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A Case Study: Monitoring and Prediction for Convergence of Shield Tunnel with Wireless Sensor Network and Long Short-Term Network.

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Abstract: Convergence is key indicator of tunnel security and it is of great significance to predict the trend of convergence and give early warning in time based on the previous monitoring data. Wireless tilt sensors have the advantages of real-time monitoring, flexibility and ease of installation, no interruption to tunnel operation and no demand of inter-visibility. A wireless sensor network system is placed in Shanghai Metro Line 1 and Line 2 and the over-10-months returned monitoring data is collected. This paper builds a prediction model for convergence variation of tunnel in soft soil based on wireless tilt monitoring returned data with Long Short-term Memory (LSTM) network and proposes appropriate prediction time step and sampling interval. LSTM method is introduced to analyze the returned monitoring data time series. Prediction results shows that there is a spearman's ρ greater than 0.7 and a Pearson correlation coefficient greater than 0.8 between monitored data and the prediction values 7 steps ago, which demonstrates the prediction model's feasibility. By utilizing the data by certain interval to simulate different sampling interval, the network shows better performance with lager interval and make more detailed prediction with small interval. This paper demonstrates that LSTM network can meet the requirement of accuracy and cost with time steps 7 and sampling interval 12 hours.

Keywords: convergence monitoring; shield tunnel; wireless sensors network; Long Short-term Memory(LSTM) network.

1 Instruction

With more tunnels built, the importance of tunnel risk management and health monitoring is growing rapidly. In current practice, horizontal convergence is key indicator of tunnel section deformation because of convergence's tight link with tunnel defects in cross section like joint opening and concrete crushing and convenience of collection in daily monitoring. At present, the main technologies for convergence monitoring are total station observation technology, digital close-range photogrammetry technology and point direct measurement technology (Li, Xu, & Liu, 2015). These convergence monitoring methods can hardly be regarded as real-time monitoring because of either disturbance to tunnel usage or strict working condition. Considering that real-time monitoring, a convergence monitoring method based on wireless sensor network is proposed and this method has been applied in metro tunnels monitoring and approved effective in many metropolises such as London and Shanghai (Bennett et al., 2010; Huang et al., 2013). A wireless sensor network (WSN) for tunnel convergence monitoring is consist of tilt sensors and gateways and once installed network can monitor the tunnel convergence in preset frequency by segment tilt angle without need for contact or inter-visibility. Furthermore, WSN system can continuously monitor the key parts of the tunnel intensively for a long time, which can get a large amount of monitoring data that shows the characteristics of time series.

In recent years, many researchers proposed many methods for time series data and some methods have been well verified in the field of geotechnical analysis. A monitoring and prediction method based on LSTM method for convergence of mountain tunnel was proposed and the performance of practical engineering application proved the effectiveness (Wang ,2020). However, studies on real-time wireless sensor network security perception and prediction of shield tunnels are still insufficient.

The rest of this paper is structured as follows: first, the project and the WSN system are introduced and monitoring data are preprocessed; second, LSTM network method is used to predict the trend of deformation; third, some discussion about tunnel structure health monitoring are made; finally, reasonable conclusions are drawn.

2 WSN Monitoring System and Data Preprocessing

2.1 Project profile

Shanghai is the city with the longest rail transit mileage (831 kilometers by Dec. 2021) in China. Shanghai Metro Line 1 and Line 2 were built in 1993 and 2000 connecting Shanghai South Railway Station to Shanghai Railway Station, Hongqiao Transport Hub to Pudong International Airport. Tunnel structures of Shanghai Metro Line 1 and Line 2 are both consisted of 6 segments with inner diameter 5.5 meters and segment thickness 0.35 meters. The tunnel structure has been inevitably deformed in the long-term service process. In order to ensure the safe operation of Metro Line 1 and Line 2, the WSN monitoring system is settled at 15 sectione with relatively unfavorable conditions for long-term deformation monitoring.

