CHAPTER 5 MODELING FOR THE ONE-DIMENSIONAL MOVING BEHAVIORS

This chapter attempts to develop fuzzy-based motorcycle-following models and to compare the results with conventional GM-based models. Section 5.1 presents the significant factors affecting motorcycle-following behaviors, which are used for model construction. Conventional GM models are attempted to explain the motorcycle's following behaviors in 5.2. Furthermore, fuzzy-based motorcycle-following model is proposed in 5.3. A brief discussion follows.

5.1 Factors Affecting Motorcycle-following Behaviors

Dijker, et al. (1998) conducted a car-following study and concluded that most of the following cars have time headway less than 3.5 seconds. The size of motorcycle is smaller than the car, thus we use 3.0 seconds as the maximum time headway to identify a motorcycle with following behaviors. Based on this, a following motorcycle with velocity of 40 kph (upper speed limit in Taipei), time headway of 3.0 seconds, shall follow the lead vehicle at least 30 meters without lateral displacement (In this paper, the one with displacement less than 0.5 meters is treated as a following motorcycle). Hence, we trace and record each vehicle in the field within the range of 30 meters.

According to the field data in chapter 4, a total of 3,064 such samples have been observed. Of these total, only 422 motorcycles (13.8%) are found with following behaviors, the others (86.2%) are treated as "sneaking" or "lane-changes" because their moving paths are either in between two adjacent vehicles or with lateral displacements greater than 0.5 meters. In accordance with the categorizing in chapter 4, the chapter also divides the 422 following samples into two cases: (I) only one lead vehicle existent in front; and (II) lead vehicles existent in front and either left-front or right-front or both as depicted in Figure 4-3. In case (I) we observe 195 samples and in case (II) we observe 227 samples.

The analysis and statistical testing of the field observation are summarized as follows:

Case (I) Only one lead vehicle existent in front

More than 90% of the observed motorcycles have traveled along the curbside. They appear within 5.0-7.0 meter, measuring from the separated island, in the 10-meter width slow lane. 89% of them have lateral displacement less than 0.5 meters within the observation range of 30 meters. If the lead vehicle is a motorcycle, the average space headway of the following motorcycle is 8.51 meters; if the lead vehicle is a car, the average space headway is 10.99 meters. 87% of the total observations have traveled at speed ranging from 25 to 55 kph and acceleration rate ranging from –4.15-2.93 m/s^2.

We further perform a statistical test on the significance of correlation coefficients between following motorcycle's acceleration rate and some measured factors. It shows that at 1% significant level, the space headway with respect to the lead vehicle, the speed and acceleration rate of the lead vehicle, and the relative velocity of the lead vehicle and the following motorcycle are the four factors significantly affecting the following motorcycle's acceleration rate. Speed of the following motorcycle has no significant influence on the acceleration rate. We will construct fuzzy-neural model based on these significant factors.

Case (II) lead vehicles existent in front and either left-front or right-front or both

More than 85% of the observed motorcycles have traveled along the curbside. They appear within 3.5-7.0 meter, measuring from the separated island, in the 10-meter width slow lane. 92.5% of them have lateral displacement less than 0.5 meters within the observation range of 30 meters. If the lead vehicle is a motorcycle, the average space headway of the following motorcycle is 9.14 meters; if the lead vehicle is a car, the average space headway is 10.05 meters. 90% of the total observations have traveled at speed ranging from 25 to 55 kph and acceleration rate ranging from –2.97-2.91 m/s^2.

Again, we perform a statistical test on the significance of correlation coefficients between following motorcycle's acceleration rate and some measured factors. It concludes that at 1% significant level, the space headway with respect to the in front lead vehicle, the acceleration rate of the in front lead vehicle, and the relative velocity of the in front lead vehicle and the following motorcycle are the three factors significantly affecting the following motorcycle's acceleration rate. Speeds of the following motorcycle and of the in front, left-front, and right-front vehicles have no significant influence on the following motorcycle's acceleration rate. (see Table 5.1) The fuzzy-neural model is constructed based on these significant factors.

