

Optimal Control of Coupled Systems

Current Methods and Perspectives

Roland Griesse



Numerical Mathematics

MPI Magdeburg
December 1–2, 2008

Coupled systems

- systems of (partial) differential equations
- often subsystems with different characteristics

Optimal control

- often driven by application
- tool to understand system dynamics

Goal of this talk

- present a toolbox of methods
- applicable to a broad range of applications

- 1 Parametric Sensitivity Analysis
- 2 Problems Promoting Sparsity
- 3 Free Boundary Value Problems

Observation

Real-life (optimization) problems usually involve **uncertain data**.

Modeling uncertainty

Two points of view:

- stochastic (not considered here)
- deterministic

Sources for uncertain data

- model parameters not exactly known
- model parameters have changed since solution was computed

Parametric optimization problems

$$\begin{aligned} & \text{Minimize} && f(x, p) && \text{w.r.t. } x \\ & \text{subject to} && g(x, p) = 0 && \text{(NLP}(p)) \\ & && \text{and } h(x, p) \leq 0 \end{aligned}$$

Parametric optimization problems

$$\begin{aligned} & \text{Minimize} && f(x, p) && \text{w.r.t. } x \\ & \text{subject to} && g(x, p) = 0 && \text{(NLP}(p)) \\ & && \text{and } h(x, p) \leq 0 \end{aligned}$$

Purpose of parametric sensitivity analysis

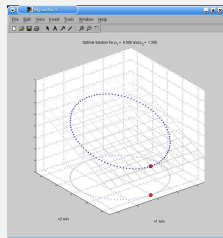
- analyze the dependence of (local) optimal solution $x^*(p)$ on p
- yields both qualitative and quantitative information
- later: $g(x, p) = 0 \Leftrightarrow$ partial differential equation

A simple example

Minimize $p_1 x_1 + p_2 x_2$ over $x \in \mathbb{R}^2$

s.t. $x_1^2 + x_2^2 = 1$

(and $x_1 \geq 0$)



Definition

parametric sensitivity derivative $:= D x^*(p; \delta p)$

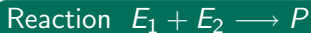
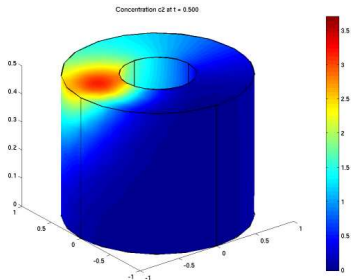
Benefits

- qualitative and quantitative assessment of stability w.r.t. perturbations
- fast update schemes, real-time control

Computational effort

- solve one simple (QP) problem per perturbation direction
- same structure, same algorithm as original problem
- perfectly parallelizable

Reaction Diffusion Model Problem



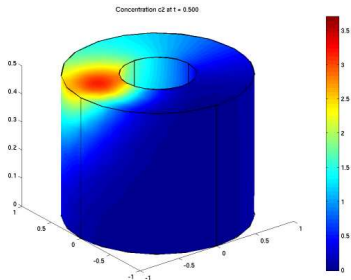
$$\frac{\partial}{\partial t} c_1 = D_1 \Delta c_1 - k c_1 c_2$$

$$\frac{\partial}{\partial t} c_2 = D_2 \Delta c_2 - k c_1 c_2$$

concentrations c_1, c_2

reaction rate $\sim c_1 c_2$

Reaction Diffusion Model Problem



Reaction $E_1 + E_2 \longrightarrow P$

$$\frac{\partial}{\partial t} c_1 = D_1 \Delta c_1 - k c_1 c_2$$

$$\frac{\partial}{\partial t} c_2 = D_2 \Delta c_2 - k c_1 c_2$$

concentrations c_1, c_2

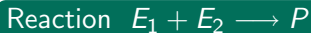
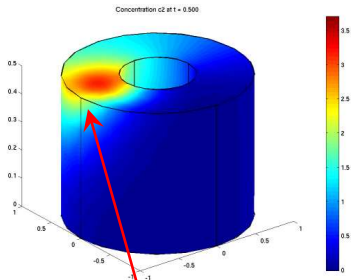
reaction rate $\sim c_1 c_2$

Boundary conditions

$$\frac{\partial}{\partial n} c_{1,2} = 0$$

$$\frac{\partial}{\partial n} c_2 = u(t) \alpha(x, t) |_{\Gamma_c}$$

Reaction Diffusion Model Problem



$$\frac{\partial}{\partial t} c_1 = D_1 \Delta c_1 - k c_1 c_2$$

$$\frac{\partial}{\partial t} c_2 = D_2 \Delta c_2 - k c_1 c_2$$

concentrations c_1, c_2

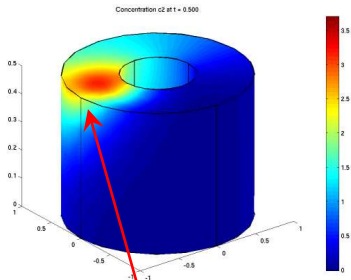
reaction rate $\sim c_1 c_2$

Boundary conditions

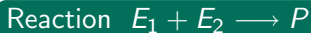
$$\frac{\partial}{\partial n} c_{1,2} = 0$$

