

Online Parameter Identification in ODEs and PDEs

Philipp Kuegler
Industrial Mathematics Institute and RICAM, Linz, Austria

Problem Statement

- Given a dynamical system

$$u_t = f(u, q_*)$$
$$u(0) = u_0$$

that describes the time evolution of the physical state variable u , e.g.,

- ★ an ODE model from aircraft dynamics
 - ★ a PDE model from heat conduction ■
- and the possibility to perform measurements of

$$z(t) = Hu(t),$$

e.g.,

- ★ observations of airspeed and altitude of the aircraft
- ★ observations of boundary temperatures

- Task: Given an initial guess q_0 at $t = 0$, identify the unknown model parameters q_* , e.g.,
 - ★ lift and drag coefficients
 - ★ heat conductivitysimultaneously to the evolution of the system ■
- Online algorithms become necessary whenever the mathematical model is needed to support decisions that have to be taken during the operation of the real system (adaptive control)

Ill-Posedness

- Parameter identification is typically ill-posed:
 - ★ the solution, if it exists, need not be unique
 - ★ and will not depend continuously on the data z
- Need for regularization methods
 - ★ regularization means to replace the ill-posed problem by a family of neighboring well-posed problems
- Especially crucial for computations in the presence of noisy data!

Basic Sketch of an Online Estimator

- see extra slide

Approaches given in Literature

- **Linear and Finite Dimensional Problems (P. Ioannou, J. Slotine,...):**

Assumption of a linear relation between q_* and observation $z(t)$

$$z(t) = A(t)q_* \text{ with } A(t) \in \mathbb{R}^{m \times n} \blacksquare$$

- **Online Identification in PDEs (J. Baumeister, M. Demetriou,...):**

Estimators exploit particular structures of underlying PDE-operators such that full state observation is necessary, i.e., $z = u$ \blacksquare

- **Continuous extended Kalman filter for nonlinear ODEs (M. Grewal, A. Andrews, ...):**

Estimation of extended state x in

$$x_t = \begin{pmatrix} u_t \\ q_{*t} \end{pmatrix} = \begin{pmatrix} f(u, q_*) \\ 0 \end{pmatrix}$$

from observations of $z(t) = Bx(t) = Hu(t)$

Linear and Finite Dimensional Case

- J. Slotine et al. (2000): Given a linear relation between q_* and observation $z(t)$

$$z(t) = A(t)q_* \blacksquare$$

- Using estimate $q(t)$ at time t , the output can be simulated by

$$z_{\text{sim}}(\tau) = A(\tau)q(t) \text{ for } \tau \leq t \blacksquare$$

- Time-derivative of the first order necessary condition for

$$\int_0^t e^{-\alpha(\tau-t)} \|z(\tau) - z_{\text{sim}}(\tau)\|^2 d\tau \rightarrow \min_{q(t)} \blacksquare$$

- yields the parameter update law

$$\begin{aligned} q_t &= G(t)A(t)^T(z(t) - z_{\text{sim}}(t)), & q(0) &= q_0 \\ G_t &= \alpha G(t) - G(t)A(t)^T A(t)G(t), & G(0) &= G_0 \end{aligned}$$

Persistence of Excitation

- Parameter convergence

$$q(t) \rightarrow q_* \text{ as } t \rightarrow \infty$$

is proven under a so-called persistence of excitation condition

$$\exists \gamma, \beta > 0 \forall t \in \mathbb{R}^+ \int_t^{t+\beta} A(\tau)^T A(\tau) d\tau \geq \gamma I \blacksquare$$

- Signals have to be strong enough in order to generate a rich data set \blacksquare
- Motivation: Consider normal equation

$$A^T(t)A(t)q_* = A^T(t)z(t);$$

if $\int A^T(\tau)A(\tau) d\tau$ is positive definite, then q_* is uniquely determined

Nonlinear and Infinite-Dimensional Case

- Define the nonlinear prediction operator

$$F(\cdot, \tilde{t}) : q \rightarrow z_{\text{sim}}(\tilde{t}) = Hu(\tilde{t}), \blacksquare$$

evaluated via integration up to time \tilde{t} of

$$u_t = f(u, q), \quad u(0) = u_0 \blacksquare$$

- Update law motivated by approach in linear case

$$\begin{aligned} q_t(t) &= G(t)F'(q, t)^*(z(t) - z_{\text{sim}}(t)), \quad q(0) = q_0, \\ G_t(t) &= \alpha(G(t) - G(t)\bar{G}^{-1}G(t)) - G(t)F'(q, t)^*F'(q, t)G(t), \quad G(0) = G_0. \blacksquare \end{aligned}$$

- F' is defined via the linearized dynamical system
- \bar{G} acts as an upper bound for $G(t)$

Convergence Theory

- In case of exact data, convergence

$$q(t) \rightarrow q_* \text{ as } t \rightarrow \infty$$

if persistence of excitation condition

$$\exists \gamma, \beta > 0 \forall t \in \mathbb{R}^+ \int_t^{t+\beta} F'(q, \tau)^* F'(q, \tau) d\tau \geq \gamma I$$

as well as a condition restricting the nonlinearity of F is satisfied ■

- Idea of proof: show that

$$V(e, t) = (G^{-1}(t)e, e)$$

with

$$e(t) = q(t) - q_*$$

is a Lyapunov function

Case of Noisy Data

- Given an error bound for noisy data z^δ

$$\|z^\delta(t) - z(t)\| \leq \delta \text{ for all } t$$

- Dead zone approach

$$q_t = \begin{cases} \text{as for exact data} & \text{if } \|z^\delta(t) - z_{\text{sim}}(t)\| \geq \tau\delta \\ 0 & \text{if } \|z^\delta(t) - z_{\text{sim}}(t)\| < \tau\delta \end{cases}$$

Update of q only if the error between data and prediction lies above the noise level

