# Shape and topology optimization of structures built by additive manufacturing

Grégoire ALLAIRE, M. Bihr, B. Bogosel, M. Boissier, C. Dapogny, F. Feppon, A. Ferrer, P. Geoffroy-Donders, M. Godoy, L. Jakabcin, O. Pantz

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#### Outline of the course



- 1 Introduction: a review of additive manufacturing
- 2 Parametric optimization and the adjoint method
- 3 Geometric optimization and Hadamard method
- 4 Topology optimization and the level set method
- 5 Typical constraints from additive manufacturing
- 6 Optimization of lattice materials
- 7 Coupled shape and laser path optimization

A "hot" topic with a lot of room for new ideas and modeling...



## Outline of the second chapter



#### Chapter 2 - Parametric optimization and the adjoint method

- I Introduction and motivation
- II Thickness optimization
- III Computation of a gradient
- IV Self-adjoint case: the compliance
- V Numerical algorithm and results
- G. Allaire, *Conception optimale de structures*, Mathématiques et Applications, Vol. 58, Springer (2007).
- G. Allaire, L. Cavallina, N. Miyake, T. Oka, T. Yachimura, *The homogenization method for topology optimization of structures: old and new*, Interdisciplinary Information Sciences, 25(2), pp.75-146 (2019).

#### I - Introduction and motivation



A problem of optimal design (or shape optimization) for structures is defined by three ingredients:

- a model (typically a partial differential equation) to evaluate (or analyse) the mechanical behavior of a structure,
- an objective function which has to be minimized or maximized, or sometimes several objectives (also called cost functions or criteria),
- a set of admissible designs which precisely defines the optimization variables, including possible constraints.

#### Classification of optimal design problems



Optimal design problems can roughly be classified in three categories from the "easiest" ones to the "most difficult" ones:

- parametric or sizing optimization for which designs are parametrized by a few variables (for example, thickness or member sizes), implying that the set of admissible designs is considerably simplified,
- geometric or shape optimization for which all designs are obtained from an initial guess by moving its boundary (without changing its topology, i.e., its number of holes in 2-d),
- topology optimization where both the shape and the topology of the admissible designs can vary without any explicit or implicit restrictions.



#### Why studying parametric optimization?



The three categories of optimal design problems (parametric, geometric, topology) share some common features in terms of:

- applications,
- sensitivities or gradients,
- adjoint method.

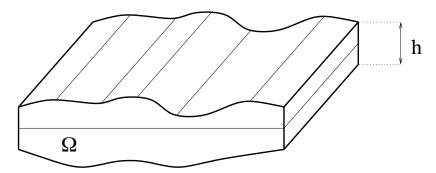
To simplify the exposition, we start with the simplest case of parametric optimization.

**Remark:** some topology optimization methods (like SIMP or homogenization) are very similar to parametric optimization...

#### II - Thickness optimization



One example of parametric optimization is thickness optimization of an elastic membrane.



- $\Omega =$  mean surface of a (plane) membrane
- $\bullet$  h = thickness in the normal direction to the mean surface



The membrane deformation is modeled by its vertical displacement  $u(x): \Omega \to \mathbb{R}$ , solution of the following partial differential equation (p.d.e.), the so-called **membrane model**,

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

with the thickness h, bounded by minimum and maximum values

$$0 < h_{min} \le h(x) \le h_{max} < +\infty.$$

The thickness h is the optimization variable.

It is a sizing or parametric optimal design problem because the computational domain  $\Omega$  does not change.

#### Variational formulation



We assume that  $\Omega$  is bounded and Lipschitz and  $f \in L^2(\Omega)$ .

The variational formulation of the membrane model is: find  $u \in H_0^1(\Omega)$  such that, for any  $v \in H_0^1(\Omega)$ 

$$\int_{\Omega} h \nabla u \cdot \nabla v \, dx = \int_{\Omega} f v \, dx$$

By Lax-Milgram lemma, there exists a unique solution  $u \in H_0^1(\Omega)$ .

