Factor analysis for choosing input variables of a car-following model

J. Hongfei\textsuperscript{1}, J. Zhicai\textsuperscript{2} & L. Xia\textsuperscript{1}
\textsuperscript{1}Department of Transportation & Traffic, Jilin University, Changchun City, Jilin Province, People’s Republic of China
\textsuperscript{2}Institute of transportation, Shanghai Jiaotong University, Shanghai City, People’s Republic of China

Abstract

The driver car-following behavior is a very complex phenomenon and it is very hard to realistically simulate the driver behavior which under the influence of many factors that can not be identified. Most of the existing car-following models were developed on the basis of a sensible understanding of traffic phenomena, and some have made statistical analysis of the field data, but the question “which factors affect driver car-following behavior” is not well answered. Namely, the input variables of car-following models are usually chosen empirically and no further theoretical studies are done. In this paper, the nonlinear statistical method of factor analysis is used to extract useful information from representative field data and those endogenous variables with higher information are selected as input variables to establish a car-following model. Finally, the model is verified used data collected through the Five-Wheel systems experiment.

Keywords: traffic flow; input variable; factor analysis; car-following model.

1 Introduction

As the computers are more popular and reliable nowadays, the utilization of simulation techniques in every aspect of engineering is becoming invaluable tools of data gathering, forecasting and testing. The area of traffic engineering relies on the simulation tools when actual data collection is not feasible or possible. Among the traffic engineering tools, the most significant ones are the microscopic simulation models or the car-following models. The car-following
models attempt to explain the behavior of vehicles in traffic and platoons. The vehicles that are in platoons or in car-following dictate the conditions of the highways, arterials and all the other traffic facilities. The behavior of these vehicles reflects the operational characteristics of the highway facilities. Ergo, the car-following models that simulate the behavior of the vehicles in platoons are the backbone of the traffic simulation tools and becoming the main ways to study and evaluate Intelligent Transportation Systems (ITS) [1]. The accuracy of the car-following models determines the success and reliability of the traffic simulation.

The driver car-following behavior is a very complex phenomenon and it is very hard to realistically simulate the driver behavior which under the influence of many factors that can not be identified. In order to establish a realistic and reliable car-following model, not only the psychophysical characteristics of the drivers, such as the course of perception, judgment and decision should be studied, but also the car-following field data should be analyzed carefully to find the factors affecting the driver behavior and avoid the disturbance to simulation output caused by information overlapping. In other words, for establishing a car-following model, besides the drivers’ reaction time and perception threshold, the emphasis should be put on the correct selection of the model input variables which can reflect driver behavior realistically. Popular car-following models NETSIM, INTRAS, FRESIM and CARSIM have been widely used in simulation of various traffic conditions. Although, the simulation results are substituted in place of the real data in most cases, there is not adequate information available in the literature related to this models assumptions and capabilities, especially no theoretical foundation for the choice of input variables is provided. In this paper, the nonlinear statistical method of factor analysis is used to extract the useful information from field data of those variables which are most used in the existing car-following models, such as the relevant distance and velocity between two vehicles in following condition, the velocity of the follower, and the acceleration of this two vehicle, to seek the endogenous variables with higher information as the input variables of car-following mode.

2 Data collection

The field data is collected through the Five-Wheel systems experiment in which two experimental vehicles, both as small passenger cars are settled with velocity automatic record system and velocity values can be recorded in small time intervals, such as 0.1 seconds during the following course [2,3]. The data showed as in Table I (see appendix A) is a small part of those 40,000 data used for input variables selection and calibration.

3 Data analysis

Previous studies on car-following models in most cases based on the perceptual knowledge for traffic phenomena and did not directly involve the selective problems to input variables as well. Utilizing factor analysis to perform
statistical analysis on typical field data and choosing relatively independent factors whose common factor loading is higher (namely, higher information loaded) as input variables to a car-following model thus we can avoid the disturbances to simulation and information overlapping caused by multi-collinearity between a few of variables.

Figure 1: Algorithm of factor analysis.

