Motion Planning and Differential Flatness

Marcus Greiff
marcus.greiff@control.lth.se

15/10-2020

Guest Lecture - Linköping

Context

- 4th-year PhD student at Lund Universtiry
- Supervised by Anders Robertsson
- K. Berntorp (former student, now at MERL)
- B. Olofsson (former student, now at LiU/LU)

- [1] M. Greiff and K. Berntorp, "Projections in Adaptive Mixture Kalman Filtering for GNSS Positioning", ACC, 2020.
- [2] M. Greiff, K. Berntorp and A. Robertsson, "Measurement dimension reduction in Gaussian filtering", CCTA, 2020.
- [3] M. Greiff, K. Berntorp and A. Robertsson, "Exploiting Linear Substructure In LRKFs (Extended)", CDC, 2020.
- [4] E. Lefeber, M. Greiff and A. Robertsson, "Filtered Output Feedback Tracking Control of a Quadrotor UAV", IFAC, 2020.
- [5] M. Greiff, Z. Sun and A. Robertsson, "Attitude Control on SU(2): Stability, Robustness, and Similarities", L-CSS, 2020.

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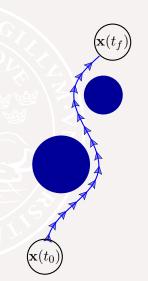
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Current work

- (i) MERL Estimation Theory
 - Satellite positioning [1]
 - Nonlinear Filtering [2, 3]
- (ii) LU Nonlinear and Robust Control
 - Focus on aerial vehicles
 - Filtered output feedback [4, 5]
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Motion planning?

- Necessary in practical experiments
- Taught by Björn at LU in 2017

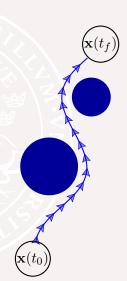


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Disclaimer

- Not an expert in the field
- Share some useful ideas



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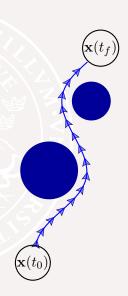
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Presentation Purpose

- + Introduce differential flatness (DF)
- Convex polynomial optimization (CPO)
- Sequential quadratic programming (SQP)
- Theoretical and practical examples



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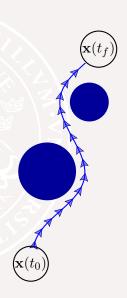
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- + Introduce differential flatness (DF)
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Motivation

- DF Applicable to ground, surface, and aerial vehicles
- CPO Powerful method enabled by DF
- SQP Generally useful, enforce constraints in CPO



Motion planning

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

$$\mathbf{x}(t) \in \mathcal{X}, \quad \mathbf{u}(t) \in \mathcal{U}$$

$$t \in [t_0, t_f]$$

[6] T. Glück et al., "Swing-up control of a triple pendulum", Automatica, 2013.

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Approaches

- Collocation-based (BVPs) [6]
- Sampling-based (RRT, PF methods)
- Optimization-based (MPC, SQP [7], CPO [8])

Simulation example A

The BVP-method in [6] applied to a variation of the under-actuated two-pendulum cart problem, and solved with the bvp5c() function in Matlab.



Under-actuated two-pendulum cart process.

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Simulation example B

A minimum torque SQP-method in [7] initialized with an interpolation between

$$\theta_1(t_0) = 0 \qquad \theta_1(t_f) = \pi$$

$$\theta_2(t_0) = \frac{-\pi}{2} \qquad \theta_2(t_f) = \frac{\pi}{2}$$



A fully actuated planar two-link robotic arm.

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Simulation example C

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$$\theta_1(t_0) = 0 \qquad \quad \theta_1(t_f) = \pi + 2\pi$$

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Older and newer solutions combined

- Defining a set of flat outputs
- Path planning by polynomial optimization
- Form QP to speed up/slow down time

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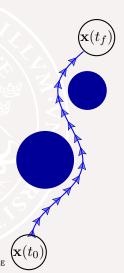
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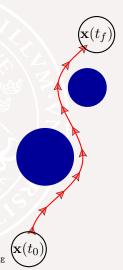
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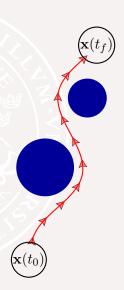
Problem formulation

Find (1) a flat output space \mathcal{F} , and (2) a feasible flat-output trajectory $\gamma(t) \in \mathcal{F}$, which drives the system from an initial state $\mathbf{x}(t_0)$ to a terminal state $\mathbf{x}(t_f)$, and (3) find an augmented trajectory, $\gamma^*(t)$, minimising t_f without altering the shape of $\gamma(t)$ in \mathcal{F} given constraints in $\mathbf{x}(t) \in \mathcal{X}$ and $\mathbf{u}(t) \in \mathcal{U}$.



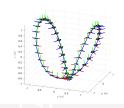
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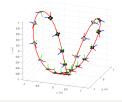
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Outline

- Introduce the concept of differential flatness
- 2 Plan path in flat output space \mathcal{F}
- 3 QP to warp the rate at which time flows [9]
- Open Demonstrate approach in three control examples



Swedish	English	Meaning
Platthet	Flatness	Having a level surface without raised areas or indentations. Lack of emotion or enthusiasm.
Plattityd	Platitude	A statement which is considered meaningless and boring.

