IROS 2022, 13th Workshop on Planning, Perception and Navigation for Intelligent Vehicles (PPNIV22)

Learning from Human Driver Data for Humanized Autonomous Driving at Dynamic Scenes

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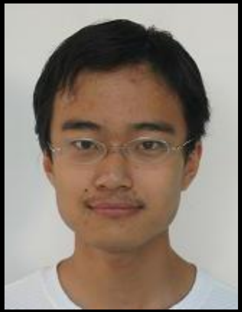
This Talk

1. Our naturalistic driving behavior study (2011~)
2. Learning from naturalistic driving data for human-like autonomous highway driving
3. Imitation learning for humanized autonomous navigation at crowded intersections

Wen Yao



Donghao Xu

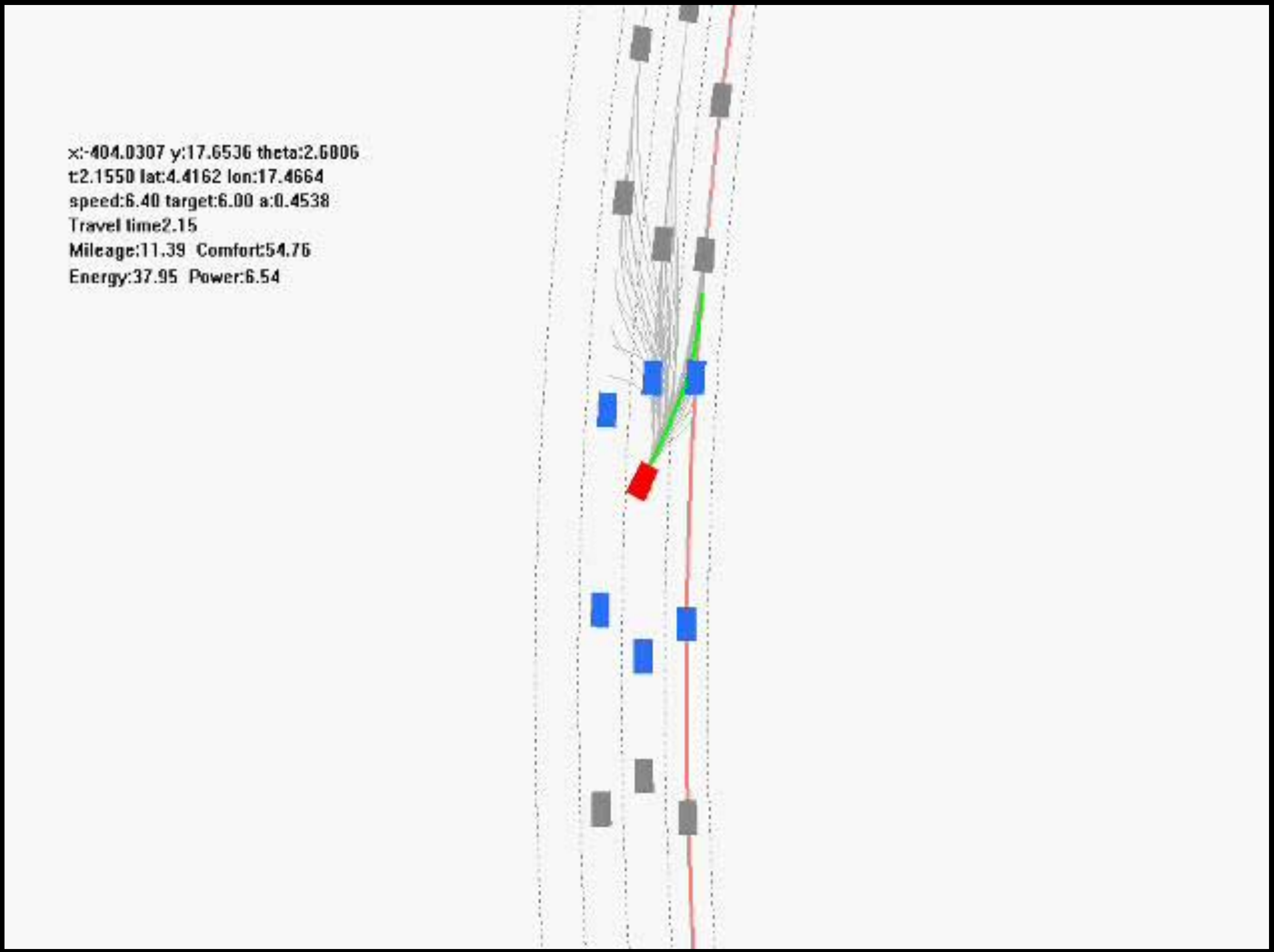
Zhezhang Ding

Zeyu Zhu

Xu He

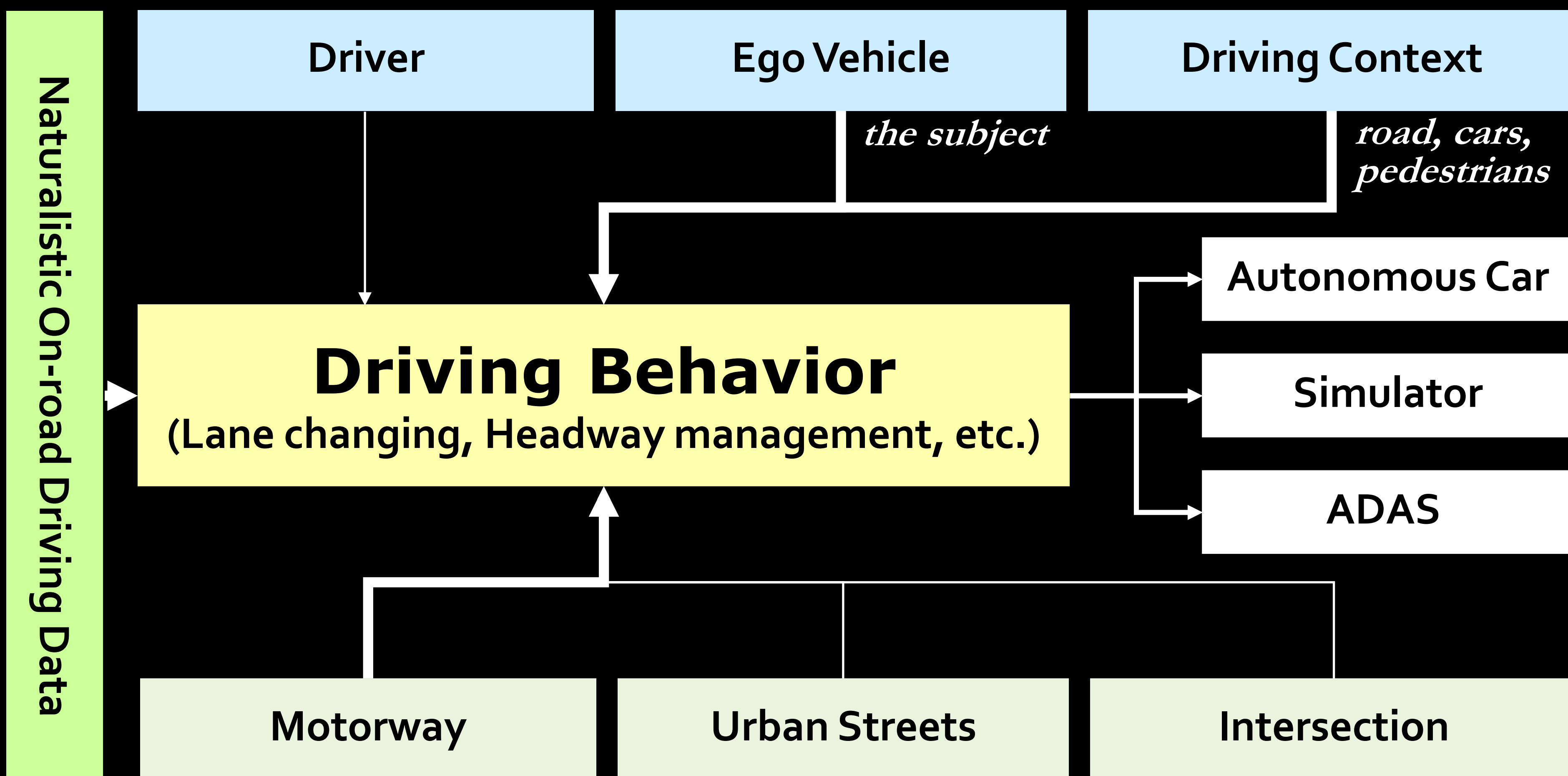
The leading students of these works!

