



HAL
open science

Affordance-based Agent model for road traffic simulation

Feirouz Ksontini, René Mandiau, Zahia Guessoum, Stéphane Espié

► **To cite this version:**

Feirouz Ksontini, René Mandiau, Zahia Guessoum, Stéphane Espié. Affordance-based Agent model for road traffic simulation. *Autonomous Agents and Multi-Agent Systems*, 2015, 29 (5), pp.821-849. 10.1007/s10458-014-9269-x . hal-01168839

HAL Id: hal-01168839

<https://hal.science/hal-01168839v1>

Submitted on 21 Oct 2024

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

Affordance-based agent model for road traffic simulation

Feirouz Ksontini · René Mandiau · Zahia Guessoum · Stéphane Espié

Abstract Existing traffic simulations often consider normative driver behavior. Drivers do not always use physically delineated lanes: sometimes drivers use the entire road surface. Thus, current traffic simulations do not reproduce all observed urban and suburban traffic phenomena. To improve the validity of urban and suburban traffic simulations, we propose to consider driving context and driver behavior in terms of occupied space. We endow driver agents with an ego-centered representation of the environment based on the concept of affordances and virtual lanes. Affordances thus identify the possible space occupation actions afforded by the environment and by other agents. The proposed model was implemented using our *ArchiSim* tool. We show that this model is more efficient and realistic than existing models. The experiments also reproduce real traffic situations and compare simulated data to real data.

Keywords Multi-agent simulation · Affordances · Traffic simulation · Virtual lanes · Driver behavior · Ego-centered representation · Space occupation

1 Introduction

Traffic modeling and simulation have generated a lot of interest in terms of improving the planning, design and operations of transportation systems. In urban areas with high traffic density, roads are often divided into lanes and drivers must respect road space divisions. However, studies have shown that this static organization is not always the most efficient. Subsequently, many European governments are studying dynamic road space reorganization and its potential positive influence on traffic.

Multi-agent systems (MAS) provide a suitable solution for traffic simulation problems, traffic management and traffic signal control [2,3,6,37]. Several multi-agent solutions have been proposed to study road space occupation and related emergent phenomena [4,9,17,21]. In these models, the lanes used by drivers are defined by road markings. These models do not consider maneuvers between vehicles or dynamic lane allocation. Bonte et al. [4] and Lee et al. [21] proposed solutions for two-wheeled vehicles. However, the proposed solutions cannot be generalized to other vehicles. They are developed for one particular type of driver and cannot be applied to other situations such as traffic jams that occur following a particular event or that result from toll plazas.

The purpose of this paper is to model road space occupation behavior, particularly in urban areas with high traffic density or a high rate of specific event occurrence. Our model focuses on filtering maneuvers between passenger or two-wheeled vehicles, road space re-adaptation, specific events (stranded or improperly parked vehicles) and dynamic lane allocation. The presence of road markings does not always prevent drivers from re-adapting road space to meet their own goals and to conform to their context. We introduce a novel approach to endowing agents with an ego-centered representation of the environment that permits the agents to make a decision regarding space occupation. Our approach is based on the theory of Affordances [15]—the ways in which an agent can interact with its environment. Note that the concept of affordances was already used in MAS [27,29,35]. However, the affordances are often considered as static properties perceived by agents in their environment.

This paper is structured as follows. After the introductory section, the second section presents general information about the affordances concept and introduces the problems pertaining to occupying space in road traffic simulation contexts. The third and fourth sections describe our affordance-based model and the notion of virtual lanes for road space occupation. This model is part of *ArchiSim*, the behavioral traffic simulation model developed by IFSTTAR¹ [12]. These sections also provide the results of different experiments. The last section concludes the paper and provides suggestions for future research.

2 Affordances and space occupation

We present a novel approach to dealing with space occupation in a multi-agent traffic simulation. There are two key elements in our approach. First, we use the concept of affordances to identify potential space occupation actions afforded by the environment. Second, we use an ego-centered representation of the situation surrounding an agent.

¹ The French National Institute for Transport and Safety Research (ex-INRETS).

2.1 Affordances

An affordance is a quality of an object or an environment that allows a situational agent to perform an action. The theory of Affordances is derived from psychological models and has been applied to design multi-agent models.

2.1.1 Psychological models

The theory of Affordances was introduced by Gibson [15]. It is based on ecological psychology, which argues that perception is a direct process. The theory of Affordances states that affordances are action possibilities or opportunities that humans (and animals) perceive in the environment. This description strongly suggests a set of specific design requirements to manage the interaction between an agent and its environment. An agent needs to perceive possible actions or action opportunities directly in the environment.

Many researchers state that Gibson's theory is insufficient to explain perception because it neglects the processes of cognition [28,32]. These authors consider this theory to result from the mental interpretation of things based on past knowledge and experience, which affect the perception of these things. Raubal [32] used an expanded theory of Affordances within a functional model for affordance-based agents. This theory supplements Gibson's theory of perception with cognitive elements, situational aspects and social constraints. Cornwell et al. [8] have also shown that integrating affordances into agent architectures is an elegant solution to the problem of providing both rapid scenario development and simulations of individual differences in perception, culture and emotion.

2.1.2 Affordances in multi-agent contexts

The concept of affordances has been used, especially in multi-agent simulations, robotics, path-finding problems and military operations simulations [27,29,35,43]. For example, Kapadia et al. [18] proposed a navigation and path planning framework for pedestrian simulation. They use affordances to represent the different potential interactions between an agent and its environment. Each agent perceives the environment through a set of vectors and scalar fields that are represented in its local space. Therefore, an agent represents the different fields in an ego-centered location-space. The authors suggest affordance fields as a powerful way to combine sensory information and define variable resolution, where information accuracy decreases as distance from the origin increases. This prevents wasteful computations and storage costs generated by longer distances and plans that are re-computed sooner than they are used. The authors define a fitness function to evaluate affordances and select the most suitable one. The final decision is the affordance associated with optimal fitness. This scalable technique provides robust steering. However, the agent's perception field is limited. In other words, the agent does not consider all perception fields that may affect its decision, which cannot be anticipated in any event.

If we refer to Gibson's theory, affordances must be set in the environment and not in the procedural memory of the agents. Nevertheless, an agent must intuit affordances for decision-making. In this sense, Papisimeon et al. [29] propose two different approaches for modeling affordances. The first approach is entirely based on the theory of Affordances presented by Gibson and stores all affordances in an environment, while the second uses a more flexible definition and considers the affordances to be in the agent's memory.

The first approach, *i.e.*, affordances described in the environment, has several advantages. The most significant advantage is that the approach corresponds more closely to the represen-

tation of the theory of Affordances as described in ecological psychology. Another advantage to this approach is that it places more importance on the environment and enables some of the intelligence in the environment to be transferred. However, in the context of this proposal, the environment model requires all the necessary relationships to be taken into consideration to calculate affordances (including information about individual agents) as well as to determine the affordances for each agent. Conversely, the agents must be able to perceive the affordances, to evaluate them and to select those that are suitable. Furthermore, the simulation architecture must be able to provide appropriate interface mechanisms between the agent and the environment so that the agent can collect relevant affordances from the environment. The main disadvantage of this approach is that the impact of the design results in a large number of subsystems in the simulation architecture. Therefore, introducing affordances means reconsidering not only agent and environmental design but also the interaction between the two. This can be difficult if affordances are introduced into an existing simulation and require multiple environmental and agent changes.

The advantage of the second approach is that it is easier to introduce the concept of affordances into an existing multi-agent simulation since affordances can be introduced into the reasoning process of an agent without affecting the rest of the architecture. In the approach of Papasimeon et al. [29], the concept of affordances may also be integrated into a BDI (beliefs, desires, intentions) architecture [30,31]. An affordance-based agent reasoning model means that affordances are treated as just another type of mental attitude: affordances may be interpreted as a type of belief regarding action possibilities. The interaction models in multi-agent simulations are thus more plausible and realistic in their representation of how agents interact with their environment. Another advantage of the BDI model is the ability to better understand agent reasoning. The computational design of this “augmented” BDI architecture for real-life situations remains an unresolved issue. Moreover, in real world systems such as road traffic simulations, agents represent human drivers: they are situated, *i.e.*, they are able to employ a reasoning mechanism and are located in a specific environment, and are thus considered “embodied reasoners”. However, modeling affordances as mental attitudes does not approach the theory of affordances as described in ecological psychology. This theory of affordances considers that the affordances exist as a result of the interactions between an agent and its environment, and not as a construct of an agent or of the environment. Each agent perceives affordances in the environment: affordances as mental attitudes bypass this concept of “direct perception” (*i.e.*, meaningful information is available in the environment for agents to perceive without any filtered reasoning about what they can perceive).

The theory of affordances has been applied in the context of pedestrian movement [18], but to our knowledge, it has not been applied to road traffic simulations. The concept is suitable for road space occupation. Affordances allow to identify potential space occupation actions generated by the interaction of the perceived entities and the environment.

Therefore, we propose an affordance-based driver agent model for space occupation. Each agent perceives its environment. It builds a set of intervals representing the free space around it and depicts these different intervals in an ego-centered representation. It then uses Allen’s algebra to analyze these intervals and deduce affordances. Subsequently, the latter define the space occupation opportunities for an agent. The agent uses a fitness function to evaluate its affordances and select the most suitable one.

2.2 Road space occupation

We are interested in reproducing road space occupation practices, particularly in urban areas with high traffic density or frequent specific events (*e.g.*, emergency vehicles, stranded vehi-

cles). Drivers do not always use the road configuration provided by the existing, marked physical lanes. Rather, drivers may occupy free space according to their goals and their contexts. For example, two-wheeled vehicles tend to ignore road markings. To improve heterogeneous traffic simulations, we need to understand the behavior of different types of drivers. Some empirical studies [25,26] aim to interpret two-wheeled vehicle behavior and the properties of mixed traffic flows.

This section gives an overview of several multi-agent traffic simulation models, and then focuses on traffic simulation models that consider virtual lanes.

2.2.1 Traffic simulation models

Most existing traffic simulation models highlight the interaction between drivers and their environment. Two theories have been proposed to deal with the representation of the environment and provide a generic solution that considers driver practices in terms of space occupation: allo-centered and ego-centered representations [7,38]. In ego-centered representations, spatial relations are generally directly related to the agent, who builds a representation using a reference system with terms such as left, right, forward or backward. When the context changes, all spatial relations should be updated. An allo-centered representation locates points within the agents' environment and generates the representation without considering the agents' positions, *i.e.*, a framework external to the agents generates the representation independently of their positions. Allo-centered representations are more stable, but are also more difficult to acquire. In addition, there are more spatial relationships since all relationships between different objects in the environment are considered. Moreover, the number of agents to be simulated can be highest in real applications. In these representations, the computational costs for the model increase to adapt the common representation of this environment to a particular context for each agent.

