Study on Driving Safety Influence of Rampway Length

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***Abstract*—The driving safety influence formation was effected distinctly by the highway ramp length. The ramp length and automobile velocity were adopted to build driving safety influence formatting model in the highway ramp environment. The fuzzy logic reasoning rules were applied to construct the computing layers of driving safety cognizing formatting neural network. The driving safety influence experimental samples in the different ramp length were gained under different experimental automobile velocity. Weights of fuzzy-neural network layers were trained and was to analog compute effects on the driving safety influences under different ramp length with different experimental velocity. The resulting analyzing to prove that the relations between the typical ramp length and driving safety influence were calculated accurately. The trained neural network structure of driving safety influence based on the utilizing fuzzy inferences is helpful to improve driving safety influences of the highway ramp under different automobile velocity.**

Keywords—rampway length, driving safety influence, velocity, fuzzy rules, neural network

I. INTRODUCTION

The small ramp length non-complete transition curve have been frequently used in the entrance ramp design of large-sized interchange in the city highway, especially in the expressway. The highway ramp section is most commonly used as the corridor linking with the main way, and changing the ramp length would affect greatly on driving safety operation and influences [1, 2]. When automobiles are running with different velocity in the traffic system, drivers are changed into the information receivers, decision maker, and operators. Drivers have to get continuously traffic information from surrounding environment as driving automobiles. Surrounding information is dealt to be cognize exactly and to drive automobile correctly [3]. The ramp way length not only effects on the automobile velocity, but also effects on the drivers' safety influences being made by the driving feeling, feedback and decision. The study on the changing ramp way length effects on the driving safety influences under different velocities[4]. It is favorable for ramp way length fitting design and operating velocity on the highway ramp. Fitting ramp way length would lead to the decline of traffic accident occurrence[5,6]. In the driver-automobile-road environments traffic system, the driving safety influence forming process is built up with the self-learning neural network and fuzzy logic rules of inside and outside correlative factors[7]. The method and model provide effective means for resolving driving safety influence's simulation and application analysis.

II. RAMPWAY INFLUENCING FACTORS

The highway ramp length is the visually directed leading role in the highway traffic system. While automobile are running in the ramp way, the driver have to be adjusted the automobile's direction and velocity constantly. The driver would become more sensitive to ramp way environment. As the automobile's velocity couldn't be controlled to match with the ramp way length, not only driving judgments and operations would be affected, but also the serious spirit pressure on driving influence would be produced. The driving safety influence and driving estimation have been take into account when the highway design stage ramp way length affection caused by. In ramp way length design criterion, when the velocity road designed velocity is higher than 40 km/h, driving safety under the target velocity on the highway ramp length needs to be evaluated. Moreover, some foreign researchers study show that the driving safety influence in different ramp way length have an obvious effects on the automobile running speed being over 96km/h[8]. As the automobile velocity is more bigger, the influences gradually become more important. Driving safety influence is a result of the interactions between ramp way length and drivers' physiology activities. From these analysis, study, judgment of drivers, the safety influence forming process is shown in figure 1.

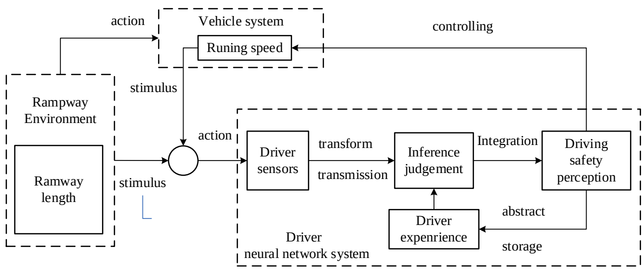

Figure 1. Rampway driving safety influence forming

III. RAMPWAY DRIVING SAFETY INFLUENCE

The ramp way driving safety influence is set up using the feed forward neural network and is improved by the fuzzy logic rules as figure 2. And the driving safety influence is emulated in Matlab.

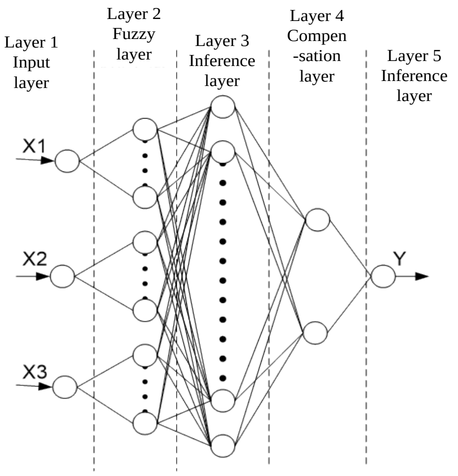

Figure 2. Rampway driving fuzzy neural network

The ramp way length (m), driving years (year) and velocity ($km \cdot h^{-1}$) are inputting samples as figure 3. Driving safety influence, the fuzzy logic space [NB, NS, PS, PB] are outputting variables. The fuzzy membership function space is [0, 1]. The simplified expression formula is as (1).

