Lecture 5: Real-Time Parameter Estimation

- Least Squares and Recursive Computations
- Estimating Parameters in Dynamical Systems
- Persistent Excitation and Linear Filtering
- Examples

Theorem (Persistent Excitation for FIR model):

Assume that data are generated by the following FIR model:

$$y(t) = g_1 u(t-1) + g_2 u(t-2) + \cdots + g_n u(t-n) + e(t)$$

with $E\{e(t)\}=0$, and mutually independent e(t). Then, one can use Recursive Least Square algorithm with

$$\phi(t,m{n})^{ \mathrm{\scriptscriptstyle T} }=\left[u(t-1),\,u(t-2),\,\ldots,\,u(t-m{n})
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 to estimate $heta^0(m{n})=\left[g_1,\,g_2,\,\ldots,\,g_n
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If the signal u(t) is persistently exciting of at least order n, the estimate is unbiased. Possible conditions to check is

$$\lim_{N o\infty}rac{1}{N}\left[egin{array}{c} \phi(n,oldsymbol{n})^{{\scriptscriptstyle T}}\ \phi(n,oldsymbol{n})^{{\scriptscriptstyle T}}\ \phi(n+1,oldsymbol{n})^{{\scriptscriptstyle T}}\ \end{array}
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Persistence of Excitation (Def 1):

Definition 1: Given a signal u(t), i.e. a sequence of numbers

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and if

$$C_{m{n}} = egin{bmatrix} c(0) & c(1) & \ldots & c(m{n}-1) \ c(1) & c(0) & \ldots & c(m{n}-2) \ dots & & & & \ c(m{n}-1) & c(m{n}-2) & \ldots & c(0) \end{bmatrix} > 0$$

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Persistence of Excitation (Def 2):

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It is called persistently exciting of order n if for all t there exists an integer m such that

$$ho_1 I_{oldsymbol{n}} > \sum_{k=t}^{t+m} \phi(k, oldsymbol{n}) \phi(k, oldsymbol{n})^{ \mathrm{\scriptscriptstyle T} } >
ho_2 I_{oldsymbol{n}}$$

where ho_1 , $ho_2 > 0$ and

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It can be shown that conditions of Def. 2 imply the ones of Def. 1.

Polynomial Conditions for Persistent Excitation:

The signal with the property that limits

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exist, is PE of order n if and only if

$$L=\lim_{N o\infty}rac{1}{N}\sum_{k=1}^{N}\left[A(q)\,u(k)
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Proof: with
$$A(q) = a_0 \, q^{n-1} + \dots + a_{n-1}$$
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Corollary: if u(t) satisfies a polynomial equation of degree n for $t \geq t_0$ with some t_0 , then it can be at most PE of order n.

Examples of computing order of PE:

Example 1: The STEP signal

$$u(t)=0$$
 for $t<0,$ $u(t)=1$ for $t\geq 0$ satisfies: $(q-1)u(t)=0$ for $t\geq 0$

and
$$c(1) = \lim_{t \to \infty} \frac{1}{t} \sum_{k=1}^t u^2(t) = 1.$$

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Example 2: Any m-PERIODIC signal:

$$u(t+m)=u(t)$$
 for $\forall t$

satisfies $(q^m-1)u=0$, so, it can be at most PE of order m.

Example 3: consider the signal

$$u(t) = \sin(\omega_0 t), \quad \text{with} \quad 0 < \omega_0 < \pi$$

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It is not hard to show [using $\sin(a+b) = \sin(a)\cos(b) + \sin(b)\cos(a)$] that

$$\left(q^2-2\,q\,\cos(\omega_0)+1
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Hence, it can at most be PE of order 2.

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<u>Definition:</u> A signal u(t) is called stationary if the limit

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Note: $R_u(k) = R_u(-k)$ and $R_u(k) = c(k)$ is called covariance of u(t).

