Research Article

Braking Intention Recognition Method Based on the Fuzzy Neural Network

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This paper focuses on a braking intention recognition method based on the adaptive network-based fuzzy inference system (ANFIS) and the data of braking tests. The displacement of brake pedal and its change rate were selected as the parameters of braking intention recognition; the braking conditions were divided into light braking, medium braking, and emergency braking. The test scheme of braking intention identification was designed, the braking test platform was built based on a vehicle, and the sample data of multiple groups of braking conditions were obtained. The parameters of braking intention recognition were fuzzed, the model of braking intention recognition was constructed based on ANFIS, and the recognition model was trained and tested. For the above three typical braking conditions, the constructed model of braking intention recognition was verified offline by using the data of the braking test. The results show that the proposed braking intention recognition method has high accuracy of braking intention recognition, which provides a theoretical basis for further application research.

1. Introduction

Friction braking by wire, motor regenerative braking, and electromagnetic auxiliary braking are the current research focus and main development directions of vehicle braking technology. Since the braking actuators of friction brake by wire, motor regenerative brake, and electromagnetic auxiliary brake are decoupled from the brake pedal mechanism, accurate and timely identification of the driver’s braking intention is the prerequisite for the normal operation of the above three. The recognition results of braking intention directly affect the distribution strategies of vehicle braking torque, the control effect of friction braking torque, the recovery efficiency of motor regenerative brake, the participation proportion of electromagnetic auxiliary brake, and the comprehensive braking performance of vehicles. Therefore, the identification method of braking intention is one of the key problems of vehicle braking technology, which has attracted more and more attention and research [1].

The identification methods of braking intention may be divided into two categories: the identification method before braking implementation and the identification method during braking implementation. The former refers to identifying the driver’s braking intention by detecting the EEG signals or EMG signals of drivers, driving conditions of vehicles, and external driving environment before braking, which can shorten the braking response time and improve the comprehensive braking performances of vehicles. However, the current relevant technologies are not mature and the reliability of them is not high [2–6]. The latter refers to identifying the driver’s braking intention by detecting the driver’s braking operation signals, driving conditions of vehicles, and external driving environment during braking, which can shorten the braking response time and improve the comprehensive braking performances of vehicles.
mainstream form of braking intention identification methods [11–16]. At present, the braking intention recognition methods mainly include fuzzy recognition algorithm, neural network algorithm, support vector machine algorithm, and fuzzy neural network algorithm. Among them, the fuzzy neural network algorithm combines the advantages of the fuzzy recognition algorithm and neural network algorithm and has obvious advantages in the existing braking intention recognition methods. However, most of the sample data used in the current braking intention recognition methods based on the fuzzy neural network algorithm come from the simulation test platforms, and few test data of vehicle braking are used.

Therefore, this paper explores a braking intention recognition method based on ANFIS and the braking test data of vehicles. The following contents are arranged as follows. In the second section, the braking intention identification parameters were selected, and the braking conditions were divided into light braking, medium braking, and emergency braking. In the third section, the test scheme of braking intention identification was designed, the test platform of vehicle braking was built, and the sample data of multiple groups of braking conditions were obtained. In the fourth section, the parameters of braking intention recognition were fuzzed, the recognition model of braking intention based on ANFIS was constructed, and the recognition model was trained and tested. In the fifth section, the constructed recognition model of braking intention was tested offline to verify the feasibility and effectiveness based on the actual test data.

2. Identification Parameters and Classification of Braking Intention

The essence of braking intention recognition is pattern recognition, and the key of pattern recognition is the selection of recognition parameters. Braking intention classification is not only the premise of braking intention recognition but also the output target of braking intention recognition. From the perspective of the closed-loop system including drivers, vehicles, and driving environment, the braking intentions directly come from the drivers. The braking intentions should be identified and classified with the drivers’ thinking as the core. However, so far, it is difficult for the drivers’ thinking to be read directly and accurately by the electronic control units. Although the braking intention recognition methods based on the drivers’ EEG signals or EMG signals mentioned above can directly detect the drivers’ braking intentions, their reliability and stability are not high enough. Therefore, the vast majority of scholars at home and abroad take vehicles as the core to carry out the research on braking intention recognition technologies.

At present, the parameters used for braking intention recognition mainly include the displacement of brake pedal, the change rate of brake pedal displacement, the acceleration of brake pedal, the force of brake pedal, the speed of vehicle, the braking deceleration, the pressure of the braking master cylinder, the pressure of the braking wheel cylinder, etc. As an exploration of braking intention recognition technology, the brake pedal displacement and its change rate which have good mapping relationship with braking intention were selected as the parameters of braking intention recognition in this paper. And the braking intentions were divided into

Figure 1: Test platform of braking intention identification for the vehicle.

