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A Novel Decision Making Technique at the Intersection Based on Perception Navigation

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Abstract

This research aims to develop a strategy of decision making technique at the intersection scenario based on Perception Navigation (P-Navi). The multi-sensor system is applied in this research. The sensor data are fused through Constraint Unscented Kalman Filter (CUKF). The intersection policy is formulated as a convex optimization problem. Once P-Navi gives a fixed result of position, the decision making module will calculate the characteristic information of the intersection as a constraint for solving the optimization problem.

Keywords: intersection strategy, perception navigation, optimization

1 Introduction

Since the automobile was invented, the intersection has always been a nightmare for all of drivers. According to the report form the National Highway Traffic Safety Administration (NHTSA) [1], the intersection related pre-crash event is one of the most commonly happened car crash event, as shown in Fig. 1. Thus, the automated decision making and vehicle motion control can be used at the intersection to improve the driver safety and keep the traffic smooth.

The most important variable for intersection decision making strategy is the geometric information of the intersection. The geometric information not only includes static variables like the number of lane, width of each lane but also includes dynamic variables like distance to the intersection and which lane the vehicle is driving in. To obtain those variables, the algorithm rely on the fusion of multi-sensors system. For all variables, the first data needed is the absolute position of the vehicle and commonly referring to GPS. However, GPS is known to be inaccurate and noisy without other argument techniques like differential global positioning system (DGPS) or real time kinematic (RTK) satellite navigation. The purpose of P-Navi is using the other sensors to enhance the accuracy of GPS without DGPS and RTK. This solution will leads the cost of P-Navi much lower than the one with RTK and makes the product become more competitive. There also many solutions have been developed to enhance the accuracy of GPS without RTK. Li *et al*. [2] proposed a method to fuse GPS and digital map data. This map-added approach combines GPS/INS and map throught constraint unscented Kalman filter. The benefit of using Kalman filter is the flexibility of sensor redundancy. It allows to fuse sensor data simply by giving a set of weighting parameters to each sensor measurement results. The constraint condition in the algorithm provides a reasonable physical restriction to adjust the value of covariance matrix which will affect the result that thrusts the estimation (update by dynamic equation) or

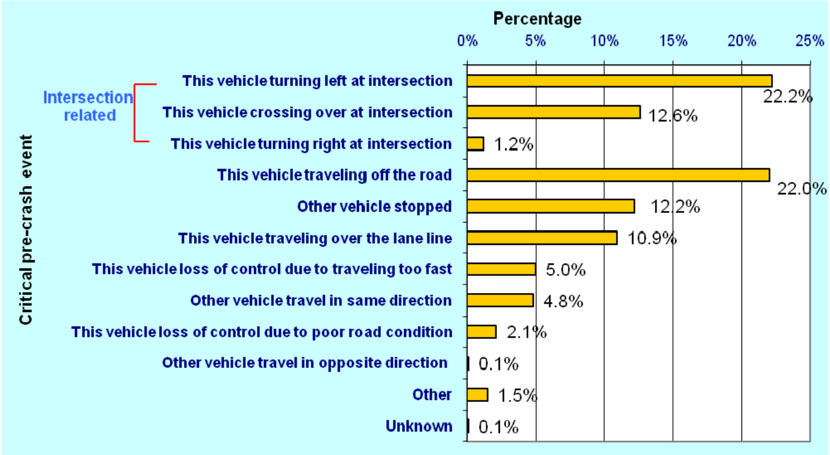

Figure1: Distribution of critical pre-crash event [1]

Data Source: NMVCCS 2005-2007

the measurements (update by sensors) more. For example, the position of vehicle driving on the roal located outside the road is impossible. Thus, the road boundary is one of the constraint for CUKF algorithm.

