Equipment State Assessment Based on Convolutional Neural Network

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Abstract. Aiming at the problem of the defect of less-information and poor reliability of assessment results when assessing equipment state, this paper proposes a method of equipment status assessment based on convolution neural network by utilizing the ability of equipment under cognitive testability design to easily obtain multi-source information. The assessment system is divided into feature layer and information layer. In the feature layer assessment, the analytic hierarchy process is used to determine the constant weight, then the variable weight theory is used to realize the real-time adjustment of the weight. And the convolutional neural network model is used in the assessment of the information layer. Finally, through the example verification and comparison with BP algorithm, it can be seen that this assessment method has fast recognition speed, high accuracy, more reliable assessment results, and has certain versatility and application value in engineering.

1. Introduction
Under the impetus of the development of basic science and technology, especially the advancement of big data technology, modern weapons have the characteristics of networking and intellectualization. At the same time, cognitive testability design is becoming one of the inherent design characteristics of modern weapons. Equipment under cognitive testability design can collect multi-source information closely related to the equipment. This paper mainly studies how to use these multi-source information to intelligently assess equipment status.

The traditional state assessment mainly uses historical statistics[1], and the assessment results are one-sided and lack of effectiveness. The assessment system established in [2] considers the factors insufficient, the established weights are fixed and the practicality is poor. Reference [3] uses fuzzy comprehensive assessment, but the traditional membership function cannot describe the ambiguity and randomness in the evaluation language. In view of the above deficiencies, under the cognitive testability design, this paper proposes a method based on convolutional neural network to assess the equipment state. From the perspective of multi-source information, the assessment system is divided into two layers: feature layer and information layer. On the basis of the analytic hierarchy process, the feature layer uses the variable weight theory to realize the real-time adjustment of the weights, and the
information layer uses the convolutional neural network method to realize the state assessment of the equipment.

2. Equipment status assessment element model

With the development of information technology, modern equipment has gradually formed a network-based equipment system. The use of information processing centers with big data characteristics for state assessment is the main basis for cognitive testability maintenance decisions. The comprehensive utilization of the multi-source information of the information processing center will greatly improve the accuracy of the state assessment[4], and the accurate state assessment is the basis of the cognitive testability maintenance decision.

2.1 Selection of Equipment Assessment Index

In the cognitive testability framework, the equipment state assessment should comprehensively utilize the various information of the equipment. Therefore, based on the completeness of equipment information as the assessment index selection principle, self status information, environmental information, historical information and rear support information are selected as the assessment indicators of the information layer, and the feature included in each information is used as the evaluation index of the feature layer.

![Figure 1. State assessment indicators system of the Equipment](image)

When selecting the feature contained in each information, the selected feature should be sufficient and reasonable according to the actual situation and the analysis of the operation mechanism of the equipment. Through the analysis of self status information, environmental information, historical information and rear support information, the overall equipment evaluation system is established as shown in Figure 1.

2.2 Normalization of feature data

The feature value $b_u$ should accurately reflect the equipment state, so it is characterized by the relative deterioration degree $x_u$, which refers to the degree of deviation between the feature value and the corresponding normal value, $x_u \in [0,1]$, “0” representation has not deteriorated, and “1” representation has completely deteriorated. According to the feature classification, there are two calculation methods[5].

The smaller the feature value, the better the type: $x_u = \frac{b_u - b^{\circ}_u}{b^{\max}_u - b^{\circ}_u}$  \hspace{1cm} (1)

The larger the feature value, the better the type: $x_u = \frac{b^{\circ}_u - b_u}{b^{\circ}_u - b^{\min}_u}$  \hspace{1cm} (2)

In the formula, $b_u$ is the feature value, $b^{\max}_u$ and $b^{\min}_u$ are the possible maximum and minimum eigenvalues, and $b^{\circ}_u$ is the optimal value.
3. Equipment State Assessment Model

3.1 Feature Layer Assessment Model Based on Variable Weight Theory

3.1.1 Determination of the constant weights. It can be seen from fig. 1 that the equipment assessment system is divided into a feature layer and an information layer. For the feature layer, the analytic hierarchy process (AHP) [6] is used to determine its constant weight.

