Blind Modulation Classification: An Idea Whose Time Has Come

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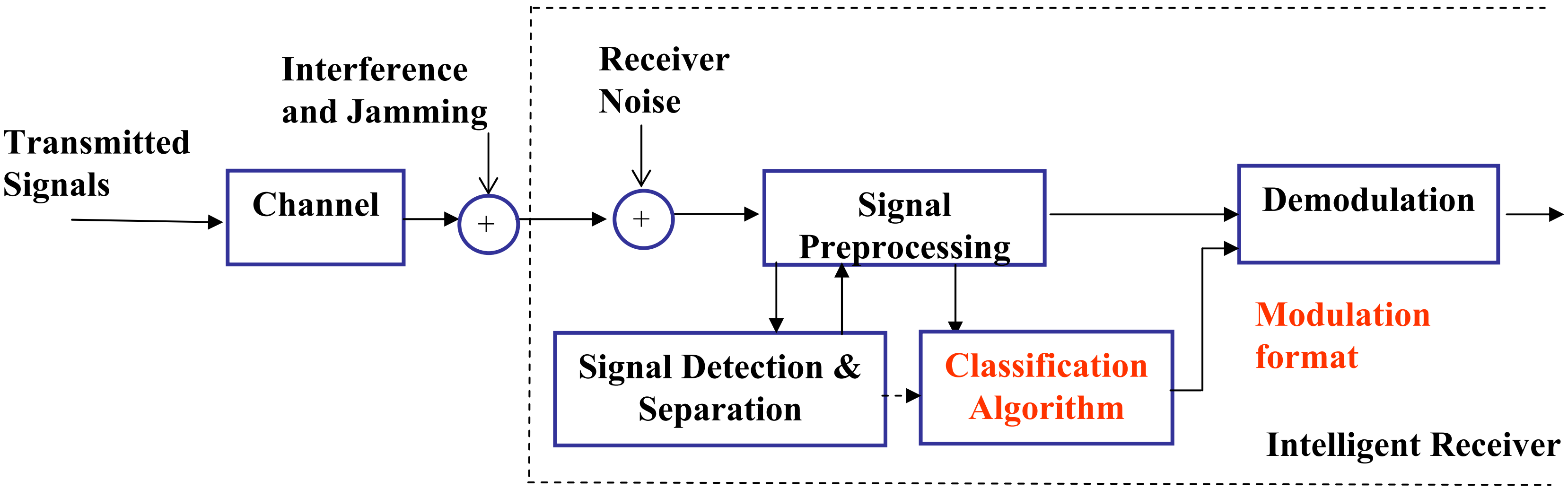
Outline

- Blind Modulation Classification (MC) : Problem Formulation
- Approaches to MC
  - Likelihood-Based (LB) Approach
  - Feature-Based (FB) Approach
- Spatial Receive Diversity for MC
- Conclusion
- Ongoing and Future Work

MC: Problem Formulation

- ***System Block Diagram***



•***Preprocessing Tasks:*** *signal bandwidth and carrier frequency estimation, signal and noise power estimation, carrier, timing and waveform recovery, compensation for fading and interferences, etc.*

MC: Problem Formulation (cont'd)

- ***Requirements for the Modulation Classification Algorithm***

  ✓ Capability to recognize many different modulations in different types of environments,

  ✓ High classification performance for low SNR in a short observation interval,

  ✓ Rely less on preprocessing,

  ✓ Robustness to non-ideal conditions, such as carrier frequency offset, timing errors, residual channel effects,

  ✓ Real-time functionality and low complexity.

Approaches to MC

- *Classification Approaches*

  ✓ ***Likelihood-Based (LB) Approach***

  Requires computation of the likelihood function (LF) of the received signal. Likelihood ratio tests (LRTs) are used for decision-making.

  ✓ ***Feature-Based (FB) Approach***

  Features common to different modulations are used, and the decision is made based on their differences.
  Such features are selected in an ad-hoc way.

Likelihood-Based (LB) Approach

LB Approach

- **MC is a multiple composite hypothesis-testing problem**

H_i : the detected signal has the ith modulation format, $i=1,\ldots,N_{mod}$.

Example: $N_{mod}=2$

LB Approach

ALRT (Average LRT)

$$\frac{\Xi_A(\mathbf{r}\,|\,H_1)}{\Xi_A(\mathbf{r}\,|\,H_2)} = \frac{\int p(\mathbf{r}\,|\,\mathbf{u}_{H_1},H_1)\,p(\mathbf{u}_{H_1})\,d\mathbf{u}_{H_1}}{\int p(\mathbf{r}\,|\,\mathbf{u}_{H_2},H_2)\,p(\mathbf{u}_{H_2})\,d\mathbf{u}_{H_2}} \underset{H_2}{\overset{H_1}{\gtrless}} \gamma_A$$

GLRT (Generalized LRT)

$$\frac{\Xi_G(\mathbf{r}\,|\,H_1)}{\Xi_G(\mathbf{r}\,|\,H_2)} = \frac{\max_{\mathbf{u}_{H_1}} p(\mathbf{r};\mathbf{u}_{H_1}\,|\,H_1)}{\max_{\mathbf{u}_{H_2}} p(\mathbf{r};\mathbf{u}_{H_2}\,|\,H_2)} \underset{H_2}{\overset{H_1}{\gtrless}} \gamma_G$$

HLRT (Hybrid LRT)

$$\frac{\Xi_H(\mathbf{r}\,|\,H_1)}{\Xi_H(\mathbf{r}\,|\,H_2)} = \frac{\int \max_{\mathbf{u}_{1H_1}} p(\mathbf{r};\,\mathbf{u}_{1H_1}\,|\,\mathbf{u}_{2H_1},H_1)\,p(\mathbf{u}_{2H_1})\,d\mathbf{u}_{2H_1}}{\int \max_{\mathbf{u}_{1H_2}} p(\mathbf{r};\,\mathbf{u}_{1H_2}\,|\,\mathbf{u}_{2H_2},H_2)\,p(\mathbf{u}_{2H_2})\,d\mathbf{u}_{2H_2}} \underset{H_2}{\overset{H_1}{\gtrless}} \gamma_H$$

$\mathbf{u}_{H_i}$ is the vector of unknown quantities, i.e., unknown data symbols and parameters (frequency, phase and timing offsets, etc.).

LB Approach (cont'd)

- ***Signal Model***

We have mostly investigated classification of **Single Carrier Linear Digital Modulations (SCLD)**, in **AWGN and Block-Fading** Channels,

under the assumption that Waveform recovery, Timing recovery, and Compensation for the Carrier Frequency Offset are performed in the preprocessing step.

Received Baseband Signal

$$r_{SCLD}(t) = \alpha e^{j\varphi} \sum_k s_k^{(i)} u_T\left(t - kT\right) + w(t), \quad 0 \le t \le KT$$

The signal samples (taken at the symbol rate) at the output of the receive matched filter are used to compute the LF.

LB Approach: ALRT

- **Unknowns** $\mathbf{u}_i = [\{s_k^{(i)}\}_{k=1}^K]$ **, AWGN**

- *Complexity*

$$\Xi_{A-AWGN}[\mathbf{r} \mid H_i] = \prod_{k=1}^{K} E_{s_k^{(i)}} \left[\exp\left\{ \frac{2\alpha}{N} \mathrm{Re}[e^{-j\varphi} R_k^{(i)}] - \frac{\alpha^2 T}{N} \mid s_k^{(i)} \mid^2 \right\} \right]$$

$\mathcal{O}(M_i K)$

- **Unknowns** $\mathbf{u}_i = [\varphi \ \{s_k^{(i)}\}_{k=1}^K]^\dagger$ **, AWGN**

[Abdi, Dobre, Choudhry, Bar-Ness, and Su, 2004]

The phase φ is uniformly distributed over $[-\pi, \pi)$.

$$\Xi_{A-CP}[\mathbf{r} \mid H_i] = E_{\{s_k^{(i)}\}_{k=1}^K} \left[I_0\left(\frac{2\alpha}{N} \mid \Psi_K^{(i)} \mid \right) \exp\left\{ -\frac{\alpha^2 T}{N} \eta_K^{(i)} \right\} \right]$$

$\mathcal{O}(M_i^K)$

- **Unknowns** $\mathbf{u}_i = [\alpha \ \varphi \ \{s_k^{(i)}\}_{k=1}^K]^\dagger$ **, Rayleigh Fading**

$\mathcal{O}(M_i^K)$

$$\Xi_{A-Rayleigh}[\mathbf{r} \mid H_i] = E_{\{s_k^{(i)}\}_{k=1}^K} \left[\left(1 + \frac{\Omega T \eta_K^{(i)}}{N}\right)^{-1} \exp\left\{ \left(1 + \frac{\Omega T \eta_K^{(i)}}{N}\right)^{-1} \frac{\Omega \mid \Psi_K^{(i)} \mid^2}{N^2} \right\} \right].$$

where M_i is the number of points in signal constellation, $\eta_K^{(i)} = \sum_{k=1}^{K} \mid s_k^{(i)} \mid^2$, $\Psi_K^{(i)} = \sum_{k=1}^{K} R_k^{(i)}$,

$\Omega = E[\alpha^2]$ is the average fading power and $R_k^{(i)} = \int_{(k-1)T_0}^{kT_0} r(t) s_k^{(i)^*}(t) dt, \ k = 1, \dots, K, \ i = 1, \dots, N_{\mathrm{mod}}.$

LB Approach: ALRT (cont'd)

▪ *Remarks on ALRT for MC*

✓ When increasing the number of unknown parameters, the computation of the LF becomes very difficult, even mathematically intractable. Thus, in many cases of practical interest, the ALRT-based classifier becomes impractical.

✓ The ALRT-based classifier requires a priori knowledge of the distribution of the unknown parameters.

✓ In addition, it usually results in structures that may not be applicable to environments other than the ones assumed.

✓ The ALRT-based classifier provides an optimum solution, in the sense that it minimizes the probability of misclassification.

✓ With no unknown parameters in AWGN (ideal case), the ALRT-based classifier represents a benchmark, against which performance of other classifiers is compared.

LB Approach: GLRT and HLRT

- **Unknowns** $\mathbf{u}_i = [\varphi \ \{s_k^{(i)}\}_{k=1}^{K}]^{\dagger}$, **AWGN**

GLRT [Panagiotou, Anastasopoulos, and Polydoros, 2000]

$$\Xi_{G-CP}[\mathbf{r} \mid H_i] = \max_{\varphi} \left\{ \sum_{k=1}^{K} \max_{\mathbf{s}_\mathbf{k}^{(\mathbf{i})}} \left\{ \mathrm{Re}[s_k^{(i)*} r_k e^{-j\varphi}] - 2^{-1}\alpha^2 T \mid s_k^{(i)} \mid^2 \right\} \right\}.$$

HLRT [Panagiotou, Anastasopoulos, and Polydoros, 2000]

$$\Xi_{H-CP}[\mathbf{r} \mid H_i] = \max_{\varphi} \left\{ \prod_{k=1}^{K} \mathbf{E}_{\mathbf{s}_\mathbf{k}^{(\mathbf{i})}} \left[\exp\left[2\alpha N^{-1} \mathrm{Re}[s_k^{(i)*} r_k e^{-j\varphi}] - \alpha^2 T N^{-1} \mid s_k^{(i)} \mid^2 \right] \right] \right\}.$$

LB Approach: GLRT and HLRT (cont'd)

▪ *Remarks on GLRT and HLRT for MC*

✓ GLRT displays some implementation advantages over ALRT and HLRT, as it avoids the calculation of exponential functions and does not require the knowledge of noise power to compute the LF.

✓ However, with GLRT maximization over data symbols can lead to equal LFs for nested signal constellations, e.g., 16-QAM and 64-QAM, which in turn leads to incorrect classification [Panagiotou, Anastasopoulos, and Polydoros, 2000] .

✓ Averaging over data symbols in HLRT removes the nested constellations problem of GLRT.

✓ GLRT and HLRT do not depend on the distribution chosen for the unknown parameters (usually, with HLRT, average is performed over unknown symbols only).

LB Approach: HLRT (cont'd)

- **Unknowns** $\mathbf{u}_i = [\alpha \ \varphi \ N \ \{s_k^{(i)}\}_{k=1}^{K}]^\dagger$ **, Block-Fading Channel**

HLRT [Dobre and Hameed, 2006]

$$\Xi_{H-Rayleigh}[\mathbf{r} \mid H_i] = \left(\frac{K}{\pi e M_i \|\mathbf{r}\|^2} \right)^K \sum_{m=1}^{M_i^K} \frac{1}{(1-\rho_m^{(i)2})^K}$$

$$\rho_m^{(i)} = |\mathbf{r}^H \mathbf{s}_m^{(i)}| / (\|\mathbf{r}\| \cdot \|\mathbf{s}_m^{(i)}\|)$$

- ***Complexity*** $\mathcal{O}(M_i^K)$

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LB Approach: HLRT (cont'd)

- ***Further Remarks on HLRT for MC***

  ✓ With several unknown parameters, HLRT is not a good solution either, as it suffers of high computational complexity .

  ✓ **Low-complexity estimators** can be used instead, leading to the so-called **Quasi-HLRT** classifiers.

