Research on Dynamic Perception Algorithm for High Speed Maglev Track Irregularity

Sansan Ding¹, Fujie Jiang¹, Xiangdong Sun¹, Jingyu Huang², Dongshuai Li² and Huibai Li²

¹ CRRC QINGDAO SIFANG CO., LTD, Qingdao 266000, China
² School of Tongji University, Shanghai 201804, China
Email: lifrankli@qq.com

Abstract. The high-speed maglev track irregularity is an important factor affecting the safety and stability of high-speed maglev trains. Based on the basic principle of high-speed maglev vehicle orbit, the deep neural network is used to establish the relationship between the vibration acceleration of the vehicle body and the track irregularity, so as to realize the real vehicle detection of the track irregularity. The results show that the relative error of the prediction of the track irregularity by the deep neural network is 6.04%, which basically meets the actual measurement requirements in the project. At the same time, it is demonstrated that the model with 8 input nodes has higher prediction accuracy and the high-speed maglev track is not smooth. Measurement provides theoretical support.

1. Introduction
Track irregularity is the main source of disturbance of train vibration, which is the main reason for the action between the rails. It has an important impact on the safety, stability and passenger comfort of the train. As a new type of traffic transportation mode, the high-speed magnetic floating system has the characteristics of wheel-rail non-contact type, which guarantees a significant increase in speed compared to the wheel-rail. It is expected to lead a new generation of transportation technology revolution. However, its high speed makes the dynamic effect of the high-speed maglev vehicle and the line more obvious, and the train vibration effect caused by this is also more serious. Therefore, it is necessary to conduct in-depth research on the irregularity of the high-speed maglev track.

2. High-Speed Maglev Track Irregularity Research Method
In the current track irregularity measurement of high-speed maglev, the main system used is still based on the principle of inertial reference method [1], on the maglev train The laser displacement sensor and the acceleration sensor are arranged, and the irregularity of the maglev track plate is calculated by solving the secondary integral of the acceleration. Literature [2, 3] indicates that there is hysteresis between vehicle vibration and track irregularity, so the orbit at the change point is calculated using the acceleration of the current point. It is not reasonable to be not smooth. The inertial reference method can only be applied to the irregularity of the track, and the calculation accuracy error for the horizontal irregularity is large [2].

At present, with the continuous improvement of computer computing power, using the basic principle of inertial benchmarking method combined with deep learning platform to study the dynamic response of vehicles has become the mainstream of academic research. Literature [4, 5] constructed a
three-dimensional model considering the irregularity of the track, and established a reverse model to identify the track irregularity by the vibration acceleration of the vehicle.

At present, the use of deep learning platform to construct the relationship between vehicle vibration acceleration and track irregularity has the following problems: 1. Constructing a model using a single fully connected network, failing to fully consider the characteristics of the vehicle's hysteresis under the track irregularity excitation; Most of the modeling of high and low irregularities, less research on horizontal irregularities. 2. The amount of data is small, and the model is prone to over-fitting, resulting in poor generalization of the model [6,7].

In summary, based on the theory of vehicle orbit coupling dynamics, this paper fully considers the hysteresis characteristics of vehicle vibration and irregularity excitation, makes reasonable adjustments to the model structure, and constructs a model suitable for track smoothing state detection based on the vehicle body dynamics policy. Data model verification, the model can be applied to the track smoothing state detection scene.

3. Maglev Vehicle-Track Coupling Dynamics Principle
The structure of the maglev vehicle is mainly composed of a vehicle body and a suspension frame, and the upper part of the suspension frame and the bottom plate of the vehicle body pass through an air spring. The rocker arm, the swing rod, the traction rod and the like are connected, and the suspension frame is a vehicle shape-removing mechanism, and the function is to load the electromagnet, and transmit the suspension force, the guiding force, the traction force and the braking force to the vehicle body through the second-line suspension system. The structure of the secondary suspension system mainly includes air springs, bolsters, pendulum bars, lateral springs (or rubber), etc., to ensure the stability of the vehicle operation.

After analysis, it can be seen that the following kinematic relations exist between the various components of the TR08 maglev vehicle:

1. The suspension frame has six degrees of freedom of telescopic, sunken, traversing, rolling, nodding and shaking. The suspension and guiding electromagnets are elastically connected to the suspension frame. The suspension electromagnet considers the two degrees of freedom of floating and nodding relative to the suspension frame. The guiding electromagnet considers two degrees of freedom of traverse and shaking.

2. The anti-rolling bolster is connected to the suspension frame by a rotating pin, and has a degree of freedom of roll movement relative to the suspension frame, and the left and right bolsters are elastically connected by the rubber member.

3. The car body also has the same six degrees of freedom of movement as the suspension frame. The pendulum rod is connected to the suspension frame, and the pendulum bar rotates in the x and Y directions with respect to the bolster and the car body.

