ADAPTIVE SEMI-BLIND SPACE-TIME EQUALIZATION FOR FREQUENCY SELECTIVE RAYLEIGH FADING MIMO SYSTEMS

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Motivations

Space-time equalization : an effective means of suppressing both ISI and CCI for frequency selective MIMO systems

① Training based adaptation: simple but considerably reduces achievable system throughput

② Blind based adaptation: inherently high complexity and slow convergence, also suffering from unavoidable estimation and decision ambiguities

③ Semi-blind based adaptation: provide good performance with high convergence speed and simple computation complexity with minimum training overhead

Existing Works

- Semi-blind stochastic-gradient(SG) based spatial equalizer for stationary frequency nonselective MIMO
  - SG-based concurrent Constant Modulus Algorithm and Soft Decision-Directed adaptation (SG-CMA+SDD)
  - high performance with minimum training
- Semi-blind gradient-Newton(GN) based spatial equalizer for stationary frequency selective MIMO
  - GN-based concurrent Constant Modulus Algorithm and Soft Decision-Directed adaptation (GN-CMA+SDD)
  - high performance with minimum training
- For time-varying MIMOs, no results has been produced

Contribution

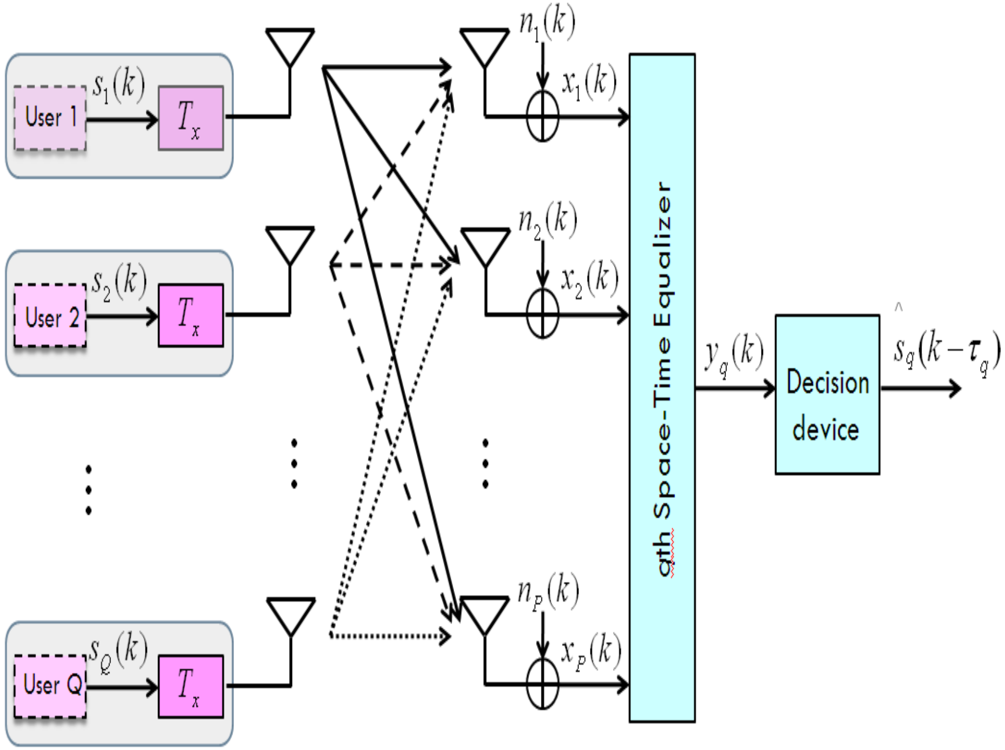
We investigate tracking performance of semi-blind GN-CMA+SDD STE operating in dispersive Rayleigh fading MIMOs

- Continuously Training-based recursive least squares (RLS) STE
  - Offering a low bound of the system's achievable performance
  - Impossible to realize
- Tracking performance is close to the continuously training-based RLS algorithm
- Offering a practical way to adapt a STE in the hostile dispersive fading MIMO environment

MIMO channels

- Q users, *P* receive antennas, and channel impulse response (CIR) connecting *q*th transmit antenna to *p*th receive antenna of length n_C

$$\mathbf{c}_{p,q}(k) = \begin{bmatrix} c_{0,p,q}(k) \\ c_{1,p,q}(k) \\ \vdots \\ c_{n_c-1,p,q}(k) \end{bmatrix}$$



- CIR taps $c_{i,p,q}$: Rayleigh magnitudes with normalized Doppler frequency f_d and unity power
- Continuously fluctuating fading, different fading magnitude and phase for each $c_{i,p,q}$ at each *k*

