

Optimal Reconstruction of Constitutive Relations in Complex Multiphysics Systems

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Agenda

1 Introduction

- Motivation
- Model Problem
- Differentiability of Map $\mu \rightarrow T$

2 Parameter Estimation as Optimization Problem

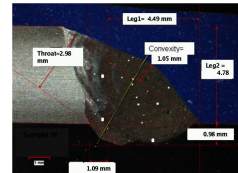
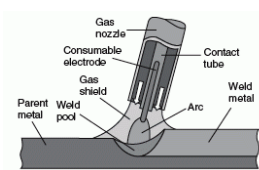
- Formulation
- Adjoint Equations and Gradients
- Algorithm

3 Computational Results

- Set-Up
- Validation of Gradients
- Reconstruction Results

Modeling & Optimization of Thermo–Fluid Phenomena

- Application: Welding in Automotive Industry



- Problem: Unknown Material Properties of Alloys in Liquid Phase

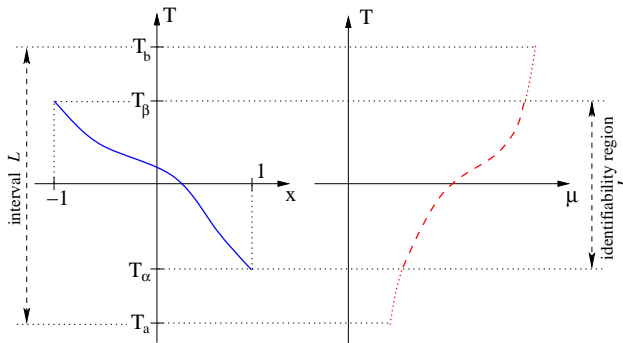
- viscosity $\mu(T)$
 - thermal conductivity $k(T)$
 - electric conductivity $\sigma(T)$
 - surface tension $\gamma(T)$
- } all functions of temperature T

- Goal: Reconstruct $\mu(T)$, $K(T)$, $\sigma(T)$, $\gamma(T)$, etc., based on available measurements

Parameter Estimation as Optimization Problem

Two distinct formulations of an inverse problem of the parameter estimation:

- a) material properties dependent on the **space** variable, i.e., the **independent** variable, and
- b) material properties dependent on the **state** variable, i.e., the **dependent variable** (very few results in the literature)



Problem

Develop and validate a computational method for reconstruction of state-dependent material properties based on incomplete and noisy measurements

- **Strategy:**
 - Inverse problem formulated as **partial differential equation (PDE)–constrained optimization** problem which can be solved using an **adjoint–based gradient method**.
 - Implement an “**optimize–then–discretize**” approach where the optimality conditions and the optimization algorithm are both formulated based on the **continuous (PDE)** setting.
- **Earlier Work: Chavent & Lemonnier (1974, in French)**
 - Existence of solutions, gradients $\nabla \mathcal{J}$ discontinuous and difficult to compute, reconstruction on the identifiability interval only
- **Our Main Contributions:**
 - Developed an efficient computational approach to evaluate cost functional gradients using adjoint variables
 - Extension of reconstruction beyond the Identifiability Region \mathcal{I}

Result of Chavent & Lemonnier (1974)

Posons pour cela:

$$\phi(x, t) = \sum_{i=1}^n \frac{\partial y}{\partial x_i}(x, t) \frac{\partial p}{\partial x_i}(x, t) \quad \phi \in L^1(Q). \quad (80)$$

Pour tout $\zeta \in \mathbb{R}$ posons:

$$Q_\zeta = \{(x, t) \in Q \mid y(x, t) \geq \zeta\} \quad (81)$$

$$\gamma(\zeta) = \int_{Q_\zeta} \phi(x, t) \, dx \, dt \quad (82)$$

L'ensemble Q_ζ est défini à un ensemble de mesure nulle près, mais la fonction $\gamma(\zeta)$ est définie sans équivoque.

