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A video-based approach to calibrating car-following parameters in VISSIM for urban traffic

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ABSTRACT

Microscopic simulation models need to be calibrated to represent realistic local traffic conditions. Traditional calibration methods are conducted by searching for the model parameter set that minimizes the discrepancies of certain macroscopic metrics between simulation results and field observations. However, this process could easily lead to inappropriate selection of calibration parameters and thus erroneous simulation results. This paper proposes a video-based approach to incorporate direct measurements of car-following parameters into the process of VISSIM model calibration. The proposed method applies automated video processing techniques to extract vehicle trajectory data and utilizes the trajectory data to determine values of certain car-following parameters in VISSIM. This paper first describes the calibration procedure step by step, and then applies the method to a case study of simulating traffic at a signalized intersection in VISSIM. From the field-collected video footage, trajectories of 1229 through-movement vehicles were extracted and analyzed to calibrate three car-following parameters regarding desired speed, desired acceleration, and safe following distance, respectively. The case study demonstrates the advantages and feasibility of the proposed approach.

Introduction

With the increasing complexity of traffic network and traffic management systems, microscopic traffic simulation has become one of the major tools to evaluate and optimize various traffic management and control systems.

Microscopic traffic simulation models replicate real-world traffic network dynamics by simulating individual vehicles' movement in the network. One of the essential components of any microscopic traffic simulation model is the driver behavior models that define how drivers are making decisions in terms of lane selection, car-following, and route choice. All driver behavior models include parameters that must be appropriately calibrated before a simulation can be used. For example, a car-following model contains multiple parameters describing distribution of drivers' following behavior (microscopic parameters). Model calibration is essential as drivers' behaviors vary significantly over location and driving conditions (time

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of the day, weather, etc.). The default parameters of the simulation software rarely represent local traffic characteristics and conditions. Because the increasing popularity of microscopic simulation and the importance of model calibration, numerous methods have been proposed to calibrate model parameters (Hollander and Liu, 2008). Due to the difficulties in measuring microscopic parameters directly, most of these methods use field-measured macroscopic traffic flow parameters as measures of effectiveness (MOEs) to calibrate microscopic driving behavior parameters. Macroscopic parameters, e.g., average travel time, are aggregated measures defining the state of traffic flow. These methods assume that the microscopic parameter set that generates the minimum estimation error in terms of certain macroscopic measures between simulation and field observations is optimal. Upon this assumption, different search techniques have been proposed to find the optimal parameter set. Traditionally, this task was conducted manually, based on users' experience (Benekohal and Abu-Lebdeh, 1994; Daigle et al., 1998; Hellinga, 2015). Recently, several optimization based approaches have been proposed, such as, gradient search, simplex-based, and genetic algorithm (GA) aiming at automate the calibration process (Kleijnen, 1995; Ma and Abdulhai, 2002; Kim and Rilett, 2003; Dowling et al., 2004; Park and Qi, 2005; Ishaque and Noland, 2009). Among these approaches, GA is the most widely applied method due to its simplicity, computational efficiency, and ability to find near optimal solution to a global optimization problem. However, despite the sophistication of applied search techniques, the basic assumption underlying these methods is questionable as the microscopic parameter set generating the least error of certain macroscopic parameters may not accurately reflect local traffic conditions, especially when the selection of the calibration parameters is inappropriate (Kim et al., 2005). The agreement in the system behavior at macro level is a necessary but not a sufficient condition for accurate calibration results on microscopic parameters. The premise of microscopic simulation is that the consistency with the real world behavior at a micro level is robust and likely to capture drivers' response to changes in system conditions (e.g., new controls and regulations) (Barceló et al., 2005).

