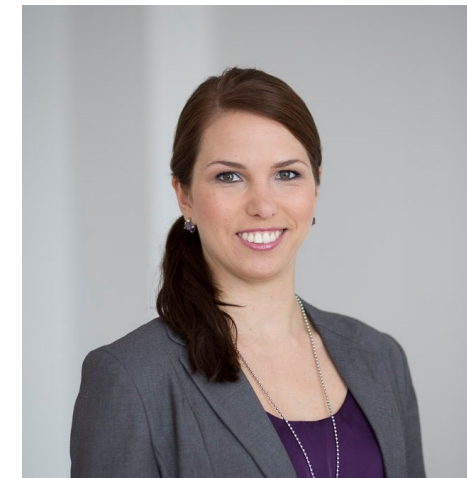




- **How to defend connected intelligent vehicles: Transferring established Information Security best practices to the vehicular world**
Miriam Gruber and Jan Lange, Volkswagen
- **Detection is not enough: Low-cost Attack Recovery for Autonomous Robotic Vehicles (RVs)**
Karthik Pattabiraman, University of British Columbia
- **Design and Assessment of Safe Autonomous Vehicles (AVs)**
Saurabh Jha, IBM T. J. Watson Research
- *Session Chair: Andrea Ceccarelli, University of Florence*
- *Rapporteur: Homa Alemzadeh, University of Virginia*



- **Collision of two worlds:** Information security and automotive safety
- **From prevention to active defense**
 - **Prevention:** Interface protection, SW integrity, authenticated communication
 - **Defense:** Intrusion detection, intrusion reaction, active defense, and recovery
 - **Challenges:**
 - New technology, timing constraints, increasing complexity, fixed rules
- **Incident response:**
 - **Active Attack Detection**
 - **Response**
- **AI-based defense:**
 - **AI-based Detection:**
 - Learn from real-world attack scenarios, not enough data
 - **AI-based Response:**
 - Too risky, needs absolute certainty, not enough real-world data to train on





- **Active Attack Detection**

- **Steps:**

- **Vehicle:** Collect data from vehicle => Apply anomaly detection rules
- **Backend (Cloud):** Aggregate data (fleet-wide) => More in-depth detection

- **Challenges:**

- **What data?** Data from ECUs, interfaces (e.g., Wifi, Bluetooth), V2V communications
- **How much data?** Just enough to analyze the attacks and the infrastructure

- **Best practices:**

- Asset register (ECUs), asset use cases, review by service owners

- **Response**

- **Goals:**

- Contain or mitigate attacks => Stop incident => Recover => Lessons learned

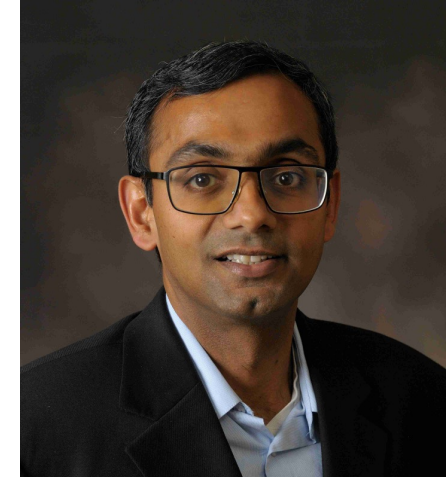
- **Challenges:**

- Variety of attack models with different levels of intelligence and complexity

- **Best practices:**

- Safety-critical context/usage, context-specific fall-back, automated vs. manual response

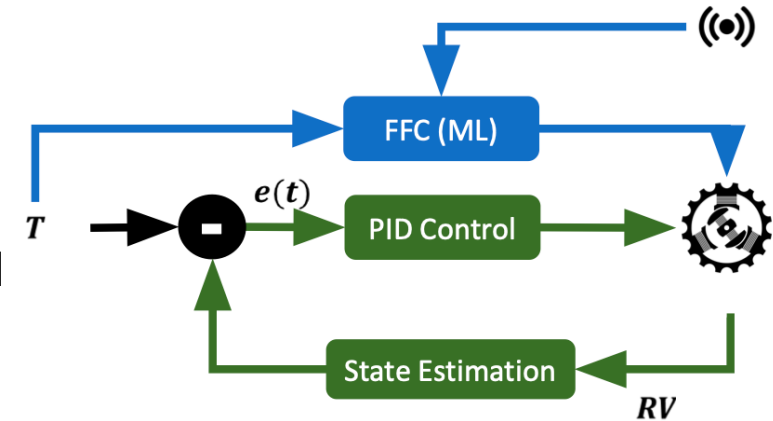
- **Perception in RVs**
 - Sensor attacks
 - Can RVs continue to operate safely despite sensor attacks?
- **State-of-the-art Attack Detection and Recovery**
 - **Detection:** Invariant-based and model-based
 - **Recovery:** Fail-safe mechanisms (emergency landing)
- **Attack Recovery without mission failure or crash**
 - Prevent erroneous physical states AND prevent erroneous actuator signals
 - **PID-Piper**
 - **Problem:** PID overcompensation under attacks => good for faults, not for attacks
 - **Solution:** Redundant feed-forward controller (FFC)
 - **DeLorean**
 - **Problem:** Multiple sensors under attack
 - **Solution:** Identify attacked sensors, isolate them, substitute sequence, recover by replay



