Estimation method of sensor node missing value in granary storage grain weight detection system based on DNN

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Abstract

The lack of node data in the sensor network affects the accuracy of the detection in the granary storage weight detection system. In order to avoid the impact of sensor node data loss in sensor networks, a method based on deep neural network for sensor missing value estimation is proposed. The deep neural network estimation method based on spatial attributes and time attributes is mainly studied, and relevant simulation experiments and actual verifications are carried out. The results show that the sensor missing value estimation method based on deep neural network has high accuracy and simple implementation, which provides a new method for estimating the missing value of the sensor.

Keywords

Sensor network; deep neural network; estimation; high accuracy.

1. Introduction

With the rapid development of the Internet of Things, information intelligence and communication intelligence have been proposed one after another, making the sensor network widely used, and the research on sensor networks has become a research hotspot [1-3]. In recent years, the weight measurement method for granary storage grain has been rapidly developed. In the past, the traditional weighing measurement method was unable to meet the modernization needs due to low work efficiency and high cost. At present, the more popular granary storage grain weight measurement methods are mainly based on image recognition, pressure sensor, laser scanning and other methods. Among them, the pressure sensor measurement method has received extensive attention from scholars because of its practicability and reliability[4]. Based on the pressure sensor measurement method, the pressure value of the measurement point is obtained by arranging a plurality of pressure sensors, thereby deducing the weight of the stored grain in the granary by a theoretical method [5-9]. However, due to the inherent characteristics of the sensor network, the lack of sensor node data has become an inevitable problem. If the sensor node network is suddenly disconnected, the sensor node is unstable, etc., the sensor node data is missing or unavailable. This brings greater uncertainty to the measurement results. Therefore, how to effectively fill in the missing values of the sensor nodes and make the real response monitoring of the sensor network is an urgent problem to be solved.

At present, the research on sensor missing value compensation is mainly based on the correlation between time and space correlation, attribute correlation and support vector machine estimation [10-12]. Although the above studies have been well demonstrated and developed, most of them are based on common sensor network applications. In the study of the weight of grain storage grain based on pressure sensors, the sensor node data is not only sometimes empty, but also affected by grain in the granary. The effects of fluidity, ventilation, temperature and humidity, and even granary effects. Therefore, the missing value estimation method in the literature [10] does not satisfactorily meet the compensation requirements for missing values in such cases. Based on the sensor network layout model and related data in [5], this paper proposes a deep neural network (DNN) based pressure sensor data missing value compensation method, and introduces the commonly used average substitution method and literature [The method in 3] is compared. The results show that in this case, the deep sensor neural network-based pressure sensor data missing value compensation method is more accurate and can meet the application requirements of the granary storage grain weight detection system.

2. Basic principles of deep neural networks

Deep neural network can be understood as a multi-layer artificial neural network, which includes not only the input layer and the output layer, but also multiple hidden layers between the two layers. The advantage of adding a hidden layer is that it can approximate complex decision functions. . The artificial neural network includes an input layer, a hidden layer, and an output layer. Among them, the upper and lower neurons are completely connected, and the neurons in the same layer are not connected. Artificial neural networks can approximate arbitrarily complex nonlinear relationships due to strong learning, adaptive capabilities, and good nonlinear mapping capabilities [13]. The artificial neural network structure is shown in Figure 1.

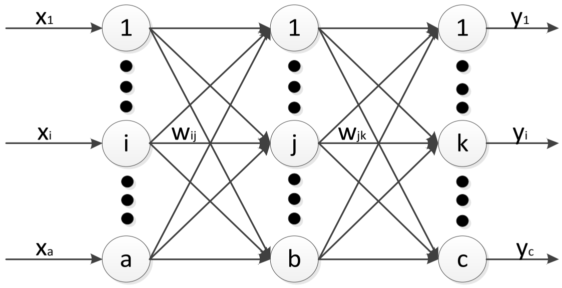

Fig.1 Artificial neural network structure

Let the number of input layer nodes be a, the number of hidden layer nodes be b, the number ofoutput layer nodes be c, the learning sample set has a total of S samples (X_p, Y_p), then the qth sample (q=1, 2,..., S), node i The input sum is recorded as net_{qi},