Figure 2: Brake pedal displacement sensor.

Figure 3: Network structure of the first-order ANFIS model.
three types: light braking, medium braking, and emergency braking.

Their main features are as follows:

(1) Light braking: the driver gently steps on the brake pedal, and the displacement and its change rate of the brake pedal are relatively small

(2) Emergency braking: the driver quickly steps on the brake pedal, and the displacement of the brake pedal quickly increases to near the maximum

(3) Medium braking: the driver purposefully steps on the brake pedal, and the displacement and its change rate of the brake pedal are between the light braking condition and the emergency braking condition

3. Obtain Test Data of Braking Intention Identification Parameters

3.1. Design of the Test Scheme for Braking Intention Identification. In this test for braking intention identification, a certain type of car was selected as the test vehicle, the test site was a flat and horizontal road, and the test data were collected by using the VBOX III test system of vehicle performances. According to the identification parameters and classification of braking intention given above, the test data mainly included the brake pedal displacement and its change rate, the speed of vehicle, and the driving track.

The test conditions were divided into emergency braking, light braking, and medium braking. The corresponding test conditions were designed as follows:

(1) Emergency braking: when the driver heard the stop command, he (or she) immediately stepped on the brake pedal with all his (or her) strength, without any preparation

(2) Light braking: after hearing the stop command, the driver gently stepped on the brake pedal, and the vehicle slowed down slowly until it stopped

(3) Medium braking: a simulated obstacle was set in front of the vehicle, and the driver stopped the vehicle purposefully after hearing the stop command

3.2. Construction of the Test Platform for Braking Intention Identification. The test platform of braking intention identification for vehicle based on the VBOX III test system is shown in Figure 1.

The main module and sensors used in the test were as follows:

3.2.1. GPS Locator. Two GPS locators were fixed on the top of the vehicle along the positive direction of the vehicle through suction cups, and the distance between the two suction cups was 1 m. When the vehicle was driving, the two GPS locators worked at the same time, and the speed information and the motion track of vehicle can be obtained.

3.2.2. Brake Pedal Displacement Sensor. The brake pedal displacement sensor with a pull wire was used to measure the displacement of the brake pedal, which is shown in Figure 2. During installation, the main body part of the sensor was fixed on the internal component of the vehicle above the brake pedal firstly; then, one end of the pull wire was pulled out and fixed on the brake pedal. After installation, based on the software of Racelogic VBOX Tools, the initial value of brake pedal displacement was set to zero.

Based on the established test platform of braking intention identification, the multiple groups of braking tests were carried out under the three braking conditions of emergency braking, light braking, and medium braking according to the test plan, to obtain the original data of brake pedal displacement and its change rate with respect to time change during braking. In order to obtain a representative sample data and improve the classification effect of braking intentions, the measured original data were processed by the Kalman filter and intercepted by the test software.

| Parameter name | S      | M      | B      |
|----------------|--------|--------|--------|
| Brake pedal displacement (mm) | 0-28   | 29-43  | 44-70  |
| Change rate of brake pedal displacement (mm/s) | 0-68   | 69-128 | 129-170 |

| Brake pedal displacement/its change rate | 1 | 2 | 3 |
|------------------------------------------|---|---|---|
| S/S                                      | 11| 0 | 0 |
| S/M                                      | 50| 0 | 0 |
| S/B                                      | 1 | 0 | 0 |
| M/S                                      | 39| 77| 0 |
| M/M                                      | 0 | 20| 0 |
| M/B                                      | 0 | 0 | 35|
| B/S                                      | 0 | 3 | 5 |
| B/M                                      | 0 | 0 | 33|
| B/B                                      | 0 | 0 | 27|

| Change rate of brake pedal displacement | S | M | B |
|----------------------------------------|---|---|---|
| S                                       | 1 | 1 | 1 |
| M                                       | 2 | 2 | 3 |
| B                                       | 3 | 3 | 3 |

Table 1: Fuzzification of identification parameters.

Table 2: Statistical results of frequency.

Table 3: Fuzzy inference rules.
4. Modeling of Braking Intention Recognition Based on ANFIS

4.1. Basic Principles of ANFIS. ANFIS is an adaptive neuro fuzzy inference system based on the Takagi-Sugeno model. It uses the learning mechanism of the neural network to automatically extract rules from sample data to form an adaptive neuro fuzzy controller to realize fuzzification, fuzzy inference, and antifuzzification of fuzzy control.

