Memorias del XVI Congreso Latinoamericano
de Control Automático, CLCA 2014
Octubre 14-17, 2014. Cancún, Quintana Roo, México

Calibration and Comparison of Two Microscopic Traffic Models

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Abstract— **Microscopic models of traffic have a main use in driving behavior because they focus on individual agents, giving a closer approach to the relations that can affect the interactions among neighbour vehicles.**

In this work we have performed a series of experiments to measure relative velocities and positions of pairs of cars while driving. Then, we use those sets of data to estimate sensitivity parameters that represent the level of reactivity of the follower driver in such pairs.

Once we have obtained these values by estimation, we use them to perform comparisons between two very similar models in order to test them to perform simulations.

Keywords: Microscopic traffic models, Parameter identification, Driving behavior.

I. INTRODUCTION

Microscopic traffic systems are those which focus on values of individual units of the traffic phenomena (May, 1990). In these models, cars and drivers are represented dynamically in their responses in order to be approached to real behavior (Gazis and Edie, 1968; Brackstone and MacDonald, 1999; Weng and Wu, 2001; Lárraga et al., 2005). Most of these models have as a main assumption that cars move on a one-lane road. This feature includes the consequence and assumption that there are not overtakes among vehicles (even though some special conditions must be taken into account in order to model lane changes) being known as car-following models.

Many of the key issues related to driving, such as perception, decision making and control belong to the study of how human intelligence is related to information processing. The car-following models, in general, try to take into account as much as possible all factors that can be identifiable. Depending on the precision searched, many of them can be entered on consideration, as for example drivers' perception on other leading vehicles (Helly, 1959), the time history of the relative speed (Lee, 1966) or the assumption that some of such factors are rather functions of other involved variables (Gazis et al, 1961).

For a very simple formulation, it is possible to express the mechanism of driving by Equation (1).

$$\text{Response} = \lambda \cdot \text{Stimulus} \qquad (1)$$

where λ is a factor that measures reactivity of the follower. Many specialists have been conducting their research in order to design and calibrate terms of this type (Brackstone and MacDonald, 1999; Chung et al., 2005; Kesting and Treiber, 2008). As it will be seen later, a quantity like λ encloses a large number of features related to the human response. It is for that reason that more precise and detailed models have arose (Ioannou et al., 2008). In this work, two of them are described and compared.

For the purpose of this work, we consider in Section II of this document a microscopic model that includes a constant sensitivity factor λ, and on the other hand a derivation of such a model which takes into account if a driver is accelerating or decelerating, in an attempt to reach a higher precision in our calculations. In Section III we present the methodology we have followed to obtain data through sets of experiments. In Section IV we describe the estimation process for the calculation of the sensitivity parameters, which comparison and further analysis is accomplished in Section V where some results of simulations achieved by these calibrations are presented, as well as the relation of the different values of the sensitivity factors versus relative distances between cars, which reveals interesting results on human driving behavior. We conclude with some remarks.

II. CONSIDERED MODELS

A. Pipes' Model

We have considered the microscopic model developed by L. A. Pipes (1953) to perform a series of experiments on driving (Rosas-Jaimes et al., 2013). In this microscopic traffic model, the author observes that the stimulus for car movement is related to keep up with the leading vehicle and to avoid collisions, expressed as relative speeds.

$$\text{Stimulus} = v_l(t) - v_f(t) \qquad (2)$$

where:

$v_l(t)$: Leader's velocity at time t
$v_f(t)$: Follower's velocity at time t

In turn, the response function at the left side of Equation (1) is linked to the follower's vehicle acceleration, because this response is influenced by the change in the leader's vehicle speed.

In other words, the follower will increase his/her velocity $v_f(t)$ if he/she perceives that the velocity of the leader $v_l(t)$ is higher, but will decrease it if he/she perceives that it is lower. These changes in follower's velocity are expressed as acceleration

$$\text{Response} = a_f(t) \tag{3}$$

Both sides of Equation (1), expressed respectively by Equations (2) and (3), are aggregated in Equation (4) by means of a factor λ.

$$a_f(t) = \lambda[v_l(t) - v_f(t)] \tag{4}$$

For this model, the sensitivity factor λ is assumed to be constant, and it is physically interpreted as a measure of the follower's reaction with respect to the leader, i.e. for lower values of λ correspond less reactive followers than those with larger values, implying psycho-physiological aspects implicit in such a parameter that spans $\lambda \in [0, 1]$.

