



# Discussion on own Works

## *Channel Estimation of MB-OFDM UWB Systems in Interfering Environments*

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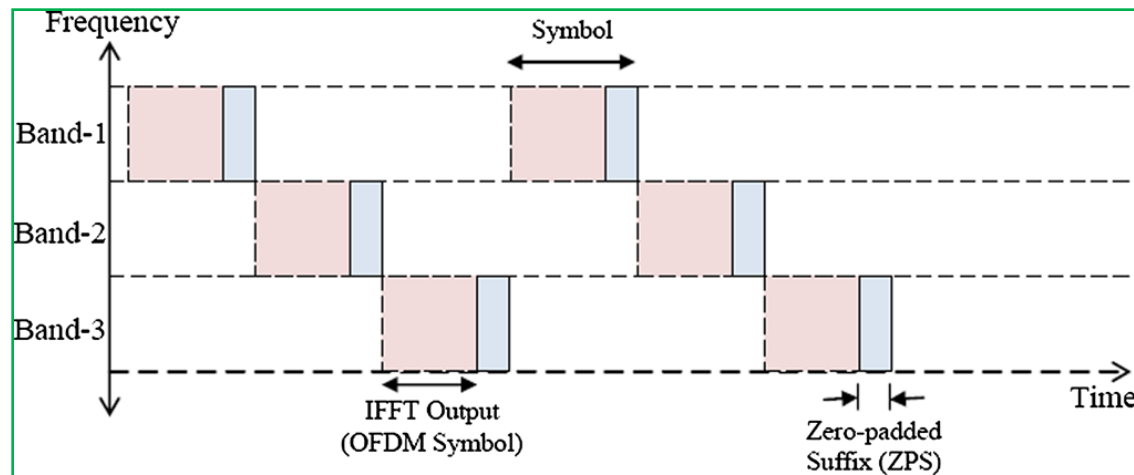


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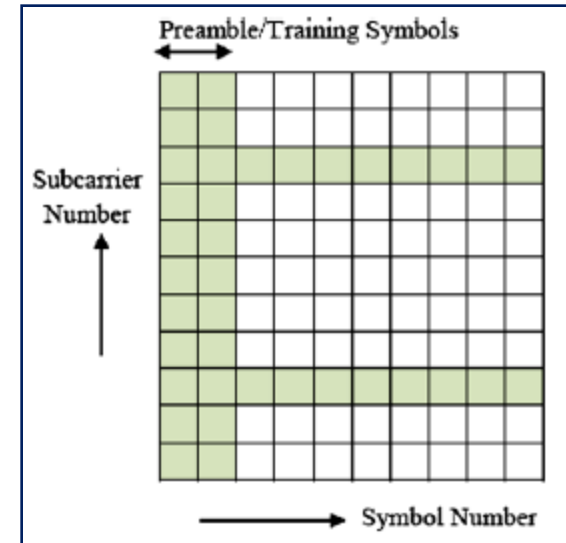
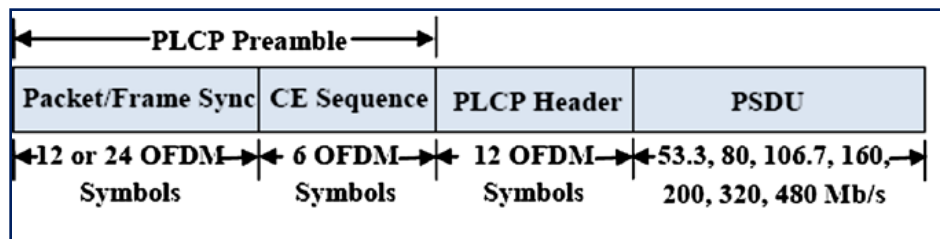
- MB-OFDM PHY in ECMA-368
- Channel estimation in MAI and NBI environments
- Channel estimation with unknown NBI
- Iterative interpolation & weighted channel estimation

