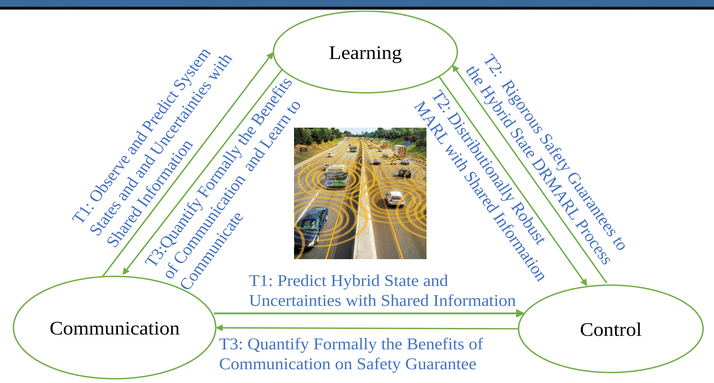
CAREER: Distributionally Robust Learning, Control, and Benefits Analysis of Information Sharing for Connected and Autonomous Vehicles

PI: Fei Miao, Pratt & Whitney Associate Professor, School of Computing, University of Connecticut

http://feimiao.org/research.html, http://feimiao.org/CAREER_CAV_MARL.html, fei.miao@uconn.edu

	5-Year Career Goals	10-Year Career Goals
Research	Improve CAVs State Prediction with Comm Model CAVs State Uncertainties with Comm DRMARL with Shared Information for CAVs Integrate Learning and Safety Control for CAVs Quantify the Value of Comm Formally for CAVs Learn to Comm for CAVs in Various Scenarios	Networked CPS State Prediction with Comm Networked CPS Model Uncertainties with Comm Robust Cooperative and Competitive Safe MARL Integrated CPS Comm, Learning, and Control Quantify the Value of Comm and Learn to Comm **Security Challenges for Networked CPS**
Education	Educational Tool; K-12 Outreach; Minorities	Education with Research; Increase STEM Minorities



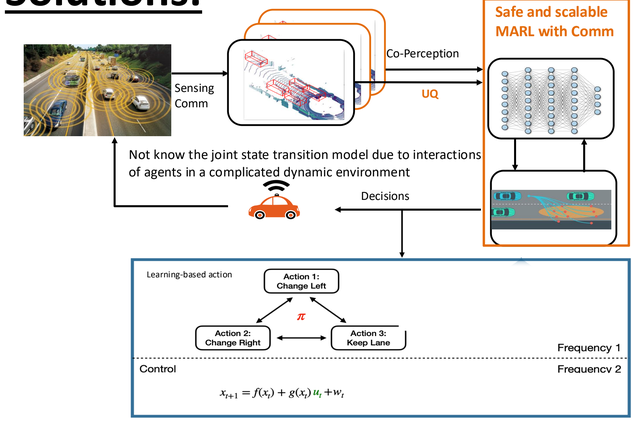
Challenges:

- Understand the tridirectional relationship among communication, learning, and control of networked CPS
- Uncertainty quantification for computer vision tasks
- Safe and robust learning and control decisions with respect to the system model and state uncertainties

Scientific Impact:

Develop integrated communication, learning and control frameworks that are robust to system model uncertainties and improve the performance of ***embodied AI and networked CPS*** by rigorously guaranteeing on their ***safety, efficiency, robustness*** and ***security***

Solutions:



1. Safe and Efficient Multi-Agent Reinforcement Learning (MARL) for Behavior Planning of CAVs

S. Han and Fei Miao et.al, IEEE Transactions on ITS, Jan. 24

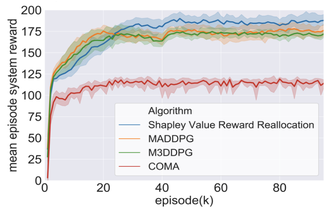
Theorem 1 Truncated Q-function: utilize information sharing, increase scalability, not rely on the global states and global actions: proved approximation error.

Theorem 2 Safe action mapping: map any action in the action space to the safe action set: provably safety guarantee for the actions during training and execution.

2. Stable and Efficient Shapley Value-Based Reward Reallocation for Multi-Agent Reinforcement Learning of Autonomous Vehicles, S.Han, Fei Miao et.al, ICRA'22

Theorem 1: Shapley value is an efficient reward reallocation.

Theorem 2: For a convex game, Shapley value is a stable reward reallocation: all agents (CAVs) will stay within the coalition.



