An integrated lane change prediction model incorporating traffic context based on trajectory data

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contents

When lane change behaviors

- Improve their driving condition
- Merge or diverge across multilane traffic streams

↓

- Requires the interaction between the subject vehicle and surrounding vehicle
- Disturbances in traffic flow
- Speed decreases
- Increase the probability of collisions

Existing Studies

- Do not consider the effect of traffic context on lane change maneuvers (traffic level and vehicle type)

Goals

- Integrated lane change prediction model incorporating traffic context
- Reduce collision risks caused by lane change maneuvers
- Improve traffic management and driving safety

1. Introduction

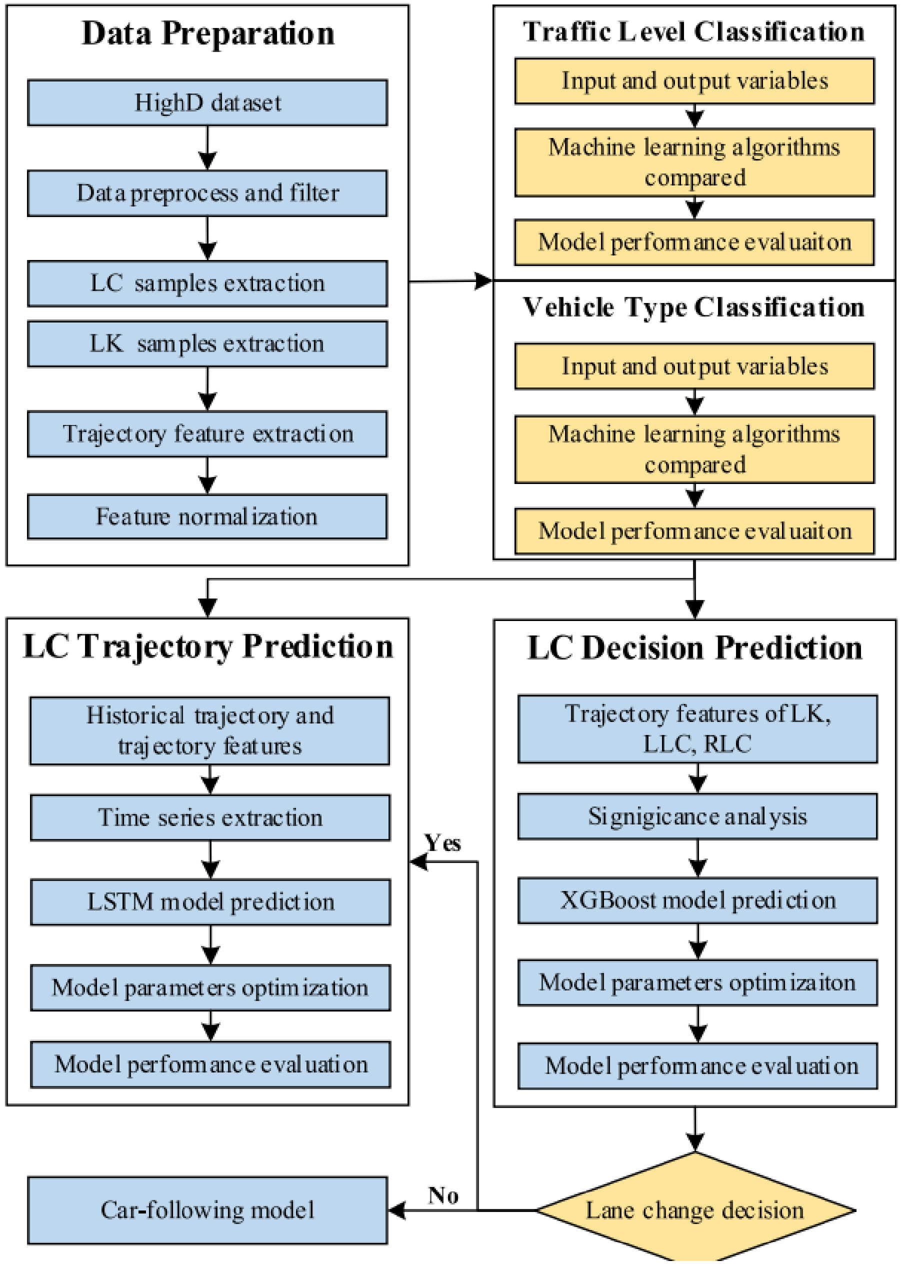


Fig. 1. The framework of the integrated lane change prediction model.

4 phases

Data Preparation

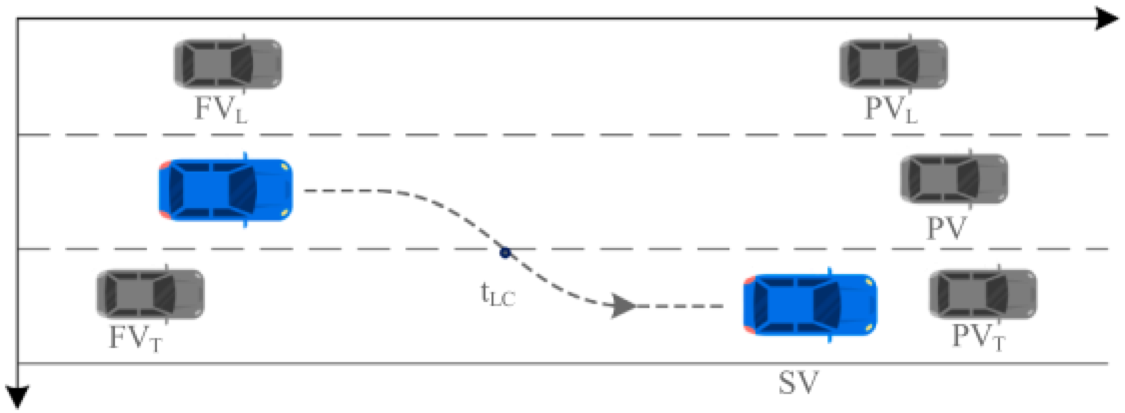
Traffic Level Classification

LC Trajectory Prediction

LC Decision Prediction

XG Boost & LSTM

2.1. Methods



LLC : Left Line Change

RLC : Right Line Change

LK : Line Keeping

	Variables	Description
Single-vehicle variables	$\boxed{v}$	The longitudinal velocity of *SV* during the lane change (m/s)
	$\boxed{a}$	The longitudinal acceleration of *SV* during the lane change (m/s^2)
	v_{lat}	The lateral velocity of *SV* during the lane change (m/s)
	a_{lat}	The lateral acceleration of *SV* during the lane change (m/s^2)
	$\varphi(t)$	The degree between vehicle trajectory and road vertical line
Multivehicle variables	$\boxed{v_{r1}}$	The relative speeds of *SV* and *PV* (m/s)
	$\boxed{v_{r2}}$	The relative speeds of PV_T and *SV* (m/s)
	$\boxed{v_{r3}}$	The relative speeds of FV_T and *SV* (m/s)
	$\boxed{v_{r4}}$	The relative speeds of PV_L and *SV* (m/s)
	$\boxed{v_{r5}}$	The relative speeds of FV_L and *SV* (m/s)
	$\boxed{d_1}$	The space headway between *SV* and *PV* (m)
	$\boxed{d_2}$	The space headway between PV_T and *SV* (m)
	$\boxed{d_3}$	The space headway between FV_T and *SV* (m)
	$\boxed{d_4}$	The space headway between PV_L and *SV* (m)
	$\boxed{d_5}$	The space headway between FV_L and *SV* (m)

