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ORIGINAL RESEARCH

A robustness approach to the distributed management of traffic intersections

Cesar L. González[1] · Jorge L. Zapotecatl[2] · Carlos Gershenson[2] · Juan M. Alberola[3] · Vicente Julian[3]

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Abstract

Nowadays, the development of autonomous vehicles has emerged as an approach to considerably improve the traffic management in urban zones. Thanks to automation in vehicles as well as in other sectors, the probability of errors, typically due to repetitive tasks, has been drastically reduced. Therefore, technological aids in current driving systems are aimed to avoid or reduce human errors like imprudences or distractions. According to this, it is possible to tackle complex scenarios such as the automation of the vehicles traffic at intersections, as this is one of the points with the highest probability of accidents. In this sense, the coordination of autonomous vehicles at intersections is a trending topic. In the last few years, several approaches have been proposed using centralized solutions. However, centralized systems for traffic coordination have a limited fault-tolerance. This paper proposes a distributed coordination management system for intersections of autonomous vehicles through the employment of some well-defined rules to be followed by vehicles. To validate our proposal, we have developed different experiments in order to compare our proposal with other centralized approaches. Furthermore, we have incorporated the management of communication faults during the execution in our proposal. This improvement has also been tested in front of centralized or semi-centralized solutions. The introduction of failures in the communication process demonstrates the sensitivity of the system to possible disturbances, providing a satisfactory coordination of vehicles during the intersection. As final result, our proposal is kept with a suitable flow of autonomous vehicles still with a high communication fails rate.

Keywords Traffic intersection management · Vehicle coordination · Self-organized systems · Multiagent systems

1 Introduction

Traffic management has become increasingly complex as the number of vehicles in current cities increase. This requires more complex interactions between different elements, such as: vehicle to vehicle (V2V), vehicles to infrastructure (V2X), and vehicles to signals and traffic management devices (V2X) (Gregor et al. 2016).

In order to deal with this issue, several proposals have appeared in order to include automation at different levels: autonomous vehicles, sensing, wireless communications, etc. (Gregor et al. 2016). These proposals are focused on improving the connection between vehicles and infrastructure (interaction with all of the elements of a traffic system) and the self-driving in vehicles (achieving levels where each time is less necessary the intervention of human on the vehicle).

One of the main critical points in traffic management are intersections. This is caused due to the large number of interactions between the different elements (mainly vehicles)

✉ Vicente Julian
vjulian@upv.es

Cesar L. González
cegonpin@dsic.upv.es

Jorge L. Zapotecatl
zapotecatl@gmail.com

Carlos Gershenson
cgg@unam.mx

Juan M. Alberola
jalberola@dsic.upv.es

[1] Universitat Politècnica de València, D. Sistemas Informáticos y Computación, Universidad ECCI, Bogotá, Colombia

[2] D. de Ciencias de la Computación, I. de Investigaciones en Matemáticas Aplicadas y en Sistemas, Centro de Ciencias de la Complejidad, Universidad Nacional Autónoma de México, Mexico City, Mexico

[3] Universitat Politècnica de València, D. Sistemas Informáticos y Computación, Florida Universitària, Catarroja, Spain

that share lanes or have conflicting points. Some proposals include other elements such as pedestrians, bicycles, motorbikes, and other transportation systems (Rasouli and Tsotsos 2019; Rothenbücher et al. 2016; Zangenehpour et al. 2015). These proposals consider interactions between vehicles and humans that cross the same intersection, including irregular behaviors that can appear. The autonomous vehicles are able to recognize these behaviors, considering all the elements that share the intersection.

In the last few years, different strategies have been proposed to manage and control the traffic in intersections. These strategies are focused on avoiding collisions while maximizing the traffic flow (Ahn et al. 2016, 2014; Zapotecatl et al. 2017).

In the literature, we can find different centralized solutions for the problem of traffic intersection management (Bazzan and Klügl 2014; Wu et al. 2012; Dresner and Stone 2008; Guo et al. 2003). In these approaches, there is a unique control system that is the responsible of communication and coordination among all the elements in an intersection (vehicles, signals, traffic lights, etc.).

Centralized control systems take are in charged of taking the decision about which vehicles must cross first and which must keep waiting. Thus, if there are at least two vehicles that find a conflict point in the intersection, the centralized control system gives the crossing priority to one of them. Hence, an appropriate amount of space and time should be assigned to each vehicle in order to avoid conflict points in its trajectory.

Even though existing approaches have reported the benefits of using centralized traffic management systems, problems can arise when some changes in the environment appear, such as devices failures. Despite the fact that centralized proposals provide support to intersection management, there are still some challenges to be addressed in order to improve the vehicle management at intersections. These challenges are focused on decreasing the delay time, increasing the flow of vehicles, and making more tolerant the system against possible failures. This would result in avoiding traffic collapse at intersections, as well as requiring lower energy consumption.

In this paper we propose a distributed approach for efficient traffic management of autonomous vehicles at intersections. We define different behavior rules that should be followed by vehicles (Gonzalez et al. 2018). These rules define the coordination among the vehicles involved in the same intersection in order to determine the crossing priority. This approach has been tested with different densities of traffic and it has been compared with other centralized solutions, using the simulator toolkit provided in Zapotecatl (2014); Zapotecatl et al. (2017). In addition, this approach also takes into account possible communication failures during the execution. To do this, we define new rules that allow vehicles to take decisions when a vehicle loses its communication capabilities. This failure management has been compared with the semi-centralized approach proposed in Gershenson (2004). In this semi-centralized approach, the priority is given by the traffic lights, while our approach does not require external devices, such as traffic lights, or sensors on the infrastructure. In this sense, a cooperative behavior emerges in order due to the negotiation process among vehicles, which determines the crossing priority event with communication problems. In contrast, in centralized and semi-centralized systems, the autonomous vehicles cannot be organized and the traffic flow decreases abruptly even with low levels of vehicles density.

The rest of the paper is structured as follows. In Sect. 2, different related works with traffic intersection approaches have been analyzed. Section 3 defines the proposed model for the distributed traffic management including possible failures in communication processes. Section 4 shows the different tests made in order to compare the performance of our model in front of other approaches. Finally, in Sect. 5, main conclusions of this work and some future research lines are presented.