$$\frac{\partial}{\partial n} c_2 = u(t) \alpha(x, t) |_{\Gamma_c}$$

Reaction Diffusion Model Problem



intensity (control)



$$\frac{\partial}{\partial t} c_1 = D_1 \Delta c_1 - k c_1 c_2$$

$$\frac{\partial}{\partial t} c_2 = D_2 \Delta c_2 - k c_1 c_2$$

concentrations c_1, c_2

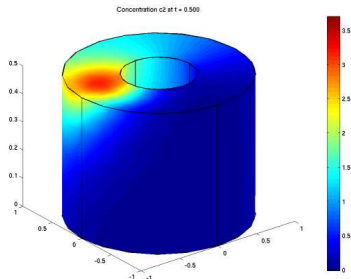
reaction rate $\sim c_1 c_2$

Boundary conditions

$$\frac{\partial}{\partial n} c_{1,2} = 0$$

$$\frac{\partial}{\partial n} c_2 = u(t) \alpha(x, t) |_{\Gamma_c}$$

Reaction Diffusion Model Problem



$$\frac{\partial}{\partial t} c_1 = D_1 \Delta c_1 - k c_1 c_2$$

$$\frac{\partial}{\partial t} c_2 = D_2 \Delta c_2 - k c_1 c_2$$

concentrations c_1, c_2

reaction rate $\sim c_1 c_2$

Initial conditions

$$c_1(\cdot, 0) = c_{10}$$

$$c_2(\cdot, 0) = c_{20}$$

Boundary conditions

$$\frac{\partial}{\partial n} c_{1,2} = 0$$

$$\frac{\partial}{\partial n} c_2 = u(t) \alpha(x, t) |_{\Gamma_c}$$

problem statement

Minimize deviation from desired states c_{iT} plus control cost

$$f(c_1, c_2, u) = \sum_{i=1}^2 \frac{\beta_i}{2} \int_{\Omega} |c_i(x, T) - c_{iT}(x)|^2 dx + \frac{\gamma}{2} \int_0^T |u(t)|^2 dt$$

subject to the RD model and control constraints

$$a(t) \leq u(t) \leq b(t)$$

Perturbed problem statement

Minimize deviation from desired states c_{iT} plus control cost

$$f(c_1, c_2, u, p) = \sum_{i=1}^2 \frac{\beta_i}{2} \int_{\Omega} |c_i(x, T) - c_{iT}(x)|^2 dx + \frac{\gamma}{2} \int_0^T |u(t)|^2 dt$$

subject to the RD model and control constraints

$$a(t) \leq u(t) \leq b(t)$$

Perturbed problem statement

Minimize deviation from desired states c_{iT} plus control cost

$$f(c_1, c_2, u, p) = \sum_{i=1}^2 \frac{\beta_i}{2} \int_{\Omega} |c_i(x, T) - c_{iT}(x)|^2 dx + \frac{\gamma}{2} \int_0^T |u(t)|^2 dt$$

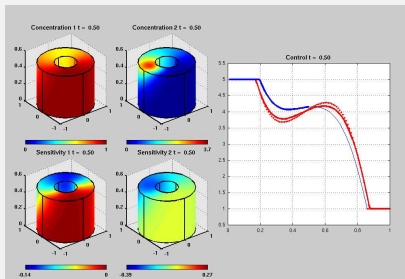
subject to the **perturbed** RD model and control constraints

$$a(t) \leq u(t) \leq b(t)$$

Note

The parameter p may be infinite-dimensional!

Movie: Optimal control and parametric sensitivities



Objective

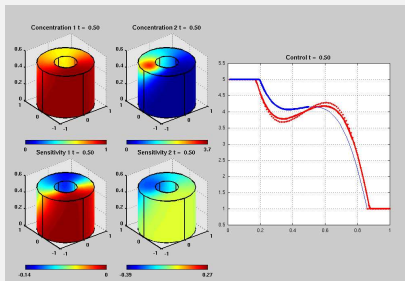
to consume educt E_1

Reaction constant

nominal $k = 1.0$

perturbed $k = 1.5$

Movie: Optimal control and parametric sensitivities



Objective

to consume educt E_1

Reaction constant

nominal $k = 1.0$

perturbed $k = 1.5$

Summary

- qualitative and quantitative sensitivity information
- fast update schemes, real-time control
- efficient computation

References: Parametric Sensitivity Analysis



K. Brandes and R. Griesse.

Quantitative stability analysis of optimal solutions in PDE-constrained optimization.

Journal of Computational and Applied Mathematics, 206(2):908–926, 2007.



R. Griesse, T. Grund, and D. Wachsmuth.

Update strategies for perturbed nonsmooth equations.

Optimization Methods and Software, 23(3):321–343, 2008.



