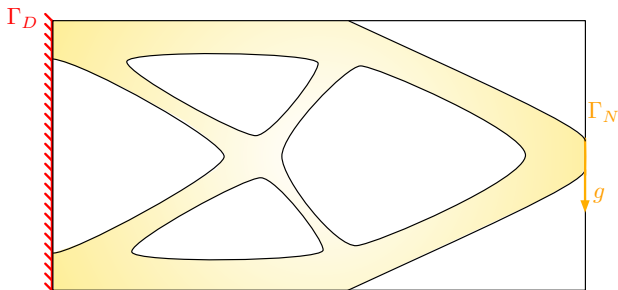
Shape accounted for by a level set description

## The level set method for shape optimization: numerical examples

- In the context of **linear elasticity**, one aims to minimize the **compliance**  $C(\Omega)$  of a cantilever beam:

$$C(\Omega) = \int_{\Omega} A e(u_{\Omega}) : e(u_{\Omega}) dx.$$

- A volume constraint is imposed.



## The level set method for geometric optimization (IV)

### Assets of the level set method

- A clear representation of the shape  $\Omega$  is possible.
- Yet, the method is robust, and arbitrary deformations of  $\Omega$  are possible.
- Recent progress in remeshing techniques make it possible to additionally enjoy an **exact mesh** of the shape throughout the process.

### Drawbacks

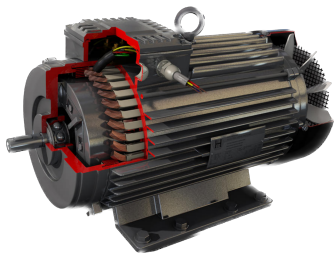
- The mathematical framework is more difficult.
- The implementation is slightly more subtle too.

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# Optimization of the shape of an electric motor (I)

Joint work with A. Cesarano & P. Gangl

- **Electric machines** convert electrical energy into mechanical work.
- The physics at play is **magneto-quasi-static** electromagnetism:
  - An electric current is powered in the coils of the outermost **stator** part.
  - It induces a magnetic field in the inner, **rotor** part, provoking its rotation.
  - The resulting mechanical energy is collected by a central shaft.
- Electric motors are seen as promising answers to the environmental crisis and the needs for energy savings.



(Left) Overview of a motor [Hau]; (right) Cross-section of a motor, by Hanning Elektro-Werke GmbH & Co KG.



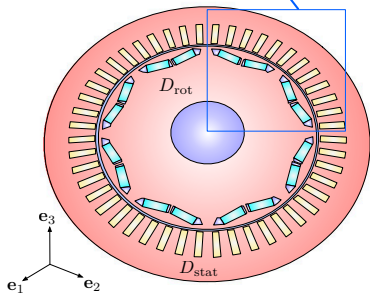
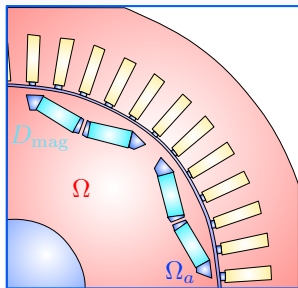
## Optimization of the shape of an electric motor (II)

- The cross-section  $D$  of a motor is made of the **stator**, the **rotor**, separated by an **air gap**:

$$\overline{D} = \overline{D_{\text{rot}}} \cup \overline{D_{\text{gap}}} \cup \overline{D_{\text{stat}}}.$$

- The stator  $D_{\text{stat}}$  consists of:
  - A region filled with ferromagnetic material;
  - A region made of air;
  - The coils, featuring copper wires.
- At rest, the rotor  $D_{\text{rot}}$  is composed of:
  - A **ferromagnetic** core, occupying the **optimized region  $\Omega$** ;
  - **Air**, occupying the region  $\Omega_a$ ;
  - **Permanent magnets** in  $D_{\text{mag}}$ .
- The internal geometry of the rotor undergoes a **rotating motion**  $\varphi_t$ :

$$\Omega(t) = \varphi_t(\Omega), \quad \Omega_a(t) = \varphi_t(\Omega_a), \quad \text{etc.}$$