## Admissible designs



#### The set of admissible thicknesses is

$$\mathcal{U}_{ad} = \left\{ h(x) \in L^2(\Omega) \text{ such that } \begin{cases} 0 < h_{min} \le h(x) \le h_{max} \\ \int_{\Omega} h(x) \, dx = h_0 |\Omega| \end{cases} \right\},$$

where  $h_0$  is an imposed average thickness.

**Possible additional "feasibility" constraints:** according to the production process of membranes, the thickness h(x) can be discontinuous, or on the contrary continuous; its derivative h'(x) can be uniformly bounded (molding-type constraint) or even its second-order derivative h''(x), linked to the curvature radius (milling-type constraint).

## Optimization criterion



The **optimization criterion** is linked to some mechanical property of the membrane, evaluated through its displacement u, solution of the p.d.e.,

$$J(h)=\int_{\Omega}j(u)\,dx,$$

where, of course, u depends on h. For example, the global rigidity of a structure is often measured by its **compliance**, or work done by the load: the smaller the work, the larger the rigidity (be careful! compliance = - rigidity). In such a case,

$$j(u) = fu$$
.

Another example amounts to achieve (at least approximately) a **target displacement**  $u_0(x)$ , which means

$$j(u)=|u-u_0|^2.$$



#### Conditions on the objective function



$$J(h) = \int_{\Omega} j(u) \, dx$$

To ensure that the criterion J(h) is well-defined and will be differentiable, we assume:

- j is a  $C^1$  function from  $\mathbb{R}$  to  $\mathbb{R}$ ,
- $\bullet |j(u)| \leq C(u^2+1) ,$
- $|j'(u)| \leq C(|u|+1)$ .

Since  $u \in H_0^1(\Omega)$ , we have

$$J(h)<+\infty$$
 and  $j'(u)\in L^2(\Omega)$ .



## Continuity of the cost function



**Proposition.** The application

$$h \to J(h) = \int_{\Omega} j(u) dx$$

is continuous from  $\mathcal{U}_{ad}$  into  $\mathbb{R}$ .

Proof. Exercise!

#### Non-existence theory



In full generality, there does not exist a solution of the optimization problem

$$\inf_{h\in\mathcal{U}_{ad}}J(h)=\int_{\Omega}j(u)\,dx$$

where u depends on h as the solution in  $H_0^1(\Omega)$  of

$$\int_{\Omega} h \nabla u \cdot \nabla v \, dx = \int_{\Omega} f v \, dx \quad \forall \, v \in H_0^1(\Omega).$$

- There are precise mathematical counter-examples (based on homogenization).
- It shows up numerically: non convergence, instabilities...
- Compliance is a miracle: existence of solutions.



## Existence theory



For a given positive constant R, replace  $\mathcal{U}_{ad}$  by

$$\mathcal{U}^R_{ad} = \left\{ h \in \mathcal{U}_{ad} \cap H^1(\Omega) \;, \quad \|h\|_{H^1(\Omega)} \leq R \right\}.$$

**Theorem.** There exists a solution  $h^R$  of the optimization problem

$$\inf_{h \in \mathcal{U}_{ad}^R} J(h) = \int_{\Omega} j(u) \, dx$$

where u depends on h as the solution in  $H_0^1(\Omega)$  of

$$\int_{\Omega} h \nabla u \cdot \nabla v \, dx = \int_{\Omega} f v \, dx \quad \forall \, v \in H_0^1(\Omega).$$

**Proof.** Exercise by using a compactness argument.

**Remark.** The bound R is the same for all elements of  $\mathcal{U}_{ad}^R$ .



#### III - Computation of a gradient



$$\begin{cases} -\operatorname{div}(h\nabla u) = f & \text{in } \Omega \\ u = 0 & \text{on } \partial\Omega. \end{cases}$$

$$\mathcal{U} = \{ h \in L^{\infty}(\Omega) \;, \quad \exists h_* > 0 \text{ such that } h(x) \geq h_* \text{ in } \Omega \} \,.$$