Human drivers (considered situated agents) “discover” situations (or update their previous knowledge) when moving. They need to know what happens around them to make decisions (go straight, move to the left or right lane). From this point of view, ego-centered representations are more intuitive in traffic simulation environments, for which there is a need to have a contextual and dynamic representation of what is happening around the agent. Furthermore, the ego-centered representation is suitable for dynamic contexts because the number of relationships to be updated is lower than for an allo-centered representation. However, in this case, redundancy in contextual information (difficulties in detecting inconsistencies in different pieces of information) may also create implementation problems.

El Hadouaj et al. [11] use an ego-centered environmental representation that is composed of physical lanes created by road markings. This representation cannot identify free road space or reproduce the road space occupation observed in the simulation like for two-wheeled vehicles. The idea is to create an environmental representation that considers the physical constraints of the environment, the context and the driver goals.

Several multi-agent traffic simulation models were introduced to study driving behavior. In these models, drivers consider road space in terms of physical lanes and are always positioned in the middle of their lane [17]. The models do not consider all observed road space occupation phenomena.

2.2.2 Virtual lanes

Existing simulation models do not consider that real driver behavior does not often respect traffic rules [4,9,17,21]. Subsequently, the related simulations do not always correspond to

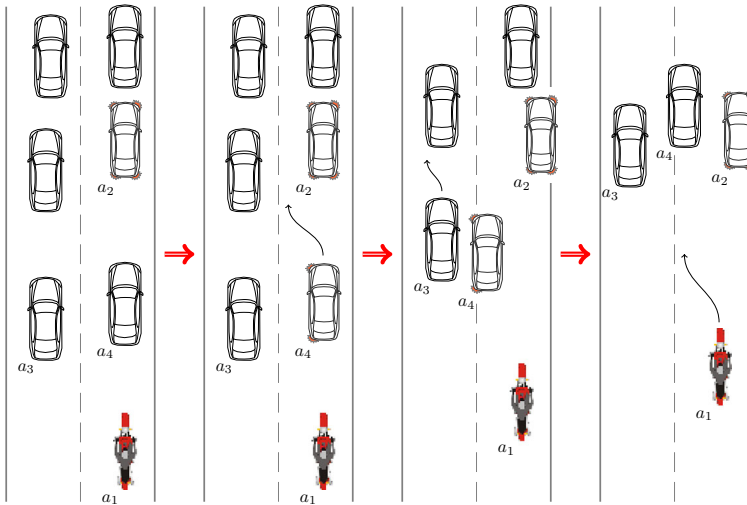


Fig. 1 Non-normative behaviors in a situation representing a badly-parked vehicle

the real observed phenomena. For instance, actual observed practices show that drivers often do not comply with regulations in order to be more efficient, such as in terms of travel time (sometimes at a group level but more often for personal gain). Drivers tend to adapt to given road space by building their own environmental representation, which may not comply with norms (defined here as compliance with traffic rules). By definition, “normative behavior” (or “norm-compliant”) means that the driver respects the traffic rules (defined by norms). If the driver does not respect these rules, the driver’s behavior is considered “non-normative behavior”.

Figure 1 illustrates a traffic situation where vehicle a_2 turns on its hazard lights. Vehicle a_2 decides to stop on the roadside. Vehicle a_4 is hindered by a_2 , which decides to pull over to the roadside, where it will be badly parked. Vehicle a_4 perceives vehicle a_3 because it considers it a danger: The driver will thus be constrained by vehicle a_3 , which is approaching because it is driving more slowly. Two situations are thus possible. In the first case, the driver displays “normative behavior” and chooses to move to another lane (using the physically delineated lane) if this is possible. In the second case (described on this figure), driver a_4 observes the situation and perceives a free space on the road between vehicles a_2 and a_3 . The driver chooses this emergent space. Vehicle a_3 perceives the lane change for a_4 and if it is cooperative, a_3 will shift to the left. The behavior of both drivers in this case is non-normative. Finally, a_1 also decides to shift to avoid vehicle a_2 .

To reproduce this kind of non-normative behavior, Fellendorf and Vortisch [13] use VIS-SIM, a commercial simulation tool that employs mathematical models to describe ongoing lateral movements in heterogeneous traffic situations. Drivers choose the lateral position where they have the longest longitudinal time-to-collision. To find this position, a driver divides the available road width into virtual lanes. These virtual lanes are created on the right and left sides of the vehicles on the road in front of the driver with some lateral space for a margin of safety. In our opinion, this configuration is insufficient because target lateral position selection is only based on an instantaneous evaluation. Lee et al. [21] propose a simulation model for two-wheeled vehicles. This proposed model is based on the Gipps [16] car-following model to describe the movement of both passenger cars and two-wheeled vehi-

cles with some modifications to take the kinematic parameters of the two wheeled-vehicles into consideration and provide the most suitable lateral movement. These interaction rules are integrated into an agent-based simulation model. The latter considers a limited number of parameters (of the vehicle in front or to the side) and does not enable drivers to significantly anticipate the traffic surrounding them.

Bonte et al. [5] proposed a multi-agent solution for two-wheeled vehicles to reproduce behaviors specific to them, such as driving between cars. In this context, the authors introduced the concept of virtual lanes to represent the free space on the road. The lanes are called “virtual” because they are not outlined on the road with markings like physical lanes. Virtual lanes are specific to an individual in a situation and they emerge according to the context. The authors thus propose an algorithm for breaking down road space into free and occupied “bands”. This results in two types of virtual lanes: forbidden virtual lanes and authorized virtual lanes. A forbidden lane is a virtual lane avoided by two-wheeled vehicle drivers. However, an authorized lane is a virtual lane that two-wheeled vehicle drivers can take. These lanes rely on the free space on the road between vehicles and the shoulder. In the proposed model, vehicle size only is considered in virtual lane identification. The evaluation of the lane does not consider the driver’s distance from the norm. This type of parameter can affect our decision-making, particularly in the case of non-normative practices. To build an agent’s environmental representation, the authors systematically and geometrically break down the entire road space into free and occupied lanes according to vehicle size and road position. This breakdown leads to a variable, and sometimes very high, number of virtual lanes, especially in situations with multi-lane roads. Moreover, the authors use the control zones initially defined by El Hadouaj et al. [11].

2.3 Discussion

Generally, the majority of existing simulation tools assume that the positioning of vehicles on a road results from the existence of physical lanes. This modeling does not simulate observed space occupation phenomena. Very few studies on multi-agent traffic simulations employ these practices. They essentially model the behavior of two-wheeled vehicles for which these practices are common. In this context, we basically presented the work of Bonte et al. [4] and Lee et al. [21]. Both solutions were developed specifically for two-wheeled vehicles and cannot be applied to other vehicle types or other situations, such as event-related traffic jams or toll plazas. To address these limitations, we are interested in studying how drivers represent the environment around them.

We propose to endow agents with an ego-centered environmental representation in which an agent identifies its own affordances and may determine the possible actions offered by the environment in terms of space occupation. Our ego-centered representation of the environment is composed of the identified affordances. For example, if a driver does not have the possibility to continue forward in its lane (due to a lane closure), the driver will not necessarily add this lane to its mental representation of the environment (*i.e.*, the affordance identified for this lane will not be defined in its representation) because this lane will be prohibited. We can also consider the filtering behavior of two-wheeled vehicles: if there is enough space between two lanes of vehicles, the emergent lane (*i.e.*, a new affordance has been identified) should be added to the ego-centered representation that the agent builds of its environment because it affords an action opportunity that is different from that provided by the marked physical lanes.

The virtual lanes correspond to the affordances available to the agent in terms of opportunities to occupy pavement space. Identified affordances will be used to build a dynamic

ego-centered and contextual representation of the environment based on the possibilities offered by the interaction between road users and their environment. Agents do not all interpret the opportunities offered by the environment in the same way. Therefore, representations of a given traffic situation may vary with the point of view of the agents. For example, a passenger car driver will not interpret the gaps that emerge on the road the same way a motorcyclist will. This difference is mainly due to the physical characteristics of vehicles (size, mobility) and the individual behavior of drivers (extent of norm violation for each agent).

The following section is devoted to proposing an agent model to take into account real life space occupation behaviors based on an agent’s ego-centered environmental representation.

3 Affordance-based agent model

This section provides useful definitions (3.1) and reasoning mechanisms for each agent (3.2 and 3.3).

3.1 Definitions

3.1.1 Definition of virtual lanes

Figure 2 illustrates a situation with four agents (a_1 , a_2 , a_3 and a_4). In this example, we focus on the reasoning of agent a_1 . This agent perceives three other agents (a_2 , a_3 , a_4), considers them obstacles and builds three virtual lanes (from VV_1 to VV_3). Each virtual lane is characterized by different properties. For example, the width of virtual lane VV_2 —denoted $width(VV_2)$ —is determined by the space available between the vehicles a_2 and a_3 ; its length is determined by the distance separating the two vehicles, denoted $dist(a_1, a_4)$, which determines the virtual lane as extending from a_1 to obstacle a_4 .

In the following, we will demonstrate that the virtual lanes are built from virtual intervals. We also assume that the physical properties of the virtual intervals and the virtual lanes are similar.

Definition 1 (Obstacle) Let $OB = \{ob_1, \dots, ob_{|OB|}\}$ be the set of obstacles. An obstacle is characterized by all elements (*i.e.*, defined either as a vehicle or a road closure) perceived on the road by an agent.

Definition 2 (Virtual interval) Let $IV = \{iv_1, \dots, iv_{|IV|}\}$ be the set of virtual intervals. Each Virtual Interval is characterized by its width and is defined by the available space between the agent and an obstacle (*i.e.*, empty space in front of the vehicle).

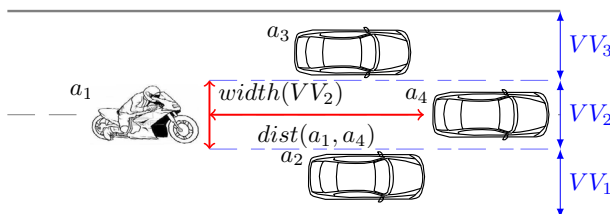


Fig. 2 Description of virtual lanes

Definition 3 (*Virtual lane*) Let $VV = \{VV_1, \dots, VV_j, \dots, VV_l\}$ be the set of virtual lanes. A virtual lane is one virtual interval or a subset of virtual intervals. Each virtual lane is referred to as VV_j and is characterized by a set of properties $P_j = \{p_{1j}, p_{2j}, \dots, p_{qj}\}$.

Let $P = \{P_1, P_2, \dots, P_j, \dots, P_l\}$ be the set of all these properties with respect to the set VV . These properties can be broken down into three classes: physical properties, flow-related properties and environmental properties to the left and right (wall effect).

The physical properties of a lane are defined as those properties that mark out the space occupied by this lane.

Definition 4 (*Physical properties*) The physical properties of virtual lane VV_j are defined by $\langle width(VV_j), dist(VV_j) \rangle$:

- Lane width $width(VV_j)$ characterizes an interval with starting position $pd(VV_j)$ and end position $pf(VV_j)$.
- Lane length $dist(VV_j)$ has been represented by the distance from agent a_i to obstacle ob_k , and can also be denoted $dist(a_i, ob_k)$, *i.e.*, the distance from which the lane remains available.

