

Study on the Prediction of Driving Braking Behaviour Based on FPNN

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Abstract. The driving braking recognized and predicted was complicated. The driving braking samples of various braking actions were gained, by means of 3 setting of driving braking including braking of automobile in front, roadblocks cutting off in other lane were planned and simulated in the real road environment. Experimental data of driving actions including automobile velocity, braking velocity and sustained action time were acquired by the driving action collecting system. Taking advantage of fuzzy aggregation analysis, the driving braking action sample was unified for the fuzzy probabilistic neural network (FPNN). Under different action groups of braking action information selected from braking action samples, the FPNN network was constructed and trained. The analytical results show that the hit rate is 95.3 % when the training braking action data number is 46. Meanwhile, the results show that the relative fuzzy unified and FPNN is useful with sufficient driving braking action data. The driving FPNN are a valid way for prediction of driving action time.

1. Introduction

Domestic and international study and analysis show that with using of normal braking assist system in general automobiles, the driving braking time is decreased, and following distance is reduced effectively with 3% or more, then the number of road accidents is less. At same time, by means of prediction of driving braking actions, controlling braking lights time, braking action would be judged, would gain the more braking reaction time. The driving braking reaction time would be decreased with 0.8 s, and the automobile rear-end collision risk can be lower[1,2]. For sake of controlling automobile braking action and braking lights working time, braking actions, especially driving operating time, should be predicted correctly.

Because of nonlinearity, fuzziness of driving judgments and operations [3,4], driving braking behaviour action would be identified by neural network and fuzzy aggregation. Braking operating parameters were gathered in different automobile braking velocity in driving action settings with different following automobiles or roadblocks settings. By means of lots of braking action factors were involved, accurately reflect relatively reactions volatility of each driving factor. The fuzzy membership was used to unify driving action data, hence the accurate and effective operation data for braking model and driving braking training were provided. The consequence show that the FPPN model has precise mapping and action recognition ability [5,6,7], so the FPNN model of driving actions is set up, based on PNN and fuzzy aggregation, to realize braking actions identification and tracking. Finally, tracking ability and accuracy of braking action identification are analysed with driving braking action data.



2. Probability Mapping Relations

So as to depict driving action model precisely, action factors should be considered when automobile is braking. The automobiles drivers would take controlling operations according to following distance and distance to roadblocks [8,9]. The driving operation shows that distances are the leading factors to effect and describe the drivers' operation condition. The changing rate of braking pedal velocity is far over distinct factor in normal driving actions [10, 11]. So, braking velocity fluctuation is the key factor of driving action factors[12]. Under the variant braking velocity, different braking actions would be used according to following distance, velocity and time. Automobile braking velocity of driving action would be considered as the key factor. At last, factors V of braking actions are gained.

$$V = (V1, V2, V3, V4, V5) \quad (1)$$

$V1, V2, V3, V4$ and $V5$ are the automobile velocity, following distance, braking velocity and action time severally in formula (1). The Impact factor of driving and normal driving actions are set as the same number. The driving action probability mathematic model z_V is gained.

$$\text{If } z_A p_A > z_B p_B, \text{ then } z_V \in A; \text{ if } z_A p_A < z_B p_B, \text{ then } z_V \in B \quad (2)$$

In formula (2), z_A, z_B are driving probability according to the non-normal driving actions A and the normal driving B , $z_A = L_A/L, z_B = L_B/L$, z_A, z_B are driving training sampling size of action A and action B , p_A, p_B are PDF (probability density function) of driving action A and action B , z_V is the driving action model A or B . Braking model mapping space is foundation of probability neural network model. The event 0 and event 1 correspond to braking action space A and B respectively.

3. Braking Data Unified Disposal

Based on above analyses, four estimated sub parameters are used in the normal driving action model: automobile velocity, following distance, braking velocity and action time. If there are n groups of action sample data, then the driving action sample numerical matrix M is gained.

$$M = (m_{ij})_{n \times 4} \quad (3)$$

The m_{ij} is no. j sub parameter of no. i braking action sample, assumed to be no. i braking action vector in formula (3). The raw normal driving action samples is not unified. The data change range is much bigger. The driving action FPPN tracking accuracy would be affected. Then the action samples dada are pre-processed with 3 steps.

