



- ✓ Motivation and Signal Model
- Semi-blind Channel Estimation for MC-CDMA
- ✓ (Asymptotic) analytical characterization
- Conclusions



Motivation and Signal model

 The received signal in a MC-CDMA system with codemultiplexed training pilots over N existing carriers can be expressed as:



Motivation and Signal model

 Schematic representation of a MC-CDMA system with codemultiplexed training pilots and multicode capabilities:



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Semi-blind CE for MC-CDMA (I)

- \checkmark The unknown symbols are modeled as deterministic parameters and are then taken into account in the channel estimation procedure.
- ✓ The ML estimators for both data and channel impulse response can be obtained by minimizing the following negative log-likelihood function:

$$N \ln \left(\boldsymbol{\pi} \sigma^2 \right) + \frac{1}{\sigma^2} \left\| \mathbf{y} - \mathbf{\Lambda} \mathbf{G}^H \mathbf{h} \right\|_2^2$$

 \checkmark In particular, the channel estimate can be obtained as

$$\mathbf{\hat{h}} = \left(\mathbf{G} \mathbf{\hat{\Lambda}}^{H} \mathbf{\hat{\Lambda}} \mathbf{G}^{H} \right)^{-1} \mathbf{G} \mathbf{\hat{\Lambda}}^{H} \mathbf{y}$$

that introduced into the previous likelihood function gives us a new cost function with a reduced parameter space

with
$$\mathbf{P}_{\mathbf{\Omega}} = \mathbf{\hat{\Lambda}}\mathbf{G}^{H} \left(\mathbf{G}\mathbf{\hat{\Lambda}}^{H}\mathbf{\hat{\Lambda}}\mathbf{G}^{H}\right)^{-1} \mathbf{G}\mathbf{\hat{\Lambda}}^{H}$$



Semi-blind CE for MC-CDMA(II)

✓ The semi-blind CML parameter estimates are then obtained from the following optimization problem

$$\mathbf{\hat{s}} = \arg\min_{\mathbf{s}} f(\mathbf{s}) = \arg\min_{\mathbf{s}} \left\| \mathbf{P}_{\mathbf{\Omega}}^{\perp} \mathbf{y} \right\|_{2}^{2}$$

✓ Since the objective function is quadratic separable in its two unknown variables both parameters can be iteratively estimated as

$$\hat{\mathbf{s}}_{k+1} = \left(\mathbf{C}^{H} \hat{\mathbf{\Lambda}}_{H(k)}^{H} \hat{\mathbf{\Lambda}}_{H(k)} \mathbf{C} \right)^{-1} \mathbf{C}^{H} \hat{\mathbf{\Lambda}}_{H(k)}^{H} \left(\mathbf{y} - \hat{\mathbf{\Lambda}}_{H(k)} \mathbf{p} \right)$$
$$\hat{\mathbf{\Lambda}}_{H(k)} = Diag \left(\mathbf{G}^{H} \hat{\mathbf{h}}_{k} \right)$$
and
$$\hat{\mathbf{h}}_{k} = \left(\mathbf{G} \hat{\mathbf{\Lambda}}_{(k)}^{H} \hat{\mathbf{\Lambda}}_{(k)} \mathbf{G}^{H} \right)^{-1} \mathbf{G} \hat{\mathbf{\Lambda}}_{(k)}^{H} \mathbf{y}$$
$$\hat{\mathbf{\Lambda}} = \hat{\mathbf{\Lambda}}_{s} + \mathbf{\Lambda}_{p} \qquad \hat{\mathbf{\Lambda}}_{s} = Diag \left(\hat{\mathbf{s}} \right)$$

for a reliable enough first estimate obtained by fixing $\mathbf{s}_1 = 0$ (e.g. training-only approach!)



Asymptotic results

✓ <u>RESULT 1</u>. Let A be an NxN complex matrix with bounded spectral radius for all N. Let $s = [s_1, ..., s_N]$, whose entries are i.i.d. complex r.v. and $N^{1/2} s_i$ has zero mean, unit variance and finite eighth order moment. Let r be a similar vector independent of r, then

$$\mathbf{s}^{H}\mathbf{A}\mathbf{s} - \frac{1}{N}\operatorname{tr}[\mathbf{A}] \to 0 \qquad \mathbf{s}^{H}\mathbf{A}\mathbf{r} \to 0$$

almost surely as $N \rightarrow \inf [Evans-Tse, IT-Trans.'00]$

✓ <u>RESULT 2</u>. Consider the projection matrix $P_G = G^H (GG^H)^{-1}G$ and the following NxN complex diagonal deterministic matrix

$$\mathbf{D} = \underset{k=0...K-1}{\text{diag}} \left[D\left(\frac{k}{K}\right) \right]$$

where D(f) is a bounded Riemann integrable function defined on [0,1]. Then, as N,L and K go to infinity at the same rate [Mestre, SP-Trans.'04]

$$\frac{1}{K}\operatorname{tr}\left[\mathbf{P}_{G}\mathbf{D}\right] \to \frac{L}{N}\int_{0}^{1}D\left(f\right)df$$

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Algorithm characterization

- Under these assumptions the asymptotic expression for the symbol estimate is seen to be

$$\mathbf{\hat{s}}_{k+1} = f\left(\mathbf{\hat{s}}_k, SNR, \beta\right)$$

✓ Further, considering \mathbf{s}_1 =0, it is found that

$$\mathbf{\hat{s}}_{k+1} = \eta_{k+1} \mathbf{s}_{k+1}$$

where η is a real positive scalar

$$\eta_{k+1} = f\left(\eta_k, SNR, \beta\right)$$

so that the analysis of the convergence of the algorithm can be approached by studying the evolution of $\eta_{\rm k}$



Estimator performance

\succ Evolution of parameter η for different values of SNR and β



 $\mathrm{SNR}=(\mathrm{p_s}{+}\mathrm{p_p})/\sigma^2$

Regardless of the SNR, the algorithm converges always to the same point for a fixed degree of channel frequency selectivity. It is only the number of iterations until convergence that actually depends on the value of SNR.

Although it need not converge to 1 the analytical tracking of the value of this parameter can be an important aid in the detection task

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➢ We have shortly presented the performance of an iterative ML channel estimation algorithm for MC-CDMA that exploits the code-multiplexing of training pilots.

- ➢ We considered an asymptotic analysis that allows us to analytically characterize the ultimate symbol estimate quality in terms of a parameter related to its evolution through the iterations.
- The previous analytical characterization can further be employed for detection purposes, whereby it turns out to be of most benefit if applied to nonconstant-amplitude modulations like M-ary QAM.





≻Main reference:

F. Rubio and X. Mestre,

"Semi-blind ML Channel Estimation for MC-CDMA Systems with Code-multiplexed Pilots", SPAWC'05.

