Towards Effective Traffic Signal Safety and Optimization Using Fisheye Video

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Abstract: Most traffic authorities across the US usually collect high-resolution (10 Hz) loop detector and signal state data and video data. The multiple modalities of data that are readily available can be utilized for better traffic operations management and improving safety. In this work, we show that the fusion of widely deployed loop detector data with trajectory information collected through video cameras can augment intersection safety and operational efficiency analysis. The additional information that can be extracted from the object's (vehicle and pedestrian) trajectory derived from video data when fused with signal state data leads to several interesting safety analyses. Data analysis shows a significant variance in turn-movement counts, pedestrian behaviors, vehicle composition, etc., temporally (hour-of-day, day-of-week, etc.) and spatially (approach-wise). We present a simulation-based approach for customizing signal timing plans based on the traffic behavior at the intersections at various times. When used to drive simulations in demand generation, we show that the fused data calibrating the simulation parameters can lead to potential improvements in existing signal timing plans that match reality and can greatly help improve intersection safety and operational efficiency by providing planners with data-driven insights.

1 INTRODUCTION

With rapid urbanization ocurring worldwide, the growing volume of vehicles and increasing complexity of road networks have led to problems such as congestion, traffic jams, and traffic incidents (Rao and Rao, 2012; Carson et al., 2010). These have been shown to affect productivity in a negative way and also the local economy(Weisbrod et al., 2003), societal well-being (Levy et al., 2010), and the environment (Zhang and Batterman, 2013). Therefore, the smooth flow of traffic and safety are important concerns for traffic authorities.

Intelligent Transportation Systems is (ITS) a fast-growing field (Alam et al., 2016; Borgi et al., 2017) and some commonly seen aspects of ITS (Gordon, 2016) include:

- Use of microprocessor-based traffic signals that are "coordinated" to optimize traffic flow across a corridor. These use embedded road sensors to relay vehicle detection counts
- Collection and storage of high-resolution (10 Hz) induction loop detector actuations along with detailed signal state information, as well as visualization of derived metrics called Automated Traffic Signal Performance Measures[1]
- Use of video cameras (with computer vision processing) at intersections to detect traffic signal violations, vehicle tracking, queue length estimation, etc.

Most traffic authorities across the United States of America usually collect high-resolution (10 Hz) loop detectors and signal state data (Figure 1). However, there are significant drawbacks, such as the inability to collect precise trajectory information, turn-movement counts, pedestrian walking behaviors, etc. We focus on using data obtained from fisheye lens

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[1] Link: atspm.cflsmartroads.com/ATSPM/

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SignalID	Timestamp	EventCode	EventParam
1490	2018-08-01 00:00:00.000100	82	3
1490	2018-08-01 00:00:00.000300	82	8
1490	2018-08-01 00:00:00.000300	0	2
1490	2018-08-01 00:00:00.000300	0	6
1490	2018-08-01 00:00:00.000300	46	1
1490	2018-08-01 00:00:00.000300	46	2
1490	2018-08-01 00:00:00.000300	46	3

Figure 1: A sample of high-resolution loop detector and signal state data.

	Pre-existing ATSPM	Fisheye Video
a. Granular vehicle flow information	●	●
b. Granular turning-movement counts		●
c. Accurate pedestrian demand, clearance, safety		●
d. Heavy Vehicles (Delivery Trucks, Buses)		●
e. Trajectory, speed, acceleration/deceleration profiles		●
f. Phase-wise vehicle composition and length information		●

Figure 2: Table showing the benefits of using fisheye lens video data compared to the pre-existing high-resolution loop detector and signal state data.

cameras, which can mitigate some of these deficiencies.

As shown in Figure 2, items ‘ a’ and ‘b’ help compute descriptive statistics of the overall intersection dynamics. Items ‘c’ and ‘d’ are vital for intersection safety, whereas ‘a’,‘b’, ‘c’, ‘d’, ‘e’, and ‘f’ are essential for building an accurate, calibrated simulation model for signal timing optimization.

The collection, processing, and application of information extracted from fisheye video data can be effectively augmented with high-resolution loop detectors and signal state data for applications in safety analyses and improving traffic operations. The additional information that can be extracted from a user’s (vehicle or pedestrian) trajectory, such as speed profiles, vehicle-to-vehicle interactions, vehicle-to-pedestrian interactions, abrupt braking, etc., can be helpful to qualitatively and quantitatively understand intersection safety. Also, this information when combined with signal state data can lead to further interesting analysis, such as red-light violations, vehicle movements during red clearance intervals, etc.

