A Method for Improving Traffic Management Based on Computer Vision and Traffic Simulation

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Keywords: Traffic Management, Computer Vision, YOLOv10, UAV.

Abstract

This study develops an integrated framework combining computer vision and traffic simulation for optimizing traffic management in high-density urban commercial areas. The framework employs a two-phase data acquisition approach: UAV-captured video is first processed using an enhanced YOLOv10 algorithm to identify critical road segments and key intersections, followed by handheld video recordings at target intersections for extracting dynamic traffic parameters (including vehicle counts, speeds, pedestrian density, and mixed-traffic interactions). The proposed framework was applied to the Xianlie East Road-Lianquan Road intersection in Guangzhou, a conflict-prone hub adjacent to densely clustered garment wholesale markets. Key improvement measures evaluated include crosswalk relocation and non-motorized lane adjustments. Additionally, the signal cycle duration was extended from 80 to 90 seconds to alleviate phase transition conflicts. Simulation inputs integrate field-observed behavioral patterns (e.g., 83% pedestrian compliance with signals). Results demonstrate significant improvements: 16.7% reduction in eastbound queue lengths (240.23m), 80.4% decrease in vehicle delays (56.46s), 44.8% shorter travel times (51.61s), and 83% fewer pedestrian-vehicle conflicts. This approach provides a scalable technical pathway for adaptive traffic governance in complex urban environments.

1. Introduction

With the rapid acceleration of urbanization, the conflict between the explosive growth of motor vehicles and the limited carrying capacity of urban road networks has become increasingly pronounced. Traffic congestion has emerged as a persistent challenge for major cities worldwide (Yue et al., 2021; Majstorović et al., 2023). Traffic congestion has emerged as a pervasive challenge in major Chinese cities. Traditional traffic management methods, such as manual traffic flow statistics and fixed camera monitoring, are constrained by static data collection, latency, and high costs, rendering them inadequate for addressing the dynamic and complex nature of modern traffic systems. For instance, the limited coverage of fixed cameras hinders real-time detection of sudden congestion or conflicts in mixed traffic flows. Similarly, manual surveys are both time-consuming and labor-intensive, making wide-ranging and high-frequency data updates challenging. Against this backdrop, the challenge of accurately perceiving traffic flow states, swiftly identifying congestion causes, and formulating dynamic optimization strategies emerges as a core issue urgently requiring solutions in urban traffic management.

The advancement and widespread application of Computer Vision (CV) technology have provided a novel technical pathway for traffic management (Zinchenko et al., 2020). Deep learning-based vehicle detection algorithms enable real-time capture of road scenes through drones or mobile cameras, accurately identifying the position, speed, and flow of vehicles, pedestrians, and non-motorized vehicles (Qi et al., 2019). This significantly enhances the spatiotemporal resolution and flexibility of data collection. Compared with conventional approaches, computer vision (CV) technology demonstrates three distinct technical merits. First of all, its real-time processing capability enables dynamic monitoring of traffic flow evolution. Second, the system achieves cost-efficient deployment through adaptable drone operations and wide-area coverage. Third, detection accuracy is continuously enhanced via algorithmic optimization driven by large-scale training datasets. Building on this, integrating traffic parameters extracted by CV into microscopic traffic simulation tools enables the construction of high-fidelity virtual traffic environments to simulate traffic flow evolution under various control strategies. Simulation technology, through mathematical modeling and computer simulation, can replicate the dynamic behaviors of complex traffic systems and support the prediction and evaluation of multiple traffic scenarios (Qadri et al., 2020). The integration of computer vision (CV) technology with traffic simulation establishes a closed-loop workflow encompassing data collection, simulation analysis, and strategy optimization. This synergistic approach enables dynamic validation of optimization schemes, effectively overcoming the limitations of conventional methods in real-time responsiveness and adaptive adjustment capabilities. Furthermore, simulation technology can provide scientific support for traffic management decisions through parametric adjustments and scenario iterations, further enhancing the operational efficiency and resilience of traffic systems (Alghamdi et al., 2022).