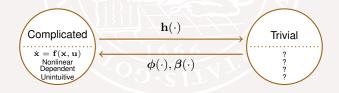
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Remark (Jokingly by Anders and Rolf)

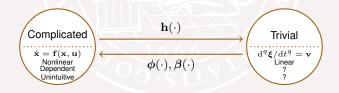
Differentiell platthet är bara en plattityd Differential flatness is only a platitude

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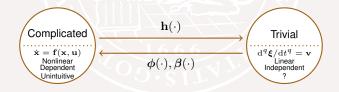
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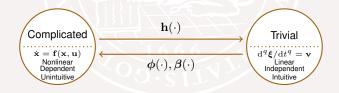
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Definition (Differential Flatness [10])

A system, $\dot{\mathbf{x}} = \mathbf{f}(\mathbf{x}, \mathbf{u})$, with $\mathbf{x} \in \mathbb{R}^n$, $\mathbf{u} \in \mathbb{R}^m$, where \mathbf{f} is a smooth vector field is *differentially flat* if there exists a set of *flat outputs*,

$$\gamma = \mathbf{h}(\mathbf{x}, \mathbf{u}, \dot{\mathbf{u}}, \cdots, \mathbf{u}^{(r)}) \in \mathbb{R}^m,$$

such that

$$\mathbf{x} = \boldsymbol{\phi}(\boldsymbol{\gamma}, \dot{\boldsymbol{\gamma}}, \cdots, \boldsymbol{\gamma}^{(q)}), \qquad \mathbf{u} = \boldsymbol{\beta}(\boldsymbol{\gamma}, \dot{\boldsymbol{\gamma}}, \cdots, \boldsymbol{\gamma}^{(q)}),$$

where $\{\mathbf{h}, \boldsymbol{\phi}, \boldsymbol{\beta}\}$ are smooth functions.

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where $\{\mathbf{h}, \boldsymbol{\phi}, \boldsymbol{\beta}\}$ are smooth functions.

Useful? Which of (A) and (B) would you rather do planning for?

(A)
$$\frac{d\mathbf{x}}{dt} = \mathbf{f}(\mathbf{x}, \mathbf{u}),$$

(B) $\frac{d^q \gamma}{dt^q} = \mathbf{v}(t)$

$$(B) \frac{\mathrm{d}^q \gamma}{\mathrm{d}t^q} = \mathbf{v}(t)$$

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(A)
$$\frac{\mathrm{d}\mathbf{x}}{\mathrm{d}t} = \mathbf{f}(\mathbf{x}, \mathbf{u}),$$

$$(B) \begin{array}{c} \mathbf{d} \\ \dot{\mathbf{r}} \\ \vdots \\ \boldsymbol{\gamma}^{q-1} \end{array} = \begin{bmatrix} \mathbf{0}_m & \mathbf{I}_m & \cdots & \mathbf{0}_m \\ \mathbf{0}_m & \mathbf{0}_m & \ddots & \mathbf{0}_m \\ \vdots & \ddots & \ddots & \vdots \\ \mathbf{0}_m & \mathbf{0}_m & \cdots & \mathbf{0}_m \end{bmatrix} \begin{bmatrix} \boldsymbol{\gamma} \\ \dot{\boldsymbol{\gamma}} \\ \vdots \\ \boldsymbol{\gamma}^{q-1} \end{bmatrix} + \begin{bmatrix} \mathbf{0}_m \\ \mathbf{0}_m \\ \vdots \\ \mathbf{I}_m \end{bmatrix} \mathbf{v}$$

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$$(A) \frac{\mathrm{d}\mathbf{x}}{\mathrm{d}t} = \mathbf{f}(\mathbf{x}, \mathbf{u}),$$

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Constructive? Yes, but it can be challenging to find $\{h, \phi, \beta\}$...!

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Example: Feedback-linearization, Chapter 13 in [12]

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^[11] G. Rigatos, "Nonlinear control and filtering using differential flatness approaches," 2015.

^[12] H. Khalil et al., "Nonlinear Systems", available online as a pdf.

Consider a system $\dot{\mathbf{x}} = \mathbf{f}(\mathbf{x}) + \mathbf{g}(\mathbf{x})u$, configured on $\mathcal{C} = \mathbb{R}^3$, where

$$\mathbf{f}(\mathbf{x}) = \begin{bmatrix} -x_1 + x_2 \\ x_1 - x_2 - x_1 x_3 \\ x_1 + x_1 x_2 - 2x_3 \end{bmatrix}, \quad \mathbf{g}(\mathbf{x}) = \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix}$$

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- Show how to derive flat outputs
- Enough details to do it yourselves
- Temporarily a bit more mathematical
- Don't worry if it is a bit tricky to follow

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Definition (Lie Derivative [12])

The so-called Lie-derivative of h with respect to f,

$$(\mathcal{L}_{\mathbf{f}}\mathbf{h})(\mathbf{x}) = \frac{\partial \mathbf{h}}{\partial \mathbf{x}}\mathbf{f}(\mathbf{x})$$

denotes a change in h along the trajectories of the system $\dot{\mathbf{x}} = \mathbf{f}(\mathbf{x})$

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• Find an output $\gamma = h(\mathbf{x})$ yielding full relative degree, i.e. such that

$$L_{\mathbf{g}}h(\mathbf{x}) = 0$$
$$L_{\mathbf{g}}L_{\mathbf{f}}h(\mathbf{x}) = 0$$
$$L_{\mathbf{g}}L_{\mathbf{f}}^{2}h(\mathbf{x}) \neq 0$$

^[12] H. Khalil et al., "Nonlinear Systems", available online as a pdf.

