Linear Quadratic Regulator(LQR) for Discrete-Time System

Baboo J. Cui

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Contents

LQR is related to optimal control problem, many problems can be formulated into it. It's one of the fundamental way to achieve optimal control.

1 Problem Formulation

Given a discrete LTI system:

$$x[k+1] = Ax[k] + Bu[k], x[0] = x_0$$

given a time horizon $k \in \{0, 1, \ldots, N\}$, where N may be infinity, find the optimal input sequence $U = \{u[0], u[1], \ldots, u[N-1]\}$ that minimize the **cost function**:

$$J(U) = \sum_{k=0}^{N-1} \left(x^T[k]Qx[k] + u^T[k]Ru[k]\right) + x^T[N]Q_f x[N]$$

- **state weight matrix**: $Q = Q^T \succeq 0$
- **control weight matrix**: $R = R^T \succ 0$, indicate that there is no free control input
- **final state weight matrix**: $Q_f = Q_f^T \succeq 0$
- **running cost**: the value of the first term in $J(u)$
- **terminal cost**: the value of the second term in $J(u)$
- **infinite case**: N is infinity, in this case, $Q_f = 0$

Note that all these case can be generalized into time-varying cases.

2 Examples of Implementations

Many problem can be formulated into LQR form, and here are some examples, though they look differently.

2.1 Energy Efficient Stabilization

Starting from $x[0] = x_0$, find control sequence U that minimize

$$J(U) = \alpha \sum_{k=0}^{n-1} ||u[k]||^2 + \beta \sum_{k=0}^{N} ||x[k]||^2$$

to make it into LQR form, choose:

- $Q = \beta I$
- $R = \alpha I$
- $Q_f = \beta I$

Note that:

- cost function try to make state trajectory stay close to zero and use the least control energy simultaneously
- α and β determine the emphasis

Sometime state cannot be obtained directly, in this case, system output y can be used for evaluating running cost. Suppose output equation(Du part can be eliminate) is

$$y = Cx$$

in this case choose $Q = \beta C^T C$. Here is the proof:

$$\begin{aligned}
\beta \sum_{k=0}^{N} ||y[k]||^2 &= \sum_{k=0}^{N} y^T[k]\beta I y[k] \\
&= \sum_{k=0}^{N} (Cx[k])^T \beta I C x[k] \\
&= \sum_{k=0}^{N} x^T[k] C^T \beta I C x[k] = \sum_{k=0}^{N} x^T[k](\beta C^T C) x[k]
\end{aligned}$$

this is a very import conclusion.

2.2 Minimum Energy Steering

Starting from $x[0] = x_0$, find control sequence U to use least energy to steer the final state to $x[N] = 0$ without lost generosity, the cost is:

$$J(U) = \sum_{k=0}^{N-1} ||u[k]||^2$$

to make it into LQR form, choose:

- $Q = 0$
- $R = I$
- $Q_f = \infty I$

By setting $Q_f \to \infty I$, there is a big penalty if $X[N]$ is far from 0, note that this won't lead to a analytic solution, but the **approximation** is good enough.

2.3 LQR for Tracking(VIP TOPIC)

Find efficient sequence U for the state to track a given **reference trajectory** x_k^*(may be time-varying):

$$J(U) = \alpha \sum_{k=0}^{N-1} ||u[k]||^2 + \beta \sum_{k=0}^{N} ||x[k] - x_k^*||^2$$

note that $||x[k]-x_k^*||^2$ is not homogeneous quadratic, it should be formulate. It can be expanded(refer math proof in last part):

$$\begin{aligned} ||x[k]-x_k^*||^2 &= x^T[k]x[k] - 2x^T[k]x_k^* + (x_k^*)^T x_k^* \\ &= \begin{bmatrix} x[k] & 1 \end{bmatrix} \begin{bmatrix} I & x_k^* \\ (x_k^*)^T & (x_k^*)^T x_k^* \end{bmatrix} \begin{bmatrix} x[k] \\ 1 \end{bmatrix} \quad \text{dimension augmentation} \end{aligned}$$

