DECISION-MAKING AND CONTROL FOR ADVANTAGEOUS LANE CHANGING: COLLISION CONE BASED

A Thesis

by

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ABSTRACT

In this paper, we propose a lane changing model based on the collision cone approach. Specifically, we show how a vehicle decides whether to change lanes using the collision cone algorithm based on the velocity and the location of surrounding vehicles. The model not only checks the safety of a lane change but also compares the current and target lane with a new measure of driving advantages. In addition, it determines if there are any existing driving advantages such as free space and speed by lane changing. This is proved by showing how the subject vehicle behaves in different situations. Moreover, a new methodology of lane changing for collision avoidance, which is based on line of sight (LOS) with a target leader in a target lane, is suggested with a model predictive controller (MPC). Additionally, we show that the model makes reliable decisions and generates acceptable lane changing trajectories.

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1. INTRODUCTION*

1.1 Motivation

People today are facing various traffic problems. For instance, 1.2 million people are killed on the world's roads every year, and in America alone, 33,000 people are killed each year. Traffic is also getting worse. In America, between 1990 and 2010, the miles traveled by vehicles increased by 38 percent, meaning that traffic is substantially worse. In order to deal with such problems, many researchers have been trying to accomplish the full automation of vehicles. In fact, the development of intelligent vehicles is a rapidly developing field in transportation and is attracting much attention.

Among diverse maneuvers that can be done by intelligent vehicles, the lane changing maneuver in Figure. 1.1 happens most frequently and is complicated in the sense that it

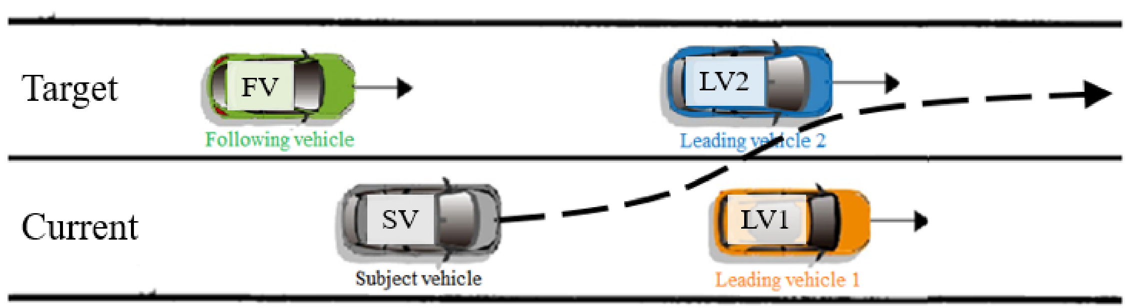

Figure 1.1: Lane changing maneuver

involves longitudinal and lateral control together. Moreover, a driver must check not only the current lane but also the target lane into which the driver intends to move. In fact, lane

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changing involves complex interactions with the surrounding traffic as in Figure 1.1, and many human drivers feel stressed while performing this task according to [1].

However, reasonable lane changing can have positive effects on traffic flow. It is sometimes inevitable because it helps avoid a dangerous situation, like when a leading vehicle rapidly slows down. Therefore, it is regarded as a dangerous but necessary operation for drivers, and researchers have been suggesting a variety of methodologies to build a robust lane changing model that can give the best answer no matter how complicated a situation is. However, there is still a need to develop a more realistic lane changing model.

1.2 Literature Review

1.2.1 Lane Changing Decision Making Model

In [2], the author presented a structure for the lane changing decision to deterministically model the driver's possible behavior. A decision to change lanes is made after answering whether or not lane changing is necessary, desirable, and safe. To answer these questions, various factors like the following are considered:

- whether lane changing is physically possible and safe from a collision
- the location of permanent obstructions
- the presence of transit lanes
- the driver's intended turning movement
- the presence of heavy vehicles
- the possibility to gain speed advantage

The author produced a model that could deal with as many situations as possible that may occur in driving.

In [3], the decision tree in Figure 1.2 is implemented. Specifically, the following are

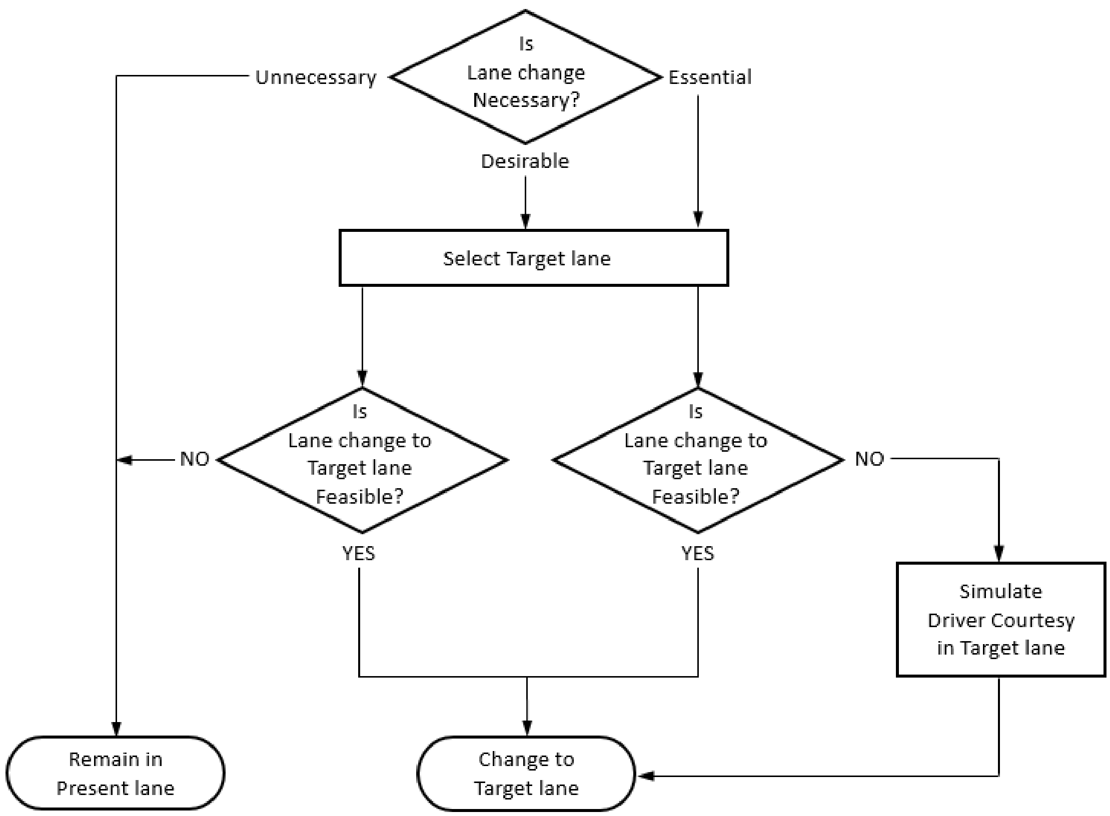

Figure 1.2: Lane changing process in [3]

considered to check if lane changing is necessary and evaluate reasons for lane changing:

- Turning movement
- End-of-lane
- Lane blockage
- Transit lane
- Speed advantage

- Queue advantage

Then, after the selection of a proper target lane, considering the reason for lane changing, feasibility of lane changing is checked. If the gap into which the vehicle moves has sufficient size so that lane changing can be done without forcing other vehicles to rapidly accelerate or decelerate, then lane changing is determined to be feasible. In this step, using the car-following algorithm from [2], the required acceleration or deceleration is obtained and then used as a standard to determine if the gap is acceptable.

In [4], the author built the decision tree in Figure 1.3 to handle the three steps for lane changing: deciding whether to change lanes, determining the target lane and checking if

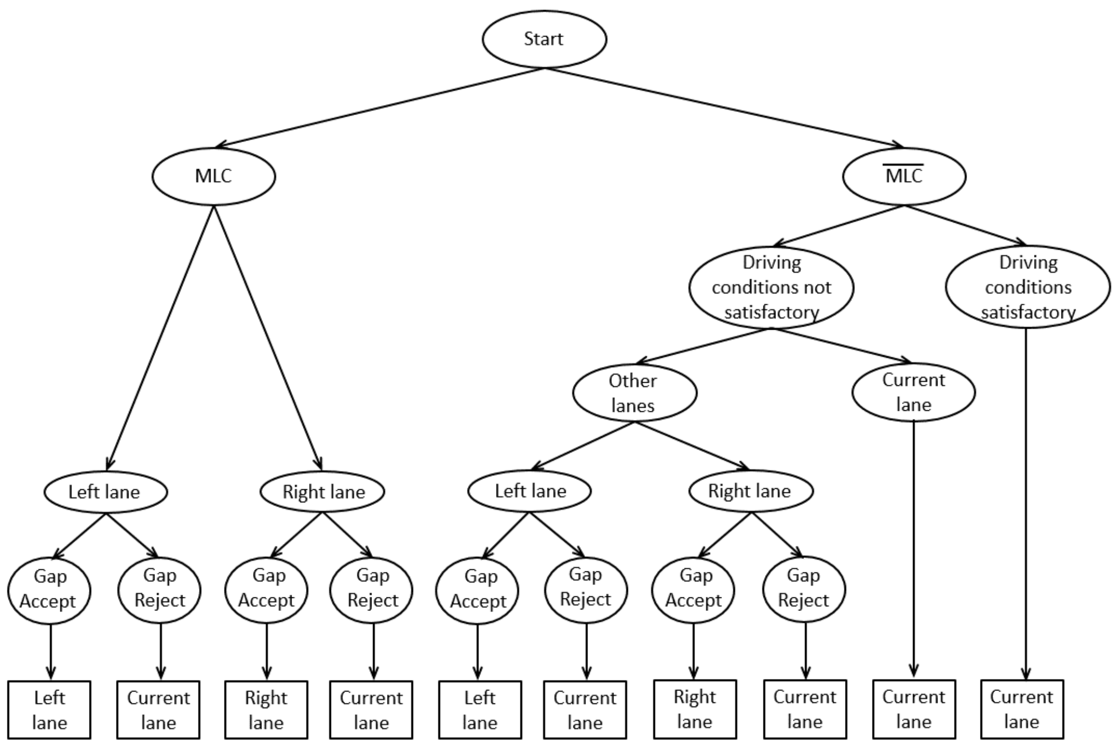

Figure 1.3: Lane changing process in [4]

the gap in the target lane is acceptable. Depending on whether lane changing is mandatory or discretionary, the author estimated different parameters to use for the evaluation of acceptance of the gap into which the driver wants to move. Other than [4], there have been many various approaches based on the notion of 'critical gap,' the minimum gap the driver would be willing to accept for lane changing. There are other studies that use related geometric interpretations. In [5], the authors tried to find a minimum initial distance between vehicles for safe lane changing. Then, the authors presented graphs that show relationships between relative velocity and initial distance for safe lane changing.

Similarly, with the increasing interest in intelligent algorithms, new approaches have been applied, some of which are based on fuzzy logic. In those papers, the authors commonly used membership functions of various parameters for decision-making. In [6], a fuzzy logic controller outputs a steering angle based on speed and lateral displacement. Game theory is yet another interesting approach. By assuming a traffic situation as a game among vehicles, several papers have tried to find the best decision in a given situation. The bigger issue in this approach is how to design the payoff matrix and the utility function. In particular, in [7, 8], the authors provided a rather realistic solution to this problem using Stackelberg game theory by considering utility functions that factor in both the free space and human aggressiveness in a unified approach. There are additional studies that continue to explore the issue, although no single approach appears to dominate the field.

1.2.2 Model Predictive Control (MPC)

Model Predictive Control (MPC) has been successfully applied to various industrial applications, as well as for vehicle control in [9, 10]. MPC generally has the following structure in Figure 1.4.

The goal of MPC is to obtain an optimized vector for control input such that the cost function has a desired value. Calculation of the optimized vector is done based on a pre-

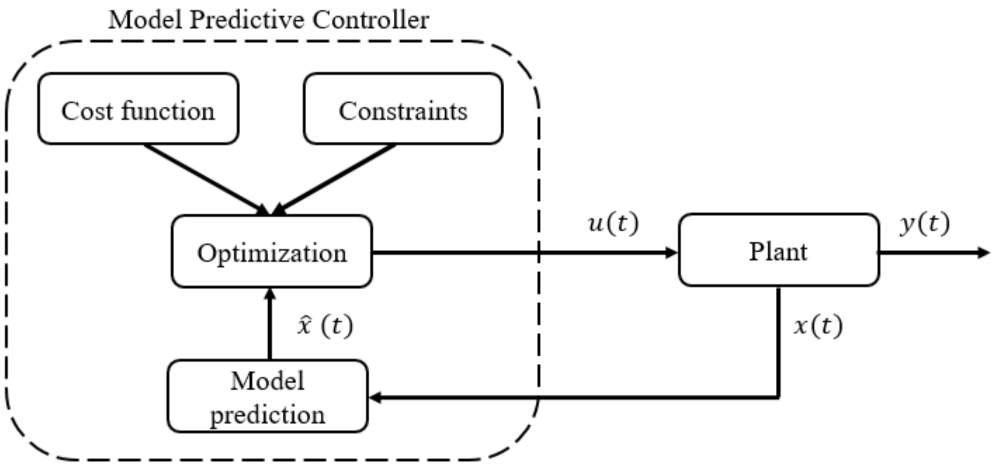

Figure 1.4: General structure of MPC

dicted future states of the plant in the presence of the constraints, and the plant behaves as we want it to by making an adjustment of the cost function. As an example, in [10], the author implemented MPC to minimize any tracking errors between a vehicles' predicted trajectory and a given reference trajectory as shown in Figure 1.5.

