Simultaneous Design and Control of Built Environments Using Reinforcement Learning

Background

Designing safe and efficient urban environments remains a critical challenge in urban planning. According to the National Highway Traffic Safety Administration (NHTSA), in 2022, pedestrian fatalities in the United States reached 7,508 deaths—the highest number in 41 years—averaging approximately 21 deaths per day [1, 2]. Of these fatalities, 84% occurred in urban settings, with 76% of deaths occurring on non-intersection locations (such as mid-block crossings and commercial strips) and 24% at intersections [3]. Studies including the Federal Highway Administration (FHWA) have demonstrated that the placement and design of crosswalks significantly influence pedestrian behavior and safety outcomes, with non-compliance with safety rules often directly linked to infrastructure design choices [4]. For example, poorly placed crosswalks frequently lead pedestrians to engage in risky behaviors such as jaywalking rather than walking to designated crossing points. However, addressing this challenge by simply adding more crosswalks can lead to unintended consequences, as excessive crosswalk placement can cause unnecessary vehicle delays, reduce overall traffic throughput, and increase development and maintenance costs. This highlights the competing objectives between pedestrian safety, traffic efficiency, and economic considerations. **Pedestrians want safe, convenient places to cross; drivers want smooth traffic flow with minimal delays; and planners need to ensure that projects are both cost-effective and practical**.

Proposal

I propose a research effort to develop a novel hierarchical reinforcement learning (RL) framework to optimize the design and real-time traffic (vehicle and pedestrian) control in built environments. Recognizing the complex interplay between pedestrian flow, vehicle movement, and broader urban design considerations such as cost, the proposed framework employs a two-stage learning process: a high-level agent designs the placement and size of signalized crosswalks, while a low-level agent learns adaptive traffic control policies given the proposed design. By incorporating real-world pedestrian behavior and traffic demand data into its learning process, this data-driven approach leverages the power of artificial intelligence to move beyond traditional heuristic-based methods, ultimately enhancing the safety, efficiency, and cost-effectiveness of urban spaces. Successful completion of this project will provide traffic engineers and urban planners with a powerful tool to develop optimal design and adaptive signal control strategies in urban settings.

Intellectual Merit

For crosswalk design, urban planners and traffic engineers have traditionally relied on established heuristics derived from fields such as urban planning, civil engineering, and transportation engineering [5, 6, 7], with guidelines specifying requirements like minimum spacing between crosswalks, minimum distances from intersections, and proximity to pedestrian areas to ensure adequate access. While these principles provide valuable starting points, they often leave planners to rely on guesswork when weighing competing priorities from other stakeholders such as vehicles and budget constraints. While on the control side, conventional traffic management systems either use fixed timing that cannot adapt to varying demands (seasonal or throughout the day) or actuated systems that typically prioritize vehicular flow over pedestrian needs, leading to excessive delays and safety risks for pedestrians. Furthermore, these traditional approaches treat design and control as sepa-

