Collision Pattern Modeling and Real-Time Collision Detection at Road Intersections

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Flora Dilys Salim
RMIT University

Seng Wai Loke
Deakin University

A. Rakotonirainy
Queensland University of Technology

Srinivasan Bala
Monash University (Australia)

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Collision Pattern Modeling and Real-Time Collision Detection at Road Intersections

Flora Dilys Salim, Seng Wai Loke, Andry Rakotonirainy, Bala Srinivasan, Shonali Krishnaswamy

Abstract— **The crash rate in road intersection demonstrates the need for a fast and accurate collision detection system. Ubiquitous computing research provides a significant opportunity to develop novel ways of improving road intersection safety. The existing intersection collision warning or avoidance systems are mostly built to suit a particular intersection. We suggest that an intersection collision detection system should be able to adapt to different types of intersections by acquiring the collision patterns of the intersection through data mining. Collision patterns that are specific to that intersection are stored in a knowledge base to select vehicles which are exposed to a high risk of collision. This algorithm increases the speed of collision detection calculation, as detection is not applied on all possible pairs in an intersection. The performance and accuracy of the algorithm are evaluated. This evaluation is done on a developed simulation bed and the results are presented.**

I. Introduction

The rate of fatalities of road intersection collisions has not significantly changed in more than two decades, regardless of improved intersection design, innovation of vehicles, and more sophisticated ITS technology [1]. Intersections are among the most hazardous sites on U.S. roads [2]. The statistic of crashes in the year 2002 in the USA reported that 50 percents of all reported crashes, approximately 3.2 million crashes, were intersection-related [1]. 22 percents of the total fatalities on the road, which was 9,612 fatalities, and roughly 1.5 million injuries and 3 million collisions, happened at intersection surroundings. In Japan, more than half of all traffic collisions took place at intersections [2]. The high crash rate in intersections is chiefly determined by the complexity at each intersection. Each intersection is unique because of the diversity of intersections' characteristics [2], [3], such as different intersection shapes, number of intersection legs, signalized/ unsignalized, traffic volume, rural / urban setting, types of vehicles using the intersection, various average traffic speed, median width, road turn types, and number of lanes [3]. Therefore, the complex nature of intersection collisions requires systems that warn drivers about possible collisions. In addition, given the uniqueness of each intersection, rather than manually fine-tuning a system for each intersection, an intelligent system for intersection safety should be able to adapt to different types of intersections automatically [4]. Different attributes of intersections such as intersection legs, traffic controls, permissible manoeuvres and turns, can cause a different set of collision patterns. Hence, it is necessary to identify these collision patterns for each intersection so that warning, avoidance, and mitigation strategies can be deployed.

Collision patterns and hazardous traffic and driver behaviours can be learnt by mining traffic and collision data. Since intersection collision depends on the characteristics of an intersection, there is a need to build a knowledge base which captures not only the traffic pattern and driver behaviours, but also the characteristics of collisions. For this purpose, mining is done to understand the cause of collisions. The mining results are stored as patterns in the knowledge base. This knowledge base assists identification of potential collisions. Since collision identification needs to be done in real-time, a novel method of storing, searching and matching of those patterns are proposed and a pair-wise vehicle contention algorithm is used for collision detection. The algorithm is evaluated not only for the speed of detection, but also the precision and coverage of incident detection. This evaluation is done on a developed simulation bed and the results are presented.

