

# Time Varying Carrier Frequency Offset Estimation in Multicarrier Underwater Acoustic Communication

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Supervised by **Prof. Israel Cohen** and **Dr. Alon Amar**



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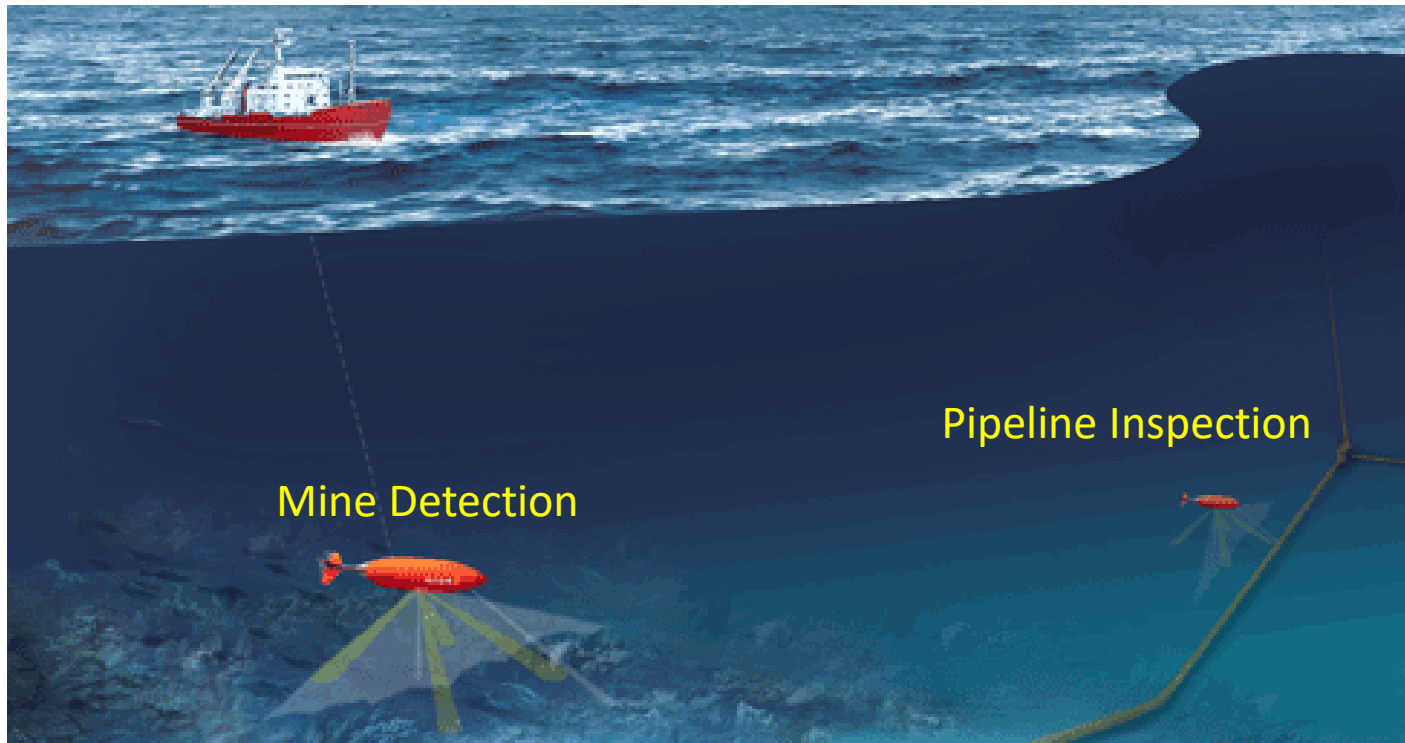
- Introduction
- Signal Space Estimation
- Pilot Design Optimization
- Time-Varying CFO Estimation
- Conclusions

# Introduction

introduction



# Why underwater communications?



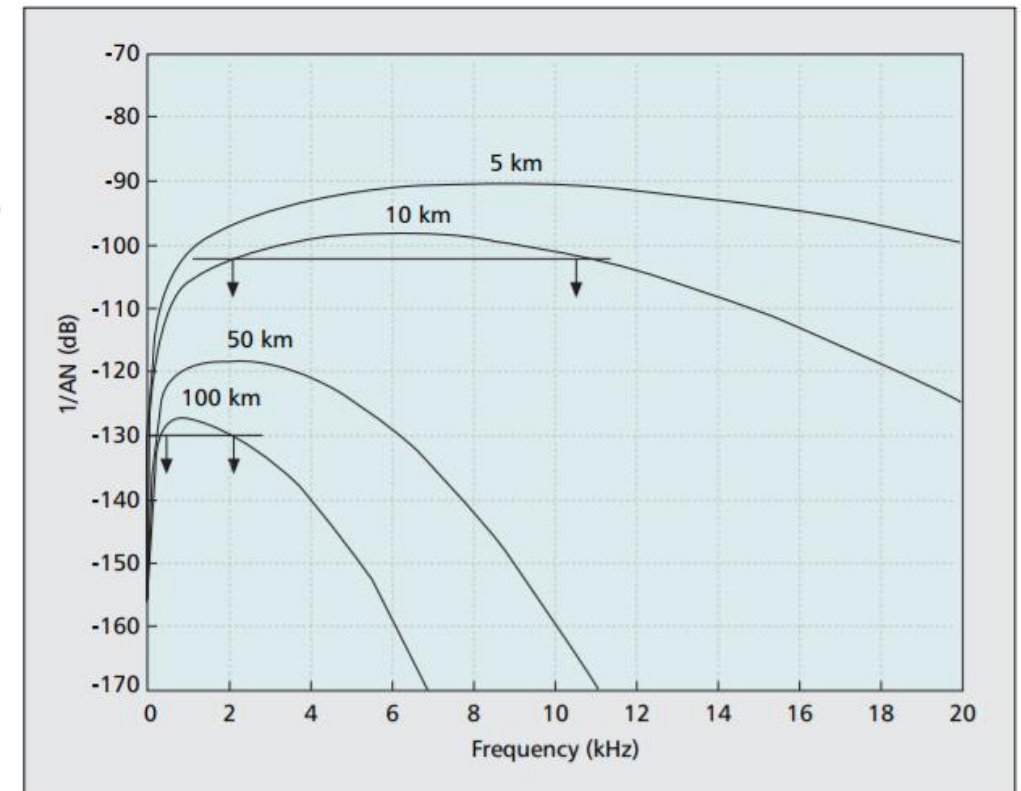
Autonomous Underwater Vehicles



Manned Vehicles

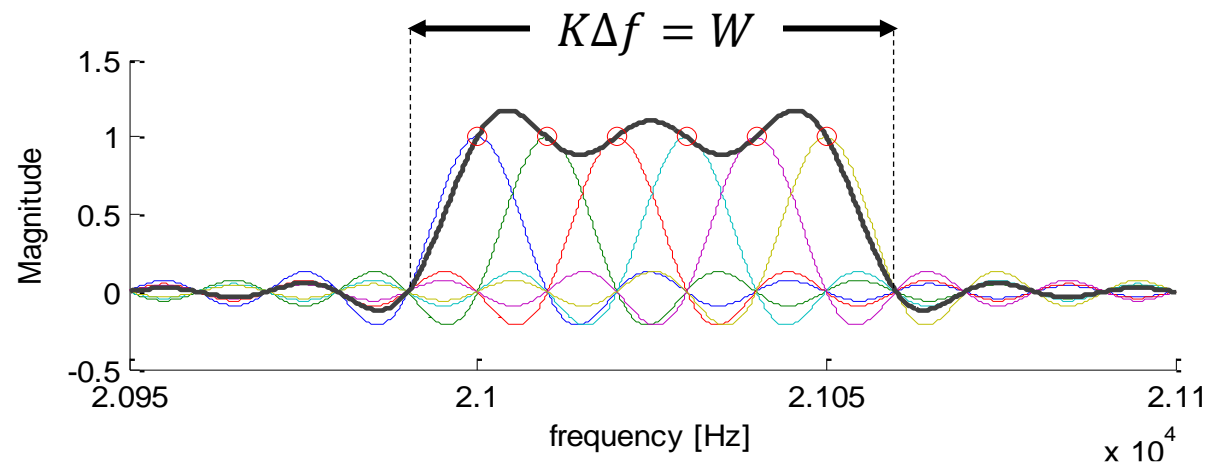
# Challenges of Underwater Communications

- EM signals are attenuated quickly in the UW medium → pressure waves (sound) have been chosen for long range communications
- Sound waves characteristics:
  - Propagation speed: 1500 m/s (times 200,000 slower than EM waves!)
  - Frequency dependent losses
  - Frequency related ambient noise



# Orthogonal Frequency Division Multiplexing

- The comm. bandwidth is divided into sub-carriers
- Each subcarrier is modulated to carry a digital communication symbol
- Pros:
  - Easy to implement using FFT operations
  - Robustness to frequency selective channels
  - Simple channel equalizer
- Cons:
  - Very sensitive to frequency shifts
  - High peak-to-average power ratio (PAPR)

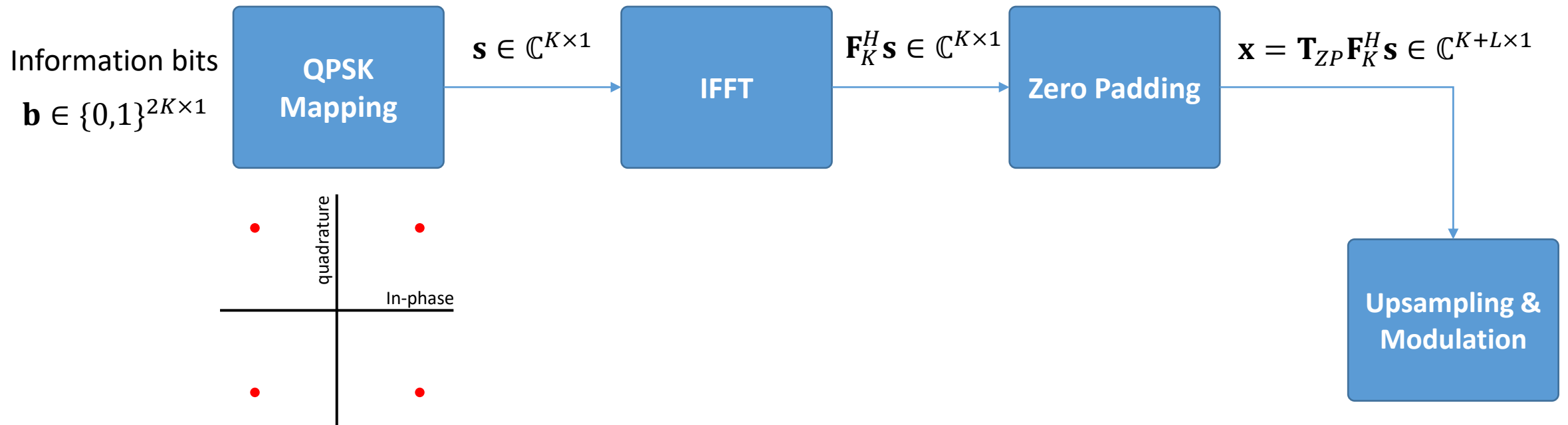


Orthogonality is achieved by  $\Delta f = \frac{1}{T}$

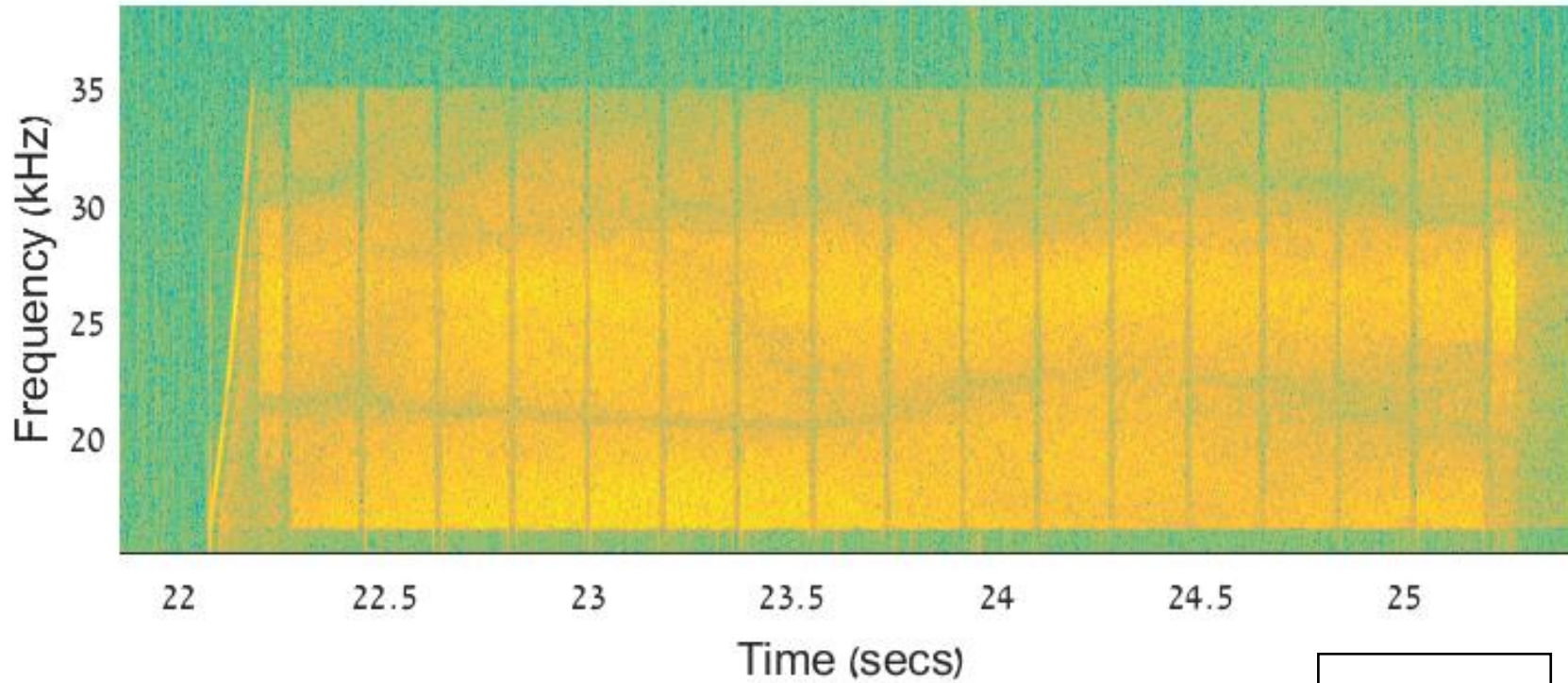
# OFDM modulation

The baseband OFDM signal:

