Blind Modulation Identification for MIMO Systems

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Abstract—Modulation type is one of the most important characteristics used in signal waveform identification and classification. In this paper, an algorithm for blind digital modulation identification for multiple-input multiple-output (MIMO) systems is proposed. The suggested algorithm is verified using higher order statistical moments and cumulants of the received signal. A multi-layer neural network trained with resilient backpropagation learning algorithm is proposed as a classifier. The purpose is to discriminate among different M-ary shift keying linear modulation types and the modulation order without any priori signal information. This study covers different MIMO systems with and without channel state information (CSI). The proposed classifier is evaluated through the probability of identification where we show that our proposed algorithm is capable of identifying the modulation scheme with high accuracy in excellent signal-to-noise ratio (SNR) range.

Index Terms—Higher order statistics, multiple-input multiple-output, modulation identification, neural networks, spatial multiplexing, space-time block coding.

I. INTRODUCTION

Over the last decade Multiple-Input Multiple-Output (MIMO) systems have shown a great importance as they provide a reliable and high-data-rate wireless communications. Nowadays, MIMO is considered one of the promising technologies for developing the next generation of wireless systems. 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 MIMO signals.

Modulation identification has its roots in military applications such as; communication intelligence (COMINT), electronic support measures (ESM), spectrum surveillance, threat evaluation and interference identification. Also recent and rapid developments in software defined radio (SDR) in the context of cognitive radio (CR) have given modulation identification a more prominence in civil applications.

Many modulation identification algorithms have been developed for Single-Input Single-Output (SISO) systems [1]. These algorithms are generally divided into two categories. The first category is based on decision theoretic approach while the second on pattern recognition. The decision theoretic approach is a probabilistic solution based on a priori knowledge of probability functions and certain hypotheses [2], [3]. On the other hand, the pattern recognition approach is based on extracting some basic characteristics of the received signal called features [4]–[10]. This approach is generally divided into two subsystems: the features extraction subsystem and the classifier subsystem. However, the second approach is more robust and easier to implement if the proper features set is chosen.

In the past, much work has been conducted on modulation identification [4]–[10]. The identification techniques, which have been employed to extract the signal features necessary for digital modulation identification, include spectral based features set [4], [5], higher order statistics (HOS) [6], [7], constellation shape [8], and wavelets transforms [9], [10]. With their efficient performance in pattern recognition problems (e.g., modulation classification), many studies have proposed the application of artificial neural networks (ANNs) as classifiers [5], [10].

In [11], Swami et. al proposed a simple yet very low complexity method, based on elementary fourth-order cumulants for the classification of digital modulation schemes. The robustness of this approach comes about not only from the resistance of HOS to additive colored Gaussian noise, but also from a natural robustness to constellation rotation and phase jitter. Also additive non-Gaussian noise can be handled if its fourth-order cumulants are known, or via simple preprocessing.

So far, few researches have considered the application of modulation identification techniques in MIMO systems. For instance, Choqueuse et. al [12] adopted a maximum likelihood approach for the blind recognition of the modulation for MIMO systems using spatial multiplexing (SM). In their work the authors proposed two Likelihood based classifiers. The first one, called Average Likelihood Ratio Tests (ALRT), is optimal in the Bayesian sense but requires the knowledge of the channel matrix. The second classifier, called Hybrid Likelihood Ratio Tests (HLRT), approximates the ALRT by replacing the channel matrix with its estimate. The major drawbacks of these methods are the high computational complexity and its need of perfect knowledge of the noise variance at the receiver side.

In this paper we introduce a pattern recognition approach for modulation identification in MIMO systems. In our approach, the features extraction subsystem is based on the higher order cumulants (HOC) and the higher order moments (HOM) of the received signal. Our proposed classifier is a multi-layer artificial neural network trained using the resilient backpropagation learning algorithm (RPROP). Modulation identification is performed without any priori information of the received signal (e.g. probability functions, noise statistics, etc.). Then, our proposed algorithm is considered as semi-blind when
assuming a perfect channel state information (CSI) knowledge at the receiver side. Conversely, this algorithm is completely blind when using erroneous channel estimation. The modulation identification is investigated for MIMO systems using spatial multiplexing (SM) and space-time block coding (STBC). The proposed algorithm has the capability to identify M-ary amplitude shift keying (M-ASK), M-ary phase shift keying (M-PSK) and M-ary quadratic amplitude modulated (M-QAM) signals and the order of the identified modulation. The performance of this algorithm is examined through the probability of identification.

