Massive MIMO Power Reduction

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The University of Texas at Austin
WHAT STARTS HERE CHANGES THE WORLD

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ESPL

Overview

Selected Topics from Sept. 2017 – Dec. 2018

Overview

Receiver Design

1. Resolution-Adaptive ADC
2. Two-stage analog combining
3. Antenna selection
4. Learning-based one-bit detection

Channel Estimation

1. MmWave One-bit ADC
2. Deterministic beamforming design

User Scheduling

1. New user scheduling criteria
2. Partial CSI-based scheduling

*GAMP: generalized approximate message passing

Overview

❑ Channel Estimation

- Compressive-sensing (CS)-based millimeter wave channel estimation in hybrid beamforming systems

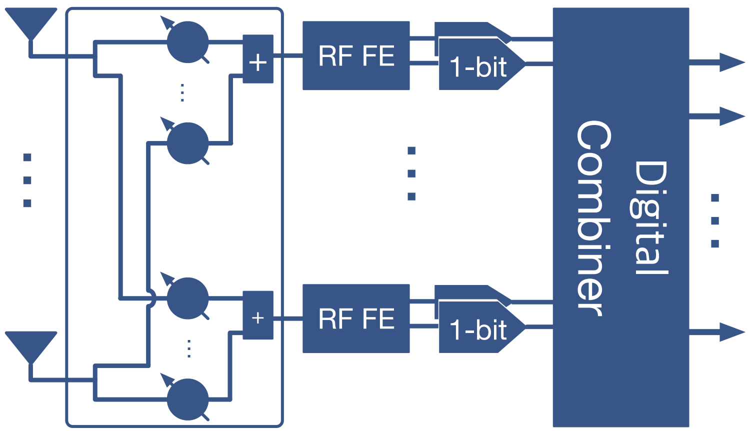
Hybrid Beamforming with One-bit ADCs

System

- PS Hybrid Architecture w/ 1-bit ADC
- Frequency-Flat Channels
- Beamformer w/ Random Configuration
- Downlink

Key Technique

- Modified one-bit GAMP*



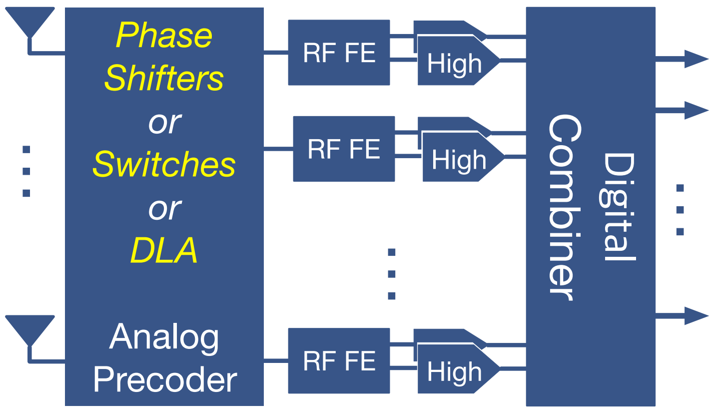
Universal and Deterministic Beamformer Design

System

- PS/SW/Lens Hybrid Architecture
- Frequency-Flat Channels
- Beamformer w/ Deterministic Configuration
- Downlink

Key Technique

- Deterministic optimal beamformer design

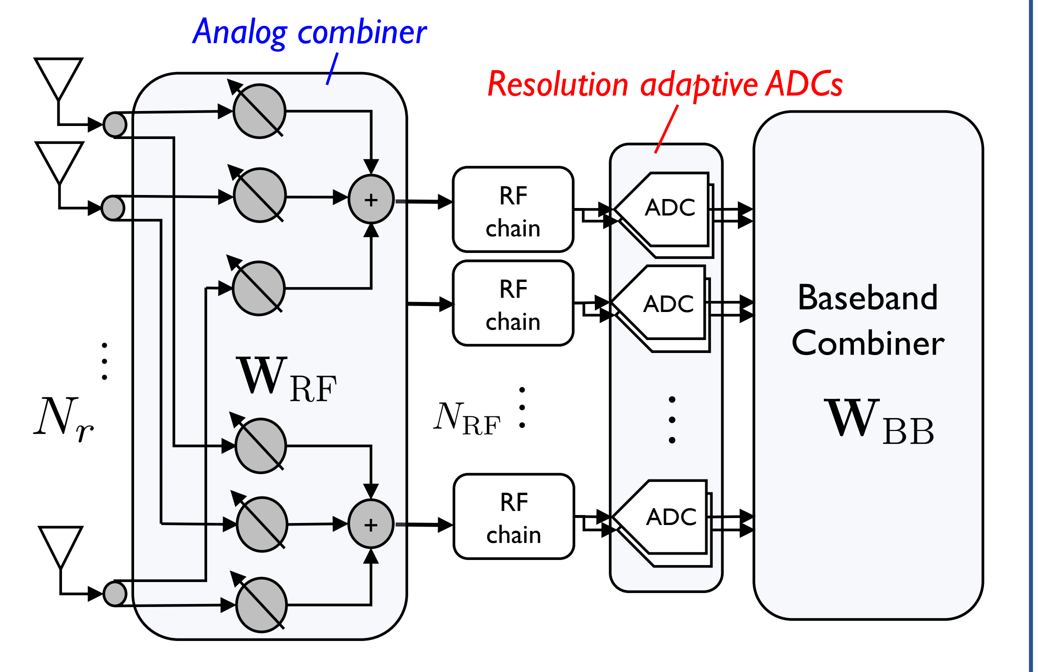


*GAMP: generalized approximate message passing

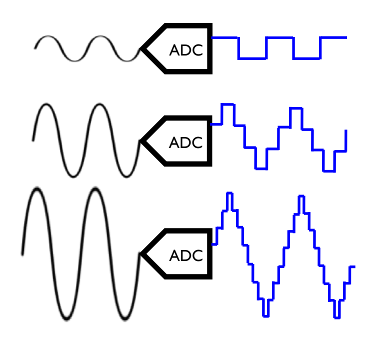
Overview

❑ Receiver Design 1-2

Resolution-Adaptive ADC

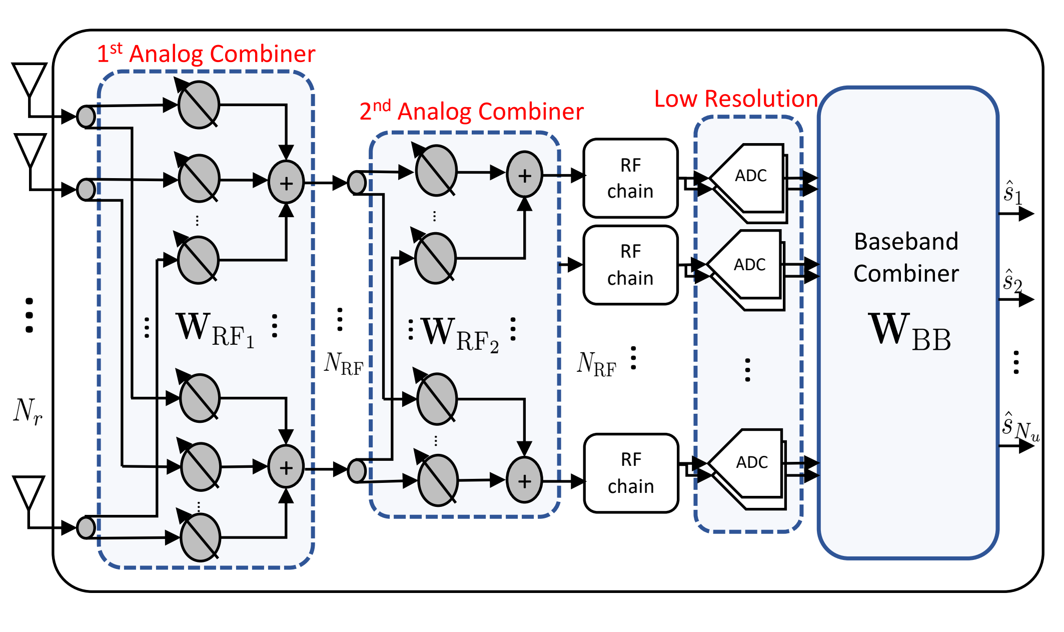


Resolution-adaptive ADC

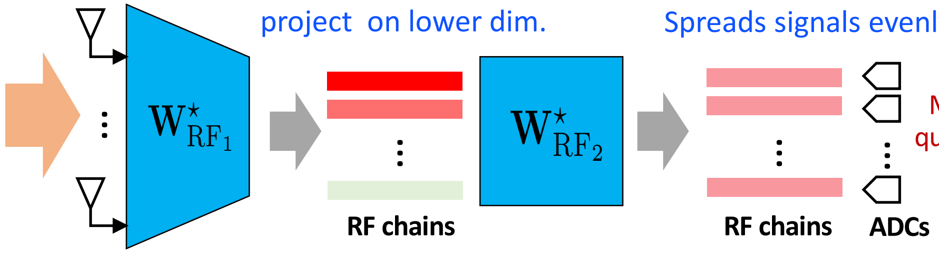


Changes quantization resolution depending on channels

Two-Stage Analog Combining



Two-stage solution

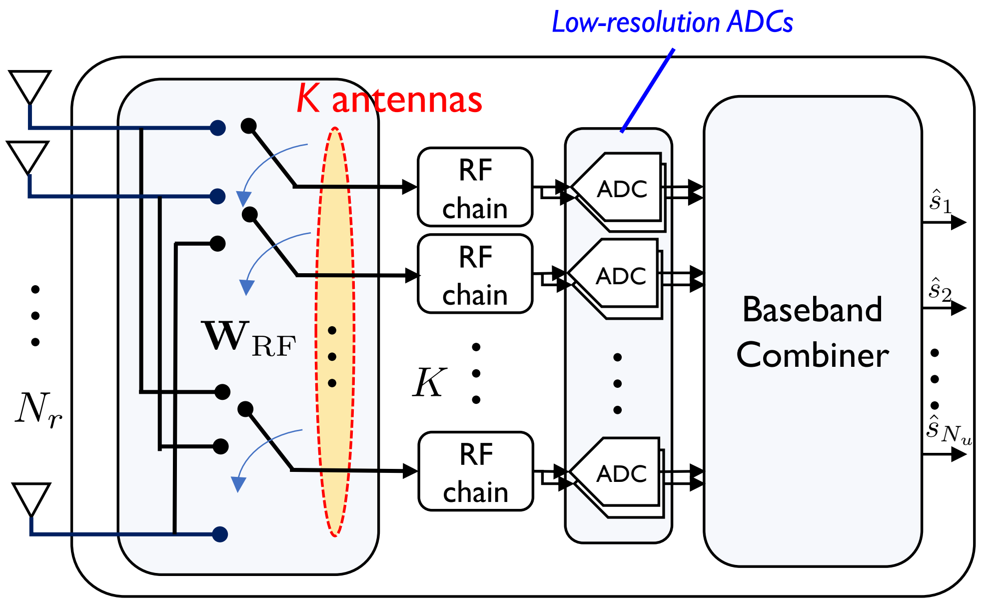


Overview

*GAMP: generalized approximate message passing

❑ Receiver Design 3-4

Antenna Selection



$K \leq N_r$

Greedy selection criterion

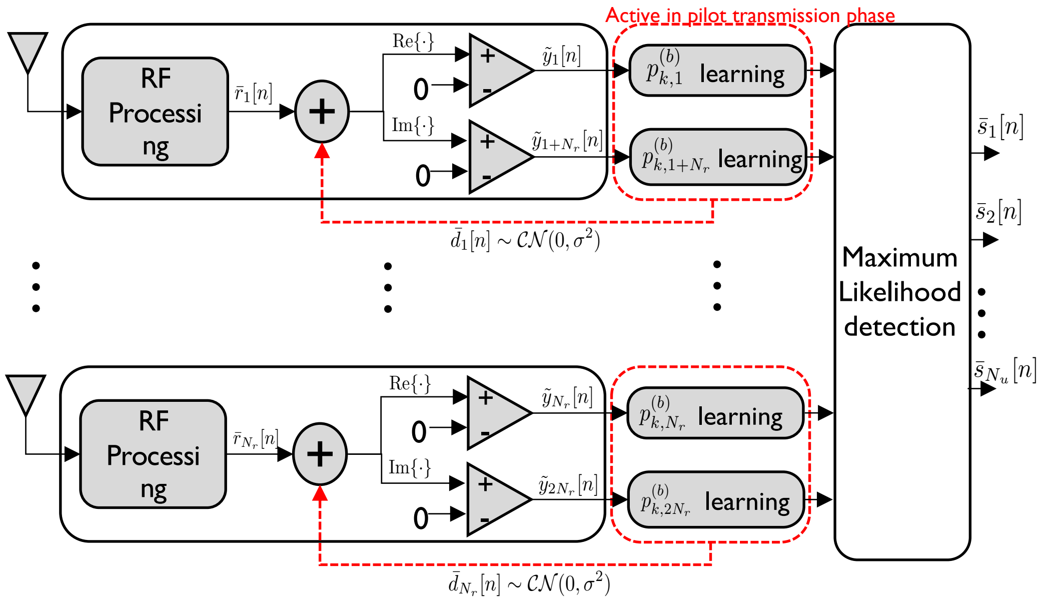
$$J = \arg\max_j \frac{c_{j,n}}{d_j}$$

channel gain from selecting antenna j

quantization error from selecting antenna j

Gain vs. Penalty

Robust Learning-based 1-Bit Detection



Dithering-and-learning

- Maximum likelihood detection
  - Add dithering to robustly learn likelihood probability

