A Low Complexity Modulation Classification Algorithm for MIMO Systems

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***Abstract*—A novel algorithm is proposed for automatic modulation classification in multiple-input multiple-output spatial multiplexing systems, which employs fourth-order cumulants of the estimated transmit signal streams as discriminating features and a likelihood ratio test (LRT) for decision making. The asymptotic likelihood function of the estimated feature vector is analytically derived and used with the LRT. Hence, the algorithm can be considered as asymptotically optimal for the employed feature vector when the channel matrix and noise variance are known. Both the case with perfect channel knowledge and the practically more relevant case with blind channel estimation are considered. The results show that the proposed algorithm provides a good classification performance while exhibiting a significantly lower computational complexity when compared with conventional algorithms.**

***Index Terms*—Automatic modulation classification, multiple-input multiple-output, fourth-order cumulant**

I. INTRODUCTION

Automatic modulation classification (AMC) of unknown communication signals finds application in cognitive radio, spectrum surveillance, signal intelligence, and electronic warfare [1], [2]. AMC can be considered as a multiple hypothesis-testing problem, with each hypothesis $\mathcal{H}_q$ corresponding to a modulation type M_q. The decision on $M_q \in \mathcal{M}$, with $\mathcal{M}$ as the set of possible modulation types, is made based on a finite number of observations of the received signal corrupted by fading and noise. Two different approaches to the AMC problem exist in the literature for conventional single-input single-output systems, i.e., the likelihood- and feature-based algorithms, respectively [1]. The former relies on the likelihood function of the received signal, while the latter employs extracted signal features.

The recent advance of multiple-input multiple-output (MIMO) technology has given rise to a need for new AMC algorithms, able to operate in such environments. The research in this area is at a very incipient stage, and only a few works are available in the literature [3]–[5]. In [3], Choqueuse et al. proposed an average likelihood ratio test (ALRT) for spatially multiplexed MIMO systems that is optimal in the Bayesian sense, given that the channel matrix and the noise variance are known; hence, its classification performance can be regarded as an upper performance bound for the AMC problem. In the same work, a suboptimal hybrid likelihood ratio test (HLRT) is presented, which employs blind channel estimation, and is therefore more practical. However, both algorithms exhibit a high computational complexity, which severely limits their applicability. The feature-based approach is followed in [4] and [5]. Diverse higher-order signal statistics are used as features in [4] with a neural network-based algorithm that requires prior training and is sensitive to channel estimation errors. The algorithm in [5] employs higher-order signal statistics with a sub-optimal criterion of decision.

In this work, we propose a novel feature-based AMC algorithm for spatially multiplexed MIMO systems, which relies on fourth-order cumulants as discriminating features. We derive the expression for the asymptotic likelihood function of the estimated feature vector and use a likelihood ratio test (LRT) for decision making. The algorithm is asymptotically optimal for the employed feature vector in the case of perfectly known channel matrix and noise variance. For the practically more relevant case when the channel matrix is not available, a blind channel estimation scheme is employed prior to the feature extraction and classification, and the asymptotic likelihood function is evaluated using the blind channel estimate. The classification performance and computational complexity of the proposed algorithm are investigated and compared with those of ALRT and HLRT.

II. SYSTEM MODEL

We consider an $N_t \times N_r$ spatially multiplexed MIMO system with N_t transmit and N_r receive antennas, $N_r \geq N_t$. The received signal vector $\mathbf{r}[k] = [r_1[k], \ldots, r_{N_r}[k]]^T$ at time instant $k = 1, \ldots, N$ is expressed as

$$\mathbf{r}[k] = \mathbf{H}\mathbf{s}[k] + \mathbf{w}[k] \,, \tag{1}$$

where $\mathbf{s}[k] = [s_1[k], \ldots, s_{N_t}[k]]^T$ is the vector of baseband transmit symbols, $\mathbf{w}[k]$ is the circular complex additive white Gaussian noise vector with variance σ_w^2, and $\mathbf{H}$ is the $N_r \times N_t$ channel matrix whose elements h_{n_r,n_t}, $n_r = 1, \ldots, N_r$, $n_t = 1, \ldots, N_t$, represent the channel coefficients between the n_r-th receive and n_t-th transmit antenna, which are modeled as independent zero-mean circular complex Gaussian random variables with unit variance. We assume a flat block fading channel over the observation interval. Without loss of generality, we assume unit power transmit signals; hence, the average signal-to-noise ratio (SNR) is expressed as $\mathrm{SNR} = \frac{N_t}{\sigma_w^2}$ [3].

