Evaluate the driving model through analyzing various driving characters

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EXTENDED ABSTRACT

In order to solve the chronic traffic problem of a city's crowded downtown area, we developed the MITRAM, with that is a traffic simulator helps to find the possible solutions.

In reality, drivers normally control the car especially the speed by information they collect on the road while driving. But the drivers' judgments are sometimes unspecific and ambiguous. Fuzzy Control applies to the analysis of the target of no specific judgment. MITRAM links a Fuzzy Inference Process, which has two inputs and one output. It builds a model of driving operation by using the network. The construction of the model then can be close to the real situation from human's perspective.

Moreover, We integrate the fuzzy neural network (FNN) to the construction of FMV, thus the construction of FMV will no longer rely on the designer's experience but through the actual driving can be simulated through learning the vehicle's movement data. In the analysis and evaluation of the traffic simulator uses FMV in consecutive time series, the data of vehicular gap is very close to the actual data.

Besides, we can build car-following models of different driving characters by just changing the actual running data as learning data, because the model is built automatically through learning these data.

In this research, we set the lead car whose velocity variation similar to a sine wave in order to understand the influences on the vehicle troop caused by different driving operations.

We assume the lead car on a one-way road with no signals, and use more FMV following the lead car to simulate.

In ***simulation 1***, we use 9 identical car-following FMV in organizing the vehicle troop in order to observe how the velocity variation of the lead car influences the vehicle troop. According to the results of ***simulation 1***, we found that the larger the frequency of the lead car's velocity variation had been, the more the vehicular gap of the following cars is close to a sine wave. On the contrary, if the velocity variation of the lead car is smaller, the velocity variation of the vehicular gap will be more obvious.

In ***simulation 2***, in order to understand how the different sequence of car-following FMV influence the vehicle troop, we used the same lead car as in ***simulation 1***, and used 4 different car-following FMV, different sequences to organize a vehicle troop. We selected the longest length of a vehicle troop as a criterion of evaluation.

In ***simulation 2***, the larger the frequency of the lead car's velocity variation is, the smaller the largest length of vehicle troop as well as the range of variation will be. Besides, the largest length of vehicle troop will be different according to the following car's sequence even we use the same lead car.

From analyzing the results of ***simulation1*** and ***simulation 2***, we found in the motion of the vehicle troop, the sharper the sate of the lead car is, the bigger the impact on the following cars is. There will be conflicts if the following cars can't follow the state of the lead car. On the other hand, when the state variation of the lead car is slower, the driving characters of the following car will be exhibited more easily. At the same time, the influence caused by different driving characters will have a greater impact on the vehicle troop. Especially in the traffic jams in the city area, it's a common phenomenon that the velocity of vehicles on the road are decided by the lead cars that the acceleration are slightly fluctuated. Therefore we argue that the driving character of the moving vehicles will influence the vehicle troop easily. Based on the understanding of this point, we further argue that it's necessary to analyze the driving character from microcosmic perspective in doing the simulation of city traffic.

1. INTRODUCTION

Unstoppable increase of vehicle in recent years causes the chronic traffic jam in most cities, and inevitably brings the further serious social problems. In order to validate the effectiveness of specific solutions aiming at solving the traffic problems, the computer-based simulation is getting more and more attention. As a result, many traffic simulators have been developed and proposed these years.

Amongst those proposed traffic simulators, there are two different approaches of modeling. One is macroscopic methodology and the other is microscopic methodology. The former assumes the traffic flow as a kind of fluid, while the latter focuses on the movement of every single vehicle. Especially in the urban areas, the movement of every single vehicle affects surrounding traffic. Therefore we should build driving model through microscopic view in order to take into consideration the influence from the driving character of every single vehicle on the overall traffic flow.

But the actual methodology of modeling in research in this field is not the case. The congruence of the observed value and some macro indexes such as traffic capacity or congestion length is regarded as the main methodology in building the models in this field. Obviously this kind of modeling not only affects the maneuverability and the understandability of the model, but also raises the difficulty of evaluating driving character's influencing on the overall traffic flow.

