

Level Set Methods For Inverse Obstacle Problems

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Outline

- Introduction
- Level Set Methods
- Optimal Geometries
- Inverse Obstacle Problems & Shape Optimization
- Sensitivity Analysis
- Level Set Methods based on Gradient Flows
- Numerical Methods



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Introduction

Many applications deal with the reconstruction and optimization of geometries (shapes, topologies);

e.g.:

- Identification of piecewise constant parameters
- Inverse obstacle scattering
- Inclusion detection
- Structural optimization
- Optimal design of photonic bandgap structures
-



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Introduction

In such applications, there is no natural a-priori information on shapes or topological structures of the solution (number of connected components, star-shapedness, convexity, ...)

→ flexible representations of the shapes needed!



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Level Set Methods

Osher & Sethian, JCP 1987
Osher & Fedkiw, Springer, 2002

Basic idea: implicit shape representation

$$\Omega = \{ x \mid \Phi(x) < 0 \}$$

$$\partial\Omega = \{ x \mid \Phi(x) = 0 \}$$

with continuous level-set function

$$\Phi : \mathbb{R}^d \rightarrow \mathbb{R}$$

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Level Set Methods

Evolution of a curve $\Gamma = \partial\Omega$
with velocity \mathbf{V} ; $\Gamma(t) = \{ \mathbf{x}(S, t) \mid S \in \Sigma \}$
 $\frac{\partial \mathbf{x}}{\partial t} = \mathbf{V}(\mathbf{x}, t)$; $\mathbf{x} \in \Gamma(t)$

Implicit representation

$$\Gamma(t) = \{ \mathbf{x} \mid \Phi(\mathbf{x}, t) = 0 \}$$

$$\Rightarrow 0 = \frac{d}{dt} \Phi(\mathbf{x}(S, t), t) = \frac{\partial \Phi}{\partial t} + \nabla \Phi \cdot \frac{\partial \mathbf{x}}{\partial t}$$

$$\Rightarrow \frac{\partial \Phi}{\partial t} + \mathbf{V}(\mathbf{x}, t) \cdot \nabla \Phi = 0$$

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Geometric Motion

Tangential velocity $\mathbf{V} \cdot \boldsymbol{\tau}$ corresponds to
change of parametrization only, i.e.

$$\{ \Phi_1 < 0 \} = \{ \Phi_2 < 0 \}$$

if $\frac{\partial \Phi_j}{\partial t} + \mathbf{V}_j \cdot \nabla \Phi_j = 0$

and $\mathbf{V}_1 \cdot \mathbf{n} = \mathbf{V}_2 \cdot \mathbf{n}$

Restriction to normal velocities is
natural: $\mathbf{V} = v \mathbf{n}$

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Geometric Motion

Normal can be computed from level set
function Φ :

$$\frac{\partial}{\partial S} \Phi(\mathbf{x}(S, t), t) = 0$$

$$\Rightarrow \nabla \Phi \cdot \frac{\partial \mathbf{x}}{\partial S} = 0$$

$$\frac{\partial \mathbf{x}}{\partial S} = \lambda \boldsymbol{\tau} \Rightarrow \nabla \Phi \text{ is normal direction}$$

$$\Rightarrow \mathbf{n}(S, t) = \frac{\nabla \Phi}{|\nabla \Phi|}(\mathbf{x}(S, t))$$

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Geometric Motion

Evolution becomes nonlinear transport equation: $\frac{\partial \Phi}{\partial t} + v |\nabla \Phi| = 0$

In general, normal velocity v may depend on the geometric properties of Γ , e.g.

$$v = v(x, t; \mathbf{n}, \kappa)$$

$$\mathbf{n} = \frac{\nabla \Phi}{|\nabla \Phi|} \text{ normal vector}$$

$$\kappa = \operatorname{div}(\mathbf{n}) = \operatorname{div}\left(\frac{\nabla \Phi}{|\nabla \Phi|}\right) \text{ mean curvature}$$



Geometric Motion

$$\rightarrow v = \tilde{v}(x, t; \nabla \Phi, D^2 \Phi)$$

\tilde{v} is homogeneous extension.

Fully nonlinear parabolic equation

$$\frac{\partial \Phi}{\partial t} + \tilde{v}(x, t; \nabla \Phi, D^2 \Phi) = 0$$



Geometric Motion

Classical geometric motions:

Eikonal equation

$$\frac{\partial \Phi}{\partial t} + v(x) |\nabla \Phi| = 0, \quad v(x) \geq 0$$

computes minimal arrival times

$$T(x) = \min_{\Phi(x,t)=0} t$$

in a velocity field v



Geometric Motion

Mean curvature flow

$$v = -\kappa$$

$$\frac{\partial \Phi}{\partial t} = |\nabla \Phi| \operatorname{div}\left(\frac{\nabla \Phi}{|\nabla \Phi|}\right)$$



Properties of Level Sets

Level sets are independent of chosen initial value:

$$\{\Phi_0 < 0\} = \{\tilde{\Phi}_0 < 0\}$$

$$\Phi_t + v | \nabla \Phi | = 0$$

$$\tilde{\Phi}_t + v | \nabla \tilde{\Phi} | = 0$$

$$\Rightarrow \{\Phi < 0\} = \{\tilde{\Phi} < 0\} \text{ for all } t \in \mathbb{R}^+$$

Properties of Level Sets

Comparison:

$$\{\Phi_0 < 0\} \subset \{\tilde{\Phi}_0 < 0\}$$

$$\Rightarrow \{\Phi < 0\} \subset \{\tilde{\Phi} < 0\} \text{ for all } t$$

In particular

$$\{\Phi_0 < p\} \subset \{\Phi_0 < q\}$$

$$\Rightarrow \{\Phi < p\} \subset \{\Phi < q\} \text{ for all } t$$

Higher-Order Evolutions

Comparison results still hold for second order evolutions like mean curvature.

No comparison results for higher order evolutions, e.g. surface diffusion

$$v = -\Delta_S \kappa$$

(4th order)

Higher-Order Evolutions

Mullins-Sekerka: $v = \left[\frac{\partial u}{\partial n} \right]$

$$\Delta u = 0$$

$$u = \kappa \text{ on } \Gamma$$

(3rd order)

➡ No global level set method!