R. Griesse and B. Vexler.

Numerical sensitivity analysis for the quantity of interest in PDE-constrained optimization.

SIAM Journal on Scientific Computing, 29(1):22–48, 2007.



R. Griesse and D. Wachsmuth.

Sensitivity analysis and the adjoint update strategy for optimal control problems with mixed control-state constraints.

Computational Optimization and Applications, to appear.

- 1 Parametric Sensitivity Analysis
- 2 Problems Promoting Sparsity
- 3 Free Boundary Value Problems

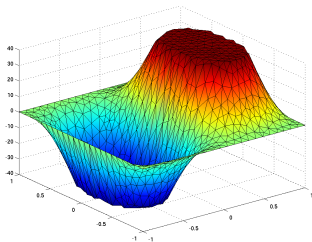
standard opt. control problem

$$\text{Minimize } \frac{1}{2} \|y - y_d\|_{L^2}^2 + \frac{\alpha}{2} \|u\|_{L^2}^2$$

$$\text{s.t. } \begin{cases} -\Delta y = u & \text{in } \Omega \\ y = 0 & \text{on } \Gamma \end{cases}$$

$$\text{and } u_a \leq u \leq u_b$$

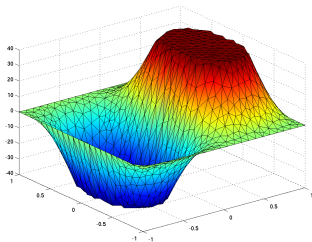
$$\|u\|_{L^2}^2 = \int_{\Omega} |u(x)|^2 dx$$



standard opt. control problem

$$\begin{aligned} & \text{Minimize} && \frac{1}{2} \|y - y_d\|_{L^2}^2 + \frac{\alpha}{2} \|u\|_{L^2}^2 \\ & \text{s.t.} && \begin{cases} -\Delta y = u & \text{in } \Omega \\ y = 0 & \text{on } \Gamma \end{cases} \\ & \text{and} && u_a \leq u \leq u_b \end{aligned}$$

$$\|u\|_{L^2}^2 = \int_{\Omega} |u(x)|^2 dx$$

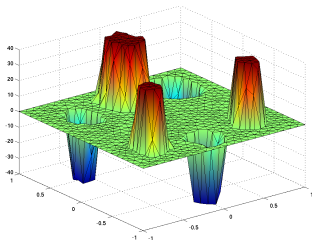


Features

- optimal control u is $\neq 0$ everywhere
- differentiable optimization problem

problem with sparsity term

$$\begin{aligned} &\text{Minimize} && \frac{1}{2} \|y - y_d\|_{L^2}^2 + \beta \|u\|_{L^1} \\ &\text{s.t.} && \begin{cases} -\Delta y = u & \text{in } \Omega \\ y = 0 & \text{on } \Gamma \end{cases} \\ &\text{and} && u_a \leq u \leq u_b \end{aligned}$$



$$\|u\|_{L^2}^2 = \int_{\Omega} |u(x)|^2 dx, \quad \|u\|_{L^1} = \int_{\Omega} |u(x)| dx$$

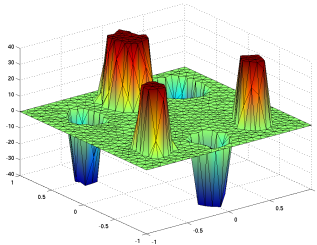
Features

- optimal control u is **sparse**
- **non-differentiable** (convex) optimization problem

[Stadler (2008)]

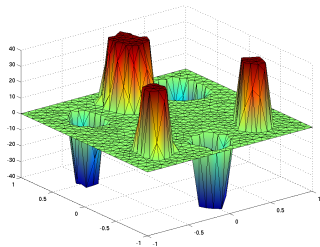
Examples

- sparse placement of actuators
- sparse identification of relevant mechanisms
 - in regulatory networks (systems biology)
 - in reaction kinetics (chemical engineering)



Examples

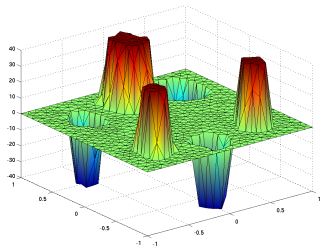
- sparse placement of actuators
- sparse identification of relevant mechanisms
 - in regulatory networks (systems biology)
 - in reaction kinetics (chemical engineering)



	A	B	C	D	E	F	G	H	I
A	x	x	x	x	x	x	x	x	x
B	x	x	x	x	x	x	x	x	x
C	x	x	x	x	x	x	x	x	x
D	x	x	x	x	x	x	x	x	x
E	x	x	x	x	x	x	x	x	x
F	x	x	x	x	x	x	x	x	x
G	x	x	x	x	x	x	x	x	x
H	x	x	x	x	x	x	x	x	x
I	x	x	x	x	x	x	x	x	x

Examples

- sparse placement of actuators
- sparse identification of relevant mechanisms
 - in regulatory networks (systems biology)
 - in reaction kinetics (chemical engineering)



