Joint modulation classification and antenna number detection for MIMO systems

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Joint Modulation Classification and Antenna Number Detection for MIMO systems

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***Abstract*—Non-cooperative classification of the modulation type of communication signals finds application in both civilian and military contexts. Existing modulation classification methods for Multiple Input Multiple Output (MIMO) communication systems commonly require a-priori information on the number of transmit antennas employed by the multiantenna transmitter, which, in most of the non-cooperative scenarios involving modulation classification, is unknown and needs to be blindly extracted from the received signal. Since the problems of MIMO modulation classification and detection of the number of transmit antennas are highly coupled, we propose a decision theoretic approach for spatial multiplexing MIMO systems that considers these two tasks as a joint multiple hypothesis testing problem. The proposed method exhibits a high performance even in moderate to low SNR regimes while requiring no a-priori knowledge of the channel state information and the noise variance.**

Keywords*—*Automatic modulation classification, multiple-input multiple-output, minimum description length.

I. Introduction

Automatic classification of the modulation type of communication signals originating from unknown or partly known sources is a popular research area which finds widespread application, e.g. in electronic warfare, radio surveillance, signal interception, civilian spectrum monitoring, and cognitive radio. Due to the continuous increase in the complexity and diversity of the transmission technologies used in both civilian and military communications, the methods used in automatic modulation classification (AMC) need to be constantly extended and updated to be able to handle the newly emerging transmission techniques. Multiple Input Multiple Output (MIMO) communications systems emerging in the last decade, which use multiple antennas for transmission and reception, represent such an example: Conventional AMC schemes designed for the single input single output (SISO) signal model cannot be employed for MIMO signals, since such algorithms are based on the fundamental assumption that only a single signal from a single transmit antenna is present at the receiver side for classification. Thus, the approaches used in AMC need to be reconsidered to accommodate multiantenna transmission, where multiple signals, one from each transmit antenna, arrive at a receiver, which also employs multiple antennas.

In [1], Choqueuse et al. proposed an average likelihood ratio test (ALRT) for MIMO signals employing spatial multiplexing (SM), which, with the assumption of known channel matrix and noise variance, can be considered as optimal in the Bayesian sense, thus, its classification performance constitutes an upper bound for the MIMO modulation classification problem for SM systems. In the same work, a suboptimal hybrid likelihood ratio test (HLRT) is presented, which relaxes the requirement of a-priori knowledge of the channel matrix by employing blind channel estimation, and is therefore more relevant for practical application scenarios. This approach is also employed in feature based AMC algorithms such as in [2], where diverse higher-order signal statistics are used as discriminating features between different modulation types with a neural network-based decision algorithm, in [3], which employs higher-order cumulant based features with a suboptimal criterion of decision, and in [4], that makes use of the asymptotic likelihood function of a feature vector consisting of 4th order cumulants for decision.

Most of the MIMO AMC methods existing in the literature require, ideally, the channel matrix itself, or, in practically relevant scenarios, its blind estimate in order to perform the classification. This inherently implies the presence of a-priori information on the number of transmit antennas employed by the transmitter at the receiver side, due to the fact that the size of the channel matrix is required for estimation purposes. This common assumption, made by most AMC methods in the literature, is not realistic in scenarios, where the transmitter is unknown and no cooperation between the transmitter and receiver is possible. In this work, in contrast to the existing literature, the MIMO modulation classification problem is investigated in a realistic non-cooperative environment, where the number of transmit antennas is unknown and needs to be extracted from the received signal in a blind manner, in addition to the channel matrix and the noise variance.

Detection of the number of sources impinging on a sensor array is a well investigated problem within various different contexts, such as in array signal processing and direction of arrival estimation. In the literature, the most common approach found for this task is to employ an information theoretic criterion such as the minimum description length (MDL) [5], which can be considered as a general approach for choosing a probabilistic model that best fits the received signal from a set of candidate models[1]. However, the use of such information theoretic criteria requires a-priori knowledge on the probability distributions of the individual sources, i.e. the distributions of the transmit signals from each antenna, which are specified by the modulation employed at the multiantenna transmitter [7]. In the non-cooperative classification scenarios considered in this work, this information is not available at the receiver side prior to the classification of the modulation type, thus, the problems of MIMO modulation classification and antenna

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[1]For recent alternative approaches to antenna number detection, see [6] and the references therein.

number detection are highly coupled: Performing the former requires a-priori information on the latter and vice versa.

