

# Optimization Case Study

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# Outline section 1

## 1 Exercises

## 2 Assignments

- Fitting problems
- Optimal control problems
- Trajectory generation using invariant representations

# Exercises

## **Fitting problems**

ex: a2 (Huber)

## **Optimal control problems**

ex: b3 (Bicycle)

## **Trajectory generation using invariant representations**

ex: c2 (Exact integration), c7 (geometric FS),  
c14 (Spline invariants)

# Outline section 2

## 1 Exercises

## 2 Assignments

- Fitting problems
- Optimal control problems
- Trajectory generation using invariant representations

# Outline subsection 1

## 1 Exercises

## 2 Assignments

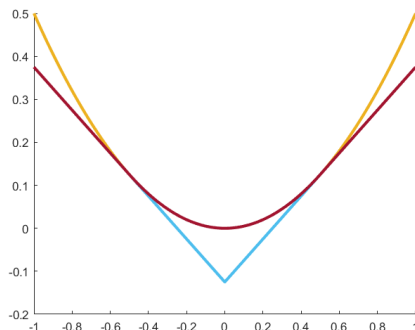
- Fitting problems
- Optimal control problems
- Trajectory generation using invariant representations

# Fitting problems

## Exercise a2: Huber norm

Huber norm  $\rightarrow$  combination of L1- and L2-norm

$$h(x) = \begin{cases} \frac{1}{2}x^2 & |x| < \delta. \\ \delta(|x| - \frac{1}{2}\delta) & \text{otherwise.} \end{cases}$$



# Fitting problems

## Exercise a2: Huber norm

Optimization problem with slack variables:

$$\min \sum s_i$$

$$\text{subject to } -s_i \leq h(e_i) \leq s_i$$

where

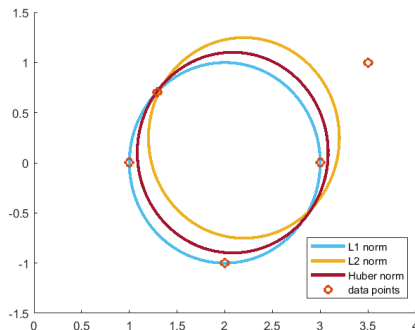
$$e_i = \left\| \begin{bmatrix} x_i - x_c \\ y_i - y_c \end{bmatrix} \right\|_2 - R$$

# Fitting problems

## Exercise a2: Huber norm

Depending on 'cut-off' value delta, closer to L1- or L2-norm fit

$$h(x) = (x < -\delta) * (\delta(-x - 0.5 * \delta)) + \\ (-\delta \leq x) * (x \leq \delta) * (0.5 * x^2) + (x > \delta) * (\delta(x - 0.5 * \delta))$$





# Outline subsection 2

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# Optimal control problems

## Exercise b3: Bicycle

### Bicycle model

$$\text{Ode's} \quad \begin{cases} \dot{x} = V * \cos(\theta) \\ \dot{y} = V * \sin(\theta) \\ \dot{\theta} = \frac{V}{L} * \tan(\delta) \\ \dot{V} = a \end{cases} \quad \text{with} \quad \begin{cases} L = 1.5m \\ m = 80kg \end{cases}$$

$$\text{Inputs} \quad \begin{cases} \text{acceleration } a \\ \text{steering angle } \delta \end{cases}$$

# Optimal control problems

## Exercise b3: Bicycle

Optimization problem

$$\min T$$

Subject to

$$\text{Input constraints} \quad \begin{cases} |F| = |m * a| < 100 \text{ N} \\ |\delta| < \pi/4 \end{cases}$$

$$\text{State constraints} \quad \begin{cases} |V| < 5 \text{ m/s} \\ \text{integrated dynamics (rk4)} \end{cases}$$

$$\text{Time constraint} \quad \begin{cases} T > 0 \end{cases}$$

# Optimal control problems

## Exercise b3: Bicycle

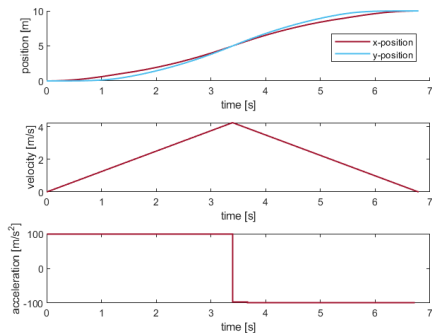


Figure 3: Position, velocity and acceleration.