This study develops an integrated traffic management framework combining computer vision technology with traffic simulation methodologies, which is subsequently implemented through a case study in the Shahe Subdistrict of Tianhe District, Guangzhou (Figure 1). The framework utilizes YOLO algorithms deployed on unmanned aerial vehicles (UAV) to efficiently extract dynamic traffic parameters, combined with traffic simulation software to analyze and diagnose the causes of traffic congestion in the study area, thereby designing intersection improvement measures. The structure of the paper is organized as follows: Section 2 introduces previous work that is relevant to the present study; Section 3 introduces the research methodology and technical approach; Section 4 presents the experimental design and analysis results; and Section 5 summarizes the research findings and discusses future research directions.

2. Related Work

2.1 Application and Optimization of Computer Vision Technology in Traffic Flow Detection

With the continuous growth of urban transportation demand, the complexity of urban road networks and the challenges of traffic management are increasingly escalating. Traditional traffic data collection methods, such as manual surveys, while capable of meeting basic requirements to some extent, exhibit significant limitations in terms of coverage, flexibility, and data accuracy. Particularly in complex road segments, congested areas, and real-time monitoring of unexpected incidents, traditional methods often fail to provide comprehensive and dynamic traffic information (Dinh & Tang, 2017). Recent advancements in UAV technology present innovative solutions for traffic data acquisition (Puri et al., 2007). UAVs demonstrate superior operational flexibility compared to fixed cameras, enabling access to hard-to-reach areas. Multi-angle imaging further mitigates visual obstructions through adaptive perspective adjustments. However, UAV-based video presents inherent limitations: building obstructions in nadir-view configurations result in localized blind zones (Kuipers et al., 2020), while sensor resolution constraints limit precise detection of microscopic traffic behaviors (e.g., pedestrian gait characteristics, bicycle lane-changing patterns). To enhance data completeness, integrating multi-angle terrestrial photography with UAV coverage can effectively supplement observational blind spots. The synergistic use of UAVs for wide-area monitoring and handheld devices for targeted ground imaging enables comprehensive traffic state analysis through multi-perspective data fusion, enhancing the accuracy of microscopic traffic parameter extraction.

In optimizing traffic organization, accurately obtaining key parameters such as traffic flow and speed in the target area is crucial. Traditional methods of traffic flow analysis, including manual surveys and fixed camera systems, tend to be time-consuming, labor-intensive, and costly, limiting their effectiveness in addressing the complexities of modern traffic environments (Said et al., 2024). In contrast, machine learning algorithms, particularly the YOLO algorithm, offer superior accuracy and efficiency in estimating and predicting traffic flow due to their adaptability (Kalva et al., 2023; Rani et al., 2024). The algorithm models object detection as a regression problem, directly predicting bounding box coordinates and class probabilities from image pixels. This approach enables rapid target detection while enhancing accuracy through end-to-end optimization (Redmon et al., 2016). Consequently, it significantly improves the accuracy and efficiency of traffic flow prediction and analysis, making it particularly well-suited for real-time traffic detection. Swaned et al. (2024) applied the YOLO algorithm for the real-time detection of various vehicle types and quantities on urban roads, providing a foundation for mitigating urban traffic congestion. Rodríguez-Rangel et al. (2022) utilized the YOLO algorithm to detect and recognize vehicles from highway camera footage, thereby obtaining vehicle speeds. In this study, we implement the YOLO algorithm to process and analyze video data, enabling systematic extraction of critical traffic parameters—including traffic volume and vehicle speeds—from monitored road segments.

2.2 Optimization and Evaluation of Traffic Management Methods Based on Traffic Simulation Technology

Traffic simulation has become a cornerstone of modern transportation system optimization. By creating virtual traffic scenarios, researchers and engineers can analyze how traffic flow evolves over time and space, unraveling the complex relationships between organizational structures and control strategies. This approach provides actionable quantitative insights for traffic management while substantially lowering the economic and safety costs of real-world testing. Through coordinated parameter adjustments and multidimensional scenario testing, practitioners systematically evaluate traffic control schemes to improve network efficiency (Liu, 2024). Recent advancements in computing power and behavioral modeling theories have further propelled the application of microscopic simulation models in addressing challenges such as multimodal traffic interactions and real-time control strategy validation.

