ICC 2007 Presentation

Joint Maximum Likelihood Channel Estimation and Data Detection for MIMO Systems

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Outline

- Motivations for **joint maximum likelihood** channel estimation and data detection for MIMO

- MIMO Signal model and proposed semi-blind joint ML **channel estimation** and **data detection**

- Simulation investigation and performance comparison

Motivations

- Knowledge of **channel state information** is critical to achieve capacity enhancement promised by MIMO, but perfect CSI is often unavailable
- Estimating MIMO channel matrix is a tough job, and **training**-based channel estimation is simple but it reduces achievable throughput
- **Blind** joint channel estimation and data detection does not reduce achievable throughput but is computationally complex
- To resolve **ambiguities** in channel estimation and symbol detection, a few pilot symbols, i.e. some training, are necessary
- We propose a **semi-blind** joint maximum likelihood channel estimation and data detection scheme

Signal Model

- MIMO system of n_T transmitters/n_R receivers with flat fading channels

$$\mathbf{y}(k) = \mathbf{H}\,\mathbf{s}(k) + \mathbf{n}(k)$$

- Transmitted symbol vector $\mathbf{s}(k) = [s_1(k)\ s_2(k) \cdots s_{n_T}(k)]^T$

  Received signal vector $\mathbf{y}(k) = [y_1(k)\ y_2(k) \cdots y_{n_R}(k)]^T$

  Channel AWGN vector $\mathbf{n}(k) = [n_1(k)\ n_2(k) \cdots n_{n_R}(k)]^T$

- $n_R \times n_T$ channel matrix $\mathbf{H}$ with $\mathbf{H}(p,m) = h_{p,m}$, for $1 \leq p \leq n_R$ and $1 \leq m \leq n_T$

- $h_{p,m}$ is a complex Gaussian process with zero mean and $E[|h_{p,m}|^2] = 1$

- Block fading is assumed, where $h_{p,m}$ is kept constant over small block of N symbols

Known Channel or Known Data

- Define $n_R \times N$ matrix of received data

$$\mathbf{Y} = [\mathbf{y}(1)\ \mathbf{y}(2) \cdots \mathbf{y}(N)]$$

and corresponding $n_T \times N$ matrix of transmitted data

$$\mathbf{S} = [\mathbf{s}(1)\ \mathbf{s}(2) \cdots \mathbf{s}(N)]$$

- Knowing data $\mathbf{S}$, channel $\mathbf{H}$ can be estimated by **LSCE**

$$\hat{\mathbf{H}}_{LSCE} = \mathbf{Y}\mathbf{S}^H \left(\mathbf{S}\mathbf{S}^H\right)^{-1}$$

- Knowing channel $\mathbf{H}$, **ML detection** of $\mathbf{S}$ can be performed using OHRSA

J. Akhtman, A. Wolfgang, S. Chen and L. Hanzo, "An optimized-hierarchy-aided approximate Log-MAP detector for MIMO systems," *IEEE Trans. Wireless Communications*, Vol.6, No.5, pp.1900–1909, 2007

Joint Channel and Data Estimation

- Both channel and data are **unknown**, joint ML channel and data estimation is defined by

$$(\hat{\mathbf{S}}, \hat{\mathbf{H}}) = \arg\left\{ \min_{\check{\mathbf{S}}, \check{\mathbf{H}}} J_{ML}(\check{\mathbf{S}}, \check{\mathbf{H}}) \right\}$$

where

$$J_{ML}(\check{\mathbf{S}}, \check{\mathbf{H}}) = \frac{1}{n_R \times N} \sum_{k=1}^{N} \left\| \mathbf{y}(k) - \check{\mathbf{H}}\, \check{\mathbf{s}}(k) \right\|^2$$

but this joint ML search is computationally **prohibitive**

- Joint optimisation can be decomposed into tractable **iterative loop** first over all possible data and then over all possible channels

$$(\hat{\mathbf{S}}, \hat{\mathbf{H}}) = \arg\left\{ \min_{\check{\mathbf{H}}} \left[\min_{\check{\mathbf{S}}} J_{ML}(\check{\mathbf{S}}, \check{\mathbf{H}}) \right] \right\}$$

Joint ML Estimation (continue)

