

Iterative Equalization for Single Carrier Cyclic Prefix in Doubly-Dispersive Channels

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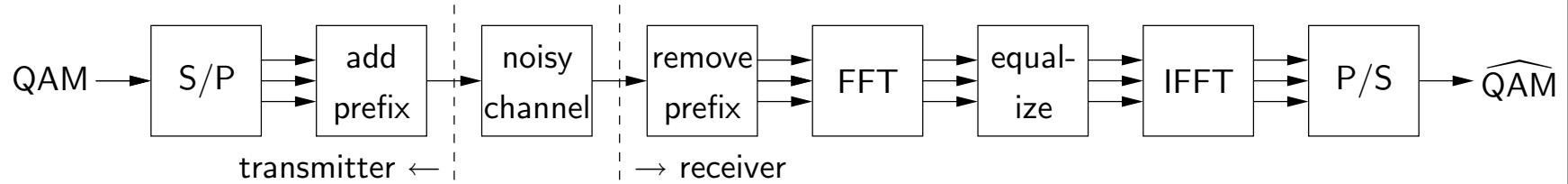


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Background:

- First, consider communication over time-dispersive channels.
- Options:
 1. Single-Carrier Modulation with Time-Domain Equalization
 - $\mathcal{O}(N_h)$ operations/symbol for chan length N_h .
 - low peak-to-average-power ratio (PAPR).
 2. Multi-Carrier Modulation with Freq-Domain Equalization
 - $\mathcal{O}(\log N)$ operations/symbol for block length N .
 - high PAPR.
 - “OFDM.”
 3. Single-Carrier Modulation with Freq-Domain Equalization
 - $\mathcal{O}(\log N)$ operations/symbol for block length N .
 - low PAPR.
 - “single carrier cyclic prefix (**SCCP**).”

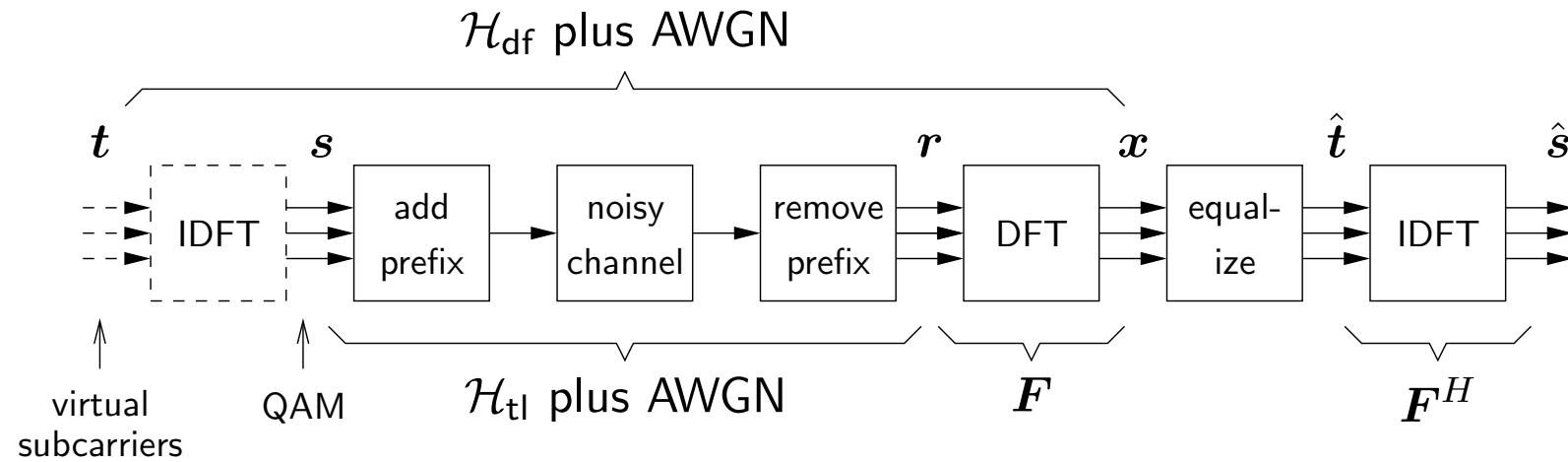
Single-Carrier Cyclic Prefix (SCCP):



- SCCP is like OFDM with both FFTs at the receiver.
- Freq-domain equalization requires only one mult-per-symbol if:
 1. cyclic prefix length > channel delay spread,
 2. channel time-invariant over the FFT-block interval.
- Our final goal, however, is communication over *time-dispersive and frequency-dispersive* channels.

