Deep Learning-based Modulation Detection for NOMA Systems

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Abstract

Since the signal with strong power should be demodulated first for successive interference cancellation (SIC) demodulation in non-orthogonal multiple access (NOMA) systems, the base station (BS) must inform modulation mode of the far user terminal (UT). To avoid unnecessary signaling overhead in this process, a blind detection algorithm of NOMA signal modulation mode is designed in this paper. Taking the joint constellation density diagrams of NOMA signal as the detection features, deep residual network was built for classification, so as to detect the modulation mode of NOMA signal. In view of the fact that the joint constellation diagrams are easily polluted by high intensity noise and loses its real distribution pattern, the wavelet denoising method is adopted to improve the quality of constellations. The simulation results represent that the proposed algorithm can achieve satisfactory detection accuracy in NOMA systems. In addition, the factors affecting the recognition performance are also verified and analyzed.

Keywords: Modulation Detection, NOMA, Joint Constellation Diagrams, Wavelet Denoising, Residual Network

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1. Introduction

The communication of massive Internet of Things (IoT) requires wireless networks with higher spectral efficiency, lower latency and larger transmission capacity under 5G era. In the face of the above requirements for higher communication quality, a new multiple access multiplexing method, namely non-orthogonal multiple access (NOMA) was proposed [1]. The research object of this paper is the power domain NOMA, which is the NOMA protocol commonly used at present. In NOMA systems, the base station (BS) exploits the power domain by allocating the same communication resource but different power level to multiple-user (MU) for downlink transmissions. However, it is impractical to superimpose all users on the same resource block because of the large decoding delays and serious error propagation, so it is necessary to reduce the number of users superimposed on the same resource block by grouping users [2]. Although interference information is introduced in NOMA system, successive interference cancellation (SIC) technology can be utilized at user terminal (UT) for removing it [3], and thus higher spectral efficiency can be achieved. The signals received by SIC receiver are mixed signals of MU. From the perspective of modulation mode, the signals transmitted by the BS may have different modulation modes. Due to the protocol of NOMA technology, SIC receiver needs to first demodulate the signal desired to far UT, which requires the knowledge of modulation mode for that signal. The general solution is to inform the UT through signaling which can lead to a higher transmission delay in massive IoT scenarios containing enormous devices. Therefore, the implementation of blind modulation detection at near user can reduce signaling overhead and further improve the quality of service in NOMA systems.

The NOMA signal is essentially a time-frequency overlapped modulation signal, in which case, the previous single signal modulation recognition algorithm is often no longer applicable. Some researches done
have been for the modulation recognition of overlapped signals in orthogonal multiple access (OMA) systems, such as using cyclo-stationary theory to extract the feature of signal component [4]. In [5], the maximum likelihood algorithm is used to implement the modulation detection in NOMA systems, which is extended by the ML algorithm in OMA systems [6]. However, the ML algorithm often has a high computational complexity. The work of [7] studied the detection of interference modulation order in downlink NOMA systems, which extracts feature based on Anderson-Darling and then classifies by machine learning.

Recently, artificial intelligence technology provides the chance of designing beyond-5G wireless communication systems, which has become a research hotspot in the industry [8, 9]. G. Gui [10] uses long short-term memory (LSTM) network to design a deep learning (DL)-aided NOMA system, which can detect the channel characteristics intelligently. In addition, the algorithm of modulation recognition in MIMO system based on DL has been studied in [11]. The application of DL into signal recognition, especially on modulation classification, has attracted most research interests due to its strong feature learning ability [12-14]. NE [12] surveys the performance gain of general deep neural network architectures for modulation classification is similar when the input data of network is baseband I/Q signals. The key to the improvement of recognition performance is to find more discriminative representations of modulated signals for neural network. The constellation diagrams and spectrogram images are used as the input features of convolutional neural networks (CNN) in [13, 14].

