International Journal of Control and Automation
Vol. 9, No. 4 (2016), pp. 171-186
http://dx.doi.org/10.14257/ijca.2016.9.4.17

Inter-Vehicle Communication Aided Trajectory Planning for Automated Vehicles

Dan Shao*, Jianan Wu, Yinfei Dai

College of Computer Science and Technology, Changchun University, Changchun 130022, China
sdsister@163.com

Abstract

Trajectory planning is a key to achieve safe and efficient driving of automated vehicles. We propose a trajectory-planning suite that enables the generation of a safe and comfortable trajectory through receiving cooperative messages (e.g. CAM and DENM) to detect the obstacle vehicles. We also present a collision probability model to improve the accuracy of vehicles' decision-making. Our approach mainly experiences three steps. The trajectory generation module first generates a candidate set of eligible trajectories by synthetically considering the current yaw angle, velocity, and physical characteristics of the vehicle. Then the state prediction module predicts the position and velocity of the potential obstacle vehicle with respect to the transmission delay. The trajectory selection module finally chooses a best suitable trajectory to follow in terms of the current context. Moreover, we also investigate the effects of the communication performance on the trajectory planning. The extensive simulations show that the proposed trajectory-planning scheme is capable of guiding vehicles smoothly and safely across a common traffic situation against other obstacle vehicles.

Keywords*: Vehicular ad-hoc network; automated vehicle; trajectory planning; delay-tolerant*

1. Introduction

Trajectory planning is one of the important and challenging tasks in achieving a perfect automated driving experience. Despite various trajectory planning possibilities proposed by researchers, the sensing of the vehicle environment is still the basis and precondition of well-running trajectory planning. Without a reliable knowledge of the vehicle environment, a suitable and optimized trajectory cannot be planned. The existing approaches to trajectory planning often rely on only autonomous sensors, including lasers, radars, and cameras. Thanks to the upcoming deployment of wireless technologies for communications between vehicles and with the roadside infrastructure (V2X) for safer and more efficient road traffic, vehicles can soon be able to exchange information with its surroundings (vehicles and infrastructures in their vicinity). Information exchange allow vehicles to plan their trajectory in a cooperative manner, *i.e.*, cooperative trajectory planning. Because it can have a larger "view" of the environment, a cooperative trajectory planning has capability of realizing safer and more efficient trajectory control.

A Vehicular Ad-hoc Network (VANET) enables the information dissemination between vehicles (V2V) and with nearby roadside infrastructures (V2I) in their vicinity for numerous attractive and exciting applications with purpose to create a safer and more efficient road environment [1]. Vehicular networking is extensively considered as an applicable and efficient technology for making the current transportation systems more efficient and safe [2]. A large number of academia, industries, and authorities put much effort towards improving its satisfactory applicability and promoting its populated

ISSN: 2005-4297 IJCA
Copyrightⓒ 2016 SERSC

deployment. The European profile of IEEE 802.11p for inter-vehicle communications specifically utilizes a dedicated 10 MHz control channel to safety-critical data, which is largely shared by Cooperative Awareness Message (CAM) and Decentralized Environmental Notification Message (DENM) [3]. CAM is a time-driven periodic message for updating state information of presence located within a single hop distance, such as position and speed. DENM is an event-triggered warning that particularly provides specific driving environment event and dangerous traffic information to other ITS stations, *e.g.*, accident. All ITS stations that participate in vehicular networks shall be able to generate, send, and receive CAMs and DENMs, by which the receiving automated vehicle can collect various information, *e.g.*, position, velocity, size, and acceleration from other obstacle vehicles, and is timely aware of the surrounding context.

Thanks to CAM and DENM, the trajectory planning of automated vehicles can obtain an enhanced improvement of performance and accuracy [4]. The current automated vehicles mainly employ such techniques as 77GHz and 24GHz radars, lasers, and cameras to sense their located surroundings, which are confined within the visual range. Without a global awareness of the surrounding traffic environment, an optimal trajectory fails to be reliably planned especially in a complicated situation. For example, two approaching vehicles cannot be perceived with each other by the camera due to the shielding of the buildings and parked vehicles at the corner of the intersection, which is a common reason for the collision accident at intersections. The problem of the traditional trajectory planning faced in using cameras and radars is expectedly solved by introducing inter-vehicle communication. Information can be timely exchanged between vehicles as soon as they enter into the communication range of each other, while the obstacles are not yet recognized by the camera at that moment.

Unlike most the previous trajectory planning methods that use anonymous sensors, we propose an inter-vehicle communication aided trajectory-planning suite. In order to achieve a better global awareness by fully utilizing the capability of inter-vehicle communication, we not only propose a side-collision probability model regarding the overlap time and a rear-end-collision probability model in terms of velocity obstacles to facilitate the selection of the suitable trajectory, but also take the transmission delay and communication range into consideration. The proposed trajectory-planning suite is composed of the following modules. (i) The External Interface Module is in charge of perceiving the change of traffic flow through receiving CAMs and DENMs from other traffic vehicles. (ii) The State Prediction Module is responsible for mitigating the negative effects of transmission delay. (iii) The Vehicle Kinematic Module mainly addresses the vehicle kinematic issues. (iv) The Vehicle State Module collects the states of the host vehicle. (v) The Trajectory Generation Module creates a candidate trajectory cluster and outputs to the (vi) Trajectory Selection Module that decides the optimal trajectory regarding the results of both the (vii) Dubins Distance Module that calculates the minimal distance away to the target and the (viii) Collision Probability Model that estimates the collision risk.

The rest of the paper is structured as follows. Section 2 overviews the related work. In Section 3, we introduce the proposed trajectory-planning approach in details. In Section 4, we provide the extensive simulations and numerical results. Finally, some conclusions and future work are outlined in Section 5.

