

NON-DATA-AIDED DIGITAL SYNCHRONIZATION

Unconditional (or Stochastic) ML (UML)

Conditional (or Deterministic) ML (CML)

Minimum Conditioned Variance Compressed
Maximum Likelihood (MCV-CML)

SIGNAL MODEL

$$r(t) = \sum_{n=-\infty}^{+\infty} c_n g(t - nT - \tau) e^{j(\theta_o + \omega t)} + w(t)$$

$$r(kT_s) = \sum_{n=-\infty}^{+\infty} c_n g(kT_s - nT - \tau) e^{j(\theta_o + \omega kT_s)} + w(kT_s)$$

$\Theta = [\tau, \nu]^T$ Signal parameters of interest to be estimated



$$\nu = \frac{\omega}{2\pi} T \quad \text{Normalized frequency error}$$

Nuisance parameters: carrier phase error and the transmitted symbols

Nss samples per symbol

Observation interval $2M+1$ samples

If a single pulse is transmitted, the $2M+1$ samples of the pulse are:

$$\mathbf{a}_n(\Theta) = e^{-j\frac{2\pi}{N_{ss}}n_0v} \begin{bmatrix} g(-nT - MT_s - \tau) e^{-j\frac{2\pi}{N_{ss}}Mv} \\ g(-nT - (M-1)T_s - \tau) e^{-j\frac{2\pi}{N_{ss}}(M-1)v} \\ \mathbf{M} \\ g(-nT + (M-1)T_s - \tau) e^{j\frac{2\pi}{N_{ss}}(M-1)v} \\ g(-nT + MT_s - \tau) e^{j\frac{2\pi}{N_{ss}}Mv} \end{bmatrix}$$

n_0 constant that reflects the time origin

TDMA (Time Division Multiple Access) : the transmitter sends a burst of $2k+1$ symbols.

SCPC (Single Carrier Per Channel): the received data vector \mathbf{r} will be affected by all the transmitted symbols, but, for a given pulse shape, only $2K+1$ symbols will effectively be involved in the $2M+1$ samples of the observation interval.

$$\mathbf{r} = \mathbf{A}(\Theta)\mathbf{x} + \mathbf{w}$$

$$\mathbf{A}(\Theta) = [\mathbf{a}_{-K}(\Theta) \quad \mathbf{a}_{-K+1}(\Theta) \quad \text{L} \quad \mathbf{a}_{K-1}(\Theta) \quad \mathbf{a}_K(\Theta)]$$

$$\mathbf{x} = [x_{-K} \quad x_{-K+1} \quad \text{L} \quad x_{K-1} \quad x_K]^T$$

$$x_n = c_n e^{j\theta_0} \quad n = -K, \dots, K$$

THE LINEAR SIGNAL MODEL INCLUDES:

- LINEAR MODULATIONS (*ASK, PSK, APK, QAM*).
- SPREAD SPECTRUM MODULATIONS (*DS-CDMA*):
 - The pulse shape $g(t)$ is the user signature, which includes the PN spreading sequence and the chip pulse.
- MULTI-CARRIER MODULATIONS (*OFDM*):
 - The signal model includes an arbitrary number of superimposed signals.
 - The shape pulses are complex.

$$x(t) = \sum_l \sum_{m=0}^{J-1} c_l^m \psi_m(t - lT) \quad \longleftarrow \quad \int_0^T \psi_k(t) \psi_i^*(t) dt = \delta_{ik}$$

NON-LINEAR MODULATIONS

- CONTINUOUS PHASE (Binary CPM): constant envelope and spectral efficiency.

$$r(t) = \sqrt{\frac{2E_s}{T}} e^{j\Phi(t;\alpha)} + w(t)$$

$$\Phi(t;\alpha) = 2\pi h \sum_n \alpha_n \int_{-\infty}^t q(t-nT) dt = \sum_n \alpha_n p(t-nT)$$

\downarrow
 $q(t) \neq 0 \text{ for } 0 \leq t \leq LT$
 $q(t) = q(LT-t)$

- LAURENT EXPANSION:

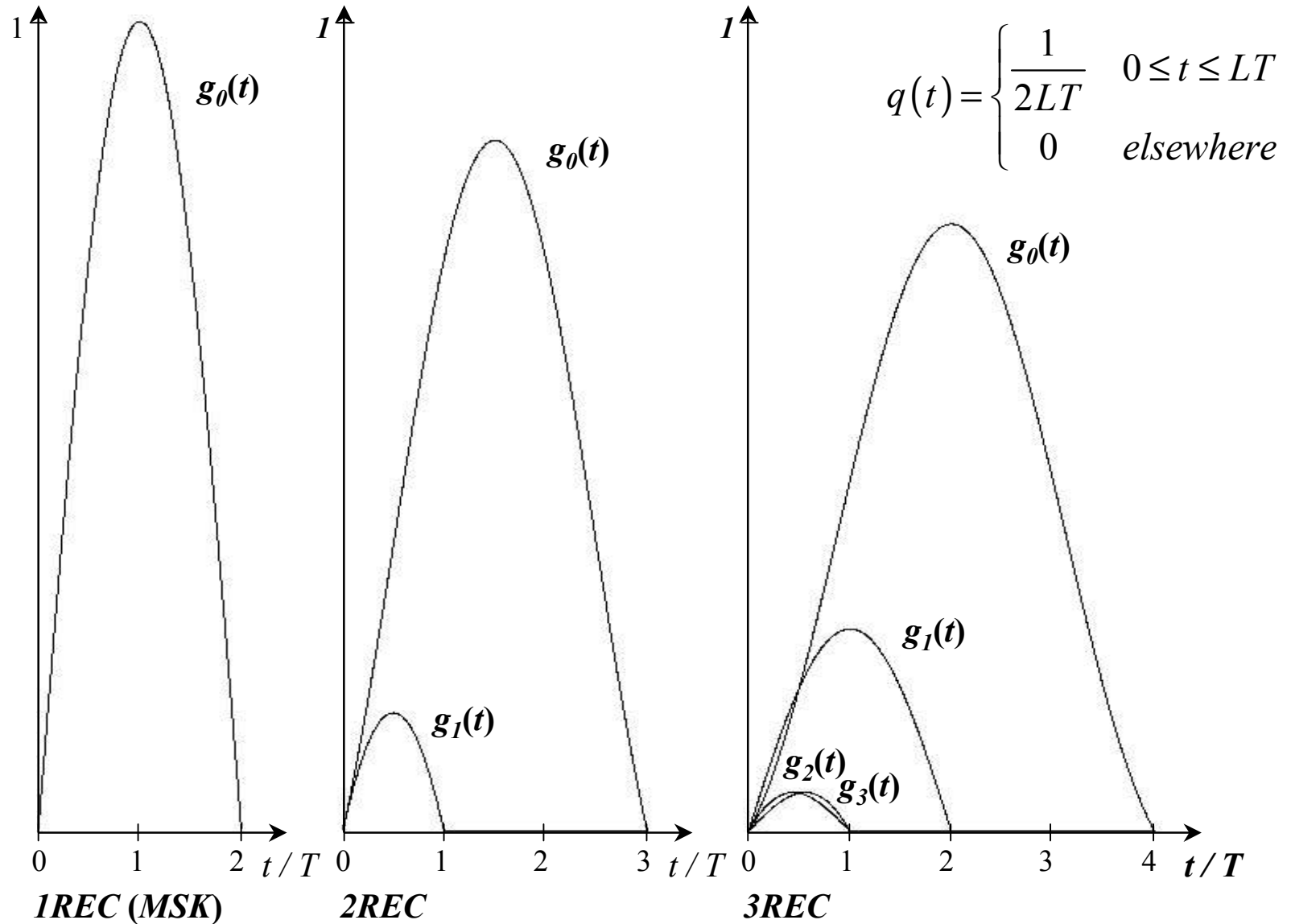
$$r(t) = \sum_{n=-\infty}^{+\infty} \sum_{m=0}^{J-1} c_{m,n} g_m(t-nT-\tau) e^{j(\theta_0 + \omega t)} + w(t) \quad J = 2^{L-1}$$

