

# Optimal control for continuous-time systems CHEATSHEET

Indirect approach via calculus of variations

## 1 Calculus of variations

Minimization over smooth enough (at least  $C^1$ ) functions

$$\min_{y(x) \in C^1[a,b]} J(y(x)).$$

Beware:  $x$  is the independent variable (often spatial position),  $y()$  is a function.

*Strong* vs. *weak* minimum (easier theory for the weak).

Variation  $\delta y()$  of a function (compare with  $dx$  in calculus)

$$y(x) = y^*(x) + \delta y(x)$$

Variation of a functional (=first-order approximation to  $\Delta J$ )

$$\delta J = \int_a^b \underbrace{\frac{\delta J}{\delta y(x)}}_{\text{variational derivative}} \delta y(x) dx$$

First-order necessary condition of optimality

$$\delta J = 0, \quad \text{hence} \quad \frac{\delta J}{\delta y(x)} = 0$$

Recall in calculus  $dJ = (\nabla J)^T dx = 0$ , hence  $\nabla J = 0$ .

For the (cost) functional

$$J(y) = \int_a^b L(x, y, y') dx$$

subject to

$$y(a) = y_a, \quad y(b) = y_b,$$

the necessary conditions of optimality = *Euler-Lagrange equation*

$$\frac{\partial L(x, y, y')}{\partial y} - \frac{d}{dx} \frac{\partial L(x, y, y')}{\partial y'} = 0$$

EL equation is a second-order ODE

$$L_y - L_{y'x} - L_{y'y'} - L_{y'y''} = 0.$$

hence two initial/boundary conditions needed.

Extensions for constrained problems (Lagrange multipliers).

Sufficiency difficult. Legendre condition

$$L_{y'y'} > 0$$

not sufficient. Jacobi condition needed (but not discussed).

## 2 General optimal control for a nonlinear system

$$\begin{aligned} & \text{minimize}_{\mathbf{x}(t), \mathbf{u}(t)} \left[ \phi(\mathbf{x}(t_f), t_f) + \int_{t_i}^{t_f} L(\mathbf{x}(t), \mathbf{u}(t), t) dt \right] \\ & \text{subject to} \quad \dot{\mathbf{x}}(t) = \mathbf{f}(\mathbf{x}, \mathbf{u}, t) \\ & \quad \mathbf{x}(t_i) = \mathbf{r}_i \\ & \quad \mathbf{x}(t_f) = \mathbf{r}_f \text{ or } \mathbf{x}(t_f) \text{ unspecified.} \end{aligned}$$

Hamiltonian (two conventions!)

as in physics

$$H(t, \mathbf{x}, \mathbf{u}, \boldsymbol{\lambda}) = \boldsymbol{\lambda}^T(t) \mathbf{f}(\mathbf{x}, \mathbf{u}, t) - L(t, \mathbf{x}, \mathbf{u}),$$

as favored in control theory

$$H(t, \mathbf{x}, \mathbf{u}, \boldsymbol{\lambda}) = L(t, \mathbf{x}, \mathbf{u}) + \boldsymbol{\lambda}^T(t) \mathbf{f}(\mathbf{x}, \mathbf{u}, t)$$

First-order necessary conditions—two-point boundary value problem (TP-BVP): *state* and *costate* ODEs plus *stationarity* equation.

$$\begin{aligned} \mathbf{x}' &= \nabla_{\mathbf{x}} H(t, \mathbf{x}, \mathbf{u}, \boldsymbol{\lambda}) \\ \boldsymbol{\lambda}' &= -\nabla_{\boldsymbol{\lambda}} H(t, \mathbf{x}, \mathbf{u}, \boldsymbol{\lambda}) \\ \mathbf{0} &= \nabla_{\mathbf{u}} H(t, \mathbf{x}, \mathbf{u}, \boldsymbol{\lambda}). \end{aligned}$$

If  $\mathbf{u}$  eliminated, the resulting “true” canonical Hamiltonian ODEs solvable numerically (shooting, multiple shooting, collocation). In Matlab: `bvp4c` and `bvp5c`.

For “physics-convention” Hamiltonian

$$\begin{aligned} \dot{\mathbf{x}} &= \mathbf{f}(\mathbf{x}, \mathbf{u}, t) \\ \dot{\boldsymbol{\lambda}} &= \nabla_{\mathbf{x}} L - \nabla_{\mathbf{x}} \mathbf{f} \boldsymbol{\lambda}, \\ \mathbf{0} &= \nabla_{\mathbf{u}} L - \nabla_{\mathbf{u}} \mathbf{f} \boldsymbol{\lambda} \\ \mathbf{x}(t_i) &= \mathbf{r}_i \\ \mathbf{x}(t_f) &= \mathbf{r}_f \text{ or } \boldsymbol{\lambda}(t_f) = -\nabla \phi(\mathbf{x}(t_f)) \end{aligned}$$

For “control-convention” Hamiltonian

$$\begin{aligned} \dot{\mathbf{x}} &= \mathbf{f}(\mathbf{x}, \mathbf{u}, t) \\ \dot{\boldsymbol{\lambda}} &= -\nabla_{\mathbf{x}} L - \nabla_{\mathbf{x}} \mathbf{f} \boldsymbol{\lambda}, \\ \mathbf{0} &= \nabla_{\mathbf{u}} L + \nabla_{\mathbf{u}} \mathbf{f} \boldsymbol{\lambda} \\ \mathbf{x}(t_i) &= \mathbf{r}_i \\ \mathbf{x}(t_f) &= \mathbf{r}_f \text{ or } \boldsymbol{\lambda}(t_f) = \nabla \phi(\mathbf{x}(t_f)) \end{aligned}$$

