Traffic Intersections of the Future*

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Abstract

Few concepts embody the goals of artificial intelligence as well as fully autonomous robots. Countless films and stories have been made that focus on a future filled with autonomous agents that complete menial tasks or run errands that humans do not want or are too busy to carry out. One such task is driving automobiles. In this paper, we summarize the work we have done towards a future of fully-autonomous vehicles, specifically coordinating such vehicles safely and efficiently at intersections. We then discuss the implications this work has for other areas of AI, including planning, multiagent learning, and computer vision.

Introduction

Few concepts embody the goals of artificial intelligence as well as fully autonomous robots. Countless films and stories have been made that focus on a future filled with autonomous agents that complete menial tasks or run errands that humans do not want or are too busy to carry out. One such task is driving automobiles.

In modern urban settings, automobile traffic and collisions lead to endless frustration as well as significant loss of life, property, and productivity. A recent study of 85 U.S. cities (Texas Transportation Institute 2004) put the annual time spent waiting in traffic at 46 hours per capita, up from 16 hours in 1982. A recent report estimates the annual societal cost of automobile collisions in the U.S. to be \$230 billion (National Highway Traffic Safety Administration 2002). Meanwhile, recent advances in artificial intelligence suggest that autonomous vehicle navigation may soon be more than just a science-fiction staple. Cars can now be equipped with features such as adaptive cruise control, GPS-based route planning (Rogers, Flechter, & Langley 1999; Schonberg *et al.* 1995), and autonomous steering (Pomerleau 1993; Reynolds 1999). As more and more cars become autonomous, the possibility of autonomous interactions among multiple vehicles becomes more realistic.

Arguably, vehicles experience the most sensitive interactions at intersections. Intersections are a serious point of failure for automobile traffic. Due to their small size and the fact that they support traffic traveling in many different directions, intersections play a part in a disproportionately high number of collisions. Furthermore, the innefficiency of intersections can be blamed for a large part of the waste and delay associated with automobile travel.

Multiagent Systems (MAS) is the subfield of AI that aims to provide both principles for construction of complex systems involving multiple agents and mechanisms for coordination of independent agents' behaviors (Stone & Veloso 2000). In two recent AAMAS papers and an AAMAS workshop paper, we have proposed and — in simulation — implemented and tested a multiagent, reservation-based mechanism for controlling intersections (Dresner & Stone 2004b; 2005; 2006b; 2006a). These papers form the basis of our Autonomous Intersection Management project, whose website can be found at http://www.cs.utexas.edu/users/kdresner/aim.

The Reservation System

Our approach to the autonomous intersection management problem is built on a multiagent *reservation system*. This system consists of two types of agents: *intersection managers* and *driver agents*. For each intersection, there is a corresponding intersection manager, and for each vehicle, a driver agent. Intersection managers are responsible for directing the vehicles through the intersection, while the driver agents are responsible for controlling the vehicles to which they are assigned.

To improve the throughput and efficiency of the system, the driver agents "call ahead" to the intersection manager and request space-time in the intersection. The intersection manager then determines whether or not these requests can be met based on an *intersection control policy*. Depending on the decision (and subsequent response) the intersection manager makes, the driver agent either records the parameters of the response message (the *reservation*) and attempts to meet them, or it receives a rejection message and makes another request at a later time. If a vehicle has a reservation, it can request that its reservation be changed or can cancel the reservation. It also sends a special message when it finishes crossing the intersection indicating to the intersection manager that it has done so.

The interaction among these agents is governed by a shared protocol (Dresner & Stone 2004a). In addition to

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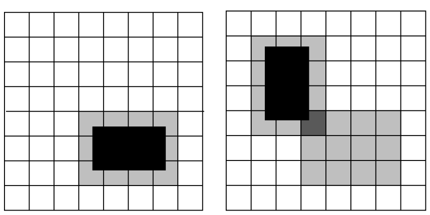
message types (e.g. REQUEST, CONFIRM, and CANCEL), this protocol includes some rules, the most important of which are (1) that a vehicle may not enter the intersection unless it is within the parameters of a reservation made by that vehicle's driver agent, (2) that if a vehicle follows its reservation parameters, the intersection manager can guarantee a safe crossing for the vehicle, and (3) a driver agent may have only one reservation at a time. While some may argue that insisting a vehicle adhere to the parameters of such a reservation is too strict a requirement, it is useful to note that vehicles today are already governed by a similar (although much less precise) protocol; if a driver goes through a red light at a busy intersection, a collision may be unavoidable. Aside from this protocol, no agent needs to know how the other agents work — each vehicle manufacturer (or third party) can program a separate driver agent, each city or state can create their own intersection control policies (which can even change on the fly), and as long as each agent adheres to the protocol, the vehicles will move safely through the intersection.