$$r(kT_s) = \sum_{n=-\infty}^{+\infty} \sum_{m=0}^{J-1} c_{m,n} g_m(kT_s - nT - \tau) e^{j(\theta_0 + \omega kT_s)} + w(kT_s)$$

Uncorrelated Pseudosymbols: $E[c_{m,n} c_{m',n'}^*] = \delta_{m,m'} \delta_{n,n'}$

Asynchronous DS-CDMA $\{\tau_i\}_{0 \leq i \leq J-1}$

Pulses in LREC binary CPM modulations

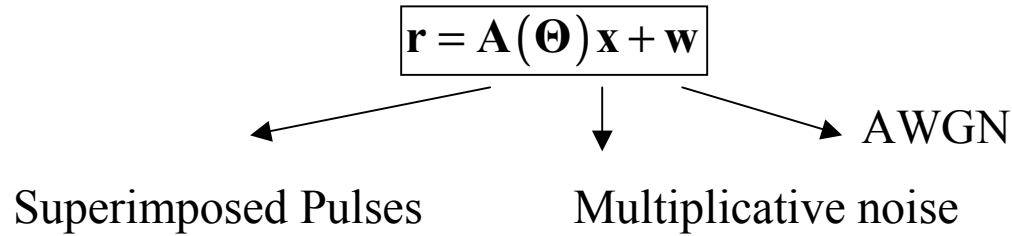


If a single pulse is transmitted, the $2M+1$ samples of the pulse are:

$$\mathbf{a}_{m,n}(\Theta) = e^{-j\frac{2\pi}{N_{ss}}n_0v} \begin{bmatrix} g_m(-nT - MT_s - \tau) e^{-j\frac{2\pi}{N_{ss}}Mv} \\ g_m(-nT - (M-1)T_s - \tau) e^{-j\frac{2\pi}{N_{ss}}(M-1)v} \\ \mathbf{M} \\ g_m(-nT + (M-1)T_s - \tau) e^{j\frac{2\pi}{N_{ss}}(M-1)v} \\ g_m(-nT + MT_s - \tau) e^{j\frac{2\pi}{N_{ss}}Mv} \end{bmatrix}$$

$$m = 0, 1, \dots, J-1 \quad n = -K, \dots, K$$

n_0 constant that reflects the time origin



$$\mathbf{A}(\Theta) = [\mathbf{A}_0(\Theta) \quad \mathbf{A}_1(\Theta) \quad \text{L} \quad \mathbf{A}_{J-1}(\Theta)]$$

$$\mathbf{A}_m(\Theta) = [\mathbf{a}_{m,-K}(\Theta) \quad \mathbf{a}_{m,-K+1}(\Theta) \quad \text{L} \quad \mathbf{a}_{m,K-1}(\Theta) \quad \mathbf{a}_{m,K}(\Theta)]$$

$$\mathbf{x} = [\mathbf{x}_0^T \quad \mathbf{x}_1^T \quad \text{L} \quad \mathbf{x}_{J-1}^T]^T$$

$$\mathbf{x}_m = [x_{m,-K} \quad x_{m,-K+1} \quad \text{L} \quad x_{m,K-1} \quad x_{m,K}]^T$$

$$x_{m,n} = c_{m,n} e^{j\theta_0}$$

$$n = -K, \dots, K \quad m = 0, 1, \dots, J-1$$

UNCONDITIONAL ML (UML)

$$\Lambda(\mathbf{r} / \Theta, \mathbf{x}) = C \exp\left(-\frac{1}{\sigma^2} q(\mathbf{r} / \Theta, \mathbf{x})\right)$$

$$q(\mathbf{r} / \Theta, \mathbf{x}) = \|\mathbf{r} - \mathbf{A}(\Theta)\mathbf{x}\|^2$$

The nuisance parameters in \mathbf{x} are considered random.