## Optimization of the shape of an electric motor (III)

- Due to the cylindrical structure of the motor, the problem amounts to a **2d evolution problem** for the transverse component  $u_\Omega$  of the **vector potential**:

$$\begin{cases} \sigma_{\Omega(t)} \frac{du_\Omega}{dt} - \operatorname{div} (\nu_{\Omega(t)}(x, |\nabla u_\Omega|) \nabla u_\Omega) = f & \text{in } (0, T) \times D, \\ u_\Omega(t, x) = 0 & \text{for } t \in (0, T), x \in \partial D, \\ u_\Omega(0, x) = u_\Omega(T, x) & \text{for } x \in D_{\text{mag}}, \end{cases} \quad (\text{MQS})$$

where  $\sigma$  and  $\nu$  are the **conductivity** and **reluctivity** coefficients.

- This problem is **non linear**, because of the behavior of the **ferromagnetic material**.
- It is of **mixed parabolic – elliptic** type:

$$\sigma_{\Omega(t)}(x) = \begin{cases} \sigma_m & \text{for } x \in D_{\text{mag}}(t), \\ 0 & \text{otherwise.} \end{cases}$$

- It is posed on a **moving geometry**:

$\sigma_{\Omega(t)}$  and  $\nu_{\Omega(t)}(x, |\nabla u_\Omega|)$  depend on the motion of the rotor.

- The **mechanical torque** is maximized:

$$\max_{\Omega \subset D_{\text{rot}}} J(\Omega), \text{ where } J(\Omega) = \int_0^T \int_D j(\nabla u_\Omega) dx dt, \text{ for a function } j : \mathbb{R}^2 \rightarrow \mathbb{R}.$$

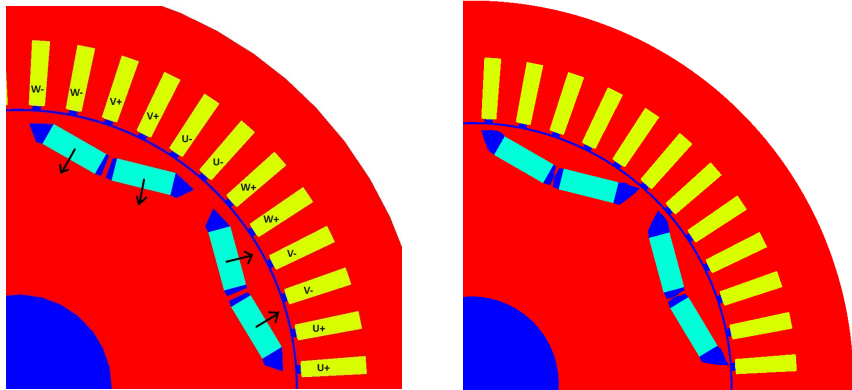
## Optimization of the shape of an electric motor (IV)

- Since “small” deformations of  $\Omega$  are expected, a **Lagrangian mesh deformation method** is used.
- The solution of (MQS) is tackled by a **space-time finite element method**:

*“The whole space-time cylinder  $D \times (0, T)$  is meshed by a tetrahedral  $(2 + 1)$  dimensional mesh”.*

- This practice naturally incorporates time periodic boundary conditions.
  - It allows to handle moving in time geometries.
  - It leaves the room for **mesh adaptation** and **domain decomposition** in space-time.
- A **Newton-Raphson method** is used to treat the non linear term.

# Optimization of the shape of an electric motor (V)



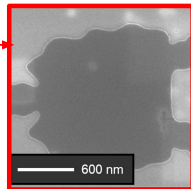
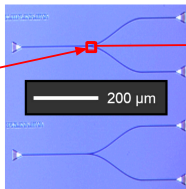
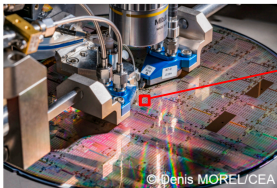
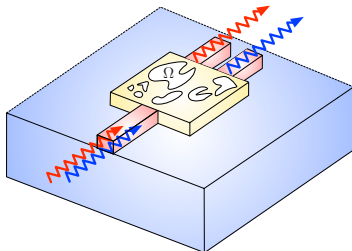
(Left) Initial, (right) Optimized design of the rotor part; the torque is increased by 12% during the process.

