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Unit 2: Rough Draft
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THE PATH TO AUTONOMOUS VEHICLES

Introduction

Modern transport relies heavily cars. They are flexible enough to travel over most terrain, powerful enough to transport goods, and efficient enough to travel hundreds of miles at a reasonable price. Unfortunately, they are also the leading cause of traumatic injury—primarily due to our own failings as drivers.

In the past five years or so, self-driving vehicles have begun the move from proof-of-concept research to sellable products. These new intelligent vehicles will eliminate most, if not all, crashes that result from human negligence. Furthermore, as the technology matures, new abilities such as collaborative traffic control will become available, enabling us to optimize performance and eliminate billions of dollars each year in wasted time and fuel.

This paper will cover the, as of yet, pubescent field of planning for self-driving cars. It will discuss requirements for a base self-sufficient vehicle and recent research into control algorithms and artificial intelligence aimed at achieving these goals. It will also touch on the ability for autonomous vehicles to collaborate to improve efficiency and safety. This paper will take a high-level approach to the subject, touching only on intelligent features. As such, we will not go into concepts such as PID controllers or hardware.

Self Sufficiency

At a base level, an autonomous vehicle must be able to localize itself within an environment, plan a path from its current location to any reachable location, and drive toward the destination following that path so as to arrive at the destination in some optimal quantity of time, fuel, or distance. It cannot rely on other vehicles or infrastructure to do so, since it is inefficient, insecure, and unstable. Furthermore, the infrastructure may not exist. This section discusses each of these abilities and research to achieve them.

Localization

Localization is the process of using information from sensors to find where you are in the world. This is incredibly important, because actions in the physical world don't map exactly to the virtual world that autonomous vehicles and other robots use to plan; as time progresses, this error accumulates until the car has no idea where it is. Additionally, the car if the car were towed, its previous location would be inaccurate.

There are several different sensors commonly used in the field of autonomous vehicles. The ones that are most commonly used are GPS (Global Positioning System), LiDAR (Light Detection and Ranging), accelerometers, gyroscopes, wheel odometers, and cameras, although others exist and may provide better results depending on the environment. SOURCE TO CONFIRM

Over the years, the algorithm that has become standard for localizing autonomous robots using multiple data sources is Extended Kalman Filtering (EKF). This algorithm takes each data source, weights it by the expected accuracy of the source, and combines it with other sources to obtain the most likely location. Hidden Markov Models is another algorithm that does almost the same thing for a discrete (not continuous) state space, but does not assume that the error lies on a Gaussian (bell) curve. SOURCE. Research has shown that fuzzy subsets improves the accuracy of location results [1]. MORE.

Path Planning

We refer to path planning in this section as a separate concept from trajectory planning. Path planning refers to the process of finding a sequence of roads that will take the vehicle from the source to the destination (hopefully in optimal time.) This is another problem that has been mostly solved.

A* (A-star) is a well-known graph algorithm that expands a set of frontier nodes from a source by choosing the next node in the frontier that has the lowest total expected cost and adding its previously unseen neighbors to the frontier. This repeats until the destination is reached. The concept of lowest expected cost is integral to this algorithm and it combines two sources of data. The first source is the expected cost to reach the next node (intersection) by traveling down the link (road). This is added to the second source, a heuristic regarding the expected cost to reach the destination from that new node. As long as this expected remaining cost is always less than the sum of edge costs along the optimal path, and the heuristic costs always obey the triangle inequality theorem, the algorithm will choose the optimal path from the source to the destination. Note that these are all expected values of distance, time, fuel consumption, etc., meaning that implementing the path may result in a different time and a suboptimal path depending on unexpected factors such as weather and traffic. A good example of a data source would be the average vehicle speed, which we could obtain using tools discussed in the section on collaboration.[2]

Several variations of A* exist, which improve features such as re-computation efficiency in dynamic environments, however, A* is an incredible algorithm that offers both average case efficiency and optimal results. Unless additional features are required, it is the go-to tool for path planning.

Trajectory Planning

Whereas path planning involves finding an optimal path from the current location to a destination, trajectory planning refers to how a vehicle should move within the road so as to avoid obstacles, conserve fuel, create a comfortable ride, show intention to other drivers, etc. Trajectories must be precise or cars run the risk of crashing. Furthermore, they are impacted by very real, physical concerns such as acceleration, momentum, turn radius, and tire grip, as well as legal concerns such as speed limits, stop signs, and right-of-way. Due to these and myriad other concerns, this is still a field of research.

