Radar Signal Separation Recognition Method based on Semantic Segmentation

Jiajun Ai
Harbin Engineering University
College of information and communication engineering
Harbin, China
aijiajun123456780@163.com

Lijie Hua
Harbin Engineering University
College of information and communication engineering
Harbin, China
hualijie@hrbeu.edu.cn

Jin Liu
Harbin Engineering University
College of information and communication engineering
Harbin, China
1727391387@qq.com

Shunshun Chen
Harbin Engineering University
College of information and communication engineering
Harbin, China
15546135809@163.com

Yongjian Xu
Harbin Engineering University
College of information and communication engineering
Harbin, China
xuyongjian@hrbeu.edu.cn

Changbo Hou*
Key Laboratory of Advanced Marine Communication and Information Technology, Ministry of Industry and Information Technology
Harbin Engineering University
Harbin, Heilongjiang, China
houchangbo@hrbeu.edu.cn

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***Abstract*—With the increasing application of electronic technology in military field, electronic countermeasure technology has been developed gradually. The separation and identification of radar signal is an important part of electronic countermeasure. Only when the enemy's information is fully grasped in the war, can the absolute advantage be obtained in the battle, which makes the separation and identification of radar signal play a very important role. However, radar signal identification is faced with serious time-frequency domain overlap problem, and the analysis of multi-component radar signals and the acquisition of valuable information are still faced with great difficulties, which is an urgent problem to be solved in radar reconnaissance system. In this paper, a one-dimensional signal is represented as a time-frequency graph (TFIS) by using the Choi-Williams distribution (CWD), and then the recognition results are obtained by using UNet to segment the time-frequency image of the signal, and the recognition results are visualized. The simulation results show that the proposed method can effectively solve the multi-signal separation and recognition of time-frequency aliasing.**

Keywords: radar signal; Separation and identification; Choi - Williams distribution; UNet;

I. INTRODUCTION

With the development of modern information technology and the rapid development of new weapons and equipment with electronic information as the core, modern warfare has entered the era of electronic warfare. It is becoming more and more important to obtain enemy information by means of electronic reconnaissance technology. The more information obtained, the greater the initiative on the battlefield [1]. Radar, as an important part of information countermeasure, has serious cross-interference in the frequency domain due to its complex modulation form and the aliasing of different signals in the same channel, so it is still a difficult point in the research to accurately separate and identify the signals required by many signals.

II. CURRENT STATUS OF RADAR SIGNAL

Blind Source Separation (BSS) [2] is a technology that realizes signal Separation only on the assumption of independence and sparsity when the number of Source signals is unknown or only known. At present, the research of pulse modulated separation recognition for radar signal has achieved good results in single component signal. Single component radar signal pulse modulation identification methods can be divided into the following three categories: traditional feature extraction methods, deep learning-based methods and modulation recognition methods based on multi-modes. However, traditional feature extraction methods cannot automatically extract the optimal features, so researchers have been looking for better radar signal separation and recognition methods.

With the development of deep learning, researchers began to try to apply convolutional neural network (CNN) to the separation and recognition of radar signals. Zhang [3] et al. proposed a feature fusion scheme of automatic modulation classification (AMC) based on CNN. In this scheme, different images and handmade signal features are fused to obtain more features. When the signal-to-noise ratio is -4dB, the classification accuracy can reach 92.5%. Hou et al. [4] integrated the characteristics of electromagnetic signal constellation and complex I/Q data, making the signal classification accuracy reach 100% when the SNR is 2dB. Gao et al. [5] proposed a separation technology based on fractional Fourier transform, which decomposes the received radar signal into multiple components, and then uses CNN and fusion features to identify each signal component respectively. The system can accurately identify binary phase-shift keying (BPSK), linear frequency modulation (LFM), continuous wave (CW), Costas, Frankcode and P1~P4 codes. When the SNR is 0 dB, the recognition rate of single signal and double signal can reach 96.23% and 72%, respectively. Liu et al. [6] proposed a Deep Convolutional Neural Network (DCNN) based separation and recognition method for radar mixed

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signals. The main method was to segment the time-frequency graph and classify the selected region with DCNN. The classification accuracy is more than 92% when the SNR is 0dB, and more than 98% when the SNR is 5dB. However, this method can identify only a few kinds of signals, so the identification method of multi-component radar signal is still faced with a huge challenge.

