Looking at Intersections: A Survey of Intersection Monitoring, Behavior and Safety Analysis of Recent Studies

Mohammad Shokrolah Shirazi[1], *Student Member, IEEE,* Brendan Tran Morris[1], *Member, IEEE*

***Abstract*—Intersections are known for their integral and complex nature due to a variety of the participants behaviors and interactions. This article presents a review of recent studies on behavior at intersections and safety analysis for three types of participants at intersections: vehicles, drivers, and pedestrians. The paper emphasize on techniques which are strong candidates for automation with visual sensing technology. A new behavior and safety classification is presented based on key features used for intersection design, planning, and safety. In addition, performance metrics are introduced to evaluate different studies and insights are provided regarding the state of the art, inputs, algorithms, challenges, and shortcomings.**

I. INTRODUCTION

INTERSECTIONS are well-known targets for monitoring because of the high number of reported accidents and collisions. According to [1] about 40 percent of the estimated 5,811,000 crashes that occurred in the United States in 2008 were intersection-related crashes. As a consequence, accident avoidance and safety improvement is a prime focus addressed by advanced driver assistance and safety systems.

Behavior and safety assessments are fundamental elements used for improving safety and preventing accidents at intersections. Although behavior assessment is mostly used for intersection design and planning, it can also be used for safety analysis. For example, Hamed et al. [2] showed that longer waiting time makes pedestrians impatient to cross which affects their collision risk. Another study examined gap acceptance behavior of drivers for the design of Advanced Driver Assistance Systems (ADAS) [3]. Fig. 1 shows the interrelationships among data collection, behavior analysis, and safety analysis. Specifically, both behavior and safety assessment consist of modeling and inference in order to analyze safety at intersections.

In order to perform intersection safety analysis, the first step requires collecting and organizing data from various sources regarding intersection participants into datasets. Complementary data such as recorded videos and survey forms can be used to enhance inference and models to find the contributing factors for the specific behavior or the safety issue.

The collected data can then be used for modeling which is required for behavior and safety inference. A model is built using participants patterns (e.g., motion), probability distribution functions, and characteristics (e.g., sex, age) as references for future predictions. The complexity of a model is chosen based on the variation, complication, and amount of the collected data; this can vary from simple linear regression models to more complicated learning algorithms, such as support vector machines (SVM) or neural networks (NN). However, this step can be ignored if simple estimations are needed, for example, the crossing speed of pedestrians or the speed of vehicles.

The behavior and safety inference provides high-level understanding from observed patterns. This varies from a simple examination of trajectories, such as calculating the crossing speed of pedestrians, to more complicated predictions, such as the driver's turning intention. Complicated inference methods usually require high dimensional data along with human characteristics in order to rationalize and predict specific behavior. For example, when predicting turning intentions of drivers, the effects of such driver characteristics, as gender and age, are investigated.

Several literature surveys on pedestrians have focused mostly on vision-based pedestrian-detection methods [4], [5]. For example, Gandhi and Trivedi [4] reviewed studies on collision prediction and pedestrian behavior analysis and Gernimo et al. [5] focused on pedestrian detection methods for ADAS. Recent surveys on vehicles focused only on vision-based detection and tracking for urban traffic and behavior analyses [6], [7]. No comprehensive survey exists specifically addressing behavior and safety analyses at intersections.

This paper presents a review of behavior, and safety studies at intersections, concentrating on studies since 2000 with emphasis on techniques that are strong candidates for automation with advanced sensing technology. Unlike other specialized reviews, this survey considers all intersection participants including pedestrians, vehicles, and drivers due to the following reasons:

1) Different behaviors are manifested by the various intersection participants and behaviors can provide a multitude of design objectives. For example, pedestrian waiting time and crossing behavior can be used for the design of crosswalk signals [8] or driver braking behavior can be used for design of ADAS systems [9].
2) The observation and analysis techniques for each participant type while similar will have specialization [10]. For instance, probabilistic methods are required for more variable pedestrian motion prediction while deterministic techniques may be suitable for vehicular traffic.

[1]M. S. Shirazi and and B. T. Morris are with the Electrical and Computer Engineering Department, University of Nevada, Las Vegas, NV 89154, USA `shirazi@unlv.nevada.edu`, `brendan.morris@unlv.edu`

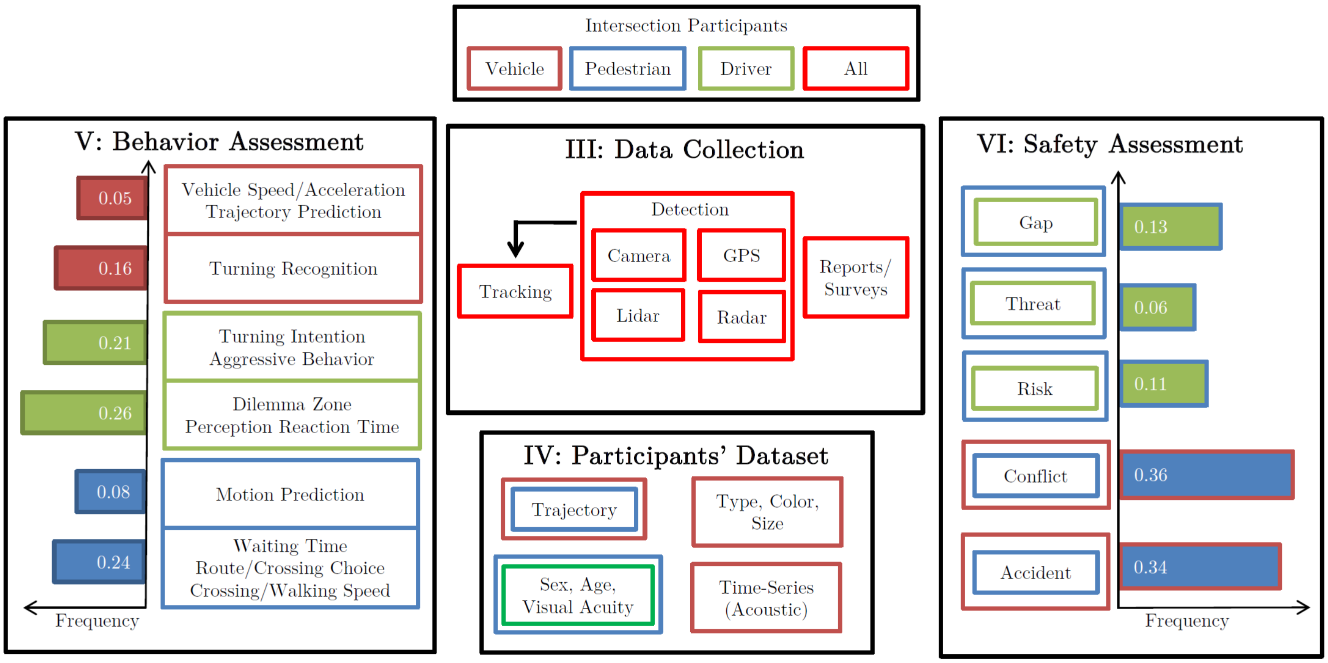


Fig. 1: The inter-relationship of data collection, participant's dataset and safety analysis. Two probability distributions are shown for behavior and safety subjects of intersection studies.

3) While pedestrians [4], [5] and vehicles [7], [11] behaviors have been extensively studied, there is no existing comprehensive survey that considers the unique properties of intersections.

The paper suggests a new approach of grouping and classification for safety analysis at intersections. Intersection studies are grouped into behavior assessments, safety assessments and safety systems (e.g., ADAS) and evaluation metrics are introduced accordingly. The studies of each group are compared based on predefined performance metrics and critically assessed. The intersection safety systems are finally described and possible directions for future research are suggested.

II. EVALUATION CRITERIA & APPLICATIONS

In order to critically compare and assess intersection literature, a concrete set of performance criteria are provided as well as a characterization for different intersection applications.

A. Criteria

The following criteria are used as metrics for comparing different intersection analysis techniques and as a basis for comment and suggestion of possible improvements.

1) Data Collection Cost (DCC): The DCC indicates the feasibility of large scale data collection. Data collection cost is considered as an aggregate of hardware and monitoring costs. The hardware cost is affected by sensor type since expensive sensors usually provide high level of accuracy. If data collection is performed automatically, monitoring cost is considered low.

2) Output Accuracy (OA): The OA describes the required level of correctness of models, inferences, and results. This metric relies on the output of the system which can be affected by erroneous data collection. Another effective criterion is the type of method used according to an specified objective. For example, when an objective is behavior assessment of pedestrians, future motion prediction of pedestrians require a probabilistic framework to deal with uncertainty problem or the early prediction of road users is highly desirable in safety systems (i.e., ADAS).

3) Response Speed (RS): The RS measures the system capability to provide a solution in a timely fashion after data collection. This parameter is important for safety systems such as collision avoidance systems (CAS) which are a type of ADAS. These types of system must avoid high computational cost which prohibits real-time capabilities. However, the emergence of computing platforms geared toward parallelization, such as multicore processors and Graphics Processing Units (GPUs), are helping to alleviate the computational problems.

B. Applications

Behavior assessment, safety assessment and safety systems are three major applications for intersection studies. They are utilized by transportation engineers and researchers to analyze safety and will provide a guideline for grouping the literature.

1) Behavior assessment: The behavior assessment of road user is helpful when the intersection is at design or planning stage (i.e., crosswalk, signal) and sufficient operational data (to quantitatively identify the safety problems) or historical data (e.g., collision, volume) is not available.

2) Safety assessment: Safety assessment is a process of finding hazardous locations, detecting accidents and underlying reasons using crash reports. Gap, risk and conflict studies

TABLE I: Acceptable metrics required for different applications (L: Low, M: Medium, H: High, Very high: V)

Application	Data Collection Cost (DCC)	Output Accuracy (OA)	Response Speed (RS)
Behavior assessment	Medium	Medium	Medium
Safety assessment	Medium	High	High
Safety systems	High	Very high	Very high

are assigned to safety assessment category since a behavior of one road user is investigated according to another participant (i.e., gap acceptance behavior) or their interaction is studied (i.e., conflict, accident).

3) Safety systems: Although some studies analyze road user behaviors, their ultimate goal is designing a safety system. Since method should be practically evaluated it requires different metrics (i.e., RS) than two other groups.

Acceptable metrics are shown in TABLE I for different application types. A method can be evaluated based on application grouping and a check on how well it matches acceptable metrics in TABLE I. An optimized method for behavior or safety assessment should have low DCC. However, it is difficult to provide low DCC in practice since most traditional methods still use surveys and human observation for data collection. Safety systems in contrast may have high DCC but require very high RS and accuracy for a practical system [12].

III. DATA COLLECTION

Before performing any type of behavior and safety analysis data must be collected to understand the intersection scenario. Although there has been a recent trend towards automatic detection and tracking from sensors (e.g., GPS or vision-based detection and tracking systems), a number of useful techniques exist for obtaining rich behavioral data.

