An Intra-Pulse Modulation Type Recognition Algorithm for Radar Signals Based on the Improved Residual Network

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Abstract. For purpose of solve the problem of poor discrimination and robustness of intra-pulse signal features extracted by the traditional methods, this paper proposes a radar signal intra-pulse modulation type recognition algorithm based on the improved residual network. Firstly, one-dimensional time-domain radar signal is converted into two-dimensional time-frequency image by Smoothing Pseudo Wigner-Ville Distribution; Then the time-frequency image is preprocessed; ResNet-50 network is chosen as the framework. In order to retain the feature map information as much as possible, the convolution kernel is increased in the residual module. The cross entropy loss function and the center loss function are used as the loss function to speed up the convergence of the network. The improved residual network is used to realize the intra-pulse modulation type recognition of radar signal. The simulation experiments show that when the SNR is -14dB, the overall average recognition accuracy of the improved algorithm for eight kinds of radar signals (CM, LFM, NLFM, BLFM, BPSK, QPSK, OPSK, LFM+BPSK) can reach 97.29%, which shows the effectiveness.

1. Introduction
In recent years, with the significant development of radar technology and the electromagnetic environment has become increasingly complex, signal types have varied, making traditional radar signal recognition algorithms difficult to meet the actual needs of radar signal classification [1]. Considering that new radar signal often contain rich intra-pulse information, radar signal classification and recognition algorithms based on intra-pulse information have gradually become a research hotspot.

Many methods that can be used for pulse modulation recognition of radar signal have been proposed. Literature [2] extracts the image coefficient, entropy, complexity and wavelet packet of the radar signal. Literature [3] uses Wigner-Ville Distribution in the field of radar signal recognition. Literature [4] extracted the pseudo zernike moments from the image obtained by the radar signal Chio-Williams Distribution. However, these methods are very sensitive to noise. At low signal-to-noise ratio(SNR), the recognition performance drops sharply, which is difficult to meet current needs. Therefore, scholars have introduced more intelligent machine learning and deep learning algorithms to improve the performance of intra-pulse modulation type recognition. Literature [5] obtained the time-frequency image of the signal through the Chio-Williams Distribution, and...
further extracted the singular value entropy of the time-frequency image and the fractal dimension of the signal spectrum and finally adopted the classification based on Support Vector Machine(SVM).

When the SNR is greater than or equal to 1dB, the recognition rate of eight kinds of radar signals reaches 95%. Literature [6] first extracted the shape and texture features of the radar signal time-frequency image to form a fusion feature and then inputs the fusion feature into the random forest classifier for recognition. The recognition accuracy of this algorithm is more than 90% when the SNR is -2dB. Although these algorithms have achieved good recognition results, there are still some problems: 1) The recognition effect is not very good under low SNR and the generalization ability is weak; 2) There is less attention to composite modulation type radar signal.

To the above problems, this paper combines time-frequency analysis and deep learning theory to propose a radar signal intra-pulse modulation type recognition algorithm based on the improved residual network. The radar signal is obtained by three time-frequency analysis methods of Short-Time Fourier Transform(STFT) [7], Wigner-Vile Distribution(WVD) [8] and Smooth Pseudo Wigner-Vile Distribution(SPWVD) [9] to obtain the radar signal time-frequency images and compare their experimental effects under low SNR, SPWVD time-frequency images have more obvious time-frequency characteristics, and the recognition rate can reach 97.29% when SNR=-14dB, and the recognition effect is the best. In the same data set, the recognition rate of this algorithm is higher than that of common algorithms VGG11, VGG19, ResNet18 and ResNet50.

2. Radar signal preprocessing based on time-frequency analysis

This paper focuses on the research on eight types of radar signal intra-pulse modulation, which are Conventional Modulation(CM), Linear Frequency Modulation(LFM), Bilinear Frequency Modulation(BLFM), Nonlinear Frequency Modulation(NLFM), Binary Phase Shift Keying(BPSK), Quadrature Phase Shift Keying(QPSK), Octal Phase Shift Keying(OPS K) and mixed modulation signal (LFM+BPSK).

