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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

\[
y(k) = H s(k) + n(k)
\]

- Transmitted symbol vector \( s(k) = [s_1(k) \ s_2(k) \cdot \cdot \cdot s_{n_T}(k)]^T \)
  Received signal vector \( y(k) = [y_1(k) \ y_2(k) \cdot \cdot \cdot y_{n_R}(k)]^T \)
  Channel AWGN vector \( n(k) = [n_1(k) \ n_2(k) \cdot \cdot \cdot n_{n_R}(k)]^T \)

- \( n_R \times n_T \) channel matrix \( H \) with \( H(p, m) = h_{p,m} \), 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

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

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

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

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

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

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

Joint Channel and Data Estimation

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

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

where

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

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

$$\hat{(\hat{S}, \hat{H})} = \arg \left\{ \min_{\hat{H}} \left[ \min_{\hat{s}} J_{ML}(\hat{s}, \hat{H}) \right] \right\}$$
Joint ML Estimation (continue)

- **Upper-level Optimisation**: RWBS\(^\dagger\) searches MIMO channel space to find optimal channel estimate \(\hat{H}\) by minimising MSE

\[
J_{MSE}(\hat{H}) = J_{ML}(\hat{S}(\hat{H}), \hat{H})
\]

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

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

\(\hat{S}(\hat{H})\) feeds back corresponding ML metric \(J_{MSE}(\hat{H})\) to upper level

Semi-Blind Joint ML Estimation

- Pure **blind** joint ML estimation converges slowly and solution ($\hat{S}, \hat{H}$) 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

$$Y_t = [y(1) \ y(2) \cdots y(t)], \ S_t = [s(1) \ s(2) \cdots s(t)]$$

To provide an initial LSCE $\hat{H}_{LSCE} = Y_t S_t^H (S_t S_t^H)^{-1}$ for adding RWBS†

† RWBS evolves population of channels $\{\hat{H}_i^{(g)}\}_{i=1}^{PS}$ over a number of generations $1 \leq g \leq N_G$. $\hat{H}_{LSCE}$ is used to initialise the search population
Repeted Weighted Boosting Search

- **Algorithm initialisation**: \( \tilde{H}_{\text{best}}^{(0)} = \tilde{H}_{\text{LSCE}} \)

- **Generation loop**: for \((g = 1; g \leq N_G; g++)\) {
  - **Generation initialisation**: \( \tilde{H}_1^{(g)} = \tilde{H}_{\text{best}}^{(g-1)} \)

  \[
  \tilde{H}_i^{(g)} = \tilde{H}_1^{(g)} + (1 + j1)\eta, \quad 2 \leq i \leq P_S
  \]

  \(\eta\) being random variable uniformly distribution in \([-\gamma, \gamma]\)

- **OHRSA ML detector**: \( \{ \hat{S}(\tilde{H}_i^{(g)}) \}_{g=1}^{P_S} \)

- **Weighted boosting search**: for \((l = 1; l \leq N_I; l++)\) {
  - WBS/OHRSA: evolve \( \{ \tilde{H}_i^{(g)}, \hat{S}(\tilde{H}_i^{(g)}) \}_{i=1}^{P_S} \)
  - } End of weighted boosting search

- **Solution**: \( \tilde{H}_{\text{best}}^{(g)} \)

- } End of generation loop

- **Solution**: \( \left( \tilde{H}_{\text{best}}^{(N_G)}, \hat{S}(\tilde{H}_{\text{best}}^{(N_G)}) \right) \)
Simulation Set Up

- \( n_T = 4 \) and \( n_R = 4 \): 4 \( \times \) 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 \( J_{MSE}(\hat{H}(n_{ev})) \) and MCE \( J_{MCE}(\hat{H}(n_{ev})) \), with

\[
J_{MCE}(\hat{H}(n_{ev})) = \sum_{m=1}^{n_T} \sum_{p=1}^{n_R} |h_{p,m} - \hat{h}_{p,m}(n_{ev})|^2
\]

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