In this work, we propose a novel decision theoretic approach to modulation classification for SM MIMO systems, capable of operating in non-cooperative scenarios, where not only the channel matrix and the noise variance are unknown, but also no a-priori information on the number of transmit antennas is available, by considering, for the first time in the literature, the tasks of AMC and antenna number detection as a joint multiple hypothesis testing problem. We restrict our study to the general class of linear and memoryless modulations and employ an extended and modified version of the MDL as a criterion of decision, where the maximum likelihood estimates of the noise variance and channel matrix for each hypothesis are replaced with more practical blind estimates based on second and higher order statistics of the signal, respectively.

II. System Model and Problem Formulation

We consider a spatial multiplexing MIMO system with N_t transmit and N_r receive antennas. The received signal vector $\mathbf{y}[k] = [y_1[k], \ldots, y_{N_r}[k]]^T$ at time instant $k = 1, \ldots, N$ can be expressed as

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

where $\mathbf{s}[k] = [s_1[k], \ldots, s_{N_t}[k]]^T$ is the modulated transmit signal vector, $\mathbf{w}[k]$ is a complex circular white Gaussian noise vector with variance σ^2, and $\mathbf{H}$ is an $N_r \times N_t$ channel matrix whose elements 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. With the assumption of unit power transmit signals, the signal-to-noise ratio (SNR) is given as: $\mathrm{SNR} = \frac{N_t}{\sigma^2}$ [1].

MIMO modulation classification can be considered as a multiple hypothesis testing problem where each hypothesis corresponds to a modulation type $M_p \in \mathcal{M}$ with $\mathcal{M}$ the set of possible modulation types. The decision on the modulation type $\hat{M}$ is made based on the received signal block $\mathbf{Y} = [\mathbf{y}[0], \ldots, \mathbf{y}[N-1]]$ of length N. Using the fact that the transmit signal in an SM system is an independent and identically distributed sequence belonging to a discrete alphabet specified by the employed modulation type, the average likelihood function of $\mathbf{Y}$ is given as [1]:

$$\Lambda(\mathbf{Y}|\mathbf{H}, \sigma^2, M_p, N_t) = \frac{1}{(K_{M_p})^{NN_t}(\pi\sigma^2)^{N_r}} \times \prod_{k=0}^{(N-1)} \sum_{\mathbf{s}^{(p)} \in M_p} \exp\left(\frac{-1}{\sigma^2}|\mathbf{y}[k] - \mathbf{H}\mathbf{s}^{(p)}|^2\right), \tag{2}$$

where K_{M_p} is the number of discrete states in the modulation type M_p and the sum is taken over $(K_{M_p})^{N_t}$ possible values of $\mathbf{s}^{(p)}$, which represents all the possible modulated data vectors for the modulation type M_p. The likelihood based MIMO AMC algorithms in the literature are essentially based on the maximization of this function or, in more realistic cases, some approximation of it with an estimate of $\mathbf{H}$ instead of its actual value, with respect to the modulation type M_p. Clearly, this approach requires the presence of the a-priori knowledge of the parameter N_t at the receiver both for computing (2) and estimating $\mathbf{H}$. This information is usually unavailable in non-cooperative scenarios, and has to be extracted from the received signal block $\mathbf{Y}$. In the literature, information theoretic methods such as the MDL are employed for this task.