A. Reports & Surveys

The use of survey forms [13], human field observations [14]–[16] as well as, user interviews [2] have been used extensively in the transportation field. These traditional methods rely on manual data collection while more contemporary techniques leverage the infrastructure of intelligent transportation systems (ITS) to obtain data [17].

Manual data collection, while providing rich behavioral cues, has a high monitoring cost since people must be hired for field observations. The data collection method requires significant time to record useful information through forms, interviews, surveys, and accident reports which limit the number of locations that can be analyzed. Further, while human analysis is often used as a "gold standard" (ground truth), this may only be true over limited time scales since there is a possibility of miscalculation or missing an event due to fatigue or other human factors. Hence, automated analysis is better suited for long-term analysis but generally provides less detailed data measurements with less semantic meaning.

B. Detection

A variety of sensors have been used for vehicle and pedestrian detection at intersections [4], including global positioning systems (GPS), light detection and ranging (LIDAR), radar and cameras. Simulation environments and driver simulators [30] have been very popular to use for driving studies due to their ability to setup and examine a scenario precisely.

With new emphasis in self-driving and intelligent vehicles with ADAS systems, new sensors on instrumented vehicles are in play at intersections. Radar and laser scanners are used as an active sensors to detect obstacles by estimating speed and relative velocity and cameras are passive sensors which are used to track road users and capture blind spots. The monitoring cost in vehicles are low since it is conducted automatically through on-board computers but the equipment cost is high since it requires a vehicle along with a sensor package (e.g., the popular Velodyne LIDAR).

The use of cameras is common since they are inexpensive and easy to install. In addition, they provide wide field of view (FOV), have recoding capabilities that facilitate the observation process, and are often available as capital investments for transportation management. TABLE III compares different sensors for data collection at intersections.

TABLE III: Comparison of sensors

Sensor	Perceived Energy	Raw Measurement	Hardware Cost	Units	FOV
GPS	Microwave radio signal	Distance to satellite	Low	Miles	Wide
Radar	Millimeter wave radio signal	Distance	Medium	Meters	Small
Lidar	Nanometer wave laser signal	Distance	High	Meters	Wide
Camera	Visible light	Light intensity	Low	Pixels	Wide

1) GPS: Current collection trends use trajectory data from GPS receivers in dash navigation systems of vehicles and mobile smart devices. GPS satellites, which provide localization messages for receivers, work well in open areas and provide network level coverage. However, accuracy is limited in areas with obstructed views of the sky, known as the urban canyon effect. In addition, commercial GPS has coarse spatial resolution limiting its safety application. Another drawback for safety is that not all intersection participants can be expected to have a device.

2) Radar: Radar technology usually is mounted on poles or embedded in vehicles to detect surrounding vehicles [7] and pedestrians [4]. Although radar works well in varied weather and illumination conditions, the FOV is generally narrow. For instance, four radars were used by Aoude et al. [31] to detect vehicles and measure speed, range, and lateral position at a rate of 20 Hz with distance of 150 m away from an intersection. Several studies demonstrated the limitations of Doppler radar in terms of FOV as well as the ability to detect stopped vehicles [32].

TABLE II: Tracking Schemes and Their Limitations for Intersection Monitoring

Technique	Methodology and/or Advantage	Limitations	DCC/OA/RS
Region-based [18], [19]	• Tracking foreground regions extracted by background subtraction. Kalman filter usually track blobs using shape characteristics (i.e., area, perimeter, color, and texture). • Low computational cost.	• It should deal with noise, light, shadow, bimodal distribution of background pixels, and it requires an occlusion handling method. • Poor performance for stationary and slow moving objects.	L/M/V
Feature-based [20]	• Selecting features (i.e., color, edge, corner) with nearby pixels, and clustering features based on some criteria, such as movement displacement and location. • Robustness against partial occlusion.	• Problem of grouping features, and feature detection varies by image quality affecting tracking performance. • It fails in cluttered and complex environments.	L/M/H
Optical Flow [21]–[26]	• Calculated by matching pixels or features between two frames by assuming brightness constancy [27], [28]. • Robustness against partial occlusion.	• Computational load is increased regarding number of flow pairs, and poor performance for stationary and slow moving objects. • Over grouping of large objects.	L/H/H
Particle Filter [29]	• Sampling a curve (i.e., distribution) built from an attribute of object such as color or edge. Samples are weighted using an observation model. • High performance tracking and robustness against partial occlusion.	• High computation cost due to sampling and resampling processes.	L/V/M

3) LIDAR: Recently, LIDARs have become quite popular due to reduced cost and high fidelity of point cloud measurements which can be used for accurate identification of objects. LIDARs provide clearer measurements than radars and they have wider FOV [7]. Several studies use laser scanners inside an ego-vehicle to detect and track other vehicles and enhance driver safety at intersections by warning them about possible collisions and risks [33]–[38].

4) Optical Cameras: Cameras provide wide FOV and data stream which is natural human observation or computer vision techniques for scene understanding. Although other imaging sensors are useful in providing robustness against light (e.g., low light sensitive night-vision or thermal cameras), they are not as widely deployed as visible light sensors due to their higher cost.

C. Tracking

Tracking aims to generate the trajectory of an object by locating object position over time. There are numerous methods for tracking, e.g, [4], [7], and [39] which have been discussed extensively in other survey papers such as [5], [7]. Thus, we briefly discuss and evaluate those tracking methods that have been used by intersection monitoring systems in TABLE II. Since only cameras are used, DCC is low for all studies. However, the main difference is for OA and RS parameters. The region-based and optical flow methods are the most often utilized methods in literature. However, region-based techniques while fast do not handle occlusion well. Optical flow is the best well suited for intersections due to accuracy and speed.

IV. PARTICIPANTS' DATASET

The data collected of intersection participants is reorganized into datasets for behavior and safety analysis. Motion trajectories, commonly provided by tracking methods, are the most valuable data used for predictions (e.g., trajectory prediction), measurements (e.g., vehicle speed), models (e.g., waiting time distribution) and inferences. Human characteristics such as gender and age [14], [15], [30], [40] can be reliably obtained by means of videos and survey forms. These information can be utilized to understand which detailed attributes contribute to pedestrian and driver behavior. Hence, complementary data collection methods are required for comprehensive individual data.

Vision acuity, a measure of how well a person is able to perceive, is an important factor affecting behavior and safety of pedestrians and drivers. This factor was investigated in some studies due to two major reasons:

1) Vision acuity of drivers being tested is verified when data collection is conducted using driving simulators [41] [42] [43]. Since drivers must pass a vision test in order to get their driving license, this helps to obtain unbiased data which imitates real driving scenarios.
2) There can be significant differences between different types of drivers (e.g., young versus old) due to vision impairments which hampers driver safety and performance.

The type, color and size of vehicles are collected in some studies [41] since such driving behaviors as gap acceptance is affected by the type and size of oncoming vehicles (e.g., a sedan versus a truck). Crash and incident signals have been shown to be another important set of data for accident recognition [44]. Acoustic signals obtained from vehicles undergoing dramatic deceleration have also been shown to be another important set of data for accident recognition. However it is challenging to develop signal processing techniques to distinguish accidents from background traffic and environmental noise

V. BEHAVIOR ASSESSMENT

A behavior that belongs to the object of interest can be a single event (e.g., braking behavior) or a sequence of events indicating an action (e.g., turning right behavior includes a declaration as well as braking behavior). The behavior assessment in this manuscript is organized based on the distribution of intersection objectives found in literature. The distribution shown in the left of Fig. 1 shows the six major topics for behavior analysis of vehicles, drivers and pedestrians that are discussed in this paper. As an example, perception reaction time (PRT) including dilemma zone were the most often occurring at over 26% of studies.

A. Vehicle Behavior

1) Trajectory Prediction, Vehicle Speed, and Acceleration: This includes measuring and learning vehicle kinematics, dynamics, and making predictions [50]. Assessing vehicle speed and acceleration [45], [46] are major areas of research. For instance, Kumar et al. [46] contextually defined check-post areas and evaluated vehicles speed on these predefined locations. The performance of kinematic trajectory evaluation is relatively strong for typical traffic but degrades during congestion. This is due to difficulties dealing with occlusion using background subtraction techniques for region-based tracking.

2) Turning Recognition: Turning movements are of particular interest for safety since these paths intersect with one another and may lead to hazardous situations. Predicting turning behavior involves learning turning patterns, building a model and finding a match for observed vehicle patterns with the model. There are two major methods to recognize turnings. The deterministic method recognizes turnings using learned prototypes such as longest common subsequence (LCSS) [47], [51] in video surveillance. The more elaborate methods consider variations in human driver behaviors within probabilistic frameworks since vehicle behavior is affected by the driver which is a human with complex behavioral models. This perspective of vehicle behavior mainly focuses on safety regarding other vehicles using various applications in ADAS.

Kafer et al. [47] predicts probability values of turning left, turning right, and going straight by using a quaternion-based rotationally invariant longest common subsequence (QRLCS). This work predicts the long-term future trajectory of other vehicles, using particle filters and motion databases. Particle filters are efficient methods, in this context, and they can be applied for different scenarios. For example, Tran and Firl [38] improved upon their previous research [37] in trajectory prediction by using particle filters instead of an extended Kalman filter in order to recognize a maneuver by finding the best match from Gaussian regression models. However, the number of particles and observation models should be carefully introduced since sampling from each trajectory pair can be computationally expensive and prohibits the real-time performance.

There is a trend towards using a probabilistic framework as a simple map to explain a vehicle behavior by case-based reasoning [48] and state-based diagrams [52] since they are simple to understand and use by drivers. These methods aim to imitate a person's natural reasoning process; however, they become challenging when burdensome states, conducted by a driver, become complicated. In addition, most accidents occur in a quite short amount of time without rigidly following predefined rules. Therefore, they should benefit on-line learning with probabilistic methods [48] to deal with different driving models with the uncertainty problem. For instance, Hulnhagen et al. [48] used a probabilistic finite state machine to model the compound driving maneuvers by breaking them into simple fundamental states such as braking, and following a vehicle. A Bayesian filter approach infers the driving maneuver by computing the probability of each basic element in the context of the 'maneuver' model.

TABLE IV shows representative works for vehicle behavior analysis with respect to learning algorithms, applications, major features, and their limitations. The behavior assessment studies [45], [46] provide medium level of output accuracy due to tracking limitation (i.e., region-based tracking) which can be improved by optical flow method. The small reduction in RS due to usage of optical flow can be handled by GPUs. Safety assessment studies [47], [48] do not address real-time processing since they analyze trajectories off-line. The recognition algorithm should be evaluated on board with extracted models to provide real-time applicability.

B. Driver Behavior

Driver behavior analysis includes measuring, learning, and predicting driver intention [9], [31], [53]–[57], perception reaction time (PRT) [32], [58], [59], and braking response at junctions and dilemma zones. Since such driving behaviors as lane changing and overtaking have been studied in [7], [60], highly frequent behaviors such as driver intention (i.e., turning intention, aggressive behavior) and PRT are investigated separately. The distribution of Fig. 1 shows these two groups of studies contribute a higher portion of attention among all 6 objectives of intersection studies.