	A	B	C	D	E	F	G	H	I
A					X				
B								X	X
C									
D				X					
E							X		
F					X				
G	X								
H		X	X						
I					X				

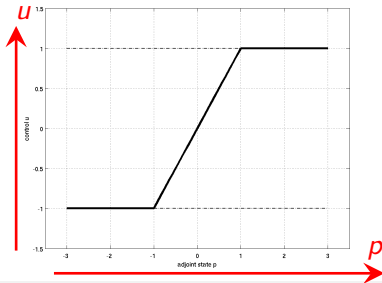
Adjoint equation for example problem

$$\begin{aligned} -\Delta p &= y - y_d && \text{in } \Omega \\ p &= 0 && \text{on } \Gamma \end{aligned}$$

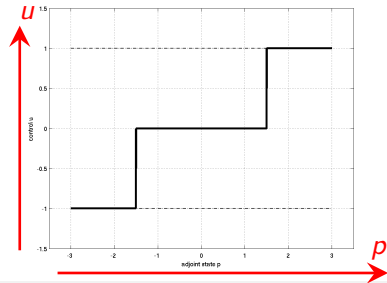
Adjoint equation for example problem

$$\begin{aligned} -\Delta p &= y - y_d && \text{in } \Omega \\ p &= 0 && \text{on } \Gamma \end{aligned}$$

Problem with $\frac{\alpha}{2} \|u\|_{L^2}^2$



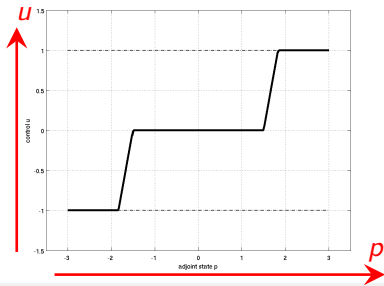
Problem with $\beta \|u\|_{L^2}$



Regularized formulation

$$\begin{aligned} \text{Minimize} \quad & \frac{1}{2} \|y - y_d\|_{L^2}^2 + \frac{\alpha}{2} \|u\|_{L^2}^2 + \beta \|u\|_{L^1} \\ \text{s.t.} \quad & \text{PDE and } u_a \leq u \leq u_b. \end{aligned}$$

Sparsity is maintained



Regularized formulation

$$\begin{aligned} \text{Minimize} \quad & \frac{1}{2} \|y - y_d\|_{L^2}^2 + \frac{\alpha}{2} \|u\|_{L^2}^2 + \beta \|u\|_{L^1} \\ \text{s.t.} \quad & \text{PDE and } u_a \leq u \leq u_b. \end{aligned}$$

Optimality conditions

$$\mu = p - \alpha u$$

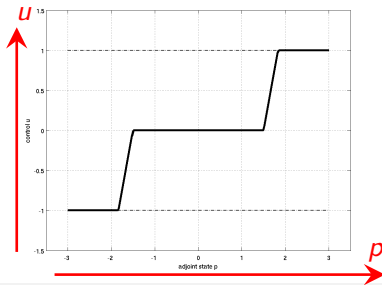
$$u = \max\{0, u + c(\mu - \beta)\}$$

$$+ \min\{0, u + c(\mu + \beta)\}$$

$$- \max\{0, u - u_b + c(\mu - \beta)\}$$

$$- \min\{0, u - u_a + c(\mu + \beta)\}$$

Sparsity is maintained



Regularized formulation

$$\begin{aligned} \text{Minimize} \quad & \frac{1}{2} \|y - y_d\|_{L^2}^2 + \frac{\alpha}{2} \|u\|_{L^2}^2 + \beta \|u\|_{L^1} \\ \text{s.t.} \quad & \text{PDE and } u_a \leq u \leq u_b. \end{aligned}$$

Optimality conditions

$$\mu = p - \alpha u$$

$$u = \max\{0, u + c(\mu - \beta)\}$$

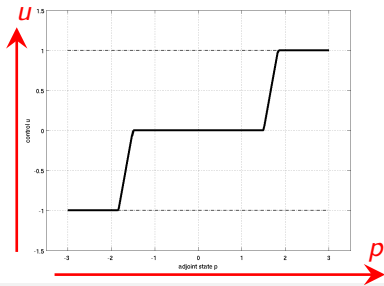
$$+ \min\{0, u + c(\mu + \beta)\}$$

$$- \max\{0, u - u_b + c(\mu - \beta)\}$$

$$- \min\{0, u - u_a + c(\mu + \beta)\}$$

Newton differentiable for $\alpha > 0$

Sparsity is maintained



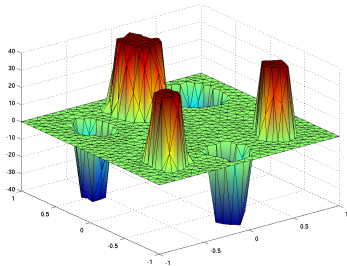
Solution of regularized problems ($\alpha > 0$)

