A Radar Signal Deinterleaving Method Based on Semantic Segmentation Thought with Neural Network

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Abstract—Radar signal deinterleaving is an important content of electronic reconnaissance. In this paper, a new radar signal deinterleaving method based on semantic segmentation thought is proposed. We select representative sequence modeling neural network architectures, and input the difference of time of arrival (DTOA) of pulse stream to them. According to the semantics contained in different categories of radar signals, each pulse in the pulse stream is marked according to the category of semantics contained, and radar signals are deinterleaved. Compared with the traditional deinterleaving method, this method can adapt to any pulse repetition interval (PRI) modulation mode and does not require PRI periodicity. Compared with other deinterleaving methods using neural network, this method does not need to digitize the data and train a network for each type of target. This method also eliminates the need to iterate the input and output of data. The proposed method has high robustness under the condition of pulse loss and noise pulses. The research also shows that recurrent neural network (RNN) still has more advantages than convolutional neural network (CNN) in this sequence modeling problem.

Index Terms—Radar signal deinterleaving, semantic segmentation, difference of time of arrival (DTOA), bidirectional Gated Recurrent Unit (BGRU); dilated convolutional network (DCN).

I. INTRODUCTION

In electronic warfare, in order to obtain the information of target radar, it is necessary to use electronic reconnaissance equipment to carry out reconnaissance and intercept the corresponding target radar signal. In the actual electromagnetic environment, there are often other electromagnetic signals besides the target radar signal. In this case, the data collected by the electronic reconnaissance equipment will contain information from different targets, and the intercepted pulse stream also contains interleaved pulses from different radiation sources, as shown in Fig. 1. Full pulse data is the pulse description words for each pulse output in chronological order in electronic reconnaissance equipment. The pulse description words include the arrival time, arrival direction, pulse width, frequency, amplitude and other information of each pulse. Radar signal deinterleaving, which is an important content of electronic reconnaissance, is essentially to deinterleave the interleaved pulse description words belonging to different radiation sources in the full pulse data.

Semantic segmentation is an important task in image processing. It uses the feature information of different categories of targets, namely semantics, to mark each pixel in an image according to the category of the target the pixel belonged to. This method can segment different types of targets in the image, and is also known as dense prediction. In recent years, neural network has become the most important tool and hotspot in the research of image semantic segmentation.

In this paper, the thought of semantic segmentation is applied to radar signal deinterleaving. According to the feature information of different categories of radar signals, each pulse of interleaved pulse stream is marked according to the category of target with the help of neural network, so as to realize the deinterleaving of different categories of radar signals in the pulse stream. This method can realize the signal deinterleaving of multiple radar targets through one network and one step, and has significant advantages over other methods.

The following parts are included in this paper. Section II introduces the related work about radar signal deinterleaving and neural network for image semantic segmentation and sequence modeling. The characteristics and data model of this task are discussed in section III. Based on the analysis of sections II and III, we determine the neural network architecture and deinterleaving strategy adopted by the proposed method in Section IV. Section V is the experimental results and analysis. Section VI concludes the whole paper.

II. RELATED WORK

A. Radar signal deinterleaving

The research of radar signal deinterleaving can be divided into two categories: deinterleaving based on multi-parameter and deinterleaving based on arrival time information. The former makes comprehensive use of the arrival direction, pulse
width (PW), frequency, amplitude and time of arrival (TOA) of the pulses. The latter uses only the arrival time information. This paper studies the deinterleaving method based on arrival time information.

The radar pulse repetition interval (PRI) is the interval between fronts of adjacent pulses when the radar transmits signal. In the deinterleaving methods based on arrival time information, an important idea is to use the periodicity of radar PRI. This idea first finds the radar PRI from the information about the difference of time of the arrival (DTOA) of the pulse stream, and then uses the found PRI to search the target radar pulse from the pulse stream. Some methods use the histogram of DTOA to obtain radar PRI, while others use DTOA matrix to find pulse repetition interval. Another method is to obtain the spectrum of PRI through the transformation of arrival time, and then extract the real PRI. In other methods, radar pulse stream with periodical PRI is modeled as a linear dynamic model, and Kalman filter is used for deinterleaving. Some researchers also tried to apply Hidden Markov Model to radar signal deinterleaving.