*How can we handle SCCP with significant
channel variation over the block interval?*

System Model:



$$\mathbf{r} = \mathcal{H}_{\text{tl}} \mathbf{s} + \boldsymbol{\nu}$$

$$\mathbf{x} = \underbrace{\mathbf{F} \mathcal{H}_{\text{tl}} \mathbf{F}^H}_{\mathcal{H}_{\text{df}}} \underbrace{\mathbf{F} \mathbf{s}}_{\hat{\mathbf{t}}} + \underbrace{\mathbf{F} \boldsymbol{\nu}}_{\mathbf{w}}$$

where

\mathcal{H}_{tl} = circular-convolution matrix,

\mathcal{H}_{df} = “virtual-subcarrier” coupling matrix.

→ \mathcal{H}_{df} diagonal iff channel is LTI and prefix-length is adequate.

Virtual-Subcarrier Coupling Matrix \mathcal{H}_{df} :

$$\mathcal{H}_{\text{df}} = \begin{pmatrix} h_{\text{df}}(0, 0) & h_{\text{df}}(-1, 1) & \dots & h_{\text{df}}(1-N, N-1) \\ h_{\text{df}}(1, 0) & h_{\text{df}}(0, 1) & \dots & h_{\text{df}}(2-N, N-1) \\ \vdots & \vdots & \ddots & \vdots \\ h_{\text{df}}(N-1, 0) & h_{\text{df}}(N-2, 1) & \dots & h_{\text{df}}(0, N-1) \end{pmatrix}$$

$$h_{\text{df}}(\nu, k) := \frac{1}{N} \sum_{n=0}^{N-1} \sum_{l=0}^{N-1} h_{\text{tl}}(n, l) e^{-j \frac{2\pi}{N} n\nu} e^{-j \frac{2\pi}{N} lk}$$

= response at carrier $k+\nu$ to an impulse applied at carrier k

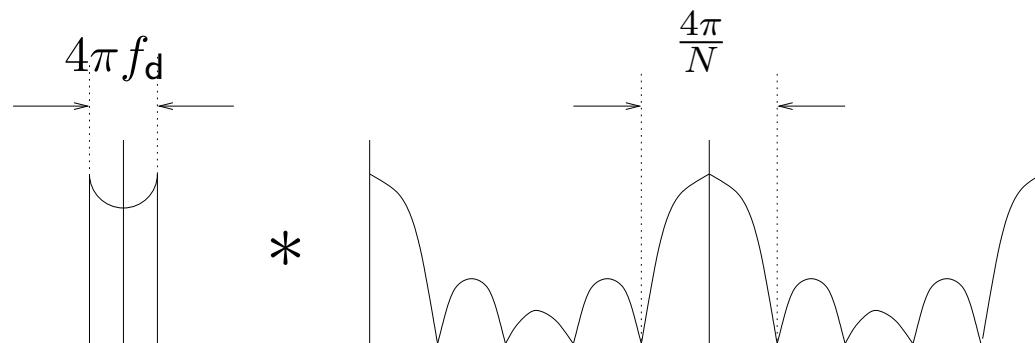
$$h_{\text{tl}}(n, l) := \text{response at time } n \text{ to an impulse applied at time } n - l$$

Inter-Carrier Interference Mechanism:

Doppler Spread meets Finite Block Length:

