Investigation of representation of accidents in car-following models

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ABSTRACT

We are selecting the second candidate project as the term project for the CEE 551 course. Our project investigates the representation of accidents by different car-following models and the performance of different car-following models in the evaluation of traffic safety.

It has become more commonplace for researchers and industries to utilize microscopic traffic simulators to evaluate the efficiency and safety of road designs and assisted or autonomous vehicle control systems. As a result, it is also ever more important for the underlying car-following models of such simulators to accurately represent the behavior of both autonomous vehicles and human-driven ones, especially under abnormal, near-accident situations. However, even given the increasing complexity of rules-based, analytical models and the emergence of novel machine learning and data-based car-following algorithms, not all such models may be up to this task of accurately reflecting traffic crash probabilities and replicating near-crash scenarios in the real world.

We will investigate this issue from the following different perspectives. Firstly, we shall demonstrate that even car-following models that do not account for driver miscues or high-risk scenarios (“accident-free") can also produce accidents in simulations, using arithmetic calculations with the Intelligent Driver Model (IDM). We shall then review various ways in the literature to modify traditional, rules-based, accident-free models to account for high-risk or crash situations, as well as how to calibrate such modifications, using the Gipps model as an example. Lastly, we will turn to more novel, data-based models that utilize machine learning and neural networks to predict vehicle trajectories. We shall evaluate their primary characteristics and drawback in modeling high-risk or accident riving scenarios using the example of a Long Short-Term Memory (LSTM) model, and provide suggestions on improving the capabilities of data-driven models in the safety evaluation of car-following behavior.

1. Introduction

This report presents our studies into car-following models and their suitability in the evaluation of safety performance and crash rates of vehicles. As the research into the control systems of connected and automated vehicles (CAV) progresses, the need for more efficient and accurate car-following models to both facilitate CAV control and validate CAV behavior in mixed traffic flows in simulations has only grown. A key part of the development and validation of any CAV control system is its safety performance, and hence the importance of simulating traffic flows that can accurately reflect the risk factors and potential crash scenarios of real-world traffic systems. At the backbone of this all lies the basic car-following model that CAVs and simulated vehicles follow to plan their trajectories and to avoid (and sometimes intentionally cause) dangerous driving situations and/or traffic crashes. The ability of car-following models to accurately reflect real-world crash risks thus forms the core of our research interests for this study.

It is worth mentioning the definition of some of the terminologies applied throughout this report. Our study is centered around the dichotomy of “accident-free" versus “accident-aware" car-following models. The former term refers to car-following models that expect idealistic, optimal behavior from each entity and does not factor in potential objective and subjective factors that may increase the risk of or outright cause traffic accidents. The latter term refers to car-following models that do take such risk factors into account in the formulation processes of the models. In the meantime, another way to classify car-following models is between “rules-based" and “data-driven" models. The former term refers to models based on arithmetic representations of vehicle dynamics, trip planning, and/or other human factors in the car-following behavior stack, with a finite number of variables and configurable parameters. The latter term refers to models that are purely formulated from extrapolating potential patterns from existing datasets, without any underlying arithmetic formula.

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Table 1
IDM parameters, adopted from Kesting, Treiber and Helbing (2010)

Parameter	Value
Desired speed, v_0	120 km/h
Free acceleration exponent, δ	4
Desired time gap, T	1.5 seconds
Jam space headway, s_0	2.0 m
Maximum acceleration, a	1.4 $\mathrm{m} \cdot \mathrm{s}^{-2}$
Desired deceleration, b	2.0 $\mathrm{m} \cdot \mathrm{s}^{-2}$

The rest of this report is structured as follows. Section 2 presents our response to the first prompt of the Candidate Project 2 assignment, where we demonstrate the generation of accidents by running a simulation of the supposedly "accident-free" Intelligent Driver Model (Treiber, Hennecke and Helbing, 2000). Section 3 presents our response to the second prompt of the assignment, where we demonstrate necessary changes that has to be made to the rules-based Gipps model (Gipps, 1981) to reflect the risk factors in traffic accidents. Section 4 presents our response to the third prompt of the assignment, where we review the literature on data-driven, machine learning-based car-following models. A summary of the characteristics and drawbacks that these models bring to the safety evaluation of autonomous vehicles will be provided, using a Long Short-Term Memory mode (Huang, Sun and Sun, 2018) as an example. We will also provide suggestions on improving the capabilities of such data-driven models with regard to safety evaluation.

2. Accident generation by accident-free model

This section is devoted to the investigation of the safety performances of rules-based accident-free car-following models. We shall use the Intelligent Driver Model (Treiber et al., 2000), a simple car-following model that is widely employed in the study of traffic flow and the control of connected and automated vehicles. After presenting the definition of this model, we shall put it through a simple simulation scenario and evaluate its capabilities in responding to high-risk driving scenarios that potentially involve crashes.

2.1. Definition of IDM

The Intelligent Driver Model is described as follows (Treiber et al., 2000).

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

The optimal space headway value s^* is defined as follows.

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

In the preceding equations, v' refers to the desired acceleration for the ego vehicle, s refers to the spacing between the ego vehicle and a preceding vehicle, and Δv refers to the difference in velocity between the ego vehicle and a preceding vehicle. Various constant parameters are defined in Table 1.

2.2. Simulation scenario

We shall construct the following high-risk driving scenario to put the IDM to the test. We are using Python with Jupyter Notebook (Pérez and Granger, 2007) to run the simulation. The source code for the simulation can be found at the following link: `https://colab.research.google.com/drive/1cgKzm8OyOhIjPFF4Hz82fjq7sXlYzFFf?usp=sharing`.

