

A Low-Complexity LS Turbo Channel Estimation Technique for MU-MIMO Systems

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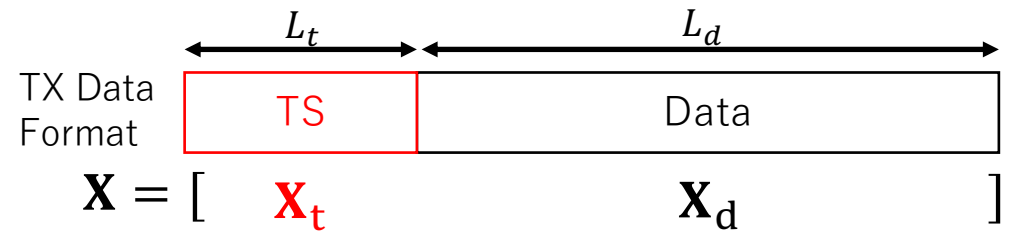
Summary

- Turbo Receiver improves the MUI problem in MU-MIMO sys.
- However, the complexity expands as Num. of ANT increases
- Because, in order to deal Spatial matrix $\mathbf{\Gamma}$ correctly

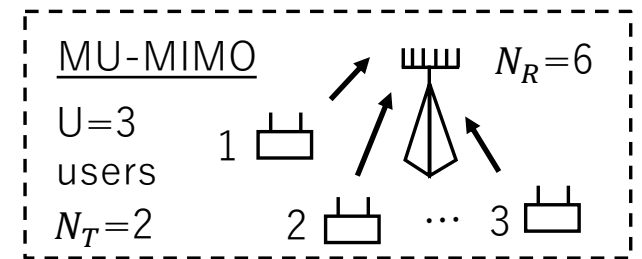
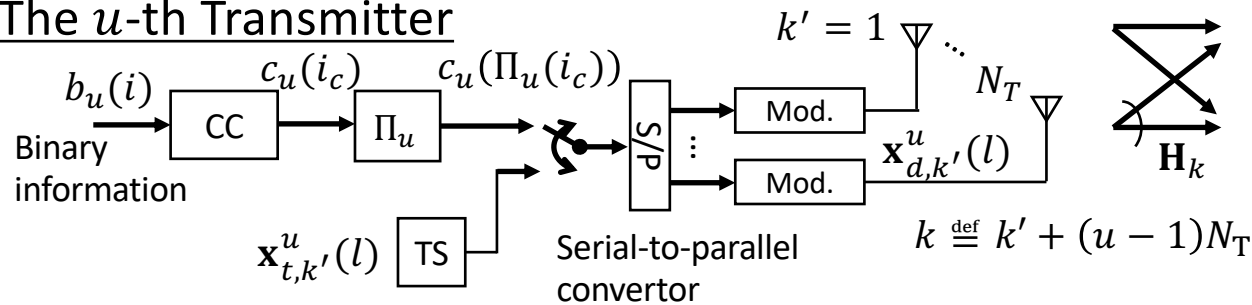
NEW: Low complexity LS algo. for Turbo receiver

- Independent of Rx Ants.: $\mathcal{O}(\kappa^3 N_T^3) \leftarrow \mathcal{O}(\kappa^3 N_T^3 N_R^3)$
- **No Accuracy Deterioration !**
- Algebraic property of Cov. Matrix $\mathfrak{R}_{\mathbf{X}\mathbf{X}}$ is utilized

