Risk-Based Lane Change Maneuver for Intelligent Vehicle

Department of Mechanical Engineering
College of Engineering
National Taiwan University

Wei-Lin Pai

Advisor: Kuei-Yuan Chan, Ph.D.

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Abstract

Traffic risk quantifies human sense or prediction of potentially dangerous, which often refers to an accident or collision in traffic. Any behavior that forces other drivers to change their current intention can be interpreted as the source of traffic risk. Human drivers often make their driving decisions based on the risk they perceive or predict. In this undergraduate research report, a risk calculation model, a driver reaction model, and a motion prediction model are proposed to describe the risk-based driving decision in a two-dimension traffic environment. We use the pygame package to visualize three lane-change scenarios. Based on our study, we propose a two-dimensional risk to define the sense of potential traffic danger for future advanced driving technique.

1 Introduction

The enhancement of the network communication and the improving computing performance boost a rapid development of the autonomous vehicles (AVs). Until now, more than 200 companies[1] in the U.S. have conducted research and invested in the self-driving industry, including companies such as Waymo, Cruise, and Tesla. Meanwhile, self-driving test cars with human safety drivers have become a constant sight in many cities in the US such as San Francisco.

This growing trend constructs a mixed traffic flow of human-driven vehicles (HDVs) and autonomous vehicles (AVs) on a traffic network, where they share the same road space and the same right. Considering that there is still a long way to construct a highly automated traffic ecology, the adaptive stage in Bertoncello[2] can be imagined to become mainstream. Due to the lack of communication protocol standards and the issue of information security, vehicles still cannot construct reliable communication with each other. Hence, AVs must be able to interact with humans in traffic without connectivity. However, AVs may act too carefully or cautiously if they do not understand the complex decision mechanism behind human drivers. This leads to conflict with HDVs and makes AVs an insufficient or dangerous drivers in a mixed traffic flow. Thus, understanding human drivers' behavior and predicting their intention is a crucial issue and challenge for AVs.

2 Problem Formulation

Lane change maneuver is one of the riskiest maneuvers on a highway and can be perceived as challenging since it involves both the longitudinal and lateral motion as well as movement in the presence of other moving vehicles. In this report, the AV should perform a lane change maneuver, determine in which inter-vehicle traffic gap and at what time instance the maneuver should be performed, and calculate a feasible maneuver in terms of a longitudinal and a lateral trajectory. The decision and planning are all based on the calculated risk.

As Figure (1), assume the ego AV **E** (white) is driving on the right side of a double-lane highway, it does not have the right-of-way, so it must adapt its behavior to the surrounding traffic. There is a vehicle **Front Car** (red) in the front of the driving lane, a vehicle **Rear Car** (red) in the rear of the driving lane, a vehicle **Left Front Car** (red) in the front of the left lane, and a vehicle **Left Rear Car** (red) in the rear of the left lane. All four of them are driven by human drivers.

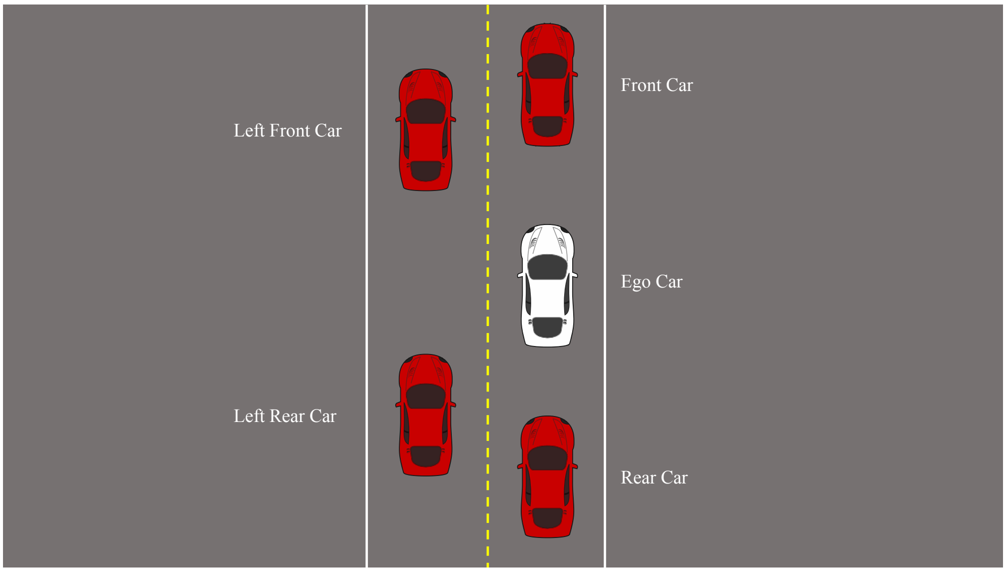

Figure 1: 2-D Lane change schema

In this scenario, the goal of ego AV is to conduct lane change in a way other human road users can predict or assume. The lane change maneuver is triggered when the risk for the ego vehicle to maintain its optimal velocity is greater than a threshold value, which is usually the risk from the front vehicle. Also, the risk between **E** and **Rear Car**, **Left Front Car**, and **Left Rear Car** are taken into consideration to decide when and how to perform lane change.

The proposed solution is based on the following assumptions:

1. **E** is equipped with sensors that can measure the velocity and position of other vehicles correctly.

2. Mixed traffic flow. An ego vehicle is an AV, other vehicles are driven by humans.

3. There is no connection between ego AVs and human-driven vehicles, i.e. the AVs cannot send the message to the human drivers.

3 Model Architecture

Our proposed risk-based decision-making model combines a risk calculation model, a driver reaction model, and a motion prediction model. Assuming the sensor can provide precise data of other vehicles' velocity and position, the risk calculation model will receive the data and calculate the according risk. Based on the risk, the driver reaction model will decide the instant optimal velocity and thus motion prediction model can conduct prediction. Once the prediction of lane change is feasible, a control command will be sent to the vehicle.

