Application of Convolutional Neural Networks in Radio Station Link Establishment Behaviors Recognition

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Abstract: For the problem that it is difficult to recognize the type of link establishment (LE) behaviors of radio station whose communication protocol is unknown, a method is proposed to solve the problem by using convolutional neural network (CNN) to recognize LE behaviors. The method processes physical layer signals directly and breaks through limitation of unknown protocol standard. Three classical CNN models are optimized through experiments so that they become more suitable for recognition of one-dimensional time series signals. Experimental results show CNN can effectively recognize the different link establishment behaviors with a large number of training samples. Moreover, DenseNet whose recognition accuracy can reach 96% when the signal-to-noise ratio (SNR) is 0dB has the best performance compared to GoogLeNet and ResNet.

Keywords: Recognition, Link Establishment Behavior, Short-wave Radio Station, Convolutional Neural Network.

1. Introduction
The LE behaviors of radio station mean communication behaviors of the station at the beginning of its communication, such as call, handshake, notification, time offset, group time broadcast, broadcast and scanning call. The recognition of LE behaviors was an important and difficult problem in the field of electronic countermeasures. If we could grasp the non-collaborative organization's LE behaviors, the communication intention and work status of the radio station could be inferred, which provided a reference for further inferring the topological structure and tactical position of the radio station.

As can be seen from the third-generation short-wave communication protocol standard (MIL-STD-188-141B), there were mainly five burst waveforms (BW), which correspond to different communication behaviors or states respectively. The LE behaviors of radio station only used the same burst waveform BW0 for communication. The number of original valid bits in the BW0 waveform data frame was 26, and the original bits corresponding to different LE behaviors were slightly different, as shown in Fig.1. And these valid bits should be transmitted through BW0 burst waveform, and the transmission scheme was shown in Fig.2.
The research on LE behaviors of communication stations at home and abroad was often based on the analysis of communication protocols standard [1]. It was a relatively novel technique to analyze LE behaviors directly by recognizing physical layer signals. Liu et al. [2-3] could accurately find the communication relationships of wireless communication station from the monitored physical layer signals, and there was no need to crack the content information carried by signals. The research combined with deep learning (DL) was the demand for intelligent battlefield reconnaissance, which could effectively break through the frequency hopping, demodulation and other technical limitations of unknown protocol standard. And DL would help to recognize LE behaviors of radiostations. As an important network model in the field of DL, CNN could extract the deep features of signals [4-7]. GoogLeNet [8-9], ResNet [10-12] and DenseNet [13-14] were classic representatives of the series of CNN. Based on the analysis of LE behaviors signals of short-wave radio station, it could be seen that different LE behaviors signals specified in the MIL-STD-188-141B [15] were very similar. However, a series of CNN can automatically extract the deep differences between signals. We would mainly explore the application of classic CNN with different structure, such as inception block [16], residual block and dense block in LE behaviors recognition of short-wave radio station.
In this paper, the type of LE behaviors of radio station was deduced directly by analyzing physical layer signals, avoiding difficulty that the communication protocol was unknown in the process of reconnaissance. Through the analysis of MIL-STD-188-141B, we simulated the LE behaviors signals of short-wave radio station. Then we explored the performance of different CNN models for recognition of LE behaviors. Experimental results have shown that network models based on CNN can effectively infer the LE behaviors.

2. Application of CNN in LE behaviors recognition

CNN has a strong ability for extracting features automatically [17-21], which can be exactly used to extract deeper features of LE behaviors signals. The basic structure of CNN for one-dimensional time-domain signal is shown in Fig.3.

![Fig.3 Basic structure of CNN.](image)

Different convolutional kernels could extract different deep features of signals. Pooling layer can effectively compress data and prevent overfitting. The development of CNN benefits from the emergence of novel network blocks, such as inception block, residual block and dense block.

Actually, the inception block was first proposed in GoogLeNet and it had better performance due to its low amount of model parameters. GoogLeNet often refers to a network model constructed from the Inception v1, as shown in Fig.4.

![Fig.4 Structure of Inception v1.](image)

Moreover, the basic residual block effectively solved the problem of gradient disappearance in deep network by adding shortcut connections between network layers. And the basic idea of dense block was similar to that of the residual block, and its dense connection between all the front layers and the last layer improved the reverse propagation capacity of the gradient and achieved feature reuse.

Considering the application background of battlefield reconnaissance, the LE behaviors recognition of short-wave radio station must be fast. However, a complex network model required a large number of parameters to be trained, and the training time cost was high. Therefore, a relatively simple and effective network model must be adopted to recognizing LE behaviors. Inspired by inception block, residual block, and dense block, this paper would use these three basic network models for experiments. These blocks used in this paper were shown in Fig.5.
As shown in Fig.5 (5888, 1) represented dimension of signal. And (16, 1, same) represented the convolutional operation, the number of convolutional kernels was 16, the size of convolutional kernel was 1, step length default to 1, and “same” meant that matrix of signal could be padded by zero when necessary.