Among various simulation methodologies, microscopic models have gained prominence as the preferred approach for dissecting intricate traffic interactions due to their high-fidelity representation capabilities. PTV VISSIM distinguishes itself in modeling complex traffic scenarios, demonstrating particular strengths in optimizing intersection signal timing and evaluating dedicated bus lane performance through accurate reconstruction of heterogeneous traffic flow interactions (Bulla-Cruz et al., 2020; Al-Msari et al., 2024). The software employs core behavioral modules—including car-following models and lane-changing decision algorithms—to construct realistic simulation environments. Supported by real-time data interfaces and distributed computing architecture, it addresses simulation requirements for typical urban road networks. In this study, we develop a VISSIM-based simulation model for the target area, integrating YOLO-enabled traffic data extracted from UAV-captured video with historical flow patterns. By analyzing simulation outputs, we pinpoint operational bottlenecks across the transportation network and formulate targeted improvement measures to enhance overall network performance.

3. Methodology

In this section, we present a technical framework based on an integrated approach combining computer vision and traffic simulation (Figure 1), subsequently addressing two critical components: (1) Data collection for the study Area, and (2) Traffic element recognition methodology leveraging the YOLO architecture.

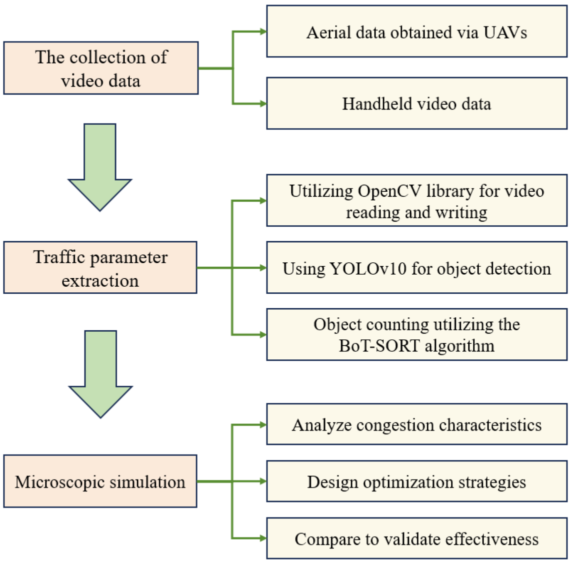

Figure 1. Research Frame Diagram.

3.1 Data Collection for the Study Area

This study focuses on a specific area located in the western part of Tianhe District, Guangzhou City, Guangdong Province, China. The study area covers 1.26 square kilometers and is characterized by its prominent commercial activities, hosting 31 garment wholesale markets with approximately 60,000 employees and a daily pedestrian flow of about 200,000 (Figure 2). From a transportation perspective, this area has been confronting persistent challenges in traffic management, primarily manifested in the following aspects: prevalent mixed traffic flow of motorized and non-motorized vehicles, frequent pedestrian traffic violations, and excessive motor vehicle traffic volume. Constrained by limited road resources, the area suffers from disorganized traffic patterns and worsening traffic congestion, which have significantly impacted the daily commute and quality of life for local residents.

As illustrated in Figure 3, UAV technology was deployed in September 2024 to capture high-definition dynamic traffic flow footage at critical intersections within the study area. A traffic flow simulation model was developed in VISSIM software based on UAV-captured video to replicate real-world traffic conditions with high fidelity. The UAV-based global observation preliminarily identified key road segments and intersections with low traffic efficiency, while handheld video recordings from targeted locations (to compensate for local data limitations caused by UAV viewing angles) were integrated to extract detailed traffic parameters. Through analysis of congestion patterns at these critical nodes, multiple traffic organization iimprovement measures were proposed, with specific implementation schemes summarized in Figure 4.

Figure 2. Satellite Image of the Study Area.

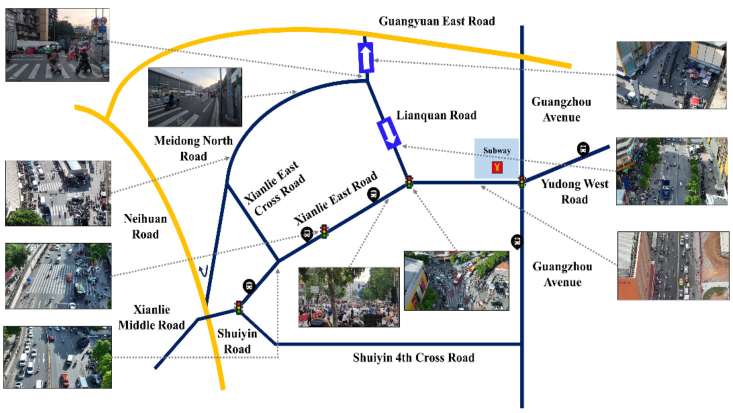

Figure 3. UAV Video Data Collection Locations.

