



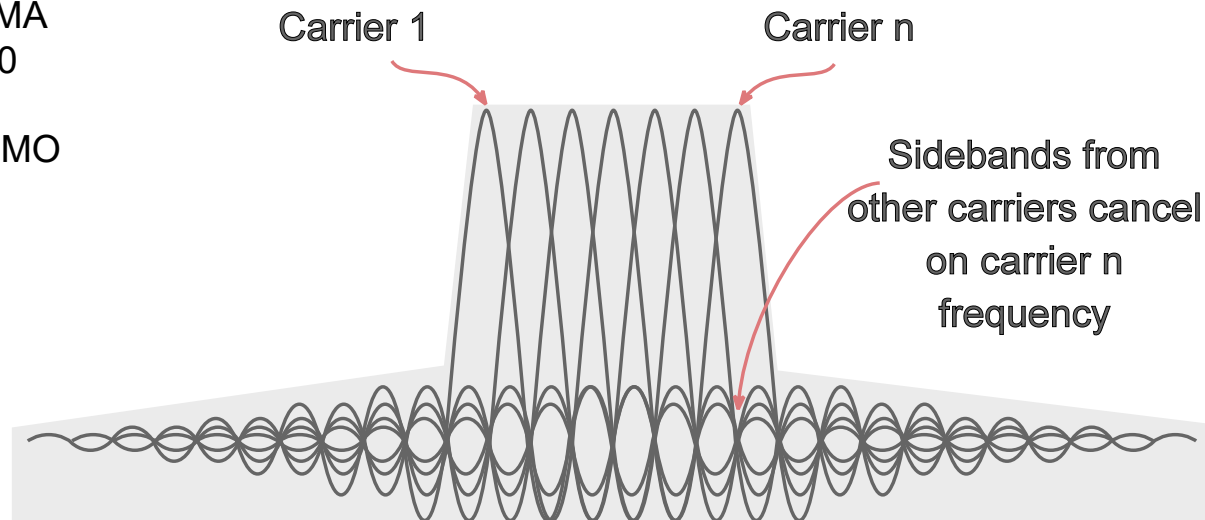
Northeastern

Recovering Clipped OFDM Symbols with Bayesian Inference

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OFDM System

- Orthogonal Frequency-Division Multiplexing (OFDM) is a method of encoding digital data on multiple orthogonal carrier frequencies.
- OFDM was first introduced in 1966 (Bell Lab)
- OFDM is one of the basic idea of 4G LTE.
 - 1G -> Analog System
 - 2G -> TDMA, CDMA
 - 3G -> CDMA-2000
 - 4G -> OFDM
 - 5G -> Massive MIMO



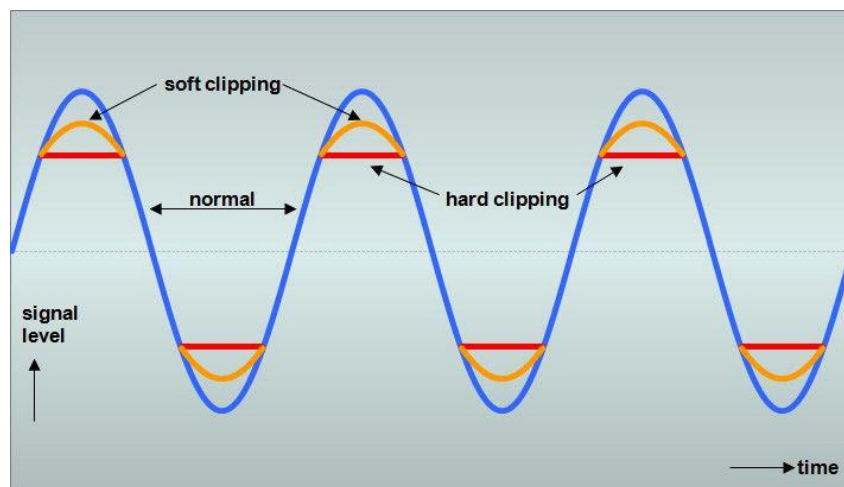
Clipping Distortion

- Frequency domain signal is drawn from a finite set (Constellation)

$$X_l \in \mathcal{S}, \quad |\mathcal{S}| = Q$$

- Time domain signal may have high peak power

$$x_n = \frac{1}{\sqrt{N}} \sum_{l=1}^N X_l e^{2\pi j \frac{ln}{N}} \quad \tilde{x}_n = \begin{cases} x_n & , \text{ if } |x_n| \leq A \\ Ae^{j\text{Arg}(x_n)} & , \text{ if } |x_n| > A \end{cases}$$



