

A New Radar Detection Effectiveness Estimation Method Based on Deep Learning

Feng Zhu^{1,2(✉)}, Xiaofeng Hu¹, Xiaoyuan He¹, Kaiming Li³,
and Lu Yang^{4,5}

¹ The Department of Information Operation and Command Training,
National Defense University, Beijing 100091, China
zhufeng_83@126.com

² No. 93682 Unit of PLA, Beijing 101300, China

³ Information and Navigation Institute, AFEU, Xi'an 710077, Shaanxi, China

⁴ Air and Missile Defense College, AFEU, Xi'an 710051, Shaanxi, China

⁵ No. 91053 Unit of PLA, Beijing 100070, China

Abstract. Some of traditional analytical processes with non-linear characteristics are difficult to manage. For example, many issues of radar detection effectiveness estimation relying on human experience are hardly to suggest by using the traditional analytical methods. Therefore, some explored researches aimed at this problem are carried out. The main purpose of the paper is some reasonable ways are tried to designed to replace the analytical process, so as to complete the radar detection effectiveness evaluation. As well known, Deep Learning which is the typical models of deep neural network has a very good capability for expressing non-linear contents. Hence, it could be brought into studying the issue of the radar detection effectiveness evaluation, and this new idea and relative new method are proposed in the paper. Furthermore, the CNN as one of the typical network models or algorithms of the Deep Learning would be employed to execute relative researches. In the proposed method, the input sample data set which CNN needs can be constructed through designing the spatial distribution images composed of the radar radiation domain and the target location. And the labels for present or absent missing alarm can be obtained according to some rules. Then, the CNN model with five hidden layers is established to complete the non-linear mapping from input sample set to output labels, in order to achieve the estimated results. Simulation results prove the validity of the proposed method.

Keywords: Radar detection effectiveness estimation · Deep Learning
Convolution Neural Network · Missing alarm · Non-linear

1 Introduction

Radar as a tool to detect, identifying and tracking the targets, has played an increasingly important role in military and other fields. Radar detection effectiveness is a comprehensive evaluation of discovery probability, target recognition rate, information refresh rate of radar and so on. Through the valid evaluation of radar detection effectiveness, the shortcoming of the using of radar can be detected in time, adjustment

and deployment being carried out timely. It can be seen that radar detection effectiveness evaluation is an important prerequisite for commander's command decision, which is essential for guiding victory of battle [1].

For the evaluation of radar detection effectiveness, the non-linear analysis via the reasonable expression or calculation is usually used [2–4]. Some analytical process is relatively simple, but with the continuous development of information technology, radar work mode more and more complex, The effectiveness of the play also becomes more difficult to grasp, which makes some difficult to analyze the expression, and even use the current analytical methods cannot be completed, such as many rely on human experience and intuitive assessment. In fact, the researches on the issues of radar detection effectiveness evaluation must be considered as the typical and explored studies for complex system. Therefore, the explored breakthroughs with new assessment methods which are from another new angle around the analytical process are necessary, in order to complete the assessment, especially some estimations are hardly to be carried out by using the traditional analysis processes.

Deep Learning is a new field in artificial intelligence technology research in 2006 [5, 6], which originated in a typical technique of machine learning within artificial neural network, which is a process of simulating the study of human brain analysis, and has the deep network model. Based on this network model, the Deep Learning can complete the comprehensive study of a large number of samples by synthetically using multiple combinations, underlying information learning, finding correlation, layering, and so on, so as to discover the essential features of data, which is conducive to the extraction and classification of the deep features of things. At present, Deep Learning has been known as the closest to the human brain intelligent learning methods. It has a wide range of applications in many areas (including: classification, identification, assessment, etc.) [7, 8].

Some explored introduction of Deep Learning into the radar detection effectiveness evaluation study is given in the paper. Compared with the traditional effectiveness evaluation technology, the new ideas and ways are brought into executing relative researches. In the proposed method, the rich internal information within the complex system can be better described, mainly due to the good non-linear expression of Deep Learning. Therefore, the new ideas and ways can be provided from another new angle for assessing radar detection effectiveness which is difficult to express by the traditional nonlinear analytical process.

Convolution Neural Network (CNN) is an important and typical model in Deep Learning [9]. It has the advantages of powerful image processing and image information extraction. Therefore, CNN is used to construct the evaluation model of examining radar detection effectiveness. The new approach and the new idea of radar detection effectiveness evaluation based on Deep Learning are explored and studied in the paper. Finally, the validity of the proposed method can be verified by the simulation results.

