CALIBRATION OF THE IDM CAR-FOLLOWING MODEL USING TRAJECTORY DATA

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Abstract

Car-following models describe the longitudinal movement of vehicles and are a major component of microscopic simulation packages. As car-following models seek to replicate the behaviour of individual drivers, their mathematical formulation usually includes a large set of adjustable parameters. The calibration of the model is essential to achieve accurate results, but as it may be a complex and expensive task, users often rely on default values or on simple techniques that offer poor transferability. In this paper we describe a calibration technique for the Intelligent Driver Model (IDM) that explicitly accounts for the physical meaning of each parameter. Trajectory data was collected for a sample of Portuguese drivers using an instrumented vehicle and covers the most relevant cases, such as unconstrained acceleration and deceleration manoeuvres and car following in steady-state conditions. A two-step calibration technique was followed: first, subsets of parameters with clear physical meanings were manually adjusted to replicate the velocity profiles of simple driving patterns; second, the results were used to define the bounds of values within an automatic calibration procedure for normal driving conditions. First results show that the calibration procedure allows to accurately replicate the real trajectories. There is still the concern with the transferability of results and further work is required to understand how to reach the best compromise between the model's descriptive and predictive capacities.

Keywords: IDM, car-following, estimation, calibration, trajectories

1 Introduction

Car-following (CF) models describe the longitudinal movement of vehicles and are a major component of microscopic simulation packages. As CF models seek to replicate the behaviour of individual drivers, their mathematical formulation usually includes a large set of adjustable parameters. Some calibration approaches rely on the use of macroscopic traffic data, such as counts and speeds at detectors, and look for the parameter values that best replicate the measured relationships of speed, flow and density. However, many authors defend that the most exact procedure to calibrate CF models requires trajectory data, that is, velocities and relative distances between pairs of leader-follower vehicles. Trajectory data can be obtained using driving simulators [1], instrumented vehicles [2, 3]; or from aerial images, collected either from tall buildings [4], helicopters [5] or drones [6]. These types of experiments are expensive and complex, which may explain why only a small fraction (9 %) of recent papers related to “car-following” and/or “adaptive cruise control” attempted to calibrate the CF models [7].

In this paper we describe a simple and low-cost calibration technique for the Intelligent Driver Model (IDM) [9] that explicitly accounts for the physical meaning of each parameter. Continuing a previous work [8], trajectory data was collected for a sample of Portuguese drivers using instrumented vehicles and covers the most relevant cases, such as unconstrained acceleration and deceleration manoeuvres and car-following in steady-state conditions.

2 The IDM car-following model

2.1 Model structure

The Intelligent Driver Model is a deterministic CF (time-continuous and autonomous) model in the optimal velocity family, with additional clauses to make it accident-free. It is described by the acceleration equation – eqn (1).

$$\dot{v} = a\left[1-\left(\frac{v}{v_0}\right)^{\delta}-\left(\frac{s^*(v,\Delta v)}{s}\right)^2\right] \tag{1}$$

$$s^*(v,\Delta v) = s_0 + vT + \frac{v\Delta v}{2\sqrt{ab}} \tag{2}$$

The acceleration depends on the variables v (vehicle velocity at a given time step), Δv (velocity difference for the leader, positive when approaching) and s (gap, bumper-to-bumper distance to the leading vehicle). v_0, s_0{\displaystyle s_{0}}, T{\displaystyle T}, a{\displaystyle a}, {\displaystyle b}b and δ are parameters which have the following meaning: v_0 (desired velocity, the velocity the vehicle would drive at in free traffic), s_0 (minimum spacing, a minimum desired net distance), T (desired headway, the minimum possible time to the vehicle in front), a (the maximum vehicle acceleration), b (comfortable braking deceleration) and δ (acceleration exponent, specifies how the acceleration decreases when approaching the desired velocity).
The acceleration consists of two terms, one comparing the current velocity v to the desired velocity v_0, and one comparing the current gap s to the desired gap s*. The vehicle velocity and position are updated using a numeric integration scheme assuming constant acceleration during finite time intervals Δt as described by the eqns (3) and (4).

