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Towards an integrated longitudinal and lateral movement data-driven model for mixed traffic

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Abstract

In recent years, there has been an increasing interest in modeling driving behavior in developing countries, where conditions, such as non–lane discipline and heterogeneity in vehicle types, prevail. Traffic flow in such conditions is very complex in nature and safety issues arise. Traffic simulation models have been formulated for lane–based conditions. The existing models do not consider the wider range of situations that drivers in mixed traffic may face compared to drivers in homogeneous lane–based traffic, such as multiple–leader following, and passing and lateral shifts. In this research, we define the concept of virtual lanes for modeling mixed traffic conditions. A methodology based on temporary virtual lanes and data–driven approaches is developed to simulate driving behavior in developing countries. The role of vehicle type in model efficiency is also explored. The proposed methodology is validated on mixed traffic trajectory data from India.

Keywords: mixed traffic; data–driven models; virtual traffic lanes

1. Introduction

Modeling driving behavior in mixed traffic streams is still a challenge. Heterogeneous mixture of vehicle types and violation of lane discipline are common characteristics of cities in the developing countries. These characteristics are difficult to be simulated using typical microscopic models. In cases of car–following situations, there is difficulty in the determination of leader–follower pairs due to multiple-leader following. Furthermore, in cases of lane changing situations there is difficulty in the determination of lanes, as drivers do not obey the real lane marks. In addition, the vehicle type seems to play a significant role in driving behavior, as it is evident by Papathanasopoulou and Antoniou (2017). Thus, vehicle–type dependent following behavior should be taken into consideration in traffic simulation.

Nowadays, the rapid development of technology has contributed to the availability of high–quality traffic data, leading the way for the development of more advanced microscopic models. Limitations of conventional models

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have been the motivation to explore an alternative methodology for the estimation of microscopic models, combining flexible data–driven components. Such methods have been used in several transport–related applications. The objective of this research is to develop a methodology based on temporary virtual lanes and including data-driven approaches to simulate driving behavior in mixed traffic conditions.

2. Literature review and state–of–the–art

Asaithambi et al. (2016) review driver behavior models under mixed traffic conditions and have pointed out limitations of current models, arguing that the main limitation is that they do not explicitly consider the wider range of situations that drivers in mixed traffic face. Munigety and Mathew (2016) have identified that due to weak lane discipline, drivers maneuvering in mixed traffic streams exhibit some peculiar patterns, such as maintaining shorter headways, swerving, and filtering. They have also proposed that the lane should be divided into small strips in order to handle virtual lane movements. Li et al. (2015) have proposed a car–following model that considers the effect of two–sided lateral gaps and have shown that their model has larger stable region compared to a car–following model that captures the impacts from the lateral gap on only one side. In addition, Parsuvanathan (2015) has used proxy lanes between the main lanes. It is assumed that free space is perceived as lanes by small vehicles. However, distribution and types of vehicles could affect the width of the lanes. A grid-based modeling approach akin to cellular automata (Gundaliya et al., 2008) and a strip-based modelling method (Mathew et al., 2013) have also been proposed. Mathew et al. (2013) have based their idea on portions of traffic queues instead of regular main lane queues. Kanagaraj et al. (2013) have evaluated the performance of different car following models under mixed traffic conditions. However, they have not taken into account the fact that a vehicle may not be exactly in line with its leading vehicle due to weak lane discipline in mixed traffic. Metkari et al. (2013) have modified an existing car-following model in order to take into account lateral movements and include mixed traffic conditions. Choudhury and Islam (2016) have developed a latent leader acceleration model.

The majority of models could not represent driving characteristics as vary with traffic conditions, in particular in mixed traffic conditions. The use of data–driven approaches for mixed traffic modeling is limited. On the other hand, various machine learning techniques have been used in other transport applications in recent years. More than ten years ago, Antoniou and Koutsopoulos (2006b) developed a framework for speed estimation using machine learning concepts, including locally weighted regression (loess) and clustering algorithms. Antoniou and Koutsopoulos (2006a) compared a number of machine learning techniques for speed estimation, including loess, support vector regression, and neural networks. Other uses of data–driven methods include neural networks (Huval et al., 2015), Gaussian processes (Chen et al., 2014) and Kernel methods offering similar capabilities (Karlaftis and Vlahogianni, 2011). Antoniou et al. (2013) developed a framework for dynamic traffic state estimation and prediction using machine learning methods. Focusing on microscopic data–driven models, data–driven approaches have already been used in developing a fully adaptive cruise control system (Simonelli et al., 2009; Bifulco et al., 2013) and in modeling car–following behavior via artificial neural networks (Colombaroni and Fusco, 2014; Chong et al., 2013). Kumar et al. (2013) have proposed a learning–based approach, based on Support Vector Machine and Bayesian filtering, for online lane–change intention prediction.