Even though the main advantage of Pipe's model is simplicity and enough understanding of the main physics involved in car-following phenomena, it is also easy to notice that there are some drawbacks that undermine its accuracy. One of them is that the only stimulus taken into account is the relative speeds among cars. It has been tested and proven (Chung et al., 2005) that drivers also consider a safety distance between bumps to avoid collisions. Another inconsistency in model (4) is that the arithmetic difference between velocities can result in zero values, resulting in zero acceleration $a_f(t)$, which is not realistic (Helly, 1959).

However, in spite of these troublesome points, the model can be considered adequate, useful in most of the cases and simple to manage, as other experts have been able to try and prove (Rakha and Crowther, 2002).

B. Asymmetric Model

A way to succeed in a more precise representation of reality based on what Pipes suggests is by dividing this type of model into two schemes, based on the idea that a driver's response is different when accelerates or when brakes. If we identify those intervals of positive change in velocity from those with a negative one, and associate to each of such sets of values distinct sensitive parameters λ_+ and λ_- respectively, then an alternate expression for such a model is

$$\dot{v}_f(t) = \begin{cases} \lambda_+ \left[v_l(t) - v_f(t)\right], & v_l(t) - v_f(t) \geq 0 \\ \lambda_- \left[v_l(t) - v_f(t)\right], & v_l(t) - v_f(t) < 0 \end{cases} \tag{5}$$

This is an attempt to enclose the asymmetric nature of driving as has been noticed since some decades ago (Newell, 1961), based on the observation that the drivers' reaction is different in these two situations, that is to say, he/she must control the acceleration by putting on or getting off the accelerator and the brakes in such a way that it can be possible to maintain a safe velocity according to the motion of the preceding vehicle (Bando et al., 1995), something that is closely related to the perception while driving and therefore a distinct way to react is not only expected, but it is possible to measure.

III. EXPERIMENTAL DATA

We conducted series of experiments to obtain speed data from pairs of vehicles. Table I shows the features of 6 cars with their respective drivers that were included to perform related activities.

TABLE I: Vehicles driven and drivers data

Vehicle				Driver	
Car Company	Brand	Vehicle	Year	Gender	Age
Volkswagen	Jetta	1	2003	Male	52
		2	2004	Male	23
Nissan	Sentra	3	2008	Male	21
		4	2013	Female	43
Toyota	Yaris	5	2010	Male	40
		6	2010	Male	52

As can be observed, the selected cars were categorized in pairs, because we wanted to perform leader-follower trials using as similar as possible automobiles to diminish the influence of the specifications of each car and to leave a bigger influence on the drivers' performance. In that manner, vehicles 1 and 2 were driven in such a way that one of them acted as a leader and the other as a follower for a first trial, and then the roles changed for a second trial. The other two pairs of cars were involved in the same activities (Figure 1).

Fig. 1: Two-car Experiments

Suitable OBD (On-Board Diagnostics) hardware and software were utilized to obtain velocity from the on-board computer of every involved car. Drivers were asked to drive their vehicles in a loop of approximately 2.5 km, which represent the University Campus perimeter (Figure 2). This loop is located in an urban area, where two sets of traffic lights and six bumps exist as part of the road circuit. Four of the six trials (with vehicles 1-4) were performed on a Saturday morning, where moderate traffic influence in the surrounding streets was taken as part of the conditions of the experiment. Another pair of trials with vehicles 5 and 6 were performed during Sunday light traffic.

We stress the drivers' performance above any other conditions as the main factor to take into account for our experiments.

