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A Machine Learning Based Blind Detection on Interference Modulation Order in NOMA Systems

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***Abstract*—In order to blindly detect the modulation order of interference signals in downlink non-orthogonal multiple access (NOMA) systems, a machine learning (ML) algorithm based on Anderson-Darling test is proposed in this letter. The proposed algorithm adopts ML to determine the modulation order of interference user equipment (UE) from the raw received constellation points automatically. In feature extraction, a novel feature is introduced to improve the accuracy of blind detection. To evaluate the performance of blind detection, the detection rate as well as the throughput are simulated under different scenarios. Simulation results show that the proposed algorithm outperforms conventional algorithm on modulation order detection.**

***Index Terms*—Blind detection, machine learning, Anderson-Darling test, modulation order, NOMA.**

I. Introduction

NON-ORTHOGONAL multiple access (NOMA) has become one of the key technologies in the fifth generation (5G) systems [1]–[5]. One of candidate receiver schemes is codeword level successive interference cancellation (CWIC) receiver, which uses successive interference cancellation (SIC) technique [6]. Assistance information, including modulation order of interference user, is required for CWIC receiver to cancel the inter-superposition-layer interference [6]. Methods, which may be considered for obtaining assistance information, include blind detection (BD), signaling, etc [6]. However, signaling will consume extra resources, which would increase the burden of control channel. Thus, BD is a practical method in real systems, and has been discussed by researchers [7], [8].

Generally, the solutions of BD can be divided into likelihood based (LB) and feature based (FB) [9]. In LB area, exact or approximated likelihood function is used to solve the classification problem. Heunchul Lee *et al* propose a algorithm based on max-log approximation [10]. In FB area, high-order cumulants are widely used. Huang *et al* propose a cumulant-based maximum likelihood algorithm [11]. Existing blind detection algorithms do not use any prior experience and cause performance degradation. This letter proposes a machine learning algorithm based on Anderson-Darling test (MLAD), which uses prior experience to blindly detect the modulation order of interference user in power-domain NOMA. Anderson-Darling test (AD) extracts features from received constellation points and its introduction makes machine learning algorithm feasible in blind detection area.

The technical contributions of this letter include:

- Proposing a new feature of received constellation points after equalization with Anderson-Darling test.
- Introducing machine learning algorithm to blind detection area in communication discipline.
- Proposing a new blind detection algorithm based on Anderson-Darling test and machine learning algorithm.

II. System Model

This letter considers a downlink single-cell scenario which consists one base station (BS) and N user equipments (UEs). The UEs are denoted as $U_i, i = 1 \cdots N$. And the system model considers a multiple carrier channel scenario. The available NOMA scheme can broadly be divided into power-domain NOMA and code-domain NOMA [1]. This letter focuses on the power-domain NOMA. Based on the concept of power-domain NOMA, signals of two or more users are superposed together with specified power ratios and are transmitted on the same time-frequency resource. This process is called superposition coding (SC) and can be written as [1], [6]

$$\boldsymbol{t} = \sum_{i=1}^{N_c} \sqrt{\alpha_i P_r} \boldsymbol{x}^{(i)}, \qquad N_c \le N \tag{1}$$

where N_c is the number of superposed UEs, and P_r denotes the total radiation power. α_i is the portion of P_r assigned to U_i, which satisfies $\sum_{i=1}^{N_c} \alpha_i = 1$. $\boldsymbol{x}^{(i)}$ is the signal of U_i and can be written as $\boldsymbol{x}^{(i)} = [x_1^{(i)}, x_2^{(i)}, \cdots, x_K^{(i)}]^T$, where $i = 1, \cdots, N_c$. $(\cdot)^T$ denotes the transpose of a vector, $x_k^{(i)}$ and K denote the k-th symbol for user U_i and the number of symbols, respectively. Symbol $x_k^{(i)}$ is chosen from a constellation set $\mathbb{C}_{p^{(i)}}$, whose cardinality is denoted by $|\mathbb{C}_{p^{(i)}}|$ and $p^{(i)}$ represents the modulation order of U_i. The k-th symbol in $\boldsymbol{t}$, denoted by t_k, is chosen from a composite constellation set $\mathbb{C}_{p_c}$,