LB Approach: QHLRT

- **Unknowns** $\mathbf{u}_i = [\alpha \ \varphi \ N \ \{s_k^{(i)}\}_{k=1}^{K}]^{\dagger}$ **, Block-Fading Channel**

QHLRT [Dobre and Hameed, 2006]

With **Method-of-Moments (MoM) estimates** of the unknown parameters, the LF is

$$\Xi_{QH-Rayleigh}[\mathbf{r} \mid H_i] = \prod_{k=1}^{K} E_{s_k^{(i)}} \left[\frac{1}{\pi \hat{N}^{(i)}} \exp\{-\frac{1}{\hat{N}^{(i)}} \mid r_k - \hat{\alpha}^{(i)} e^{j\hat{\varphi}^{(i)}} s_{k,m}^{(i)} \mid^2\} \right]$$

$$\hat{\alpha}^{(i)} = \left(\frac{\hat{M}_{42}^2 - 2\hat{M}_{21}^2}{b^{(i)} - 2} \right)^{1/4} \left(\mathrm{E}[\mid s_k^{(i)} \mid^2] \right)^{-1/2}$$

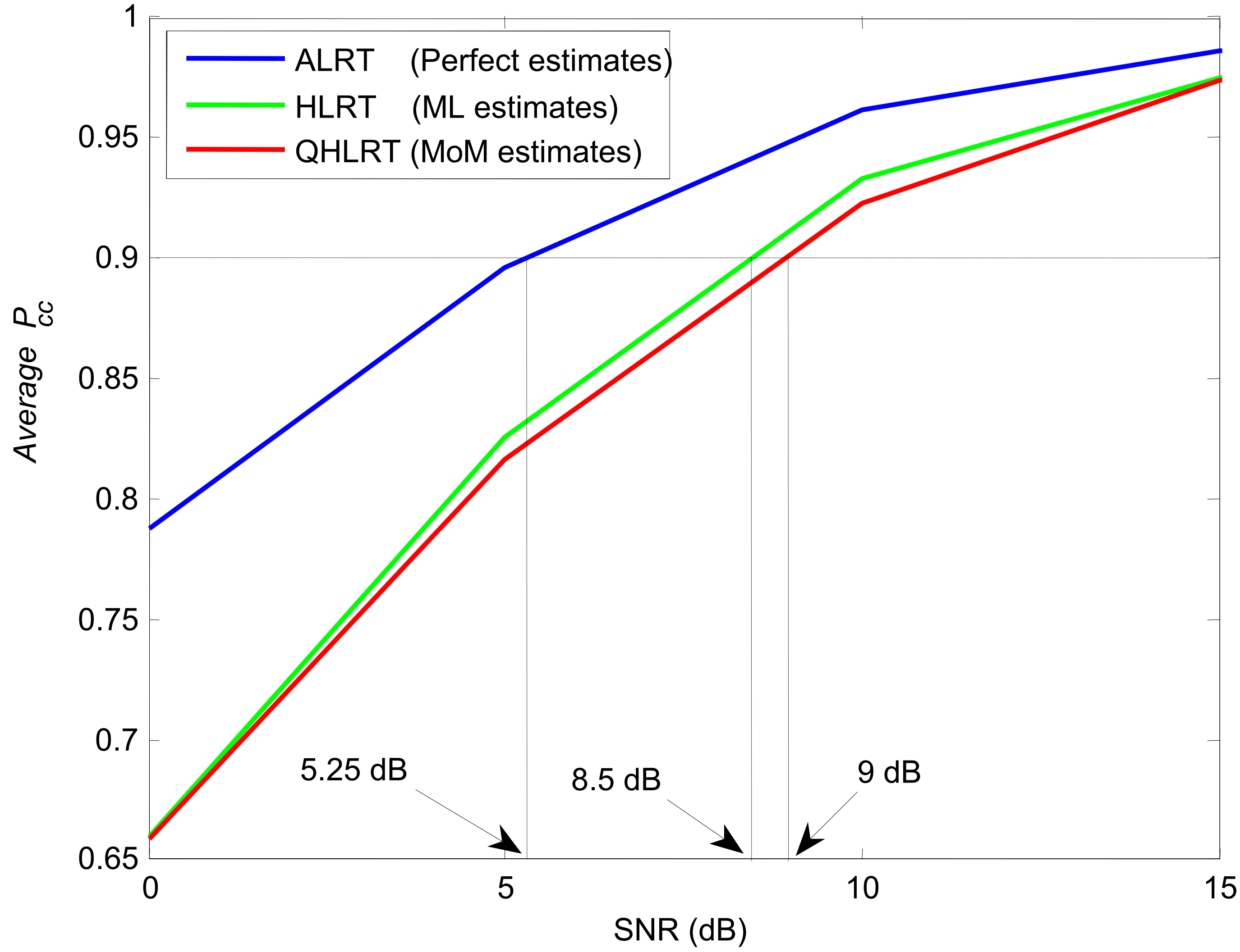
$$\hat{N}^{(i)} = \hat{M}_{21} - \left(\frac{\hat{M}_{42}^2 - 2\hat{M}_{21}^2}{b^{(i)} - 2} \right)^{1/2}$$

$$\hat{\varphi}_{M\text{-}PSK}^{(i)} = M_i^{-1} \arg(\sum_{k=1}^{K} r_k^{M_i})$$

$$\hat{\varphi}_{M\text{-}QAM}^{(i)} = 4^{-1} \arg(\sum_{k=1}^{K} r_k^{4})$$

LB Approach: QHLRT (cont'd)

HLRT Versus QHLRT in Rayleigh Fading, *K*=10 (BPSK/QPSK)



LB Approach: QHLRT

- ***Remarks on QHLRT for MC***

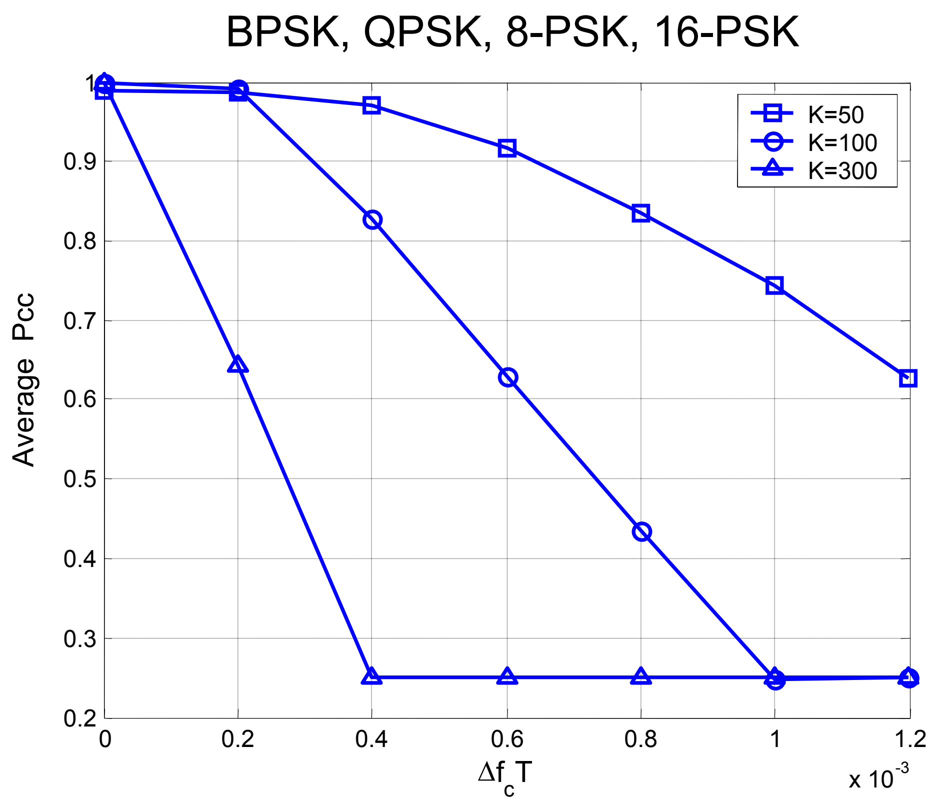
✓ The QHLRT-based classification algorithm is less complex, applicable to any distribution of the unknown parameters, yet providing a good classification performance.

✓ Methods for joint parameter estimation, less complex, yet accurate, need to be devised.

LB Approach: Sensitivity Analysis

- **Unknowns** $\mathbf{u}_i = [\{s_k^{(i)}\}_{k=1}^{K}]$ **, AWGN**

Carrier frequency offset, Δf_c $r_{SCLD}(t) = \alpha e^{j\varphi} e^{j2\pi\Delta f_c t} \sum_{k=1}^{K} s_k^{(i)} u_T(t-kT) + w(t)$



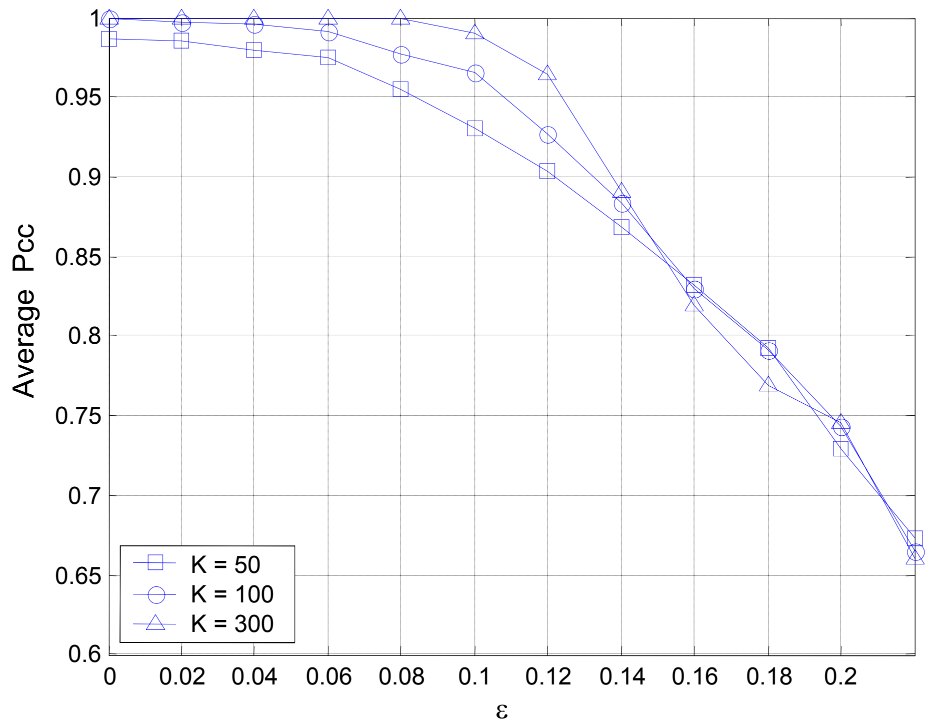
SNR=12dB

LB Approach: Sensitivity Analysis (cont'd)

- **Unknowns** $\mathbf{u}_i = [\{s_k^{(i)}\}_{k=1}^{K}]$ **, AWGN**

Synchronization errors, ε $r_{SCLD}(t) = \alpha e^{j\varphi} \sum_{k=1}^{K} s_k^{(i)} u_T(t - kT - \boldsymbol{\varepsilon T}) + w(t)$

BPSK, QPSK, 8PSK, 16PSK



SNR=12dB

LB Approach: Sensitivity Analysis (cont'd)

- ***Remarks on LB for MC***

✓ The LB-based classifier is sensitive to model mismatches, such as carrier frequency and timing errors. Here we have presented the individual effect of model mismatches on the classification performance. Apparently, the performance will degrade further under the cumulative effect of model mismatches.

LB Approach: Conclusion

- ***Remarks on the LB Approach to MC***

  ✓ The ALRT-, GLRT- and HLRT- based algorithms suffer of high computational complexity.

  ✓ The QHLRT-based classification algorithm is less complex, applicable to any distribution of the unknown parameters, yet providing a good classification performance.

  ✓ Methods for joint parameter estimation, less complex, yet accurate, need to be devised.

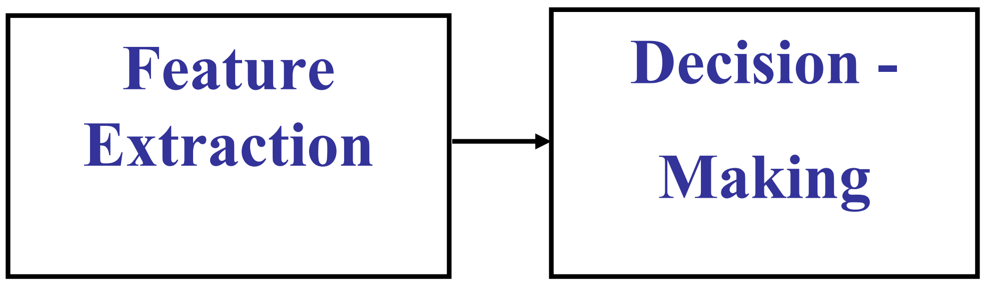
  ✓ The LB-based classifier is sensitive to model mismatches, such as carrier frequency and timing errors.

  ✓ The LB-based classifier is not suitable to classify different modulation types, such as digital against analog modulations.

Feature-Based (FB) Approach

FB Approach

- ***Feature-Based Classifier***



✓ ***The features*** show unique characteristics for every specific modulation.

✓ ***Decision-making*** is based on the difference of the features for diverse modulations.

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FB Approach (cont'd)

- **Examples of features:**

FB Method

- Instantaneous Amplitude, Phase, and Frequency
- Signal Statistics: Moments, Cumulants, Cyclic Cumulants (CC)
- Wavelet Transform
- Information in the Zero-Crossing Sequence

- **Examples of decision criteria:**

  - Euclidian distance between estimated and prescribed values of the features, - Correlation between estimated and theoretical features,
  - The probability density function of a feature estimator.

FB Approach: Signal Cyclostationarity

We have explored signal cyclostationarity for MC.

Why Signal Cyclostationarity?

- Cyclic statistics (CS) provide supplementary information through the cycle frequency domain.
- CS-based features can be used to classify a large number of modulation types.
- CS-based features can be robust to model mismatches.

Signal Cyclostationarity

for Modulation Classification (MC)

- Signal Cyclostationarity: Definitions
- Exploitation of Signal Cyclostationarity for MC

Signal Cyclostationarity:

Definitions

FB Approach: Signal Cyclostationarity - Definitions

Cyclostationary Signals

- **Definition**: ***A stochastic process r(t) is said to be cyclostationary of order n (for a given conjugation configuration, i.e., q conjugate) if its cumulants up to order n (assuming they exist) are (almost)-periodic functions of time.***

  The nth-order/q-conjugate moments are also (almost)-periodic functions of time.

