Modulation Recognition of Composite Signal Based on ResNet and Frequency Domain Graph

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Abstract. Aiming at the problem of composite signal recognition in measurement and control system, a modulation recognition method of composite signal is proposed based on clipped internal modulation signal frequency image and residual network. Residual network has the advantages of fast convergence and high recognition accuracy, which is used to realize the recognition of different modulation modes and different bandwidth signals. The experimental results show that, compared with the traditional decision tree algorithm and the constellation based CNN recognition algorithm, the recognition performance of the proposed method is improved by more than 3dB for the variable bandwidth composite modulation signal set (BPSK-FM and QPSK-FM with internal modulation bandwidth of 128kHz, BPSK-FM and QPSK-FM with internal modulation bandwidth of 2kHz and 2FSK-FM with internal modulation bandwidth of 32kHz and 2kHz).

Keywords. Composite signal; modulation recognition; ResNet; frequency domain graph.

1. Introduction

Measurement and control signals are widely used in satellite communication link [1]. The research on modulation recognition algorithm of composite modulation signals is mainly based on the decision tree algorithm of artificial feature extraction. In reference [2], the recognition of AM-MSK and FM-MSK is realized through the nonlinear transform spectrum and square spectrum features of composite modulation signal. This algorithm has a simple process and strong adaptability, but the recognition performance needs to be improved. Reference [3] realized the identification of BPSK-FM, QPSK-FM, and FSK-FM signals by extracting the envelope features and quadratic spectrum features of the internal modulation signal. The algorithm has high recognition performance and strong anti-jamming ability, but its performance degrades rapidly at low SNR. Reference [4] proposed an algorithm based on FRFT (Fractional Fourier Transform) and phase difference method for composite signal recognition, which effectively realized the recognition of LFM and BPSK-LFM signals. This method has good anti-noise performance and high recognition accuracy rate. The above-mentioned traditional decision tree recognition method based on artificial feature...
extraction has poor generalization ability of the extracted features, and the performance of recognition for signal sets with variable bandwidth is degraded.

In recent years, the research on modulation recognition of communication signals based on convolutional neural network and other depth learning methods has begun to rise [5]. Reference [6] uses the peak density clustering algorithm to realize the identification of QPSK, 8QAM, 8PSK, and 16QAM signals by drawing density-distance graphs and K-Nearest Neighbor regression algorithm. Reference [7] uses k-means clustering method combined with KNN and SVM algorithms to realize the modulation recognition of MQAM, MASK and MPSK signals. However, due to the large amount of calculation, slow learning speed, and low prediction accuracy of rare categories in the KNN model, the recognition accuracy of the above algorithm needs to be improved. Reference [8] proposed a precise modulation classification method using CNN and constellation features to achieve accurate recognition of digital signals such as BPSK, QPSK, 16QAM, and 64QAM under low SNR. For the composite modulation signal set with variable bandwidth addressed in this paper, the performance of training and recognition using the features mentioned above degrades rapidly. Because it is difficult to obtain the difference between the internal modulation signals by directly extracting the features of composite signal. Constellation and clustering features are difficult to distinguish signals with different bandwidth. Under the condition of low signal-to-noise ratio, the contrast of feature image decreases, so when using CNN network to train and recognize the feature image of the signal set [9], we need to continuously improve the network depth to ensure the recognition performance. However, with the increase of network depth, the gradient of CNN model will disappear, which will lead to the deterioration of the recognition performance.

Therefore, this paper proposed a modulation recognition method of composite signal, which firstly demodulate the internal modulation signal based on the digital receiver, then highlights the frequency domain difference between different signals by extracting the moving clipping image features of the internal modulation signal frequency domain, and finally use the residual network to realize the modulation recognition of the Composite modulation signals.