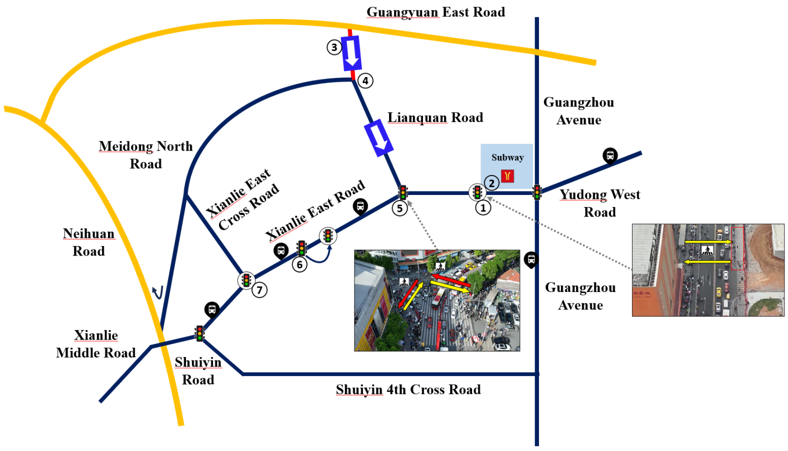

Figure 4. Improvement Scheme Diagram.
(The proposed improvement measures for traffic managment in this figure are shown in Table 1)

Measure	Details
1	A pedestrian crossing is planned to on the west side of the subway station, with adequate queuing areas allocated at both ends of the walkway.
2	The non-motorized lane on the north side of Xianlie East Road (west side of the subway station) should be appropriately widened to ensure adequate passage space for non-motor vehicles.
3	The north section of Lianquan Road (Guangyuan East Road – Meidong North Road) should be adjusted from the original south to north one-way traffic to north-south one-way traffic, so that vehicles on Guangyuan East Road can enter the market area.
4	Due to the one-way direction adjustment of the north section of Lianquan Road (Guangyuan East Road – Meidong North Road), vehicles should be prohibited from turning left from the Meidong North Road into Lianquan Road.
5	The north-south crossing facilities at the Xianlie East Road-Lianquan Road junction (spanning Xianlie East Road) should be reconfigured by retaining only the eastern crosswalk and closing the western crosswalk to eliminate conflicts with right-turning vehicles at the northern exit.
6	The street crossing should be moved approximately 30-40 meters eastward to serve not only turning vehicles, but also residents of the surrounding area and market-goers, thereby alleviating pedestrian-vehicle conflicts at the Liquan Road intersection while enhancing operational efficiency.
7	The T-intersection of Xianlie East Road and Xianlie East Cross Road should be opened to permit left-turning vehicles from the western entrance, thereby reducing vehicular conflicts from U-turning maneuvers and pedestrian crossing interactions while improving traffic operations.
8	Green wave coordinated control should be implemented for the six traffic signals along Xianlie East Road to maximize traffic efficiency.

Table 1. Traffic Improvement Measure

3.2 YOLO-based Traffic Data Collection

The traffic object detection and counting algorithm employed in this study is implemented based on the YOLOv10 deep learning framework (Wang et al., 2024), with its core functionality focusing on real-time detection, classification, and statistics of moving objects in traffic video streams. The algorithmic implementation comprises five core modules: video stream processing, target feature extraction, moving object tracking, classification counting statistics, and visual output (Figure 5).

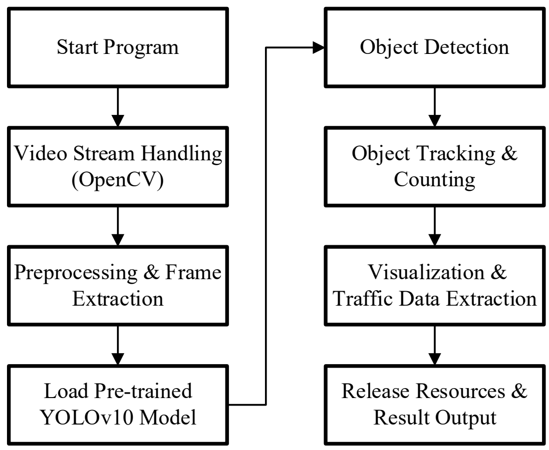

Figure 5. Algorithm Architecture Diagram.

