Reconstruction of Hierarchical Fuzzy Driving Logic for Road Transportation Simulator with Using Measurement Data Reference Simulation Method

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Abstract : We have already proposed a road transportation simulator for analyzing traffic jam, and called it MITRAM. The MITRAM consisted of microscopic models for vehicles. The model for a vehicle had capability of own decision-making through the fuzzy logic. This model is called Fuzzy Model Vehicle (FMV) which has hierarchical fuzzy driving logic. The driving logic was constructed by neural networks which learned measurement data of actual driving. We have simulated driving of a succeeding vehicle through the FMV, assuming only two vehicles (a preceding actual vehicle and a succeeding FMV) existed. The succeeding FMV was made to learn many kinds of measurement data (e.g. the preceding vehicle speed and acceleration). When the FMV came into the driving states that were not included in the measurement data which we made the FMV learn, the FMV could not always move correctly and sometimes collided with the preceding vehicle in the simulation. Only the measurement data were not enough for the FMV to learn the actual driving. In this paper, we proposed a measurement data reference simulation method. We could always refer to the measurement data during simulation so that we calculated the ideal driving of FMV which was close to the measurement data. The FMV was made to move by not the same but the nearly ideal driving in the measurement data reference simulation which provided new learning data for the FMV. The FMV was reconstructed by both the new learning data and the measurement data. The succeeding vehicle driving was simulated through the reconstructed FMV. This method was repeated until the succeeding FMV did not collide with the preceding vehicle. We found that reconstruction for the FMV with using measurement data reference simulation method was useful for modeling of the FMV.

1. INTRODUCTION

We have already proposed MITRAM [Satoh et al., 1992]. The MITRAM is a new simulator of road transportation system for analyzing traffic jam. The MITRAM consists of microscopic models for individual vehicles. The microscopic model has capability of driver's decision-making through an application of fuzzy logic. This microscopic model is called Fuzzy Model Vehicle (FMV). The fuzzy logic of the FMV was automatically determined by measurement data with using a neural network [Itakura et al., 1993a; 1993b]. The FMV is constructed with this neural network.

We have simulated acceleration and deceleration operations of a succeeding vehicle through the FMV, assuming only a preceding and a succeeding vehicles existed. We assumed that the preceding vehicle would be an actual vehicle and the succeeding vehicle would be the FMV. Data of the succeeding vehicle speed, the relative speed of the succeeding to the preceding vehicle and so on, were obtained as the simulation data. The simulation data were compared with the measurement data to evaluate the FMV [Itakura et al., 1994; 1995]. The simulation data were sometimes different from the measurement data.

We could not always make the FMV get actual acceleration and deceleration operations by making the FMV learn only the measurement data. The FMV could not deal with the states that were not included in the measurement data, and sometimes fell into these states during simulation. It was necessary to make the FMV learn a lot of data measured in various states. However, these data could not be obtained easily.

In this paper, a Measurement Data Reference (MDR) simulation was proposed. The MDR simulation provided learning data for the FMV, instead of measurement of actual driving. The FMV was reconstructed by using those learning data. This reconstruction process was repeated several times. We compared the FMV which was reconstructed several times with the FMV which was constructed by only the measurement data. We discussed the effect of the MDR simulation method on the FMV modeling.

2. MODEL FOR FMV

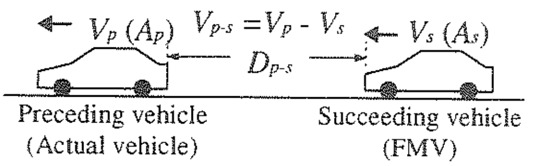


Figure 1 Simulation for the FMV.

We have simulated one pair of a preceding and a succeeding vehicles as shown in Figure 1. A_s and V_s shown in Figure 1 are acceleration and speed of the succeeding vehicle. A_p and V_p are those of the preceding vehicle. The relative speed of the succeeding to the preceding vehicle is $V_{p\text{-}s}$, and the spacing distance between the succeeding and the preceding vehicles is $D_{p\text{-}s}$.

