

EM725

Control Adaptivo de Sistemas

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8.0 Observadores Adaptivos

Introducción

- Teoría de Observadores adaptivos fines 60's primeros resultados principios 70's.

Caroll & Lindorff, U. de Connecticut

Lüders & Narendra, U. de Yale.

- Estimar el estado y los parámetros (A, B, C, D) del sistema a partir del conocimiento de la entrada $u(t)$ y salida $y(t)$.
- Teoría "clásica" y realizaciones mínimas y no mínimas de observadores adaptivos.
- Observadores adaptivos "mejorados" 4 tipos.
- Aplicación al control adaptivo.

Planteamiento del problema

$$\text{Planta} \begin{cases} \dot{x}_p(t) = Ax_p(t) + bu(t), & x_p(t_0) = x_{p0} \\ y_p(t) = c^T x(t) \end{cases}$$

A partir del conocimiento de

$$(u(t), y(t)) \quad \forall t \in [t_0, \infty)$$

Estimar simultáneamente A, b, c y $x_p(t)$

(c^T, A, b) : n^2+2n parámetros

2n parámetros son suficientes

Realización mínima

$$\dot{x}_p(t) = [a; \bar{A}] x_p(t) + bu(t)$$

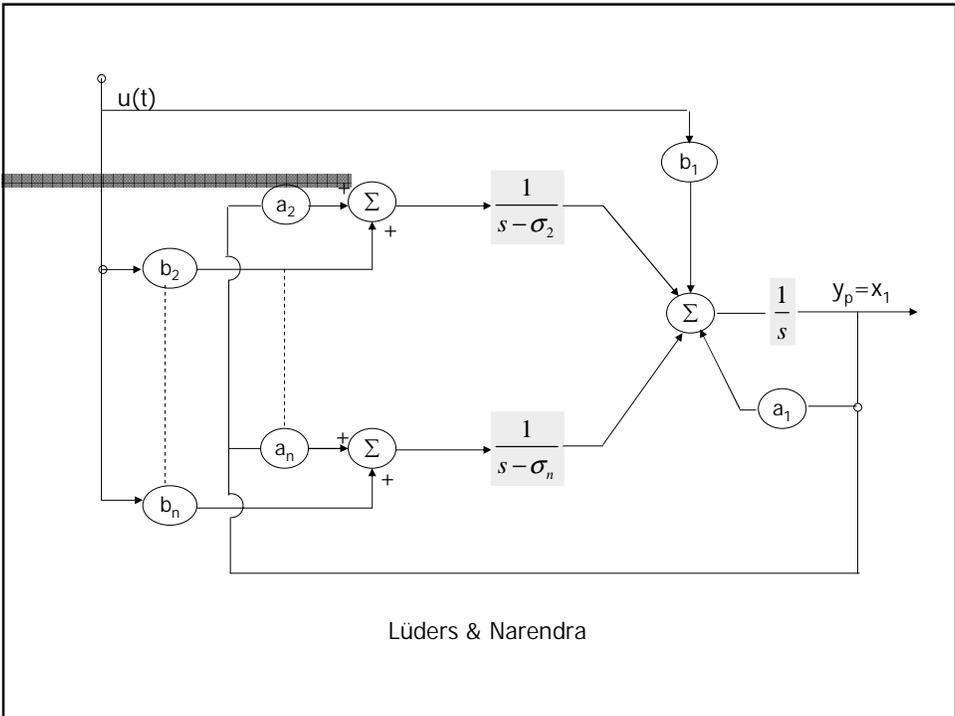
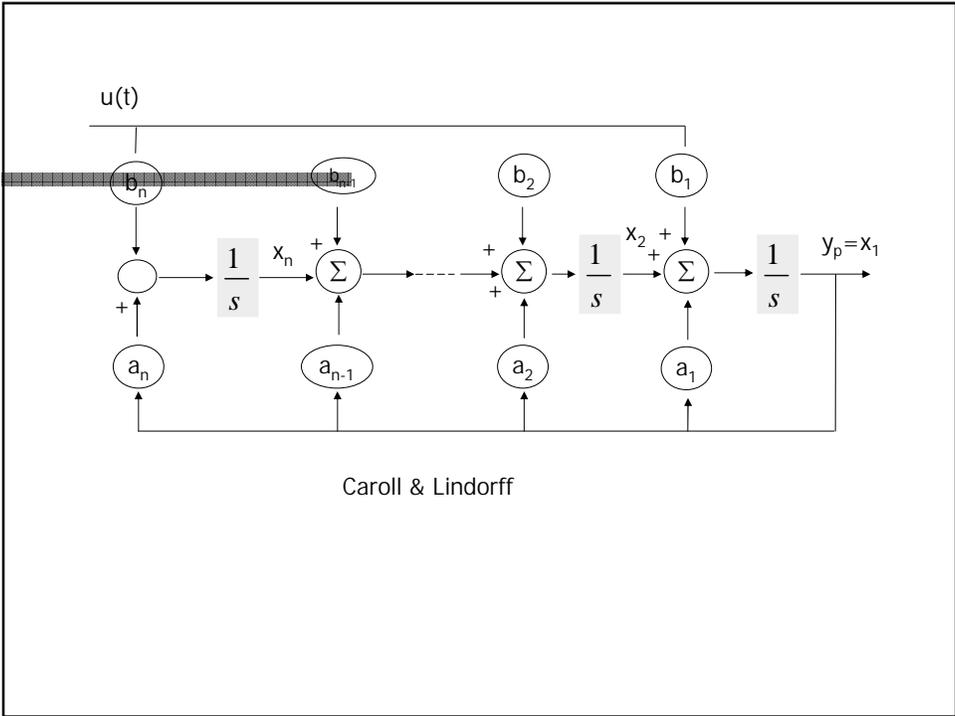
$$y_p(t) = c^T x_p(t) = x_1(t)$$