Consider a system $\dot{\mathbf{x}} = \mathbf{f}(\mathbf{x}) + \mathbf{g}(\mathbf{x})u$, configured on $\mathcal{C} = \mathbb{R}^3$, where

$$\mathbf{f}(\mathbf{x}) = \begin{bmatrix} -x_1 + x_2 \\ x_1 - x_2 - x_1 x_3 \\ x_1 + x_1 x_2 - 2x_3 \end{bmatrix}, \quad \mathbf{g}(\mathbf{x}) = \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix}$$

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such as

$$h(\mathbf{x}) = a\left(\frac{1}{2}x_1^2 - x_3\right) + b, \quad a \in \mathbb{R} \setminus \{0\}, b \in \mathbb{R}.$$

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- lacktriangle Find an output $\gamma=h(\mathbf{x})$ yielding full relative degree, i.e. such that
- ② With a=1,b=0, we find a feedback linearization

$$\begin{split} \gamma &= L_{\mathbf{f}}^0 h(x) = x_1^2/2 - x_3 \\ \dot{\gamma} &= L_{\mathbf{f}}^1 h(x) = -x_1^2 - x_1 + 2x_3 \\ \ddot{\gamma} &= L_{\mathbf{f}}^2 h(x) = 2x_1^2 + 3x_1 - x_2 - 4x_3 \end{split}$$

which (surprisingly) turns out to be a surjective map $\mathbf{x} = \phi(\gamma, \dot{\gamma}, \ddot{\gamma})$.

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- Find an output $\gamma = h(\mathbf{x})$ yielding full relative degree, i.e. such that
- With a=1,b=0, we find a surjective map $\mathbf{x}=\phi(\gamma,\dot{\gamma},\ddot{\gamma})$.
- 3 With $\gamma(t)=h(\mathbf{x})$, the endogenous feedback law

$$u = \frac{1}{L_{\mathbf{g}} L_{\mathbf{f}}^2 h(\mathbf{x})} [-L_{\mathbf{f}}^3 h(\mathbf{x}) + v] = 4x_2 - 8x_1 + 8x_3 + x_1 x_3 - 4x_1^2 - v$$

results in a system

$$\frac{d^3\gamma(t)}{dt^3} = v(t),$$

As \mathbf{x} is known from ϕ , and v is known from $\ddot{\gamma}$, we also know $u = \beta(\gamma, \dot{\gamma}, \ddot{\gamma}, \ddot{\gamma})$.

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Consider a system $\dot{\mathbf{x}} = \mathbf{f}(\mathbf{x}) + \mathbf{g}(\mathbf{x})u$, configured on $\mathcal{C} = \mathbb{R}^3$, where

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As ${\bf x}$ is known from ϕ , and v is known from $\dddot{\gamma}$, we also know $u=\beta(\gamma,\dot{\gamma},\ddot{\gamma},\dddot{\gamma})$.

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Disclaimer: Not always possible. What about other systems?

^[12] H. Khalil et al., "Nonlinear Systems", available online as a pdf.

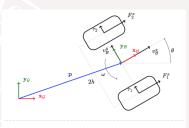
1. Differentially Flat Dynamics - UGV (unconstrained)

Unmanned ground vehicle (UGV) configured on C = SE(2),

$$\mathbf{x} = \begin{bmatrix} \theta \\ p_{\mathcal{G}}^x \\ p_{\mathcal{G}}^y \\ \omega \\ v_{\mathcal{B}}^y \\ v_{\mathcal{B}}^y \end{bmatrix} \qquad \begin{array}{ll} \text{Attitude} \\ \text{Translation in } \mathbf{x}_{\mathcal{G}} \\ \text{Attitude rate} \\ \text{Velocity in } \mathbf{x}_{\mathcal{B}} \\ \text{Velocity in } \mathbf{y}_{\mathcal{B}} \\ \end{bmatrix} \\ \mathbf{u} = \begin{bmatrix} \tau_1 \\ \tau_2 \end{bmatrix} \qquad \begin{array}{ll} \text{Torque along } \mathbf{x}_{\mathcal{B}} \text{ at wheel 1} \\ \text{Torque along } \mathbf{y}_{\mathcal{B}} \text{ at wheel 2} \\ \end{array}$$

with $\mathcal{X}\subseteq\mathbb{R}^6$, $\mathcal{U}\subseteq\mathbb{R}^2$, and dynamics

