

Nonlinear and Switched Systems: Geometric Motion Planning, Non-monotonic Lyapunov Functions and Input-to-State Stability

Final Exam

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1 Motion planning via geometric approach

- Review
- Motion planning for systems with drift
- Extensions

2 Stability analysis via non-monotonic Lyapunov function

- Review
- Show ISS via almost Lyapunov functions
- Show ISS via higher order derivatives of Lyapunov functions

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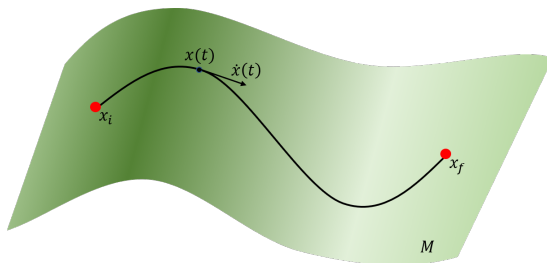
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Motion planning problem

Given a system

$$\dot{x} = f(x, u) \quad (1)$$

and two points $x_i, x_f \in M$, find a control $u^*(t)$ that steers the system from x_i to x_f in T units of time.



- Motion planning has been widely studied (see, e.g., [Laumond, 1998], [LaValle, 2006])
- One of the early control papers which addresses the issue of motion planning for non-holonomic systems is [Brockett, 1982], where motion planning is stated as a **sub-Riemannian geodesic** problem. See also the monograph [Jean, 2014] for a recent survey of this line of work.
- Other motion planning methods include but are not limited to LQR-tree method [Tedrake et al., 2010], sum-of-square techniques [Majumdar and Tedrake, 2013], motion primitives [Murphey, 2006] [Woodruff and Lynch, 2017], random sampling-based [Karaman and Frazzoli, 2011], graph-based [Kuffner et al., 2003] and optimization-based approaches [Dai et al., 2014], etc.

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Difficulties in motion planning

- non-holonomic dynamics,
- drift,
- constraints on the inputs/states.

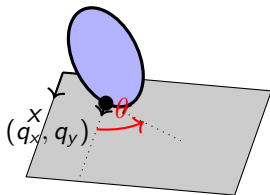
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“Deforming” a curve in order to make it feasible.



$$\underbrace{\begin{pmatrix} \dot{q}_x \\ \dot{q}_y \\ \dot{\theta} \end{pmatrix}}_{\dot{x}} = \underbrace{\begin{pmatrix} \cos \theta \\ \sin \theta \\ 0 \end{pmatrix}}_{f_1} u_1 + \underbrace{\begin{pmatrix} 0 \\ 0 \\ 1 \end{pmatrix}}_{f_2} u_2. \quad (2)$$

“Deforming” a curve in order to minimize its “length”.

- What is “length”? Answer: **Riemannian metric** – encodes dynamics, constraints, etc.
- How to “deform”? Answer: **Homotopies** – achieved by solving PDEs.

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Riemannian metric

- A Riemannian metric on M is a family of positive definite matrices $G(x), x \in M$.
- A curve on M has length $\mathcal{L} = \int_0^T \sqrt{\dot{x}^\top G(x) \dot{x}} dt$ w.r.t. Riemannian metric G . e.g., identity matrix $G(x) \equiv I$ gives usual Euclidean length.
- Consider the driftless system affine in control

$$\dot{x} = F(x)u \quad (3)$$

To encode non-holonomic constraints, we set

$$G(x) = (\bar{F}(x)^{-1})^\top D \bar{F}(x)^{-1},$$

where $D = \text{diag}(\underbrace{\lambda, \dots, \lambda}_{n-m}, \underbrace{1, \dots, 1}_m)$ for some large $\lambda > 0$ and

$\bar{F}(x) = (F_c(x) | F(x)) \in \mathbb{R}^{n \times n}$ so that it is full rank.

- $\dot{x}^\top G(x) \dot{x} \approx \left(|\mathbf{P}_{\mathcal{F}} \dot{x}|^2 + \lambda |\mathbf{P}_{\mathcal{F}^\perp} \dot{x}|^2 \right)$

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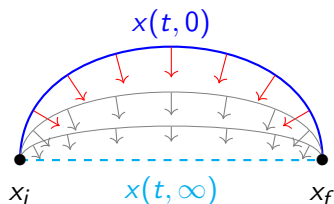
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Geometric heat flow (GHF)

For the driftless system (3),

$$\frac{\partial x(t, s)}{\partial s} = \nabla_{\dot{x}(t, s)} \dot{x}(t, s) \quad (4)$$

yields a curve of minimal length when $s \rightarrow \infty$ [Jost, 1995].



$$\nabla_f g := \frac{df}{dt} + \sum_{i,j,k} \Gamma_{ij}^k f_i g_j e^k,$$

$$\Gamma_{jk}^i(x) := \frac{1}{2} \sum_l (G^{-1})_{il} \left(\frac{\partial G_{lj}}{\partial x_k} + \frac{\partial G_{lk}}{\partial x_j} - \frac{\partial G_{jk}}{\partial x_l} \right)$$

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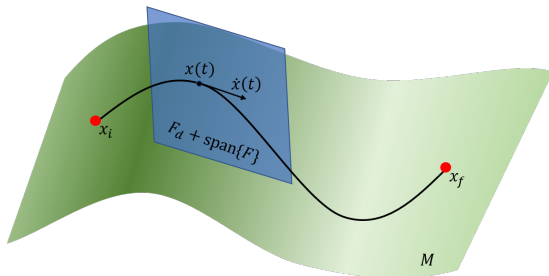
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System with affine controls

$$\dot{x} = F_d(x) + F(x)u \quad (5)$$



Assumption A

Both $F_d(x)$, $F(x)$ are assumed to be at least C^2 , Lipschitz with constants L_1 , L_2 respectively;
 $F(x)$ is of rank m almost everywhere on M .

