Research on trouble diagnosis method of braking anti-lock system based on vehicle data flow

Tianhao Zhang*, Shuquan Xu† and Fujia Liu†

†Research Institute of Highway Ministry of Transport, No.8 Xitucheng Road, Haidian District, Beijing, 100088, China
*Corresponding author’s e-mail: zfsn_chd@163.com

Abstract. Trouble diagnosis method of anti-lock braking system based on vehicle data flow was proposed. The selection principles of trouble diagnosis parameters and trouble modes were analyzed firstly, then 3 trouble modes and 9 parameters including four wheels’ speed, vehicle speed, brake pedal position, steering wheel angle, lateral acceleration and yaw rate were selected based on SAE J1939, 48 sets of test data were obtained by vehicle trouble simulation test. The test data were pretreated to form 32 sets of training samples and 16 sets of test samples, and then neural network models were trained and validated. The accuracy of the test results reach 100% by adjusting and optimizing smoothing factor values. The results show that the neural network model based on vehicle data flow can achieve accurate trouble diagnosis.

1. Introduction
The braking anti-lock system is one of the active safety devices of vehicle, and it is of great significance to detect or diagnose its troubles in time for safe driving. Traditional trouble diagnosis methods cannot be self-learning, adaptive and real-time analysis and processing. A trouble diagnosis method based on machine learning was proposed in this paper, the safe operation state of vehicles was monitored through real-time analysis and processing of vehicle data flow, which was helpful to improve the level of road traffic safety.

The electronic-signal-assisted diagnosis of troubles was first applied in the field of aerospace and military industry, and then gradually extended to the automotive industry, the core part of which was signal preprocessing, trouble feature extraction, the establishment of appropriate diagnostic model, state recognition and decision making. The detection result of the anti-lock braking system is essentially a pattern recognition problem[1]. The processing methods include fuzzy theory[2], expert system[3-4], neural network[5-6] and so on. The neural network has the advantages of parallel computing, adaptive adjustment and incomplete information[7], which is the preferred solution for fault diagnosis of automobile anti-lock braking system.

There are many researches on trouble diagnosis based on neural network, but there are few researches on fusion analysis based on vehicle real-time data flow. Aiming at the electronic control system of vehicle anti-lock braking system, this paper obtained the data flow of vehicle trouble condition through the real vehicle test, which was used to train and validate the neural network. Finally, the trouble diagnosis function was realized. The technical scheme is shown in figure 1.
2. Neural network model and trouble diagnosis

2.1. Introduction to neural network model
Artificial neural network is a kind of data processing model established under the Enlightenment of biological neural network, which is calculated by a large number of artificial neuron connections, and the input data is modeled by adjusting the weights between neurons, and finally has the ability to solve practical problems. Its connection weights are adjustable. It connects a series of nodes with simple processing power through weights. When the weights are adjusted to appropriate values, the correct results can be output.

2.2. Selection of neural network models
The neural network model is subdivided into different types according to its structural characteristics, which makes it excellent in many fields such as pattern classification, clustering, regression and fitting, optimization calculation and data compression.

The application of trouble diagnosis based on the real-time data flow of the vehicle has the following characteristics: first, it is necessary to process the data flow data in real time, which requires the fast operation speed of the model. Second, the newly collected data should be included in the training sample, which requires the model can be self-adaptive. Third, the number of trouble types will be gradually increases, which requires that the model should have good expansion performance.

The probabilistic neural Network can be regarded as a radial basis function neural network, which combines density function estimation and Bayesian decision theory based on radial basis function neural network. It can realize arbitrary nonlinear approximation, and has the advantages of fast convergence speed, good expansion performance and strong fault tolerance, which is very suitable for real-time processing. Therefore, the probabilistic neural network model is used herein.