$$\text{if } X_1^k \text{ and } X_2^k \text{ and } X_3^k \text{ then } Y^k \tag{1}$$

Inputting and outputting fuzzy membership functions could be gained with the occurrence frequency table in (1). The driving safety influence neural network is built up using the fuzzy logic rules and functions in the ramp way. Gauss fuzzy membership functions are applied in the fuzzy neural network. The $\mu_{x_i^k}(x)$ and $\mu_{y^k}(y)$ are the membership functions. Then mean and variance of $\mu_{x_i^k}(x)$, $\mu_{y^k}(y)$ are a_i^k , σ_i^k , b^k and δ^k . In the figure 3, driving safety fuzzy membership functions are shown.

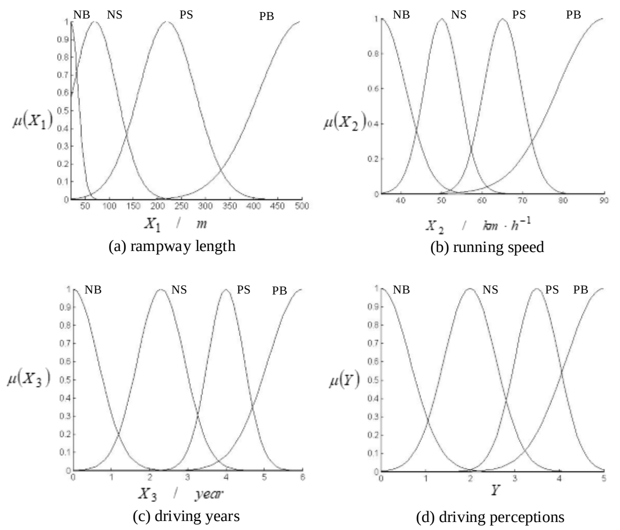

Figure 3. Membership functions

The fuzzy outputting reasoning algorithm of fuzzy neural network system is written as the formula (2).

$$f\left(x^p\right)=\sum_{k=1}^{m} b^k \delta^k\left[\prod_{i=1}^{3} \mu_{x_i^k}\left(x_i^p\right)\right] / \sum_{k=1}^{m} \delta^k\left[\prod_{i=1}^{3} \mu_{x_i^k}\left(x_i^p\right)\right] \tag{2}$$

The layer 1th, layer 2th, layer 3th, layer 4th are inputting, fuzzy, inference, and anti-fuzzy layer respectively in fuzzy reasoning neural network structure. The anti-fuzzy layer is adopted the neural cell. The each layer neural cell number is determined by the fuzzy reasoning rules in fuzzy neural network system. And the fitting precision of fuzzy neural network is improved by the compensation layer being as the layer 4th in system. The global optimization is adopted the passive positive fuzzy neural cell. The system compensation algorithm is written as the formula (3).

$$\mu_{x_1^k \times x_2^k \times x_3^k}\left(x^p\right)=\left[\prod_{i=1}^{3} \mu_{x_i^k}\left(x_i^p\right)\right]^{1-\gamma+\gamma/3} \tag{3}$$

The layer 5th of system outputting is shown as the formula (4).

$$f\left(x^p\right)=\frac{\sum_{k=1}^{m} b^k \delta^k\left[\prod_{i=1}^{3} \mu_{x_i^k}\left(x_i^p\right)\right]^{1-\gamma+\gamma/3}}{\sum_{k=1}^{m} \delta^k\left[\prod_{i=1}^{3} \mu_{x_i^k}\left(x_i^p\right)\right]^{1-\gamma+\gamma/3}} \tag{4}$$

The global optimization algorithm function is written as the formula (5).

$$E^p = 1/2\left[f\left(x^p\right)-y^p\right]^2 \tag{5}$$

The inputting and outputting membership functions using gradient descend algorithm shown from the formula (6) to the formula (10).

$$b^k(t+1)=b^k(t)-\eta \left.\frac{\partial E^p}{\partial b^k}\right|_t \tag{6}$$

$$\delta^k(t+1)=\delta^k(t)-\eta \left.\frac{\partial E^p}{\partial \delta^k}\right|_t \tag{7}$$

$$a_i^k(t+1)=a_i^k(t)-\eta \left.\frac{\partial E^p}{\partial a_i^k}\right|_t \tag{8}$$

$$\sigma_i^k(t+1)=\sigma_i^k(t)-\eta \left.\frac{\partial E^p}{\partial \sigma_i^k}\right|_t \tag{9}$$

$$\gamma(t+1)=\gamma(t)-\eta \left.\frac{\partial E^p}{\partial \gamma}\right|_t \tag{10}$$

$\left.\frac{\partial E^p}{\partial b^k}\right|_t$, $\left.\frac{\partial E^p}{\partial \delta^k}\right|_t$, $\left.\frac{\partial E^p}{\partial a_i^k}\right|_t$, $\left.\frac{\partial E^p}{\partial \sigma_i^k}\right|_t$ and $\left.\frac{\partial E^p}{\partial \gamma}\right|_t$ are inputting and outputting variance, mean and compensation gradients. The optimal learning efficiency is $\eta\,(\eta = 0.96)$.

