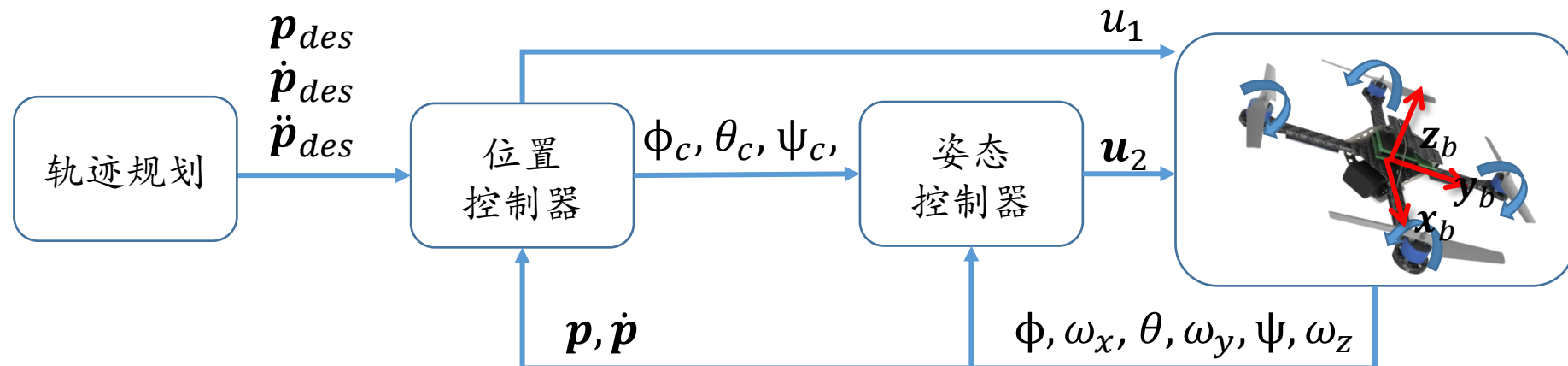


# 线性控制器



- 位置控制

PID:  $\ddot{\mathbf{p}}_{i,c} = \ddot{\mathbf{p}}_i^{des} + K_{d,i}(\dot{\mathbf{p}}_i^{des} - \dot{\mathbf{p}}_i) + K_{p,i}(\mathbf{p}_i^{des} - \mathbf{p}_i)$

模型:  $u_1 = m(g + \ddot{\mathbf{p}}_{3,c})$  (牛顿方程)

$$\phi_c = \frac{1}{g} (\ddot{\mathbf{p}}_{1,c} \sin \psi - \ddot{\mathbf{p}}_{2,c} \cos \psi) \quad \theta_c = \frac{1}{g} (\ddot{\mathbf{p}}_{1,c} \cos \psi + \ddot{\mathbf{p}}_{2,c} \sin \psi)$$

注意: 这些是当前测量的yaw, 不是期望的yaw

- 姿态控制

PID: 
$$\begin{bmatrix} \ddot{\phi}_c \\ \ddot{\theta}_c \\ \ddot{\psi}_c \end{bmatrix} = \begin{bmatrix} K_{p,\phi}(\phi_c - \phi) + K_{d,\phi}(\dot{\phi}_c - \dot{\phi}) \\ K_{p,\theta}(\theta_c - \theta) + K_{d,\theta}(\dot{\theta}_c - \dot{\theta}) \\ K_{p,\psi}(\psi_c - \psi) + K_{d,\psi}(\dot{\psi}_c - \dot{\psi}) \end{bmatrix}$$

模型: 
$$\mathbf{u}_2 = \mathbf{I} \cdot \begin{bmatrix} \ddot{\phi}_c \\ \ddot{\theta}_c \\ \ddot{\psi}_c \end{bmatrix} + \begin{bmatrix} \omega_x \\ \omega_y \\ \omega_z \end{bmatrix} \times \mathbf{I} \cdot \begin{bmatrix} \omega_x \\ \omega_y \\ \omega_z \end{bmatrix} \quad \text{(欧拉方程)}$$

# 总结

- 两者都是串级控制，外环控制位置，内环控制姿态。但相比于Linear Controller，SE(3) Controller有两个特点：
1. 根据误差计算期望的推力向量，用其根据微分平坦计算姿态误差（用旋转矩阵表示而非欧拉角，且没有小角度假设）。
  2. 推力控制输入是期望的推力向量投影到当前测量的姿态Z轴上的分量。



## 欧拉角

$$\bullet R_x(\phi) = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos \phi & -\sin \phi \\ 0 & \sin \phi & \cos \phi \end{bmatrix}$$

$$\bullet R_y(\theta) = \begin{bmatrix} \cos \theta & 0 & \sin \theta \\ 0 & 1 & 0 \\ -\sin \theta & 0 & \cos \theta \end{bmatrix}$$

$$\bullet R_z(\psi) = \begin{bmatrix} \cos \psi & -\sin \psi & 0 \\ \sin \psi & \cos \psi & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

$$R_z(\psi) \cdot R_x(\phi) \cdot R_y(\theta) \Rightarrow R$$

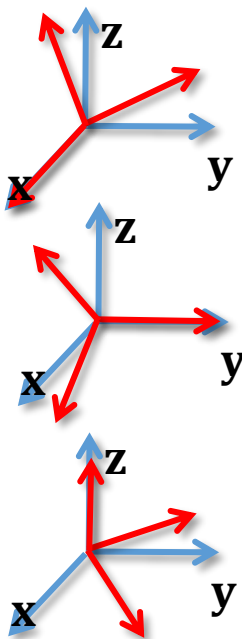
## 系统状态

$$\mathbf{x} = [x \ \dot{x} \ y \ \dot{y} \ z \ \dot{z} \ \phi \ \dot{\phi} \ \theta \ \dot{\theta} \ \psi \ \dot{\psi}]$$

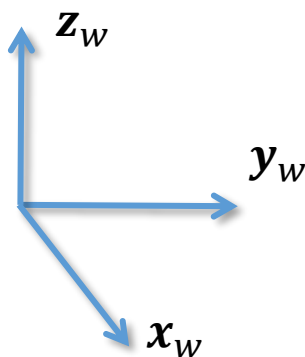
## 系统输入

$$\mathbf{u} = [U_1 \ U_2 \ U_3 \ U_4]$$

合推力 X, Y, Z三轴力矩



$R$ : body to world (ZXY)  
( $\phi, \theta, \psi$  分别对应于X-Y-Z Euler)

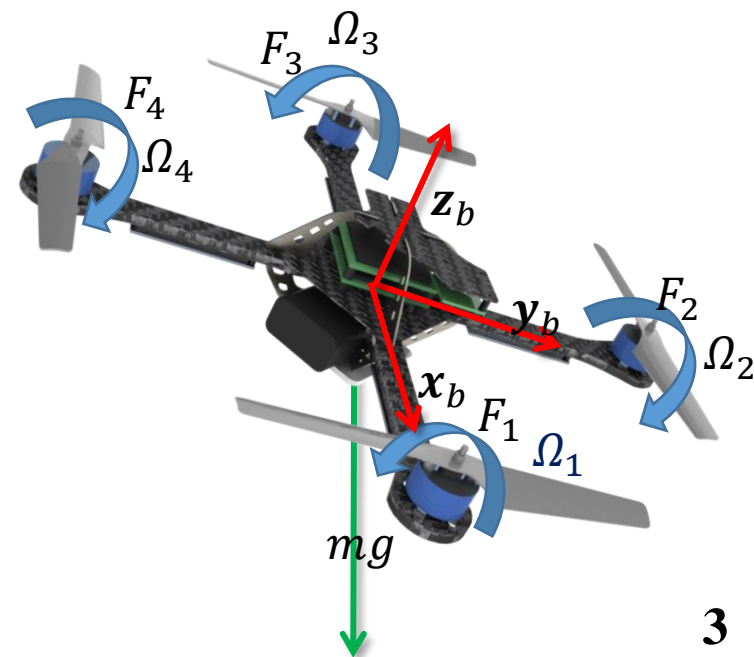


$l$ 是四轴飞行器中心与螺旋桨中心之间的距离,  $b$ 和 $d$ 分别是推力和反扭矩系数

$$\mathbf{u} = \begin{bmatrix} b & b & b & b \\ 0 & bl & 0 & -bl \\ -bl & 0 & bl & 0 \\ d & -d & d & -d \end{bmatrix} \begin{bmatrix} \Omega_1^2 \\ \Omega_2^2 \\ \Omega_3^2 \\ \Omega_4^2 \end{bmatrix}$$

混控矩阵

螺旋桨的速度 $\Omega_1, \Omega_2, \Omega_3, \Omega_4$





由空气动力学可知四轴转桨推力 $F_1, F_2, F_3, F_4$ 正比于螺旋桨的速度 $\Omega_1, \Omega_2, \Omega_3, \Omega_4$ 的平方。  
 $l$ 是四轴飞行器中心与螺旋桨中心之间的距离， $b$ 和 $d$ 分别是推力和反扭矩系数

$$F_i = b\Omega_i^2 \quad \text{单桨推力}$$

$$U_1 = F_1 + F_2 + F_3 + F_4 \quad \text{合推力}$$

$$U_2, U_3, U_4 \quad \text{三轴力矩}$$

$$J_r \quad \text{总转动惯量}$$

$$I_x, I_y, I_z \quad \text{三轴转动惯量}$$

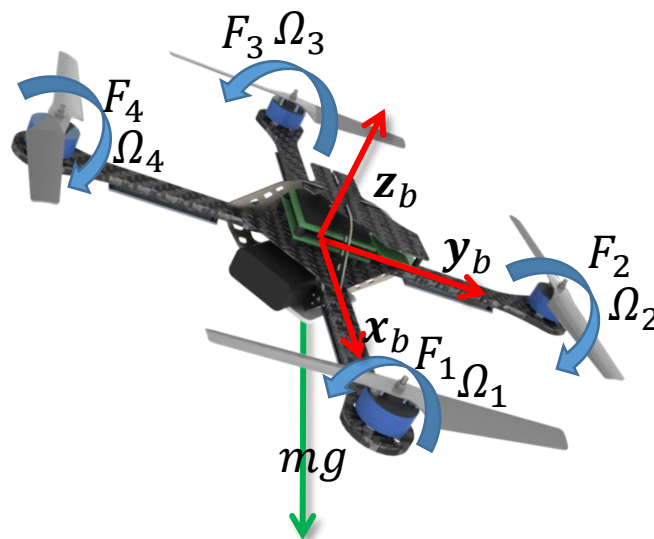
系统状态

$$\mathbf{x} = [x \ \dot{x} \ y \ \dot{y} \ z \ \dot{z} \ \phi \ \dot{\phi} \ \theta \ \dot{\theta} \ \psi \ \dot{\psi}]$$