2.2 The traffic context label

Traffic density is the primary determinate of the traffic flow level

↓

Adopt this parameter to label the traffic level

< Traffic Density >

- Density of the road section / Number of lanes

$$k(t) = \frac{n(t)}{L}$$

n(t) : number of the vehicles on the road at time t

L : length of the road section

< K-means >

- Label the traffic flow level based traffic density

$$k = \sum_{t_1}^{t_2} k(t)/(t_2 - t_1)$$

average density of the LC manuver during t_1 and t_2

- Clustered groups

↪ Different traffic density

↪ Different traffic levels

$$\bar{k} = k/x$$

average density of each lane is the overall density of the road section divided by the number of lanes x

2.3.1 traffic level classification model

Characteristics of lane change trajectory vary with different traffic levels

↓

Traffic flow should be classified into different levels to facilitate lane change prediction

< Traffic level classification model >

$$y_t = \{v(t), a(t), ST_R(t)\}$$

v(t) : longitudinal speed
a(t) : acceleration

$$ST_R(t) = \{v_{r1}(t), v_{r2}(t), v_{r3}(t), v_{r4}(t), v_{r5}(t), \quad d_1(t), d_2(t), d_3(t), d_4(t), d_5(t)\}$$

Relative trajectory between SV and five vehicles

$ST_R(t)$ → predict the model

2.3.2 The vehicle type classification model

Car and Truck driver’s driving preferences are significantly different

↓

Vehicle type should be considered

< Recognition model >

$$y_v = \{\varphi(t), v(t), a(t), ST_R(t)\}$$

highD dataset can provide vehicle type

Vehicle type cannot be recognized directly

2.4. The integrated lane change prediction model

Traffic Level

+

Traffic Density

+

Vehicle Type

Traffic Context

Lane Change Decision Predict

↪ LLC, RLC, LK

Lane Change Trajectory Predict

↪ Trajectory

2.4.1. The lane change decision prediction model

Lane change process usually lasts for several seconds

↓

Predict whether the lane change decision will be conducted in the next few seconds

$$y_d = \{v(t), a(t), \varphi(t), v_{lat}(t), a_{lat}(t), ST_R(t), y_t, y\}_v$$

yd : lane change decision
vlat(t) : lateral velocity
alat(t) : acceleration

Traffic level classification model output

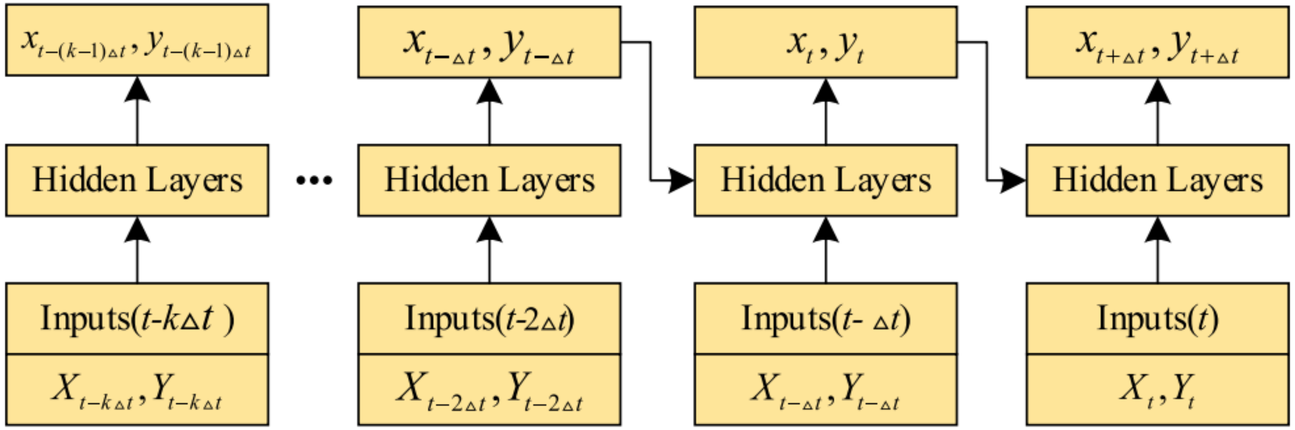
Vehicle type recognition model output

→ LLC or RLC or LK

2.4.2. The lane change trajectory prediction model

Lane change decision predicted
↓
Lane change trajectory is also predicted

< LSTM >



$$Y_t = \{y(t), y(t-\Delta t), y(t-2\Delta t), y(t-3\Delta t)...y(t-k\Delta t)\}$$

Location of the SV
↪ lateral x(t + Δt), longitudinal y(t + Δt)

Collected k preceding time step before time t + Δt to predict the position of the SV at the time t + Δt

- Recall rate
- Precision rate
- Accuracy rate
- F1-score
- MSE

2.5. Key feature extraction

1. Time-domain features

- SM : statistical method

2. Frequency-domain features

- DWT : Discrete wavelet transform

  ↪ Decompose the signal into multiple steps of lower resolution

- DFT : Discrete Fourier transform

  ↪ Time domain to frequency domain conversion

3.1. Data description

highD dataset

- Contains postprocessed trajectories of vehicles
- Six different German highways around Cologne
- 2017 & 2018
- Collected by a drone
- Range 420m
- Computer vision algorithms with 25Hz

Maintain a similar driving environment

- 373 vehicles (316 cars, 57 trucks)
- 9:30 ~ 11:00
- Six straight lanes without intersection or ramp
- Speed limit 120km/h
- Frame ID
- Vehicle ID
- Position, width and length of the vehicle
- Velocity and acceleration
- Lane ID
- Surrounding vehicles IDs

3.1. Data description

Duration of lane change implementation.

Duration of lane change implementation	Number of vehicles	Proportion
≤2 s	4	0.0107
2–3 s	17	0.0456
3–4 s	177	0.4745
4–5 s	118	0.3164
5–6 s	41	0.1099
6–8 s	16	0.0429
Total	373	1.0000

Trucks : 5~8s

Cars : no more than 5s

Implementation process time of 2~6s account for nearly 95% of the vehicles

10s covers the whole lane change process

Less than 6s or more than 10s removed

3.1. Data description

The statistics of congested and normal traffic.

Variables	Normal	Congested
Density (pc/mile/ln)	28.84	41.46
LOS	C	E

LOS criteria for basic freeway segments.

