

Efficient Communication Over Highly Spread Underwater Acoustic Channels

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Introduction:

Goal: *Communication over large-delay/Doppler-spread channels that is reliable, spectrally efficient, and computationally efficient.*

Prior Art:

- single-carrier/DFE [Stojanovic/Proakis JOE 95], [Preisig JASA 05]
 - unsatisfactory in surf zone ($2f_D T_h \approx 0.1$) [Preisig/Deane JASA 04]
- ZP-OFDM [Li/Zhou/et al. OCEANS 06], [Stojanovic OCEANS 06]
 - $\left\{ \begin{array}{l} \text{negligible ICI (-25dB)} \rightarrow 2f_D T_s = 0.06 \\ T_s = 7T_h \end{array} \right\} \Rightarrow 2f_D T_h = 0.008$
- MCM (ICI-free but ISI-inducing) [Morozov/Preisig OCEANS 06]
 - $2f_D T_h = 0.007$ simulated, $2f_D T_h = 0.004$ experimental

Conclusion: *Need a new approach to the problem.*

Our approach to comm over highly spread channels:

- Suppressing *both* ISI and ICI mandates a low spectral efficiency (Balien-Low theorem) [Strohmer/Beaver TCOM 03]. Solution: *allow a small span of ICI* [Schniter Allerton 03].
- When channel-estimation and data-detection are decoupled, guardbands are required for good performance, thereby decreasing spectral efficiency. Solution: *joint estimation/detection*, which can achieve the high-SNR capacity $(1 - 2f_D T_h) \log_2 \text{SNR}$ [Kannu/Schniter Allerton 06].
- For joint estimation/detection, PSP-VA/Kalman is complex and PSP-VA/LMS is poor performing. Solution: *use fast tree-search*.
- Channel sparseness is complicated to track (e.g., $\mathcal{O}(N_h^2)$ [Li/Preisig OCEANS 06]) and seldom combined with MCM. Solution: *to be described...*

Summary of our approach:

We use...

1. **multicarrier modulation** that allows a small ICI span,
2. **joint estimation/detection** (i.e., noncoherent decoding)
3. **fast tree-search** (i.e., sequential decoding),
4. a novel means of **tracking/exploiting delay-domain channel sparseness**.

In the near future, we plan to incorporate

4. **bit-interleaved coded modulation** and **soft tree search**.

Next, we detail our approach...

Multicarrier Modulation:

Modulation:

$$s(t) = \sum_{n=-\infty}^{\infty} \sum_{k=0}^{N-1} [\mathbf{s}(n)]_k \alpha(t - nT_s) e^{j2\pi k F_s (t - nT_s)}$$

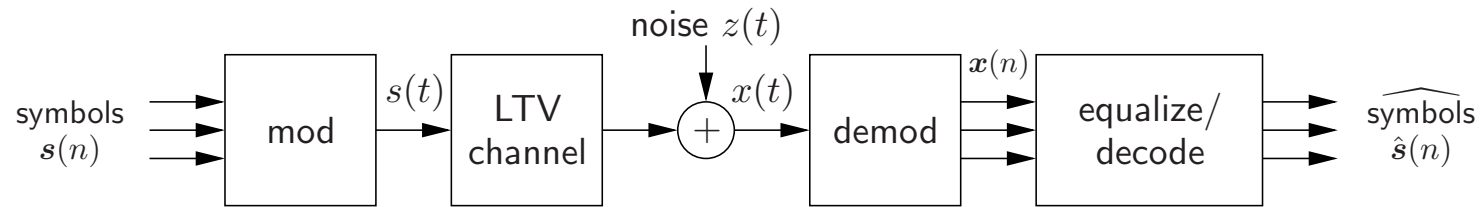
Doubly dispersive channel:

$$x(t) = \int_0^{T_h} h(t, \tau) s(t - \tau) d\tau + w(t)$$

Demodulation:

$$[\mathbf{x}(n)]_k = \int_{-\infty}^{\infty} x(t) \beta^*(t - nT_s) e^{-j2\pi k F_s (t - nT_s)}$$

