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A Modern Intersection Data Analytics System for Pedestrian and Vehicular Safety

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Abstract— **As a part of road safety initiatives, surrogate road safety approaches have gained popularity due to the rapid advancement of video collection and processing technologies. This paper presents an end-to-end software pipeline for processing traffic videos and running a safety analysis based on surrogate safety measures. We developed algorithms and software to determine trajectory movement and phases that, when combined with signal timing data, enable us to perform accurate event detection and categorization in terms of the type of conflict for both pedestrian-vehicle and vehicle-vehicle interactions. Using this information, we introduce a new surrogate safety measure, "severe event," which is quantified by multiple existing metrics such as time-to-collision (TTC) and post-encroachment time (PET) as recorded in the event, deceleration, and speed. We present an efficient multistage event filtering approach followed by a multi-attribute decision tree algorithm that prunes the extensive set of conflicting interactions to a robust set of severe events. The above pipeline was used to process traffic videos from several intersections in multiple cities to measure and compare pedestrian and vehicle safety. Detailed experimental results are presented to demonstrate the effectiveness of this pipeline.**

I. Introduction

Intersection safety is an active area of research because traffic intersections are prone to crashes. USDOT estimates more than 50% of road crashes leading to fatality or injury happen at or near traffic intersections. Road crashes have been one of the leading causes of death worldwide. With the rapid advancement in technology, many intersections now have video cameras deployed as sensors to monitor these intersections. The videos are streamed over the Web, stored, and processed for safety assessment. Existing intersection safety assessment methodologies often require the analysis of historical data to infer current and future intersection user behavior. Although helpful, these data are often biased to what has been reported, are incomplete, and retrospective. This paper will present our end-to-end intersection safety methodology, starting with processing intersection videos and ending at computing existing and new "surrogate safety measures."

Based on decades of safety research using crash data, it is generally acknowledged that using surrogate measures of safety could provide further insights into enhancing the safety of roadways. These surrogate measures rely on maneuvers (trajectories) of vehicles and pedestrians. By understanding trajectories that could have led to a crash, countermeasures can be developed to reduce or even eliminate such unsafe maneuvers. The most common surrogate safety measure is the "near miss" or the "traffic conflict." Near misses involve a vehicle's trajectory coming "very close" to that of another vehicle or a pedestrian without an actual collision. The proximity of the trajectories is measured on a temporal scale using metrics such as time-to-collision (TTC) [1] and post-encroachment time (PET) [2]. The severity of the near-miss event can be determined based on both the temporal proximity measures (TTC and PET) and the velocities of the vehicles or pedestrians involved. Typically, shorter TTC and PET, combined with higher relative speeds, imply a greater severity of the near miss (i.e., the lesser likelihood of not avoiding the potential crash and higher injury severity had the crash not been avoided). Unlike the case of crashes, there are currently no clear thresholds or categories for classifying near misses by severity. In this paper, we introduce a new surrogate safety measure, "severe event," that includes all near-miss events as well as unsafe behavior exhibited by road users.

While surrogate safety measures offer a great opportunity to understand site-specific and time-specific safety issues and develop countermeasures, a great practical impediment in using surrogate measures for safety analysis is the need to process large volumes of video data to determine trajectories, identify the conflicts in these trajectories, and filter these down to a subset of critical unsafe maneuvers for further analysis. In the context of signalized intersections, it is also necessary to analyze the unsafe maneuvers for the ongoing signal phasing data to identify the appropriate countermeasures. For example, unsafe maneuvers that happen during a *permitted* left-turn phase may suggest the need for a *protected* left-turn phase. Similarly, conflicts between right-turning vehicles and crossing pedestrians may suggest separating the signal phases for these two movements (no right turn on red or leading pedestrian phase). This paper makes several contributions to the field of intersection safety analysis, described as follows:

- The algorithms to decompose pedestrian and vehicle trajectories while fusing signal timing data to derive features useful for safety analysis.
- Introduction of a new surrogate safety measure, severe event, which is quantified by multiple existing metrics such as TTC or PET as recorded in the event, deceleration, and speed.
- Categorization of severe events based on the directional movement of vehicles and/or pedestrian movements and

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phase information. This is then used for relative weighting of severe events (based on the potential for damage) and deriving a weighted average to reflect a comparative safety rating for each intersection. This comparison can also consider the exposure rate (determined by total number of vehicles and pedestrians crossing the intersection).

- An efficient multistage event filtering approach followed by a multi-attribute decision tree approach that subsets the extensive set of conflicting interactions to a robust set of severe events.

We have applied our algorithms to multiple intersections in two different cities. Our extensive results demonstrate the usefulness of the software by exposing key insights into severe conflicts by the day of the week and hour of the day analysis.

The rest of the paper is organized as follows. Section II presents the related work in the field of traffic safety analysis using surrogate safety measures. Section III presents the overall methodology we developed, starting with trajectory generation and computation of features from the trajectories, our strategy of classification of serious conflicts, and the introduction of the new surrogate safety measure, severe event, that we developed as a part of this work. We present a set of event filters that we use to automatically filter out events that are not potentially dangerous. Section IV presents our experimental results, and we conclude in Section V.

