Data Mining, Machine Learning Algorithms, and their usage for Autonomous Vehicles

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***Abstract*—This paper is a literature review based on the usage of Data Mining and Machine Learning Algorithms in the Motor industry, specifically for the self-driving capabilities of Autonomous Vehicles. In this paper I review and discuss five papers based on the different types of algorithms used to facilitate autonomous driving, both rule-based and learning-based algorithms are compared to give an relevant understanding of the technologies being used for autonomous vehicles and the future for the industry. Additionally, I examine the means in which these vehicles use to collect and analyse data, and how experiments are conducted, either through real world driving or simulated environments.**

I. Introduction

As technology is advancing many industries are trying to implement new technology in their products to be competitive and continue to gain market share.

The motor industry is no different, and the technology that is being pushed by the media and motor companies such as Tesla, is Autonomous Vehicles. Cars and Trucks that will have the ability to drive themselves with no control or input from a human driver.

Autonomous Driving is said to revolutionise the motor industry, with many companies investing in the future of Autonomous vehicles such as Google, Apple, Intel, Uber, Samsung and Huawei. However, its not only Tech Giants and Software companies that are invested in developing Autonomous Vehicles, the Traditional Motor industry veterans like BMW, Volkswagen,Volvo, Fiat Chysler, Audi, Toyota, General Motors, Ford, and Mercedes-Benz are investing also.

It seems like every company, from both the tech-sector and the motor industry are believers in the future of driving being autonomous.

So that brings us to the research question, what is Autonomous Driving, how is it being performed, how is Data Mining and Machine Learning algorithms facilitating this self driving revolution for the motor industry?

This paper will review and discuss research papers that use Data Mining and Machine Learning algorithms to test and measure the performance of autonomous vehicles and their ability to handle different driving situations, specifically difficult situations such as uncontrolled intersections, with Speed and Safety being measures of Success and Failure.

II. Related Work

The papers researched for this literature review to answer the research question of how data mining and machine learning is used for the purpose of autonomous driving are all from 2018 - 2019. I chose more recent papers as I wanted to get an accurate and relevant understanding of what is happening in the research area of today, and what is being done to improve upon the work that has been done in the past.

The first paper that I will discuss is ”Decision-Making Framework for Autonomous Driving at Road Intersections: Safeguarding Against Collision, Overly Conservative Behavior, and Violation Vehicles” by Samyeul Noh. [1] This paper is a good paper to introduce the topic as it explains the different types of sensors, cameras and technologies that are attached to an Experimental Vehicle, commonly referred to as the EGO amongst all these papers. The paper then goes on to explain its usage of these sensors to inform a decision-making framework for autonomous driving. This Decision-making framework is what would be categorised as a Rule-based algorithm, where a set of rules are created around a set of data, and when data that has been analysed though the sensors meets these set rules, a decision is made by the algorithm.

I will then follow up the decision making framework from Noh with another paper that utilises a similar Rule-based algorithm ”A Hybrid Control Design for Autonomous Vehicles at Uncontrolled Intersections” by Nitin R. Kapania. [2] This paper proposes a novel hybrid control architecture to allow safe interaction between autonomous vehicles and pedestrians at uncontrolled intersections. This hybrid control functions similarly to a Rule-based algorithm and is compared to the Mixed-observable Markov Decision Process (MOMDP), which is often used as a base control to compare Rule-based autonomous driving algorithms against, and appear multiple times throughout the selected research papers.

These papers give a strong understanding of what has been done in the autonomous vehicle research area with relation to Rule-based algorithms, and their strength when it comes to absolute safety. However the future of autonomous vehicles is the power of Learning-based algorithms, such as the Deep Reinforced Learning algorithm Deep Q-learning. The remaining papers all utilise or improve upon Deep Q to try and assess its downsides and create a perfect Deep Reinforced Learning algorithm that can be scaled to handle any uncontrolled intersection or difficult autonomous driving task.