2. Related Work

The trajectory planning of the current well-known self-driving vehicles, including Google car [5] and PROUD car [6], is mostly accomplished by solely using autonomous sensors (*e.g.* radars and cameras), and thus the trajectory planning can be performed only within a limited area. The communication technology has been considered in some of the recent R&D projects on autonomous driving. In the project of “Have it” [7], the

 Copyrightⓒ 2016 SERSC

trajectory is selected from the multiplicity of possible ego-vehicle trajectories through balanced optimizing the safety, comfortability, consumption and traffic regulations for the maneuver. The project "SARTRE" [8] seeks to a solution that allows vehicles to drive in a platoon following a lead human-driven vehicle through V2X communications for information dissemination and autonomous sensors (*i.e.* radars, lidars, and cameras) for position measurement. However, the comprehensive cooperative trajectory planning is not their objective. In the project of "Connected-Car" [9], the cooperative trajectory planning is considered. However, a fixed central unit (*e.g.* roadside unit) is employed to collect information from the various traffic participants and to determine an optimal trajectory for each vehicle. Then the optimized trajectory result is transmitted back to the corresponding vehicle again, by which the fixed central unit undoubtedly becomes the bottleneck for the task of cooperative trajectory planning.

Some achievements are already available and are presented in literatures with respect to the trajectory planning. Wei *et al.* [10] proposed a prediction and cost-function-based algorithm to implement the robust freeway driving of autonomous vehicles. Michael and Joel [11] presented a set of potential function components to assist an automated or semi-automated vehicle in navigating a highway based on the potential field method [12]. The resulted potential field is constructed as a superposition of disparate functions for lane-keeping, road-staying, speed preference, and vehicle avoidance and passing. However, one drawback of the potential filed method is that the vehicle may get trapped among a cluttered obstacles without escape. Due to this reason, a number of methods are proposed to escape the local minima [13-16]. But these methods suffer from unaffordable computation time or storage space cost. Choi [17] proposed a moving obstacle avoidance method through expanding the paradigm of velocity obstacles [18]. Qu *et. al.* [19] explicitly transformed the kinematic model into a chained form so that the family of feasible trajectories and their corresponding steering controls are expressed in terms of one adjustable parameter with aims to collision avoidance. But it fails to select the suitable trajectory without a consideration on the driving comfortability while the vehicle kinematic is involved. Yang [20] extended this work and selected the feasible trajectories regarding the near-shortest distance and the near-minimal control energy. Macek *et al.* [21] combined this method with a sampling method called rapidly exploring random trees [22]. Tao *et al.* [23] designed a method to build two dimensional visual landmarks feature map for the navigation of wheeled mobile robot. Liu *et al.* [24] proposed an improved method for mobile robot path planning. These methods only focus on how to avoid obstacles but ignore either the vehicle kinematic or the driving comfortability, resulting in difficulty to deploy these algorithms into the practice.

The inter-vehicle communication aided trajectory planning approach outperforms the traditional way in terms of three advantages. Firstly, the inter-vehicle communication provides a wide view of perception by utilizing CAMs and DENMs. The radio waves can travel over long distance and across obstacles, while the perception of using cameras is restricted into the scope of visibility. Next, the inter-vehicle communication can enrich the perceived state collections, *e.g.* acceleration value and yaw angle, by which the planned trajectory is obviously more efficient and accurate. At last, the inter-vehicle communication aided trajectory planning only relies on the positioning and communication devices whose cost is significantly less than the current available autonomous vehicle equipped with 360-degree sensing installment. In spite of many benefits of the inter-vehicle communication aided trajectory planning, the comprehensive work in this area is still rare.

In summary, how to avoid moving obstacles but without compromising any comfortability is still not perfectly solved yet. In addition, the time delay and communication range inevitably affect the feasibility and applicability of the planned trajectory. Therefore, our main contributions are summarized as follows: (i) a collision probability model regarding the communication delay of CAMs and DENMs, (ii) a

Copyright ⓒ2016 SERSC

dynamic trajectory planning suite that accommodates the vehicle kinematics as well as the driving comfortability, and (iii) a detailed investigation on the influence of communication performance on the proposed trajectory-planning suite.

3. System Models

The task of the trajectory planning is to dynamically decide a collision-free trajectory for the manipulator under a given initial state and a short-term target. In order to timely satisfy the practical use in an urban scenario, the trajectory planning should be able to perceive and response to the surroundings as quickly and accurately as possible and to plan a safe and comfortable trajectory. In this paper, we only focus on the trajectory planner since the short-term target is provided in advance by a route planner.

The proposed trajectory-planning suite divides the planning procedure into several short-time cycles. At the beginning of each planning cycle, the External Interface Module perceives the surrounding traffic through receiving CAMs and DENMs from other traffic vehicles. Then the State Prediction Module takes the transmission delay of CAMs and DENMs into consideration to predict the current obstacle vehicles' states, which is a feasible way to alleviate the negative effects of the experienced delay. The Vehicle Kinematic Module characterizes the vehicle kinematics and responses to various control inputs in real time. The Vehicle State Module collects the host vehicle's state information via various on-board sensors. The Trajectory Generation Module receives the response from the Vehicle Kinematic Module and then generates a candidate cluster of trajectories. The Collision Probability Module assesses the collision probability utilizing the received CAMs and DENMs. The Dubins Distance Module calculates the minimum distance away from the current position to the short-term target. The Trajectory Selection Module utilizes the results of the Collision Probability Module to optimize the trajectory. The Control Unit generates the corresponding control maneuvers such as throttle, gear, brake and more to track the optimal trajectory. The states of the host vehicle are constantly updated per planning cycle. The mainly focused modules here are marked in green colure, and we use the term of host vehicle to indicate the automated vehicle in the rest context.

3.1. Trajectory Generation Module

The Trajectory Generation Module utilizes the current yaw angle, velocity, mass, wheelbase, cornering stiffness, and more, which are provided by the Vehicle Kinematic Module, to calculate a candidate cluster of trajectories within a planning cycle Δt, and then outputs the result to the Collision Probability Module.

The prediction accuracy on the obstacle vehicles' future state is significantly reduced as the prediction window Δt increases. Moreover, the allowable maximal sent time interval between two successive CAMs cannot exceed 50ms [3]. Obviously, Δt should be set quite short, so it is reasonable to assume that the host vehicle keeps the velocity and steering angle as a constant during Δt.