LOS	Density (pc/mile/ln)
A	11
B	18
C	26
D	35
E	45

LOS : Level of Service

373 LC sample

240 LK sample

LOS C (Normal) 208 sample

LOS E (Congested) 268 sample

Limited samples for the truck-congested

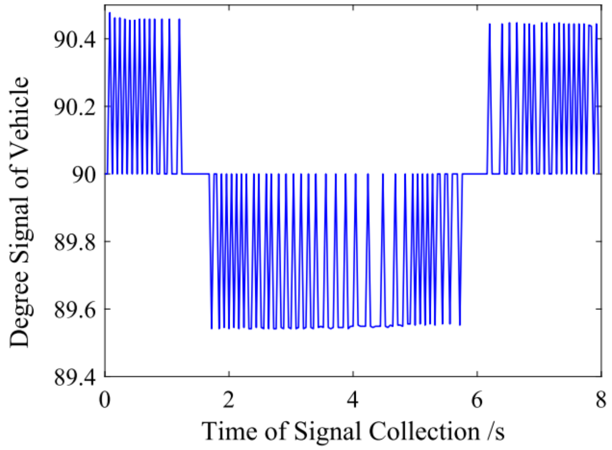
- Car-normal
- Car-congested
- Truck-normal

Sample distribution under different traffic contexts.

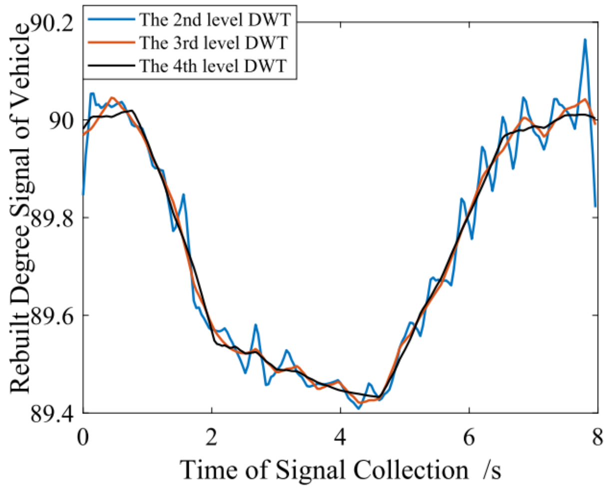
Context	**LLC**	**RLC**	**LK**	**All**
Car-normal	59	69	80	208
Car-congested	68	120	80	268
Truck-normal	27	30	80	137
All	154	219	240	613

3.2.1. Features extraction comparison

< DWT >

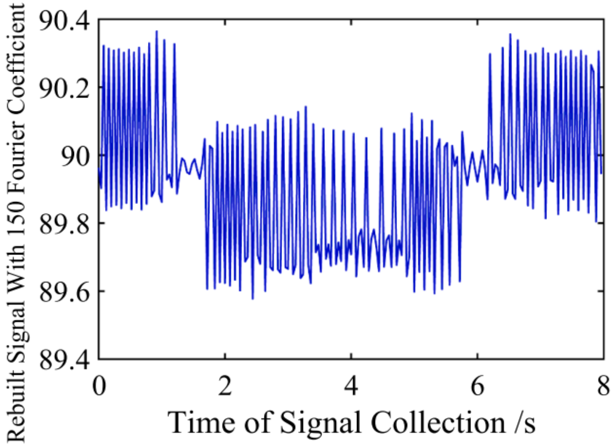


Original signal

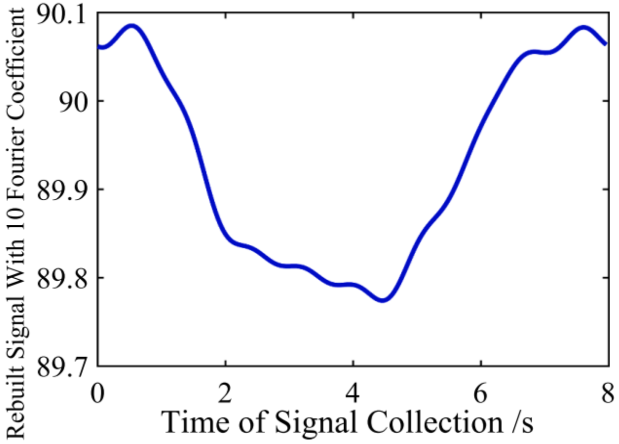


Reconstructed signal with different levels of DWT

< DFT >



Reconstructed signal with 150 Fourier coefficients



Reconstructed signal with 10 Fourier coefficients

Increase in the number of decomposition layer

↓

Signal lose more details and become smoother

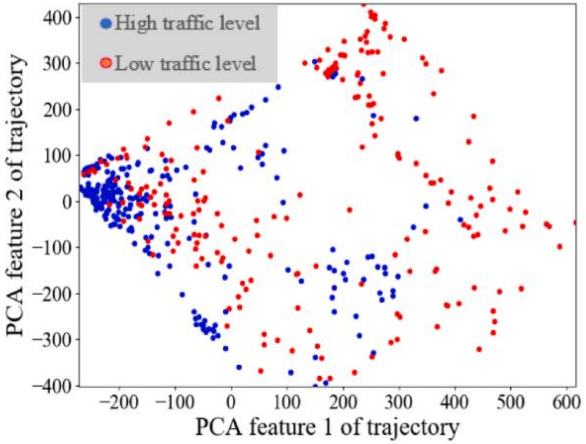
Features of DWT much less than those of DFT

