Lane change decision on highways, literature review

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1 Problem Description

- Mandatory lane change: Mandatory lane changes de- fine the situations where drivers must perform a lane change due to strict road rules and situations, such as lane endings or lane blockages
- Discretionary lane change: Discretionary lane changes are performed by drivers when the observa- tion indicates that, there is another lane with better driving conditions for the host vehicle.
- Anticipatory Lane change: Finally, an- ticipatory lane changes are performed to improve road conditions for other road actors, such as allowing a faster vehicle to pass .

Aim to determine when and how to execute a lane change maneouver. Under efficiency, safety and comfort criteria.

3 categories of approaches to solve this problem

- Microscopic traffic models and decision trees
- Markov decision process
- Reinforcement learning.

task expected from a decision-making module is to increase safety and comfort while maintaining the desired speed.

2 Approaches From Literuature

2.1 Automated Lane Change Decision Making in Highway using a Hybrid Approach Caldıran et al

2.1.1 literature review

Gipps(1986) introduced a decision-making model that covers various urban driving situations. . Driver's behavior is governed by two basic considerations: maintaining the desired speed and being in the correct lane for an intended turning maneuver. Ahmed (1999) proposed lane change decision-making models based on utility functions to model microscopic highway traffic scenarios. The probability of lane change was calculated based on the output of a softmax function and the decisions of the drivers to make lane changes were modeled using a decision tree. Ardelt et al. (2012) integrated the ideas from Ahmed (1999) and Toledo (2003), and implemented a decision tree- based framework based on utilities of adjacent lanes, on an actual car. In the first phase, utilities of the lanes are computed with a decision tree mechanism. If the utilities indicate that a lane-change maneuver is profitable, the feasibility of this lane change is then controlled. If the lane change maneuver is not fea- sible, a lane change gap approach protocol, whose details were not provided, is activated. Nilsson et al.

(2016) computed three types of utilities of adjacent lanes and assessed the quality of gaps for a lane change. A drawback of these utility-based methods is their limited capacity regarding the incorporation of the other traffic participants actions and their possible ef- fects on the decisions. n this regard, the Markov Decision Process (MDP) and Partially Observable Markov Decision Processes (PO-MDP) offer princi- pled solutions to modeling and decision-making processes. However, the implementation of MDPs or PO- MDPs poses practical problems due to their computa- tional complexity for real-time bound systems such as autonomous cars. For example, Brechtel (2015) outlines highway driving scenarios as a generic Markov Decision Pro- cess with continuous states and action spaces based on the dynamics and inputs of a car.

2.1.2 Method

We discretize the time from past the future and calculate the utilities of lanes that belong to specific time inter- vals. We created a utility table to keep utility values from past to future, and we update the table at each time step with the incoming utilities.

For future state prediction, we use linear future state estimator functions that cal- culate possible future velocities and positions of dy- namic objects.

Utility functions:

- Longitudinal Velocity: The longitudinal velocity util- ity represents the difference between the desired ve- locity of ego and the actual velocity of ego
- Average Time Gap: The average time gap of a lane represents the average of the time gaps between ve- hicles in the corresponding lane. For the calculation, the time gaps between longitudinally adjacent cars are calculated and the average of these time gaps are used as a utility factor.
- Average Longitudinal/Lateral Velocity: These factors denotes the average longitudinal and lateral velocities in a specific lane. Based on the desired velocity of ego, these factors can be used as hints to determine which lane to keep.
- Relative Leader Velocity: This factor denotes the highest relative velocities in each lane. Even though it is similar to the other velocity-related factors, know- ing the fastest objects in lanes may help the driver with the decision of keeping the current lane or not.
- Presence of Heavy Vehicles: Presence of heavy ve- hicles is an indicator of the inconvenient of a lane. Lanes with heavy vehicles tend to be flowing slower
- Required Number of Lane Changes: Required num- ber of lane changes to reach a lane is an impor- tant factor regarding driving safety and comfort. We should avoid targeting far lanes as much as possible and choose adjacent lanes to be sure about safety and comfort

- Presence of Tailgating: Tailgating is an undesirable situation that can easily cause accidents. If a behind vehicle is driving too closely, especially in the left- most lane, the ego vehicle should make a lane change to allow the vehicle to pass

- Left/Right Most Lane Check: In highway, keeping the left-most lane and right-most lane for a long time is generally inhibited. Thus, keeping these lanes for de- creases the utility of that lane over time.

