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Robust Learning-Based ML Detection for Massive MIMO Systems with One-bit Quantized Signals

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I MOTIVATION

Problem

- Improve communication reliability using one-bit I/Q converters

Goal

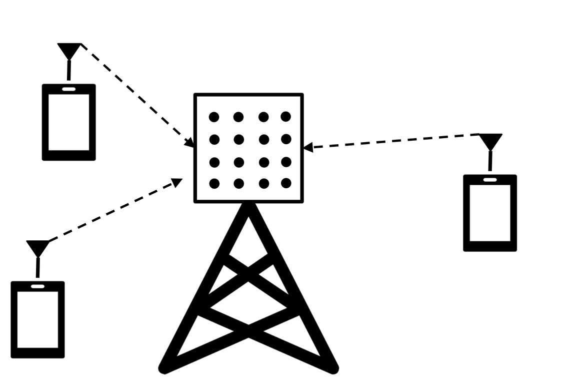
- Apply maximum likelihood (ML) detection without channel estimation

Solution

- Adding dither to improve ML detection

II MODELS

Multiuser-MIMO Communication



One-bit quantized observation

$$\mathbf{y}[n] = \mathcal{Q}(\mathbf{r}[n]) = \mathcal{Q}(\sqrt{\rho}\mathbf{H}\mathbf{s}[n] + \mathbf{n}[n])$$

Optimal ML detection

ML detection rule

$$k^\star[n] = \underset{k\in\mathcal{K}}{\operatorname{argmax}} \prod_{i=1}^{2N_r} p_k(y_i[n])$$

$$p_k(y_i[t]) = \mathbb{P}(y_i[t]|\mathbf{h}_i, \mathbf{s}_k) = \begin{cases} \Phi(\psi_{k,i}), & \text{if } y_i[t] = 1 \\ 1 - \Phi(\psi_{k,i}), & \text{if } y_i[t] = -1. \end{cases}$$

: likelihood function for ith antenna for vector $\mathbf{s}_k$

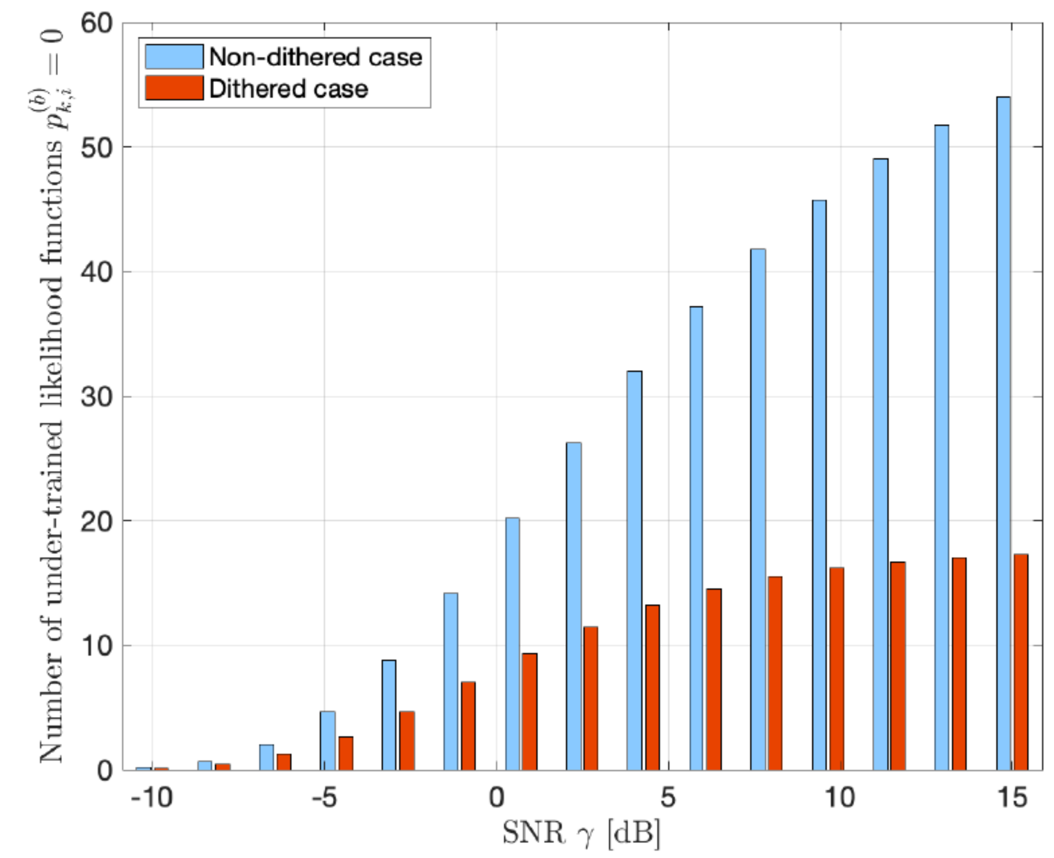
: requires CSI $\psi_{k,i} = \sqrt{\frac{\rho}{N_0/2}}\mathbf{h}_i^H\mathbf{s}_k$