The primary aim of this paper is to propose a method for the knowledge acquisition of intersection accidents and real-time collision detection. Section II reviews the related works in intersection collision warning system, robotic collision avoidance, and collision detection algorithm. Section III discusses the research challenges and framework. Section IV discusses the need of knowledge base and the process of knowledge acquisition through data mining. Section V discusses real time collision detection. Section VI presents

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F. D. Salim is with the Caulfield School of Information Technology, Monash University, Caulfield East, VIC 3145, Australia (e-mail: Flora.Salim@infotech.monash.edu.au).
S. W. Loke is with Department of Computer Science & Computer Engineering at La Trobe University, Bundoora, Victoria 3086, Australia (e-mail: s.loke@latrobe.edu.au).
A. Rakotonirainy is with the Centre for Accident Research and Road Safety Queensland, Queensland University of Technology, Carseldine, QLD 4034, Australia (e-mail: a.rakotonirainy@qut.edu.au).
B. Srinivasan is with the Clayton School of Information Technology, Monash University, Clayton, VIC 3168, Australia (e-mail: Bala.Srinivasan@infotech.monash.edu.au).
S. Krishnaswamy is with the Caulfield School of Information Technology, Monash University, Caulfield East, VIC 3145, Australia (e-mail: Shonali.Krishnaswamy@infotech.monash.edu.au).

the evaluation methods and initial results. Section VII concludes the paper.

II. Related Work

A. Intersection Collision Warning and/or Avoidance Systems

There have been a number of initiatives in developing intersection collision warning systems and/or avoidance systems. Currently, no existing intersection collision warning and avoidance systems can tackle intersection collision problems entirely. Many existing Intersection Collision Warning Systems are still infrastructure-only systems, and are limited in certain aspects, which are as described in [4]. The main issue that is occurring in each system is that it is developed for a particular intersection and cannot be generalised for other types of intersections, and therefore, each application requires a field study on that intersection.

Vehicle-based intersection collision warning systems are fairly effective for a single vehicle [4]. However, in an intersection, the potential danger normally impacts more than one vehicle, therefore, a cooperative system is preferred [4]. However, to our knowledge, existing research projects in cooperative systems for intersection safety do not mention techniques to discover crash patterns and pre-crash behaviour associations [4], which are essential to detecting and reacting to potential threats. A generic framework that can automatically adapt to different intersections is required for efficient deployment.

B. Robotic Collision Avoidance

Studies in robotic collision avoidance have existed for many years [4]. Robots need to be able to find their own way to their destination as well as to avoid obstacles on their path. Although it seems that robotic collision avoidance has much resemblance to the problem of road collision avoidance, those two subjects differ in many aspects [4], which are as follows:

1) Robotic collision avoidance mostly focuses on static obstacles, such as walls. Whereas in road collision avoidance, we deal mostly with dynamic obstacles; therefore, the movement attributes of all objects must be taken into account, and a knowledge base should be updateable.
2) Robotic collision avoidance focuses on the goal of the robotic tasks such as to find a way out of a room. Road intersection collision avoidance focuses on getting to the destination safely.
3) Robotic collision avoidance, a path is the outcome of a collision avoidance process. However, in road collision avoidance, intended path of the driver is known to a certain extent by using sensors and is decided before a collision avoidance process.
4) Road collision avoidance does not require full automation such as robot collision avoidance. The output of road collision avoidance is primarily warning to drivers or other road users, whereas robot collision avoidance requires autonomous actions.

Due to the above differences, we need to approach road collision avoidance issues differently from robotic collision avoidance.

C. Collision Detection Algorithm

A multiagent based collision warning system [5], proposed a collision detection algorithm that can calculate a future collision point (x_+, y_+), where θ is the angle between the horizontal line and car trajectory:

$$x_+ = \frac{(y_2 - y_1) - (x_2 \tan\theta_2 - x_1 \tan\theta_1)}{\tan\theta_1 - \tan\theta_2}$$
$$y_+ = \frac{(x_2 - x_1) - (y_2 \cot\theta_2 - y_1 \cot\theta_1)}{\cot\theta_1 - \cot\theta_2} \quad (1)$$

The time for each car to reach the future collision point (TTX), where v is velocity of each car and r is the vector of the coordinate (x, y) [5] is calculated by:

$$TTX_1 = \frac{|\vec{r}_+ - \vec{r}_1|}{|\vec{v}_1|} sign((\vec{r}_+ - \vec{r}_1).\vec{v}_1)$$
$$TTX_2 = \frac{|\vec{r}_+ - \vec{r}_2|}{|\vec{v}_2|} sign((\vec{r}_+ - \vec{r}_2).\vec{v}_2) \quad (2)$$