II. Related Work

Several surrogate safety measures have been developed relying on physical properties (time, distance, and speed) of vehicle trajectories. Measures such as TTC and PET which are based on temporal proximity of the road users are perhaps the most widely used indicators, especially in the context of intersections, which are the focus of this paper. TTC is the time remaining to avoid a collision, from the time the road user takes an action to the point where the collision can occur [1]. PET is the time difference between the time at which the first road user leaves one point and the time at which the second road user arrives at that same point [2]. Lower values of TTC and PET indicate higher risks of collision. There are several other measures that have been proposed which are based on either spatial proximity or acceleration-deceleration patterns of vehicles [3][4]. A very extensive synthesis of literature on surrogate safety measures was recently provided by Arun et al. [5].

Just as all traffic crashes are not equally severe (some could lead to fatalities while a vast majority are minor crashes with only property damage but no injuries), all temporally proximal interactions among road users need not be "safety-critical" events. Even though Hydén [6] proposed over three decades ago that there is a hierarchy of traffic events varying in severity, Arun et al. [5] note that there is still no consensus on what constitutes a safety-critical event or a near miss.

One approach to identifying the critical events is by applying thresholds on surrogate safety measures. For example, thresholds on TTC range from 1.5 to 3.0 seconds [7-10], while those for PET range from 1.0 to 1.5 sec [11,12]. Broadly, the perception-reaction time of road users (the time taken by a road user to understand a situation and react to it) are considered as benchmarks in determining these thresholds.

Surrogate safety measures primarily reflect the possible interactions (or "events") between road users, and not all of them are critical from the standpoint of safety. Therefore, it is important to distinguish between safer and critical interactions. Safety-critical events are also known as near-misses or sometimes as traffic conflicts, but the definition of a traffic conflict has remained contentious over years [5]. The early definitions of traffic conflicts indicate that only the most extreme of traffic interactions have been considered as safety critical [13]. Hydén [6] proposed that there is a hierarchy of traffic events varying in severity, and Arun et al. [5] note that there is still no consensus on what constitutes a safety-critical event or a near miss.

A second approach to identifying critical conflicts is the "Swedish Traffic Conflict Technique" [14]. This approach considers both the surrogate measure and the speed of the conflicting road users. In general, events representing a combination of lower times to crash and a higher conflict speed are considered more serious events. An example of conflict curves is presented in Fig. 1. Vehicle-vehicle conflicts placed above curve 26 are considered serious while vehicle-pedestrian conflicts placed above curve 24 are considered serious [20].

The determination of surrogate safety measures and critical safety events requires trajectories of road users (vehicles and pedestrians) as inputs. These trajectories may be obtained from traffic simulators or from processing of real-world video data. The Surrogate Safety Assessment Model (SSAM) has been

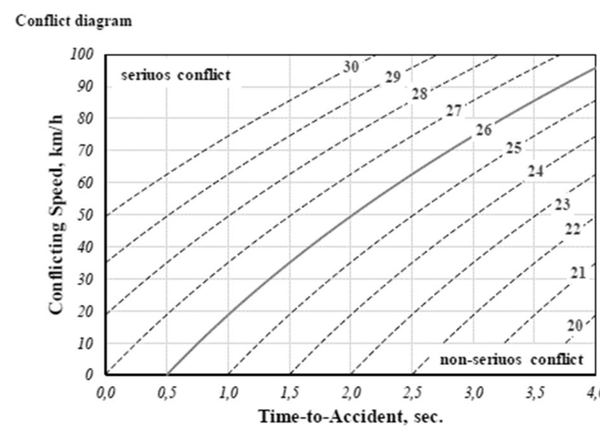

Figure 1. Swedish technique conflict diagram (reproduced from Laureshyn & Várhelyi [14]).

developed as a post-processor to estimate the number and severity of conflicts based on vehicle trajectory data [16][17]. The outputs of SSAM include the number, the type, the severity, and the locations of three types (crossing, lane changing, and rear-end) of simulated conflicts. The conflict type is identified according to the lane and link information or the angle between the two converging vehicles.

Commercial applications for processing trajectory data from videos to determine surrogate measures include those developed by DERQ, AMAG, Currux, and Transoft Solutions. Our paper is closely related to the work in [21], where the authors use video analysis for intersection traffic analysis. The main difference is [21] has not treated pedestrian-vehicle conflicts. Further, only PET was used as a safety indicator. In contrast, we use a holistic approach to compute and use PET and TTC as is appropriate, speed, deceleration, and distance between the road users as active features for severe-event detection. In combination, these features give a deeper insight into the event's nature and get us nearer to the events that are indeed close calls.

III. Methodology

The methodology used for this work is described as follows. Section III.A presents the salient features generated by our software to better qualify the events and their use for safety analysis. Section III.B introduces a new surrogate safety measure, severe event, and describes a categorization scheme for vehicle-vehicle and pedestrian-vehicle events. Section III.C describes a filtering process, which is an event sieve that helps narrow down the events to keep only the most critical events. Finally, Section III.D describes a multi-attribute decision tree approach to isolate high intensity regions in feature space that contain most of the severe events.