However, the accuracy of position results requires a reliable ground truth resource. Lidar, Radar or camera are most commonly seen sensors used in ADAS to provide ground truth data. There are advantages and disadvantages of each sensor. Lidar and Radar measure the distance accuratly to surroundings and camera captures the image frames. For enhancing the accuracy of positioning result, camera is better than the others because the range sensors is hard to recognize the pattern of the object. For example, those range sensors do detected where the sign is but do not know what kind of the sign it is. However, a camera can recognize the pattern well due to the color information. The approximately position can be estimated under some assumptions although a camera connot give the position of the object directly. For road markers lying on the surface of the road, the high of them is zero. That is, the position can be estimated by coordinate transformation with the pxiel position of road markers and other parameters like focal length, camera mounted position and true objection vertical position which is zero. LIM *et al.* [3] proposed an efficient hybrid positioning method combining a single frequency GPS receiver and a monocular vision sensor. the method measures absolute heading angle based on the images of straight road segments and use this message to correct the GPS positioning result. However, this method requires no external map aiding that lose opportunity of using more road marker messages.

This paper proposes a new method called P-Navi which combines the advantages of the above two methods. The combination of the stop sign location in camera and digital map allows to correct the GPS positioning results in both lateral and longitudinal direction and makes the intersection decision making strategy become more reliable. Some intersection strategies focus on the traffic flow rate. Wang *et al.* [4] controled the timing of the traffic signal to optimize the queue length based on the cooperative game theory. Jiang *et al* [5] controled the traffic signal to improve the traffic flow. These methods assume that all vehicles follow the stastic model. Once a colliction occurs, a piece of area in the intersection will be closed. The same signal control strategy might no longer work, or even let things become worse. Some studies consider the collision avoidance problem and coordiante vehicles by controlling vehicle itself. P. Dai *et al.* [6] linearized collision avoidance constraints by designing a schedule rule and solved a convex optimization problem that transformed form the objective of quantitatively capturing the quality of travel experience. S. Lefèvre *et al.* [7] considered the V2X commumication privacy strategies on intersection collision avoidance systems. The ID of each vehicle is no longer consistent with respect to time. That is, the probabilistic motion model is applied to deal with the variation of information form V2X commumication. Gabriel R. Campos *et al.* [8] presented a decentralized coordination approach, combining optimal control with model-based heuristics.

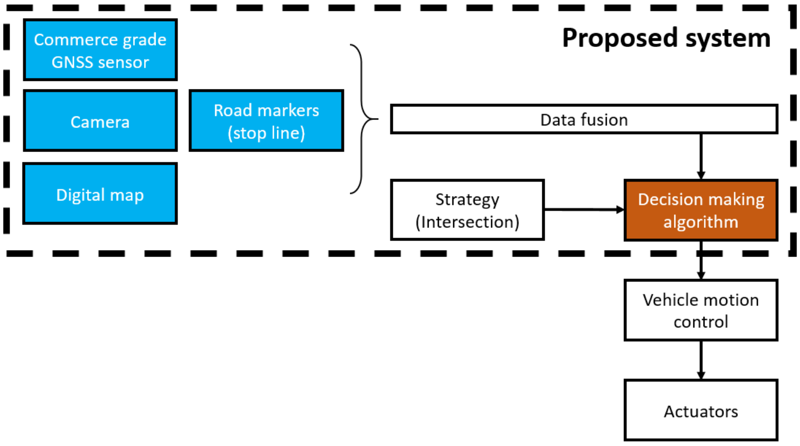

Figure2: System structure

The vehicle movement is classification into several patterns. Vehicles which follow their patterns are coordinated that do not appear in the same region at the same time. Those strategies assume that all vehicle is controllable and always follow the instruction from central controll unit. For intersection decision making strategy, the intersection geometry is also import as vehicles. In this paper, the perception navigation based decision making technique is proposed to deal with the geometric information. Moreover, a vehicle is only considered to be controllable. This scenario is designed for upcoming early stage of automonous vehicle. Only very few self driving car on the road.

The remainder of this paper is organized as follows. In Section 2, the proposed system is presented including perception navigation and the intersection decision making technique. Simulation results are given in Section 3, and the conclusions are presented in section 4.

2 System Overview

The propose system has two mainly components which are P-Navi and decision making technique as shown in Fig. 2. The fused multi-sensor data and strategy at the intersection are referred by the decision making algorithm and then the motion control unit sends the proper signals to actuators which includes the throttle, the brake pedal and the steering wheel.