1) Turning Intention & Aggressive Behavior: Predicting the drivers' intention including turnings is different from turning prediction methods used for vehicles because it requires not only vehicle dynamics but other high resolution data sources as well such as human factor measures (e.g., look direction). The uncertainty of the driver's intention demands probabilistic methods such as Bayesian networks [54] and hidden Markov models [56]. In a few recent studies, SVM was used as a learning framework for binary classification [31], [53] since training SVMs involves an optimization problem of a convex function which makes an optimal solution a global one. For instance, Aoude et al. [31] used SVM to classify violating drivers who do not stop behind the stop bar. However, a variety of violating behaviors should be considered in the literature.

Other traditional learning methods- Bayesian networks and hidden Markov models (HMM)- still are used extensively since they are simple, capable methods to model dynamic stochastic processes and they do not need large quantities of data for their training. For instance, a model developed by Streubel and Hoffman [56] learned behavior HMMs by using the calculated speed, acceleration, and yaw rate for each direction: straight, left, and right. Although this method was used to evaluate a large database of real driving data, it could not be applied to arbitrary intersections. Lefevre et al. [54] used a Bayesian network to address arbitrary intersections by incorporating knowledge about the layout of the intersection using contextual information from a digital map.

2) Perception Reaction Time (PRT): PRT is defined as the time difference between the onset of the yellow phase and

TABLE IV: Vehicle Behavior Analysis at Intersections

Study	Application	Data Source & Features	Goal	Classification, Inference or Approach	DCC/OA/RS: Comments
Viti et al. 2008 [45]	Behavior assessment	Video: Trajectory	Analyzed speed and acceleration behavior	Probability density functions using trajectories	L/M/H: Region-based tracker fails to track stopped vehicles.
Kumar et al. 2005 [46]	Behavior assessment	Video: Trajectory, velocity, convex hull	Behavior recognition	Bayesian network	L/M/H: Region-based tracker fails to track stopped vehicles, contextual information is required.
Kafer et al. 2010 [47]	Safety system	GPS: Position, velocity, yaw rate	Long term trajectory prediction	Quaternion-based rotationally invariant LCS (QRLCS)	L/M/L: Offline analysis and high computational cost result in low RS, prediction in 1-2 s but ideal is 2-4 s.
Hulnhagen et al. 2010 [48]	Safety system	Observer: Trajectory, velocity, acceleration, steering angle	Maneuver recognition	Fuzzy logic system with a Bayesian filter	H/M/L: Improvements are required for complex behaviors and early maneuver recognition, RS is lows due to offline evaluation.
Wang et al. 2015 [49]	Behavior assessment	Video: Trajectory	Real-time vehicle counting under fisheye camera	Vehicle count by predefined zone areas	L/M/H/: Optical flow fails to track stopped vehicles.

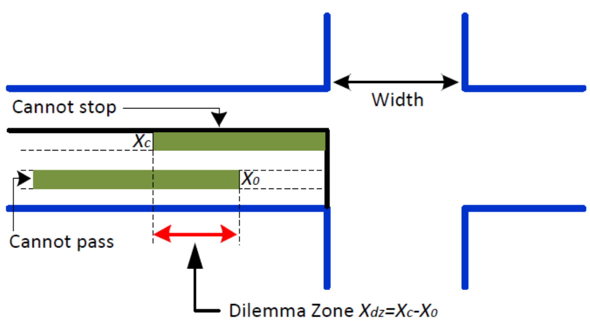


Fig. 2: A graphical illustration of a dilemma zone at a signalized intersection [61]

the activation of the vehicle's brake lights, and it is a critical measure for the design of intersections and timers. Moreover, PRT of drivers is usually studied to estimate a dilemma zone. A dilemma zone is a range in which a vehicle approaching the intersection during the yellow phase can neither safely clear the intersection nor stop comfortably at the stop line (see Fig. 2). Dilemma zones have been the subject of much attention for observing behaviors since there is a high possibility of collisions due to hesitancy by a driver to stop or pass the traffic signal.

The collisions within a dilemma zone can be avoided if the location and the length of a dilemma zone is known for an intersection. The dilemma zone can be estimated using stopping x_c and clearing x_0 distances, as shown in Fig. 2,

$$x_c = v\sigma + \frac{v^2}{2a},\ x_0 = v\tau - (W + L) \tag{1}$$

where v is the speed of the approaching vehicle, σ is the perception reaction time of the driver, a is the maximum deceleration rate of the vehicle, τ is the length of the amber signal, W is the width of the intersection, and L is the length of the vehicle. A segment of a dilemma zone approaching the stop-line is said to exist when $x_c > x_0$. In literature, the critical PRT value is normally 1-s which is $\geq 85\%$ of the PRT cumulative distribution [40], [62], [63].

There are two major problems regarding to dilemma zone estimation:

1) A dilemma zone distribution varies for different drivers regarding their age and gender [15]. As a result, some studies incorporate these measurements to find a model for dilemma zone distribution [15], [40].
2) The dynamic nature of a dilemma zone is difficult to measure [61], [64] since the acceleration/deceleration rate and the PRT should be captured at the onset time of the yellow light. As a result, naturalistic observation of videos is preferred since other methods, such as simulators and controlled roads, produce practice effects. Although, difficult to obtain generally, traffic phase data could be collected by video recordings, and drivers' characteristics could be obtained by some complementary methods, such as the communication between vehicles and infrastructure-based systems at intersections.

There are various ways to control the dilemma zone for purposes of avoiding a collision. For instance, Tarko et al. [65] used a probabilistic approach to control dilemma occurrence by developing a dilemma likelihood function and finding the optimal green extension to minimize this likelihood. To be truly effective, a green phase extension requires driver information regarding sex, age, and time to intersection. Dilemma zone protection systems will be discussed later in Section VII on safety systems.

TABLE. V shows the representative works of driver behavior regarding their goals, features, applications, limitations and important findings. Probabilistically and applicability on arbitrary intersections are two constraints affecting OA for the subject of turning intention & aggressive behavior. The evaluation of literature using the survey metrics shows that behavior analysis requires a high data collection cost. However, Gates et al. [58], and Liu and Tao [61] showed reasonable results and cost due to usage of video recording to estimate parameters used in Eq. 1 to calculate dilemma zone distribution. This shows the effectiveness of using video recordings to estimate PRT and dilemma zones. The fully automated vision-based system can significantly help if there is a prior knowledge about signal timings.

C. Pedestrian Behavior

Pedestrians behavior studies can be grouped into "prediction-based" and "observation-based" methods. The early prediction of a future trajectory is the main focus for prediction-based methods since it can be used in safety systems (e.g., ADAS) to avoid collisions. The question, "Will the pedestrian cross?" should be answered early and promptly [66]. However, the question is difficult to answer since it is not simple to infer the current state of pedestrians due to the localization problem [67]; pedestrians' behavior is highly dynamic as well.

1) Motion Prediction: One way to perform a prediction relies on the closed-form solutions of a Bayesian filter, such as Kalman filtering; however, non-parametric stochastic models are preferred due to non-linearity of pedestrians' motion patterns. Possible trajectories are generated by Monte Carlo simulations using dynamical models. For instance, Abramson and Steux [68] combined a constant motion model with particle filtering but constant motion model loses its accuracy for standing pedestrians around the crosswalk.

Markovian models also have been used to model pedestrians' motion [67], using fours states of a Markov chain, corresponding to 'stand still', 'walking', 'jogging' and 'running'. However, the model does not explicitly address the 'pedestrian crossing' state in the traffic safety domain. Predicting pedestrian future states as crossing or not requires a binary classifier with more features than just positions and velocities. As a result, SVM is ideal for this task, and the most meaningful features can be verified to make a reliable prediction about the pedestrians' future behavior. Pedestrians' distance to the curb and the crosswalk should be considered as important features for training models and making predictions.

2) Waiting Time, Walking Speed, Crossing Speed and Choices: Measuring waiting times and speeds are used in numerous studies [2], [69], [70] since they are valuable metrics for intersection design and signal control. Walking and crossing speeds are two major elements to characterize pedestrians' behaviors [16], [71], [72], and contributing factors include age, gender, and group size [72] [16]. Pedestrian routes and crossing choices are two other important factors considered during behavior analysis since they might lead to hazardous situations, such as walking or crossing at unmarked locations [13], [73], [74].

The methods require evaluating over a long period with high accuracy, followed by statistical evaluations including t and χ^2 tests. The statistical methods look at the aggregates from the samples of large populations to determine the significant differences between studying behaviors and factors.

TABLE VI shows key factors used for pedestrian behavior analysis, various findings, and limitations in representative studies. Most pedestrian behavior studies suffer from high data collection cost. However, this extensive data collection resulted in important findings. We suggest automated vision-based system using fusion of appearance and motion with optical flow and supplement with survey forms, and interviews as complementary methods to decrease DCC. For example, recorded videos help to verify incidents and correct observations, and pedestrian age and gender information can be obtained by using high resolution cameras.

VI. SAFETY ASSESSMENT

Safety inference refers to two different tasks. One is an assessment process undertaken by pedestrians or drivers at the decision making level to avoid an accident as follows:

- Gap: An available time/space for a maneuver or between leading and trailing vehicles in a car following model.
- Risk: The uncertain level of danger introduced by other vehicles for the subject vehicle under a specific mission (e.g., turning risk, or crossing risk).
- Threat: The possible danger of imminent collisions introduced by other vehicles.

The second task involves models and predictions for conflicts (i.e., near-accidents) and accidents built from safety measurements, crash datasets and police reports. The second distribution plot on the right side of Fig. 1 shows the importance of five safety assessment topics discussed in this paper. Conflict and accident analysis are the most frequent addressed topics by intersection studies.

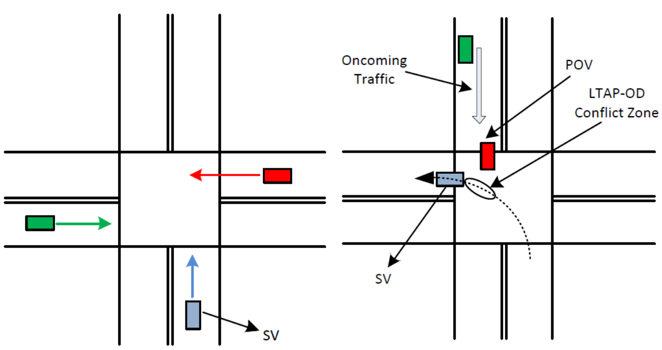
A. Gap

While pedestrians and drivers are making the decision to pass or cross at intersections, they check the sequence of gaps that can be rejected or accepted. An accident or near-accident may be caused when the accepted gap is small. Gap analysis consists statistical inference and modeling of accepted gaps, which are studied at intersections due to two major reasons:

1) The first and second most common types of accidents at controlled intersections having two stop signs involve scenarios for a) a straight crossing path (at over 45%) and b) a left turn access path/opposite direction (at around 25%) [32]. They happen when drivers in the subject vehicle are not able to accurately judge the speed of the approaching vehicles and the available time gap to complete their turning or crossing maneuver. The scenarios are shown in Fig. 3.
2) If gap acceptance behavior is accurately estimated for drivers or pedestrians, intersection decision support (IDS) systems can correctly predict the turning or crossing time by monitoring approaching vehicles. This branch of warning systems are explained in Section VII with more details.

