Efficient Near Optimal Joint Modulation Classification and Detection for MU-MIMO Systems

Hadi Sarieddeen*, Mohammad M. Mansour*, Louay M.A. Jalloul†, and Ali Chehab*

* Department of Electrical and Computer Engineering, American University of Beirut, Beirut, Lebanon - {has63, mmansour, chehab}@aub.edu.lb
† Qualcomm Inc. San Jose, CA, USA - jalloul@ieee.org

Introduction

A joint maximum likelihood (ML) modulation classification (MC) of the co-scheduled user and data detection receiver is developed

Reference MU-MIMO Detection Schemes:

- Interference Ignoring
- Interference Rejection Combining (IRC) and MMSE
  Only make use of the channel estimate of the interferer
- Interference Assuming
  Say 16-QAM for example
- Interference Estimation
  Add a MC routine
  Feed estimate to a regular Interference Aware (IA) receiver

Modulation Classification Schemes:

- Likelihood-based
- Feature-based

System Model

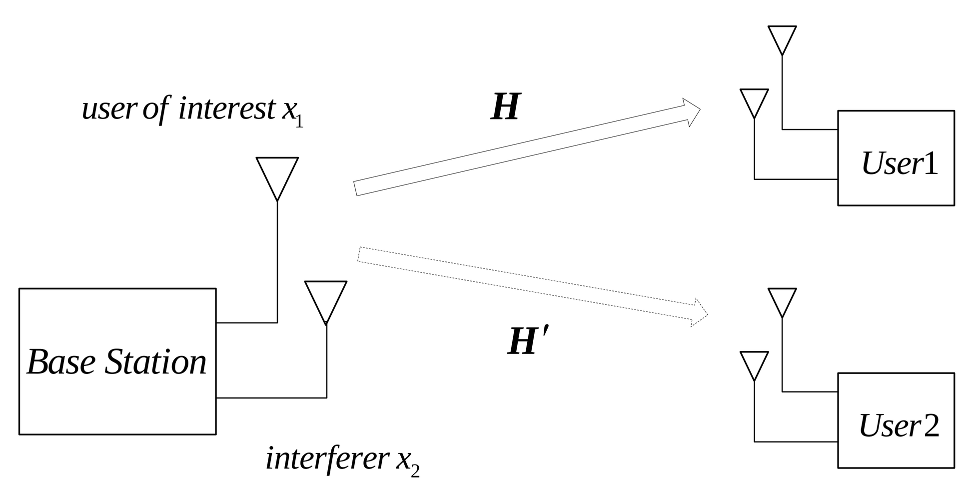
$$\mathbf{y} = \mathbf{H}\mathbf{x} + \mathbf{n}$$

- $\mathbf{H} = N_r \times N_t$ channel matrix
- $\mathbf{x}$ transmitted QAM symbols
- $\mathbf{n}$ complex additive white Gaussian noise with zero mean and variance $\sigma^2 = \frac{N_t}{\text{SNR}}$

We consider the case $N_r = N_t = 2$ $\quad \mathbf{y} = \mathbf{h}_1 x_1 + \mathbf{h}_2 x_2 + \mathbf{n}$

$\bar{\Lambda}$ is the constellation of user of interest

Λ_0 is $\emptyset$ (no interference) - Λ_1 is QPSK - Λ_2 is 16-QAM - Λ_3 is 64-QAM



Proposed Joint MC and Detection

Bayesian formulation: 4-ary hypothesis testing

$$\begin{cases} \theta_0: \mathbf{y} \sim P(\mathbf{y}; x_1 \in \bar{\Lambda}, x_2 \in \Lambda_0) \\ \theta_1: \mathbf{y} \sim P(\mathbf{y}; x_1 \in \bar{\Lambda}, x_2 \in \Lambda_1) \\ \theta_2: \mathbf{y} \sim P(\mathbf{y}; x_1 \in \bar{\Lambda}, x_2 \in \Lambda_2) \\ \theta_3: \mathbf{y} \sim P(\mathbf{y}; x_1 \in \bar{\Lambda}, x_2 \in \Lambda_3) \end{cases}$$

