

Ordered Iterative Methods for Low-Complexity Massive MIMO Detection

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Importance of MIMO

- Function: significantly improve the spectral and energy efficiency
- Role: a key pillar in 5G communication networks

with the growing number of antennas at the both sides of MIMO systems $N_r \geq N_t$

Challenge upon the Uplink Signal Detection

Linear Detection (ZF and MMSE)

- Advantage:
achieve near-optimal ML detection performance
- Disadvantage:
still with **computational complexity** $\mathcal{O}(N_t^3)$

Sub-optimal Iterative Detectors

Jacobi

Gauss-Seidel (GS)

Successive Over Relaxation (SOR)



Deep Learning (DL)

Combine the internal structure of certain model-based algorithms with the remarkable power of **deep neural networks (DNN)**

Data-driven DL detectors

- **DetNet**
- unfold projected gradient descent via DNN
- achieve better performance than MMSE detector

Model-driven DL detectors

- **OAMPNet**
- exploit full domain knowledge with a few trainable parameters optimized
- outperform the original OAMP

Achieve comparable performance via DL in massive MIMO detection

System Model

$$\mathbf{y} = \mathbf{H}\mathbf{x} + \mathbf{n}$$

Detection

Optimal ML

$$\hat{\mathbf{x}} = \underset{\mathbf{x} \in \mathcal{A}^{N_t}}{\operatorname{argmin}} \|\mathbf{y} - \mathbf{H}\mathbf{x}\|^2 \quad \text{Exponentially increased complexity}$$

Linear Detection

$$\tilde{\mathbf{x}}_{\text{MMSE}} = \left(\mathbf{H}^H \mathbf{H} + \sigma_n^2 \mathbf{I} \right)^{-1} \mathbf{H}^H \mathbf{y} \quad \hat{\mathbf{x}}_{\text{MMSE}} = Q(\tilde{\mathbf{x}}_{\text{MMSE}}) \in \mathcal{A}^{N_t}$$

To bypass the matrix inversion

$$\mathbf{b} = \mathbf{H}^H \mathbf{y}$$

$$\mathbf{A} = \mathbf{H}^H \mathbf{H} + \sigma_n^2 \mathbf{I}$$

$$\mathbf{A}\mathbf{x} = \mathbf{b}$$

Iterative methods are proposed to solve this linear equation

2 System model



Jacobi

$$x_i^{(t+1)} = x_i^{(t)} + \frac{1}{a_{ii}} \left(b_i - \sum_{j=1}^{i-1} a_{ij} x_j^{(t)} - \sum_{j=i+1}^n a_{ij} x_j^{(t)} \right)$$

Parallel Structure

Gauss-Seidel (GS)

$$x_i^{(t+1)} = x_i^{(t)} + \frac{1}{a_{ii}} \left(b_i - \sum_{j=1}^{i-1} a_{ij} x_j^{(t+1)} - \sum_{j=i+1}^n a_{ij} x_j^{(t)} \right)$$

Conventionally in a Sequential Order

Successive Over Relaxation (SOR)

$$x_i^{(t+1)} = x_i^{(t)} + \frac{\omega}{a_{ii}} \left(b_i - \sum_{j=1}^{i-1} a_{ij} x_j^{(t+1)} - \sum_{j=i+1}^n a_{ij} x_j^{(t)} \right)$$



For a better presentation

Update Component

$$\mathbf{x}^{(t+1)} = \mathbf{x}^{(t)} + \frac{\omega}{a_{ii}} r_i^{(t)} \mathbf{e}_i, \quad r_i^{(t)} = b_i - \mathbf{a}_i^H \mathbf{x}^{(t)}$$