First, invite a number of experts or engineering maintenance personnel who are familiar with the equipment to give the relative importance judgment of each feature in the feature layer under the four information according to the standard of Table 1.

| bₜ | ratio | Identified | Slightly strong | Strong | Very strong | Absolutely strong |
|----|-------|------------|-----------------|--------|-------------|-------------------|
| aᵢ |   1   |             |                 |        |             |                   |
| 3  |       |             |                 |        |             |                   |
| 5  |       |             |                 |        |             |                   |
| 7  |       |             |                 |        |             |                   |
| 9  |       |             |                 |        |             |                   |

If the judgment is between adjacent grades, the judgment is expressed by 2, 4, 6 and 8, and the formula is satisfied: \( a'_i = 1/a'_j \)

The judgment matrix is as follows: \( A_t = \begin{bmatrix} a'_{11} & a'_{12} & \cdots & a'_{1n} \\ a'_{21} & a'_{22} & \cdots & a'_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a'_{n1} & a'_{n2} & \cdots & a'_{nn} \end{bmatrix} \)

Among them, \( t = 1,2,3,4 \) respectively correspond to the input of the convolutional neural network is \( b_1,b_2,b_3,b_4 \). These four input characteristics are used to determine the current state of the equipment, and the current health state of the equipment is analyzed according to the historical state. The settings of the equipment health status corresponding to each state are listed in Table 2.

Self state information, environment information, history information and rear support information in the information layer. The consistency check is first performed on the judgment matrix \( A_t \). After passing the consistency test, the eigenvector method is used to obtain the eigenvector \( W^0 \) corresponding to the maximum eigenvalue of \( A_t \). After normalization, the constant weight \( w^0 = [w^0_1,w^0_2,\cdots,w^0_n] \) of the feature can be obtained which describe the relative importance of the feature. The detailed steps are referenced [7].

3.1.2 Calculation of the variable weights. The constant weights obtained by the analytic hierarchy process reflects the relative importance of the feature. However, when a certain feature is seriously abnormal, it may be unable to be reflected in the information layer because its corresponding feature weight is small. The constant weights can not form a "Short Board Effect", affecting the results of the assessment. In response to this phenomenon, the variable weight theory [8] is used to strengthen the relative weight of the anomaly feature, realizing the real-time adjustment of the feature weight, and making the assessment result more reasonable and accurate.

According to the theory of variable weight, there is the following formula:

\[
w_i = \frac{w^0_i}{x_i} \sum_{i=1}^{n} \frac{w^0_i}{x_i} \tag{3}
\]

In the formula, \( x_i \) is the feature value, \( n \) is the number of featur, \( w^0_i \) is the constant weight of the \( i \) feature under the \( t \) information, \( w_i \) is the variable weight of the \( i \) feature under the \( t \) information. In summary, the assessment of the feature under the \( t \) information of the information layer is as follows:
3.2 Information layer assessment model based on convolutional neural network

3.2.1 Model construction. For the assessment of information layer, this paper adopts the convolution neural network method\[9\], which includes a convolution layer, sampling layer, full connection layer and output layer. The input data only takes \(b_1, b_2, b_3, b_4\) as parameters of information layer. The data structure is relatively simple. Improving the number of convolution layer and sampling layer will increase the network complexity and network time. Because the input data is one-dimensional, the convolution core is set as one-dimensional convolution core, and different convolution kernels extract different characteristics of input data. Through dimension reduction operation of sampling layer, the output nodes of sampling layer are reduced. Finally, the probabilities of various equipment states are obtained through full connection layer and output layer. The network model structure diagram\[10\] used in this paper is shown in Figure 2.

