Numerical Optimization of Partial Differential Equations

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Goal ("key learning outcome"):

introduction to state-of-the-art computational approaches to solution of PDE optimization problems, including actual computer implementation

Key Challenge:

dealing with the PDE constraint

Applications of PDE Optimization

- Open-loop optimal control of distributed systems
  - flow control problems in fluid mechanics (e.g., optimization of lift and/or drag, mixing, etc.)
  - structural optimization is solid mechanics
  - process optimization in chemical engineering
  - portfolio optimization in investing
- State and parameter estimation for distributed systems
  - inverse problems for PDEs (e.g., medical imaging)
  - data assimilation in Numerical Weather Prediction ("4D VAR")

General Framework

- Equation-constrained optimization problem

$$(\star) \qquad \begin{cases} \inf_{(x,\varphi)} \widetilde{\mathcal{J}}(x,\varphi) \\ \text{subject to:} \quad S(x,\varphi) = 0 \end{cases}$$

  where:
  - $x \in \mathcal{X}$ — the state variable ($\mathcal{X}$ is a suitable function space)
  - $\varphi \in \mathcal{U}$ — the control variable ($\mathcal{U}$ is a suitable function (Hilbert) space)
  - $\widetilde{\mathcal{J}} \; : \; \mathcal{X} \times \mathcal{U} \to \mathbb{R}$ — the objective functional
  - $S \; : \; \mathcal{X} \times \mathcal{U} \to \mathcal{X}^*$ — constraint (PDE with initial/boundary conditions)

- The constraint $S(x,\varphi)=0$ be handled by introducing the *Lagrange multiplier* $\lambda \in \mathcal{X}$, such that we can define the Lagrangian

$$\mathcal{L}(x,\varphi,\lambda) = \widetilde{\mathcal{J}}(x,\varphi) - \langle \lambda, S(x,\varphi)\rangle_{\mathcal{X}\times\mathcal{X}^*}$$

- The constrained minimizers are then defined by the variational problem

$$\sup_{\lambda\in\mathcal{X}} \inf_{(x,\varphi)\in\mathcal{X}\times\mathcal{U}} \mathcal{L}(x,\varphi,\lambda)$$

- Stationary points $(\widetilde{x},\widetilde{\varphi},\widetilde{\lambda})$ of the Lagrangian are solutions of the Euler-Lagrange equations

$$\nabla_\lambda \mathcal{L}(\widetilde{x},\widetilde{\varphi},\widetilde{\lambda}) = 0$$
$$\nabla_x \mathcal{L}(\widetilde{x},\widetilde{\varphi},\widetilde{\lambda}) = 0$$
$$\nabla_\varphi \mathcal{L}(\widetilde{x},\widetilde{\varphi},\widetilde{\lambda}) = 0$$

- The stationary points $(\widetilde{x},\widetilde{\varphi},\widetilde{\lambda})$ are saddle points. The problem is hard so solve and we will advocate for a different formulation.

- If the constraint equation $S(x, \varphi) = 0$ can be solved for x (cf. implicit function theorem), then $x = x(\varphi)$ and one can define the *reduced* objective functional

$$\mathcal{J}(\varphi) := \widetilde{\mathcal{J}}(x(\varphi), \varphi)$$

- Constrained optimization problem $(\star)$ can then replaced with the following equivalent unconstrained problem

$$\min_{\varphi \in \mathcal{U}} \mathcal{J}(\varphi)$$

- *Inequality* constraints are more difficult to handle, especially in the context of PDE optimization, and will not be considered here

- How to find a local minimizer $\widetilde{\varphi}$?
- Consider the following initial-value problem in the space $\mathcal{U}$, known as the *gradient flow*

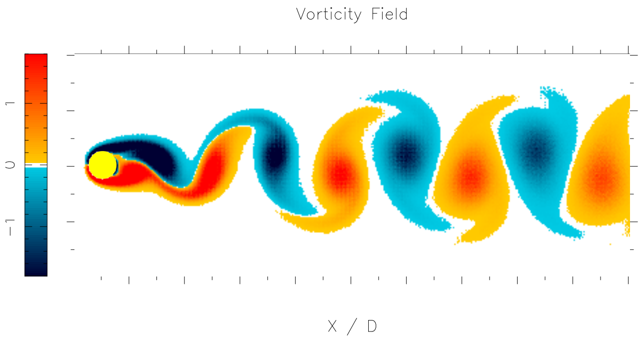
$$(\mathrm{GF}) \qquad \begin{cases} \dfrac{d\varphi(\tau)}{d\tau} = -\nabla\widetilde{\mathcal{J}}(\varphi(\tau)), & \tau > 0, \\ \varphi(0) = \varphi_0, \end{cases}$$

  where
  - τ is a "pseudo-time" (a parametrization)
  - φ_0 is a suitable initial guess
- Then, $\lim_{\tau\to\infty}\varphi(\tau) = \widetilde{\varphi}$