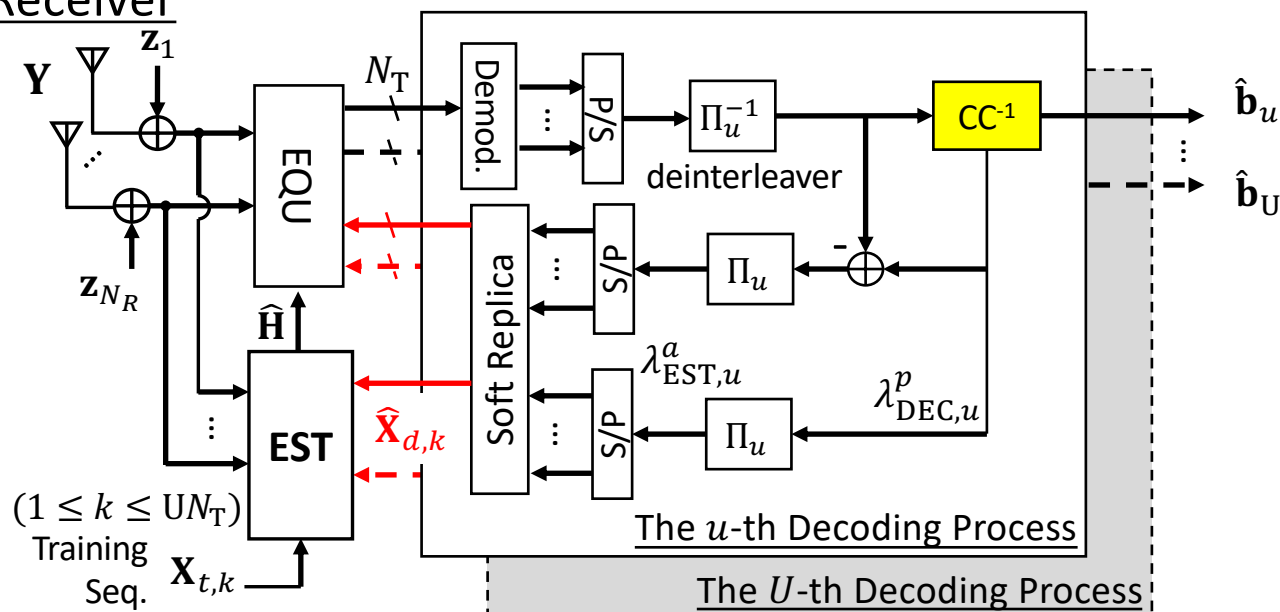
System Model



The u -th Transmitter



Receiver

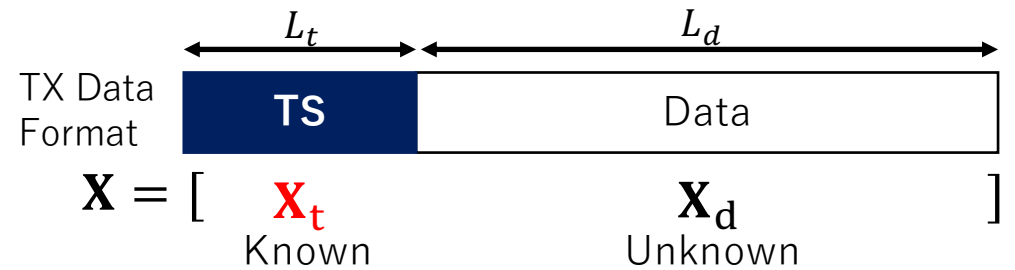


Turbo Receiver

$\hat{\mathbf{X}}_{d,k}$: Replica of TX Data can be obtained from Decoder's feedback info.

LS Channel Estimation

$$\begin{aligned}\hat{\mathbf{H}} &= \operatorname{argmin}_{\mathbf{H}} \mathcal{L}_t(\mathbf{H}) \\ &= \mathbf{Y}_t \mathbf{X}_t^+ = \mathbf{Y}_t \mathbf{X}_t^H (\mathbf{X}_t \mathbf{X}_t^H)^{-1} \\ \mathcal{L}_t(\mathbf{H}) &= \frac{1}{\sigma_z^2} \|\mathbf{Y}_t - \mathbf{H} \mathbf{X}_t\|^2\end{aligned}$$



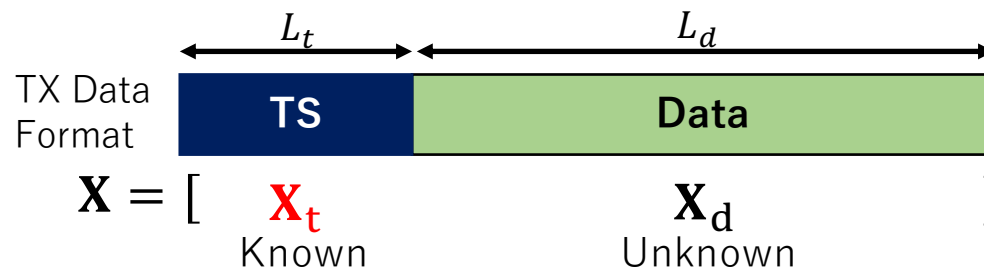
Rx Signal: $\mathbf{Y} = \mathbf{H} \mathbf{X} + \mathbf{Z}$