III. CLASSIFICATION ALGORITHM

We propose an AMC algorithm for spatially multiplexed MIMO signals, which relies on the fourth-order cumulants with zero and with two conjugates, i.e., $\kappa^{(4,0)}$ and $\kappa^{(4,2)}$,

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TABLE I
FOURTH-ORDER CUMULANTS FOR UNIT VARIANCE CONSTELLATIONS.

	BPSK	QPSK	8-PSK	16-QAM	64-QAM
$\kappa_q^{(4,0)}$	-2	1	0	-0.68	-0.619
$\kappa_q^{(4,2)}$	-2	-1	-1	-0.68	-0.619

respectively, as discriminating features. For a zero-mean stationary random sequence $s[k]$, these are given as [6]

$$\kappa^{(4,0)} = \mu^{(4,0)} - 3(\mu^{(2,0)})^2, \tag{2}$$

and

$$\kappa^{(4,2)} = \mu^{(4,2)} - |\mu^{(2,0)}|^2 - 2(\mu^{(2,1)})^2, \tag{3}$$

where $\mu^{(\beta,\gamma)} = \mathrm{E}\{s[k]^{\beta-\gamma}s[k]^{*\gamma}\}$ is the moment of order β with γ conjugates and $\mathrm{E}\{\cdot\}$ is the statistical expectation operator. Theoretical values of $\kappa^{(4,0)}$ and $\kappa^{(4,2)}$ for different unit variance constellations are provided in Table I. For the theoretical values of the corresponding moments, the reader is referred to [1]. Note that the estimates of $\kappa^{(4,0)}$ and $\kappa^{(4,2)}$ are obtained from (2) and (3) with the moments replaced by their corresponding finite sample estimates [6].

Clearly, the cumulant features cannot be directly estimated from $\mathbf{r}[k]$ in (1) due to the channel effects, which are required to be compensated for prior to feature estimation. In the following, we consider both the ideal case with perfectly known channel matrix $\mathbf{H}$ and the more realistic case where a blind estimation of $\mathbf{H}$ is employed.

A. Classification with Perfect Channel Knowledge

If the channel matrix is perfectly known, the transmit signal is estimated as

$$\hat{\mathbf{s}}[k] = (\mathbf{H}^\dagger\mathbf{H})^{-1}\mathbf{H}^\dagger\mathbf{r}[k] = \mathbf{s}[k] + \tilde{\mathbf{w}}[k], \tag{4}$$

where $\dagger$ represents the Hermitian transpose operation and the noise term term $\tilde{\mathbf{w}}[k]$ is non-white. The cumulant features are estimated from $\hat{\mathbf{s}}[k]$, i.e.,

$$\begin{aligned}\hat{\boldsymbol{\kappa}} &= [\hat{\boldsymbol{\kappa}}^{(4,0)T}, \hat{\boldsymbol{\kappa}}^{(4,2)T}]^T \\ &= [\hat{\kappa}_1^{(4,0)}, \ldots, \hat{\kappa}_{N_t}^{(4,0)}, \hat{\kappa}_1^{(4,2)}, \ldots, \hat{\kappa}_{N_t}^{(4,2)}]^T,\end{aligned} \tag{5}$$

where $\hat{\kappa}_{n_t}^{(4,0)}$ and $\hat{\kappa}_{n_t}^{(4,2)}$ are the estimates of the cumulants corresponding to the estimated symbol stream from the n_t-th transmit antenna, $\hat{s}_{n_t}[k]$, $n_t = 1, \ldots, N_t$.