Much of the research in this field relies on a form of algorithm called fuzzy logic, so we shall give a brief explanation to aid those unfamiliar with the subject. Fuzzy logic shares similar properties with binary logic in that they both involve rules that map to behaviors. The difference is that the variables in fuzzy logic are floating point numbers ranging from 0 to 1 rather than Boolean true or false values. Fuzzy logic uses membership functions to map input from sensors or other computation to these values. A simple ruleset and membership function are shown below.

FIGURE 1 RULES THAT MAP VARIABLES ACTIONS

Value	Action
COLD	HEAT
WARM	OFF
HOT	COOL

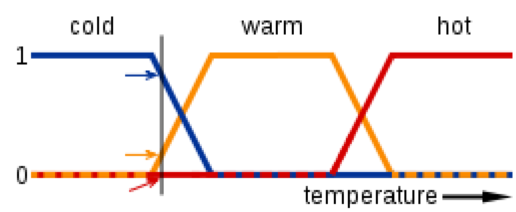

FIGURE 2 A MEMBERSHIP FUNCTION THAT MAPS TEMPERATURE TO 3 VARIABLES[3]

Farhi et al. researched fuzzy control algorithms to optimally control the trajectory of a car within a road. They took sensor data regarding the distance to the curb on either side of the car and the distance to the curb in front of the car, and fed them into a membership functions that defined variables. Braking reserve became either ZERO, MIDDLE, or HIGH, and delta distance front became CLOSER, CONSTANT, or FURTHER. Their algorithm utilized two weighted rule sets find the optimal curve while staying within the lane of the road. The power of this algorithm is that the rules for matching the environment were weighted higher than the goal rules. This meant that the car could push towards the optimal goal curve as much as possible but never drive off the road. [4]

Milanés et al. also used fuzzy logic to control vehicle trajectories; however, in this case, they applied it to create an intelligent overtaking system that relied on vision for vehicle detection. They used stereoscopic cameras measure the width, length, and time-to-collision for the vehicle that they wanted to overtake. From here they calculated the angle at which to turn using fuzzy logic that maintained both comfort and safety by taking into account the velocity of the overtaking car. Overtake speed was calculated as a function of the relative velocities of the vehicles and the length of the overtaken vehicle, limited by the speed limit. As a result, the overtake maneuver is activated automatically when the autonomous vehicle becomes aware that a collision will occur. The autonomous vehicle changes to the overtake lane, accelerates to reduce the overtake time, and finally merges back into the slow lane in front of the overtaken vehicle [5].

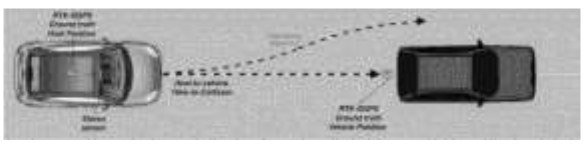

FIGURE 3 A DEPICTION OF THE SCENARIO STUDIED IN MILANÉS ET AL. [5]

Milanés et al. also used fuzzy logic to create a vision-based active safety system for automatically stopping to avoid collisions with pedestrians. As with [5], they used stereographic cameras to locate and range pedestrians in the road. From this information they calculated the time-to-collision, as a function of distance and vehicle speed. From here they used fuzzy logic on the inputs of time-to-collision and probability of wheel-slip given road conditions to determine the course of braking action. Tests at urban speeds under 50 Km/h had good results [6].

Much of the research in trajectory planning that we have discussed so far has focused on urban environments. Fassbender et al. researched trajectory planning in unknown, unstructured, obstacle-rich environments. The input to the algorithm is a series of GPS waypoints, however, the algorithm they designed does not assume that the waypoints are reachable or that paths between them are drivable. Instead, the algorithm utilizes LiDAR and camera data to map its environment and generate a trajectory that moves towards the goal [7].

Choi et al. also researched driving in rural, off-road environments. Like Fassbender et al. they also based their system on cameras and Lidar; however, they designed their vehicle to detect speed bumps and pedestrian crossings. Using the camera, they build a local map of the world that the car could then use to navigate. This research seemed the most dynamic and powerful seen thus far [8].

