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Department: Information Science and Engineering

Technical Seminar(15ISS86)

Title: Lane-change Intention Estimation for Car following Control in Autonomous Driving

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Introduction

- Lane change is driving maneuver that moves a vehicle from one lane to another lanes.
- Lane change should happen before the target vehicle crosses the lane line.
- Due to rapid development in vehicle manufactures have focused on commercialization of autonomous driving.

Overview of Technology

- Autonomous driving is capable of sensing its environment and navigating without human input.

- Autonomous Driving mainly uses ADAS aim to assist drivers during lane change maneuvers.

- A system that is developed for average drivers or all drivers will have to be conservative for safety reasons to cover all the driver type.

- It takes into account the dynamics and characteristics of each individual vehicle system during lane change maneuvers will be more effective and more acceptable to drivers with safety and reliability.

Motivation

- Digitization of automobile industry.
- Road safety with vision zero.
- Traffic Management is automated.
- Increase in number of accidents occurs in lane change should be reduced.

Problem Statement

- To design and develop a lane change intention estimation based on contextual traffic information using Autonomous Driving(AD).

Purpose & Scope

- The main purpose of the Autonomous Driving is to Estimate and predict of driving behaviour of the vehicle.

- Future in self driving car.
- In future research, safety and reliability, control in acceleration, complicated scenarios.

Literature Survey

- A model that uses ADAS in order to perform lane change traffic configuration.
- It also uses sinusoidal lane change model, GMM, Manuever shape prediction for lane change and lane merging.

- <u>Demerits</u>: Lane changes only applicable for minimum no of vehicle with increase in gap acceptance.

Vadim A. Butakov and Petros Ioannou[1], “Personalized driver lane change models for ADAS,” *IEEE Trans Intell. Transp. Syst.*, vol. 64, no. 10, pp. 4422-4431, Oct. 2018

Literature Survey

- POMDP to build a general models for other vehicles uncertain intentions.
- The policy generation algorithm produces candidate strategies and a deterministic HMM and GMM to recognize vehicle’s lateral and longitudinal motion intentions.
- Interactive situation predicts driving intention and cooperative driving behavior.

- Demerits: Complexity in POMDP model

Weilong, et al[2], “Intention aware decision making in Urban lane change scenario for Autonomous Driving,” *Journal of Field Robotics*, vol. 24, no. 10, pp. 425-434, Sep. 2018

Literature Survey

- Analysis of driver Behaviour, automated driving principles and manual driving.
- Combined braking and steering, driver eye movement was investigated for safety critical driving scenario.

- Demerits – Lane changes was done only on Long combination vehicles.
- Time gap and relative speed was not considered.

Peter et al[3] ‘‘A simulator study comparing characteristics of manual and Automated Driving during lane changes of long combination vehicles’’. *IEEE Trans Intell. Transp. Syst.*, vol. 18, no. 9, pp. 2514-2524, Sep. 2017