Space-time Equalizer (STE)

- Received signal vector

$$\mathbf{x}(k) = \mathbf{C}(k)\mathbf{s}(k) + \mathbf{n}(k)$$

  - $\mathbf{s}(k)$ is the transmitted symbol vector $\mathbf{s}(k) = \left[\mathbf{s}_1^T(k) \quad \mathbf{s}_2^T(k) \quad \cdots \quad \mathbf{s}_Q^T(k)\right]^T$ with user-*q*'s data $\mathbf{s}_q(k) = \left[s_q(k) \quad s_q(k-1) \quad \cdots \quad s_q(k-D-n_C+2)\right]^T$, where *D* is the temporal filter length
  - $\mathbf{n}(k)$ is the AWGN vector $\mathbf{n}(k) = \left[\mathbf{n}_1^T(k) \quad \mathbf{n}_2^T(k) \quad \cdots \quad \mathbf{n}_P^T(k)\right]^T$ with $\mathbf{n}_p(k) = \left[n_p(k) \quad n_p(k-1) \quad \cdots \quad n_p(k-D+1)\right]^T$
  - $\mathbf{C}(k)$ is overall system's CIR matrix
- *q*th STE output for detecting user-*q*'s data $s_q(k-\tau_q)$, where τ_q is decision delay

$$y_q(k) = \mathbf{w}_q^H(k)\mathbf{x}(k)$$

  - *q*th STE weight vector $\mathbf{w}_q(k) = \left[\mathbf{w}_{1,q}^T(k) \quad \mathbf{w}_{2,q}^T(k) \quad \cdots \quad \mathbf{w}_{P,q}^T(k)\right]^T$ with *p*th filter $\mathbf{w}_{p,q}(k) = \left[\mathbf{w}_{0,p,q}(k) \quad \mathbf{w}_{2,p,q}(k) \quad \cdots \quad \mathbf{w}_{D-1,p,q}(k)\right]^T$

Least Squares Estimate

- *K* available training symbols, and available training data:

$$\begin{cases} \mathbf{X}_K = [\mathbf{x}(1) \quad \mathbf{x}(2) \quad \cdots \quad \mathbf{x}(K)], \\ \bar{\mathbf{s}}_{K,q} = [s_q(1-\tau_q) \quad s_q(1-\tau_q) \quad \cdots \quad s_q(1-\tau_q)]^T \end{cases}$$

- Least Square (LS) estimate of STE's weight vector

$$\mathbf{w}_q(0) = \left(\mathbf{X}_K \mathbf{X}_K^H\right)^{-1} \mathbf{X}_K \bar{\mathbf{s}}_{K,q}^*$$

- To ensure full rank of $\mathbf{X}_K \mathbf{X}_K^H$, $K \geq N_{STE}$, the dimension of STE

$N_{STE} = P \cdot D$

- To maintain throughput, we choose minimum training length

$K \approx N_{STE}$

Gradient-Newton Adaptation

- SG adaptation suffers from slow convergence and high steady-state misadjustment in highly correlated signal environments
- Similar to RLS, GN adaptation is effective in such hostile signal environments, at cost of increased complexity
  - "Kalman" gain

$$\mathbf{g}(k) = \frac{\lambda^{-1}\mathbf{P}(k-1)\mathbf{x}(k)}{1+\lambda^{-1}\mathbf{x}^H(k)\mathbf{P}(k-1)\mathbf{x}(k)}$$

  - Inverse "autocorrelation" matrix

$$\mathbf{P}(k) = \lambda^{-1}\mathbf{P}(k-1) - \lambda^{-1}\mathbf{g}(k)\mathbf{x}^H(k)\mathbf{P}(k-1)$$

  - Forgetting factor $0 < \lambda < 1$, and initial $\mathbf{P}(0) = \left(\mathbf{X}_K \mathbf{X}_K^H\right)^{-1}$

GN-CMA

- Given initial LS estimate , split STE's weight vector to two parts

$$\mathbf{w}_q(k) = \mathbf{w}_{q,c}(k) + \mathbf{w}_{q,d}(k)$$

  with $\mathbf{w}_{q,c}(0) = \mathbf{w}_{q,d}(0) = 0.5\mathbf{w}_q(0)$

- Gradient-Newton constant modulus algorithm for $\mathbf{w}_{q,c}(k)$
  - Given $\Delta = E[|s_q(k)|^4]/E[|s_q(k)|^2]$, error signal is

$$\varepsilon(k) = y_q(k)\left(\Delta - \left|y_q(k)\right|^2\right)$$

  - Given step size μ_{CMA}, weight adaptation

$$\mathbf{w}_{q,c}(k+1) = \mathbf{w}_{q,c}(k) + \mu_{CMA}\mathbf{P}(k)\varepsilon^*(k)\mathbf{x}(k)$$