2 Intersection control approaches

Several studies related to traffic control have focused on the coordination of vehicles in intersections (Bazzan 2005). One of the most popular techniques is the green wave, which uses a centralized coordinator that manages traffic lights. These traffic lights change periodically, given time to each of the different vehicle lanes to cross the intersection without collisions. However, these techniques usually do not provide adaptation in the decision making process when changes in the environment occur (Bazzan 2005). As an example, the time given for each lane does not automatically change in cases where there is a traffic jam in a blocked lane where the opposite crossing lane is empty of traffic.

In order to solve this issue, more flexible approaches that consider autonomous and semi-autonomous vehicles have appeared. Dresner and Stone (2005, 2006, 2008) present a centralized solution called Autonomous Intersection Management (AIM). This solution provides a control system that is in charge of defining the crossing priority to autonomous vehicles in a conflict intersection. The IAM receives requests from the autonomous vehicles as they are approaching to the intersection. This manager denies or accept each request depending on the collision risk. In case that some collision possibility may exist, the request is denied, otherwise, it is accepted. When a request is accepted, the IAM makes a reservation of space and time during intersection by following a FIFO policy, which avoids extremely long waiting periods. However, the fault tolerance of this type of techniques is quite limited, since the centralized manager can be overloaded of requests or it can even fail.

Another centralized proposal is presented in Ahn et al. (2014), Ahn et al. (2016), Ahn et al. (2016). In this case, a less restrictive supervisor is used to schedule the vehicles crossing at the intersection. This supervisor queues crossing requests as scheduled jobs and it only acts if there is two or more job entries that overlap each other. This model determines the time at which each vehicle is expected to arrive at the intersection, the time required to cross, and the time required to leave the intersection. The advantage of this model is that the autonomous vehicles are operating by themselves until the supervisor detects that a collision can appear. This gives more efficiency in terms of response time than the previous approach. However, the scalability of this model is still limited since it has been tested in a single intersection but not in a large city with hundreds of intersections to be managed. Other approaches related to automation and control also provide centralized models for crossing management in intersections, such as Bazzan and Klügl (2014). Guo et al. (2003) and Wang (2005) show the use of a control system that includes different control levels. In this approach, the centralized manager gives always the crossing priority as long as exists a request by the vehicles over the intersection.

As it can be observed, the use of centralized intersections management systems has become very popular. Authors of centralized proposals state that keeping all the information in a single system guarantees an arrangement of orders to cross without collisions. However, as we commented above, efficiency, fault-tolerance and scalability may become critical issues. Other approaches, focus the crossing management problem in a distributed fashion. Wu et al. (2012) and Grünewald et al. (2006) present a distributed control that gives the autonomous vehicles the responsibility of reaching an agreement when crossing intersections. This may cause that an autonomous vehicle decides to cross by itself, causing a collision or blocking the intersection.

Multiagent systems and other Artificial Intelligence techniques such as fuzzy inference have been also used for intersections management. Kosonen (2003) propose a multiagent system to change the traffic lights state. In this approach, a negotiation is carried out between an agent manager and her neighbors in order to determine the crossing priority. Parameters such as density, behavior, or flow are taken into account during the negotiation. In Koźlak (2008), a multiagent system is used to guide the intersection by forecasting the traffic flow of the vehicles. Roozemond (2001) propose a multiagent system composed by a road agent, a control agent and an intersection agent in order to manage intersection crossing.

In the literature we can also find works related to swarm intelligence (De Oliveira et al. 2005) and self-organization (Gershenson 2007), which approach the problem from the perspective of cooperative intelligence. In these approaches, a complex system is coordinated to reach a main goal. In the first work, a swarm intelligence algorithm is applied, in which agents interact to each other without the control of a centralized entity. Authors show in their research that agents reach a significant performance but this require a long time. This can be a negative issue in complex and dynamic environments that require a real-time response. In the second work, the traffic lights are capable of self-organize by themselves, giving the autonomous vehicles the possibility of crossing fluently with few stops. This proposal integrates rules that give crossing priority to convoys over single vehicles.

Although distributed approaches may overcome the efficiency and scalability problems of centralized approaches, there is still some lack of support for fault-tolerance. In this sense, autonomous vehicles are expected to work properly in order to coordinate to each other in a distributed fashion. One of the main advantages of distributed systems for crossing management is the robustness when failures occur. In contrast to centralized approaches, bottlenecks can be avoided and thus, the system may respond properly without causing an operative decrease in efficiency or even collapsing. In this paper, we present a distributed proposal for crossing management in intersections that consider failures in vehicles. When a failure is detected, the system can respond to manage intersection crossing without collisions

3 Distributed intersection management model (DIM)

In the last few years, technological advances have allowed the development of devices used in the automotive industry (autonomous vehicles, communications systems such as V2V and V2X, intelligent algorithms, images and video recognition, network processing, etc). These technologies, give the automotive industry important improvements related to energy consumption, fewer traffic accidents, fewer emissions and reduction of traffic jams (Bagloee et al. 2016).

Nowadays, a high growth in prototypes of autonomous vehicles can be seen in different companies: the models of Google (Waymo), Tesla Motors, Aptiv (Delphi Technologies), Zenuity (Autoliv and Volvo Cars), Baidu, BMW-Intel-Mobileye, Daimler-Bosch, CISCO-Hyundai, Ford-ARGO, GM-Lyft, Nvidia-Paccar, Honda, Uber, Nissan-Renault, Toyota-University of Michigan, Volkswagen, Waymo-FCA (Fiat Chrysler Automobiles). These companies and many others have been dabbled inside this technology with the joint effort to show a first generation of autonomous vehicles in the following 6 years (2023) (Knight 2013; Kaplan 2018). In short, the use of autonomous vehicles is expected to give passengers safer journeys with the possibility of avoiding crashes. One way of dealing with the development of this type of autonomous system is to emulate behaviors of natural systems such as cooperative systems, in order to coordinate autonomous vehicles promoting the interaction among them (Ioannou 2013).