We assume that each agent has a perception field that depends on its individual characteristics (such as speed). Each agent uses these characteristics to estimate the lane's flow-related properties and wall effect properties.

Definition 5 (*Flow-related properties*) Properties related to traffic flow correspond to a characterization of the traffic in the lane. These properties are defined by a triplet $\langle d, v_{Avg}, \sigma \rangle$:

- Traffic density d defines the number of vehicles in the lane.
- Average vehicle speed v_{Avg} reflects the speeds of different vehicles.
- The standard deviation of driving speed σ measures the distribution of vehicular speed throughout the lane. A high standard deviation would mean that traffic speeds are unstable and therefore unpredictable.

In addition to physical and flow-related characteristics, we also consider other properties, which in our opinion are important to characterize a lane, especially since they have an impact on agent behavior. These properties are related to the *wall effect*. Studies in the psychology of driving highlight the impact of this effect on a driver's operating speed and lateral positioning within lane [22,36]. It may be related to infrastructure (lane width, tunnel walls) or road context (*e.g.*, the effect of the existence of trucks in adjacent lanes, adjacent lane speed variability).

Definition 6 (*Wall effect properties*) The wall effect represents the impact of the surrounding environment (adjacent lanes or shoulder) on driver behavior. This effect is a triplet, $\langle v_{wall}, st_{wall}, prox_{wall} \rangle$ that relies on the following characteristics (affecting lateral position and applied speed):

- The speed of each wall— v_{wall} (the speed of the slowest vehicle in the lane that defines the wall or 0 if the slowest vehicle is roadside).
- The stability of the walls— st_{wall} (the difference between the average speeds of the walls and the hypothesis that, when the speeds of the right and left walls are similar, the wall effect can be considered stable).
- The proximity of the walls— $prox_{wall}$ (the available space between the vehicle and the boundaries).

3.1.2 Definition of affordances and ego-centered representation

According to our application, we define situated agents and their characteristics (which may be perceived by the other agents) in their environment.

Definition 7 (*Situated agents*) Let $\mathcal{A} = \{a_1, a_2, \dots, a_i, \dots, a_{|\mathcal{A}|}\}$ be a set of situated agents in environment \mathcal{E} . At a given maximal distance, we assume that each agent a_i perceives the other agents $A \subseteq \mathcal{A}$ around it and a subset of their individual characteristics C :

- Let $A = \{a_1, a_2, \dots, a_n\}$ be a subset of \mathcal{A}
- Let $C = \{C_1, C_2, \dots, C_n\}$ be a subset of the perceived characteristics of the agents (*e.g.*, position, distance to the norm, speed, type, width). Each C_i is thus a set of properties describing each $a_i \in A$.

In our approach, we use an expanded version of the affordances concept enriched with cognition. Affordances rely on environmental constraints and the mental capacities of the agent. Therefore, we consider the “situational” interpretation of the environment by the agents. To identify opportunities afforded by the interaction of perceived entities with the environment, an agent takes into account the context, the properties of the other agents and its own individual properties (capabilities, intentions, goals and behavioral properties, like distance to the norm²). The affordances identified by one agent may be different from those identified by another agent in the same context.

Definition 8 (*Affordance*) An affordance corresponds to a space occupation opportunity resulting from the relationship between an agent and the entities it perceives in its physical environment.

Affordances are used in the ego-centered representation, which has been defined for each agent a_i .

Definition 9 (*Ego-centered environmental representation*) Let $EE R_{a_i}$ be the ego-centered environmental representation. $EE R_{a_i}$ is defined by the tuple $\langle A, Aff, R \rangle$:

- $A = \{a_1, a_2, \dots, a_n\}$ is a subset of all agents perceived by agent a_i , at a given viewing distance.
- $Aff = \{V V_1, V V_2, \dots, V V_l\}$ denotes the set of affordances identified by agent a_i in its environment. Those affordances may be different from the physical lanes initially defined by the road markings.
- $R = \{r_{a_i}(w_k)/w_k \in A \cup Aff\}$ is the set of relations. Each $r_{a_i}(w_k)$ establishes a binary relation between agent a_i and each agent a_k from A reflecting the spatial relationship between the two agents (*e.g.*, to the right, to the left, in front, behind) or a binary relationship between agent a_i and each virtual lane $V V_k$ of Aff reflecting the relationship between the agent and the lane in question (*e.g.*, the agent lane, the adjacent lane to the left, the adjacent lane to the right).

Agent a_i perceives its environment (road and other agents) and considers P , the set of perceived properties for virtual lanes, and C , the set of individual characteristics for the perceived agents.

The agent reasoning process a_i is split into three steps according to the “Perception–Decision–Action” loop (Fig. 3).

² The distance to the norm (traffic rules) is randomly specified during agent initialization; it denotes the degree of compliance with norms and ensures heterogeneity for the agents.

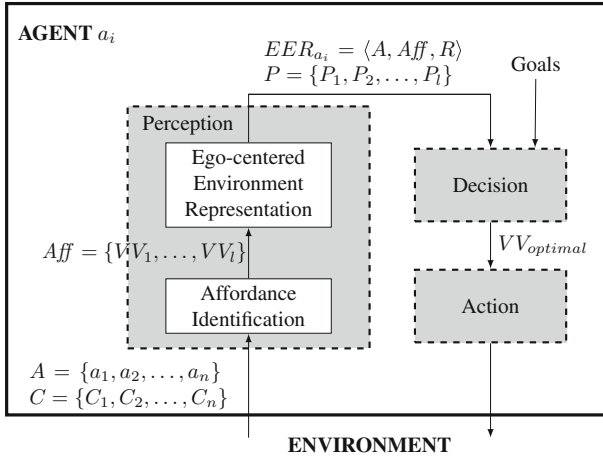


Fig. 3 Agent a_i 's architecture

3.2 Perception

The affordances result from the interactions of perceived agents (their individual characteristics) with the road configuration. The determination of affordances requires a cognitive process of perceiving information to identify what space occupation possibilities are afforded to the agent. This process verifies whether or not an identified affordance truly corresponds to a suitable action. It is performed using a payoff function, identified as *payoff*, which evaluates one possibility and determines if it can be a potential action.

Agent a_i builds its ego-centered representation of the environment based on the detected affordances. Note that each ego-centered representation $EE R_{a_i}$ depends on the agent context. It is composed of the identified affordances and a set of affordance properties, P . These affordances correspond to space occupation possibilities. This representation corresponds to an explicit mental representation of the situation, and therefore evaluates affordances and enables a decision to be made.

The details of this process are given in the next sections.

3.2.1 Affordance identification

We propose a model to manage interactions with the environment. Figure 4 gives an overview of our affordance-based model. The environment includes several agents and entities. The latter may correspond to road objects such as equipment, signs, markings or other agents. Decision-making relies on the context and must deal with environmental changes. The entities in the environment can offer different action possibilities or affordances to agents. In the context of space occupation, agents identify a set of available and occupied intervals. These intervals correspond to elements designated by α , β and γ . For example, at time t , agent a_1 identifies intervals α and β ; agent a_2 identifies intervals α and γ . The agents reason about these intervals to evaluate action possibilities based on space occupation criteria. These evaluation and reasoning steps allow agent a_1 to identify the affordance resulting from the merging of α and β and allow agent a_2 to identify the affordances α and γ . The environment is dynamic and complex: the environment thus changes from time step t to time step t' . At time step t' , these reasoning steps allow agent a_1 to identify affordance α (β is no longer detected by this

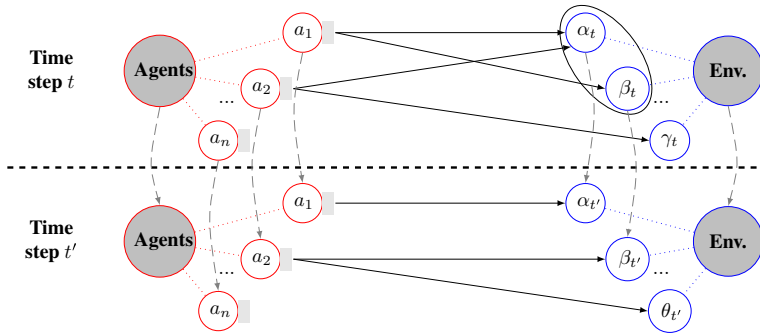


Fig. 4 Agents—environment interaction model

agent) and allow agent a_2 to identify two affordances β (β becomes visible for this agent) and θ (a new affordance perceived by a_2).

An affordance corresponds to the potential space occupation resulting from interactions between the perceived entities and the road configuration. The space occupation practices are not normative because agents do not always follow road markings. The representation of individual agent characteristics (*e.g.*, distance to the norm, vehicle type) enables heterogeneous behaviors to occur. For example, a given space will offer different opportunities to an agent driving a two-wheeled vehicle compared with an agent driving a truck, as it will afford different possibilities to an agent engaging in normative behaviors (*i.e.*, an agent who does not consider inter-lanes spaces to be a possibility) compared with an agent engaging in non-normative behaviors.

In the context of our application, we assume that there cannot be more than five affordances. The affordances correspond to the following possibilities:

- Stay in own lane
- Move left towards an adjacent lane
- Move right towards an adjacent lane
- Move left to reach a space to the left of the adjacent lane
- Move to right to reach a space to the right of the adjacent lane

The latter two possibilities represent “reachable” opportunities to the left or right, just beyond the adjacent lanes. These lanes are not necessarily adjacent to adjacent lanes. Rather, they indicate lanes that are reachable by a series of potentially unfavorable lane-changing maneuvers.

This choice is based on the following analysis. In a given interactive traffic situation, a driver can choose between staying in his lane and adapting to the constraint or changing lanes (to the left or to the right). To perform lane-changing maneuvers, a driver needs to have information on what is happening ahead (in his own lane) and laterally (lanes directly adjacent to the left and to the right). In addition, a driver needs to have information beyond the immediate environment in order to detect the most favorable options that can only be reached through iterated maneuvers. Lane changes can be an immediate solution to the constraint or a transitional step towards the goal if the driver tries to reach a favorable lane by crossing unfavorable ones.

Affordances are identified when the agent browses its environment starting with what is closest and moving towards what is furthest away.

Before	Overlaps	Meets	During	Starts	Finishes	Equals
$X < Y$	$X o Y$	$X m Y$	$X d Y$	$X s Y$	$X f Y$	
After	Overlapped	Met by	Contains	Started by	Finished by	
$Y > X$	$Y oi X$	$X mi Y$	$X di Y$	$X si Y$	$X fi Y$	

Fig. 5 Allen's relationships between two intervals X and Y

3.2.2 Identification mechanisms

We describe the different steps to determine the list of affordances available to the agent. From the list of perceived agents (ordered according to their lateral position from the right edge of the road to the left edge), the agent identifies set of virtual intervals IV . In this case, there may be overlapping intervals or an interval that is included within another due to the position of vehicles on the roadway. To identify and distinguish free intervals from those that are occupied, we will use the model introduced by Allen [1] for reasoning about the construct of virtual intervals.