For a given initial state $\{x(t0), y(t0), \theta(t0)\}$, the possible future state $\{x(t), y(t), \theta(t)\}$ during Δt, $t \in (t0, t0+\Delta t)$ is expressed by:

$$x(t) = x(t_0) + \frac{L\left(1 + Kv(t)^2\right)}{\delta(t)} \sin\left(\frac{v(t)\delta(t)}{L\left(1 + Kv(t)^2\right)} t\right), t \in (t_0, t_0 + \Delta t] \tag{1}$$

$$y(t) = y(t_0) + \frac{L\left(1 + Kv(t)^2\right)}{\delta(t)} \left(1 - \cos\left(\frac{v(t)\delta(t)}{L\left(1 + Kv(t)^2\right)} t\right)\right), t \in (t_0, t_0 + \Delta t] \tag{2}$$

 Copyrightⓒ 2016 SERSC

$$\theta(t) = \theta(t_0) + \frac{v(t)\delta(t)}{L\left(1 + Kv(t)^2\right)}t, t \in (t_0, t_0 + \Delta t] \tag{3}$$

Equations (1), (2), and (3) capture the responses of the host vehicle kinematics to the various inputs v(t), δ(t), t∈(t0,t0+Δt] under the given v(t0) and θ(t0), which displays the satisfactory accuracy and computational efficiency within a short-time interval.

We perform a sampling process over the velocity space v(t)∈[vmin,vmax] and steering angle space δ(t)∈[δmin, δmax], where t∈(t0,t0+Δt], and the sampled result is termed as $\dot{v} \in \left[v_{\min}, v_{\max}\right], \dot{\delta} \in \left[\delta_{\min}, \delta_{\max}\right]$. So the host vehicle state {x(t0+Δt), y(t0+Δt), θ(t0+Δt)} and the candidate trajectory $l\left(t_0, \Delta t, \dot{v}, \dot{\delta}\right)$ can be obtained through (9), (10), and (11). When the entire velocity space and steering angle space are traversed, the cluster L(t0, Δt, v(t), δ(t)) of all the possible trajectories during the current planning cycle is expressed:

$$L\left(t_0, \Delta t, v(t), \delta(t)\right) = \bigcup_{\substack{\forall \dot{\delta} \in \dot{\delta}(t) \\ \forall \dot{v} \in \dot{v}(t)}} l\left(t_0, \Delta t, \dot{v}, \dot{\delta}\right), t \in (t_0, t_0 + \Delta t] \tag{4}$$

The host vehicle repeats the above process and accordingly deliveries the candidate trajectory cluster L(t0, Δt, v(t), δ(t)) to the Dubins Distance Module and Collision Probability Module.

3.2. State Prediction Module

The State Prediction Module utilizes the vehicle state involved in CAMs and DENMs received from the External Interface Module to predict the current state of the obstacle vehicle, and then outputs the result to the Collision Probability Module for the collision risk assessment.

The sending interval and transmission delay might cause a lag error of the received vehicle state. To address this issue effectively, we use a non-parameter method called unicycle method [1] to predict the actual position of the surrounding obstacle vehicle at the received moment. This approach only relies on gyroscopic devices and wheel speed sensors to perform the required measurements with a sufficient confidence level and without needing additional sensor cost and much time consumption, so it is not hard to be implemented and deployed on the existing vehicles.

The predicted position at time t0+T is:

$$\Delta x(t0,T)=R(t0)\sin(\Delta\theta(t0,T)) \tag{5}$$

$$\Delta y(t0,T)=R(t0)(1-\cos(\Delta\theta(t0,T))) \tag{6}$$

$$x(t0+T)=x(t0)+\Delta x(t0,T)\cos(\theta(t0))-\Delta y(t0,T)\sin(\theta(t0)) \tag{7}$$

$$y(t0+T)=y(t0)+\Delta x(t0,T)\sin(\theta(t0))+\Delta y(t0,T)\cos(\theta(t0)) \tag{8}$$

$$\theta(t0+T)=\theta(t0)+\Delta\theta(t0,T) \tag{9}$$

Also there are some other prediction models available except the unicycle method, *e.g.* the classic bicycle (CB) model and the numerical integration CB model. Table 1 lists their RMS errors and computation time [1], where vehicles experience 3km in 55km/h.

Table 1 1 Root mean square (RMS) predicted position error (in meters) and computation time (in milliseconds) comparison for the three deterministic prediction approaches. The vehicle was traveling around a 3 km test course at an average speed of 55 km/h.

Copyright ⓒ2016 SERSC

Table 1. Root Mean Square (RMS) Predicted Position Error (In Meters) and Computation Time (In Milliseconds) Comparison for the Three Deterministic Prediction Approaches

Prediction horizon	RMS Error (m)			Computation Time (ms)		
	unicycle	Linearized CB	Integrated CB	unicycle	Linearized CB	Integrated CB
1s	0.31	0.60	0.31	0.003	9.12	7.11
2s	1.17	2.15	1.12	0.004	17.6	11.1
3s	3.28	5.31	3.09	0.004	27.8	14.6
4s	7.05	10.4	6.62	0.004	34.7	18.9
5s	12.6	17.2	11.8	0.004	42.8	22.2

In Table 1, the non-parameter unicycle approach significantly outperforms the numerical integration CB model in the aspect of computation time and without compromising any accuracy of prediction. Additionally, considering the maximum broadcast interval is short enough, we reasonably employ the unicycle approach to predicting the position of the obstacle vehicle. We sample all of the allowable accelerations of each obstacle vehicle to profile the entire possible space of position and velocity. Accordingly, the collision probability with a consideration on the transmission delay is quantified as to average the collision probabilities at all the possible positions and velocities.

3.3. Collision Probability Module

The Collision Probability Module utilizes both the candidate cluster of trajectories outputted from the Trajectory Generation Module and the state prediction on the obstacle vehicles made by the State Prediction Module to assess the risk of each available trajectory and then outputs the assessment result to the Trajectory Selection Module for the subsequent decision-making.

