Prediction of estimated lane change distance on highway: based on traffic information

Yujin Kim, Seok Youl Yang , Myo Taeg Lim
Hyundai Motor Company, Korea University

현대자동차그룹 연구장학생

Introduction

❖ Motivation

- In order for an autonomous vehicle to drive to its final destination, the decision of the lane change timing should be given to perform the mandatory lane change.
- When driving on the highway, where including numbers of ramps and interchanges, the information about the ramp is given, but not the distance required for changing lanes.

❖ Objectives

- In this study, we propose the lane change decision model based on given real time road information.
- The model predicts the minimum safe distance for a lane change from the current lane to the target lane.
- We validate the predicted measurements through simulation.

Method

❖ Dataset & Key Word

- Highway Drone Dataset (levelxdata)
- US Highway 101 Dataset (U.S Department of transportation)
- Interstate 80 Freeway Dataset (U.S Department of transportation)

✓ Congestion Level

Road congestion level reflecting the number and average speed of vehicles passing through the target lane for a unit time (5 minutes)

$$C_{i^{th}} = \frac{Traffic\ of\ i^{th} lane}{Avg.speed\ of\ i^{th} lane}$$

$$Traffic\ of\ i^{th} lane = total\ number\ of\ vehicles\ at\ i^{th} lane\ /recording\ time$$

Level 1	Level 2	Level 3	Level 4	Level 5	Level 6
[0.50, 2.66]	[2.66, 3.07]	[3.07, 3.41]	[3.41, 4.14]	[4.14, 4.87]	[4.87, 28.20]

✓ Acceptance Gap

Acceptance gap is the minimum distance between vehicles in the target lane required for lane change. The acceptance gap is calculated under UN regulation No. 79 and No.157.

❖ Dataset Analysis

The inter-vehicle distance (gap) distribution is analyzed in the dataset. From the density of gaps on the road, the probability of occurrence of an acceptable gap is showing the log-logistic distribution.