We shall construct a platoon of three (3) connected and automated vehicles traveling along a long, straight highway. The leading vehicle, the first following vehicle, and the second following vehicle will start at positions $x = 0$, $x = 30$, and $x = 60$, respectively. The three vehicles' starting velocities will be 20 m/s, 30 m/s, and 40 m/s, respectively. We shall control the car-following behavior of the two following vehicles with IDM, updating their accelerations and velocities with a time step measuring 0.01 seconds long, for 100 seconds, while placing particular attention to the vehicle dynamics and interactions within the first 10 seconds.

We wish to investigate the performance of the IDM under both idealistic, unbounded driving scenarios and more realistic scenarios (in both the real world and in some driving simulators such as CARLA (Dosovitskiy, Ros, Codevilla, Lopez and Koltun, 2017)) where the maximum acceleration and deceleration of vehicles are oftentimes constrained by their physical capabilities. In our latter constrained scenarios, our IDM model would output acceleration values strictly within the range of $-b \leq a_n \leq a$, where a_n is the acceleration of vehicle n, $a = 1.4$ is the maximum acceleration, and $b = 2.0$ is the maximum deceleration.

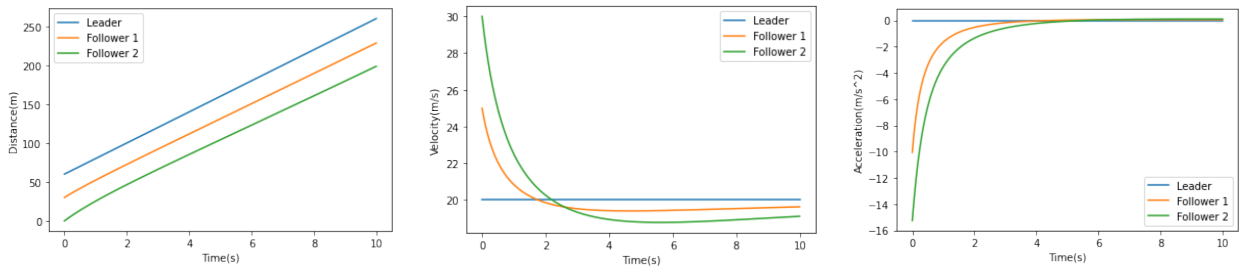
2.3. Simulation results

We shall provide the vehicle trajectory, velocity, and acceleration graphs with regard to simulation time below, for both the unbounded IDM model and the acceleration-constrained IDM model. We utilized the Matplotlib (Hunter, 2007) library to generate the following visualizations.

2.3.1. *Unbounded IDM model*

The simulation results of the unbounded IDM model for the three-vehicle platoon are shown below.

Figure 1: Trajectory, velocity, and acceleration data of vehicle platoon controlled by unbounded IDM



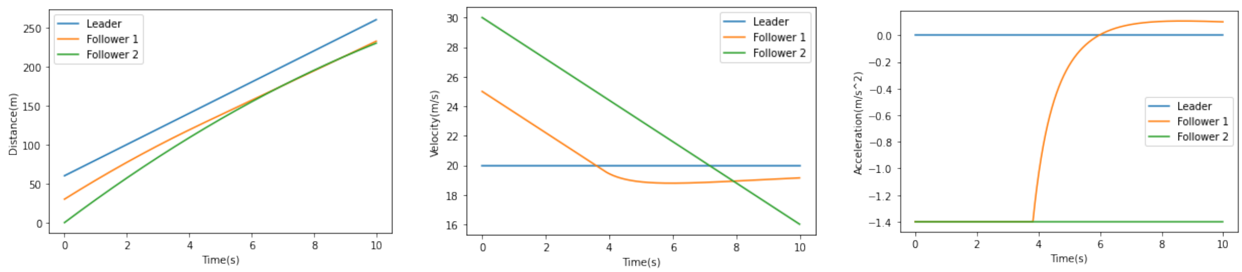
It can be observed that under ideal scenarios, the spacing of the vehicles would converge towards the value of 30 meters after some initial fluctuations, the velocities would converge towards that of the leading vehicle, or 20 m/s, and the accelerations would converge towards the value of zero. We can claim that by running the IDM for long periods of time under ideal vehicle performances would indeed generate a nearly accident-free scenario.

However, we can also identify potential hazards in some of the IDM's proposed control schemes. Most notably, we can identify some unreasonable large deceleration values that the second following vehicle goes through (as great as 16 $\mathrm{m \cdot s^{-2}}$). Ramifications of this phenomenon will be described in the following section.

2.3.2. *Constrained IDM model*

The simulation results of the acceleration-constrained IDM model for the three-vehicle platoon are shown below.

Figure 2: Trajectory, velocity, and acceleration data of vehicle platoon controlled by unbounded IDM



We can identify the intersection in the trajectories of the first and second vehicles at approximately time $t = 7$, signifying an accidental collision. Upon further review, we can identify that the cause of the collision is that the first following vehicle did not maintain the correct speed to ensure positive amounts of space headway between itself and its preceding and following vehicle. One can argue that it did not go fast enough to avoid a rear-end collision with its following vehicle.