$$\mathbb{C}_{p_c} = \left\{ c_{(i,j)} | c_{(i,j)} = \sum_{i=1}^{N_c} \sum_{j=1}^{|\mathbb{C}_p^{(i)}|} \mathbb{C}_{(p^{(i)},j)} \right\}, \tag{2}$$

where $p_c = \sum_{i=1}^{N_c} p^{(i)}$ and $\mathbb{C}_{(p^{(i)},j)}$ is the j-th point in $\mathbb{C}_{p^{(i)}}$. p_c is termed as the composite modulation order of the superposed transmission. A schematic diagram is given in Fig. 1 to show how superposition coding is performed.

Defining $\boldsymbol{r}^{(i)}$ as the received constellation points vector after equalization at the user U_i. Then, $\boldsymbol{r}^{(i)}$ can be written as

$$\boldsymbol{r}^{(i)} = \boldsymbol{H}^{(i)} \boldsymbol{t} + \boldsymbol{n}^{(i)}, \tag{3}$$

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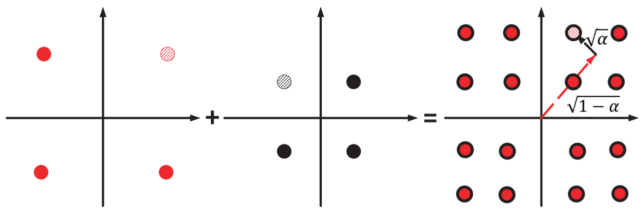

Fig. 1. An example of composite constellation generated from two QPSK constellations with different power ratios

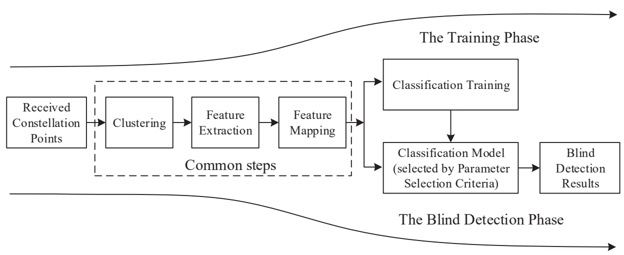

Fig. 2. The diagram of MLAD, including two phases: training phase and blind detection phase

where $\boldsymbol{H}^{(i)}$ denotes the channel matrix after equalization, and $\boldsymbol{n}^{(i)}$ is the additive noise vector, whose elements are independent and identically-distributed (i.i.d.) complex Gaussian. $\mathbb{E}[|\boldsymbol{n}^{(i)}|^2] = \sigma_i^2$, where $\mathbb{E}[\cdot]$ denotes the expectation operator, and $|\cdot|$ represents the absolute value of a complex number. The aim of blind detection is to determine the modulation order of interference user from $\boldsymbol{r}^{(i)}$.

III. Proposed Algorithm

In this section, we introduce a new feature of received constellation points $\boldsymbol{r}^{(i)}$ and propose a MLAD algorithm, including clustering, feature extraction, classification training and model parameter selection criteria. Its block diagram is shown in Fig. 2. Without loss of generality, two users are considered in the remainder of this letter.

A. Training Phase

1) Clustering: Assuming that the noise at the receiver is additive white Gaussian noise (AWGN). Defining $\mathbb{S}_j$ as a cluster of received points. $\mathbb{S}_j$ has the minimum Euclidean norm to the j-th composite constellation point from $\mathbb{C}_{p_c}$, which can be written as

$$\mathbb{S}_j = \{r_k^{(i)}\}, \tag{4}$$
$$\text{s.t.} \quad ||r_k^{(i)} - c_j|| < ||r_k^{(i)} - c_z||, c_j, c_z \in \mathbb{C}_{p_c}, c_j \neq c_z.$$

where j is in the range of $[1 \dots 2^{p_c}]$ and p_c is one of candidate composite modulation orders.