The use of microscopic simulation to understand intersection dynamics, including the impact of different signal timing plans, is quite common. In order to ensure that the traffic flow dynamics in a simulator align with real-world observations, incorporating real-world data into simulations for demand generation and calibration of simulation parameters is a crucial aspect. The controller log data can be used to obtain granular vehicle flow data in the simulator. However, video data can provide accurate turning movement counts (especially for combined turn lanes such as through-right turning lanes), vehicle compositions, speed/acceleration profiles, accurate pedestrian demand, and walking speeds. These can be used to fine-tune and calibrate the simulation and thus make it more realistic.

Using data collected from real traffic intersections, we show that potential improvements in the existing signal timing can be made using controller log data and additional information from video data.

We have deployed a fisheye video collection system at a vital intersection in a dense urban region with time-varying vehicular and pedestrian traffic. We have processed the video obtained and extracted trajectory information for vehicles and pedestrians. Our data analysis shows a significant variance in turn-movement counts, pedestrian behaviors, vehicle composition, etc., temporally (hour-of-day, day-of-week, etc.) and spatially (approach-wise). Such analysis can significantly help improve intersection safety and operational efficiency by providing planners with data-driven insights. The overall system flowchart is presented in Figure 3. The main contributions of the paper are as follows:

- We quantitatively and qualitatively present safety analyses at an intersection by fusing controller log data with trajectory information obtained through video cameras.
- We present a simulation-based approach for customizing signal timing plans at an intersection at various times. When used to drive simulations, the fused data can lead to potential improvements in existing signal timing plans that match reality.

The rest of the paper is organized as follows. Section 2 discusses the background information. Section 3 presents the details of our field implementation. We also review the data obtained and present some descriptive statistics. We describe the application of the data obtained to intersection safety in Section 4 and signal timing optimization in Section 5. We conclude and present future work in Section 6.

2 BACKGROUND

We now discuss the data collection methodology and the simulation software.

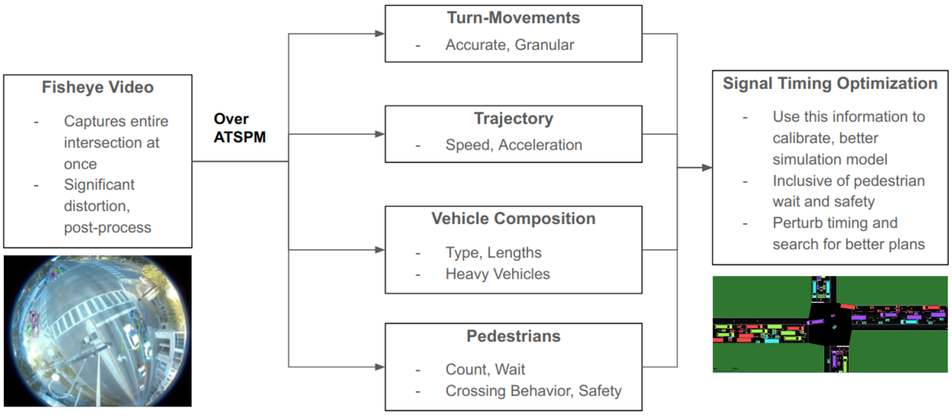


Figure 3: Flowchart showing the workflow for using fisheye video data to improve safety and signal timing of an intersection using a traffic microsimulation framework. Fisheye video data provides vital information on different aspects of the intersection dynamics, which can then be used to improve modeling.

2.1 Fisheye Lens Camera Data: Collection and Processing

A fisheye lens is a type of camera lens that produces a distortion that allows for an ultra-wide-angle field of view, often 100 to 180 degrees. This allows a single camera to capture a much larger scene than regular camera lenses. Such lenses are often paired with video cameras to record the dynamics of traffic intersections. Additional video processing techniques are required to perform object-tracking in such distorted videos.

While computer vision using regular non-distorted video data at traffic intersections is well-explored (Mondal et al., 2019; Buch et al., 2011; Santhosh et al., 2020), there needs to be more research using fisheye video data. (Huang et al., 2020) uses an integrated two-stream convolutional networks architecture that performs real-time detection, tracking, and near-accident detection of different road users (pedestrains and vehicles) in traffic video from a fisheye lens camera; (Yeh et al., 2020) details a system for automatically identifying and tracking vehicles and processing their trajectories; (Chen et al., 2021) describes a visualization tool for analyzing trajectories from fisheye video data; (Zhao et al., 2021) discusses a system for pedestrian detection and re-identification.