- Leakage approach

$$q_t(t) = G(t)F'(q, t)^*(z^\delta(t) - z_{\text{sim}}(t)) - \sigma G(q - q_0)$$

enforces q to stay within a neighborhood of q_0

ODE Example

- The longitudinal motion of an aircraft (pitching and translation in the vertical plane) can be described by

$$\begin{aligned}m\dot{V}_T &= F_T \cos(\alpha) - D - mg_D \sin(\theta - \alpha) \\m\dot{\alpha}V_T &= -F_T \sin(\alpha) - L + mg_D \cos(\theta - \alpha) + mV_T Q \\ \dot{\theta} &= Q \\ \dot{Q} &= M/J_Y \\ \dot{h} &= V_T \sin(\theta - \alpha) \blacksquare\end{aligned}$$

- ★ for airspeed V_T , angle of attack α , pitch attitude θ , pitch rate Q and altitude h \blacksquare
- ★ with mass m , thrust F_T , inertia J_Y \blacksquare
- ★ and drag D , lift L and moment M

- Drag, lift and pitching moment are given by

$$D \sim V_T^2 S C_D$$

$$L \sim V_T^2 S C_L$$

$$M \sim V_T^2 S C_M$$

with wing area S , airspeed V_T and aerodynamic coefficients

$$C_{D,L,M} = C_{D,L,M}(\alpha, \text{mach number, thrust, altitude } h, \text{Re} \dots) \blacksquare$$

- Ansatz for aerodynamic coefficients

$$C_L = q_2 + q_1 \alpha$$

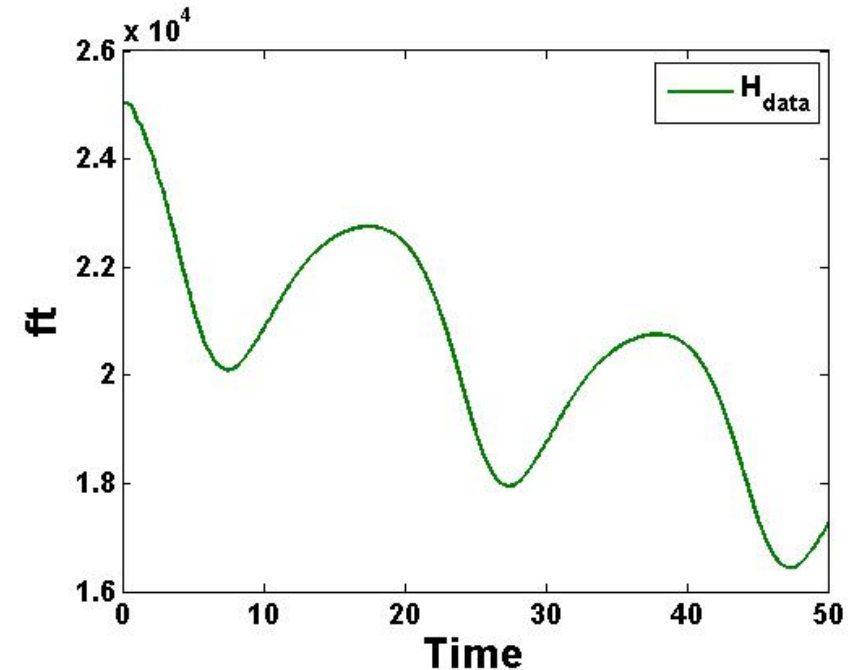
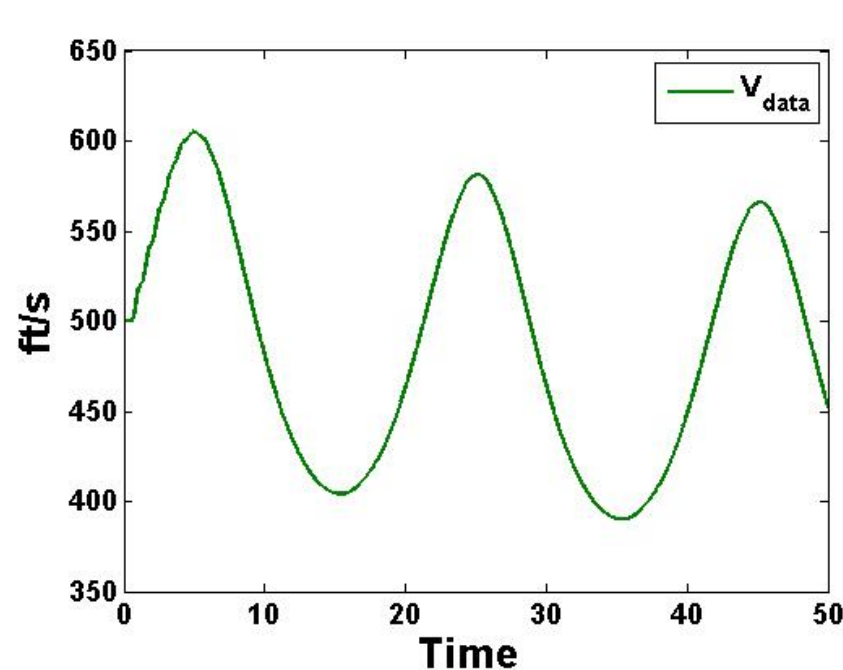
$$C_D = q_3 + C_L^2 \blacksquare$$