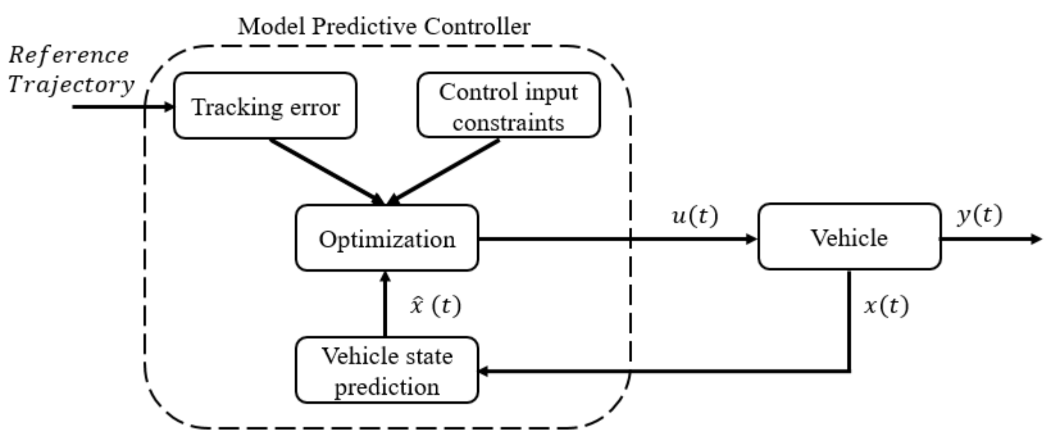

Figure 1.5: Structure of MPC in [10]

1.3 Research Objectives

The objective of this thesis is to build a lane-changing decision model based on a concept called the collision cone approach [11]. Moreover, in control level, a design of MPC for longitudinal and lateral control both for lane changing and deceleration is another objective.

1.3.1 Design of Lane Changing Decision-Making Model

In the thesis, I will design a novel decision-making model, and the model will be designed to check the following: safety and driving advantage. Out of many aspects, driving advantage like speed advantage and free space is considered important. In all cases lane changing is discretionary, which means it is not mandatory, whether the driver can benefit from lane changing or not is the main question the model has to answer. However, there has never been a way to clearly measure driving advantage. There is a need to introduce the lane changing model based on a measure of driving advantage. I will explain a driving advantage measure based on collision cone algorithm and how come it is possible to measure it with the algorithm. Moreover, I will also show how to use the collision cone algorithm as the main concept for the safety check of lane changing.

To evaluate the model, I will provide various scenarios with different conditions in terms of safety and advantages as follows:

- Changing lane is dangerous, but advantageous
- Changing lane is safe, but disadvantageous
- Changing lane is safe, but advantageous

and how the model responds to these scenarios will be given for the evaluation.

1.3.2 Design of MPC

Once a decision is made by the model, a vehicle has to be controlled to follow the decision by the model. In the thesis, I will show a new concept that lane changing is executed by following a target leading vehicle, LV2, in the target lane. MPC will be designed in a way that the subject vehicle can follow the line of sight (LOS) of the target leader.

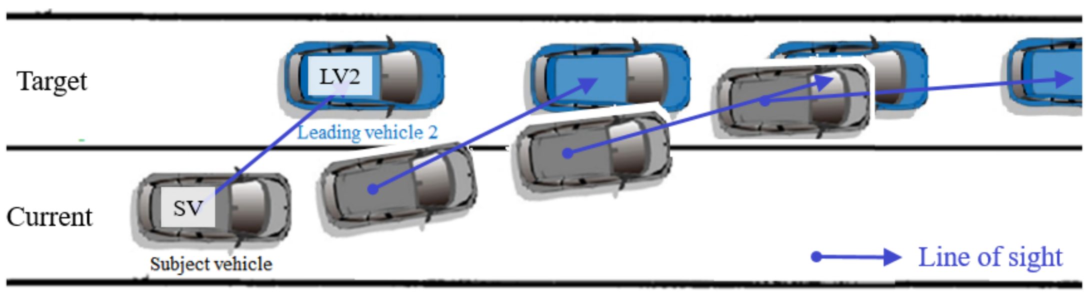

Figure 1.6: LOS following lane changing model

To make the research realistic, control input efforts, which are steering angle and acceleration in the research, will be limited as a part of MPC formulation. For details, I will show how to define proper parameters for MPC, such as prediction horizon and weights in a cost function, depending on diverse scenarios.

2. COLLISION CONE ALGORITHM

Everything about lane changing decision model starts from understanding of the collision cone algorithm [11] and fundamentals of the algorithm can be introduced by understanding of the geometric relationship between two points moving at different constant velocities.

2.1 Collision Geometry between Points

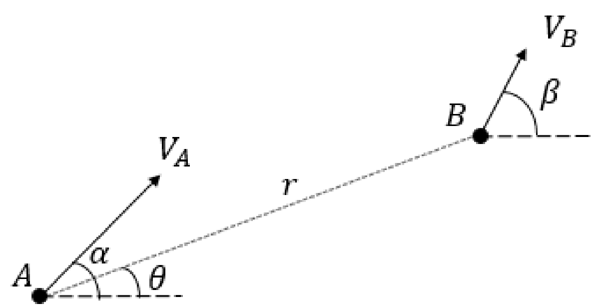

Figure 2.1: Collision geometry between points

When there exist two constantly moving points, we can define V_r and V_θ, two components of relative velocity of point B with respect to A. V_r is the relative velocity along LOS, and the other one, V_θ, is the relative velocity perpendicular to LOS, θ.

$$V_r = \dot{r} = V_B \cos(\beta - \theta) - V_A \cos(\alpha - \theta) \tag{2.1}$$

$$V_\theta = r\dot{\theta} = V_B \sin(\beta - \theta) - V_A \sin(\alpha - \theta) \tag{2.2}$$

And, we can obtain the following by differentiating (2.1) and (2.2)

$$\dot{V}_r = \dot{\theta} V_B \sin(\beta - \theta) - \dot{\theta} V_A \sin(\alpha - \theta) = \dot{\theta} V_\theta \tag{2.3}$$

$$\dot{V}_\theta = -\dot{\theta} V_B \cos(\beta - \theta) + \dot{\theta} V_A \cos(\alpha - \theta) = -\dot{\theta} V_r \tag{2.4}$$

Dividing (2.3) by (2.4) and cross-multiplying , we can get

$$\dot{V}_r V_r + \dot{V}_\theta V_\theta = 0 \tag{2.5}$$

which, on integration, yields :

$$V_r^2 + V_\theta^2 = V_{r0}^2 + V_{\theta 0}^2 \tag{2.6}$$

The equation above shows that the trajectory of V_r, V_θ is a circle with a center at the origin with a radius equal to the initial relative velocity between A and B in Figure 2.1. This also implies that the relative velocity is a constant with respect to time when A and

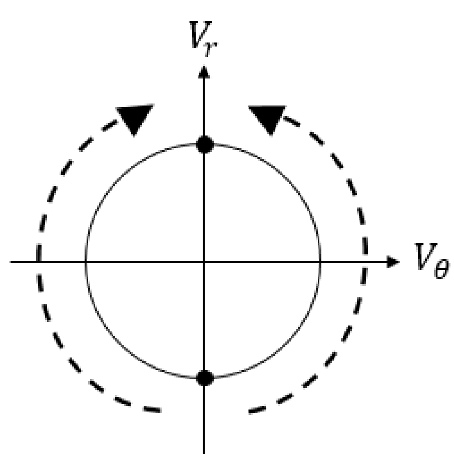

Figure 2.2: (V_r,V_θ) plane and points satisfying V_θ = 0

B move with constant velocity vectors, V_A and V_B.

In such a case, once the following condition on a relative velocity component is met,

$$V_\theta = 0 \tag{2.7}$$

then, it possible to infer the following from (2.2).

$$\dot{\theta} = 0 \tag{2.8}$$

Moreover, substituting (2.8) to (2.3) and (2.4) leads to

$$\dot{V}_r = 0 \text{ and } \dot{V}_\theta = 0 \tag{2.9}$$

, which means black points, which satisfy (2.7), are stationary on the plane in Figure 2.2.

Therefore, a sufficient and necessary condition for a collision to occur can be established with respect to initial relative velocity components as

$$V_{\theta 0} = 0 \text{ and } V_{r0} < 0. \tag{2.10}$$

(2.10) means the following from (2.9)

$$V_\theta = 0 \text{ and } V_r < 0 \text{ for time } t > 0. \tag{2.11}$$

And, the condition's sufficiency can be proved by following inference from (2.11)

- θ is constant from (2.8)
- $V_r = \dot{r} < 0$ for future from (2.9)

In other words, θ is constant without any rotation and the distance between two points along θ, r, keeps decreasing for the future time. Therefore, we can predict a collision with the sufficient condition. However, we also need to check if there are any other cases than a collision from the sufficient condition by checking the necessity of (2.10) for a collision.

For the necessity, let us consider Figure 2.3.

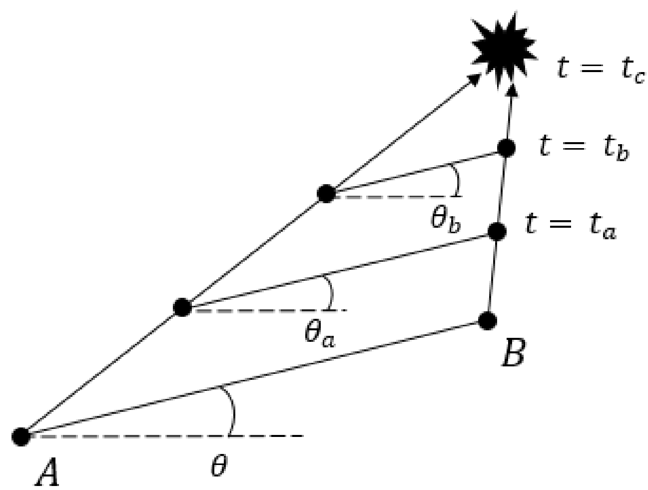

Figure 2.3: Collision steps between points

Let us say a collision between A and B occurs at time t_c. In Figure 2.3, because velocities of A and B are assumed to be constant, LOS made between A and B at any time before time = t_c are parallel to each other, which means

$$\dot{\theta} = 0 \tag{2.12}$$

Furthermore, the presence of a collision means

$$V_r < 0 \text{ at time } t_c^-. \tag{2.13}$$

In such a case, we can infer the following initial condition from (2.2), (2.4), and (2.9).

$$V_\theta = \dot{V}_\theta = 0 \text{ before time } t_c^-.$$
$$V_r < 0 \text{ before time } t_c^-. \tag{2.14}$$

As a result, the following can be newly defined as the necessary and sufficient initial condition for a collision.

$$V_{\theta 0} = 0 \text{ and } V_{r0} < 0. \tag{2.15}$$

2.2 Collision Geometry between a Point and a Circle

Consider a possibility of a collision between A and B, a point and a circle in Figure 2.4.

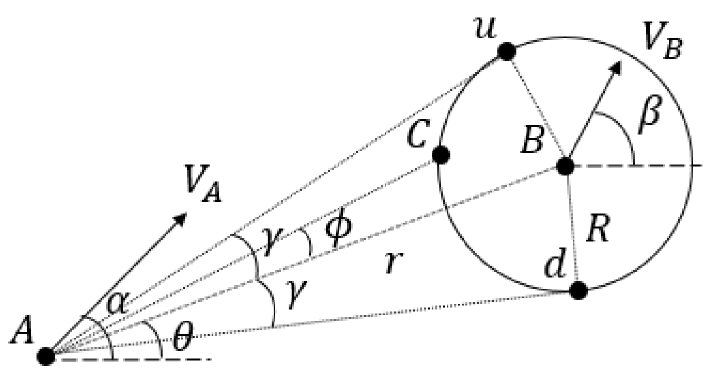

Figure 2.4: Collision geometry between a point and a circle

We basically need to check if there exist an arbitrary point C on the circle B that satisfies the condition (2.15) with the subject point A, which means

$$(V_\theta)_{AC} = 0 \text{ and } (V_r)_{AB} < 0. \tag{2.16}$$

Because C is an arbitrary point, instead of $(V_\theta)_{AC} = 0$, we can use the following condition about upper tangent Au and lower tangent Ad to the circle B.

$$(V_\theta)_{Au} \cdot (V_\theta)_{Ad} \leq 0 \tag{2.17}$$

Proof: Relative velocity of an arbitrary point C perpendicular to corresponding LOS, $\theta + \phi$, can be written as :

$$(V_\theta)_{AC} = V_B \sin(\beta - (\theta + \phi)) - V_A \sin(\alpha - (\theta + \phi)). \tag{2.18}$$

Here, an arbitrary point C can be defined by the angle ϕ, which is bounded by $[-r, r]$ according to two tangent lines Ad and Au. Based on that $(V_\theta)_{AC}$ is a continuous function, we can infer that $(V_\theta)_{AC} = 0$ means that $(V_\theta)_{Au}$ and $(V_\theta)_{Ad}$ are always of opposite sign hence the product $(V_\theta)_{Au} \cdot (V_\theta)_{Ad}$ is also negative.