Allen's interval algebra [1] has been introduced for temporal reasoning. The calculus defines possible relationships between time intervals and provides compositional rules that can be used as a basis for reasoning about temporal event descriptions. Let X and Y be two intervals: the relationships identified by Allen to reason about intervals are provided in Fig. 5.

In our model, we adapt these relationships to a spatial representation to allow the agent to identify and reorganize virtual intervals. These relationships are useful for identifying conflicts that may exist between spatial intervals. The free and occupied intervals obtained in this way must cover the entire width of the road. Therefore, two adjacent intervals should have end up meeting. The agent starts by identifying the intervals resulting from free spaces and occupied spaces (detection of an obstacle). For occupied intervals, we defined a distance to the obstacle as the distance between agent a_i , who is calculating intervals, and obstacle ob_X characterizing interval X . This distance is estimated by $dist(a_i, ob_X)$ (same definition for interval Y).

Based on these relationships, an agent identifies the intervals that may cause problems. The latter correspond to the following cases:

- One interval overlaps another
- One interval contains another
- One interval begins with another
- One interval ends with another

In the following, we do not develop the inverse relationships, which can be easily deduced. If two intervals X and Y overlap, the agent must merge them to consider one:

$$(X o Y) \wedge (width(a_i) > (pf(Y) - pf(X))) \rightarrow merge(X, Y)$$

If interval X contains interval Y (X during Y), then the agent keeps the interval with the highest width in the interval set:

$$(X d Y) \wedge (width(X) < width(Y)) \rightarrow IV \setminus \{X\}$$

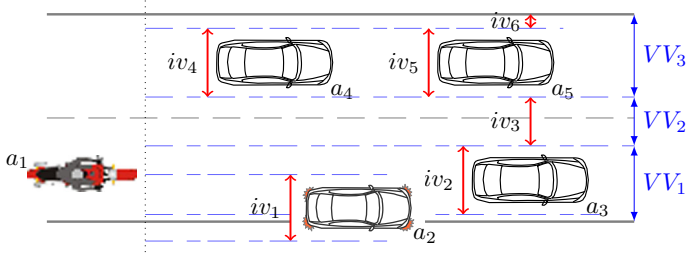


Fig. 6 Detection of virtual lanes for agent a_1

If interval X starts with Y , the rule is:

$$(X \text{ s } Y) \wedge (\text{width}(X) < \text{width}(Y)) \rightarrow IV \setminus \{X\}$$

If interval X ends with interval Y , the rule is:

$$(X \text{ f } Y) \wedge (\text{width}(X) < \text{width}(Y)) \rightarrow IV \setminus \{X\}$$

If interval X is equal to interval Y , the agent keeps the closest interval:

$$(X = Y) \wedge (\text{dist}(a_i, \text{ob}_X) < \text{dist}(a_i, \text{ob}_Y)) \rightarrow IV \setminus \{Y\}$$

To illustrate this reasoning, we consider the situation shown in Fig. 6. We assume that the reasoning is performed by agent a_1 . This agent detects four other agents: illegally parked agent a_2 , and three agents a_3 , a_4 and a_5 on the road. In this case, agent a_1 builds the set of virtual intervals $IV = \{iv_1, iv_2, iv_3, iv_4, iv_5, iv_6\}$. Interval iv_1 corresponding to the width of vehicle a_2 (iv_2 for a_3 , iv_4 for a_4 and iv_5 for a_5), and iv_3 and iv_6 for the rest of this road. Firstly, there are two overlapping intervals iv_1 and iv_2 . The agent applies the first merging rule to solve the conflict of spatial representation. Since $\text{space}(pf(iv_2) - pf(iv_1))$ is not wide enough to allow the two-wheeled vehicle to continue its trajectory, agent a_1 considers that these two intervals should be merged into a single interval (it does consider the road markings, thereby reducing this interval). In the figure, this interval will be considered virtual lane VV_1 . Secondly, virtual interval iv_3 has not been changed and also will be considered as virtual lane VV_2 . Finally, vehicles a_4 and a_5 move on the same lane (the last rule can be applied and iv_5 has been omitted). Moreover, the size of interval iv_6 is insufficient for a_1 : this interval should be merged with previous interval iv_4 into a single interval. This interval resulting from iv_4 , iv_5 and iv_6 will be thus considered as virtual lane VV_3 . Analyzing this situation gives us three virtual lanes $\{VV_1, VV_2, VV_3\}$.

All these rules allow the agent to reason about intervals to identify sources of conflict and reorganize free and occupied spaces. From the list of virtual intervals resulting from the above reasoning, the agent identifies the list of affordances by browsing intervals from closest to farthest (in the position lateral to the agent and the start and end positions of each interval). The agent starts by identifying and characterizing its immediate environment (its own lane), its adjacent environment (lanes to the left and the right), and finally the non-adjacent environment (non-adjacent lanes to the left and right).

Immediate environment: The agent browses set IV and identifies interval iv_k to which it belongs according to its lateral position. This interval is transformed into virtual lane VV_j by defining the aforementioned parameters, such as depth (distance to the obstacle in the lane in question), speed and density. This lane is then added to affordance set Aff . This new affordance corresponds to the action “stay in own lane and go straight”.

Adjacent environment: From the agents' immediate environment (*i.e.*, their own lane), they check the space to the left and to the right to identify possible affordances. The agent starts by evaluating the first interval. If the agent considers that this lane is more beneficial, it adds this possibility to its list of affordances. Otherwise it merges this lane with the next one (if there is no physical marking in this interval) or it merges intervals until a road marking is reached. The agent adds this new lane to its affordances set.

The evaluation mechanism is based on the lane properties identified above. Each agent has a choice between two actions: stay in current lane or change. This evaluation is performed through a function that compares the current speed of the agent with the estimated speed the agent could have in the target lane. The agent selects the lane that improves its speed. The agent estimates the speed of the identified lane and decides whether or not to choose this lane. For example, for the situation illustrated in Fig. 6, agent a_1 will decide to choose virtual lane VV_2 ; because it enables the agent to attain a higher speed than its current speed in its current lane (the virtual lane is empty, whereas lanes VV_1 and VV_3 are occupied by several vehicles). This evaluation function is provided by the difference between the two speeds³:

$$payoff(vc_{a_i}) = \tau * v_{a_i}(VV_j) - vc_{a_i} \quad (1)$$

where a_i represents an agent, VV_j the lane, $v_{a_i}(VV_j)$ the expected agent speed in lane VV_j , vc_{a_i} the agent's current speed and $\tau \in [0, 1]$ the social acceptance of the filtering, which varies with vehicle type (*e.g.*, two-wheeled vehicle, passenger car, bus). $v_{a_i}(VV_j)$ ⁴ depends on the following parameters:

- $f_{a_i}(VV_j)$: reflects the traffic flow characteristics of lane VV_j and depends on lane density and average lane speed.
- $g_{a_i}(VV_j)$: reflects the wall effect of lane VV_j and depends on the closeness of the walls and their stability in terms of speed.
- $h_{a_i}(VV_j)$: is related to the individual characteristics of each agent and translates the agent's distance to the norm (normative/non-normative behavior).

The evaluation function is positive when the target lane is appropriate for the agent (in terms of speed). This estimation takes into account lane characteristics (width, distance to obstacle), wall characteristics (stability, proximity) and individual agent characteristics, especially distance to the norm.

Distant environment: For affordances that are not immediately adjacent, we propose to evaluate the lane by browsing the road space from the immediately adjacent lane to the edge of the road (laterally, to the left and to the right) and to select the lane if its characteristics are better than those of the current lane (browsing is performed on set IV). Such a lane allows the agent to expect a benefit, according to its own criteria, and this depends on individual characteristics. The result of this step is a set of affordances corresponding to all the opportunities identified by the agent.

After identifying the affordances set, agent a_i builds its ego-centered representation of the environment based on the affordances it detected, $EE R_{a_i}$.

3.3 Decision and action

The ego-centered environmental representation allows an agent to make a decision by choosing the optimal affordance. The result (or output) of the decision mechanism is a possible

³ This function choice is completely empirical: we chose the parameters that affect agent behavior based on psychological studies.

⁴ The expected agent speed in lane VV_j is given by the weighted sum of the parameters mentioned below.

virtual lane with properties such as width, position on the road, lane speed and lane wall speed. These properties provide the agent with a future lateral position and a potential lateral speed.

With a generalization of the virtual lanes and an enrichment of lane properties, we expect that the alternative to choosing a virtual lane (between two rows of vehicles) will not be systematic, especially for automobiles, trucks and buses, where there is low “tolerance” for using such lanes and minimal time-savings. For these users, choosing a virtual lane would be more favorable when specific events occur (badly-parked vehicles, emergency vehicles). Filtering maneuvers are better suited to two-wheeled vehicles because there is greater tolerance for these vehicles and significant travel time-savings. The proposed solution is also expected to improve the validity of the model for situations in which there is a high number of lanes, such as in “complex” toll plazas.

The agent is endowed with a decision-making mechanism to select an affordance to adopt from its affordance-based ego-centered environmental representation. It computes a fitness (score, interest value) for each affordance of Aff set. This fitness quantifies the relative “strength” or “attractiveness” of all the affordances. It relies on the agent’s target goals (In our context, the goals correspond to objectives defined by the agent’s itinerary) and its representation of the environment. Let $F(VV_j)$ be the fitness for given affordance VV_j .

$$F(VV_j) = f(p_{1j}, p_{2j}, \dots, p_{qj}, goals) \quad (2)$$

where function $f(\cdot)$ is defined in such that $F(VV_j)$ provides a numerical value indicating the strength (expected utility) of a particular affordance. It is given by a weighted sum of affordance parameters $p_{1j}, p_{2j}, \dots, p_{qj}$ such as width of the lane and average speed.

Choosing optimal affordance thus takes place after evaluating all identified affordances. The final system output is the affordance (space occupation possibility) VV_j associated with optimal value $F(VV_j)$. Optimality is defined by maximizing $f(\cdot)$.

$$VV_{optimal} = arg \max F(VV_j) \quad (3)$$

More generally, action selection in the BDI model may be defined by the following steps [31]: When an agent wants to fulfill a desire, it searches for a plan to do this. A hypothesis for these models relies on the fact that agents have different “plans”. The plans may be defined in different ways: the addition of a new desire, changes in beliefs, or the execution of a primitive action. These recipes have some conditions (external data from the environment or an internal agent state), which must be satisfied to adopt these plans as intentions. If there are some plans that can be simultaneously activated, an arbitrary mechanism selects the plan. If the plan becomes an intention, each action must be executed until a new action is selected. This new selection may be useful if a new desire appears: the plan is then completely terminated/fails or a new event is observed in the environment.

In our approach, the agent builds its contextual representation based on affordances and selects an optimal affordance (the agents have no predetermined plans). The selected affordance determines the action to be executed (stay in the virtual lane or go towards this new virtual lane). At the next time step, the agent builds a new contextual representation and once again selects a new optimal affordance (it may be different from the previous one).