III. Modulation and Time-frequency Analysis of Radar Signal

A. Radar Signal

In this paper, an image semantic segmentation method is proposed to separate and recognize radar signals. This method can randomly identify six typical radar signals, including LFM, SFM, BPSK, 2FSK, CW, and Frank codes.The form of the signal is shown in TABLE I:

TABLE I. RADAR SIGNAL FORMULA

Signal type	Formula
LFM	$s(t)=\begin{cases} A\left\{exp\left(j2\pi ft+\frac{1}{2}kt^2\right)+\varphi\right\} & 0\le t\le T \\ 0 & \text{else} \end{cases}$
SFM	$s(t)=A\ exp[j2\pi f_c t+jm_f sin(2\pi f_m t)]$
BPSK	$s(t)=A\sum_{i=1}^{n} exp\{j2\pi f_c t+\varphi_i)\}uT_p(t-iT_p)$
2FSK	$s(t)=[\sum a_n g(t-nT_s)]\cos(w_1+\theta_n)+[\sum \bar{a}_n g(t-nT_s)]\cos(w_2+\varphi_n)$
CW	$s(t)=\begin{cases} Aexp(j2\pi f_c t+\varphi) & 0\le t\le T \\ 0 & \text{else} \end{cases}$
Frank	$s(t)=Aexp[j(2\pi f_c t+\varphi_k)]$

B. Time-frequency analysis

Time-frequency Analysis is the abbreviation of Joint Time-Frequency Analysis (JTFA), which is a powerful tool for analyzing time-varying non-stationary signals. Through the joint distribution information of time domain and frequency domain, JTFA can express the relationship between signal frequency and time. The basic idea is to design a time-frequency joint function to determine the energy density and intensity of the signal in different time domain and frequency domain. At present, the commonly used time-frequency analysis functions include Short Time Fourier Transform (STFT), Wavelet Transform, WVD, Cohen-type time-frequency distribution, etc. If the signal is multiplied by a time-limited window function H(t) before taking its Fourier transform, the short-time Fourier transform of the signal can be obtained [7]. The window function H(t) of STFT moves along the time axis, and the signal is decomposed segment by segment for analysis, thus the local spectrum of the signal can be obtained. However, because the window function of STFT is fixed, it is not adaptive, which is not conducive to blind signal recognition. In order to overcome the disadvantage that the size of STFT window function does not change with frequency, the wavelet transform [8] adopts the operation of stretching and shifting to realize the multi-scale refinement analysis of the signal. Wigner-Ville Distribution algorithm [9] (WVD) is one of the time-frequency distributions for non-stationary signal analysis. WVD has good time-frequency aggregation, and this time-frequency analysis method can obtain relatively ideal resolution in both time domain and frequency domain. However, since it is the second time-frequency of the signal, So there must be cross - interference term for multi - component signal. This means that WVD cannot directly and accurately identify the modulated signal when processing the stacking signal, and further processing is needed.

Cohen class time-frequency distribution [10] is an improvement of WVD. A variety of time-frequency analysis methods can be obtained by adding different kernel functions to WVD. The mathematical expression of time-frequency distribution of Cohen class is shown in Equations (1) and (2).

$$C(t,w)=\frac{1}{4\pi^2}\iint AF(\tau,v)\varphi(\tau,v)\exp(-jvt-jw\tau)dvd\tau \quad (1)$$

$$AF(\tau,v)=\int x\left(u+\frac{\tau}{2}\right)x^*\left(u-\frac{\tau}{2}\right)\exp(-jvu)du \quad (2)$$

In the formula, $x(u)$ is the received signal, $AF(\tau,v)$ is the ambiguity function of the received signal, τ and v represent the delay and frequency offset, respectively, and $\varphi(\tau,v)$ is the kernel function.

Aiming at the aliasing problem of radar signal separation and identification, the Choi-Williams distribution (CWD) selected in this paper has good time-frequency resolution and strong anti-noise ability, and can effectively suppress the cross terms. The kernel function used by CWD is the Gaussian function, namely $\varphi(\tau,v)=\exp\left[-\frac{(\tau v)^2}{\sigma}\right]$.

IV. Semantic segmentation of UNET

The computer calculates the probability of each pixel in the image, finds out the category of each pixel, classifies it, and marks the same kind of pixel with the same semantics. According to the content of the image, the process of segmentation of different objects in the image from the perspective of pixels is the semantic segmentation of the image.

UNet is a semantic segmentation method based on CNN (Convolutional Neural Networks) proposed by Olaf Ronneberger, Phillip Fischer and Thomas Brox [11] in 2015. The framework of its network is shown in Figure 1.

The entire network of UNet adopts a symmetric structure. The purple arrow in Figure 1 represents the 3×3 convolutional layer and the ReLU activation function. The red arrow indicates the maximum pooled layer of 2×2. The green arrow represents the 2×2 upper sampling layer. The blue arrow represents the 1×1 convolution layer and the Sigmoid activation function.

