Near-explosion failure of elman neural network based on bootstrap

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Abstract. In this paper, for the fuze of a certain type of fuze, there is a phenomenon that the fuze function of the fuze is invalid. The method of using the Bootstrap method to resample the experimental data, increase the sample size, and obtain the regular data, and use the back propagation neural network to establish the fuze near-failure learning model, and obtain a more accurate model by training the model. Test data is brought into the model and its accuracy is verified to ensure the accuracy of the model. It provides model support for the analysis of the weak condition of the fuze near-explosion function failure, and provides reference for the analysis of other fuzes.

1. Introduction
As a starting device for ammunition, the fuze plays a vital role in the accurate strike and effective hit of the ammunition. Under the new technology conditions, the type and function of the fuze are constantly expanding, providing technical support for ammunition to complete various tactical missions. For a near-explosion fuze, the near-explosion function of the fuze is the core capability of the fuze, and it is also a manifestation of the ammunition's damage power. During a Near-explosion function test of a certain type of fuze, if a total of 480 shots are fired, the Near-explosion function fails 20 rounds. Although the near-explosion function meets the requirements for use, it is in the purpose of being responsible for the product and responsible for the army. This paper proposes the Bootstrap Elman neural network modeling of the Near-explosion Failure of this type of fuze to simulate the weak link of the fuze to provide technical support for the army to avoid firing at the weak link. At the same time, it provides model methods for other fuze near-explosion function tests [1,2].

Neural network is a mathematical model that imitates the structure and function of neural networks of living things, and is also an adaptive computing model. It changes the internal structure of the system by sensing changes in external information, and adjusts related parameters to meet certain rules. A neural network consists of many neurons, and the neurons are interconnected to form a huge network of information processing. Assuming there are multiple ways to do one thing, the neural network will tell the designer which way is best. The advantage of a neural network is that it is a self-learning, summarizing, and inductive method that uses existing data to generate an intelligent recognition system [3-6]. In this paper, Elman neural network has the characteristics of supervised learning. It continuously learns and selects feature parameters from samples, establishes a discriminant function for the classifier, and classifies the identified samples. At the same time, the bootstrap method is used to resample the test data [7-9], generating multiple sets of test data, showing the relevant...
characteristics of the test data, providing more effective prior data for accurate recognition classification of Elman neural network [10].

2. Bootstrap basic theory

The Bootstrap is a method proposed by professor Bradle Efron at Stanford University in the United States, in 1979 in order to accurately determine the estimated value. The basic idea is to use the obtained original sample to copy the observation information, without the need to make distribution assumptions or add new sample information, a statistical method for statistical inference of the overall distribution characteristics. The mathematical description is as follows [11]:

Let \( x = (x_1, \ldots, x_n) \) be a set of independent and identically distributed data from the distribution of \( F \), with the mean of \( \mu \) and the variance of \( \sigma^2 \). From the mean of \( \bar{x} \) obeying the distribution of \( \bar{x} \sim \left( \mu, \frac{\sigma^2}{n} \right) \), we can know that the standard deviation of the mean is \( \text{se}_F(\bar{x}) = \left( \frac{\sigma^2}{n} \right)^{1/2} \). Let the sample of \( F^* \) be returned to the sample group of \( F \), where is a set of independent and identically distributed data of \( x^* = (x^*_1, \ldots, x^*_s) \) from the distribution of \( F^* \), \( \text{se}_F(\bar{x}^*) = \text{se}_F(\bar{x}) \) is called the Bootstrap estimate of \( F \) [12].

When the expression parameters of the distribution of \( F \) cannot be known, no parameter assumptions are made on it. And the observation data is directly resampled with replacement to obtain a set of samples of \( \hat{F} \). This process is called non-parametric Bootstrap estimation. The mathematical representation process is:

A. First select a sample of capacity \( n \) of \( (\hat{x}_1^1, \ldots, \hat{x}_s^1) \) from the sample of \( (x_1, \ldots, x_n) \). After the sample of \( (x_1, \ldots, x_n) \) is put back, a sample with a capacity of \( n \) is taken again, and the sampling is repeated \( m \) times to extract a total of \( m \) groups of samples;

B. From \( \hat{\theta}_b = T(\hat{x}_n^b), \ b = 1, \ldots, m \), \( \hat{\theta}_b \) is the standard deviation of \( \hat{\theta} \), obtained as an independent sample of \( (\hat{\theta}_1, \ldots, \hat{\theta}_m) \);

C. Using the Bootstrap statistics of \( (\hat{\theta}_1, \ldots, \hat{\theta}_m) \) of \( m \) groups generated above, the distribution of unknown parameters of \( \hat{\theta} \) and related eigenvalues can be obtained according to the statistics.

