




Digital Communications Adaptive Equalization



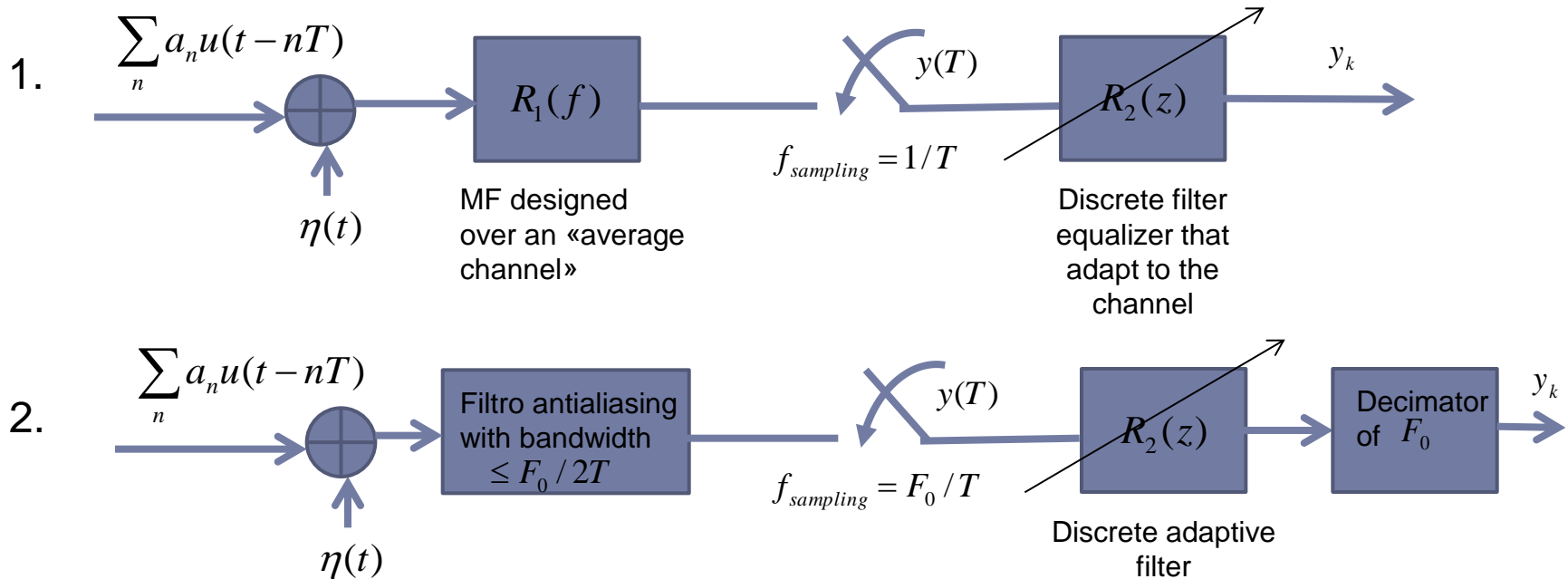
Dott.ssa Ernestina Cianca
a.a. 2016-2017

DIGITAL COMMUNICATION SYSTEM

Adaptive Equalization

When the channel is NOT know or it is time-varying, the receiver must estimate the channel and ADAPT its behavior to it.

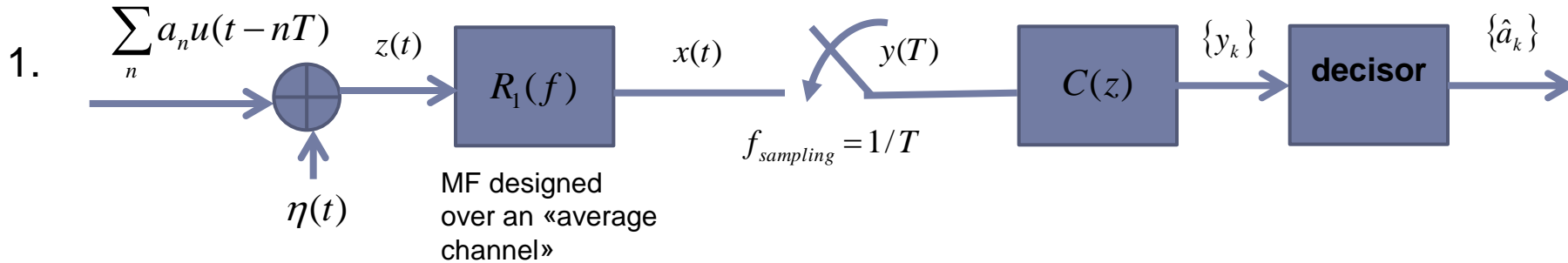
Two approaches:



DIGITAL COMMUNICATION SYSTEM

Adaptive Equalization

Let us consider the approach 1.



$$z(t) = \sum_i a_i u(t - iT) + \eta(t)$$

$$g(t) = u(t) * r_1(t)$$

$$x(t) = \sum_i a_i g(t - iT) + n(t)$$

$$n(t) = \eta(t) * r_1(t)$$

$$C(z) = \sum_{m=-\frac{N-1}{2}}^{\frac{N-1}{2}} c_m z^{-m}$$

Not causal for sake of simplicity → central tap c_0 with zero delay

$$C(e^{j2\pi fT}) = T \sum_{m=-\frac{N-1}{2}}^{\frac{N-1}{2}} c_m e^{-j2\pi f m T}$$

AFTER THE SAMPLER

$$x_k = \sum_i a_i g_{k-i} + n_k$$



$$X(z) = A(z)G(z) + N(z)$$

$$y_k = \sum_{m=-\frac{N-1}{2}}^{\frac{N-1}{2}} c_m x_{k-m}$$

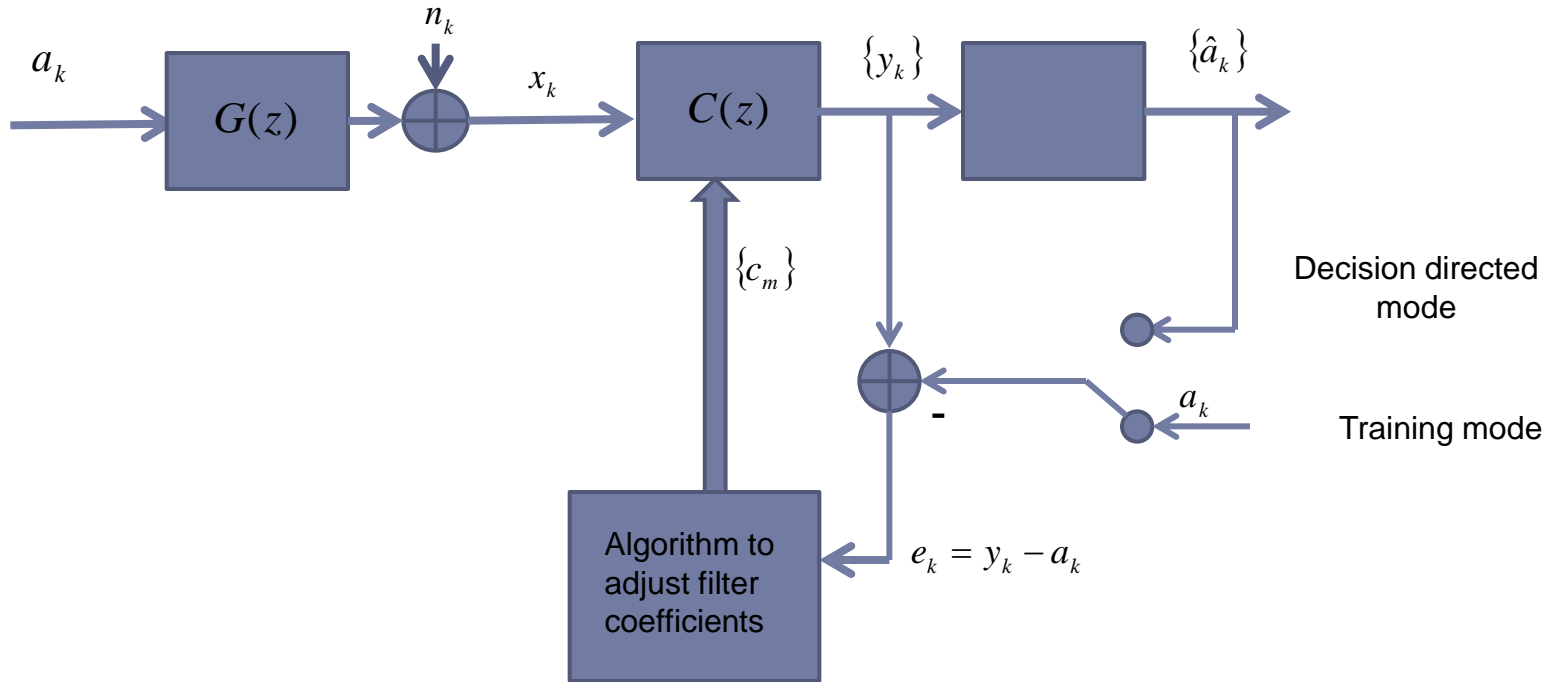


$$Y(z) = C(z)X(z)$$

DIGITAL COMMUNICATION SYSTEM

Adaptive Equalization

Discrete equivalent scheme of the receiver



1. Decision directed mode: $e_k = y_k - \hat{a}_k$
2. Training mode: $e_k = y_k - a_k$ in the training sequence, the transmitted symbols are known.