In addition, we can obtain ϕ that satisfies $(V_\theta)_{AC} = 0$ from (2.18).

$$\tan\phi = \frac{V_B \sin(\beta - \theta) - V_A \sin(\alpha - \theta)}{V_B \cos(\beta - \theta) - V_A \cos(\alpha - \theta)} \tag{2.19}$$

In (2.19), $\tan\phi$ is a function with a period of π, which means $(V_\theta)_{AC} = 0$ has a unique. This is because ϕ is bounded by $[-\gamma, \gamma]$ and γ is less than $\pi/2$ by the following.

$$\gamma = \arcsin\frac{R}{r} \text{ and } r \geq R \tag{2.20}$$

Therefore, ϕ satisfying $(V_\theta)_{AC} = 0$ is unique all the time.

Furthermore, we can expand (2.17) by substitution of ϕ with γ and $-\gamma$ and obtain :

$$\begin{aligned}
&V_B^2 \sin(\beta - (\theta + r)) \sin(\beta - (\theta - r)) \\
&-V_A V_B \sin(\alpha - (\theta + r)) \sin(\beta - (\theta - r)) \\
&-V_A V_B \sin(\alpha - (\theta - r)) \sin(\beta - (\theta + r)) \\
&+V_A^2 \sin(\alpha - (\theta + r)) \sin(\alpha - (\theta - r)) \leq 0.
\end{aligned} \tag{2.21}$$

(2.21) can be simplified in terms of $(V_r)_{AB}, (V_\theta)_{AB}$, two relative velocity components with respect to LOS between the point A and the center of B, as :

$$r^2 (V_\theta)_{AB}^2 \leq R^2 \{(V_r)_{AB}^2 + (V_\theta)_{AB}^2\}. \tag{2.22}$$

Therefore, with (2.22), we can rewrite (2.16) with respect to initial conditions like

$$\begin{aligned}
&(V_{r0})_{AB} < 0 \\
&r^2 (V_{\theta 0})_{AB}^2 \leq R^2 \{(V_{r0})_{AB}^2 + (V_{\theta 0})_{AB}^2\}
\end{aligned} \tag{2.23}$$

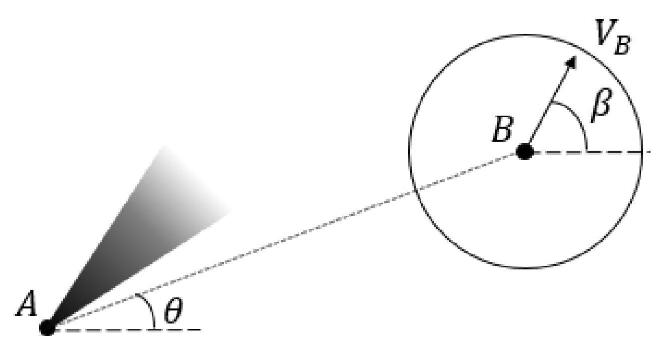

Figure 2.5: Collision Cone between a point and a circle

2.3 Collision Geometry between Circles

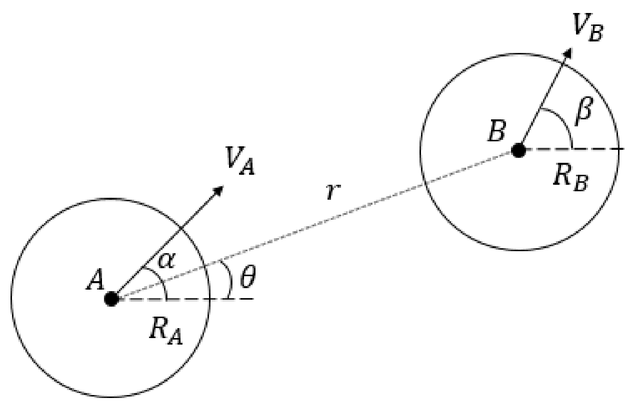

Figure 2.6: Collision geometry between circles

It is also possible to predict a collision between two circles A and B in Figure 2.6. According to the algorithm, it is the same as predicting a collision between a point and an enlarged circle with the radius of $R_A + R_B$ as in Figure 2.7.

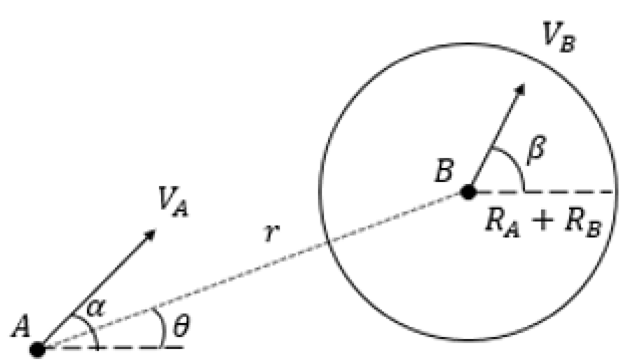

Figure 2.7: Collision geometry between a point and an enlarged circle

Therefore, the necessary and sufficient condition for a collision between two circles can be defined as :

$$
\begin{aligned}
(V_{r0})_{AB} &< 0 \\
r^2(V_{\theta 0})^2_{AB} &\leq (R_A + R_B)^2\{(V_{r0})^2_{AB} + (V_{\theta 0})^2_{AB}\}.
\end{aligned}
\tag{2.24}
$$

If we consider vehicles as moving circles in Figure 2.6, we can calculate collision cones about surrounding vehicles on the road with respect to the subject vehicle. Considering that a collision cone is calculated using current location and velocity, it is possible to measure a chance of a collision and to estimate driving advantages such as free distance and speed advantage using (2.24). Therefore, once reliable information is obtained, the model can decide if lane changing is safe and advantageous in a robust and simple way by interpreting collision cones.

3. DECISION-MAKING MODEL*

3.1 Structure for Decision-Making

The overall schematic of the decision-making model for collision avoidance is depicted in Figure 3.1. This architecture was used to simulate several cases of highway

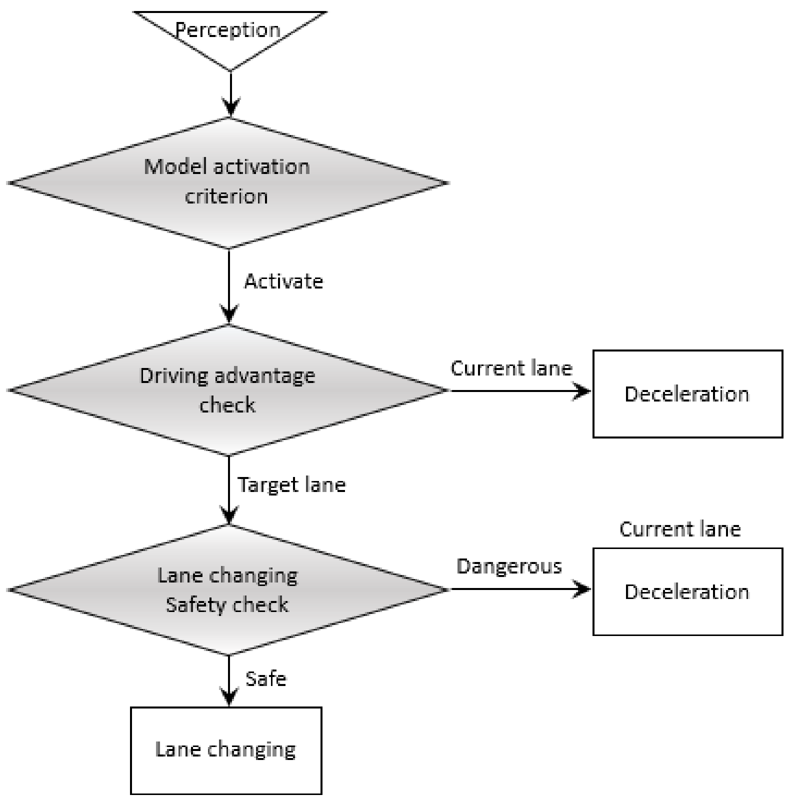

Figure 3.1: Structure of decision-making model

driving. Measured information (velocity and location of surrounding vehicles relative to

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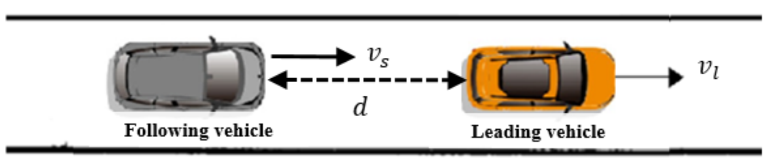
the subject) is used for making a decision as to whether to change lane or not but also for planning a safe path for lane-changing.

3.2 Model Activation Criterion

It is important to set a good model activation criterion. False activation by an inefficient criterion can become a nuisance to a driver by causing unnecessary lane changing or deceleration [12]. Moreover, because activation criterion defines driving condition on a current lane that a vehicle moves in, the criterion is directly related to the target lane condition that leads to lane changing. Therefore, activation conditions need to be proper so that the decision-making model makes a proper decision.

We used two danger measures, time to collision (TTC) and time headway(TH). TTC is defined as the time that it would take a following vehicle to collide with a leading vehicle. TTC measures actual danger [13] by calculating how long is left until collision and



$$\frac{d}{v_s - v_l} \text{ when } v_s > v_l$$

Figure 3.2: Time to collision

many researchers have been suggesting TTC values that can distinguish safe and unsafe conditions for driving [14], but none of them is considered as dominant. So, I used TTC of 2.5 sec [12], which is one of the generally used values to distinguish dangerous driving. Using TTC has the drawback that TTC only applies to when a following vehicle is faster. In some cases, TTC cannot measure potential danger that comes from a short gap that is not decreasing. Therefore, I also considered TH not to overlook potential danger [13] that TTC cannot cover. TH means time headway and is defined as the time that passes between

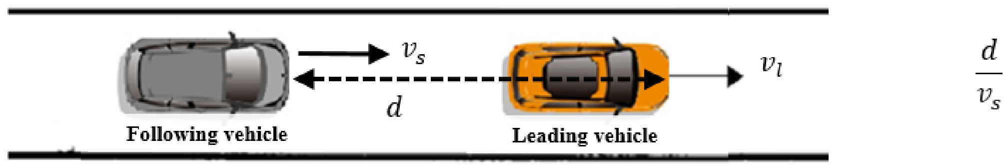


Figure 3.3: Time headway

two vehicles'reaching the same location. It is used to measure potential danger like a very short distance between vehicles regardless of relative velocity. Drivers are most likely to accept TH of 1-2 sec [15], in fact, and at least when TH = 0.5 sec, drivers generally feel threatened and try to change lanes. In conclusion, I designed a model activation criterion as in Table 3.1 considering actual danger and potential danger. If it is indicated that any of two threats exists according to Table 3.1, then the model is triggered.

Table 3.1: Model Activation Criterion

	TH$\leq$0.5 sec	TH$>$0.5 sec
TTC$\leq$2.5 sec	Activation	Activation
TTC$>$2.5 sec	Activation	Deactivation

To validate if these two conditions can work together properly, I obtained the size of the gap between two vehicles according to TTC of 2.5 and TH of 0.5 sec. Here I have four plots and each plot shows a gap between two vehicles in Figure 3.2 depending on the velocity of a leading vehicle for a particular velocity of a following vehicle. In Figure 3.4

