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# *Target Signal Recognition Method for 5G Communication Supporting Machine Learning*

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***Abstract:*** The identification of 5G communication target signal type may be the premise and foundation of modulation mode identification, signal demodulation and other links. Therefore, the identification of 5G communication target signal type has become an indispensable technical link in the intelligent signal processing system. In order to solve the shortcomings of existing agricultural machine vision system research, this paper discusses the composition and key technologies of agricultural machine vision system and machine learning algorithm, and then simply discusses the hardware selection and software development environment of the system in which the algorithm proposed in this paper is applied. And the overall results of agricultural machine vision monitoring system are designed and discussed. RCNN and K-means algorithms in machine learning are used to study the identification and classification of seedlings in images. Finally, through the experimental analysis of selected samples, it is known that the accuracy of RCNN and K-means algorithm in image recognition detection in agricultural machine vision monitoring system is up to 94.25%. Therefore, it is verified that machine learning algorithm has high practical value in agricultural machine vision system.

## 1. Introduction

With the emergence and development of machine learning, the research scope of feature based 5G communication target signal recognition method is becoming wider and wider, and the 5G communication target signal recognition method based on likelihood ratio decision theory has been greatly improved. However, in the recognition process, the method must first realize the two challenges of human feature extraction and improving SNR in signal preprocessing.

Nowadays, more and more scholars have done a lot of research in 5G communication target signal recognition methods through various technologies and system tools, and have also made certain research achievements through practical research. Bonvard established the transmission signal identification model of 5G multi-mode terminal multi antenna system by using multi-sensor joint tracking and identification method. Combining the narrowband distributed source characteristics of MIMO system; the receiver signal detection model is established. In order to improve the beam integration ability of 5G output signal, the adaptive beam forming algorithm is adopted, and the optimal array mode and detection filter of 5G multi-mode terminal multi antenna are designed by using matched filter [1]. The higher-order cumulant used by Ribaupierre S D can have a good anti noise performance. First, high-order cumulants can be extracted as eigenvalues of signals. Finally, the traditional SVM recognition algorithm is improved. Compared with conventional SVM alone, the corresponding average modulation recognition rate can be improved by more than 25%. Especially when the signal-to-noise ratio is 5dB, the recognition rate can reach 90%, and the system is easy to implement, which shows that high-order cumulants have broad application prospects in signal recognition and parameter estimation [2]. SdA proposes a recognition method based on multi-dimensional signal feature fusion to solve the problem of 5G communication target signal recognition. Firstly, the multi-dimensional features of RF signal are extracted from time domain, frequency domain and high-order spectrum domain respectively, and then the features are fused. Finally, the SVM classifier of PSO algorithm is used to classify and recognize signals. The experiment shows that the recognition method can have a good classification and recognition effect [3]. Although the existing 5G communication target signal recognition methods are very rich, there are still some limitations in the application of machine learning algorithms.

This paper first introduces the 5G communication concept and maximum likelihood classifier. The derived likelihood function in AWGN channel in 5G communication target signal recognition and common 5G communication signal recognition features are introduced. Secondly, the recognition training features of AlexNet convolution neural network and VGGNet neural network in machine learning are analyzed. Then, the collected data are processed and sent to BP neural network and ResNet neural network for classification and recognition. The 5G communication target signal recognition model based on Alex Net convolution neural network and VGGNet neural network is established. Finally, the experimental results show that the performance of this algorithm is better than the other two algorithms.

## 2. Design and Research of 5G Communication Target Signal Recognition Method Supporting Machine Learning

### 2.1. 5G Communication Target Signal Identification

(1) 5G communication

The fifth generation mobile phone mobile communication standard, also known as the fifth generation mobile communication technology (5G) [4]. It is greatly different from the mobile communication of 4G and its predecessors. The network speed of 5G communication can reach 5M/S-6M/S. One of its important capability indicators is called "Gbps user experience rate". Advanced technologies represented by large-scale antenna array, ultra dense networking, new multiple access, full spectrum access and new network architecture are the guarantee of this capability indicator [5].