3 Ordering Iterative Detection Scheme

Iterative \longrightarrow underlying error propagation

A. Ordering Iterative Detection

$$\begin{aligned} \mathbf{x}^{(t+1)} &= \mathbf{x}^{(t)} + \frac{\omega}{a_{ii}} (b_i - \mathbf{a}_i^H \mathbf{x}^{(t)}) \mathbf{e}_i \\ &= \mathbf{x}^{(t)} - \frac{\omega}{a_{ii}} \mathbf{a}_i^H \mathbf{x}^{(t)} \mathbf{e}_i + \frac{\omega}{a_{ii}} b_i \mathbf{e}_i \end{aligned}$$

$$\mathbf{b} = \mathbf{H}^H \mathbf{y} = \mathbf{H}^H (\mathbf{H}\mathbf{x} + \mathbf{n}) = \mathbf{H}^H \mathbf{H}\mathbf{x} + \mathbf{H}^H \mathbf{n}$$

$$\mathbf{x}^{(t+1)} = \mathbf{x}^{(t)} - \frac{\omega}{a_{ii}} \mathbf{a}_i^H \mathbf{x}^{(t)} \mathbf{e}_i + \frac{\omega}{a_{ii}} \mathbf{g}_i^H \mathbf{x}^{(t)} \mathbf{e}_i + \underbrace{\frac{\omega}{a_{ii}} (\mathbf{h}_i)^H \mathbf{n} \mathbf{e}_i}_{\text{noise part}}$$

Criterion: suppress the effect of noise

$$\begin{aligned} \left\| \frac{\omega}{a_{ii}} (\mathbf{h}_i)^H \mathbf{n} \right\|^2 &\leq \omega^2 \frac{\|\mathbf{h}_i\|^2}{|a_{ii}|^2} \|\mathbf{n}\|^2 \\ &= \omega^2 \|\mathbf{n}\|^2 \frac{(\mathbf{h}_i)^H \mathbf{h}_i}{|a_{ii}|^2} \\ &= \omega^2 \|\mathbf{n}\|^2 \frac{|a_{ii} - \sigma_n^2|}{|a_{ii}|^2} \end{aligned}$$

$$\propto \frac{1}{|a_{ii}|}$$

Update in the descending order of $|a_{ii}|$

3 Ordering Iterative Detection Scheme

Restriction on OID: fixed order ; cyclic traversal iteration

B. Modified Ordered Iterative Detection

Dynamic Ordering Strategy

$$\mathbf{x}^{(t+1)} - \mathbf{x}^{(t)} = \Delta \mathbf{x} = \frac{\omega}{a_{ii}} r_i^{(t)} \mathbf{e}_i, \quad r_i^{(t)} = b_i - \mathbf{a}_i^H \mathbf{x}^{(t)}$$

A large size $\Delta \mathbf{x}$

A large change of the iteration

Positive impact upon the convergence

Update in the descending

order of $\left| \frac{r_i^{(t)}}{a_{ii}} \right|$

3 Ordering Iterative Detection Scheme

C. Complexity Analysis

Algorithm 1: OID

Input $\mathbf{A} = \mathbf{H}^H \mathbf{H} + \sigma_n^2 \mathbf{I}$, $\mathbf{b} = \mathbf{H}^H \mathbf{y}$, $\mathbf{x}^{(0)} = \mathbf{0}$, T

Output near MMSE detection solution $\hat{\mathbf{x}}^{(t)}$

- 1: **for** $t = 0, 1, \dots, T - 1$ **do**
- 2: Select i coordinate in descending order of $|a_{ii}|$
- 3: Update $\mathbf{x}^{(t+1)} = \mathbf{x}^{(t)} + \frac{\omega}{a_{ii}} r_i^{(t)} \mathbf{e}_i$
- 4: **end for**
- 5: output $\hat{\mathbf{x}}^{(t)}$ by rounding $\mathbf{x}^{(t)}$ based on constellation \mathcal{A}^{N_t}

Preprocess operation, reduce the complexity

TABLE I

COMPUTATIONAL COMPLEXITY OF ITERATIVE DETECTION SCHEMES

MIMO detection	Multiplication	Summation
SOR [12]	$N_t^2 + N_t$	$N_t^2 + N_t$
OID	$N_t^2 + 2N_t$	$N_t^2 + N_t$
MOID	$2N_t^2 + 3N_t$	$N_t^2 + N_t$

Algorithm 2: MOID

Input $\mathbf{A} = \mathbf{H}^H \mathbf{H} + \sigma_n^2 \mathbf{I}$, $\mathbf{b} = \mathbf{H}^H \mathbf{y}$, $\mathbf{x}^{(0)} = \mathbf{0}$, T