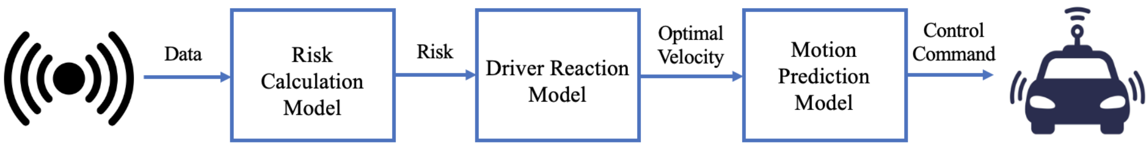

Figure 2: Model Architecture

3.1 Risk Calculation Model

Inspired by the approach used for pedestrian movement in congested traffic, Cheng[3] map the conflict probability based on the minimum distance between two vehicles' geometry space. However, instead of using Gaussian distribution, the probability is modeled to have a negative exponential relation to the distance, where the idea comes from the repulsive potential exponential function in the Social Force model[4]. As Figure 3 depicts, the elliptic zone is generated on the two-dimensional road plane around a vehicle as vehicle geometry. The egg-like shape is chosen to model the fact that drivers' awareness of collision is higher in the front and less in the side as well as back.

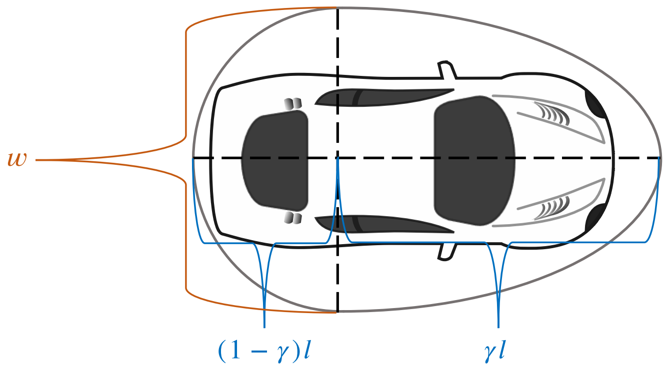

Figure 3: Safety shape for Exponential Distribution Model

l and w stands for the approximate length and width of the ego vehicle.γ is the parameter to locate the mass along the approximate length of the vehicle, 0.6 is selected in this report.

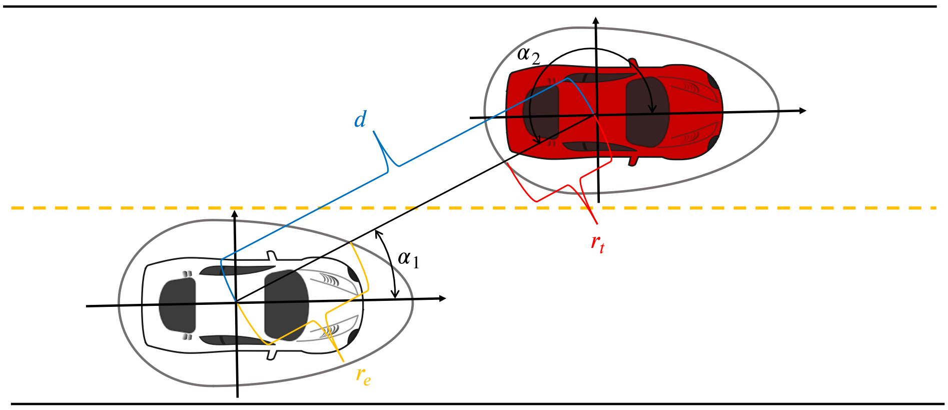

Figure 4: Two dimension distance for exponential distribution model

As Figure 4 depicts, α represents the angle between the heading of the ego vehicle and the neighbor vehicle.d stands for the center distance between two vehicles. r_e and r_t stand for the respective radii for the ego vehicle and target vehicle and d_{min} represents the remaining distance between two elliptic zones.

Equation(1), (2) calculate the radius of the elliptic space:

$$r_e = \begin{cases} \sqrt{(\gamma * l * \cos\alpha_1)^2 + (\frac{w}{2} * \sin\alpha_1)} & if \quad \alpha_1 \in [-90°, 90°] \\ \sqrt{((1-\gamma) * l * \cos\alpha_1)^2 + (\frac{w}{2} * \sin\alpha_1)} & else \end{cases} \tag{1}$$

$$r_t = \begin{cases} \sqrt{(\gamma * l * \cos\alpha_2)^2 + (\frac{w}{2} * \sin\alpha_2)} & if \quad \alpha_2 \in [-90°, 90°] \\ \sqrt{((1-\gamma) * l * \cos\alpha_2)^2 + (\frac{w}{2} * \sin\alpha_2)} & else \end{cases} \tag{2}$$

Equation(3) computes the conflict probability using the probability density function with an exponential distribution. The rate parameter λ_1 in the exponential formula is set to 1. When two elliptic spaces overlap, meaning that the neighbor vehicle position is inside the ego vehicle's vehicle geometry, the probability is set to 1.

$$p(d) = \begin{cases} \lambda_1 e^{-\lambda_2 d_{min}} & if \quad d_{min} > 0 \\ 1 & else \end{cases} \tag{3}$$

$$d_{min} = d - r_e - r_t \tag{4}$$

3.2 Driver Reaction Model

3.2.1 Optimal Velocity Model

The optimal velocity (OV) model introduced by Bando[5] observes the macroscopic feature of traffic flow in a microscopic view. In the OV model, the acceleration of the nth vehicle is decided by the difference between an optimal velocity V and actual velocity v_n within a period τ.

$$\frac{dv_n}{dt} = \frac{1}{\tau} \left(V(\Delta x_n) - v_n \right) \tag{5}$$

In every period, the vehicle will chase on an optimal velocity which depends on the headway Δx_n to the front car, the relationship is modeled using the hyperbolic tangent function:

$$V(\Delta x_n) = V_0 \left[tanh \left(\frac{\Delta x_n - D}{b} - C_1 \right) + C_2 \right] \tag{6}$$

$$\Delta x_n = x_{n-1} - x_n \tag{7}$$

x_n and x_{n-1} is the position of the nth and preceding car. D represents the car length and b is the length scale. V_0, C_1 and C_2 are constant.