2.4. Discussions

We can conclude from this extremely simple simulation of the IDM that even accident-free models are absolutely capable of generating accidents. Even though such models can be stable and safe in the long term, this does not excuse them from generating accidents given particular edge cases. In other words, even accident-free models can generate accidents and destabilizing effects on traffic flows when they produce unrealistic dynamics when simulating under realistic reaction times and/or physical constraints (Treiber, Kesting and Helbing, 2006).

In the case of IDM, it is true that running the model with desirable initial conditions and few dynamic constraints can result in considerable long-term stability that prevents the emergence of high-risk or outright crash scenarios. However, given certain adverse, high-risk initial conditions and certain constraints that disallow the arbitrary acceleration or deceleration values that IDM generates, such an accident-free model can still inadvertently produce accidents. This might be due to the fact that IDM places large amounts of emphasis on an “ideal" space headway between two vehicles, often at the cost of vehicle performance or safety, instead of a “minimum allowable" headway that is also compatible with other preceding or following vehicle(s) in a traffic system.

Another major caveat here, though, is that even though accident-free, rules-based models are capable of producing traffic accidents, the frequencies and mechanisms of such “edge case" accidents can be vastly different from what happens in the real world. In order to correctly fit the frequencies and mechanisms of real-world accident occurrences, we might need to modify our rules-based models and introduce extra parameters to capture such high-risk behaviors.

3. Anatomy of a rules-based, accident-aware model

Despite the possibility of accident-free models generating read-end accidents in car-following scenarios, substantial changes would have to be made to those models in order for them to be genuinely aware of real-world safety risk factors, and for them to be able to replicate the complex safety situation present in real-world traffic systems. This section will discuss the necessary additional factors that a rules-based model would have to take into account to become “accident-aware," provide ideas on the types of data needed to calibrate those factors, and analyze an example of modifications to the Gipps model (Gipps, 1981).

3.1. Factors affecting safety performance of car-following models

There have been many opinions in the literature on the contributing factors of safety risks in car-following scenarios, and also considerable numbers of review studies that attempt to aggregate such opinions in order to aid the development of accident-aware car-following models. One of the most comprehensive among such reviews is by Saifuzzaman and Zheng (2014). This section will review some of the factors proposed by this review article, as well as provide our reflection on the implication of such factors.

3.1.1. Human factors

One of the primary sources of safety risks in car-following scenarios is the limited perception capabilities and poor judgment by human drivers. Saifuzzaman and Zheng (2014) presented the following list of possible human factors that may affect the safety performance of car-following models., taking into account the works of Hamdar (2012) and Treiber and Kesting (2013).

1. Socio-economic characteristics
2. Reaction time, estimation errors, distraction
3. Perception threshold, temporal and spatial anticipation
4. Desired speed, spacing, time headway
5. Driving skills, imperfect driving
6. Driving needs, aggressiveness or risk-taking propensity

It can be seen that not all of the above factors can be perfectly represented in a few simple numerical parameters in an accident-aware car-following model. However, we can anticipate that the factors of reaction time (and the effects of distraction), perception threshold, desired speed, spacing, time headway, driving skills (in terms of random noise to simulate imperfect controls), and risk-taking propensity (and the effects of driving needs and urgency) can all be incorporated into car-following models.

Of the above, we consider that the term “perceptual threshold" warrants additional discussion. Wiedemann (1974) introduced the term “perceptual threshold" to define the minimum value of the stimulus a driver can perceive and will react to. The psycho-physical thresholds are defined as follows.

1. **AX** – The desired spacing between the front sides of two successive vehicles in a standing queue
2. **BX** – The desired minimum following distance, which is a function of AX, the safety distance, and speed
3. **SDV** – The action point where a driver consciously observes that he/she is approaching a slower leading vehicle; SDV increases with increasing speed difference
4. **CLDV** – Closing delta velocity (CLDV) is an additional threshold that accounts for additional deceleration by the application of brakes
5. **OPDV** – The action point where a driver notices that he/she is slower than the leading vehicle and starts to accelerate again
6. **SDX** – A perception threshold to model the maximum following distance, which is approximately 1.5–2.5 times BX

A modified version of the original Wiedemann model has been used in the commercial micro-simulation software VISSIM (Fellendorf and Vortisch, 2010). Several calibration attempts for VISSIM model exist in the literature.

In the meantime, we have also found the works of Hamdar and Mahmassani (2008) and Hamdar, Mahmassani and Treiber (2015) in the development of a driver behavior model to model risk-taking behavior using Kahneman and Tversky (1979)’s prospect theory.

3.1.2. Other factors

Apart from the subjective driver behavior factors discussed above, there are also other factors that may influence the safety performance of accident-aware car-following models. For example, different vehicles have varying acceleration and deceleration capabilities under different weather and road conditions (reflected in the a and b parameters in the Intelligent Driver Model, for instance), and dynamically modifying these parameters may also introduce uncertainties and risk factors in a car-following traffic system. The varying lengths of individual vehicles may also be a simple factor that can interfere with the perception of space headway in car-following behavior.

3.2. Necessary datasets to calibrate accident-aware models

Even most of the accident-aware models available today are calibrated on nothing more than vehicle trajectory datasets or other dynamic information (for instance, Hamdar and Mahmassani (2008) and Yang and Peng (2010)). This is based upon the assumption of the fact that any effect of the various factors discussed above would inevitably reflect in a vehicle’s trajectory, and we can attempt to estimate the values of each parameter through extensive regression operations.