$$k^\star = \operatorname*{argmax}_{k \in \mathcal{K}} \prod_{i=1}^{2N_r} p_{k,i}^{(b)} = \begin{cases} p_{k,i}^{(1)} = \frac{1}{N_{tr}} \sum_{t=1}^{N_{tr}} \mathbb{1}(y_i[(k-1)N_{tr}+t] = 1) \\ p_{k,i}^{(-1)} = 1 - p_{k,i}^{1} \end{cases}$$

Overview

*GAMP: generalized approximate message passing

❑ User Scheduling

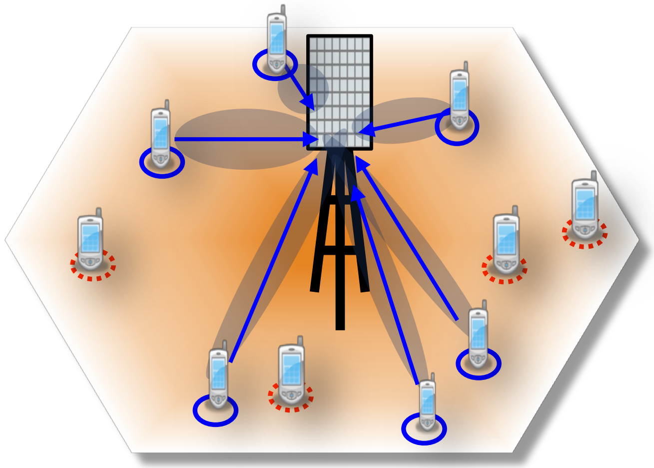
:To mitigate quantization error by effectively scheduling users

- **Key idea**
  - Derive new scheduling criteria that reduce quantization error
- **Optimization results**
  - Maximum sum rate user scheduling

New criteria

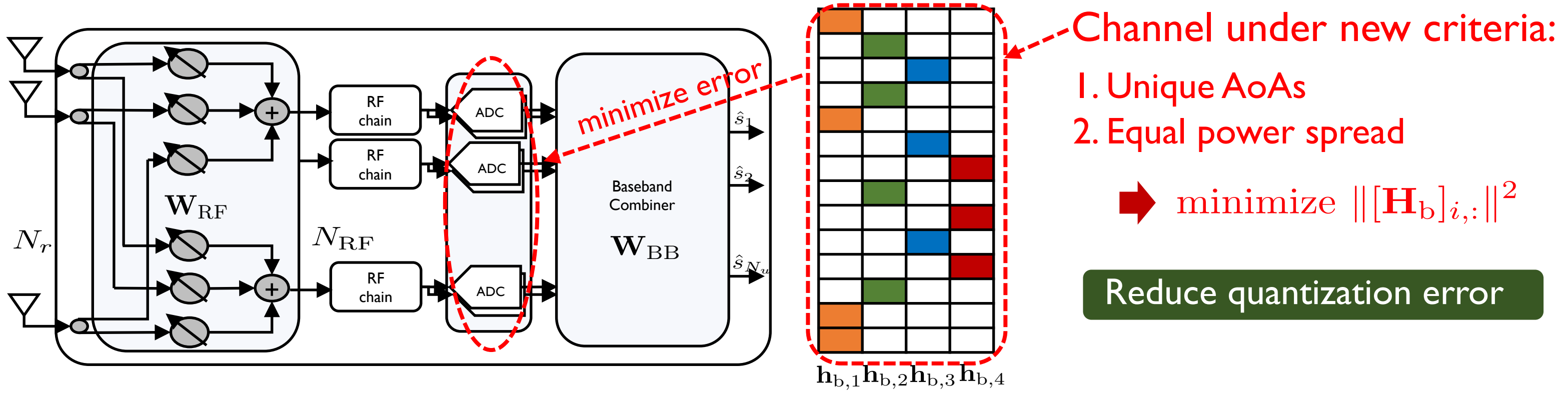
*Angle of arrivals

1. Unique *AoAs for channel paths of each scheduled user
2. Equal power spread across complex path gains



Uplink user scheduling

Intuition



One-bit MIMO Detection

with Coding Theoretical Approach

Related publications:

[1]. Yunseong Cho, Seonho Kim, and Songnam Hong, "Successive Cancellation Soft-Output Detector for Uplink MIMO system with One-bit ADCs", IEEE ICC 2018, Kansas city, MO, USA.

[2]. Songnam Hong, Seonho Kim, and Namyoon Lee, "A Weighted Minimum Distance Decoding for Uplink Multiuser MIMO Systems With Low-Resoultion ADCs", *IEEE Transactions on Communications,* 2018.

System Model

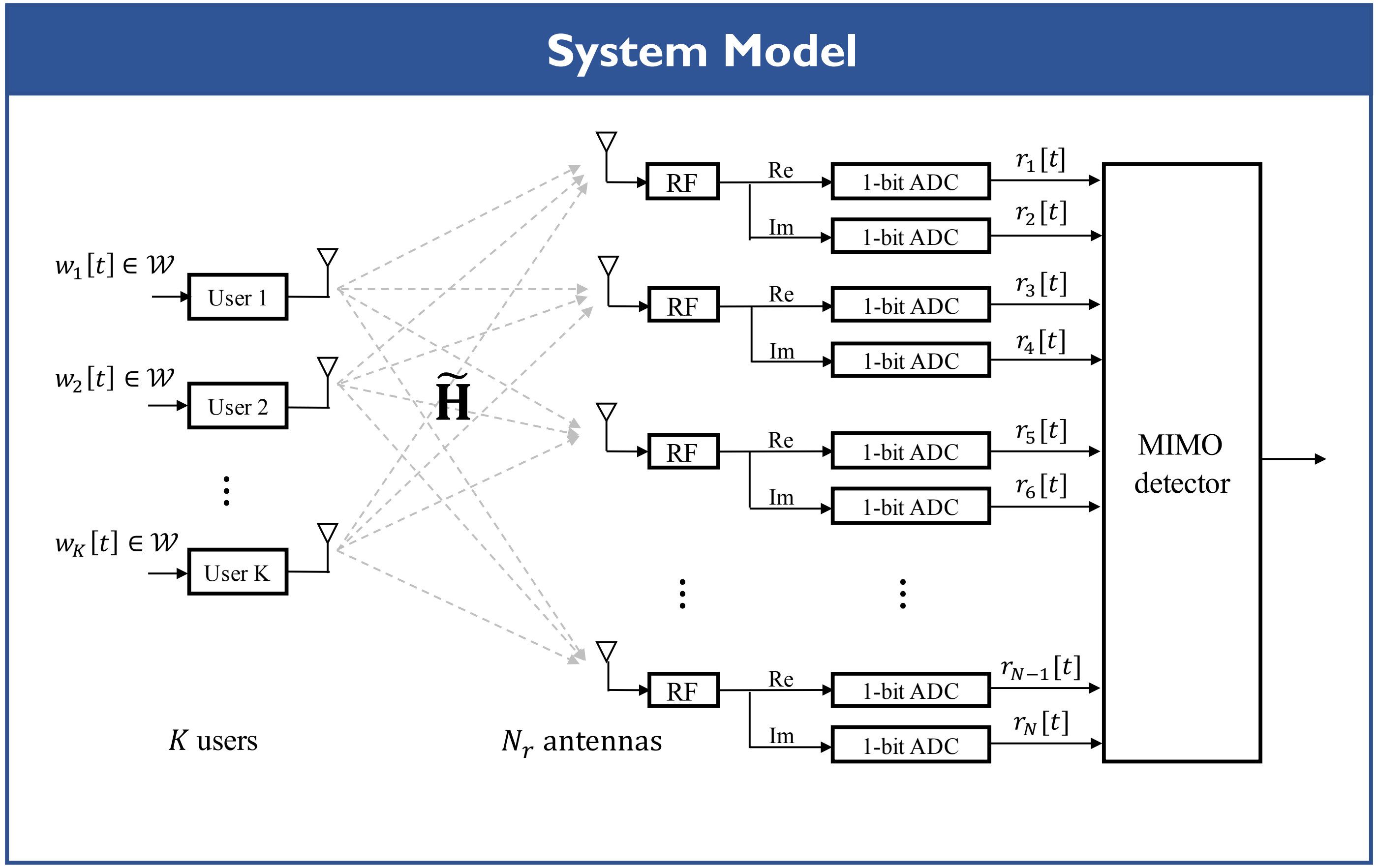
- Multi-user MIMO uplink system
  - Single cell environment
  - Serves K users w. single antenna
  - BS is equipped with N_r antennas
- Quantized signal
  - M-QAM constellation
  - Encoded input $\boldsymbol{\tau}$ for a given sequence $\mathbf{b}$
  - Corresponding symbol

$$w_k[t] = \left[\tau_k[pt], \ldots, \tau_k[pt-p+1]\right]_{(p)}$$

$$\mathrm{x}_k[t] = f(w_k[t]) \in \mathcal{S}$$

- Quantized signal

$$\mathbf{r}[t] = \mathrm{sign}(\mathbf{H}\mathbf{x}(\mathbf{w}[t]) + \mathbf{z}[t]) \in \{1, -1\}^{2N_r}$$



Real-valued channel

System Model

❑ Channel Input

- Maps all possible combinations into code
- Fully characterized by **H**

$$c_l = \left[\text{sign}\left(\mathbf{h}_1^{\text{T}} f(\mathbf{w}[\text{t}])\right), \ldots, \text{sign}\left(\mathbf{h}_{\text{N}}^{\text{T}} f(\mathbf{w}[\text{t}])\right)\right]^{\text{T}}$$

[Example]

