Towards Safe Learning-Based Control

Performance & Constraint Satisfaction under Uncertainties

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Variable speed control of compressors
ABB drives control the compressors of the world's longest gas export pipeline
Performance and Safety
Go Together

no knowledge of safety boundaries

![Graph with time = 0.02 seconds and no knowledge of safety boundaries.]

with knowledge of safety boundaries

![Graph with time = 0.02 seconds and with knowledge of safety boundaries.]

Video courtesy of Kene Akametalu
Variable speed control of compressors

ABB drives control the compressors of the world's longest gas export pipeline.

- Safety
- Performance

Model
- System dynamics
- Constraints
- Computation
The Quest for a Good Model

Model Uncertainty

\[
\dot{x} = f(x, u, t, d) \quad g(x, u, t, d) \leq 0
\]

- **Complexity**
- **External effects**
- **Variation**

[Images of complexity, external effects, and variation]
Optimization-based Control
High Performance for Constrained Systems

\[
\min \sum_{k=0}^{N} l(x(k), u(k)) + g(x(N)) \\
\text{s.t. } x(k+1) = f(x(k), u(k), d(k)) \\
(x(k), u(k)) \in \mathbb{X}
\]
Optimization-based Control
High Performance for Constrained Systems

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\]

- High performance
- Recursive constraint satisfaction
- Stability by design
- Automatic synthesis

Rely on system model
Automatic Synthesis
Of High Performance, Safe Controllers

Specifications + Online data

Learning & Controller

Software/Implementation

Performance & Safety

Dynamical System

Online data

Learning-based controller

Environment

Human

control input

measurements
Previous Work
Real-time Constraints in Optimization-based Control

- Real-time model predictive control [Zeilinger et al., 2008 – 2014]
- High-speed, certified optimization [Domahidi, Z. et al., 2012; Pu, Z. et al., 2014, 2016]

$$\begin{align*}
\min_{k=0}^{N} & \  l(x(k), u(k)) + g(x(N)) \\
\text{s.t.} \ & \ x(k+1) = f(x(k), u(k), d(k)) \\
& \ (x(k), u(k)) \in X
\end{align*}$$
Outline

This talk:

1. Learning for performance: Tailoring optimal controllers online
2. Safety guarantees: Constraint satisfaction for any performance controller
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2. Safety guarantees: Constraint satisfaction for any performance controller

\[
\min \sum_{k=0}^{N} l(x(k), u(k)) + g(x(N))
\]

s.t. \( x(k+1) = f(x(k), u(k), d(k)) \), \( (x(k), u(k)) \in \mathbb{X} \)

How to predict complex behavior, quantify & reduce uncertainties?
Quantifying Uncertain Predictions From Online Data

Infer function $d(t)$ online:

- Measured states: $\{x(t_k)\}_{k=0}^{K}$
- Applied inputs: $\{u(t_k)\}_{k=0}^{K}$

Dynamical Model

Regression

Inferred function $\hat{d}(t)$

\[ x(k + 1) = f(x(k), u(k), d(k)) \]

E.g., $x(k + 1)$

\[ = f(x(k), u(k)) + d(x, u, k) \]
Quantifying Uncertain Predictions From Online Data Using Gaussian Process Regression

Infer function $d(t)$ online:

- Measured states: $\{x(t_k)\}_{k=0}^K$
- Applied inputs: $\{u(t_k)\}_{k=0}^K$

Dynamical Model:

$x(k + 1) = f(x(k), u(k), d(k))$

GP Regression:

Estimated:

$\{\tilde{d}(t_k)\}_{k=0}^K$

Predictive distribution:

$\hat{d}(t)$

GP prior:

- Mean + covariance function

Mean function: $\bar{d}(t)$

Variance: $\sigma_d^2(t)$
Quantifying Uncertain Predictions From Online Data Using Gaussian Process Regression

Infer function $d(t)$ online:

- Measured states: $\{x(t_k)\}_{k=0}^{K}$
- Applied inputs: $\{u(t_k)\}_{k=0}^{K}$
- Estimated function: $\{\tilde{d}(t_k)\}_{k=0}^{K}$
- Mean function: $\bar{d}(t)$
- Variance: $\sigma_d^2(t)$

Dynamical Model:

$$x(k + 1) = f(x(k), u(k), d(k))$$

GP Regression:

GP prior: mean + covariance fn

$\Rightarrow$ Predictive distribution

Examples:

- Mechanical errors
- Prediction of loads, efficiencies etc. in energy systems
- Unknown nonlinear dynamics (e.g. ground effects)
Example:
Telescope Guiding

