Vehicle Intersection Collision Monitoring Algorithm Based on VANETs and Uncertain Trajectory

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***Abstract*—In order to ensure driving safely, the driving safety assistance system must be able to aware of potential collision accidents in advance, especially significant for the intersection where traffic accidents occur more frequently. Considering that VANETs is one of the most important applications for improving the safety of driving, furthermore, vehicles have an inherent uncertainty of location because the exact position of a moving object is known, with certainty, only at the time of an update on position information. In order to reduce the accident rate at intersection and combine the driving characteristics of vehicles at traffic intersections, a vehicle intersection collision monitoring algorithm based on VANETs and uncertain trajectory is proposed. The algorithm is divided into two categories: uncertain trajectory prediction algorithm and vehicle collision monitoring algorithm. The proposed approach provides approximate answers to the user at the users required level of accuracy while achieving near-optimal communication and computational costs. Finally, extensive experiments were conducted to show the efficiency and efficacy of the proposed approach.**

***Index Terms*—collision monitor, intersection, uncertain trajectory, VANETs**

I. INTRODUCTION

Collision avoidance is one of the most critical concerns in traffic safety, and it is becoming increasingly important as traffic volume increases. Recently, with changes in social needs and automotive technology, autonomous driving has become an important concern. Collision avoidance system has been becoming a significant component in the current autonomous driving research to ensure driving safety[1].

According to traffic accident statistics from the Road Traffic Authority, approximately 75% of fatal traffic accidents resulted in collisions among vehicles in recent years[2].In particular, more than 40% of all crashes causing injuries or fatalities worldwide occur in intersection. Therefore, a number of solutions have been proposed to mitigate or avoid collision[3].

Collision avoidance systems provide a service based on the locations of moving objects; therefore, the accuracy of the location information has a direct influence on the service quality of the system. The key factor of system quality is to know the exact present position of a vehicle, and to predict its future position accurately by monitoring the movement of a vehicle for collision avoidance [4] [5].

Positioning systems utilizing technology such as a GPS device in a vehicle and roadside sensors can provide location samples only at discrete time instants. Thus, the location of a moving object is never definite between two consecutive samples. Because a vehicle moves continuously, the moving information such as position, velocity, and direction of a vehicle changes constantly[6].

Therefore, this paper introduces a collision monitor model considering the location uncertainty of vehicles in the intersection to increase the accuracy of collision risk detection.The primary contributions of this paper are summarized as follows:

- This paper introduces a novel uncertain trajectory prediction method, which combined with uncertain position and the main line of trajectory.
- This paper introduce a novel collision monitor algorithm which which predicts collision possibilities based on VANETs and the uncertain trajectory.
- This study addresses this issue by proposing a method that achieves minimal use of wireless network bandwidth and optimal computational cost while not missing true warnings.
- A series of simulations are conducted to demonstrate that the proposed algorithm markedly outperforms a conventional solution in terms of reducing collision risks and the computational consumption.

The remainder of this paper is organized as follows: Section II discusses related work, Section III details the system model, Section IV proposed approach for collision avoidance monitoring algorithm, Section V presents and analyze simulation results, and Section VI concludes this paper.

II. RELATED WORK

In recent years, significant research and development activities have been performed to avoid collisions.

When a vehicle predicts collisions within a black zone, it has one to many relationships with other vehicles. By evaluating information independently, the objects also assess the situation independently and make separate decisions on whether the situation is critical or not, and different judgments cause traffic congestion and conflicts[7]. To resolve these problems, a supervisory role that manages the overall situation of a black zone is necessary. Therefore, this study uses a centralized approach to solve priority and information conflicts for improving safety.

Many proposed collision-predicting methods assume that position data of moving vehicles are precise, and the future positions of vehicles are predicted based on periodically updated information such as position and velocity at every time instant (e.g., 0.1 s). However, these approaches can cause undesirable consequences such as missing a true warning and poor response times. In addition, in real traffic scenarios, thousands of vehicles operate in the same district at the same time. It is unlikely for a server to fulfill the task of cooperative localization owing to limited computational resources as well as limited network bandwidth[5] [8]. This study addresses this issue by proposing a method that achieves minimal use of wireless network bandwidth and optimal computational cost while not missing true warnings.