$$net_{pi} = \sum_{i=1}^{a} W_{ij}O_{pi} \tag{1}$$

among them:

$$O_{pi} = f(net_{pi}) \tag{2}$$

When the initial value of the network is changed, the error E of the input sample q, the total network output and the expected output is:

$$E = \sum_{p=1}^{M} E_p = [\sum_{i=1}^{a} (d_{pi} - O_{pi})^2] / 2 \tag{3}$$

The weight correction formula of BP neural network is:

$$W_{ij} = W_{ij}(t) + \mu\delta_{pi}O_{pi} \tag{4}$$

Where $W_{ij}(t)$ is the weight at time t, and

$$\delta_{pi} = \begin{cases} f(net_{pi})(d_{pi} - O_{pi}), \text{ For input node} \\ f(net_{pi})\sum_{k=1}^{a} \delta_{pk}W_{ki}, \text{ For output node} \end{cases} \tag{5}$$

In equation (4): μ is a positive, adjustable learning rate, the choice affects the convergence speed of the network.

Due to the small number of hidden layers, artificial neural networks may have problems such as gradient sparseness and convergence to local minimum during learning and training. Compared with the traditional artificial neural network, the deep neural network has more hidden layers in the process of learning, which can be regarded as a multi-level logic regression, which realizes the conversion of complex functions mainly through multiple hidden layers. The prediction model is implemented by continuously updating the weights of hidden nodes in each hidden layer through a large number of tagged training samples.

3. Experimental design and results analysis

3.1 Data set selection

The experiment selected two data sets for testing and verification, which are the experimental data sets of the experimental warehouses 1 to 6 in the literature [5] and the data collections of the sensors 1 to 6 of the Qihe 31 granary. There are generally two ways to estimate the missing data of the sensor node. One is the time-based estimation of the sensor single node, that is, the purpose of estimating the data of the sensor node over time. The other is to estimate the value of the missing data sensor node by the spatial correlation of the sensor network, that is, to estimate the missing data value through the overall change law and correlation of the sensor network. The experiment takes the two attributes of space and time as the design and test objectives.

3.2 Experimental design and results analysis

The experiment is combined with the above data set and implemented by R language, wherein the learning rate and the threshold are set to 0.1 and 0.05, respectively. The selection of the number of hidden layer nodes in the deep neural network can be designed according to the method in [13]. After trying to compare the 1st, 2nd, and 3rd deep neural network models respectively, the deep neural network model of the 3 hidden layers with the best prediction effect is determined as the final prediction model structure. The number of hidden layer nodes is shown in Table 1.

Tab.1 Deep neural network structure

	Number of node	Connection method
First hidden layer	4	Fully connected
Second hidden layer	6	Fully connected
Third hidden layer	5	Fully connected
Out layer	1	Fully connected

First, the missing values of the spatial attribute sensor nodes are predicted. The first 70 samples of the sensor data of the experimental warehouses 1 to 6 are used as modeling samples. The input format of each modeling sample is IPm={In1m, In2m, In3m, In4m, In5m,In6m}, where In1m to In6m represent the measured values of sensors 1 to 6, and m represents the sample number. The last 8 pieces of data are used as test samples, and the sensor data of each test sample No. 1 to No. 5 is used as an input to predict the data value of sensor No. 6, that is, In6m is predicted by inputting IPm={In1m, In2m, In3m, In4m, In5m}. The value. The predicted results are shown in Figure 2.

