# Likelihood-Based Modulation Classification for MU-MIMO Systems


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# Outline:

**Introduction**
- Motivation
- Literature Review
- System Model

**Proposed Work**
- Likelihood-Based Modulation Classification
- Log-MAP and Max-Log-MAP
- Closest_N, CMLD, CMLD1, and CMLD2

**Results**
- Complexity Study
- Simulation Scenario
- Simulation Results

**Summary & future work**

# Motivation

- Multiuser MIMO (MU-MIMO) is part of 3GPP
  - Multiple users on same physical resources on the downlink
- Optimal detection uses co-scheduled user's signal
  - Maximum likelihood (ML) detection
- Modulation classification is required
  - Interfering user's constellation is unknown at the receiver in current standards
- Optimal MC techniques are likelihood-based
- We seek joint likelihood-based MC and detection that is
  - Near optimal
  - With low complexity

# MIMO Detection

- Linear detection
  - Least complex
  - Sub-optimal
  - Zero-Forcing (ZF)
  - Minimum Mean Square Error (MMSE)

- Non-linear maximum likelihood (ML) detection
  - Optimal
  - Exhaustive

- Performance/complexity tradeoff in between
  - Sphere Detector (SD) and its variants
  - Subspace detection schemes
    - Layered Orthogonal Lattice Detector (LORD)

# MU-MIMO Detection

- Interference Ignoring
  - Solve as if interferer does not exist
- Maximum Ration Combining (MRC) and MMSE
  - Proven to be equivalent in MU-MIMO
  - Make use of the channel estimate of the interferer
  - But not the modulation type of the interferer
- Assume Interferer
  - Make an assumption on the interfering modulation type
  - It captures the geometry of the interfering constellation
  - Say 16-QAM for example
- Estimate Interferer
  - Optimal approach
  - Start by a MC routine
  - Feed estimate to a regular Interference Aware (IA) receiver

# Modulation Classification

- Likelihood based
  - Multiple hypotheses
  - Choose the modulation with highest probability
    - Optimal in the Bayesian sense
  - Average Likelihood Ratio Test (ALRT)
    - Unknown random variable with known distributions
  - Generalized Likelihood Ratio Test (GLRT)
    - Deterministic but unknown
  - Hybrid Likelihood Ratio Test (HLRT)
    - Combination of both

- Feature based
  - Classification based on statistical properties
  - Exploit inherent characteristics of the received signal
    - Higher order correlation
    - Hierarchical cumulants
    - Zero-crossing rate
    - Power estimation

# System Model (1)

We assume an LTE scenario

- Transmission modes (TMs) 7, 8, and 9
- Estimates of desired and co-scheduled user channels are available at the User Equipment (UE)

Received signal at resource element (RE) is given by:

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

$\mathbf{H} = N_r \times N_t$ channel matrix

$\mathbf{x}$ transmitted QAM symbols

$\mathbf{n}$ complex additive white Gaussian noise with zero mean and variance $\sigma^2$

$$\sigma^2 = \frac{N_t}{\text{SNR}}$$

# System Model (2)

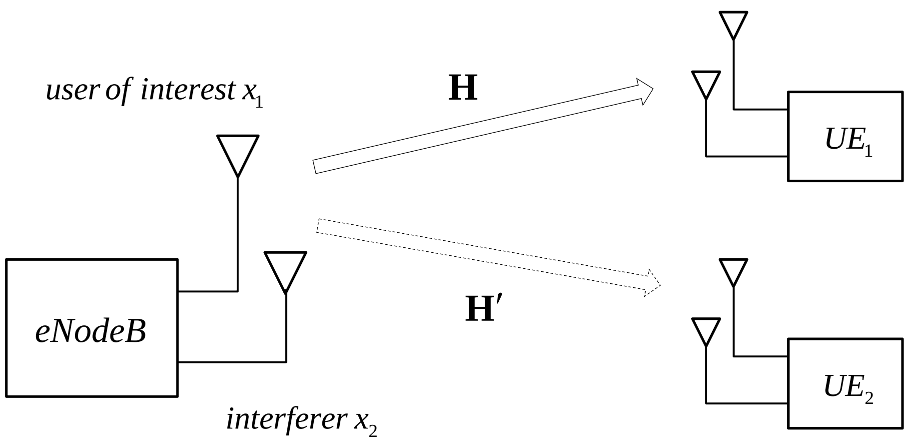
We consider the case $N_r = N_t = 2$

$$\mathbf{y} = \mathbf{h}_1 x_1 + \mathbf{h}_2 x_2 + \mathbf{n}$$

$\mathbf{h}_1$ : channel coefficients of user of interest
$\mathbf{h}_2$: channel coefficients of interferer