III. System model

A. Cooperative vehicle infrastructure system within an intersection

VANETs are created by applying the principles of mobile ad hoc networks. It is the spontaneous creation of a wireless network for data exchange to the domain of vehicles. VANETs consist of a set of moving objects (e.g., vehicles, pedestrian with mobile devices) and servers (e.g., RSUs). In VANETs, V2I communication, communication between vehicles and a server of roadsides, corresponds to a server-clients communication in mobile environments. This study uses a server-centric approach based on the cooperation of objects passing through an intersection and a server[9].The intersection mark points can help determine whether vehicles are in the intersection.

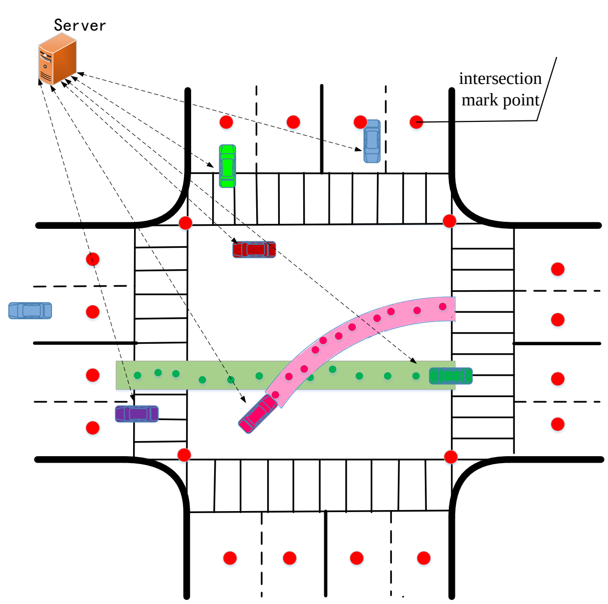

Fig. 1. Vehicle cooperation communication system

Figure.1 shows the vehicle cooperative communication system at the intersection. The system is mainly composed of three parts:

Server: Stored the intersection information on the number of lanes, the coordinates of intersections, key point coordinates of lanes, and the size of intersections; it communicates with the OBU on-board unit and receives information on vehicles' position, speed, and direction. According to calculating the range of uncertain trajectories to predict the possible collisions;Broadcasting warning information to relevant vehicles.

OBU on-board unit: Equipped with a global positioning system receiving device and an 802.11P communication device and a sensor capable of acquiring information such as the position, direction, speed, and acceleration of the vehicle, those information are sent to the server and receive collision warning information from the server.

Communication links based on 802.11p: Vehicles that have entered the intersection or are about to enter the intersection will establish a connection with the roadside unit at the intersection through DSRC (Transportation Short Range Communication). The communication is achieved through the 802.11P protocol to ensure normal communication under high-speed environment and ensure the accuracy of information in real time.

In this paper, a report is a message transferred from a target vehicle to a server. It is assumed that moving objects o_1 through o_{10} are vehicles, and o_i is a target vehicle that communicates with a server for collision monitor. In addition, moving objects o_1 through o_{10} can be the target vehicle o_i. A server monitors target vehicle o_i and determine if there is a collision, based on the information from o_i and that of its peers (i.e., o_1-o_{10}) within the intersection area. When a moving vehicles o_i approaching the intersection. The server predicts the uncertain trajectory of the target vehicle o_i and monitors collision probability with other vehicles in the intersection, based on the reports from other vehicles[10]. The server then sends the target vehicle the first warning if the collision probability is higher than the desired accuracy of o_i. The target vehicle o_i, based on the warning and notification messages received from the server, may take action to avoid collisions (e.g., speed adjustment within the safe reaction distance).

B. Uncertainty region and report delivery

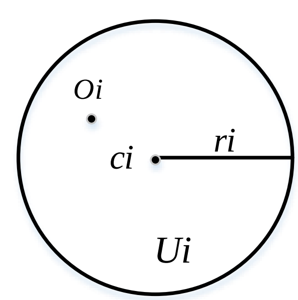

Fig. 2. Uncertainty position of o_i

This study assumes that a moving vehicle is located anywhere in the uncertainty region at a given point in time. Fig.2

shows the location uncertainty of vehicle o_i at time t. Target vehicle o_i is denoted by the point, and its uncertainty region is denoted by a solid-line circle U_i with center C_i, and radius r_i. The smaller the difference between the expected location and the actual location, the smaller the radius of the circle presenting the uncertainty region.