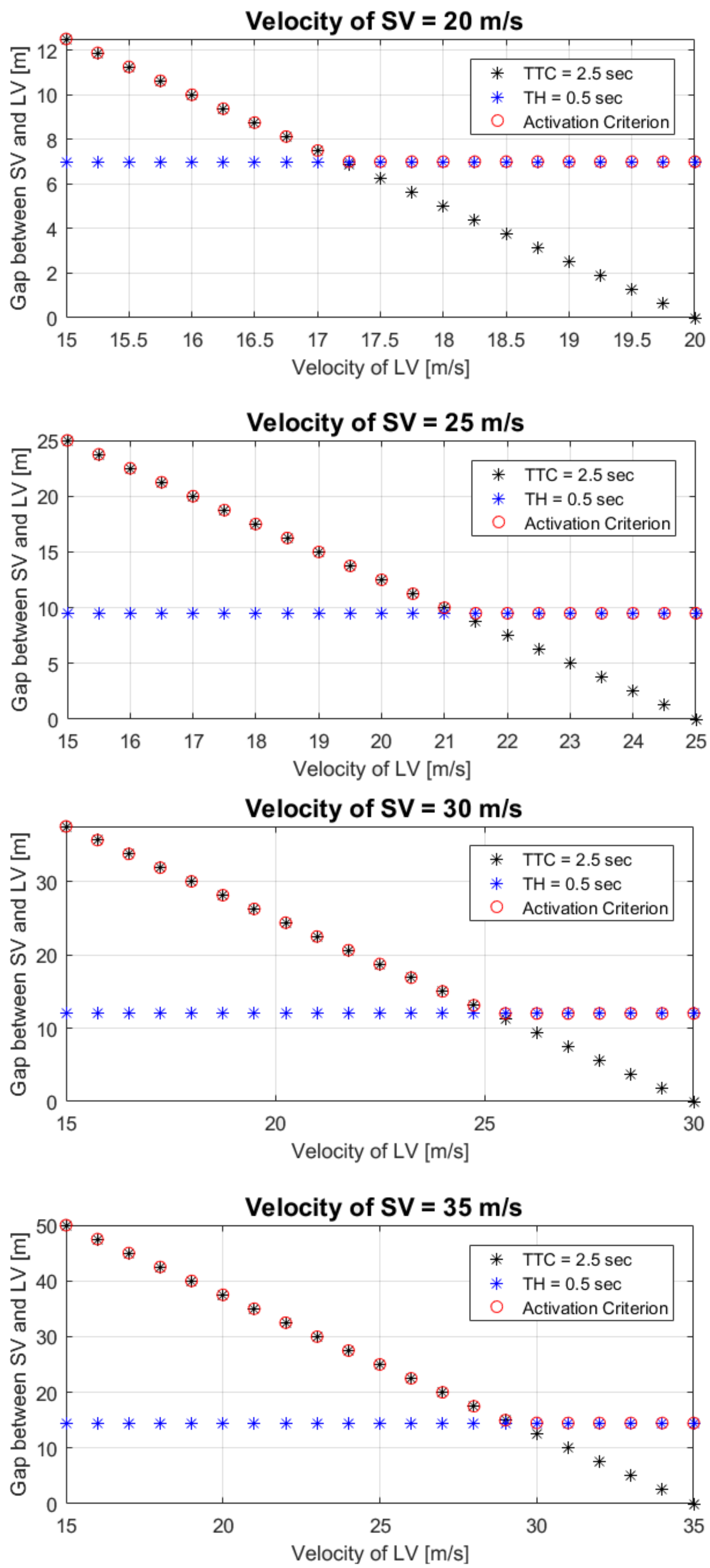


Figure 3.4: Gap according to Table 3.1

Black stars represents the gap based on TTC value 2.5 sec, and blue stars represents the gap based on TH value 0.5 sec. When the leader is a lot slower compared to the follower, TTC condition gives sufficient gap for safety, which means the gap according to TTC condition gives TH bigger than 0.5 sec. However, when there is not a big difference between their velocities, TH condition, not TTC condition, needs to be considered first for safe driving from both actual danger and potential danger. With TH condition, the model knows when to trigger the model according to the minimum gap only depending on velocity of SV even without actual threat from the leader. Therefore, the model is triggered according to red-circle line that indicates the gap determined by Table 3.1.

3.3 Driving Advantage Check

3.3.1 Driving Advantage Measure

In Figure 3.5, we assume that SV(the black vehicle in the current lane) assesses driving condition of the target lane in view of the presence of the contending lead vehicle LV2(the blue vehicle in the target lane). In case SV is faster than LV2, we can determine the blue collision cone, and we prepared a few examples to show how the cone changes depending on the target leader LV2.

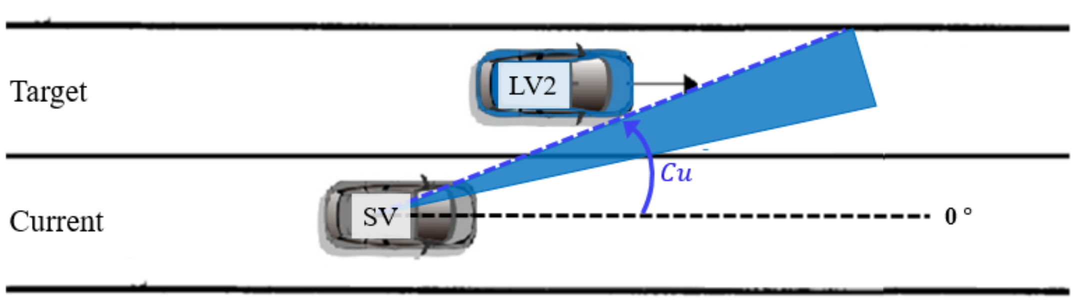


Figure 3.5: Vehicles and a collision cone

Example 1: Consider Figure 3.6 where the contending lead vehicle is assumed to be in the target lane (LV2, the blue vehicle in the target lane). LV2 is slightly slower than SV, and the blue collision cone exists.

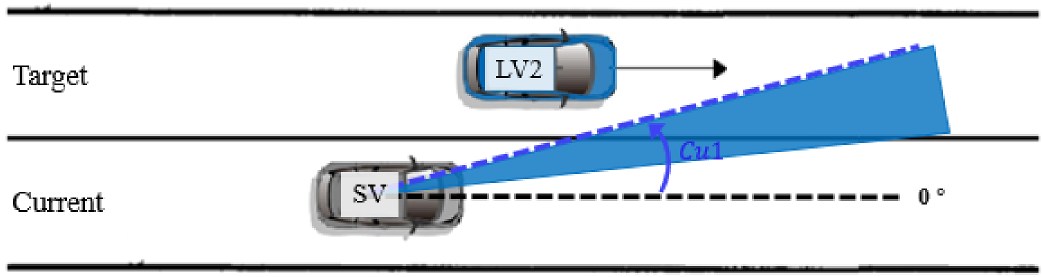


Figure 3.6: Schematic of *Example 1* : $Cu1$

Example 2: The difference relative to *Example 1* is that LV2 is assumed to be moving at a slower rate (hence the shorter velocity arrow) and therefore moving to the left gives a smaller speed advantage, where the total driving advantage produced by the lane-change would be smaller. This decrease can be easily checked with the blue collision cone by LV2, which produces a bigger upper boundary angle, $Cu2$, in Figure 3.7.

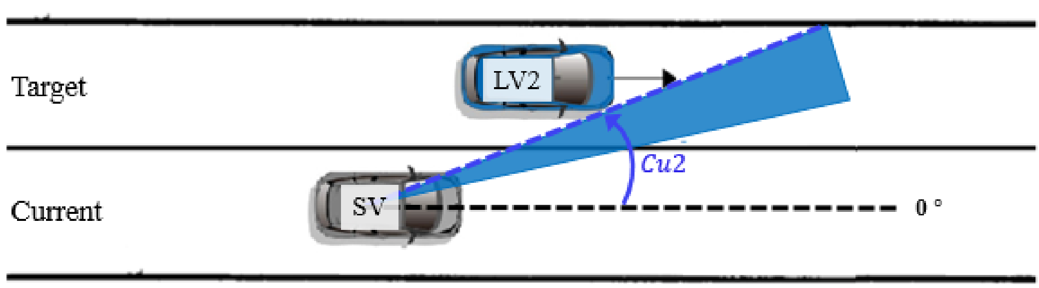


Figure 3.7: Schematic of *Example 2* : $Cu2 > Cu1$

Example 3: Here as shown in Figure 3.8, LV2 has been moved slightly forward so that SV can obtain a larger free longitudinal space by moving into the target lane. Even though the speed advantage given by LV2 does not change, the upper boundary angle of the collision cone decreases by increased total driving advantage from LV2.

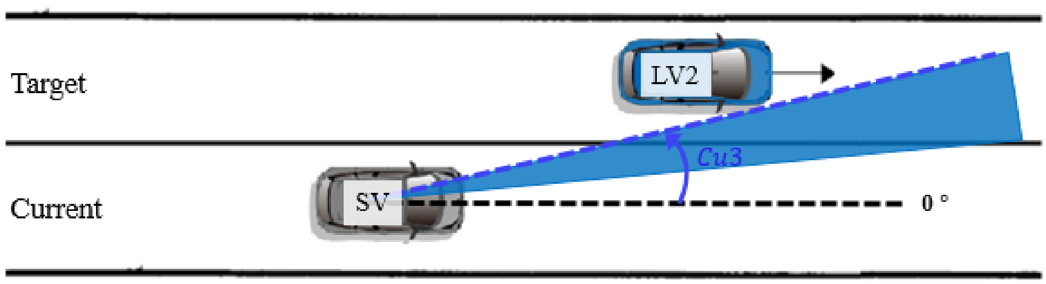


Figure 3.8: Schematic of *Example 3* : $Cu3 < Cu2$

Remark 1: It is possible to use Cu, the angle made by upper boundary of the collision cone, as a measure for driving advantage factoring in speed advantage and free space.

For more details, collision geometry between the vehicles in previous examples can be depicted as in Figure 3.9. In Figure 3.9, we can think of vehicles as circular objects. And, by considering tangents to circle B with radius of $R_A + R_B$, we can define ζ and θ, and use (2.24) for derivation of Cu.

We first made following assumptions for application of the collision cone algorithm to scenario that we are interested in, which is between SV and LV2.

- Radius of the circles A, B : $R_A, R_B = 1.5$ meter
- Longitudinal distance to B from A : $0 < d < 50$ meter
- Direction of V_B : $\beta = 0°$

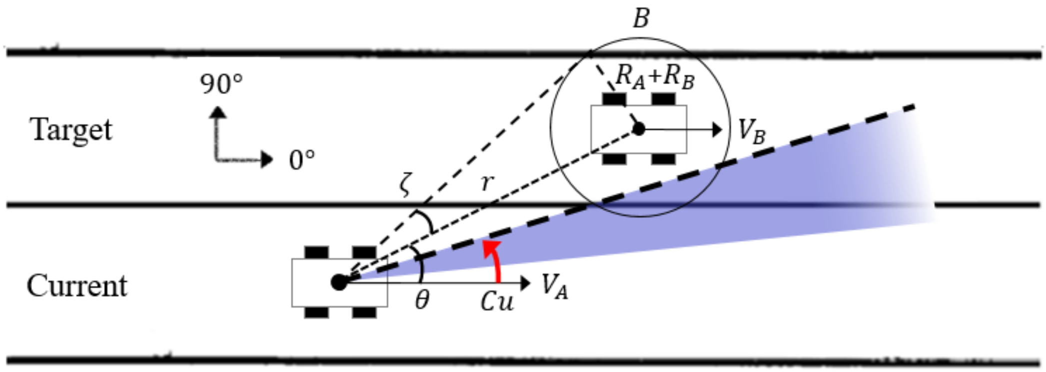
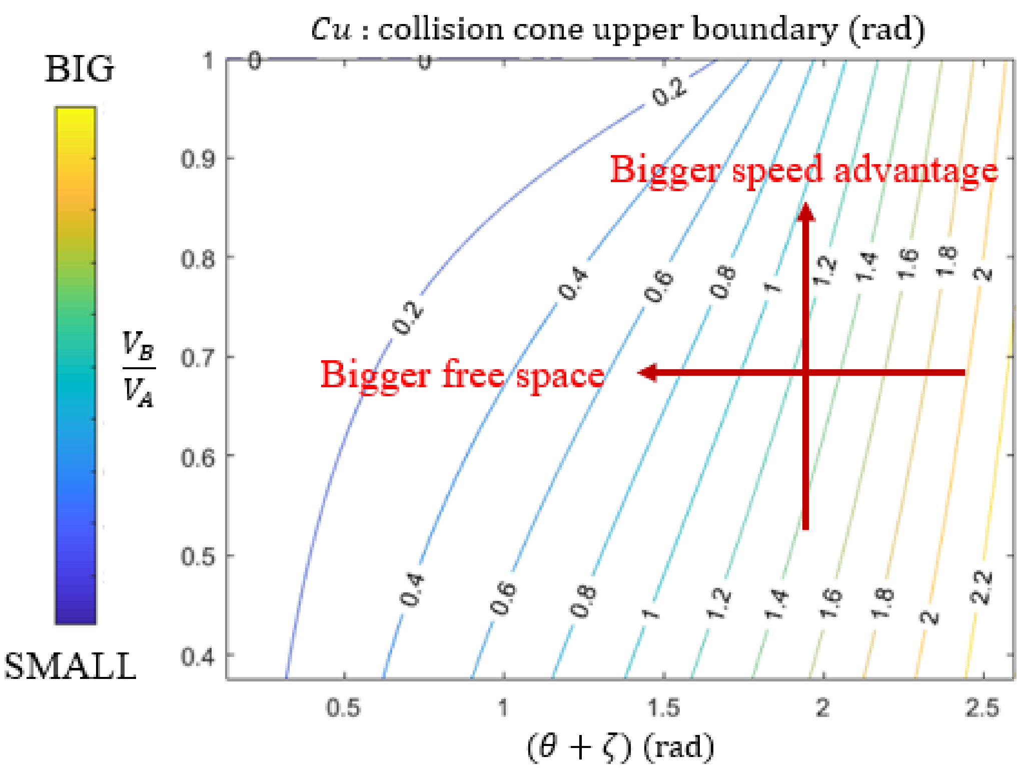


Figure 3.9: Collision geometry between SV and LV2

- Speed of V_A, V_B : $15\text{m/s} \leq V_A, V_B \leq 40\text{m/s}$ and constant

With the assumptions, we simplified the collision cone algorithm [11] and obtained

$$Cu = (\theta + \zeta) - \arcsin\left[\frac{V_B}{V_A} \cdot \sin(\theta + \zeta)\right]. \tag{3.1}$$



In (3.1), $(\theta + \zeta)$ is the angle made by the upper tangent to the circle B with respect to the horizontal lane, and V_B/V_A is the velocity ratio. $(\theta + \zeta)$ and V_B/V_A are both related to driving advantage from B. $(\theta + \zeta)$ is inversely proportional to d, and V_B/V_A is related to speed advantage from V_B. We considered when $V_A > V_B$, and we checked how Cu changes depending on $(\theta + \zeta)$ and V_B/V_A under the assumptions for Figure 3.9. The value of Cu depending on $(\theta + \zeta)$ and V_B/V_A is given above, and we concluded that there is a clear tendency. The bigger driving advantage is, the smaller Cu is.