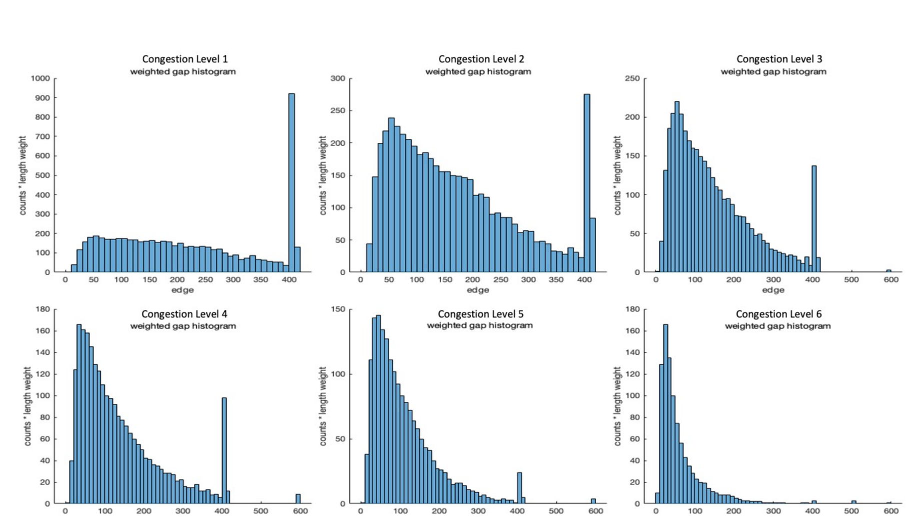

Figure 1. Distribution of inter-vehicle spacing by congestion level

❖ Model Description

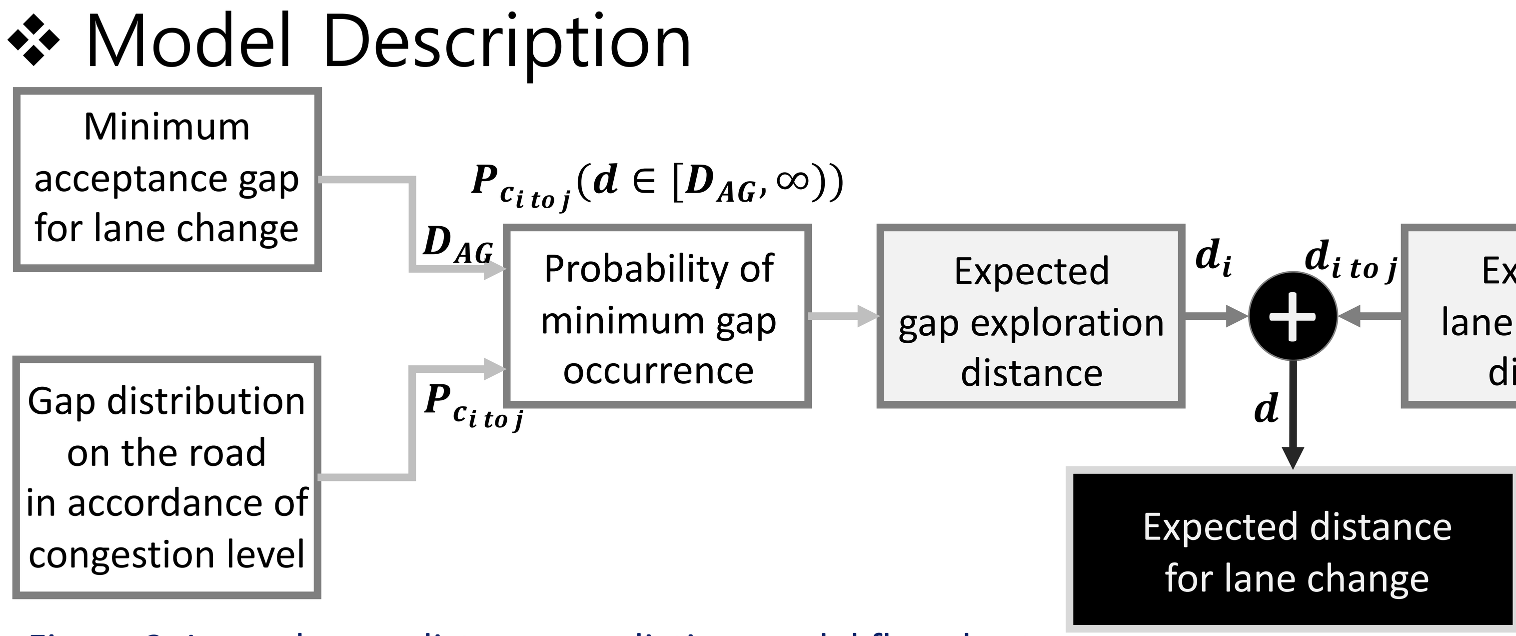

Figure 2. Lane change distance prediction model flowchart.

With the lane change distance prediction model, we can generate lane change decision timing on the road. The model is tested under recorded traffic in the dataset.

- Lane change point prediction (US Highway101 Dataset)
  - ❖ Input
    : 5^{th}lane -> 6^{th}lane(off ramp) lane change
  - ❖ Given (previous 5 minutes of traffic information)
    5^{th}lane : road congestion level 5 (Avg. velocity 50.84km/h)
    6^{th}lane : road congestion level 6 (Avg. velocity 58.77km/h)
  - ❖ Output
    Minimum acceptance gap : 49.17m
    Gap occurrence probability : 80.47%
    Expected gap exploration distance = 111.24m
    Expected lane changing distance = 51.64m
    ✓ Expected lane change distance = 162.88m
  - ❖ Description
    : **Prepare to change lane before 162.88m from turn-off**