In this step, all candidates of modulation order for interference user should be used to cluster received constellation points. For the sake of simplicity, the set of clusters are denoted by

$$\mathbb{D}_{p_c} = \{\cdots, \mathbb{S}_j, \cdots\}, \quad j = 1, \cdots, 2^{p_c}. \tag{5}$$

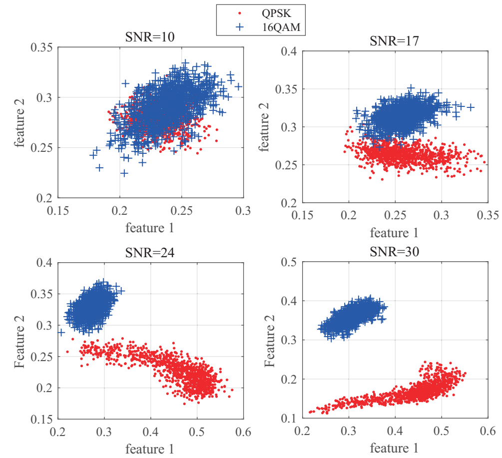

Fig. 3. The features of QPSK and 16QAM when modulation order of target user is 64QAM on different SNRs

2) Feature Extraction: Feature extraction is the most important part in the proposed algorithm. It reduces the complexity of received constellation points. The goal of this step is to extract accurate features of received constellation points. AD test is used to extract features which can be written as [12]

$$A^2 = -K - \sum_{k=1}^{K} \frac{2k-1}{K}[\ln(F(r_k^{(i)})) + \ln(1 - F(r_{K+1-k}^{(i)}))], \tag{6}$$

where $F(\cdot)$ is hypothesized distribution function and $\{r_1^{(i)} < r_2^{(i)} < \cdots < r_K^{(i)}\}$ is the ordered data. Stephens shows that for the case where the mean (μ) and variance (σ) are estimated from data, the statistic must be corrected according to [12]

$$A_*^2 = A^2(1 + \frac{4}{n} - \frac{25}{n^2}). \tag{7}$$

The formula for p-value depends on the value of AD statistic. There are two methods to calculate p-value, which can be found in [13]. Assuming that the p-value of $\mathbb{S}_j$ in $\mathbb{D}_{p_c}$ is $p_j^{(p_c)}$. Then, the feature of received signals is

$$f_i = \frac{1}{2^{p_c}} \sum_{j=1}^{2^{p_c}} p_j^{(p_c)} \qquad i = 1, \cdots, w, \tag{8}$$

where w is the number of candidate modulation orders for interference user. The physical meaning of f_i is the average extent that each cluster obeys Gaussian distribution when we split received constellation into 2^{p_c} clusters. After performing feature extraction, we can get a feature vector

$$\boldsymbol{f} = [\cdots, f_i, \cdots]^T, i = 1, \cdots, w. \tag{9}$$

To make it easier to understand, the features extracted from different combinations of modulation orders and SNRs are shown in Fig. 3.

3) Classification Training: The goal of classification training is to find a model parameter of logistic regression model. Based on the features extracted from previous step, the model estimates the probability of modulation order that interference user may use. From Fig. 3, we can find that clusters are well-separated. But some cases are non-linear separable. A better

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way to fit the data well is to create more features. We choose a simple method to map features and it can be written as

$$\tilde{\boldsymbol{f}} = [1, f_1, f_2, \cdots, f_w, f_1^2, f_2^2, \cdots, f_w^2, \cdots, f_1^l, f_2^l, \cdots, f_w^l], \tag{10}$$

where f_i is the i-the feature in the feature vector $\boldsymbol{f}$. l is the highest degree and is also one of parameters in logistic regression. Based on this higher-dimension feature vector, the trained model will have a more complex decision boundary. To avoid overfitting, a regularized logistic regression is used in this step.