3. Trouble diagnosis based on real-time data flow
9 parameters and 3 fault modes were selected, a total of 48 groups of tests were carried out in 4 different driving conditions, the test data were formed by frequency unification and clipping, the probabilistic neural network model was analyzed, and the prediction accuracy of 100% was adjusted by adjusting the optimization smoothing factor.
3.1. Vehicle trouble simulation test

3.1.1. Selection of parameters. It is helpful to improve the accuracy of model prediction and the speed of neural network model operation by selecting the right parameters. 3 principles are set to select parameters.

First, the selected parameters should have significant characteristics. CAN messages contain many parameters, most of which are independent of the working status of the anti-lock braking system. It is not scientific and reasonable to read and collect all of them. Therefore, the selected parameters include parameters directly generated by the anti-lock braking system, parameters directly related to the anti-lock braking system, and parameters that change due to the operating state of the vehicle due to the anti-lock braking operating state.

Second, the number of parameters should be appropriate. The more parameters, the more accurate the model training will be, but the amount of computation will increase exponentially, and the convergence speed will be too slow or even error. Therefore, the number of parameters should be controlled within a reasonable range. According to experience, 8-12 parameters were determined to be selected generally.

Third, the parameters should be easy to obtain, which is related to the configuration of the vehicle. The test vehicle is equipped with electronically controlled brake system, can easily obtain "EBC1", "EBC2", "CCVS1", "VDC2" and other messages data.

In summary, the following 9 parameters were finally determined to be collected, they are “left front wheel speed”, “right front wheel speed”, “left rear wheel speed”, “right rear wheel speed”, “vehicle speed”, “brake pedal position”, “steering wheel angle”, “lateral acceleration”, and “yaw rate”, of which the wheel speed are relative to the front axle. The message name corresponding to each parameter is shown in table 1.

Table 1. Message name corresponding to each parameter.

| Parameters               | Message name                                           |
|--------------------------|--------------------------------------------------------|
| left front wheel speed    | SAE_Chassis__EBC2__Relative_Speed_FA_Left_Wheel        |
| right front wheel speed   | SAE_Chassis__EBC2__Relative_Speed_FA_Right_Wheel       |
| left rear wheel speed     | SAE_Chassis__EBC2__Relative_Speed_RA_1_Left_Wheel      |
| right rear wheel speed    | SAE_Chassis__EBC2__Relative_Speed_RA_1_Right_Wheel     |
| vehicle speed             | SAE_Chassis__CCVS1_E__Wheel_Based_Vehicle_Speed        |
| brake pedal position      | SAE_Chassis__EBC1__Brake_Pedal_Position                |
| lateral acceleration      | SAE_Chassis__VDC2__Lateral_Acltn                       |
| steering wheel angle      | SAE_Chassis__VDC2__Steering_Wheel_Angle_VDC2           |
| yaw rate                  | SAE_Chassis__VDC2__Yaw_Rate                            |

3.1.2. Selection of trouble modes. The selection of right trouble modes is convenient for vehicle trouble simulation test. Similarly, 3 principles were set to determine the trouble modes. First, the trouble should be representative. It is necessary to cover all troubles of a single wheel as much as possible, and to avoid repeated types of troubles. Second, the characteristics of the trouble should be obvious. The trouble should cause obvious changes in the data flow. Third, the trouble should be easy to simulate. In summary, 3 trouble modes were selected to simulate, as shown in table 2.

Table 2. Trouble modes of vehicle trouble simulation test.

| Trouble location           | Simulation operation                  |
|---------------------------|--------------------------------------|
| Sensor of left front wheel | Short circuit                        |
|                           | Adjust the gap so that it has no signal|
| Solenoid valve of left front wheel | Disconnect the power supply          |

3.1.3. Test scheme and data collection. The WABCO heavy duty Truck Tractor (Type: HOWO T7H) was selected as the test vehicle. The Chuangxin Technology CAN Analyzer (Type: CANALYST-II) was used for data collection, The CANalyzer software was used for record and analyze the data.
According to the principle of single variable, the test was subdivided into 16 groups according to the failure mode, test situation and initial conditions. Each group of tests was carried out three times, so that a total of 48 groups of test data were obtained. The specific grouping is shown in Table 3.