- 1 Foreword
- 2 General overview
  - General statement and application examples
  - Various paradigms for optimal design
- 3 A few basic notions
  - Differentiation with respect to the design
  - The adjoint method
  - A worked example
- 4 A generic algorithm, and a few popular numerical strategies
  - The historic “Lagrangian” approaches
  - Density-based topology optimization
  - The level set method for geometric optimization
- 5 **Two applications in the field of electromagnetism**
  - Optimization of the section of an electric motor
  - **Optimization nanophotonic devices**

# Optimization of nanophotonic devices (I)

Joint work with A. Gliere, K. Hassan, N. Lebbe & E. Oudet

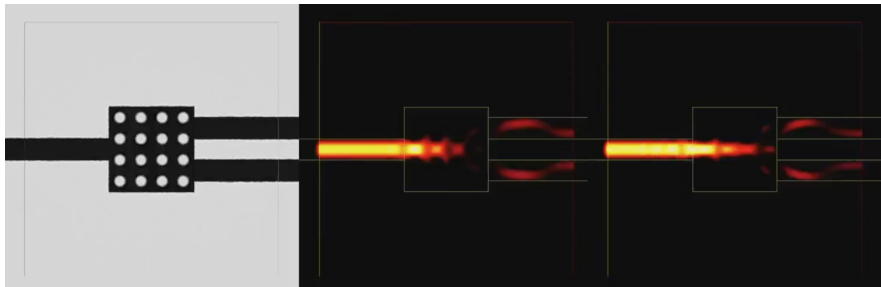
- **Nanophotonic devices** are the basic components of **photonic integrated circuits**.
- In these, **light** is transported by **wave guides**.
- The **electric** and **magnetic fields** are governed by the **time-harmonic Maxwell's equations**.
- The shape  $\Omega$  of **air inclusions** in the **Si** core is optimized to achieve particular effects.



*One nanophotonic component inside a complete photonic circuit.*

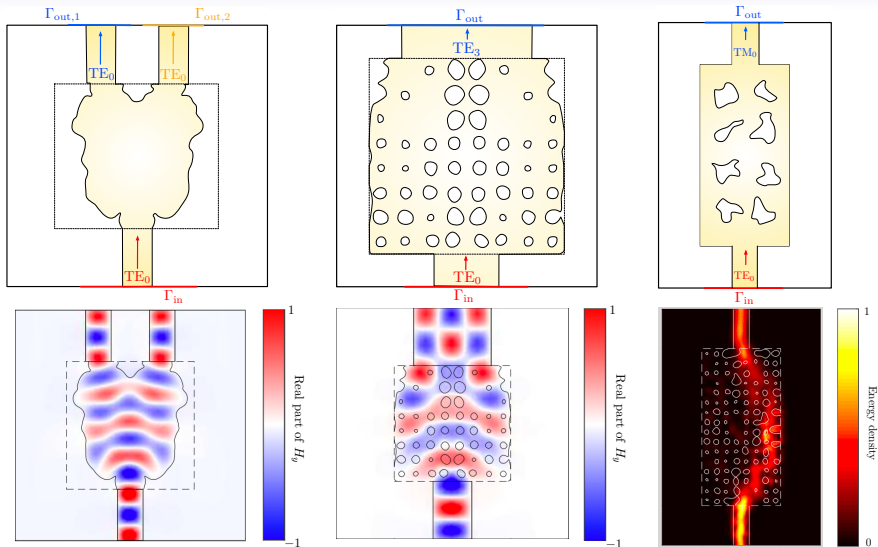
## Optimization of nanophotonic devices (II)

**Duplexers** steer incoming waves to different output channels, depending on their wavelength.



*Optimization of the shape of a nanophotonic duplexer.*

# Optimization of other nanophotonic devices



Optimization of (left) A power divider; (center) A mode converter; (right) A polarization converter.



