Federated learning in Intelligent Transportation Systems and Connected Vehicles

Objectives, Methods, Results, and Future Directions

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Papers Studied

- (Paper 1) Federated Learning in Intelligent Transportation Systems: Recent Applications and Open Problems, 2023, arXiv:2309.11039v1
- (Paper 2) A Survey of Federated Learning for Connected and Automated Vehicles, 2023, arXiv:2303.10677v1

Introduction

Intelligent Transportation Systems (ITS) and Connected Automated Vehicles (CAVs) generate **huge amounts of data** (trajectories, images, sensors).

Traditional centralized machine learning **struggles** due to:

- High latency for real-time decisions
- Privacy concerns (vehicle location, driver info)
- Data scattered across multiple vehicles (**data islands**)

Federated Learning (FL) allows vehicles to **learn collaboratively without sharing raw data**, preserving privacy while improving traffic intelligence.

Objectives

- Survey FL applications in ITS
- Explain why FL is needed (privacy, latency, scalability)
- Categorize FL applications: Object recognition, traffic status, traffic management, service provision
- Identify challenges & future directions
- Review FL applications for connected and automated vehicles
- Summarize data types (images, LiDAR, vehicle status)
- Review FL algorithms, security methods, and autonomous driving applications
- Highlight challenges and research directions

Example to relate:

- FL in ITS can optimize **traffic signals**, while FL in CAVs can improve **vehicle trajectory prediction** for safer driving.

Methods / Application Scenarios (Paper 1)

1. Object Recognition

- License plate detection, traffic signs
- Models: YOLO, R-CNN with FL
- Semi-supervised FL for limited labeled data

2. Traffic Status Identification

- GPS correction, trajectory classification, flow prediction
- Models: LSTM, Graph Neural Networks

3. Traffic Management

- Parking space estimation, traffic signal control
- FL + Reinforcement Learning

4. Service Providing

- EV charging prediction, edge content caching, knowledge sharing

Methods / Application Scenarios (Paper 2)

Data modalities in CAVs:

- **RGB Images** → steering, traffic sign detection (CNN, ResNet, YOLO)
  LiDAR Point Clouds → 3D object detection
- **Vehicle Status** → trajectory prediction, motion control (LSTM, RNN, RL)

FL Algorithms:

- FedAvg (weighted average), FedProx, Fed-ADAM, DFP, Federated Distillation

Applications:

1. Driver distraction & fatigue monitoring
2. Steering wheel angle prediction (critical for autonomous driving)
3. Vehicle trajectory prediction (using NGSIM data)
4. Object detection in adverse weather
5. Motion control: target speed, throttle, brake

Results / Key Findings

From Paper 1 (ITS FL):

- Privacy preserved: data remains on vehicles
- Communication-efficient: only model updates shared
- Scalable: vehicles join/leave dynamically
- Robust: handles node failures
- Non-IID data handling: models cope with uneven data

From Paper 2 (CAVs FL):

- FL can train models **without central server** dependency
- Improves prediction of rare events (accidents, weather)
- Enhances object detection in adverse conditions (snow, fog)
- Efficient for massive data (CAVs generate 1–2 TB/day)

Challenges

Paper 1 (ITS):

- Computational efficiency on resource-constrained vehicles
- Security & privacy attacks
- Real-world deployment gaps
- Sensor fusion optimization

Paper 2 (CAVs):

- Resource limitations (massive parallel vehicles)
- Catastrophic forgetting in global model updates
- Fairness & incentive mechanisms
- Evaluation difficulty for new vehicles

Future Directions

Paper 1:

- Lightweight encryption for vehicles
- Semi-supervised learning to handle limited labeled data
- Edge cache authentication & trust
- Compression/pruning to reduce communication overhead
- Specialized FL architectures for ITS tasks

Paper 2:

- Decentralized FL (remove central server)
- Communication-efficient model compression
- Defense against backdoor attacks
- Homomorphic encryption and differential privacy
- Cross-domain transfer learning for CAV-specific tasks

Example for audience:

- Imagine autonomous cars learning collectively to handle rare snowstorms or accidents while keeping driver privacy intact.

Conclusion

- Federated Learning enables **collaborative, privacy-preserving learning** for ITS and CAVs.
- Real-world benefits: safer roads, optimized traffic, better autonomous driving decisions.
- Challenges remain: security, computational efficiency, deployment in real traffic.
- Future research: lightweight privacy-preserving methods, decentralized FL, and specialized FL frameworks for vehicles.

References

- Zhang et al., *Federated Learning in Intelligent Transportation Systems: Recent Applications and Open Problems*, 2023, arXiv:2309.11039v1
- Chellapandi et al., *A Survey of Federated Learning for Connected and Automated Vehicles*, 2023, arXiv:2303.10677v1