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SEMINAR REPORT

on

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

Submitted in partial fulfillment of the requirement for the award of the degree of

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in

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by

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Under the Guidance of

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B.N.M. Institute of Technology

Approved by AICTE, Affiliated to VTU, Accredited as grade A Institution by NAAC.
All UG branches – CSE, ECE, EEE, ISE & Mech.E accredited by NBA for academic years 2018-19 to 2020-21 & valid upto 30.06.2021

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CERTIFICATE

Certified that the seminar entitled **"Lane-change Intention Estimation for Car-following Control in Autonomous Driving"** is carried out by Ms. **Rutuja R** bearing USN **1BG15IS041** the bonafide student of **B.N.M Institute of Technology** in partial fulfillment for the award of **Bachelor of Engineering** in **Information Science & Engineering** of the **Visvesvaraya Technological University**, Belagavi during the year 2018-2019. It is certified that all corrections / suggestions indicated for Internal Assessment have been incorporated in the report. The seminar has been approved as it satisfies the academic requirements in respect of seminar prescribed for the said Degree.

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ABSTRACT

Lane changes are stressful maneuvers for drivers, particularly during high-speed traffic flows. Advanced driver assistance systems (ADAS) aim to assist drivers during lane change maneuvers. A system that is developed for an average driver or all drivers will have to be conservative for safety reasons to cover all driver/vehicle types. Such a conservative system may not be acceptable to aggressive drivers and could be perceived as too aggressive by the more passive drivers.

An ADAS that takes into account the dynamics and characteristics of each individual vehicle/driver system during lane change maneuvers will be more effective and more acceptable to drivers without sacrificing safety. We develop a methodology that learns the characteristics of an individual driver/vehicle response before and during lane changes and under different driving environments.

Car-following is the most general behavior in highway driving. It is crucial to recognize the cut-in intention of vehicles from an adjacent lane for safe and cooperative driving. A method of behavior estimation is proposed to recognize and predict the lane change intentions based on the contextual traffic information. A model predictive controller is designed to optimize the acceleration sequences by incorporating the lane-change intentions of other vehicles. The public data set of next generation simulation is labeled and then published as a benchmarking platform for the research community. Experimental results demonstrate that the proposed method can accurately estimate vehicle behavior and therefore outperform the traditional car-following control.

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CHAPTER 1

INTRODUCTION

With increase in number of vehicle and accidents on the road, many research institutes and vehicle manufacturers have focused on the commercialization of autonomous driving systems. Safety and reliability are fundamental for self driving cars on roads. Most car crashes are caused by human mistakes, and many of these occur during lane changes. Furthermore, fewer than 50% of drivers use turn signals when they change lanes. In order to guarantee the safety of driving, it is important for self-driving cars to estimate the driving behavior of surrounding vehicles and predict their intension of lane change before they cross lane lines.

A lane change is defined as a driving maneuver that moves a vehicle from one lane to another where both lanes have the same direction of travel. Events involving lateral motion onto the shoulder of the road or into an oncoming lane are not considered. The beginning of a lane change is defined using criteria adopted from the driver initiates a steering input intended to change the direction of the vehicle relative to the lane. This criterion was predominantly used to establish lane-change initiation. The vehicle begins to move laterally relative to the lane. This criterion was used when in-vehicle video footage was not available, during night-time driving when the in-vehicle image contrast was low, and when the vehicle was performing a lane change on a curved highway segment. The driver returns his/her gaze to the forward view upon glancing at his/her mirrors or side windows. The lane change ends when the vehicle position in the adjacent lane normalizes. One analyst determined the beginning and end points of each lane change in this investigation. Since this report set out to investigate lane-change events with respect to struck and striking drivers, two types of lane-change maneuvers were identified: planned lane changes and unexpected lane changes

1.1 Overview of Technology

Autonomous driving mainly uses advanced driver assist system (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. An autonomous driving that 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.

The related work is divided into two parts: one is on the estimation and prediction of driving behavior by using various kinds of information, the other is on car-following control including mathematical models, control methods and ACC systems.