**Lemma.** The application  $h \to u(h)$ , which gives the solution  $u(h) \in H_0^1(\Omega)$  for  $h \in \mathcal{U}$ , is differentiable and its directional derivative at h in the direction  $k \in L^{\infty}(\Omega)$  is given by

$$\langle u'(h), k \rangle = v,$$

where v is the unique solution in  $H_0^1(\Omega)$  of

$$\begin{cases} -\operatorname{div}(h\nabla v) = \operatorname{div}(k\nabla u) & \text{in } \Omega \\ v = 0 & \text{on } \partial\Omega. \end{cases}$$



#### Proof of differentiability



**Proof.** Formally, one simply computes the directional derivative. Define h(t) = h + tk for t > 0. Let u(t) be the solution for the thickness h(t). Deriving with respect to t leads to

$$\left\{ \begin{array}{ll} -\operatorname{div}\left(h(t)\nabla u'(t)\right) = \,\operatorname{div}\left(h'(t)\nabla u(t)\right) & \text{in } \Omega \\ u'(t) = 0 & \text{on } \partial\Omega, \end{array} \right.$$

and, since h'(0) = k, we deduce u'(0) = v.

More rigorously, one could use an implicit function theorem for the variational formulation.

## Directional derivative of the objective function



**Lemma.** For  $h \in \mathcal{U}$ , let u(h) be the state in  $H_0^1(\Omega)$  and

$$J(h) = \int_{\Omega} j(u(h)) dx.$$

The application J(h), from  $\mathcal{U}$  into  $\mathbb{R}$ , is differentiable and its directional derivative at h in the direction  $k \in L^{\infty}(\Omega)$  is given by

$$\langle J'(h), k \rangle = \int_{\Omega} j'(u(h)) v \, dx ,$$

where  $v = \langle u'(h), k \rangle$  is the unique solution in  $H_0^1(\Omega)$  of

$$\begin{cases} -\operatorname{div}(h\nabla v) = \operatorname{div}(k\nabla u) & \text{in } \Omega \\ v = 0 & \text{on } \partial\Omega. \end{cases}$$

**Proof.** By simple composition of differentiable applications.

This formula is useless because v is implicit in k!

## The adjoint trick



We introduce an adjoint state p defined as the unique solution in  $H_0^1(\Omega)$  of

$$\left\{ \begin{array}{ll} -\operatorname{div}\left(h\nabla p\right)=-j'(u) & \text{ in } \Omega\\ p=0 & \text{ on } \partial\Omega. \end{array} \right.$$

**Theorem.** The cost function J(h) is differentiable on  $\mathcal{U}$  and

$$J'(h) = \nabla u \cdot \nabla p .$$

Remark. Here, the full gradient is explicitly given !

#### Proof of the theorem



**Proof.** To make explicit J'(h), we must eliminate  $v = \langle u'(h), k \rangle$ . We use the adjoint state for that: multiplying the equation for v by p and that for p by v, we integrate by parts

$$\int_{\Omega} h \nabla p \cdot \nabla v \, dx = -\int_{\Omega} j'(u) v \, dx$$
$$\int_{\Omega} h \nabla v \cdot \nabla p \, dx = -\int_{\Omega} k \nabla u \cdot \nabla p \, dx$$

Comparing these two equalities we deduce

$$\langle J'(h), k \rangle = \int_{\Omega} j'(u) v \, dx = \int_{\Omega} k \nabla u \cdot \nabla p \, dx,$$

for any  $k \in L^{\infty}(\Omega)$ . Since  $\nabla u \cdot \nabla p$  belongs to  $L^{1}(\Omega)$ , we check that J'(h) is continuous on  $L^{\infty}(\Omega)$ .



We explain that the adjoint is not a trick but it comes naturally as the Lagrange multiplier of a constrained optimization problem.