To improve the reliability and credibility of traditional simulation calibration procedure, researchers have attempted to utilize microscopic trajectory data during the calibration process. For example, Brockfeld et al. (2004) calibrated various car-following models using data provide by ten probe vehicles equipped with Global Positioning System (GPS). Also, some studies use naturalistic driving data from the Next Generation SIMulation (NGSIM) (NGSIM, 2007) to calibrate or validate car-following models (Cunto and Saccomanno, 2008; Chen et al., 2010; Higgs et al., 2011). However, due to the characteristics of probe vehicle data, these studies are usually based on trajectories from relatively small sample size of drivers; moreover, NGSIM data can hardly be applied to model local variability. In recent years, vide-based automated trajectory analysis presents a feasible means to directly derive accurate driving behavior parameters. The automated video processing techniques can provide individual vehicles' trajectory data in the form of positions over time series, and then the velocity and acceleration vectors can be derived by simple differentiation of position and subsequently velocity over time (St-Aubin et al., 2015). Fu et al. (2016) used the manually observed speed as "ground truth" to evaluate the accuracy of speed information automatically extracted from video footage collected by regular and thermal cameras. The evaluation criteria are mean relative error, relative accuracy error, and relative precision error. The results suggest that the method of extracting speed from video is robust under various environmental conditions. The decreasing cost and increasing prevalence of video sensors along with the reliable automated techniques of extracting microscopic parameters from videos provide a very promising opportunity to apply video-extracted information to the simulation calibration. The large amount of video information enables traffic practitioners to calibrate simulation models accounting for the local variability at a relatively low cost.

The objective of this paper is to develop a reliable and practical method for calibrating car-following parameters for urban traffic in VISSIM. The method is expected to be robust as it includes direct measurements of microscopic parameters from video footage as inputs to the model and benchmark for the model output. The following parts of the paper first give a step-by-step description of the proposed method, and then further demonstrate the method through a case study of simulating traffic at a signalized intersection in VISSIM. Lastly, the paper summarizes the research findings and proposes the future work.

Proposed methodology

The proposed procedure for calibrating microscopic simulation models consists of six main steps: field data collection, parameter selection, sensitivity analysis, microscopic parameter extraction, parameter calibration, and model evaluation. This procedure generally agrees with the framework proposed in Park and Qi (2005). The main innovation lies in the addition of the step microscopic parameter extraction. The inclusion of direct measurements of microscopic parameters strengthens the credibility of the method. Detailed description of each step is descried as follows.

Field data collection

Traffic video data are required for the calibration method proposed in this paper. The traffic video data are used to both determine measures of effectiveness (MOEs) and extract certain microscopic calibration parameters. When video data are collected from the study site, several situations need to be avoided in order to facilitate automatic video data processing: 1. glare from sun; 2. frost/raindrop on camera; 3. reflection; 4. obstacle in between (Fu et al., 2015). Moreover, the field-collected video data should meet the requirements of spatial coverage, temporal coverage, and event coverage.

Parameter selection

This paper mainly focuses on calibrating car-following models in the VISSIM microscopic simulation environment. VISSIM contains two psycho-physical perception car-following models: Widedemann 74 and Wiedemann 99 (VISSIM 7 User Manual, 2015). Widedemann 74 is more commonly used to model urban traffic while Widemann 99 is more suitable for modeling traffic on freeway. Since the proposed paper mainly addresses calibration issues for urban traffic, the car-following model appeared in the remainder of this paper refers to the Widedemann 74 model. The basic concept of the model is that a driver decelerates when his or her perception threshold has been met, and this threshold depends on the relative speed and distance to the leading vehicle. Otherwise, the driver travels at or accelerates to his or her desired speed (Wiedemann, 1974). The difference within drivers is taken into consideration with stochastic distribution functions of driving behavior parameters (VISSIM 7 User Manual, 2015).

Three main categories of parameters are used in VISSIM to define car-following behaviors: desired speed, acceleration/deceleration, and safe following distance. Desired speed is defined as the speed at which a driver travels if not hindered by other vehicles or network objects, e.g., signal controls (VISSIM 7 User Manual, 2015). Desired speed distribution for drivers of different vehicle types can be modified by model users, and so do desired acceleration/deceleration distribution parameters. Safe following distance parameters define the spacing-based threshold which a driver uses to decide whether to decelerate or not.