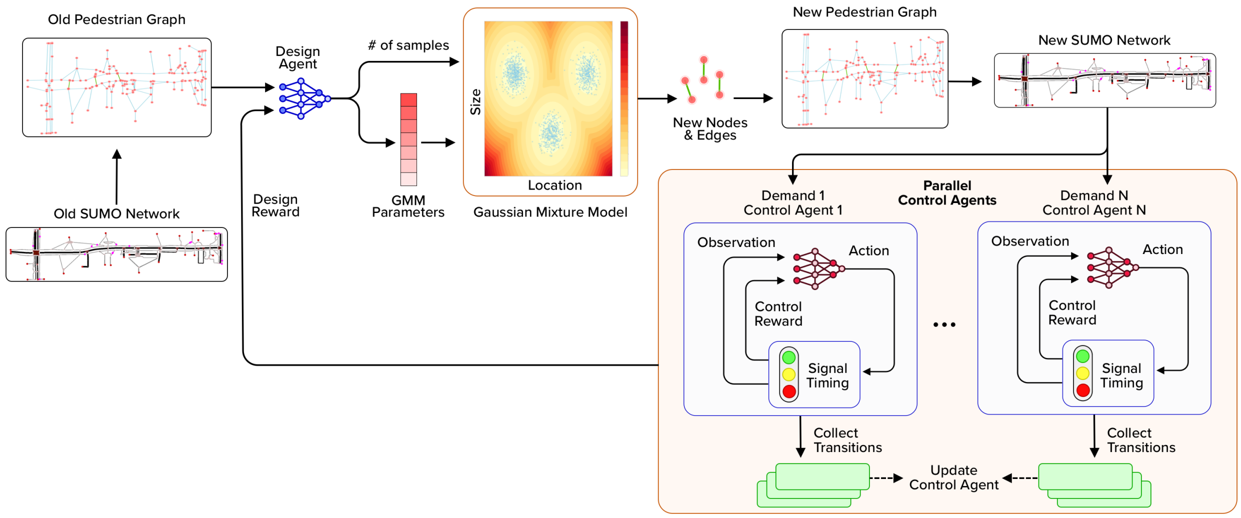

Figure 1: Illustration of the proposed hierarchical two-stage reinforcement learning framework for joint design and control of built environments. The process begins (left) with a real-world roadway-—encompassing both vehicle and pedestrian components—-and its corresponding Simulation of Urban Mobility (SUMO) network. From this network, a pedestrian graph is extracted and provided to the higher level (design) agent, which predicts the parameters of a Gaussian Mixture Model (GMM) to capture the relationships between input graph and optimal crosswalk location and size. The design agent also specifies how many times to sample from the GMM, thereby generating new crosswalk configurations (nodes and edges) and updating the pedestrian graph accordingly. This updated graph is then integrated back into the SUMO network, creating a modified urban environment. In the second stage, multiple low-level (control) agents operate in parallel, each under distinct traffic demand scenarios. While the design agent receives global rewards related to high-level metrics like pedestrian arrival travel time and overall cost, each control agent focuses on local rewards such as vehicle wait times and flow. Both sets of agents learn from their respective reward feedback and continuously adjust the policies until the entire system converges toward a design configuration and control timing that fulfills the required objectives.

rate issues, failing to account for their interconnectedness– a limitation reflected in the alarming rise of pedestrian fatalities. Reinforcement learning offers a promising data-driven alternative by formulating this as a multi-objective optimization problem that can navigate the interdependencies between design and control as well as competing objectives of various stakeholders. The system design is illustrated in Figure 1, where through iterative simulation of various designs and demands, the framework produces an optimized infrastructure design that aligns with actual pedestrian desire lines and an adaptive control strategy that responds dynamically to changing traffic patterns.

Research Plan

Within my Ph.D. research, I have primarily focused on traffic control and coordination [8, 9, 10]. Through this work, I have found that data-driven methods outperform (and offer significant advantages over) traditional approaches in optimizing urban traffic systems. The proposed research will build on this foundation. The research plan is structured into four distinct phases:

Phase 1: Real-world Network Setup and Data Collection: This phase involves establishing a real-world Simulation of Urban Mobility (SUMO) [11] network within a built environment such as a campus or city center. Data on pedestrian trips will be collected using cellular and Wi-Fi signals to capture actual pedestrian movement patterns. Additionally, vehicle traffic data, including turn counts, will be gathered to capture the dynamics of vehicular flow. This data collection is essential for creating an accurate and representative model of the urban traffic environment.

Phase 2: Framework Development and Implementation: In this phase, a bi-level hierarchical reinforcement learning framework will be developed and implemented. The design agent within this framework will utilize a Gaussian Mixture Model (GMM) to propose a variable number of crosswalks in each iteration, determining their optimal locations and sizes. Concurrently, the control agent will learn real-time adaptive control policies for existing traffic signals and crosswalks. The learning process will be executed using algorithms such as Proximal Policy Optimization [12].

Phase 3: Tuning and Training: This phase focuses on hyper-parameter tuning and adjusting various learning-related settings, such as discount factor, learning rate, and the reward function, to optimize the performance of the agents.

Phase 4: Validation and Testing: The final phase involves benchmarking the developed framework against real-world designs using performance metrics such as total vehicle travel time, total pedestrian travel time, queue lengths, and wait times. The framework will also be compared against baselines including human designers and traditional control methods, to assess its effectiveness.

Broader Impacts

This research has the potential to significantly impact urban planning and transportation management by providing a data-driven framework for designing and controlling built environments. The outcomes of this research would lead to several key benefits:
Improved Safety: By optimizing crosswalk placement and traffic signal control, the framework can contribute to reducing pedestrian-vehicle conflicts and improving overall pedestrian safety. This directly helps create safer urban environments, especially for vulnerable populations like children, the elderly, and people with disabilities.
Improved Traffic Efficiency and Reduced Congestion: Optimized designs and adaptive control strategies can minimize travel times, wait times, and queue lengths for both vehicles and pedestrians. This leads to a more efficient transportation system with reduced congestion.
Cost-Effectiveness: The framework provides urban planners and traffic engineers with a powerful tool to explore a wider range of design options and evaluate their cost-effectiveness before implementation. This leads to more informed decision-making, potentially reducing infrastructure costs and maximizing the return on investment for public funds.
Sustainable Urban Development: By optimizing traffic flow (reducing vehicle idling time), the framework can decrease fuel consumption and greenhouse gas emissions from urban transportation. According to the Environmental Protection Agency, the transportation sector accounts for 28% of US greenhouse gas emissions [13], with majority of transportation activities concentrated in cities and urban areas.

The project results will be disseminated through top-tier peer-reviewed publications in transportation and urban planning (IEEE Transactions on ITS, TR_C, Cities), as well as machine learning and robotics venues (ICML, CoRL, RLC, ICRA, and IROS), contributing to the broader scientific community and informing practitioners in the field. The framework and codebase developed during this research will be made publicly available through GitHub, promoting transparency and enabling further research and development in this area.

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