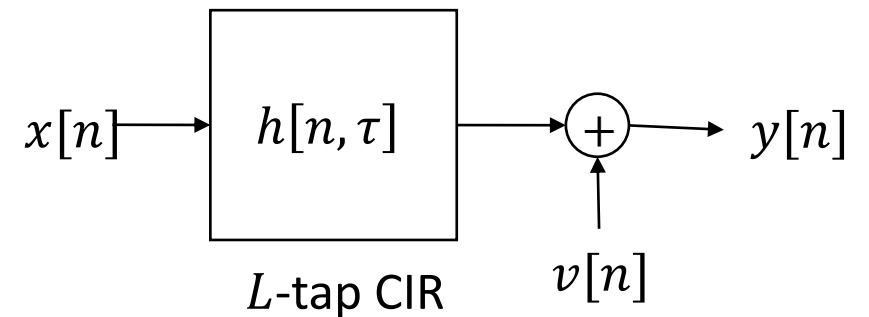
$$x[n] = g[n] \sum_{k=0}^{K-1} s[k] e^{j2\pi\left(\frac{n}{W}\right)f_k} = g[n] \sum_{k=0}^{K-1} s[k] e^{j2\pi\left(\frac{n}{W}\right)k\Delta f} = g[n] \sum_{k=0}^{K-1} s[k] e^{\frac{j2\pi nk}{K}} = \frac{g[n]}{\sqrt{K}} \text{IDFT}\{s[k]\}$$



# Sea Trial OFDM Signal



Recording from sea trial in the Mediterranean, December 2016



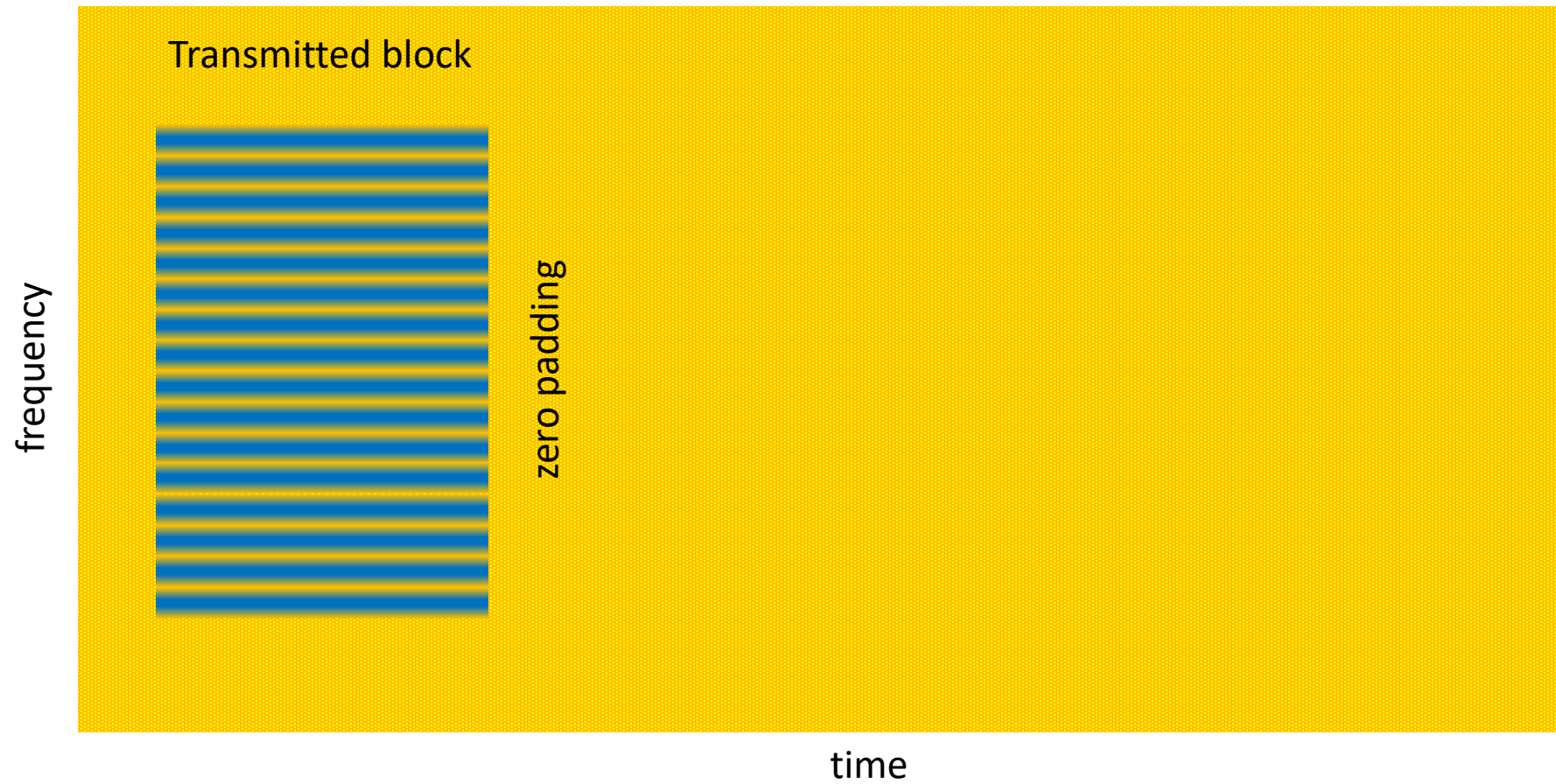


# Research Goal

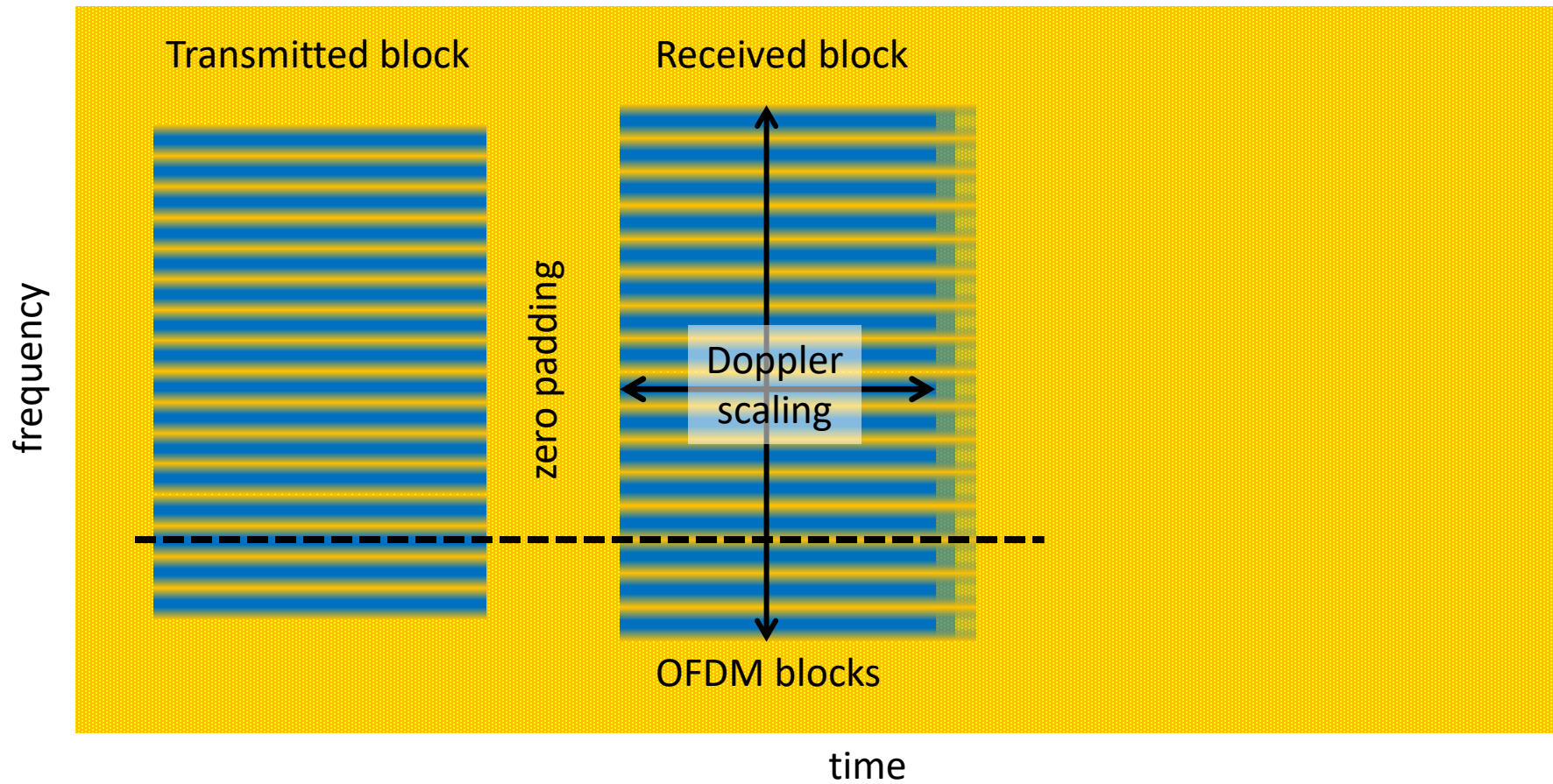
Develop a carrier frequency offset estimator for underwater acoustic OFDM modems.

The solution is required to be **computationally efficient** and practical for the **underwater acoustic channel**.