MDL is a general approach employed in the model selection problem, i.e., choosing a probabilistic model that fits the received data best from a class of possible models in presence of unknown parameters [5]. Given a parameterized class of probability densities $f^{(q)}(\mathbf{Y}|\mathbf{\Theta}^{(q)})$ with the unknown parameter vector $\mathbf{\Theta}^{(q)}$, the MDL criterion decides for the q'th model in the class that satisfies

$$\hat{q} = \arg\min_q \{-\log\left(f^{(q)}(\mathbf{Y}|\hat{\mathbf{\Theta}}^{q})\right)\} + \frac{1}{2}|\mathbf{\Theta}|_q \log(N) \tag{3}$$

where $\hat{\mathbf{\Theta}}^{(q)}$ represents the maximum likelihood estimates of the parameters $\mathbf{\Theta}$, $f(\mathbf{Y}|\hat{\mathbf{\Theta}}^{(q)})$ is the likelihood function of the received signal and $|\mathbf{\Theta}|_q$ is the number of parameters to be estimated, all of which are computed with the assumption of the q'th class of distributions. In [7], the MDL approach has been employed for the source number detection problem with sources using linear digital modulations, which leads to:

$$\hat{N}_t = \arg\min_q \{-\log\left(\Lambda(\mathbf{Y}|\hat{\mathbf{H}}^{(q)}, \hat{\sigma}^2_{(q)}, M\right) + \frac{1}{2}(2qN_r + 1)\log(N)\}, \tag{4}$$

where $\Lambda(\mathbf{Y}|\hat{\mathbf{H}}^{(q)}, \hat{\sigma}^2_{(q)}, M)$ is the average likelihood function given in (2) for the known modulation type M, approximated with the maximum likelihood (ML) estimates of the channel matrix and the noise variance. Clearly, the use of the MDL criterion for this case requires the a-priori knowledge on the modulation type employed in the transmitter.

III. Proposed Algorithm

The main objective of this work is to perform modulation classification in a non-cooperative MIMO environment with an unknown number of transmit antennas. Since modulation classification and antenna number detection are two deeply intertwined signal processing tasks, we propose to employ a joint hypothesis testing approach for this purpose. We employ the MDL criterion for decision, by extending the class of probability distributions considered in the model selection problem in (3), where only distributions for a known modulation type under different number of sources is considered [7], to also include all possible distributions $f^{(q)}(\mathbf{Y}|\hat{\mathbf{\Theta}}^{(q)})$ that correspond to all the modulation types $M_p \in \mathcal{M}$. The resulting joint classifier decides for the modulation type and antenna number pair that jointly minimize the extended MDL criterion:

$$(\hat{N}_t, \hat{M}) = \arg\min_{i \in \mathcal{I}; M_p \in \mathcal{M}} \{-\log\left(\Lambda(\mathbf{Y}|\hat{\mathbf{H}}^{(i,p)}, \hat{\sigma}^2_{(i,p)}, M_p, i\right) + \frac{1}{2}(2iN_r + 1)\log(N)\}, \tag{5}$$

where $\mathcal{I} = \{1, 2 \ldots, K\}$ is the set of all possible values considered for N_t, $\hat{\mathbf{H}}^{(i,p)}$ and $\hat{\sigma}^2_{(i,p)}$ are the blind ML estimates of the channel matrix and the noise variance, respectively, generated with the assumption that the modulation type M_p is employed by a transmitter with i antennas.

In the literature, blind ML estimation of these parameters is usually carried out using the expectation maximization approach (see, for example [8]), however, such methods display a high computational complexity, which, considering the fact that the estimation needs to be performed for each possible antenna number and modulation pair, is prohibitive for practical applications. In this work, we propose a computationally less intensive approach that approximates the MDL cost function in (5) by substituting the ML estimates of σ^2 and $\mathbf{H}$ with estimates based on second and higher order statistics of the signal, respectively.

1) Estimation of the channel matrix: In this work, we employ a blind channel estimation strategy consisting of two steps. First, we use the higher order statistics (HOS) based MIMO blind channel matrix estimation algorithm proposed in [9], which employs a blind source separation (BSS) approach by applying a kurtosis-based cost minimization procedure, to form a pre-estimate of the channel matrix. It should be noted that for the classical BSS model, where the signal components are assumed to be independent, the channel matrix estimate contains phase ambiguities which needs to be resolved prior to the classification. Furthermore, in contrast to the EM based ML approaches such as in [8], the use of [9] for estimation requires the presence of a larger number of receive antennas than transmit antennas, i.e. $N_r > N_t$.