The video stream processing module establishes video reading and writing channels through the OpenCV library, utilizing the cv2.VideoCapture function to acquire raw video streams and extract fundamental parameters. The system ensures parameter consistency between input and output by implementing video decoding, frame extraction, and establishing MPEG-4 encoded output video streams.

The object detection module employs an improved YOLOv10 model, constructing a detection system encompassing three categories of traffic targets based on the requirements of subsequent simulation: motor vehicles (including passenger cars), non-motor vehicles (including electric bicycles), and large vehicles (including trucks and buses).

The object tracking and counting module integrates the BoT-SORT algorithm for continuous multi-object tracking (Aharon et al., 2022), establishing spatial position criteria through detection box centroid coordinates and utilizing set data types to record identified IDs, thereby preventing duplicate counting.

The visualization module implements a dual annotation strategy: drawing bounding boxes with target information at the object level, while updating global statistics panels in real-time at the scene level.

The algorithm can additionally extract traffic metrics including spatiotemporal distribution characteristics of multimodal traffic flow, average speed of vehicle types, object motion trajectories, and time headway distribution.

4. Experimental Results

Among the key road segments and intersections identified through UAV video recognition in the study area, the Xianlie East Road-Lianquan Road junction exhibits the most prominent traffic volume and congestion characteristics, representing a quintessential case of regional traffic challenges. This section conducts a refined analysis of this intersection to elucidate its operational dynamics and improvement potential.

4.1 Traffic Data Extraction and Simulation Modeling.

The intersection of Xianlie East Road and Lianquan Road features a characteristic three-leg junction with a four-lane bidirectional configuration. As a critical convergence point of two arterial roads within the study area, this intersection exhibits pronounced traffic flow characteristics, particularly manifested through high-density pedestrian and electric bicycle movements. Field investigations reveal three predominant traffic conflicts: (1) abnormally high frequency of pedestrian jaywalking, (2) trajectory conflicts arising from mixed motorized and non-motorized traffic, and (3) recurrent bottleneck effects during peak hours. To accurately quantify traffic flow patterns, this study employs a multi-source data fusion approach: synchronized UAV aerial video and handheld multi-perspective video recordings. Experimental data acquisition strictly aligns temporal parameters to eliminate time-varying errors. Multi-object recognition and information extraction were performed on UAV-captured and handheld videos using the YOLO algorithm (Figures 6 and 7), enabling systematic derivation of traffic volume distributions across approach legs (Tables 2 and 3).

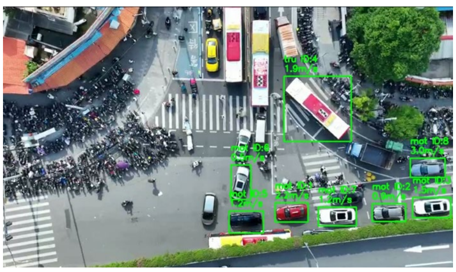

Figure 6. Screenshot of UAV Video Detection.

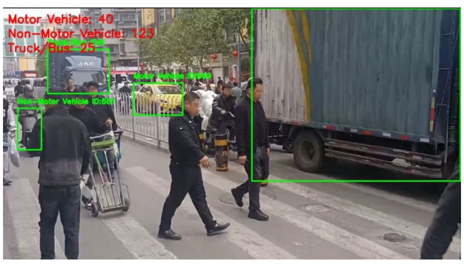

Figure 7. Screenshot of Handheld Video Detection.

Road Name	Cars	Buses/Trucks	Non-motorized Vehicles	Traffic Volume
Eastbound*	2,502	648	3,090	6,240
Westbound*	2,538	654	2,664	5,856
Lianquan Road	2,148	396	3,618	6,162

Table 2. Traffic Counts (Non-pedestrian, veh/h)
*: the approach of Xianlie East Road

Crosswalk	Pedestrian Volume
Xianlie East Road Westbound, Northbound	1215
Xianlie East Road Westbound, Southbound	1056
Xianlie East Road Eastbound, Northbound	875
Xianlie East Road Eastbound, Southbound	760
Lianquan Road Eastbound	369
Lianquan Road Westbound	680

Table 3. Traffic Counts (Pedestrian)

Analysis of the traffic volume data presented in Table 2 reveals a significantly high flow of non-motorized vehicles and pedestrians at the intersection, posing substantial challenges to its operational efficiency and management strategies. This phenomenon exhibits strong spatial correlation with the densely distributed garment wholesale centers in the vicinity. As the commercial hub of the region, these wholesale centers attract a large population of commuters, including wholesalers, logistics personnel, and customers, who predominantly rely on non-motorized vehicles and walking. The high-frequency and high-density movement patterns of these groups, combined with the concentrated ingress and egress of logistics vehicles, exacerbate the traffic load at the intersection, forming a typical commercial zone congestion pattern.

