A unified modeling framework for lane change intention recognition and vehicle status prediction

Renteng Yuan, Mohamed Abdel-Aty, Xin Gu, Ou Zheng, Qiaojun Xiang

SCH Univ.
Dept. of AI and Bigdata
Seokjun Hong
Drone Vision Traffic Prediction

SOON CHUN HYANG UNIVERSITY

Contents

1. Introduction

LC → Significantly impact road traffic efficiency and safety

Accurately identifying and Prediction

↪ Anticipate potential safety risks

↪ Execute appropriate response strategies

1. Introduction

① Lane Change Intention Recognition and Status Prediction (LC-IR-SP)

② TCN-ATM

③ Multi-task learning models (MTL-LSTM, MTL-TCN, MTL-TCN-ATM)

2. Related Research

2. Related Works

A summary of the representative research for LC intention recognition.

Study	Data	Method	Number of Samples	Advance time	Accuracy (%)
([77]	Image	CNN	637	–	73.97
([31]	Image	GoogleNet & LSTM	714	3.76 s	74.46
([45]		Vision-cloud	-– 2(Pts)	–	79.2
([25]	Simulator	AT-BiLSTM	-– 2(5Pts)	3 s	93.33
([26]		BN	–(1 Pt)	–	95.4
([92]	Naturalistic	HMM	–(58 Pts)	–	83.22
([36]		SVM	139(6 Pts)	1.3	80
([73]		EBiLSTM	201(3 Pts)	0.5 s	96.1
([41]		HMM	642(50 Pts)	0.5 s	90.3
([20]		LSTM	814(6 Pts)	–	88.26
([17]		RVM	903(8 Pts)	3 s	88.51
([91]	Trajectory	NN	Above 1000	–	73.33
([72]		LSTM	—	2.5 s	92.40
([51]		Logit	Above 1000	–	66.41
([66]		LSTM	Above 1000	2 s	86.21
([76]		HMM	3410	6 s	94.4
([1]		Extra trees classifier	Above 1000	2 s	82
([32]		SVM	351	3 s	85

① Vision based behavior recognition methods low classification accuracy

② Simulators and natural experiments hard to generalizability

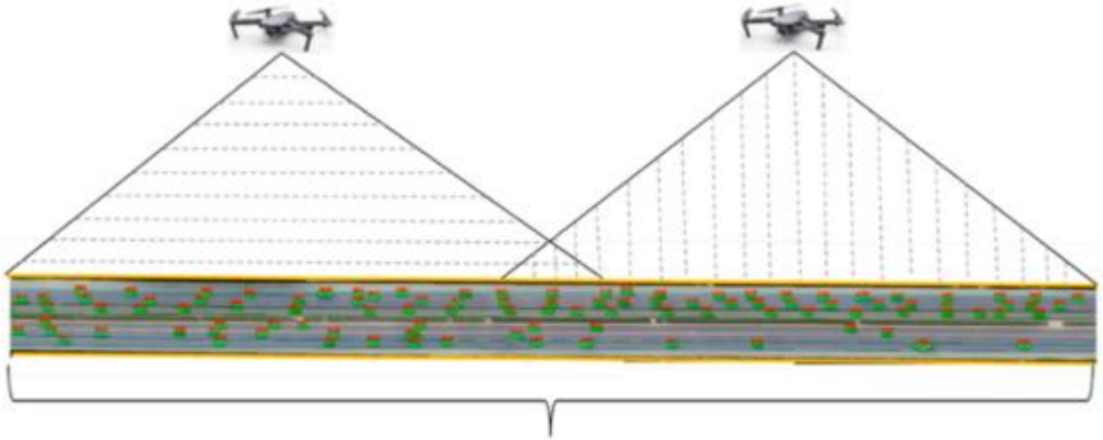
③ ML-based models better classification accuracy compared to ST-based models

④ LSTM has excellent potential to improve classification accuracy

3. Data

3. Data

< CitySim Dataset >



680m

1023 vehicle

LC : 545 → RLC : 240, LLC : 305

LK : 475

1) Removing Abnormal Data

    - Frame

2) Data Smoothing

    - Moving Average

3) Indicator Calculation

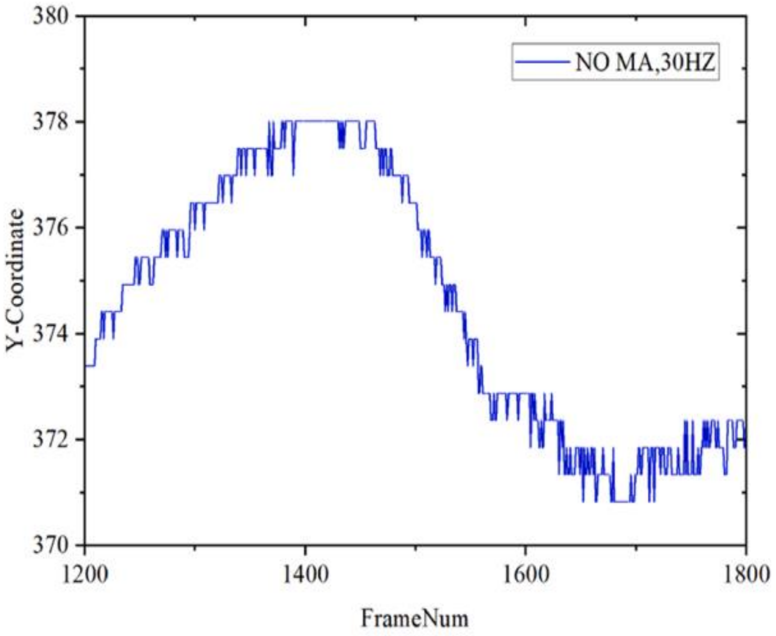
    - Longitudinal · Lateral velocity, acceleration …

4) Normalization

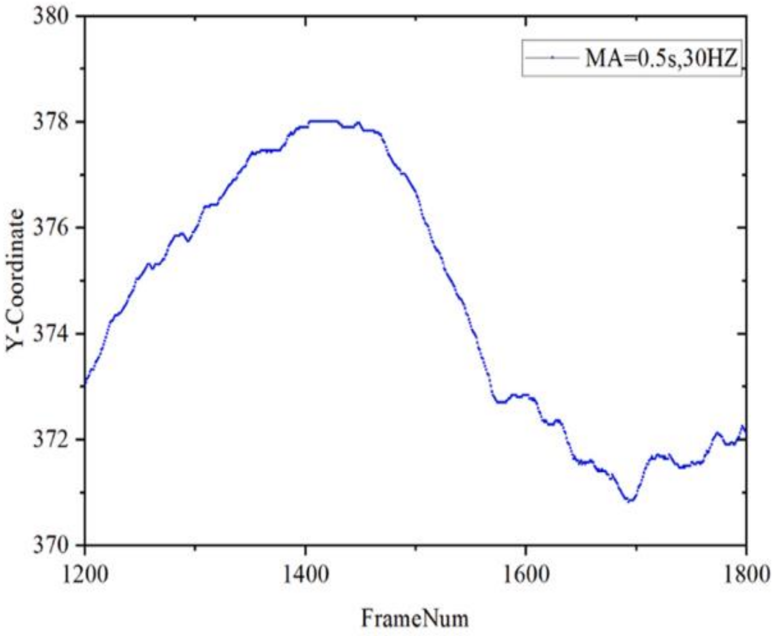
    - Min-Max Normalization

3. Data

▸ 3.1. Data processing



Raw Data



Processed Data

Moving Average

- Moving Average smooths trends by averaging data points over set periods

- It's used to identify trends, reduce noise, and forecast in various fields

3. Data

▸ 3.1. Data processing

$$v_n(t) = \frac{s(t+n) - s(t-n)}{2 \cdot nT}$$

t : Current frame

T : 1/30

n : 1~8

s(t+n) : Vehicle's position in the frame t+n

$$a(t) = \frac{v(t+1) - v(t-1)}{2 \cdot T}$$

t : Current frame

T : 1/30

v(t+1) : Vehicle's velocity in the frame t+1

$$\theta_n(t) = \arctan\left(\frac{y_H(t+n) - y_R(t-n)}{x_H(t+n) - x_R(t-n)}\right)$$