$\mathrm{E}[x_1 . x_1^*] = \mathrm{E}[x_1 . x_1^*] = 1$ Transmission power normalized to unity

$x_1$ and $x_2$ are drawn from QPSK, 16-QAM or 64-QAM



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# Likelihood-Based MC

Bayesian formulation
- 4-ary hypothesis testing

$$\begin{cases} \theta_{\mathbf{0}}:\ \mathbf{y} \sim P(\mathbf{y}; x_1 \in \bar{\Lambda}, x_2 \in \Lambda_0) \\ \theta_{\mathbf{1}}:\ \mathbf{y} \sim P(\mathbf{y}; x_1 \in \bar{\Lambda}, x_2 \in \Lambda_1) \\ \theta_{\mathbf{2}}:\ \mathbf{y} \sim P(\mathbf{y}; x_1 \in \bar{\Lambda}, x_2 \in \Lambda_2) \\ \theta_{\mathbf{3}}:\ \mathbf{y} \sim P(\mathbf{y}; x_1 \in \bar{\Lambda}, x_2 \in \Lambda_3) \end{cases}$$

$P(.)$ : probability density function
$\bar{\Lambda}$ : constellation of user of interest
$\Lambda_0$ : $\emptyset$ (no interference)
$\Lambda_1$ : QPSK
$\Lambda_2$ : 16-QAM
$\Lambda_3$ : 64-QAM

Probability of each hypothesis is given by:

$$P(\mathbf{y}; \Lambda_n) = \sum_{x_1 \in \bar{\Lambda}, x_2 \in \Lambda_n} P(\mathbf{y}|x_1, x_2) P(x_1, x_2)$$

$x_1$and $x_1$ are independent, $P(x_2) = 1/|\Lambda_n|$, and $P(x_1) = 1/|\bar{\Lambda}|$ is fixed over hypotheses

$$\hat{n} = \underset{n=0,1,2,3}{\operatorname{argmax}} \sum_{x_1 \in \bar{\Lambda}, x_2 \in \Lambda_n} P(\mathbf{y}|x_1, x_2) \frac{1}{|\Lambda_n|}$$

# Log-MAP and Max-Log-MAP

Knowing that $$P(\mathbf{y}|x_1,x_2)=\frac{1}{(\pi\sigma^2)^2}\exp\left(-\frac{1}{\sigma^2}\|\mathbf{y}-\mathbf{H}\mathbf{x}\|^2\right)$$

the term $\frac{1}{(\pi\sigma^2)^2}$ is fixed over hypotheses

We take the logarithm to obtain the Log-MAP equation of the ALRT solution:

$$\hat{n}_{\mathrm{Log-MAP}}=\underset{n=0,1,2,3}{\operatorname{argmax}}\left(\log\frac{1}{|\Lambda_n|}+\sum_{x_1\in\bar{\Lambda},x_2\in\Lambda_n}\exp\left(-\frac{1}{\sigma^2}\|\mathbf{y}-\mathbf{H}\mathbf{x}\|^2\right)\right)$$

For each $n$, $|\bar{\Lambda}|\times|\Lambda_n|$ exponential terms are computed, but the ML distance is dominant

$$d_{\mathrm{ML},n}=\min_{x_1\in\bar{\Lambda},x_2\in\Lambda_n}\varphi(\mathbf{x})\qquad\qquad\varphi(\mathbf{x})=\frac{1}{\sigma^2}\|\mathbf{y}-\mathbf{H}\mathbf{x}\|^2$$

The Max-Log-MAP classifier equation is thus:

$$\hat{n}_{\mathrm{Max-Log-MAP}}=\underset{n=0,1,2,3}{\operatorname{argmax}}\left(\log\frac{1}{|\Lambda_n|}-d_{\mathrm{ML},n}\right)$$