Computing Viscosity Solutions

First-order equations

$$\Phi_t + v |\nabla \Phi| = 0$$

Explicit time discretization

$$\Phi^{k+1} = F(\Phi^k)$$

Stability bound

$$\Delta t \cdot \max_x |V(x, t)| \leq \Delta x$$

„CFL-condition“

Computing Viscosity Solutions

As in numerical schemes for conservation laws,
first-order Hamilton-Jacobi equations

$$\Phi_t + H(\Phi_x, \Phi_y) = 0$$

are solved by a scheme of the form

$$\frac{\Phi^{k+1} - \Phi^k}{\Delta t} = \tilde{H}(D_+^x \Phi^k, D_-^x \Phi^k, D_+^y \Phi^k, D_-^y \Phi^k)$$

with approximate numerical flux \tilde{H} - analogous
to conservation laws (Godunov, Lax-Friedrichs, ENO, WENO)

Computing Viscosity Solutions

Mean curvature type equation

$$\Phi_t - |\nabla \Phi| \left(\operatorname{div} \frac{\nabla \Phi}{|\nabla \Phi|} - v \right) = 0$$

Set $Q = \sqrt{|\nabla \Phi|^2 + \epsilon}$, $\epsilon > 0$

$$\frac{\Phi_t}{Q} - \operatorname{div} \left(\frac{\nabla Q}{Q} \right) = -v$$

Computing Viscosity Solutions

Discretization with linear finite elements
(Q , $\nabla \Phi$ piecewise constant)

$$\sum_T \frac{1}{Q_T} \left(\int_T \Phi_t v \, dx + |T| (\nabla \Phi)_T (\nabla \Psi)_T \right) = - \sum_T \int_T v \Psi \, dx$$

Convergence to viscosity solution as
 $\epsilon \rightarrow 0$ (Deckelnick, Dziuk, 2002)

Redistancing

In order to prevent fattening
 $(\nabla\Phi \approx 0 \text{ around } \{\Phi = 0\})$
 and for initial values, Φ should be close to
 signed distance function b .

b is limit of Ψ solving

$$\frac{\partial\Psi}{\partial s} + \text{sign}(\Phi)(|\nabla\Psi| - 1) = 0$$

$$\Psi(s=0) = \Phi$$

as $s \rightarrow \infty$ (Osher, Sussman, Smereka, 1994)

Redistancing

Upwind scheme, first order

$$\Phi_{ij}(t + \Delta t) = \Phi_{ij}(t) - \Delta t S(\Phi_{ij}^0) G(\Phi)_{ij}$$

$$S(\Phi) = \frac{\Phi}{\sqrt{\Phi^2 + \Delta x^2}}$$

Redistancing

$$G(\Phi)_{ij} = \begin{cases} \sqrt{\max(a_+^2, b_-^2) + \max(c_+^2, d_-^2)} - 1 \\ \sqrt{\max(a_-^2, b_+^2) + \max(c_-^2, d_+^2)} - 1 \end{cases}$$

$$a = D_x^- \Phi_{ij} = \frac{\Phi_{ij} - \Phi_{i-1j}}{\Delta x}$$

$$b = D_x^+ \Phi_{ij} = \frac{\Phi_{i+1j} - \Phi_{ij}}{\Delta x}$$

$$c = D_y^- \Phi_{ij} = \frac{\Phi_{ij} - \Phi_{ij-1}}{\Delta x}$$

$$d = D_y^+ \Phi_{ij} = \frac{\Phi_{ij+1} - \Phi_{ij}}{\Delta x}$$

Velocity Extension

In many cases, natural velocity is given
 on the interface Γ only.

Simplest extension is constant in normal
 direction:

$$\nabla v \cdot n = \nabla v \cdot \nabla \Phi = 0, \text{ on } \mathbb{R}^d - \Gamma$$

Extension velocity is the limit of the linear
 transport equation

$$\frac{\partial v}{\partial s} + \text{sign}(\Phi)(\nabla v \cdot \nabla \Phi) = 0 \text{ as } S \rightarrow \infty$$

Velocity Extension

Upwind scheme, first order

$$v_{ij}(t + \Delta t) = v_{ij} - \Delta t G(v, \Phi)_{ij}$$

$$S(\Phi) = \frac{\Phi}{\sqrt{\Phi^2 + \Delta x^2}}$$

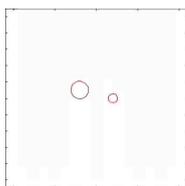
$$(D_x \Phi)_{ij} = \frac{\Phi_{i+1j} - \Phi_{i-1j}}{2\Delta x}$$

$$(D_y \Phi)_{ij} = \frac{\Phi_{ij+1} - \Phi_{ij-1}}{2\Delta x}$$

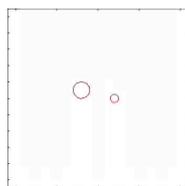
Velocity Extension

$$G(v, \Phi)_{ij} = \max(S(\Phi_{ij})(D_x \Phi)_{ij}, 0) \cdot \left(\frac{v_{ij} - v_{i-1j}}{\Delta x} \right) \\ + \min(S(\Phi_{ij})(D_x \Phi)_{ij}, 0) \cdot \left(\frac{v_{i+1j} - v_{ij}}{\Delta x} \right) \\ + \max(S(\Phi_{ij})(D_y \Phi)_{ij}, 0) \cdot \left(\frac{v_{ij} - v_{ij-1}}{\Delta x} \right) \\ + \min(S(\Phi_{ij})(D_y \Phi)_{ij}, 0) \cdot \left(\frac{v_{ij+1} - v_{ij}}{\Delta x} \right)$$

Example: Eikonal Equation



$$v(x) \equiv 1$$



$$v(x) = 1 - ax_2$$

Optimal Geometries

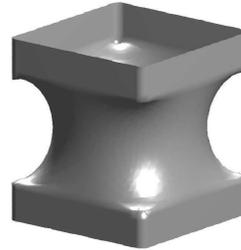
Optimal Geometries

Classical problem for optimal geometry:
PLATEAU PROBLEM
 (MINIMAL SURFACE PROBLEM)

Minimize area of surface between fixed
 boundary curves.

Optimal Geometries

Minimal surface (L.T.Cheng, PhD 2002)



Optimal Geometries

Wulff-Shapes: crystals tend to minimize
 energy at fixed volume.

Pure surface energy:

$$J(\Omega) = \int_{\partial\Omega} \varphi(v) ds \rightarrow \min$$

subject to $\int_{\Omega} 1 dx = V_0$

v is the normal on $\partial\Omega$

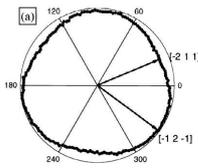
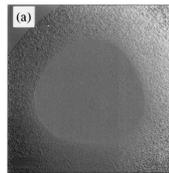
$$\varphi : S^{d-1} \rightarrow \mathbb{R}$$

given anisotropic surface tension

Optimal Geometries

Wulff-Shapes: Pb[111] in Cu[111]

Surnev et al, J.Vacuum Sci. Tech. A, 1998



Optimal Geometries

Isotropic case: $\varphi(v) = |v| = 1$
 Minimization of perimeter, yields ball Ω

Optimal Geometries

Free discontinuity problems:
 find the set of discontinuity Γ from a
 noisy observation \tilde{u} of a function.