DIGITAL COMUNICATION SYSTEM

Adaptive Equalization: strategy

1. Choice of the performance metric J that depends from the coefficient $\{c_m\}$
e.g.: MSE criteria $J = E[|e_k|^2]$

2. Choice of the strategy to update the coefficient

e.g. steepest descendent method

$$\underline{c}^{k+1} = \underline{c}^k - \mu^k \frac{\partial}{\partial \underline{c}^k} J$$

It is not easy to calculate that gradient



It is possible to estimate the gradient from x_k and e_k



$$\underline{c}^{k+1} = \underline{c}^k - \mu^k \frac{\partial J}{\partial \underline{c}^k}$$



DIGITAL COMMUNICATION SYSTEM

MSE adaptive algorithm

$$J = E[|e_k|^2] = E[|y_k - a_k|^2] = E \left[\left| \sum_{j=-\frac{N-1}{2}}^{\frac{N-1}{2}} c_j x_{k-j} - a_k \right|^2 \right]$$

$$\boxed{\frac{\partial J}{\partial \underline{c}_l} = 0}$$



$$2E[(y_k - a_k)x_{k-l}^*] = 0$$



$$\sum_{j=-\frac{N-1}{2}}^{\frac{N-1}{2}} c_j E[x_{k-j}x_{k-l}^*] = E[a_k x_{k-l}^*]$$

$$R_x(l-j) \quad V(l)$$

$$\underline{R}_x = E[\underline{x}_k^* \underline{x}_k^T] = \begin{bmatrix} R_x(0) & R_x(-1) & \cdot & R_x(-(N-1)) \\ R_x(1) & R_x(0) & \cdot & \cdot \\ \cdot & \cdot & \cdot & R_x(-1) \\ R_x(N-1) & \cdot & R_x(1) & R_x(0) \end{bmatrix}$$

$$y_k = \underline{c} \underline{x}_k$$

$$\underline{c} = \begin{bmatrix} c_{\frac{N-1}{2}} \\ \cdot \\ c_0 \\ \cdot \\ c_{-\frac{N-1}{2}} \end{bmatrix} \quad \underline{x}_k = \begin{bmatrix} x_{k+\frac{N-1}{2}} \\ \cdot \\ x_k \\ \cdot \\ x_{k-\frac{N-1}{2}} \end{bmatrix}$$

Autocorrelation matrix of
the sampled PAM signal

$$\underline{V} = E[a_k \underline{x}_k^*]$$



DIGITAL COMMUNICATION SYSTEM

MSE adaptive algorithm

$$J = \underline{c}^{*T} \underline{R}_x \underline{c} - 2 \operatorname{Re}[\underline{c}^{*T} \underline{V}] + \alpha_0$$

Properties of the matrix \underline{R}_x

1) It is Hermitian: $\underline{R}_x^{*T} = \underline{R}_x \quad \longrightarrow \quad \begin{aligned} \operatorname{Re}[\underline{R}_x] &= \operatorname{Re}[\underline{R}_x^T] \\ \operatorname{Im}[\underline{R}_x] &= \operatorname{Im}[\underline{R}_x^T] \end{aligned}$

2) It is Toeplitz: all diagonal have the same element

3) It is semi-definite positive: $\underline{x}^{*T} \underline{R}_x \underline{x} \geq 0 \quad \forall \underline{x}$

$$\underline{c} = \underline{c}_{\operatorname{Re}} + j\underline{c}_{\operatorname{Im}} \quad \underline{V} = \underline{V}_{\operatorname{Re}} + j\underline{V}_{\operatorname{Im}} \quad \underline{R}_x = \underline{R}_{x\operatorname{Re}} + j\underline{R}_{x\operatorname{Im}}$$

Gradient with respect to a vector:

$$\nabla_{\underline{c}} = \nabla_{\underline{c}_{\operatorname{Re}}} + j\nabla_{\underline{c}_{\operatorname{Im}}}$$