Discrete-time Vector Representation:



$$\mathbf{x}(n) = \sum_{m=-\infty}^{\infty} \mathbf{H}(n, m) \mathbf{s}(n - m) + \mathbf{w}(n)$$

“ISI+ICI channel”

$\mathbf{s}(n) \in \mathbb{C}^N$ multi-carrier symbol vector

$\mathbf{H}(n, m) \in \mathbb{C}^{N \times N}$ sub-carrier coupling matrix at time- n and lag- m

$\mathbf{x}(n) \in \mathbb{C}^N$ multi-carrier observation vector

$\mathbf{w}(n) \in \mathbb{C}^N$ noise vector

Quasi-Banded Model:

With properly chosen pulse shapes $\alpha(t)$ and $\beta(t)$, and with a smoothly varying channel, we can make the ISI-free approximation

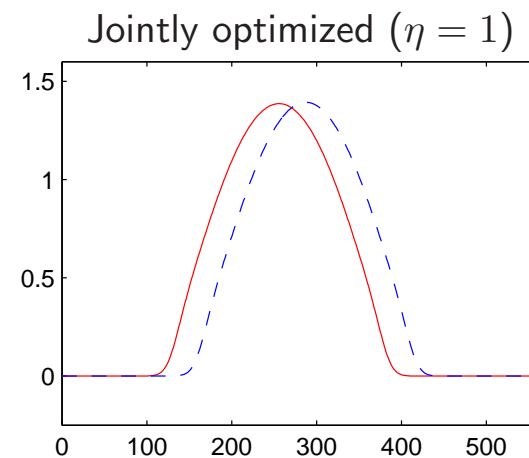
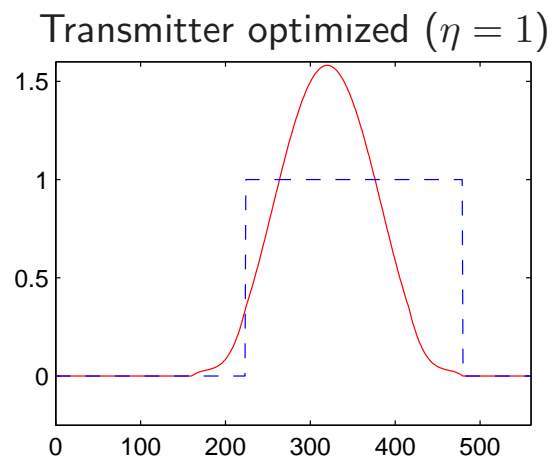
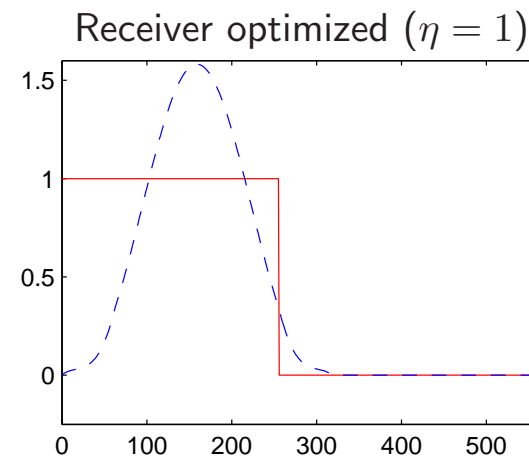
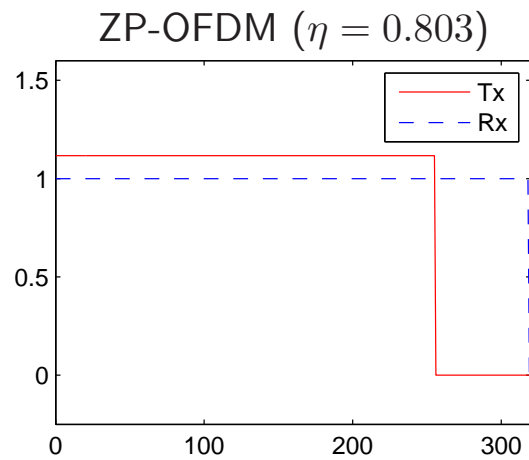
$$\begin{aligned} \mathbf{x}(n) &= \sum_{m=-\infty}^{\infty} \mathbf{H}(n, m) \mathbf{s}(n - m) + \mathbf{w}(n) \\ &\approx \mathbf{H}(n, 0) \mathbf{s}(n) + \mathbf{w}(n) \end{aligned}$$