Defining $\mathbb{T}_{\mathrm{SNR},p^{\mathrm{tar}}}$ as the training set. $\mathbb{T}_{\mathrm{SNR},p^{\mathrm{tar}}}$ is made up of mapped features and labels. The labels are actual modulation order of interference user, which are explicitly known in the training phase. $\mathbb{T}_{\mathrm{SNR},p^{\mathrm{tar}}}$ can be written as

$$\mathbb{T}_{\mathrm{SNR},p^{\mathrm{tar}}} = \begin{bmatrix} (\tilde{\boldsymbol{f}}^{(1)})^T & y^{(1)} \\ (\tilde{\boldsymbol{f}}^{(2)})^T & y^{(2)} \\ \vdots & \vdots \\ (\tilde{\boldsymbol{f}}^{(m)})^T & y^{(m)} \end{bmatrix}, \tag{11}$$

where m is the number of training examples and $y^{(i)}$ is the label. The subscript SNR and p^{tar} represent Signal-to-Noise ratio and the modulation of target user, respectively. Then, conventional logistic regression process, such as cost function computing and gradient descent, should be executed to find optimal model parameters. Moreover, receiver operating characteristic curve (ROC), learning curve and precision-recall (P-R) curve should be used to select the best model parameter in training phase.

B. Blind Detection Phase

1) Model Parameter Selection Criteria: Model parameter selection criteria is a method to choose one model parameter for the classification model. After the training phase, a series of model parameters for classification model have been established on different SNRs and p^{tar}s. Those SNRs are denoted by S_l, $l = 1, \cdots, L$, where L is the number of SNRs. As shown in blind detection phase in Fig. 2, the common steps in dashed block should be performed repeatedly on each candidate modulation order of interference user. After that, a feature vector of received constellation points $\boldsymbol{f_e}$ is generated.

Assuming that the estimated SNR is S_e, and the modulation of target user is p_e^{tar}. S_e is generated in channel estimation process. Then, the model parameter whose SNR has the minimum distance to S_e and satisfies $p^{\mathrm{tar}} = p_e^{\mathrm{tar}}$ is chosen. The selection criteria can be written as

$$\begin{aligned} p^{\mathrm{tar}} &= p_e^{\mathrm{tar}}, \\ \mathrm{SNR} &= \arg\min_i |S_e - S_i|, \quad i = 1, \cdots, L \end{aligned} \tag{12}$$

Then model parameter can be uniquely determined by (12).

2) Blind Detection: Inputing the feature vector $\boldsymbol{f_e}$ to the logistic regression model, and the output is the modulation order of interference user.

TABLE I
SIMULATION PARAMETERS

Parameter	Value	Parameter	Value
Bandwidth	10 MHz	Carrier frequency	2 GHz
Sampling rates	15.36 MHz	TTI size	14 OFDM
CFI	2	Channel estimation	MMSE
Cyclic Prefix	Normal	HARQ	Disabled
FFT size	1024	CSI reporting	PUCCH 2-0
Fast fading	Rayleigh	No. of PRBs	50
Propagation	EPA	Receiver type	CWIC

TABLE II
MODULATION COMBINATIONS OF TARGET AND INTERFERENCE USER

Target user	Interference user
16QAM	None, QPSK, 16QAM, 64QAM
64QAM	None, QPSK, 16QAM, 64QAM

IV. SIMULATIONS AND COMPARISON

In this section, we provide a series of simulation results to verify the efficacy and accuracy of the proposed algorithm. We use the blind detection rate and throughput as the measurements of pros and cons of the proposed algorithm. The definition of blind detection rate is $R = v/Z$, where R is the detection rate, v is the number of transmissions which blindly detect the modulation order of interference user successfully and Z is the total number of transmissions. As the performance of blind detection only affects target user, the throughputs of target user are compared. Moreover, the throughput comparison of orthogonal multiple access (OMA) and NOMA is also considered, and the definition of total throughput of NOMA is the throughput on the same time-frequency resource block. To demonstrate its effectiveness, the performance of max-log likelihood based blind detection algorithm is used as benchmark [10]. The legends, which contain “ideal” in Fig. 5 and Fig. 6, are best performance curves where receiver always knows the modulation order of interference user. Simulation parameters and modulation combinations are listed in Table I and Table II, respectively. The word “None” in Table II represents that there is no interference user.

