



Discrete Gradient Flows for a Shape Optimization Problem

Marco Verani

MOX - Dipartimento di Matematica “F. Brioschi”,
Politecnico di Milano

<http://mox.polimi.it>

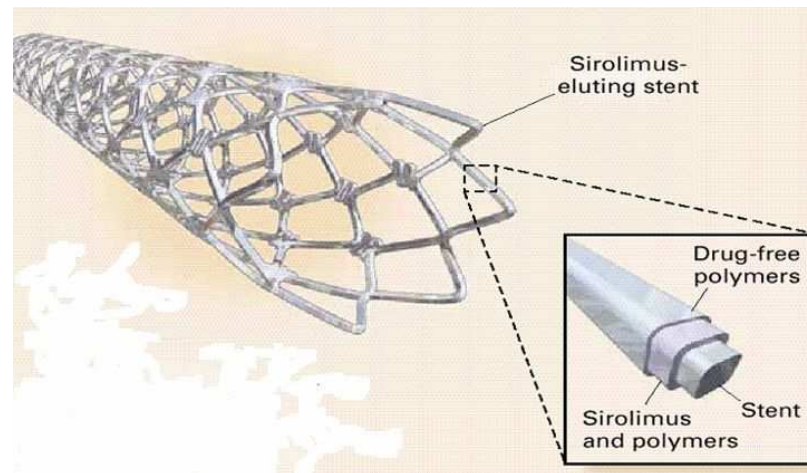
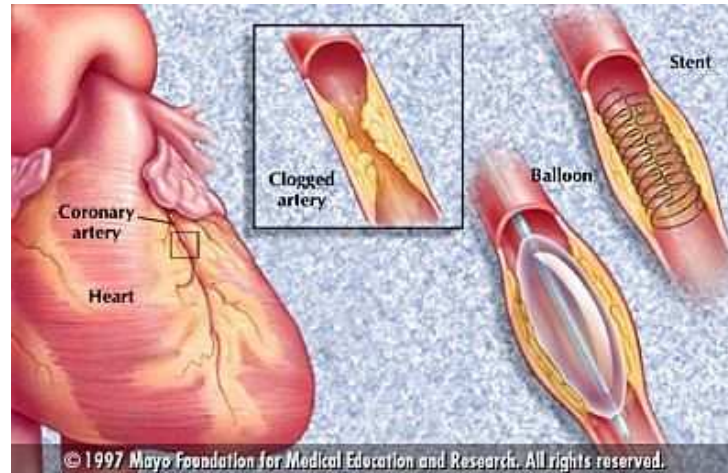
(joint work with P. Morin and R.H. Nochetto)

Benasque, Spain, August 2007

Outline

- Motivation
- Shape Calculus
- Numerical Approximation

Drug Eluting Stents



Abstract Problem

$$\Omega^* \in \mathcal{U}_{ad} : \quad J(\Omega^*, y(\Omega^*)) = \inf_{\Omega \in \mathcal{U}_{ad}} J(\Omega, y(\Omega)),$$
$$y(\Omega): \quad Ly(\Omega) = f, \quad \text{in } \Omega.$$

Mathematical problems:

- Continuous dependence of $y(\Omega)$ with respect to Ω
- Existence (and uniqueness) of Ω^*
- Optimality Conditions
- Algorithms for the numerical approximation of Ω^*
- ...

Toy Problem

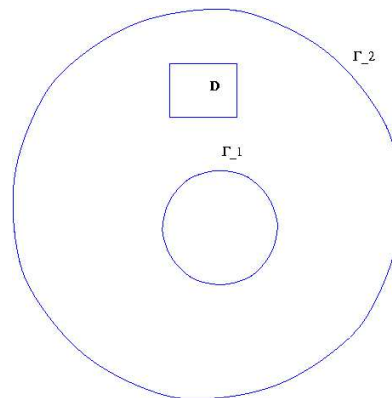
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z_g given and $y = y(\Omega)$ solution of

$$\begin{cases} -\Delta y = 0, & \text{in } \Omega \\ y = 0, & \text{on } \Gamma_2 \\ \frac{\partial y}{\partial n} = 1, & \text{on } \Gamma_1, \end{cases}$$