# Realization of RF Tx Signal using 3 Bands



**MB-OFDM Approach; 14 Sub-Bands; 528 MHz BW; TFC; ZPS**

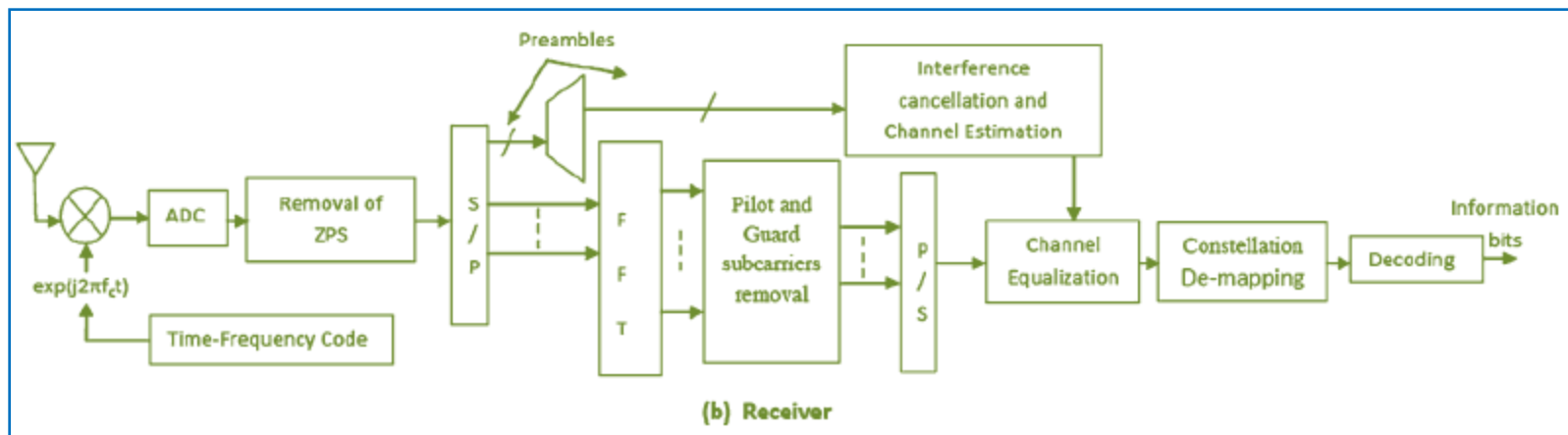
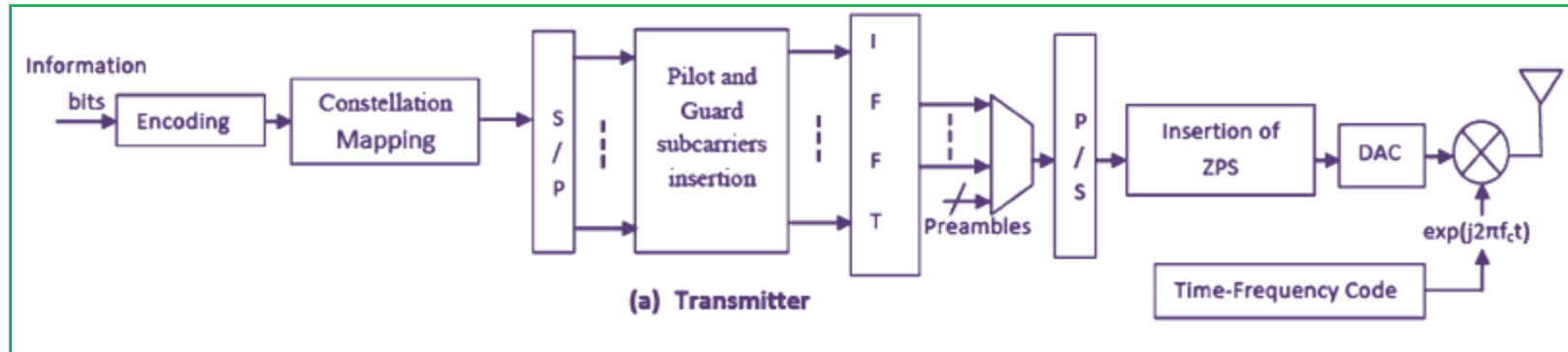
# PLCP Packet Data Unit (PPDU)



PLCP= Packet Layer Convergence Protocol

PSDU= PLCP Service Data Unit

# SISO Architecture



# DFT Properties

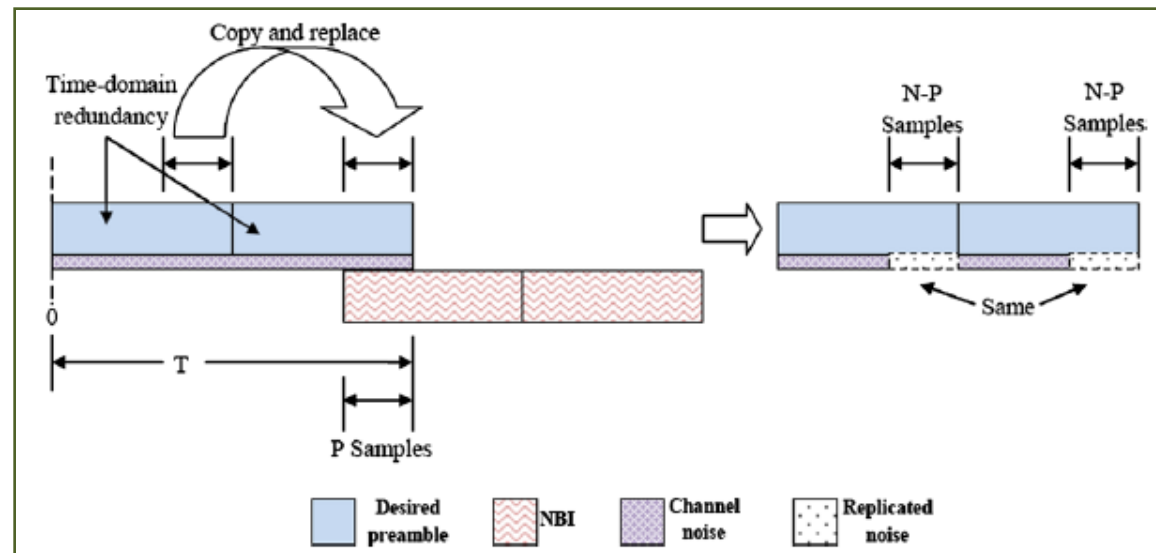
- **Principle:** Subcarrier/Sample Nulling provides TR/FR property