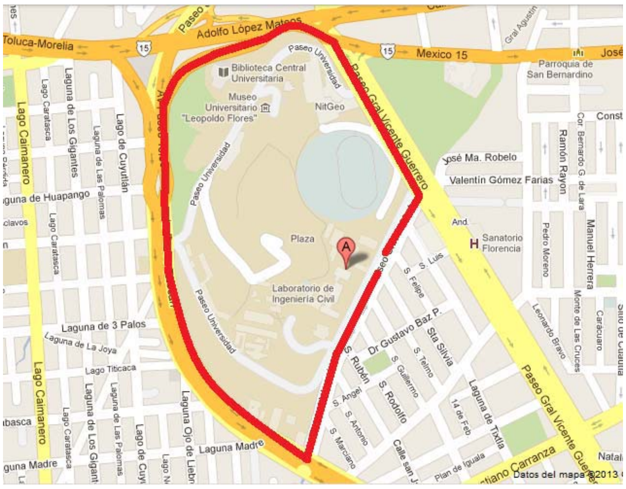


Fig. 2: UAEM Campus and loop performed in the set of experiments with cars

In fact, all of the drivers were asked to drive as they normally would, with only two restrictions:

1) Followers should not overtake leaders.
2) Followers should not permit any external car to be located between them and the leaders, except if safety was at risk.

Six sampling circuits were performed outside the University Campus in the already described loop, organizing the trials as presented in Table II, where the identification numbers given to cars in Table I indicate the role as leader or as follower.

TABLE II: Organization of the trials

Sampling Circuit	Vehicle Identification	Car Number Relationship	
		Leader	Follower
A	Jetta	1	2
B		2	1
C	Sentra	4	3
D		3	4
E	Yaris	6	5
F		5	6

The data obtained had to be processed and refined, i.e. a synchronization-type treatment had to be performed. Because an operator is accompanied to each driver to manage the software in each computer where data were captured, the starting times to record the data differ as do the stopping times.

By monitoring convenient and similar times between data sets, it is possible to establish analogous time series for all the pairs of vehicles for each trial. Once identified, velocity data for the leader-follower pair has an aspect similar to those shown in the plots of Figure 3.

In the same figure it is possible to see that there is a shift-like behavior for all followers in relation to their respective leader, which is an expected result because of the not-overtaking condition.

This aspect also corresponds with the intention of keeping behind the leader by the followers, depicted by the speed profiles being very similar among the two involved drivers. However, even though these resemblances are very close, they are not identical, which revels the followers' necessity to be in expectancy and to react to the behavior of the leaders' unknown intentions.

IV. SENSITIVITY PARAMETER ESTIMATION

From the last data sets it is possible to perform an estimation of the sensitivity parameter λ as it appears in the linear expression (4), which can be written in a discrete approximation form like in (6).

$$\frac{v_f(t+\Delta t)-v_f(t)}{\Delta t}\approx\lambda\left[v_l(t)-v_f(t)\right] \tag{6}$$

The left side of (6) is the derivative approximation for two very close sample points of the time series.

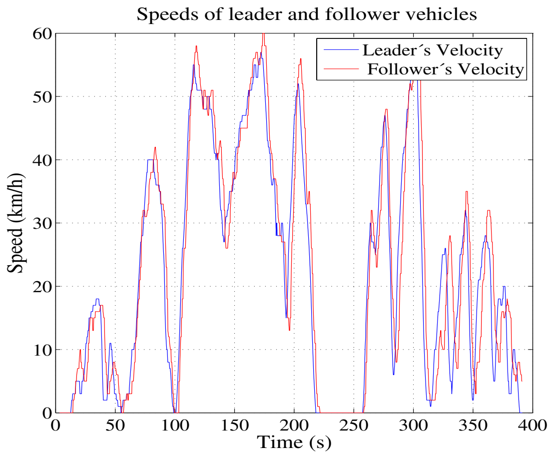


Fig. 3: Speed profile for trial A as listed in Table II

Equation (6) has the additional advantage of having all its quantities known but one; as a result, it is convenient to determine the value of λ to obtain Equation (7)

$$\lambda\approx\frac{1}{v_l(t)-v_f(t)}\cdot\frac{v_f(t+\Delta t)-v_f(t)}{\Delta t} \tag{7}$$

By substituting leader and follower velocities for each case in Equation (7), estimations of λ are achieved.