Taking inspiration from the GHF, we introduce AGHF as below:

$$\frac{\partial x(t, s)}{\partial s} = \nabla_{\dot{x}(t, s)} (\dot{x}(t, s) - F_d) + r(x(t, s), \dot{x}(t, s)) \quad (6)$$

where

$$r(x, \dot{x}) = G^{-1} \left(\left(\frac{\partial F_d}{\partial x} \right)^\top G(\dot{x} - F_d) + \frac{1}{2} \begin{pmatrix} (\dot{x} - F_d)^\top \frac{\partial G}{\partial x_1} F_d \\ \vdots \\ (\dot{x} - F_d)^\top \frac{\partial G}{\partial x_n} F_d \end{pmatrix} \right)$$

Geometric interpretation

$$\frac{\partial x(t, s)}{\partial s} = \nabla_{\dot{x}(t, s)} (\dot{x}(t, s) - F_d) + r(x(t, s), \dot{x}(t, s)) \quad (6)$$

- $\nabla_{\dot{x}} (\dot{x} - F_d)$ is the covariant derivative of $\dot{x} - F_d$ in the direction \dot{x} , which updates the curve in the direction of decreasing its “curvature” and hence minimizing the “length”.
- $-r(x, \dot{x})$ is the scaled **gradient** of the point-wise map

$$P_f : M \rightarrow \mathbb{R} : x \mapsto \langle F_d(x) - f, F_d(x) \rangle$$

with $f = \dot{x}$ and $\langle f, h \rangle := f^\top G(x)h$. This map reaches its minimal value when $F_d(x)$ is aligned with \dot{x} .

- $\mathcal{L} = \int_0^T g(x(t), \dot{x}(t))^{\frac{1}{2}} dt$ where $g(x, \dot{x}) \approx \left(|\mathbf{P}_{\mathcal{F}}(\dot{x} - F_d(x))|^2 + \lambda |\mathbf{P}_{\mathcal{F}^\perp}(\dot{x} - F_d(x))|^2 \right)$.

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Convergence of AGHF

Our AGHF minimizes the **action functional**

$$\mathcal{A}(x(\cdot)) := \frac{1}{2} \int_0^T (\dot{x} - F_d(x))^T G(x) (\dot{x} - F_d(x)) dt \quad (7)$$

Lemma

Let $x^(t)$ be a steady-state solution of the AGHF (6). Then $x^*(t)$ is an extremal curve for \mathcal{A} in (7). Furthermore, \mathcal{A} decreases along the solutions of the AGHF; i.e. if $x(t, s)$ is such a solution, then $\frac{d}{ds} \mathcal{A}(x(\cdot, s)) \leq 0$, and equality holds only if $x(\cdot, s)$ is an extremal curve for \mathcal{A} .*

Algorithm

Step 1: Encode system dynamics into the Riemannian metric G ;

Step 2: Solve the AGHF (6) with boundary conditions

$$x(0, s) = x_i, x(T, s) = x_f \quad \forall s \geq 0$$

and an initial condition

$$x(t, 0) = y(t), \quad t \in [0, T]$$

for some $y(\cdot) \in \mathcal{X}'$;

Step 3: Evaluate

$$u(t) := F(x(t, s_{\max}))^\dagger (\dot{x}(t, s_{\max}) - F_d(x(t, s_{\max}))). \quad (8)$$

Output: The control $u(t)$ obtained in (8) is our solution to the motion planning problem. When integrating (5) with initial state x_i and input $u(t)$, the **integrated path** $\tilde{x}(t)$ approximately ends with $\tilde{x}(T) \approx x_f$.

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On convergence guarantees for motion planning

Theorem

Consider the system (5) and let $x_i, x_f \in \mathbb{R}^n$. Assume that the motion planning problem from x_i to x_f is feasible and that Assumption A is met. Then there exists $C > 0$ such that for any $\lambda > 0$, there exists an open set $\Omega_\lambda \subseteq \mathcal{X}'$ (with respect to $\|\cdot\|_{AC}$) so that as long as the initial curve $y \in \Omega_\lambda$, the integrated path $\tilde{x}(t)$ from our algorithm with sufficiently large s_{\max} has the property that

$$|\tilde{x}(T) - x_f| \leq \sqrt{\frac{3TC}{\lambda}} \exp\left(\frac{3T}{2}(L_2^2 T + L_1^2 C)\right). \quad (9)$$

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- Our algorithm gives a solution to the **relaxed motion planning problem**:

Relaxed motion planning problem

Given $x_i, x_f \in \mathbb{R}^n$, $T > 0, \epsilon > 0$, find an integrable u (potentially continuous u) such that the corresponding solution of (5) with initial condition $x(0) = x_i$ satisfies $|x(T) - x_f| \leq \epsilon$.