Output near MMSE detection solution $\hat{\mathbf{x}}^{(t)}$

- 1: **for** $t = 0, 1, \dots, T - 1$ **do**
- 2: Update the descending order $o(i)$ by $|\frac{r_i^{(t)}}{a_{ii}}|$ when $t = 0, N_t, 2N_t, \dots$
- 3: Select i coordinate in descending order of $o(i)$
- 4: Update $\mathbf{x}^{(t+1)} = \mathbf{x}^{(t)} + \frac{\omega}{a_{ii}} r_i^{(t)} \mathbf{e}_i$
- 5: **end for**
- 6: output $\hat{\mathbf{x}}^{(t)}$ by rounding $\mathbf{x}^{(t)}$ based on constellation \mathcal{A}^{N_t}

Loosely dynamic ordering strategy

OID and MOID maintain $\mathcal{O}(N_t^2)$

$$\omega_{opt} = \frac{2}{1 + \sqrt{1 - \rho^2(J)}}, \rho(J) = \left(1 + \sqrt{\frac{N_t}{N_r}} \right)^2 - 1$$

Not Optimal

For a better detection performance, upgrade the proposed MOID algorithm with DNN

Projection Operation

$$\mathbf{x}_k^{(T)} = \mathbf{x}_k^{(T-1)} + \frac{\omega_k}{a_{ii}} r_i^{(T)} \mathbf{e}_i$$

$$\mathbf{z}_k = \text{ReLU}(\mathbf{W}_z \mathbf{x}_k^{(T)} + \mathbf{p}_z)$$

$$\mathbf{x}_{oh,k+1} = \mathbf{W}_x \mathbf{z}_k + \mathbf{p}_x$$

$$\mathbf{x}_{k+1}^{(0)} = f_{oh}(\mathbf{x}_{oh,k+1})$$

Learning parameters

$$\theta = \{\mathbf{W}_z, \mathbf{W}_x, \mathbf{p}_z, \mathbf{p}_x, \omega_k\}$$

Trained by minimizing MSE loss function

$$l(\mathbf{x}; \hat{\mathbf{x}}) = \sum_{k=1}^K \log(k) \|\mathbf{x}_l - \hat{\mathbf{x}}_k\|^2$$

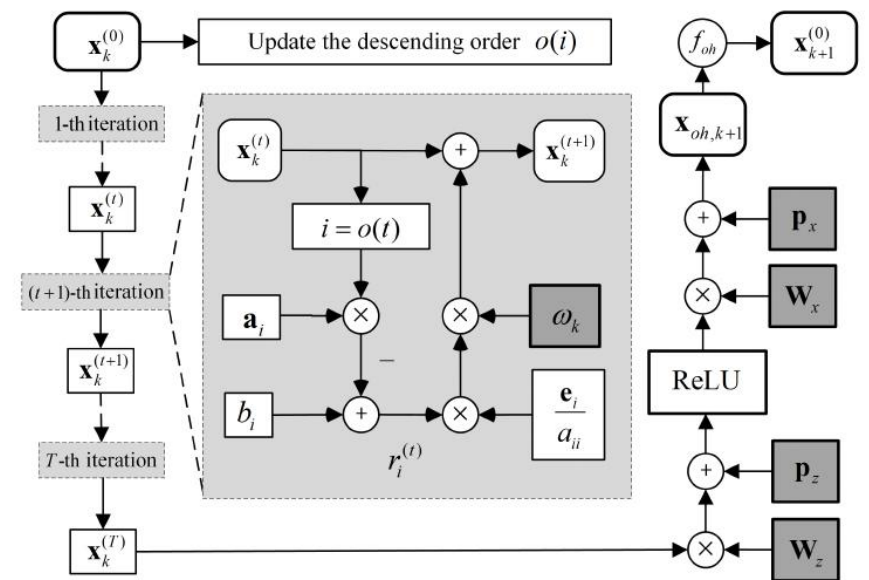


Fig. 1. The architecture of the MOID-Net detector.

5 Simulations

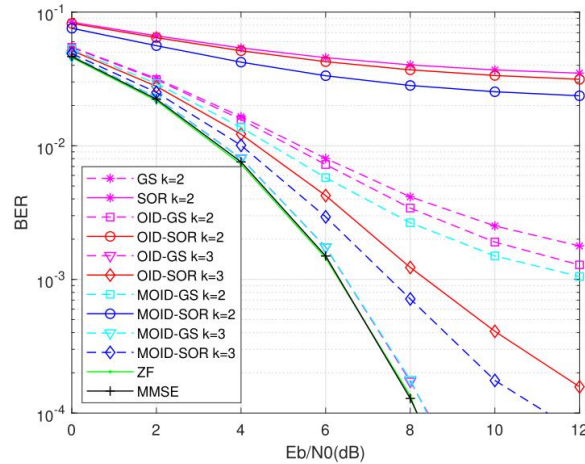


Fig. 2. Performance comparison under 64-QAM scheme of size 128×16 .

