Improved Road Crossing Behavior with Active Perception Approach

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ABSTRACT

Nowadays, micro-simulation is a common approach to study the behaviors of drivers in the road traffic. The main concern of most microscopic simulators is the network efficiency evaluation. The micro-simulation approach relies on major models such as car following, lane changing and road crossing. Each of these models has a strong theoretical base, and corresponds to a specific road section and a specific driver's intention. Moreover, the micro-simulation approach can be used to investigate an accident or near accident situation. Some approaches tackle the individual behavior in these micro-simulations. For these approaches, a more detailed behavioral model, which is referred to the nanoscopic simulation, is required. In this paper, we focus on the road crossing behavior of drivers. Although various researches have been addressing this subject, existing approaches seem inadequate to simulate accurately drivers' behavior in the conflict area (the center of intersection) or in the crossroads exit. We are developing an active perception model following a nanoscopic approach, which will palliate this inadequacy. The aim of this paper is to make a qualitative comparison between our approach and the existing gap acceptance model. Our model allows to simulate the interaction between drivers at the center of intersection. Future work will consist in integrating the pedestrians in the road crossing scenario.

INTRODUCTION

Vehicle movements can be described using appropriate microscopic models; car following models, lane changing models and gap acceptance models are the most used in the simulation tools. The car following and the lane changing models depict longitudinal and lateral movements of individual vehicles respectively, while the gap acceptance is used to depict road crossing. Different types of car following models have been proposed *(1,2,3)*. These models describe the driver's speed control behavior on the road section. To simulate the lane changing and road crossing behaviors, the gap acceptance model is broadly used. The gap acceptance models provide realistic results with some limitations to understand the drivers' behavior in conflict area (or intersection area) at crossroads.

One of the major issues for the cities are traffic jams. The events which occur at an intersection are sometimes at the origin of these jams. Indeed the throughput mainly depends on the way the drivers solve their conflict at intersections. To reject an adequate gap may lead to a delay, and the acceptance of an inadequate gap may lead to a collision. Traffic simulation can be used to evaluate the impact of a new infrastructure designed to improve the situations. This is possible provided that the studied solution deals with local phenomena. But to study intersections and their centre, it is necessary to take into account the driver's behaviors. Nevertheless, in many traffic studies the authors do not really consider this point *(4)*, and when they do, they often introduce normative behaviors in their models *(5)*, *e.g.* they follow the rules from the Highway Code. Many papers deal with intersections. And in most of them, the centre of the intersections, called conflict area, is almost never used. An autonomous simulated vehicle cannot stop in the conflict area, whatever the model to solve the conflicts *(6,7)*: if the driver enters the conflict area, he has to leave the intersection. Thus, he follows the rule, he has normative behavior. Unfortunately, driver’s behaviors are not normative, moreover in some crossroads situations they may create their own informal rules *(8)*, which can differ from the established ones. In crossroads situations, most of the traffic simulation do not deal much with the management of the interactions in the conflict area. And when they do, they use a kind of supervisor at the crossroads to manage the conflict. This supervisor is represented by either virtual road signs in the conflict area in order to reproduce the storage in the centre, or by a virtual (or not) policeman, in order to limit the number of vehicles in the centre at the same time. In both cases, the simulated driver's behaviors are not always representative of the actual situations.

In addition, the micro-simulation approach can be used to investigate an accident or near accident situation *e.g.* incidents between pedestrians and drivers in right-turn situations. For instance, one may study the correlation between accident and critical gap. Some approaches tackle the individual behavior in these micro-simulations *(9)*. For these approaches, a more detailed behavioral model, which is referred to as the nanoscopic simulation, is required.

In this paper, we propose a contribution to an existing model *(10)* which allows taking into consideration the drivers' behaviors. Our contribution consists in the development of an active perception model which corresponds to a decision process. This perception model relies on cognitive science researches and the substantial model of active perception in Artificial Intelligence.

In the following section, we discuss the gap acceptance model and its applications. In the third section, we describe the framework of our model and, in the fourth section, active perception approach. Next, we present our model applied to the traffic context. Then, some preliminary results are shown, based on an actual urban intersection. Lastly, we discuss the limits of the proposed model and we propose some perspectives.