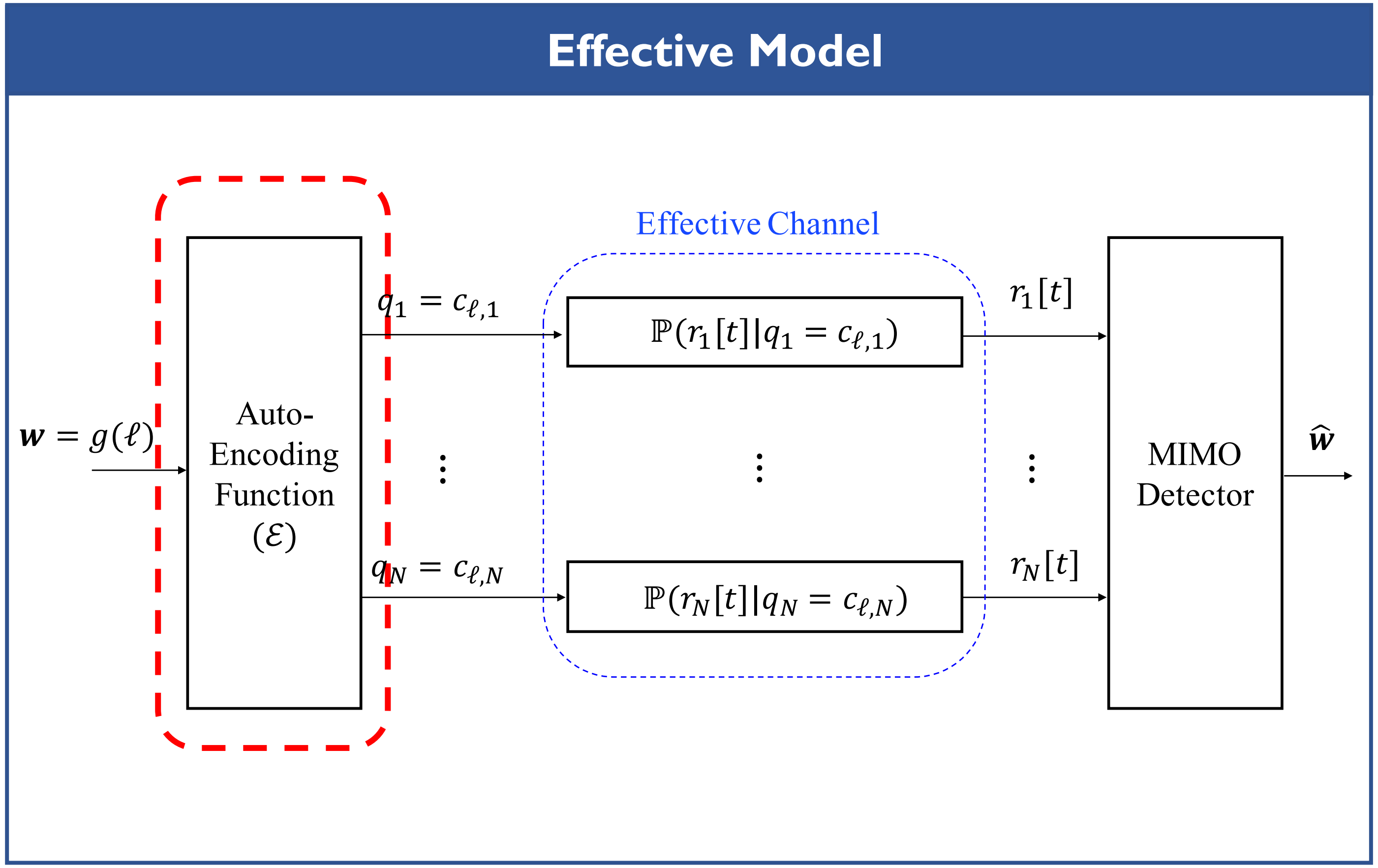
Consider a system with $N = 1, K = 1$ and $m = 2$ (QPSK) with a channel realization $\hat{H} = 0.1 + i1$

$$c_0 = Q\left(\begin{bmatrix} 0.1 & -1 \\ 1 & 0.1 \end{bmatrix} \begin{bmatrix} 1 \\ 1 \end{bmatrix}\right) = \begin{bmatrix} 1 \\ 0 \end{bmatrix}$$

$$c_1 = Q\left(\begin{bmatrix} 0.1 & -1 \\ 1 & 0.1 \end{bmatrix} \begin{bmatrix} 1 \\ -1 \end{bmatrix}\right) = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$$c_2 = Q\left(\begin{bmatrix} 0.1 & -1 \\ 1 & 0.1 \end{bmatrix} \begin{bmatrix} -1 \\ 1 \end{bmatrix}\right) = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$$

$$c_3 = Q\left(\begin{bmatrix} 0.1 & -1 \\ 1 & 0.1 \end{bmatrix} \begin{bmatrix} -1 \\ -1 \end{bmatrix}\right) = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$$



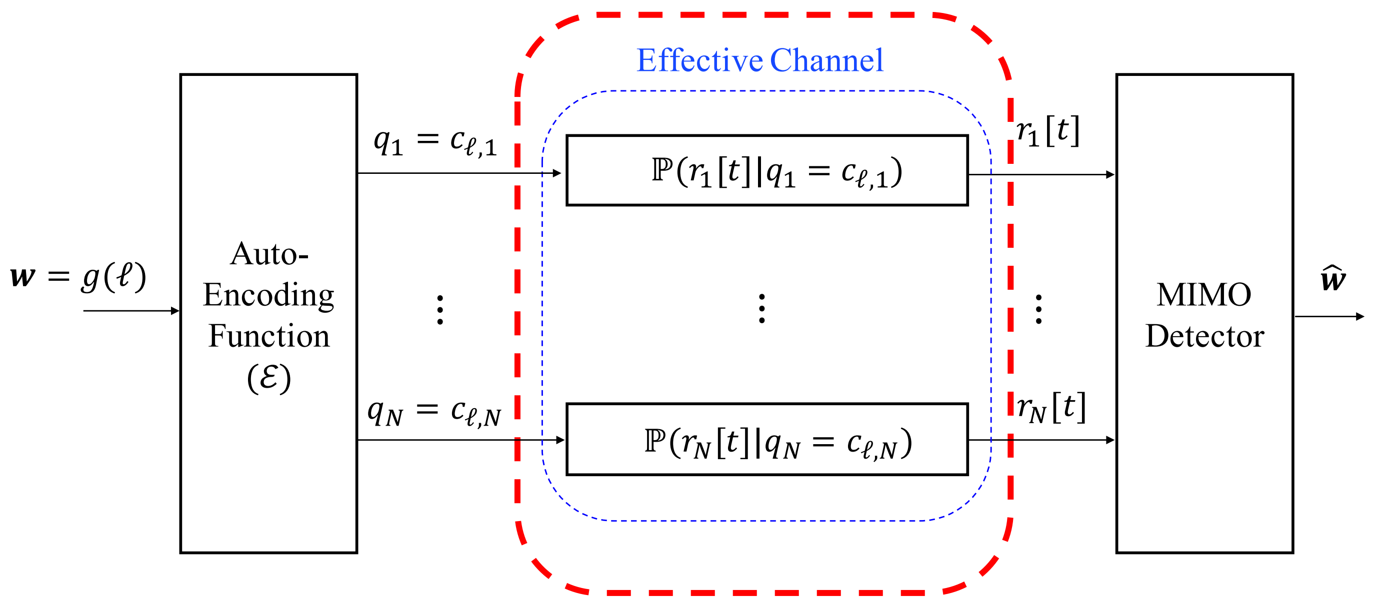
System Model

❑ Effective Channel

- Composed of N_r parallel BSCs
- Each sub-channel has cross probability

$$\epsilon_i = Q(|\mathbf{h}_i^{\mathrm{T}} f(\mathbf{w}[\mathrm{t}])|)$$

Effective Model



System Model

❑ Effective Channel

- Composed of N_r parallel BSCs
- Each sub-channel has cross probability

$$\epsilon_i = Q(|\mathbf{h}_i^{\mathrm{T}} f(\mathbf{w}[\mathrm{t}])|)$$

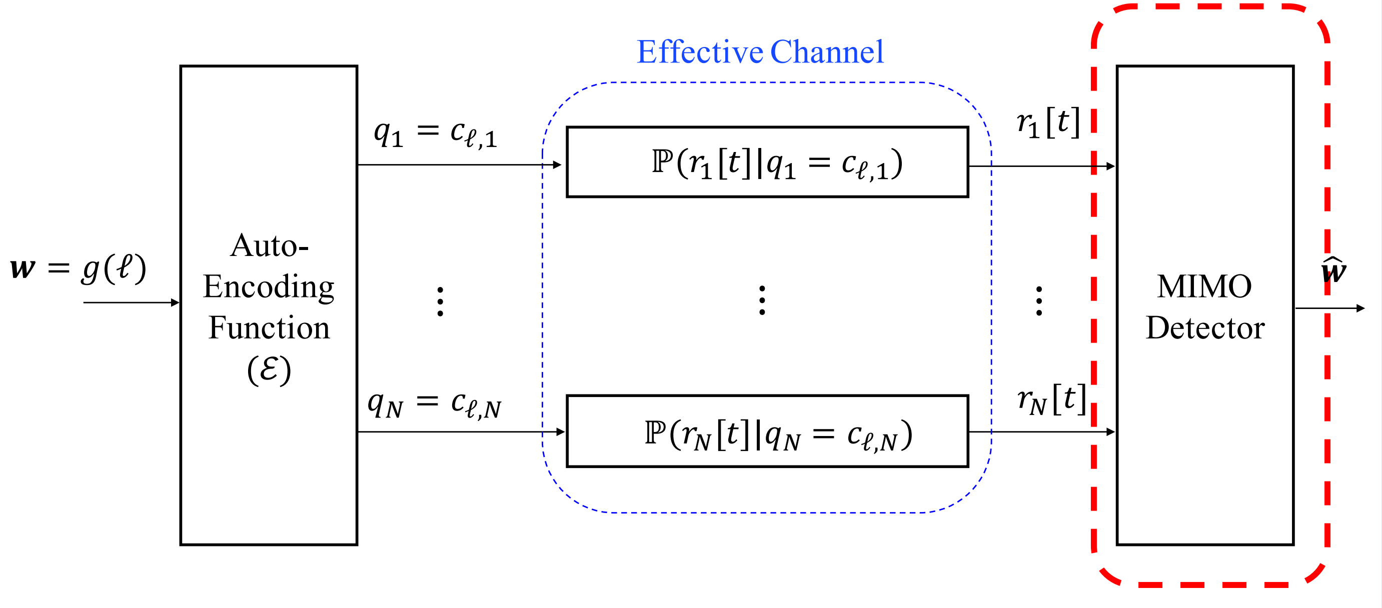
❑ Detector

- Introduces *weighted Hamming distance*

$$d_{wh}(\mathbf{x}, \mathbf{y}; \boldsymbol{\alpha}) \equiv \sum_{i=1}^{N} \alpha_i 1_{\{x_i \neq y_i\}}$$

$$\hat{l} = \operatorname*{argmin}_{l} d_{wh}(\mathbf{r}, \mathbf{c}_l; \log \frac{1}{\boldsymbol{\epsilon}_l})$$

Effective Model



Detection Phase

Soft-Output

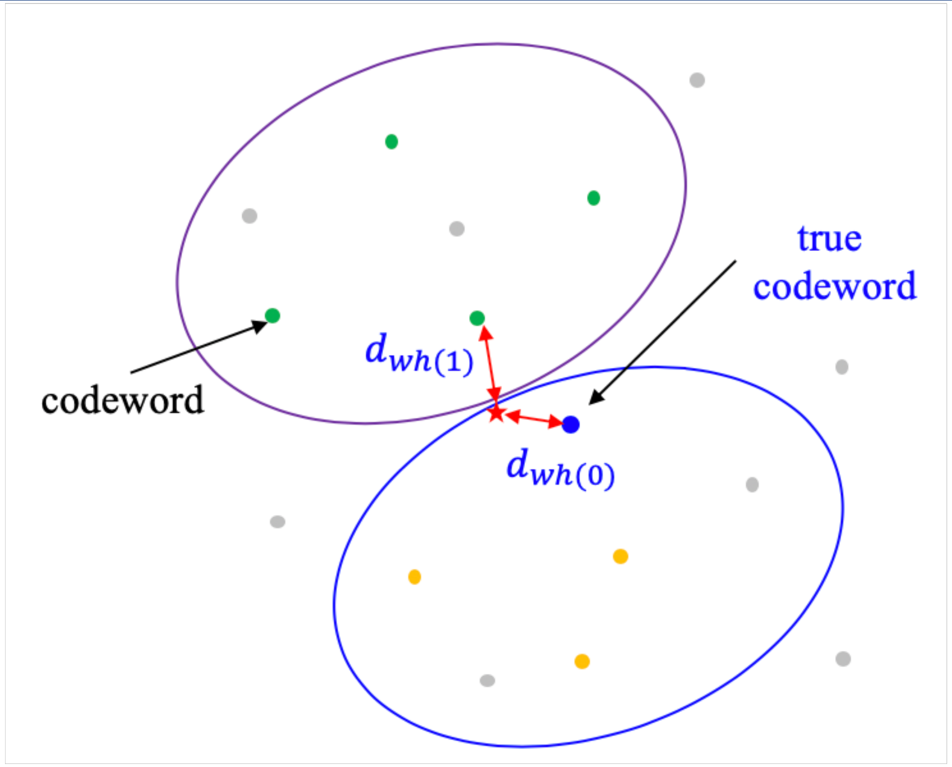
- Log-likelihood ratio (LLR)
  - Distance between two subsets

$$L^k_{pt-(i-1)}(\mathbf{r}[t]) = \min_{\mathbf{c}_\ell \in \mathcal{B}^k_{(i,1)}} d_{\mathrm{wh}}(\mathbf{r}[t], \mathbf{c}_\ell; \{\log \epsilon^{-1}_{\ell,i}\}) - \min_{\mathbf{c}_\ell \in \mathcal{B}^k_{(i,0)}} d_{\mathrm{wh}}(\mathbf{r}[t], \mathbf{c}_\ell; \{\log \epsilon^{-1}_{\ell,i}\}).$$