Sensitivity analysis

Due to the complexity of the microscopic simulation models, the number of calibration parameters has a significant effect on the computation time. The objective of the sensitivity analysis is to identify key model parameters affecting MOEs. In a sensitivity analysis, parameters chosen from the step parameter selection are tested to assess their level of influence on MOEs. A baseline scenario is first developed using default values for all initially selected parameters. Afterward, the value of parameters is changed one at a time, while other parameters are kept to default values. Values of MOEs are collected for all scenarios. The trend of how the MOEs change over the varying parameter value demonstrates the intensity of the relationship between MOEs and this parameter. Based on the sensitivity analysis results, parameters with low effect on MOEs are excluded.

Microscopic parameter extraction

Certain microscopic calibration parameters can be directly measured from vehicle trajectories. In this paper, an open-source software called Traffic Intelligence is used to track individual vehicle trajectories from video data. The software has been applied in several studies with its feature-based tracking technique (Saunier and Syed, 2006). It can provide reliable results of vehicle trajectories in world coordinates (2-D) even the video are recorded by a camera with a wide-angle lens (Saunier, 2016). First, individual pixel trajectories (features) are detected using the robust Kanade-Lucas-Tomasi feature tracker. Second, those features are grouped into objects, each representing a moving vehicle. The grouping of features is based on their relative distance and motion to each other. $D_{connection}$ and $D_{segmentation}$ are maximum relative distance and motion thresholds for features to be grouped as one object. These values can be adjusted by users to adapt various video filming heights, angels, and resolutions.

The implementation steps of extracting trajectories from video using Traffic Intelligence are demonstrated as follows:

1. Prepare a screenshot of the video and a high-resolution aerial map of the filming area. By matching multiple corresponding points on the screenshot and map, a homography matrix is computed to convert image coordinates into world coordinates.
2. Run feature-tracking scripts to generate feature trajectories.
3. Run feature-grouping scripts to generate object trajectories. Depending on the trajectory extraction quality (users can visually review object trajectory animations after feature-grouping), users iteratively calibrate the values of $D_{connection}$ and $D_{segmentation}$ to achieve a balance between oversegmentation and overgrouping.

After the video is processed, Traffic Intelligence outputs temporal series of individual vehicle positions in world-space coordinates. A screenshot of the Traffic Intelligence's object-reviewing interface is provided in Fig. 1.

Then, vehicle speed and acceleration/deceleration information can be obtained from trajectory data by a simple differentiation of position and subsequent speed over time. This information can be used to determine values of calibration parameters regarding desired speed and acceleration/deceleration. Due to the complexity of measuring front-rear distance between vehicles in video, parameters related to safe following distance are not directly measured from video data in this paper; their values are later obtained in the step parameter calibration.

Parameter calibration

Since safe following distance parameters remain to be calibrated, optimization algorithms are applied to search for optimal values of these parameters to match the simulated MOEs with field-measured MOEs. The choice of appropriate

Fig. 1. Traffic Intelligence object-reviewing interface.

algorithm is influenced by the number of calibration parameters, relationship between MOEs and calibration parameters, computing time constraints, and acceptable error level.

Model evaluation

Once model parameters are calibrated, an evaluation is conducted to assess the credibility of the model. First, simulation animations are viewed to check whether there is significant difference with the real-world traffic. In the next step, quantitative indictors are selected to compare results from calibrated simulations and field observations. If no discrepancy has been found from either animations or quantitative indicators, the model can be regarded as successfully calibrated. Otherwise, the model user needs to re-calibrate the model from parameter selection.

Furthermore, model variability needs to be evaluated. VISSIM uses random seeds within the simulation to generate stochastic results. To acquire credible simulation results, multiple runs are necessary. The required running times are dependent on the result variability, acceptable error, and significance level.

