Research on Damage Evaluation of Radar Target Based on Deep Learning

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Abstract: In view of the evaluation of the damage effect of a radar on a damaged object, considering the nonlinearity and complexity of the target damage assessment, deep learning can be used to evaluate the radar target damage effect. Determine the network parameters and network node structure characteristics according to the characteristics of damage information; use the appropriate software and tools to build a modular network model; train the damage assessment network to make the network have strong expert experience.

1. Evaluation of damage effect based on deep learning

1.1 Basic principles of deep learning
Deep learning is an important part of the machine learning field, and it is widely used in data analysis, fault diagnosis, speech recognition, language processing and prediction evaluation. Deep learning is essentially a network model that simulates the human brain and learns various kinds of information. The information can be text, audio, images, and so on. The basic idea of deep learning is to obtain information useful for the learning objectives and to interpret the data or objects by learning a model with multiple hidden layers and training a large amount of data as much as possible. Fig.1 shows a deep learning model with multiple hidden layers.

![Deep learning model with multiple hidden layers](image)

Fig.1 Deep learning model with multiple hidden layers

Deep learning involves three steps:
Step 1: Get the initial parameters of the network by unsupervised learning. By training a large amount of unmarked data, the learning data of the next layer network is obtained. Then the learning data is input, and the data of the latter layer network is obtained. This process is iterated layer by layer until the complete network is learned.
Step 2: Adjust local networks through supervised learning. Supervised learning is based on unsupervised learning. Using some data with annotations, the initial parameters obtained by unsupervised learning are finely adjusted, so that the network parameters are closer to the training data, thus improving the classification accuracy.

Step 3: Test results by sample test. Use part of the "unknown" data (data that the system has not touched) to check the effect of deep learning.

With the deepening of deep learning research, many scholars have proposed many deep learning methods. This paper focuses on convolutional neural networks and restricted Boltzmann machines[1].

(1) Convolutional neural network

CNN[2-3] is an extension of neural network. It adds convolution action based on BP neural network. Therefore, CNN can simulate human visual system more realistically. Due to its high efficiency and stability, CNN has a wide range of applications in image recognition, predictive estimation, feature extraction, and pattern classification. The CNN structure consists of five parts: input layer, convolution layer, activation function, pooling layer[4] and fully connected layer.

(2) Restricted Boltzmann machine

The Boltzmann Machine (BM) is a network model consisting of a visual layer and a hidden layer random unit. Fig.2 shows a typical BM model.

As can be seen from Fig.2, in the BM structure, there are edges between the nodes of the visible layer and the hidden layer, that is, full connections, the model is very complicated, and the learning efficiency is relatively low. The Restricted Boltzmann Machine (RBM) is improved on the basis of BM. The RBM determines that the values of the nodes in the visible layer and the hidden layer in the network structure are all 0, that is, the contact weight is 0, there is no connection inside each layer, and the layers are fully connected. Fig.3 shows a typical RBM model. The energy function of RBM can be calculated by equation (1):

$$ E(v, h | \theta) = -v W h - b v - d h $$

In the formula, $\theta = \{W, b, d\}$ represents the parameters of the RBM, $v \in \{0,1\}^d_v$ represents the visual layer which is the input data, $h \in \{0,1\}^d_h$ represents the hidden layer, $W$ is the connection weight matrix of the two layers, $b$ and $d$ represent the thresholds of the visible layer and the hidden layer respectively. According to formula (1), we can find that there is an energy relationship between the unit of the visible layer and the unit of the hidden layer, and there is no energy relationship between the internal units of the same layer.

