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Comparison of Reaction Time-based Collaborative Velocity Control and Intelligent Driver Model for Agent-based Simulation of Autonomous Car

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Abstract

Based on historical records, driving in hazardous weather conditions is one of the most serious causes that lead to fatal accidents on roads in general and in United Arab Emirates (UAE) highways in particular. One solution to improve road safety is to equip vehicles and infrastructure with connected and smart devices and convert them into autonomous vehicles. Before deploying a concrete solution to the field, it must be validated by simulation, and more specifically by agent-based simulation. In this paper, we propose to implement the Reaction Time-Based Collaborative Velocity Control (RT-CVC) model that was implemented in autonomous cars into an agent-based simulator. This model is compared to the Intelligent Driver Model (IDM) , which is one of the standard longitudinal driving behaviors in simulation environments. The experimental results show that RT-CVC generates traffic flows with fewer vehicle collisions and shorter travel times. This positive analysis is balanced by the fact that RT-CVC is designed for autonomous cars, and IDM is designed to model human-drive decisions. Using RT-CVC for modeling a human driver may be counter productive in simulation experiments.

Keywords: Driving model; Microsimulation; Agent-oriented model; Comparison;

1. Introduction

Many environmental factors, e.g., fog or rain, impact road traffic safety because of their drastic effect on reducing drivers' visibility and its ability to alter driving behavior. To provide accurate results, a high-resolution spatial model should be established that represents the state of the traffic infrastructure and the driving population. An agent-based

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model (ABM) is a class of computational models for simulating the actions and interactions of autonomous agents [1, 6]. ABM is now widely used for modeling increasingly complex systems, and especially transportation behavior modeling [5]. Although traditional modeling tools cannot capture the complexity, ABM can do it by modeling the interaction of autonomous agents and deducing the rules for such a system.

Several agent models and frameworks have been proposed to simulate traffic flows, connected vehicles, autonomous vehicles, connected objects, or put together several of the previous aspects. According to our knowledge, most of the driver simulation models are considering the drivers as humans, and not as an artificial intelligence embedded in an autonomous car. Therefore, we propose to implement the Reaction Time-Based Collaborative Velocity Control (RT-CVC) [3] model in order to be used in an agent-oriented model of autonomous car. RT-CVC model was specifically designed for being embedded in an autonomous car as a control algorithm for the longitudinal speed. Outcomes of RT-CVC are compared to those of a standard model for driver simulation, i.e. the Intelligent Driver Model (IDM) [10], which is used in standard traffic simulation tools. Even if RT-CVC and IDM models are used to simulate cars on roads, there are fundamental differences between them. RT-CVC and IDM are not designed to represent the same type of driving behavior. Indeed, RT-CVC is specifically designed for the control of autonomous cars; when IDM is dedicated to the modeling of human drivers. This target difference is expected to be highlighted in this study in terms of the reaction time of the model with respect to unexpected events, such as a vehicle appearing in the field of view in foggy weather conditions. It is also important to understand these differences to allow researchers to create simulators with mixed types of drivers. In fact, a transition period is expected to occur to move from full human-driver flows to autonomous vehicle flows during which both types of driver will co-habit. This research is a first step for understanding the key differences between the different longitudinal driving models to enable the selection of the best model for fitting simulation requirements. This paper is the first step toward complete validation of RT-CVC and its comparison with standard driver models.

The paper is structured as follows. Section 2 contains the definition of the RT-CVC and IDM models. The description of the evaluation scenario based on an agent-based simulation is provided in Section 3. Section 4 provides the simulation results and related discussions regarding the comparison of RT-CVC and IDM. Related works are briefly described in Section 5. Section 6 concludes this paper.