$$\begin{split} \dot{\theta}(t) &= \omega_{\mathcal{B}}(t) \\ \dot{p}_{\mathcal{G}}^x(t) &= v_{\mathcal{B}}^x(t)\cos(\theta(t)) - v_{\mathcal{B}}^y(t)\sin(\theta(t)) \\ \dot{p}_{\mathcal{G}}^y(t) &= v_{\mathcal{B}}^x(t)\sin(\theta(t)) + v_{\mathcal{B}}^y(t)\cos(\theta(t)) \\ \dot{\omega}(t) &= (h/(Jr))(\tau_1(t) - \tau_2(t)) \\ \dot{v}_{\mathcal{B}}^x(t) &= \omega(t)v_{\mathcal{B}}^x(t) + (r/m)(\tau_1(t) + \tau_2(t)) \\ \dot{v}_{\mathcal{B}}^y(t) &= -\omega(t)v_{\mathcal{B}}^x(t) \end{split}$$





1. Differentially Flat Dynamics - UGV (unconstrained)

Unmanned ground vehicle (UGV) configured on C = SE(2),

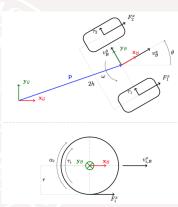
$$\mathbf{x} = \begin{bmatrix} \theta \\ p_{\mathcal{G}}^x \\ p_{\mathcal{G}}^y \\ p_{\mathcal{G}}^y \\ \omega \\ v_{\mathcal{B}}^x \\ v_{\mathcal{B}}^y \end{bmatrix} \qquad \begin{array}{ll} \text{Attitude} \\ \text{Translation in } \mathbf{x}_{\mathcal{G}} \\ \text{Translation in } \mathbf{y}_{\mathcal{G}} \\ \text{Attitude rate} \\ \text{Velocity in } \mathbf{x}_{\mathcal{B}} \\ \text{Velocity in } \mathbf{y}_{\mathcal{B}} \\ \end{array}$$

 $\mathbf{u} = \begin{bmatrix} \tau_1 \\ \tau_2 \end{bmatrix} \qquad \begin{array}{l} \text{Torque along } \mathbf{x}_{\mathcal{B}} \text{ at wheel 1} \\ \text{Torque along } \mathbf{y}_{\mathcal{B}} \text{ at wheel 2} \end{array}$

with $\mathcal{X}\subseteq\mathbb{R}^6$, $\mathcal{U}\subseteq\mathbb{R}^2$, and flat outputs

$$\gamma(t) = \mathbf{h}(\mathbf{x}(t)) = \begin{bmatrix} p_{\mathcal{G}}^x(t) & p_{\mathcal{G}}^y(t) \end{bmatrix}^T \in C^3(\mathbb{R}^2)$$

in the flat output space \mathcal{F} .



1. Differentially Flat Dynamics - UGV (constrained)

Constrained UGV with no lateral slip configured on C = SE(2),

$$\mathbf{x} = \begin{bmatrix} p_{\mathcal{G}}^x \\ p_{\mathcal{G}}^y \\ \theta \\ \dot{\alpha}_1 \\ \dot{\alpha}_2 \end{bmatrix} \qquad \begin{array}{ll} \text{Attitude} \\ \text{Translation in } \mathbf{x}_{\mathcal{G}} \\ \text{Translation in } \mathbf{y}_{\mathcal{G}} \\ \text{Angular rate of wheel 1} \\ \text{Angular rate of wheel 2} \\ \end{array}$$

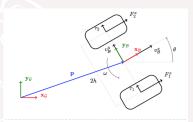
$$\mathbf{u} = egin{bmatrix} au_1 \ au_2 \end{bmatrix}$$
 Torque along $\mathbf{x}_{\mathcal{B}}$ at wheel 1 Torque along $\mathbf{y}_{\mathcal{B}}$ at wheel 2

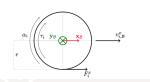


$$\begin{split} \dot{p}_{\mathcal{G}}^{x}(t) &= (\dot{\alpha}_{1}(t) + \dot{\alpha}_{2}(t))(r/2)\cos(\theta) \\ \dot{p}_{\mathcal{G}}^{y}(t) &= (\dot{\alpha}_{1}(t) + \dot{\alpha}_{2}(t))(r/2)\sin(\theta) \\ \dot{\theta}(t) &= (\dot{\alpha}_{2} - \dot{\alpha}_{1}(t))/(2h) \end{split}$$

$$\ddot{\alpha}_1(t) = J_1^{-1} \tau_1(t)$$

$$\ddot{\alpha}_2(t) = J_2^{-1} \tau_2(t)$$





1. Differentially Flat Dynamics - UGV (constrained)

Constrained UGV with no lateral slip configured on C = SE(2),

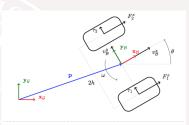
$$\mathbf{x} = egin{bmatrix} p_{\mathcal{G}}^x \\ p_{\mathcal{G}}^y \\ \theta \\ \dot{\alpha}_1 \\ \dot{\alpha}_2 \end{bmatrix} \qquad egin{bmatrix} \text{Attitude} \\ \text{Translation in } \mathbf{x}_{\mathcal{G}} \\ \text{Angular rate of wheel 1} \\ \text{Angular rate of wheel 2} \\ \hline \left[au_1 \right] \qquad \textbf{Torque along } \mathbf{x}_{\mathcal{B}} \text{ at wheel 1} \\ \end{bmatrix}$$

