Design of Intelligent Forecasting System for ITS Application

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Abstract - **The classification of vehicle is one of more important parameter in the view of traffic congestion forecasting and it's control. Generally, traditional ITS(Intelligent Transportation System) could not be detected the tailgating cars at same speed. In this paper, we purpose an intelligent forecasting system for traffic congestion. The proposed system includes the ILD(Inductive Loop Detector) and the FNN(Fuzzy-Neural Network) and it's effectiveness should be determined by the computer simulation using the standard data of KTDB(Korea Transport Database).**

Ⅰ Introduction

In modern cities, it has become more difficult that the road area expand for the number of vehicles which increases by geometric progression, and it is required enormous expenses. In addition to the construction of new roads, therefore, the advanced countries have introduced the ITS(Intelligent Transportation System) to make use of roads effectively and to assure of smooth traffic flow: The Korean Government also is introducing the ITS to the roads at some areas, the highways and the national roads, etc.

The ITS always needs traffic information collection system that can give the Traffic Control Center statistical information on passing vehicles. The ITS requires precise and exact measuring system enough to assure reliability: Current Inductive Loop Detector (ILD) cannot detect a vehicle's class exactly in case that vehicles are passing through the detector in the case of bumper to bumper. Wrong information may produce a critical error of the ITS.

In this paper, the Fuzzy Logic System was used to elevate the accuracy of existing vehicle information collection system and to inspect its performance. Being based on expert's knowledge and information, the Fuzzy Logic System cannot learn and adapt of vehicle dimension information as well as various road environment that may change periodically. Therefore, in this paper designed a simulator with the Fuzzy-Neural Network enough to make information collection system of vehicles, and evidenced its efficiency.

Ⅱ Application Fuzzy Based Neural Network

Fig. 1 shows the configuration of the proposed FNN which is a feedforward architecture with five layers.