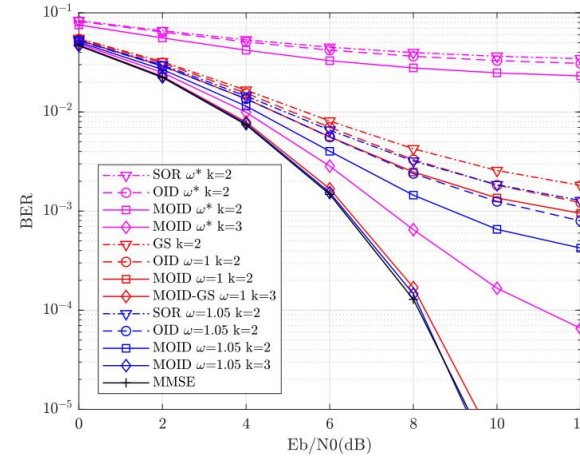


Fig. 3. Performance comparison under 64-QAM scheme of size 128×16 with different ω .

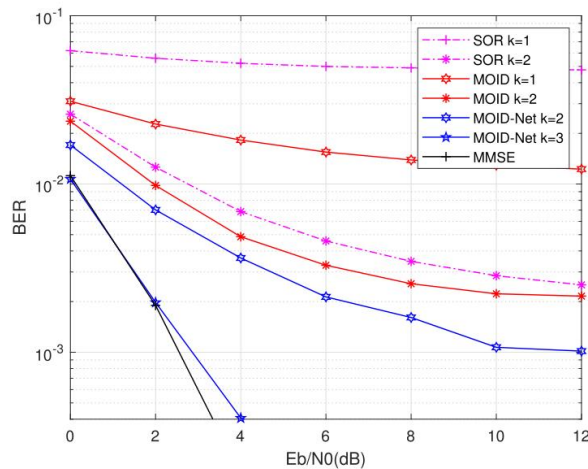


Fig. 4. Performance comparison under 16-QAM scheme of size 128×16 .

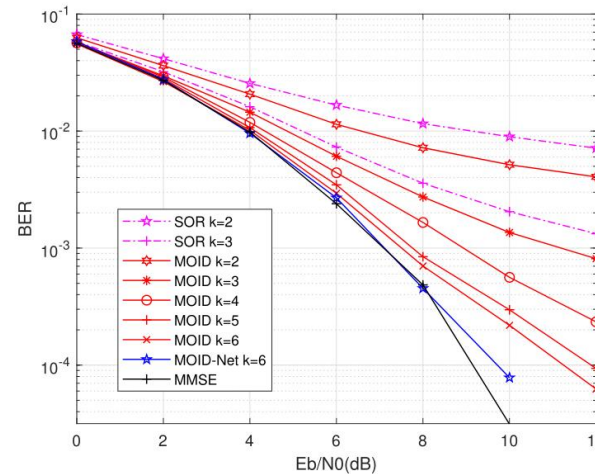


Fig. 5. Performance comparison under 4-QAM scheme of size 32×16 .

Detection Performance

MOID > OID
> Conventional Iterative Method

- MMSE detection is applied as the **baseline**
- ω has a great effect on the convergence

MOID-Net > MOID
> Conventional Iterative Method

- More iteration numbers needed with the loss of receive diversity

Propose two **ordered** iterative detection methods for better signal detection performance in massive MIMO systems.

OID

- To **reduce error propagation** in the traditional iterative detection schemes with sequential order
- Achieves a **better detection performance** with **low complexity**

MOID

- Convergence chiefly depends on the **residual component** during the iterations.
- A **dynamic** ordering strategy
- Further **performance improvement**

MOID-Net

- Extend the proposed algorithm via **DNN** and **relaxation factor are trained** to optimal
- Further **performance gain**

Thank you for your watching

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