$$\begin{aligned}
 x_{\text{even}}[n + M] &= \frac{1}{2M} \sum_{k'=0}^{M-1} X[2k'] \times e^{\frac{j2\pi(2k')(n+M)}{2M}} \\
 &= \frac{1}{2M} \sum_{k'=0}^{M-1} X[2k'] \times e^{\frac{j2\pi(2k')n}{2M}} \times e^{j2\pi k'} \\
 &= x_{\text{even}}[n], \quad n = 0, 1, \dots, M - 1.
 \end{aligned}$$

$$\begin{aligned}
 X_{\text{even}}[k + M] &= \sum_{n'=0}^{M-1} x[2n'] \times e^{\frac{j2\pi(2n')(k+M)}{2M}} \\
 &= \sum_{n'=0}^{M-1} x[2n'] \times e^{\frac{j2\pi(2n')k}{2M}} \times e^{j2\pi n'} \\
 &= X_{\text{even}}[k], \quad k = 0, 1, \dots, M - 1,
 \end{aligned}$$

# MAI Rejection

Multiple Access Interference



Adaptive Select and Replace (ASR) Scheme

# NBI Position

$$x[n] = x[n + N], \quad n = 0, \dots, N_{ZPS} - 1$$

$$y[n] = y[n + N], \quad n = L - 1, L, \dots, N_{ZPS} - 1$$

$$q[n] \triangleq y[n + N] - y[n] \\ = \alpha e^{j\theta} (e^{j\omega N} - 1) e^{j\omega n} + w[n],$$

$$\bar{q}[n] = [q[n] \quad q[n + 1] \quad \dots \quad q[n + P - 1]]^T \\ = \alpha e^{j\theta n} (e^{j\omega N} - 1) \sqrt{P} \bar{s} + \bar{w}[n],$$

$$\mathbf{C}_{\bar{q}} \triangleq E\{\bar{q}[n](\bar{q}[n])^H\},$$

$$\mathbf{C}_{\bar{q}} = \alpha^2 P |e^{j\omega N} - 1|^2 \bar{s} \bar{s}^H + \sigma_w^2 \mathbf{I},$$

$$\mathbf{C}_{\bar{q}} = (\bar{\mathbf{u}}_{\bar{s}} \quad \bar{\mathbf{U}}_{\bar{w}}) \begin{pmatrix} \lambda + \sigma_w^2 & 0 & \dots & 0 \\ 0 & \sigma_w^2 & 0 & \vdots \\ \vdots & 0 & \ddots & 0 \\ 0 & \dots & 0 & \sigma_w^2 \end{pmatrix} \begin{pmatrix} \bar{\mathbf{u}}_{\bar{s}}^H \\ \bar{\mathbf{U}}_{\bar{w}}^H \end{pmatrix},$$

$$\hat{\mathbf{C}}_{\bar{q}} = \frac{1}{L_2} \sum_{n=L-1}^{N_{ZPS}-1} \bar{q}[n](\bar{q}[n])^H,$$