2.2 WSN monitoring system and layout

WSN is a distributed sensor network, which connects various sensor nodes through wireless communication technology. WSN system includes data acquisition node, relay node, gateway and cloud server. The monitoring data is collected by data acquisition node, transmitted to the gateway through the relay node based on ZigBee communication protocol, and finally transmitted to the cloud server through the 4G network. In the monitoring process, authorized users can use any mobile terminals at any time to process and analyze the monitoring data in the cloud server. The data acquisition nodes are shown in Figure 1 and the parameters of two kinds of node are shown in Table 1. WSN monitoring system can control the monitoring frequency artificially to accommodate different requirements. In this paper, the frequency of monitoring system is set to one time per 20 minutes for real-time monitoring.

(a) (b)

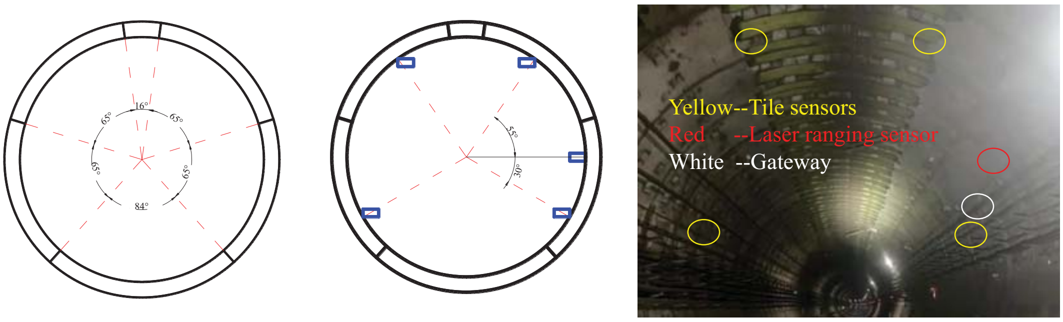
Figure 1. Data acquisition nodes object picture (a)tilt sensor; (b) laser ranging sensor

Table 1. Parameters of data acquisition nodes

Node	Tilt sensors WISENMESHNET® 1305	Laser ranging sensors WISENMESHNET® 1F06
Range	from -90° to 90°	from 0.05m to 33m
Accuracy	72″	0.5mm
Resolution	0.36″	0.1mm
Weight	0.43kg	Less than 0.65kg
Size	80mm*75mm*57mm	100mm*100mm*60mm
Waterproof	P6	P6

Shield tunnel lining is consisted of numbers of prefabricated segments and its deformation can be regarded as superposition of segment deformation and joint deformation. Research shows that the deformation of shield tunnel is dominated by the shield segment rotation around the joint and the deformation of segment itself only effect little on the structure deformation (Wang, 2016). Theoretically, the deformation of tunnels' cross-section is mainly determined by the relative rotation of segments. This mechanism provides a new monitoring method for convergence variation that can be obtained by segment inclination variation.

Research shows that under the condition of symmetrical deformation, the ideal installation position of tilt sensor node on both sides is about 120 degrees away from arch roof where the variation of inclination monitoring data is almost the same as the segment rotation angle around joint (Wang, 2020). In order to perceive the deformation of tunnel cross section more accurately, another two tilt sensors are installed at 35 degrees from the arch roof. In addition, to obtain the real convergence data, a laser ranging sensors is installed at about the horizontal diameter position and the return data will be regarded as the truth value after processing. In total, four tilt sensors and one laser ranging sensors are applied in a monitoring section. The layout of WSN monitoring system is shown in Figure 2.