- Associated subcodes
  - Divides space in terms of the specific bit

$$\mathcal{B}^k_{(i,j)} = \bigcup_{\mathbf{b} \in \{0,1\}^p : b_i = j} \mathcal{C}_{|\{w_k[t] = [\mathbf{b}]_p\}}$$

SO Detector



$$\ell \in \begin{Bmatrix} 0 = [000]_{(2)} \\ 1 = [001]_{(2)} \\ 2 = [010]_{(2)} \\ 3 = [011]_{(2)} \\ 4 = [100]_{(2)} \\ 5 = [101]_{(2)} \\ 6 = [110]_{(2)} \\ 7 = [111]_{(2)} \end{Bmatrix}$$

There are 2^{N_u} noiseless outputs among all possible 2^{N_r} vectors

Detection Phase

❑ Successive Cancellation

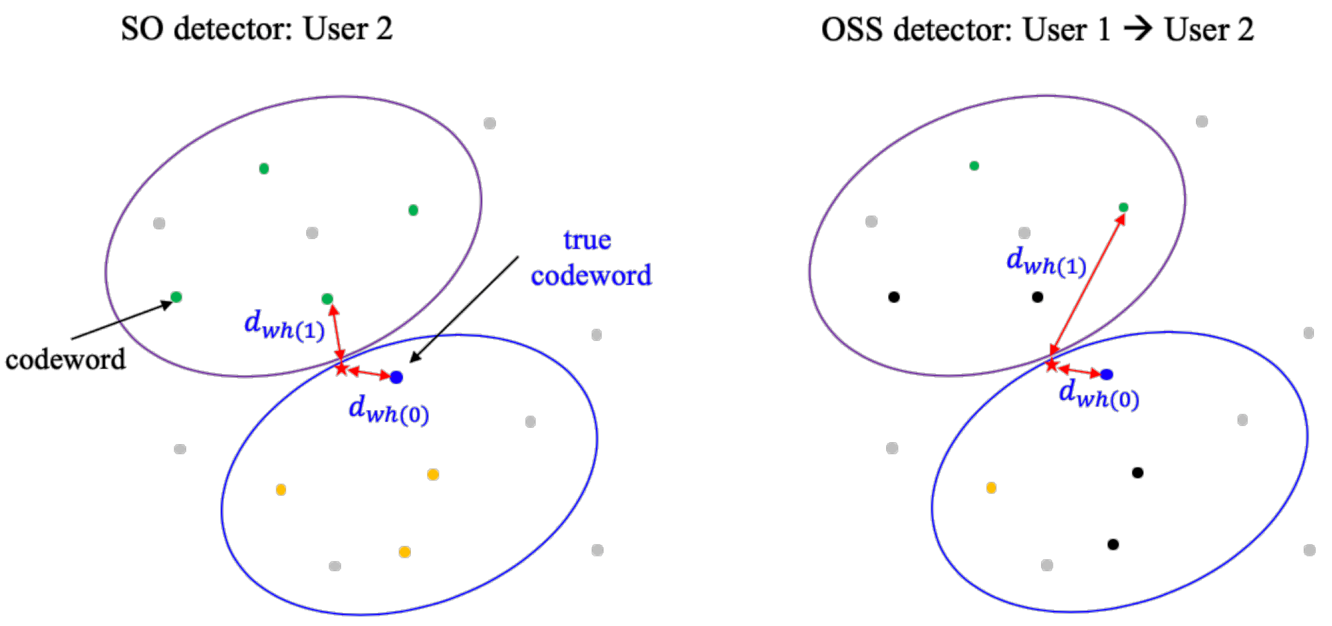
- Enhanced LLR
  - Using a previously detected message

$$\tilde{L}^{k}_{pt-(i-1)}(\mathbf{r}[t],\ \hat{\mathbf{w}}_1^{k-1}[t]) = \min_{\mathbf{c}_\ell \in \mathcal{B}^k_{(i,1|\hat{\mathbf{w}}_1^{k-1}[t])}} d_{\mathrm{wh}}\left(\mathbf{r}[t], \mathbf{c}_\ell; \left\{\log \epsilon_{\ell,i}^{-1}\right\}\right) - \min_{\mathbf{c}_\ell \in \mathcal{B}^k_{(i,0|\hat{\mathbf{w}}_1^{k-1}[t])}} d_{\mathrm{wh}}\left(\mathbf{r}[t], \mathbf{c}_\ell; \left\{\log \epsilon_{\ell,i}^{-1}\right\}\right)$$

- Refined subcodes
  - Decreases the size by half
  - Removes an ambiguity

$$\mathcal{B}^k_{(i,j|\hat{\mathbf{w}}_1^{k-1}[t])} = \bigcup_{\mathbf{b}\in\{0,1\}^p : b_i = j} \mathcal{C}_{|\{w_k[t]=[\mathbf{b}]_p,\ \mathbf{w}_1^{k-1}[t]=\hat{\mathbf{w}}_1^{k-1}[t]\}}$$

SO and SCSO detectors



$L = d_{\mathrm{wh}}(1) - d_{\mathrm{wh}}(0)$ $\qquad$ $\tilde{L} = d_{\mathrm{wh}}(1) - d_{\mathrm{wh}}(0)$

There are 2^{N_u} noiseless outputs among all possible 2^{N_r} vectors

Ordering

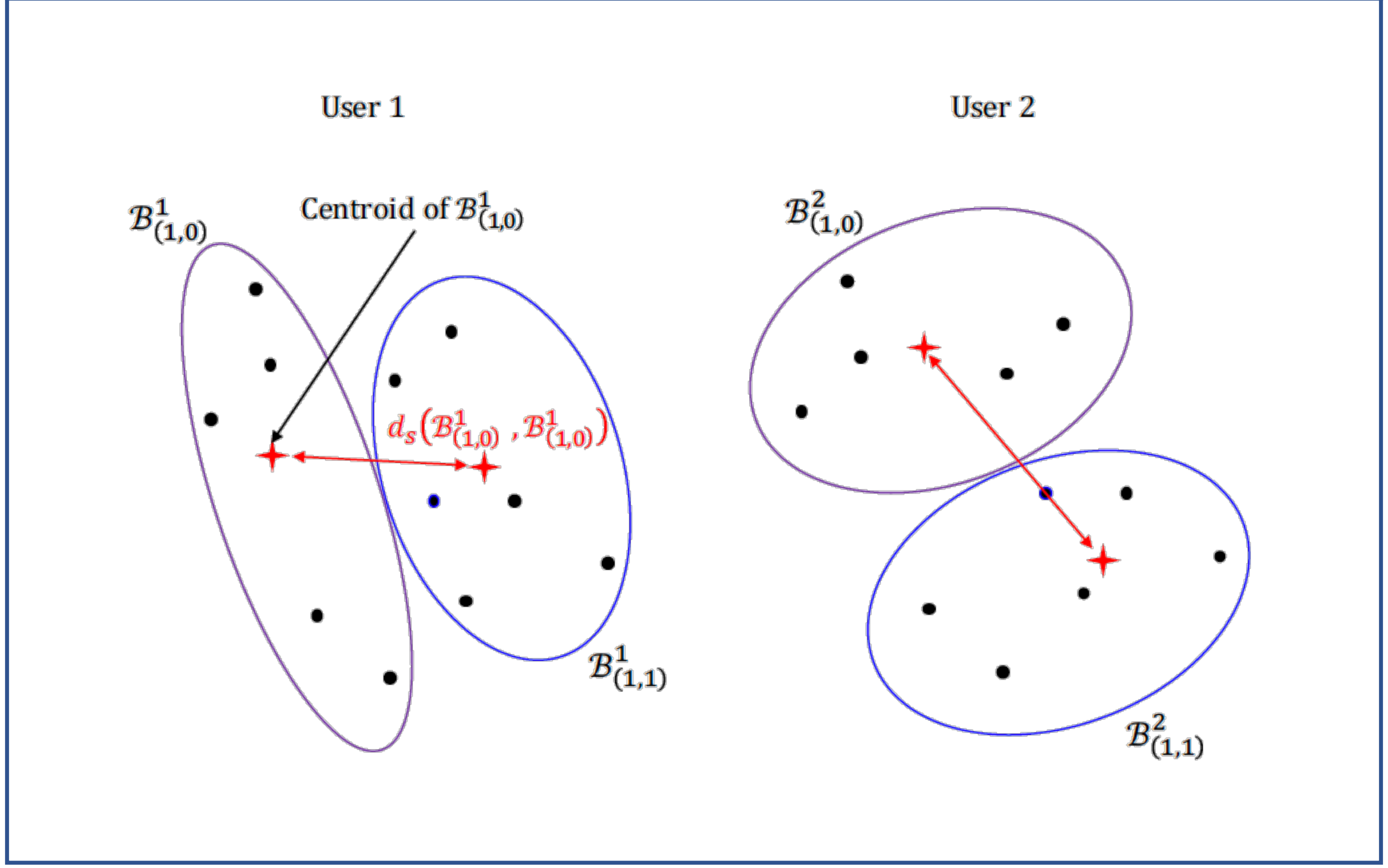
- Efficient order
  - Distance between Centroids
    - Measures strength for each user
    - Larger gap leads to more reliable LLR

$$d_s(\mathcal{C}_1, \mathcal{C}_2) \triangleq \left| \frac{1}{|\mathcal{C}_1|} \sum_{\mathbf{c} \in \mathcal{C}_1} \mathbf{c} - \frac{1}{|\mathcal{C}_2|} \sum_{\mathbf{c} \in \mathcal{C}_2} \mathbf{c} \right|^2$$

  - Order
    - Sorts in terms of the strength
    - Can be done during the training phase

$$k_i = \underset{k \in \langle K \rangle \setminus \{k_1, \ldots, k_{i-1}\}}{\operatorname{argmax}} \quad d^k$$