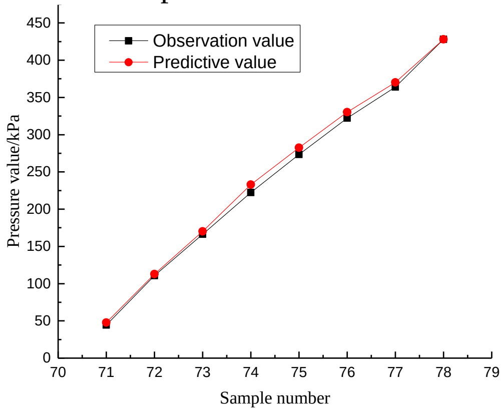

Fig.2 Spatial property experimental warehouse forecast results

It can be seen from the results in Fig. 2 that the model has a high degree of fit, a good predictive effect, and a consistent trend, with a predicted average error of 3.01%.

To predict the missing value of the time attribute sensor node, the input data set format needs to be modified. Convert from a spatial property to a time property. The input format of each modeling sample is InPrn={T1rn, T2rn, T3rn, T4rn, T5rn}, where T1rn to T5rn represent the measured values of sensor nodes for five consecutive time points, r represents the sensor number, and n represents the sample number. The first 448 data sets of the data set are used as model samples for model training, and the last 20 data are used as test samples to test the model fit, and the data values collected at the first four time points of each test sample are used as input to predict. The value of the fifth time point sensor is predicted by inputting InPrn={T1rn, T2rn, T3rn, T4rn}. The predicted results are shown in Figure 3.

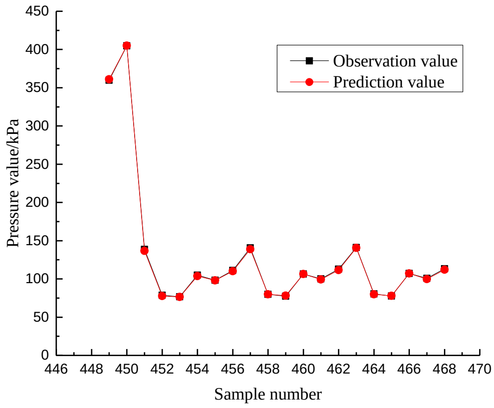

Fig.3 Time attribute experiment warehouse forecast results

It can be seen from the results in Fig. 3 that the observation results are highly fitted to the prediction results and the trends are consistent. The predicted average error is only 0.65%.

Comparing the results of Fig. 2 and Fig. 3, it can be seen that due to the volume of the small granary, the grain in the granary is greatly affected by the friction of the sidewall, and therefore the accuracy of the sensor node pressure value based on the spatial property is poor, but the small granary is stored due to the grain. The weight is light, and the sedimentation effect is small, so the accuracy of the sensor node pressure value prediction based on the time attribute is high.

3.3 Qihe Grain Depot Verification Results

Align the pressure sensor data of the No. 31 Grain Depot sensor node for prediction. The predictive model structure still uses the deep neural network structure of Table 1, and the learning rate and threshold are set to 0.1 and 0.05, respectively. Select sensors 1 to 6 as the research object. Based on the spatial properties, select 1050 sample data as the research, in which the first 1000 are used as modeling samples, the last 50 are used as test samples, and the sensors 1 to 5 are used as input. The value of sensor No. 6 is predicted, and the predicted result is shown in Fig. 4. The average prediction error is only 0.03%.

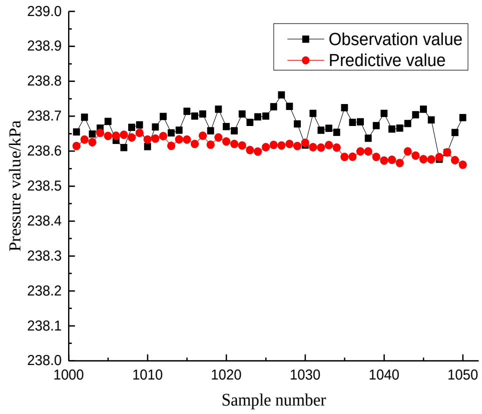

Fig.4 Spatial attribute real warehouse forecast results

Based on the time attribute, 610 sample data were selected as the study, in which the first 600 were used as modeling samples and the last 10 were used as test samples, and the values of the previous four moments were used as inputs to predict the sensor node values at the next moment. The prediction results are shown in Figure 5. The average prediction error is 2.99%.