However, it would no doubt be more efficient if we had access to alternative sources of data other than vehicle trajectories. With the advancements in driver state monitoring technology (Melnicuk, Birrell, Crundall and Jennings, 2016), we can now collect first-hand data of the cognitive distraction, mental workload, mental fatigue, and the emotions of drivers, namely in car-following scenarios. Calibrating models with these data can certainly enable a more accurate representation of the human factors in an accident-aware car-following model. Meanwhile, with the ever more widespread deployment of assisted and/or automated driving systems and the suite of sensors that accompany such systems, we can also collect information on vehicle perception and actuation performance, and compare it to the externally observed trajectory data to gain a more thorough understanding of car-following behavior.

3.3. Example of accident-aware car-following model

In this section, we shall present an example of accident-aware modifications to a rules-based car-following model, the Gipps model (Gipps, 1981). We shall incorporate a Task-Capability Interface (Fuller, 2005) to the Gipps model, introduce our measure of safety using aggregated time-to-collision values, and present the results of our simulation.

3.3.1. The Gipps Model

The car-following model developed by Gipps (1981) is a popular rules-based safety distance model. The model assumes that the speed is selected by the driver in a way to ensure that the vehicle can be safely stopped in case the preceding vehicle should suddenly brakes. The Gipps model includes two modes of driving: free-flow and car-following. The driver chooses the smaller one from the speeds obtained from the free-flow and car-following modes.

$$V_{a,n}(t+\tau_n) = V_n(t) + 2.5\tilde{a}_n\tau_n(1-\frac{V_n(t)}{\tilde{V}_n})(0.025+\frac{V_n(t)}{\tilde{V}_n})^{\frac{1}{2}} \tag{3}$$

$$V_{b,n}(t+\tau_n) = \tilde{b_n}\tau_n + \sqrt{\tilde{b}_n^2\tau_n^2 - \tilde{b}_n[2(\Delta X_n(t) - L_n - s_n) - V_n(t)\tau_n - \frac{V_{n-1}(t)^2}{\hat{b}_n}]} \tag{4}$$

$$V_n(t+\tau_n) = \min\{V_{a,n}(t+\tau_n), V_{b,n}(t+\tau_n)\} \tag{5}$$

, where V_n denotes the speed of the subject vehicle, n,$\tilde{a}_n$ is the desired acceleration $\tilde{b}_n$ is the desired deceleration, ΔX_n is the space headway between the subject and preceding vehicles ($\Delta X_n = x_{n-1} - x_n$); where x_n is the position of the vehicle n). L_n is the vehicle length, s_n is the minimum spacing at a standstill situation, $\tilde{b}_n$ is an estimation of the deceleration applied by the preceding vehicle (b_{n-1}), and $\tilde{V}_n$ is the desired speed of vehicle n, and τ_n is the reaction time.

The advantage of the Gipps model is in its ability to model driving behavior following some cognitive thinking that may be adopted by the driver; moreover, the Gipps model showed an acceptable degree of stability (relatively low number of accidents) when relaxing its safety constraints (Hamdar and Mahmassani, 2008).

However, the engineering of Gipps' car following model provides a less psychologically plausible characterization of how humans think about, and address the driving problem. Besides, Gipps' model is not capable of reproducing human factor-induced collisions. In normal and often complex driving situations, humans adopt strategies that are adequate rather than optimal because of their incomplete knowledge or insufficient time to evaluate all possible alternatives. If the current driving situation is acceptable, there is no reason to look for opportunities to overtake. The phenomenon contradicts traditional car following models where optimality requires that drivers expand all resources on trying to improve performance.

Therefore, Saifuzzaman, Zheng, Haque and Washington (2015) et al. propose an improved Gipps' model by integrating it with Task–Capability Interface (TCI) (Fuller, 2005) to model human factors in high-risk and/or traffic crash scenarios.

3.3.2. The Task–Capability Interface

From the human factors perspective, Fuller (2005) presents the Task-Capability Interface (TCI) model where the difficulty of driving task dominates driver behavior. In this model, task difficulty (TD) arises out of the dynamic interaction between driver capability and driving task demand. Driver capacity is assumed to be limited by constitutional characteristics and biological characteristics. Although driver's capacity is hard to evaluate, past studies(Saifuzzaman et al., 2015) have discovered a correlation between driver capacity and time headway selection.

According to the TCI model, task difficulty (TD) can be expressed as an interaction between task demand and driver capacity. And it assumes this interaction as the ratio of task demand and driving capability. Fuller (2002) explains that the task demand at ant instance could be explained by the speed of the driven vehicle and the spacing from the preceding vehicle proposed in the following equation.

$$TD_n(t) = \left(\frac{V_n(t-\tau'_n)\tilde{T}_n}{(1-\delta)S_n(t-\tau'_n)}\right)^\gamma \tag{6}$$

where TD_n represents task difficulty as perceived by driver n at time t. S_n is spacing measured as the distance between the front of the subject vehicle to the back of the preceding; V_n is speed of the subject vehicle; $\tilde{T}_n$ is desired time headway, δ_n is the risk parameter, τ'_n is the modified reaction time including the original reaction time τ_n and reaction time increment ϕ'_n; and γ is a sensitivity parameter which is used to capture driver;s sensitivity toward the risk difficulty is lagged by the reaction time, which means that it produces the perceived task difficulty at time t based on the observations at time $(t-\tau'_n)$. In addiction, the same task that is easy to one driver may be difficult to another, depending on their desired time headway, which is consistent with observations and reflects the soundness of the task difficulty.