For the overall utility calculation, we follow the formulation in Ardelt et al. (2012). For each discrete timestamp, we calculate the utilities of a lane from past to future and get an overall utility value. Even though past utilities are useful for a better assessment of a traffic situation, they can imply wrong predictions and slow down the utility process.

At first they do not think about where are the gaps and is it okay to do a lane change they just asses the lane as a complete thing. Then there is a module to do a gap selection. When a lane change decision is made, our gap se- lection algorithm searches for inter-vehicular gaps that comply with certain safety and comfort crite- ria. To find the best gap, the decision-making mod- ule requires the kinematic information of the vehicles around the ego vehicle for the whole 360○ from the environment perception modules. The sensor fusion module, which is the core com- ponent of the environment perception modules, uses Kalman Filters to track the surrounding vehicles and hence assumes a normal distribution for the uncer- tainty in the estimated states of these vehicles. Our gap selection algorithm considers both the estimated kinematic states and their uncertainties for a feasi- ble lane change as in Ardelt et al. (2012), i.e., the rear/front bumper of a lead/follow vehicle is consid- ered to be 3 standard deviations away from its es- timated mean.

Furthermore, we estimate the future positions of the surrounding vehicles using a constant acceleration model to predict the future states of the inter-vehicular gaps. Therefore, we can anticipate feasible but un- reachable gaps to be reachable in a certain time hori- zon and plan accordingly. Nevertheless, gaps that are expected to be reach- able in the future are not guaranteed to be reachable or feasible in the expected time horizon (see Fig. 2a and 2b). Therefore, gaps that are temporally closer to the current time frame are more desirable.

Moreover, aligning with a feasible gap might require a deviation from the desired velocity, thus rendering the gap to be less desirable. These criteria lead to another multi- criteria selection problem among gaps. Similar to the lane utility functions, we defined the following crite- ria: • Uto : Time for the gap opening • Udur : Duration of the gap feasibility • Utr : Time to reach the gap • Uddv : Difference to desired velocity,

2.2 Design of a utility-based lane change decision making algorithm and a motion planning for energy-efficient highway driving Sahar Zeinali

2.2.1 literature review

2.2.2 Method

The overall process of lane change can be divided into two steps, including decision making, and planning and control. In the first step, the desirability of the maneuver is checked via a decision making algorithm. In the case of a desirable maneuver, its feasibility is checked by an MPC-based trajectory planning. If the maneuver is feasible, a lateral controller finds appropriate control inputs to execute the lane change. The desirability of a lane change maneuver is checked via a decision making algorithm, which is based on a utility function. This function considers different aspects of the maneuver Li et al. (2020) and Nilsson et al. (2016), such as: 1. Average travel time in lane , 2. Remaining travel time in lane , 3. Energy consumption in lane , 4. Traffic rules.

- Average travel time Ulv This variable shows the deviation of the average travel time of the lane from the average travel time as expected from the desired velocity vdes, set by the driver. It is defined as

  where vdes and vl are the desired longitudinal velocity for the EV and the average longitudinal velocity of the lanes l = c or l = t, respectively. Also, gama ¿ 0 is a parameter to avoid division by zero and dmax is the maximum travel distance, defined as dmax = Bvdes, (2) where B is a positive constant. The average velocity of a lane is calculated by taking an average of the velocities of the leading and trailing vehicles in the lane.

- Remaining travel time Uld This parameter shows the time duration that the EV can stay in the current lane l and is defined as Uld = min(dmax, dend)/vdes where dend is the distance to the end point of the lane l

- Energy consumption Ule This variable shows the desirability of the lane change maneuver from an energy efficiency point of view. In other words, by incorporat- ing this variable, the lane with an average velocity closer to the optimal operating point of the energy map is selected.

- Traffic rules Ulr In order to incorporate the rule of driving in the rightmost lane as much as possible, the following utility function is considered: Ulr = -L where L is the number of lanes to the right-hand side of the lane l.

  A lane change maneuver is desirable if the utility function of the target lane is higher than that of the current lane. In other words, if Ut ¿ (1 + e)Uc , where Uc and Ut are the total utility functions of the current and target lane, respectively, and e is a positive parameter. If a lane change is desirable, then in the next step, MPC as the longitudinal planner, tries to find an appropriate engine or brake torque to position the EV in the gap between the leading and trailing vehicles in the target lane. For this purpose, the longitudinal dynamical model is discussed in the next section, and then the energy-efficient MPC design is presented in Section 4

The motion of the TVs during the prediction horizon is predicted by a constant velocity assumption.