- sparsity is maintained for regularized problems
- efficient solution using **semi-smooth Newton method** for $\alpha > 0$
- continuation method as $\alpha \searrow 0$
- convergence rates up to $\alpha^{1/3}$

[Hintermüller, Ito, Kunisch (2002)]

[Ulbrich (2003)]

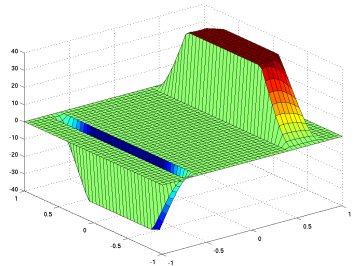
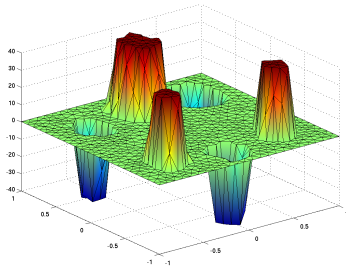
Sparsity



Objective function

$$\frac{1}{2} \|y - y_d\|_{L^2}^2 + \beta \|u\|_{L^1}$$

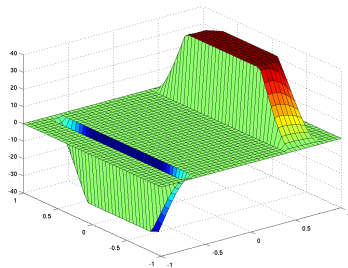
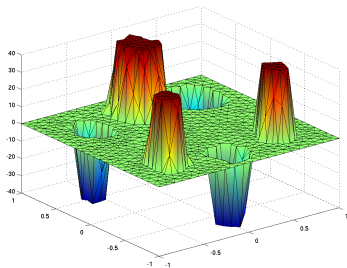
Sparsity vs. directional sparsity



Objective function

$$\frac{1}{2} \|y - y_d\|_{L^2}^2 + \beta \|u\|_{L^1}$$

Sparsity vs. directional sparsity



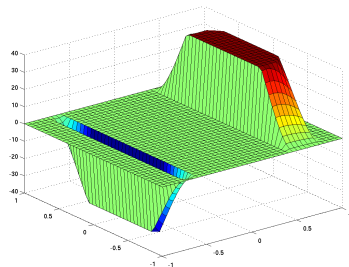
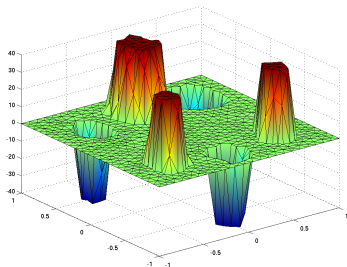
Objective function

$$\frac{1}{2} \|y - y_d\|_{L^2}^2 + \beta \|u\|_{L^1}$$

Objective function

$$\frac{1}{2} \|y - y_d\|_{L^2}^2 + \beta \|u\|_{L^1(L^2)}$$

Sparsity vs. directional sparsity



Properties

- no structural assumptions made

Properties

- exploits known or desired group sparsity structure

Fixed point property

\bar{u} is optimal $\Leftrightarrow \bar{u}$ solves

$$\begin{aligned} \text{Minimize} \quad & \frac{1}{2} \|y - y_d\|_{L^2}^2 + \frac{1}{2} \int_{\Omega^+} \left(\alpha + \frac{\beta}{\|\bar{u}(x_1, \cdot)\|_{L^2}} \right) u(x)^2 dx \\ \text{s.t.} \quad & \text{PDE and } u_a \leq u \leq u_b \end{aligned}$$

and if it satisfies the complementarity property

$$\|p(x_1, \cdot)\|_{L^2} \leq \beta \quad \text{where } \bar{u}(x_1, \cdot) = 0.$$

Fixed point property

\bar{u} is optimal $\Leftrightarrow \bar{u}$ solves

$$\begin{aligned} \text{Minimize} \quad & \frac{1}{2} \|y - y_d\|_{L^2}^2 + \frac{1}{2} \int_{\Omega^+} \left(\alpha + \frac{\beta}{\|\bar{u}(x_1, \cdot)\|_{L^2}} \right) u(x)^2 dx \\ \text{s.t.} \quad & \text{PDE and } u_a \leq u \leq u_b \end{aligned}$$

and if it satisfies the complementarity property

$$\|p(x_1, \cdot)\|_{L^2} \leq \beta \quad \text{where } \bar{u}(x_1, \cdot) = 0.$$

Numerical solution

- fixed-point iteration for $\|\bar{u}(x_1, \cdot)\|_{L^2}$, semi-smooth Newton method inside
- alternative: complementarity formulation, semi-smooth Newton method

Applications

- sparse placement of actuators
- sparse identification of relevant mechanisms
- directional sparsity as a new device

Algorithmics

- regularized problems for $\alpha > 0$
- efficient semi-smooth Newton algorithm
- directional sparsity: fixed-point formulation (globalization)

References: Problems Promoting Sparsity



R. Griesse and D. Lorenz.

A semismooth Newton method for Tikhonov functionals with sparsity constraints.