2.1 Perception Navigation

GPS positioning result is the most important information for navigation. However, the satellite’s signal is usually blocked by the buildings in urban area. The error of commerce grade GNSS sensor is larger than three meters and not precise enough to navigate an autonomous vehicle. On the other hand, the intersection without lane markers cannot provide the information that the autonomous vehicle passes through by following the path refereeing to lane markers. Furthermore, the bigger intersection contains the road with multi-lane. A lane-level positioning result is needed for navigating an autonomous vehicle in the intersection. Fig. 3 illustrates how the sensor fusion algorithm works and Fig. 4 shows the flow chart for P-Navi.

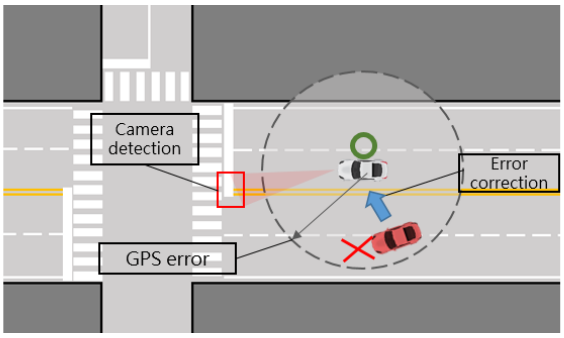

Figure3: Illustration of perception navigation

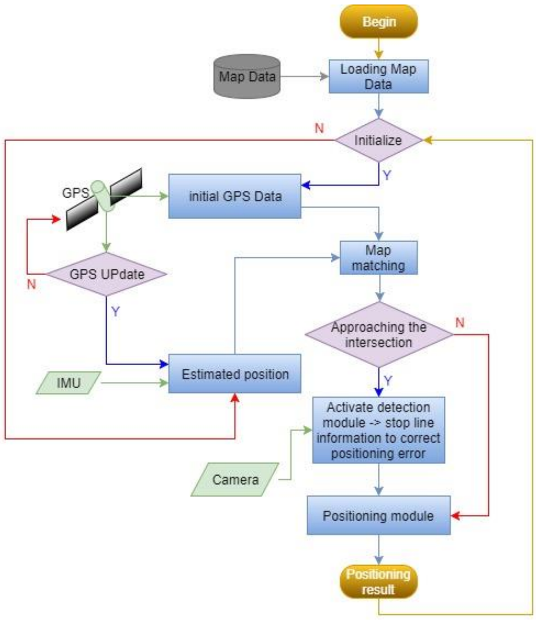

Figure4: Sensor fusion process

The algorithm first load the pre-build digital map including the stop line informations at all intersections. For the initialization, the raw GPS positioning result is referred to locate the initial position of the vehicle with digital map. After that, the referred positioning result is from the GPS/INS fused result. Then, the algorithm will check if the vehicle approaches intersection to decide when the stop line detection module should be activated. This operation would save the computation load for the computer vision program at general situation. Finally, the correction information from camera and computer vision algorithm fix the GPS/INS result of positioning.

A general discrete nonlinear system can be expressed in Eq. 1. The sensor fusion result can be obtained through CUKF algorithm at Eq. 2~7. The covariance matrices (Eq. 2~4) are calculate by the dynamic modes and measurement model at Eq. 1. The idea is to calculate the statistic result of the model updated sigma points (state variables scatter referring the last updating system covariance by Eq. 7). That is, the constraint can be added as moving those sigma points which are out of boundary back in the boundary. Finally the fused result is determined by combining the estimated value and measurement data together with a proportion of measurement and cross (measurement and dynamic update) covariance matrices as shown in Eq. 6.

$$\begin{cases} X_{k+1} & = & f\left(X_k, U_k\right) + \omega_k \\ Y_k & = & h\left(X_k, U_k\right) + \upsilon_k \end{cases} \tag{1}$$

$$P_k^- = \sum_{i=1}^{2L} W_i^{(c)} \left[x_{i,k|k-1}^x - \hat{x}_k^- \right] \left[x_{i,k|k-1}^x - \hat{x}_k^- \right]^T + Q \tag{2}$$

$$P_{\hat{y}_k \hat{y}_k} = \sum_{i=1}^{2L} W_i^{(c)} \left[y_{i,k|k-1} - \hat{y}_k^- \right] \left[y_{i,k|k-1} - \hat{y}_k^- \right]^T + R \tag{3}$$