$y_H(t+n)$: Head point longitudinal position in the frame t + n

$x_R(t-n)$: Tail point horizontal position in frame t – n

arctan : $\tan^{-1}$

$$\Delta\theta(t) = \frac{\theta(t+1) - \theta(t-1)}{2T}$$

t : Current frame

T : 1/30

θ(t+1) : Vehicle's angle in the frame t+1

$$X' = \frac{X - Xmin}{Xmax - Xmin}$$

Min-Max Normalization

- Min-Max Normalization rescales data to a 0-1 range, enhancing algorithm performance
- It standardizes data, crucial for machine learning and data mining
- Xmin : Denotes the minimum value in the dataset
- Xmax : Denotes the maximum value in the dataset

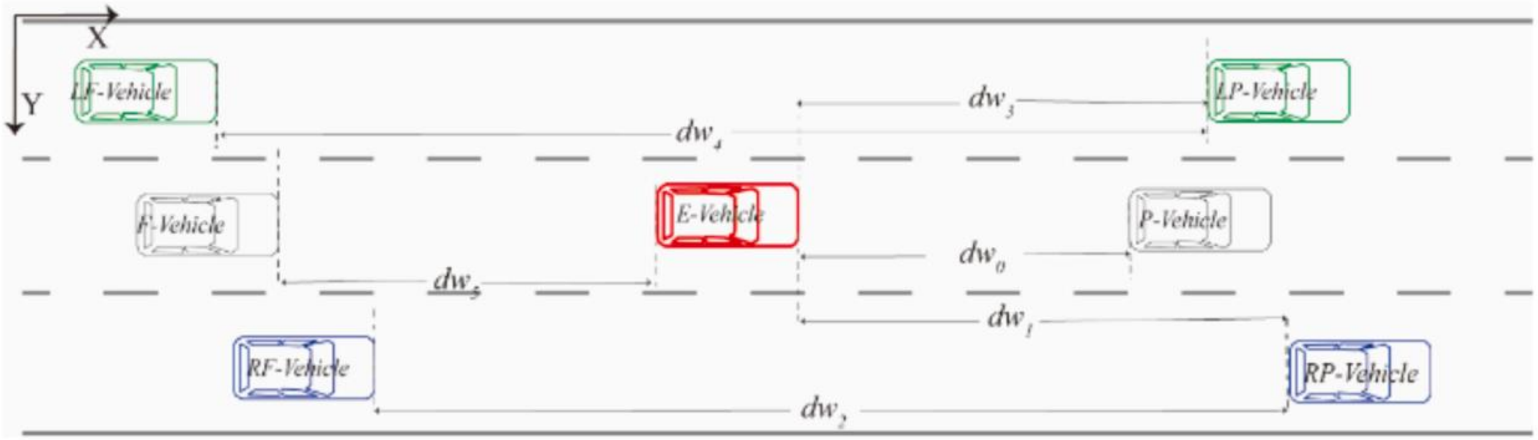
3. Data

▸ 3.2. Input indicator

Input indicators of the model.

Inputs Variable	Variable descriptions
E-, P-, F-, LP-, LF-, RP-, RF-v_x	The longitudinal velocity of E-vehicle and surrounding vehicle (ft/ sec)
E-, P-, F-, LP-, LF-, RP-, RF-v_y	The lateral velocity of E-vehicle and surrounding vehicle (ft/ sec)
E-, P-, F-, LP-, LF-, RP-, RF-a_x	The longitudinal acceleration of E-vehicle and surrounding vehicle (ft/ sec^2)
E-, P-, F-, LP-, LF-, RP-, RF-a_y	The lateral acceleration of E-vehicle and surrounding vehicle (ft/ sec^2)
E-, P-, F-, LP-, LF -, RP-, RF-θ	The heading of E-vehicle and surrounding vehicle (degree)
E-, P-, F-, LP-, LF -, RP-, RF-$\Delta\theta$	The yawRate of E-vehicle and surrounding vehicle (degrees/sec)
dw_0, dw_1, dw_2, dw_3, dw_4, dw_5	Space headway between E-vehicle and surrounding vehicle (ft)
P-, F-, LP-, LF -, RP-, RF-val	0 means it has recorded trajectory information; 1 means the trajectory information is missing

Note: "E-" represents the ego vehicle; "P-" represents the closest preceding vehicle in the same lane; "F-" represents the closest following vehicle in the same lane; "LP-" represents the closest preceding vehicle in the adjacent left lane; "LF-" represents the closest following vehicle in the adjacent left lane; "RP-" represents the closest preceding vehicle in the adjacent right lane; "RF-" represents the closest following vehicle in the adjacent right lane.