A. Generating Features from Trajectories

Trajectories are generated by processing the intersection videos. The safety analysis system takes fisheye video footage as input, then annotates objects with bounding boxes, maps those coordinates from the fisheye image to rectilinear space, and then stores the results in the trajectory table. The object detection and tracking module utilizes YOLOv4 [19] to detect different kinds of road participants, including vehicles, pedestrians, cyclists, and motorcyclists. A modified DeepSORT algorithm is used to associate detections across frames and assign a unique ID for each object. As the trajectories from fisheye videos are usually of unnatural shapes caused by distortion, we perform rectification and alignment to Google Maps images before feeding the trajectories to downstream modules. Our solution for rectification includes two steps: fisheye-to-perspective transformation followed by thin-plate spline (TPS) warping.

Separately, Automated Traffic Signal Performance Measures (ATSPM) data provided by the city are collected, which provides the signal information for each traffic light per intersection over time. These signals are merged with object trajectories, which enables analyses that are concerned with object location and signal states over time, such as signal violations, lingering mid-trajectory, and others. One issue that arises however is the synchronization of city provided signal changes and video-recorded signal changes, which usually vary by a few seconds. A purpose-built computer vision model is trained to output signal states, which is compared to ATSPM signal changes to yield the time delay between video and city data. If a signal is not visible, then the start-up time of a vehicle is used under the assumption that driver reaction time is roughly one and a half seconds, but this time is configurable in the software.

We have computed a comprehensive set of features for every conflict event. A feature in this context is an individual measurable property or characteristic of a conflicting event. The following is a list of the key features that we compute:

1. Standard near-miss attributes: We compute the common risk assessment metrics such as TTC and PET for every event.
2. Signal phase information: The fused video and ATSPM dataset is used to determine features such as the ongoing vehicle signal, ongoing pedestrian signal, and if the event occurs during the beginning, middle, or end of the current signaling phase.
3. Trajectory features: The trajectory-related features are the trajectory's movement, phases, and lanes.
4. Speed features: These include the current speeds and accelerations for vehicle-vehicle interactions.
5. Distance: Spatial distance between two users at the time of the conflict.

B. Categorization of Severe Events

The categorization of the vehicle-vehicle and pedestrian-vehicle conflicts are described in this section.

1) Pedestrian-vehicle (P2V) Events:

The following are the main conflict events between vehicles and pedestrians at signalized intersections:

- Conflict Types 1 and 2: Right-turning vehicle with the pedestrian in an adjacent parallel crosswalk (Fig. 2a) and near-side crosswalk (Fig. 2d), respectively.
- Conflict Types 3 and 4: Left-turning vehicle with the pedestrian in the far-side crosswalk (Fig. 2b) and near-side crosswalk (Fig. 2d), respectively.
- Conflict Types 5 and 6: Through vehicle with pedestrian in the far-side crosswalk (Fig. 2c) and the near-side crosswalk (Fig. 2d) respectively.

Among these conflicts, Conflict Types 1 and 3 are feasible conflicts between pedestrians and vehicles at signalized intersections if all vehicles and pedestrians strictly follow the traffic rules (assuming a three- or four-leg intersection, which are the most common).

2) Vehicle-vehicle (V2V) Events: As the primary purpose of signalization is to reduce or eliminate conflicting movements on the intersection, the following are the feasible conflicts between vehicles at signalized intersections if all vehicles strictly follow the traffic rules (assuming a three- or four-leg intersection, which are the most common):

- Left turn and opposing through (LOT): A left-turning vehicle in a permitted phase conflicts with an opposing through movement (Fig. 2e).
- U-turn and opposing through: A U-turning vehicle in a permitted phase conflicts with an opposing through movement (Fig. 2f).
- Through and right turn (RMT): A right-turning vehicle merging on the same lane as a through vehicle (Fig. 2g).
- U-turn and a following left-turn (UFL): A leading U-turn with a following left-turning vehicle (Fig. 2h).
- Right turn and a following through (RFT): A leading right-turning vehicle with a following through vehicle (Fig. 2i).
- Lane change and adjacent through (LCC): A lane-changing vehicle conflicting with adjacent through (Fig. 2j).
- Rear-end conflicts: A leading vehicle moves slower than the following vehicle on the same lane.
- A U-turn and an adjacent right turn.

If one or more vehicles do not strictly follow the traffic rules (e.g., run the red light), other conflicts are also possible, namely, adjacent through movements and left turn and adjacent through.

Some conflict types may be inherently more dangerous than the other types. For example, the left-turn and opposing through conflicts may lead to a more serious crash than a merging, a diverging, or a rear-end conflict. Further, the left

