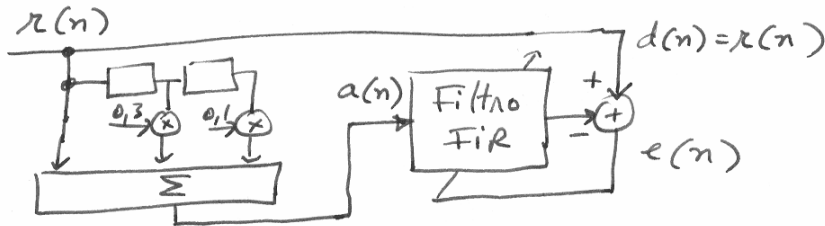


1) $a(n) = r(n) + 0,3 r(n-1) + 0,1 r(n-2)$



$E[d^2(n)] = E[r^2(n)] = 10$
 σ^2

$R = E[\underline{a}(n) \underline{a}^T(n)]$, $P = E[d(n) \underline{a}(n)]$

Seja R_k o termo genérico da 1ª linha de R .

$R_k = E[a(n) a(n-k)] = E\{[r(n) + 0,3 r(n-1) + 0,1 r(n-2)] \times [r(n-k) + 0,3 r(n-k-1) + 0,1 r(n-k-2)]\} =$
 $= 1,1 \delta(k) + 0,33 [\delta(k+1) + \delta(k-1)] + 0,1 [\delta(k+2) + \delta(k-2)]$

(Considerou-se, para simplificar a expressão, que $E[r(n) r(n-k)] = \delta(k) = \begin{cases} \sigma^2 = 1/2 & k=0 \\ 0 & k \neq 0 \end{cases}$, visto as amostras de ruído branco serem decorrelacionadas entre si)

Da mesma forma, $P = E[d(n) \underline{a}(n)] \Rightarrow P_k = E[d(n) a(n-k)]$

$\Rightarrow P_k = E[r(n) [r(n-k) + 0,3 r(n-k-1) + 0,1 r(n-k-2)]] =$
 $= \delta(k) + 0,3 \delta(k+1) + 0,1 \delta(k+2)$

a) $N=5$ coeficientes

$R = \sigma^2 \begin{bmatrix} 1,1 & 0,33 & 0,1 & 0 & 0 \\ 0,33 & 1,1 & 0,33 & 0,1 & 0 \\ 0,1 & 0,33 & 1,1 & 0,33 & 0,1 \\ 0 & 0,1 & 0,33 & 1,1 & 0,33 \\ 0 & 0 & 0,1 & 0,33 & 1,1 \end{bmatrix} = \begin{bmatrix} 11 & 3,3 & 1 & 0 & 0 \\ 3,3 & 11 & 3,3 & 1 & 0 \\ 1 & 3,3 & 11 & 3,3 & 1 \\ 0 & 1 & 3,3 & 11 & 3,3 \\ 0 & 0 & 1 & 3,3 & 11 \end{bmatrix}$ (c/ $\sigma^2=10$)

$P = \sigma^2 [1 \ 0 \ 0 \ 0 \ 0]^T = [10 \ 0 \ 0 \ 0 \ 0]^T$

$$b) N=2 \Rightarrow \underline{R} = \frac{1}{\sigma^2} \begin{bmatrix} 1,1 & 0,33 \\ 0,33 & 1,1 \end{bmatrix} \quad \text{e} \quad \underline{p} = \begin{bmatrix} \sigma^2 \\ 0 \end{bmatrix} \quad (2)$$

$$\underline{c}_{opt} = \underline{R}^{-1} \underline{p} = \begin{bmatrix} 0,9990 \\ -0,2997 \end{bmatrix} \quad (\text{Valor independente de } \sigma^2)$$

$$\left(\underline{R}^{-1} = \frac{1}{\sigma^2} \begin{bmatrix} 0,9990 & -0,2997 \\ -0,2997 & 0,9990 \end{bmatrix} \right)$$

$$c) \text{ Do formulário: } \varepsilon = E[d^2(n)] - 2\underline{c}^T \underline{p} + \underline{c}^T \underline{R} \underline{c}$$

$$\varepsilon_{min} = E[d^2(n)] - \underline{p}^T \underline{c}_{opt}$$

$$\underline{c}_{opt} = \underline{R}^{-1} \underline{p} \Rightarrow \underline{p} = \underline{R} \underline{c}_{opt}$$