- **Time-Variant and Cyclic Statistics** [Spooner and Gardner, 1994]

  Time-varying nth-order/q-conjugate cumulant

  $$c_r(t;\boldsymbol{\tau})_{n,q} = \sum_{\kappa_{n,q}} c_r(\beta;\boldsymbol{\tau})_{n,q} e^{j2\pi\beta t}$$

  The nth-order/q-conjugate cyclic cumulant (CC) the cycle frequency (CF) β (**Used in Our Work**)

  $$c_r(\beta;\boldsymbol{\tau})_{n,q} = \lim_{T\to\infty} \frac{1}{T} \int_{-T/2}^{T/2} c_r(t;\boldsymbol{\tau})_{n,q} e^{-j2\pi\beta t} dt$$

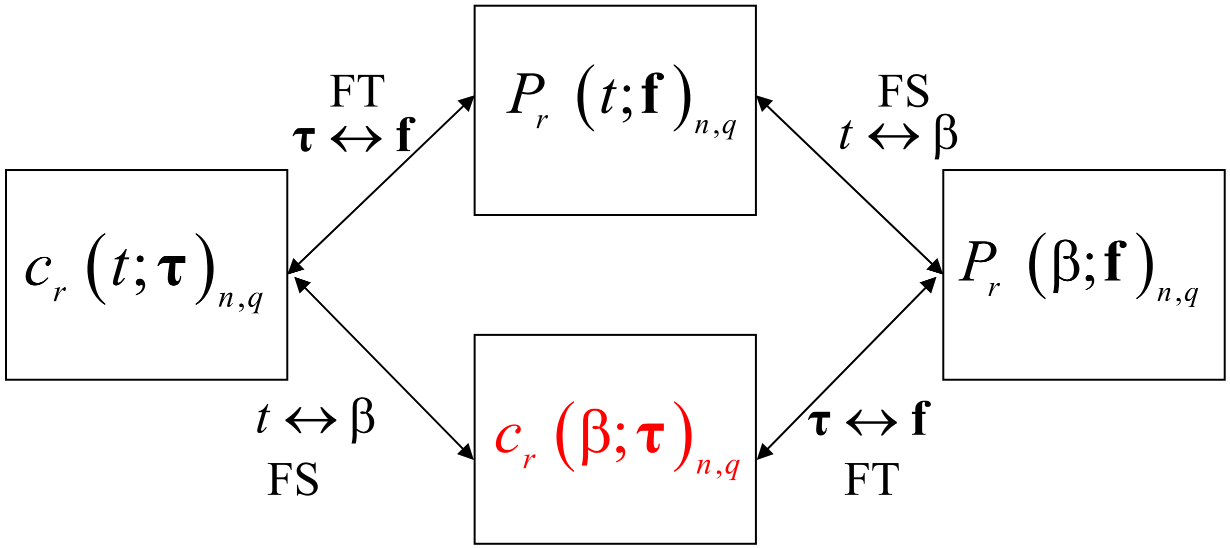
  The (nth-order) cycle frequencies

  $$\kappa_{n,q} = \{\beta \mid c_r(\beta;\boldsymbol{\tau})_{n,q} \neq 0\}$$

  where $\boldsymbol{\tau} = [\tau_1 \ldots \tau_{n-1}]^{\dagger}$ is the delay-vector.

FB Approach: Signal Cyclostationarity - Definitions

- *Cyclostationary Signals (cont'd)*



Interrelationships between time-, cyclic-, and frequency-domain

$c_r(t;\boldsymbol{\tau})_{n,q}$ ***The nth-order/q conjugate time-varying cumulant (q conjugations)***

$c_r(\beta;\boldsymbol{\tau})_{n,q}$ ***The nth-order/q conjugate cyclic cumulant (CC) at cycle frequency (CF) β***

$P_r(t;\mathbf{f})_{n,q}$ ***The nth-order/q conjugate time-varying cumulant polyspectrum***

$P_r(\beta;\mathbf{f})_{n,q}$ ***The nth-order/q conjugate cyclic cumulant polyspectrum (CP) at CF β***

Exploitation of Signal Cyclostationarity for Modulation Classification (MC)

FB Approach: Signal Cyclostationarity for MC (cont'd)

GOAL*: *DEVELOP A GENERAL CLASSIFIER BASED ON SIGNAL CYCLOSTATIONARITY

Exploitation of first-order cyclostationarity

AM (detection of a single CF)

***M*-ary FSK (detection of *M* CFs)**

OFDM, CP-SCLD, SCLD (no first-order CFs)

Exploitation of second-order cyclostationarity

OFDM

CP-SCLD

Exploitation of higher-order cyclostationarity

Modulation Type

SCLD

Exploitation of higher-order cyclostationarity

Modulation Type

SCLD: Single Carrier Linear Digital Modulation

CP-SCLD: Cyclically Prefixed SCLD

OFDM: Orthogonal Frequency Division Multiplexing

FSK: Frequency Shift Keying

AM: Amplitude Modulation

FB Approach: Signal Cyclostationarity for MC (cont'd)

- ***Signal Models***

$$r_{FSK}(t) = \alpha e^{j\varphi} e^{j2\pi\Delta f_c t} \sum_k e^{j2\pi f_d s_k^{(i)}(t-kT-\varepsilon T)} g(t-kT-\varepsilon T) + w(t)$$

$$r_{AM}(t) = \alpha e^{j\varphi} e^{j2\pi\Delta f_c t} (1 + \mu_A m(t - t_0)) + w(t)$$

ε	is the timing offset	Δf_c	is the carrier frequency offset
φ	is the phase	f_d	is the frequency deviation
α	is the signal power	i	denotes the modulation format
T	is the symbol period	$w(t)$	is complex zero-mean additive Gaussian noise
		t_0	time delay
$g(t)$	is the pulse shape	μ_A	modulating index

$m(t)$ is the zero-mean modulating signal convolved with Rx filter impulse response

$s_k^{(i)}$ is the symbol transmitted within the *k*th period, with values drawn from an alphabet $A_{MFSK}=\{\pm 1, \pm 3, \ldots, \pm(M-1)\}$

FB Approach: Signal Cyclostationarity for MC (cont'd)

▪ *Signal Models (cont'd)*

$$r_{\text{SCLD}}(t) = \alpha e^{j\varphi} e^{j2\pi \Delta f_c t} \sum_{k=-\infty}^{\infty} s_k^{(i)} g(t - kT - \varepsilon T) + w(t)$$

$$r_{\text{CP-SCLD}}(t) = \alpha e^{j\varphi} e^{j2\pi \Delta f_c t} \sum_{b=-\infty}^{\infty} \sum_{l=0}^{N+L-1} s_{b,l}^{(i)} g(t - b(N+L)T - lT - \varepsilon T) + w(t)$$

$$\mathbf{s}_b^{(i)} = [\underbrace{s_{b.N-L+1}^{(i)} \quad \cdots \quad s_{b,N}^{(i)}}_{\text{cyclic prefix}} \quad \underbrace{s_{b,1}^{(i)} \quad \cdots \quad s_{b,N}^{(i)}}_{\text{information data symbols}} \quad]$$

N	is the number of information data symbols in a block	*L*	is the number of symbols in the cyclic prefix
b	is the block index	*l*	is the symbol index within a block
$s_{b,l}^{(i)}$	is the symbol transmitted within the *l*th symbol period of block *b*, with modulation *i*		

FB Approach: Signal Cyclostationarity for MC (cont'd)

- ***Signal Models (cont'd)***

$$r_{\mathrm{OFDM}}(t) = \alpha e^{j\varphi} e^{j2\pi \Delta f_c t} \sum_{k=-\infty}^{\infty} \sum_{v=0}^{V-1} s_{u,k}^{(i)} e^{j2\pi k v \Delta f_V (t-kT-\varepsilon T)} g(t-kT-\varepsilon T) + w(t)$$

V	number of subcarriers	Δf_V	frequency separation between two adjacent subcarriers

T symbol period; OFDM: $T = T_u + T_{cp}$, $T_u = 1/\Delta f_V$ and T_{cp} is the cyclic prefix.

$s_{v,k}^{(i)}$ is the symbol transmitted over the *k*th symbol interval and *v*th subcarrier, with *i* denoting the modulation type on each subcarrier.

The signals are oversampled at the receive-side.

FB Approach: Signal Cyclostationarity for MC (cont'd)

▪ *First-order Cyclic Cumulant (CC) of Discrete-time Signals*

[Dobre, Rajan, and Inkol, 2007]

$$c_{r_{FSK}}(\beta)_{1,0} = M^{-1}\alpha\, e^{j\varphi} e^{-j2\pi\gamma f_s T\varepsilon}$$

$$\kappa_{1,0}^{FSK} = \{\, \beta \in [-1/2, 1/2) \mid \beta = \Delta f_c f_s^{-1} + \gamma,\ \gamma = pT^{-1} f_s^{-1},\ p = \pm l, \ldots, \pm(M-1)l \}$$

if $f_d = lT^{-1}$.

***M*-FSK**: *M* first-order cycle frequencies.

$$c_{r_{AM}}(\beta)_{1,0} = \alpha e^{j\varphi}$$

AM: A single first-order cycle frequencies.

$$\kappa_{1,0}^{AM} = \{\, \beta \in [-1/2, 1/2) \mid \beta = \Delta f_c f_s^{-1} \}$$

The first-order CC of the other signals, i.e., **SCLD, CP-SCLD, and OFDM**, equals zero. In other words, there are no first-order cycle frequencies.

Discriminating Signal Feature: Number of Detected First-Order Cycle Frequencies [Dobre, Rajan, and Inkol, 2007]

FB Approach: Signal Cyclostationarity for MC (cont'd)

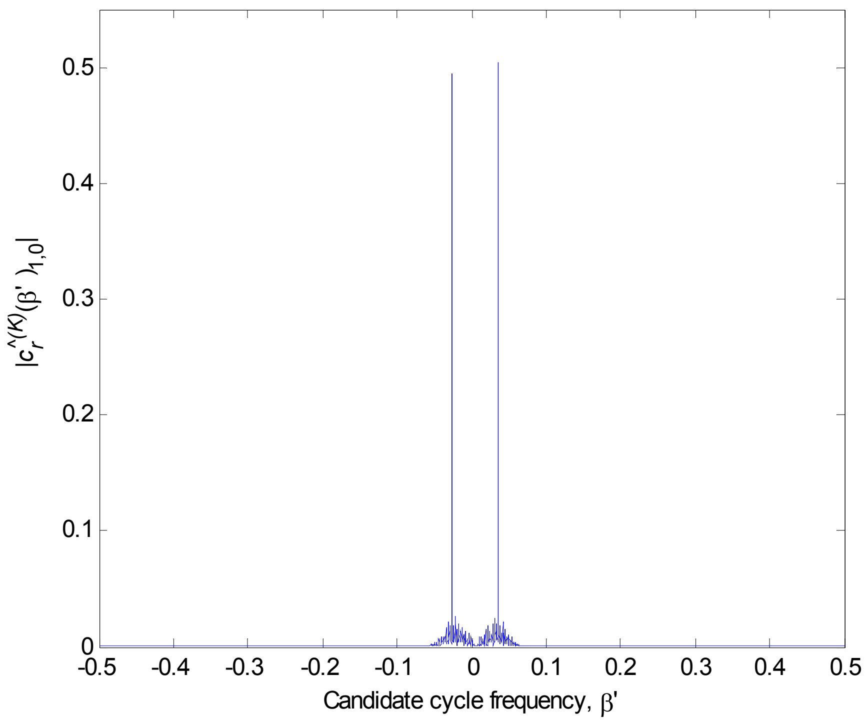
First-order CC of Discrete-time Signals (cont'd)

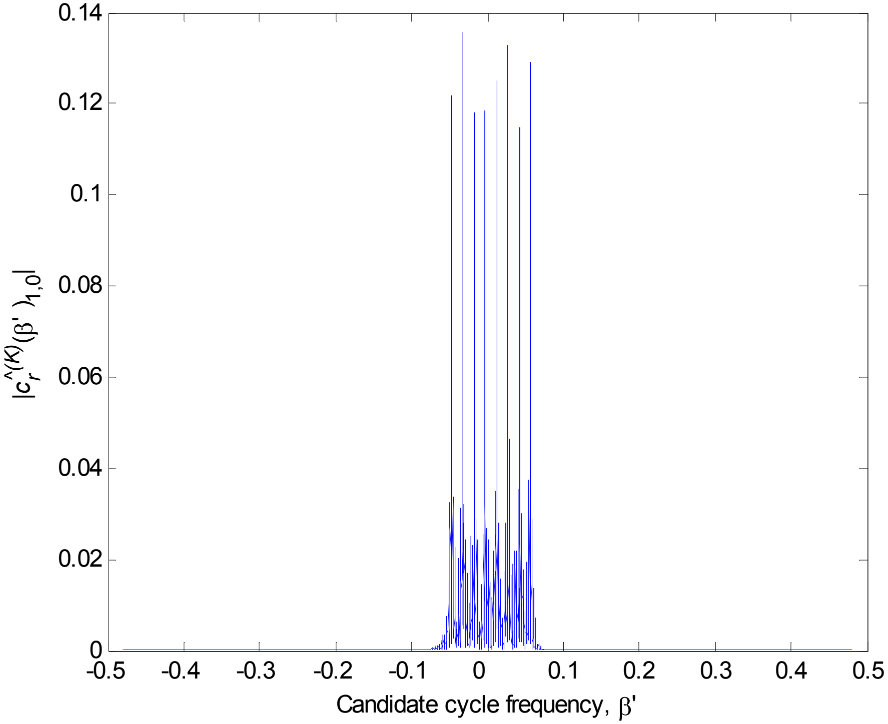
2-FSK $|c_{r_{FSK}}(\beta)_{1,0}| = \alpha M^{-1},\ \alpha = 1,\ M = 2$

$$\beta = \Delta f_c f_s^{-1} \pm T^{-1} f_s^{-1}$$

8-FSK $|c_{r_{FSK}}(\beta)_{1,0}| = \alpha M^{-1},\ \alpha = 1,\ M = 8$

$$\beta = \Delta f_c f_s^{-1} + pT^{-1} f_s^{-1},\ p = \pm 1, \pm 3, \pm 5, \pm 7$$