4. One end of the traction rod is connected by the arm seat at the bottom of the vehicle body, and the other end is elastically connected to the suspension frame, which plays the role of transmitting longitudinal force, and has the freedom of movement in the Y direction of the rotating arm seat.

The TR08 has a total of 138 degrees of freedom, as shown in table 1.

4. BP Neural Network
BP neural network is a neural network trained according to the error back propagation algorithm. It generally includes three structures: input layer, hidden layer and output layer, as shown in figure 1.

The BP neural network mainly consists of two stages, the forward propagation stage, the input layer obtains the output layer through the BP neural network, and obtains the predicted value of the output vector; the error back propagation stage calculates the error between the predicted value and the output value, thereby The propagation algorithm adjusts the weight distribution in the BP neural network. Therefore, the main calculation steps of the BP neural network algorithm are as follows:

1. Set the initial weight of the BP neural network $\omega_j^{(0)}$, $b_j^{(0)}$. 


Table 1. Freedoms of Components of a Single Vehicle.

| Vehicle parts  | Telescopic | Traverse | Sinking | Rolling | Nodding | Shaking head |
|----------------|------------|----------|---------|---------|---------|--------------|
| Car body       | √          | √        | √       | √       | √       | √            |
| Bolster        | -          | -        | -       | -       | -       | -            |
| Suspension     | √          | -        | -       | -       | -       | -            |
| Suspension electromagnet | - | √      | -       | -       | -       | -            |
| Guided electromagnet | - | -      | -       | √       | -       | √            |

3. Back Propagation (BP)

2. Forward propagation phase:
To calculate the output value of the jth node of the lth layer, the forward propagation formula is as follows:

\[ z_j^l = \sum_{i=1}^{n} a_{ij}^{l-1} w_{ij}^l - b_j^l \]

(1)

Let:
\( a_{ij}^{l-1} \): The weight of the i-th node from the l-1th layer to the j-th node of the l-th layer
\( a_j^l \): Output value of the i-th node of the l-1th layer
\( b_j^l \): Offset value of the jth node of the 1st layer
\( z_j^l \): Output value of the jth node of the first layer
Let the output value of the final i-th node $\hat{y}_i$, the real value, define the error function, and the derivative of the calculation error with respect to each weight is:

$$
\frac{\partial E}{\partial \omega_{ij}} = \frac{\partial E}{\partial a_j} \frac{\partial a_j}{\partial z_j} \frac{\partial z_j}{\partial \omega_{ij}} = \frac{\partial E}{\partial a_j} g'(z_j') \omega_{ij}^{l-1}
$$

(2)

4. Weight update

$$
\omega_{ij}^{(t)} = \omega_{ij}^{(t-1)} - \eta \frac{\partial E}{\partial \omega_{ij}}
$$

(3)

Let $\eta$ learning rate.

5. Track Irregularity Prediction Based on BP Neural Network

In this paper, the high-low magnetic irregularity of K0+000-K2+880 2880 m is measured in a certain place. The sampling interval of the irregularity is 0.024m, and there are 12000 sampling points in the section. Based on the theory of vehicle orbit coupling dynamics, with reference to the dynamic characteristics of the TR08 model of the Shanghai high-speed maglev demonstration line, the telescopic, traverse, ups and downs, roll, nod and head movements between the vehicle body and the suspension frame are fully considered, and 138 is established. The multi-body dynamics model of degrees of freedom uses simpack to construct the multi-body dynamics model of the above TR08 vehicle, as shown in figure 2.

![Figure 2](image_url)

Figure 2. High Speed Maglev Vehicle-Line Dynamic Model.

A three-axis acceleration sensor is respectively arranged in the front and rear of the vehicle body for measuring the vertical vibration acceleration of the vehicle body in the section, and the measured vertical acceleration vibration curve of the vehicle body is shown in figure 3.
5.1. Data Preprocessing

Data preprocessing is mainly divided into data enhancement and data normalization. Data enhancement is a commonly used method in deep neural networks to solve the problem of less data. In this case, the 1*120000 uneven vector can be equally divided into 2000*60 two-dimensional matrices, and a single sample uses 60 points to predict the track irregularity, which can expand the sample size. Data normalization is to eliminate the dimensional impact between indicators and to resolve comparability between data indicators. At the same time, the convergence speed is accelerated. The commonly used data normalization methods have maximum and minimum normalization and mean variance (Z-score) normalization. In this case, the maximum and minimum normalization are used. The formula is as follows:

$$\overline{X} = \frac{X - \max(X)}{\max(X) - \min(X)}$$  \hspace{1cm} (4)

5.2. Construction of BP Neural Network

The construction of the BP neural network is mainly to reasonably select the number of network layers and the number of input parameters, including:

5.2.1. Number of Network Layers. The number of network layers depends mainly on the number of sample sizes. The deeper network layer can fit the training set to the greatest extent, but it will reduce the generalization ability of the model, the comprehensive sample size and the comprehensive consideration of the track irregularity nonlinearity. Prediction of track irregularity using a 3-layer BP network

5.2.2. Number of Input and Output Parameters. After the data of 5.1 is enhanced, the input dimension of a single sample becomes 1*60, and the following BP neural network can be constructed to predict the sequence characteristics of input and output. The process is shown in Figure 4.
Can be expressed by
\[
\delta_i = f(a_i, a_{i+1}, ..., a_{i+k})
\]  
(5)

Let: \( f \) : Expression for generalized BP neural network.