The reason for our naturalistic driving behavior study



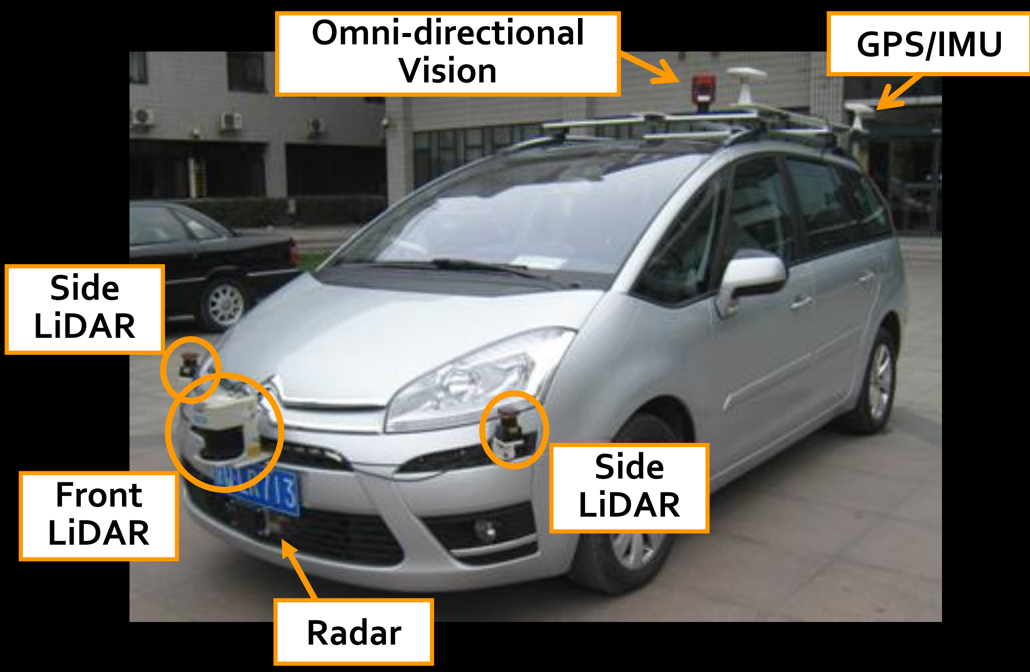
By Wenda Xu, 2010

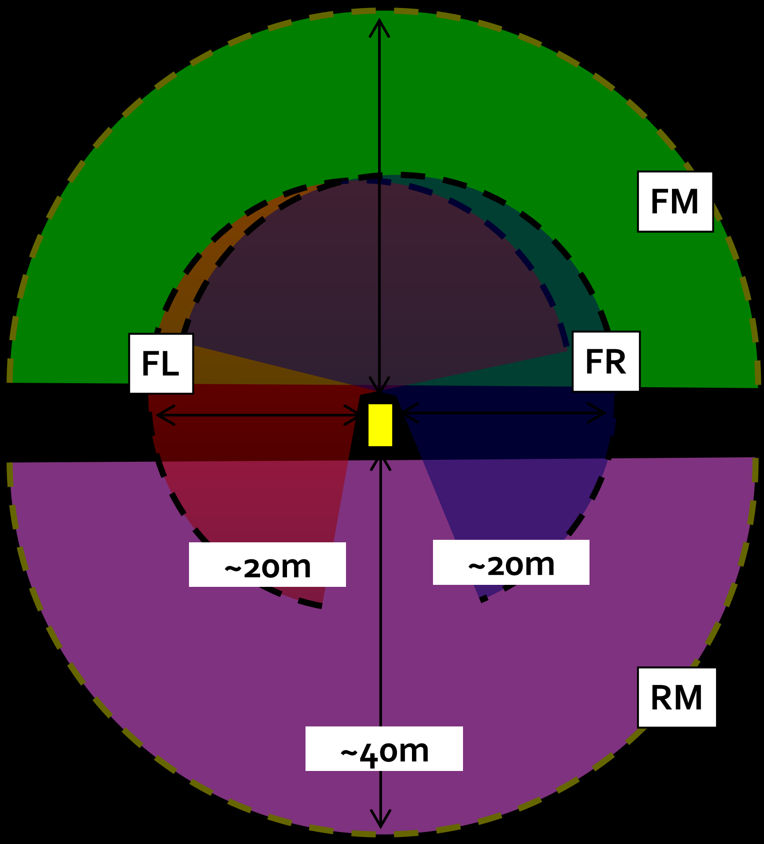
Naturalistic Driving Behavior Study

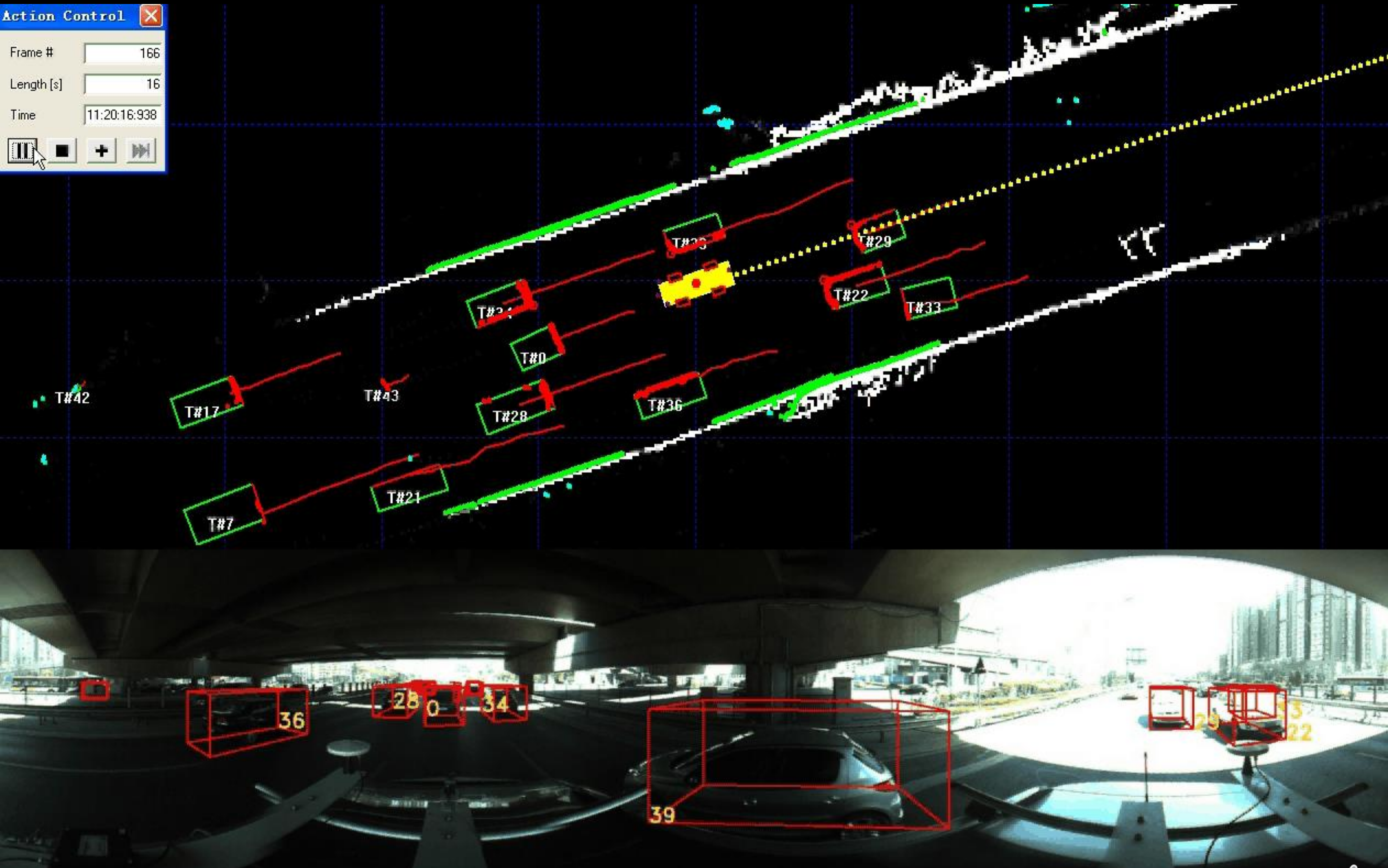


2011

PSA-PKU OpenLab Program [2012~2019]