  - If $\mathbf{P}(k) = \mathbf{I}$ ⟹ Stochastic-gradient CMA

SDD Scheme

- For M-QAM, divide complex plane into $M/4$ regions:

  $$S_{i,l} = \{s_{r,m}, r = 2i-1, 2i, m = 2l-1, 2l\}$$

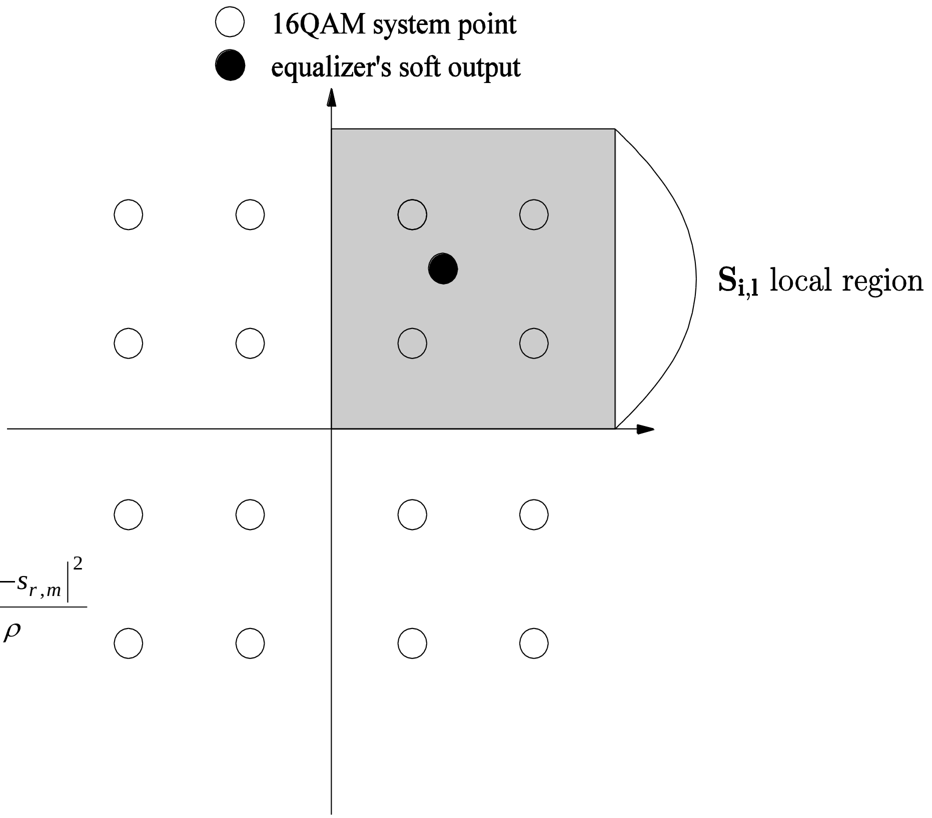
  where $1 \le i, l \le \sqrt{M}/2$

- If STE's output $y_q(k) \in S_{i,l}$, local approximation of marginal PDF

  $$\hat{p}(\mathbf{w}_q(k), y_q(k)) \approx \sum_{r-2i-1}^{2i} \sum_{m=2l-1}^{2l} \frac{1}{8\pi\rho} e^{-\frac{|y_q(k)-s_{r,m}|^2}{2\rho}}$$

- SDD: "maximize"

  $$J_{LMAP}(\mathbf{w}_q(k), k) = \rho \log\left(\hat{p}(\mathbf{w}_q(k, y_q(k))\right)$$



GN-SDD

- Gradient-Newton soft decision directed adaptation for $\mathbf{w}_{q,d}(k)$

$$\mathbf{w}_{q,d}(k+1) = \mathbf{w}_{q,d}(k) + \mu_{SDD}\mathbf{P}(k)\frac{\partial J_{LMAP}\left(\mathbf{w}_q(k), k\right)}{\partial \mathbf{w}_{q,d}}$$

