Eigenfilter-based Automatic Modulation Classification with Offsets for Distributed Antenna Systems

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***Abstract*—Automatic modulation classification (AMC) schemes are crucial for cognitive radio applications in 5G systems as well as for military scenarios. Current AMC schemes do not exploit the redundant information of distributed antenna systems (DAS). Moreover, in case of DAS, an offset should be taken into account. In this paper, we propose an eigenfilter and higher-order cumulants based AMC scheme with offsets. By including different offsets during the training phase of the artificial neural network (ANN), we can exploit all the cumulants achieving a very high accuracy. Moreover, by combining the captured signals by the DAS with the eigenfilter, we can successfully exploit the array gain.**

I. Introduction

Automatic Modulation Classification (AMC) allows the identification of a modulation scheme of a signal at a single antenna receiver. In military applications, it is an essential step in the identification of the modulation type of the intercepted signals [2].

AMC approaches have two general classes, namely, likelihood based and features based. Due to the incomplete knowledge of the probability density function, likelihood based AMC schemes are sub-optimal classifiers [1]-[3]. On the other hand, features based AMC schemes achieve near-optimal performance and have a much lower computational complexity in comparison with the likelihood based counterparts [1]-[3].

AMC for single antenna receivers are susceptible to the channel and SNR conditions. Therefore, in distributed antenna systems (DAS), the exploitation of multiple antennas gives a higher classification accuracy.

In this work, we assume a simple communication system composed of a single narrowband transmitter, i.e. no interference, and a receiver equipped with an antenna array in a scenario where the time delay of the multipath components is negligible in comparison with the line-of-sight (LOS) component. In order to solve to improve AMC, we propose an eigenfilter and higher-order cumulants based automatic modulation classification with offsets. By including different offsets during the training of the artificial neural network (ANN), we can exploit all the cumulants achieving a very high accuracy. Moreover, by combining the captured signals with the eigenfilter, we obtain a gain proportional to the amount of antennas.

The remainder of this work is divided into five sections: In Section II, we present the data model used for AMC in DAS systems; In Section III, we present the proposed classifier in detail; In Section IV, the simulations results are discussed; Finally, in Section V, the conclusions are drawn.

II. Data Model

The distributted antenna system(DAS) is composed of two parts: the distributed antennas and a base station. The antennas only purpose is to collect signal samples and transmit them to the base station via a wired high-bandwidth low-latency dedicated connection. The base station is responsable for all the processing and automatic modulation classification of the received signals. Assuming signals received from the distributed antennas are narrowband, the baseband complex envelope of the signal received at the base station can be written as

$$\mathbf{y}(n) = \mathbf{a}s(n) + \mathbf{g}(n), \tag{1}$$

where m is the number of distributed antennas, $\mathbf{a} = [a_1 \cdots a_M]^{\mathrm{T}} \in \mathbb{C}^M$ consists of the amplitudes and phase offsets of the signals received at each sensor, $s(n)$ are the transmitted symbols and $\mathbf{g}(n)$ is the additive white Gaussian noise vector.

III. Proposed Eigenfilter-based AMC with Offsets

As shown in Fig. 2, our proposed scheme is composed of three main steps. In step 1, we apply the eigenfilter in order to estimate the transmitted signal $\hat{s}(n)$. Note that the estimated signal $\hat{s}(n)$ includes an offset. In step 2, we extract the features from the estimated signal with offset. Here the features are the fourth and sixth order cumulants of $\hat{s}(n)$. In step 3, given the computed cumulants as inputs, a trained ANN returns the modulation scheme. We propose to train the ANN not only for all possible modulations, but also for all possible values of offsets. Note that the bold blocks in Figure 2 are the innovative steps proposed in this paper. The signals received from the distributed antennas are filtered using the eigenfilter, which gives a stronger output signal. The filtered signal is given by

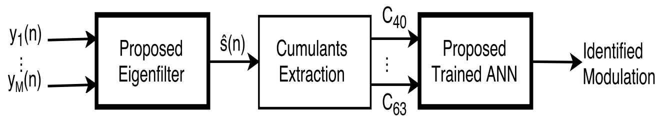

Fig. 1. Proposed system block diagram.

$\hat{s}(n) = \mathbf{w}^H \mathbf{y}(n)$, where $\mathbf{w} \in \mathbb{C}^M$ is the vector of mixing weights, chosen such that the SNR of the filtered signal is maximized.

If the signal power is higher than the noise power, by constrainig $\mathbf{w}$ to unitary magnitude, we can approximate the SNR as

$$\mathrm{SNR} = \frac{\mathbf{w}^{\mathrm{H}} \mathbf{R_{yy}} \mathbf{w}}{\sigma_{\mathrm{g}}^2}, \tag{2}$$

where σ_g^2 is the variance of the noise and $\mathbf{R_{yy}}$ is the covariance matrix of $\mathbf{y}(n)$. The SNR can be maximized by choosing $\mathbf{w}$ equal to the eigenvector associated to the highest eigenvalue of $\mathbf{R_{yy}}$.