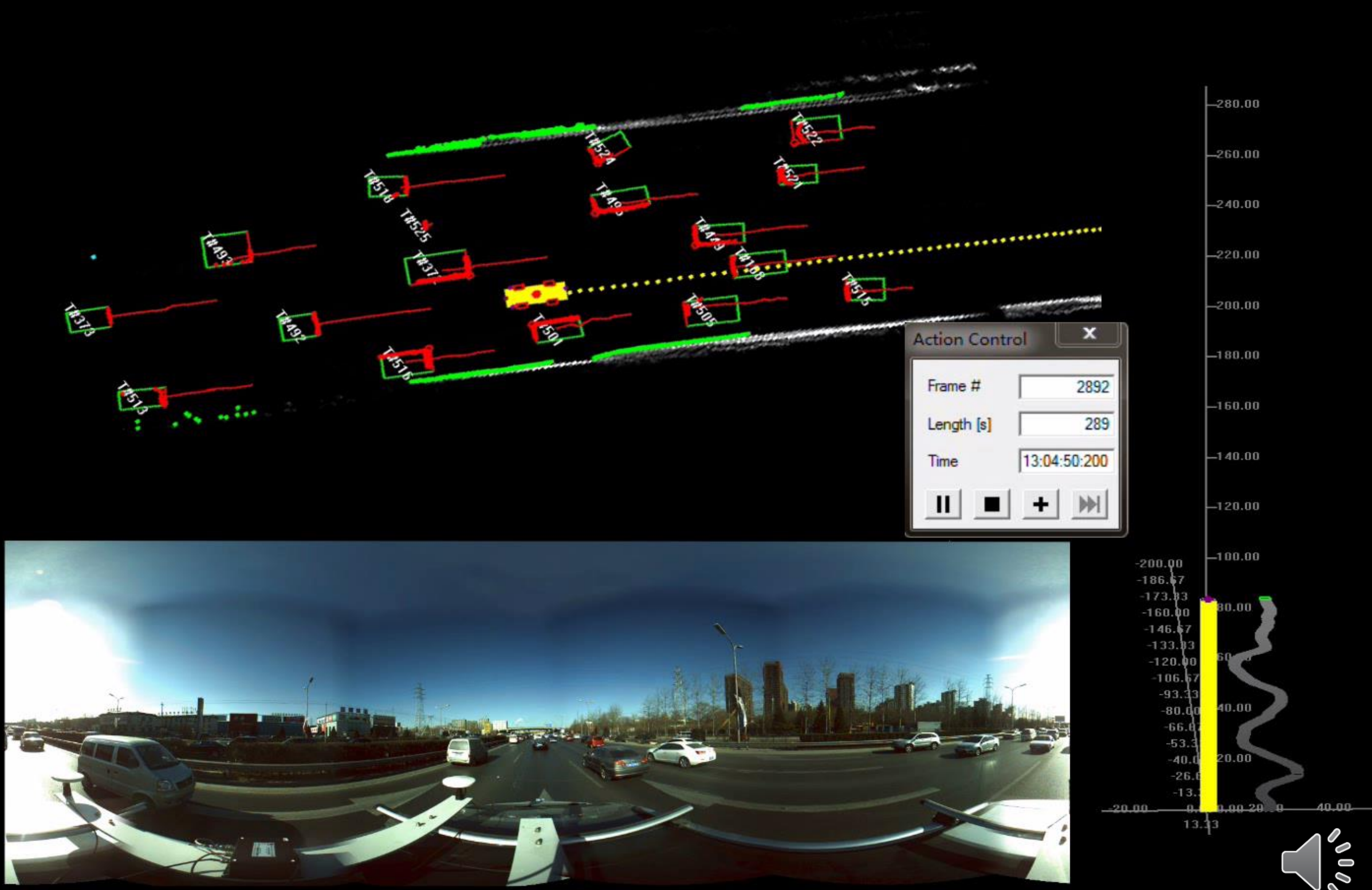




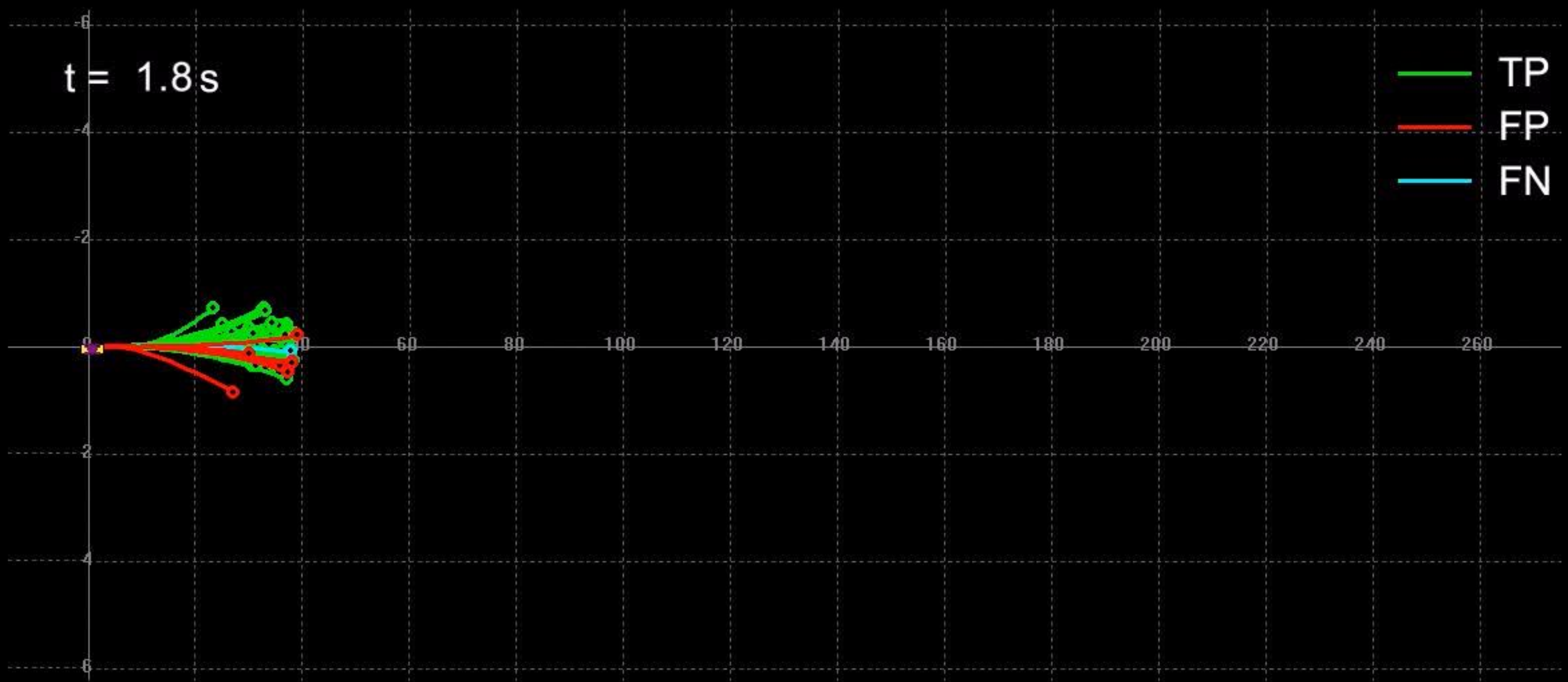


Action Control
Frame #
166
Length [s]
16
Time
11:20:16:938
T#42
T#17
T#43
T#0
T#28
T#36
T#21
T#7
T#22
T#33
T#29
36
28
0
34
39

A Car following Data

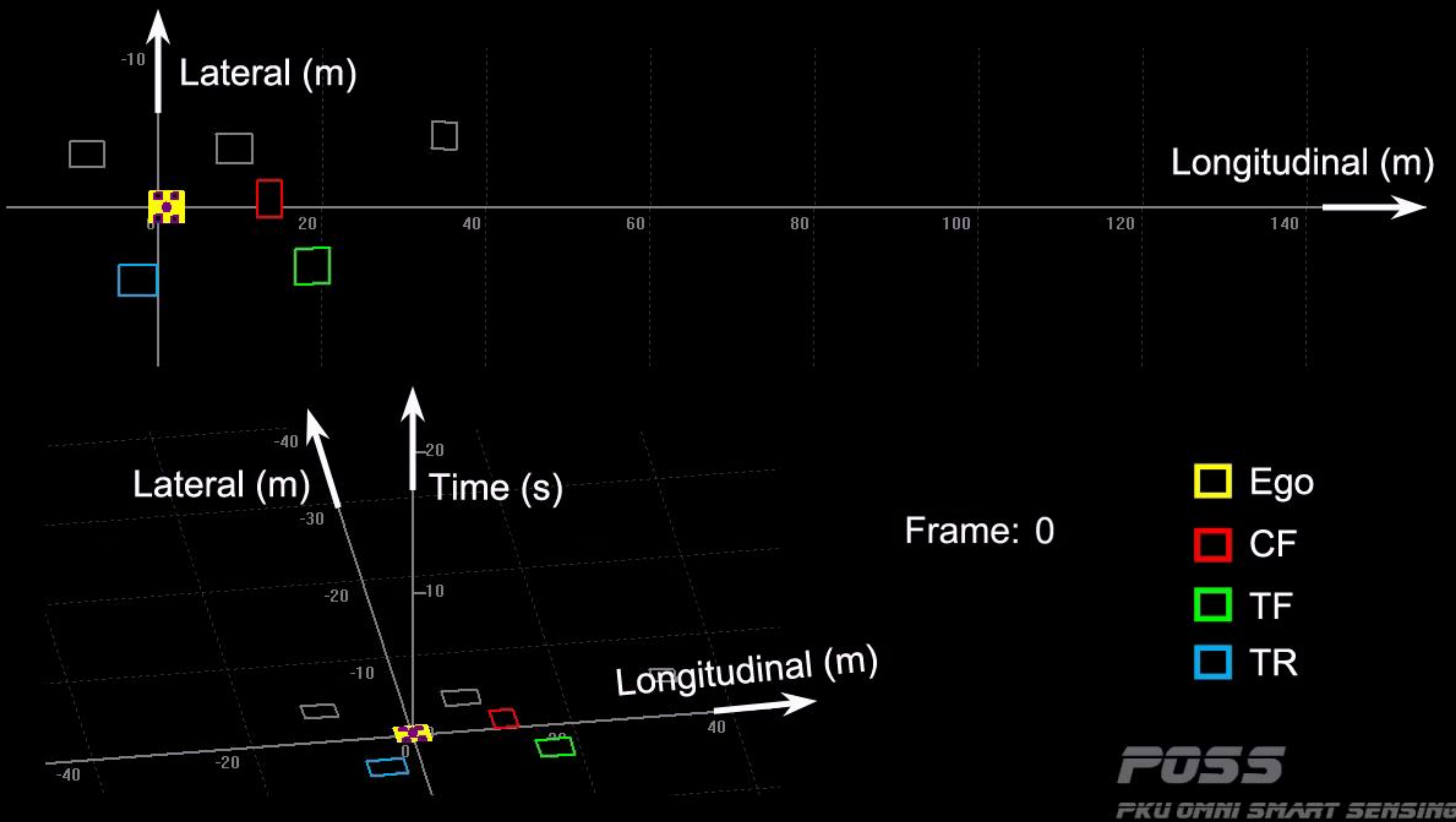


Lane Change Segment Extraction



Day 1 round 1

POSS
PKU OMNI SMART SENSING



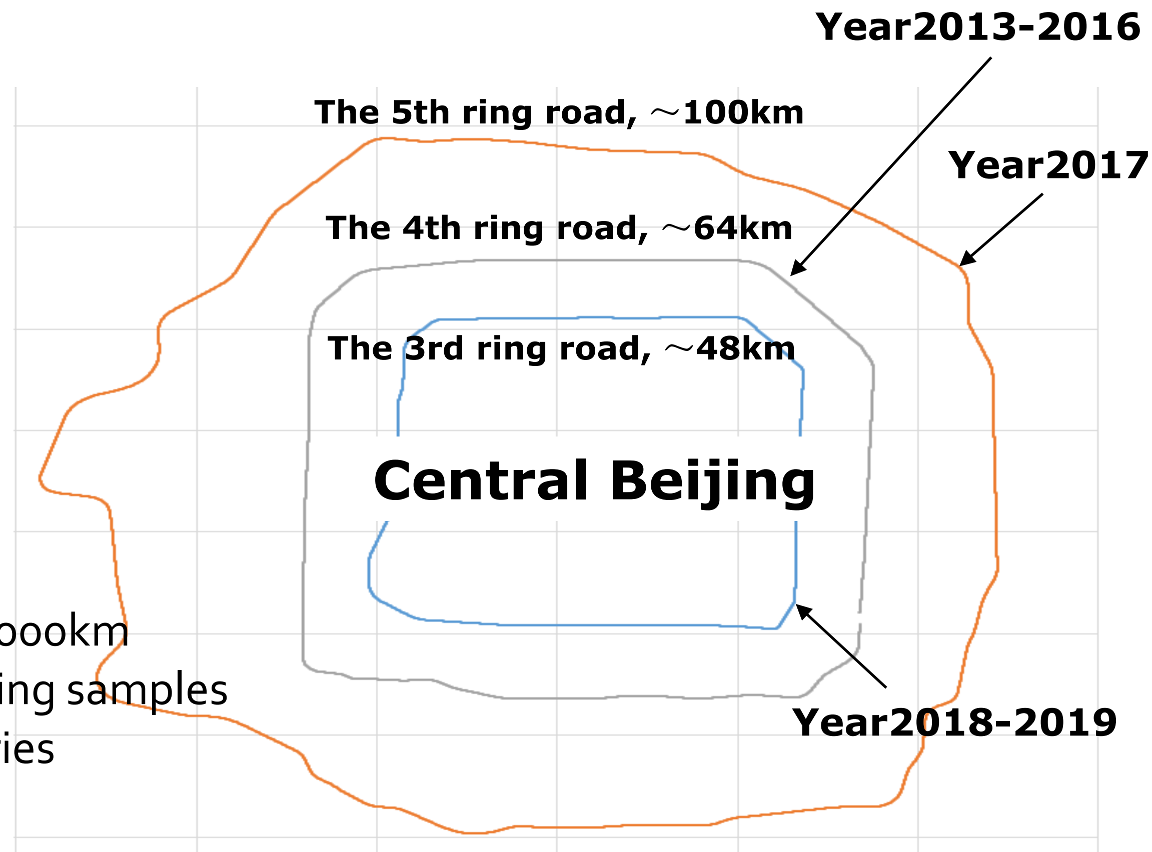
Lateral (m)
Longitudinal (m)
-10
20
40
60
80
100
120
140
Lateral (m)
Time (s)
Longitudinal (m)
-40
-30
-20
-10
20
10
-40
-20
0
40
Frame: 0
Ego
CF
TF
TR
POSS
PKU OMNI SMART SENSING

On-road Data Collection (2013-2019)