\mathbf{H} : Channel

\mathbf{X} : TX Signal

\mathbf{Z} : AWGN $\sim \mathcal{CN}(0, \sigma_z^2)$

LS Turbo Channel Estimation



$$\hat{\mathbf{H}} = \operatorname{argmin}_{\mathbf{H}} \mathcal{L}_{td}(\mathbf{H}), \text{ where } \mathcal{L}_{td}(\mathbf{H}) = \mathcal{L}_t(\mathbf{H}) + \mathcal{L}_d(\mathbf{H})$$

$$\left\{ \begin{aligned} \mathcal{L}_d(\mathbf{H}) &= \frac{1}{\sigma_z^2} \|\mathbf{Y}_t - \mathbf{H}\hat{\mathbf{X}}_d\|_{\mathbf{\Gamma}}^2 \\ &= \frac{1}{\sigma_z^2} \operatorname{tr} \left\{ (\mathbf{Y}_d - \mathbf{H}\hat{\mathbf{X}}_d)^H \mathbf{\Gamma} (\mathbf{Y}_d - \mathbf{H}\hat{\mathbf{X}}_d) \right\} \end{aligned} \right.$$

Joint Log-Likelihood Function

$$\mathbf{\Gamma} = (\mathbf{I}_{N_R} + \sum_u \frac{\Delta\sigma_d^2}{\sigma_z^2} \mathbf{R}_{H,u})$$

Spatial Weight Matrix

LS Solution:

$$\text{vec}\{\hat{\mathbf{H}}\} = \mathfrak{R}_{\mathbf{XX}}^{-1} \cdot \text{vec}\{\mathbf{R}_{\mathbf{YX}}\}$$

Gaussian Elimination?
 $\mathcal{O}((WUN_T N_R)^3)$

Matrix size

$$\mathbf{X}_t : WUN_T \times L_t$$

$$\hat{\mathbf{X}}_d : WUN_T \times L_d$$

$$\mathbf{Y}_t : N_R \times L_t$$

$$\mathbf{Y}_d : N_R \times L_d$$

System Size

W : CIR length

U : Num. of Users

N_T, N_R : Tx, Rx Ants.

L_t, L_d : TS, Data Len.

$WUN_T N_R \times WUN_T N_R$ Matrix

$$\mathfrak{R}_{\mathbf{XX}} = \mathbf{R}_{\mathbf{XX}_t}^T \otimes \mathbf{I}_{N_R} + \hat{\mathbf{R}}_{\mathbf{XX}_d}^T \otimes \mathbf{\Gamma}$$

$$\mathbf{R}_{\mathbf{YX}} = \mathbf{R}_{\mathbf{YX}_t} + \mathbf{\Gamma} \hat{\mathbf{R}}_{\mathbf{YX}_d}$$

$$\mathbf{R}_{\mathbf{XX}_t} = \mathbf{X}_t \mathbf{X}_t^H \quad \mathbf{R}_{\mathbf{YX}_t} = \mathbf{Y}_t \mathbf{X}_t^H$$

$$\hat{\mathbf{R}}_{\mathbf{XX}_d} = \hat{\mathbf{X}}_d \hat{\mathbf{X}}_d^H \quad \mathbf{R}_{\mathbf{YX}_d} = \mathbf{Y}_d \hat{\mathbf{X}}_d^H$$

$$\underbrace{\hspace{10em}}_{\mathcal{O}((WUN_T)^2 L_{td})}$$

$$\underbrace{\hspace{10em}}_{\mathcal{O}(N_R^2 L_{td})}$$

$$L_{td} = L_t + L_d$$

$$\mathfrak{R}_{\mathbf{X}\mathbf{X}} = \mathbf{R}_{\mathbf{X}\mathbf{X}_t}^T \otimes \mathbf{I}_{N_R} + \widehat{\mathbf{R}}_{\mathbf{X}\mathbf{X}_d}^T \otimes \mathbf{\Gamma}$$