Table 5.1 Correlation coefficients between following motorcycle's acceleration rate and some measured factors

Factors	Case (I): acceleration rate $a_{n+1}(t+\Delta t)$, (m/sec^2)			Case (II): acceleration rate $a_{n+1}(t+\Delta t)$, (m/sec^2)		
	Correlation coefficients	P value	n	Correlation coefficients	P value	n
Following motorcycle's speed ($V_{n+1}(t+\Delta t)$, kph)	.035	.397	589	-.007	.850	692
Space headway (ΔS, m)	.150*	.000	589	.122*	.001	692
Lead vehicle's speed ($V_n(t)$, kph)	.132	.001	589	-.036	.338	692
Lead vehicle's acceleration rate ($a_n(t)$, m/sec^2)	.211*	.000	440	.286*	.000	516
Relative speed (ΔV, kph)	.506*	.000	589	.287*	.000	692
Left-front vehicle's speed (kph)	—	—	—	.026	.622	366
Gap with corresponding left-front vehicle (m)	—	—	—	.130	.011	388
Right-front vehicle's speed (kph)	—	—	—	-.151	.015	256
Gap with corresponding right-front vehicle (m)	—	—	—	.110	.072	268

Note 1: $H_0: \rho = 0, H_1: \rho \neq 0$;
Note 2: *at 1% significant level, the correlation coefficients rejects the $H_0: \rho = 0$ (p-value<0.005);
Note 3: $\Delta t = 0.5$ sec.

5.2 Construction of GM Models

The fifth generation of GM car-following model takes the form as follows:

$$a_{n+1}(t+\Delta t) = \frac{\alpha [V_{n+1}(t+\Delta t)]^m}{\Delta S^l}[V_n(t) - V_{n+1}(t)] \tag{5.1}$$

where

$a_{n+1}(t+\Delta t)$ =acceleration rate of the following vehicle at time $t+\Delta t$

$[V_n(t) - V_{n+1}(t)]$=relative velocity of the lead vehicle and the following vehicle at time t

ΔS = space headway between the lead vehicle and the following vehicle

$V_{n+1}(t+\Delta t)$=velocity of the following vehicle at time $t+\Delta t$

α, m, l = parameters to be estimated

We apply Eq (5.1) directly to describe the motorcycle following behaviors. Assume that the reaction time for the following motorcycle is $\Delta t = 0.5$ sec. The coefficients of Eq (5.1) are estimated with SPSS package as follows. We also attempt to estimate the coefficients of fourth, third, second and first generation of GM car-following model. Table 5.2 and 5.3 are the estimated results for case (I) and case (II), respectively. These tables show that the parameters, m, for speed of motorcycle in fifth generation of GM car-following model are not significant (t value $<$ $t^*_{(0.975,\infty)} = 1.96$).

Table 5.2 The results of GM models for case (I)

Parameter	The 5th model	The 4th model	The 3rd model	The 2nd $\Delta S \le 10$ meters	The 2nd $\Delta S > 10$ meters	The 1st model
α (t value)	0.2367 (6.8821)	0.0093 (12.2835)	0.3820 (12.6241)	0.1314 (11.9944)	0.0726 (9.4824)	0.0937 (14.4577)
m (t value)	0.0102 (0.4538)	1	0	0	0	0
l (t value)	0.4852 (6.0746)	1	1	0	0	0
R^2	0.2950	0.2042	0.2132	0.2398	0.2637	0.2623
$RMSE$	0.76	0.81	0.80	0.79	0.73	0.78

Note: $RMSE = \sqrt{\frac{\sum(a_i - \hat{a}_i)^2}{n}}$, m/sec^2; a_i is observed accelerate rate; $\hat{a}_i$ is estimated accelerate rate; n is sample size.