$$P_{\hat{x}_k \hat{y}_k} = \sum_{i=1}^{2L} W_i^{(c)} \left[x_{i,k|k-1}^x - \hat{x}_k^- \right] \left[y_{i,k|k-1} - \hat{y}_k^- \right]^T \tag{4}$$

$$K = P_{\hat{x}_k \hat{y}_k} P_{\hat{y}_k \hat{y}_k}^{-1} \tag{5}$$

$$x_k = \hat{x}_k^- + K\left(y_k - \hat{y}_k^-\right) \tag{6}$$

$$P_k = P_k^- - K P_{\hat{x}_k \hat{y}_k} K^T \tag{7}$$

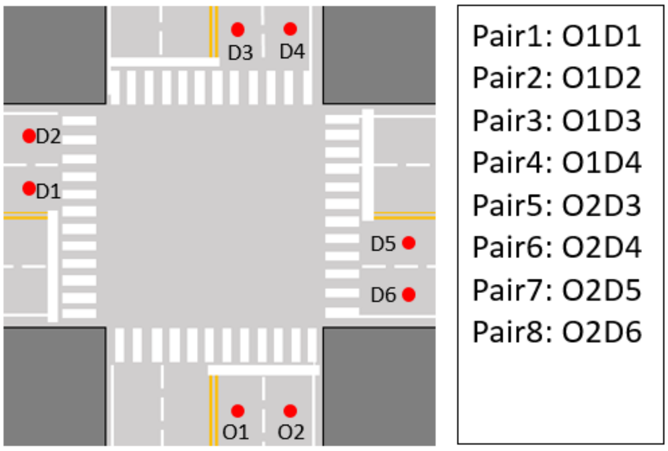

Figure5: The origin-destination (OD) pairs

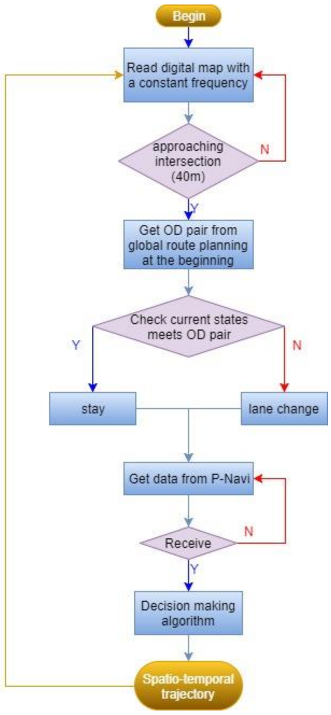

Figure6: The decision making strategy

2.2 Decision Making Technique

The scenario is considered in a cross-intersection which is the most representative intersection type in an urban area. The cross-intersection is assumed that contains four lanes in a road. That is, each direction has two lanes for left turn and right turn group of vehicles, as shown in Fig. 5. All vehicles follow the rules that left turn vehicle should pre-change or stay in the inner lane and so does right turn vehicle in the outer lane. For the decision making technique, the origin-destination (OD) is given from P-Navi and the route planning algorithm. There eight different OD pairs are defined in this paper and illustrated in Fig. 5. Pairs 1 and 2 are for turning left, 3~6 are for driving across the intersection, 7 and 8 are for turning right.

The decision making strategy first reads the digital map and matches it with GPS position. When the distance between the vehicle and the intersection is roughly smaller than 40m (consider the positioning error of GPS), the strategy will get an OD pair from global route planning module. If the lane that the vehicle is driven on is not matches the OD pair, it will make the vehicle do the lane change task. Otherwise, the vehicle stays. For example, the vehicle should do the lane change task lane when it is driven on the inner lane but the destination is D6. After checking the OD pair matching status, the system waits the positioning correction result from P-Navi. Once the position of the vehicle is fixed by the stop line information, the decision making algorithm tries to find a trajectory that the vehicle can pass through the intersection.

