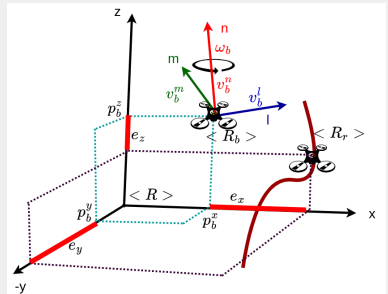


MOTION PLANNING FOR AUTONOMOUS VEHICLES

LINEAR QUADRATIC REGULATOR (LQR)

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LINEAR QUADRATIC REGULATOR

- LQR Formulation
- LQR via least squares
- Hamilton Jacobi Bellman (HJB) Approach
- Bellman Optimality
- LQR with HJB
- Hamiltonian formulation to find the optimal control policy
- Linear quadratic optimal tracking
- Optimal reference trajectory tracking with LQR

LQR FORMULATION

In general, discrete linear system, which can be either LTI or LTV, dynamics is described by:

$$\mathbf{x}_{k+1} = \mathbf{f}_d(\mathbf{x}_k, \mathbf{u}_k) = A_k \mathbf{x}_k + B_k \mathbf{u}_k, \quad (1)$$

where $k = 0, \dots, n$, $\mathbf{x}_k \in \mathbb{R}^n$, and $\mathbf{u}_k \in \mathbb{R}^m$. For the continuous time system

$$\dot{\mathbf{x}} = \mathbf{f}_c(t) = A(t)\mathbf{x}(t) + B(t)\mathbf{u}(t) \quad (2)$$

If the system dynamics is non-linear, A_k and B_k are recalculated by linearizing the \mathbf{f}_c at each time index.

Since linearization has to be carried out in each iteration, **ILQR** and **ELQR** are such variants, consider nominal trajectory, $\mathbf{x}_0(\mathbf{t}), \mathbf{u}_0(\mathbf{t}) \quad \forall t[t_1, t_2]$.

Using first-order Taylor series approximation, the increment $\Delta \dot{\mathbf{x}} = \dot{\mathbf{x}} - \dot{\mathbf{x}}_0 = \mathbf{f}_c(\mathbf{x}, \mathbf{u}) - \mathbf{f}_c(\mathbf{x}_0, \mathbf{u}_0)$ can be expressed by

$$\begin{aligned}\Delta \dot{\mathbf{x}} &\approx \mathbf{f}_c(\mathbf{x}_0, \mathbf{u}_0) + \frac{\partial \mathbf{f}_c(\mathbf{x}_0, \mathbf{u}_0)}{\partial \mathbf{x}}(\mathbf{x} - \mathbf{x}_0) + \frac{\partial \mathbf{f}_c(\mathbf{x}_0, \mathbf{u}_0)}{\partial \mathbf{u}}(\mathbf{u} - \mathbf{u}_0) - \mathbf{f}_c(\mathbf{x}_0, \mathbf{u}_0) \\ &= A(t)\Delta \mathbf{x}(t) + B(t)\Delta \mathbf{u}(t)\end{aligned}\tag{3}$$

where $\Delta \mathbf{x}(t) = \mathbf{x}(t) - \mathbf{x}(t_0)$ and $\Delta \mathbf{u}(t) = \mathbf{u}(t) - \mathbf{u}(t_0)$ and $A(t) = \frac{\partial \mathbf{f}_c}{\partial \mathbf{x}}(\mathbf{x}_0, \mathbf{u}_0)$, $B(t) = \frac{\partial \mathbf{f}_c}{\partial \mathbf{u}}(\mathbf{x}_0, \mathbf{u}_0)$.

Consider **initial state** x_0 at each time instance t_0 is given, the objective is to **find the optimal control input sequence \mathbf{u}** for a given initial condition x_0 , to reach the final state x_T , i.e., **estimate the optimal state prediction**, an optimal control sequence (or **control policy**) has to be calculated.

LQR FORMULATION

Such a **control policy** can be estimated by minimizing the following quadratic cost:

$$J(\mathbf{x}, \mathbf{u}) = \underbrace{\|x_n\|_{Q_n}^2}_{\text{terminal cost}} + \underbrace{\sum_{k=0}^{n-1} \|x_k\|_Q^2 + \|u_k\|_R^2}_{\text{running cost}} \quad (4)$$

$$J(\mathbf{x}, \mathbf{u}) = \int_0^\infty \left(\|x(t)\|_Q^2 + \|u(t)\|_R^2 \right) dt,$$

where $k \in \{0, 1, \dots, n-1\}$, $Q, Q_n \in \mathbb{R}^{n_x \times n_x}$, $R \in \mathbb{R}^{n_u \times n_u}$, $P \in \mathbb{R}^{n_x \times n_x}$ are predefined in which $\mathbf{Q} = \mathbf{Q}^\top \geq \mathbf{0}$ is a **positive definite** and $\mathbf{R} = \mathbf{R}^\top > \mathbf{0}$ is a **positive semi-definite**. However, if the **system is nonlinear**, need to estimate the **second-order approximation of the non-linear cost functions** to **define $\mathbf{Q}(\mathbf{t})$ and $\mathbf{R}(\mathbf{t})$** .

LQR VIA LEAST SQUARES

- For a linear system

$$\begin{aligned} \min_{\mathbf{u}} \quad & \sum_{k=0}^{n-1} \mathbf{x}_k^\top \mathbf{Q}_k \mathbf{x}_k + \mathbf{u}_k^\top \mathbf{R}_k \mathbf{u}_k + \mathbf{x}_n^\top \mathbf{Q}_n \mathbf{x}_n, \mathbf{Q}_k = \mathbf{Q}_k^\top \geq 0, \mathbf{R}_k = \mathbf{R}_k^\top > 0 \\ \text{s.t.} \quad & \mathbf{x}_{k+1} = \mathbf{A}\mathbf{x}_k + \mathbf{B}\mathbf{u}_k \\ & \mathbf{x}_0 \end{aligned} \tag{5}$$

LQR VIA LEAST SQUARES

- For a linear system

$$\begin{aligned} \min_{\mathbf{u}} \quad & \sum_{k=0}^{n-1} \mathbf{x}_k^\top \mathbf{Q}_k \mathbf{x}_k + \mathbf{u}_k^\top \mathbf{R}_k \mathbf{u}_k + \mathbf{x}_n^\top \mathbf{Q}_n \mathbf{x}_n, \mathbf{Q}_k = \mathbf{Q}_k^\top \geq 0, \mathbf{R}_k = \mathbf{R}_k^\top > 0 \\ \text{s.t.} \quad & \mathbf{x}_{k+1} = \mathbf{A}\mathbf{x}_k + \mathbf{B}\mathbf{u}_k \\ & \mathbf{x}_0 \end{aligned} \tag{5}$$

- The state prediction sequence can be written in a compact sequence as follows:

$$\mathbf{x} = Mx_0 + C\mathbf{u}, \quad M = \begin{bmatrix} I \\ A \\ A^2 \\ \vdots \\ A^N \end{bmatrix}, \quad C = \begin{bmatrix} 0 & 0 & \dots & 0 \\ B & & & \\ AB & B & & \\ \vdots & \vdots & \ddots & \\ A^{N-1}B & A^{N-2}B & \dots & B \end{bmatrix}$$