As vehicles have variation in size, collision can no longer be expressed as a point; instead as a region. The α parameter is used to represent the size of the region, depends on the vehicle size. Therefore, a future collision is detected if time for both vehicles to reach the collision point is the equal or nearly equal [5], that is

$$\left|TTX_1 - TTX_2\right| < \alpha \quad (3)$$

While the technique can be used for collision detection, we found that there are two limitations of such an approach: firstly, high computational cost. The algorithm requires calculation for each possible pair of vehicles in the intersection; therefore, computational cost is high. Therefore, real time detection is doubtful when the number of vehicles increases abruptly in the intersection. Secondly, high communication cost. The algorithms require very frequently updated information due to split second velocity and location changes, thereby incurring high communication costs.

The challenges of the research are concluded in the next section, and a framework to answer the requirement of fast and accurate collision detection is presented.

III. Research Challenges & Framework

A. Challenges

An intersection safety system should be able to detect collision in real time, since collision warning must be delivered in time before collision occurs. An early and accurate detection should allow time for the system to warn a potential collision, for drivers to respond to warnings, and for avoidance systems or drivers to steer clear from the potential collision. Firstly, the collision detection algorithm should be simple and optimized. Secondly, reducing the number of vehicle pairs to be calculated in real time can reduce the computational time, because calculating each possible pair of vehicles located at an intersection for a potential collision is not prudent due to time constraints.

A means of filtering and matching vehicle pairs that have the potential of colliding with each other can be implemented to reduce the number of collision detection computation. We suggest that patterns of collisions that are accurate can be used as selection criteria for finding and matching a pair of vehicles, and therefore reduces the number of vehicle pairs to be calculated by the collision detection algorithm. Therefore, we store collision patterns in a dynamic knowledge base, which is populated through data mining of historical traffic and collision data. The usage of collision patterns has been customary in intersection safety studies, although it is not for the purpose of improving the performance of detecting potential collisions.

In order to improve the safety and design of an interesection, one of the first procedures is to execute a field observation and statistical analysis of collision patterns. Understanding patterns of collisions in an intersection can assist in planning for countermeasures. It is necessary to have a comprehensive collision patterns in an intersection safety system, in order not to miss detecting a potential collision, since the system can only detect and warn vehicles that match those patterns kept in the knowledge base.

The process of learning patterns of collisions is mainly done manually and repeated for each intersection. Results of those studies cannot be applied for all types of intersections due to uniqueness of each intersection. An intersection safety system should be able to adjust to different types of intersection through computer based pattern acquisition, not manual field observation.

B. Framework

We implemented the Ubiquitous Intersection Awareness (U & I Aware) framework (Fig. 1) [4], which aims to achieve holistic situation recognition at road intersections.

Currently, collision warning systems mostly react to events that might cause collision. Intersection collision warning systems should also evolve by adapting to information gained from analysis of sensor and historical data in the intersection. By learning from historical data of collision and near-collision events, improved detection and reactive behaviour can be achieved since the knowledge base of the intersection is evolving in the U & I Aware (Fig. 1). Thus, the system can gain better knowledge of any intersection where it is installed for better crash prediction. As this paper only focuses on collision learning and detection, the knowledge base and the knowledge acquisition process are described next.