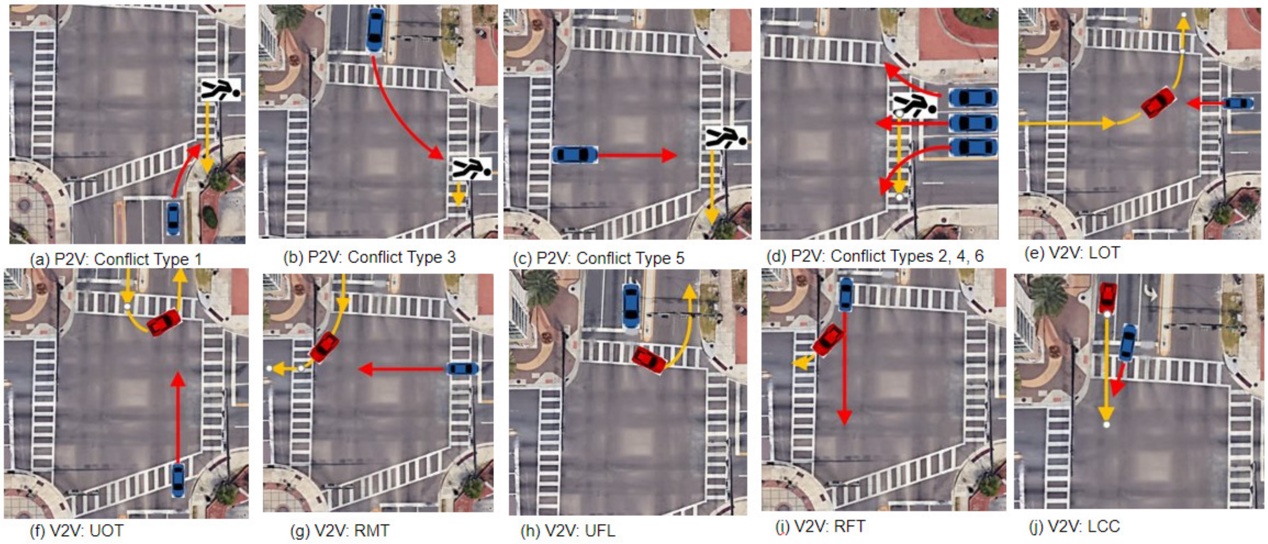

Figure 2. Pedestrian-vehicle (P2V) and vehicle-vehicle (V2V) conflicts at signalized intersections. Some conflicts are infeasible if the road users are strictly following the traffic rules. However, such an assumption is far from reality and in our analysis, we pick up quite a handful of conflicts that happened because the road users did not follow the basic traffic rules.

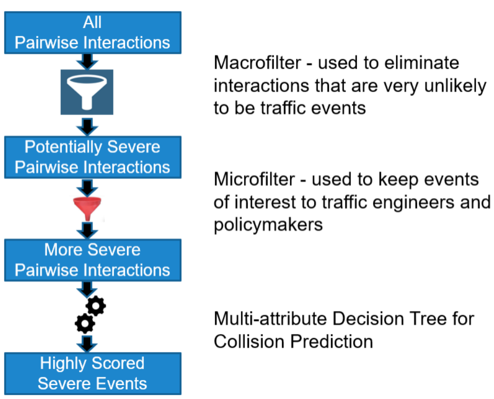

Figure 3. Event filtering sieve. The macrofilter checks for movement phases of conflicting trajectories, the timing, and distance features. The microfilter checks finer aspects such as whether yields were properly given.

turn and opposing through conflict is dangerous when the slow left-turning vehicle is the first one to cross the conflict point. The less dangerous and common occurrence is when the left-turning vehicles yield to the through vehicles before completing the turn.

C. *Event Filtering*

Fig. 3 shows the multistage event filter we employ to prune the set of events. The macrofiltering stage checks the following conditions for two road users who happen to be at the intersection in the same time frame: (1) Are they in a conflicting traffic phase? (2) Is the TTC or PET within a user-defined threshold, say, 10 seconds? (3) Are they spatially within or close to the intersection and within a user-defined threshold, say, 10 meters from each other? and (4) Are both the road users moving?

When all these conditions are satisfied, the event passes through to the microfilter. The first check for vehicle-vehicle interactions in the microfilter is whether an event is recorded more than once from separate TTC and PET computations. If the event did not result in a post-encroachment and there is no corresponding PET, the event must last for more than one decisecond for it to be considered severe. The second check for vehicle-vehicle interactions is whether the vehicles properly yielded to the other as per the traffic rules in case of a conflicting movement. If so, the event is filtered away.

For pedestrian-vehicle interactions, the first check in the microfilter is to find if the pedestrian is violating the pedestrian signal, and if so, the event is considered severe, even if there are no vehicles nearby. Highlighting the behavior allows practitioners to be aware if there is a pattern and adjust signal timing if needed. Suppose the pedestrian follows the signal, yet the event already made it through the macrofilter (indicating a conflicting maneuver), in that case, the microfilter checks if the distance between the pedestrian and the vehicle is 5 meters or less. If so, then the event is considered severe. On the other hand, if the pedestrian is about to enter the crosswalk and the vehicle is close by, the filter checks if the pedestrian's distance is less than 1 meter, and in that case, the event is considered severe.

All the thresholds mentioned in this section are easily configurable by the user based on specific intersection geometry and user characteristics.

Figure 4. Four pedestrian phases, P2, P4, P6, and P8, and the eight vehicle phases, 1, 2, 3, 4, 5, 6, 7, and 8, are shown for University Ave & 13th St.