In this paper, the joint constellation density diagrams of NOMA signals are selected as the shallow representation, and then a deep residual network [15] for feature learning and classification is designed for realizing the detection of modulation mode of far UT's signal in NOMA system. The main contributions of
this paper include:

- Introducing deep learning algorithm to detect modulation mode of NOMA signals.
- Designing preprocessing algorithm to improve the classification performance, which includes wavelet denoising and density extraction.
- Analyzing two factors that affect the detection performance of NOMA modulation signal by numerical experiments.

2. System Model

The scenario considered in this paper is that there are two UTs in the NOMA downlink, so the BS must prepare two modulators to encode the corresponding bitstream into two complex signals, which are superimposed by the adder according to different power factors. The superposition coding [16] method is that the bit arrangement of constellation points after superposition does not meet the gray mapping rule. The process of superposition coding is shown in Fig. 1.

\[
s(i) = h(i)(\sqrt{\alpha_1}P_1x_1(i) + \sqrt{\alpha_2}P_2x_2(i)) + n(i), \quad i = 1, 2, ..., N
\]
where \( x_1(i), x_2(i) \) is modulated signal sent to near user and far user respectively. \( \alpha_1, \alpha_2 \) denotes power factor, which satisfies \( \alpha_1 + \alpha_2 = 1 \) and \( \alpha_1 > \alpha_2 \). \( P_t \) is total transmitting power. \( h(i) \) represents channel gain and \( n(i) \) is white gaussian noise. \( N \) is the length of bitstream.

The traditional power allocation algorithms can be divided into optimal and suboptimal allocation algorithms [17]. Among them, since the optimal power distribution algorithms, such as the iterative water-filling algorithm, often has too much computation, fractional transmit power allocation algorithms is adopted in this system model. The transmission power of UT \( j \) is expressed as

\[
\beta(j) = \frac{1}{\sum_{k \in S} \left( g(k) / n(k) \right)^{-\alpha_{pce}}} \left( g(j) / n(j) \right)^{-\alpha_{pce}}
\]

where \( g(j) \) represents channel gain vector. \( n(j) \) is the power of noise and interference signals. \( S \) is a set of UTs. \( \alpha_{pce} \) denotes the decay factor, which satisfies \( 0 < \alpha_{pce} \leq 1 \). As \( \alpha_{pce} \) increases, more power is allocated to the Far UT since its channel condition is poor.

3. Proposed Algorithm

3.1 The joint constellation density diagrams

The constellation of NOMA signal is the superposition of the constellation of multiple users, which is called the joint constellation diagram. When the component signals of NOMA signal are modulated in different ways or different power allocation ratio, the distribution of its joint constellation will change. So the joint constellation can be used as a feature of NOMA modulation detection. Since the constellation matrix is directly used as the input of the neural network in this paper, it is necessary to convert the joint constellation diagram to a feature matrix, which can be realized by Alg. 1.
Algorithm 1. The joint constellation diagram

Input: NOMA signal $s(i)$
Output: The joint constellation diagram matrix $C$

1: Into two orthogonal groups:
   
   $x = \text{imag}(s_i), \quad y = \text{real}(s_i)$

2: finding the minimum of $x$ and $y$:

   $\min_x = \min(x), \quad \min_y = \min(y)$

3: Matrix coordinate transformation:

   $x = \text{ceil}(x - \min(x)), \quad y = \text{ceil}(y - \min(y))$

4: generating the joint constellation matrix $C$:

   $\text{for } i \text{ in range(length}(x)\text{)} \text{ do}$
   
   $\text{for } j \text{ in range(length}(y)\text{)} \text{ do}$
   
   $C(x, y) = 1$
   
   $\text{end for}$
   
   $\text{end for}$

When the signal to noise ratio (SNR) is not ideal, the distribution pattern of the constellations will be easily lost, so the quality of the joint constellation diagrams should be improved by denoising first. The traditional denoising method is to filter out the frequency part of the noise by passing the band-pass filter. When the frequency band of the noise is very wide, it is difficult to separate the noise from the effective signal. The multiresolution of wavelet transform (WT) can make the active components of non-stationary signal and noise show different characteristics respectively [18]. The amplitude of wavelet coefficients
generated by the WT of the effective signal is larger than the wavelet coefficients of the noise. The WT of signal \( x(t) \) can be written as

\[
WT_x(a,b) = \frac{1}{\sqrt{a}} \int x(t)\psi^*\left(\frac{t-b}{a}\right)dt
\]

(3)

where \( b \) is time shifting and \( a \) represent scale factor. \( \psi(t) \) is denoted basic wavelet, * represents the conjugate.