Taking the system with two inputs \(x_1, x_2\) and one output \(y\) as an example, it has the following two fuzzy rules:

Rule 1: if \(x_1\) is \(A_1\) and \(x_2\) is \(B_1\), then \(f_1 = p_1x_1 + q_1x_2 + r_1\).

| Serial number | Displacement | Change rate | Braking intention | Serial number | Displacement | Change rate | Braking intention |
|---------------|--------------|-------------|-------------------|---------------|--------------|-------------|-------------------|
| 1             | 7.69         | 47.07       | 1                 | 19            | 18.95        | 22.72       | 1                 |
| 2             | 63.80        | 167.80      | 3                 | 20            | 42.84        | 144.73      | 3                 |
| 3             | 53.28        | 26.38       | 2                 | 21            | 37.95        | 38.44       | 2                 |
| 4             | 26.36        | 15.49       | 2                 | 22            | 13.21        | 127.00      | 1                 |
| 5             | 16.23        | 30.20       | 1                 | 23            | 41.45        | 138.81      | 3                 |
| 6             | 61.74        | 75.52       | 3                 | 24            | 31.95        | 37.06       | 2                 |
| 7             | 16.63        | 34.93       | 1                 | 25            | 6.14         | 32.94       | 1                 |
| 8             | 31.42        | 39.51       | 2                 | 26            | 67.24        | 113.14      | 3                 |
| 9             | 53.08        | 89.96       | 3                 | 27            | 30.73        | 8.46        | 2                 |
| 10            | 63.33        | 125.73      | 3                 | 28            | 16.92        | 7.51        | 1                 |
| 11            | 11.48        | 40.31       | 1                 | 29            | 9.67         | 35.58       | 1                 |
| 12            | 35.04        | 13.55       | 2                 | 30            | 68.38        | 85.79       | 3                 |
| 13            | 33.81        | 4.53        | 2                 | 31            | 19.83        | 7.03        | 2                 |
| 14            | 11.03        | 31.91       | 1                 | 32            | 48.97        | 163.10      | 3                 |
| 15            | 40.73        | 132.42      | 3                 | 33            | 39.88        | 17.60       | 2                 |
| 16            | 20.50        | 9.20        | 2                 | 34            | 35.15        | 51.36       | 2                 |
| 17            | 17.27        | 35.96       | 1                 | 35            | 17.26        | 17.86       | 1                 |
| 18            | 58.13        | 77.48       | 3                 |               |              |             |                   |

Table 4: Training data samples.

Table 5: Inspection data samples.
The ANFIS model is composed of the adaptive network and the fuzzy inference system, which inherits the interpretability of the fuzzy inference system and the learning ability of the adaptive network. It can change the parameters of the system according to the prior knowledge and make the outputs of the system closer to the real outputs [17, 18].

For the first-order Takagi-Sugeno fuzzy model, the network structure of ANFIS is shown in Figure 3.

Layer 1: fuzzification of input variables. The parameters of this layer are variable. Each node is a square node represented by node function, which can be expressed as

\[
\begin{align*}
O_{i,j} &= \mu_{A_i}(x_1), \quad i = 1, 2, \\
O_{i,j} &= \mu_{B_{(i-2)}}(x_2), \quad i = 3, 4, \\
\end{align*}
\]

(1)

where \(x_1\) and \(x_2\) are the inputs of nodes; \(O_{1,i}\) is the membership function of fuzzy set \(A_i\) or \(B_{(i-2)}\), and the parameters of the membership function are the premise parameters.

Layer 2: operation of the fuzzy set. Multiply the input signals and their product as output:

\[
o_{2,i} = \omega_i = \mu_{A_i}(x_1)\mu_{B_{(i-1)}}(x_2), \quad i = 1, 2. 
\]

(2)

Layer 3: calculate the ratio between each rule \(\omega_i\) and the sum of all rules \(\omega\):

\[
O_{3,i} = \hat{O}_i = \frac{\omega_i}{\omega_1 + \omega_2}, \quad i = 1, 2. 
\]

(3)

Layer 4: calculate each rule’s output as

\[
O_{4,i} = \hat{O}_i f_i = \hat{O}_i (p_i x_1 + q_i x_2 + r_i), \quad i = 1, 2, 
\]

(4)

where \(\{p_i, q_i, r_i\} (i = 1, 2)\) are the conclusion parameters.

Layer 5: calculate the total output of all input signals as

\[
O_{5,j} = \sum_i \hat{O}_i f_i = \sum_i \frac{\omega_i f_i}{\sum_i \omega_i}, \quad i = 1, 2. 
\]

(5)

ANFIS provides a learning method that can extract fuzzy rules from datasets. Through learning, the optimal values of premise parameters and conclusion parameters can be calculated, so that the designed fuzzy inference system can well simulate the expected input-output relationship and then provide an effective tool for braking intention recognition.