It is possible to note that the present model takes into account one parameter only and this fact makes possible to determine λ in this simple manner. Other models with this same feature (Ioannou et al., 2008) can be treated in this same way in order to obtain numerical values for single parameters. Other existing models include more than one parameter, making necessary different process to perform such a task as, for example, identification by regression approaches (Ioannou, 1996), with which a number of parameters can be identified simultaneously if suitable and proper data is available.

The estimations of λ are not series of constant values. In many intervals these estimated values tend frequently to infinity because, as previously mentioned, $v_l(t) - v_f(t)$ approaches zero. In addition, there were also calculations that resulted in non-expected values, such as some finite values being out of the range $\lambda \in [0, 1]$. It was necessary for us to identify and eliminate such values without losing the inherent significance of this parameter.

The remaining estimations were consistent enough to be suitable of calculation of their means. The fourth column of Table III shows the sensitivity parameter λ for each follower in his/her respective sampling circuit. The mean sample time values Δt are also shown. Due to car's computer has different inner clock signals, those Δt values are distinct in each case.

These same sets of data can be used to perform estimations for the asymmetric approach sensitivity parameters λ_+ and λ_-, making use of similar expressions like (7), with the difference that it is necessary to carry on a classification of speed values into two sets, those which show a tendency to accelerate and those which tendency is to decelerate. Our estimation then must switch between intervals of these two different data sets to make the identification of each sensitivity parameter. The fifth and sixth columns of Table III includes these values for each trial.

V. DICUSSION

A. *Efficiency of the models*

The main purpose to calibrate a parameter such as λ, or as λ_+ and λ_-, involves having a model that can be used in simulations of real phenomena that are as close as possible to reality. Once such an objective is achieved, it is possible to estimate other useful quantities, such as travel times, travel distances, levels of congestion and bottleneck places in a network.

The plots in Figure 4 depicts comparisons between the speed profiles of followers against the speed profiles obtained by calculation of model (4), with the corresponding substitution of λ in trial A. Similar profiles were obtained for trials B to F performed by the pairs of cars in our experiments. For each follower we have run the respective simulation with λ.

In the same manner, making use of λ_+ (for those times in which the derivative of velocity is positive) and λ_- (for those cases where that derivative is negative) in a single simulation, has the aspect shown in Figure 5, where it is evident that a good match between real and calculated data is also achieved.

In order to measure the efficiency of each approach, we have obtained the relative error for the two models (Table IV). As it can be seen, at least for our set of six trials, there is no significance among the differences that could be observed and both models seem to achieved very similar efficiency.

This result is also important, in the sense that we have an evidence of the performance of these two models, which in turn allows us to conclude that none of them is predominant over the other in the results that each one can achieve. However, the simplicity of Pipes' model is an advantage over the relative more complex scheme of the Asymmetric model. In this sense, it is then preferable, based on this evidence, to make use of that model due to it uses a lower computational load.

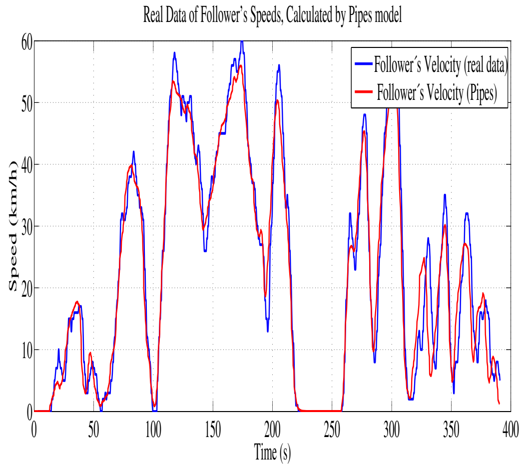


Fig. 4: Comparison between measured data of Trial A and the calculation of Pipes' Model with λ = 0.5586