Radar signal is a kind of non-stationary signal and time-frequency analysis can clearly describe the law of non-stationary signal frequency changing with time. For this reason, this section will use STFT, WVD and SPWVD, these three time-frequency analysis methods to perform time-frequency conversion on the above eight modulation signals. In order to explore the advantages of the time-frequency analysis method under low SNR and to make the simulated signal closer to the real electromagnetic environment, the SNR is set to -14dB to 0dB with an interval of 2dB, and there are a total of eight SNR points. Next, select a representative SNR point of 0dB, and analyze the characteristics and performance of different transformations.

2.1. Preprocessing of radar signal by STFT

![STFT time-frequency image when SNR=0dB](image)

*Figure 1. STFT time-frequency image when SNR=0dB*

It can be seen from the above Figure 1 that no matter what kind of signal, when SNR=0dB, the time-frequency images from STFT have a little background interference, but the time-frequency image of the eight kinds of signals are all very well gathered.
2.2. Preprocessing of radar signal by WVD

As shown in the Figure 2, at 0dB, all eight signals can be distinguished from the time-frequency image. The time-frequency curve of the BLFM signal has cross-curve interference, and the time-frequency aggregation of the BPSK, QPSK and OPSK signals is not ideal, which may affect the subsequent recognition accuracy.

2.3. Preprocessing of radar signal by SPWVD

It can be seen from the above Figure 3 that no matter what kind of signal, when SNR=0dB, the time-frequency characteristic curves can be separated easily.

3. Methods of this paper

3.1. The network framework of this paper

In this section, an improved residual network is designed based on ResNet-50 [10]. The improved network framework is shown in Figure 4, compared with the common ResNet structure, this paper increases the convolution kernel size of the residual module, in order to prevent the loss of information in the feature graph during training. The cross entropy loss function and the center loss function are selected as the loss function, which can speed up the network convergence. The improved residual block are shown in Figure 5.
In Figure 5, path C goes through 3x3 convolution in turn to complete the channel shrinkage, and the step size is set as two to achieve downsampling, then through 3x3 convolution, the number of channels remains unchanged, the main feature is extracted, and finally the number of channels expansion is completed through 3x3 convolution. According to the data set, the types of intra-pulse modulation are very complex, the signal lengths and the change modes are different. If the 1x1 convolution kernel size and step size of two are used for downsampling, a lot of the information will be lost. Take a 5x5 feature map as an example, as shown in Figure 6, when the convolution kernel is 1x1, only the information in the red squares can be passed to the next layer, and the white squares does not participate in the convolution operation.

It can be seen that it is not appropriate to perform downsampling on a 1x1 convolution kernel. It is better to perform downsampling on a 3x3 convolution kernel. As shown in Figure 7, since the convolution kernel width is greater than the step size, the convolution kernel can traverse all the information on the feature map in the process of moving.
3.2. Loss function

Generally speaking, softmax cross entropy loss (CE loss) is usually used for the field of image classification. The center loss proposed in [11] can make the distance between classes larger and the distance within classes smaller.

The total loss in this paper is the weighted combination of the two losses, \( L_s \) represents CE loss, where \( \alpha \) is a parameter to control \( L_c \).

\[
L = L_s + \alpha L_c
\]  

(1)

4. Simulation experiment and result analysis

4.1. Dataset and simulation experiment

To improve the recognition rate of radar signal intra-pulse modulation type recognition under low SNR, the neural network must fully learn the time-frequency characteristics of the signal under low SNR, so the data set needs to be expanded to ensure sufficient data. Radar signals get time-frequency images through SPWVD, set the SNR to -14dB to 0dB, 400 images are simulated for each modulation type at each SNR points. The sampling frequency(Fs), pulse width(PW) and bandwidth(B) parameters setting are shown in Table 1.

| Radar Signal | SNR(dB) | Fs(MHz) | PW(us) | B(MHz) |
|--------------|---------|---------|--------|--------|
| CM           | -14 to 0| 400, 500| 3, 4   |        |
| LFM          | -14 to 0| 70, 200 | 5, 20  | 8, 20  |
| NLFM         | -14 to 0| 200, 250| 5, 40  | 10     |
| BLFM         | -14 to 0| 200, 250| 5, 12  | 5, 10  |
| BPSK         | -14 to 0| 450, 500| 10, 11 |        |
| QPSK         | -14 to 0| 200, 500| 10, 13 |        |
| OPSK         | -14 to 0| 300, 500| 10, 16 |        |
| LFM+BPSK     | -14 to 0| 200, 450| 12, 14 | 20, 30 |