The goal of the decision making algorithm is to design a trajectory that the vehicle can arrive the destination in finite time and avoid collisions. The obstacles or the other vehicles are assumed to be static or conditionally dynamic that it will remain the constant speed and steering. That is, the motion of the moving obstacles is easy to predict. Then, the decision can be formulated as the optimal function, as shown in Eq. 8:

$$\min_{U} J(X,U)\,, X = x_{tN}, U = u_0, \cdots, u_{tN} \tag{8a}$$

Subject to

$$\dot{x} = f(x,u) \tag{8b}$$

$$x < L_i \tag{8c}$$

$$x < \sum O_j(t) \tag{8d}$$

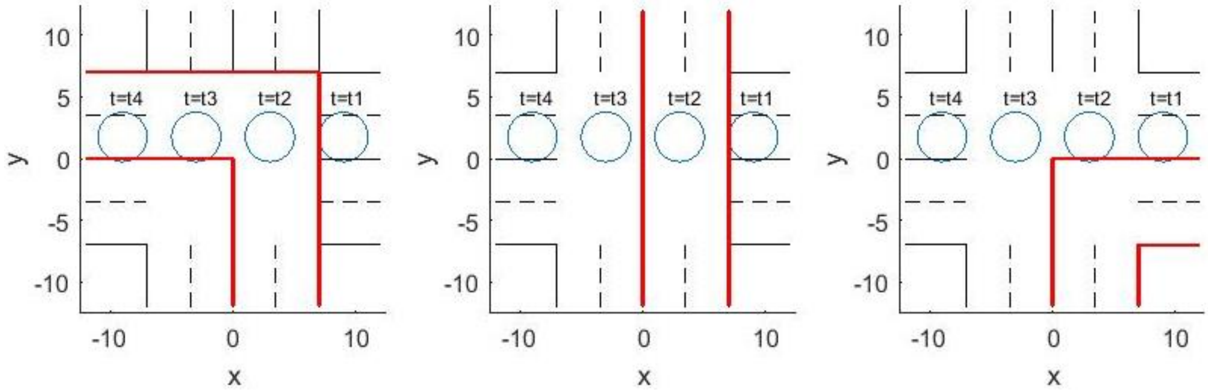

Figure7: illustration of spatial constraints. The red line in left figure is type 1 road constraint. The red line in middle figure is type 2 road constraint. The red line in right figure is the type 3 road constraint. The blue circle is the moving obstacle constraint and it will change its position with respect to time.

$$x_{lb} < x < x_{ub} \tag{8e}$$

$$u_{lb} < u < u_{ub} \tag{8f}$$

The cost (8a) is composed by the integration of square of control inputs and the Euclidean distance between the position of vehicle at time t_N and the destination (D1~D6). The former part is designed for saving the energy consumption as possible as it can. The equality constraint (8b) represents the vehicle dynamics. Where state variable $x = [x_v, y_v, v, \varphi]$ are position, longitudinal velocity, and heading angle respectively. The control inputs $u = [\delta, T]$ denotes the steering and the trust. For the concern of computational complexity, the simplified Ackerman steering model is adopted in this paper. For the other applications, please refer to the research by X. Li *et al*. [9]. Ackerman steering model is an approach of vehicle dynamics in low speed driving scenario. Eq. (8c) and (8d) are the road boundary constraint and the moving obstacle constraint respectively, as shown in Fig. 7. There are three types of the road boundary constraint for vehicle turning left, right and driving straight. The road boundary is determined after P-Navi giving the accuracy vehicle location. It can reversely refer to the digital map to find the road boundary information when the position of the vehicle is known. The moving obstacle constraint are formulated as circles around the obstacles. The position of these circular constraints changes with respect to time and with simple constant moving patterns. It is assumed that the speed, yaw rate and the destination of the other vehicle can be obtained via V2V communication device and the relative position can be obtained via range sensors like lidar or radar. That is, these spatial constraints can be avoided during solving the optimization problem. Eq. 8e and Eq. 8f are the limitation of speed and the control signal for a vehicle respectively. Note that the result from solving Eq. 8 is a pair of control signals which are the steering wheel angle and depth of the throttle. The ideal trajectory is obtained through solving the vehicle dynamic equations with these control signals. Thus, this trajectory is a spatio-temporal data that the vehicle should follow it not only at the right place but also at the right time.