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Example: unicycle with constant linear velocity

$$\underbrace{\begin{pmatrix} \dot{q}_x \\ \dot{q}_y \\ \dot{\theta} \end{pmatrix}}_{\dot{x}} = \underbrace{\begin{pmatrix} \cos \theta \\ \sin \theta \\ 0 \end{pmatrix}}_{F_d} + \underbrace{\begin{pmatrix} 0 \\ 0 \\ 1 \end{pmatrix}}_F u. \quad (10)$$

Figure: Two different scenarios for parallel parking. Both start with $x_i = (0, 0, 0)^\top$. Left: $x_f = (0, 1, 0)^\top$. Right: $x_f = (0, 1, 2\pi)^\top$

Example: dynamic unicycle

$$\underbrace{\begin{pmatrix} \dot{q}_x \\ \dot{q}_y \\ \dot{\theta} \\ \dot{u}_1 \\ \dot{u}_2 \end{pmatrix}}_{\dot{x}} = \underbrace{\begin{pmatrix} u_1 \cos \theta \\ u_1 \sin \theta \\ u_2 \\ 0 \\ 0 \end{pmatrix}}_{F_d} + \underbrace{\begin{pmatrix} 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 1 & 0 \\ 0 & 1 \end{pmatrix}}_F \underbrace{\begin{pmatrix} v_1 \\ v_2 \end{pmatrix}}_v \quad (11)$$

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Our algorithm can also be modified to tackle variants of the basic motion planning problems, including but not limited to **state constraints**, **input constraints**, **holonomic constraints**, **indefinite boundary conditions** and **free terminal time**.

State constraints (obstacles)

- Suppose $\Omega \subset M$ is the set of obstacles that the system should avoid. Design a **barrier function** $b : M \setminus \Omega \rightarrow \mathbb{R}$ such that
 - 1 $b(x)$ is positive and differentiable for all $x \in M \setminus \Omega$
 - 2 $b(x) \rightarrow \infty$ as $x \rightarrow \partial\Omega$,
 - 3 $b(x) = 1$ when x is far away from Ω .
- Let the new Riemannian metric be

$$G(x) = b(x)(\bar{F}(x)^{-1})^\top D\bar{F}(x)^{-1},$$

- Intuitively, $G(x)$ becomes larger when x is close to obstacles. Since our algorithm minimizes the “length” of the curve, AGHF deforms the curve such that it avoids obstacles while still satisfying the dynamic constraints.

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Input constraints

For the general control system with input constraints

$$\begin{aligned}\dot{x} &= f(x, u) \\ l(x(t), u(t)) &\geq 0, \quad \forall t \in [0, T],\end{aligned}\tag{12}$$

- Define $\dot{u} = v$ and also define the **augmented state** $y = \begin{pmatrix} x \\ u \end{pmatrix} \in \mathbb{R}^{n+m}$, then we can set

$$\dot{y} = \begin{pmatrix} \dot{x} \\ \dot{u} \end{pmatrix} = \underbrace{\begin{pmatrix} f(x, u) \\ 0 \end{pmatrix}}_{F_d} + \underbrace{\begin{pmatrix} 0 \\ I_{m \times m} \end{pmatrix}}_F v,\tag{13}$$

which is a system with affine control and drift, similar to (5).

- Input constraints become state constraints; they can be implemented using the **augmented barrier function** $b(y)$.

Input constraints

For the general control system with input constraints

$$\begin{aligned}\dot{x} &= f(x, u) \\ l(x(t), u(t)) &\geq 0, \quad \forall t \in [0, T],\end{aligned}\tag{12}$$

- Define $\dot{u} = v$ and also define the **augmented state** $y = \begin{pmatrix} x \\ u \end{pmatrix} \in \mathbb{R}^{n+m}$, then we can set

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Holonomic constraints

- Holonomic constraints can be written as $q_i(x) = 0$, $i = 1, 2, \dots, k$, which, after differentiating with respect to time, give $\nabla q_i(x) \cdot \dot{x} = 0$, $i = 1, 2, \dots, k$.

- An affine control system with drift and holonomic constraints can be written as

$$\begin{aligned}\dot{x} &= F_d(x) + F(x)u, \\ H(x)\dot{x} &= 0.\end{aligned}\tag{14}$$

- Solution exists if and only if $H(x)F_d(x) \in \text{span } H(x)F(x)$.
- When solution exists, the motion planning problem of system (14) is equivalent to the motion planning problem for the system

$$\dot{x} = \tilde{F}_d(x) + \tilde{F}(x)v\tag{15}$$

where $\tilde{F}_d(x) = \left(I + (H(x)F(x))^{\dagger}H(x)\right)F_d(x)$ and $\tilde{F}(x) = F(x)A(x)$, $A(x) = \{a_1(x), \dots, a_l(x)\}$ is the basis of $\ker H(x)F(x)$.

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Indefinite boundary condition

- For physical systems with no external inputs, the conservation of momentum imposes constraints on the initial and final configuration of the system.
- Arbitrary choice of the pair $x_i, x_f \in M$ may result in no solution; the relation between x_i, x_f is implicit.
- Let $S_{bc} \subset S := \{1, \dots, d\} \times \{0, T\}$. For element-wise specified boundary states:

$$x_i(t, s) = x^{bc}(i, t) \quad \forall (i, t) \in S_{bc}, s \geq 0 \quad (16)$$

For unspecified boundary states:

$$\frac{\partial L}{\partial (x_t)_i}(x(t, s), x_t(t, s)) = 0 \quad \forall (i, t) \in S \setminus S_{bc}, s \geq 0 \quad (17)$$

- (16) together with (17) give the correct number of boundary conditions when solving our AGHF (6).