![Convolutional neural network structure](image)

**Figure 2. Convolutional neural network structure**

The input of the convolutional neural network is \(b_1, b_2, b_3, b_4\). These four input characteristics are used to determine the current state of the equipment, and the current health state of the equipment is analyzed according to the historical state. The settings of the equipment health status\[11\] corresponding to each state are listed in Table 2.

| Status serial number | Status grade | State description |
|----------------------|-------------|------------------|
| 1                    | Fault       | Equipment failure, can not continue to work, need to repair or replace components |
| 2                    | Warning     | Equipment performance degradation is serious, function degradation, must be maintained. |
| 3                    | Abnormality | The performance of the equipment is deteriorated and its function is slightly affected, but the equipment can still complete its normal work. The equipment is in sub-health and needs to be maintained. |
| 4                    | Degeneration | Equipment performance degradation is weak, basically does not affect equipment function, can not be maintained. |
| 5                    | Normal      | Equipment healthy, no maintenance required |

In this paper, a single input sample\[12\] is represented by \(X\), which contains four elements. The number of convolution kernels is \(N\) and the size of each convolution kernels is \(M\times1\). Therefore, the size of output characteristics corresponding to each convolution kernels is \((7-M)\times1\). The number of
connections between convolution layer and input layer is \((7-M)\times(M+1)\times N\), and the number of trainable parameters is \((M+1)\times N\). The concrete formulas are as follows:

\[
A_{c_{i,k}} = f\left(\sum_{j=0}^{M} W_{k,j}^{(i)} \cdot X_{k,j}^{(i)} + b_{k}\right)
\]  

(5)

Where \(A_{c_{i,k}}\) represents the \(i\) element of the output of the \(k\) convolution core; \(W_{k,j}^{(i)}\) represents the \(j\) element of the \(k\) convolution core; \(b_{k}\) represents the bias of the \(k\) convolution core; \(f\) represents the activation function of the convolution layer.

The sampling layer\(^{\text{[13]}}\) adopts the mean sampling operation, the sampling width is \(q\times1\), and the sampling output corresponding to each feature is \(((q \times 1)/q)\times1\), so the output result of the sampling layer corresponding to the \(k\) convolution kernel is:

\[
A_{s_{i,k}} = \frac{\sum_{i=q}^{M} A_{c_{i,k}}}{q}
\]  

(6)

The output of the sampling layer is connected with a full connection layer, and then classified output. The output of the neuron is the probability value, the sum of which is 1.

The model is trained by the backpropagation algorithm, and the objective function is converged to a minimum through continuous iteration. The objective function is expressed as the sum of the squares of the error between the ideal output and the actual output. The formula is as follows:

\[
E_k = \frac{1}{2} \sum_{i=1}^{R} (Y_i - O_i)^2
\]  

(7)

Where \(O_i\) represents the actual output, \(Y_i\) represents the ideal output, \(E_k\) represents the objective function of backpropagation, and \(R\) represents the total number of neurons.

Finally, the optimal parameters are obtained by the objective function and the error derivatives of each level of the model:

\[
W_k(t+1) = W_k(t) - \alpha \frac{\partial E_k}{\partial W_k(t)}
\]  

(8)

Among them, \(t\) denotes the number of iterations; \(W_k(t+1)\) denotes the parameters of each layer of the model in the \(t\) order, such as weights, biases, neuron parameters; \(\frac{\partial E_k}{\partial W_k(t)}\) denotes the derivative of the error to the model layer; \(\alpha\) denotes the learning rate, which ranges between 0 and 1.

3.2.2 Training Convolutional Neural Network Model. A total of 700 experimental data of the measurement equipment of unmanned aerial vehicle(UAV) were used as the convolutional neural network training data. The training samples are listed in Table 3. The sample data in the table are calculated by the feature layer according to formula (4).

| Serial number | \(b_1\) | \(b_2\) | \(b_3\) | \(b_4\) | Current state |
|---------------|--------|--------|--------|--------|---------------|
| 1             | 0.32   | 0.51   | 0.24   | 0.48   | 3             |
| 2             | 0.27   | 0.25   | 0.33   | 0.51   | 2             |
| ...           |        |        |        |        |               |
| 700           | 0.57   | 0.34   | 0.87   | 0.61   | 1             |

According to the comprehensive analysis, the sampling width of the convolutional neural network model is \(2\times1\), the number of convolution kernels is 6, and the size of the convolution kernel is \(4\times1\).
4. Example analysis

Taking UAV measurement equipment as an example, the related data of measurement equipment are shown in Table 4.