3.3.2 Driving Advantage Comparison

In order to decide whether to actually change lanes, we introduced an additional notion, a virtual vehicle (hereafter VV), which SV needs to compare with LV2, an actual target leader, in order to decide whether a lane change is warranted in the first place.

Remark 2: VV, as a standard for the comparison, represents driving advantages that SV can take by staying in the current lane assuming that VV is the same vehicle as LV1, in terms of longitudinal position and speed as in Figure 3.10. However, by positioning VV in the target lane and measuring Cu by VV, the model is able to compare LV1 and LV2, which are in two different lanes.

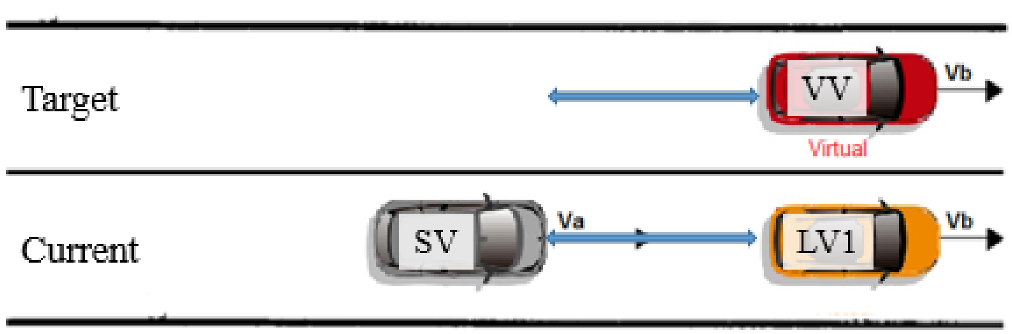


Figure 3.10: Schematic of virtual vehicle concept

This is very similar to how a driver decides whether to change lanes or not in the sense that people approximate driving conditions of both target lane and current lane, and compare them. I used a geometric concept in the middle of the process to measure it more precisely. This approach is straightforward and powerful at the same time.

Example 4: Let's consider the situation in Figure 3.11. SV is faster than LV1, and SV needs either to change lanes or to decelerate for safe driving. In the target lane, LV2 drives faster than LV1 and give more free space to SV in comparison to LV1 as in Table 3.2.

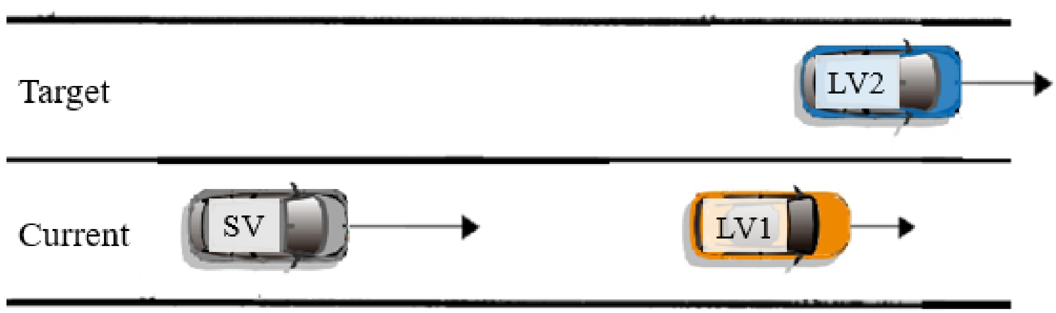


Figure 3.11: Schematic of *Example 4*

Table 3.2: Driving advantage comparison

	LV1(current lane)	LV2(target lane)
Longitudinal space	15m	20m
Speed advantage	-5m/s	-2m/s

Considering Table 3.2, it is undeniable that the target lane is preferred. This can be easily concluded by comparing the upper boundary angles of collision cones in Figure 3.12. In

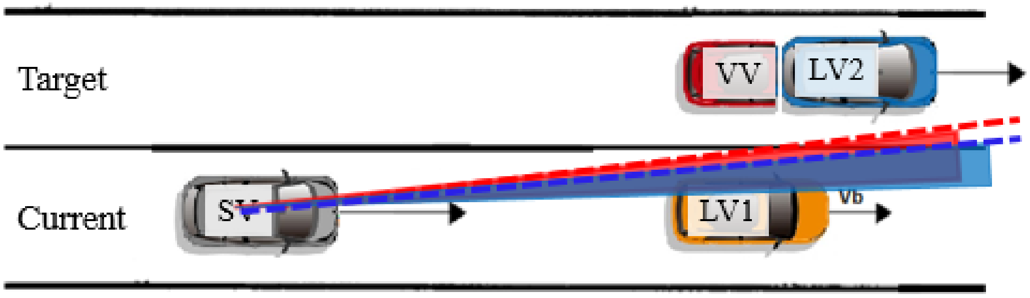


Figure 3.12: Schematic of *Example 4*

Table 3.3: Driving Advantage Comparison by Cu

	VV(current lane)	LV2(target lane)
Cu	3.518°	1.049°

Table 3.3, Cu by LV2 is smaller than one by VV, which means SV can achieve a bigger driving advantage by moving into the target lane and following LV2. The model easily figures out which option is better with Cu, the new driving advantage measure.

3.4 Lane Changing Safety Check

For safe lane changing, two types of collisions are considered. One of them is the lateral collision that can happen while moving into the target lane and the other one is the rear-end collision that can happen after a vehicle safely arrives in the target lane.

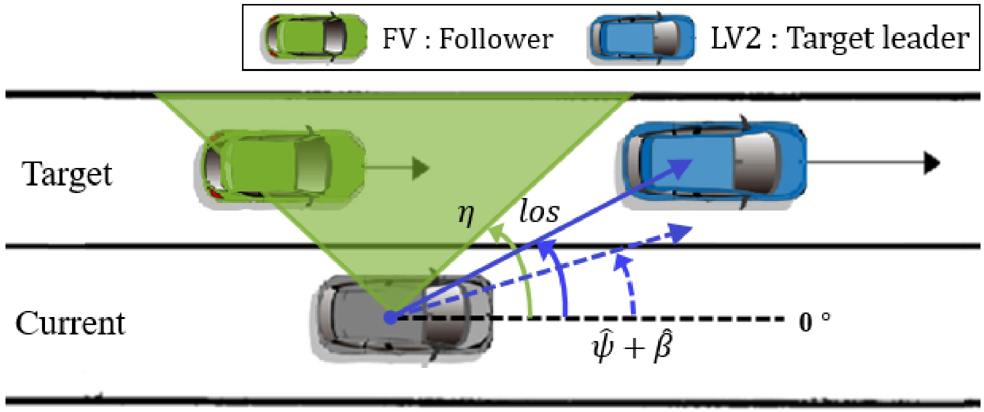


Figure 3.13: Lateral collision free condition

3.4.1 Lateral Collision Free

Lateral collision can happen right after a lane change starts. In Figure 3.13, lateral collision is considered when FV is too close to SV such that there is a high chance of lateral collision while in transition. For lateral collision-free, we used the collision cone algorithm. Because we assumed that FV moves straight along the horizontal target lane, the heading direction of SV outside the collision cone with FV can guarantee a collision-free situation at least at the beginning of lane changing. Therefore, the model needs to see if the velocity direction, the summation of yaw and vehicle slip side angle, is outside the collision cone with FV, which means $\eta > \hat{\psi} + \hat{\beta}$ in Figure 3.13.

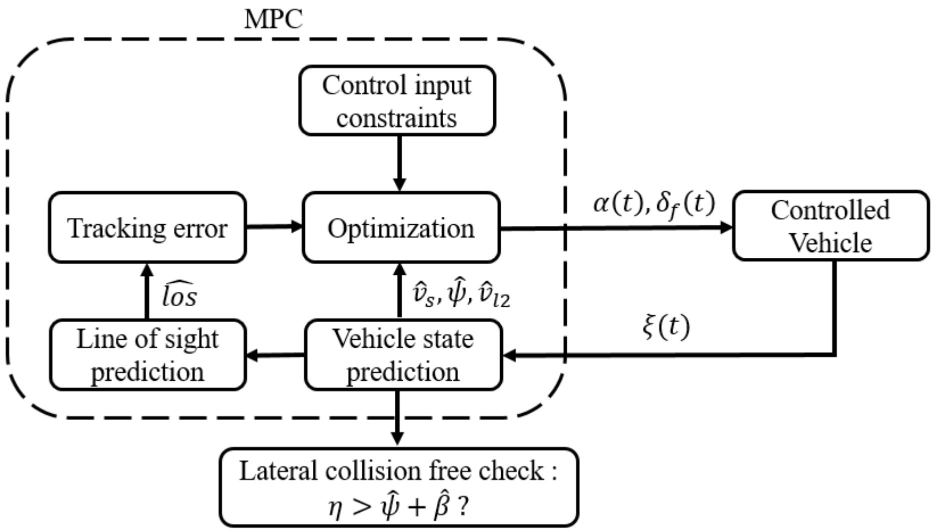


Figure 3.14: MPC with lateral collision free condition

Figure 3.14 is the structure of MPC with lateral safety check while lane changing. After calculation of control input based according to the new method, the model uses vehicles' predicted states to check if generated control input by MPC using LOS with a target leader is safe from a possibility of a collision.

3.4.2 Rear-end Collision Free

One more aspect to consider is safety after lane changing. In case FV is faster than SV($v_f > v_s$) in Figure 3.13, considering only the collision cone cannot guarantee safety when SV moves along the target lane as a new leader of FV after lane changing. we also considered if FV can safely slow down and accept SV as a new leader. To define the rear-end collision free condition, we assumed the following conditions on FV.

- Reaction time of FV : R_t = 1.5 sec
- Maximum deceleration that SV and FV are willing to accept : a_m = - 4 $\mathrm{m/s^2}$

It was assumed that FV starts to decelerate at most a_m to avoid a rear-end collision with SV after R_t, time until a human driver normally reacts and starts to slow down. According to the assumptions, we can have Figure 3.15 and Figure 3.16.Two graphs show assumed velocity profiles of FV for deceleration. For rear-end collision free, shaded area S_m, the decreasing distance between FV and SV while FV's deceleration, needs to be shorter than the current gap.

$$\text{current gap} > S_m \tag{3.2}$$

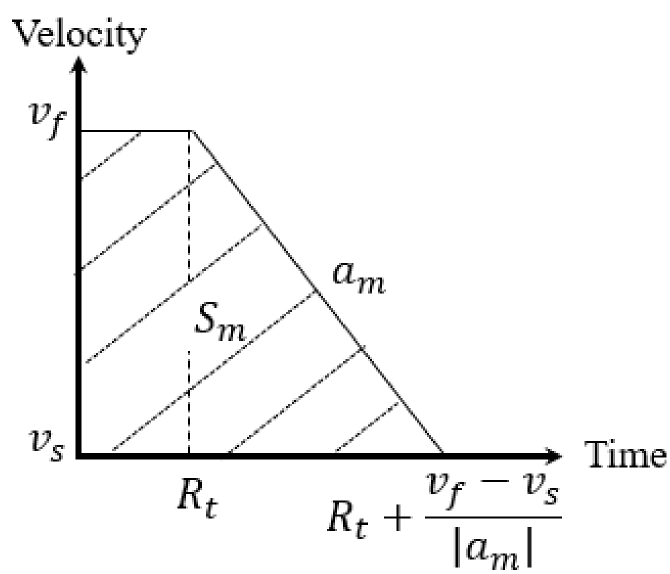


Figure 3.15: Velocity of FV while deceleration ($v_{l2} \geq v_s$)

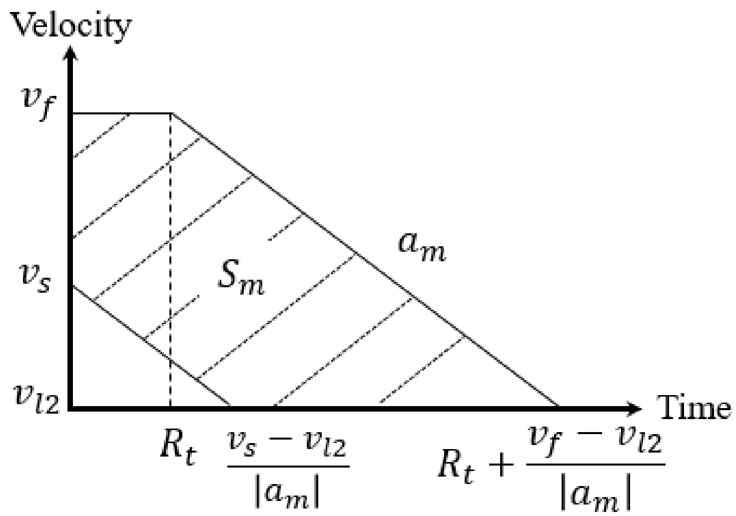


Figure 3.16: Velocity of FV while deceleration ($v_s > v_{l2}$)

Therefore, we can define (3.3) and (3.4) as the minimum size of the gap required for rear-end collision free when SV does not need to slow down and when SV needs to slow down

$$\text{current gap} > (v_f - v_s) * R_t + \frac{1}{2} * \frac{(v_f - v_s)^2}{|a_m|} \tag{3.3}$$

$$\text{current gap} > (v_f - v_{l2}) * R_t + \frac{1}{2} * \frac{(v_f - v_{l2})^2}{|a_m|} - \frac{1}{2} * \frac{(v_s - v_{l2})^2}{|a_m|} \tag{3.4}$$

to v_{l2} respectively. In Figure 3.16, the model also needs to consider deceleration of SV. Therefore, another condition (3.4) on minimum gap was defined in the same way as in (3.3) to see if the current gap is sufficient even if SV rapidly decelerates with -4m/s^2. Depending on vehicles' velocity, TTC, reaction time R_t, and affordable deceleration, the safety check for rear-end collision can be done with the inequalities on the gap size.