SNR=20dB

1 sec observation interval

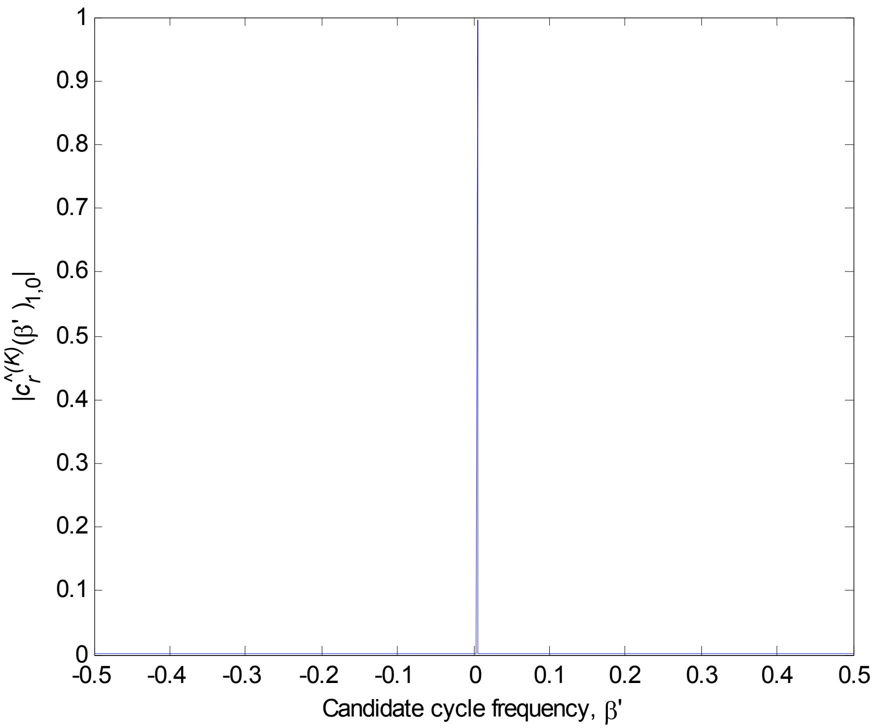
▪ *First-order CC of Discrete-time Signals (cont'd)*

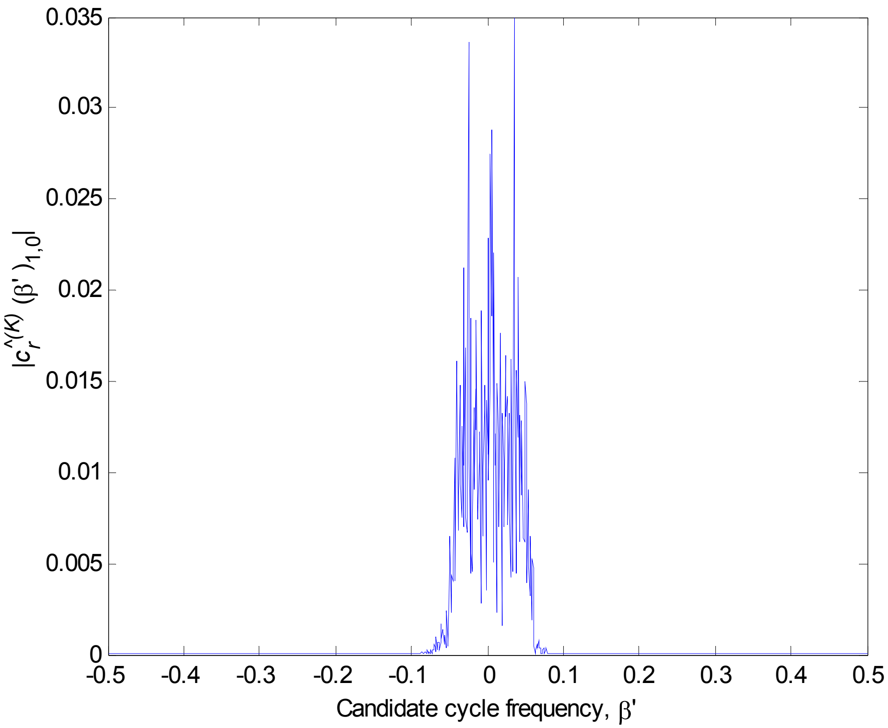
AM $|c_{r_{AM}}(\beta)_{1,0}| = \alpha, \ \alpha = 1$

$\beta = \Delta f_c f_s^{-1}$

2-PSK $|c_{r_{2-PSK}}(\beta')_{1,0}| = 0$

any β'





SNR=20dB

1 sec observation interval

FB Approach: Signal Cyclostationarity for MC (cont'd)

- **_Second-order/ One-conjugate CC of Discrete-time Signals_**

$$c_{r_{\mathrm{SCLD}}}(\beta;\tau)_{2,1} = \alpha^2 c_{s,2,1}\rho^{-1} e^{-j2\pi\beta\varepsilon\rho} e^{j\frac{2\pi}{\rho}\Delta f_c T\tau} \sum_m g(m) g^*(m+\tau) e^{-j2\pi\beta m} + c_w(\beta;\tau)_{2,1}$$

$$\kappa_{2,1}^{\mathrm{SCLD}} = \{\ \beta \in [-1/2, 1/2) \mid \ \beta = l\rho^{-1},\ l \text{ is an integer and } \rho \text{ is the oversampling factor}\}$$

$$c_{r_{\mathrm{CP\text{-}SCLD}}}(\beta;\tau)_{2,1} = \begin{cases} \alpha^2 c_{s,2,1}\rho^{-1} e^{-j2\pi\beta\varepsilon\rho} e^{-j\frac{2\pi}{\rho}\Delta f_c T\tau} \sum\limits_{m=-\infty}^{\infty} g(m) g^*(m+\tau) e^{-j2\pi\beta m} + c_w(\beta;\tau)_{2,1}, \\ \text{for delays around } \tau = 0 \text{ and } \beta = k\rho^{-1},\ k \text{ integer} \\ \alpha^2 c_{s,2,1}[(N+L)\rho]^{-1} e^{-j2\pi\beta\varepsilon\rho} e^{-j\frac{2\pi}{\rho}\Delta f_c T\tau} \sum\limits_{l=0}^{L-1}\sum\limits_{m=-\infty}^{\infty} g(m-l\rho) g^*(m-l\rho-N\rho+\tau) e^{-j2\pi\beta m} + c_w(\beta;\tau)_{2,1}, \\ \text{for delays around } \tau = \rho N \text{ and } \beta = b[(N+L)\rho]^{-1},\ b \text{ integer} \\ \alpha^2 c_{s,2,1}[(N+L)\rho]^{-1} e^{-j2\pi\beta\varepsilon\rho} e^{-j\frac{2\pi}{\rho}\Delta f_c T\tau} \sum\limits_{l=0}^{L-1}\sum\limits_{m=-\infty}^{\infty} g(m-l\rho) g^*(m-l\rho+N\rho+\tau) e^{-j2\pi\beta m} + c_w(\beta;\tau)_{2,1}, \\ \text{for delays around } \tau = -\rho N \text{ and } \beta = b[(N+L)\rho]^{-1},\ b \text{ integer} \end{cases}$$

[Dobre, Zhang, Rajan, and Inkol, 2008]

FB Approach: Signal Cyclostationarity for MC (cont'd)

- ***Second-order/ One-conjugate CC of Discrete-time Signals (cont'd)***

$$c_{r_{\text{OFDM}}}(\beta;\tau)_{2,1} = \alpha^2 c_{s,2,1} D^{-1} e^{-j2\pi\beta\varepsilon D} e^{j\frac{2\pi}{\rho V}\Delta f_c T_u \tau} \Xi_V(\tau) \sum_m g(m) g^*(m+\tau) e^{-j2\pi\beta m} + c_w(\beta;\tau)_{2,1}$$

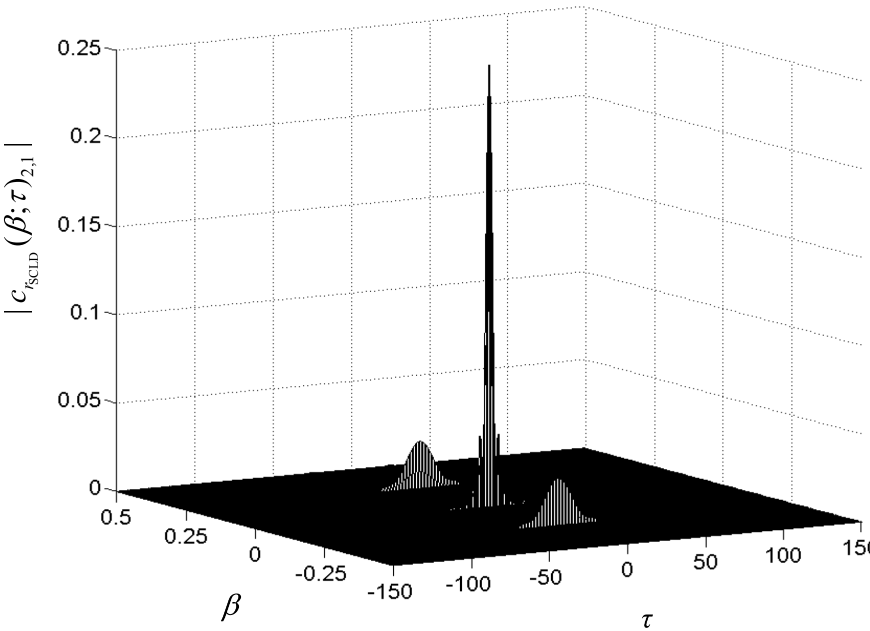
$$\kappa_{2,1}^{\text{OFDM}} = \{\beta \in [-1/2, 1/2) \mid \beta = lD^{-1},\ l \text{ is an integer and } D \text{ is the oversampling factor}\}$$

$$\Xi_V(\tau) = \sum_{v=0}^{V-1} e^{j\frac{2\pi}{\rho V} v\tau} = e^{j\frac{\pi}{\rho V}(V-1)\tau} \frac{\sin(\pi\tau/\rho)}{\sin(\pi\tau/\rho V)}$$

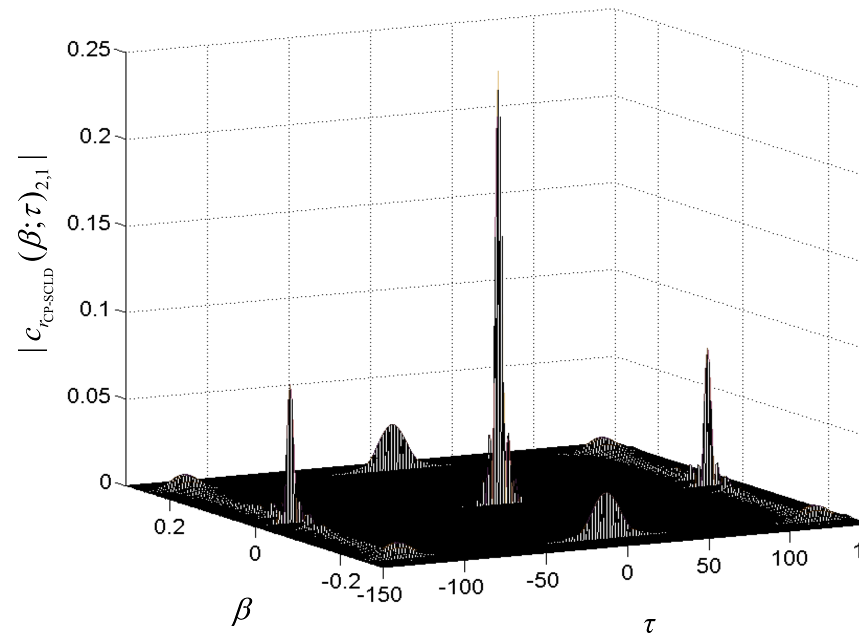
The additional factor $\Xi_V(\tau)$ yields significant peaks in the second order/one conjugate CC at delays equals to $\tau = v\rho V$, v integer.

FB Approach: Signal Cyclostationarity for MC (cont'd)

- *Second-order/ One-conjugate CC of Discrete-time Signals (cont'd)*



a)

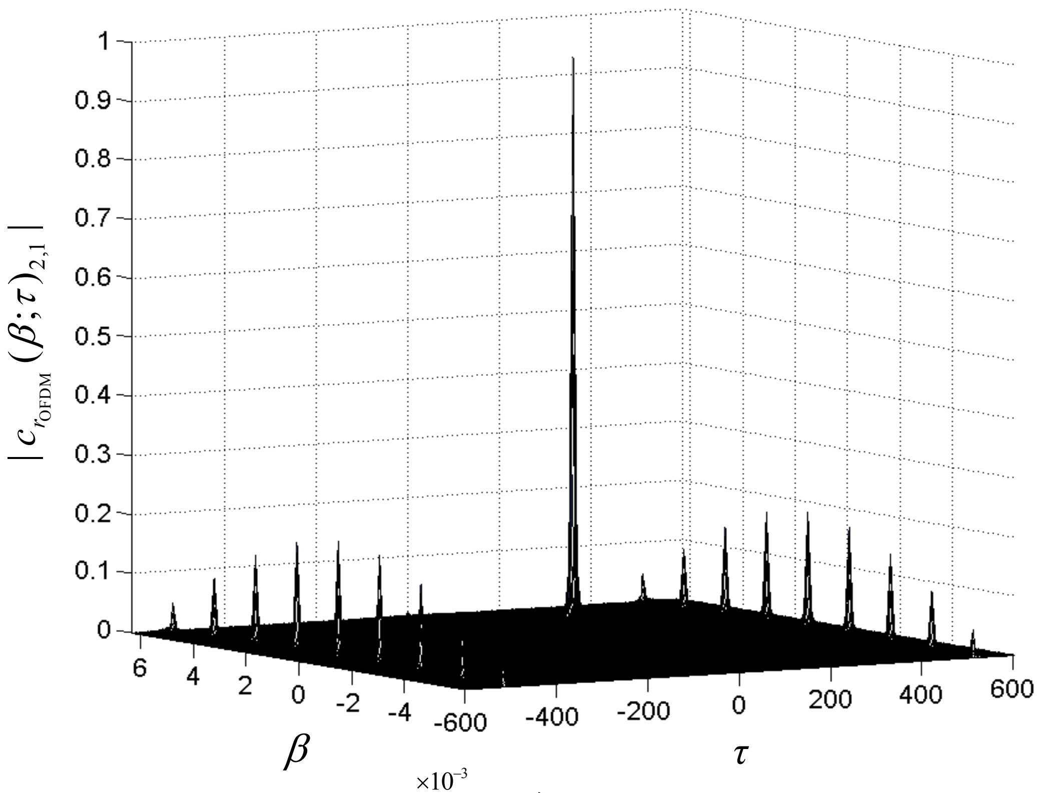


b)

The magnitude of second-order / one-conjugate CC versus cycle frequency and delay (in the absence of noise) for a) SCLD and b) CP-SCLD signals.