The remainder of the paper is organized as follows: Section II defines the system model and introduces the different assumptions. Section III describes the process of feature extraction using HOS. Section IV focuses on the classifier structure. The results and algorithm performance analysis are presented in section V. Finally, conclusions and perspectives of the research work are presented in section VI.

II. SYSTEM MODEL

A MIMO system with $N_t$ transmitting antennas and $N_r$ receiving antennas is considered ($N_r \geq N_t$). Under the assumption of a frequency flat and time invariant MIMO channel, the baseband received symbols vector at the instant $k$ is described as:

$$y(k) = Hx(k) + n(k)$$

where $y(k) = [y_1(k), ..., y_{N_r}(k)]^T$ is an $(N_r \times 1)$ received signal vector without any time oversampling and optimum symbol timing, $x(k) = [x_1(k), ..., x_{N_t}(k)]^T$ is the $(N_t \times 1)$ vector representing the transmitted symbols, and $n(k) = [n_1(k), ..., n_{N_r}(k)]^T$ is an $(N_r \times 1)$ vector corresponds to the additive zero-mean spatially-white circularly complex Gaussian noise with variance $\sigma_n^2$; i.e. $n(k) \sim \mathcal{CN}(0, \sigma_n^2 I_{N_r})$, where $I_{N_r}$ is the identity matrix of size $N_r$. $H$ corresponds to the $(N_r \times N_t)$ full rank gain matrix of the MIMO channel. The entries of $H$ follows a circularly symmetric complex Gaussian distribution with zero-mean and unit variance.

The signals $X$ are transmitted after space-time encoding is applied to the source signal $s$, as follows:

$$X = C(s)$$

where $C$ is the space-time coding matrix, that encodes a block of input symbols of size $N_t$ represented by $s = [s_1, ..., s_{N_t}]^T$ into $(N_t \times T)$ transmitted symbols where $T$ is the code length. This defines the code rate by $R_{MIMO} = N_t/T$. In this paper, we consider both spatial multiplexing (SM) and space-time block coded (STBC) MIMO systems.

When considering MIMO system using SM, $R_{MIMO} = N_t$ since $N_r = N_t$ and $T = 1$; i.e. $X = [s_1, ..., s_{N_t}]^T$.

The several orthogonal space-time block coded (OSTBC) MIMO systems are examined in this study. We consider full-rate Alamouti [13] scheme defined by:

$$X = \begin{pmatrix} s_1 & -s_2^* \\ s_2 & s_1^* \end{pmatrix}$$

and MIMO systems with $N_t = 3, 4$ using OSTBC with $R_{MIMO} = \frac{1}{2}$, $\frac{3}{4}$. In what follows we use the notation $R_{MIMO}$/OSTBC $N_t$ to represent different codes, for example, $\frac{1}{2}$OSTBC3 and $\frac{3}{4}$OSTBC3 are given respectively by [14]:

$$X = \begin{pmatrix} s_1 & -s_2 & -s_3 & s_4 \\ s_2 & s_1 & -s_3 & s_4 \\ s_3 & s_1 & -s_2 & -s_4 \\ s_4 & -s_1 & s_2 & -s_3 \end{pmatrix}$$

The zero-forcing (ZF) technique is applied to reveal some ambiguity from the received symbols. This technique consists of applying an equalizing matrix $W$ on the received vector. This matrix $W$ is defined by:

$$W = (H^H H)^{-1} H^H$$

where the estimation of the transmitted symbols is given by:

$$\hat{x}(k) = W y(k) = x(k) + (H^H H)^{-1} H^H n(k).$$

Then the estimated vector $\hat{x}(k) = [\hat{x}_1(k), ..., \hat{x}_{N_t}(k)]^T$ is applied to the modulation identifier or more precisely the features extraction subsystem.

Here we assume perfect CSI at the receiver side (semi-blind classifier). If it is not the case, channel estimation has to be performed and the modulation is blindly identified. In the literature, many blind channel estimation works have been proposed [12], [15]. In this paper, we are interested in investigating the impact of channel estimation error on the modulation identification rather than the estimation process. Hence, we model the estimated channel as:

$$\hat{H} = H + E$$

where $E$ is the estimation error matrix with entries being i.i.d with zero-mean circularly symmetric complex Gaussian variables and variance $\sigma_e^2$.