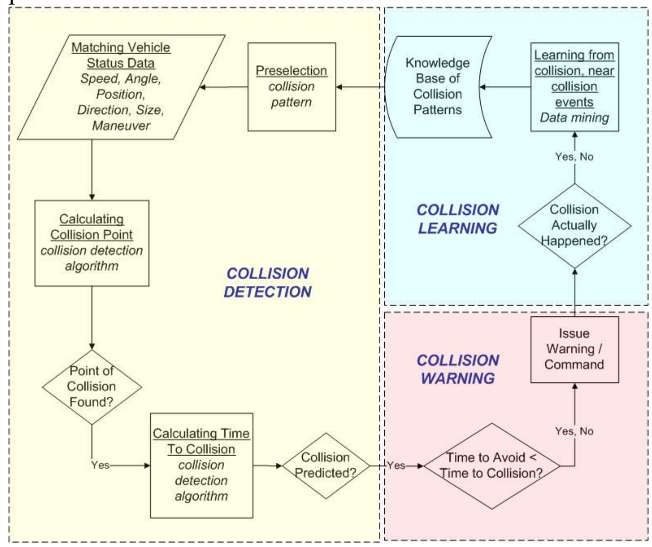

Fig. 1. U & I Aware Framework Strategy

IV. KNOWLEDGE BASE & KNOWLEDGE ACQUISITION

Ubiquitous computing research provides a significant opportunity to develop novel ways of improving road intersection safety. In-vehicle sensors have received considerable research and development focus and are now a reality in today's roads. The increased proliferation of such sensors has brought with it the question of how the sensory data can be leveraged for effective and efficient road safety enhancement. First, given the large amount of sensor data that are obtained from intersections and sensor-equipped cars, analysis and learning from these data can help detecting intersection accident patterns. Second, such patterns can be incorporated in accident detection systems. These patterns can be learnt through the historical collision and traffic data, which are collected from roadside sensors. We can also incorporate positive/negative results of the past collision warning ("collision actually happened?"), which can be communicated by the system in the vehicle, for refinement of the collision patterns. Data mining is proven to be effective for extracting traffic patterns and trends [6], [7].

In opposite to static knowledge base, dynamic knowledge base involves learning to accumulate and refine rules in knowledge base to adapt to situational changes. The dynamic knowledge base in an intersection collision detection system should contain valid and comprehensive collision patterns. Collision pattern learning is performed by using classification rules of data mining. New events are matched with the existing classes in the patterns repository of the intersection central agent or the car agent, depending on where learning happens. If a collision happens outside a known pattern, a learning process can detect and add a new collision pattern. There are a number of improvements and enhancements that can be added to the plain collision warning system that is based only on trajectory calculations.

These are done via mining of data from our simulation, assumed to be obtained from on the road sensors in order to characterize collision patterns. The sensor data simulated in our system resembles the real world data gathering from sensors installed on freeway by The Pantheon Gateway Project [7].

The simulated sensor data has six attributes, three of which (i.e. *direction, manoeuvre, and angle*) are from colliding vehicle pairs. Whenever there is a collision or near-collision event in our intersection simulation, data from the colliding (or near-colliding) pair of vehicles are collected and mined. In the real world, such data can be collected with conventional sensors such as inductive loop detectors on the road, or speedometer in the vehicle. We have successfully classified types of side collisions or perpendicular crashes in a cross intersection using the C4.5 decision tree (J48 classifier from Weka [8]) and the second vehicle direction (*Veh2_Direction*) attribute is nominated as the class. The implementation results also exhibit the most common crash patterns that exist within the particular intersection where the traffic data is acquired. Then, to realise all the possible crash patterns that involve a specific driving manoeuvre (e.g. straight) in an intersection, a Bayesian Network classifier [8] is used to classify the same data. The crash patterns enumerate four possible straight driving directions in a four legs cross intersection, which are left, right, up, and down. The classification shows all the possible collision patterns that might happen with the probability rate of each crash pattern (See Fig. 2). The highest probability of a crash pattern in each direction is circled in red in Fig. 2. Out of all the collisions that occur to vehicles that travel from the right leg to the left leg (i.e. "LEFT" direction), 93.1% of the collisions occur with vehicles from the lower leg to the upper leg (i.e. "UP" direction). Based on the result, we can also deduce that vehicles that travel with a straight manoeuvre from the left leg to the right leg of the intersection ("RIGHT" direction) tend to collide with vehicles that travel with a straight manoeuvre from the upper leg to the lower leg ("DOWN" direction). Note that these results were obtained from our simulated data for one intersection. Applying the same technique to a different intersection (with different data) could lead to different likely situations for collisions – the point is that applying such learning techniques would enable such collision situations to be recognized automatically and identified as "dangerous" patterns.