FB Approach: Signal Cyclostationarity for MC (cont'd)

- ***Second-order/ One-conjugate CC of Discrete-time Signals (cont'd)***



c)

The magnitude of second-order/ one-conjugate CC versus cycle frequency and delay (in the absence of noise) for OFDM signals.

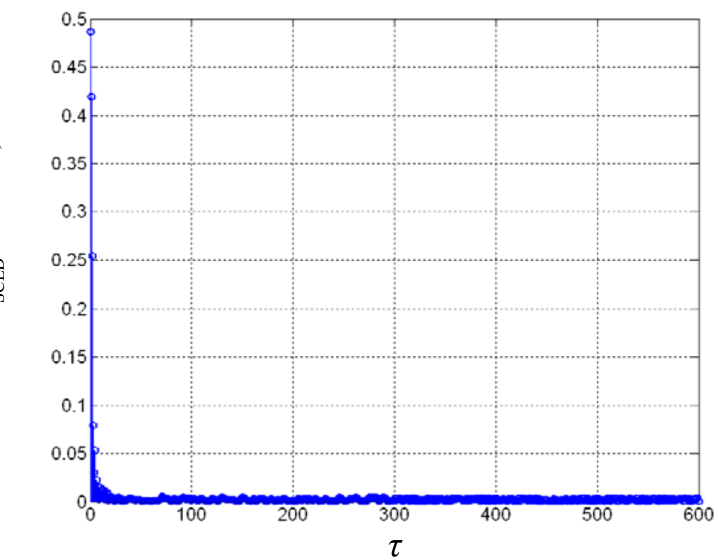
FB Approach: Signal Cyclostationarity for MC (cont'd)

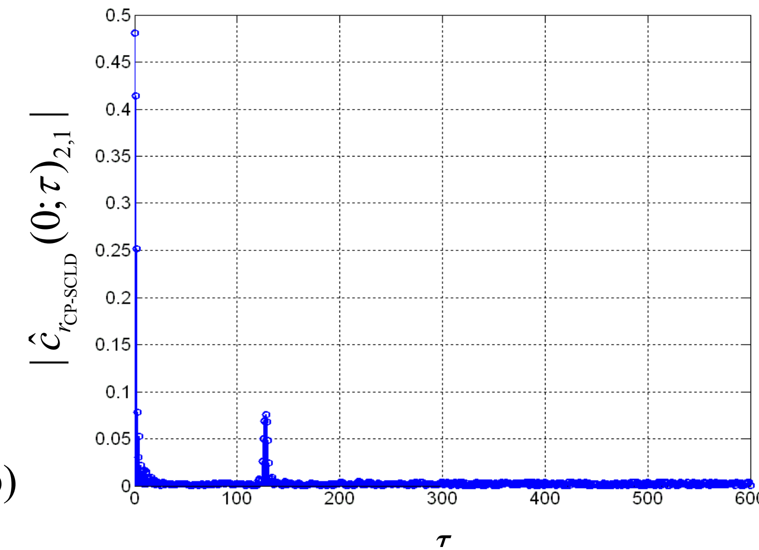
- ***Second-order/ One-conjugate CC of Discrete-time Signals (cont'd)***

- The second-order/ one-conjugate CC of the SCLD signals is non-zero only for delays around zero. This differs from the case of CP-SCLD and OFDM signals, in which non-zero values are also obtained for delays around $\pm\rho N$ and $\pm\rho V$, respectively, due to the existence of the cyclic prefix (CP).
- For the SCLD signals, peaks in the CC magnitude appear at zero and $\pm\rho^{-1}$ CFs for delays around zero. The CC and CFs of the CP-SCLD signals are the same as for SCLD signals for delays around zero. For the OFDM signals, the CC magnitude at non-zero CFs and zero delay is close to zero.
- For the OFDM signals, the peaks in the CC magnitude which appear at delays around $\pm\rho V$, are at CFs integer multiples of D^{-1}. For the CP-SCLD signals, such peaks appear at delays around $\pm\rho N$ and CFs integer multiples of $[(N+L)\rho]^{-1}$.

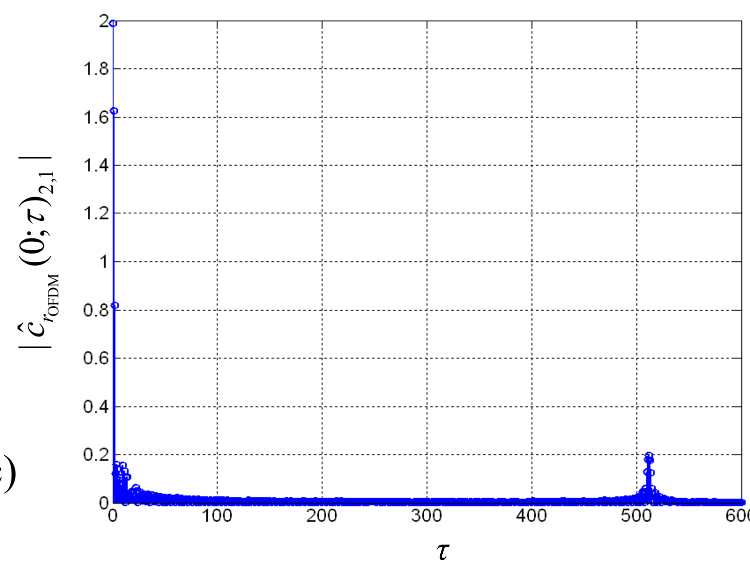
FB Approach: Signal Cyclostationarity for MC (cont'd)

- *Second-order/ One-conjugate CC of Discrete-time Signals (cont'd)*
  - *SCLD against CP-SCLD and OFDM*

a)


b)


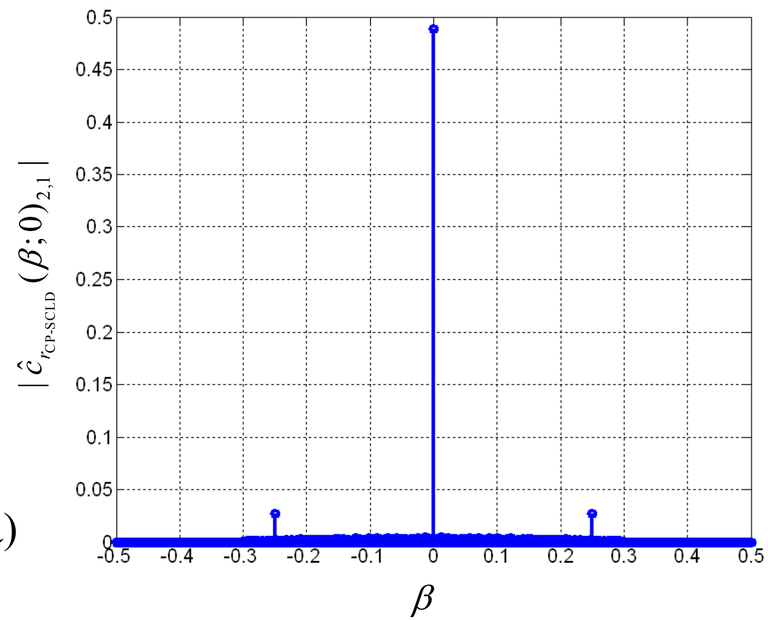
The magnitude of estimated second-order / one-conjugate CC versus positive delays, at zero CF and 0 dB SNR, for a) SCLD, b) CP-SCLD, and c) OFDM signals.

c)


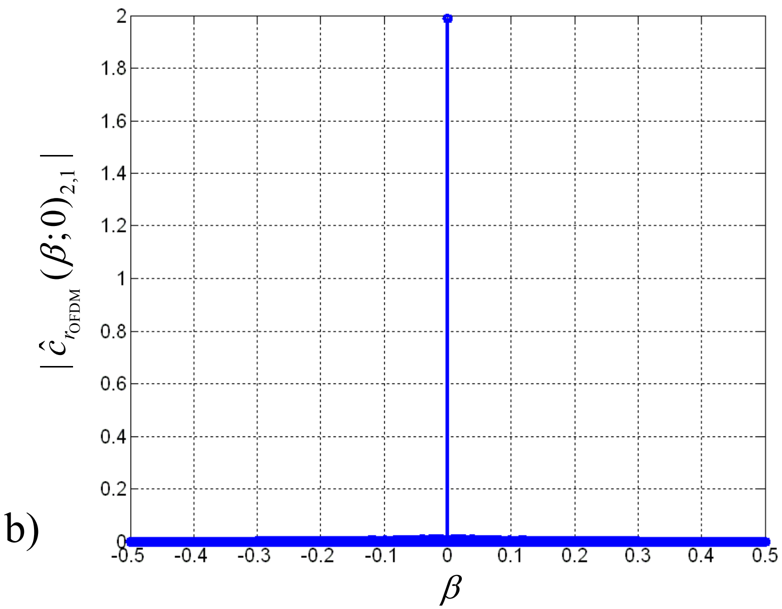
FB Approach: Signal Cyclostationarity for MC (cont'd)

- **Second-order/ One-conjugate CC of Discrete-time Signals (cont'd)**
  - **CP-SCLD against OFDM**

a)



b)



The magnitude of estimated second-order (one-conjugate) CC over the cycle frequency domain, at zero delay and 0 dB SNR, for a) CP-SCLD and b) OFDM signals.

FB Approach: Signal Cyclostationarity for MC (cont'd)

- ***CC-Based Classification Algorithm***

(Example: SCLD against CP-SCLD and OFDM)

Step 1: The magnitude of the second-order/ one-conjugate CC of the baseband received signal is estimated at zero CF and over a range of positive delay values.

Over the considered delay range, we select that delay value for which the CC magnitude reaches a maximum.

Step 2: A cyclostationarity test [Dandawate and Giannakis, 1995] is used to check whether or not zero is indeed a CF for the delay selected in Step 1.

If $\beta = 0$ is found to be a CF, then we decide that the signal belongs to the class OFDM and CP-SCLD; otherwise, we declare it as SCLD.

FB Approach: Signal Cyclostationarity for MC (cont'd)

- ***Test to Verify the Presence of a Cycle Frequency*** [Dandawate and Giannakis 95]

H_0 : the tested candidate CF $\beta' = 0$ is not a CF.

H_1 : the tested candidate CF $\beta' = 0$ is a CF.

Steps (test applied for zero CF):

<u>Step 1</u>: Estimation of the CC at candidate CF, β', from K samples, $\hat{c}_r^{(K)}(\beta';\tau)_{2,1}$ and calculation of $\hat{\mathbf{c}}_{r,2,1} := [\mathrm{Re}\{\hat{c}_r^{(K)}(\beta';\tau)_{2,1}\} \;\; \mathrm{Im}\{\hat{c}_r^{(K)}(\beta';\tau)_{2,1}\}]$

<u>Step 2</u>: Calculate $\mathcal{T}_{2,1} = K\hat{\mathbf{c}}_{r,2,1}\hat{\Sigma}_{r,2,1}^{-1}\hat{\mathbf{c}}_{r,2,1}^{\dagger}$, where $\hat{\Sigma}_{r,2,1}$ is the estimate of

$$\Sigma_{r,2,1} = \begin{bmatrix} \mathrm{Re}\left\{(Q_{2,0}+Q_{2,1})/2\right\} & \mathrm{Im}\left\{(Q_{2,0}-Q_{2,1})/2\right\} \\ \mathrm{Im}\left\{(Q_{2,0}+Q_{2,1})/2\right\} & \mathrm{Re}\left\{(Q_{2,0}-Q_{2,1})/2\right\} \end{bmatrix}, \text{ with}$$

$$Q_{2,0} := \lim_{K\to\infty} \mathrm{Cum}[\hat{c}_r^{(K)}(\beta';\tau)_{2,1}, \hat{c}_r^{(K)}(\beta';\tau)_{2,1}]$$

$$Q_{2,1} := \lim_{K\to\infty} \mathrm{Cum}[\hat{c}_r^{(K)}(\beta';\tau)_{n,q}, \hat{c}_r^{*}(\beta';\tau)_{2,1}]$$

FB Approach: Signal Cyclostationarity for MC (cont'd)

- ***Test to Verify the Presence of a Cycle Frequency (cont'd)***

Step 3: The statistic is compared again a threshold for decision-making.

If $\mathcal{T}_{2,1} \geq \Gamma$

$$\Downarrow$$

One decides that the tested candidate CF is indeed a CF for the selected delay.

Otherwise it is not declared a CF.

Threshold Setting: $P_F = \Pr\{\mathcal{T}_{2,1} \geq \Gamma \mid H_0\}$

$\mathcal{T}_{2,1}$ has an asymptotic χ^2 distribution with two degrees of freedom under H_0.