Marginal Likelihood function of the wanted parameters: $\Lambda(\mathbf{r} / \Theta) = E_{\mathbf{x}} [\Lambda(\mathbf{r} / \Theta, \mathbf{x})]$

Low SNR:
$$\Lambda(\mathbf{r} / \Theta, \mathbf{x}) \cong C - \frac{1}{\sigma^2} q(\mathbf{r} / \Theta, \mathbf{x}) + \frac{1}{2\sigma^4} q^2(\mathbf{r} / \Theta, \mathbf{x})$$

$$\Lambda(\mathbf{r} / \Theta, \mathbf{x}) \cong C - \frac{1}{\sigma^2} \left(2 \operatorname{Re}[\mathbf{x}^H \mathbf{A}^H \mathbf{r}] - \mathbf{x}^H \mathbf{A}^H \mathbf{A} \mathbf{x}\right) + \frac{1}{2\sigma^4} \left(2 \operatorname{Re}[\mathbf{x}^H \mathbf{A}^H \mathbf{r}] - \mathbf{x}^H \mathbf{A}^H \mathbf{A} \mathbf{x}\right)^2$$

$\mathbf{A}^H \mathbf{A}$ does not depend on the parameters

$$\Lambda(\mathbf{r} / \Theta, \mathbf{x}) \cong C - \frac{2}{\sigma^2} \operatorname{Re}[\mathbf{x}^H \mathbf{A}^H \mathbf{r}] + \frac{2}{\sigma^4} \operatorname{Re}^2[\mathbf{x}^H \mathbf{A}^H \mathbf{r}]$$

$$\Lambda(\mathbf{r} / \Theta) \cong C + \frac{1}{\sigma^4} \mathbf{r}^H \mathbf{A} \Gamma \mathbf{A}^H \mathbf{r}$$

$$\Gamma = E[\mathbf{x} \mathbf{x}^H]$$

$$L_{UML}(\mathbf{r} / \Theta) = \ln(\Lambda(\mathbf{r} / \Theta)) \approx \mathbf{r}^H \mathbf{A} \Gamma \mathbf{A}^H \mathbf{r} = \left\| \Gamma^{1/2} \underbrace{\mathbf{A}^H \mathbf{r}} \right\|^2$$

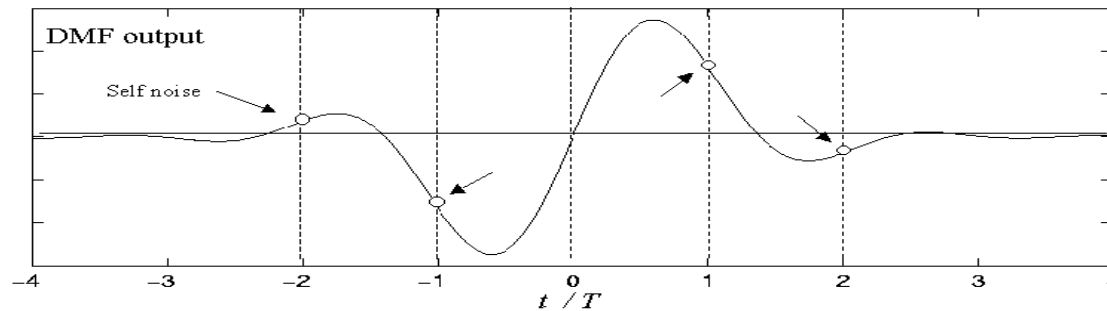
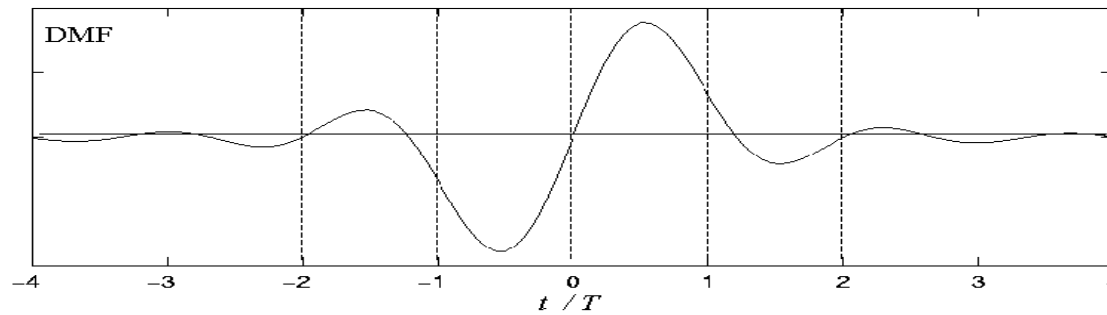
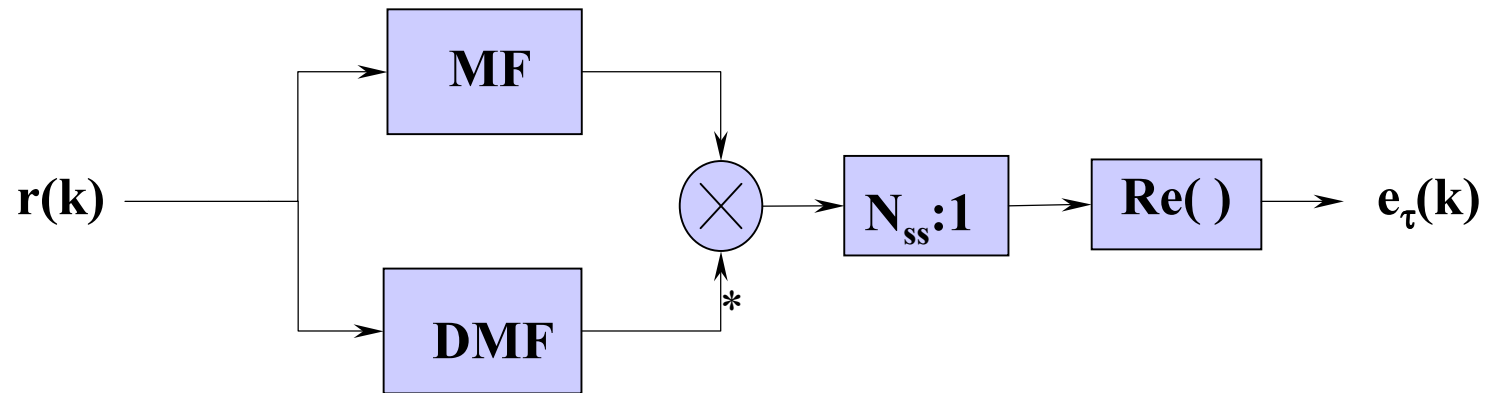
Matched filter
output