In the training phase, the range of SNR is 0-30 dB with an interval of 1 dB and different types of modulation and coding scheme (MCS) are performed to embody the superiority of proposed algorithm. The blind detection rate curves of different algorithms are shown in Fig. 4, and throughput comparisons are shown in Fig. 5 and Fig. 6.

From Fig. 4, it can be seen that the proposed algorithm is more accuracy than the conventional max-log algorithm on modulation order blind detection. There are two reasons for this phenomenon. One is that the features of received constellation points are extracted properly, and they can represent the modulation order parameter. Another is that the proposed algorithm has more prior experience than benchmark scheme. The prior experience is learned from numbers of training examples in the training phase, and it is saved in model parameter.

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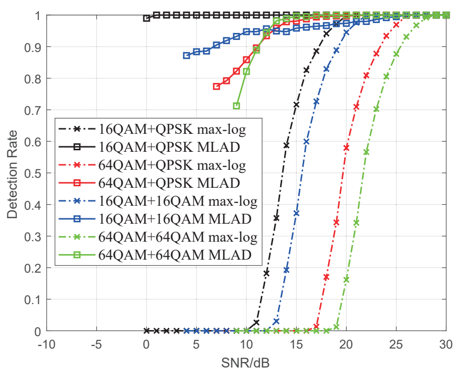

Fig. 4. Blind detection rate comparisons on different detection algorithms.

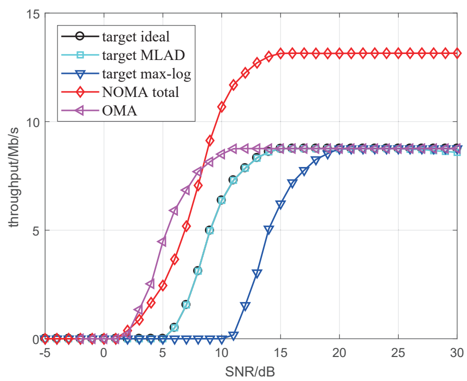

Fig. 5. Throughput comparisons on different detection algorithms. Target user: 16QAM (MCS=11), Interference user: QPSK (MCS=5).

The accuracy improvement of blind detection improves the throughput performance. From Fig. 5, it is clear that the throughput of the proposed algorithm is very closed to the ideal curve, and achieves larger gains compared to max-log algorithm. The throughputs of NOMA and OMA are also addressed in Fig. 5. Due to the failure blind detection of modulation order and imperfect SIC receiver, the throughput for target user in NOMA systems may be worse than that of OMA, but the total throughput of NOMA is better than that of OMA in most SNR regions.

Fig. 6 shows the throughput comparison with different MCS levels for both algorithms. It can be seen that the proposed algorithm brings a mild throughput improvement with the increasing of MCS level. This is because high MCS levels are usually scheduled in high SNR region where the blind detection rates for MLAD and max-log benchmark are both optimistic.

V. Conclusion

In this paper, we introduce new features to represent the modulation order parameter, and propose an MLAD algorithm to blindly detect that parameter of interference user in downlink NOMA systems. The algorithm consists of two phases and four main steps, including clustering, feature extraction, classification training and model parameter selection criteria. Simulation results have proved that the performance of the proposed method outperforms max-log algorithm.

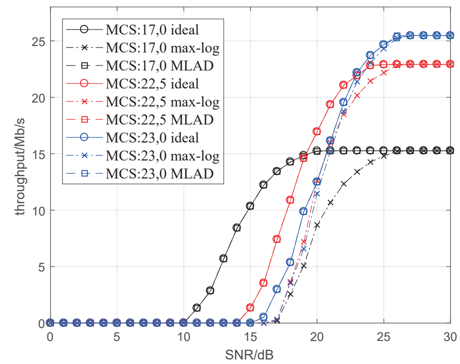

Fig. 6. Throughput comparison on different detection algorithms. Target user: 64QAM, Interference user: QPSK.

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