A MACHINE LEARNING BASED INTERFERENCE MODULATION ORDER DETECTION OF LSTM NETWORK BASED 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. Let us propose a novel and effective deep learning (DL)-aided NOMA system, in which several NOMA users with random deployment are served by one base station (BS). Since DL is advantageous in that it allows training the input signals and detecting sharply changing channel conditions, let us exploit it to address wireless NOMA channels in an end-to-end manner. Specifically, it is employed in the proposed NOMA system to learn a completely unknown channel environment. A Long short-term memory (LSTM) network based on DL is incorporated into a typical NOMA system that enables the posed system to detect the channel characteristics automatically. In addition, the accuracy of the LST Maidedp NOMA scheme is studied by introducing the well-known 10-fold cross-validation procedure.

KEY WORDS: 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].

Practically, channel state information (CSI) has great impact on the performance of the NOMA system and a lot of works have been devoted to realize channel estimation based on the NOMA scenarios. Meanwhile, due to the CSI is hard to be obtained through traditional methods, some scholars turn to investigate the NOMA based strategies in different CSI scenarios. The performance of NOMA under a non-ideal setup and two power allocation algorithms were provided under imperfect CSI [12]. Also, based on the uplink NOMA systems, the authors revealed that imperfect CSI leads to not only extra interference on the desired signal but also the incorrect decoding order [13]. Hence, how to derive an efficient way to acquire perfect CSI is an important issue in the field of NOMA based means and new methods should be exploited to resolve this problem.

Motivated by the aforementioned considerations, a comprehensive study is conducted to optimize the NOMA system based on the DL technique in terms of effectiveness and reliability. 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:

- To the best of our knowledge, by establishing a NOMA system with the aid of DL, our first attempt is to use deep learning methods instead of traditional online learning to analyze the complex channel characteristics of NOMA. To promote the performance of the DL framework, the pre-training process of the DL network is modified.
- 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 consist 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]

$$t = \sum_{i=1}^{N_c} \sqrt{\alpha_i P_r}\, x^{(i)}, \; N_c \leq N \quad \text{----- (1)}$$

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 $\sum_{i=1}^{N_c} \alpha_i = 1 \cdot x^{(i)}$ is the signal of U_i Which can be written as $x^{(i)} = \left[x_1^{(i)}, x_2^{(i)}, x_3^{(i)} \cdots, x_K^{(i)}\right]^T$ where $i = 1, \cdots, N_c \cdot (\cdot)^T$ 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 $\left|\mathbb{C}_{P^{(i)}}\right|$ and $P^{(i)}$ represents the modulation order of U_i. The k-th symbol in t, denoted by t_k, is chosen from a composite constellation set $\mathbb{C}_{P_c}$,

$$\mathbb{C}_{P_c} = \left\{ C_{(i,j)} \middle| C_{(i,j)} = \sum_{i=1}^{N_c} \sum_{j=1}^{\left|\mathbb{C}_P^{(i)}\right|} \mathbb{C}_{(P^{(i)},j)} \right\} \text{-- (2)}$$

Where $P_c = \sum_{i=1}^{N_c} P^{(i)}$ and $\mathbb{C}_{(P^{(i)},j)}$ is the j-th point in $\mathbb{C}_{P^{(i)}} \cdot P_c$ is termed as the composite modulation order of the superposed transmission. Defining $r^{(i)}$ as the received constellation points vector after equalization at the user U_i. Then, $r^{(i)}$ can be written as

$$r^{(i)} = H^{(i)} t + n^{(i)} \text{ ------ (3)}$$

Here, $H^{(i)}$ denotes the channel matrix after equalization and $n^{(i)}$ is the additive noise vector, whose elements are independent and identically-distributed (i.i.d.) complex Gaussian $\mathbb{E}\left[\left|n^{(i)}\right|^2\right] = \sigma_i^2$, 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 $r^{(i)}$.

III. PROPOSED ALGORITHM

In this section, a new feature of MLAD is introduced to detect received constellation points $r^{(i)}$ and consider a novel scheme that adopts the LSTM network into the NOMA framework. Thus, after developing a strategy based on Restricted Boltzmann machines (RBM) to train the initial input, LSTM is employed to learn the channel characteristics of NOMA systems and its end-to-end performance is simulated via offline training and online training.

A. TRAINING PHASE

1. Pre-training based on the RBM

For the sake of enhancing the generalization ability of the network and reducing the dimension of the input data, the RBM is implemented to train the original input of the LSTM. In other words, the RBM is used as the pre-training structure for promoting the performance of the LSTM. Generally speaking, messages are converted into a sequence of transmitted symbols that represent different transmitted signals in digital communication systems. Based on our analysis above, let the unknown signal vector $x_i = \{x_{i,1}, x_{i,2}, \cdots x_{i,q}\}$ be a finite sequence of all transmission symbols, where q denotes the amount of samples in the sequence at U_i. Meanwhile, the transmitted symbols will be corrupted by complex noise and degraded by the poly-tropic environment and the corresponding output y_i can be detected at the receiver. Specifically, this relation can be represented by a channel model, which can be illustrated by the probability density function (PDF) as $p(y_i | x_i)$. In this procedure, each RBM independently trains the framework based on its local unknown input signal by a stochastic gradient descent (SGD) algorithm. Thus, for the first sample, we can work out the training data set as follows:

$$\{(s_{i,1}^1, y_{i,1}^1), (s_{i,1}^2, y_{i,1}^2), \cdots, (s_{i,1}^k, y_{i,1}^k)\} \text{ -- (5)}$$

