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Research on Prediction Method of Pipe Gallery Environment based on LSTM Circular Convolution Neural Network

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Abstract

At present, there are many blind spots in the management of the multi-purpose network for underground pipelines in cities, while its security mechanism is not so improved. A pipe gallery accident can pose a threat to the urban functions, and the security of life as well as that of property, no matter it is a gas leak or explosion in the pipelines entering the gallery, or a failure occurs in the equipment attached to the cabin.To realize the safe operation and efficient management of the underground integrated pipe gallery, our project is based on the data recorded in authentic operations, employs the neural network algorithm to predict its environmental parameters under authentic operations, and also apples LSTM algorithm to detect abnormal states. The designed model has a high accuracy rate in calculating and can evaluate the running state of the pipe gallery.

Keywords

Neural network, LSTM, Pipe gallery.

1. Introduction

Today our society has witnessed high-speed economic development, and the pace of urbanization is constantly stepping closer to the intelligentization. In many big cities of our country, the construction of utility tunnel is improving day by day. In recent years, China has paid more and more attention to the construction of underground integrated pipe gallery [1]. In 2015, the underground integrated pipe gallery began to operate in 10 cities of China on a pilot [1]. Prensently, the construction of underground integrated pipe is in full swing in many cities in our country, such as Suzhou, Hangzhou, Guangzhou, Zhongshan and many other places. With the increasing of the scale and number of integrated pipe gallery, building an intelligentized and informatized pipe gallery has become an urgent problem to be solved.

The pipe gallery system is required to be of high qualify on safety, for there are important pipelines carrying gas, water, natural gas, and electricity in the pipe gallery, and the underground pipe gallery can be regarded as the blood vessels of the cities, because it is an impartible part of the cities' normal operation.It's a common way for who monitoring the pipe gallery to do real-time detections of abnormal temperature and humidity to determine whether the water pipeline is leaking or damaged.However, this way always brings a lag, which may cause some economic losses. If we can predict the environmental parameters of the pipe gallery through deep learning algorithm, and take actions before the accident appears, the risk of major failures can be effectively reduced, and the economic loss can also be greatly reduced.

LSTM (Long-Short Term Memory RNN) is in the range of RNN, and a special implementation of it. It is mainly for us to solve the problem of gradient disappearance and explosion during the long training sequences. In simple terms, compared to the ordinary RNNs, LSTM can perform better in

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longer sequences. This article uses the LSTM recurrent neural network to learn and adjust to the network weights and offsets based on the historical data in the environmental parameters of the pipe gallery to realize the prediction of the environmental parameters with an absolute error of 2%.

2. LSTM neural network design

2.1 The introduction of LSTM neural network

The change in humidity of the pipe gallery is a process of faults accumulation and their continuous development. The state change is not only related to the monitoring information at the current moment, but also the monitoring values in the past. The traditional neural network only considers the current monitoring state value, so it is difficult to characterize the degradation and development process of humidity over time. Recurrent Neural Network (RNN) is a memory neural network that can consider the memory data of the current and also the historical periods to realize the prediction process.Therefore, it can overcome the drawbacks of traditional neural networks which cannot make full use of historical data. RNN recurrent neural network has a certain memory function, but due to the difficulty of RNN training and the problems of gradient diffusion and explosion, it cannot handle long-term dependence issues well.

Long-short-term memory neural network (Long.Short-Term.Memory, LSTM) is an improved time-speed regression neural network based on the recurrent neural network. The network was first proposed by Professor Schmidhuber and Professor Hochreiter in 1997 to solve the problems of gradient disappearance and a lack of long-term memory in the process of RNN calculation, so that RNN can be effectively used for large-scale temporal information.