construct new state variable $\tilde{x}[k] = [x[k] \quad 1]^T$, new system dynamic will be:

$$\tilde{x}[k+1] = \begin{bmatrix} A & 0 \\ 0 & 1 \end{bmatrix} \tilde{x}[k] + \begin{bmatrix} B \\ 0 \end{bmatrix} u[k]$$

and the origin cost can be reformed as:

$$J(U) = \alpha \sum_{k=0}^{N-1} ||u[k]||^2 + \beta \sum_{k=0}^{N} \tilde{x}^T[k]\tilde{Q}_k\tilde{x}[k]$$

where

$$\tilde{Q}_k = \begin{bmatrix} I & x_k^* \\ (x_k^*)^T & (x_k^*)^T x_k^* \end{bmatrix}$$

clearly, the system is LTI and the cost function is LTV.

2.4 LQR for System with Perturbation

Suppose system is:

$$x[k+1] = Ax[k] + Bu[k] + w[k]$$

To achieve LQR formulation, new state vector is constructed as:

$$\tilde{x}[k] = [x[k] \quad z[k]] \quad \text{dimension augmentation}$$

recall that $x \in \mathbb{R}^n$, and $z[k] \in \mathbb{R}$, set $z[k] = z[k+1] = 1$, new system dynamic will be:

$$\tilde{x}[k+1] = \begin{bmatrix} A & w[k] \\ 0 & 1 \end{bmatrix} \tilde{x}[k] + \begin{bmatrix} B \\ 0 \end{bmatrix} u[k]$$

and system initial condition is $\tilde{x}[0] = [x[0] \quad 1]$. R will be the original one and $\tilde{Q}$ is:

$$\tilde{Q}_k = \begin{bmatrix} Q & 0 \\ 0 & 0 \end{bmatrix}$$

clearly, the system is LTV and the cost function is LTI. In this case, u is not changed, x is augmented.

3 Direct Approach to Solve LQR

LQR problem can be directly formulated as a least square problem

4 Extra

4.1 Matlab Functions

- lqrd(): for discrete-time system
- lqr(): for continuous-time system

4.2 Quadratic Expansion

The general length of a vector $x \in \mathbb{R}^n$ is also called the L_2 norm. It is defined as:

$$||x||^2 = x^T x = \sum_{i=1}^{n} x_i^2, \text{ where } x_i \in \mathbb{R}$$

if another vector $y \in \mathbb{R}^n$, the norm of the difference is:

$$\begin{aligned} ||x-y||^2 &= ||y-x||^2 \quad \text{identity property} \\ &= (x-y)^T(x-y) \quad \text{definition} \\ &= x^T x - x^T y - y^T x + y^T y \quad \text{distributive property} \\ &= ||x||^2 - 2x^T y + ||y||^2 \end{aligned}$$

recall that:

$$x^T y = y^T x \quad \text{property of inner product}$$

4.3 Direct Approach

Formulate the LQR problem as a least square problem: Under the constraint:

$$\underbrace{\begin{bmatrix} x[1] \\ x[2] \\ \vdots \\ x[N] \end{bmatrix}}_{\widetilde{X}} = \underbrace{\begin{bmatrix} B & 0 & \cdots & \\ AB & B & 0 & \cdots \\ \vdots & \vdots & \ddots & \\ A^{N-1}B & A^{N-2}B & \cdots & B \end{bmatrix}}_{\widetilde{G}} \underbrace{\begin{bmatrix} u[0] \\ u[1] \\ \vdots \\ u[N-1] \end{bmatrix}}_{\widetilde{U}} + \underbrace{\begin{bmatrix} A \\ A^2 \\ \vdots \\ A^N \end{bmatrix}}_{\widetilde{H}} x_0$$

