Intelligent Traffic Monitoring and Control

A Hybrid IoT and Q-Learning Approach

CS974 (Internet of Things)

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Overview

Overview

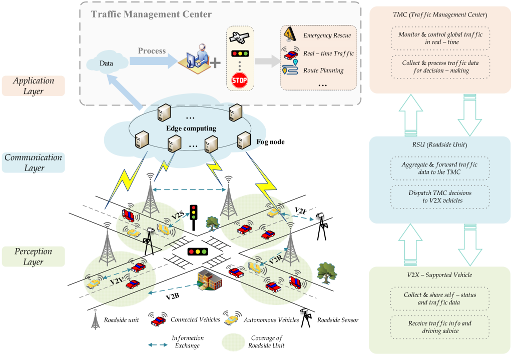
Problem Statement

- Urban traffic congestion caused by static signal systems [Li et al. (2020)]
- Consequences:
  - Time loss, fuel wastage, environmental pollution
  - Delayed emergency response
- Need for real-time adaptive solutions

Overview

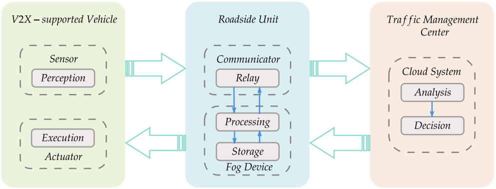
IoT Architecture for Urban Intelligence

- Three-layer architecture:
  - **Application Layer**: Traffic Management Center (TMC) with cloud/fog computing
  - **Communication Layer**: RSUs, 5G/V2V/V2I networks [Lu et al. (2014)]
  - **Perception Layer**: Sensors, cameras, V2X-supported vehicles
- Key components:
  - Vehicle-to-Everything (V2X) communication
  - Real-time data collection and processing



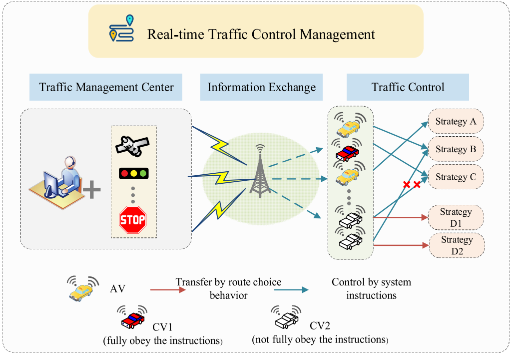
Key IoT Components

- **V2X-Supported Vehicles**:
  - Equipped with GPS, sensors, and communication modules
  - Share real-time position and speed data [Chavhan et al. (2019)]
- **Roadside Units (RSUs)**:
  - Aggregate traffic data within coverage zones
  - Act as fog computing nodes
- **Traffic Management Center (TMC)**:
  - Centralized cloud system for decision-making
  - Implements optimal control strategies



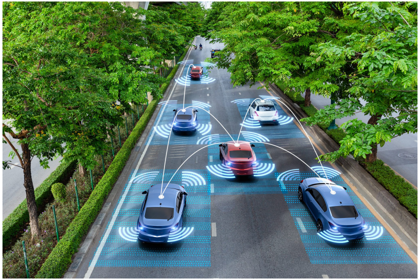
IoT-Enabled Traffic Control Strategies

- **Strategy A**: Idle capacity-based rerouting
- **Strategy B**: Dynamic edge connectivity-based rerouting
- **Strategy C**: Edge betweenness-based rerouting
- **Emergency Priority**: Dynamic lane clearance for emergency vehicles
- **Performance Metrics**: Congestion levels (TTI), recovery time



Challenges and Solutions

- **Data Reliability**:
  - Challenge: Sensor noise/outliers
  - Solution: Redundant data sources and validation
- **Latency**:
  - Challenge: Real-time decision requirements
  - Solution: Edge computing with RSUs
- **Scalability**:
  - Challenge: City-wide deployment
  - Solution: Modular zone-based architecture



Overview

Q-Learning for Signal Optimization

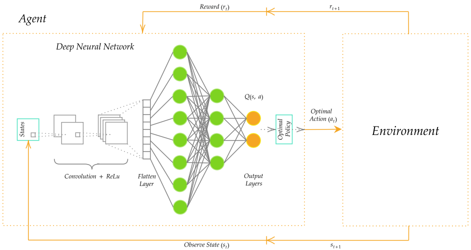
- **Objective**: Minimize cumulative waiting time
- **State Space**: Vehicle counts per lane, signal phase
- **Action Space**: Signal duration adjustments
- **Reward Function**: Negative of waiting time [Olayode et al. (2020)]

Theorem 3.1: Update Rule

$$Q(s,a) \leftarrow Q(s,a) + \alpha[r + \gamma \max_{a'} Q(s',a') - Q(s,a)]$$

Deep Q-Network Design

- **Input Layer**: Traffic state (16 features)
- **Convolutional Layers**:
  - Layer 1: 16 filters (4x4), stride 2, ReLU
  - Layer 2: 32 filters (2x2), stride 1, ReLU
- **Fully Connected Layers**:
  - FC1: 128 units, ReLU
  - FC2: 64 units, ReLU
- **Output Layer**: Q-values for each action
- **Experience Replay**: Stabilizes training [Zhao et al. (2024)]



Overview

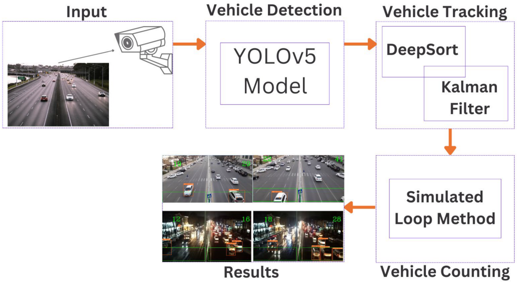
1. Problem Statement
2. IoT Architecture for Urban Intelligence
3. Q-Learning for Signal Optimization
4. Performance Results
   - Synergy of IoT and Q-Learning
   - Conclusion

Performance Results

- **Benchmark Comparison**:
  - Static system: 330k seconds waiting time
  - Our model: 190k seconds (avg), 126k seconds (best)
- **Improvement**: 61.8% reduction in waiting time
- **Key Advantages**:
  - Adapts to real-time traffic conditions [Zhang et al. (2011)]
  - Scalable to complex intersections [Gao and Wang (2021)]

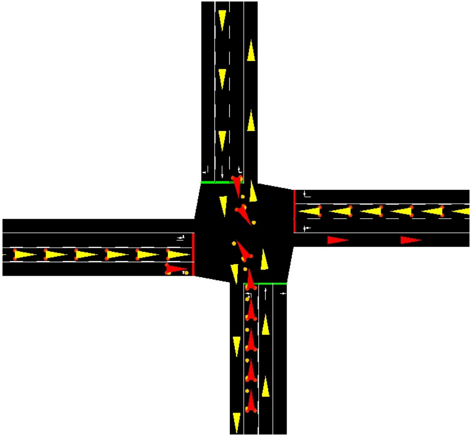
Synergy of IoT and Q-Learning

- **IoT Provides**:
  - Real-time traffic data collection
  - City-wide coordination capability
- **Q-Learning Provides**:
  - Local intersection optimization
  - Adaptive learning without explicit programming
- **Combined Benefit**: Macro-micro control integration



Conclusion

- Demonstrated 61.8% improvement over static systems
- IoT enables real-time monitoring and control
- Q-learning provides adaptive optimization
- Future work:
  - Multi-agent coordination for city-scale deployment [Liang et al. (2022)]



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