Information sharing among autonomous vehicles crossing an intersection

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Abstract— **In this paper we compare the performance of autonomous vehicles at intersections with respect to the type of information shared. For this purpose we consider the cases where vehicles share or not information about their inertia and their intention at the intersection. An existing control method based on navigation functions is modified in order to take into account such information. The results show that if autonomous vehicles know each other's inertia they achieve significantly smoother paths, use less fuel and more often avoid full stops.**

Keywords- Autonomous vehicles, intersection, multi-agent system, communication

I. INTRODUCTION

Recent researches in intelligent transportation systems envisage that autonomous vehicles operating in modern urban areas are soon going to be a reality [1–3]. In this paper, we focus on the coordination of autonomous vehicles at intersections. Nowadays, traffic lights, stops or priority signs assist human drivers to safely cross intersections. However, in the future, with computers behind the wheels, innovative driver assistance systems or autopilots have to be designed. One of the challenges in this area of research is to find coordination methods improving vehicle performances at intersections. There are generally two different approaches to solve this problem. One approach is to design a centralized controller for an intersection or an urban area. Autonomous intersection management project is based on this approach [4]. A second approach is to rely on decentralized control to increase reliability and robustness and to decrease communication costs by reducing complexities.

The problem of coordinating autonomous vehicles at intersections in a decentralized way was first touched in [5] where a decentralized navigation function is introduced. Navigation functions are practical tools introduced in robotics for solving collision avoidance problems [6] such as formation [7], rendezvous and consensus scenarios. Decentralized navigation functions have two great benefits. First, compared with centralized approaches, navigation functions show a relatively low complexity with respect to the number of agents, in our case vehicles [8]. Second, it is possible to consider dynamic models for vehicles rather than simple kinematic ones.

When using decentralized navigation function method for vehicles crossing an intersection, one main question is which type of information is required for every vehicle to cross the intersection without collision. There is a trade off between the complexity of the communication and efficiency of the method.

In this paper we investigate how sharing additional information rather than just the position of the vehicles could improve the performance of the whole system. For this purpose we consider the cases where vehicles can share information about their inertia and their intention at the intersection. To be able to use this information, we add appropriate terms to the initial navigation function. So, the vehicles use this information to coordinate and pass the intersection without collision.

The remainder of this paper is organized as follows. In section 2 the problem of passing an intersection is formulated and a dynamical model of the vehicles is introduced. It is simple enough to enable the handling of complex traffic situations and complex enough to capture real-world limitations. In section 3, a decentralized navigation function that enables taking dynamical constraints into account is proposed. In section 4, modified navigation functions based on available information are presented. The evaluation of the proposed approached is presented in section 5. Results of this evaluation are discussed in section 5. Section 6 briefly explores some avenues for future research and concludes.

II. PROBLEM FORMULATION

We consider the system as an intersection scenario involving autonomous vehicles (Fig. 1). The considered multi-vehicle system considered consists of N autonomous vehicles. The goal of each vehicle is to cross the intersection without having any collision with other vehicles.

The position of vehicle i is known as $q_i = (x_i, y_i)$ in a global frame attached to the intersection. The path of the vehicle is predefined for the vehicle and can be described by path parameter s_i. Therefore, the position of the vehicle in the global frame is directly calculated from its location along the path using the parametric function $q_i = f_k(s_i)$ corresponding to the path k the vehicle chooses. This parametric function is an injective function, which means that computing the location of the vehicles along its path is straightforward knowing its global location and the path it has chosen. The motion of each vehicle along its path is modeled using second order dynamics along the path:

$$\ddot{s}_i = a_i \tag{1}$$

a_i is the acceleration of the vehicle along the path. The proposed dynamic model is realistic as the assumption of predefined paths is valid for autonomous vehicles driving to their destinations. Additionally, using this dynamic model, it is possible to introduce real-word acceleration and braking constraints, defined as $a_{\max}$ and braking $b_{\max}$, respectively.

The speed limit is given by a function of the path parameter $v_{\max} = v_{\lim}(s_i)$ such that the centripetal acceleration in the bends remains below a certain value. So, the speed of vehicle along its path $\dot{s}_i$ is bounded to the interval $[0, v_{\max}]$.