3 Results

The performance of P-Navi is evaluated in a route which contains four intersections and there are seven stop lines in this route. Fig. 8 shows the positioning result without and with detecting the stop line. Note that the positioning data is from the experiment the vehicle is driven by human. However, the stop line detection algorithm is simulated through directly using the ground truth data from GPS with RTK because the computer vision algorithm for detecting the stop line was not ready. The entire post-processed result is shown in Fig. 9. The distance to the stop line (orange line) is not continuous because the effectively detection range is assumed to be 25 meters in this paper. It can be observed that the positioning error holds under 30 cm when the stop line is assumed to be detected. Although the error grows after lose detecting the stop line, the data fusion technique prevent the positioning result diverges immediately because the covariance matrix of CUKF is adjusted during the correction.

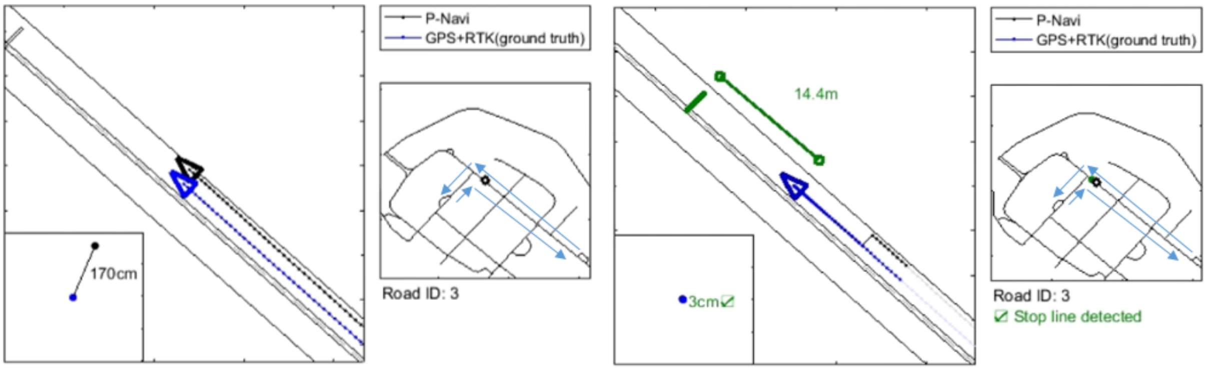

Figure8: Positioning result without (left) and with (right) detecting the stop line

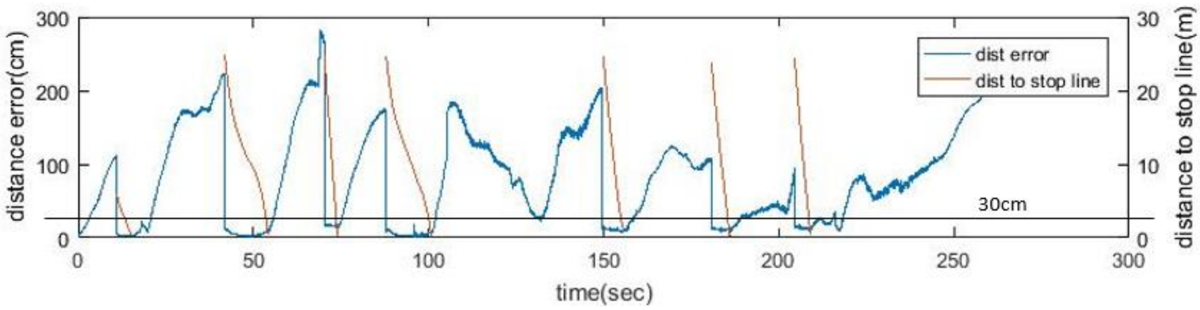

Figure9: the post-processed result for P-Navi

Figure 10 and 11 show that the decision making results with two scenarios. One is that the obstacle is moving faster, the other is that the obstacle is moving slower. In former case, the optimization algorithm finds the solution that the vehicle do not need to change its direction for driving to the destination whereas the trajectory of the latter case slightly changes the direction that the vehicle can avoid the upcoming collision. Note that the optimization algorithm of the latter case didn't slow the speed down because the estimated time of arrival (ETA) from the origin to the destination is concerned. The solution shows that it rather travels with longer distance than slows down and waits for the obstacle passing. However, this design can be replaced with a variable ETA form the origin to the destination. If it allows the vehicle to arrive the destination with plenty time, it will plan a spatio-temporal trajectory that saves the extra steering energy by slowing speed of the vehicle which should reach, as shown in Fig. 12.