Subtraindo ε_{min} a ε e desembaraçando de $\underline{p} = \underline{R} \underline{c}_{opt}$ obtemos:

$$\varepsilon - \varepsilon_{min} = \underline{c}^T \underline{R} \underline{c} - (\underline{c} - \underline{c}_{opt})^T \underline{p} = \underline{c}^T \underline{R} \underline{c} - \underline{c}^T \underline{p} - (\underline{c} - \underline{c}_{opt})^T \underline{p} =$$

$$= \underline{c}^T \underline{R} \underline{c} - \underline{c}^T \underline{R} \underline{c}_{opt} - (\underline{c} - \underline{c}_{opt})^T \underline{R} \underline{c}_{opt}$$

$$= \underbrace{\underline{c}^T \underline{R} (\underline{c} - \underline{c}_{opt})} - (\underline{c} - \underline{c}_{opt})^T \underline{R} \underline{c}_{opt} =$$

$$(\underline{c} - \underline{c}_{opt})^T \underline{R} \underline{c}$$

$$= (\underline{c} - \underline{c}_{opt})^T \underline{R} (\underline{c} - \underline{c}_{opt}) = \underline{c}_e^T \underline{R} \underline{c}_e$$

$$\text{Mas } \underline{R} = \underline{Q} \underline{\Lambda} \underline{Q}^T \Rightarrow \varepsilon - \varepsilon_{min} = \underline{c}_e^T \underline{Q} \underline{\Lambda} \underline{Q}^T \underline{c}_e =$$

$$\text{Ora } \underline{v} = \begin{bmatrix} v_0 \\ v_1 \end{bmatrix} \text{ e } \underline{\Lambda} = \begin{bmatrix} \lambda_0 & 0 \\ 0 & \lambda_1 \end{bmatrix} \Rightarrow \varepsilon - \varepsilon_{min} = \underbrace{(\underline{Q}^T \underline{c}_e)^T}_{\underline{v}^T} \underline{\Lambda} \underline{v} = \underline{v}^T \underline{\Lambda} \underline{v}$$

$$\Rightarrow \varepsilon - \varepsilon_{min} = [v_0 \ v_1] \begin{bmatrix} \lambda_0 & 0 \\ 0 & \lambda_1 \end{bmatrix} \begin{bmatrix} v_0 \\ v_1 \end{bmatrix} = \lambda_0 v_0^2 + \lambda_1 v_1^2$$

As curvas de nível obtêm-se fazendo $\varepsilon - \varepsilon_{min} = \text{const.} = K$

$$\Rightarrow \lambda_0 v_0^2 + \lambda_1 v_1^2 = K \Rightarrow \frac{v_0^2}{K/\lambda_0} + \frac{v_1^2}{K/\lambda_1} = 1 \quad \text{c.g.d.}$$

Os semi-eixos valem: eixo dos xx : $a = \sqrt{K/\lambda_0} = \sqrt{\frac{\varepsilon - \varepsilon_{min}}{\lambda_0}}$

eixo dos yy : $b = \sqrt{K/\lambda_1} = \sqrt{\frac{\varepsilon - \varepsilon_{min}}{\lambda_1}}$

2- $\Lambda = \begin{bmatrix} 1 & 0 \\ 0 & 5 \end{bmatrix}$ $Q = \frac{1}{\sqrt{2}} \begin{bmatrix} -1 & 1 \\ 1 & 1 \end{bmatrix}$ $P = \begin{bmatrix} 5 \\ 3 \end{bmatrix}$
 $\epsilon_{min} = 0,6$

a) $R = Q\Lambda Q^T = \begin{bmatrix} 3 & 2 \\ 2 & 3 \end{bmatrix}$

Do formulário: $\epsilon_{min} = E[d^2(n)] - P^T c_{opt}$

$\Rightarrow E[d^2(n)] = \epsilon_{min} + P^T c_{opt}$

Eq. Wiener-Hopf: $c_{opt} = R^{-1} P = \begin{bmatrix} 1,8 \\ -0,2 \end{bmatrix}$

