

Research on LSTM-based Model for Predicting Deformation of Tunnel Section During Construction Period

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Abstract— In order to ensure the smooth construction of highway tunnel construction project, it is necessary to monitor and analyze the tunnel deformation. Most of the existing monitoring systems at home and abroad are for independent projects or independent equipment monitoring, the system application scope is small, and the data processing is not perfect. Based on this, this paper takes the tunnel deformation monitoring during highway tunnel construction as the research object, and adopts LSTM to predict the tunnel section deformation. The short-duration memory neural network model can learn from memory and then predict the subsequent information. After establishing the neural network model, the model parameters such as learning rate, number of hidden nodes, number of iteration steps and unit input are tested and adjusted by comparative experiment, and the best fitting effect is obtained at last. The tunnel prediction model can predict the deformation of tunnel section in real time, and has high precision. At the same time, it can leave enough reaction time for construction personnel. It can be predicted that it has good development potential in the future.

Keywords— Tunnel Deformation, Deformation Prediction, Model Testing, LSTM Model, Model Evaluation

I. INTRODUCTION

In the modern tunnel construction project, the stable deformation monitoring of surrounding rock is an important condition to ensure the construction safety. As technology advances, methods such as manual and visual inspection are replaced by more accurate equipment and systems; The shift from scales and total stations to more accurate monitoring equipment, such as geodesy [1], optical fiber sensing technology [2], distributed optical fiber systems [3], and resistance strain gauges [4], has made tunnel monitoring more accurate. Ariznavarreta-Fernandez (2016) used CANG (convergence by Angle sensor) to measure tunnel convergence, which achieved an accuracy of about $\pm 0.5\text{mm}$ in laboratory tests, but poor accuracy under real conditions [5]. Kazuko Sugimoto (2018) realized long-range non-contact acoustics based on a long-range acoustic device and a laser Doppler vibrometer, which can detect internal defects of concrete

structures at a depth of 10 cm [6]. Leanne Attard (2018) uses photogrammetry and computer vision technology (CV) for image processing (IP) to automate different tunnel inspection procedures to achieve different measurement objectives [7]. Alireza Afshani (2019) adopted passive thermal infrared method to carry out non-contact non-destructive testing for defect detection of concrete lined box tunnels and shield tunnels [8]. Based on 3D laser scanning monitoring data, Zhang L (2018) proposed an elliptic fitting method based on the 1-norm minimum residual algorithm criterion to analyze the tunnel surrounding rock section and improve the accuracy of the monitoring data to reflect the tunnel deformation [9]. Xiangyang Xu (2019) proposed Gaussian filtering based on signal-to-noise ratio gradient to automatically identify and extract cracks in ground laser scanning measurement point cloud data [10]. Timothy Nuttens (2016) uses a high-speed phase laser scanner for tunnel monitoring with an accuracy of 0.5 mm and a standard deviation between 0.34 and 0.58 mm [11]. Zrelli (2017) studied the tunnel health monitoring architecture based on wireless sensor networks, and tried to use wireless sensor and civil engineering technology to measure and locate tunnel damage vibration [12].

II. DISPLACEMENT DEFORMATION MONITORING AND PREDICTION

The neural network model has the advantages of self-learning, associative storage, and high-speed search for optimized solutions. Therefore, tunnel deformation monitoring and warning are achieved through the neural network prediction model. In ordinary neural network models, there is no arithmetic connection between the inputs of the network in a fixed layer, resulting in the model cannot represent the relationship between the "contexts" of the inputs, resulting in a Recurrent Neural Network (RNN). Long Short-Term Memory (LSTM) is an improved derivative model of recurrent neural network, which can solve the problem of gradient explosion or vanishing caused by the poor dependence on long-distance information in recurrent neural networks. It is mainly used for the prediction judgment of temporal information, which meets the requirements of this

monitoring system for monitoring prediction. By comparing the deformation monitoring prediction results with the permissible relative displacements and combining with other monitoring information, such as the monitoring results of the tilt sensor used in this system, an early warning judgment is made.