Minimize the function:

$$X^T \underbrace{\begin{bmatrix} Q & & & \\ & Q & & \\ & & \ddots & \\ & & & Q_f \end{bmatrix}}_{\widetilde{Q}} X + U^T \underbrace{\begin{bmatrix} R & & & \\ & R & & \\ & & \ddots & \\ & & & R \end{bmatrix}}_{\widetilde{R}} U$$

4.4 Limitations of Direct Approach

- Matrix inversion needed to find optimal control
- Problem(matrices) dimension increases with time horizon N
- Imprarical for large N let alone infinite horizon case
- Sensitivity of solutions to numerical errors

Observations:

- Problem easier to solve for shorter time horizon N
- $(N+1)$-horizon solution related to N-horizon solution
- Explpoit this relation to design an iterative solution procedure

Dynamic programming approach

- Reuse results for smaller N to solve for large N case
- In each iteration only need to deal with a problem of fixed size

4.5 Movitating Example

- Start from point A
- Try to reach point B
- Each step only move right
- Cost labeled on each edge

Problem: The least costly path from A to B?

4.6 Formulated as an Optimal Control Problem

- $A = (0, 0),\ B = (3, 3)$
- State $x[k]$ with
$$x[0] = A,\ x[6] = B$$
- Control $u[k] = \pm 1$
- Dynamics:
$$x[k+1] = \begin{cases} x[k] + (0,1) & u[k] = 1 \\ x[k] + (1,0) & u[k] = -1 \end{cases}$$
- Cost to be minimized:
$$\sum_{k=0}^{5} \underbrace{w(x[k], u[k])}_{\text{edge weight}}$$

4.7 Direct Solution

Enumerate all possible legal from A to B and compare their costs to find the one with the least cost.

- A total of 20 possible paths

  For ℓ-by-ℓ grid, the total number of legal paths is
$$\frac{(2\ell)!}{(\ell!)^2}$$
- Grows extremely fast as problem size ℓ increases
- Solution impractical for large ℓ

4.8 Value Function

Definition: At any point z, the value function(optimal cast-to-go) $V(z)$ is the least possible cost to reach B from z.

- Obtained by solve shorter time horizon problems

Original problem is to find $V(A)$

4.9 Value Function Property

Principle of Optimality: If a least-cost path from A to B is

$$x_0^* = A \to x_1^* \to x_2^* \to \cdots \to x_6^* = B,$$

Then any truncation of it at the end:

$$x_t^* \to x_{t+1}^* \to \cdots \to x_6^* = B$$

is also a least-cost path from x_t^* to B.
As a result, value function at any point z satisfies

$$\begin{aligned} V(z) &= \min\left\{w_u + V\left(z_u'\right), w_d + V\left(z_d'\right)\right\} \\ &= \min_{u \in \pm 1}\left[w(z,u) + V\left(z'\right)\right] \end{aligned}$$

- $V(z)$: Cost-to-go from current position
- $w(z,u)$: Running cost of current step
- $V(z')$: Cost-to-go from next state position

4.10 Value Function Iteration

Idea: Use above to iteratively evaluate $V(z)$ from right to left

4.11 Value Function Iteration

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4.12 Value Function Iteration

Conclusion: The least cost from A to B is 40

4.13 Recover the Optimal Control

Optimal control $u[0]$ is recovered from $V(A) = \min\{5+35,\ 7+36\}$

4.14 Advantages of Dynamic Programming

Reduced computational complexity: for ℓ-by-ℓ grid

- Only need to compute ℓ^2 value functions
- No need to enumerate $\frac{(2\ell)!}{(\ell!)^2}$ paths
- Solve an optimization problem of fixed size in each iteration

Provide solutions to a family of optimal control problems

- Even if starting from a different initial position (e.g. due to perturbation), there is no need for re-computation

4.15 Back to LQR Problem

A discrete-time LTI system

$$x[k+1] = Ax[k] + Bu[k], \quad x[0] = x_0$$

Problem: Given a time horizon $k \in \{0, 1, ..., N\}$, find the optimal input sequence $U = \{u[0], ..., u[N-1]\}$ that minimizes the cost function

$$J(U) = \sum_{k=0}^{N-1} \underbrace{(x[k]^T Qx[k] + u[k]^T Ru[k])}_{running\ cost} + \underbrace{x[N]^T Q_f x[N]}_{terminal cost}$$

Quenstions: Can we apply dynamic programming method to LQR problem?

