Journal of Southeast University (English Edition) Vol. 31, No. 3, pp. 424 - 426 Sept. 2015 ISSN 1003—7985

Complexity and applicability analysis among OVM, GFM and FVDM models

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Abstract: The complexity and applicability of three relative car-following models are investigated and they are the optimal velocity model (OVM), the generalized force model (GFM) and the full velocity difference model (FVDM). The vehicle trajectory data used is collected from the digital pictures obtained at a 30-storey building near I-80 freeway. Three different calibrating methods are used to estimate the model parameters and to study the relationships between model complexity and applicability from overall, inter-driver and intra-driver analysis. Results of the three methods of the OVM, GFM and FVDM show that the complexity and applicability are not consistent and the complicated models are not always superior to the simple ones in modeling car-following. The findings of this study can provide useful information for car-following behavior modeling.

Key words: car-following; complexity; applicability; trajectory

doi: 10.3969/j.issn.1003 - 7985.2015.03.022

The car-following model, one of the most important types of microscopic models in traffic flow field, has been developed for more than five decades[1-2]. In recent years, some researchers draw a common conclusion that the complicated models with less fitting errors are better than the simple ones due to more parameters, which can be misleading in reality[3-5].

The prime objective of this study is to analyze the complexity and applicability of different car-following models. The optimal velocity model (OVM), the generalized force model (GFM) and the full velocity difference model (FVDM) are investigated in this paper. Large amounts of measured data are also used to calibrate and cross-compare the three car-following models with different complexities. The applicability takes the overall performances, inter-driver differences and intra-driver differences into account.

Received 2015-01-22.

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Foundation items: The National Basic Research Program of China (973 Program) (No. 2012CB725402), the National Natural Science Foundation of China (No. 51478113).

Citation: Li Ye, Wang Hao, Wang Wei, et al. Complexity and applicability analysis among OVM, GFM and FVDM models[J]. Journal of Southeast University (English Edition), 2015, 31(3): 424 - 426. [doi: 10.3969/j.issn.1003 - 7985.2015.03.022]

1 Car-Following Models

The OVM introduced by Bando[6] is used in this paper. Aslo, the GFM[7] and FVDM[8], which are derived from the OVM, are used. In these models, the acceleration of the n-th velocity is determined by the difference between the actual velocity v_n and the optimal velocity $V(\Delta x_{n-1,n})$, and the speed difference $\Delta v_{n-1,n}$. Tab. 1 summarizes different models with various driving factors, and FVDM has the highest complexity and most comprehensive considerations of diversified conditions.

Tab. 1 Complexity analysis of three different models

Model	$V(\Delta x_{n-1,n})$	v_n	$\Delta v_{n-1,n}(<0)$	$\Delta v_{n-1,n}(>0)$
OVM	✓	✓		
GFM	✓	✓	✓	
FVDM	✓	✓	✓	✓

2 Data Source

The trajectory data used for calibrating the three car-following models is collected on a section on I-80 freeway, USA, which is approximately 500 m in length, with an on-ramp at Powell Street. The data is collected from a 15-min video between 16:00 and 16:15 on April 13, 2005. To obtain the suitable leader-follower combinations among all the trajectories, all the vehicles are filtered according to two criteria: 1) The trajectories of the leader-follower combinations should cover a period at least 15 s; 2) The following car has a unique leader, which ensures that the follower is concerned with cars in the same lane. Following the data selecting procedures, all the vehicles are filtered and 100 valid sets of leader-follower combinations are available for analysis.

3 Calibration Methods

3.1 Calibration for overall analysis

For overall analysis, the models are calibrated for all drivers with the following approach: The measured data of the leader is served as input for three different car-following models. The models calculate the acceleration of the follower and obtain the velocity and position. In this case, the models can simulate the movements of each following car. Comparing the measured data and simulated date of the follower (the driver n), we can obtain the error term ε for each driver and calculate the overall error term E for all the drivers. The error term ε is defined as