Mumford-Shah functional

$$J(u, \Gamma) = \lambda \int_D |u - \tilde{u}|^2 dx + \int_{D \setminus \Gamma} |\nabla u|^2 dx + \alpha \text{Per}(\Gamma)$$

Again, u solves partial differential
 equation with interface condition on Γ .

Optimal Geometries

Structural topology optimization

$$J(\Omega) = \tilde{J}(\mathbf{u}_\Omega, \Omega)$$

subject to

$$\int_\Omega 1 dx = V_0$$

$$-\text{div}(\sigma(\mathbf{u}_\Omega)) = 0 \text{ in } \Omega$$

+ boundary conditions on $\partial\Omega$

Design of Photonic Crystals,
 Semiconductor Design, Electromagnetic
 Design, ...

Optimal Geometries

Inverse Obstacle Problems

E.g., inclusion detection

$$\int_{\Gamma_n} |u - f|^2 ds \rightarrow \min$$

$$-\Delta u = 0 \text{ in } D \setminus \Omega$$

$$\frac{\partial u}{\partial n} = g \text{ on } \Gamma_n \subset \partial D$$

$$u = 0 \text{ on } \Gamma_d \subset \partial D$$

$$\frac{\partial u}{\partial n} = 0 \text{ on } \partial\Omega$$

Inverse Obstacle Scattering, Impedance
 Tomography, Identification of Discontinuities
 in PDE Coefficients, ...

Gradient Flows

Physical Processes tend to minimize energy E by a gradient flow:

$$\frac{\partial u}{\partial t} = -E'(u)$$

E.g., heat diffusion, thermal energy

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

$$\frac{\partial u}{\partial t} = -E'(u) = \Delta u$$

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Gradient Flows

Gradient flow can be obtained as limit of variational problems

$$E(u(t + \Delta t)) + \frac{1}{2\Delta t} \|u(t + \Delta t) - u(t)\|^2 \rightarrow \min_{u(t+\Delta t)}$$

for $\Delta t \rightarrow 0$

(Fife 1978; „Minimizing movements“, De Giorgi 1974)

Scales of gradient flows are obtained by changing the norm.

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Geometric Gradient Flows

For geometric motion, there is no natural Hilbert space setting, generalized notion of gradient flow needed.

Natural velocity replacing $\frac{\partial u}{\partial t}$ is normal velocity v on $\partial\Omega$.

$$\rightarrow E(\Omega(t + \Delta t)) + \frac{\Delta t}{2} \|v\|_{\mathcal{H}(t)}^2 \rightarrow \min_{v \in \mathcal{H}(t)}$$

Where $\Omega(t + \Delta t)$ is the shape obtained by the motion of $\Omega(t)$ with normal velocity v (Almgren-Taylor 1994)

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Geometric Gradient Flows

Scale of geometric gradient flows obtained, in the limit $\Delta t \rightarrow 0$ by using different Hilbert spaces $\mathcal{H}(t)$ for the velocity v .

Variational form for $\Delta t \rightarrow 0$:

$$E'(\Omega)w + \langle v, w \rangle_{\mathcal{H}(t)} = 0, \quad \forall w \in \mathcal{H}(t)$$

where $E'(\Omega)$ is the shape derivative

$$E'(\Omega) = \frac{d}{dt} E(\Omega(t))$$

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Geometric Gradient Flows

$$E(\Omega) = - |\Omega|$$

$$E'(\Omega) w = - \int_{\partial\Omega} w \, ds$$

$$\mathcal{H}(t) = L^2(\partial\Omega(t))$$

$$\rightarrow \int_{\partial\Omega(t)} (-1 + v) w \, ds = 0 \quad \forall w$$

$$\rightarrow v = 1, \text{ Eikonal Equation}$$

Geometric Gradient Flows

$$E(\Omega) = \int_{\partial\Omega} 1 \, ds = \mathcal{H}^{d-1}(\partial\Omega)$$

$$E'(\Omega) = - \int_{\partial\Omega} \kappa v \, ds$$

$$\kappa \dots \text{ mean curvature} = \text{div}(n)$$

$$\mathcal{H}(t) = L^2(\partial\Omega(t))$$

$$\rightarrow v = \kappa, \text{ mean-curvature flow}$$

Geometric Gradient Flows

$$\mathcal{H}(t) = \{w \in L^2(\partial\Omega(t)) \mid \int_{\partial\Omega(t)} w \, ds = 0\}$$

$$\rightarrow v = \kappa + \lambda, \quad \lambda = - \int_{\partial\Omega(t)} \kappa \, ds$$

volume-conserving mean curvature flow

Geometric Gradient Flows

$$E(\Omega) = \int_{\partial\Omega} 1 \, ds$$

$$E'(\Omega) = - \int_{\partial\Omega} \kappa v \, ds$$

$$\mathcal{H}(t) = H^{-1}(\partial\Omega(t))$$

$$\|w\|_{\mathcal{H}(t)}^2 = \int_{\partial\Omega(t)} |\nabla_s \Psi|^2 \, ds$$

$$-\Delta_s \Psi = w$$

$$\int_{\partial\Omega(t)} \Psi \, ds = 0$$

$$\rightarrow v = -\Delta_s \kappa \text{ surface diffusion}$$

Geometric Gradient Flows

$$E(\Omega) = \int_{\partial\Omega} 1 \, ds$$

$$E'(\Omega) = - \int_{\partial\Omega} \kappa \, v \, ds$$

$$\mathcal{H}(t) = H^{-\frac{1}{2}}(\partial\Omega(t))$$

$$\|w\|_{\mathcal{H}(t)}^2 = \int_D |\nabla\Psi|^2 \, dx$$

$$-\Delta\Psi = 0 \quad \text{in } D \supset \Omega(t)$$

$$\Psi = w \quad \text{on } \partial\Omega(t)$$

$$\rightarrow v = - \left[\frac{\partial\Psi}{\partial n} \right]_{\partial\Omega(t)}, \quad w = \kappa$$