3. Elman neural network

Elman neural network is a feedback neural network proposed by Jeffrey L. Elman in 1990. The main structure of Elman neural network is similar to feedforward neural network, including input layer, hidden layer and output layer. The difference is that it adds a special hidden layer on the basis of traditional hidden layer, which is generally called the receiving layer or association. The receiving layer receives feedback signals from the hidden layer, and each neuron of the hidden layer corresponds to a neuron node of the receiving layer. The role of the association layer is to use the associative memory to use the state of the hidden layer at the previous moment and the network input at the current moment as the input of the current hidden layer, similar to the mechanism of state feedback. For the Elman neural network, the transfer function of the hidden layer is a Sigmoid function; both the receiving layer and the output layer are linear functions. A simple Elman neural network structure is shown in figure 1. The characteristics of the Elman neural network are that the output of the hidden layer is automatically connected to the input of the hidden layer by accepting the storage of the layer. This connection method will make the model compare the historical state data. Sensitive, and the
addition of the internal support layer also increases the dynamic processing capacity of the Elman neural network [13].

The training process of the Elman neural network is: first initialize the weights of each network layer, then pass the samples into the input layer and calculate the output layer output, and then input the output of the input layer and the output of the receiving layer into the hidden layer and calculate the hidden layer's Input, the output of the hidden layer is transmitted to the output layer and the receiving layer at the same time. Pass to the output layer to calculate the error, and then back-propagate to adjust the weight; pass to the acceptor layer as the input for the next hidden layer.

The input layer vector of Elman neural network is \( n \) dimensional of \( X \), that is \( X = [x_1, x_2, x_3, \ldots, x_n]^T \); the output layer vector is \( m \) dimensional of \( Y \), that is \( Y = [y_1, y_2, y_3, \ldots, y_n]^T \); the output vector of the hidden layer is \( k \) dimensional of \( U \), that is \( U = [u_1, u_2, u_3, \ldots, u_k]^T \); the output vector of the receiving layer is also \( k \) dimensional of \( U \), that is \( U = [u_1, u_2, u_3, \ldots, u_k]^T \). The weight of the hidden layer to the output layer id \( w^1 \). \( w^2 \) is the weight of the input layer to the hidden layer, and the weight of the receiving layer to the hidden layer is \( w^3 \). \( f \) that is the activation function of the receiving layer is the Sigmoid function. \( g \) represents the activation function of the neurons in the output layer. \( h \) represents the activation function of the neurons in the hidden layer. \( t \) represents the different moments of the neural network. Output represents the output of a layer, with \( a \) represents the input layer and \( b \) denotes the receiving layer.

For the output layer, exists \( y(t+1) = g(Output_{m}(t+1)) \), and for \( Output_{m}(t+1) \), the calculation formula is as follows:

\[
Output_{m}(t+1) = \sum w_i(t+1)u_i(t+1)
\]

For the hidden layer, there exists \( u_i(t+1) = f(Output_{i}(t+1)) \), and \( Output_{i}(t+1) = \sum w_i(t)v_i(t) \).

Where

\[
w^1(t) = \begin{cases} w^2, \text{if } i \in a \\ w^3, \text{if } i \in b \end{cases}, \quad v_i(t) = \begin{cases} x_i(t), \text{if } i \in a \\ u_{in}(t), \text{if } i \in b \end{cases}
\]
For the receiving layer of \( \text{Output}_c(t) = \sum_{i=1}^{k} w_i(t-1)h_i(t-1) \), and \( u_c(t) = h(\text{Output}_n(t)) \), iterative reasoning can be performed according to the above process. It is worth noting that the defined objective function can be the following formula:

\[
E = \sum_{k=1}^{T} (y_k - y'_k)^2
\]

Where: \( y_k \) is the actual output of the Elman neural network. \( y'_k \) represents the output of the expected model.