4.2. The influence of the loss functions

This section, the influence of the center loss function on the classification recognition rate is evaluated. This experiment uses the data of SPWVD time-frequency image at -10dB. According to Figure 8, for the model without the center loss and the model with the center loss, the loss values show a downward trend. The training recognition rates also gradually increase with the number of iterations. However, it can be found from the test accuracy rate that for the model without the center loss, when the number of epochs is 17, the test accuracy rate can reach about 97% and gradually tend to be stable. For a model with center loss, when the number of epoch is 8, the test accuracy can be increased to about 97%, and it maintains a gradual upward trend, reaching a maximum of about 99%. From the above experimental data, the center loss can accelerate the convergence of the model and narrow the gap within the class can improve performance.

![Figure 8. Loss comparison experiment](image)
4.3. The influence of different time-frequency analysis methods

This section mainly evaluates the impact of different time-frequency analysis methods (STFT, WVD, and SPWVD) on recognition accuracy. The recognition accuracy of each SNR point are shown in Table 2.

| SNR/dB | STFT  | WVD   | SPWVD |
|--------|-------|-------|-------|
| -14    | 96.84 | 90.46 | 97.29 |
| -12    | 97.07 | 91.07 | 97.81 |
| -10    | 97.52 | 92.32 | 99.84 |
| -8     | 98.86 | 96.57 | 100   |
| -6     | 100   | 99.85 | 100   |
| -4     | 100   | 100   | 100   |
| -2     | 100   | 100   | 100   |
| 0      | 100   | 100   | 100   |

From Table 2, the improved residual network has good anti-noise performance on the three kinds of time-frequency images. At the SNR is more than -4dB, the recognition accuracy of these three time-frequency analysis methods can all reach 100%. When the SNR is -14dB to -6dB, the recognition rate based on SPWVD time-frequency analysis method is better than that based on STFT and WVD time-frequency analysis method. Even at the SNR is -14dB, the recognition rate based on the SPWVD time-frequency analysis method can still reach more than 97%, which shows that SPWVD is more suitable for time-frequency analysis of radar signal.

4.4. Algorithm comparison experiment

For purpose of further analyze the performance of ours algorithm in low SNR, we compare ours algorithm with common algorithms. The experimental data used SPWVD time-frequency image at -14dB to 0dB. As shown in Table 3, it can be seen that the recognition accuracy of the improved algorithm is better than other conventional algorithms. Even at -14dB, the overall average recognition accuracy of eight radar signals modulation type can still reach 97.29%. This is because the automatic mining of high-dimensional features in time-frequency domain based on SPWVD time-frequency analysis and improved ResNet algorithm has stronger representation ability, what’s more, the anti-noise and generalization ability of the model are better.

| SNR/dB | VGG11 | VGG19 | ResNet18 | ResNet50 | Ours |
|--------|-------|-------|----------|----------|------|
| -14    | 93.49 | 96.20 | 95.63    | 96.03    | 97.29|
| -12    | 94.32 | 97.25 | 95.83    | 96.25    | 97.81|
| -10    | 98.12 | 98.29 | 97.51    | 98.86    | 99.84|
| -8     | 99.36 | 99.51 | 99.63    | 99.89    | 100  |
| -6     | 100   | 100   | 100      | 100      | 100  |
| -4     | 100   | 100   | 100      | 100      | 100  |
| -2     | 100   | 100   | 100      | 100      | 100  |
| 0      | 100   | 100   | 100      | 100      | 100  |

5. Conclusions

In this study, we have proposed a deep learning algorithm based on time-frequency analysis and improved residual network under low SNR, which is used in the classification and recognition of radar signals. The conclusions are as follows: 1)The CE loss function and the Center loss function combined
as the loss function can speed up the network convergence; 2) In addition, the feature representation abilities of STFT, WVD and SPWVD are compared through the simulation experiments, and the results show that the SPWVD is the best of them; 3) When the SNR is -14dB, the average recognition rate of eight kinds of radar signals can reach 97.29%, and it has high anti-noise performance and generalization ability, which verifies the effectiveness and accuracy of the algorithm.

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