$$\hat{\sigma}_w^2 = \frac{1}{P-1} \sum_{i=1}^{P-1} \rho_i$$

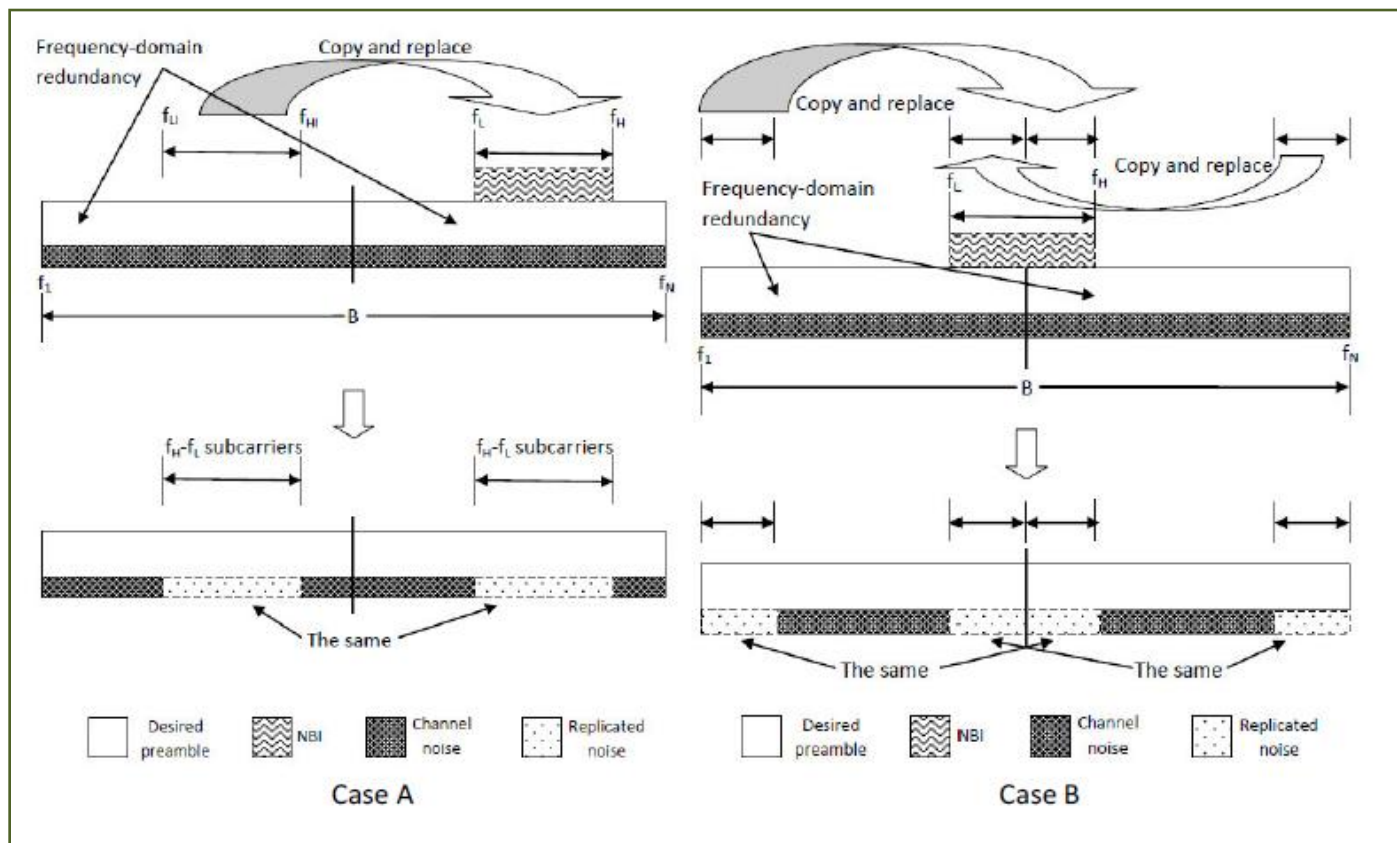
$$\hat{\mathbf{s}} = [\hat{s}_0 \quad \hat{s}_1 \quad \dots \quad \hat{s}_{P-1}]^T,$$

$$\hat{\omega} = \frac{1}{P-1} \sum_{n=0}^{P-2} \text{Im} \left\{ \ln \left( \frac{\hat{s}_{n+1}}{\hat{s}_n} \right) \right\},$$

# NBI Rejection

## Narrowband Interference

### Adaptive Band Select and Replace (ABSR) Scheme



# Channel Filtering and Windowing

Power Delay profile

$$P_z = \sum_{i=1}^2 \left| \sum_{j=z}^{z+N} y_{i,j} \times x_{i,j-z} \right|^2$$

Profile Vector

$$g_z = \begin{cases} 1, & P_z \geq \frac{1}{K} \max\{P_z\}_0^{Z-1} \\ 0, & P_z < \frac{1}{K} \max\{P_z\}_0^{Z-1} \end{cases}$$