↓

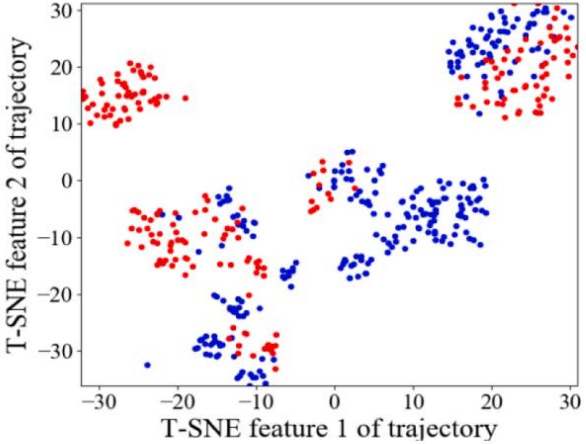
Reducing the computational complexity

DWT apply to extract frequency-domain features

3.2.2. Key features visualization



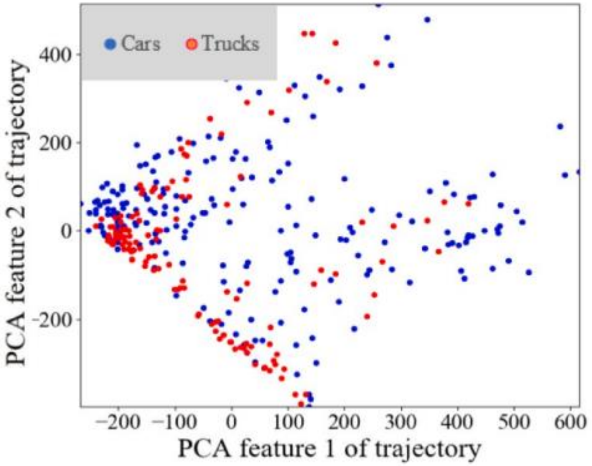
PCA feature distribution



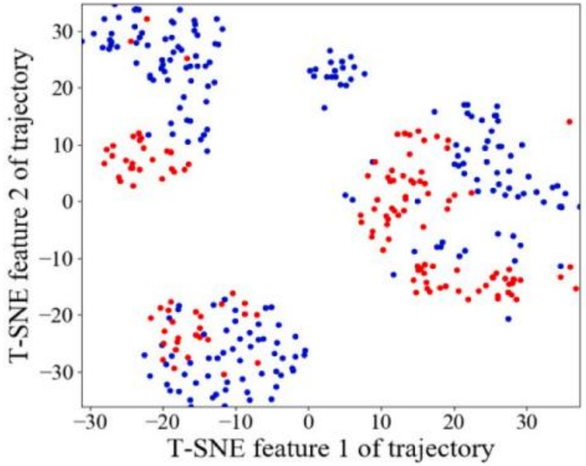
t-SNE feature distribution

High traffic level / Low traffic level

- High and low traffic levels nonlinearly separable



PCA feature distribution

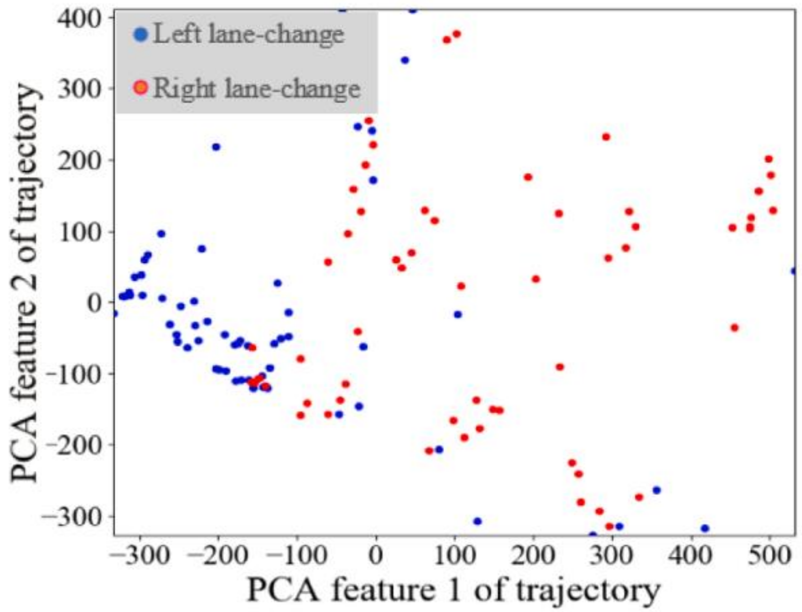


t-SNE feature distribution

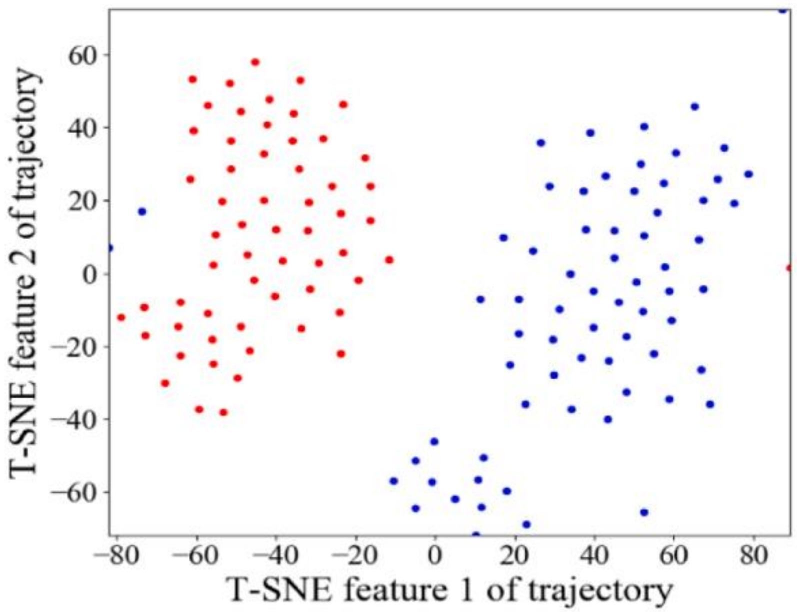
Cars / Trucks

- Vehicle type classification model large complexity
- Requires powerful classification algorithm

3.2.2. Key features visualization



PCA feature distribution



t-SNE feature distribution

Left lane-change / Right lane-change

- LLC and RLC maneuvers linearly separable

3.3.1. The traffic level classification model evaluation

Significance analysis between trajectory features for normal and congested traffic.

Variables	Congested		Normal		F-value
	Mean	**Std**	**Mean**	**Std**	
v	$\boxed{25.235}$	26.975	$\boxed{31.173}$	8.159	**0.000****
a	0.122	0.186	−0.002	0.138	**0.000****
v_{lat}	$\boxed{0.019}$	0.262	$\boxed{0.304}$	0.119	**0.000****
a_{lat}	0.015	0.040	0.108	0.018	**0.000****
v_{r1}	−0.759	5.930	−0.510	17.621	**0.000****
v_{r2}	−0.349	17.787	1.087	25.272	**0.000****
v_r	1.081	38.711	5.690	121.966	**0.000****
d_1	43.225	1728.473	82.877	6031.493	**0.000****
d_2	46.256	3748.281	104.806	9307.097	**0.000****
d_3	60.032	8681.355	103.975	13794.015	**0.000****

** Significance correlation at the 0.01 level (bilateral).

- Significant difference between the trajectory variables
- Congested < Normal
- Space headway and relative speed between SV and PV, PVt, FVt

  ↪ Much smaller under congested traffic

  ↪ Lane change maneuvers more aggressively

3.3.1. The traffic level classification model evaluation

Traffic level classification results of frequency-domain features.

Algorithms	Class name	Precision (%)	Recall (%)	F1-score (%)	Accuracy (%)	MSE
XGBoost	Congested	91.24	93.63	**91.35**	**91.36**	**0.086**
	Normal	91.54	88.46			
AdaBoost	Congested	91.51	92.88	91.14	91.16	0.088
	Normal	90.68	88.94			
NB	Congested	88.97	84.64	85.51	85.47	0.145
	Normal	81.44	86.53			
SVM (linear)	Congested	90.29	90.63	89.26	89.26	0.107
	Normal	87.92	87.50			
DT	Congested	88.89	92.88	89.43	89.47	0.105
	Normal	90.30	85.09			

Comparison of classification results.

Algorithms	Frequency-based features		Time-based features	
	Accuracy (%)	MSE	Accuracy (%)	MSE
XGBoost	91.36	0.086	90.32	0.096
AdaBoost	91.16	0.088	91.78	0.082
NB	85.47	0.145	71.15	0.288
SVM (linear)	89.26	0.107	81.89	0.181
DT	89.47	0.105	86.52	0.134
Average	**89.34**	**0.106**	**84.33**	**0.156**

3.3.2. Vehicle type classification model evaluation

Significance analysis between trajectory variables for car and truck drivers.