- Ego vehicle
- Surrounding vehicle
- Relative position
- 54 input variables

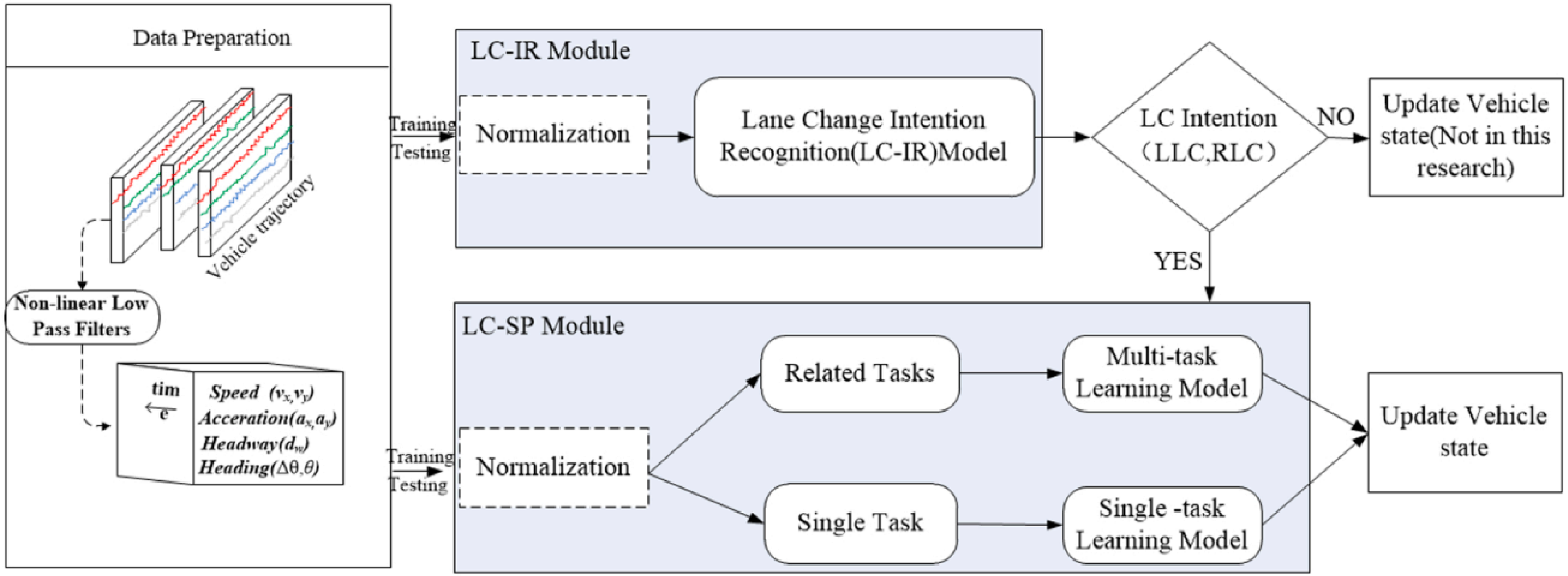
< Vehicle status >

0 : Recorded trajectory

1 : Missing trajectory

4. Method

4. Method



Data Preparation
Vehicle trajectory
Non-linear Low Pass Filters
time
Speed (v_x,v_y)
Acceration(a_x,a_y)
Headway(d_w)
Heading$(\Delta\theta,\theta)$
Training
Testing
LC-IR Module
Normalization
Lane Change Intention Recognition(LC-IR)Model
LC Intention (LLC,RLC)
NO
Update Vehicle state(Not in this research)
YES
LC-SP Module
Training
Testing
Normalization
Related Tasks
Multi-task Learning Model
Single Task
Single -task Learning Model
Update Vehicle state

① LC-IR module

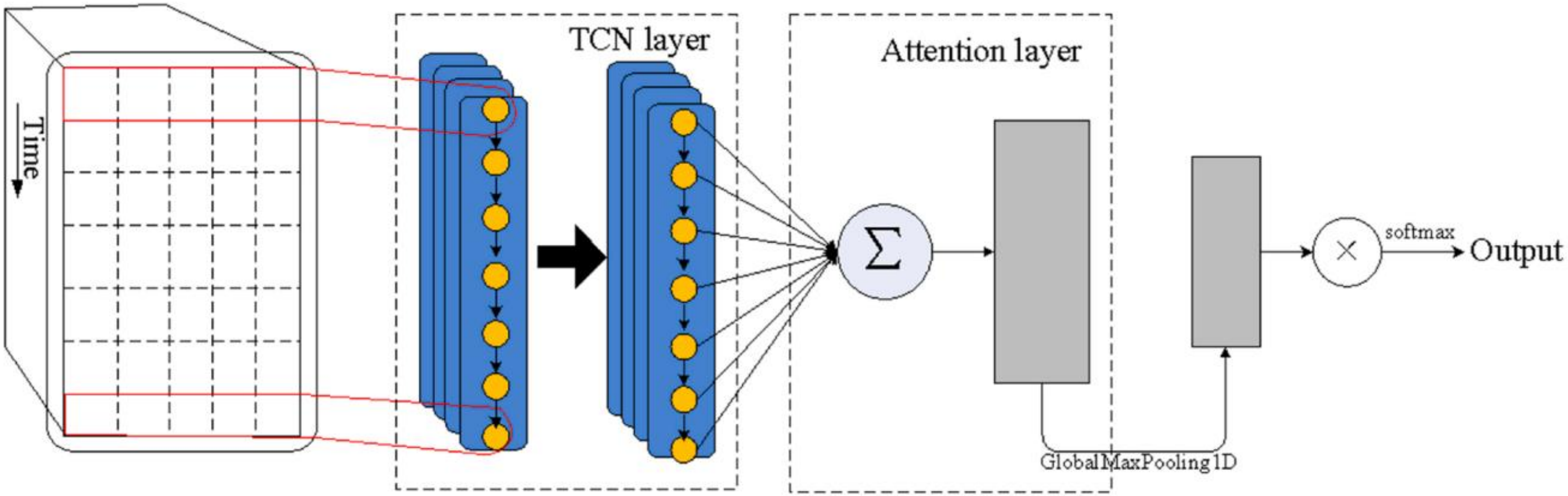
- Intention Recognition
- LK : 1
- RLC : 2
- LLC : 3

② LC-SP module

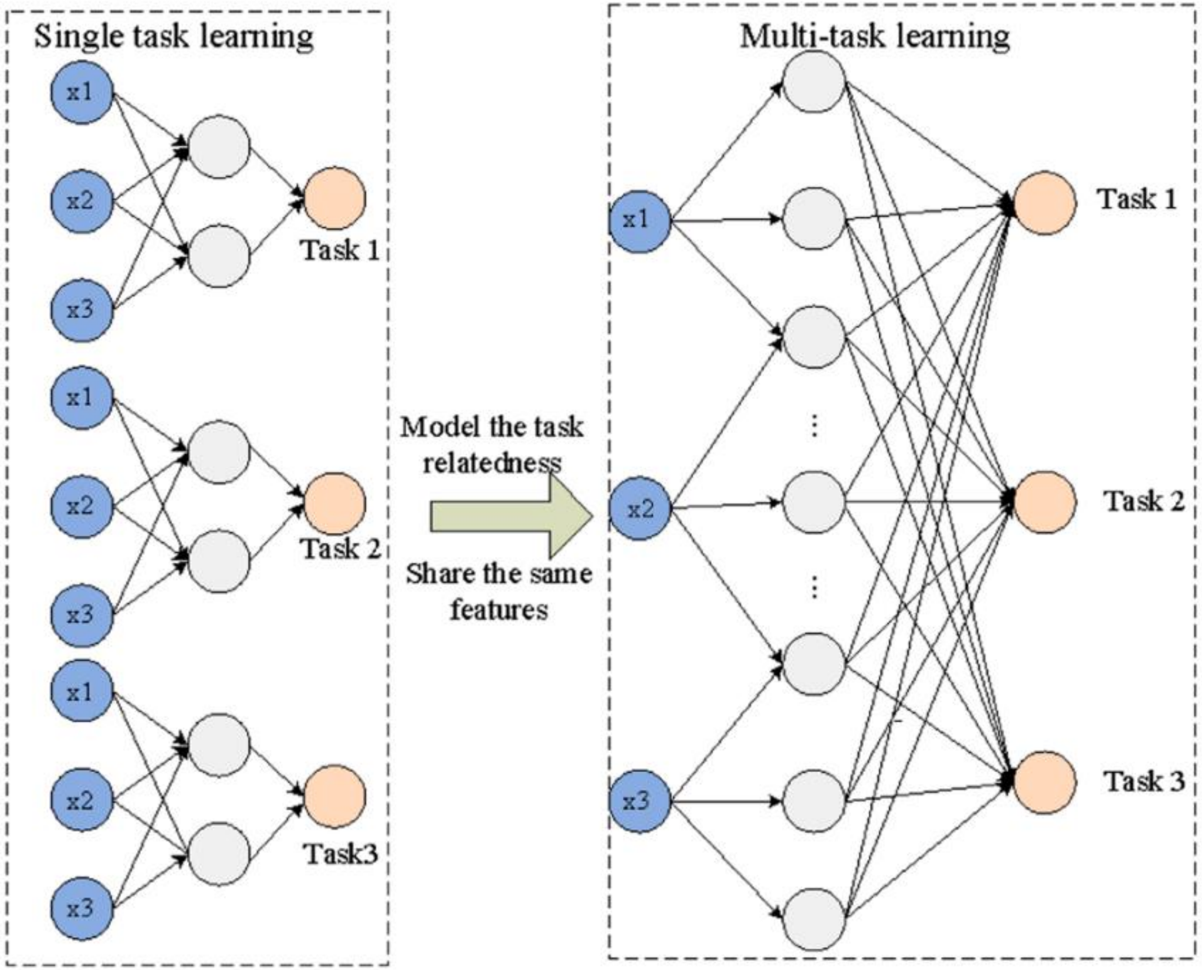
- Status Prediction
- v_x, v_y, a_x, a_y, θ, $\Delta\theta$
- 1s interval, next 2s predict

