FuzzyLight Framework: A Review

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1 Problem Description

Traffic congestion remains a persistent challenge in urban areas, contributing to increased travel time, pollution, and economic inefficiencies. Conventional traffic signal control (TSC) systems rely on predefined timing rules or adaptive strategies using sensor data or expert events. However, these approaches struggle to cope with real-time traffic fluctuations, are unable to optimally manage large traffic volumes, or perform poorly due to sensor inaccuracies. Reinforcement Learning (RL) has recently emerged as a promising solution, but its deployment faces challenges such as unstable learning processes (owing to the need for exploration before convergence), noisy sensor data, and the absence of phase duration decisions (since many recent models focus solely on phase selection).

To address these challenges, the ***FuzzyLight*** *framework is introduced. It enhances TSC by integrating* ***fuzzy logic and RL*** *into a two-stage process that improves robustness to noise while optimizing both phase selection and duration. Unlike existing RL-based TSC systems, which often require extensive real-world training and can produce unsafe decisions during early exploration,* ***FuzzyLight*** *mitigates these risks by leveraging compressed sensing and fuzzy rules, ensuring* ***safe and efficient traffic management*** *across multiple intersections.*

2 Technical Approach

At each intersection, the framework first identifies the number of **incoming lanes**, denoted by

$$L_{in}^{i},$$

and then defines the **phase duration** (i.e., the duration a traffic signal remains green)

$$t_{\text{duration}}.$$

Each intersection is modeled using lane-specific state representations that include:

– **Total number of vehicles per lane**:

$$x(l), \quad l \in L_{in}^{i}.$$

– **Lane segmentation**:

$$x_i(l), \quad \text{where } x_i(l) \text{ represents a segmentation of vehicles on lane } l.$$

– **Queue length**, which tracks the number of vehicles waiting at an intersection:

$$q(l), \quad l \in L^i_{in}.$$

3 Sensor Data Compression

The approach also incorporates sensor data compression to mitigate noise. Compressed sensing is employed to reconstruct the signal from a reduced set of measurements, avoiding the high sampling rate mandated by the traditional Nyquist theorem. This technique is based on the equation

$$y = Ax + h,$$

which is then reformulated as an optimization problem solvable by linear programming—a well-established method in signal processing. This approach efficiently extracts the most critical features from the sensor data while filtering out noise.

4 Reinforcement Learning Model

The problem is formulated as a Markov Decision Process (MDP), where the goal is to maximize the cumulative discounted reward:

$$\sum_{n=0}^{\infty} \gamma^n r_{t+n}.$$

In the **FuzzyLight** framework, a unified RL algorithm is employed to calculate both the optimal traffic signal phase (phase selection) and its corresponding duration (phase duration).

RL-Based Phase Selection and Duration Optimization: The RL agent receives the current state of the intersection—including features such as the number of vehicles per lane, lane segmentation, and queue lengths—as input. Based on this state, the agent outputs an action that comprises two components: the chosen traffic signal phase and the optimal duration for which the phase should be active. The RL algorithm is trained to maximize the cumulative reward, which reflects improvements in traffic throughput, reductions in congestion, and decreases in average waiting times. By jointly optimizing phase selection and duration, the system dynamically adapts to real-time traffic conditions, ensuring smooth transitions and efficient traffic management even in the presence of sensor noise.

5 Study Results

The experiments were conducted using both real-life data and simulated environments. Data were collected from two cities: Hangzou and JiNan.

The **FuzzyLight** approach was evaluated across **22 intersections** in two different cities and was also implemented in real-life traffic control systems. Experimental results demonstrated a **49% increase in traffic efficiency** compared to traditional TSC methods. It also outperformed other RL-only methods, primarily due to its enhanced handling of noise. These improvements were quantified using metrics such as reduced congestion, smoother vehicle flow, and lower average waiting times.

Simulation experiments, conducted on **six real-world datasets**, confirmed that **FuzzyLight** outperforms conventional **fixed-time**, **max-pressure**, and **RL-based** approaches. The improvements were particularly notable during peak traffic hours:

- **City 1:** Throughput increased by **36%**, and the number of stops decreased by **46%**.
- **City 2:** Throughput increased by **24%**, and the number of stops decreased by **38%**.

Even under noise-intensive conditions, **FuzzyLight** maintained performance close to its noise-free baseline, demonstrating **state-of-the-art (SOTA) robustness** compared to models such as **MPLight**, **CoLight**, and **DualLight**.

6 Critical Analysis

The integration of **compressed sensing** and **fuzzy logic** significantly enhances FuzzyLight's decision-making capabilities, offering a reliable alternative to purely RL-based methods. The unified RL approach for phase selection and duration optimization addresses a critical gap in current TSC research.

However, several limitations remain:

1. **Sensor Dependency:**
   While noise resilience is improved, the system still relies on high-quality sensor data. Moreover, sensors have limited range capabilities, which may lead to inaccuracies in traffic estimation. Increasing sensor quality often results in higher costs, making the proposal less feasible for commercial TSC applications.

2. **Computational Complexity:**
   The fusion of fuzzy logic and RL introduces additional computational overhead, which could present challenges for real-time, large-scale deployments.

3. **Adaptability to Rare Events:**
   Although effective under typical conditions, the framework may not adequately handle unexpected disruptions, such as sudden road closures or significant traffic surges, which might still require manual intervention. While RL systems using online learning may eventually adapt, there exists a tradeoff between the allowable margin for error and the resultant slower traffic flow during adaptation.

4. **Extreme Conditions:**
   The paper does not provide a clear analysis of how extreme weather conditions or network failures may affect system performance.

5. **Traffic Pattern Assumptions:**
   The model's reliance on historical data assumes relatively stable traffic patterns. Abrupt, non-repetitive changes in traffic flow could challenge the model's adaptability.

7 Future Research Opportunities

Several avenues for future research could further enhance **FuzzyLight's** capabilities:

1. **Vehicle and Network Communication:**
   Integrating vehicle data into the decision-making process may further improve traffic control and routing, enhancing overall performance.

2. **Multi-Intersection Optimization:**
   Extending the system to optimize a network of intersections collectively—rather than treating each intersection independently—could significantly improve urban traffic management. This integrated approach may help address large-scale congestion problems resulting from urbanization.

3. **Autonomous Safety Mechanisms:**
   Developing automated systems to detect and respond to traffic anomalies could further enhance safety and reduce congestion. Such systems might also detect accidents and facilitate a faster, coordinated emergency response.

4. **Online and Continual Learning:**
   Future work could explore online or continual learning strategies to continuously adapt the models to new data, thereby optimizing performance in dynamic traffic environments.

By addressing these limitations and pursuing the proposed research directions, **FuzzyLight** has the potential to evolve into a **scalable, adaptive, and resilient** traffic control system, transforming urban mobility and paving the way for smarter cities.