Hybrid Algorithms for Parameter Estimation in Static and Dynamical Systems

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- Abrupt changes in the dynamics (changes in the environment,

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Approach:



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Model continuous and discrete behavior using dynamical models that are hybrid.



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How can we systematically design such systems featuring switching and intermittency of information with provable robustness to uncertainties arising in real-world environments?

Approach:

- Model continuous and discrete behavior using dynamical models that are hybrid.
- Develop systematic control theoretical tools for stability, invariance, safety, and temporal logic, with robustness.

Outline of Recent Results



1. Estimation

- Finite-time Parameter Estimation via Hybrid Methods ACC 21a, ACC 21b, ACC 21c (all submitted), + CoE collab
- Observers for Hybrid Systems ACC 20, CDC 19, CDC 20, Automatica (submitted)
- 2. Safety
 - Reachable maps for hybrid systems and regularity HSCC 20, TAC 19, NAHS 20, HSCC 20, CDC 20 (submitted)
 - (Necessary and Sufficient) Safety Certificates, with Events ACC 21a, ACC 21d (submitted), TAC 20 + CoE collab

3. Optimization

- High Performance Optimization via Uniting Control ACC 19, MTNS 20, ACC 20e (submitted) + AFRL/RV collab.
- ► Model Predictive Control for Hybrid Systems ACC 20, CDC 20, IFAC WC 20 Workshop



$$\mathcal{H} \quad \left\{ \begin{array}{rrr} \dot{x} & = & F(x) & \quad x \in C \\ x^+ & = & G(x) & \quad x \in D \end{array} \right.$$

where x is the *state*

- ► C is the *flow set*
- ► F is the *flow map*

- ► *D* is the *jump set*
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Solutions are functions parameterized by hybrid time (t, j):

- Flows parameterized by $t \in \mathbb{R}_{\geq 0} := [0, +\infty)$
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The state x can have logic, memory, and timer components.



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The hybrid system \mathcal{H} satisfies the hybrid basic conditions if C, D are closed and F, G are "continuous"

Linear regression models of the form

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Hybrid methods enable the following:

- Finite-time estimation of θ using a hybrid algorithm that triggers jumps in the estimates
- Asymptotic estimation of θ using a hybrid algorithm for the case when the regressor model or the dynamic model is hybrid

with robustness and safety, under appropriate PE conditions.

Robust Finite-Time Parameter Estimation Using Hybrid Dynamical Systems

Ryan S. Johnson and Ricardo G. Sanfelice

Duke

Hybrid Systems Laboratory University of California, Santa Cruz

October 29, 2020

















- 1. Context and Motivation
 - Preliminaries
 - Problem statement
- 2. A Hybrid Algorithm for Finite-Time Parameter Estimation
 - Hybrid model
 - Main results
 - Numerical examples
- 3. References





Parameter estimation algorithms seek to determine the values of unknown parameters in a dynamical system whose data is partially known.



Parameter estimation algorithms seek to determine the values of unknown parameters in a dynamical system whose data is partially known.

For example, consider the nonlinear system of the form

$$\dot{x} = f(x) + g(x)\theta \tag{1}$$

where $t \mapsto x(t) \in \mathbb{R}^n$ is the known state vector, $f(x) \in \mathbb{R}^n$ and $g(x) \in \mathbb{R}^{n \times p}$ are known continuous functions of the state, and $\theta \in \mathbb{R}^p$ is an unknown vector of parameters.



Assumptions [1-4]

- The unknown parameter vector θ is constant or piecewise constant.
- ► The function g is *persistently exciting*, that is, there exist $\sigma_1, \sigma_2 > 0$ such that for any $t_0 \ge 0$ and any solution $t \mapsto \phi_x(t)$ to (1),

$$\int_{t_0}^{t_0+\sigma_1} g^{\top}(\phi_x(s))g(\phi_x(s))ds \ge \sigma_2 I.$$
(2)

Problem Statement



Problem

Given a nonlinear system of the form

$$\dot{x} = f(x) + g(x)\theta \tag{3}$$

where $t \mapsto x(t) \in \mathbb{R}^n$ is the known state vector, $f(x) \in \mathbb{R}^n$ and $g(x) \in \mathbb{R}^{n \times p}$ are known continuous functions of the state, and $\theta \in \mathbb{R}^p$ is an unknown vector of parameters.