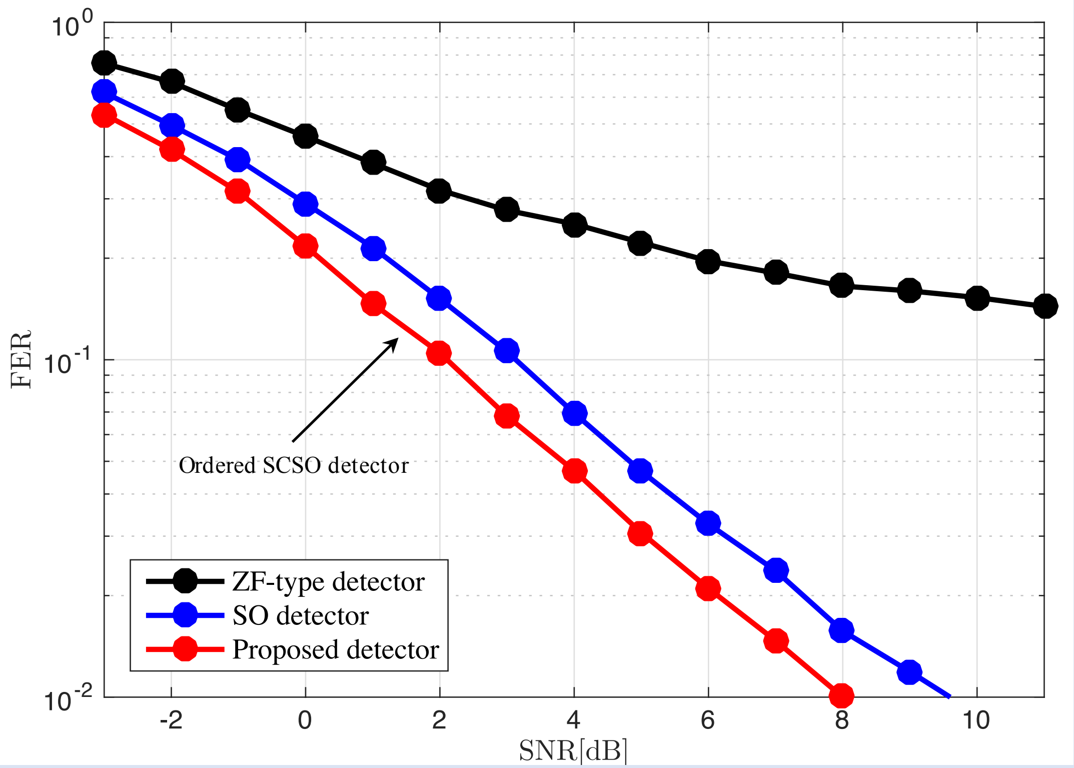
Distance



Simulation Results

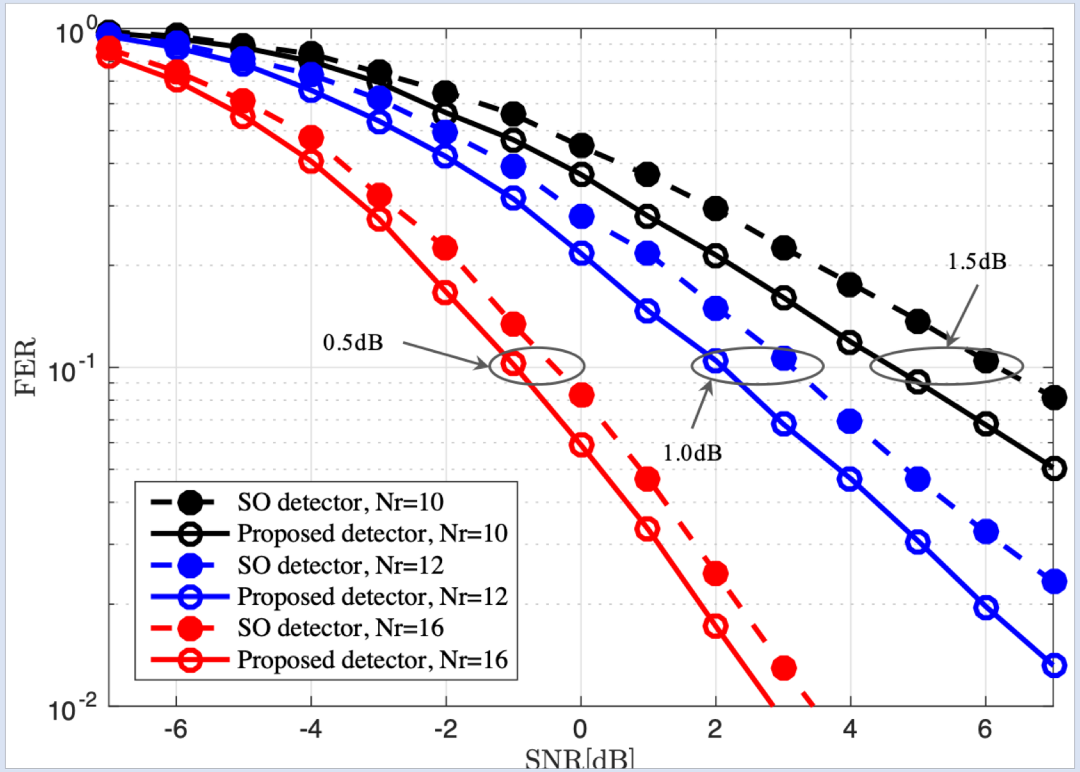
- Polar encoding and decoding with 128 length is used

Various detectors



(N_u = 6, N_r = 12, Po)

Various N_r



(N_u = 6)

Uplink Antenna Selection for Low-Resolution ADC Systems

Related publications:

[1]. Jinseok Choi, Junmo Sung, Brian L. Evans, and Alan Gatherer, "Antenna selection for large-scale MIMO systems with low-resolution ADCs", IEEE ICASSP 2018, Calgary, Alberta, Canada.

[2]. Jinseok Choi and Brian L. Evans, "Analysis of ergodic rate for transmit antenna selection in low-resolution ADC systems", submitted to *IEEE Transactions on Vehicular Technology*, 2018.

Wideband Extension

❑ MIMO-OFDM Systems

- Mutual information (MI) for subcarrier *n*

MI: $$\mathcal{R}_n(\mathcal{K}) = \log_2 \left| \mathbf{I}_K + \rho\alpha_b^2(\alpha_b^2\mathbf{I}_K + \mathbf{R}_{\mathbf{q}_n\mathbf{q}_n})^{-1}\mathbf{G}_{n,\mathcal{K}}\mathbf{G}_{n,\mathcal{K}}^H \right|$$

- Maximum sum MI problem
  - All subcarriers share same subset of antennas

$$\mathcal{K}^{\star\star} = \underset{\mathcal{K}\subseteq\mathcal{S}:|\mathcal{K}|=K\geq N_{\mathrm{MS}}}{\arg\max} \; \mathcal{C}(\mathcal{K})$$

where $\mathcal{C}(\mathcal{K}) = \frac{1}{Nc}\sum_{n=1}^{N_c}\mathcal{R}_n(\mathcal{K})$

MIMO-OFDM Greedy Antenna Selection

❑ Greedy approach

- Greedy selection problem can reduce to simpler form

Greedy problem

$$J = \arg \max_{j \in \mathcal{S} \backslash \mathcal{K}_t} \sum_{n=1}^{N_c} \mathcal{R}_n^{\text{ul}} \left(\mathcal{K}_t \cup \{j\} \right)$$

Simplified greedy problem

$$J = \arg \max_{j \in \mathcal{S} \backslash \mathcal{K}_t} \sum_{n=1}^{N_c} \log_2 \left(1 + \frac{\rho \alpha_b}{d_j} c_{n,t}(j) \right)$$

$$\mathcal{R}_n^{\text{ul}}(\mathcal{K}_t \cup \{j\}) = \mathcal{R}_n^{\text{ul}}(\mathcal{K}_t) + \log_2 \left(1 + \frac{\rho \alpha_b}{d_j} c_{n,t}(j) \right)$$

where $c_{n,t}(j) = \mathbf{f}_{n,j}^H \left(\mathbf{I}_{N_{\text{MS}}} + \rho \alpha_b \mathbf{G}_{n,\mathcal{K}_t}^H \mathbf{D}_{n,\mathcal{K}_t}^{-1} \mathbf{G}_{n,\mathcal{K}_t} \right)^{-1} \mathbf{f}_{n,j}.$

❑ Complexity Reduction

- For each subcarrier, avoid matrix inversion in $c_{n,t}(j)$

$$c_{n,t+1}(j) = \mathbf{f}_n(j)^H (\mathbf{Q}_{n,t} - \mathbf{a}\mathbf{a}^H) \mathbf{f}_n(j)$$
$$= c_{n,t} - |\mathbf{f}_n(j)^H \mathbf{a}|^2$$

where

$$\mathbf{a} = \left(c_{n,t}(j) + \frac{d(j)}{p_u \alpha} \right)^{-1/2} \mathbf{Q}_{n,t} \mathbf{f}_n(j)$$

$$\mathbf{Q}_{n,\mathcal{K}_t} = \left(\mathbf{I} + p_u \alpha \mathbf{H}_{n,\mathcal{K}_t}^H \mathbf{D}_{n,\mathcal{K}_t}^{-1} \mathbf{H}_{n,\mathcal{K}_t} \right)^{-1}$$

Linear complexity increase by # of subcarrier compared to narrowband channel

Performance Bounds

❑ Theoretical Lower Bound

Theorem

The performance of solving simplified greedy problem is lower bounded by

$$\sum_{n=1}^{N_c} \mathcal{R}_n(\mathcal{K}_G) \geq \left(1 - \frac{1}{e}\right) \sum_{n=1}^{N_c} \mathcal{R}_n(\mathcal{K}^\star)$$

Proof: submodularity is closed under non-negative linear sum

❑ Numerical Upper Bound

- Markov Chain Monte Carlo (MCMC) method

(+) Provides approximation of optimal solution
(+) Converges with iterations
(-) High Complexity (sampling and iterations)

Performance Bounds

❑ MCMC Antenna Selection

- **Problem reformulation**

$$\max_{\mathcal{K}\subseteq\mathcal{S}:|\mathcal{K}|=K\geq N_{\mathrm{MS}}} \mathcal{C}(\mathcal{K}) \quad \Rightarrow \quad \max_{\mathcal{K}\subseteq\mathcal{S}:|\mathcal{K}|=K\geq N_{\mathrm{MS}}} \exp\left(\frac{\mathcal{C}(\mathcal{K})}{\tau}\right)/\Gamma$$

Normalization factor

$$\Gamma = \sum_{\mathcal{K}} \exp\left(\frac{\mathcal{C}(\mathcal{K})}{\tau}\right)$$

τ: Rate constant

$\pi(\mathcal{K})$: Original distribution

- **Proposal distribution** [Liu 2009]

$\boldsymbol{\omega}_q$: binary codeword vector with ones and zeros

$$g(\boldsymbol{\omega}_q;\mathbf{p}) = \frac{\prod_{i=1}^{M_R} p_i^{[\boldsymbol{\omega}_q]_i}(1-p_i)^{1-[\boldsymbol{\omega}_q]_i}}{\Gamma'} \propto \prod_{i=1}^{M_R} p_i^{[\boldsymbol{\omega}_q]_i}(1-p_i)^{1-[\boldsymbol{\omega}_q]_i}$$

q: codebook index from all possible combinations

p_i: probability of antenna *i* to be selected

Performance Bounds

❑ MCMC Antenna Selection

- **Step1: Sampling by Metropolized independence sampler**

1. Given current sample $\boldsymbol{\omega}_q^{(i)}$, draw candidate sample $\boldsymbol{\omega}_q^{(\text{new})}$ from proposal distribution $g(\boldsymbol{\omega}_q; \mathbf{p})$
2. Accept $\boldsymbol{\omega}_q^{(\text{new})}$ depending on accepting probability: $\min\left\{1, \left(\frac{\pi(\mathbf{w}_q^{(\text{new})})}{\pi(\mathbf{w}_q^{(i)})}\right)\left(\frac{g(\mathbf{w}_q^{(i)})}{g(\mathbf{w}_q^{(\text{new})})}\right)\right\}$
3. If not accepted, use current sample $\boldsymbol{\omega}_q^{(i)}$ as accepted sample
4. Repeat until collecting N_{MCMC} samples

- **Step 2: Parameter update** [Liu 2009]
  - Maximizing Kullback-Leibler divergence between original and proposal distributions

$$p_j^{(t+1)} = p_j^{(t)} + r^{(t+1)}\left(\frac{1}{N_{\text{MCMC}}}\sum_{n=1}^{N_{\text{MCMC}}}\left[\boldsymbol{\omega}_q^{(n)}\right]_j - p_j^{(t)}\right)$$