Experimental Setting
- Ring Road in Beijing
- Length: 65～100 km

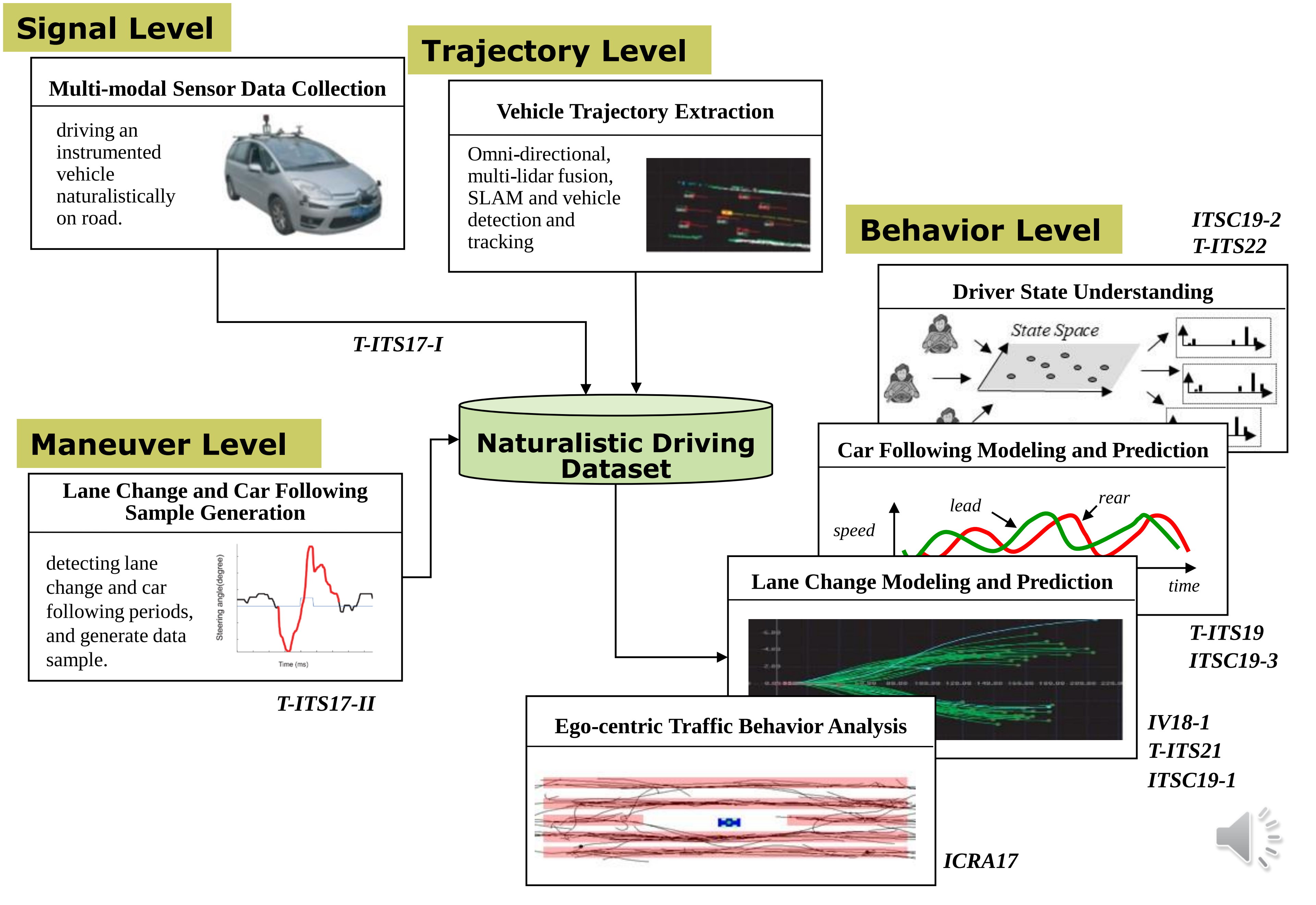
Three Axes
- Different drivers
- Different highways
- Heavy traffic

Data Collection
- >10 drivers, >100 days, >15000km
- lane change and car following samples
- all-around vehicle trajectories



Trajectory Quality Examination
Zhao,H et al., On-road Vehicle Trajectory Collection and Scene-based Lane Change Analysis: Part I, IEEE T-ITS, 18(1), 192-205, 2017.

Naturalistic Driving Behavior Study

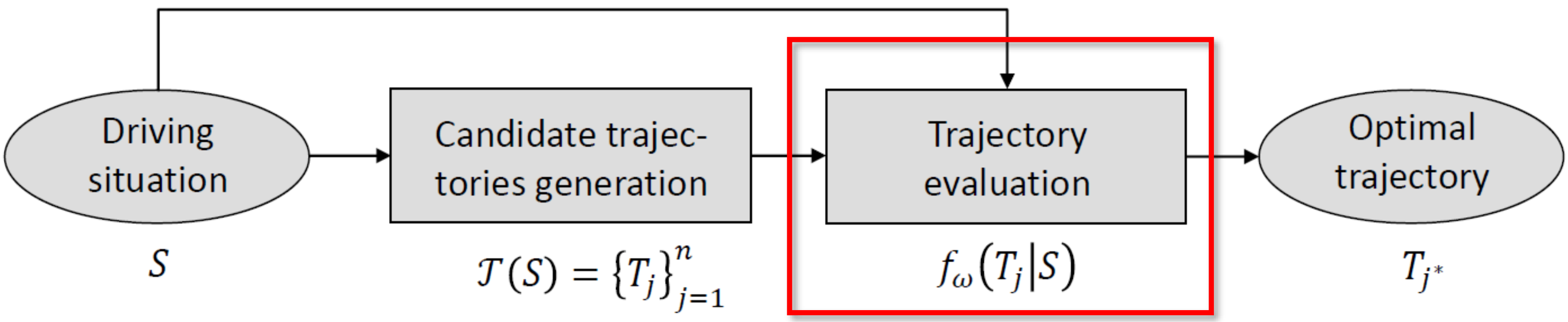


Aware the Scene - Naturalistic Driving Behavior Study

1. **Scene Aware Lane Change Analysis**
   - ✓ Lane Change Extraction and Interactive Behavior Modeling **[T.ITS17-II]**
   - ✓ Naturalistic Lane Change Analysis for Human-Like Trajectory Generation **[IV18-1]**
2. **Trajectory planning for human-like autonomous driving**
   - ✓ A Human-like Trajectory Planning Method by Learning from Naturalistic Driving Data **[IV18-2]**
   - ✓ Human-like Highway Trajectory Modeling based on Inverse Reinforcement Learning **[ITSC19-1]**
   - ✓ Learning From Naturalistic Driving Data for Human-Like Autonomous Highway Driving **[T.ITS21]**
3. **Multi-state car following behavior modeling and reasoning**
   - ✓ Aware of Scene Vehicles - Probabilistic Modeling of Car-Following Behaviors in Real-World Traffic **[IV17, T.ITS19]**
   - ✓ Driver Identification through Multi-state Car Following Modeling **[T.ITS22]**
   - ✓ Backpropagation through Simulation: A Training Method for Neural Network-based Car-following Models **[ITSC19-3]**
4. **Ego-centric Traffic Behavior Analysis**
   - ✓ Ego centered traffic behavior understanding through multi-level vehicle trajectory analysis **[ICRA17]**

** These works were supported in part by the Groupe PSA's OpenLab Program and co-authored with Groupe PSA.*

Human-Like Trajectory Planning by Learning from Naturalistic Driving Data



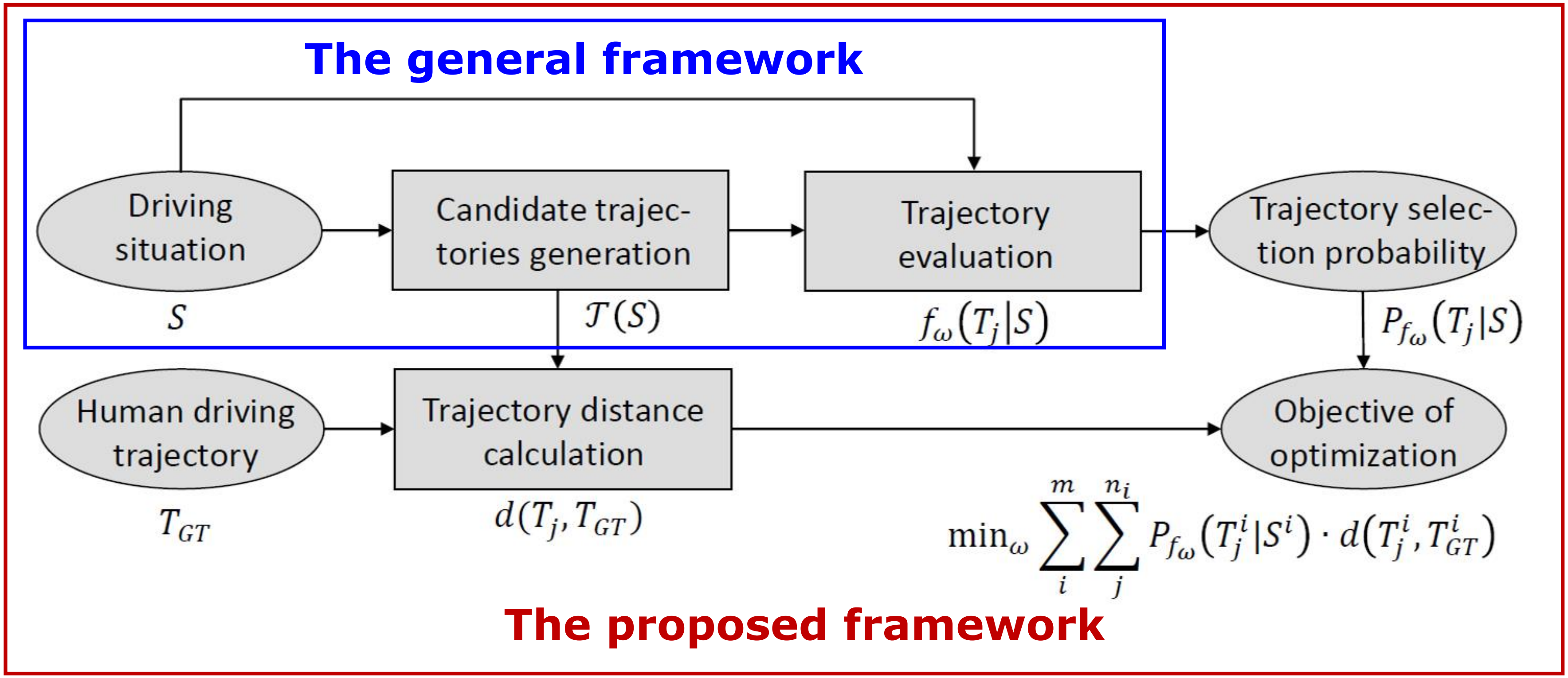
A general framework of trajectory planning

Finding a proper cost function to evaluate trajectories is non-trivial!