# Proposed Closest_N and CMLDs (1)

The more distance metrics that we include, the better the approximation

Closest_N accumulates the N most dominant distances

Instead, we can consider counter-ML distances

$$d_{\mathrm{CML},n,j,i} = \begin{cases} \min\limits_{x_1 \in \bar{\Lambda}, x_2 \in \Lambda_n | b_{i,j}=0} \varphi(\mathbf{x}) & b_{i,j}^{(\mathrm{ML},n)} = 1 \\ \min\limits_{x_1 \in \bar{\Lambda}, x_2 \in \Lambda_n | b_{i,j}=1} \varphi(\mathbf{x}) & b_{i,j}^{(\mathrm{ML},n)} = 0 \end{cases}$$

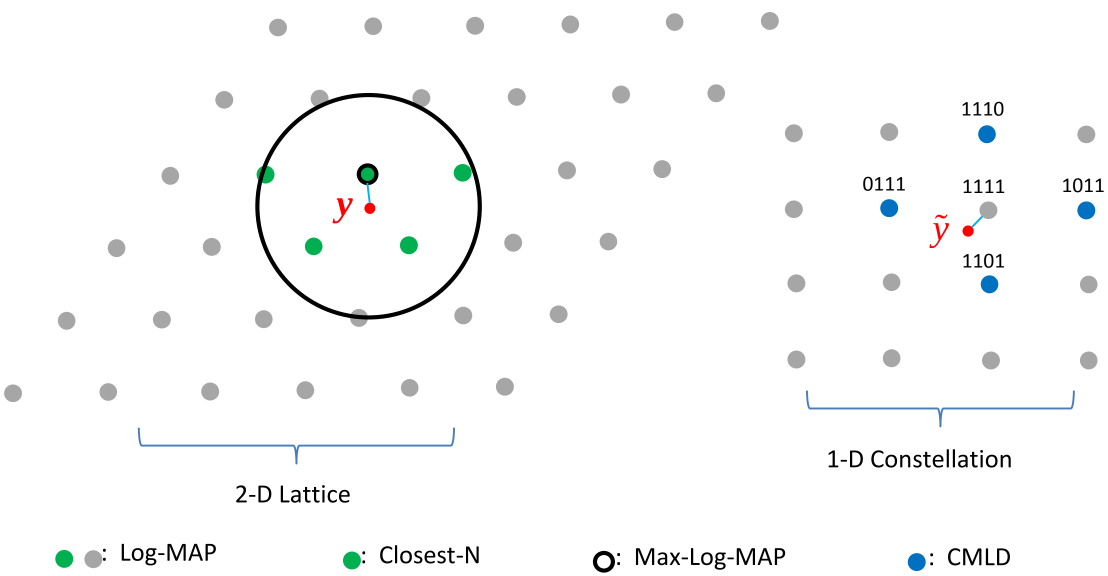
where $b_{i,j} \in \{0,1\}$ denotes the *i*th bit of the *j*th symbol $x_j$

- CMLD1: accumulates $K_1$ counter-ML distances of bits of $x_1$ + $d_{\mathrm{ML},n}$
- CMLD2: accumulates $K_2$ counter-ML distances of bits of $x_2$ + $d_{\mathrm{ML},n}$
- CMLD: accumulates $K$ counter-ML distances of bits of $\mathbf{x}$ + $d_{\mathrm{ML},n}$