The FMV evaluated in this paper was a model in which driving operations could be changed according to various conditions. It was shown by Itakura et al. [1996]. In order to give any function of changing the driving operations according to various conditions, it is necessary to give selective learning method depending on conditions to the FMV. Consequently, we have proposed the model shown in Figure 2.

This model consists of four neural networks (NN1, NN2, NN3, and NN4). The FMV was constructed by this model with a back propagation method learning the measurement data. $V_{p\text{-}s}(t)$ and $V_s(t)$ are inputs and $A_s(t+1)$ is a output. $W11$, $W12$, $W21$, and $W22$ are changed according to each value of $A_p(t)$ and $D_{p\text{-}s}(t)$. Membership functions ($W11$, $W12$, $W21$, and $W22$) are used to unify Y_1, Y_2, Y_3, and Y_4. The output $A_s(t+1)$ is given as follows:

$$Y_{12} = W11 \times Y_1 + W12 \times Y_2,$$
$$Y_{34} = W11 \times Y_3 + W12 \times Y_4,$$
$$A_s(t+1) = W21 \times Y_{12} + W22 \times Y_{34}. \qquad (1)$$

When the value of $A_p(t)$ is small, $W11$ is the larger and $W12$ is the smaller so that the influence of Y_1 on Y_{12} is stronger than that of Y_2. On the other hand, when the value of $A_p(t)$ is large, $W12$ is the larger and $W11$ is the smaller so that the influence of Y_2 on Y_{12} is stronger than that of Y_1. The error at Y_{12} is distributed to NN1 and NN2 at the ratio of $W11$:$W12$ during learning with a back propagation method. As a result, the logic in the case where the value of $A_p(t)$ is small can be built into the NN1, and the logic in the case where the value of $A_p(t)$ is large can be built into the NN2. We thought that the simulation model shown in Figure 2 was a model in which driving operations could be changed according to the values of $A_p(t)$ and $D_{p\text{-}s}(t)$.

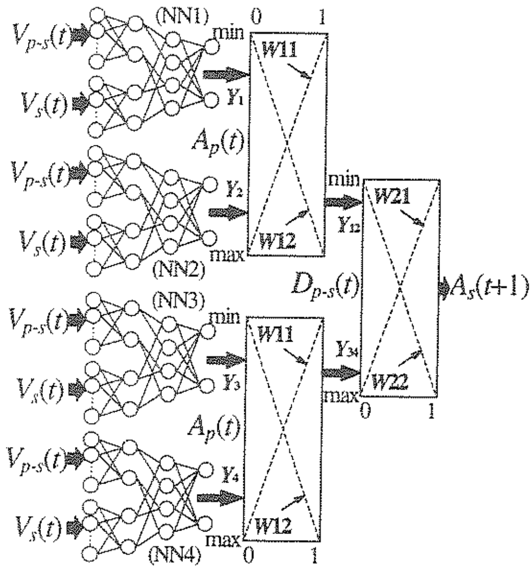


Figure 2 Model for the FMV.

Learning data, which were obtained through measurement of actual traffic condition, were given to the inputs and the output of the FMV. The values of synapse weights corresponding to the membership functions of the FMV could be automatically obtained with using a back propagation method.

We drove two vehicles at roads in a city area to obtain measurement data. The speed of the vehicles and the spacing distance between the vehicles were measured at discrete intervals of 1 second only when there were no other vehicles between our vehicles. The data sets for learning of the FMV were chosen except on the condition both the preceding and the succeeding vehicles did not move at the same time. The total number of the data sets was 45 sets. The 45 data sets were each named Data1, Data2, ..., and Data45. The total time for all the data sets was 4252 seconds. The back propagation method for the FMV was repeated 150 times per one data set.