$$\varepsilon[v_n^{\text{sim}}(\boldsymbol{\beta}), \Delta x_{n-1,n}^{\text{sim}}(\boldsymbol{\beta})] = \frac{\sqrt{\sum[v_n^{\text{obs}}(t) - v_n^{\text{sim}}(t,\boldsymbol{\beta})]^2}}{\sqrt{\sum[v_n^{\text{obs}}(t)]^2}} + \frac{\sqrt{\sum[\Delta x_{n-1,n}^{\text{obs}}(t) - \Delta x_{n-1,n}^{\text{sim}}(t,\boldsymbol{\beta})]^2}}{\sqrt{\sum[\Delta x_{n-1,n}^{\text{obs}}(t)]^2}} \tag{1}$$

where $v_n^{\text{obs}}(t)$ is the observed speed of the following car at time t; $v_n^{\text{sim}}(t,\boldsymbol{\beta})$ is the simulated speed of the following car at time t with parameter vector $\boldsymbol{\beta}$; $\Delta x_{n-1,n}^{\text{obs}}(t)$ is the observed spacing between the leader and the follower at time t; and $\Delta x_{n-1,n}^{\text{sim}}(t,\boldsymbol{\beta})$ is the simulated spacing between the leader and the follower at time t with parameter vector $\boldsymbol{\beta}$.

The overall error term E used as the combination objective function is calculated as

$$E = \frac{1}{N}\sum_{1}^{N}\varepsilon[v_n^{\text{sim}}(\boldsymbol{\beta}), \Delta x_{n-1,n}^{\text{sim}}(\boldsymbol{\beta})] \tag{2}$$

where N is the number of vehicles.

3.2 Calibration for inter-driver analysis

For inter-driver analysis, the real data of the leader is also served as input for the models to calculate the simulation data of the follower, acceleration, velocity and position. Using the measured data and the simulated data, the error term of each vehicle for inter-driver difference analysis is calculated from Eq. (1). For each driver, the parameter vector is calibrated separately. Therefore, the objective function is applied for all the vehicles independently and is defined in a similar way:

$$E_n = \varepsilon_n[v_n^{\text{sim}}(\boldsymbol{\beta}), \Delta x_{n-1,n}^{\text{sim}}(\boldsymbol{\beta})] \tag{3}$$

3.3 Calibration for intra-driver analysis

For intra-driver analysis, the data of all the leader-follower combinations are split into two parts equally first. Each part has at least 75 observations. Then, part Ⅰ and part Ⅱ are calibrated with the method mentioned in the calibration for inter-driver analysis, respectively. For each vehicle in the two parts, the error term ε_n^J is defined as

$$\varepsilon_n^J[v_n^{\text{sim},J}(\boldsymbol{\beta}), \Delta x_{n-1,n}^{\text{sim},J}(\boldsymbol{\beta})] = \frac{\sqrt{\sum[v_n^{\text{obs},J}(t) - v_n^{\text{sim},J}(t,\boldsymbol{\beta})]^2}}{\sqrt{\sum[v_n^{\text{obs},J}(t)]^2}} + \frac{\sqrt{\sum[\Delta x_{n-1,n}^{\text{obs},J}(t) - \Delta x_{n-1,n}^{\text{sim},J}(t,\boldsymbol{\beta})]^2}}{\sqrt{\sum[\Delta x_{n-1,n}^{\text{obs},J}(t)]^2}} \tag{4}$$

where $J \in \{\text{Part Ⅰ}, \text{Part Ⅱ}\}$.

In the two parts, the parameter vector of each vehicle is calibrated in the same way, with the independent objective function as follows:

$$E_n^J = \varepsilon_n^J[v_n^{\text{sim},J}(\boldsymbol{\beta}), \Delta x_{n-1,n}^{\text{sim},J}(\boldsymbol{\beta})] \tag{5}$$

4 Results

4.1 Results of overall analysis

The calibration process of overall analysis is conducted three times, and the results are shown in Tab. 2 and Tab. 3. The results show that the OVM has the highest average error of 0.13, which means that the OVM does not perform as well as the other two models at a relative macroscopic level for all the vehicles. The GFM and FVDM perform well, with average errors of 0.09 and 0.08, respectively. These results are in accordance with the existing research results; i.e., FVDM has the highest complexity among the three models and can simulate the car-following behavior more sophisticatedly. The time-consuming T of each calibration is also recorded, which indicates that the models' precision and efficiency are contradictory.