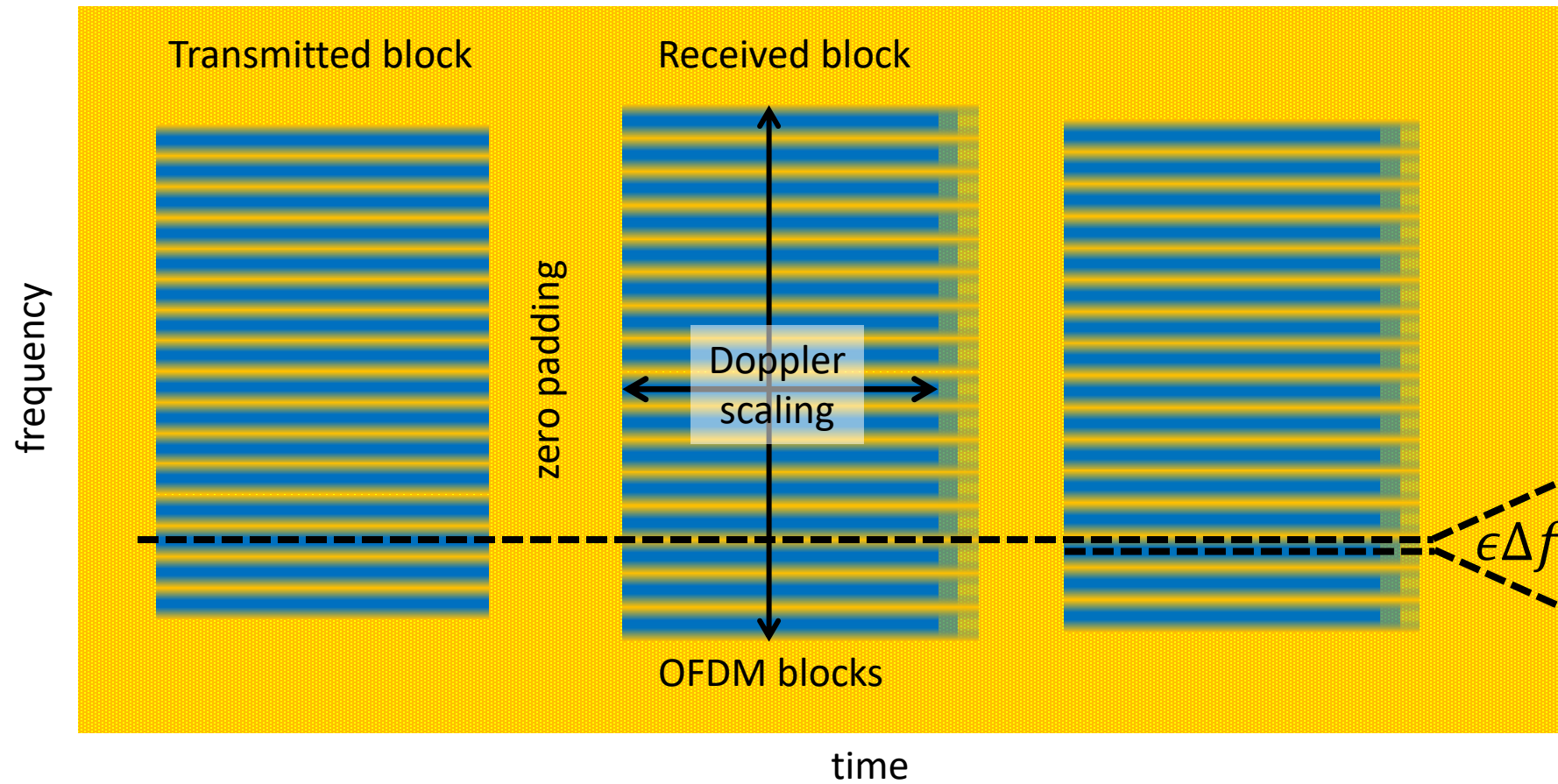
# Multicarrier UAC Effects



# Multicarrier UAC Effects



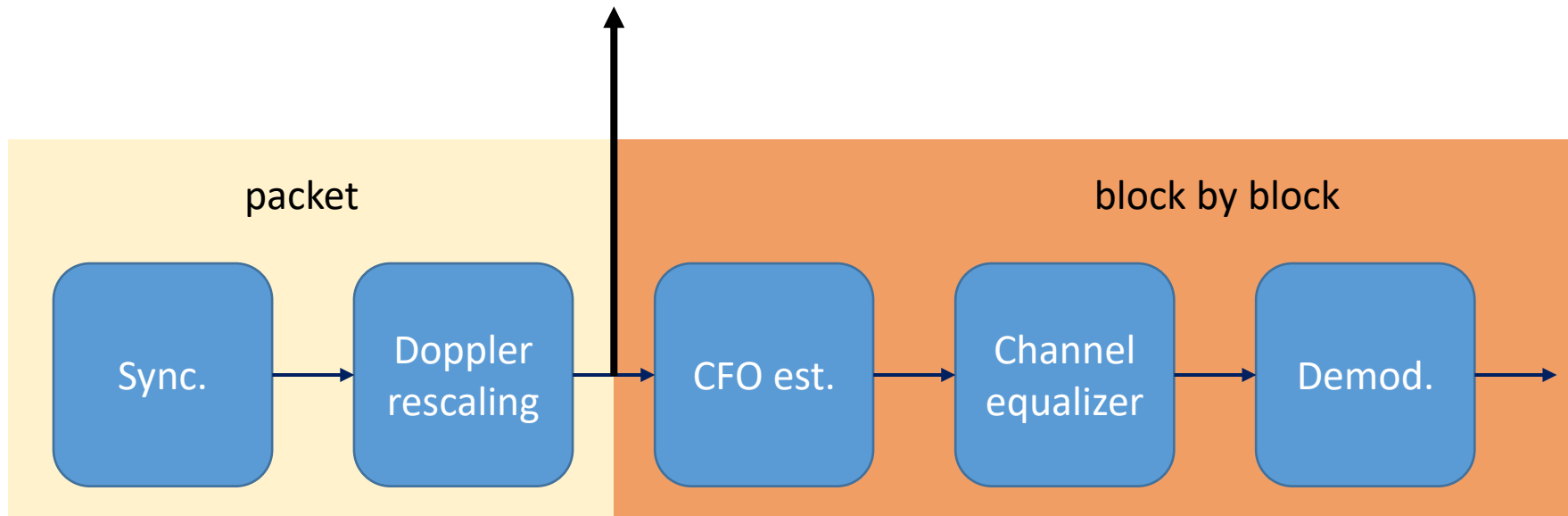
# Multicarrier UAC Effects



# Received Signal Model

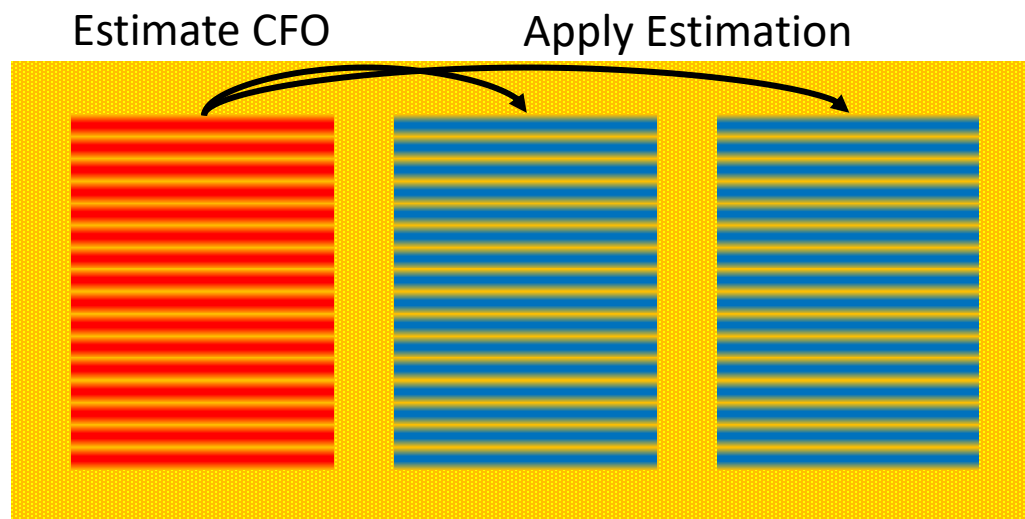
Li et al. '08

$$y[n] = e^{\frac{j2\pi\epsilon_0 n}{K}} h[n] * x[n] + v[n] \quad \text{or in matrix form} \quad \mathbf{y} = \mathbf{\Gamma}_K(\epsilon_0) \underbrace{\mathbf{H}\mathbf{x}}_{\mathbf{z}} + \mathbf{v}$$

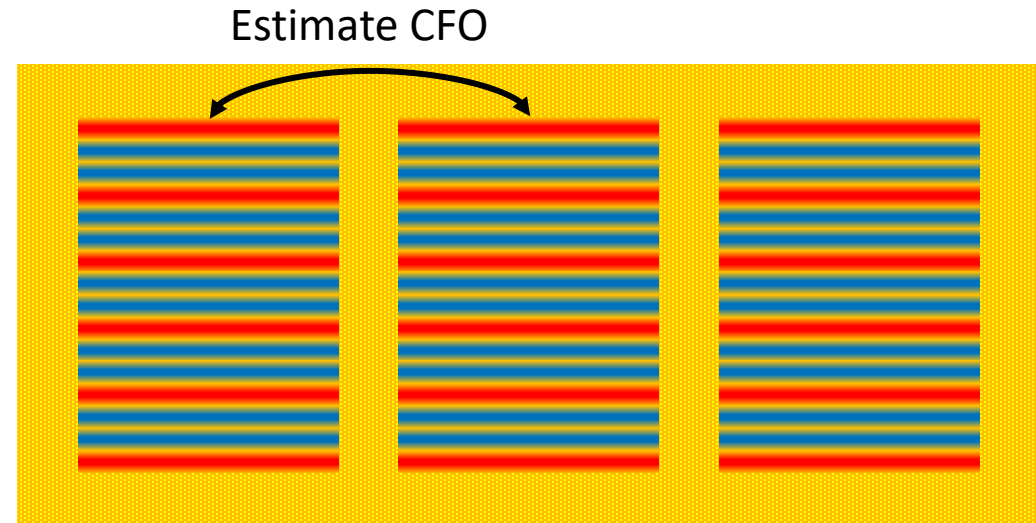


# Radio Frequency Approaches

**Training blocks** with periodic characteristics  
(Classen & Meyer '94)



**Block to block** pilot signal cross-correlation  
(Schmidl & Cox '97)



In UAC – CFO varies between adjacent blocks

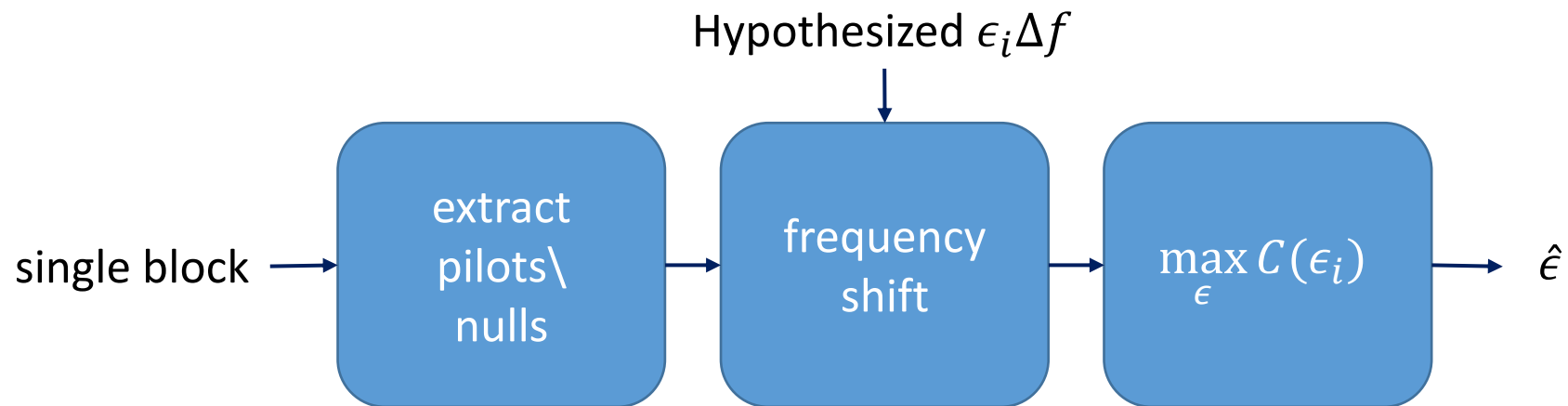
# UAC Approaches

## Null Carriers

Minimum variance  
(Li et al. '08)

## Pilot aided

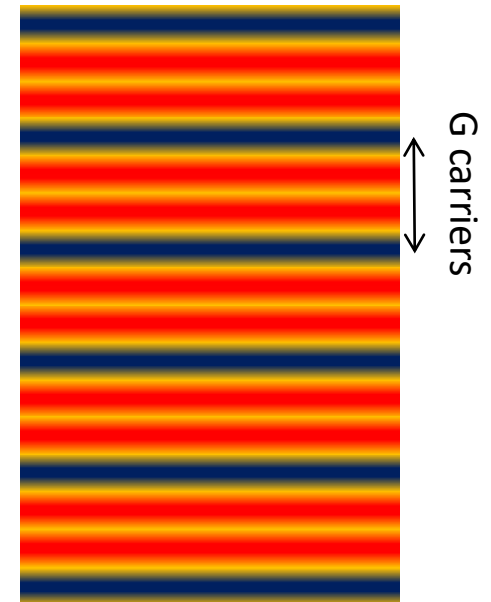
Maximum power  
(Li et al. '06)



Requires exhaustive grid search

# Pilot Based Estimation

$$x[n] = \frac{1}{\sqrt{K}} \sum_{k=0}^{K-1} s(k) e^{\frac{j2\pi nk}{K}}$$



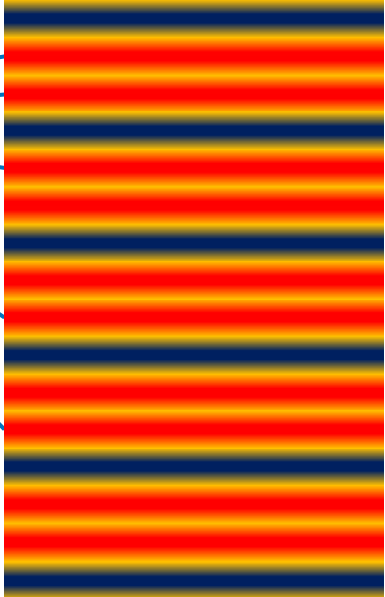


# Pilot Based Estimation

$$x[n] = \frac{1}{\sqrt{K}} \sum_{k=0}^{K-1} s(k) e^{\frac{j2\pi nk}{K}} =$$

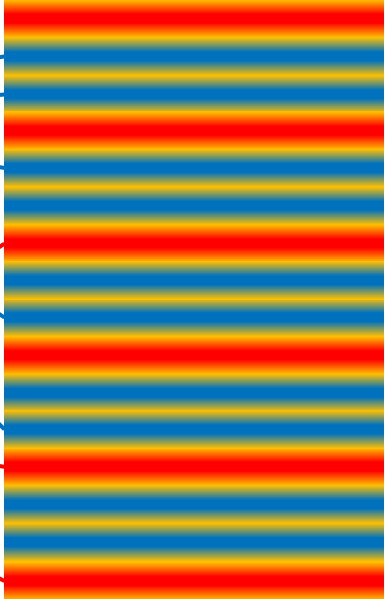
data signal  $\sim \mathcal{N}\left(0, \frac{K-Q}{Q}\right)$

$$\frac{1}{\sqrt{K}} \sum_{k \in S_D} s(k) e^{\frac{j2\pi nk}{K}}$$



G carriers

# Pilot Based Estimation

$$x[n] = \frac{1}{\sqrt{K}} \sum_{k=0}^{K-1} s(k) e^{\frac{j2\pi nk}{K}} = \underbrace{\frac{1}{\sqrt{K}} \sum_{k \in S_D} s(k) e^{\frac{j2\pi nk}{K}}}_{\text{data signal } \sim \mathcal{N}\left(0, \frac{K-Q}{Q}\right)} + \underbrace{\frac{1}{\sqrt{K}} \sum_{q=0}^{Q-1} s(qG) e^{\frac{j2\pi nq}{Q}}}_{\text{pilot signal } Q\text{-periodic}}$$


G carriers

**Idea:** Use correlation between periods of the pilot signal

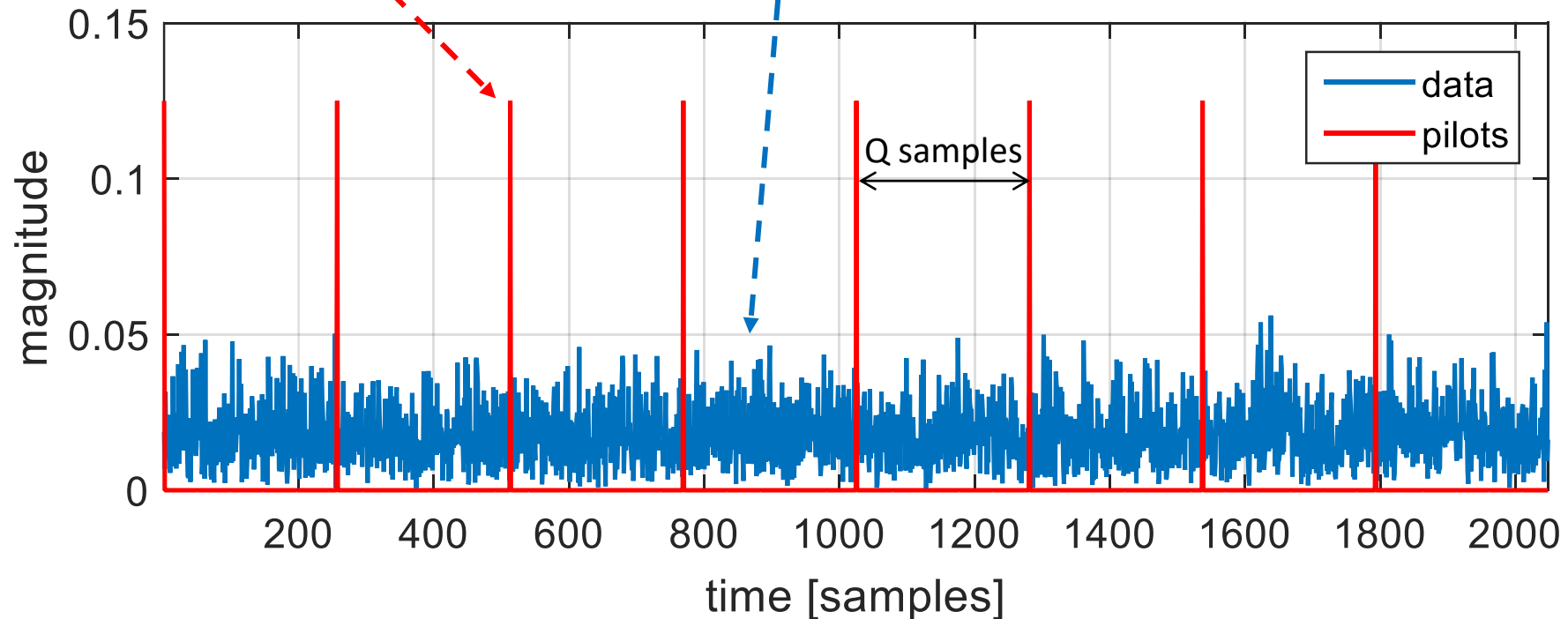
**Problem:** Low “SNR” – Pilot to Data Ratio (PDR)