The previous construction process for the FMV was shown in Figure 3. The FMV whose model was shown in Figure 2 was made to learn only the measurement data. After learning of the FMV, the $A_s(t+1)$ of the FMV which succeeded the preceding actual vehicle was calculated every t time during simulation in order to obtain simulation data. We call these simulation data "normal simulation data" in order to distinguish between normal simulation data and measurement data reference (MDR) simulation data. The MDR simulation are explained in the next section. The normal simulation data were used to evaluate the FMV by comparing with the measurement data.

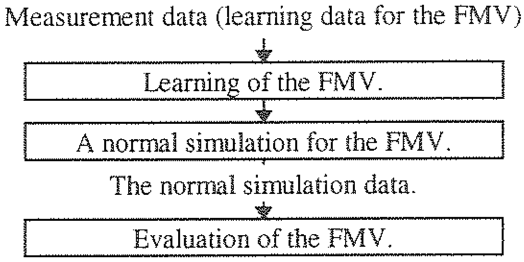


Figure 3 Previous construction process for the FMV.

The learning data for the FMV were only the measurement data in the previous study. The FMV could not deal with the states that were not included in the measurement data and sometimes fell into these states during the normal simulation. As the number of the data in the measurement data sets that the FMV was made to learn decreased, the number of the states that were not included in the measurement data sets was larger. The normal simulation data were sometimes different from the measurement data because the number of the data in the measurement data sets was not always large. Therefore, it was necessary to make the FMV learn a lot of data measured in various states.

In this study, we proposed the measurement data reference (MDR) simulation, instead of measurement for actual driving in various states. The MDR simulation provided the learning data for the FMV. The FMV was reconstructed by using these learning data. The reconstruction process was repeated several times.

3. RECONSTRUCTION OF FMV

3.1 Measurement Data Reference Simulation

We would like to explain the MDR simulation with Figure 4. The open squares in Figure 4 show the $D_{p\text{-}s}$ of the MDR simulation data obtained by the MDR simulation. The open circles and the closed squares show the measurement data and the normal simulation data respectively. If the $D_{p\text{-}s}(t)$ of the normal simulation data was different from that of the measurement data, the $D_{p\text{-}s}(t+1)$ of the normal simulation data would be also different from that of the measurement data because the FMV could not deal with the states that were not included in the measurement data.

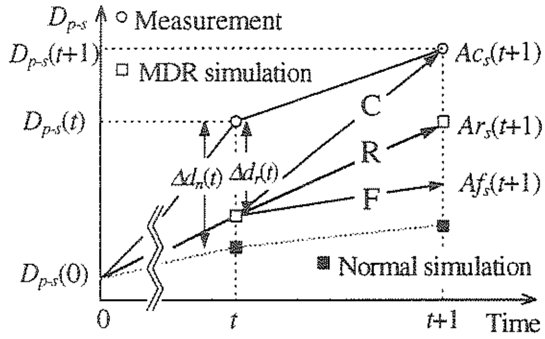


Figure 4 The MDR simulation.

The $Af_s(t+1)$, the $Ar_s(t+1)$ and the $Ac_s(t+1)$ are the accelerations of the succeeding vehicle at $t+1$ time. The transition F, R and C shown in Figure 4 result from the $Af_s(t+1)$, the $Ar_s(t+1)$ and the $Ac_s(t+1)$ respectively. The value of $Af_s(t+1)$ is given from the output of the FMV shown in Figure 2. The $Ac_s(t+1)$ is an acceleration which made the $D_{p\text{-}s}(t+1)$ of the MDR simulation data equal to that of the measurement data. During simulation, $D_{p\text{-}s}(t+1)$ is calculated as

$$D_{p\text{-}s}(t+1)=D_{p\text{-}s}(t)+V_{p\text{-}s}(t)+A_p(t+1)-A_s(t+1) \quad (2)$$

so that the value of $Ac_s(t+1)$ can be calculated by

$$Ac_s(t+1)=D_{p\text{-}s}(t)+V_{p\text{-}s}(t)+A_p(t+1)-D_{p\text{-}s}(t+1), \quad (3)$$