In two ways, task difficulty function includes human factors, the risk parameter δ and modified reaction time. The risk parameter $\delta \leq 1$ capture the perceived risk that arise from human factors. A positive risk parameter indicates that the driver acknowledges the impairment caused by human factors and perceives the risk of driving with reduced capacity. Consequently the perceived level of task difficulty increase. A negative risk parameter indicates aggressive driving where the driver underestimated the risk. For instance, a drunk or sleepy driver lack of concern for safety and lead to aggressive behavior. In regular driving the driver can drive with the full capacity, and thus the risk parameter will be zero, which also represents in absence of human factors. Besides, a modification time is used with is calculated as $\tau'_n = \tau_n + \phi_n$, where ϕ_n denotes the reaction time increase.

A task difficulty homeostasis theory is used to incorporate TD_n in car-following model. Therefore, task difficulty applied to Gipps' model as below.

$$V_{a,n}(t+\tau_n) = V_n(t) + 2.5\frac{\tilde{a_n}\tau_n}{TD_n(t+\tau'_n)}(1-\frac{V_n(t)}{\tilde{V_n}})(0.025+\frac{V_n(t)}{\tilde{V_n}})^{\frac{1}{2}} \tag{7}$$

$$V_{b,n}(t+\tau_n) = \tilde{b_n}\tau_n TD_n(t+\tau'_n) + \sqrt{\tilde{b}_n^2\tau_n^2 - \tilde{b}_n[2(\Delta X_n(t) - L_n - s_n) - V_n(t)\tau_n - \frac{V_{n-1}(t)^2}{\hat{b}_n}]} \tag{8}$$

$$V_{c,n}(t+\tau_n) = V_n(t) + a_n^{max}\tau'_n \tag{9}$$

$$V_{c,n}(t+\tau_n) = \max\{0, V_n(t) + b_n^{max}\tau'_n\} \tag{10}$$

$$V_n(t+\tau_n) = \max\{V_{d,n}(t+\tau_n), \min\{V_{a,n}(t+\tau_n), V_{b,n}(t+\tau_n), V_{c,n}(t+\tau_n)\}\} \tag{11}$$

3.3.3. Time-to-collision as safety performance metric

Rear-end crashes are one of the most widespread crashes types ever observed. In a microscopic simulation model, mainly the Time to Collision (TTC) and Short following headways are selected as metrics to evaluate accident probability, which directly show the following metrics. TTC is a proximal safety indicator initially introduced by Hayward (Hayward, 1972).

Time to Collision(TTC) refers to the time required for two vehicles to collide if they continue at their speed and on the same path.

$$TTC_i = \frac{x_{i-1}(t) - x_i(t) - l_i}{\dot{x}_i(t) - \dot{x_{i-1}}(t)} \tag{12}$$

Several studies employed TTC, to evaluate traffic safety, and the critical time to collision, is about 3 seconds to 5 seconds 4sec or 5,3.5 seconds. Time Integrated TTC (TIT) (Bonte, Espié, Mathieu et al., 2007) is an integral value of the TTC profile. Once the TTC falls below a threshold, TIT can present an index of severity. So the indicator is chosen to choose the trajectories which are critical.

headway is a measure of driver risk. Evan and Wasielewski's research on a large number of vehicles within the traffic stream shows that accident-involved and offensive drivers have a "higher level of risk in everyday driving" which means they have close following distances (Evans and Wasielewski, 1983).

3.3.4. Simulation of the updated Gipps' model

In this section, we use Next Generation Simulation (NGSIM) vehicle trajectories (Colyar and Halkias, 2007) dataset to test Gipps' model and TDGipps' model performance. The car-following trajectory is collected on the US-101 freeway in Los Angeles, CA.

The calibration of basic Grips model refers to **?** that Soria et. al simulated Gipps' car-following model in a simulator. Soria's simulated car following in different driving types, traffic conditions, and environmental conditions. It builds seven scenarios, including three driving types (aggressive, average, conservative) and four environmental regimes (rainy or not rainy, congested or uncongested). This paper calibrate three parameter: acceleration rate$n$, deceleration rate $\underline{n}$, and the desired speed $\hat{V}$. The result shows that the conservative and aggressive drivers both have large deceleration; and driver has less deceleration rate in congestion or rainy weather.

The parameters value in our simulation is $[a_n, b_n, b, \tau] = [3.3, \bar{-}3.4, -3.4, 1]$ based on **?**'s paper. Our trajectory data is collected in the early morning, traffic condition is relatively good which eases the driver's driving task difficulty, and we set task difficulty value TD_n as 0.5.

Figure 3 and Figure 4 are examples of two vehicle's car-following trajectory data and 3b, 4c shows four regimes of TDGipps' model and compared with two regimes Gipps' model in Figure 4a, 4b, TDGipps' has upper and lower bound of acceleration, resulting in lower RMSE value. RMSE values in examples are 0.75 and 0.6 of DTGipps' model which outweigh the RMSE value of Gipps' model 1.4 and 0.91 respectively. What is important, in these examples, car-following regime in DTGipps' model are more smooth, since the human factors involvement in car-following model that allows traditional CF model reflect the driving task difficulty and risk compared with driver's acceptable limitation.

3.4. Conclusion

In conclusion, DTGipps' model includes human factors in conventional car-following model, the human factor's parameter in DTGipps' model correspondingly learn how environmental and traffic conditions impact driver's perception. Thereby, DTGipps' model benefits traffic safety when use in Collision Prevention System.