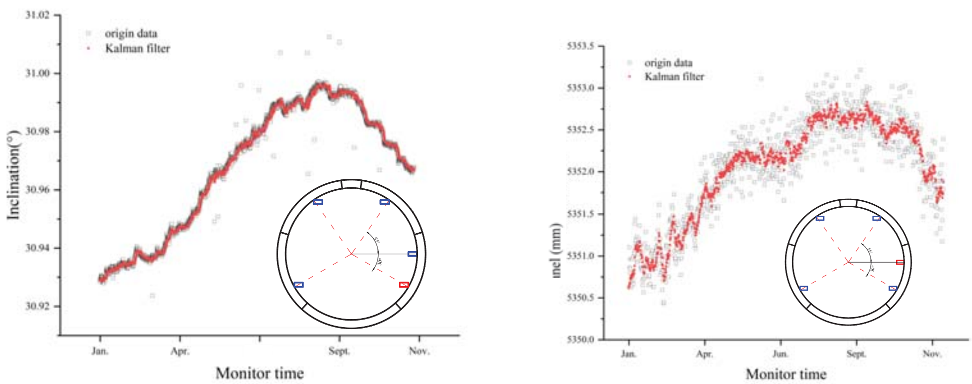


(a) (b) (c)

Figure 2. (a) six-segments metro tunnels (b) WSN layout (c) WSN layout on site

2.3 Monitoring data preprocessing

To consider tunnel deformation as quasi-static problem in long-time deformation monitor, data preprocessing is introduced to reduce the influence of vibration caused by normal operation of metro line. The Kalman filter algorithm can real-time denoise data without variation of data size (Kalman, 1960). In essence, it is carried out through the cycle of prediction, measurement and correction. The measured values are used to reconstruct the system state parameters, eliminate random interference, reduce uncertainty, and carry out the optimal estimation of the system state. Therefore, Kalman filtering algorithm is used to denoise the monitoring data in order to reduce the impact of noise data and high frequency cyclic loads such as train vibration. For some missing data caused by train block-out, linear interpolation method is used to complete. The error of the denoised data is within the acceptable range, and the data are more reasonable and credible. How the data preprocessing works is shown in Figure 3.



(a) (b)

Figure 3. Data preprocessing for return data of (a) tile sensor and (b) laser ranging sensor

3 Tunnel Convergence Time Series Prediction

3.1 LSTM network

Long short-term memory (LSTM) network is a modified recurrent neural network (RNN) and LSTM network improves the performance when facing the long-term dependence problem (Hochreiter & Schmidhuber,1997). LSTM network introduce the gate mechanism to control iteration and loss of features. Each LSTM unit has three gates: input gate, output gate and forget gate. Input gate decide whether the new information will be remembered; forget gate decide whether the old information will be forgotten and output gate decide what information the cell will pass to next cell. The renewal of memory cell state comes from new information (input gate), remaining information (forget gate) and the memory cell state in last time (output gate of last cell). Compared with traditional RNN network, LSTM can weight value of information and choose to remember more useful information with the gate mechanism, so LSTM will perform better in time series data analysis.

3.2 Monitoring section convergence prediction

This paper builds a 3 layers LSTM network to predict the tunnel convergence with the inclination monitoring data. The first and the second layers are both LSTM layers with dimensionality of the output space 8 and the last layer is fully connected layer where all the vector are use as input to calculate a value. The preprocessed data is used to train the LSTM network. The ratio of the training set to the test set is 2:1. The inclination monitoring data is used as input data(X) and the return values of laser ranging sensor is regarded as truth value(Y). To avoid overfitting and keep generalization performance of LSTM network, L2 regularization is introduced as penalty.

The parameters of data processing and hyperparameter of this network is shown in the Table 2. This final loss function of training process is shown in Eq. (1).

Table 2. The parameters of data processing and hyperparameter of LSTM network.

Sampling interval /h	LSTM layers	Epoch	Batch size	Moving time window /timestep	Prediction time gap /timestep	Loss function	L2 regularization parameters λ
8	2	1500	128	30	7	Mean squared error	0.001

$$Loss = \frac{1}{n}\sum_{i=1}^{n}(y_i - \bar{y})^2 + \frac{\lambda}{2n}\sum_{w} w^2 \tag{1}$$

Shanghai is divided by two parts by Huangpu River and many metro lines, urban roads and bridges share the traffic pressure of going across the river. In this project, the WSN monitoring system is applied at ring 710 of tunnel between East Nanjing Road-Lujiazui where underlying at the bottom of the Huangpu River connecting the east and west of Shanghai together and the return data of this section is used as samples for network training and prediction.