The second step is the features extraction. The features are given by the fourth and the sixth order cumulants of $\hat{s}(n)$. For a complex valued stationary signal, we define the p^{th} order moments as [1]

$$\hat{M}_{pq} = \frac{1}{N} \sum_{n=1}^{N} y(n)^{p-q} (y^*(n))^q \tag{3}$$

The 4^{th} and 6^{th} order cumulants used as features are defined as

$$\begin{aligned}
\hat{C}_{40} =& \hat{M}40 - 3\hat{M}_{20}^2, \\
\hat{C}_{41} =& \hat{M}_{41} - 3\hat{M}_{20}\hat{M}_{21}, \\
\hat{C}_{42} =& \hat{M}_{42} - 2\hat{M}_{21}^2 - \hat{M}_{20}\hat{M}_{22}, \\
\hat{C}_{60} =& \hat{M}_{60} - 15\hat{M}_{40}\hat{M}_{20} + 30\hat{M}_{20}^3, \\
\hat{C}_{61} =& \hat{M}_{61} - 5\hat{M}_{40}\hat{M}_{21} - 10\hat{M}_{41}\hat{M}_{20} + 30\hat{M}_{20}^2\hat{M}_{21} \\
\hat{C}_{63} =& \hat{M}_{63} - 3\hat{M}_{41}\hat{M}_{22} - 9\hat{M}_{42}\hat{M}_{21} - 3\hat{M}_{20}\hat{M}_{43} \\
& + 18\hat{M}_{20}\hat{M}_{21}\hat{M}_{22} + 12\hat{M}_{21}^3.
\end{aligned} \tag{4}$$

After extracting the cumulants, the classification of the modulation type is performed using a proposed trained ANN. Only the cumulants $\hat{C}_{42}$ e $\hat{C}_{63}$ are insensitive to offsets and, therefore, only these two cumulants should be used in scenarios with offsets. On the other hand, not using the other cumulants means that less information is taken into account for the classification of the modulation type. In order to relax such limitation, we propose to train an ANN considering different types of modulations with different values of offsets. For the training phase of the ANN, we assume an offset given by a zero mean Gaussian distributed random variable with variance σ_θ^2.

IV. Simulation Results

In this section, we present the simulation results comparing the performance of our proposed classifier with the state-of-the-art approach proposed in [5]. For the sake of simplicity, we consider four types of modulations, namely, BPSK, QPSK, 8PSK and 16QAM. For each modulation type, we generate 10000 signals with 1024 samples. The SNR is given with respect to one antenna of the DAS, while the other antennas are multiplied by a factor with mean 1 and variance 0.1. The offset of each antenna of the DAS follows a zero Gaussian distribution with variance 0.1.

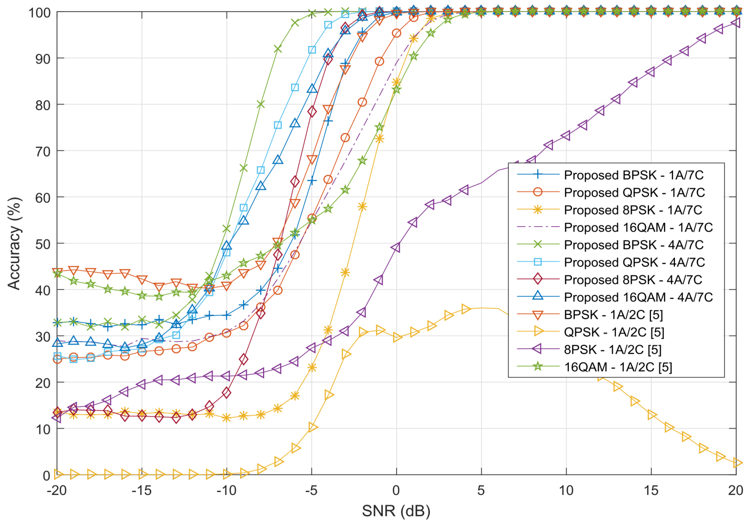

Fig. 2. Classifier performance under various settings.

Figure 3 depicts the curves of the accuracy for each AMC scheme by varying the SNR. In the legend, the state-of-the-art schemes have a suffix [5] corresponding to the reference, while the proposed AMC schemes have a prefix proposed. Note that the proposed schemes can exploit seven cumulants (7C) due the proposed trained ANN, while the state-of-the-art approach only exploits two cumulants (2C) due the limitation of the other cumulants with respect to offsets. In addition, we also compare the proposed scheme with eigenfilter considering four antennas (4A) and without eigenfilter considering one antenna (1A).

Note that, for the same modulation, the proposed scheme with one antenna and the state-of-the-art scheme have only a similar performance in the case of BPSK modulation. For other types of modulations, our proposed approach provides a considerable gain. Our proposed approach with more antennas using eigenfilter provides a significant gain with respect to our approach with only one antenna.

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