(2) Target signal recognition

The classical method of traditional 5G communication target signal recognition and classification is maximum likelihood classifier. In this paper, we will focus on the likelihood function in AWGN channel [6].

Assuming that the collected data sample $f(m)$ is the probability that the likelihood function of modulation method $N$ can use the signal data $f(m)$ collected in AWGN channel when modulation method $N$ is used, equation (1) holds [7].

$$\gamma(f(m)|N,\partial)=G(f(m)|N,\partial) \tag{1}$$

(2) The complex form probability density function of the imported signal in AWGN is shown as follows:

$$\gamma(f(m)|N,\partial)=\sum_{x=1}^{X}\frac{1}{X}\frac{1}{2\pi\partial^2}r^{\frac{|f(m)-Dx|^2}{2\partial^2}} \tag{2}$$

Where $D=\{\tilde{D},...,\tilde{D}_X\}$ is the set of all possible transmitted symbol vectors, where $X$ represents the number of clusters, and $X=G^M$. When the modulation symbol of data sample $f(m)$ is unknown, the likelihood is generally calculated by using the average of the likelihood values between the data sample and the modulation symbol $\tilde{D}_X$ [8]. The joint possibility of multiple observation samples is calculated by multiplying all the likelihood of each sample, as follows:

$$\gamma(F|N,\partial)=\prod_{m=1}^{M}\sum_{x=1}^{K}\frac{1}{X}\frac{1}{2\pi\partial^2}r^{\frac{|f(m)-Dx|^2}{2\partial^2}} \tag{3}$$

### 2.2. Common Communication Signal Identification Features

(1) Instantaneous parameter signal

Instantaneous parameters include instantaneous amplitude, instantaneous phase and instantaneous frequency of signal. Modulation information is reflected in the fluctuation of these instantaneous parameters [9]. The characteristics of some signals often exist in the changes of the spectrum, so the characteristics can also be found by observing the spectrum to complete modulation recognition [10].

(2) Higher-order cumulant

A cumulant is a statistical characteristic of a signal or sequence. For non Gaussian signals, the hidden signal information cannot be completely represented by second-order cumulants; For non Gaussian and non minimum phase signals, second-order cumulants cannot express the phase characteristics of such signals [11].

(3) Time frequency domain

The method based on feature theory focuses on the characteristics of time-frequency transform domain. Wavelet transform and short-time Fourier transform have strong real-time property. They can process non-stationary signals more precisely and express the process of the change of the signal's spectral content with time [12]. Therefore, some special features of the signal can only be displayed in this field, and cannot be extracted by other forms of transformation [13].

(4) Cyclic spectrum

Because of the potential periodicity of signals, many time signals can be modeled as periodic stationary signals. For such signals, their mean and autocorrelation are periodic [14]. A variety of weak signals with large noise can be modulated and identified by taking the signal periodic stationary spectrum as the feature [15].

## 2.3. Machine Learning

In fact, deep learning is a technology to realize machine learning, which abstractly expresses data characteristics based on self-learning mechanism. In this paper, the three most widely used machine learning algorithms are comprehensively studied, including: AlexNet neural network and VGGNet neural network and the latter two are mainly discussed in this paper.

(1) ResNet neural network

The network pays attention to the "degradation problem" of accuracy, and realizes the direct transmission of upper layer learning results to the lower layer through the introduction of residual structure. Even if the network level continues to deepen, the error can still be well controlled, thus enhancing the convergence performance of ResNet network and the accuracy of classification and recognition [16].

On the whole, the characteristics and advantages of ResNet are mainly reflected in the following aspects:

1) The network layer is very deep, but the hidden layer is relatively small, which can reasonably control the parameters;

2) As long as the number of layers increases, the number of convolutional feature maps will also increase accordingly, which improves the learning efficiency and enhances the level of feature expression;

3) Through data sampling, reduce the amount of low pooling layers as much as possible to enhance the forward propagation efficiency;

4) No Dropout layer, regularization processing is completed through Meanpool, effectively ensuring the training progress;

(2) VGGNet neural network

The advantage of VGGNet is that it tests the relationship between network depth and model performance. The network has a diversified structure system [17].