$$a = [a_1, a_2, \dots, a_n]^T, \quad b = [b_1, b_2, \dots, b_n]^T$$

$$c = [1, 0, \dots, 0]^T, \quad \bar{A} \in \mathfrak{R}^{n \times (n-1)} \text{ conocida}$$

$$\bar{A} = \begin{bmatrix} I_{n-1} \\ \dots \\ 0 \end{bmatrix} \quad \text{Caroll \& Lindorff 1973}$$

$$\bar{A} = \begin{bmatrix} 1 & \dots & 1 \\ \sigma_2 & & \\ & \ddots & \\ & & \sigma_n \end{bmatrix} \quad \text{Lüders \& Narendra 1973}$$



Reexpresada como:

$$\begin{aligned}\dot{x}_p(t) &= [-k : \bar{A}] x_p(t) + g y_p(t) + b u(t) \\ y_p(t) &= c^T x_p(t) = x_1(t) \\ k &= [k_1 k_2 \dots k_n]^T \quad K = [-k : \bar{A}] \quad \text{asintóticamente estable} \\ g &= k + a\end{aligned}$$

Parámetros desconocidos $g, b \in \mathfrak{R}^n$

Observador L & N

$$\begin{aligned}\dot{\hat{x}}_p(t) &= K \hat{x}_p(t) + \hat{g}(t) y_p(t) + \hat{b}(t) u(t) + v_1(t) + v_2(t) \\ v_1, v_2 & \text{ señales auxiliares} \\ \hat{b}(t), \hat{g}(t) & \text{ estimados de } b \text{ y } g \text{ en } 't'. \\ \hat{y}_p(t) &= c^T \hat{x}_p(t)\end{aligned}$$

Ley de ajuste de parámetros

$$\begin{aligned}\dot{\hat{g}}(t) &= -e_1(t) w^2(t) = -\Gamma_2(t) w^2(t) e_1(t) \\ \dot{\hat{b}}(t) &= -e_1(t) w^1(t) = -\Gamma_1(t) w^1(t) e_1(t) \\ \Gamma_i(t) &> 0, \text{ ganancias adaptivas} \\ e_1(t) &= \hat{y}_p(t) - y_p(t), \quad w^1(t) = G(s)u(t), \quad w^2(t) = G(s)y_p(t) \\ G(s) &= [G_1(s), G_2(s), \dots, G_n(s)]^T\end{aligned}$$