Filtered

$$\hat{H}_{Filtered} = G_z \otimes \hat{H},$$

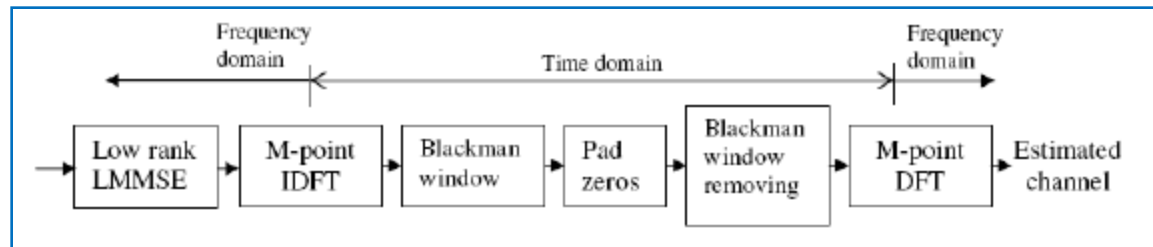
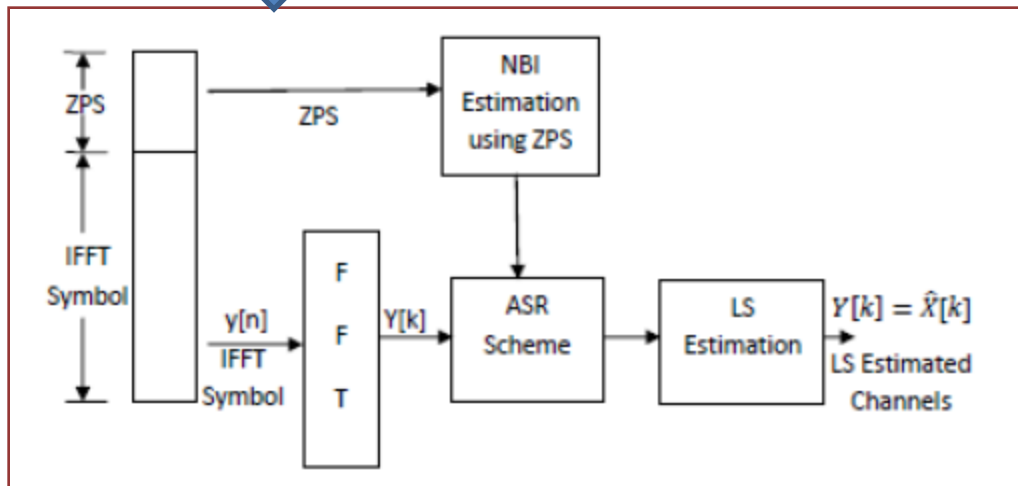
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$$h_{lrLMMSE}(i) = \frac{1}{M} \sum_{k=0}^{M-1} \hat{H}_{lrLMMSE}(k) e^{j2\pi \frac{ki}{M}}$$

Blackman Windowing

$$d(i) = 0.42 - 0.5 \cos\left(\frac{2\pi i}{M-1}\right) + 0.08 \cos\left(\frac{4\pi i}{M-1}\right), \quad i = 0, 1, \dots, M-1$$

# Refined Channel and Blackman Windowing



# System and Signal Model

- **Principle:** the interference power on each subcarrier is treated as a nuisance parameter which is averaged out from the corresponding likelihood function

$$H(n) = \sum_{l=1}^L h(l) e^{-j2\pi n(l-1)/N} \quad -N_\alpha \leq n \leq N_\alpha$$

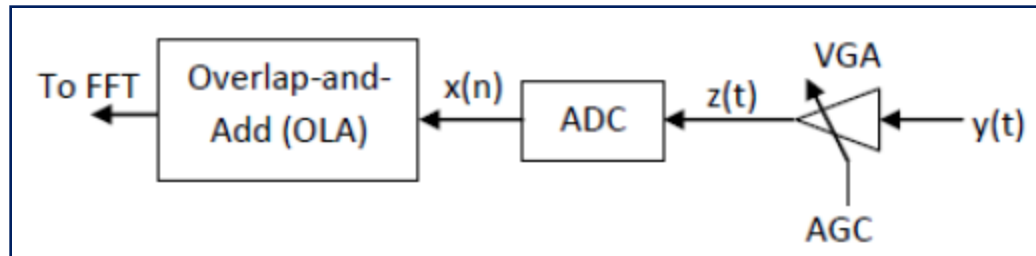
$$Y(n, k) = s(n, k)H(n) + w(n, k) \quad -N_\alpha \leq n \leq N_\alpha$$

$$\boxed{Y(k) = S(k)Fh + w(k)} \longrightarrow \sigma^2(n) = \sigma_w^2 + \sigma_I^2(n)$$

$$S(k) = \text{diag}\{s(n, k); 1 \leq n \leq N\}$$

$$H = Fh \longrightarrow \hat{H} = F\hat{h}$$

# Impacts of NBI on Channel Estimation



The ADC output is given by

$$x(n) = G \left( \sum_{l=0}^{L-1} s(n-l)h(l) + w(n) \right) + q(n)$$

$$SINR = \frac{\bar{\sigma}_c^2}{(\bar{\sigma}_c^2 + \sigma^2(n))/\gamma_q + \sigma^2(n)}$$

$$\begin{aligned} J_{hh} &= E_{Y(k)|h} \left( \frac{\partial \ln p(Y(k)|h)}{\partial h^*} \right) \left( \frac{\partial \ln p(Y(k)|h)}{\partial h^*} \right)^H \\ &= \frac{1}{\sigma^4} E_{Y(k)|h} \left[ \frac{\partial}{\partial h^*} (Y(k) - Bh)^H (Y(k) - Bh) \right] \left[ \frac{\partial}{\partial h^*} (Y(k) - Bh)^H (Y(k) - Bh) \right]^H \\ &= \frac{1}{\sigma^2} B^H B \end{aligned} \quad (13)$$