The first half of the UNet network is the component of the encoder for feature extraction, and the upsampling module of the second half is the decoder for feature fusion. The most important feature of UNet network is that the feature of channel dimension is fused by splicing method, which makes the feature layer formed more accurate. When the image is input into the semantic segmentation system, a feature of the same scale is first output by 3×3 convolution for two consecutive times, and then a maximum pooling is carried out for the output feature. The encoder part repeats the above operation 4 times to enter the decoder. The output of the encoder fuses a same-scale feature after every up-sampling in the decoder, and the fused feature is convolved for two consecutive 3×3 times. The encoder section repeats the above operation 4 times to obtain the final output. The code in this paper uses VGG16 as the encoder part and uses its pre-training weight to train.

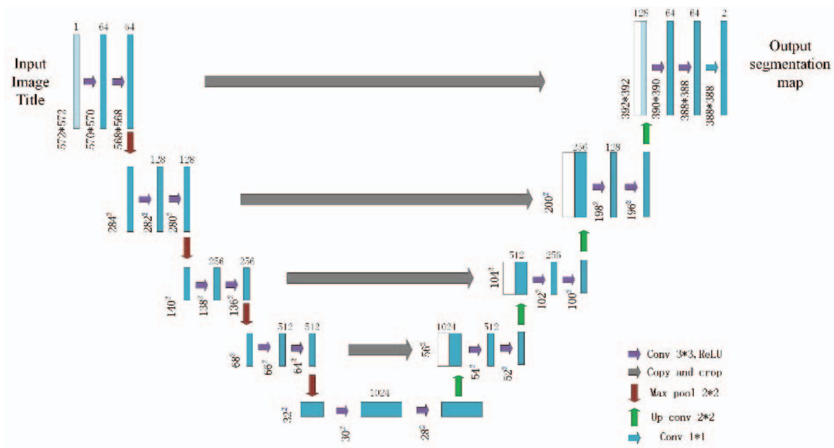


Figure 1. UNet network model

V. Experiment and Results

In this paper, the specific steps of the algorithm mainly include the following three parts: radar signal time-frequency processing, signal separation and recognition and visualization results. Figure 2 is the algorithm flow chart of this paper. In the first part, we generate the time-frequency image of the received signal through CWD transformation, which is used as the input of the semantic segmentation network encoder. In the second part, the semantic segmentation of radar signal time-frequency image is carried out by using UNet network. In the third part, the result of recognition is visualized.

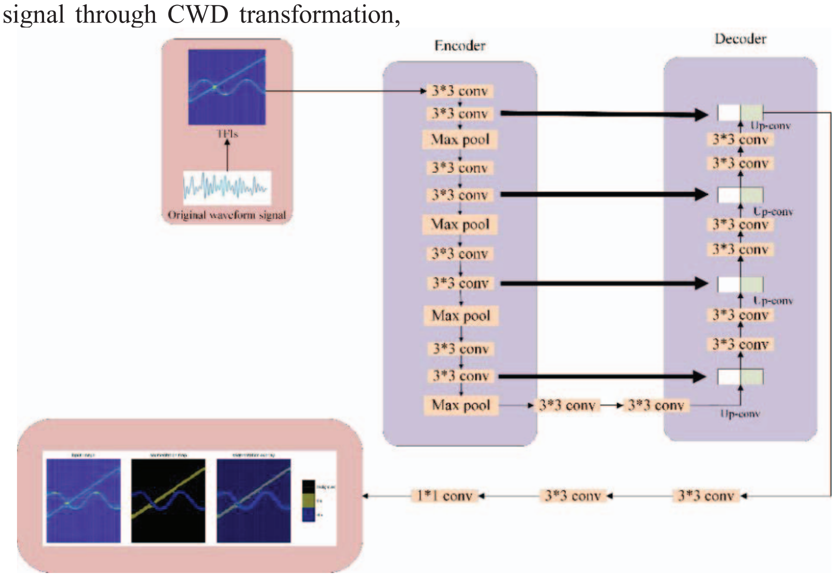


Figure 2. Algorithm flow chart

First, six common radar signals are generated for modulation identification processing. The parameters of these six digital signals are shown in TABLE II below.

TABLE II. RADAR SIGNAL PARAMETERS

Signal type	Parameter	Range
CW	Carrier frequency f_0	0.1~0.4
LFM	The initial frequency f_c bandwidth Δf	0.05~0.45 0.05~0.4
SFM	The minimum frequency f_{min} bandwidth Δf	0.05~0.15 0.05~0.35
2FSK	Carrier frequency f_1, f_2 Yards wide T_b	0.15~0.35 1/16~1/8 N
BPSK	Carrier frequency Barker code	0.1~0.4 [7,9,13]
Frank	Carrier frequency f_0 The step frequency M	0.1~0.3 [4,8]

In this paper, the CWD transformation of the six modulated identification signals is carried out to obtain the time-frequency diagram. The SNR range was set as 0 ~ 10dB, and the step size was 2dB. Every two signals generate 20 images at each SNR. The data set includes 3 * 20 * 6 = 360 images. The verification set contains 70 images and the training set contains 616 images. Because of the small number of images, it is a small sample data set.

