Adaptive Coordination in Autonomous Driving: Motivations and Perspectives

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***Abstract*—As autonomous cars are entering mainstream, new research directions are opening involving several domains, from hardware design to control systems, from energy efficiency to computer vision. An exciting direction of research is represented by the coordination of the different vehicles, moving the focus from the single one to a collective system.**

In this paper we propose some challenging examples that show the motivations for a coordination approach in autonomous driving. Moreover, we present some techniques borrowed from distributed artificial intelligence that can be exploited to tackle the previously mentioned challenges.

***Index Terms*—adaptation, autonomous driving, socio-technical systems.**

I. Introduction

The next generation of cars will be composed of fully- and partly-automated vehicles that drive in our streets with little or no human intervention. Despite fully fledged Self-Driving Cars will be commercialized only in 10-15 years, vehicles with limited autonomous capabilities (the so-called Advanced Driving Assistant Systems, or ADAS) are already part of our lives, and prototypes such as Google Car [1] and the Tesla ADAS [2] already performed thousands of kilometers of testing/validation. Interestingly, as of today, researchers mainly focus on the problem for each of the three main ADAS sub-systems (perception-planning-actuation), but only at the level of the *single* vehicle. We believe that is extremely interesting, and to some extent crucial, to enlarge our perspective, and taking into the picture *multiple* vehicles that interact and coordinate among themselves while driving in the street. Algorithms from artificial vision, real-time scheduling and energy/power reduction might benefit from the additional information coming from other vehicles, and decisions i.e., on path planning can be taken accordingly to other cars' needs.

Until now, prototype of autonomous cars have been tested in a sort of protected environment, always *alone*: the only interaction with other vehicles has been recognizing them by cameras and avoiding to collide with them. The next step is to enable a *proactive interaction* among autonomous vehicles, in order to better exploit resources and to facilitate goal achievement.

We must consider two kinds of interaction: *collaborative* and *competitive*; in the former, the considered vehicles have the same goal and collaborate to achieve it; in the latter, each vehicle is self-interested and must compete with other vehicles to achieve its goal.

Several researches have addressed the Vehicle-to-Vehicle (V2V) or Vehicle-to-Infrastructure (V2I) collaboration [3], mainly supported by Vehicular Ad hoc NETworks (VANETs) [4], and they can be considered at the base of vehicles coordination. However, they focus more on the communication between vehicles, not on higher-level collaboration algorithms, and they do not take into consideration autonomous vehicles.

II. Motivations

In this section we present some challenging examples and situations that can benefit from applying adaptive coordination in autonomous driving.

A. Crossings

Being deployed on a 2D plane, our streets must intersect with each other forming *crossings*. Having vehicles coming from at least three ways, they have to coordinate to exploit the "crossing resource" in such a way to avoid collisions. The traditional way to coordinate vehicles in a crossing is to use *traffic lights*, which however do not enable the best exploitation of the "crossing resource", because they stop vehicles even when no other vehicles are crossing.

Another approach is to exploit *roundabouts*, which are circular street intersections where vehicles must yield to the vehicles coming from left. This is more adaptive than traffic lights, and the "crossing resource" is not wasted. However, roundabouts can be built where enough space is available, typically not in the city centers; moreover, *starvation* is possible when one of crossing street has a high flow of traffic.

In this example, an approach to manage the crossing access in an adaptive and decentralized way is deserved. *Adaptive* because it must adapt the management to different conditions, priorities and constraints; *decentralized* to avoid bottlenecks and single point of failures

B. Turning Left

Connected to the previous example, *turning left* (or right in some countries) represents another interesting case for autonomous driving, where, differently from the previous case, the crossing could be not regulated by a traffic light. Turning left requires the coordination with the vehicles coming from the opposite direction, which have the right of way and the turning vehicle must yield. This example exhibit issues similar to the previous one.

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C. Parking

As known by people living in big cities, parking can be a nightmare in given periods and/or given areas. One first aspect is the *valet parking*, which means that the car parks autonomously once a free slot is found. Even if solutions have been proposed at the end of the last century [5], only now some cars are equipped with appropriate devices to enact automatic valet parking. We can foresee a near future when drivers can leave their cars at the entrance of a parking area and the cars autonomously find a free slot where to wait for their owners. The second aspect is more complex but useful as well. We envision a world where vehicles can "book" parking slots in advance. Of course, to avoid resource waste, a coordination with the vehicle(s) that will leave the slot at the right time is needed. In addition, in smart cities, it will be possible to automatically detect free parking spots in the whole city area, thanks to IoT-capable monitoring cameras. In this case, both V2V and V2I are involved. We remark that a centralized infrastructure can be exploited to provide vehicles with needed information, but it is not feasible to take decision, due to scalability and dynamism requirements.

D. Behavior Learning

We can imagine that autonomous vehicles will learn from the environment where they drive how to behave. With "environment" we aim at being very general, from the street conditions to the typical weather, from the traffic load to the user herself, who can specify some preferences. Of course, the learned behavior is related to the environment where typically the user moves by the vehicle. However, when the user drives in a new environment (e.g., during holidays), the environment can change and the vehicle is likely to need to learn a new behavior. To this purpose, the vehicle can interact with other vehicles in the new environment, which are used to that environment and can provide information about the roads, the weather, the traffic, and so on. We remark that this learning is not trivial, because the vehicle can be flood by information from other vehicles, and a careful coordination is needed to avoid "garbage" pieces of information.