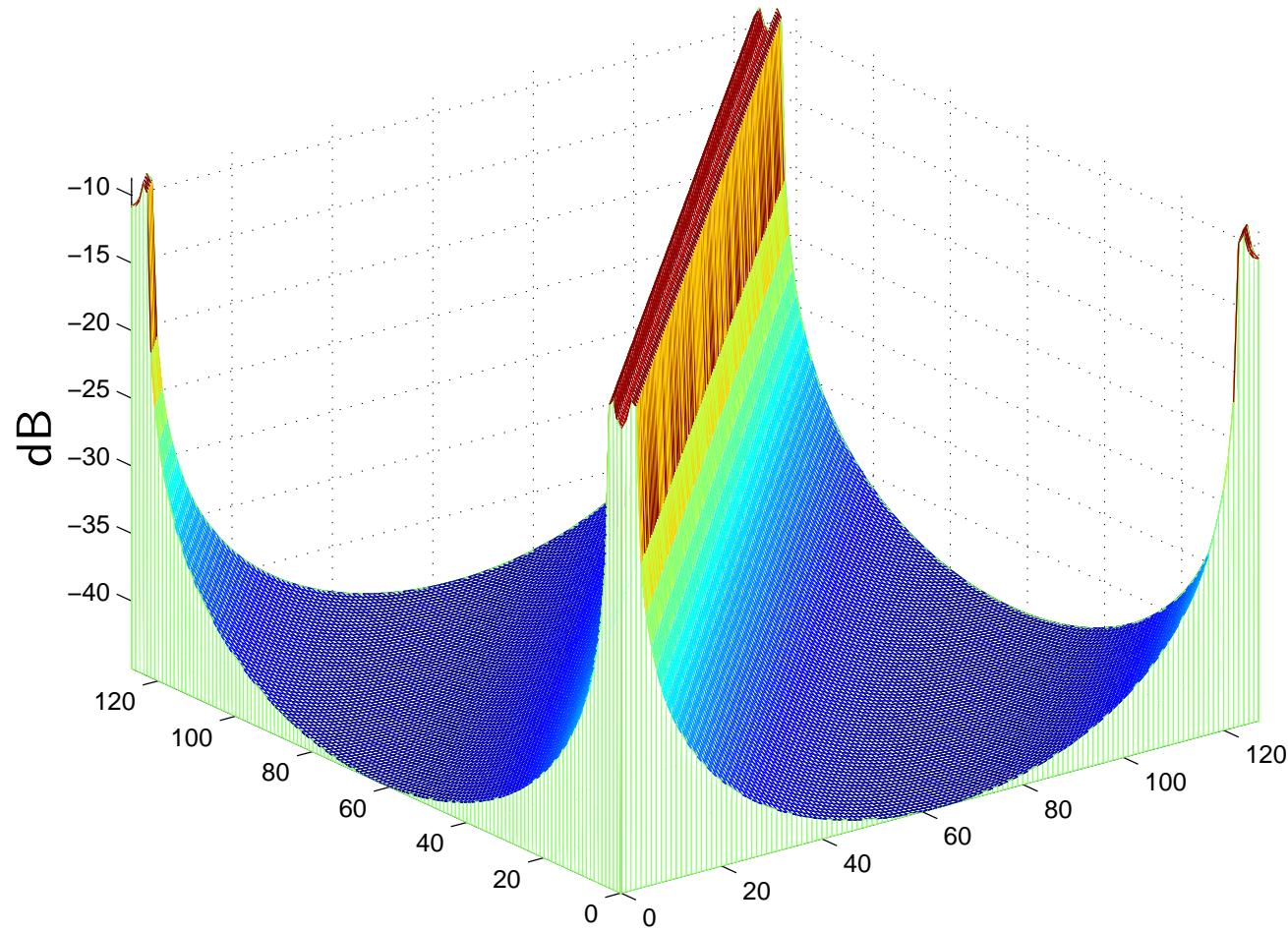
$$\mathbb{E}\{|h_{\text{df}}(\nu, k)|^2\} = \underbrace{\left(\frac{I_{[0, 2\pi f_d)}(|\phi|) \sum_l \sigma_l^2}{\sqrt{(2\pi f_d)^2 - \phi^2}} \right)}_{\text{assuming WSSUS Rayleigh}} * \underbrace{\left(\frac{\sin(\phi N/2)}{N \sin(\phi/2)} \right)^2}_{\text{block length } N} \Big|_{\phi = \frac{2\pi}{N} \nu}$$