2.2 LSTM network design

RNN can be seen as multiple copies of the same neural network. Each neural network module will pass the information to the next one. When the input is a time series, the loop structure can be expanded as shown in Figure 2.1:

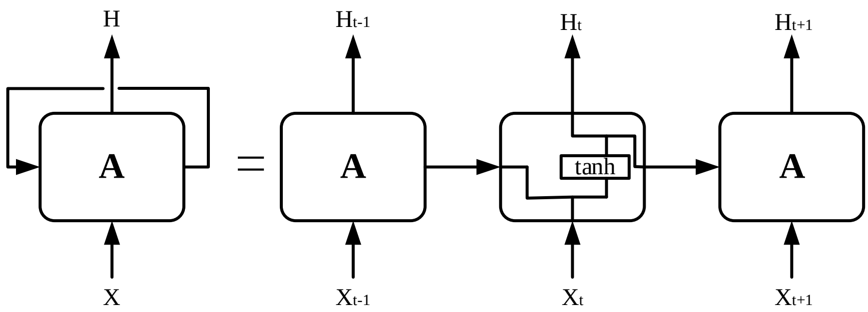

Fig. 1 The recurrent structure of RNN

Among them, $X=(x_1, x_2 \cdots, x_t)$ is input sequence information, and $H=(h_{0,} h_1, \cdots, h_t)$ is the state vector at the corresponding moment. RNN is composed of input layer, hidden layer, and state layer. RNN recurrent neural network has a certain memory.However, there is a problem of long-term dependence, because the predicted value relies too much on the historical data, it is difficult for a simple RNN to learn the corresponding information.The main idea of LSTM is to use gating to control the weight of the self-loop, instead of the traditional fixed weight. The weight of the LSTM unit takes into account all inputs, that is, the weight of the current time step is determined by the input context information. This feature makes that even if the parameters of each LSTM unit are the same, it will dynamically change at each time step due to the different input context information of the current time step. So we can learn the long-term sequence dependency. The specific structure is shown in Figure 2:

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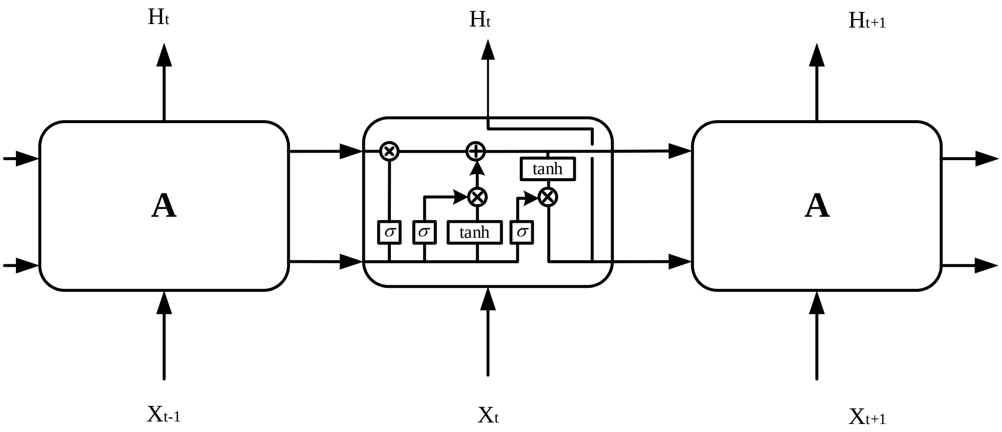