4. DRIVER DRIVING MODEL*

4.1 Vehicle Model

MPC requires an analytical model of the vehicle dynamics. In the research, the simplified kinematic model in Figure 4.1 from [16, 17] has been adopted. The model is defined

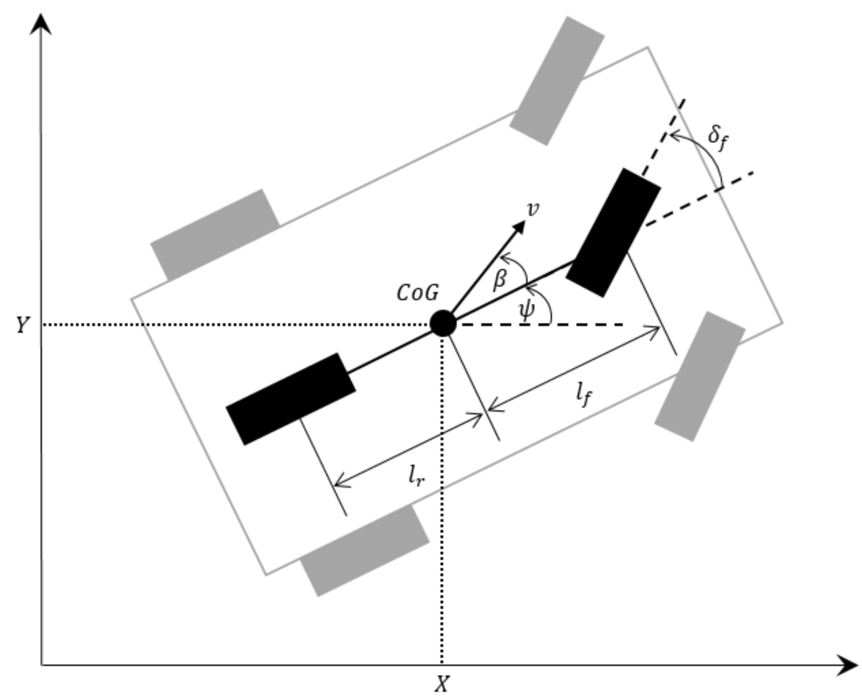


Figure 4.1: 2-DOF vehicle model

by non-linear relationships between four state variables: vehicle X, Y coordinates in the global frame, yaw ψ and velocity v. Their relationships are represented by four non-linear differential equations.

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$$\dot{X} = v\cos(\psi + \beta) \tag{4.1}$$

$$\dot{Y} = v\sin(\psi + \beta) \tag{4.2}$$

$$\dot{\psi} = -\frac{v\cos(\beta)}{l_f + l_r}\tan(\delta_f) \tag{4.3}$$

$$\dot{v} = \alpha \tag{4.4}$$

where l_f = 1.232 m, l_r = 1.468 m and vehicle side slip angle β

$$\beta = \arctan\left(\frac{l_r}{l_f + l_r}\tan(\delta_f)\right). \tag{4.5}$$

The front wheel steering angle δ_f and acceleration α are the control inputs to the vehicle model, and l_f and l_r are the distances to the front and rear tires from the vehicle's center of gravity. Therefore, the whole system with a state vector $\xi = [X, Y, \psi, v]$, an output vector $y = [X, Y]$ and a control input vector $u = [\delta_f, \alpha]$ can be rewritten as

$$\begin{aligned} \dot{\xi} &= f(\xi(t), u(t)) \\ y &= C\xi. \end{aligned} \tag{4.6}$$

For integration of the vehicle model in the control design process using MPC, we discretized the differential equation (4.6) using the Euler method and obtained the following.

$$\begin{aligned} \xi(k+1) &= f(\xi(k), \triangle u(k)) \\ y(k) &= \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix} \xi(k) \end{aligned} \tag{4.7}$$

where $\triangle u(k) = u(k) - u(k-1)$.

4.2 MPC Controller Design

4.2.1 Deceleration

Once lane changing either dangerous or disadvantageous, the subject vehicle chooses the current lane as the better option, and longitudinal control should be applied for vehicle platooning in the current lane. In Figure 4.2, SV needs to adjust its speed to have the desired distance for safety, and Constant Time headway(CTH)-based spacing is chosen as a spacing strategy. As a popular strategy for vehicle platooning [18, 19, 20], desirable safe distance is proportional to the velocity of SV, v_s.

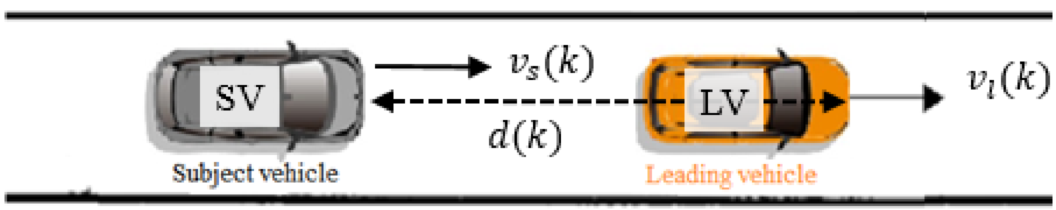

Figure 4.2: Variables for platooning

Based on perception of the leading vehicle LV, MPC outputs deceleration for spacing two vehicles. In Figure 4.2, depending on v_s, v_l, and d, MPC will generate optimized acceleration sequence under the presence of constraints for control input effort. Those optimized values will be control inputs to the vehicle model so that d will be adjusted according to CTH strategy under the penalty on rapid change of acceleration and big acceleration. We have adopted 1 sec as a preferred TH to be kept based on [15]. Longitudinal dynamics in Figure 4.2 can be described as the following equations.

$$
\begin{aligned}
v_s(k+1) &= v_s(k) + \alpha_s(k) T_s \\
d(k+1) &= d(k) + \left(v_l(k) - v_l(k)\right) T_s + \frac{1}{2}\left(\alpha_l(k) - \alpha_s(k)\right) T_s^2
\end{aligned}
\tag{4.8}
$$

We considered the following as cost function for CTH based spacing.

$$
\min_{\triangle u_t} \sum_{i=1}^{N_p} \left(||\hat{v}_{s_{(k+i/k)}} - \hat{d}_{(k+i/k)}||_{R_1}^2 + ||\triangle\alpha_{(k+i/k)}||_{R_2}^2 + ||\alpha_{(k+i/k)}||_{R_3}^2 \right) \tag{4.9}
$$

$$
\begin{aligned}
\text{subject to: } \xi s_{k+1} &= f(\xi s_k, \triangle\alpha_k) \\
y_k &= C\xi s_k \\
k &= t, ..., t + N_p
\end{aligned}
\tag{4.10}
$$

$$
\begin{aligned}
\triangle\alpha_{min} \leq &\triangle\alpha_k \leq \triangle\alpha_{max} \\
\alpha_k &= \alpha_{k-1} + \triangle\alpha_k \\
k &= t, ..., t + N_p
\end{aligned}
\tag{4.11}
$$

- Sampling time : T_S = 0.05 sec
- Prediction horizon : N_P = 25 steps
- Constraints on acceleration rate change per T_S : -0.25m/s$^2 \leq \triangle\alpha_k \leq 0.25$m/s^2

- Weights

Activation	Weights		
	R_1	R_2	R_3
TTC≤2.5 sec	0.48	200	1.25→1.5
TH≤0.5 sec	0.48	200	1.5

The first term of (4.9) is about the safety distance according to TH = 1 sec. Therefore, control efforts will be generated such that d can be equivalent to v_s. Depending on whether the model activated by TTC condition or TH condition, the model is designed to decelerate differently by different weights for R_3. In case a vehicle is threatened by actual danger, the TTC condition, relatively bigger deceleration is allowed at the beginning of braking compared to when triggered by the TH condition. After v_s reaches v_l with, SV comfortably adjusts its speed by increasing R_3.

4.2.2 Lane Changing

4.2.2.1 Strategy

In this research, lane changing is done by instantly swerving, and we did not consider changing lanes that occur after SV overtakes LV2 where it requires SV to accelerate. Moreover, changing lanes takes place based on the driving advantage measure Cu so that it happens only either when acceptable deceleration is required compared to staying in the current lane or when there is no need to decelerate to safely follow LV2. Therefore, LOS with LV2 was considered as a variable los in Figure 4.3, a reference value for steering while lane changing.

Lane change duration is one of the important aspects. According to [21], a lane change is not instantaneous, and its duration is 5-6 sec on average. Therefore, when it comes to the

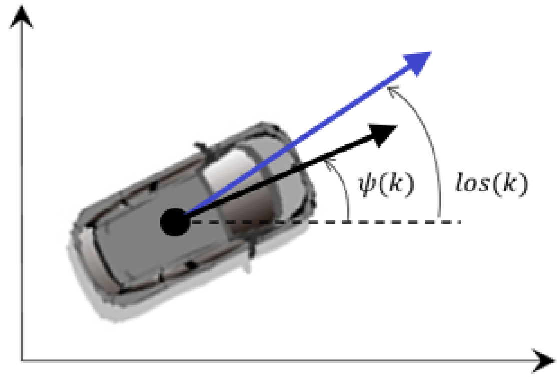

Figure 4.3: Variables for steering

design of the model, it is necessary to make sure that the methodology for lane changing results in a safe lane change and that it doesn't have a negative impact on traffic flow. With our model, the duration is affected by velocities of vehicles, and it is longer when LV2 is faster than SV ($v_{l2} > v_s$). In such a case, los is small, and it takes a long time until SV arrives in the target lane, which can be dangerous. Therefore, the variable los becomes LOS with a virtual vehicle that starts to move with v_s from the position at which LV2 is located at the moment when a decision is made based on actual LV2.

We designed MPC such that tracking error between predicted SV's yaw angle ψ and predicted los in Figure 4.3 can be minimized.

$$\min_{\triangle u_t} \sum_{i=1}^{N_p} \Bigg(||\hat{\psi}_{(k+i,k)} - \hat{los}_{(k+i,k)}||^2_{Q_1} + ||\triangle\delta_{(k+i,k)}||^2_{Q_2} \\ + ||\hat{v}_{s_{(k+i,k)}} - \hat{v}_{l2_{(k+i,k)}}||^2_{R_1} + ||\triangle\alpha_{(k+i,k)}||^2_{R_2} + ||\alpha_{(k+i,k)}||^2_{R_3} \Bigg) \tag{4.12}$$

$$\min_{\triangle u_t} \sum_{i=1}^{N_p} \left(||\hat{\psi}_{(k+i,k)} - \hat{los}_{(k+i,k)}||^2_{Q_1} + ||\triangle\delta_{(k+i,k)}||^2_{Q_2} \right) \tag{4.13}$$

$$\text{subject to: } \xi s_{k+1} = f(\xi s_k, \triangle\alpha_k, \triangle\delta_k)$$
$$y_k = C\xi s_k \tag{4.14}$$
$$k = t, ..., t + N_p$$

$$los = \arctan \frac{Y_{l2} - Y_s}{X_{l2} - X_s} \tag{4.15}$$

$$\triangle\alpha_{min} \leq \triangle\alpha_k \leq \triangle\alpha_{max}$$
$$\alpha_k = \alpha_{k-1} + \triangle\alpha_k \tag{4.16}$$
$$k = t, ..., t + N_p$$

$$\triangle\delta_{min} \leq \triangle\delta_k \leq \triangle\delta_{max}$$
$$\delta_k = \delta_{k-1} + \triangle\delta_k \tag{4.17}$$
$$k = t, ..., t + N_p$$

In (4.12) and (4.13), there commonly exist two terms for steering while lane changing. The first term reflects the penalty on the reference tracking error between los and ψ, while the second term is to penalize the rapid change of steering angle. Which cost function MPC uses depends on whether deceleration of SV is required or not. When SV is faster than LV2 ($v_s > v_{l2}$), SV has to adjust its velocity to safely follow a new leader LV2 after its arrival in the target lane. The controller adopts (4.13) with three additional terms as the

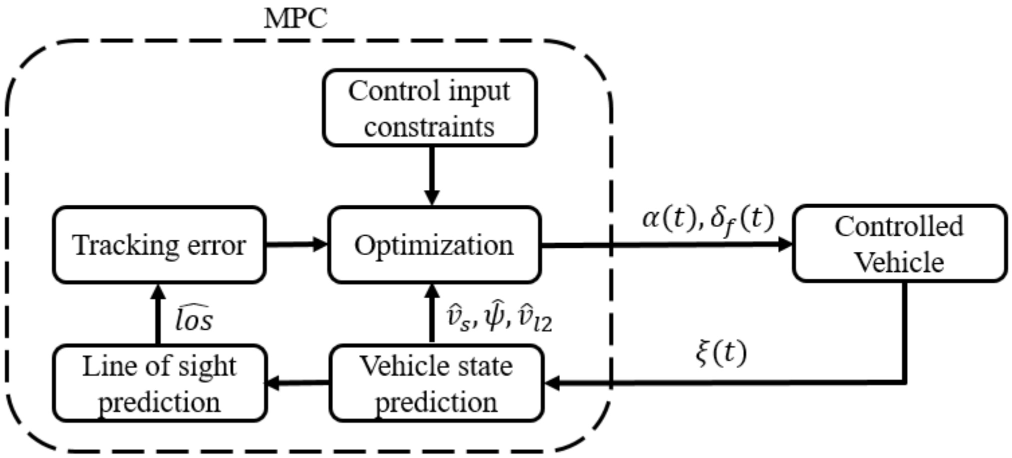

Figure 4.4: Structure of MPC controller for lane changing

cost function. These three terms are for the deceleration of v_s to v_{l2} under the penalty for big acceleration and rapid acceleration change.