Input-BackOff:

$$(IBO)_{dB} = 10 \log_{10} \left(\frac{A^2}{\mathbf{E}[x_n^2]} \right)$$

Channel

- We assume time invariant frequency selective channel

$$y_n = \sum_{m=0}^{M-1} h_m \tilde{x}_{n-m} + w_n$$

- Also assume perfect sync. and equalization

$$\bar{Y}_l = \frac{Y_l}{H_l} = \tilde{X}_l + \frac{W_l}{H_l}$$

$$\bar{y}_n = \tilde{x}_n + \epsilon_n, \sigma_\epsilon^2 = \frac{\sigma_w^2}{N} \sum_{l=1}^N \frac{1}{|H_l|^2}$$

MAP Approach

- Set hyperparameter z_n

$$\bar{y}_n = \tilde{x}_n + \epsilon_n = x_n(1 - z_n) + Ae^{j\text{Arg}(x_n)}z_n + \epsilon_n, \quad z_n \in \{0, 1\}$$

- Prior

$$\Pr(z_n) = \begin{cases} 1/2 & , z_n = 0 \\ 1/2 & , z_n = 1 \end{cases}$$

$$\Pr(X_l = S_u) = \frac{1}{Q}$$

$$\Pr(\sigma_\epsilon^2) = \mathcal{IG}(a_0, b_0)$$

MAP Approach

- Likelihood

$$\begin{aligned}\Pr(\bar{\mathbf{y}}|\mathbf{x}, \mathbf{z}, \sigma_\epsilon^2) &= \prod_{n=1}^N \Pr(\bar{y}_n|x_n, z_n, \sigma_\epsilon^2) \\ &= \prod_{n:z_n=0} \mathcal{N}(\bar{y}_n|x_n, \sigma_\epsilon^2) \times \prod_{n:z_n=1} \mathcal{N}(\bar{y}_n|Ae^{j\phi_{x_n}}, \sigma_\epsilon^2)\end{aligned}$$

- Directly maximizing the full posterior w.r.t all variables would be hard to implement because the parameter space is too large

Iterative MAP Approach

- We introduce iterative/stochastic algorithm, update each variable separately.
- This approach can be interpreted as an extension of EM strategy.

Algorithm 1: Iterative/Stochastic MAP Estimation

Result: transmitted signal $\hat{\mathbf{x}}$, hyperparameter $\hat{\mathbf{z}}$, receiver noise power $\hat{\sigma}_\epsilon^2$

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1 Compute  $\bar{\mathbf{y}}$  at the receiver;  
2 Start point  $\mathbf{x}^{(0)}, \mathbf{z}^{(0)}, \sigma_\epsilon^{(0)}$  drawn from the given prior;  
3  $k \leftarrow 1$ ;  
4 do  
5   Drawn  $\mathbf{z}^{(k)} \sim \Pr(\mathbf{z}|\mathbf{x}^{(k-1)}, \sigma_\epsilon^{(k-1)}, \bar{\mathbf{y}})$ ;  
6   Update:  $\mathbf{x}^{(k)} = \arg \max_{\mathbf{x}} \Pr(\mathbf{x}|\mathbf{z}^{(k)}, \sigma_\epsilon^{(k-1)}, \bar{\mathbf{y}})$ ;  
7   Drawn  $(\sigma_\epsilon^2)^{(k)} \sim \Pr(\sigma_\epsilon^2|\mathbf{z}^{(k)}, \mathbf{x}^{(k)}, \bar{\mathbf{y}})$ ;  
8    $k \leftarrow k + 1$ ;  
9 while  $k \leq K_{max}$ ;  
10 return  $(\hat{\mathbf{x}}, \hat{\mathbf{z}}, \hat{\sigma}_\epsilon^2) \leftarrow (\mathbf{x}^{(k)}, \mathbf{z}^{(k)}, (\sigma_\epsilon^2)^{(k)})$ 
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Iterative MAP Approach (Algorithm)

- Detail conditional posterior

- \mathbf{Z}_n

$$p = \frac{\Pr(z_n = 1 | \bar{y}_n, x_n, \sigma_\epsilon^2)}{\Pr(z_n = 0 | \bar{y}_n, x_n, \sigma_\epsilon^2) + \Pr(z_n = 1 | \bar{y}_n, x_n, \sigma_\epsilon^2)}$$
$$= \text{Sigmoid}\left(\frac{1}{\sigma_\epsilon^2} \left[|\bar{y}_n - Ae^{j\phi_{x_n}}|^2 - |\bar{y}_n - x_n|^2 \right]\right)$$