Fig. 2 The memory module of LSTM

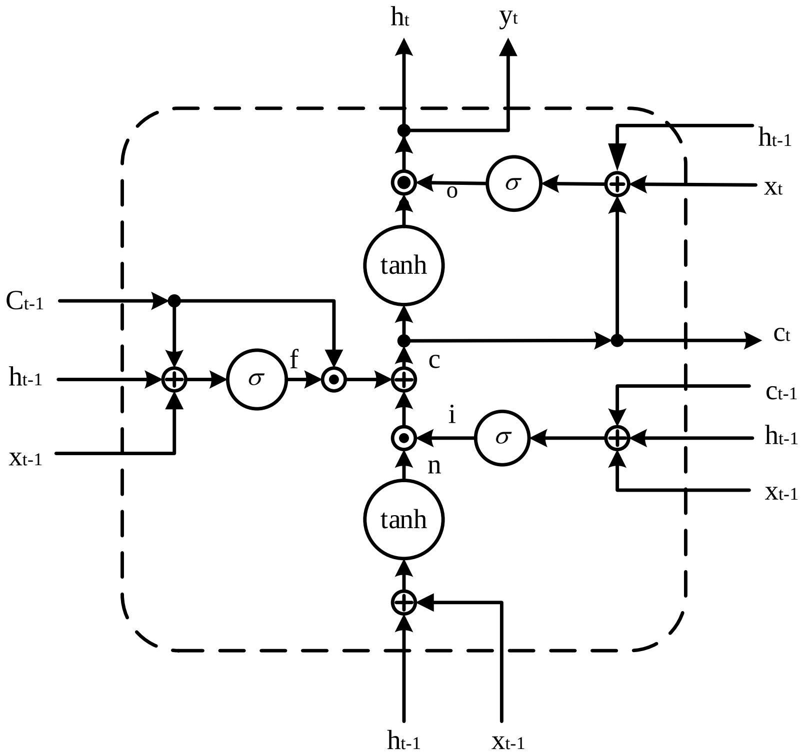

Fig. 3 LSTM hidden layer cell structure

The LSTM network has three gate structures: input gates, forget gates, and output gates to maintain and update the cell state. The $sigmoid$ layer of the forget door mainly determines the forgetting information from the cell state. The information stored in the cell is mainly composed of two parts: one is the $sigmoid$ layer determined by the input gate; the other is the new vector created by the $tanh$ layer to update the old cell state (forget the old information and save the new information). The output information is determined by the output gate. Firstly we use the $sigmoid$ layer to determine the part of the cell state information to be output, and then use $tanh$ to process the cell state. The product of the two parts is the output value. The forward propagation of the LSTM recurrent neural network can be expressed as:

$$i_t = \delta(W_i x_i + U_i h_{i-1} + V_i c_{i-1} + b_i) \tag{1}$$

$$f_t = \delta(W_f x_t + U_f h_{i-1} + V_f c_{t-1} + b_f) \tag{2}$$

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$$c_t = f_t \cdot c_{t-1} + i_t \cdot \tanh(W_c x_t + U_c h_{t-1} + b_c) \tag{3}$$

$$o_t = \delta(W_o x_t + U_o h_{t-1} + V_o C_t + b_o) \tag{4}$$

$$h_t = o_t \cdot \tanh(c_t) \tag{5}$$

Among them c_t represents the calculation rule of the LSTM cell at time t; h_t represents the output of the calculation unit at time t; W, U and V are all parameter matrices; b represents the offset item; $\delta(\cdot)$ is the sigmoid activation function used in this article; $\tanh(\cdot)$ is the hyperbolic tangent activation Function; i_t, f_t, o_t respectively represent the calculation rules of output, forget gate and output at time t.

The pipe gallery environment prediction model based on LSTM recurrent neural network includes an input layer, a hidden layer and an output layer: the training framework is shown in the figure:

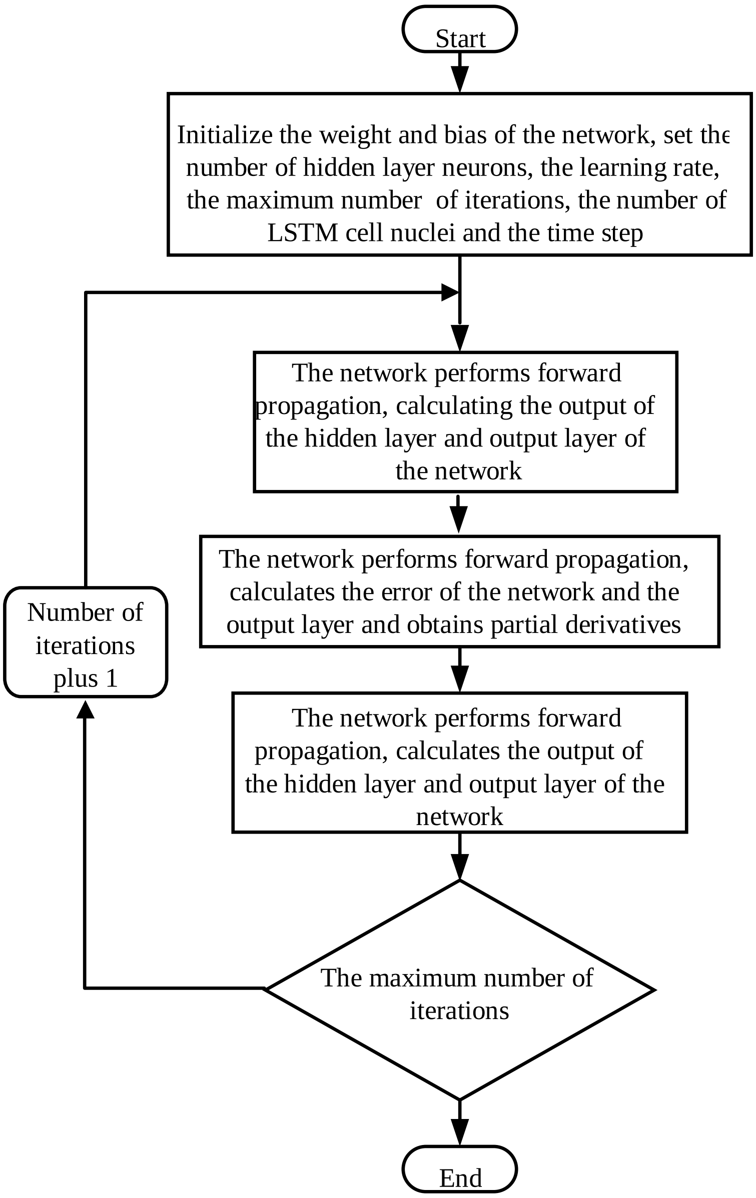

Fig. 4 Model training framework

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The long-short term memory neural network is trained by the Back Propagation Through Time (BPTT) algorithm. The error is counterpropagated through the time dimension.The gradient optimization algorithm uses the Adam algorithm for optimization. This algorithm combines the advantages of the momentum gradient descent method and the RMSProp algorithm. It can calculate the adaptability of different parameters while occupying less processor resources. Compared with other optimization algorithms, Adam shows a very big advantage in practical use.

3. Analysis of results

3.1 Data declaration

Suzhou Chengbei Road-Chengyang Road pipeline gallery, with a total length of 3.24 kilometers, a total project investment of 324 million yuan, a cross-sectional size of 6.5 meters × 3.65 meters, the pipeline gallery is located in the central green belt of Chengyang Road. There are five types of municipal pipelines for water, electricity, communications, limited cables, and reserved water in the pipe gallery. The pipe gallery is equipped with an electronic real-time monitoring system to facilitate daily maintenance. The source of the data for this design is the actual operating data of the Suzhou Chengbei Road-Chengyang Road Pipe Gallery. The humidity data from January 2, 2019 to January 21, 2019 was selected in the design to realize the content of this design.