The problem is now to find a decentralized controller that guarantees safety of vehicles and high capacity of intersection while facing the mentioned real-world limitations related to acceleration, speed and braking. The proposed method is a navigation function for each vehicle, which gives the possibility to control the vehicles in a decentralized manner.

III. DECENTRALIZED NAVIGATION FUNCTION

A navigation function is practically a smooth mapping which should be analytic in the workspace of every vehicle and its gradient would be attractive to its destination and repulsive from other vehicles. So, an appropriate navigation function could be combined with a proper control law in order to obtain a trajectory for every vehicle leading to the destination and avoiding collisions. Although the navigation functions presented in [9] and [10] provide a stable solution and exhibit strong analytical properties, it has not been studied from scalability and computation point of views. In the navigation problem as formulated in [5], the main purpose is to modify the navigation function to take into account the dynamical characteristics of the vehicles. In our work the main concern is the opportunity to add different type of information about other vehicles to the navigation function. This actually adds the possibility of energy optimization at the intersections, by limiting as much as possible the costly velocity changes.

As a consequence, it is well conditioned to handle local traffic conditions in which many vehicles are involved.

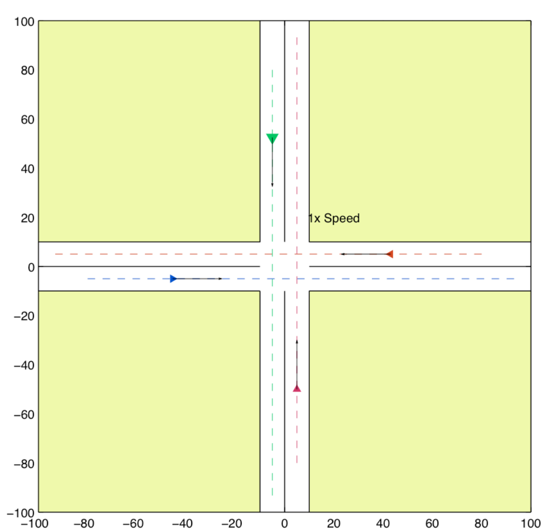


Figure 1 intersection scenario with autonomous vehicles

$$\phi_i = \lambda_1 \left\| q_i - q_{di} \right\|^2 + \lambda_2 \sum_{i \neq j} \frac{1}{\beta_\sigma(q_i, q_j)} \quad (2)$$

The proposed function (2) is composed of two terms. The first term is the squared distance of vehicle i from its destination and attains small values as the vehicle approaches the goal. The second term aims at avoiding collision between vehicle i and all other vehicles located in its visibility zone. Various functions can be chosen for $\beta_\sigma(.)$, providing that core properties are kept. These properties are directly connected to the visibility zone of the vehicles and the fact that the navigation function should be an analytic mapping. This function should be small when vehicle j is in the visibility zone of vehicle i in order to create a strong repulsive force and avoid collision risks. This function should be equal to 1 when the vehicle j is out of visibility zone of vehicle i. The function $\beta_\sigma(.)$ given in (3) has been chosen. Its value is close to zero for very short distances between two vehicles and is equal to 1 at distance σ.

$$\beta_\sigma(q_i, q_j) = \begin{cases} 3\left(\frac{\| q_i - q_j \|}{\sigma}\right)^2 - 2\left(\frac{\| q_i - q_j \|}{\sigma}\right)^3 & if \ \| q_i - q_j \| < \sigma \\ 1 & else \end{cases} \quad (3)$$

According to the navigation function presented in (2) and the vehicles dynamics defined in (1), the following control law is proposed:

$$u_i = -k_i \nabla_{q_i} \phi_i \quad (4)$$

In every step, the vehicle will move according to gradient descent method. k_i is step-size parameter that could be tuned in order to have a collision free crossing. As it has been mentioned before all vehicles move in their predefined lane. This means that vehicles do not move laterally.

IV. AVAILABILITY OF INFORMATION

In this work, we investigate the impact of the type of information shared with other vehicles on performances. The navigation function introduced in the previous section relies on the position of all vehicles. Every vehicle needs its position, velocity and the path. This information could be easily derived from onboard or GPS instruments.