Before building LSTM network, the monitoring data is sampled with 8 hours interval to simulate that the monitoring system work at a frequency of 3 times per day. The historical data moving time window and prediction time gap are set to 30 and 7 artificially. That is, the prediction task of LSTM network is to get the predicted value in the future (after 7 timesteps) based on the historical monitoring data (30 timesteps), as shown in Eq. (2). The detail of monitoring data and prediction value is shown in Figure 4. LSTM performs very well in either trend or values with high correlation and low mean squared error which are shown in Table 3. LSTM network prediction can more accurately reflect the deformation details of tunnel monitoring cross section. It is certified that prediction for variation of convergence after 7 timesteps can satisfy the precision requirement.

$$X_{(t-29):t} \xrightarrow{\text{LSTM network}} Y_{t+7} \tag{2}$$

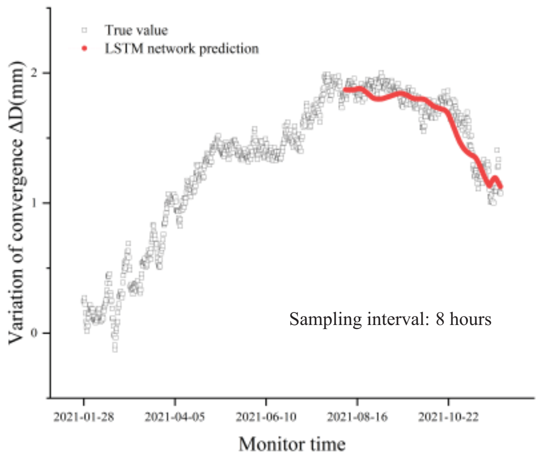


Figure 4. Prediction for horizontal convergence of Ring 710 in East Nanjing Road-Lujiazui (Line 2) with 8h sampling interval

Table 3. LSTM neural network evaluation index with sampling interval 8h

Set	Mean squared error	Pearson correlation coefficient	Spearman's ρ
Train set	0.0067	0.989	0.968
Test set	0.0108	0.922	0.815

4 Discussion

4.1 Analysis of monitoring results

The deformation of operation tunnels usually comes from the impact of dead load like self-weight load, live load like train load and dynamic load. For shield tunnels in soft soil area, vertical load provided by overlying soil pressure and subgrade reaction is usually larger than horizontal load provided by lateral pressure of soil. Hence, most of round metro operation tunnel section in Shanghai tend to be elliptical with longer horizontal diameter and shorter vertical diameter. In addition, the elliptical tunnel has more area in horizontal direction which cause lager vertical load promoting tunnel more elliptical.

Monitoring results shows that from January to July, the horizontal convergence is increasing reaching a high in a year on July, stay in high until September and begin to decrease from October. Rainy season in Shanghai begins at the end of March and lasts till end of September. Heavy rains occur more frequently in the rainy season than in dry season and cause water level of the Huangpu River rise and stay in high position and when rainy season ends, the water level begins to fall. Higher water level cause higher water pressure on the tunnel underlying the river and make horizontal convergence bigger, the joint pressed on the inside of tunnel and open on the outside.

4.2 Performance of LSTM network under different sampling interval

Sensors in WSN monitoring system is powered by battery and battery will run out faster in high monitoring frequency. In past one-year monitoring, the monitoring frequency is set to 1 time per 20 minutes, and in such a high frequency the incoming manual maintenance will bring extra burden to manager. Appropriate monitoring frequencies need to be determined to balance the cost and of monitoring system and performance of prediction. The return data is sampled in certain time interval to simulate the situation where monitoring frequency is set to the same as sampling time interval. LSTM networks which have same parameter in Table 2 are trained by the data after sampling and the performance of prediction will also be evaluated by mean squared error, Pearson's correlation coefficient and Spearman' ρ.