- \mathbf{X}_l

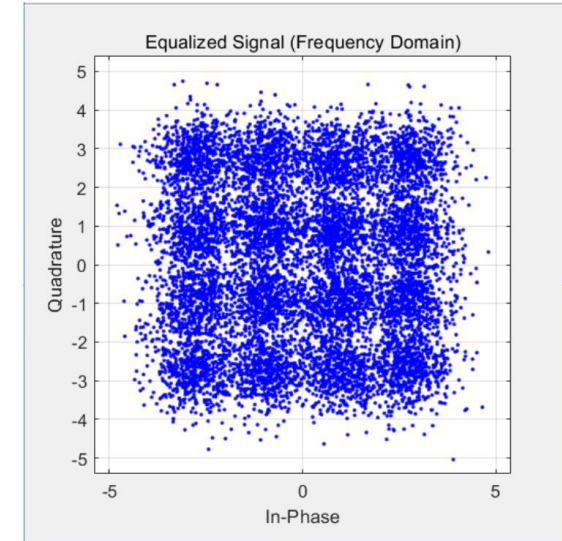
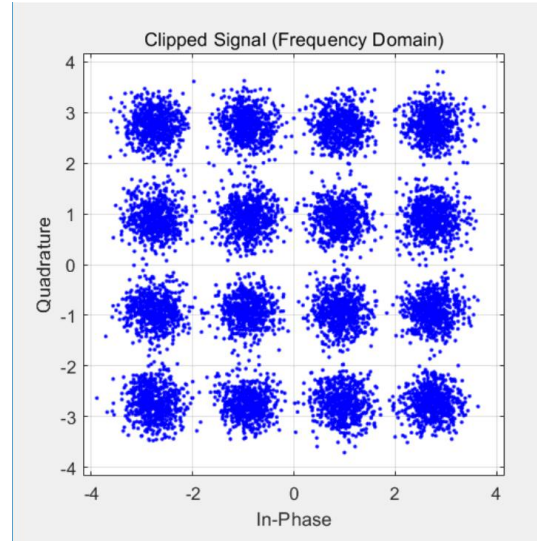
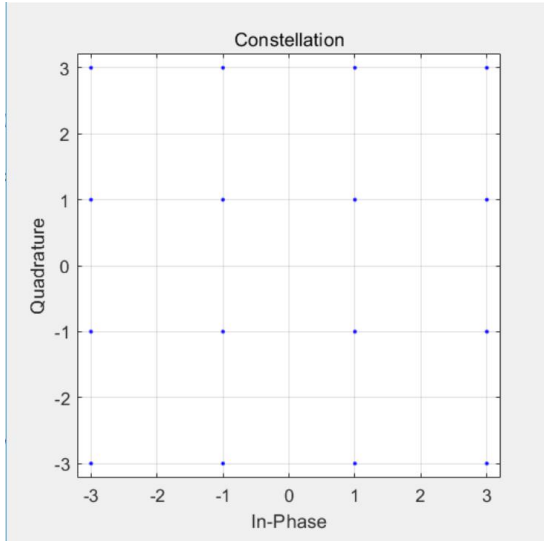
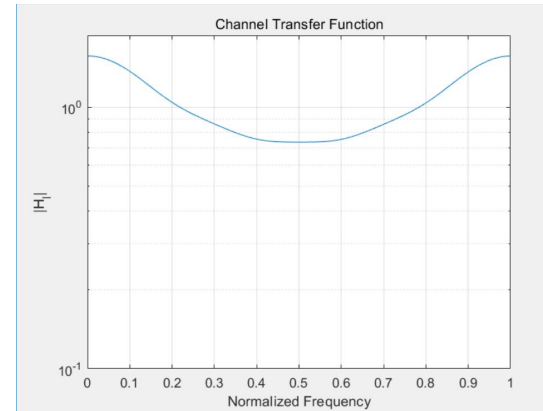
$$\hat{X}_l = \arg \max_{S_u} \Pr(X_l = S_u | \mathbf{X}_{-l}, \bar{\mathbf{y}}, \mathbf{z}, \sigma_\epsilon^2)$$
$$= \arg \max_{S_u} \sum_{n: z_n=0} |\bar{y}_n - x_{n, X_l=S_u}|^2 + \sum_{n: z_n=1} \left| \bar{y}_n - Ae^{j\phi_{x_n, X_l=S_u}} \right|^2$$

- σ_ϵ

$$\Pr(\sigma_\epsilon^2 | \bar{\mathbf{y}}, \mathbf{x}, \mathbf{z}) \propto \Pr(\bar{\mathbf{y}} | \mathbf{x}, \mathbf{z}, \sigma_\epsilon^2) \Pr(\sigma_\epsilon^2)$$
$$\propto \mathcal{IG}(a_N, b_N)$$
$$a_N = a_0 + \frac{N}{2}$$
$$b_N = b_0 + \frac{1}{2} \sum_{n=1}^N \left(\bar{y}_n - x_n(1 - z_n) - Ae^{j\phi_{x_n} z_n} \right)^2$$

Implementation

- Simple convolution channel
- 16QAM Constellation



Implementation

- $N = 100000$, $\text{IBO} = 2.93\text{dB}$, $K_{\text{Max}} = 10$
- 20 trials
- Time Complexity: $O(KQN^2)$

