

On the linear quadratic data-driven control

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Notation

w — # of external variables, m — # of inputs, p — # of outputs

$\mathbb{N} := \{1, 2, \dots\}$ — time axis

$\mathcal{B}(A, B, C, D)$ — the system defined by

$$\begin{aligned} \sigma x &= Ax + Bu \\ y &= Cx + Du \end{aligned}$$

Restriction of the system behavior \mathcal{B} to the interval $1, 2, \dots, t$

$$\mathcal{B}_t := \{w_p \in (\mathbb{R}^w)^t \mid \text{there is } w_f \text{ such that } (w_p, w_f) \in \mathcal{B}\}$$

$\text{lag}(\mathcal{B})$ — lag of \mathcal{B} (observability index of I/S/O repr.)

$\text{order}(\mathcal{B})$ — order of \mathcal{B}

We assume that an input/output partition of the variables is given.

“Data-driven” control methods

data-driven = model-free = model-less = ...

1995	Skelton, Furuta	LQG design using Markov par.
1996	Hjalmarsson, Gevers	iterative feedback tuning
1997	Safonov	unfalsified control
1999	Favoreel, De Moor	subspace based LQG control
2001	Woodley	subspace based \mathcal{H}_∞ control
2002	Campi, Lecchini	virtual reference feedback tuning
2004	Ikeda, Fujisaki	subspace based LQ tracking

Our work is in the spirit of the “subspace based” methods.

The simulation problem

Classical simulation problem: Given

- system $\mathcal{B} := \mathcal{B}(A, B, C, D)$,
- input $u \in (\mathbb{R}^m)^t$, and
- initial conditions $x_{\text{ini}} \in \mathbb{R}^n$,

find the response y of \mathcal{B} to u and ini. cond. x_{ini} .

Data-driven simulation problem: Given

- trajectory $w_d = (u_d, y_d) \in (\mathbb{R}^w)^T$ of \mathcal{B} ,
- input $u \in (\mathbb{R}^m)^t$, and
- initial trajectory $w_{\text{ini}} \in (\mathbb{R}^w)^{T_{\text{ini}}}$, $w_{\text{ini}} \in \mathcal{B}_{T_{\text{ini}}}$,

find the response y of \mathcal{B} to u , such that $(w_{\text{ini}}, (u, y)) \in \mathcal{B}_{T_{\text{ini}}+t}$.

Notes:

- \mathcal{B} is specified implicitly by w_d ,
- the initial condition x_{ini} is specified implicitly by w_{ini} .

Algorithm 1: data-driven simulation, using I/S/O repr.

1. identification $w_d \mapsto (A, B, C, D)$
2. observer $(w_{ini}, (A, B, C, D)) \mapsto x_{ini}$
3. classical simulation $(u, x_{ini}, (A, B, C, D)) \mapsto y$

Can we find y without deriving an explicit representation of \mathcal{B} ?

Basic idea

Assuming that w_d is a trajectory of \mathcal{B} (exact data),

lin. comb. of the columns of $\mathcal{H}_t(w_d)$ are trajectories of \mathcal{B} , i.e.,

$$\text{for all } g, \quad \mathcal{H}_t(w_d)g \in \mathcal{B}_t$$

Under additional conditions—persistency of excitation of u_d and controllability of \mathcal{B} —every trajectory can be generated that way.

In what follows, we assume that these conditions are satisfied.

⇒ computing the response of \mathcal{B} to given input and initial conditions from data w_d , requires choosing a suitable g

Notation for Hankel matrices

Given a signal $w = (w(1), \dots, w(T))$ and $t \leq T$, define

$$\mathcal{H}_t(w) := \begin{bmatrix} w(1) & w(2) & w(3) & \cdots & w(T-t+1) \\ w(2) & w(3) & w(4) & \cdots & w(T-t+2) \\ w(3) & w(4) & w(5) & \cdots & w(T-t+3) \\ \vdots & \vdots & \vdots & & \vdots \\ w(t) & w(t+1) & w(t+2) & \cdots & w(T) \end{bmatrix}$$

block-Hankel matrix with t block-rows, composed of w

Construction of responses from data

Problem: Find y , such that $(w_{ini}, (u, y)) \in \mathcal{B}$, where w_{ini}, u are given, and \mathcal{B} is implicitly defined by w_d .