In our video processing pipeline based on (Chen et al., 2021; Huang et al., 2020), raw video data from the fisheye lens was processed, and trajectory information of vehicles and pedestrians was obtained. Object detection was done using YOLOV4(Bochkovskiy et al., 2020) Deep Neural Network, and multiple-object tracking was built upon Deep SORT(Wojke et al., 2017). Camera calibration was performed, and landmark points were mapped from the fisheye camera image of the intersection to the top-view satellite map image of the intersection. Thin-Plate Spline (Bookstein, 1989; Chui and Rangarajan, 2000) was used as the basis function for coordinate mappings from the reference to the target. Thus, object trajectories seen in the fisheye videos were projected onto the satellite map of the intersection. Outlier detection and smoothing techniques were used to stabilize trajectories. Manual annotation and checking were also performed to get a final accuracy of over 95 percent for detecting vehicles and pedestrians. The details of the performance of the vision processing algorithms can be found in (Chen et al., 2021; Huang et al., 2020).

2.2 Traffic Simulation Software

Traffic simulation frameworks (US DOT FHWA, 2020; DLR, 2020) are computational implementations of traffic models with dynamic components (vehicles, traffic signals, pedestrians, etc.) and static components (road geometry and linkages, etc.). A traffic simulation consists of a traffic scenario with a base map that defines the static features, such as the topology of roads with lanes, junctions that connect these roads, etc. These static components usually remain the same in the short term (i.e., in seconds or minutes). On this base map, dynamic components usually change their states based on predefined behaviors (i.e., cars will change their locations based on their speeds and accelerations, traffic signals will change their light configuration based on the signal plan, etc.). The simulation is started and is allowed to evolve in time. We can thus simulate a variety of base maps and behaviors and estimate different measures of effectiveness (such as queue lengths and travel times).

One such essential simulation software is Simulation of Urban MObility (SUMO) (Lopez et al., 2018). SUMO is an open-source, microscopic, agent-based road traffic simulation package that is designed to handle large road networks. SUMO uses its file formats for traffic networks, but it can import files encoded in other popular formats like OpenStreetMap (OpenStreetMap contributors, 2017), VISSIM (Lownes and Machemehl, 2006) etc. SUMO is implemented in C++ and uses only portable libraries, thus making it lightweight and fast. SUMO is single-threaded, i.e., it uses only one CPU core, but several parallel SUMO processes can be spawned, allowing for parallel simulations.

3 FIELD IMPLEMENTATION AND DESCRIPTIVE STATISTICS

A critical intersection at a major urban center in the United States of America was analyzed for this demonstration. The intersection borders a large university. Several residential complexes and commercial establishments (especially restaurants) in the area give rise to significant pedestrian traffic and vehicular traffic. On the median, a single fisheye video camera is mounted 13 feet (3.96 meters) above the intersection at the southbound approach.

Raw data from the intersection (fisheye video data, high-resolution loop detector, and signal state data) was captured and stored in a cloud database. Three weeks of data, spanning October-November 2021, with time ranges from 6 am to 8 pm, was considered. This time range captures the AM (morning), PM (evening), and midday traffic peaks but also ensures sufficient ambient light for the camera to function. The Major flow (i.e., North-South direction) usually sees higher flows than the Minor flow (i.e., East-West direction), with the Major flow (North-South combined) reaching 1400-1800 vph (vehicles per hour) at peak and Minor flow (East-West combined) reaching 800-1200 vph.

We then analyze the data given the hour-of-day and day-of-week. We look for both variations and similarities. These will help us identify periods where significant pedestrian traffic co-exists with vehicular traffic and also inform us where segmented customized signal timing plans may be needed.

4 APPLICATION TO IMPROVE INTERSECTION SAFETY

Fisheye cameras provide a crucial piece of information: turn-movement counts. This data is challenging to obtain from loop-detector-based ATSPM data without exit detectors. Intersections frequently have lanes that accommodate multiple movements, such as the right-most lane allowing through and right-turning traffic. Fisheye lens tracking can count these vehicles, which loop detectors cannot differentiate. Fisheye data is necessary to analyze direction-wise flows (see Figure 4). In addition, fisheye cameras also allow us to track individual pedestrians. This allows us to estimate the number of pedestrians crossing in various directions. This contrasts with ATSPM data that tracks the number of pedestrian calls but has no way of estimating the actual number of pedestrians (Figure 5, Figure 7). With accurate trajectories of vehicles and pedestrians, it is possible to study, both qualitatively and quantitatively, the safety aspects of the intersection. Visualizations (Figure 4, Figure 5, Figure 7) can help determine overlapping times and directions where vehicles and pedestrians have intersecting trajectories. This can support traffic authorities in modifying intersection signaling (e.g., restricting right turns, etc.) for those times and directions.

