

Linear Prediction

(1)

FLP given M previous values $[u(n-1), \dots, u(n-M)]$
 (predict) estimate $u(n)$

$$\underline{u}_M(n-1) = \begin{bmatrix} u(n-1) \\ u(n-2) \\ \vdots \\ u(n-M) \end{bmatrix}$$

$$\text{FLP error} \quad \hat{e}_M(n) = u(n) - \sum_{k=1}^M w_{f,k}^* u(n-k) = u(n) - \underline{w}_f^H \underline{u}_M(n-1)$$

Stoxos : No bpedn to \underline{w}_f t.o.w. $E[|\hat{e}_M(n)|^2] \rightarrow \underline{\text{min}}$

λvga W#E $\underline{R}_M \circ \underline{w}_f = \underline{t}_M$ (1) $\Rightarrow \underline{w}_f = \underline{R}_M^{-1} \underline{t}_M$

o/oo $\underline{R}_M = \begin{bmatrix} r(0) & r(1) \\ r^*(1) & \\ \vdots & \\ r^*(M-1) & \end{bmatrix}$ $\underline{w}_f = \begin{bmatrix} w_{f,1} \\ w_{f,2} \\ \vdots \\ w_{f,M} \end{bmatrix}$ $\underline{t}_M = \begin{bmatrix} r^*(1) \\ r^*(2) \\ \vdots \\ r^*(M) \end{bmatrix}$

$M \times M$ $M \times 1$ $M \times 1$

Igxos too σfor/atos, P_M : Mean-squared Error.

$$P_M = E[|\hat{e}_M(n)|^2] \stackrel{\text{ano W#E}}{=} \underline{t}_M^H - \underline{t}_M^H \underline{w}_f = \underline{t}_M^H - \underline{t}_M^H \underline{R}_M^{-1} \underline{t}_M \quad (2)$$

$$P_M = E[|\hat{e}_M(n)|^2] \stackrel{\text{ano W#E}}{=} \sigma_d^2 - \underline{t}_M^H \underline{w}_f = \underline{t}_M^H - \underline{t}_M^H \underline{R}_M^{-1} \underline{t}_M$$

\downarrow \underline{w}_f ano W#E $\Rightarrow \underline{w}_f = \underline{R}_M^{-1} \underline{t}_M$

$d(n) = u(n) \Rightarrow \sigma_d^2 = r(0)$ $u(n)$ is zero mean.
 $\underline{t}_M^H = E[\underline{u}_M(n-1) u^*(n)] = \underline{t}_M$

Augmented WHE for FLP

$$\textcircled{1} \& \textcircled{2} \rightarrow \begin{bmatrix} \Gamma(0) & \Gamma^H \\ \vdots & \vdots \\ \Gamma & \underline{R}_M \end{bmatrix} \begin{bmatrix} \underline{1} \\ \vdots \\ -\underline{w}_F \end{bmatrix} = \begin{bmatrix} \underline{P}_M \\ \underline{0} \end{bmatrix}$$

$\underbrace{\hspace{10em}}_{\substack{R \\ = M+1}} \quad \underbrace{\hspace{10em}}_{\substack{1 \\ \underline{a}_M}}$

$$\text{όπως } \underline{a}_{M,k} = \begin{cases} \underline{1} & \gamma \alpha \quad k=0 \\ -w_{F,k} & \gamma \alpha \quad k=1, \dots, M \end{cases}$$

το διάνυσμα \underline{a}_M έχη τούς συσχετισμούς τω φηττος FP

$$F_M(u) = u(n) - w_{F,1}^* u(n-1) - \dots - w_{F,M}^* u(n-M)$$

$$= \underline{a}_M^H \underline{u}_M(n)$$

BLP given M future values $[u(n), u(n-1), \dots, u(n-M+1)] = \underline{u}_M(n)$
 estimate the value $u(n-M)$

$$\underline{u}_M(n) = \begin{bmatrix} u(n) \\ u(n-1) \\ u(n-2) \\ \vdots \\ u(n-M+1) \end{bmatrix}$$

BLP error: $b_M(n) = u(n-M) - \sum_{k=L}^M w_{b,k}^* u(n-k+1)$

στόχος: Να βρεθεί το \underline{w}_b τ.ω $E[|b_M(n)|^2] \rightarrow \text{min}$

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WHE : $\underline{R} \cdot \underline{W} = \underline{P}$

