Modulation Recognition for MIMO Relaying Broadcast Channels with Direct Link

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***Abstract*—In this letter, we investigate the performance of modulation identification based on pattern recognition approach using the decision tree (J48) classifier, for multiple-input multiple-output (MIMO) relaying broadcast channels with direct link (source-to-destination). The proposed system identifies the modulation type and order among different M-ary shift-keying linear modulations used by broadband technologies such as long term evolution-advanced (LTE-A) and worldwide interoperability for microwave access (WiMAX). The system under study employs features extraction based on higher order statistics (HOS) of the received signal. Based on receiver operating characteristic (ROC) curves, our study shows that J48 classifier is more efficient than the multilayer perceptron (MLP) classifier trained with resilient backpropagation training algorithm (RPROP) where it achieves close to perfect detection rate (over 99%) with reasonable training time in acceptable signal-to-noise ratio (SNR) range. We also show that the performance of the MIMO relaying broadcast network is remarkably better than the traditional MIMO one.**

***Index Terms*—Higher order statistics, multiple-input multiple-output relaying broadcast channels, modulation identification, multilayer perceptron, decision tree, spatial multiplexing.**

I. Introduction

RECENTLY, blind algorithms and techniques for MIMO signals interception have gained more attention. One essential step in the signal interception process is to blindly identify the modulation scheme of traditional MIMO signals [1], [2], [3]. Modulation identification has attracted considerable interest in military for many applications such as; communication intelligence (COMINT), electronic support measures (ESM) and spectrum surveillance. Also recent and rapid developments in software defined radio (SDR) in the context of cognitive radio (CR) have given modulation identification more prominence in civil applications. Cooperative communications through user collaboration have received a growing interest [4], [5], [6], [7].

Ignoring the direct link is reasonable in some scenarios such as; where the distance between the source and destination is very large, causing significant link loss and absorption of the source signal. Practically, this consideration is not always true. In fact, cooperative systems based on relaying with direct link [8], [9], [10] can improve the recognition performance of modulation types, where spatial diversity is improved and the coverage of wireless networks is extended. To the best of our knowledge, no previous work addressed the problem of modulation identification in the context of MIMO relaying broadcast channels with direct link.

In this letter, we investigate a pattern recognition approach for modulation identification in MIMO relaying broadcast with direct link using spatial multiplexing (SM) and the decision tree (J48) classifier. The purpose is to distinguish among M-ary phase shift keying (M-PSK) and M-ary quadratic amplitude modulated (M-QAM) signals and to identify the order of modulation without any priori signal information. Since we assume Rayleigh fading channels for backward, forward and direct links with perfect channel state information (CSI), our proposed algorithm is considered as semi-blind classifier. Here, we apply a linear transmission strategy to design the linear precoding matrix at the source node ($\mathcal{S}$) and the beamforming matrix at the relay node ($\mathcal{R}$). At the destination node ($\mathcal{D}$), after combining the received signal replicas from the direct link ($\mathcal{SD}$) and the forward link ($\mathcal{RD}$), two subsystems are employed. The first subsystem is features extraction based on combining higher order moments (HOM) and higher order cumulants (HOC). The second subsystem is the classifier. In this work, in order to prove the effectiveness of J48 classifier in our proposed algorithm, we compare it to the multilayer perceptron (MLP) classifier using the backpropagation training algorithm (RPROP). Moreover, through the probability of identification, we evaluate the modulation identification gain for cooperative MIMO scheme relative to non-cooperative one.

The remainder of this letter is organized as follows; we present the system model in Section II. In Section III, we describe the pattern recognition approach, then we evaluate the performance of our proposal in Section IV. Finally, we conclude this letter with Section V.

Notations $E(.)$, $\mathrm{tr}(\cdot)$, $(\cdot)^{-1}$, $(\cdot)^{T}$,$\bar{(\cdot)}$ and $(\cdot)^{H}$ denote expectation, trace, inverse, transpose, conjugate and conjugate transpose operations, respectively. $\mathbf{I}_N$ is an $N \times N$ identity matrix. $\mathcal{C}^{M\times N}$ represents the set of $M \times N$ matrices over complex field, and $\mathcal{CN}(x, y)$ denotes a circularly symmetric complex Gaussian distribution with mean x and covariance y.