In the Collision Probability Module, we respectively propose a side-collision and a rear-end-collision probability model. The term x0 denotes the host vehicle and xk, k=1, 2 for the others. The collision probability between vehicles x0 and xk is expressed as P_{c,x_0x_k}, which can be calculated by using the side-collision and rear-end-collision probability models on the basis of the angle between vehicles x0 and xk. The common adopted indicators of estimating the collision risk include [25] time difference of arrival, overlap time of arrival, and time to collision (TTC), which intuitively reflect the risk of collision and have been widely used as the indicators of collision risk. The presented side-collision probability model employs the concept of overlap time of arrival, while the calculation of time to collision (TTC) in the rear-end collision probability model.

3.3.1. Side Probability Model: Our side-collision probability model is an extension of the work in [26] through utilizing a triangular distribution to approximate the future acceleration. For facilitating computation, the vehicle is assumed in of round shape with a radius r. If the trajectories of vehicles A and B happen to have an intersection point O, there will be a potential collision event at point O. For convenience and without losing generality, we define a concept of collision zone as a circular zone Carea (O,rc) with the center point O and radius rc, rc=max(rA, rB). Accordingly, the collision-free condition can be expressed that vehicle B should have already left the collision zone prior to the arrival of vehicle A, or vice versa. Say event E means that vehicle A enters the collision zone while vehicle B has already left, and event F implies that vehicle A leaves the collision zone prior to the arrive of vehicle B, then the probability Pc,AB of a side-collision occurring between vehicles A and B can be formulated as:

$$Pc,AB=(1-P(tBE<tAE))(1-P(tAF<tBF)) \quad (10)$$

 Copyright⓪ 2016 SERSC

Where tAF and tBE are the needed time of vehicles A and B passing across the collision zone, and tAE and tBF are the time prior to the reach of vehicles A and B to the collision zone.

3.3.2. Rear-end Collision Model: Another common accident case is the rear-end collision in which we can use the relative longitudinal velocity to estimate the happening of a potential rear-end collision. But in the actual urban environment, due to the frequent lane changing and overtaking operations, it is essential to develop a new method that accommodates the factor of heading orientation. We extend the approach of Velocity Obstacle in [18].

Velocity Obstacle (VO) is proposed to address dynamic trajectory planning in order to avoid multiple moving and static obstacles through enabling the choice of those collision-free velocities in the velocity space in light of the current velocities and positions of the vehicle and its surrounding obstacles. VO is illustrated in Figure 2 where A and B indicate two moving circular objects in the velocity vA(t0) and vB(t0). We assume A represents the main vehicle while B represents the obstacle, provided that vA(t0) and vB(t0) never change, VO is able to predict if a possible collision between A and B in the future through reducing A to the point A′, and enlarging B to the B′ by the radius of A. Accordingly, we define a collision cone CCA,B:

$$CCA,B=\{vA,B(t0)|\lambda A,B(t0)\cap B'\neq\emptyset\} \tag{11}$$

where vA,B(t0) specifies the relative velocity of A′, B′ at time t0, and λA,B(t0) refers to the line containing vA,B(t0). The collision cone CCA, B is a planar sector with the apex A′ and bounded by the two tangents λf and λr from A′ to B′. Any relative velocity within the collision cone might lead to a potential collision in the future. An equivalent partition of the absolute velocity of A could be established by adding each velocity within CCA,B to the velocity of B′:

$$VOA,B(t0)=CCA,B(t0)\oplus vB(t0) \tag{12}$$

where the operator $\oplus$ is the Minkowski vector sum, and VOA, B(t0) separates the absolute velocity of A into two parts: collision with B and not collision with B. If vA(t0) does not fall into VOA,B(t0), a collision cannot occur between A and B under the guarantee:

$$A(t)\cap B(t)=\emptyset \ if\ v_A(t_0)\cap VO_{A,B}(t_0)=\emptyset, t\in(t_0,\infty) \tag{13}$$

In order to avoid multiple moving obstacles, we need to ensure that the absolute velocity vA(t0) of A does not have intersection with any individual velocity obstacle, as expressed by:

$$VO_A(t_0)=\bigcup_{i=1}^{n} VO_{A,B_i}(t_0), \forall i=1,2... \tag{14}$$

If selecting a velocity outside VOA(t0), A has no possibility to collide with any moving obstacle. Additionally, we can calculate TTC of the possible collision:

$$TTC_{A,B_i}=Min\, t, \forall t\in\left\{t\mid A+t\left(v_A(t_0)-v_{B_i}(t_0)\right)=B_i\right\}, \forall B_i\in\left\{B_i\mid v_A(t_0)\cap VO_{A,B_i}(t_0)\neq\emptyset\right\} \tag{15}$$

3.4. Trajectory Selection Module

The Trajectory Selection Module utilizes the potential minimal lengths received from the Dubins Distance Module and the corresponding collision probability outputted from the Collision Probability Module to decide an optimal trajectory for each planning cycle, and then outputs the selection to the Control Unit to follow the trajectory.

In a planning cycle [ti, ti+Δt] , the Trajectory Selection Module uses the potential

Copyright ⓒ2016 SERSC

collision probability of each candidate trajectory to calculate its safe probability $P_{safe,x_0,l(t_i,\Delta t,\dot{v},\dot{\delta})}$:

$$P_{safe,x_0}\left(l\left(t_i,\Delta t,\dot{v},\dot{\delta}\right)\right)=\prod_{k=1}^{K}\left(1-P_{c,x_0x_k}\left(l\left(t_i,\Delta t,\dot{v},\dot{\delta}\right)\right)\right) \tag{16}$$

Where K indicates the number of obstacles. Then the Trajectory Selection Module utilizes each minimal distance away to the target of each candidate trajectory to generate an optimal assessment index J, which is a reasonable balance between safety and efficiency. The Trajectory Selection Module always selects the {δ(t), v(t)} that minimizes the assessment index J and then outputs to the Control Unit to perform the corresponding control operations, as expressed by:

$$J\left(t_i,\Delta t,\dot{v},\dot{\delta}\right)=\frac{S_{\min}\left(l\left(t_i,\Delta t,\dot{v},\dot{\delta}\right)\right)}{P_{safe,x_0}\left(l\left(t_i,\Delta t,\dot{v},\dot{\delta}\right)\right)} \tag{17}$$

$$J_{\min}=\min\left\{J\left(t_i,\Delta t,\dot{v},\dot{\delta}\right)\mid\mu\left(\dot{v},\dot{\delta}\right)\le 0.25)\in\right\},\forall\dot{v}\in v\left(t\right),\forall\dot{\delta}\in\delta\left(t\right) \tag{18}$$

4. Simulations

4.1. Effects of the Planning Cycle

The autonomous vehicle keeps a constant velocity and steering angle during a planning cycle Δt, so the minimal distance away to obstacles should be significantly reduced if Δt is set too long. Conversely, the curvature will be frequently changed if too short, resulting in an intolerant uncomfortability. In order to confirm the optimal time length of Δt, we collect the relevant data that corresponds an average of more than 20 times of simulations in a continuous overtake scenario, as shown in Table 2.