$\underline{R} \xrightarrow{\text{WH}} \underline{R} = E[\underline{u}(n) \underline{u}^H(n)] = \begin{bmatrix} r(0) & r(1) & \dots & r(N-1) \\ r^*(1) & & & \\ \vdots & & & \\ r^*(N-1) & & & r(0) \end{bmatrix}$

$\underline{W} \rightarrow \underline{W}_b = [w_{b,1}, w_{b,2}, \dots, w_{b,M}]^T$

$\underline{P} = E[\underline{u}(n) \cdot d^*(n)] \rightarrow E[\underline{u}(n) \cdot u^*(n-M)] = \begin{bmatrix} r(M) \\ r(M-1) \\ \vdots \\ r(1) \end{bmatrix} = \underline{r}_M^{*B}$

order n fixed $\rightarrow \underline{R} \underline{W}_b = \underline{r}_M^{*B}$

opto WHE : $E[|b_M(n)|^2] = \sigma_d^2 - \underline{P}^H \underline{W}_b = r(0) - \underline{r}_M^{BT} \underline{W}_b$

Augmented WH Eq for BLP

$\begin{bmatrix} \underline{R} & \underline{r}_M^{*B} \\ \underline{r}_M^{BT} & r(0) \end{bmatrix} \begin{bmatrix} -\underline{W}_b \\ 1 \end{bmatrix} = \begin{bmatrix} 0 \\ \underline{P}_M \end{bmatrix}$

$\underline{0} \Rightarrow M \times M$

$\underline{R}_{M+1} \quad \underline{C}_M$

opto $C_{M,k} = \begin{cases} -w_{b,k+1} & k=0,1,\dots,M-1 \\ 1 & k=M \end{cases}$

To solve for \underline{C}_M gives us backward prediction error filter

$b_M(n) = u(n-M) - \underline{W}_b^H \underline{u}(n) = \sum_{k=0}^M C_{M,k}^* u(n-k)$

Σχεδιά προαγωγή FLP & BLP

α. 6x604 προαγωγή των φητρωων

FLP : $\underline{R} \cdot \underline{W}_F = \underline{\Gamma}$

BLP : $\underline{R} \cdot \underline{W}_B = \underline{\Gamma}^{B*} \Leftrightarrow E [\underline{u}(w) \cdot \underline{u}^H(w) \cdot \underline{W}_B] = \underline{\Gamma}^{B*} \Leftrightarrow$

$E [\underline{u}(w) \cdot \underline{u}^{BH}(w) \underline{W}_B^B] = \underline{\Gamma}^{B*} \Leftrightarrow$

$(E [\underline{u}(w) \cdot \underline{u}^{BH}(w) \underline{W}_B^B])^B = (\underline{\Gamma}^{B*})^B \Leftrightarrow$

$E [\underline{u}^B(w) \cdot \underline{u}^{BH}(w) \underline{W}_B^B] = \underline{\Gamma}^{B*} \Leftrightarrow$

$E [\underline{u}^B(w) \cdot \underline{u}^{BH}] \cdot \underline{W}_B^B = \underline{\Gamma}^{B*} \Leftrightarrow \underline{R}^T \cdot \underline{W}_B^B = \underline{\Gamma}^{B*} \Leftrightarrow$
 $\underline{R}^T = \underline{R}^T - 1$

$\underline{R}^{T*} \cdot \underline{W}_B^{B*} = \underline{\Gamma} \Leftrightarrow \underline{R}^H \cdot \underline{W}_B^{B*} = \underline{\Gamma} \Leftrightarrow \underline{R}^H = \underline{R}$

$\underline{R} \cdot \underline{W}_B^{B*} = \underline{\Gamma} \} \Rightarrow \underline{W}_B^{B*} = \underline{W}_F$
 $\underline{R} \cdot \underline{W}_F = \underline{\Gamma}$

β. 6x604 προαγωγή των 16x1000 των φητρωων

FPE : $P_M = E [|f_M(w)|^2] = f(0) - \underline{\Gamma}^H \underline{W}_F$

BPE : $E [|b_M(w)|^2] = f(0) - \underline{\Gamma}^{BT} \underline{W}_B = f(0) - \underline{\Gamma}^T \underline{W}_B^B =$
 $= f(0) - \underline{\Gamma}^{T*} \underline{W}_B^{B*} = f(0) - \underline{\Gamma}^H \underline{W}_F = P_M$