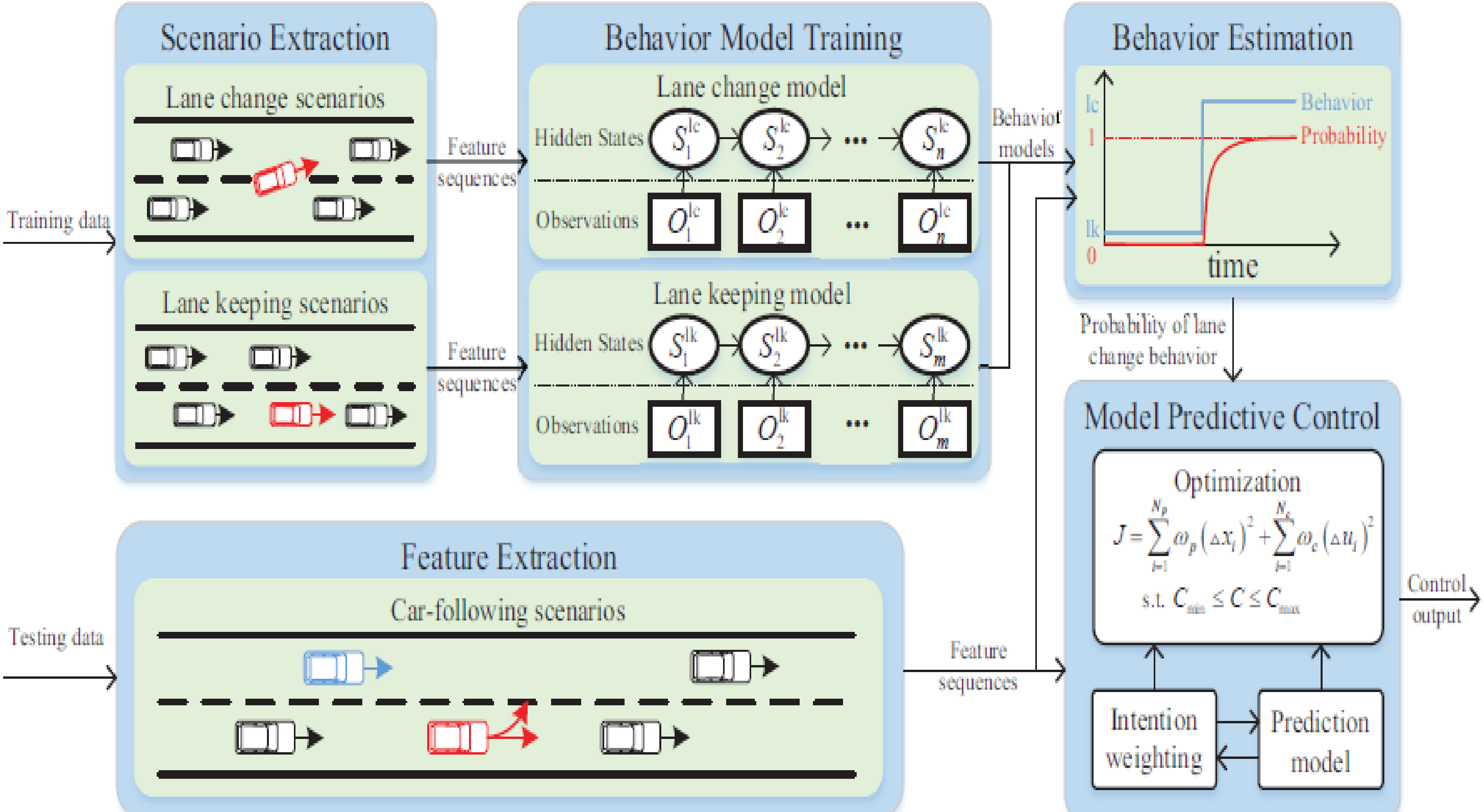
Literature Survey

- A stochastic model aims to smooth and safe driving behavior with safety in collision risk road situation.
- Lane change and risk monitoring features extracted from motion planning algorithm.

- Demerits: It was not able to analyse for unexpected traffic.

Jongsang Suh et al[4] ‘‘Stochastic Model predictive control for lane change decision of automated driving vehicles ’’. *IEEE Trans Intell. Transp. Syst.*, vol. 67, no. 6, pp. 2514-2524, Jun. 2018