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<u>Definition:</u> The Fourier transform of the covariance, $\Phi_{u}(\omega)$, is called the frequency spectrum of u(t):

$$R_{u}(k) = \frac{1}{2\pi} \int_{-\pi}^{\pi} e^{j\omega k} \Phi_{u}(\omega) d\omega, \qquad j = \sqrt{-1}$$

$$\Phi_{u}(\omega) = \sum_{k=-\infty}^{+\infty} R_{u}(k) e^{-j\omega k} = \left| \frac{1}{2\pi} \int_{-\infty}^{+\infty} u(t) e^{-j\omega t} dt \right|^{2}$$

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Example: for the signal

$$u(t) = \sin(\omega_0 t), \quad \text{with} \quad 0 < \omega_0 < \pi$$

we have

$$R_u(k) = rac{1}{2}\cos(\omega_0\,k), \qquad \Phi_u(\omega) = rac{\pi}{2} \Big[\delta(\omega - \omega_0) + \delta(\omega + \omega_0)\Big]$$

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<u>Lemma</u>: A stationary signal is PE of order n if its frequency spectrum is non zero for at least n points.

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<u>Lemma</u>: A stationary signal is PE of order n if its frequency spectrum is non zero for at least n points.

Example: white noise is PE of any order, while the signal

$$u(t) = \sum_{i=1}^m A_i \, \sin(\omega_i \, t + arphi_i), \qquad ext{with} \quad 0 < \omega_i < \pi, \quad \omega_i
eq \omega_j$$

is PE of order 2 m.

Theorem (Persistent Excitation for ARMA model):

Assume that data are generated by the following ARMA model:

$$\underbrace{(q^n + a_1 q^{n-1} + \dots + a_n)}_{A(q)} y(t) = \underbrace{(b_1 q^{m-1} + b_2 q^{m-2} + \dots + b_m)}_{B(q)} u(t)$$

with n > m. Then, one can use RLS algorithm with

$$\phi(t-1)^{ \mathrm{\scriptscriptstyle T} }= \Big[-y(t-1),\ldots,-y(t-n),u(t-n+m-1),\ldots,u(t-n)\Big]$$
 to estimate $heta^0=\Big[a_1,\,\ldots,\,a_n,\,b_1,\,\ldots,\,b_m\Big]^{ \mathrm{\scriptscriptstyle T} }.$

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$$\lim_{t o\infty}rac{1}{t}\Big[\Phi(t-1)^{{ \mathrm{\scriptscriptstyle T} }}\Phi(t-1)\Big] = \lim_{t o\infty}rac{1}{t} \left[egin{array}{c} \phi(n)^{{ \mathrm{\scriptscriptstyle T} }} \ \phi(n+1)^{{ \mathrm{\scriptscriptstyle T} }} \ \vdots \ \phi(t-1)^{{ \mathrm{\scriptscriptstyle T} }} \end{array}
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Persistent Excitation for $\ A(q)y(t)=B(q)u(t)$

$$\phi(t-1) = egin{bmatrix} -y(t-1) \ \cdots \ -y(t-n) \ u(t-n+m-1) \ \cdots \ u(t-n) \end{bmatrix}$$

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$$\phi(t-1) = \begin{bmatrix} -y(t-1) \\ \dots \\ -y(t-n) \\ u(t-n+m-1) \\ \dots \\ u(t-n) \end{bmatrix} = \begin{bmatrix} -q^{-1}y(t) \\ \dots \\ q^{-n+m-1}u(t) \\ \dots \\ q^{-n}u(t) \end{bmatrix} = \frac{q^m}{A(q)} \begin{bmatrix} -q^{-1-m}A(q)y(t) \\ \dots \\ q^{-n-m}A(q)y(t) \\ q^{-n-1}A(q)u(t) \\ \dots \\ q^{-n-m}A(q)u(t) \end{bmatrix}$$

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$$\phi(t-1) = \begin{bmatrix} -y(t-1) \\ \dots \\ -y(t-n) \\ u(t-n+m-1) \\ \dots \\ u(t-n) \end{bmatrix} = \frac{q^m}{A(q)} \begin{bmatrix} -q^{-1-m}B(q)u(t) \\ -q^{-n-m}B(q)u(t) \\ q^{-n-1}A(q)u(t) \\ \dots \\ q^{-n-m}A(q)u(t) \end{bmatrix} = S \begin{bmatrix} -q^{-1}v(t) \\ \dots \\ -q^{-n}v(t) \\ q^{-n-1}v(t) \\ \dots \\ q^{-n-m}v(t) \end{bmatrix}$$

where $v(t)=rac{q^m}{A(q)}\,u(t)$ and S is not singular in the case when A(q) and B(q) are relatively prime.