Recall the definition of a Lagrangian for the following simple optimization problem

$$\inf_{x \in \mathbb{R}^n, C(x) = 0} F(x)$$

where C, F are two functions from  $\mathbb{R}^n$  into  $\mathbb{R}$ . The Lagrangian  $\mathcal{L}(x, \lambda)$  is defined from  $\mathbb{R}^n \times$  into  $\mathbb{R}$  by

$$\mathcal{L}(x,\lambda) = F(x) + \lambda C(x)$$

A simple computation yields

$$\inf_{x \in \mathbb{R}^n} \sup_{\lambda \in \mathbb{R}} \mathcal{L}(x, \lambda) = \inf_{x \in \mathbb{R}^n, C(x) = 0} F(x)$$





Here, the constraint is the variational formulation of the state equation.

**Definition.** For independent variables

$$(h,\hat{u},\hat{\rho}) \in L^{\infty}(\Omega) \times H^1_0(\Omega) \times H^1_0(\Omega)$$
, the Lagrangian is defined by

$$\mathcal{L}(h,\hat{u},\hat{p}) = \int_{\Omega} j(\hat{u}) dx + \int_{\Omega} \hat{p} \left(-\operatorname{div}(h\nabla \hat{u}) - f\right) dx,$$

where  $\hat{p}$  is a Lagrange multiplier (a function) for the constraint which connects u to h.

By integration by parts we get

$$\mathcal{L}(h, \hat{u}, \hat{p}) = \int_{\Omega} j(\hat{u}) dx + \int_{\Omega} (h \nabla \hat{p} \cdot \nabla \hat{u} - f \hat{p}) dx.$$



#### Lagrangian for thickness optimization



By definition (because the Lagrangian is linear in  $\hat{p}$ ), the partial derivative of  $\mathcal{L}$  with respect to p in the direction  $\phi \in H_0^1(\Omega)$  is

$$\langle \frac{\partial \mathcal{L}}{\partial p}(h, \hat{u}, \hat{p}), \phi \rangle = \int_{\Omega} (h \nabla \hat{u} \cdot \nabla \phi - f \phi) dx,$$

which, when it vanishes, is nothing else than the variational formulation of the state equation.

**Definition.** The adjoint  $p \in H_0^1(\Omega)$  is defined as the solution of the variational formulation

$$\langle \frac{\partial \mathcal{L}}{\partial u}(h, \hat{u}, \hat{p}), \phi \rangle = 0 \quad \forall \phi \in H_0^1(\Omega).$$





A simple computation shows that

$$\langle \frac{\partial \mathcal{L}}{\partial u}(h,\hat{u},\hat{p}),\phi \rangle = \int_{\Omega} j'(\hat{u})\phi \,dx + \int_{\Omega} (h\nabla \hat{p}\cdot\nabla \phi) \,dx.$$

Therefore,

$$\langle \frac{\partial \mathcal{L}}{\partial u}(h,\hat{u},\hat{p}),\phi \rangle = 0 \quad \forall \, \phi \in H_0^1(\Omega).$$

is indeed equivalent to our previous variational formulation of the adjoint equation

$$\int_{\Omega} j'(\hat{u})\phi \, dx + \int_{\Omega} (h\nabla \hat{p} \cdot \nabla \phi) \, dx = 0 \quad \forall \, \phi \in H_0^1(\Omega).$$



**Theorem.** The differential of the objective function is given by

$$J'(h) = \frac{\partial \mathcal{L}}{\partial h}(h, u, p)$$

where u is the state and p is the adjoint.

**Proof.** Since *u* satisfies its variational formulation, we have

$$J(h) = \mathcal{L}(h, u, \hat{p}) \quad \forall \hat{p} \in H_0^1(\Omega).$$

Thus, if u(h) is differentiable, we get

$$\langle J'(h), k \rangle = \langle \frac{\partial \mathcal{L}}{\partial h}(h, u, \hat{p}), k \rangle + \langle \frac{\partial \mathcal{L}}{\partial u}(h, u, \hat{p}), \frac{\partial u}{\partial h}(k) \rangle$$

Then, taking  $\hat{p} = p$ , the second term vanishes to yield

$$\langle J'(h), k \rangle = \langle \frac{\partial \mathcal{L}}{\partial h}(h, u, p), k \rangle$$



#### Conclusion



#### This approach is called the adjoint method.

- Introduce a Lagrangian  $\mathcal{L}(h, \hat{u}, \hat{p})$  for independent variables.
- The notation  $\hat{u}$ ,  $\hat{p}$  indicates that these functions are not solutions of any equations...
- The partial derivative of  $\mathcal{L}$  with respect to p gives the variational formulation of the state equation for u.
- The partial derivative of  $\mathcal{L}$  with respect to u gives the variational formulation of the adjoint equation for p.
- The partial derivative of  $\mathcal{L}$  with respect to h, evaluated at u and p, gives the formula of the differential J'(h).
- This method is simple but does not prove that one can differentiate J(h).