Papathanasopoulou and Antoniou (2017) have proposed data–driven approaches for modeling mixed traffic and virtual lanes for weak lane discipline conditions. This research is based on this analysis but the proposed methodology is further explored and implemented. The existing approaches for mixed traffic conditions do not adapt dynamically to the current conditions. Lanes, strips or cells with a predefined width, which are used to simulate mixed traffic, do not ensure that the appropriate width has been selected, as half vehicle or two vehicles may fit into this width. Heterogeneity in vehicle types lead to various widths of virtual lanes. On the other hand, temporary virtual lanes allow only one vehicle to fit in each lane. Furthermore, in this research the incorporation of vehicle type is explored as an additional explanatory categorical variable. Data-driven models are validated on non-disciplinary trajectory data with heterogeneous mixture of vehicle types and could be a promising perspective for microscopic traffic simulation in the developing countries.

3. Methodology

The methodology consists of three main components: the determination of virtual lane changes, the identification of pair leader–follower and data–driven microscopic modeling including the incorporation of the vehicle type in the model.

3.1. Determination of virtual lanes

In this section, we define the concept of virtual lane. It is considered that a vehicle follows the virtual lane i. While there are small lateral movements, it is considered that it does not change lane. However, when its movement is constrained by another vehicle, it is considered that it changes lane and then follows virtual lane i+1. The challenge is that vehicles are moving constantly laterally. This could be addressed in two distinct ways. The first one is using change detection algorithms (such as 'strucchange' package by Zeileis et al. (2001)) that could identify the appropriate breakpoints and has been explored by Papathanasopoulou and Antoniou (2018). The second one is to estimate the threshold that indicated a lane change, as outlined in Figure 1a. The subject vehicle is moving in virtual lane i, until its movement is constrained by the hatched vehicle. When the subject vehicle exceeds a threshold for lateral movements at a position, then it is assumed that it changes lane and follows virtual lane i+1.

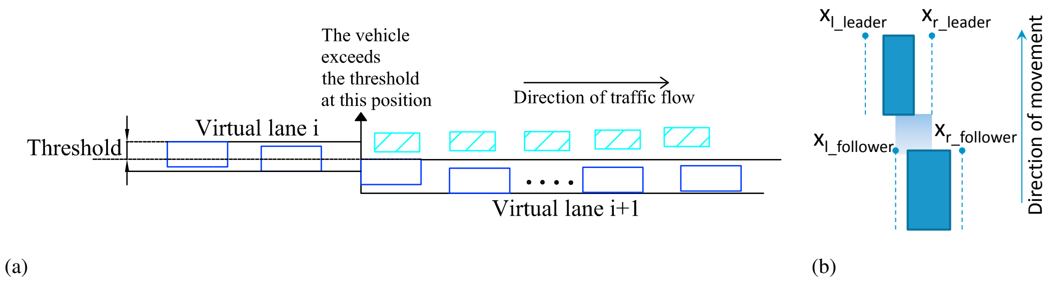


Fig. 1. (a) Determination of temporary virtual lanes by setting a threshold, (b) Overlap of vehicle trajectories

3.2. Identification of pair leader–follower

The probability of a given front vehicle to be the governing leader depends on the type of the lead vehicle and the extent of lateral overlap with the following vehicle (Choudhury and Islam, 2016). In order to apply a microscopic model, it should be determined whether there is a vehicle pair of follower–leader. The main characteristic of mixed traffic is that the size of overlap between the leader and the follower varies. Assuming that the lateral and longitudinal coordinates of the front center of each vehicle (x_{c_i}, x_{c_i}) are known, it could be defined which vehicle follows the other. The coordinates for the left and the right lateral bound of each vehicle are estimated per time instant t by Equations 1 and 2 (as shown in Figure 1b).

$$x_{l_i}(t) = x_{c_i}(t) - \frac{w_i}{2} - s_i(t) \tag{1}$$

$$x_{r_i}(t) = x_{c_i}(t) + \frac{w_i}{2} + s_i(t) \tag{2}$$

where i: 0,1,2,n vehicle index x_{c_i}: lateral coordinate of the front center of vehicle i, x_{l_i}: lateral coordinate of the front left bound of vehicle i, x_{r_i}: lateral coordinate of the front right bound of vehicle i, w_i: width of vehicle i s_i: a lateral safety distance for vehicle i.