As we assume every AV is well connected, there will be no time delay t_d included considering the effect of driver reaction time. One optimal velocity model is constructed by Sugiyama[6] to reproduce the highway characteristics of a Japan freeway

$$V(\Delta x) = 16.8[tanh(0.086(-25)) + 0.913] \tag{8}$$

Based on the distance, the model can be divided into a reaction section and a free section. When the distance between the ego vehicle and the neighbor vehicle is smaller than a threshold value, the model falls into the reaction section, the velocity will alter according to the distance. In the free section, the distance with the neighbor vehicle is longer, the vehicle will maintain the optimal velocity, which is normally the speed limit of the road.

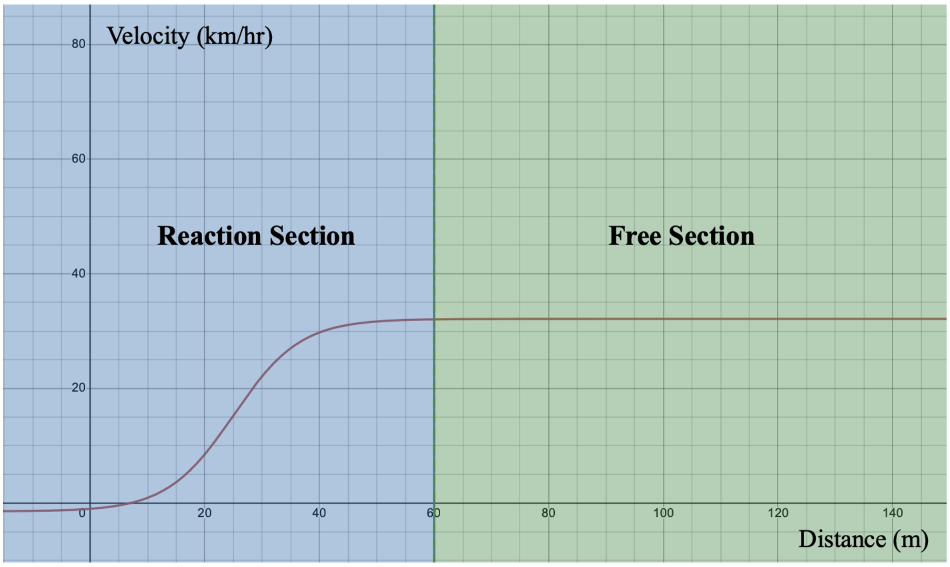

Figure 5: Optimal velocity model

The optimal velocity model (OV) describes the optimal velocity of traffic flow using distance and hyperbolic tangent. In this report, distance is replaced by risk P as a variable of optimal velocity V. Conflict probability of 0.55 is selected as the index for half of the ideal velocity.

$$V(P) = \frac{V_{ideal}}{2}(1 - \tanh 7(P - 0.55)) \tag{9}$$

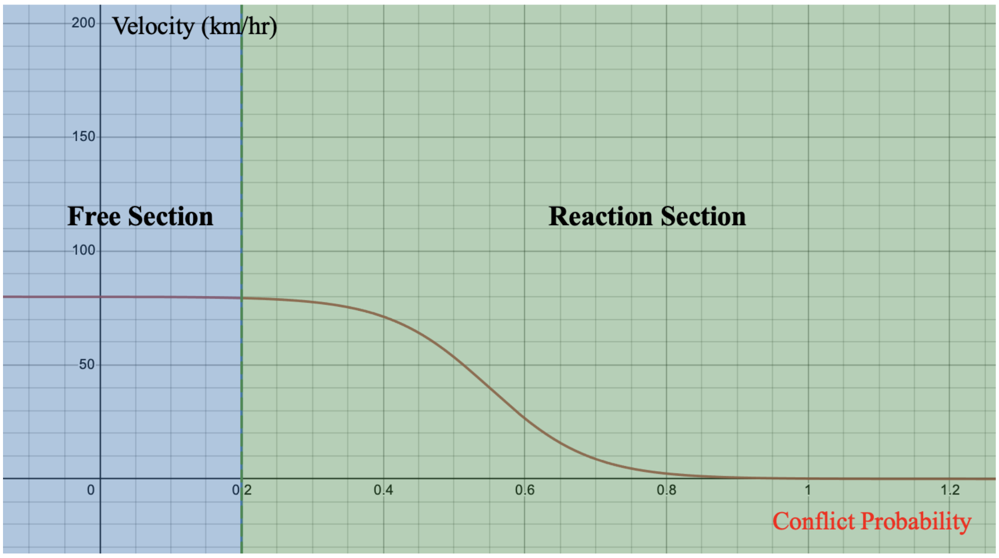

Figure 6: Optimal velocity model based on risk

3.2.2 Driver Awareness

As the velocity of the vehicle gets higher, the driver should have a more sensitive awareness, the sensitivity is considered by altering the power index λ_2. As Figure (7), lower λ_2 indicates higher awareness, which means higher risk estimated under the same distance. 0.5 is selected as a benchmark value when the vehicle is driving at its ideal velocity.