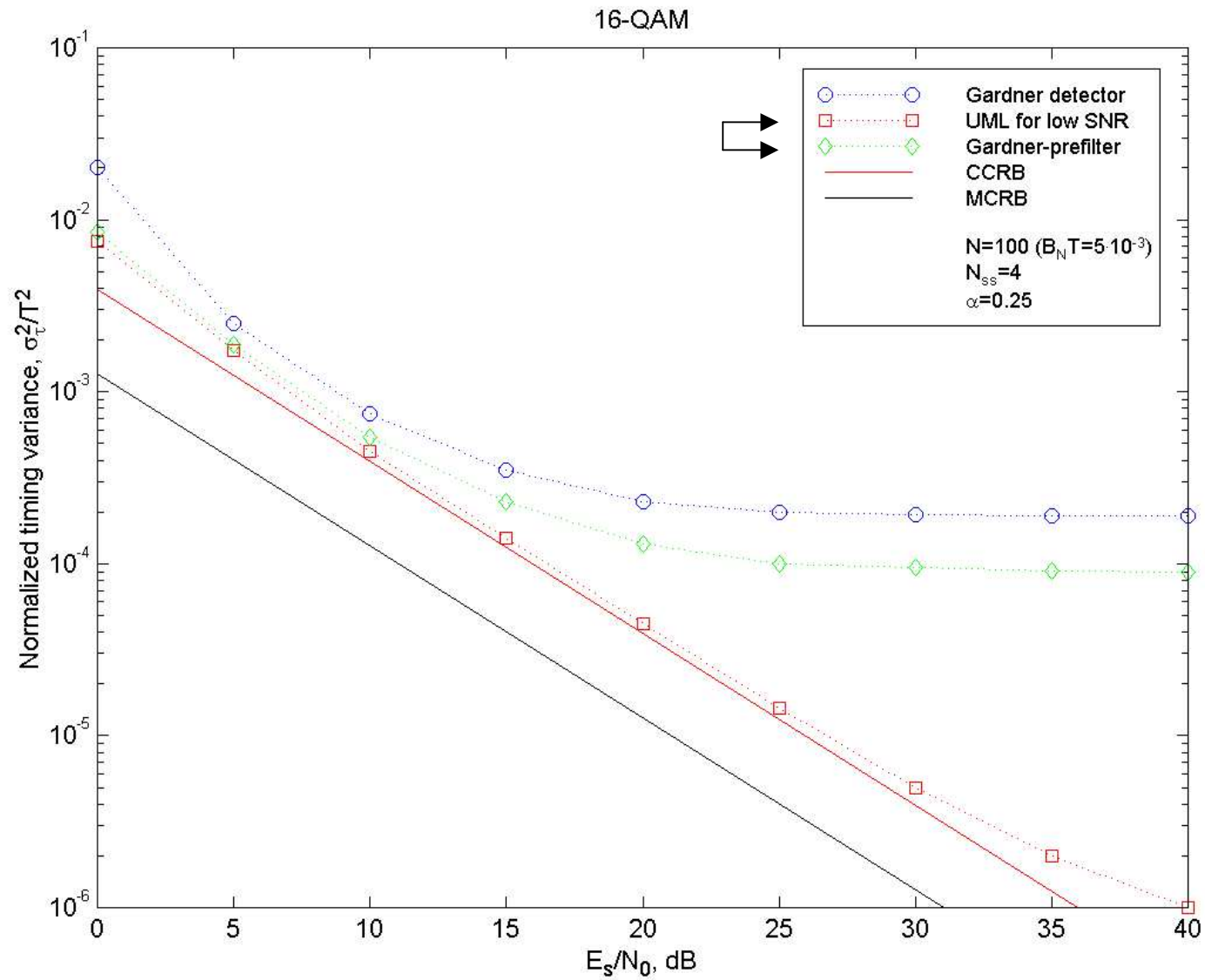
$$\frac{\partial}{\partial \Theta} L_{UML}(\mathbf{r} / \Theta) = \text{Re} \left[\mathbf{r}^H \mathbf{D} \Gamma \underbrace{\mathbf{A}^H \mathbf{r}} \right]$$

Matched filter output

$$\mathbf{D}(\Theta) = \frac{\partial}{\partial \Theta} \mathbf{A}(\Theta)$$

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CONDITIONAL ML (CML)

The nuisance parameters in \mathbf{x} are unknown deterministic variables.

$$\mathbf{r} = \mathbf{A}(\Theta)\mathbf{x} + \mathbf{w}$$

$$\hat{\mathbf{x}} = \mathbf{A}^\#(\Theta)\mathbf{r} = \mathbf{x} + \mathbf{A}^\#(\Theta)\mathbf{w} \quad \begin{array}{l} \text{ZERO FORCER} \\ \text{EQUALIZER} \end{array}$$

$$\mathbf{A}^\# = (\mathbf{A}^H \mathbf{A})^{-1} \mathbf{A}^H \longrightarrow \text{Symbol decorrelating matrix}$$

$$L_{CML}(\mathbf{r} / \Theta) = \ln(\Lambda(\mathbf{r} / \Theta, \hat{\mathbf{x}})) = \mathbf{r}^H \mathbf{A} \mathbf{A}^\# \mathbf{r}$$

$$\hat{\Theta}_{CML} \rightarrow \max_{\Theta} \mathbf{r}^H \mathbf{A} \mathbf{A}^\# \mathbf{r} \longrightarrow \text{Insensitive to the symbol autocorrelation matrix}$$

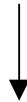
$$\hat{\Theta}_{CML} \rightarrow \min_{\Theta} \text{Tr}[\mathbf{P}_A^\perp \mathbf{r} \mathbf{r}^H]$$

$$\mathbf{P}_A^\perp = \mathbf{I} - \mathbf{A} \mathbf{A}^\# \longrightarrow \text{Projection matrix onto the orthogonal signal subspace}$$

$$\frac{\partial}{\partial \Theta} L_{CML}(\mathbf{r} / \Theta) = \text{Re} \left[\underbrace{\mathbf{r}^H \mathbf{P}_A^\perp \mathbf{D}}_{\text{Orthogonal Derivative Matched Filter (ODMF) output}} \underbrace{\mathbf{A}^\# \mathbf{r}}_{\text{Decorrelation of the symbols}} \right]$$