A. Long Short-Term Memory

The Long Short-Term Memory neural network is essentially an improved recurrent neural network, and the neural network structure is shown in Figure 1. Three gate concepts are introduced in LSTM: forgetting control gate, input control gate, and output control gate, which add or delete information to the unit state to improve the recurrent neural network. With the increase of incoming data, it is difficult to learn the relationship between nodes at different times, which leads to the ineffectiveness of the long-range dependency problem. The "gate" is a selective passage of information, and its output is composed of a σ layer and point by point product composition, where the output of the σ layer between $[0,1]$, which determines the degree of passing of each component, with a value of 0 indicating that passage is not allowed at all and a value of 1 indicating that passage is allowed at all. The forgetting control gate is used to determine which information in the previous hidden layer state is important, the input control gate is used to determine which information in the current state is important, and the output control gate is used to determine the next hidden layer state.

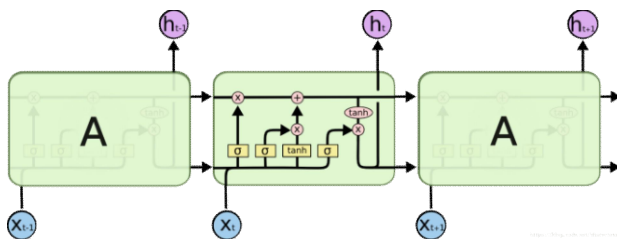


Figure 1. Structure of Long Short-Term Memory neural networks

The Long Short-Term Memory neural network is mainly used to predict the subsequent information after memory learning through the processing of temporal information. According to the state of tunnel deformation to predict the future degree of deformation, determine the magnitude of deformation, and provide data support for tunnel warning and judgment.

III. MODEL TESTING

For the monitoring data collected in this project, as the data collection is done every second with minimal changes, the data is averaged and the average value per minute is used as the data point for deformation prediction processing. After averaging, a total of 12000 pieces of data are collected. The Long Short-Term Memory neural network is used for model testing, and various parameters of the neural network model are adjusted to obtain the optimal solution. The main parameters of the neural network selected in this article are learning rate, the number of hidden nodes, the number of

iterations and the input of the unit. The parameters were adjusted by controlling variables, and the number of iteration steps, mean square error, and model running time for data convergence predicted by the adjusted neural network were compared to make a reasonable choice of parameters. The Long Short-Term Memory neural network model selected for this study contains two layers of neural network with default parameters of learning rate 0.01, number of hidden nodes 4, iteration step 500, unit input 1. The first 70% of the monitoring data is selected by default as a training set of 8400 data, and the second 30% as a test set of 3600 data for co-computation.

A. Selection of Learning Rate

The learning rate is used by The Long Short-Term Memory neural network to determine the location of the next selection point during iteration when performing the fitting of real monitoring data. In this paper, the parameters of the learning rate are selected as 0.1, 0.01, 0.001, 0.0001, and the number of hidden nodes and iterations as well as the unit inputs are predicted using the default values of the neural network for monitoring data. The results of the training are shown in Table 1, and the impact of learning rate on iterative convergence during data prediction is shown in Figure 2.

The processing data is shown in Figure 2, the size of the learning rate has little effect on the overall computation time of the neural network, but it has a significant effect on the convergence during the test. When the learning rate is 0.1 and 0.01, the mean square error of convergence is similar, and the number of iteration steps when the convergence is stabilized is also similar, which is 203 and 237 respectively. When the learning rate is 0.001, the required iteration steps for data convergence are 496, and the mean square error of convergence is 0.00022, which is an order of magnitude higher than when the learning rate is 0.1 and 0.01; When the learning rate is 0.0001, the data does not converge to the prediction.

From Figure 2, it is obvious that the data mean square error is large and cannot converge when the learning rate is 0.0001, the curve changes more slowly when the learning rate is 0.01 and cannot fully converge under the default number of iterations. The data convergence is better with the learning rates of 0.1 and 0.01. However, there is an abnormal fluctuation in the mean square error after data convergence when the learning rate is 0.1, and when the number of iterations is 308 ~ 346 and 499 ~ 500 iterations, indicating a state of data overfitting. Therefore, in comparison, a learning rate of 0.01, the shortest running time, and a small mean square error during convergence were selected.