2. Signal Modulation Model

The variable bandwidth composite modulation signals addressed in this paper include: BPSK-FM and QPSK-FM with internal modulation bandwidth of 128 kHz, BPSK-FM and QPSK-FM with internal modulation bandwidth of 2 kHz, and 2FSK-FM with internal modulation bandwidth of 32 kHz and 2 kHz. The expression of BPSK-FM is as follows:

\[ s(n)_{\text{BPSK-FM}} = A \cos[2\pi f_c n T_s + 2\pi K_f a(k) \cos(2\pi f_s k T_s) + \sin(2\pi f_s k T_s)] T_s \]

(1)

In equation (1), \( A \) represents the signal amplitude, \( T_s \) represents the sampling period, and \( K_f \) is the frequency modulation coefficient, \( f_c \) represents the carrier frequency, \( f_s \) represents the subcarrier frequency, and \( a(k) \) represents the bipolar baseband signal [10], and its bandwidth is 2 kHz or 128 kHz. The expression of QPSK-FM signal is as follows:

\[ s(n)_{\text{QPSK-FM}} = A \cos[2\pi f_c n T_s + 2\pi K_f \{a(k) \cos(2\pi f_s k T_s) + b(k) \sin(2\pi f_s k T_s)\}] T_s \]

(2)

where \( a(k) \) and \( b(k) \) represent the bipolar baseband signal with the same symbol rate and bandwidth. The expression of 2FSK-FM signal is as follows:

\[ s(n)_{\text{2FSK-FM}} = A \cos[2\pi f_c n T_s + 2\pi K_f \{s_1(k) \cos(2\pi f_s k T_s) + s_2(k) \cos(2\pi f_s k T_s)\}] T_s \]

(3)
where $f_1$ and $f_2$ are two subcarrier frequencies, and the frequency difference $f_2 - f_1$ is 2 kHz or 32 kHz, $s_1(k)$ and $s_2(k)$ represent unipolar binary pulse sequence [10], and its bandwidth is 2 kHz or 32 kHz. When $s_1(k)=1$, $s_2(k)=0$ and vice versa. In order to facilitate the subsequent operation, the part of the internal modulation signal in (1), (2) and (3) is expressed as $m(k)$, and the expression of FM composite modulation signal is as follows:

$$s(n) = A\cos(2\pi f_c n T_s + 2\pi K \sum_{n=0}^{N} m(k) T_s)$$

3. Feature Image Construction of Composite Modulation Signal Based on Digital Receiver

In order to realize the recognition of composite signals with different internal modulation bandwidth, this article firstly obtains the internal modulation signal by the digital receiver, then constructs the frequency domain moving clipping images features, to highlight the differences between the signal feature images with different bandwidth and different modulation types.

3.1. Internal Modulation Signal Extraction Based on FM Receiver

This paper uses the receiver structure as shown in figure 1 to extract the internal modulation signal of the composite signal.

![Figure 1. Principle of digital receiver.](image)

The expression of $S_i(n)$ and $S_q(n)$ are as follows:

$$S_i(n) = \cos[2\pi \Delta f n T_s + 2\pi K \sum_{n=0}^{N} m(k) T_s - \theta(n)]$$

$$S_q(n) = \sin[2\pi \Delta f n T_s + 2\pi K \sum_{n=0}^{N} m(k) T_s - \theta(n)]$$

where $\Delta f = f_2 - f_1$ represents the difference between the signal and the NCO (Numerical Control Oscillator) output frequency, $\theta(n)$ represents the initial phase of NCO. The expression of phase detector is as follows:

$$\phi(n) = \arctan \frac{S_i(n)}{S_q(n)}$$

The output of the loop filter is as follows:
\[ \tau(n) = C_2 \phi(n) + \lambda(n) \] (8)

In the above equation, \( \lambda(n) = C_1 \phi(n) + \lambda(n-1) \). where C1 and C2 are loop filter coefficients and their values are constants. Supposing the output phase of the numerically controlled oscillator is \( f_n(n) \), then it can be expressed as follows:

\[ f_n(n) = f_n(n-1) + \tau(n) \] (9)

It can be seen by substituting (5)-(8) into equation (9), when \( \Delta f \to 0 \) and the initial phase of NCO output signal \( \theta(n) \to 2\pi K, m(k)T_s \), the loop becomes stable. Then, the phase discrimination output can be obtained by formula (5)-(8) as follows:

\[ \phi(n) = 2\pi K, m(n)T_s \] (10)

Since \( K_f \) and \( T_s \) are constants, the value \( \phi(n) \) after phase discrimination is equal to the internal modulation signal \( m(n) \). The time domain features of the internal modulation signal obtained by the phase discrimination error are susceptible to noise, but its frequency domain features are relatively stable.