Design a hybrid algorithm to estimate θ in finite-time.





As in [2], we define a state estimate given by

$$\dot{\hat{x}} = f(x) + g(x)\hat{\theta} + k(x - \hat{x}) + wh(x)$$

then the state prediction error $e=x-\hat{x}$ has dynamics

$$\dot{e} = g(x)\tilde{\theta} - k(x - \hat{x}) - wh(x)$$

where $\tilde{\theta}=\theta-\hat{\theta}$ and $\hat{\theta}$ is generated the parameter update law given by

$$\hat{\theta} = \gamma (w^\top + g(x)^\top) (x - \hat{x}) =: h(x).$$

where $\gamma = \gamma^\top > 0.$



Hybrid Modeling

Next, define $t \mapsto \eta(t)$ and $t \mapsto w(t)$ with dynamics

$$\dot{\eta} = -k(x - \hat{x}), \qquad \dot{w} = g(x).$$



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It can be shown that integration of $\dot{\eta}$ over an interval $[t_0, t_1]$ from an initial condition with $\hat{x}_0 = x$, $w_0 = 0$, and $\eta_0 = 0$ yields

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Premultiplying each side of the above by w^{\top} yields

$$w^{\top}\eta = w^{\top}e - w^{\top}w\tilde{\theta}.$$
 (4)



Hybrid Modeling

Then, (4) may be rearranged to solve for $\tilde{\theta}$ as

$$\tilde{\theta} = (w^\top w)^{-1} w^\top (e - \eta) =: \psi$$

Thus, whenever the inverse of $w^\top w$ is well defined, we may solve for θ as

$$\hat{\theta} + \tilde{\theta} = \hat{\theta} + \psi = \theta$$

Closed-loop system

(5)



The hybrid system is denoted $\mathcal{H}=(C,F,D,G)$ with state $z=(x,\hat{x},\hat{\theta},\eta,w)\in\mathcal{X}$ where

- ► *x*: plant state vector
- \hat{x} : plant state vector estimate
- \triangleright $\hat{\theta}$: parameter vector estimate
- ▶ η, w : auxiliary state variables and data

$$\dot{z} \in F(z)$$
 $z \in C$
 $z^+ \in G(z)$ $z \in D$

Closed-loop system



where

$$F(z) := \begin{cases} f(x) + g(x)\theta \\ f(x) + g(x)\hat{\theta} + k(x - \hat{x}) + wh(z) \\ h(z) \\ -k(x - \hat{x}) \\ g(x) \end{cases} \qquad z \in C$$

$$G(z) := (x, x, \theta + \psi, 0, 0) \qquad z \in D$$

$$\psi := (w^{\top}w)^{-1}w^{\top}(x - \hat{x} - \eta)$$

$$C := \{z \in \mathcal{X} : \det(w^{\top}w) \le \varepsilon \}$$

$$D := \{z \in \mathcal{X} : \det(w^{\top}w) \ge \varepsilon \}$$

and $h(z) = \gamma(w^{\top} + g(x)^{\top})(x - \hat{x})$, $k = k_1 + \frac{1}{4}g\gamma g$, $k_1 = k_1^{\top} > 0$, $\gamma > 0$, and $\varepsilon > 0$.

Closed-loop system



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$$F(z) := \begin{cases} f(x) + g(x)\theta \\ f(x) + g(x)\hat{\theta} + k(x - \hat{x}) + wh(z) \\ h(z) \\ -k(x - \hat{x}) \\ g(x) \end{cases} \qquad z \in C$$
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and $h(z) = \gamma(w^{\top} + g(x)^{\top})(x - \hat{x})$, $k = k_1 + \frac{1}{4}g\gamma g$, $k_1 = k_1^{\top} > 0$, $\gamma > 0$, and $\varepsilon > 0$.