The above methods have several shortcomings. First, these methods require the target radar PRI to have a certain periodicity, which cannot solve the deinterleaving problem of targets without periodical PRI. Second, for the radar pulses of staggered PRI, these methods require deinterleaving the target radar pulses in batches as several targets, and then merging them into one single target. Third, in order to obtain accurate PRI from statistical features, these methods are effective only if the pulse stream is long enough. Fourthly, these methods are sensitive to pulse loss and random noise pulses.

People have tried to use neural networks to classify pulses very early, but since neural networks were not fully developed at that time, they could only deal with relatively simple problems. The recurrent neural network (RNN) is introduced to deinterleave radar signal. It treats the deinterleaving problem as a prediction problem, so only unidirectional information of the pulse sequence is used to judge the attribution of each pulse. Autoencoders are used to remove random noise pulses, but cannot sort out target pulses. When Autoencoders are used to sort out target pulses, accurate prior information about target pulse parameters is required. In order to facilitate neural network processing of radar full pulse data, these methods use small time units to digitize time information such as TOA, DTOA, PRI, PW. This operation brings three problems: first, it brings errors and reduces the accuracy of time information; second, when there are more than one pulses in a time unit, only one pulse is presented, and the information of other pulses will be covered. Third, it is possible to mark the position without pulse as having pulse. In addition, the above method needs to train a network for each category of radar signal, and only one target can be deinterleaved in each output step. In other words, the existing method completes a binary classification task in each output step, so it is necessary to iterate the input and output of data repeatedly.

Finite Automata is also used for radar signal deinterleaving by researchers, but it also requires accurate prior information of target pulse parameters.

B. Neural networks for semantic segmentation and sequence modeling

In recent years, the application of neural network in the field of image semantic segmentation has been deeply studied, and some important results have been produced. To achieve a good semantic segmentation effectiveness, some important ideas are proposed, such as “fully convolutional network (FCN), ” “multi-path refinement network,” “U-Net architecture,” “encoder decoder architecture,” “fully connected conditional random field (CFR),” “atrous spatial pyramid pooling (ASPP).” These ideas have produced excellent effectiveness in image semantic segmentation.

Neural networks are widely used in sequence modeling tasks. Recurrent neural network is the most influential sequence modeling architecture so far, and has been considered as the best architecture for a long time. People began to study RNN model in the 1980s, and proposed Jordan Network in 1986 and Elman Network in 1990. The latter became the basis of some RNN architectures with higher application value. In 1997, Jurgen Schmidhuber proposed Long Short-Term Memory (LSTM) architecture, which uses gated unit and memory mechanism to improve RNN in training. In the same year, Mike Schuster proposed the Bidirectional RNN model (BRNN), which enables RNN to simultaneously use sequence information in both forward and backward directions. The development of Gated Recurrent Unit (GRU) further improved the training problem of RNN. The application of RNN Encoder-Decoder solves sequence to sequence(seq2seq) problem very well. The introduction of attention-based models model greatly improves the effect of RNN-based model on many tasks. The use of transformer models pushes attention-based models to new heights and abandons the RNN architecture.

The application of convolutional neural networks in sequence modeling tasks can also be traced back to the 1980s. In recent years, convolutional neural network-based models have also performed excellently in some sequence modeling tasks, including audio synthesis, word-level language modeling and machine translation, and can reach state-of-the-art in some tasks. These results prompt people to think: can CNN architecture perform better than the RNN architecture in more tasks, or is it just limited to some specific tasks? Shaojie Bai et al conducted an empirical study on this problem and proved that CNN architecture performed better than RNN architecture in many sequence modeling tasks, while these tasks are on the RNN’s "home Turf". The authors summarize this CNN architecture as temporal convolutional network (TCN).
III. TASK CHARACTERISTICS AND DATA MODEL

A. Input and output form

In order to make the input data have smaller variance and facilitate neural network processing, the method in this paper input DTOA of the pulse stream into the neural network instead of TOA. When the pulse stream contains only a single radar target, the DTOA of the pulse stream is the real PRI of the target. When the pulse stream contains pulses from multiple radiation sources, or pulses from a single target arrive through multipath, the DTOA of the pulse stream is chaotic. In order to make DTOA and TOA equal in length, we add 0 before DTOA as the first value of DTOA. The output of this method is the label information of the category of each pulse. When training the neural network, the DTOA and pulse labels to input are as shown in Fig. 1.

Different from the existing deinterleaving methods using neural network [18], [19], [20], the method in this paper does not digitize the time information when input, so as to avoid the adverse effects caused by it. In the output, each pulse is judged to belong to which class of target, rather than whether it belongs to the target we want. In other words, so the processing result of the method in this paper is multi-classification, while the existing methods are usually binary classification.