MODELING DRIVERS' BEHAVIOR IN ROAD CROSSING

In the literature of gap acceptance, most of the papers aim estimating the critical gap of drivers *(11,12)*. Mahmassani et al. *(12)* present the impact of waiting times on critical gaps. They show that the critical gap of drivers decreases as their waiting time at the stop line increases.

There are some different research results in the gap acceptance model. In *(13)*, the authors claim that the distance separating a turning driver from an opposing vehicle is the most reliably associated with gap choice in the left turning. Schaap et al. *(14)*, after presenting current researches about the gap acceptance with the inefficiency to simulate accident and near accident situations, suggest an extended gap acceptance model considering 4 successive weighted gaps with different criteria. This approach is implemented at a T-junction. The gap is the combination of two gaps in the main flow from right and from left. This is an attempt to find a better description of the drivers' behavior before the intersection area and to estimate accident rate accurately.

A report of U.S. Department of Transportation Federal Highway Administration *(15)* compares the microscopic simulation tools with respect to the simulation of surrogate safety measures. This report finds out that some modification, upgrade or enhancement are required to support the derivation of surrogate safety measures in all of these micro-simulation tools: both internal enhancements to the source code and external enhancements for additional output file(s), statistics, and possibly new input value(s). Hidas *(16)* stated that AIMSUN is the only one among the main commercial simulators (q-paramics, vissim, aimsun) which takes into account the effect of waiting time during congestion onto the variability of critical gap. According to Jones et al. *(17)*, this allows AIMSUN to provide the most realistic road crossing behaviors. AIMSUN's user manual *(18)* explains the main points of the implemented gap acceptance model. This model is used to model give way behavior. The gap acceptance model becomes invalid in an intersection without any sign, because all people incoming the crossroads consider themselves as prior. This situation creates an unrealistic outcome in the simulation. If there is a stop or a yield sign, the AIMSUN road crossing decision model takes into account the distance of vehicle to the theoretical collision point and calculates the estimated time needed to reach this collision point using speed and acceleration rate. According to the time to collision point of the other vehicles, the driver model decides to go or to stop. If there are several theoretical collision points, the driver does not move until he finds a gap that corresponds all of these potential conflicts. In AIMSUN, the stop line for any give way sign is defined at the end of road section. The gap acceptance is applied when the driver is approaching this line. It means that each stop line is equivalent to a decision procedure. In a turning move, we can define several stop lines in order to allow the driver to decide partially and sequentially. Hence, the agent does not have to apply his decision procedure continuously. We can consider each stop line in the conflict area as a waiting (storage) point where the agents stop and wait for the next acceptable gap.

AIMSUN has a particular parameter: maximum give way time. When the driver cannot find a gap, he gets impatient. In this case, the driver waits for this maximum give way time and, then starts to modify his critical gap linearly reducing the safety margin to 0. This safety margin equals twice the reaction time (*i.e.* another parameter of the simulation). This improvement seems adequate but not enough. It means that the priority reversal situations (*e.g.* forcing gap, politely allowing others) have been reduced to the variance of the safety margin.

In a nutshell, AIMSUN road crossing model based on the gap acceptance theory, which has the most realistic outputs according to some authors, does not model driver's behavior sufficiently. The model does not allow the storage of the vehicle in the intersection area without a stop line specified by the designer. The driver's model cannot question his decision during the trip in the crossroads.

Moreover, Brilon and Wu *(19)* criticize the gap acceptance model on four points:

- The determination of the critical gap is a complicated process based on some arbitrary definitions of details.
- The gap estimation loses its theoretical base with pragmatical simplifications. The models only provide approximate results.
- The gap acceptance is inadequate to simulate the situations including non normative behavior *e.g.* forcing gap, politely allowing others (priority reversal).
- The gap acceptance theory is not applicable to intersections containing pedestrians or cyclists because of the complexity and variability of the rules and behaviors.

Spek et al. *(20)* suggest that the gap acceptance model should take into account the limitations of human perception. The speed of an approaching vehicle influences the perception of its estimated speed and its estimated distance. Low speed vehicles create a slight change on the perceiving driver and hinder speed and distance estimation.

Furthermore, Wong and Huang *(21)* clearly specify the requirement of the modeling drivers' visual attention to understand the accident and near accident scenarios. In their work, Young et al. *(22)* investigate the efficiency of Incident Reduction System in Sweden, and point out the need for driver's model with greater detail.