4. Method

▸ 4.2. TCN with attention mechanism model



▸ 4.3. Multi-task prediction model



< Multi-Task Learning >

- Share information among different tasks

- Reduce training time

↪ Improve the efficiency of data utilization

- Single-task : Building three separate models

- Multi-task : Only one model

$$Loss_{total} = \sum_i \omega_i Loss_i$$

4. Method

▸ 4.4. Evaluation indexes

$$Accuracy = \frac{T}{T + F}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Rcall = \frac{TP}{TP + FN}$$

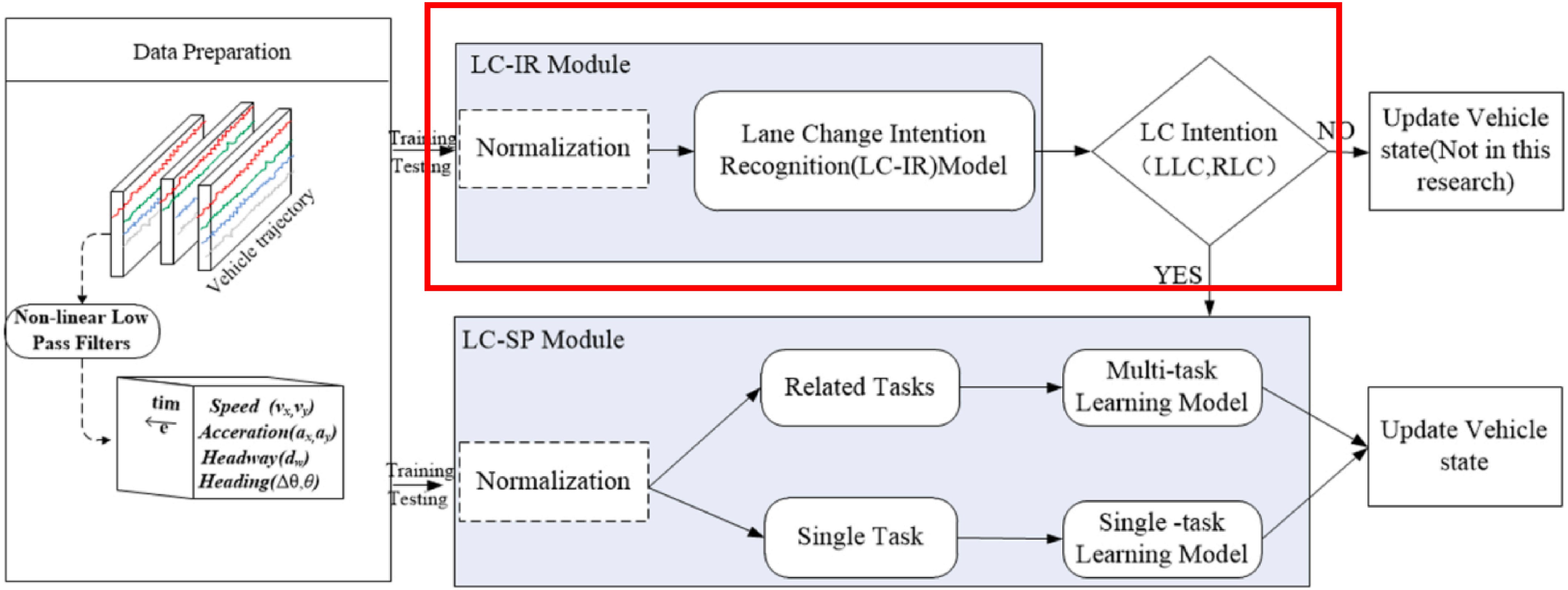
$$MAE = \frac{1}{N} \sum_{i=1}^{N} |y_i - \widehat{y}_i|$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (y_i - \widehat{y}_i)^2}$$