The first of these papers,”Navigating Occluded Intersections with Autonomous Vehicles using Deep Reinforcement Learning” by David Isele [3] Explores the effectiveness of Deep Reinforced Learning to handle intersection problems and compares it to commonly-used heuristic approaches, such as the rule-based algorithms found in first papers. It compares two Deep Q-networks (DQNs), Sequential Action, and Time-to-Go, against a standard rule-based algorithm TTC, which uses Time-To-Collision as a measure of safety for when the car should cross the intersection. These algorithms were tested using the Simulation of Urban Mobility (SUMO) simulator which is an open source traffic simulation package. [3]

Following Isele, "Automatically Generated Curriculum based Reinforcement Learning for Autonomous Vehicles in Urban Environment" by Zhiqian Qiao [4], tries to improve upon some of the shortcomings that arise when using Deep Reinforced Learning algorithms, such as DQNs. While they can create a strong algorithm for autonomous vehicles, as the problems they encounter become more complex, they need a higher number of training iterations, which results in a long training period to get acceptable results. [4] Therefore, Qiao proposes that a novel algorithm, Automatically Generating Curriculum (AGC) can help solve tasks for the DRL with fewer iterations than the DRL.

Finally, "Human-like Autonomous Vehicle Speed Control by Deep Reinforcement Learning with Double Q-Learning" by Yi Zhang [5] attempts to use an improvement on Deep Q-learning, called Double Q-learning to iterate on the popular DRL algorithm and compare it to the traditional Deep Q-learning algorithm.

III. Methodologies

Different algorithms and approaches are used across the research papers to deal with the problems that arise for autonomous vehicles, In this section I will go through each of the methodologies, referencing their usage in which papers, their individual strengths and weaknesses, and compare them.

A. Sensors and Data Mining

Throughout these papers, both simulated and real world vehicles will be using a collection of sensors and camera technology to analyse the environment around them, referred to as the State-space. The decision-framework proposed by Noh is broken down into three distinct modules: situation awareness, Situation assessment, and Manoeuvre decision. The situation awareness module is the part of Nohs framework that uses the technology equipped in the experimental vehicle to gather data about the state-space. [1]

It creates a detailed, precise digital map to predict at the lane level all possible future motion paths of all observed vehicles, it also uses its sensors to identify physical areas at the intersection where predicted future motion paths of observed vehicles intersect with the global path of the autonomous vehicle and classifies them as potential collision areas. (CAs) [1]

The experimental vehicle has several sensors to estimate its pose and perceive its environment. Vehicle pose is the angle and shape of an observed vehicle, using cameras and sensors the autonomous vehicle can identify observed vehicles and understand their road direction and vehicle type. It allows the autonomous vehicle to truly observe other vehicles.

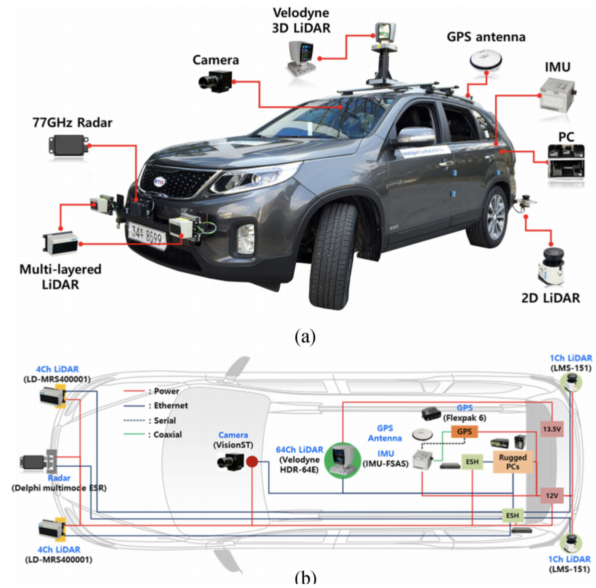

Fig. 1: Noh's Experimental vehicle configuration

It uses a vision sensor on the windshield to detect traffic signals, a 77-GHz long- and midrange Delphi multimode ESR radar attached to the front bumper, two multilayered LD-MRS LiDARs attached to the front edge, two two-dimensional (2-D) SICK LMS LiDARs attached to the rear edge, and a 3-D Velodyne HDL-64 LiDAR attached to the roof are all used to detect and track surrounding vehicles. [1]

Another paper, by Zhang constructs its environment using data from the Shanghai Naturalistic Driving Study, created by Tongji University and an automotive company, it is the first natural driving study in China. [5]

This data was gathered under normal driving conditions without interference and experiments, this allows the reinforcement learning algorithm to learn human decision-making and judging ability. [5]

The data acquisition system is very similar to Nohs, using an accelerometer with three axes, a LIDAR system that can track 8 targets, a GPS system that can fix position and a camera with four directions. [5]