Photograph by Robert Vanderbei, La Palma, 2012
Infer function $d(t)$ online:

- Measured states: $\{x(t_k)\}_{k=0}^{K}$
- Applied inputs: $\{u(t_k)\}_{k=0}^{K}$

**Dynamical Model**

\[
x(k + 1) = Ax(k) + Bu(k) + d(k)
\]

linear system + gear effect

**GP Regression**

\[
\{\tilde{d}(t_k)\}_{k=0}^{K}
\]

estimated

mean function $\tilde{d}(t)$

variance $\sigma^2_d(t)$

Gaussian Process regression with ‘weakly periodic’ kernel
Comparison to State of the Art
Open Source Software PHD Guiding by Edgar Klenske

Tracking Algorithm of PHD2 Guiding 2.5.0

Tracking with GP Prediction

RMS(error) = 0.4174

26% reduction

RMS(error) = 0.3080

Currently own branch on github.com/OpenPHDG Guiding/phd2
Tracking in “Darkness”
Robustness through Improved Predictions

![Graph showing accumulated gear error RA over time](image)
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2. Safety guarantees: Constraint satisfaction for any performance controller

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\begin{align*}
\min_{k=0}^{N} \sum_{k=0}^{N} l(x(k), u(k)) + g(x(N)) \\
\text{s.t. } x(k + 1) = f(x(k), u(k), d(k)) \\
(x(k), u(k)) \in \mathbb{X}
\end{align*}
\]
The Issue of The Transient
An Example

What if we have to learn while satisfying constraints?

Stanford Autonomous Helicopter – Tic-toc learning from scratch
[Abbeel, Coates, Quigley, Ng, NIPS 2007]

Transients make system traverse through unsafe behavior

Goal: Safe online learning in control
Safety Guarantees
Invariance & Stability

Model: \( \dot{x}(t) = f(x(t), u(t)) \)
states \( x \in \mathcal{X} \), inputs \( u \in \mathcal{U} \)

**Constraint satisfaction**
Satisfy constraints now & in future

→ Utilize feasible, invariant set

\[ \mathcal{O} = \{ x \in \mathbb{R}^n \mid \exists u(\cdot) \in \mathcal{U}_t \} \]

s.t. \( \forall \tau \in [0, \infty) \),

\( \phi(\tau; x, t, u(\cdot)) \in \mathcal{X} \)

**Stability**
Control system to output target

→ Show Lyapunov function

\( V(x) \) positive definite, bounded

\( \dot{V}(x) \leq -\alpha(|x|) \forall x \in \mathcal{X} \)
Safety Guarantees
Invariance & Stability for Uncertain Systems

Model: \( \dot{x}(t) = f(x(t), u(t), d(t)) \)
states \( x \in X \), inputs \( u \in U \), disturbances \( d \in D \)

**Robust Invariance**

Satisfy constraints now & in future

→ Utilize feasible, robust invariant set

\[ \mathcal{O} = \{ x \in \mathbb{R}^n \mid \exists u(\cdot) \in U_t \}
\]
s.t. \( \forall \tau \in [0, \infty), \forall d(\cdot) \in D_t \)

\[ \phi(\tau; x, t, u(\cdot), d(\cdot)) \in X \}\]

**Input-to-State Stability (ISS)**

Control system to output target

→ Show ISS Lyapunov function

\[ V(x) \text{ positive definite, bounded} \]

\[ \dot{V}(x, d) \leq -\alpha(|x|) + \gamma(|d|) \]

\( \forall x \in X, d \in D \)

Alternative: Constraint relaxation

→ Soft constraints with stability guarantees

[Zeilinger et al., TAC 2014]
Safety Guarantees
Invariance & Stability for Uncertain Systems

Robust Invariance
Satisfy constraints now & in future

→ Utilize feasible, robust invariant set

\[ \mathcal{O} = \{ x \in \mathbb{R}^n \mid \exists u(\cdot) \in U_t \}
\]
\[ s.t. \ \forall \tau \in [0, \infty), \forall d(\cdot) \in D_t \]
\[ \phi(\tau; x, t, u(\cdot), d(\cdot)) \in \mathcal{X} \}

Input-to-State Stability (ISS)
Control system to output target

→ Show ISS Lyapunov function

\[ V(x) \] positive definite, bounded
\[ \dot{V}(x, d) \leq -\alpha(|x|) + \gamma(|d|) \]
\[ \forall x \in \mathcal{X}, d \in D \]

Invariant set is based on system model

→ Common practice: Use conservative bound on model uncertainties

→ Small safe set restricts performance
Quantifying Model Uncertainties
Using Gaussian Process Regression