When the parameters of the model are known, the joint probability distribution can be derived using the energy function:

$$ p(v, h) = \frac{e^{-E(v, h | \theta)}}{Z} $$

$$ Z = \sum_{v, h} e^{-E(v, h | \theta)} $$

Then the probability distributions of the visible layer and the hidden layer are obtained in turn. The probability distribution of the visible layer element $v$ is:
The probability distribution of hidden layer element $h$ is:

$$p(h) = \frac{1}{Z} \sum_v e^{-E(v, h|\theta)}$$

(4)

In the RBM model, each neuron is independent of each other, therefore,

$$p(h|v) = \prod_i p(h_i|v)$$

(5)

1.2 Damage assessment based on deep learning

The damage assessment based on deep learning is mainly divided into five steps:

Step1: Obtain the damage information and establish a data set. The evaluation information of the damage assessment factors is obtained by various means, and then integrated into a complete data set as a training set for deep learning.

Step2: Establish a deep learning network model. Identify the appropriate learning model, then map the evaluation factors to the deep learning network and build the corresponding models.

Step3: Determine the network parameters. The initial parameters of the deep learning network are determined by data analysis or expert consultation.

Step4: Learn to train. Enter the training data set for learning training.

Step5: Output training results. After the training is completed, the training results are output and analyzed to map the results to the corresponding damage assessment metrics.

2. Damage Assessment Network Construction Based on NeuroSolutions

2.1 Damage Information Structure and Modular Network Model

A radar consists of different parts. The structure and function of each part are different. The physical meaning of the damage information of different parts is different, and the data format of the damage information[5-6] is not the same. In general, the data format of the damage information generally includes three types: real numbers in the range of 0 to 1, such as the proportion of the damaged area of the sub-objective outer armor; 0 to a specific value The real type inside, such as the spectrum range of the radar antenna; the Boolean type of 0 or 1, such as the continuity of the power supply line, whether the personnel in the vehicle are effectively killed, etc..

For different types of data, the commonly used network structure is Modular Neural Network (MNN). The MNN network is a special type of feedforward multilayer perceptron cluster.

For MNN, this article will define the quaternion for its characteristics: $MNN = \langle X, SN, IU, Y \rangle$.

In the above definition, an input vector of the system is expressed as $X \in R^n$; a set of sub-networks is expressed as $SN$; $IU$ is the conclusion synthesis unit of the system; the output vector of the system is expressed by $Y \in R^n$. In summary, the MNN system structure can be visually represented as shown in Fig.4:

![Fig.4 Schematic diagram of the network topology of the RNM](image-url)
In Fig. 4, the dimension of the output vector $Y$ is same as the dimension of $y_i (i = 1, 2, \cdots, K)$; $w_i (i = 1, 2, \cdots, K)$ is the connection weight corresponding to each sub-network of the entire network, that is, it determines the proportion of the corresponding sub-network in the whole network, then the output of corresponding system is:

$$Y = \sum_{i=1}^{K} w_i y_i$$  \hspace{1cm} (7)

### 2.2 Modular network construction based on NeuroSolutions

Building a modular network with NeuroSolutions generally consists of two methods. One is to select the network mode to be built according to the network construction wizard, build the network according to the wizard prompts, set network parameters and select training data. The other is the most direct way to create a network, that is, the manual creation method.

Considering that the damage information of the radar can be divided into five categories, this paper adopts the manual creation method. This method mainly includes two steps: selecting network components one by one, setting up a network structure and performing connectivity; adding learning data and control, displaying components, adjusting network width and control parameters.

A network structure with five modules is created, and each module adds its own input file, and the input file is the damage information data of each of the five sub-objects. By setting the respective input files, it is possible to selectively input different types of damage information as different modules.

The hidden layer axons use the Bias transfer function:

$$f(x_i, w_i) = x_i + w_i$$  \hspace{1cm} (8)

Connect the cusps between the layers of the spurs to select the Fully Synchronized FullSynapse, whose transfer function can be expressed as:

$$f(x_i(t-d), w_j) = w_j x_j(t-d)$$  \hspace{1cm} (9)