Table 2. Safety and Comfort Indexes Comparison for the Different Δt

Δt	cycles	$D_{\min}$	D_{mean}	K_{sum}	D	I
0.1	66	1.2929	2.4644	5.2376	1.8786	2.788
0.2	37	1.1687	2.2748	2.7172	1.7218	1.578
0.3	27	1.2130	2.1587	1.2813	1.6859	0.760
0.4	21	1.0632	2.1145	1.0559	1.5889	0.665
0.5	18	1.1054	2.1087	0.9833	1.5020	0.612
0.6	15	1.0280	2.1131	0.5612	1.4792	0.357
0.7	13	0.3759	1.3670	0.3850	0.8714	0.442
0.8	12	0.2032	1.3417	0.4024	0.7725	0.521
0.9	12	0.2017	1.3365	0.4025	0.7691	0.523
1.0	10	0.2006	1.2764	0.3850	0.7385	0.521

$$D=0.5(Dmin+Dmean) \tag{19}$$

$$I=\frac{K_{sum}}{D} \tag{20}$$

where Dmin and Dmean indicate the minimal and average distances away to obstacles, respectively. Ksum represents the total number of the changing times of curvature. We select the optimal Δt with respect to minimizing the index I. So Δt=0.6s where the index I reaches the minimum, Dmean=1.9303 and Ksum=0.5612.

4.2. Effects of Communication Profile

The transmission delay undoubtedly reduces the perception accuracy while the

 Copyrightⓒ 2016 SERSC

transmission range affects the perception range. Since the increase of the transmission range, more stations have opportunities to join in the channel competition, resulting in a deteriorated transmission delay of CAMs and DENMs. We separate the transmission delay tdelay into two parts, *i.e.* the transmission time ttr from the beginning of sending to the time that the message has been received by the receiver, and the average channel competition time twait that the message has to be waited in the queue until having the opportunity to be sent.

$$\text{tdelay=ttr+twait} \tag{21}$$

$$t_{tr} = \frac{l_{package}}{BR} + DIFS + \tau, l_{package} = l_{PHY} + l_{MAC} + l_{data} \tag{22}$$

$$t_{wait} = \frac{1}{\omega}\sum_{i=0}^{\omega-1} i\left[(1-P_b)t_{slot} + P_b(t_{slot} + t_{tr})\right] \tag{23}$$

$$\text{Pb=1-[1-Pt(1-P0)]n-1} \tag{24}$$

$$P_t = \frac{2}{\omega + 1} \tag{25}$$

Where DIFS is the DCF Interframe Space, τ is the propagation delay, lPHY and lMAC represent the lengths of the frame header of PHY and MAC layers, respectively, and BR is the bit rate. Pb is the probability of busy channel. n indicates the number of stations within the transmission range. P0 is the probability of without message to send, and P0=0 in the simulations because we mainly focus on the saturated state.

The simulations are performed in a scenario that includes a 500m highway, 60 obstacle vehicles, and the initial velocity 10m /s of the host vehicle. The detailed parameters can be found in Table 3.

Table 3. Simulation Parameters

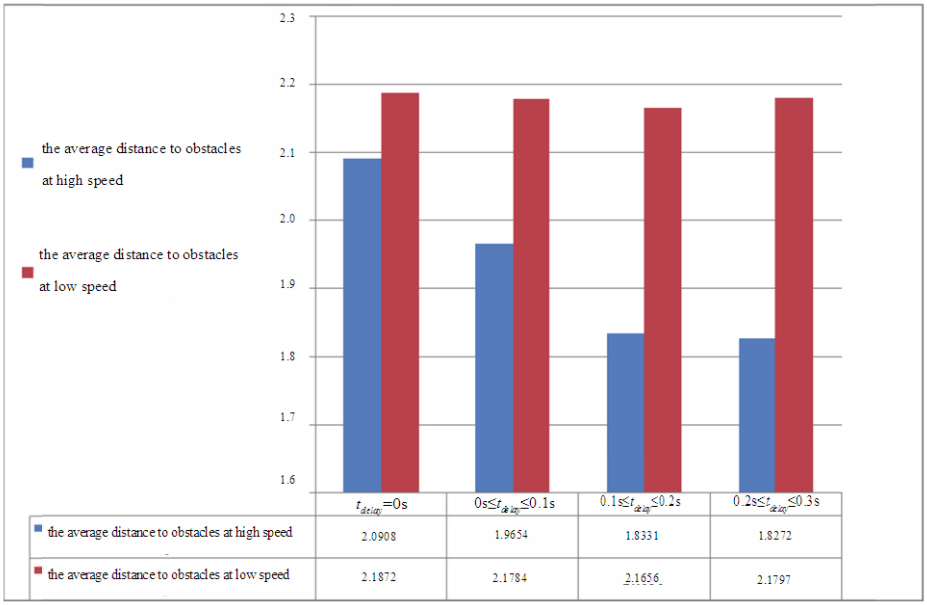
Parameter	Meaning	Value
S	Highway length	500m
N	Obstacle vehicle number	60
DIFS	DCF inter Frame Space	58μs
t_{slot}	Slot time	13μs
l_{PHY}	Physical layer header size	24*8 bits
l_{data}	Packet size	100*8 bits
λ	Bit rate	12Mbit/s
γ	Transmission range	50m, 100m, 200m, 300m
ω	Contention window	2^i, i = 3, 4, 5...
τ	Propagation delay	1μs

4.3. Effects of Time Delay

Compared to other scenarios, the continuous overtaking scenario is more challenging, so we mainly focus on the worst case, where v=10m/s and vobs=6m/s under the low-speed condition while v=20m/s and vobs =10m/s in the high-speed scenario. The allowable maximum transmission delay does not exceed 300ms. We example some high-priority safety applications identified by NHTSA and VSCC, *e.g.* pre-crash sensing, collision warning, lane-change warning, the allowed latency is less than 100ms [1]. So it is acceptable that the maximum delay is assumed not to exceed 300ms. We observe the average inter-vehicle distance and average velocity of the host vehicle. The results

correspond to an average over at least 20 times.