4. Data-driven car-following models for safety evaluation

It is true that we can keep refining existing rule-based models with more parameters and more intricate mathematical formulations, but there certainly exists a point where such models grow to become too complex for efficient application. This is why data-driven car-following models, ones that are only based on extrapolating patterns from a mass of empirical data without manual intervention (Huang et al., 2018), come in. In particular, there has been growing interest in utilizing emerging technologies in machine learning to construct computer models that can predict prospective car-following behavior given current perceptual cues after being trained with existing datasets of car-following behavior.

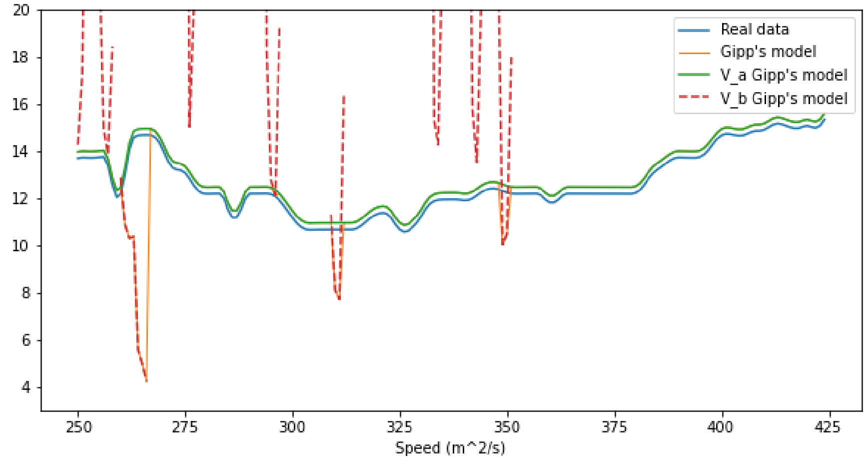
This section will first provide an overview of different types of data-driven and machine learning-based car-following models in the literature. Then we shall discuss the potential pitfalls and drawbacks of these models in terms of their applicability in safety performance evaluation, using a Long Short-Term Memory model published by Huang et al. (2018) as a case study. Finally, we shall provide our opinions on how these drawbacks can be remediated and how we can make the best use of data-driven models to produce accident-aware representations of real-world driving behavior.

4.1. Classifications

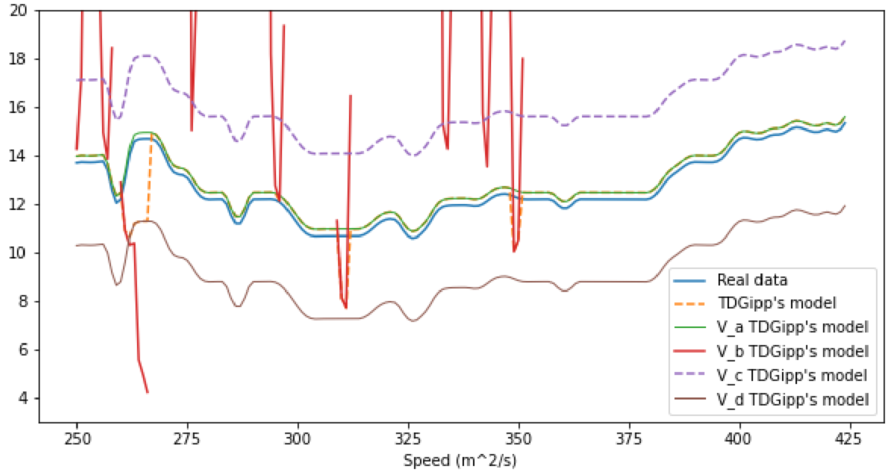
Among the first data-driven car-following models, and perhaps the most prominent to date, are models built with artificial neural networks. Neural networks are built upon interconnected computing cells known as "neurons," each applying their own set of weights and parameters to specific data inputs. Networks of these neurons can come together to form layers of functional abstractions of the biological neural structures of the central nervous system, and can be powerful pattern recognizers and classifiers (Adeli, 2001). We have first seen small-scale neural networks applied towards car-following tasks with hand-crafted neurons and layers from Jia, Juan and Ni (2003).

Recent advances in this field focus on using much deeper (i.e., more layers) and denser (i.e., more neurons at each layer) neural networks with millions of parameters to learn car-following behavior on several levels of hierarchical representations of driving behavior. This approach is also known as "deep learning," with Wang, Jiang, Li, Lin, Zheng and Wang (2018), Huang et al. (2018), Zhang, Sun, Qi and Sun (2019), Cao, Bıyık, Wang, Raventos, Gaidon, Rosman and Sadigh (2020) as a few notable examples.