TABLE V: Driver Behavior Analysis at Intersections

Study	Application	Data Source	Description	Important Findings	DCC/OA/RS: Comments
Gates, et al. 2007 [58]	Behavior assessment at dilemma zone.	Video	Deceleration rates and brake response times were estimated by manual calculation of related parameters such as approaching speed, brake response time, and headway.	PRT is significantly affected by • approach speed • distance to intersection at onset of yellow • deceleration rate.	M/H/-: Drivers sex and age are not incorporated since manual video observation is used and DCC is not low.
Rakha et al. 2007 [40]	Behavior assessment at the onset of the yellow-phase.	Instrumented vehicle	Distribution of PRT and the probability of stopping/running versus the distance to the stop bar was estimated.	• Males have low probability of stopping • 1 sec PRT is valid • Older drivers less likely clear intersections at short yellow trigger distances.	V/H/-: Practice effects are produced since drivers know that they are under observation. Instrumented vehicle results in very high DCC.
Papaioannou et al. 2007 [15]	Behavior assessment at dilemma zones.	Radar, video, observer	Measurements related to the dilemma zone at the onset of a yellow signal was extracted for different age groups of males and females.	Female drivers demonstrate a more obedient behavior and their average speed is lower than the speed limits.	V/H/-: The work can be further improved by estimating dilemma zone distribution using PRT and maximum deceleration rate.
Liu and Tao 2006 [61]	Behavior assessment to estimate dilemma zone.	Video	Velocities, acceleration/deceleration rates, distance, and expected time to the stop line were measured to find the dilemma-zone distribution for three groups: conservative, normal, and aggressive drivers.	Dilemma zone is dynamic in nature and its location varies with the driving populations.	M/H/-: Can be improved by showing the dynamic nature of dilemma zone for different drivers regarding age, gender, safety/violation record and experience.
Caired et al. 2007 [30]	Behavior assessment to estimate PRT.	Driver simulator	Dependent variables including the stop/go percentage, velocity, PRT, deceleration, stopping accuracy, and intersection clearance for each age group were evaluated using statistic software package (i.e., UNIONOVA).	PRT of 1 sec is sufficient to accommodate older drivers.	V/H/-: Results of driving simulators differ from real driving scenarios. DCC is high due to usage of driver simulator.
Kaysi and Abbany 2007 [14]	Behavior assessment to model aggressive behavior.	Observer	Distribution of aggressive driving estimated for driver characteristics (gender and age), car characteristics (type and model year), and traffic attributes. Aggression defined for turning vehicle that forces major road to slow.	Indicators of aggressive behavior are • age • car performance • average speed on major road.	V/H/-: More data would validate and enhance the obtained model, and investigate the significance of other parameters in explaining the aggressive behavior.



(a) Straight crossing path [75] (b) LTAP/OD [32]

Fig. 3: Two common accident scenarios

Gap inference includes estimating the frequency of accepted gaps, the median acceptable gap size, and gap orders [41] [42]; usually, these are modeled by probability distribution functions, regression models, and logistic functions [3]. However, it is difficult to implement a gap inference for real traffic scenarios since it should be customized based on age and gender of the drivers and pedestrians. For instance, the probability distribution of accepted gaps were studied in [41] [42] for different driver characteristics (e.g., females versus males) using driving simulators; it was found that males more likely accept smaller gaps than females. Other important factors were observed on gap acceptance behavior, such as the velocity of the oncoming vehicles. Drivers would accept a smaller gap size for scenarios of higher speeds on major roads [42].

Few studies have investigated pedestrians gap acceptance (PGA) due to the difficulty in data collection and the lack of supporting safety systems for pedestrians. For instance, Sun et al. [76] modeled PGA by estimating the probability of the acceptable gap size, and Banerjee et al. [77] evaluated the presence of pedestrians on drivers gap acceptance in the LTAP/OD scenario. Sun et al. [76] studied the probabilistic gap acceptance behavior as a random variable that best fits the training data. Since the pedestrian decision is to reject or accept the available gap, the binary logit model with such factors as waiting time and number of waiting pedestrians on the curb side was used in their study. The waiting time was incorporated in [76] since it was shown by Hamed et al. [2] that high waiting times make pedestrians impatient to cross.

TABLE VII describes gap analysis studies with more details including goals and important findings. Most studies expose high cost except those use manual observation of videos. since

TABLE VI: Pedestrian Behavior Analysis at Intersections

Study	Application	Data Source	Description	Important Findings	DCC/OA/RS: Comments
Hamed 2001 [2]	Behavior assessment: Modeled waiting time and crossing attempts for signal design.	Observers, interview	A risk function models waiting times and Maximum Likelihood Estimate (MLE) is used to model parameters.	A pedestrian's expected waiting time significantly affect required attempts to make a successful crossing.	V/H/-: Video recording can reduces DCC.
Sisiopiku and Akin 2003 [13]	Behavior assessment: Analyzed perceptions, and preferences for design & planning.	Video, survey forms	Sidewalk cameras for movement data and survey for complementary information. Compliance rate (ratio of ped. count over total peds. including jaywalkers) is used for comparison.	Mid-block crosswalk is most influential facility. Distance of crosswalk to desired destination is most influential factor in decision to cross.	H/H/-: Work can be improved by conducting the data collection part automatically with a vision-based system. However, contextual information of facilities and destinations should be provided for each intersection.
Lam and Cheung 2000 [71]	Behavior assessment: Analyzed walking types for design & planning.	Video	Estimated walking speeds and flow relationships for commercial and shopping areas.	Pedestrians tend to walk faster in commercial areas than in shopping areas. Pedestrians generally walk slower on crosswalks with mid-block than those crosswalks without mid-block.	M/H/-: Automatic data collection can improve the data collection process and waiting time estimation can be added to complement behavior analyses.
Keegan and Mahony 2003 [73]	Behavior assessment: Evaluating timers effect on crossing behavior.	Video, survey forms	Extracted relationship between green cycle length and number of pedestrian crossings. A survey was used to determine pedestrians' characteristics, such as age and gender.	The count-down timer induced a reduction in the number of individuals who crossed during the red signal.	H/H/-: A vision-based system would enhance the data collection and evaluation process. The signal timing information can be inferred by queue length estimation.
Bernhoft and Carstensen 2008 [74]	Behavior assessment of old pedestrians versus pedestrians' ages 40-49.	Questionnaire forms	The χ^2 test showed a significant difference between old versus young respondents and men versus women. A linear regression was used to build a model.	The younger group generally finds it important to move fast but older group shows more cautious behavior.	H/H/-: A work only relies on questionnaire form for data collection which limits the long time evaluation.
Tarawneh 2001 [72]	Behavior assessment: Analyzed crossing speeds for individuals and groups for safe signal design.	Observers	A four-factor analysis of variance (ANOVA) was performed with the mean speed as the dependent variable and age, gender, group size, and street width as independent variables.	Age, gender, group size and street width significantly contribute to a pedestrian speed.	V/H/-: Data collection was time consuming since it was conducted by four individuals. Videos facilitates the process and decreases DCC.
Shirazi and Morris 2016 [69]	Behavior assessment: Estimating crossing speed, count and waiting time.	Video	The fusion of motion and appearance cues provide robust detections. Optical flow tracks pedestrians to handle partial occlusion.	Contextual fusion of appearance and motion improves performance of vision-based tracking.	L/H/H: Tracking speed can be improved using GPU.

videos facilitate a field observation process, medium level of DCC was assigned to it. Moreover, they all lack real time applicability, which is desirable for safety systems, since they just use simulation environment. Although driving simulators facilitate the gap estimation process (e.g., they provide the location and speed of oncoming vehicles), they suffer from the sickness problem. In particular, simulator sickness is correlated with turning maneuvers and braking behaviors [42].

B. Threat

Some studies evaluated threat assessment [79]–[81] by predicting the possible threats of other vehicles [79] or by calculating the safety measurements [81]. Predictions were made based on combining the intention predictor and an efficient threat assessor by using rapidly-exploring random trees. The threat assessor computed the threat level, and the corresponding maneuver for the best escape route. Chan et al. [81] assessed the threat of opposing traffic by finding the time to intersection (TTI) value. When TTI is greater than a threshold, a time window is open for the SV to take its maneuver. Other threat assessment studies [79]–[81] collected data using instrumented vehicles and vision based systems. A threat assessment method has real applicability in ADAS systems as long as collected trajectories are evaluated in real-time fashion to determine the possible threat levels of opposing traffic.

C. Risk

Risk assessment is the process of detecting a dangerous situation that might cause by drivers' error, for example, perception failure, misunderstanding of the situation, or a wrong decision. Drivers mostly evaluate the risk of collision with other vehicles by assessing the other drivers intentions. Driver intention should be predicted and compared against the expectation [82] in order to determine the probability of the risk. As an alternative approach, the collision risk of an intended path could be compared against all possible paths of other vehicles according to probabilistic models [33].

TABLE VII: Gap Analysis at Intersections

Study	Application	Data Source	Subject	Important Findings	DCC/OA/RS
Alexander et al. 2002 [41]	Safety assessment: building a model by regression to predict incidents (i.e., an accident or near-accident) from gap and driver characteristics.	Driving simulator, survey forms	Driver	Male and young drivers more likely accept smaller gaps in comparison with female and elderly drivers.	V/H/-
Yan et al. 2007 [42]	Safety assessment: investigation of vehicle speed, driver age, and gender on left- turn gap acceptance.	Driving simulator, survey forms	Driver	The major road traffic speed and driver age and gender have significant effects on the gap acceptance maneuver.	V/H/-
Ragland et al. 2005 [3]	Safety systems: modeling gap acceptance of left-turner subject vehicle (SV) in order to design Intersection Decision Support (IDS) systems.	Video	Driver	Presented gap to the driver of SV has a log-normal distribution. Accepted gap ranged from 3 to 12 seconds.	M/H/-
Chan et al. 2004 [78]	Safety systems: extracting time gap acceptance (TGA) to design IDS systems.	Video	Driver	Warnings should issue in the range $t = -5$ to $t = -3$ of driver decision. Pedestrians' presence significantly affects driver behavior.	M/H/-
Leung and Starmer 2005 [43]	Safety assessment: Evaluation of age and alcohol use on gap acceptance behavior.	Driving simulator, survey forms	Driver	Young drivers demonstrated and increased tendency to engage in risky tactics.	V/H/-
Sun et al. 2003 [76]	Safety assessment: modeling pedestrian gap acceptance using deterministic, probabilistic, and binary logit methods.	Video	Pedestrian	The minimum accepted gap by younger pedestrians is less. The mean of accepted gap increases marginally with waiting time.	M/H/-

The Bayesian network and HMM are two popular learning frameworks in this context [33], [82].