„Mullins-Sekerka Problem“, Bulk diffusion

Geometric Gradient Flows

$$E(\Omega) = \int_{\partial\Omega} 1 \, ds$$

$$E'(\Omega) = - \int_{\partial\Omega} \kappa \, v \, ds$$

$$\mathcal{H}(t) = H^1(\partial\Omega(t))$$

$$\rightarrow -\Delta_s v + v = \kappa$$

Geometric Gradient Flows

$$\mathcal{H}(t) = H^{\frac{1}{2}}(\partial\Omega(t))$$

$$\|w\|_{\mathcal{H}(t)}^2 = \int_D |\nabla\Psi|^2 \, dx$$

$$-\Delta\Psi = 0 \quad \text{in } D \supset \Omega(t)$$

$$- \left[\frac{\partial\Psi}{\partial n} \right] = w \quad \text{on } \partial\Omega(t)$$

$$\rightarrow v = \Psi_{\partial\Omega(t)}, \quad w = \kappa$$

Inverse Obstacle Problems & Shape Optimization

Inverse Obstacle Problem

$\mathcal{F} : \mathcal{D} \rightarrow X$

\mathcal{D} ... Set of shapes

X ... Hilbert space

\mathcal{F} ... Nonlinear operator

Given noisy measurement z^δ for $z := \mathcal{F}(\hat{\Omega})$
find a shape Ω approximating $\hat{\Omega}$.

$\Omega = \Omega(\delta) \rightarrow \hat{\Omega}$ as $z^\delta \rightarrow z$

Associated Least-Squares Problem

$$J_0(\Omega) := \|\mathcal{F}(\Omega) - z^\delta\|^2 \rightarrow \min_{\Omega}$$

Inverse Obstacle Problem

In general, minimization of $J_0(\Omega)$

is ill-posed:

$J_0(\Omega_k) \rightarrow 0$ without convergence of a
subsequence Ω_k possible.

No stable dependence of minimizer (if
existing) on the data z^δ .

Inverse Obstacle Problem

Ill-posedness causes need for
Regularization.

(i) **Tikhonov-type regularization**

$$\frac{1}{\alpha} J_0(\Omega) + R(\Omega) \rightarrow \min_{\Omega}$$

with regularization functional

$$R : \mathcal{D} \rightarrow \mathbb{R}$$

Inverse Obstacle Problem

(ii) **Iterative regularization concept**

Apply iterative (level set) method directly
to J_0 , use appropriate stopping
criterion, e.g. stop at the first iteration
where residual is less than τ^* (noise
level), $\tau > 1$.

Inverse Obstacle Problem

Regularization functional $R : \mathcal{D} \rightarrow \mathbb{R}$ must be defined on general class of shapes (multiply connected, no fixed parametrization with respect to reference shape, ...).

Popular choice: Perimeter

$$R(\Omega) = \mathcal{H}^{d-1}(\partial\Omega) = TV(\chi^\Omega)$$

χ^Ω ----- Ω

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Inverse Obstacle Problem

Other possibilities for regularization functionals:

based on distance function d_Ω .

Reference (starting) shape Ω_0 :

$$R(\Omega) = \int_{\Omega \Delta \Omega_0} |d_{\Omega_0}|^p dx, \quad p \geq 1$$

$$R(\Omega) = \int_{\Omega \Delta \Omega_0} |d_\Omega|^p dx, \quad p \geq 1$$

$$R(\Omega) = \int_{\partial\Omega_0} |d_\Omega|^p ds, \quad p \geq 1$$

$$R(\Omega) = \int_{\partial\Omega} |d_{\Omega_0}|^p ds, \quad p \geq 1$$

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Shape Optimization

$$J(\Omega) \rightarrow \min$$

$$e(\Omega) = 0$$

$$c(\Omega) \leq 0$$

$J : \mathcal{D} \rightarrow \mathbb{R}$ shape functional

$e : \mathcal{D} \rightarrow X$ equality constraints in Banach space

$c : \mathcal{D} \rightarrow Y$ inequality constraints in ordered Banach space

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Shape Optimization

In general, existence of minimizer not guaranteed (except simple 2D cases, e.g. Chambolle 2001)

➔ Perimeter constraint $P(\Omega) \leq p^*$ or penalization by perimeter

$$J(\Omega) + \alpha P(\Omega) \rightarrow \min_{\Omega}$$

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Metrics on Shapes

For analysis of inverse obstacle and shape optimization problems, metrics on classes of shapes are needed!

- Transformation-metrics
- L^1 -metric
- Hausdorff-metric

Transformation Metrics

Transformation metrics are based on cost of transformation of shapes:

$$d_T(\Omega_0, \Omega_1) := \inf_{v \in \mathcal{D}} \int_0^1 \|v(\cdot, t)\|^2 dt$$

subject to $\Phi_t + v|\nabla\Phi| = 0$

$$\Omega_0 = \{\Phi(\cdot, 0) < 0\}$$

$$\Omega_1 = \{\Phi(\cdot, 1) < 0\}$$

Transformation Metrics

→ use any appropriate Hilbert space norm

→ used e.g. for conformal mappings

→ restricts class of admissible shapes

L^1 -metric

L^1 -metric measures distance of shapes via their indicator functions:

$$d_1(\Omega_0, \Omega_1) = \|\chi_{\Omega_1} - \chi_{\Omega_2}\|_{L^1}$$

Many shape functionals are lower semicontinuous with respect to L^1 -metric, typically if

$$J(\Omega) = \tilde{J}(\chi_\Omega)$$

L^1 -metric

Perimeter is weakly lower semicontinuous with respect to L^1 -metric

$\{\Omega : P(\Omega) \leq c\}$ is pre-compact with respect to L^1 -metric

Hausdorff Metric

Natural metric of shapes (?)

$$d_{\mathcal{H}}(\Omega_0, \Omega_1) := \left\{ \sup_{x \in \partial\Omega_0} d_{\Omega_1}(x) \quad \sup_{x \in \partial\Omega_1} d_{\Omega_0}(x) \right\}$$

Perimeter is lower-semicontinuous with respect to $d_{\mathcal{H}}$ on the class of compact sets in \mathbb{R}^2 with finite number of connected components (Golab's Theorem)

Hausdorff Metric

Neumann-Problems for elliptic partial differential equations are lower semicontinuous with respect to $d_{\mathcal{H}}$ on the class of compact sets in \mathbb{R}^2 with finite number of connected components (Chambolle 2002, DalMaso-Toader 2002)

Regularization by Perimeter

Assumptions: $\|z - z^\delta\| \leq \delta$
 $\mathcal{F}(\Omega) = \tilde{\mathcal{F}}(\chi_\Omega)$
 \mathcal{F} continuous on L^1
 $\alpha \rightarrow 0, \frac{\delta^2}{\alpha}, \text{ as } \delta \rightarrow 0$