- Requires a significant amount of hand-engineering by experts;
- Hard to incorporate the likelihood to human driver's behavior;
- The cost function can be furthermore used for trajectory prediction.

-> Learning from Naturalistic Driving Data !

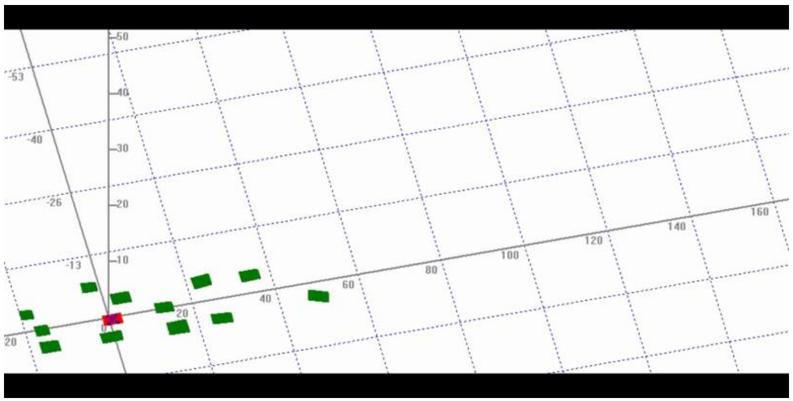
Learning Cost Function for Trajectory Selection

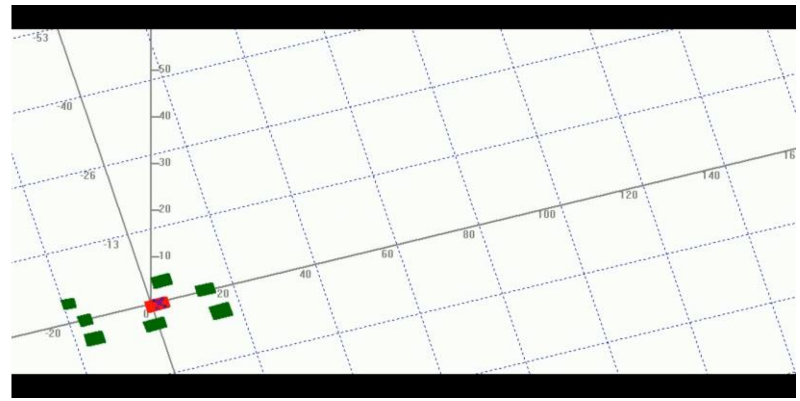


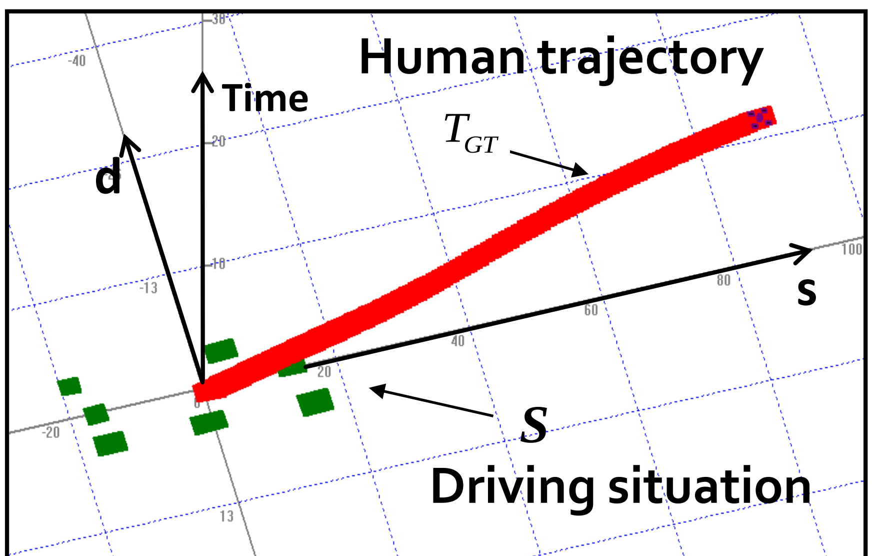
$$f_\omega(T_j) = \omega_1 * f_{Comfort} + \omega_2 * f_{Efficiency} + \omega_3 * f_{Safety} + \omega_4 * f_{LaneIncentive}$$

Fitting the coefficients of the cost function on human driving data.

Human Driven Data Sample

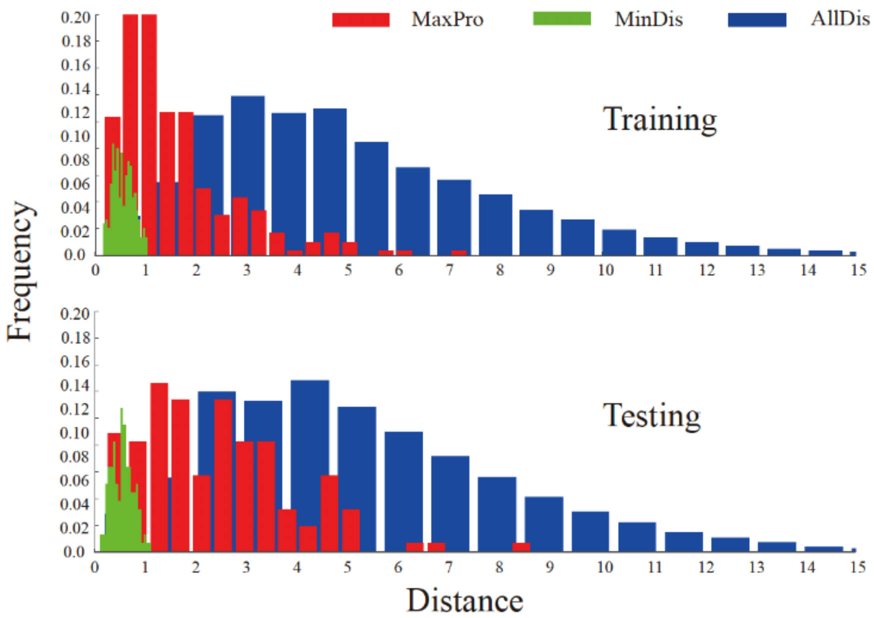






A data sample

Experimental Results

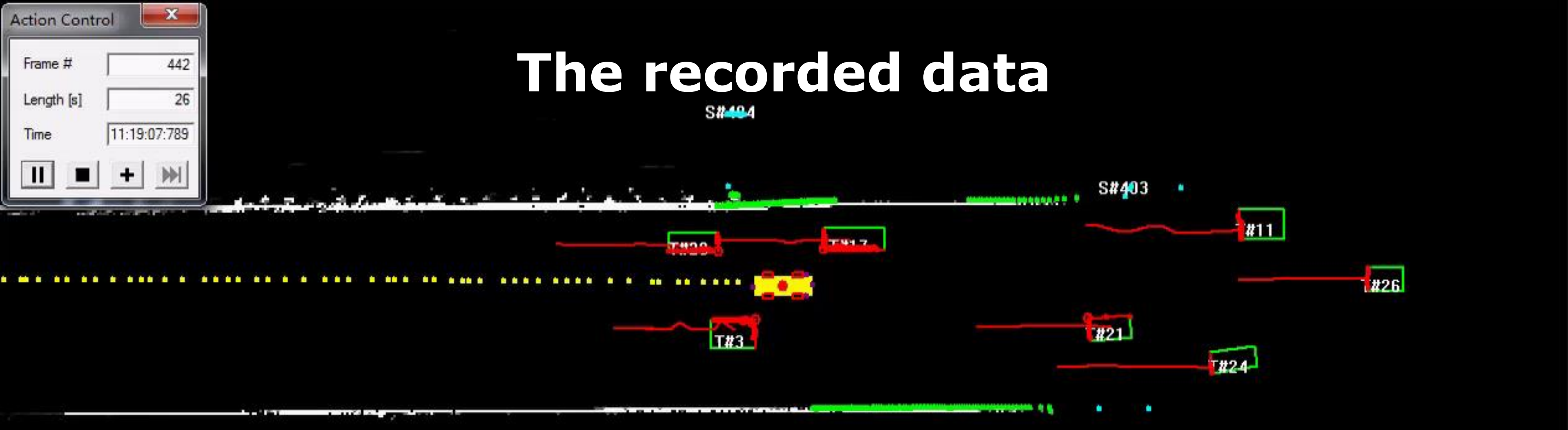


Similarity of the Planned Trajectory

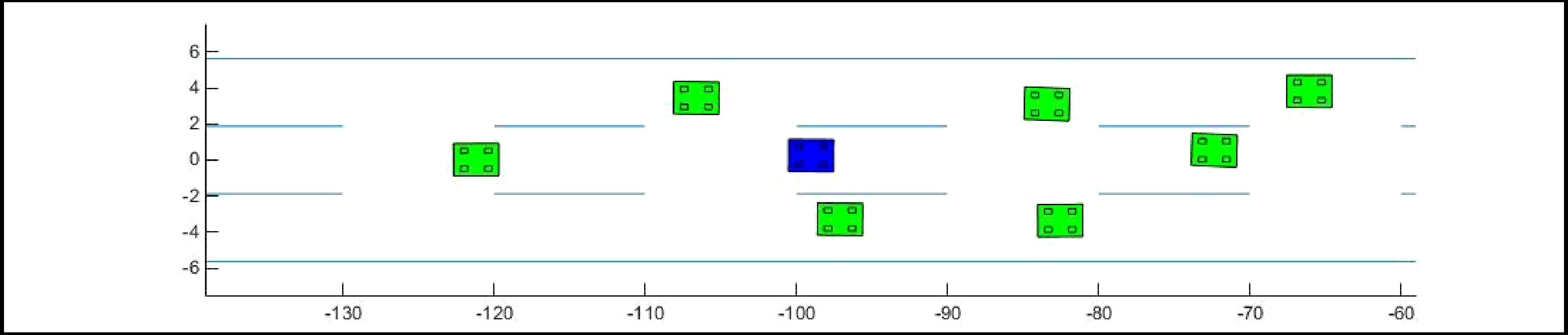
	Training			Testing		
	CF(H)	LLC(H)	RLC(H)	CF(H)	LLC(H)	RLC(H)
CF(P)	**77**	4	8	**34**	2	10
LLC(P)	9	**83**	3	11	**38**	2
RLC(P)	4	3	**79**	8	5	**33**
Accuracy	85.6%	92.2%	87.8%	64.2%	84.4%	73.3%

Similarity of the maneuver decision

The recorded data



Replay the data of scene vehicle, simulate the trajectory candidates of different similarity