- Short form with $u = [V_T, \alpha, \theta, Q, h]$ and $q_* = [q_1, q_2, q_3]$

$$u_t = f(u, q_*)$$

Exact Data

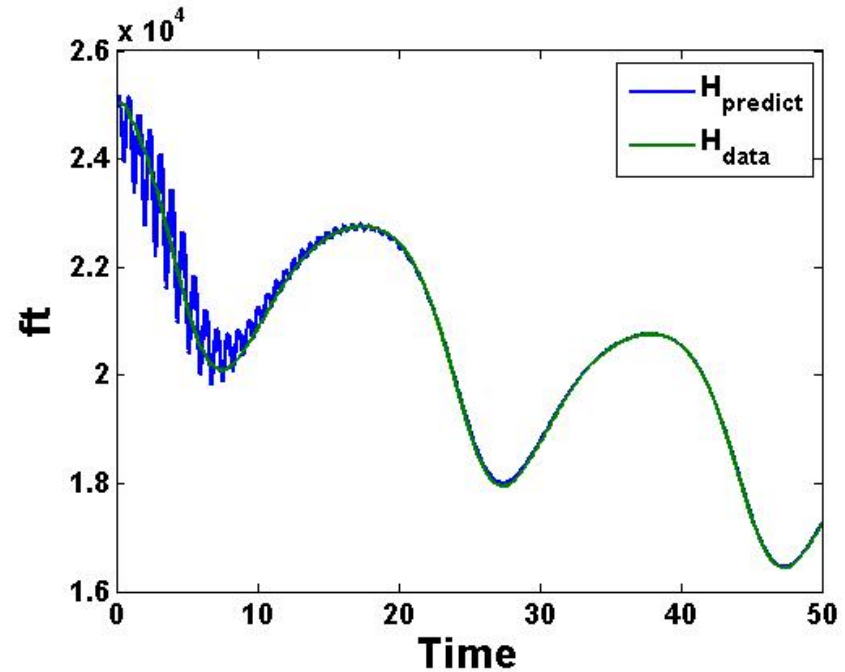
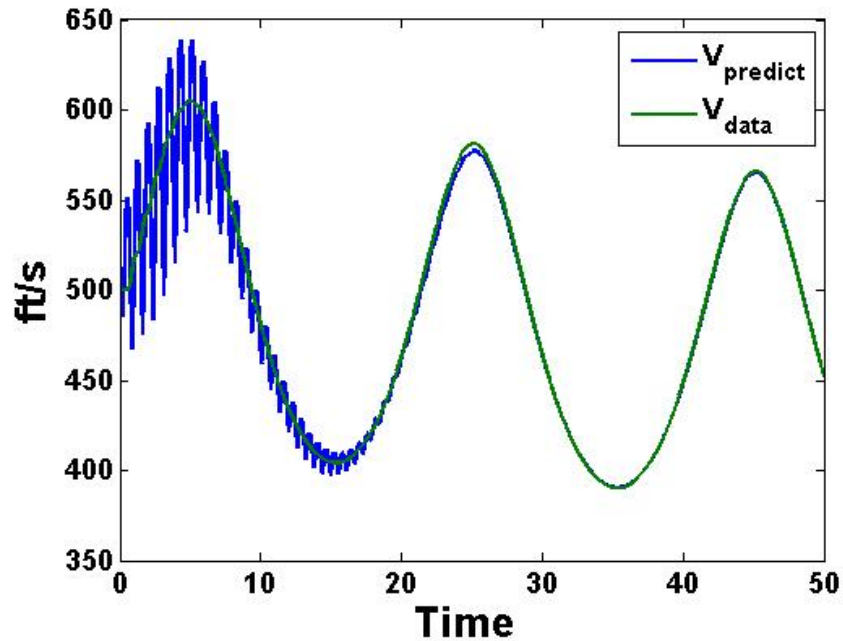
- Measurements of airspeed and altitude



while the aircraft is climbing and falling due to changes in thrust and elevation controllers

- Simulated with true parameter $q_* = [0.85, 1., 1.6]$
- Initial guess q_0 with 25% deviation from q_* in each component

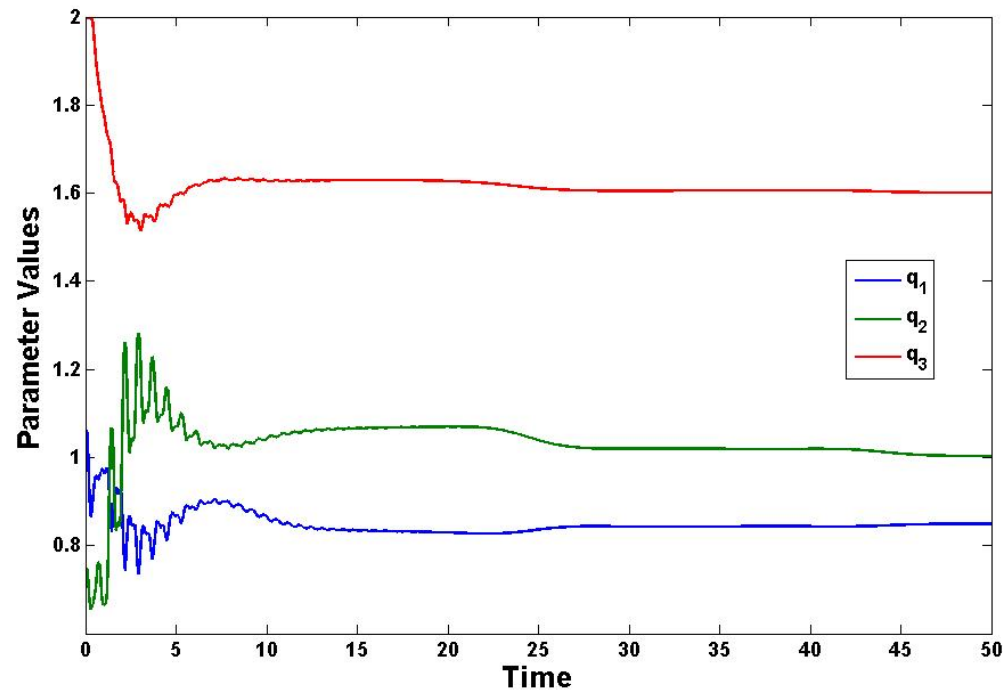
Online Result for Exact Data



- After some time, the simulated output z_{sim} follows the data z
→ data tracking

Online Result for Exact Data

- Data allow for a unique identification



- Parameter convergence, i.e., $q(50) = [0.849, 1.003, 1.6008]$
- Conjecture: persistence of excitation is given