# Proposed Closest_N and CMLDs (2)

In general, for a group of distance metrics $S$, and after $T$ observations

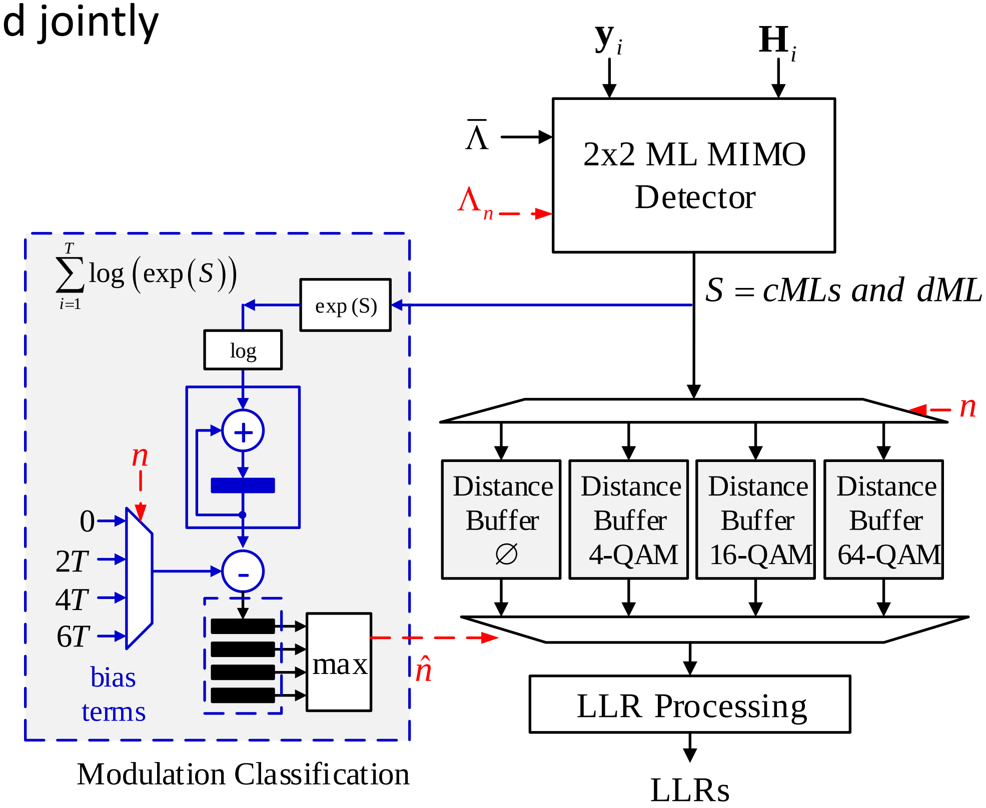
$$\hat{n} = \underset{n=0,1,2,3}{\operatorname{argmax}} \sum_{t=1}^{T} \left( \log \frac{1}{|\Lambda_n|} + \sum_{\mathbf{x} \in S} \exp\left( -\frac{1}{\sigma^2} \|\mathbf{y} - \mathbf{H}\mathbf{x}\|^2 \right) \right)$$



# Proposed Joint MC and Detection

CMLD1 MC and soft-output ML detection compute the same distance metrics

They can be executed jointly



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# Complexity Study

The computational complexity of the MC approaches is expressed in terms of:

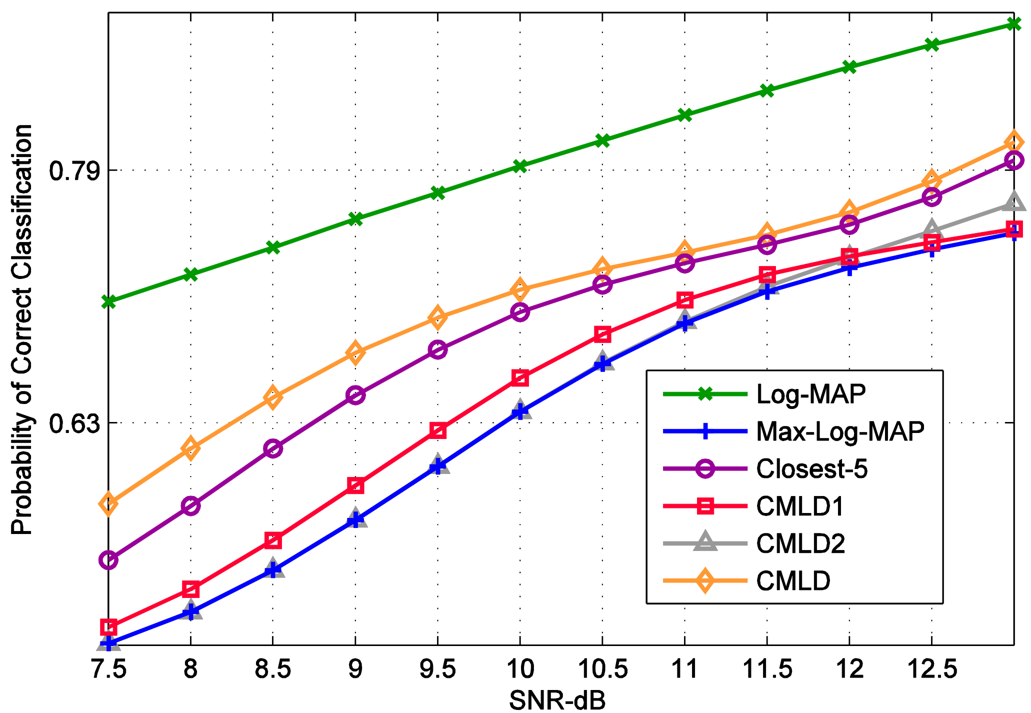
- Distance computations D
- Exponential operations E
- Logarithmic operations L