系统输入

$$\mathbf{u} = [U_1 U_2 U_3 U_4]$$

$$\mathbf{u} = \begin{bmatrix} b & b & b & b \\ 0 & bl & 0 & -bl \\ -bl & 0 & bl & 0 \\ d & -d & d & -d \end{bmatrix} \begin{bmatrix} \Omega_1^2 \\ \Omega_2^2 \\ \Omega_3^2 \\ \Omega_4^2 \end{bmatrix}$$



## 完整模型

$$\Omega_r = -\Omega_1 + \Omega_2 - \Omega_3 + \Omega_4$$

$$\ddot{x} = (\sin\psi\sin\phi + \cos\phi\sin\theta\cos\psi) \frac{U_1}{m}$$

$$\ddot{y} = (-\cos\psi\sin\phi + \sin\psi\sin\theta\cos\phi) \frac{U_1}{m}$$

$$\ddot{z} = -g + (\cos\theta\cos\phi) \frac{U_1}{m}$$

$$\ddot{\phi} = \frac{I_y - I_z}{I_x} \dot{\theta} \dot{\psi} - \frac{J_r}{I_x} \dot{\theta} \Omega_r + \frac{U_2}{I_x}$$

$$\ddot{\theta} = \frac{I_z - I_x}{I_y} \dot{\phi} \dot{\psi} + \frac{J_r}{I_y} \dot{\phi} \Omega_r + \frac{U_3}{I_y}$$

$$\ddot{\psi} = \frac{I_x - I_y}{I_z} \dot{\phi} \dot{\theta} + \frac{U_4}{I_z}$$

## • 线性简化模型

平衡悬停态  $(\phi_0 \sim 0, \theta_0 \sim 0, u_{1,0} \sim mg)$

牛顿方程  $m\ddot{\mathbf{p}} = \begin{bmatrix} 0 \\ 0 \\ -mg \end{bmatrix} + \mathbf{R} \begin{bmatrix} 0 \\ 0 \\ F_1 + F_2 + F_3 + F_4 \end{bmatrix}$

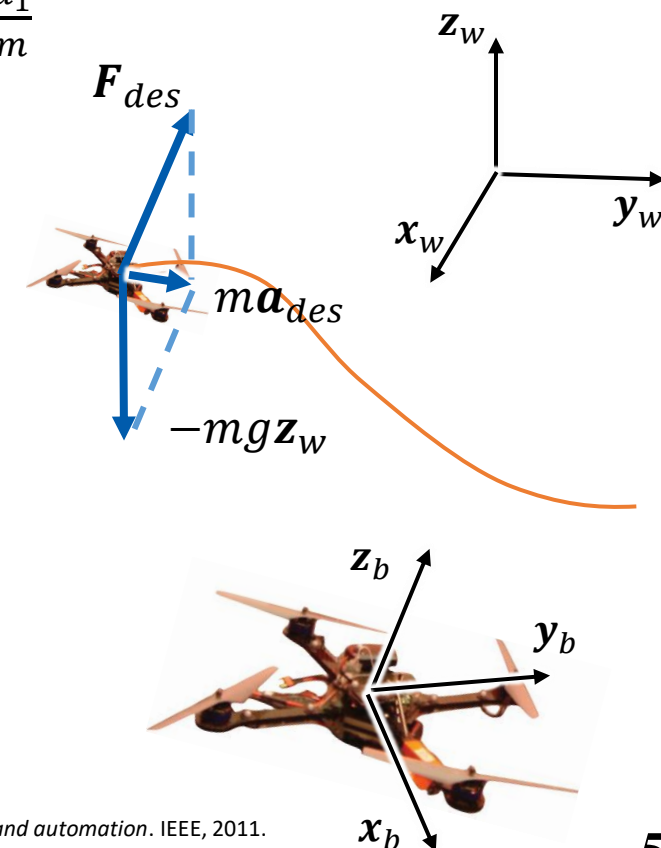
$$\mathbf{R} = \begin{bmatrix} c\psi c\theta - s\phi s\psi s\theta & -c\phi s\psi & c\psi s\theta + c\theta s\phi s\psi \\ c\theta s\psi + c\psi s\phi s\theta & c\phi c\psi & s\psi s\theta - c\psi c\theta s\phi \\ -c\phi s\theta & s\phi & c\phi c\theta \end{bmatrix}$$

$$\begin{aligned} \ddot{p}_1 &= \ddot{x} = g(\theta \cos\psi + \phi \sin\psi) \\ \ddot{p}_2 &= \ddot{y} = g(\theta \sin\psi - \phi \cos\psi) \\ \ddot{p}_3 &= \ddot{z} = -g + \frac{u_1}{m} \end{aligned}$$

欧拉角微分  $\begin{bmatrix} \omega_x \\ \omega_y \\ \omega_z \end{bmatrix} = \begin{bmatrix} c\theta & 0 & -c\phi s\theta \\ 0 & 1 & s\phi \\ s\theta & 0 & c\phi c\theta \end{bmatrix} \begin{bmatrix} \dot{\phi} \\ \dot{\theta} \\ \dot{\psi} \end{bmatrix}$

$$\begin{bmatrix} \omega_x \\ \omega_y \\ \omega_z \end{bmatrix} = \begin{bmatrix} \dot{\phi} \\ \dot{\theta} \\ \dot{\psi} \end{bmatrix}$$

欧拉方程:  $\mathbf{I} \cdot \begin{bmatrix} \ddot{\phi} \\ \ddot{\theta} \\ \ddot{\psi} \end{bmatrix} + \begin{bmatrix} \omega_x \\ \omega_y \\ \omega_z \end{bmatrix} \times \mathbf{I} \cdot \begin{bmatrix} \omega_x \\ \omega_y \\ \omega_z \end{bmatrix} = \begin{bmatrix} l(F_2 - F_4) \\ l(F_3 - F_1) \\ M_1 - M_2 + M_3 - M_4 \end{bmatrix} = \begin{bmatrix} U_2 \\ U_3 \\ U_4 \end{bmatrix}$



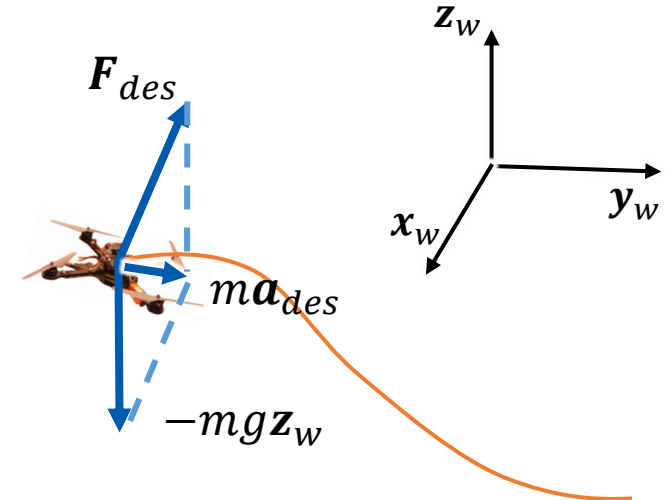


## 控制目标:

### • 理想情况:

$$m\mathbf{a} = \mathbf{F} - mg\mathbf{z}_w$$

$$\underline{\mathbf{F}}_{des} = mg\mathbf{z}_w + m\mathbf{a}_{des} \quad \mathbf{z}_{b,des} = \frac{\mathbf{F}_{des}}{\|\mathbf{F}_{des}\|}$$



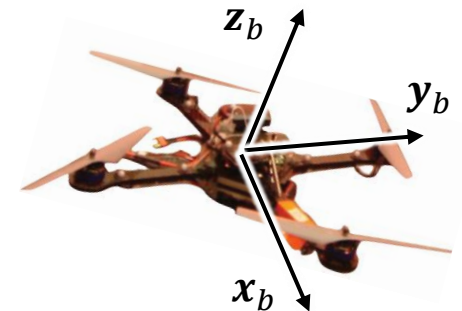
### • 现实情况: $\mathbf{q}_{des} = \mathbf{q}_z \otimes \mathbf{q}_\psi$ 期望推力与姿态 $\longrightarrow$ 自驾仪 Autopilot

$$\mathbf{e}_p = \mathbf{p} - \mathbf{p}_{des}, \quad \mathbf{e}_v = \mathbf{v} - \mathbf{v}_{des} \quad \text{位置与速度误差}$$

$$\mathbf{F}_{des} = -\underline{K_p}\mathbf{e}_p - \underline{K_v}\mathbf{e}_v + mg\mathbf{z}_w + m\mathbf{a}_{des}$$

增益

反应式控制





## 优势

- 易于实现
- 考虑误差

## 缺陷

- 对于复杂系统实现Non-trivial
- 增益项手动调整
- 对于耦合系统与约束无处理
- 忽略未来的决定

腿式机器人：  
太过复杂



无人机，车：  
分解为姿态位置或  
横向纵向控制器，  
忽略状态耦合





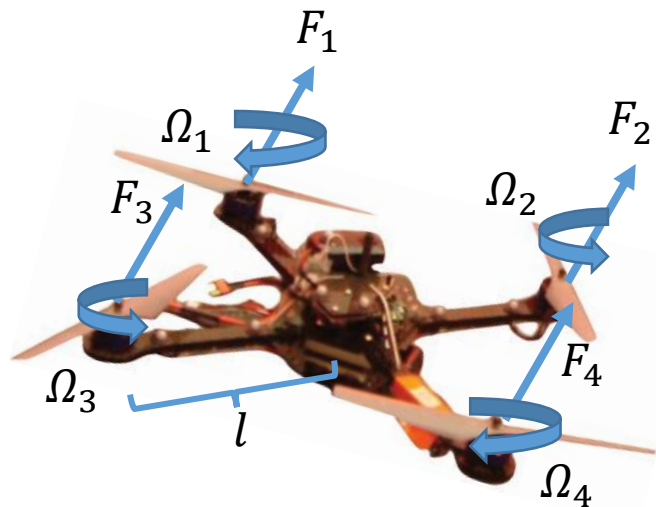
## • 最优控制

## • 系统模型

$$\begin{aligned} \dot{x} &= f_c(x, u) \\ x_{k+1} &= f_d(x_k, u_k) \quad x_0 \text{ 初始条件} \end{aligned}$$