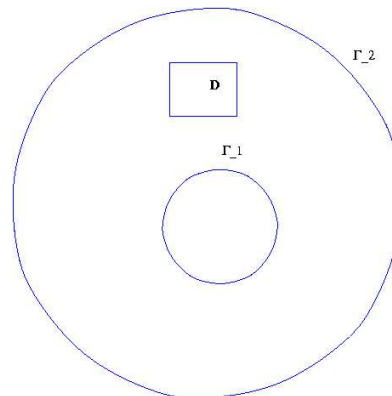
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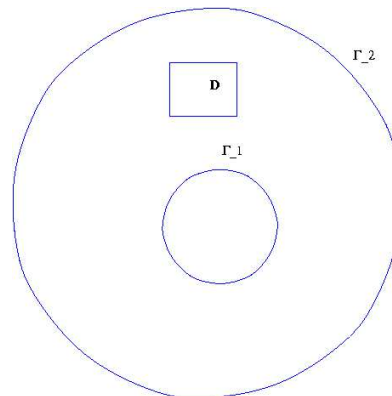
Toy Problem

$$\min_{\Omega \in \mathcal{U}_{ad}} J(\Omega) := \min_{\Omega \in \mathcal{U}_{ad}} \frac{1}{2} \int_D (y(\Omega) - z_g)^2 dx + \gamma \int_{\Gamma_1} ds$$

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Deformation of Domains: the Speed Method

- \vec{V} given
- Consider the function $X(\cdot, t) : x \in \mathbb{R}^n \longrightarrow X(x, t) \in \mathbb{R}^n$ defined by

$$\frac{dX}{dt} = \vec{V}(X(x, t)), \quad X(x, 0) = x \in \Omega, \quad (\Omega := \Omega_0)$$

- $\Omega_t = \{X(x, t) : x \in \Omega_0\}$
- \vec{V} "regular" \longrightarrow regularity of Ω is preserved for $t > 0$.

[Cea et al, 1974], [Sokolowski and Zolesio, 1992], ...

Shape sensitivity

- Eulerian derivative in direction \vec{V} :

$$dJ(\Omega; \vec{V}) = \lim_{t \rightarrow 0} \frac{1}{t} (J(\Omega_t) - J(\Omega))$$

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- Shape derivative:

$$y'(\Omega; \vec{V}) = \underbrace{\dot{y}(\Omega; \vec{V})}_{\text{material derivative}} - \underbrace{\langle \nabla y(\Omega), \vec{V} \rangle}_{\text{space derivative}}$$

material derivative

space derivative

Examples I $(V = \vec{V} \cdot \vec{\nu})$

$$J(t) = \int_{\alpha_-(t)}^{\alpha_+(t)} \phi(x, t) dx \Rightarrow \frac{dJ}{dt} = \int_{\alpha_-(t)}^{\alpha_+(t)} \partial_t \phi(x, t) dx \pm \phi(\alpha_{\pm}(t)) \alpha'_{\pm}(t)$$

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$$J(\Omega) = \int_{\Omega} \phi(\cdot, \Omega) dx \Rightarrow dJ(\Omega, \vec{V}) = \int_{\Omega} \phi'(\Omega, \vec{V}) + \int_{\Gamma} \phi V dx$$

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Shape sensitivity for the toy problem I $(V = \vec{V} \cdot \vec{\nu})$

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$$\left\{ \begin{array}{ll} -\Delta y' = 0, & \text{in } \Omega \\ y' = -\frac{\partial y}{\partial n} V = 0, & \text{on } \Gamma_2 \text{ (fix)} \\ \frac{\partial y'}{\partial n} = \text{div}_\Gamma(V \nabla_\Gamma y) + \kappa V, & \text{on } \Gamma_1 \end{array} \right.$$

Shape sensitivity for the toy problem II

Let $J(\Omega) = \frac{1}{2} \int_D (y(\Omega) - z_g)^2$ and p s.t.

$$\begin{cases} -\Delta p = \chi_D (y - z_g), & \text{in } \Omega \\ p = 0, & \text{on } \Gamma_2 \\ \frac{\partial p}{\partial n} = 0, & \text{on } \Gamma_1, \end{cases}$$

then

$$\begin{aligned} dJ(\Omega; \vec{V}) &= \int_D (y - z_g) y' = - \int_{\Omega} \Delta p y' \\ &= \int_{\Gamma_1} \underbrace{(-\nabla_{\Gamma} y \nabla_{\Gamma} p + k p)}_{:= G} V \end{aligned}$$

Shape sensitivity for the toy problem II

Let $J(\Omega) = \frac{1}{2} \int_D (y(\Omega) - z_g)^2 + \gamma \int_{\Gamma_1} d\Gamma$ and p s.t.