Infer disturbance function \( d(x) \) online:

\[
\dot{x} = f(x, u, d(x))
\]

\[
\hat{D}(x) = [\bar{d}(x) - m\sigma_d(x), \bar{d}(x) + m\sigma_d(x)]
\]

\( m \) chosen according to desired probability \( p \)
(e.g. \( m=3 \) for \( p=99.7\% \))
Safety Based on Robust Invariance

Main Idea

Goal: Guarantee safety for any online controller

Idea: Utilize robust invariant safe set

Example:
Quadrotor tracking up and down reference (e.g. pick-up task)

\[ \dot{x} = f(x, u) + d(x) \]

states: vertical position velocity
control: thrust
model: uncertainty
Safety Based on Reachability

Main Idea

Goal: Guarantee safety for any online controller

Idea: Utilize robust invariant safe set

1. **Inside:** Apply performance controller
2. **On boundary:** Apply safety controller

→ Control law: \( u = \begin{cases} u^P(x), & \text{if } x \text{ inside} \\ u^S(x), & \text{otherwise} \end{cases} \)

→ Guaranteed constraint satisfaction, if model captures true system dynamics

[Gillula & Tomlin, ICRA 2012]
Safety Based on Reachability and Online Model Validation

Goal: Leverage online data to improve performance and safety properties

Idea: Utilize robust invariant safe set

1. Learn model from online data and compute safe set
2. On boundary: Apply safety controller
3. Inside: Apply performance controller

\[
\dot{x} = f(x, u) + d_1(x)
\]
\[
d_1(x) \in \mathcal{D}_1(x)
\]
Safety Based on Reachability and Online Model Validation

Goal: Leverage online data to improve performance and safety properties

Idea: Utilize robust invariant safe set

1. Learn model from online data and compute safe set
2. On boundary: Apply safety controller
3. Inside: Apply performance controller

\[
\dot{x} = f(x, u) + d_2(x), \quad d_2(x) \in D_2(x)
\]

[Akametalu, Fernandez-Fisac, Zeilinger, Tomlin CDC 2014]
Safety Based on Reachability and Online Model Validation

Goal: Leverage online data to improve performance and safety properties

Idea: Utilize robust invariant safe set

1. Learn model from online data and compute safe set

2. On boundary: Apply safety controller

3. Inside: Check confidence in model
   - If confident: Apply performance-maximizing controller
   - If unconfident: Contract safe set and apply safety controller

\[
\dot{x} = f(x, u) + d_2(x) \\
D_2(x) \subseteq \mathcal{D}_2(x)
\]

[Jayakumar, Fernandez-Fisac, Zeilinger, Tomlin CDC 2014]
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[ Akametalu, Fernandez-Fisac, Zeilinger, Tomlin CDC 2014 ]
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Safety by combining learning and control theoretic techniques

[Akametalu, Fernandez-Fisac, Zeilinger, Tomlin CDC 2014]
Reaction to Incorrect Model
With Model Validation, No Re-computation of Safe Set

No online validation

Online disturbance validation

Detect unmodeled disturbance
→ Contract safe set
→ Wait for recomputation of safe set
Safe Online Learning
With Model Learning and Validation

Initial **Inaccurate** Improved

- First updated model is invalid
- Method detects inconsistency, slightly contracts safe set
- Improved tracking after next model update

System never leaves converged safe set
Safety Based on Reachability and Online Model Validation

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Safety by combining learning and control theoretic techniques

[ Akametalu, Fernandez-Fisac, Zeilinger, Tomlin CDC 2014]
The Safe Set

Hamilton-Jacobi-Isaacs Formulation

Stay in $\mathcal{K}$:
Control $u$ vs. disturbance $d$

Goal: Compute safe set
= maximum robust control invariant subset

Model: $\dot{x} = f(x, u, d)$  $u \in \mathcal{U}, d \in \mathcal{D}$

Constraint Set $\mathcal{K}$
The Safe Set

Hamilton-Jacobi-Isaacs Formulation

Stay in $\mathcal{K}$:
Control $u$ vs. disturbance $d$

$l(x)$: positive in set
and negative otherwise

Modified HJI equation:

$$\frac{\partial J(x, t)}{\partial t} = - \min \left\{ 0, \max_{u \in \mathcal{U}} \min_{d \in \mathcal{D}} \frac{\partial J(x, t)}{\partial x}^T f(x, u, d) \right\}$$

$$J(x, \emptyset) = l(x)$$

Safe Set:

$$\{ x : J(x) \geq 0 \}$$

= Largest robust control invariant set
= Set of states for which disturbance cannot win!