Thus, our objective is to make a more realistic perception model to enhance the level of the realistic behavior in the conflict area of crossroads. The decision and perception will be done continuously for a better adaptation to the situational changes. In addition, with a more detailed perception module, we will present a better understanding of the drivers' behavior with a high level of detail. This approach will allow to study the causes of near accident situations, in particular for example the incidents between pedestrians and drivers in the right-turn situations.

MODEL FRAMEWORK

The nanoscopic traffic simulation aims to combine the technical knowledge of the traffic and the knowledge of human perception and cognition into one entity. This approach is based on the enhancement of the microscopic models with behavioral rules. The nanoscopic model allows studying and better understanding traffic safety issues. The nanoscopic simulation approach has been discovered in some research projects: ARCHISIM *(23)*, HUTSIM *(24)*.

The microscopic and nanoscopic traffic simulations present a distributed and complex context that is well-adapted for agent-based modeling which is a subdomain of Artificial Intelligence. “An agent is a computer system situated in some environment, and that is capable of *autonomous action* in this environment in order to meet its design objectives” *(25)*. In agent-based traffic simulation, the driver is an autonomous social agent, sharing a common environment with other similar agents. The interactions among the agents and the relation between the agents and the environment are the key concepts.

Improving the microscopic simulation with agent concept has been applied many times *(26,27,28,29)*. A global model of agent contains 3 modules: Perception, Decision and Action. In agent based traffic modeling, the decision module includes a different behavioral submodule for each task (*e.g.* car following, road crossing, over taking etc.). The agent percepts (*i.e.* the perceived stimuli) are processed by each of these submodules . The agent selects the most conservative rule (output) and applies it *(28)*. We can find a detailed explanation about the decision module in *(26,27)*. In order to create a more realistic output, the requirement of the detailed perception module has been specified in *(26,27)*.

ACTIVE PERCEPTION

Perception is not a direct understanding of the current environmental state. It includes a process to interpret raw data. An agent perceives its environment through sensors. In a simulation context, the sensors are at the interface between the environment entities and the agent. First, data about the environment are provided by the surrounding entities and the other agents. Then the agent interprets these data to build a representation of the environment.

In the basic perception-decision-action cycle of the agent, the perception is generally taken in its passive sense in traffic simulations, *i.e.* as the reception of external stimuli by the agent's sensors. In passive perception, the agent acquires as much data as possible during the sensing phase. This approach does not require the agents to deliberate explicitly about their sensing needs.

Conversely, active perception is supervised by the current intention or action *(30)*. Active perception enables the agent to perceive what is necessary for its current goals. This minimizes the useless information, and thus the use of unnecessary resource, and maximizes useful information acquisition.

Before making some propositions to improve the microscopic traffic simulation perception model with psychological notions, we must define these notions. In cognitive science, perception and attention are important research topics *(31,32)*. Two main cognitive processes characterize perception: top-down and bottom-up. Perception is a balance between these two information processes.

- The top-down information process is goal-driven: Humans (or agents) pay attention to some environmental elements in order to achieve their goal (or intention). Thus, the current goal determines the relevance of the collected information. Active perception is an appropriate framework to implement this top-down information process.
- The bottom-up information process is data-driven: Salient data attracts the agent's attention. Non-salient items are not (or weakly) perceived; the implementation of this principle needs some ideas about the object's salience, in a way which only depends on environmental properties.

Furthermore, humans have *limited perception capacity*. They can process simultaneously a limited amount of data *(33)*. If the current goal needs an amount of data above the agent's capacity, the most relevant percepts must be selected. We have integrated the active perception approach to the driver agent model, on the basis of current cognitive psychology knowledge *(34,35)*. In the remainder of this section, we present how these concepts can be used in relation with the simulation of the agent's resource-bounded active perception.