- **Upper-level Optimisation**: RWBS[†] searches MIMO channel space to find optimal channel estimate $\hat{\mathbf{H}}$ by minimising MSE

$$J_{MSE}(\check{\mathbf{H}}) = J_{ML}(\hat{\mathbf{S}}(\check{\mathbf{H}}), \check{\mathbf{H}})$$

  ☆ $\hat{\mathbf{S}}(\check{\mathbf{H}})$ denotes ML estimate of transmitted data for given channel $\check{\mathbf{H}}$

- **Lower-level Optimisation**: Given MIMO channel matrix $\check{\mathbf{H}}$, OHRSA detector finds ML estimate of transmitted data $\hat{\mathbf{S}}(\check{\mathbf{H}})$

  ☆ Feeds back corresponding ML metric $J_{MSE}(\check{\mathbf{H}})$ to upper level

[†] S. Chen, X.X. Wang and C.J. Harris, "Experiments with repeating weighted boosting search for optimization in signal processing applications," *IEEE Trans. Systems, Man and Cybernetics, Part B*, Vol.35, No.4, pp.682–693, 2005

Semi-Blind Joint ML Estimation

- Pure **blind** joint ML estimation converges slowly and solution $(\hat{\mathbf{S}}, \hat{\mathbf{H}})$ suffers from inherent permutation and scaling **ambiguity** problem

- Effective means of resolving ambiguities is to employ a few **pilot symbols** to determine **unitary** $n_T \times n_T$ permutation and scaling matrix

- Since we have a few pilots, it is **semi-blind**

- Let number of pilots be t, we can further use **training** data

$$\mathbf{Y}_t = [\mathbf{y}(1)\ \mathbf{y}(2) \cdots \mathbf{y}(t)],\ \mathbf{S}_t = [\mathbf{s}(1)\ \mathbf{s}(2) \cdots \mathbf{s}(t)]$$

  to provide an initial LSCE $\check{\mathbf{H}}_{LSCE} = \mathbf{Y}_t \mathbf{S}_t^H \left(\mathbf{S}_t \mathbf{S}_t^H\right)^{-1}$ for adding RWBS[†]

[†] RWBS evolves population of channels $\{\check{\mathbf{H}}_i^{(g)}\}_{i=1}^{P_S}$ over a number of generations $1 \leq g \leq N_G$. $\check{\mathbf{H}}_{LSCE}$ is used to initialise the search population

Repeated Weighted Boosting Search

- **Algorithm initialisation**: $\check{\mathbf{H}}_{\text{best}}^{(0)} = \check{\mathbf{H}}_{LSCE}$
- **Generation loop**: for $(g = 1; g \le N_G; g++)$ {
  - **Generation initialisation**: $\check{\mathbf{H}}_1^{(g)} = \check{\mathbf{H}}_{\text{best}}^{(g-1)}$

    $$\check{\mathbf{H}}_i^{(g)} = \check{\mathbf{H}}_1^{(g)} + (\mathbf{1} + j\mathbf{1})\eta, \ 2 \le i \le P_S$$

    η being random variable uniformly distribution in $[-\gamma, \quad \gamma]$
  - **OHRSA ML detector**: $\{\hat{\mathbf{S}}(\check{\mathbf{H}}_i^{(g)})\}_{g=1}^{P_S}$
  - **Weighted boosting search**: for $(l = 1; l \le N_I; l++)$ {
    WBS/OHRSA: evolve $\{\check{\mathbf{H}}_i^{(g)}, \hat{\mathbf{S}}(\check{\mathbf{H}}_i^{(g)})\}_{i=1}^{P_S}$
  - } **End of weighted boosting search**
  - Solution: $\check{\mathbf{H}}_{\text{best}}^{(g)}$
- } **End of generation loop**
- **Solution**: $\left(\check{\mathbf{H}}_{\text{best}}^{(N_G)}, \hat{\mathbf{S}}(\check{\mathbf{H}}_{\text{best}}^{(N_G)})\right)$