$$= \left(\mathbf{R}_{\mathbf{X}\mathbf{X}_t}^{T/2} \otimes \mathbf{I}_{N_R} \right) \mathbf{J} \left(\mathbf{R}_{\mathbf{X}\mathbf{X}_t}^{T/2} \otimes \mathbf{I}_{N_R} \right)^H$$

$$\mathbf{J} = \mathbf{I}_{WUN_T} \otimes \mathbf{I}_{N_R} + \mathbf{R}_{\mathbf{X}\mathbf{X}_t}^{-H/2} \widehat{\mathbf{R}}_{\mathbf{X}\mathbf{X}_d}^T \mathbf{R}_{\mathbf{X}\mathbf{X}_t}^{-1/2} \otimes \mathbf{\Gamma}$$

$$= (\mathbf{U}_Q \otimes \mathbf{U}_\Gamma) \mathbf{\Sigma}_J (\mathbf{U}_Q \otimes \mathbf{U}_\Gamma)^H$$

$$\mathcal{O}(WUN_T N_R)$$

$$\mathfrak{R}_{\mathbf{X}\mathbf{X}}^{-1} = (\tilde{\mathbf{U}}_Q \otimes \mathbf{U}_\Gamma) \mathbf{\Sigma}_J^{-1} (\tilde{\mathbf{U}}_Q \otimes \mathbf{U}_\Gamma)^H$$

Unitary **Diagonal** Unitary

SVD:
 $\mathcal{O}(N_R^3)$

$$\mathbf{Q} = \mathbf{U}_Q \mathbf{\Sigma}_Q \mathbf{U}_Q^H$$

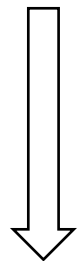
$$\mathbf{\Gamma} = \mathbf{U}_\Gamma \mathbf{\Sigma}_\Gamma \mathbf{U}_\Gamma^H$$

$$\mathbf{\Sigma}_J = \mathbf{I}_{WUN_T N_R} + \mathbf{\Sigma}_Q \otimes \mathbf{\Sigma}_\Gamma$$

$$\tilde{\mathbf{U}}_Q = \mathbf{R}_{\mathbf{X}\mathbf{X}_t}^{*/2} \mathbf{U}_Q$$

Multiplications of **Huge** Matrices ? $\mathcal{O}((WUN_T N_R)^3)$

$$\text{vec}\{\hat{\mathbf{H}}\} = \mathfrak{R}_{\mathbf{XX}}^{-1} \cdot \text{vec}\{\mathbf{R}_{\mathbf{YX}}\}$$



$$\mathfrak{R}_{\mathbf{XX}}^{-1} = (\tilde{\mathbf{U}}_Q \otimes \mathbf{U}_\Gamma) \cdot \boldsymbol{\Sigma}_J^{-1} \cdot (\tilde{\mathbf{U}}_Q \otimes \mathbf{U}_\Gamma)^H$$

Revert **vec**-operation
 $(\mathbf{C}^T \otimes \mathbf{A}) \text{vec}\{\mathbf{B}\} = \text{vec}\{\mathbf{ABC}\}$

$$\begin{aligned} \hat{\mathbf{H}} &= \text{mat}_{N_R}[\text{vec}\{\hat{\mathbf{H}}\}] \\ &= \mathbf{U}_\Gamma \text{mat}_{N_R}[\mathbf{v}] \tilde{\mathbf{U}}_Q^T \end{aligned}$$