Orthogonal Derivative Matched Filter (ODMF) output

Decorrelation of the symbols



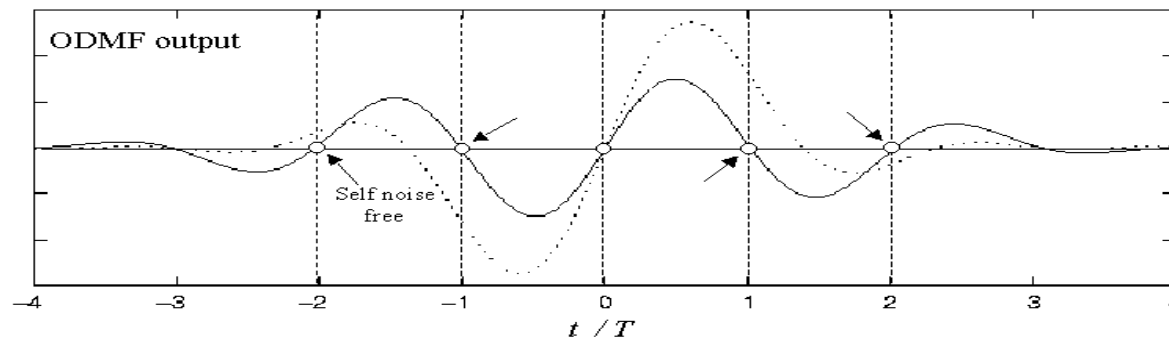
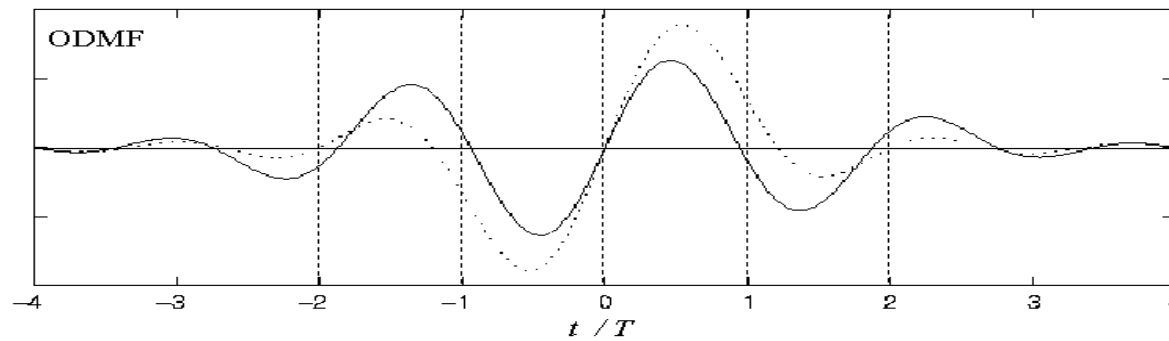
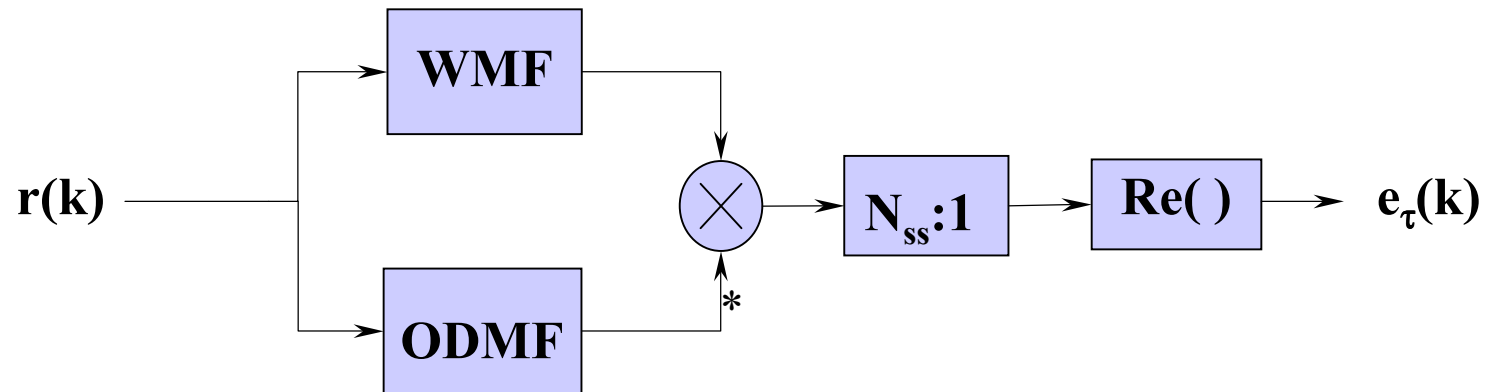
No self-noise