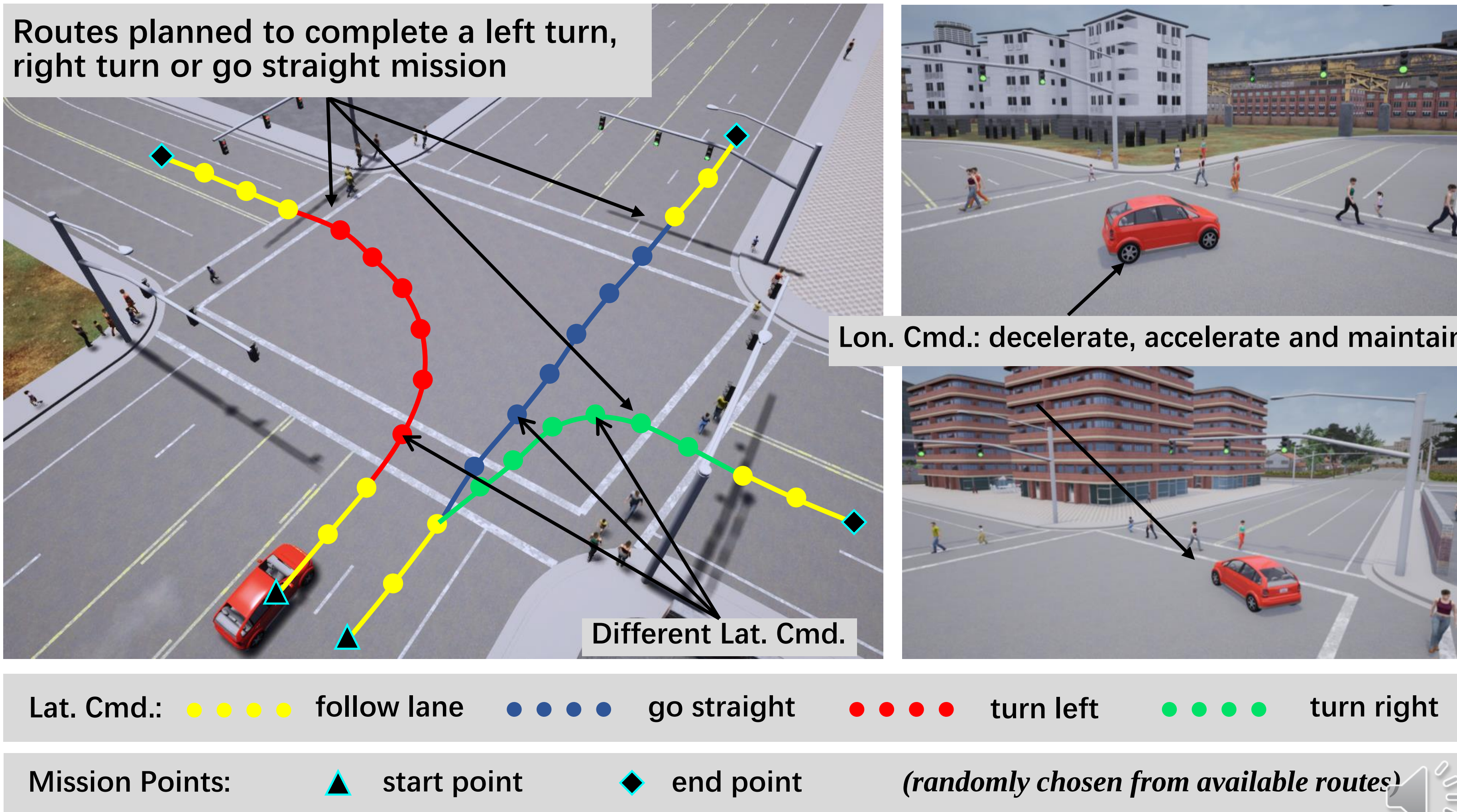
Bottlenecks of the Naturalistic Driving Behavior Study

- Can not perform closed-loop test
  - The learnt model can only be evaluated on dataset.
  - However, evaluating control models on static datasets is not enough due to compounding error caused by covariate shift.

  → **High-fidelity simulator CARLA**
- Inaccurate trajectory data
  - The accuracy of the estimated acceleration of surrounding vehicles is poor.
  - In densely interacting traffic scenarios, such as crowded intersections, the accuracy of the trajectory greatly limits the accuracy of the model.

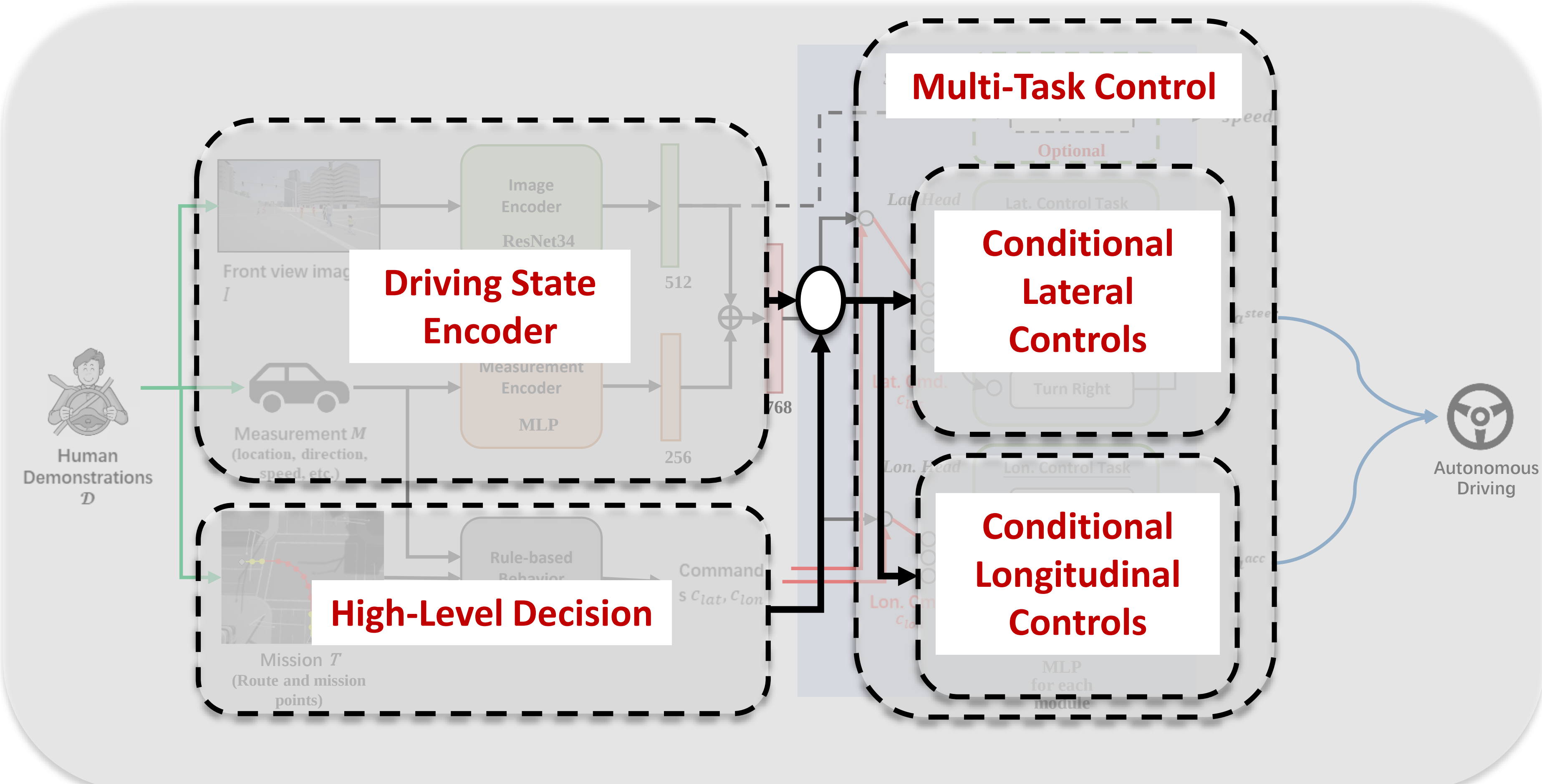
  → **End-to-end driving policy learning at intersection scenes**

Imitation learning for humanized autonomous navigation at crowded intersections using CARLA Simulator