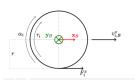
$$\mathbf{u} = egin{bmatrix} au_1 \ au_2 \end{bmatrix}$$
 Torque along $\mathbf{x}_\mathcal{B}$ at wheel 1 Torque along $\mathbf{y}_\mathcal{B}$ at wheel 2

with $\mathcal{X}\subseteq\mathbb{R}^5$, $\mathcal{U}\subseteq\mathbb{R}^2$, and flat outputs

$$\boldsymbol{\gamma}(t) = \mathbf{h}(\mathbf{x}(t)) = \begin{bmatrix} p_{\mathcal{G}}^x(t) & p_{\mathcal{G}}^y(t) \end{bmatrix}^T \in C^2(\mathbb{R}^2)$$

in the flat output space \mathcal{F} .





1. Differentially Flat Dynamics - UAV

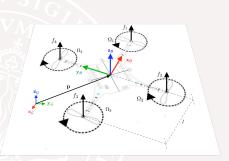
Unmanned Aerial Vehicle (UAV) configured on C = SE(3),

$$\mathbf{x} = egin{bmatrix} \mathbf{p}_{\mathcal{G}} \\ \mathbf{R} \\ \mathbf{v}_{\mathcal{G}} \\ \boldsymbol{\omega} \end{bmatrix}$$
 Translation Attitude Translational Velocity Angular rate

$$\mathbf{u} = \begin{bmatrix} f_z \\ \tau_x \\ \tau_y \\ \tau_z \end{bmatrix} \qquad \begin{array}{ll} \text{Positive force along } \mathbf{z}_\mathcal{B} \\ \text{Torque along } \mathbf{x}_\mathcal{B} \\ \text{Torque along } \mathbf{y}_\mathcal{B} \\ \text{Torque along } \mathbf{z}_\mathcal{B} \end{array}$$

with $\mathcal{X} \subseteq \mathbb{R}^9 \times \mathbb{S}^2$, $\mathcal{U} \subseteq \mathbb{R}^4$, but we may instead use rotor speeds $\Omega = [\Omega_1, \cdots, \Omega_4]$ as inputs

$$\begin{bmatrix} f_z(t) \\ \tau_x(t) \\ \tau_y(t) \\ \tau_z(t) \end{bmatrix} = \begin{bmatrix} k \sum_{i=1}^4 \Omega_i^2(t) \\ kl(-\Omega_2^2(t) + \Omega_4^2(t)) \\ kl(-\Omega_1^2(t) + \Omega_3^2(t)) \\ \sum_{i=1}^4 b\Omega_i^2(t) + I_M\dot{\Omega}_i(t) \end{bmatrix}$$



1. Differentially Flat Dynamics - UAV

Unmanned Aerial Vehicle (UAV) configured on $\mathcal{C} = SE(3)$,

$$\mathbf{x} = egin{bmatrix} \mathbf{p}_{\mathcal{G}} \\ \mathbf{R} \\ \mathbf{v}_{\mathcal{G}} \\ \boldsymbol{\omega} \end{bmatrix}$$
 Translation Attitude Translational Velocity Angular rate

Angular rate

$$\mathbf{u} = \begin{bmatrix} f_z \\ \tau_x \\ \tau_y \\ \tau_z \end{bmatrix}$$

 $\mathbf{u} = \begin{bmatrix} f_z \\ \tau_x \\ \tau_y \\ \tau_z \end{bmatrix} \qquad \begin{array}{l} \text{Positive io. 2.} \\ \text{Torque along } \mathbf{x}_{\mathcal{B}} \\ \text{Torque along } \mathbf{z}_{\mathcal{B}} \\ \end{array}$ Positive force along z_B

with $\mathcal{X} \subseteq \mathbb{R}^9 \times \mathbb{S}^2$, $\mathcal{U} \subseteq \mathbb{R}^4$, and flat outputs in \mathbf{u} or Ω ,

$$\gamma(t) = \mathbf{h}(\mathbf{x}(t)) = \begin{bmatrix} \mathbf{p}_{\mathcal{G}}^T(t) & \psi(t) \end{bmatrix}^T \in C^5(\mathbb{R}^4)$$

defines the flat outputs [13, 14].

^[13] D. W. Mellinger, "Trajectory generation and control for quadrotors", PhD Thesis, 2012, available online as a pdf.

^[14] M. Greiff, "Modelling and control of the crazyflie quadrotor", M.Sc. Thesis, 2017, available online as a pdf.