where $\mathbf{H}(n, 0)$ is quasi-banded with $2D + 1$ active diagonals:

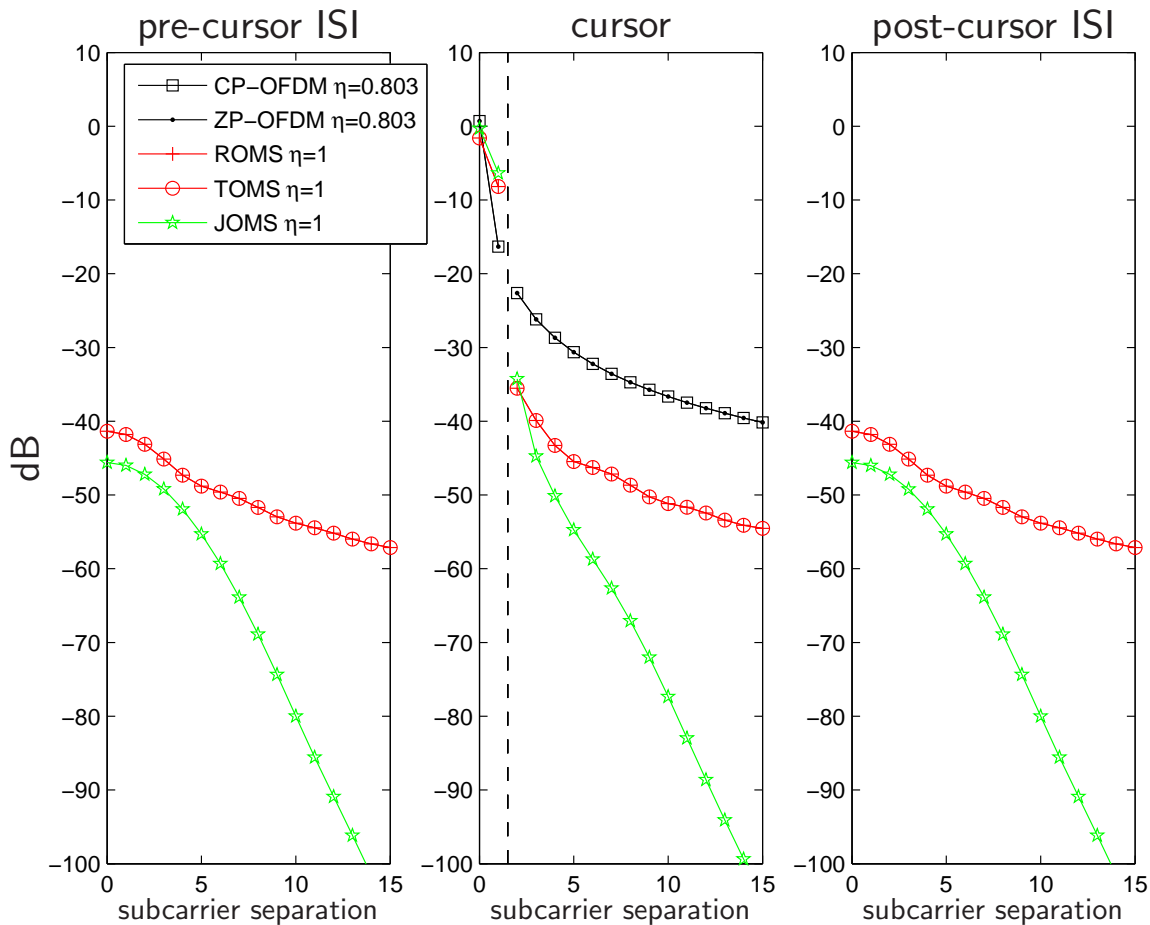
$$\mathbf{x}(n) \approx \mathbf{H}(n, 0) \mathbf{s}(n) + \mathbf{w}(n)$$

In other words, ISI becomes negligible and ICI is effectively limited to a radius of D subcarriers. (Typically $D = 1$.)