Driving Behavior Classification: The behaviour of following and passing a vehicle was modeled and recognized using HMMs and Gaussian mixture model. In a maneuver-based method was proposed to estimate the driving state of a driver and to predict the future trajectory considering the information of its leading vehicle. In car-following scenarios, it is important to monitor the situation in the adjacent lanes to deal with the behavior of lane change.

The Adaptive Cruise Control (ACC) systems have been in market since their performance in terms of smoothness is frequently interrupted by cut-in vehicles from adjacent lanes. More attention should be paid to the intention of other vehicles for a more reliable ACC.

1.2 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.

1.3 Problem Statement

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

1.4 Purpose and Scope

The proposed Autonomous Driving considers:

- Estimate and predict of driving behavior of the vehicle.
- Reduction in human errors

- An autonomous driving algorithm helps in analyze of behavior and improve the safety and reliability.
- A method of behavior estimation is proposed to recognize and predict the lane change intentions based on the contextual traffic information. A model predictive controller is designed to optimize the acceleration sequences by incorporating the lane-change intentions of other vehicles.
- Future in self driving car.

CHAPTER 2

LITERATURE SURVEY

The aim of proposed model is to recognize and predict the lane change intentions based on the contextual traffic information. A model predictive controller is designed to optimize the acceleration sequences by incorporating the lane-change intentions of other vehicles. The public dataset of Next Generation Simulation are labeled and then published as a benchmarking platform for the research community. Experimental results demonstrate that the proposed method can accurately estimate vehicle behavior and therefore outperform the traditional car-following control.

2.1 Alternate Approaches

Vadim A. Butakov et al[1] has proposed a model that uses ADAS in order to perform lane change traffic configuration. Methodology combines advantages of stochastic and kinematic modeling techniques to come up with models that can run in real time with the capability of adjusting their parameters as new data are received for better accuracy. The models capture the behavior that involves adjusting longitudinal position and speed before the lane change maneuver, gap acceptance to initiate the maneuver, and the kinematics of the maneuver. This personalized modeling framework can be used to develop a lane change driver-assistance system as part of ADAS to provide appropriate and desirable recommendations to the driver that are personalized to his/her driving characteristics and dynamics.

Weilong, et al[2] built a 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.

Peter et al[3] has proposed a back-to-back performance comparison of lane-change manoeuvres, conducted in a driving simulator using an A-double long combination vehicle, applying two automated driving approaches and manual driving. Combined braking and steering, driver eye movement was investigated for safety critical driving scenario. The results provide evidence that both the time gap and relative speed to the adjacent lead vehicle are important for manual lane-change initiation. In addition, converting the time gap and relative speed into optical variables leads to similar indications of the possibility of safe lane-change initiation.

Jongsang Suh et al[4] A probabilistic and deterministic prediction based lane change motion planning and control algorithm for automated driving was developed, and the performance of the proposed algorithm was evaluated via computer simulation and test vehicle. To deal with the potential risk of the lane change situation, the current states and possible risk behaviors of the surrounding environment during a finite time horizon were simultaneously considered to determine lane keeping and change motion, and to maintain a safe driving envelope with risk monitoring. The control architecture based on a SMPC approach was used to calculate the desired steering angle and longitudinal acceleration with probabilistic constraints from uncertainties and disturbances.

2.2Demerits

- Lane changes only applicable for minimum no of vehicle with increase in gap acceptance[1]
- Complexity in POMDP model[2]
- Lane changes was done only on Long combination vehicles[3]
- Time gap and relative speed was not considered[3]
- It was not able to analyse for unexpected traffic[4]

2.3 Proposed Method

In the NGSIM dataset, separated scenarios for each vehicle are extracted where surrounding vehicles remain the same. Two types of behavior models, i.e., lane keeping and lane change, are learned using GMM-HMMs. In the testing phase, the likelihood of sequences is computed using a forward algorithm and is compared with a threshold for the final recognition. The probability of lane-change is calculated and integrated into the MPC framework to control the car following behavior of the host vehicle. Fig 2.3.1 is the framework of proposed method.