Let $\tilde{\mathbf{H}}^{(i)}$ be the pre-estimate of the channel matrix formed by the HOS algorithm under the assumption $N_t = i$. We first recover an estimate of the transmit signal vector $\mathbf{s}[k]$ using this pre-estimate:

$$\tilde{\mathbf{s}}[k] = (\tilde{\mathbf{H}}^{(i)\dagger}\tilde{\mathbf{H}}^{(i)})^{-1}\tilde{\mathbf{H}}^{(i)\dagger}\mathbf{y}[k]. \quad (6)$$

Due to the phase ambiguities inherent to the estimator, the components of the recovered signal vector $\tilde{\mathbf{s}}[k]$ are noisy and phase-rotated versions of the components of the actual transmit signal $\mathbf{s}[k]$, i.e. $\tilde{s}_l[k] = e^{j\varphi_l}s_l[k] + n_l[k]$ where $n_l[k]$ is a noise term and φ_l is the phase offset of the l'th component, which can now be estimated using blind phase recovery, with the assumption that the modulation type M_p has been transmitted. Similar to [1], we employ the blind phase recovery algorithm in [10], exploiting the higher order moments of $s_l[k]$ to estimate the phase offset. Assuming that a modulation has been transmitted, which has a $\frac{2\pi}{Q_p}$ rotationally symmetric constellation, the phase offset estimate is given as

$$\hat{\varphi}_l^{(p)} = \frac{1}{Q_p}\arg\left(\mu_p^{(Q_p)}\sum_{k=1}^{N}\tilde{s}_l[k]^{Q_p}\right), \quad (7)$$

where $\mu_p^{(Q_p)} = E\{(s_p^*)^{Q_p}\}$ is the Q_p'th order moment of a signal using the modulation M_p. Following the estimation the phase offset for each component of $\tilde{\mathbf{s}}[k]$, the final phase corrected channel estimate under the assumption of the modulation type M_p and $N_t = i$ is expressed as

$$\tilde{\mathbf{H}}^{(i,p)} = \tilde{\mathbf{H}}^{(i)}\tilde{\mathbf{\Phi}}^{(i,p)} \quad (8)$$

where the phase correction matrix $\tilde{\mathbf{\Phi}}^{(i,p)}$ is an $i \times i$ diagonal matrix with elements $[\tilde{\mathbf{\Phi}}^{(i,p)}]_{l,l} = e^{-j\hat{\varphi}_l^{(p)}}$.

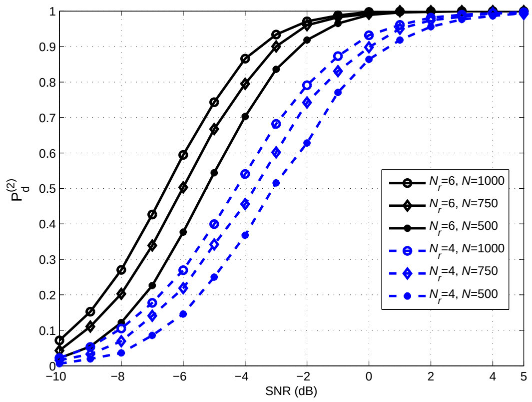

Fig. 1. Performance of the proposed algorithm for $N_t = 2$, $N_r = 4, 6$; $N = 500, 750, 1000$.

2) Estimation of the noise variance: In the HOS based blind channel estimation algorithm in [9], the main assumption is that the signal components in the transmit signal vector have unit power. This assumption is employed as a constraint in solving the kurtosis based cost minimization, hence, it is straightforward to show that a method-of-moments estimator for the noise variance, with the assumption that the modulation type M_p has been employed with $N_t = i$, can be given as

$$\tilde{\sigma}^2_{(i,p)} = \frac{1}{i}\text{trace}\Big((\tilde{\mathbf{H}}^{(i,p)})^{\dagger}\tilde{\mathbf{H}}^{(i,p)}(\hat{\mathbf{\Sigma}} - \mathbf{I})\Big) \quad (9)$$

where $\hat{\mathbf{\Sigma}} = \frac{1}{N}\sum_{k=0}^{N-1}\tilde{\mathbf{s}}[k]\tilde{\mathbf{s}}^{\dagger}[k]$ is the sample covariance matrix of the transmit signal recovered with the blind channel estimate. Finally, the proposed joint modulation classification and antenna number detection algorithm is obtained by substituting the ML estimates $\hat{\mathbf{H}}^{(i,p)}$ and $\hat{\sigma}^2_{(i,p)}$ in eq. (5) with the estimates $\tilde{\mathbf{H}}^{(i,p)}$ and $\tilde{\sigma}^2_{(i,p)}$ given in equations (8) and (9).