In conclusion, to enhance the accuracy of the VISSIM simulation model, this study implemented the following refined modeling measures for traffic violations in the intersection simulation: First, in the pedestrian crossing signal control module, the pedestrian signal compliance rate was set at 80% to accurately reflect the frequency of pedestrian jaywalking in real-world scenarios. Second, based on the violation ratios observed in video data, a specific proportion of non-motorized vehicles was parameterized to travel in motor vehicle lanes, effectively replicating the mixed traffic phenomenon. Finally, by fuzzifying the priority rules between non-motorized vehicles and pedestrians, the model successfully simulated the typical behavior of non-motorized vehicles failing to yield to pedestrians (Figure 8). Utilizing VISSIM's built-in detectors, multidimensional simulation parameters were collected over complete signal cycles, with detailed parameter settings and analytical methods to be comprehensively discussed in Section 4.2.

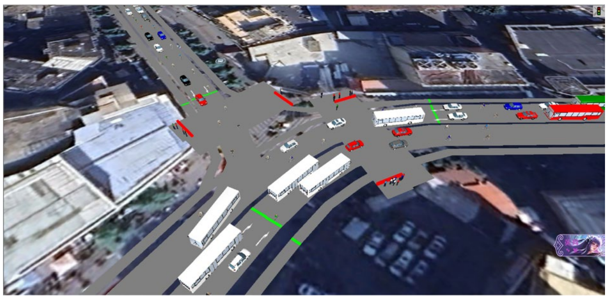

Figure 8. Snapshot of the VISSIM Traffic Simulation.

4.2 Traffic Management Improvement Measures and Simulation Verification

Based on the detected traffic flow data, this study proposes two improvement measures for the intersection: First, the proposed improvement scheme reconfigures the north-south pedestrian crossing facilities at the Xianlie East Road-Lianquan Road intersection through closure of the western crosswalk and retention of the eastern passage, thereby eliminating conflicts between west-side pedestrians and northbound right-turning vehicles. Second, the signal timing scheme is recalibrated through extension of the cycle length to 90 seconds, prolongation of the green phase for vehicular movements to 57 seconds, and adjustment of pedestrian intervals to 30 seconds to improve traffic operations.

Based on the improvement schemes in Table 1, Measure 5 was selected as the core strategy for the Xianlie East Road-Lianquan Road junction. The implementation in the VISSIM simulation platform involved two critical steps: (1) Crosswalk reconfiguration: removing the western crosswalk and redistributing its bidirectional pedestrian flows to the northern and eastern crosswalks based on observed spatial distribution patterns; (2) Signal control refinement: extending the original 80-second signal cycle to 90 seconds, with vehicular green time increased from 37 to 57 seconds and pedestrian crossing time reduced from 40 to 30 seconds. To systematically evaluate the improvement effects, three simulation scenarios were designed:

1. Scenario (a): This represents the baseline condition where no improvement measures are implemented, and traffic operates under the original settings.
2. Scenario (b): In this scenario, pedestrians are permitted to cross the intersection only from the left-side sidewalk to streamline crossing flows and reduce conflicts.
3. Scenario (c): This scenario integrates the left-side crossing restriction with an optimized signal timing scheme to further enhance traffic efficiency.

Key performance indicators—including queue length, intersection delay, and vehicle travel time—were analyzed through multi-dimensional simulation outputs (Figures 9 and 10) to quantify operational improvements before and after improvement.