  - μ_{SDD} is step size
  - ρ is the cluster width

$$\frac{\partial J_{LMAP}}{\partial \mathbf{w}_{q,d}} = \frac{1}{Z_N}\sum_{r-2i-1}^{2i}\sum_{m=2l-1}^{2l} e^{-\frac{\left|y_q(k)-s_{r,m}\right|^2}{2\rho}}\left(s_{r,m} - y_q(k)\right)^* \mathbf{x}(k)$$

where $$Z_N = \sum_{r=2r-1}^{2i}\sum_{m=2l-1}^{2l}\exp\left(-\frac{\left|y_q(k) - s_{r,m}\right|^2}{2\rho}\right)$$

  - If $\mathbf{P}(k) = \mathbf{I}$ ⟶ Stochastic-gradient SDD

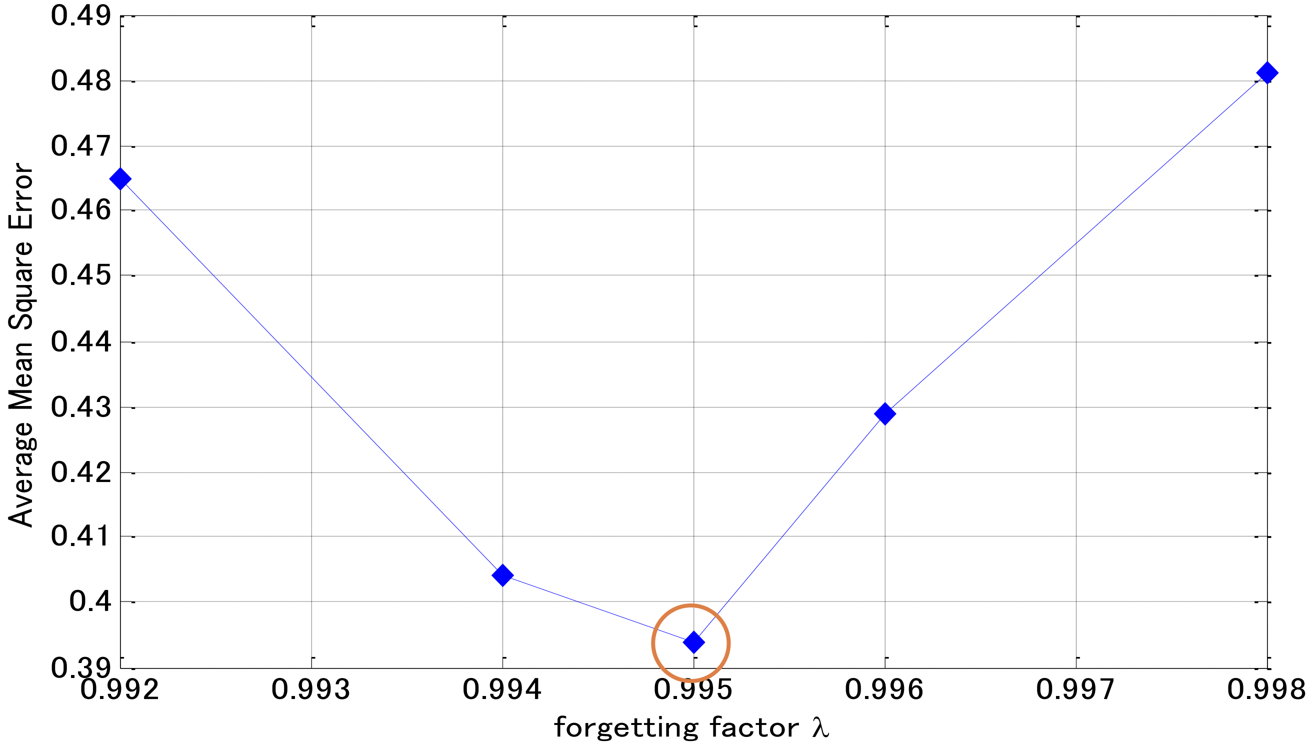
Simulation Setting

- Q = 3 users with 16-QAM, and *P* = 4 receive antennas
  - Each of $P \cdot Q = 12$ CIRs had $n_C = 3$ taps
  - Continuously fluctuating fading with normalized Doppler frequency $f_d = 5$, and CIRs' taps changed at each *k*
  - STE's temporal filter order *D* = 5, and three STE decision delays $\tau_1 = \tau_2 = \tau_3 = 2$
- Semi-blind GN-CMA+SDD is compared with semi-blind SG-CMA+SDD, with training based RLS STE as benchmark
  - Number of training symbols for semi-blind STEs was *K* = 24, slightly larger than STE's dimension N_{STE}
  - RLS STE kept training continuously, which was impractical but offered lower bound of achievable performance

