Application of MIV-NARX to Identify Road Roughness

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Abstract. Aiming at the deficiencies in the existing research on road roughness recognition based on neural networks, the road roughness and 16 vehicle response data are simulated based on the filtered white noise model and the smoothness seven-degree-of-freedom model, NARX neural network is built to identify road roughness. The coefficient of determination and the root mean square error are introduced as the evaluation indicators of the model, the MIV method is used to evaluate and screen each input response. Research shows that MIV method improves the performance of NARX neural networks, MIV-NARX can effectively identify road roughness.

1. Introduction
Road roughness refers to the deviation of the road surface from the ideal plane. It is usually used to describe the degree of undulation of the road surface. It is the main excitation during the car driving process, which affects the ride comfort, handling stability, component fatigue, transportation efficiency, fuel consumption and so on [1]. Although the traditional pavement roughness measurement method can accurately identify the pavement roughness, it requires special equipment and sensors, which are expensive, inefficient and will cost a lot of manpower. With the development of machine learning and deep learning, the research of using neural network to identify road roughness based on vehicle response appears accordingly. Compared with traditional measurement methods, such methods have advantages such as low cost and simple operation [2].

The recognition methods of road roughness based on neural network mainly include BP neural network [3], RBF neural network [4], Wavelet neural network [5] and NARX neural network [6]. Li et al. have compared these four neural networks and found that NARX neural network is the optimal neural network for recognizing road roughness [7].

Throughout previous studies, it can be found that most of the vehicle ride comfort models select 1/4 vehicle model and half-vehicle model, which results in limited response choices, and road data sampling points are few, which is not convincing. In addition, the research seldom considers the evaluation and screening of each response, the screening method is complicated, and the accuracy of algorithm recognition needs to be further improved. In response to the above problems, a seven-degree-of-freedom model was established to obtain the vehicle ride comfort evaluation index, the NARX neural network was used to identify the road roughness, and MIV was selected as an index to evaluate the importance of each response to the dependent variable. Screening is carried out to determine the optimal plan, in order to provide a theoretical and methodological basis for practical applications.

2. Principle and evaluation index of NARX neural network

2.1. Principles of NARX neural network
The NARX (Nonlinear Auto Regressive models with Exogenous Inputs) is the most widely used neural
network in nonlinear dynamic systems. Because the neural network contains multi-step input and output delays, it can reflect the historical state information of the system, it can be defined as:

\[ y(t) = f[y(t - 1), y(t - 2), \cdots y(t - ny), x(t - 1), x(t - 2), \cdots x(t - nx)] \]  

(1)

Where \( f(\cdot) \) represents the nonlinear process function implemented by neural network, and its structure is shown in Figure 1.

![Figure 1. The structure of NARX](image)

2.2. Evaluation Index

Determination coefficient \( (R^2) \) and root mean square error \( (RMSE) \) are introduced as evaluation indexes:

\[ R^2 = 1 - \frac{\sum_{i=1}^{m}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{m}(y_i - \bar{y})^2} \]  

(2)

\[ RMSE = \sqrt{\frac{\sum_{i=1}^{m}(y_i - \hat{y}_i)^2}{m}} \]  

(3)

Where \( y \) is the true value, \( \hat{y} \) is the predicted result, \( \bar{y} \) is the mean value of the true value, and \( m \) is the number of samples.

\( R^2 \) is generally used in the regression model to evaluate the degree of agreement between the predicted value and the actual value. The closer \( R^2 \) is to 1, the better the interpretation of the dependent variable by the independent variable in the regression analysis; \( RMSE \) represents the stability of the recognition results; the smaller the value, the better and more stable the recognition result.

3. Smoothness model of seven degrees of freedom

3.1. Filtered white noise model of four-wheel road roughness

The simulation methods of road roughness include harmonic superposition method, white noise filtering method, inverse Fourier transform method and time series model method, among which white noise filtering method is the most common method used at present.

For the white noise filtering method, the road roughness of the left front wheel \( q_1(t) \) can be expressed as:

\[ \dot{q}_1(t) = -2\pi n_u u q_1(t) + 2\pi n_0 \sqrt{G_q(n_0)} u w(t) \]  

(4)

Where \( n_u \) is the cut-off frequency under space, take 0.01; \( u \) is the vehicle speed.\( n_0 \) is the reference space frequency, set as 0.1; \( G_q(n_0) \) is the road roughness coefficient; \( w(t) \) is the standard Gaussian white noise.