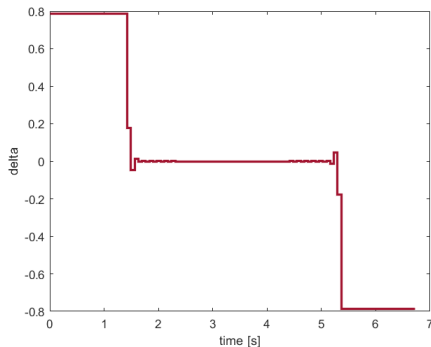


Figure 4: Steering angle.

# Optimal control problems

## Exercise b3: Bicycle

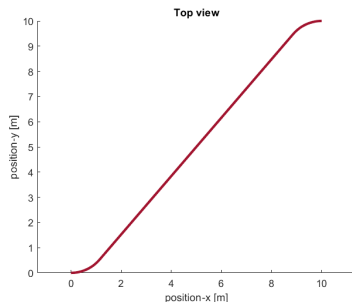


Figure 5:  $\theta_{init} = 0^\circ$  &  $\theta_{final} = 0^\circ$

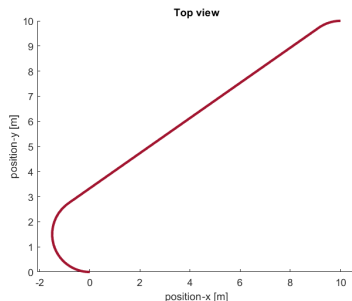


Figure 6:  $\theta_{init} = 180^\circ$  &  $\theta_{final} = 0^\circ$

# Outline subsection 3

## 1 Exercises

## 2 Assignments

- Fitting problems
- Optimal control problems
- Trajectory generation using invariant representations

# Trajectory generation using invariant representations

## Exercise c2: Exact integration

Rewrite differential equation representing motion:

$$\dot{p}(t) = R_t(t) \begin{bmatrix} i_1(t) & 0 & 0 \end{bmatrix}^T$$

$$\dot{R}_t(t) = R_t(t) \text{skew}(\begin{bmatrix} i_3(t) & i_2(t) & 0 \end{bmatrix}^T)$$

as

$$\dot{X} = HX \tag{1}$$

where  $X = [p(t); R_t(t)(:)]$

# Trajectory generation using invariant representations

## Exercise c2: Exact integration

Then

$$H = \begin{bmatrix} 0 & 0 & 0 & \mathbf{i}_1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \mathbf{i}_1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & \mathbf{i}_1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -\mathbf{i}_2 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -\mathbf{i}_2 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -\mathbf{i}_2 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \mathbf{i}_3 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \mathbf{i}_3 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \mathbf{i}_3 \\ 0 & 0 & 0 & \mathbf{i}_2 & 0 & 0 & -\mathbf{i}_3 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \mathbf{i}_2 & 0 & 0 & -\mathbf{i}_3 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & \mathbf{i}_2 & 0 & 0 & -\mathbf{i}_3 & 0 & 0 & 0 \end{bmatrix}$$