II. System Model and Preliminaries

In this work, we investigate the MIMO relaying broadcast channel with $\mathcal{S}$, $\mathcal{R}$ and $\mathcal{D}$ nodes as depicted in Figure 1. Our transmission model assumes that $\mathcal{S}$, $\mathcal{R}$ and $\mathcal{D}$ are equipped with M_s, M_r and M_d antennas, respectively. A two-phase protocol can be used to transmit data from $\mathcal{S}$ to $\mathcal{D}$ via the direct link $\mathcal{SD}$ and the cooperative one $\mathcal{SR}-\mathcal{RD}$.

When $\mathcal{S}$ implements SM, the requirements $\{M_d \geq M_s, M_r \geq M_s\}$ must be satisfied if $\mathcal{D}$ and $\mathcal{R}$ are to support all the K independent substreams simultaneously ($K \leq M_s$).

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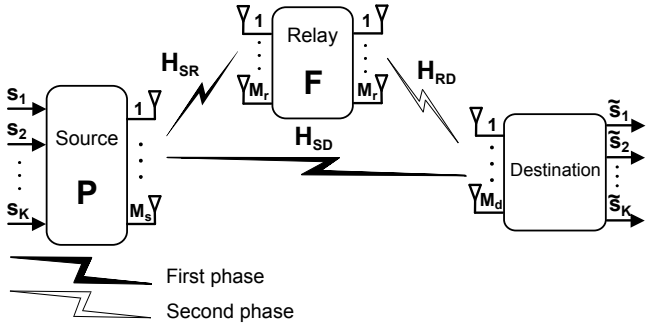

Fig. 1. MIMO relaying broadcast network with source, relay and destination nodes using two-phase protocol.

For simplicity, we assume that $M_s = M_r = M_d = K$. We also assume that a non-regenerative and half-duplex relaying scheme applied at $\mathcal{R}$ to process and forward the received signals [11].

A. Source node precoding design based on regularized zero forcing (RZF)

During the first phase, a RZF [12] is applied to the data vector $\mathbf{x} = \{[x_1, x_2, ..., x_K]^T$, x_k is the symbol intended for the kth antenna at $\mathcal{D}\}$.

The RZF is defined by a linear precoding matrix $\mathbf{P}$ as

$$\mathbf{P} = \mathbf{H}_{SD}^H \left(\mathbf{H}_{SD}\mathbf{H}_{SD}^H + \alpha \mathbf{I}_K\right)^{-1}, \tag{1}$$

where $\mathbf{H}_{SD} \in \mathcal{C}^{K\times K}$ is the full rank gain matrix of the $\mathcal{SD}$ MIMO channel and α is equal to the ratio of total noise variance to the total transmit power (i.e, $\alpha = K\sigma_{SD}^2/P_s$) [12]. The entries of $\mathbf{H}_{SD}$ follow a circularly symmetric complex Gaussian distribution with zero-mean and unit variance. Thereafter, $\mathcal{S}$ will broadcast the K precoded data streams to $\mathcal{R}$ and $\mathcal{D}$ simultaneously. Here, the received signal vectors at $\mathcal{D}$ and $\mathcal{R}$, respectively, can be expressed as

$$\mathbf{y}_{SD} = [y_{SD1}, y_{SD2}, ..., y_{SDK}]^T = \rho_s \mathbf{H}_{SD}\mathbf{P}\mathbf{x} + \mathbf{n}_{SD}, \tag{2}$$

$$\mathbf{y}_{SR} = \rho_s \mathbf{H}_{SR}\mathbf{P}\mathbf{x} + \mathbf{n}_{SR}, \tag{3}$$

where $\rho_s = \sqrt{P_s/\mathrm{tr}\left(\mathbf{P}\mathbf{P}^H\right)}$ is the source power control factor. $\mathbf{H}_{SR} \in \mathcal{C}^{K\times K}$ is the full rank gain matrix of the $\mathcal{SR}$ MIMO channel. The entries of $\mathbf{H}_{SR}$ follow a circularly symmetric complex Gaussian distribution with zero-mean and unit variance. Each $\mathbf{n}_i = \{[n_{i1}, n_{i2}, ..., n_{iK}]^T \sim \mathcal{CN}\left(0, \sigma_i^2 \mathbf{I}_K\right)$, $i = SD,\ SR\}$, is a vector corresponds to the additive zero-mean spatially-white circularly complex Gaussian noise with variances σ_i^2.