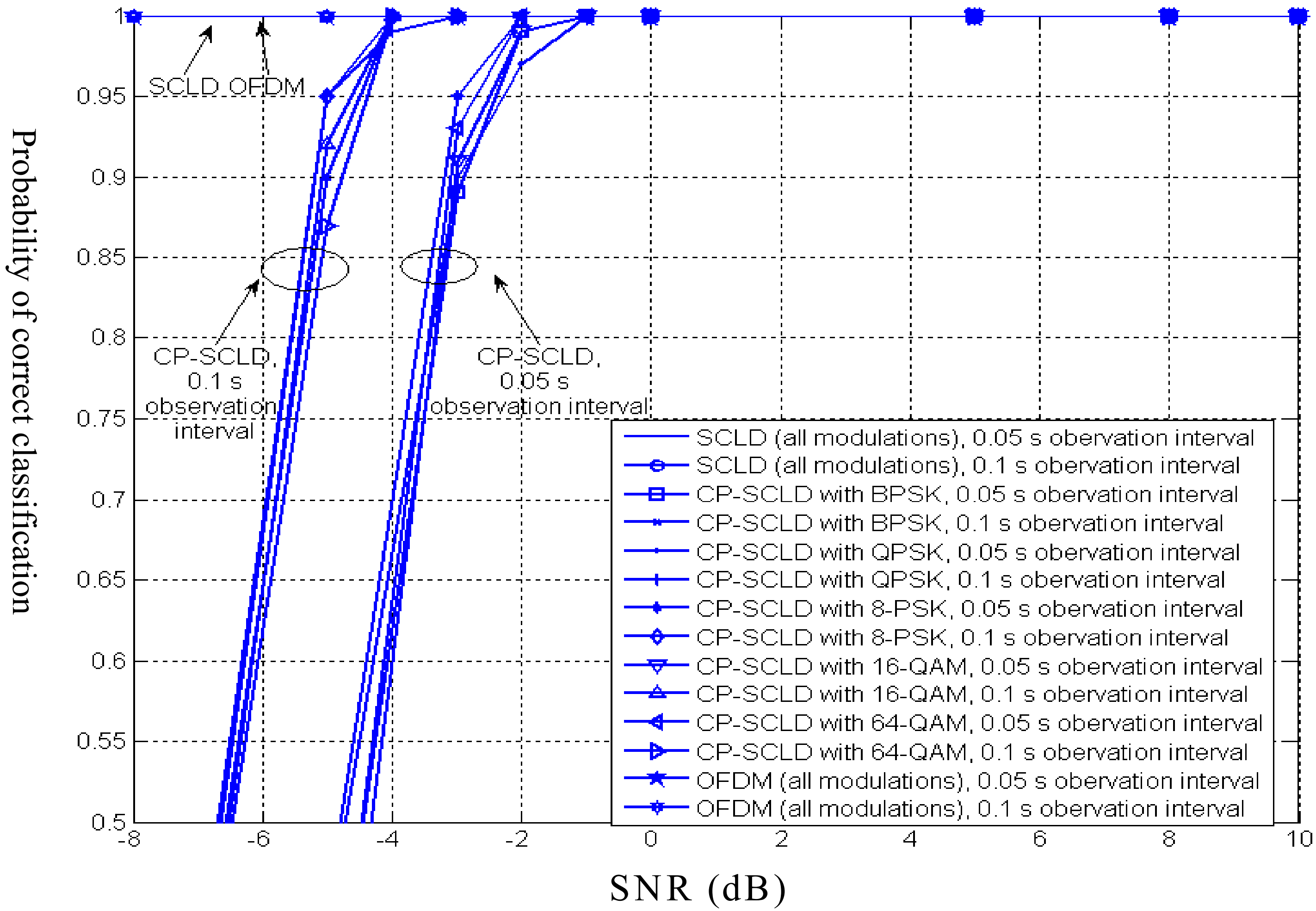
FB Approach: Signal Cyclostationarity for MC (cont'd)

- *Simulation Setup*

- SCLD and CP-SCLD modulations: BPSK, QPSK, 8-PSK, 16-QAM and 64-QAM.
- The transmit filter is root-raised cosine, with 0.35 roll-off factor. The signal bandwidth is 40 kHz.
- We simulate unit variance constellations.
- For OFDM signal generation we use raised cosine windowing function with 0.025 roll-off factor. The number of subcarriers is set to 128, the bandwidth to 800 kHz, the useful time period to 160 μs and the cycle prefix to 40 μs.
- The observation interval available at the receiver is 0.1 and 0.05 seconds, respectively.
- At the receive-side, a low-pass filter is used to eliminate the out of band noise.
- The oversampling factor per symbol per subcarrier is set to 4. The sampling frequency for SCLD and CP-SCLD is set to 160 kHz, whereas to 3.2 MHz for OFDM.
- The phase θ is uniformly distributed in the interval [- π, π). The carrier frequency offset is set to $\Delta f_c f_s^{-1} = 0.1$, and the timing offset to $\varepsilon = 0.75$.

FB Approach: Signal Cyclostationarity for MC (cont'd)

- ***Classification Performance***



FB Approach: Signal Cyclostationarity for MC (cont'd)

- *Remarks*

✓ We are currently investigating the effect of the number of processed symbols on the classification performance, i.e., what is the minimum number of symbols required to achieve a certain performance at a given SNR.

✓ In addition, we are extending the algorithm(s) to time-dispersive channels, and looking into the complexity of the algorithm(s). Results for classifying OFDM against SCLD in time dispersive channel has been already reported [Dobre, Punchihewa, Rajan, and Inkol, 2008].

FB Approach: Signal Cyclostationarity for MC (cont'd)

We have investigated higher-order cyclic cumulants (CCs) of the baseband signal at the output of the receive filter as features to classify SCLD (CP-SCLD) signals in AWGN and block fading channels.

Why Higher-Order Cyclic Cumulants?

- ***First- and second-order cyclostationarity cannot be used to classify SCLD (CP-SCLD) signals (see results presented in slide #40).***
- ***Higher-order CCs have particular properties, which make them attractive for MC, e.g.,***
  - tolerance to stationary noise
  - CC-based features are robust to phase and timing offsets.

FB Approach: Signal Cyclostationarity for MC (cont'd)

Signal Model

$$r_{SCLD}(t) = \alpha e^{j\varphi} e^{j2\pi\Delta f_c t} \sum_k s_k^{(i)} g\left(t - kT - \varepsilon T\right) + w(t)$$

[Dobre, Bar-Ness, and Su, 2003]

The nth-order Cyclic Cumulant (q conjugations, q=0,…,n) of the discrete-time signal $r(m) = r(t)|_{t=mT/\rho}$ *(no aliasing condition)*

$$c_{r_{SCLD}}(\gamma;\boldsymbol{\tau})_{n,q} = \alpha^n c_{s^{(i)},n,q} \rho^{-1} e^{-j2\pi\beta\varepsilon\rho} e^{j(n-2q)\varphi} e^{j2\pi\Delta f_c T\rho^{-1}\sum_{u=1}^{n}(-)_u \tau_u}$$

$$\times \sum_m \prod_{u=1}^{n} g^{(*)_u}(m+\tau_u) e^{-j2\pi\beta m},$$

The Cycle Frequencies are given by

$$\left\{\gamma \in [-1/2;1/2) \mid \gamma = \beta + (n-2q)\Delta f_c T/\rho,\ \beta = \nu/\rho,\ \nu \text{ integer},\ c_{r_{SCLD}}(\gamma;\boldsymbol{\tau})_{n,q} \neq 0\right\}$$

where ν is an integer and $\boldsymbol{\tau} = [\tau_1, \ldots, \tau_n]^{\dagger}\big|_{\tau_n=0}$ is the delay-vector.

FB Approach: Signal Cyclostationarity for MC (cont'd)

The nth-order/ q-conjugate CC Magnitude

$$|c_{r_{SCLD}}(\gamma;\boldsymbol{\tau})_{n,q}| = \alpha^n \, |c_{s^{(i)},n,q}| \, \rho^{-1} \left| \sum_m \prod_{p=1}^{n} g^{(*)_p}(m+\tau_p) e^{-j2\pi\beta m} \right|$$

is robust to a time-invariant phase and timing errors.

We need to choose the:

- order	***n***
- number of conjugations	***q***
- delay-vector	$\boldsymbol{\tau}$
- cycle frequency	β

to achieve the best discrimination capability for a specific pool of modulations.

FB Approach: Signal Cyclostationarity for MC (cont'd)

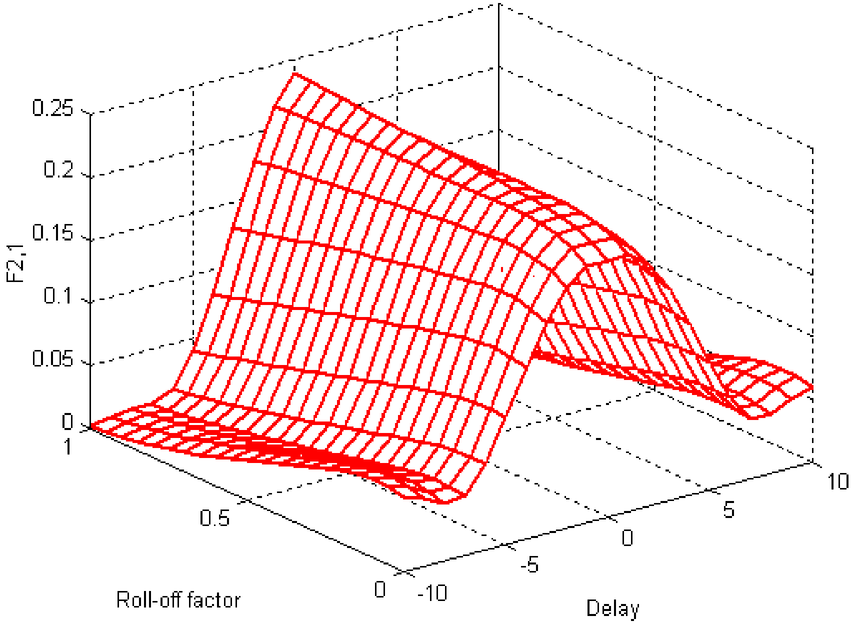
Cumulants of the Normalized Noise-Free Signal Constellations

	4ASK	8ASK	BPSK	QPSK	8PSK	16PSK	16QAM	32QAM	64QAM
c_{20}	1	1	1	0	0	0	0	0	0
c_{21}	1	1	1	1	1	1	1	1	1
c_{40}	-1.36	-1.2381	-2	1	0	0	-0.6800	-0.1900	-0.619
c_{41}	-1.36	-1.2381	-2	0	0	0	0	0	0
c_{42}	-1.36	-1.2381	-2	-1	-1	-1	-0.6800	-0.6900	-0.619
c_{60}	8.32	7.1889	16	0	0	0	0	0	0
c_{61}	8.32	7.1889	16	-4	0	0	2.08	0.5700	1.7972
c_{62}	8.32	7.1889	16	0	0	0	0	0	0
c_{63}	8.32	7.1889	16	4	4	4	2.08	2.1100	1.7972
c_{80}	-111.8464	-92.018	-272	-34	1	0	-13.9808	-1.9926	-11.5022
c_{81}	-111.8464	-92.018	-272	0	0	0	0	0	0
c_{82}	-111.8464	-92.018	-272	34	0	0	-13.9808	-3.8446	-11.5022
c_{83}	-111.8464	-92.018	-272	0	0	0	0	0	0
c_{84}	-111.8464	-92.018	-272	-34	-33	-33	-13.9808	-13.7862	-11.5022

FB Approach: Signal Cyclostationarity for MC (cont'd)

- ***CC magnitude dependency on the delay-vector and roll-off factor***

$$F_{n,q}(\boldsymbol{\tau}, r, \beta) = \rho^{-1} \left| \sum_m \prod_{p=1}^{n} g^{(*)_p}(m+\tau_p) e^{-j2\pi\beta m} \right|$$



- maximum reached at zero delay vector.
- maximum increases with the roll-off factor.
- maximum decreases as increasing β .

FB Approach: Signal Cyclostationarity for MC (cont'd)

- ***Selected Features***

$$|c_{r_{SCLD}}(\gamma;\boldsymbol{\tau})_{n,q}| = \alpha^n |c_{s^{(i)},n,q}| \rho^{-1} \left| \sum_m \prod_{p=1}^{n} g^{(*)_p}(m+\tau_p) e^{-j2\pi\beta m} \right|$$

Order	- n=8 (M-ASK, M-PSK (maximum order M=8), M-QAM * n=4,6,8 (Rectangular QAM)
Number of conjugations	- q=0,…,8 * q=n/2
Cycle frequency	$\gamma=1/\rho+(n-2q)\Delta f_c T/\rho$ (discrimination distance decreases with an increase in CF)
Delay-vector	$\tau=0_8$ (the features reach maximum)

-Robust to carrier phase, φ, and timing errors, ε.

*Also robust to carrier frequency offset Δf_c and phase noise [Dobre, Bar-Ness, and Su, 2004].

FB Approach: Signal Cyclostationarity for MC (cont'd)

- **A feature vector $\Upsilon^{(i)}$ is formed** for each $i = 1,\ldots, N_{mod}$ and saved in a look-up table.

  Estimates of the signal amplitude and pulse shape are needed to compute these features. We assume perfect (error free) estimates.

- **An estimate $\overline{\Upsilon}$ of the feature vector is computed** for the received signal from $K\rho$ samples (K symbol length observation interval) taken at the output of the receive filter.

- **Decision Criterion**

  Choose $\overline{i}$ as the received modulation if $\overline{i} = \arg\min_{i=1,\ldots,N_{\text{mod}}} d(\overline{\Upsilon}, \Upsilon^{(i)})$

  where $d(.,.)$ is the Euclidian distance.

FB Approach: Signal Cyclostationarity for MC (cont'd)

▪ *Remarks on CC-based Features for MC*

✓ The CC-based features have the capability of classifying a large number of modulations. In addition, these have the advantage of relying less on preprocessing, being robust to carrier phase and timing errors (see, for example, classification of M-ASK, M-QAM, and M-PSK signals).

✓ First-order cyclostationarity can be used to classify AM, FSK, and SCLD, CP-SCLD, and OFDM (as a signal class), second-order cyclostionarity to distinguish between SCLD, CP-SCLD, and OFDM signal classes, and higher-order cyclostationarity to identify signals within SCLD and CP-SCLD signal classes.

✓ The CC-based features are also robust to carrier frequency offset and phase noise when classifying rectangular QAM constellations [Dobre, Bar-Ness, and Su, 2004].

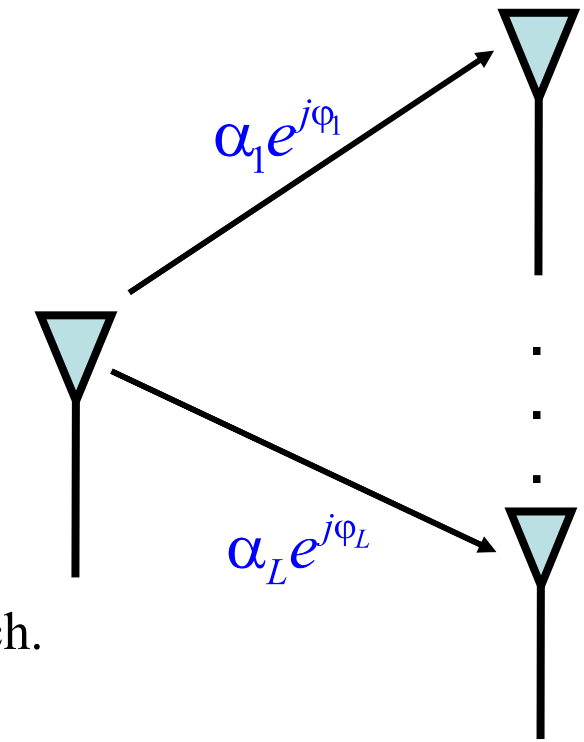
✓ When higher-order statistics are employed, a large observation interval is required to obtain accurate feature estimates.