A lot of work has been dedicated to planning trajectories in urban environments. This is likely due to the sheer complexity of such environments in comparison to empty country roads. However, it would be nice to have a single comprehensive algorithm that could handle various environments intuitively rather than needing programmers to implement algorithms for environment-specific features. While fuzzy logic is incredibly powerful and easy to reason about, it’s also a shame that we don’t have better intelligent learning systems which can do the same thing. Such systems would remove the burden from programmers, since we would no longer need to come up with square shaped rules for round holes. In a way, this is asking for traits of a strong AI, which we are still somewhat far some achieving. I expect that future research will attempt to combine the afore-mentioned algorithms with intelligent learning systems so as to create something that resembles this single comprehensive model.

Communication & Collaboration

One of the major advantages that autonomous vehicles have over human drivers is that they can communicate with each other and with centralized servers in real time. The result of this is that they can use the best, most up-to-date information to make decisions, and they can coordinate their efforts precisely to improve safety and efficiency for everyone on the road.

Infrastructure based Pedestrian Detection

As mentioned in the section regarding trajectory planning, protecting pedestrians is a primary goal for autonomous cars. When the car can see the pedestrian, this is a simple problem addressed by Milanés et al. using fuzzy logic. If, however, the pedestrian is hidden behind a car in a busy business district, the autonomous vehicle may not have time to react. Kohler et al. researched a system that relies on infrastructure based prediction of pedestrian intentions to inform vehicles, so they may autonomously evade the hidden civilian. This system used networked cameras located at public hotspots to detect pedestrians and predict their intentions based on gait. At this point, the system notifies cars in the area, so they can move laterally or break to avoid the pedestrian. In trials this system had an accuracy of about 80% using 35 Hz video; however, this increased to 96% if the pedestrian stood still before starting. [9]

Intersection Algorithms

One of the major inefficiencies in our road systems today are intersections. At any one time, at least half of the cars at the intersection are waiting for their turn. This is unavoidable with human drivers, since we lack the communication skills to coordinate ourselves safely, but it isn't with autonomous cars. If autonomous cars were to hit a threshold number, we would be able to replace standard stop-and-wait algorithms with efficient algorithms that rely on real time communication between vehicles.

Makarem et al. researched "a decentralized model of predictive control for the coordination of autonomous vehicles at intersections," [10] building on their prior work in [11]. In their previous work they had developed a distributed algorithm that took expected time of arrival of vehicles at the intersection. This addition enabled them to eliminate cases where all cars would suddenly stop [11]. In [10], they extended this algorithm further by framing it as an "finite horizon optimal control problem", which each vehicle solves independently using decentralized model predictive controllers that take into account vehicle velocity and acceleration. The result of this these changes is a near-optimal solution that minimizes energy consumption and maintains a smooth trajectory.

At the same time as he published [11], Makarem et al. also published a paper called "Information sharing among autonomous vehicles crossing an intersection". In this paper, they discuss how the type of information that vehicles share with each other as they enter an intersection affects performance as they travel through said intersection. Using simulations, they show that sharing inertia and destination information drastically increase the path smoothness of participants while minimizing energy expenditure, communication cost, and full stops [12].

Overall, it seems like very few people are researching this field, but it shows a lot of promise. While their results are limited to simulations, Makarem et al. have shown that it is possible to use autonomous vehicle communication to improve the efficiency of intersections. The biggest issue that may present a problem is that by complicating intersections, we would effectively prevent un-networked vehicles such as bicyclists from crossing. As autonomous vehicles enter the roads, and this research can be implemented, I expect that these issues will be resolved by algorithmic improvements or modifications to infrastructure.

Traffic Shaping and Platooning

On an autonomous cruising traffic flow simulator including inter-vehicle and road-to-vehicle communication networks I'm already at 2500 words. Can expand this if needed. [13]

Collision avoidance in vehicle following systems I'm already at 2500 words. Can expand this if needed. [14]

Conclusion

Autonomous vehicles are just beginning to enter the realm of plausibility. While research is incredibly promising, there is still a way to go before we achieve fully autonomous cars that can communicate and solve problems interactively. So far, problems regarding localization and path planning have been solved, although the solutions could be tweaked for improved performance.

Trajectory planning is still a field of research, and I expect that it will grow and mature along with intelligent machine-learning algorithms, enabling us to build cars that predict and preempt disaster before it happens. Finally, autonomous vehicle communication and collaboration is a problem that we will not really get a chance to study until more autonomous vehicles are on our roads. While we can build models and theorize about potential improvements, we currently lack the infrastructure and prevalence to study or support it. Overall, though, autonomous vehicles are coming. The field is maturing, and there is no doubt that they will enter the road en mass within the near future.

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