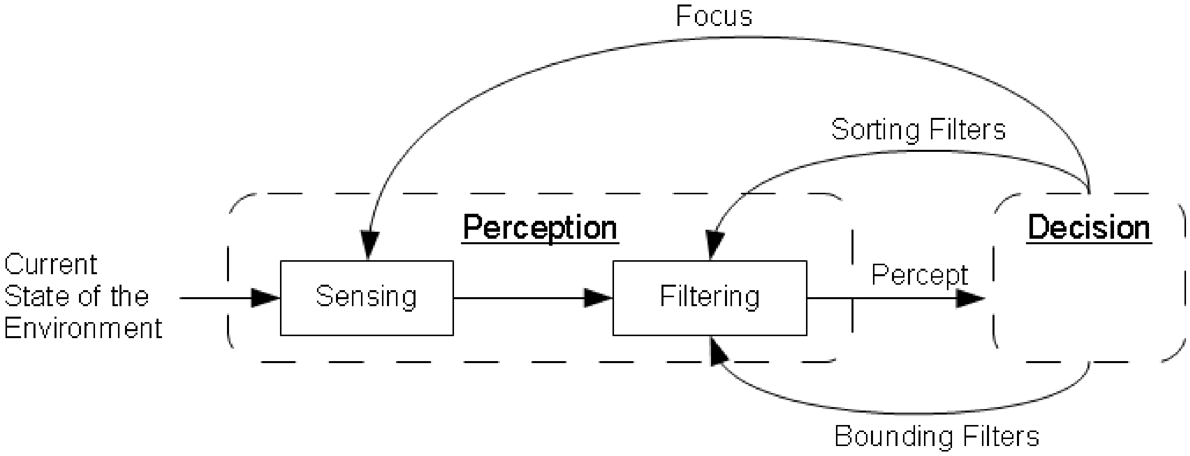


FIGURE 1 The model of bounded active perception.

In the following, we focus on the top-down information process and limited perception. We have extended an existing model of active perception in the literature of Multi-Agent System *(36)*. We use 3 main concepts in order to implement these psychological concepts :

- **Focus:** A focus is a domain of interest in the spatial sense. For example, some parts of the spatial domain are scanned in order to achieve the current intention. Therefore the focus is directed by the decision module. For instance when the agent's intention is crossing the intersection without any conflict, the agent's focus covers the conflict area and the incoming ways towards the crossroads.
- **Sorting Percepts with respect to Relevance:** The relevance of a percept depends on the agent's current intention. To achieve its goals, a rational agent makes a plan, composed of ordered tasks. The effective realization of a task depends on the state of specific objects in the environment. Because the situation changes in dynamic environments, these states must be continuously updated. The agent must emphasize the current task and the inputs needed for this task. If a percept is related to the current intention, its relevance is higher than the relevance of the other percepts. This kind of filter is implemented in order to sort the percepts (see “Sorting Filters” in Fig. 1) according to the current task. In road crossing mode, the agent sorts the percepts according to the adjacency to conflict point, in other words, to the probability of having an accident.
- **Resource-Bounded Perception:** To achieve a realistic simulation of human perception, the limits due to the workload must be taken into account. (see “Bounding Filters” in Fig. 1). The complexity of the current tasks, *i.e.* the cognitive workload, can modify this limit. This is discussed further in the paper.

DRIVER AGENT MODEL FOR A MULTI-AGENT TRAFFIC SIMULATION

We have demonstrated the effect of limited resource with our microscopic traffic simulation in a previous work *(37)*. In this work, the behavior of driver agent follows one of two behavioral rules: one for straight lanes, one for road crossing. On straight sections, the agent’s speed tends to reach the desired speed, unless other drivers prevent to do so. The interaction between two consecutive agents is described in the road traffic literature as a “car following task”. We have implemented this classical task as a speed regulation behavior according to what is described in *(2)*.

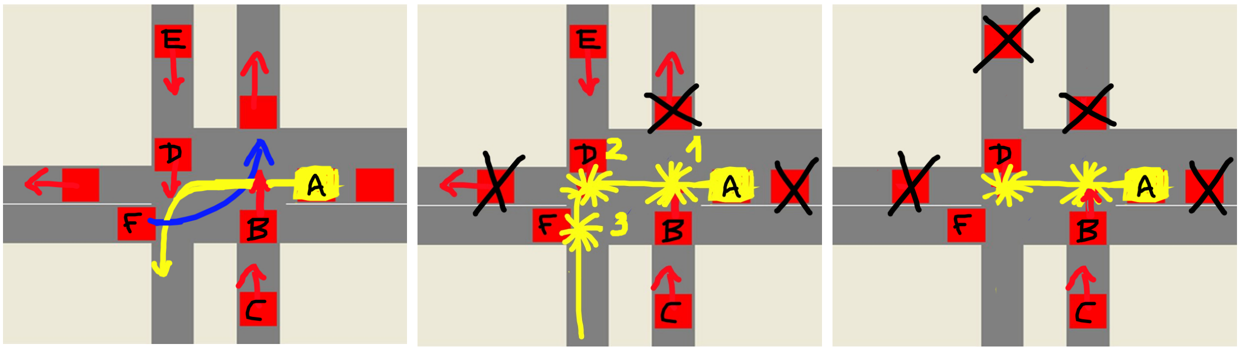
One tough issue in agent-based traffic models is the “road crossing”, which may explain why most agent-based traffic simulations shun urban situations. The key problem is the complexity of the agents' interactions, and the number of agents simultaneously involved in the road crossing.