3.1. Braking Sample Mini-Max Uniformization

The bigger quantitative parameters in clustering rank directly to original braking action sample data process may be focused. The non-quantitative method is applied in braking action samples. The action sample data will be changed into the range $[0, 1]$ with a certain rate. The original braking action samples are processed using mini-max uniformization method.

$$m_{ij} = (m_{ij} - m_{jmin}) / (m_{jmax} - m_{jmin}) \quad (4)$$

The m_{jmax} and m_{jmin} in formula(4) are mini and max braking action data of no. j parameter respectively.

3.2. Braking Sample Fuzzy Clustering

The fuzzy braking action relationship matrix S with the uniformization method is built. The similar parameter s_{ij} is constructed using the cosine angle method.

$$s_{ij} = \sum_{j=1}^4 m_{ij} m_{kj} / \sqrt{\sum_{j=1}^4 m_{ij}^2 \sum_{j=1}^4 m_{kj}^2} \quad (5)$$

The property of transitivity doesn't in the braking action relationship matrix S . The S has to be calculated. When $S^k = S^{2k}$, the matrix S calculation will be stopped. If $S' = S^{2k}$, then the fuzzy relationship matrix is S' . $\beta \in [0,1]$ of the braking action fuzzy relationship matrix S' is built up. If the

sample quantitative value is bigger, then β is set 1. If the sample quantitative value is smaller, then β is set 0. The cut matrix of β is gained. Based on this way, the braking action samples will be divided into the smaller cluster sample.

3.3. Braking Action Sample Standardization

The average value \bar{m}_m of braking action samples using with the clustering ranking method can be obtained.

$$\bar{m}_m = \sum_{l=1}^h m_l / h \quad (6)$$

The clustering rank m'_m of no. m is taken as the driving action sample h in formula (6). The m_l is taken as the braking action sample. When setting $m_i \in m'$, the braking action sample is regrouped. The v_l is the braking action original sample according to m'_m ($l = 1, 2, \dots, h$). The original braking action sample m_i , that is v_l , is standardized with fuzzy clustering rank of no. m .

$$r_m = [(v_l - \bar{m}_m)^2 / (h - 1)]^{0.5} \quad (7)$$

$$v_{lj} = v_{lj} - \bar{m}_{mj} / r_m \quad (8)$$

The β is bigger, the driving action sample classification is better. When β is 0.925, the processed braking action samples simplified with above methods are applied in the normal braking action recognition.

4. Braking Action Neural Network

There are total 4 layers in the braking action neural network structure based on Bayes' rule of PNN. The in-put layer has 4 nodes standing as automobile velocity, following distance, braking velocity and time based on above analyses about normal braking action parameters and probability function. The braking action neural network is shown as Fig. 1.

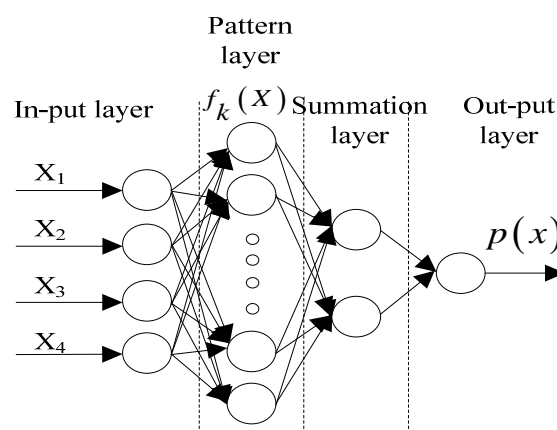


Figure 1. Driving action neural network

The no. 2 layer of braking action neural network adopted the radial basis function as the algorithm. The Parzen method is used Probability density function $p_k(V)$ to build the probability density function from braking action samples.

$$p_k(V) = 1 / (2\pi)^{p/2} \alpha^p N_k \sum_{j=1}^{N_k} [\|V - W_{ij}\|^2 / 2\alpha^2] \quad (9)$$