In this work, we propose a classification strategy, which is based on the asymptotic likelihood function of the feature vector $\hat{\boldsymbol{\kappa}}$. It is well known that the finite sample estimates of cumulants are consistent and asymptotically (as the sample size $N \to \infty$) unbiased and Gaussian distributed [7]. Thus, the asymptotic likelihood function of the feature vector under the hypothesis $\mathcal{H}_q$ is given as

$$p(\hat{\boldsymbol{\kappa}}|M_q, \sigma_w^2, \mathbf{H}) = \frac{1}{\pi^{2N_t}|\boldsymbol{\Sigma}_{q,\sigma_w^2,\mathbf{H}}|}\exp(-(\hat{\boldsymbol{\kappa}} - \boldsymbol{\kappa}_q)^\dagger\boldsymbol{\Sigma}_{q,\sigma_w^2,\mathbf{H}}^{-1}(\hat{\boldsymbol{\kappa}} - \boldsymbol{\kappa}_q)), \tag{6}$$

with the mean

$$\boldsymbol{\kappa}_q = [\kappa_q^{(4,0)}\mathbf{1}_{Nt}^T, \kappa_q^{(4,2)}\mathbf{1}_{Nt}^T]^T, \tag{7}$$

and the covariance matrix

$$\boldsymbol{\Sigma}_{q,\sigma_w^2,\mathbf{H}} = \begin{bmatrix} \boldsymbol{\Sigma}_{q,\sigma_w^2,\mathbf{H}}^{(4,0)} & \boldsymbol{\Sigma}_{q,\sigma_w^2,\mathbf{H}}^{(4,0),(4,2)} \\ \boldsymbol{\Sigma}_{q,\sigma_w^2,\mathbf{H}}^{(4,2),(4,0)} & \boldsymbol{\Sigma}_{q,\sigma_w^2,\mathbf{H}}^{(4,2)} \end{bmatrix}, \tag{8}$$

where $\mathbf{1}_{N_t}$ is an $N_t \times 1$ vector of ones, $\boldsymbol{\Sigma}_{q,\sigma_w^2,\mathbf{H}}^{(4,0)}$ and $\boldsymbol{\Sigma}_{q,\sigma_w^2,\mathbf{H}}^{(4,2)}$ are the covariance matrices of $\hat{\boldsymbol{\kappa}}^{(4,0)}$ and $\hat{\boldsymbol{\kappa}}^{(4,2)}$, respectively, and $\boldsymbol{\Sigma}_{q,\sigma_w^2,\mathbf{H}}^{(4,0),(4,2)}$ is the cross-covariance matrix of $\hat{\boldsymbol{\kappa}}^{(4,0)}$ and $\hat{\boldsymbol{\kappa}}^{(4,2)}$. The mean of the feature vector depends on the modulation type M_q, while its covariance matrix additionally depends on the channel matrix $\mathbf{H}$ and the noise variance σ_w^2. By using the independence of the transmit signal and noise, the expressions of the cumulant estimators [7] and those of the higher-order joint moments of the non-white noise $\tilde{\mathbf{w}}[k]$ calculated according to the Isserlis' theorem [8], and neglecting the terms proportional to N^{-2} and N^{-3} for large N, one can show that the covariance matrices $\boldsymbol{\Sigma}_{q,\sigma_w^2,\mathbf{H}}^{(4,0)}$ and $\boldsymbol{\Sigma}_{q,\sigma_w^2,\mathbf{H}}^{(4,2)}$ can be approximated as

$$\begin{aligned}\boldsymbol{\Sigma}_{q,\sigma_w^2,\mathbf{H}}^{(4,0)} \approx{}& \frac{1}{N}24\sigma_w^8((\mathbf{H}^\dagger\mathbf{H})^{-1})^{\circ 4} + \frac{1}{N}\mathbf{I}_{Nt}\circ \\ &((16\mu_q^{(6,3)} - 96\mu_q^{(2,0)}\mu_q^{(4,1)} + 144(\mu_q^{(2,0)})^2\mu_q^{(2,1)})\sigma_w^2(\mathbf{H}^\dagger\mathbf{H})^{-1} \\ &+ (72\mu_q^{(4,2)} - 72(\mu_q^{(2,0)})^2)\sigma_w^4((\mathbf{H}^\dagger\mathbf{H})^{-1})^{\circ 2} \\ &+ 96\sigma_w^6\mu_q^{(2,1)}((\mathbf{H}^\dagger\mathbf{H})^{-1})^{\circ 3} + \mathbf{I}_{N_t}(\mu_q^{(8,4)} - 12\mu_q^{(2,0)}\mu_q^{(6,2)} \\ &+ 12(\mu_q^{(2,0)})^2\mu_q^{(4,0)} + 36(\mu_q^{(2,0)})^2\mu_q^{(4,2)} - 36(\mu_q^{(2,0)})^4) \\ &- (\mu_q^{(4,0)})^2),\end{aligned} \tag{9}$$