According to the correlation of road roughness of left and right wheels, road roughness of right front wheels \( q_2(t) \) can be expressed as:

\[ \dot{q}_2(t) = \left( \frac{2u}{B} + 2\pi n_u u \right) q_1(t) - \frac{2u}{B} q_2(t) - 2\pi n_0 \sqrt{G_q(n_0)} u w(t) \]  

(5)

Where \( B \) is the wheelbase.

For the input of road roughness of the left rear wheel and the right rear wheel, time delay is added on the basis of the front formula, and the delay time is the ratio of the length of the car body to the speed.

3.2. Seven degrees of freedom model for vehicle comfort

The seven-degree-of-freedom (DOF) model of vehicle comfort includes the vertical motion, pitch
motion and roll motion of the vehicle body and the vertical motion of the four wheels, with a total of seven degrees of freedom.

According to Lagrange's equation, the vibration equation of the vehicle can be obtained as follows:

\[ M\ddot{Z} + C\dot{Z} + KZ = K_fQ \]  

(6)

Where \( Z \) is the displacement vector of each degree of freedom of the vehicle; \( M \) is the mass matrix; \( K \) is the stiffness matrix; \( C \) is the damping matrix; \( K_f \) is tire stiffness matrix; \( Q \) is the input vector of the road surface. Specific parameters can be found in literature [8]

Set \( X = [Z, \dot{Z}]^T \), then the equation of state can be described as:

\[ \dot{X} = AX + BQ \]  

(7)

\[ Y = CX + DQ \]  

(8)

Where \( A = \begin{bmatrix} C & M \\ M & 0 \end{bmatrix}^{-1} \begin{bmatrix} K & 0 \\ 0 & -M \end{bmatrix} \), \( B = \begin{bmatrix} C \\ M \end{bmatrix}^{-1} \). \( C \) and \( D \) are adjusted with the output selection of \( Y \).

4. Road roughness identification

4.1. NARX neural network data source

When considering the input vehicle response, priority should be given to the indexes related to vehicle ride comfort. The indexes of vehicle ride comfort evaluation mainly include: vertical acceleration at center of mass \( \dddot{z}_b \), pitch angular acceleration \( \dddot{z}_{by} \), roll angular acceleration \( \dddot{z}_{bx} \), vertical speed at center of mass \( \dot{z}_b \), pitch angular velocity \( \dot{z}_{by} \), roll angular velocity \( \dot{z}_{bx} \), pitch angle \( \dot{z}_b \), roll angle \( \dot{z}_b \), wheel dynamic load \( F_{d1}, F_{d2}, F_{d3}, F_{d4} \), suspension dynamic deflection \( f_{d1}, f_{d2}, f_{d3}, f_{d4} \), a total of 16 input responses.

The road roughness of the four wheels is obtained from Equations (4) and (5), the vehicle response is obtained from equations (6)-(8). Corresponding models can be built in Simulink. In the actual simulation, a certain car parameter was used, the road surface level was selected as B, the vehicle operating condition was set to a constant speed of 20m/s. The simulation time was set to 100s, so the total number of sampling points was 68324. Taking the left front wheel as an example, the generated road roughness and power spectral density are shown in Figure 2. Take \( \dddot{z}_b \) and \( \dddot{z}_{bx} \) as an example, the simulation results are shown in Figure 3.

![Figure 2. Road roughness and PSD of the left front wheel](image-url)
4.2. MIV assessment

There are 16 vehicle responses that can be used to input NARX, but too many input variables will cause the network size to be too large, the convergence speed to be slow, the computation amount of the network will be increased, and the generalization of the model will be worse. Therefore, input variables need to be filtered to improve the performance of the model. There are many methods to screen input variables, and Mean Impact Value (MIV) is regarded as one of the best indicators to evaluate the correlation of variables in the neural network.