2 Design of Radar Detection Effectiveness Evaluation Sample Set for CNN

2.1 Design of Radar Detection Effectiveness Data Set for CNN

Considering that the main advantages of CNN are to extract the image feature information, we intend to construct a matrix that characterizes the image as the input data set. And the image contains a lot of pixels, and these pixels can constitute the whole image matrix. According to the spatial distribution of the radar and its detection ability, the radar detection model is equivalent to the image matrix $S_{A \times B}$. The matrix shows the geographical distribution of the radar detection effectiveness in the north-south L_M km-wide and east-west L_N km wide range on a high-altitude plane. $S_{A \times B}$ has $A \times B$ elements total. Each element is the image of the pixels, the value of the integer value within $[0, 255]$, A is the number of pixels in the direction of the latitude, B is the number of pixels in the longitude direction, we can see

$$L_A = A \cdot D_A \quad (1)$$

$$L_B = B \cdot D_B \quad (2)$$

where D_A km, D_B km are the latitude and longitude resolutions, respectively.

Thus, we assume that there are N radars in the figure, the coordinates of each radar latitude and longitude is (Lat_n, Lon_n) , the actual radiation radius of R_n km, $n = 1, 2, \dots, N$. Assuming that there are I targets in the figure, each target latitude and longitude coordinates is (Lat_i, Lon_i) , $i = 1, 2, \dots, I$, respectively. The radar position and the radiation radius are all fixed, and the target position is randomly generated. The area where the actual radiation of the radar can be covered is filled with a pixel value P_1 , each target is marked with another pixel value P_2 , and the other pixel values are all P_3 . Thus the sample set is assigned to generate.

2.2 Preprocessing the Input Dataset

We need to normalize the sample dataset in order to fit the unit dimension of the Deep Learning network training. The concrete details as follows.

For all elements of image matrix $S_{A \times B}$, i.e., x_i , $i = 1, 2, \dots, A \times B$, the normalized processing can be expressed as follows.

$$\tilde{x}_i = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \quad (3)$$

where

$$x_{\min} = \min\{x_1, x_2, \dots, x_{A \times B}\} \quad (4)$$

$$x_{\max} = \max\{x_1, x_2, \dots, x_{A \times B}\} \quad (5)$$

\tilde{x}_i is the result of normalized processing for x_i . From these results, we can see that the normalized method can be used to map different data into $[0, 1]$ space to unify the unit dimensions of different data, so as to construct the input sample set suitable for the Deep Learning network.

2.3 Design of Radar Detection Effectiveness Evaluation Label (i.e., Evaluation Criterion) for CNN

Taking into account the assessment of radar detection effectiveness is an important factor is the missing alarm situation, we have built the whether there is the missing alarm as an evaluation criterion of the radar detection effectiveness [10], assuming that the radar should be able to detect for reaching everywhere in the image $S_{A \times B}$, whether there is the missing alarm can be described as follows.

$$C = \begin{cases} 1, & \forall \text{ target is out of real detection domain of radar} \\ 0, & \text{all targets are in real detection domain of radar} \end{cases} \quad (6)$$

where the situation that the target is beyond the actual detection domain is occurred, i.e., $\exists i, n, i = 1, 2, \dots, I, n = 1, 2, \dots, N$, s.t.,

$$R_{in} \leq R_n \quad (7)$$

where

$$R_{in} = \sqrt{(Lat_n - Lat_i)^2 + (Lon_n - Lon_i)^2} \quad (8)$$

the situation that all targets are within the actual detection domain is shown, i.e., $\forall i, n, i = 1, 2, \dots, I, n = 1, 2, \dots, N$, s.t.,

$$R_{in} > R_n \quad (9)$$

According to these principles, the label of each image, i.e., the input sample set for CNN, can be achieved.

3 CNN Model

CNN is a multi-layer neural network. In CNN, each layer consists of multiple two-dimensional planes, and each plane consists of multiple independent neurons. Usually, the net structure of CNN contains the feature extraction layer, the down sampling layer and the full connection layer and so on. The feature extraction layer and the down sampling layer emerge alternately in the net structure, and the full connection layer is constructed in the end of the CNN to obtain the output results. The neurons of the feature extraction layer can extract the key features by the convolution operation aimed at the previous layer. And the adjacent pixels of the feature results obtained by the upper layer are averaged in the down sampling layer to obtain the new feature

map. Furthermore, the above steps are repeated a number of times and then the resulted pixel values are rasterized and connected to become an input vector which can be brought into the conventional neural network to run and obtain the output results.

Based on this principle, we construct the radar detection effectiveness evaluation CNN model, as shown in Fig. 1.