In this section, we present the Distributed Intersection Management (DIM), which is a system to provide autonomous vehicles with the capacity to negotiate and manage crossings at intersections (Gonzalez et al. 2018). This system is aimed at being scalable and flexible as well as achieving similar levels of efficiency than a centralized system. In addition, this model incorporates fault-tolerance in order to efficiently respond to failures in vehicles. The DIM model is composed by three parts: the traffic flow model, the autonomous vehicle model, and behavioral roles.

3.1 Traffic flow model

We require the support of a dynamic model that shows the behavior of vehicles with a specific trajectory as well as their relationship with the rest of vehicles that are around them. The traffic flow model of DIM is based on the LAI (Lárraga and Alvarez-Icaza 2010) model for large traffic networks simulation. LAI is a model for traffic flow that captures the vehicles' reactions in a real environment. Specifically, the model incorporates individual characteristics and acceleration constraints of vehicles in the definition of lane changing decision process in order to simulate asymmetric two-lane traffic flow. According to this model, three main rules are used to represent the behavior of a vehicle:

- A vehicle a_i can accelerate as long as exists a distance D_{acc} between this vehicle and the vehicle that comes before a_{i+1}.
- A vehicle a_i keeps its velocity as long as exists a distance $D_{keep} < D_{acc}$ between this vehicle and the vehicle that comes before a_{i+1}.
- A vehicle a_i has to decrease its velocity if exists a distance $D_{brake} < D_{keep}$ between this vehicle and the vehicle that comes before a_{i+1}.

The above three rules provide the mechanism to maintain safe distances among the vehicles, guaranteeing safe driving. As long as safe distances exists between a vehicle and its predecessor, collisions will be avoided between these vehicles.

The LAI model defines three equations to calculate safe distances according to the above rules (Lárraga and Alvarez-Icaza 2010). These equations are incorporated into the DIM model to describe the dynamics of the vehicles on the same trajectory and lane. In addition, we based our distributed model on the centralized negotiation model proposed by Gershenson (2004) Cools et al. (2013) and Gershenson and Rosenblueth (2012), which is used as the basic model for the design of the distributed rules for autonomous vehicles.

3.2 Autonomous vehicle model

We assume a group of agents $A = a_0, \dots, a_n$ that represent autonomous vehicles moving through the different streets of a city. Each vehicle a_i includes sensors to detect other vehicles that are inside an area. Each vehicle is also provided with a wireless communication system to send messages and request information to other vehicles.

To represent this, each autonomous vehicle a_i defines two radius: the perception radius and the communication radius. The perception radius P_r defines a detection area inside which, other autonomous vehicles are detected by the sensors of a_i. This radius simulates LIDAR[1] sensors (see Fig. 1a).

The communication radius C_r defines a communication area inside which, other autonomous vehicles receive messages sent by a_i. Messages can be delivered to specific receivers or can be broadcasted to any receiver inside this area (see Fig. 1b).

3.3 Behavioral roles

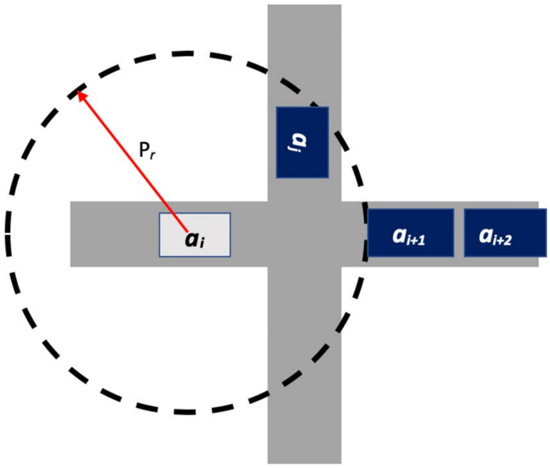
An autonomous vehicle can play two different roles: follower and negotiator. The role played by an autonomous vehicle depends of information that receives and the actions the vehicle can take. This is similar to the approach already proposed in the context of automated highway systems in the 1990s (Li et al. 1997).

The follower role (represented as F_v) is played by autonomous vehicles that are moving just behind another vehicle. At the beginning of the execution, every autonomous vehicle has associated this role. An autonomous vehicle a_i plays F_v if it detects another vehicle a_{i+1} driving before it, inside the detection area defined by P_r. In this situation, a_i has the goal of keeping its safe distance with a_{i+1} (see Fig. 3a).

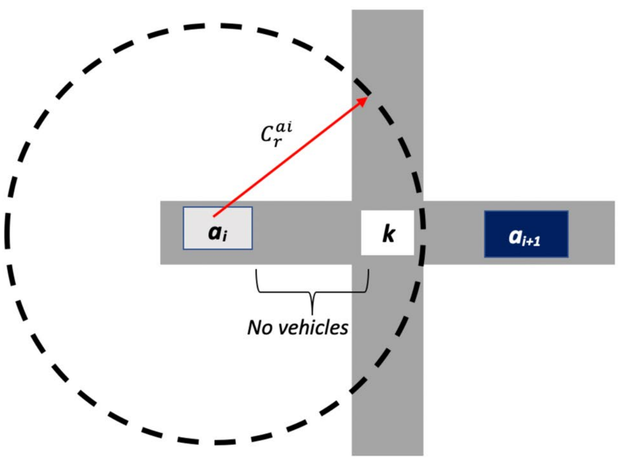
A vehicle a_i playing F_v is able to detect the distance with respect to the vehicle that comes before a_{i+1}. Taking into account its safe distance, it could decide to increase, to keep or to decrease its velocity according to the above commented LAI model rules.

The negotiator role (represented as N_v) is played by autonomous vehicles that do not detect other vehicles inside their communication areas and before the next intersection k (see Fig. 2b).

[1] https://news.voyage.auto/an-introduction-to-lidar-the-key-self-driving-car-sensor-a7e405590cff.