$$p(d) = \begin{cases} \lambda_1 e^{-\lambda_2 d_{min}} & if \quad d_{min} > 0 \\ 1 & else \end{cases} \tag{10}$$

$$\lambda_2 = 0.5 - \frac{V - V_{ideal}}{V_{ideal}} \tag{11}$$

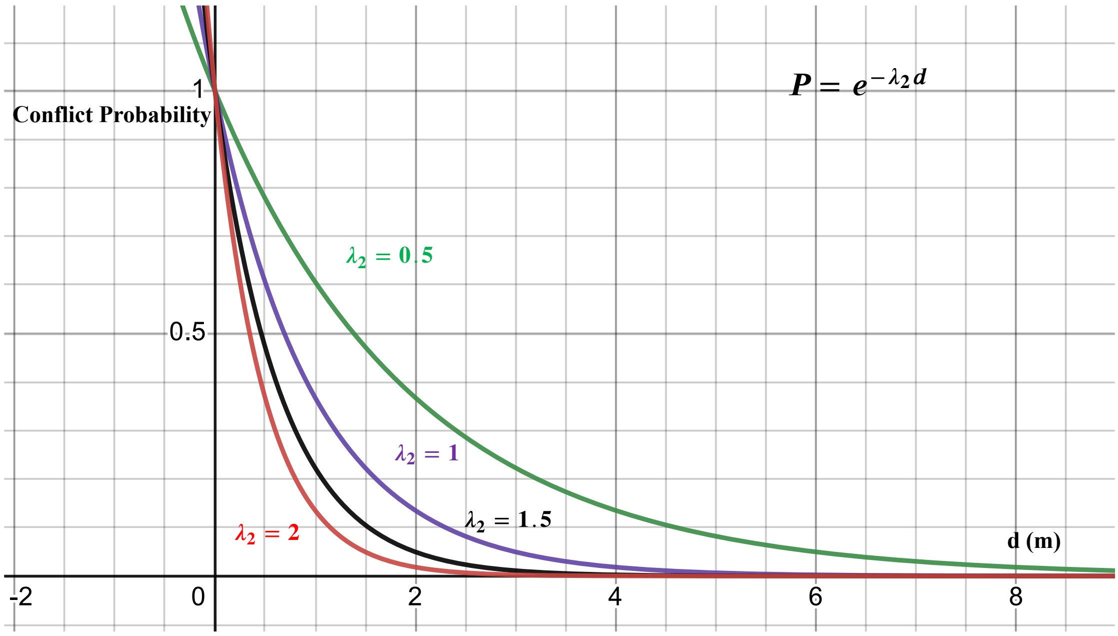

Figure 7: Driver awareness adjustment

3.3 Motion Prediction Model

3.3.1 Bezier Curve

During the lane change maneuver, the path of the lane change maneuver has to be tangential to the path of the target lane and current lane. The Cubic Bezier curve, a smooth curve generated by four discrete points, was shown to be suitable for tracing vehicles many researches.

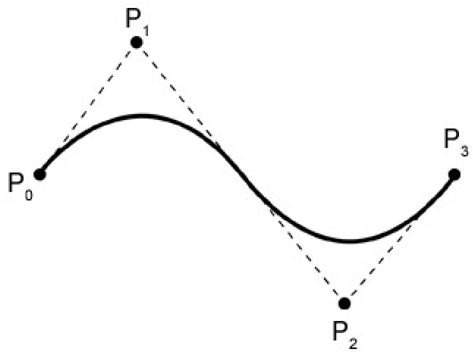

Figure 8: Cubic Bezier Curve

As Figure (8), to generate a cubic bezier curve suitable for lane changing, P_0, P_1, P_2, and P_3 need to be decided. Having the first point P_0 as the starting point, P_1 should be selected where $\overrightarrow{P_0P_1}$ is parallel to the current lane direction so that the curve will be tangential to the current lane. Then, choose P_3 as the terminal point of the curve, P_3 should be then located such that $\overrightarrow{P_2P_3}$ parallel to the target lane. The curve will then be generated using equation (12):

$$B(t) = (1-t)^3 P_0 + 3(1-t)^2 t P_1 + 3(1-t)t^2 P_2 + t^3 P_3,\ 0 \leq t \leq 1 \tag{12}$$

By knowing the current position P_0 and target position P_3, we can decide the curve by changing P_1 and P_2. In the current simulation,P_1 will be 10 meters in front of P_0 and P_2 will be 10 meters behind P_3 along the target lane. To consider risk when planning the curve, the different selection criteria of P_1 and P_2 is still in progress.

3.3.2 Driver Behavior Uncertainty

As the assumption has mentioned, there is no communication between each vehicle. Hence, AV can get the instant position and velocity of other HDVs but cannot know their acceleration intention. In a few cases, the driver may have a sudden acceleration or deceleration. But under most circumstances, the driver will tend to maintain its current status, or just have a slight adjustment on the velocity.

To consider this uncertainty in prediction, the Gaussian distribution is selected to model the driving behavior. In this report, mean μ is set to be 0 as the vehicles are assumed to prefer to maintain this current velocity. Standard deviation σ is set to be 0.1 time of the gravitational acceleration g since the 0-100 acceleration of most of the car is about $0.2g$. In the traffic, 95.5 percent of the drivers are assumed to behave less severely than performing straight-line acceleration.

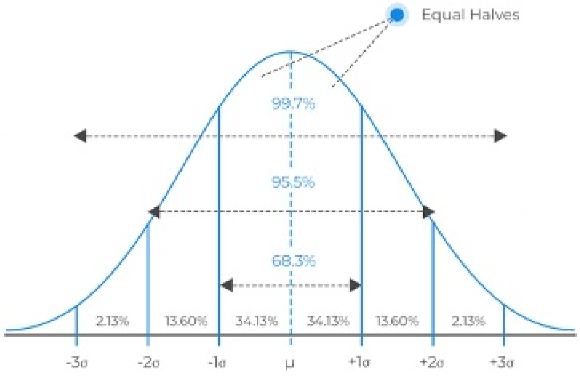

Figure 9: Gaussian Distribution

4 Scenario Simulation

4.1 Lane Change Maneuver

As Figure (10), the lane change maneuver has three stages: before lane change, during lane change, and after lane change. The motion prediction model will predict the potential risk before conducting lane change, where the vehicle is still in the current lane following **Front Car**. Once the prediction is feasible, **E** will start lane change and will alter its velocity based on risk to a different surrounding vehicle in a different scenario.