= Samples of

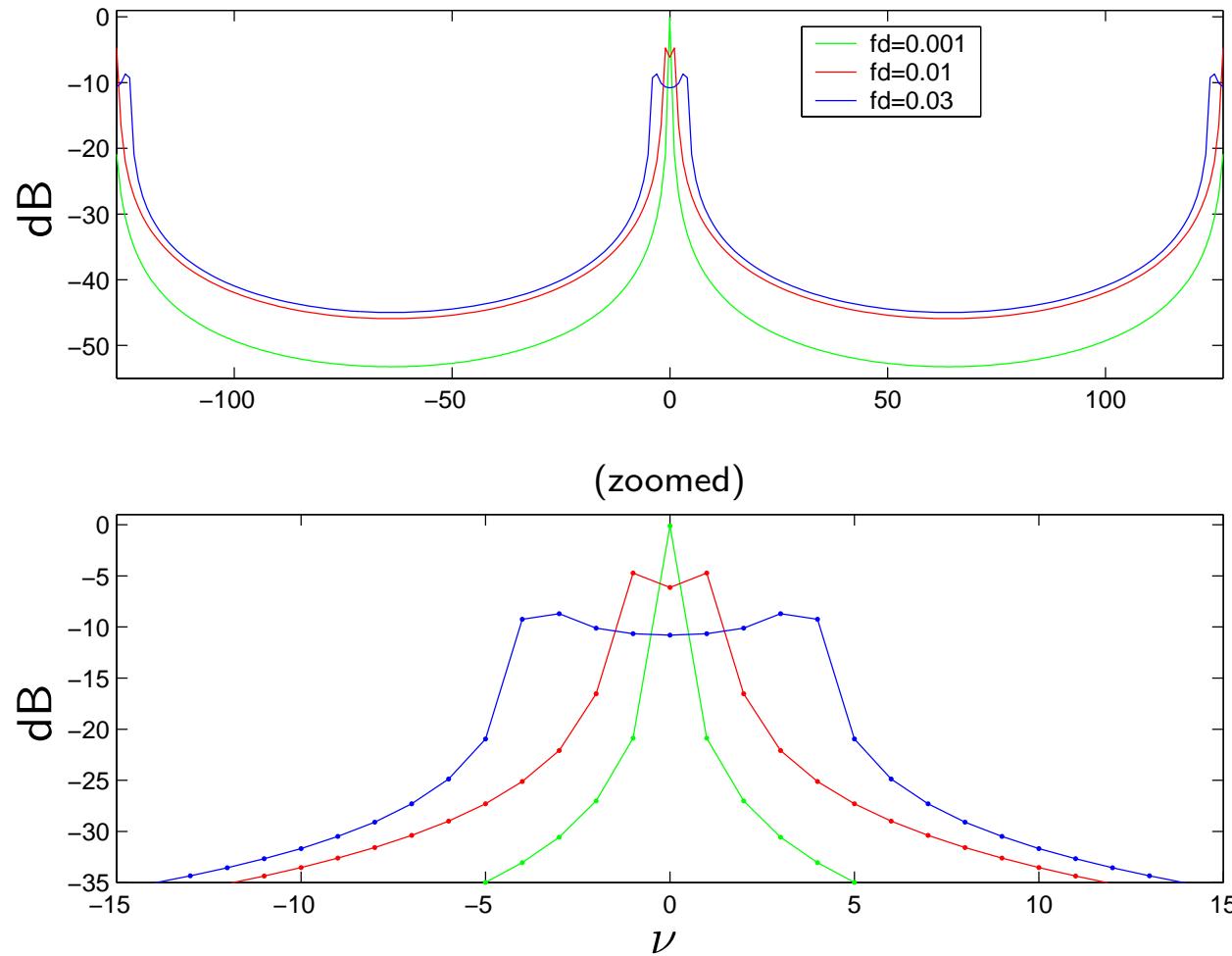


Note: Zero Doppler spread \Rightarrow Sample at sinc nulls \Rightarrow Zero ICI

Rayleigh $E\{|h_{df}(\nu, k)|^2\}$ for $N = 128$ and $f_d = 0.03$:



Rayleigh $E\{|h_{df}(\nu, \cdot)|^2\}$ for $N = 128$ and various f_d :



SCCP Equalization/Detection:

Objective: Recover finite-alphabet vector s from $\boxed{x = \mathcal{H}_{\text{df}} F s + w}$.

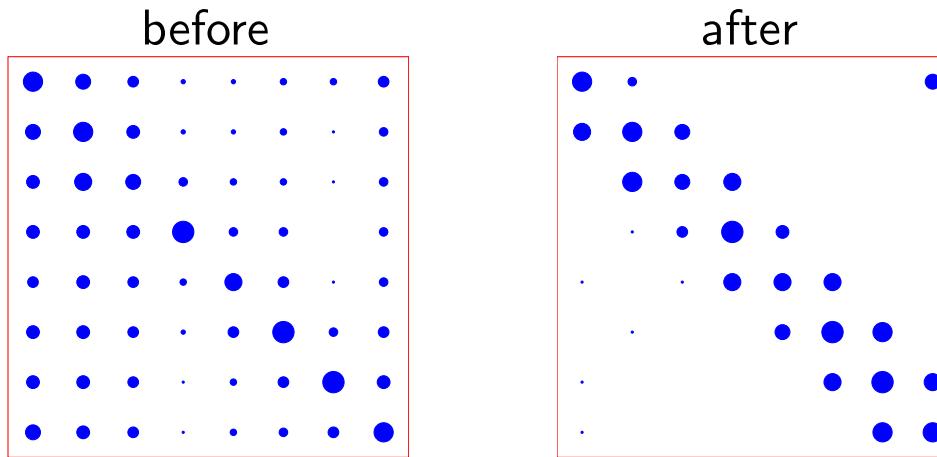
Classical Strategies:

- ZF, LS: $\hat{s}_{\text{zf}} = \text{slice}\left[\mathbf{F}^H \mathcal{H}_{\text{df}}^{-1} \mathbf{x}\right]$
- MMSE: $\hat{s}_{\text{mmse}} = \text{slice}\left[\mathbf{F}^H \mathcal{H}_{\text{df}}^H (\mathcal{H}_{\text{df}} \mathcal{H}_{\text{df}}^H + \sigma_w^2 \mathbf{I})^{-1} \mathbf{x}\right]$
- MLSD: $\hat{s}_{\text{mlsd}} = \arg \max_s \|x - \mathcal{H}_{\text{df}} F s\|^2$

With LTV channel: \rightsquigarrow Equalization requires $\geq O(N^3)$ operations
 \rightsquigarrow Low-complexity advantage of SCCP is lost!

Linear Pre-Processing to Simplify Detection:

- Use linear pre-processing to simplify detection.
 - Want to make \mathcal{H}_{df} sparse
 - ICI-response “shortening”
 - Reminiscent of ISI-shortening for single-carrier MLSD
- Time-domain windowing = Doppler-domain convolution!