Simulation Set Up

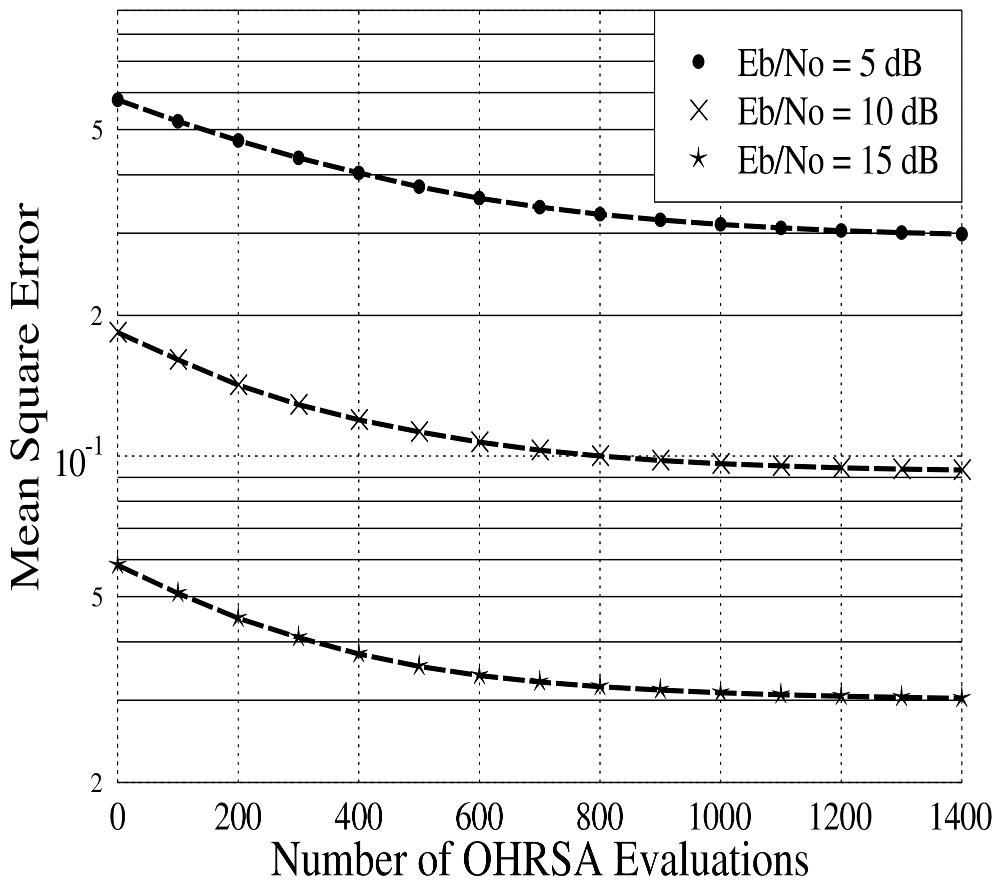
- $n_T = 4$ and $n_R = 4$: 4×4 MIMO system with flat fading channel
- Each channel $h_{p,m}$ was complex Gaussian process with zero mean and $E[|h_{p,m}|^2] = 1$, block faded, i.e. kept constant over block of N symbols
- Modulation scheme: BPSK, data block: $N = 50$, pilot symbols: $t = 4$
- Simulation was averaged over 100 runs, **complexity** was determined by number of OHRSA(N) evaluations, n_{ev}
- **Convergence metrics**: MSE $J_{MSE}(\hat{\mathbf{H}}(n_{\text{ev}}))$ and MCE $J_{MCE}(\hat{\mathbf{H}}(n_{\text{ev}}))$, with