The training and testing samples were collected from the ramp way driving experiment. Ramp way sections is the city express way. The ramp way length(X_1/m), the velocity($X_2/km\cdot h^{-1}$), driving years($X_3/year$), and driving safety influence(Y^p) are grouped to be test. The partial driving influence samples are shown in table I.

TABLE I. DRIVING SAFETY SAMPLES

X,Y	Driving Samples							
X_1/m	346	154	157	164	250	400	192	258
$X_2/km\cdot h^{-1}$	56	34	40	36	46	37	41	33
$X_3/year$	10	4	20	2	12	1	20	21
Y^p	1.3	2.2	1.6	1.8	2.2	2.7	1.9	2.7

The 120 groups samples are grouped into training and testing sample by the different ramp way length. The fitting outputting results of the fuzzy neural network and the actual outputting data of the safety influence tests are compared in figure 4.

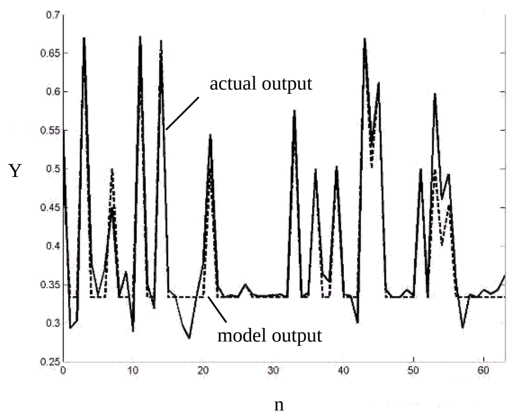

Figure 4. Driving safety influence comparison

The driving safety influences can be deduced and calculated precisely by the fuzzy neural network. The inputting sample amount is more large and the fitting results of the neural network is more precise.

IV. APPLIED ANALYSIS

The driving safety influences of the typical ramp way length are gained using of the fuzzy neural network reasoning ability. The ramp way length have markedly affects on the driving safety influence under different velocity by the driving tests and analysis. The driving safety influences by the ramp way length under the automobile velocity range [20, 90] km/h is shown in figure 5.When the ramp way length changing range is [56, 600] m, the ramp way length 156 m, 310 m and 520 m are changed into sudden changing point of driving safety influence. As the rampway length is shorter than 56 m, the driving safety influence is bad and worse. The driver have to operate the automobile with the lower speed pass safely this typical ram way. When the ramp way length is longer than 310 m, the driving safety influence in lower speed range is better. In designing ramp way length, the value of rampway length should be not shorter than 310 m. And the automobile velocity in this ramp way section should be not more than 50 km/h. Drivers are easy to pass the ramp way with good feelings.

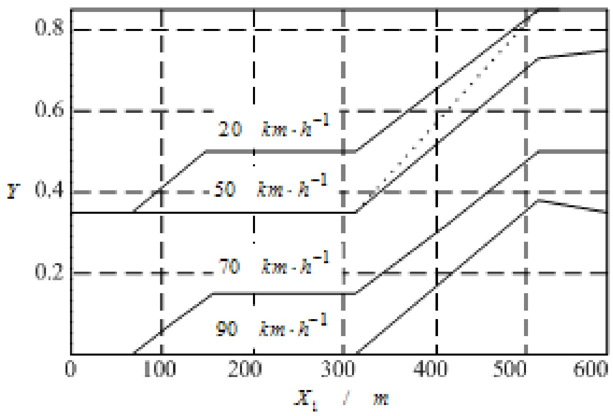

Figure 5. Ram way driving safety influences

With the above analysis, the length of a rampway section connecting with the highway is important safety influence factor in the reconstructed road. The results prove that the driving safety influence is generally fitted by the fuzzy inference and neural network. And the driving safety influence could be calculated and forecasted when ramp way are in design stage. The rampway length can be designed actively to make driving safety influence consistent to actual safety design requirements.

V. CONCLUSIONS

Via research on the driving safety influenced by velocity, rampway length, and driving years, the driving safety influence fuzzy neural network structure was set up. The driving safety influence fitting precision meet the needs of the ramp way length reconstruction in the design stage.

The analysis shows that in the typical ramp way length ranges is the key factor to the driving safety influence when the rampway length is shorter than certain fixed values. No matter the velocity is lower or higher, the rampway length is the predominant factor to driving safety changes.

Using of the fuzzy neural network model is rather meaningful to the ramp way length subjective safety evaluation, the ramp way reconstruction and velocity setting.

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