Additional Parameter Component

- Consider

$$C_L = q_2 + q_1\alpha$$

$$C_D = q_3 + C_L^2$$

$$C_M = q_4 + c_1\alpha + c_2C_L$$

with

$$q_* = [0.85, 1, 1.6, 0.5]$$

which gives exactly the same data as before

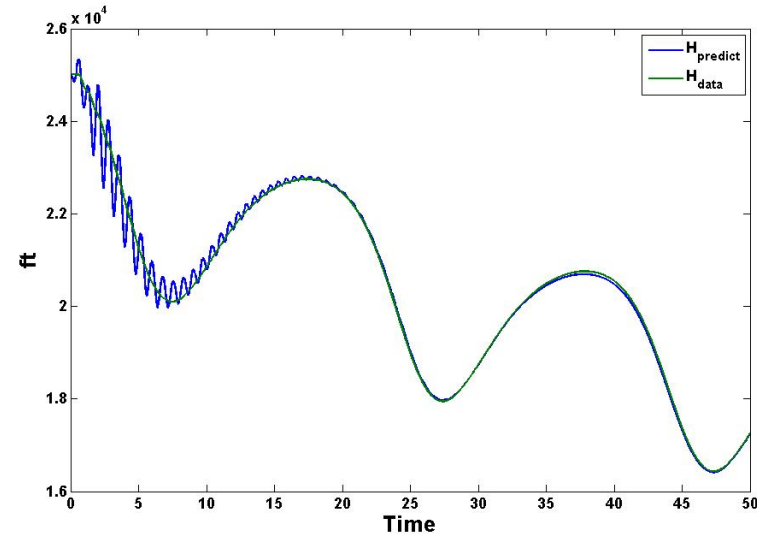
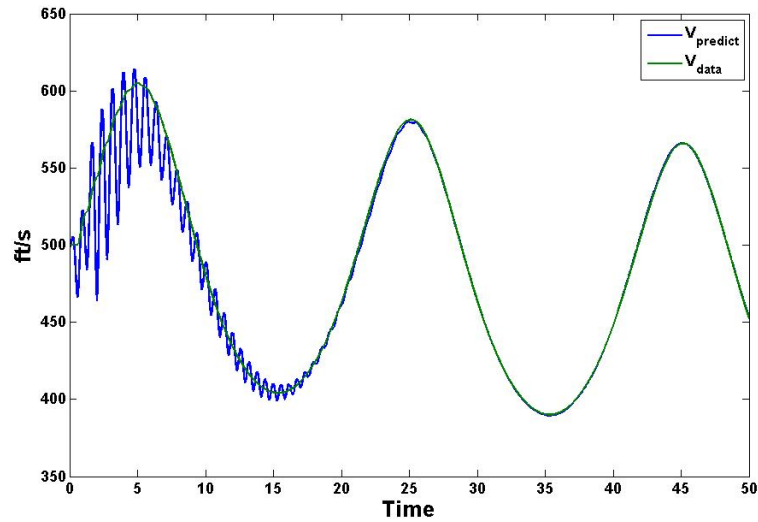
- Offline result for exact data
 - ★ quasi Newton-technique for

$$\|z - F(q)\|^2 \rightarrow \min_q$$

yields $q = [0.8496, 0.8312, 1.5994, 0.5872]$

- Non-uniqueness

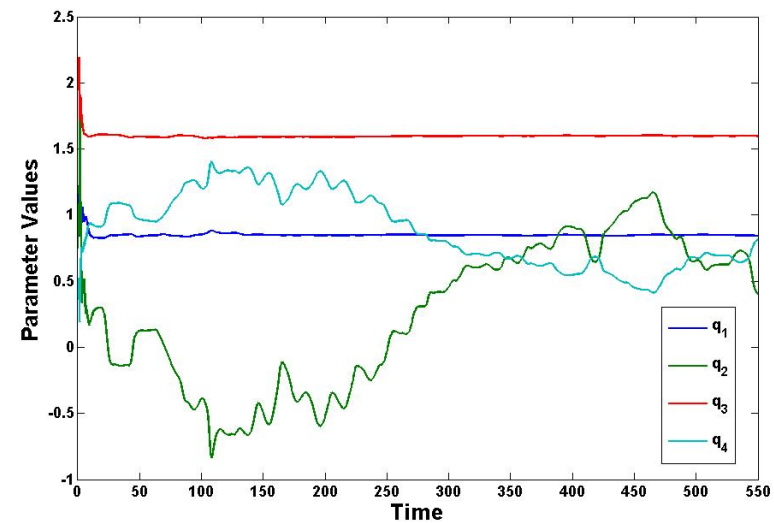
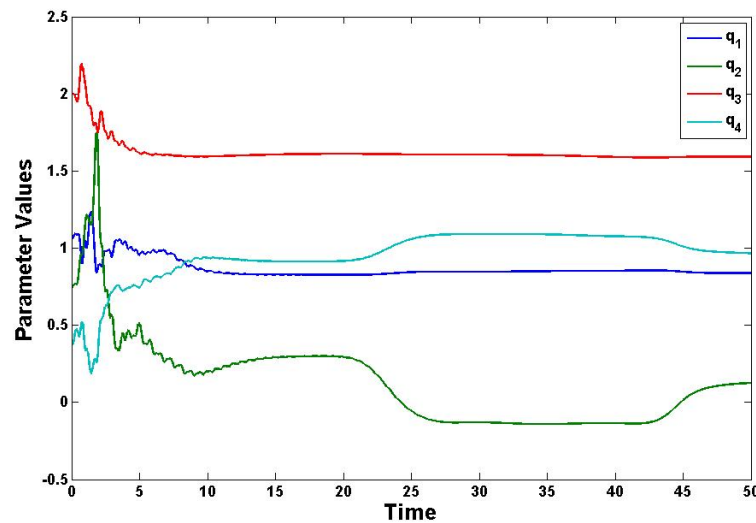
Online Result for Exact Data - Output Space