**Solution:** Design pilot signal with “Good” auto-correlation

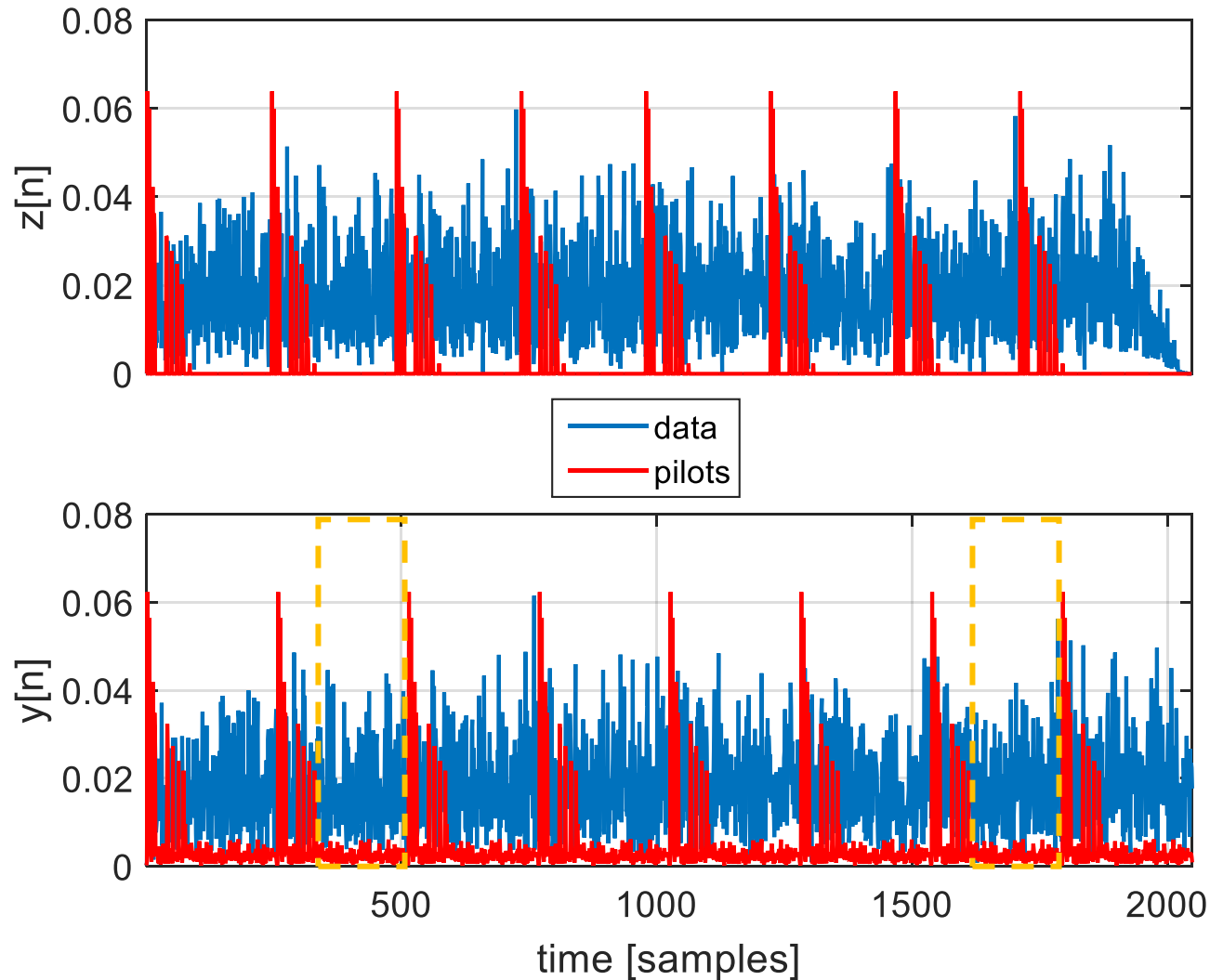
# Best auto correlation: identical pilots

Amar, Avrashi, Stojanovic '16

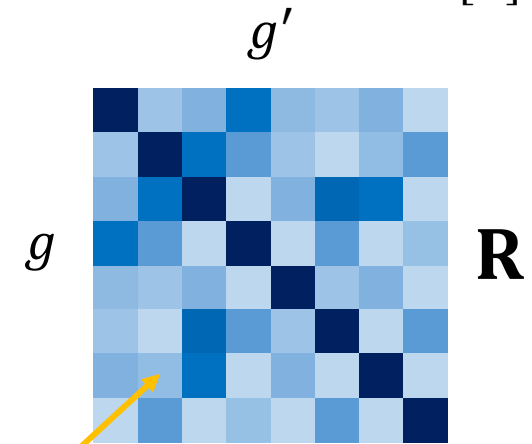
$$\tilde{s}[n] = \frac{1}{\sqrt{K}} \sum_{q=0}^{Q-1} u e^{\frac{j2\pi nq}{Q}} + \frac{1}{\sqrt{K}} \sum_{k \in S_D} s(k) e^{\frac{j2\pi nk}{K}}$$



# Exploiting Inter-Segment Correlations



$$y[n] = e^{\frac{j2\pi\epsilon_0 n}{K}} \underbrace{h[n] * x[n]}_{z[n]}$$



$$\mathbf{y}_g^H \mathbf{y}_{g'} = \underbrace{\left( e^{-j\frac{2\pi}{G}\epsilon_0} \right)^{g'-g}}_{\alpha(\epsilon_0)} \mathbf{z}_g^H \mathbf{z}_{g'}$$

# Eigen Value Decomposition

The cost function in matrix formulation

We look for  $\hat{\epsilon}$  that **minimizes** (**maximizes**)

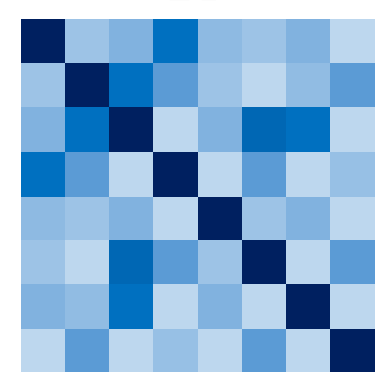
$$l = \boldsymbol{\alpha}(\epsilon)^H \mathbf{R} \boldsymbol{\alpha}(\epsilon)$$

Under two constraints:

- $\|\boldsymbol{\alpha}\| = 1$
- $\arg(\boldsymbol{\alpha}) \propto \epsilon$

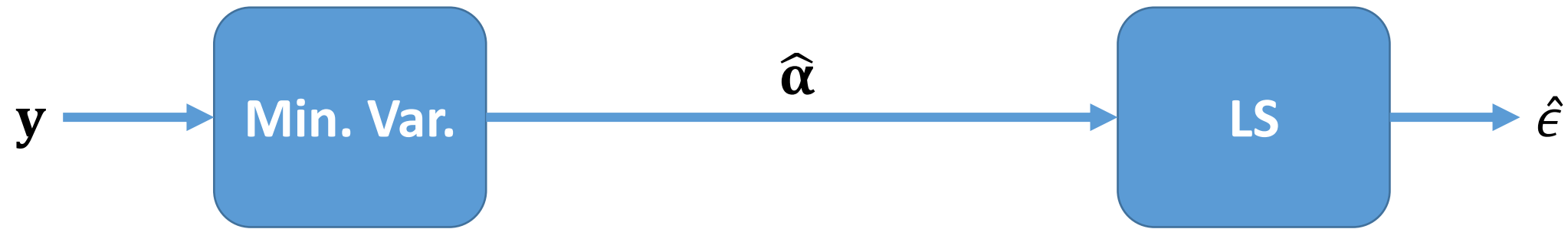
$$\frac{1}{G} [1 \quad \alpha^{-1} \quad \dots \quad \alpha^{-(G-1)}]$$

**R**



$$\begin{bmatrix} 1 \\ \alpha^1 \\ \vdots \\ \alpha^{G-1} \end{bmatrix}$$

# EVD estimator



$$\min_{\alpha} \alpha^H \mathbf{R} \alpha \quad \text{s. t.} \quad \alpha^H \alpha = 1$$

$$\rightarrow \hat{\alpha} = \mathbf{V}_{\min}(\mathbf{R})$$

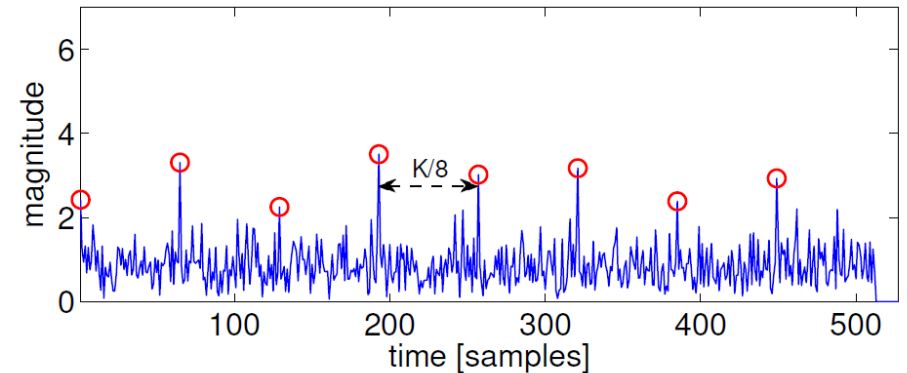
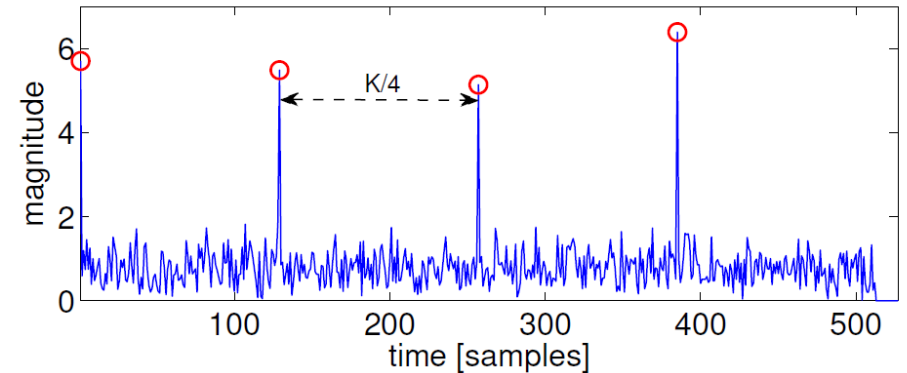
$$\arg[\hat{\alpha}] \approx -\frac{2\pi}{G} \mathbf{g}^E$$

$$\rightarrow \hat{\epsilon} = -\frac{G}{2\pi} \frac{\sum_{g=0}^{G-1} g [\arg[\hat{\alpha}]]_g}{\sum_{g=0}^{G-1} g^2}$$

**Decompose  $\mathbf{R}$  → find the eigenvector of the smallest EV → extract  $\hat{\epsilon}$**

# Research objectives

- The EVD-based estimator has two drawbacks:
  - High PAPR
  - Requires constant CFO during the block
- **Our goal:** Propose a CFO estimator for UAC with the following characteristics:
  - Low complexity
  - Negligible PAPR
  - Adjustable for time-varying channels

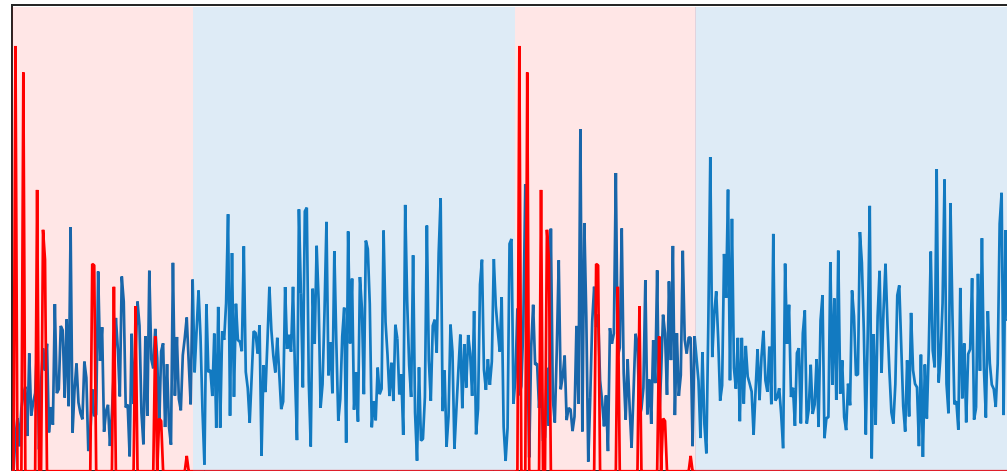
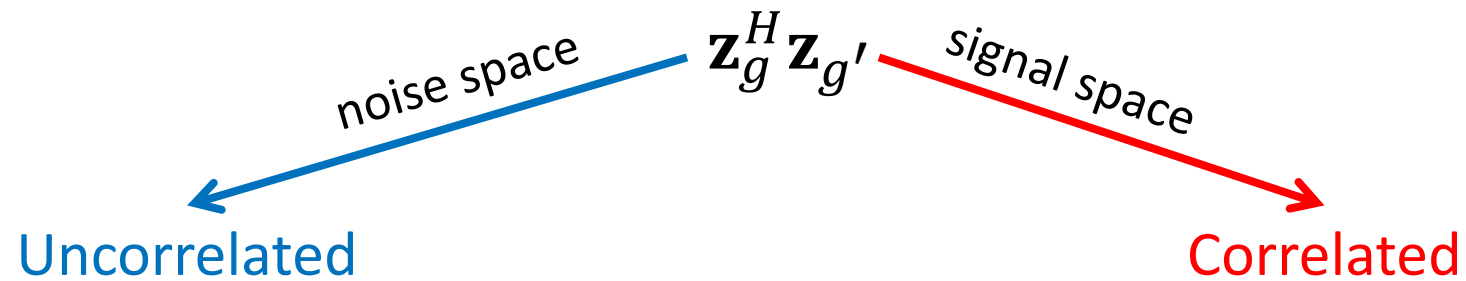