On a alors le

Théorème 8. Avec les hypothèses et notations du théorème 7, plus (80) à (82), la fonction γ définie en (82) est bornée et continue sur \mathbb{R} . Elle définit en particulier une distribution sur \mathbb{R} , et on a

$$\begin{cases} \forall \delta a \in \mathcal{A}: \\ J'(a)\delta a = \langle \frac{d\gamma}{d\zeta}, \delta a \rangle. \end{cases} \quad (83)$$

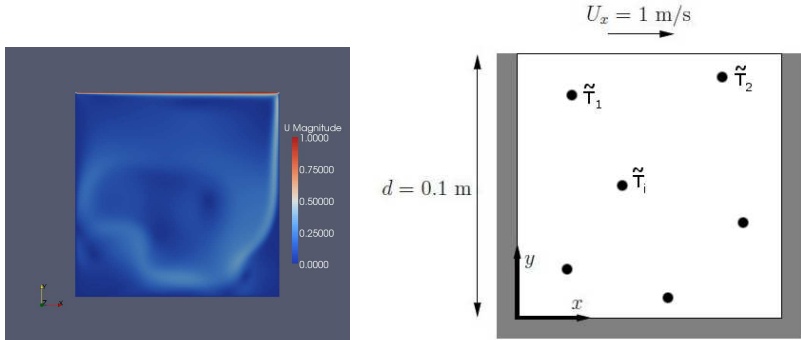
Démonstration: Pour tout $\zeta \in \mathbb{R}$ on a: $|\gamma'(\zeta)| \leq \|\phi\|_{L^1(Q)}$, donc γ est bornée sur \mathbb{R} . Posons:

$$Y(\zeta) = \begin{cases} 1 & \text{si } \zeta \geq 0 \\ 0 & \text{si } \zeta < 0 \end{cases} \quad \forall \zeta \in \mathbb{R}.$$

Alors en notant y un représentant de la classe de fonctions y , (82) se réécrit:

$$\gamma(\zeta) = \int_Q Y(y(x, t) - \zeta) \phi(x, t) \, dx \, dt. \quad (84)$$

- **Model System:** Unsteady Mass, Momentum & Energy Transfer
- **Geometry:** 2D Lid-Driven Cavity Problem with Heat Transfer



- **Measurements:** (pointwise) temperature measurements $\{\tilde{T}_i\}_{i=1}^M$ at a number of points $\{\mathbf{x}_i\}_{i=1}^M$ in the domain Ω

- **Governing System:**

- Navier–Stokes equation with temperature–dependent viscosity
- Energy equation

$$\partial_t \mathbf{u} + \mathbf{u} \cdot \nabla \mathbf{u} + \nabla p - \nabla \cdot \left[\mu(T) [\nabla \mathbf{u} + (\nabla \mathbf{u})^T] \right] = 0 \quad \text{in } \Omega,$$

$$\nabla \cdot \mathbf{u} = 0 \quad \text{in } \Omega,$$

$$\partial_t T + \mathbf{u} \cdot \nabla T + \nabla \cdot [k \nabla T] = 0 \quad \text{in } \Omega.$$

subject to

$$\mathbf{u} = 0 \quad \text{on } \partial\Omega,$$

$$T = T_b \quad \text{on } \partial\Omega,$$

$$\mathbf{u}(0) = \mathbf{u}_0, \quad T(0) = T_0.$$

- **Goal:** Reconstruct $\mu(T)$ based on temperature measurements $\{\tilde{T}_i\}_{i=1}^M$ inside the domain Ω
- **Remark:** $\mu(T) > 0$ required for well–posedness
(\Rightarrow second principle of thermodynamics)

Differentiability of Map $\mu \rightarrow T$

Simplified Model: solving parameter estimation problem for

$$\begin{aligned} -\nabla \cdot [\mu(T) \nabla T] &= g && \text{in } \Omega, \\ T &= T_0 && \text{on } \partial\Omega. \end{aligned} \quad (1)$$

is equivalent in a suitably-defined variational (weak) setting to finding the solution to the operator equation

$$\mathcal{F}(\mu) = T, \quad (2)$$

where $\mathcal{F} : \mathcal{K} \rightarrow L_2(\Omega)$ and \mathcal{K} is the set of constitutive relations

$$\mathcal{K} = \{\mu(T) \text{ piecewise } C^1 \text{ on } \mathcal{L}; 0 < m_k < \mu(T) < M_k, \forall T \in \mathcal{L}\}.$$

Theorem

Assume that m_k is sufficiently large and solutions of (1) satisfy $\|\nabla T\|_{L^\infty(\Omega)} < \infty$. Then the map $\mu \rightarrow T(\cdot; k)$ from \mathcal{K} to $L_2(\Omega)$ is Fréchet-differentiable in the norm $H^1(\mathcal{I})$.