Table 3. Specific grouping of the test.

| Trouble modes                      | Road   | Initial state                        | Times |
|------------------------------------|--------|--------------------------------------|-------|
| No trouble                         | Straight/At an initial speed of 30 km/h | 3      |
|                                    | Curve/At an initial speed of 40 km/h  | 3      |
|                                    | Straight/Initial speed 35 km/h, the radius of the curve is 200 m | 3      |
|                                    | Curve/Initial speed 35 km/h, the radius of the curve is 300 m | 3      |
| Short Circuit                      | Straight/At an initial speed of 30 km/h | 3      |
| of Left Front Wheel Speed Sensor   | Curve/At an initial speed of 40 km/h  | 3      |
|                                    | Straight/Initial speed 35 km/h, the radius of the curve is 200 m | 3      |
|                                    | Curve/Initial speed 35 km/h, the radius of the curve is 300 m | 3      |
| Left Front wheel speed sensor gap  | Straight/At an initial speed of 30 km/h | 3      |
| too large leads to no signal       | Curve/At an initial speed of 40 km/h  | 3      |
|                                    | Straight/Initial speed 35 km/h, the radius of the curve is 200 m | 3      |
|                                    | Curve/Initial speed 35 km/h, the radius of the curve is 300 m | 3      |
| Left Front solenoid valve disconnect| Straight/At an initial speed of 30 km/h | 3      |
|                                    | Curve/At an initial speed of 40 km/h  | 3      |
|                                    | Straight/Initial speed 35 km/h, the radius of the curve is 200 m | 3      |
|                                    | Curve/Initial speed 35 km/h, the radius of the curve is 300 m | 3      |

3.2. Training and validation of neural network model

The collected 48 sets of data were preprocessed as training samples and test samples, and then the nonlinear mapping relationship between the real-time data flow of the vehicle and the trouble types was established by training and verifying the probabilistic neural network models.

3.2.1. Data preprocessing. The collected data was processed into training samples and test samples available for the neural network through frequency unification and data clipping.

The transmission frequency of the 9 parameters in the CAN bus is different, as shown in Table 4. In order to reflect the change of parameters value over time, it is necessary to obtain 9 parameter values at the same time point, so the frequency of 9 parameters should be unified. Theoretically, the higher frequency of the data is, the more obvious features are. Therefore, the frequency of all the parameters was unified to 10 Hz.

Table 4. The transmission frequency of the 9 parameters.

| Parameters                                    | Transmission frequency |
|-----------------------------------------------|------------------------|
| Wheel speed, vehicle speed, brake pedal position | 10 Hz                  |
| lateral acceleration, steering wheel angle, yaw rate | 100 Hz                 |

The purpose of data clipping is to make each set of test data have the same length. In order to facilitate the data length, the test data was divided into 3 stages, as shown in Figure 2.

The first stage is the uniform driving stage. After starting up, the vehicle accelerated to the specified by the test and drove at a uniform speed. The duration of this stage is uncertain. In this stage, the vehicle speed is maintained at 30-40 km/h, and other parameter data do not change significantly.

The second stage is the emergency braking phase. This stage is from the moment when the position of brake pedal starts to change from “0” to the moment when the vehicle speed gradually decreases to “0”. The parameters change a lot in this stage. For example, the speed decreases gradually from the initial speed to “0”, and the brake pedal position increases first and then decreases.

The third stage is the end of braking. This stage is from the moment when the vehicle speed decreases to “0” to the end of the test. At this stage, the vehicle speed is always “0”, the brake pedal position is gradually reduced from a certain value to “0”, the rest of the parameters have slight changes, and all parameters no longer change after 2-3 seconds.
Any data that had changed can help improve the accuracy of model predictions. All the data of the second stage and part of the data of the third stage were selected to form training samples and test samples. Finally, 5s data were selected for each group of tests, through the statistical analysis of 48 sets of test data.

3.2.2. Model Training and validation. The training samples are used to establish the parameters of the mathematical model, and the test samples are used to verify the match between the model and the facts. In general, training samples and test samples are independent of each other and use different data. In each set of tests, the data of the first 2 trials of 3 trials were selected as training samples, and the third trials of 3 trials were selected as test samples.

