

# Online Parameter Estimation for LTI systems

Recap:  $\dot{x} = Ax + bu$   $y, u \in \mathbb{R}$  (SISO)  
 $y = c^T x$   $x \in \mathbb{R}^n$   
 $A \in \mathbb{R}^{n \times n}, b \in \mathbb{R}^n, c \in \mathbb{R}^n$

i/o description:

$$y(t) = c^T e^{At} x(0) + \int_0^t c^T e^{A(t-s)} b u(s) ds, \quad t \geq 0$$

linear parametrization:

$$Y(s) = G(s) U(s) \quad (\text{freq. domain})$$

$$G(s) = c^T (sI_n - A)^{-1} b$$
$$= \frac{b_{n-1}s^{n-1} + b_{n-2}s^{n-2} + \dots + b_1s + b_0}{s^n + a_{n-1}s^{n-1} + \dots + a_1s + a_0}$$

$n$ th-order controlled ODE (output  $y$  is controlled by input  $u$ )

$$(s^n + a_{n-1}s^{n-1} + \dots + a_1s + a_0)Y(s) = (b_{n-1}s^{n-1} + \dots + b_1s + b_0)U(s) \quad [FD]$$

$$y^{(n)} + a_{n-1}y^{(n-1)} + \dots + a_1y' + a_0y = b_{n-1}u^{(n-1)} + \dots + b_1u' + b_0u \quad [TD]$$

Linear parametrization:

$$y^{(n)} = \Theta^T v$$

where  $\Theta := (b_{n-1}, \dots, b_1, b_0, a_{n-1}, \dots, a_1, a_0)^T$  is the vector of sys. parameters

$$v(t) := (u^{(n-1)}(t), \dots, u'(t), u(t), -y^{(n-1)}(t), \dots, -y'(t), -y(t))^T$$

$$s^n Y(s) = \Theta^T V(s)$$

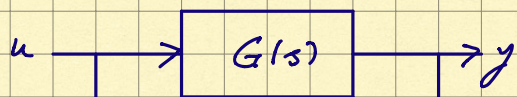
$$Z(s) := \frac{s^n}{\lambda(s)}, \quad \Phi(s) = \left( \frac{s^{n-1}}{\lambda(s)} U(s), \dots, \frac{1}{\lambda(s)} U(s), -\frac{s^{n-1}}{\lambda(s)} Y(s), \dots, -\frac{1}{\lambda(s)} Y(s) \right)^T$$

where  $\lambda(s) = s^n + \lambda_{n-1}s^{n-1} + \dots + \lambda_1s + \lambda_0$  is a polynomial with stable roots:

$\frac{s^n}{\lambda(s)}, \frac{s^{n-1}}{\lambda(s)}, \dots, \frac{s}{\lambda(s)}, \frac{1}{\lambda(s)}$  are stable filters

Back to time domain:

$$z(t) = \Theta^T \phi(t)$$



$$G(s) = c^T (sI_n - A)^{-1} b$$

← do not depend on  $A, b, c$

$z(t)$   $\phi(t)$

$$z(t) = \Theta^T \phi(t), \quad \Theta \in \mathbb{R}^{2n}$$

$\phi(t)$  is the vector of regressors

Upshot: we can process  $u, y$  in an online manner to get  $z, \phi$  and estimate  $\Theta$  online using  $(\phi, z)$  as data.

$$J_t(\vec{\Theta}) := \frac{1}{2} (\hat{z}(t) - z(t))^2, \quad \hat{z}(t) = \vec{\Theta}^T \phi(t)$$

(instantaneous cost)

$$\bar{J}_t(\vec{\Theta}) := \frac{1}{2} (\bar{z}(t) - \bar{z}(t))^2, \quad \bar{z}(t) = \Theta^T \bar{\phi}(t)$$

$$\hat{z}(t) = \vec{\Theta}^T \bar{\phi}(t)$$

$$\bar{\phi}(t) := \frac{\phi(t)}{m(t)}$$

where  $m(t)$  is a positive signal chosen so that  $\frac{\phi}{m} \in \mathcal{L}_\infty$   
 e.g.  $m(t) = 1 + \phi(t)^T \phi(t)$ .