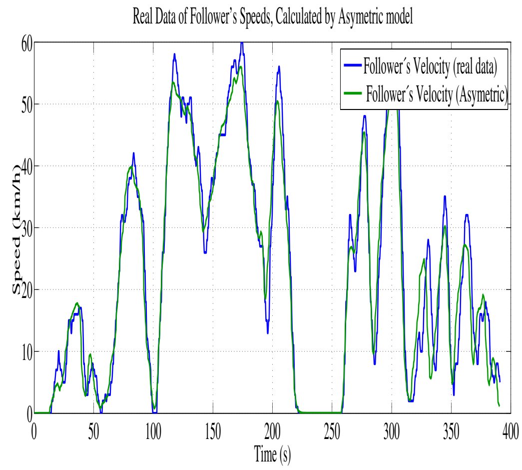


Fig. 5: Comparison between measured data of Trial A and the calculation of Asymmetric Model with λ_+ = 0.5867 (accelerating) and λ_- = 0.5470 (decelerating)

B. *Human Response Measure*

Sensitivity parameter is a measurement of follower's reactivity to the actions of the leading vehicle being, as stated previously, is greater for higher values of λ. In other words, there is a value of this parameter for each driver. However, it is also true that, even for a specific individual, this value can change depending on the level of fatigue or the individual's mood. In this manner, this quantity involves some psycho-physiological aspects.

TABLE III: Average value of the sensitivity parameter λ for each trial. Mean sample time values Δt are included for each case.

Sampling Trial	Δt	$s_l(t) - s_f(t)$ [m]	λ [s^{-1}]	λ_+ [s^{-1}]	λ_- [s^{-1}]
A	0.4300	43.38	0.559	0.547	0.587
B	0.4391	43.72	0.522	0.504	0.536
C	0.1899	19.28	0.754	0.756	0.756
D	0.1880	11.98	0.804	0.803	0.817
E	0.1858	44.74	0.778	0.444	0.619
F	0.1886	53.40	0.622	0.453	0.621

It is impossible to distinguish all different factors that affect the value of λ, but it is possible to use this parameter as a junction among physical data and psycho-physiological factors. From speed profiles such as those shown in Figure 4, and knowing the initial separation among pairs of cars for each trial, it is possible to estimate the position of the cars by means of (8).

$$S(t) \approx s_o + \sum_{i=1}^{n} v_{fi}(\Delta t)_i \quad (8)$$

where:

$S(t)$: separation between centres of cars at time t
s_o: initial separation between centres of cars
v_{fi}: follower car velocity at the end of interval i
$(\Delta t)_i$: i-th sample time interval

As a consequence of expression (8), it is possible to generate position profiles for each trial, as shown in Figure 6. With such data sets, we are able to calculate the relative separation of cars for each trial by subtracting follower's position $s_f(t)$ from leader's position $s_l(t)$. The third column of Table III lists the average for such separations related to each trial.

TABLE IV: Relative error among calculated and measured velocities for simulations performed over data from trials A to E, using Pipes' model and Asymmetric model

Trial Sampling	Pipes	Asymmetric
A	19.42	19.52
B	31.58	31.68
C	20.55	20.58
D	16.58	16.62
E	14.07	13.09
F	19.66	19.38

A close observation of Table III reveals a tendency in which there is an inverse relation among the relative positions of cars and the λ parameters, that is to say, for larger λ there exist smaller $s_l(t) - s_f(t)$ differences (Figure 7).

This observation should not be a surprise. A direct means to measure reaction levels on drivers that follow another car in front of them is through the separation the follower permits to exist between both vehicles. Many authors (van Winsun, 1999; Chung et al., 2005) report that this gap is a primary factor to take into account not only to model human driving behavior but also to model microscopic traffic.