Pedestrians' risk exposures were estimated using data-mining techniques on observed data, reported accidents, and collision datasets. For example, King et al. [83] used crash datasets and observation data for illegal crossings, such as walking against the red light and crossing away from the signals but within 20 m. In their studies, relative risk ratios were calculated for these categories using annual crash reports, and experimental results indicated eight times higher risk of illegal crossings.

Tiwari et al. [84] observed video recordings of seven intersections to determine the number of safe and unsafe crossings, waiting times, and survival times. Survival analysis leverages waiting time, the number of waiting pedestrians, and unsafe crossings in order to provide the probability of initiating an unsafe crossing. Tiwari et al. [84] applied this idea to investigate the variant nature of pedestrian risk as a function of time. Leden [85] investigated police reports of accidents to determine the correlation between pedestrians' risk and vehicles' flow. Risk decreased with increasing pedestrian flow and increased with increasing vehicle flow. In addition, left-turning vehicles caused higher risk for pedestrians than right-turning vehicles.

Unfortunately, risk analysis studies usually introduce their own definition regarding near-accidents or unsafe situations. Further efforts are required to codify universally consistent definitions. Since accident dataset is a valuable source for risk analysis, a comprehensive dataset is necessary regarding pedestrians and drivers with their accident records. In addition, accident records, specifically for pedestrians and drivers, are critical for risk analysis. The accuracy of risk analysis is thus subject to the accuracy of collected accident data. Currently, these are obtained manually from video recordings and automated vision-based systems could greatly facilitate this branch of safety studies. Since representative work of risk analysis used accident report as data source, they have been listed at the end of TABLE X along with their methods and important findings.

D. *Conflict*

A traffic conflict mostly is used in safety analysis defined by Amundsen and Hyden [86] as: "An observable situation in which two or more road users approach each other in space and time to such an extent that there is a risk of collision if their movements remained unchanged". Fig. 4 shows a hierarchical concept of using conflicts that implies critical observations used in safety analysis. In this section, surrogate safety measurements are explained with their application for safety quantification, and finally conflict-based studies at intersections are presented.

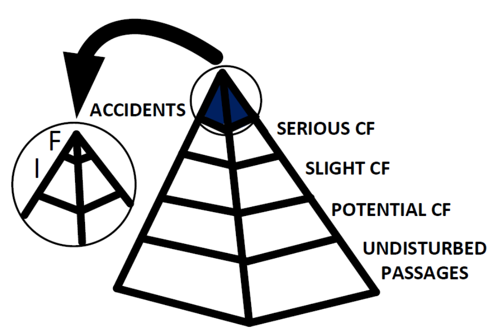


Fig. 4: Traffic safety pyramid measurement showing the hierarchy of traffic events (CF=Conflicts, F= Fatal, I=Injury) [87]

1) Surrogate Safety Measurements: Important safety measurements used in intersection studies are shown in Table VIII.

Low values of time to collision (TTC) and post-encroachment time (PET) are used in literature to imply a high probability of collisions. Headway is another safety indicator in a car-following model [88], and departure headway is an important variant of headway used to measure the intersection capacity and time of traffic signals. It is usually defined as the time that elapses between consecutive vehicles when vehicles in a queue start crossing the stop line (or any other reference line) at a signalized intersection, after the light turns green [89], [90]. Since the inaccurate estimation of departure flow often leads to an inappropriate signal-timing plan, many investigations had been carried out to study the statistics of departure headways regarding such external influence factors as the number of lanes and vehicle types. For instance, Jin et al. [89] and Yin et al. [91] showed that departure headways follow a certain log-normal distribution for each vehicle position in queue with different mean and variance values. This distribution is suggested intuitively to interpret the outcome of the interactions between the vehicles in the discharging queue.

Since availability and quality problems are associated with collision data, some studies have relied upon traffic conflict analysis as an alternative or a complementary approach to analyze traffic safety. Traffic safety analysis has been investigated separately for vehicle-vehicle and vehicle- pedestrian conflicts. For vehicle-vehicle conflicts, safety measurements include distance to intersection (DTI) [92], [94], [97] Headway [59], and TTC [93].

Chan et al. [92], [97] addressed the LTAP/OD scenario (See Fig. 3) to assess the left-turn conflicts. The data acquisition system included radars to capture vehicle position and speed relative to the intersection and a video camera to provide complementary data. This group showed the effectiveness of PET and TTC values to compare and quantify safety at three different intersections. However, the safety quantification method should be conducted for all scenarios since various turning behaviors are manifested from vehicles at a typical intersection.

Automated vision-based systems address all turning scenarios by providing reliable trajectories of intersection participants and directly estimating the surrogate safety measurements during tracking. For instance, Sayed et al. [93] leveraged TTC measurements to identify the safety deficiencies at regions of interest. The accuracy of the direct methods was affected by the reliability of individual vehicle and pedestrian tracks which would be noisy for occluded and stopped vehicles. As an alternative way (i.e., indirect conflict detection), trajectories are clustered to learn the typical models using probabilistic frameworks. For instance, statistical sequence clustering by HMM was used in [24] to learn models of conflicting trajectories. However, HMMs require considerable data for the reliable estimation of the model parameters. Determining the model parameters, especially the number of model components in HMM-based clustering, is a complicated and uncertain process.

Conflicts at intersections are defined in some studies as abnormal or unexpected behavior of vehicles. Vehicles approaching an intersection follow a certain model that helps to determine their abnormal behavior as shown in Fig. 5.

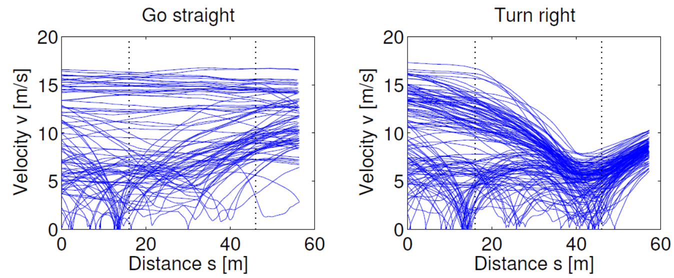


Fig. 5: Velocity profiles of vehicles for going straight and turning right. The position of the stop line and that of the pedestrian crossing are indicated by dotted lines [55], [94].

Akamutsu et al. [94] developed the Bayesian framework to learn a model and detect conflicts on the onset of braking using vehicle velocity and DTI. However, the model requires improvement using on-line updating methods, since a variety of driving patterns are introduced by different drivers.

2) Turning Conflicts: For vehicle-pedestrian conflicts, violations by pedestrians and their conflicts with right- or left-turning vehicles were studied. Ismail et al. [25], [26] extracted DTI, PET, and TTC; and Zaki et al. [22] investigated pedestrian violations by comparing a given track and normal movement prototypes. Sayed et al. [23] relied on the development of a database to cover all interactions between road users, including TTC and other measurements. Most vehicle-pedestrian conflict analyses use cameras and a tracking system with optical flow to provide trajectories of pedestrians and vehicles. Although feature-based tracking with optical flow can tackle the partial occlusion problem, it is challenging for stopped pedestrians with small size. In addition, grouping the features regarding road users is another problem which is addressed by hierarchical clustering. Hierarchical clustering requires perfect criteria for the segmentation process; however, road users are prone to the over segmentation problem [21].

In general, the main threat to pedestrian safety rises from the interaction with turning vehicles since crossing pedestrians and turning vehicles share the common phase of signal. Since left-turn conflicts with pedestrians frequently occur, some studies addressed that issue by extracting vehicle speed and PET [96] or by using regression models to find the greatest contributing factors [98]. The conflict point was determined in [96] by predicting future trajectories using predefined models, such as the speed profile, gap acceptance and stopping and clearing profiles. The accuracy of the system is affected by cubic functions used to estimate model parameters and situation results do not reflect real driving scenarios.

TABLE IX shows representative studies of conflict based safety analysis methods and highlights their applications and limitations. Among the presented methods, those with automated vision-based methods using optical flow (OF) [23]–[26] demonstrated better performance. The tracking accuracy is high due to robustness against partial occlusions and the limitation in tracking of stopped vehicles does not affect TTC and PET calculations.

TABLE VIII: Safety Measurements Used in Intersection Studies

Parameter	Definition
Time To Collision (TTC)	The time for two vehicles (or a vehicle and pedestrian) to collide if they continue at their present speeds on their paths. [23], [25], [26], [43], [55], [92]–[94]
Distance To Intersection (DTI)	The distance until a vehicle reaches to stop bar with current speed. Stop bar is used as reference point. [15], [25], [26], [30], [32], [40], [55], [61], [63], [78], [93]–[95]
Time To Intersection (TTI)	The time remains until a vehicle reaches the stop bar with its current speed. Stop bar is used as a reference point. [30], [40], [56], [61], [63], [78], [81], [92]
Time Headway	Elapsed time between the front of the lead vehicle passing a point on the roadway and the front of the following vehicle passing the same point. [43], [58], [59]
Post-Encroachment Time (PET)	Time lapse between end of encroachment of a turning vehicle and the time that the through vehicle (or pedestrian) actually arrives at the potential point of collision. [23], [25], [26], [93], [96]

TABLE IX: Conflict-based Safety Analysis at Intersections

Study	Application	Data Source	Participants	Classification, Inference or Approach	DCC/OA/RS: Comments
Chan and Bougler 2005 [97]	Safety system (CAS): Assessed conflicts by cooperative roadside and vehicle-based data collection.	Video, vehicle, radar, loops	Vehicle-Vehicle	Estimated the distribution of some measurements, such as TTC, steering wheels and angles.	V/H/-: LTAP/OD scenario is evaluated. Offline evaluation doesn't provide RS metric.
Saunier and Sayed 2006 [24]	Safety assessment: Traffic conflict detection.	Video	Vehicle-Vehicle	Used HMM for clustering trajectories of traffic conflicts.	L/H/H: Validation is needed by comparison with the ground truth.
Ismail et al. 2010 [25], [26]	Safety assessment: Localized conflicts using heat map.	Video	Vehicle-Pedestrian	Optical flow tracking, classification of pedestrians and vehicles by speed and trajectory prototypes.	L/H/H: Motion-based tracking method fails for stationary participants but doesn't affect TTC calculation.
Alhajyaseen et al. 2012 [96]	Safety assessment: Conflict analysis with left turning vehicles.	Video	Vehicle-Pedestrian	Manual video observations; estimated vehicle speed profiles, PET.	M/H/-: Trajectory predictions by models can be improved using non parametric Bayesian methods (e.g., particle filtering).
Sayed et al. 2012 [23]	Safety assessment: Localized rear-end and merging conflicts by heat map.	Video	Vehicle-Pedestrian	Optical flow tracking; estimated distribution of TTC and the severity index.	L/H/H: Motion-based tracking method fails for stationary participants but doesn't affect TTC calculation.
Hussein et al. 2015 [99]	Safety assessment: Assessed pedestrian conflicts.	Video	Vehicle-Pedestrian	Optical flow tracking; investigated pedestrians' violation realtion with TTC.	L/H/H: Motion-based tracking method fails for estimating waiting time but doesn't affect TTC.