The results show that the proposed approach can effectively support a satisfactory travel with safety (see Figure 1) and velocity (see Figure 2). The ideal average distance of the host vehicle away to the obstacles is nearly 2.1m in the high- and low-speed conditions and tdelay=0. With the increase of tdelay, the average distance is significantly reduced in the high-speed condition, while is slightly changed in the low-speed condition. This is because the prediction range to the obstacle vehicle is enlarged as vobs increases, which causes a deviation between the actual and estimated collision probabilities. Such deviation becomes much more in the high-speed condition. The negative influence of tdelay is capable of being minimized via the appropriate prediction method but not completely eliminated. In order to keep robust to the transmission delay, we should restrict the average distance beyond a certain threshold. One can see that the average distance is 1.8331m at 0.1s≤tdelay≤0.2s. As tdelay increases to 0.2s≤tdelay≤0.3s, the average distance should be over 1.8m.



	t_{delay}=0s	0s≤t_{delay}≤0.1s	0.1s≤t_{delay}≤0.2s	0.2s≤t_{delay}≤0.3s
the average distance to obstacles at high speed	2.0908	1.9654	1.8331	1.8272
the average distance to obstacles at low speed	2.1872	2.1784	2.1656	2.1797

Figure 1. The Effects of the Transmission Delay Tdelay on the Average Distance Away from Obstacles at the Worst Case

Copyrightⓒ 2016 SERSC

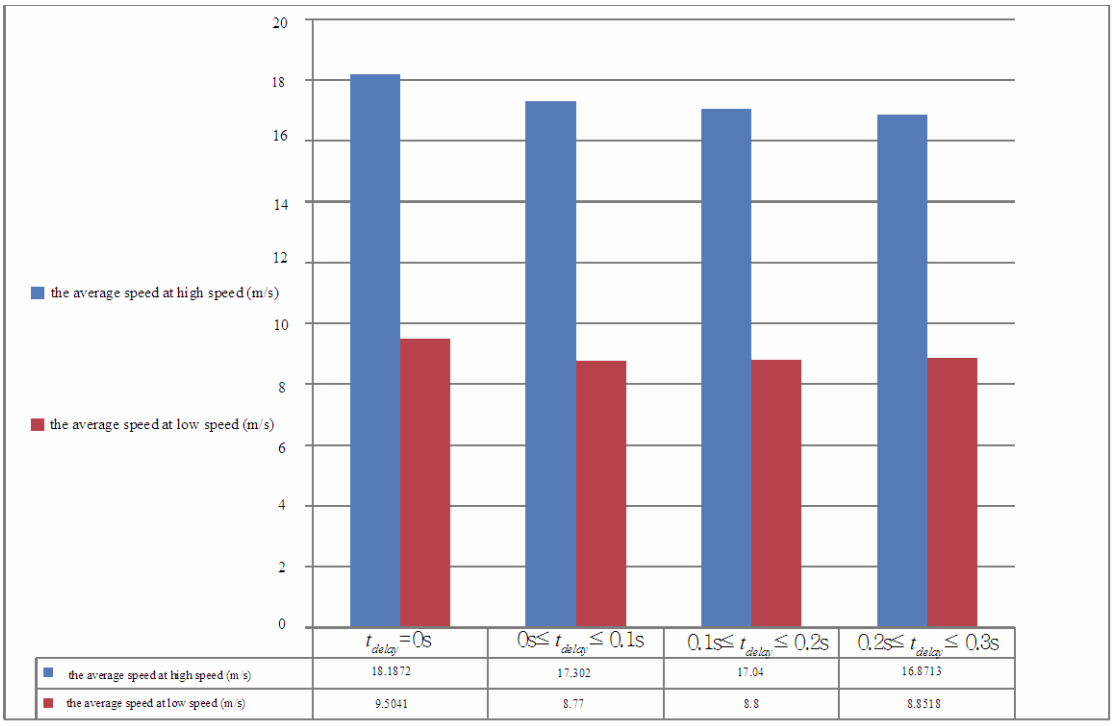


Figure 2. The Effects of the Transmission Delay Tdelay on the Average Speed at the Worst Case

4.4. Effects of Transmission Range

We consider the signal should be successfully perceived beyond at least 50m, *i.e.* $\gamma \geq 50$m. As γ increases, tdelay is slightly increases but far from 0.3s, so the resulted trajectories are basically the same (see Figure 3). Another reason is that the collision probability is close to zero if the obstacle vehicles are far away from the host vehicle. The results in Section 4.3 show that the host vehicle is able to behave well at $0.2\text{s} \leq \text{tdelay} \leq 0.3\text{s}$, so we point out that the increase of γ does not destroy the automated driving of the host vehicle, at least acceptable. A large value of γ implies more global awareness, which might potentially increase the performance. Our approach belongs to a local trajectory planner, so the benefits are not uncovered in the scope of this paper, but the current results show that a relatively big value of γ is advisable.