Variables	Car		Truck		F-value
	Mean	Std	Mean	Std	
v	$\boxed{31.702}$	8.563	$\boxed{25.830}$	6.832	**0.000****
a	$\boxed{0.048}$	0.100	$\boxed{0.012}$	0.044	**0.000****
v_{lat}	0.490	0.105	0.491	0.101	0.967
a_{lat}	0.180	0.015	0.178	0.015	0.432
v_{r1}	−0.606	25.964	2.202	22.304	**0.000****
v_{r2}	0.627	17.861	2.937	17.483	**0.000****
v_r	4.141	28.374	0.245	33.147	**0.000****
d_1	101.720	8669.554	88.231	6294.753	**0.000****
d_2	94.570	6346.226	84.236	6614.721	**0.000****
d_3	94.648	12188.109	87.021	9132.504	**0.000****

** Significance correlation at the 0.01 level (bilateral).

- Car > Truck
- Truck drivers tend to perform lane change with larger headway distances to preceding vehicles
- Driving trajectories of truck drivers greatly different from those of car drivers

3.3.2. Vehicle type classification model evaluation

The vehicle type classification results of frequency-domain features.

Algorithms	Class name	Precision (%)	Recall (%)	F1-score (%)	Accuracy (%)	MSE
XGBoost	Car	97.56	96.61	**96.51**	**96.51**	**0.035**
	Truck	94.96	96.35			
AdaBoost	Car	95.63	95.16	94.48	94.47	0.055
	Truck	92.75	93.43			
NB	Car	91.25	70.53	78.39	78.19	0.218
	Truck	66.84	89.78			
SVM (linear)	Car	95.16	95.16	94.18	94.18	0.058
	Truck	92.70	92.70			
DT	Car	94.73	95.65	94.17	94.18	0.058
	Truck	93.33	91.97			

3.4.1. The lane change decision prediction model evaluation

Significance analysis between trajectory variables for LLC and RLC.

Variables	RLC		LLC		F-value
	Mean	SE	Mean	SE	
v	32.562	5.912	30.692	9.793	**0.000****
a	$\boxed{-0.027}$	0.052	$\boxed{0.135}$	0.143	**0.000****
v_{lat}	0.514	0.099	0.462	0.111	**0.000****
a_{lat}	0.178	0.013	0.182	0.017	0.068
v_{r1}	2.801	13.914	−4.612	10.430	**0.000****
v_{r2}	−1.117	16.745	2.677	11.397	**0.000****
v_r	6.443	8.247	1.436	38.492	**0.000****
d_1	146.593	11216.042	48.975	528.090	**0.000****
d_2	114.061	6201.082	71.659	5546.351	**0.000****
d_3	59.073	7193.516	136.464	14824.403	**0.000****

** Significance correlation at the 0.01 level (bilateral).

- Speed of PVt in the target lane > speed of the PV in the original lane

  ↪ LLC (passing lane left), safer environment for vehicles to accelerate
- LLC more aggressive acceleration
- SV much closer to preceding vehicles
- Headway between SV and FV for RLC longer → limited view of drivers (left sit)

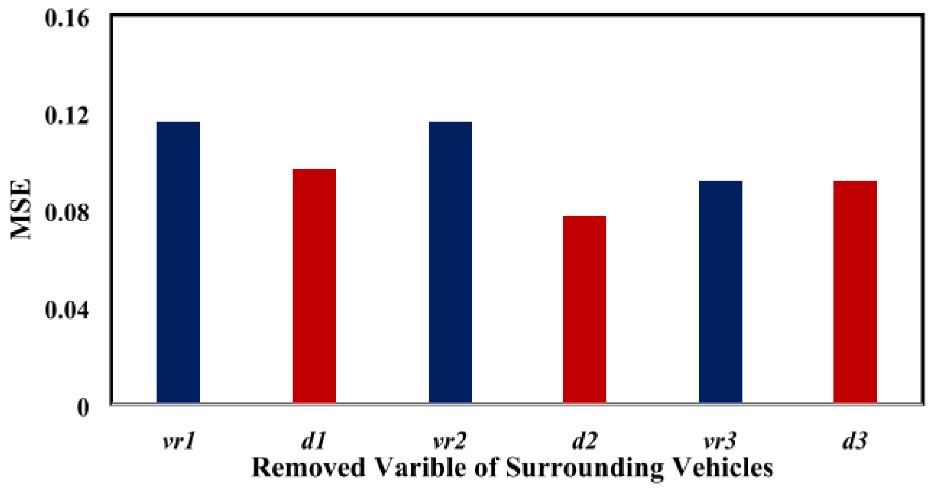
3.4.1. The lane change decision prediction model evaluation

Lane change decision prediction performance based on the XGBoost algorithm.

Time	Class name	Precision (%)	Recall (%)	F1-score (%)	Accuracy (%)	MSE
0.5 s	LK	97.91	97.50	**98.20**	**98.20**	**0.043**
	RLC	99.07	98.61			
	LLC	97.44	98.70			
1.0 s	LK	96.25	96.25	97.10	97.10	0.087
	RLC	97.05	97.05			
	LLC	98.30	98.30			
1.5 s	LK	96.20	95.00	96.61	96.61	0.106
	RLC	95.65	97.05			
	LLC	98.30	98.30			
2.0 s	LK	91.66	96.25	95.19	96.17	0.120
	RLC	98.46	94.11			
	LLC	96.55	94.91			

- Trajectory before vehicle cross lines
- Predict whether vehicle would perform the lane change maneuver a few seconds later
- Prediction accuracy is higher when it approaches the lane change time
- RLC, LLC, LK = 97.06%, 97.86%, 95.39% (average prediction precision)
- LLC higher than RLC, LK → system more sensitive

3.4.1. The lane change decision prediction model evaluation



- Remove relative speeds and space headway
- Increases MSE
- Important traffic context

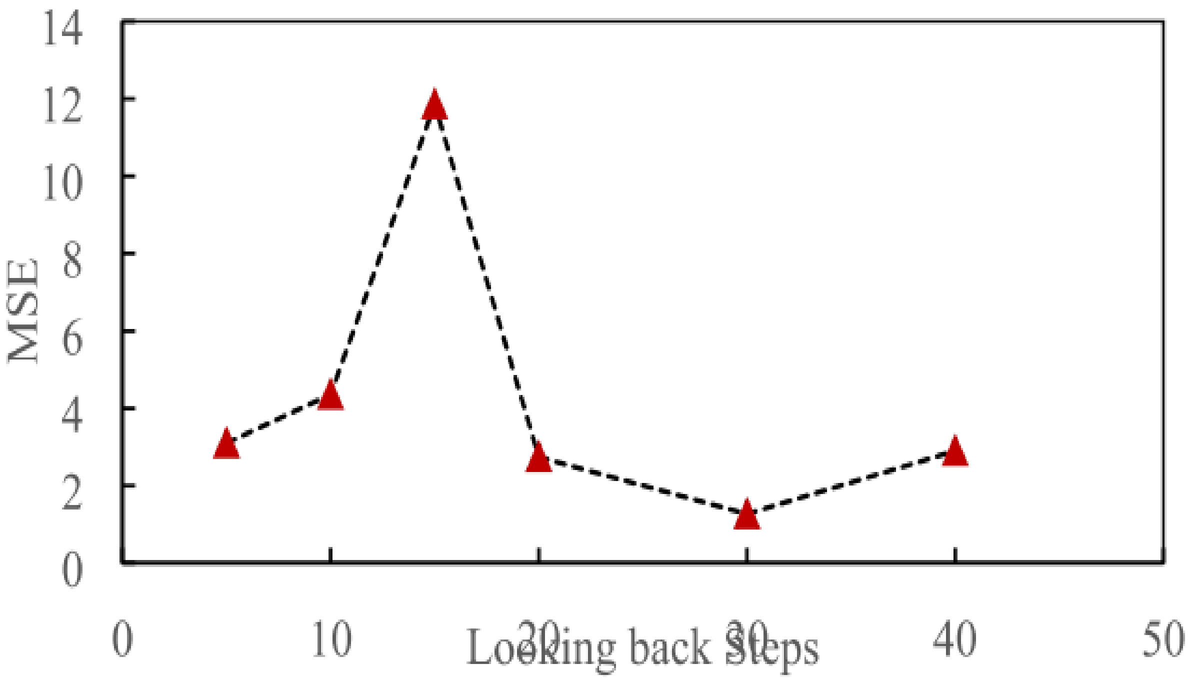
MSE of lane change decision prediction when one input is removed.