B. Difference of this task from image semantic segmentation and other sequence modeling tasks

Radar signal deinterleaving based on semantic segmentation thought is a problem of mapping input sequence to output sequence. It is obviously different from image semantic segmentation and seq2seq tasks such as natural language processing.

1) Target points are unconcentrated and throughout the sequence: In the pulse stream, the pulses of different targets are interleaved and the information about the same target runs through the whole pulse stream. But in the task of image semantic segmentation, the pixels of the same object are usually concentrated in one or several regions.

2) There is a strict mathematical relationship between the data at each input point of the sequence: Since the input is DTOA, the information loss of one point will completely change the information in the pulse stream, so pooling is not allowed. Image semantic segmentation and seq2seq tasks do not have this feature.

3) The input and output are of equal length: The input and output of this task are equal length sequences. In some sequence modeling tasks such as machine translation, the input and output are often not equal length.

4) The input at each point is meaningless on its own: Similar to the image data, the input data of each point in this task does not have any meaning by itself. Only when it is calculated together with the input before and after, can the information be reflected. But in natural language processing tasks, each input word itself has a specific meaning.

5) Forward and backward information are equivalent: In the deinterleaving task, the forward and reverse information of the sequence is completely equivalent, which is significantly different from many sequence modeling tasks. Therefore, in this task, using the bidirectional information of the sequence at the same time is more conducive to accurately judge the category of each pulse.

C. Limitations of deinterleaving method based on semantic segmentation thought and the solution

The deinterleaving method based on the semantic segmentation thought faces the same problem as image semantic segmentation, that is, it cannot distinguish multiple objects belonging to the same category in a single input. In image processing, this problem is solved by instance segmentation [49], [50], [51], which usually consists of two contents: semantic segmentation and object detection, as shown in Fig. 2 [49]. However, this idea cannot be applied to radar signal deinterleaving, because in the image, the pixels belonging to the same target concentrated, while in the pulse stream, the pulses belonging to the same target are not. Pulses from one target are interleaved with pulses from other targets, and distributed in the whole pulse stream. The method to solve this problem is to extract more different semantics from target radar signals, and divide radar signals into more classes. This will be discussed in section IV.

D. Data model

PRI modulation mode has an important effect on radar function and performance. In this paper, we define and use the following PRI modulation modes in simulation experiments. The DTOA of radar signals with these three PRI modulation modes is shown in Fig. 3 [35]. The subfigures show the DTOA of radar signals under different conditions respectively: a) DTOA of non-destructive radar signal, that is, PRI of radar signal; b) DTOA of radar signal with pulse loss; c) DTOA of radar signal with random noise pulses; d) DTOA of radar signal with pulse loss and random noise pulses.

1) Constant PRI: The radar pulse repetition interval remains a constant, and the PRI sequence can be represented as:

\[ PRI_n = PRI_0, n = 1, 2, 3, \ldots \]  \hspace{1cm} (1)

2) Dwell and Switch (D&S) PRI: Radar PRI changes in groups, with the same number of pulses in each group.
The value of PRI changes periodically between groups. Its mathematical model is shown:

\[ PRI_n = PRI_{n+j}, 0 \leq j < J, \]

\[ PRI_n = PRI_{n+N*K}. \]

\( PRI_n \) is the first PRI in each group, \( J \) is the number of pulses in each group, \( K \) is the number of pulse groups in one period, that is, the number of PRI values in a period.

3) Staggered PRI: Radar PRI consists of several fixed values and changes periodically. The PRI sequence can be described as follows:

\[ PRI_n = PRI_{n+M}. \]

\( M \) is the number of PRI values in a period.

IV. NEURAL NETWORK ARCHITECTURE AND DEINTERLEAVING STRATEGY

A. What kind of neural network should be selected for this task

According to the basic thought of the method in this paper, when we select neural network, it is required to have good semantic segmentation ability for sequence data with strong mathematical relations. In section III, we analyzed the difference of this task from image semantic segmentation and seq2seq tasks such as natural language processing. Therefore, the neural network need to meet the following conditions: good ability at sequence modeling, full use of all the information of the whole sequence (or a large enough receptive field), equal length of input and output, and no pooling.

Accordingly, we select BRNN and dilated convolutional network (DCN), but abandon the classical neural networks used for image semantic segmentation \[1, 22, 23, 24, 25, 26, 27, 28\] and used for seq2seq tasks, \[35, 36, 37, 38, 39\], e.g. encoder-decoder structures architecture.