| Approach | S | L | E | D |
|---|---|---|---|---|
| Log-MAP | All | T | $T \times \lvert\bar{\Lambda}\rvert \times (\lvert\Lambda_0\rvert + \lvert\Lambda_1\rvert + \lvert\Lambda_2\rvert + \lvert\Lambda_3\rvert)$ | $T \times \lvert\bar{\Lambda}\rvert \times (\lvert\Lambda_0\rvert + \lvert\Lambda_1\rvert + \lvert\Lambda_2\rvert + \lvert\Lambda_3\rvert)$ |
| Closest_N | Closest N | T | $T \times 4 \times N$ | $T \times \lvert\bar{\Lambda}\rvert \times (\lvert\Lambda_0\rvert + \lvert\Lambda_1\rvert + \lvert\Lambda_2\rvert + \lvert\Lambda_3\rvert)$ |
| CMLD | ML+CMLs of $\mathbf{x}$ | T | $T\left[4 \times (K_1 + 1)\right.$ | $T \times \lvert\bar{\Lambda}\rvert \times (\lvert\Lambda_0\rvert + \lvert\Lambda_1\rvert + \lvert\Lambda_2\rvert + \lvert\Lambda_3\rvert)$ |
| CMLD1 | ML+CMLs of $x_1$ | T | $4 \times T \times (K_1 + 1)$ | $T \times \lvert\bar{\Lambda}\rvert \times (\lvert\Lambda_0\rvert + \lvert\Lambda_1\rvert + \lvert\Lambda_2\rvert + \lvert\Lambda_3\rvert)$ |
| CMLD2 | ML+CMLs of $x_2$ | T | $T\left(K_2^{(0)} + K_2^{(1)} + K_2^{(2)} + K_2^{(3)} + 4\right)$ | $T \times \lvert\bar{\Lambda}\rvert \times (\lvert\Lambda_0\rvert + \lvert\Lambda_1\rvert + \lvert\Lambda_2\rvert + \lvert\Lambda_3\rvert)$ |
| Max-Log-MAP | ML | T | $4 \times T$ | $T \times \lvert\bar{\Lambda}\rvert \times (\lvert\Lambda_0\rvert + \lvert\Lambda_1\rvert + \lvert\Lambda_2\rvert + \lvert\Lambda_3\rvert)$ |