III. FEATURES EXTRACTION

One of the important aspects of modulation identification is the selection of the proper identification features. Previous works have shown that higher order cumulants (HOC) and higher order moments (HOM) of the received signal are one of the best candidates for signal identification in SISO systems [7], [11].
Higher order moments of a signal $x$ are defined by [16]:

$$M_{km} = E[x^{k-m}(x^*)^m]$$  \hspace{1cm} (9)

where $k$ is the moment order. The cumulant of order $k$ of the zero-mean signal $x$ is defined by:

$$C_{km} = Cum[ x, ..., x, x^*, ..., x^*, \text{ (k-m) times m times }]$$  \hspace{1cm} (10)

Also, the relation between moments and cumulants can be expressed as:

$$Cum[x_1, ..., x_n] = \sum_{\Omega} (\alpha - 1)! (-1)^{\alpha - 1} \prod_{v \in \Omega} E(\prod_i x_i)$$  \hspace{1cm} (11)

where $\Omega$ runs through the list of all partitions of $\{1, ..., n\}$, $v$ runs through the list of all blocks of the partition $\Omega$, and $\alpha$ is the number of elements in the partition $\Omega$. For instance, the fourth-order cumulant of zero-mean signals $x$, $y$, $z$ and $w$ is given by:

$$Cum[x, y, z, w] = E(xyzw) - E(xy)E(zw) - E(xz)E(yw) - E(xw)E(yz).$$  \hspace{1cm} (12)

Based on (11), moments estimation leads to estimate the cumulants. Given a signal $x$ with $N$ samples, one can estimate the moments as:

$$\hat{M}_{km} = \frac{1}{N} \sum_{i=1}^{N} x^{k-m}(i)x^*^m(i).$$  \hspace{1cm} (13)

The natural robustness to constellation rotation and phase jitter and the resistance of HOS to additive colored Gaussian noise makes this approach very robust as proved in [11]. Based on that, the features set we employ consists of a combination of HOM and HOC up to order four. The features extraction subsystem inputs are the estimated signals from the zero-forcing receiver. By considering $L$ consecutive equalized vectors, we have:

$$\hat{X}(n) = [\hat{x}(n), \hat{x}(n-1), ..., \hat{x}(n-L-1)]$$

$$= \begin{bmatrix} \hat{x}_1(n) & \cdots & \hat{x}_1(n-L-1) \\ \vdots & \ddots & \vdots \\ \hat{x}_{N_t}(n) & \cdots & \hat{x}_{N_t}(n-L-1) \end{bmatrix}$$  \hspace{1cm} (14)

where the combination of HOM and HOC is calculated for the $N_t$ estimated signals i.e. $x_1, ..., x_{N_t}$. Finally, the signal identification will be based on all the combined features.

Note that the complexity of (13) is of order $N$ where estimating a moment of order $k$ requires only about $N$ complex additions and $k \times N$ complex multiplications. Based on (11), cumulant calculation is of order $N$. Of course, the computational cost of the features calculation for each of the above mentioned $N_t$ signals is of the same order. Then, the features extraction process has a very low complexity $O(N)$.

IV. CLASSIFIER

After extracting the proper features, the modulation identification problem can be considered as a pattern recognition problem. Knowing that ANN is one of the best solutions for pattern recognition problems, many researchers have focused on ANNs to develop high performance modulation classifiers of the various M-ary shift keying linear modulation types [5], [10]. In this study, the proposed classifier is a backpropagation artificial neural network employed for the MIMO system.

The network structure including the number of hidden layers, the number of nodes in each layer and the transfer function of each node has been chosen through intensive simulations. This structure is directly related to network training speed and identification precision. Speeding the learning process of the network and improving the identification accuracy can be achieved by normalizing the features set and selecting the optimal subset for the discrimination process. Here, a feature subset selection based on the principal component analysis (PCA) is applied to select the best subset of the combined HOM and HOC features set [17].

After pre-processing and features subset selection, the training process is triggered. The initiated artificial neural network is trained using the resilient backpropagation learning algorithm (RPROP) introduced in [18], known by its high performance on pattern recognition problems. After training, a test phase is launched, and the classifier is evaluated through the probability of identification.

Since the outputs of a layer in ANN are considered as linear combinations among the inputs of this layer, then the computational cost of the classifier is related to the number of nodes at each layer. Considering the static and predefined structure of ANN, and the small number of nodes at each layer, the required number of operations to obtain the classifier output is fixed and inexpensive.