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Free terminal time

- For a driftless affine system, If $u(\cdot) : [0, 1] \rightarrow \mathbb{R}^m$ gives an admissible path satisfying the boundary condition $x(0) = x_i, x(1) = x_f$, then $\frac{1}{T}u\left(\frac{t}{T}\right)$ gives a time scaled admissible path with $x'(0) = x_i, x'(T) = x_f$.
- This is not true for systems with drift; minimization of the action functional \mathcal{A} in (7) as studied in Lemma 1 should be with respect to T as well.
- In addition, unlike the driftless case, the reachable space of an affine system with drift or constrained inputs may be related to the terminal time T .
- To tackle free terminal time motion planning, we have introduced a **true time** state τ and under smoothness assumptions, let $\dot{\tau}(t) = a(t)^2, \dot{a}(t) = u_0(t)$.
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Summary

Motion Planning Problem	Appears in
Driftless	ACC '17
Driftless + Obstacle	
Driftless + Holonomic constraints	arXiv
Drift	NOLCOS '19
Drift + Obstacle	
Drift + Input constraints	
Drift + Holonomic constraints	Only in dissertation
Drift + Indefinite boundary condition	WROCO '19
Drift + Free terminal time	arXiv

Conclusion

- In our research we have proposed an innovative motion planning algorithm for dynamical system affine in controls and with or without drift.
- We have formulated the (A)GHF equation, obeying which the initial curve is deformed to a curve with locally minimal “length”. Controls are extracted from this minimizer and the integrated path is derived by feeding the system with the extracted control, which gives us a solution to the relaxed motion planning problem.
- Variants of the basic motion planning problems are also studied, including obstacle avoidance, input constraints, holonomic constraints, indefinite boundary conditions and free terminal time.
- Our algorithm is demonstrated on many canonical examples and the simulations show great potential of our algorithm.

Stability analysis via non-monotonic Lyapunov function

1 Motion planning via geometric approach

- Review
- Motion planning for systems with drift
- Extensions

2 Stability analysis via non-monotonic Lyapunov function

- Review
- Show ISS via almost Lyapunov functions
- Show ISS via higher order derivatives of Lyapunov functions

Background

- Lyapunov's direct method tells that a time invariant, autonomous system

$$\dot{x} = f(x) \quad (18)$$

has a globally asymptotically stable origin if there exists a **positive definite**, radially unbounded function $V(x)$ such that $\dot{V}(x) := \langle \frac{d}{dx} V(x), f(x) \rangle$ is **negative definite** [Khalil, 2002].

- Finding such V satisfying the opposite sign definite constraints is difficult.
- **Non-monotonic** Lyapunov functions are widely studied [Aeyels and Peuteman, 1998, Ahmadi and Parrilo, 2008, Karafyllis, 2011, Meigoli and Nikraves, 2012]
- The time varying nature and presence of inputs complicate the analysis: $\dot{x} = f(t, x, u)$.

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“ $V(x(t))$ decreases more than it increases over any long enough time”

which can be guaranteed by

- 1 Considering the finite step difference of Lyapunov function, i.e., existence of $T > 0$ such that $V(x(T)) - V(x(0)) < 0$ for all $x(0) \neq 0$ [Aeyels and Peuteman, 1998]; or
- 2 Imposing some conditions on the higher order derivatives of V [Meigoli and Nikraves, 2009]; or
- 3 The study of almost Lyapunov functions such that $\Omega := \{x \in \mathbb{R}^n : \dot{V}(x) > -aV(x)\}$ is small enough [Liu et al., 2016, Liu et al., 2020].

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Global asymptotic stability

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- The system (18) is **globally asymptotically stable** (GAS) if there exists $\beta \in \mathcal{KL}$ such that

$$|x(t)| \leq \beta(|x_0|, t) \quad \forall x_0 \in \mathbb{R}^n, t \geq 0. \quad (19)$$

- GAS can be shown via a Lyapunov function $V(x) : \mathbb{R}^n \rightarrow \mathbb{R}_{\geq 0}$ such that for some $\alpha_1, \alpha_2 \in \mathcal{K}_\infty, a > 0$ such that

$$\alpha_1(|x|) \leq V(x) \leq \alpha_2(|x|) \quad \forall x \in \mathbb{R}^n, \quad (20)$$

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Almost Lyapunov functions for autonomous systems

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 - 1 Poor choice of V ;
 - 2 Numerical computation;
 - 3 System perturbation;
 - 4 ...
- The inequality (21) may not be satisfied for $x \in \Omega \subset \mathbb{R}^n$.
- Our work [Liu et al., 2020] shows that as long as the volume of the connected components of Ω are small enough, the system (18) is GAS.

Almost Lyapunov functions for autonomous systems

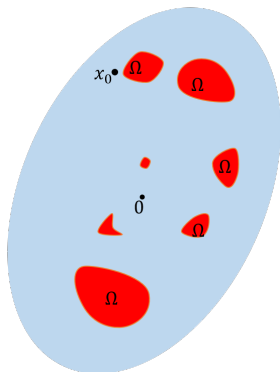
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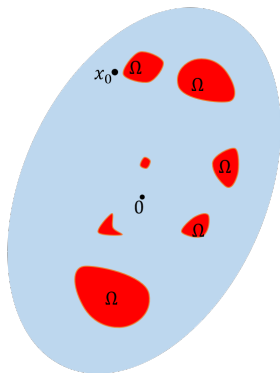
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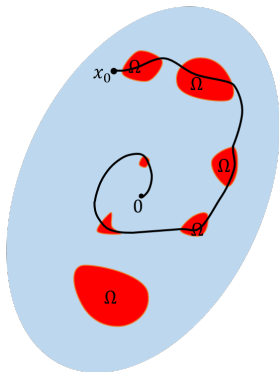
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Higher order derivatives of V for autonomous systems

$$\dot{x} = f(x) \quad (18)$$

Not necessarily $\dot{V}(x) < 0$ for all $x \neq 0$.