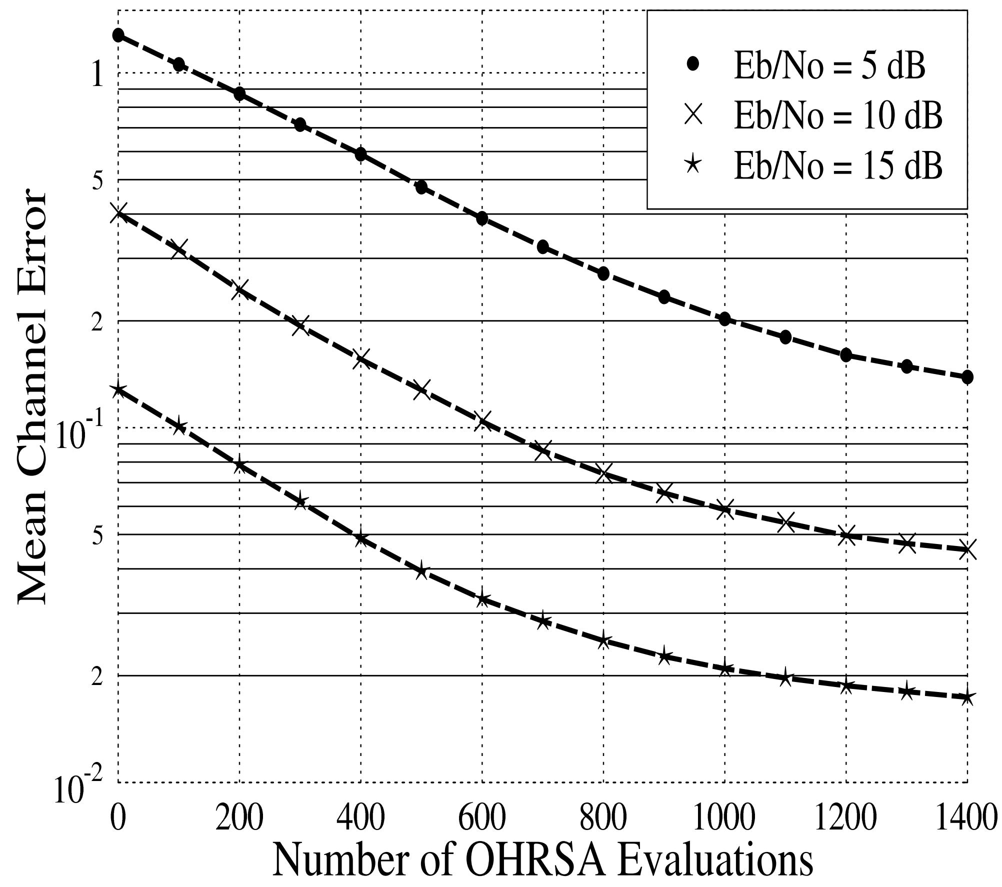
$$J_{MCE}(\hat{\mathbf{H}}(n_{\text{ev}})) = \sum_{m=1}^{n_T} \sum_{p=1}^{n_R} \left| h_{p,m} - \hat{h}_{p,m}(n_{\text{ev}}) \right|^2$$

where $\hat{\mathbf{H}}(n_{\text{ev}})$ was channel estimate after n_{ev} OHRSA(N) evaluations

Convergence Investigation

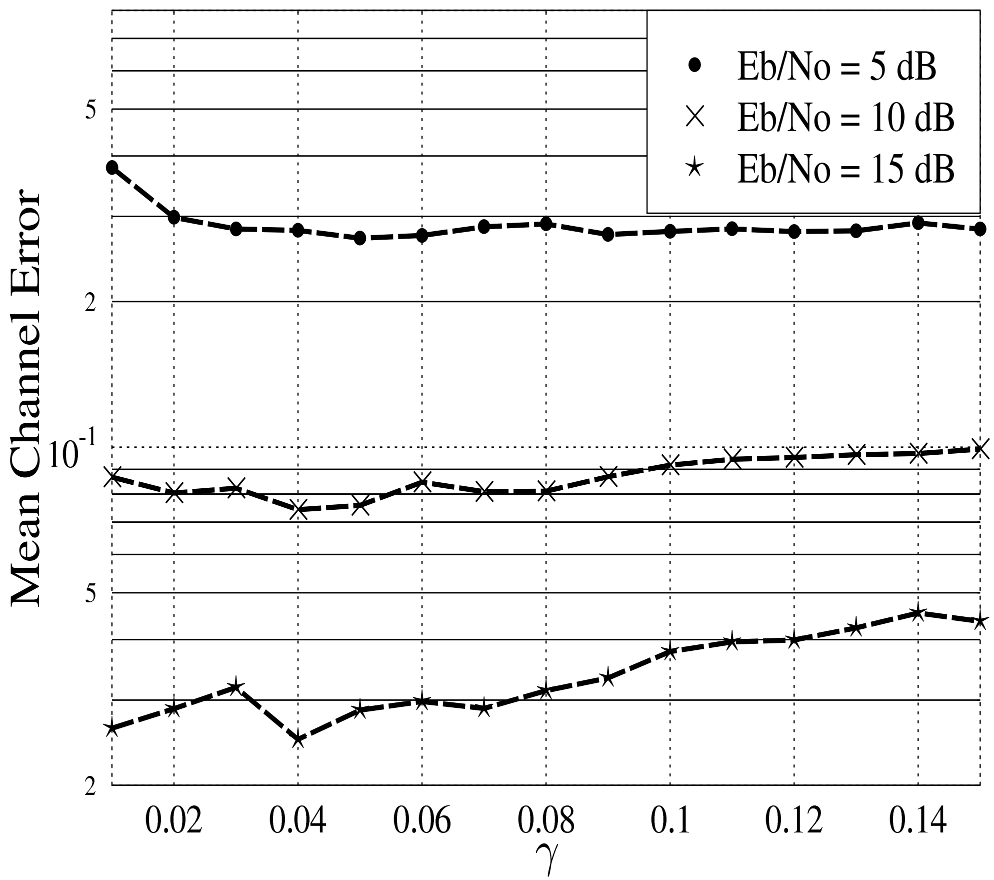
Convergence performance, **mean square error** and **mean channel error**, of proposed semi-blind joint ML estimation algorithm, with $\gamma = 0.04$

