

Announcements:

- HW 3 out, due 3/20
- Mid-semester survey out, due 3/17
- Project milestone due 3/11
- 2-6 pg.
- intro/related work, problem def, timeline

Last time:

- dynamic programming

Today's q: How do we apply to nonlinear sys?

Recall:
$$\min_{x_{0:T}, u_{0:T}} c_T(x_T) + \sum_{t=0}^{T-1} c_t(x_t, u_t)$$

$$\text{s.t. } x_0 = x(0)$$

$$x_{t+1} = f(x_t, u_t)$$

$$x_t \in \mathcal{X}$$

$$u_t \in \mathcal{U}$$

1. Trajectory opt: $x_{0:T}^*, u_{0:T-1}^*$

2. Dynamic programming

$V_t^*(x)$ "value function" "cost-to-go"

$$V_t^*(x) = \min_{u \in \mathcal{U}} \{ c_t(x, u) + V_{t+1}^*(f(x, u)) \}$$

$$\Pi_t^*(x) = \arg \min_{u \in \mathcal{U}} \{ \dots \}$$

special case: LQR (two views coincide)

Q: How do we extend these results?

e.g.) (cart pole)



$$x = [p, \theta, \dot{p}, \dot{\theta}]$$

$$u = [f]$$

goal: $x_t \rightarrow 0$

cost: $Q_T = \begin{bmatrix} 1 & & & \\ & 10 & & \\ & & 1 & \\ & & & 1 \end{bmatrix}$ $Q_t = \begin{bmatrix} 1 & & & \\ & & & \\ & & & \\ & & & 1 \end{bmatrix}$

$$R_t = [0.1]$$

problem: nonlinear dynamics!

How can we do this?

1. Linearize system about \bar{x} , use LQR
2. Linearize about many points, look LQR gains
3. iLQR

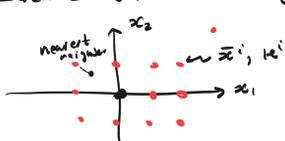
suppose $\theta \approx 0$

$$A = \frac{\partial f}{\partial x} \Big|_{\bar{x}=0} \quad B = \frac{\partial f}{\partial u} \Big|_{\bar{x}=0}$$

apply infinite-horizon LQR gain w/ these matrices

- Pros: - dead simple
- for $x \approx 0$ it tends to work well
- cons: for $x \neq 0$, it doesn't

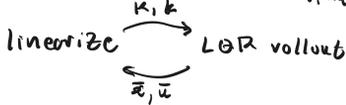
Idea 2: Gain scheduling



Idea 3: Iterative LQR

suppose we have initial guess $\bar{x}_{0:T}, \bar{u}_{0:T-1}$

key idea: $A_t = \frac{\partial f}{\partial x} \Big|_{\bar{x}_t, \bar{u}_t} \quad B_t = \frac{\partial f}{\partial u} \Big|_{\bar{x}_t, \bar{u}_t}$



To derive this, we use Taylor expansions of the cost/dynamics

$$\delta x_t = x_t - \bar{x}_t \quad \delta u_t = u_t - \bar{u}_t$$

$$c_t(\delta x_t, \delta u_t) = \text{const} + \begin{bmatrix} \delta x_t \\ \delta u_t \end{bmatrix}^T \begin{bmatrix} q_t \\ r_t \end{bmatrix} + \frac{1}{2} \begin{bmatrix} \delta x_t \\ \delta u_t \end{bmatrix}^T \begin{bmatrix} Q_t & S_t \\ S_t^T & R_t \end{bmatrix} \begin{bmatrix} \delta x_t \\ \delta u_t \end{bmatrix} + \dots$$

$$q_t = \nabla_x^2 c_t \quad Q_t = \nabla_{xx}^2 c_t \quad S_t = \nabla_{xu}^2 c_t$$

$$r_t = \nabla_u^2 c_t \quad R_t = \nabla_{uu}^2 c_t$$

$$\delta x_{t+1} = f(\delta x_t, \delta u_t) = A_t \delta x_t + B_t \delta u_t$$

$$A_t = \frac{\partial f}{\partial x} \Big|_{\bar{x}_t, \bar{u}_t} \quad B_t = \frac{\partial f}{\partial u} \Big|_{\bar{x}_t, \bar{u}_t}$$

For this variation of LQR,

$$u_t^* = -\bar{K}_t x_t - \bar{k}_t \quad \bar{K}_t \in \mathbb{R}^{m \times n} \quad \bar{k}_t \in \mathbb{R}^m$$

feedback \leftarrow \bar{k}_t feedforward

$$V_t^*(\delta x_t) = \bar{P}_t^T \delta x_t + \frac{1}{2} \delta x_t^T \bar{P}_t \delta x_t$$

We can define "the Q-function"

$$Q_t(\delta x_t, \delta u_t) = c_t(\delta x_t, \delta u_t) + V_{t+1}^*(f(\delta x_t, \delta u_t))$$

\uparrow apply δu_t @ time t , \uparrow then act optimally $\tau > t$

$$V_t^*(\delta x_t, \delta u_t) = \min_{\delta u_t} \{ Q_t(\delta x_t, \delta u_t) \}$$

$$Q_t(\delta x_t, \delta u_t) = \begin{bmatrix} h_x \\ h_u \end{bmatrix}^T \begin{bmatrix} \delta x_t \\ \delta u_t \end{bmatrix} + \frac{1}{2} \begin{bmatrix} \delta x_t \\ \delta u_t \end{bmatrix}^T \begin{bmatrix} H_{xx} & H_{xu} \\ H_{xu} & H_{uu} \end{bmatrix} \begin{bmatrix} \delta x_t \\ \delta u_t \end{bmatrix}$$

$$h_x = q_t + A_t^T \bar{P}_{t+1} \quad H_{xx} = Q_t + A_t^T \bar{P}_{t+1} A_t$$

$$h_u = r_t + B_t^T \bar{P}_{t+1} \quad H_{uu} = R_t + B_t^T \bar{P}_{t+1} B_t$$

$$H_{xu} = S_t + A_t^T \bar{P}_{t+1} B_t$$

$$\nabla_{\delta u_t} Q(\delta x_t, \delta u_t^*) = 0$$

$$h_u + H_{uu} \delta u_t^* + H_{xu} \delta x_t = 0$$

$$\delta u_t^* = -(H_{uu})^{-1} (H_{xu} \delta x_t + h_u)$$

Get an LQR-style recursion

$$\bar{P}_t = H_{xx} - H_{xu} \bar{K}_t \quad \bar{P}_t = h_x - H_{xu} \bar{k}_t$$

Alg) (iLQR)

input: $\bar{x}_{0:T}, \bar{u}_{0:T-1}$ // initial guess

repeat until convergence

$$\bar{K}_t, \bar{k}_t \leftarrow \text{backward}(\bar{x}_{0:T}, \bar{u}_{0:T-1})$$

for $t=0, \dots, T-1$ // forward

$$u_t = \bar{u}_t - \bar{K}_t (x_t - \bar{x}_t) - \bar{k}_t$$

$$x_{t+1} = f(x_t, u_t) \quad (-\alpha \bar{k}_t)$$

end for

$$\bar{x}_{0:T} \leftarrow x_{0:T}$$

$$\bar{u}_{0:T-1} \leftarrow u_{0:T-1}$$

Discussion:

- no convergence guarantees $\ddot{}$
- very sensitive to initialization
- provides you w/ feedback
- need to add reg. to H_{uu}

$$(H_{uu} + \lambda I)^{-1} \quad \lambda > 0$$

- often linesearch over \bar{k}_t