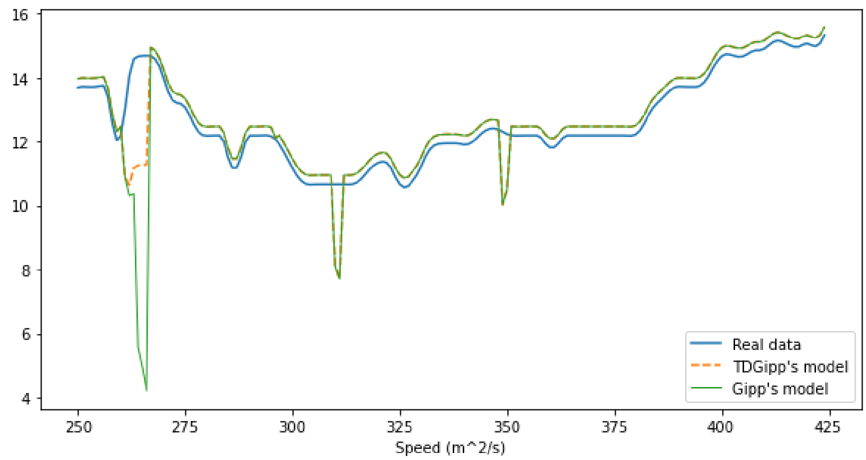
Given the inherent complexities and difficulties in training ever deeper and more massive neural networks, there have also been studies that look at alternative methods to achieve machine learning of car-following data. One such method is known as instance learning, where a computer simply stores a repository of known car-following behavior data given a set of external stimuli. When similar stimuli are again detected in the deployment of the car-following model, the computer simply fetches one or more sets of past responses to the stimuli, applies some sort of post-processing to the data, and outputs the processed response as the response of the car-following model. Examples



(a) Gipp’s Model different regimes

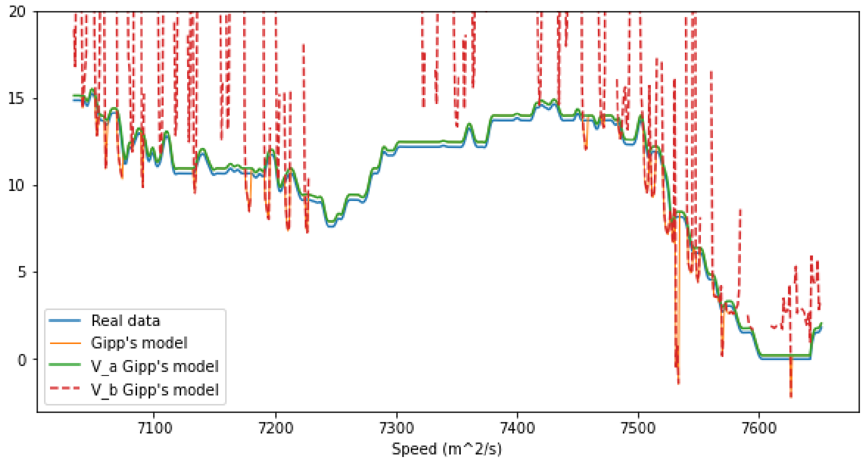


(b) TDGipp’s model regimes

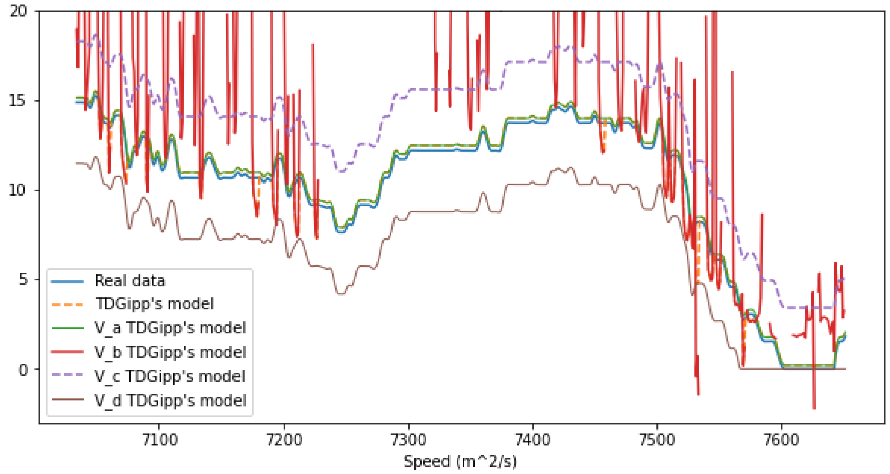


(c) Result of Gipp’s model and DTGipp’s model

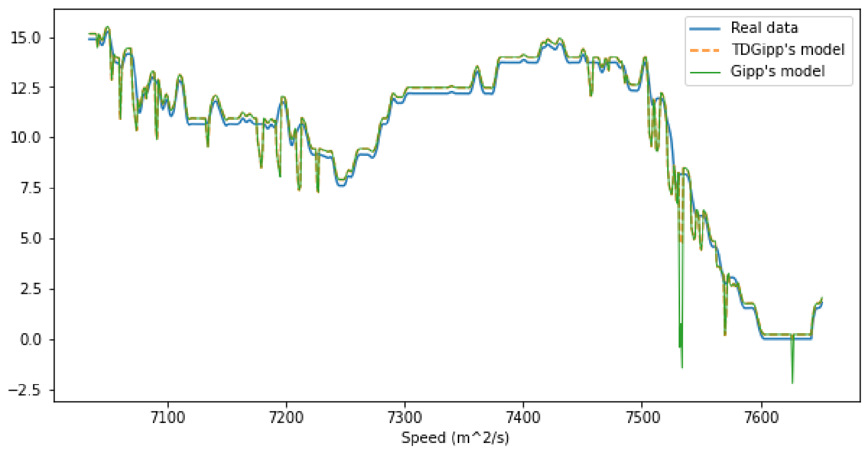
Figure 3: Comparison between TDGipps’ model and Gipp’s model



(a) Gipp's Model different regimes



(b) TDGipp's model regimes



(c) Result of Gipp's model and DTGipp's model

Figure 4: Comparison between TDGipps' model and Gipp's model

can be seen with the work of Toledo, Koutsopoulos and Ahmed (2007) and Papathanasopoulou and Antoniou (2015) with locally weighted regression and He, Li, Lin and Zhu (2013) with K-means clustering.