In fact, with $D > 0$, the pulses $\{\alpha(t), \beta(t)\}$ can be designed to make the approximation accurate *without compromising spectral efficiency*.
 Example pulse shapes:



Corresponding ISI/ICI Energy Profiles (same for each subcarrier):



for $N_h = 64$, $f_D T_c = 7.6 \times 10^{-4}$, $2f_D T_h = 0.1$, $D = 1$, $\text{SNR} = 15\text{dB}$
(e.g., $T_h = 7\text{ms}$, $f_D = 7\text{Hz}$, $\text{BW} = 9.2\text{kHz}$)

A Sparse Basis-Expansion Model:

From multicarrier model

$$\begin{aligned}\mathbf{x}(n) &= \mathbf{H}(n, 0)\mathbf{s}(n) + \mathbf{w}(n) \\ &= \mathbf{S}(n)\mathbf{h}(n) + \mathbf{w}(n) \quad \mathbf{h}(n) \in \mathbb{C}^{(2D+1)N} \quad \text{ICI coefs}\end{aligned}$$

we can use a basis-expansion model (BEM)

$$\begin{aligned}\mathbf{h}(n) &= \mathbf{B}\boldsymbol{\theta}(n) & \boldsymbol{\theta}(n) &\in \mathbb{C}^{(2D+1)N_h} \quad \text{delay/Doppler coefs} \\ \mathbf{B} &= \begin{pmatrix} \mathbf{F} & & \\ & \ddots & \\ & & \mathbf{F} \end{pmatrix} & \mathbf{F} &\in \mathbb{C}^{N \times N_h} \quad \text{Fourier basis matrix}\end{aligned}$$

to rewrite the observation as

$$\mathbf{x}(n) = \mathbf{S}(n)\mathbf{B}\boldsymbol{\theta}(n) + \mathbf{w}(n)$$

where *sparseness in the delay profile implies sparseness in $\boldsymbol{\theta}(n)$* .

Thus, ignore negligible coefs in $\boldsymbol{\theta}(n)$ and corresponding columns in \mathbf{B} !

Noncoherent ML Decoding:

Treating (non-negligible) delay/Doppler coeffs $\boldsymbol{\theta}$ as nuisance parameters,

$$\begin{aligned}\hat{\mathbf{s}}_{\text{ML}} &= \arg \max_{\mathbf{s}} p(\mathbf{x}|\mathbf{s}) \\ &= \arg \max_{\mathbf{s}} \int_{\boldsymbol{\theta}} p(\mathbf{x}|\mathbf{s}, \boldsymbol{\theta}) p(\boldsymbol{\theta}) d\boldsymbol{\theta}\end{aligned}$$

Assuming $\boldsymbol{\theta} \sim \mathcal{CN}(\mathbf{0}, \mathbf{R}_{\theta})$,

$$\begin{aligned}\hat{\mathbf{s}}_{\text{ML}} &= \arg \max_{\mathbf{s}} \left\{ \mathbf{x}^H \mathbf{S} \mathbf{B} \boldsymbol{\Sigma}^{-1} \mathbf{B}^H \mathbf{S}^H \mathbf{x} - \sigma^2 \log |\boldsymbol{\Sigma}| \right\} \\ &\approx \arg \max_{\mathbf{s}} \left\{ \mathbf{x}^H \mathbf{S} \mathbf{B} \boldsymbol{\Sigma}^{-1} \mathbf{B}^H \mathbf{S}^H \mathbf{x} \right\} \text{ for SNRs of interest} \\ \boldsymbol{\Sigma} &:= \mathbf{B}^H \mathbf{S}^H \mathbf{S} \mathbf{B} + \sigma^2 \mathbf{R}_{\theta}^{-1}.\end{aligned}$$