Many traffic models concerned with intersections are based on the gap acceptance theory. With these models it is very difficult to simulate the drivers behaviors which are observed in actual situations, in the conflict area. An insufficient perception and a normative behavior are often the consequence of these difficulties. An alternative approach, recently proposed by Mandiau et al. *(10)*, takes into account the drivers' behavior in the intersection context. This approach is derived from the game theory, where a driver selects a number of players when approaching a road crossing, and decides at each time step to GO or to STOP depending on his evaluation of the relative priorities with the other players selected in the game. The GO/STOP decision is then translated into an acceleration for the driver's vehicle, and the process is iterated at each time step. Based on this approach, we have implemented an active bounded perception for the selection of the players, which now depends on the traffic context and more specifically on how this context is perceived by the agent. With active perception, we have tried to make more detailed perception of a driver-agent, in order to get more realistic emerging behaviors in crossroads.

In the road crossing mode, the driver senses the entities in the perception domain constrained by foci. The driver's top-down focus covers the incoming ways towards the road crossing; this limits the perception. Due to its location in the environment, each agent has a different representation of his vicinity.

The first step of the top-down filtering is the relevance ranking. The driver ranks the percepts with respect to their relevance for the current task. We have chosen the time to conflict as a ranking criterion. After this sorting process, the agent takes the σ most relevant percepts and sends them to the Decision module.

Example of Bounded Active Perception



(a) *(b)* *(c)*

FIGURE 2 The simulated crossroads with the drivers' trajectory (a), the identified conflict points before filtering (b) and the conflict points after the filtering with respect to threshold $\sigma = 4$ (c).

Figure 2(a) illustrates the crossroads which has been modeled (the squares represent the vehicles and the arrows represent their directions). This model is derived from an intersection in Reggio Calabria, Italy. The roads North, West and South have two lanes; one for oncoming, other for outgoing vehicles. The East road, however, has three lanes; two for oncoming, one for outgoing vehicles. We have chosen this crossroads to apply our model for its vehicle storage capacity.

In the traffic simulation context, the relevance of the percepts is represented by a ranking of the other drivers according to their distance to the collision point. To be more specific about the top-down procedure, the scenario is explained step by step from the point of view of agent A which has a capacity of perceiving maximum σ (=4) percepts.

At the beginning, the agent perceives the vehicles in his foci. The foci are the interest zones where the subject agent probably finds other agents with which it shares a collision point. Therefore the focus of A are over the conflict area and the incoming lanes to intersection.

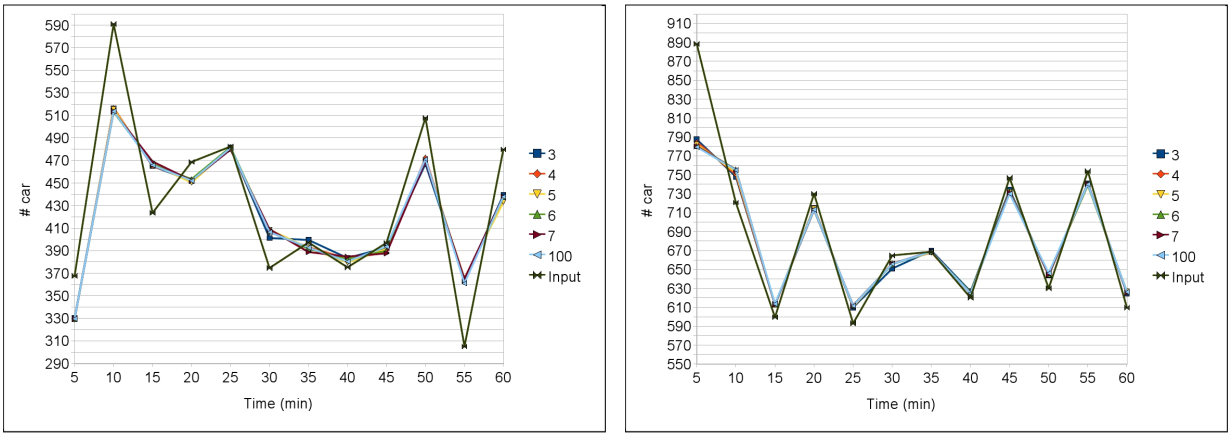
Namely, agent A perceives agents B,C,D,E,F in parallel and detects the potential collision points with them (Figure 2(b)). The sorted list of the collision points (CP) of agent A are:

- CP 1: with B,C and F
- CP 2: with D and E
- CP 3: with D,E and F

After this detection stage of CP, the top-down process sorts the percepts according to distance to the CP. The agent takes into consideration the first σ (=4) percepts and discards the remainder. The agent starts by CP 1 which is the closest collision point hence it has 3 percepts. The agent has only one available resource to handle the rest (CP 2 and CP 3). Next, thanks to sorting, A finds the closest agent with which it shares CP 2 : D. Finally, because of the lack of available resource, the agent cannot handle CP 3. At the end of this detection and selection phase, agent A has the representation as Figure 2(c) :

- CP1 : with B,C and F
- CP2 : with D

RESULTS



(a) *(b)*

FIGURE 3 The flow rate of East(a) and North(b) entrance of the intersection for the different values of σ (from 3 to 100) with respect to time.

In this paper, we have explored the impacts of the perception limit parameter σ comparing the mean of the traffic performance (flow), the number of accidents, the time of execution and the number of deadlock in the intersection on 100 simulations. We have compared the flow rate with the real data observed at a crossroads in Italy (Reggio Calabria). We are aware that this kind of comparison is not a validation. However, it allows us to examine the consistency of our algorithm. Our hypothesis is that if the input flows (evaluated at the entrance of intersection) are close to the real life (observed) data, our model improves the level of details without degrading the traffic performance.

The deviation has been measured using RMSE (Root Mean Square Error) indicator. The results are presented in Table 1.

$$RMSE=\sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(x_i^{simu}-x_i^{obs}\right)^2}$$

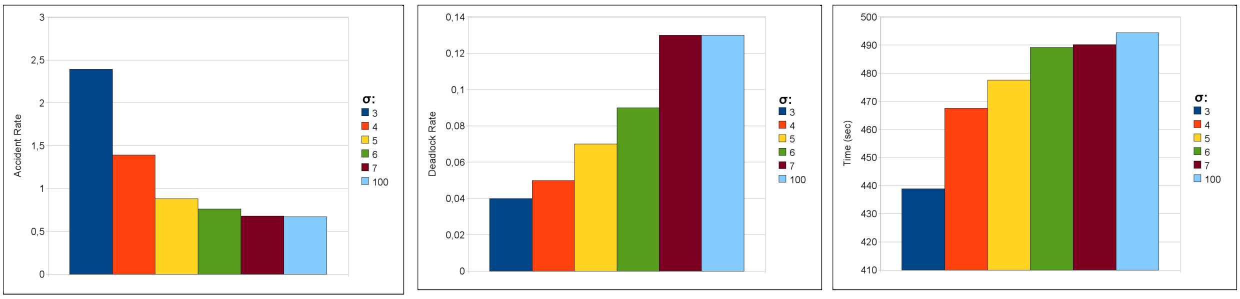
Because of the low flow rate on the West branch, the outputs of this branch of the crossroads are not significant. We can note that the active perception algorithm does not degrade the traffic performance of the simulation in term of the flow rate (Figure 3) compared to results in *(10,38)*, because the average deviation of (RMSE%) is lower than 10 %.

We had expected that the deviation between the observed flow rate on the entrance of intersection and the simulated flow rate on the entrance of the intersection would decrease with σ. We realized that the deviation remains limited in any case. It is in favor of the proposed model. The agent handles with a low quantity of information without any performance lost.