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

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

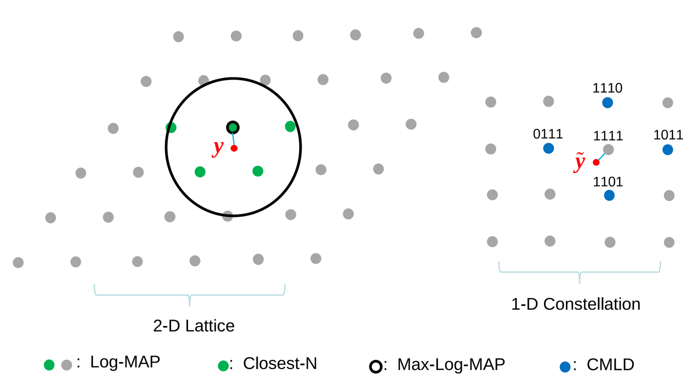
$$d_{\text{ML},n} = \min_{x_1 \in \bar{\Lambda}, x_2 \in \Lambda_n} \varphi(\mathbf{x}) \qquad \varphi(\mathbf{x}) = \frac{1}{\sigma^2} \|\mathbf{y} - \mathbf{H}\mathbf{x}\|^2$$

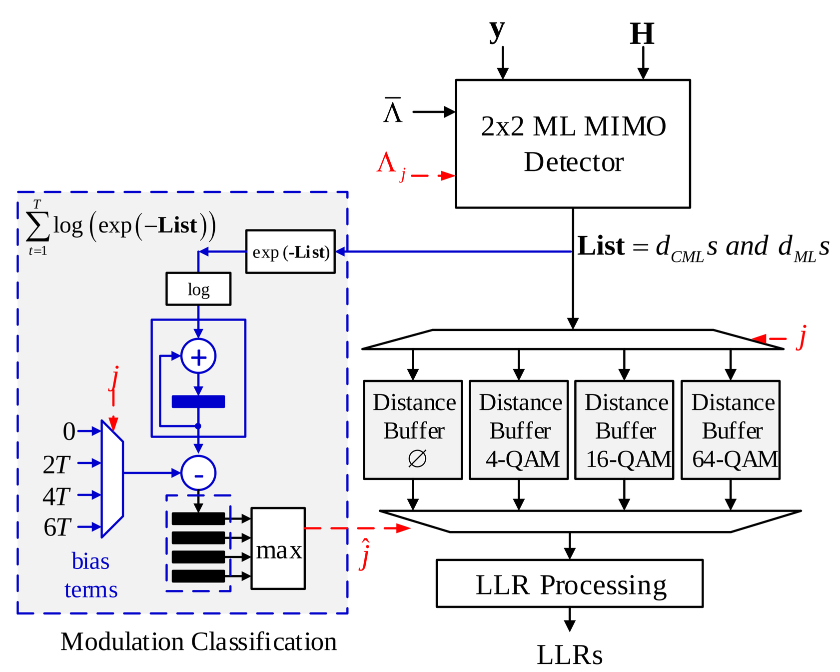
$$\hat{n}_{\text{Max-Log-MAP}} = \underset{n=0,1,2,3}{\text{argmax}} \left(\log \frac{1}{|\Lambda_n|} - d_{\text{ML},n} \right)$$

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

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

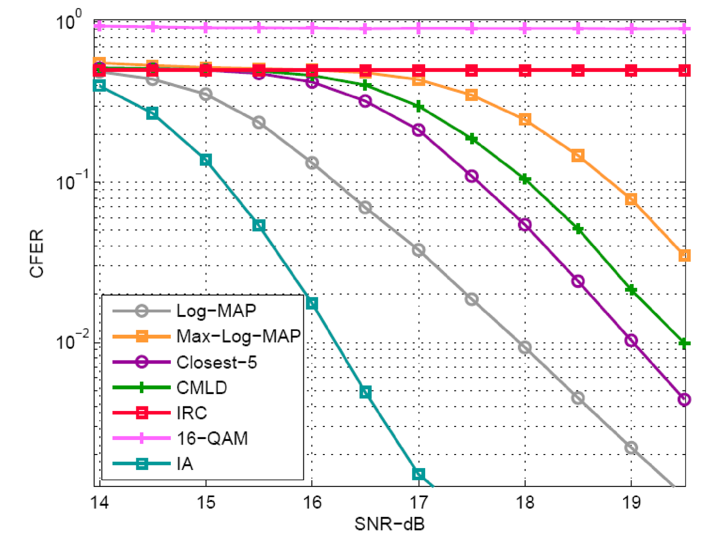
- Closest_N: S consists of points corresponding to smallest N distance metrics.
- CMLD: S consists of points corresponding to ML and counter-ML distances.