because the $A_p(t+1)$ and the $D_{p\text{-}s}(t+1)$ are given from the measurement data. The $Ar_s(t+1)$ is the acceleration selected in the MDR simulation and the value of $Ar_s(t+1)$ is given as follows:

$$Ar_s(t+1) = G(t)\cdot \Delta Ac_s(t+1) + Af_s(t+1),$$
$$\Delta Ac_s(t+1) = Ac_s(t+1) - Af_s(t+1), \quad (4)$$

where $G(t)$ is a correcting coefficient. The MDR simulation data become close to the measurement data in the case of $G(t)$=0 ~ 1, and are equal to the measurement data in the case of $G(t)$=1. We thought that the MDR simulation data were useful for learning of the FMV in the case where the number of the measurement data was small.

In this study, we investigated the effect of the $G(t)$ on the reconstruction of FMV. The $G(t)$ was set at a constant value (type C) or variable values (type V) during the MDR simulation. Under the type C, the $G(t)$ had a constant value between 0 and 1. Under the type V, the $G(t)$ had variable values ranging from 0 to 1, and is set as follows:

$$G(t) = \alpha \times [\Delta d_r(t) - \theta] \quad (\Delta d_r(t) \geq \theta),$$
$$G(t) = 0 \quad (\Delta d_r(t) < \theta), \quad (5)$$

where θ is a threshold given as follows:

$$\theta = \beta \times M\Delta d_n, \quad (6)$$

and α and β are coefficients which were investigated. The $\Delta d_r(t)$ represents an error between the measurement and the MDR simulation data at $D_{p\text{-}s}(t)$, and the $\Delta d_n(t)$ represents an error between the measurement and the normal simulation data. The "$M\Delta d_n(t)$" represents the mean $\Delta d_n(t)$ during the normal simulation.

We investigated what $G(t)$ had a good effect and which type had a better effect on the reconstruction process for the FMV. The measurement data plus the MDR simulation data were used as the learning data for the FMV. The FMV was reconstructed by these learning data. The next section gives full details of the reconstruction process for the FMV.

3.2 Reconstruction Processes for FMV

Figure 5 shows the reconstruction processes for the FMV. All the reconstruction processes consisted of the 0^{th} to the N^{th} reconstruction processes. The 0^{th} reconstruction process equals to the previous construction process for the FMV shown in Figure 4.

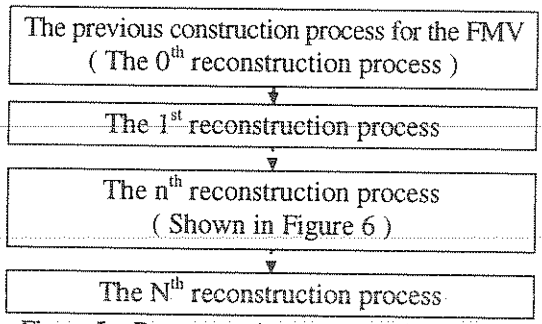
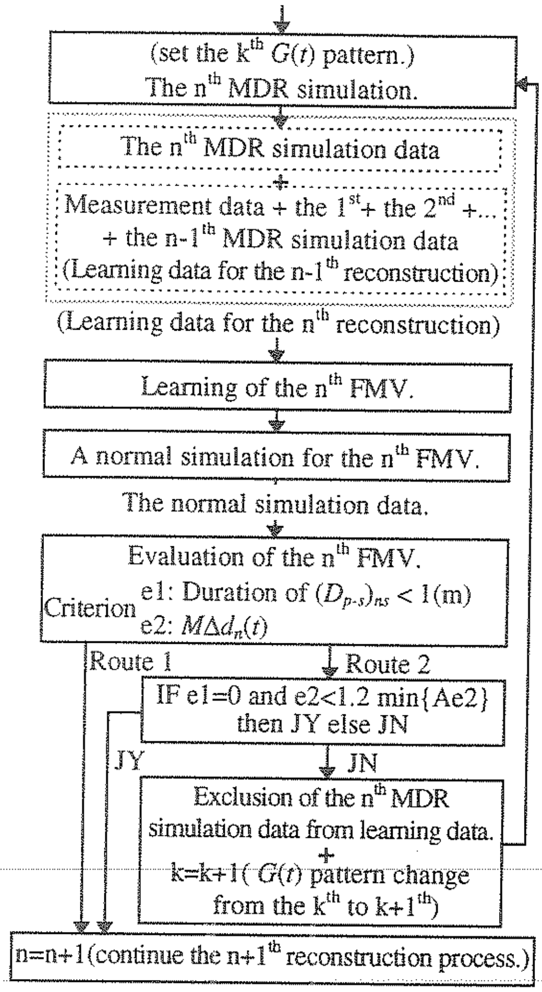