- Again, tracking property is given

Online Result for Exact Data - Parameter Space

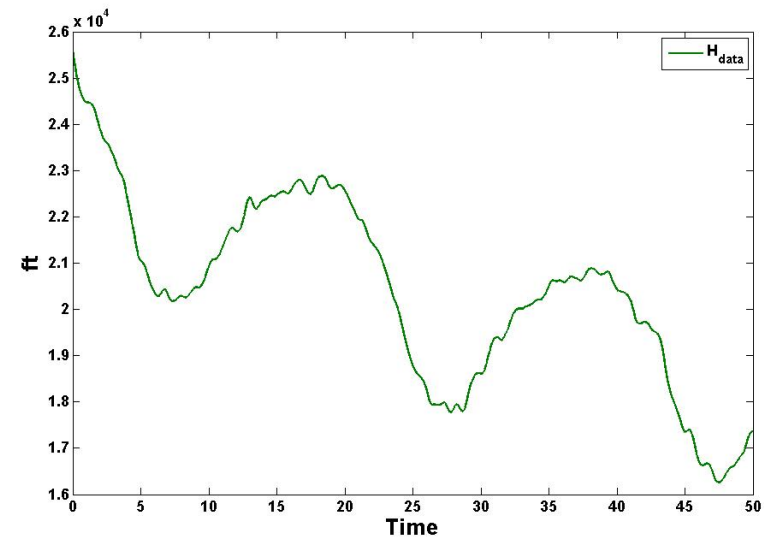
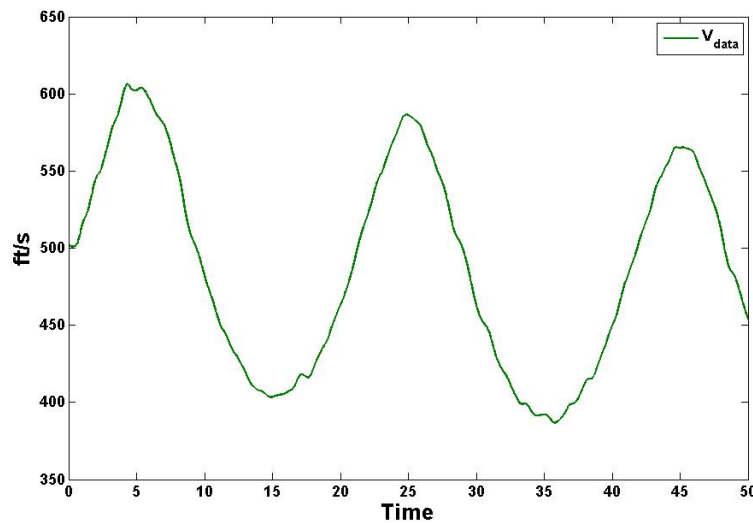
- However, convergence only in two components



- Conjecture: no persistence of excitation

Noisy Data

- Perturbed measurements of airspeed and altitude

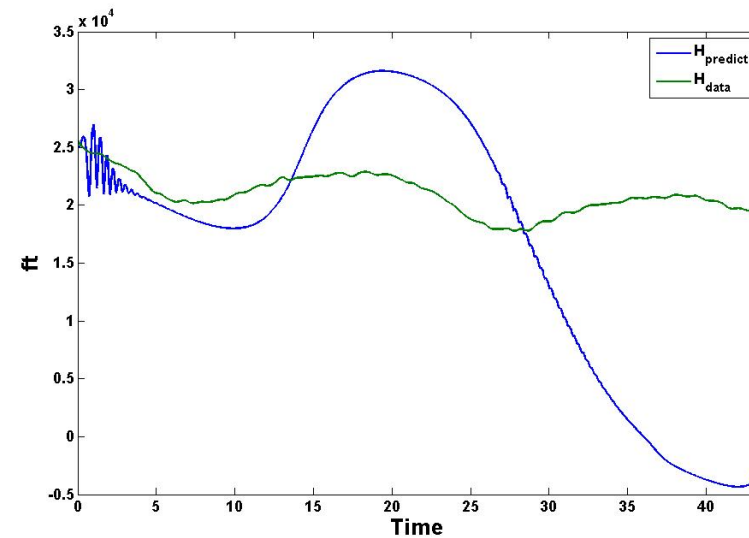
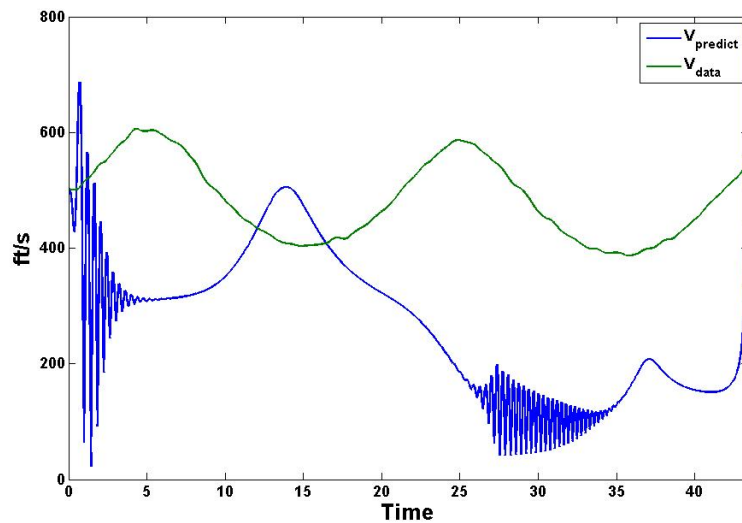


- Error bounds

$$\frac{|z_V^\delta(t) - z_V(t)|}{|z_V(t)|} \leq 0.0142 \quad \text{and} \quad \frac{|z_H^\delta(t) - z_H(t)|}{|z_H(t)|} \leq 0.025$$