4 Factor analysis principle

As poly-statistics method, factor analysis requests for data basic structure and classifies variables or samples. Firstly developed on psychology, it has been extensively applied to many fields in natural and social science at present. In this paper, we adopt factor analysis to “purify” the information involved in field data samples (as shown in Table 1) and seek the endogenous variables that to the greatest extent reflect car-following phenomenon as basis of establishing microscopic traffic simulation. For the word limitation, only algorithm of factor analysis is shown in Figure 1, the principles, explanations to statistical significance for factor loading and algorithm of orthogonal rotation with maximum variance are shown in reference [4] etc.
5 Data analysis

Utilizing the above data (see Table 1), we firstly select seven variables such as leader velocity \((v_{n-1})\), follower velocity \((v_n)\), relative speed \((v_{n-1}-v_n)\), leader position \((x_{n-1})\), follower position \((x_n)\), relative distance \((x_{n-1}-x_n)\) leader acceleration \((a_{n-1})\) and so forth then build factor model to carry out statistical analysis. The mutual relation between variables is shown in Table 1. Table II (see appendix A) gives variance explanation after convergence with six iterations in different condition that before and after factors extraction and after orthogonal rotation with maximum variance. As known from Table II, the accumulative information provided by the first four common factors \((x_{n-1}, v_{n-1}, a_{n-1}, x_n)\) variance “distribution” takes more than 99.5 percent of all the information after preliminary extraction, and the rest supplied from other factors just only does less than 0.5 percent, the fourth factor \((x_n)\) offered over 5 percent, hence microscopic simulation with higher requisites could not be negligible.

Figure 2 apparently shows information content of each factor. In order to avoid that the multi-collinearity decreases covariance correlative coefficient when calibrating with regression, the first four factors are chosen as main influential factors to perform further detailed analysis. Table 2 gives factor loaded matrix reflected factor structure.

From factor structure provided by Table 2, we know that loaded coefficients in matrix reach the polarity between 0 and 1 after orthogonal rotation with maximum variance.

<table>
<thead>
<tr>
<th>Correlative Matrix</th>
<th>(x_{n-1}) (m)</th>
<th>(v_{n-1}) (m/sec)</th>
<th>(a_{n-1}) (m/sec^2)</th>
<th>(x_n) (m)</th>
<th>(v_n) (m/sec)</th>
<th>(v_{n-1}-v_n) (m/sec)</th>
<th>(x_{n-1}-x_n) (m)</th>
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<td>-.027</td>
<td>-.339</td>
<td>.999</td>
<td>.202</td>
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<td>.356</td>
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<td>(v_{n-1}) (m/sec)</td>
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<td>1.000</td>
<td>-.074</td>
<td>-.077</td>
<td>.944</td>
<td>.471</td>
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<td>(a_{n-1}) (m/sec^2)</td>
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<td>-.074</td>
<td>1.000</td>
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<td>-.212</td>
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<td>(v_{n-1}-v_n) (m/sec)</td>
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<td>(x_{n-1}-x_n) (m)</td>
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Table 2: Factor matrix after rotation.

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<td>.964</td>
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<td>-1.648E-02</td>
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<td>(a_{n-1}) (m/sec^2)</td>
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<td>-.180</td>
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<td>.123</td>
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<td>(x_n) (m)</td>
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<td>(v_n) (m/sec)</td>
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<td>6.848E-02</td>
<td>-8.806E-02</td>
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<td>(v_{n-1}-v_n) (m/sec)</td>
<td>.213</td>
<td>-.477</td>
<td>.187</td>
<td>.832</td>
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<td>-8.943E-02</td>
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Horizontally to see, the common ground of leader velocity, follower velocity and spatial headway variables is very high, all of them have 96.5 percent information reflected in main four factors. The common ground of others variables falls between 0.7 and 0.8, which reflects the main four factors to extremity “squeeze” information of previous seven variables. To vertically analyze, the fourth main factor to the greatest degree embodies the information of velocity variation, therefore, it was firstly selected out as input variables in microscopic simulation. It also can be noticed that leader velocity shades highest weight in third main factor. As a consequence, this variable should be picked up as one of input variables. For first common factor, follower velocity takes greatest weight in factor space then it also becomes input variable. To second common factor, leader and follower displacement have higher weight in factor space, meanwhile spatial headway has been more generally representative (although it’s load is less than velocity variation value in the same column, because velocity variation has been taken out, so when given another choice, it must be spatial headway), consequently it should be selected as another input variable.

6 Models verification

The car-following model calculates a vehicle’s acceleration rate in terms of its relationship with the leading vehicle. In this paper, a vehicle is classified into one of two stages: distance control and velocity control. Each one of these stages corresponds to a required acceleration/deceleration rate (see Figure 3).