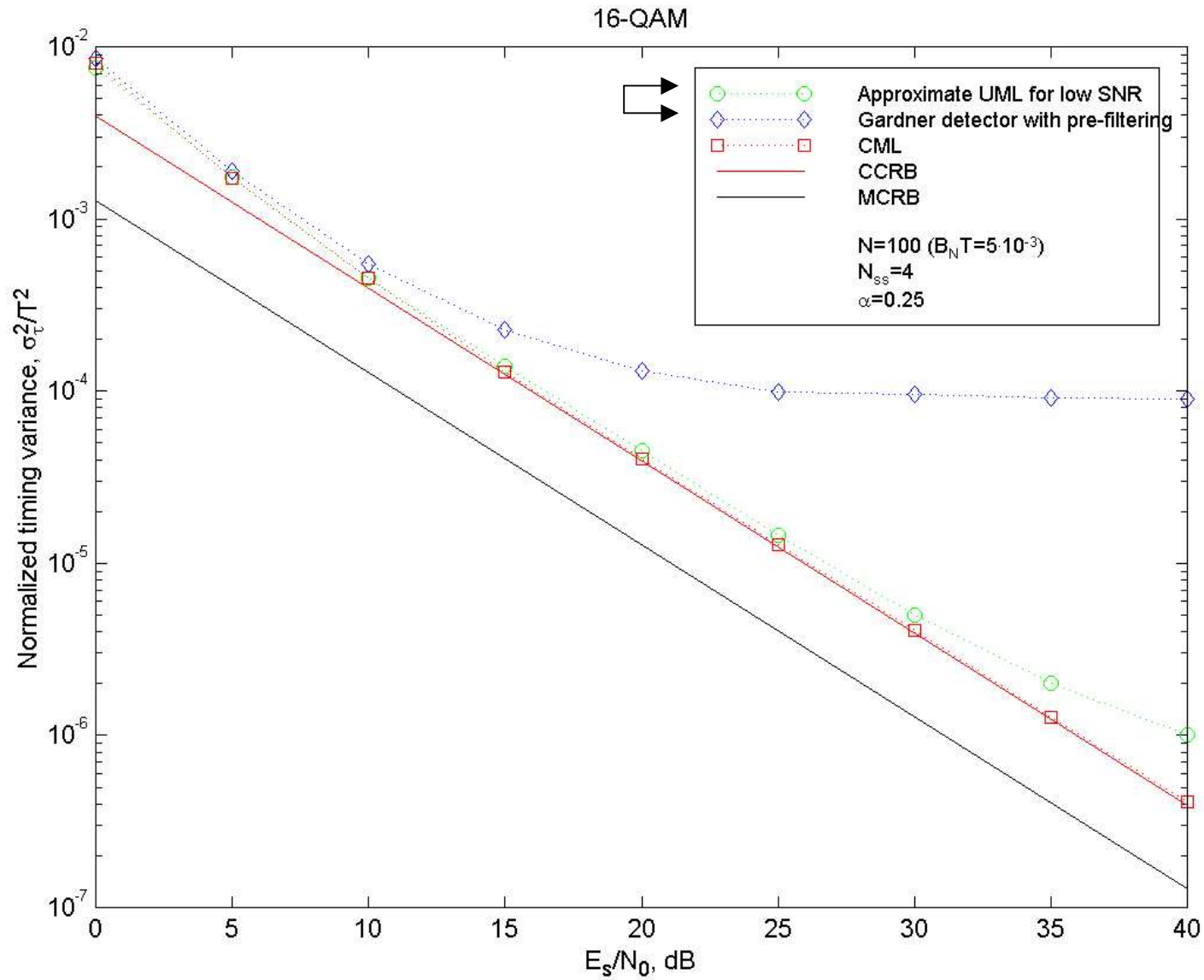
Increase of the noise

in the noiseless case:

$$\mathbf{r}^H \mathbf{P}_A^\perp \mathbf{D} \Big|_{\hat{\tau}=\tau, \hat{\nu}=\nu} = 0$$

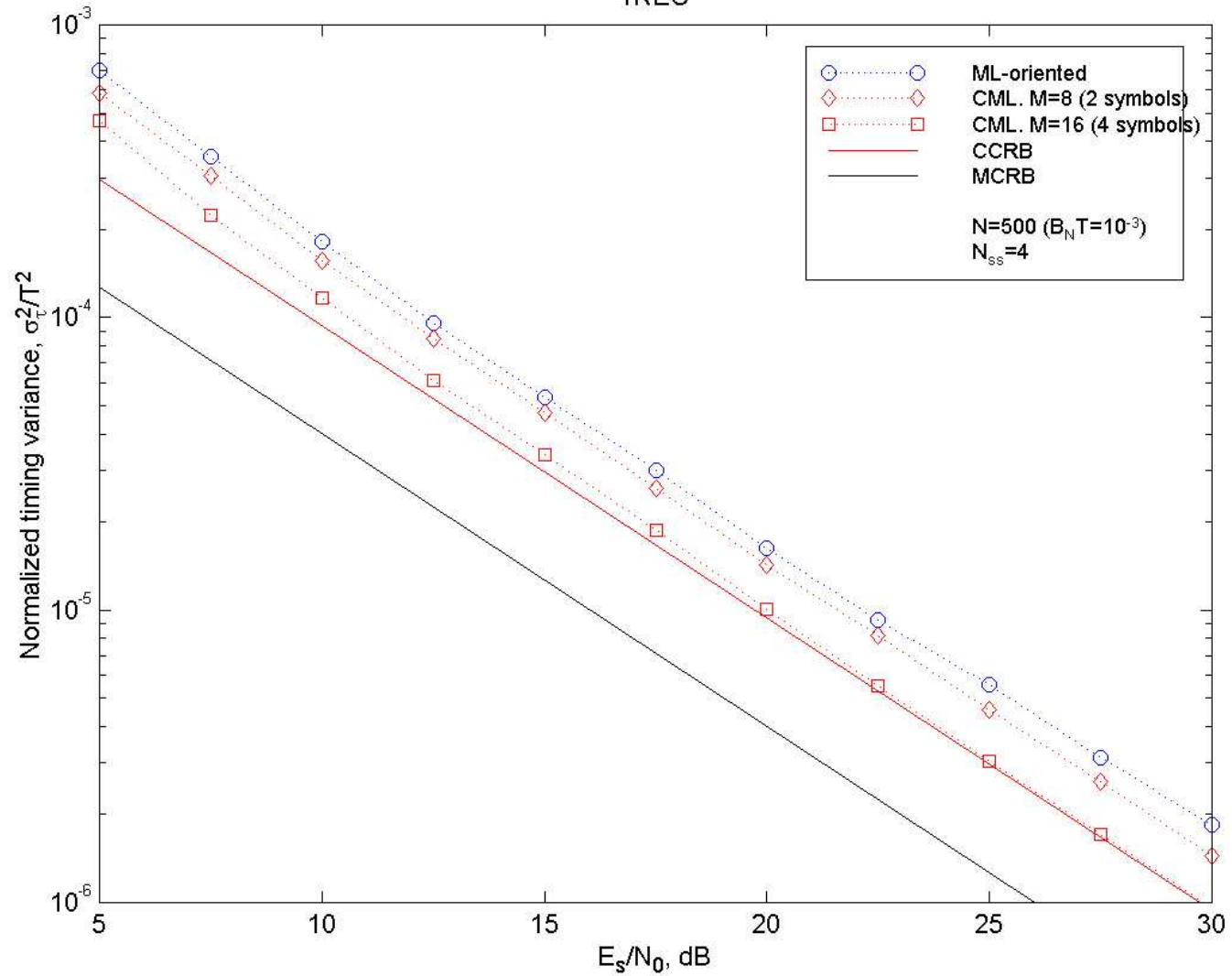
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MSK (1REC)

1REC



MINIMUM CONDITIONED VARIANCE COMPRESSED MAXIMUM LIKELIHOOD (MCV-CML)

The wanted parameter vector is defined such that the received data vector is best fitted, under a minimum square-error sense, to the regenerated data from the best linear estimate of the nuisance parameter vector:

$$\hat{\mathbf{x}} = E[\mathbf{x}/\mathbf{r}] = \mathbf{A}^H (\mathbf{A}\mathbf{A}^H + \sigma^2\mathbf{I})^{-1} \mathbf{r} = \mathbf{C}\mathbf{r}$$

$$L_{MCV}(\mathbf{r}/\Theta) = \|\mathbf{r} - \mathbf{A}\hat{\mathbf{x}}\|^2 = \|\mathbf{r} - \mathbf{A}\mathbf{C}\mathbf{r}\|^2 = \|(\mathbf{I} - \mathbf{A}\mathbf{C})\mathbf{r}\|^2$$

$$\frac{\partial}{\partial \Theta} L_{MCV}(\mathbf{r}/\Theta) = -2 \operatorname{Re} \left[\mathbf{r}^H (\mathbf{I} - \mathbf{A}\mathbf{C}) \left(\mathbf{D}\mathbf{C} + \mathbf{A} \frac{\partial}{\partial \Theta} \mathbf{C} \right) \mathbf{r} \right]$$

$$(\mathbf{I} - \mathbf{A}\mathbf{C})\mathbf{D}\mathbf{C} + (\mathbf{I} - \mathbf{A}\mathbf{C})\mathbf{A} \frac{\partial}{\partial \Theta} \mathbf{C}$$