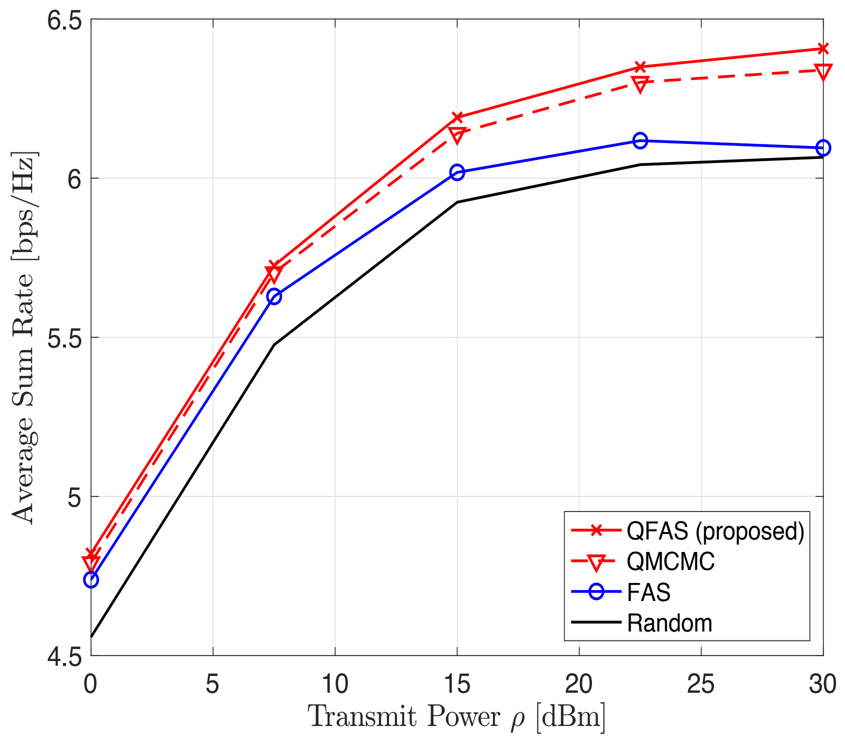
- **Step3: update maximum objective function** if $\pi(\boldsymbol{\omega}_q^{(n)}) > \pi(\hat{\boldsymbol{\omega}})$

Simulation Results

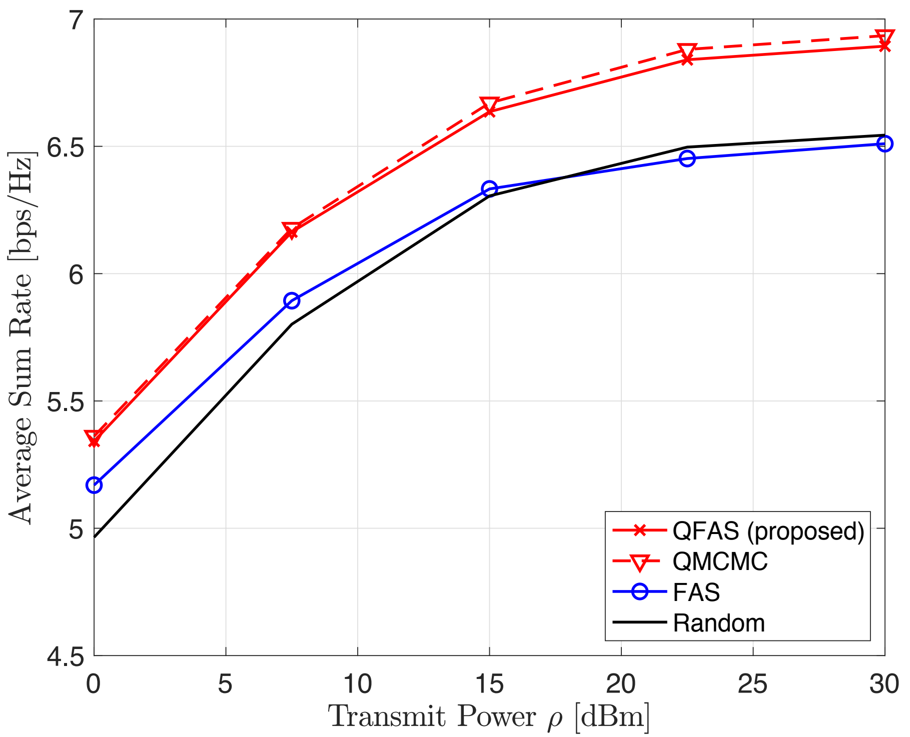
Average Mutual Information vs. Transmit Power

Settings
16 BS antennas
4 selected antennas
4 users
2-bit ADCs
2.4 GHz fc
10 MHz bandwidth,
4 delay taps
64 subcarriers
Rayleigh fading
1km cell radius

Low sampling / iteration (10, 10)



Medium sampling / iteration (50, 50)

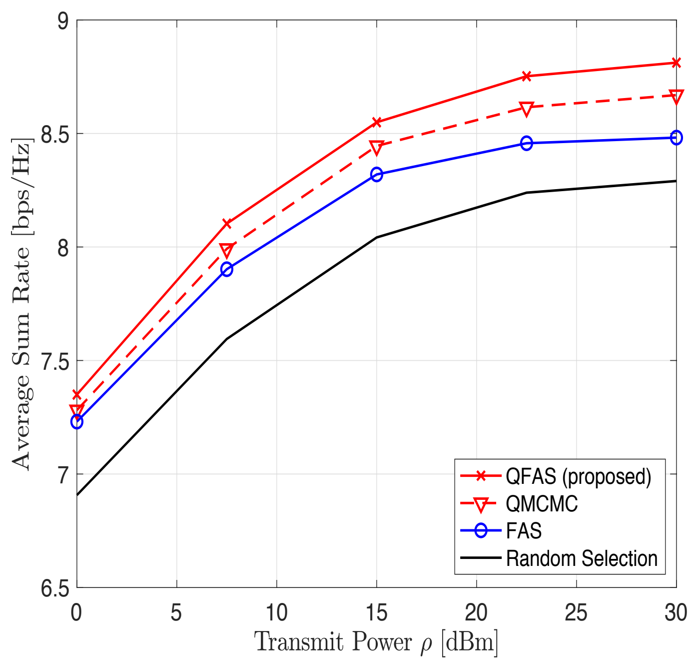


Simulation Results

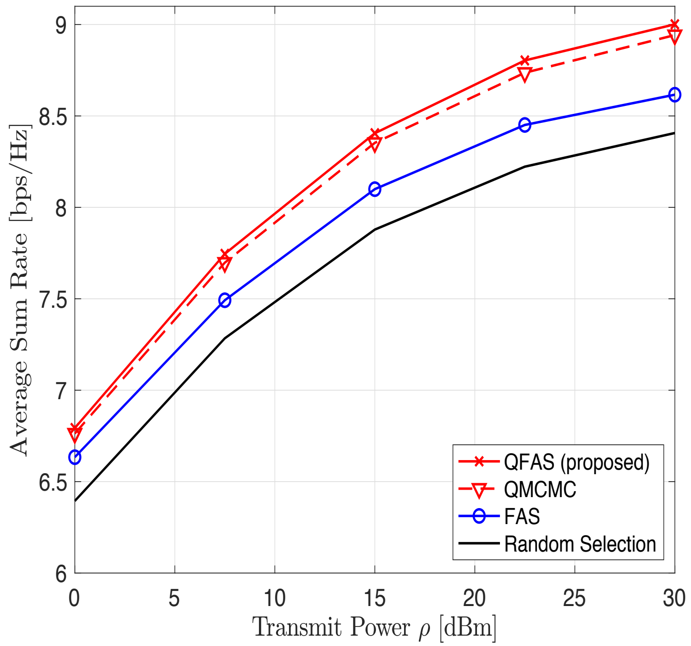
Average Mutual Information vs. Transmit Power

(16 BS antennas, 4 selected antennas) x2 (32 BS antennas, 8 selected antennas)

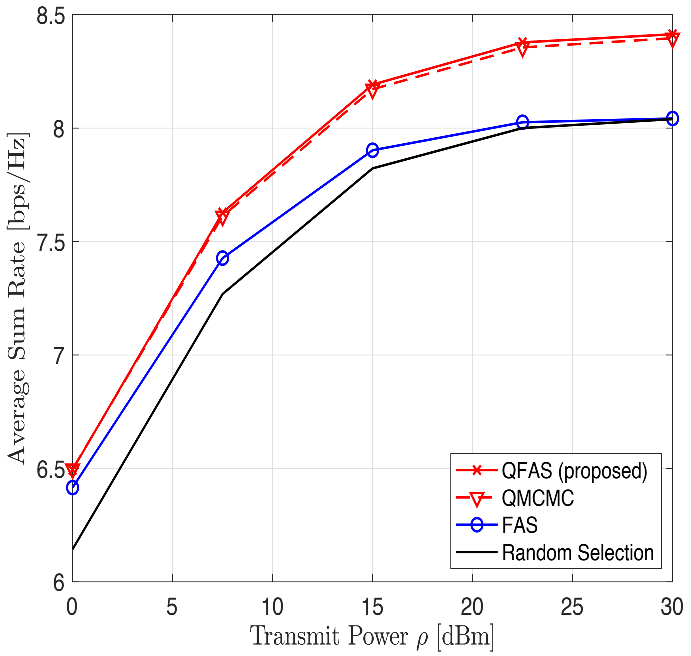
Low sampling / iteration (10, 10)



Medium sampling / iteration (50, 50)



Large sampling / iteration (100, 100)



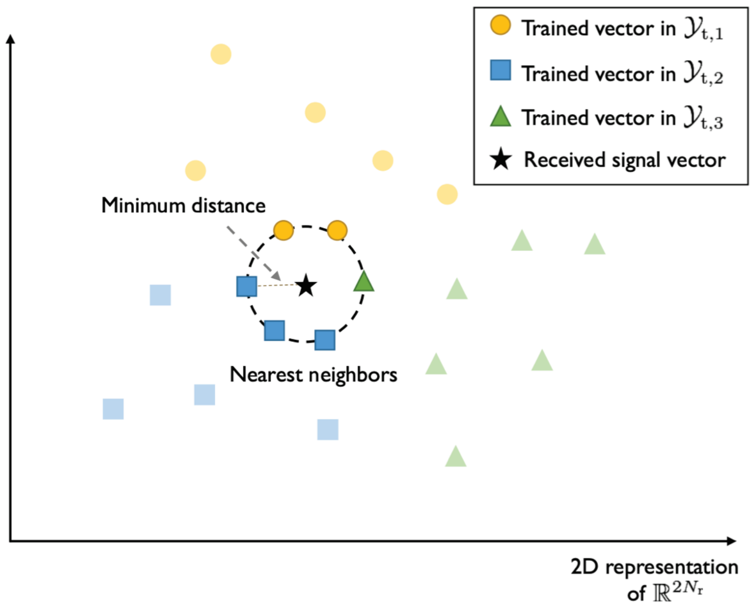
Robust Learning-Based One-Bit ADC Detection

Related publications:

[1]. Jinseok Choi, Yunseong Cho, Brian L. Evans, and Alan Gatherer, "Robust Learning-Based ML Detection for Massive MIMO Systems with One-Bit Quantized Signals", submitted to IEEE Int. Conf. on Communications, 2019.