1. Differentially flat systems - Summary

Main takeaways

- A very large number of systems are "boring" [11, 15]
- Ways of finding flat outputs exists (feedback linearization)
- Almost always found as functions of the system configurations
- Independent planning in flat output dimensions
- $oldsymbol{\circ}$ Plan for smoothness in γ instead of explicitly enforcing $\dot{\mathbf{x}} = \mathbf{f}(\mathbf{x}, \mathbf{u})$ in time.

```
 \begin{array}{ll} \text{Toy example} & \gamma \in C^2(\mathbb{R}^1) \\ \text{UGV (unconstrained)} & \gamma \in C^3(\mathbb{R}^2) \\ \text{UGV (constrained)} & \gamma \in C^2(\mathbb{R}^2) \\ \text{UAV} & \gamma \in C^5(\mathbb{R}^4) \end{array}
```

^[11] G. Rigatos, "Nonlinear control and filtering using differential flatness approaches," 2015.

^[15] R. Murray et al., "Differential flatness of mechanical control systems," 1995.

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- **6** Plan for smoothness in γ instead of explicitly enforcing $\dot{\mathbf{x}} = \mathbf{f}(\mathbf{x}, \mathbf{u})$ in time.

Toy example
$$\gamma \in C^2(\mathbb{R}^1)$$
 UGV (unconstrained) $\gamma \in C^3(\mathbb{R}^2)$ UGV (constrained) $\gamma \in C^2(\mathbb{R}^2)$ UAV $\gamma \in C^5(\mathbb{R}^4)$

Suitable parameterizations of the flat trajectories?

- Sinusoids
- Bezier curves
- LP-filtered signals
- Polynomials

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Suitable parameterizations of the flat trajectories?

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Path planning with polynomials (CPO) [8]

① Consider n polynomial splines $P_1(t),...,P_n(t)$ with $\deg(P_k)=N$, as

$$P_k(t) = \sum_{i=0}^{N} p_{k,i} t^i = \mathbf{p}_{(k)}^T \mathbf{t}(t), \qquad t \in [0, T_k], \qquad \mathbf{p}_{(k)} = [p_{k,0}, ..., p_{k,N}]^T$$

Path planning with polynomials (CPO) [8]

- Onsider n polynomial splines $P_1(t),...,P_n(t)$ with $\deg(P_k)=N$
- Integral cost associated with sum of spline derivatives

$$J(T_k) = \sum_{i=0}^{N} \int_{0}^{T_k} c_i \left\| \frac{dP_k^{(i)}(t)}{dt} \right\|_{2}^{2} dt = \mathbf{p}_{(k)}^{T} \mathbf{Q}_{(k)} \mathbf{p}_{(k)}$$

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Remark (Regarding the cost)

Spline	Name	Objective	
$P_k(t)$	Position	Small/Large (often $c_0 = 0$)	
$\begin{vmatrix} \frac{\mathrm{d}^1}{\mathrm{d}t^1} P_k(t) \\ \frac{\mathrm{d}^2}{\mathrm{d}t^2} P_k(t) \\ \frac{\mathrm{d}^3}{\mathrm{d}t^3} P_k(t) \end{vmatrix}$	Velocity	Small/Large (often $c_1=0$)	
$\frac{\mathrm{d}^2}{\mathrm{d}t^2}P_k(t)$	Acceleration	Small	(often $c_2 > 0$)
$\frac{\mathrm{d}^3}{\mathrm{d}t^3}P_k(t)$	Jerk	Small	(often $c_3 > 0$)
$\frac{\mathrm{d}^4}{\mathrm{d}t^4} P_k(t)$	Snap	Small	(often $c_4 \gg 0$)

Minimum snap: $c_4 > 0$, $c_i = 0 \forall i \neq 4$.

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Remark (Regarding the smoothness)

If we need a function $C^M(\mathbb{R})$, add constraint

$$\frac{\mathrm{d}^m}{\mathrm{d}t^m} P_k(T_k) = \frac{\mathrm{d}^m}{\mathrm{d}t^m} P_{k+1}(0) \quad \forall m = 0, ..., M, \quad k = 1, ..., n-1$$
 (4)

which is linear in $\mathbf{p}_{(k)}$ and $\mathbf{p}_{(k+1)}$ given T_k .

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- Integral cost associated with sum of spline derivatives

$$J(T_k) = \sum_{i=0}^{N} \int_{0}^{T_k} c_i \left\| \frac{dP_k^{(i)}(t)}{dt} \right\|_{2}^{2} dt = \mathbf{p}_{(k)}^T \mathbf{Q}_{(k)} \mathbf{p}_{(k)}$$

 $\textbf{ § Sum cost over all splines with } \mathbf{p} = [\mathbf{p}_{(1)}^T,...,\mathbf{p}_{(n)}^T]^T$

Subject to
$$P_k(t) \in C^M(\mathbb{R}) \ \forall k=1,..,n \quad \Rightarrow \quad \text{Subject to} \ \mathbf{Ap} - \mathbf{b} = \mathbf{0}.$$

O bo this independently for each flat dimension

Path planning with polynomials (CPO) [8]

- Consider n polynomials $P_1(t),...,P_n(t)$ with $\deg(P_k)=N$
- Integral cost associated with sum of spline derivatives
- Sum cost over all splines
- What happens between the endpoints?