Low SNR: \mathbf{C} corresponds to the matched filter of the transmitted pulses: $\mathbf{C} = \sigma^{-2} \mathbf{A}^H$

$$(\mathbf{I} - \mathbf{A}\mathbf{C})\mathbf{D}\mathbf{C} + (\mathbf{I} - \mathbf{A}\mathbf{C})\mathbf{A} \frac{\partial}{\partial \Theta} \mathbf{C} \cong \sigma^{-2} (\mathbf{D}\mathbf{A}^H + \mathbf{A}\mathbf{D}^H)$$

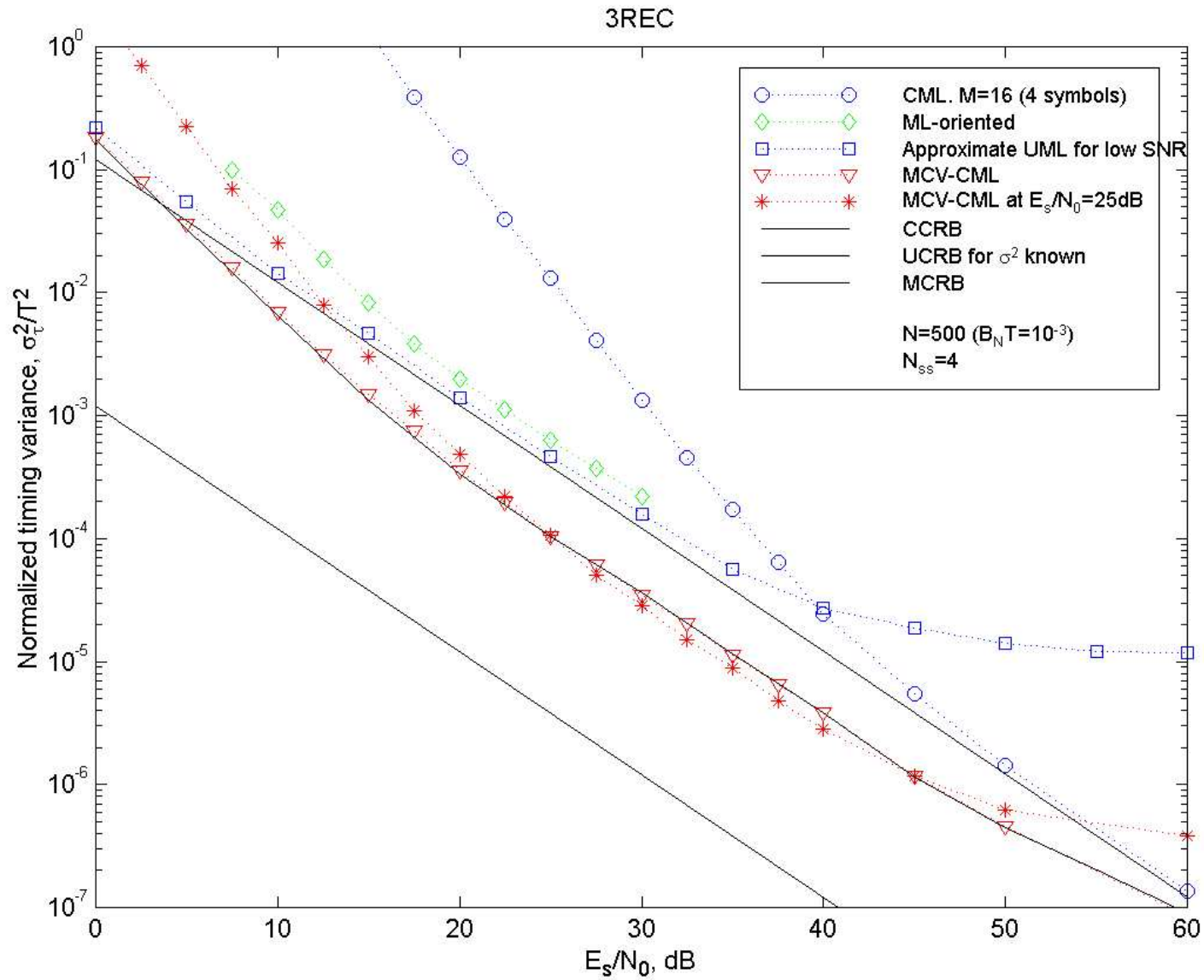
$$\frac{\partial}{\partial \Theta} L_{MCV}(\mathbf{r}/\Theta) = -\frac{2}{\sigma^2} \text{Re}[\mathbf{r}^H [(\mathbf{D}\mathbf{A}^H + \mathbf{A}\mathbf{D}^H)] \mathbf{r}] = -\frac{4}{\sigma^2} \text{Re}[\mathbf{r}^H \mathbf{D}\mathbf{A}^H \mathbf{r}] \rightarrow \text{Low-SNR UML}$$