Attack Recovery Methods

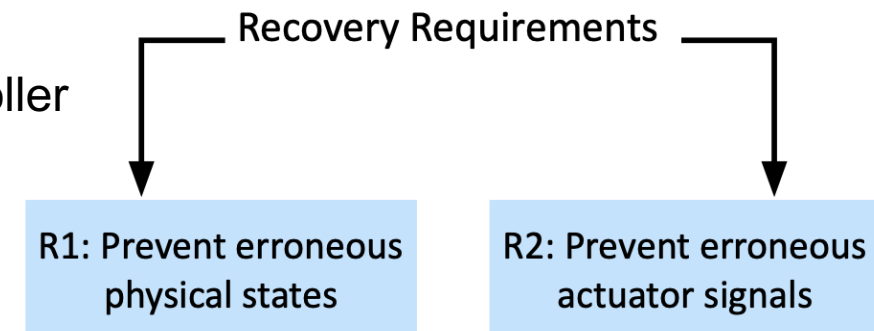
– PID-Piper

- Redundant feed-forward controller to address PID overcompensation
- ML trained on sensor and waypoint data to predict recovery actions
- Switched to upon attack detection and active for the attack duration
- **Higher mission success, low false positives, negligible overhead**



– DeLorean

- Detect the attacked sensors
- Prevent erroneous physical states: isolating sensor(s) from controller
- Prevent erroneous actuator signals: substituting input sequence
- Discard corrupted states and replay historic states
- **First work to recover from multiple sensor attacks with little overhead**



- **Vulnerabilities in AVs**

- Much worse than non-AVs
- Increased attack surface: ML uncertainty, training data quality, unknown unknowns

- **Identifying safety-critical vulnerabilities**

- **Problem:** State-space exploration to find the faults that lead to safety hazards

- **What/Where to inject faults?**

- **Solution:** Accelerate testing by only doing FI based on ML inference

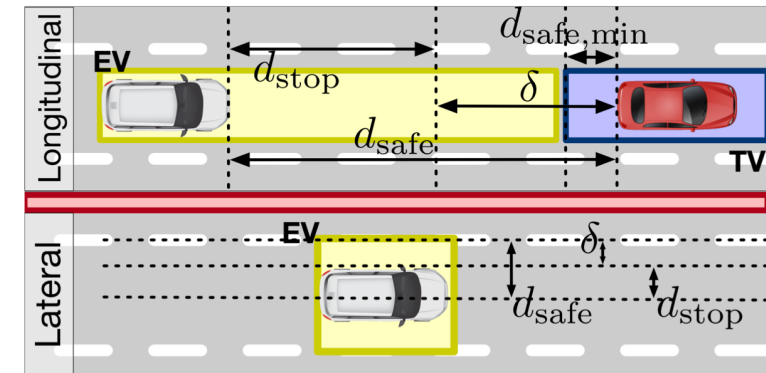
- Probabilistic Graph Models (PGMs) to model fault propagation
- Training on observational data
- Model fault injection as an inference query on PGM

- **What/How/When to launch attacks?**

- **Solution:** Design ML-driven attacks that can evade detection
 - Alter objects trajectories by corrupting pixels or perception output
 - ML inference of low safety potential and minimum time to hazards

- **Much faster and more efficient identification of safety-critical scenarios than random FI**

- **Runtime threat assessment for safety**





▪ Current Challenges

- IT to AV transfer of security and safety methods and best practices
- Lack of realistic incident data and labels for training detection and response models
- Effect of ML uncertainties and quality of training data
- Timing constraints, computational overhead, and side consequences of methods at runtime

▪ Future Directions

- ML/AI driven models for fault injection, safety assessment, attack detection and recovery
- Combined model and data-driven methods, situationally-aware methods, both online and offline
- Simulation to real transfer of safety models, fault and driving scenarios, and datasets
- Community standards for quantifying the quality of ML models and datasets