2. Definition of the Longitudinal Driving Models

2.1. Reaction Time-Based Collaborative Velocity Control

RT-CVC model [3] is developed to deal with the occupancy of a conflict zone. From the point of view of car following, the conflict zone could be considered as a location on road before the following vehicle. This model is implemented as a control algorithm for real autonomous cars [3]. The acceleration a_r of a vehicle is provided by Equation 1. This acceleration is used by the following vehicle for braking or acceleration during the next simulation step Δt.

$$a_r = \frac{b_f\tau - 2v_f \pm 2b_f\sqrt{\dfrac{b_f b_l \tau^2 + 4b_l v_f \tau + 4v_l^2 - 8b_l s}{4b_f b_l}}}{2\tau} \quad (1)$$

where: s is the distance between the two successive vehicles. If s becomes lower to the minimal safety distance for breaking s_0, the vehicle starts its emergency braking behavior. v_f and v_l are the current velocity of the follower and leader, respectively. b_f and b_l are the respective maximum decelerations of the follower and the leader. And τ is the reaction time of the driver. In some unusual cases, the bumper-to-bumper distance may be less than the minimal headway s_0. Consequently, the final control equation is given by Equation 2.

$$a_r = \begin{cases} b_f & \text{if } s < 0 \\ \dfrac{b_f\tau - 2v_f - 2b_f a^*}{2\tau} & \text{if } s \geq 0 \end{cases} \tag{2}$$

where:

$$a^* = \sqrt{\frac{b_f b_l \tau^2 + 4b_l v_f \tau + 4v_l^2 - 8b_l s}{4b_f b_l}} \tag{3}$$

2.2. Intelligent Driver Model

IDM is a time-continuous car following model for the simulation of freeways and urban traffic [10]. It describes the dynamic of the positions and velocities of a vehicle, as defined in equations 4 and 5.

$$\frac{dv}{dt} = a \cdot \left[1 - \left(\frac{v_\alpha}{v_0}\right)^4 - \left(\frac{s^*(v_\alpha, \Delta v_\alpha)}{s}\right)^2\right] \tag{4}$$

$$s^*(v_\alpha, \Delta v_\alpha) = s + v_\alpha T + \frac{v_\alpha \Delta v_\alpha}{2\sqrt{ab}} \tag{5}$$

where: a is the comfortable acceleration, v_α is the current speed of the vehicle α, v_0 is the desired speed, and s_0 is the minimum distance between the current vehicle and the front vehicle. T is the desired time headway. Δv_α is the speed difference with the leader. s is the current distance headway and b is the comfortable deceleration. IDM shows realistic shockwave patterns, but has a macroscopic capacity of just below $1,900$ veh/h. In order to reach a reasonable capacity, the desired time headway needs to be lowered to unreasonable values. The initial model is adapted to the progression of discrete time by evaluating one of the following equations at each time step: the free road $\dot{v}_\alpha^{\text{free}}$ and the interaction $\dot{v}_\alpha^{\text{int}}$ terms, which are detailed in equations 6 and 7, respectively. The first is used when the distance from the next obstacle is greater than a certain threshold, which is equivalent to the absence of an obstacle. The second term is used when there is an obstacle close enough to have to adapt the speed according to this obstacle.

$$\dot{v}_\alpha^{\text{free}} = a\left(1 - \left(\frac{v_\alpha}{V_\alpha}\right)^\delta\right) \tag{6}$$

$$\dot{v}_\alpha^{\text{int}} = -a\left(\frac{s_0 + v_\alpha T}{s} + \frac{v_\alpha \Delta v_\alpha}{2s\sqrt{ab}}\right)^2 \tag{7}$$

where: V_α is the maximum speed of the vehicle α. δ is a constant usually set to 4.