Copyright ⓒ2016 SERSC

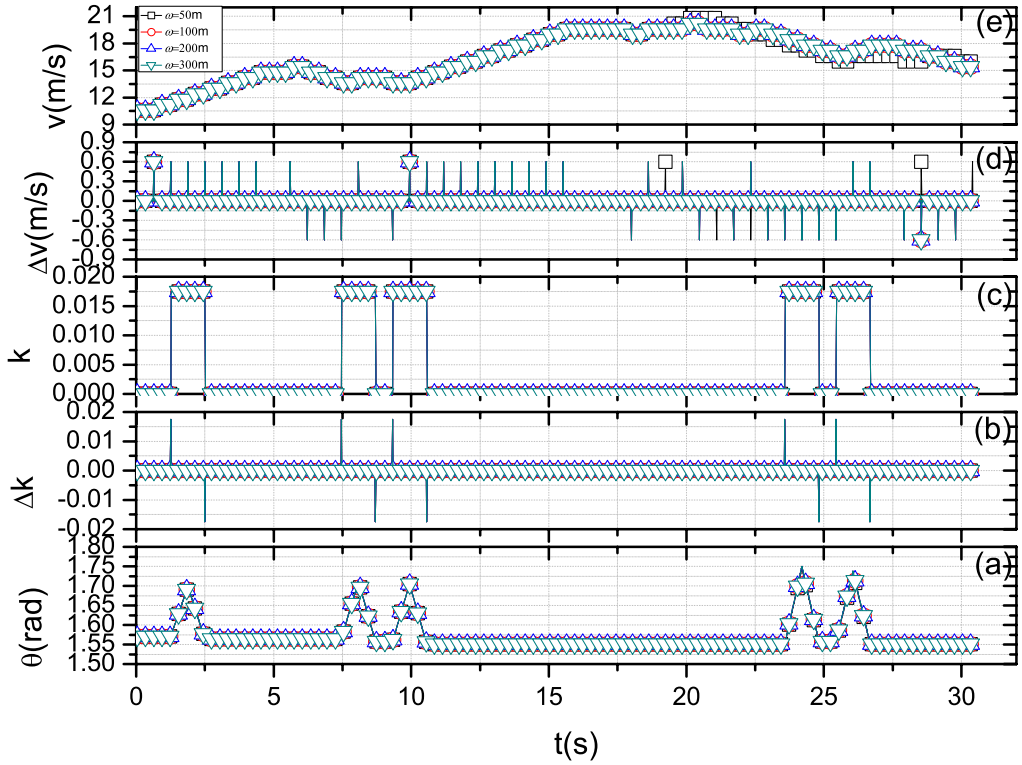


Figure 3. The Effects of the Transmission Range TR At C=0.5,Vobs=9m/S On (a) Yaw Angle (b) Curvature Change (c) Curvature (d) Velocity Change (e) Velocity

5. Conclusions

In this paper, we present a novel delay-tolerant trajectory planner aided by the inter-vehicle communication. The Trajectory Generation Module is in charge of creating a cluster of the safe and comfortable candidate trajectories, and the Trajectory Selection Module can select the optimal trajectory regarding the collision probability and minimal distance away to the short-term target. The simulations show that the proposed approach is able to keep comfortable and safe adaptive to various combinations of the traffic density, average velocity of the obstacle vehicles, and transmission delay. Combined with some existing global trajectory planners, *e.g.* Hybrid A* [27] and consider the average velocity of the related lane and traffic density, this approach is expected to achieve much better performance through utilizing global awareness. Our simulations are performed by extending the work of Choi [17] whose result in the continuous overtaking situation is presented in Figure 10. One can easily find that several crash cases occur in overtaking, which implies that simply depending on the sum of the cost function is possible to cause an unexpected danger in the practice.

Copyright⓪ 2016 SERSC

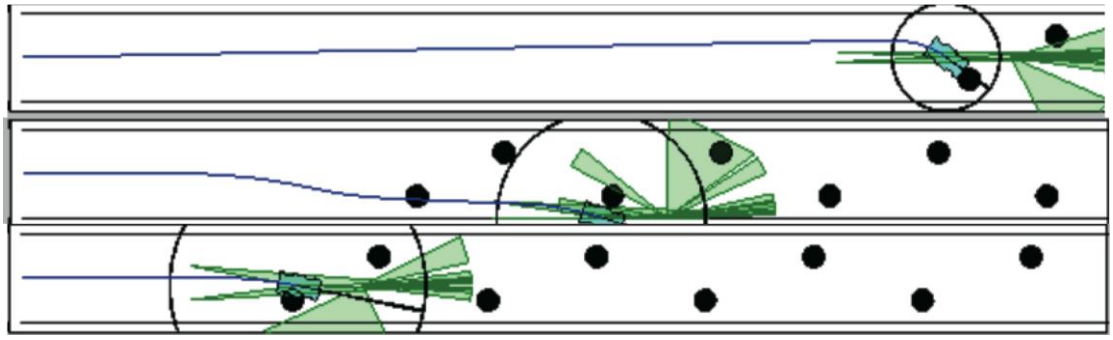


Figure 4. The Method in [7] Operates Against the Continuous Overtake

It is worth mentioning that the choice of the estimation model on the obstacle position is dependent on the requirement and characteristic of the serving application. In this paper, we employ the non-parameter unicycle model that has the ability to provide sufficient accuracy but little computation time in most cases. However, if the vehicle happens to slide or rotate on an icy road, the unicycle method is not applicable, which is because the yaw rate measured by the gyroscopic device is not reliably used to estimate the road curvature any more. It is necessary to consider more physical variables such as the wheel slip angle and wheel longitudinal slip in the icy road or something like this. The traditional trajectory planner is hard to acquire the accurate wheel slip angle and wheel longitudinal slip while the inter-vehicle communication enables it. In the future, we will focus on the cooperative trajectory planning, which is helpful to significantly improve the performance of the vehicle platoon.

Acknowledgments

This work was supported Jilin Provincial Science and Technology Development Foundation [20130206040GX].