1) BRNN: For DTOA data, forward and reverse information are equivalent. In order to make full use of the complete information of the sequence when determining the category of each pulse, bidirectional RNN is used in this paper to process DTOA data. Then the output of each step of RNN is connected with the full connection layer to realize the classification of each time step. As is shown in Fig. 6. This paper chooses GRU architecture of RNN to achieve this task, that is, bidirectional GRU (BGRU).

2) DCN: Due to TCN’s outstanding performance in sequence modeling task, this paper took TCN as reference when constructing DCN. It is the same in the construction of residual module, that is, a residual module contains two dilated convolution layers and two nonlinear layers. The dilation factors of the convolution kernel within the module is the
same, and the dilation factors between modules increases exponentially with the network depth.

The difference is that, in order to keep the length of the feature map unchanged in each convolution step, both sides of the feature map are padded symmetrically rather than adopting causal convolution, as shown in the Fig. 7. This operation takes into account the equivalence of forward and reverse information. In this paper, we set the convolution kernel size of DCN as 3, and 8 residual modules. This makes the receptive field of each convolution kernel in the last layer of the network sufficient to cover the length of the input data.

After the residual module, we use a common convolution to reduce the number of channels to the number of target classes, to achieve the classification of each pulse, as shown in Fig. 8.

### Table I: Semantic information for radar signal deinterleaving

| semantic information | category |
|----------------------|----------|
| PRI modulation mode  | category 1: constant PRI<br>category 2: D&S PRI<br>category 3: staggered PRI |
| value range of constant PRI | category 1: (a, b)<br>category 2: (b, c)<br>category 3: (c, d) |
| center value range of jittered PRI | category 1: (a, b)<br>category 2: (b, c)<br>category 3: (c, d) |
| mean value range of staggered/sliding/wobulated PRI | category 1: (a, b)<br>category 2: (b, c)<br>category 3: (c, d) |
| number of values of staggered/sliding/wobulated PRI in a period | category 1: 3 values in a period<br>category 2: 4 values in a period<br>category 3: 5 values in a period |

**B. How to use semantic information - deinterleaving strategy**

Semantic segmentation is based on the characteristics of different categories of objects. Analysis in section III indicates that in order to achieve good deinterleaving effect, enough different semantics need to be extracted from radar signal. This section mainly analyzes how to deinterleave radar signal using PRI modulation mode and PRI parameters as semantics separately, and how to use both for deinterleaving comprehensively.

1) Take PRI modulation mode as semantic information: Different PRI modulation modes represent different information, that is, contain different semantics, as shown in Table I. The target radar signals can be divided into different classes accordingly. When the intercepted radar pulse stream contains multiple targets with different PRI modulation modes, PRI modulation information can be used as semantic information, and the category of each pulse can be predicted based on this to achieve radar signal deinterleaving.

2) Take PRI parameters as semantic information: When multiple target radars adopt the same PRI modulation mode, the deinterleaving method based on semantic segmentation with PRI modulation mode will be limited and cannot distinguish such multiple targets. In this case, PRI parameter information can be used as semantics to distinguish different targets. For the targets with constant PRI or jittered PRI, the value can be used as semantic information. E. g., When the value of constant PRI or the center value of jittered PRI is in (a, b), it is the first subclass, in (b, c) the second subclass, (c, d) the third subclass, and so on. For the targets with periodically changing PRI, such as staggered PRI, sliding PRI, and wobulated PRI, the number of typical values within a period can be used as semantics. E. g., for the staggered PRI, with 3 PRI values in a period is the first subclass, with 4 PRI values in a period is the second class, and with 5 PRI values in a period is the third class. The mean value of PRI can also be used as semantic information for targets with periodically changing PRI. How to set the specific value of the subclass depends on the signal and the specific task environment.

3) Comprehensive use of PRI modulation modes and PRI parameters: It was pointed out in Section III, Part D, that to solve the problem of having multiple targets in the same
class, we need enough semantics to divide the radar pulses into different classes. Now we have proposed deinterleaving methods using PRI modulation and PRI parameters as semantic information, respectively. In this section, two methods are proposed to make comprehensive use of these information for deinterleaving. One is a parallel deinterleaving method, using PRI modulation modes and PRI parameters at the same time, as shown in Fig. 9. The second is the serial deinterleaving method, which first uses PRI modulation and then uses PRI parameters for deinterleaving, as shown in Fig. 10. The former has fewer deinterleaving steps and needs only one neural network. The latter needs to be completed step by step, and uses multiple neural networks. But the latter can adapt to more complex deinterleaving environment, e. g., when the semantic categories of radar pulses are diverse and the capacity of neural networks is limited.