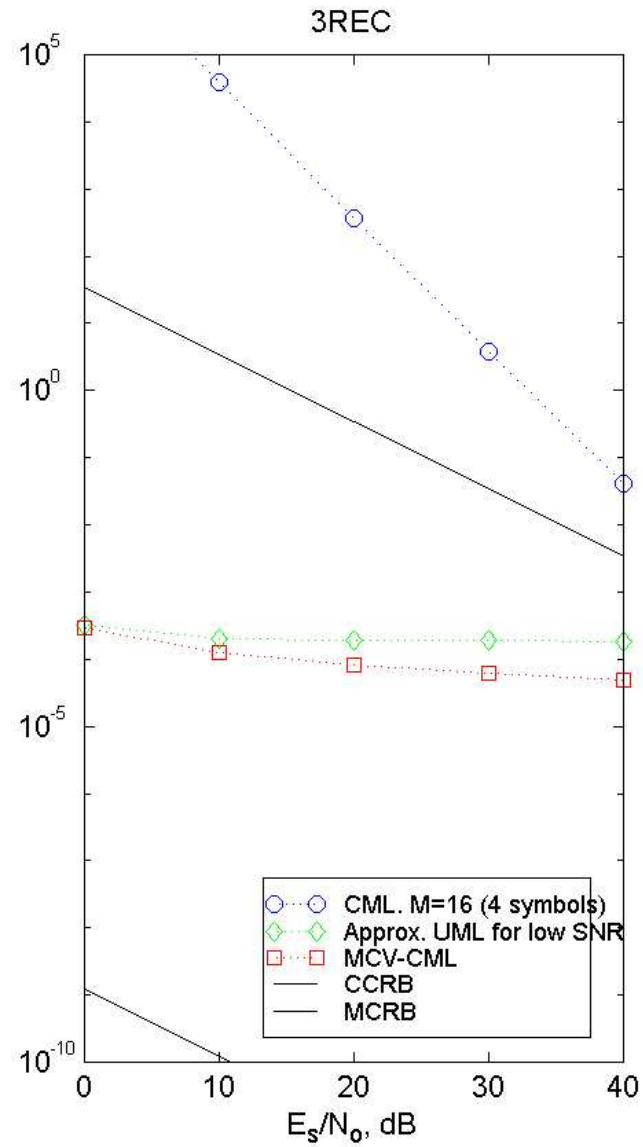
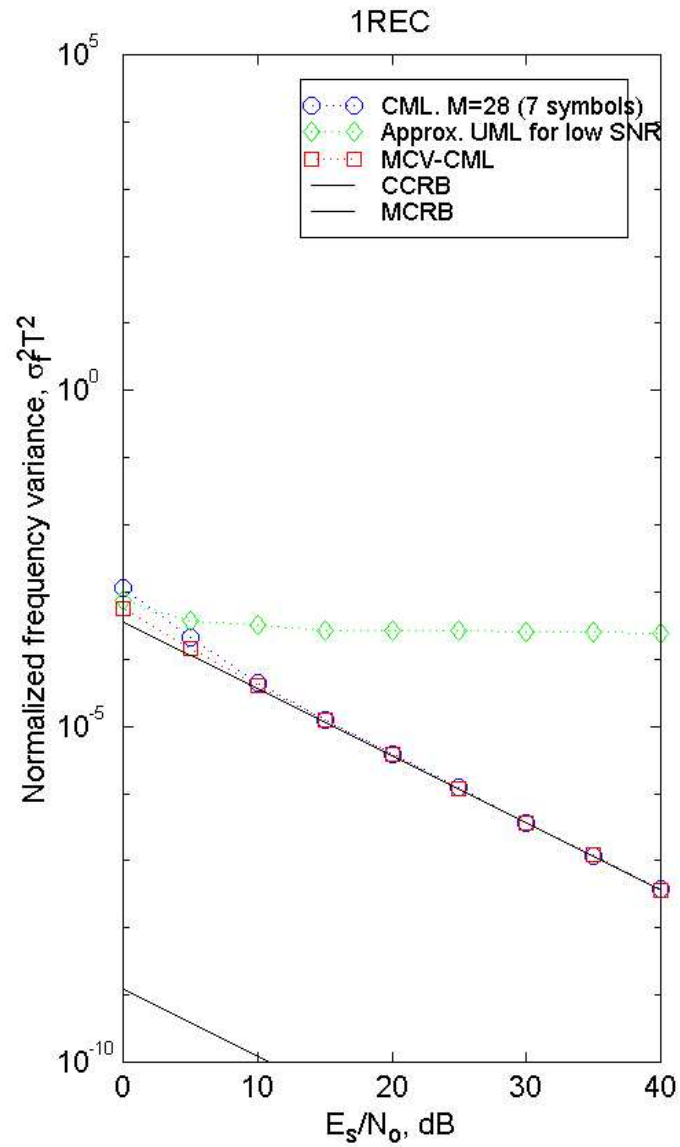
High SNR: \mathbf{C} pseudo-inverse of \mathbf{A} : $\mathbf{C} = \mathbf{A}^\#$

$$(\mathbf{I} - \mathbf{A}\mathbf{C})\mathbf{A} \frac{\partial}{\partial \Theta} \mathbf{C} \cong (\mathbf{I} - \mathbf{A}\mathbf{A}^\#) \mathbf{A} \frac{\partial}{\partial \Theta} \mathbf{A}^\# = \mathbf{P}_A^\perp \mathbf{A} \frac{\partial}{\partial \Theta} \mathbf{A}^\# \equiv 0$$

$$\frac{\partial}{\partial \Theta} L_{MCV}(\mathbf{r}/\Theta) = -2 \text{Re}[\mathbf{r}^H \mathbf{P}_A^\perp \mathbf{D} \mathbf{A}^\# \mathbf{r}] \longrightarrow \text{CML}$$

$$\boxed{\frac{\partial}{\partial \Theta} L_{MCV}(\mathbf{r}/\Theta) \approx \text{Re}[\mathbf{r}^H (\mathbf{I} - \mathbf{A}\mathbf{C}) \mathbf{D} \mathbf{C}^H \mathbf{r}]}$$





PERFORMANCE LIMITS

$$CRB(\lambda) = \frac{1}{E_{\mathbf{r}} \left\{ \left| \frac{\partial}{\partial \lambda} \ln E_{\mathbf{x}} \Lambda(\mathbf{r} / \Theta, \mathbf{x}) \right|^2 \right\}}$$

$$MCRB(\lambda) = \frac{1}{E_{\mathbf{r}, \mathbf{x}} \left\{ \left| \frac{\partial}{\partial \lambda} \ln \Lambda(\mathbf{r} / \Theta, \mathbf{x}) \right|^2 \right\}} = \frac{\sigma^2}{2Tr(\mathbf{D}_{\lambda}^H \mathbf{D}_{\lambda} \Gamma)}$$

$$CCRB(\lambda) = \frac{1}{E_{\mathbf{r}} \left\{ \left| \frac{\partial}{\partial \lambda} \ln \Lambda(\mathbf{r} / \Theta, \hat{\mathbf{x}}) \right|^2 \right\}} = \frac{\sigma^2}{2\mathbf{x}^H \mathbf{D}_{\lambda}^H \mathbf{P}_{\Lambda}^{\perp} \mathbf{D}_{\lambda} \mathbf{x}}$$