Table 5.3 The results of GM models for case (II)

Parameter	The 5th model	The 4th model	The 3rd model	The 2nd $\Delta S \le 10$ meters	The 2nd $\Delta S > 10$ meters	The 1st model
α (t value)	0.1350 (2.2087)	0.0070 (7.4456)	0.3073 (7.6470)	0.0750 (7.6595)	0.0359 (3.4383)	0.0549 (7.7241)
m (t value)	0.0010 (0.2943)	1	0	0	0	0
l (t value)	0.3956 (1.9610)	1	1	0	0	0
R^2	0.1030	0.0943	0.0980	0.1386	0.0645	0.0995
$RMSE$	0.92	0.93	0.93	0.89	0.97	0.93

Note: $RMSE$ is the same as that in Table 5.1.

Note that rather low values of R^2 (below 0.27) and rather high values of $RMSE$ (0.73~0.97) for the above two equations reveal that GM based models poorly explain the motorcycle-following behaviors for both cases. The main reason for the poor fitness is perhaps due to the misspecification of sensitivity term for GM models. According to the field observation, the space headway, speed and acceleration rate of the lead vehicle significantly affect the following motorcycle's acceleration in case (I) while in case (II) the space headway and acceleration rate of the in front lead vehicle dominate. However, the fifth generation of GM model takes the combination of speed and space headway of the following vehicle as the sensitivity measurement.

5.3 Construction of Fuzzy-based Models

According to the field investigation on the 422 motorcycles with following behaviors, we have found that the following motorcycle's acceleration rate $a_{n+1}(t+\Delta t)$ is significantly affected by the space headway ΔS and relative speed ΔV, which are the same as GM model. The difference between field observation and GM model is that the speed $V_n(t)$ and acceleration rate $a_n(t)$ of lead vehicle are significant factors affecting the following motorcycle's acceleration, while the following vehicle's speed $V_{n+1}(t+\Delta t)$ is not. This finding concurs with Chakroborty and Kikuchi (1999). As above-mentioned, the poor fitness of GM based regression model may result from inclusion of the following vehicle's speed $V_{n+1}(t+\Delta t)$ as a sensitivity term and omission of the lead vehicle's speed and/or acceleration.

Also notice from the field observation that the same magnitudes of relative speed ΔV, space headway ΔS and lead vehicle's speed $V_n(t)$ do not necessarily result in the same magnitudes of the following motorcycles' acceleration rate $a_{n+1}(t+\Delta t)$. Thus, instead of using the same sensitivity terms as GM model, we use the significant factors, relative speed ΔV, space headway ΔS and acceleration rate $a_n(t)$ of lead vehicle from field observation to construct adaptive network fuzzy-based models.

5.3.1 Structure of models

This fuzzy-based model is composed of five layers as depicted in Figure 5-1. The fuzzy inference rule is of Sugeno-type and backpropagation gradient descent method is employed for network training. The fuzzy inference rules and node operations are narrated in detail as follows:

(1) Fuzzy inference rule

R_i : IF(ΔS is ΔS_{m_1}) and (a_n(t) is $a_n(t)_{m_2}$) and (ΔV is ΔV_{m_3})

THEN$\left[a_{n+1}(t+\Delta t) = f_i\left(\Delta S, a_n(t), \Delta V\right)\right]$

$m_1 = 1 \sim l_1,\ m_2 = 1 \sim l_2,\ m_3 = 1 \sim l_3,\ \ i = 1 \sim l_1 \times l_2 \times l_3$

ΔS = space headway from the lead vehicle at time t (10 meters);

$a_n(t)$ = acceleration rate of the lead vehicle at time t (m/s^2);

ΔV = relative speed of the lead vehicle and the following motorcycle at time t (10kph);

$a_{n+1}(t+\Delta t)$ = acceleration rate of the following motorcycle at time t+0.5sec (m/s^2);

l_1, l_2, l_3 = linguistic degrees of membership function for ΔS, $a_n(t)$ and ΔV.