RLS

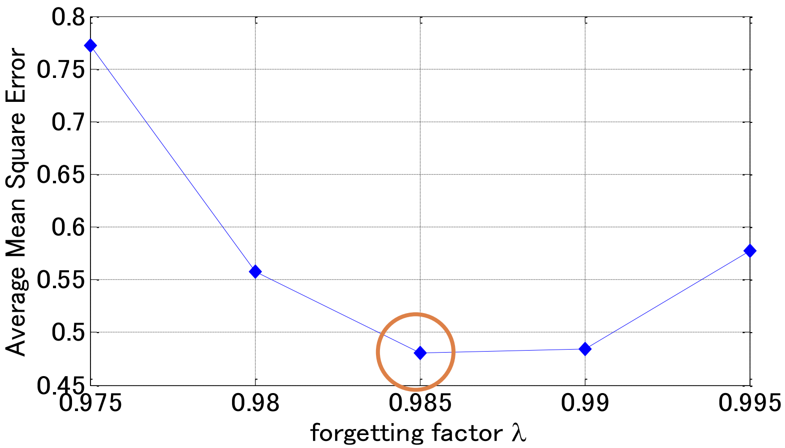
- Forgetting factor $\lambda = 0.995$ for training-based RLS algorithm

Influence of λ to average MSE of training-based RLS algorithm (SNR of 20 dB, averaged over all three users and over 50 runs)

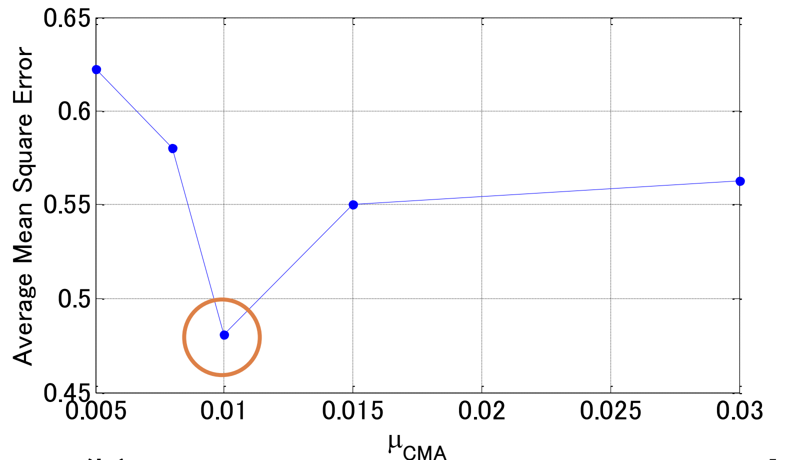


GN-CMA+SDD

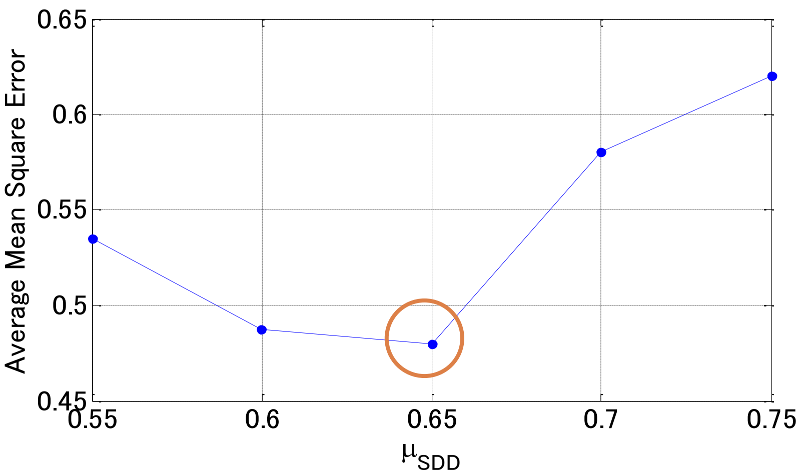
- $\lambda = 0.985$, $\mu_{SDD} = 0.65$, $\mu_{CMA} = 0.01$ and $\rho = 0.4$ for GN-CMA+SDD algorithm