Other Approaches

Empirical ML Detection



(a) Empirical-maximum-likelihood detection (eMLD)

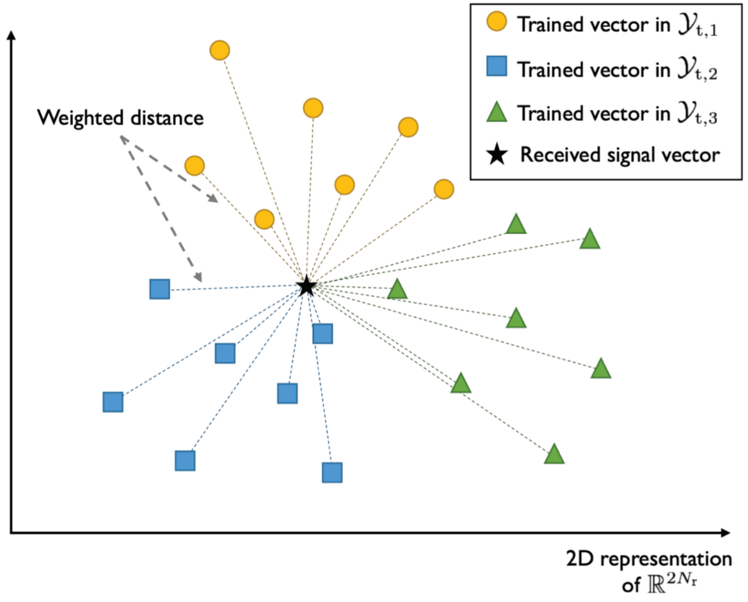
- Set generation

$$\mathcal{N}(\mathbf{y}[n]) = \left\{\mathbf{y}_t \,\middle|\, \|\mathbf{y}[n] - \mathbf{y}_t\|_2 = R_{\min}[n],\, \mathbf{y}_t \in \mathcal{Y}_t\right\}$$

- Detection rule

$$f_{\mathrm{eMLD}}(\mathbf{y}[n]) = \operatorname*{argmax}_k \sum_{\mathbf{y} \in \mathcal{N}(\mathbf{y}[n])} \hat{p}(\mathbf{y}|\mathbf{x}_k).$$

Minimum Mean-Distance Detection

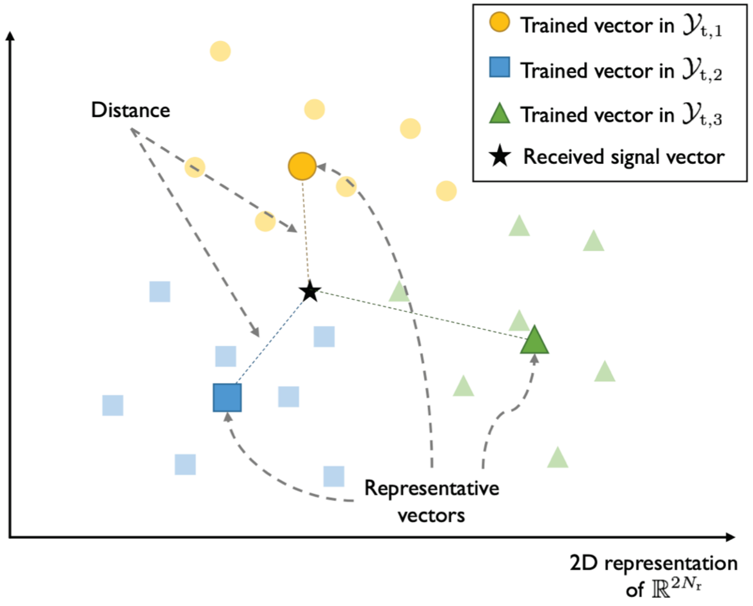


(b) Minimum-mean-distance detection (MMD)

- Detection rule

$$\begin{aligned} f_{\mathrm{MMD}}(\mathbf{y}[n]) &= \operatorname*{argmin}_k \mathbb{E}_{\mathbf{y}_t}\left[\|\mathbf{y}[n] - \mathbf{y}_t\|_2 \,\middle|\, \mathbf{x} = \mathbf{x}_k\right] \\ &= \operatorname*{argmin}_k \sum_{\mathbf{y}_t \in \mathcal{Y}_{t,k}} \|\mathbf{y}[n] - \mathbf{y}_t\|_2\, \hat{p}(\mathbf{y}_t|\mathbf{x}_k), \end{aligned}$$

Minimum Center-Distance Detection



(c) Minimum-center-distance detection (MCD)

- Set generation

$$\bar{\mathbf{y}}_{t,k} \triangleq \mathbb{E}_{\mathbf{y}_t}[\mathbf{y}_t|\mathbf{x} = \mathbf{x}_k] = \sum_{\mathbf{y}_t \in \mathcal{Y}_{t,k}} \mathbf{y}_t \hat{p}(\mathbf{y}_t|\mathbf{x}_k).$$

- Detection rule

$$f_{\mathrm{MCD}}(\mathbf{y}[n]) = \operatorname*{argmin}_k \left\|\mathbf{y}[n] - \bar{\mathbf{y}}_{t,k}\right\|_2$$

Robust, but far from ML detection with high complexity

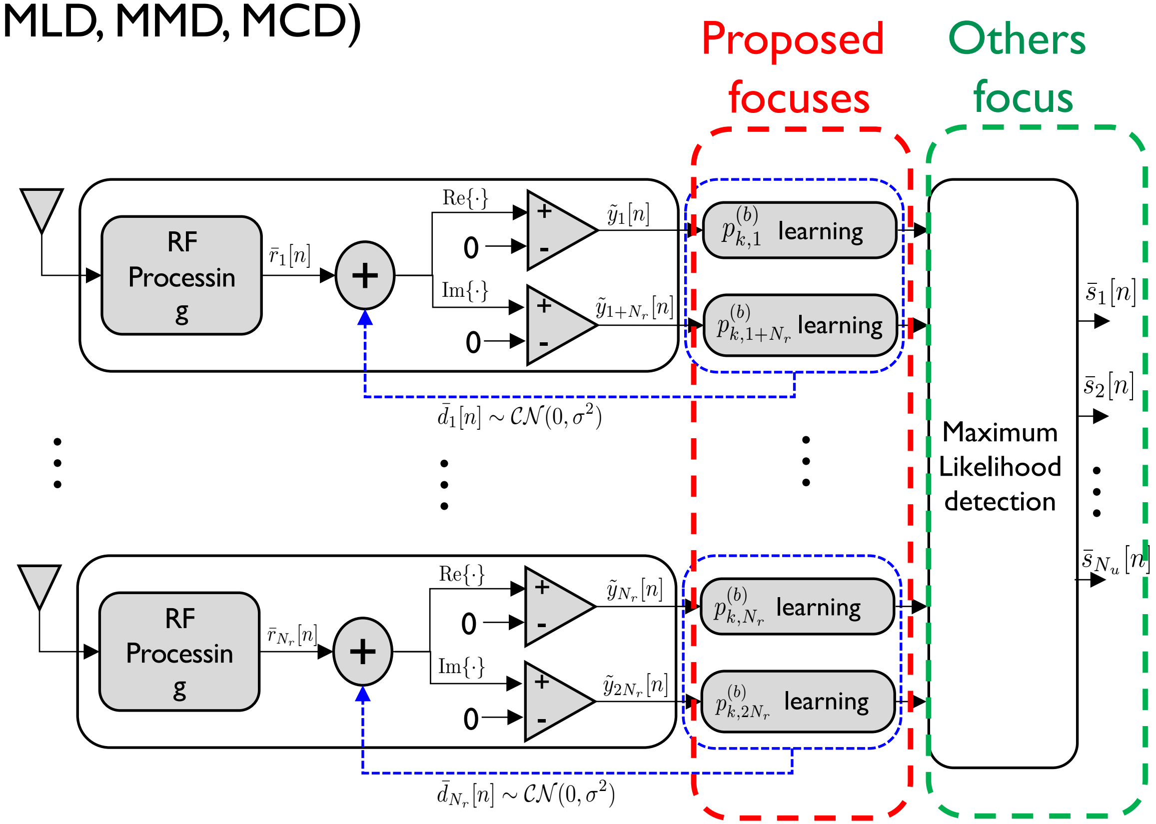
Comparison

❑ Proposed method

- **Main goal**
  - how to learn transition probability well
- **Advantages**
  - can be directly applied for ML detection
  - can be directly applied for other approaches (ex. eMLD, MMD, MCD)
- **Disadvantages**
  - depends on dithering variance
  - needs to estimate SNR value

❑ Other approaches

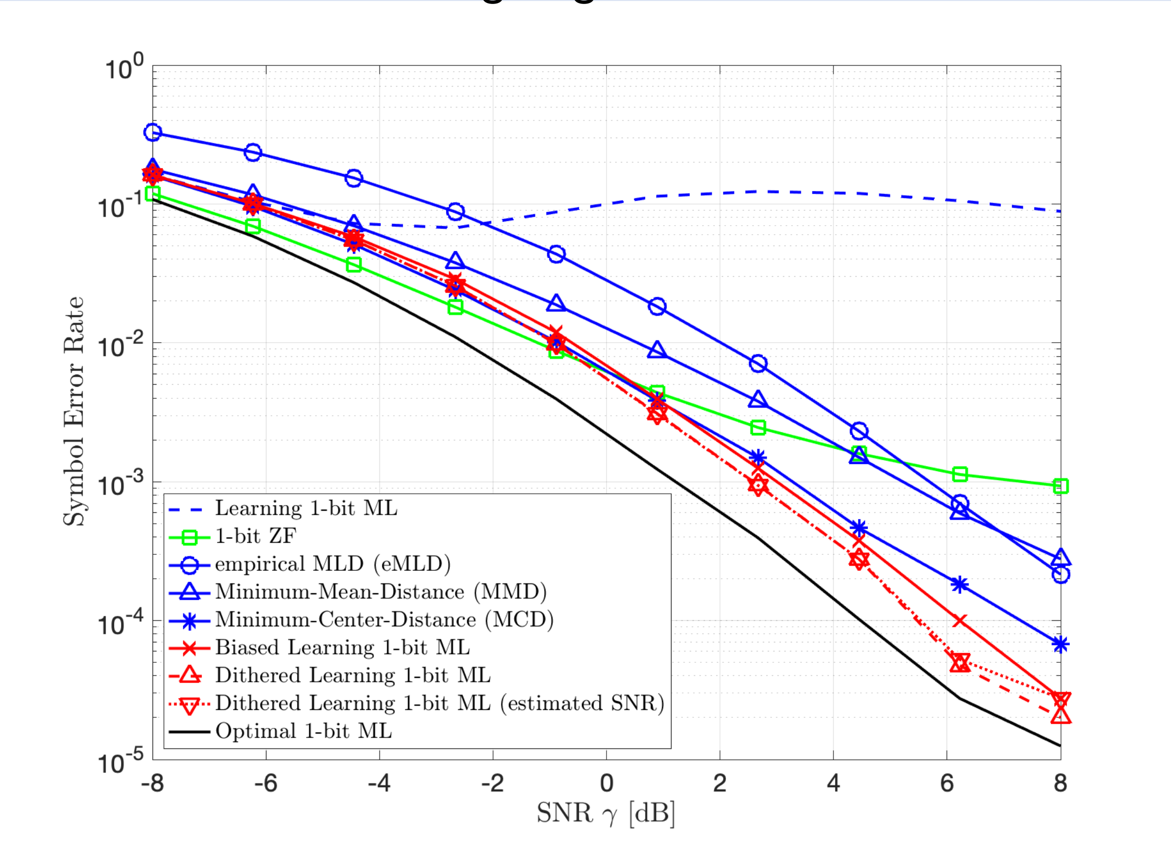
- **Main goal**
  - how to design detection method well
- **Advantages**
  - need trained transition probability only
- **Disadvantages**
  - not ML detection
  - high complexity