# Impacts of NBI on Channel Estimation

Thus, using (10), the variance of the estimator is bounded as

$$\begin{aligned}
 E \left[ \|\widehat{\mathbf{h}} - E(\widehat{\mathbf{h}})\|^2 \right] &= E \left[ \|\widehat{\mathbf{h}} - \mathbf{h}\|^2 \right] \\
 &= \text{tr}[\mathbf{R}_{\widehat{\mathbf{h}}}] \geq \frac{\sigma^2}{\sigma_s^2} [\text{tr}\{(\mathbf{F}^H \mathbf{S}(k)^H \mathbf{S}(k) \mathbf{F})^{-1}\}] \\
 &\geq \frac{1}{\text{SINR}} [\text{tr}\{(\mathbf{F}^H \mathbf{S}(k)^H \mathbf{S}(k) \mathbf{F})^{-1}\}] \\
 &= \frac{(\bar{\sigma}_c^2 + \sigma^2(n))/\gamma_q + \sigma^2(n)}{\bar{\sigma}_c^2} [\text{tr}\{(\mathbf{F}^H \mathbf{S}(k)^H \mathbf{S}(k) \mathbf{F})^{-1}\}] \\
 &= \frac{(\bar{\sigma}_c^2 + \sigma_w^2 + \sigma_l^2(n))/\gamma_q + \sigma_w^2 + \sigma_l^2(n)}{\bar{\sigma}_c^2} [\text{tr}\{(\mathbf{F}^H \mathbf{S}(k)^H \mathbf{S}(k) \mathbf{F})^{-1}\}] \quad (15)
 \end{aligned}$$

- it is evident that as the NBI power increases, the variance of the estimator increases and thus the estimator performance gets worse

# ML Channel Estimation

Given the unknown parameters  $(\mathbf{h}, \sigma^2)$ , vectors  $\{\mathbf{Y}(k)\}$  in (4) are statistically independent and Gaussian distributed with mean  $\mathbf{S}(k)\mathbf{F}\mathbf{h}$  and covariance matrix  $\mathbf{C}$ . Therefore, their joint pdf gets the form

$$p(\mathbf{Y}|\check{\mathbf{h}}, \check{\sigma}^2) = \prod_{n=1}^N \frac{1}{[\pi\check{\sigma}^2(n)]^2} \exp\left\{-\frac{1}{\check{\sigma}^2(n)} \sum_{k=1}^2 |Z_k(n, \check{\mathbf{h}})|^2\right\} \quad (16)$$

where

$$Z_k(n, \check{\mathbf{h}}) = Y(n, k) - s(n, k) \sum_{l=1}^L \check{h}(l) e^{\frac{j2\pi n(l-1)}{N}} \quad (17)$$

$$p(\sigma^2; \alpha, \beta) = \frac{\beta^\alpha}{\Gamma(\alpha)} (\sigma^2)^{-\alpha-1} \exp\left(-\frac{\beta}{\sigma^2}\right) \quad (18)$$

Taking the value of shape parameter  $\alpha = 1$ , (18) becomes

$$p(\sigma^2) = \frac{\beta}{\sigma^4} \exp\left(-\frac{\beta}{\sigma^2}\right) \quad (19)$$

where the scale parameter  $\beta$  is thought as a suitable design parameter.

# ML Channel Estimation

The marginal log-likelihood function (LLF) is thus given by

$$\ln[p(\mathbf{Y}|\tilde{\mathbf{h}})] = N \ln\left(\beta \frac{2}{\pi^2}\right) - 3 \sum_{n=1}^N \ln\left[\beta + \sum_{k=1}^2 |Z_k(n, \tilde{\mathbf{h}})|^2\right] \quad (22)$$

$$\Phi(\tilde{\mathbf{h}}) = - \sum_{n=1}^N \ln\left[\beta + \sum_{k=1}^2 |Z_k(n, \tilde{\mathbf{h}})|^2\right]$$