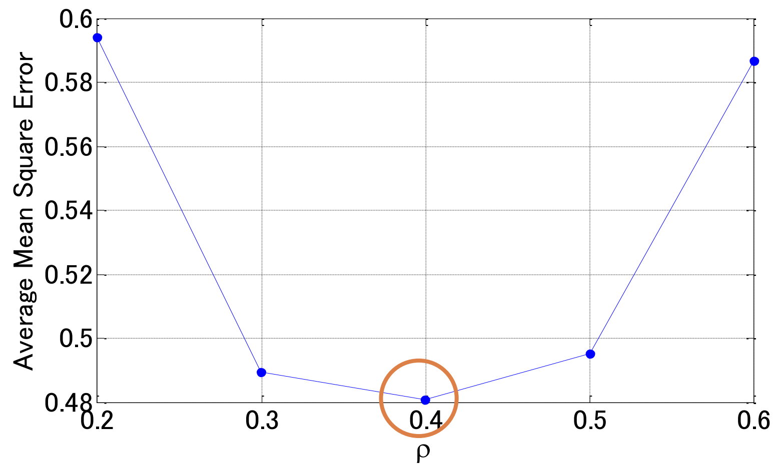
(a) $\mu_{CMA} = 0.01$, $\mu_{SDD} = 0.65$, $\rho = 0.4$, $SNR = 20dB$



(b) $\lambda = 0.985$, $\mu_{SDD} = 0.65$, $\rho = 0.4$, $SNR = 20dB$



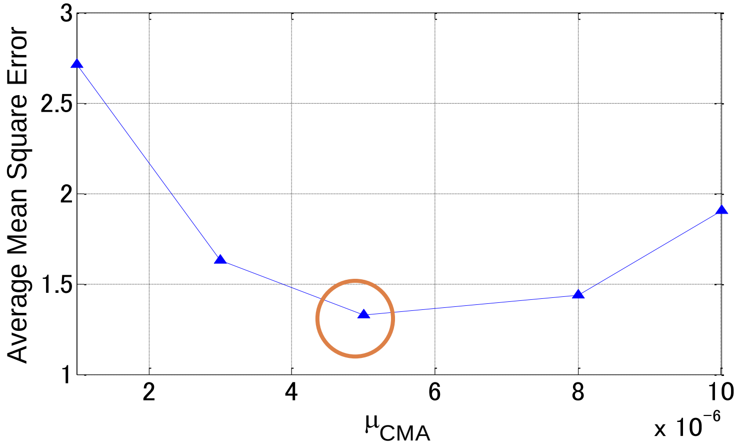
(c) $\lambda = 0.985$, $\mu_{CMA} = 0.01$, $\rho = 0.4$, $SNR = 20dB$



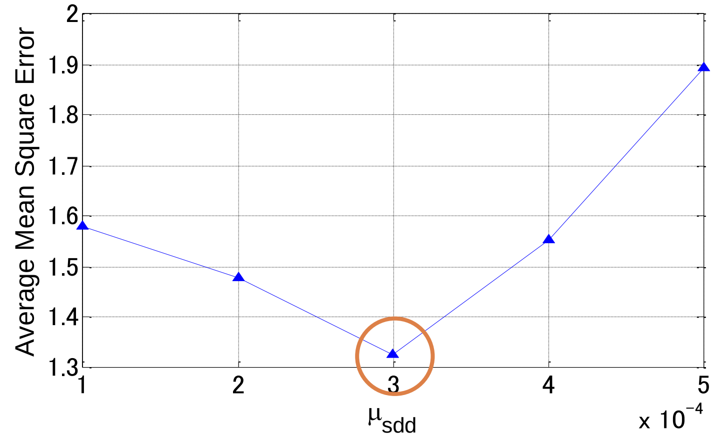
(d) $\lambda = 0.985$, $\mu_{CMA} = 0.01$, $\mu_{SDD} = 0.65$, $SNR = 20dB$

SG-CMA+SDD

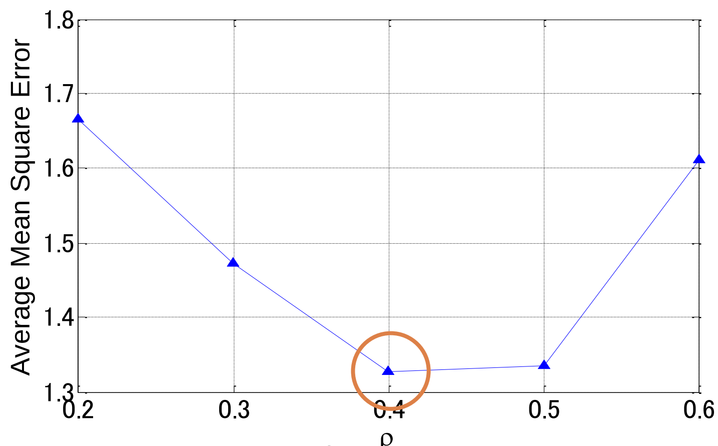
- $\mu_{CMA} = 5\times10^{-6}$, $\mu_{SDD} = 3\times10^{-4}$ and $\rho = 0.4$ for SG-CMA+SDD algorithm