#### IV - Self-adjoint case: the compliance



When j(u) = fu, we find p = -u since j'(u) = f. This particular case is said to be **self-adjoint**.

More can be said! We use the dual or complementary energy

$$\int_{\Omega} fu \, dx = \min_{\substack{\tau \in L^2(\Omega)^N \\ -\operatorname{div}\tau = f \text{ in } \Omega}} \int_{\Omega} h^{-1} |\tau|^2 dx .$$

We can rewrite the optimization problem as a double minimization

$$\inf_{h \in \mathcal{U}_{ad}} \min_{\substack{\tau \in L^2(\Omega)^N \\ -\text{div}\tau = f \text{ in } \Omega}} \int_{\Omega} h^{-1} |\tau|^2 dx ,$$

and the order of minimization is irrelevant.



#### Compliance minimization



**Lemma.** The function  $\phi(a, \sigma) = a^{-1} |\sigma|^2$ , defined from  $\mathbb{R}^+ \times \mathbb{R}^N$  into  $\mathbb{R}$ , is convex and satisfies

$$\phi(a,\sigma) = \phi(a_0,\sigma_0) + \phi'(a_0,\sigma_0) \cdot (a-a_0,\sigma-\sigma_0) + \phi(a,\sigma-\frac{a}{a_0}\sigma_0),$$

where the derivative is given by

$$\phi'(a_0,\sigma_0)\cdot(b,\tau) = -\frac{b}{a_0^2}|\sigma_0|^2 + \frac{2}{a_0}\sigma_0\cdot\tau.$$

**Theorem.** There exists a minimizer to the compliance minimization problem.

**Proof.** Use the direct method fo the calculus of variations and the convexity property of  $\phi(a, \sigma)$ .



## Optimality condition



**Lemma.** Take  $\tau \in L^2(\Omega)^N$ . The problem

$$\min_{h \in \mathcal{U}_{ad}} \int_{\Omega} h^{-1} |\tau|^2 dx$$

admits a minimizer  $\mathit{h}(\tau)$  in  $\mathcal{U}_{\mathit{ad}}$  given by

$$h(\tau)(x) = \left\{ \begin{array}{ll} h^*(x) & \text{if } h_{\min} < h^*(x) < h_{\max} \\ h_{\min} & \text{if } h^*(x) \leq h_{\min} \\ h_{\max} & \text{if } h^*(x) \geq h_{\max} \end{array} \right. \quad \text{with } h^*(x) = \frac{|\tau(x)|}{\sqrt{\ell}},$$

where  $\ell \in \mathbb{R}^+$  is the Lagrange multiplier such that

$$\int_{\Omega} h(x) dx = h_0 |\Omega|.$$

This is at the root of a numerical algorithm called "optimality criteria" or "alternate minimization".



#### V - Numerical algorithm and results



#### Projected gradient

- **1** Initialization of the thickness  $h_0 \in \mathcal{U}_{ad}$  (for example, a constant function which satisfies the constraints).
- 2 Iterations until convergence, for  $n \ge 0$ :

$$h_{n+1} = P_{\mathcal{U}_{ad}}\Big(h_n - \mu J'(h_n)\Big),\,$$

where  $\mu>0$  is a descent step,  $P_{\mathcal{U}_{ad}}$  is the projection operator on the closed convex set  $\mathcal{U}_{ad}$  and the derivative is given by

$$J'(h_n) = \nabla u_n \cdot \nabla p_n$$

with the state  $u_n$  and the adjoint  $p_n$  (associated to the thickness  $h_n$ ).