3.2. Frequency Domain Feature Image Construction of Internal Modulation Signal

The power spectral density expression of 2FSK-FM internal modulation signal is obtained from equation (3):

\[ P_{2\text{FSK-FM}}(f) = \frac{1}{4}[P_1(f + f_1) + P_2(f + f_2) + P_2(f - f_2)] \] (11)

where \( P_1(f) \) and \( P_2(f) \) are unipolar baseband signal power spectrum [10]. According to the formula, there is a single spectral line in the power spectrum at \( f_1 \) and \( f_2 \), and the spectrum should be bimodal, and its spectral line bandwidth is 2 kHz or 32 kHz. The expressions of internal modulation power spectral density of BPSK-FM and QPSK-FM signals can be written as follows:

\[ P_{\text{MPSK-FM}}(f) = \frac{1}{4}[P_1(f + f_1) + P_2(f - f_1)] \] (12)

where MPSK is the general name of BPSK and QPSK signals, \( P_3 \) is bipolar baseband signal power spectrum [10].

Therefore, the internal modulation spectrum of BPSK-FM and QPSK-FM signals shows a single peak image, and the bandwidth of the spectrum line is 2 kHz or 128 kHz. The digital receiver is used to demodulate the internal modulation signals of six kinds of composite modulation signals at 10 dB SNR, and then the spectrum can be obtained by Fast Fourier Transform (FFT), as shown in figure 2.

It can be seen from equations (11) and (12) that there should be differences in the bandwidth and the number of spectral peaks of the above signals. However, it can be seen from figure 2 that the feature images obtained by FFT of internal modulation signal are very similar, and the difference cannot be reflected. The features of 2FSK-FM with 32 kHz bandwidth, 2FSK-FM with 2 kHz bandwidth, BPSK-FM with 2 kHz bandwidth and QPSK-FM are almost identical, so it is difficult to distinguish them effectively. Therefore, this paper improves the frequency resolution by down sampling the data and moves the spectral front position to the center of the image, according to the maximum bandwidth of 128 kHz of the signal to
be classified, the image is clipped to get the structure of feature image which can highlight the difference of spectrum image. The feature image obtained by moving and clipping is shown in figure 3.

As can be seen from figure 3, the difference between 2FSK-FM signal with 32 kHz bandwidth and 2FSK-FM signal with 2 kHz bandwidth and other images is obvious. MPSK-FM signal with 2 kHz bandwidth and MPSK signal with 128 kHz bandwidth also have significant differences, which can be used as the basis for classification. But at the same time, (a), (b), (d), (E) in figure 3 also show that BPSK-FM and QPSK-FM signals with the same bandwidth cannot be distinguished only by spectral image. So in this paper, BPSK-FM and QPSK-FM signals with the same bandwidth are recognized by constructing the square spectrum feature image of internal modulation signal.

\[
m^2(n) = a^2(n)\cos^2(2\pi \frac{f_b}{nT_f}) + b^2(n)\sin^2(2\pi \frac{f_b}{nT_f}) + 2a(n)b(n)\cos(2\pi \frac{f_b}{nT_f})\sin(2\pi \frac{f_b}{nT_f})
\]

Since both \(a(n)\) and \(b(n)\) are bipolar codes with amplitude of \(\pm 1\), equation (13) is simplified as follows:

\[
m^2(n) = 1 + a(n)b(n)\sin(4\pi \frac{f_b}{nT_f} + 2\phi_b)
\]

For BPSK-FM signal, \(a(n)\) and \(b(n)\) are the same bipolar codes, so equation (14) can be rewritten as follows:

\[
m_{\text{BPSK}}^2(n) = 1 + \sin(4\pi \frac{f_b}{nT_f} + 2\phi_b)
\]

\(\text{Figure 2.} \) Spectrum image of internal modulation signal before clipping.
Figure 3. The spectrum image of the internal modulation signal after being moved and clipped.