III ROBUST LEARNING WITHOUT CSI

Learning technique during pilot transmission phase

$$\hat{p}_{k,i}^{(b)} = \begin{cases} \hat{p}_{k,i}^{(1)} = \frac{1}{N_{tr}}\sum_{t=1}^{N_{tr}} \mathbf{1}(y_i[(k-1)N_{tr} + t] = 1) \\ \hat{p}_{k,i}^{(-1)} = 1 - \hat{p}_{k,i}^{(1)} \end{cases}$$

: massive number of zeros at high SNR



The number of zero probabilities

Robust learning-based One-Bit ADCs

Signal model with dithering noise

$$\tilde{\mathbf{r}}[n] = \mathbf{r}[n] + \mathbf{d}[n] \qquad \mathbf{d}[n] \sim \mathcal{N}(\mathbf{0}, \sigma^2/2\mathbf{I}_{2N_r})$$
$$= \sqrt{\rho}\mathbf{H}\mathbf{s}_k + \mathbf{n}[n] + \mathbf{d}[n]$$

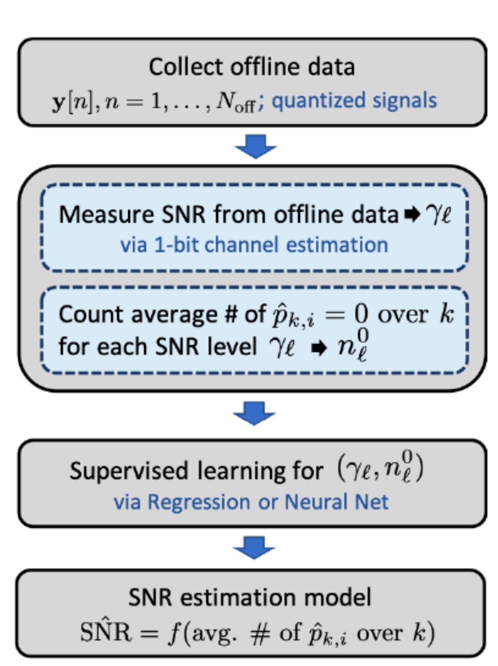
: known to BS

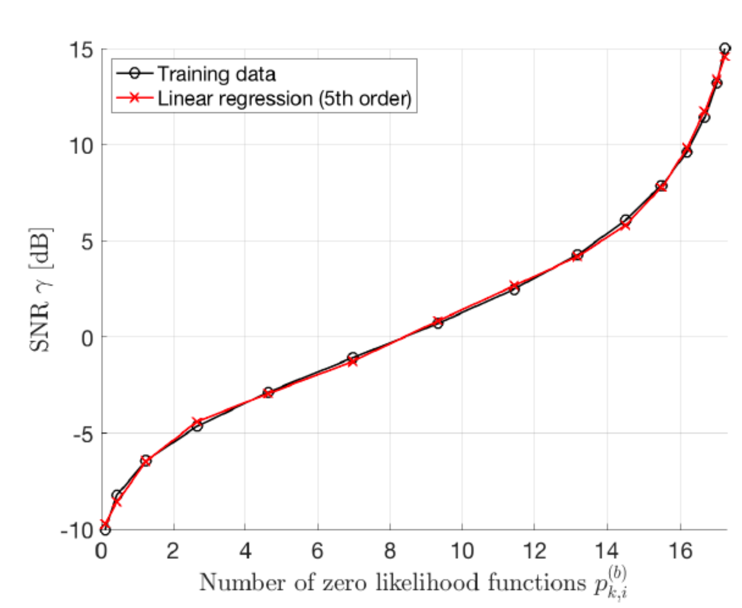
Trained probability is derived as $\tilde{p}_{k,i}^{(+1)} \approx \Phi\left(\sqrt{\frac{2\rho}{N_0 + \sigma^2}}\tilde{\mathbf{h}}_i^\top\mathbf{s}_k\right)$

- Sets $\tilde{p}_{k,i}^{(b)} = p_{bias}$ and $\tilde{p}_{k,i}^{(-b)} = 1 - p_{bias}$, if $\hat{p}_{k,i}^{(b)} = 0$
- p_{bias} has to be less that $1/N_{tr}$