5. Results

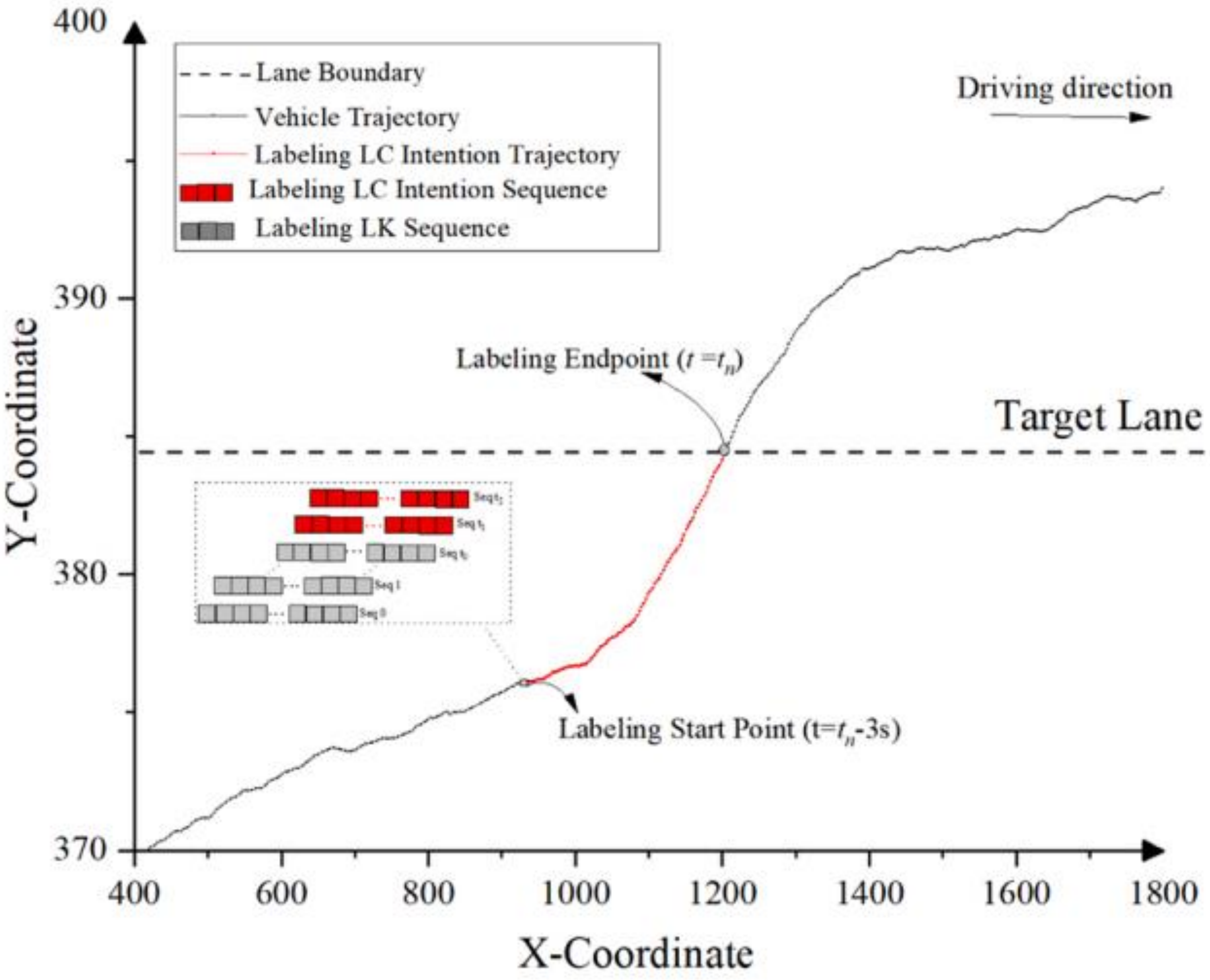
5. Results

▸ 5.1. Lane change intention recognition



5. Results

▸ 5.1.1. Lane change intention labeling

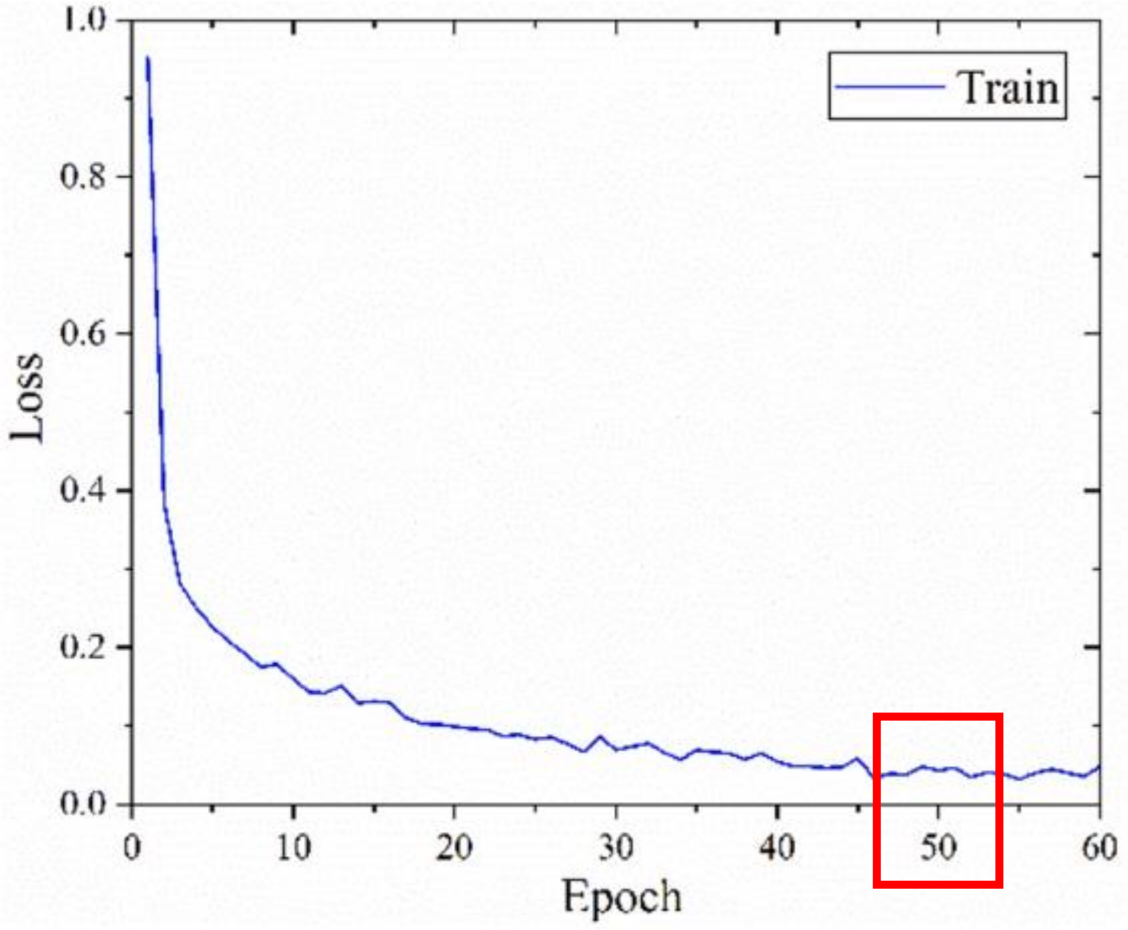


< Labeling >

- Labeling endpoint + 3s
- RLC : 24,092 frame
- LLC : 19,792 frame
- Train : 80% / Test : 20%