Proposed Methodology



Proposed Methodology

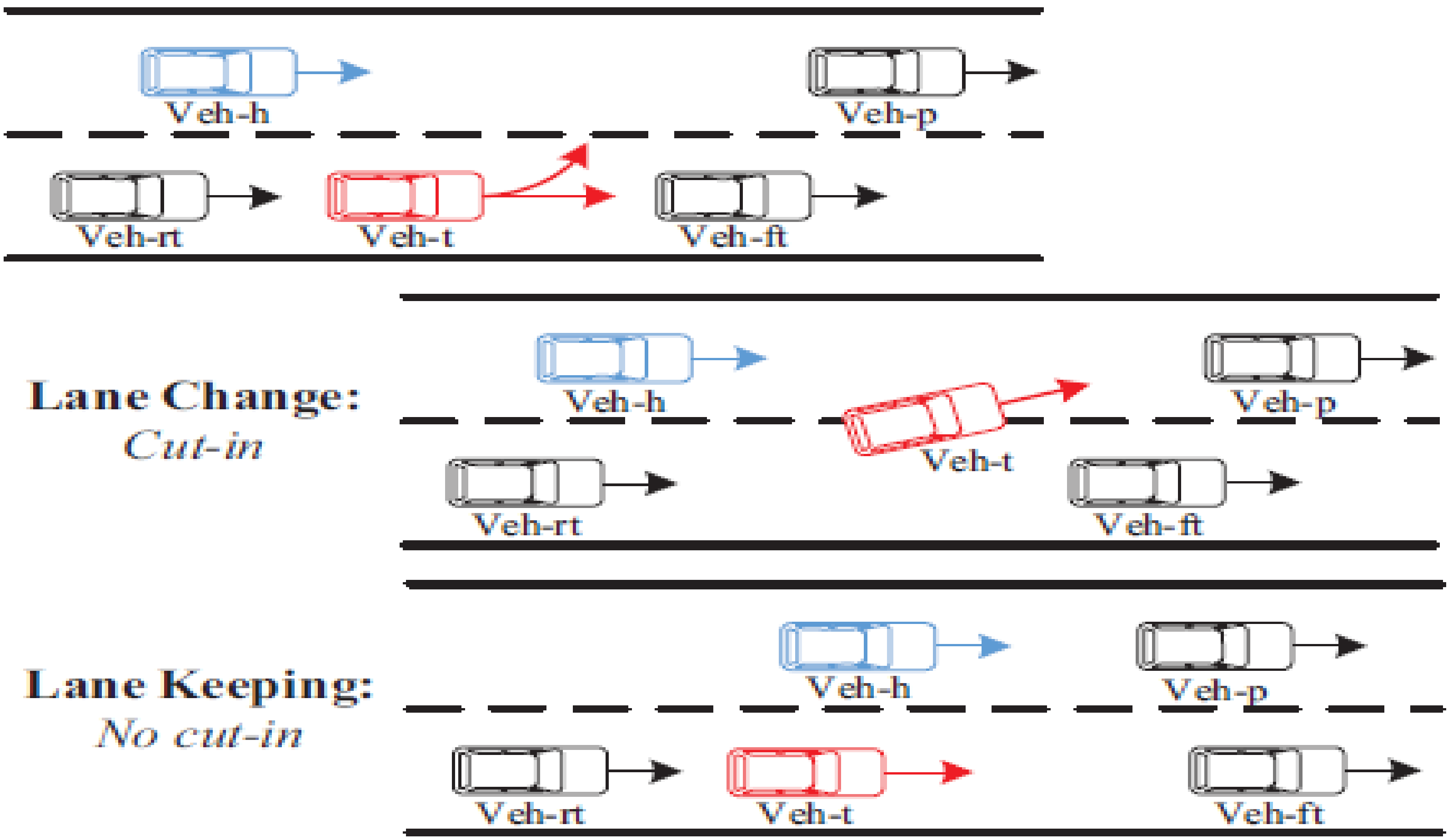
A Scenario definition and extraction

1. Data Description(NGSIM)

Proposed Methodology

A Scenario definition and extraction

2. Scenario Segmentation



Proposed Methodology

B Behavior Model

1. GMM(Gaussian Mixture Model)

$$\xi_t = \Big[\left[v_{\mathrm{x}}(t), v_{\mathrm{y}}(t), d_{\mathrm{o}}(t)\right], \left[\Delta v_{\mathrm{t,p}}(t), \Delta v_{\mathrm{t,h}}(t), \Delta x_{\mathrm{t,p}}(t), \Delta x_{\mathrm{t,h}}(t)\right], \left[\Delta v_{\mathrm{t,ft}}(t), \Delta v_{\mathrm{t,rt}}(t), \Delta x_{\mathrm{t,ft}}(t), \Delta x_{\mathrm{t,rt}}(t)\right] \Big]^{\mathrm{T}}$$

EM likelihood

$$\mathcal{L}(\hat{\theta}^{j+1}) = \sum_{t=1}^{n} \mathcal{L}(\hat{\theta}^{j})$$

2. HMM(Hidden Markov Model)

$$\lambda = \{\mathcal{S}, \mathcal{Z}, \mathcal{A}, \mathcal{B}, \pi\}$$

$$\mathcal{R} = \frac{P(\xi_{1:t}|\lambda_{\mathrm{lc}})}{P(\xi_{1:t}|\lambda_{\mathrm{lk}})}$$

Proposed Methodology

C Model Predictive Control

- Intention Estimation
- Prediction Model
- Receding horizon optimization
  - Tracking errors
  - Comfort and smoothness

Experimental Results

Classification Evaluation

TABLE IV: Performance index comparison at FPR = 5%.