B. Rule-Based Algorithms

Noh's Decision-based framework is our first example of a Rule-Based algorithm. As discussed in the Sensors and Data mining section, Noh's framework is broken down into three distant modules: situation awareness, situation assessment, and manoeuvre decision. The situation awareness module is what allows the autonomous vehicle to analyse and detect what exists in the environment, such as other vehicles and different lanes. However it is the situation assessment module that applies predictions to these classifications, assuming multiple potential future paths that an observed vehicle can take, using the information gained from the situation awareness module should an observed vehicle be locked within an intersection, the proposed framework will consider the vehicles heading

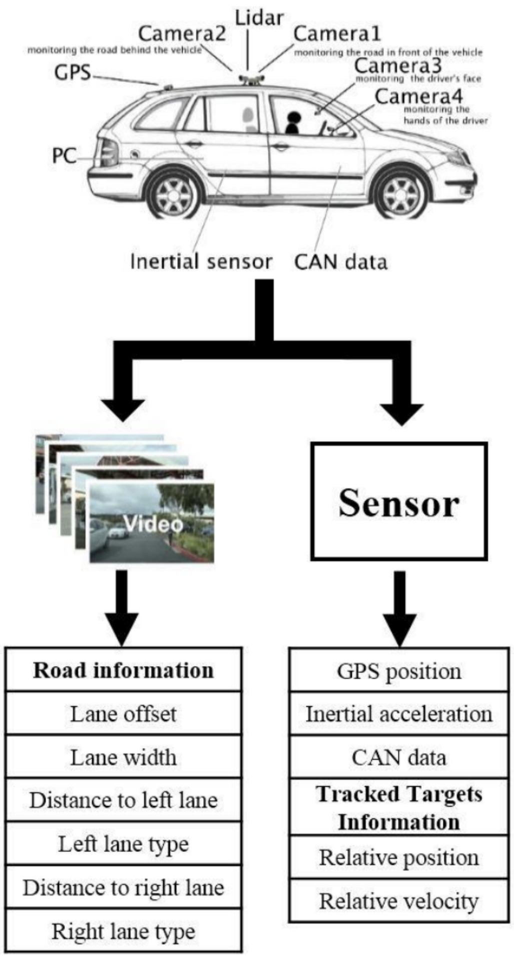

Fig. 2: Zhang's Experimental vehicle configuration

when determining a finite set of future paths for the vehicle. [1]

The situation assessment module uses an independent and distributed reasoning structure to asses a given situation effectively and systematically. [1]

Under this structure, the module groups observed vehicles according to their CA; vehicles that have a common collision area (CCA) form a group, each group is then assigned an independent reasoning agent who analyse the spatial relationship between the autonomous vehicle and the relevant vehicles, and establishes a threat level for each vehicle of the group by using Bayesian networks. [1] A Bayesian network is a type of probabilistic graphical model that is used for probability calculations, essentially calculating the probability of a given threat to the autonomous vehicle. To measure the threat of relevant vehicles a threat measure is used, the conventional threat measure that is used is TTC, Time-to-Collison, however Noh chooses to use Time-to-Enter (TTE) instead. This is a slightly modified version of TTC for collision avoidance.

The final module is the manoeuvre decision module which calculates all of the variables collected and analysed within the situation assessment module to make a manoeuvre Decision based on the data given to it. This allows the decision-framework to navigate safely and efficiently across an intersection, it can be scaled to any type of intersection as it uses predictions on the lane level, established by the situation awareness module. This makes it a very robust and reliable framework for handing intersections. It ensures that the autonomous vehicle avoids collisions, but simultaneously Is not overly conservative which can cause traffic and even accidents. The downsides of Nohs Decision-framework are that it doesnt have a full grasp of observed driver intentions and it is uncertain how the algorithm could handle dilemma zones such as traffic signals at signalled intersections.

Kapania also uses Rule-Based algorithm for their autonomous vehicle tests, however they specifically focus on the reliability of autonomous vehicles when dealing with pedestrians at a crosswalk and how a vehicle should act. This algorithm focuses on a factor in uncontrolled intersections called gap acceptance, defined as the accepted gap is a measure of how much time there is before the vehicle would enter the crosswalk if it kept its current speed. [2]

This relatively simplistic algorithm proposes four separates states for the autonomous vehicle, Driving, Yielding, Hard Braking or Speed up. Driving is the normal state of the vehicle as it attempts to drive through the crosswalk naturally, the instant the vehicle details a pedestrian a calculation is taking place. The algorithm will calculate a Time Advantage value to estimate whether stopping is needed. If the time advantage value is not sufficient for the vehicle to pass, Yielding will occur and the vehicle will begin to decelerate. In the unlikely event the pedestrian crosses when the Time Gap is low, the vehicle will prioritise a complete stop. Alternatively, a case where the pedestrian enters the crosswalk just as the vehicle is crossing, the vehicle must prioritise speeding up or else it will risk being rear-ended by other drivers. [2]

C. *Learning-based algorithms*

Learning-based algorithms such as Deep Q-learning are used in the next selection of papers, recently Deep Q become popular due to its ability to control and beat various games on the Atari 2600 gaming console, which showed that it might have potential for autonomous vehicles, specifically autonomous vehicles in simulated environments.