Therefore, the selection of the input parameter \( k \) in the BP neural network will directly determine the effect of the model. In this case, a single hidden layer neural network with \( k \) from 5 to 12 is designed to predict the track irregularity.

6. Neural Network Prediction Accuracy Analysis

The vehicle's vibration response data is modeled and analyzed using a single hidden layer BP neural network with 5-12 input nodes. The final error is measured by mean square error (MSE) and relative error (MPE). The effect is as follows in Table 2.

| Input Nodes | Training set | Valid set |
|-------------|--------------|-----------|
|             | MSE (mm^2)   | MPE (%)   | MSE (mm^2) | MPE (%) |
| 5           | 0.111937     | 8.44      | 0.104547   | 12.96   |
| 6           | 0.10391      | 7.56      | 0.10097    | 8.93    |
| 7           | 0.096139     | 6.59      | 0.094647   | 6.37    |
| 8           | 0.087592     | 5.97      | 0.083574   | 6.04    |
| 9           | 0.080686     | 5.48      | 0.102337   | 7.26    |
| 10          | 0.064596     | 5.02      | 0.102056   | 8.54    |
| 11          | 0.048136     | 4.88      | 0.1161     | 9.91    |
| 12          | 0.016748     | 4.71      | 0.012016   | 11.72   |

From the results of the BP model, it can be seen that:

1. Using the BP neural network model can better predict the track irregularity, the average relative error is 5.02%, the error is the largest, and the measurement accuracy of the track height and roughness is initially satisfied.

2. From the relationship between the MSE and the number of input nodes, it can be seen that as the number of input nodes increases gradually, the initial training loss and the valid loss gradually decrease, which proves that the model can fit the data well and the model. The generalization ability is also increasing, and then the training loss is decreasing, but the valid loss is rising, which proves that although the model can fit the training set well, the generalization ability of the model decreases.
In summary, combined with the degree of fitting of the model to the data set and the comprehensive consideration of the generalization ability of the model, the number of input nodes of the model is determined to be 8 nodes.

7. Conclusion

According to the changing characteristics of the track irregularity, according to the basic principle of high-speed maglev vehicle track system dynamics, the vehicle track coupling dynamics model is constructed by simpack, and the dynamic vibration response of the vehicle body under the irregularity of the track is calculated. The BP neural network is used to achieve high-precision measurement of track irregularity according to the vehicle vertical vibration acceleration.

From the prediction results of the model, the training model of the 8-input node has better performance in both the generalization performance and the training set fitting degree. Subsequent increases in the number of nodes do not lead to further improvements in model generalization performance.

Acknowledgments

This work was financially supported by National "13th Five-Year" Plan for Science & Technology Support ‘Research on High-Speed Maglev Transportation Engineering key technology’ (2016YFB1200602) fund.

Reference

[1] Wu Xiangming. Maglev train [M]. Shanghai: Shanghai Science and Technology Press, 2003.

[2] Li Huibai, Huang Jingyu. Research on Maximum Longitudinal Slope Value of High Speed Maglev Line[J]. Urban Rail Transit Research, 2018, 21(11): 44-48.

[3] Zhou Hewang. Dynamics simulation analysis of high-speed railway circular curve parameters based on 3D line model [D]. Southwest Jiaotong University, 2014.

[4] Deng Xiaoxing. Research on Dynamics Performance of Medium and Low Speed Maglev Vehicle System[D]. Southwest Jiaotong University, 2009.

[5] Ministry of Housing and Urban-Rural Development of the People's Republic of China, National Development and Reform Commission of the People's Republic of China. High-speed Maglev Traffic Construction Standards (Trial) [S]. Jianbiao 161-2012.

[6] Shi Jin, Feng Yawei, School of Civil Engineering and Architecture, Beijing Jiaotong University, Beijing. Research on main technical parameters of flat vertical curve of high-speed maglev traffic line[J]. 2005 National Doctoral Academic Forum - Transportation Engineering, 2010.

[7] Xie Weimin. Research on simulation model of magnetic suspension vehicle-line coupling dynamics [D]. Southwest Jiaotong University, 2005.