Levinson - Durbin Algorithm (1)

Forward

$$\underline{R}_M \circ \underline{W}_f = \underline{\Gamma}_M$$

$$\underline{R}_M = \begin{bmatrix} r(0) & r(1) & \dots & r(N-1) \\ r^*(1) & r(0) & & r(N-2) \\ r^*(2) & & & r(N-3) \\ \vdots & & & \vdots \\ r^*(N-1) & r^*(N-2) & & r(0) \end{bmatrix}$$

$$\underline{W}_f = \begin{bmatrix} W_{f,1} \\ W_{f,2} \\ W_{f,3} \\ \vdots \\ W_{f,M} \end{bmatrix}$$

$$\underline{\Gamma}_M = \begin{bmatrix} r^*(1) \\ r^*(2) \\ \vdots \\ r^*(M) \end{bmatrix}$$

Offce :

dan ya $(M-1)^{th}$ tugas FLP iter 16x07

$$R_{=M-1} \cdot W_{=M-1} = \Gamma_{M-1} \quad (3)$$

kali ya $(M-1)^{th}$ tugas BLP iter 16x07

$$R_{=M-1} W_{=M-1}^{B*} = \Gamma_{M-1}^{B*} \quad (4)$$

atau dengan cara lain BLP: $R_{=M-1} W_b = \Gamma_{M-1}^{B*}$
 dan $W_b^{B*} = W_f \Rightarrow \frac{W_b^{B*}}{W_b} = \frac{W_f}{W_b} \Rightarrow \frac{W_b^{B*}}{W_b} = \frac{W_f}{W_b}$

$$\Rightarrow R_{=M-1} \frac{W_b^{B*}}{W_f} = \Gamma_{M-1}^{B*} \Rightarrow R_{=M-1} W_b^{B*} = \Gamma_{M-1}^{B*} W_f$$

(1) $\xrightarrow{(3)(4)}$ $R_{=M-1} \cdot \frac{W}{M} + R_{=M-1} \frac{W_{M,M}^{B*}}{W_{M,M}} = R_{=M-1} \cdot \frac{W}{M-1}$

$\frac{R_{=M-1}}{R_{=M-1}} \times$ $\frac{W}{M} + \frac{W_{M,M}^{B*}}{W_{M,M}} = \frac{W}{M-1} \Rightarrow$

$$\frac{W}{M} = \frac{W}{M-1} - \frac{W_{M,M}^{B*}}{W_{M,M}} \quad (5)$$

(2) $\xrightarrow{(5)}$ $\Gamma_{=M-1}^{BT} \left(\frac{W}{M-1} - \frac{W_{M,M}^{B*}}{W_{M,M}} \right) + \Gamma(0) W_{M,M} = \Gamma^*(U) \Rightarrow$

$$\Rightarrow \Gamma_{=M-1}^{BT} \frac{W}{M-1} - \Gamma_{=M-1}^{BT} \frac{W_{M,M}^{B*}}{W_{M,M}} + \Gamma(0) W_{M,M} = \Gamma^*(U) \Rightarrow$$

$$\Rightarrow W_{M,M} = \frac{\Gamma^*(U) - \Gamma_{=M-1}^{BT} \frac{W}{M-1}}{\Gamma(0) - \Gamma_{=M-1}^{BT} \frac{W_{M,M}^{B*}}{W_{M,M}}} \quad (6)$$