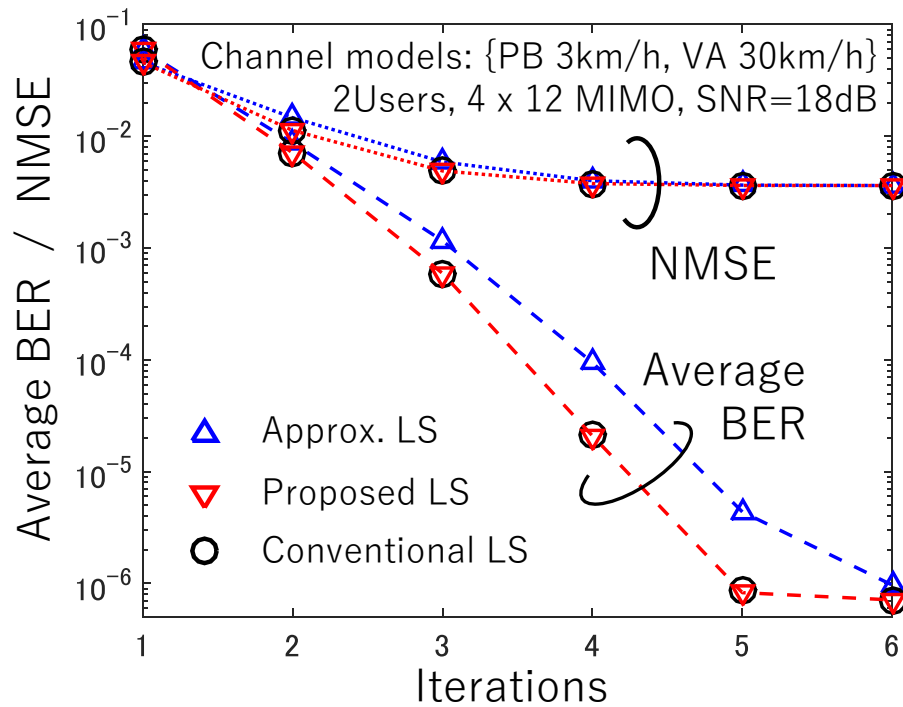
Small
 Matrices
 $\mathcal{O}(N_R^3)$

$$\mathbf{v} = \text{diag}\{\boldsymbol{\Sigma}_J^{-1}\} \odot \text{vec}\{\tilde{\mathbf{U}}_Q^H \mathbf{R}_{\mathbf{YX}} \mathbf{U}_\Gamma^*\}$$

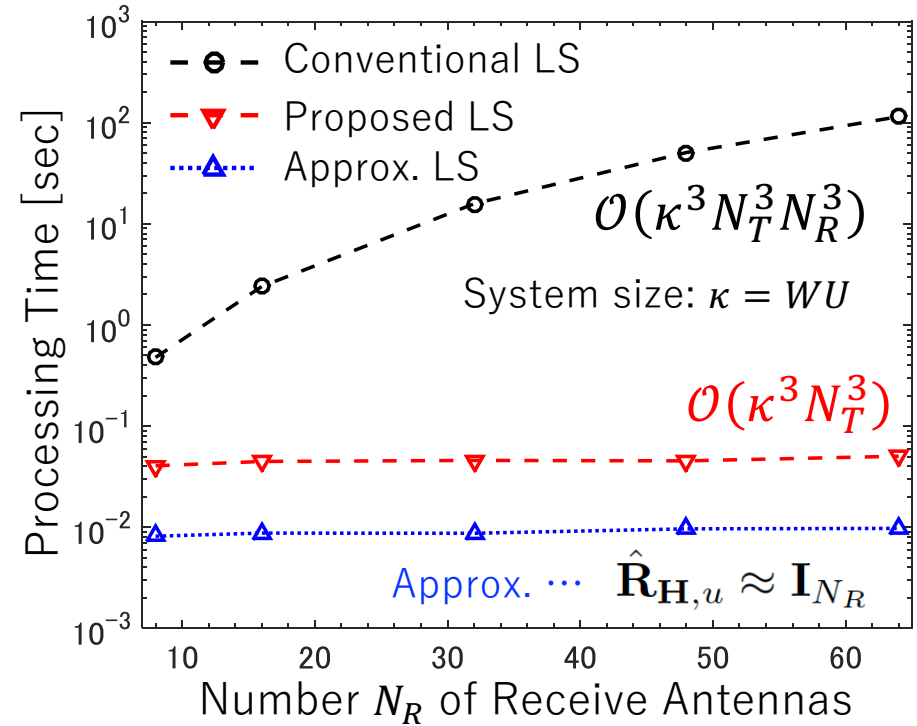
Consequently, $\mathcal{O}((WUN_T)^3)$ when $WUN_T \ll N_R$
 $\leftarrow \mathcal{O}\left((WUN_T)^3 + N_R^3 + (WUN_T)^2 L_{td}\right)$

Numerical Results

No Performance Degradation



Complexity is Independent of Rx antennas



[1] Y. Takano, H. J. Su, "A low-complexity LS turbo channel estimation technique for MU-MIMO systems," *IEEE Signal Proc. Lett.*, vol. 25, no. 5, pp. 710-714, May 2018.