Lateral Trajectory planner: Utilizing a sigmoid function is another way to design the trajectory. This function has beneficial mathematical charac- teristics, such as continuity, differentiability, and a simple closed-form expression. Furthermore, this function allows us to consider the dy- namic and geometric constraints of the system, which is the most important advantage

2.3 Lane Change Decision-making through Deep Reinforcement Learning with Rule-based Constraints Wang et al

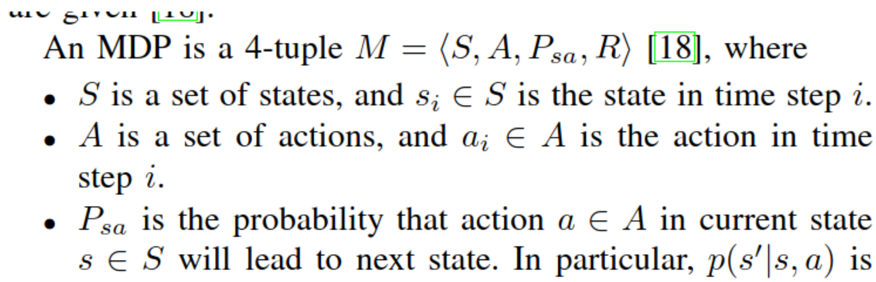
2.4 DQN deep q network

2.4.1 literature review

Wolf et al. [16] presented a method for teaching an agent to drive a car in a simulation environment by using DQN. The input of the network was the front-facing camera image with a shape of 48×27, and the action space, i.e. the network output, was discrete—5 actions were defined and each corresponding to a different steering angle. The reward function depended on the distance from the lane center and some relative items (such as the error of the angle between the vehicle and the center line). Hoel et al. [17] also used DQN to deal with the problem of vehicle speed and lane change decision-making in a simulation environment. Different from previous work mentioned above, the Q-network input in [17] was defined as a one-dimensional vector of the relative po- sition, speed, and lane of surrounding vehicles, rather than front-facing images. Two different agents were defined with the discrete action space. The first agent considered only the lateral lane change control, while the second considered both the lane change and speed control. The result showed that the second agent outperforms the former when CNNs were both utilized. However, how to guarantee the decisions' safety of the learning-based method should be further considered.

2.4.2 Method

The task of the decision-making module is to make an appropriate driving decision according to the sensor information from the perception module, and then plan a drivable path to the control module **Nevertheless, how to make a reliable decision is still a problem for the rule-based methods owing to their poor ability to generalize to unknown situations [11]**


An MDP is a 4-tuple $M = \langle S, A, P_{sa}, R \rangle$ [18], where

- S is a set of states, and $s_i \in S$ is the state in time step i.
- A is a set of actions, and $a_i \in A$ is the action in time step i.
- P_{sa} is the probability that action $a \in A$ in current state $s \in S$ will lead to next state. In particular, $p(s'|s, a)$ is

Figure 1: approach from paper 3.

2.5 A Reinforcement Learning Based Approach for Automated Lane Change Maneuvers *******

2.6 literature review

C. Vallon, Z. Ercan, A. Carvalho, F. Borrelli. A machine learning approach for personalized autonomous lane change initiation and control. IEEE Intelligent Vehicles Symposium (IV), Los Angeles, 2017.proposed to use Support Vector Machine to make the lane change decision tailored to the driver's individual driving preferences. After the lane change demand is generated, the maneuver is executed using a MPC.

Reinforcement learning, one promising category in the machine learning family, has the capability of dealing with time-sequential problems and seeking optimal policies for long-term objectives by learning from trials and errors, without resorting to an off-line collected database.

*** In our case, the driving environment involves the interaction with other vehicles whose behaviors may be cooperative or adversarial. For example, when a vehicle reveals its intention of a lane change by turning on the turning signal, the lag vehicle on the target lane may cooperatively decelerate or change its path to yield, or it may adversarially accelerate just to deter the vehicle from cutting into its course of motion. Consequently, it is not trivial to model the environment explicitly with all possible future situations. Thus, we resort to a model-free approach to find the optimal policy.*** YOU CAN NOT MODEL EVERY CASE. IF you dont do reinforcement learning

2.6.1 Method

** They train with yaw accelaration. This means for every state of the environment they find an ideal yaw accelaration**

chosen state as tate space includes the ego vehicle's speed v, longitudinal acceleration a, position X, y , yaw angle theta, target lane id, lane width w, and road curvature c. s = v, a, X, y, theta, id, w, c = S