Substituindo valores: $E[d^2(n)] = 0,6 + \underbrace{\begin{bmatrix} 5 & 3 \end{bmatrix} \begin{bmatrix} 1,8 \\ -0,2 \end{bmatrix}}_{8,4} = 9$

b) $\epsilon = \epsilon_{min} + c_e^T R c_e = 0,6 + 0,1 = 0,7$
 (c/c_e = [0,1 0,1]^T)

c) Gama máxima: $0 < \mu < \frac{1}{\lambda_{max}} = \frac{1}{5} = 0,2$

Gama reduzida: $0 < \mu < \frac{1}{\lambda_{max}[R]} = \frac{1}{6}$

d) $\mu_{opt} = \frac{1}{\lambda_{min} + \lambda_{max}} = \frac{1}{1+5} = \frac{1}{6}$

e) O modo natural associado ao valor próprio mais elevado converge mais rapidamente (pois nesse caso $1-2\mu\lambda$ é menor). Portanto, sendo $\lambda_0=1$ e $\lambda_1=5$, o modo natural mais rápido é v_1 .

f) $c_e(0) = [-1,8 \ 0,2]^T$. Sabemos que (ver alínea b)
 $\epsilon = \epsilon_{min} + c_e^T R c_e = \epsilon_{min} + c_e^T Q\Lambda Q^T c_e = \epsilon_{min} + v^T \Lambda v$

Explicitando a iteração n temos

$\epsilon(n) = \epsilon_{min} + v^T(n) \Lambda v(n)$

Mas $v(n) = (I - 2\mu\Lambda)^n v(0)$

De $\underline{v}(0) = Q^T \underline{c}_e(0)$ temos

$$\underline{v}(0) = \frac{1}{\sqrt{2}} \begin{bmatrix} -1 & 1 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} -1,8 \\ 0,2 \end{bmatrix} = \frac{1}{\sqrt{2}} \begin{bmatrix} 2 \\ -1,6 \end{bmatrix}$$

$$\begin{aligned} \text{Temos também } (\mathbf{I} - 2\mu\Lambda)^n &= \begin{bmatrix} (1-2\mu\lambda_0)^n & 0 \\ 0 & (1-2\mu\lambda_1)^n \end{bmatrix} = \\ &= \begin{bmatrix} 0,7^n & 0 \\ 0 & (-0,5)^n \end{bmatrix} \end{aligned}$$

Substituindo valores e desenvolvendo:

$$\underline{v}(n) = \frac{1}{\sqrt{2}} [2 \times 0,7^n \quad -1,6 \times (-0,5)^n]^T$$

$$E(n) = \underbrace{E_{\min}}_{0,6} + 2 \times 0,7^{2n} + 6,4 \times (0,5)^{2n}$$

Verificações:

$$E(0) = \underbrace{E_{\min}}_{0,6} + 2 + 6,4 = 9$$

Note-se que se $\underline{c}_e(0) = [-1,8 \quad 0,2]^T$

e $\underline{c}_{opt} = [1,8 \quad -0,2]^T$ (alínea a)

então $\underline{c}(0) = [0 \quad 0]^T$

$$\Rightarrow E(0) = E[d^2(n)] - \underbrace{2\underline{c}^T p + \underline{c}^T R \underline{c}}_0 =$$

$$= E[d^2(n)] = 9 \text{ (alínea a)}$$

$$E(4) = \underbrace{E_{\min}}_{0,6} + \underbrace{2 \times 0,7^8 + 6,4 \times (0,5)^8}_{0,140} = 0,74 \text{ (tal como está no enunciado)}$$

$$3- \quad J(n) = E[e^2(n)] + \gamma \underline{c}^T(n) \underline{c}(n)$$

$$a) \quad \text{Equação de actualização: } \underline{c}(n+1) = \underline{c}(n) - \mu \hat{\nabla}(n)$$

$$\nabla(n) = \frac{dJ(n)}{d\underline{c}(n)} = 2 E \left[e(n) \frac{de(n)}{d\underline{c}} \right] + 2\gamma \underline{c}(n)$$

$$\text{Mas } e(n) = d(n) - \underline{c}^T(n) \underline{a}(n) \Rightarrow \frac{de(n)}{d\underline{c}} = -\underline{a}(n)$$

$$\Rightarrow \nabla(n) = -2 E[e(n) \underline{a}(n)] + 2\gamma \underline{c}(n)$$

$$\text{Simplificando: } \hat{\nabla}(n) = -2 e(n) \underline{a}(n) + 2\gamma \underline{c}(n)$$

$$\Rightarrow \underline{c}(n+1) = \underline{c}(n) + 2\mu e(n) \underline{a}(n) - 2\mu\gamma \underline{c}(n) =$$

$$= (1 - 2\mu\gamma) \underline{c}(n) + 2\mu e(n) \underline{a}(n) \quad \text{c.q.d.}$$