In order to define the car–following vehicle pairs, the longitudinal position of the leader should be in front of the following vehicle and in a distance L that could influence the movement of the following vehicle (Equation 3). In addition, a part of the front side of a vehicle should overlap a part of the front side of another vehicle (Equation 5). This overlap is evident in Figure 1b with light blue color. Each vehicle i is considered as follower and then a leader vehicle is required to fulfill the conditions, described by Equations 3– 5, at the same instant t:

$$y_{follower}(t) \leq y_{leader}(t) \leq y_{follower}(t) + L \tag{3}$$

$$x_{l_{follower}}(t) \leq x_{r_{leader}}(t) \tag{4}$$

$$x_{l_{leader}}(t) \leq x_{r_{follower}}(t) \tag{5}$$

A scenario with two leaders and one follower case is also possible. For instance, a bus could be the follower and a part of its front side may overlap with two leaders such as two motorcycles or a small vehicle and a motorcycle. In this case the closest vehicle according to the direction of movement is chosen as the most critical leader (Papathanasopoulou and Antoniou, 2017). If no vehicles are identified as leaders, then the driving situation of the vehicle is free flow.

3.3. Data-driven modeling – Vehicle–dependent models

3.3.1. Overall framework

The data–driven approach includes two parts: training and application. First the required explanatory variables of the model are determined and the appropriate surveillance data are collected. In the training step traffic models are estimated according to the available surveillance data using a flexible regression technique, while in the application step the fitted model is applied to provide predictions using new observations. The data–driven modeling approach is further analyzed by Papathanasopoulou and Antoniou (2015). Some of the alternative methods that can be applied in this context include locally weighted regression, Gaussian Processes, Kernel support vector machines (KSVM), regression splines and neural networks. In this work locally weighted regression and KSVM have been applied and analyzed in the following section. Correlations between observations of the response variable and predictor variables are identified. In a previous work (Papathanasopoulou and Antoniou, 2017), $v(t)$, $v_{front}(t)$, $D_{front}(t)$) have been used as predictor variables and v(t+τ) as the response variable. However, in this research, the vehicle type is added as an explanatory variable in order to further improve model performance and develop vehicle–dependent models.

3.3.2. Locally weighted regression

Locally weighted regression (loess) could be considered as a generalization of the k-nearest neighbor method (Mitchell et al., 1997). It was firstly introduced by Cleveland (1979) and further details can be found on Cleveland and Devlin (1988). Locally weighted regression $y_i = g(x_i) + \epsilon_i$, where i=1,. . . ,n index of observations, g is the regression function and ϵ_i are residual errors, provides an estimate g(x) of each regression surface at any value x in the d-dimensional space of the independent variables. Correlations between observations of the response variable y_i and the vector with the observations d–tuples x_i of d predictor variables are identified. Local regression provides an estimation of function g(x) near x = x_0 according to its value in a particular parametric class. This estimation could be achieved by adapting a regression surface to the data points within a neighborhood of the point x_0, which is bounded by a smoothing parameter: span. The span determines the percentage of data that are considered for each local fit and hence the smoothness of the estimated surface is influenced (Cohen, 1999). The span ranges from 0 (wavy curve) to 1 (smooth curve). Each local regression uses either a first or a second degree polynomial that it is specified by the value of the degree parameter of the method (degree=1 or degree=2).

The data are weighted according to their distance from the center of neighborhood x, therefore a distance and a weight function are required. As a distance function p, Euclidean distance could be used for a single independent variable. A weight function defines the size of influence on fit for each data point taking for granted that nearby points have higher influence than the most distant. Therefore the weight function calculates the distances between each point and the estimation point and higher values in a scale from 0 to 1 are set for the nearest observations. A weight function should meet the requirements determined by Cleveland (1979) and the most common one is the tri–cube function:

$$W(u) = \begin{cases} (1-u^3)^3, 0 \le u \le 1 \\ \\ 0, otherwise \end{cases} \tag{6}$$

The weight of each observation (y_i, x_i) is defined as following:

$$w_i(x) = W[p(x, x_i)/d(x)] = (1 - (\frac{x_i - x}{d(x)})^3)^3 \tag{7}$$

$$\sum_{n=1}^{n} w_i \cdot \epsilon_i^2 \tag{8}$$

where d(x) is the distance of the most distant predictor value within the area of influence. In the loess method, weighted least squares are used so as linear or quadratic functions of the independent variables could be fitted at the centers of neighborhoods Cleveland (1979). The objective function that should be minimized is Equation 8.