The main idea behind the intersection control policies we've developed is dividing the intersection into a grid of *reservation tiles* (see Figure 1). When an intersection manager receives a request, it simulates the journey of the vehicle through the intersection, and based on the resulting trajectory, determines which tiles are required at each time step. Then, similarly to how a reservation clerk at a hotel would record, grant, or deny reservations, the intersection manager acts appropriately and responds to the vehicle with information regarding its decision. In some cases, the intersection manager can even respond with a counter-offer, the same way that the hotel's reservation clerk might make a counter-offer after examining the reservation book.



(a) Successful (b) Rejected

Figure 1: A granularity-8 FCFS policy. In 1(a), vehicle A's request reserves tiles at time t. In 1(b), vehicle B's request is rejected because it requires a tile used by A at t.

Experiments

To evaluate the efficacy of our work, we developed a custom simulator that models discrete time steps. For our experiments we used a time step of 0.02 seconds, although this parameter is completely adjustable. In our paper we have shown that the system has many attractive properties — vehicles experience vastly lower delays, intersections have significantly increased throughput, emergency vehicles can get preferential treatment, and humans can use the system in a backward-compatible mode. We have even demonstrated that the system can effect a smooth transition between modern-day traffic lights and the streamlined, accident-free, super-efficient highways of the future.

Lower Delay and Increased Throughput

To measure the performance of the intersection manager, we define a quantity called *delay*, which is the amount of additional time a vehicle takes to complete its journey due to the intersection. Using our multiagent mechanism, autonomous vehicles can get across the intersection with a delay on the order of tenths of a second instead of tens of seconds. In addition, the intersection can move many more vehicles through without causing backups. At twice the level of traffic at which a traffic light would break down and cause unbounded delays, the autonomous intersection is still running smoothly.

Incremental Deployability

While an intersection control mechanism for autonomous vehicles will someday be very useful, there will always be people who enjoy driving. Additionally, there will be a fairly long transitional period between the current situation (all human drivers) and one in which human drivers are a rarity. Even if switching to a system comprised solely of autonomous vehicles were possible, pedestrians and cyclists must also be able to traverse intersections in a controlled and safe manner. Fortunately, we have been able to create intersection control policies that can accomodate human drivers, whether they make up the majority of drivers or show up very rarely. Because these policies can handle both cases and many in between, they enable incremental deployability, without which such a system might never be realized. In Figure 2 note how delays can be decreased across the board, while increasing capacity, as the proportion of human drivers decreases.

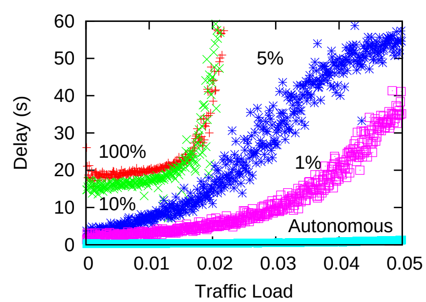


Figure 2: As human vehicles become more and more sparse, delays experienced by the average vehicle decreases.

Emergency Vehicles

In addition to decreases in delay across the board, our system as implemented allows us to give a slight preference to emergency vehicles. When emergency vehicles make reservations, they send a special message indicating that they are an emergency vehicle (and that they are in an emergency situation). By granting reservations only to vehicles in lanes with emergency vehicles, the emergency vehicles experience significantly lower delays (around 1/2 that of other vehicles).

A Multiagent Learning Domain

In addition to being a good domain for creating a robust multiagent framework, our work offers many opportunities for multiagent learning. Both the intersection manager and the driver agents could potentially benefit from their experience.

Delayed Response and Priorities

As explained above, intersection managers process requests on a first come, first served basis. This means that if two vehicles send requests that require the same space-time in the intersection, whichever vehicle sends the request first will get the reservation. To take this to an extreme, imagine a set of n vehicles $v_1, v_2, \ldots, v_n$ such that v_1's reservation request conflicts with every other vehicle, but that $v_i, 2 < i < n$ do not conflict in any way with one another. If v_1 sends its request first, it will be granted and all other vehicles will have to wait. If it sends its request last instead, the other $n-1$ vehicles will make it through and only one vehicle, v_1 will have to wait. If the intersection were able to wait until it had received all n requests, it could reorder them such that as many vehicles as possible make it through unhindered. In other scenarios, emergency vehicles may be given priority over commuters, or low-emission vehicles can be given priority over "gas-guzzlers".