Theorem ([Meigoli and Nikraves, 2009])

Let $V(x) : \mathbb{R}^n \rightarrow \mathbb{R}_{\geq 0}$ be a Lyapunov function. If there exists $m \in \mathbb{N}_{\geq 2}$ and $a_1, \dots, a_{m-1} \geq 0$ such that V is $m - 1$ times differentiable and f is $m - 2$ times differentiable and

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for all $x \neq 0$, then (18) is GAS.

Higher order derivatives of V for autonomous systems

$$\dot{x} = f(x) \quad (18)$$

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Preliminaries in the presence of inputs

$$\dot{x} = f(t, x, u) \quad (22)$$

- The system (22) is **globally uniformly asymptotically stable** (GUAS) if there exists $\beta \in \mathcal{KL}$ such that

$$|x(t; t_0, x_0, u)| \leq \beta(|x_0|, t - t_0) \quad (23)$$

for all $x_0 \in \mathbb{R}^n$, $t \geq t_0 \geq 0$ and $u \in \mathcal{U} \subset \mathbb{R}^m$.

- GUAS can be shown via a **time varying** Lyapunov function $V(t, x) : \mathbb{R}_{\geq 0} \times \mathbb{R}^n \rightarrow \mathbb{R}_{\geq 0}$ such that for some $\alpha_1, \alpha_2 \in \mathcal{K}_\infty$ and a positive definite function $\psi : \mathbb{R}_{\geq 0} \rightarrow \mathbb{R}_{\geq 0}$ such that

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$$\dot{V}(t, x, u) := \frac{\partial}{\partial t} V(t, x) + \left\langle \frac{\partial}{\partial x} V(t, x, u), f(t, x, u) \right\rangle \leq -\psi(|x|) \quad (25)$$

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- The system (22) is **input-to-state stable** (ISS) [Sontag, 1989] if there exists $\beta \in \mathcal{KL}, \gamma \in \mathcal{K}_\infty$ such that

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for all $x_0 \in \mathbb{R}^n, t \geq t_0 \geq 0$ and $u \in \mathcal{U} \subseteq \mathbb{R}^m$.

Lemma ([Sontag and Wang, 1996])

The system

$$\dot{x} = f(t, x, u) \quad (22)$$

is ISS if and only if its auxiliary system

$$\dot{x} = f_\rho(t, x, d) := f(t, x, \rho(|x|)d) \quad (27)$$

is GUAS with $d \in \mathcal{U} = \mathbb{B}_1^m$ for some $\rho \in \mathcal{K}_\infty$.

1 Motion planning via geometric approach

- Review
- Motion planning for systems with drift
- Extensions

2 Stability analysis via non-monotonic Lyapunov function

- Review
- Show ISS via almost Lyapunov functions
- Show ISS via higher order derivatives of Lyapunov functions

Problem set up

Consider a time invariant system with input

$$\dot{x} = f(x, u) \quad (28)$$

- If there exist a Lyapunov function satisfying (20) and some $\rho \in \mathcal{K}_\infty$, $a > 0$ such that $\dot{V}(x) = \left\langle \frac{d}{dx} V(x), f_\rho(x, d) \right\rangle \leq -aV(x)$ for all $|d| \leq 1$, $x \in \mathbb{R}^n$, then (28) is ISS. Equivalently, we need

$$V'(x) := \sup_{|d| \leq 1} \left\langle \frac{d}{dx} V(x), f_\rho(x, d) \right\rangle \leq -aV(x). \quad (29)$$

- Appealing to our almost Lyapunov function framework, we allow (29) to be violated for $x \in \Omega \subset \mathbb{R}^n$.
- Can we still show ISS if we only have (29) for all $x \in \mathbb{R}^n \setminus \Omega$, while Ω is **small** enough?

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How to quantify the size of Ω ?

- Although volume of Ω in Euclidean space is used in our previous work, it is conservative.
- Small Ω does not necessarily imply $x_\rho(t; x_0, d)$ will stay inside Ω for finite time.
- Instead, we directly impose assumptions on the Ω dwell time:

$$T := \sup_{x_0 \in \Omega, \|d\| \leq 1} \inf_{t \geq 0} \{t : x_\rho(t; x_0, d) \notin \Omega\} \quad (30)$$

- Only upper bound of T is needed; depending on the size and shape of Ω and the vector field $f(x, u)$, it can be estimated without computing the solutions of the system.

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Let $V \in C^1(\mathbb{R}^n \rightarrow \mathbb{R}_{\geq 0})$ be a positive definite function and assume the system (22) has an equilibrium at 0. Then V' defined via (31) exists for all $x \in \mathbb{R}^n$ and is Lipschitz when both $f_\rho(x, d)$, $\frac{d}{dx} V(x)$ are Lipschitz in x .