5. Results

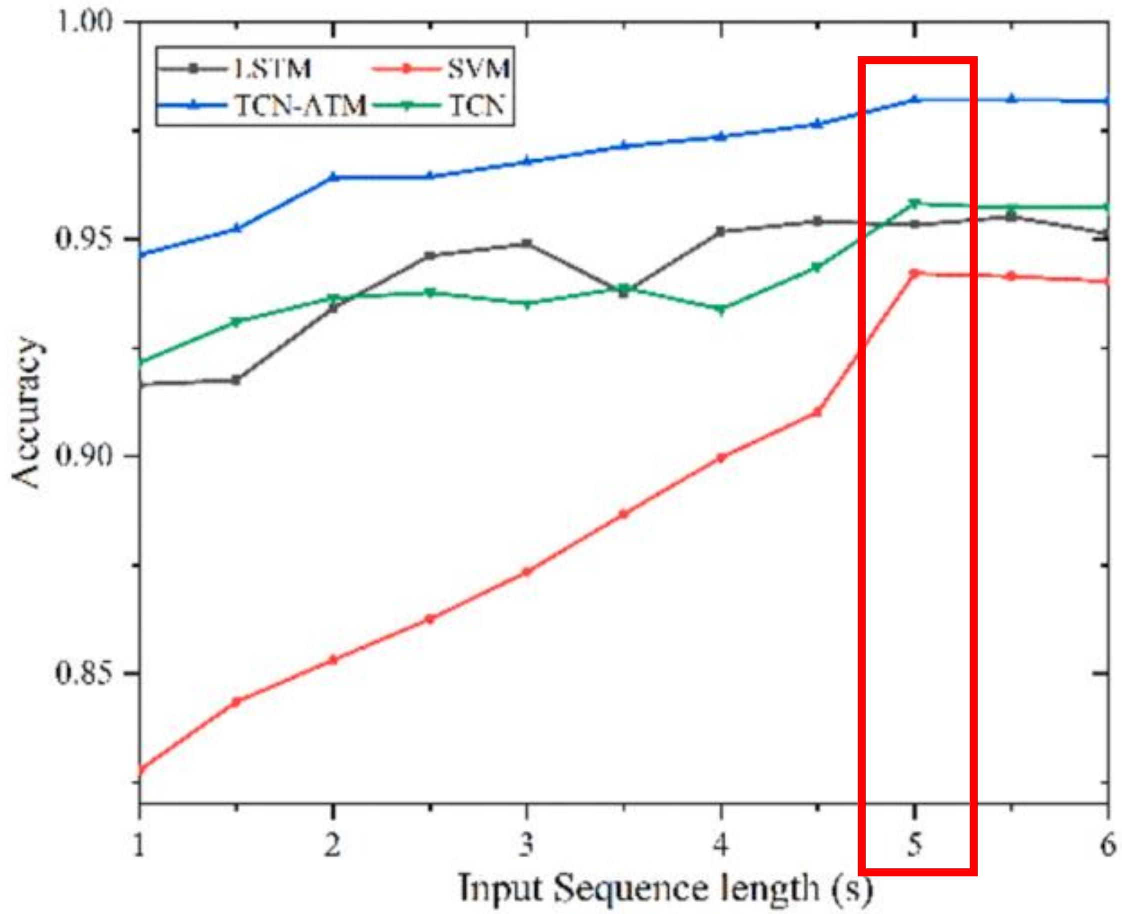
▸ 5.1.2. Results of LC intention recognition models

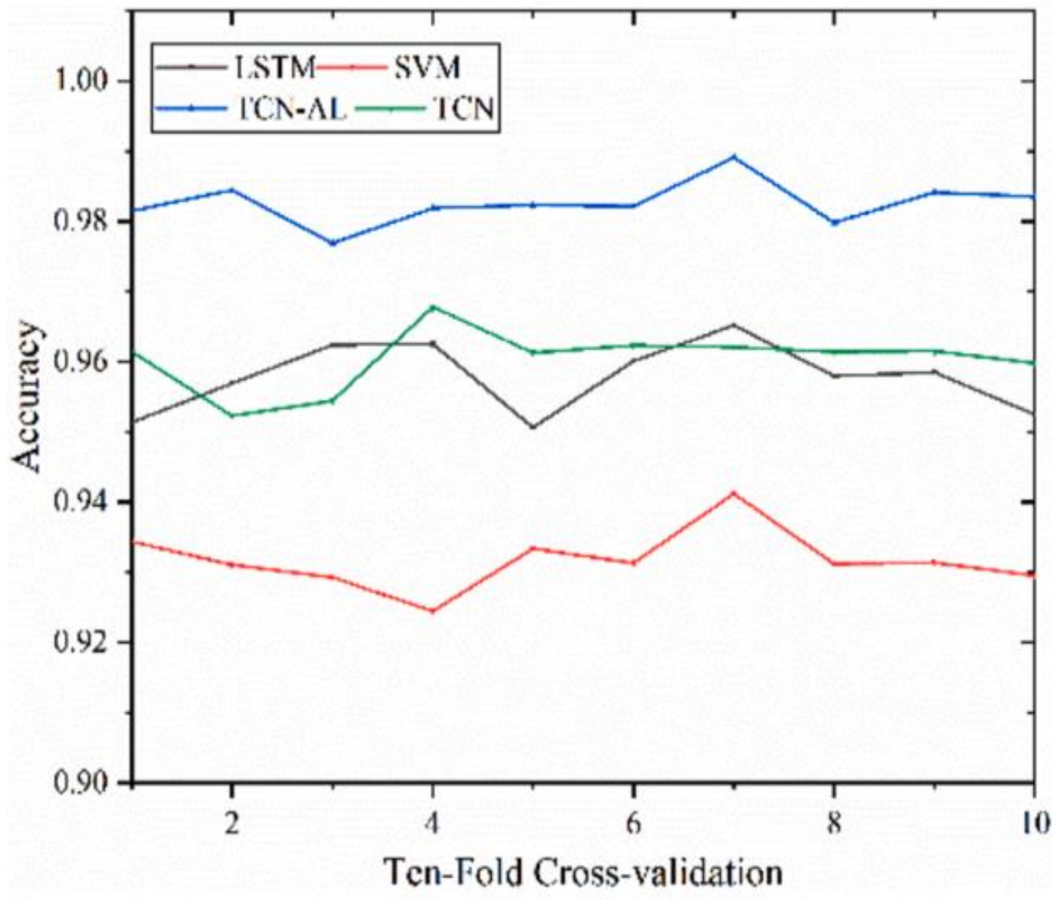


Optimizer	Adam
Loss function	Cross Entropy
Epoch	50
Filter	64
Batch size	128
Dropout	0.3

5. Results

▸ 5.1.2. Results of LC intention recognition models





5. Results

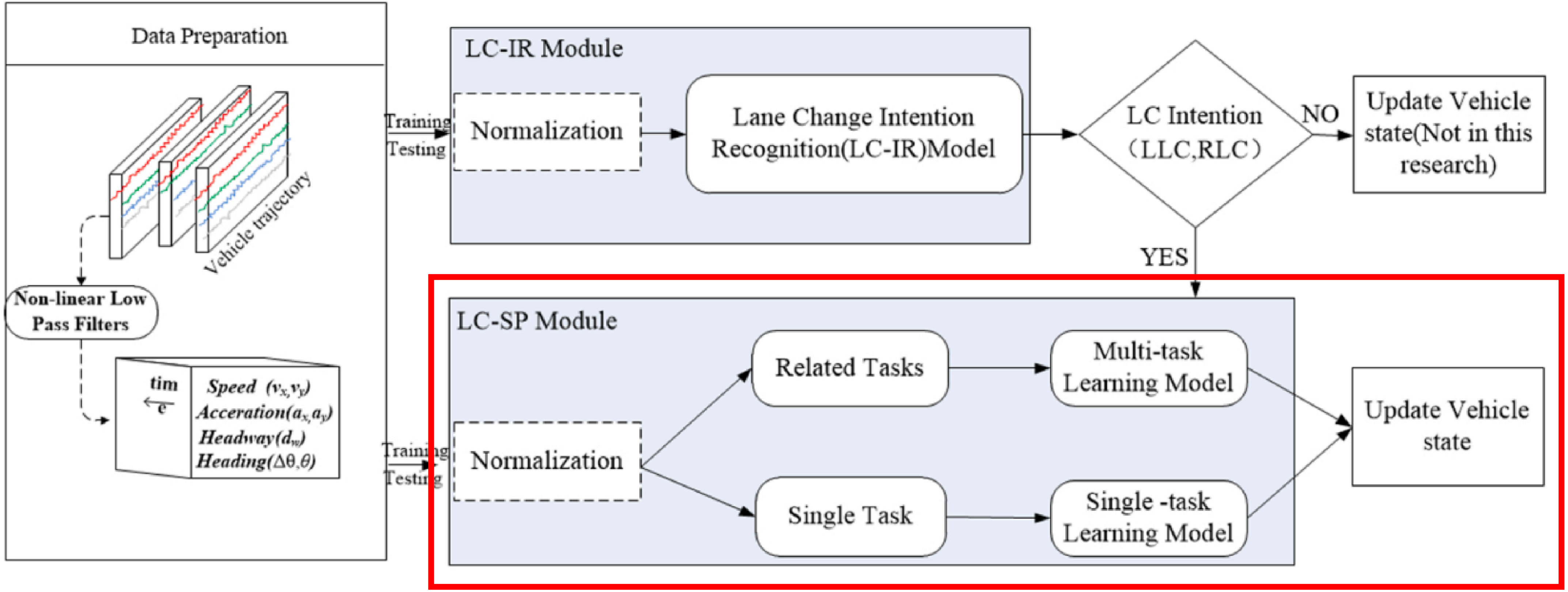
▸ 5.1.2. Results of LC intention recognition models