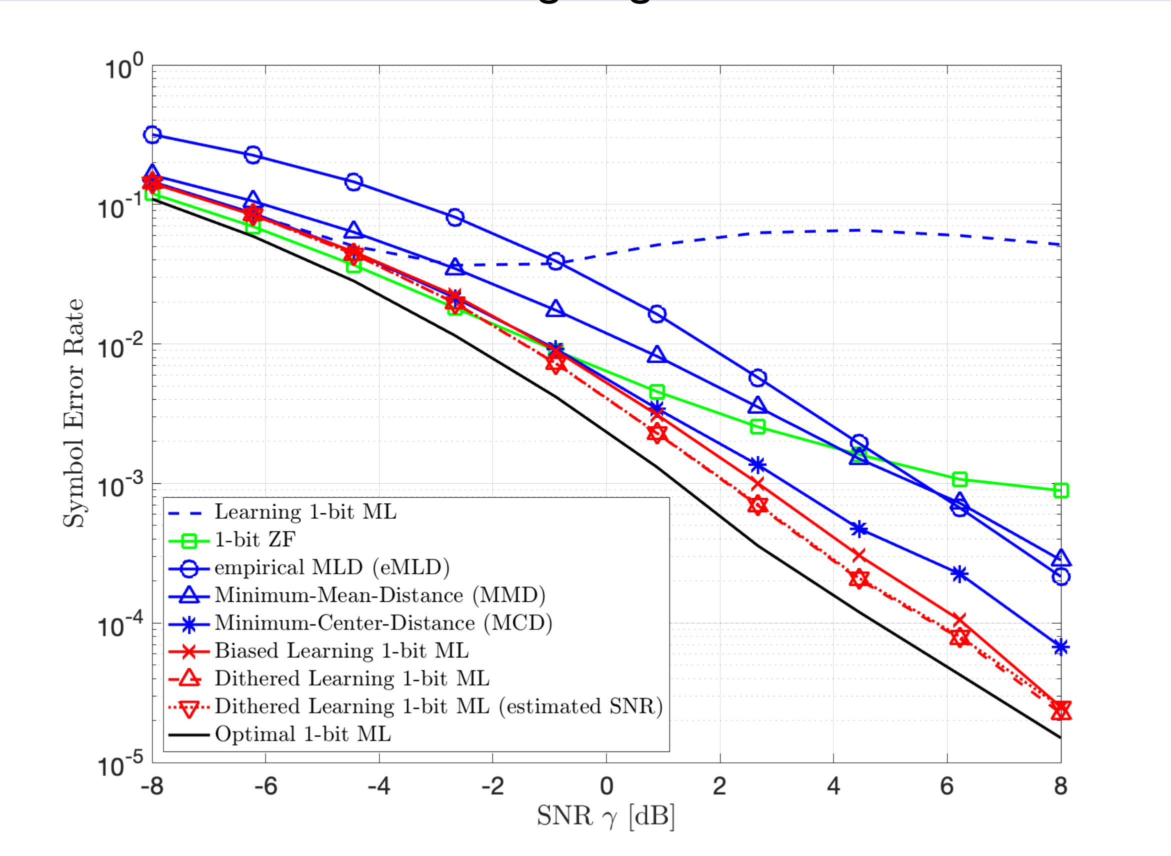
Simulation Results

Symbol Error Rate vs. Transmit Power

Training length: N_{tr} = 30



Training length: N_{tr} = 30



Settings: 32 BS antennas, 4 users, 4-QAM, 1-bit ADCs, Rayleigh fading

Future Work

Extension of Robust-Learning 1-Bit Detection

Deterministic Channel Estimation

Learning-Based One-Bit Detection (Extension 1)

❑ Weighted minimum distance detection (wMDD)

- Weighted hamming distance

$$d_{\mathrm{wh}}(\mathbf{x},\mathbf{y};\{\alpha_i\},\{\beta_i\}) \triangleq \sum_{i=1}^{N} \alpha_i \mathbf{1}_{\{x_i=y_i\}} + \sum_{i=1}^{N} \beta_i \mathbf{1}_{\{x_i\neq y_i\}},$$

- Scalable to any number of bits
- More robust than conventional ML detection

ML detection

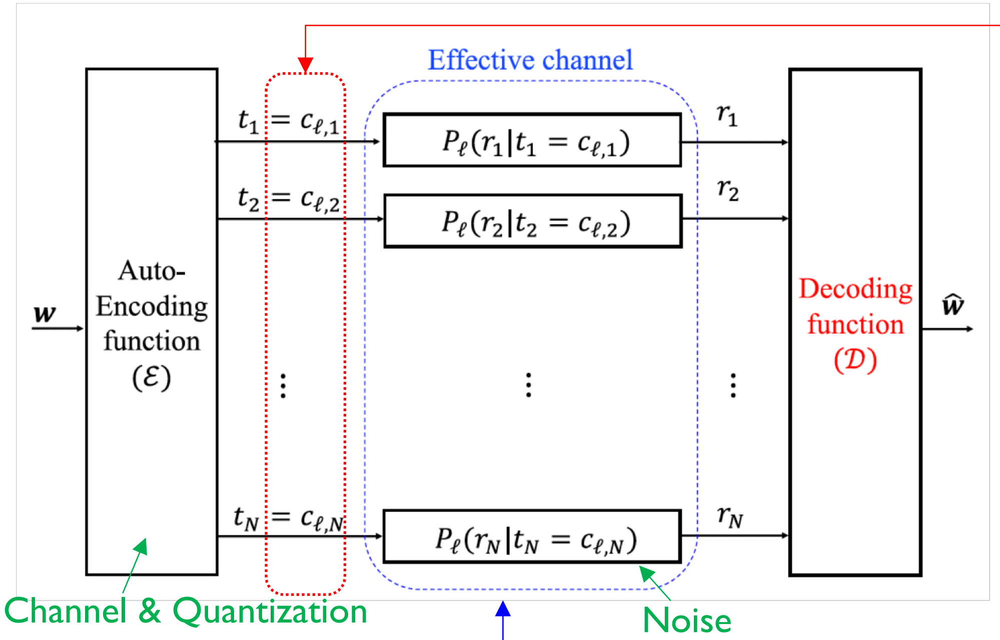
$$\alpha_{\ell,i} = -\log\left(1-\epsilon_{\ell,i}\right)$$

$$\beta_{\ell,i} = -\log \epsilon_{\ell,i},$$

wMMD

ϵ : error probability

$c_i \neq r_i$



Need to estimate during training phase

$$\mathbf{c}_\ell = \left[\phi_p\left(\mathbf{h}_1^{\mathsf{T}}\mathbf{x}(g(\ell))\right), \ldots, \phi_p\left(\mathbf{h}_N^{\mathsf{T}}\mathbf{x}(g(\ell))\right)\right]^{\mathsf{T}}$$

By using majority rule

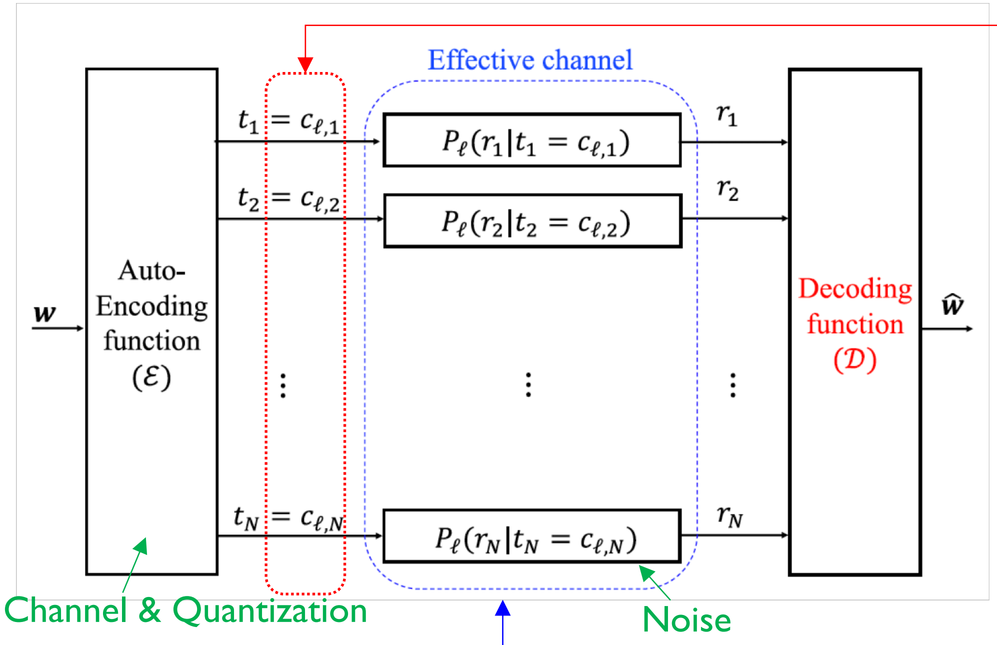
Need to estimate during training phase

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

Learning-Based One-Bit Detection (Extension 1)

❑ Weighted minimum distance detection (wMDD)

- Extension with dithering
  - decreases estimation accuracy of **c** & increase estimation accuracy of **p**
  - provides tradeoff between estimating **c** and **p**
  - needs to maximize tradeoff by finding optimal dithering variance



Need to estimate during training phase

$$\mathbf{c}_\ell = \left[\phi_p\left(\mathbf{h}_1^\top \mathbf{x}(g(\ell))\right), \ldots, \phi_p\left(\mathbf{h}_N^\top \mathbf{x}(g(\ell))\right)\right]^\top$$

By using majority rule

Need to estimate during training phase

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

Learning-Based One-Bit Detection (Extension II)

❑ Channel coded system

- Proposes soft matric operation
  - To use state-of-the-art channel codings
  - Proper low-complexity scheme

$$L^u_{mn-(p-1)}(\mathbf{y}[n]) = \log \frac{\prod_{k\in\mathcal{A}^u_{(p,0)}} \prod_{i=1}^{2N_r} \left\{\hat{p}^{(1)}_{k,i}\mathbf{1}(y_i[n]=1) + \hat{p}^{(-1)}_{k,i}\mathbf{1}(y_i[n]=-1)\right\}}{\prod_{k\in\mathcal{A}^u_{(p,1)}} \prod_{i=1}^{2N_r} \left\{\hat{p}^{(1)}_{k,i}\mathbf{1}(y_i[n]=1) + \hat{p}^{(-1)}_{k,i}\mathbf{1}(y_i[n]=-1)\right\}}$$

$$\mathcal{A}^u_{(p,j)} = \bigcup_{\mathbf{b}\in\{0,1\}^m,\, b_p=j} \{k: \mathcal{S}^u = f(\mathbf{b})\}$$

where

$u \in \{1, \ldots, N_u\}$

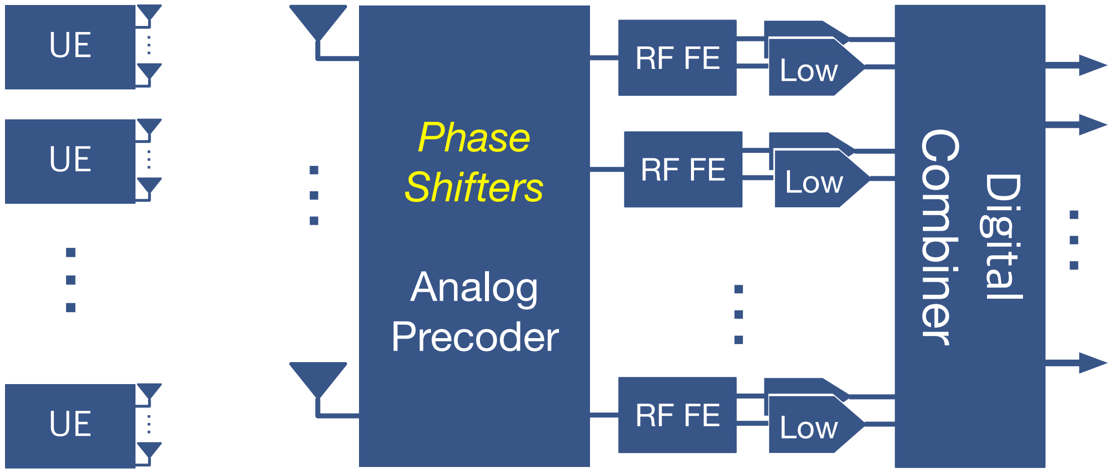
$f: M - \text{QAM modulation}$

$m = \log_2 M$

$p \in \{1, \ldots, m\}$

Channel Estimation (Extension)

Deterministic hybrid beamformer design for channel estimation



Extension covers:

- Compressed sensing based algorithms
- Millimeter wave frequencies
- Frequency-selective channels
- Phase shifter based architecture
- Low-resolution ADCs
- Uplink

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[13] Songnam Hong, Seonho Kim, and Namyoon Lee, "A Weighted Minimum Distance Decoding for Uplink Multiuser MIMO Systems With Low-Resoultion ADCs", IEEE Transactions on Communications, 2018.