Intersection as a Market

Another avenue for investigation is framing the intersection as a marketplace. Using a micropayment or credit system, vehicles could be required to pay for their reservations. The intersection can then be designed to maximize its revenue. This would have the effect of either earning actual currency or balancing the system. If each vehicle is given a fixed number of credits, it can spend those credits when in a rush, and collect them back in less pressing times.

Learning Driver Agents

The market scenario is also one in which the driver agents have an opportunity to learn. Each vehicle would like to minimize its delay, but also minimize the cost it incurs in making the appropriate reservations. Other opportunities for driver agent learning present themselves as well. Imagine that each reservation request has associated with it a fee, perhaps to discourage flooding the intersection manager with requests. Each vehicle would then have to learn to make reservations that are likely to be granted, in order to avoid incurring large costs with multiple requests.

Multiple Intersections

Because each intersection (along with the vehicles near it) comprises a standalone multiagent system, linking together multiple intersections should be mostly straightforward. Unless the intersections are close enough such that a vehicle exiting one intersection would not have time to stop before entering the second intersection (not likely), each one can make its own decisions, independent of the other intersections. Modern-day traffic lights are constantly tuned with data that is expensive and time-consuming to gather. The idea is to time the lights such that a wave of green lights allows a vehicle to continue without having to stop very often. In practice, this works to some extent, but it is inflexible and cannot adjust for different levels or patterns of traffic. If multiple autonomous intersections could communicate, they might be able to reduce delays even further by setting up similar patterns of traffic. Explicit communication may not even be necessary, as simulations indicate that the intersection manager naturally coerces vehicles into wave-like groups.

Other Areas of AI

Machine learning and multiagent systems are the two parts of AI most closely related to this domain, insofar as it is implemented in simulation. However, as with any project involving fully-autonomous robots, many different parts of AI will be required if a system like this is to be implemented in the real world. Advanced vision algorithms to detect, classify, and track vehicles, cyclists, and pedestrians will be extremely important. Additionally, sensor fusion techniques that can allow an agent to utilize information from laser range finders, radar, sonar as well as cameras (including infrared) will be vital. Even with all the sensor data coming in, accurate localization algorithms will be required to enable smaller safety buffers and thus more efficient intersections. Vehicles will then have to use this position information to keep themselves in their lanes and/or away from other vehicles (Pomerleau 1993; Reynolds 1999). Once all this is put together, the vehicles will still need to plan the routes to their destinations (Rogers, Flechter, & Langley 1999; Schonberg *et al.* 1995).

Related Work

Rasche and Naumann have worked extensively on decentralized solutions to intersection collision avoidance problems (Naumann & Rasche 1997; Rasche *et al.* 1997). Others focus on improving current technology (systems of traffic lights). For example, Roozemond allows intersections to act autonomously, sharing the data they gather (Roozemond 1999). The intersections then use this information to make both short- and long-term predictions about the traffic and adjust accordingly. This approach still assumes human-controlled vehicles. Bazzan has used an approach using both MAS and evolutionary game theory which involves multiple intersection managers (agents) that must focus not only on local goals, but also on global goals (Bazzan 2005).

Hallé and Chaib-draa have taken a MAS approach to collaborative driving by allowing vehicles to form *platoons*, groups of varying degrees of autonomy, that then coordinate using a hierarchical driving agent architecture (Hallé & Chaib-draa 2005). While not focusing on intersections, Moriarty and Langley have shown that reinforcement learning can train efficient driver agents for lane, speed, and route selection during freeway driving (Moriarty & Langley 1998). On real autonomous vehicles, Kolodko and Vlacic have created a small-scale system for intersection control which is very similar a reservation system with only 1 reservation tile (Kolodko & Vlacic 2003).

Actual systems in practice (not MAS) for traffic light optimization include TRANSYT (Robertson 1969), an off-line system requiring extensive data gathering and analysis, and

SCOOT (Hunt *et al.* 1981), which is an advancement over TRANSYT, responding to changes in traffic loads on-line. However, all methods for controlling automobiles in practice or discussed above still rely on traditional signals.

Conclusion

The Autonomous Intersection Management project aims to tackle a complicated real-world problem in a way that will have lasting and far-reaching consequences in the daily lives of billions of people. The problem is inherently a multiagent problem — the sheer number of vehicles in any given city is enough to overwhelm even the most powerful of computer systems. Furthermore, even if it were possible to control all the vehicles in a city or country with one computer, that computer would be a highly critical point of failure for the system — nobody could get anywhere if something happened to that machine.

In simulation, the project has achieved some notable results. Delays for vehicles can be reduced and almost eliminated as more and more autonomous vehicles take to the streets. The system can be deployed incrementally in a backwards-compatible mode that accomodates human drivers, pedestrians, and cyclists. Emergency vehicles experience half the delays of normal vehicles, without significantly deteriorating performance of the system as a whole.