Reinforced learning uses a SAR framework, in which a state S, takes an action A, and is given reward R. Essentially, allowing an algorithm to train itself based on a reward structure, the goal of reinforced learning is to choose a sequence of actions starting at time T, that will maximise the return R. This means that over multiple iterations, an algorithm will eventually discover the highest reward in the best time, the downside being the high number of iterations that will have to be run to find this optimal return. In Q-learning, an action value Q is set and has an expected return. This Q value is given to the algorithm, and the algorithm can determine how close or far away their action A was from Q, and adjust accordingly. This

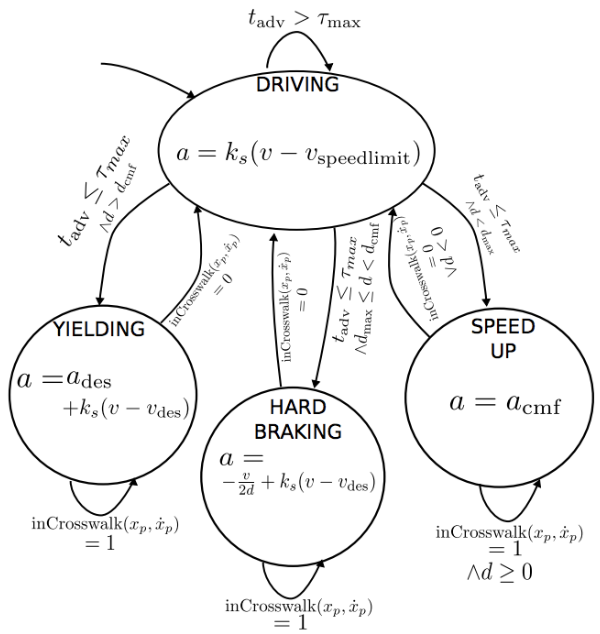

Fig. 3: Kapina's Hybrid Control Design

is an improvement over regular Reinforced learning algorithms and should result in lower training iterations. [3]

In his paper, Isele uses this Deep reinforced learning structure to train the algorithm to handle the complex problem space of crossing an occluded intersection, essentially forcing the autonomous vehicle to only use what it can perceive from its cameras and sensors. Isele creates two different DQNs, Sequential and Time-to-Go. [3]

Sequential scenario allows for more complex behaviours, allowing the vehicle to slow down halfway though an intersection and allowing oncoming traffic to pass, Meanwhile Time-to-Go more closely compares the standard TTC algorithm which places a high importance on time of departure. [3]

(a) *Right* (b) *Left* (c) *Left2* (d) *Forward* (e) *Challenge*

Fig. 4: Isele's tests for Deep Q

These two algorithms are then compared to TTC amongst a variety to tests. Right, Left, Left2, Forward and Challenge. Conducted in the SIMO simulator for safety reasons, the data generated by the simulator are qualitative similar to representations collected from real vehicular data, and therefore are apt. [3]

The variety of tests are just different ways a car can interact with an intersection, going different directions, the only novel test being challenge, where the autonomous vehicle must cross a six lane intersection safely.

The tests were then ran 10,000 times and percentages were collected.

TABLE I: Comparison of Different Algorithms

Scenario	Metric	*TTC*	*DQN-Sequential*	*DQN-Time-to-Go*
Right	% Success	99.61	99.5	**99.96**
	% Collisions	**0.0**	0.47	0.04
	Avg. Time	6.46s	5.47s	**4.63s**
	Avg. Brake	**0.31s**	0.88s	0.45s
Left	% Success	99.7	**99.99**	**99.99**
	% Collisions	**0.0**	**0.0**	0.01
	Avg. Time	6.97s	5.26s	**5.24s**
	Avg. Brake	0.52s	**0.38s**	0.46s
Left2	% Success	99.42	99.79	**99.99**
	% Collisions	**0.0**	0.11	0.01
	Avg. Time	7.59s	7.13s	**5.40s**
	Avg. Brake	0.21s	0.22s	**0.20s**
Forward	% Success	**99.91**	99.76	99.78
	% Collisions	**0.0**	0.14	0.01
	Avg. Time	6.19s	**4.40s**	4.63s
	Avg. Brake	0.57s	0.61s	**0.48s**
Challenge	% Success	39.2	82.97	**98.46**
	% Collisions	**0.0**	1.37	0.84
	Avg. Time	12.55s	9.94s	**7.94s**
	Avg. Brake	**1.65s**	1.94s	1.98s