Define $k_M \triangleq -w_{M,M}$ (reflection coefficients) (4)

also we (5)
$$\underline{w}_M = \begin{bmatrix} w_{M,1} \\ w_{M,2} \\ \vdots \\ w_{M,M} \end{bmatrix} = \begin{bmatrix} \underline{w}_M \\ w_{M,M} \end{bmatrix} \stackrel{(5)}{=} \begin{bmatrix} \underline{w}_{M-1} - \frac{w_{M-1}^{B*}}{M-1} w_{M,M} \\ w_{M,M} \end{bmatrix} =$$

$$= \begin{bmatrix} \underline{w}_{M-1} \\ 0 \end{bmatrix} - w_{M,M} \begin{bmatrix} \frac{w_{M-1}^{B*}}{M-1} \\ -1 \end{bmatrix} = 0$$

$$\Rightarrow \underline{w}_M = \begin{bmatrix} \underline{w}_{M-1} \\ 0 \end{bmatrix} + k_M \begin{bmatrix} \frac{w_{M-1}^{B*}}{M-1} \\ -1 \end{bmatrix} \quad (7)$$

optimal $\underline{a}_M = \begin{bmatrix} 1 \\ -\underline{w}_M \end{bmatrix}$ and $\underline{a}_{M-1} = \begin{bmatrix} 1 \\ -\underline{w}_{M-1} \end{bmatrix}$

optimal
$$\underline{a}_M = \begin{bmatrix} 1 \\ -\underline{w}_M \end{bmatrix} \stackrel{(7)}{=} \begin{bmatrix} 1 \\ -\underline{w}_{M-1} \\ 0 \end{bmatrix} + k_M \begin{bmatrix} -\frac{w_{M-1}^{B*}}{M-1} \\ +1 \end{bmatrix} =$$

$$= \begin{bmatrix} 1 + 0 \\ -\underline{w}_{M-1} \\ 0 \end{bmatrix} + k_M \begin{bmatrix} \frac{w_{M-1}^{B*}}{M-1} \\ -1 \end{bmatrix} = \begin{bmatrix} 1 \\ -\underline{w}_{M-1} \\ 0 \end{bmatrix} + k_M \begin{bmatrix} 0 \\ -\frac{w_{M-1}^{B*}}{M-1} \\ +1 \end{bmatrix} =$$

$$= \begin{bmatrix} \underline{a}_{M-1} \\ 0 \end{bmatrix} + k_M \begin{bmatrix} 0 \\ -\underline{a}_{M-1}^{B*} \end{bmatrix} = \underline{a}_M \quad (8)$$

In scalar form

Algo 8

$$a_{-M} = \begin{bmatrix} 1 \\ -w_{M,1} \\ -w_{M,2} \\ -w_{M,3} \\ \vdots \\ -w_{M,M} \end{bmatrix} = \begin{bmatrix} 1 \\ -w_{M-1,1} \\ -w_{M-1,2} \\ -w_{M-1,3} \\ \vdots \\ -w_{M-1,M-1} \\ 0 \end{bmatrix} + k_M \begin{bmatrix} 0 \\ -w_{M-1,1}^* \\ -w_{M-1,2}^* \\ -w_{M-1,3}^* \\ \vdots \\ -w_{M-1,1}^* \\ 1 \end{bmatrix} \Rightarrow$$

$$a_{-M} = \begin{bmatrix} 1 \\ a_{M,1} \\ a_{M,2} \\ \vdots \\ a_{M,M} \end{bmatrix} = \begin{bmatrix} 1 \\ a_{M-1,1} \\ a_{M-1,2} \\ \vdots \\ a_{M-1,M-1} \end{bmatrix} + k_M \begin{bmatrix} 0 \\ a_{M-1,1}^* \\ a_{M-1,2}^* \\ \vdots \\ a_{M-1,1}^* \\ 1 \end{bmatrix} = A$$

$$a_{M,k} = a_{M-1,k} + k_M a_{M-1, M-k}^*, \quad k=0, 1, 2, \dots, M-1$$

ke $a_{M,0} = 1$ dan $a_{M-1,0} = 1$

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Algo 6 opifw

kon aprofman ws:

$$\Delta_{M-1} \triangleq F^*(M) - \Gamma_{M-1}^{BT} \frac{W}{M-1} =$$

$$= F^*(M) \cdot 1 - \Gamma_{M-1}^{BT} \frac{W}{M-1} \quad \underline{a_{M-1} = [-w_{M-1}]} \quad \Gamma_{M-1}^{BT} \cdot \frac{W}{M-1} = F^*(k) = F^*(k)$$

because P is hermitian

$$= \sum_{l=0}^{M-1} a_{M-1,l} F(l-M) = E \left[b_{M-1}(n-1) F_{M-1}^*(n) \right]$$

iterasi ke M
proses ini di ulangi
3x 6 per 00 k ke M-1

opou $b_M(n) = u(n-M) - \sum_{k=1}^M w_{b,k}^* u(n-k+1)$ backward prediction error

dan $F_M(n) = u(n) - \sum_{k=1}^M w_{f,k}^* u(n-k)$ forward prediction error

α) Ορισμοί: $r(t)$ είναι σταθερό n τοξός των $t=0, \dots, T$ LBP

(6)