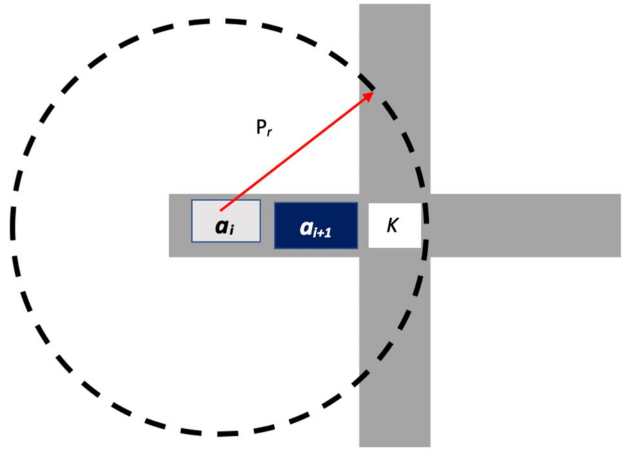


(a) Perception radius.

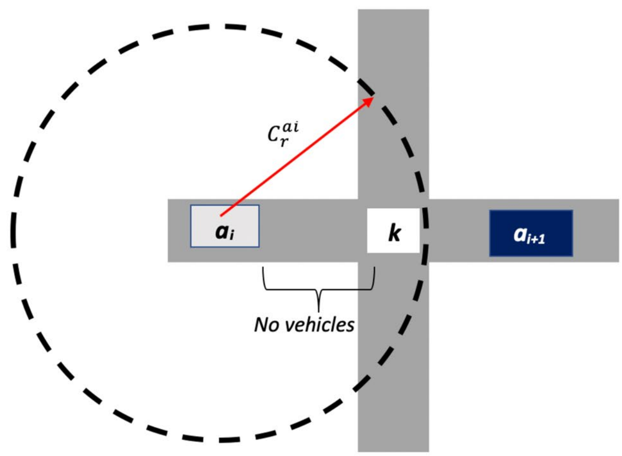


(b) Communication radius.

Fig. 1 Example of the perception radius and the communication radius



(a) a_i plays F_v, keeping safe distances with a_{i+1}.



(b) a_i plays N_v.

Fig. 2 Examples of the roles played by a vehicle

When a vehicle a_i starts playing role N_v, this vehicle broadcasts a message with information of its position and velocity with respect to intersection k. If a vehicle a_i playing role N_v intersects its $C_r^{a_i}$ (communication radius of vehicle a_i) with the $C_r^{a_j}$ (communication radius of vehicle a_j) of another vehicle a_j playing role N_v in a conflict way, they must share the information of velocity and positions in order to negotiate who should be the first to cross at the intersection (see Fig. 3).

Finally, a vehicle playing role N_v leaves this role, when it enters in the intersection and shares its messages to the new vehicle with role N_v behind it.

3.4 Negotiation between autonomous vehicles

When crossing an intersection, a set of priority rules must be followed by each autonomous vehicle that is trying to cross it. These priority rules determine a negotiation process among the vehicles that obtains the priority to cross that should be cooperatively fulfilled in order to achieve the expected behavior of the system. Following, we define these priority rules in more detail.

3.4.1 Intersection blocking avoidance

The first priority rule is called *Intersection blocking avoidance* and it is defined in order to prevent any blocking situation in the intersection. Let us suppose a vehicle a_i playing role N_v that is arriving to an intersection k. If a_i detects

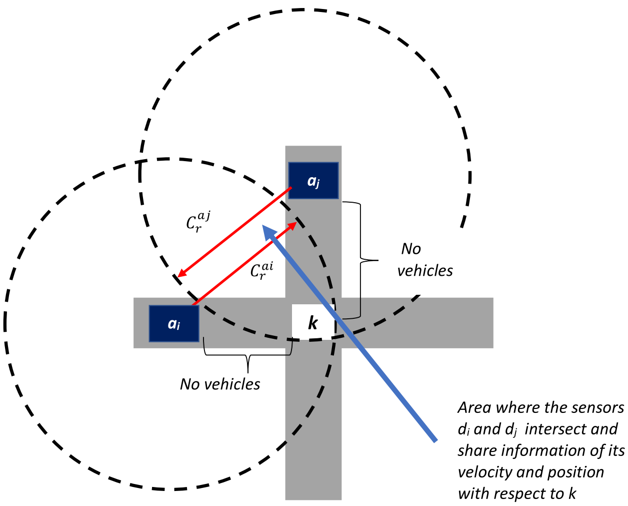


Fig. 3 vehicle a_i playing role N_v sharing information with vehicle a_j playing role N_v in a conflict way intersecting their communication radius ($C_r^{a_i}$ and $C_r^{a_j}$)

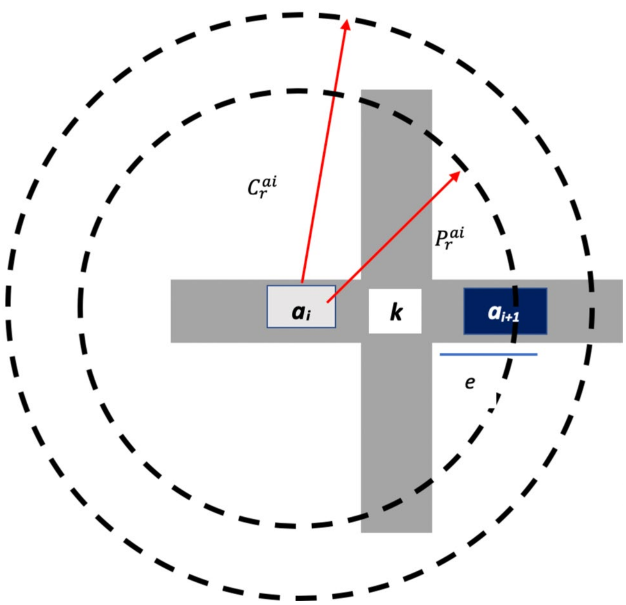


Fig. 4 a_i avoids crossing the intersection k if a_{i+1} is in a distance shorter than e from the intersection

another vehicle a_{i+1} inside its communication radius $C_r^{a_i}$ or its perception radius P_r that has crossed the intersection k but it still remains in a distance lower than e with respect to the intersection, the vehicle a_i must start decreasing the speed before arriving to the intersection. In this case, a_i avoids crossing the intersection k until vehicle a_{i+1} is in distance large than e from the intersection. As a last resort, vehicle a_i must stop before the intersection (see Fig. 4).