$$\begin{aligned}\boldsymbol{\Sigma}_{q,\sigma_w^2,\mathbf{H}}^{(4,2)} \approx{}& \frac{1}{N}\mathbf{I}_{Nt} \circ (4\sigma_w^8((\mathbf{H}^\dagger\mathbf{H})^{-1})^{\circ 4} \\ &+ 16\sigma_w^6\mu_q^{(2,1)}((\mathbf{H}^\dagger\mathbf{H})^{-1})^{\circ 3} + (20\mu_q^{(4,2)} - 4(\mu_q^{(2,0)})^2 \\ &- 16(\mu_q^{(2,1)})^2)\sigma_w^4((\mathbf{H}^\dagger\mathbf{H})^{-1})^{\circ 2} + (8\mu_q^{(6,3)} - 32\mu_q^{(2,1)}\mu_q^{(4,2)} \\ &- 16\mu_q^{(2,0)}\mu_q^{(4,1)} + 40(\mu_q^{(2,0)})^2\mu_q^{(2,1)} \\ &+ 32(\mu_q^{(2,1)})^3)\sigma_w^2(\mathbf{H}^\dagger\mathbf{H})^{-1} + \mathbf{I}_{N_t}(\mu_q^{(8,4)} - (\mu_q^{(4,2)})^2 \\ &- 4\mu_q^{(2,0)}\mu_q^{(6,2)} - 8\mu_q^{(2,1)}\mu_q^{(6,3)} + 6(\mu_q^{(2,0)})^2\mu_q^{(4,2)} \\ &+ 24(\mu_q^{(2,1)})^2\mu_q^{(4,2)} + 2(\mu_q^{(2,0)})^2\mu_q^{(4,0)} + 16\mu_q^{(2,0)}\mu_q^{(2,1)}\mu_q^{(4,1)} \\ &- 16(\mu_q^{(2,0)})^2(\mu_q^{(2,1)})^2 - 16(\mu_q^{(2,1)})^4 - 4(\mu_q^{(2,0)})^4)),\end{aligned} \tag{10}$$

where $\mathbf{I}_{N_t}$ is the $N_t \times N_t$ identity matrix, $\circ$ denotes the Hadamard product, $\mathbf{H}^{\circ\alpha} = \mathbf{H} \circ \mathbf{H} \circ \ldots \circ \mathbf{H}$ (α times), and $\mu_q^{(\beta,\gamma)}$ is the β-th order moment with γ conjugates for the modulation type M_q. The expression for $\boldsymbol{\Sigma}_{q,\sigma_w^2,\mathbf{H}}^{(4,0),(4,2)}$ and derivation of the covariance matrices are omitted due to space considerations. The classification of the modulation type is performed by choosing the hypothesis that maximizes the asymptotic likelihood function in (6), i.e.

$$\hat{M} = \arg\max_{M_q \in \mathcal{M}} p(\hat{\boldsymbol{\kappa}}|M_q, \sigma_w^2, \mathbf{H}), \tag{11}$$

which can be considered as asymptotically optimal for the employed feature vector, assuming equiprobable hypotheses. We use the average probability of correct classification P_{cc} as a performance measure, which is given as

$$P_{cc} = \sum_{q=1}^{|\mathcal{M}|} P(\hat{M} = M_q|M_q)P(M_q), \tag{12}$$

where $P(\hat{M} = M_q|M_q)$ is the probability that the transmitted modulation M_q is classified correctly, and $P(M_q) = \frac{1}{|\mathcal{M}|}$ is the *a priori* probability of M_q. For the proposed algorithm, it can be expressed as

$$P_{cc} = E_{\mathbf{H}}\Big\{\frac{1}{|\mathcal{M}|}\sum_{q=1}^{|\mathcal{M}|}\int_{\mathcal{R}_q} p(\hat{\boldsymbol{\kappa}}|M_q, \sigma_w^2, \mathbf{H})\mathrm{d}\hat{\boldsymbol{\kappa}}\Big\}, \tag{13}$$

where $E_{\mathbf{H}}\{\cdot\}$ is the expectation operation with respect to the random channel matrix $\mathbf{H}$, and $\mathcal{R}_q = \{\hat{\boldsymbol{\kappa}} \in \mathbb{C}^{2N_t} : p(\hat{\boldsymbol{\kappa}}|M_q, \sigma_w^2, \mathbf{H}) \geq p(\hat{\boldsymbol{\kappa}}|M_p, \sigma_w^2, \mathbf{H})\ \forall q \neq p\}$. Unfortunately, (13) is analytically intractable; however, it can be evaluated numerically.