Fig. 5: Isele's Deep Q-Learning Results

From the table above you can see that although the success rate of both DQN-sequential and DQN-Time-to-Go is very strong, the issue remains that they still occasionally result in collisions.

Ultimately, although both of Iseles DQNs are capable of learning exploratory behaviours to more fully understand a scene, and have better efficient and success rates that the rule based method, the difficulty the algorithm has in identifying occluded intersections leads to a high amount of collisions that is completely unsustainable, which Isele himself admits and concludes that further research is required to increase robustness. [3]

Although Isele found difficulty with Deep Q for traversing Intersections, that doesnt mean Deep Q Is definitively unreliable for autonomous driving. In their paper, Qiao address the shortcomings of DRL and proposes that a novel algorithm, Automatically Generating Curriculum (AGC) can help solve tasks for the DRL with fewer iterations than the DRL. The application of this AGC-based DRL should allow the autonomous vehicle to learn for a complex autonomous driving scenario by only using the information of other simulated vehicles within the EGO vehicles visibility range, essentially forgoing the long learning process that hinder traditional DRL algorithms. [4]

Using Reinforced learning, again an algorithm is trained to perform in a set amount of time for a reward, and over multiple iterations a max reward function will be found. For Qiao's proposed problem, the reward function is designed in terms of percentage of trip that has finished, with a negative constant reward for a time penalty. Therefore, the Ego vehicle is required to complete the goal fast, as to reduce the constant negative reward aligned with time. There is a negative reward that will be added if the ego vehicle gets too close to a target vehicle, and another if a crash happens. [4]

Where Qiao iterates on Isele use of Deep Q is the implementation of the ACG-based reinforcement learning. In this scenario the ACG is tasked with creating a optimum curriculum for the DRL to use, Qiao contrasts this with a random curriculum that would be generated for the DRL normally. [4]

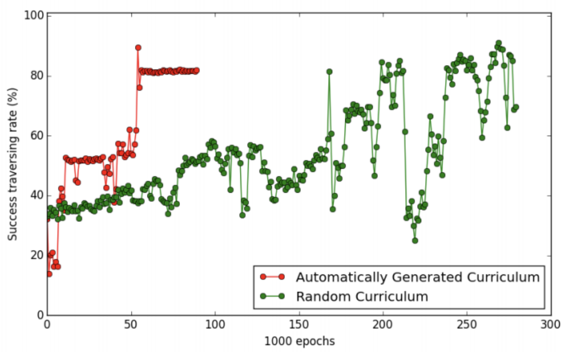

Fig. 6: Success rate of Random Curricula and AGC-based Model for the intersection traversing case

Above you can see that the ACG based learning is faster at reaching a higher success traversing rate than random learning, measured in epohcs, which is a measurement of time.

Similarly to Qiao, Zhang attempts an improvement upon Deep Q with their own Double Q-learning methodology, however this is only performed for speed control and doesnt have the inherent complexities of islesoccluded intersections. Zhangs paper has been discussed briefly in the Sensors and Data mining section, so this will be a brief overview of this paper.

Again, the basis of this algorithm is Deep Q-learning, and all of the applications of Reinforced learning outlined above are applied here, a reward function given over time to find the ultimate value and maximise reward.