4. **Build a training model**

4.1. *Bootstrap Elman neural network*

The Bootstrap resampling method is used to sample the test data to increase the overall sample size and bring it into the Elman neural network process. The flowchart for obtaining the Bootstrap Elman neural network is shown in figure 2:

![Figure 2. Bootstrap Elman neural network flowchart.](image)

4.2. *Sampling data*

This article collects the characteristics of the near-explosion data during the test, and classifies the data by the type of ammunition, the charge number, the temperature of the projectile, the shooting angle, the falling angle, the attack target, the type of the near-explosion and the effect. The integration is completed as shown in table 1:
### Table 1. Test table of near-explosion performance.

| Type                  | Number | Charge (#) | Temperature (°C) | Shooting angle (°) | Falling angle (°) | Attack target | Near-explosion failure |
|-----------------------|--------|------------|------------------|-------------------|-------------------|---------------|------------------------|
| **The type of I ammunition** |        |            |                  |                   |                   |               |                        |
| 10                    | 0      | 15         | 45               | 46                |                   | Arable land   |                        |
| 10                    | 4      | 15         | 69               | 74                |                   | Arable land   |                        |
| 10                    | 6      | 15         | 58               | 66                |                   | Arable land   |                        |
| 11                    | 4      | -40        | 55               | 61                |                   | Arable land   | 1                      |
| 21                    | 6      | 15         | 45               | 55                |                   | Water surface | 1                      |
| 12                    | 6      | 15         | 58               | 66                |                   | Arable land   | 2                      |
| 11                    | 3      | 60         | 75               | 77                |                   | Arable land   |                        |
| 11                    | 6      | 60         | 44               | 54                |                   | Water surface |                        |
| 12                    | 4      | 25         | 60               | 66                |                   | Desert        |                        |
| 11                    | 2      | -40        | 75               | 77                |                   | Arable land   |                        |
| 11                    | 5      | 15         | 83               | 85                |                   | Arable land   | 1                      |
| 12                    | 0      | 25         | 70               | 71                |                   | Treetop       | 2                      |
| 10                    | 6      | 15         | 45               | 55                |                   | Arable land   |                        |
| 12                    | 5      | 25         | 37               | 40                |                   | Incline       | 1                      |
| 10                    | 0      | 25         | 80               | 80                |                   | Plateau       | 2                      |
| 10                    | 4      | 15         | 70               | 73                |                   | Treetop       |                        |
| **The type of II ammunition** |        |            |                  |                   |                   |               |                        |
| 12                    | 1      | -40        | 80               | 80.5              |                   | Arable land   |                        |
| 12                    | 3      | 15         | 65               | 68                |                   | Arable land   |                        |
| 12                    | 8      | 60         | 44               | 54                |                   | Arable land   |                        |
| 10                    | 5      | 15         | 75               | 77.5              |                   | Arable land   |                        |
| 10                    | all    | 15         | 45               | 55                |                   | Arable land   |                        |
| 10                    | all    | 15         | 44               | 54                |                   | Arable land   |                        |
| **The type of III ammunition** |        |            |                  |                   |                   |               |                        |
| 11                    | all    | 25         | 81               | 83.1              |                   | Arable land   |                        |
| 11                    | all    | 60         | 44               | 54                |                   | Arable land   |                        |
| 11                    | 2      | -40        | 35               | 38                |                   | Arable land   | 2                      |
| 12                    | all    | -40        | 70               | 74                |                   | Arable land   |                        |
| 11                    | 3      | 15         | 60               | 63                |                   | Arable land   |                        |
| 10                    | all    | 15         | 65               | 70                |                   | Arable land   |                        |
| **The type of IV ammunition** |        |            |                  |                   |                   |               |                        |
| 12                    | 6      | 15         | 35               | 42                |                   | Water surface |                        |
| 11                    | 1      | 15         | 80               | 82                |                   | Arable land   |                        |
| 11                    | 3      | 15         | 43               | 54                |                   | Arable land   |                        |
| 11                    | 6      | 15         | 60               | 72                |                   | Arable land   |                        |
| 11                    | 6      | 60         | 70               | 78                |                   | Arable land   |                        |
| 11                    | 4      | -40        | 50               | 62                |                   | Arable land   |                        |
| **The type of V ammunition** |        |            |                  |                   |                   |               |                        |
| 11                    | 2      | 15         | 45               | 55                |                   | Water surface |                        |
The type of VI ammunition

| 11 | 2  | 15 | 65 | 71 | Arable land |
| 11 | 4  | 15 | 45 | 58 | Arable land  |
| 10 | 5  | 15 | 54 | 66 | Arable land  |
| 11 | 0  | 60 | 45 | 49 | Arable land  |
| 11 | 3  | -40| 50 | 61 | Arable land  |
| 11 | 5  | 15 | 70 | 77 | Water surface|