Both approaches are highly reactive to different events observed in the environment. The BDI model selects the action, which depends on the agents’ new desires/intentions, whereas action selection in our approach depends only on new information from the environment.

4 Validation

We implemented our agent model in a traffic simulation tool (4.1), called *ArchiSim* [12], and then proposed a validation for our approach (4.2).

4.1 *ArchiSim*: traffic simulation platform

ArchiSim is a traffic simulation platform that is implemented with the MODULA 2 language. This language has features that make programming easier. These features include a built-in time scale and random generators for a range of distributions.

ArchiSim considers general road traffic to be a set of interactions between different actors (road users such as vehicle drivers, motorcyclists and pedestrians) with road infrastructure (road signs and markings). The platform can simulate a realistic traffic environment for a human driver. The behavioral models are based on driving psychology studies [33] that analyze a driver's behavior in realistic situations. The model's objectives are to identify human driver knowledge and decision-making strategies.

ArchiSim is based on a MAS in which each simulated driver is an autonomous software agent evolving in a virtual environment and interacting with other simulated agents (or human drivers) to reach their goals in accordance with their current skills and situation. At each step of the simulation, an agent receives information describing the surrounding environment (its context). Based on this information, agents develop perceptions of their environments and make their decisions accordingly.

ArchiSim has been validated for different actors, such as the drivers of two-wheeled vehicles [4], passenger vehicles [10, 11, 24] and heavy trucks [34] for different highway and urban situations. Preliminary research was conducted on this model to apply it to the *ArchiSim* tool [20].

Results were obtained on a computer equipped with dual-core 2.5 GHz Intel Core i5 CPU and 4GB of RAM.

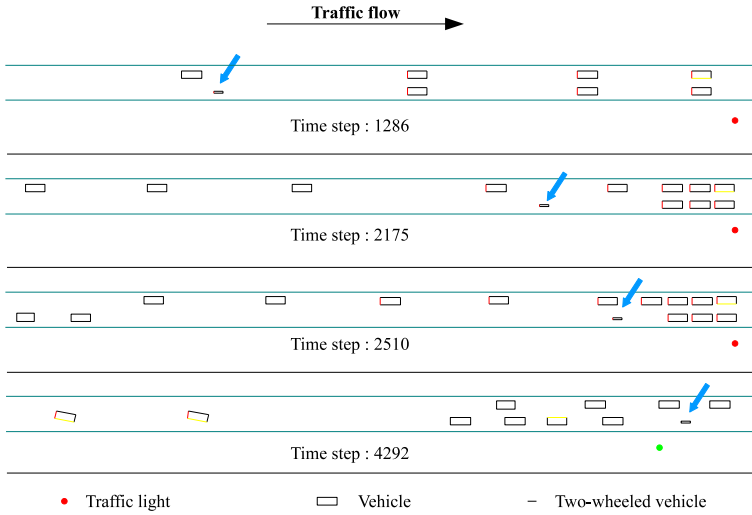
4.2 Experiments

The first part of our evaluation involves a visual assessment of simulated driver behavior. We begin our experiments by evaluating individual agent behavior in terms of road space positioning in various scenarios.

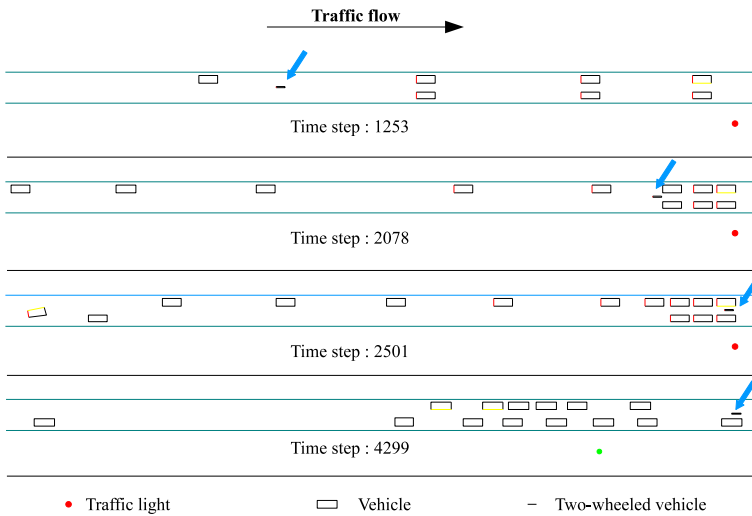
The scenarios described in the following sub-sections allowed us to estimate our model in traffic situations involving two-wheeled vehicle moving up in a road with a traffic light (4.2.1) or vehicles moving up at an intersection with turning left or right (4.2.2). Finally, we validated the macroscopic aspects of our model by comparing real data collected on a route with simulation data (4.2.3) and a situation in which an emergency vehicle arrives (4.2.4). We began by validating the usual behavior for two-wheeled vehicles in motion [19].

4.2.1 *Experiment 1: a situation with a traffic light*

The aim of this experiment was to verify the filtering maneuver behavior of two-wheeled vehicles at a traffic light. We considered a road (1 km in length) with two physical lanes and we put a traffic light on this road at 800 m. We considered 20 vehicles (19 cars and 1 motorcycle). The initial position, initial speed and desired speed of each vehicle were provided by the simulation designer.



(a) Reference model (without affordance-based model)



(b) with affordance-based model

Fig. 7 The behavior of a two-wheeled vehicle in a situation with a traffic light: a reference model **(a)** and an affordance-based model **(b)**

We ran the simulations 20 times with the same parameters. We compared the reference model simulations (the *ArchiSim* model without an affordance-based model) with the simulations using our model (affordance-based model). The observed behaviors were similar for the 20 simulations.

Figure 7 presents one of the 20 simulations performed. Figure 7a (reference model) shows that the agent stays behind the different vehicles and stays in the same lane. At time step 2510, the agent is still at the back of a lane of stopped vehicles. It continues to move in

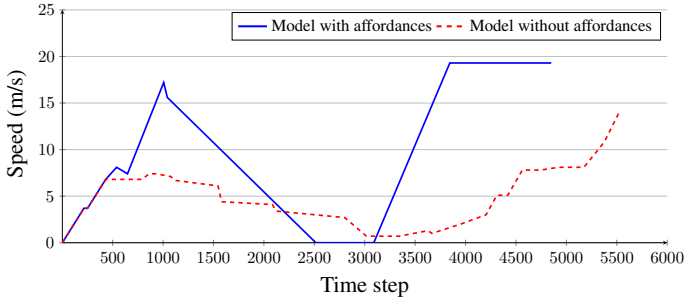


Fig. 8 Speed of the two-wheeled vehicle with/without affordance-based model

its lane when the traffic light changes from red to green. Figure 7b illustrates that for our model, at time step 1253, the agent driving the two-wheeled vehicle chose to fit and filter between the two rows of vehicles, moving to the head of a lane and stopping at the traffic light (step 2501). The behavior of the two-wheeled vehicle in our model results from the affordance-based ego-centered environmental representation. The two-wheeled agent detects the potential emergence of a virtual lane (between the two rows of vehicles) afforded by the interaction of the other agents with the physical road structure.

This kind of behavior does not appear in the reference model (*ArchiSim* without the affordance-based model), since the lanes correspond to physical ones. These two physical lanes are occupied by vehicles in front. Therefore, the two-wheeled vehicle driver gets stuck behind stopped vehicles and has no other opportunity until the light turns green. This kind of behavior does not always correspond to the two-wheeled agent’s behavior in an actual traffic situation. Our model reproduces behaviors that are often observed in reality.

Figure 8 shows a typical example in which the model reproduces the observed behaviors. This figure compares the speed profiles for two-wheeled vehicles in both the affordance-based model and the reference model (without affordances). Between time-steps 0 and 1006, the two-wheeled vehicle accelerates faster in our model than in the reference model. This behavior is the result of using the virtual lane in our model, whereas in the reference model, the two-wheeled vehicle is blocked behind a row of slower vehicles. Between steps 1006 and 2515, the speed variation is much lower for the model without affordances than for our model. Between steps 2515 and 3090, the two-wheeled vehicle in our model must stop at the red traffic light, while in the reference model, it continues to decelerate (it has not yet arrived at the traffic light). At step 3090 in our model, the traffic light changes to green and the two-wheeled vehicle begins to accelerate; in the reference model, it continues to move with a speed close to 0 km/h. After step 3090, the two-wheeled vehicle accelerated faster in our model than in the reference model: it is at the head of the lane in our approach; in the reference model, it is again blocked behind different vehicles.

There are fewer variations for our model than for the reference model; the two-wheeled vehicle is alone in the virtual lane (it decelerates only for a red traffic light); while in the reference model, the two-wheeled vehicle adapts the speed to the speed of the vehicles in front of it.

4.2.2 Experiment 2: a situation with an intersection

The objective of the second scenario is to evaluate a situation at an intersection with left- and right-turning vehicles and a single vehicle moving straight ahead. More specifically,

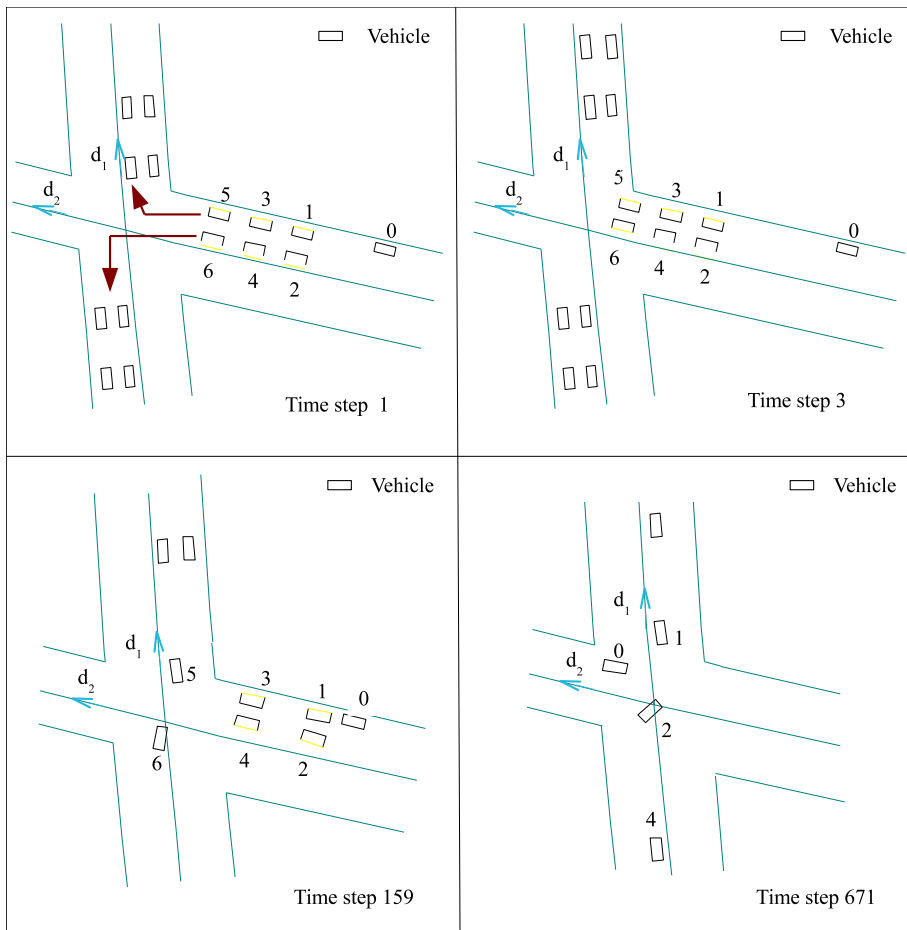


Fig. 9 Simulation in an intersection without an affordance-based model

this scenario aims to reproduce a behavior that we often observe at intersections. Generally, vehicles that turn right shift to the right, while those that turn left shift to the left, in order to allow vehicles moving straight ahead to pass.