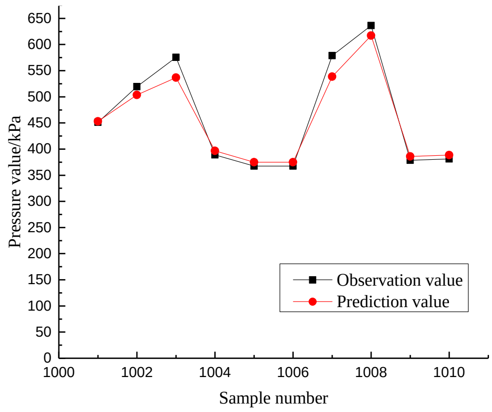

Fig.5 Time attribute real warehouse forecast results

Comparing the results of Fig. 4 and Fig. 5, it can be seen that the large granary is bulky, and the grain in the granary is less affected by the friction of the side wall. Therefore, the prediction result of the pressure value of the sensor node based on the spatial attribute is high, but the weight of the large granary is heavy. It is greatly affected by factors such as sedimentation, so the accuracy of the sensor node pressure value prediction based on time attribute is poor.

3.4 Comparison of prediction methods by different methods

In order to study the validity and feasibility of the deep neural network prediction model, the average replacement method commonly used in practice and the linear regression method in the literature [3] are introduced for comparison. The first 1000 samples of the Qihe Grain Depot spatial attribute data set are used. Modeled samples, 1001 to 1010 samples were used as test samples. The comparison of the prediction results of each method is shown in Fig. 6.

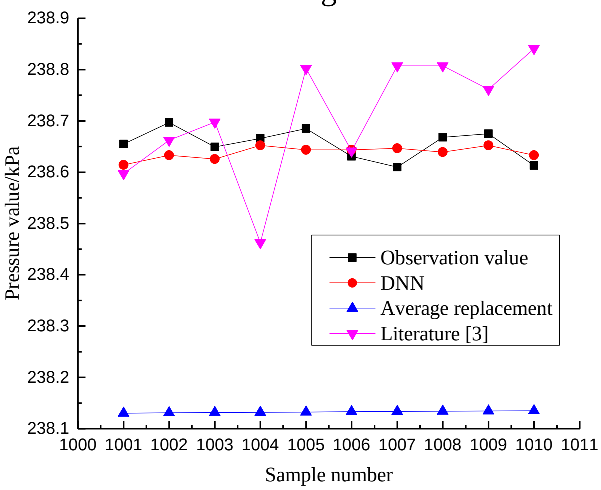

Fig.6 Comparison of prediction results of different methods

It can be seen from the prediction results of each method in Fig. 6. The average prediction error based on the depth neural network prediction model is only 0.0128%, and the error of the average value substitution method commonly used in practice is the largest, which is 0.2188%. The prediction error of the linear regression method in the literature [3] is 0.0471%. It can be seen that the sensor node missing value prediction method based on deep neural network has higher prediction accuracy.

4. Conclusion

In summary, the main conclusions of this paper are:

(1) Based on the principle analysis, a data compensation method for sensor missing nodes based on deep neural network is proposed.

(2) Through simulation experiments and actual verification, the feasibility of the data loss method based on deep neural network for sensor missing nodes is proved from two properties of space and time. By comparing with the commonly used methods and the compensation methods proposed in

other literatures, it is proved that the sensor node missing value estimation method based on deep neural network is more suitable for the granary storage grain weight detection system.

(3) There are also deficiencies in this paper. For example, under the condition of pursuing precision, the implementation complexity caused by adding hidden layers in the model is not fully considered. This is also the key issue of the next study.

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