TABLE 1 Comparison between simulated flow and observed flow on the roads South, North and East with respect to σ (RMSE % = RMSE * 100 / Mean Flow Rate)

σ :	3		4		5		6		7		100	
RMSE	RMSE	RMSE %	RMSE	RMSE %	RMSE	RMSE %	RMSE	RMSE %	RMSE	RMSE %	RMSE	RMSE %
South	64.1	7.86	64.46	7.9	65.74	8.06	64.82	7.94	64.7	7.93	66.31	8.13
North	37.03	8.65	37.12	8.67	38.43	8.98	37.94	8.86	38.68	9.04	37.23	8.7
East	31.02	4.53	31.94	4.66	32.9	4.8	33.79	4.93	33.77	4.93	34.06	4.97

Moreover, with the implementation of the bounded active perception algorithm can emerge a phenomenon where one branch prevents the fluidity of the other branches of the intersection. Through the obtained results, we have confirmed that this model does not impact negatively the performance of the simulation.



(a) *(b)* *(c)*

FIGURE 4 Accident rate (a), deadlock rate (b) and run time (c) with respect to perception limite σ.

Accident

An accident is detected when the distance between the vehicles is lower than the size of the vehicle. As we expected and as we can see on the chart, the accident rate is highly correlated with σ (Figure 4(a)). The more the agent perceives, the more complete representation of environment it has and the fewer accident it has.

Besides, the difference is weak among the results obtained for the values σ between 5 and 100, whereas it increases distinctly for the values 3 and 4. In case of an accident, the drivers continue to drive with their current speed ignoring the other vehicle with which they participate the same accident and the simulation does not halt. This allows us to compare the simulation performance between each other.

Deadlock

The agents can not occupy the same space except in case of accident as aforementioned. Hence, an agent can be locked (it can not move forward more) at the intersection if it perceives another agent over his trajectory. The deadlock is defined in our simulation with the existence of mutually locked vehicles. If the vehicle is included in a string of lock (*e.g.* A locks B, B locks C, C locks D and D locks A), the deadlock is then detected. In this case, the situation is unlocked allowing all vehicles in the deadlock to drive ignoring the existence of other vehicles in the deadlock. Thus, the simulation does not halt, this allows us to compare the simulation performance between each other.

The number of deadlocks per simulation increases with the number of percepts σ (Figure 4(b)). This concordance between the number of percepts and the number of deadlocks is probably depending on the time spent in the conflict area. We can explain that if the agents deliberate with several percepts, they become more careful and spend more time in the conflict area. This cautiousness decreases the accident rate but increases the deadlock rate.

Run time

The run time increases with increasing σ : if the agent takes into account fewer percepts, the deliberation process takes less time. This is particularly visible on the variance of the run time between the values 3 and 4 (Figure 4(c)).

CONCLUSION AND DISCUSSION

In order to create more credible simulated behaviors with a high level of detail, we have improved the existing model of micro-simulation with a bounded active perception approach. We have implemented a top-down process which allows us to study the impacts of a variable threshold of perception on several indicators (flow rate, accidents rate, deadlock rate, run time). We note that there is no significant behavioral difference among the tests with different scenarios down to a specific threshold of perception (around 5). Nevertheless, the less the agent perceives, the less calculus it has to do. These results show the redundancy of simulating the perception of the entire entity on the scene and the utility of selecting some relevant percepts using bounded active perception. Furthermore, this selection yields a benefit on the run time indicator. The deadlock is a disadvantage of our approach until we are able to model threading one's way through the blockage behavior.

We have simulated and investigated the impact of a constant threshold. However, in order to model completely and augment the credibility of the simulated behavior, we must implement a variable threshold according to the complexity of the current decision and action. For instance, in an intersection, the left turn decision and action is more complex and requires more available resources than the right turn. Thus, a right turn creates less workload, and more resources remain available for the perception.

This notion can be studied in future works.

Some salient entity can attract the attention of the driver while it is not relevant. The salience depends on the visual characteristics of an object. The salient elements are perceived in bottom-up manner. The salience is the essential notion to build bottom-up perception. In our future works, we will work in order to integrate this bottom-up perception into our model.

This bottom-up process will be modeled as a distractor of the top-down process. It will be useful for simulating the non-detection of the pedestrian at the end of trajectory in conflict area (accident or near accident situation) which is one our objectives in the medium term. This will be an attempt to fulfill the requirement of the "less-than-perfect" perception model as it is specified in *(9)*.

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