There is g , such that

$$\mathcal{H}_{T_{ini}+t}(w_d)g = (w_{ini}, (u, y)).$$

The eqns with RHS y , define y , for given g . The others restrict g .

Generic data-driven simulation algorithm:

1. compute any solution g of the equations with RHS w_{ini}, u
2. substitute g in the equations for y

Define

$$U := \mathcal{H}_{T_{\text{ini}}+t}(u_d), \quad Y := \mathcal{H}_{T_{\text{ini}}+t}(y_d)$$

and the partitionings

$$U =: \begin{bmatrix} U_p \\ U_f \end{bmatrix}, \quad Y =: \begin{bmatrix} Y_p \\ Y_f \end{bmatrix}.$$

Algorithm 2: data-driven simulation

1. compute the least norm solution of

$$\begin{bmatrix} U_p \\ Y_p \\ U_f \end{bmatrix} g = \begin{bmatrix} u_{\text{ini}} \\ y_{\text{ini}} \\ u \end{bmatrix}.$$

2. compute $y := Y_f g$.

Special case $w_{\text{ini}} = 0$: zero initial cond. response

Let h be the impulse response of \mathcal{B} , and define

$$\mathcal{T}_t(h) := \begin{bmatrix} h(0) & & & & \\ h(1) & h(0) & & & \\ h(2) & h(1) & h(0) & & \\ \vdots & \ddots & \ddots & \ddots & \\ h(t-1) & \dots & \dots & h(1) & h(0) \end{bmatrix}$$

For any $w = \text{col}(u, y) \in \mathcal{B}_t$,

$$y = \mathcal{O} x_{\text{ini}} + \mathcal{T}_t(h)u$$

We can compute a basis for $\mathcal{B}_{0,t} := \text{image}(\mathcal{T}_t(h))$ from data, by finding t_m lin. indep. zero initial cond. responses.

Special case $u = 0$: free response

Allows to compute an **observability matrix** \mathcal{O} of \mathcal{B} from data, by finding $n \geq \text{order}(\mathcal{B})$ linearly indep. free responses.

Let l_{max} be an **upper bound for the lag of** \mathcal{B} and take $T_{\text{ini}} = l_{\text{max}}$.

Algorithm 3: compute an observability matrix \mathcal{O}

1. compute the least norm solution of

$$\begin{bmatrix} U_p \\ Y_p \\ U_f \end{bmatrix} G = \begin{bmatrix} U_p \\ Y_p \\ 0 \end{bmatrix}$$

2. compute $Y := Y_f G$
3. compute a **rank revealing factorization** $Y = \mathcal{O} X_{\text{ini}}$

Algorithm 4: compute a basis of $\mathcal{B}_{0,t}$

1. compute the least norm solution of

$$\begin{bmatrix} U_p \\ Y_p \\ U_f \end{bmatrix} G = \begin{bmatrix} 0 \\ 0 \\ \mathcal{H}_{t,t_m}(u_d) \end{bmatrix}$$

2. compute $Y_0 := Y_f G$

Then **image**(Y_0) = **image**($\mathcal{T}_t(h)$) = $\mathcal{B}_{0,t}$.

Special case $w_{\text{ini}} = 0$, $u = I\delta$: impulse response

With the same construction we can find the first t Markov parameters of \mathcal{B} , which is a **system identification method**.

Algorithm 5: compute the impulse response

1. compute the least norm solution of

$$\begin{bmatrix} U_p \\ Y_p \\ U_f \end{bmatrix} G = \begin{bmatrix} 0 \\ 0 \\ \text{col}(I_m, 0) \end{bmatrix}$$

2. compute $h := Y_f G$

Solution using an I/S/O representation

The classical but indirect solution is:

Algorithm 7: data-driven LQ tracking, using I/S/O repr.