3. Optimization of CNN models

All kinds of CNN were originally applied in the field of image processing. In order to make them play better roles in the field of radio signal, we needed to discuss the recognition performance of different CNN models with different internal structures. Afterwards, we would obtain more appropriate network model for recognizing different LE behaviors. MIL-STD-188-141B specified that the white Gaussian noise channel could be used as an analog channel for communication, so the signal data set whose SNR was 0dB could be used to train and test the network model during optimization of network models. In actual battlefield conditions, the network structure with more network layers was difficult to be trained and cannot meet the needs of actual reconnaissance, so the network model used in our experiments must be relatively simple. Therefore, the influence of the number of convolutional layers inside residual block and dense block on the recognition performance was experimentally analyzed, and then the influence of the number of inception block, residual block, and dense block on the recognition performance in different network models was investigated. These experiments could not only make the network model have better recognition performance, but also lower training time cost because the network model was simple.

In order to reduce the influence of initial learning rate on experimental results, batch normalization (BN) was added to the full connection layer and classifier. Batch size is equal to 16, Adam is used as optimizer and epoch is equal to 10.

Experimental environment: (NVIDIA GeForce GTX 950M) *1, TensorFlow1.12.0 and Keras2.2.5.

3.1. Influence of internal structure of network blocks on recognition performance
In the research on the influence of internal structure of residual block and dense block on the recognition performance, all these network models would use one network block respectively, and then connect to flatten layer. The internal structures of residual block were set as A, B and C shown in Fig.6(a). The internal structures of dense block were set as D, E and F shown in Fig.6(b).

![Different residual blocks](image)

![Different dense blocks](image)

**Fig.6** Different blocks with different CNN models

There were all 14,000 LE behaviors signals containing seven kinds of behaviors simulated in this work. And 8,400 LE behaviors signals were randomly selected as the training set, and the remaining 5,600 samples were taken as the test set. The corresponding recognition performances with different internal structures of network blocks were shown in Tab.1.

| Different networks | ResNet  | DenseNet |
|--------------------|---------|----------|
| Different structures| A       | B        | C       | D     | E     | F     |
| Accuracy           | 0.865   | 0.8977   | 0.9507  | 0.953 | 0.9635| 0.9625|

**Tab.1** Recognition performance with different internal structures of network blocks

As shown in Tab.1, there were more convolutional layers in residual block, the better recognition performance would be. When condition was C, the recognition accuracy of the ResNet model can reach 95%. When condition was E, the recognition accuracy of the DenseNet model was slightly higher, however, all the recognition accuracy were roughly the same.

### 3.2. Influence of the number of network blocks on recognition performance

In order to explore the performance of the network models containing different number of network blocks on recognizing LE behaviors, the internal structures of residual block and dense block were fixed as C and E due to experiment results in subsection 3.1. The inception block was shown in Fig.4. The network model recognition performance with different number of network block was shown in Tab.2.

| Different networks | ResNet | DenseNet | InceptionNet |
|--------------------|--------|----------|--------------|
| Different structures| one    | two      | three        | one    | two    | three |
| Accuracy           |        |          |              |        |        |       |
4. Research on the recognition performance of network model based on CNN

In order to fully explore the recognition performance of different network models based on CNN for recognizing LE behaviors of short-wave radio station, it was necessary to explore the recognition performance of network models when SNR=-5, 0, 5dB. The structures of network models was set as C and E due to experiments in section 3, and each network model contained a residual block, a dense block, or an inception block. In order to reduce the influence of initial learning rate on experimental results, BN layer was added to the full connection layer. In various SNR, the variation of loss and test accuracy of each CNN network model was shown in Fig.7.

![Variation of loss in different network models](image1)

(a) Variations of loss in different network models when SNR=-5

![Variation of test accuracy in different network models](image2)

(b) Variations of test accuracy in different network models when SNR=-5

![Variation of loss in different network models](image3)

(c) Variations of loss in different network models when SNR=0

![Variation of test accuracy in different network models](image4)

(d) Variations of test accuracy in different network models when SNR=0

| structures | Accuracy |
|------------|----------|
|            | 0.95     | 0.94     | 0.92     | 0.96     | 0.97     | 0.96     |
|            | 07       | 73       | 62       | 45       | 23       | 79       |
|            | 0.93     | 0.96     |
|            | 81       | 00       |

Tab.2 Recognition performance with different number of network block

As shown in Tab.2, after the network models were trained, the more basic network blocks were used in ResNet, the poorer recognition performance of the network model was. Because the network model became more difficult to be trained while the complexity of the network model was increasing. In terms of DenseNet and InceptionNet, the change in the number of basic dense blocks and basic inception blocks did not have a significant impact on the final recognition accuracy, mainly because of their complex network structure.
As shown in Fig.7, the loss of DenseNet declined the fastest, followed by ResNet and InceptionNet. On the whole the loss of each network model gradually declined and finally tended to be stable. DenseNet had the highest testing accuracy, while the ResNet model was slightly higher than the Inception Net model. In addition, the higher the SNR was, the faster the training speed of each network model was, and the better the recognition performance was. Actually, DenseNet model had the best performance, ResNet and Inception Net model had similar performance, but the performance of Inception Net model was unstable.

5. Conclusion
According to MIL-STD-188-141B, seven kinds of LE behaviors signals of short-wave radio station were simulated. Then considering the time cost of network model in battlefield application, three kinds of mainstream basic CNN models were used to intelligently recognize LE behaviors signals, and network models were improved and optimized. Experimental results have shown that when SNR was greater than 0dB, each network model had better recognition performance and DenseNet model had the best performance. The LE behaviors recognition of radio stations was of great significance to graspradiostation's work state and tactical position in the wireless communication network.

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