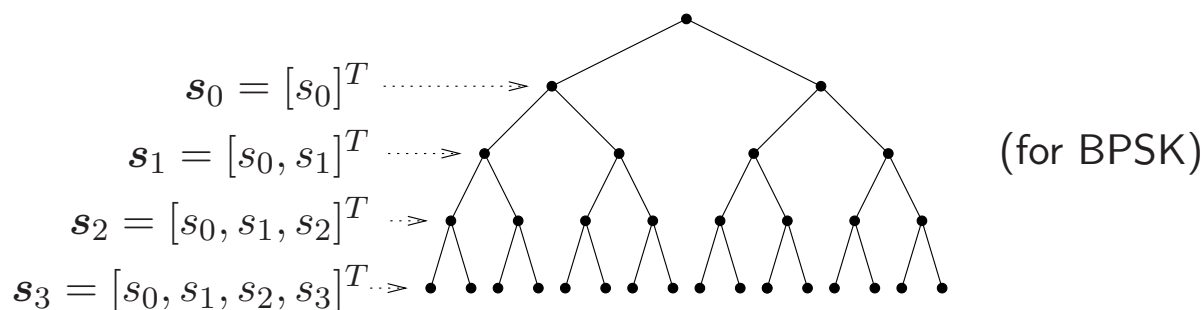
where it is interesting to note that $\hat{\boldsymbol{\theta}}_{\text{MMSE}}|\mathbf{s} = \boldsymbol{\Sigma}^{-1} \mathbf{B}^H \mathbf{S}^H \mathbf{x}$.

But how do we avoid an exhaustive search for symbols \mathbf{s} ?

Fast Sequential Decoding:

By turning off the first and last D subcarriers, the ICI model becomes “causal,” facilitating the use of **tree-search**.

$$\mathbf{x} = \mathbf{H} \mathbf{s} + \mathbf{w}$$



The important thing here is that the partial ML metric

$$\mu(\mathbf{s}_k) = \mathbf{x}_k^H \mathbf{S}_k \mathbf{B}_k \boldsymbol{\Sigma}_k^{-1} \mathbf{B}_k^H \mathbf{S}_k^H \mathbf{x}_k$$

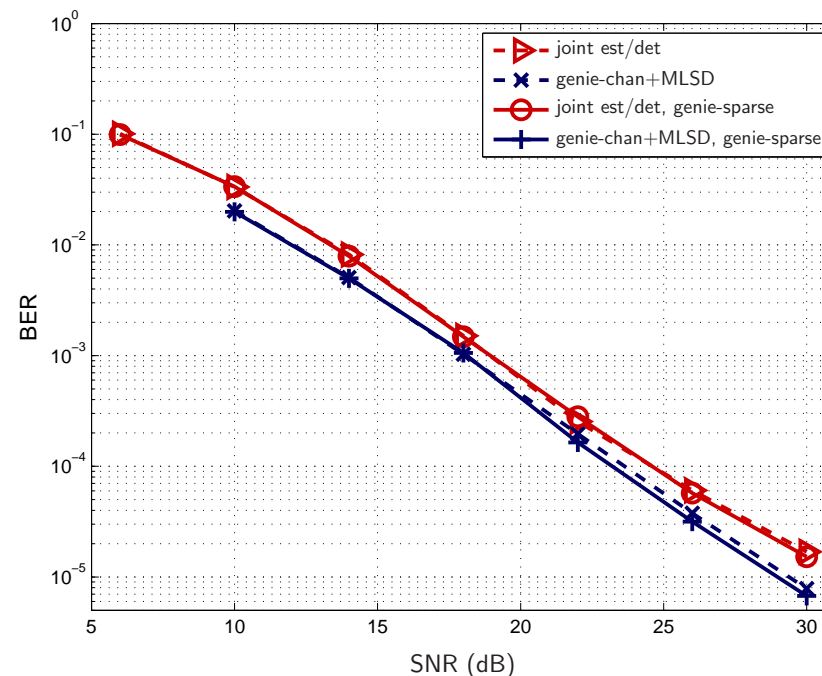
can be computed *recursively*. Thus, total search complexity via the M -algorithm is only about