V is braking action sample vector. N_k is number of braking action samples, k is A or B , α is the smoothing factor. Weight vector W_{ij} is made by w_{ij} connecting no.1 layer, no.2 layer and no.3 layers. The i is the in-put layer's nodes. The j is the hidden layer's nodes. A competitive nerve unit is used in the out-put layer as the out-put of braking action neural network. The out-put unit adopts the equation $z(v)$ shown as the formula (10).

$$z(v) = \begin{cases} 1, & \max_N(z(v)_{N_A}, z(v)_{N_B}) \\ 0, & \text{others} \end{cases} \quad (10)$$

If the input data is normal driving samples, then the out-put results of FPNN would be 1. The FPNN provides possibility to recognize braking actions.

5. Driving Action Sample Acquisition

Driving action samples were acquired in the professional testing ground. The automobile different automobile velocity and following distance were simulated under normal and non-normal braking actions. The professional drivers were selected with the age range is 26 to 50 years. The driving years range is 5 to 20. And the experimental automobile was a car. The experimental car followed the car in front under different testing velocity. The velocity range was 50 and 90 km/h. The following distance range was 30 and 80m. Driving action settings included the car in front braking action, sudden reducing velocity action, and human form blocks suddenly crossing the road. The driving action times in one setting traffic environment was be limited to 2 times. These experimental requirements prevented from being familiar with traffic settings. Driving action samples were recorded with driving action acquisition system shown in Fig. 2.

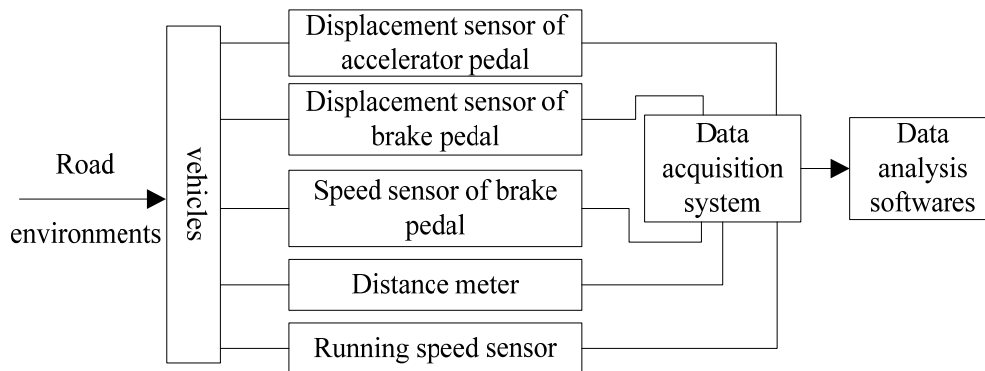


Figure 2. Driving action acquisition system

The braking action sample of simulation normal actions experiment is processed. The processed braking action sample in Table 1. The formula (5) is used to process the driving action samples in table1 and in table 2 with unification algorithm. In table 3, the action samples is translated into cut-off matrix at $\beta = 0.925$. Five classes ($m_{1,2,3,4,5}$, $m_{6,7,8}$, $m_{9,10,11,12}$, m_{13} , $m_{14,15,16}$) are gained from 16 groups braking action samples. Then, in table 4 the braking action training sample class and the trained class are gained.

Table 1. Driving action samples

Car velocity	Following distance	Braking velocity	Action time
76.21	35.90	54.62	0.98
78.70	32.46	55.69	0.86
76.52	36.21	56.60	0.77
79.03	34.97	55.30	0.72
69.27	30.78	46.05	0.77
69.36	45.63	39.86	0.76
70.95	44.32	34.65	0.78
69.58	42.68	33.04	0.79

Table 2. Driving action sample with fuzzy unification algorithm

Car velocity	Following distance	Action velocity	Action time
0.9433	0.0447	0.7404	1.0026
1.0010	0.0013	0.9729	0.7947
0.9610	0.0233	1.0012	0.9374
0.9735	0.0148	0.8990	0.6742
0.7234	0.0398	0.6194	0.4111
0.6456	0.3594	0.1597	0.3594
0.6847	0.3484	0.2182	0.4337
0.7490	0.2916	0.2148	0.5193