In addition to sharing position, we investigate in this section the benefit for the vehicles to share information about their inertia and their intention at the intersection (i.e. the path they will follow). To be able to use the information, we add appropriate terms to the initial navigation function so the vehicles use this information to coordinate and pass the intersection without collision. In all the options we take into account the fact that vehicles can communicate when they are at a distance less than their communication range. Modifications of the navigation function are detailed in the next subsections.

A. Inertia of the vehicles

The inertias of the other vehicles are used in order to give indirect priority to heavier vehicles to cross the intersection. This indirect priority assignment lets the heavier vehicles to cross the intersection on a smoother trajectory. Avoiding abrupt changes in velocity of heavier vehicles leads in less energy consumption. For this purpose we introduce the matrix of inertias (5).

$$V(i,j)=\frac{m_i}{m_j} \tag{5}$$

This matrix of inertia gives weights to the second term of the navigation function, which guarantees the collision avoidance. Lighter vehicles will sense stronger propulsive force from heavier vehicles. So the navigation function will be modified as follows: First give the new NF and then detailed the terms

$$\phi_i=\lambda_1\|q_i-q_{di}\|^2+\lambda_2\sum_{i\neq j}V(i,j)\frac{1}{\beta_\sigma(q_i,q_j)} \tag{6}$$

B. Destination of vehicles

So far, the navigation function avoids collision with all the vehicles entering the intersection. However, all the vehicles are not potential threads. For instance, if a vehicle is turning right, any other vehicle crossing the intersection straight from the opposite side do not induce no collision risk. Therefore, knowing the intention of the vehicles at the intersection can help the vehicles to have smoother trajectories. Furthermore, each vehicle, as an autonomous agent, may have privacy concerns, which should be respected. So, vehicles can communicate their intention in the current intersection but not their global destination.

We use the intention of the vehicles at the intersection to determine the risk of collision. If there is no risk of collision between vehicle *i* and vehicle *j*, their corresponding term in the navigation function will be put to one.

V. Simulation and Results

In this section, the simulation scenario for the crossing of autonomous vehicles is explained. As the proposed method is a decentralized control of autonomous vehicles, there should be individual controller for each vehicle. In addition, an environment is needed to simulate the whole intersection and animate all vehicles. We have developed a platform in MATLAB in order to evaluate the performance of our approach when using different type of information and compare them with traffic lights.

A. Simulation environment

The intersection consists of one junction and eight sections which correspond to 4 two-way roads (Fig. 1). The length of each road is 100 meters, which makes an isolated intersection at the junction point. The maximum speed is 50 km/h, like the standard speed limit in urban areas. This speed limit is considered in the decentralized navigation function method as well as for traffic lights by putting an upper bound for speed.

In terms of liability and controllability, traffic lights are an efficient way to guide vehicles with human drivers. In this work, the traffic lights are fully actuated, thanks to detectors integrated in all sections. To obtain useful information, the detectors are set at a long distance from the stop line (50 meters). No pedestrian pass time is considered to enable comparison with the autonomous approaches. Detectors count the number of vehicles entering the roads in red and yellow intervals in order to prepare the light for green. The controller is designed as a single ring with minimum green light of 20s and maximum green light of 50s.

Vehicles entering the intersection are of two types. The specifications of the vehicles such as inertias, acceleration limits and braking limits are given in Table 1. In all the sets of simulations, the number of type one vehicles is four times the number of type two.

The chosen simulation step is 20 ms. The parameters chosen for the navigation function are $\lambda_1=0.02$, $\lambda_1=0.8$, and $\sigma=0.3$ meters.

The sets of simulations have been carried out with three alternatives. The vehicles could go straight, turn left or turn right, with the same probability. The simulations have been carried out for 5 sets, each set corresponding to one hour of real traffic.

B. Results

The various approaches are compared using performance indexes, which are defined in the next subsections. These indexes are chosen to show the overall performance at the intersection. The results of these comparisons are shown in Fig. 2 to Fig. 5.