Therefore, we use fuzzy logic in developing MITRAM (microscopic model for analyzing Traffic jam in the city area). The driver's actual driving condition is exhibited by fuzzy model vehicle (FMV), thus the movement of each vehicle can be simulated. We integrate the fuzzy neural network (FNN) to the construction of FMV, thus the construction of FMV won't be dependent on the experience of the model builder, but the actual driving can be simulated through learning the vehicle's movement data. According to the evaluation of simulators use FMV conducted in time series, we found the vehicular gap generated by the simulator is pretty much closer to the actual data.

Besides, we can build car-following models of different driving characters by just changing the actual running data as learning data, because the model is built automatically through learning these data.

However it's still so difficult to elaborate the car-following characteristics, because of the diversities of people's driving manipulation. The simulation conducted by the driving model built on incomplete data inevitably has its limitation. In order to solve this problem, we must at first understand how much influence the driving characters bring to the movement of the vehicle troop.

So, in this research, we build following acceleration control FMV through using 47 sets actual car-following data, (3474 sets timing points, seconds in total). Through using these FMV constitute troop of vehicles to evaluate the influence what the different driving characters bring to the troop.

2. CAR-FOLLOWING FMV

We build the car-following model by using the car-following driving data. In building this car-following model, we use fuzzy neural network. We name this model as car-following FMV. Figure 1. Illustrates its core concept.

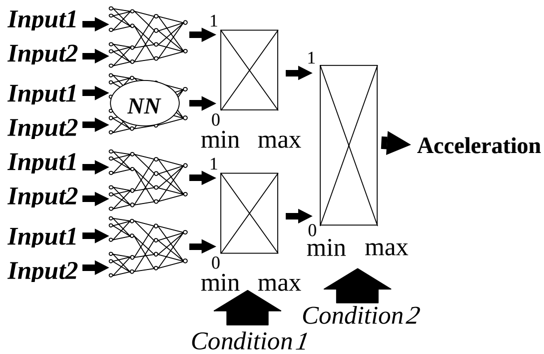

Figure 1. FNN for the acceleration control FMV

Here is the process of modeling:

1. Input Signal of Neural Network

These input signals come from the actual driving data of both the preceding vehicle and the succeeding one. They are acceleration, velocity and the vehicular gap (following distance).

2. Teacher Signal

The acceleration and vehicular gap of the succeeding vehicle in the next time series are regarded as the teacher signal.

It enables the neural network to learn by using the back-propagation algorithm by which the model was built.

By utilizing this methodology, we are able to assemble the car-following model by car-following driving data. Input the data of preceding and succeeding vehicles at every time point into the fuzzy neural network. By learning actual car-following driving data, the driving characters remain in the model.

By using the above methods, the result of building the model by using 47 sets of actual car-following data as well as the result of the comparison of the error of vehicle gap between simulation and actual data. In Table 1, we can see the result that the average error is only 1.2[m].

Table 1. The average error of vehicle gap

	Min.	*Max.*	*Ave.*
Error [m]	0.3	5.3	1.2

One of the simulation results display in Figure 2.

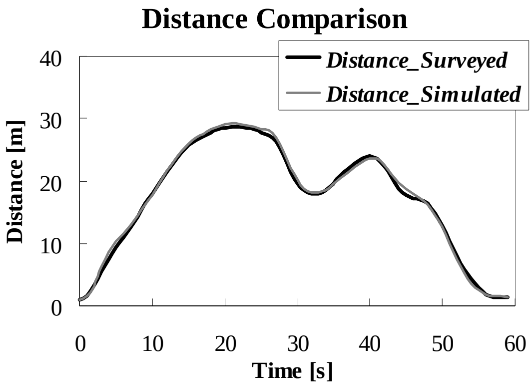

Figure 2. Comparison of vehicle gap

3. THE MOVEMENT OF VEHICLE TROOP FORMED BY FMV

During observing the vehicle troop with microscopic perspective, the lead car's state is delivered to the following cars by interacted with various car-following movements. But we do not know what will be the influences that the lead car affect the following cars, and what the variety is made to the vehicle troop's movement by the car-following appearing order.