Zhangs Double DQN algorithm attempts to improve upon the base DQN by decoupling the max operation in the target into action selection and action evaluation. By separating the action into two distinct parts, the Double DQN algorithm can estimate the value of an action prior to selecting it, in theory this allows Double DQN to select better actions and in turn gain a better reward. [5]

Zhang has also changed the reward structure for Double DQN, he designs a reward network that changes the level of reward based on which direction the ideal action is held. For example, if the ideal action is to go at a certain speed, the algorithm will gain positive reward for how closely it climbs to the ideal action, and if the algorithm goes away from the ideal action, such as reducing speed or stopping instead of moving at the speed determined by the ideal action, the DQN will receive negative reward. This is built to encourage the DQN to always adjust itself to the ideal action. [5]

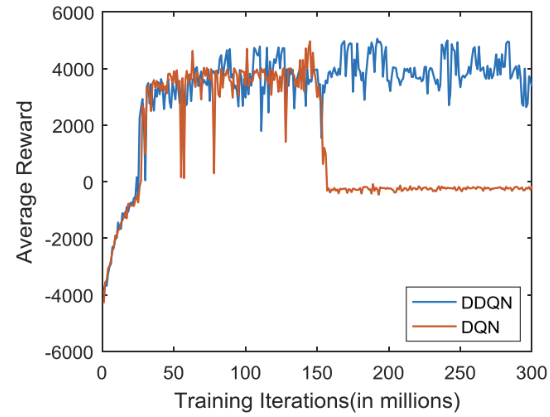

Fig. 7: Track of reward: Double DQN vs DQN

Ultimately, Zhangs Double Deep Q-learning algorithm is can successfully reduce the instability that DQN can have, and result in more stable and reliable learning, this can be seen in the graph above with the wild fluctuations DQN has when it comes to average reward. However more testing is needed and this is a smaller scope as it Is only tested on an autonomous vehicles speed control, and not the complexity of full control, attempted by Isele and Qiao.

IV. Conclusion

Ultimately, we are at a cross roads when it comes to Rule-based Algorithms and Learning-based Algorithms. Rule-Based Algorithms have advantages over their Learning-based counterparts, specifically the ability to tune parts of the Algorithm to make certain assurances. Time-to-Collision is an excellent algorithm because it can ensure safety every single time, which is absolutely critical for something as dangerous as driving can be. That is why nearly every learning-based algorithm in all of these excellent research papers compare their algorithm to it. It is a perfect standard for learning-based algorithms to be compared to, despite it's flaws. However, its downsides are significant, in multiple tests the Time-to-Collision algorithm failed the test simply because it waited too long, it was waiting for the Time-to-Collision value to reach 0, to ensure absolute safety. Although this is unrealistic when it comes to real world driving scenarios.

Learning-based algorithms have their downsides, namely being the lack of absolute certainty of 0 collisions, something rule-based algorithms perform so strongly at. However that doesn't mean that Learning-based algorithms are completely irrelevant when it comes to autonomous driving. The advances made by Deep Q-learning and its various improvements are significant, and with time I believe Learning-based algorithms will perfect autonomous driving, as their results are very close to the same as Time-to-Collision.

V. Future work

Going forward, Learning-based algorithms have a lot of work to do before comfortably being able to control an autonomous vehicle with an absolute certainty of safety. However, it is ever inching closer to that reality. The work that has been done in this area has impressed me and I genuinely enjoyed learning about the different algorithms and their application to the area of autonomous vehicles. I would like to research this topic again in the future to see the advancements that this technology with take in the coming years, this is an exciting time for autonomous vehicles, and the companies that are heavily invested in autonomous vehicles are valid in their assumptions about the future of the motor industry.

References

[1] Samyeul Noh. Decision-making framework for autonomous driving at road intersections: Safeguarding against collision, overly conservative behavior, and violation vehicles. *IEEE, Vol 66, No.4, 3275-3286*, 2018.

[2] N. R. Kapania, V. Govindarajan, F. Borrelli, and J. C. Gerdes. A Hybrid Control Design for Autonomous Vehicles at Uncontrolled Intersections. *arXiv e-prints*, February 2019.

[3] D. Isele, R. Rahimi, A. Cosgun, K. Subramanian, and K. Fujimura. Navigating occluded intersections with autonomous vehicles using deep reinforcement learning. In *2018 IEEE International Conference on Robotics and Automation (ICRA)*, pages 2034–2039, May 2018.

[4] Z. Qiao, K. Muelling, J. M. Dolan, P. Palanisamy, and P. Mudalige. Automatically generated curriculum based reinforcement learning for autonomous vehicles in urban environment. In *2018 IEEE Intelligent Vehicles Symposium (IV)*, pages 1233–1238, June 2018.

[5] Y. Zhang, P. Sun, Y. Yin, L. Lin, and X. Wang. Human-like autonomous vehicle speed control by deep reinforcement learning with double q-learning. In *2018 IEEE Intelligent Vehicles Symposium (IV)*, pages 1251–1256, June 2018.