$$2M|\mathcal{S}|(2D + 1)^2 N_{h\text{-sparse}}^2 \text{ mults per scalar-symbol!!}$$

Complexity Reduction via Pilots:

- With noncoherent decoding, only a single pilot subcarrier is required to resolve gain/phase ambiguity.
- But, as number of pilots increase, the initial channel estimate $\hat{\theta}$ improves, allowing more aggressive branch pruning (i.e., smaller M) without a sacrifice in performance.

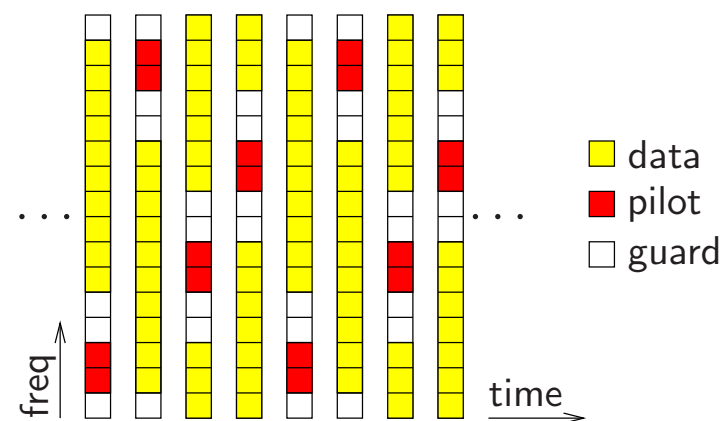
- Example: M-algorithm (BPSK, 25% pilots, $M=8$) compared to coherent MLSD with genie-aided $\hat{\theta}_{\text{MMSE}}$:



Tracking the Sparseness Pattern:

- To apply the sparse BEM, need to know “active tap” locations.
- To learn active taps, we can use pilots to estimate the delay-power profile (DPP), then
 1. choose $N_{h\text{-sparse}}$ largest taps (for fixed complexity), *or*
 2. choose all taps above a threshold (for fixed performance).
- Note: the same pilots are used for DPP and tree-search initialization.

Example pilot/data pattern:



Residual-Tap Compensation:

- Since the interference from residual (i.e., non-active) taps is treated as additive noise, the effective noise power is unknown and time-varying.
- Solution: estimate noise power from

$$\hat{\boldsymbol{w}}(n) = \boldsymbol{x}(n) - \hat{\boldsymbol{S}}(n)\boldsymbol{B}\hat{\boldsymbol{\theta}}(n).$$

Simulation Setup:

Channel:

- 4 paths with Rayleigh-fading gains and slowly varying delays.
- $\left\{ \begin{array}{l} \text{delay spread } N_h = 20 \\ \text{Doppler spread } 2f_D T_c = 0.005 \end{array} \right\} \Rightarrow 2f_D T_h = 0.1 \text{ (surf zone).}$

which corresponds to

BW= T_c^{-1}	T_h	$2f_D$
10kHz	2ms	50Hz
5kHz	4ms	25Hz
1kHz	20ms	5Hz

Transmitter:

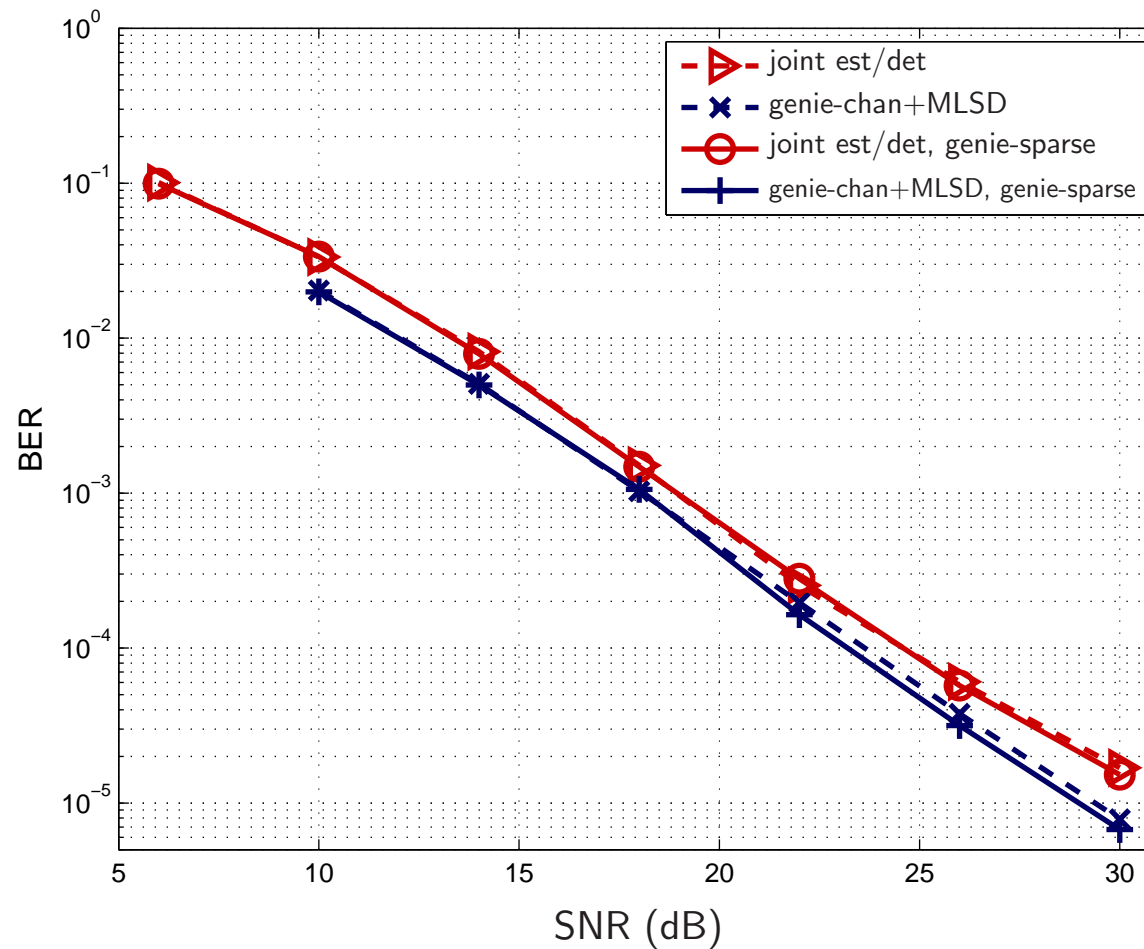
- max-SINR pulse, $N=64$ carriers, 18 pilots, $\eta=0.72 \frac{\text{symbols}}{\text{sec/Hz}}$, QPSK.

Receiver:

- rectangular pulse, ICI radius $D = 1$, M-alg parameter $M = 8$,
 $N_{h\text{-sparse}} = 8$.