Since we consider MIMO system using SM, the signals $\mathbf{x}$ are given by,

$$\mathbf{x} = [s_1, s_2, ..., s_K]^T, \tag{4}$$

where the source symbols $\mathbf{s}$ are assumed to be independent, identically distributed (i.i.d), and mutually independent.

B. Relay node beamforming design based on ZF-RZF

During the second phase, $\mathcal{R}$ forwards the received signal vector to $\mathcal{D}$ after applying a linear beamforming matrix $\mathbf{F}$, based on ZF-RZF [9], given by

$$\mathbf{F} = \mathbf{H}_{RD}^H \left(\mathbf{H}_{RD}\mathbf{H}_{RD}^H + \gamma \mathbf{I}_K\right)^{-1} \left(\mathbf{P}^H \mathbf{H}_{SR}^H \mathbf{H}_{SR}\mathbf{P}\right)^{-1} \mathbf{P}^H \mathbf{H}_{SR}^H, \tag{5}$$

where $\mathbf{H}_{RD} \in \mathcal{C}^{K\times K}$ is the full rank gain matrix of the $\mathcal{RD}$ MIMO channel and γ is equal to the ratio of total noise variance to the total transmit power (i.e, $\gamma = K\sigma_{RD}^2/P_r$) [12]. The entries of $\mathbf{H}_{RD}$ follow a circularly symmetric complex Gaussian distribution with zero-mean and unit variance.

Therefore, the received signal vector at $\mathcal{D}$ can be expressed as

$$\begin{aligned} \mathbf{y}_{RD} &= [y_{RD1}, y_{RD2}, ..., y_{RDK}]^T \\ &= \rho_r \rho_s \mathbf{H}_{RD}\mathbf{F}\mathbf{H}_{SR}\mathbf{P}\mathbf{x} + \rho_r \mathbf{H}_{RD}\mathbf{F}\mathbf{n}_{SR} + \mathbf{n}_{RD}, \end{aligned} \tag{6}$$

where $\rho_r = \sqrt{P_r/\mathrm{tr}\left(\rho_s^2 \mathbf{F}\mathbf{H}_{SR}\mathbf{P}\mathbf{P}^H\mathbf{H}_{SR}^H\mathbf{F}^H + \sigma_{RD}^2\mathbf{F}\mathbf{F}^H\right)}$ is the relay power control factor and $\mathbf{n}_{RD} \sim \mathcal{CN}\left(0, \sigma_{RD}^2 \mathbf{I}_K\right)$ is a vector corresponds to the additive zero-mean spatially-white circularly complex Gaussian noise with variances σ_{RD}^2.

C. Destination node combining

The destination receives two representations of the data vector $\mathbf{x}$; $\mathbf{y}_{SD}$ (2) and $\mathbf{y}_{RD}$ (6) through $\mathcal{SD}$ and $\mathcal{SR}-\mathcal{RD}$, respectively. In order to maximize the combined SNR at $\mathcal{D}$, the received signal vector $\mathbf{y}_D$ can be expressed as

$$\mathbf{y}_D = [y_{D1}, y_{D2}, ..., y_{DK}]^T = \mathbf{y}_{SD} + \mathbf{y}_{RD}. \tag{7}$$

In the following, to implement the classifier, features must be extracted for each signal $\mathbf{y}_D$ to provide a basis for discriminating between the modulation types.

III. Pattern Recognition Approach

Our proposal is based on pattern recognition to distinguish among different modulation types. This approach is generally divided into two subsystems: the features extraction subsystem and the classifier subsystem.

A. Features extraction

Previous works have shown that HOC and HOM of the received signal are one of the best candidates for modulation identification in single-input single-output (SISO) systems [13], [14] and traditional MIMO systems [2]. In this work, based on [15], we employ the features with a combination of HOM and HOC up to order eight for the case of cooperative MIMO systems since they can discriminate the different modulation schemes.

HOM of a signal $\mathbf{x}$ are defined by [16]

$$M_{jm}(\mathbf{x}) = E\left[x^{j-m}\left(\overline{x}\right)^m\right], \tag{8}$$

where j is the moment order.