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Problem 1

Given Ω , how to choose \vec{V} such that $dJ(\Omega; \vec{V}) < 0$?

Gradient Flow

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Choice of a scalar product

- $L^2(\Gamma)$: $b(V, W) = \int_{\Gamma} VW$
- $H^1(\Gamma)$: $b(V, W) = \int_{\Gamma} \alpha \nabla_{\Gamma} V \nabla_{\Gamma} W + \beta VW$
- $H^{-1}(\Gamma)$: $b(V, W) = \int_{\Gamma} (-\Delta_{\Gamma})^{-1} VW$

[Cea, Zolesio, ...]

Problem 2

Given Ω^0 , how to build $\{\Omega^k\}_k$ such that $J(\Omega^{k+1}) \leq J(\Omega^k)$?

Time Discretization (discrete Gradient Flow)

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Linearization: Semi-Implicit method

$$b_{n+1}(V^{n+1}, W) = - \int_{\Gamma_1^{n+1}} G^{n+1} W \quad \forall W$$

Linearization: Semi-Implicit method

- Replace in optimality condition:

$$\Omega_{n+1} \rightarrow \Omega_n, \vec{V}^{n+1} \rightarrow \vec{V}^n, G^{n+1} \rightarrow G^n$$

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$$b_n(V^{n+1}, W) = - \int_{\Gamma_1^n} G^n W \quad \forall W$$

$$G = -\nabla_{\Gamma} y \nabla_{\Gamma} p - k(p + \gamma)$$

How to proceed?

$$\Omega^n \rightarrow \Omega^{n+1}: \quad \vec{X}^{(n+1)} = \vec{X}^n + \tau \vec{V}^{(n+1)}$$

$$\vec{k}^{(n+1)} + \tau \Delta_\Gamma \vec{V}^{(n+1)} = -\Delta_\Gamma \vec{X}^n$$

$$k^{(n+1)} - \vec{k}^{(n+1)} \cdot \vec{\nu}^{(n)} = 0$$

$$\mathcal{B}V^{n+1} = \nabla_\Gamma y^{(n)} \nabla_\Gamma p^{(n)} - k^{(n+1)} (p^{(n)} + \gamma)$$

$$\vec{V}^{(n+1)} - V^{(n+1)} \vec{\nu}^n = 0$$

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$$\mathcal{L}V^{(n+1)} = \nabla_\Gamma y^{(n)} \nabla_\Gamma p^{(n)} - k^{(n+1)}(p^{(n)} + \gamma)$$

$$\vec{V}^{(n+1)} - V^{(n+1)} \vec{\nu}^n = 0$$

$$\mathcal{L} = -\text{div}_\Gamma(\alpha \nabla_\Gamma \cdot) + \beta I$$

FEM discretization

Let $\mathcal{V}(\Gamma) \subset H^1(\Gamma)$. Find $\vec{V}, \vec{k} \in \vec{\mathcal{V}}(\Gamma)$, $V, k \in \mathcal{V}(\Gamma)$, s.t.

$$\langle \vec{k}, \vec{\phi} \rangle - \tau \langle \nabla_{\Gamma} \vec{V}, \nabla_{\Gamma} \vec{\phi} \rangle = - \langle \nabla_{\Gamma} \vec{X}, \nabla_{\Gamma} \vec{\phi} \rangle$$

$$\langle k, \phi \rangle - \langle \vec{k} \cdot \vec{\nu}, \phi \rangle = 0$$

$$\langle \alpha \nabla_{\Gamma} V, \nabla_{\Gamma} \phi \rangle + \langle \beta V, \phi \rangle + \langle kp, \phi \rangle = \langle \nabla_{\Gamma} y \nabla_{\Gamma} p, \phi \rangle$$

$$\langle \vec{V}, \vec{\phi} \rangle - \langle V, \vec{\phi} \cdot \vec{\nu} \rangle = 0$$