Therefore, the square spectrum of the modulated signal in BPSK-FM has a peak value at DC and twice carrier frequency. However, for QPSK-FM signal, $a(n)$ and $b(n)$ are not the same, and the product jumps between positive and negative 1. Its square spectrum does not contain double carrier frequency component, and only has peak value at DC. The processed square spectrum image is shown in figure 4.

Figure 4. Square spectrum characteristic image of MPSK-FM internal modulation signal demodulated.
It can be seen from figure 4 that QPSK-FM and BPSK-FM signals have large discrimination on the square spectrum image of the internal modulation signal. Therefore, the spectrum and square spectrum image features of internal modulation signal can be used as the basis to distinguish the above six kinds of signals.

4. Modulation Recognition Based on Residual Network

4.1. Image Feature Classification in Internal Modulation Frequency Domain Based on ResNet50

According to the analysis in Section 2.2, when MPSK-FM signal and 2FSK-FM signal have the same internal modulation bandwidth, the difference of spectrum image features is small. When using traditional CNN network to train and recognize the spectrum, it is necessary to continuously improve the model depth to ensure the recognition performance. However, with the increase of the depth of the model, the convergence difficulty of CNN will be greatly improved, and the recognition performance may decline due to the disappearance of the gradient. The residual network can effectively solve the degradation problem of deep convolution neural network caused by gradient explosion, and can maintain good generalization ability.

This is because in deep neural networks, CNN usually directly fits a potential identical mapping function $H(x) = x$, but this mapping relationship is difficult to converge in deep neural networks. The residual network constructs the residual unit through cross layer connection, and a path from input to output is set before and after two common convolution layers. The mapping relation can be expressed as $H(x) = F(x) + x$. By training and learning residual function $F(x) = H(x) - x$, when $F(x) = 0$, an identity mapping $H(x) = x$ is formed. In deep neural network, such mapping relation is easier to get. In this paper, the training and recognition of frequency domain images of different signals are realized based on 50 layer residual network (ResNet50) structure. The structure is shown in figure 5:

![Figure 5. ResNet50 network structure.](image)

The network firstly through a $7 \times 7$ convolution layer, and then connect a maximum pooling layer, and then through stacking residual blocks, connect a global average pooling at the end of the network. Finally, the data classification is realized through the full connection layer and the activation function SOFTMAX.

4.2. Identification Scheme Design

The signals to be identified are collected by China Electronics Technology Group Corporation, including 6 signals, namely BPSK-FM, QPSK-FM and 2FSK-FM signals with 2k internal modulation bandwidth, BPSK-FM and QPSK-FM signals with 128 kHz internal modulation bandwidth and 2FSK-FM signals with 32 kHz internal modulation bandwidth. The process of the identification scheme is shown in figure 6:
Figure 6. Recognition process of composite signal based on residual network and digital receiver.

Firstly, the input FM composite modulation signal is demodulated by digital receiver on FPGA, and the processed internal modulation signal spectrum and square spectrum pattern are acquired by down sampling and moving clipping image. Secondly, the spectrum feature image is input into the residual network classifier, and the signals are divided into four categories: 2FSK-FM signal with 2 kHz bandwidth, MPSK-FM signal with 128 kHz bandwidth, and 2FSK-FM signal with 32 kHz bandwidth. Finally, the square spectrum image marked as MPSK-FM signal is put into the classifier to realize the modulation recognition of BPSK-FM and QPSK-FM signals with 2 kHz bandwidth, and BPSK-FM and QPSK-FM signals with 128 kHz bandwidth.