TABLE 1. COMPUTATIONAL RESULTS FOR DIFFERENT LEARNING RATES

Learning rate	0.1	0.01	0.001	0.0001
Computation time	33.8648	33.6472	33.8109	33.9416
Convergence mean square error	0.00002	0.00003	0.00022	-
Convergent iteration steps	203	237	496	-

B. Selecting the Number of Hidden Nodes

The number of hidden nodes is the number of hidden nodes of the unit in the recurrent layer of the neural network (default 2-layer recurrent layer for modeling) for multidimensional processing of input data. Based on the determination of the learning rate of 0.01, the number of hidden nodes is parameterized, and the number of hidden nodes is selected in an incremental manner to be 4, 8, 16, 32, 64 and 128 six parameters for prediction training of monitoring data.

The results of the training are organized as shown in Table 2, and the state of the influence of the number of hidden nodes on the iterative convergence during data prediction is shown in Figure 2. From Table 2, it can be seen that the increase in the number of nodes has a certain impact on the operation time, when the number of hidden nodes is less than 32, the degree of impact on the operation time increases more, in less than 32, the time change is not obvious. For the six hidden node parameters selected, the neural network prediction model can achieve convergence, and the mean square error at convergence is similar and smaller, to meet the requirements of convergence, the convergence effect is better. The data can reach convergence before iteration to 300, and most of them can realize convergence before 200 steps. Because the data convergence changes mainly in the first 150 iterations, so in order to highlight the iteration changes in the state, the plotting of the results of the first 150 iterations, and at the same time due to the convergence of the mean-square error is small, will be greater than 1 mean-square error (a total of three points: the number of hidden nodes is 8, the number of iterations is 1, the mean-square error is 1.03579; the number of hidden nodes is 128, the number of iterations is 3, the mean-square error is 8.80421; when the number of hidden nodes is 128 and the number of iterations is 4, the mean square error is 1.8788) is changed to 1 for plotting to highlight the trend of the mean square error when the data converge. When the number of hidden nodes is 64, 128, the model computing time is longer, and the mean square error iteration curve fluctuates more, and the data prediction is unstable; when the number of hidden nodes is 4, 8, the mean square error fluctuates more at the beginning of the iteration, and the curve is more variable; the number of hidden nodes with relatively more stable changes in the mean square error is 16, 32, and the model takes less computing time when the number

of hidden nodes is 16, and the iteration converges with a The number of hidden nodes is 16.

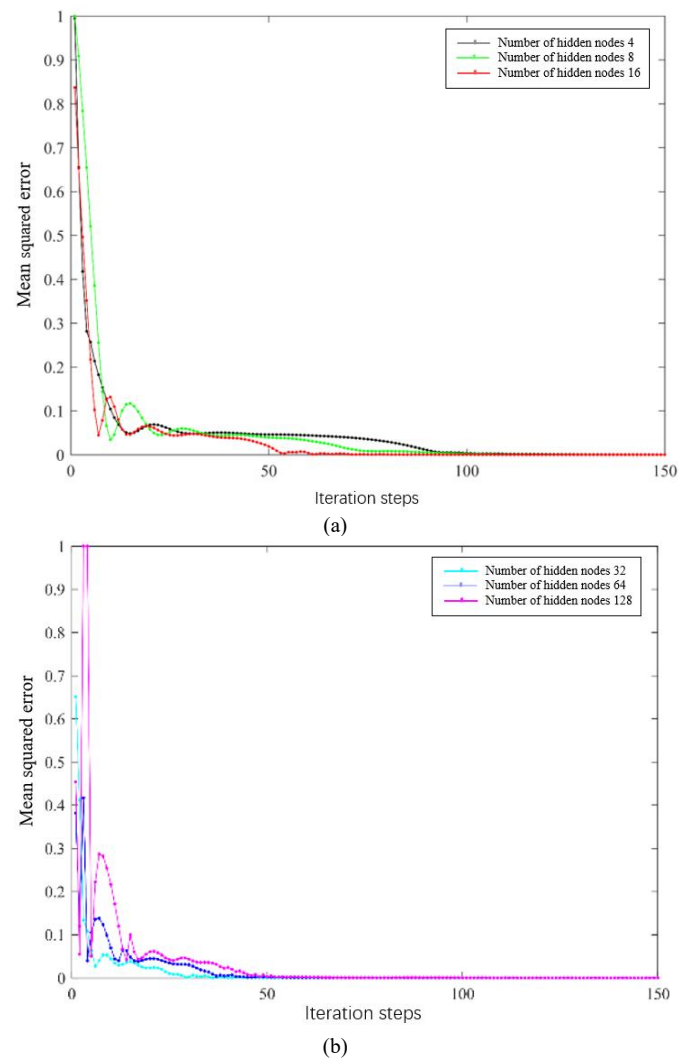
**Figure 2.** Iterative convergence plot for different number of hidden nodes