Our research will use car-following FMV constructed by actual data to simulate and observe the movement of vehicle troop.

3.1. The Vehicle Troop Used in This Research

In the condition that one lane doesn't have passing car-following traffic flow, we can consider that movement of lead car will continuously deliver to the following cars.

In this research, we design velocity ***v*** of the lead car, just as Formula 1, to vary like the state of sine wave. And according to this, the simulation of vehicle troop's movement of non-intersection is conducted.

$$V_0 = \frac{V_{\max}}{2}\sin\left(2\pi ft + \frac{3}{2}\pi\right) + \frac{V_{\max}}{2} \qquad \ldots (1)$$

In the Formula 1, velocity V_{max} of the lead car is 14[m/s], and ***f*** from 0.01[s^{-1}] to 0.05[s^{-1}] carry on 5 kind variety (The variation of lead car accelerant range is displayed in Table 2), and running time is 4 cycles.

Table 2. Lead car accelerant range

f **[s^{-1}]**	**0.01**	**0.02**	**0.03**	**0.04**	**0.05**
Acce. Range ± [m/s^2]	0.4	0.9	1.3	1.8	2.2

In the simulation, initial state (t = 0) of vehicle troop is as below.

$$V_i(0) = 0\ [m/s],\ D_i(0) = 1[m].$$

V_i is velocity of ***No.i*** running car, and D_i is vehicular gap between ***No.i*** and ***No.i*+1** running car.

3.2. *Simulation 1*:The Troop Consists of 4 different Car-following FMV.

In order to observe how the variation in velocity of the lead car in vehicle troop delivers, in ***simulation 1*** we arrange 9 identical car-following FMV to make up the vehicle troop. Using FMV with the same car-following driving characters in the vehicle troop, purpose to avoid the complication that educed interferences from the difference of driving characters.

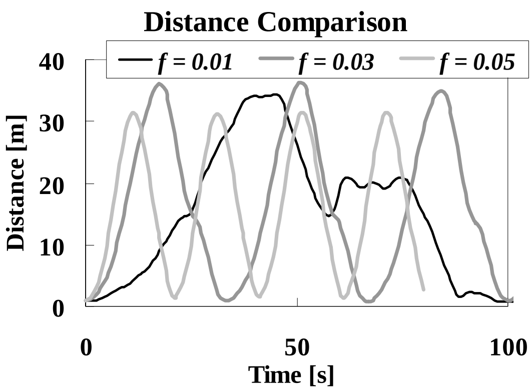

Figure 3. Vehicular gap in ***simulation 1*** ($D_{i=0}$)

In the simulation, there are totally 235 categories of vehicle troops. {Lead car 5 categories (one vehicle) × following car 47 categories (9 of same model)=235 categories}

First, we analyze what will be the influences that the variation of velocity of the lead car affects the first following car. The result displays, when the f in Formula 1 became larger, the vehicle gap between the lead car and the first following car is also approaching to the state of sine wave. Figure 3 displays one of the examples (FMV Model ***No***.47)

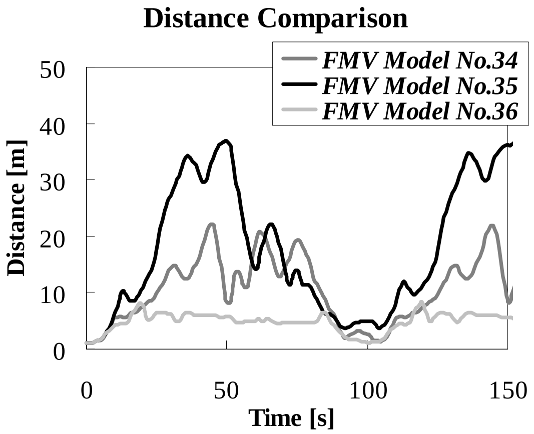

Figure4. Vehicular gaps ($D_{i=0}$) while $f = 0.01$[s^{-1}]