Theorem

Suppose g in (3) is persistently exciting as in (2). Consider the hybrid system \mathcal{H} in (5) with

$$h(z) = \gamma(w^{\top} + g(x)^{\top})(x - \hat{x}),$$

$$k = k_1 + \frac{1}{4}g\gamma g, \quad k_1 = k_1^{\top} > 0.$$

and
$$\varepsilon > 0$$
. Then, the set
 $\mathcal{A} = \left\{ z \in \mathcal{X} : \hat{x} = x, \ \hat{\theta} = \theta, \ \eta = 0 \right\}$
(6)

is globally finite time stable for \mathcal{H} .



Proof sketch

To prove this result, we show:

Since g is persistently exciting, the set

$$\mathcal{A}_0 = \{ z \in \mathcal{X} : \eta = 0, w = 0 \}$$

is globally finite-time attractive for \mathcal{H} .



Proof sketch

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• It can be shown that for any $\phi \in S_{\mathcal{H}}$ there exist $\varepsilon > 0$ and $\delta > 0$ such that

$$|\phi(0,0)|_{\mathcal{A}} \leq \delta \implies |\phi(t,j)|_{\mathcal{A}} \leq \varepsilon$$

Thus, the set \mathcal{A} is globally finite time stable for \mathcal{H} .



A parameter estimation algorithm is proposed in [1-2] which provides finite-time estimation of the parameter vector θ in (1). However, this scheme suffers from the following issues:

Issues with current implementation

- The algorithm in [1-2] may require a large amount of memory implement.
- ► The algorithm in [1-2] may take a long time to converge for some functions g(·).

Numerical Example



Example 1.1

Consider the frequency estimation problem for a signal $t \mapsto y(t) = \gamma \sin(\nu t)$ where $\gamma \in \mathbb{R}_{>0}$ is the magnitude and $\nu \in \mathbb{R}_{>0}$ is the frequency. Globally estimate ν from measurements of y.

This problem may be rewritten as the problem of estimating θ for a system with state $x=(x_1,x_2)$ such that $x_1=y$ and $\dot{x}_1=x_2$ and dynamics

$$\dot{x} = Ax + g(x)\theta$$

where

$$A = \begin{bmatrix} 0 & 1 \\ -1 & 0 \end{bmatrix} \qquad \qquad g(x) = \begin{bmatrix} 0 \\ -x_1 \end{bmatrix}$$

and $\theta = \nu^2 - 1$.

Numerical Example





Numerical Example



Example 1.2

Next, consider the problem of estimating $\boldsymbol{\theta}$ for the following perturbed model

$$\dot{x} = Ax + g(x)\theta + d$$

where

$$A = \begin{bmatrix} 0 & 1 \\ -1 & 0 \end{bmatrix} \qquad \qquad g(x) = \begin{bmatrix} 0 \\ -x_1 \end{bmatrix}$$

and d is an unknown perturbation on the state \boldsymbol{x} given by

$$d = \begin{bmatrix} \sin(5t) \\ \cos(5t) \end{bmatrix}.$$



Numerical Example with Noise





Summary:

- We proposed a finite-time estimation algorithm for a class of nonlinear systems.
- The proposed algorithm may provide faster convergence compared to the schemes available in the literature.
- The proposed algorithm utilizes a state vector with > 30% fewer elements compared to schemes in the literature, thereby requiring less memory.

Future work:

Extend the proposed estimation scheme to switched systems and hybrid systems.



Thank You!

- M. Hartman, N. Bauer, and A. R. Teel, "Robust finite-time parameter estimation using a hybrid systems framework," *IEEE Transactions on Automatic Control*, vol. 57, no. 11, pp. 2956–2962, 2012.
- [2] V. Adetola and M. Guay, "Finite-time parameter estimation in adaptive control of nonlinear systems," *IEEE Transactions on Automatic Control*, vol. 53, no. 3, pp. 807–811, 2008.
- [3] Y. Li and R. G. Sanfelice, "Finite time stability of sets for hybrid dynamical systems," *Automatica*, vol. 100, pp. 200–211, 02/2019 2019.
- [4] G. C. Goodwin and R. Payne, *Dynamic System Identification:* Experiment Design and Data Analysis. Academic Press, 1977.
- [5] R. Goebel, R. G. Sanfelice, and A. R. Teel, *Hybrid Dynamical Systems: Modeling, Stability, and Robustness.* Princeton University Press, 2012.