$$v(t+\Delta t) = x(t) + v(t)\Delta t \tag{3}$$

$$x(t+\Delta t) = x(t) + v\Delta t + \frac{1}{2}\dot{v}\Delta t^2 \tag{4}$$

2.2 Model decomposition

Each parameter describes a main aspect of the driving behaviour, suggesting the possibility of conducting a sequential calibration procedure. A two-part calibration is followed: first, the most relevant parameters for a set of elementary driving conditions were identified and calibrated; after that the initial parameter values were used to define the minimum and maximum bounds of an automatic calibration procedure that looks for the full set of parameters that provides the best fit under typical driving conditions. The elementary driving conditions considered for the first part are:

1. Unrestricted acceleration to the desired velocity: when s $\to \infty$ the second term of the acceleration function tends to zero. The acceleration decreases as v approaches v_0 and depends only on the parameters a, δ and v_0, given by eqn (5).

$$\dot{v} = a\left[1-\left(\frac{v}{v_0}\right)^{\delta}\right]a \tag{5}$$

2. Following a vehicle with constant velocity (steady-state equilibrium): by setting $\dot{v} = \Delta v = 0$, we obtain the equilibrium gap s (eqn (6)) with the velocity being the independent variable. Under congested traffic ($v \ll v_0$) the gap increases linearly with the v and depends mostly on the parameters s_0 and T.

$$s = \frac{s_0 + vT}{\sqrt{1-\left(\frac{v}{v_0}\right)^{\delta}}} \tag{6}$$

3. Deceleration to a complete stop: this driving condition can be modelled by considering that at a given instant the driver notices a stopped vehicle ahead; the deceleration is controlled mostly by the parameter b.

3 Data collection

The full data collection process involved multiple drivers and vehicles. For the sake of simplicity, data is presented for only one leader follower pair. The leader vehicle is a 2007 Opel Corsa, the follower is a 2015 Mercedes C220 with automatic transmission, equipped with a datalogger device from Race Technology Ltd (DL1 Club), Figure 1. The data logger has internal accelerometers and a 20Hz GPS. Positional accuracy is about 3 m (circular error probability) and the velocity accuracy is better than 0.1 km/h. A LIDAR rangefinder (ULS, from Laser Technology Inc.) was connected to the datalogger to provide real time distances to the leading vehicle. The data analysis was based on the Race Technology software which, with a maximum frequency of 20 Hz, allows the extraction of time series for any measured variable. The variables of interest to the calibration were the follower's position, velocity, acceleration, and bumper-to-bumper gap. Some experiments required a single vehicle and were conducted with the Mercedes. The driver is a male adult with more than 20 years of driving experience. The work focused on a heterogeneous urban route with 4.4 km on each direction (Figure 2). The route has arterial, multilane roads in sections 1-2, 3-4 and distributer, single lane roads in section 2-3. After leaving the university campus, drivers were instructed to follow the leader vehicle between points 1 and 4 according to their normal driving style. Section 4-5 was reserved for unrestricted acceleration and deceleration manoeuvres: acceleration from stop to a steady velocity and then deceleration to a stop. Drivers were asked to repeat 9 times these manoeuvres using smooth (3x), normal (3x), and aggressive (3x) driving styles, allowing to identify minimum and maximum bounds for the corresponding parameters. The kinematic data was combined with the LIDAR measurements. The time series were filtered to remove outliers and resampled to 4 Hz, resulting in small files and fast optimization procedures.