3. Simulation Scenario

The comparison scenario is based on the simulation of roads in the United Arab Emirates in a foggy weather situation. The agent environment must be defined to allow comparison of results, that is, a 10-km long two-lane highway, without exit, entry, or interchange ramps. Vehicles are injected into the simulation at one end of the simulated highway, and a fog area is defined at the other end of the highway. The maximum visibility distance in fog is set at 40 meters. Figure 1 shows a simplified view of the scenario. Speed-limit panels are regular panels, i.e., they are neither smart nor connected. The car drivers perceive the objects in front of their car with a maximum distance of 250 meters. The safety distance sd is the minimum distance between vehicles under which it is assumed that it is hard to avoid a collision with the front car. It is defined in Equation 8, where γ_r is the duration of the reaction in seconds by the driver (usually 1 second) and γ_s is the expected time to stop the vehicle in case of emergency (usually 5 seconds). $\dot{v}$ is the current speed of the vehicle (km/h). α is an approximation factor that is usually a constant.

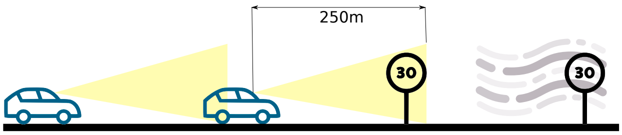

Fig. 1. Scenario 1 includes neither communication between the infrastructure and the vehicles, nor between the vehicles

$$sd = \alpha\,(\gamma_r + \gamma_s)\,\frac{1000\dot{v}}{3600} \tag{8}$$

The simulator is implemented in the SARL agent-oriented environment [8] and available online[1]. Because of the limited size of this article, details on the implementation of longitudinal driving models in the SARL agent framework could be found in [7] or in the source code mentioned previously.

4. Results and Discussion

One hundred different experiments are carried out for the scenario explained in the previous section. Several indicators were measured to validate the general behavior of the simulator related to the evolution of vehicle speeds, travel duration, measured accidents, and simulator runtime performance.

Figure 2 illustrates the evolution of the vehicles' speeds, regardless the position of the vehicles inside or outside the fog. The average values and standard deviation can be found in Table 1, and for the speeds inside and outside the foggy weather area. Three different stages could be shown. Average speed increases because none of the vehicles has encountered a foggy weather situation. Then, around time 500, the vehicles start to enter the fog, which has the consequence of decreasing the average speed and making it stable until all vehicles have entered the fog. Average speed increases again at the end of the simulation because the drivers accelerate after exiting from the fog. Figure 3 shows the average speed of the vehicles when they are inside the fog zone. This speed value is stable around 17 $m.s^{-1}$ for RT-CVC and 12 $m.s^{-1}$ for IDM, which corresponds to the maximum speed to reach safety with a maximum perception distance of 40 meters. The higher values at the beginning and at the end of the simulation are explained by the small number of vehicles into the simulation. Therefore, the individual impact of each on the average speed is increasing. The drivers are accelerating into the fog because they are perceiving the end of the fog wall, even if they are still physically into the fog area.

[1] Source Code: https://bitbucket.org/sgalland/zayed-fogsimu/

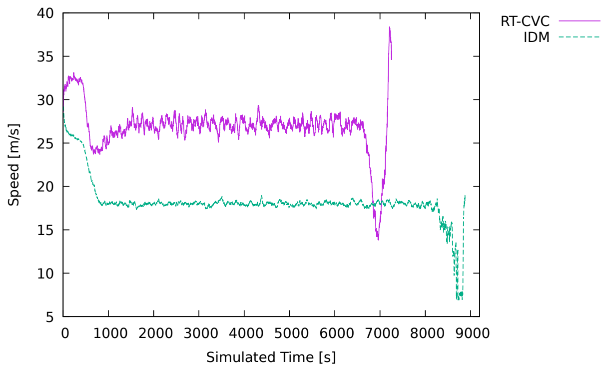

Fig. 2. Average speed of the simulated vehicles over the simulated time into the entire road network