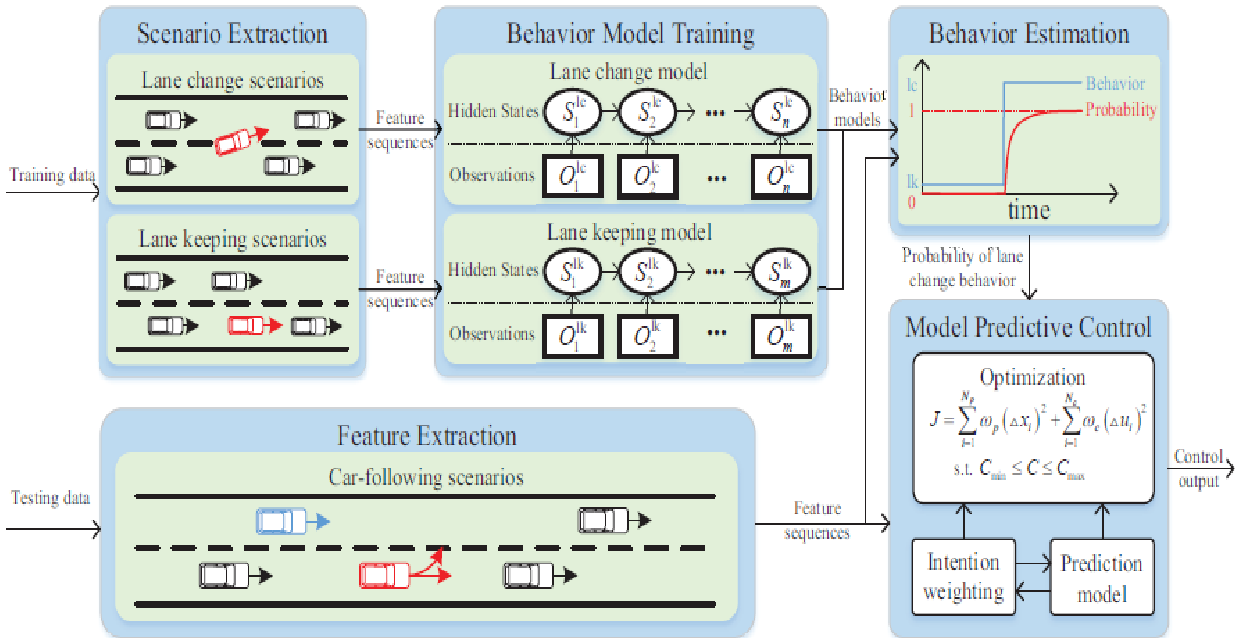
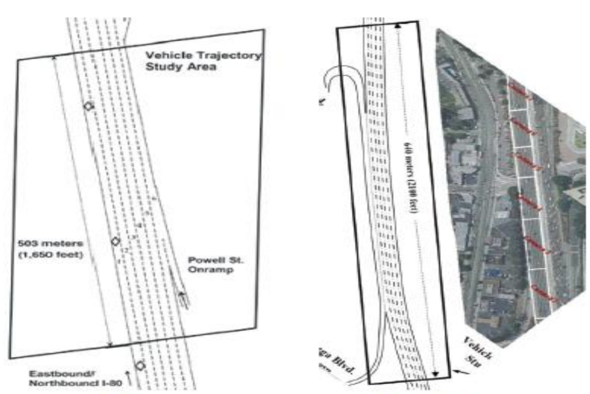


Fig. 2.3.1: Framework of proposed method

A. <u>Scenario definition and extraction</u>

In the following, the NGSIM dataset is described in detail and the scenarios used in this paper are defined.

1) Data Description: This paper uses the public datasets of individual vehicle trajectories from NGSIM, a program funded by the U.S. Federal Highway Administration. These trajectory data are thus far unique in the history of traffic research and provide a valuable basis for the research of driving behavior on structured roads. All the experiments are performed on the datasets of I-80 and US-101. The road structures of both scenarios are shown in Fig. 2.3.2. The labeled scenario data are open-sourced



(a) I-80 scenario (b) US-101 scenario

Fig. 2.3.2: Overview of study area on two NGSIM datasets

The I-80 dataset consists of three 15-minute periods: 4:00 pm to 4:15 pm, 5:00 pm to 5:15 pm, and 5:15 pm to 5:30 pm. These periods represent respectively a buildup of congestion, a transition between uncongested and congested conditions, and full congestion. A total of 45 minutes of data are available in the US-101 dataset, which are segmented into three 15-minute periods: 7:50 am to 8:05 am, 8:05 am to 8:20 am, and 8:20 am to 8:35 am. The vehicle trajectories in both datasets data include the precise location of each vehicle within the study area and the data were sampled at a rate of 10 Hz.