Where, K is the number of iterations. This data set is applied to pre-train the DL scheme and then employed to train the LSTM network (the data generation procedure is depicted below). Also, $\{(s_i^t, y_i^t)\}_{t=1}^k$ is formed as a (label, feature) pair of the DL network. Since the NOMA based network is very complex, a well-known Pearson Correlation mean to extract the features automatically will be used.

2. LSTM scheme based on the NOMA system

In this subsection, a novel framework is proposed which integrates the improved LSTM network into the NOMA model, as shown in Figure (1). This LSTM network with different layers is used for complex data processing. For the purpose of keeping the training set small, the LSTM is extended with additional layers (i.e., hidden layers) to promote the representation and learning capacities of the network. It is indicated that these layers have no trainable parameters, which perform a certain action, such as mixing distortion and propagate only one symbol to the node of the next layer with the same form.

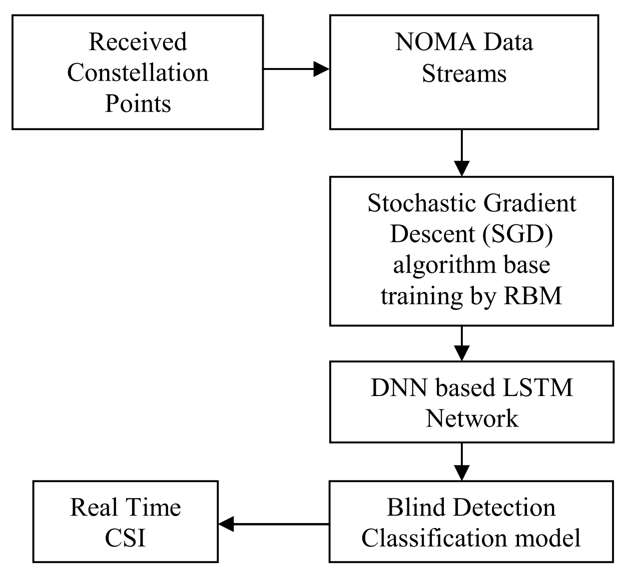

Fig. 1: PROPOSED MODEL OF INTERFERENCE MODULATION ORDER DETECTION

Specifically, this LSTM network consists of 8 layers, in which 6 layers are hidden layers that are employed to carry out training and recognition. Each hidden layer of this branch of the DNN (Deep Neural Network) is equipped with multiple neurons and an output is the weighted sum of these neurons with a nonlinear function. The input layer is processed by the RBM network, while the output layer is processed by the sigmoid function. Also all the hidden layers are processed by the Rectified Linear Unit (RLU) function. Here, in our LSTM framework, let us denote the length of each training sequence as L, which is the dimension of the input layer. This layer is a fully connected layer that includes 128 neurons, serving as the input of the transmitted signal vectors and conveying important features to the first hidden layer. The second hidden layer and the third hidden layer are dense layers that consist of 500 neurons and 256 neurons, respectively. With these two hidden layers, the encoding procedure is conducted based on the output of the input layer. Then, the next layer is designed as a noise layer with 200 neurons, and the processed signal is corrupted by the AWGN in this layer. Afterwards, the remaining two hidden layers comprise 128 neurons and 64 neurons, which act as a decoder. Additionally, the output layer is the linear layer, providing the estimated output signal vectors based on the NOMA system.

B. BLIND DETECTION PHASE

1) Model Parameter Selection Criteria: Model parameter selection criterion 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 f_e is generated. Assuming that the estimated SNR is S_e, and the modulation of target user is p^{tar}. S_e, is generated in channel estimation process. Then, the model parameter whose SNR has the minimum distance to Se and satisfies $p^{tar} = p_e^{tar}$ is chosen. The selection criteria can be written as

$$p^{tar} = p_e^{tar}$$

$$\mathrm{SNR} = \arg\min_i |S_e - S_i|, i = 1, \cdots, L \text{ ----- } (12)$$

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

2) Blind Detection: Input the feature vector f_e to the logistic regression model and the output is the modulation order of interference user.

IV. SIMULATIONS AND COMPARISON

Here, to gain further insight into the performance of the proposed scheme with other DL frameworks, the same data set will be used to formulate the F-score of the proposed LSTM scheme and other typical DL networks (convolution neural network (CNN), linear neural network (LNN) and deep belief network (DBN)). Also, the activation function and number of the hidden layers are designed as the proposed LSTM based algorithm. The results show that the proposed scheme outperforms all others, as illustrated in Figure (2).