## 3 LQ-optimal regulation on a finite time horizon 4 LQR on an infinite time horizon

$$\begin{aligned} & \text{minimize}_{\mathbf{x}(t), \mathbf{u}(t)} \left[ \mathbf{x}^T(t_f) \underbrace{\mathbf{S}_f}_{\geq 0} \mathbf{x}(t_f) \right. \\ & \quad \left. + \int_0^{t_f} \left( \mathbf{x}^T(t) \underbrace{\mathbf{Q}}_{\geq 0} \mathbf{x}(t) + \mathbf{u}^T(t) \underbrace{\mathbf{R}}_{> 0} \mathbf{u}(t) \right) dt \right] \end{aligned}$$

subject to  $\dot{\mathbf{x}}(t) = \mathbf{A}\mathbf{x}(t) + \mathbf{B}\mathbf{u}(t)$ ,

$$\mathbf{x}(0) = \mathbf{r}_0,$$

$$\mathbf{x}(t_f) = \mathbf{r}_f \text{ or } \mathbf{x}(t_f) \text{ unspecified.}$$

Could be also time-varying:  $\mathbf{A}(t)$ ,  $\mathbf{B}(t)$ .

First-order necessary cond's (“physical Hamiltonian”)

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

$$\dot{\boldsymbol{\lambda}} = \mathbf{Q}\mathbf{x} - \mathbf{A}^T \boldsymbol{\lambda}$$

$$\mathbf{0} = \mathbf{R}\mathbf{u} - \mathbf{B}^T \boldsymbol{\lambda}$$

$$\mathbf{x}(t_i) = \mathbf{r}_i$$

$$\mathbf{x}(t_f) = \mathbf{r}_f \text{ or } \boldsymbol{\lambda}(t_f) = -\mathbf{S}_f \mathbf{x}(t_f)$$

Sufficiency (luckily) trivial:  $\frac{\partial^2 J}{\partial \mathbf{u}^2} = \mathbf{R} > 0$ .

Thanks to nonsingularity of  $\mathbf{R}$ , from the stationarity equation express  $\mathbf{u}$  and substitute to the state and costate equations to get Hamilton canonical equations

$$\begin{bmatrix} \dot{\mathbf{x}} \\ \dot{\boldsymbol{\lambda}} \end{bmatrix} = \begin{bmatrix} \mathbf{A} & \mathbf{B}\mathbf{R}^{-1}\mathbf{B}^T \\ \mathbf{Q} & -\mathbf{A}^T \end{bmatrix} \begin{bmatrix} \mathbf{x} \\ \boldsymbol{\lambda} \end{bmatrix}$$

For fixed-final state, the optimal control is a precomputed function/signal (the formula contains an inversion of weighted finite horizon controllability Gramian).

For free-final state, the optimal control is given by a state-feedback control

$$\mathbf{u}(t) = -\underbrace{\mathbf{R}^{-1}\mathbf{B}^T\mathbf{S}(t)}_{\mathbf{K}(t)} \mathbf{x}(t).$$

where  $\mathbf{S}(t) \geq 0$  is a positive semidefinite solution of (matrix) differential Riccati equation

$$-\dot{\mathbf{S}} = \mathbf{S}\mathbf{A} + \mathbf{A}^T\mathbf{S} + \mathbf{Q} - \mathbf{S}\mathbf{B}\mathbf{R}^{-1}\mathbf{B}^T\mathbf{S}.$$

For long enough time horizon,  $\mathbf{S}(t)$  (hence  $\mathbf{K}(t)$ ) is most of time steady (constant).

$$\begin{aligned} & \text{minimize}_{\mathbf{x}(t), \mathbf{u}(t)} \int_0^{\infty} (\mathbf{x}^T(t)\mathbf{Q}\mathbf{x}(t) + \mathbf{u}^T(t)\mathbf{R}\mathbf{u}(t)) dt \\ & \text{subject to} \quad \dot{\mathbf{x}}(t) = \mathbf{A}\mathbf{x}(t) + \mathbf{B}\mathbf{u}(t), \\ & \quad \mathbf{x}(0) = \mathbf{r}_0. \end{aligned}$$

Steady-state solution to the differential Riccati equation found by solving Algebraic Riccati equation (ARE)

$$\mathbf{0} = \mathbf{S}\mathbf{A} + \mathbf{A}^T\mathbf{S} + \mathbf{Q} - \mathbf{S}\mathbf{B}\mathbf{R}^{-1}\mathbf{B}^T\mathbf{S}. \quad (1)$$

But ARE is a quadratic (matrix) equation and has more than one solution. We need a unique stabilizing  $\mathbf{S} \geq 0$ . Conditions:

- $(A, B)$  stabilizable
- $(A, \sqrt{Q})$  detectable. If  $(A, \sqrt{Q})$  observable,  $\mathbf{S} > 0$  (nonzero feedback controller for stable systems).

LTI state-feedback

$$\mathbf{u}(t) = -\underbrace{\mathbf{R}^{-1}\mathbf{B}^T\mathbf{S}}_{\mathbf{K}} \mathbf{x}(t).$$

Solvers for ARE in Matlab (`icare`), Mathematica, Octave, Scilab, Julia, ...

Conservative robustness guarantees ( $GM_+ = 2, GM_- = 1/2, PM = \pm 60^\circ$ ).

## 5 LQ-optimal tracking, tracking+LQR

Optimal for an apriori known reference (not discussed). Tracking for class of references (steps, ramps, ...): proportional feedforward, integral control, state augmentation.