The type of VII ammunition

| 10 | 0  | -40| 75 | 76 | Arable land |

The type of VIII ammunition

| 10 | 0  | -40| 74 | 75 | Arable land |

4.3. Model establishment

The collected test data is simply processed, and the firing situation of each round is used as a separate input element to establish grid data of 480 rounds. By dividing data elements into training data, test data, and prediction data. Six types of conditions are used as input for the type of bomb, charge, temperature, shooting angle, falling angle, and attack target, and whether the near-explosion function fails as an output. The neural network model is shown in figure 3:

5. Experimental comparison

Take 352 rounds as the training amount, 50 rounds as the test amount, and 78 rounds as the prediction amount. The Elman neural network and Bootstrap Elman neural network were used to process and train the data. The experimental situation is shown in figure 4:
Figure 4. Comparison of experimental conditions.

The accuracy comparison of experimental prediction data is shown in figure 5:

Figure 5. Comparison of prediction data accuracy.

According to the predicted data set and predicted value shown in figure 5, the accurate number and accuracy of the predictions are shown in table 2:

| Experimental method       | Exact quantity | Accuracy  |
|---------------------------|----------------|-----------|
| **Elman neural network**  | 64             | 82.05%    |
| **Bootstrap Elman neural network** | 67             | 85.90%    |

The specific near-failure failure prediction data set and prediction value are shown in table 3:
### Table 3. Comparison table of prediction data set and prediction value of near-explosion failure.

| No. | Near-explosion failure | Value Elman prediction | Bootstrap Elman prediction |
|-----|------------------------|------------------------|----------------------------|
|     | 1 2 3 4 5 6 7 8 9     | 0 0 0 0 1 1 0 0 0 0 0 0 | 0 0 0 0 1 1 1 1 1 1 0 0 0 |
|     | 1 2 3 4 5 6 7 8 9     | 0 0 0 0 1 1 1 1 1 1 0 0 0 | 0 0 0 0 1 1 1 1 1 1 0 0 0 |
|     | 2 2 2 2 2 2 2 2 2     | 0 0 0 0 1 1 1 1 1 1 0 0 0 | 0 0 0 0 1 1 1 1 1 1 0 0 0 |
|     | 2 2 3 3 3 3 3 3 3     | 0 0 0 0 1 1 1 1 1 1 0 0 0 | 0 0 0 0 1 1 1 1 1 1 0 0 0 |
|     | 4 4 4 4 4 4 4 4 4     | 0 0 0 0 1 1 1 1 1 1 0 0 0 | 0 0 0 0 1 1 1 1 1 1 0 0 0 |
|     | 5 5 5 5 5 5 5 5 5     | 0 0 0 0 1 1 1 1 1 1 0 0 0 | 0 0 0 0 1 1 1 1 1 1 0 0 0 |
|     | 6 6 6 6 6 6 6 6 6     | 0 0 0 0 1 1 1 1 1 1 0 0 0 | 0 0 0 0 1 1 1 1 1 1 0 0 0 |
|     | 7 7 7 7 7 7 7 7 7     | 0 0 0 0 1 1 1 1 1 1 0 0 0 | 0 0 0 0 1 1 1 1 1 1 0 0 0 |
|     | 8 9 8 9 8 9 8 9 8     | 0 0 0 0 1 1 1 1 1 1 0 0 0 | 0 0 0 0 1 1 1 1 1 1 0 0 0 |
|     | 9 0 9 0 9 0 9 0 9     | 0 0 0 0 1 1 1 1 1 1 0 0 0 | 0 0 0 0 1 1 1 1 1 1 0 0 0 |

6. Conclusion
In this paper, a Bootstrap Elman neural network is used to build a neural network model. According to the training and testing of the model, the neural network prediction is performed on the prediction data to obtain the accurate amount and accuracy of the prediction data. At the same time, the model
established with the Elman neural network is used. By comparison, it is found that this method improves the accurate quantity and accuracy of the prediction data, and can better reflect the inherent connection of the fuze near-explosion failure. A preliminary determination has been made that fuze near-explosion failure often occur under certain conditions, and it has certain guiding significance. It provides technical support for the use of subsequent fuze and other fuze near-explosion tests. The neural network model was subsequently improved, and the input conditions were refined to obtain more input condition correspondences, which improved the prediction accuracy of the Bootstrap Elman neural network.

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