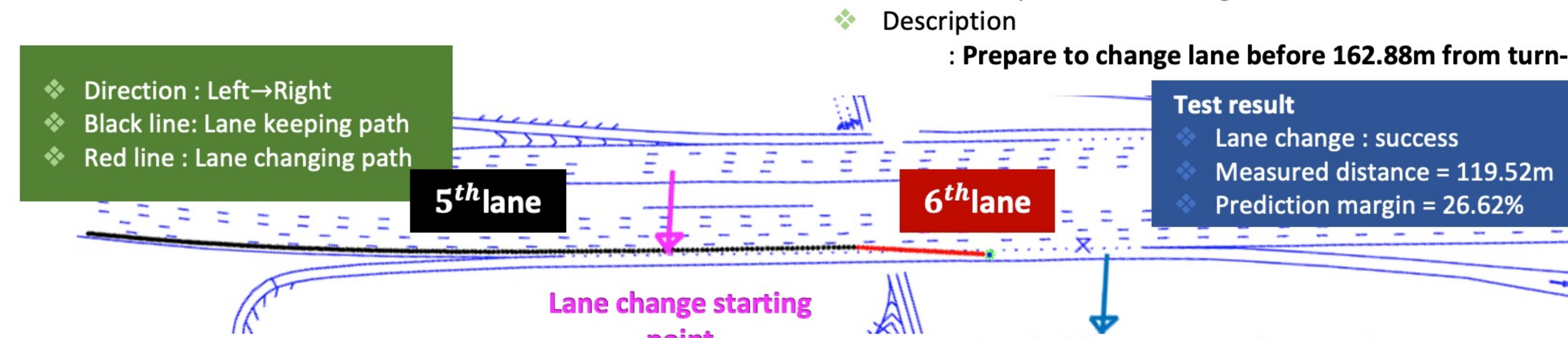

Figure 3. Lane change starting point generation process

Result

❖ Simulation result

Firstly, we compared the required distance for the lane change of proposed model to observed distance from the dataset. The heat map on Figure 4 is showing the distances according to the congestion level of current lane to target lane.