Effective channel

$$\tilde{\psi}_{k,i} = \sqrt{\frac{\rho}{N_0/2}}\tilde{\mathbf{h}}_i^\top\mathbf{s}_k$$
$$= \sqrt{1 + \frac{\sigma^2}{N_0}}\Phi^{-1}\left(\tilde{p}_{k,i}^{(+1)}\right)$$





SNR training

IV POST UPDATE

- Divides data transmission into D subframes
- Each subframe has length N_d^{sub} ($N_d = DN_d^{\text{sub}}$)
- CRC is added to each frame, and checked as BS

Biased-learning approach

- $\hat{p}_{k,i}^{(b)}$ is updated using $N_{tr} + d_k(j)$
- $d_k(j)$ is number of $\mathbf{s}_k$ in first successfully decoded subframes

Dither-and-learning method

- $\hat{p}_{k,i}^{(b)}$ is updated after successfully decoding each subframe

Post updated likelihood function

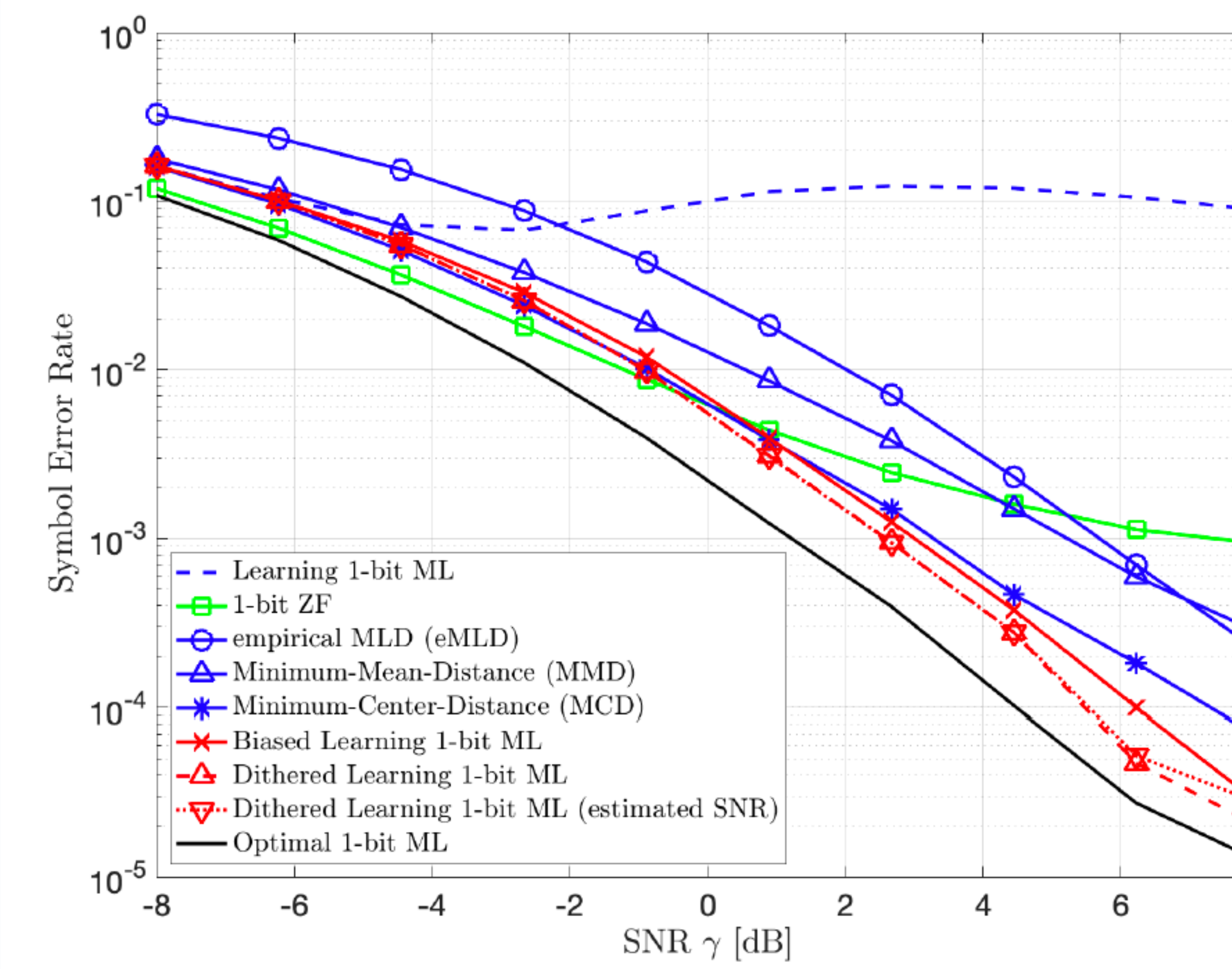
$$\hat{p}_{k,i}^{(b)} = \alpha_{k,i}(v_j)\hat{p}_{k,i}^{(b)}(0) + (1 - \alpha_{k,i}(v_j))\hat{p}_{k,i}^{(b)}(v_j)$$