1. $w_d \xrightarrow{\text{Identification}} (A, B, C, D)$
2. $(w_{\text{ini}}, (A, B, C, D)) \xrightarrow{\text{Observer (1,2)}} x_{\text{ini}}$
3. $(\Phi, w_r, x_{\text{ini}}, (A, B, C, D)) \xrightarrow{\text{Synthesis (3,4,5)}} w_f^*$

We aim to find algorithms that do not derive a repr. of \mathcal{B} .

Linear quadratic tracking problem

Given

- trajectory $w_d = (u_d, y_d) \in (\mathbb{R}^w)^T$ of \mathcal{B} ,
- initial trajectory $w_{\text{ini}} \in (\mathbb{R}^w)^{T_{\text{ini}}}$, $w_{\text{ini}} \in \mathcal{B}_{T_{\text{ini}}}$,
- reference trajectory $w_r \in (\mathbb{R}^w)^{T_r}$, and
- positive definite matrix $\Phi \in \mathbb{R}^{w \times w}$,

find a trajectory of \mathcal{B} that is optimal with respect to the criterion

$$J(w_r, w) := (w_r - w)^\top \Phi (w_r - w)$$

and has as a prefix the initial trajectory w_{ini} , i.e., find

$$w_f^* := \arg \min_{w_f} J(w_r, w_f) \quad \text{subject to} \quad (w_{\text{ini}}, w_f) \in \mathcal{B}_{T_{\text{ini}} + T_r}.$$

Observer

Let h be the impulse response of \mathcal{B} . We have,

$$y_{\text{ini}} = \mathcal{O}(A, C) \mathbf{x}(1) + \mathcal{T}_{T_{\text{ini}}}(h) u_{\text{ini}}, \quad (1)$$

where

$$\mathcal{O}(A, C) := \text{col}(C, CA, \dots, CA^{T_{\text{ini}}-1})$$

defines a system of equations for the initial state $\mathbf{x}(1)$.

$$\begin{aligned} w_{\text{ini}} \in \mathcal{B}_{T_{\text{ini}}} &\implies \text{existence of solution} \\ (A, B, C, D) \text{ minimal} &\implies \text{uniqueness} \end{aligned}$$

$$x_{\text{ini}} := \mathbf{x}(T_{\text{ini}} + 1) = A^{T_{\text{ini}}} \mathbf{x}(1) + [A^{T_{\text{ini}}-1} B \quad A^{T_{\text{ini}}-2} B \quad \dots \quad B] u_{\text{ini}}. \quad (2)$$

LQ Regulator

LQ tracking problem:

$$\begin{aligned} \min_{x,u,y} & (w_r - \text{col}(u, y))^T \Phi (w_r - \text{col}(u, y)) \\ \text{subject to} & \quad x(t+1) = Ax(t) + Bu(t), \quad x(1) = x_{\text{ini}} \\ & \quad y(t) = Cx(t) + Du(t), \quad \text{for } t = 1, \dots, T_r. \end{aligned}$$

The solution for the $w_r = 0$ case (regulation problem) is

$$\begin{aligned} x^*(t+1) &= (A - BL_t)x^*(t), \quad x(1) = x_{\text{ini}} \\ w_f^*(t) &= \begin{bmatrix} -L_t \\ C - DL_t \end{bmatrix} x^*(t) \end{aligned} \quad (3)$$

a state feedback.

Solution using the impulse response representation

LQ tracking problem:

$$\min_{w_f} (w_r - w_f)^T \Phi (w_r - w_f) \quad \text{subject to} \quad (w_{\text{ini}}, w_f) \in \mathcal{B}_{T_{\text{ini}}+T_r}$$

Let $y_{f,0}$ be the free response of \mathcal{B} initiated by w_{ini} .

$$y_f = y_{f,0} + \mathcal{T}_r(h)u_f$$

so that the tracking problem becomes

$$\min_{u_f} (w_r - w_f)^T \Phi (w_r - w_f) \quad \text{subject to} \quad y_f = \mathcal{T}_r(h)u_f + y_{f,0}$$

a weighted least squares problem.