TABLE 1: DESCRIPTION OF THE SIX INTERSECTIONS THAT WERE THE SUBJECT FOR OUR ANALYSIS, INCLUDING THE LOCATION OF THESE INTERSECTIONS, THEIR SPEED LIMITS ALONG THE MAJOR AND THE MINOR STREETS, TOTAL TRAFFIC OBSERVED OVER A WEEK, THE PERCENTAGE OF PEDESTRIAN TRAFFIC, WHETHER THE INTERSECTION SERVED PROTECTED, PERMISSIVE, OR A COMBINATION OF THE PROTECTED AND PERMISSIVE LEFT.

ID	Intersection	City	Speed Limit (Major/Minor) Mph	Pedestrian Presence (% of total traffic)	Total Volume	Left Turn Type
1	University Ave & 13th St	Gainesville	35/25	18.5	146,133	Protected
2	University Ave & 17th St	Gainesville	25/25	41.8	67,550	Protected/Permissive
3	University Ave & 20th Dr	Gainesville	25/25	2.9	105,590	Protected/Permissive
4	NW 23rd Ave & NW 55th St	Gainesville	45/30	1.6	97,173	Protected/Permissive
5	Post Office & Rhinehart	Orlando	45/45	1.2	61,530	Protected/Permissive
6	Lake Mary & Rhinehart	Orlando	45/45	0.2	55,889	Protected

D. Event Modeling

Although the event filters were efficient in pruning the event set, manually reviewing the filtered videos still constitutes a significant investment of human resources. For this reason, we utilize a simple algorithm to determine high-intensity regions in the feature space for severe events, where these events have been annotated manually. Since the event count after applying the filters is small compared to the total number of features for the events, there is a high chance of over-fitting if a feature space with all the features is considered. So, to determine the high-intensity regions, we use only three features: the speed, acceleration, and TTC or PET, as appropriate for that event. The algorithm plots 2D scatter plots of the events for each pair of features from the three-feature set and then sweeps the 2D space with a straight line to find the best intercept for which the line separates the severe and the non-severe events. The straight-line acts as a separator of the 2D feature space, and we consider several such lines with different slopes to arrive at a near-optimal partitioning. This process is repeated for each of the two partitions if a partition is not purely from one class of events and contains a good mix of severe and non-severe events. In any case, the process is repeated up to a maximum of three levels of recursion. This algorithm could lead to more than one high-intensity region for the same dataset, which once identified, can be conveniently used as a classifier for severe events. An example is presented in the experiments section. Human ratings of events are used to validate the model's predictions.

IV. EXPERIMENTS

We applied our video processing algorithms end-to-end on six different intersections for the first week in November 2021. We collected data between 6 AM and 7 PM for each intersection, so a total of 546 hours of video data were processed using our software and analyzed for intersection safety. Table 1 gives the intersection details. Based on video analysis, Table 1 also presents the total traffic and the percentage of pedestrians versus drivers. Three intersections are on an arterial adjacent to a university (ID: 1, 2, 3), one intersection is adjacent to a high school (ID: 4), and the two other intersections are in a city (ID: 5, 6). Though all these intersections have right-hand-drive traffic, our algorithms can also analyze intersections with left-hand-drive traffic.

We present our results on conflict analysis separately for pedestrians and vehicles in Sections IVA and IVB, respectively. While Table 1 gives an aggregate volume of the total number of pedestrians observed during the study period, we can further disaggregate the pedestrian count by the pedestrian phases and by day of the week and hour of the day. We present this analysis for the intersection of University Ave & 13th Street, but the other intersections may be analyzed similarly. The four pedestrian phases P2, P4, P6, and P8, and the eight vehicle phases, 1–8, for the University Ave & 13th Street intersection are shown in Fig. 4.

Fig. 5 shows the pedestrian volumes for the four pedestrian phases at the University Avenue & 13th Street intersection by day of week and hour of the day. We observe that (i) the volume on phase 4 is the highest, (ii) the volume on a Saturday, November 13, 2021, is the highest because there was a football game at the University stadium on the University Avenue, (iii) the volumes on Monday and Tuesday are higher than the rest of the weekdays, and (iv) this intersection is large, so the pedestrians on the closest crosswalks are the best processed by the video processor. The

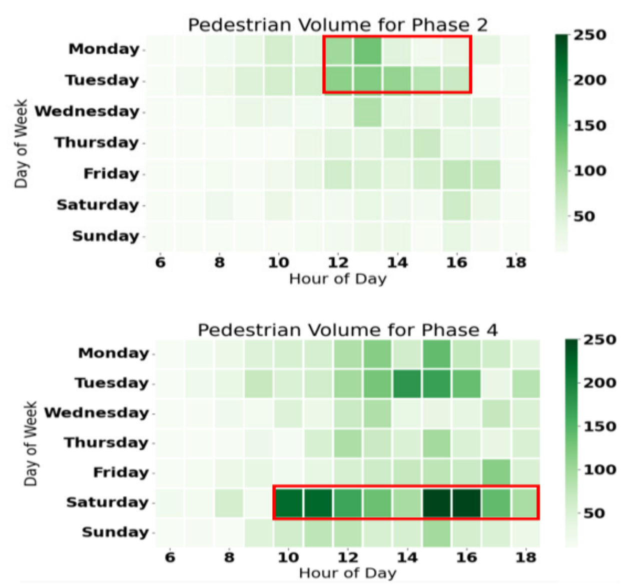

Figure 5. Pedestrian volumes by the four pedestrian phases at the University Avenue & 13th Street intersection. Among the weekdays, Monday and Tuesday are busier at this intersection. On Saturday, November 13, 2021, pedestrian traffic was especially high because of a football game being held at the University Stadium.