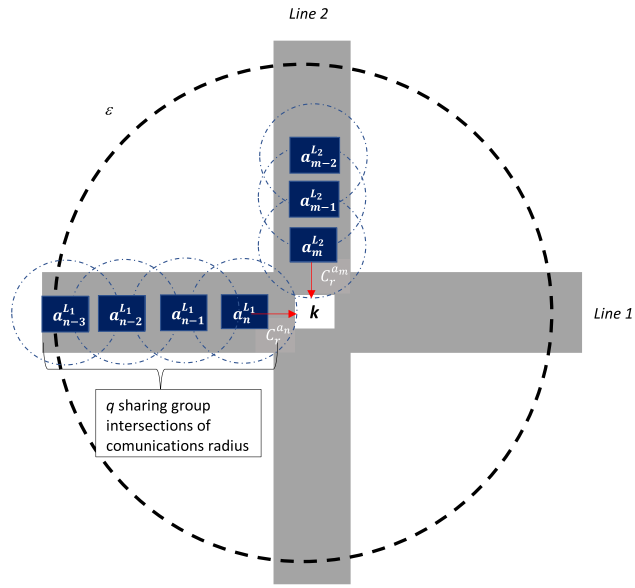


Fig. 5 The queue of vehicles in lane 1 has priority to cross over vehicles in lane 2

If there exists two conflict lanes L_1 and L_2 with a vehicle in each line (a_n and a_m, respectively) in a distance shorter than e from the intersection k, then, this priority rule is executed until any of the two lanes gets a distance larger than e. If both lanes achieves this condition at the same time, then the vehicle playing role N_v whose waiting time is larger gets the priority to cross.

3.4.2 Convoy

The *Convoy* priority rule is defined to allow crossing convoys of vehicles. We define a convoys as a group of autonomous vehicles that are in the same lane. In this sense, this priority rule determines that convoys have priority for crossing over individual vehicles. According to this, a vehicle a_n playing role N_v in lane L_1 has priority for crossing over the lanes in conflict L_2 if the amount of vehicles q behind a_n is greater than the vehicles of lane L_2. To calculate this q, we introduce a threshold ϵ which indicates the distance limit of a queue of vehicles in the same lane before an intersection (see Fig. 5).

3.4.3 Waiting time limit

We define a third priority rule called *Waiting time limit* in order to prevent vehicles to be stopped at the intersection during more than a waiting time limit. This limit depends on the vehicle playing role N_v that complete a convoy of vehicles q_t such that:

$$q_t = \sum_{i=1}^{n} c \tag{1}$$

where c is the number of vehicles detected by N_v in each step of time i and n represents the number of steps required in order to change the lane (Eq. 2).

$$\gamma - q_t < 0 \tag{2}$$

where γ represents a threshold such that if it is exceeded, the priority of crossing is changed.

3.5 Communication failures

Most of the distributed systems for managing intersections assume that the different elements involved in the management process are working properly. However, these systems may become unpredictable when failures occur in some devices, such as, autonomous vehicles. In this sense, interactions may not be monitored with the same accuracy than in centralized approaches and collisions can appear.

According to this, apart from the efficiency and the scalability, distributed systems are required to be fault-tolerant and robust against failures. Therefore, the DIM model integrates support for communication failures of autonomous vehicles. In this sense, sensors are used to supply these failures.

We represent as Cf_v the role played by an autonomous vehicle a_i that has a communication failure, i.e. this vehicle is not capable of sending and receiving messages to other vehicles. In this situation, a_i only has activated its $P_r^{a_i}$. This vehicle uses the perception radius to safely cross the intersection when there is not any other vehicle in the conflict lane, stopped, or that has just crossed the intersection but it is still in a distance lower than e with respect to the intersection. Otherwise, the vehicle a_i stops before the intersection.

Each vehicle that is playing the role Cf_v must stop during a waiting time depending whether the corresponding vehicle playing role N_v has exceeded the threshold γ or not. If this occurs, the last vehicle N_v that exceeded the threshold acquires the Behavioral role with communication failures.

If all the vehicles are playing the role Cf_v, then the crossing would be carried out one by one, giving the priority to one of the lanes.

4 Experiments

In this section, we show different experiments in order to test the DIM model. To do this, we use the simulator tool developed by Zapotecatl (2014), which is based on a cellular automata. This tool simulates the dynamics of traffic in cities composed by streets and intersections. It has been developed following the rules of LAIE's[2] model (Zapotecatl 2014; Gershenson and Rosenblueth 2012; Zubillaga 2014).

We compare the performance of our DIM model with two other traffic intersection management systems. The first system (Green Wave) is a traditional approach in which traffic lights are the responsible of setting the priority in each intersection. In this approach, the traffic light switches between green and red light every period of time, giving priority to the vehicles located in the line with green light. The second system (semi-centralized) is the self-organizing proposal developed by Gershenson (2004), Gershenson and Rosenblueth (2012) and Cools et al. (2013). This system can adapt the traffic lights in order to give priority to lanes that complies with features as clustering of vehicles or convoys, free lanes forward of the intersection, and empty intersections.

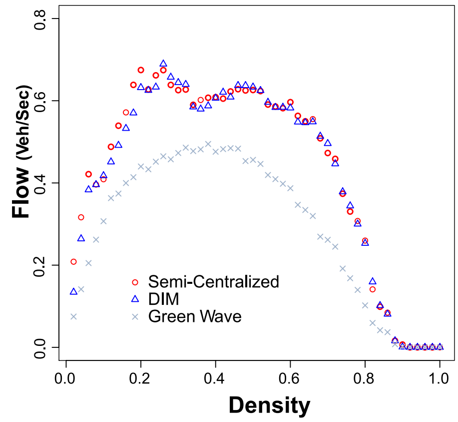
The experiments evaluate performance of the three systems in a Manhattan-style grid with a first setting of 4 intersections, afterward 25 intersections, 100 intersections and finally a setting with 225 intersections. We start from a traffic density of 0.02 and we increase this density until reaching 1 (that means a collapse where no vehicle is moving because all spaces are occupied). Each density was repeated 20 times with different initial random positions of vehicles.