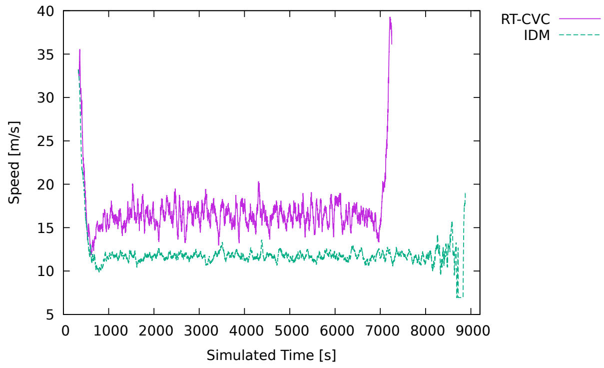

Fig. 3. Average speed of the simulated vehicles over the simulated time into the foggy weather zone

Table 1. Indicators for the RT-CVC and IDM models

Criteria	RT-CVC			IDM		
	Avg.	Std. Dev.	Avg. Spread	Avg.	Std. . Dev.	Avg. Spread
Number of vehicles	86.6	22.2	14.1	105.1	23.7	15.6
Vehicle speed [m/s]	26.9	2.8	1.5	18.2	2.5	1.0
Vehicle speed in fog [m/s]	16.9	3.2	1.6	11.9	2.1	0.8
Travel duration [s]	314.1	12.8	6.5	466.0	16.9	4.0
Execution time [s]	0.0594	0.0179	0.0137	0.0749	0.0231	0.0189

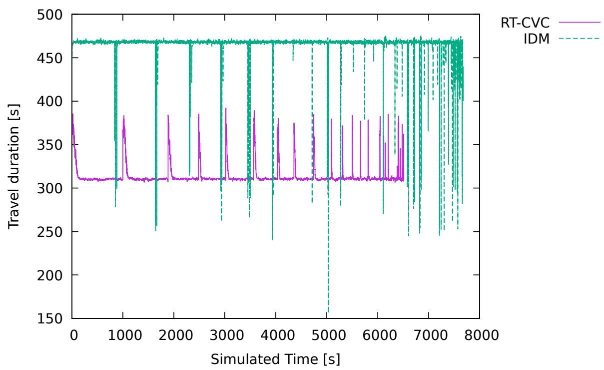

Fig. 4. Average duration for the vehicles to traverse the experimental area

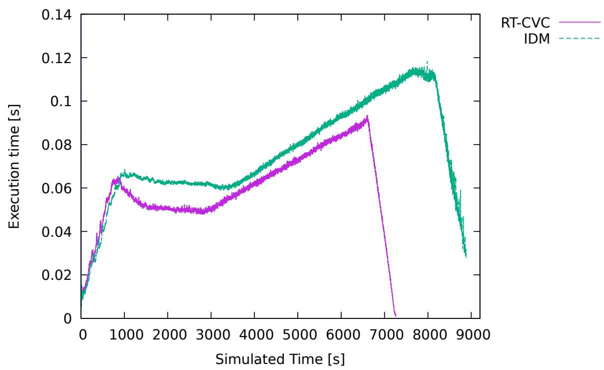

Fig. 5. Average duration of the execution of a single simulation step, which includes the computation of the agent perceptions, the execution of the agent behavior, and the application of the agent actions

One of the notable differences between the two models is the travel duration that is more important for IDM than RT-CVC. Figure 4 provides the simulation results related to the vehicle travel time. The associated average values and standard deviation can be found in Table 1. The vehicles simulated with RT-CVC spend around $310s$ to travel the simulated road, and it takes $460s$ for IDM-based vehicles. We could observe the typical accordion effect in traffic for both models. It is illustrated by the punctual increase (resp. decrease) of the travel duration for the RT-CVC (resp. IDM) model.

For both RT-CVC and IDM, the probability of observing an accident, that is, a vehicle colliding with another vehicle, is defined as $\lim P(accident) = 0$. This is due to the values of the constants in the equations, e.g., $\gamma_r = 1$, which are the recommended ones, and the driving behavior model that is implemented in the simulator is designed to be efficient in extreme cases with these specific parameters' values. When the reaction time γ_r is randomly selected in [0.5; 1.5], then $P(accident) = 0.27$ for IDM. RT-CVC still does not generate an accident. The difference between these two accident probabilities could be explained by the fact that RT-CVC is specifically designed for controling an autonomous car under advertorial conditions. It is able to react efficiently to any event that the agent in the neighborhood perceives. In fact, RT-CVC was implemented by Hao [3] on the embedded computer of CIAD's autonomous cars with success[2]. On the other hand, the IDM model is designed to represent human driving behavior.