HOC of order j of the zero-mean signal $\mathbf{x}$ are defined by

$$C_{jm}(\mathbf{x}) = Cum\left[\underbrace{x, ..., x}_{(j-m)\ times}, \underbrace{\overline{x}, ..., \overline{x}}_{m\ times}\right]. \quad (9)$$

Also, the relation between HOM and HOC can be expressed as

$$Cum[x_1, ..., x_n] = \sum_{\Phi} (-1)^{\alpha-1} (\alpha-1)! \prod_{\nu\in\Phi} E\left(\prod_{i\in\nu} x_i\right), \quad (10)$$

where Φ runs through the list of all partitions of $\{1, \cdots, n\}$, ν runs through the list of all blocks of the partition Φ, and α is the number of elements in the partition Φ.

In order to mitigate the effect of the increase of the cumulants magnitude with their order, we raise each cumulant to the power $2/j$ [17].

B. Classifier

After extracting the proper features, the modulation identification problem can be considered as a pattern recognition problem. Knowing that classifiers typically employ two phases of processing: training and testing. Our purpose is to have a well generalized network, which has a good prediction for all sample sets. For this, some processing of data set are highly recommended before launching training phase. First, the extracted set of features are normalized to have zero mean and unit variance. Then, the best subset of the combined HOM and HOC features set is selected through the principal component analysis (PCA) technique [18]. After pre-processing and features subset selection, the training process is triggered. After training, a test phase is launched, and the classifier is evaluated through the probability of identification.

In the following, we describe J48 and MLP classifiers.

1) Decision Tree (J48): A decision tree is a decision support tool that uses a tree graph of decisions and their possible consequences. It is an excellent tool for helping to decide between several courses of action. In our work we use C4.5 decision tree. In fact, C4.5 creates a model based on a tree structure [19]. In the tree, nodes and branches correspond to features and possible values connecting features, respectively. A leaf that symbolizes the class, terminates a set of nodes and branches. Thus, tracing the path of nodes and branches to the terminating leaf leads to determine the class of an instance. J48 algorithm is an implementation of the C4.5.

2) MLP: Many researchers have focused on artificial neural network (ANN) to develop high performance modulation classifiers of the various M-ary shift keying linear modulation types [2], [20]. In addition, many ANN models have been developed, where MLP network is the most widely used. Here, the proposed classifier is a MLP using the RPROP introduced in [21], known by its high performance on pattern recognition problems. MLP is composed of an input layer, one or more hidden layers and an output layer, where each neuron of a layer is connected to all the neurons of the next layer. The addition of this hidden layer allows the network to model the functions of complex nonlinear decision between any input and output space. However, ANN approaches suffer from complex network structure, large training time and low convergence speed.

C. Metrics for performance evaluation of classifier

The efficiency indicators used in the evaluation of classification applications are numerous. An effective way for the evaluation of detection performance is to plot the receiver operating characteristic (ROC) curve [22]. By computing the area under the curve ROC (AUC) [23], we can compare multiple classifiers. Indeed, the most efficient classifier is one that has the largest AUC.

IV. Results and Discussion

Our proposed system was verified and validated for digital modulation schemes $\Theta = \{2-PSK,\ 4-PSK,\ 8-PSK,\ 16-QAM,\ 64-QAM,\ 256-QAM\}$ for MIMO systems using VBALST. First, 200 realizations of testing MIMO signals with $512\times K$ symbols are generated. The combined HOM and HOC of the equalized signals (i.e., $\mathbf{y}_D$) are calculated to form the features set. Then, pre-processing and features subset selection is performed as a preparation of J48 and MLP training.

In order to evaluate our proposed system, we use the data mining tool Weka [24] for classification. Through intensive simulations, we show that the optimal MLP structure to be used for this algorithm is a two hidden layers network (excluding the input and the output layer), where the first layer consists of 10 nodes and the second of 15 nodes. Thus, we compare the recognition performance of J48 classifier to this structure of MLP classifier using the ROC curves.

All results are based on 1000 Monte Carlo trials for each modulation scheme i.e. 6000 Monte Carlo trials in total. For each trial, K testing signals of 512 i.i.d symbols are used as input messages. We assume Rayleigh fading channels for $\mathcal{SR}$, $\mathcal{RD}$ and $\mathcal{SD}$ links with perfect CSI. Also, we assume that the SNRs for sub-channels $\mathcal{SD}$ and $\mathcal{RD}$ are equal (i.e., $SNR = SNR_{SD} = SNR_{RD}$). However, the SNR for sub-channel $\mathcal{SR}$ (i.e., SNR_{SR}) can be different.