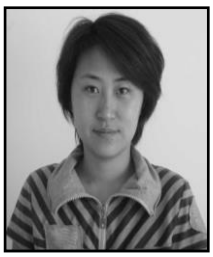
References

[1] H. Hartenstein, "VANET: vehicular applications and inter-networking technologies", Chichester: Wiley. **(2010)**.
[2] A. M. Vegni, M. Biagi, and R. Cusani, "Smart vehicles, technologies and main applications in vehicular ad hoc networks". **(2013)**.
[3] ETSI EN 302 637-2 V1.3.0, "Technical Specification Intelligent Transport Systems (ITS); Vehicular Communications; Basic Set of Applications; Part 2", Specification of Cooperative Awareness Basic Service, **(2013)** August.
[4] S. Wang, B. Dipl.-Ing. -Benjamin-Hesse, T. Brandt and D. Schramm, "Cooperative Trajectory Planning Based on Car-to-X Communication", ATZ World, vol. 113, no. 4, **(2011)**, pp. 60-64.
[5] Wikipedia, **(2014)**. Google driverless car. [online] Available at: http://en.wikipedia.org/wiki/Google_driverless_car [Accessed 8 May. 2014].
[6] Vislab.it, **(2014).** PROUD Car Test 2013|VisLab. [online] Available at: http://vislab.it/proud/ [Accessed 8 May. 2014].
[7] Hoeger, R., Amditis, A., Kunert, M., Hoess, A., Flemish, F., Krueger, H. P., and Pagle, K. "Highly automated vehicles for intelligent transport", Have-it approach. In 15th World Congress on Intelligent Transport Systems and ITS America's 2008 Annual Meeting. **(2008)**.
[8] Chan, E., Gilhead, P., Jelínek, P., Krejci, P., and Robinson, T., "Cooperative control of SARTRE automated platoon vehicles". In Proceedings of the 19th ITS World Congress. **(2012)**.
[9] J. I. Peters and D. S. Elston. "Recent International Activity in Cooperative Vehicle–Highway Automation Systems", Technical report, FHWA-HRT-12-033, **(2012)** December.
[10] Wei, J., Dolan, J. M., and Litkouhi, B. (2010, June). A prediction-and cost function-based algorithm for robust autonomous freeway driving. In Intelligent Vehicles Symposium (IV), 2010 IEEE, IEEE, pp. 512-517.
[11] M. T. Wolf and J. W. Burdick, "Artificial potential functions for highway driving with collision avoidance", In Robotics and Automation, 2008. ICRA 2008. IEEE International Conference on. IEEE. **(2008)** May. pp. 3731-3736.

Copyright ⓒ2016 SERSC

[12] O. Khatib, "Real-time obstacle avoidance for manipulators and mobile robots". The international journal of robotics research, vol. 5, no. 1, **(1986)**. pp. 90-98.
[13] L. Kavraki and J. C. Latombe, "Randomized preprocessing of configuration for fast path planning", In Robotics and Automation", 1994 Proceedings, 1994 IEEE International Conference on IEEE. **(1994)** May, pp. 2138-2145.
[14] J. Barraquand and J. C. Latombe, "Robot motion planning: A distributed representation approach", The International Journal of Robotics Research, vol. 10, no. 6, **(1991)**, pp. 628-649.
[15] M. Chen and A. Zalzala, "A genetic approach to motion planning of redundant mobile manipulator systems considering safety and configuration", Journal of Robotic Systems, vol. 14, no. 7, **(1997)**, pp. 529-544.
[16] A. McLean and S. Cameron, "The virtual springs method: Path planning and collision avoidance for redundant manipulators", The International journal of robotics research, vol. 15, no. 4, **(1996)**, pp. 300-319.
[17] J.W. Choi, "Real-time obstacle avoiding motion planning for autonomous ground vehicles", University of California, Santa Cruz. **(2011)**.
[18] P. Fiorini and Z. Shiller, "Motion planning in dynamic environments using the relative velocity paradigm". In Robotics and Automation, 1993. Proceedings. 1993 IEEE International Conference on. IEEE. **(1993)** May. pp. 560-565.
[19] Z. Qu, J. Wang, and C. E. Plaisted, "A new analytical solution to mobile robot trajectory generation in the presence of moving obstacles". Robotics, IEEE Transactions on, vol. 20, no. 6, **(2004)**, pp. 978-993.
[20] J. Yang, "Real-time trajectory planning for ground and aerial vehicles in a dynamic environment", ProQuest. **(2008)**.
[21] K. Macek, M. Becked and R. Siegwart, "Motion planning for car-like vehicles in dynamic urban scenarios". In Intelligent Robots and Systems, 2006 IEEE/RSJ International Conference on. IEEE. **(2006)** October. pp. 4375-4380.
[22] S. M. LaValle, "Rapidly-Exploring Random Trees A New Tool for Path Planning". **(1998)**.
[23] H. Tao, H. Wu, L. Cheng, X. Zhang, and S. Yang, "The Research of Wheeled Mobile Robot FastSLAM algorithm". Journal of Harbin University of Science and Technology, vol. 16, no. 1, **(2011)**, pp. 42-47.
[24] C. Liu, Y. Liang and J. Yang, "A Method for Solving Local Minimum Problem of Path Planning Based on Potential Field in Complex Environments". Journal of Harbin University of Science and Technology, vol. 17, no. 4, **(2012)**, pp.78-82.
[25] O. Kwon, S. H. Lee, J. S. Kim, M. S. Kim and K. J. Li, "Collision prediction at intersection in sensor network environment. In Intelligent Transportation Systems" Conference, 2006. ITSC'06. IEEE. **(2006)**. pp. 982-987.
[26] S. Joerer, M. Segata, B. Bloess, R. Lo Cigno, C. Sommer and F. Dressler, "A Vehicular Networking Perspective on Estimating Vehicle Collision Probability at Intersections". **(2013)**.
[27] D. Dolgov, S. Thrun, M. Montemerlo and J. Diebel, "Practical search techniques in path planning for autonomous driving". Ann Arbor 1001, **(2008)**. 48105.

Authors



Dan Shao, College of Computer Science and Technology, Changchun University, Changchun 130022, China.

Jianan Wu, College of Computer Science and Technology, Changchun University, Changchun 130022, China

 Copyright⓪ 2016 SERSC

Yinfei Dai, College of Computer Science and Technology, Changchun University, Changchun 130022, China

Copyright ⓒ2016 SERSC

Copyrightⓒ 2016 SERSC