First theoretical analysis of MARL under state uncertainties

3. What is the Solution for State-Adversarial Multi-Agent Reinforcement Learning?

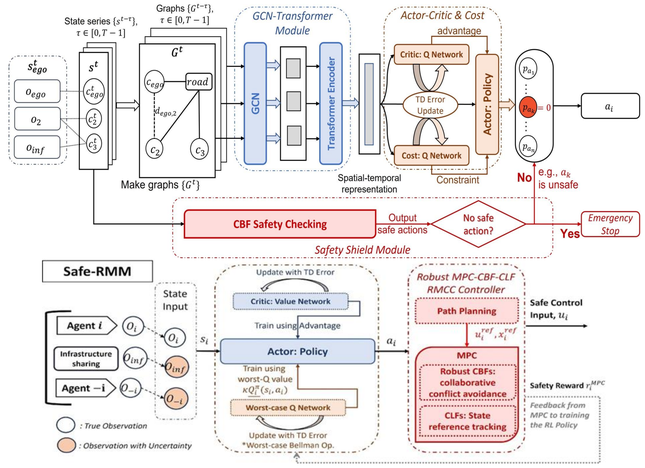
S. Han, Fei Miao, et.al, Transactions on Machine Learning Research, Jan. 2024

https://openreview.net/pdf?id=HyqSwNhM3x

4. Robust Multi-Agent Reinforcement Learning with Adversarial State Uncertainties

Sihong He, Fei Miao et.al, Transactions on Machine Learning Research, Jun. 2023,

https://openreview.net/forum?id=CqTkapZ6H9



Method	Uncertainty: None	ϵ^{rand}	ERR^{V}	ERR^{T}
Intersection				
Safe-RMM[1]	0, 162.9	0, 161.4	0, 162.2	0, 161.8
Safe-MM[2]	0, 157.9	0, 155.7	0, 155.9	0, 155.7
MCP[3]	3, 65.7	2, 60.6	0, 66.2	2, 67.7
MP[4]	33, 148.4	41, 149.1	36, 145.9	30, 139.0
RULE[5]	2, 120.9	1, 113.9	3, 105.5	2, 112.3

Method	Uncertainty: None	ϵ^{rand}	ERR^{V}	ERR^{T}
Highway				
Safe-RMM	0, 162.0	0, 169.4	0, 166.4	0, 161.8
Safe-MM	0, 161.3	0, 168.7	0, 168.7	0, 163.0
MCP	0, 56.8	2, 55.8	1, 60.7	2, 58.4
MP	35, 74.1	34, 74.5	38, 73.8	38, 74.5

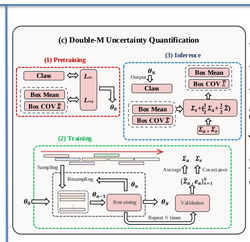
5.Spatial-Temporal-Aware Safe MARL of CAVs in Challenging Scenarios

Zhili Zhang and Fei Miao et.al, ICRA'23, arXiv:2210.02300

6. Safety Guaranteed Robust Multi-Agent Reinforcement Learning with Hierarchical Control for Connected and Automated Vehicles

Z.Zhang, Fei Miao et.al, ICRA'25 arxiv:2309.11057.

7.Multi-Agent Reinforcement Learning Guided by Signal Temporal Logic Specifications, under review, J.Wang, Fei Miao et. al, arXiv:2306.06808.

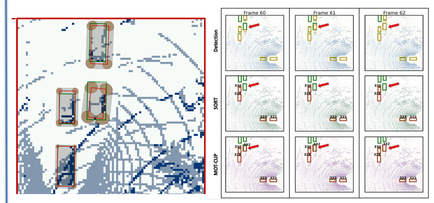


- Double-M: Direct Modeling (DM)+ Moving Block Bootstrap (MBB)
- Double-M achieves up to 4x Improvement in uncertainty reduction
- Double-M improves up to 3.13% in accuracy

8. Uncertainty Quantification of Collaborative Object Detection for CAVs

S. Su, F. Miao et al. , ICRA'23, arXiv:2209.08162

Website: https://coperception.github.io/double-m-quantification/

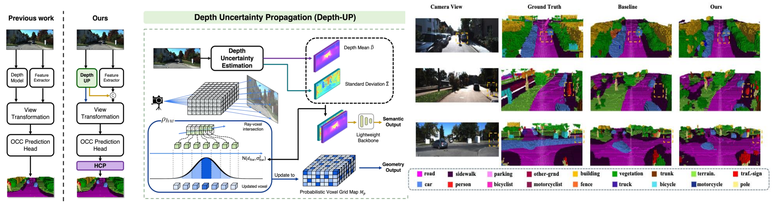


9. Collaborative Multi-Object Tracking with Conformal Uncertainty Propagation

S.Su, Fei Miao et.al, IEEE Robotics and Automation Letters, Feb.24, DOI: 10.1109/LRA.2024.3364450

--MOT-CUP: UQ in detection input to tracking direct modeling + conformal prediction.

--Improved accuracy and reduced uncertainty, especially high occlusion cases.



10. "α-OCC: Uncertainty-Aware Camera-based 3D Semantic Occupancy Prediction"

S.Su, Fei Miao et.al, under review, https://arxiv.org/abs/2406.11021, Oct. 2024

Depth-UP: Uncertainty propagation framework to improve the Semantic Occupancy Prediction (OCC). **Hierarchical Conformal Prediction (HCP)** to improve the uncertainty quantification (UQ) under high class imbalance of OCC. Depth uncertainty propagation and hierarchical conformal prediction **improves rare class (human) occupancy prediction**

Broader Impact:

- Full-size CAVs (buses) and the testing ground under development at Uconn with industry partners and DOT
- Opensource code and data; K-12 students and under representative students participate research, F1/10th racing car experiments