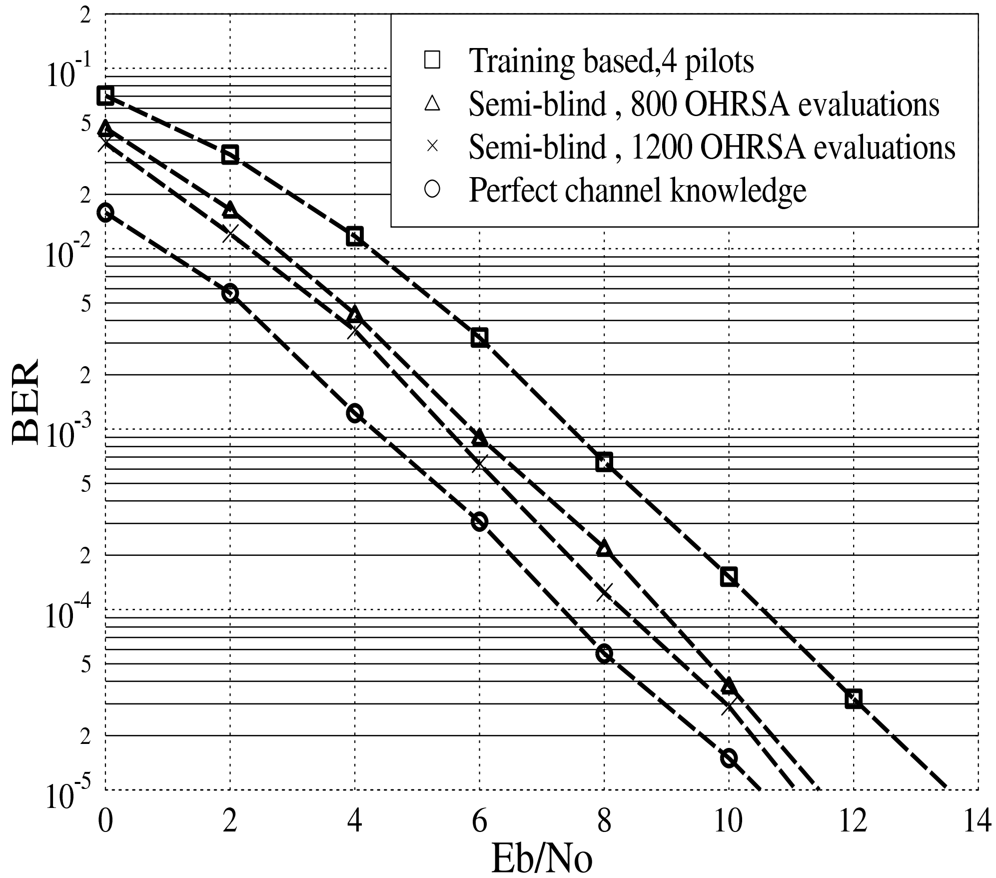




Performance Investigation

Influence of **algorithmic parameter** γ to MCE at 800 OHRSA(N) evaluations, and **bit error ratio** comparison with $\gamma = 0.04$ for semi-blind scheme





Conclusions

- An algorithm has been proposed for MIMO semi-blind joint maximum likelihood channel estimation and data detection
- The scheme uses RWBS to search MIMO channel space and OHRSA to provide ML data estimates for channel population
- A few pilot symbols are used to resolve ambiguity of blind joint ML estimate and to add RWBS search
- Effectiveness of proposed semi-blind joint ML scheme has been demonstrated using simulation

THANK YOU.

The financial support of the EU under the auspice of the Newcom project is gratefully acknowledged