Max-SINR Window Coefficients:

- Say we allow $2D$ diagonals of controlled ICI.
- Max-SINR window coefficients \mathbf{b}_* are

$$\mathbf{b}_* = \text{gen-evec}_{\max} \left(\mathbf{A} \odot \mathbf{R}^*, \text{diag}(\mathbf{R} + \sigma^2 \mathbf{I}) - \mathbf{A} \odot \mathbf{R}^* \right)$$

where, for WSSUS Rayleigh fading,

$$[\mathbf{A}]_{m,n} = \frac{\sin\left(\frac{\pi}{N}(2D+1)(n-m)\right)}{N \sin\left(\frac{\pi}{N}(n-m)\right)}$$

$$[\mathbf{R}]_{n,m} = J_0\left(2\pi f_d(n-m)\right) \sum_{l=0}^{N_h-1} \sigma_l^2$$

- Note that \mathbf{b}_* is a function of $\left\{ D, N, f_d, \frac{\sum \sigma_l^2}{\sigma^2} \right\}$

Windowed-System Model:

- Apply windowing before first receiver DFT:

$$\begin{aligned}
 \breve{\mathbf{x}} &= \mathbf{F} \mathcal{D}(\mathbf{b}) \mathbf{r} \\
 &= \underbrace{\mathbf{F} \mathcal{D}(\mathbf{b}) \mathbf{F}^H}_{\mathcal{C}(\boldsymbol{\beta})} \underbrace{\mathbf{F} \mathbf{r}}_{\mathbf{x}} \quad \text{for } \boldsymbol{\beta} = \mathbf{F} \mathbf{b} / \sqrt{N} \\
 &= \underbrace{\mathcal{C}(\boldsymbol{\beta}) \breve{\mathcal{H}}_{\text{df}}}_{\text{nearly banded}} \underbrace{\mathbf{F} \mathbf{s}}_{\mathbf{t}} + \mathcal{C}(\boldsymbol{\beta}) \mathbf{w}
 \end{aligned}$$

- *Goal:*

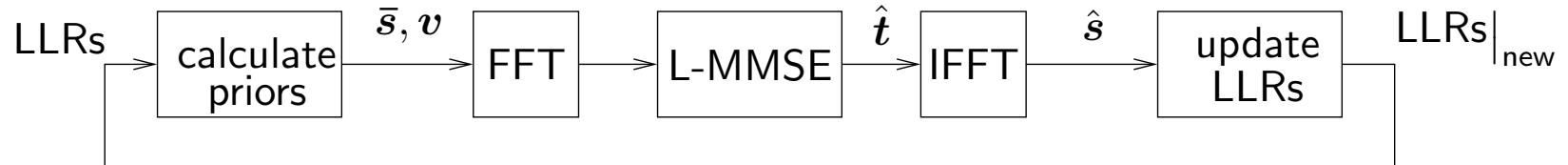
Estimate finite-alphabet $\{s_0, \dots, s_{N-1}\}$ given $\breve{\mathcal{H}}_{\text{df}}$, $\boldsymbol{\beta}$, and $\breve{\mathbf{x}}$.

- *Approach:*

Leverage sparse $\breve{\mathcal{H}}_{\text{df}}$ to estimate \mathbf{t} , then relate $\mathbf{t} \rightarrow \mathbf{s}$.

Iterative MMSE Estimation:

Block Iteration:



L-MMSE step for each k :

$$\check{x}_k = \begin{bmatrix} \text{---} & \text{---} & \text{---} & \text{---} & \text{---} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \text{---} & \text{---} & \text{---} & \text{---} & \text{---} \end{bmatrix} = \begin{bmatrix} \text{---} & \text{---} & \text{---} & \text{---} & \text{---} \\ \text{---} & \text{---} & \text{---} & \text{---} & \text{---} \\ \text{---} & \text{---} & \text{---} & \text{---} & \text{---} \\ \text{---} & \text{---} & \text{---} & \text{---} & \text{---} \\ \text{---} & \text{---} & \text{---} & \text{---} & \text{---} \end{bmatrix} \check{h}_k + \begin{bmatrix} \text{---} & \text{---} & \text{---} & \text{---} & \text{---} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \text{---} & \text{---} & \text{---} & \text{---} & \text{---} \end{bmatrix} t_k + \begin{bmatrix} \text{---} & \text{---} & \text{---} & \text{---} & \text{---} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \text{---} & \text{---} & \text{---} & \text{---} & \text{---} \end{bmatrix} C_k + \begin{bmatrix} w \\ \vdots \\ w \end{bmatrix}$$

The diagram shows the L-MMSE step for each k . It consists of a sum of four terms: a vector \check{x}_k , a product of a channel matrix $\check{\mathcal{H}}_k$ and a vector \check{h}_k , a vector t_k , and a vector C_k . The vector w is also shown.