Probability Distribution Table For Veh1_Direction

Veh2_Direction	UP	DOWN	RIGHT	LEFT
UP	0.014	0.014	0.042	0.931
DOWN	0.022	0.065	0.891	0.022
LEFT	0.583	0.25	0.083	0.083
RIGHT	0.611	0.278	0.056	0.056

Fig 2. Collision Patterns based on Vehicle Direction classified with Bayesian Network

Later, we also included data of rear collision events that occur in the simulation. The test data now contain 7 attributes, i.e. *direction, manoeuvre, and angle* from each vehicle in a colliding pair, and *collision type* (side collision or rear end collision) and 20 – 30 rows in a file [6]. In this particular intersection, when Bayesian Network classification is applied with *collision type* nominated as the class, the result shows that rear end collision occurs much more often than side collisions in this particular intersection (Fig. 3). Using the same set of data, when the EM is applied, it also exhibits the same highest probability of side collision patterns as in Fig. 2.

Probability Distribution Table For Coll_Type

Veh1_Direction	SideCollision	RearEndCollision
DOWN	0.411	0.589
UP	0.023	0.977
RIGHT	0.044	0.956
LEFT	0.145	0.855

Fig. 3. Collision Patterns based on Collision Types as classified by Bayesian Network

In order to find trends in manoeuvre involved in certain collisions, we use EM clustering and the C4.5 decision tree. Visualization of EM results shows clusters of side collision with stopped maneuver, rear end collision with straight maneuver, and rear end collision with stopping maneuver. This is confirmed by C4.5 result (Fig. 4). We conclude that in this particular intersection, most side collisions occur when one of the vehicle pair is stopped and rear end collisions happen mostly when both vehicles are on the move with straight manoeuvres and secondly when both vehicles are stopping.

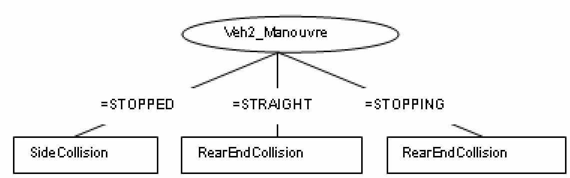

Fig. 4. Classification of Collision Types based on Vehicle Maneuvers

Based on the results of knowledge acquisition, there are two types of collisions in this particular intersection, which are rear-end collisions and side collisions. Each of this collision type consists of a number of sub-types. For example, rear-end collision with stopping maneuvers and rear-end collision with straight maneuvers. The collision patterns are stored in the system's knowledge base. The knowledge base in our system has a hashtable of collision patterns. Each pattern stores information about a pair of colliding trajectory, which is represented in vehicle's direction, manoeuvre and leg position. We use the collision patterns in the knowledge base to improve the speed of detection by preselection technique, which is discussed in the next section.

V. EVALUATION

As an implementation testbed, we use a computer based simulation of two different scenarios: intersection with traffic lights (Fig. 5) and without traffic lights. At this stage, computer based simulation is an acceptable proof of concept, since the scenarios that we implement involve collisions that are difficult to be simulated in the real world due to the constraint of resources and technology. The simulation parameters are as follows:

1) Intersection module: intersection type, leg, lane, lane group, traffic control.
2) vehicle: speed, acceleration, size, type, position, angle, maneuver.
3) driver: profile, intended destination, choices of maneuver.