$\swarrow$  状态       $\searrow$  输入

## • 动力学模型



$U_1$  合推力  
 $U_2 U_3 U_4$  三轴力矩

系统状态:

$$\begin{bmatrix} x \\ \dot{x} \\ y \\ \dot{y} \\ z \\ \dot{z} \\ \phi \\ \dot{\phi} \\ \theta \\ \dot{\theta} \\ \psi \\ \dot{\psi} \end{bmatrix}$$

系统输入:

$$\begin{bmatrix} U_1 \\ U_2 \\ U_3 \\ U_4 \end{bmatrix}$$

$$\begin{aligned} \ddot{x} &= (\sin\psi\sin\phi + \cos\phi\sin\theta\cos\psi) \frac{U_1}{m} \\ \ddot{y} &= (-\cos\psi\sin\phi + \sin\psi\sin\theta\cos\phi) \frac{U_1}{m} \\ \ddot{z} &= -g + (\cos\theta\cos\phi) \frac{U_1}{m} \\ \ddot{\phi} &= \frac{I_y - I_z}{I_x} \dot{\theta} \dot{\psi} - \frac{J_r}{I_x} \dot{\theta} \Omega_r + \frac{U_2}{I_x} \\ \ddot{\theta} &= \frac{I_z - I_x}{I_y} \dot{\phi} \dot{\psi} + \frac{J_r}{I_y} \dot{\phi} \Omega_r + \frac{U_3}{I_y} \\ \ddot{\psi} &= \frac{I_x - I_y}{I_z} \dot{\phi} \dot{\theta} + \frac{U_4}{I_z} \end{aligned}$$

$$\dot{x} = f_c(x, u) = \begin{pmatrix} \dot{x} \\ u_x \frac{1}{m} U_1 \\ \dot{y} \\ u_y \frac{1}{m} U_1 \\ \dot{z} \\ -g + (\cos\theta\cos\phi) \frac{1}{m} U_1 \\ \dot{\phi} \\ a_1 \dot{\theta} \dot{\psi} - a_2 \dot{\theta} \Omega_r + b_1 U_2 \\ \dot{\theta} \\ a_3 \dot{\phi} \dot{\psi} + a_4 \dot{\phi} \Omega_r + b_2 U_3 \\ \dot{\psi} \\ a_5 \dot{\phi} \dot{\theta} + b_3 U_4 \end{pmatrix}$$

$$\begin{aligned} a_1 &= \frac{I_y - I_z}{I_x} & b_1 &= \frac{1}{I_x} \\ a_2 &= \frac{J_r}{I_x} & b_2 &= \frac{1}{I_y} \\ a_3 &= \frac{I_z - I_x}{I_y} & b_3 &= \frac{1}{I_z} \\ a_4 &= \frac{J_r}{I_y} \\ a_5 &= \frac{I_x - I_y}{I_z} \end{aligned}$$

$$\begin{aligned} u_x &= (\sin\psi\sin\phi + \cos\psi\sin\theta\cos\phi) \\ u_y &= (-\cos\psi\sin\phi + \sin\psi\sin\theta\cos\phi) \end{aligned}$$

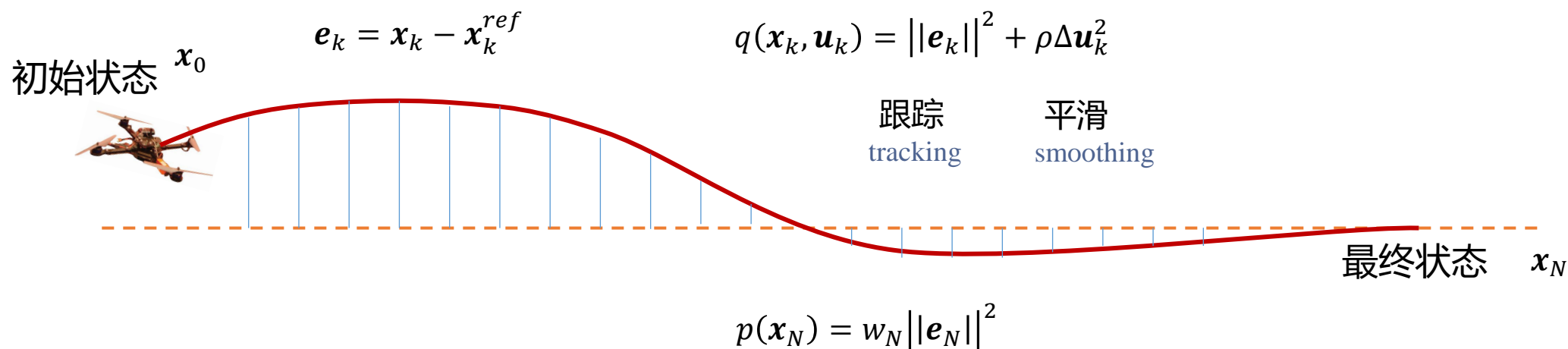




- 目标最小化函数

$$\min_{u_{0:N-1}} \sum_{k=0}^{N-1} \underbrace{q(\mathbf{x}_k, \mathbf{u}_k)}_{\substack{\text{阶段代价} \\ \text{(stage cost)}}} + \underbrace{p(\mathbf{x}_N)}_{\substack{\text{终端代价} \\ \text{(terminal cost)}}}$$

- 跟踪任务(tracking)举例:





- 目标最小化函数

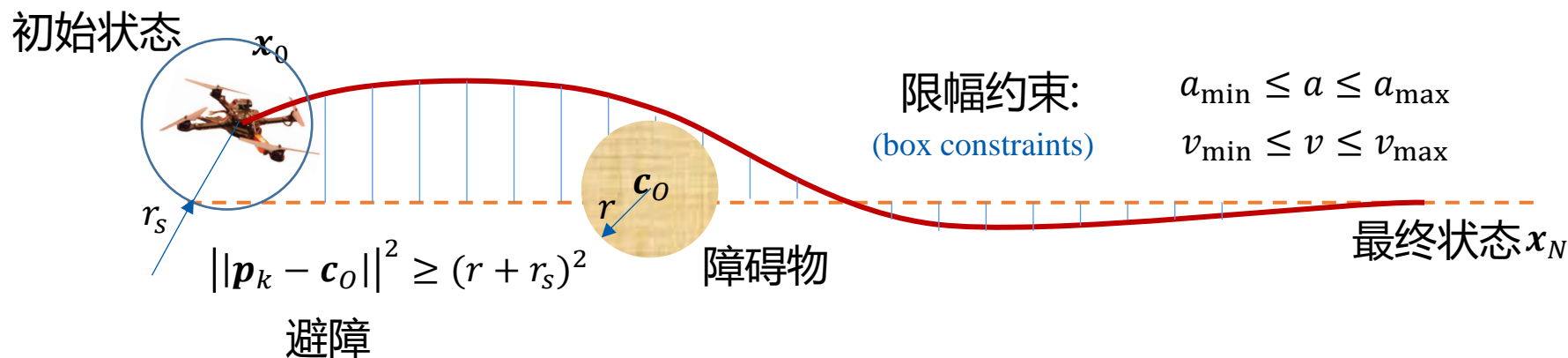
$$\min_{u_{0:N-1}} \sum_{k=0}^{N-1} \underbrace{q(\mathbf{x}_k, \mathbf{u}_k)}_{\text{阶段代价 (stage cost)}} + \underbrace{p(\mathbf{x}_N)}_{\text{终端代价 (terminal cost)}}$$

- 约束项

$$\mathbf{x}_{k+1} = f_d(\mathbf{x}_k, \mathbf{u}_k)$$

$$h(\mathbf{x}_k, \mathbf{u}_k) = 0 \quad \text{等式约束}$$

$$g(\mathbf{x}_k, \mathbf{u}_k) \leq 0 \quad \text{不等式约束}$$





- 最优控制

- 目标最小化函数

$$\min_{u_{0:N-1}} \sum_{k=0}^{N-1} \underbrace{q(\mathbf{x}_k, \mathbf{u}_k)}_{\substack{\text{阶段代价} \\ \text{(stage cost)}}} + \underbrace{p(\mathbf{x}_N)}_{\substack{\text{终端代价} \\ \text{(terminal cost)}}}$$

- 约束项

$$\mathbf{x}_{k+1} = f_d(\mathbf{x}_k, \mathbf{u}_k)$$

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$$g(\mathbf{x}_k, \mathbf{u}_k) \leq 0 \quad \text{不等式约束}$$

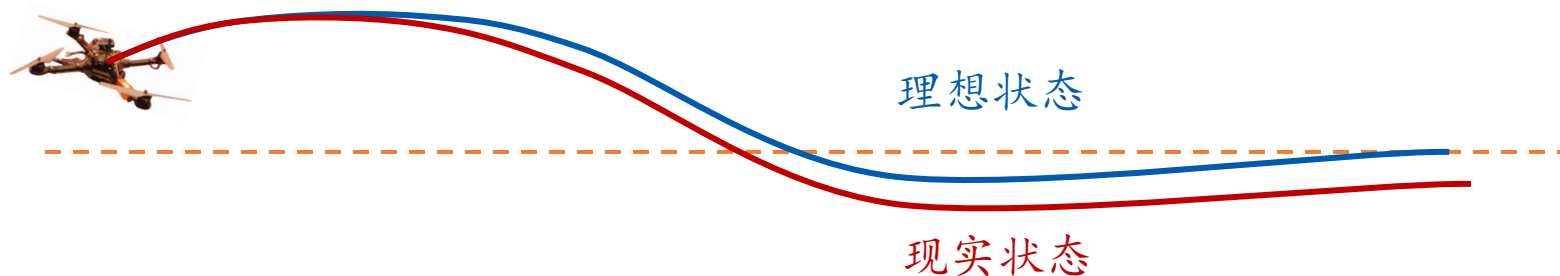
- 最优解

$$\mathbf{z}^* = [\mathbf{u}_0^T, \dots, \mathbf{u}_{N-1}^T]^T \quad \text{最优序列}$$

理想情况下用最优解 $\mathbf{z}^*$ 作为系统的控制输入!