The NOMA signal was separated into real part and imaginary part and computed the wavelet decomposition respectively. Then soft thresholding is applied to the detail wavelet coefficients and wavelet reconstruction is realized according to the original approximation coefficients and the modified detail coefficients. Lastly, the denoising results of the real and imaginary parts are combined to achieve the overall denoising of NOMA signal. Fig. 4 shows the preprocessing of the joint constellation diagram. Simulation parameters are listed in Table I. The joint constellation diagram has more obvious characteristics and tends to an ideal distribution by wavelet denoising.

| Parameter                     | Value          | Parameter                  | value          |
|-------------------------------|----------------|----------------------------|----------------|
| Near UT modulation mode       | QAM16          | Basic wavelet              | sym8           |
| Far UT modulation mode        | \( \pi/2 \)-BPSK| Thresholding rule          | heursure       |
| Near UT SNR                   | 16 dB          | Thresholding type          | Soft thresholding |
| Far UT SNR                    | 10 dB          | The level of the WT        | 2              |
| Decay factor                  | 0.5            | The size of output matrix  | \( 100 \times 100 \) |
Considering there may be multiple signal sample points within the range of one pixel, so the constellation density is calculated by counting the number of sample points in the fixed region. Then normalizes the constellation density and converts it into the pixel value of the region. Finally, a grayscale image is generated.

The whole process can be described by Alg. 2.

**Algorithm 2.** The joint constellation density diagram

Input: The joint constellation diagram matrix $C$ after denoising

Output: The joint constellation density diagram matrix $G$ with size of $N \times N$

1: The size of constellation matrix
   $[x, y] = \text{size}(C)$

2: Determining statistical area
   $W = \text{fix}(x/N), H = \text{fix}(y/N)$

3: generating the constellation statistical matrix $CT$
   
   for $k$ in range($N$) do
     for $l$ in range($N$) do
       for $i$ in range($W$) do
         for $j$ in range($N$) do
           if $C(i, j) == 1$ then
             $CT(k, l)++$
           end if
         end for
       end for
     end for
   end for

4: Normalization to grayscale matrix $G$
   
   $G(i, j) = \frac{CT(i, j) - \min(CT)}{(CT) - \min(CT)}$
After the operation of density extraction, the joint constellation density diagram, which is shown as Fig. 5, not only strengthened the differentiation, but also adjusted the size of the image to make it more suitable as an input for neural network.

3.2 Deep Residual Network

When the neural network have reached a certain depth, which may have reached the optimal network structure, and then still increase the number of network layers, the classification accuracy of neural network will often become worse which is called network degradation. He [15] designed a residual learning framework to ease the training of networks. With the introduction of residual learning, it is easier for the redundancy layer to realize identity mapping, so as to solve the problem of network degradation.

In this paper, deep residual network is designed to detect the modulation mode of NOMA signal. The input of the network is the joint constellation density diagrams with size of matrix. The whole network can be divided into three stages, which is shown as Fig. 6(a).
In the first stage, the network extracts the characteristics of the bottom layer through a baseline convolution layer. Batch Normalization layer is added after convolution, which pulls the data distribution back to the standard normal distribution with a mean of 0 and a variance of 1, so that the input value of the nonlinear transformation ReLU function falls into the region that is more sensitive to the input, so as to avoid the gradient disappearance problem. Then feature maps are downsampled by max-pooling. In the second stage, the deep features are excavated through 6 residual blocks. There are two types of residual blocks in Fig. 6(b), (c). One is the identity block in the case of consistent input and output, which is denoted by ID BLOCK. The other is the convolutional block in the case of inconsistent input and output, which is denoted by CONV BLOCK. It includes the convolution operation in the shortcut, and the output matrix is half the size of the input matrix for each CONV BLOCK. In the last stage, the feature matrixes are downsampled by average-pooling first. After flattening, it passes through a fully connected layer and get 4 outputs. The last layer calculates the softmax with cross-entropy loss of output to determine the results of classification, which is shown in (4).

$$J = -\sum_i y_i \ln \frac{e^{a_i}}{\sum_k e^{a_k}}$$  \hspace{1cm} (4)
where $T$ are all categories of NOMA modulation scheme. $y_i$, $a_i$ represents the i-th output of the network and expected output respectively.