τοξός $n-1$: $r(0) - \frac{r^{BT}}{n-1} \cdot \frac{W^{B*}}{n-1} = P_{n-1}$

Επίσης (6.10) Haykin: $P_M = r(0) - \frac{r^H}{M} \frac{W}{f_{1,M}} = r(0) - \frac{r^T}{n} \frac{W^*}{f_{1,n}} =$
 $= r(0) - \frac{r^{TB}}{n} \cdot \frac{W^{B*}}{f_{1,n}}$

Ορίζω n σχέση (6) γίνονται

$$k_M \triangleq -W_{M,M} = \frac{-\Delta_{M-1}}{P_{M-1}} = \frac{-\sum_{l=0}^{M-1} \alpha_{M-1,l} r(l-M)}{P_{M-1}} = \frac{-E[b_{M-1}^{(n-1)} F_{M-1}^*]}{E[|F_{M-1}|^2]}$$

\Rightarrow $k_M = \frac{-\sum_{l=0}^{M-1} \alpha_{M-1,l} r(l-M)}{P_{M-1}}$ (10) [αναστροφική σχέση]

και από βολό Haykin: $P_M = r(0) - \frac{r^H}{M} \cdot \frac{W}{M} \stackrel{(4)}{\Rightarrow}$

$$P_M = r(0) - \frac{r^H}{M} \left(\begin{bmatrix} W_{M-1} \\ 0 \end{bmatrix} + k_M \begin{bmatrix} W_{M-1}^{B*} \\ -1 \end{bmatrix} \right) =$$

$$r(0) - \frac{r^H}{M-1} \frac{W}{M-1} - k_M \frac{r^H}{M-1} \frac{W^{B*}}{M-1} + k_M r(M) \Rightarrow$$

$\underbrace{r(0) - \frac{r^H}{M-1} \frac{W}{M-1}}_{P_{M-1}}$

$$P_M = P_{M-1} + k_M \left(r(M) - \frac{r^H}{M-1} \frac{W^{B*}}{M-1} \right) = P_{M-1} + k_M \left(r(M) - \frac{r^{BH*}}{M-1} \frac{W^*}{M-1} \right) =$$

$$P_{M-1} + k_M \left(r(M) - \frac{r^{BT}}{M-1} \frac{W}{M-1} \right)^* \Rightarrow P_M = P_{M-1} + k_M \Delta_{M-1} \stackrel{(10)}{\Rightarrow}$$

$\underbrace{\Delta_{M-1}}_{-k_M P_{M-1}}$

$$P_M = P_{M-1} + k_M (-k_M P_{M-1}) \Rightarrow P_M = P_{M-1} - |k_M|^2 P_{M-1} \Rightarrow$$

\Rightarrow $P_M = (1 - |k_M|^2) P_{M-1} = P_0 \prod_{l=1}^M (1 - |k_l|^2)$ (11)

αναστροφική σχέση

Όπως ο αλγόριθμος Levinson-Durbin (7)

- $P_0 = 1$

- $m = 1, 2, 3, 4, \dots, M$

$$k_m = a_{m,m} = \frac{-\Delta_{m-1}}{P_{m-1}} = -\frac{\sum_{l=0}^{m-1} a_{m-1,l} r^{(l-m)}}{P_{m-1}}$$

$$\left[\begin{aligned} \Delta_0 &= \sum_{l=0}^0 a_{0,0} r^{(0-1)} = \\ &= a_{0,0} r^{(-1)} = r^{(-1)} = r^* \end{aligned} \right]$$

- $k = 0, 1, 2, \dots, m-1$

$$a_{m,k} = a_{m-1,k} + k_m a_{m-1,m-k}^* \quad (a_{l,m} = 0 ; m > l)$$

end

↪ $\text{execu}(a)$

$$P_m = (1 - |k_m|^2) P_{m-1}$$

end