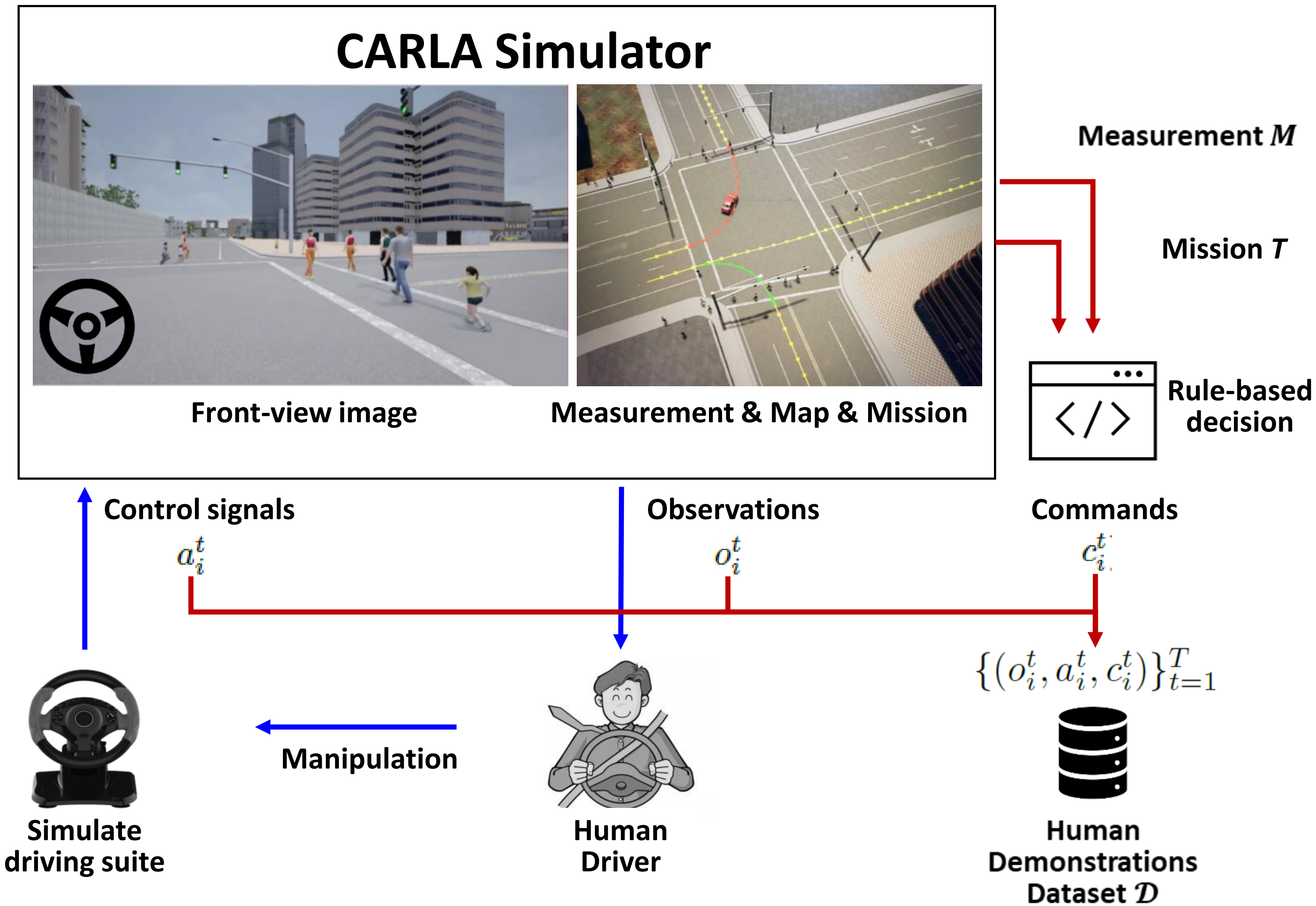
Methodology

Multi-Task Conditional Imitation Learning



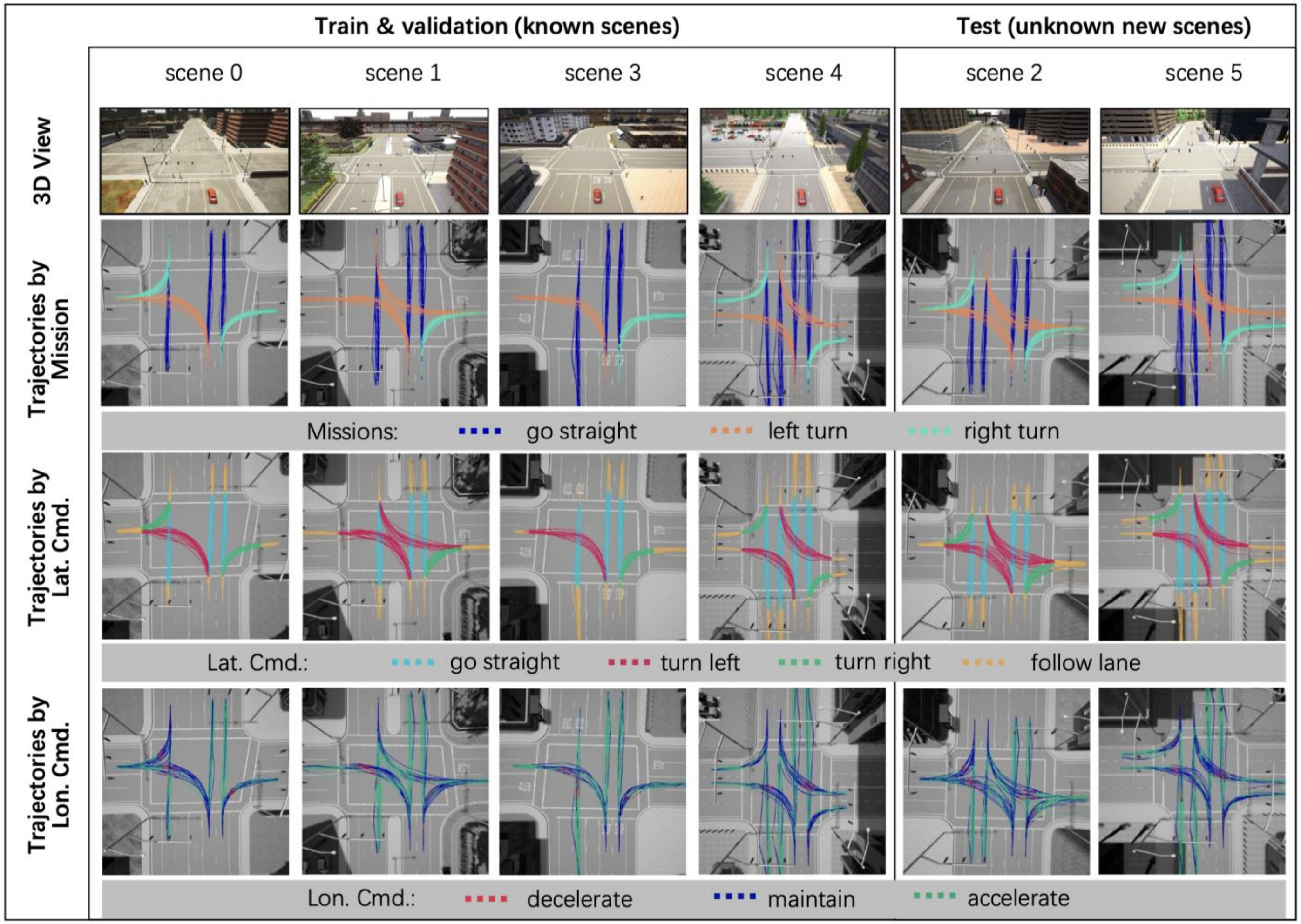
Zeyu Zhu, Huijing Zhao, Multi-Task Conditional Imitation Learning for Autonomous Navigation at Crowded Intersections, arXiv:2202.10124v1.

Human Driving Data Collection



New Benchmark "IntersectNav" on CARLA

https://github.com/zhackzey/IntersectNav

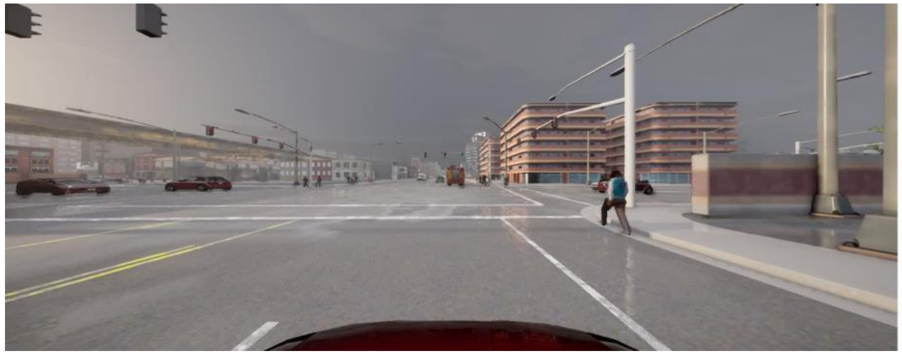


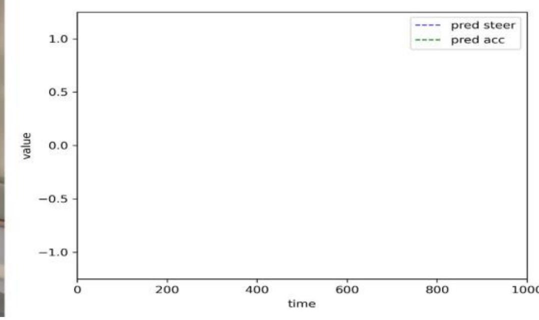
6 intersections, 8 weather conditions
2 dataset: Ped-Only, Ped-Veh, over 1300 trajectories and 40 hours data