4.16 Value Function of LQR Problem

The value function at time $t \in \{0, 1, ..., N\}$ and state $x \in \mathbb{R}^n$ is

$$V_t(x) = \min_{u[t],...,u[N-1]} \sum_{k=t}^{N-1} (x[k]^T Qx[k] + u[k]^T Ru[k]) + x[N]^T Q_f x[N]$$

with the initial condtion $x[t] = x$

- **Cost-to-go**, namely, optimal cost of the LQR problem over the time horizon $\{t, t+1, ..., N\}$, starting from $x[t] = x$.

4.17 Solution of LQR Problem via Value Functions

Preview of results:

- The value function at the final time is quadratic: $V_N(x) = x^T Q_f x$
- We will see that the value function at any time t is also quadratic: $V_t(x) = x^T P_t x$ for some $P_t \geqslant 0$
- P_t can be obtained from P_{t+1}

Solution algorithm:

(1) Start from $P_N = Q_f$ at time $t = N$

(2) For $t = N - 1 : 0$ do

- Compute P_t from P_{t+1} by the above recursion

(3) Recover optimal control sequence from value functions

4.18 How are Value Functions Related?

(Hamilton-Jacobi-)Bellman equation:

$$\begin{aligned} V_t(x) &= \min_{u[t]=v} [x^T Q x + v^T R v + V_{t+1}(Ax + Bv)] \\ &= x^T Q x + \min_{u[t]=v} [v^T R v + V_{t+1}(Ax + Bv)] \end{aligned}$$

Optimality principle: For optimal case, cost-to-go form next state $x[t+1]$ should also be optimal, i.e., $V_{t+1}(x[t+1])$.

4.19 $t = N$ case

Value function at time N is quadratic:

$$V_N(x) = x^T P_N x, \quad \forall x \in \mathbb{R}^n, \quad \text{where } P_N = Q_f$$

4.20 $t = N - 1$ case

Value function at time $N - 1$ is:

$$\begin{aligned} V_{N-1}(x) &= x^T Q x + \min_v [v^T R v + V_N(Ax + Bv)] \\ &= x^T Q x + \min_v [v^T R v + (Ax + Bv)^T P_N (Ax + Bv)] \end{aligned}$$

4.21 General Case

Suppose value function at time $t + 1$ is quadratic: $V_{t+1}(x) = x^T P_{t+1} x$

- Value function at time t is also quadratic:

$$V_t(x) = x^T P_t x, \quad \forall x \in \mathbb{R}^n,$$

- P_t obtained from P_{t+1} according to the **Riccati recursion**:

$$P_t = Q + A^T P_{t+1} A - A^T P_{t+1} B (R + B^T P_{t+1} B)^{-1} B^T P_{t+1} A$$

- Optimal control at time t for the given state $x[t] = x$ is:

$$u^*[t] = -(R + B^T P_{t+1} B)^{-1} B^T P_{t+1} A x = -K_t x$$

  which is a linear state feedback control!