Figure 5 Reconstruction processes for the FMV.

Figure 6 shows the n^{th} reconstruction process. At first, the n^{th} MDR simulation using the n-1^{th} FMV were carried out. The n^{th} MDR simulation data were obtained from the n^{th} MDR simulation. The n^{th} MDR simulation data and the learning data for the n-1^{th} reconstruction were included in the learning data for the n^{th} reconstruction. The learning data for the n-1^{th} reconstruction consisted of the measurement data and from the 1^{st} to the n-1^{th} MDR simulation data. The FMV whose model was shown in Figure 2 was made to learn those learning data for the n^{th} reconstruction.

After learning of the FMV, the normal simulation was carried out to obtain the normal simulation data. The normal simulation data were used to evaluate the FMV. Criteria for the FMV are the duration when the $D_{p\text{-}s}(t)$ of the normal simulation data is less than 1 meter (e1), and the "$M\Delta d_n(t)$" (e2).

When we investigated the $G(t)$ effect on the reconstruction process for the FMV, we selected Route 1 in Figure 6. Then, we continued the n+1^{th} reconstruction process.



$(D_{p\text{-}s})_{ns}$: $D_{p\text{-}s}$ of the normal simulation data.
$M\Delta d_n(t)$: The mean $\Delta d_n(t)$.
Ae2: all the e2 obtained until the n-1^{th} FMV.

Figure 6 The n^{th} reconstruction process.

When we tried to automatically reconstruct the FMV for each measurement data set, we selected Route 2 in Figure 6. When the Route 2 was selected and if the criterion e1 equaled to 0 and the criterion e2 was 1.2 times smaller than minimum value among all the e2 obtained until the n-1^{th} FMV, then JY would be selected, else JN would be selected. When the JN was selected, the n^{th} MDR simulation data were excluded from the learning data for the n^{th} reconstruction and the $G(t)$ patterns were changed from the k^{th} to the k+1^{th}.

4. RESULTS

4.1 Comparison between $G(t)$ Patterns

The FMV that we made learn the measurement data set named Data1 had the largest $M\Delta d_n$(t) in those of the 45 data sets. Therefore, we used Data1 to investigate the reconstruction for the FMV

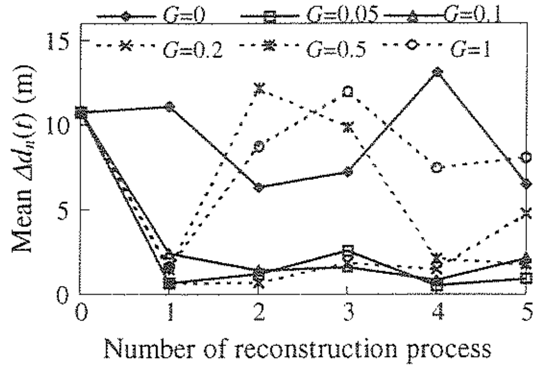


Figure 7 Results of reconstruction for the FMV under Type C (Data1).