MIV is an indicator used to determine the influence size of input neurons on output neurons. Its symbol represents the relevant direction, and the absolute value represents the relative importance of the influence. The specific operation steps are as follows:

① On the basis of the trained network model, the i-th input variable in the training sample (set as X) is increased by 10% and reduced by 10% on the basis of the original value to form two new training samples X1 and X2;
② Taking X1 and X2 as training samples respectively and calculating on the established neural network, two simulation results Y1 and Y2 can be obtained;
③ Calculating the difference between Y1 and Y2, which is the Impact Value (IV) of the variable on the output Value;
④ Averaging IV according to the number of sample points is the average impact value (MIV) of the input variable on the output;
⑤ The relative contribution rate of the i-th input variable to the output can be further obtained from Equation (9)\(^9\).

\[
\delta_l = \frac{\sum_1^{|MIV|}}{\sum_1^{m}|MIV|} \times 100
\]

4.3. Network Training

The number of neurons in the hidden layer was set as 15. The input delay and output delay were set as 1:2. The activation function was set as trainbr. After network training, the input variables were evaluated by MIV, and then the input variables were screened according to the cumulative relevant contribution rate, and then the neural network was constructed and evaluated. The average value of the evaluation index was taken as the result of five training sessions, as shown in Table 1.

| The cumulative relative contribution | Input variable number | RMSE  | \(R^2\)  |
|-----------------------------------|----------------------|-------|--------|
| 100%                              | 16                   | 0.0049| 0.884  |
| 99.9%                             | 14                   | 0.0047| 0.903  |
| 99%                               | 10                   | 0.0070| 0.781  |
| 90%                               | 8                    | 0.0119| 0.504  |

It can be found that when the number of input variables is 14 is the optimal input scheme, that is \(\hat{z}_{bx}\) and \(\hat{z}_{bx}\) are deleted on the basis of the original 16 input variables. The RMSE is 0.0047, \(R^2\) is 0.903.
Compared with no MIV variable screening, the model has a better fitting effect while reducing the training time. The trained NARX model is used to predict the test set data, and the results are shown in Figure 4. It can be seen that the variation trend of the model fitting results is very similar to the variation trend of the real value.

Figure 4. Prediction results of test set

5. Conclusion
In this paper, the road roughness and vehicle response data are obtained by filtering the white noise model and the smoothness 7-degree-of-freedom model. The NARX neural network model is built to identify the road roughness. The MIV method is used to reduce the number of input responses from 16 to 14, the evaluation index RMSE of the model is 0.0047, and R² is 0.903, indicating that MIV-NARX can effectively identify road roughness.

There are still some limitations in the research. Firstly, the vehicle driving conditions only considers the uniform speed, and the influence of the speed change on the model is not studied. Secondly, the responses of some vehicles are difficult to obtain in practical applications, so it can be considered to use a small amount of easily obtained responses in the Internet of vehicles environment, and rely on the recognition results of multiple vehicles to improve the accuracy of the final road identification. These questions will become the important direction of the follow-up research.

References
[1] Duan H.M, Shi F, Xie F, Zhang K.B. (2009) Summary of Research on Road Roughness. Vibration and Shock, 28(09): 95-101.
[2] Guo X.X, Xu Z, Li M.L, Yang Bo, Wang B. (2009) Summary of Research on Road Roughness Measurement Technology. China and Foreign Highway, 29(05): 47-51.
[3] Zhang Z.W. (2019) Power function model identification of road surface statistical characteristics based on international roughness index and vehicle vibration response.
[4] Mahdi Y, Shahram A, Abbas S. (2010) Road profile estimation using neural network algorithm. 24(3):743-754.
[5] Zhang L, Zhang H, Pan F. (2014) Research on highway surface roughness recognition Structural Engineer, 30(04): 105-111.
[6] Ali S, Shahram A, Reza K. (2012) Road profile estimation using wavelet neural network and 7-DOF vehicle dynamic systems., 26(10):3029-3036.
[7] Ngwangwa H.M, Heyns P.S. (2014) Breytenbach, et al. Reconstruction of road defects and road roughness classification using Artificial Neural Networks simulation and vehicle dynamic responses: Application to experimental data, 53:1-18.

[8] Zhao Q, Wang W, Luo L, Zheng L, Li J. (2017) Time-domain modeling and simulation of car ride comfort based on space model. Science Technology and Engineering, 17(04): 99-104.

[9] Xu G.Y, Peter S, Yang H.L. (2019) Determining China's CO2 emissions peak with a dynamic nonlinear artificial neural network approach and scenario analysis, 128:752-762.