E. Traffic

In general, the traffic jam situations represents an interesting case study for our aims. Currently, each vehicle is equipped with a personal navigator device that provides information about the routing. Connected vehicles can retrieve information about the traffic and their navigators can suggest alternative paths to avoid traffic jams. However, this can lead to an odd situation where a lot of vehicles "choose" an alternative path, causing its congestion as well. In this case, a coordination of several vehicles is required. However, a *centralized* coordination is very hard to be enacted, because the situation can change dynamically in a very fast way; vehicles can enter and exit the interested area, drivers can change their target, accident can happen, and so on.

III. Perspectives

In our work we have evaluated some possible techniques to apply to autonomous driving, taken from multi-agent systems [6], autonomic computing [7] and self-organizing systems [8]. We discuss how traditional auction based approach might be implemented to serve ADAS scenarios as well as alternative paradigms of coordination that takes inspiration from swarm intelligence [9], such as bio-inspired approaches and other environment mediated coordination strategies. Several approaches have been proposed that take inspiration from nature, biology and similar disciplines [10]. In fact, living beings enact coordination mechanisms and policies that are likely to be the result of the evolution in several hundreds or thousands of years, so they are effective for their purposes. Even is their purposes are often simple, the advantage is twofold: from the one hand, we can take inspiration from simple living beings, so their mechanism are easier to understand and to replicate on artificial beings; on the other hand, there are no centralized control, avoiding bottlenecks and single points of failure, and improving scalability and robustness [11] in highly distributed complex systems. The next subsections will provide more details regarding these approaches, while TABLE I summarizes their applicability to the case studies.

A. Auctions

A first, well-know and wide-adopted technique is represented by the auctions [12]. They have been applied to the management of intersections [13], but in our opinion can be exploited for a broader range of situations. In fact, this is quite simple yet flexible and effective, and requires a little centralization. The entities that aim at using a resource "bid" for that resource and an authority collects the bids and define the winner (usually the highest bid, but variations are possible); auctions can be held in a given period of time, during which bidders can change their bid. In our case, a vehicle can bid for a "slot" in an intersection or in a parking area; of course, the bid amount depends on different aspects (availability of slots, available time, agreement with friends, hurry, and so on).

B. Ant Colony Optimization

Another deep-studied technique to coordinate software components is the one inspired by ant behavior [14]. This technique is quite simple but can be very effective; it is based on the fact that ants leave signals (called "pheromones") on their path, and those signals fan be enforced (if more ants leave the signal in the same place) or decreased (they "evaporate" after a given time) depending on the interest on the path. An interesting aspect of this approach is that it exploits the environment to enable communication among coordinated entities. In our scenario, it can be applied to autonomous vehicles even if they do not know each other and do not have the capability of communicate directly. For instance, a traffic jam can be faced (and avoided) by "putting" specific signal information in the environment.

C. Distributed Learning

Deep learning [15] is now the most widely adopted machine-learning model for enabling vehicles to detect pedestrians, street lanes and many other features needed to perform safe autonomous driving [16]. As of now, car manufacturers are collecting huge amount of data in (mostly) centralized servers to perform the off-line learning phase; elaborated data (such as weights and topology of the resulting deep neural networks) are then offloaded to the autonomous vehicles. We argue that in the future such model might be further enhanced with continuous learning networks, in which the experience of different cars can serve for improving previously stored neural networks, so to have online distributed refinement of weights and topologies for continuously evolving networks. Simulated scenarios already discussed some possible algorithms for these approaches [17].

D. Field-based Approaches

The metaphor of the *physic field* has been exploited in distributed coordination because of its simplicity and expressiveness [18]. In this kind of approach, the environment provides one or more location-dependent values that represent information for the components living in the environment. This approach has been enforced by distributed tuple spaces in the SAPERE project [19]. These mechanisms have been successfully tested in urban scale crowd steering scenarios [20], which might be easily adopted for avoiding traffic congestions.

TABLE I
CASE STUDIES AND POSSIBLE APPROACHES

Case study	**Techniques**
Crossings and Turning left	Auctions
Parking	Auctions
Behavior learning	ACO, Distributed learning
Traffic Jam	ACO, field-based

E. What Is Missing

From the previous sections, it seems that several technologies and techniques are available to manage a set of autonomous vehicles. However, we point out that the real scenario of autonomous vehicles has not been explored yet, and can exhibits peculiar issues that have not been faced in the previous research. In particular, we point out two issues: (i) there is no comprehensive approach to apply coordination approaches to the autonomous driving scenario; (ii) there are no real experiments on applying the mentioned techniques to physical vehicles. Therefore, to pursue our research objective, we aim at defining a global approach and at testing the previously mentioned technology with real vehicles.

Testing on real-vehicles, will then be carried out by two ways: (i) A first bunch of experiments will be performed by using scale cars; (ii) next experiments will be performed in a real area of the city of Modena, called “Smart-area”, which is going to be equipped by the local administration with sensors, actuators, and, above all, a connection infrastructure that will enable the communication among vehicles.

IV. CONCLUSIONS

In this paper we have presented some *examples* as motivations to introduce adaptive coordination in autonomous driving, along with the challenges they introduce. We have also presented some *techniques* that can be exploited to enact adaptive coordination in the considered scenario. From our consideration, a lack of a comprehensive approach and of real experiments emerges.

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