# Signal Space Estimation





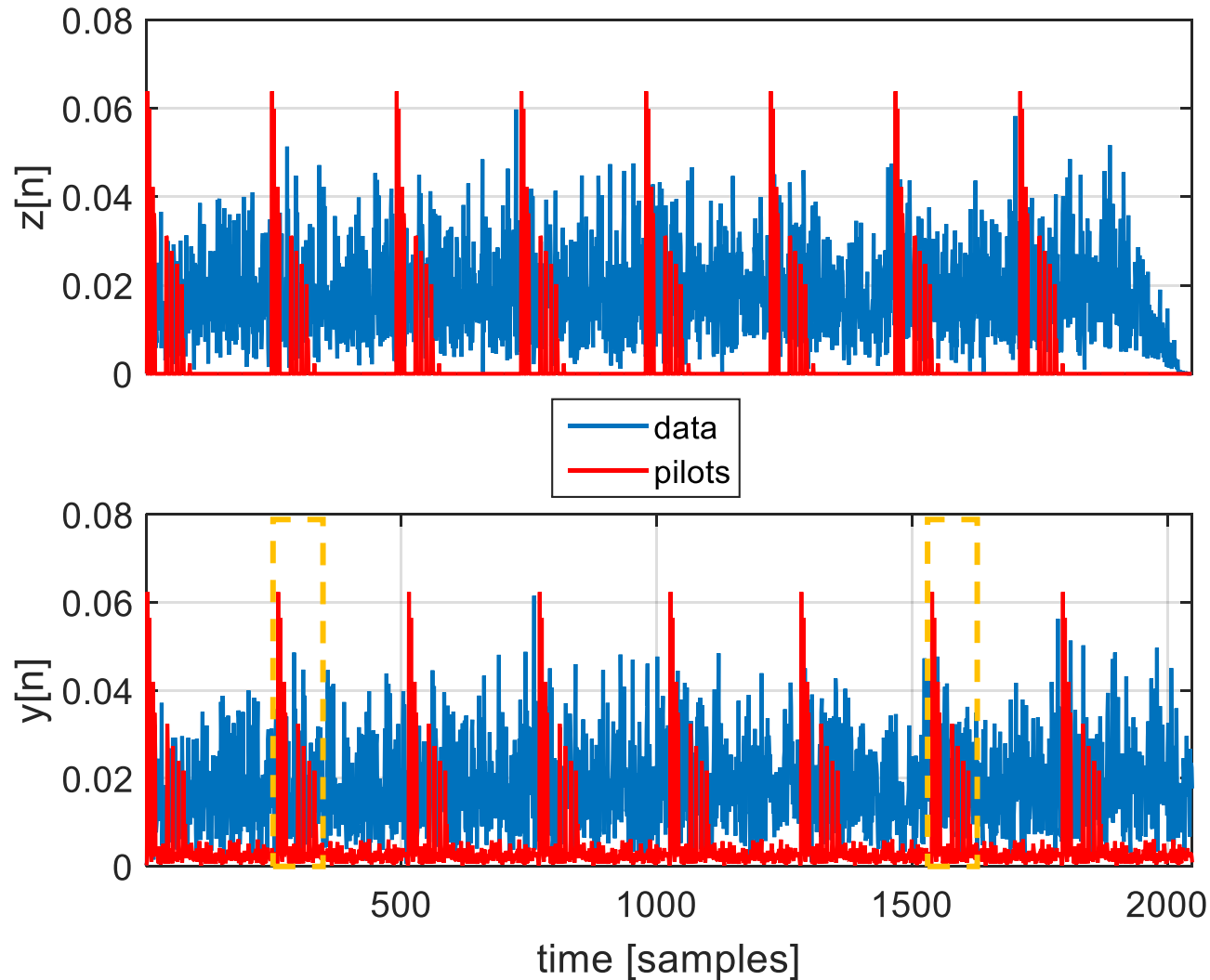
# Two sides of the same coin



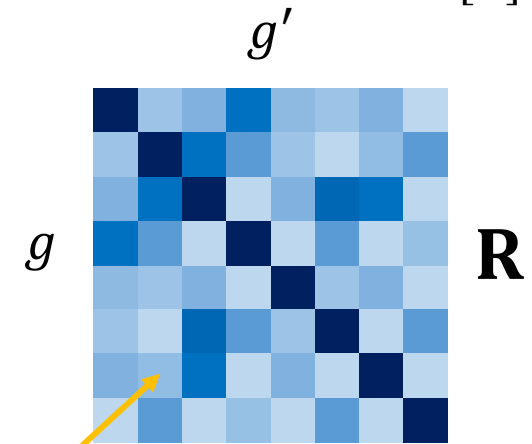
**array processing interpretation**

Steering  $\epsilon$  in the **noise**\signal space to achieve **lowest**\highest SNR

# Exploiting Inter-Segment Correlations

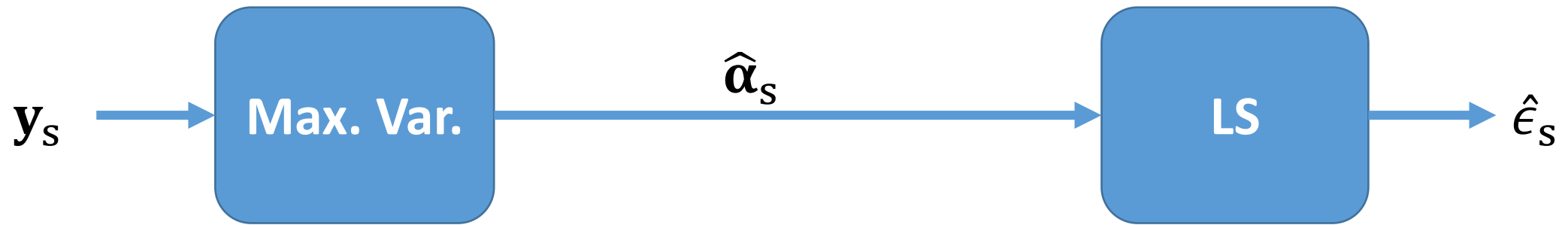


$$y[n] = e^{\frac{j2\pi\epsilon_0 n}{K}} \underbrace{h[n] * x[n]}_{z[n]}$$



$$\mathbf{y}_g^H \mathbf{y}_{g'} = \underbrace{\left( e^{-j\frac{2\pi}{G}\epsilon_0} \right)^{g'-g}}_{\alpha(\epsilon_0)} \mathbf{z}_g^H \mathbf{z}_{g'}$$

# EVD in Signal Space



$$\max_{\alpha} \alpha^H \mathbf{R}_s \alpha \quad \text{s.t.} \quad \alpha^H \alpha = 1$$

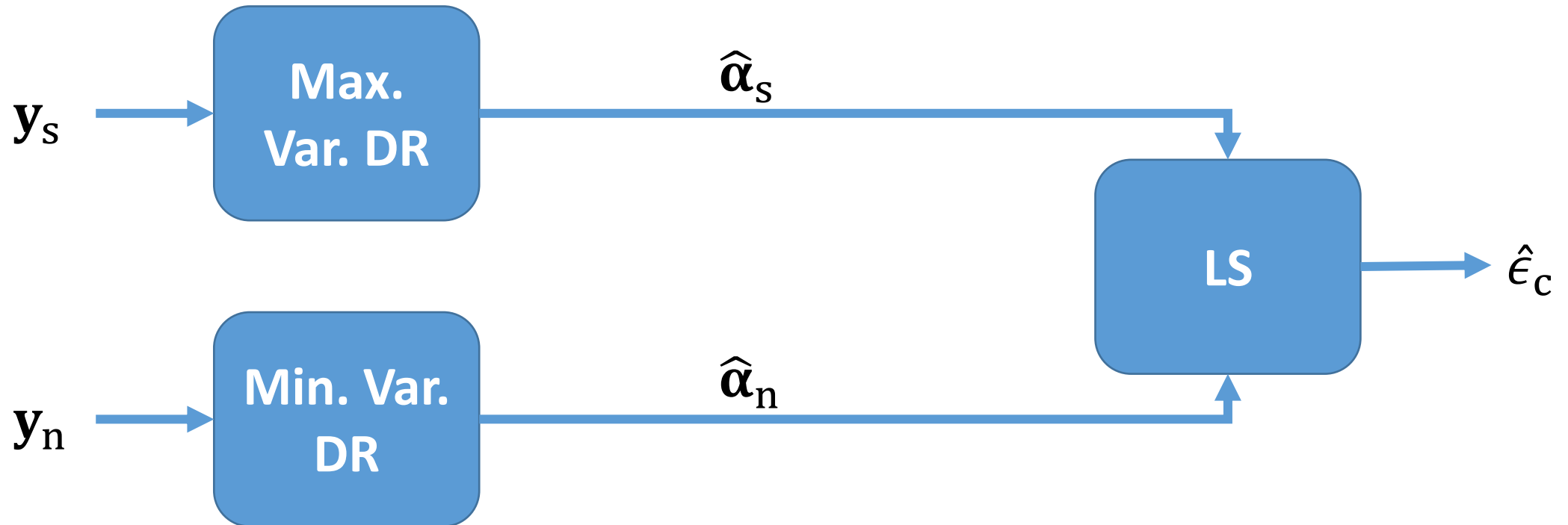
$$\rightarrow \hat{\alpha}_s = \mathbf{V}_{\max}(\mathbf{R}_s)$$

$$\arg[\hat{\alpha}] \approx -\frac{2\pi}{G} \mathbf{g}^T \epsilon$$

$$\rightarrow \hat{\epsilon} = -\frac{G}{2\pi} \frac{\sum_{g=0}^{G-1} g [\arg[\hat{\alpha}]]_g}{\sum_{g=0}^{G-1} g^2}$$

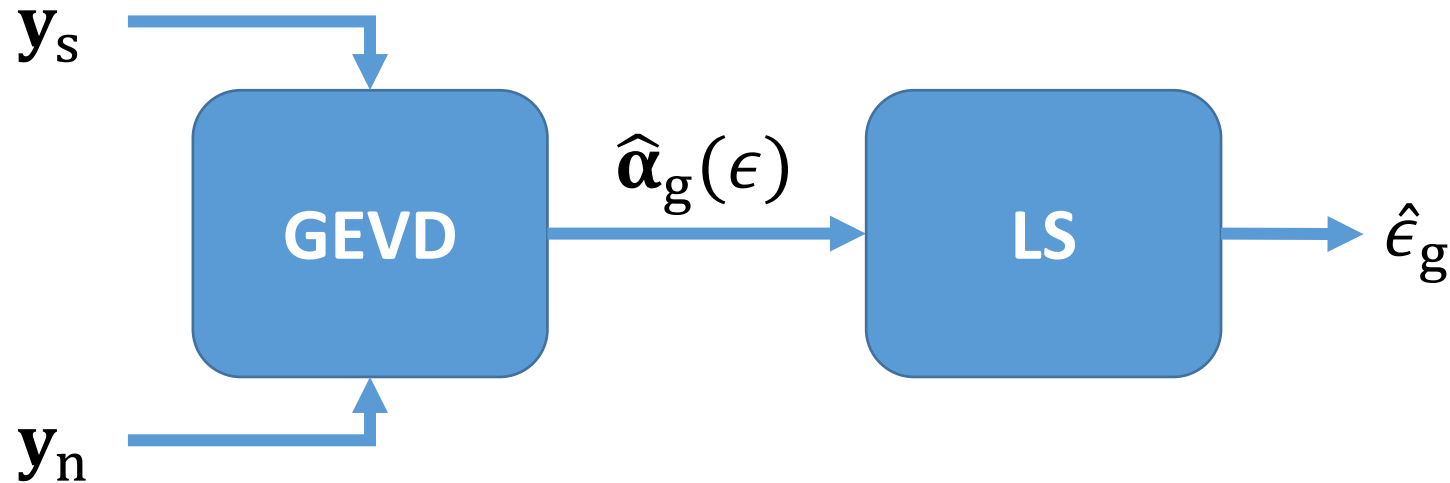
**Decompose  $\mathbf{R}_s$**   $\rightarrow$  find the eigenvector of the largest EV  $\rightarrow$  extract  $\hat{\epsilon}$

# Combined LS estimate



$$\hat{\epsilon}_c = \beta \hat{\epsilon}_n + (1 - \beta) \hat{\epsilon}_s, \quad 0 \leq \beta \leq 1$$

# Generalized EVD



$$\max_{\alpha} \frac{\alpha^H \mathbf{R}_s \alpha}{\alpha^H \mathbf{R}_n \alpha} \quad \text{s. t. } \alpha^H \alpha = 1$$

$$\rightarrow \hat{\alpha}_g = \mathbf{V}_{\max}(\mathbf{R}_n^{-1} \mathbf{R}_s)$$

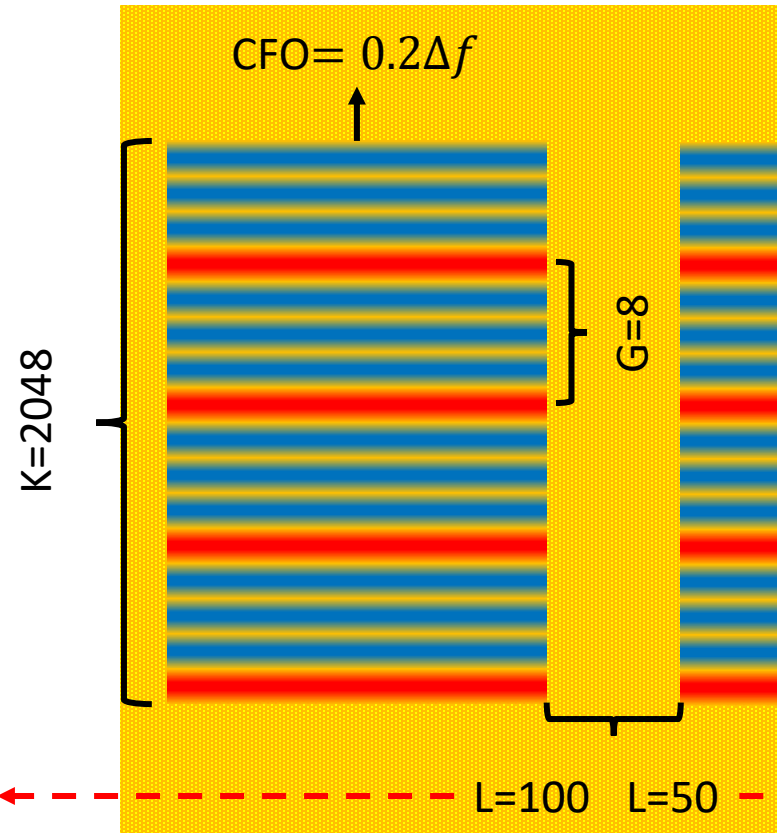
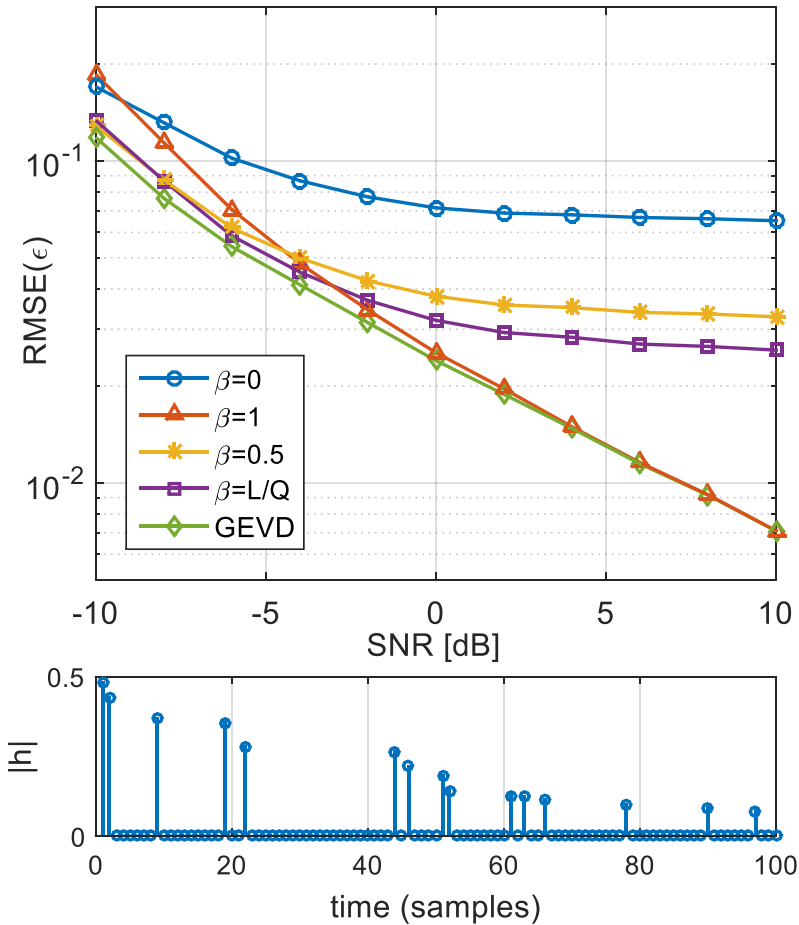
**Decompose  $\mathbf{R}_n^{-1} \mathbf{R}_s$   $\rightarrow$  find the eigenvector of the largest EV  $\rightarrow$  extract  $\hat{\epsilon}$**