4.2. Fuzzification of Identification Parameters. The problems of braking intention recognition were transformed into the mathematical problems. The displacement of the brake pedal and its change rate were expressed as \(x\) and \(ds\), respectively. Based on the actual test data, the ranges of both were set as \([0 \text{ mm}, 70 \text{ mm}]\) and \([0 \text{ mm/s}, 170 \text{ mm/s}]\), respectively. The displacement of the brake pedal and its change rate were fuzzified, as shown in Table 1. Among them, “S,” “M,” and “B” represent “small,” “medium,” and “large,” respectively.

The outputs of three braking conditions by braking intention identification: light braking, medium braking, and emergency braking, which were represented by numbers 1, 2, and 3, respectively. Based on the braking test mentioned above, 100 groups of data were selected for classification and statistics under each braking condition, and the fuzzy inference rules were designed based on the principle of probability maximization. The obtained statistical results of frequency are shown in Table 2, and the fuzzy inference rules are shown in Table 3.

4.3. Modeling of Braking Intention Recognition. Among the previously obtained data of the braking test, 35 training data samples and 35 inspection data samples were selected, respectively, as shown in Tables 4 and 5.

The above training data samples and test data samples were imported into the ANFIS editor, respectively, as shown in Figure 4.

Based on the editing dialog box of FIS, the brake pedal displacement and its change rate were named as “weiyi” and “weiyi_rate”, respectively, and the output of brake intention was named as “yt.” The obtained ANFIS network structure for braking intention identification is shown in Figure 5.

The membership functions of brake pedal displacement, the change rate of brake pedal displacement, and the output of brake intention were set one by one. The fuzzy inference rules of braking intention recognition were edited. The surface view of fuzzy inference rules was formed, as shown in Figure 6.

4.4. Training and Testing of the Recognition Model. The training method was set as "backpropa," the error tolerance was set as 0.001, the training time was set as 1082, and the output error after training was about 0.082, which can meet the actual requirements, as shown in Figure 7.

The above ANFIS model was tested with the test data samples shown in Table 5, and the test result is shown in Figure 8.

It can be seen from the figure that the output values of the ANFIS model are in good agreement with the test data, and the small difference between them will not have a great impact on the recognition of braking intention. Therefore, the model of braking intention recognition based on ANFIS can effectively identify the driver’s braking intention.
5. Verification of the Braking Intention Recognition Model

From the actual test data, a group of characteristic parameter data of light braking, medium braking, and emergency braking was intercepted as verification data. They were imported into the trained ANFIS model in the specified format to predict and identify the braking intentions. The time interval of sample points was set to 0.2 s, and the braking intention recognition results were as follows:

5.1. Light Braking. The intercepted data corresponded to a light braking process with duration of about 28 s. A total of 142 sample points were selected in this light braking process, including 139 correctly identified sample points and 3 incorrectly identified sample points. The classification accuracy was about 97.8873%.

5.2. Medium Braking. The intercepted data corresponded to a medium braking process with duration of about 10 s from braking start to full stop. A total of 51 sample points were selected in this medium braking process, including 49 correctly identified sample points and 2 incorrectly identified sample points. The classification accuracy was about 96.0784%.

5.3. Emergency Braking. The intercepted data corresponded to an emergency braking process with duration of about 3 s. A total of 17 sample points were selected in this emergency braking process, including 17 correctly identified sample points and 0 incorrectly identified sample point. The classification accuracy was 100%. Considering the short duration of emergency braking, the sampling time interval
of 0.2 s may not truly reflect the prediction effect, so the sampling time interval was set to 0.05 s. The test data of emergency braking were screened again for prediction. The prediction results showed that 63 sample points were selected in the emergency braking process, including 62 correctly identified sample points and 1 incorrectly identified sample point. The classification accuracy was about 98.4127%.

According to the above prediction results, it can be found that the braking intention recognition model based on ANFIS has a good prediction effect for the three braking conditions of light braking, medium braking, and emergency braking, and it can effectively reflect the driver’s braking intention, so it has certain superiority and practical application value.

6. Conclusion

On the basis of the analysis of the research status of braking intention recognition technologies, a kind of braking intention recognition method was explored based on braking test data and ANFIS in this paper.

(1) The brake pedal displacement and its change rate were selected as the identification parameters of braking intention, and the braking conditions were divided into three types: light braking, medium braking, and emergency braking

(2) Based on the VBOX III test system for vehicle performances, the test platform of braking intention identification was built. Multiple groups of braking tests were carried out for the above three typical braking conditions, and the test data of braking intention identification parameters were obtained

(3) The braking intention recognition model was constructed based on ANFIS, and the actual braking test data were used to predict and verify the constructed ANFIS model. The results show that the constructed ANFIS model has high classification accuracy of braking intentions, which provides a theoretical basis and reference basis for the subsequent practical application

Data Availability

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Conflicts of Interest

The authors declare no conflict of interest.

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