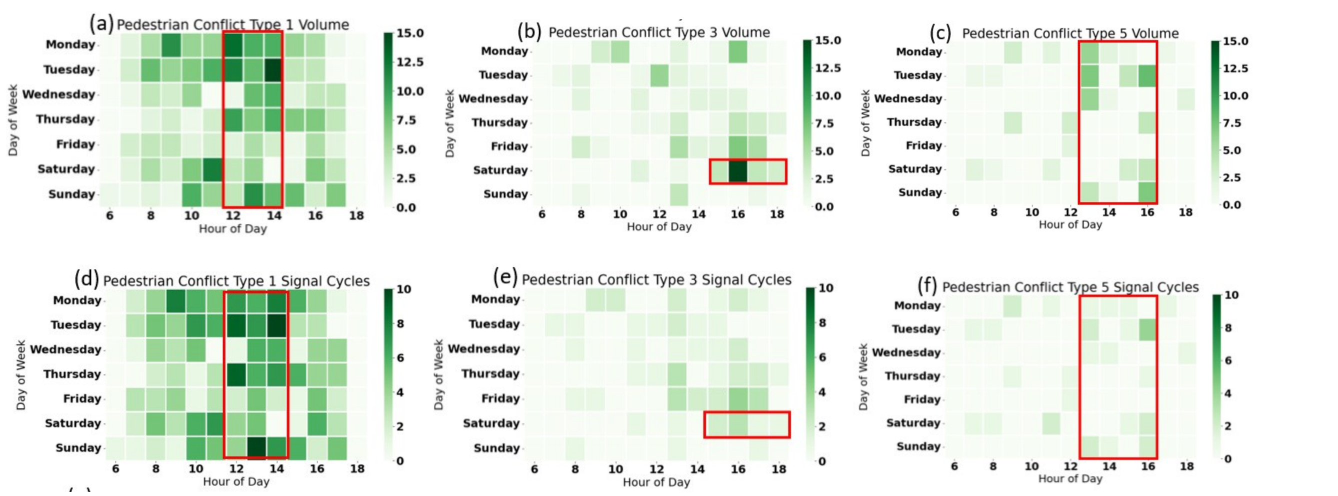

Figure 6. The pedestrian-vehicle conflict events are categorized into six conflict types and counted by day of the week and hour of the day. Figures (a), (b), and (c) give the raw event count for Conflict Types 1, 3, and 5, while figures (d), (e), and (f) give a count of signal cycles with at least one conflict. Conflict Type 1 occurs most frequently and is more likely to happen between 12 and 2 PM. Saturday, November 13, 2021, was a game day, and there was an uptick on the conflict counts from (c). However, these conflicts are clustered and fewer signal cycles are affected as can be seen from (d), Conflict Type 5, which is through vehicle with pedestrian in the far-side crosswalk, a dangerous conflict that happens more frequently during 1–4 PM.

crosswalks may be ordered as phases 4, 2, 6, and 8 by their proximity to the camera.

A. Pedestrian-vehicle Conflict Analysis

Fig. 6 counts pedestrian-vehicle conflicts by the conflict type and conflict cycles on the University Avenue & 13th Street intersection. The conflicts are shown by day of the week and hour of the day. We observe: (i) Conflict Type 1, which is a right-turning vehicle with a pedestrian on the adjacent parallel crosswalk, occurs most frequently; (ii) Conflict Type 1 happens throughout the day but are more likely to happen around 12–2 PM; (iii) Conflict Type 3, which is a left-turning vehicle with a pedestrian on the far-side crosswalk, happens most frequently on game day; (iv) Conflict Type 5, which is a through vehicle with a pedestrian on the far-side crosswalk, a dangerous conflict, happens more frequently during 1–4 PM.

Each conflict type can be analyzed further by the vehicular movements, and Fig. 7 shows a sample of such an analysis. We observe that the afternoons and weekends are when pedestrians are more prone to violate the traffic light and undertake dangerous crossings. We found that for Conflict Type 1, the movements west-bound right (WBR) and south-bound right (SBR) happen most frequently, and these events happen on both weekdays and weekends.

Such detailed analysis of pedestrian-vehicle conflicts could give insights into countermeasures that could lead to reduced conflicts.

B. Vehicle-vehicle Conflict Analysis

Table 2 shows the number of potentially conflicting interactions over a week and the performance of the two-level macro- and microfilters in filtering the events. The events include both vehicle-vehicle and pedestrian-vehicle conflicts. All pedestrian-vehicle events that remain after applying the microfilter are considered severe by default because of the vulnerable nature of pedestrians. We manually verified for vehicle-vehicle events that between 30%–60% of these may be regarded as severe. We further applied our multi-attribute decision tree algorithm for classifying an unseen event automatically as severe or non-severe. The results of this step are presented in the Vehicle-Vehicle Multi-Attribute Decision Tree (V2V MADT) column that further reduces the count of severe events, which then may be quickly evaluated manually for insights into applicable countermeasures. Thus, starting from millions of potential conflict interactions, our filtering scheme reduced the events to a small set of severe events.

