

# OPTIMAL DESIGN OF STRUCTURES (MAP 562)

G. ALLAIRE

January 23rd, 2019

Department of Applied Mathematics, Ecole Polytechnique

## CHAPTER IV

# OPTIMAL CONTROL

Optimization of distributed systems:  
Computing a gradient by the adjoint method

## Control of an elastic membrane

For  $f \in L^2(\Omega)$ , the vertical displacement  $u$  of the membrane is solution of

$$\begin{cases} -\Delta u = f + v & \text{in } \Omega \\ u = 0 & \text{on } \partial\Omega, \end{cases}$$

where  $v$  is a **control force** which is our optimization variable (for example, a piezzo-electric actuator). We define the set of admissible controls

$$K = \{v \in L^2(\omega) \mid v_{min}(x) \leq v(x) \leq v_{max}(x) \text{ in } \omega \text{ and } v = 0 \text{ in } \Omega \setminus \omega\}.$$

We want to **control the membrane** in order to reach a prescribed displacement  $u_0 \in L^2(\Omega)$  by minimizing ( $c > 0$ )

$$\inf_{v \in K} \left\{ J(v) = \frac{1}{2} \int_{\Omega} (|u - u_0|^2 + c|v|^2) dx \right\}.$$

## Existence of an optimal control

### Proposition.

There exists a unique optimal control  $\bar{v} \in K$ .

**Proof.**  $v \rightarrow u$  is an affine function from  $K$  into  $H_0^1(\Omega)$ .

The integrand of  $J$  is a positive "polynomial" of degree two in  $v$ .

$v \rightarrow J(v)$  is strongly convex on  $K$  which is convex.

**Remark.** The existence is often more delicate to prove, but the important thing here is to compute a gradient  $J'(v)$  for numerical purposes.

**Important notice:** the solution  $u$  of the p.d.e. depends on the control  $v$ .

## Gradient and optimality condition

The safest and simplest way of **computing a gradient** is to evaluate the **directional derivative**

$$j(t) = J(v + tw) \quad \Rightarrow \quad j'(0) = \langle J'(v), w \rangle = \int_{\Omega} J'(v)w \, dx .$$

By linearity, we have  $u(v + tw) = u(v) + t\tilde{u}(w)$  with

$$\begin{cases} -\Delta \tilde{u}(w) = w & \text{in } \Omega \\ \tilde{u}(w) = 0 & \text{on } \partial\Omega. \end{cases}$$

In other words,  $\tilde{u}(w) = \langle u'(v), w \rangle$ .

Since  $J(v)$  is quadratic the computation is very simple and we obtain

$$\int_{\Omega} J'(v)w \, dx = \int_{\Omega} \left( (u(v) - u_0)\tilde{u}(w) + cvw \right) dx,$$

**Unfortunately  $J'(v)$  is not explicit because we cannot factorize out  $w$  in  $\tilde{u}(w)$  !**

### Adjoint state

To simplify the gradient formula we use the so-called **adjoint state**  $p$ , defined as the unique solution in  $H_0^1(\Omega)$  of

$$\begin{cases} -\Delta p = u - u_0 & \text{in } \Omega \\ p = 0 & \text{on } \partial\Omega. \end{cases}$$

We multiply the equation for  $\tilde{u}(w)$  by  $p$  and conversely

$$\text{equation for } p \times \tilde{u}(w) \Rightarrow \int_{\Omega} \nabla p \cdot \nabla \tilde{u}(w) \, dx = \int_{\Omega} (u - u_0) \tilde{u}(w) \, dx$$

$$\text{equation for } \tilde{u}(w) \times p \Rightarrow \int_{\Omega} \nabla \tilde{u}(w) \cdot \nabla p \, dx = \int_{\Omega} w p \, dx$$

Comparing these two equalities we deduce that

$$\int_{\Omega} (u - u_0) \tilde{u}(w) \, dx = \int_{\Omega} w p \, dx \Rightarrow \int_{\Omega} J'(v) w \, dx = \int_{\Omega} (p + cv) w \, dx.$$

## Conclusion on the adjoint state

We found an **explicit formula** of the gradient

$$J'(v) = p + cv.$$

- ✎ **Adjoint method**: computation of the gradient by solving **2** boundary value problems ( $u$  and  $p$ ).
- ✎ If one does not use the adjoint: for **each** direction  $w$  one must solve **2** boundary value problems ( $u$  and  $\tilde{u}(w)$ ) to evaluate  $\langle J'(v), w \rangle$ .  
For example, if  $J'(v)$  is a vector of dimension  $n$ , its  $n$  components are obtained by solving  $(n + 1)$  problems !
- ✎ Very efficient in practice: it is the best possible method.
- ✎ Inconvenient: if one uses a **black-box** software to compute  $u$ , it can be very difficult to modify it in order to get the adjoint state  $p$ .

### Further remarks on the notion of adjoint state

- ☞ If the state equation is not self-adjoint (the bilinear form is not symmetric), the operator of the adjoint equation is the transposed or **adjoint** of the direct operator.
- ☞ If the state equation is time dependent with an initial condition, then the adjoint equation is time dependent too, but **backward** with a final condition.
- ☞ If the state equation is non-linear, the adjoint equation is linear.