Figure 6a shows the performance of the three intersection management systems in a city with four intersections. In the figure it is shown the vehicles flow performance as vehicles density increases. As it can be observed, the behavior of the three systems is similar for low traffic densities. However, as the density is greater than 0.2, the behavior of the Green Wave system is worse than the other two systems. This is caused because the lights turning system causes that vehicles gets more collapsed as the number of vehicles increases. In contrast, the other two systems are more scalable and both maintain good taxes of performance until values of density of 0.7. From this moment on, the performance of both systems considerably decrease. The maximum flow achieved by Green Wave is 0.49 for density 0.38, while the performance of the other two systems is very similar, achieving a maximum flow of 0.68 in DIM and 0.67 in the semi-centralized approach.

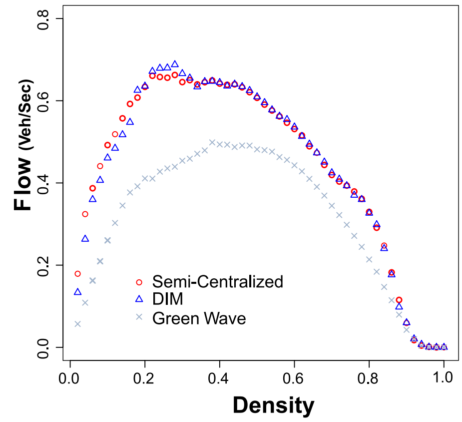
Figure 6b shows the performance of the three systems in a city with 25 intersections. Similarly than the previous experiment, the performance of Green Wave is worse than the other two systems, whose performance is quite similar in the whole experiment. In contrast to the previous experiment, the performance decrease of DIM and the semi-centralized system is not so abrupt than for the city of four intersections. However, this decrease starts earlier, around density values of 0.5 on.

[2] The LAIE's model is an extension of the LAI model, which introduces conflict ways but maintaining the same dynamic model.

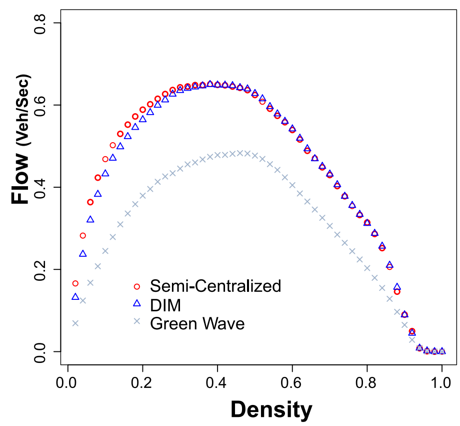
Fig. 6 Results of experimentation (flow vs density)



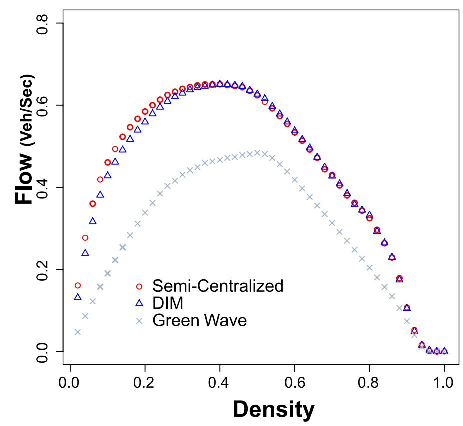
(a) Flow vs Density. City Manhattan style of 4 intersections.



(b) Flow vs Density. City Manhattan style of 25 intersections.



(c) Flow vs Density. City Manhattan style of 100 intersections.



(d) Flow vs Density. City Manhattan style of 225 intersections.

Figure 6c, d show the performance of the three systems in cities of 100 and 225 intersections, respectively. Both experiments show similar behaviors than the previous experiments. However, as the density increases, the behavior of Green Wave is significantly lower than the other two approaches. In this sense, the maximum flow achieved by Green Wave is 0.48 for density 0.5, while the performance of the other two systems achieves a traffic flow of 0.65, maintaining similar values for density ranging from 0.2 to 0.6. As it can be observed, the performance of the DIM system is quite similar to the semi-centralized approach.

Figure 7a–d show the average velocity reached by the vehicles during intersections for the four types of cities. It can be observed that the performance of Green Wave is again lower than the other systems for density values up to 0.5. In this sense, the velocity differences between Green Wave and the other two systems are higher for low values of densities. This reflects that DIM and the semi-centralized approaches can manage situations of low traffic better than Green Wave. For densities greater than 0.5, the performance of the three systems is quite similar. This is caused due to as the density increase, the average velocity tends to decrease until the city is collapsed by vehicles and the velocity reaches 0.

Figure 8a–d show the performance of the three systems for the four types of cities in terms of average waiting time in intersections. Similar to the previous experiments, the performance of Green Wave is worse than the other systems. In this case, the maximum difference appears with the lowest density values. This is because vehicles stop several times during the execution because they find some red lights. In contrast, DIM and the semi-centralized system show very short waiting times with low densities. This is caused by the rules for dynamically changing the traffic lights in the case of the semi-centralized approach and by the reactive