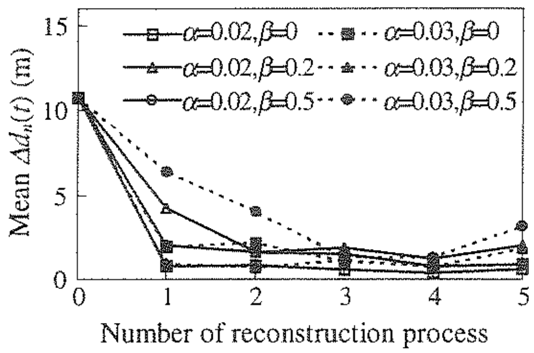


Figure 8 Results of reconstruction for the FMV under Type V (Data1).

Figure 7 shows the results of the reconstruction for the FMV. The several $G(t)$ patterns under Type C were investigated.

The $M\Delta d_n(t)$ values at $G(t)$=1, $G(t)$=0.5 and $G(t)$=0 patterns sometimes became larger than that of the 0th FMV. The $M\Delta d_n(t)$ value of the 1st FMV at $G(t)$=1 became smaller than that of the 0th FMV. However the $M\Delta d_n(t)$ value of the 2nd FMV became larger. The 1st FMV and the 2nd FMV at $G(t)$=1 mean that the FMV was made to learn only one measurement data set until 300 times and 450 times respectively. We thought that the $M\Delta d_n(t)$ values did not always become smaller even if the back propagation method for the FMV was repeated a lot of times per one measurement data set.

As for $G(t)$=0, the $M\Delta d_n(t)$ values from the 1st to 5th FMVs did not always become smaller because the normal simulation data of Data1 were different from the measurement data. On the other side, the $M\Delta d_n(t)$ values from the 1st to 5th FMVs always became smaller about $G(t)$=0.05 and $G(t)$=0.2 .

Figure 8 shows the results of the reconstruction for the FMV under Type V. All the $M\Delta d_n(t)$ values from the 1st to 5th FMVs always became smaller under Type V. Especially, the 4th FMV about α=0.02 and β=0 had the smallest $M\Delta d_n(t)$ value. We could not found the best pattern for α and β because all the $M\Delta d_n(t)$ values became smaller and the difference between the $M\Delta d_n(t)$ values were slight.

Table 1 shows the minimum $M\Delta d_n(t)$ value among $M\Delta d_n(t)$ values from the 1st to 5th FMV. Every minimum $M\Delta d_n(t)$ was smaller than that of the 0th FMV at every $G(t)$ pattern. The mesh cells in Table 1 indicate the minimum value in the same column for each type. Comparing the values in the mesh cells, all the minimum $M\Delta d_n(t)$ values under Type V were smaller than those under Type C.

Table 1 The minimum $M\Delta d_n(t)$ value (m) among $M\Delta d_n(t)$ values from the 1st to the 5th FMVs.

		Data1	Data5	Data36	Data43
The 0th FMV		10.7	2.51	3.47	3.18
Type C	$G(t)$=0	6.29	2.04	2.89	2.92
	$G(t)$=0.05	0.51	1.76	2.12	2.86
	$G(t)$=0.1	0.83	1.48	2.61	2.92
	$G(t)$=0.2	0.66	1.65	2.29	3.12
	$G(t)$=0.5	1.49	1.34	2.22	2.80
	$G(t)$=1	1.62	2.47	2.92	2.60
Type V	α=0.02, β=0	0.38	1.76	2.27	2.60
	α=0.02,β=0.2	1.25	1.32	2.32	2.69
	α=0.02,β=0.5	0.79	1.29	2.28	2.55
	α=0.03, β=0	0.78	1.75	2.01	2.84
	α=0.03,β=0.2	0.70	1.43	1.89	2.51
	α=0.03,β=0.5	1.31	1.41	2.02	2.21

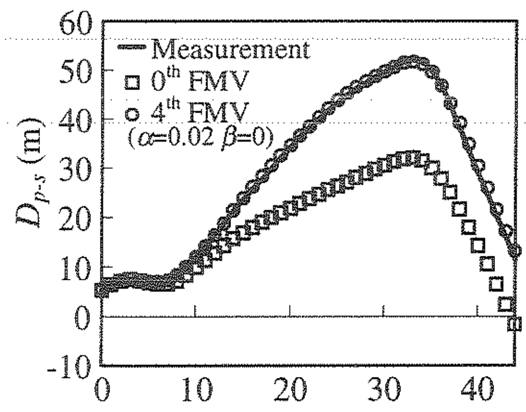


Figure 9 Time series of $D_{p\text{-}s}$ for the FMV(Data1).