C. Loss function

In this task, each sample input to the neural network is the DTOA of a pulse stream. The predicted loss of each sample by the neural network is the average of the predicted loss of all pulses in the pulse stream, i.e.,

$$Loss = \frac{1}{N} \sum_{n=1}^{N} loss_n.$$  

(5)

loss_n is the predicted loss of the nth pulse by the neural network. We use cross-entropy loss function to evaluate the prediction performance of each pulse of the neural network, which can be described below

$$loss = - \sum_{c=1}^{C} P_c \log(\hat{P}_c).$$  

(6)

C is the category number of radar signal in pulse stream. P_c is whether the current pulse belongs to the cth category of radar signal, and the value is 0 or 1. \(\hat{P}_c\) represents the probability that the current pulse belongs to the cth category of radar signal in the prediction of neural network.

V. EXPERIMENTS

A. Data simulation

According to the definition of PRI modulation modes in Section III, Part D, the following designs are made for simulation data.

1) For all PRI modulation modes, the PRI value satisfy the condition \(20 < PRI < 100\).

2) For the D&S PRI, the number of pulses in each group satisfy the condition \(4 \leq J \leq 6\), the number of pulse groups in one period satisfy the condition \(4 \leq K \leq 6\).

3) For the staggered PRI, the number of PRI values in a period satisfy the condition \(3 \leq M \leq 10\).

4) In this paper, Gaussian distributed deviation is added to TOA to simulate measurement error, the standard deviation (STD) is 0.1. Then the DTOA is generated on this basis, and the length of DTOA is 1000.

5) In this paper, the problem of target pulse loss and random noise pulses in intercepted pulse stream is considered. The pulse loss rate of target is represented by \(\rho_l\), and the ratio of the number of random noise pulses to the average number of the target radars pulses in the intercepted pulse stream is represented by \(\rho_n\). The proportion of the number of random noise pulses to the total number of pulses can be calculated by \(\frac{\rho_n}{\rho_n + D}\), and D represents the number of target radars.

B. Design of experiments

According to the deinterleaving strategies proposed in Section IV, 5 experiments are designed to verify the feasibility of the proposed deinterleaving method and compare the performance of different neural networks in dealing with this problem. Experiment 1 is to verify the feasibility of deinterleaving radar signal taking PRI modulation modes as semantics. Experiment 2 and 3 are to verify the feasibility of deinterleaving radar signal taking PRI parameters as semantics. Experiment 4 is to verify the parallel deinterleaving method using PRI modulation modes and PRI parameters simultaneously. Experiment 5 is to verify the first step of the serial deinterleaving method, deinterleaving radar signal with PRI modulation modes when there are multiple targets per PRI modulation mode, experiment 2 and 3 can be used to verify the second step. \(\rho_l\) and \(\rho_n\) of each sample of training data is randomly chosen within a certain range.

1) Experiment 1-Deinterleaving radar signal with PRI modulation modes: The target settings are shown in Table III. For the training data, \(\rho_l < 0.25\), \(\rho_n < 0.25\).

2) Experiment 2-Deinterleaving radar signal of constant PRI with PRI values: The target settings are shown in Table III. For the Training data, \(\rho_l < 0.5\), \(\rho_n < 0.5\).
### Table II: The target settings in Experiment 1

| category | PRI modulation mode | number of targets |
|----------|---------------------|-------------------|
| 1        | constant            | 1                 |
| 2        | D&S                 | 1                 |
| 3        | staggered           | 1                 |
| 4        | random noise pulse  |                   |

### Table III: The target settings in Experiment 2

| category | value range of constant PRI | number of targets |
|----------|------------------------------|-------------------|
| 1        | (20,40)                      | 1                 |
| 2        | (40,60)                      |                   |
| 3        | (60,80)                      |                   |
| 4        | (80,100)                     |                   |
| 5        | random noise pulse           |                   |

### Table IV: The target settings in Experiment 3

| category | number of values of staggered PRI in a period | number of targets |
|----------|-----------------------------------------------|-------------------|
| 1        | 3                                             | 1                 |
| 2        | 4                                             | 1                 |
| 3        | random noise pulse                            |                   |