Standard safety metrics(Mullakkal Babu et al., 2017) such as Time-To-Collision (TTC) and Post-Encroachment Time (PET) can also be calculated. Our intersection safety research (Banerjee et al., 2022) has involved computing TTC and PET, along with other factors such as speed, deceleration, proximity between conflicting users, to determine severe events. These metrics are solely obtainable from trajectory datasets that are processed through video. In (Mishra et al., 2022), we presented a study that showed how the day of the week and time of day can affect the frequency and severity of events at intersections. This analysis enables us to pinpoint the busiest periods and conflict-prone locations at intersections. The data can then be utilized to evaluate safety countermeasures with minimal disruption to intersection efficiency.

The fisheye video also lets us detect heavy motor vehicles, i.e., large vehicles such as delivery trucks and buses (Figure 6). These large vehicles often have a long braking distance and significant blind spots. Given that this intersection borders the University and has several shopping and eating locations nearby, these large vehicles may pose a safety concern for pedestrians. Their movement can be restricted or rerouted based on such data. Using this information to adjust signal timing plans for transit priority is also

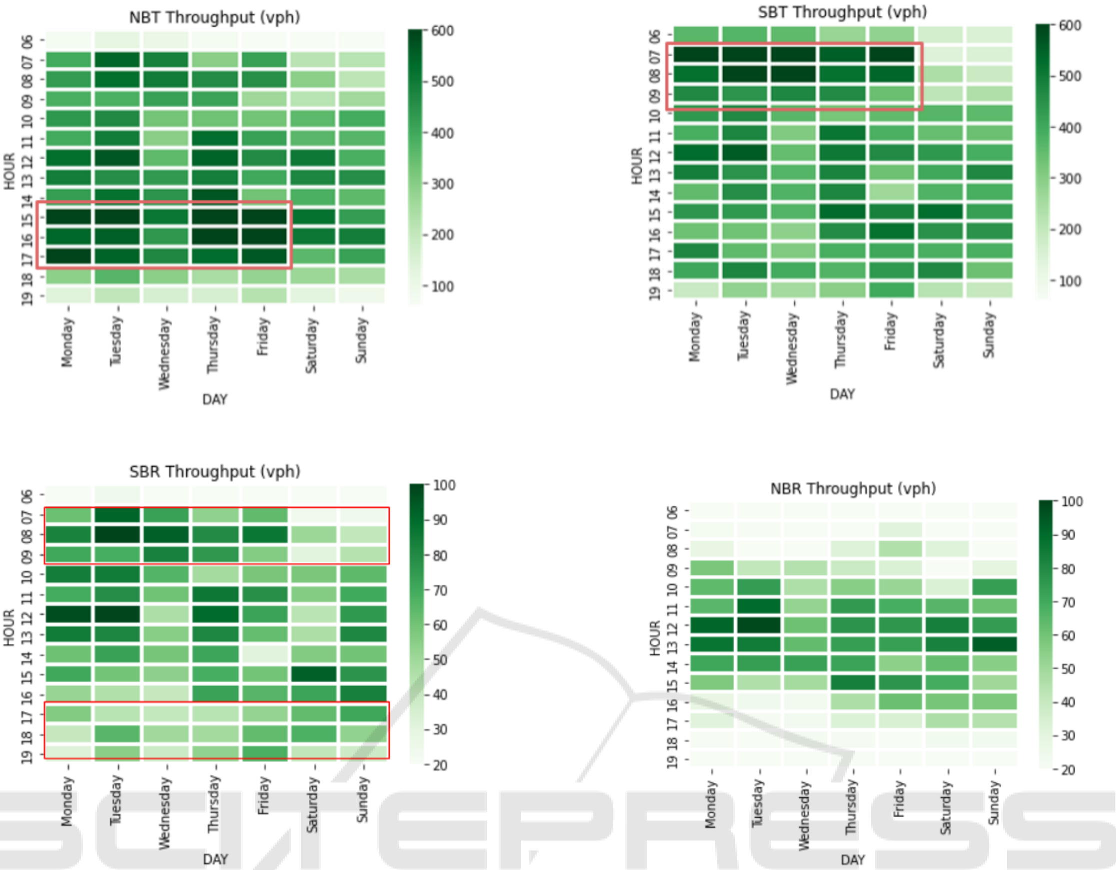


Figure 4: Heatmap showing the intensity of vehicles per hour for various hours of the day across the week. We can see that the Southbound-through direction has a larger AM peak, and the Northbound-through direction sees a larger PM peak. This is likely because the University is south of the intersection, with people coming to work in the morning and leaving in the evening. Similarly, for Southbound-Right and Northbound-Right directions, we can see that both AM and PM peaks for Southbound-Right are larger. Loop detectors do not usually capture right turns as they share the same lane as through movements. Right turns are vital for pedestrian safety, as drivers may neglect pedestrians while focusing on merging at the right turn.