A report rpt consists of six attributes, $< rpt = o_i, C_i, V_i, r_i, t_s, \delta_{min} >$ Where o_i indicates the target object, C_i and V_i indicate the center position (x, y) and velocity (v_x, v_y) respectively, of target object o_i at time stamp t_s, and r_i is radius of the uncertain area. δ_{min} is the accuracy of the approximate answer, which reflects the users required level of accuracy. A report is generated when a vehicle deviates from its uncertainty region, which is sent to the server.

C. Collision risk considering uncertain trajectory within a dangerous area

A moving object o_i may have a probability of collision with any other objects that appear in the black zone between the times when the target object enters and exits the black zone. Let t_b and t_e be the times when target object o_i enters and leaves the black zone, respectively. The movements of o_i within a black zone depend on the number of vehicles in the black zone and the nature of the black zone such as layout or traffic pattern. Assume that $B = o_1, o_2, ..., o_{|n|}$ is a subset of O, which has moving objects appearing within the black zone for the time interval $[t_b, t_e]$, and they have a collision probability with o_i. Let T_{ri} be an uncertain trajectory of moving object o_i and $S = T_{r1}, T_{r2}, ..., T_{rn}$ be a set of the uncertain trajectories of moving objects.

Consider the scenario depicted in Fig.4, which illustrates four trajectories: T_{r1}, T_{r2}, T_{r3}, and T_{ri}, which are based on the initial positions and velocity of object o_1, o_2, o_3, and o_i, respectively. The uncertain trajectories run through the time interval $[t_b, t_e]$.Clearly, a moving object that does not have an overlapping area with uncertain trajectories of other objects has little collision probability. The shaded parts in the sheared oval cylinders have a larger collision probability between o_i and one of the other objects o_1, o_2, o_3, if considering location.Ignoring location uncertainty, the nonzero collision risk neighbors of T_{ri} are only T_{r2} at t_2. However, if location uncertainty is considered, T_{ri} has collision risk possibilities with T_{r2} and T_{r1} within $[t_1, t_3]$ and $[t_4, t_5]$, respectively, as well as at t_2. In addition, If only consider the overlap of trajectories, T_{r3} has no collision risk with T_{r3} in $[t_b, t_e]$.

IV. METHODOLOGY

A. Uncertain trajectory prediction algorithm for vehicles

According to the driving intention of the vehicle at the intersection, we divide the trajectory of the vehicle into two types:going straight and turning. For determining the range of uncertain trajectory for vehicles, we need to calculate the main line equation of the trajectory firstly.Then according to the trajectory main line equation and the definition of uncertain position, we can get the range of uncertain trajectory of the vehicle.The following is a brief introduction of the solution to the main line of uncertain trajectory when going straight and turning.

going straight: The linear expression of the trajectory main line when the vehicle going straight can be determined in combination with the current position (x_0, y_0) and the rotation angle φ of the front wheel of the vehicle.

$$y - y_0 = \frac{\varphi}{90}(x - x_0) \tag{1}$$

turning: Because the trajectory curve of the vehicle and the curvature of the curve are continuous, we describe the vehicle's trajectory using cubic curve interpolation. Each segment of the Vehicle's trajectory can use a cubic equation to describe.

$$S_i(x) = a_i + b_i(x-x_i) + c_i(x-x_i)^2 + d_i(x-x_i)^3, i = 1, 2, \cdots, n-1 \tag{2}$$

Where coefficient a_i, b_i, c_i, d_i can be determined by the properties of the cubic curve, x_i is the abscissa of the vehicle's location.

An uncertain trajectory T_{ri} is a path consisting of all uncertainty regions of moving object o_i in a time interval. In Fig. 3, it is assumed that moving object o_i moves along a straight line with a constant speed, which is based on the velocity (v_x, v_y) at current time (t_0). Thus, the expected location of o_i at time t is evaluated under the assumption that it is based on the current velocity (v_x, v_y) of oi with acceleration $a = 0$.