The vehicles are randomly generated at a fixed time period (deterministic traffic flow / distribution) with different speeds, maneuvers, position and trajectory at the end of each intersection leg. Each vehicle is should observe the traffic light signals, safe following distance (3 seconds), safe stopping distance (2 seconds), and the speed limit. Random "naughty" vehicles (that will violate speed limit or perform red light running) are generated in the simulation to test the ability of the collision detection and learning algorithms. The probability of naughty vehicles in the intersection is 1:5. When a naughty vehicle is generated, its speed will be a random number up to 40 km/h above the speed limit.

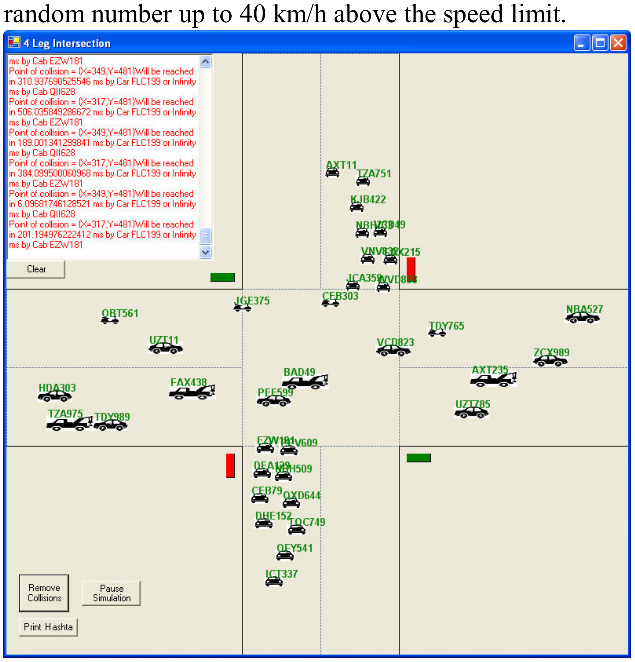

Fig. 5. Intersection Simulation

We implemented a pattern matching method, namely preselection algorithm, so that collision detection is only performed on pairs of cars that have the possibility of collisions based on the known intersection collision patterns. Preselection is implemented by choosing only the vehicles that exhibits behaviours, location, and driving manoeuvres that match the collision patterns in the knowledge base. The crash pattern knowledge base is implemented as a hash table filled with crash pattern class objects. Each crash pattern consists of a name, a manoeuvre, a direction, an intersection leg location, and a delegate function to find conflicting direction and manoeuvres. For example, given there is a cross intersection and the knowledge base contains a collision pattern named "perpendicular paths", which means collision normally happens between vehicles that have straight manoeuvre movement when entering the intersection, their conflicting paths will intersect at an angle of around 90 degrees. If a car enters the intersection from the south leg of the cross intersection detection with a straight manoeuvre movement, collision detection will be performed on this car against every other car that is currently located on perpendicular paths (i.e., west and east legs of the intersection), or moving straight towards the intersection. Therefore, performance is improved by not needing to check every pair of cars at the intersection for possible collision. The implementation of the preselection algorithm is further described in [6].

Currently, the algorithm implemented for pair-wise collision detection is only for side collision detection, which comes from [5], as has previously discussed. The algorithm for side collision detection cannot be used for rear-end collision detection as rear-end collisions have a different facets from side-collision in terms of chain effects, where there can be a number of cars following a rear-end collision. At this stage, we have not yet found an effective algorithm for multiple rear-end collision detections that are results of the chain effect, as this is not the main focus of the research.

We evaluate our approach using the following methods:

1) Speed of detection
2) Performance/accuracy: precision and coverage

Each of this method is performed in our system in two ways: first, the side collision detection is performed without knowledge base and preselection (i.e. pure implementation of pair-wise collision algorithm [5] where each possible pair of all the vehicles in the intersection is calculated); second, the side collision detection is performed after applying preselection criteria from the knowledge base). Those methods are further discussed in the following subsections.