Case study

The proposed procedure for calibrating car following parameters in microscopic simulator VISSIM is illustrated by a case study conducted in Waterloo, Ontario, Canada. It should be noted that although the case study only shows an example of calibrating simulation models at signalized intersections, the method can also be easily applied to traffic on road segments. However, the selection of MOEs and calibration parameters could be different between simulation of uninterrupted traffic flow and interrupted traffic flow.

Field data collection

The intersection of University Avenue and Seagram Drive in Waterloo was selected as the study site. We collected two hours of video data from a day in spring 2015 using a portable video data collection device called Miovision Scout. The camera was situated 21 feet above the road surface. The study site and video location settings are shown in Fig. 2.

Average saturation headway on through lanes was selected as the MOE for model calibration, as it is crucial to the performance of signal timing plans and able to be measured from both field data and simulation (Sharma and Swami, 2012). Saturation headway on through lanes for each cycle was estimated using the field measurement method described in Highway Capacity Manual (2010). According to HCM 2010, the first four vehicles in the cycle are expected to experience start-up delay. Therefore, vehicles after the fourth and until the last one that was in the initial queue (the queue at the beginning of the green) comprise the saturation status. The procedure is described as follows: 1. manually record the time when each vehicle's rear axle passes the stop line from video, 2. calculate headway between vehicles by subtracting the time when the leading vehicle's rear axle passes the stop line from the time when the following vehicle's rear axle passes the line, 3. for each cycle, calculate the average headway between vehicles in the saturated status. This average value is then used as the estimation of saturation headway for the cycle. Following the guidelines, cycles with less than eight vehicles in the initial queue were excluded from the analysis in order to achieve significant results.

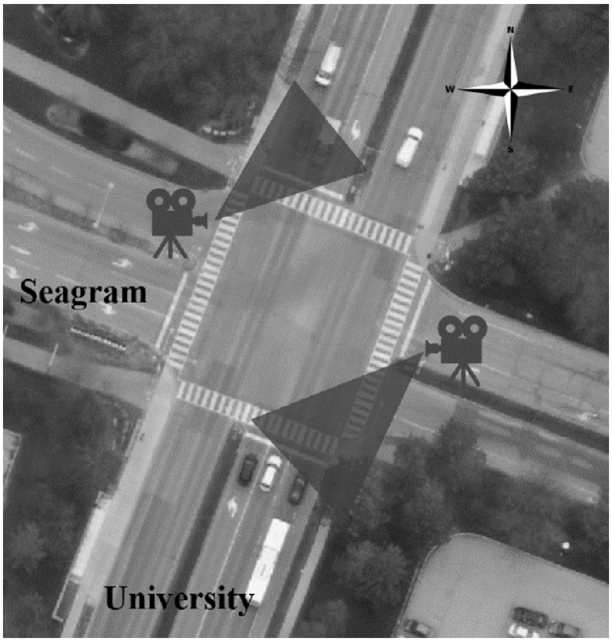

Fig. 2. Study site and filming locations.

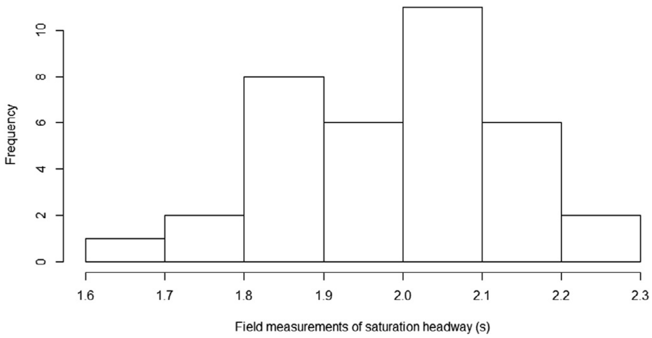

Fig. 3. Histogram of field measurements of saturation headway.