Let $L(o_i, t)$ be the expected location of vehicle o_i at time t. (x_{i0}, y_{i0}) and (v_x, v_y) denote the location and velocity, respectively, of o_i at current time (t_0). Then, the expected location $L(o_i, t)$ of o_i at time instant (t_k) is given by:

$$L(oi, t_k) = (x_{ik}, y_{ik}) = (x_{i0} + v_{ix}(t_k - t_0), y_{i0} + v_{iy}(t_k - t_0)) \tag{3}$$

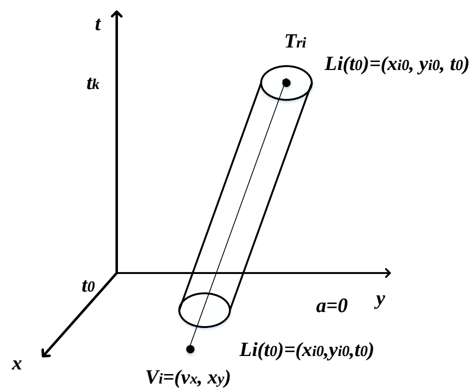

Fig. 3. Uncertain trajectory of o_i

B. Collision probability between moving objects

This section computes the collision probability mathematically. Assume that target vehicle o_i and the other vehicle o_j are located anywhere in uncertainty region U_i and U_j at time t. If at time t the uncertainty location U_i of target vehicle o_i has an intersection area (C) with uncertainty location U_j of another vehicle o_j, then there is a possibility of collision. Fig.5 illustrates the computation of the collision risk probability of o_i and o_j at time t when both o_i and o_j are located in the red area (C). As shown in the figure, $p_c = \frac{area(C)}{area(U_i)} \times \frac{area(C)}{area(U_j)}$

Fig.6 considers there cases separately: $(a) dist(c_i, c_j, t) > (r_i + r_j), (b) dist(c_i, c_j, t) < |r_i - r_j|$ and $(c)|r_i - r_j| <$

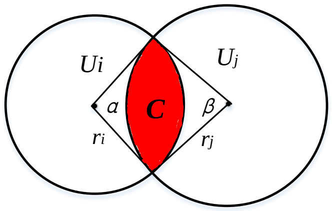

Fig. 4. U_i and U_j intersect area

$dis(c_i, c_j) < (r_i + r_j)$. As shown in Fig.6(a), when $dist(o_i, o_j, t) > (r_i + r_j)$, then $p_c = 0$, because there is no area(C). In Fig.6(b), if $dist(o_i, o_j, t) < |r_i - r_j|$, then $P_c = \frac{area(U_i)}{area(U_j)}$ when $(r_j > r_i)$ or $P_c = \frac{area(U_j)}{area(U_i)}$ when $(r_i > r_j)$. In Fig.6(c), if $|r_i - r_j| < dis(c_i, c_j, t) < (r_i + r_j)$, then $p_c = \frac{area(C)}{area(U_i)} \times \frac{area(C)}{area(U_j)}$.The area of U_i,U_j,and C can be determined

$$area(U_i) = \pi r_i^2 \tag{4}$$

$$area(U_j) = \pi r_j^2 \tag{5}$$

$$area(C) = r_i^2(\alpha - \sin(\frac{\alpha}{2}) - r_j^2(\beta - \sin(\frac{\beta}{2}) \tag{6}$$

where

$$\alpha = 2 \cdot \arccos(\frac{r_i^2 + dist(o_i, o_j, t) - r_j^2}{2 \cdot r_i \cdot dist(o_i, o_j, t)}) \tag{7}$$

$$\beta = 2 \cdot \arccos(\frac{r_j^2 + dist(o_i, o_j, t) - r_i^2}{2 \cdot r_j \cdot dist(o_i, o_j, t)}) \tag{8}$$

Finally, Table I summarizes the collision probability p_c of U_i and U_j.