Define

$$\Phi =: \begin{bmatrix} \Phi_u & \Phi_{uy} \\ \Phi_{yu} & \Phi_y \end{bmatrix}.$$

The optimal input is a **state feedback with time-varying gain**

$$L_t := (B^T S_{t+1} B + \Phi_u + \Phi_{uy} D + D^T \Phi_{uy}^T + D^T \Phi_y D)^{-1} \times (B^T S_{t+1} A + \Phi_{uy} C + D^T \Phi_y C) \quad (4)$$

where S is given by the **Riccati difference equation**

$$\begin{aligned} S_t &= A^T S_{t+1} A + C^T \Phi_y C - (B^T S_{t+1} A + \Phi_{uy} C + D^T \Phi_y C)^T \\ &\quad \times (B^T S_{t+1} B + \Phi_u + \Phi_{uy} D + D^T \Phi_{uy}^T + D^T \Phi_y D)^{-1} \\ &\quad \times (B^T S_{t+1} A + \Phi_{uy} C + D^T \Phi_y C), \quad S_{T_r} = 0. \end{aligned} \quad (5)$$

With $\tilde{h} := \text{col}(I\delta, h)$,

$$w_f := \left(\text{col}(u_f(1), y_f(1)), \dots, \text{col}(u_f(T_r), y_f(T_r)) \right) = \mathcal{T}_{T_r}(\tilde{h})u_f$$

Then

$$w_f = \mathcal{T}_{T_r}(\tilde{h})u_f + w_{f,0}, \quad \text{where} \quad w_{f,0} := \text{col}(0, y_{f,0})$$

The tracking problem becomes

$$\min_{u_f} (w_r - w_{f,0} - \mathcal{T}_{T_r}(\tilde{h})u_f)^T \Phi (w_r - w_{f,0} - \mathcal{T}_{T_r}(\tilde{h})u_f)$$

and the solution is

$$\begin{aligned} u_f^* &= (\mathcal{T}_{T_r}^T(\tilde{h})\Phi\mathcal{T}_{T_r}(\tilde{h}))^{-1} \mathcal{T}_{T_r}^T(\tilde{h})\Phi(w_r - w_{f,0}) \\ y_f^* &= \mathcal{T}_{T_r}(h)u_f^* + y_{f,0} \end{aligned} \quad (6)$$

Ingredients of the solution:

- the free response $y_{f,0}$ and
- the impulse response h .

We can compute them directly from w_d .

Algorithm 8: data-driven LQ tracking, using impulse resp. repr.

1. $(w_{ini}, w_d, T_r) \xrightarrow{\text{Algorithm 2}} y_{f,0}$
2. $(w_d, T_r) \xrightarrow{\text{Algorithm 6}} h$
3. $(\Phi, w_r, w_{f,0}, h) \xrightarrow{(6)} w_f^*$

Proof

Any zero initial conditions trajectory $w = \text{col}(u, y) \in (\mathbb{R}^w)^{T_r}$ is of the form $w = \mathcal{T}_{T_r}(\tilde{h})u$. Therefore,

$$\mathcal{B}_{0,T_r} = \text{image}(\mathcal{T}_{T_r}(\tilde{h})) = \text{image}(W_0)$$

Consider the space $\mathcal{W} = (\mathbb{R}^w)^{T_r}$ with inner product defined by $\langle w_1, w_2 \rangle = w_1^\top \Phi w_2$. The **projector on \mathcal{B}_{0,T_r} in \mathcal{W}** is

$$\mathcal{T}_{T_r}(\tilde{h})(\mathcal{T}_{T_r}^\top(\tilde{h})\Phi\mathcal{T}_{T_r}(\tilde{h}))^{-1}\mathcal{T}_{T_r}^\top(\tilde{h})\Phi = W_0(W_0^\top\Phi W_0)^+W_0^\top\Phi$$

Then the data-driven solution (7) follows from the solution (6), using the impulse response representation.