E. Accident

Accident-based safety analysis includes various methods used to learn and model accident patterns, making predictions to prevent accidents and using data mining techniques on accident reports.

1) Automated Accident Detection: Automated vision-based methods are available that can address accidents and collisions, based on predicting the future state of the vehicle by using vehicle dynamics. Collisions are detected if there is an overlap between the predicted 3D cubic models of vehicles at the same time. As a typical example of vision-based work, Kamijo et al. [100] addressed three types of accidents 1) bumping accidents, 2) stop and start in tandem, and 3) passing. These types of collisions were detected using HMM to learn the crash patterns. Akoz [101] used continuous HMM for clustering paths, and linear regression for recognizing the severity of an accident.

The major difficulty of vision-based systems is to provide a robust tracker against occlusion, which is an undesired effect of accidents. This manifests as well when vehicles get too close and the segmentation of vehicles becomes highly challenging. Region-based tracking using background subtraction is still a good solution for accident prediction since 3D model of object can be inferred using foreground mask [102].

As an alternative way, extracting different features regarding shape and motion tracks (e.g., variation rate of velocity, position, area, and direction) are quite common for accident detection [103]. For instance, Atev et al. [104], [105] inferred all possible pairs of rectangles that intersect in current and future time steps, based on the estimated position, orientation, and size of the vehicles. In studies by Hu et al. [102], [106] motion patterns were learned by neural networks, and the probability of accidents was calculated for partial trajectories obtained by 3D model tracking of vehicles [102].

Since automatic accident detection from videos is a complicated task, non-vision-based techniques rely on other sensors for vehicle detection. Harlow and Wang [44] used acoustic signals to automatically detect accidents by creating a database from traffic features and accident sounds. In a study by Streib et al. [34] LIDAR data was used to detect vehicles, and the severity of collisions was detected using a 3D model estimation of the target by an extended Kalman filter. Salim et al. [107], [108] used a simulation environment. So, they did not need to address tracking problems and collision patterns were stored in a knowledge base for statistical inference operations.

2) Data Mining: Data mining algorithms work on data of accident reports to find cause of accidents and contributing factors. Vehicle-pedestrian accidents are addressed through the non-vision based studies using real crash datasets and police reports. Since real datasets are used, statistical inferences are more accurate and valuable. Finding reasons for the accidents [109], [110] with regard to the types of vehicles [111], time, location, and injury [112] are the common subjects for these intersection studies. Crash datasets is also used to build a model based on pedestrian intersection safety indices ($PED\ ISI$), used to determine the safety index score for a single pedestrian crossing. The model is defined in (2),

$$\begin{aligned} PED\ ISI = 2.372 - 1.867(S) - 1.807(St) + 0.335(Tl) \\ + 0.018(Sp) + 0.238(Cm) + 0.006(Ma)(S) \end{aligned} \quad (2)$$

where S, St, and Cm are binary values indicating signal controlled, stop signs, and predominantly commercial areas. Tl is the number of through lanes, Sp is the 85% speed of the street being crossed, and Ma is the main street traffic volume.

TABLE X shows safety analysis methods based on accident reports including important findings and limitations. The major problem involves limited availability of real crash datasets which are required for informative predictions. Moreover, the update of estimated models and new inferences undergoes a long time period since real accident data is the rare event which firstly need to be collected and reported by police. Vision-based systems have better performance for collecting accident events due to lower cost and automated analysis.

VII. INTERSECTION SAFETY SYSTEMS

Intersection safety systems help drivers to make safe decisions at intersection junctions and avoid accidents. They can be coarsely divided into two groups, infrastructure-based systems and advanced driver assistant systems (ADAS). Both approaches require understanding the traffic scene, assessing the criticality of the solution and guiding drivers with the necessary information, or intervening into the vehicle's control system autonomously. Fig. 6 depicts a simple diagram of safety systems at intersections.

A. Advanced Driver Assistant Systems

ADAS is expected to cooperatively work through the mutual understanding of a driver and a vehicle; this is difficult due to the uncertainties regarding driver behavior and intention. ADAS supports a driver through three major steps: perception enhancement, action suggestion, and function delegation. Since a general survey with more details is presented in [115], the following is a discussion regarding intersection studies.

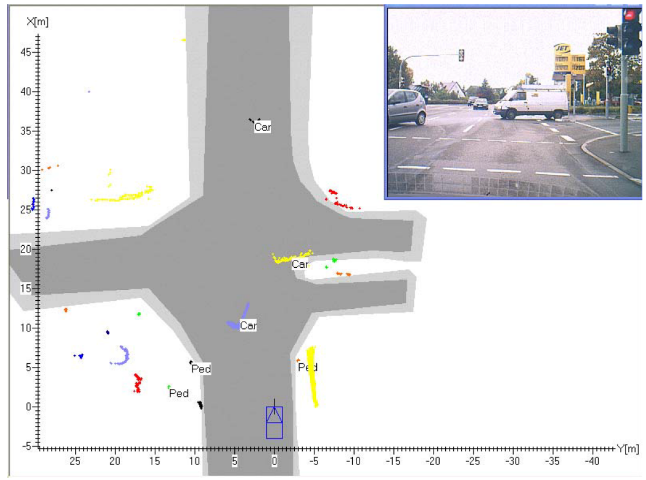


Fig. 7: The visual display of a feature-level map, which shows the road users [35]. Unseen pedestrians are shown on the map, and the host vehicle is drawn as a blue rectangle at (0,0) position.

1) Driver Perception Enhancement: The goal of driver perception enhancement is to enhance the sensing capability of drivers through outside vehicle lighting systems, inside vehicle displays, and by filtering noisy signals. This is referred to 'as mild ADAS' since information is directly provided to drivers, and their decisions and actions are required to handle undesired situations [115]. This is a great help for older drivers since they are overrepresented in accident reports [41], [42]. This also helps people with low vision acuity since small undetected objects can be shown to drivers on high resolution screens.

Driver perception is highly enhanced by means of feature level map [116]. This map is a database of knowledge for all the dynamic components at an intersection, including vehicles' and pedestrians' movement, traffic signal timing, and drivers' intent. The information is fused contextually with GIS map, and can be drawn with a friendly interface to drivers. Fig. 7 shows a typical display of the feature-level map. The efficiency of the map is related to the performance of the fusion techniques using different sensors. Since vehicle-based cameras provide a limited field of view, infrastructure-based sensors provide complementary data. As a result, data collected from infrastructure-based sensors, such as RADAR [117] and GPS corrections [75], [118], [119], should be communicated to the vehicles.

2) Action Suggestion Systems and Human Driver Interface : Action suggestion systems are known as a moderate ADAS [115] since they allow drivers to take an appropriate action besides providing related information for them. The general action suggestion systems are visual information, voice navigation guidance, decision support and warning systems. An intersection decision support (IDS) system focuses on enhancing the driver's ability to successfully negotiate rural intersections. The system uses sensing and communication technology to identify the safe gaps in traffic on a high-speed rural expressway and communicate this information to

TABLE X: Risk & Accident-based Safety Analysis at Intersections

Study	Application	Data Source	Participants	Classification, Inference or Approach	Important Findings	DCC/OA/RS: Comments
Atev et al. 2005 [104], [105]	Safety assessment: Collision prediction.	Video	Vehicle-Vehicle	Position and 3D model shape estimation	A novel method for three-dimensional vehicle size estimation is presented to predict collisions.	L/H/V: Background subtraction fails to detect occlusion, stopped vehicles and shadow.
Ki and Lee 2007 [103]	Safety assessment: Accident detection and reporting model.	Video	Vehicle-Vehicle	Extracted features with a predefined threshold value	The proposed system detected some accidents which were not reported by police in two weeks evaluation.	L/M/V: frame differencing does not update background model, fail for occlusion and stopped vehicles
Salim et al. 2007 [107], [108]	Safety assessment: Collision detection.	Simulation environment	Vehicle-Vehicle	Data mining	A collision system is able to adapt to a new intersection settings through mining the intersection patterns of collisions.	L/M/-: Simulation environment doesn't exactly reflect the real traffic scenario.
Harlow and Wang 2001 [44]	Safety assessment: Accident detection.	Acoustic signals	Vehicle-Vehicle	Feed forward neural network	Classifying acoustic signals showed a promising results to recognize accident events.	L/-/H: Supervise learning is required to distinguish crash signals.
Lee 2005 [109]	Safety assessment: Analysis of vehicle-pedestrian crashes.	Crash dataset	Vehicle-Pedestrian	Developed two types of models to analyze frequency and injury severity of pedestrian crashes	Middle age (25-64) and male drivers are more involved in crashes. Higher average traffic volume increases the number of pedestrian crashes.	H/H/-: The work can be further improved to find the reasons of pedestrian crashes.
Al-ghamdi 2002 [111]	Safety assessment: Association analysis between crash severity and such variables as age, gender and nationality.	Crash dataset	Vehicle-Pedestrian	Chi-square and odd ratio techniques	77% of pedestrians were struck while crossing a roadway outside of crosswalk area. More than one third of fatal injuries were located on the head and chest.	H/H/-: Limited number of pedestrian-vehicle crashes (i.e., total of 638) were investigated during the period 1997-1999.
Preusser et al. 2003 [110]	Safety assessment: Extracted crash type versus culpability pedestrians and drivers	Crash dataset	Vehicle-Pedestrian	Extracting information from crash datasets reported by the police	Pedestrians were slightly more likely to be judged culpable. Turning vehicle crashes typically involves driver's failure to yield pedestrians.	H/H/-: Very old datasets of two cities (Washington, Baltimore) at 1970 were used.
Zeeger et al. 2007 [113]	Safety assessment: Safety effects of installing crosswalks at uncontrolled locations.	Video	Vehicle-Pedestrian	Manual observation, poisson and negative binomial regressive models	Pedestrians' crash severity of marked versus unmarked locations didn't differ significantly for two-lane roads but it did for multi-lane roads.	M/H/-: Unfair evaluation due to comparison of unmarked crosswalk with opposite leg of intersection as marked crosswalk.
LaScala et al. 2000 [114]	Safety assessment: The effects of environmental and demographic characteristics on pedestrian injury collisions.	Crash dataset	Vehicle-Pedestrian	Spatial analysis	Injuries in pedestrian crashes are greater in the areas with higher population density and average daily traffic.	H/H/-: Estimated variables of the model depend on available crash datasets.
Leden 2001 [85]	Safety assessment: Estimation of risk relation with flow.	Accident database	Vehicle-Pedestrian	Generalized linear interactive modeling	• Greater left- than right-turn risk for peds. • Risk decreased with higher pedestrian flow. • Risk increased with higher vehicle flow.	H/H/-: Automated vision-based methods or manual observation of videos can help to reduce the data collection cost.
King et al. 2009 [83]	Safety assessment: Estimation of annual crash/crossings vs. legal, red-light, and $>$ 20 m from signal crossings.	Observers, accident reports	Vehicle-Pedestrian	Compositional Data Analysis by CoDaPack software	• $8\times$ risk of pedestrian crash for illegal crossing at signalized intersection.	V/H/-: Manual observation plus survey forms causes very high (V) cost in data collection.