B. Classification with Blind Channel Estimation

In practical scenarios involving AMC, no cooperation between the transmitter and receiver is possible; thus the channel matrix is unknown to the receiver and needs to be estimated blindly. In this work, we employ a blind channel estimation strategy consisting of two steps [3]. First, an independent component analysis (ICA) method is used to estimate the channel matrix blindly up to a phase offset matrix. Then, the phase offset corresponding to each transmit signal stream is estimated for each hypothesis $\mathcal{H}_q$.

Independent Component Analysis

The term ICA refers to a family of computational methods that are employed to blindly separate linear mixtures of statistically independent random processes into their individual components. Since the received signal for a spatially multiplexed system consists of a linear mixture of independent transmit symbol streams and noise, the ICA framework proves itself to be a useful tool for blind estimation and compensation of the channel matrix. Here, we employ the joint approximate diagonalization of eigen-matrices (JADE) algorithm proposed in [9] to form pre-estimates of the channel matrix $\tilde{\mathbf{H}}$ and the transmit symbol streams $\tilde{\mathbf{s}}[k]$. Note that like many ICA algorithms, JADE is able to estimate the channel matrix and separate the independent signal components up to a phase rotation. Thus, the transmit signal vector, $\tilde{\mathbf{s}}[k] = (\tilde{\mathbf{H}}^\dagger\tilde{\mathbf{H}})^{-1}\tilde{\mathbf{H}}^\dagger\mathbf{r}[k]$, separated by JADE, contains phase offsets that need to be estimated and compensated for prior to feature estimation and classification.

Estimation of the Phase Offsets

For the estimation of the phase offsets in $\tilde{\mathbf{s}}[k]$, we use the algorithm in [10]. Under hypothesis $\mathcal{H}_q$, the phase offset estimate corresponding to the n_t-th transmit symbol stream is

$$\hat{\varphi}_{n_t(q)} = \frac{1}{Q}\arg\left(\mu_q^{(Q,Q)}\sum_{k=1}^{N}\tilde{s}_{n_t}[k]^Q\right), \tag{14}$$

where Q is the modulation order for phase-shift-keying (PSK), while it equals four for quadrature amplitude modulations (QAM).

The phase corrected channel estimate under hypothesis $\mathcal{H}_q$ is expressed as

$$\hat{\mathbf{H}}_q = \tilde{\mathbf{H}}\hat{\boldsymbol{\Phi}}_q, \tag{15}$$

with

$$\hat{\boldsymbol{\Phi}}_q = \begin{bmatrix} \exp\{-j\hat{\varphi}_{1,(q)}\} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \exp\{-j\hat{\varphi}_{N_t,(q)}\} \end{bmatrix}. \tag{16}$$

The classification is performed as described in Section III-A, with the asymptotic likelihood function evaluated by using the estimated channel matrix $\hat{\mathbf{H}}_q$ for each hypothesis. The proposed classification algorithm is summarized as follows:

Proposed algorithm

Input: Receive signal $\mathbf{r}[k]$ and noise variance σ_w^2
Form the pre-estimates of the channel matrix $\tilde{\mathbf{H}}$ and the transmit signal $\tilde{\mathbf{s}}[k]$ using JADE
for each hypothesis $\mathcal{H}_q$ **do**
  Estimate phase offset $\hat{\boldsymbol{\Phi}}_q$ using (14) and (16)
  Estimate the channel matrix $\hat{\mathbf{H}}_q$ using (15)
  Estimate the transmit symbols $\hat{\mathbf{s}}[k]$ using (4)
  Estimate the feature vector $\hat{\boldsymbol{\kappa}}$ using (2) and (3), with the moments replaced by their estimates
  Calculate $\boldsymbol{\Sigma}_{q,\sigma_w^2,\hat{\mathbf{H}}_q}$ using (9) and (10), with $\mathbf{H}$ replaced by $\hat{\mathbf{H}}_q$
  Evaluate the likelihood function $p(\hat{\boldsymbol{\kappa}}|M_q, \sigma_w^2, \hat{\mathbf{H}}_q)$ using (6), with $\boldsymbol{\Sigma}_{q,\sigma_w^2,\mathbf{H_q}}$ replaced by $\boldsymbol{\Sigma}_{q,\sigma_w^2,\hat{\mathbf{H}}_q}$
end for
Output: Choose $\hat{M} = \arg\max_{M_q \in \mathcal{M}} p(\hat{\boldsymbol{\kappa}}|M_q, \sigma_w^2, \hat{\mathbf{H}}_q)$