TABLE 2. CALCULATION RESULTS OF DIFFERENT HIDDEN NODE NUMBERS

Iteration steps	4	8	16	32	64	128
Computation time min	33.6472	34.5205	34.3415	35.8493	38.6670	47.7782
Convergence mean square error	0.00003	0.00001	0.00002	0.00001	0.00002	0.00001
Number of convergent iteration steps	237	199	152	213	129	132

C. Iteration Steps

The already determined learning rate of 0.01 and the number of hidden nodes 16 were used as a basis to parameterize the number of iteration steps. The chosen iteration step parameters are 100, 200, 300, 400, 500 and 600 to train the data for prediction. The results of the training are organized as shown in Table 4.10, and the influence of the number of iteration steps on the state of iterative convergence in data prediction is shown.

As can be seen from Table 3, the neural network prediction convergence is generally at 120~300 iterations, and the mean square error after iteration is 0.00004~0.00001, which has a small effect on the mean square error. However, the increase in the number of iteration steps is almost exponential growth in the computing time of the model, which is because in the model calculation, the running time required for each iteration is basically the same, so the increase in the number of iterations makes the computing time lengthening, but the convergence of the model convergence of the measurement of the mean-square error shows a tendency to decrease. Therefore, the more reasonable iteration steps are 200, 300, 400 iterations.

In order to show the change of the mean square error in the previous iteration, the convergence of the mean square error in the first 150 iterations of each model is selected for plotting, and the results are shown in Figure 3. Only 100 iterations are not able to meet the need for iterative convergence; when 200 iterations are performed, the number of times for the convergence of the mean square error is just enough to satisfy the demand, which is not suitable for use in consideration of the redundancy of the model operation. When iteration 300, 400 times, the initial mean square error of the data is relatively small, and the curve changes slowly. Considering that the mean square error after convergence of the iteration is similar and the mean square error is smaller when the iteration is 400 times, and the number of steps in this iteration when the convergence of the receipts is concentrated in 290 times, in order to provide redundancy in the number of iterative steps to ensure the accuracy of the iteration results, the number of iterations selected is 400 times.

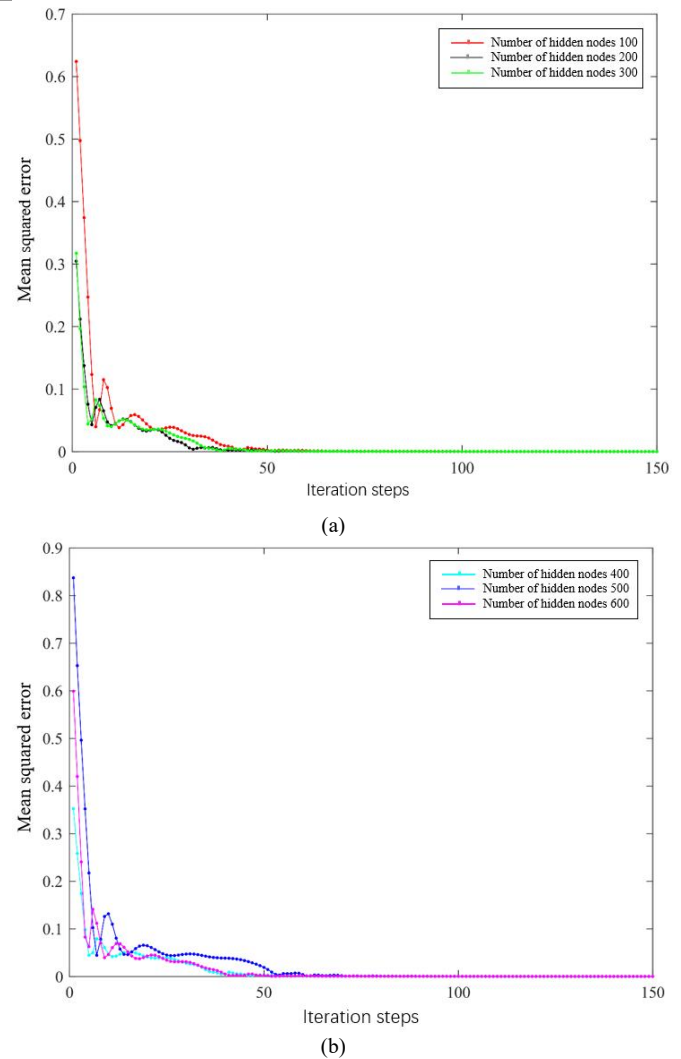
**Figure 3.** Iterative convergence plots for different number of iteration steps