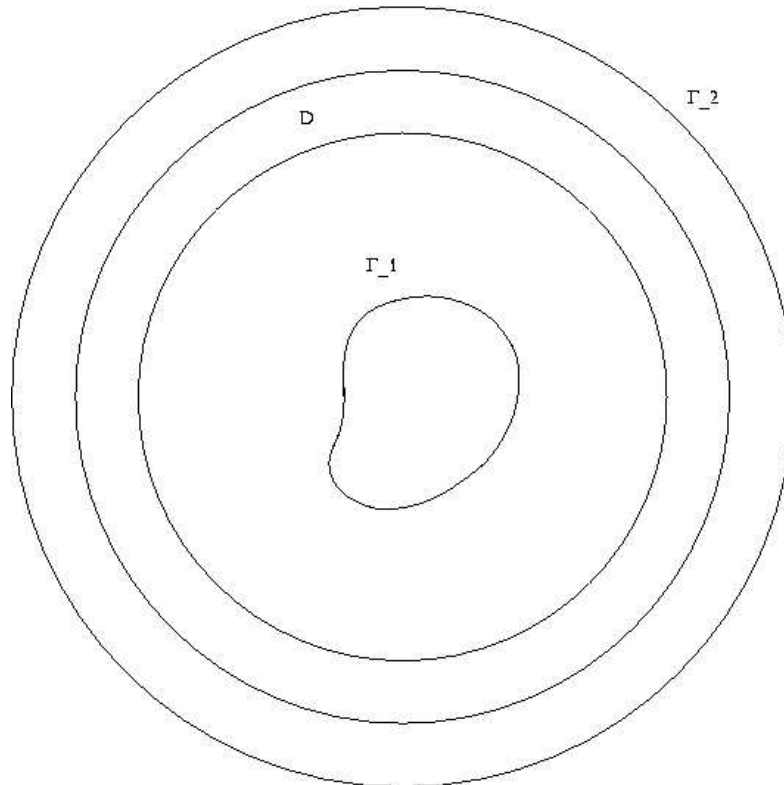
$$\forall \vec{\phi} \in \vec{\mathcal{V}}(\Gamma), \phi \in \mathcal{V}(\Gamma)$$

Schur complement

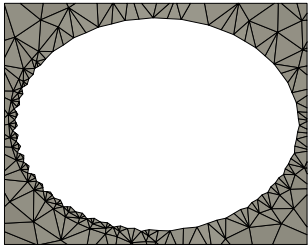
$$(\tau M_p M^{-1} \vec{N} \vec{M}^{-1} \vec{A} \vec{M}^{-1} \vec{N}^T + M + A) V = -f - M_p M^{-1} \vec{N} \vec{M}^{-1} \vec{A} \vec{X}_n$$

Test case

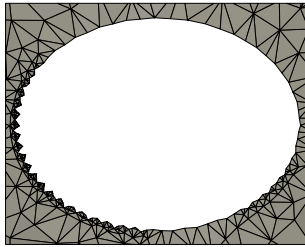
- $\min_{\Omega \in \mathcal{U}_{ad}} \frac{1}{2} \int_D [y(\Omega) - (\log(3) - \log(\rho(x)))]^2$
- $D = \{x \in \mathbb{R}^2 : 2 \leq \rho(x) \leq 2.5\}$
- \mathcal{U}_{ad} : Γ_2 fix and move Γ_1 s.t. $\Gamma_1 \cap D = \emptyset$.



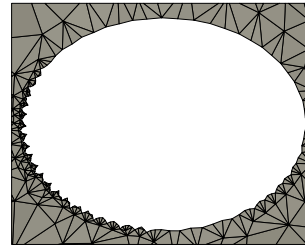
L^2 Flow



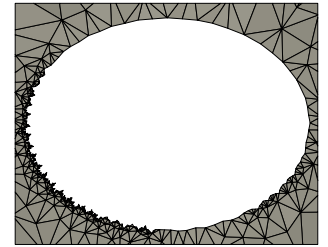
$$J(3) = 0.09879199$$



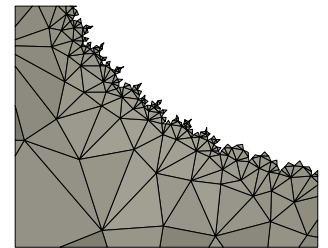
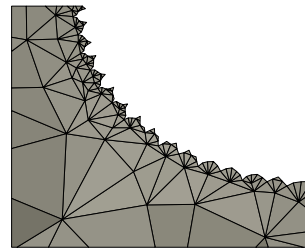
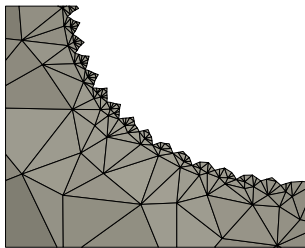
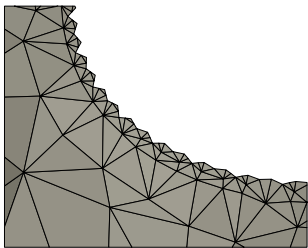
$$J(6) = 0.08488141$$