Gradient flow:  $\dot{\vec{\Theta}} = -\Gamma \nabla \bar{J}_t(\vec{\Theta})$

where  $\Gamma = \Gamma^T > 0$  is a fixed adaptation gain matrix

$$\begin{aligned} \bar{e}(t) &:= \frac{1}{z}(t) - \bar{z}(t) \\ &= (\bar{\theta}(t) - \theta)^T \bar{\phi}(t) \quad \text{-- (normalized) prediction error} \end{aligned}$$

### Theorem (Ioannou-Sun)

(i)  $\bar{\theta} \in L_\infty$  and  $\bar{e}, \dot{\bar{\theta}} \in L_2 \cap L_\infty$

(ii) if  $\bar{\phi} = \frac{\phi}{m}$  is persistently exciting<sup>(\*)</sup>, then

$$\bar{\theta}(t) \rightarrow \theta \quad \text{as } t \rightarrow \infty$$

exponentially fast.

### Remarks:

1)  $\bar{\theta} \in L_\infty \Leftrightarrow \sup_{t \geq 0} |\bar{\theta}(t)| < \infty$

(parameter estimates don't escape to  $\infty$ )

2)  $\bar{e}, \dot{\bar{\theta}} \in L_2 \cap L_\infty$

$$\bar{e}(t) := \frac{1}{z}(t) - \bar{z}(t)$$

$$= \underbrace{(\bar{\theta}(t) - \theta)^T}_{\tilde{\theta}(t)} \bar{\phi}(t) \quad \bar{\phi} = \frac{\phi}{m} \in L_\infty$$

-- param-estimation error

$$\sup_{t \geq 0} |\bar{e}(t)| < \infty \quad (\bar{e} \in L_\infty)$$

$$\int_0^\infty \bar{e}(t)^2 dt < \infty \quad (\bar{e} \in L_2)$$

Same applies to  $\dot{\bar{\theta}}$  (sensitivity to data)

$$\dot{\bar{\theta}} \in L_\infty \quad (\text{bdd rate of change of } \bar{\theta})$$

$$\dot{\bar{\theta}} \in L_2 \quad (\text{slow adaptation})$$

### 3) PE for vector-valued signals

$$\bar{J}_t(\hat{\theta}) = \frac{1}{2} (\hat{\theta} - \theta)^T \bar{\phi}(t) \bar{\phi}(t)^T (\hat{\theta} - \theta)$$

$$\nabla \bar{J}_t(\hat{\theta}) = \bar{\phi}(t) \bar{\phi}(t)^T (\hat{\theta} - \theta)$$

$$\nabla^2 \bar{J}_t(\hat{\theta}) = \bar{\phi}(t) \bar{\phi}(t)^T \quad \text{— rank-1 positive semidefinite}$$

—  $\nabla^2 \bar{J}_t$  is a singular matrix  $\forall t \geq 0$

Integrated cost:

$$\begin{aligned} \bar{\bar{J}}_t(\hat{\theta}) &= \int_0^t \bar{J}_s(\hat{\theta}) ds \\ &= \frac{1}{2} (\hat{\theta} - \theta)^T \int_0^t \bar{\phi}(s) \bar{\phi}(s)^T ds (\hat{\theta} - \theta) \end{aligned}$$

$$\nabla^2 \bar{\bar{J}}_t(\hat{\theta}) = \int_0^t \bar{\phi}(s) \bar{\phi}(s)^T ds$$

— can be nonsingular if  $\bar{\phi}$  persistently moves around

Def:  $\bar{\phi}$  is PE if  $\exists \alpha_0, T_0 > 0$  s.t.