TABLE 3. BUDGET RESULTS FOR DIFFERENT ITERATION STEPS

Iteration steps	100	200	300	400	500	600
Computation time min	7.0099	14.4948	21.0900	27.9834	34.3415	41.9887
Convergence mean square error	-	0.00004	0.00003	0.00002	0.00002	0.00001
Number of convergent iteration steps	-	125	173	294	291	291

D. Unit Input

The unit input is the number of input data in each pass of data in the recurrent network, and the data prediction is done by splitting the overall data sample into individual units before modeling. Based on the already determined learning rate of 0.01, the number of hidden nodes 16 and the number of iteration steps 300 times, the unit input parameters of 1, 10, 20, 30 and 60 are selected to train the data for prediction. Due to the pre-processing of the data, the unit input parameters are equivalent to the monitoring of the data for early warning prediction at intervals of: 1, 10, 20, 30 and 60 minutes. The results of the training are organized as shown in Table 4, and the state of influence of the unit inputs on the convergence of the iterations during data prediction is shown in Figure 4.

As can be seen from Table 4, based on the previously selected learning rate, the number of hidden nodes and the number of iteration steps of the model in the case of different unit inputs, in the iteration of about 300 steps can achieve the effect of convergence of the mean squared error, and the convergence of the mean squared error can be achieved enough small, the value of the difference is not large, compared with the number of iterative steps in the convergence of the iterative convergence is required to converge to a certain number of iterative convergence of the number of steps after the redundancy to determine that the convergence has been Achieve stability, compared to the final convergence of the mean square error, smaller means that the effect of storage is better, to determine the appropriate unit input 1, 20, 60. different unit inputs on the model operation time has a greater impact, in the input of 10, compared with the input of 1 there is a 7-fold difference, but the subsequent 10, 20, 30, 60 unit inputs between the time gap is smaller, the impact on the operation time gap is basically within 2~0.6 minutes. Considering that tunnel deformation monitoring needs to provide construction personnel and management personnel with sufficient response time and evacuation time, the monitoring and warning operation response time should be as fast as possible, while the monitoring and warning interval should not be too long, so as not to cause injuries or deaths due to the inability to provide timely warnings in the event of sudden changes in the tunnel construction, the appropriate inputs of the unit are 10, 20, 30. In summary, the most appropriate input of the unit is 20

Due to the iterative convergence of the mean square error changes are mainly reflected in the early stage, so in order to

fully reflect the different units of input, iterative operation when the mean square error convergence, selected the first 100 iterations of iterative convergence plotting, as shown in Figure 4, the convergence of different units of input changes in the mean square error convergence is basically the same, the early stage of the fluctuation is large, the late curve changes gently and gradually decrease tends to 0, indicating that the fit state is good to achieve a good prediction effect. It shows that the fitting state is good and achieves a better prediction effect.