Dataset		I-80						US-101					
Cases		I	II	III	IV	V	Average	I	II	III	IV	V	Average
TPR	srd	**0.9158**	**0.8055**	0.8056	**0.8425**	**0.8037**	**0.8346**	**0.8091**	0.7478	0.8108	**0.8091**	**0.7727**	**0.7898**
	tgt	0.7757	0.7407	**0.8241**	0.5278	0.6168	0.6971	0.6546	**0.8378**	**0.8738**	0.5909	0.7636	0.7441
FPR	srd	**0.0654**	**0.0648**	0.0740	0.0740	**0.0654**	**0.0688**	**0.0636**	**0.0811**	**0.0811**	**0.0909**	**0.0727**	**0.0778**
	tgt	0.0841	0.0741	**0.0648**	**0.0648**	**0.0654**	0.0706	0.0909	0.0991	0.0901	0.1000	0.0909	0.0942
ACC	srd	**0.9252**	**0.8703**	0.8657	**0.8842**	**0.8691**	**0.8829**	**0.8727**	0.8333	0.8648	**0.8591**	**0.8501**	**0.8561**
	tgt	0.8458	0.8333	**0.8796**	0.7315	0.7757	0.8132	0.7818	**0.8694**	**0.8919**	0.7455	0.8364	0.8249
PRE	srd	**0.9333**	**0.9255**	0.9157	**0.9191**	**0.9247**	**0.9237**	**0.9271**	**0.9022**	**0.9091**	**0.8989**	**0.9139**	**0.9103**
	tgt	0.9022	0.9091	**0.9271**	0.8906	0.9041	0.9066	0.8781	0.8942	0.9066	0.8553	0.8936	0.8855
F_1	srd	**0.9245**	**0.8614**	0.8571	**0.8792**	**0.8600**	**0.8765**	**0.8641**	0.8177	0.8571	**0.8516**	**0.8374**	**0.8456**
	tgt	0.8342	0.8163	**0.8725**	0.6627	0.7333	0.7838	0.7501	**0.8651**	**0.8899**	0.6989	0.8235	0.8055

Experimental Results

- Lane change prediction

TABLE V: Lane change prediction time τ_t in second.

Cases	I	II	III	IV	V	Average
srd-I-80	5.16	5.21	4.97	3.11	3.49	4.39
tgt-I-80	4.12	3.42	2.99	2.58	2.49	3.12
srd-US-101	4.67	4.96	5.38	4.24	4.43	4.73
tgt-US-101	2.67	2.81	3.12	2.23	2.41	2.65

Experimental Results

- Car following testing results

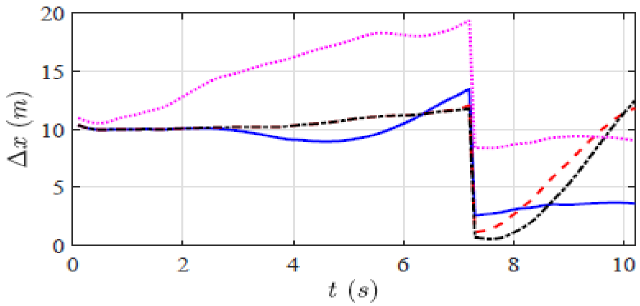
TABLE VII: Performance index comparison of MPCs.

Dataset		I-80						US-101					
Cases		I	II	III	IV	V	Average	I	II	III	IV	V	Average
v_h (m/s)	srd-MPC	6.3667	7.5950	6.2163	6.0926	6.1791	6.4899	10.1505	10.4960	10.2020	10.9406	9.7350	10.3048
	tgt-MPC	6.3292	7.5994	6.1411	5.8433	5.9667	6.3759	10.3989	10.7071	10.5165	11.0393	9.8605	10.5045
	Only-MPC	6.9295	7.5845	6.2827	6.0988	6.2823	**6.6356**	10.6237	10.9072	10.6093	11.2079	9.8176	**10.6331**
a_h (m/s^2)	srd-MPC	1.1624	1.0795	1.1589	1.1845	1.2646	**1.1700**	1.1609	1.3325	1.0661	1.7717	1.4109	**1.3484**
	tgt-MPC	1.1974	1.5522	1.3786	1.2096	1.4739	1.3623	1.1632	1.6061	1.4135	1.8874	1.4795	1.5099
	Only-MPC	1.4067	1.5785	1.4746	1.3482	1.4555	1.4527	1.4798	1.6183	1.4058	1.9159	1.7556	1.6351
Δa_h (m/s^3)	srd-MPC	0.1253	0.1399	0.1378	0.1409	0.1548	**0.1397**	0.1245	0.1526	0.1145	0.1787	0.1550	**0.1451**
	tgt-MPC	0.1263	0.1836	0.1569	0.1498	0.1783	0.1590	0.1320	0.1710	0.1511	0.1841	0.1619	0.1600
	Only-MPC	0.1625	0.1892	0.1732	0.1606	0.1734	0.1718	0.1698	0.1730	0.1515	0.1827	0.1850	0.1724
HI	srd-MPC	0.0310	0.0214	0.2641	0.3888	0.4185	**0.2248**	0.2664	0.3675	0.1517	1.0301	0.4928	**0.4617**
	tgt-MPC	0.1245	0.4692	0.2650	0.4297	0.8305	0.4238	0.2865	0.8062	0.7836	1.2306	0.7578	0.7729
	Only-MPC	0.6393	0.4705	0.2821	0.6097	0.9959	0.5995	0.6062	0.8269	1.1758	1.3458	1.0394	0.9988
CR	srd-MPC	0/29	0/22	1/25	2/25	2/21	**0.0430**	2/35	2/28	1/40	6/31	2/36	**0.0805**
	tgt-MPC	1/29	3/22	1/25	3/25	3/21	0.0947	2/35	6/28	5/40	8/31	4/36	0.1531
	Only-MPC	4/29	3/22	1/25	4/25	4/21	0.1330	4/35	6/28	8/40	8/31	6/36	0.1907