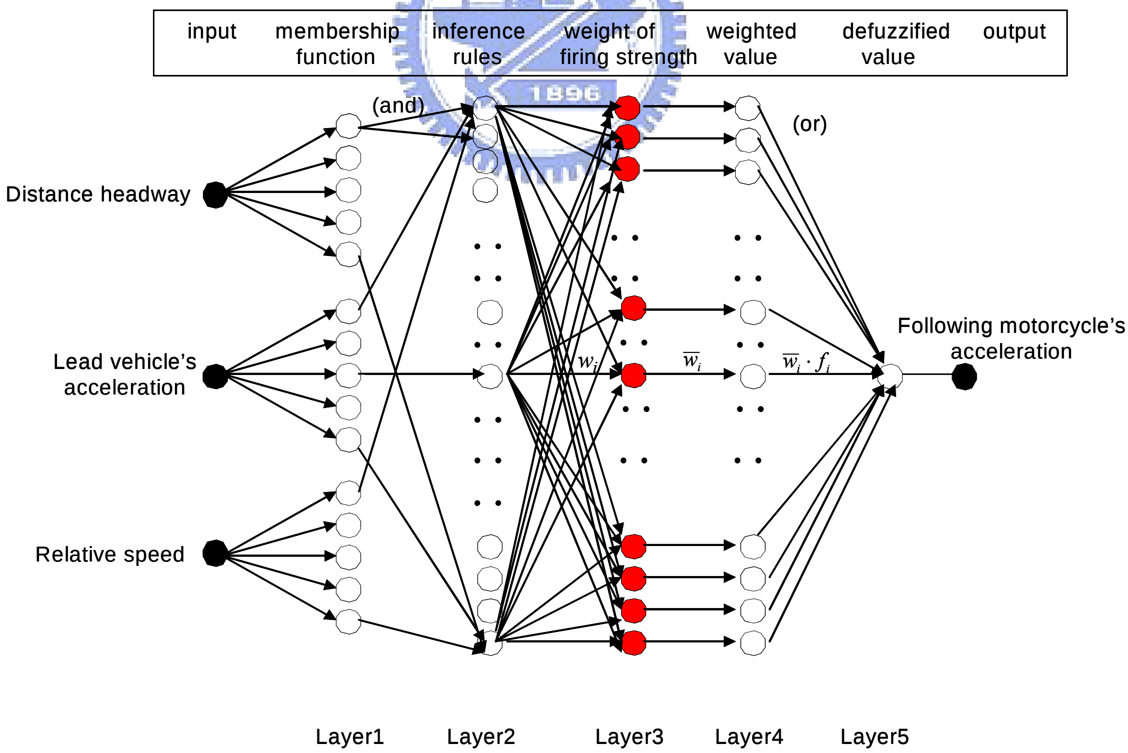

Figure 5-1 Structure of fuzzy-based models

(2) Node operation

1st layer: In this layer, there are three linguistic variables including "space headway from the lead vehicle," "lead vehicle's acceleration," and "relative speed." Each variable has five linguistic degrees (NL: negatively large, NS: negatively small, ZE: zero, PS: positively small, PL: positively large). The main function for this layer is to fuzzify the output values from the input values by utilizing Gaussian membership function and then to determine membership degrees of input variables. The function is expressed mathematically as follows.

$$O^1_{m_i} = \mu_{m_i}(x) = \exp\left[-\frac{1}{2}\left(\frac{x - c_{m_i}}{a_{m_i}}\right)^2\right] \tag{5.2}$$

$O^1_{m_i}$ = the output value of m_i th node at layer one;

$\mu_{m_i}(x)$ = the membership degree of the input value x at layer one;

where, $x = \Delta S$ represents gap length from the lead vehicle ($i = 1$), $x = a_n(t)$ represents lead vehicle's acceleration ($i = 2$), and $x = \Delta V$ represents relative speed ($i = 3$).