The probability of identification is given in percentage and estimated by $\frac{N_c}{N_{total}} \times 100$, where $N_{total} = 6000$ is the total number of trials and N_c is given by

$$N_c = \sum_{\theta_i\in\Theta} N_{\theta_i}, \quad (11)$$

where N_{θ_i} is the number of trials for which the modulation $\theta_i \in \Theta$ is correctly identified.

Figure 2 depicts the ROC curves for both J48 and MLP methods for cooperative MIMO system using VBLAST technique with $K = 4$, $SNR_{SR} = 30dB$ and $SNR = 5dB$. Here, it is clear that the AUC of J48 is larger than that MLP. Indeed, J48 and MLP methods can identify perfectly the 16, 64 and 256-QAM (i.e., $AUC = 1$). However, for 2, 4 and 8-PSK, by comparing the ROC curves of these two methods, we can conclude that the J48 classifier is more efficient as it offers better AUC.

To confirm these results, we show the probability of identification for J48 and MLP methods in the case of MIMO systems using VBLAST technique with $K = 4$ in Figure 3. As seen from these results, at 95% of identification, the J48 classifier offers SNR gain of about $0.7dB$ and $2.1dB$ compared to the MLP for the cooperative and the non-cooperative cases, respectively.

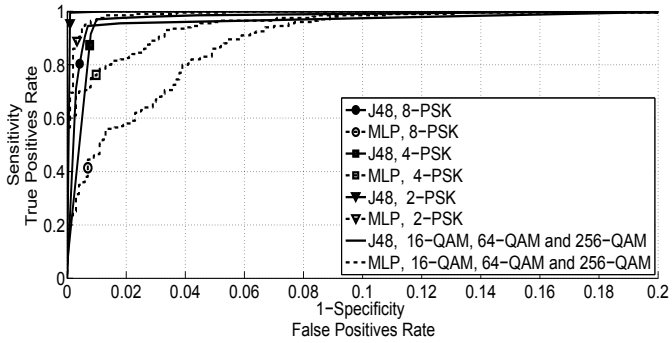

Fig. 2. ROC curves of J48 and MLP methods for each type of modulation (in the case of VBLAST MIMO scheme, $K = 4$, $SNR_{SR} = 30dB$ and $SNR = 5dB$).

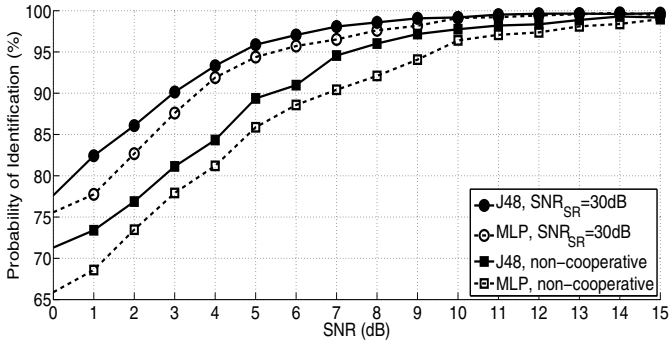

Fig. 3. Probability of identification versus SNR for Θ in VBLAST MIMO scheme for $K = 4$ using J48 and MLP classifiers.

It is worth noting that the duration of the training phase for J48 and MLP given by the data mining tool Weka are 0.19 and 8.59 seconds, respectively. Therefore, the J48 method is more adapted for our proposed system in terms of both performance of modulation identification and training time.

V. Conclusion

We have presented an algorithm for modulation identification dedicated for cooperative MIMO networks based on pattern recognition approach. Through the ROC curves and the learning period time, we carried out a comparative study of J48 and MLP classifiers. Indeed, our study showed the superiority of J48 classifier to discriminate among different linear modulation types with reasonable training time. Consequently, J48 classifier allows for better monitoring of the intercepted signals in broadband technologies with reduced complexity. We have also shown that the effectiveness of modulation recognition based on cooperative schemes is remarkably better than the non-cooperative case.

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