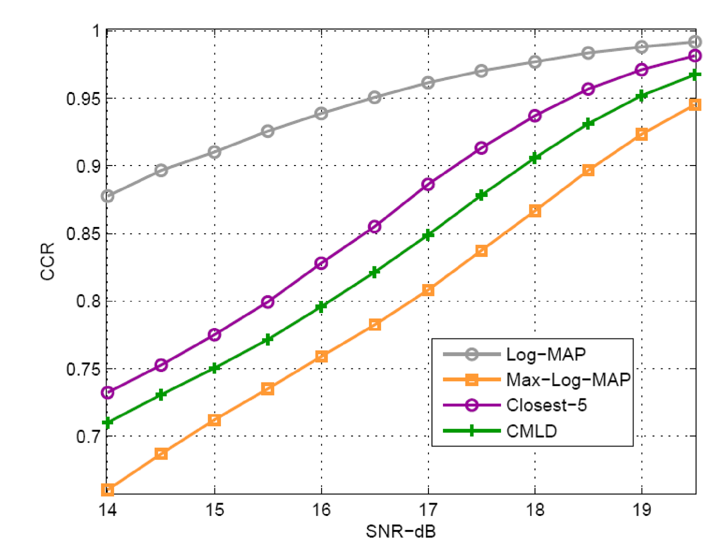


Results

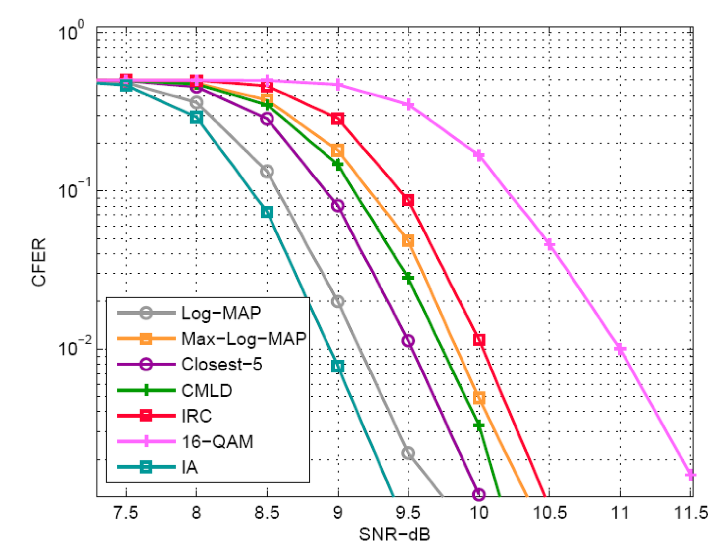
- Correct Classification Ratio (CCR) of classifiers
- Coded frame error rate (CFER) of detectors



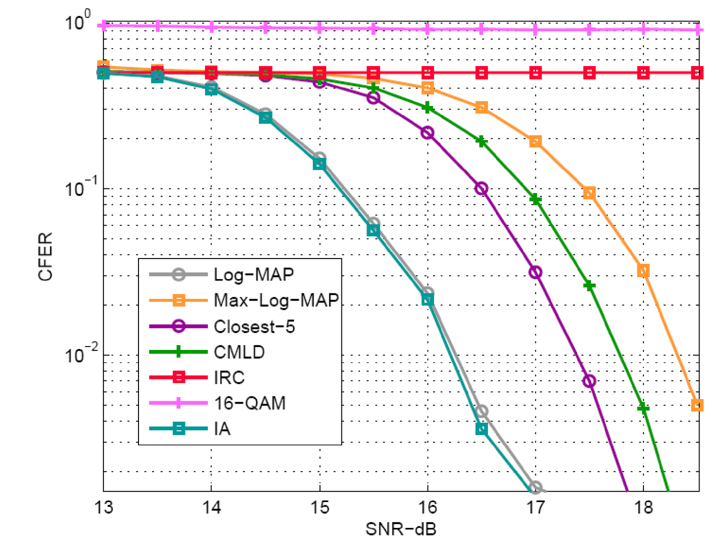
CFER Performance - T = 12 - Correlated Channels



CCR Performance - T = 12 - Correlated Channels



CFER Performance - T = 12 - Uncorrelated Channels



CFER Performance - T = 52 - Correlated Channels

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	$T\left[4 \times (K_1 + 1) + \left(K_2^{(0)} + K_2^{(1)} + K_2^{(2)} + K_2^{(3)} + 4\right)\right]$	$T \times \lvert\bar{\Lambda}\rvert \times (\lvert\Lambda_0\rvert + \lvert\Lambda_1\rvert + \lvert\Lambda_2\rvert + \lvert\Lambda_3\rvert)$
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	$4 \times T$	$T \times \lvert\bar{\Lambda}\rvert \times (\lvert\Lambda_0\rvert + \lvert\Lambda_1\rvert + \lvert\Lambda_2\rvert + \lvert\Lambda_3\rvert)$

In the Context of WiFi

- From 52 to 234 data tones
- large number of OFDM symbols (L)
- Constant interferer over T tones and L symbols
- MC executes on one OFDM symbol in the frame
- $\frac{3}{L}$% increase in distance computations
- L takes values from 8 to more than 1024