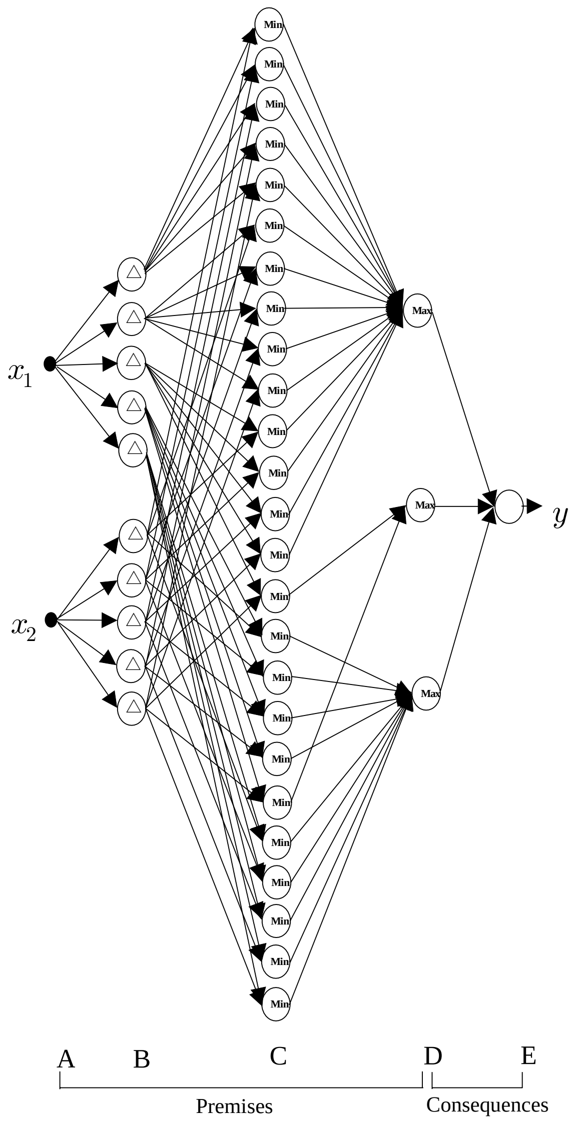

Fig. 1. Architecture of the proposed feedforward FNN

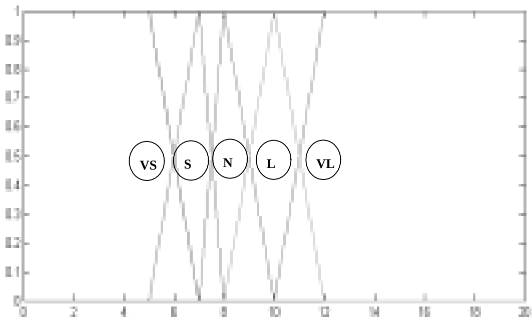

Fig. 2. Membership Functions of Length

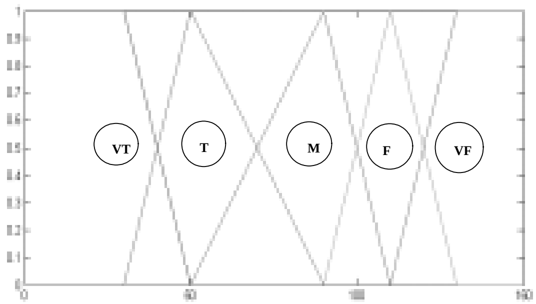

Fig. 3. Membership Functions of Speed

In the layer A, x_1 represents length and x_2 speed. The second layer B is divided into two groups of neurons. Each neuron in the layer B represents a discrete universe of discourse. Once input data come into the layer B, Membership value of each input are calculated in each neuron by Equation (1).

$$F_B = \mu_B = \begin{cases} 1 - \dfrac{x-c}{\omega_R} & when\ c \leqq x \leqq c + \omega_R \\ 1 + \dfrac{x-c}{\omega_L} & when\ c - \omega_L \leqq x \leqq c \\ 0 & otherwise \end{cases} \qquad (1)$$

Where c, ω_R and ω_L are nodal value and bounds of the triangle fuzzy numbers. In Equation (1), c, ω_R and ω_L are initially determined in each fuzzy partition by the membership functions of the inputs shown in Fig. 2 and Fig. 3.

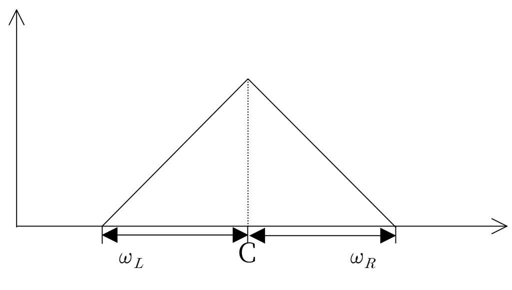

Fig. 4. Triangle Membership Function

Layer C and D play a role as a fuzzy inference specifically Mamdani's MAX-MIN operator. The number of the neurons in the layer C is the number of the fuzzy rules.

And in the layer E, an appropriate car class is acquired by defuzzification. As the defuzzifier to obtain a crisp output. Simplified Center of Gravity Method has been used as follow.

$$y^*_{COA} = \frac{\sum_{j=1}^{n} \mu_{Di}(y_i)\, y_i}{\sum_{j=1}^{n} \mu_{Di}(y_i)} \qquad (2)$$

Where y^* is an optimal car class and y_i, is a center of each universe of discourse.

The error function can be defined by

$$E = -\frac{(d-y^*)^2}{2} \qquad (3)$$

The error signal of the output layer in the FNN is derived as,

$$\frac{\partial E}{\partial y^*} = -(d - y^*) \qquad (4)$$

where d is the target car class.