Lemma

Assume Ω is bounded and all the assumptions in the above lemma hold. Then $\frac{d}{dx} V'$ exists almost everywhere in Ω . In addition, there exists $c > 0$ such that for all $x \in \Omega$ where $\frac{d}{dx} V'(x)$ exists,

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- $f_\rho(x, d) := f(x, \rho(|x|)d)$ is Lipschitz in x ;
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Theorem

Consider a system with input (28) with the assumptions listed in the previous slide satisfied with some $a, c > 0$. There exists an increasing function $\alpha : [0, 1) \rightarrow [0, \infty)$ with $\alpha(0) = 0$, $\lim_{t \rightarrow 1^-} \alpha(t) = \infty$ such that as long as the Ω dwell time T satisfies

$$T < \frac{1}{\sqrt{c}} \min \left\{ \frac{\pi}{2}, \alpha \left(\frac{a}{\sqrt{c}} \right) \right\}, \quad (33)$$

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$$\alpha(t) = \ln \left(\frac{1+t}{1-t} \right) + 2 \arccos \left(\frac{1}{\sqrt{t^2 + 1}} \right) \quad (34)$$

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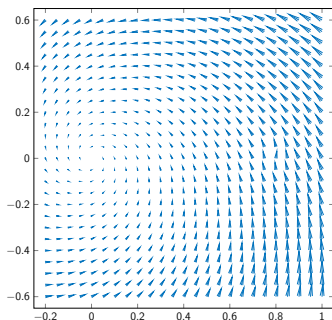
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Example

$$\dot{x} = \begin{pmatrix} -\lambda(x) & -\mu \\ \mu & -\lambda(x) \end{pmatrix} x + u, \quad (35)$$

where $\lambda(x) = \left(\frac{a+b}{2}\right) \min\left\{\frac{|x-x_c|}{r}, 1\right\} - \frac{b}{2} + k$.

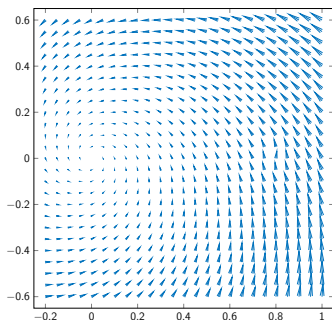


- Take $V = \frac{1}{2}|x|^2$, $\rho(s) = ks$.
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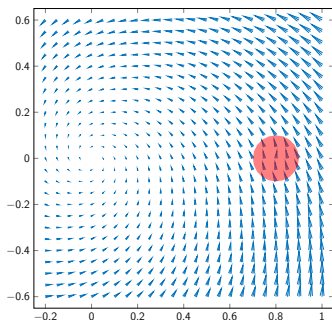


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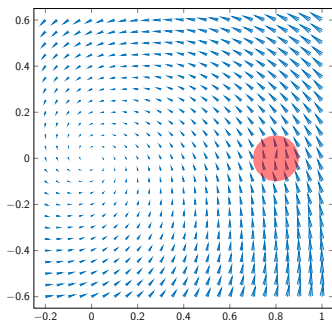


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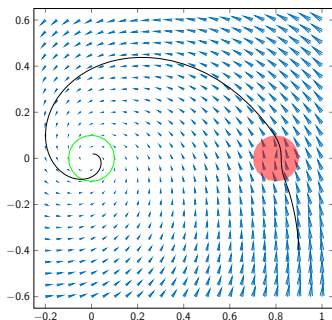


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Sketch of proof

- Let t_1, t_2 be the time the solution trajectory $x_\rho(t; x_0, d)$ enters and leaves Ω . We want to ultimately show $V(x_\rho(t_2; x_0, d)) \leq \eta V(x_\rho(t_1; x_0, d))$ for some $\eta < 1$.
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- For any $t \in [t_1, t_2]$, It is proven that

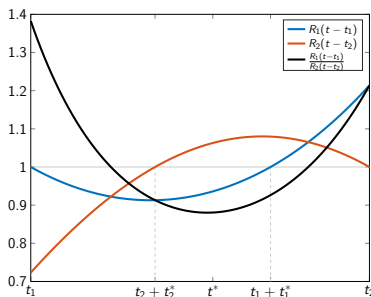
$$\frac{V(x_\rho(t; x_0, d))}{V(x_\rho(t_1; x_0, d))} \leq R_1(t - t_1),$$

$$\frac{V(x_\rho(t; x_0, d))}{V(x_\rho(t_2; x_0, d))} \geq R_2(t - t_2)$$

where

$$R_1(s) := \left(\cosh \sqrt{c}s - \frac{a}{\sqrt{c}} \sinh \sqrt{c}s \right),$$

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- It is then shown that when (33) holds, there always exists $t^* \in [t_1, t_2]$ such that $R_1(t^* - t_1) \leq \eta_1 < 1$, $R_2(t^* - t_2) \geq \eta_2 > 1$ and thus

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Sketch of proof

- For any $t \in [t_1, t_2]$, It is proven that

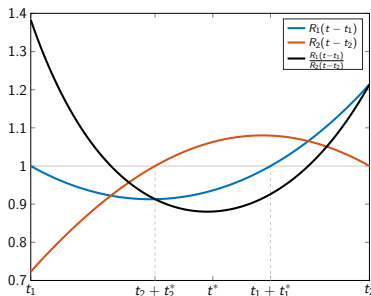
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1 Motion planning via geometric approach

- Review
- Motion planning for systems with drift
- Extensions

2 Stability analysis via non-monotonic Lyapunov function

- Review
- Show ISS via almost Lyapunov functions
- Show ISS via higher order derivatives of Lyapunov functions

Problem set up

$$\dot{x} = f(t, x, u) \quad (22)$$

- Known some $V(t, x)$ satisfying the “sandwich condition” (24) and $\rho \in \mathcal{K}_\infty$; but not necessarily

$$\dot{V}(t, x, d) := \frac{\partial}{\partial t} V(t, x) + \left\langle \frac{\partial}{\partial x} V(t, x, d), f_\rho(t, x, d) \right\rangle \leq -\psi(|x|) \quad (25)$$

for all $x \in \mathbb{R}^n, t \geq t_0$ and $|d| \leq 1$.