By adjusting and selecting the parameters of the adopted long and short-term memory neural network model in this subsection, the model parameters applicable to the monitoring system of this study are obtained as learning rate 0.01, number of hidden nodes 16, number of iterations 400, and unit input 20, and the selection of the above parameters can achieve the effect of fast modeling speed, good convergence of iterations, and shorter deformation prediction time interval.

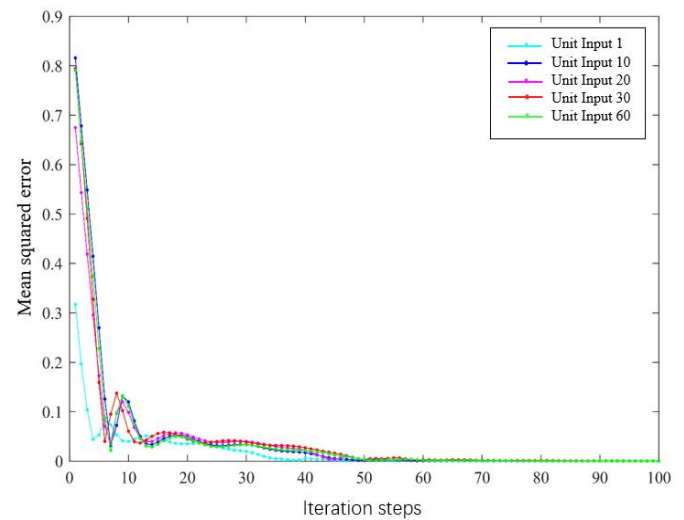
**Figure 4.** Iterative convergence plot for different cell inputs

TABLE 4. ARITHMETIC RESULTS FOR DIFFERENT CELL INPUTS

Unit Input	1	10	20	30	60
Computation time min	27.9834	3.9132	2.2041	1.5913	0.9354
Convergence mean square error	0.00002	0.00007	0.00003	0.00005	0.00002
Number of convergent iteration steps	294	316	291	301	275

TABLE 5. REPEAT EXPERIMENT RESULTS

Experiment number	Computation time min	Convergence mean square error	Number of convergent iteration steps
1	2.2031	0.00005	314
2	2.1691	0.00001	260
3	2.2040	0.00005	305
4	2.2176	0.00006	321
5	2.1991	0.00001	246
6	2.1960	0.00003	328
7	2.1928	0.00001	197
8	2.1904	0.00001	188
9	2.2015	0.00001	226
10	2.1943	0.00002	311
Average	2.1968	0.000026	270

IV. EVALUATION OF FORECASTING MODEL RESULTS

In order to judge the reliability of the parameter-adjusted long and short-term memory neural network model for deformation monitoring prediction, the parameter-adjusted model was used to conduct several repeated experimental predictions on the acquired monitoring data samples, and the results of the predictions were compared for evaluation.

Ten repetitive experiments were carried out on the monitoring data using the parameter-adjusted neural network model, and the experimental results were recorded as shown in Table 5, from which it can be seen that the maximum difference between the model's operation time and the average value in the results of the 10 repetitive experiments was 0.0064 min, indicating that the model runs stably and has less influence on the time to ensure the timeliness of the prediction. The 10 predictions carried out can reach the result of model convergence, and the average value of the mean square error of convergence is 0.000026, which indicates that the model convergence effect is better, and the accuracy of prediction can be ensured. The number of iterative steps for the neural network model to reach convergence is between 188 and 326, with an average value of 270, indicating that the number of iterative steps is selected appropriately to ensure that the prediction of the monitoring data can reach convergence with a certain degree of redundancy to ensure the stability of convergence and the accuracy of the prediction.

V. CONCLUSIONS

LSTM is selected to predict the monitoring data, the learning rate of the model, the number of hidden nodes, the number of iterative steps and unit inputs are adjusted, and compared with the parameter adjustment of the model operation time, the number of iterative convergence steps and the mean squared error of the iterative convergence of the parameter selection, select the learning rate of 0.01, the number of hidden nodes 16, the number of iterative steps of 400 and unit inputs of 20, and utilize the model for Multiple repetitive experiments, the average computing time is 2.1968 min, the average number of iterative convergence steps is 270, the average convergence mean square error is 0.000026, and the prediction results are well fitted to the measured data.

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