possible. Thus, we have seen the usefulness of fisheye lens camera videos in providing us with statistics and visualizations of various road users, including heavy vehicles and pedestrians. Such analysis can lead to better policy decisions, especially for pedestrian safety.

5 APPLICATION TO SIGNAL TIMING OPTIMIZATION

In this section, we present our efforts in utilizing the fisheye lens camera data for modeling the intersection dynamics in simulation. We can then vary various signal timing parameters to improve performance.

We build a simulation (Figure 9) of the chosen intersection. We then input flows by the cycle with the correct turn-movement counts. We also replicate the effect of pedestrian calls within the ring-and-barrier actuated signal timing plan we have implemented in the simulation. Using bounding box information, we can further calibrate vehicle lengths and types in the simulation.

Significant variations in different aspects of traffic patterns will indicate to us that customized signal timing plans may be required. The similarities across such sections suggest which signal timing plan can be effectively applied in the future. We plot and analyze the weekly traffic throughput in Figure 10. This leads us to identify four crucial stable high-volume traffic patterns:

- Weekday AM peak,
- Weekday midday peak
- Weekday PM peak
- Weekend PM peak

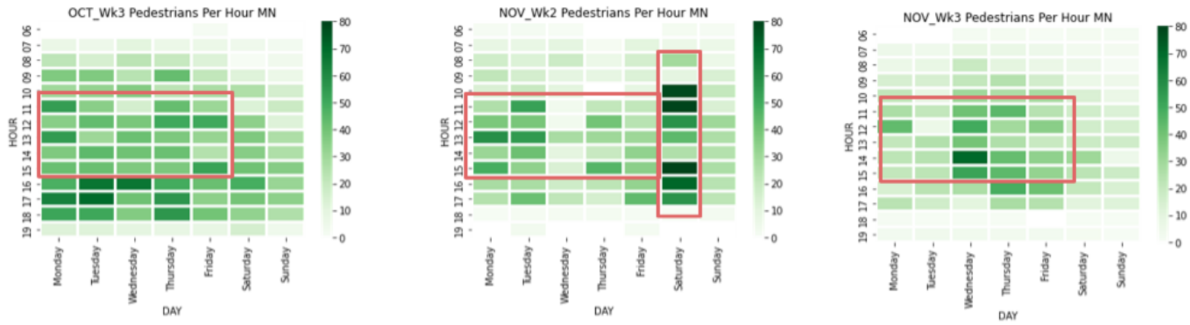


Figure 5: Heatmap showing the intensity of pedestrians per hour for various hours of the day, across three weeks along the Minor Phase (i.e., East-West direction). We see high activity around lunch hours on weekdays. An unusual peak was seen on Saturday in the second week of November. This can be explained due to an important football game that day. Such anomalies can be inferred from this data.

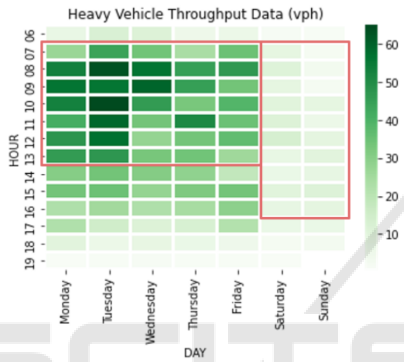


Figure 6: Heatmap showing the intensity of heavy vehicles per hour for various hours of the day across the week. We can see that heavy vehicles are usually limited to weekday mornings. Additional measures, such as restricting right-turns, re-routing, etc., can be put into effect at those times for safety reasons.