IV. Simulation Results

In this section, the performance of the proposed classification algorithm is evaluated using simulations. We consider the set of possible modulation types $\mathcal{M} = \{BPSK, QPSK, 8PSK, 16QAM\}$, and $K = N_t + 1$. For each hypothesis, 1000 Monte Carlo trials have been performed. We use the joint probability of correct decision $P_d^{(N_t)}$ as a performance measure, i.e. the probability of correctly determining both the modulation and the antenna number, given that N_t transmit antennas have been employed. Assuming equiprobable modulation types, this probability is given as

$$P_d^{(N_t)} = \frac{1}{|\mathcal{M}|}\sum_{p=1}^{|\mathcal{M}|}P\Big((\hat{N}_t = N_t, \hat{M} = M_p)|(N_t, M_p)\Big), \quad (10)$$

where $P\Big((\hat{N}_t = N_t, \hat{M}= M_p)|(N_t, M_p)\Big)$ is the joint probability of correctly deciding for the modulation type M_p and antenna number N_t and $|\mathcal{M}|$ is the cardinality of the set $\mathcal{M}$.

Figures 1 and 2 display the performance of the proposed algorithm for $N_t = 2$ and 3 respectively. For both cases, three different values of the observation length $N = 500, 750$ and 1000 has been considered. For $N_t = 2$, the classification is performed for $N_r = 4$ and 6, whereas for $N_t = 3$, $N_r = 6$ and

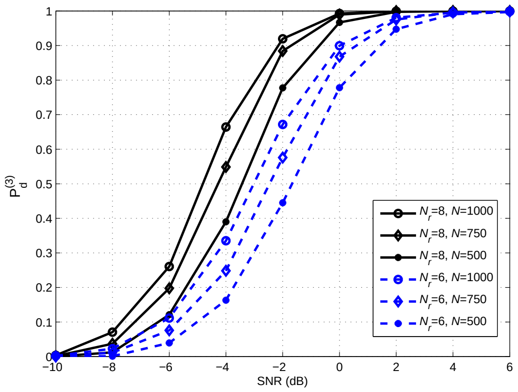

Fig. 2. Performance of the proposed algorithm for $N_t = 3$; $N_r = 6, 8$; $N = 500, 750, 1000$.

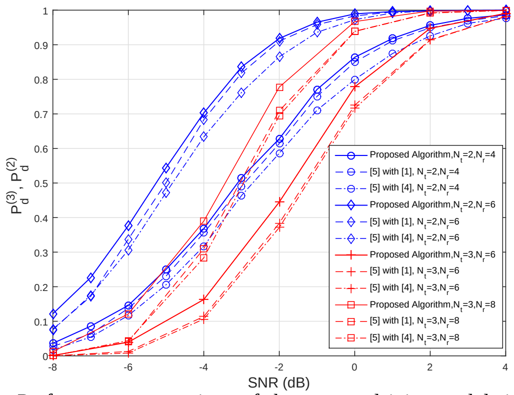

Fig. 3. Performance comparison of the proposed joint modulation classification and antenna number detection approach with the AMC algorithms in [1] and [4], combined with the antenna detection scheme in [5], N=500

8 is considered. The simulation results show that the proposed algorithm achieves a good performance both for $N_t = 2$ and $N_t = 3$ even in the low SNR regime. Clearly, the numbers of receive and transmit antennas are essential parameters effecting the performance of the algorithm: Increasing N_r for a fixed N_t both improves the quality of the blind estimates of the unknown parameters and provides a diversity effect, leading to an increase in the classification performance, whereas increasing N_t for a fixed N_r results in an opposite effect, as seen by comparing figures 1 and 2. As expected, the performance of the algorithm increases as the number of observed vector samples N increases.