Moreover, as it shows in Figure 4, when the frequency f goes down, its vehicular gap $D_{i=0}$ also changes noticeably because of the car-following FMV difference. We believe that, the slower velocity change of lead car is, the easier the character of following car will be displayed.

On the other hand, when the frequency f became larger, the time that the lead car approaches max velocity V_{max} is shorter, the accelerate change of the lead car is larger. However, the stimulation made by the lead car on the following car will be stronger, the following car reacts that the velocity change approach to the state of sine wave.

In addition, how the variation of the vehicular gap between the lead car and the first following car ($D_{i=0}$) is delivered to the following cars? We use $R_{xy}(\tau)$ to analyze. It is explained in the following formula.

$$R_{xy} = \frac{\{\varphi_{xy}(0,\tau) - m_x(0)m_y(\tau)\}}{\sqrt{\{\varphi_x(0) - m_x^2(0)\}\{\varphi_y(\tau) - m_y^2(\tau)\}}} \cdots (2)$$

In Formula 2, x is vehicular gap data $D_{i=0}$ of each time point, y is vehicular gap data $D_{i=n}$ ($n = 1$ to 8). m_x, m_y is the average data. φ_x, φ_y is auto-correlation function. φ_{xy} is cross-correlation function, produced by $\varphi_{xy}(\tau) = E[x(t)y(t+\tau)]$.

We use Formula 2, varies τ to get correlation coefficient of $D_{i=n}$ ($n = 1$ to 8) and $D_{i=0}$, while f = 0.01[s^{-1}] or f = 0.05 [s^{-1}]. And consider the max of correlation coefficient as evaluating parameter. The average of max correlation coefficient ($i=n$) is displayed in Table 3.

Table3. The average of correlation coefficient (between $D_{i=n}$ and $D_{i=0}$) in the maximum

$D_{i=n}$	f=0.01[s^{-1}]	f=0.05[s^{-1}]
$n = 1$	0.924	0.940
$n = 2$	0.880	0.932
$n = 3$	0.840	0.912
$n = 4$	0.813	0.885
$n = 5$	0.787	0.800
$n = 6$	0.754	0.612
$n = 7$	0.727	0.434
$n = 8$	0.707	0.323

From Table 3, we find that the bigger the n is, the lower the relation between $D_{i=n}$ and $D_{i=0}$ is. In other words, more rear the car is, the weaker car-following affecting by lead car is.

Besides, we also find that when i = 6, 7, 8 , correlation coefficient of frequency f = 0.05[s^{-1}], comparing to that f = 0.01[s^{-1}], is low. Therefore, we observe the vehicle troop when f = 0.05[s^{-1}], and analyze how the velocity variation of the lead car is delivered to the rear. The result is that we find the variation of the last following car in the vehicle troop, as in Figure 5 and Figure 6, is generally divided into two kinds.

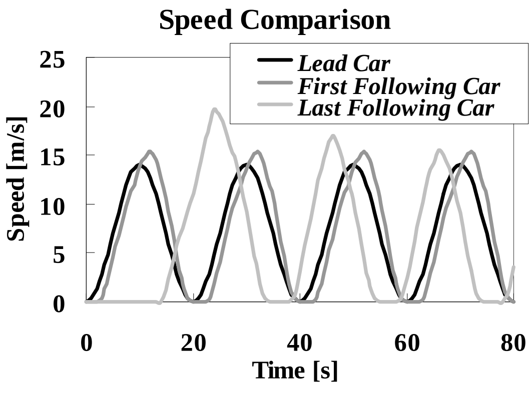

Figure 5. Velocity variety while f=0.05[s^{-1}] (FMV Model ***No***.29)

From Figure 5,we should find vibrate extent of velocity of the last following car is larger than the first following car. In other words, comparing to the first following car, its velocity variety has to become larger, therefore it's easy to crash into the preceding car.