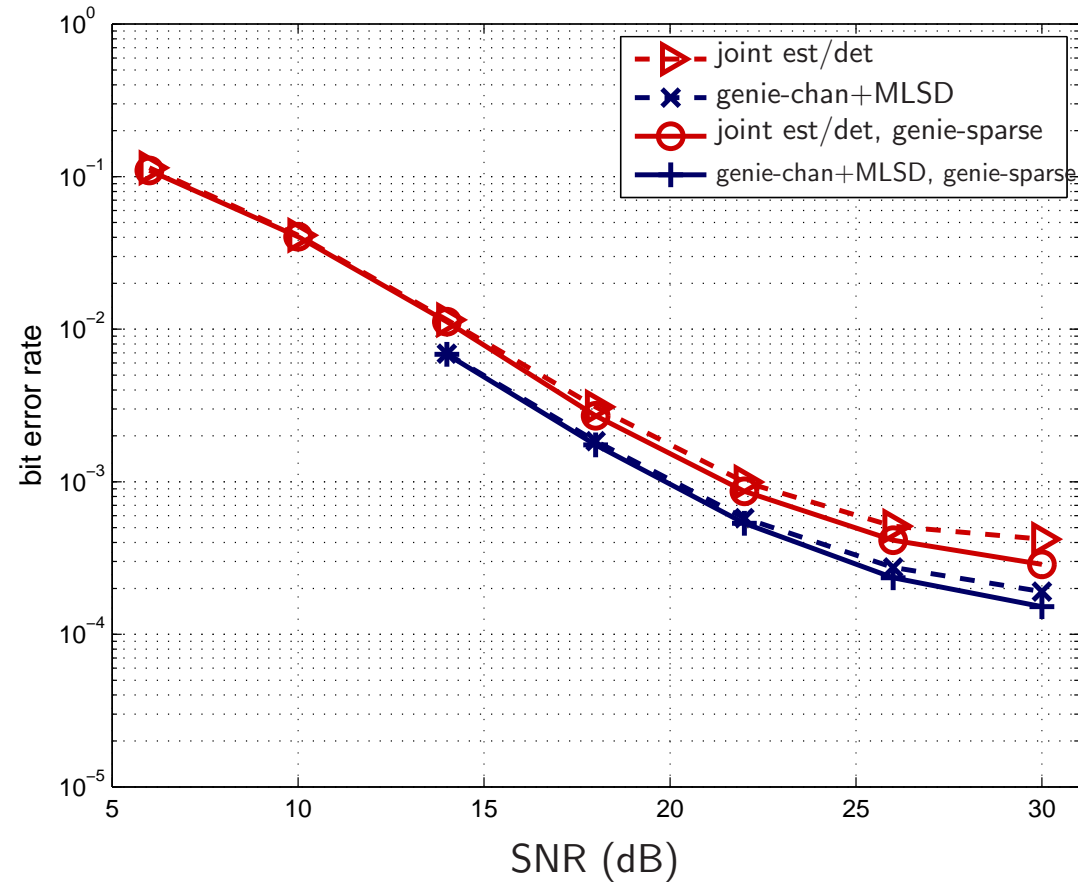
Simulation Results (Perfectly Sparse Channel):

“Non-active” taps are zero-valued.



Simulation Results (Nearly Sparse Channel):

2% of “active tap” energy leaked to “non-active” taps.



Note: Can lower BER-floor by increasing $N_{h\text{-sparse}}$.

Possible Improvements from Coding:

- With 3 ICI taps, the uncoded system will achieve a diversity order of at most 3 (and simulations indicate diversity order ≈ 2).
- Through the use of coding, an MCM system can extract additional diversity from the channel's delay-spread.
- One option would be to use bit-interleaved coded modulation (BICM) in conjunction with turbo reception. We expect significant gains from this approach.

Conclusions:

We proposed a multi-carrier scheme for communication over highly spread underwater acoustic channels that

- allows ICI from neighboring subcarriers, eliminating the need for time-domain guards,
- estimates symbols and sparse-channel-parameters jointly using a fast tree-search algorithm that requires only about $2M|\mathcal{S}|(2D+1)^2 N_{h\text{-sparse}}^2$ multiplications per QPSK symbol,
- uses pilots to reduce search complexity (i.e., tolerate low M)
- uses the same pilots to track the sparseness pattern.

For surf-zone-like channels (i.e., $2f_D T_h = 0.1$), simulations indicate

- performance approximately 1dB away from genie-channel MLSD.