Inverse Problems, 24(3):035007 (19pp), 2008.



R. Griesse, G. Stadler, and G. Wachsmuth.

Elliptic optimal control problems with directional sparsity terms.

in preparation.



G. Stadler.

Elliptic optimal control problems with L^1 -control cost and applications for the placement of control devices.

Computational Optimization and Applications, to appear.

- 1 Parametric Sensitivity Analysis
- 2 Problems Promoting Sparsity
- 3 Free Boundary Value Problems**

Examples

- phase transitions in solidification and melting processes
- Stefan problem
- multi-phase fluid flow, fluid-structure interaction

Features

- **domain** of definition of the underlying equation is a priori **unknown**
- it is determined along with the solution
- **coupled system** with differing characteristics:
 - heat equation (temperature)
 - geometric evolution equation (free boundary)

The Stefan Problem

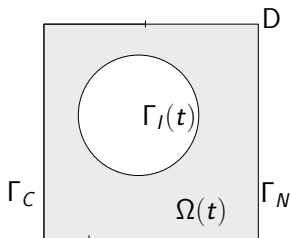




Heat equation

$$\begin{aligned} \rho c_p y_t - k \Delta y &= f && \text{in } \Omega(t) \\ y &= 0 && \text{auf } \Gamma_I(t) \end{aligned}$$

[Stefan 1889]



Heat equation

$$\rho c_p y_t - k \Delta y = f \quad \text{in } \Omega(t)$$

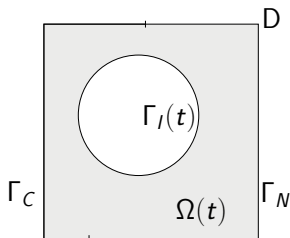
$$y = 0 \quad \text{auf } \Gamma_I(t)$$

$$k \frac{\partial y}{\partial n} = u \quad \text{auf } \Gamma_C$$

$$k \frac{\partial y}{\partial n} = g \quad \text{auf } \Gamma_N$$

$$y(0) = y_0 \quad \text{in } \Omega(0)$$

[Stefan 1889]



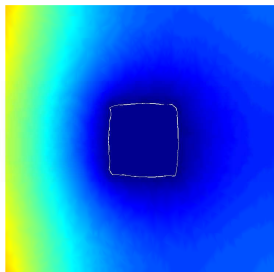
Heat equation

$$\begin{aligned} \rho c_p y_t - k \Delta y &= f && \text{in } \Omega(t) \\ y &= 0 && \text{auf } \Gamma_I(t) \\ k \frac{\partial y}{\partial n} &= u && \text{auf } \Gamma_C \\ k \frac{\partial y}{\partial n} &= g && \text{auf } \Gamma_N \\ y(0) &= y_0 && \text{in } \Omega(0) \end{aligned}$$

Stefan condition

$$\rho L F \cdot n = k \frac{\partial y}{\partial n} \quad \text{auf } \Gamma_I(t)$$

[Stefan 1889]



Heat equation

$$\varrho c_p y_t - k \Delta y = f \quad \text{in } \Omega(t)$$

$$y = 0 \quad \text{auf } \Gamma_I(t)$$

$$k \frac{\partial y}{\partial n} = u \quad \text{auf } \Gamma_C$$

$$k \frac{\partial y}{\partial n} = g \quad \text{auf } \Gamma_N$$

$$y(0) = y_0 \quad \text{in } \Omega(0)$$

Stefan condition

$$\varrho L F \cdot n = k \frac{\partial y}{\partial n} \quad \text{auf } \Gamma_I(t)$$

[Stefan 1889]

- Signed distance function:

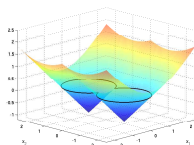
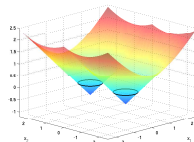
$$\phi(x, t) \begin{cases} < 0 & \text{in } \Omega(t) \\ = 0 & \text{on } \Gamma_I(t) \\ > 0 & \text{in } D \setminus \Omega(t) \end{cases}$$

- Linear transport equation:

$$0 = \phi_t + F \cdot \nabla \phi.$$

- Level-set equation:

$$n = \frac{\nabla \phi}{|\nabla \phi|} \Rightarrow 0 = \phi_t + F_n |\nabla \phi|.$$



- Signed distance function:

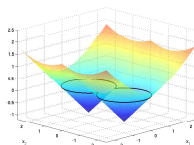
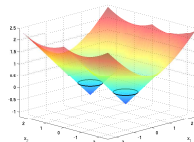
$$\phi(x, t) \begin{cases} < 0 & \text{in } \Omega(t) \\ = 0 & \text{on } \Gamma_I(t) \\ > 0 & \text{in } D \setminus \Omega(t) \end{cases}$$

- Linear transport equation:

$$0 = \phi_t + F \cdot \nabla \phi.$$

- Level-set equation:

$$n = \frac{\nabla \phi}{|\nabla \phi|} \Rightarrow 0 = \phi_t + F_n |\nabla \phi|.$$



Flexible.