Figure 1. Probability of identification versus SNR for $\Theta$ in several VBLAST MIMO systems with $N_1 \times N_f$ antenna configuration (including SISO up to $4 \times 4$ system).
V. RESULTS AND DISCUSSION

The proposed algorithm was verified and validated for various orders of linear digital modulation schemes. First, 100 realizations of testing MIMO signals with \( 512 \times N_t \) symbols are generated. The combined HOM and HOC of the equalized signals are calculated to form the features set. Then, preprocessing and features subset selection is performed as a preparation of ANN training. Extensive simulations show that the optimal ANN 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.

The following modulation schemes are considered in all of our simulations:

\[
\Theta = \{16 - QAM, 32 - QAM, 64 - QAM, 2 - PSK, 8 - PSK, 4 - ASK, 8 - ASK\} \]

All results are based on 1000 Monte Carlo trials for each modulation scheme i.e. 7000 Monte Carlo trials in total. For each Monte Carlo trial, \( N_t \) testing signals of 512 i.i.d symbols are used as input messages. For different values of SNR, a spatially-white circularly complex Gaussian noise with variance \( \sigma_n^2 \) is added such as \( SNR = 10 \log_{10}(\frac{\sigma_n^2}{\sigma_s^2}) \) where \( \sigma_s^2 \) is the average transmitted power. A Rayleigh channel is considered; i.e. the entries of channel matrix are circularly symmetric complex Gaussian random variables with zero-mean and unit variance.

The probability of identification is given in percentage and estimated by \( \frac{N_c}{N_{total}} \times 100 \), where \( N_{total} = 7000 \) is the total number of trials and \( N_c \) is given by:

\[
N_c = \sum_{\theta_i \in \Theta} N_{\theta_i}
\]

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

The proposed classifier has shown an excellent performance even at low SNRs for MIMO systems using VBLAST, as it is clear in Fig. 1. Note that the probability of identification is more than 99% when SNR is not lower than 5dB for all antenna configurations. Also, the performance will increase when the difference \( N_r - N_t \) increases. We also find that the performance is better when using more transmitters for the same antenna difference. These results are perfectly normal since increasing \( N_r - N_t \) will increase the diversity gain which will degrade the symbol error probability and improve the probability of identification.

Fig. 2 shows the simulations results for MIMO systems using different OSTBCs. The proposed classifier shows an excellent performance even at low SNRs. Similar to the results in Fig. 1, for the same \( R_{MIMO} \), increasing the difference \( N_r - N_t \) will improve the performance. For the same
antenna configuration increasing the code rate will decrease the performance.

Comparing classifier performances among MIMO systems using VBLAST and OSTBC techniques will reveal that for the same antenna configuration, the probability of identification is better when considering OSTBC MIMO systems as shown in Fig. 3. This is expected since the equalization is more robust when employing OSTBC techniques instead of SM ones.

The probability of identification was examined for different values of \( L \) (i.e. the number of considered symbols). Increasing \( L \) will improve the performance since this will raise the accuracy of HOM estimation (13). Fig. 4 shows the performances for several values of \( L \). One can notice that for each duplication of the number of symbols, a gain of \(-2dB\) will be achieved when SNR<\(-5dB\).

The effect of channel estimation error on modulation scheme identification has been examined and the results are displayed in Fig. 5. As noticed, the performances will drop rapidly for an error variance \( \sigma^2 > 0.1 \). The proposed algorithm is sensitive to channel estimation errors. One of the proposed solutions is to use more robust equalization technique instead of ZF. Minimum mean square error (MMSE) equalizer could improve the performance, but it requires the knowledge of the SNR. Another solution is to use a blind source separation (BSS) technique where the channel estimation is not required. For instance several BSS algorithms could be used (Constant Modulus Algorithm (CMA), Multi-Modulus Algorithm (MMA) or Analytical Multi-Modulus Algorithm (AMMA)). It should be noted that the proposed algorithm shows better performance than [12] without noise variance knowledge and with a very low complexity.

VI. Conclusions

We presented an algorithm for modulation identification aimed for MIMO systems based on HOS as features extraction subsystem and a neural network trained with resilient backpropagation learning algorithm as classifier subsystem. The proposed algorithm is capable of recognizing different linear digital modulation schemes with high accuracy at low SNRs. Our classifier has high modulation identification performance when the SNR is not lower than 5dB for systems employing SM or STBC. For the same antenna configuration, the probability of identification is shown to be more accurate when using STBC.

One major improvement to our algorithm is to use a blind source separation technique where the channel estimation is not required.

REFERENCES