1) Vehicle average speed

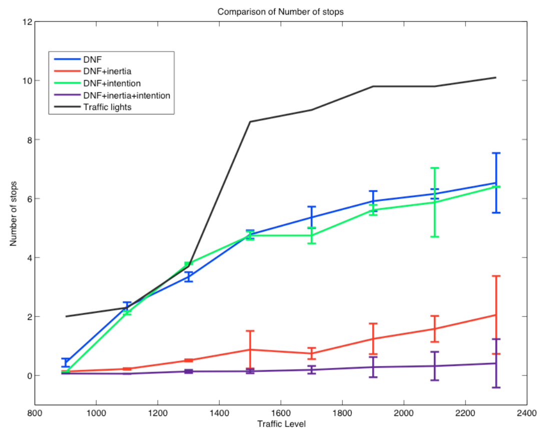
This index of performance is the average speed for all vehicles that have left the network. This is computed using the mean journey speed for each vehicle and then averaged it over the total number of vehicles that have exited the network.

2) Number of stops

The number of stops is the average number of stops of every vehicle averaged over all the vehicles that have left the network.

Table 1 Technical specifications of two different types of vehicles in the system [11]

	Mass [m]	Maximum deceleration [m/s^2]	Maximum acceleration [m/s^2]
Type1	1300	80.0	30.47
Type2	20000	20.9	10.54



Average number of stops of all passed vehicles for the four different cases where different types of information are shared among vehicles. Decentralized navigation function controller using only the position of other vehicles is shown in blue. The same controller in presence of information about the inertias of other vehicles is shown in red. Decentralized navigation function taking into account the intention of the vehicles at the intersection is shown in green. Purple line shows the average number of stops of vehicles where information about both inertia and intention of vehicles are available. Results for adaptive traffic lights are shown in black. For decentralized navigation function, the error bars are showing the standard deviation. The horizontal axis shows the total vehicle input to the network.

3) *Vehicle throughput*

Vehicle throughput or flow is the average number of vehicles per hour that have passed through the network during the simulation time. It is worth mentioning that the vehicles are counted when leaving the network. This means that if a blockade occurs the flow of the vehicles would decrease significantly. The average number of vehicles that should enter the network is defined using the O/D matrix of the network.

4) *Fuel consumption*

Fuel consumption of each vehicle is computed using the model presented in [11]. In this model, every vehicle is

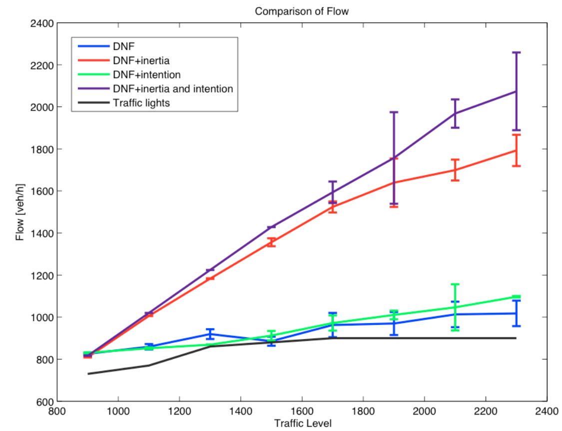


Figure 4. Flow of all passed vehicles for the four different cases where different types of information are shared among vehicles. Color code compatible with Fig.2

considered either as idling, or cruising at a constant speed, or accelerating or decelerating. The state of each vehicle is determined and the model then uses the appropriate relation to compute the fuel consumed for that state. For idling and decelerating vehicles, the rate is assumed to be constant. Fuel consumption during these four phases is shown in table 2.

For the first type of vehicles that we modeled, the constants c_1 , c_2 , F_i and F_d are 0.42, 0.26, 0.333 and 0.537 respectively. v_m is also the speed at which the fuel consumption rate is at its minimum value for a vehicle cruising at constant speed. This speed is 50km/h for cars simulated in this work. For the second type of vehicles, the constants c_1 , c_2 , F_i and F_d are 0.84,, 3.37 ,0.333 and 7.7 respectively.