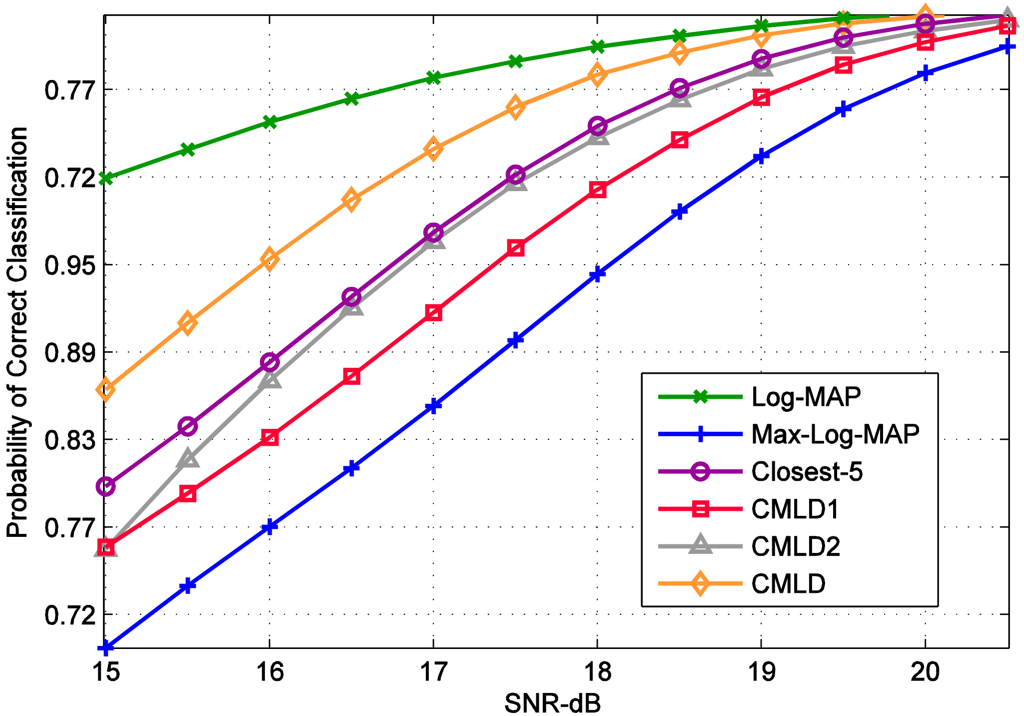
# Simulation Scenario

- A MC-assited ML detector was implemented
  - System model in introduction
- 12 tones observed before classification decision
  - Constant interferer over 12 tones
  - 1 OFDM symbol in LTE
- Turbo coding/decoding
  - Code rate 1/3
  - 4 iterations
- User of interest uses 16-QAM
  - Equiprobable interference (4 hypotheses)
- Two channel types
  - Uncorrelated (rich scattering)
  - Highly correlated ($\alpha = 0.9$)
- Performance measures
  - Correct Classification Rate (CCR)
  - Frame Error Rate (FER)