c_{m_i} = the cortex of a Gaussian membership function

a_{m_i} = the distance between left and right point of a Gaussian membership function

2nd layer: This layer estimates the firing strength of each fuzzy inference rule. In this paper, the nodes at this layer will perform a minimum operation as follows.

$$\begin{aligned} O^2_i = w_i &= \mu_{m_1}(\Delta S) \times \mu_{m_2}(\Delta V) \times \mu_{m_3}(a_n(t)) \\ &= Min\ \{\ \mu_{m_1}(\Delta S), \mu_{m_2}(\Delta V), \mu_{m_3}(a_n(t))\} \end{aligned} \tag{5.3}$$

O^2_i = the output value of i th node at layer two

w_i = the firing strength of i th inference rule

3rd layer: This layer computes the weight of each rule's firing strength.

$$O_i^3 = \overline{w}_i = \frac{w_i}{\sum_i w_i} \tag{5.4}$$

O_i^3 = the output value of i^{th} node at third layer

4th layer: This layer computes the corresponding value of each weighted rule.

$$O_i^4 = \overline{w}_i f_i = \overline{w}_i \left(p_i \Delta S + q_i \Delta V + r_i a_n(t) + s_i \right) \tag{5.5}$$

O_i^4 = the output value of i^{th} node at fourth layer

p_i, q_i, r_i, s_i are parameters of i^{th} inference rule's membership function.

5th layer: This layer executes defuzzification to obtain the numerical output values, the acceleration rate of the following motorcycle.

$$O_1^5 = \sum_i \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{5.6}$$

O_1^5 = the output value of i^{th} node at fifth layer

5.3.2 Training process

The training process for the fuzzy-based model is to construct the training set and then to adjust the connection weights and parameters. In this way, the model can learn to predict the following motorcycle's acceleration via such variables as space headway and relative speed of the lead vehicle and following motorcycle, and speed or acceleration of the lead vehicle.

A gradient decent modification procedure, also known as backpropagation training method, is used to adjust the connection weights and membership function parameters. This training method repetitively sends the error signals backward to renew the parameters so that the network can learn to mapping between inputs and the output. An error signal is then obtained by subtracting the network-generated output from the real output. The signal is backpropagated throughout the network, in which the error is used to modify the connection weights and membership function parameters.

The training process continues until the network can successfully predict the following motorcycle's acceleration in the training examples. Root mean square errors (RMSE), defined in eq. (5.7), is used as the performance index. Once the RMSE converges, the training is completed.

$$RMSE = \frac{1}{K}\sum_{k=1}^{K}[a_{n+1}(k) - O_1^5(k)]^2 \tag{5.7}$$

where a_{n+1} and O_1^5 represent network-generated output and the real output, respectively. k represents training examples.

Let E represent the energy function, also known as mean square error (E is a square of RMSE) and let $\delta_{i,j}$ represent the error signal of j^{th} node at i^{th} layer. The training process is as follows:

5th layer:

$$\delta_{5,1} = \frac{\partial E}{\partial O_1^5} = -2[a_{n+1} - O_1^5] \tag{5.8}$$

4th layer:

$$\delta_{4,i} = \frac{\partial E}{\partial O_i^4} = \frac{\partial E}{\partial O_1^5}\frac{\partial O_1^5}{\partial O_i^4} = \delta_{5,1}\frac{\partial O_1^5}{\partial O_i^4} \tag{5.9}$$

$$\frac{\partial E}{\partial p_i} = \frac{\partial E}{\partial O_i^4}\frac{\partial O_i^4}{\partial p_i} = \delta_{4,i}\cdot \overline{w}_i \cdot \Delta S \tag{5.10}$$