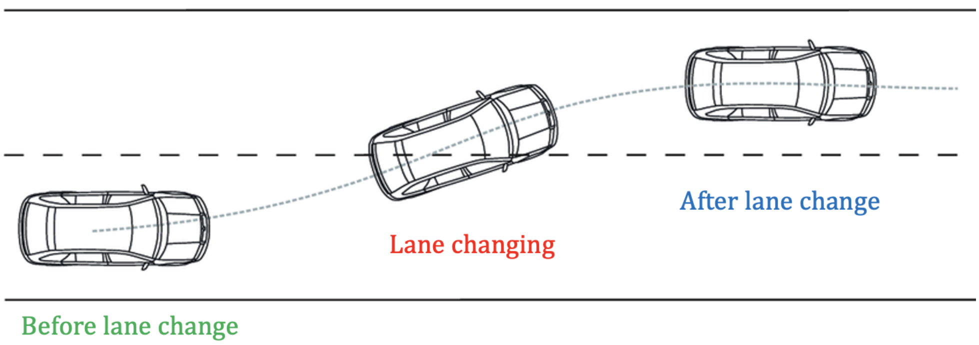

Figure 10: Three lane change stages

According to the vehicle position on the target lane (left lane), three scenarios are proposed to thoroughly inspect the possible traffic conditions. The three scenarios will be merging, overtaking, and following.

4.2 Merging Scenario

As Figure (11) depicts, when the target lane change position for **E** is between **Left Front Car** and **Left Rear Car**, this condition is classified as "Merging".

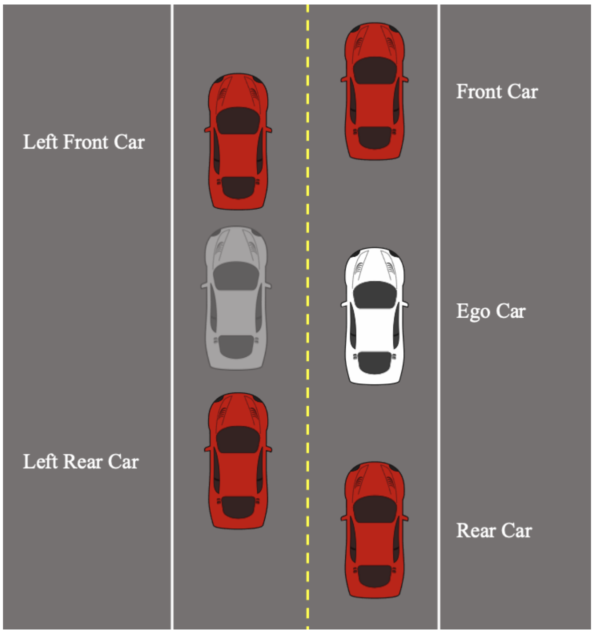

Figure 11: Merging Scenario

In this scenario, the lane change strategy is listed in Table (1). Before lane changing **E** will alter its velocity according to the optimal velocity model and the risk to the **Front Car**. The risk to **Left Front Car** is taken into consideration when performing lane change and will then follow **Left Front Car** after merging into the left lane.

Once the lane change condition is triggered, the motion prediction model will start to predict and calculate the possible risk for performing lane change. The average risks to different vehicle when performing lane change are chosen as the index to decide the feasibility of the motion prediction. The respective risk value of 0.4, 0.5, and 0.3 are adjustable, if the limits are set lower, the lane change prediction will be more conservative. The interpretation of risk value will be discussed later in conclusion section.

Following	
Before	Front Car
During	Left Front Car
After	Left Front Car
Prediction	
Avg_Risk1 (< 0.4)	Front Car
Avg_Risk2 (< 0.5)	Left Front Car
Avg_Risk3 (< 0.3)	Left Rear Car

Table 1: Merging Strategy

4.3 Overtaking Scenario

When the target lane change position for **E** is in front of **Left Front Car**, the scenario is classified as "Overtaking".

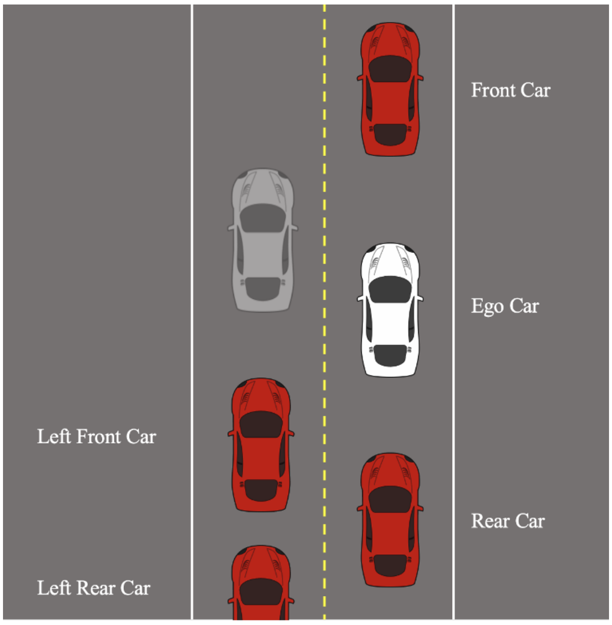

Figure 12: Overtaking Scenario

The lane change strategy when overtaking is listed in Table (2). Before lane changing **E** will alter its velocity according to the optimal velocity model and the risk to the **Front Car**. The risk to **Front Car** is taken into consideration when performing lane change and will then maintain its optimal velocity after merging into the left lane. The risk to **Front Car** and **Left Front Car** are calculated in the motion prediction model and are selected as index.

Following	
Before	Front Car
During	Front Car
After	N/A
Prediction	
Avg_Risk1 (< 0.4)	Front Car
Avg_Risk2 (< 0.5)	Left Front Car
Avg_Risk3 (< 0.3)	0

Table 2: Overtaking Strategy

4.4 Following Scenario

If the target lane change position for **E** is behind **Left Rear Car**, the scenario falls into following.