TABLE I
SUMMARY OF COLLISION PROBABILITY p_c OF U_i AND U_j

Distance between o_i and o_j	Collision probability p_c
If $dist(c_i, c_j, t) > (r_i + r_j)$	0
if $dist(c_i, c_j, t) < \|r_i - r_j\|$	if $(r_i > r_j)$, $\frac{r_j^2}{r_i^2}$ if $(r_i < r_j)$, $\frac{r_i^2}{r_j^2}$
if $\|r_i - r_j\| < dis(c_i, c_j) < (r_i + r_j)$	$\frac{area(C)}{area(U_i)} \times \frac{area(C)}{area(U_j)}$

C. Monitoring algorithm for collision avoidance

Naturally, the server administering a dangerous area has all relevant information such as the location and layout of the area. The server has received the reports rpt from the vehicles which are going to driving into the intersection. Each vehicle is not only a target vehicle but also another vehicle for each target vehicle within the monitored intersection.

Algorithm1 provides the detailed steps of the monitoring algorithm for collision avoidance. The algorithm receives a new report rpt from a target vehicle in the monitored intersection and returns the approximate answer A (of collision candidates) satisfying the minimum required accuracy δ_{min}. The algorithm consists of filter and refinement steps. The first step filters out any vehicles that has no collision probability with o_j. The refinement step computes the collision probability with o_i for each other vehicles o_j which remain after the filter step.It returns the answer set A (of collision candidates) satisfying δ_{min}. When a new report arrives,the server investigates whether this update affects the query result.

The new report rpt satisfies the following condition: (1) the report comes from a new vehicle, or (2) the object o_i of set O deviates from the uncertainty region. First, the filter step should determine the time interval $[t_b, t_e]$ of o_i based on the information of new report rpt. Then, it decides B, which is a set of objects existing within the intersection area for the time interval $[t_b, t_e]$. Next, to calculate the overlap area C between the trajectory T_{ri} of o_i and the trajectory T_{rj} of the other vehicles o_j. Finally,the refinement step computes the collision probability with o_i for each candidate o_j. This step determines the answer set A satisfying $P_{cj} > \delta_{min}$.In addition, in order to avoidance too many early and inaccuracy warning message, the answer set should satisfy $t - t_0 \leq 2s$ as well, where t is the collision time, t_0 is the current time.

Algorithm 1 Vehicle Collision Monitoring Algorithm

Input: rpt new report
Output: A: an approximate answer set with a required accuracy level

while receiving a rpt **do**
  for the rtp from o_i **do**
    if $o_i \notin O$ **then**
      put o_i into O;
      determine $[t_b, t_e]$ of o_i;
      decide B as a set of objects existing in the intersection during $[t_b, t_e]$ of o_i;
      for each peer $o_j \in B$ **do**
        if $C \leq 0$ **then**
          CONTINUE
        else
          if time interval I is not included in $[t_b, t_e]$ **then**
            CONTINUE
          else
            if $P_{cj} > \delta_{min} \bigcap t - t_0 \leq 2s$ **then**
              $o_j \in A \leftarrow o_j$;
              send A as an answer set to o_i;
            end if
          end if
        end if
      end for
    end if
  end for
end while

V. EXPERIMENT AND ANALYSIS

This section evaluates the performance of CAMA using three metrics: (1) the communication cost, which measures the total number of messages transferred between vehicles and a server administering an intersection; (2) the computational cost, which measures the query processing time of a message per minute; and (3) the quality of the approximate query answer, which can reflect the accuracy of collision avoidance monitor algorithm.

TABLE II
SIMULATION PARAMETER SETTINGS.

Parameter	Range
simulation environment	MATLAB_R2014a
the size of intersection	$20m * 20m$
traffic flow density (vehicles/line/hour)	$600, 800, 1000, 1200, 1400, 1600, \mathbf{18}$
the average speed of vehicle	$2, \mathbf{3}, 4, 5, 6, 7, 8, 9, 10m/s$
number of lanes	4 (no signal lights)
radius of uncertainty region	$3(m)$
ratio of vehicles that deviate from the driving attention of vehicles	10 (%) go straight, turning left, turning right
message size	128 bytes
beacon interval	0.1 (sec)
number of query issuer (vehicles)	$10, 20, \mathbf{30}, 40, 50$
the accuracy of approximate answer (δ_{min})	0.20

Finally, Table II summarizes the parameters and relevant values used in the simulations. Each simulation was conducted with a variety of ranges for a single parameter, while keeping the other parameters at the default values which are shown in bold in Table II.