Evaluation results of nine different models.

Model	Type	Precision	Recall	Accuracy	Model	Type	Precision	Recall	Accuracy
SVM	LK	88.31%	97.29%	94.21%	ET	LK	94.41%	95.74%	96.53%
	RLC	97.23%	93.46%			RLC	97.03%	97.30%	
	LLC	96.88%	92.10%			LLC	98.44%	96.37%	
RF	LK	90.36%	94.56%	94.39%	LSTM	LK	90.10%	96.21%	95.33%
	RLC	95.72%	95.02%			RLC	97.83%	95.78%	
	LLC	97.69%	93.28%			LLC	97.79%	93.73%	
GRU	LK	91.96%	86.39%	92.19%	CNN	LK	62.86%	99.42%	78.71%
	RLC	96.03%	95.15%			RLC	80.64%	79.63%	
	LLC	86.81%	95.52%			LLC	94.94%	66.69%	
TCN	LK	90.47%	97.36%	95.83%	TCN-LSTM	LK	94.19%	95.70%	96.67%
	RLC	98.17%	95.77%			RLC	98.99%	97.13%	
	LLC	98.81%	94.28%			LLC	96.37%	97.16%	
TCN-ATM	LK	95.09%	99.41%	98.20%					
	RLC	99.63%	97.65%						
	LLC	99.83%	97.64%						

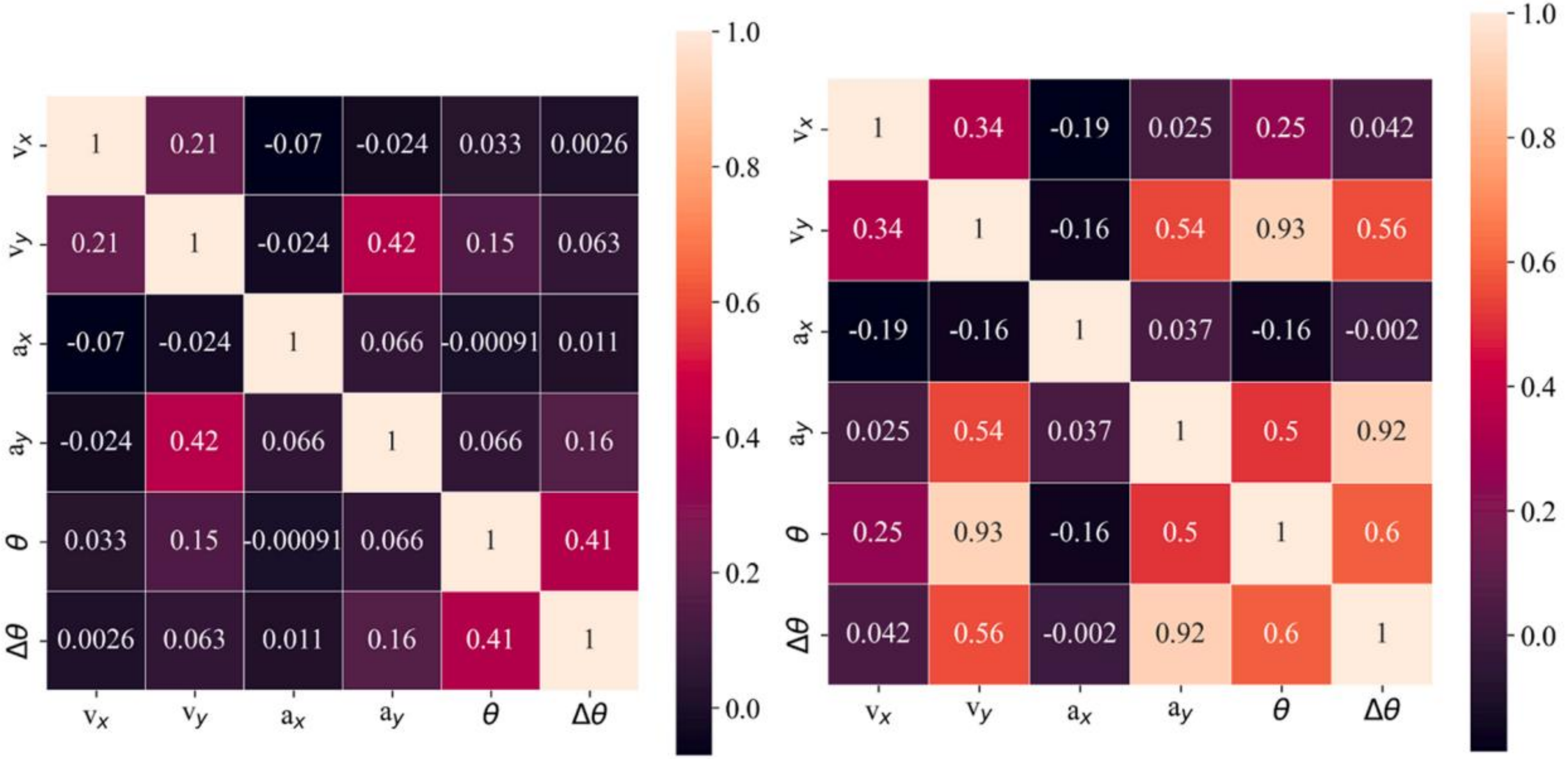
5. Results

▸ 5.2. Lane change status prediction



5. Results

▸ 5.2.1. Correlation analysis



(a) Indicators Extracted from LK Sequences (b) Indicators Extracted from LC Sequences

vx & θ(0.25), vy & Δθ(0.56), ay & θ(0.92), vy & θ(0.93)

↪ LC → Adjust their driving direction and velocity

5. Results

▸ 5.2.2. Results of LC status prediction model

Model result comparison.