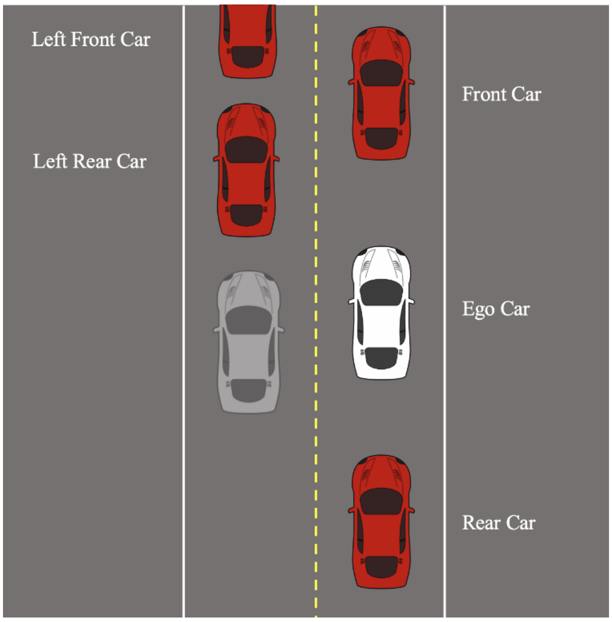

Figure 13: Following Scenario

The lane change prediction and strategy are listed in Table (3). The lane change and prediction strategy are similar to those in overtaking, where **Left Front Car** is replaced by **Left Rear Car**

Following	
Before	Front Car
During	Left Rear Car
After	Left Rear Car
Prediction	
Avg_Risk1 (< 0.4)	Front Car
Avg_Risk2 (< 0.5)	Left Rear Car
Avg_Risk3 (< 0.3)	0

Table 3: Following Strategy

4.5 Pseudo Code

$EndTime = SimulationTime$
$P_i \leftarrow Start\,Position$
$V_i \leftarrow Optimal\,Velocity$
$N \leftarrow Vehicle\,Number$
while Time < End Time **do**
  for i = 1 to N **do**
    Calculate $\alpha_1(i), \alpha_2(i), r_e(i), r_t(i), d_{min}(i)$
    $V_i = Optimal\,Vlocity(Risk_i)$
    if Lane Change Triggered **then**
      Motion Prediction Model(Scenario)
      if Predict lane change feasible **then**
        Decide P_0, P_1, P_2, P_3
        B = Bezier Curve(P_0, P_1, P_2, P_3)
        Lane Changing = True
      end if
    end if
    if Lane Changing **then**
      Car Move(B)
    else
      Car Move(V_i)
    end if

end for
Time = Time + 0.1
end while

5 Simulation Result

5.1 Merging Scenario

Figure (14) shows the risk to **Front Car**, **Left Front Car**, and **Left Rear Car** in merging scenario. At about 6.3 seconds the risk to the **Front Car** is greater than the threshold value 0.1, the intention of lane change is triggered. The motion prediction model then calculate the predicted risks for lane change within about 0.006 second, the predicted risks to surrounding vehicle are showed in Figure (15), which are **Front Car**, **Left Front Car**, and **Left Rear Car**. Totally 16 sample positions are chosen to predict risk. Once the predicted is asserted feasible, **E** conduct lane change where the risk to **Front Car** decrease and the risks to **Left Front Car** and **Left Rear Car** increase. A point should be notice is that after 14 seconds the risk to **Left Front Car** and **Left Rear Car** maintain at around 0.35, which means **E** is following **Left Front Car** and **Left Rear Car** is following **E** in a same lane. The risk value of 0.35 is the result of optimal velocity curve mentioned in previous section.