# Computational Complexity

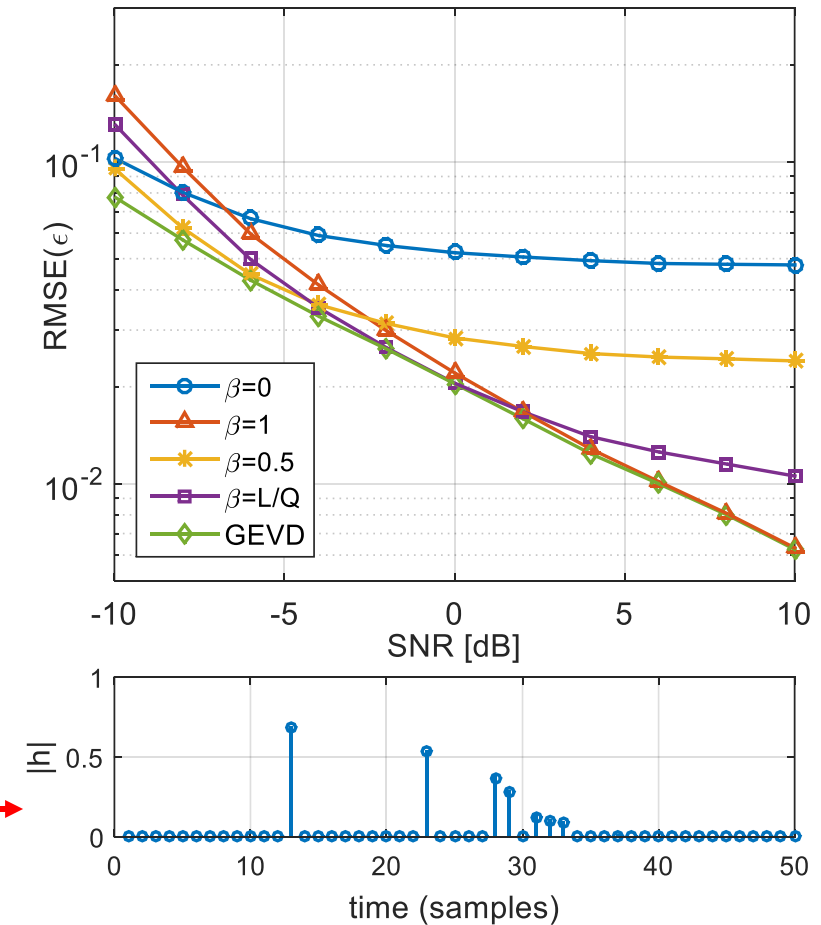
Method	Complexity
Grid Search	$\mathcal{O}(K\sqrt{K})$
Noise Space EVD	$\mathcal{O}(G^2(Q - L)) = \mathcal{O}(KG)$
Signal Space EVD	$\mathcal{O}(G^2L)$
Combined LS	$\mathcal{O}(G^2 \max\{Q - L, L\})$
Generalized EVD	$\mathcal{O}(G^2 \max\{Q - L, L\})$

# RMSE vs SNR

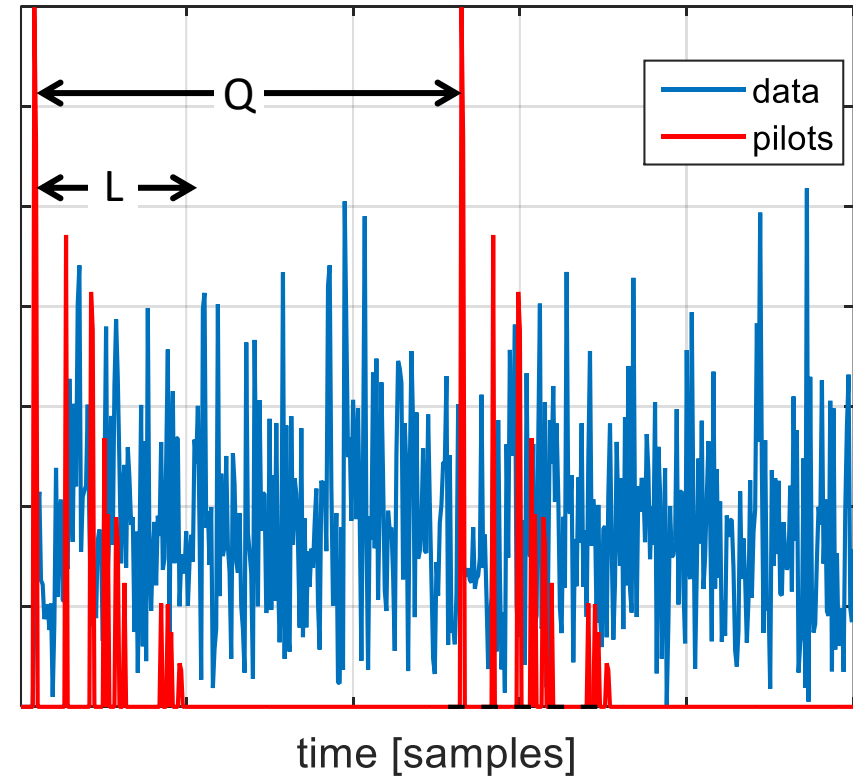
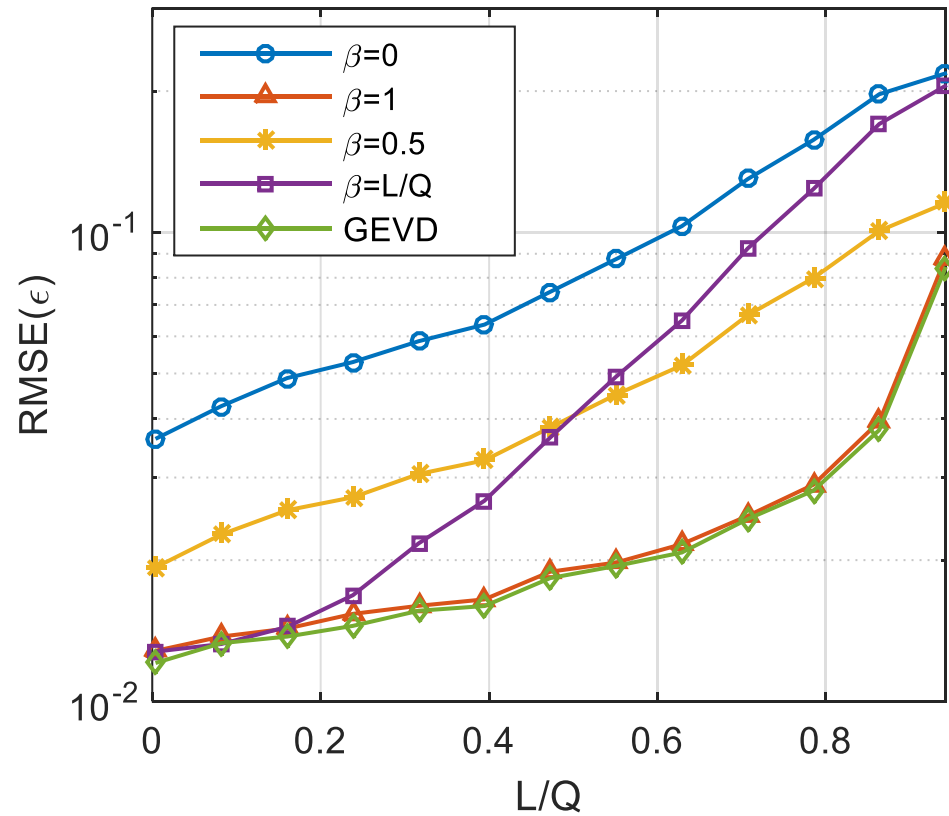
## Long Delay Spread



## Short Delay Spread

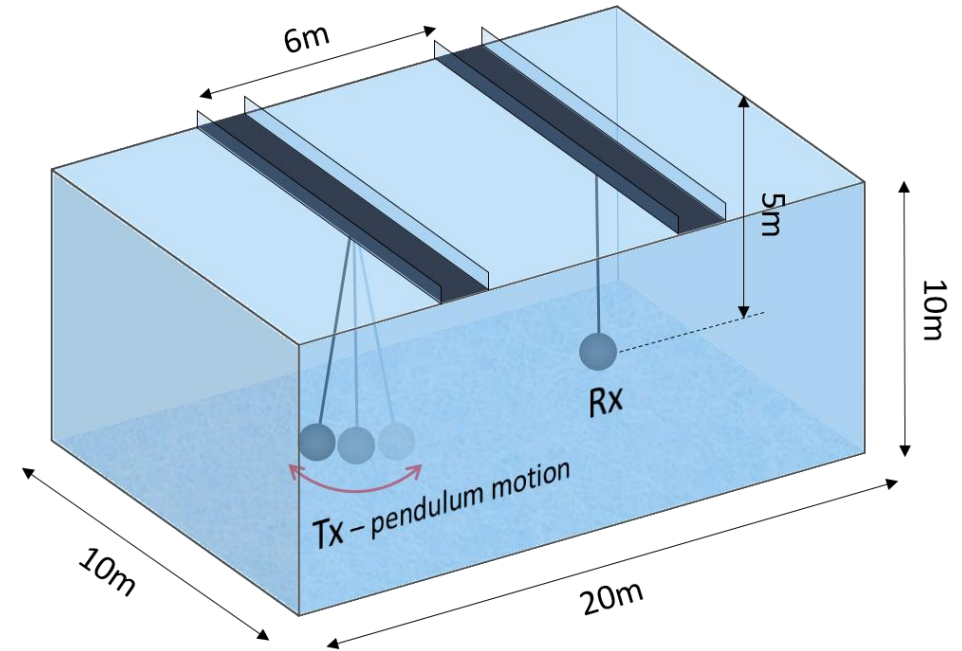
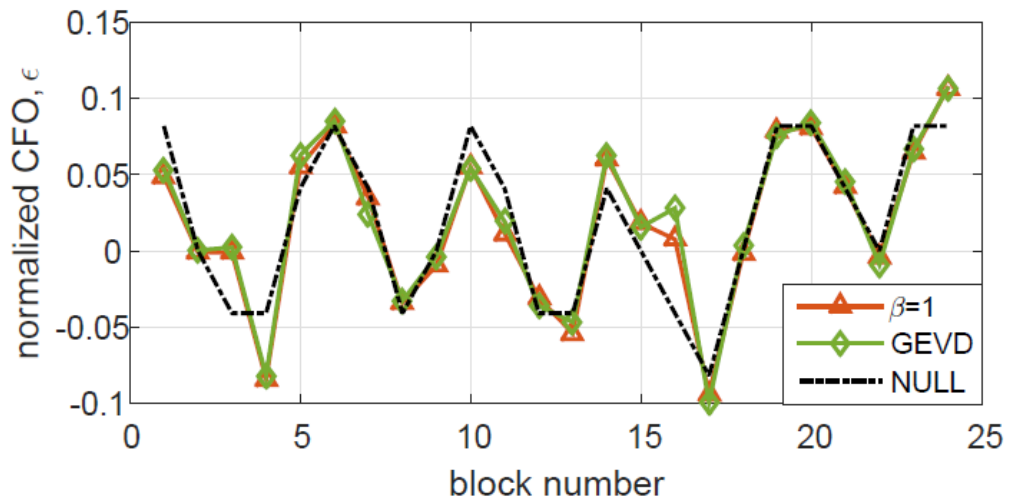
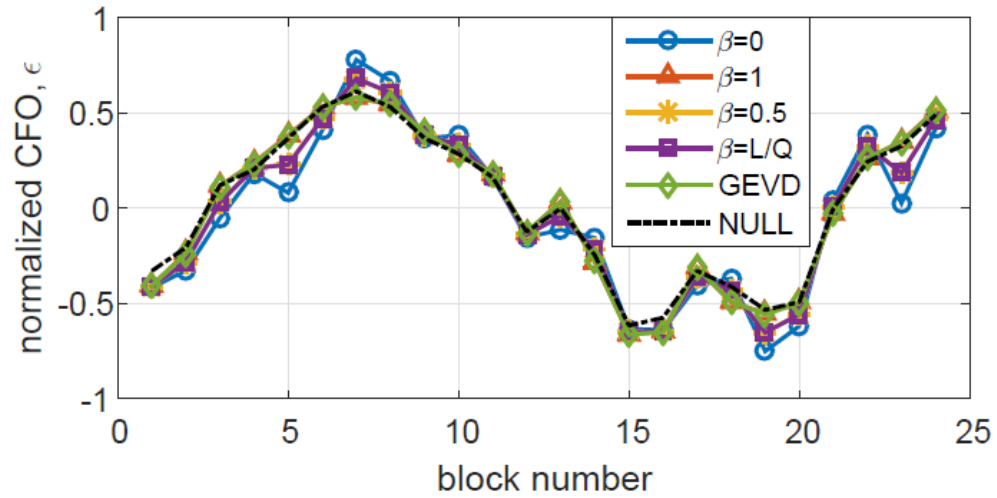