Let Ω_α^δ be minimizer of

$$\frac{1}{\alpha} \|\mathcal{F}(\Omega) - z^\delta\|^2 + P(\Omega) \rightarrow \min_{\Omega}$$

Regularization by Perimeter

Respectively

$$\frac{1}{\alpha} \|\tilde{\mathcal{F}}(\chi_\Omega) - z^\delta\|^2 + TV(\chi_\Omega) \rightarrow \min$$

$$\chi_\Omega \in BV(D; \{0, 1\})$$

Then there exists subsequence (δ_k, α_k)
such that $\Omega_{\alpha_k}^{\delta_k} \rightarrow \hat{\Omega}$ as $\delta_k \rightarrow 0$

$$\text{where } \hat{\Omega} \text{ solves } P(\hat{\Omega}) \rightarrow \min \\ \text{s.t. } \mathcal{F}(\hat{\Omega}) = z$$

Regularization by Perimeter

Uniqueness of the limit problem implies

$$\Omega_\alpha^\delta \rightarrow \hat{\Omega}$$

as $\delta \rightarrow 0$.

Shape Sensitivity Analysis

Sensitivity Analysis

As usual for optimization problems
sensitivities (derivatives) are needed.

Gateaux-Derivatives in Banach spaces

$$J'(u)v = \lim_{\epsilon \downarrow 0} \frac{J(u + \epsilon v) - J(u)}{\epsilon}$$

Sensitivity Analysis

Alternative definition:

$$J'(u)v = \frac{d}{dt}J(u(t))|_{t=0}$$

$$\frac{du}{dt}(t) = v, \quad t \in (0, \epsilon)$$

$$u(0) = u$$

„Speed Method“

Speed Method

Analogous to Gateaux-Derivative define
„Shape Derivative“ of Ω

$$J'(\Omega)v = \frac{d}{dt}J(\Omega(t))|_{t=0}$$

$$\Omega(t) = \{\Phi(\cdot, t) < 0\}$$

$$\frac{\partial \Phi}{\partial t} + v |\nabla \Phi| = 0$$

Speed Method

Classical definition for smooth shapes (C^1)
and velocities (C^2)

→ extension via level set method

Volume Functionals

Let $J(\Omega) := \int_{\Omega} g \, dx$

Level-set formulation, $D \supset \Omega$

$$\tilde{J}(\Phi) = \int_D H(\Phi) g \, dx$$

with Heaviside function H .

Volume Functionals

Formal derivative:

$$\begin{aligned} \frac{d}{dt} \tilde{J}(\Phi(\cdot, t)) &= \int_D \delta(\Phi) \frac{\partial \Phi}{\partial t} g \, dx \\ &= - \int_D \delta(\Phi) |\nabla \Phi| v g \, dx \end{aligned}$$

with Dirac δ -distribution

$$\delta = H'$$

Surface Functionals

$$\begin{aligned} \text{Let } J(\Omega) &= \int_{\Gamma} g \, ds \\ \Gamma &= \partial\Omega \end{aligned}$$

Level-set formulation, $D \supset \Omega$

$$\tilde{J}(\Phi) = \int_D \delta(\Phi) |\nabla \Phi| g \, dx$$

Formal derivative

$$\begin{aligned} \frac{d}{dt} \tilde{J}(\Phi(\cdot, t)) &= \int_D (\delta'(\Phi) |\nabla \Phi| \frac{\partial \Phi}{\partial t} \\ &\quad + \delta(\Phi) \frac{\nabla \Phi}{|\nabla \Phi|} \cdot \nabla \left(\frac{\partial \Phi}{\partial t} \right) g \, dx \end{aligned}$$

Surface Functionals

$$\begin{aligned} \frac{d}{dt} \tilde{J}(\Phi(\cdot, t)) &= - \int_D (\delta'(\Phi) \nabla \Phi \cdot \nabla \Phi v \\ &\quad + \delta(\Phi) \frac{\nabla \Phi}{|\nabla \Phi|} \cdot \nabla (v |\nabla \Phi|) g \, dx \end{aligned}$$

Extension of v , arbitrary on $D \setminus \Gamma$

→ use constant normal extension

$$\nabla v \cdot \nabla \Phi = \nabla v \cdot \mathbf{n} \, |\nabla \Phi| = 0$$

Surface Functionals

Use $\delta'(\Phi) \nabla \Phi = \nabla(\delta(\Phi))$ and
Gauss-Theorem:

$$\begin{aligned} \frac{d}{dt} \tilde{J}(\Phi(\cdot, t)) &= \int_D \delta(\Phi) (\text{div}(g v \nabla \Phi) \\ &\quad - \frac{\nabla \Phi}{|\nabla \Phi|} \cdot \nabla (|\nabla \Phi|) g) \, dx \\ &= \int_D \delta(\Phi) |\nabla \Phi| v (g \text{div} \left(\frac{\nabla \Phi}{|\nabla \Phi|} \right) + \nabla g \cdot \frac{\nabla \Phi}{|\nabla \Phi|}) \, dx \\ &= \int_{\Gamma} v (g \kappa + \frac{\partial g}{\partial n}) \, ds \end{aligned}$$

Level Set Methods Based on Gradient Flows

Gradient Flows

In the above framework of gradient flows,
we can derive equations for velocity v
by minimizing

$$J(\Omega(t + \Delta t)) + \frac{\Delta t}{2} \|v\|_{\mathcal{H}(t)}^2$$

with respect to $v \in \mathcal{H}(t)$
and $\Delta t \rightarrow 0$

Gradient Methods

Variational equation for v

$$\langle v, w \rangle_{\mathcal{H}(t)} = -J'(\Omega(t)) w$$

yields continuous time evolution for v .

Classical gradient method is explicit time
discretization of gradient flow.

Gradient Methods

Set $t = 0, k = 0$, initial value Φ_0

Loop:

- Set $\Omega_k := \{\Phi(\cdot, t_k) < 0\}$
- Compute v_k from variational equation at time t_k
- Select time step $\Delta t_k, t_{k+1} = t_k + \Delta t_k$
- Solve $\frac{\partial \Phi}{\partial t} + v_k |\nabla \Phi| = 0$ in (t_k, t_{k+1})
- $k = k + 1$

Gradient Methods

Lemma: v_k is descent direction, i.e.

$$J(\Omega_{k+1}) < J(\Omega_k)$$

If $v_k \neq 0$, Δt_k sufficiently small.