With the sampling time interval increasing, the performance of network better however prediction become less detailed and the detail performance is shown in Table 4 and Figure 5. Large sampling interval helps to make a long-term but relative rough prediction and small sampling interval helps to make a short-term but detailed prediction which will works better when small disturbance occurs in a short time. Managers can choose sampling time interval considering their need and cost of monitoring system. Since only one monitoring section is considered in this paper, the selected data cannot reflect the deformation law of tunnel under various deformation modes. Therefore, for different monitoring sections, the hyperparameters in LSTM neural network still need to be adjusted.

Table 4. Performance of LSTM network with different sampling interval

Evaluation index	Mean squared error				Pearson correlation coefficient				Spearman's ρ			
Sampling time interval	1h	2h	4h	12h	1h	2h	4h	12h	1h	2h	4h	12h
Train set	0.0176	0.0170	0.0141	0.0121	0.977	0.976	0.980	0.983	0.952	0.952	0.960	0.955
Test set	0.0341	0.0296	0.0172	0.0119	0.807	0.832	0.896	0.931	0.740	0.806	0.720	0.867

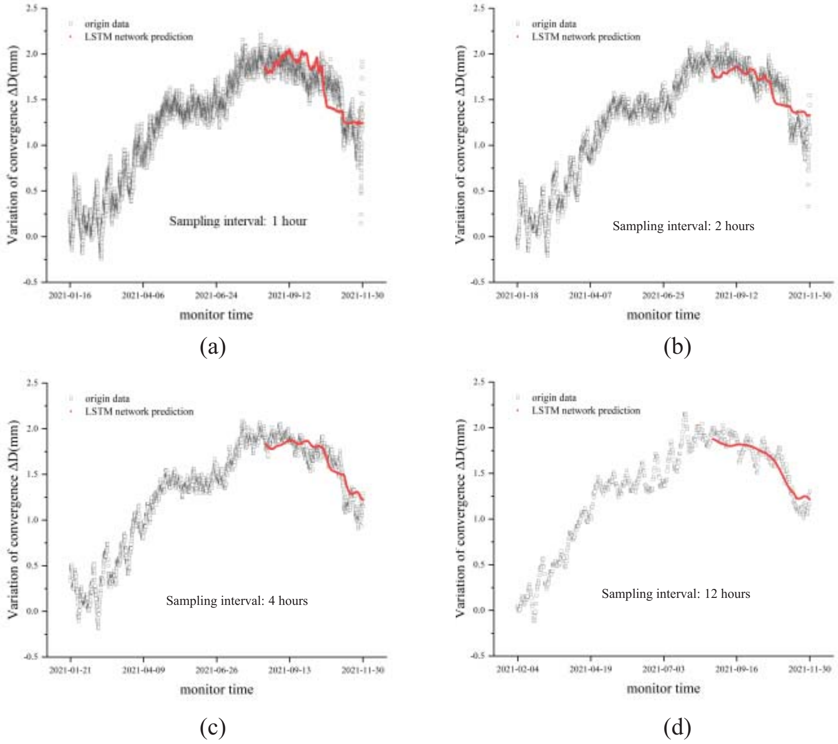


Figure 5. LSTM network performance under sampling time interval (a) 1 hour (b) 2 hours (c) 4 hours (d) 12 hours

5 Conclusion

Based on WSN system in shield tunnel of Shanghai Metro Line 1 and Line 2, this paper uses LSTM network to predict the convergence deformation of monitoring position based on the time series of monitoring data. The main conclusions are as follows:

(1) The WSN system is deployed in the shield tunnel of Shanghai rail transit, and the dip angle and horizontal convergence of the monitoring section are effectively monitored, which proves that the WSN system has certain engineering feasibility and application value for long-term deformation monitoring of shield tunnel during operation.

(2) The LSTM network is introduced to predict the convergence deformation value of shield tunnel. With machine learning method, large amount of data obtained by WSN system can more accurately reflect the process of tunnel section deformation.

(3) The performance of convergence prediction LSTM network under different monitoring frequency is tested. Effectively selecting the appropriate frequency can reduce the monitoring cost and improve the monitoring accuracy.

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