Model:

$$\dot{x} = f(x, u, d) \quad u \in \mathcal{U}, d \in \mathcal{D}$$

$J(x)$

$\mathcal{K}$

Constraint Set

$\emptyset$

Safe Set

$\mathcal{D}$

$\mathcal{U}$

$\emptyset$

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The Safe Set

Hamilton-Jacobi-Isaacs Formulation

Stay in $\mathcal{K}$:
Control $u$ vs. disturbance $d$

$l(x) :$ positive in set
and negative otherwise

Modified HJI equation:

$$\frac{\partial J(x, t)}{\partial t} = -\min \left\{ 0, \max_{u \in \mathcal{U}} \min_{d \in \mathcal{D}} \frac{\partial J(x, t)^T}{\partial x} f(x, u, d) \right\}$$

$J(x, \emptyset) = l(x)$

Safe Set: $\{ x : J(x) \geq 0 \}$
= Largest robust control invariant set
= Set of states for which disturbance cannot win!

Safety controller: $u^s(x) = \arg \max_{u \in \mathcal{U}} \min_{d \in \mathcal{D}} \frac{\partial J(x)^T}{\partial x} f(x, u, d)$

[Mitchell, Bayen, Tomlin, TAC 2005]
Safety Based on Reachability and Online Model Validation

Goal: Leverage online data to improve performance and safety properties

Idea: Utilize robust invariant safe set

1. **Learn** model from online data and compute safe set
2. **On boundary:** Apply safety controller
3. **Inside:** Check confidence in model
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Safety by combining learning and control theoretic techniques

[ Akametalu, Fernandez-Fisac, Zeilinger, Tomlin CDC 2014]
Benefit of HJI Formulation
Infinite Number of Invariant Sets

\[
\frac{\partial J(x, t)}{\partial t} = - \min \left\{ 0, \max_{u \in \mathcal{U}} \min_{d \in \mathcal{D}} \frac{\partial J(x, t)}{\partial x}^T f(x, u, d) \right\}
\]

Safe Set: \( \{ x : J(x) \geq 0 \} \)

Lemma:

Any nonnegative superlevel set of \( J(x) \), i.e. \( \{ x \mid J(x) \geq \alpha, \alpha \geq 0 \} \), is robust control invariant w.r.t. \( d \in \mathcal{D} \)
Safety Strategy with Online Model Validation

Given: $\hat{D}(x), J(x)$

- **Initialize:**
  - Active safe set = biggest candidate set
  - Critical level $J_L = 0$

- **At each time step:**
  - Check confidence in $\hat{D}(x)$
  - If not confident:
    - $J_L = \max\{J(x), J_L\}$
  - Contract safe set to include current state

- **Control law**
  
  $u = \begin{cases} 
  u^p(x), & \text{if } J(x) > J_L \\
  u^s(x), & \text{otherwise}
  \end{cases}$

  Standard: $J(x) > 0$
Safety Strategy with Online Model Validation

Given: \( \hat{D}(x), J(x) \)

- Initialize:
  \[ \text{Active safe set} = \text{biggest candidate set} \]
  \[ \rightarrow \text{Critical level } J_L = 0 \]

- At each time step:
  Check confidence in \( \hat{D}(x) \)
  If not confident:
  \[ J_L = \max\{J(x), J_L\} \]

  Contract safe set to include current state

- Control law
  \[ u = \begin{cases} 
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  - \( u = \begin{cases} 
  u^p(x), & \text{if } J(x) > J_L \\
  u^s(x), & \text{otherwise} 
  \end{cases} \)
Safety Strategy with Online Model Validation

Global Guarantees

Theorem:
If for some state $z$ the model confidence is low and $\exists J_S \in [0, J(z)]$ such that $d(x) \in \hat{D}(x) \ \forall x \in \{x|J(x) = J_S\}$, then the control law is guaranteed to keep the state within the constraints at all times.

Intuitively:
Safety guaranteed, if there exists some superlevel set, such that disturbance is captured on its boundary

[Akametalu, Fernandez-Fisac, Zeilinger, Tomlin CDC 2014]
Safety

A First Experiment with Humans

Safer to stay above this altitude

Model inconsistency
Summary

Performance & Safety for Learning-based Control

- Online model learning provides automatic enhancement of prediction & controller performance
  → Important to characterize residual uncertainty

  \[\text{[Klenske et al., TCST 2015]}\]

- Invariant sets provide safe exploration space, but require system model

- Model validation critical when learning online
  → Iteratively identify safe set

  \[\text{[Akametalu, Fisac et al., CDC 2014]}\]

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