In this case study, the number of valid signal cycles used to calculate average saturation headway was 36. The sample size satisfies the HCM requirement of 15. The average saturation headway obtained from these 36 cycles was 1.995 s. The standard deviation of the 36 samples was 0.15 s. The distribution of the sample data is shown in Fig. 3.

It should be noted that the average saturation headway measured from VISSIM used the same methodology as the one used in the field measurements. In simulation, the saturation headway for one scenario was the average of saturation headways from 30 simulated cycles to reduce stochastic variability. The VISSIM model was coded using inputs, i.e., road geometry, traffic demand, and signal timing plans, measured from the field.

Parameter selection

As noted previously, calibration parameters were selected from three categories: desired speed, desired acceleration/deceleration, and safe following distance.

Desired speed

By default, the driver's desired traveling speed has a uniform distribution ranging from 48 km/h to 58 km/h in VISSIM. In this case study, desired speed was assumed to follow a uniform distribution, with two parameters being selected for calibration: the mean μ_s and range r_s of the distribution.

Desired acceleration/deceleration

Desired acceleration/deceleration values vary at different traveling speeds. In the default settings of VISSIM, the median acceleration/deceleration rate has a linear relationship with traveling speed. The intercepts are 3.5 m/s^2 and -2.75 m/s^2 for acceleration and deceleration by default. In the case study, acceleration rate and deceleration rate at speed 0, i.e., a_0 and d_0, were chosen as calibration parameters.

Safe following distance

In VISSIM, the desired safe distance is the sum of two components, ax and bx; ax represents the average desired standstill distance between two cars, and bx is the additional desired distance for moving vehicles. In this research, we assume that there is little need to modify ax values for local uses as their distribution is not expected to vary significantly over various conditions; bx is more preferable to be calibrated to reflect local drivers' aggressiveness. bx is determined by

$$bx = (bx_{add} + bx_{mult} \cdot z) \cdot \sqrt{v} \tag{1}$$

where bx_{add} and bx_{mult} are two VISSIM built-in parameters used for computing the desired safe following distance, and z is a normally distributed variable with mean of 0.5 and standard deviation of 0.15; v represents vehicle speed (m/s). Therefore, bx is positively proportional to $\sqrt{v}$, and the coefficient obeys a normal distribution with mean of $(0.5bx_{mult} + bx_{add})$ and standard deviation of $0.15bx_{mult}$. In order to separate the parameters' impact on the mean and variance, a new parameter bx_{new} is introduced as

$$bx_{new} = bx_{add} + 0.5bx_{mult} \tag{2}$$

By substituting bx_{add} with bx_{new}, Eq. (2) is expressed as

$$bx = [bx_{new} + (z - 0.5) \cdot bx_{mult}] \cdot \sqrt{v} \tag{3}$$

Thus, the coefficient distribution is centered at bx_{new} with standard deviation of $0.15bx_{mult}$. bx_{new} and bx_{mult} were then selected as calibration parameters.

Sensitivity analysis

Sensitivity analysis was performed on the five parameters selected from the previous step, i.e., $\mu_s, r_s, a_0, d_0, bx_{new}$, and bx_{mult}. The relationship between each of these parameters and through lane average saturation headway was examined one at a time, while other parameters were set to default values. The results are shown in Fig. 4. It can be observed that μ_s, a_0, and bx_{new} have a strong effect on the through-movement average saturation headway; whereas, the influences of r_s, d_0, and bx_{mult} on the MOE were negligible. Therefore, the former three parameters were selected as the calibration parameters.

Microscopic parameter extraction

As previously mentioned, the traffic video data were processed using the Traffic Intelligence tool to generate vehicle trajectories. In this study, 1229 through-movement vehicles in the video were detected by Traffic Intelligence. Their trajectories were stored in the format of time series of positions on a planar surface. Speed and acceleration information about vehicles were obtained by a simple differentiation of position and subsequent speed over time. Thus, μ_s and a_0 were estimated according to the parameter definitions in VISSIM.