2.7 P. Wang, C. Chan, Formulation of Deep Reinforcement Learning Architecture Toward Autonomous Driving for On-Ramp Merge. IEEE 20th International Conference on ITS, JAPAN, 2017

2.8 Rule-Based Safety-Critical Control Design using Control Barrier Functions with Application to Autonomous Lane Change

2.8.1 literature review

ccording to statistics provided by US National Highway Traffic Safety Administration (NHTSA) in [1], about 9 percent of all vehicle crashes involved lane change maneuvers. B. Sen, J. D. Smith, W. G. Najm et al., "Analysis of lane change crashes," United States. National Highway Traffic Safety Administration, Tech. Rep., 2003

2.8.2 Method

2.9 Integrated driving behavior modeling Toledo

2.9.1 literature review

2.9.2 Method

2.10 implementation from github

https://medium.com/@madhusudhan.d/path-planning-for-self-driving-cars-in-a-virtual-highway-fb266ba6713b The goal of the project to make a ego car drive around a virtual highway in dense traffic by adhering to following constraints for minimum 4.32 Miles.

No collision at any time with other vehicles Maximum speed of 50 MPH (80 KMH) Maximum acceleration of 10 m/s^2 Maximum jerk of 10 m/s^3 Vehicle cannot be in between lanes for more than 3 seconds Vehicle cannot go outside the 3 lanes of the highway Vehicle cannot drive on the wrong side of the highway

planning code should output the trajectory of planned path to the term 3 simulator provided by Udacity, which will then visualize the ego behavior and output dynamic parameter like velocity, acceleration, jerk etc.

the simulator takes in position data in Cartesian coordinate system. However it can output position in Cartesian and Frenet Coordinate system.

This module is heavily simplified in this project by using a Linear point model or constant velocity model for all the vehicles around the ego car. Given the duration for which the prediction is required, the new position of all the vehicles are calculated.

The basis of trajectory planning in this project is the map of highway given as text file highway map.csv. It is a cloud of points with each point described as both in cartesian and Frenet coordinate system. Format is as follows [X,Y,s,dx,dy].

I think for path generation part part of this map is isolated using the last 2 points in previous path and three more points selected over 90 m range. These five points are transformed from map coordinate system to vehicle coordinate system and interpolated using open source Spline function. For spline function they used https://kluge.in-chemnitz.de/opensource/spline/ The end result will be a spline starting from last position in previous path extending over 90 m along the track.

They use a simulator which executes every point input in 20ms so the spacing between 2 points determines the vehicle speed. Then these points are transformed back the xy coordinate system.

They use 2 step system similar in the papers I looked for. First lanes are ranked by cost functions and you choose the ideal lane to be in. Then as a second step you choose the vacant area in that lane and make the change.

They used a fsm approach with 5 states, Keep Lane: Prepare for Lane Change Left : Prepare for Lane Change Right: Lane Change Left Lane Change Right

Costs:

- goal_lane_cost : This function imposes higher cost on trajectories with vehicle in first or third lane and zero cost if the vehicle is in middle lane. Being in middle is efficient
- inefficiency_cost : This function imposes higher cost on trajectories with intended and final lane that have traffic slower than the vehicle's target speed. The function promotes lane change to maintain vehicle speed.
- lane_change_safety_cost : This function imposes higher cost on trajectories that attempt lane change when speed difference between current lane and goal lane is less than 7 Kmph. This limits potential for accidents during lane change in heavy traffic lane_chane_safe_dist_cost : This function imposes higher cost on trajectories that attempt a lane change when front cars in both goal lane and current lane travel at same speed and distance ahead of ego car .This prevents waggling of ego cars

2.11 Code decryption

generate predictions() of the class::Vehicle for the surrounding vehicle's state estimation with **constant velocity assumption**

The getXY helper function calculates the X and Y value given s and d in frenet coordinate system

Behavior planning implementation is available in Vehicle.cpp . The function successor states() creates all these states. All the above states are coded in the functions keep lane trajectory(), prep lane change trajectory(), lane change trajectory(). These functions after checking for their respective conditions will call the function get kinematics() to calculate new position, velocity and acceleration. All these trajectories are then evaluated in test func() and trajectory with minimal cost is returned.

All the cost functions are implemented in Cost.cpp. The function calculate_cost() calculates weighted mean of the individual cost values.