Online Result for Noisy Data - Output Space

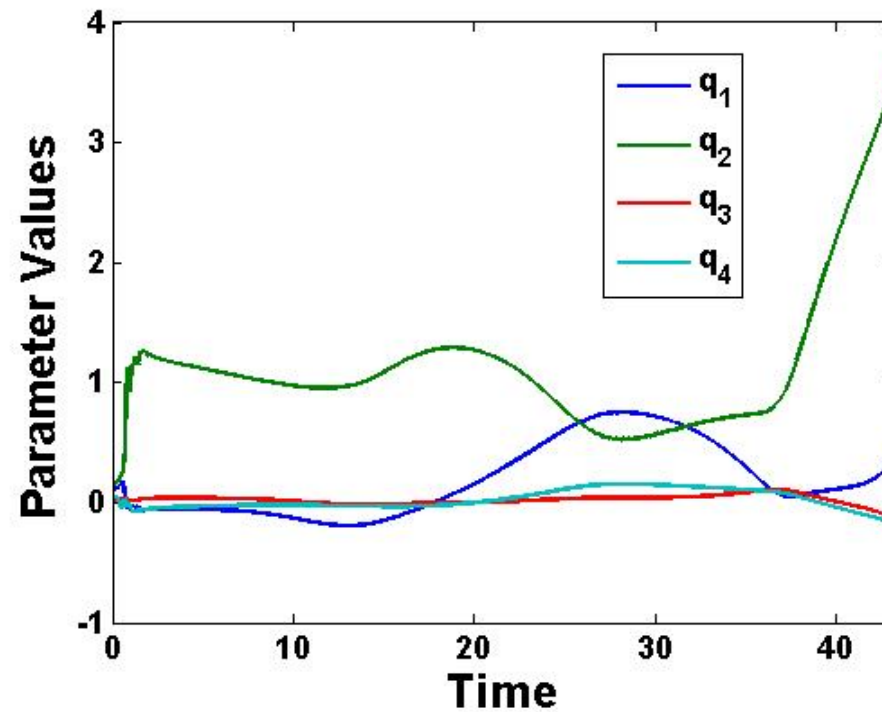
- No regularization



- Data tracking property is lost

Online Result for Noisy Data - Parameter Space

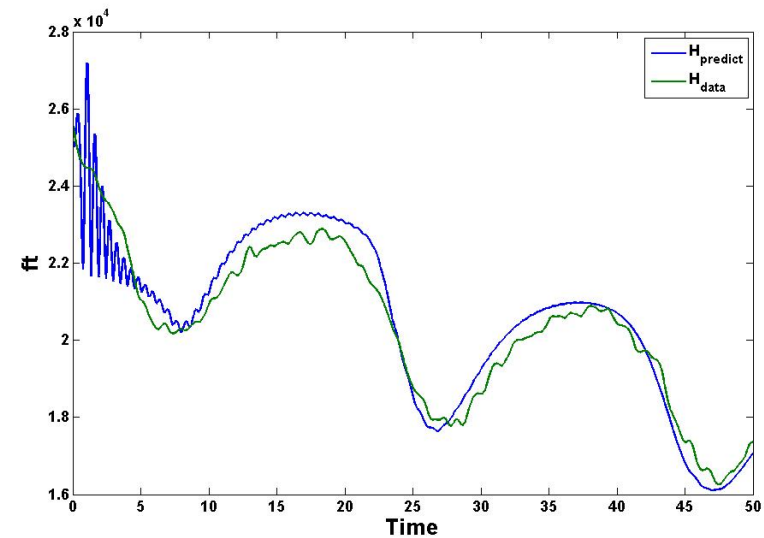
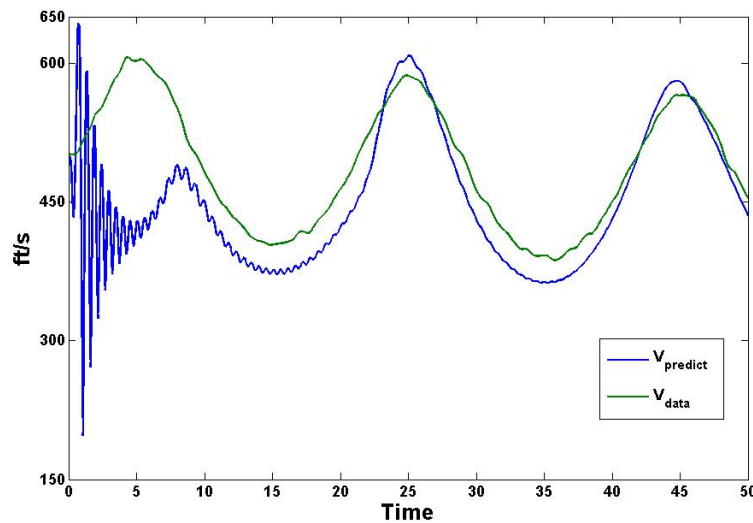
- No regularization



- Parameter divergence

Online Result for Noisy Data - Output Space

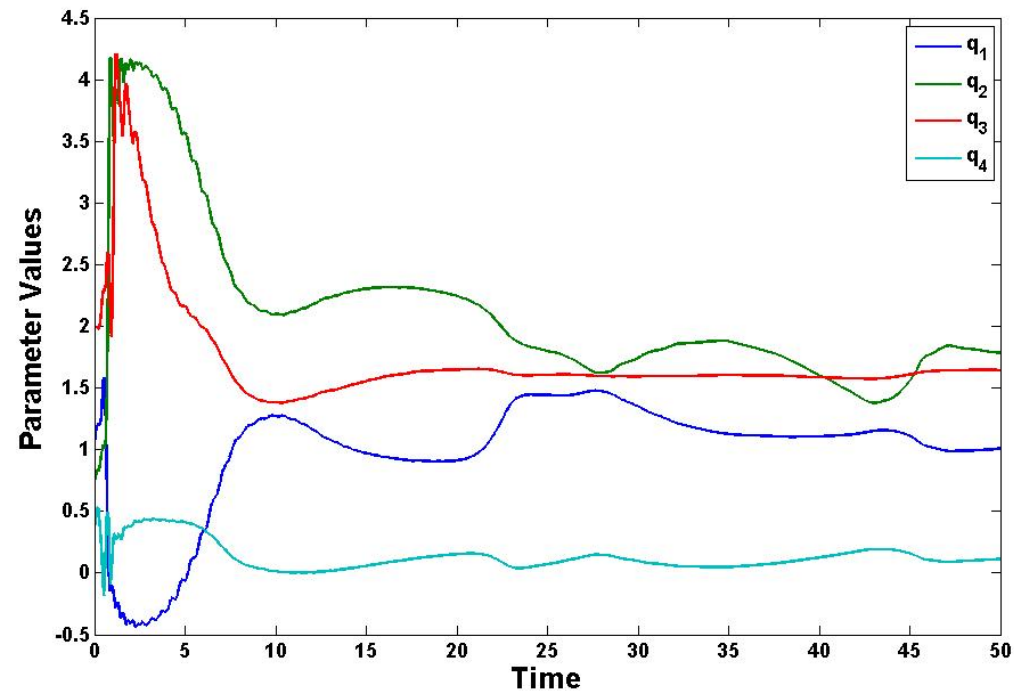
- Use of leakage term



- Data tracking property within certain tolerance restored

Online Result for Noisy Data - Parameter Space

- Use of leakage term



- Parameter divergence is suppressed
- $\hat{q}(t)$ stays in a neighborhood of q^*