- 开环最优控制难点
  - 系统模型不准确，长时间下累计更多误差
  - 最优解 $z^*$ 无法被准确执行
  - 较长的预测时域使得问题难以求解
  - 系统可能受到外界扰动





- 使用动力学模型预测未来走向选择最佳的控制输入

有限的预测时域

- 测量信息的反馈

- 测量信息的反馈

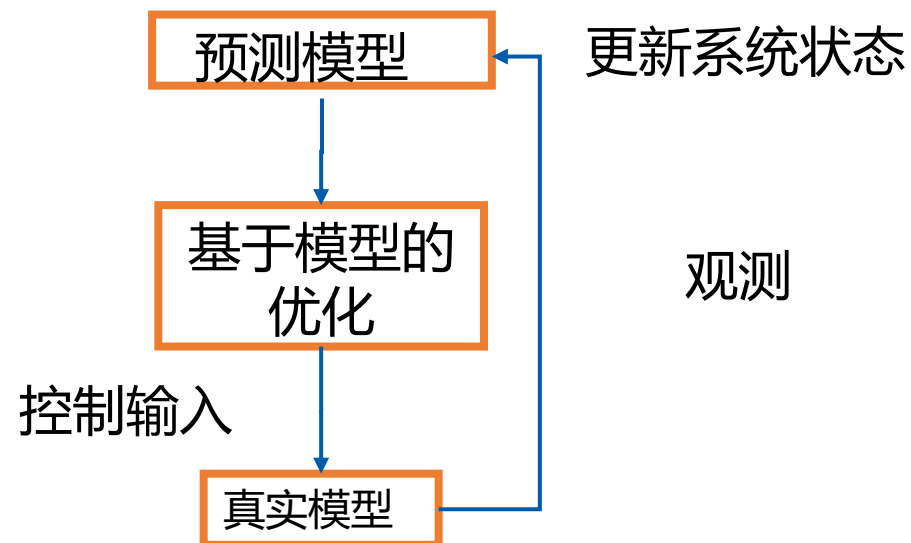
→ 从估计的当前状态开始

- 优化最佳的控制序列

→ 在有限的预测时域内找到最佳的控制输入序列

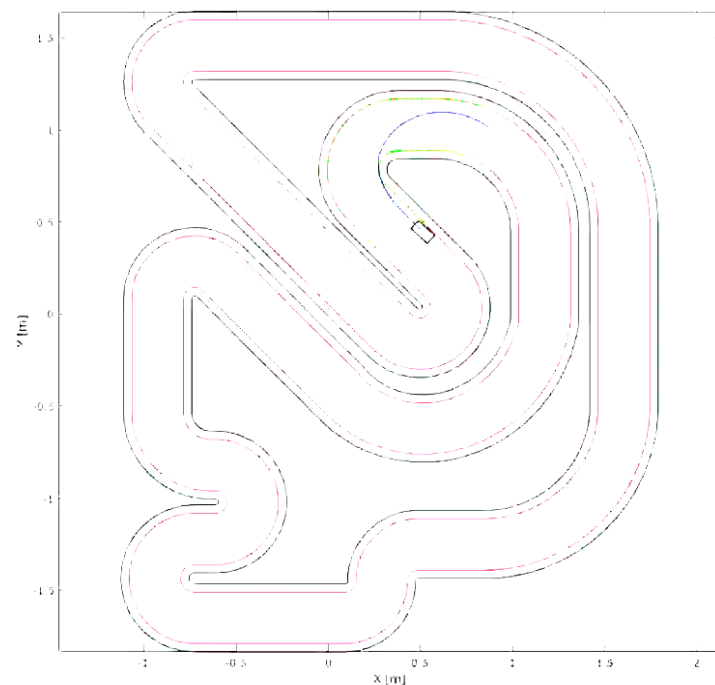
- 滚动预测框架

→ 执行第一个最佳的控制输入，更新状态重规划





- 滚动优化框架





- 使用动力学模型预测未来走向选择最佳的控制输入
- 跟踪目标为例

$$\min_{u_0, u_1, \dots, u_N} \sum_k^N \|p_k - r(t)\|^2 + \rho \Delta u_k^2$$

$$\text{s. t. } \mathbf{x}_{k+1} = f(\mathbf{x}_k, \mathbf{u}_k)$$

$$\mathbf{y}_k = g(\mathbf{x}_k)$$

$$\mathbf{x}_{\min} \leq \mathbf{x}_k \leq \mathbf{x}_{\max}$$

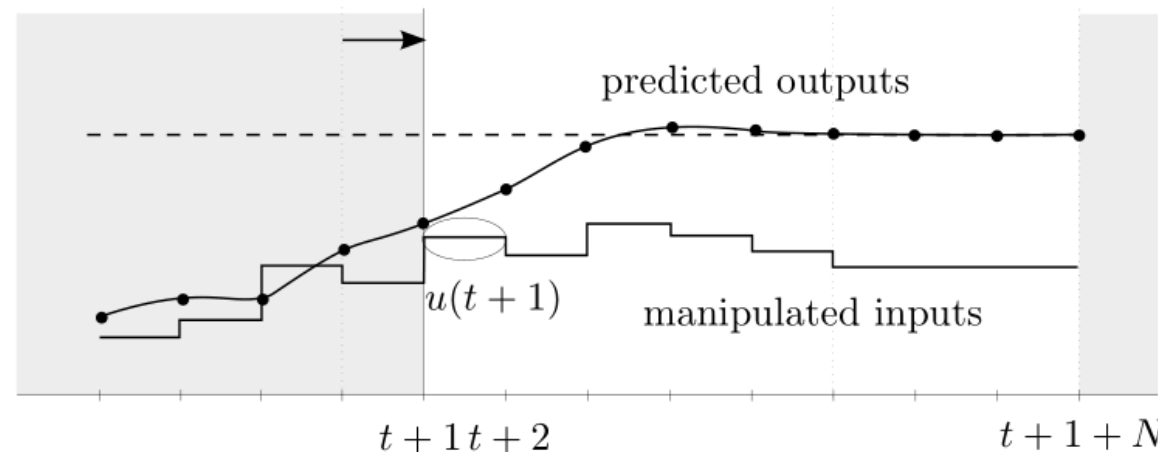
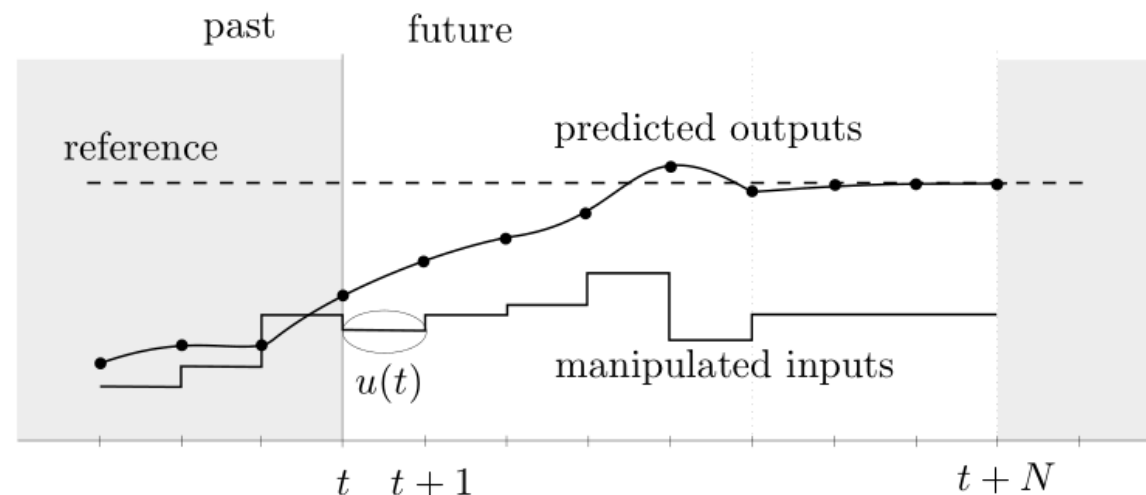
$$\mathbf{u}_{\min} \leq \mathbf{u}_k \leq \mathbf{u}_{\max}$$

$$\mathbf{x}_0 = \mathbf{x}(t)$$

预测模型

约束

状态反馈





- 别名
  - 开环最优反馈(Open Loop Optimal Feedback)
  - 反应式规划(Reactive Scheduling)
  - 滚动优化控制(Receding Horizon Control)
- 优势
  - 考虑未来时域 (尽管有限)
  - 考虑误差
  - 减小问题规模 (求解器一般有warm-start, 由上次最优解开始作为初值)





- 机器人当中运用



非线性MPC用于容错控制



Whole-body MPC 用于轮腿式机器人



- MPC的参数选择
- 模型的选择。效率与准确性之间权衡

$$\dot{\mathbf{x}} = f_c(\mathbf{x}, u) = \begin{pmatrix} \dot{z} \\ -g + \frac{1}{m}U_1 \cos \phi \\ \dot{y} \\ -\frac{1}{m}U_1 \sin \phi \\ \dot{\phi} \\ \frac{1}{I_x}U_2 \end{pmatrix}$$

平衡悬停态  $\theta = \dot{\theta} = \psi = \dot{\psi} \sim 0$

系统状态  $\mathbf{x} = [z, \dot{z}, y, \dot{y}, \phi, \dot{\phi}]$   
系统输入  $\mathbf{u} = [U_1, U_2]$

二维简化模型  
简易性

VS

$$\dot{\mathbf{x}} = f_c(\mathbf{x}, u) = \begin{pmatrix} \dot{x} \\ u_x \frac{1}{m}U_1 \\ \dot{y} \\ u_y \frac{1}{m}U_1 \\ \dot{z} \\ -g + (\cos \theta \cos \phi) \frac{1}{m}U_1 \\ \dot{\phi} \\ a_1 \dot{\theta} \dot{\psi} - a_2 \dot{\theta} \Omega_r + b_1 U_2 \\ \dot{\theta} \\ a_3 \dot{\phi} \dot{\psi} + a_4 \dot{\phi} \Omega_r + b_2 U_3 \\ \dot{\psi} \\ a_5 \dot{\phi} \dot{\theta} + b_3 U_4 \end{pmatrix}$$