Model	Metrics	Task					
		v_x	v_y	a_x	a_y	$\Delta\theta$	θ
LSTM	MAE	2.817	0.572	1.256	0.692	2.375	1.420
	RMSE	3.926	0.704	1.662	0.937	3.049	1.845
MTL-LSTM	MAE	**1.288**	**0.502**	–	**0.632**	2.042	**0.838**
	RMSE	**1.712**	**0.684**	–	**0.866**	2.510	**1.080**
TCN	MAE	2.977	0.596	1.064	0.669	8.159	1.894
	RMSE	4.134	0.793	1.402	0.922	10.60	2.408
MTL-TCN	MAE	1.982	0.547	–	0.648	2.945	1.566
	RMSE	2.534	0.751	–	0.916	3.875	2.062
TCN-ATM	MAE	1.749	0.561	**0.975**	0.875	**0.560**	1.002
	RMSE	2.080	0.693	**1.235**	1.188	**0.799**	1.293
MTL-TCN-ATM	MAE	17.18	1.751	–	0.869	0.601	1.775
	RMSE	19.88	2.081	–	1.183	0.858	1.464

5. Results

▸ 5.2.2. Results of LC status prediction model

Performance improvement rate of prediction (%).

Model	Index	v_x	v_y	a_y	$\Delta\theta$	θ
MTL-LSTM vs LSTM	MAE	54.28	12.24	8.67	14.02	40.99
	RSME	56.39	2.84	7.58	17.68	41.46
MTL-TCN vs TCN	MAE	33.42	8.22	3.14	63.90	17.32
	RSME	38.70	5.30	0.65	63.44	14.37
MTL-TCN-ATM vs TCN-ATM	MAE	-882.2	-212.12	0.69	-7.32	-77.15
	RSME	-855.77	-200.29	0.42	-7.38	-13.23

$$p_i = 1 - \frac{m_i}{s_i}$$

m_i : RMSE, MSE value of i th task using multi-task model

S_i : RMSE, MSE value of i th task using single-task model

P_i : Evaluation index improvement ration of task

- Task competition and conflicts
- Optimization challenges
- Feature conflicts

6. Conclusion

6. Conclusion

- Developed integrated models for lane change recognition and prediction using TCN-ATM and MTL

- Achieved high accuracy in identifying lane change intentions and vehicle status prediction

- Enhanced autonomous vehicle capabilities

  ↪ Future improvements suggested through adaptive loss functions

7. How To Apply

7. How To Apply

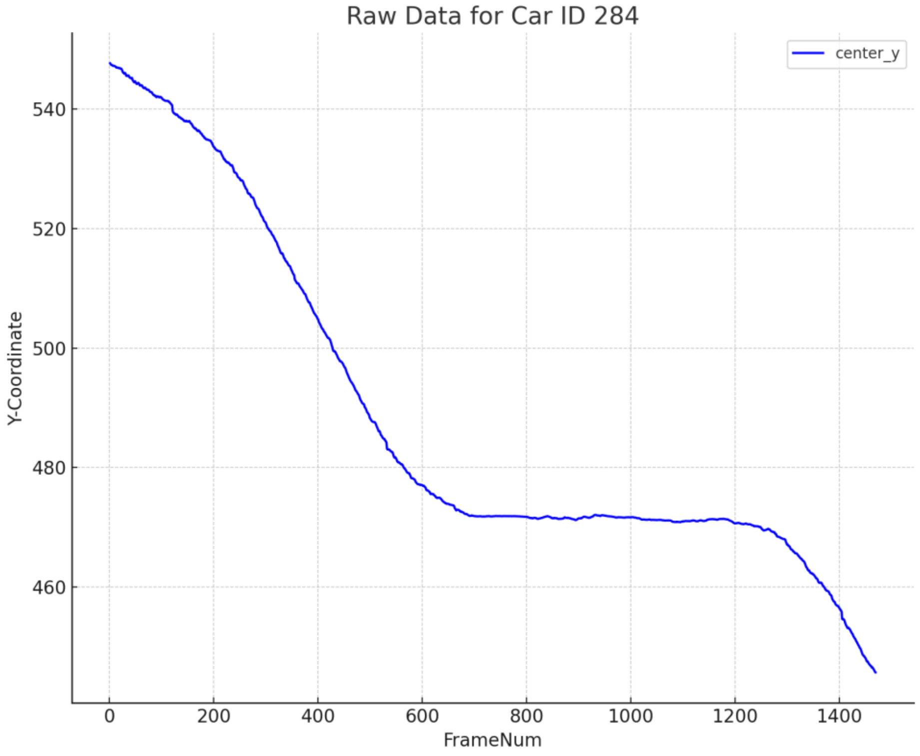
▸ 7.1. Data processing

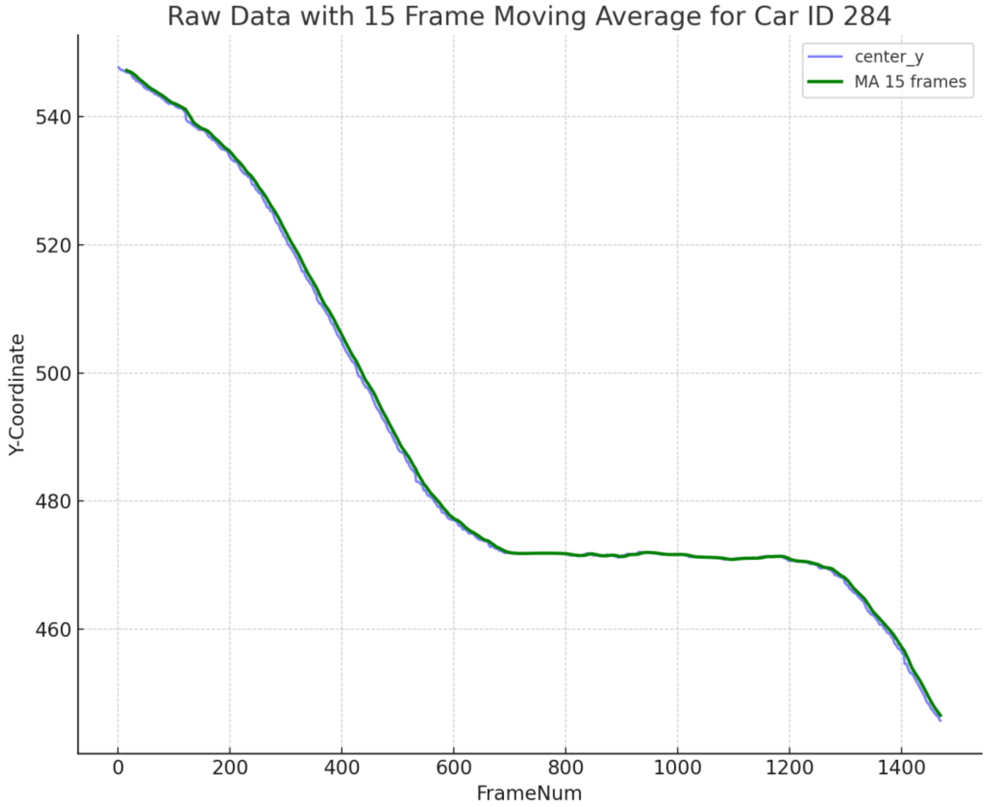
$$\boxed{v_n(t) = \frac{s(t+n) - s(t-n)}{2 \cdot nT}}$$

$$\boxed{Vn(t) = \frac{s(t) - s(t-1)}{T}}$$

7. How To Apply

▸ 7.1. Data processing





Thank You

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