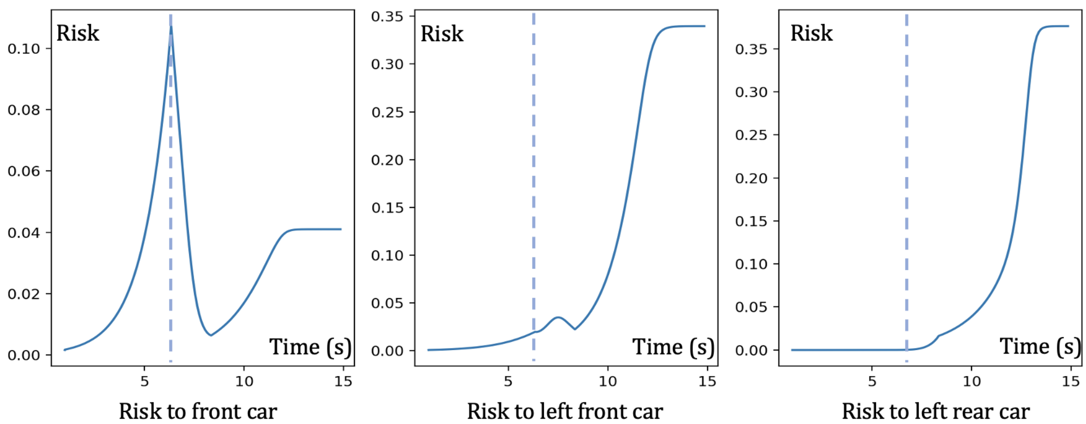

Figure 14: Risk plot in merging scenario

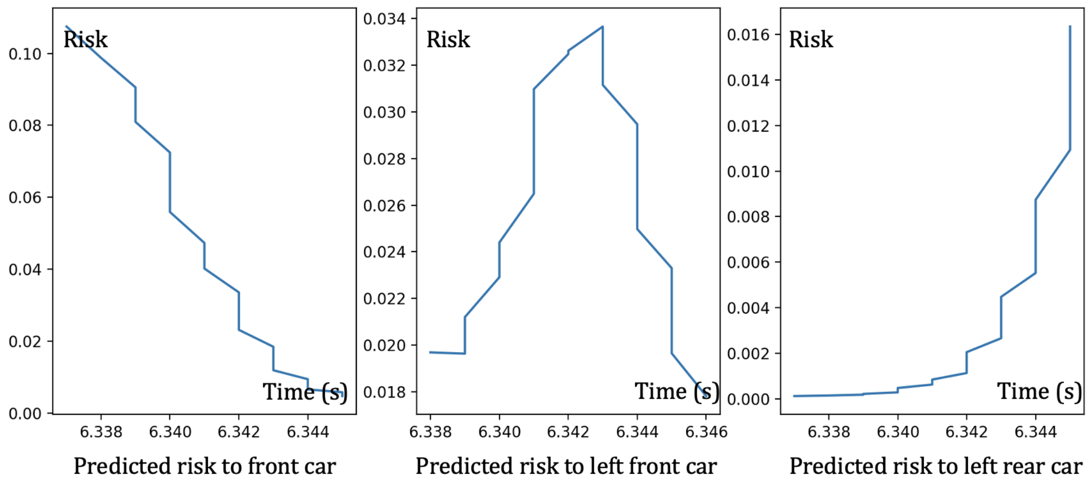

Figure 15: Predicted risk in merging scenario

5.2 Overtaking Scenario

Figure (16) shows the risk to **Front Car**, **Left Front Car**, and **Left Rear Car** in overtaking scenario. The intention of lane change is same as merging scenario. Figure (17) shows the predicted risk to **Front Car**, **Left Front Car** and costs only 0.06 seconds.

The prediction has a high precision as Figure (17) shows that the risk to **Left Front Car** may rise to nearly 0.5 and the risk to **Left Front Car** do rise up to 0.5 when lane change is conducted. The risk to **Front Car** rises and drops from 10 to 20 seconds when **E** just pass by **Front Car** in another lane. This is because the two-dimension risk calculation model consider the risk of vehicle in another lane rather than only the vehicle in same lane.

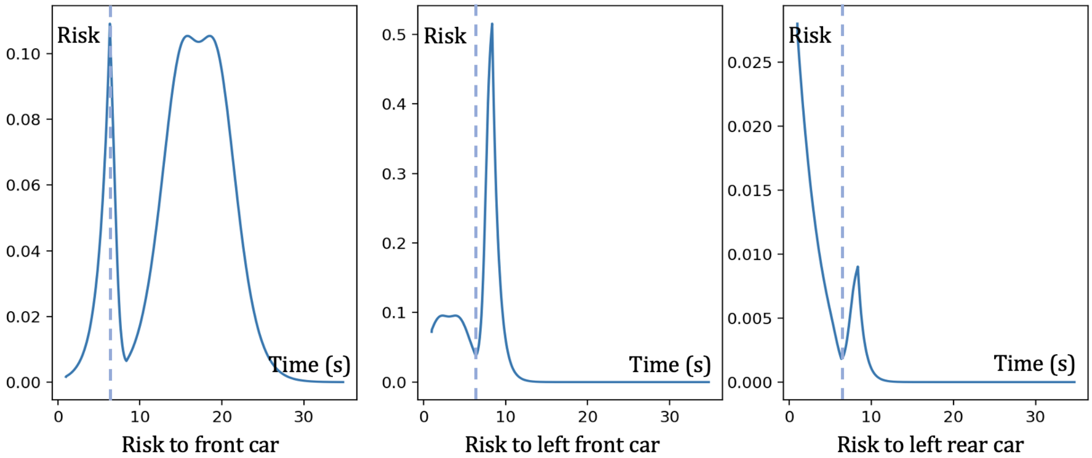

Figure 16: Risk plot in overtaking scenario

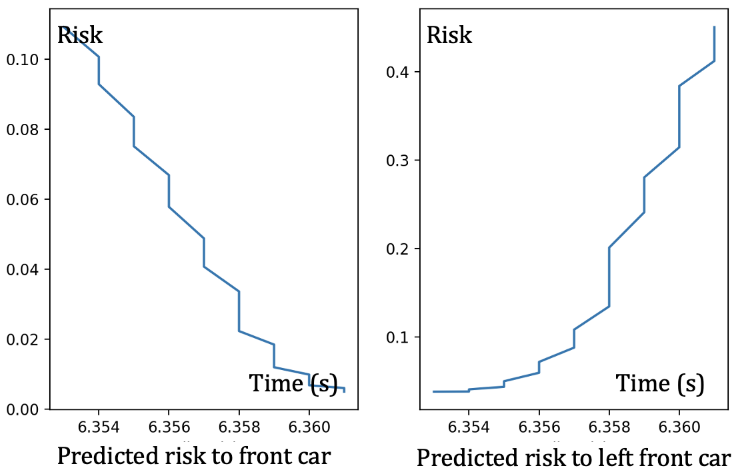

Figure 17: Predicted risk in overtaking scenario

5.3 Following Scenario

Figure (18) shows the risk to **Front Car**, **Left Front Car**, and **Left Rear Car** in overtaking scenario. The intention of lane change is same as merging scenario. Figure (19) shows the predicted risk to **Front Car** and **Left Rear Car** and costs only also 0.06 seconds.

The predicted risk2 in Figure(19) rises before it drops, which matches the actual risk after conducting lane change in Figure (18).