# Effect of Delay Spread





# Pool Trial

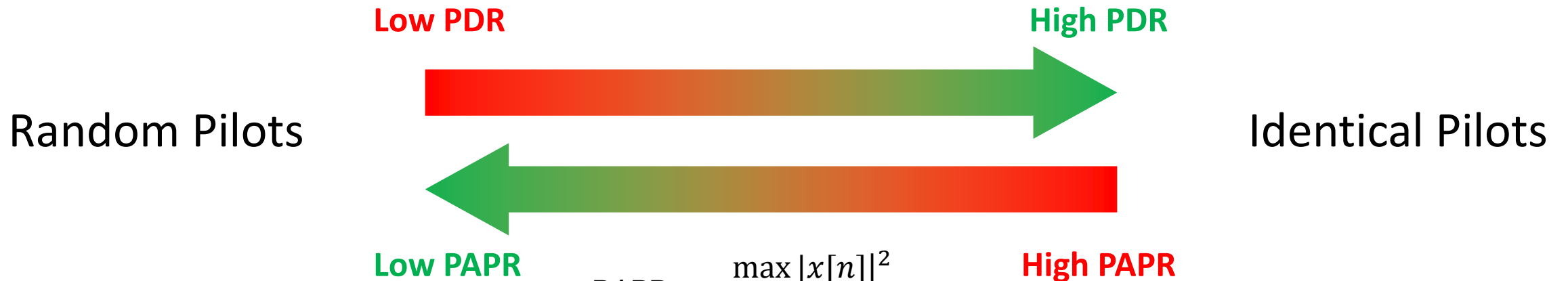


# Pilot Design Optimization

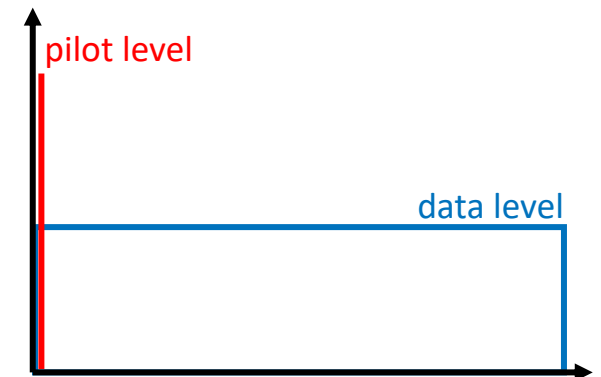
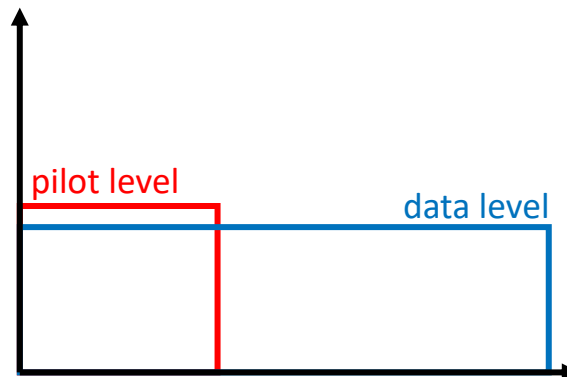
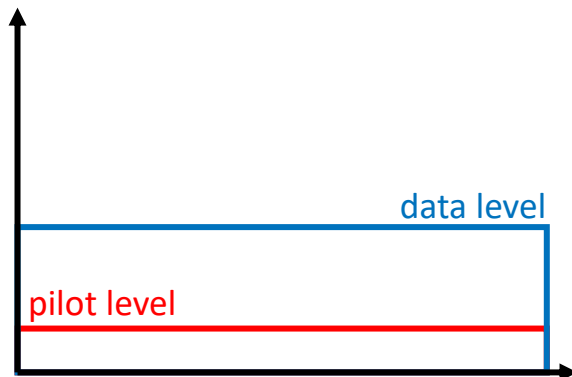
Pilot Design Optimization



# PDR and PAPR tradeoff



$$\text{PAPR} = \frac{\max |x[n]|^2}{\frac{1}{K} \sum_{n=1}^K |x[n]|^2}$$



# Proposed pilot design formulation

Pilot tones:  $\phi[k] = s[qG] = e^{j\phi_k}$

Pilot signal (one period):  $\psi[n] = \frac{1}{\sqrt{Q}} \text{IDFT}\{\phi[k]\}$

Unit amplitude

Known envelope

Find the phases  $\phi_k$

$$w_{L_p}[n] = \begin{cases} \frac{1}{\sqrt{L_p}}, & n < L_p \\ 0, & n \geq L_p \end{cases}$$

Phase retrieval problem:  $\min_{\psi, \phi} \left\| \mathbf{W}_{L_p} \boldsymbol{\Psi} - \mathbf{F}_Q^H \boldsymbol{\Phi} \right\|^2$

# Pilot design – generalized GSA algorithm

Initialize  $\phi_0 = \text{rand}(Q, 1)$ ,  $J = \infty$

while  $J > \eta$  do

$$\psi_i = e^{j\angle[\text{IFFT}\{\phi_{i-1}\}]}$$

$$\phi_i = e^{j\angle[\text{FFT}\{\mathbf{W}\psi_i\}]}$$

$$\varepsilon = \|\text{IFFT}\{\phi_i\} - \mathbf{w}\|^2$$

$$p = \frac{\max |\text{IFFT}\{\phi_i\}|^2}{\frac{1}{Q} \sum_{n=1}^Q |\text{IFFT}\{\phi_i\}|^2}$$

$$J = \alpha\varepsilon + \beta p$$

end while

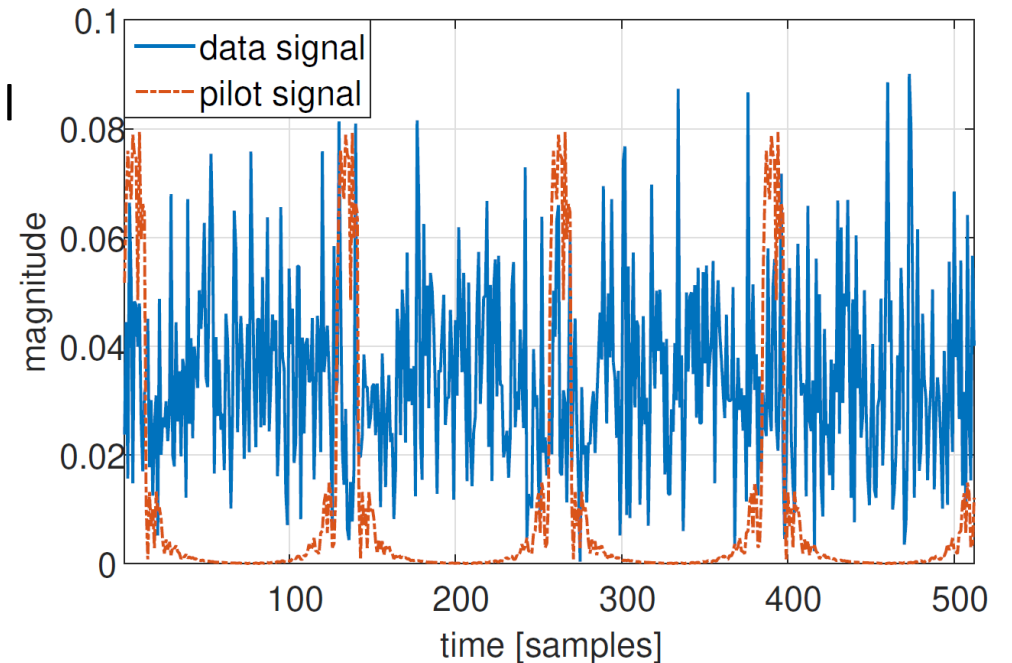
return  $\phi_i$

time domain pilot signal

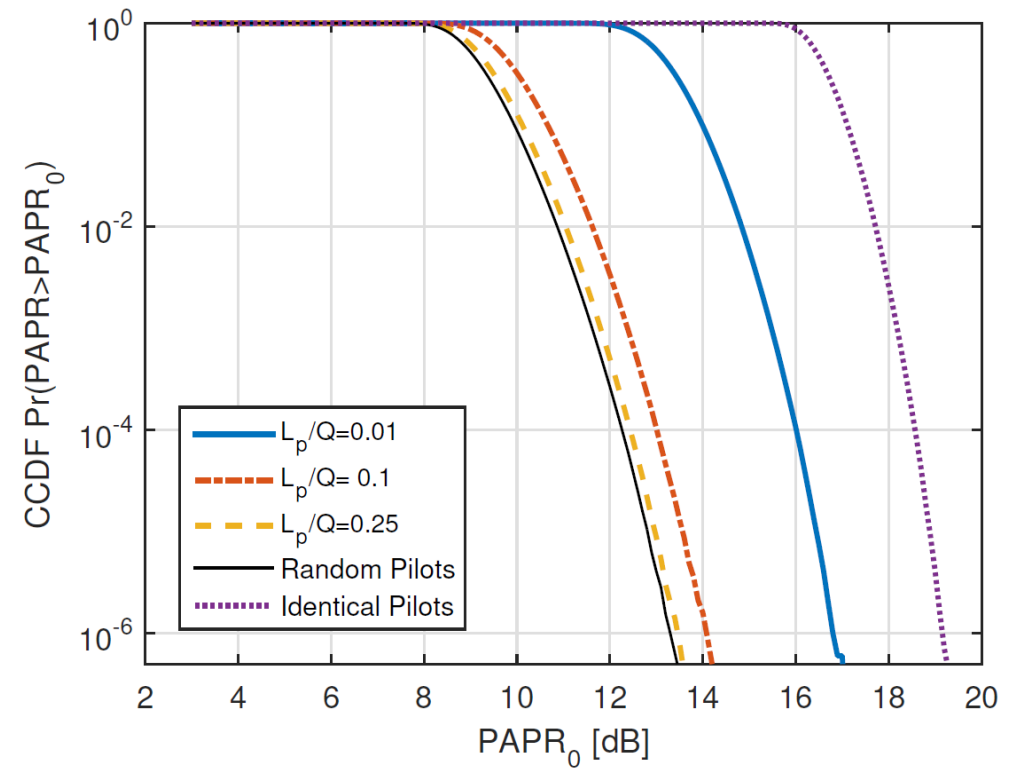
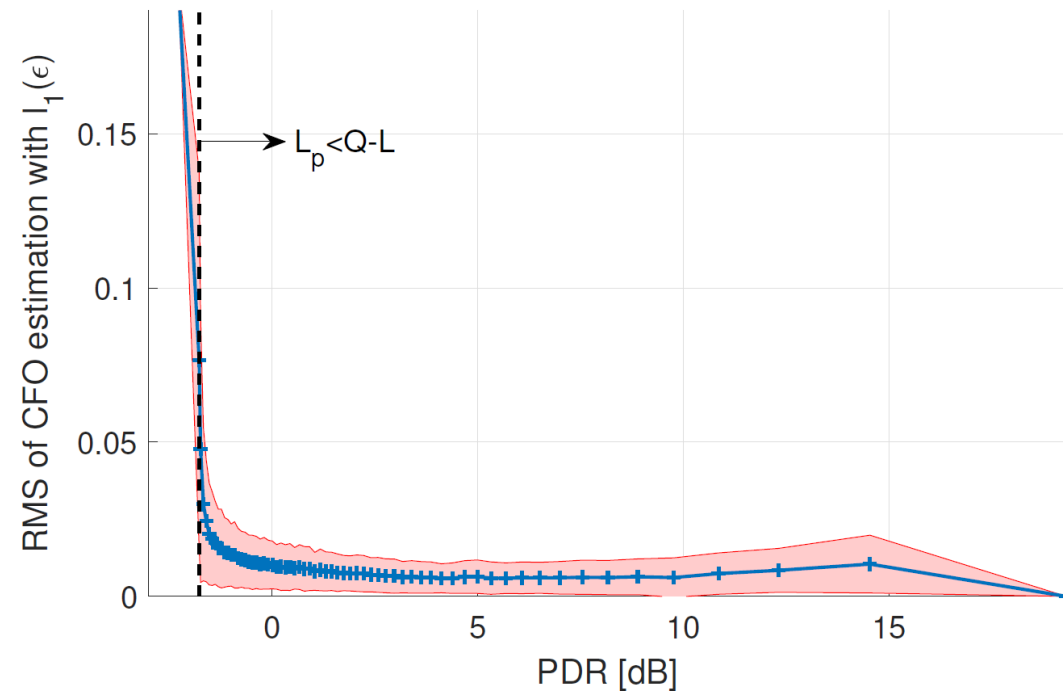
pilot tones

envelope error norm

PAPR



# Simulation results



# Time-Varying CFO Estimation

Time-Varying CFO Estimation



# How can we capture TV-CFO?

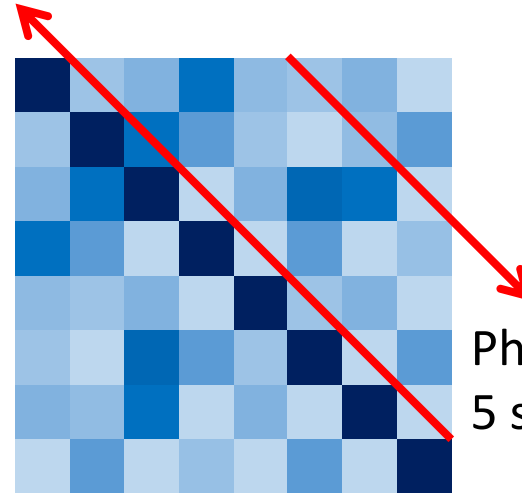
$\mathbf{R}(\epsilon, g)$  becomes  $\mathbf{R}(\epsilon, g, n)$ :

$$\mathbf{R}_{g,g'} = \mathbf{y}_g^H \mathbf{y}_{g'} = \mathbf{z}_g^H \mathbf{\Gamma}_g^H(\epsilon, n) \mathbf{\Gamma}_{g'}(\epsilon, n) \mathbf{z}_{g'}$$

$\mathbf{\Gamma}_g^H(\epsilon, n) \mathbf{\Gamma}_{g'}(\epsilon, n)$  is a diagonal matrix

For constant CFO the diagonal is  $d_{g,g'} = \alpha_g^* \alpha_{g'}$

Phases accumulated within  
1 sub-segment duration



Phases accumulated within  
5 sub-segment duration



# Polynomial Model

- Time variations are decomposed to its Taylor series:

$$\epsilon[n] = \sum_{l=0}^{\infty} \epsilon_l n^l \quad , \quad 0 \leq n \leq K - 1$$