Test Results - Succeed Cases

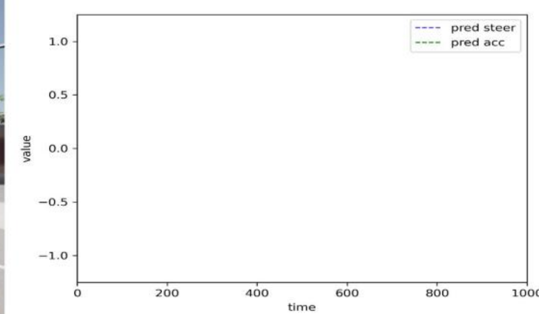
Train weather

Train scene

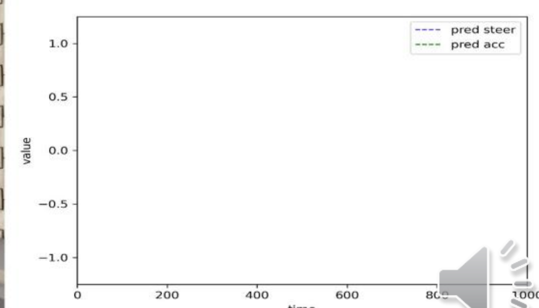




Train scene



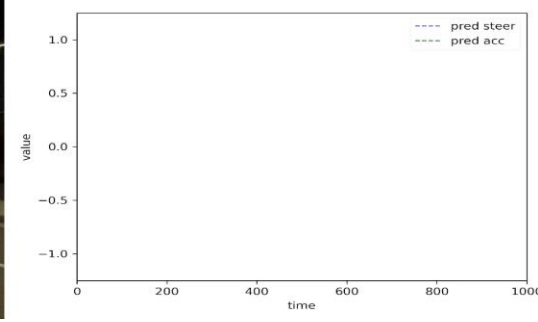
New scene



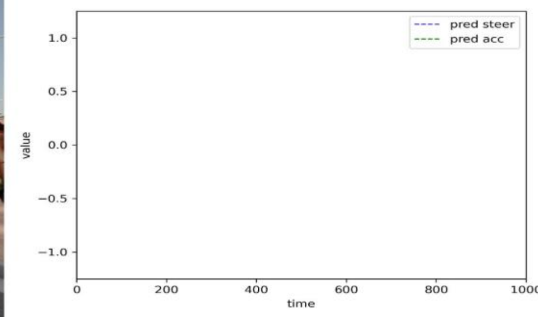
Test Results - Succeed Cases

New weather

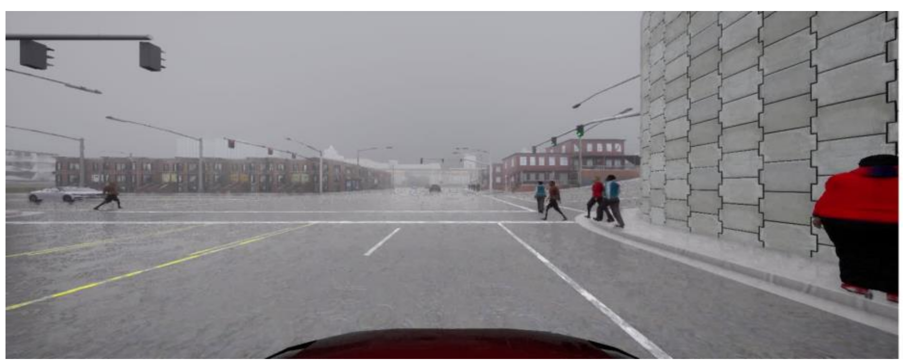
Train scene

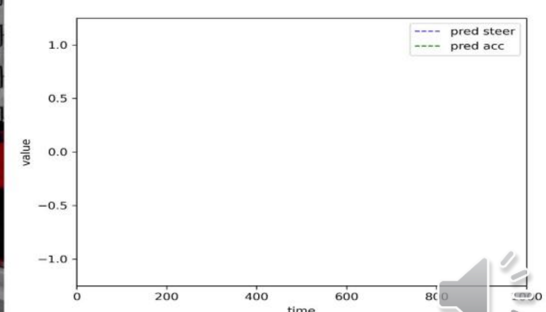


New scene



New scene



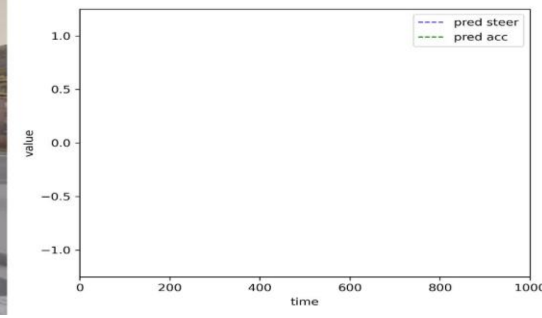


Test Results - Failed Cases

Train weather

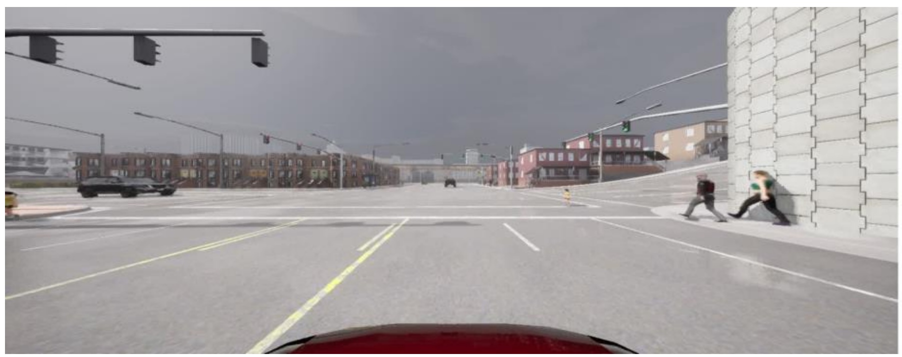
Train scene

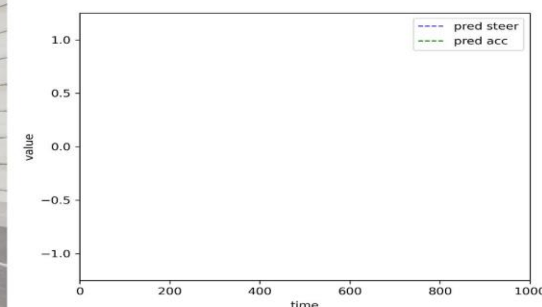
Collision



New scene

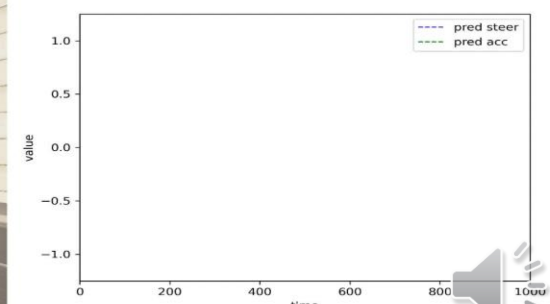
Collision





New scene

Timeout

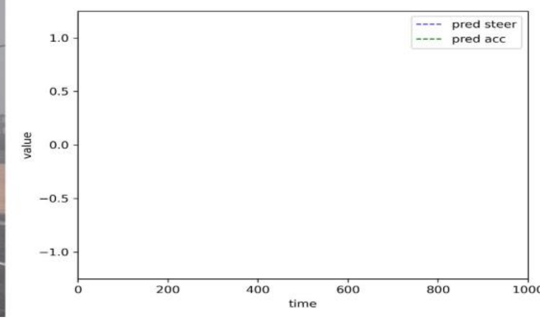


Test Results - Failed Cases

New weather

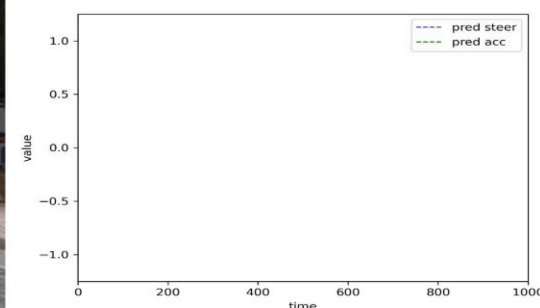
New scene

Lane Invasion



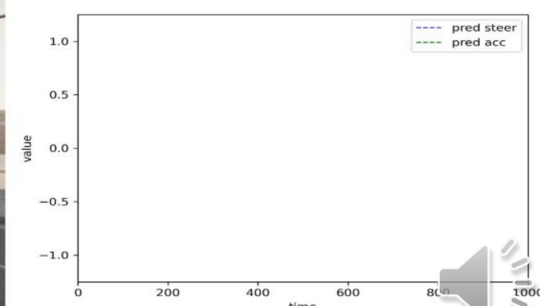
New scene

Collision



New scene

Lane Invasion



Closed-loop Evaluation on task completion and control quality

Models	Succ. Rt.	Time. Rt.	Lane. Rt.	Colli. Rt.
TS & TW	(%) ↑	(%) ↓	(%) ↓	(%) ↓
CIL	57.3 ± 2.5	21.1 ± 2.6	5.3 ± 1.7	16.3 ± 2.6
CILRS	67.5 ± 2.7	9.1 ± 3.5	6.4 ± 2.2	17.0 ± 2.8
Ours	**91.2 ± 2.0**	**1.6 ± 2.6**	**4.5 ± 1.8**	**2.7 ± 1.9**
TS & NW				
CIL	52.5 ± 3.1	21.9 ± 3.4	4.8 ± 1.4	20.8 ± 2.5
CILRS	46.7 ± 5.3	33.9 ± 5.6	2.1 ± 1.4	17.3 ± 2.2
Ours	**88.6 ± 2.0**	**1.9 ± 2.6**	6.6 ± 1.8	**2.9 ± 1.9**
NS& TW				
CIL	50.4 ± 2.4	23.3 ± 4.2	4.6 ± 3.1	21.7 ± 3.1
CILRS	53.3 ± 2.8	28.7 ± 3.3	2.5 ± 2.4	15.5 ± 2.8
Ours	**88.8 ± 3.7**	**3.1 ± 2.6**	4.6 ± 1.6	**3.5 ± 1.6**
NS & NW				
CIL	40.8 ± 4.9	27.1 ± 8.5	1.3 ± 1.7	30.8 ± 5.7
CILRS	32.1 ± 5.5	46.3 ± 6.1	0.4 ± 0.8	21.2 ± 3.3
Ours	**86.8 ± 3.6**	**3.8 ± 2.5**	4.7 ± 1.6	**4.7 ± 1.6**

Models	Intense Actions	Disruption to Pedestrians	Deviation from Waypoint	Deviation from Destination	Heading Angle Deviation	Total Steps
TS & TW	#, ↓	#, ↓	m, ↓	m, ↓	°, ↓	#, ↓
CIL	0.440 ± 0.108	88.848 ± 35.771	1.988 ± 0.233	7.365 ± 0.272	17.187 ± 3.157	385.013 ± 18.176
CILRS	1.300 ± 0.503	75.448 ± 29.667	1.107 ± 0.085	4.598 ± 0.375	14.271 ± 1.615	310.642 ± 33.795
Ours	**0.000 ± 0.000**	**17.219 ± 17.671**	**0.520 ± 0.029**	**1.253 ± 0.396**	**4.368 ± 0.466**	**308.376 ± 14.951**
TS & NW						
CIL	0.064 ± 0.035	34.435 ± 7.286	1.527 ± 0.147	9.114 ± 0.814	17.467 ± 1.143	375.848 ± 24.455
CILRS	0.003 ± 0.005	124.845 ± 54.668	1.117 ± 0.126	9.123 ± 0.949	20.901 ± 1.420	482.261 ± 39.933
Ours	**0.000 ± 0.000**	**17.224 ± 17.680**	**0.520 ± 0.029**	**1.253 ± 0.396**	**4.369 ± 0.464**	**308.392 ± 14.944**
NS & TW						
CIL	0.167 ± 0.137	110.867 ± 39.536	1.853 ± 0.376	9.502 ± 0.600	21.407 ± 1.808	376.825 ± 16.704
CILRS	0.267 ± 0.077	192.037 ± 36.298	1.361 ± 0.166	7.922 ± 1.098	19.161 ± 3.063	514.867 ± 29.989
Ours	**0.000 ± 0.000**	**36.458 ± 31.388**	**0.581 ± 0.012**	**1.390 ± 0.472**	**5.437 ± 0.679**	**339.292 ± 16.309**
NS & NW						
CIL	0.104 ± 0.077	35.142 ± 8.137	1.159 ± 0.148	10.471 ± 0.942	24.189 ± 2.445	425.917 ± 64.926
CILRS	0.004 ± 0.008	144.762 ± 46.157	0.868 ± 0.165	14.279 ± 1.106	26.983 ± 0.170	578.217 ± 40.494
Ours	**0.000 ± 0.000**	37.492 ± 32.246	**0.582 ± 0.012**	**1.426 ± 0.381**	**5.988 ± 0.111**	**346.625 ± 15.805**

Conclusion and Future Works

- **Learning from Human Driver Data for Humanized Autonomous Driving at Dynamic Scenes**
  - **Early works**: on-road naturalistic driving data based study, traditional modular-based approach using trajectory data as the input
    - **Pros**: real-world data, the model is explainable
    - **Cons**: no closed loop evaluation, difficult at densely interacting scenes due to poor trajectory accuracy
  - **Current work**: CARLA simulator-based study, end-to-end approach using front image as the input
    - **Pros**: closed loop evaluation, adapt to densely interacting scenes
    - **Cons**: simulation is unreal, reliability of end-to-end model faces still big challenges
- **Future works: close the sim-to-real loop; combine the mo end-to-end approaches**

IntersectNav Benchmark:
https://github.com/zhackzey/IntersectNav

POSS Dataset:
http://www.poss.pku.edu.cn/download.html

More Information of POSS-Lab:
http://www.poss.pku.edu.cn/

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