Figure 3 compares the performance of the joint multiple hypothesis testing approach proposed in this work with a more conventional approach, where the antenna number detection is performed prior to the modulation classification, providing the modulation classifier with the information on the number of transmit antennas. Since this approach can only be employed with a sub optimal antenna number detection method that does not require the modulation type of the transmit signal, we use the MDL criterion derived for gaussian distributed sources in [5], which, as shown in [11], provides relatively good detection results even when the distributions of the transmit signals are non-Gaussian or unknown. For the subsequent modulation classification, we consider the AMC algorithms proposed in [1] (the HLRT) and in [4]. In the simulations, the same antenna configurations are considered as above with $N = 500$. The proposed joint approach clearly outperforms the alternative approaches in all cases, and the performance gap increases with increasing N_r, N_t.

V. Conclusion

This work presents a novel approach to the modulation classification problem for SM MIMO systems by considering non cooperative scenarios where the number of antennas employed by the transmitter is not available to the classifier and has to be extracted from the received signal, in contrast to the existing literature, where this parameter is commonly assumed to be perfectly known. The proposed approach, for the first time in the literature, treats the detection of the number of antennas and classification of the modulation as a joint multiple hypothesis testing problem and uses a criterion based on MDL to perform the decision. The numerical results show that the proposed algorithm exhibits a good performance for relatively low values of SNR.

Compared to existing MIMO AMC algorithms, the proposed method can be considered as more suitable for blind and non-cooperative scenarios due to the fact that it requires a considerably less amount of a-priori information for classification.

References

[1] V. Choqueuse, S. Azou, K. Yao, L. Collin, and G. Burel, "Blind modulation recognition for MIMO systems," *MTA Review*, vol. 19, no. 2, pp. 183–196, Jun. 2009.

[2] K. Hassan, I. Dayoub, W. Hamouda, C. Nzeza, and M. Berbineau, "Blind Digital Modulation Identification for Spatially-Correlated MIMO systems," *IEEE Trans. Wireless Commun.*, vol. 11, no. 2, pp. 683–693, Feb. 2012.

[3] M. Muhlhaus, M. Oner, O. Dobre, H. Jakel, and F. Jondral, "A novel algorithm for MIMO signal classification using higher-order cumulants," in *Radio and Wireless Symposium (RWS), 2013 IEEE*, Jan 2013, pp. 7–9.

[4] M. Muhlhaus, M. Oner, O. Dobre, and F. Jondral, "A Low Complexity Modulation Classification Algorithm for MIMO Systems," *Communications Letters, IEEE*, vol. 17, no. 10, pp. 1881–1884, October 2013.

[5] M. Wax and T. Kailath, "Detection of Signals by Information Theoretic Criteria," *IEEE Transactions on Acoustics, Speech and Signal Processing*, vol. 33, no. 2, pp. 387–392, Apr. 1985.

[6] M. Mohammadkarimi, E. Karami, and O. Dobre, "A novel algorithm for blind detection of the number of transmit antennas,," in *IEEE Crowncom 2015*, April 2015.

[7] E. Fishler, M. Grosman, and H. Messer, "Determining the Number of Discrete Alphabet Sources from Sensor Data," *EURASIP Journal on Applied Signal Processing*, vol. 2005, pp. 4–12, Jan. 2005.

[8] A. Belouchrani and E. Cardoso, "Maximum Likelihood Source Separation for Discrete Sources," in *EUSIPCO*, Edinburgh, Sep 1994, pp. 768–771.

[9] V. Choqueuse, A. Mansour, G. Burel, L. Collin, and K. Yao, "Blind Channel Estimation for STBC Systems Using Higher-Order Statistics," *Wireless Communications, IEEE Transactions on*, vol. 10, no. 2, pp. 495–505, Feb 2011.

[10] M. Moeneclaey and G. de Jonghe, "ML-oriented NDA Carrier Synchronization for General Rotationally Symmetric Signal Constellations," *IEEE Trans. Commun.*, vol. 42, no. 8, pp. 2531–2533, Aug. 1994.

[11] E. Fishler, M. Grosmann, and H. Messer, "Detection of Signals by Information Theoretic Criteria: General Asymptotic Performance Analysis," *Signal Processing, IEEE Transactions on*, vol. 50, no. 5, pp. 1027–1036, May 2002.