Mean desired speed (μ_s)

From the video, 59 vehicles were observed and identified as traveling at desired speed (not hindered by other factors). The average speed for each one of these vehicles was calculated by dividing the traversed trajectory length by its travel time. This average speed was regarded as the driver's desired speed. The mean desired speed of the 59 vehicles was 48.53 km/h. The margin of error of the mean desired speed was 1.70 km/h with confidence level of 99%. The error level was acceptable. Thus, value of 48.53 km/h was then used as the μ_s input in the calibration process.

Median desired acceleration rate at speed 0 (a_0)

In the case study, only the first vehicle departing from the stop line within each cycle was chosen to measure the desired acceleration rate. The reason was that, following vehicles may not accelerate at their desired rate due to the interference from leading vehicles. From the video, 30 vehicles met the criteria. For each of these vehicles, the desired acceleration rate at speed 0 was estimated as the equivalent constant acceleration rate at which a vehicle traveled its first five meters from a stationary position. Sample median a_0 from these 30 vehicles was 2.40 m/s^2 which was used as the a_0 input. Since the standard error of median was estimated to be 0.075, the margin of error was 0.21 m/s^2. The small margin of error justified the sample size. Histograms of the sample desired speeds and desired accelerations are provided in Fig. 5.

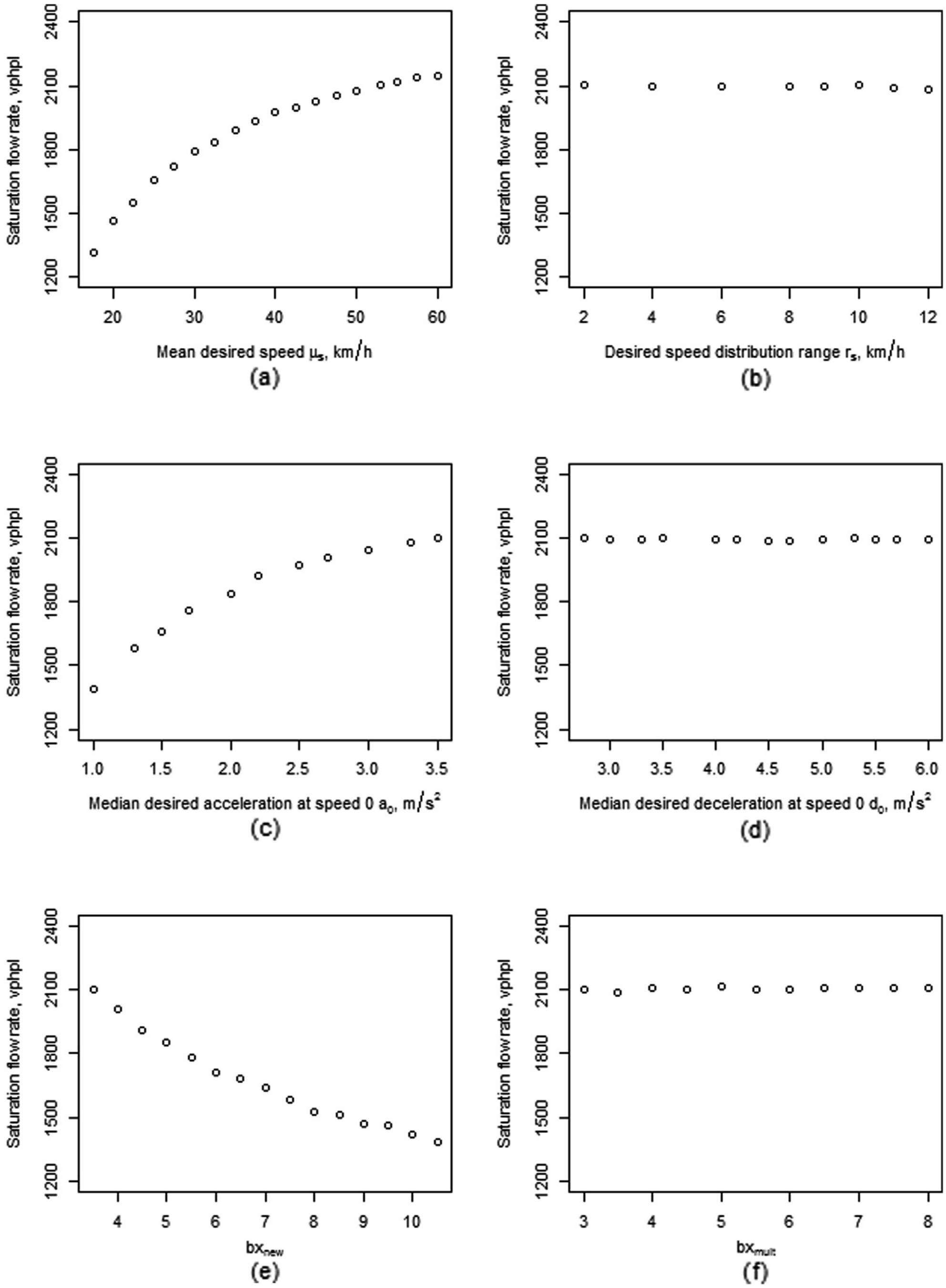

Fig. 4. Sensitivity analysis on: (a) $\boldsymbol{\mu_s}$, (b) $\mathbf{r_s}$, (c) $\mathbf{a}_0$, (d) $\mathbf{d}_0$, (e) $\mathbf{bx_{new}}$, and (f) $\mathbf{bx_{mult}}$.

Parameter calibration

As values of μ_s and a_0 were directly measured, bx_{new} was the only parameter remaining undetermined. In this case study, golden section search was applied to search for optimal value of bx_{new} to minimize the difference in average saturation headway between simulation outputs and field observations. Golden section search is a common technique used to find the minimum of a unimodal continuous function over an interval without using derivatives. It is conducted by continuously refining the bracket which contains the optimal parameter value until the bracket is tight enough to match the predefined criteria. The technique derives its name from the fact that the search algorithm refines the bracket based on the function values for

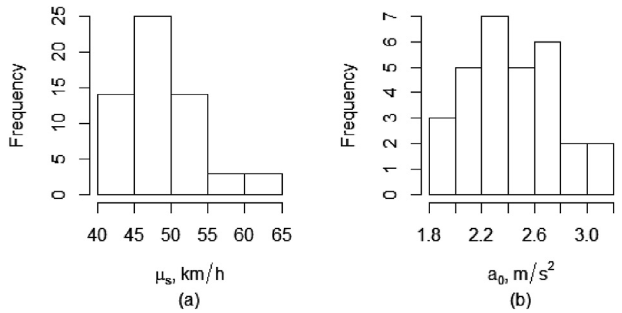

Fig. 5. Histogram of (a) sample desired speeds, and (b) sample desired acceleration.

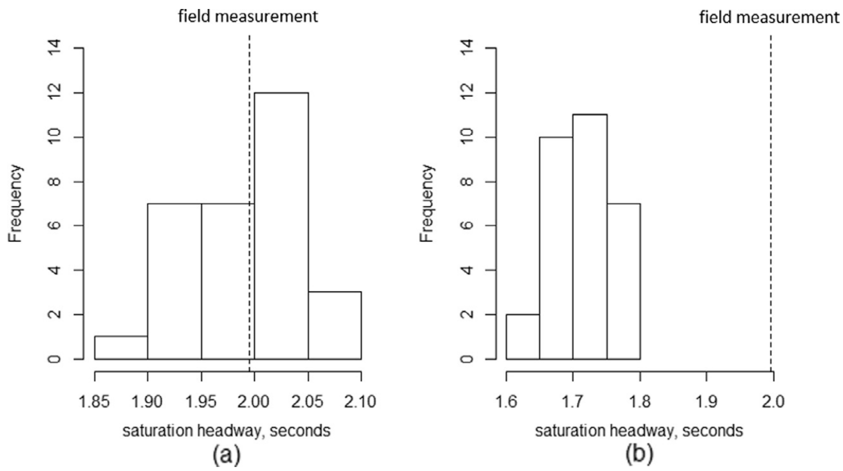

Fig. 6. Histogram of saturation headways of 30 cycles from (a) the calibrated VISSIM model and (b) a default-setting model.