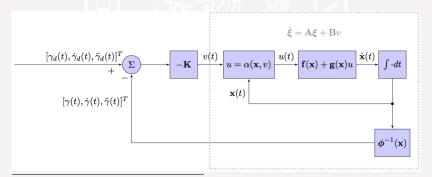
Reconsider the toy example

$$\dot{\mathbf{x}} = \mathbf{f}(\mathbf{x}) + \mathbf{g}(\mathbf{x})u, \quad \mathbf{f}(\mathbf{x}) = \begin{bmatrix} -x_1 + x_2 \\ x_1 - x_2 - x_1 x_3 \\ x_1 + x_1 x_2 - 2x_3 \end{bmatrix}, \quad \mathbf{g}(\mathbf{x}) = \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix}$$

[8] C. Richter, "Polynomial trajectory planning for aggressive quadrotor flight in dense indoor environments", 2013.

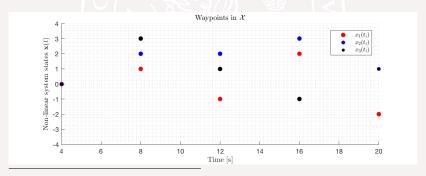
Path planning with polynomials (CPO) [8]

- Consider n polynomials $P_1(t), ..., P_n(t)$ with $\deg(P_k) = N$
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- Sum cost over all splines
- What happens between the endpoints?



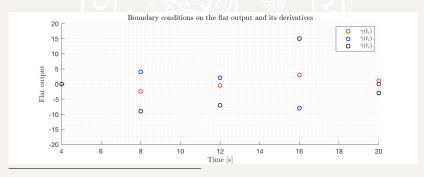
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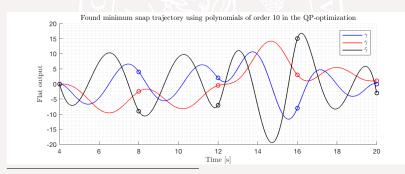
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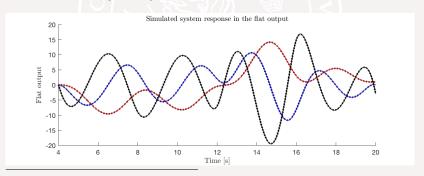
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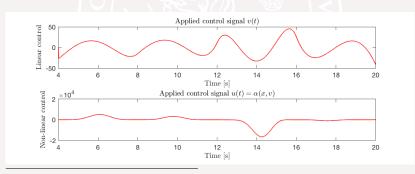
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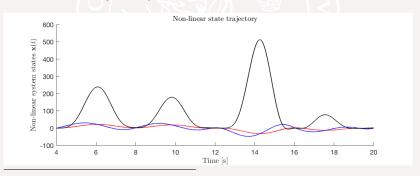
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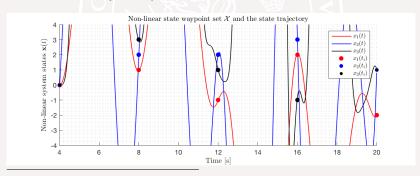
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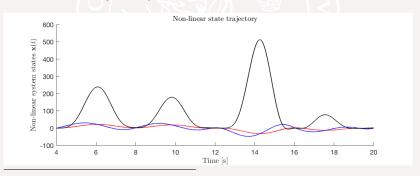
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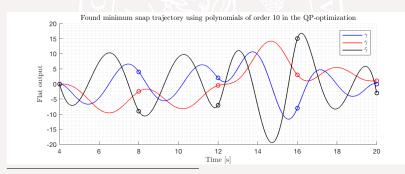
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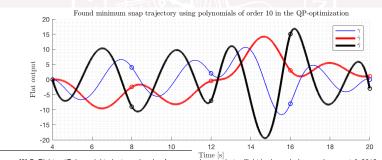
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Reconsider the toy example



[8] C. Richter, "Polynomial trajectory planning for aggressive quadrotor flight in dense indoor environments", 2013.

3. Time-warping transformation

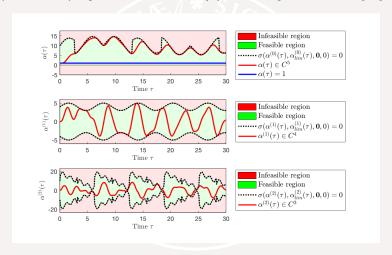
Remark (Change the rate of time)

Let a trajectory $\gamma(\tau)$ be generated in terms of the time unit τ , relating to a second time unit t on which the system evolves, such that $\alpha(\tau)d\tau=dt$ for some $\alpha(\tau)>0$.



3. Time-warping transformation

Optimization program to maximize $\alpha(\tau)$, enforcing smoothness [16]



3. Formulating a QP

Given the maps $\{\mathbf{h},\phi,\beta\}$ for a differentially flat system, and

- ullet A feasible flat trajectory $\gamma(au) \in C^M$
- A smoothness constraint on $\alpha(\tau) \in C^{M-1}$

minimize the time t_f-t_0 taken to traverse $\pmb{\gamma}(t)$ by maximising $\alpha(\tau)$

3. Formulating a QP

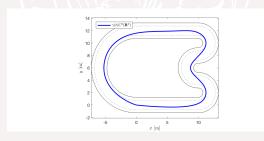
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minimize the time t_f-t_0 taken to traverse ${m \gamma}(t)$ by maximising ${m lpha}(au)$