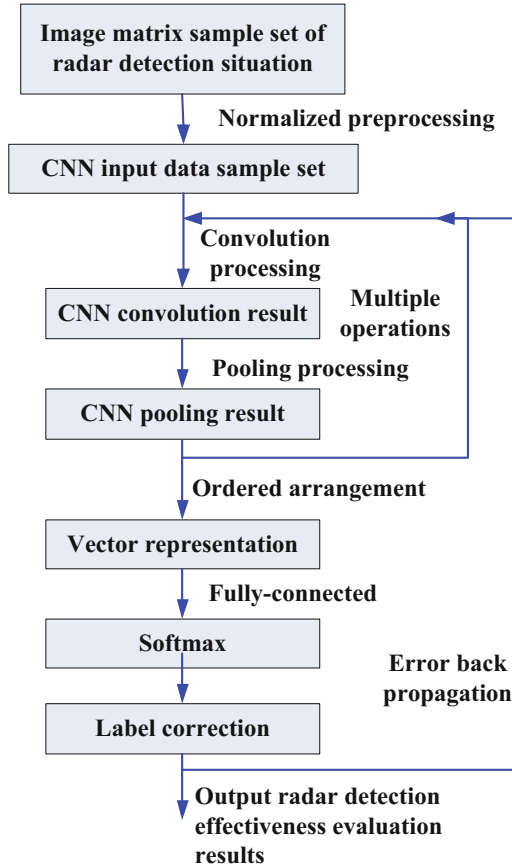


Fig. 1. Evaluation model of radar detection effectiveness based on CNN

4 Simulation Results

For the sake of validating the availability of the method proposed in the paper, the following simulation experiments are executed. Assuming that the rated detection radius of the X-band radar is 98 km, the actual detection radius is 65 km, and the resolution of the image matrix $S_{A \times B}$ is 5 km. Assuming that the 5 radars networking work to detect 10 targets, $P_1 = 200$, $P_2 = 100$, $P_3 = 0$, thus the sample images can be generated, as shown in Fig. 2. Figure 2(a) and (b) represent the radar detection situation and the input sample image, respectively, when there is the missing alarm, i.e.,

when some target is not detected, and the corresponding label is 1. Figure 2(b) and (c) represent the radar detection situation and the input sample image, where there is no missing alarm, that is, all targets are detected, and the corresponding label is 0.

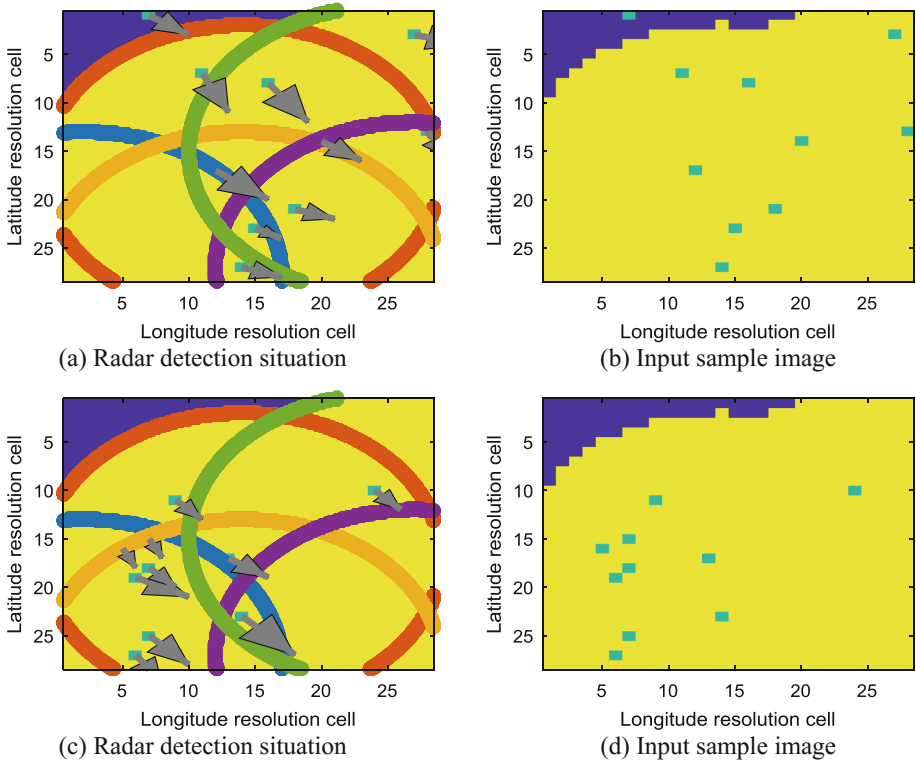


Fig. 2. Sample image, where (a) and (b) represent there is the missing alarm, and (c) and (d) represent there is no missing alarm

Thus, we constructed 70000 input sample data for CNN, as shown in Table 1.