5. Experiment and Result Analysis
In order to verify the recognition performance of the proposed method based on the spectrum and square spectrum image of internal modulation signal and residual neural network. In the simulation, the vector signal generator SMBV100A-2 was used to transmit the 2FSK-FM composite signal with 2 kHz and 32 kHz internal modulation signal bandwidth, the BPSK-FM and QPSK-FM signals with internal modulation bandwidth of 2 kHz and 128 kHz. The FM frequency modulation coefficient is 0.05, the sampling rate $f_s = 12.8$ MHz, the signal carrier frequency $f_c = 500$ kHz, and the sub-carrier frequency is 1000 kHz. Then, a digital receiver was implemented on the Intel cortex IV E series EP4CE180F17C8N FPGA chip to extract the spectrum and square spectrum data of the internal modulation signal in the composite modulation signal. Finally, based on MATLAB software, ResNet50 is used for training and modulation recognition. The computer CPU is Intel (R) Core (TM) i7-8700, CPU@3.2 GHz 3.19 GHz, 8 GB memory.

Two hundred samples are generated for each SNR at 1dB intervals between -5dB and 20dB, while 100 are training data and others are test data. The loss function decline curve of residual network is obtained as shown in figure 7.

From the above figure, we can see that the loss function has basically no longer decreased after the 400th iteration, which shows that the model has converged. In order to illustrate the advantages of proposed algorithm, the performance of proposed algorithm is compared with the CNN based constellation algorithm and the traditional decision tree algorithm respectively. The comparison image of recognition rate is shown in figures 8 and 9.
Figure 7. The decline curve of the loss function of residual network.

Figure 8. The recognition rate of the proposed method is compared with that of CNN based on constellation [8].

It can be seen from figure 8 that the recognition performance of the proposed algorithm is better than the CNN algorithm based on constellation [8], and the advantage is more prominent when the SNR is lower than -2dB. When the SNR is very low, the recognition rate of CNN based constellation features decreases rapidly, and almost completely loses the classification ability at -5dB. The recognition rate of the proposed method is still above 90% at -5dB. This is because for the composite modulation signal, it needs to go through two demodulation processes of FM receiver and MPSK/FSK receiver to obtain its constellation features, in this case, the noise has a great impact on the demodulation effect. Therefore, it is difficult for the receiver to recover the constellation feature under the condition of low SNR. Moreover, the classification ability of CNN model for similar constellation images in low SNR is poor, so the anti-noise ability of this method is weak. In this paper, the feature extraction based on frequency domain image only uses FM receiver, and uses the residual network which has stronger recognition ability for similar images to avoid the above problems. Therefore, it can achieve good recognition performance at lower SNR.
It can be seen from figure 9 that the recognition performance of the proposed algorithm is better than the decision tree algorithm [3] based on frequency domain envelope feature and quadratic spectrum parameter feature. When SNR is 0 dB, the average recognition rate of decision tree is about 70%, while the recognition rate of proposed method is still close to 100%. When the SNR is further reduced, the decision tree algorithm [3] cannot effectively distinguish various signals with the same bandwidth, and the classification accuracy of different signals with the same bandwidth is greatly reduced. This is because the noise has a great influence on the feature parameters when the SNR is low. The decision based on threshold is easy to make mistakes. At the same time, the error accumulation of decision tree algorithm leads to the rapid decline of recognition performance. The frequency domain features extracted by the proposed algorithm have stronger stability at low SNR, and the residual network classifier can extract the deep features of the signal and has stronger anti-noise ability, so it has higher recognition rate at low SNR.

6. Conclusion
In this paper, a composite modulation signal recognition algorithm based on digital receiver and residual network classifier is proposed. In this algorithm, the feature difference of the composite modulation signal with different bandwidth is enhanced by constructing the frequency domain moving and clipping image feature, which effectively improves the anti-noise ability. And the residual network model is used to improve the recognition performance of similar signals in frequency domain images.

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