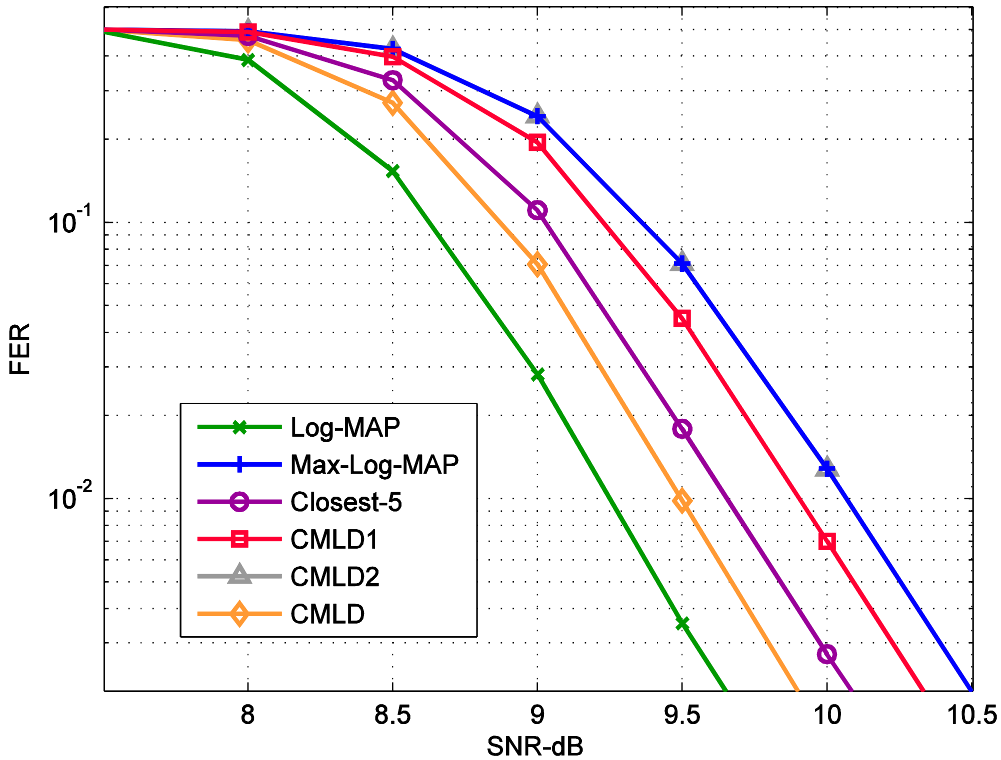
# CCR - Uncorrelated



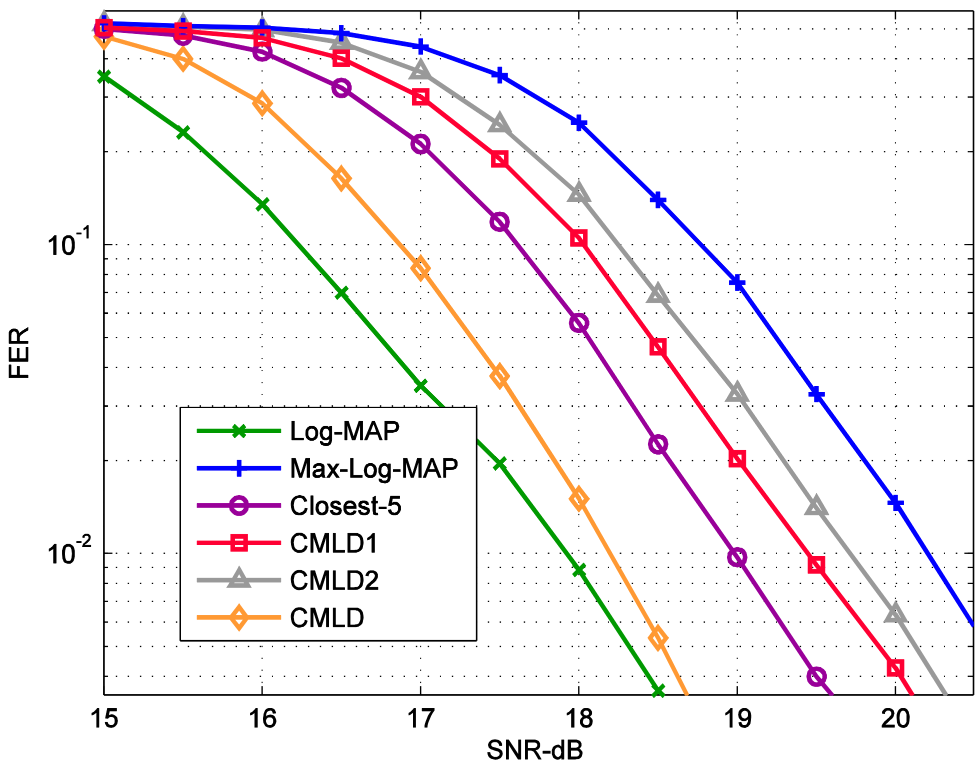
# CCR - Correlated



# FER - Uncorrelated



# FER - Correlated



# Discussion

- Performance depends on $K_1$ and $K_2$
  - If $K_1 + 1 > N$ CMLD1 can outperform Closest_N
  - If $K_1 + 1 \leq N$ Closest_N is the winner
  - CMLD2 is biased towards larger constellations
  - CMLD outperforms CMLD1 and CMLD2
- CMLD1 is better suited for joint MC and detection setup
  - Even in case of sphere detection
- Closest_N can also be used in a joint setup
  - Especially with list sphere decoding
- Proposed algorithm applies to 802.11ac (WiFi)
  - More observations (tones) can be accumulated
  - At lest 52 tones
- The proposed algorithm can make use of further approximations
  - Constant Max-Log-MAP
  - Linear Max-Log-MAP

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# Summary

- **ML MC** scheme **for 2 × 2 LTE MU-MIMO** systems was investigated.
- The decision metric for **likelihood-based MC** was shown to be an accumulation over a **set of tones of Euclidean distance computations**.
- Several **simplified** versions of MC were proposed.
- Compared to the **Max-Log-MAP**, the proposed schemes achieved an average **FER gain of 0.4dB with uncorrelated** channels and **1.5dB with correlated channels**.
- The classifier **CMLD1** was argued to be of a **practical interest**.

# Future Work

- Higher Order MU-MIMO.
- Joint MC and sub-optimal detection.
- Higher order constellations.
- Low complexity implementations.

# Thanks for listening

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