3.3.3. Kernel support vector machines (KSVM)

Support vector machines are based on the Structural Risk Minimization principle (Cortes and Vapnik, 1995). An SVM model is a representation of training data as points in space. Training a support vector machine (SVM) leads to the following quadratic optimization problem with bound constraints and one linear equality constraint (Cortes and Vapnik, 1995).

$$W(a_1 \dots a_n) = -\sum_{i=1}^{n} a_i + \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n} y_i \cdot y_j \cdot a_i \cdot a_j \cdot K(x_i, x_j) \tag{9}$$

$$\sum_{n=1}^{n} y_i \cdot a_i, 0 < a_i < C \tag{10}$$

Where n is the dimensionality of α_i, each component α_i corresponds to a training example (x_i, y_i), K(x_i,x_j) is the kernel function which is used as a similarity measure between objects x_i and x_j and C is an upper bound on α_i.

3.3.4. Evaluation of modeling performance

The performance of the models presented in this paper is evaluated using several goodness–of–fit measures: RMSN, RMSPE, MPE and Theils U, U_m and U_s coefficients (for details and a discussion of these metrics, see e.g. Antoniou et al. (2013)). Different measures are used so that the properties of the calibration and validation results could be quantified from different views. For example, the normalized root mean square error (RMSN) assesses the overall error and performance of each method estimating the difference between the observed values Y_n^{obs} and their simulated counterparts Y_n^{sim}. The root mean square percentage error (RMSPE) penalizes large errors more heavily than small errors and the mean prediction error (MPE) indicates the existence of systematic under– or over–estimation in the simulated values. The measure of Theil's inequality coefficient U has been applied in transport model validation and includes three error proportions: the bias (U_m), the variance (U_s) and the covariance (U_c), whose sum is one. Values close to zero for U_m and U_s measures indicate an ideal fit, while values close to 1 suggest the worst fit.

4. Case study set–up

4.1. Data

In order to evaluate the feasibility of the methodological framework on mixed traffic trajectory data, data collected in India were used (Kanagaraj et al., 2015). The video data were collected on a six–lane separated urban arterial road at the Maraimalai Adigalar Bridge in Saidapet, Chennai, India. The section was on a bridge, which ensured that the road geometry was uniform and that there were no nearby intersections or other side factors that could affect drivers behavior. A detailed description of the data is provided by Kanagaraj et al. (2015). The data are presented in two parts– two excel files for the data collected in the periods 2:45–3:00 PM and 3:00–3:15 PM, on February 13, 2014. Each excel sheet contains columns of variables, such as time, vehicle type, length and width, longitudinal position, speed, acceleration and lateral position, speed, acceleration. Longitudinal position is the position of the front of the vehicle, measured from the upstream end of the section, while lateral position is the position of the center of the vehicle, measured from the left-most side of the roadway. The trajectory data are available at the address http://toledo.net.technion.ac.il/downloads/.

As coordinates of the front center of each vehicle, longitudinal and lateral positions are used. Regarding the considered speed for each vehicle, the resultant speed of horizontal and vertical direction is estimated. Due to the nature of mixed traffic data, the next step was to define the car–following sequence, namely which vehicle is in front of the other. Kanagaraj et al. (2015) have identified that in 45% of the observations the overlap between the leader and the follower is less than half the follower width. The methodology described in methodology section was adopted for the identification of the front vehicle. Observations that correspond to vehicles with no leading vehicle were excluded. As lateral safety distance, s=0.20m is considered for each vehicle on both sides. As distance L in Equation 3, L=200m is considered. If no vehicles are identified as leaders, then these observations are omitted, as they do not correspond to car-following state. The same procedure was also used with the validation on dataset data300. Finally, dataset data245 includes 47036 observations corresponding to 1511 vehicle pairs and dataset data300 45982 observations corresponding to 1488 vehicle pairs.

5. Results

5.1. Reference model

A conventional car–following model, the Gipps model (Gipps, 1981), is used as reference benchmark in order to monitor and evaluate the effectiveness of data–driven modeling. The calibration of the model was implemented using the Improved Stochastic Ranking Evolution Strategy (ISRES) algorithm, which is included in the package nloptr (Runarsson and Yao, 2005) and is appropriate for nonlinearly constrained global optimization. This method is implemented in a simple way and supports arbitrary nonlinear inequality and equality constraints in addition to the bound constraints. For further details on Gipps' model calibration see Papathanasopoulou and Antoniou (2017).