2) Scenario segmentation: The segmented scenarios in Fig 2.3 have the following properties:

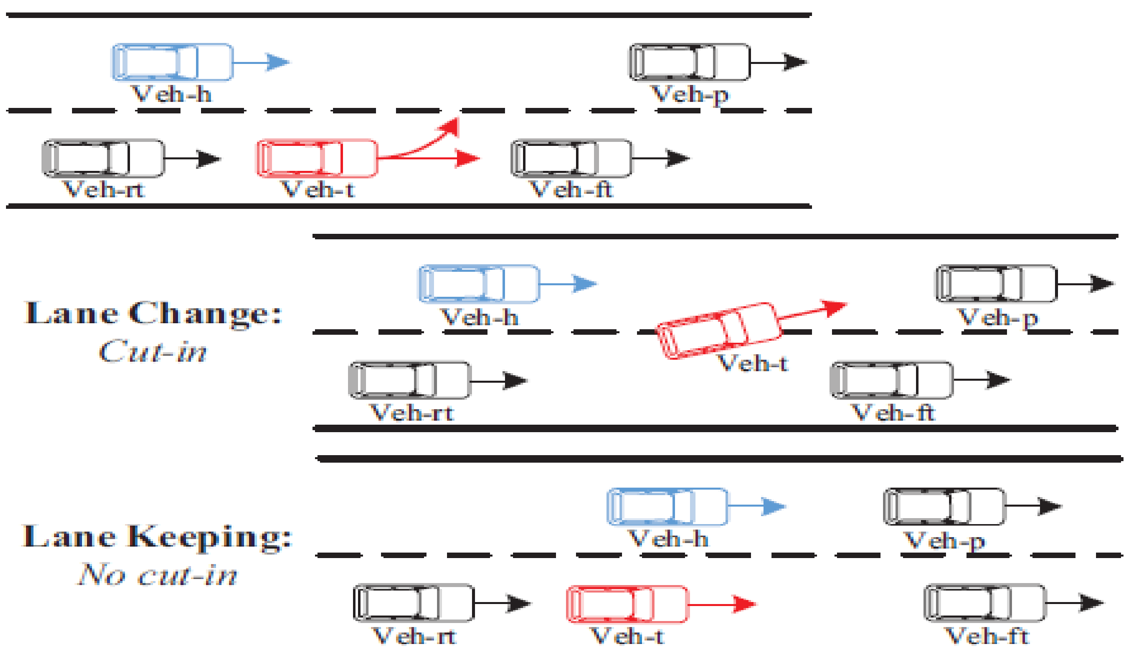


Fig. 2.3.3: Multi-lane car-following scenarios

- In each scenario, the surrounding vehicles (Veh-h, Veh-p, Veh-ft, Veh-rt) of a target vehicle (Veh-t) remain the same.
- We set the relative distance to 150 m and the relative speed to 0 for any missing surrounding vehicles.
- A scenario ends when a target vehicle crosses a lane line (merge), passes Veh-p, or yields to Veh-h.
- A new scenario restarts immediately once the preceeding scenario is finished to ensure continuity between driving scenarios.