On the other hand, as we can see in Figure 6, the farther the following vehicle is in the troop, the closer the velocity will change to a certain velocity.

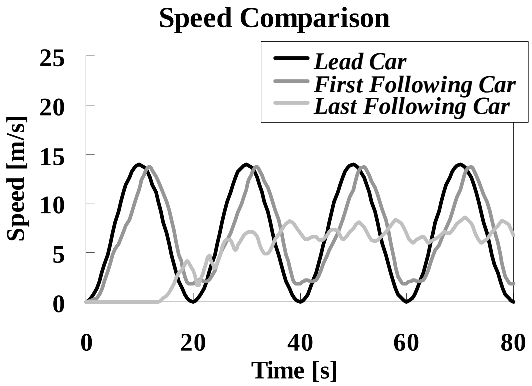

Figure 6. Velocity variety while $f=0.05$[s^{-1}] (FMV Model ***No***.30)

In order to find the difference between Figure 5 and Figure 6, let's first look at Figure 4: There are great differences of vehicular gaps although the lead car was exactly the same one. We finally found the max following distance had the proportional relations by comparing the actual running data with the results of simulation. Table 4 shows the result.

Table 4. The max following distance from actual running data and simulation result [m]

FMV Model	***No.34***	***No.35***	***No.36***
Result Data	18.5	42.3	9.3
f = ***0.01*** [s^{-1}]	22.0	37.1	8.3
f = ***0.02*** [s^{-1}]	26.7	38.8	9.7
f = ***0.03*** [s^{-1}]	25.4	37.8	8.9
f = ***0.04*** [s^{-1}]	31.8	35.3	10.1
f = ***0.05*** [s^{-1}]	24.2	31.1	13.1

Table 5. Character of actual running data

Data No.	D_{max} **[m]**	A_p **[m/s²]**		A_s **[m/s²]**	
		Min.	***Max.***	***Min.***	***Max.***
01	51.3	-1.5	1.2	-1.5	1.1
29	28.3	-1.4	1.4	-1.8	1.4
30	32.9	-2.0	1.3	-1.8	1.1
46	49.6	-2.5	1.9	-2.6	1.8
47	34.5	-1.5	1.3	-1.9	1.4

Because the car-following FMV is constructed through learning actual running data, we think that the max following distance from actual data is remained in the model. Therefore, the difference of the simulation results is caused by the difference in the characteristics of actual data constructed these models.

The actual driving data include parameters $\boldsymbol{D_{max}}$ (max vehicular gap), $\boldsymbol{A_p}$ (acceleration of preceding car) and $\boldsymbol{A_s}$ (acceleration of succeeding car). So we consider the maximum and minimum of them as the characteristic of the actual data. As example, data displayed in Table 5, we analyzed the difference between the data with clashes and those without clashes in this simulation.

As it shows in Table 2, the lead car when frequency of velocity variation $\boldsymbol{f}$ = 0.05[s^{-1}], the variation range of acceleration is ∓2.2[m/s^2]. But about ***No.***29 in Table 5, we find the variation in acceleration of the lead car is only ∓1.4[m/s^2]. Is the variation range of acceleration in the actual data constructed model so small to cause the clash?

From Table 5, about the acceleration range of the preceding car, the ***No***.29 is close to the ***No***.01 and the ***No***.47. But in the simulation constructed by FMV, the ***No***.29 clashed, and the ***No***.01, the ***No***.47 didn't clash. We consider that though the parameters of the actual running data as above is connected with the running of following driving model, it is not enough to appraise the character of following driving.