$$\frac{\partial E}{\partial q_i} = \frac{\partial E}{\partial O_i^4}\frac{\partial O_i^4}{\partial q_i} = \delta_{4,i}\cdot \overline{w}_i \cdot \Delta V \tag{5.11}$$

$$\frac{\partial E}{\partial r_i} = \frac{\partial E}{\partial O_i^4}\frac{\partial O_i^4}{\partial r_i} = \delta_{4,i}\cdot \overline{w}_i \cdot a_n \tag{5.12}$$

$$\frac{\partial E}{\partial s_i} = \frac{\partial E}{\partial O_i^4}\frac{\partial O_i^4}{\partial s_i} = \delta_{4,i}\cdot \overline{w}_i \tag{5.13}$$

Parameters p_i, q_i, r_i, s_i are renewed by the following equations. η represents the learning rate.

$$p_i(t+1) = p_i(t) - \eta \frac{\partial E}{\partial p_i} \tag{5.14}$$

$$q_i(t+1) = q_i(t) - \eta \frac{\partial E}{\partial q_i} \tag{5.15}$$

$$r_i(t+1) = r_i(t) - \eta \frac{\partial E}{\partial r_i} \tag{5.16}$$

$$s_i(t+1) = s_i(t) - \eta \frac{\partial E}{\partial s_i} \tag{5.17}$$

3rd layer:

$$\delta_{3,i} = \frac{\partial E}{\partial O_i^3} = \frac{\partial E}{\partial O_i^4}\frac{\partial O_i^4}{\partial O_i^3} = \delta_{4,i}\frac{\partial O_i^4}{\partial O_i^3} \tag{5.18}$$

2nd layer:

$$\delta_{2,i} = \frac{\partial E}{\partial O_i^2} = \sum_{j=1} \frac{\partial E}{\partial O_i^3}\frac{\partial O_i^3}{\partial O_i^2} = \sum_{j=1} \delta_{3,i}\frac{\partial O_i^3}{\partial O_i^2} \tag{5.19}$$

1st layer:

$$\delta_{1,m_i} = \frac{\partial E}{\partial O_{m_i}^1} = \sum_{j=1} \frac{\partial E}{\partial O_j^2}\frac{\partial O_j^2}{\partial O_{m_i}^1} = \sum_{j=1} \delta_{2,j}\frac{\partial O_j^2}{\partial O_{m_i}^1} \tag{5.20}$$

$$\frac{\partial E}{\partial a_{m_i}} = \frac{\partial E}{\partial O_{m_i}^1}\frac{\partial O_{m_i}^1}{\partial a_{m_i}} = \delta_{1,m_i} \cdot \exp[(-\frac{1}{2}(\frac{x-c_{m_i}}{a_{m_i}})^2] \cdot \frac{(x-c_{m_i})^2}{a_{m_i}^3} \tag{5.21}$$

$$\frac{\partial E}{\partial c_{m_i}} = \frac{\partial E}{\partial O_{m_i}^1}\frac{\partial O_{m_i}^1}{\partial c_{m_i}} = \delta_{1,m_i} \cdot \exp[-\frac{1}{2}(\frac{x-c_{m_i}}{a_{m_i}})^2] \cdot (\frac{x-c_{m_i}}{a_{m_i}^2}) \tag{5.22}$$

Parameters c_{m_i} and a_{m_i} are renewed by the following two equations.

$$a_{m_i}(t+1) = a_{m_i}(t) - \eta \frac{\partial E}{\partial a_{m_i}} \tag{5.23}$$

$$c_{m_i}(t+1) = c_{m_i}(t) - \eta \frac{\partial E}{\partial c_{m_i}} \tag{5.24}$$

5.3.3 Training results and validation

Fuzzy inference rules and their corresponding Guassian membership functions are validated through the network training. The number of training cycles is set equal to 100 initially. If the RMSE value is not converged, additional 50 training cycles would be added each time until the RMSE value is converged. In this paper, we use 90% of the total samples for training and the rest 10% for validation. Table 5.4 presents the training results for both cases under various membership functions and inference rules. It is found that the one with 125 inference rules has the least RMSE value. Hence, we will use this as the final ANFIS based motorcycle following model for further validation and comparison.