- The segmented scenarios last at least two seconds to ensure complete lane-change or lane-keeping behavior

B. Behavior model

1) GMM: The variables in Table 2.1 can be classified into three categories as follows:

Symbols	Descriptions
v_x	Longitudinal speed of Veh-t
v_y	Lateral speed of Veh-t
d_0	Lateral offset from target lane line to Veh-t
$\Delta v_{t,p}$	Longitudinal speed difference between Veh-t and Veh-p
$\Delta v_{t,h}$	Longitudinal speed difference between Veh-t and Veh-h
$\Delta v_{t,ft}$	Longitudinal speed difference between Veh-t and Veh-ft
$\Delta v_{t,rt}$	Longitudinal speed difference between Veh-t and Veh-rt
$\Delta x_{t,p}$	Longitudinal distance between Veh-t and Veh-p
$\Delta x_{t,h}$	Longitudinal distance between Veh-t and Veh-h
$\Delta x_{t,ft}$	Longitudinal distance between Veh-t and Veh-ft
$\Delta x_{t,rt}$	Longitudinal distance between Veh-t and Veh-rt

TABLE 2.3.1: Features of scenario segmentation

$$\text{£}_t = [\ [v_x(t), v_y(t), d_0(t)],$$
$$[\Delta v_{t,p}(t), \Delta v_{t,h}(t), \Delta x_{t,p}(t), \Delta x_{t,h}(t)],$$
$$[\Delta v_{t,ft}(t), \Delta v_{t,rt}(t), \Delta x_{t,ft}(t), \Delta x_{t,rt}(t)]\ ]^T$$

Note that £t is used to model the behaviors. We assume that the distribution of the observation £ is a weighted sum of multivariate Gaussian distribution functions:

$$\mathrm{p}(\text{£}_\mathrm{t}; \theta) = \sum_{\mathrm{k}=1}^{\mathrm{K}} \mathrm{w_k}\, N(\text{£}_\mathrm{t}; v_k, \textstyle\sum_\mathrm{k})$$

$$= \textstyle\sum_{\mathrm{k}=1}^{\mathrm{K}} \mathrm{w_k}.\exp(-1/2(\text{£}_t - v_k)^t \sum_k^{-1}(\text{£}_\mathrm{t} - v_k))/\sqrt{(2\pi)^{11}\det(\sum_\mathrm{k})}$$

Given a data sequence $\text{£}_{1:n}$ the maximum-likelihood estimation method is used to find a Θ that maximizes the likelihood of the GMM function:

$$L(\theta)=\sum_{t=1}^{n} \ln(p(£_t;\theta))$$

The expectation-maximization algorithm is to search for the optimal parameter

$$\theta^*=argmax_\theta\ L(\theta)$$

In the end of each iteration, the log-likelihood is

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

The iteration will continue until the likelihood difference between two consecutive estimated models is less than a threshold, which is set to 10^{-10}.

2) HMM: Two separate HMMs are built to represent the behavior of lane change and lane keeping. The structure of the HMM is left-to-right. The HMM is represented by

$$\lambda=S,Z,A,B,\pi$$

where

- S = $\{s_{1,},..,s_n\}$ represents a finite set of N hidden states.
- Z = $\{€_t\}$ is the set of all observed states € at time t and each € consists of the eleven elements included in the GMM.
- A = $[a_{ij}]$ is the state transition matrix and a_{ij} is defined as the probability of a transition from state s_i to state s_j .
- B =$\{b_i(€)\}$ is the observation model and $b_i(€)$ represents the probability of observing £ while being in state s_i.
- π = $\{\pi_i\}$is the initial state distribution where π_i represents the probability of the state s_i being the initial state

3) Behavior recognition: In the testing phase, a binary recognition, i.e., lane change or lane keeping, is achieved in a receding horizon manner.

$$R= P(£_{1:t} \mid \lambda_{lc}) / P(£_{1:t} \mid \lambda_{lk})$$

where R indicates whether the classification is more likely to be lane change or keeping.

C. <u>Model predictive control</u>

Once the behavior model is built, a probability of lane change is calculated and integrated into the framework of model predictive control.

1) Intention estimation: The probability of the lane change intention is calculated and the likelihood is thus normalized as a probability ranging from 0 to 1.

2) Prediction model: In this paper, the longitudinal motion of the vehicle is expressed by

$$x(t+1)=x(t)+v(t)\,\Delta t+0.5a(t)\,\Delta t^2$$

$$v(t+1)=v(t)+a(t)\,\Delta t$$

where x, v, a are respectively the positions, speeds and accelerations of the host vehicle, and Δt is the sampling time.