Data-driven solution

Define the **zero initial conditions subbehavior of \mathcal{B}**

$$\mathcal{B}_{0,T_r} := \left\{ w \in (\mathbb{R}^w)^{T_r} \mid \underbrace{(0, \dots, 0)}_{\text{lag}(\mathcal{B})}, w \in \mathcal{B}_{\text{lag}(\mathcal{B})+T_r} \right\}$$

Theorem: Let $W_0 \in \mathbb{R}^{T_r \times w}$ be a matrix, such that

$$\text{image}(W_0) = \mathcal{B}_{0,T_r}$$

Then the LQ optimal trajectory is

$$w_f^* = W_0(W_0^\top\Phi W_0)^+W_0^\top\Phi(w_r - w_{f,0}) + w_{f,0} \quad (7)$$

where $w_{f,0}$ is the free response of \mathcal{B} , caused by w_{ini} .

Algorithm for data-driven LQ tracking

Algorithm 9: data-driven LQ tracking

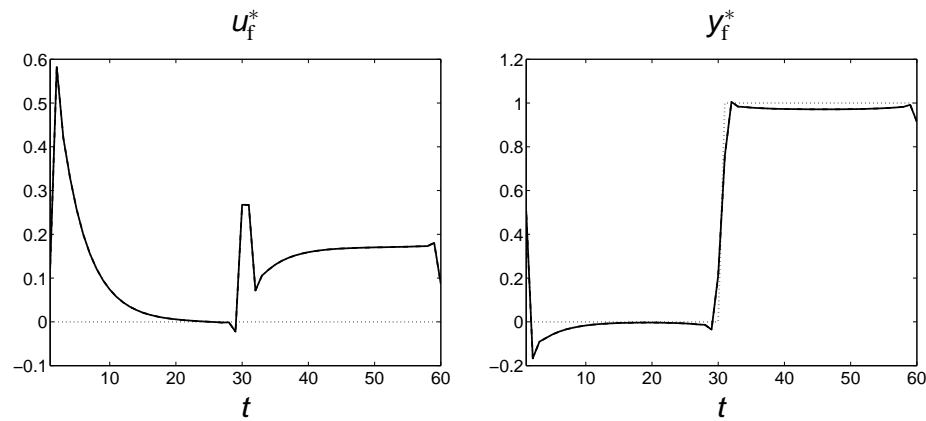
1. $(w_{ini}, w_d, T_r) \xrightarrow{\text{Algorithm 2}} y_{f,0}$
2. $(w_d, T_r) \xrightarrow{\text{Algorithm 4}} W_0$
3. $(\Phi, w_r, y_{f,0}, W_0) \xrightarrow{(7)} w_f^*$

Simulation showing the equivalence of the three methods

- \mathcal{B} — 2nd order, $m = 1$ input, $p = 1$ output
- w_d — random trajectory of \mathcal{B} with $T = 200$ samples
- Φ — identity (assign equal weights to the variables)

step tracking: $u_r = 0, \quad y_r = \text{step}, \quad w_{ini} = (1, 1)$

Simulation example



w_r — dotted line, w_f^* — solid line, $J(w_r, w_f^*) = 2.1034$

Conclusions

- Given $w_d \in \mathcal{B}_T$, we can compute feedforward LQ tracking control without deriving a repr. of \mathcal{B} . (data-driven control)
- For doing this we need
 - \mathcal{B} to be controllable,
 - u_d to be persistently exciting of sufficient order.
- The construction of the optimal control is based on
 - free response $y_{f,0}$ of \mathcal{B} under w_{ini} , and
 - zero ini. cond. trajectories W_0 (a basis for \mathcal{B}_{0,T_f}).

- Compared with previous work on subspace control, we
 - give conditions under which the problem is solvable,
 - relate the problem to data-driven simulation, and
 - derive new computational algorithms.

Thank you