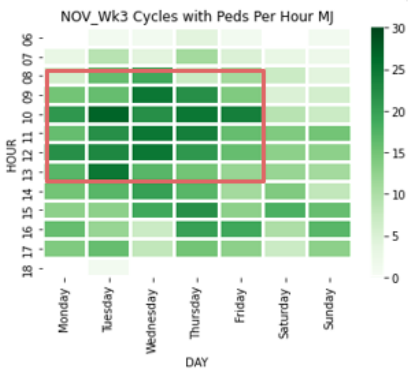


Figure 7: Heatmap showing the number of pedestrian calls per hour for various hours of the day across three weeks along the Major Phase (i.e., North-South direction). We see high activity around lunch hours on weekdays, where almost every cycle has a pedestrian call. Customized signal behavior (turn restrictions etc.) and timing plans can be implemented.

We simulate these scenarios with their respective signal timing plans, vehicle flow patterns, and pedestrian call patterns. We vary the barrier times (separating the major and minor phase rings in the Ring-and-Barrier signal plan) across a reasonable range of values and see the effect on the trade-off between the major and minor phase wait times.

We first see the impact of introducing pedestrian calls (Figure 8) and ignoring them. We can see an apparent effect of including pedestrian calls. Pedestrians require significant time to cross the road (here, 30 seconds) safely. The ring-and-barrier configuration shown, including pedestrian calls within a cycle, ensures lower time for the left-turning phases that precede them (in both major and minor directions). We can see that because this non-negotiable amount of time (here, 30 seconds) must be provided to serve the pedestrian calls, barrier times that previously had acceptable wait times for left-turning traffic are now unacceptable. Hence, these barrier times can no longer be viable when considering pedestrian calls. Thus, the inclusion of pedestrian calls is vital during simulation. We present the simulation results for the four critical traffic times we identified. The ”Major vs. Minor Wait Times wrt. Barrier Time” plots show the trade-off for (75th percentile) wait times of major and minor streets (Figures 11, 12). The ”Major and Minor Throughputs wrt. Barrier Time” plot on the right shows the change in throughput when the barrier time is changed. Thus, it is possible to understand the trade-off between the Major and Minor phase traffic flows in terms of wait times and throughputs (Figures 11, 12). Ideally, we want to lower significant wait times while not massively increasing minor phase wait times and while not lowering the throughput.

WITH PEDS

	MJ-THRU THROUGHPUT	MN-THRU THROUGHPUT	MJ-LEFT THROUGHPUT	MN-LEFT THROUGHPUT	MJ-THRU WAIT 75th PCT	MN-THRU WAIT 75th PCT	MJ-LEFT WAIT 75th PCT	MN-LEFT WAIT 75th PCT	BARRIER TIME		THRU+LEFT TOTAL
0	865	758	174	261	232	19	642	101	40		2058
1	1118	755	258	259	157	29	206	91	50		2390
2	1258	754	300	251	127	38	102	82	60		2563
3	1308	755	308	250	72	48	97	82	70		2621
4	1308	755	309	250	64	59	95	82	80		2622
5	1308	755	308	250	54	68	97	88	90	Present Plan	2621
6	1308	755	309	250	46	81	97	92	100		2622
7	1308	703	309	240	37	170	94	112	110		2560
8	1308	552	309	205	27	296	97	178	120		2374

WITHOUT PEDS

	MJ-THRU THROUGHPUT	MN-THRU THROUGHPUT	MJ-LEFT THROUGHPUT	MN-LEFT THROUGHPUT	MJ-THRU WAIT 75th PCT	MN-THRU WAIT 75th PCT	MJ-LEFT WAIT 75th PCT	MN-LEFT WAIT 75th PCT	BARRIER TIME		THRU+LEFT TOTAL
0	809	757	215	261	301	18	130	101	40		2042
1	1054	754	271	259	196	28	118	94	50		2338
2	1252	755	299	250	128	38	106	84	60		2556
3	1308	755	308	250	72	48	97	82	70		2621
4	1308	755	309	250	64	59	95	82	80		2622
5	1308	755	308	250	54	68	97	88	90	Present Plan	2621
6	1308	755	308	250	46	81	96	93	100		2621
7	1308	697	309	240	37	171	98	128	110		2554
8	1308	507	308	193	27	333	97	142	120		2316

	Phase	Phase		Phase	Phase
Ring 1	1	2		3	4
Ring 2	5	6		7	8
			BARRIER		

Figure 8: Given the ring-and-barrier scheme at this intersection, left turns are affected by the inclusion of pedestrian calls. The ring structure of the signal timing plan is shown at the bottom of the figure. The pedestrians cross parallel to the moving traffic, i.e., left-turning traffic does not interact with pedestrians for safety reasons. Hence, the left-turning phases, i.e., 1/5 and 3/7, get less when pedestrian calls are made since a non-negotiable pedestrian crossing time (here, 30 seconds) must be given. Further, barrier time restricts the total time the half-rings (i.e., major(1/5 and 2/6) and minor(3/7 and 4/8) halves) get. Taking an extreme barrier time of 40 seconds means 2/6 must get at least 30 seconds (when pedestrian calls are considered), leaving just 10 seconds for 1/5. Hence, there is a very high wait time of 642 seconds for left-turning traffic. Had pedestrian calls not been included in the simulation, the same situation would have given us a wait time of 130 seconds. Hence, it is important to include the impact of pedestrian calls while analyzing the trade-off between major and minor street wait times.