VGGNet neural network has the following characteristics:

1) VGGNet uses all 3 × Convolution Kernel of 3 and 2 × 2 pool core to improve performance by continuously deepening the network structure. The growth of network layers will not bring about an explosion in parameter quantities;

2) Compared with AlexNet neural network, VGGNet neural network has stronger learning ability of features;

3) Use 1 × 1 convolution layer to increase the linear transformation, the number of output channels does not change;

4) VGGNet first trains the simple network of level A, and then uses the weight of the network to initialize the following complex models, so that the convergence speed is faster [18].

# 3. Research on 5G Communication Target Signal Recognition Method Supporting Machine Learning

## 3.1. Experimental Parameter Setting

In this experiment, the CPU is Intei510606G, the memory size is 16G, the operating system is Windows10 environment, the signal generation uses Matlab integrated simulation tool, the signal recognition program is written in Python language, the deep learning framework Tensorflow is used, and the training process is accelerated through GPU. In the above environment, through setting different parameters, the machine learning modulation recognition algorithm proposed in this paper is simulated for many times, and its performance is recorded and analyzed. Table 1 shows the parameter settings for AlexNet network model training,

*Table 1. Relevant parameters*

| Parameter name | Parameter setting |
|---|---|
| Loss function | Cross entropy |
| Learning rate | Self-adaption(0.01-0.0003) |
| Optimizer | AdamOptimizer |
| Iterations | 15 |
| Number of studies | 20 |

This paper mainly considers the recognition of OFDM-QAM, FOFDMQAM, FBMC-OQAM, UFMC-QAM, four kinds of 5G communication modulation signals by neural network algorithm. During the modulation of bit information, the symbol rate of various signals is set to 8. The carrier frequency and transmission rate are different according to the application of wireless sensor nodes in practical applications.

*Table 2. Physical layer parameters of WSN node*

| Node Name | UAMPs-I | WecMote | Mica2/GAINS | Micaz/Tmote/GAINZ |
|---|---|---|---|---|
| Modulation mode | GFSK | ASK | FSK | O-QPSK |
| Carrier frequency/Hz | 2.4G | 916.5M | 750M | 2.4G |
| Transmission rate/bps | 1M | 115.2K | 76.8K | 250K |

### 3.2. Experimental Data Collection

In order to test the algorithm proposed in this paper, a data set was built using Matlab software. The constellation diagram of the corresponding signal was extracted through signal preprocessing. Four kinds of 5G communication modulation signals were selected, which are OFDM-QAM, FOFDMQAM, FBMC-OQAM, and UFMC-QAM signals in turn. The experimental data set has 2500 samples in the training set and 1500 samples in the test set. As the input data of AlexNet convolution neural network and VGGNet neural network models. The additive white Gaussian noise will then be introduced for all data. The signal to noise ratio range of each data set is 5-20dB, and the interval is 5dB. These four data sets with different signal-to-noise ratios will be sent into the recognition model of the depth learning convolutional neural network in turn to analyze the recognition effect of the model under different signal-to-noise ratios.

## 4. Application Research of 5G Communication Target Signal Recognition Method Supporting Machine Learning

### 4.1. Design of 5G Communication Target Signal Recognition Method Supporting Machine Learning

(1) Design of 5G Communication Target Signal Recognition Model Based on AlexNet Neural Network

For OFDM-QAM, FOFDMQAM, FBMC-OQAM and UFMC-QAM signals, four kinds of 5G communication target signals are selected as the input characteristics of the AlexNet network, and a 5G communication target signal classification algorithm is constructed. Its basic framework is shown in Figure 1.