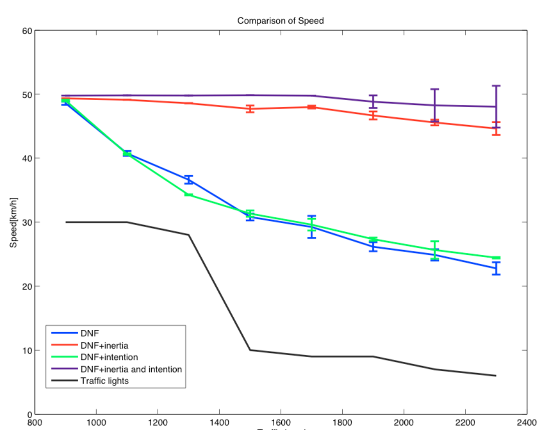


Figure 3. Average speed of all passed vehicles for the four different cases where different types of information are shared among vehicles. Color code compatible with Fig.2

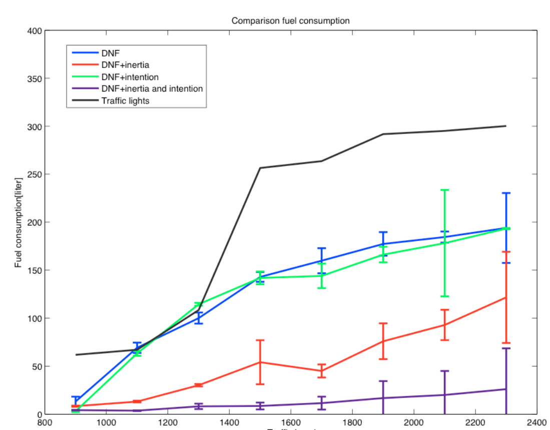


Figure 5. Fuel consumption of all passed vehicles for the four different cases where different types of information are shared among vehicles. Color code compatible with Fig.2

TABLE 1 The fuel consumption for different phases of a vehicle's journey

Vehicle phase	Fuel consumption rate
Idling	F_i
Decelerating	F_d
Accelerating with acceleration $a(\frac{m}{s^2})$ and speed $v(\frac{m}{s})$	$c_1 + c_2 a v$
Cruising at speed $v(\frac{m}{s})$	$k_1(1 + (\frac{v}{2v_m})^3) + k_2 v$

VI. DISCUSSION

The results listed in the Fig.2 to Fig.5 show that using decentralized navigation functions while vehicles share information about their positions introduces a significant improvement compared to traffic lights. All four indexes related to performance of the whole system are improved, showing the benefits of using autonomous vehicles in urban areas. By taking the inertia of the vehicles into account, the proposed method not only increases the fluency of crossing, but also optimizes energy consumption. As a matter of fact, this approach gives indirect priorities to heavier vehicles. As a consequence, the heavier vehicles that have greater impact on the fuel consumption of the whole system, consume less.

Having information about the intention of other vehicles at the intersection can also minimize energy consumption in comparison with the simple decentralized navigation function. However sharing information about inertias shows a more enhanced improvement than sharing the intentions. This happens due to the fact that, in a general case, there are more than two vehicles at the intersection. There is a great chance that every vehicle finds a potential collision risk with one other vehicle. Nevertheless, this is not a case in a scenario with navigation function with inertia where all the lighter vehicles give priority to a heavy one.

Sharing inertias and intentions of vehicles shows the highest performance among the all methods. However keeping the number of messages and amount of information transmitted to a minimum is always desired in reality. This helps the system to put more communication reliability measures in place. So, there is a trade off between sharing the intention of vehicles thus optimizing energy consumption and minimizing communication costs. The answer to this problem could be found by computing the on-board costs of communication and fuel consumption.

VII. CONCLUSION AND FUTURE WORKS

Autonomous vehicles can cross safely and smoothly at intersections. The performances of such vehicles depend of the information they share. Communicating is also costly especially using complex protocols. So there is always a tradeoff between having a simple communication protocol and increasing the performances. In this paper, our goal was to find the best alternative in terms of information sharing. We introduced four performance indexes including average speed of vehicles, number of stops, maximum flow of intersection and fuel consumption, in order to achieve a fair comparison. The results show that vehicles benefit a greater deal sharing the information about their inertia than sharing their intentions at the intersection.

Our future research directions include the statistical study of the performances of the proposed methods in multi intersection scenarios. In the future, we will also study the behavior of the vehicles under communication constraints and connection failures.

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