From Equation (1), the derivative of y^* with respect to the output membership value, μ_D, from the layer D is computed accordingly.

$$\begin{aligned} \frac{\partial y^*}{\partial \mu_{Di}} &= \frac{y_i \sum_{i=1}^{3} \mu_{Di} y_i - \sum_{i=1}^{3} \mu_{Di} y_i}{(\sum_{i=1}^{3} \mu_{Di})^2} \\ &= \frac{1}{\sum_{i=1}^{3} \mu_{Di}} \left[y_i - \frac{\sum_{i=1}^{3} \mu_{Di} y_i}{\sum_{i=1}^{3} \mu_{Di}} \right] \qquad (5) \\ &= \frac{1}{\sum_{i=1}^{3} \mu_{Di}} [y_i - y^*] \end{aligned}$$

Following the calculus suggested by Pedrycz[3], the derivatives of the Max-Min operation are defined as:

$$\frac{d \min(x, a)}{dx} = \begin{cases} 1 & when \quad x \leqq a \\ 0 & otherwise \end{cases} \qquad (6)$$

$$\frac{d\max(x,a)}{dx} = \begin{cases} 1 & when \quad x \geqq a \\ 0 & otherwise \end{cases} \qquad (7)$$

Equation (6) and (7) can be rewritten as follow.

$$\frac{\partial \mu_D}{\partial \mu_C} = \begin{cases} 1 & when\ \mu_C = \mu_D \\ 0 & otherwise \end{cases} \qquad (8)$$

$$\frac{\partial \mu_C}{\partial \mu_B} = \begin{cases} 1 & when\ \mu_B = \mu_C \\ 0 & otherwise \end{cases} \qquad (9)$$

And in the layer B, we can derive $\frac{\partial \mu_B}{\omega_L}$ and $\frac{\partial \mu_B}{\omega_R}$ from Equation (1).

$$\frac{\partial \mu_B}{\partial \omega_L} = \frac{-(x-c)}{{\omega_L}^2} \qquad (10)$$

$$\frac{\partial \mu_B}{\partial \omega_R} = \frac{(x-c)}{{\omega_R}^2} \qquad (11)$$

After all, the increments of $\omega_R(\Delta\omega_R)$ and $\omega_L(\Delta\omega_L)$ are obtained by the following equations.

$$\Delta\omega_R = -\eta \frac{\partial E}{\partial y^*} \sum \frac{\partial y^*}{\partial \mu_D} \frac{\partial \mu_D}{\partial \mu_C} \frac{\partial \mu_C}{\partial \mu_B} \frac{\partial \mu_B}{\partial \omega_R} \qquad (12)$$

$$\Delta\omega_L = -\eta \frac{\partial E}{\partial y^*} \sum \frac{\partial y^*}{\partial \mu_D} \frac{\partial \mu_D}{\partial \mu_C} \frac{\partial \mu_C}{\partial \mu_B} \frac{\partial \mu_B}{\partial \omega_L} \qquad (13)$$

With obtained $\Delta\omega_R$ and $\Delta\omega_L$, we can update ω_R and ω_L as shown in Equation (12) and (13), which is the process to minimize the error of y^*.

$${\omega_L}^{(k)} = {\omega_L}^{(k-1)} + {\Delta\omega_L}^{(k)} \qquad (14)$$

$${\omega_R}^{(k)} = {\omega_R}^{(k-1)} + {\Delta\omega_R}^{(k)} \qquad (15)$$

Overall, the learning algorithm can be summarized by the following steps:

<u>Begin</u>

▪ itialize the parameter with the membership function and rules
▪ t iteration = 0

<u>Repeat</u>

▪ pdate the parameters ω_R , ω_L by computing the adjustment $\Delta\omega_R$ and $\Delta\omega_R$
▪ eration = iteration + 1

<u>Until</u>

▪ $E \leqq E_{MAX}$ or $iteration \geqq iteration_{MAX}$

<u>END</u>

Ⅲ Evaluation of the FNN

3.1 Simulation method

In this paper using two type of simulation data and evidence its efficiency for proposed FNN System. The simulation data 1 of Table 1 generated randomly for all vehicles specification in a rolling stock company in the Korea. In this 8~10m range detected a case of tailgating car when out of standard specification that assigned domestic vehicles.

Simulation Data 2 of Table 2 is made by changing velocity within 8~10m that frequent classification error generally. Error range is 0.03, and maximum learning iteration is 100. Thus, each simulation data is used as follows. First, it simulated class classification method using ILD, generally used. Second, it shows efficiency applied fuzzy algorithm. Finally, it compared conventional system with fuzzy logic system and FNN system.