Figure 1 Data acquisition system: Left – measuring the gap to the leading vehicle; top right – datalogger; top bottom: LIDAR

Figure 2 Route used for the calibration process

4 Parameter calibration

The calibration procedure takes the form of an optimization problem [10] and it was implemented using the nonlinear programming solver in Matlab fmincon (find minimum of constrained nonlinear multivariable function). This method provides fast and accurate solutions, however, alternative techniques, such as genetic algorithms [8], may be preferable to solve more complex optimization problems. The objective function aims to minimize the difference between the measured and predicted time series of the velocity, given by the average root mean square error (RMSE), eqn (7).

$$\text{minimaze } RMS(v) = \sqrt{\frac{1}{T}\sum_{i=1}^{T}\left[v^{sim}(t)-v^{obs}(t)\right]^2} \tag{7}$$

$$\text{subject to: } LB_\beta \leq \beta \leq UB_\beta$$

where β is a vector of CF model parameters, LB_β and UB_β represent the lower and the upper bound for the parameters in β, respectively. This was done in two parts: in the first, we modelled elementary driving conditions to minimize the number of parameters involved and identify the reasonable range of values that each parameter can take; in the second, all parameters were simultaneously estimated to provide the best fit under a mix of driving conditions.

4.1 Unrestricted acceleration from stop

The objective of this first calibration step was to find estimates for the parameters a and δ. Figure 3 (left panel) shows the velocity and acceleration time series for the field (GPS) and fitted data, corresponding to one of the nine manoeuvres. The IDM trajectory was calculated using the unrestricted acceleration function (eqn 5) and, for the illustrated case, the best fit was found for a = 2.03 m/s^2, δ = 4.20 and v_0 = 14.0 m/s. The complete set of results is presented on Table 1 and Figure 3.

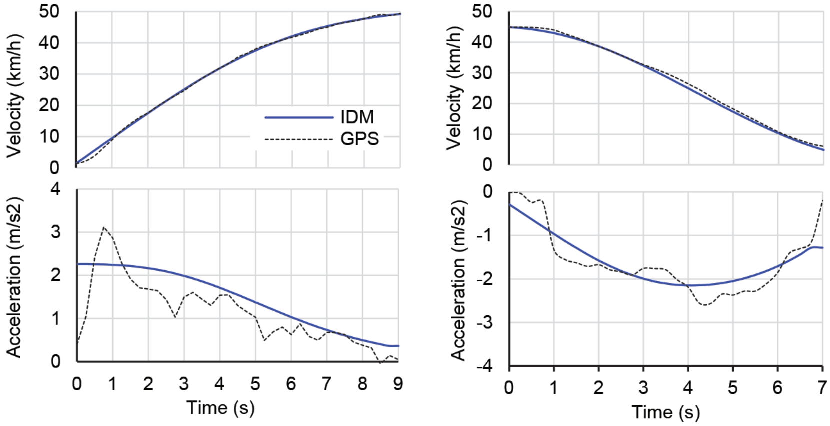

Figure 3 Field vs predicted cinematic profiles for the acceleration and deceleration manoeuvres

Table 1 Results of the calibration using elementary driving conditions

Driving style	**a** [m/s²]			**Δ**			**b** [m/s²]		
	Min	**Mean**	**Max**	**Min**	**Mean**	**Max**	**Min**	**Mean**	**Max**
Smooth	0.92	0.99	1.13	3.52	3.56	3.59	0.74	1.01	0.98
Normal	1.52	1.60	2.03	4.21	4.63	5.34	1.83	2.04	2.28
Aggressive	2.34	2.74	2.97	1.99	3.59	5.72	3.75	4.06	4.31

4.2 Car-following in steady-state conditions

The second calibration step aimed at finding estimates for the minimum spacing s_0 and the desired time headway T under a normal driving style. As given by eqn (6), for $v \ll v_0$ the bumper-to-bumper distance increases linearly with the velocity. The graphic gap vs. velocity (s – v) data was extracted manually by isolating small segments (≈ 4 s) of steady-state driving conditions (constant velocity and gap) along the sections 1-4, Figure 4. As the leading driver was imposing relatively low velocities, the term $(v/v_0)^\delta$ is small, and therefore s_0 and T are given by the slope and intersection of the fitted line (s_0 = 3.2 m, T = 0.86 s).