Tab. 2 Results of E of calibration for overall analysis

Model	E_1	E_2	E_3	E_{mean}	Relative to OVM/%
OVM	0.128 3	0.128 1	0.128 5	0.13	0.00
GFM	0.089 0	0.089 0	0.089 8	0.09	−30.41
FVDM	0.077 4	0.079 4	0.077 4	0.08	−39.19

Tab. 3 Time-consuming of calibration for overall analysis

Model	T_1/s	T_2/s	T_3/s	T_{mean}/s	Relative to OVM/%
OVM	1 033	1 033	1 125	1 064	0
GFM	1 164	1 160	1 164	1 162	9.28
FVDM	1 267	1 268	1 273	1 269	19.32

4.2 Results of inter-driver analysis

The descriptive statistics for inter-driver analysis shown in Tab. 4 indicate that the complex model is inferior in certain aspects, especially in inter-driver heterogeneity. The coefficient of variation (CV), defined as the ratio of the standard deviation divided by the mean, is used to evaluate the degree of dispersion of different model parameters. The mean CV values of all the parameters illustrate that the simplest model OVM has the smallest CV, which implies the minimum degree of dispersion of model parameters. The large CV value of the FVDM means that the model cannot be used to model all the vehicles with the unique parameters due to inter-driver heterogeneity. From this perspective, the complex models are not always applicable for modelling car-following.

Tab. 4 Descriptive statistics for inter-driver analysis

Model	Statistics	α	λ	v_{max}	h_c	Mean
OVM	Mean	0.35		38.91	53.87	
	SD	0.37		16.38	17.00	
	CV	1.06		0.42	0.32	0.60
GFM	Mean	0.11	0.80	64.82	45.51	
	SD	0.12	0.52	32.43	19.82	
	CV	1.11	0.65	0.50	0.44	0.67
FVDM	Mean	0.10	0.43	53.67	53.53	
	SD	0.25	0.27	33.82	22.44	
	CV	2.58	0.62	0.63	0.42	1.06

4.3 Results of intra-driver analysis

The Theil's U[9] is applied to compare the intra-driver differences of the two parts. As shown in Tab. 5, it is clear that the simplest model OVM has the smallest mean U value of 0.361 8, which means that the OVM has the minimum degree of dispersion of parameters for the different driving periods of the same driver. In contrast, the complicated FVDM has the largest average U value of 0.416 9, which means that the model cannot model different periods of the same vehicle with the uniform parameters. The results show that complicated models (such as the FVDM) do not have better performances considering intra-driver heterogeneity.

Tab. 5 Results of calibration for intra-driver analysis

Model	$U(\alpha)$	$U(\lambda)$	$U(v_{max})$	$U(h_c)$	U_{mean}
OVM	0.524 1		0.312 1	0.249 1	0.361 8
GFM	0.649 3	0.406 0	0.313 1	0.270 6	0.409 8
FVDM	0.636 3	0.360 5	0.350 8	0.320 2	0.416 9

5 Conclusion

An approach is proposed to investigate the relationship between complexity and applicability of car-following models by using trajectory data. The most important result from the inter-driver and intra-driver analysis is that the complexity and applicability are not consistent. Therefore, in future research, the standard determining the appropriate car-following models of different research goals is urgently needed.

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OVM,GFM 及 FVDM 模型的复杂性与应用性分析

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摘要:对优化速度模型(OVM)、广义力模型(GFM)、全速差模型(FVDM)3 种相关跟驰模型的复杂性与适应性进行了研究.采用美国Ⅰ-80 高速公路附近 30 层高楼上所拍摄数字图像,并提取车辆轨迹数据,通过 3 种不同的标定方式对跟驰模型进行了参数标定,进而从总体、驾驶员间异质性、驾驶员自身异质性 3 个方面对模型复杂性与应用性进行了对比分析.研究结果表明,OVM,GFM,FVDM 三种模型的应用性和复杂度并不具有一致性,复杂度高的模型在模拟跟驰的应用性上并不一定优于简单模型.研究结果为跟驰行为的建模研究提供了有效信息.

关键词:跟驰;复杂性;应用性;轨迹

中图分类号:U491