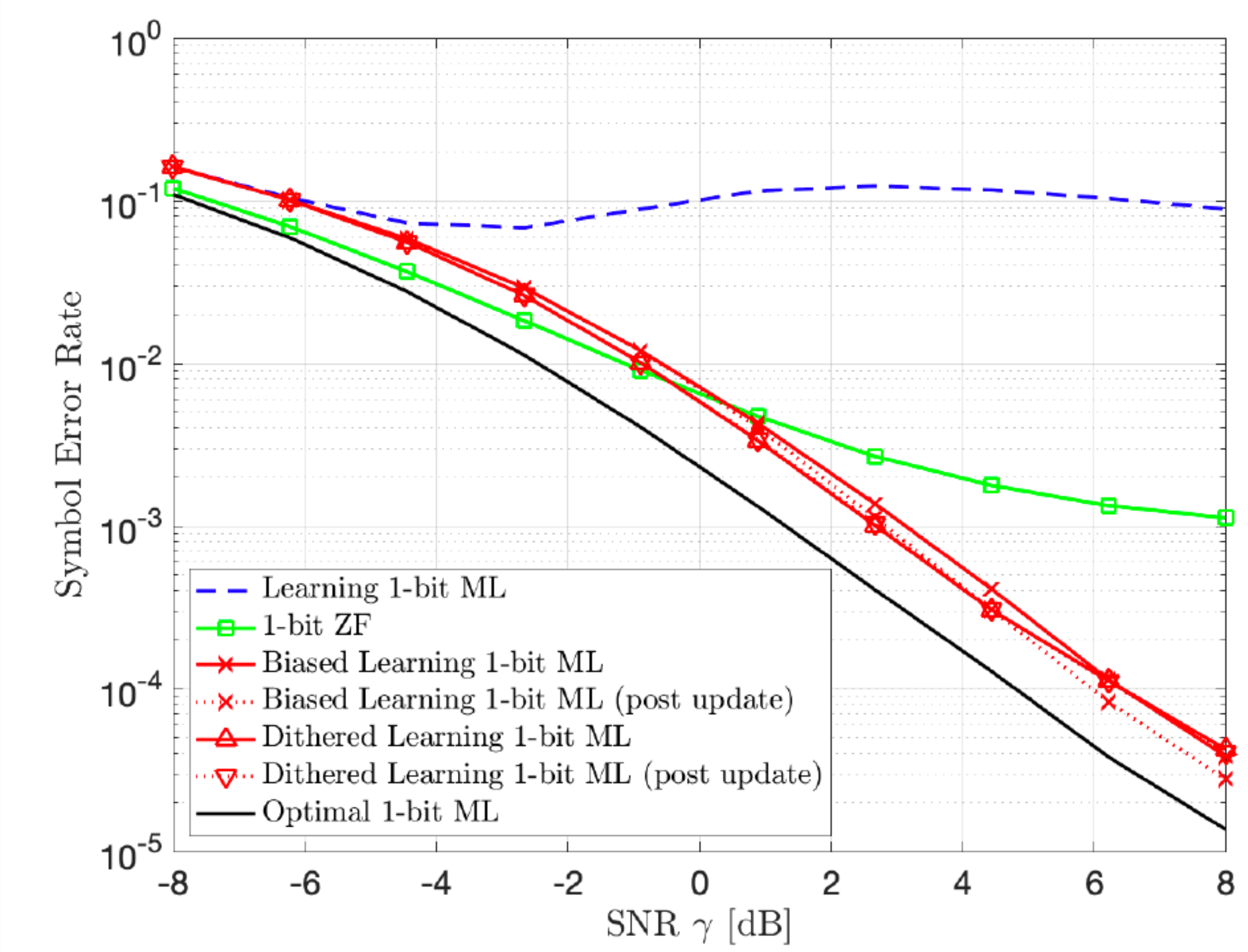
v_j: # of successfully decoded subframes during first j subframes

$\alpha_{k,i}(v_j)$: update rate after jth subframe

: optimal parameter should be designed

V VALIDATION & CONCLUSIONS





System parameters	
N_u	4
N_r	32
N_{tr}	30
Modulation	4-QAM
D	80
N_d^{sub}	128

Conclusions

- Robust learning-based one-bit ML detection
- Likelihood probabilities with reasonable number of N_{tr}
- Post update has better performance
- Optimization is needed

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