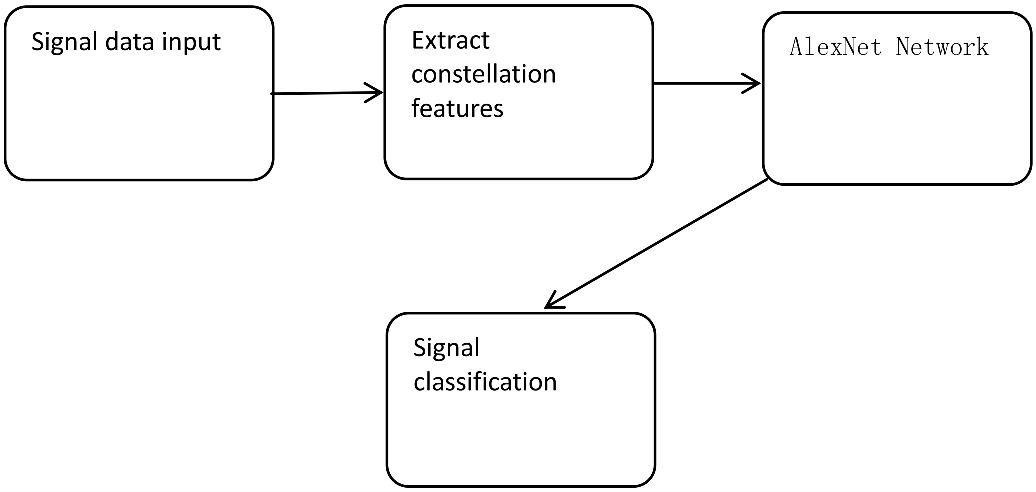


*Figure 1. 5G communication target signal recognition model based on AlexNet neural network*

The signal recognition of this algorithm can be divided into four main steps, as follows:

1) Obtain four 5G communication target signal data sets;

2) Extracting constellation features from signals;

3) Input the extracted features into AlexNet neural network for classification training;

4) Signal classification is realized according to the trained AlexNet neural network.

(2) Design of 5G Communication Target Signal Recognition Model Based on ResNet Neural Network

As an improved version of AlexNet, VGGNet introduces a convolutional group structure into its network structure. In order to improve the performance of 5G communication target signal algorithm, this section takes it as a neural network classifier, and studies a 5G communication target signal recognition algorithm based on VGGNet. Its input feature selects its spectrum modulus sequence wavelet transform. In this paper, VGGNet neural network is applied to the identification of 5G communication target signals. Its training process is similar to that of AlexNet network, and its steps are as follows:;

1) Initialize the parameters of VGGNet model;

2) Randomly select appropriate samples, and define the wavelet transform modulus sequence characteristics of the trained input 5G communication target signal spectrum;

3) The training samples are imported into the VGGNet model to generate the spectral wavelet transform modulus pixel matrix, which then flows through each hidden layer, and finally gives the classification results;

4) Determine the loss function, that is, the gap between the measurement results and the target results;

5) Evaluate the number of training iterations to confirm whether the preset value is not exceeded, use the formula to complete the gradient derivation and calculation, and update the parameters of all hidden layers in reverse;

6) Jump to step (2) and enter the next training

7) If the training iterations meet the requirements, stop the training directly

8) The structure and parameters of each layer of the VGGNet model are saved to complete the verification of the test set and the evaluation of the overall performance.

## 4.2. Application of 5G Communication Target Signal Recognition Method Supporting Machine Learning

In order to verify the effectiveness of the proposed method, the simulation data set is used in the performance comparison analysis of several algorithms proposed in this paper. Table 3 shows the performance comparison of 5G communication target signal recognition of each algorithm under different signal-to-noise ratios.

*Table 3. Algorithm recognition accuracy*

| Algorithm | AlexNet | VGGNet | VMD | EMD |
|---|---|---|---|---|
| 5 | 0.90 | 0.87 | 0.78 | 0.83 |
| 10 | 0.92 | 0.89 | 0.80 | 0.86 |
| 15 | 0.95 | 0.91 | 0.82 | 0.88 |
| 25 | 0.99 | 0.93 | 0.84 | 0.90 |