(a) $\mu_{SDD} = 5\times10^{-4}$, $\rho = 0.4$, $SNR = 20dB$



(b) $\mu_{CMA} = 5\times10^{-6}$, $\rho = 0.4$, $SNR = 20dB$

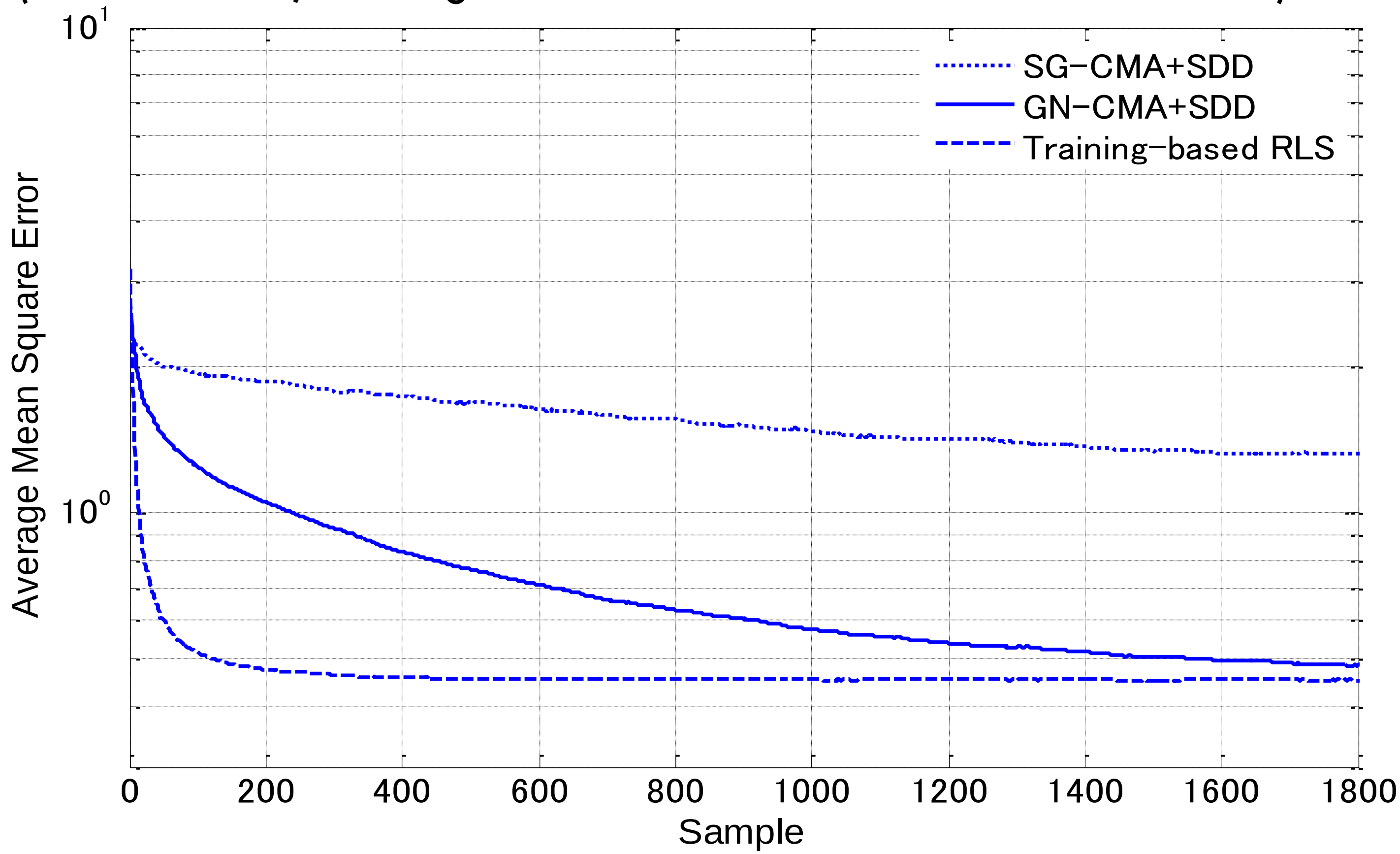


(c) $\mu_{CMA} = 5\times10^{-6}$, $\mu_{SDD} = 5\times10^{-4}$, $SNR = 20dB$

MSE Performance

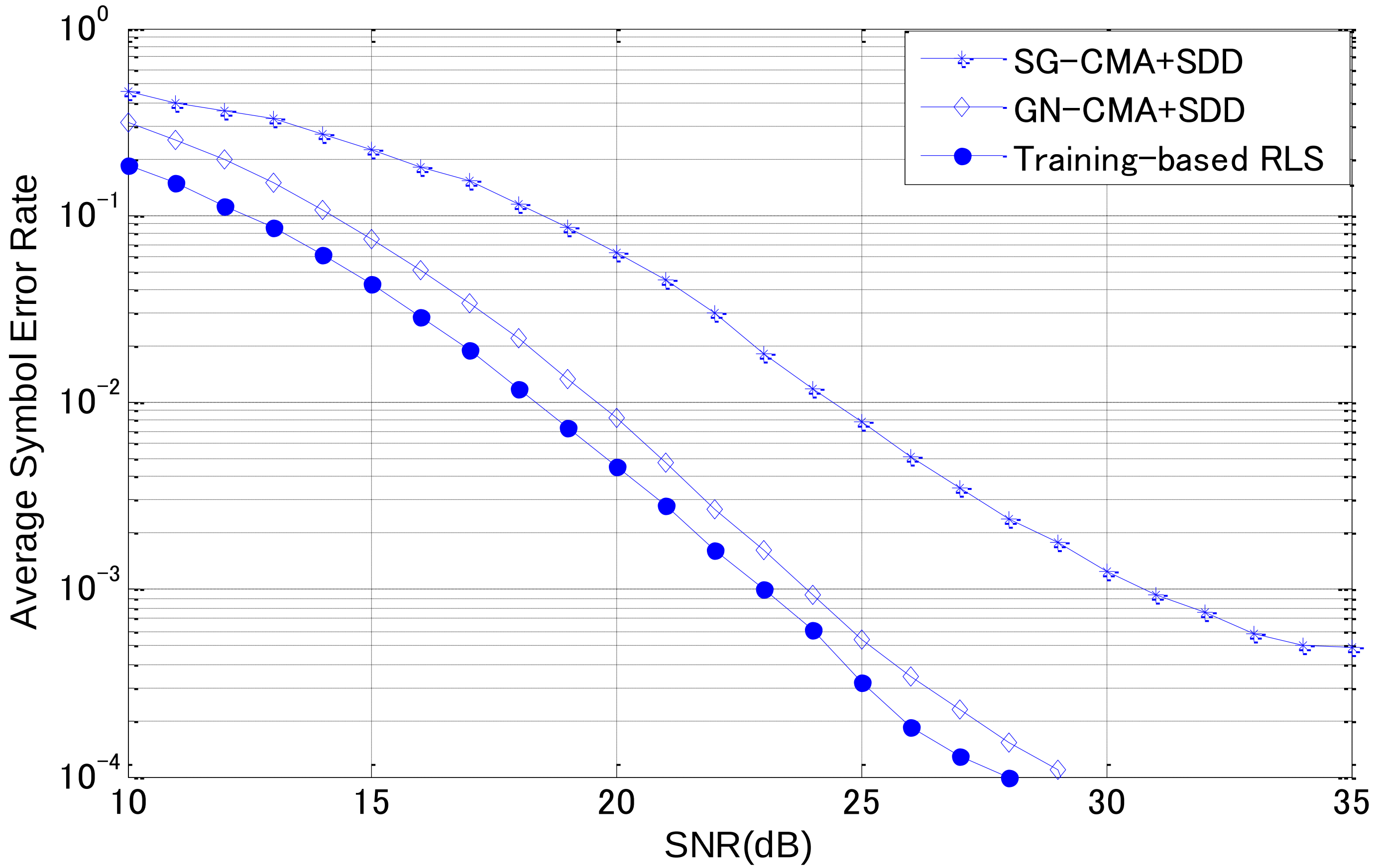
- MSE tracking performance of continuously training RLS, semi-blind SG-CMA+SDD and semi-blind GN-CMA+SDD

(SNR= 20 dB, average over all three users and over 50 runs)



SER Performance

- SER, averaged over all three users, of continuously training RLS, semi-blind SG-CMA+SDD and semi-blind GN-CMA+SDD



Conclusion

We have investigated semi-blind GN-CMA+SDD STE operating in dispersive Rayleigh fading MIMO environments

- Tracking performance of this semi-blind algorithm is close to continuously training-based RLS
- Continuously training-based RLS STE is impractical, and its SER offers a low bound of achievable performance
- This semi-blind GN-CMA+SDD algorithm offers a practical means to adapt STE in hostile dispersive fading MIMOs