$$A_i = \begin{bmatrix} 0 & -d_i & -d_{i+1} & \cdots & -d_n & 0 & \cdots & 0 \\ 0 & 0 & -d_i & \cdots & -d_{n-1} & -d_n & 0 & 0 \\ \vdots & \ddots & \ddots & & & & & \\ 0 & \cdots & 0 & -d_i & -d_{i+1} & \cdots & : & d_n \\ 0 & 1 & d_2 & d_3 & \cdots & d_{i-1} & 0 \cdots & 0 \\ 0 & 0 & 1 & d_2 & \cdots & \cdots & d_{i-1} \cdots & 0 \\ \vdots & \ddots & \ddots & & & & & \\ 0 & & 0 & 1 & d_2 & d_3 & \cdots & d_{i-1} \end{bmatrix}$$

$A_i \in \mathcal{R}^{n \times n}, i=1,2,\dots,n$

$$G_i(s) = \frac{s^{n-i}}{s^n + d_2 s^{n-2} + \cdots + d_n} \quad i=1,2,\dots,n$$

$$d = [1, d_2, \dots, d_n]^T \quad \text{t.q.} \quad c^T (sI - k)^{-1} d \text{ sea e.r.p.}$$

$$v_1^T(t) = \hat{b}^T(t) [0, A_2 w^1(t), \dots, A_n w^1(t)]$$

$$v_2^T(t) = \hat{g}^T(t) [0, A_2 w^2(t), \dots, A_n w^2(t)]$$

$A_i, i=2,\dots,n$ se definen en términos de d

Se puede demostrar:

- i) El sistema globalmente uniformemente estable (todas las señales uniformemente acotadas).