$$\int_{t_0}^{t_0+T_0} \bar{\phi}(t) \bar{\phi}(t)^T dt \geq \alpha_0 T_0 I, \quad \forall t_0 \geq 0$$

$$\text{or } \int_{t_0}^{t_0+T_0} v^T \bar{\phi}(t) \bar{\phi}(t)^T v dt \geq \alpha_0 T_0 |v|^2,$$

for all  $t_0 \geq 0$  and all  $v \in \mathbb{R}^{2n}$ .

$$\dot{\hat{\theta}} = -\Gamma \nabla \bar{J}_t(\hat{\theta})$$

$$\Gamma = \Gamma^T > 0$$

$$\tilde{\theta} = \hat{\theta} - \theta$$

$$\Gamma^{-1} \text{ exists}$$

$$\dot{\tilde{\theta}} = \dot{\hat{\theta}}$$

Proof

(i) Introduce candidate Lyapunov fcn

$$V(\tilde{\theta}) := \frac{1}{2} \tilde{\theta}^T \Gamma^{-1} \tilde{\theta}$$

$$\begin{aligned} \dot{V} &= \tilde{\theta}^T \Gamma^{-1} \dot{\tilde{\theta}} & (\Gamma^{-1} = (\Gamma^{-1})^T > 0) \\ &= \tilde{\theta}^T \Gamma^{-1} \dot{\theta} \\ &= -\tilde{\theta}^T \Gamma^{-1} \Gamma \nabla \bar{J}_t(\hat{\theta}) \\ &= -\tilde{\theta}^T \nabla \bar{J}_t(\hat{\theta}) \end{aligned}$$

$$\begin{aligned} \nabla \bar{J}_t(\hat{\theta}) &= \bar{\phi} \bar{\phi}^T (\hat{\theta} - \theta) \\ &= \underbrace{(\hat{\theta} - \theta)^T \bar{\phi}}_{\bar{e}} \bar{\phi} \end{aligned}$$

$$\begin{aligned} \bar{e}(t) &= \frac{1}{2} (\hat{\theta}(t) - \theta) \\ &= (\hat{\theta}(t) - \theta)^T \bar{\phi}(t) \\ &= \tilde{\theta}(t)^T \bar{\phi}(t) \end{aligned}$$

$$\begin{aligned} \Rightarrow \dot{V} &= -\tilde{\theta}^T \bar{\phi} \bar{e} \\ &= -\bar{e}^2 \leq 0 \end{aligned}$$

So:  $V(\tilde{\theta}(t))$  is nonnegative, decreasing

$$0 \leq V(\tilde{\theta}(t)) \leq V(\tilde{\theta}(0))$$

$$\frac{1}{2} \tilde{\theta}(t)^T \Gamma^{-1} \tilde{\theta}(t) \leq \frac{1}{2} \tilde{\theta}(0)^T \Gamma^{-1} \tilde{\theta}(0)$$

$$\sup_{t \geq 0} |\tilde{\theta}(t)| < \infty \quad \Rightarrow \quad \tilde{\theta} \in L_\infty \quad \Rightarrow \quad \boxed{\bar{\theta} \in L_\infty}$$

$$\begin{aligned} \text{Now, } 0 \leq \int_0^t \bar{e}^2(s) ds &= - \int_0^t \dot{V}(\tilde{\theta}(s)) ds \\ &= V(\tilde{\theta}(0)) - V(\tilde{\theta}(t)) \\ &\leq V(\tilde{\theta}(0)) < \infty \quad \forall t \geq 0 \end{aligned}$$

$$\Rightarrow \bar{e} \in L_2$$

$$\bar{e} = \tilde{\theta}^T \bar{\phi}$$

$$|\bar{e}| \leq |\tilde{\theta}| |\bar{\phi}| \quad \begin{matrix} \nearrow L_\infty \\ \nearrow L_\infty \end{matrix} \quad \Rightarrow \quad \bar{e} \in L_\infty$$