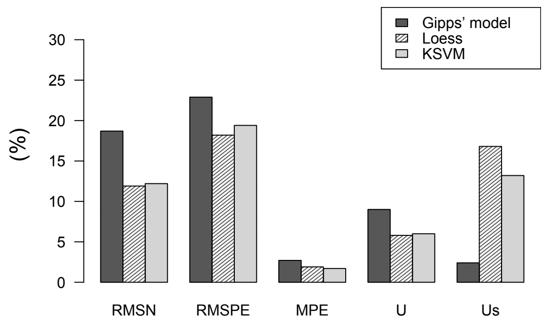
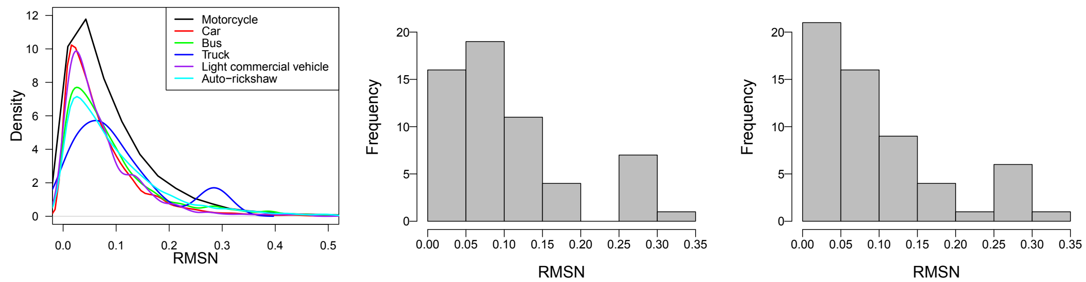


Fig. 2. Validation results using goodness–of–fit measures

5.2. Data–driven modeling

A machine learning method identifies the relationships between predictor variables ($v_{leader}(t)$, $v_{follower}(t)$, the distance $D(t)$ between the two vehicles) and the response data $v_{follower}(t+\tau)$, where time step is τ=0.5s. First, a loess models with span= 0.75 and degree=1 has been trained using dataset data245. Then, a KSVM is trained using 38823 Support Vectors. The hyperparameter sigma, the inverse kernel width for the Radial Basis kernel function "Gaussian" (rbfdot), is estimated using automatic sigma estimation for the regression by the kernlab package. For the available data the estimated value is sigma = 0.68. In Figure 2 validation results for dataset data300, data–driven models outperform Gipps' model. Loess model seems to provide the best results for the available data. In Figure 3a, the densities of RMSN are outlined per vehicle type using loess model. Better results were achieved for cars and light commercial vehicles compared to other vehicle type categories. The worst performance is observed for trucks and thus this vehicle type category is further explored. In Figure 3b, RMSN histogram is presented for trucks using speeds and distances as explanatory variables in loess model (validation on data300). In Figure 3c, the validation results are presented when incorporating vehicle type as an additional explanatory categorical variable in the model. Improvement in model efficiency is evident.



(a) (b) (c)

Fig. 3. (a) RMSN densities per vehicle type using loess model, (b) RMSN histogram for trucks using speeds and distances as explanatory variables in loess model (validation on data300), (c) RMSN histogram for trucks using speeds, distances and vehicle type as explanatory variables in loess model (validation on data300)

6. Discussion and future prospects

Models developed for lane–based traffic conditions may not be appropriate to simulate traffic situations in developing countries, where weak lane discipline is often observed. Traffic in the developing world is so heterogeneous that often lane–based models cannot be realistic. To overcome some of the associated limitations, in this research a methodology is proposed using temporary virtual lanes in order to capture heterogeneity in vehicle width. An integrated methodological framework is proposed for modeling mixed traffic conditions with weak–lane discipline and heterogeneity in vehicle types. Vehicle–dependent models need to be developed in case of heterogeneous traffic, as the drivers of vehicles with unequal dimensions tend to have different driving behaviors; furthermore, different vehicle types are characterized by varying vehicle kinematics. The results indicate that the incorporation of vehicle type in the model may be critical. Thus, it is foreseen that further exploration into this could open up opportunities to understand and simulate driving behavior in mixed traffic conditions. Computational models allow the fitting to data, without the explicit specification of a functional form. On the other hand, data–driven models may not provide as much insight into traffic flow theory as the traditional models. As future prospect, more computational methods could be tested for validation of the proposed methodology and an overall comparison of the available methods is required.

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