Spatial Receive Diversity for Modulation Classification

Spatial Receive Diversity for MC

GOAL: improve the performance of classifiers in fading channels with multiple receive antennas.

- ***Signal and noise models***



Let us consider an L branch antenna array.

$$r_\ell(t) = s_\ell(t;\mathbf{u}_i) + w_\ell(t),\ 0 \le t \le KT,\ \ell = 1,2,\ldots,L$$

- Independent AWGN processes from branch to branch.
- Independent fading among L branches.
- Channel amplitudes and phases are constant over K symbols (block fading model).

LB and Spatial Receive Diversity

[Abdi, Dobre, Choudhry, Bar-Ness, and Su, 2004]

- **Unknowns** $\mathbf{u}_i = [\{s_k^{(i)}\}_{k=1}^{K}]$ **, AWGN**

$$\Xi_{A-Array}[\mathbf{r} \mid H_i] = \prod_{k=1}^{K} E_{s_k^{(i)}}\left[\exp\left\{\frac{2}{N}\mathrm{Re}\left[\sum_{\ell=1}^{L}\alpha_\ell e^{-j\varphi_\ell}R_{k,\ell}^{(i)}\right] - \frac{T}{N}\left(\sum_{\ell=1}^{L}\alpha_\ell^2\right)\mid s_k^{(i)}\mid^2\right\}\right].$$

When there are unknown parameters, e.g., $\{\alpha_\ell\}_{\ell=1}^{L}$ and $\{\varphi_\ell\}_{\ell=1}^{L}$, integration over the unknown parameters becomes more difficult for the array classifier.

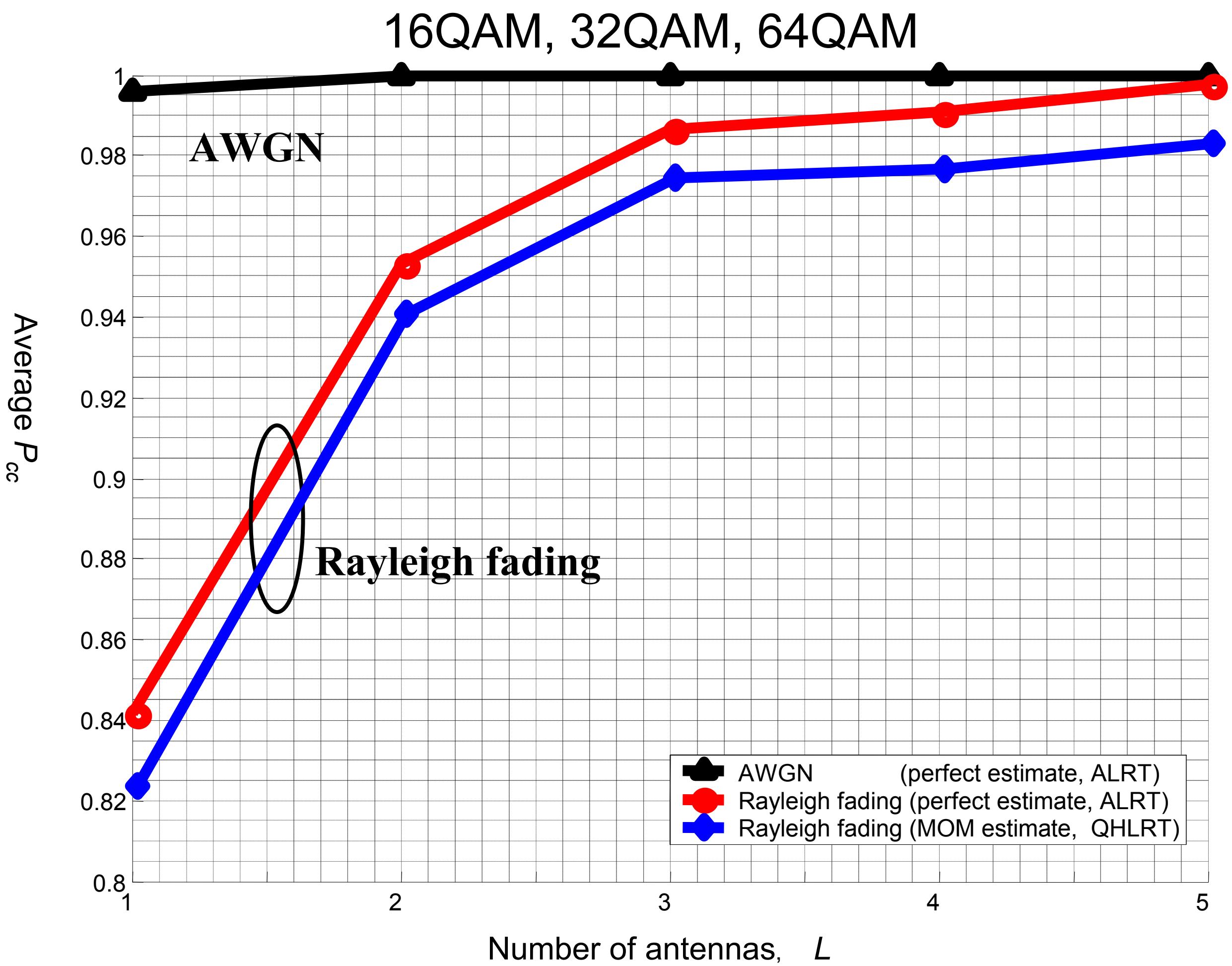
- **Unknowns** $\mathbf{u}_i = [\{\alpha_\ell\}_{\ell=1}^{L}\ \{\varphi_\ell\}_{\ell=1}^{L}\ \{s_k^{(i)}\}_{k=1}^{K}]$ **, Rayleigh Fading**

$$\Xi_{QH-Array}[\mathbf{r} \mid H_i] = \prod_{k=1}^{K} E_{s_k^{(i)}}\left[\exp\left\{\frac{2}{N}\mathrm{Re}\left[\sum_{\ell=1}^{L}\widehat{\alpha}_\ell e^{-j\widehat{\varphi}_\ell}R_{k,\ell}^{(i)}\right] - \frac{T}{N}\left(\sum_{\ell=1}^{L}\widehat{\alpha}_\ell^2\right)\mid s_k^{(i)}\mid^2\right\}\right],$$

The Maximal Ratio Combiner is used to combine the replicas of the received signal.

QHLRT and Spatial Receive Diversity (cont'd)

- **Effect of Number of Antennas**



SNR=12dB

500 symbols

QHLRT and Spatial Receive Diversity (cont'd)

■ *Effect of the Correlation among the Antennas*

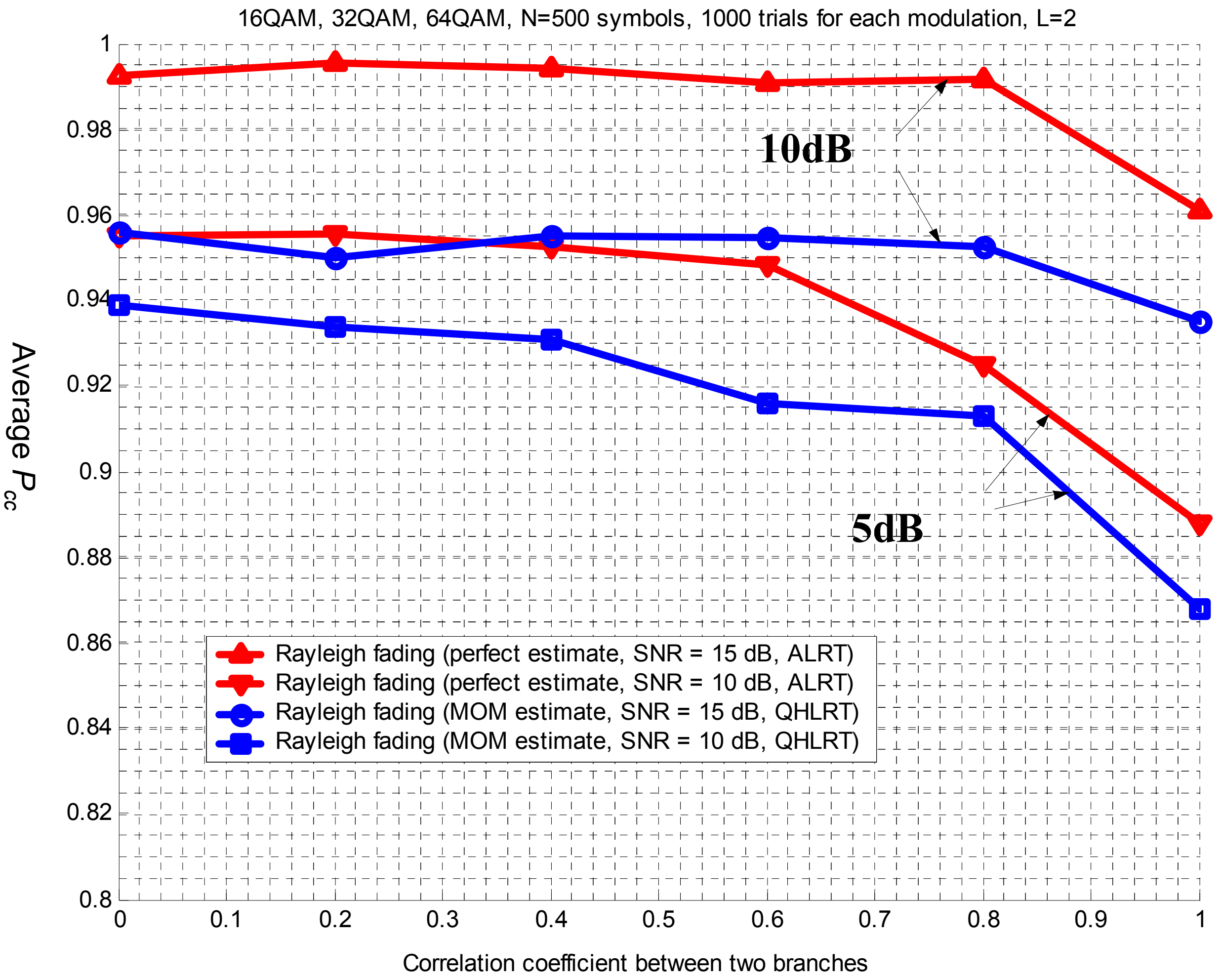
The correlation coefficient between two branches

$$\varsigma_{12} = E[z_1 z_2^*]$$

where

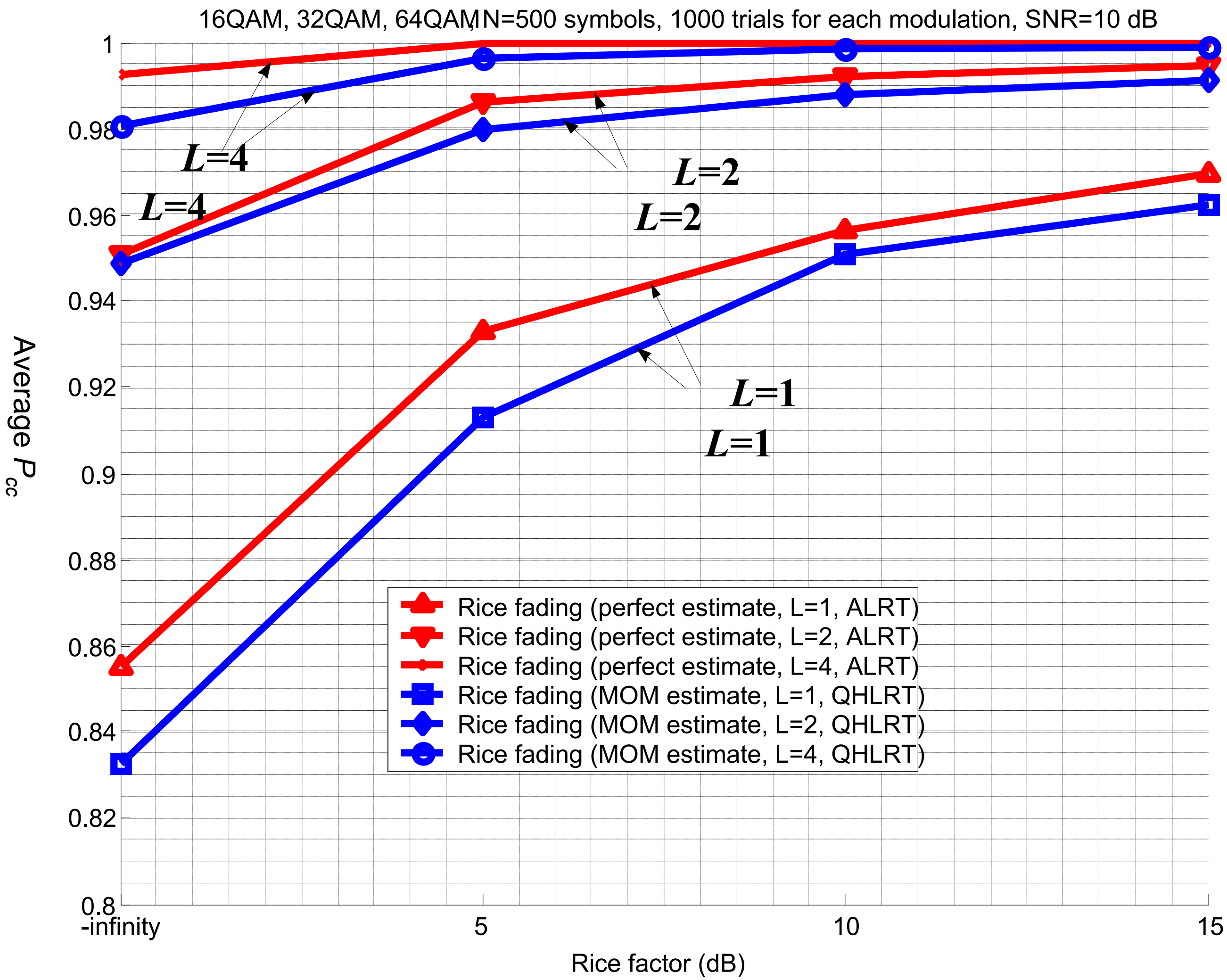
$$z_1 = \alpha_1 e^{j\varphi_1},\ z_2 = \alpha_2 e^{j\varphi_2}$$

are two zero-mean complex Gaussian variables.