[Proof: see Bukshytynov, Volkov & Protas (2011)]

Reformulation as Minimization Problem:

- Define cost functional $\mathcal{J} : \mathcal{X} \rightarrow \mathbb{R}$ as

$$\mathcal{J}(\mu) \triangleq \frac{1}{2} \int_0^{t_f} \sum_{i=1}^M \left[T(\mathbf{x}_i; \mu) - \tilde{T}_i \right]^2$$

- Optimal reconstruction $\hat{\mu}$ obtained as an unconstrained minimizer of cost functional \mathcal{J}

$$\hat{\mu} = \underset{\mu \in \mathcal{X}}{\operatorname{argmin}} \mathcal{J}(\mu)$$

[positivity condition $\mu(T) > 0$ not taken into account yet]

- Minimizer $\hat{\mu}$ computed with the gradient descent algorithm as $\hat{\mu} = \lim_{n \rightarrow \infty} \mu^{(n)}$, where

$$\begin{cases} \mu^{(n+1)} &= \mu^{(n)} - \tau^{(n)} \nabla_{\mu} \mathcal{J}(\mu^{(n)}), & n = 1, \dots \\ \mu^{(1)} &= \mu_0 \end{cases}$$

Computation of cost functional gradient $\nabla_{\mu} \mathcal{J}(\mu)$:

1 Direct problem

$$\begin{aligned} \partial_t \mathbf{u} + \mathbf{u} \cdot \nabla \mathbf{u} + \nabla p - \nabla \cdot [\mu(T) [\nabla \mathbf{u} + (\nabla \mathbf{u})^T]] &= 0 & \text{in } \Omega, \\ \nabla \cdot \mathbf{u} &= 0 & \text{in } \Omega, \\ \partial_t T + \mathbf{u} \cdot \nabla T - \nabla \cdot [k \nabla T] &= 0 & \text{in } \Omega. \end{aligned}$$

2 Adjoint problem

$$\begin{aligned} -\partial_t \mathbf{u}^* - \mathbf{u} \cdot \nabla \mathbf{u}^* - \nabla \cdot \sigma^* + \mathbf{u}^* \cdot (\nabla \mathbf{u})^T + T^* \nabla T &= 0 & \text{in } \Omega, \\ \nabla \cdot \mathbf{u}^* &= 0 & \text{in } \Omega, \\ -\partial_t T^* - \mathbf{u} \cdot \nabla T^* - \nabla \cdot [k \nabla T^*] + \frac{d\bar{\mu}}{dT}(T) [\nabla \mathbf{u}^* + (\nabla \mathbf{u}^*)^T] : \nabla \mathbf{u} &= \\ &= \sum_{i=1}^M [T(\mathbf{x}_i; \mu) - \tilde{T}_i] \delta(\mathbf{x} - \mathbf{x}_i) & \text{in } \Omega. \end{aligned}$$

3 Cost functional (integration over level sets $T(\mathbf{x}) = s$)

$$\nabla_{\mu}^{L_2} \mathcal{J}(s) = - \int_0^{t_f} \int_{\Omega} \delta(T(\mathbf{x}) - s) [\nabla \mathbf{u}^* + (\nabla \mathbf{u}^*)^T] : \nabla \mathbf{u} \, d\mathbf{x} \, d\tau.$$

Ensuring Smoothness of Reconstructed Constitutive Relations:

- ① Since constitutive relations must possess some smoothness, i.e.,

$$\mathcal{K} = \{\mu(T) \text{ piecewise } C^1 \text{ on } \mathcal{L}; 0 < m_k < \mu(T) < M_k, \forall T \in \mathcal{L}\},$$

the “classical” L_2 gradients may (and in fact do!) lead to discontinuities in $\mu(T)$

- ② From mathematical analysis: $\mu \in H^1(\mathcal{L})$ (Sobolev space)

- ③ By Riesz Representation Theorem, Sobolev gradient $\nabla_{\mu}^{H^1} \mathcal{J}$ obtained from $\nabla_{\mu}^{L_2} \mathcal{J}$ through an elliptic boundary-value problem (with T an independent variable)