Table 3 categorizes the vehicle-vehicle conflict types into the previously defined classes. There were some conflicts that did not belong to any of our defined conflict types. Among the known conflict types, left opposing through is the most severe as it could lead to significant damage to life and property if any of the conflicts results in a collision. The other conflict types

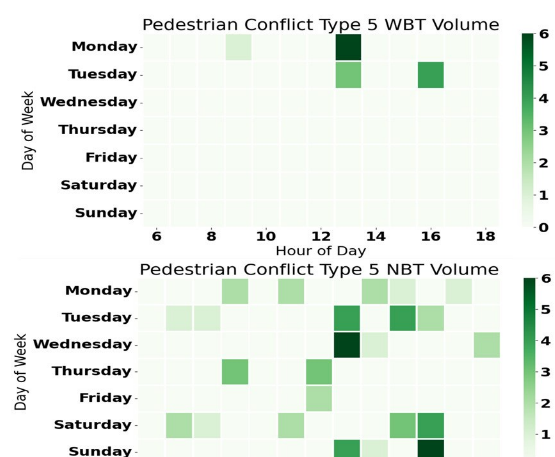

Figure 7. Volume of pedestrian-vehicle Conflict Type 5 by vehicle movement. This conflict type, between a through vehicle and a pedestrian in the far-side crosswalk, is the most dangerous. In almost all these cases, we have watched the video and found that pedestrians are violating their

TABLE 2. TOTAL NUMBER OF POTENTIALLY CONFLICTING INTERACTIONS OVER A WEEK FOR DIFFERENT INTERSECTIONS AND PERFORMANCE OF THE TWO-LEVEL MACRO- AND MICROFILTERS IN FILTERING THE EVENTS TO A HANDFUL FOR FURTHER MANUAL ANALYSIS. THE COLUMN V2V MADT CONTAINS THE EVENT COUNTS AFTER APPLYING OUR MULTI-ATTRIBUTE DECISION TREE ALGORITHM.

Intersection	Conflicts	Macrofilter	Microfilter	P2V Events	V2V	V2V MADT
University Ave & 13th St	1,918,822	5152	888	722	166	125
University Ave & 17th St	459,995	5370	1045	959	86	42
University Ave & 20th Dr	2,247,395	5433	403	259	144	85
NW 23rd Ave & NW 55th St	947,921	5938	217	63	154	112
Post Office & Rhinehart	362,354	344	95	67	28	28
Lake Mary & Rhinehart	1,279,019	956	28	0	28	28

TABLE 3: TOTAL VEHICLE-VEHICLE CONFLICTS BY CONFLICT TYPE AND AGGREGATED AS (I) TOTAL, WHICH IS THE SUM OF ALL CONFLICTS, (II) WEIGHTED, WHICH IS A WEIGHTED TOTAL OF CONFLICTS WITH A WEIGHT OF 4 ASSIGNED TO THE LEFT OPPOSING THROUGH AND 1 TO THE REST OF THE CONFLICTS, BASED ON POTENTIAL SEVERITY OF THE CONFLICT, (III) NORMALIZED, WHICH IS OBTAINED BY DIVIDING THE WEIGHTED CONFLICTS BY THE CORRESPONDING EXPOSURE METRIC, AND MULTIPLYING BY 10,000, TO GIVE THE NUMBER OF WEIGHTED CONFLICTS PER 10,000 VEHICLES MAKING THE SAME MANEUVERS.

Intersection	Left Opposing Through	Right Merging Through	Right Following Through	Rear-End Conflict	Others	Total	Weighted	Normalized
University Ave & 13th St	15	2	37	28	84	166	211	24
University Ave & 17th St	33	2	15	9	27	86	185	21
University Ave & 20th Dr	91	5	9	3	36	144	417	62
NW 23rd Ave & NW 55th	73	6	22	6	47	154	373	43
Post Office & Rhinehart	12	0	7	1	8	28	64	15
Lake Mary & Rhinehart	1	1	0	2	24	28	31	14

TABLE 4: TRAFFIC EXPOSURE METRIC SUITABLE FOR EACH TYPE OF CONFLICTING MOVEMENT COMBINATION. FOR EXAMPLE, FOR LEFT OPPOSING THROUGH CONFLICTS, WE DEFINE THE EXPOSURE METRIC AS THE SUM OF VEHICLES MAKING LEFT TURNS AND OPPOSING THROUGH MOVEMENTS.

Intersection	Left Opposing Through	Right Merging Through	Right Following Through	Rear-End Conflict	Total Vehicles
University Ave & 13th St	53,484	27,663	72,735	191,788	146,133
University Ave & 17th St	99,974	28,030	63,826	179,082	67,550
University Ave & 20th Dr	66,774	59,706	31,596	121,966	105,590
NW 23rd Ave & NW 55th St	97,810	45,988	36,814	63,782	97,173
Post Office & Rhinehart	47,759	23,568	20,459	23,294	61,530
Lake Mary & Rhinehart	8450	8884	N/A	11,542	55,889

are merging or diverging conflicts, and any resulting collision yields a very low impact crash. So, event categorization helps emphasize only the more dangerous conflict types by placing more weight on the dangerous conflict types. For example, in Table 3, the column titled "Total" is a simple sum of all conflict types, whereas the column titled "Weighted" gives a weighted total, where the left opposing through conflicts have been assigned a weight of 4. The "Normalized" column computes the conflict volume per 10,000 road users. These numbers are obtained by dividing the weighted conflicts by the corresponding exposure metric (explained in the next paragraph) and multiplying by 10,000. The "Normalized" conflicts allow us to rank the intersections by safety. For example, we can conclude from Table 3 that the Lake Mary & Rhinehart intersection is the safest.