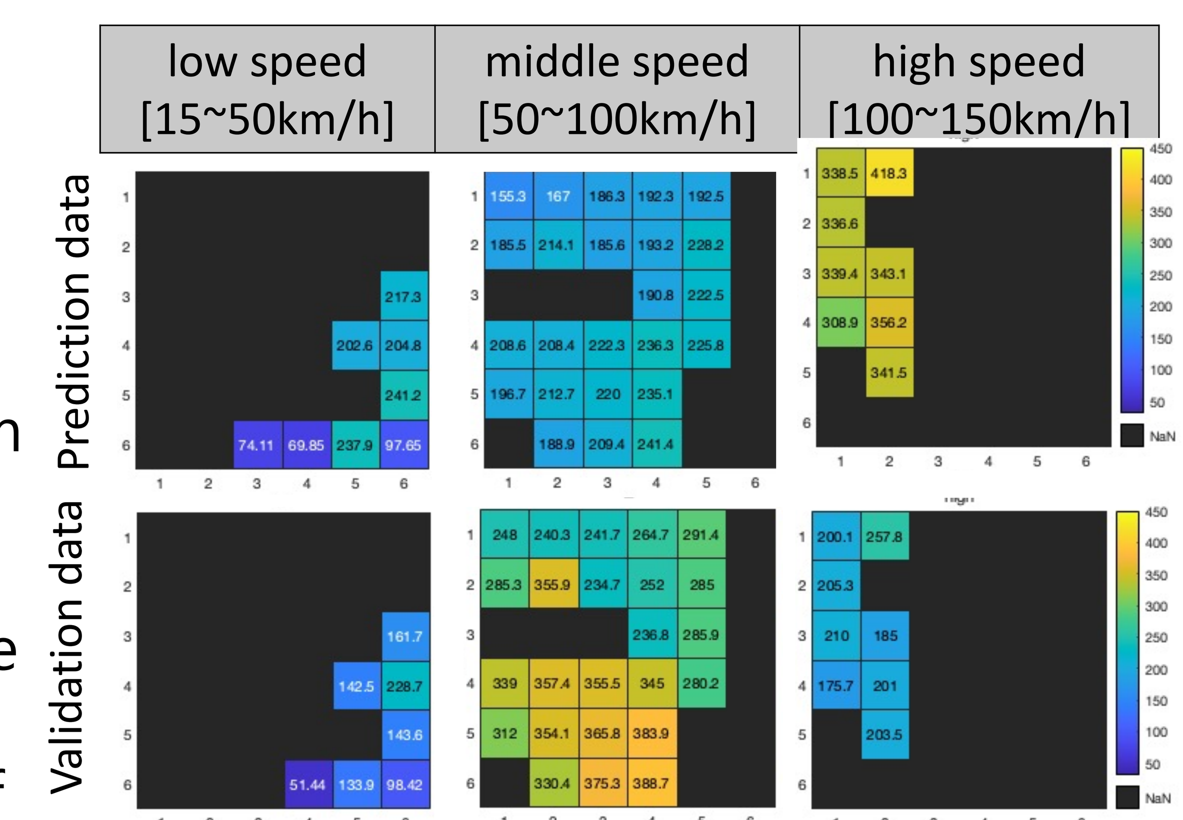

Figure 4. Model prediction and validation from the dataset. Congestion level : column -> target lane, row -> current lane.

The predicted lane change distance is tested with the dataset. All vehicles are driving along the trajectory recorded in the dataset, and the controlled vehicle is changing lanes from the distance behind the model prediction at the intersection. We ran a total of 1800 simulations using 600 cases each of low, medium, and high speeds. For medium and high speed, more than 95% of cases, controlled vehicle succeeded to reach to the target lane before the intersection. In low speed setting, we got only 48.67%. We analyze these results in the following discussion.

❖ Discussion

We categorize the lane change failure case in low speed setting (Table 1). Case 1. Minor velocity difference between current and target lane. Case 2. Underestimation of lane change distance. Failures of case 1 are inevitable with the trajectory planner we have used in the experiment, as it does not have an accelerate/decelerate techniques for the lane change. The success rate(SR) of case 2 can be improved by mitigating the acceptance gap. We re-analyze the SR and prediction error by varying the acceptance gap in low speed setting (SR-I :case 1+case2 / SR-II :Case2 only). The SR are shown in Figure 5 and maximum SR-II scores 98.67% by increasing the acceptance gap to 120%.

acceptance gap	Failure Case		Total failure case
	Case 1 Minor dV	Case 2 Underestimation	
100%	201	107	308
80%	197	157	354
90%	201	121	322
110%	201	56	257
120%	201	8	209

Table 1. Case study with varying acceptance gap

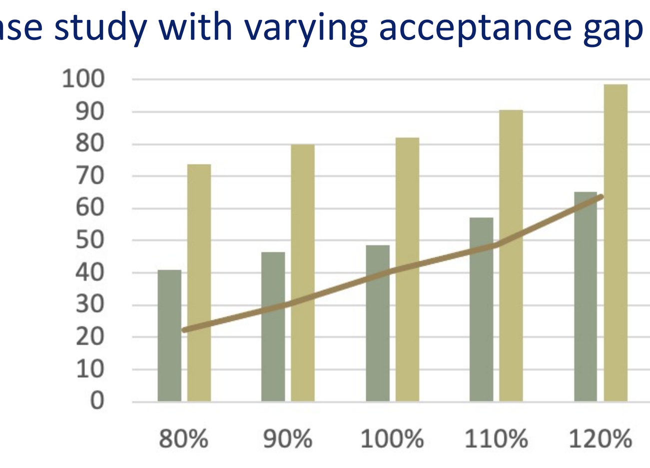

Figure 5. Lane change success rates and prediction margin