$$\lim_{t \rightarrow \infty} e_1(t) = 0$$

ii) Si $u(t)$ es tal que $w(t) = [w^{1T}(t), w^{2T}(t)]^T \in \mathfrak{R}^{2n}$

es de excitación persistente en \mathfrak{R}^{2n} entonces

$$\lim_{t \rightarrow \infty} e(t) = \hat{x}_p(t) - x_p(t) = 0$$

$$\lim_{t \rightarrow \infty} \hat{g}(t) = g$$

$$\lim_{t \rightarrow \infty} \hat{b}(t) = b$$

Realización No mínima

Representación 1

$$\dot{x}_p(t) = A x_p(t) + b u(t)$$

$$y_p(t) = h^T x_p(t)$$

$$\dot{x}_1(t) = -\lambda x_1(t) + \theta^T \omega(t)$$

$$\dot{\omega}_1(t) = \Lambda \omega_1(t) + \ell u(t)$$

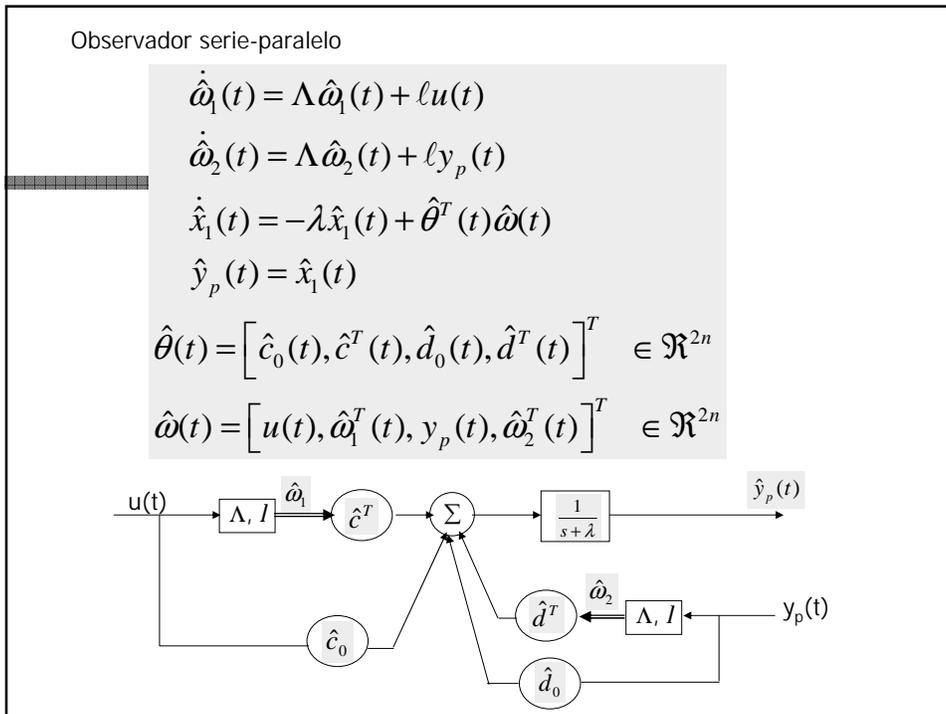
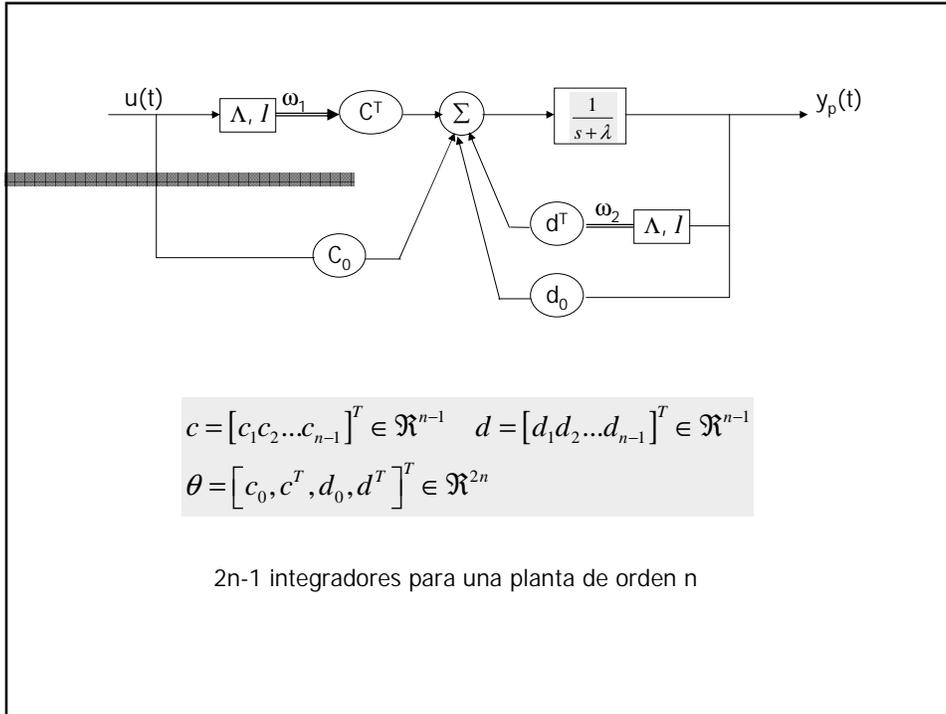
$$\dot{\omega}_2(t) = \Lambda \omega_2(t) + \ell y_p(t)$$

$$y_p(t) = x_1(t)$$

$\theta \in \mathfrak{R}^{2n}$ Vector de parámetros

$$\omega(t) \in \mathfrak{R}^{2n}, \quad \omega(t) = [u(t), \omega_1^T(t), y_p(t), \omega_2^T(t)]$$

$$(\Lambda, \ell) \text{ c.c.}, \quad \Lambda \in \mathfrak{R}^{(n-1) \times (n-1)}, \quad \lambda > 0, \quad \Lambda \text{ a.e.}$$



$$e_1(t) = \hat{y}_p(t) - y_p(t)$$

$$\dot{\hat{\theta}}_1(t) = -\lambda e_1(t) + \phi^T(t) \hat{\omega}(t) + \theta^T \tilde{\omega}(t) \quad (\text{Modelo de Error 2})$$