3) Receding horizon optimization: The cost function of the MPC is designed to meet the following objectives:

- Tracking errors
- Comfort and smoothness

2.4 Results

Classification Evaluation

In order to highlight the effects of surrounding vehicles, the model only considering the information of target vehicles is also studied in the following experiments, which is designated "tgt" for only considering target vehicle. The proposed method is designated "srd" for considering surrounding vehicles. Besides the AUC evaluation, the following quantitative metrics are also introduced for a comprehensive evaluation in the table 2.4.1.

Datasets		I-80						US-101					
Cases		I	II	III	IV	V	AVG	I	II	III	IV	V	AVG
TPR	srd	0.9158	0.8055	0.8056	0.8425	0.8307	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	0.0948
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
F1	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

Table 2.4.1: Performance index comparison at FPR = 5%.

Lane change prediction

A further challenge is to predict lane change before the target vehicle crosses lane lines shown in TABLE 2.4.2

Cases	I	II	III	IV	V	AVG
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	7.96	5.38	4.24	4.43	4.73
tgt-US-101	2.67	2.81	3.12	2.23	2.41	2.65

Table 2.4.2: Lane change prediction time T in second

Car following testing results

The scenarios containing the host and target vehicles in the NGSIM dataset are extracted for the car-following control test. The information of the surrounding vehicles are used as the observation of the host vehicle As shown in Table IV, five metrics are selected to evaluate the proposed method and three methods are compared to demonstrate the influences of the cut-in situations. The proposed method is denoted by “srd-MPC”, which means the intention of the target vehicle is estimated by considering the information of all the surrounding vehicles. The method “tgt-MPC” represents the MPC controller with the intention estimated only using the information of the target vehicle. The method “Only-MPC” is the pure MPC method without considering the cut-in intentions of target vehicles. The speeds, accelerations and jerks listed in Table 2.4.3 are the average value in each test.

Datasets		I-80						US-101					
Cases		I	II	III	IV	V	AVG	I	II	III	IV	V	AVG
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	0.8061	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

Table 2.4.3: Performance index comparison of MPCs

Two detailed examples from the testing data are illustrated to explain the advantage of the proposed method in Fig. 2.4, where the real data is from human drivers in the dataset.

The first example is a cut-in scenario in the I-80 dataset as shown in Fig. 2.4.1. In this scenario, the cut-in behavior happens when the target vehicle is slow and wants to give way to a faster following vehicle. As shown in Fig. 2.4.2 the lane change intention of the target vehicle is detected at 1.8 s by the proposed method, and the target vehicle crosses the lane lines at 7.3 s, where the sudden change of relative distance is shown in Fig. 2.4.1

Such an intention is detected at 6.6 s using the target vehicle information only. By using the proposed method, the host vehicle is able to take an earlier intervention control of slowing down before the cut-in, therefore obtains smooth accelerations and avoids a hard brake.

Another example from the US-101 dataset is shown in Fig. 2.4.3. The target vehicle in this scenarios is trying to merge into the lane of the host vehicle to speed up. The proposed method estimates the cut-in behavior at 1.1 s, while the target vehicle crosses the lane lines at 8.2 s. Similarly to the last scenarios, an earlier and smoother control can be seen in the Jerk subplot. Without the intention estimation, the host vehicle controlled by the pure MPC fails to avoid the collision due to the sudden cut-in in Fig. 2.4.4.