$$\phi(t-1) = \begin{bmatrix} -y(t-1) \\ \dots \\ -y(t-n) \\ u(t-n+m-1) \\ \dots \\ u(t-n) \end{bmatrix} = \frac{q^m}{A(q)} \begin{bmatrix} -q^{-1-m}B(q)u(t) \\ \dots \\ -q^{-n-m}B(q)u(t) \\ q^{-n-1}A(q)u(t) \\ \dots \\ q^{-n-m}A(q)u(t) \end{bmatrix} = S \underbrace{\begin{bmatrix} -v(t-1) \\ \dots \\ -v(t-n) \\ v(t-n-1) \\ \dots \\ v(t-n-m) \end{bmatrix}}_{\psi(t-1)}$$

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where $v(t)=rac{q^m}{A(q)}\,u(t)$ and S is not singular in the case when A(q) and B(q) are relatively prime.

$$\lim_{t \to \infty} \frac{1}{t} \Big[\Phi(t-1)^{ \mathrm{\scriptscriptstyle T} } \, \Phi(t-1) \Big] = S \left(\lim_{t \to \infty} \frac{1}{t} \Big[\Psi(t-1)^{ \mathrm{\scriptscriptstyle T} } \, \Psi(t-1) \Big] \right) S^{ \mathrm{\scriptscriptstyle T} } > 0$$

)Leonid Freidovich. April 15, 2010. Elements of Iterative Learning and Adaptive Control: Lecture 5 -- p.11/15

The conditions for parameter convergence, formulated in the case of FIR model for the signal u(t), are similar in the case of ARMA model, but should be concerning the signal

$$v(t) = rac{q^m}{A(q)} u(t)$$

 $n>m,\,q^m$ is stable, $q^m/A(q)$ is stable and minimum phase.

Hence,
$$\left|\Phi_v(\omega)=\left|rac{e^{jm\omega}}{A(e^{j\omega})}
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ight|.$$

Theorem (Persistent Excitation for ARMA model):

Suppose that

- 1. A(q) and B(q) are relatively prime,
- 2. A(q) is stable (i.e. all roots are inside the unite circle),
- 3. u(t) is a stationary signal such that $\Phi_u(\omega)$ is nonzero for at least (n+m) points.

Then, RLS algorithm converges to the correct value.

Example

Consider the system

$$y(t) + a_1 y(t-1) + a_2 y(t-2) = b_1 u(t-1) + b_2 u(t-2)$$

Choose a nice (as simple as possible) input signal, which is rich enough to ensure parameters convergence.

Example

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Choose a nice (as simple as possible) input signal, which is rich enough to ensure parameters convergence.

Solution:

$$A(q) = q^2 + a_1 q + a_2, \qquad B(q) = b_1 q + b_2 q^2$$

Since n=2 and m=2, we can take

$$u(t) = A_1 \sin(\omega_1 t) + A_2 \sin(\omega_2 t), \qquad \omega_1 \neq \omega_2, \quad 0 < \omega_{1,2} < \pi.$$

to have exactly 4 non zero points in $\Phi_u(\omega)$.

Example 2.12 (book)

Consider the system y(t) + a y(t-1) = b u(t-1) + e(t) with a = -0.8, b = 0.5, e(t) – zero mean white noise with standard deviation $\sigma = 0.5$.

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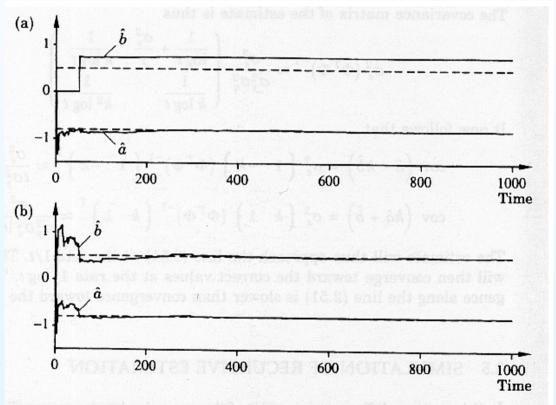


Figure 2.7 The estimated (solid line) and true (dashed line) parameter values in estimating the parameters in the model (2.53). The input signal u(t) is (a) a unit pulse at t = 50, (b) a unit amplitude square wave with period 100.

Next Lecture / Assignments:

Next meeting (April 19, 13:00-15:00, in A205Tekn): Recitations

Homework problem: repeat the simulation for Example 2.12 shown above (see pages 71–72), taking $P(0)=100\,I_2$ and $\hat{\theta}(0)=0$.