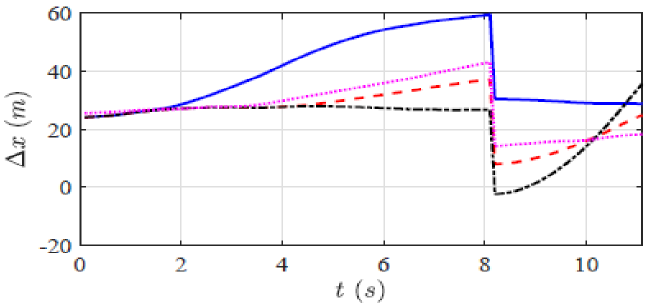
Experimental Results

- Relative distance

I-80

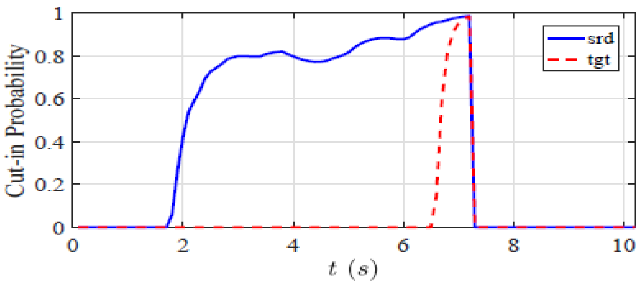


US-101

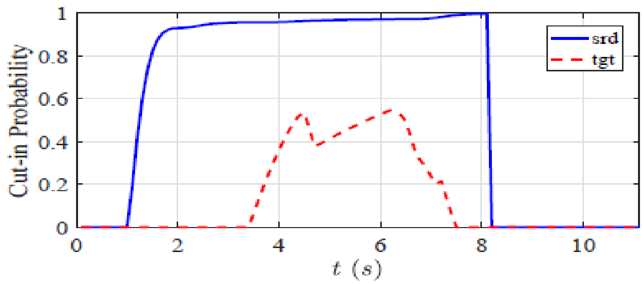


- Cut in probability

I-80



US-101



Comparative study

- Lane change should happen in both the ways
  - ❑ Left to right
  - ❑ Right to left

- Lane change occurs on speed and acceleration of the vehicle.

- Nonholonomic constraints.

Conclusion

- Lane change should happen in time.
- Speed of the vehicle can able to change the lane.
- Behavior model of the target vehicle is able to achieve over 85% of the true positive rate and the lane change behavior is predicted about 4sec before the target vehicle crosses the lane lines.
- MPC achieves superior performance of safety and ride comfort.

References

[1] Vadim A. Butakov and Petros Ioannou, ‘‘Personalized driver lane change models for ADAS,” IEEE Trans Intell. Transp. Syst., vol. 64, no. 10, pp. 4422-4431, Oct. 2018.

[2] Weilong, Bo Su, Gaungming Xiong and Shengfei Li, ‘‘Intention aware decision making in Urban lane change scenario for Autonomous Driving,” Journal of Field Robotics, vol. 24, no. 10, pp. 425-434, Sep. 2018.

[3] Peter Nilsson, Leo Laine and Bengt Jacobson, ‘‘A simulator study comparing characteristics of manual and Automated Driving during lane changes of long combination vehicles”. IEEE Trans Intell. Transp. Syst., vol. 18, no. 9, pp. 2514-2524, Sep. 2017.

[4] Jongsang Suh, Heungseok Chae and Kyongsu Yi,‘ ‘Stochastic Model predictive control for lane change decision of automated driving vehicles ”. IEEE Trans Intell. Transp. Syst., vol. 67, no. 6, pp. 2514-2524, Jun. 2018.

Thank you!