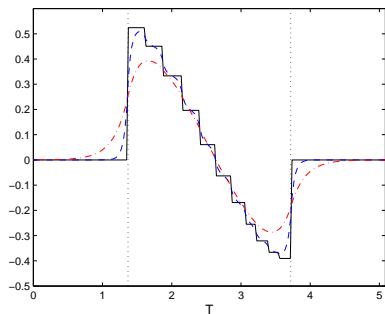
Variant 1

$$\begin{aligned} \nabla_k^{H^1} \mathcal{J} - l^2 \frac{d^2}{ds^2} \nabla_k^{H^1} \mathcal{J} &= \nabla_k^{L_2} \mathcal{J} && \text{on } (T_a, T_b), \\ \frac{d}{ds} \nabla_k^{H^1} \mathcal{J} &= 0 && \text{for } s = T_a, T_b \end{aligned}$$

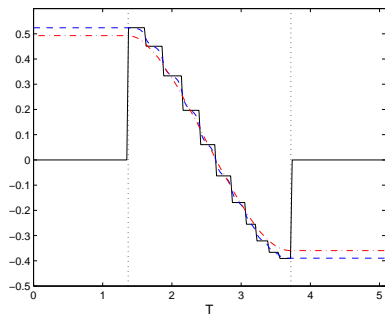
Variant 2

$$\begin{aligned} \nabla_k^{H^1} \mathcal{J} - l^2 \frac{d^2}{ds^2} \nabla_k^{H^1} \mathcal{J} &= \nabla_k^{L_2} \mathcal{J} && \text{on } (T_{\alpha}, T_{\beta}), \\ \frac{d}{ds} \nabla_k^{H^1} \mathcal{J} &= 0 && \text{for } s = T_{\alpha}, T_{\beta}, \\ \nabla_k^{H^1} \mathcal{J}(s) &= \nabla_k^{H^1} \mathcal{J}(T_{\alpha}) && \text{for } s \in [T_a, T_{\alpha}], \\ \nabla_k^{H^1} \mathcal{J}(s) &= \nabla_k^{H^1} \mathcal{J}(T_{\beta}) && \text{for } s \in [T_{\beta}, T_b] \end{aligned}$$

L_2 vs. H^1 Gradients as Functions of T



Variant 1



Variant 2

(blue) $l = 0.05$, (red) $l = 0.2$

Computational Algorithm:

0. provide initial guess $\mu^{(0)}(s)$
1. Solve governing system for $\{\mathbf{u}, T\}$
2. Solve adjoint system for $\{\mathbf{u}^*, T^*\}$
3. Use \mathbf{u} and \mathbf{u}^* to compute $\nabla_{\mu}^{H^1} \mathcal{J}$
4. update the constitutive relation according to

$$\mu^{(n+1)} = \mu^{(n)} - \tau^{(n)} \nabla_{\mu} \mathcal{J}(\mu^{(n)})$$
5. iterate 1. through 4. until convergence, i.e. until $\nabla_{\mu}^{H^1} \mathcal{J} \simeq 0$

Set up for Numerical Simulations

- algebraic expressions for **viscosity** $\mu(T)$

$$\mu(T) = C_1 e^{C_2/(C_3+T)} \quad (\text{Arrhenius})$$

$$\mu(T) = C_1 e^{C_2/T} \quad (\text{Andrade})$$

with $C_1 = \frac{U_{max}}{Re}$ and $C_2 = 10^{-3} \div 10^3$

- for simplicity, **thermal conductivity**

$$k = 0.002 = \text{const}$$

- $Re = 100$

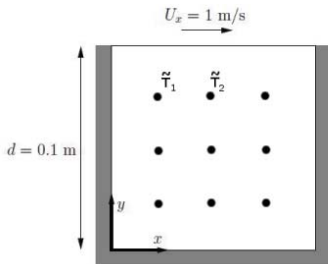
- geometry:** 2D lid-driven cavity flow

- boundary conditions**

top boundary: $u_x = U = 1$, $u_y = 0$,
 $T = 500$

other boundaries: $u_x = u_y = 0$, $T = 300$

- “synthetic” temperature measurements:** 9 thermal sensors uniformly distributed inside the cavity to capture the temperature corresponding to unknown $\mu(T)$