Moreover, in (4.15), los according to X, Y coordinates of SV and LV2 needs to be predicted. Therefore, we designed MPC controller such that it knows how los would change and decide how to steer front wheels to smoothly follow predicted los. $\triangle u_t = \triangle u_{t,t}, .., \triangle u_{t+N_p-1,t}$, the optimized control input vector at time t over the prediction horizon time N_p, is generated by MPC and SV's state over N_p is predicted by applying $\triangle u_t$ to the current state of SV at time t. As a result, the overall structure of MPC for lane changing operation can be depicted as Figure 4.4.

4.2.2.2 Choice of Parameter

We have estimated suitable prediction length and weights for MPC.

- Sampling time : T_S = 0.05 sec
- Prediction horizon : N_P = 35 steps

- Constraints on steering angle change per T_S : -0.0175 rad $\leq \triangle\delta_k \leq 0.0175$ rad
- Constraints on acceleration change per T_S : $-0.25\text{m/s}^2 \leq \triangle\alpha_k \leq 0.25\text{m/s}^2$
- Weights ($R1, R2, R3 = 0$ for (4.13))

d	R_1	R_2	R_3	Q_1	Q_2
0m< d ≤5m	10	500	5	10→45	450000
5m< d ≤10m	5			10→25	250000
10m< d ≤15m	3			10→15	150000
15m< d ≤20m	2			10	100000

Weights are important aspects that influence lane changing. In this optimization, it is deciding where we put more value either driving comfort or better moving directions exactly following los. $Q2$ is given a different value considering that LOS can be different depending on the longitudinal distance between SV and LV2, d, and a bigger value for $Q2$ is to prevent rapid steering angle change when d is short. On the contrary, los is small when d is relatively long, which causes lane changing to take long. In this case, following los does not cause big driving discomfort, therefore by putting a small value for $Q2$, the model can generate smooth trajectories free from the big penalty of rapid change of steering angle. Moreover, depending on $Q2$, there is a difference of change in $Q1$ as SV enters the target lane, and small tracking errors exist in the first term of the cost functions. We chose different $Q1$ so that SV can follow los under a different penalty depending on $Q2$. Furthermore, different values are chosen for $R1$ considering urgency depending on how short d is.

5. RESULTS*

In the simulation, we have two goals. The first goal is to see if the model has the ability to make a reliable decision. The result of collision cone angle based decision-making should be benefit to the vehicle and safety conditions needs to guarantee safe lane changing. In order to demonstrate the ability of the proposed model to select preferred lane, we tested if the model can decide whether or not a lane change is safe and advantageous in diverse traffic scenarios, and saw if its decisions are reliable.

The second goal is to show if lane changing by MPC controller is affordable. We will show how the trajectory changes depending on factors that affect LOS, such as velocity and distance between vehicles. For the evaluation, we focused on trajectory shape and lateral acceleration while lane changing.

5.1 Decision-Making Model Evaluation

We simulated several cases of highway driving. We assumed that surrounding vehicles move at constant speeds, and SV considers moving into the gap between LV2 and FV to avoid a collision with LV1. Moreover, FV is willing to slow down to yield to SV with acceptable deceleration smaller than -4m/s^2. All the results here are based on the lane changing model, and these are presented to show how SV decides and behaves depending on different road conditions in terms of their safety and driving advantage as in Table 5.1. We tested four cases in Table 5.1 where the driver needs to immediately make a decision. In Figure 5.1, SV (black circle) moves in the current lane, and there are two leading vehicles. One of them, LV1, is in the current lane (orange circle), and the other one, LV2, is in

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Table 5.1: Possible Scenarios

	Disadvantageous	Advantageous
Dangerous	·	*Case1*
Safe	*Case2*	*Case3*, *Case4*

the target lane (blue circle). These two vehicles are not affected by SV, and they keep their current velocity. In each situation, LV1 and LV2 have either different velocities or begin moving at different points longitudinally. VV(red circle) has LV1's velocity and longitudinal position, and LV2's lateral position. FV is also important in the sense that FV(green circle) affects the safety of lane changing, and we used different values for velocity and location of FV to determine safety condition that we want to test. The bigger circles in each trajectory plot represent vehicles at the moment when the decision is made.

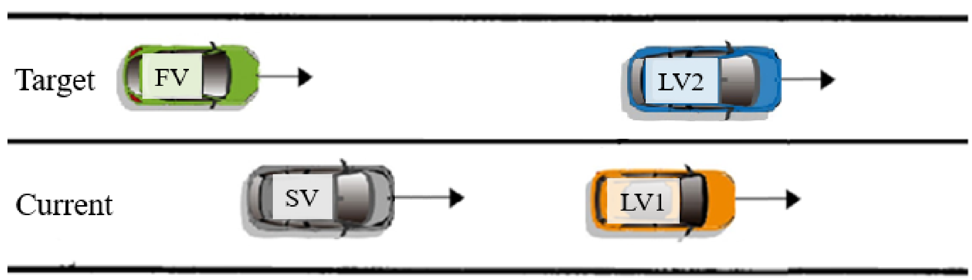


Figure 5.1: Simulation scenario considering SV, LV1, LV2, and FV on a two-lane road

Case 1: SV does not change lanes. Because FV moves too fast to slow down and accept SV as a new leader, SV finds that moving into the target lane and decelerating to v_{l2} would be dangerous. According to Table 5.2, even though SV can enter in the target lane without lateral collision, but the gap is not sufficient and shorter than the minimum gap for rear-end collision free after lane changing.

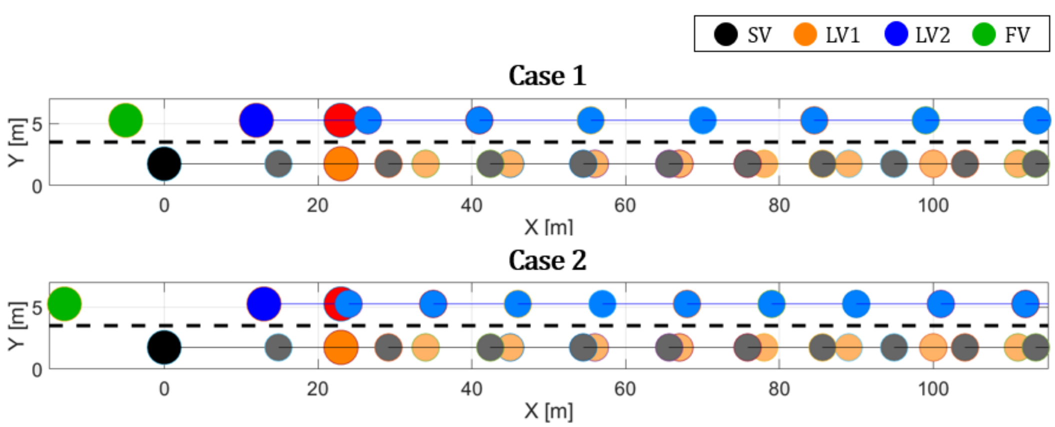
Table 5.2: *Case 1*: Dangerous and Advantageous

SV(30m/s at 0m)	**FV**(33m/s at -2m)	**LV2**(29m/s at +9m)	**VV**(22m/s at +20m)
Gap $> S_m$	Dangerous	.	.
$\eta > \hat{\psi} + \hat{\beta}$	Safe	.	.
Cu	.	1.10°	4.35°
Decision	**Deceleration**		

Case 2: Safety is guaranteed by the existence of velocity direction in collision free area and sufficient gap that between FV and SV. When it comes to driving advantage, Cu with LV2 is bigger than the one with VV, which means bigger driving advantage exists in the current lane. There is no reason for SV to move into the target lane.

Table 5.3: *Case 2*: Safe and Disadvantageous

SV(30m/s at 0m)	**FV**(32m/s at -10m)	**LV2**(22m/s at +10m)	**VV**(22m/s at +20m)
(Gap $> S_m$) & ($\eta > \hat{\psi} + \hat{\beta}$)	Safe	.	.
Cu	.	7.84°	4.35°
Decision	**Deceleration**		



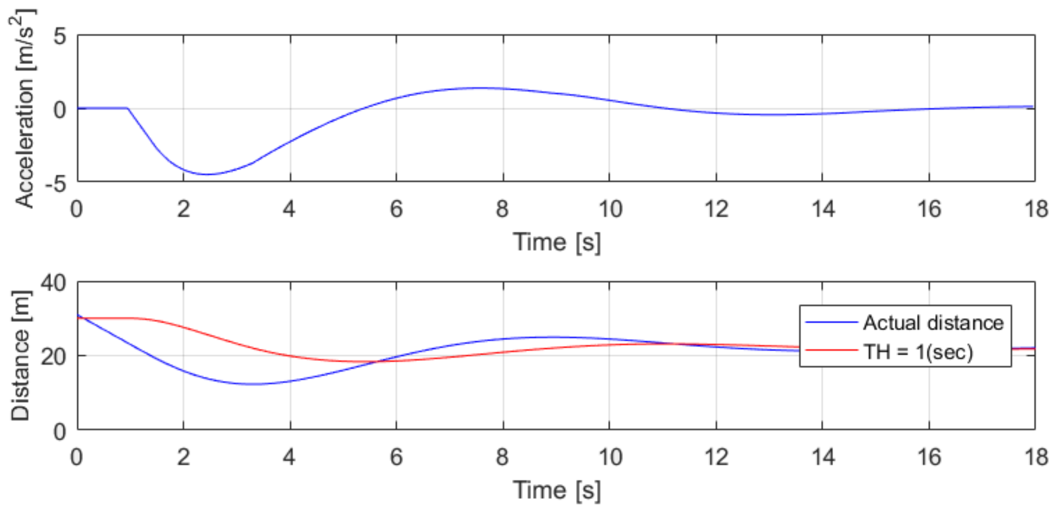


Figure 5.2: Lane change rejection : *Case 1 and Case 2*

Case 3: SV intends to change a lane. Even though current free space given by LV2 is smaller, the total driving advantage in the target lane is bigger due to the much bigger speed advantage from LV2. This can be easily explained by the following Table.

Table 5.4: *Case 3*: Safe and Advantageous (Slower target lane)

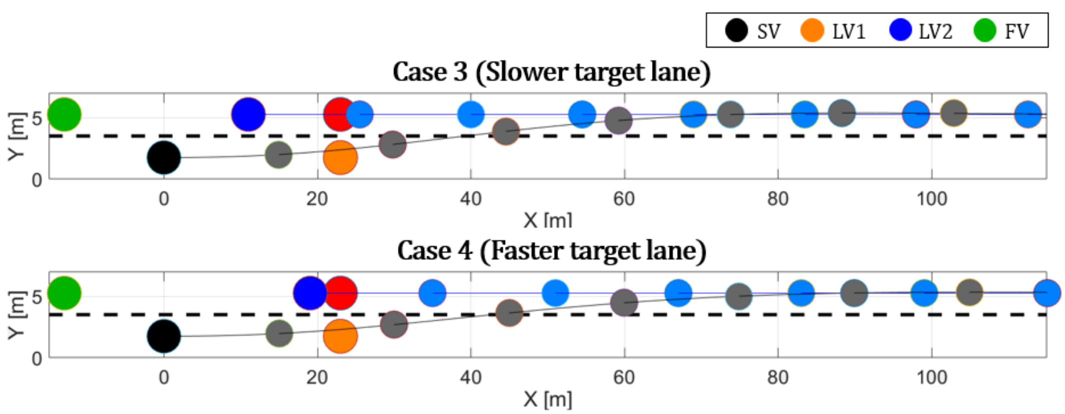
SV(30m/s at 0m)	**FV**(32m/s at -10m)	**LV2**(29m/s at +8m)	**VV**(22m/s at +20m)
(Gap $> S_m$) & ($\eta > \hat{\psi} + \hat{\beta}$)	Safe	.	.
Cu	.	1.25°	4.35°
Decision	**Lane Changing**		

Case 4: The fourth case (Discretionary lane changing: Faster target lane) also shows when changing a lane is preferred. In this case, because LV2 is faster than not only LV1 but also SV, there is little possibility of the collision with LV2 even without deceleration, which means lane changing is much better. Figure 5.3 shows the corresponding control

inputs, yaw angle and lateral acceleration profiles while lane changing by MPC. The front steering angle should vary smoothly within a limited range not only for driving comfort but also from the standpoint of vehicle dynamic constraints. In the simulation, these conditions are obtained by limiting the change rate of control inputs, and the results show that smooth steering angle was generated by MPC.