A science-fiction future with self-driving cars is becoming more and more believable. As intelligent vehicle research moves forward, it is important that we prepare to take advantage of the high-precision abilities autonomous vehicles have to offer. Efficient, fast, and safe automobile transporation is not a fantasy scenario light-years away, but rather a goal toward which we can make worthwhile progress.

References

Bazzan, A. L. C. 2005. A distributed approach for coordination of traffic signal agents. *Autonomous Agents and Multi-Agent Systems* 10(2):131–164.

Dresner, K., and Stone, P. 2004a. Multiagent traffic management: A protocol for defining intersection control policies. Technical Report UT-AI-TR-04-315, The University of Texas at Austin, Department of Computer Sciences, AI Laboratory.

Dresner, K., and Stone, P. 2004b. Multiagent traffic management: A reservation-based intersection control mechanism. In *The Third International Joint Conference on Autonomous Agents and Multiagent Systems*, 530–537.

Dresner, K., and Stone, P. 2005. Multiagent traffic management: An improved intersection control mechanism. In *The Fourth International Joint Conference on Autonomous Agents and Multiagent Systems*, 471–477.

Dresner, K., and Stone, P. 2006a. Human-usable and emergency vehicle–aware control policies for autonomous intersection management. In *The Fourth Workshop on Agents in Traffic and Transportation (ATT 06)*. To appear.

Dresner, K., and Stone, P. 2006b. Multiagent traffic management: Opportunities for multiagent learning. In K. Tuyls et al., ed., *LAMAS 2005*, volume 3898 of *Lecture Notes In Artificial Intelligence*. Berlin: Springer Verlag.

Hallé, S., and Chaib-draa, B. 2005. A collaborative driving system based on multiagent modelling and simulations. *Journal of Transportation Research Part C (TRC-C): Emergent Technologies* 13:320–345.

Hunt, P. B.; Robertson, D. I.; Bretherton, R. D.; and Winton, R. I. 1981. SCOOT - a traffic responsive method of co-ordinating signals. Technical Report 1014, TRL Laboratory.

Kolodko, J., and Vlacic, L. 2003. Cooperative autonomous driving at the intelligent control systems laboratory. *IEEE Intelligent Systems* 18(4):8–11.

Moriarty, D., and Langley, P. 1998. Learning cooperative lane selection strategies for highways. In *Proceedings of the Fifeenth National Conference on Artificial Intelligence*, 684–691. Madison, WI: AAAI Press.

National Highway Traffic Safety Administration. 2002. Economic impact of U.S. motor vehicle crashes reaches $230.6 billion, new NHTSA study shows. NHTSA Press Release 38-02. Available at `http://www.nhtsa.dot.gov`.

Naumann, R., and Rasche, R. 1997. Intersection collision avoidance by means of decentralized security and communication management of autonomous vehicles. In *Proceedings of the 30th ISATA - ATT/IST Conference*.

Pomerleau, D. A. 1993. *Neural Network Perception for Mobile Robot Guidance*. Kluwer Academic Publishers.

Rasche, R.; Naumann, R.; Tacken, J.; and Tahedl, C. 1997. Validation and simulation of decentralized intersection collision avoidance algorithm. In *Proceedings of IEEE Conference on Intelligent Transportation Systems (ITSC 97)*.

Reynolds, C. W. 1999. Steering behaviors for autonomous characters. In *Proceedings of the Game Developers Conference*, 763–782.

Robertson, D. I. 1969. TRANSYT — a traffic network study tool. Technical Report TRRL-LR-253, Transport and Road Research Laboratory, Crowthorne.

Rogers, S.; Flechter, C.-N.; and Langley, P. 1999. An adaptive interactive agent for route advice. In Etzioni, O.; Müller, J. P.; and Bradshaw, J. M., eds., *Proceedings of the Third International Conference on Autonomous Agents (Agents'99)*, 198–205. Seattle, WA, USA: ACM Press.

Roozemond, D. A. 1999. Using intelligent agents for urban traffic control control systems. In *Proceedings of the International Conference on Artificial Intelligence in Transportation Systems and Science*, 69–79.

Schonberg, T.; Ojala, M.; Suomela, J.; Torpo, A.; and Halme, A. 1995. Positioning an autonomous off-road vehicle by using fused DGPS and inertial navigation. In *2nd IFAC Conference on Intelligent Autonomous Vehicles*, 226–231.

Stone, P., and Veloso, M. 2000. Multiagent systems: A survey from a machine learning perspective. *Autonomous Robots* 8(3):345–383.

Texas Transportation Institute. 2004. 2004 urban mobility report. Accessed at `http://mobility.tamu.edu/ums` in December 2004.