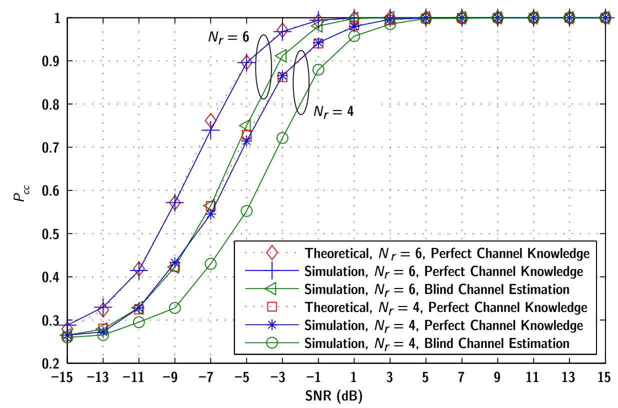

Fig. 1. Performance of the proposed algorithm for $N_t = 2$ and $N_r = 4, 6$, with perfect channel knowledge and blind channel estimation, respectively. For the case of perfect channel knowledge, both simulations and theoretical results are presented.

IV. Simulation Results

In the simulations, the number of transmit antennas was set to $N_t = 2$. Unless otherwise mentioned, the observation length was $N = 1000$. For each SNR value, 2000 Monte Carlo trials were used to calculate P_{cc}. The set of modulations was chosen as $\mathcal{M} = \{\mathrm{BPSK}, \mathrm{QPSK}, 8-\mathrm{PSK}, 16-\mathrm{QAM}\}$.

Performance evaluation of the proposed algorithm

Fig. 1 shows the classification performance of the proposed algorithm for $N_r = 4$ and 6 with perfect channel knowledge and blind channel estimation, respectively. Both simulation and theoretical results, with the latter calculated by numerically evaluating (13), are displayed in the case of perfect channel knowledge. These results are in agreement, which indicates the validity of the asymptotic Gaussian approximation for the likelihood function. It can be noticed that using blind channel estimation leads to a performance loss of about 2 dB when compared with the case of perfect channel knowledge, at $P_{cc} = 0.9$. As expected, the classification performance increases as N_r increases.

The observation length N is also a significant parameter that affects the classification performance. In Fig. 2, the performance of the proposed algorithm with blind channel estimation is shown for $N_r = 4$ and different values of N. As expected, an improved performance is achieved with an increased number of observed symbols. Simulations were also run to investigate the performance of the proposed algorithm with blind channel estimation for the set of modulations $\mathcal{M}$ = {BPSK, QPSK, 8-PSK, 16-QAM, 64-QAM}. Results

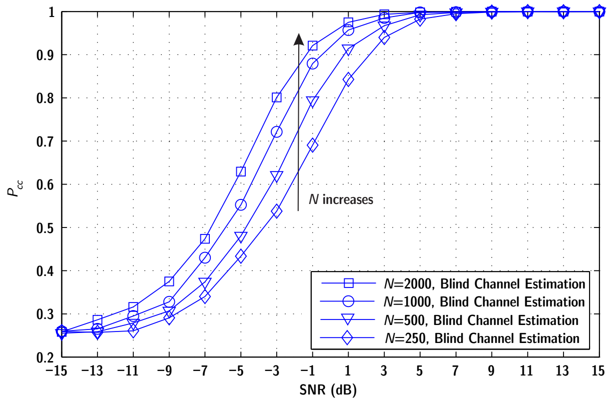

Fig. 2. Performance of the proposed algorithm for $N_t = 2$ and $N_r = 4$ with different observation lengths and blind channel estimation.