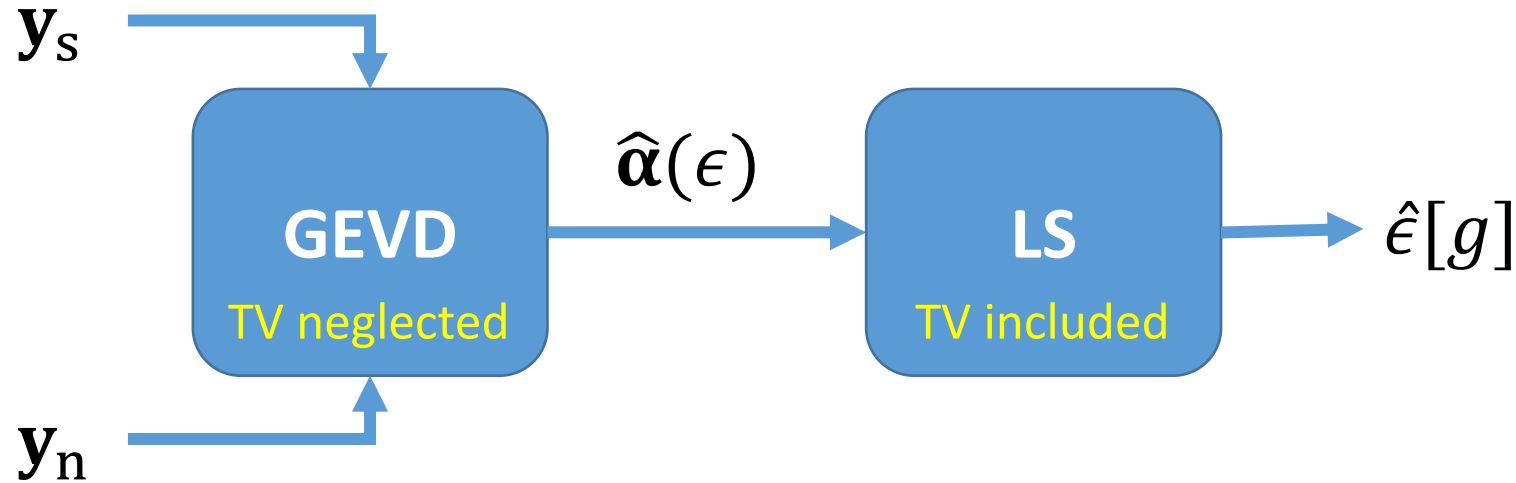
- The diagonal of  $\mathbf{\Gamma}_g^H(\epsilon, n)\mathbf{\Gamma}_{g'}(\epsilon, n)$  becomes

$$d_{g,g'} = \alpha_g^* \exp \left\{ \frac{j2\pi}{K} \sum_{l=1}^{\infty} \epsilon_l [r_l(n, g') - r_l(n, g)] \right\} \alpha_{g'}$$

$$\alpha_g = \exp \left\{ \frac{2\pi}{G} \sum_{l=1}^{G-1} g^l Q^{l-1} \epsilon_{l-1} \right\}$$

$$r_{l(n,g)} = \sum_{k=1}^{l-1} \binom{l}{k} n^{l-k} (gQ)^k$$

# Approximated solution



$$\max_{\alpha} \frac{\alpha^H \mathbf{R}_s \alpha}{\alpha^H \mathbf{R}_n \alpha} \quad \text{s. t. } \alpha^H \alpha = 1$$

$$\rightarrow \hat{\alpha} = \mathbf{V}_{\max}(\mathbf{R}_n^{-1} \mathbf{R}_s)$$

$$\arg[\hat{\alpha}] \approx -\frac{2\pi}{G} \mathbf{A} \mathbf{Q} \epsilon$$

$$\rightarrow \hat{\epsilon} = -\frac{G}{2\pi} \mathbf{Q}^{-1} (\mathbf{A}^T \mathbf{A})^{-1} \mathbf{A}^T \arg[\hat{\alpha}]$$

# Piecewise-Constant Model

- Time variations are represented as piecewise-constant:

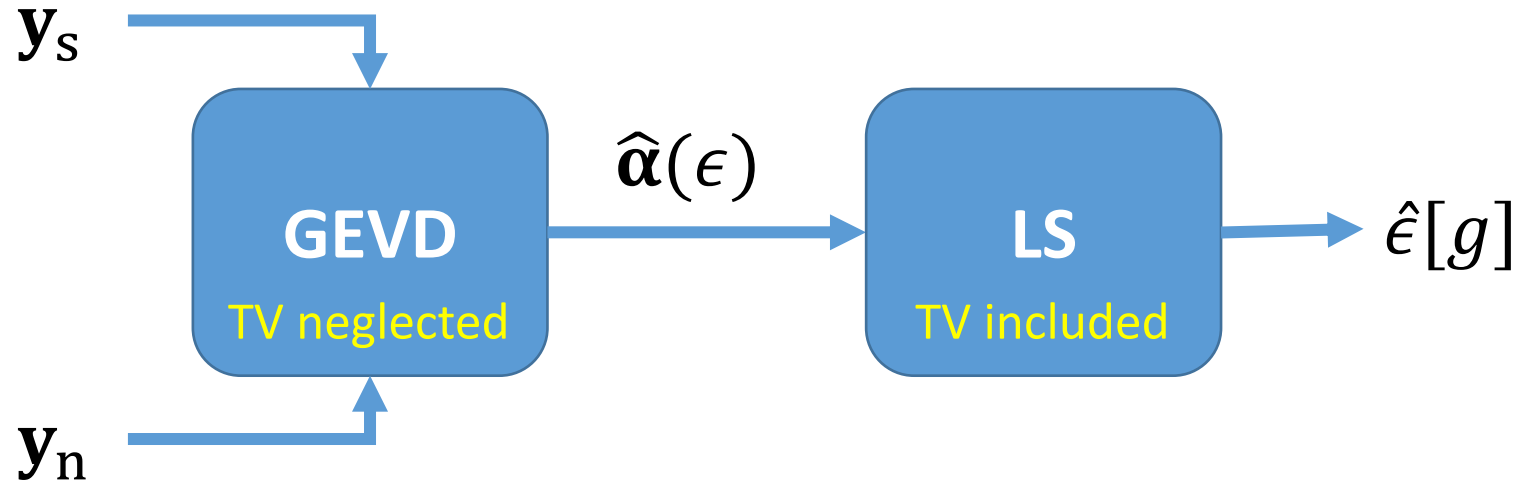
$$\epsilon[n] = \sum_{g=0}^{G-1} \epsilon_g u_g[n] \quad , \quad 0 \leq n \leq K - 1$$

- The diagonal of  $\mathbf{\Gamma}_g^H(\epsilon, n) \mathbf{\Gamma}_{g'}(\epsilon, n)$  becomes

$$d_{g,g'} = \alpha_g^* \exp \left\{ \frac{j2\pi}{K} \sum_{l=1}^{\infty} (\epsilon_{g'} - \epsilon_g) n \right\} \alpha_{g'} \quad , \quad \alpha_g = e^{\frac{2\pi}{G} \epsilon_g g}$$

The time varying component is bounded by  $\exp \left\{ \frac{j2\pi}{K} |\epsilon_{g'} - \epsilon_g| Q \right\}$

# Approximated solution



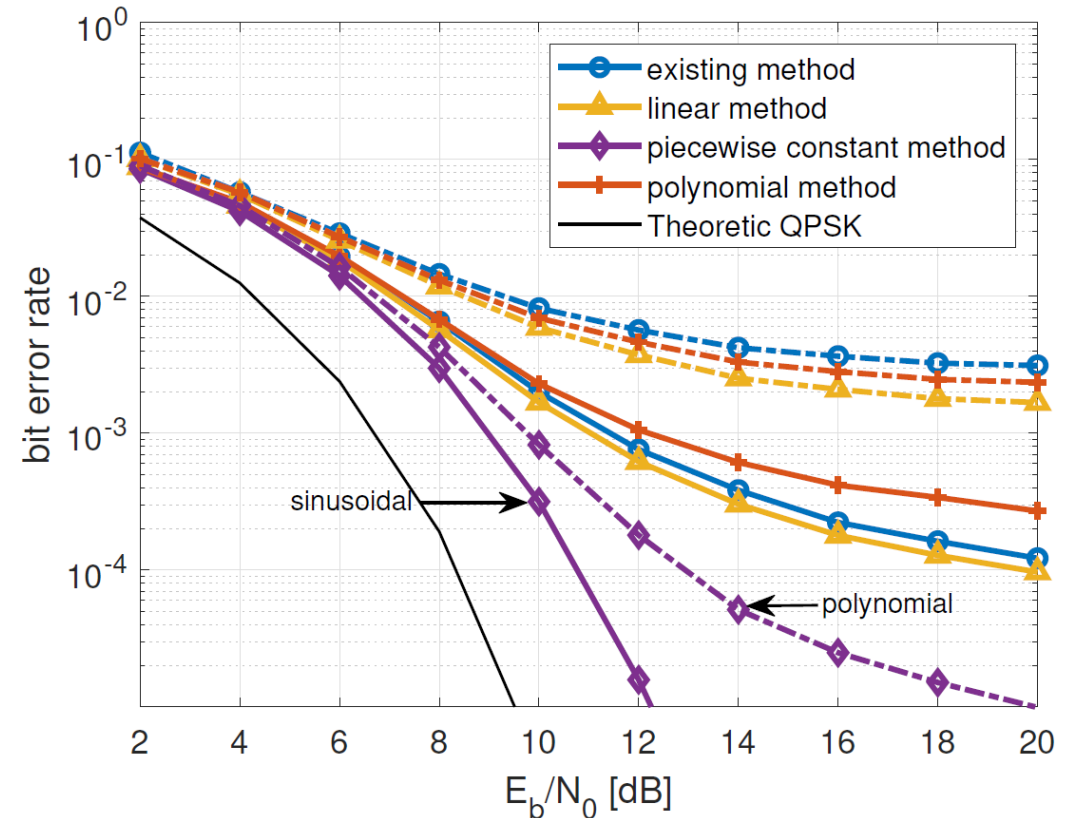
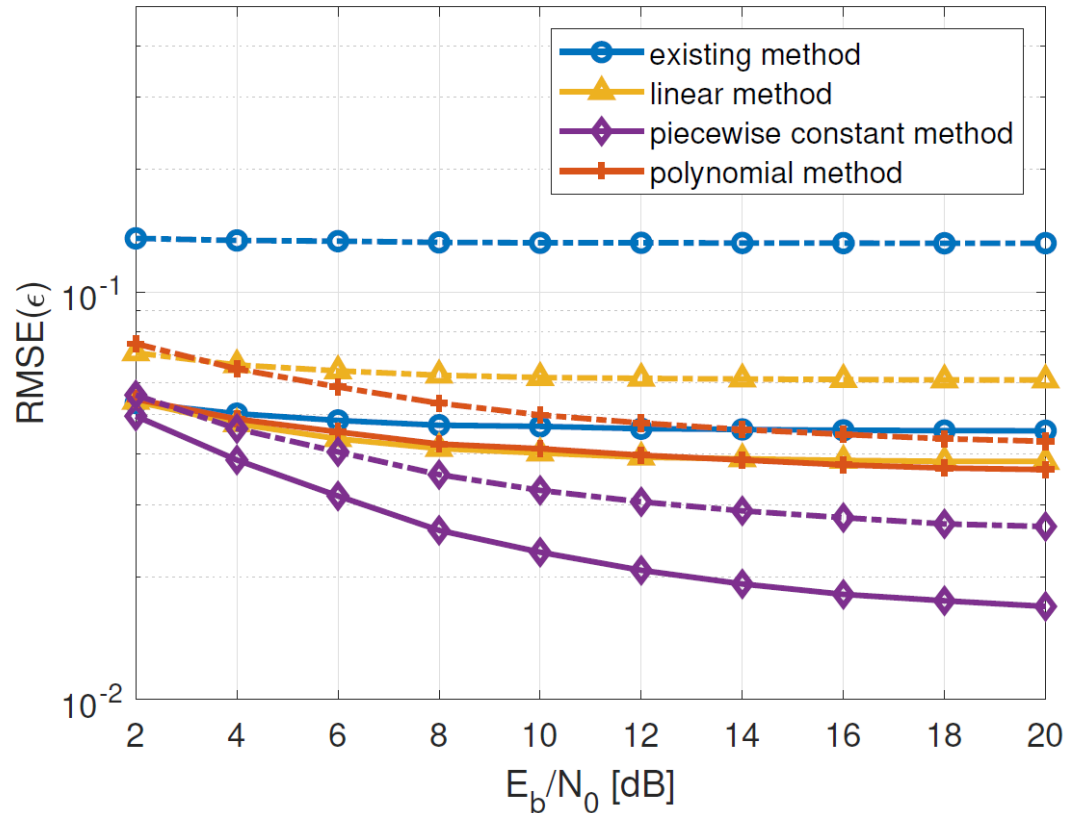
$$\max_{\boldsymbol{\alpha}} \frac{\boldsymbol{\alpha}^H \mathbf{R}_s \boldsymbol{\alpha}}{\boldsymbol{\alpha}^H \mathbf{R}_n \boldsymbol{\alpha}} \quad \text{s. t. } \boldsymbol{\alpha}^H \boldsymbol{\alpha} = 1$$

$$\rightarrow \hat{\boldsymbol{\alpha}} = \mathbf{V}_{\max}(\mathbf{R}_n^{-1} \mathbf{R}_s)$$

$$\arg[\hat{\boldsymbol{\alpha}}] \approx -\frac{2\pi}{G} \mathbf{G}\boldsymbol{\epsilon}$$

$$\rightarrow \hat{\epsilon} = -\frac{G}{2\pi} \mathbf{G}^{-1} \arg[\hat{\boldsymbol{\alpha}}]$$

# Simulation results



Polynomial model:  $\epsilon[n] = \sum_{l=0}^4 \frac{b_l}{K^l} n^l$  ,  $b_l \sim U[-0.25, 0.25]$

Sinusoidal model:  $\epsilon[n] = \Delta f \left[ A_0 + A \sin \left( 2\pi n \frac{f_{\sin}}{K} \right) \right]$  ,  $A_0, A \sim U[-0.25, 0.25]$  ,  $f_{\sin} \sim U[0.25, 2]$

# Conclusions and Future Research

- A complete Tx-Rx scheme was suggested:
  - Reduced complexity closed form CFO estimation
  - Pilot design resolves the PAPR problem and makes the solution practical
  - Time-varying model allows deployment in harsh environments
- Future Research
  - Time Varying CIR
  - Combined pilots-data PAPR reduction
  - Proving the solution in sea trials
  - Model order estimation and channel sensing for the TV estimator