Classification method for spatial targets based on convolutional neural network

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ABSTRACT

In this paper, we constructed a one-dimensional convolutional neural network as a classifier model for spatial object classification. Considering that there are few available training samples obtained from actual measurement, combining with the characteristics of actual measurement data, we simulated a large amount of data for training and testing. The simulation results show that our method has a high classification accuracy and can overcome the problems existing in actual measurement, such as tracking mixed batches to a certain extent, and it can also effectively solve the problem that it is difficult to directly train neural networks because of the small number of spatial target samples, which take advantage of neural network autonomous learning and memory to reliably identify features.

Keywords: Network, spatial targets, simulation

1. INTRODUCTION

Spatial targets mainly include normally working satellites, rocket body and space debris[1]. The typical attitudes of space targets include three-axis stable attitude, spin-stabilized attitude and rolling attitude. Among them, the rollover attitude is an abnormal attitude, which may occur on out-of-control satellites and abandoned rocket boosters. Such targets either do not have an attitude adjustment system or exhaust the energy used for attitude balance. Under the action of external forces such as the earth's gravity, they will eventually roll over. Tumble is a way of rotation of space targets. The tumbling period is related to the moment of the target. For example, the final stage rocket has a large difference in the length ratio of the vertical and horizontal axes (or the size in one direction). Generally, the tumbling axis and the long axis of the target are different. Orthogonal spin-stabilized space satellites have a relatively fast spin angular velocity, and the rotation period is generally tens to more than one hundred revolutions per minute.

RCS (Radar Cross section) is an index that reflects the ability of a target to scatter radar signals[2]. Generally speaking, the larger the target area in the direction of the radar line of sight, the larger the RCS. According to the average value of multiple RCS measurements, the size of the target can be roughly determined. In general, the movement of the space target along the orbit will cause the attitude to change relative to the radar line of sight, so that the data of the fluctuation of the RCS with the attitude angle can be obtained.

We propose a method to classify and identify spatial targets based on a one-dimensional convolutional network using RCS sequence values measured by radar as characteristic data, and output the three types of target recognition results of satellite targets, rocket body targets and space debris targets in real-time. Simulation proves that this method has a high classification accuracy.

2. NEURAL NETWORK CONSTRUCTION

2.1 Feature extraction

In order to extract the feature information of the RCS sequence for training, we found a total of 14 features for training, forming an N*14 target set. These features include a time sequence, an amplitude sequence, 6 sequences of amplitude statistics, and 6 sequence of window amplitude statistics. Defining the RCS amplitude sequence of a target relative to time t as $R_a = \{r_a(t_i)\}, i = 1,2,...,N$, the extracted features are as follows[3]:

(1) RCS Amplitude Sequence

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$$R_a(i) = \{r_a(t_i)\}, i = 1,2,...,N \tag{1}$$

(2) Time Sequence

$$t_a(i) = t_i - t_{i-1}, i = 1,2,...,N \tag{2}$$

(3) RCS Amplitude Average Sequence

$$\bar{r}_a(i) = \frac{\sum_{j=1}^{i} r_a(t_j)}{i}, i = 1,2,...,N \tag{3}$$

(4) RCS Amplitude Maximum Sequence

$$r_{a\max}(i) = \max\{r_a(t_i)\}, i = 1,2,...,N \tag{4}$$

(5) RCS Amplitude Minima Sequence

$$r_{a\min}(i) = \min\{r_a(t_i)\}, i = 1,2,...,N \tag{5}$$

(6) RCS Amplitude Range Sequence

$$r_{a\max-\min}(i) = r_{a\max} - r_{a\min} \tag{6}$$

(7) RCS Amplitude Range-Mean Sequence

$$r_{amean}(i) = \frac{\sum_{j=1}^{i} \frac{|r_a(t_j) - r_a(t_{j-1})|}{t_j}}{i} i = 1,2,...,N \tag{7}$$

(8) RCS Amplitude Standard Deviation Sequence

$$s_a(i) = \left(\frac{\sum_{j=1}^{i} (r_a(t_j) - \bar{r}_a)}{i-1} \right)^{\frac{1}{2}} \tag{8}$$

(9) RCS Window Amplitude Average Sequence

$$\bar{r}_{a60}(i) = \begin{cases} \bar{r}_a(i), i < 60 \\ \frac{\sum_{j=i-59}^{i} r_a(t_j)}{i}, i \geq 60 \end{cases} \tag{9}$$

(10) RCS Window Amplitude Maximum Sequence

$$r_{a\max 60}(i) = \begin{cases} r_{a\max}(i), i < 60 \\ \max\{r_a(t_i)\}, i \geq 60 \end{cases} \tag{10}$$

(11) RCS Window Minima Sequence

$$r_{a\min 60}(i) = \begin{cases} r_{a\min}(i), i < 60 \\ \min\{r_a(t_i)\}, i \geq 60 \end{cases} \tag{11}$$

(12) RCS Window Amplitude Range Sequence

$$r_{a\max-\min 60}(i)=\begin{cases} r_{a\max-\min}(i), i<60 \\ r_{a\max 60}(i)-r_{a\min 60}(i), i\geq 60 \end{cases} \tag{12}$$

(13) RCS Window Amplitude Range-Mean Sequence

$$r_{amean60}(i)=\begin{cases} r_{amean}(i), i<60 \\ \dfrac{\sum_{j=i-59}^{i}\dfrac{|r_a(t_j)-r_a(t_{j-1})|}{t_j}}{60} i\geq 60 \end{cases} \tag{13}$$