$$\phi(t) = \hat{\theta}(t) - \theta$$

$$\tilde{\omega}(t) = \hat{\omega}(t) - \omega(t)$$

$\tilde{\omega}(t)$ decae exponencialmente

Ley de ajuste

$$\dot{\hat{\theta}}(t) = -e_1(t) \hat{\omega}(t)$$

$$V = \frac{1}{2} (e_1^2 + \phi^T \phi + \beta \tilde{\omega}^T P \tilde{\omega})$$

$$i) \quad \dot{V} = -\lambda e_1^2 + e_1 \theta^T \tilde{\omega} - \frac{\beta}{2} \tilde{\omega}^T Q \tilde{\omega}$$

$$\bar{\Lambda}^T P + P \bar{\Lambda} = -Q < 0, \quad \bar{\Lambda} = \begin{bmatrix} \Lambda & 0 \\ 0 & \Lambda \end{bmatrix}$$

β Se escoge mayor que $\frac{2\|\theta\|^2}{(\lambda\lambda_Q)} \lambda_Q = \min \text{e.v. de } Q$

$$\dot{V} \leq 0$$

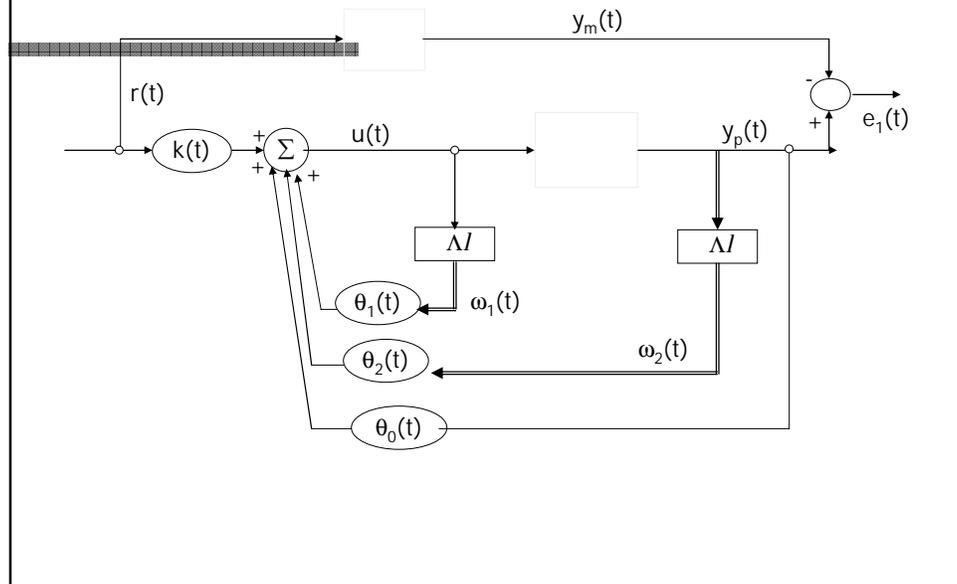
Todas las señales son acotadas

$$ii) \quad e_1 \in L^2, \quad \dot{e}_1 \in L^\infty \quad \therefore \lim_{t \rightarrow \infty} e_1(t) = 0$$

$$iii) \quad Si \quad \hat{\omega}(t) \in \Omega_{2n} \quad entonces \quad \lim_{t \rightarrow \infty} \hat{\theta}(t) = 0$$

$$\lim_{t \rightarrow \infty} \hat{x}_p(t) = x_p(t)$$

Aplicaciones de Observadores Adaptivos



$\dot{\theta}_1(t) = -e_1(t)\omega_1(t)$	$n^* = 1$
$\dot{\theta}_2(t) = -e_1(t)\omega_2(t)$	$n - m = 1$
$\dot{\theta}_0(t) = -e_1(t)y_p(t)$	$\uparrow \uparrow$
$\dot{k}(t) = -e_1(t)r(t)$	$p \quad z$

$$\lim_{t \rightarrow \infty} e_1(t) = 0$$

Todas las señales acotadas
Si $r(t)$ suficientemente rica t.q.