Table 4 shows the exposure metrics for the known conflict types. The exposure metric was computed as the sum of the total number of vehicles participating in either of the two movements that are involved in a conflict. For example, if there is a conflict between north-bound left (NBL) and south bound through (SBT), then the exposure metric for left opposing through will have a component that is the sum of all vehicles making NBL and SBT maneuvers. The exposure metric serves as a denominator in normalizing the conflict volume.

Fig. 8 shows the steps in our algorithm for isolating the high-intensity regions in the three-dimensional space of (maxSpeed, maxDeceleration, minTime). For a conflict,

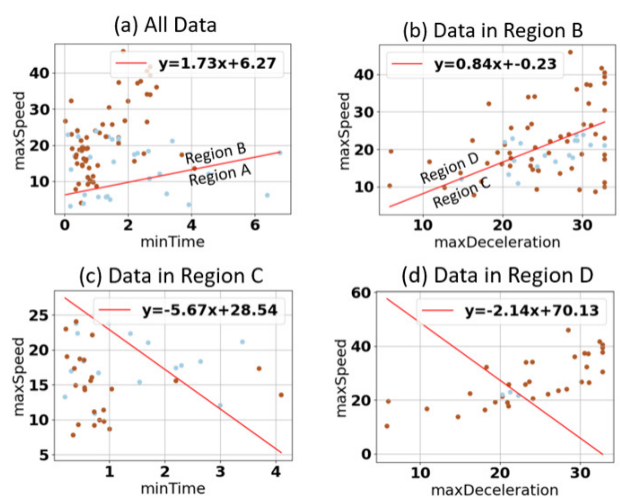

Figure 8. The steps in finding high intensity regions of severe events: (a) all data and the line that separates them. In this diagram, the red dots represent severe events, while the blue dots represent non-severe events. The data here are from the NW 23rd Avenue & NW 55th Street intersection. Region A consists of non-severe points, while in (b), Region B is further split into regions C and D. Splitting regions C and D again, in (c) and (d) respectively, gives us high-intensity regions.

maxSpeed defines the maximum speed of the two vehicles involved, while maxDeceleration is the maximum brake applied by either of the two vehicles. minTime is the minimum time for TTC or PET, which comes from the point representation of the involved vehicles and a bounding box representation of these vehicles. We take the minimum of these two times. The data used in Fig. 8 are from the NW 23rd Ave & NW 55th Street intersection. The steps in the algorithm are demonstrated in Fig. 8(a–d). The high-intensity region is obtained from randomly processing 80 of 100 filtered events from the intersections. The remaining 20 events are used to test the classifier. We manually annotated the 100 filtered events as severe or non-severe. The accuracy of this scheme is 90%, with a 92% recall and 90% precision. We used our algorithm separately for each intersection. The splits as shown in Fig. 8 are different for each intersection because the intersections have different characteristics such as speed limits, presence of a school nearby, etc. The column V2V MADT in Table 2 shows the volume of events that were further pruned by our algorithm to find high-intensity regions. We didn't apply the MADT algorithm to P2V events because pedestrians are vulnerable users and all conflicts that remain after applying the filters are considered as severe by default. The accuracy of the MADT algorithm depends on the accuracy of video processing algorithms as video processing plays a crucial role in the computation of the safety features such as speed, deceleration.

V. CONCLUSIONS

This paper developed a systematic and novel methodology for analyzing intersection safety based on video analysis. We developed algorithms that use video analysis and signal timing data to perform accurate event detection and categorization in terms of the phase and type of conflict for both pedestrian- vehicle and vehicle-vehicle interactions. We introduced a new surrogate safety measure, severe event which is quantified by multiple existing metrics such as TTC or PET as recorded in the event, deceleration, and speed. We developed an efficient multistage event filtering approach followed by a multi-attribute decision tree approach that prunes the extensive set of conflicting interactions to a robust set of severe events.

Using our analysis and based on the limited number of intersections, we found that the dominant conflicts at intersections with heavy pedestrian use are right-turning vehicle on the adjacent parallel crosswalk. We could identify the specific right-turn directions that contribute to this problem and the hours during the week when the problem peaks. Categorization of vehicle-vehicle interactions showed that for intersections with permissive left turns, the more common conflict is that between a left-turning vehicle and a through vehicle. The intersections with protected left-only displayed some merging and diverging conflicts which are inherently less severe conflicts.

We believe that our approach provides a systematic approach to diagnose key safety issues on an intersection. This information can then be used to make changes in signal timing and conduct before and after studies to see potential improvements. This is part of our ongoing work.

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