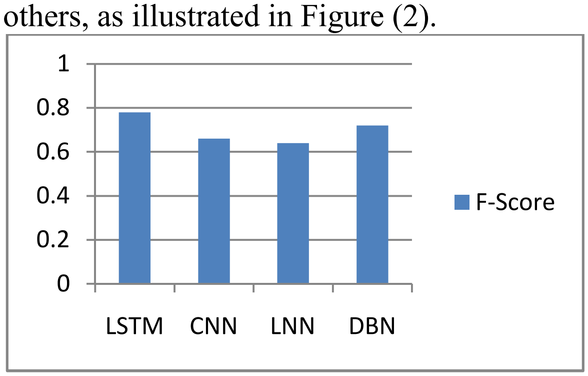

Fig. 2: F-SCORE FOR FOUR DL SCHEMES.

From Figure (3), it is clear that the throughput of the proposed algorithm is very close to the ideal curve and achieves larger gains compared to max-log algorithm. The throughputs of NOMA and Target MLAD are also addressed in Figure (3). Due to the failure blind detection of modulation order and imperfect SIC receiver, the total throughput of NOMA is better than that of OMA in most SNR regions.

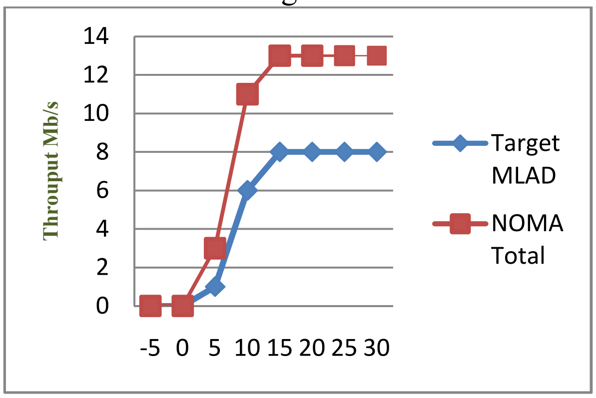

Fig. 3: THROUGHPUT PERFORMANCE OF DETECTION ALGORITHMS.

V. CONCLUSION

In this paper, new features to represent the modulation order parameter is introduced by proposing an MLAD algorithm Also an effective DL-aided NOMA scheme. MLAD algorithm is used to blindly detect that parameter of interference user in downlink NOMA systems. Taking advantage of the RBM, the input signals are processed by the RBM and then trained by the LSTM network. Also, it is shown that the proposed LSTM-aided NOMA system can achieve better performance in terms of the BLER, sum data rate, its robustness and high precision are verified. Simulation results have proved that the performance of the proposed method outperforms max-log algorithm.

VI. REFERENCES

[1] L. Xiao, Y. Li, C. Dai, H. Dai, and H. V. Poor, "Reinforcement learningbased noma power allocation in the presence of smart jamming," IEEE Transactions on Vehicular Technology, vol. 67, no. 4, pp. 3377–3389, 2018.

[2] Y. Du, B. Dong, Z. Chen, X. Wang, Z. Liu, P. Gao, and S. Li, "Efficient multi-user detection for uplink grant-free noma: Prior-information aided
adaptive compressive sensing perspective," IEEE Journal on Selected Areas in Communications, vol. 35, no. 12, pp. 2812–2828, Dec 2017.

[3] H. Huang, J. Xiong, J. Yang, G. Gui, and H. Sari, "Rate Region Analysis in a Full-Duplex-Aided Cooperative Nonorthogonal Multiple-Access System," IEEE Access, vol. 5, pp. 17869-17880, Aug. 2017.

[4] Y. Chen, L. Wang, Y. Ai, B. Jiao, and L. Hanzo, "Performance Analysis of NOMA-SM in Vehicle-to-Vehicle Massive MIMO Channels," IEEE J. Sel. Areas Commun., vol. PP, no. 99, pp. 1-1,Jul. 2017.

[5] N. Zhang, J.Wang, G. Kang, and Y. Liu, "Uplink nonorthogonal multiple access in 5g systems," IEEE Communications Letters, vol. 20, no. 3, pp. 458–461, 2016.

[6] R1-163836, "Ls on potential parameters for blind detection in must," 3GPP RAN1 #84bis, Busan, Korea, 11th - 15th April 2016.

[7] A. Bayesteh, E. Yi, H. Nikopour, and H. Baligh, "Blind detection of scma for uplink grant-free multiple-access," in Wireless Communications Systems (ISWCS), 2014 11th International Symposium on. IEEE, 2014, pp. 853–857.

[8] O. A. Dobre, A. Abdi, Y. Bar-Ness, and W. Su, "Survey of automatic modulation classification techniques: classical approaches and new trends," IET Communications, vol. 1, no. 2, pp. 137–156, April 2007.

[9] F. A. Gers, and E. Schmidhuber, "LSTM recurrent networks learn simple context-free and context-sensitive languages," IEEE Trans. Neural Networks, vol. 12, no. 6, pp. 1333-1340, Nov. 2001.

[10] M. A. Stephens, "Edf statistics for goodness of fit and some comparisons,"

Journal of the American statistical Association, vol. 69, no. 347, pp. 730–737, 1974.

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