According to the data in Table 4, the constant weight and weight of the feature layer are calculated as follows:

\[
W_1^w = [0.42, 0.27, 0.31] \quad W_2^w = [0.65, 0.35] \quad W_3^w = [0.39, 0.45, 0.16] \quad W_4^w = [0.63, 0.37] \\
W_1^v = [0.53, 0.38, 0.09] \quad W_2^v = [0.62, 0.38] \quad W_3^v = [0.56, 0.33, 0.11] \quad W_4^v = [0.31, 0.69]
\]

According to the relative deterioration degree and variable weight of the feature quantity of measuring equipment, the evaluation values of each information can be calculated as follows:

\[
h_1 = 0.44, h_2 = 0.53, h_3 = 0.57, h_4 = 0.35
\]

Substituting \(h_1, h_2, h_3, h_4\) into the training model of section 3.2.2, the output is \(\{0.0836, 0.1898, 0.2960, 0.0281\}\). According to the principle of maximum membership degree, the equipment is in state 4. In the degradation stage, the performance of the equipment is degraded, but it does not affect the function and does not need maintenance.

Comparing BP algorithm with CNN algorithm, table 5 can be obtained. From the data, it can be concluded that the training time of convolutional neural network is shorter, the recognition speed is faster, and the evaluation accuracy is higher.

### Table 4. Measuring device feature quantities

| Information layer                  | Feature layer                 | Unit     | \(V_{\text{min}}\) | \(V_{\text{opt}}\) | \(V_{\text{max}}\) | \(v_i\) |
|------------------------------------|-------------------------------|----------|---------------------|---------------------|---------------------|--------|
| Self status information            | Sampling data error           | \%       | 0                   | 0                   | 5                   | 2.3    |
|                                   | Time synchronization error    | \(\mu s\) | -1                  | 0                   | 1                   | 0.3    |
|                                   | Sampling transmission delay   | \(\mu s\) | 0                   | 0                   | 2                   | 1.6    |
|                                   | Jitter                        |          |                     |                     |                     |        |
| Environmental information         | Temperature                   | \(\degree C\) | -1                  | 20                  | 40                  | 26     |
|                                   | Humidity                      | \%       | 30                  | 50                  | 75                  | 55     |
|                                   | Service age                   | year     | 0                   | 0                   | 3                   | 1.5    |
| historical information            | Failure times                 | —        | 0                   | 0                   | 3                   | 2      |
|                                   | Family defect rate            | Times / years | 0                   | 0                   | 2                   | 1      |
| Rear Support Information          | Spare Parts Inventory         | piece    | 0                   | 3                   | 3                   | 1      |
|                                   | Maintenance staff in place rate| \%       | 0                   | 10                  | 0                   | 80     |

### Table 5. Comparison of BP and CNN

| Algorithm | Test set accuracy/% | Training time/s | Running time/s |
|-----------|---------------------|-----------------|---------------|
| BP        | 93.6                | 183.2           | 0.043         |
| CNN       | 99.6                | 132.8           | 0.036         |

5. Conclusion

Based on the analysis of the current equipment development trend, the equipment assessment system under the cognitive testability design is established. The equipment assessment system makes full use of the multi-source information of the equipment and describes the equipment status from multi-angle and multi-level. Compared with the traditional assessment system, the factors considered in this paper are more comprehensive. In the assessment of feature layer, the method of analytic hierarchy process (AHP) and variable weight theory are used to realize the real-time adjustment of the index weight, which is more practical than the traditional constant weight. In the assessment of information layer,
the convolution neural network model is established, and the data of the UAV measurement equipment is trained.

Finally, through the assessment of a UAV measurement equipment data, it can be seen that the method is reasonable and effective, and the assessment results are accurate, which can provide a scientific and reasonable basis for maintenance decision-making under cognitive testability.

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