Figure 9: Replication of intersection geometry and flows in SUMO simulator. The intersection base map was manually made. The traffic information was automatically extracted and fed to SUMO.

6 CONCLUSION AND FUTURE WORK

Fisheye data provides additional information about the intersection dynamics, such as accurate turn-movement counts and flows, vehicle lengths, and pedestrian information. Unlike regular non-distorted cameras, of which several are required to capture the intersection view, a single fisheye lens camera can be used instead. But there are significant issues due to the fisheye distortion. However, these can be overcome using the latest computer vision and smoothing techniques to yield accurate trajectories, speeds, and acceleration profiles of vehicles and pedestrians.

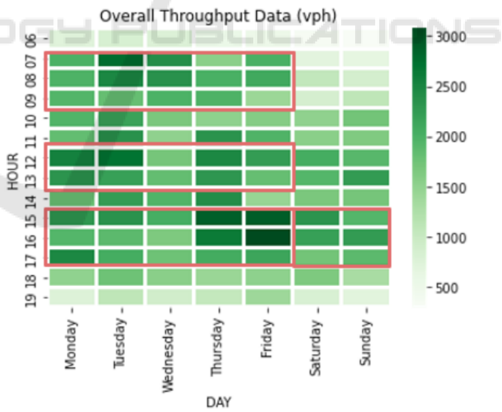
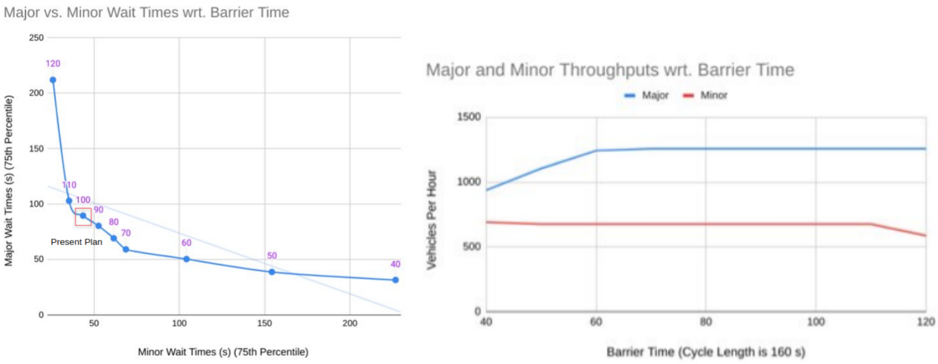
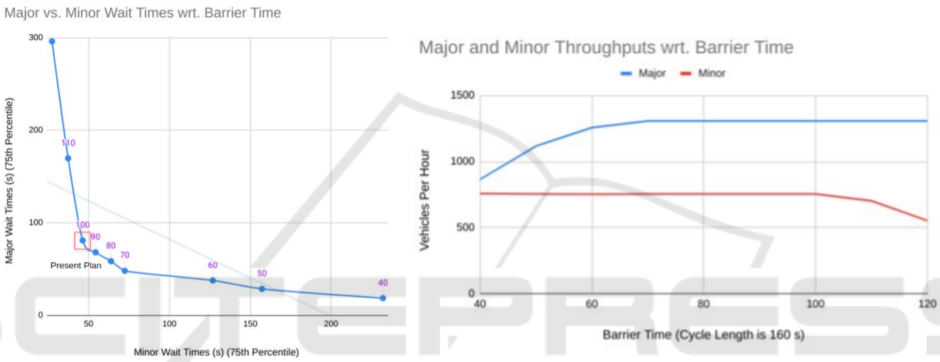


Figure 10: Overall traffic throughput shows four high-volume times for analysis: weekday AM peak, weekday midday peak, weekday PM peak, and weekend PM peak. Efforts can be focused on managing the traffic at these times.