Letting  $\psi(\tilde{\mathbf{h}}) = -\Phi(\tilde{\mathbf{h}})$ , results in

$$\psi(\tilde{\mathbf{h}}) = \sum_{n=1}^N \ln\left[\beta + \sum_{k=1}^2 |Z_k(n, \tilde{\mathbf{h}})|^2\right]$$

$$\hat{\mathbf{h}}_{MLE} = \arg \min_{\mathbf{h}} \{\psi(\tilde{\mathbf{h}})\}$$

# ML Channel Estimation

- As indicated by (26), the channel estimation problem becomes a minimization problem. However, it requires a complete search over the multidimensional domain spanned by  $\mathbf{h}$ . Accordingly, optimization algorithm should be simple enough to produce fast convergence with low computational complexity. Quasi-Newton methods, like steepest descent, require only the gradient of objective function to be supplied at each iterate

$$\hat{\mathbf{h}}_{i+1} = \hat{\mathbf{h}}_i + \Delta \hat{\mathbf{h}}_i$$

where the Newton step  $\Delta \hat{\mathbf{h}}_i$  is provided as

$$\Delta \hat{\mathbf{h}}_i = -\alpha_i \mathbf{B}_i^{-1} \nabla \psi(\tilde{\mathbf{h}}) \big|_{\hat{\mathbf{h}}_i}$$

# ML Channel Estimation

$$\mathbf{B}_{i+1} = \mathbf{B}_i + \frac{\boldsymbol{\Theta}_i \boldsymbol{\Theta}_i^T}{\boldsymbol{\Theta}_i^T \Delta \hat{\mathbf{h}}_i} - \frac{\mathbf{B}_i \Delta \hat{\mathbf{h}}_i (\mathbf{B}_i \Delta \hat{\mathbf{h}}_i)^T}{\Delta \hat{\mathbf{h}}_i^T \mathbf{B}_i \Delta \hat{\mathbf{h}}_i} \quad (29)$$

where  $\boldsymbol{\Theta}_i$  represents the change in gradient of  $\psi(\tilde{\mathbf{h}})$  expressed as

$$\boldsymbol{\Theta}_i = \nabla \psi(\tilde{\mathbf{h}})|_{\tilde{\mathbf{h}}_{i+1}} - \nabla \psi(\tilde{\mathbf{h}})|_{\tilde{\mathbf{h}}_i} \quad (30)$$

As required in (28),  $\mathbf{B}_{i+1}^{-1}$  takes the form

$$\mathbf{B}_{i+1}^{-1} = \left( \mathbf{I} - \frac{\boldsymbol{\Theta}_i \Delta \hat{\mathbf{h}}_i^T}{\boldsymbol{\Theta}_i^T \Delta \hat{\mathbf{h}}_i} \right)^T \mathbf{B}_i^{-1} \left( \mathbf{I} - \frac{\boldsymbol{\Theta}_i \Delta \hat{\mathbf{h}}_i^T}{\boldsymbol{\Theta}_i^T \Delta \hat{\mathbf{h}}_i} \right) + \frac{\Delta \hat{\mathbf{h}}_i \Delta \hat{\mathbf{h}}_i^T}{\boldsymbol{\Theta}_i^T \Delta \hat{\mathbf{h}}_i} \quad (31)$$

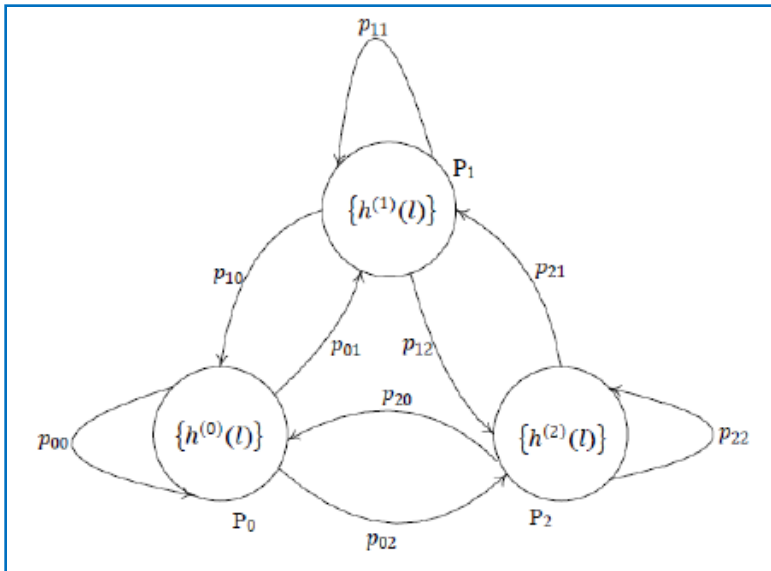
Thus, collecting (27) to (31) leads to the following quasi-Newton based channel estimation (QNCE)

$$\hat{\mathbf{h}}_{i+1} = \hat{\mathbf{h}}_i - \alpha_i \mathbf{B}_i^{-1} \nabla \psi(\tilde{\mathbf{h}})|_{\tilde{\mathbf{h}}_i} \quad (32)$$