As shown in Figure 5, the accuracy of the collision detection changes as the traffic volume increases. The collision detection accuracy rate becomes smaller as the traffic volume increases. This is because the traffic volume increases, and the trajectories of different vehicles are different. There is always a part of the collision that will be missed. The baseline is the vehicle collision prediction method proposed in [11]. Our proposed collision monitoring algorithm CAMA is obviously better than the baseline method in accuracy of the collision detection, especially when the traffic volume increases continuously.

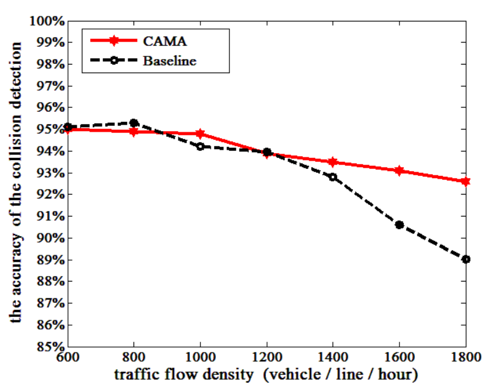

Fig. 5. The accuracy of collision monitoring

Fig. 6 and Fig. 7 shows the comparison of the results from CAMA and the baseline method in terms of the number of transmitted messages. Both of them have two types of the y-axis, because the value of the difference between CAMA and the baseline method is greater. The left y-axis is for CAMA, and the right y-axis is for the baseline method.

Fig. 6 shows the number of transmitted messages as a function of the vehicle speed. The number of transmitted messages on the baseline method are constant regardless of the objects speed, whereas CAMA shows a marginal reduction based on the vehicle speed. This is plausible in CAMA since the time interval in intersection of the query issuer decreases as the value of vehicle speed increases. With regard to the baseline method, messages are transmitted to the server every 0.1 s.

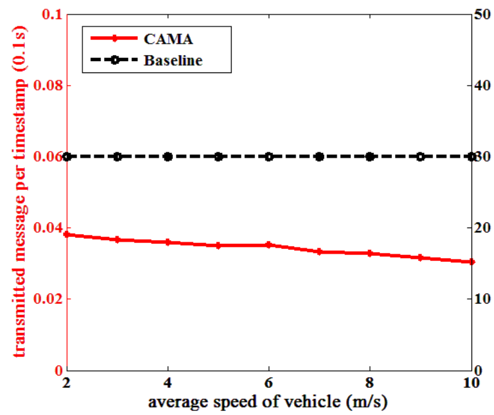

Fig. 6. Transmitted message vary with speed

Fig. 7 shows the number of transmitted messages as a function of the number of vehicles as query issuers. For the baseline method, the number of transmitted messages increases linearly with the value of query vehicles , because the number of messages increases typically with the value of query vehicles.

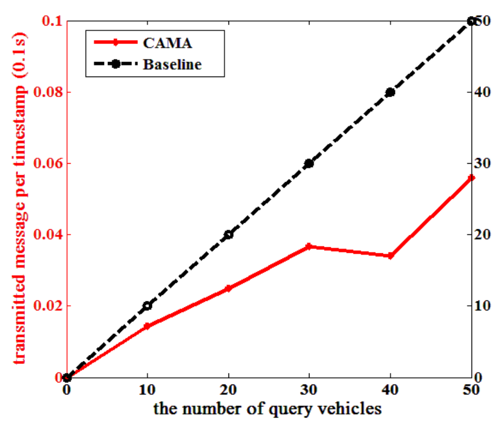

Fig. 7. Transmitted message vary with the number or vehicles

Fig.8 and Fig.9 show the results of CAMA and the baseline method in terms of the query processing time of a message under the same conditions.

Fig.8 shows that, the time interval in the intersection of the query vehicles decreases as the speed of vehicle increases.Fig.9 show that, the query processing time of both CAMA and the baseline method increases with the number of query vehicles increase.