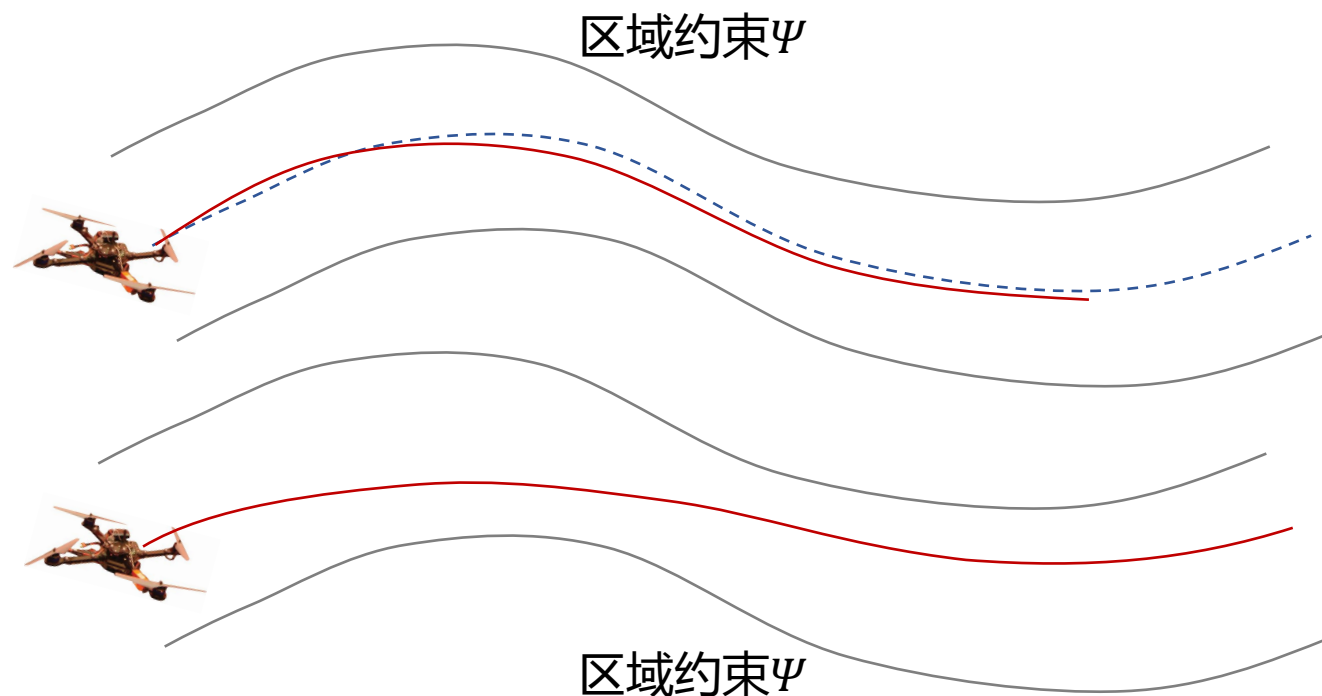
系统状态  $\mathbf{x} = [x, \dot{x}, y, \dot{y}, z, \dot{z}, \phi, \dot{\phi}, \theta, \dot{\theta}, \psi, \dot{\psi}]$   
系统输入  $\mathbf{u} = [U_1, U_2, U_3, U_4]$

完整状态模型  
准确性



- MPC的参数选择
- 代价函数的选择

## 控制器与规划器



$$\min_{u_0, u_1, \dots, u_N} \sum_k^N \|p_k - r(t)\|^2 + \rho \Delta u_k^2$$

最小化跟踪误差（控制器）

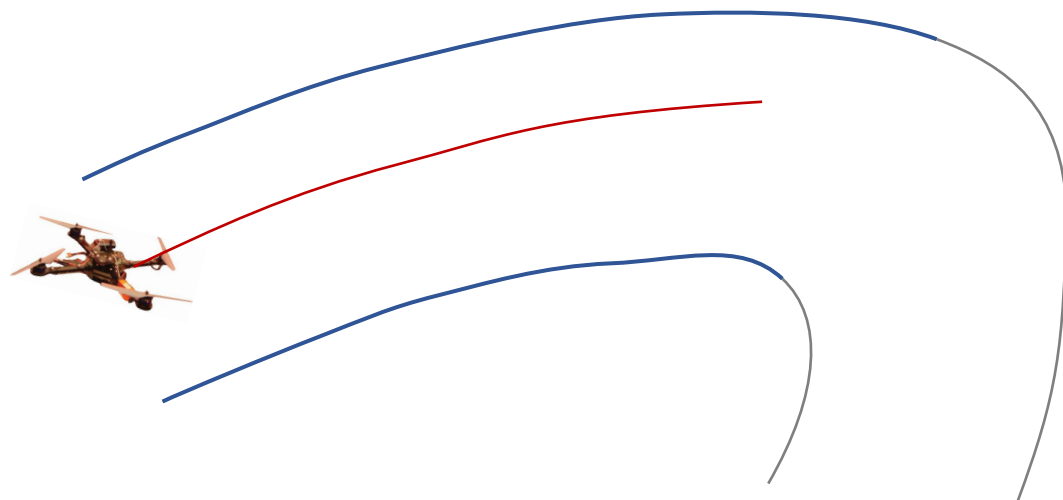
$$\min_{u(t)} \sum_k^N \rho \Delta u_k^2 + \gamma T$$

st.  $p(t) \in \Psi$

时间参数化控制指令  
最小化时间（规划器）



- MPC的参数选择
- 预测时域：计算量与解的可行性的权衡



- 较短的预测时域
  - 较小的计算量
  - 次优的解（可能不安全）
- 较长的预测时域
  - 较大的计算量
  - 更优更安全的解

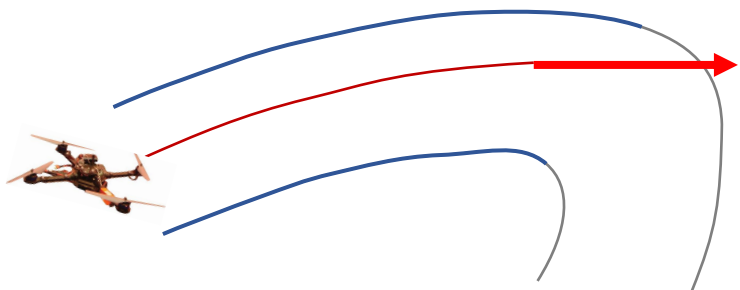


## 预测时长 (Prediction horizon) 的长短?

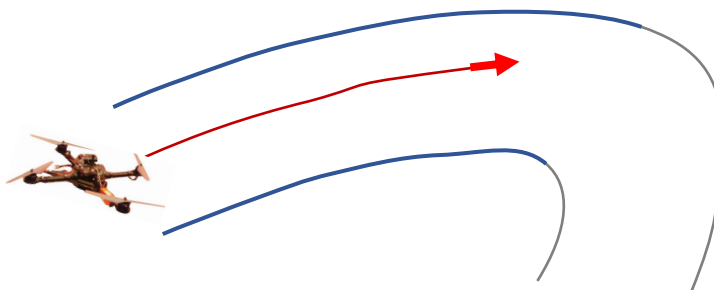
→ 权衡 计算时间 **computation overload** 和递归可行性 **recursive feasibility**

- 较短的预测时长
  - 减少计算时间
  - 短视性 (不安全)
- 末状态增加某些额外的约束可以提高 **recursive feasibility**.

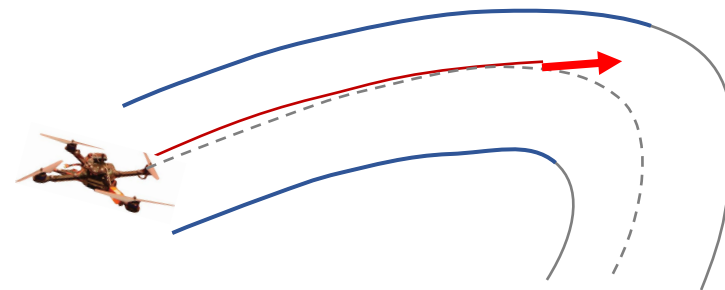
末速度无额外约束



末速度限制为0



末速度限制为全局轨迹  
该位置附近的速度





- 线性时变模型 Linear Time-Varying (LTV) model

$$\mathbf{x}_{k+1} = \mathbf{A}\mathbf{x}_k + \mathbf{B}\mathbf{u}_k \rightarrow \mathbf{x}_{k+1} = \underline{\mathbf{A}_k(t)}\mathbf{x}_k + \underline{\mathbf{B}_k(t)}\mathbf{u}_k$$

- 非线性模型

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

- 通过线性化非线性模型得到LTV

$$\dot{\mathbf{x}} \approx f(\bar{\mathbf{x}}, \bar{\mathbf{u}}) + \left. \frac{\partial f}{\partial \mathbf{x}} \right|_{\bar{\mathbf{x}}, \bar{\mathbf{u}}} (\mathbf{x} - \bar{\mathbf{x}}) + \left. \frac{\partial f}{\partial \mathbf{u}} \right|_{\bar{\mathbf{x}}, \bar{\mathbf{u}}} (\mathbf{u} - \bar{\mathbf{u}})$$

$$\dot{\mathbf{x}} = \mathbf{A}_c \mathbf{x} + \mathbf{B}_c \mathbf{u} + \mathbf{g}_c$$



- 用前向欧拉法把线性模型转化为离散形式

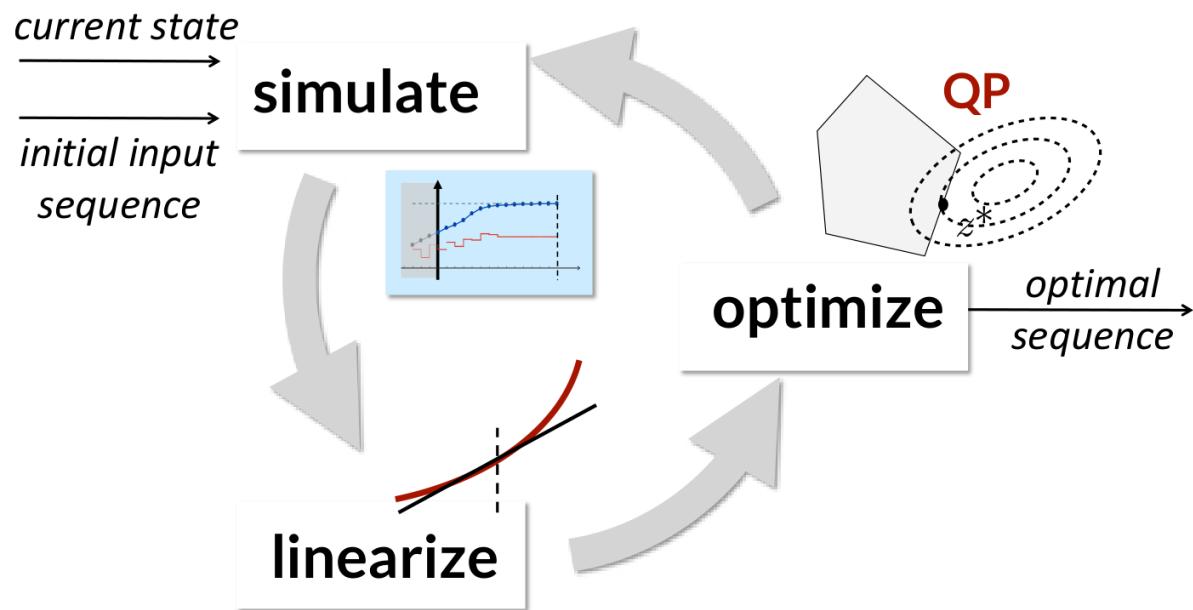
$$\dot{\mathbf{x}} = \mathbf{A}_c \mathbf{x} + \mathbf{B}_c \mathbf{u} + \mathbf{g}_c$$

$$\frac{\mathbf{x}_{k+1} - \mathbf{x}_k}{T_s} = \mathbf{A}_c \mathbf{x}_k + \mathbf{B}_c \mathbf{u}_k + \mathbf{g}_c$$

$$\mathbf{x}_{k+1} = (\mathbf{I} + T_s \mathbf{A}_c) \mathbf{x}_k + \underline{T_s \mathbf{B}_c} \mathbf{u}_k + \underline{T_s \mathbf{g}}$$

$$\mathbf{x}_{k+1} = \underline{\mathbf{A}_k} \mathbf{x}_k + \underline{\mathbf{B}_k} \mathbf{u}_k + \underline{\mathbf{g}_k}$$

- 此时可以在线求解线性MPC.