- Relative distance for I-80 dataset

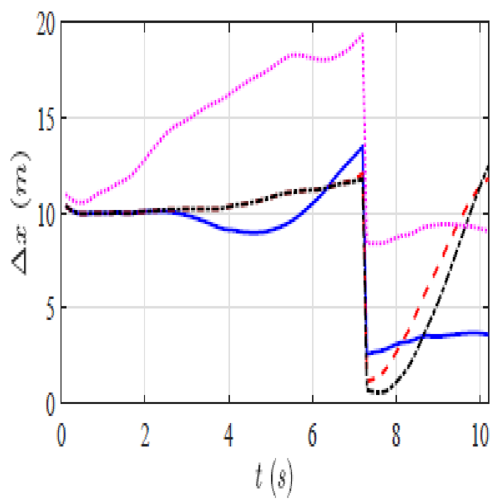


Fig. 2.4.1: Relative distance for I-80

- Cut in probability for I-80 dataset

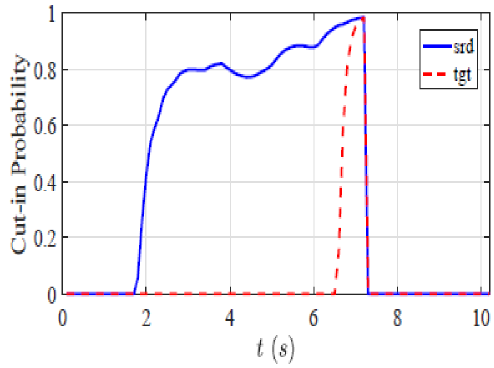


Fig. 2.4.2: Cut in probability for I-80

- Relative distance for US 101 dataset

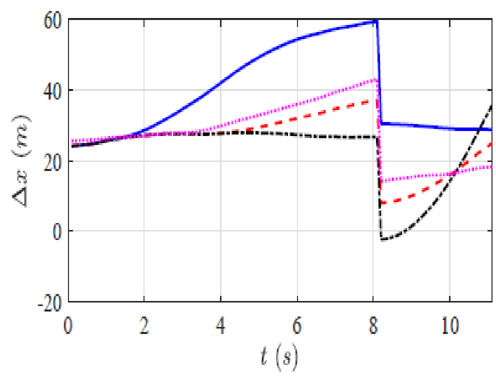


Fig. 2.4.3: Relative distance for US 101

- Cut in probability for US 101 dataset

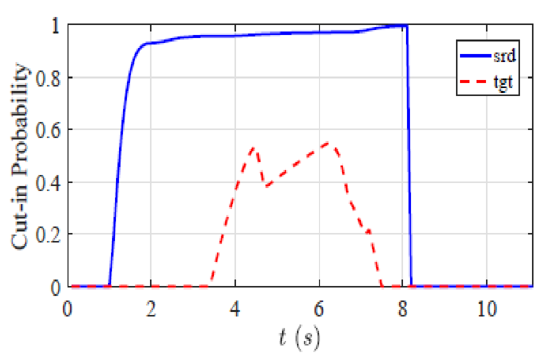


Fig. 2.4.4: Cut in probability for US 101

CHAPTER 3

COMPARITIVE STUDY

Lane change duration

The experiments for comparative study, conducted on NGSIM dataset for Autonomous driving principle, demonstrated the lane change intention estimation for the proposed method. The efficiency and effectiveness of the proposed Autonomous method is validated by evaluating the proposed model against GMM, HMM. Duration of lane change should happen 6 to 8 sec. In[3] Lane changes was done only on Long combination vehicles. Time gap and relative speed was not considered and duration took for lane change is two to three times that of previous method.

Direction of lane change

A comparative study on base paper and other reference paper. We can conclude the direction lane change should happen in both the direction.

- Right to left
- Left to right

Nonholonomic Constraints

This is applicable in generally for any dataset, this values are not constant. This constraints should be considered:

- Speed of the host vehicle
- Minimum gap should be maintained between the vehicles.
- Acceleration constraint varies in host vehicles.
- Jerk constraint of host vehicles.

CHAPTER 4

CONCLUSION

A car-following control method with the estimation of the lane-change behavior of other traffic participants. Multivariate time series data from the target vehicle and its surrounding vehicles are used to build two continuous HMM(Hidden Markov Model) representing the behavior of lane change and land keeping. A threshold-based classification method is used to estimate the target vehicle’s behavior. In the meantime, a cut-in probability is calculated based on the behavior estimation and the MPC(Model Predictive Control) method is then applied to optimize the car-following behavior of the host vehicle.

The 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 4 seconds before the target vehicle crosses the lane lines. The proposed intention-based MPC achieves superior performance of safety and ride comfort. In future, we will investigate the strategies based on intention prediction in more complicated scenarios like at intersections. The interpretation of the complicated model is also a research line. The insightful model like timed automaton would act as a promising alternative solution.

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