Suitable for 2D, 3D.

Solver for PDE \Rightarrow Effort!

F is known on $\Gamma_I(t)$ only.

Stefan condition

$$F = (F_1, F_2)^\top : \quad \rho L F \cdot n = k \frac{\partial y}{\partial n} \quad \text{on } \Gamma_I(t)$$

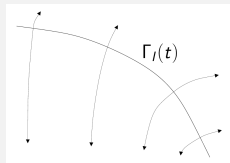
Stefan condition

$$F = (F_1, F_2)^\top : \quad \rho L F \cdot n = k \frac{\partial y}{\partial n} \quad \text{on } \Gamma_I(t)$$

Constant extension in normal direction

Find F_i , $i = 1, 2$, such that:

$$\begin{aligned} \text{sign}(\phi) \nabla F_i \cdot \nabla \phi &= 0 && \text{in } \mathbb{R}^2 \\ \rho L F_i &= k \frac{\partial y}{\partial x_i} && \text{on } \Gamma_I(t) \end{aligned}$$



- maintains signed-distance property
- fast marching schemes
- same technique is used to re-initialize level-set function

Moving mesh approach

- mesh conforms to interface
- FEM on moving mesh

Moving mesh approach

- mesh conforms to interface
- FEM on moving mesh

X-FEM approach

- keep mesh
- modify trial functions

Moving mesh approach

- mesh conforms to interface
- FEM on moving mesh

X-FEM approach

- keep mesh
- modify trial functions

$$y_h(x, t) = \sum_{i=1}^n v_i(x) y_i(t) + \sum_{j=1}^{n_{e,t}} w_j(x, t) a_j(t),$$

Moving mesh approach

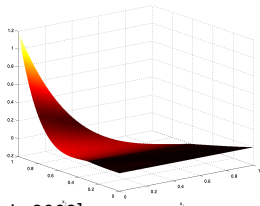
- mesh conforms to interface
- FEM on moving mesh

X-FEM approach

- keep mesh
- modify trial functions

$$y_h(x, t) = \sum_{i=1}^n v_i(x) y_i(t) + \sum_{j=1}^{n_{e,t}} w_j(x, t) a_j(t),$$

$$w_j(x, t) = v_j(x) (|\phi(x, t)| - |\phi_j(t)|)$$



[Chessa et al. 2002]

Moving mesh approach

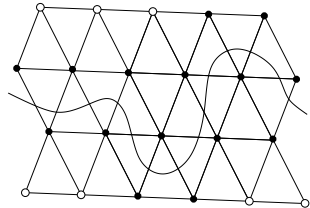
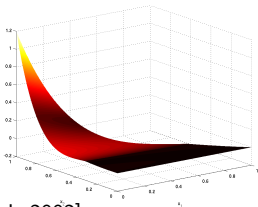
- mesh conforms to interface
- FEM on moving mesh

X-FEM approach

- keep mesh
- modify trial functions

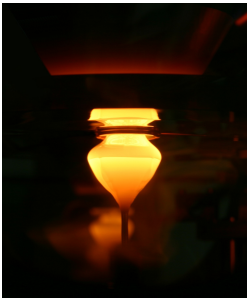
$$y_h(x, t) = \sum_{i=1}^n v_i(x) y_i(t) + \sum_{j=1}^{n_{e,t}} w_j(x, t) a_j(t),$$

$w_j(x, t) = v_j(x) (|\phi(x, t)| - |\phi_j(t)|)$ at enriched nodes:

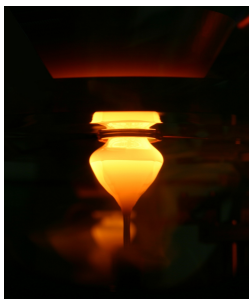


[Chessa et al. 2002]

Goal: Influence the phase boundary



Goal: Influence the phase boundary



Optimal control problem

$$\begin{aligned} \text{Minimize} \quad & \frac{\gamma_1}{2} \int_0^T \int_{\Gamma_I(t)} |\phi_d|^2 \\ & + \frac{\gamma_2}{2} \int_0^T \int_{\Omega_1(t)} |y - y_d|^2 + \frac{\gamma_3}{2} \int_0^T \int_{\Gamma_C} |u|^2 \end{aligned}$$

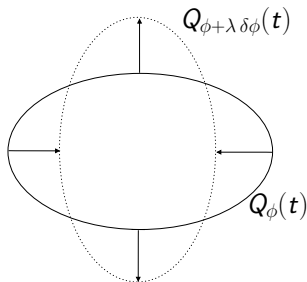
s.t. Stefan problem

$$E(\phi) = \int_0^T \int_{Q_\phi(t)} f \, dx \, dt, \quad Q_\phi(t) = \{\phi < 0\}$$

$$E'(\phi) \delta\phi = \lim_{\lambda \rightarrow 0} \frac{E(\phi + \lambda \delta\phi) - E(\phi)}{\lambda} = ?$$