Table 3. Cutting matrix of action sample

	m1	m2	m3	m4	m5	m6	m7
m1	1	1	1	1	1	0	0
m2	1	1	1	1	1	0	0
m3	1	1	1	1	1	0	0
m4	1	1	1	1	1	0	0
m5	1	1	1	1	1	0	0
m6	0	0	0	0	0	1	1
m7	0	0	0	0	0	1	1

Table 4. Driving action sample with standardization

Car velocity	Following distance	Action velocity	Action time
0.0215	0.0168	0.2144	0.0012
0.0386	-0.0221	0.4924	0.0049
0.0192	-0.0023	0.5997	0.0059
0.0619	-0.0070	0.4047	-0.0048
-0.2912	0.0121	-1.7511	-0.0016
-0.0538	0.0494	-1.1306	-0.0019
0.1507	0.0125	0.6588	0.00038
-0.1469	-0.0638	0.4618	0.00162

6. Applying Analyses

Driving action samples are normalized firstly. Using Matlab neural networking tools, the driving action neural network is constructed and verified. The tolerance of feedback calculation and connecting weights in FPNN are needless. The classifying ability and tracking accuracy of driving action FPNN is simulated and analysed. The driving action hit rate is to analyse accuracy of FPNN.

Identification precision of the driving action neural network at $\alpha \in [0.233, 0.675]$ are analysed in fig. 1. The weights is 1.0 in the no.2 layer and the no. 3 layer. The fuzzy unification algorithm is used in the no.3 layer to the no.4 layer. By means of braking action sample training, each layer weight in the input layer to pattern layer is gained. Layer weights of training samples are unified. Because the relevantly sample astringency is not involved any more, the action training process is simplified. According to action sample size and hitting rate changing tendency, the maximum hitting rate 95.3 % of trained braking action network is got at the sample number 190 in Fig. 3. The fuzzy unified samples can accurately map braking actions. The braking action neural model can reach recognition accuracy needed. The rising sample number does not affect identify accuracy at the number of braking training samples 250 and 350 respectively. When the sample number reaches 260, the identify accuracy is stabilized at 95.3%. From above analyses, the braking action neural network can correctly discern the rest of driving action samples.

7. Conclusions

Through the fuzzy unifying algorithm, braking action samples of different units are transform into the unified space. The characters of different action parameters are clearly changed into the same space providing basis for the driving action neural networking training and building.

By means of braking action neural network, samples of normal braking actions are trained and are discerned. The braking sample number impacting the identifying accuracy is achieved according to the tracking accuracy of driving action network.

Results show that while training samples are sufficient, the highest accuracy 95.3% of the driving action neural network could be reached. FPNN based on the Fuzzy cluster ranking can meet requirement of the accuracy of the normal braking action identification and prediction. The FPNN provides a valid technology method for advanced driver assistance systems.

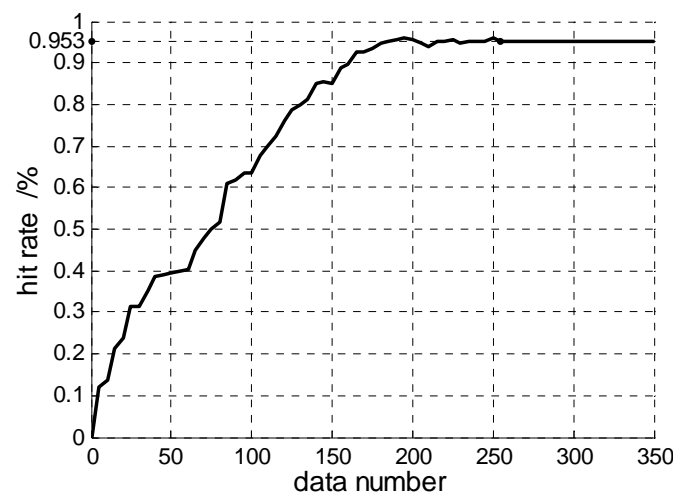


Figure 3. Results of braking behaviour neural network model

8. References

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