The adjoint is not just a trick ! It can be deduced from the Lagrangian of the problem.

General method to find the adjoint equation

We consider the state equation as a **constraint** and, for any  $(\hat{v}, \hat{u}, \hat{p}) \in L^2(\Omega) \times H_0^1(\Omega) \times H_0^1(\Omega)$ , we introduce the Lagrangian of the minimization problem

$$\mathcal{L}(\hat{v}, \hat{u}, \hat{p}) = \frac{1}{2} \int_{\Omega} (|\hat{u} - u_0|^2 + c|\hat{v}|^2) dx + \int_{\Omega} \hat{p}(\Delta \hat{u} + f + \hat{v}) dx,$$

where  $\hat{p}$  is the **Lagrange multiplier** for the constraint which links the two **independent** variables  $\hat{v}$  and  $\hat{u}$ .

Integrating by parts yields

$$\mathcal{L}(\hat{v}, \hat{u}, \hat{p}) = \frac{1}{2} \int_{\Omega} (|\hat{u} - u_0|^2 + c|\hat{v}|^2) dx + \int_{\Omega} (-\nabla \hat{p} \cdot \nabla \hat{u} + f\hat{p} + \hat{v}\hat{p}) dx.$$

**Proposition.** The optimality conditions are equivalent to the stationnarity of the Lagrangian, i.e.,

$$\frac{\partial \mathcal{L}}{\partial v} = \frac{\partial \mathcal{L}}{\partial u} = \frac{\partial \mathcal{L}}{\partial p} = 0.$$



Proof

- $\frac{\partial \mathcal{L}}{\partial p} = 0 \Rightarrow$  by definition, we recover the equation satisfied by the state  $u$ .
- $\frac{\partial \mathcal{L}}{\partial u} = 0 \Rightarrow$  equation satisfied by the adjoint state  $p$ . Indeed,

$$\ell_u(t) = \mathcal{L}(\hat{v}, \hat{u} + t\phi, \hat{p}) \quad \Rightarrow \quad \ell'_u(0) = \left\langle \frac{\partial \mathcal{L}}{\partial u}, \phi \right\rangle = \int_{\Omega} ((\hat{u} - u_0)\phi - \nabla \hat{p} \cdot \nabla \phi) dx$$

which is the variational formulation of the adjoint equation.

- $\frac{\partial \mathcal{L}}{\partial v} = 0 \Rightarrow$  formula for  $J'(v)$ . Indeed,

$$\ell_v(t) = \mathcal{L}(\hat{v} + tw, \hat{u}, \hat{p}) \quad \Rightarrow \quad \ell'_v(0) = \left\langle \frac{\partial \mathcal{L}}{\partial v}, w \right\rangle = \int_{\Omega} (c\hat{v} + \hat{p})w dx$$

Simple formula for the derivative

In the preceding proof we obtained

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

with the state  $u$  and the adjoint  $p$  (both depending on  $v$ ).

It is not a surprise ! Indeed,

$$J(v) = \mathcal{L}(v, u, \hat{p}) \quad \forall \hat{p}$$

because  $u$  is the state. Thus, if  $u(v)$  is differentiable, we get

$$\langle J'(v), w \rangle = \left\langle \frac{\partial \mathcal{L}}{\partial v}(v, u, \hat{p}), w \right\rangle + \left\langle \frac{\partial \mathcal{L}}{\partial u}(v, u, \hat{p}), \frac{\partial u}{\partial v}(w) \right\rangle$$

We then take  $\hat{p} = p$ , the adjoint, to obtain

$$\langle J'(v), w \rangle = \left\langle \frac{\partial \mathcal{L}}{\partial v}(v, u, p), w \right\rangle$$

### Another interpretation of the adjoint state

The adjoint state  $p$  is the Lagrange multiplier for the constraint of the state equation. But it is also a **sensitivity function**.

Define the Lagrangian

$$\mathcal{L}(\hat{v}, \hat{u}, \hat{p}, f) = \frac{1}{2} \int_{\Omega} (|\hat{u} - u_0|^2 + c|\hat{v}|^2) dx + \int_{\Omega} (-\nabla \hat{p} \cdot \nabla \hat{u} + f\hat{p} + \hat{v}\hat{p}) dx.$$

**We study the sensitivity of the minimum with respect to variations of  $f$ .**

We denote by  $v(f)$ ,  $u(f)$  and  $p(f)$  the optimal values, depending on  $f$ . We assume that they are differentiable with respect to  $f$ . Then

$$\nabla_f \left( J(v(f)) \right) = p(f).$$

**$p$  gives the derivative (without further computation) of the minimum with respect to  $f$  !**

Indeed  $J(v(f)) = \mathcal{L}(v(f), u(f), p(f), f)$  and  $\frac{\partial \mathcal{L}}{\partial v} = \frac{\partial \mathcal{L}}{\partial u} = \frac{\partial \mathcal{L}}{\partial p} = 0$ .