Example: Consider a UGV, path in \mathcal{F} generated by CPO, velocity constraints

$$-\begin{bmatrix} 5+2\sin(\tau) \\ 5+2\sin(\tau) \end{bmatrix} \le \gamma_t^{(1)}(\tau) \le \begin{bmatrix} 5+2\sin(\tau) \\ 5+2\sin(\tau) \end{bmatrix},$$



3. Simulation Example - UGV

Simulation example D - UGV with and without time-warping

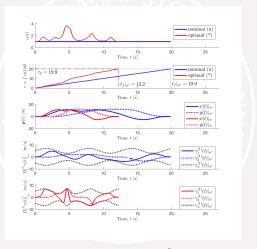


Figure 1: A nominal $\alpha^n(\tau)=1 \ \ \forall \tau$ and optimal $\alpha(\tau)\in C^3(\mathbb{R})$ subject to sinusoidal constraints.

3. Simulation Example - UGV

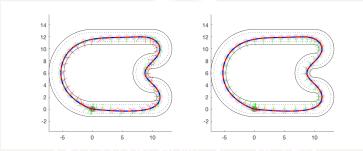


Figure 1: The nominal trajectory $\gamma^n(\tau)$ (blue) and simulated motion along the optimised flat output trajectory $\gamma^*(t)$ with the SE(2) configured UGV (left) and the non-holonomically constrained UGV (right).

Example summary

- Optimal warping found as the problem is convex
- Same flat output trajectory, very different state-trajectories
- Original dynamical system $\dim(\mathbf{x}) = \{5, 6\}, \dim(\mathbf{u}) = 2$
- System in the warping MPC formulation $\dim(\mathbf{x}_{\alpha}) = 3$, $\dim(u_{\alpha}) = 1$

3. Formulating a SQP

Example: UAV dynamics, starting and finishing in $\gamma(0)=0$, performing a looping manoeuvre defined by the path

$$\gamma(\tau) = -[\sin(\pi\tau/4), \sin(\pi\tau/2), \cos(\pi\tau/2), -\pi\tau/4]^T.$$

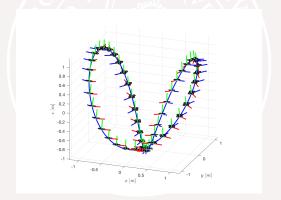


Figure 2: A looping manoeuvre with $\gamma(\tau) \in C^{\infty}(\mathbb{R}^4)$.

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Two main saturating constraints

Velocities:

$$-\begin{bmatrix} 5 \\ 5 \\ 5 \end{bmatrix} \leq \begin{bmatrix} v^x(t) \\ v^y(t) \\ v^z(t) \end{bmatrix} \leq \begin{bmatrix} 5 \\ 5 \\ 5 \end{bmatrix} \qquad [m/s] \qquad \text{(Linear in } \alpha\text{)}$$

Rotor-speeds:

$$\begin{bmatrix} 500 \\ 500 \\ 500 \\ 500 \end{bmatrix} \leq \begin{bmatrix} \Omega_1(t) \\ \Omega_2(t) \\ \Omega_3(t) \\ \Omega_4(t) \end{bmatrix} \leq \begin{bmatrix} 2400 \\ 2400 \\ 2400 \\ 2400 \end{bmatrix} [rad/s] \qquad \text{(Highly nonlinear in } \alpha\text{)}$$

3. Simulation Example - UAV

Simulation example E - Looping UAV with and without time-warping

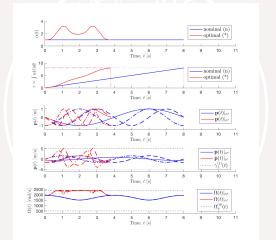


Figure 2: The nominal- (blue) and computed locally time-optimal trajectories (red) for the SE(3)-configured UAV during the looping manoeuvre with actuator constraints.

3. Simulation Example - UAV

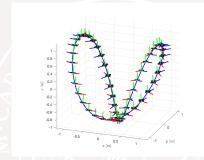


Figure 2: Nominal and locally time-optimal solutions for a looping manoeuvre given actuator constraints.

Example summary

- Locally optimal warping found (problem is now non-convex)
- The posed constraints are close to saturated at almost all times
- Original system $\dim(\mathbf{x}) = \{12, 13\}, \dim(\mathbf{u}) = 4$
- System in the SQP formulation $\dim(\mathbf{x}_{\alpha}) = 5$, $\dim(u_{\alpha}) = 1$

3. Simulation Example - UAV

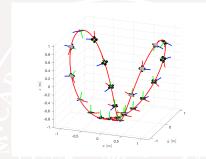


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Summary

Two-step approach

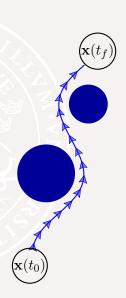
- Path planning of the flat outputs
- Augment higher order derivatives through $\alpha(\tau)$

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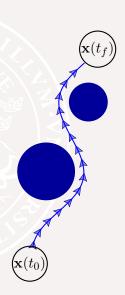
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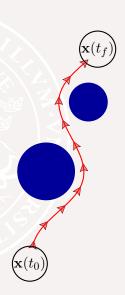
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