Removed variables	MSE	Removed variables	MSE
v_{r1}	**0.116**	d_1	**0.097**
v_{r2}	**0.116**	d_2	0.077
v_{r3}	0.092	d_3	0.092

The prediction result comparison with and without traffic context.

Comparison	Class name	Precision (%)	Recall (%)	F1-score (%)	Accuracy (%)	MSE
Traffic context	LK	97.91	97.50	**98.20**	**98.20**	**0.043**
	RLC	99.07	98.61			
	LLC	97.44	98.70			
Without considering traffic context	LK	97.41	94.17	97.00	97.02	0.065
	RLC	96.87	100.00			
	LLC	96.73	96.73			

3.4.2. The lane change trajectory prediction model evaluation



LSTM

1) Adam optimizer, learning rate = 0.005
2) Mini batch size = 32
3) Six kinds of time steps (5, 10, 15, 20, 30, 40) → minimum MSE time step set 30

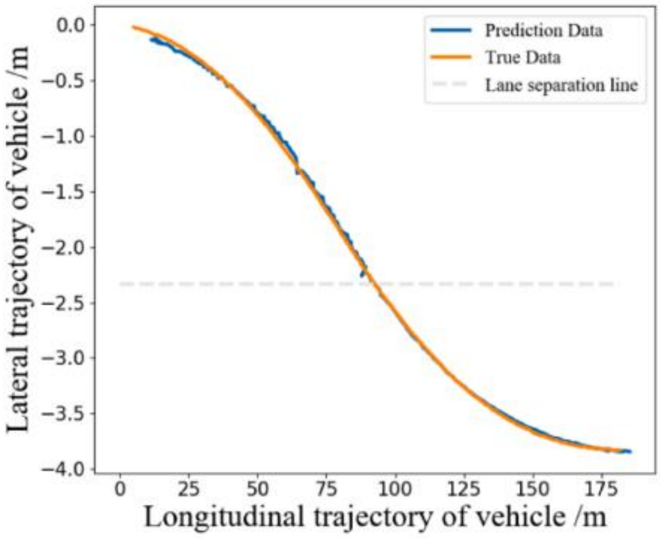
3.4.2. The lane change trajectory prediction model evaluation

The MSE of the trajectory predicted by the LSTM algorithm.

ID	MSE	ID	MSE
1	7.59	10	7.6
2	6.27	11	11.17
3	4.18	12	9.02
4	3.5	13	7.78
5	3.87	14	11.02
6	7.14	15	6.38
7	3.2	16	5.65
8	5.96	17	7.12
9	7.09	18	4.58

- Car-normal, Car-congested, Truck-normal situations for LLC and RLC → six type of sample
- MSE predicted trajectory for 18 randomly selected vehicles
- Average MSE : 6.62
- LLC MSE : 6.60, RLC MSE : 6.62 → trajectories predicted similar similarity
- Small MSE → LSTM based model capture whole lane change process well

3.4.2. The lane change trajectory prediction model evaluation



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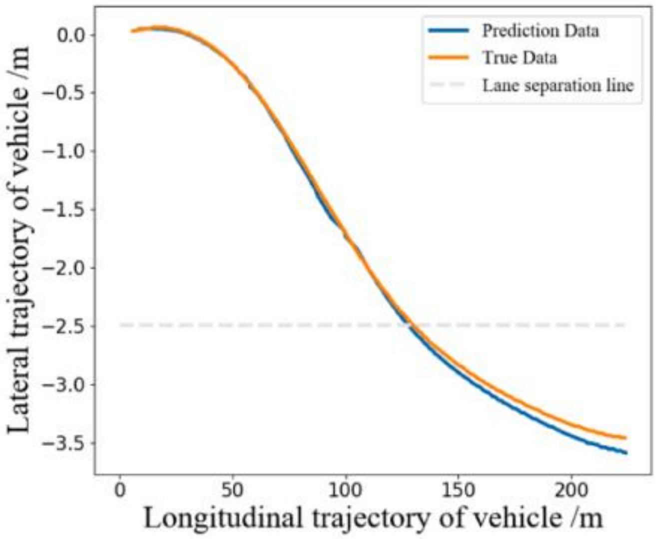

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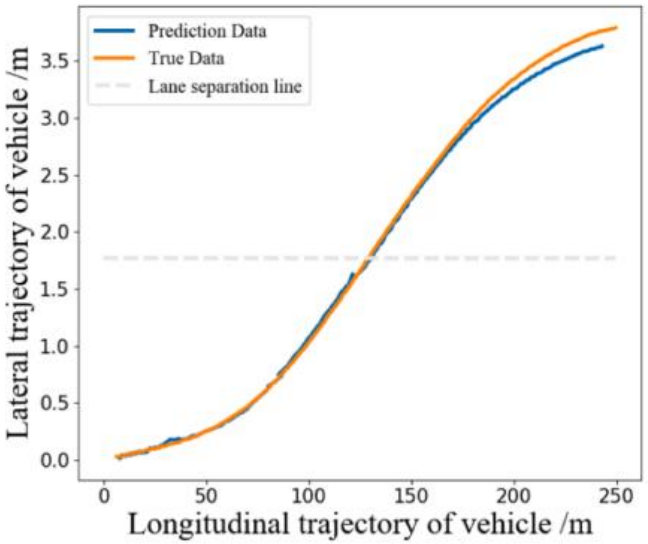