Similarly to the previous experiment, we consider a bounded number of 15 vehicles, and the initial position, initial speed and desired speed of each vehicle are provided by the simulation designer. We ran the experiments 20 times. Figures 9 and 10 present an illustration of the scenario that occurs in this type of situation.

Figure 9 shows that agents move according to physical lanes, which are delineated by road markings. We focused on the behavior of vehicle 0. Vehicles 1, 3 and 5 are going to turn right. Vehicles 2, 4 and 6 move and turn left. We notice that vehicle 0 is blocked behind the row of vehicles turning right. Only once vehicles 1, 3 and 5 turn right, does vehicle 0 cross the intersection (time step 671): it cannot cross it before.

Figure 10 presents the same scenario based on our model. Mobile 0 creates a representation of the situation. Since vehicles 1, 3 and 5 turn right, they shift towards the right edge of the road. Vehicles 2, 4 and 6 follow the same behavior; however they shift to the left. We notice

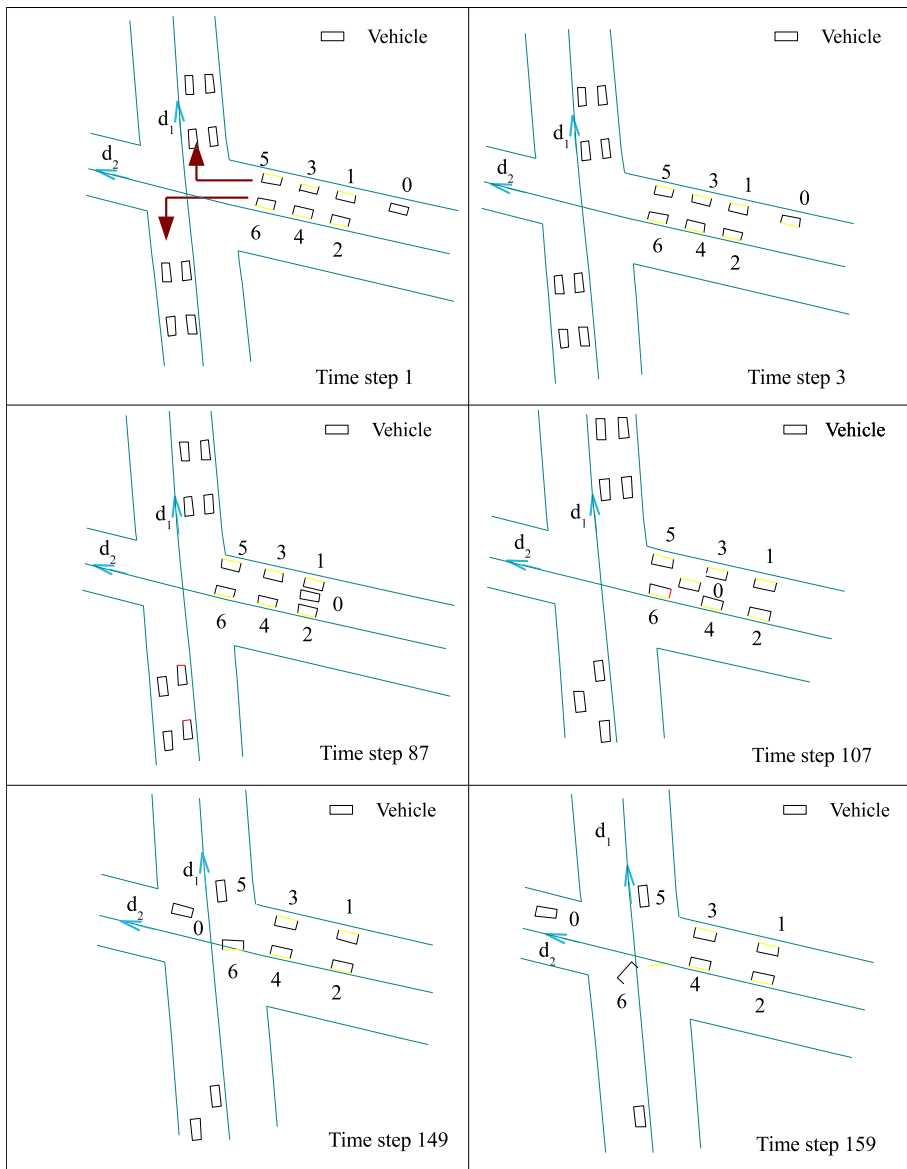


Fig. 10 Simulation in an intersection with an affordance-based model

that at time step 3, mobile 0 puts its turn signal on and starts moving in a virtual lane between the two rows of vehicles. At time step 159, mobile 0 has already crossed the intersection while at the same time step in the first simulation, it was still blocked behind the queue of vehicles. Mobile 0 creates an ego-centered representation based on affordances. For that purpose, it identifies three affordances:

- The lane furthest to the right, formed by vehicles 1, 3 and 5
- The lane furthest to the left, formed by vehicles 2, 4 and 6
- A lane that emerges in the middle, between the two rows of vehicles.

In order to make a decision, an agent evaluates the affordances and selects the most suitable, which is the virtual lane between the two rows. This lane presents better speed characteristics and allows the agent to get out from the situation and move through the intersection.

4.2.3 Experiment 3: a real traffic situation

In order to validate the macroscopic view of the traffic simulation using our affordance-based agent model, we considered a road situation with real, heavy traffic.

Real traffic context: In road traffic, it is very difficult to pick up real data on space management. So, we used the available data collected by ADEME⁵, which conducted a study in order to compare the energy consumption and emissions of two-wheeled vehicles with those of other vehicles. The considered data were collected on 23 km of a route composed of departmental roads, national roads and highways. This route represents a typical path from a driver's place of residence to work (*i.e.*, from the suburbs of Paris to the center of Paris).

The method used for collecting this traffic data involves simultaneously recording real conditions for a scooter, a motorcycle and a passenger vehicle. We assume that the motorcyclists' driving needed to be "serious", *i.e.*, they needed to obey speed limits and be able to move up in a lane of slowly moving cars. These records provided data such as average speed, travel time and number of stops.

The aim of our experiment was to simulate traffic in a context similar to the one considered by ADEME, and to compare real data with those of our simulation.

Experimental protocol: We first used *ArchiSim* to simulate a route similar to the one considered by ADEME. We used the same components (departmental roads, national roads, highways), traffic lights and road markings. We placed virtual sensors at the same kilometeric positions as on a real route. We generated heterogeneous traffic as follows:

- Each vehicle' arrival time and position were defined using Poisson distribution.
- The desired speed was generated according to Gaussian law.
- The initial speed of each vehicle was established as the lowest speed between the desired speed and the speed determined by the vehicle in front.
- The proportions of two-wheeled vehicles, trucks and buses were dependent on the number of cars.

We then added a car and a two-wheeled vehicle with the same initial and desired speeds and positions.

Results with real data versus simulated data: We carried out several experiments to pick up data and compare them with ADEME's data. These data included travel time, average speeds and numbers of stops by vehicle type (passenger car or two-wheeled vehicle). First, we compared the results of our model with those of the reference model to evaluate the impact of our agent model. Then, we compared our results to real data. Figure 11 provides real data and results obtained during simulations (with three different models) and gives the average of 20 simulations for each approach. In the first case, agents were defined by the "reference" behavior associated with the *ArchiSim* model with no virtual lane: the agents moved on the road within the physical lanes. The second case provided the results obtained by Bonte et al. [4]'s model and the last case defined the results provided by our affordance-based model.

⁵ French acronym for "The Environment and Energy Management Agency"

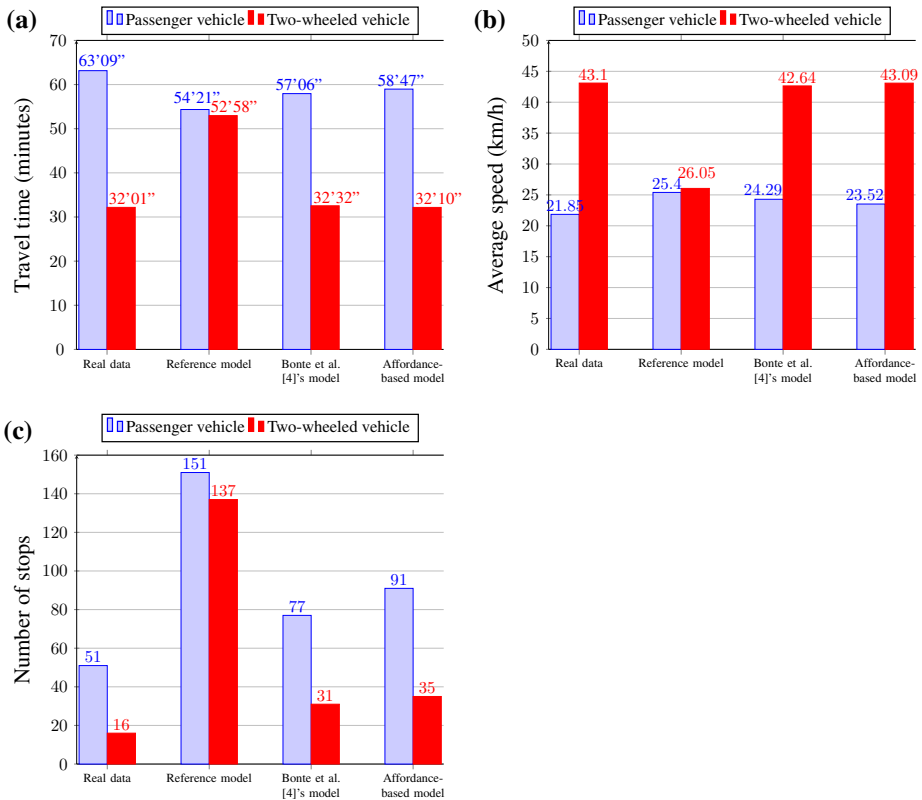


Fig. 11 Comparison between Real and Experimental measurements on a route 23 km long. **a** Travel time. **b** Average speed. **c** Number of stops

These data included travel time (Fig. 11a), average speeds (Fig. 11b) and the number of stops (Fig. 11c) by vehicle type (passenger vehicle or two-wheeled vehicle).