Proof:

$$J(\Omega_{k+1}) - J(\Omega_k) = \Delta t_k J'(\Omega_k)v_k + o(\Delta t_k)$$

$$J'(\Omega_k)v_k = -\|v_k\|_{\mathcal{H}(t)}^2 < 0$$

Example 1

$$J(\Omega) = \frac{1}{2} \int_M |u - f|^2 dx$$

$$-\Delta u = \chi_\Omega = H(\Phi) \quad \text{in } D$$

$$u = 0 \quad \text{on } \partial D$$

$\Omega \subset D$ and $M \subset D$

$$J'(\Omega)v = \int_M (u - f) u' dx$$

$$-\Delta u' = -\delta(\Phi) |\nabla \Phi| v \quad \text{in } D$$

$$u' = 0 \quad \text{on } \partial D$$

Example 1

Define adjoint state u^* via

$$-\Delta u^* = \chi_M \cdot (u - f) \quad \text{in } D$$

$$u^* = 0 \quad \text{on } \partial D$$

Example 1

$$J'(\Omega)v = \int_M (u - f) u' dx$$

$$= - \int_D \Delta u^* u' dx$$

$$= - \int_D u^* \Delta u' dx$$

$$= - \int_{\partial \Omega} u^* v ds$$

$J'(\Omega)v$ independent of u'
„Adjoint Method“

Example 1

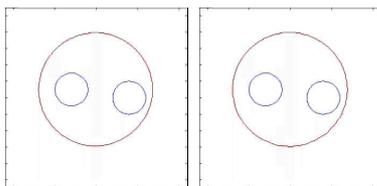
$$\begin{aligned} \mathcal{H}(t) &= L^2(\partial\Omega(t)) \\ \int_{\partial\Omega(t)} v w \, ds &= \int_{\partial\Omega(t)} u^* w \, ds \\ \Rightarrow v &= u^* \\ \mathcal{H}(t) &= H^{-\frac{1}{2}}(\partial\Omega(t)) \\ -\Delta\Psi &= 0 \quad \text{in } D \setminus \Gamma \\ \Psi &= u^* \quad \text{on } \Gamma \\ \Psi &= 0 \quad \text{on } \partial D \\ v &= - \left[\frac{\partial\Psi}{\partial n} \right] \end{aligned}$$

Example 1

Alternative: $v = \left[\frac{\partial u^*}{\partial n} \right]$

$$\begin{aligned} \rightarrow J'(\Omega) v &= - \int_{\partial\Omega} u^* \left[\frac{\partial u^*}{\partial n} \right] ds \\ &= - \int_{\Omega} |\nabla u^*|^2 dx \end{aligned}$$

Example 1

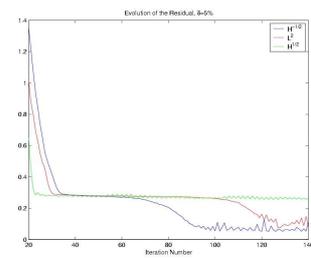


L^2 - Norm

$H^{-\frac{1}{2}}$ - Norm

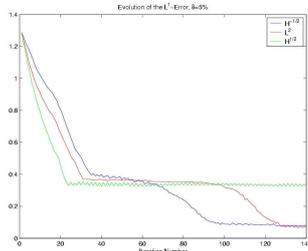
Example 1

Residual



Example 1

L^1 - error



Example 2

$$J(\Omega) = \frac{1}{2} \int_M |u - f|^2 ds$$

$$-\Delta u = 0 \quad \text{in } D \setminus \partial\Omega$$

$$\frac{\partial u}{\partial n} = 0 \quad \text{on } \partial\Omega$$

$$\frac{\partial u}{\partial n} = g \quad \text{on } \Gamma_n \subset \partial D$$

$$u = 0 \quad \text{on } \Gamma_d = \partial D \setminus \Gamma_n$$

$$\Omega \subset D, \quad M \subset \Gamma_d$$

Example 2

$$J'(\Omega) v = \int (u - f) u' ds$$

$$-\Delta u' = 0 \quad \text{in } D \setminus \partial\Omega$$

$$\frac{\partial u'}{\partial n} = -\text{div}(\nabla u \cdot n v) \quad \text{on } \partial\Omega$$

$$\frac{\partial u'}{\partial n} = 0 \quad \text{on } \Gamma_n$$

$$u' = 0 \quad \text{on } \Gamma_d$$

Example 2

Adjoint state u^* defined by

$$-\Delta u^* = 0 \quad \text{in } D \setminus \partial\Omega$$

$$\frac{\partial u^*}{\partial n} = 0 \quad \text{on } \partial\Omega$$

$$\frac{\partial u^*}{\partial n} = \chi_M(u - f) \quad \text{on } \Gamma_d$$

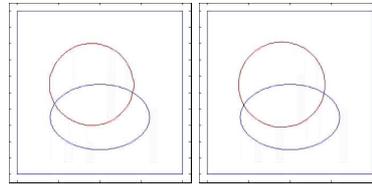
$$u^* = 0 \quad \text{on } \Gamma_n$$

$$\rightarrow J'(\Omega) v = \int_{\partial\Omega} v [\nabla u \cdot \nabla u^*] ds$$

Example 2

$$\begin{aligned} \mathcal{H} &= L^2(\partial\Omega(t)) \\ v &= -[\nabla u \cdot \nabla u^*] \text{ on } \partial\Omega \\ \mathcal{H} &= H^{\frac{1}{2}}(\partial\Omega(t)) \\ -\Delta\Psi &= 0 \text{ in } D \\ \left[\frac{\partial\Psi}{\partial n}\right] &= -[\nabla u \cdot \nabla u^*] \text{ on } \partial\Omega \\ \Psi &= 0 \text{ on } \partial D \\ v &= -\Psi \end{aligned}$$

Example 2

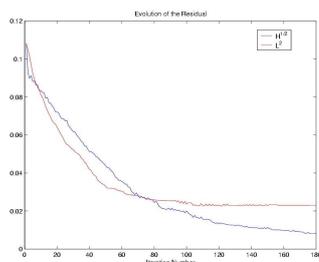


L^2 - Norm

$H^{\frac{1}{2}}$ - Norm

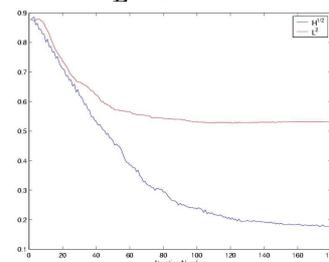
Example 2

Residual



Example 2

L^1 - error



Levenberg-Marquardt

$$J(\Omega) = \|\mathcal{F}(\Omega) - z\|^2$$

Levenberg-Marquardt obtained from first-order expansion of \mathcal{F} together with penalty on velocity

$$\|\mathcal{F}(\Omega) + \mathcal{F}'(\Omega) v - z\|^2 + \beta \|v\|_{\mathcal{H}(t)}^2 \rightarrow \min_v$$