3. b) Tomando o valor médio de ambos os membros da equação de atualização de coeficientes obtemos:

$$E[\underline{\epsilon}(n+1)] = (1-2\mu\gamma) E[\underline{\epsilon}(n)] + 2\mu E[e(n)\underline{a}(n)]$$

$$\begin{aligned} \text{Ora } E[e(n)\underline{a}(n)] &= E[(d(n) - \underbrace{\underline{a}^T(n)}_{\text{escalar} = \underline{a}^T(n)\underline{\epsilon}(n)}) \underline{a}(n)] = \\ &= E[\underbrace{d(n)\underline{a}(n)}_P] - E[\underline{a}(n) \cdot \underline{a}^T(n) \cdot \underline{\epsilon}(n)] = \end{aligned}$$

$$= P - E[\underbrace{\underline{a}(n)\underline{a}^T(n)}_R] E[\underline{\epsilon}(n)] = P - R E[\underline{\epsilon}(n)]$$

Substituindo em cima

$$\begin{aligned} E[\underline{\epsilon}(n+1)] &= (1-2\mu\gamma) E[\underline{\epsilon}(n)] + 2\mu P - 2\mu R E[\underline{\epsilon}(n)] = \\ &= [I - 2\mu(R + \gamma I)] E[\underline{\epsilon}(n)] + 2\mu P \end{aligned}$$

(No LMS era $E[\underline{\epsilon}(n+1)] = (I - 2\mu R) E[\underline{\epsilon}(n)] + 2\mu P$)

$$\text{Quando } n \rightarrow \infty : E[\underline{\epsilon}(\infty)] \approx [I - 2\mu(R + \gamma I)] E[\underline{\epsilon}(\infty)] + 2\mu P$$

$$\Rightarrow 2\mu(R + \gamma I) E[\underline{\epsilon}(\infty)] = 2\mu P$$

$$\Rightarrow E[\underline{\epsilon}(\infty)] = (R + \gamma I)^{-1} P \neq R^{-1} P = \underline{\epsilon}_{opt}$$

$$c) \quad \sigma_n^2 = \gamma \leftarrow R_n = \begin{bmatrix} \gamma & 0 & 0 \\ 0 & \gamma & 0 \\ 0 & 0 & \dots & \gamma \end{bmatrix} = \gamma I \quad \text{c. q. d.}$$



$$R = E[\underline{a}(n)\underline{a}^T(n)]$$

Como há independência entre $\underline{a}(n)$ e o "ruído" \Rightarrow matriz de auto-covariância de entrada = $R + \gamma I$

Os valores próprios desta matriz são os valores próprios de R aumentados de $\gamma \Rightarrow \lambda_0 + \gamma, \lambda_1 + \gamma, \lambda_2 + \gamma, \text{ etc.}$

$$\Rightarrow 0 < \mu < \frac{1}{\lambda_{max} + \gamma}$$

4. Da figura vemos que

$$\begin{array}{cccc} \underline{a}(0) & \underline{a}(1) & \underline{a}(2) & \underline{a}(3) \dots \\ \hline \begin{bmatrix} 1 \\ 0 \end{bmatrix} & \begin{bmatrix} -1 \\ 1 \end{bmatrix} & \begin{bmatrix} -1 \\ -1 \end{bmatrix} & \begin{bmatrix} 0 \\ -1 \end{bmatrix} \dots \end{array} \quad \begin{array}{cccc} d(0) & d(1) & d(2) & d(3) \dots \\ \hline 1 & 2 & -2 & 0 \end{array}$$

$$P(0) = 50I, \quad \alpha = 1$$

$$a) \quad \hat{R}(n) = \sum_{j=0}^n \alpha^{n-j} \underline{a}(j) \underline{a}^T(j) = \underline{a}(0) \underline{a}^T(0) + \underline{a}(1) \underline{a}^T(1) + \dots + \underline{a}(n) \underline{a}^T(n)$$