Set $\tilde{\phi} := \phi + \lambda \delta\phi$ and write

$$\int_{Q_\phi(t)} f = \int_{Q_\phi(t) \cap Q_{\tilde{\phi}}(t)} f + \int_{Q_\phi(t) \setminus Q_{\tilde{\phi}}(t)} f$$



Elements of Shape Calculus

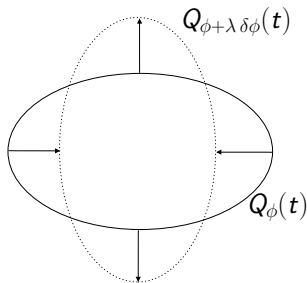


$$E(\phi) = \int_0^T \int_{Q_\phi(t)} f \, dx \, dt, \quad Q_\phi(t) = \{\phi < 0\}$$

$$E'(\phi) \delta\phi = \lim_{\lambda \rightarrow 0} \frac{E(\phi + \lambda \delta\phi) - E(\phi)}{\lambda} = ?$$

Set $\tilde{\phi} := \phi + \lambda \delta\phi$ and write

$$\int_{Q_\phi(t)} f = \int_{Q_\phi(t) \cap Q_{\tilde{\phi}}(t)} f + \int_{Q_\phi(t) \setminus Q_{\tilde{\phi}}(t)} f$$



$$\begin{aligned} \frac{E(\phi + \lambda \delta\phi) - E(\phi)}{\lambda} &= \frac{1}{\lambda} \int_0^T \left(\int_{Q_{\tilde{\phi}}(t) \setminus Q_\phi(t)} f - \int_{Q_\phi(t) \setminus Q_{\tilde{\phi}}(t)} f \right) \\ &= \frac{1}{\lambda} \int_0^T \left(\int_{\partial Q_\phi(t)} \lambda \frac{-\delta\phi}{|\nabla\phi|} f + \mathbf{o}(\lambda) \right) \xrightarrow{\lambda \rightarrow 0} \int_0^T \int_{\partial Q_\phi(t)} \frac{-\delta\phi}{|\nabla\phi|} f \, ds \, dt \end{aligned}$$

[Pironneau 1984, Santosa 1995]

$$\mathcal{L}_y \delta y = 0:$$

$$\begin{aligned} -\rho c p_t - k \Delta p &= \gamma_2 q & \Omega(t) \\ p(T, x) &= 0 & \Omega(T) \\ k \frac{\partial p}{\partial n} &= 0 & \Gamma_C \cup \Gamma_N \end{aligned}$$

$$\begin{aligned} p_I &= \rho c p k \frac{\partial y}{\partial n} - k \frac{\partial p}{\partial n} & \Gamma_I(t) \\ S_i &= -p n_i, \quad i = 1, 2 & \Gamma_I(t) \end{aligned}$$

$$\mathcal{L}_{F_i} \delta F_i = 0:$$

$$\begin{aligned} \psi \phi_{x_i} &= \text{sign}(\phi) \text{div}(G_i \nabla \phi) & \mathbb{R}^2 \\ 2|\nabla \phi| G_i &= -\rho L p n_i & \Gamma_I(t) \end{aligned}$$

$$\mathcal{L}_u \delta u = 0:$$

$$\gamma_3 u + p = 0 \quad \Gamma_C$$

$$\mathcal{L}_\phi \delta \phi = 0:$$

$$\begin{aligned} \psi_t + \text{div}(\psi F) &= \text{sign}(\phi) \text{div}(G_1 \nabla F_1) + \text{sign}(\phi) \text{div}(G_2 \nabla F_2) & \mathbb{R}^2 \\ \psi(T) &= 0 & \mathbb{R}^2 \end{aligned}$$

$$\begin{aligned} \gamma_1 \text{div} \left(\frac{|\phi_d|^2}{2} n \right) &= \rho c p y_t + k \nabla y \nabla p - f p \\ &+ \text{div} \left(((c y - L) \rho p k \frac{\partial y}{\partial n} - y k \frac{\partial p}{\partial n} - p_I y_M) n \right) & \Gamma_I(t) \end{aligned}$$

$$q = \chi_{\Omega_1(t)}(y - y_d), \quad n = \frac{\nabla \phi}{|\nabla \phi|}$$

Challenges and outlook

- optimality conditions
- in particular for problems with **constrained interfaces**
- gradient based and higher-order numerical solution techniques

Challenges and outlook

- optimality conditions
 - in particular for problems with **constrained interfaces**
 - gradient based and higher-order numerical solution techniques
-
- developed techniques applicable to other free boundary problems
 - for instance, multi-phase fluid flow problems

Optimal control

- often driven by application
- tool to understand system dynamics

Toolbox of methods applicable to a broad range of applications

- parametric sensitivity analysis
- problems with sparse solutions
- free boundary value problems