drivers who are waiting to enter the intersection from a minor road [120]. As a result, some intersection studies analyze gap acceptance and its effect on IDS systems (see TABLE VII). IDS alerts usually are designed using gap information and safety measurements collected by various sensors [121] which is not perfectly possible from the vehicle-based sensors such

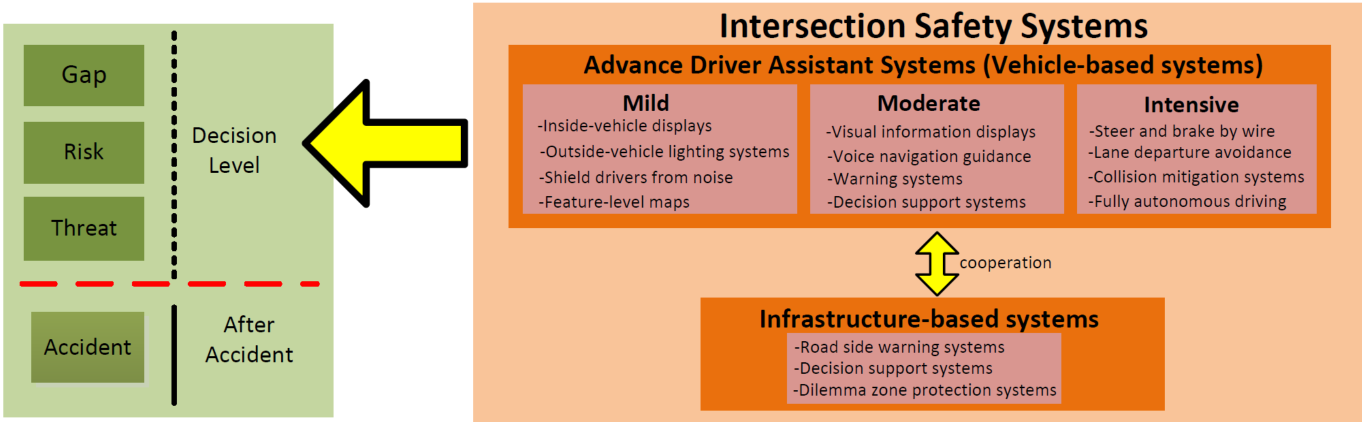


Fig. 6: Intersection Safety Systems

as LIDARs and cameras. As mentioned earlier, infrastructure-based cameras can provide better coverage at junctions that need to be transmitted and fused with available collected data by the vehicle in real-time.

Intersection warning systems boost safety by warning drivers about the possible threats within a supported range at an intersection. Warning systems have been studied in [118], [119] as part of the cooperative intersection collision avoidance system (CICAS) project for violations. Traffic signal violations and stop-sign violations are considered with respect to signalized and unsignalized intersections. Infrastructure-based and vehicle-based equipment and devices are introduced, such as GPS corrections, dedicated short-range communication (DSRC) and driver-vehicle interface. The intersection sends the signal phase and timing, positioning corrections, and a small map to the subject vehicle. After receiving this information, the subject vehicle predicts whether or not POV is violated, based on the speed and distance to the stop location [118], [119].

The practical warning systems rely on receiving portion of data from the infrastructure. Although this lightens the processing overhead for the vehicle, it limits the coverage range to detect approaching vehicles. As a result, inter-vehicle communication is preferred since the vehicle itself could cover the partial areas, and their aggregate could significantly improve the perception of the intersection scene by means of a distributed network scheme.

Inter-vehicle and wireless communication are integral parts of the network, and have been studied using simulators in [122]–[124]. The major goal is to improve the interface with the driver in order to virtually ensure that warnings are received at a high transmission rate. When Dogan et al. [122] evaluated collision warning systems by simulating 20 vehicles, they realized that packet loss under the broadcast scenario was unlikely when vehicles were 50 meters away from the intersection. However, less timing intervals to broadcast the information was required to reduce the percentage of packet loss [123].

3) Advanced Vehicle Motion Control Delegation: This is a future perspective of ADAS systems that aims to alert drivers from possible wrongdoing (i.e., lane departure warning) or even intervene into driving behaviors if high probability of risky situation is recognized (e.g., braking before a collision). As shown in [125], there are different levels of function delegation for drivers. The simplest one such as steer-by-wire corrects the human driving behavior by filtering out the human errors and stochastic disturbances. A more elaborate ADAS could adjust the steering gear ratio with regard to vehicle dynamics and driver behavior [123]. For example, brake by wire controllers should know the driving models and environmental situation in order to adjust their level of braking at an appropriate time.

Collision mitigation systems belong to motion control solutions that enhance traffic safety by evaluating certain safety considerations for near-accident situations. For example, the system applies brakes if the driver does not react to the generated warnings; when a collision is unavoidable, it tightens the seat belts of the front-seat occupants. A typical study on mitigation systems used a simulation environment to avoid or mitigate rear-end collisions and possibly head-on collisions [126]. Obviously, various types of accidents occur at intersections, and dynamic information of all surrounding vehicles are required to handle collisions soundly. Traffic control with vehicular communications [127]–[129] and a multi agent approach [130] are suggested for intersections at this level of ADAS systems.

More complicated systems are suggested to enhance safety at intersections by means of traffic control systems with vehicular communications. If vehicles' current positions and future movements are known by each vehicle, they can be guided to travel in a safe, deterministic and smooth manner. A trajectory planning algorithm [127] is a frequently used method that designs time varying velocity profiles for the encountered vehicles. A simple example of trajectory planning is shown in Fig. 8. A collision may occur, when two vehicles move to the same zone simultaneously (i.e., vehicles A and D). Different scheduling algorithms, such as schedule trees [127]–[129] are processed in real-time to discover the collision free paths of all vehicles.

Regardless of communication issues [127], the trajectory planning is difficult to implement in real traffic scenarios since most studies come up with some assumptions to generate a

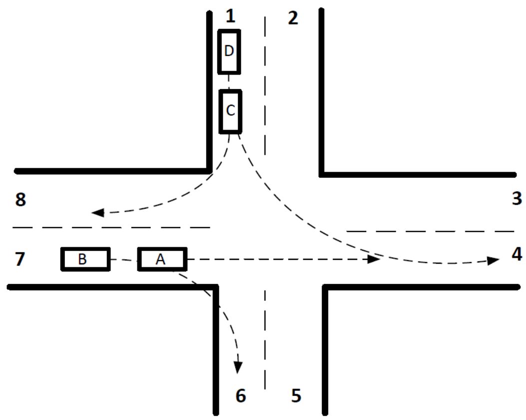


Fig. 8: Four-vehicle driving scenario for a two-lane junction [128]. A collision might happen for vehicles A and D since they enter the same zone.

collision free plan. For example, Li and Wang [128] considered low-speed vehicles without any stop signals or signs, which does not happen in reality. In addition, most methods assume that vehicles do not change their lanes within a certain distance to an intersection [128], [129]. Moreover, it is difficult to predict the long term trajectory of vehicles because of the stochastic nature of human driving behaviors.

B. Infrastructure-based Systems

1) Roadside Warning Systems: Roadside warning systems provide static or dynamic information to pedestrians and drivers. They vary from the simple count-down signal timers to more complicated ones which make the signal red for detected threatened vehicles. They offer a near term opportunity to deploy countermeasures for common intersection crashes, and could provide potential safety benefits for intersection participants. The design and effectiveness of these systems should be established by comprehensive human factor processes [75]. When a violation happens, there are various ways to convey this to participants. For example, a ”stop ahead” warning sign could be used in conjunction with a flashing amber light or else a warning light could be incorporated directly in the traffic-signal display. An intelligent rumble strip can be used to warn a violator to slow down.

2) Decision Support Systems: Infrastructure-based decision support systems provide a judgment about the available gaps by tracking all vehicles that arrive at intersections. Radars are typical sensors located along the main line of the intersection, and provide the optimal solution in terms of tracking ability, including lane assignment, coverage area, and cost [120]. Decision support systems should be designed with a simple interface that can be understood easily by drivers without increasing their mental workload. In one of the interfaces designs [120], such signs as hazard detection, count-down signs, and variable message signs (VMS) provide a real time dynamic presentation of approaching vehicles with their available gaps. The proposed interface was later evaluated by Creaser et al. [131] through the driving simulator for young and old drivers. It was shown that an IDS system is useful to encourage safer decisions regarding gap acceptance. The proposed methods should incorporate the participants’ waiting time as a significant factor contributing to aggressive driving behavior in order to imitate a real traffic scenario.

3) Dilemma Zone Protection Systems: A common method of providing dilemma-zone protection is based on placing detectors for each through lane and extending the green phase while approaching vehicles are at their dilemma zones. Although the method is effective, it fails for sequence of vehicles detected at their dilemma zones. As a result, green extension reaches to its maximum value, and there is a potential hazard for subsequent vehicles. McCoy and Pesti [132] suggested advanced warning flashers to overcome this undesirable situation. After a vehicle enabled the 3-s extension of a green phase, an advanced warning flasher with a ‘prepare to stop’ sign underneath begins to flash if gap-out (i.e., green can not further be extended) occurs. This helps subsequent vehicles prepare to stop. In comparison with more common methods, it has lower maximum allowable headway.

VIII. DISCUSSION & FUTURE DIRECTIONS

There are many open issues and further research that should be conducted to fully realize the promise of intersection analysis. The overall improvement of safety at intersections is an intricate problem due to complex behaviors and interactions between ranges of participants. The following highlights challenges and possible solutions for complete intersection safety.

A. Robust Detection and Tracking

Detailed data can be provided through manual collection techniques to extract trajectories and characteristics (e.g., gender, age, and vehicle type); however, this method is time consuming and labor intensive. Automated data collection must be improved for a wider-range of use cases including wide field of view (FOV), low equipment cost, and over long periods of time (night-time).

1) Cooperating Sensing Modalities: Each sensing technology encounters challenges for intersection use. Radars trade-off field of view for range and camera-based detection of pedestrians is difficult in highly occluded scenes and during night. Newer types of non-visible light sensors, such as thermal infrared and LIDAR, show promising results and their cost are decreasing with mass production. Sensor fusion and integration of sensing modalities with vision can be important for performance enhancement. A video provides a data stream that can be easily understood by humans while complementary sensors can simplify detection algorithms. Further, infrastructure-based sensors can complement vehicle-based sensing to develop a complete intersection description without blind spots. Practical safety systems, such as CICAS or forward warning systems, demonstrate the effectiveness of sensor cooperation.