After J iterations, the channel frequency response is eventually obtained from (6) in the form

$$\hat{\mathbf{H}}_{QNCE} = \mathbf{F} \hat{\mathbf{h}}_J \quad (33)$$

# Channel Model



$$h_{RF}^{(0)}(t) = X \sum_{l=0}^{L_h} \sum_{r=0}^R \alpha_{r,l} \delta(t - T_l - \tau_{r,l})$$

$$h_{RF}^{(1)}(t) = X \sum_{l=0}^{L_h} \sum_{r=0}^R \alpha_{r,l} \delta(t - T_l - \tau_{r,l}) - X \left[ \sum_{r=r_0}^{r_0+J-1} \alpha_{r,l} \delta(t - T_l - \tau_{r,l}) \right]_{l=L_c}$$

$$h_{RF}^{(1)}(t) = X \sum_{l=0}^{L_h} \sum_{r=0}^R \alpha_{r,l} \delta(t - T_l - \tau_{r,l}) + X \left[ \sum_{r=r_0}^{r_0+J-1} \alpha_{r,l} \delta(t - T_l - \tau_{r,l}) \right]_{l=L_c}$$

# Iterative Interpolation & Weighted Channel

- One possible solution consists of shifting the positions of pilot subcarriers in PSDU and estimating the channels at pilot subcarriers using (33) or other proven algorithm.

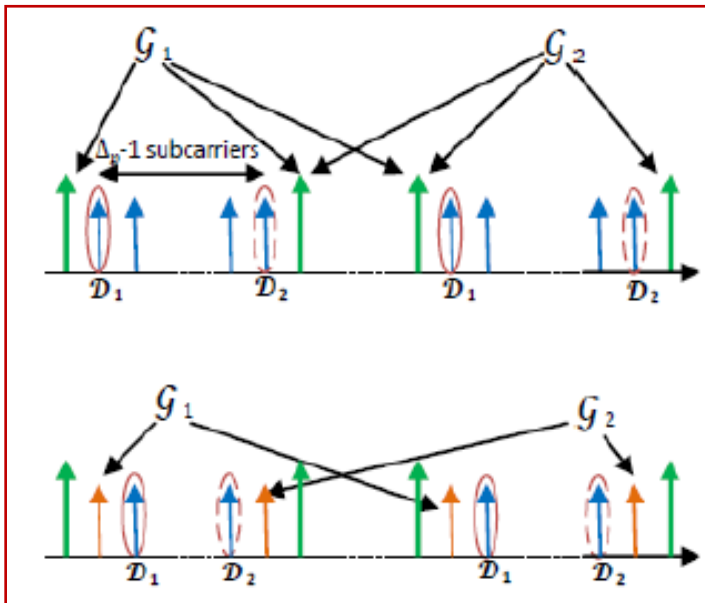
$$\hat{H}_{wgt}^{ref}(n) = \gamma \hat{H}_{QNCE}^{old}(n) + \lambda \hat{H}_{QNCE}^{new}(n)$$

- However, positions of pilot subcarriers are fixed in each OFDM symbol, according to ECMA-368 standard. This leads us to propose an alternate solution, where channels at pilot subcarriers are calculated by above Eq and channels at data subcarriers are estimated through iterative interpolation.

# Iterative Interpolation & Weighted Channel

For the  $n$ th subcarrier of group  $\mathcal{D}_1$ , the estimated channel is calculated as

$$\hat{H}_{\mathcal{D}_1}(n) = \hat{H}_{\mathcal{G}_1}(n) + \frac{\hat{H}_{\mathcal{G}_2}(n) - \hat{H}_{\mathcal{G}_1}(n)}{\Delta_p - 2(i - 1)}$$



$$\hat{H}_{\mathcal{D}_2}(n) = \hat{H}_{\mathcal{G}_1}(n) + \frac{(\Delta_p - 2i + 1) (\hat{H}_{\mathcal{G}_2}(n) - \hat{H}_{\mathcal{G}_1}(n))}{\Delta_p - 2(i - 1)}$$

$$\hat{H}_{wgt}^{ref}(n) = \gamma \hat{H}_{QNCE}^{old}(n) + \lambda \hat{H}_D(n)$$

## We Find

- Improved channel estimation with Time-domain redundancy and frequency-domain redundancy based multi-access and narrowband interference rejection.
- Further improvement using PDP-based channel filtering and Blackman windowing
- ML channel estimation with unknown NBI environment optimizing the likelihood function in iterative fashion using quasi-Newton algorithm.
- Iterative interpolation and weighted channel estimation approach for time-varying channel capturing occasional sudden channel change.

Thank you for your suggestions!