- 线性预测模型 
$$\begin{cases} \mathbf{x}_{k+1} = \mathbf{A}\mathbf{x}_k + \mathbf{B}\mathbf{u}_k \\ \mathbf{y}_k = \mathbf{C}\mathbf{x}_k \end{cases}$$

- 状态量与输入的关系 
$$\mathbf{x}_k = \mathbf{A}^k \mathbf{x}_0 + \sum_{j=0}^{k-1} \mathbf{A}^j \mathbf{B} \mathbf{u}_{k-1-j}$$

- 状态传播与计算 
$$\begin{bmatrix} \mathbf{x}_1 \\ \mathbf{x}_2 \\ \vdots \\ \mathbf{x}_{N-1} \\ \mathbf{x}_N \end{bmatrix} = \begin{bmatrix} \mathbf{B} & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{AB} & \mathbf{B} & \cdots & \mathbf{0} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{A}^{N-1}\mathbf{B} & \mathbf{A}^{N-2}\mathbf{B} & \cdots & \mathbf{B} \end{bmatrix} \begin{bmatrix} \mathbf{u}_0 \\ \mathbf{u}_1 \\ \vdots \\ \mathbf{u}_{N-1} \end{bmatrix} + \begin{bmatrix} \mathbf{A} \\ \mathbf{A}^2 \\ \vdots \\ \mathbf{A}^N \end{bmatrix} \mathbf{x}_0$$





- 线性MPC

- 二次型cost  $J = \mathbf{x}_N^T \mathbf{P} \mathbf{x}_N + \sum_{k=0}^{N-1} (\mathbf{x}_k^T \mathbf{Q} \mathbf{x}_k + \mathbf{u}_k^T \mathbf{R} \mathbf{u}_k)$

$$\mathbf{P} = \mathbf{P}^T > 0$$

$$\mathbf{Q} = \mathbf{Q}^T > 0$$

$$\mathbf{R} = \mathbf{R}^T > 0$$

半正定

- 目标：找到最优的控制序列  $\mathbf{u}_{0:N-1}^*$  最小化cost函数  $J$

$$J = \mathbf{x}_0^T \mathbf{Q} \mathbf{x}_0 + \begin{bmatrix} \mathbf{x}_1 \\ \mathbf{x}_2 \\ \vdots \\ \mathbf{x}_{N-1} \\ \mathbf{x}_N \end{bmatrix}^T \begin{bmatrix} \mathbf{Q} & \mathbf{0} & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{0} & \mathbf{Q} & \mathbf{0} & \cdots & \mathbf{0} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ \mathbf{0} & \cdots & \mathbf{0} & \mathbf{Q} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \cdots & \mathbf{0} & \mathbf{P} \end{bmatrix} \begin{bmatrix} \mathbf{x}_1 \\ \mathbf{x}_2 \\ \vdots \\ \mathbf{x}_{N-1} \\ \mathbf{x}_N \end{bmatrix} + \begin{bmatrix} \mathbf{u}_0 \\ \mathbf{u}_1 \\ \vdots \\ \mathbf{u}_{N-1} \end{bmatrix}^T \begin{bmatrix} \mathbf{R} & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{0} & \mathbf{R} & \cdots & \mathbf{0} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{0} & \cdots & \mathbf{0} & \mathbf{R} \end{bmatrix} \begin{bmatrix} \mathbf{u}_0 \\ \mathbf{u}_1 \\ \vdots \\ \mathbf{u}_{N-1} \end{bmatrix}$$



$$\begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_{N-1} \\ x_N \end{bmatrix} = \underbrace{\begin{bmatrix} B & 0 & \cdots & 0 \\ AB & B & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ A^{N-1}B & A^{N-2}B & \cdots & B \end{bmatrix}}_{\bar{S}} \underbrace{\begin{bmatrix} u_0 \\ u_1 \\ \vdots \\ u_{N-1} \end{bmatrix}}_z + \underbrace{\begin{bmatrix} A \\ A^2 \\ \vdots \\ A^N \end{bmatrix}}_{\bar{T}} x_0$$

$$J(z, x_0) = x_0^T Q x_0 + \underbrace{\begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_{N-1} \\ x_N \end{bmatrix}^T}_{\bar{Q}} \begin{bmatrix} Q & 0 & 0 & \cdots & 0 \\ 0 & Q & 0 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & \cdots & 0 & Q & 0 \\ 0 & 0 & \cdots & 0 & P \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_{N-1} \\ x_N \end{bmatrix} + \underbrace{\begin{bmatrix} u_0 \\ u_1 \\ \vdots \\ u_{N-1} \end{bmatrix}^T}_{\bar{R}} \begin{bmatrix} R & 0 & \cdots & 0 \\ 0 & R & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & \cdots & 0 & R \end{bmatrix} \begin{bmatrix} u_0 \\ u_1 \\ \vdots \\ u_{N-1} \end{bmatrix}$$

$$\begin{aligned} J(z, x_0) &= (\bar{S}z + \bar{T}x_0)^T \bar{Q} (\bar{S}z + \bar{T}x_0) + z^T \bar{R} z + x_0^T Q x_0 \\ &= \underbrace{\frac{1}{2} z^T 2 (\bar{R} + \bar{S}^T \bar{Q} \bar{S}) z}_{H} + \underbrace{x_0^T 2 \bar{T}^T \bar{Q} \bar{S} z}_{F} + \underbrace{\frac{1}{2} x_0^T 2 (Q + \bar{T}^T \bar{Q} \bar{T}) x_0}_{Y} \end{aligned}$$



$$J(\mathbf{z}, \mathbf{x}_0) = \underbrace{\frac{1}{2} \mathbf{z}^T \mathbf{H} \mathbf{z}}_{\mathbf{H}} + \underbrace{\mathbf{x}_0^T \mathbf{F} \mathbf{z}}_{\mathbf{F}} + \underbrace{\frac{1}{2} \mathbf{x}_0^T \mathbf{Y} \mathbf{x}_0}_{\mathbf{Y}}$$

- MPC的紧凑形式

$$J(\mathbf{z}, \mathbf{x}_0) = \frac{1}{2} \mathbf{z}^T \mathbf{H} \mathbf{z} + \mathbf{x}_0^T \mathbf{F} \mathbf{z} + \frac{1}{2} \mathbf{x}_0^T \mathbf{Y} \mathbf{x}_0 \quad \mathbf{z} = \begin{bmatrix} \mathbf{u}_0 \\ \mathbf{u}_1 \\ \vdots \\ \mathbf{u}_{N-1} \end{bmatrix}$$

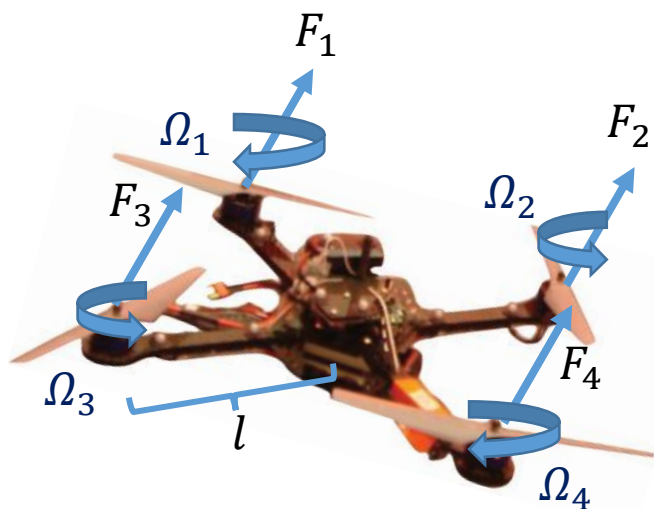
目标即是找到梯度的为零的解

$$\nabla_{\mathbf{z}} J(\mathbf{z}, \mathbf{x}_0) = \mathbf{H} \mathbf{z} + \mathbf{F}^T \mathbf{x}_0 = 0 \rightarrow \mathbf{z}^* = -\underline{\mathbf{H}^{-1}} \mathbf{F}^T \mathbf{x}_0 \quad (\text{解序列“batch” solution})$$

无约束MPC= 线性反馈控制(linear state-feedback)



- 例子：选择最佳系统输入即总推力 $U_1$ 与x轴力矩 $U_2$



这里采用二维简化模型  $\dot{\mathbf{x}} = f_c(\mathbf{x}, \mathbf{u}) =$   
平衡悬停态  $\theta = \dot{\theta} = \psi = \dot{\psi} \sim 0$

$$\begin{pmatrix} \dot{z} \\ -g + \frac{1}{m}U_1 \cos \phi \\ \dot{y} \\ -\frac{1}{m}U_1 \sin \phi \\ \dot{\phi} \\ \frac{1}{I_x}U_2 \end{pmatrix}$$

系统状态  $\mathbf{x} = [z, \dot{z}, y, \dot{y}, \phi, \dot{\phi}]$   
系统输入  $\mathbf{u} = [U_1, U_2]$



- 线性模型离散化

$$\dot{\mathbf{x}} = f_c(\mathbf{x}, u) = \begin{pmatrix} \dot{z} \\ -g + \frac{1}{m}U_1 \cos \phi \\ \dot{y} \\ -\frac{1}{m}U_1 \sin \phi \\ \dot{\phi} \\ \frac{1}{I_x}U_2 \end{pmatrix} \xrightarrow{\text{前向欧拉法}} \mathbf{x}_{t+1} = f(\mathbf{x}_t, u_t) = \begin{pmatrix} \mathbf{x}_t^1 + h\mathbf{x}_t^2 \\ \mathbf{x}_t^2 + h\left(-g + \frac{1}{m}u_t^1 \cos \mathbf{x}_t^5\right) \\ \mathbf{x}_t^3 + h\mathbf{x}_t^4 \\ \mathbf{x}_t^4 - \frac{h}{m}u_t^1 \sin \mathbf{x}_t^5 \\ \mathbf{x}_t^5 + h\mathbf{x}_t^6 \\ \mathbf{x}_t^6 + \frac{h}{I_x}u_t^2 \end{pmatrix}$$