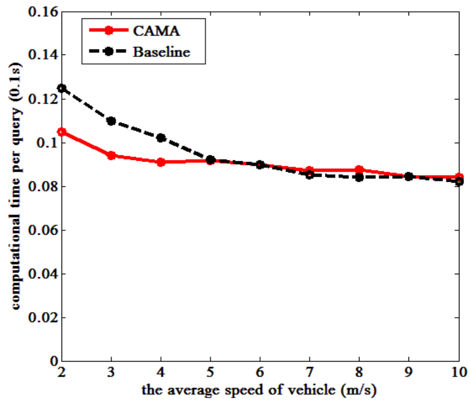

Fig. 8. The computational time per query vary with speed

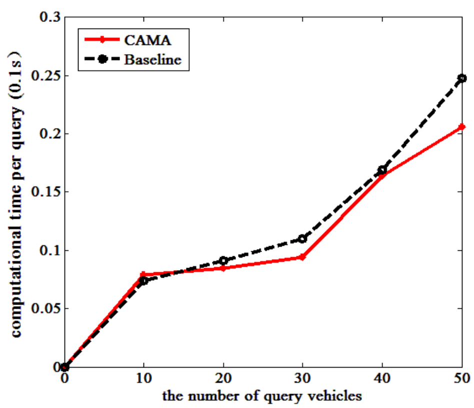

Fig. 9. The number of computational time vary with the number of vehicles

Fig. 10 and Fig.11 compares CAMA and the baseline method in terms of the query processing time considering total transmitted messages per timestamp. The query processing time of CAMA is approximately equal to that of the baseline method, but the query processing time of the total transmitted messages per time stamp in CAMA is significantly smaller than that of the baseline method. It is because the baseline method computes the collision probability between a query issuer and each object at every intersection point between two distance functions periodically throughout the time interval. Clearly, this incurs major overhead caused by unnecessary computations.

The shorter query processing time accorded to CAMA is a critical issue in vehicular ad hoc networks because the query processing of a server can cause a bottleneck in the system. As shown in Fig.10, the query processing times of CAMA and the baseline method decrease slightly as the value of vehicle speed increases. This is because, as shown in Fig.8, the time interval in the intersection of the query issuer decreases as the average speed of vehicle increases. Fig.11 show that, the query processing time of both CAMA and the baseline method increases with the number of query vehicles increase.

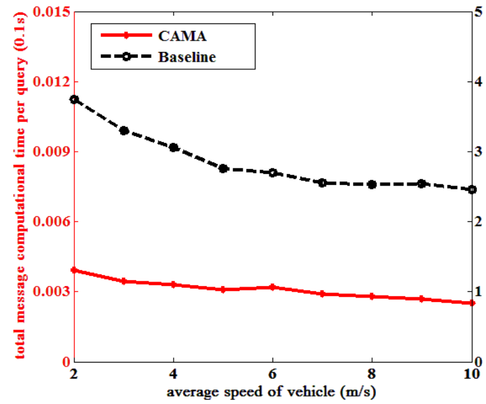

Fig. 10. The number of computational time vary with the number of vehicles

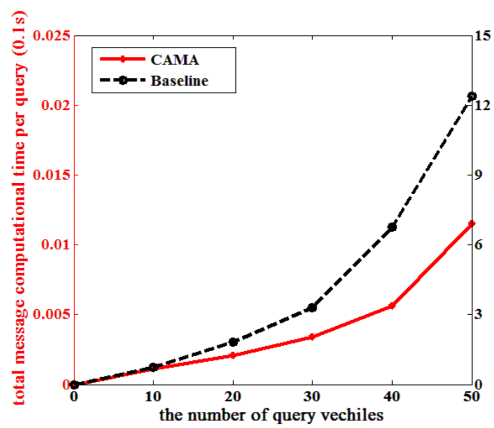

Fig. 11. The number of computational time vary with the number of vehicles

VI. Conclusion

This paper proposed a probabilistic approach called CAMA, a monitoring algorithm for collision avoidance of moving vehicles within an intersection in VANETs. To this end, this paper introduced an uncertainty region, which saves computational and communication costs. By means of a series of simulations, it has also shown that the performance of CAMA is superior to that of the existing solution in terms of communication and computational costs. As future work, a method to minimize false alarms and recommend actions to avoid collision after a warning are planned under the proposed approach for collision avoidance.

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