Experiments are done on a computer with processor Intel Bi-Xeon Platinum 8168 2.7 GHz and 3.7 GHz Turbo, with 512 Gb of DDR4 LRDIMM ECC (2,666 MHz) of memory, running Linux Ubuntu 16.02, SARL 0.10 [8] and Open JDK 1.8. Figure 5 provides the execution time for each simulation step of 0.5 seconds simulated time. The associated average values and standard deviation can be found in Table 1. In general, the performance of the model execution is stable and low ($0.06s$ for simulating the microscopic perception, behaviors, and actions for around 100 agents). Four phases could be observed. First, the number of vehicles that are generated in the simulation increase. In addition, it causes the execution time to increase. When the number of vehicles into the simulation becomes stable, the execution of the simulation decreases due to the usage of hash-tables and tree for storing the perception and action lists in the agent software. The third stage is harder to explain. Indeed, the linear increase in execution time could be explained by the types of internal data structure in the simulator or the management of threads by the SARL framework. The internal data structure is a graph of road segments in which each segment contains an ordered list of vehicles. The most expensive function to apply to this internal data structure is the determination of conflicts among the agents' influences that lead to the detection of collisions between the vehicles. The general complexity of this operation is $O(r.s._m P_m)$; where r is the number of segments that contain a least one vehicle; s is the number of segments to traverse for applying a motion of a vehicle (usually 1 or 2); and m is the number of vehicles associated to road segments. More investigation is needed on that point to determine the scalability of the proposed model when it is facing thousands of vehicles. Finally, the decrease in execution time reflects the fact that vehicles are leaving the simulation environment.

According to the experiments mentioned above, RT-CVC is expected to react more efficiently than IDM. This fact is mostly explained by the type of target, which is modeled by the equations. RT-CVC is a control algorithm for an autonomous vehicle that can react in real time to perceived events. IDM is dedicated to reproduce human driving behavior. Intrasically, RT-CVC depends on the quality of the vehicle perception sensors and the computation of the equation parameters. Specifically, the distance to the front vehicle is a key parameter. Therefore, it is important to have a very precise estimation of this distance to obtain accurate results with RT-CVC. On physical car, this distance might be precise according to the type of sensor, e.g. Laser-Range Finder, etc. In the simulation, the exact distance is computed, and a noise of 1 meter is applied with a Gaussian probability. In all of our experiments, RT-CVC exhibits a reaction time to the obstacles that is better than that of IDM.

5. Related Works

This section provides a brief summary of works from the literature that are related to longitudinal driving models. First, a set of comparison criteria is defined and presented for enabling the comparison of the different works. Then, different works are presented and compared in the fields of longitudinal driving models. Several recent research works were focusing on the study of foggy weather conditions on road traffic. Table 2 summarizes a brief comparison of the models that are mentioned in the following sections. The columns of this table correspond to the following comparison criteria:

Agent-oriented paradigm (AOP) indicates whether the model is based on the agent modeling paradigm that includes the modeling of autonomous, distributed and connected entities as defined by Ferber [1] and Wooldridge [11].

Simulation level specifies the abstraction level of the simulation model. The simulation may be mesoscopic if several elements of the model are not centered on individual properties and behaviors, microscopic if each individual entity is modeled and simulated, and submicroscopic if the components of an individual entity is simulated.

[2] CIAD autonomous cars: https://youtu.be/Hlwbhe7wntg

Environment type indicates the type of model used to represent the environment. This type may be the "graph" to represent a road network data structure based on a graph, that is, a monodimensional data structure. A $1.5D$ graph is a extension of the mono-dimensional graph with the lateral position of the vehicles on the lanes.