Variational equation

$$\begin{aligned} \langle \mathcal{F}'(\Omega) v, \mathcal{F}'(\Omega) w \rangle + \beta \langle v, w \rangle_{\mathcal{H}(t)} &= \\ = - \langle \mathcal{F}(\Omega) - z, \mathcal{F}'(\Omega) w \rangle \quad \forall w \in \mathcal{H}(t) \end{aligned}$$

Levenberg-Marquardt

Set $t_0 = 0$, $k = 0$, initial value Φ_0

Loop:

- Set $\Omega_k := \{\Phi(\cdot, t_k) < 0\}$
- Compute v_k from variational equation at time t_k
- Select time step Δt_k , $t_{k+1} = t_k + \Delta t_k$
- Solve $\frac{\partial \Phi}{\partial t} + v_k |\nabla \Phi| = 0$ in (t_k, t_{k+1})
- $k = k + 1$

Example 1

$$\mathcal{F} : \mathcal{D} \rightarrow H_0^1(D), \Omega \mapsto u_M$$

$$-\Delta u = \chi_\Omega$$

$$\mathcal{F}'(\Omega) v = u'_{v/M}$$

$$-\Delta u'_v = \delta_\Gamma v, \Gamma = \partial\Omega$$

Example 1

Levenberg-Marquardt update

$$\begin{aligned} \langle \mathcal{F}'(\Omega_k) v, \mathcal{F}'(\Omega_k) w \rangle + \beta \langle v, w \rangle &= \\ = - \langle \mathcal{F}'(\Omega_k) w, \mathcal{F}(\Omega_k) - z \rangle \end{aligned}$$

becomes

$$\begin{aligned} \int_M u'_v u'_w dx + \beta \langle v, w \rangle_{\mathcal{H}(t)} &= \\ = - \int_M u'_v (u - z) dx \end{aligned}$$

Example 1

Define Lagrange parameter λ

$$\int_M u'_v \Psi \, dx + \int_D \nabla \lambda \nabla \Psi \, dx = - \int_M u'_v (u - z) \, dx \quad \forall \Psi \in H_0^1(D)$$

$$\Psi = u'_v \Rightarrow \int_D \nabla \lambda \nabla u'_w \, dx = - \int_\Gamma w \lambda \, ds$$

Example 1

→ Primal-Dual formulation ($u' = u'_v$)

$$A(u', v; \Psi, w) = \int_M u' \Psi \, dx + \beta \langle v, w \rangle_{\mathcal{H}(t)}$$

$$B(u', v; \lambda) = \int_D \nabla u' \nabla \lambda \, dx - \int_\Gamma v \lambda \, ds$$

$$\langle \mathcal{F}, \Psi \rangle = - \int_M (u - z) \Psi \, dx$$

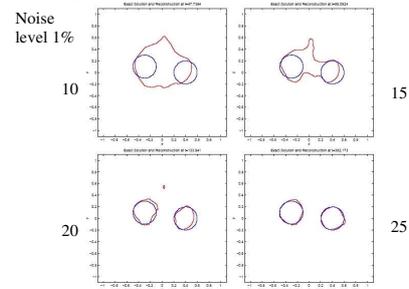
Example 1

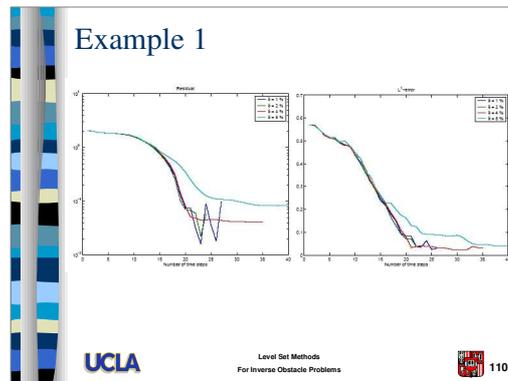
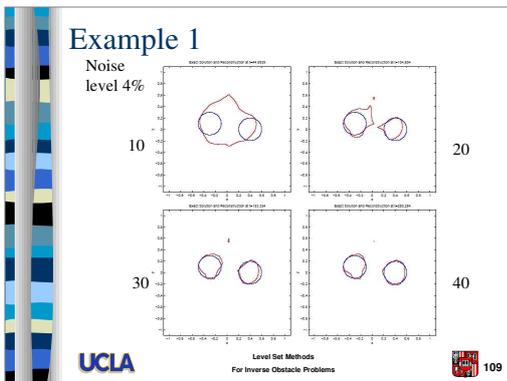
$$A(u', v; \Psi, w) + B(\Psi, w; \lambda) = \langle \mathcal{F}, \Psi \rangle$$

$$B(u', v; \mu) = 0$$

$$\forall \Psi \in H_0^1(D), v \in \mathcal{H}(t), \mu \in H_0^1(D)$$

Example 1





Example 2

$$\begin{aligned} \mathcal{F}(\Omega) &= u|_M \\ -\Delta u &= 0 \quad D \setminus \Omega \\ \frac{\partial u}{\partial n} &= 0 \quad \partial \Omega \\ \frac{\partial u}{\partial n} &= g \quad \Gamma_n \\ u &= 0 \quad \Gamma_d \\ \mathcal{F}'(\Omega) v &= u'_v|_M \\ \int_{D \setminus \Omega} \nabla u'_v \nabla \Psi \, dx &= \int_{\partial \Omega} v (\nabla u \cdot \nabla \Psi) \, ds \\ \forall \Psi &\in H^1_{0,d}(D \setminus \Omega) \end{aligned}$$

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Example 2

Primal-Dual formulation

$$\begin{aligned} A(u', v; \Psi, w) &= \int_M u' \Psi \, ds + \beta \langle v, w \rangle_{\mathcal{H}(t)} \\ B(u', v; \lambda) &= \int_{D \setminus \Omega} \nabla u' \nabla \lambda \, dx - \\ &\quad - \int_{\partial \Gamma} v (\nabla u \cdot \nabla \lambda) \, ds \\ \langle \mathcal{F}, \Psi \rangle &= - \int_M (u - z) \Psi \, ds \end{aligned}$$