$$\begin{aligned} \hat{R}(1) &= \underline{a}(0) \underline{a}^T(0) + \underline{a}(1) \underline{a}^T(1) = \begin{bmatrix} 1 \\ 0 \end{bmatrix} \begin{bmatrix} 1 & 0 \end{bmatrix} + \begin{bmatrix} -1 \\ 1 \end{bmatrix} \begin{bmatrix} -1 & 1 \end{bmatrix} = \\ &= \begin{bmatrix} 2 & -1 \\ -1 & 1 \end{bmatrix} \end{aligned}$$

$$b) \quad \hat{P}(n) = \sum_{j=0}^n \alpha^{n-j} d(j) \underline{a}(j)$$

$$\begin{aligned} \hat{P}(2) &= \sum_{j=0}^2 \alpha^{2-j} d(j) \underline{a}(j) = d(0) \underline{a}(0) + d(1) \underline{a}(1) + d(2) \underline{a}(2) = \\ &= \begin{bmatrix} 1 \\ 0 \end{bmatrix} + 2 \begin{bmatrix} -1 \\ 1 \end{bmatrix} + (-2) \begin{bmatrix} -1 \\ -1 \end{bmatrix} = \begin{bmatrix} 1 \\ 4 \end{bmatrix} \end{aligned}$$

$$c) \quad \underline{P}(n) = \frac{1}{\alpha} \left[\underline{P}(n-1) - \frac{\underline{P}(n-1) \underline{a}(n) \underline{a}^T(n) \underline{P}(n-1)}{\alpha + \underline{a}^T(n) \underline{P}(n-1) \underline{a}(n)} \right]$$

sendo $\alpha = 1$ e $\underline{P}(0) = 50I$:

$$\underline{P}(1) = \underline{P}(0) - \frac{\underline{P}(0) \underline{a}(1) \underline{a}^T(1) \underline{P}(0)}{1 + \underline{a}^T(1) \underline{P}(0) \underline{a}(1)}$$

Numerador:

$$50 \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} -1 \\ 1 \end{bmatrix} \begin{bmatrix} -1 & 1 \end{bmatrix} \times 50 \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} =$$

$$= 2500 \begin{bmatrix} 1 & -1 \\ -1 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} = 2500 \begin{bmatrix} 1 & -1 \\ -1 & 1 \end{bmatrix}$$

Denominador:

$$1 + \begin{bmatrix} -1 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} -1 \\ 1 \end{bmatrix} \times 50 = 1 + 2 \times 50 = 101$$

$$\Rightarrow \underline{P}(1) = 50 \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} - \frac{2500}{101} \begin{bmatrix} 1 & -1 \\ -1 & 1 \end{bmatrix} = \begin{bmatrix} 25,25 & 24,75 \\ 24,75 & 25,25 \end{bmatrix}$$

$\approx 24,75$

4.d) $\underline{k}(n) = \underline{P}(n) \underline{a}(n)$ - vector de ganho de Kalman

$$\Rightarrow \underline{k}(1) = \underline{P}(1) \underline{a}(1) = \begin{bmatrix} 25,25 & 24,75 \\ 24,75 & 25,25 \end{bmatrix} \begin{bmatrix} -1 \\ 1 \end{bmatrix} =$$

$$= \begin{bmatrix} -0,5 \\ 0,5 \end{bmatrix}$$

e) $e'(n) = d(n) - \underline{c}^T(n-1) \underline{a}(n)$ - erro de estimação "a priori"

$$\Rightarrow e'(1) = d(1) - \underline{c}^T(0) \underline{a}(1) =$$

$$= 2 - [0 \ 0] \begin{bmatrix} -1 \\ 1 \end{bmatrix} = 2 //$$

$$e'(2) = d(2) - \underline{c}^T(1) \underline{a}(2) = -2 - [-1 \ 1] \begin{bmatrix} -1 \\ -1 \end{bmatrix} = -2$$

f) $\underline{c}(n) = \underline{c}(n-1) + \underline{k}(n) e'(n)$

$$\Rightarrow \underline{c}(1) = \underline{c}(0) + \underline{k}(1) e'(1) = \underline{0} + \begin{bmatrix} -0,5 \\ 0,5 \end{bmatrix} \times 2 = \begin{bmatrix} -1 \\ 1 \end{bmatrix} //$$