Based on the method analysis in Section 2, the following simulation experiments are carried out. The results of the simulation experiment are shown and analyzed below. As shown in Figure 3., the time-frequency diagrams of the six radar signals in this paper, which are combined pairwise and transformed by CWD, show that there are differences in time-frequency diagrams of various signals. Therefore, the time-frequency diagrams can be used to obtain signal features for signal modulation identification.

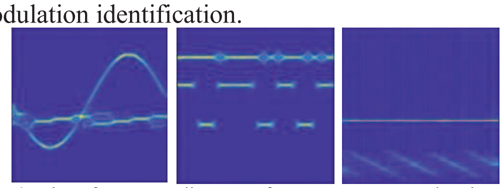
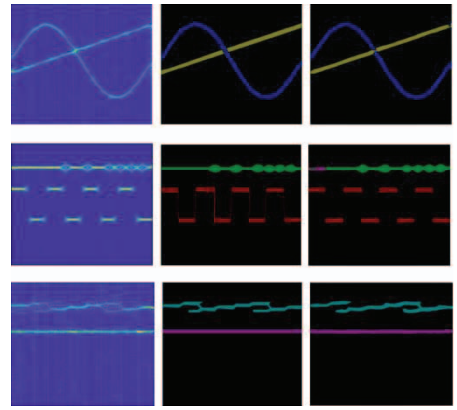


Figure 3. Time-frequency diagram of two-component radar signal in data set

Then randomly select three original images from the picture set and input them to the system we designed for recognition and segmentation. The results are shown in Figure 4. (a) is the image processed by CWD, (b) is the label image, and (c) is the segmentation result. Because the overlap situation selected in the test in this paper is different from that selected in the training, it is more general.



（a） (b) (c)

Figure 4. Simulation experiment results

In order to objectively evaluate the recognition effect of the system, Mean Intersection Over Unionm (MIoU) and Mean Pixel Accuracy (MPA) were used as evaluation indexes in this paper. MIoU calculates the cross and parallel ratio of each class between the Ground Truth image and the Prediction image on the pixel, and then calculates the average cross and parallel ratio of all classes. PA is the proportion of the correct pixel in the total pixel, while MPA is a simple improvement of PA. The proportion of the correctly classified pixels in each class is calculated, and then the average of all classes is obtained. Its mathematical expression is shown in Equations (3) and (4) :

$$MIoU = \frac{1}{k+1}\sum_{k}^{i=0}\frac{p_{ii}}{\sum_{k}^{j=0} p_{ij} + \sum_{k}^{j=0} p_{ji} - p_{ii}} \tag{3}$$

$$MPA = \frac{1}{k+1}\sum_{\mathrm{i}=0}^{K}\frac{p_{ii}}{\sum_{j=0}^{k} p_{ij}} \tag{4}$$

The formula, there are a total of category $k+1$(including a background category), p_{ij} denotes the number of points that predict category i as Category j , p_{ii} denotes the number of points that predict category i as category i , and p_{ji} denotes the number of points that predict category j as category i . The comparison of test results of data sets is shown in TABLE III. it can be seen from the table that the MIoU of other categories are more than 70% and MPA is more than 80% except CW, which has more accurate segmentation results.

TABLE III. THE EXPERIMENTAL RESULT

Classification \ Method	MIoU%	MPA%
Background	98.03	99.07
CW	67.82	77.67
LFM	73.48	83.79
SFM	76.92	86.77
2FSK	75.19	85.39
BPSK	76.37	88.20
Frank	72.32	84.50
Mean	77.16	86.48

VI. CONCLUSION

In this paper, a two-component radar signal modulation identification method based on UNet semantic segmentation is proposed.This method is suitable for the unknown number of signals, and can separate and identify the intra-frame pulse modulation modes of single-component and dual-component radar signals.It can recognize CW, LFM, SFM, 2FSK, BPSK and FRANK six typical radar signal pulse modulation types. The simulation results show that when the SNR is between 0-10dB, the MIoU of the dual-component radar signal can reach 76.92 %and MAP can reach 88.20%. This method can effectively suppress the cross interference in radar signal, and can get more accurate segmentation results with only a small amount of sample data. However, when the radar signal is greatly affected by noise at low signal-to-noise ratio (SNR), it is still a problem that needs to be solved in the future to accurately separate and identify the multi-component radar signal with low signal-to-noise ratio (SNR) and obtain a recognition system suitable for more signal types.

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