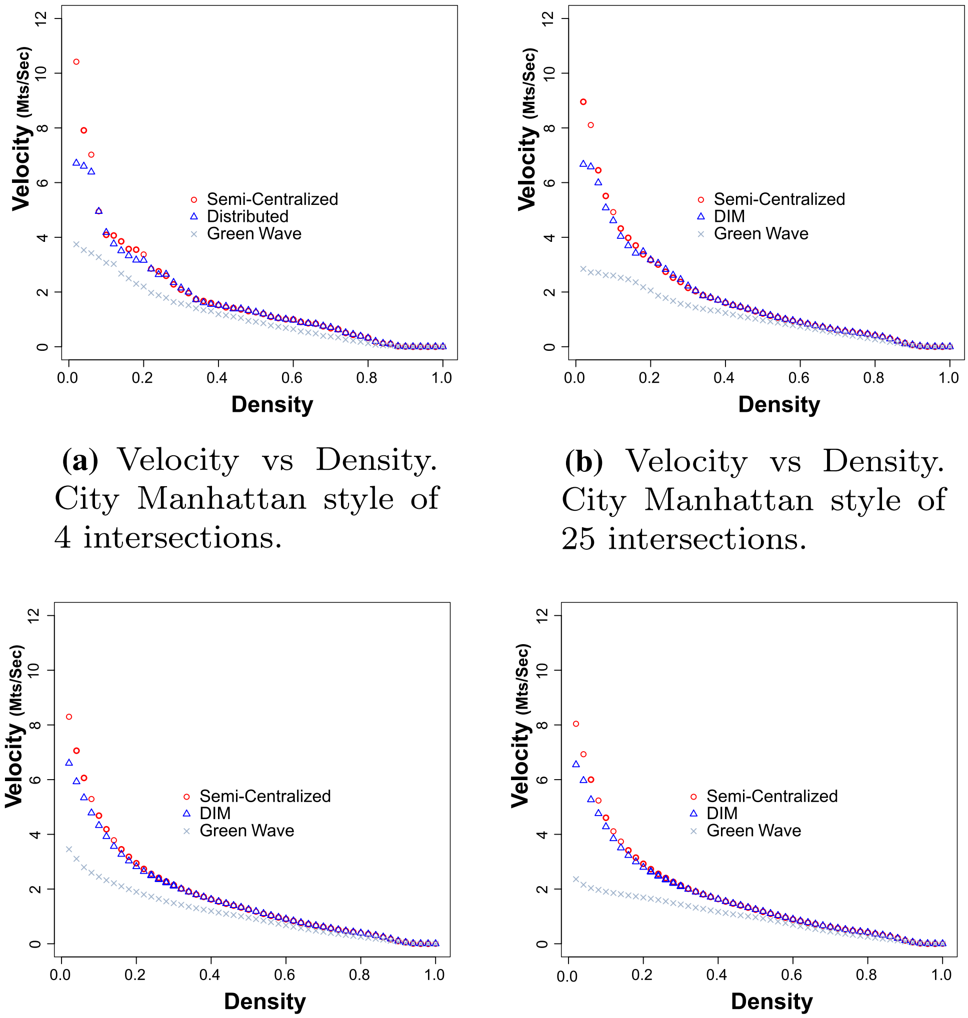


Fig. 7 Results of experimentation (velocity vs density)

(a) Velocity vs Density. City Manhattan style of 4 intersections.

(b) Velocity vs Density. City Manhattan style of 25 intersections.

(c) Velocity vs Density. City Manhattan style of 100 intersections.

(d) Velocity vs Density. City Manhattan style of 225 intersections.

negotiation in intersections in the case of the DIM system. For densities greater than 0.5, the performance of the three systems becomes similar since the traffic tends to collapse the city. Note that the average waiting time is quite similar for the four city sizes. Therefore, the number of intersections does not seem to have much influence in the performance.

4.1 Experiments on communication failures

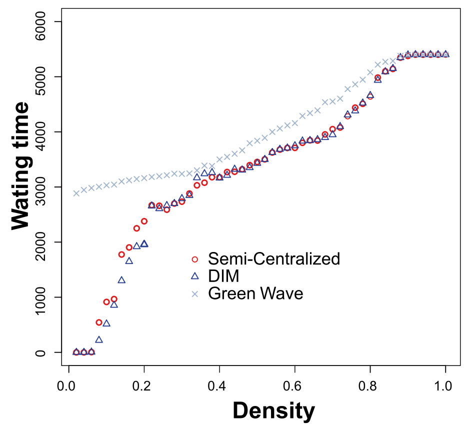
In this section, we show different experiments that test the performance of the system when some communication failure occurs. We compare the performance of our DIM model with the semi-centralized system. In the case of the semi-centralized approach, communication failures are represented as fails in the traffic lights. Therefore, vehicles are expected to cross the intersection without stopping. In the case of DIM, communication failures are represented as communication problems in the vehicles. Therefore, a vehicle with communication failures is not able to coordinate the crossing with other vehicles.

The experiments evaluate the performance of both approaches in a city represented as a Manhattan-style grid with 100 intersections. We test different percentages of vehicles with communication failures, from 25% (i.e. most of the vehicles can communicate properly) to 100% (i.e. all the vehicles have communication problems). The vehicles with communication failures are randomly selected.

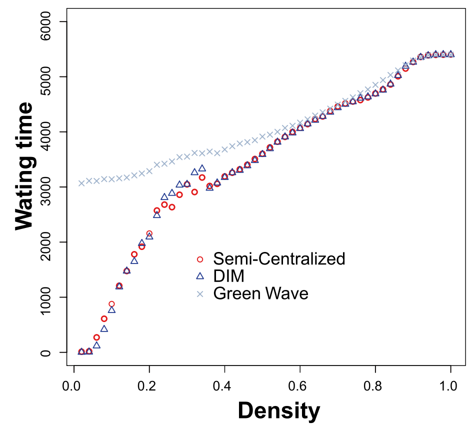
Similarly to the experiments commented above, each simulation starts from traffic density of 0.02 and this density increases until reaching 1 (i.e. the city is collapsed and all spaces are occupied by vehicles). Each density was repeated 20 times with different initial random positions of vehicles.