## Projection operator



We characterize the projection operator  $P_{\mathcal{U}_{ad}}$ 

$$(P_{\mathcal{U}_{ad}}(h))(x) = \max(h_{min}, \min(h_{max}, h(x) + \ell))$$

where  $\ell$  is the unique Lagrange multiplier such that

$$\int_{\Omega} P_{\mathcal{U}_{ad}}(h) dx = h_0 |\Omega|.$$

The determination of the constant  $\ell$  is not explicit: we must use an iterative **dichotomy** algorithm based on the monotonicity of

$$\ell o F(\ell) = \int_{\Omega} \max(h_{min}, \min(h_{max}, h(x) + \ell)) dx$$

which is strictly increasing on an interval  $[\ell^-, \ell^+]$  and constant outside.





Replace the membrane model by the 2-d elasticity equations

$$\begin{cases}
-\operatorname{div}\sigma = f & \text{in } \Omega \\
\sigma = 2\mu h e(u) + \lambda h \operatorname{tr}(e(u)) \operatorname{Id} & \text{in } \Omega \\
u = 0 & \text{on } \Gamma_D \\
\sigma n = g & \text{on } \Gamma_N
\end{cases}$$

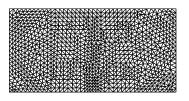
with the strain tensor  $e(u) = \frac{1}{2} (\nabla u + (\nabla u)^t)$ .

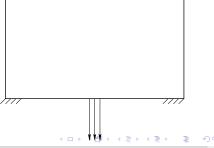
FreeFem++ computations; scripts available on the web page http://www.cmap.polytechnique.fr/~allaire/cours\_X\_annee3.html

## Compliance minimization



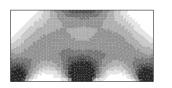
Mesh and boundary conditions:

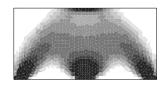


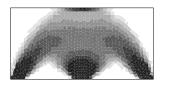


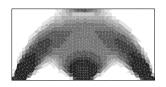
## Compliance minimization: iterations 1, 5, 10 and 30







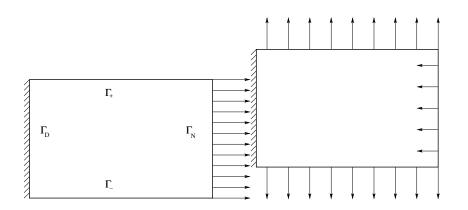




#### Least-square criterion



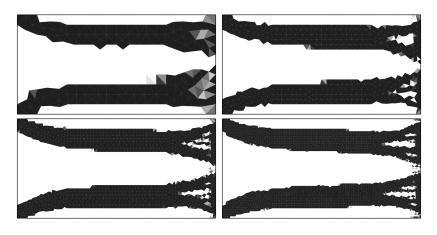
Boundary conditions and target displacement  $u_0$ :



#### Least-square criterion



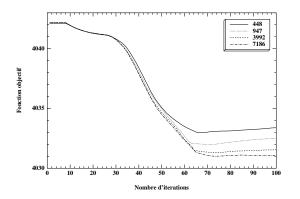
Optimal shapes for meshes with 448, 947, 3992, 7186 triangles



#### No convergence under mesh refinement!



More and more details appear when the mesh size is decreased. The value of the objective function decreases with the mesh size.



## Exercises (just in case !)



If you want to practice the adjoint method, find the adjoint and the objective differential for the following problems.

$$\left\{ \begin{array}{ll} -\operatorname{div}\left(h\nabla u\right) = f & \text{ in } \Omega \\ u = 0 & \text{ on } \Gamma_D, \\ \frac{\partial u}{\partial n} = 0 & \text{ on } \Gamma_N, \end{array} \right.$$

where  $\partial \Omega = \Gamma_D \cup \Gamma_N$ .

$$2 J_2(h) = \int_{\Omega} |h \nabla u|^2 dx$$

$$J_3(h) = \int_{\Gamma_M} |u - u_0|^2 ds$$