4. Simulation and Comparison

In the simulation, each user can choose the modulation mode supported by the current 5G standard, which are $\pi/2$-BPSK, QPSK, QAM16 and QAM64. With the same SNR, there are 1000 NOMA signal samples, and the dividing ratio of training set, validation set and test set is 6:2:2. The SNR of near UT varies from -10 dB to 20 dB with an interval of 2dB. Since the distribution of the joint constellation diagrams are mainly affected by the types of superposition modulation mode of NOMA signal and the power allocation between MU, this paper conducts simulation to verify the influence of these two factors for the modulation detection accuracy of NOMA signal.

![Fig. 7: (a) In the case of fixed power distribution ratio, the detection accuracy under different near UT, and (b) confusion matrix when near UT is QAM16 and SNR is 0dB.](image)

When the SNR is above 2dB, Fig. 7(a) represents the modulation recognition accuracy will decrease with the increase of the order of the near UT's modulation signal. Fig. 7(b) shows that when the near UT is the same, the higher order modulation of far UT will misclassify each other. Because the distribution of higher-order constellations is denser, the joint constellation diagrams of NOMA signal are more complex, which are more difficult to distinguish for the neural network. It is worth mentioning that although the
constellation of $\pi/2$-BPSK is also of fourth order, its distribution is more characteristic than QPSK. However, under 2dB, the joint constellation diagrams have been polluted by noise to a large extent, and the effect of the wavelet denoising is not obvious. Therefore, when the near UT uses the high-order modulation, the recognition rate is roughly the same.

Fig. 8: In the case of the same near UT, the detection accuracy with different power distribution ratio.

When power allocation is carried out in NOMA system, the allocation ratio is positively correlated with the SNR difference between near UT and far UT, which is denoted by ‘Delta’ in Fig. 8, and the decay factor in fractional power allocation algorithm, which is denoted by ‘alpha’ in Fig. 8. When the ‘alpha’ or the ‘Delta’ is large, the detection accuracy of modulation mode will be improved. This is because the larger the ’alpha’ or ‘Delta’ made the far UT get more large power factor, then the overall distribution of the joint constellation would be biased towards the constellation of far UT, as shown in Fig. 2(a),(b), which will be easy to implement the correct classification.

Fig. 9: the detection accuracy in different modulation recognition algorithms.
The proposed algorithm is compared with the traditional modulation recognition algorithm based on projection subtractive clustering of constellations, which is denoted by Projection Clustering in Fig. 9, and using the joint constellations without preprocessing as the input image of the network, which is denoted by Raw ResNet in Fig. 9. The projection clustering algorithm needs to calculate the number of clustering centers first. With the increase of constellation points, the complexity of the clustering algorithm in the traversal process will be higher. When the SNR is not ideal, the representation ability of the joint constellation without wavelet denoising is obviously reduced. So the modulation detection algorithm based on the joint constellation density diagrams and deep residual network is superior to the other two methods in NOMA systems.

5. Conclusion

Wireless communication channel has been considered by many researchers is the largest black box in the physical layer. NOMA signals often have a certain extent of distortion and loss at the receiving terminal. The use of machine learning algorithm to help the communication system process the unknown information in the channel, which can achieve greater benefits than traditional methods. In this paper, The NOMA signal modulation detection algorithm based on the joint constellation density diagrams and deep residual network is proposed, which will reduce the signaling overhead in the communication system and improve the demodulation efficiency of SIC. However, for the existing high-order modulation mode in 5G, such as QAM256, its constellation will be more complex, and the classification difficulty will be significantly improved, which is where further research is needed in this paper.
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