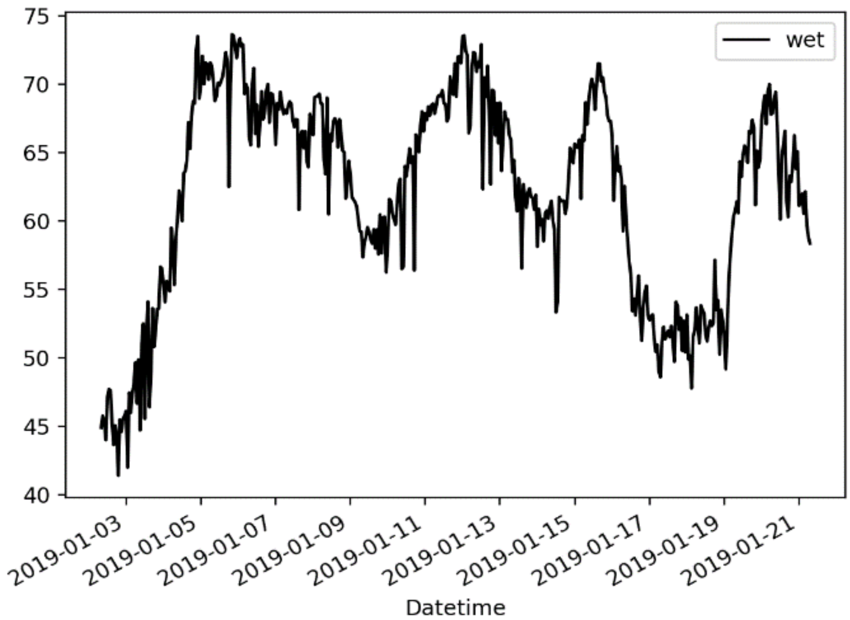

Fig. 5 Humidity data

3.2 Analysis of experimental results

Combined with the humidity data of the pipe gallery of Suzhou Chengbei Road-Chengyang Road, the LSTM prediction model proposed in Chapter 2 is used for experimental verification. A total of 438 hours of data, 395 hours withdrawn for the training set, and the next 43 hours for the test set. The prediction results based on the LSTM recurrent neural network model are compared with the real values. The statistical error is used to evaluate the performance of the LSTM recurrent neural network prediction model. The statistical error is the root mean square error and the calculation formulas are as follows:

$$e_{RMS} = \sqrt{(\sum_{i=1}^{N}(y_{es,i} - y_{a,i})^2 / N}$$

The simulation results are as follows:

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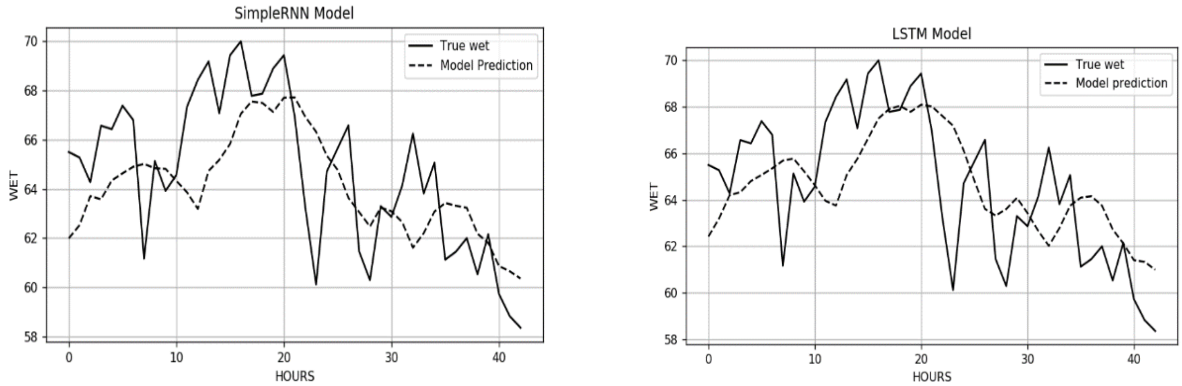

Fig. 6 Humidity prediction results

Table 1. Humidity prediction results of different models

	Simple RNN	LSTM
Test cost	0.0097	0.0088
Test accuracy	0.9903	0.9912
MSE	2.0862	2.0661
Time/s	4.2591	4.1365

As can be seen from Table 1, the accuracy P and MSE values of LSTM model are 0.9903 and 2.0862, respectively. Both evaluation indexes are superior to RNN model, which proves the feasibility and accuracy of LSTM network model in the prediction of environmental humidity of pipe corridor. Moreover, the LSTM network model takes 4.1365s, which is the fastest prediction.

4. Conclusion

The real-time change of environmental parameters is a very dynamic process. With the widespread application of artificial intelligence concepts, how to let computers learn the laws of environmental changes themselves and make predictions has become a research direction and hotspot.

This paper targeted at the safety of underground pipe gallery and an environmental early warning system is designed. The core of the system is the construction of the LSTM pipe gallery humidity prediction model, which realizes the prediction of humidity, thus sets early warning, so that the staff can take timely measures. The measures are taken to ensure that the environment of the underground pipe gallery meets the standards, thereby ensuring the safety of the city.

The fitting and prediction of the LSTM network prediction model is of high accuracy, which proves its feasibility and effectiveness in the pipe gallery, and expands the application scope of the LSTM network.

In addition, there are many directions for further research. With the development of deep learning and the emergence of new models, we can try to change the architecture of the network layer and use a better model for training to adapt to the nonlinear characteristics of the data set.

Acknowledgments

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