4.22 LQR Solution Algorithm

Set $P_N = Q_f$
for $t = N-1, N-2, ..., 0$ **do**
Compute the value functions backward in time:
$P_t = Q + A^T P_{t+1} A - A^T P_{t+1} B(R + B^T P_{t+1} B)^{-1} B^T P_{t+1} A$
end for
Return $V_0(x_0)$ as the optimal cost
Set $x^*[0] = x_0$
for $t = 0, 1, ..., N-1$ **do**
Recover the optimal control and state trajectory forward in time:
$u^*[t] = -(R + B^T P_{t+1} B)^{-1} B^T P_{t+1} A x^*[t]$
$x^*[t+1] = Ax^*[t] + Bu^*[t]$
end for
Return u^* and x^* as the optimal control and state sequences

4.23 Remarks

- Value function at any time is quadratic (easy numeric representation)
- Optimal control strategy is of the state feedback form (though with time-varying gains)
- Yield the optimal solutions for all initial conditions x_0 and all initial times $t_0 \in \{0, 1, ..., N\}$ simultaneously
- Easily extended to time-varying dynamics and costs cases

4.24 Example

$$x[k+1] = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} x[k] + \begin{bmatrix} 0 \\ 1 \end{bmatrix} u[k], \quad x[0] = \begin{bmatrix} 1 \\ 0 \end{bmatrix}$$

$$y[k] = \begin{bmatrix} 1 & 0 \end{bmatrix} \times [k]$$

Cost function to be minimized

$$J(U) = \sum_{k=0}^{N-1} \|u[k]\|^2 + \rho \sum_{k=0}^{N} \|y[k]\|^2$$

- Time horizon $N = 20$
- State weights $Q = Q_f = \rho C^T C$
- Control weight $R = 1$
- Optimal control is of the form $u^*[t] = [a_t \;\; b_t] \; x^*[t]$

4.25 Optimal Solution of Example

4.26 Steady State Optimal Control

Plot of the Kalman gain $K(k) = [K_1(k) \;\; K_2(k)]$ for $\rho = 0.1$:
After sufficient number of iterations in the example

- The value function converages to the solution of the matrix equation:

$$P_{ss} = Q + A^T P_{ss} A - A^T P_{ss} B (R + B^T P_{ss} B)^{-1} B^T P_{ss} A$$

- The Kalman gain converges to

$$K_{ss} = (R + B^T P_{ss} B)^{-1} B^T P_{ss} A$$

4.27 Convergence of Riccati Recursion

Theorem: If (A, B) is stabilizable, then Riccati recursion starting from any P_N:

$$P_t = Q + A^T P_{t+1} A - A^T P_{t+1} B (R + B^T P_{t+1} B)^{-1} B^T P_{t+1} A$$

will converge to a solution P_{ss} of the **Algebraic Riccati Equation(ARE)**

$$P_{ss} = Q + A^T P_{ss} A - A^T P_{ss} B (R + B^T P_{ss} B)^{-1} B^T P_{ss} A$$

If further $Q = C^T C$ for some C such that (C, A) is detectable, then the ARE has a unique positive semidefinite P_{ss}. Also, in this case by applying the steady-state optimal control with gain

$$K_{ss} = (R + B^T P_{ss} B)^{-1} B^T P_{ss} A$$

the closed-loop system $A_{cl} = A - BK_{ss}$ is stable.

4.28 Infinite Horizon LQR Problem

Problem: Find optimal $U = \{u[0], u[1], ...\}$ to minimize

$$J(U) = \sum_{k=0}^{\infty} \left(x[k]^T Q x[k] + u[k]^T R u[k] \right)$$

- Problem invariant to time-shift: same problem faced again and again
- Thus, value function is indepedent of time. with Bellman equation:

$$V(x) = x^T Q x + \min_v \left[v^T R v + V(Ax + Bv) \right]$$

- Infinite value function possible

Theorem: If (A, B) is stabilizable and (C, A) is detectable where $Q = C^T C$, then the value function $V(x)$ of the infinite horizon problem is $V(x) = x^T P_{ss} x$ where P_{ss} is the unique positive semidefinite solution to the discrete-time ARE and the optimal control is stationary $u^*(t) = -K_{ss} x^*(t)$.