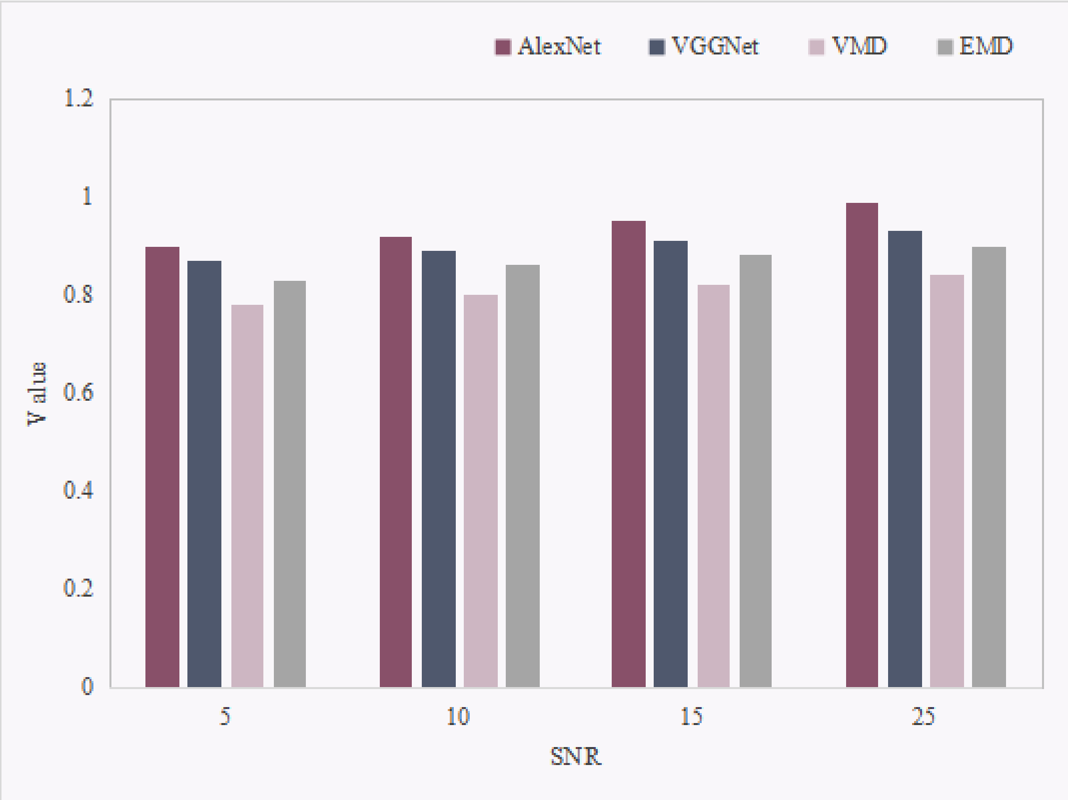


*Figure 2. Comparison of algorithm recognition performance*

It can be seen from the data in Figure 2 that the EMD based 5G communication target signal recognition algorithm has the worst performance. When the SNR is increased to 25dB, the EMD recognition accuracy reaches 95%, indicating that the algorithm has high requirements for SNR. At the same signal-to-noise ratio, the recognition performance of communication target signal based on EMD5G is worse than the modulation recognition performance based on Alex Net convolution neural network and VGGNet neural network, which shows that Alex Net algorithm has a good effect on improving the accuracy of signal recognition. Under various SNR conditions, the performance of AlexNet and VGGNet algorithm in this paper is superior to other algorithms, especially under low SNR conditions, which shows that AlexNet convolution neural network and VGGNet neural network algorithms are conducive to improving the accuracy of signal recognition.

## 5. Conclusion

This paper discusses two signal recognition algorithms based on Alex Net convolution neural network and VGGNet neural network for the recognition of four commonly used 5G communication target signals. Firstly, the classification of the recognition features of 5G communication target signals is analyzed. On this basis, the wavelet transform of the signal's spectral modulus is selected as the input feature. Then, the 5G communication target signal recognition classifiers based on AlexNet convolution neural network and VGGNet neural network are constructed respectively, and the model structure design and training process of the two neural networks are described in detail. Finally, the performance of the two algorithms proposed in this paper is simulated and analyzed through Matlab simulation, and compared with the existing algorithms comprehensively. The advantages, disadvantages and application scope of various algorithms are classified, which provides a reference for the application of algorithms in practical projects.

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## Data Availability

Data sharing is not applicable to this article as no new data were created or analysed in this study.

## Conflict of Interest

The author states that this article has no conflict of interest.

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