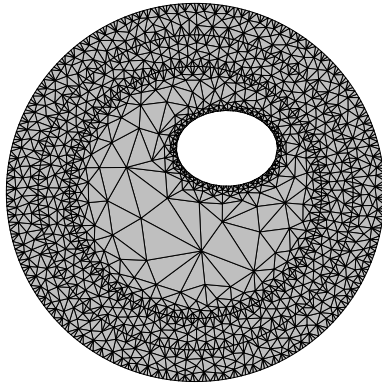
$$J(9) = 0.07282547$$



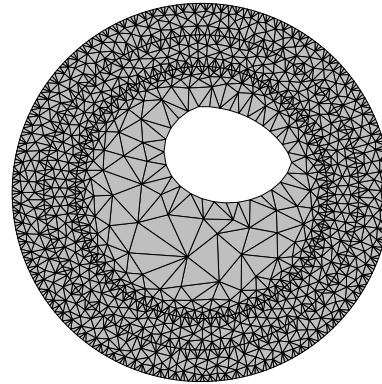
$$J(22) = 0.03951210$$



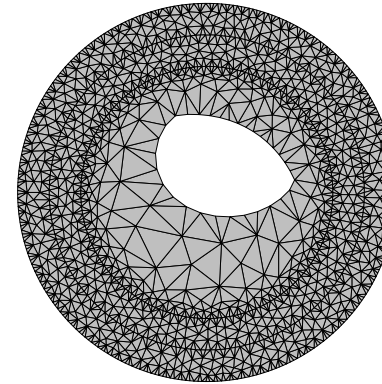
H_w^1 flow



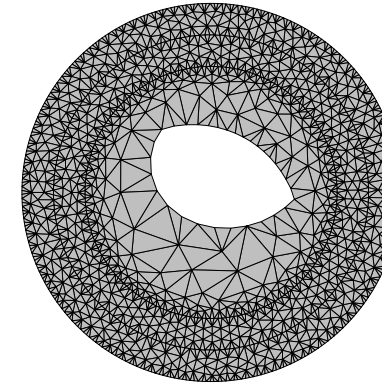
$$J(0) = 0.10257$$



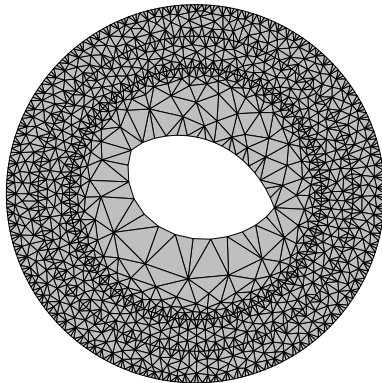
$$J(20) = 0.05646$$



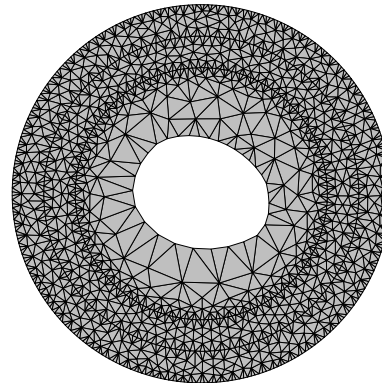
$$J(40) = 0.02642$$



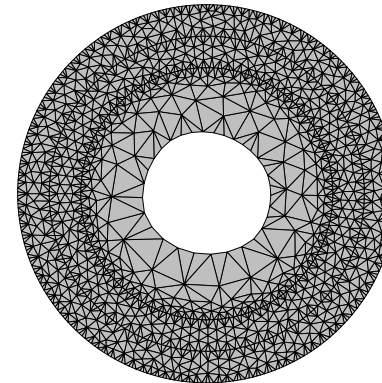
$$J(60) = 0.00973$$



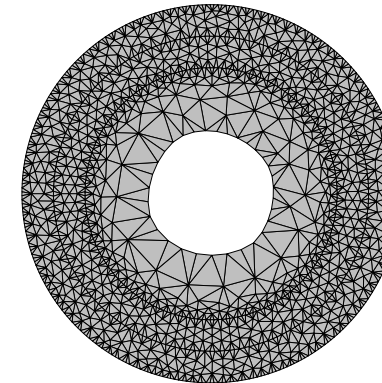
$$J(80) = 0.00232$$



$$J(100) = 0.000288$$



$$J(120) = 0.0000213$$



$$J(140) = 0.00000137$$

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