$$w(t) \in \Omega_{2n}, \quad \lim_{t \rightarrow \infty} \theta(t) = \theta^*$$

Representación 2 (No Mínima)

$$\dot{x}_p(t) = Ax_p(t) + bu(t)$$

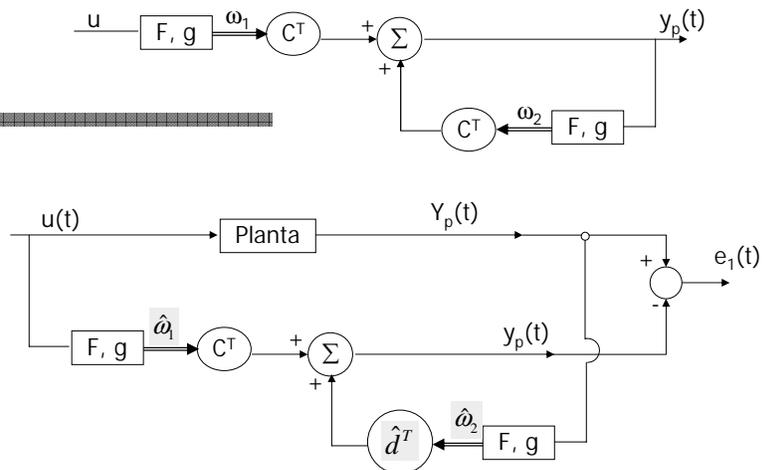
$$y_p(t) = h^T x_p(t)$$

$$\dot{\omega}_1 = F\omega_1 + gu$$

$$\dot{\omega}_2 = F\omega_2 + gy_p$$

$$y_p = \theta^T \omega = c^T \omega_1 + d^T \omega_2 \quad c, d \in \mathfrak{R}^n$$

$$F \in \mathfrak{R}^{n \times n}, \quad (F, g) \text{ c.c.}$$



$$\dot{\hat{\omega}}_1(t) = -e_1(t)\hat{\omega}_1(t)$$

$$\dot{\hat{\omega}}_2(t) = -e_1(t)\hat{\omega}_2(t)$$

$$\begin{aligned}\dot{\omega}_1(t) &= F \omega_2(t) + g u(t) & \omega_1 &\in \mathfrak{R}^n \\ \dot{\omega}_2(t) &= F \omega_2(t) + g y_p(t) & \omega_2 &\in \mathfrak{R}^n \\ y_p(t) &= \theta^T \omega(t) & \theta &\in \mathfrak{R}^{2n}, \omega \in \mathfrak{R}^{2n}\end{aligned}$$

$$\begin{aligned}\dot{\hat{\omega}}_1(t) &= F \hat{\omega}_1(t) + g u(t) & \hat{\omega}_1 &\in \mathfrak{R}^n \\ \dot{\hat{\omega}}_2(t) &= F \hat{\omega}_2(t) + g y_p(t) & \hat{\omega}_2 &\in \mathfrak{R}^n \\ \hat{y}_p(t) &= \hat{\theta}^T(t) \hat{\omega}(t) & \hat{\theta}, \hat{\omega} &\in \mathfrak{R}^{2n}\end{aligned}$$

$$e_1(t) = \hat{y}_p(t) - y_p(t) = \hat{\theta}^T(t) \hat{\omega}(t) - \theta^T \omega(t) \quad \pm \theta^T \hat{\omega}(t)$$

$$e_1(t) = (\hat{\theta}(t) - \theta)^T \hat{\omega}(t) + \theta^T \underbrace{(\hat{\omega}(t) - \omega(t))}_{\tilde{w}(t)}$$