Table 5.5: *Case 4*: Safe and Advantageous (Faster target lane)

SV(30m/s at 0m)	**FV**(32m/s at -10m)	**LV2**(32m/s at +16)	**VV**(22m/s at +20m)
(Gap $> S_m$) & ($\eta > \hat{\psi} + \hat{\beta}$)	Safe	.	.
Cu	.	no collision cone	4.35°
Decision	**Lane Changing**		



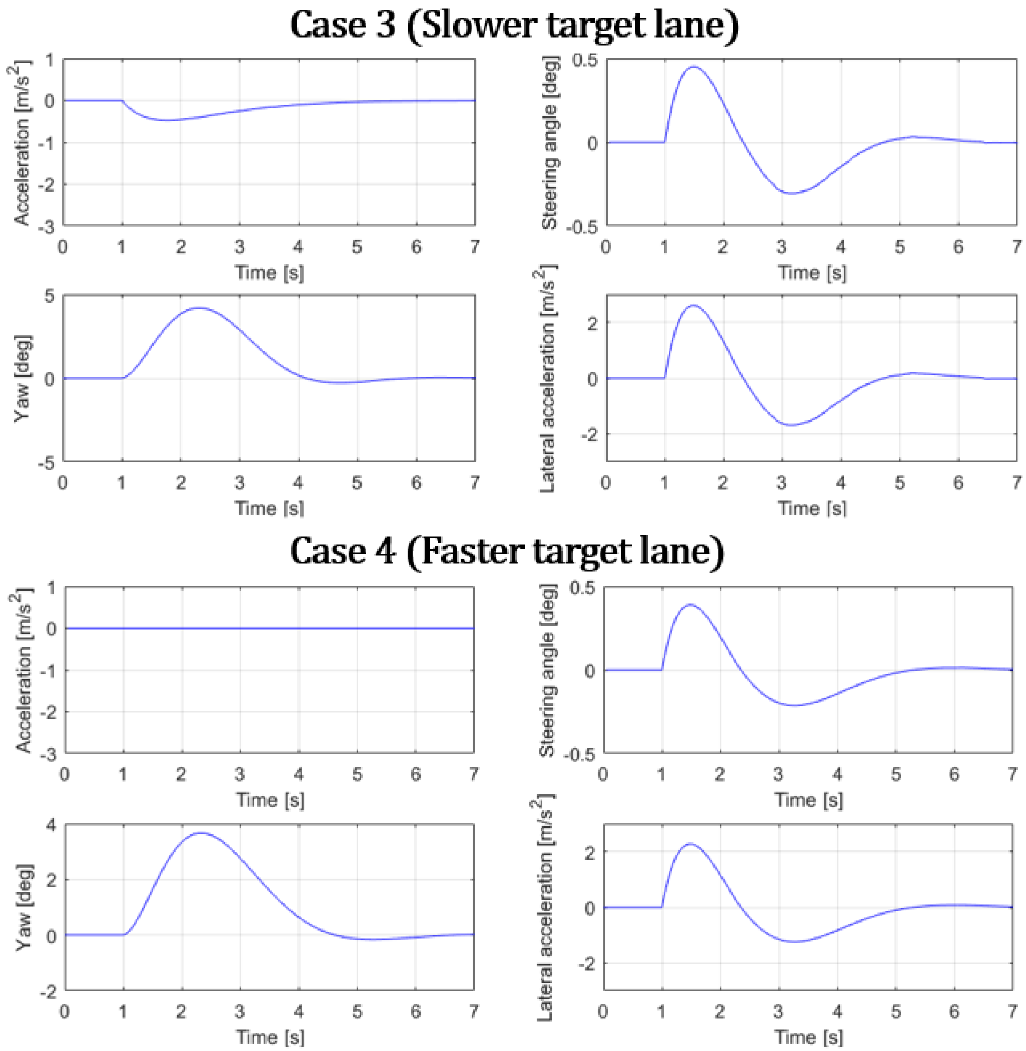


Figure 5.3: Lane change accepted : *Case 3 and Case 4*

5.2 Lane Changing Trajectory Evaluation

Another important issue that needs to be verified is whether the new methodology for a lane change gives good performance with regard to lane changing trajectory shape and driving comfort. Specifically, following LOS is dependent on leading vehicle's location and velocity, so it is important to see how the trajectory changes depending on following factors that affect LOS with LV2.

- Driving advantage decided by LV2 : d and v_{l2}

- Velocity of SV : v_s

In addition to d, we also considered the relative velocity of LV2 that affects change rate of LOS. We tested diverse cases that can represent common lane changing scenarios in terms of vehicles' velocities and locations and checked if generated trajectories would be acceptable.

In this simulation, v_s ranges from 20m/s to 35m/s, and many values of v_{l2} for advantageous lane changing are considered and tested as in Table 5.6. Consequently, we obtained

Table 5.6: Traffic scenarios for trajectory generation

SV	**LV1**	**LV2**			
20	15	≥ 18	≥ 16	≥ 13	≥ 11
25	15	≥ 22	≥ 20	≥ 18	≥ 16
30	15	≥ 27	≥ 25	≥ 22	≥ 20
35	20	≥ 32	≥ 30	≥ 27	≥ 25
Distance to LV2		5m	10m	15m	20m

trajectories that have representation in Figure 5.4. Figure 5.4 shows general forms of trajectories based on the model, and they all have a smooth shape. In order to clearly show trajectory, only initial location of vehicles are plotted in figures, and collision with LV2 has not happened at all. Each trajectory is when LV2 are 5m, 10m, 15m, and 20m ahead of SV respectively, and different colors represent different velocity of SV.

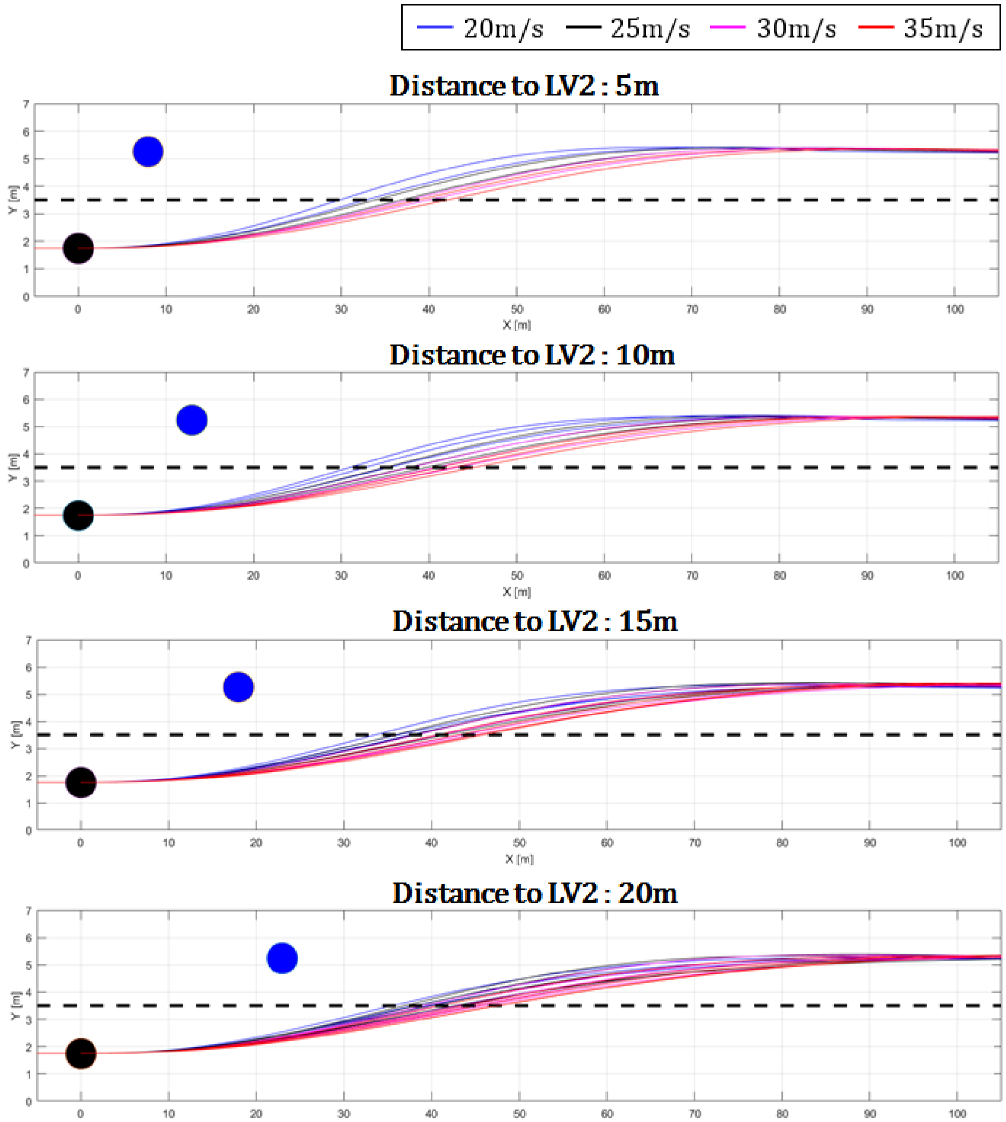


Figure 5.4: Trajectories depending on SV and LV2

A Rapidly curved trajectory is good for a quick transition to the target lane but, it can cause big lateral acceleration and the driver feel uncomfortable. In the worst case, a vehicle accident like rolling over can take place. In fact, whether lane changing is proper or not has to do with trajectory shape, and trajectory shape is also directly related to other profiles like lane changing duration and lateral acceleration[22]. Therefore, trajectory shape needs to be properly smooth for safe and comfortable lane changing.

I found a few noticeable tendencies in how the trajectory changes, which are important. First, the trajectory gets gentle when SV has a bigger velocity. This is one of required aspects for driving comfort in the sense that while driving fast, even small steering can cause a big discomfort, and regarding that, the new MPC shows good performance. Second, either when LV2 is far from SV or LV2 is fast, the trajectory gets smooth. This shows that driving advantage affects the lane changing trajectory, and the model knows to adjust how smooth the trajectory can be depending on driving advantage by using LOS as a reference value for steering. These results shown through simulation support that the lane changing model can generate acceptable trajectories, and it is very similar to the way actual human drivers change lanes.

In addition to the shape of lane changing trajectory, I obtained the maximum lateral acceleration of generated trajectories, which is important for driving comfort[23].

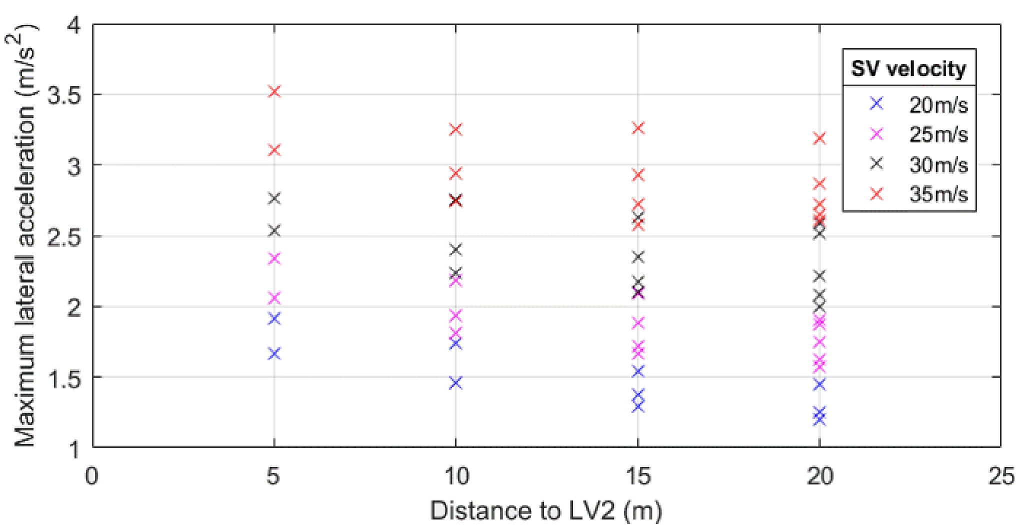


Figure 5.5: Maximum lateral acceleration

For driving comfort, maximum lateral acceleration needs to be as small as possible. In Figure 5.5, we concluded that higher v_s and shorter d result in higher lateral acceleration with a maximum value of 3.6 m/s^2, which is the medium comfort level [24]. In conclusion, through the second simulation for driving comfort check while lane changing, I could see that the shape of trajectories is smooth and obtained maximum lateral accelerations during transition are acceptable.

6. CONCLUSIONS*

6.1 Research Summary

In conclusion, this model has a drawback that it is not robust to irrational driving, such as rapid acceleration or deceleration, because collision cone algorithm is based on prediction of the future without considering other important things like human factors. Therefore, irrational cases depending on a driver that is hard to predict can easily lead to either failure of a reliable decision or affordable lane change trajectory.

Other than that, assuming that drivers are rational, I could make sure that decision-making of the model is reliable in the sense that it considers surrounding vehicles for safety and driving advantage check. Furthermore, MPC of the model always provided a trajectory with a smooth shape and acceptable lateral acceleration, which are important for comfortable lane changing.

6.2 Directions for Future Research

We can validate this lane changing model by comparing it with a human driver using a more functional driving simulator accessible to the project team (dSPACE.) Secondly, although the geometric concept plays an important role, there are other improvements that can be made by involving new factors. For example, human factors, such as a driver's aggressiveness, can be considered as well, to make the approach more realistic. Thirdly, we will introduce a new collision cone where an important factor, namely acceleration, is considered.

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