Beside, we also analyzed the influence caused by the study error of FNN. In Table 6, it shows the max study error in getting the distance between vehicles generated by both the simulation and the actual running.

Table 6. The max error of following distance

Data No.	**01**	**29**	**30**	**46**	**47**
Max Error [m]	0.8	0.6	0.5	3.2	2.7

In Table 6, it says that the simulation result of FMV Model ***No***.29 is closer to the actual running data than that of ***No***.46, ***No***.47. But in this simulation (***simulation 1***) we find that the movement of vehicle troop which used FMV Model ***No***.46 or ***No***.47 is stability, and the ***No***.29 had the clash with the preceding car. Therefore, we drew the conclusion that the study error of constructing the model has no relationship with the error of the non-intersection running of the following cars.

3.3. *Simulation 2*: The Troop Consists of 4 Different Car-following FMV

Just the same as in ***simulation 1***, 4 different car-following FMV will be arrayed to follow the lead car like Formula 1. It's for the observation of the influence on the troop by different kind of arrays. The other 4 FMV used in ***simulation 2*** were FMV Model ***No***.01, ***No***.30, ***No***.46 and ***No***.47, which have no clashes in ***simulation 1***.

The troop of ***simulation 2*** consists of the lead car (the 5^{th} category) and 4 following cars, which represent totally 120 ways of troop arrays.

Table 7. The max length of different vehicle troops

f **[s^{-1}]**	**0.01**	**0.02**	**0.03**	**0.04**	**0.05**
Max.	146.4	138.2	123.9	122.6	103.1
Min.	128.3	126	114.2	106.7	96.8
Difference	18.1	12.2	9.7	15.9	6.3

In ***simulation 2***, we investigated the longest length of each troop in order to understand the impact on the troop generated by the different arrays of car-following FMV.

From Table 7, we find that if the velocity's periodic variation of the lead car in the vehicle troop − ***f*** is bigger, maximum and minimum of the largest length of the vehicle troop will be smaller, and the variation range of the largest length of the vehicle troop becomes smaller. In other words, the larger the ***f*** is, the smaller the effect to the different vehicle troop arrays.

Furthermore, we also find that the difference of lead car will influence the largest length of vehicle troop. In other words, even if the array of following cars is same, the influence on the movement of vehicle troop will be different as for the difference in the movement of the lead car. So we can find easily the complexity of the interaction and influence in the movement of vehicle troop.

4. CONCLUSIONS

As the result of ***simulation 1*** and ***simulation 2***, we know that in the movement of vehicle troop, the velocity variation of lead car is more significant, bring more great influence to following cars. If the following cars cannot follow the state change of the proceeding car, the clash will be inevitable. On the other hand, when state change of the lead car is slow, it is easy to express the driving characters of the following car in the vehicle troop. And the difference of the driving characters would be influenced even more significantly. Especially the acceleration variation of the running car is small in the traffic jam in the city area. So for the result of the simulation, we believe it is easy to affect the vehicle troop by the driving characters of the running car. It is necessary to elucidate the driving characters to do simulation in microcosmic perspective.

Furthermore, because car-following FMV used in this research was constructed by the learning of the actual data, it is necessary to evaluate the characteristic of the actual data for elucidating the operating characteristic. In addition, it is insufficient to use the value in one point in time like the largest value of following distance as a characteristic appraisal parameter of the actual data. We believe in the near future it is necessary to propose the criteria by that the characteristics of the data can be evaluated in the time series

In addition, the vehicle troop reproduced by simulation must be able to adapt to the different movement of the vehicle troop. Though the car-following FMV used in this research was built from using the limited data, it is possible to correspond to part of different state variation from the lead car.

We think it is possible to build the car-following model what can adapt to the different state of actual running with limited data. From now on, we expect that all car-following FMV can produce stable movement, if we can compare the actual data used for the car-following model of stability driving to the not, and find those differences.

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