$$\bar{e} \in L_2 \cap L_\infty$$

$$\begin{aligned} \dot{\hat{\theta}} &= -\Gamma \nabla \bar{J}_t(\hat{\theta}) \\ &= -\Gamma \bar{e} \bar{\phi} \end{aligned}$$

$$|\dot{\hat{\theta}}| = |\Gamma \bar{e} \bar{\phi}|$$

$$\leq |\Gamma| |\bar{e}| |\bar{\phi}|$$

$\downarrow$  spectral norm      $\hookrightarrow$   $\hookleftarrow$   
 $L_2 \cap L_\infty$

$$\Rightarrow \dot{\hat{\theta}} \in L_2 \cap L_\infty$$

(ii) convergence of  $\hat{\theta}$  to  $\theta$  and PE property

$$\tilde{\theta} = \hat{\theta} - \theta$$

( $\theta \in \mathbb{R}^{2n}$  — constant vector of sys. parameters)

$$\dot{\tilde{\theta}} = \dot{\hat{\theta}} = -\Gamma \bar{e} \bar{\phi}$$

where  $\bar{e} = \bar{\phi}^T \tilde{\theta}$

Define  $A(t) := -\Gamma \bar{\phi}(t) \bar{\phi}(t)^T \in \mathbb{R}^{2n \times 2n}$

$c(t) := \bar{\phi}(t) \in \mathbb{R}^{2n}$

Then we have the LTV system

$$\begin{aligned} \dot{\tilde{\theta}} &= A(t) \tilde{\theta} \\ \bar{e} &= c(t)^T \tilde{\theta} \end{aligned}$$

with "state"  $\tilde{\theta}$  and "output"  $\bar{e}$ .

We want to show  $\tilde{\theta} \rightarrow 0$  exponentially fast.

This is implied by **Uniform Complete Observability (UCO)** property of  $(A(t), c(t)^T)$ .

**Lemma (Ioannou - Sun)** An LTV system  $(A(t), c(t))$  is UCO if the pair  $(A(t) + L(t)C(t), C(t))$  is UCO for some bdd output injection matrices  $L(t)$ .

We have 
$$\begin{aligned}\dot{\tilde{\theta}} &= A(t)\tilde{\theta} \\ \tilde{e} &= c(t)^T \tilde{\theta}\end{aligned}$$

$$A(t) = -\Gamma \bar{\phi}(t) \bar{\phi}(t)^T$$

$$c(t) = \bar{\phi}(t)$$

Take  $L(t) = \Gamma \bar{\phi}(t)$

$$A(t) + L(t)c(t)^T = -\Gamma \bar{\phi}(t) \bar{\phi}(t)^T + \Gamma \bar{\phi}(t) \bar{\phi}(t)^T = 0$$

Now we look at: 
$$\begin{aligned}\dot{\tilde{\theta}} &= 0 \\ \tilde{e} &= c(t)^T \tilde{\theta}\end{aligned} \quad (A(t) + L(t)c(t)^T)$$

For this system, can write down observability Gramian easily:

$$M(t_0, t_0 + T_0) = \int_{t_0}^{t_0 + T_0} \Phi(t_0, t)^T c(t) c(t)^T \Phi(t_0, t) dt$$

where  $\Phi(t_0, t) = I \quad [\tilde{\theta}(t) = \tilde{\theta}(0)]$

$$\Rightarrow M(t_0, t_0 + T_0) = \int_{t_0}^{t_0 + T_0} \bar{\phi}(t) \bar{\phi}(t)^T dt \geq \alpha_0 T_0 I$$

(by PE assumption)

Thus, 
$$\begin{aligned}\dot{\tilde{\theta}} &= A(t)\tilde{\theta} \\ \tilde{e} &= c(t)^T \tilde{\theta}\end{aligned}$$

is UCO,  $\hookrightarrow \tilde{\theta}(t) \rightarrow 0$  exponentially fast. ▣