

# Lane change decision on highways, literature review

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# 1 Problem Description

- **Mandatory lane change:** Mandatory lane changes define 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 observation indicates that, there is another lane with better driving conditions for the host vehicle.
- **Anticipatory Lane change:** Finally, anticipatory 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 maneuver. 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 Literature

## 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 feasible, 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 effects on the decisions. In this regard, the Markov Decision Process (MDP) and Partially Observable Markov Decision Processes (PO-MDP) offer principled solutions to modeling and decision-making processes. However, the implementation of MDPs or PO-MDPs poses practical problems due to their computational complexity for real-time bound systems such as autonomous cars. For example, Brechtel (2015) outlines highway driving scenarios as a generic Markov Decision Process 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 intervals. 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 calculate possible future velocities and positions of dynamic objects.

Utility functions:

- Longitudinal Velocity: The longitudinal velocity utility represents the difference between the desired velocity 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 vehicles 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 denote 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, knowing 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 vehicles is an indicator of the inconvenience of a lane. Lanes with heavy vehicles tend to be flowing slower
- Required Number of Lane Changes: Required number of lane changes to reach a lane is an important 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 decreases the utility of that lane over time.

For the overall utility calculation, we follow the formulation in Ardelet 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 selection algorithm searches for inter-vehicular gaps that comply with certain safety and comfort criteria. To find the best gap, the decision-making module 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 component of the environment perception modules, uses Kalman Filters to track the surrounding vehicles and hence assumes a normal distribution for the uncertainty in the estimated states of these vehicles. Our gap selection algorithm considers both the estimated kinematic states and their uncertainties for a feasible lane change as in Ardelet et al. (2012), i.e., the rear/front bumper of a lead/follow vehicle is considered to be 3 standard deviations away from its estimated 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 unreachable gaps to be reachable in a certain time horizon and plan accordingly. Nevertheless, gaps that are expected to be reachable 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 criteria: •  $U_{to}$  : Time for the gap opening •  $U_{dur}$  : Duration of the gap feasibility •  $U_{tr}$  : Time to reach the gap •  $U_{ddv}$  : Difference to desired velocity,

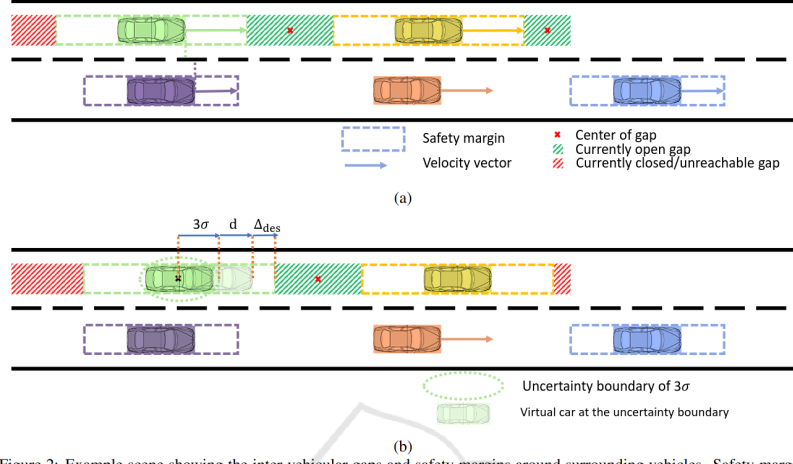


Figure 2: Example scene showing the inter-vehicular gaps and safety margins around surrounding vehicles. Safety margins are depicted with dashed-rectangles around the surrounding vehicles. (The orange-colored vehicle denotes the ego vehicle, hence does not have a safety margin around it.) In 2a, the gap in front of the adjacent left lane is defined by the lead vehicle in the left and ego lanes. In 2b, this gap is closed, and the safety margin around the following vehicle in the left lane is broken down into its parts: i.e., the vehicle dimensions  $d$ , the uncertainty of the perceived state of the vehicles ( $3\sigma$ ), and desired time gaps  $\Delta_{des}$ .

Figure 1: approach from paper 1.

## 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  $U_{lv}$  This variable shows the deviation of the average travel time of the lane from the average travel time as expected from the desired velocity  $v_{des}$ , set by the driver. It is defined as

where  $v_{des}$  and  $v_l$  are the desired longitudinal velocity for the EV and the average longitudinal velocity of the lanes  $l = c$  or  $l = t$ , respectively. Also,  $\gamma, 0$  is a parameter to avoid division by zero and  $d_{max}$  is the

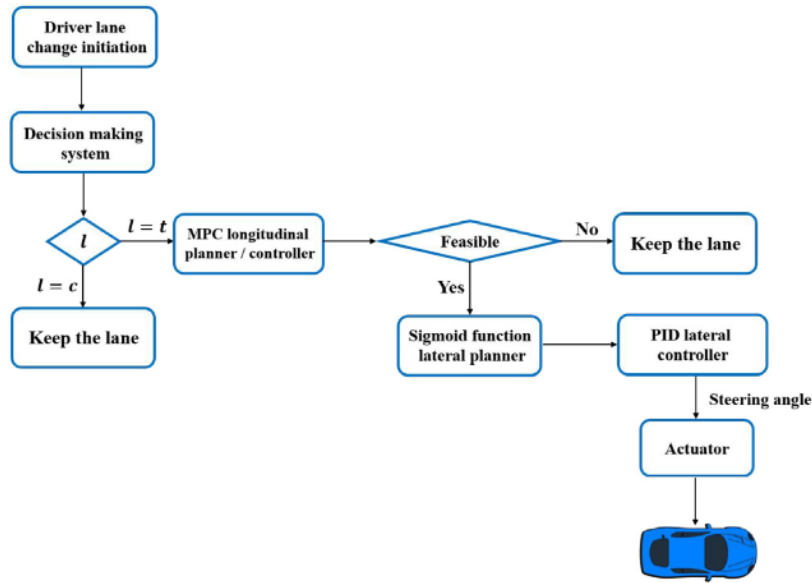


Fig. 1. Schematic diagram of the algorithm.

Figure 2: approach from paper 2.

maximum travel distance, defined as  $d_{\max} = B v_{\text{des}}$ , (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  $U_{\text{ld}}$  This parameter shows the time duration that the EV can stay in the current lane  $l$  and is defined as  $U_{\text{ld}} = \min(d_{\max}, d_{\text{end}})/v_{\text{des}}$  where  $d_{\text{end}}$  is the distance to the end point of the lane  $l$
- Energy consumption  $U_{\text{le}}$  This variable shows the desirability of the lane change maneuver from an energy efficiency point of view. In other words, by incorporating this variable, the lane with an average velocity closer to the optimal operating point of the energy map is selected.

- Traffic rules  $U_{\text{lr}}$  In order to incorporate the rule of driving in the rightmost lane as much as possible, the following utility function is considered:  $U_{\text{lr}} = -L$  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  $U_{\text{t}} \geq (1 + e)U_{\text{c}}$ , where  $U_{\text{c}}$  and  $U_{\text{t}}$  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 characteristics, such as continuity, differentiability, and a simple closed-form expression. Furthermore, this function allows us to consider the dynamic and geometric constraints of the system, which is the most important advantage

## **2.3 Paper3**

### **2.3.1 literature review**

### **2.3.2 Method**

## **2.4 Paper4**

### **2.4.1 literature review**

### **2.4.2 Method**

## **2.5 Paper5**

### **2.5.1 literature review**

### **2.5.2 Method**