triples of points whose distances form a golden ratio. From the sensitivity analysis, it was observed that bx_{new} has a monotonic relationship with the average saturation headway. Thus, the optimization of bx_{new} can be resolved using the golden section search method. Since this paper focuses on the use of video-based approach in the calibration process, a detailed description of the search algorithm is not provided here. More information on the golden search technique can be found in Miller (2014). In this research, by setting (Benekohal and Abu-Lebdeh, 1994; Ishaque and Noland, 2009) as the initial bracket and 0.1 as the acceptable bracket range, the optimal value of bx_{new} was found to be 4.12 after ten iterations.

Model evaluation

To this point the key calibration parameters were selected and quantified. An initial evaluation on the animation of the calibrated model was performed and no obvious discrepancy was found between the simulation and field video. Then, the saturation headways from the calibrated model were analyzed and compared to the results from a default-setting model (Fig. 6). Default values of μ_s, a_0, and bx_{new} are 53 km/h, 3.5 m/s^2, and 2, respectively. The figure shows that the distribution of the calibrated model's outputs is centered at 1.993 seconds, with sample standard deviation of 0.049 seconds. The calibrated model outperformed the default-setting model with mean saturation headway which was much closer to the field measurement (1.995 s).

Furthermore, averaging values from 30 cycles, as done in the case study, would result in an error (the difference between mean field measurement and mean simulation output) of 0.025 s at maximum at the significance level of 0.01. This error level was acceptable. Therefore, it was concluded that the simulation model was credible and reliable.

Conclusions and future work

This paper has presented a video-based method of calibrating car-following parameters in a microscopic simulation software VISSIM. In this method, automated video processing techniques are applied to extract massive numbers of trajectories from video footage, so that microscopic speed and acceleration parameters can be measured from these trajectories as model inputs. The proposed method was demonstrated through a case study with a typical signalized intersection. Traffic video data were collected from a camera situated 21 feet above the road surface, and the average saturation headway measured from the video was set as the MOE. Parameter selection and sensitivity analysis were conducted to select three calibration parameters: the mean desired speed μ_s, median desired acceleration rate a_0, and a new following-distance parameter bx_{new} in VISSIM. To obtain data on these microscopic parameters, an automated video processing software was used to extract vehicle trajectories in the form of a time series of positions. Values of μ_s and a_0 were then derived from these trajectories according to the parameter definition in VISSIM. The optimal value for bx_{new} was subsequently obtained using the golden section search algorithm to minimize the error between the simulated average saturation headway and the field-observed average saturation headway.

The video-based approach proposed in this research is expected to be more robust and reliable than the traditional methods. This is primarily due to the fact that certain individual parameters were estimated directly from field data using a physically consistent way in the video-based approach. In contrast, traditional methods determine the values of all calibration parameters through a try-and-error process – trying out different combinations of the parameter values and finding the one under which simulated traffic is most consistent with the field observation in terms of a few macro traffic measures. Unfortunately, the process is prone to unrealistic parameter calibration results and there are few ways to ensure the validity of each calibration parameter value under different traffic network settings. The calibration results from the proposed method are suggested to be compared with results from traditional methods to further demonstrate the advantages in the future work.

It should be noted that this paper focuses only on calibrating car following model parameters. The work, however, can be easily extended to calibrating other simulation parameters such as lane changing behaviors and route choices, which is the focus of our future research.

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