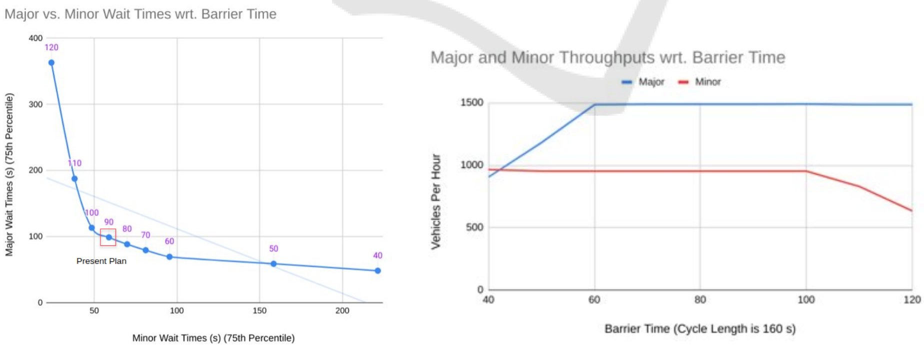
This data fusion with widely available controller log data is valuable to traffic engineers and city authorities, as it provides new insights into traffic (vehicular and pedestrian) behavior and safety. These two data sources augment each other in various ways



(a) Simulations results for Weekday AM Peak. In this scenario, we can see that major phase wait times could be decreased by lowering the barrier time to 70 or 80 seconds, with a relatively small increase in minor phase wait times. The throughput would remain unchanged. Beyond 70 seconds, there would be a massive increase in minor phase wait times, with no appreciable improvement in major wait times.

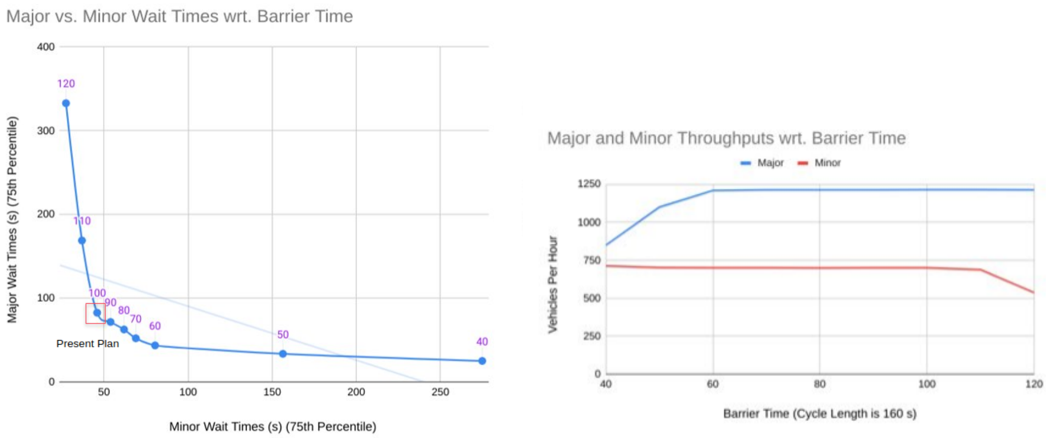


(b) Simulations results for Weekday Midday Peak. In this scenario, we can see that major phase wait times could be decreased by lowering the barrier time to 70 or 80 seconds, with a relatively small increase in minor phase wait times. The throughput would remain unchanged. Beyond 70 seconds, there would be a massive increase in minor phase wait times, with no appreciable improvement in major phase wait times.



(c) Simulations results for Weekday PM Peak. In this scenario, we can see that major phase wait times could be decreased slightly by lowering the barrier time to 60 or 70 seconds, but with a more significant increase in minor phase wait times. The throughput would remain unchanged. Beyond 60 seconds, there would be a massive increase in minor phase wait times, with no appreciable improvement in major phase wait times.

Figure 11: Simulation results for Weekday AM peak, Weekday midday peak, Weekday PM peak.



(a) Simulations results for Weekend PM Peak. In this scenario, we can see that Major phase wait times could be decreased by lowering the barrier time to 60 or 70 seconds, but with a more significant increase in minor phase wait times. The throughput would remain unchanged. Beyond 60 seconds, there would be a massive increase in minor phase wait times, with no appreciable improvement in major phase wait times.

Figure 12: Simulation results for Weekend PM peak.

and, when used together, can be helpful for safety analysis and aid data-driven traffic operations.

In the near future, we intend to build an end-to-end system. It will be capable of supporting multi-camera fisheye data fusion for large intersections. We also plan to fuse other modalities of data, such as trajectory data. The system will fully automate the tasks of cleaning, processing, and visualizing the intersection dynamics and can be easily deployed across several intersections with minimal manual effort.

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