Driver behavior heterogeneity specifies whether the model includes different driving behaviors or a single driving behavior (no heterogeneity).

Ready for an autonomous car indicates whether the model can be deployed on the embedded computer of an autonomous car without changing its definition.

Fog model specifies that a fog-weather model could be included or connected to the model. If the foggy weather model is connected, then the overall simulation model becomes a co-simulation framework.

Tan [9] propose a longitudinal driving model to investigate the impact of driver's risk illusion on traffic flow. This model is applied in scenario with foggy weather conditions. Linear stability analysis and numerical simulations of the proposed model are conducted, but they are not based on the agent paradigm. The comparison between the longitudinal driving model of Tan [9] and RT-CVC [3] will be made in a dedicated article.

Hoogendoorn et al. [4] proposes a study on adaptation effects in the case of fog in relation to two longitudinal driving behaviors (Helly and IDM). Authors show from the experiments a significant decrease in speed and a significant increase in distance to the lead vehicle. Furthermore, the results showed that acceleration significantly decreased. The effect of fog on deceleration was not significant. These effects have also been found in our experiments.

Hammit et al. [2] propose a methodology for calibrating the Wiedemann 1999 car-following behavior. This research is based on data from the SHRP2 Naturalistic Driving Study (NDS) to capture realistic driving behavior in a variety of weather conditions. This study has two primary objectives. This research was interesting and was used to find the properties of our agent-based models.

Table 2. Brief comparison of the different approaches mentioned in the related works

Model	AOP	Simulation Level	Environment Type	Driver Beh. Heterogeneity	Autonomous Car	Fog Model
GAMA	Yes	Micro meso	Graph	Yes	No	No
Hammit et al. [2]	No	Micro	Graph	Yes	No	No
RT-CVC	Partial	Micro	Graph	No	Yes	No
Hoogendoorn et al. [4]	Yes	Meso	Graph	Yes	No	No
MATSIM	Yes	Micro Meso	Graph	Yes	No	No
SUMO	Yes	Micro Meso	Graph	Yes	No	No
Tan [9]	No	Micro	n/a	No	No	No
VISSIM	Yes	Micro Meso	Graph	Yes	No	No

Table 2 provides the results of the comparison of the models mentioned above. We have also added the three standard frameworks for simulating traffic with the agent-oriented paradigm: GAMA, MATSIM, SUMO and VISSIM. These frameworks implement a standard driving behavior such as IDM. We consider that simulating connected vehicles and infrastructure, the behavior of the car (physic behavior) and the drivers, and several specific weather conditions are the key features that leads us to propose an agent simulation architecture that is described in the rest of this paper.

6. Conclusion and Perspectives

This research is in the context of safety and fluidity of road traffic when the drivers and cars are facing environmental factors reducing the visibility in the environment. It is assumed that they are the source of accidents and that the introduction of autonomous cars is a possible solution to reduce accidents. In this paper, a longitudinal control algorithm from autonomous car's literature is implemented in an agent-oriented simulator to measure the impact of autonomous vehicles on traffic and car accidents. In fact, RT-CVC is an algorithm that has been successfully implemented in real autonomous cars. It is successfully compared to IDM in a simulation scenario that includes a bad weather condition. RT-CVC provides better outcomes related to safety and fluidity than IDM. However, these positive results are balanced by the fact that RT-CVC is designed to represent an autonomous car and IDM to represent a human being.

In the near future, the RT-CVC model will be improved to decrease its reaction time when an unexpected event occurs. This improvement will enable autonomous cars, first, to avoid collisions with other vehicles when the visibility distance is very small, and second, to still move the car at the highest possible cruise speed under safety conditions. RT-CVC will be compared with more longitudinal driving behaviors (IDM+, Wiedemann, Newell, GIPPS, OVM, VDIFF, etc.), including those specifically designed for autonomous cars.

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