在工作点 $(\mathbf{x}_t^{ref}, u_t^{ref})$ 处线性展开

$$\mathbf{x}_{t+1} = f(\mathbf{x}_t, u_t) \approx f(\mathbf{x}_t^{ref}, u_t^{ref}) + \tilde{A}_t(\mathbf{x}_t - \mathbf{x}_t^{ref}) + \tilde{B}_t(u_t - u_t^{ref})$$

$$\tilde{A}_t = \left. \frac{\partial f(\mathbf{x}, u)}{\partial \mathbf{x}} \right|_{(\mathbf{x}_t^{ref}, u_t^{ref})} \longrightarrow \tilde{A}_t = \begin{bmatrix} 1 & h & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & -\frac{h}{m}u_t^{ref,1} \sin \mathbf{x}_t^{ref,5} & 0 \\ 0 & 0 & 1 & h & 0 & 0 \\ 0 & 0 & 0 & 1 & -\frac{h}{m}u_t^{ref,1} \cos \mathbf{x}_t^{ref,5} & 0 \\ 0 & 0 & 0 & 0 & 1 & h \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \quad \tilde{B}_t = \left. \frac{\partial f(\mathbf{x}, u)}{\partial u} \right|_{(\mathbf{x}_t^{ref}, u_t^{ref})} \longrightarrow \tilde{B}_t = \begin{bmatrix} 0 & 0 \\ \frac{h}{m} \cos \mathbf{x}_t^{ref,5} & 0 \\ 0 & 0 \\ -\frac{h}{m} \sin \mathbf{x}_t^{ref,5} & 0 \\ 0 & 0 \\ 0 & \frac{h}{I_x} \end{bmatrix}$$



- 线性模型离散化

$$A_t = \begin{bmatrix} 1 & h & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & -\frac{h}{m}\bar{u}_t^1 \sin \bar{\mathbf{x}}_t^5 & 0 \\ 0 & 0 & 1 & h & 0 & 0 \\ 0 & 0 & 0 & 1 & -\frac{h}{m}\bar{u}_t^1 \cos \bar{\mathbf{x}}_t^5 & 0 \\ 0 & 0 & 0 & 0 & 1 & h \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \quad B_t = \begin{bmatrix} 0 & 0 \\ \frac{h}{m} \cos \bar{\mathbf{x}}_t^5 & 0 \\ 0 & 0 \\ -\frac{h}{m} \sin \bar{\mathbf{x}}_t^5 & 0 \\ 0 & 0 \\ 0 & \frac{h}{I_x} \end{bmatrix}$$

系统状态  $\mathbf{x} = [z, \dot{z}, y, \dot{y}, \phi, \dot{\phi}]$

系统输入  $\mathbf{u} = [U_1, U_2]$

$$\mathbf{g}_t = f(\mathbf{x}_t^{ref}, u_t^{ref}) - A_t \mathbf{x}_t^{ref} - B_t u_t^{ref}$$

$$\mathbf{x}_{t+1} = A_t \mathbf{x}_t + B_t \mathbf{u}_t + \mathbf{g}_t$$



- 最小化的累加和

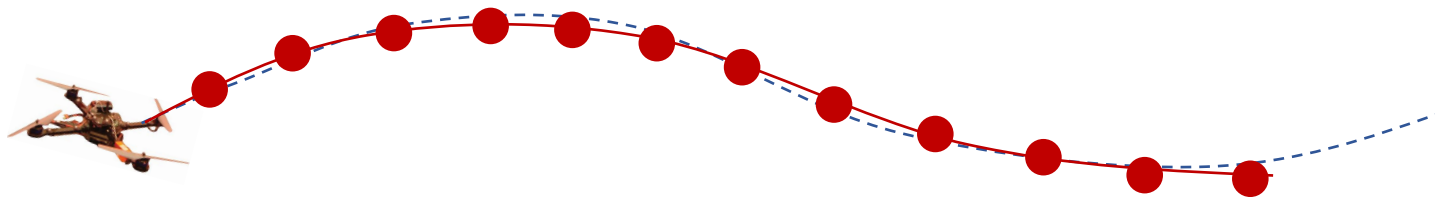
$$(p_x - x_{ref})^2 + (p_y - y_{ref})^2 + w_v \Delta a^2 + w_\delta \Delta \delta^2 \rightarrow \text{二次型}$$

- 增广模型

$$\begin{bmatrix} x \\ u \end{bmatrix}_{k+1} = \begin{bmatrix} A & B \\ 0 & I \end{bmatrix} \begin{bmatrix} x \\ u \end{bmatrix}_k + \begin{bmatrix} B \\ I \end{bmatrix} \Delta u_k \quad z = \begin{bmatrix} u_0 \\ u_1 \\ \vdots \\ u_{N-1} \end{bmatrix} \text{ or } z = \begin{bmatrix} \Delta u_0 \\ \Delta u_1 \\ \vdots \\ \Delta u_{N-1} \end{bmatrix}$$

- 约束形式

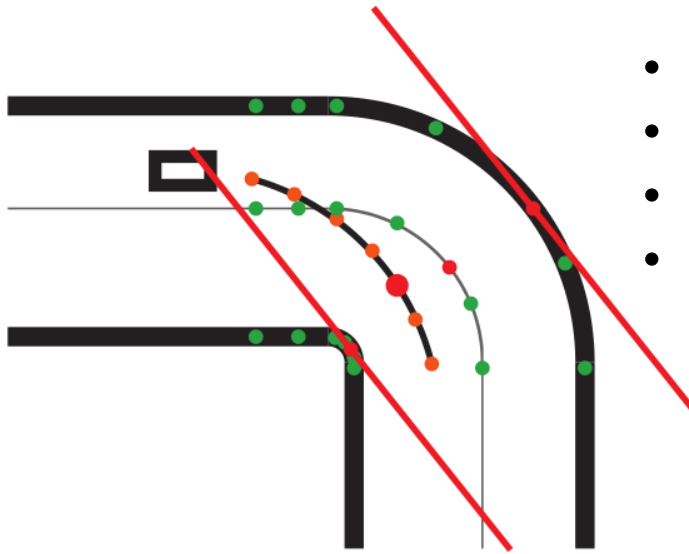
$$\begin{aligned} a_{\min} &\leq a \leq a_{\max} \\ v_{\min} &\leq v \leq v_{\max} \end{aligned} \rightarrow \text{线性约束二次型 (Linear constrained QP formulation)}$$



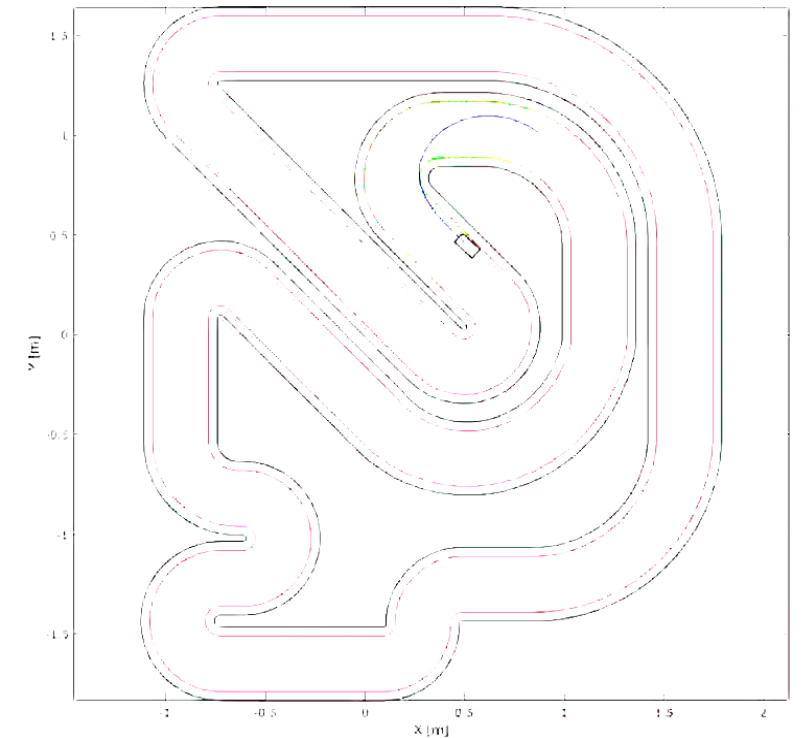
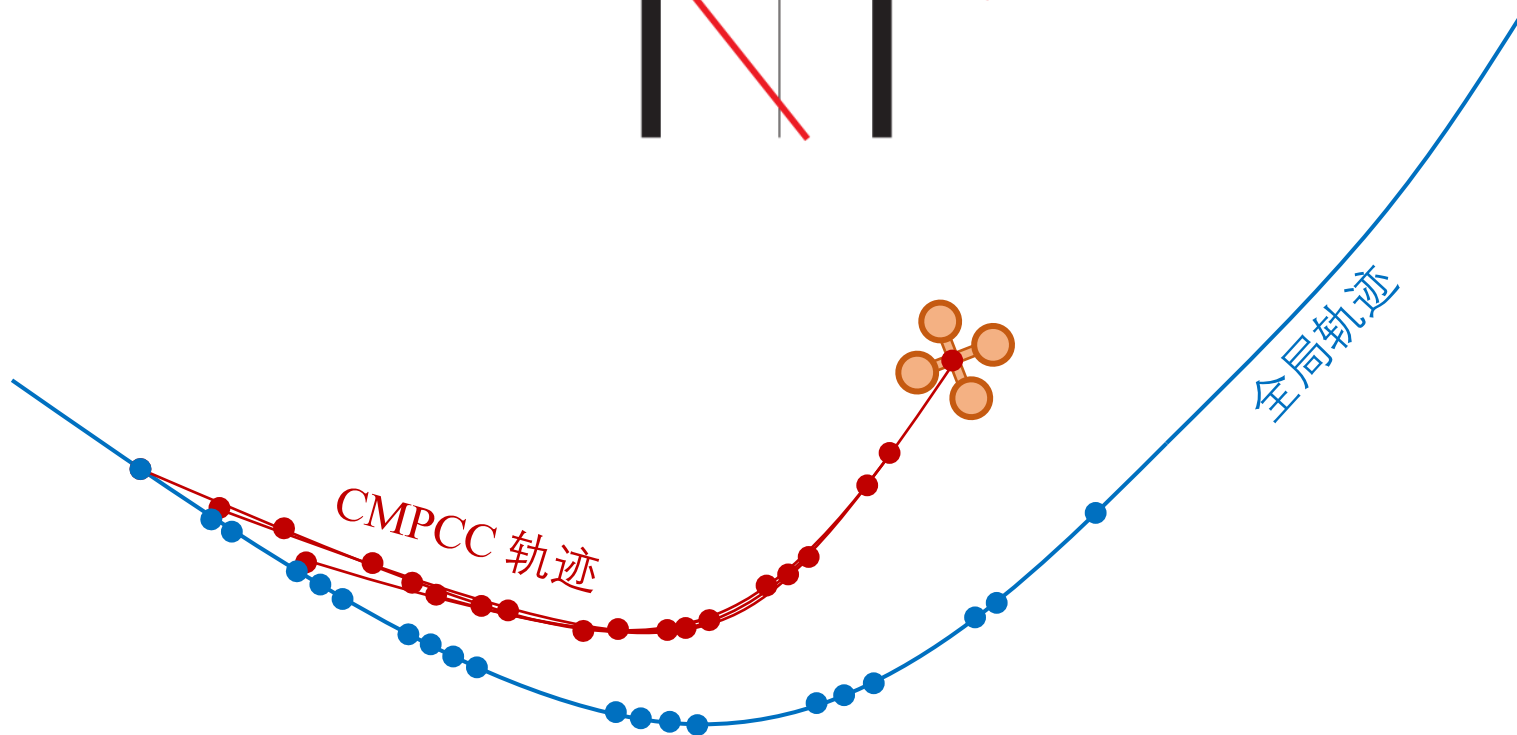
The chicken or the egg