Direct and Adjoint Fields: Vorticity

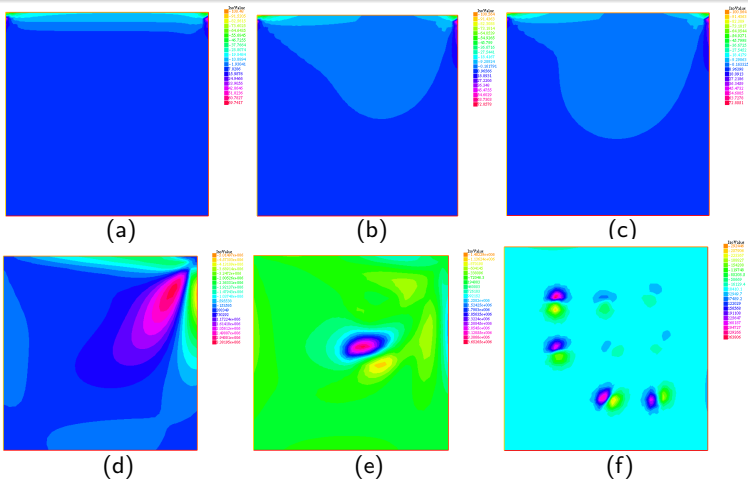


Figure: ω (a,b,c), ω^* (d,e,f) for $t = 0.2$ (a,d), $t = 3.0$ (b,e), $t = 5.8$ (c,f)

Direct and Adjoint Fields: Temperature

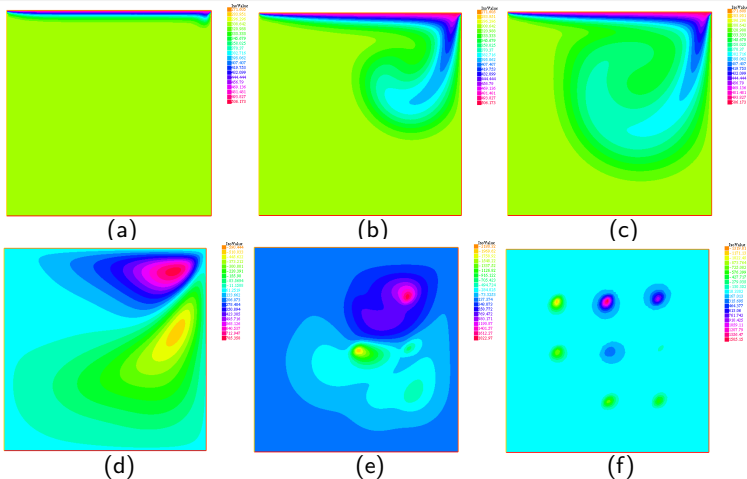
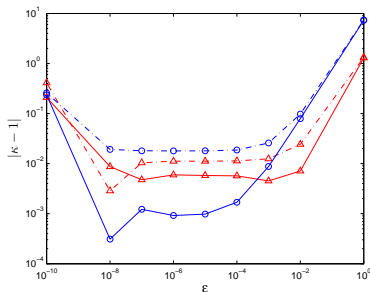
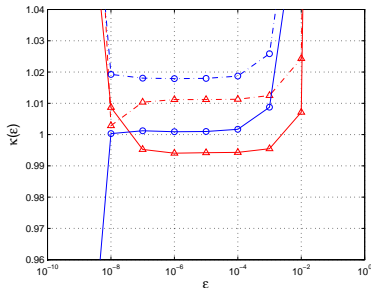


Figure: T (a,b,c), T^* (d,e,f) for $t = 0.2$ (a,d), $t = 3.0$ (b,e), $t = 5.8$ (c,f)

Validation of Gradients



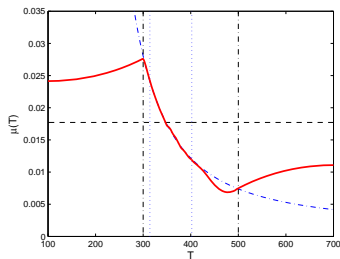
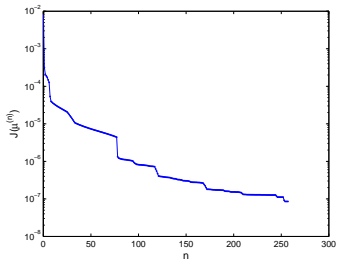
- Directional differential $\mathcal{J}'(\mu; \mu')$ obtained in two ways: finite-difference approximation and using adjoint field, ratio

$$\kappa(\epsilon) \triangleq \frac{\epsilon^{-1} [\mathcal{J}(\mu + \epsilon \mu') - \mathcal{J}(\mu)]}{\int_{-\infty}^{+\infty} \nabla_{\mu} \mathcal{J}(s) \mu'(s) ds}$$