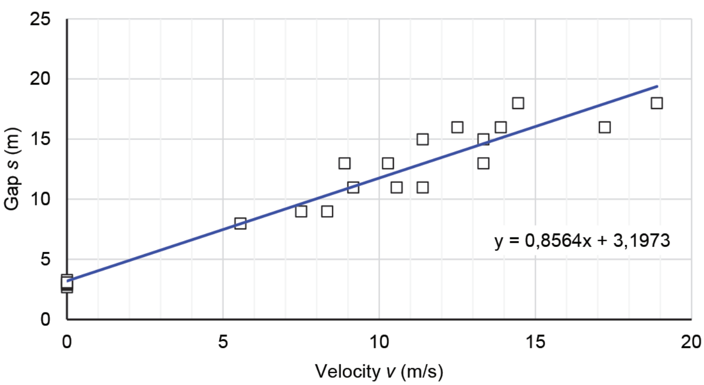

Figure 4 Linear regression of s-v data points in steady-state conditions

4.3 Deceleration to a complete stop

The third step aims at finding an estimate for the remaining parameter, the comfortable deceleration b. To calibrate this parameter, we followed a process like the one used to find a and δ, this time fitting the velocity time series of an isolated vehicle coming to a full stop, under smooth, normal, and aggressive driving styles. Since modelling this manoeuvre with IDM requires the full set of parameters, the values found in the previous calibration steps were taken as reference. Figure 3 (right panel) shows the GPS and model data for one of the nine deceleration manoeuvres (b =1.83 m/s^2).

4.4 Normal driving conditions

After obtaining the initial estimates for the parameters, the last calibration step consists of finding the full set of parameters that provides the best fit when following a leading vehicle through a sequence of urban roads. Under real conditions, there are several events that affect the driver behaviour (pedestrian jaywalking, avoiding potholes, late reaction to the green light, etc.) that cannot be easily represented by the IDM. This way, to prevent the optimization from returning unrealistic values, the following lower and upper bounds were defined, Table 2.

Table 2 Lower and upper bounds for the parameters for normal driving conditions

	a [m/s^2]	**b** [m/s^2]	**δ**	**s_0** [m]	**T** [s]	**v_0** [km/h]
Lower bound	0.9	0.7	1.9	2.0	0.5	Var.
Upper bound	3.0	4.3	5.8	5.0	1.5	Var.

The optimization procedure was run for segments of 90 – 120 s. Figure 5 compares the predicted and real trajectories of the follower vehicle, for one of those segments (west part of the section 2-3). The optimization returned the values a = 2.97 m/s^2, b = 3.71 m/s^2, δ = 3.08, s_0 = 4.95 m and T = 1.48 s. The desired velocity was manually set as v_0 = 15.3 m/s. On other segments, the calibration returned significantly different optimal values.

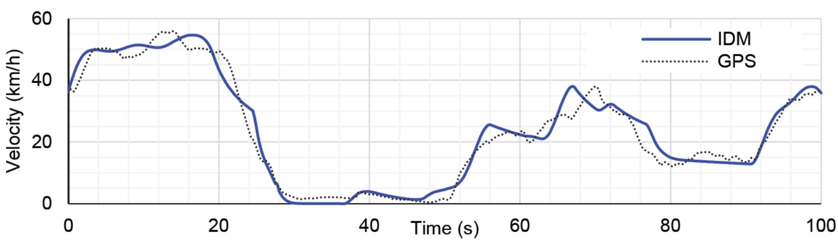

Figure 5 Filed vs predicted velocity profile for normal driving conditions

5 Conclusions

The proposed method to obtain trajectory data relies on equipment that most research teams can afford (‹2500€) and that can be easily installed on any vehicle under any driving environment. However, drivers are aware that they are being part of an experiment, which can change their behaviour.

The sequential calibration method allows to identify reasonable values for the parameters being calibrated. Simple driving manoeuvres can be accurately represented by the IDM. Good adjustments were also obtained for normal driving scenarios in short route sections, but sometimes at cost of using parameter values close to their lower or upper bounds. This suggests that the optimization may be returning unreasonable estimates, leading to an over-estimated model with limited capacity to describe the driver behaviour under a different road environment.
This way, additional work is required to understand how the parameters affect the model results and its transferability, and how to deal with intra-driver variability. It will also be necessary to further process and filter the raw data, to exclude all incidents that the IDM cannot represent.

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