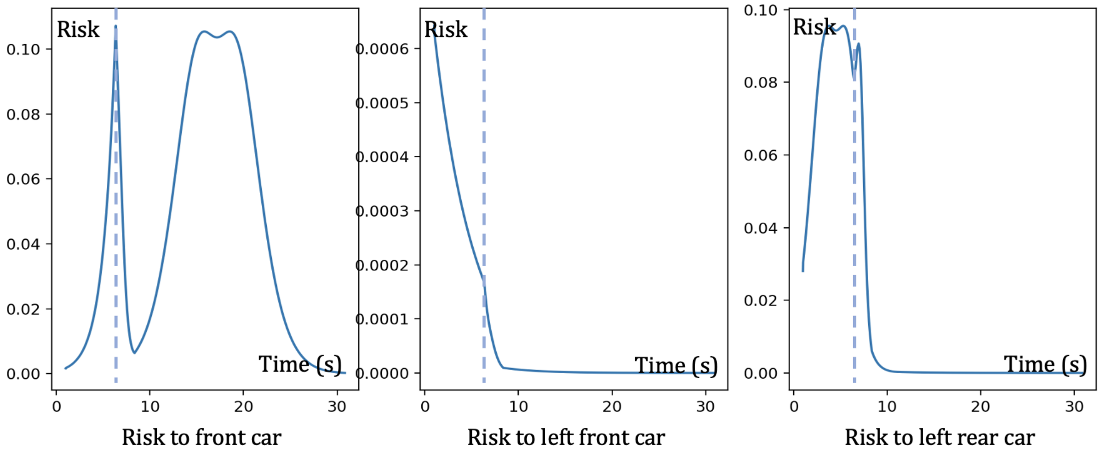

Figure 18: Risk plot in following scenario

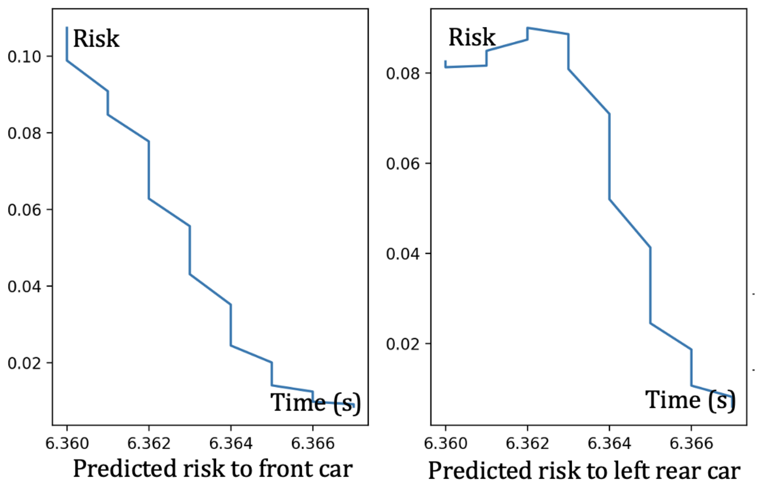

Figure 19: Predicted risk in following scenario

6 Conclusion

The risk-based model proposed can work without V2X and thus can provide decision strategy for automated vehicle even having information security issue. On the other hand, it can also serve as lane change assistance system in commercial car. The concern of high computation in prediction system may not be a problem due to the advance technology on ECU (Electronic Control Unit).

Traffic risk plays an important role in this report, almost every decision based on the calculated risk. According to the modified optimal velocity model, the risk is roughly divided into four parts, as Figure (20) depicts.

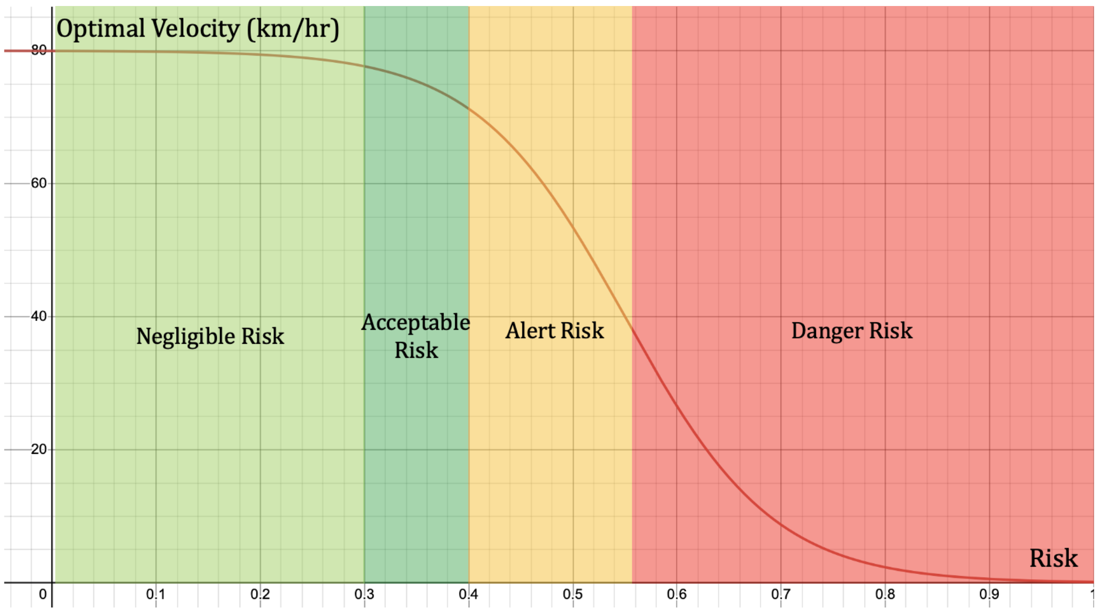

Figure 20: Risk index division

The preliminary definition of each part is as below:

1. **Negligible Risk (0 - 0.3):** In this section, the risk to the driver is negligible, the vehicle will tend to maintain its optimal (or maximum) velocity.

2. **Acceptable Risk (0.3 - 0.4):** When the risk rise to 0.3, the driver may have small reaction to the risk, such as slightly acceleration or deceleration. 0.35 is also the risk where the vehicle is following the car in the front.

3. **Alert Risk (0.4 - 0.55):** Alert refers to the potential high risk, the optimal velocity decrease rapidly in this section. The driver should make decision or reaction under this risk to prevent accident.

4. **Danger Risk (0.55 - 1):** The threshold value of 0.55 is determined by the inflection point in Equation (9). The accident is highly possible under this risk and driver must react to the traffic environment.

The scenario simulation in python shows that the exponential distribution risk model can serve as a reasonable index for lane changing, the way ego car conduct lane change seems rational and understandable. However, whether it is acceptable to public still requires more data and survey.

Furthermore, the above definition strongly depends on the optimal velocity curve, and the risk calculation also affected by the parameters in model, i.e., $w, l, \gamma, \lambda_1, \lambda_2, V_{ideal}$. Hence, to implement risk system in general transportation system still requires an well-established protocol for the definition and formulation of risk.

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