Figure 9 shows the time series for $D_{p\text{-}s}$. The open squares show the $D_{p\text{-}s}$ of the normal simulation (the 0th FMV) and the open circles show that of the 4th FMV about α=0.02 and β=0 under Type V. The $M\Delta d_n(t)$ value of the normal simulation is 10.7(m) and that of the 4th FMV is 0.38(m). The thick line shows the measurement data for Data1. We proved that the reconstruction FMV with using the MDR simulation method was useful for modeling of the FMV which could control the same acceleration or deceleration as the driver.

4.2 Automatic Reconstruction Process

We tried an automatic reconstruction process which automatically progressed the reconstruction process with the MDR simulation. The Route 2 in Figure 6 were selected for the automatic reconstruction process. The kth $G(t)$ pattern were selected from 10 patterns at random because the best $G(t)$ pattern for all the measurement data were not able to found. The 10 patterns consists of all the 6 patterns from Type V and the 4 patterns ($G(t)$=0.05, $G(t)$=0.1, $G(t)$=0.2, and $G(t)$=0.5) from Type C. A Criterion e1 is the duration when the $D_{p\text{-}s}(t)$ of the normal simulation data is less than 1 meter. A criterion e2 is the mean $\Delta d_n(t)$. The nth MDR simulation data were excluded from learning data for the nth FMV and the $G(t)$ pattern were changed from the kth to k+1th when the criterion e1 did not equal to 0 and the criterion e2 became 1.2 times larger than the minimum value in all the e2 obtained until the n-1th FMV. Therefore, the normal simulation data for the nth FMV were kept close to the measurement data because the MDR simulation data that made the FMV different from the actual driving were excluded.

Figure 10 shows the results of the automatic reconstruction process. The mean $\Delta d_n(t)$ became small gradually for all the data sets (Data5, Data 36, and Data45). We proved the automatic reconstruction process was useful for the FMV modeling because we could improve the FMV by one algorithm of this reconstruction process.

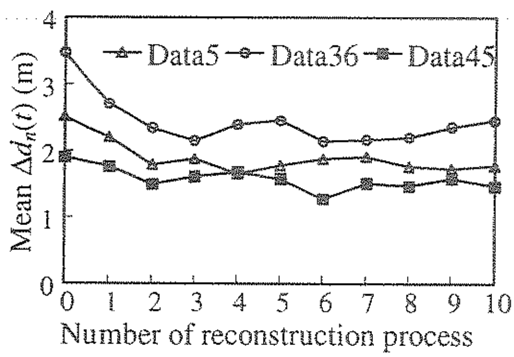


Figure 10 Results of the automatic reconstruction process.

5. CONCLUSIONS

In this study, we proposed the Measurement Data Reference (MDR) simulation. The FMV were reconstructed with the MDR simulation. We investigated the effect of the correcting coefficient $G(t)$ on the FMV modeling. The $G(t)$ was set at a constant value (type C) or variable values (type V). We also used the automatic reconstruction process.

The results are summarized as follows: 1) All the $M\Delta d_n(t)$ values from the 1st to 5th FMVs always became smaller than that of the 0th FMV under Type V. 2)The automatic reconstruction process was useful because the FMV could be improved by one algorithm of this reconstruction process.

We proved that the reconstruction process with using the MDR Simulation method was useful for modeling of the FMV which could control the same acceleration or deceleration as the driver.

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