A. Speed of Detection

Whenever a future collision event is detected for the first time, it is recorded in a log file, with attributes as follows: *registration number of both vehicles, collision point, time to collision, leg location of both vehicles, and collision type*. Afterwards, the average of detection time (*time to collision*) for each run is calculated. In each execution, the average time to collision is calculated. At the evening peak vehicle distribution model (average traffic volume 37-42 vehicles): if preselection is ignored in collision detection, the average time to collision is 5.6 seconds; However, when preselection is used, the average time to collision is 10.7 second, which is around 5 seconds earlier than the previous method. In each distribution model, preselection yields faster detection result.

Therefore, preselection is proven to speed up the process of collision detection. The greater the number of vehicles in an intersection, the more preselection is useful and effective.

B. Accuracy: Precision and Coverage

Whenever a prediction of a future collision event is issued, it is evaluated on whether the collision really happens. If it does, it is counted as a *true positive* (valid detection). However, when a predicted collision does not happen, it is counted as a *false positive* (invalid detection). When a collision occurs, and it is not previously predicted, then it is counted as *false negative* (undetected collision). The terms are described in Fig. 6.

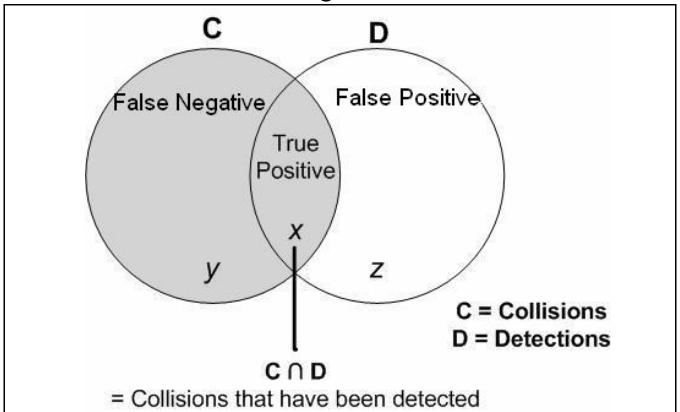

Fig. 6. Evaluation Terms

We determine performance based on the terms of *precision* (of all the detections) and *coverage* (of all the collisions), respectively:

$$precision = \frac{no.of\ valid\ Detections}{total\ collision\ Detections} \tag{4}$$

$$= \frac{true\ positive}{(true\ positive + false\ positive)} = \frac{x}{(x+z)}$$

$$Coverage = \frac{no.of\ valid\ Detections}{total\ Collisions} \tag{5}$$

$$= \frac{true\ positive}{(true\ positive + false\ negative)} = \frac{x}{(x+y)}$$

Based on the accuracy evaluation on side collision detection in our simulation, we achieve 100% precision when side collision detections are present and 100% coverage when side collisions are present. 100% precision and coverage can be realistically achieved when the collision detection algorithm is correct and effective. Besides proving the effectiveness of side collision detection in our system, this evaluation method helps to find parts of the collision detection that need improvement.

VI. Conclusion

This paper has presented the challenges faced by intersection collision detection systems and a novel approach for fast and accurate real-time collision detection. U & I Aware framework is proposed and implemented on a computer-based simulation. The collision patterns that are acquired from mining traffic and collision data are stored in the knowledge base of the collision detection system. These patterns are used for matching vehicle pairs to be calculated for the possibility of route contention and future collision events. The speed of the detection is evaluated by calculating the average of time to collision in the first detection of a future collision event. The accuracy of collision detection is evaluated using precision and coverage measurements. Real-time side collision detection can be achieved with 100% precision and 100% coverage. The experiment has been simulated in a four-leg cross intersection. For different intersection types, the same approach can be deployed but with different collision detection algorithms for other types of collisions. A broader perspective relates to *device ecologies* [9], where devices (computers and sensors) within a particular locality work together; here, the computers at the intersection and in cars within the vicinity of the intersection work together to warn drivers of impending dangers.

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