(14) RCS Window Amplitude Standard Deviation Sequence

$$s_{a60}(i)=\begin{cases} s_a(i), i<60 \\ \left(\dfrac{\sum_{j=i-59}^{i}(r_a(t_j)-\bar{r}_a)}{i-1}\right)^{\frac{1}{2}}, i\geq 60 \end{cases} \tag{14}$$

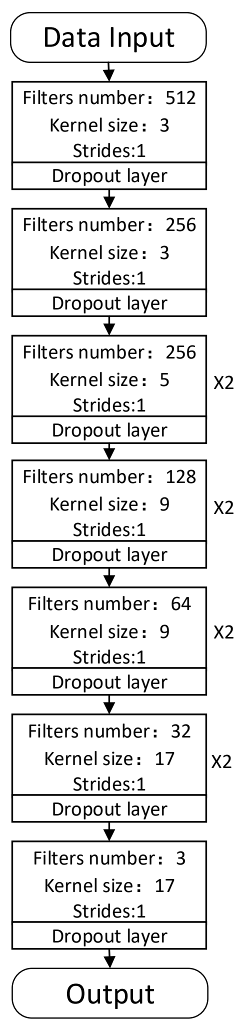

Figure 1. One-dimensional convolutional network structure.

2.2 1D convolutional network

The input of one-dimensional convolution is vector and convolution kernel, and the output is also vector[4]. Usually, the length of the input vector is much larger than the length of the convolution kernel. The length of the output vector depends on the padding scheme of the convolution operation. The length of the output vector of a constant-width convolution is equal to the length of the input vector. The length of the convolution kernel is usually odd, which is designed for symmetry.

In order to realize the classification of RCS sequences, thus realizing the classification of spatial objects, we designed an end-to-end one-dimensional convolutional network. The real-time input of the network is 14 RCS feature sequences, and the output is the RCS classification result. The network output and input has the same length. The classification and identification results include three categories, which are satellites, rocket body and space debris[5].

The one-dimensional convolutional network structure we designed is shown in Figure 1.

3. RESULTS

3.1 Dataset construction

Using the omnidirectional angular RCS data of the simulated satellite, rocket body and space debris target models, according to the simulated ballistics and the motion characteristics of various targets, combined with the frequency conversion characteristics of equipment measurement, the RCS amplitude sequence values of the three types of targets at each moment are obtained. The radar band has a great influence on the RCS measurement data, so the recognition network needs to be trained for different bands. This paper takes the recognition network trained by P-band RCS as an example for analysis. In the simulation scenario, the radar coordinates are fixed, and the space targets move at different heights and speeds. Assuming that the P-band radar observes the target well, the relevant parameters of the three types of targets are shown in Table 1:

Table 1. Parameter table of three types of targets.

	RCS magnitude	Posture stability	Number
Satellite	5~-5dB	Yes	25000
Rocket body	10~-10dB	No	20000
Space debris	-5~-20dB	No	20000

We obtained a total of 65,000 simulation data, of which 25,000 were satellite targets, 20,000 were rocket targets, and 20,000 were space debris.

3.2 Analysis of experimental results

We trained the network on the Keras neural network framework. In the training and testing part, we used the 4fold method to divide the three types of targets into four groups A, B, C, and D, and the groups do not overlap each other. We performed training and testing four times, using three of them as training samples and the other as testing samples for each training. The identification results are counted, and then the results of the four simulation experiments are summed and averaged, and the accuracy of the final stable classification results is calculated.

By training the neural network, we can get the classification of three types of targets, as shown in Table 2:

We analyze from the table that after the 4fold classification test, the classification accuracy rate of satellite targets is more than 90%, which shows that the algorithm proposed in this paper can give high-confidence recognition results. This is because the satellite target has good attitude stability characteristics, and its mean RCS has a large degree of discrimination with the other two types of targets most of the time. In addition, the rocket body target can also achieve an accuracy rate of about 80%. Due to the large size of some models in the simulation and the lack of stable attitude characteristics, a considerable number of samples were identified as rocket body targets.

Table 2. Target classification accuracy.

	Satellites classified	Rocket body classified	Space debris classified	Accuracy
Satellite	5721	318	211	91.54%
Rocket body	320	4324	356	86.48%
Space debris	258	757	3985	79.70%

4. CONCLUSION

We propose a spatial target RCS sequence recognition method based on simulation data and one-dimensional convolutional neural network. We first analyze the available features for spatial targets recognition, and then combine the characteristics of actual data measurements to design a recognizer using one-dimensional convolutional neural network, and we train it using a transfer learning approach. Simulation experiments show that the classifier obtained by this method has high accuracy and can effectively use the RCS amplitude sequences values of space targets for identification and classification. It has the advantages of machine learning and provides a new idea for the identification of space targets.

REFERENCES

[1] Lvarez, C., Mullen, A. M., Poji, M., et al., "Classification and target compounds," Food Waste Recovery (Second Edition), 21-49 (2021).
[2] Yang, N., Zhong, W., Guo, L., et al., "A method of space target attitude classification and recognition based on convolutional neural network," CN111898652A, (2020).
[3] Noh, Y. H., Kim, W., Tae, H. S., et al., "RCS feature extraction using discretized point scatterer with compressive sensing," IEEE Antennas and Wireless Propagation Letters, (2020.
[4] Kim, Y., "Convolutional neural networks for sentence classification," Eprint Arxiv, (2014).
[5] Zhao, Z. and Wu, Y., "Attention-based convolutional neural networks for sentence classification", Interspeech, (2016).