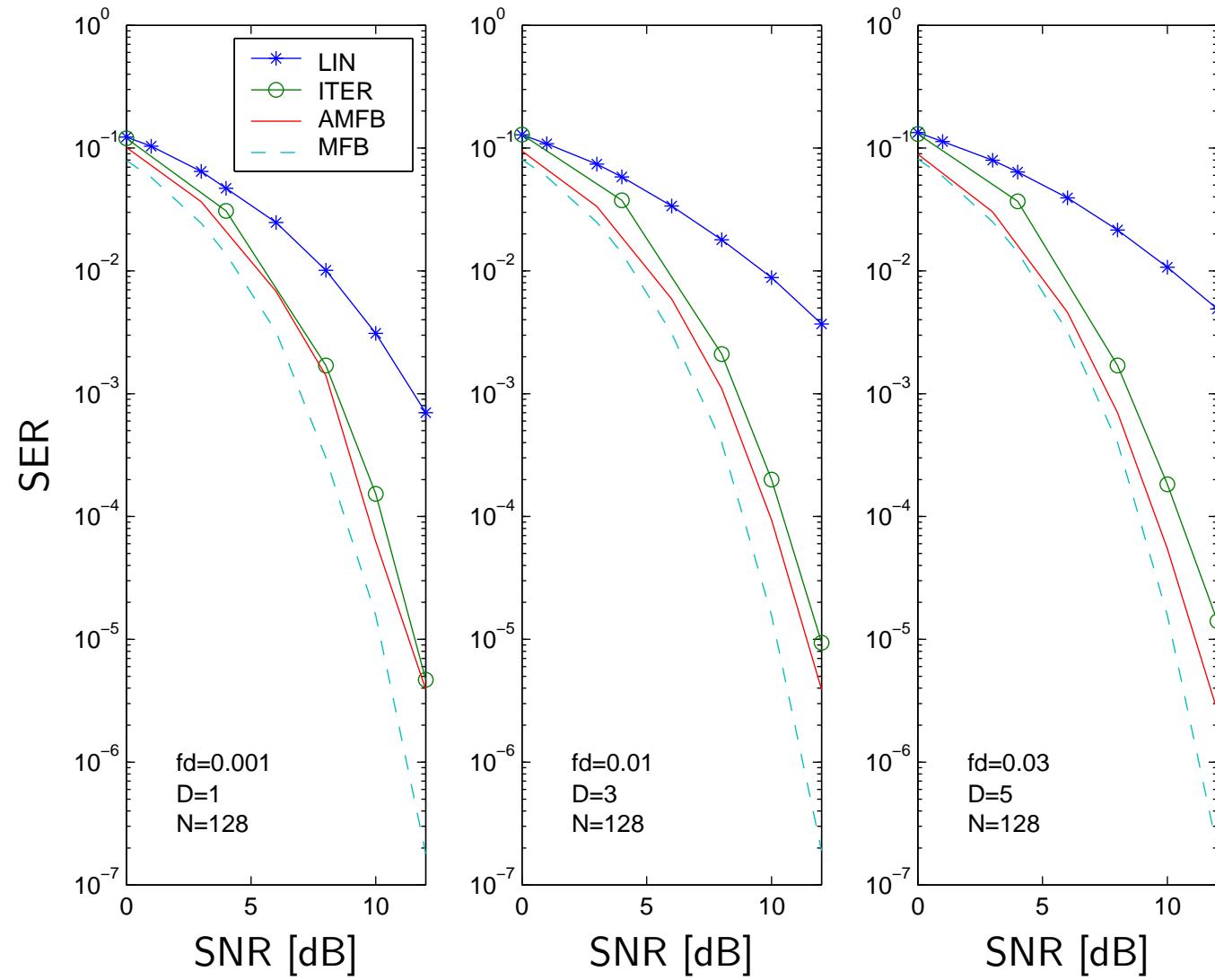
Algorithm requiring $\mathcal{O}(D^2 \log N)$ operations/symbol:

```

 $L^{(0)}(s_k) = 0 \quad \forall k$ 
for  $i = 0 \dots,$ 
    for  $k = 0 \dots N - 1,$ 
         $\bar{s}_k^{(i+1)} = \tanh(L^{(i+1)}(s_k)/2)$ 
         $v_k^{(i+1)} = 1 - (\bar{s}_k^{(i+1)})^2$ 
    end
     $\bar{\mathbf{t}}^{(i)} = \mathbf{F} \bar{\mathbf{s}}^{(i)}$ 
    for  $k = 0 \dots N - 1,$ 
         $\mathbf{g}_k^{(i)} = (\check{\mathcal{H}}_k \mathbf{F} \mathcal{D}(\mathbf{v}^{(i)}) \mathbf{F}^H \check{\mathcal{H}}_k^H + \sigma^2 \mathbf{C}_k \mathbf{C}_k^H)^{-1} \check{\mathcal{H}}_k \mathbf{F} \mathcal{D}(\mathbf{v}^{(i)}) \mathbf{F}^H \mathbf{i}_k$ 
         $\hat{t}_k^{(i)} = \bar{t}_k^{(i)} + \mathbf{g}_k^{(i)H} (\mathbf{x}_k - \check{\mathcal{H}}_k \bar{\mathbf{t}}^{(i)})$ 
    end
     $\mathbf{Q}^{(i)} = \mathbf{F}^H \left( \sum_{k=0}^{N-1} \check{\mathcal{H}}_k^H \mathbf{g}_k^{(i)} \mathbf{i}_k^H \right) \mathbf{F}$ 
     $\mathbf{P}^{(i)} = \mathbf{F}^H \left( \sum_{k=0}^{N-1} \mathbf{C}_k^H \mathbf{g}_k^{(i)} \mathbf{i}_k^H \right) \mathbf{F}$ 
     $\hat{\mathbf{s}}^{(i)} = \mathbf{F}^H \hat{\mathbf{t}}^{(i)}$ 
    for  $k = 0 \dots N - 1,$ 