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Example 2

Multiple State Equations

$$-\Delta u_k = 0, \quad \frac{\partial u_k}{\partial n} = g_k, \quad k = 1, \dots, l$$

$$\mathcal{F}(\Omega) = (u_k|_M)_{k=1, \dots, l}$$

$$\sum_k A(u'_k, v; \Psi_k, w) + \sum_k B(\Psi_k, w; \lambda_k) = \sum_k \langle \mathcal{F}_k, \Psi \rangle$$

$$\sum_k B(u'_k, v; \mu_k) = 0$$

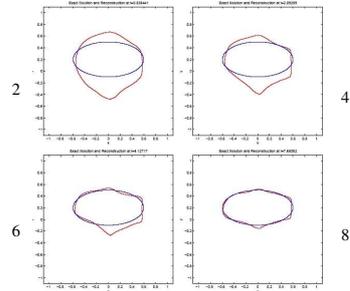
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Example 2



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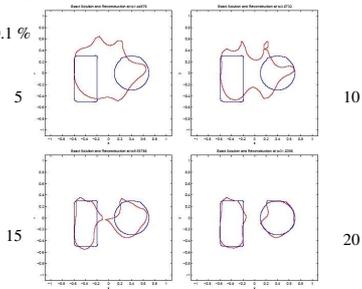
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Example 2

Noise
level 0.1 %



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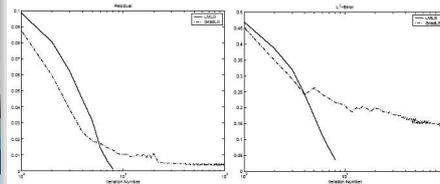
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Example 2

Comparison with Gradient method



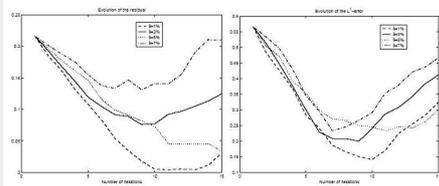
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Example 2



Newton-Type Methods

Basic structure: compute second derivative

$$J''(\Omega)(v, w) = \frac{d}{dt}(J'(\Omega(t)) v)$$

for $\Omega(t) = \{\Phi(\cdot, t) < 0\}$

$$\frac{\partial \Phi}{\partial t} + w|\nabla \Phi| = 0$$

Newton-Type Methods

Compute velocity v_k by solving

$$J''(\Omega_k)(v_k, w) = -J'(\Omega_k) w, \quad \forall w \in \mathcal{H}(t)$$

$$J(\Omega) = \int_{\partial \Omega} 1 \, ds$$

$$J'(\Omega) = \int_{\partial \Omega} \kappa v \, ds$$

$$J''(\Omega)(v, w) = \int_{\partial \Omega} [vw (\kappa^2 + \frac{\partial \kappa}{\partial n}) + \nabla v \cdot \nabla w] \, ds$$

Hintermüller, Ring, SIAP 2003

Numerical Methods

Numerical Methods

Besides computational techniques for level set evolution, (Hamilton-Jacobi solver, redistancing, velocity extension), we need numerical methods to solve partial differential equations with/on interfaces (state/adjoint equation, Newton equation, ...).

Numerical Methods

Possibilities for elliptic PDEs with interfaces:

1. Resolve interface by mesh (e.g. finite elements) accurately
→ Remeshing at each iteration step is needed. Expensive in particular in 3D, difficult.

Numerical Methods

2. Use adaptive refinement of basic mesh (fixed during iteration).
3. Moving meshes
→ Problems with too strong change of obstacle.

Numerical Methods

4. Immersed interface method: finite difference discretization on fixed grid with local connections to system matrix, around interface.
5. Partition of Unity FE/Extended Finite Element.
FE analogous to immersed interface method, fixed triangular grid + discontinuous elements around interface.

Numerical Methods

6. Fictitious Domain Methods: extend problem to larger domain, use Lagrange parameter for correction.

So far, all methods require construction of the zero level set

$$\Gamma = \{\Phi = 0\}$$

Expensive in 3D!

Numerical Methods

7. Averaged fictitious domain methods: use weighted average over several level sets.

Numerical Methods

Let $w_\epsilon \rightarrow \delta$ as $\epsilon \rightarrow 0$

$$\int_{\{\Phi < 0\}} g \, dx = \int_D H(-\Phi) g \, dx$$

$$\begin{aligned} &\rightarrow \int w_\epsilon(p) \int_D H(p - \Phi) g \, dx \, dp = \\ &= \int_D H_\epsilon(-\Phi) g \, dx \end{aligned}$$

$$H_\epsilon(t) = \int w_\epsilon(p) H(p + t) \, dp$$

$$\begin{aligned} \int_{\{\Phi=0\}} g \, ds &\rightarrow \int w_\epsilon(p) \int_{\{\Phi=p\}} g \, ds \, dp \\ &= \int_D w_\epsilon(\Phi) |\nabla \Phi| g \, dx \end{aligned}$$

Example 1

State equation, weak form

$$\begin{aligned} \int_D \nabla u \nabla \Psi \, dx &= \int_D H(-\Phi) \Psi \, dx \\ &\rightarrow \int_D \nabla u \nabla \Psi \, dx = \int_D H_\epsilon(-\Phi) \Psi \, dx \end{aligned}$$

Linearized state equation, weak form

$$\begin{aligned} \int_D \nabla u' \nabla \Psi \, dx &= \int_{\{\Phi=0\}} \Psi v \, ds \\ &\rightarrow \int_D \nabla u' \nabla \Psi \, dx = \int_D w_\epsilon(\Phi) \Psi v |\nabla \Phi| \, dx \end{aligned}$$

Use adaptize finite element method on fixed grid on D .

Example 2

State equation, weak form

$$\int_{\{\Phi > 0\}} \nabla u \cdot \nabla \Psi \, dx = \int_{\Gamma_n} g \cdot \Psi \, ds$$

„Ersatz material“, stiffness

$$A^\epsilon = \epsilon + (1 - \epsilon)H(\Phi)$$

$$\int w_\epsilon(p) \int_D A^\epsilon(\Phi) \nabla u \cdot \nabla \Psi \, dx \, dp = \int_{\Gamma_n} g \cdot \Psi \, ds$$

$$\int_D \tilde{A}^\epsilon(\Phi) \nabla u \cdot \nabla \Psi \, dx = \int_{\Gamma_n} g \cdot \Psi \, ds$$

Example 2

Linearized state equation

$$\begin{aligned} \int_D \tilde{A}^\epsilon(\Phi) \nabla u' \cdot \nabla \Psi \, dx &= \\ &= \int_D \frac{\partial \tilde{A}^\epsilon}{\partial \Phi}(\Phi) v \cdot \nabla u \cdot \nabla \Psi \, |\nabla \Phi| \, dx \end{aligned}$$