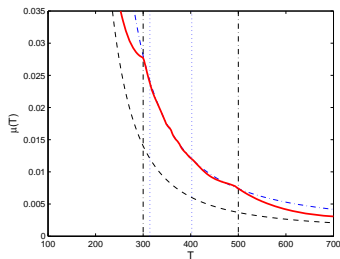
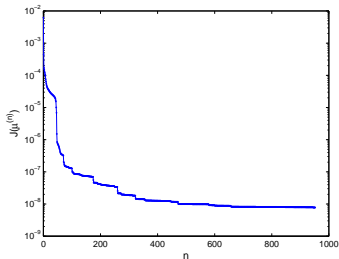
red and blue denote different perturbations μ'

- Note that $\kappa \rightarrow 1$ as $\Delta t \rightarrow 0$

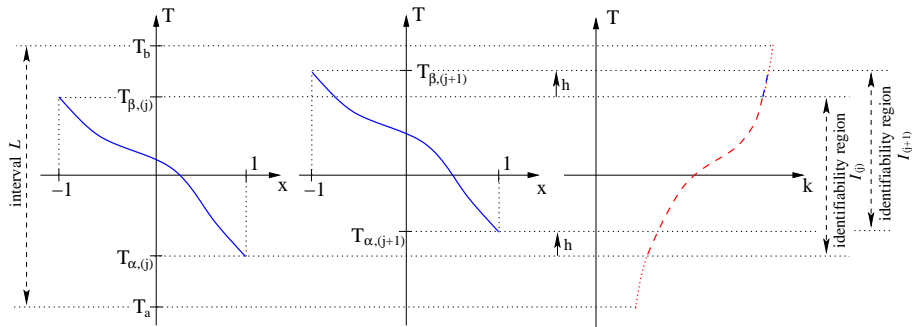
• constant initial guess $\mu^{(0)}$



• variable initial guess $\mu^{(0)}$

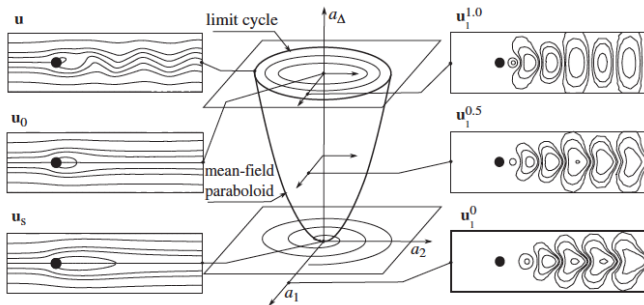


Shifting Identifiability Interval



Extensions (with B. Noack, Université de Poitiers)

- Optimal reconstruction of inertial manifolds in reduced-order models



Tadmor et al. (2011)

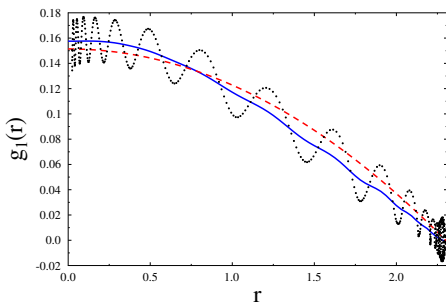
- From ∞ -dim to $\dim = 3$ (using POD modes as basis)

$$\left. \begin{aligned} \partial_t \mathbf{u} + \mathbf{u} \cdot \nabla \mathbf{u} + \nabla p - \nu \Delta \mathbf{u} &= 0 & \text{in } \Omega, \\ \nabla \cdot \mathbf{u} &= 0 & \text{in } \Omega, \end{aligned} \right\} \Rightarrow \begin{cases} \dot{r} = g_1(r) r, \\ \dot{\theta} = g_2(r), \\ a_3 = g_3(r), \end{cases}$$

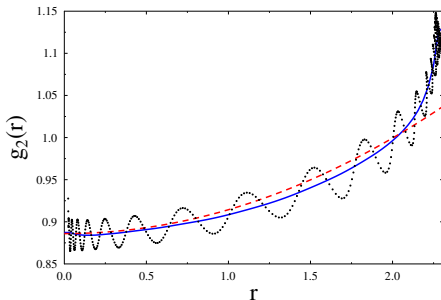
where $r := \sqrt{a_1^2 + a_2^2}$ and $\theta := \arctan(a_2/a_1)$