We focused on the behavior of a car and a two-wheeled vehicle generated with the same characteristics as for this itinerary to study the impact of our model. The real data show that the travel time for a two-wheeled vehicle is half that of a passenger car. This is not the case in the reference model, where travel times are roughly equal. This is due to the fact that, in the reference model, the behavior is the same for cars and two-wheeled vehicles. Both types of vehicles use the physical lanes provided by the road markings.

We compared our results with those of the reference results. Travel time for the same journey was shorter for the two-wheeled vehicle than for the car. The average speed of the two-wheeled vehicle was higher than the average speed of the car. We also observed that the two-wheeled vehicle made fewer stops than the cars did. Therefore, the affordance-based model allowed an agent driving a two-wheeled vehicle to identify the virtual lanes afforded by the environment. Due to their size, two-wheeled vehicles use virtual lanes more frequently than other types of vehicles. Their travel time is shorter and they make fewer stops than cars. Note that we observed the same trends when we compared results of our model with real data. The difference between the simulated results and real results may be related to the calibration of the simulation. We do not have data to precisely adjust the flow or speed of simulated vehicles.

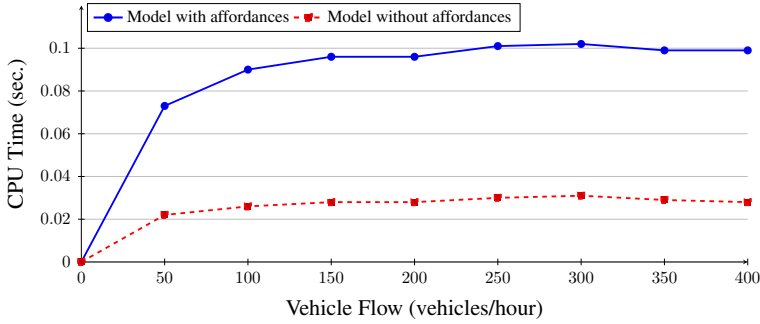


Fig. 12 Temporal performance for the perception process with/without affordances

We can conclude that our model considers that filtering is better tolerated in two-wheeled drivers than in car drivers (*i.e.*, two-wheeled vehicles make a given journey in less time). We have already outlined these different behaviors [19]: we observe that car drivers choose the virtual lane solution only if they engage in non-normative behavior (extreme cases). Choosing virtual lanes is not systematic; it depends on lane and vehicle characteristics (*e.g.*, size) and individual agent characteristics (distance to the norm). Our model is generic because it is not specific to one kind of driver. The heterogeneous behavior results from different driving contexts and individual driver characteristics coupled with generic rules.

Performance evaluation: To evaluate the performance of the proposed affordance mechanism, we considered the same route as in the previous experiments (the route similar to the one considered by ADEME). We simulated several traffic flow variations and we studied the CPU time required by the agents to perceive (*i.e.*, the time that each agent takes to build its environmental ego-centred representation). We compared our affordance-based model to the reference model (named model without affordances). For low traffic densities (fewer than 100 vehicles/h), perception time lengthens as traffic flow becomes heavier. For higher traffic densities, perception time becomes almost constant (for 250 vehicles/h, perception time approaches to 0.1 s in our model). This is due to the fact that the number of agents considered in the perception process usually does not change when the traffic density is high. In the proposed affordance-based model, the affordance mechanism is the most costly process. So, the perception times of Fig. 12 are very acceptable. However, our implementation of the affordance mechanism could be improved to reduce this cost.

4.2.4 Experiment 4: generalization regarding emergency vehicles

The comparison between real data and our approach shows that we can reproduce the observed trends. For the same itinerary, car travel time is longer (estimated ratio of 2–1) than two-wheeled vehicle travel time (when driving under the same conditions). We evaluated our simulations in the same context as the previous experiment, but we used a dynamically appearing emergency vehicle (ambulance, police car or fire truck). The purpose of this last experiment was to check the generic nature of our model.

In order to reproduce the “priority” given to this type of vehicle, we introduced a new behavior for the other agent types. This new behavior involved moving when an emergency vehicle is detected to make it easier for that vehicle to pass. Figure 13 describes the general behaviors for all agents. The presence of an emergency vehicle (vehicle 1) leads other vehicles

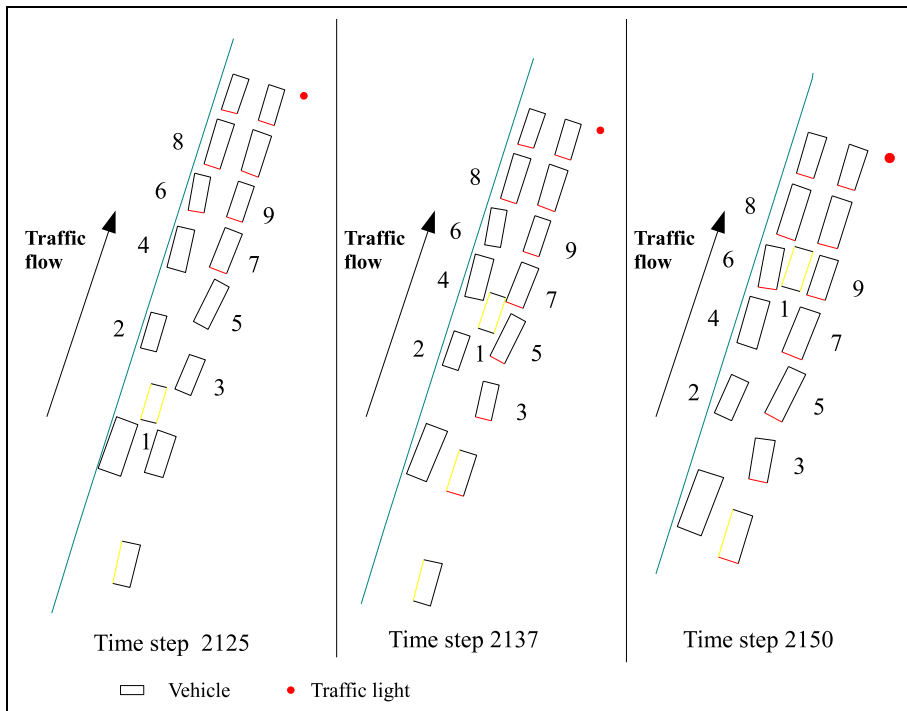


Fig. 13 Appearance of an emergency vehicle in a traffic situation

to shift to the right (vehicles 3, 5 and 7) or the left side (vehicles 2, 4, 6 and 8), if possible. When vehicle 1 disappeared, the other vehicles returned to the middle of their initial lane.

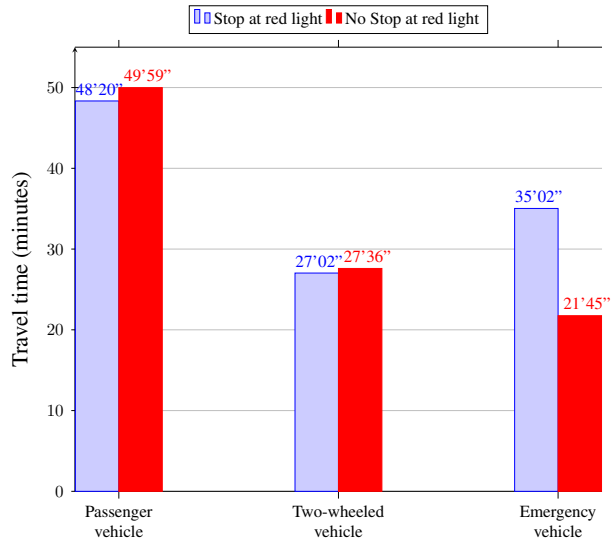
We consider that yielding to an emergency vehicle is equivalent to cooperative behaviors for the other agents. This cooperative behavior has also been observed in two-wheeled vehicles in certain situations, and especially in suburban contexts. In contrast with two-wheeled vehicles, an emergency vehicle forces its way through traffic by positioning itself between lanes: the space is insufficient to pass but the action creates space because other vehicles cooperate by moving.

We present two situations with an emergency vehicle (Fig. 14):

- In the first, we compared times for the different types of vehicles (“passenger”, “two-wheeled” and “emergency” vehicles): we assumed that the emergency vehicle stops when the light changes red. We note that the emergency vehicle takes less time than a passenger vehicle to move on the same road but it takes more time than a two-wheeled vehicle. Given the width of the vehicle, this result is understandable: two-wheeled vehicle drivers can weave through road traffic whereas emergency vehicles cannot.
- In the second situation, we assumed that the emergency vehicle goes through a red light (this situation is more “realistic” than the first). The emergency vehicle is faster than the others. The temporal difference between two-wheeled and emergency vehicles is minimal: we think that two-wheeled vehicles tend to compensate for this temporal difference by weaving in and out of traffic.

We believe that the results of the second situation are more realistic because emergency vehicles must be faster than the others in real situations. These results seem to reproduce what

Fig. 14 Travel time for different agent types based on emergency vehicle behavior



is actually seen when emergency vehicles switch lanes. New spaces are produced when agents cooperate, and allow emergency vehicles to move faster, ensuring overall traffic fluidity. Note that we have no real data about the behavior of emergency vehicles to fully validate simulated behaviors for this type of vehicle.

5 Conclusion

This article introduced an affordance-based agent model mainly based on the agents' interactions with their environment. Affordances identify the possible actions offered to agents by the environment when they interact with perceived entities, thus facilitating the agent decision-making process. The theory of Affordances was introduced by Gibson [15]. This initial theory has several advantages. However, it is not sufficient to explain the "direct perception": several studies have shown that the cognition process plays an important role in the representation of affordances. An important issue to address is the computational aspect of affordances.

To deal with this issue, we propose to consider that affordances may be directly perceived in the environment or represented in an agent's mind. This affordance-based mental representation facilitates affordance implementation in a multi-agent simulation with situated and autonomous agents.

Our work also aims to validate traffic simulations in urban and suburban areas, by focusing more on the heterogeneity of vehicles and driver behavior in terms of road space positioning and occupation. In this context, agents represent human drivers and an affordance corresponds to a possible virtual lane, perceived by the agents.

The agents follow a decision-making loop based on the usual three processes: perception, decision and action. Each agent perceives the other agents and their characteristics, as well as information from the environment (*e.g.*, road markings, signals). The perception process builds an "ego-centered representation" by analyzing the relationships between agents and the environment, and by identifying affordances. The different characteristics of agents and

the environmental properties allow each agent to build different virtual intervals. Based on Allen's interval algebra, these different virtual intervals are modified to obtain affordances (virtual lanes). Based on these affordances and its goals, each agent determines the "optimal affordance" and performs the corresponding action.

We implemented our model with *ArchiSim*, a road traffic simulation tool and we ran several experiments. The results of four experiments were reported in this paper. The first two experiments validated individual behaviors such as two-wheeled vehicles weaving in and out of traffic and passenger cars between rows of vehicles. The third experiment investigated a real traffic situation. We thus compared our affordance-based models to other models and real data. Our model gave the best results. The last experiment also illustrated a realistic situation with an emergency vehicle arriving to a traffic situation. The obtained results show that our model reproduces practices seen in real life.