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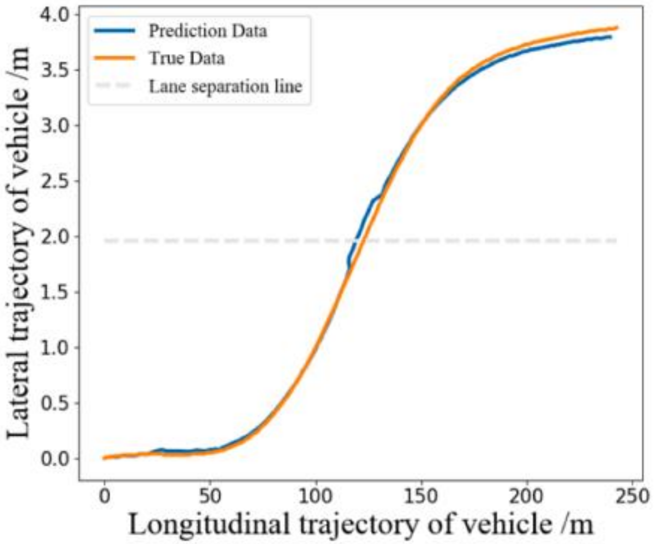

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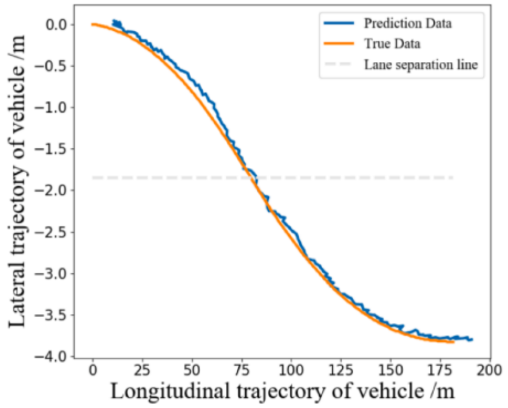
3.4.2. The lane change trajectory prediction model evaluation

The MSE comparison of considering traffic context using the LSTM-based model.

Situation	Total MSE	Average MSE	Lateral MSE	Longitudinal MSE
Considering traffic context and distinguishing LLC and RLC	119.12	6.62	0.01	13.23
Without considering traffic context and distinguishing LLC and RLC	187.68	10.42	0.01	20.85
Without considering traffic context and confusing LLC and RLC	201.80	11.21	0.01	22.42

< Without considering traffic context >



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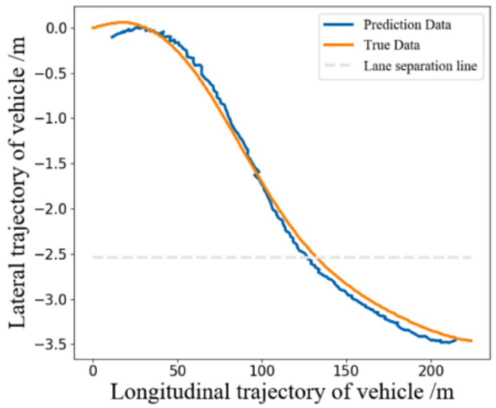

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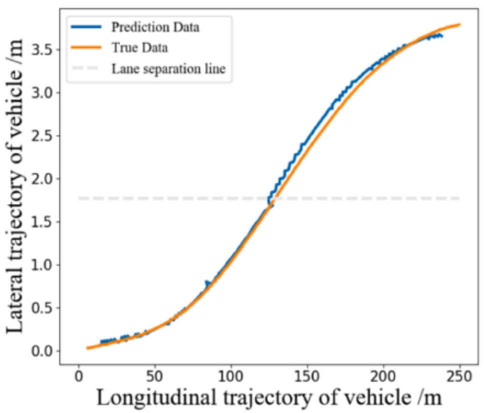

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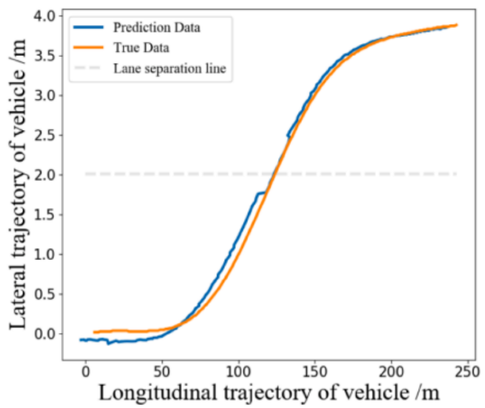

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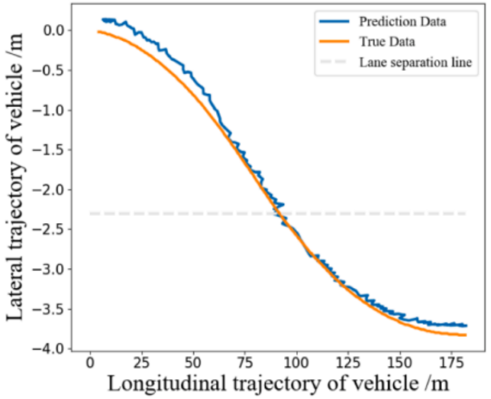
< Without considering traffic context but distinguishing RLC and LLC >



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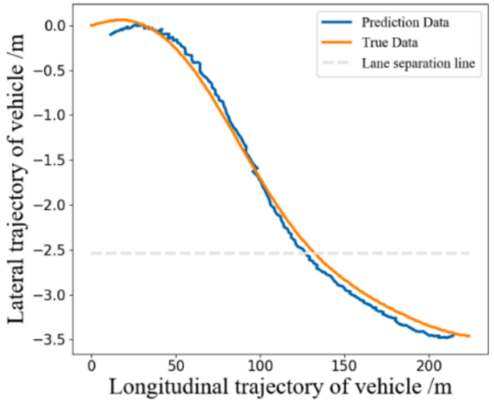

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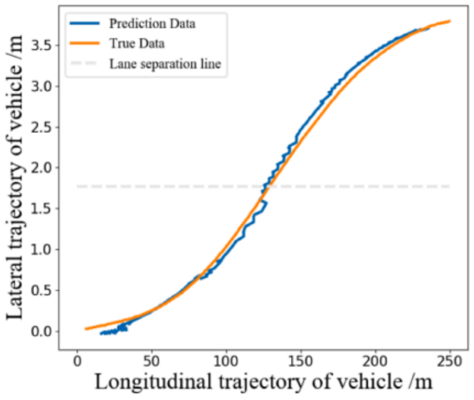

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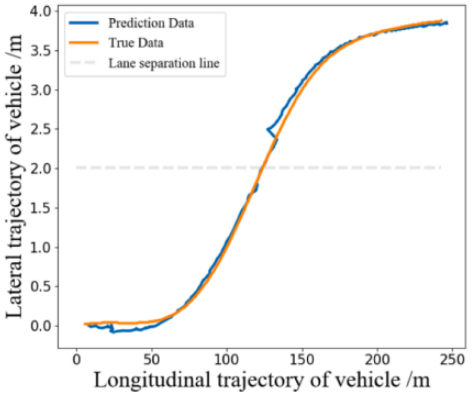

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3.5. Validation of the proposed model

NGSIM dataset

- I-80 freeway in Emeryville
- California in 2005
- 4:00 p.m. to 4:15 p.m.
- Computer vision algorithm 10Hz
- LK sample : 450
- LC sample : 509

K-means

- LOS B
- LOS D
- LOS E
- Levels of traffic flow

3.5.1. The traffic context classification

Traffic level classification results.