2) Wide FOV and Small Participants: Video-based detection and tracking can be a challenging problem in traffic videos where the FOV is wide to cover an intersection completely resulting in small objects of interest. Detection algorithms must handle pedestrians that are very small in size and scene participants that can become stationary for some time. Motion can be reliable for small objects while appearance can be used to detect stopped objects. Contextual fusion of appearance-based classifiers and motion-based detectors improves intersection detection and tracking robustness [133]. Strategies, such as optical flow, can be utilized to handle partial occlusions and further improve performance.

B. Long-Time Monitoring

Long-time monitoring of vehicles' and pedestrians' behavior is a major requirement for intersection analysis (e.g., behavior modeling or scenario understanding). As a result, monitoring system should have real-time capability to generate measurements as they occur over lengthy observation periods. Embedded systems connected to surveillance cameras is a good solution for processing with communication systems in place to share measurements (e.g. with a turning movement count). With new networking technology it may be possible to stream video, with high quality compression, and make use of cloud-based services for computation. With the cloud, less processing equipment is required and software maintenance and improvements are easier.

C. Enhancing Behavior Inference with Topic Modeling

Although tracking methods provide microscopic behavior of participants, it can be strengthened through unsupervised learning of motion patterns which provides installation flexibility since the do not require manual calibration. Machine learning approaches are used to extract meaningful patterns, in aggregate, to describe scene and identify behaviors through clustering and topic modeling [11]. Topic models, such as latent Dirichlet allocation (LDA) [134] and hierarchical Dirichlet process (HDP) [135], have become quite popular for video surveillance due to their success with natural language processing. The basic idea is to cluster motion vectors based on their co-occurrence in a video clip to describe behavior/movement patterns without any requirement of highly accurate tracking or complex detection methods. The Bayesian modeling approach makes it possible to adjust a model to address different applications (e.g., abnormal behaviors or signal phase discovery).

D. Enhanced Abnormal Behavior Detection

Accidents often occur when there are some abnormal behaviors conducted by scene participants. These abnormalities are easier to detect through the traffic monitoring cameras since they provide wide view and scene context. When these abnormalities occur, intersection participants should be warned. Recognizing crosswalks and traffic signal timings are crucial for the detection of intersection misuse, such as jaywalkers or red-light running. Vision-based crosswalk detection can be performed by corner feature detection techniques (e.g., Harris corner detection [136]). The crosswalk corners can be recognized as static features points whose position does not change and form a rectangular shape. Tracking information and cumulative waiting time distribution can be used to infer

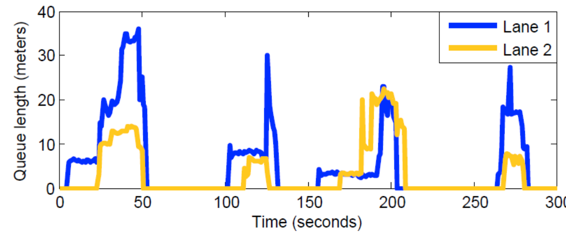


Fig. 9: Vision-based queue length estimation at intersections [137]. Traffic signal phases can be inferred from queue length analysis as green phases have no queue.

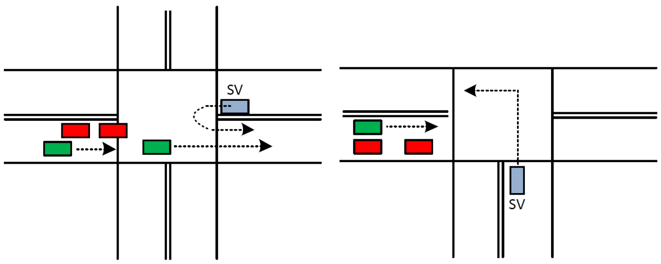
traffic signal timings [137]. In addition, that queue length estimation helps to infer the traffic phase shown in Fig. 9. Topic modeling is another way to estimate signal phase and detect abnormal behaviors without explicit tracking.

E. Human Features and Characteristics

A variety of features are required to characterize humans' behavior and estimate more accurate models. As it was mentioned earlier, some of these data can not be automatically collected from traditional intersection video (including pedestrians' and drivers' age and gender). Personal connected vehicles and smart phones can be good gateways for providing human characteristics to the infrastructure system. ADAS systems (in car or on a smart device), can learn customized driving models and patterns which can populate individual safety databases with different characteristic fields. A personalized system provides opt-in options for characteristics such as age which would not be possible to obtain otherwise and allows for the system to learn specifics based on data (e.g., route choice or average walking speed).

F. Networked Traffic Monitoring System

The technology of cooperative driving with inter-vehicle communication [138] is a potential solution to suppress traffic jams and prevent collisions. Operational trajectory planning should be solved considering potential conflicts. However, it is very difficult to infer the intention of another driver using only external sensors which increases the conflict search space. Vehicles need to send an intention signal (e.g., turn signal) to the monitoring system. Turning intentions, which are labels, along with other features would be collected by infrastructures for on-line updates and training models. Since traffic cameras have wider FOV, they can, in turn, provide more contextual data for planning and safety ADAS. Cooperation between vehicles and infrastructure can be used to augment the effective sensor coverage and provide preferential views for solving problems such as occlusion, line of sight and situational awareness [139]. As discussed in Section VII-A, the feature-level map improves situational awareness by revealing all surround participants including those that would be unseen in a blind spot. Fig. 10 shows two blocked line of sights which can be addressed through the communication of dashboard mounted camera which faces the direction of travel and infrastructure cameras that provide a complementary view.



(a) (b)

Fig. 10: Two obstructed line of sights scenarios during the gap estimation process (a) Driver (SV) to make u-turn on a flashing yellow, but waiting vehicles (red) block the driver view of a moving vehicle (green). (b) Parked cars (red) block the driver view (SV) when attempting to make a left turn at a junction.

G. Intelligent Intersections

Intelligent intersections are representative of complex hybrid systems which require the tractable distributed algorithms that guarantee safety and provide good performance. They can continuously monitored what's happening in them, communicate with participants and take an appropriate decisions to provide maximum level of safety through different collision avoidance strategies [140]. Embedding such intelligence in every road users including vehicles, and pedestrians would be a natural next step. Future cars will behave more like intelligent agents traveling in intelligent intersections and traffic control at intersections could employ cooperative driving technologies implemented over ad hoc networks, instead of relying on traffic lights [141].

H. Enhancing Pedestrian Protection Systems

Pedestrians are the most vulnerable intersection participants and require the most protection. However, common pedestrian safety approaches are within vehicle systems that only activate if a pedestrian is detected. Future research can address pedestrian safety on both sides through cooperating sensing (e.g., with cellphones). GPS and navigation data from pedestrian cellphones may be used to improve ADAS detection. The challenges are data management for real-time operation through data windowing only on relevant signals and online behavior model updates. Consumer GPS will be noisy and will require filtering and estimation techniques to have tight localization. As an example, pedestrian localization is improved by the use of WIFI signals [142].

I. Intersection Safety Map

A potential output of the safety quantification process at intersections is a safety map. Surrogate safety measures obtained through tracking or topic modeling methods could be utilized to highlight dangerous intersections on a navigation map. The danger level of a particular intersection could be used by ADAS to adjust control parameters or more simply as a warning for drivers and pedestrians to be more cautious when they are in a hazardous area.

J. Joint Warning Infrastructures

While smart devices can provide localization data, they may not be sufficient for alerts due to battery and attention issues. For more reliable notifications, cooperative warning infrastructures can be installed at known hazardous locations (as obtained from the intersection safety map). When an unsafe event is predicted through ADAS or infrastructure-based camera system, warnings (lights or sounds) can be generated; for example, a pedestrian crossing light that turns on automatically.

IX. CONCLUSION

In this article, we presented a review of recent studies for safety quantification using behavior and safety analysis of intersection participants including vehicles, drivers, and pedestrians. We grouped, commented on and compared different studies based on key factors of different participants and four major goals which are followed by various safety analyzing methods. Long term trajectory prediction, applicability on arbitrary intersections, real-time capability and dealing with human uncertainty are the four critical criteria required by safety systems. Subsequently, probabilistic methods using Bayesian frameworks are represented more in trajectory prediction literature since they can deal well with uncertainty (i.e., HMM: 0.187, Bayesian: 0.5, SVM: 0.187, LCSS: 0.125). Around 68% of safety studies use surrogate safety measurements in their evaluations since it is generally very difficult to predict and collect real accident data. TTC is the most important safety measurement used in safety analysis and automotive industries. However, DTI showed higher contribution among reviewed papers due to covering driving behavior of approaching vehicles, and gap estimation (i.e., TTC: 0.23, DTI: 0.32, TTI: 0.23, Headway: 0.8, PET :0.14). Intersection safety needs to be strengthened for all participants including vehicles, drivers, and pedestrians through communication and sharing of their dynamics and profiles. Infrastructure can be used cooperatively with well-equipped vehicles for technology enhanced safety. In addition, people should be trained through education and public awareness messages to reduce their errors and fully improve intersection safety.

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Mohammad Shokrolah Shirazi Mohammad Shokrolah Shirazi received his Ph.D. degree in electrical engineering from University of Nevada, Las Vegas (2016). He received his B.S. degree in computer engineering from Ferdowsi Univeriesity of Mashhad (2005) and his M.S. degree in computer architecture from Sharif University of Technology, Tehran, Iran (2007). He was working as a visiting professor at several universities in Tehran and he is the member of the "real-time intelligent systems laboratory" at UNLV. His dissertation Vision-based Intersection Monitoring: Behavior Analysis & Safety Issues got the second-winner place for the Best Dissertation Award of the year at UNLV. He is working on intersection safety analysis systems and his interests include computer vision, intelligent transportation systems, machine learning, computer architecture, embedded systems, and fault tolerant system design.

Brendan Tran Morris Brendan Tran Morris received the B.S. degree from the University of California, Berkeley, CA, USA, in 2002 and the Ph.D. degree from the university of California, San Diego, CA, in 2010. He is currently an Assistant Professor of electrical and computer engineering and the founding Director of the Real-Time Intelligent Systems Laboratory with the University of Nevada, Las Vegas, NV, USA. He and his team researched on computationally efficient systems that utilize computer vision and machine intelligence for situational awareness and scene understanding. Dr. Morris serves as an Associate Editor for the IEEE TRANSACTIONS ON INTELLIGENT TRANSPORTATION SYSTEMS (ITS), the IEEE ITS MAGAZINE, and IEEE Robotics and Automation Letters. His dissertation research on Understanding Activity from Trajectory Patterns was awarded the IEEE ITSS Best Dissertation Award in 2010.