Another relatively niche machine learning methodology applied to car following is support vector machine regression, proposed by Wei and Liu (2013). This algorithm first attempts to fit a "median" of car-following behavior from the training dataset with an SVM, prunes the outliers, and uses data points close to the median behavior as inputs to another regression model to produce a more error-proof car-following model.

4.2. Potential problems

It might be tempting to treat data-driven, machine learning-based models as the cure-all for car-following tasks, and a vast majority of the literature claims that whatever newly developed data-driven model can outperform all of their rules-based counterparts in specific testing scenarios similar to those in the training datasets. However, we have identified the following potential pitfalls and drawbacks in relying on data-driven models to account for high-risk and crash circumstances and to evaluate the safety performance of a traffic system.

4.2.1. Dataset biases and imperfections

The entirety of the behavior and performance of a data-driven car-following model is dependent upon what kind of data it is being trained with. However, most models in the literature only utilize somewhat homogeneous datasets of vehicle trajectories on one single road segment, without any flow disturbances or high-risk scenarios, to train their models. It would be hard to envision how such a model could react appropriately to adverse circumstances where accidents are likely to occur when the model has never been exposed to such circumstances in the first place. In the meantime, a model trained solely on vehicle trajectories would also fail to account for some of the human factors, vehicle characteristics, or environmental factors that define a true, mature accident-aware model.

4.2.2. Opacity in model construction

Machine learning-based models, especially the prevalent ones based in artificial neural networks and deep learning, possess an inherently and purposefully opaque model structure with potentially millions of parameters and dense connections between computational layers. Given this phenomenon, Papathanasopoulou and Antoniou (2015) has claimed that machine-learned models do not necessarily respect analytical traffic flow theory – rather, any agreement with such theories might just be coincidences. In turn, it is also difficult for researchers to draw meaningful conclusions about the state of the car-following model or its surrounding traffic systems just by observing the learned model structure and/or parameters, which is vastly different from rules-based models.

4.2.3. Evaluation and validation

The validation methods for data-driven car-following models in the literature can be highly inconsistent and not totally relevant to our interests in safety evaluation. Apart from dataset-based miscues such as data leakage and lack of variety in testing data, a more significant issue is that there is no uniform performance metric to evaluate the safety performance of data-driven car-following models. Most "comparisons" and "benchmarks" in the literature compare a new model with an arbitrary rules-based or data-driven model, using arbitrary physical parameters, and tend to jump to conclusions whenever there are promising signs in terms of the new model's performance on these cherry-picked parameters.

4.2.4. Case study: a Long Short-Term Memory model

A Long Short-Term Memory car-following model developed by Huang et al. (2018) provides a great example of some of the drawbacks of data-driven models from a safety performance viewpoint. The model itself is intended to emulate the varying degrees of memory that a driver may have towards previously seen car-following behavior, and the model adjusts its parameters according to the constant update of short-term memories of perceived traffic events.

The first observation we can make is that it is trained exclusively with 799 sets of vehicle trajectories from the Next Generation Simulation (NGSIM) dataset (Colyar and Halkias, 2007). This dataset, for all its benefits, is heavily biased towards one geographic region, and one road condition (i.e., a segment of the US-101 highway near Los Angeles, CA); and it does not account for high-risk or crash scenarios in its vehicle trajectory data.

In the meantime, the evaluation metrics are also a bit arbitrary in their formulations. It does not seem the correlation coefficient between simulated and actual speed, and the mean squared errors of speed and space headway can present a truly holistic picture of the performance of the car-following model. The authors also compared the LSTM model to two seemingly random alternative models: a recurrent neural network model (Schmidhuber, 2015), and a rules-based asymmetric full velocity difference model (Xu, Liu and Gong, 2013). It is thus not entirely clear how much the proclaimed significance of the LSTM model over both the RNN and ASFD models matters when it comes to traffic simulation and safety evaluation performance.

4.3. Room for Improvement

Lastly, we want to provide some of our ideas on how the previously stated drawbacks of current data-driven models can be fixed. In terms of dataset selection, future studies should specifically incorporate vehicle dynamics datasets that feature real-life driver responses to high-risk and/or crash scenarios. Such datasets can also include driver psycho-physical monitoring, vehicle performance metrics, etc., to fully account for and replicate potential risk factors in car-following scenarios. If the need arise, models that train, calibrate, and simulate concurrently on rules-based and data-driven models may be able to provide more insights to the traffic situations and the intangibles of the car-following behavior. Finally, a methodology for evaluating the safety performance of car-following models can attempt to identify high-risk driving behavior and/or crashes from simulation and compare the frequencies of such events against real-world statistics for the same or similar roadway segments and other external conditions.

5. Conclusion

This report presents our work in the exploration and evaluation of different car-following models and their suitability in modeling safety performance during car-following maneuvers. We hope that the insights we sustained and the suggestion we raised can inspire and facilitate future research efforts in accident-aware, safety-focused car-following models.

CRediT authorship contribution statement

Peijing Li: Methodology, writing – review editing; formal analysis, investigation, software, and writing – original draft for Prompt 1 (Section 2 of this report); investigation and writing – original draft for Prompt 3 (Section 4 of this report). **Zhaoming Zeng:** Conceptualization of this study; software, investigation, data curation, writing – original draft, visualization for Prompt 2 (Section 3 of this report).

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