Figure 9a, b show the performance of both approaches. As it can be observed, the vehicles flow of the semi-centralized

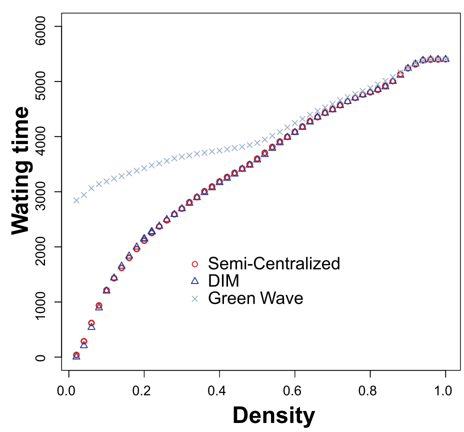
Fig. 8 Results of experimentation (waiting time vs density)



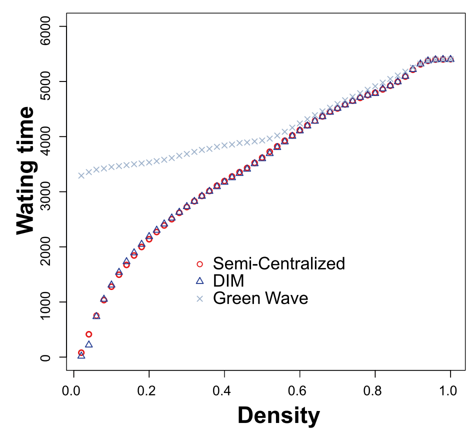
(a) WaitingTime vs Density. City Manhattan style of 4 intersections.



(b) WaitingTime vs Density. City Manhattan style of 25 intersections.



(c) WaitingTime vs Density. City Manhattan style of 100 intersections.

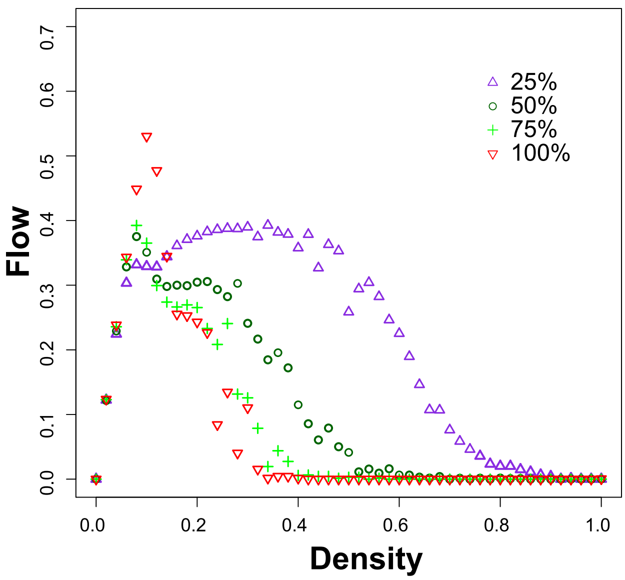


(d) WaitingTime vs Density. City Manhattan style of 225 intersections.

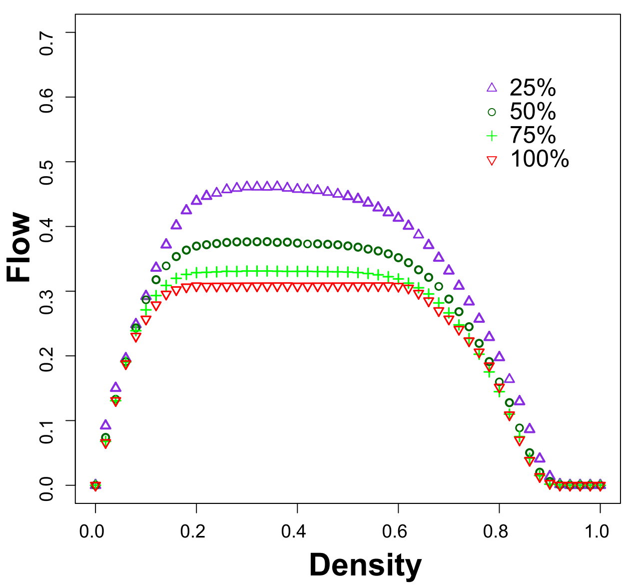
approach is influenced by the percentage of failures. For a percentage of 25%, the maximum flow does not exceed 0.4 and this flow abruptly decreases between 0.5 and 0.7, becoming close to 0 from density 0.8 on. As this percentage is increased, the results get dramatically worse. As an example, for 50% of failures, the maximum flow is around 0.3 for values of density lower than 0.3. From densities values greater than 0.5, the flow is practically null. In contrast, the DIM system shows a better behavior against failures. As it can be observed in the figure, for a percentage of 25%, the flow achieves values around 0.6 for densities values from 0.2 to 0.6. This shows a more stable behavior compared to the semi-centralized approach. What is more, this stability against failures can be observed for any percentage of failures. Although flow values are lower as the percentage of failures is increased, these values are quite similar for density values ranged between 0.2 and 0.6. In contrast to the semi-centralized approach, the abruptly decrease does not occur until large values of density (greater than 0.7). Therefore, the distributed approach provides more tolerance against failures.

5 Conclusions

In this paper, we proposed the DIM model for supporting the distributed management of traffic intersections. In this model, each autonomous vehicle uses message exchange to coordinate with other vehicles in order to safely and efficiently cross intersections. As it could be observed by the tests, the performance of the DIM model is quite similar to other centralized adaptive approaches such as



(a) Semi-centralized model.



(b) DIM model.

Fig. 9 Robustness with communication failures

the one proposed by Gershenson et al. In addition, since it is a distributed approach, it can be more robust against failures. At the same time, our proposal outperforms other conventional traffic control systems such as Green Wave in terms of velocity, waiting time and traffic flow.

The coordination of autonomous vehicles in DIM does not require a central control for management. Therefore, this distributed system is more scalable since there is not any centralized manager that could become a bottleneck. In addition, DIM is much tolerant to changes in the conditions of the environment and possible device failures.

With regard to adaptive centralized systems, the DIM model requires less hardware and road infrastructure for traffic management. Due to the roles defined for the vehicles, the negotiation rules are considered suitable for crossing intersections in a safe way without obstructing the critical areas of the intersection.

Furthermore, according to the experiments, the DIM model is more robust that the semi-centralized model against failures. As it could be observed, our proposal allows the system to maintain a constant vehicles flow with the 50% of vehicles with communication failures. In contrast, the performance of the semi-centralized model decreases when some communication failures occurs, even with low levels of traffic density.

As a future work, it is planned to include in our model the possibility of considering multiple lanes and directions. Additionally, the model will include the possibility to define vehicles with different priorities in order to have vehicles with more preference at intersections.

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