and the exact solution to (1) is

$$X(t) = \expm(Ht) * X_0$$



# Trajectory generation using invariant representations

## Exercise c2: Exact integration

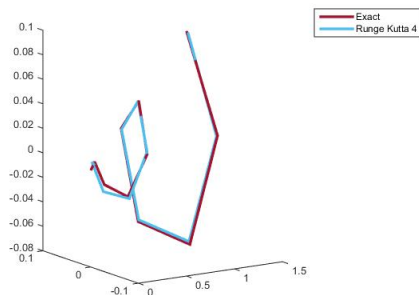


Figure 7: Simulation results of fits:  
10 Sample points

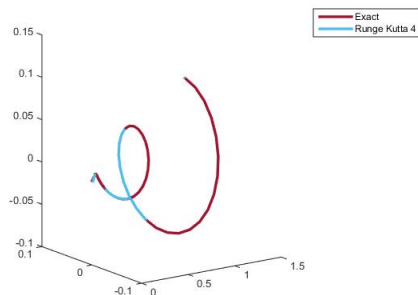


Figure 8: Simulation results of fits:  
50 Sample points

# Trajectory generation using invariant representations

## Exercise c2: Exact integration

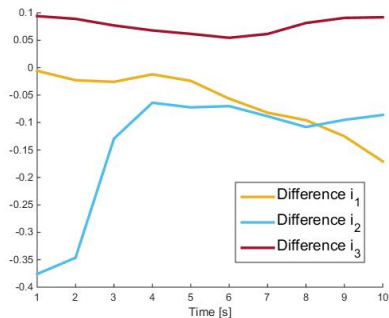


Figure 9: Relative difference Exact - RK4: 10 Sample points

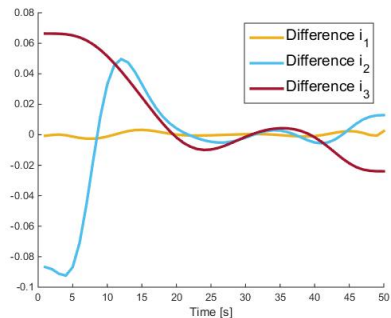


Figure 10: Relative difference Exact - RK4: 50 Sample points

# Trajectory generation using invariant representations

## Exercise c7: Geometric Frennet-Serret invariants

Revisit the differential equation representing motion, but now as function of the path-length coordinate instead of time:

$$\frac{d}{ds}R(s) = R(s)\textit{skew}(\begin{bmatrix} i_{3,s}(s) & i_{2,s}(s) & 0 \end{bmatrix}^T)$$

# Trajectory generation using invariant representations

## Exercise c7: Geometric Frennet-Serret invariants

Now use the chain rule to express the differential equation in the time domain but still with the geometric invariants  $i_{2,s}(s)$  and  $i_{3,s}(s)$ .

$$\begin{aligned}
 \frac{d}{dt}R(t) &= \left\| \frac{d\mathbf{r}(t)}{dt} \right\| * R(t) * skew([i_{3,s}(s) \quad i_{2,s}(s) \quad 0]^T) \\
 &= u * R(t) * skew([i_{3,s}(s) \quad i_{2,s}(s) \quad 0]^T) \\
 &= R(t) * skew([u * i_{3,s}(s) \quad u * i_{2,s}(s) \quad 0]^T) \\
 &= R(t) * skew([i_{3,t}(t) \quad i_{2,t}(t) \quad 0]^T)
 \end{aligned}$$

Note that  $u$  is equal to  $i_{1,t}(t)$ .