$\tilde{w} \rightarrow$ exponencialmente

$$e_1(t) = \phi^T(t) \hat{\omega}(t)$$

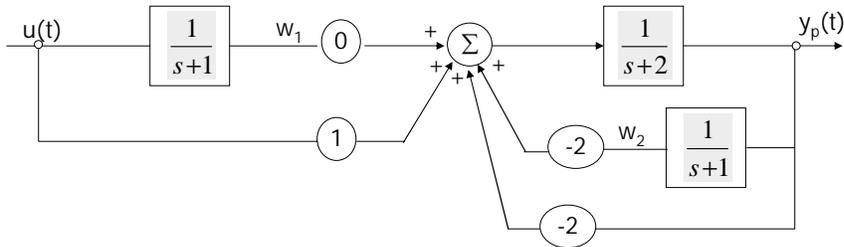
Modelo de Error 1

$$\phi(t) = \hat{\theta}(t) - \theta$$

$$\dot{\phi}(t) = \dot{\hat{\theta}}(t) = -e_1(t) \hat{\omega}(t)$$

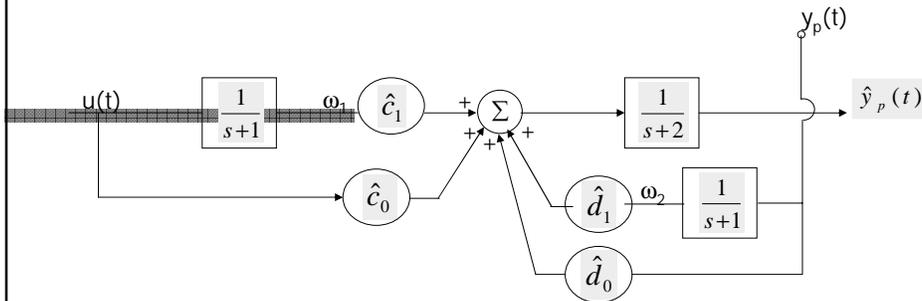
Ejemplo de Diseño

$$W_p(s) = \frac{s+1}{(s+2)(s+3)}$$



$$H(s) = \frac{1}{1 - \frac{1}{s+2} \begin{bmatrix} -2 & -2 \\ s+1 & -2 \end{bmatrix}} = \frac{s+1}{(s+2)(s+3)}$$

Observador



$$\begin{aligned} \dot{\hat{c}}_1 &= -e(t)\omega_1(t) \\ \dot{\hat{c}}_0 &= -e(t)u(t) \\ \dot{\hat{d}}_1 &= -e(t)\omega_2(t) \\ \dot{\hat{d}}_0 &= -e(t)y_p(t) \end{aligned}$$

Observadores Adaptivos Mejorados

a) Ganancias variables en el tiempo:

$$e(t) = \phi^T(t)\omega(t)$$

$$\dot{\phi} = \dot{\hat{\theta}}(t) = -\gamma\Gamma(t)e(t)\omega(t) \quad , \quad \gamma > 0$$

$$\dot{\Gamma}(t) = -\Gamma(t)\omega(t)\omega^T(t)\Gamma(t) \quad , \quad \Gamma(0) = \Gamma_0 > 0$$

$$V = \frac{1}{\gamma}\phi^T\Gamma^{-1}(t)\phi$$

$$\dot{V} = \frac{1}{\gamma}\dot{\phi}^T\Gamma^{-1}(t)\phi + \frac{1}{\gamma}\phi^T\Gamma^{-1}(t)\dot{\phi} - \frac{1}{\gamma}\phi^T\Gamma^{-1}\dot{\Gamma}\Gamma^{-1}\phi$$

$$\dot{V} = -e_1^2(t) \leq 0$$

$$\phi \in L^\infty$$

$$- \text{ si } \omega \in L^\infty \quad , \quad e \in L^\infty$$

$$e \in L^2 \quad , \quad \text{ si } \dot{\omega} \in L^\infty \quad , \quad \dot{e} \in L^\infty$$

$$\therefore \lim_{t \rightarrow \infty} e(t) = 0$$

$$- \text{ si } \omega \in \Omega_{2n} \Rightarrow \lim_{t \rightarrow \infty} \phi(t) = 0$$

$$\text{i.e. } \lim_{t \rightarrow \infty} \hat{\theta}(t) = 0$$

b) Algoritmo Integral:

$$\dot{\phi}(t) = -\gamma \int_{t_0}^t e_1(t, \delta) \omega(\delta) d\delta \quad J = \int_{t_0}^t e_1^2(t, \delta) d\delta$$

$$e_1(t, \tau) = \phi^T(t) \omega(\tau) = \hat{\theta}^T(t) \omega(\tau) - y_p(\tau)$$

$$\dot{\phi}(t) = -\mathcal{K} \phi(t) \quad J = \int_{t_0}^t e^{-q(t-\tau)} e_1^2(t, \tau) d\tau$$