Table 5.4 Training results under various inference rules

Cases		Inference Rules			
		$3\times3\times3=27$	$5\times3\times3=45$	$5\times5\times3=75$	$5\times5\times5=125$
Case (I)	Training cycles	100	100	100	100
	RMSE	0.3907	0.3236	0.2134	0.1618
Case (II)	Training cycles	100	150	150	100
	RMSE	0.5809	0.5112	0.4229	0.3416

Using 90% of the total samples for training, Table 5.5 summarizes the parameter values of membership functions after training. The corresponding RMSE values of the ANFIS motorcycle-following models for case (I) and (II) are 0.16 and 0.34, respectively. We further use the rest 10% data for validation and find that the corresponding RMSE values for case (I) and (II) are 0.1753 and 0.2948, respectively. Figure 5-2 demonstrates the scattergram between observed and predicted acceleration rates of the following motorcycles. It is found that more than 80% of the plots are located within the interval of ± 0.3 m/sec^2.

Furthermore, we conduct a Q-Q plot correlation coefficient test and find that the observed acceleration rates with respect to the predicted ones, in general, will follow a 45° line, representing a positive correlation between these two acceleration rates. Namely, $H_0:\rho=1, H_1:\rho<1$, in case (I) we cannot reject the null hypothesis that both acceleration rates are perfectly positively correlated ($\rho=1$) at 1% significant level for the statistics $r_Q=0.9778$ is slightly greater than the critical value $r^*_{Q(44,0.01)}=0.9625$. However, in case (II) we would reject the null hypothesis that both acceleration rates are perfectly positively correlated for $r_Q=0.9411$ is slightly less than the critical value $r^*_{Q(52,0.01)}=0.9681$.

Table 5.5 The parameter values of membership functions after training

Membership Functions		Case (I)		Case (II)	
		c	a	c	a
ΔS	NL	0.2661	0.2191	0.2874	0.1937
	NS	0.8120	0.0540	0.8915	0.0578
	ZE	1.2421	0.0984	1.2069	0.0307
	PS	1.7333	0.2179	1.6571	0.1870
	PL	2.2811	0.2047	2.0270	0.2114
a_n	NL	-2.3070	0.5499	-2.9330	0.6703
	NS	-1.1990	0.4649	-1.5140	0.6332
	ZE	-0.1325	0.3376	-0.1358	0.5301
	PS	0.9384	0.4663	1.2420	0.5632
	PL	2.0000	0.5650	2.6400	0.6311
ΔV	NL	-1.2410	0.3217	-1.6070	0.4056
	NS	-0.6246	0.2426	-0.8320	0.3216
	ZE	0.0128	0.0618	-0.0726	0.0854
	PS	0.5494	0.2758	0.7020	0.3472
	PL	1.1470	0.3512	1.4970	0.4131
RMSE		0.16		0.34	

Note: Gaussian membership function $\mu(x)=\exp[-\frac{1}{2}(\frac{x-c}{b})^2]$, where c is the cortex and b is the width.