# Trajectory generation using invariant representations

## Exercise c7: Geometric Frennet-Serret invariants

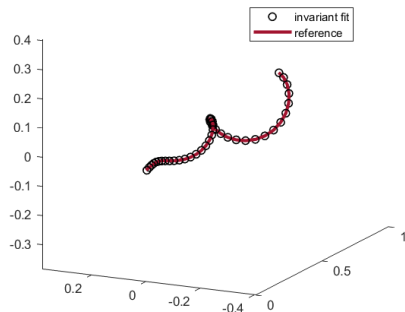


Figure 11: Invariant fit on reference

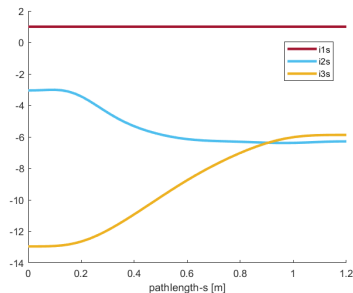


Figure 12: Invariants as a function of  $s$

# Trajectory generation using invariant representations

## Exercise c7: Geometric Frennet-Serret invariants

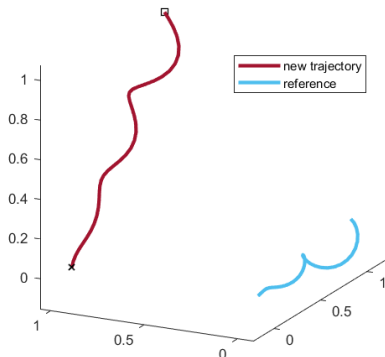


Figure 13: New vs reference trajectory

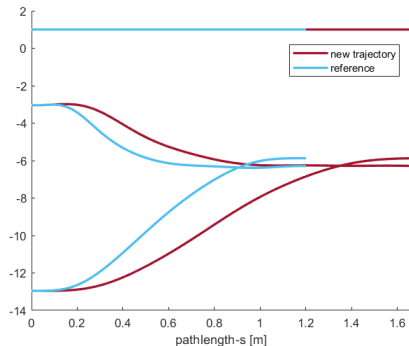


Figure 14: New vs reference trajectory invariants

# Trajectory generation using invariant representations

## Exercise c14: Spline parametrization of invariants

Instead of describing invariants using variables for each time step  $\rightarrow$   
describe each invariant as a spline function

Spline parameters

$$\begin{cases} \textit{degree} = 5 \\ \textit{domain} = [0, 1] \\ \textit{\#knots} = 15 \end{cases}$$

# Trajectory generation using invariant representations

## Exercise c14: Spline parametrization of invariants

### Fitting of reference trajectory invariants

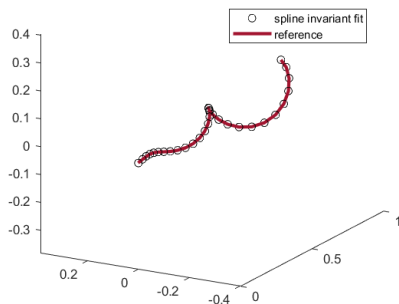


Figure 15: Spline invariant fit

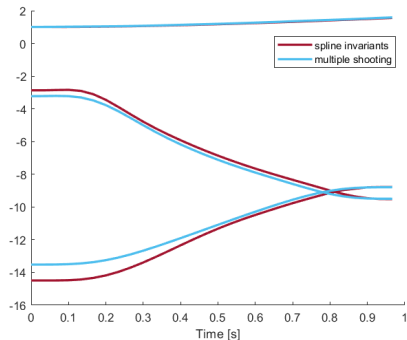


Figure 16: Spline vs multiple shooting invariants



# Trajectory generation using invariant representations

## Exercise c14: Spline parametrization of invariants

Generate new trajectory with cost function:

$$f(x) = \sum e_i^2$$

where

$$e_i = \left\| \begin{bmatrix} i_{1,new,i} - i_{1,ref,i} \\ i_{2,new,i} - i_{2,ref,i} \\ i_{3,new,i} - i_{2,ref,i} \end{bmatrix} \right\|_2$$

# Trajectory generation using invariant representations

## Exercise c14: Spline parametrization of invariants

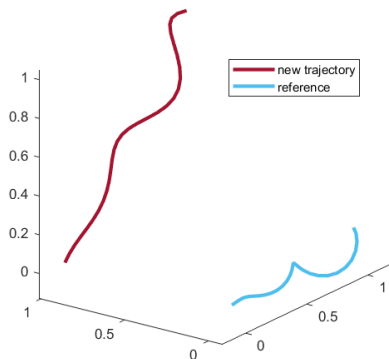


Figure 17: New vs reference trajectory

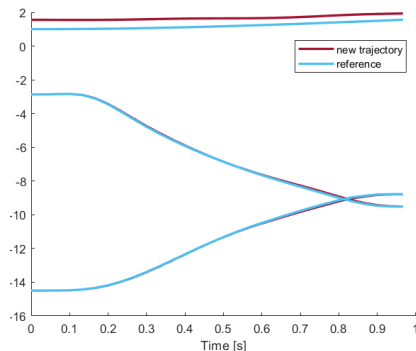


Figure 18: New vs reference trajectory invariants