- Like the autonomous case, we would like to study the “higher order derivatives” of V to show stability.
- Difficulty:** $\dot{V}(t, x, d)$ depends on d , which may not be differentiable w.r.t. time t , $\ddot{V}(t, x, d) = \frac{d}{dt} \dot{V}(t, x, d)$ does not exist in general.

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Defining higher order derivatives for systems with inputs

- The higher order derivatives of V are defined and constructed iteratively:
 - 1 $v_0(t, x) := V(t, x)$;
 - 2 $V_i(t, x) := \frac{\partial}{\partial t} v_{i-1}(t, x) + \sup_{|d| \leq 1} \langle \frac{\partial}{\partial x} v_{i-1}(t, x), f_\rho(t, x, d) \rangle$;
 - 3 Construct $v_i(t, x) \in C^1(\mathbb{R}_{\geq 0} \times \mathbb{R}^n)$ such that $v_i(t, x) \geq V_i(t, x)$ for all $x \in \mathbb{R}^n, t \geq t_0$.
- $v_i(t, x)$ is sign indefinite for $i > 0$;
- $\frac{d}{dt} v_{i-1}(t, x) \leq v_i(t, x)$.
- The higher order derivatives $v_i(t, x)$ are globally decreascent up to order $m \in \mathbb{N}$ if there exists $\phi \in \mathcal{K}_\infty$ such that

$$v_i(t, x) \leq \phi(|x|) \quad \forall x \in \mathbb{R}^n, t \geq t_0, i = 0, \dots, m.$$

Defining higher order derivatives for systems with inputs

- The higher order derivatives of V are defined and constructed iteratively:
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Defining higher order derivatives for systems with inputs

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 - 1 $v_0(t, x) := V(t, x);$
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- $v_i(t, x)$ is sign indefinite for $i > 0$;
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- The higher order derivatives $v_i(t, x)$ are globally decrescent up to order $m \in \mathbb{N}$ if there exists $\phi \in \mathcal{K}_\infty$ such that

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Defining higher order derivatives for systems with inputs

- The higher order derivatives of V are defined and constructed iteratively:
 - 1 $v_0(t, x) := V(t, x);$
 - 2 $V_i(t, x) := \frac{\partial}{\partial t} v_{i-1}(t, x) + \sup_{|d| \leq 1} \left\langle \frac{\partial}{\partial x} v_{i-1}(t, x), f_\rho(t, x, d) \right\rangle;$
 - 3 Construct $v_i(t, x) \in C^1(\mathbb{R}_{\geq 0} \times \mathbb{R}^n)$ such that $v_i(t, x) \geq V_i(t, x)$ for all $x \in \mathbb{R}^n, t \geq t_0$.
- $v_i(t, x)$ is sign indefinite for $i > 0$;
- $\frac{d}{dt} v_{i-1}(t, x) \leq v_i(t, x)$.
- The higher order derivatives $v_i(t, x)$ are **globally decrescent** up to order $m \in \mathbb{N}$ if there exists $\phi \in \mathcal{K}_\infty$ such that

$$v_i(t, x) \leq \phi(|x|) \quad \forall x \in \mathbb{R}^n, t \geq t_0, i = 0, \dots, m.$$

Theorem

Given a system (22), a C^1 positive definite function $V(t, x)$ satisfying (24) and some $\rho \in \mathcal{K}_\infty$, generate the higher order derivatives v_i by f_ρ and V . If v_i 's are globally decrescent up to order $m \in \mathbb{N}$ and there exist

$$a_0 > 0, \quad a_i \geq 0 \quad \forall i = 1, \dots, m \quad (37)$$

such that

$$\sum_{i=0}^m a_i v_i(t, x) \leq 0 \quad \forall x \in \mathbb{R}^n, t \geq t_0, \quad (38)$$

then the system (22) is ISS.

Sketch of proof

The following lemma can be proven using induction, similar to what is done in [Meigoli and Nikraves, 2009]:

Lemma

Let $x(t; t_0, x_0, d)$ be a solution of system (27). When (38) holds with some a_i 's satisfying (37) and $a_m = 1$, for any $b > 0$ if $v_0(t, x(t; t_0, x_0, d)) \geq b$ for all $t \in [t_0, t_0 + T]$ for some $T \geq 0$, then

$$v_0(t, x(t; t_0, x_0, d)) \leq -b \sum_{j=1}^m a_{m-j} \frac{(t - t_0)^j}{j!} + \sum_{j=0}^{m-1} \sum_{i=0}^j \frac{(t - t_0)^j}{j!} a_{m+i-j} v_i(t_0, x_0) \quad (39)$$

for all $t \in [t_0, t_0 + T]$, $\|d\| \leq 1$.

Sketch of proof

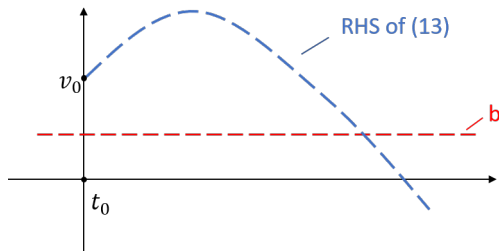
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The origin can be subsequently shown globally stable and uniformly attractive for the auxiliary system and hence it is GUAS; the original system (22) is therefore ISS.