$$\dot{\Gamma}(t) = -q\Gamma(t) + \omega(t)\omega^T(t), \quad \Gamma(t_0) = 0$$

$$\dot{\phi}(t) = -\mathcal{K}(t)\hat{\theta}(t) + \gamma\delta(t), \quad \gamma > 0$$

$$\dot{\Gamma}(t) = -q\Gamma(t) + \omega(t)\omega^T(t), \quad \Gamma(t_0) = 0$$

$$\dot{\delta}(t) = -q\delta(t) + \omega(t)y_p(t), \quad \delta(t_0) = 0$$

Todas las señales acotadas

$$\lim_{t \rightarrow \infty} e_1(t) \rightarrow 0$$

Si $w(t) \in \Omega_{2n}$, $\theta(t) \rightarrow \theta$ con una tasa de convergencia no menor que $\min\{q, H\}$

$$H = ke^{-qT}$$

$$\int_t^{t+T} \omega(\tau)\omega^T(\tau) d\tau \geq kI, \quad \forall t \geq t_0$$

c) Modelos Multiples

$$W_p(s)u(t) = y(t) \rightarrow e_1(t) = \phi^T \omega_1(t)$$

$$W_p(s) \frac{u(t)}{N(s)} = \frac{y(t)}{N(s)}$$

$$W_p(s)u_1(t) = y_1(t) \rightarrow e_2(t) = \phi^T \omega_2(t)$$

$$\vdots$$

$$e_{2n}(t) = \phi^T \omega_{2n}(t)$$

$$e(t) = \Omega(t)\phi(t)$$

$$e(t) = [e_1(t), e_2(t), \dots, e_{2n}(t)]^T$$

$$\Omega(t) = [\omega_1(t) : \omega_2(t) : \dots : \omega_{2n}(t)]^T$$

$\omega_i(t) : l.i.$

$$\dot{\phi}(t) = -\gamma \underbrace{\Omega^T(t)\Omega(t)}_{p.d.} \phi(t)$$

v.p. manejados por γ

$$\text{Si } \gamma \rightarrow \infty, \lim_{t \rightarrow \infty} \phi(t) = 0$$

d) Algoritmos Híbridos

$$e(t) = \phi^T(t)\omega(t)$$

$$\phi(t_{k+1}) = \phi(t_k) - \Gamma R(t_k) \quad , \quad \Gamma < 0$$

$$R(t_k) = \frac{1}{T_k} \int_{t_k}^{t_{k+1}} \frac{e(\tau)\omega(\tau)}{1 + \omega^T(\tau)e(\tau)} d\tau$$

$$T_k = t_{k+1} - t_k \quad \{t_k\} \quad k = 0, 1, 2, \dots$$

$$\sup_i [t_{i+1} - t_i] < \infty$$

- Todas las señales acotadas

$$\lim_{t \rightarrow \infty} e(t) = 0$$

$$\text{Si } \omega(t) \in \Omega_{2n} \Rightarrow \lim_{t \rightarrow \infty} \phi(t) = 0$$

$$\lim_{t \rightarrow \infty} \hat{\theta}(t) = \theta$$

Robusta frente a perturbaciones externas

$$V(k) = \frac{1}{2} \phi_k^T \phi_k \quad (\Gamma = I)$$

$$\Delta V(k) = V(k+1) - V(k) = \left[\phi_k^T + \frac{\Delta \phi_k^T}{2} \right] \Delta \phi_k$$

$$\Delta V(k) = -\frac{1}{2} \phi_k^T [2I - R_{k+1}] R_{k,k+1} \phi_k \leq 0$$

$$R_{k,k+1} \geq 0$$

Conclusiones

- Principales aspectos de la teoría de observadores y observadores adaptivos.
- Importancia de la elección de la parametrización de la planta y del observador.
- Observadores ↔ Realimentación del estado
- Observadores Adaptivos ↔ Control adaptivo.
- Observadores: Análisis de robustez frente a variaciones en los parámetros de la planta.
- Observadores adaptivos: Análisis en condiciones de incertidumbre; perturbaciones acotadas externas, parámetros variables en el tiempo y dinámica no modelada.