Reconstructions

$g_1(r)$ in $\dot{r} = g_1(r)$



$g_2(r)$ in $\dot{\theta} = g_2(r)$



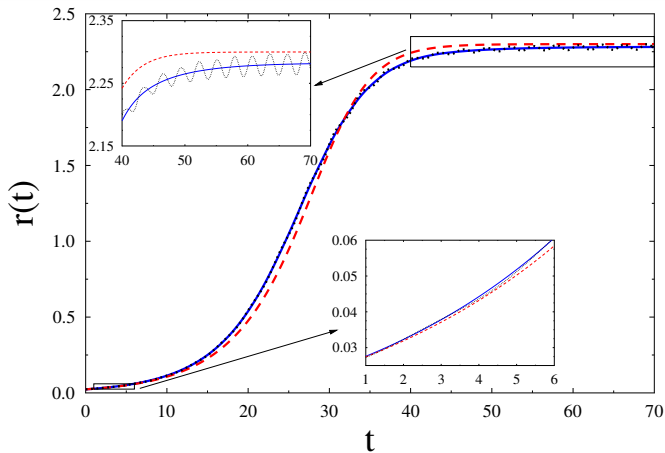
--- Initial Guess (Mean-Field Model)

$$\dot{r}(t) = [\sigma_1 - \beta_{\Delta} \alpha_{\Delta}^M r^2(t)] r(t), \quad \dot{\theta}(t) = \omega_1 + \gamma_{\Delta} \alpha_{\Delta}^M r^2(t)$$

— Optimal Reconstruction

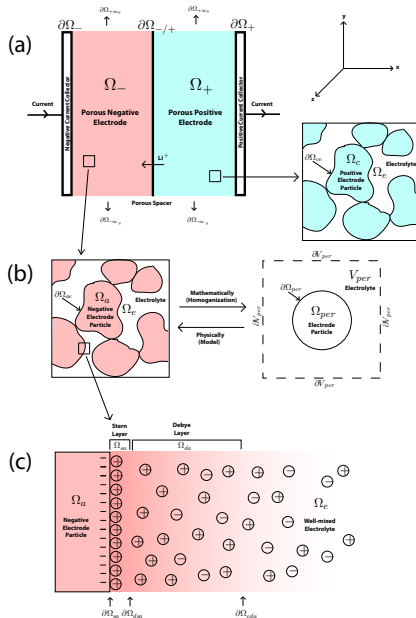
$$\dots \frac{1}{r} \frac{dr}{dt}(r(t_i)), \frac{d\theta}{dt}(r(t_i)), i = 1, \dots, N_T$$

Comparison of Output (state magnitude r)



- - - Initial Guess (Mean-Field Model), — Optimal Reconstruction,
 ... Measurement Data

Emerging Application: Multiscale Problems in Non-Equilibrium Thermodynamics (Electrochemistry in Li-Ion Batteries)



Conclusions

- Optimization-based approach to reconstruction of state-dependent constitutive relations
- Smoothness of reconstructed relations ensured by Sobolev gradients
- A systematic procedure to extend the identifiability region
- extension (reduction) to finite dimension straightforward
- Follow-up work — generalize to more complicated problems, e.g.,
 - reconstruct the surface tension $\gamma(T)$ in problems with phase change
 - “positivity” condition $k(T) > 0$ replaced by the Clausius–Duhem inequality
 - Optimal closure models in RANS and LES

$$\rho \langle \mathbf{u}' \mathbf{u}' \rangle = \nu_T [\nabla \tilde{\mathbf{u}} + (\nabla \tilde{\mathbf{u}})^T]$$

Optimal reconstruction of eddy viscosity: $\nu_T = f(\nabla \tilde{\mathbf{u}})$

References

- V. Bukshynov, O. Volkov, and B. Protas, “On Optimal Reconstruction of Constitutive Relations” *Physica D* **240**, 1228–1244, (2011).
- V. Bukshynov and B. Protas, “Optimal Reconstruction of Material Properties in Complex Multiphysics Phenomena”, (submitted), (2012).
- B. Protas, B. R. Noack and M. Morzyński, “An Optimal Model Identification For Oscillatory Dynamics With A Stable Limit Cycle”, (submitted), (2012)