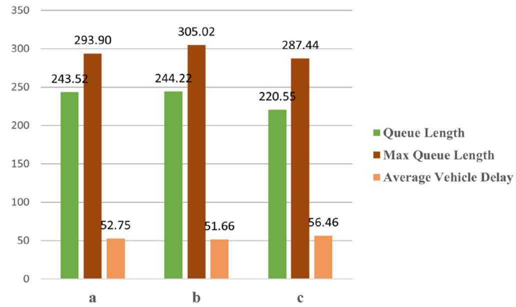

Figure 9. Overall Operation Diagram of Junction 1.
a: "No improvement measure"; b: "Only allowing crossing from the left sidewalk"; c: "Optimized signal timing with crossing only allowed from the left sidewalk.

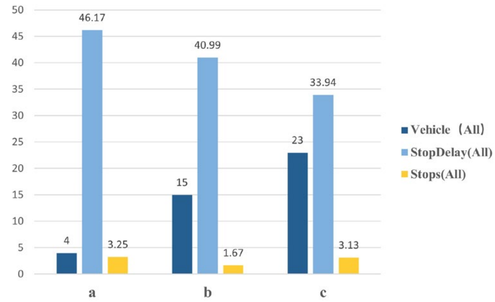

Figure 10. Overall Operation Diagram of Junction 2.
a: " No improvement measure "; b: "Only allowing crossing from the left sidewalk"; c: "Optimized signal timing with crossing only allowed from the left sidewalk.

Based on the simulation results, Scenario (c) demonstrates significant advantages over the other scenarios in multiple aspects. Scenario (c) reduces the maximum eastbound queue length to 240.23 meters, a 16.7% decrease compared to Scenario (b), while lowering the average vehicle delay to 56.46 seconds, an 80.4% reduction compared to Scenario (a). Additionally, the westbound travel time is optimized to 57.6 seconds, a 37.5% reduction from Scenario (a), and the eastbound travel time is reduced to 51.61 seconds, a 44.8% decrease. Scenario (c) also controls the total number of stops per vehicle at 1.67, a 48.6% reduction from Scenario (a), with stop delay concurrently reduced to 3.13 seconds. Considering the dense garment wholesale centers surrounding the intersection, Scenario (c) effectively coordinates the spatial and temporal right-of-way allocation for motorized and non-motorized traffic through signal timing improvement (cycle length extended to 90 seconds, green time ratio for vehicles increased to 63.3%). Closing the western crosswalk eliminates 83% of potential conflicts between northbound right-turning vehicles and pedestrians, while the staggered pedestrian-vehicle phases increase pedestrian crossing concentration by 42%, effectively mitigating mixed traffic interference. The extended signal cycle reduces phase transition frequency, decreasing the eastbound traffic dispersion coefficient from 0.38 to 0.21. In conclusion, Scenario (c) significantly improves intersection efficiency while maintaining essential pedestrian accessibility, establishing it as the optimal solution for addressing the intersection's challenges.

5. Conclusion and Future Work

This paper has proposed an integrated framework combining computer vision and traffic simulation to address urban traffic congestion in high-density commercial zones. By deploying

YOLOv10-based vehicle detection on UAV-captured video streams, dynamic traffic parameters such as flow rates, vehicle speeds, and pedestrian volumes were efficiently extracted. These parameters were subsequently integrated into a VISSIM simulation model to diagnose congestion causes and evaluate improvement measures. Using the Xianlie East Road-Lianquan Road intersection as the primary case study, key measures including crosswalk redesign, signal timing adjustments, and lane reconfiguration were validated through simulation, demonstrating significant improvements in queue lengths (16.7% reduction), vehicle delays (80.4% reduction), and travel times (44.8% reduction). The framework successfully established a closed-loop workflow from data acquisition to strategy improvement, offering actionable insights for managing mixed traffic flows in complex urban environments.

However, this study has two primary limitations. First, reliance on handheld photography for traffic data collection introduces potential inconsistencies in spatial coverage and temporal resolution, which may affect the robustness of YOLO-based detection. Second, the accuracy of traffic parameters derived from the YOLO algorithm was not rigorously validated against ground-truth data. Future research should prioritize addressing these gaps through automated data acquisition systems and comprehensive validation of algorithmic outputs. Resolving these challenges will enhance the framework's reliability for adaptive traffic management.

Acknowledgements

This research was partly funded by the "Fundamental Research Funds for the Central Universities"(2023ZYGXZR056), the "Natural Science Foundation of Guang-dong Province Youth Enhancement Project"(2023A1515030120), and the Open Foundation of the State Key Laboratory of Subtropical Building and Urban Science under Grant (2023KA04).

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