### Table V: The target settings in Experiment 4

| category | PRI modulation mode and parameters | number of targets |
|----------|------------------------------------|-------------------|
| 1        | constant PRI in (20,40)            | 1                 |
| 2        | constant PRI in (40,60)            |                   |
| 3        | staggered PRI                      |                   |
| 4        | random noise pulse                 |                   |

### Table VI: The target settings in Experiment 5

| category | PRI modulation mode and parameters | number of targets |
|----------|------------------------------------|-------------------|
| 1        | constant PRI in (20,40)            | 1                 |
| 2        | constant PRI in (40,60)            |                   |
| 3        | staggered PRI with 3 values        | 1                 |
| 4        | staggered PRI with 4 values        |                   |
| 5        | random noise pulse                 |                   |

### C. Result

The network capacity in the five experiments and the overall performance on the test set (produced under the same conditions as the training set) are shown in Table VII. In addition, we tested the trained model on data sets generated under three different conditions: a) There is pulse loss, but no random noise pulses, i.e. \( \rho_l < 0.5 \), \( \rho_n < 0.5 \); b) There is no pulse loss, i.e. \( \rho_l = 0 \), but there are random noise pulses; c) There are both pulse loss and random noise pulses, and \( \rho_l = \rho_n \). The results are shown in Fig. [11][15].

The experiments have proven the feasibility of the radar signal deinterleaving method based on semantic segmentation thought and the deinterleaving strategy proposed in Section IV. This method does not require the periodicity of PRI, can adapt to any PRI modulation mode, and has excellent accuracy and robustness. The experiments also proves that the classical RNN architecture is better than the convolution architecture in this task.
TABLE VII: The network capacity and the overall performance in the five experiments

| experiment | model size | accuracy |
|------------|------------|----------|
|            |            | DCN      | BGRU     |
| 1          | ≈611K      | 86.4     | 89.3     |
| 2          | ≈211K      | 86       | 94.1     |
| 3          | ≈611K      | 70.9     | 89.5     |
| 4          | ≈611K      | 84.2     | 90.7     |
| 5          | ≈611K      | 90.2     | 94.8     |

VI. CONCLUSION

In this paper, a radar signal deinterleaving method based on semantic segmentation thought is proposed. It uses the semantic information contained in different radar signals to label the pulses that constitute the same semantic as the same class. Two deinterleaving strategies comprehensively using PRI modulation modes and modulation parameters are also proposed. Through the research, we got the following conclusions.

1) Compared with the traditional method [2], [3], [4], [5], [6], [7], [8], [9], [10], [11], [12], [13], [52], this method can adapt to any PRI modulation mode without requiring the periodicity of PRI. There is no need to find the period of PRI first and then search the sequence to get the target radar pulses. For the targets of staggered PRI, no merging operation is required.

2) Compared with other deinterleaving methods using neural network and automata [18], [19], [20], [21], this method does not require digital processing of data, thus avoiding adverse effects; this method can output multiple targets in one step with one network, without training a network for each category of target, and without iterating the input and output of data repeatedly; only the PRI modulation modes and the PRI parameter range are required for training, without very accurate PRI value as prior information in this method.

3) The method proposed in this paper is easy to train, easy to converge, and still maintains ideal accuracy and good robustness in complex deinterleaving environments with high pulse loss rate and noise to target ratio.

4) In this paper, PRI modulation modes and PRI parameters are proposed as semantic information. However, the method proposed in this paper still have limitations when PRI modulation modes and PRI parameters are exactly the same or the PRI value range of a target is large. At this point, RF and PW can be used as semantic information to further divide the targets into more classes. The deinterleaving method based on semantic segmentation thought and multi-parameter will be our future research direction.

5) Our research shows that GRU has more obvious advantages than DCN in this task. This may indicate that although the performance of CNN architecture has exceeded RNN in representative sequence modeling tasks [48], RNN is still superior to CNN in sequences with strong mathematical relationships. This problem depends on further research and proof in the field of deep learning in the future.

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Fig. 11: Deinterleaving radar signal with PRI modulation modes.

Fig. 12: Deinterleaving radar signal of constant PRI with PRI values.

Fig. 13: Deinterleaving radar signal of staggered PRI with the number of PRI values in a period.

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Fig. 14: Deinterleaving radar signal using PRI modulation modes and PRI parameters simultaneously.

Fig. 15: Deinterleaving radar signal with PRI modulation modes when there are multiple targets per PRI modulation mode.