Table 1. Input sample set for radar detection effectiveness evaluation with CNN

	Number of train sample	Number of test sample	Total
Label is 1	32998	5431	38429
Label is 0	27002	4569	31571
Total	60000	10000	70000

And next, the 5 layers of CNN, including two convolutions, two pooled layers and one full connected sensing layer is constructed. The sample number in each training group is 50, and the whole number for training is 1 to 5. The training termination error changing curve and the correct recognition rate corresponding to the label changing curve are shown in Figs. 3 and 4, respectively. From Figs. 3 and 4, we can see that on

condition of the change of iteration number from little to large, the training termination error is gradually reduced and the correct recognition rate corresponding to the label is gradually increased. When the number of iterations reaches 5, the correct recognition rate corresponding to the label reaches 78%. At this time, the assessment for radar detection situation whether there is the missing alarm based on CNN model can be consider as being valid. Therefore, the simulation results show the validity of the proposed method.

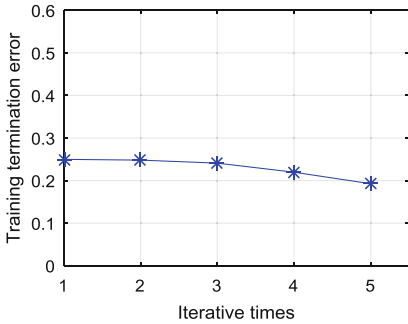


Fig. 3. Change of training termination error with increasing of iterative times

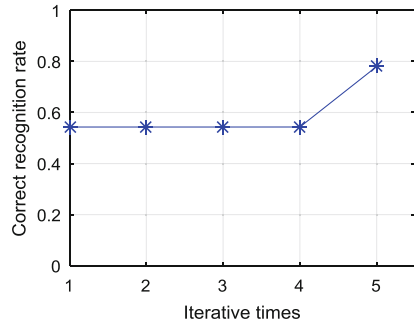


Fig. 4. Change of correct recognition rate with increasing of iterative times

5 Analysis and Discussion

According to the comprehensive analysis, compared with the traditional analytical method, the proposed method is another new solution. In fact, the method uses CNN to form a nonlinear mapping process by convolution, pooling, and all connections. This process can replace and even improve the traditional analytic process to achieve the more effective results beyond the traditional analytic process. This principle can be described and suggested in Fig. 5.

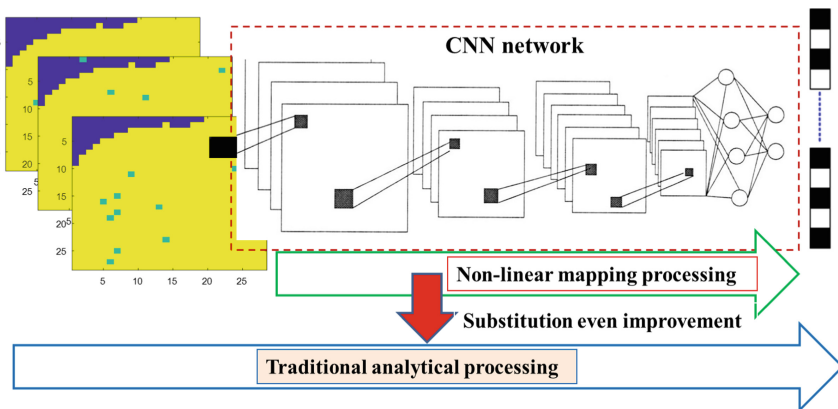


Fig. 5. Describing chart of principle within proposed method

6 Conclusions

This paper focuses on the current actual military needs, and puts forward a new method and new idea of radar detection effectiveness estimation which are engaged with Deep Learning. In the proposed method, the processes of convolution, pooling and full connection within CNN are used to complete the analysis process within the traditional evaluation, so as to realize the radar detection effectiveness evaluation. And even the proposed method has some important potential for improving and enriching the traditional assessment methods based on analytical processes. The simulation results show that the proposed method can achieve the correct recognition rate more than 78% at least aimed at the missing alarm labels. It also proves that the proposed method is valid to complete radar detection effectiveness estimations in certain extent. The research work of this paper can provide the new ideas and methods for the research on the relative issues of radar detection effectiveness evaluation, and it is also useful for studying and solving other evaluation problems. At the same time, it opens up some new spaces for the applications of Deep Learning.

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