Sketch of proof

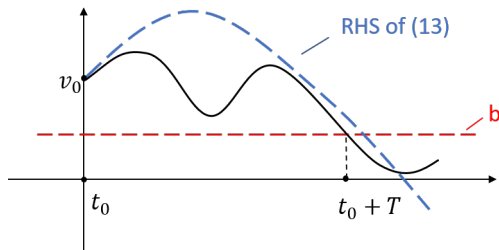
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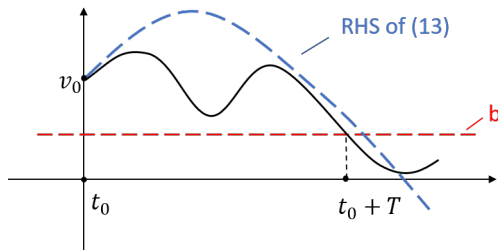
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Example: linear system with unaligned V

$$\dot{x} = f(x, u) = Ax + u, \quad A = \begin{pmatrix} -0.1 & -1 \\ 2 & -0.1 \end{pmatrix} \quad (40)$$

- Choosing $V = |x|^2$ gives $\dot{V} = -0.2(x_1 - 5x_2)^2 + 4.8x_2^2$ even if $u \equiv 0$; stability is inconclusive.
- Pick $\rho(s) = 0.05s$, Higher order derivatives are constructed:

$$v_1 = -0.1x_1^2 + 2x_1x_2 - 0.1x_2^2,$$

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$$v_3 = -1.5907x_1^2 - 15.62x_1x_2 + 1.4093x_2^2.$$

- Let $a_0 = 0.1, a_1 = 8, a_2 = 0.5, a_3 = 1$,

$$\sum_{i=0}^3 a_i v_i = -0.2257x_1^2 + 0.08x_1x_2 - 0.2257x_2^2 = -x^\top \begin{pmatrix} 0.2257 & -0.04 \\ -0.04 & 0.2257 \end{pmatrix} x$$

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Example: slowly varying between two stable linear modes

$$\dot{x} = f(t, x, u) = \sin^2(kt)A_1x + \cos^2(kt)A_2x + u =: A(k, t)x + u \quad (41)$$

where $A_1 = \begin{pmatrix} -0.1 & -1 \\ 2 & -0.1 \end{pmatrix}, A_2 = \begin{pmatrix} -0.1 & -2 \\ 1 & -0.1 \end{pmatrix}$

- No common Lyapunov function for A_1, A_2 .
- Again choose $V(t, x) = |x|^2, \rho(s) = 0.05s$. It can be shown that $v_i(t, x) = x^\top (P_i(k, t) + kp(k)Q_i(k, t))x$ where Q_i are uniformly bounded, $p(k)$ is a polynomial in k and

$$P_1 = \begin{pmatrix} -0.1 & -C \\ -C & -0.1 \end{pmatrix}, \quad P_2 = \begin{pmatrix} C^2 - 3C + 0.13 & 0.3C \\ 0.3C & C^2 + 3C + 0.13 \end{pmatrix},$$
$$P_3 = \begin{pmatrix} -0.5C^2 + 1.5C + 0.224 & -C^3 + 8.81C \\ -C^3 + 8.81C & -0.5C^2 - 1.5C + 0.224 \end{pmatrix}$$

- Pick $a_0 = 0.1, a_1 = 8, a_2 = 0.5, a_3 = 1$,
 $\sum_{i=0}^3 a_i v_i \approx \sum_{i=0}^3 a_i x^\top P_i x \leq 0$ for sufficiently small k and hence (41) is ISS.

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- No common Lyapunov function for A_1, A_2 .
- Again choose $V(t, x) = |x|^2, \rho(s) = 0.05s$. It can be shown that $v_i(t, x) = x^\top (P_i(k, t) + kp(k)Q_i(k, t))x$ where Q_i are uniformly bounded, $p(k)$ is a polynomial in k and

$$P_1 = \begin{pmatrix} -0.1 & -C \\ -C & -0.1 \end{pmatrix}, \quad P_2 = \begin{pmatrix} C^2 - 3C + 0.13 & 0.3C \\ 0.3C & C^2 + 3C + 0.13 \end{pmatrix},$$
$$P_3 = \begin{pmatrix} -0.5C^2 + 1.5C + 0.224 & -C^3 + 8.81C \\ -C^3 + 8.81C & -0.5C^2 - 1.5C + 0.224 \end{pmatrix}$$

- Pick $a_0 = 0.1, a_1 = 8, a_2 = 0.5, a_3 = 1$,
 $\sum_{i=0}^3 a_i v_i \approx \sum_{i=0}^3 a_i x^\top P_i x \leq 0$ for sufficiently small k and hence (41) is ISS.

- We have proposed two alternative methods for determining ISS for systems with inputs: via almost Lyapunov functions or via higher order derivatives of Lyapunov functions.
- In the first method, the study of almost Lyapunov functions from our previous work was generalized to systems with inputs. When there are “bad” regions Ω in the state space where V does not decrease fast enough, an upper bound of the Ω dwell time was found to guarantee that the system with inputs is still ISS.
- In the second method, it is claimed and proven that if there exists a linear combination of those higher order derivatives with non-negative coefficients (except that the coefficient of the 0-th order term needs to be positive) which is negative semi-definite, then the system is ISS.

The End



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