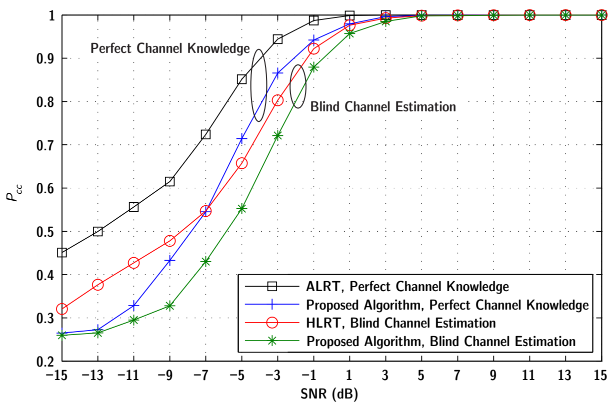

Fig. 3. Performance of the proposed algorithm for $N_t = 2$ and $N_r = 4$ with perfect channel knowledge and blind channel estimation, when compared with ALRT and HLRT, respectively.

showed that for $N = 1000$, a 3 dB SNR increase is required to reach $P_{cc} = 0.9$ when 64-QAM is additionally considered, regardless of the antenna configuration. Furthermore, it was observed that in order to attain $P_{cc} = 0.9$ at the same SNR, an increase in the number of symbols to $N = 6000$ is needed.

Comparison with ALRT and HLRT

Fig. 3 compares the performance of the proposed algorithm (perfect channel knowledge and blind channel estimation cases) with the ALRT and HLRT algorithms proposed in [3], respectively. It can be seen that ALRT achieves $P_{cc} = 0.9$ at about -4 dB SNR with perfect channel knowledge, while HLRT attains this performance at -1.5 dB SNR with blind channel estimation. Moreover, our proposed algorithm requires -2 dB SNR and -0.5 dB SNR with perfect channel knowledge and blind channel estimation, respectively. The performance of the proposed algorithm with perfect channel knowledge is about 2 dB lower when compared with ALRT, whereas the performance loss of the proposed algorithm with blind channel estimation compared with HLRT is only about 1 dB. The degradation in performance is expected since both ALRT and HLRT use the likelihood function of the receive signal for discrimination, whereas the proposed algorithm employs only the fourth-order cumulants.

However, the complexity of the proposed algorithm is significantly lower. The evaluation of the log-likelihood function employed in both ALRT and HLRT, which essentially determines their computional complexity, requires $N_r N m_q^{N_t}(N_t + 1) + 2$ complex additions, $N m_q^{N_t}(N_r(N_t+1)+1)+1$ complex multiplications, $N m_q^{N_t}$ exponentiations, and $N+1$ logarithms, with m_q as the modulation order under hypothesis $\mathcal{H}_q$. On the other hand, for the calculation of $p(\hat{\boldsymbol{\kappa}}|M_q, \sigma_w^2, \mathbf{H}_q)$, only $\frac{26}{3}N_t^3 + 4N_t^2(3 + N_r) + N_t(6N - \frac{20}{3})$ complex additions, $\frac{26}{3}N_t^3 + 30N_t^2 + N_t(\frac{22}{3} + 6N)$ complex multiplications, and one exponentiation are required. For example, for $N_t = 2$, $N_r = 4$, and $N = 1000$ symbols, the required number of additions and multiplications is respectively reduced to 0.32% and 1.67% of that needed by the log-likelihood function of ALRT and HLRT. Furthermore, only one exponentiation and no logarithms are required. It should be noted that the additional computational cost arising due to blind channel estimation is the same for both HLRT and the proposed algorithm with blind channel estimation, as both apply the JADE algorithm to estimate the channel; thus, the difference in the computational cost remains the same in the blind context.

V. Conclusion

A novel feature-based algorithm is proposed for AMC in spatially multiplexed MIMO systems. Fourth-order cumulants are used as discriminating features and the classification is based on an LRT using the asymptotic likelihood function of the feature vector estimate. The results show that the algorithm achieves a performance close to that of ALRT (with perfect channel knowledge) and HLRT (with blind channel estimation) while exhibiting a significantly lower computational complexity. Thus, the proposed algorithm is applicable in time-critical implementations like cognitive radios. Ongoing work is carried out by our group to study different higher-order feature combinations for classification; comparative results will be presented in future work.

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