- 一些工程技巧:
  - 根据参考轨迹人为给定
  - Warm-start: 在上一次求解处对模型线性化  $u_{k-1}^*, x_{k-1}^*$





- 平衡跟踪进度和执行进度.
- 走廊约束保证安全.
- 终端速度约束保证可行.
- QP方法让问题在机载电脑上求解时间少于5ms.



## ◆ 目标函数

状态:  $\mathbf{x}^{(k)} = [x, v_x, a_x, y, v_y, a_y, z, v_z, a_z, \theta, v_\theta, a_\theta]^T$

输入:  $\mathbf{u}^{(k)} = [j_x, j_y, j_z, j_\theta]^T$

$$J = \min_{\mathbf{x}, \mathbf{u}} \sum_{k=1}^N \left\{ \sum_{\mu=x,y,z} (\mu^{(k)} - p_\mu(\theta^{(k)}))^2 - q \cdot v_\theta^{(k)} \right\}$$

$$\text{s.t. } \mathbf{x}^{(k+1)} = \mathbf{A}_d \mathbf{x}^{(k)} + \mathbf{B}_d \mathbf{u}^{(k)}, k = 1, 2, 3, \dots, N-1$$

$$\mathbf{x}_l \leq \mathbf{x}^k \leq \mathbf{x}_u, k = 1, 2, 3, \dots, N-1$$

$$\mathbf{u}_l \leq \mathbf{u}^k \leq \mathbf{u}_u, k = 1, 2, 3, \dots, N-1$$

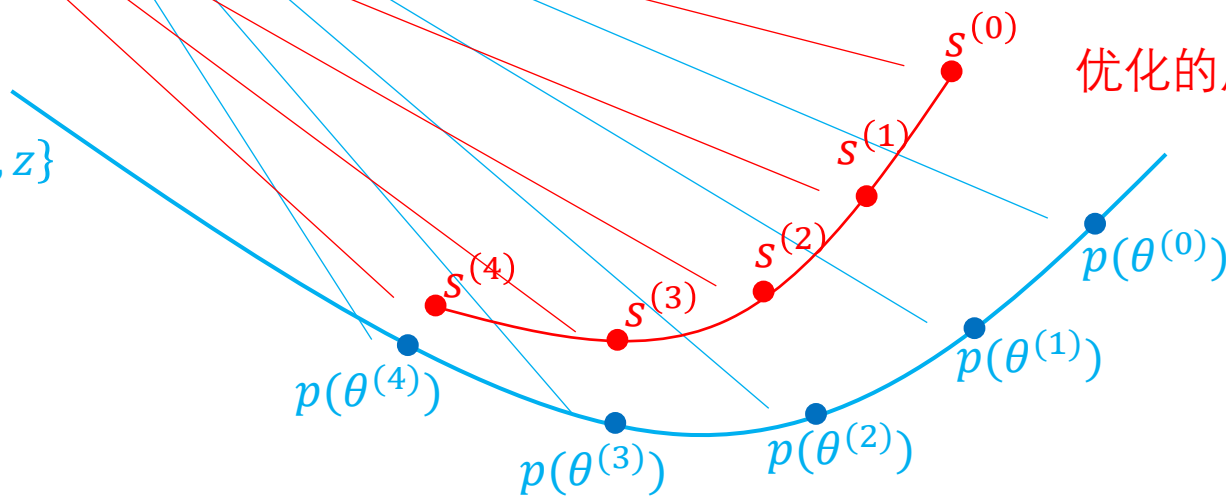
$$\mathbf{C}^k \cdot [\mathbf{x}^k, \mathbf{y}^k, \mathbf{z}^k]^T \leq \mathbf{b}^k, k = 1, 2, 3, \dots, N-1$$

$$|v_\mu^{(N)}| \leq v_{t\mu}, \mu = x, y, z$$

全局轨迹:

$$P = p_\mu(\theta), \mu \in \{x, y, z\}$$

优化的局部CMPCC 轨迹



## ◆ 目标函数

状态:  $\mathbf{x}^{(k)} = [x, v_x, a_x, y, v_y, a_y, z, v_z, a_z, \theta, v_\theta, a_\theta]^T$

输入:  $\mathbf{u}^{(k)} = [j_x, j_y, j_z, j_\theta]^T$

$$J = \min_{\mathbf{x}, \mathbf{u}} \sum_{k=1}^N \left\{ \sum_{\mu=x,y,z} (\mu^{(k)} - p_\mu(\theta^{(k)}))^2 - q \cdot v_\theta^{(k)} \right\}$$

$$\mathbf{s.t.} \quad \mathbf{x}^{(k+1)} = \mathbf{A}_d \mathbf{x}^{(k)} + \mathbf{B}_d \mathbf{u}^{(k)}, k = 1, 2, 3, \dots, N-1$$

$$\mathbf{x}_l \leq \mathbf{x}^k \leq \mathbf{x}_u, k = 1, 2, 3, \dots, N-1$$

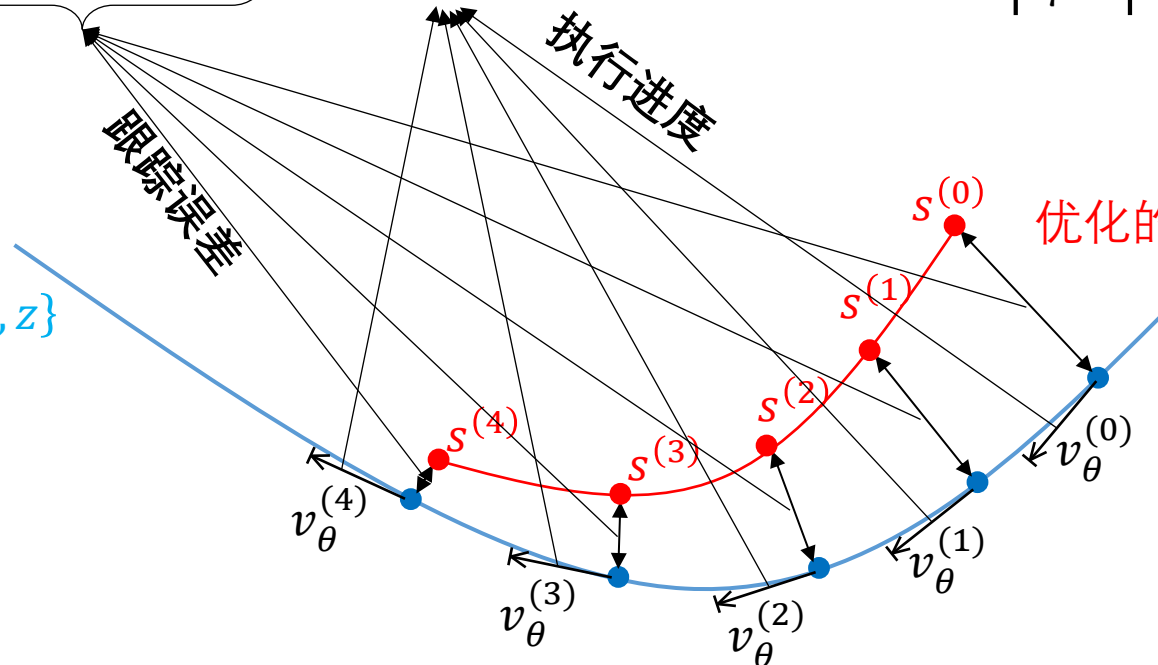
$$\mathbf{u}_l \leq \mathbf{u}^k \leq \mathbf{u}_u, k = 1, 2, 3, \dots, N-1$$

$$\mathbf{C}^k \cdot [\mathbf{x}^k, y^k, z^k]^T \leq \mathbf{b}^k, k = 1, 2, 3, \dots, N-1$$

$$|v_\mu^{(N)}| \leq v_{t\mu}, \mu = x, y, z$$

全局轨迹:

$$P = p_\mu(\theta), \mu \in \{x, y, z\}$$



优化的局部CMPCC 轨迹



## ◆ 终端速度约束

限制终端速度可确保轨迹可行性，  
同时大大缩短规划的时间。

$$\text{s.t. } \mathbf{x}^{(k+1)} = \mathbf{A}_d \mathbf{x}^{(k)} + \mathbf{B}_d \mathbf{u}^{(k)}, k = 1, 2, 3, \dots, N-1$$

$$\mathbf{x}_l \leq \mathbf{x}^k \leq \mathbf{x}_u, k = 1, 2, 3, \dots, N-1$$

$$\mathbf{u}_l \leq \mathbf{u}^k \leq \mathbf{u}_u, k = 1, 2, 3, \dots, N-1$$

$$\mathbf{C}^k \cdot [\mathbf{x}^k, y^k, z^k]^T \leq \mathbf{b}^k, k = 1, 2, 3, \dots, N-1$$

$$|v_\mu^{(N)}| \leq v_{t\mu}, \mu = x, y, z$$