Table 1. The Simulation Data 1

No.	Length(m)	Speed(Km/h)
01	3.5	60
02	4.0	90
03	4.5	120
04	5.0	120
05	5.5	60
06	6.0	90
07	6.5	120
08	7.0	60
09	7.5	90
10	8.0	120
11	8.5	130
12	9.0	100
13	9.5	120
14	10.0	90
15	10.5	120
16	11.0	60
17	11.5	90
18	12.0	120
19	12.5	60
20	13.0	100

Table 2. The Simulation Data 2

No.	Length(m)	Speed(Km/h)
01	8.0	100
02	8.0	110
03	8.0	120
04	8.0	130
05	8.5	100
06	8.5	110
07	8.5	120
08	8.5	130
09	9.0	100
10	9.0	110
11	9.0	120
12	9.0	130
13	9.5	100
14	9.5	110
15	9.5	120
16	9.5	130
17	10.0	100
18	10.0	110
19	10.0	120
20	10.0	130

3.2 Simulation result

Fig. 5 and Fig. 6 shows result that simulated traditional method, fuzzy logic algorithm and FNN. The indication is wrong measurement. Fig. 5 shows error detection of 35%, 10%, 0% about traditional system and fuzzy logic system and FNN system. Fig. 6 shows error detection of 70%, 25%, 0% about traditional system and fuzzy logic and FNN system.

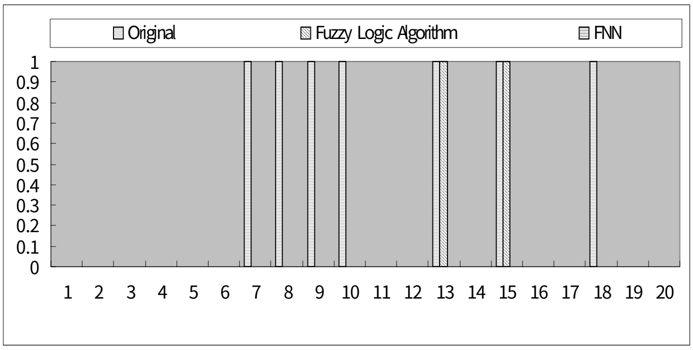

Fig. 5. Simulation Results 1

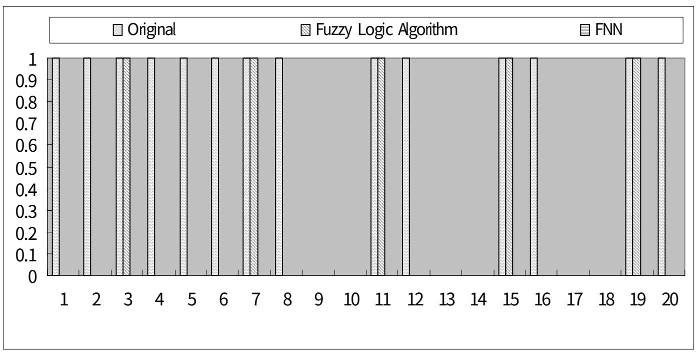

Fig. 6. Simulation Results 2

Ⅳ Conclusions

It is difficult that optimization of membership function based on expert knowledge in case of fuzzy algorithm. It can improve efficient by revision using specifications of cars, but it must be very difficult problem that modeling all cars and covering patterns or make roughly membership function with them. We improve shortage of fuzzy algorithm using feed-forward FNN and back-propagation learning method. FNN shows even if make roughly membership function, it optimize membership function by learning.

Moreover, it can expand the classified traffic system by making distribution of vehicle flow based on class classification data with FNN. It is impossible that mathematic modeling, classifying traffic flow and control by traditional method. This system has application to develop the system that classified traffic flow for traffic accident, paralysis, and so forth. The conclude it is most suitable method because it can be optimized by learning with roughly membership function using FNN applied multi layered BPN(Back-Propagation Network).

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