The information fusion between modules uses the Gaussian module, and its transfer function is:

$$f(x_i, w_i) = \exp \left[ -\beta \left( x_i + w_i \right)^2 \right]$$  \hspace{1cm} (10)

among them

$$w_i = \begin{cases} 0 & \text{Euclidean} \\ 0 & \text{Box Car} \\ \sum_{j} w_{ij}^2 & \text{Dot Product} \end{cases}$$ \hspace{1cm} (11)

the touch weight $w_{ij}$ is one of the neighbors of the weight $w_{ij}$, the parameter $\beta_i$ can be expressed as:

$$\beta_i = \frac{1}{2 \sigma^2} = \frac{P}{2 \sum_{k=1}^{P} \left\| w_{ij} - w_{kj} \right\|^2} = \frac{1}{2 \sum_{j=1}^{P} \sum_{k=1}^{P} \left( w_{ij} - w_{kj} \right)^2}$$ \hspace{1cm} (12)

The error calculation uses a second-order norm, and its calculation model is:

$$J(t) = \frac{1}{2} \sum_{j} (d_j(t) - y_j(t))^2$$  \hspace{1cm} (13)

The learning method adopts the Momentum method, and the mathematical expression is:

$$\Delta w_i(n+1) = \eta \nabla w_i + \rho \Delta w_i(n)$$  \hspace{1cm} (14)
3. Network training and radar damage assessment

3.1 Training of the damage assessment network

The purpose of training is to make the network have strong expert experience by learning the limited reconnaissance information, and can realize the process of mining and evaluating the uncertain information. Therefore, the training correction data is damaged by radar under the condition of full damage information evaluation result. It is not appropriate to use non-continuous damage level data here, and the original radar function reduction ratio is used as the correction data. At the same time, considering the range of the axon transfer function, it is necessary to standardize the input data to convert the radar function degradation ratio within the range of 0~1 into the range.

One of the difficulties in the application of deep learning networks is the training of the network. The training of deep learning networks often requires a large amount of data, the convergence of the network is difficult, and the training takes a long time. The damage data of 1000 sets of a radar was taken as the training sample of the network, and the number of trainings was taken 500 times to train the network. The output results of different stages in the training process are shown in Fig.5.

![Output after training 100 times](image1)

(a) Output after training 100 times

![Output after training 200 times](image2)

(b) Output after training 200 times

![Output after training 300 times](image3)

(c) Output after training 300 times

![Output after training 400 times](image4)

(d) Output after training 400 times

![Output after training 500 times](image5)

(e) Output after training 500 times

Fig.5 The convergence of the output in the training process

As can be seen from Fig.5, the convergence of the network is a fast-to-slow process. When the number of trainings is 100, the correlation between the output and the expected result is not high; but when the number of training reaches 200, the output is And the expected value gradually shows a strong correlation; when the number of training reaches 300 times, the output is generally close to the expected value, but some samples still have a large deviation; from 300 to 500 times, the output result Overall, there was little change, but the result correction was made for samples with large deviations. When the number of training reaches 500 times, the output result has a high degree of coincidence with the expected value.

The cost function and the average cost function in the training process gradually converge and decrease as the number of training increases. The change curve is shown in Fig.6. It can also be seen
from the figure that as the number of networks increases, the output gradually converges to the correction result, and the error gradually decreases.

![Fig.6 Convergence of error and mean error in the training process](image)

### 3.2 Verification of results

Since the network is learning and optimizing for the training data, the training data cannot be used to verify the network. Here, another 500 sets of unlearned radar damage data are used for verification.

The verification process is to input the verification data into the trained network, calculate the result and compare it with the expected result, so as to verify the performance of the network. Fig.7 shows the comparison between the calculation results of the verification data and the expected results.

![Fig.7 Comparison of verification results and expected results](image)

### 4. Conclusion

It can be seen that the network basically achieves an accurate assessment of the damage results, and the calculation results are generally consistent with the expected results. However, it can also be seen that the verification result is still slightly worse than the training result, and there are cases where the individual error is large. This is because the training and experience gained by the network are limited due to the limited training data. Therefore, one of the important means to improve the performance of network evaluation is to provide as much training data as possible, so that the network can be fully trained under as much prior information as possible.

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