Due to the dimensions of the original test samples are not uniform and the numerical values vary greatly, the convergence performance of the model may decrease. Therefore, it is necessary to normalize the sample data, by converting the formula to limit the input and output data to (0,1) or (-1,1) range. The raw data and the normalized data of the training samples are shown in figure 3.

Characteristic value should be given before training probabilistic neural network model, that is, the output value y in the nonlinear mapping relation. The given characteristic value is shown in table 6.

Different smoothing factor values will affect the training process of the model and the accuracy of the results. The smoothing factor should be selected according to the size of the sample capacity. If the value of the smoothing factor is too large or too small, the result will be inaccurate. In order to select the right smoothing factor and obtain accurate results, different smoothing factor values were selected for calculation and comparison, as shown in Table 6.

Calculation results shows that, if the smoothing factor values is 0.1, the accuracy of the test results is 25%. If the smoothing factor values is 1, 3, 15 and 30, the accuracy of the test results is 93.8%. If the smoothing factor values is 8, the accuracy of the test results is 100%. After repeated tests, if the smoothing factor value is between [6, 11], the accuracy of the test results is always 100%.
Table 5. Smoothing factor values and calculation results.

| Trouble modes                                      | The given characteristic value | 0.1 | 1  | 3  | 8  | 15 | 30 |
|---------------------------------------------------|--------------------------------|-----|----|----|----|----|----|
| No trouble                                        | 1 1 1 1 1 1 1                  |     |    |    |    |    |    |
| Short Circuit of Left Front Wheel Speed Sensor    | 2 2 2 2 2 2 2                 |     |    |    |    |    |    |
| Left Front wheel speed sensor gap too large leads to no signal | 3 3 3 3 3 3 3             |     |    |    |    |    |    |
| Left Front solenoid valve disconnect               | 4 4 4 4 4 4 4                 |     |    |    |    |    |    |
| Calculation results                                | \                            | 25% | 93.8% | 93.8% | 100% | 93.8% | 93.8% |

4. Conclusions and prospects

This paper has given a method of anti-lock braking system based on vehicle data flow. 9 parameters including four wheels’ speed, vehicle speed, brake pedal position, steering wheel angle, lateral acceleration and yaw rate were selected by analyzing the selection principles of trouble diagnosis parameters. 48 sets of test data were obtained by vehicle trouble simulation test, and then probabilistic neural network models were trained and validated. The accuracy of the test results reach 100% by adjusting and optimizing smoothing factor values. The results show that the neural network model based on vehicle data flow can complete accurate trouble diagnosis. However, the most important limitation lies in the fact that the number of troubles simulated and samples are not enough. A further study could research the method of evaluating vehicle power, braking or other performance based on vehicle real-time data flow.

References

[1] HAO Ruru. Bench detection approach and experimental study for auto anti-lock braking system[D]. Chang’an University, 2013. (In Chinese)
[2] QI Cuiqin. Study on automobile ABS faulty diagnosis based on fuzzy theory[J]. Coal Technology, 2010, 29(7):185-189. (In Chinese)
[3] Nameless. Research on the fault diagnose system of automotive ABS based on fault tree and expert system[D]. Hebei University of Technology, 2015. (In Chinese)
[4] Lv Pei. Study of ABS fault diagnoses based on artificial neural network and expert system technology[D]. Wuhan University of Technology, 2013. (In Chinese)
[5] WANG Dejun, LI Meng, WANG Lihua. Fault diagnoses of ABS of vehicles based on BP neural net[C]. China Control Conference, 2010. (In Chinese)
[6] WU Dejun. Fault mode diagnoses for automobile ABS system based on nerve network[J]. Mechanical-electrical integration, 2011(9):95-98. (In Chinese)
[7] WANG Yuhaao. Research on vehicle fault diagnosis based on genetic neural network[D]. Central South University, 2010. (In Chinese)