- When the optimization is nonconvex, “solution” mean a *local minimizer*
  - one is often interested in branches of local maximizers obtained as some parameter is varied

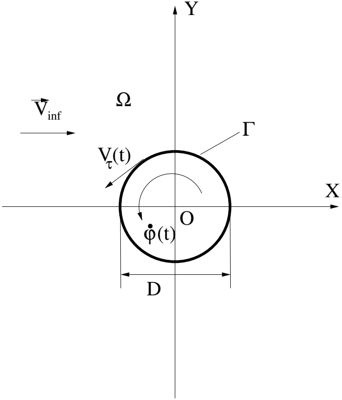
- In principle, the gradient flow may converge to a *saddle point* φ_s, where $\nabla\widetilde{\mathcal{J}}(\varphi_s) = 0$ and the Hessian $\nabla^2\widetilde{\mathcal{J}}(\varphi_s)$ is *not* positive-definite, but in actual computations this is very unlikely.

Vorticity fields on the flow past an obstacle



A Classical Flow Control Problem in Fluid Mechanics

- Flow Domain



- Assumptions:
  - viscous, incompressible flow
  - plane, infinite domain
  - $Re = 150$
- State variables:
  - velocity: $\mathbf{v} \; : \; \Omega \rightarrow \mathbb{R}^d$
  - pressure: $p \; : \; \Omega \rightarrow \mathbb{R}$
- Control variables:
  - rate of rotation:

$$\dot{\varphi} \; : \; [0, T] \rightarrow \mathbb{R}$$

Statement of the Problem (II)

- Find $\dot{\varphi}_{opt} = \operatorname{argmin}_{\dot{\varphi}\in L^2(0,T)} \mathcal{J}(\dot{\varphi})$, where

$$\begin{aligned}\mathcal{J}(\dot{\varphi}) &= \frac{1}{2}\int_0^T \left\{ \left[\begin{array}{c}\text{power related to}\\ \text{the drag force}\end{array}\right] + \left[\begin{array}{c}\text{power needed to}\\ \text{control the flow}\end{array}\right]\right\} dt \\ &= \frac{1}{2}\int_0^T \oint_{\Gamma_0} \left\{ \left[p(\dot{\varphi})\mathbf{n} - \mu \mathbf{n}\cdot \mathbf{D}(\mathbf{v}(\dot{\varphi}))\right] \cdot \left[\dot{\varphi}\,(\mathbf{e}_z \times \mathbf{r}) + \mathbf{v}_\infty\right]\right\} d\sigma dt\end{aligned}$$

- Subject to:

$$\begin{cases} \left[\begin{array}{c} \frac{\partial \mathbf{v}}{\partial t} + (\mathbf{v}\cdot\boldsymbol{\nabla})\mathbf{v} - \mu\Delta\mathbf{v} + \boldsymbol{\nabla} p \\ \boldsymbol{\nabla}\cdot\mathbf{v}\end{array}\right] = \left[\begin{array}{c}0\\0\end{array}\right] & \text{in } \Omega\times(0,T), \\ \mathbf{v} = 0 & \text{at } t = 0, \\ \mathbf{v} = \dot{\varphi}_{opt}\tau & \text{on } \Gamma \end{cases}$$

Optimization vs. Discretization

- Optimize-then-Discretize: optimality conditions and gradient expressions derived at the continuous (PDE) level and only then discretized $\Longleftarrow$ will focus on this approach
  - formulation independent of discretization
  - allows one to exploit the analytic structure of the problem (e.g., regularity, etc.)
  - works well with mesh refinement in the numerical solution of PDEs
- Discretize-then-Optimize: the PDE problem is discretized first and then treated as optimization problem in finite dimension
  - PDE discretization errors do not affect the optimization procedure
  - can take advantage of Automatic Differentiation (AD) tools
  - may be more suitable for very large problems

- Part I: basic optimization concepts in $\mathbb{R}^n$
  - gradients and gradient flows
  - fixed and optimal step sizes
  - linear and nonlinear conjugate gradients
  - constraints, projections and Lagrange multipliers
- Part II: optimization with PDE constraints
  - Riesz theorem and gradient extraction
  - adjoint calculus
  - preconditioning and Sobolev gradients
- Part III: applications
  - flow control
  - shape optimization
- All presentations available at
  http://www.math.mcmaster.ca/bprotas/lecture_notes.shtml