         $L^{(i+1)}(s_k) = L^{(i)}(s_k) + 4 \frac{\operatorname{Re}\{Q_{k,k}^{(i)}(\hat{s}_k^{(i)} - \bar{s}_k^{(i)})\} + |Q_{k,k}^{(i)}|^2 \bar{s}_k^{(i)}}{\mathbf{q}_k^{(i)H} \mathcal{D}(\mathbf{v}^{(i)}) \mathbf{q}_k^{(i)} - |Q_{k,k}^{(i)}|^2 v_k^{(i)} + \sigma^2 \|\mathbf{p}_k^{(i)}\|^2}$ 
    end
end

```

Uncoded-SER versus SNR:



Observations:

- Classical (Joint Linear) MMSE:
 - $\mathcal{O}(N^2)$ operations/symbol.
 - Worst performance.
- Iterative MMSE:
 - $\mathcal{O}(\log N)$ operations/symbol.
 - $\sim 2\text{dB}$ from MFB
 - Easily combined with decoding algorithm (i.e., turbo eq).
- Approximate MFB:
 - Uses sparse $\check{\mathcal{H}}_{\text{df}}$ with perfect interference cancellation.
- MFB:
 - Uses true $\check{\mathcal{H}}_{\text{df}}$ with perfect interference cancellation.

Summary:

- SCCP reception complicated by time-selectivity.
- Proposed a two-stage SCCP receiver for doubly-selective channels:
 1. SINR-optimal windowing,
 2. Iterative MMSE estimation.
- Like classical SCCP receivers, requires $\mathcal{O}(\log N)$ operations/symbol.
- Uncoded error rate is $\sim 2\text{dB}$ from MFB.
- Soft decoding can be easily incorporated.