PDE-Example

- Consider online identification of the space dependent heat conductivity

$$q_*(x) = 0.1 - 0.05 \sin(2\pi(x - 0.25)), \quad x \in \Omega = (0, 1),$$

in the linear heat equation

$$u_t(x, t) - \nabla(q_*(x)\nabla u(x, t)) = (4 \sin(4\pi t) + 0.001t^2)\chi_{[0.215, 0.315]}$$

$$u(0, t) = u(1, t) = 0$$

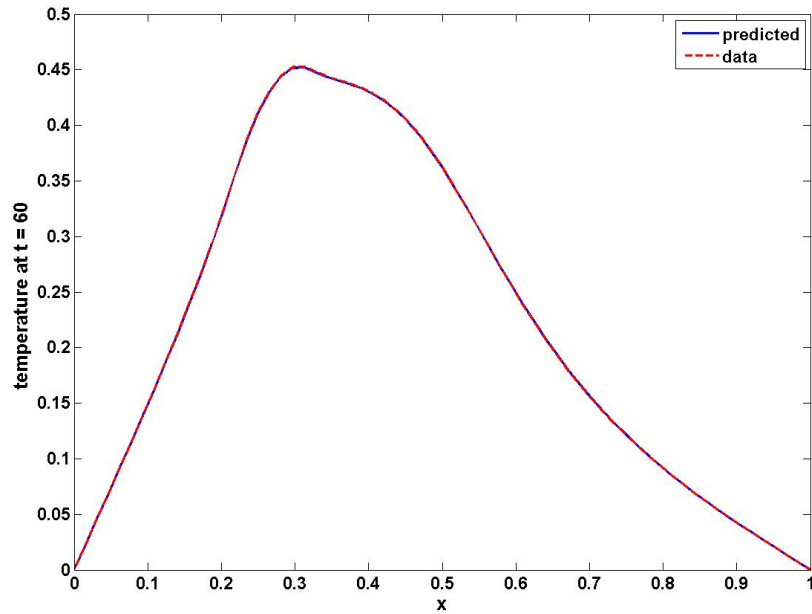
$$u(x, 0) = 0, \blacksquare$$

- the data shall either result from full temperature observations, i.e.,

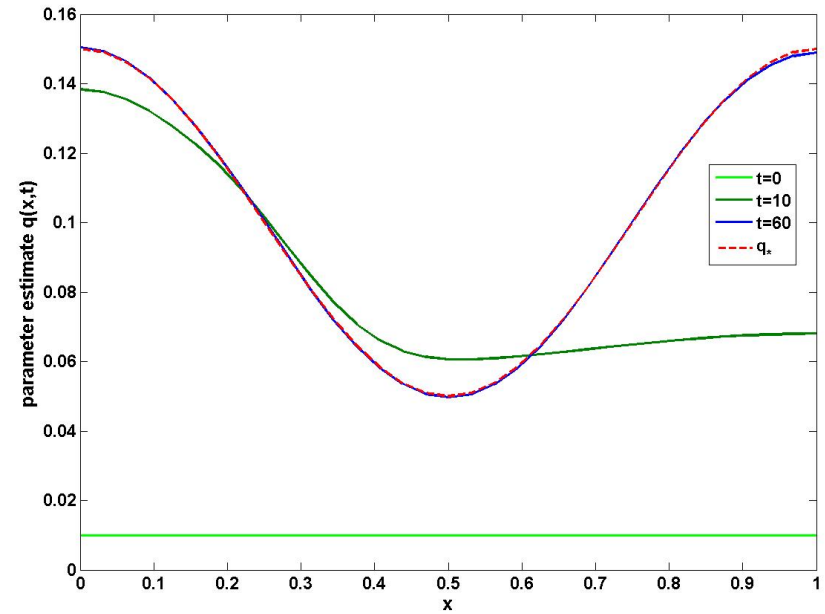
$$z(x, t) = u_{q_*}(x, t), \quad x \in [0, 1], \quad t > 0, \blacksquare$$