Algorithm	**Precision (%)**	**Recall (%)**	**F1-score (%)**	**Accuracy (%)**	**MSE**
XGBoost	85.28	84.95	83.76	**84.95**	**0.15**
AdaBoost	81.83	82.52	82.12	82.52	0.19
SVM (linear)	73.24	73.95	72.73	73.91	0.25

Vehicle type classification results.

Algorithm	**Precision (%)**	**Recall (%)**	**F1-score (%)**	**Accuracy (%)**	**MSE**
XGBoost	92.46	96.05	94.27	**96.15**	**0.08**
AdaBoost	92.42	95.03	93.72	95.06	0.09
SVM (linear)	90.46	91.12	90.59	91.37	0.11

3.5.2. The lane change decision and trajectory prediction

The prediction result comparison with and without traffic context.

Comparison	Class name	Precision (%)	Recall (%)	F1-score (%)	Accuracy (%)	MSE
Traffic context	LK	93.43	96.24	94.81	95.13	0.15
	RLC	91.30	91.30	91.30		
	LLC	97.65	94.69	96.15		
Without considering traffic context	LK	94.03	94.73	94.38	94.79	0.16
	RLC	88.00	95.65	91.66		
	LLC	96.89	94.69	95.78		

1) Lane change decision prediction

- LK sample : 450, RLC sample : 109, LLC sample : 400
- Based XGBoost
- Predict whether vehicle would perform the lane change maneuver a few seconds later

3.5.2. The lane change decision and trajectory prediction

2) Lane change trajectory prediction

The MSE of the trajectory predicted by the LSTM algorithm.

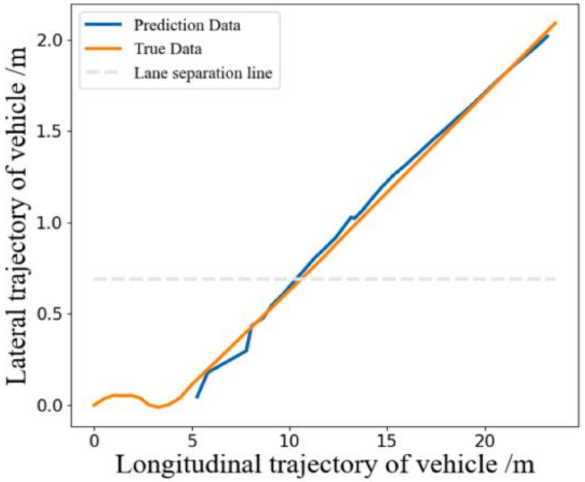
ID	MSE	ID	MSE
1	0.17	6	0.65
2	0.15	7	0.24
3	0.12	8	0.15
4	0.06	9	0.28
5	0.24	10	0.11

The MSE comparison of considering traffic context using the LSTM-based model.

Situation	Average MSE	Lateral MSE	Longitudinal MSE
Considering traffic context and distinguishing LLC and RLC	**0.22**	0.01	0.43
Without considering traffic context and distinguishing LLC and RLC	0.25	0.01	0.48
Without considering traffic context and confusing LLC and RLC	0.41	0.01	0.81

3.5.2. The lane change decision and trajectory prediction

< Considering traffic context and distinguishing RLC and LLC >



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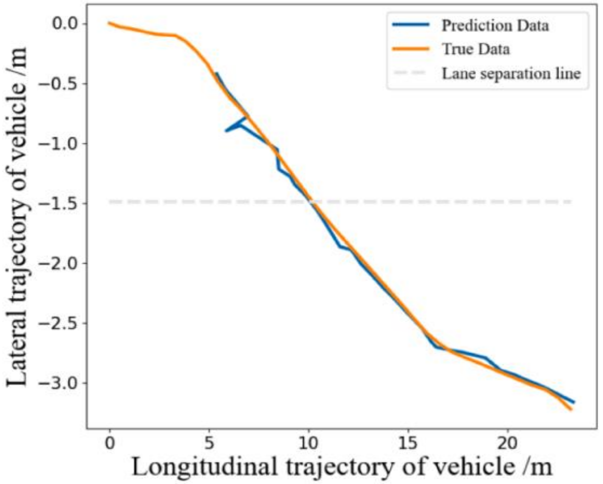

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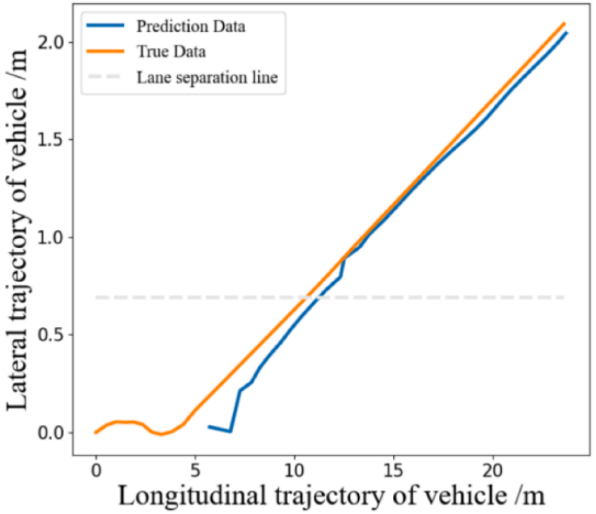
< Without considering traffic context and confusing RLC and LLC >



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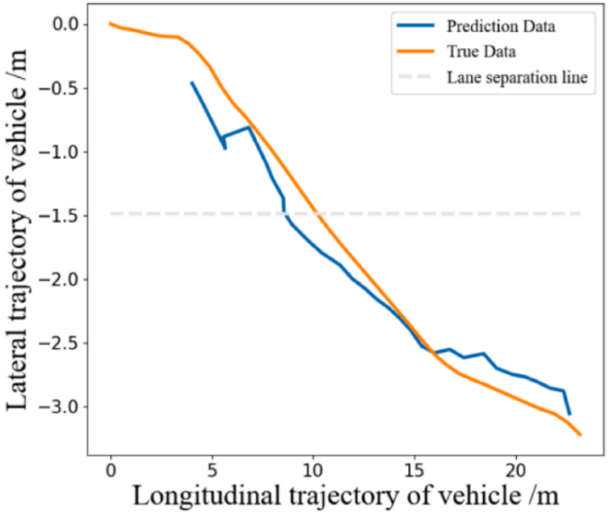

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Results

- Lane change decision prediction

↪ accuracy : 95.13%

- Lane change trajectory prediction

↪ MSE : 0.22

- Incorporating traffic context perform

↪ Better in lane change prediction

4. Conclusion

- Lane change decisions predicted - accuracy : 98.20%
- Lane change trajectory predicted - MSE : 6.62
- When not considering traffic context, lane change decisions decreases accuracy 97.02%
- When not considering traffic context and trajectory differences in LLC and RLC, MSE 11.21

- Influence of traffic context on lane change maneuver
- Different in LLC and RLC considered when predicting lane change trajectories

Limitations

1. Vehicle trajectories can only be used to recognize the on-going lane change decision

2. Some other traffic contexts such as weather conditions and road alignment

Drone Vision Traffic Predict

- The frequency-domain features are extracted by DWT and DFT algorithm
- Apply traffic context to the turn left or turn right

Thank You

☺