# A word of advertisement

A webpage gathering [lecture notes](#), [slides](#), [demonstration codes](#), etc.



<https://membres-ljk.imag.fr/Charles.Dapogny/tutosto.html>

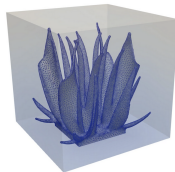


## Shape and topology optimization: online resources

The discipline of shape and topology optimization has aroused a growing enthusiasm among mathematicians, physicists and engineers since the seventies, fostered by its impressive technological and industrial achievements. Nowadays, problems pertaining to fields so diverse as mechanical engineering, fluid mechanics or quantum chemistry are currently tackled with such techniques, and raise new, challenging issues.

This webpage gather useful resources of various nature, with the aim to popularize this subject and disseminate possible numerical implementations. In particular, you will find:

- Lecture notes and review articles.
- Slides and records of graduate courses.
- Open source implementations, ranging from simple, educational toy codes, to more involved frameworks allowing to deal with challenging personal test cases.
- Useful links to similar resources, emanating from other researchers.



## Pedagogical articles and presentations

Article in the "Gazette des mathématiciens"

Large-audience presentation in prep. school

Review chapter about level set based shape optimization

Thank you!

Thank you for your attention!

# Technical appendix

## The Lax Milgram theorem

In a **Hilbert space**  $H$ , let  $a : H \times H \rightarrow \mathbb{R}$  be a bilinear form and  $\ell : H \rightarrow \mathbb{R}$  be a linear form such that:

- $a$  is **continuous**, i.e. there exists  $M > 0$  such that:

$$\forall u, v \in H, |a(u, v)| \leq M \|u\|_H \|v\|_H.$$

- $a$  is **coercive**, i.e. there exists  $\alpha > 0$  such that:

$$\forall u \in H, \alpha \|u\|_H^2 \leq a(u, u).$$

- $\ell$  is **continuous** (i.e.  $\ell$  belongs to the **dual space**  $H^*$ ):

$$\|\ell\|_{H^*} := \sup_{\substack{v \in H \\ v \neq 0}} \frac{|\ell(v)|}{\|v\|_H} < \infty.$$

### Theorem 3.

*Under the above hypotheses, the variational problem*

$$\text{Search for } u \in H \text{ s.t. for all } v \in H, a(u, v) = \ell(v)$$

*has a unique solution  $u \in H$ , which depends continuously on  $\ell$ :*

$$\|u\|_H \leq \frac{M}{\alpha} \|\ell\|_{H^*}.$$

## The implicit function theorem

The **implicit function theorem** ensures the **existence** and **smoothness** of a solution  $u = u_\theta$  to a parametrized, non linear equation of the form:

$$\mathcal{F}(\theta, u) = 0,$$

where  $u$  is the unknown and  $\theta$  is a “parameter”.

### Theorem 4 (Implicit function theorem).

Let  $\Theta, E, F$  be Banach spaces,  $\mathcal{V} \subset \Theta$ ,  $U \subset E$  be open sets. and  $\mathcal{F} : \mathcal{V} \times U \rightarrow F$  be a function of class  $\mathcal{C}^p$  for  $p \geq 1$ . Let  $(\theta_0, u_0) \in \mathcal{V} \times U$  be such that  $\mathcal{F}(\theta_0, u_0) = 0$  and:







The derivative  $\frac{\partial \mathcal{F}}{\partial u}(\theta_0, u_0) : E \rightarrow F$  is a linear **isomorphism**.

Then there exist open subsets  $\mathcal{V}' \subset \mathcal{V}$  of  $\theta_0$  in  $\Theta$  and  $U' \subset U$  of  $u_0$  in  $E$ , and a mapping  $g : \mathcal{V}' \rightarrow U'$  of class  $\mathcal{C}^p$  satisfying the properties:


- 1  $g(\theta_0) = u_0$ ,
- 2 For all  $\theta \in \mathcal{V}'$ , the equation  $\mathcal{F}(\theta, u) = 0$  has unique solution  $u = g(\theta) \in U'$ .


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