Our approach uses Allen's interval model to determine virtual intervals (free or occupied spaces). These intervals are characterized by two dimensions: width and distance to an obstacle. Allen's model has been used only to handle the width of different intervals. Therefore, it may be interesting to improve this model by using the region connection calculus model [14,23,42] to build a continuous model with these two dimensions and represent such spaces.

Finally, we think that affordance-based models may be useful to design new interactions between agents and entities that are currently present in the environment. This approach defines relationships between agents and the environment, and identifies action possibilities for a given agent. Perception and cognition mechanisms must thus be reconsidered when designing MAS. The MAS designer must focus on the "interface" between the environment and the agent perception process. Therefore, affordances are used as a mechanism for better understanding and hopefully improving the representation of agent—environment interaction. Other existing models investigate the agent-environment interaction problem. For Weyns et al. [41], the environment is defined as a first-class abstraction that provides the conditions of existence for agents and supplies an abstraction for an exploitable model for designing MAS. Similarly, Weyns et al. [40] claimed that the interactions between agents and the environment are very important when designing multi-agent applications: they defined the concept of "artifact" as "...a software entity designed to provide some kinds of services that agents can use to achieve their goals" [39]. Future research is necessary to highlight the relationships between the various models.

Acknowledgments This research was partially funded by the French Ministry of Education, Research and Technology, the Nord/Pas-de-Calais Region, the CNRS and the International Campus on Safety and Intermodality in Transportation (CISIT). We would like also to thank the anonymous reviewers for their comments.

References

1. Allen, J. (1981). An interval based representation of temporal knowledge. In: *Proceedings of the seventh International Joint Conference on Artificial Intelligence*, (pp 221–226).
2. Bazzan, A. (2005). A distributed approach for coordination of traffic signal agents. *Autonomous Agents and Multi-Agent Systems*, 10(1), 131–164.
3. Bazzan, A., & Klügl, F. (2014). A review on agent-based technology for traffic and transportation. *The Knowledge Engineering Review*, 29(3), 375–403.
4. Bonte, L., Espié, S., & Mathieu, P. (2006). Modélisation et simulation des usagers deux-roues motorisés dans archisim. In: *Actes des 14e Journées Francophones sur les Systèmes Multi-Agents (JFSMA'06)*, (pp 31–44).

5. Bonte, L., Espié, S., & Mathieu, P. (2007). Virtual lanes interest for motorcycles simulation. In *Proceedings of the fifth European Workshop on Multi-Agent Systems*, (pp 580–596).
6. Chen, B., & Cheng, H. (2010). Review of the application of agent technology in traffic and transportation systems. *IEEE Transactions on Intelligent Transportation Systems*, 11(2), 485–497.
7. Cohn, A., & Renz, J. (2008). Qualitative spatial representation and reasoning. In F. van Harmelen, V. Lifschitz, & B. Porter (Eds.), *Handbook of knowledge representation* (Vol. 3, pp. 551–596). Amsterdam: Elsevier.
8. Cornwell, J., O'Brien, K., Silverman, B., & Toth, J. (2003). Affordance theory for improving the rapid generation, composability and reusability of synthetic agents and objects. In: *Twelfth Conference on Computer Generated Forces and Behavior Representation*.
9. Dai, J., & Li, X. (2010). Multi-agent systems for simulating traffic behaviors. *Chinese Science Bulletin*, 55, 293–300.
10. Doniec, A., Mandiau, R., Piechowiak, S., & Espié, S. (2008). Anticipation based on constraint processing in a multi-agent context. *Journal of Autonomous Agents and Multi-Agent Systems (JAAMAS)*, 17(2), 339–361.
11. El Hadouaj, S., Drogoul, A., & Espié, S. (2000). How to combine reactivity and anticipation : the case of conflicts resolution in a simulated road traffic. In S. Moss & P. Davidsson (Eds.), *Multi-Agent-Based Simulation, Second International Workshop* (pp. 82–96). Boston: Springer.
12. Espié, S. (1995). Archisim, multi-actor parallel architecture for traffic simulation. In: *Proceedings of the Second World Congress on Intelligent Transport Systems*, Yokohama, vol IV.
13. Fellendorf, M., & Vortisch, P. (2010). Microscopic traffic flow simulator vissim. In J. Barceló (Ed.), *Fundamentals of Traffic Simulation, International Series in Operations Research and Management Science* (Vol. 145, pp. 63–93). New York: Springer.
14. Gerevini, A., & Nebel, B. (2002). Qualitative spatio-temporal reasoning with rcc-8 and Allen's interval calculus: Computational complexity. In F. van Harmelen (Ed.), *Proceedings of the 15th European Conference on Artificial Intelligence, ECAI'2002* (pp. 312–316). Lyon, France: IOS Press.
15. Gibson, J. (1977). The theory of affordances. In R. Shaw & J. Bransford (Eds.), *Perceiving, acting and knowing, Lawrence Erlbaum and associates*. New Jersey: Hillsdale.
16. Gipps, P. (1981). A behavioural car-following model for computer simulation. *Transportation Research Part B*, 15(2), 105–111.
17. Hidas, P. (2002). Modelling lane changing and merging in microscopic traffic simulation. *Transportation Research Part C*, 10(5–6), 351–371.
18. Kapadia, M., Singh, S., Hewlett, W., & Faloutsos, P. (2009). Egocentric affordance fields in pedestrian steering. In: *Proceedings of the 2009 symposium on Interactive 3D graphics and games*, ACM, I3D '09, (pp 215–223).
19. Ksontini, F., Espié, S., Guessoum, Z., & Mandiau, R. (2012a). Traffic behavioral simulation in urban and suburban - representation of the drivers' environment. In: *Advances in Intelligent and Soft Computing, PAAMS*, vol 155, (pp 115–125). Springer.
20. Ksontini, F., Guessoum, Z., Mandiau, R., Espié, S. (2013). Using ego-centered affordances in multi-agent traffic simulation. In M.L. Gini, O. Shehory, T. Ito, C.M. Jonker (eds) *International conference on Autonomous Agents and Multi-Agent Systems, AAMAS '13*, (pp 151–158) Saint Paul, MN, USA, May 6–10, 2013, IFAAMAS.
21. Lee, T., Polak, J., & Bell, M. (2009). New approach to modeling mixed traffic containing motorcycles in urban areas. *Transportation Research Record*, 2140, 195–205.
22. Lewis-Evans, B., & Charlton, S. G. (2006). Explicit and implicit processes in behavioural adaptation to road width. *Accident Analysis & Prevention*, 38(3), 610–617.
23. Li, S., & Ying, M. (2003). Region connection calculus: Its models and composition table. *Artificial Intelligence*, 145(1–2), 121–146.
24. Mandiau, R., Champion, A., Auberlet, J. M., Espié, S., & Kolski, C. (2008). Behaviour based on decision matrices for a coordination between agents in a urban traffic simulation. *Applied Intelligence*, 28(2), 121–138.
25. Minh, C. C., Sano, K., & Matsumoto, S. (2005a). Characteristics of passing and paired riding maneuvers of motorcycle. *Journal of the Eastern Asia Society for Transportation Studies*, 6, 186–197.
26. Minh, C. C., Sano, K., & Matsumoto, S. (2005b). The speed, flow and headway analyses of motorcycle traffic. *Journal of the Eastern Asia Society for Transportation Studies*, 6, 1496–1508.
27. Murphy, R. (1999). Case studies of applying gibson's ecological approach to mobile robots. *IEEE Transactions on Systems, Man, and Cybernetics, Part A*, 29(1), 105–111.
28. Norman, D. (1999). Affordances, conventions and design. *Interactions*, 6(3), 38–43.

29. Papisimeon, M., Pearce, A., & Goss, S. (2007). The human agent virtual environment. In: *Proceedings of the 6th international joint conference on Autonomous agents and multiagent systems*, (pp 1–8). Honolulu, Hawaii, AAMAS '07.
30. Rao, A. S., & Georgeff, M. P. (1991). Deliberation and its role in the formation of intentions. In B. D'Ambrosio & P. Smets (Eds.), *Proceedings of the Seventh Annual Conference on Uncertainty in Artificial Intelligence (UAI)* (pp. 300–307). Los Angeles, CA, USA: Morgan Kaufmann.
31. Rao, A. S., & Georgeff, M. P. (1995). Bdi agents: From theory to practice. In V. R. Lesser & L. Gasser (Eds.), *Proceedings of the First International Conference on Multiagent Systems (ICMAS)* (pp. 312–319). San Francisco, California, USA: The MIT Press.
32. Raubal, M. (2001). Ontology and epistemology for agent-based wayfinding simulation. *International Journal of Geographical Information Science*, 15(7), 653–665.
33. Saad, F. (1992). In-depth analysis of interactions between drivers and the road environment: contribution of on-board observations and subsequent verbal report. In: *Proceedings of the 4th Workshop of ICTCT*, University of Lund.
34. Six, L., Guessoum, Z., Saunier, J., & Ieng, S.S. (2013). Towards a truck-driver model using a hysteresis based analysis and verification approach. In M. L. Gini, O. Shehory, T. Ito, & C. M. Jonker (Eds.) *proceedings of the Twelfth International Conference on Autonomous Agents and Multiagent Systems (AAMAS'2013)*, IFAAMAS, (pp 1219–1220).
35. Stoytchev, A. (2005). Behavior-grounded representation of tool affordances. In *Proceedings of IEEE International Conference on Robotics and Automation (ICRA)*, (pp 3071–3076).
36. Tornros, J. (1998). Driving behavior in a real and a simulated tunnel: A validation study. *Accident Analysis & Prevention*, 30, 497–503.
37. Vasirani, M., Klugl, F., Camponogara, E., & Hattori, H. (Eds.) (2012). *Proceedings of the 7th International Workshop on Agents in Traffic and Transportation (ATT)*, AAMAS 2012, Valencia, Spain.
38. Wang, H., Kearney, J. J., & Cremer, Willemsen P. (2005). Steering behaviors for autonomous vehicles in virtual environments. In *Proceedings of the IEEE Virtual Reality Conference* (pp. 155–162). Germany: Bonn.
39. Weyns, D., & Holvoet, T. (2005). On the role of environments in multi-agent systems. *Informatica*, 29(4), 409–421.
40. Weyns, D., Schumacher, M., Ricci, A., Viroli, M., & Holvoet, T. (2005). Environments in multiagent systems. *Knowledge Engineering Review*, 20(2), 127–141.
41. Weyns, D., Omicini, A., & Odell, J. (2007). Environment as a first class abstraction in multiagent systems. *Autonomous Agents and Multi-Agent Systems*, 14(1), 5–30.
42. Xia, L., & Li, S. (2006). On minimal models of the region connection calculus. *Fundamenta Informaticae*, 69(4), 427–446.
43. Zieba, S., Polet, P., & Vanderhaegen, F. (2011). Using adjustable autonomy and human–machine cooperation to make a human–machine system resilient—application to a ground robotic system. *Information Sciences*, 181(3), 379–397.