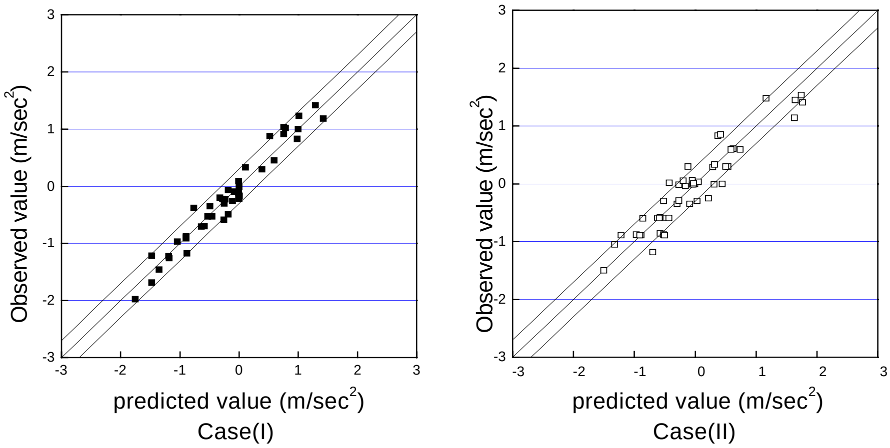

Figure 5-2 Scattergram of observed and predicted acceleration rates

5.4 Discussion

The rather low values of R^2 (0.295 and 0.103) or high RMSE values (0.76 and 0.92) of GM based models for case (I) and case (II) conclude that GM based models fail to describe the motorcycle-following behaviors. In contrast, the rather low RMSE values (0.16 and 0.34) of fuzzy-neural based models for the two cases strongly suggest that fuzzy-based models have overwhelmingly outperformed in depicting the motorcycle-following behaviors.

We attempt to use the fuzzy-based models to simulate motorcycle platoons in a motorcycle exclusive lane of two-meter width, where overtaking and parallel traveling are not possible (It is the case (I)). Assume that the lead motorcycle travels at a constant speed of 40kph. Three scenarios are simulated in such a way that the following motorcycle has space headway of 12 meters with an initial speed of 25kph, 40kph, and 55kph, respectively. Figure 5-3 presents the variations of gap length and speed for the following motorcycle. Note from this figure that all of the three scenarios have come up with stable space headway of 9.63 meters at speed of 40kph. One can easily convert this space headway and speed into time headway of 0.8667 second, which is equivalent to a flow rate of 4,150 motorcycles per hour. This result corresponds with 2001 Highway Capacity Manual of Taiwan (2001) proposes service volume for two-meter width motorcycle exclusive lane with level of service between B and C, ranging from 3,600 to 5,400 motorcycles per hour.

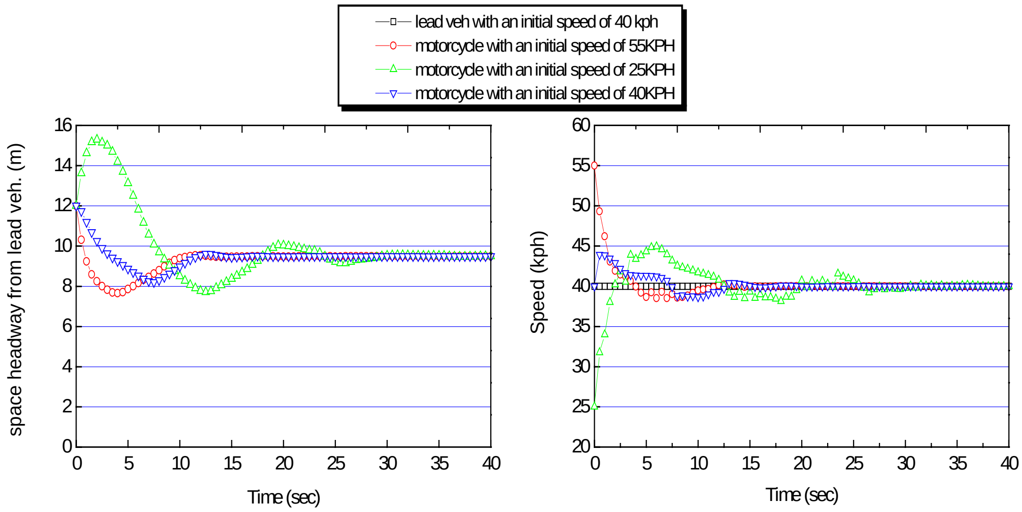

Figure 5-3 Simulation results of fuzzy-based model