

# Derivation of Levinson-Durbin Algorithm :

- m-th order predictor:

$$\underline{R}_m \underline{a}_m = -\underline{r}_m = - \begin{bmatrix} r[1] \\ \vdots \\ r[m] \end{bmatrix} = - \begin{bmatrix} r_{m-1} \\ r[m] \end{bmatrix}$$

- for order m-1:

$$\underline{R}_{m-1} \underline{a}_{m-1} = -\underline{r}_{m-1}$$

$$\underline{R}_m = \begin{bmatrix} r[0] & \underline{r}_{m-1}^T \\ \underline{r}_{m-1} & \underline{R}_{m-1} \end{bmatrix}$$

$$\underline{a}_m = -\underline{R}_m^{-1} \underline{r}_m$$

$$\underline{a}_{m-1} = -\underline{R}_{m-1}^{-1} \underline{r}_{m-1}$$

## Partitioned matrix inversion lemma:

If  $A = \begin{bmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{bmatrix}$  then

$$A^{-1} = \begin{bmatrix} E^{-1} & | & -E^{-1}A_{12}A_{22}^{-1} \\ \hline -A_{22}^{-1}A_{21}E^{-1}; & | & A_{22}^{-1} + A_{22}^{-1}A_{21}E^{-1}A_{12}A_{22}^{-1} \end{bmatrix}$$

where:  $E = A_{11} - A_{12}A_{22}^{-1}A_{21}$

Here: partition  $R_m$  such that

$$A_{11} = r[0] \text{ so that } E \text{ is } 1 \times 1 \text{ scalar}$$

$$E^{-1} = 1/E$$

and  $A_{22} = R_{m-1}$

Examine  $E$ :

$$E = r[\bar{o}] - \underline{r}_{m-1}^T \underline{R}_{m-1}^{-1} \underline{r}_{m-1}$$

$$= r[\bar{o}] - \underline{r}_{m-1}^T (-\underline{a}_{m-1})$$

$$= r[\bar{o}] + \underline{r}_{m-1}^T \underline{a}_{m-1}$$

$$= r[\bar{o}] + \sum_{k=1}^{m-1} a_{m-1}(k) r_{xx}[k]$$

$$= \mathcal{E}_{m-1}^{\min}$$

$$E^{-1} = 1 / \mathcal{E}_{m-1}^{\min}$$

$(= r_{xx}^*[k])$   
for real-valued  
 $x[n]$

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$$\begin{aligned} \underline{R}_m^{-1} &= \frac{1}{\epsilon_{m-1}^{\min}} \begin{bmatrix} 1 & & & & \\ & 1 - \underline{r}_{m-1}^T \underline{R}_{m-1}^{-1} & & & \\ & & 1 - \underline{r}_{m-1}^T \underline{R}_{m-1}^{-1} & & \\ & & & \ddots & \\ & & & & 1 - \underline{r}_{m-1}^T \underline{R}_{m-1}^{-1} \end{bmatrix} \\ &= \frac{1}{\epsilon_{m-1}^{\min}} \begin{bmatrix} 1 & & & & \underline{g}_{m-1}^T \\ & \vdots & & & \underline{g}_{m-1}^T \\ & & 1 - \underline{g}_{m-1}^T \underline{R}_{m-1}^{-1} & & \\ & & & \ddots & \\ & & & & 1 - \underline{g}_{m-1}^T \underline{R}_{m-1}^{-1} \end{bmatrix} \end{aligned}$$

Recall reverse permutation matrix

$\tilde{I}^2$  satisfies  $\tilde{I}^2 \tilde{I} = I$

Also:  $\tilde{I} \underline{R} \tilde{I} = \underline{R}_m$  (for real-valued  $x[n]$ )

Trick: pre-multiply both sides of

$$\underline{q}_m = -\underline{R}_m^{-1} \underline{r}_m \text{ by } \tilde{\underline{I}} :$$

$$\tilde{\underline{I}} \underline{q}_m = -\tilde{\underline{I}} \underline{R}_m^{-1} \tilde{\underline{I}} \tilde{\underline{I}} \underline{r}_m$$

Since  $(ABC)^{-1} = C^{-1} B^{-1} A^{-1}$  and  $\tilde{H}^{-1} = \tilde{H}$

$$\underline{R}_m^{-1} = (\tilde{\underline{I}} \underline{R}_m \tilde{\underline{I}})^{-1} = \tilde{\underline{I}} \underline{R}_m^{-1} \tilde{\underline{I}} = \underline{R}_m^{-1}$$

$$\tilde{H} \tilde{\underline{I}} \underline{q}_m = \begin{bmatrix} \underline{q}_m(m) \\ \tilde{\underline{I}} \underline{q}_m(1:m-1) \end{bmatrix} = -\underline{R}_m^{-1} \begin{bmatrix} \underline{r}[m] \\ \tilde{H} \underline{r}_{m-1} \end{bmatrix}$$

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Substituting expression for  $\underline{R}_m^{-1}$ :

$$\begin{bmatrix} \underline{a}_m(m) \\ \underline{a}_{m-1}(1:m-1) \end{bmatrix} = \frac{-1}{\underline{\epsilon}_{m-1}^{\min}} \begin{bmatrix} r[m] + \underline{a}_{m-1}^T \tilde{I} \underline{r}_{m-1} \\ \dots \\ r[m] \underline{a}_{m-1} + (\underline{a}_{m-1}^T \tilde{I} \underline{r}_{m-1}) \underline{a}_{m-1} \\ \dots \\ + \underline{\epsilon}_{m-1}^{\min} \underline{R}_{m-1}^{-1} \tilde{I} \underline{r}_{m-1} \end{bmatrix}$$

Thus:  $\underline{a}_m(m) = \frac{-\{r[m] + \underline{a}_{m-1}^T \tilde{I} \underline{r}_{m-1}\}}{\underline{\epsilon}_{m-1}^{\min}}$

and:

$$\begin{aligned} \underline{a}_m(1:m-1) &= + \underline{a}_m(m) \tilde{I} \underline{a}_{m-1} - \tilde{I} \underline{R}_{m-1}^{-1} \tilde{I} \underline{r}_{m-1} \\ &= \underline{a}_m(m) \tilde{I} \underline{a}_{m-1} - \underline{a}_{m-1} \end{aligned}$$

• End of Derivation