According to different stage, it is necessary to adopt different algorithm then correspondingly design and calibrate the models. The car-following model adopt in this paper is shown as equation 1.

\[
a_n^*(t) = \max \{ \min( a_n(t), A_{\text{max}}, \frac{V_{\text{max}} - V_n}{k \Delta t} ), B_{\text{max}} \} \tag{1}
\]

where \( A_{\text{max}} \) and \( B_{\text{max}} \) are the maximum acceleration and deceleration of the follower (n\text{th} vehicle) and \( V_{\text{max}} \) is its ideal maximum speed. Parameter \( k \) is a positive integer specified arbitrarily, which is used to avoid excessive acceleration fluctuation during the follower accelerating course. The acceleration...
Figure 3: Programme of stage judgement in car-following module.

\[ a_n(t) = \frac{(\Delta t)}{\alpha_1(\Delta t) + (\Delta t)\alpha_2 + \frac{1}{2} (\Delta t)^2} \{v_{n-1}(t) - v_n(t)\} + \]

\[ \frac{1}{(\Delta t)\alpha_2 + \frac{1}{2} (\Delta t)^2 + \alpha_1 (\Delta t)} \{x_{n-1}(t) - x_n(t) - d_n\} + \]

\[ \frac{(-\alpha_2)}{(\Delta t)\alpha_2 + \frac{1}{2} (\Delta t)^2 + \alpha_1 (\Delta t)} v_n(t) + \]

\[ \frac{1}{2} (\Delta t)^2 + \alpha_1 (\Delta t) a_{n-1}(t) - \frac{\gamma_2}{(\Delta t)\alpha_2 + \frac{1}{2} (\Delta t)^2 + \alpha_1 (\Delta t)} \]

\[ = \frac{(\Delta t)}{\alpha_1(\Delta t) + (\Delta t)\alpha_2 + \frac{1}{2} (\Delta t)^2} \{v_{n-1}(t) - v_n(t)\} + \]

\[ \frac{1}{(\Delta t)\alpha_2 + \frac{1}{2} (\Delta t)^2 + \alpha_1 (\Delta t)} \{x_{n-1}(t) - x_n(t) - d_n\} + \]

\[ \frac{(-\alpha_2)}{(\Delta t)\alpha_2 + \frac{1}{2} (\Delta t)^2 + \alpha_1 (\Delta t)} v_n(t) + \]

\[ \frac{1}{2} (\Delta t)^2 + \alpha_1 (\Delta t) a_{n-1}(t) - \frac{\gamma_2}{(\Delta t)\alpha_2 + \frac{1}{2} (\Delta t)^2 + \alpha_1 (\Delta t)} \]

\[ a_n(t) \] adopt in the free and distance controlling stage is shown as equation 2, and during velocity controlling stage, \(a_n(t)\) is calculated as equation 3.
where \( \Delta t \) is the time step for simulation; \( d_n(t) \) and \( \delta_n(t) \) is the follower’s desired distance and reaction time separately; \( \alpha_1, \alpha_2, \gamma_2 \) are factors to be calibrated.

The above models are calibrated used the data which is collected through the Five-Wheel systems experiment and can reflect different car-following stages. If want details of this part to see references [5].

Models’ verifying results are portrayed in Figure 4 and Figure 5. In Figure 4 and Figure 5, the black, red and yellow curve is represented leader, follower and simulated follower position or acceleration separately.
7 Conclusions

Traffic jams, traffic pollution and accidents have become jeopardy to human beings and society. Traffic block is a critical factor to restrict city development and economic growth. As an analytical tool, traffic flow simulation reproduces kinematical regulations of traffic flow and becomes not only an important experimental means to control and optimize traffic system but also significant tool for development and experimental study of ITS, ATMS and ATIS that are spreading launched in the filed of transportation as well. This paper studies the selection of input variables with factor analysis and field typical data, requests fundamental structure of car-following models, selects factors with higher information and relatively independent variables as input parameters for microscopic traffic simulation models, so as to avert the disturbances to simulation output caused by information overlapping. In this paper, only these variables which are most used in the existing car-following models are studied, other variables such as traffic environmental, driver characteristics should be included for further studies.

References

Appendix A

Table I: Part data for models analysis and calibration.

<table>
<thead>
<tr>
<th>Time (sec.)</th>
<th>Leader Position (m)</th>
<th>Leader Velocity (m/sec)</th>
<th>Leader Acceleration (m/sec^2)</th>
<th>Follower Position (m)</th>
<th>Follower Velocity (m/sec)</th>
<th>Follower Acceleration (m/sec^2)</th>
<th>Relative Velocity (m/sec)</th>
<th>Distance Headway (m)</th>
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Table II: Total variance explained.

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<th>Squares Sum of Factor Loading after Rotation</th>
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<td>Percentage of Total Variance (%)</td>
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