or from partial temperature observations on the right half of the domain, i.e.,

$$z(x, t) = u_{q_*}(x, t), \quad x \in [0.5, 1], \quad t > 0,$$

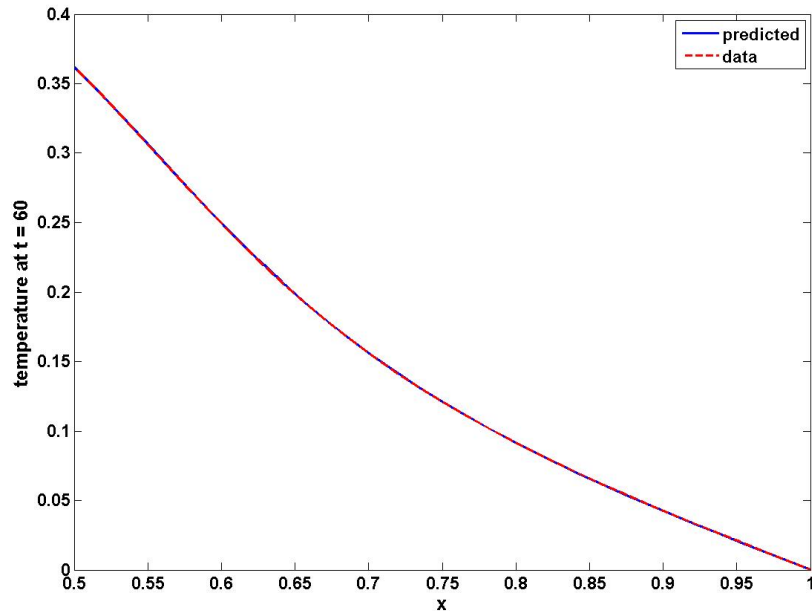


a): data and predicted output at $t = 60$

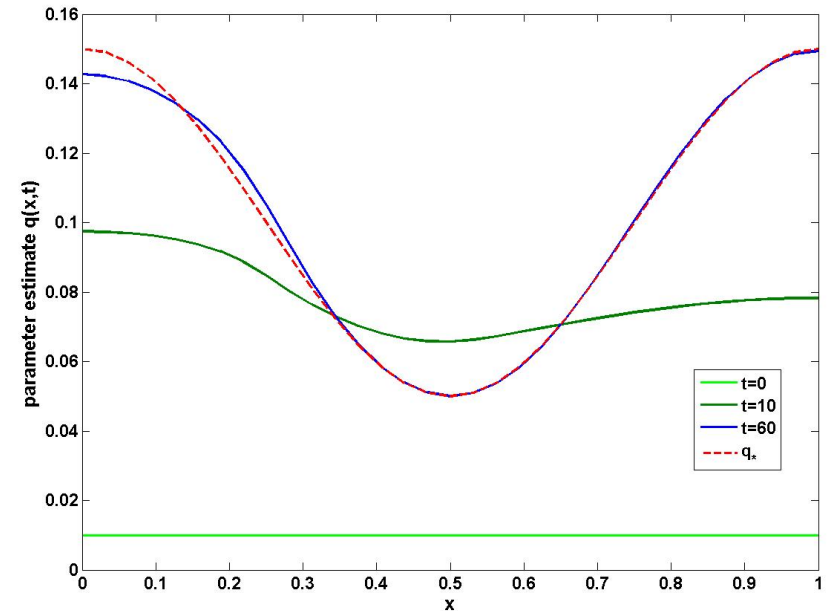


b): $q(x, t_i)$ and $q_*(x)$

full state observation:
 convergence both in output and parameter space

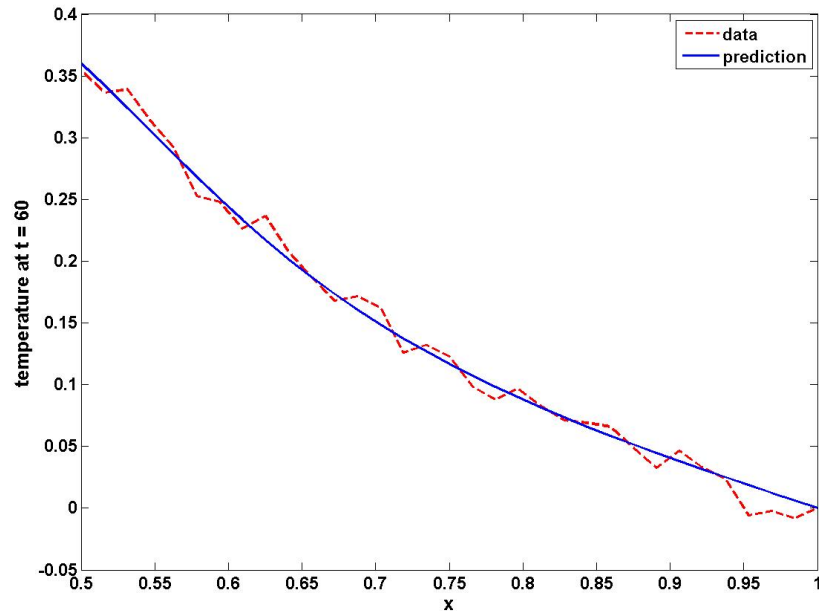


a): data and predicted output at $t = 60$

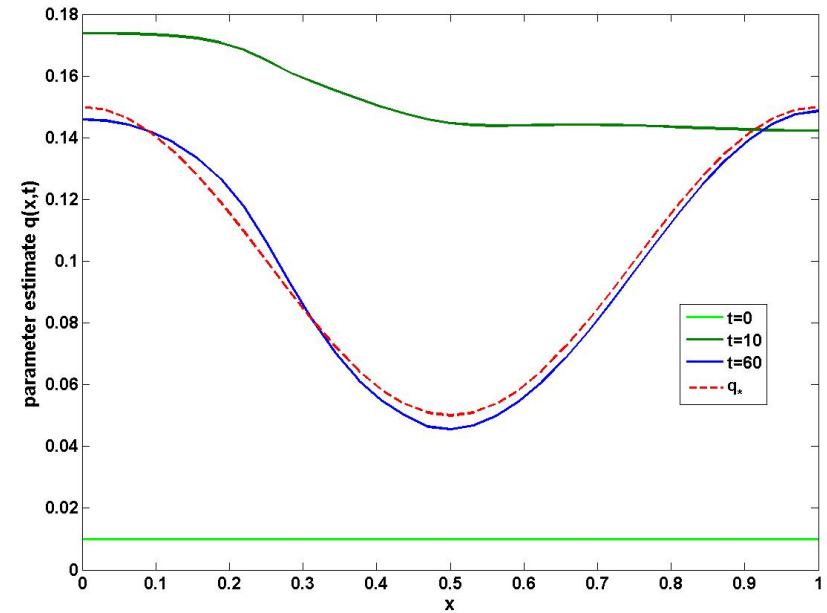


b): $q(x, t_i)$ and $q_*(x)$

partial state observation:
 convergence in output space while parameter convergence in region
 where data are taken



a): data and predicted output at $t = 60$



b): $q(x, t_i)$ and $q_*(x)$

partial state observation:
 stable result in case of noisy data by use of leakage approach

Summary and Future Topics

- We presented a nonlinear operator approach to online parameter identification in dynamical system that
 - ★ is an extension of the linear and finite dimensional approach
 - ★ applies to PDE problems without requiring full state observations ■

- In ODE case, method with $\alpha = 0$ can be understood as a Kalman filter for estimation of q_* in

$$q_{*t} = 0$$

from nonlinear observations $z(t) = F(q_*, t)$

different to extended Kalman filter for estimation of $x = [u \ q]^T$

→ comparison ■

- Choice of parameters of the method in dependence on noise level
- How to ensure/verify persistence of excitation ?
- Link to Kaczmarz type methods ?