DIGITAL COMMUNICATION SYSTEM

MSE adaptive algorithm

$$\nabla_{\underline{c}_{\text{Re}}} \underline{c}^{*T} \underline{R}_x \underline{c} = 2\underline{R}_{x_R} \underline{c}_{\text{Re}} - 2\underline{R}_{x_I} \underline{c}_I$$

$$\nabla_{\underline{c}_{\text{Re}}} \text{Re}[\underline{c}^{*T} \underline{V}] = V_{\text{Re}}$$

$$\nabla_{\underline{c}_I} \underline{c}^{*T} \underline{R}_x \underline{c} = 2\underline{R}_{x_R} \underline{c}_I + 2\underline{R}_{x_I} \underline{c}_{\text{Re}}$$

$$\nabla_{\underline{c}_I} \text{Re}[\underline{c}^{*T} \underline{V}] = V_I$$



$$\nabla_{\underline{c}} \underline{c}^{*T} \underline{R}_x \underline{c} = 2\underline{R}_x \underline{c}$$

$$\nabla_{\underline{c}} \text{Re}[\underline{c}^{*T} \underline{V}] = \underline{V}$$



$$\nabla_{\underline{c}} J = 2(\underline{R}_x \underline{c} - \underline{V})$$



$$\underline{c}_{opt} = \underline{R}_x^{-1} \underline{V}$$

$$J_{\min} = \alpha_0 - \underline{V}^{*T} \underline{c}_{opt}$$



DIGITAL COMMUNICATION SYSTEM

MSE adaptive algorithm

Orthogonality principle

when $\underline{c} = \underline{c}_{opt}$  $\underline{e}_k \perp \underline{x}_k$

$$E[\underline{e}_k \underline{x}_k^*] = E[\underline{x}_k^* (y_k - a_k)] = E[\underline{x}_k^* (\underline{x}_k^T \underline{c}_{opt} - a_k)] = \underline{R}_x \underline{c}_{opt} - \underline{V} = \underline{0}$$



DIGITAL COMUNICATION SYSTEM

MSE adaptive algorithm

Iterative algorithm: steepest descendent method

J has a minimum in \underline{c}

$$\underline{c}(n+1) = \underline{c}(n) - \mu \left(\frac{1}{2} \nabla_{\underline{c}(n)} J \right)$$

$$\nabla_{\underline{c}(n)} J = 2(\underline{R}_x \underline{c}(n) - \underline{V})$$

$$\underline{c}(n+1) = \underline{c}(n) + \mu(\underline{V} - \underline{R}_x \underline{c}(n)) = (\underline{I} - \mu \underline{R}_x) \underline{c}(n) + \mu \underline{V}$$

Let us define $\underline{q}(n) = \underline{c}(n) - \underline{c}_{opt}$



$$\underline{q}(n+1) = (\underline{I} - \mu \underline{R}_x) \underline{q}(n) = (\underline{I} - \mu \underline{R}_x)^n \underline{q}(0)$$



DIGITAL COMUNICATION SYSTEM

MSE adaptive algorithm

Iterative algorithm: Least Mean Square (or stochastic gradient)

In many cases of interest, it is not possible to know the autocorrelation matrix R_x and the previous method is not applicable

In the LMS algorithm, the statistic average is replaced by the time average



$$\begin{aligned}\min_{\underline{c}} |e_k|^2 &= |y_k - a_k|^2 = |\underline{c}^T \underline{x}_k - a_k|^2 = \\ &= \underline{c}^{*T} \underline{x}_k^* \underline{x}_k^T \underline{c} - 2 \operatorname{Re}[a_k \underline{c}^{*T} \underline{x}_k^*] + |a_k|^2\end{aligned}$$



$$\nabla_{\underline{c}} |e_k|^2 = 2e_k \underline{x}_k^*$$



DIGITAL COMUNICATION SYSTEM
MSE adaptive algorithm
Iterative algorithm: Least Mean Square (or
stocastic gradient)

$$\underline{c}_{k+1} = \underline{c}_k - \mu \left(\frac{1}{2} \nabla_{\underline{c}_k} |e_k|^2 \right)$$



$$\underline{c}_{k+1} = \underline{c}_k - \mu e_k x_k^*$$



$$\underline{c}_{k+1}(j) = \underline{c}_k(j) - \mu e_k x_{k-j}^* \quad -\frac{N-1}{2} \leq j \leq \frac{N-1}{2}$$

In the previous method, the index was the index of the iteration to solve a system of linear equations. Now, the index is the TIME, it is the number of the sample in input to the filter. Each iteration is a new sample in input. The algorithm work on the temporal average to estimate the gradient.