QHLRT and Spatial Receive Diversity (cont'd)

- *Effect of the Rice Factor*



SNR=10dB

500 symbols

QHLRT and Spatial Receive Diversity (cont'd)

- ***Remarks on Multi-Antenna ALRT and QHLRT for MC***

  - ✓ With an antenna array at the receiver, the complexity of the LB classifier increases further.
  - ✓ By adding only a second antenna, a large performance improvement is achieved in Rayleigh fading.
  - ✓ Further improvement is obtained by using more antennas.
  - ✓ The multi-antenna QHLRT classifier is reasonably robust to correlations among branches, as well as the Rice factor.

▪Multi-Antenna CC-based Classifier

Signal at the output of the Selection Combiner (SC)

$$\{r_{SC}(m)\} = \{r_{\ell'}(m)\} \qquad \ell' = \arg\max_{1\le\ell\le L} \eta_\ell$$ [Dobre, Abdi, Bar-Ness, and Su, 2005]

where η_ℓ is the received SNR on each branch.

The nth-order CC of the signal at the output of the SC

$$c^{(i)}_{r_{,SC}}(\gamma;\boldsymbol{\tau})_{n,q} = \alpha^n_{\ell'} c_{s^{(i)},n,q} \rho^{-1} e^{-j2\pi\beta_d\varepsilon_{\ell'}\rho} e^{j(n-2q)\varphi_{\ell'}} e^{j2\pi\Delta f_c T\rho^{-1}\sum_{u=1}^{n}(-)_u\tau_u}$$

$$\times \sum_m \prod_{u=1}^{n} p^{(*)_u}(m+\tau_u) e^{-j2\pi\beta m}$$

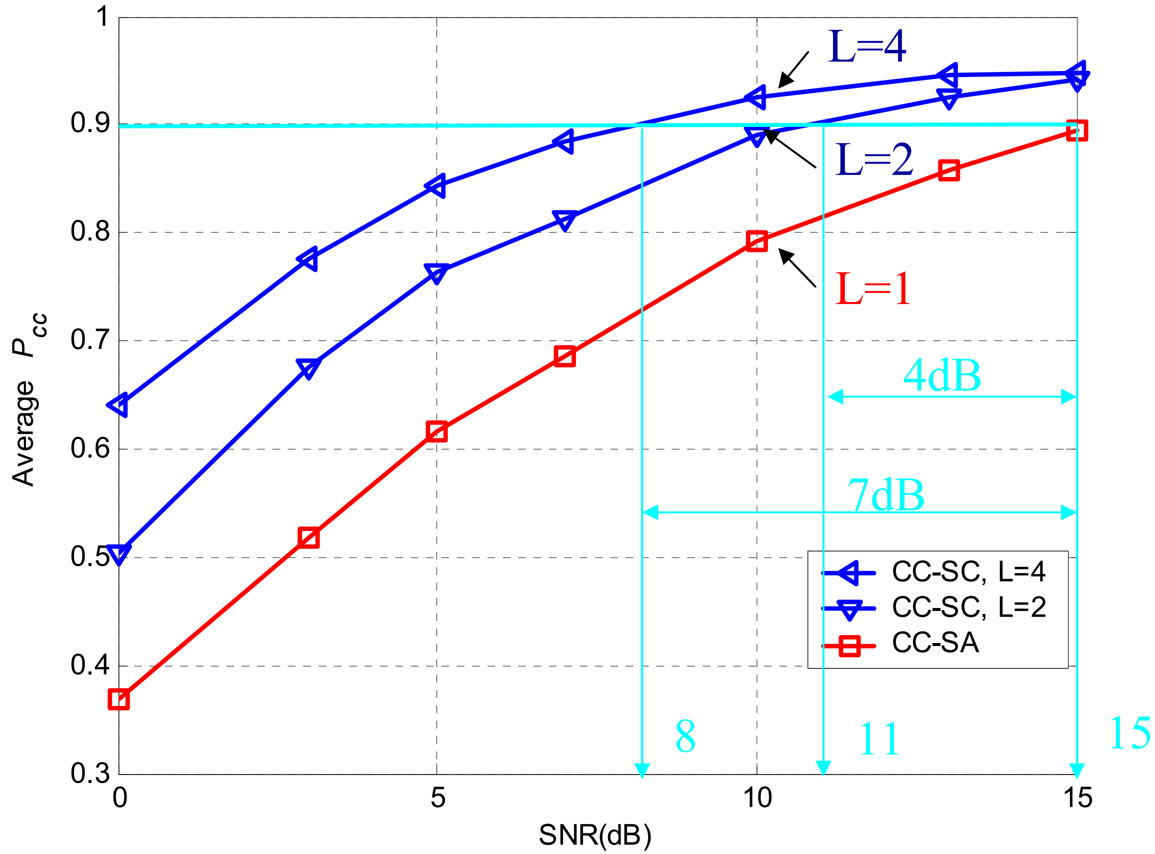
Feature Vector Υ : the same as for the single antenna case.

Decision Criterion

Choose $\bar{i}$ as the received modulation if $\bar{i} = \arg\min_{i=1,\ldots,N_{\mathrm{mod}}} d(\bar{\Upsilon}_{SC}, \Upsilon^{(i)}_{SC})$

CC-based Classifier and Spatial Receive Diversity (cont'd)

- ***Single- and Multi-Antenna CC-based Classifiers in Rayleigh Fading***
  - 4ASK, 8ASK, BPSK, QPSK, 8PSK, 16PSK, 16QAM, 32QAM, 64QAM



4000 symbols

By using two and four two antenna elements with a CC-SC classifier, we get a 4dB and 7dB SNR improvement to attain P_{cc}=0.9, respectively.

CC-based Classifier and Spatial Receive Diversity (cont'd)

■ *Effect of the Correlation among the Antennas*

4000 symbols, *L*=2

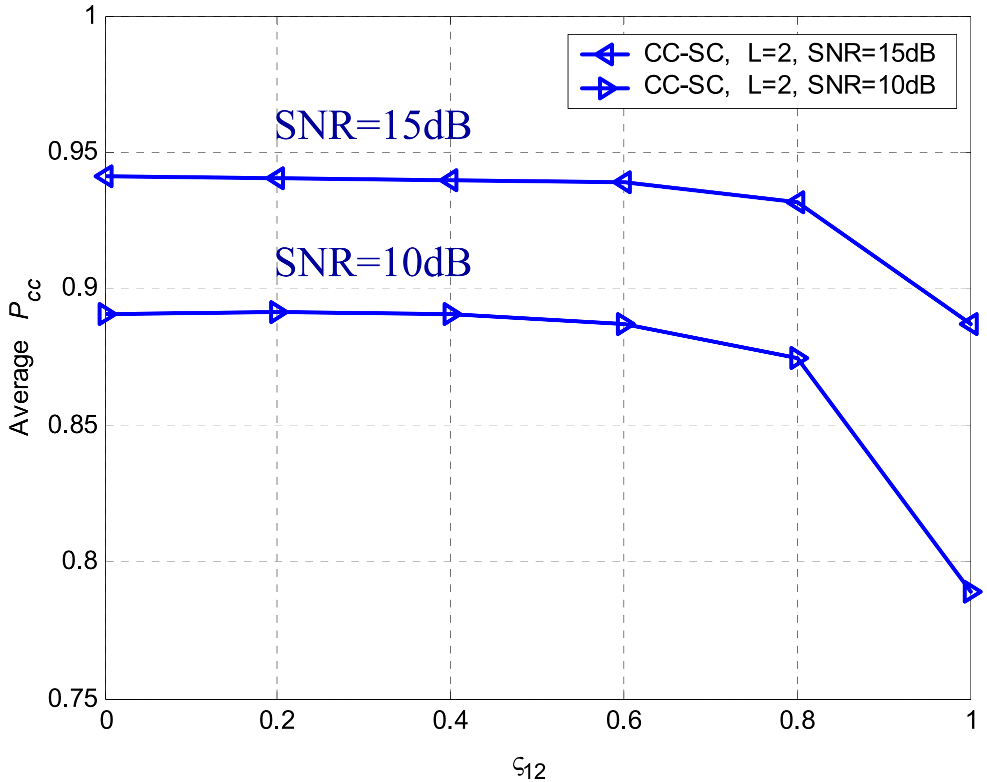
Correlation coefficient between two branches

$$\varsigma_{12} = E[z_1 z_2^*]$$

where

$$z_1 = \alpha_1 e^{j\varphi_1}, \quad z_2 = \alpha_2 e^{j\varphi_2}$$

are two zero-mean complex Gaussian variables.

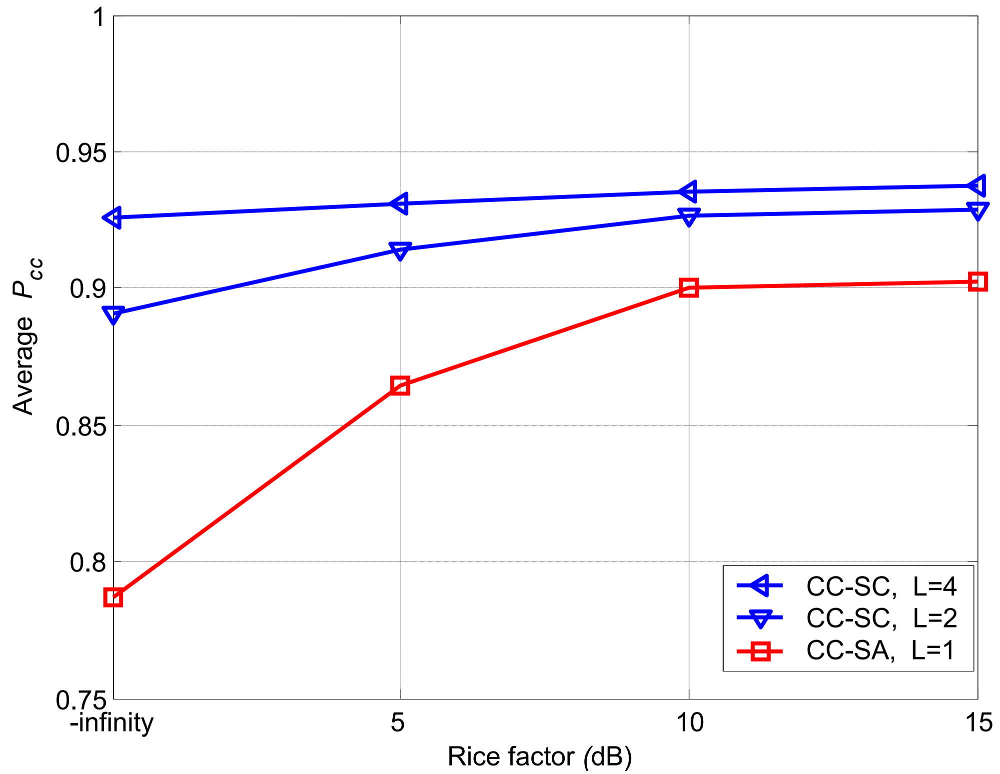


As expected, the P_{cc} decreases when the correlation coefficient increases. The performance degradation seems to be less at high SNRs. As can be noticed from the flat portion of these curves, the array classifiers appear to be reasonably robust to some possible correlations that may exist between the branches.

CC-based Classifier and Spatial Receive Diversity (cont'd)

- ***Effect of the Rice Factor***

4000 symbols



It is noteworthy to mention the significant performance enhancement by adding only one extra antenna, i.e., L=2 comparing to L=1 particularly at low values of the Rice factor (For K=0 and ∞, Rice fading reduces to Rayleigh fading and no fading, respectively.)

CC-based Classifier and Spatial Receive Diversity (cont'd)

- ***Remarks on Multi-Antenna CC-based Classifier***

✓ By adding only a second antenna, a large performance improvement is achieved in fading channels.

✓ Further improvement is obtained by using more antennas.

✓ The multi-antenna CC-SC classifier is reasonably robust to some level of correlation that may exist between branches and to the Rice factor.

Conclusion

- ***LB Approach to MC***

✓ QHLRT seems to be the approach to follow, as it is relatively simple to implement, yet providing a good classification performance.

✓ However, it suffers of sensitivity to model mismatches, such as timing errors.

✓ It cannot be applied to a large pool of modulation types, e.g., analog against digital modulations.

- ***FB Approach to MC***

✓ CC-based MC algorithms are robust to carrier phase and timing errors, and applicable to a large pool of modulations.

✓ Higher-order CCs used to discriminate SCLD signals require a large observation interval for accurate estimations.

- ***Spatial Diversity for MC***

✓ With multiple receive antennas and proper combining at the receive side, performance of the LB and FB classifiers improves.

✓ The price is the increase in complexity.

- **Ongoing Work**
- ***Cyclostationarity-based Approach to MC***

✓ Investigation of new criteria of decision, which lead to maximum probability of correct classification.

✓ Extension to more complex environments (an extension of the algorithm to identify OFDM against SCLD in time-dispersive channels has been already developed).

✓ Study of the algorithm complexity.

✓ Extension of the cyclostationarity-based MC algorithm to identify other modulation types, such as CPM.

✓ Study of the minimum number of symbols required to achieve a certain probability of correct classification at a given SNR.

Ongoing and Future Work (cont'd)

- **Future Work**

- ***FB Approach to MC***

✓ Investigation of other signal features, such as wavelet transform.

✓ Handle new classification problems raised by the emerging wireless technologies, such as classification of signals received from single and multiple transmit antennas, identification of space-time modulation format, etc.