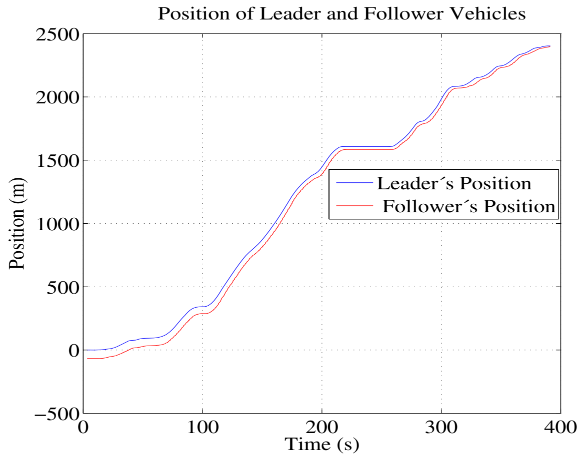


Fig. 6: Position profiles for Trial A

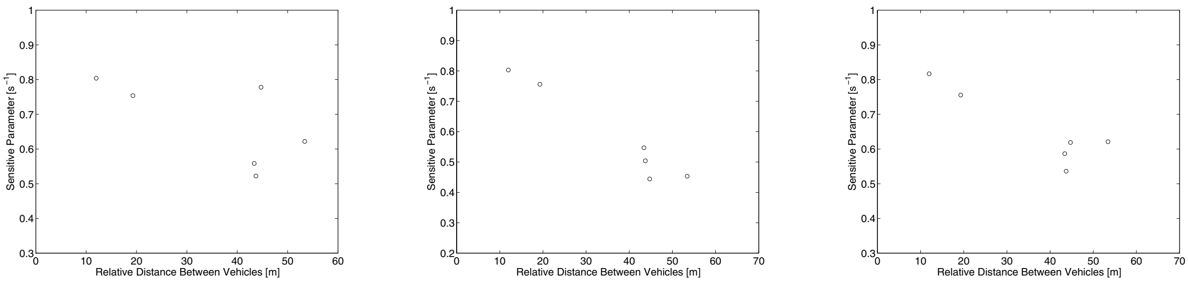
Even though Figure 7 depicts very few points to get a firm conclusion, these different plots confirm those statements about the relation between λ and the reactions that drivers can show, what is reported in other works (Kesting and Treiber, 2008; Weng and Wu, 2001).

VI. CONCLUSIONS

A model is useful for performing simulations of real phenomena but such a model requires the necessary calibrations are performed. Such calibrations are performed on model parameters that adjust such a model into specific situations of application. In this work we have obtained appropriate measuring data sets of vehicular speeds for leader-follower pairs to perform such calibrations for two well-known car-following models.

Different values of the sensitivity parameter λ and of the couple (λ_+, λ_-) were obtained in each trial, and they were then substituted in relevant programming codes in order to perform simulations, in which the speed profiles from measured data of the followers were compared with those calculated in such simulations. The resulting plots revealed a very good fitting between the pairs of points for each situation.

Both models tested show a very high and similar efficiency. It was expected that the Asymmetric model improved Pipes's model performance, but at least for our results this was not the case in a significant way.



(a) λ vs. $s_l(t) - s_f(t)$ (b) λ_+ vs. $s_l(t) - s_f(t)$ (c) λ_- vs. $s_l(t) - s_f(t)$

Fig. 7: Sensitivity parameter against relative distances between vehicles. (a) for Pipes' Model, (b) for Asymmetric Model, drivers accelerating, (c) for Asymmetric Model, drivers decelerating.

However, we can conclude of this fact that the simpler Pipes' model has the advantage to require lower calculation effort and still gives very good results. This is in agreement with experiences reported in other similar papers.

Such sensitivity values were obtained for different drivers, which reflects inherently psycho-physiological features in their driving behavior, which can be roughly related by means of this sensitivity parameter.

In order to obtain an alternative way to probe this idea, the position estimations were calculated from the speed data. By proper mathematical expressions and knowledge of the initial separation between leader and follower vehicles for each trial, it was possible to calculate the instantaneous separations and then calculate a mean in each trial, where small values of average separations tend to correspond to higher values of the sensitivity parameter λ.

If we agree that smaller gaps correspond with more reactive drivers, then we can conclude that λ values reflect such a condition. However, note that this observation does not mean that the relation between λ and the calculated separation averages can be related by a simple proportional relation; this is a matter of future work.

Both Pipes' model and Asymmetric model are simple to understand, to analyse and to manipulate. On opposition, they show conditions that misrepresent real behavior. Other microscopic models can represent in a better way those situations where these models fail. Besides this is a matter for future work also, in this communication we have been able to establish a general frame to estimate parameters like λ that appear in such models.

VII. ACKNOWLEDGEMENTS

This project is supported by the Autonomous University of the State of Mexico, funding with register FE048/2012.

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