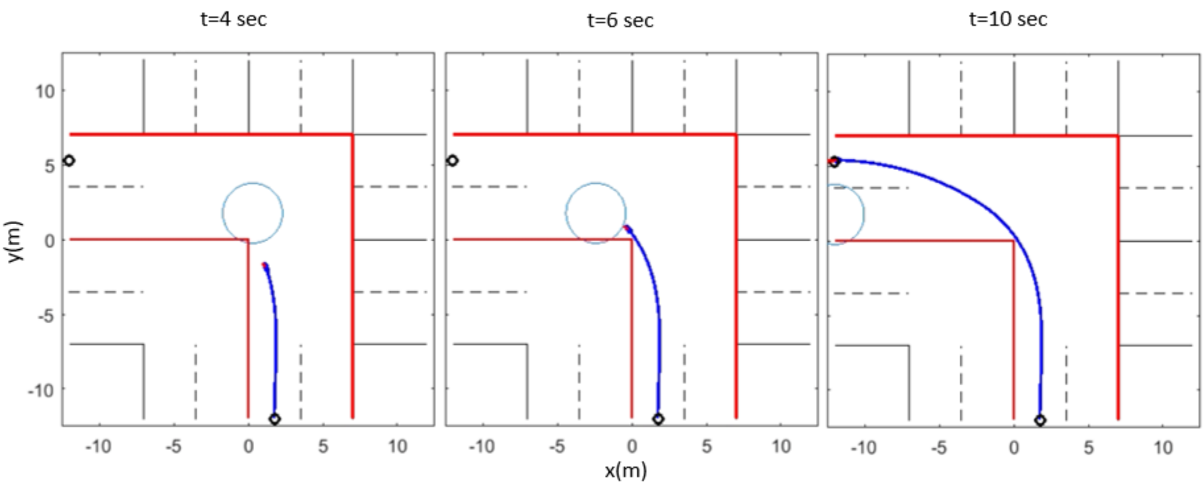

Figure10: The spatio-temporal trajectory for the obstacle which moves faster

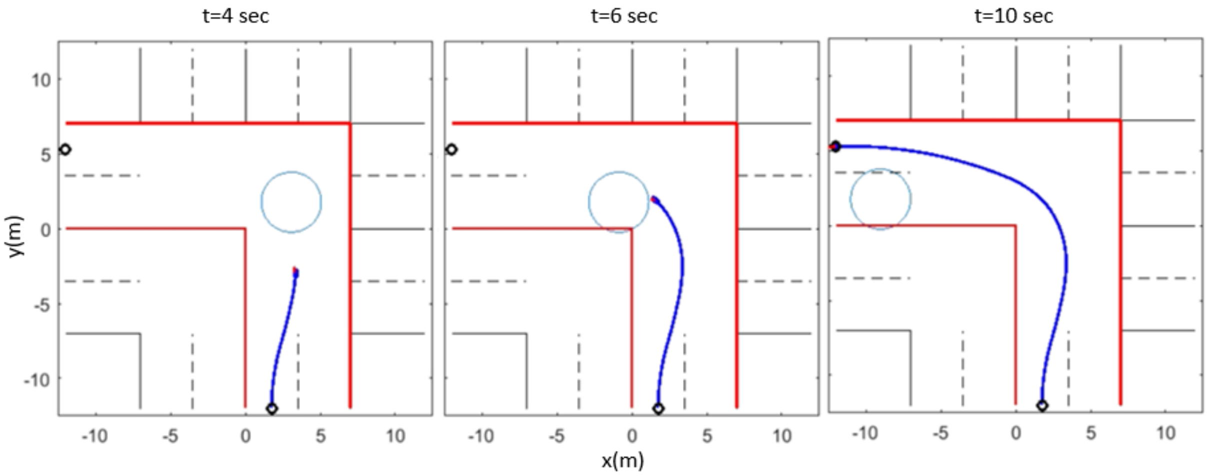

Figure11: The spatio-temporal trajectory for the obstacle which moves slower

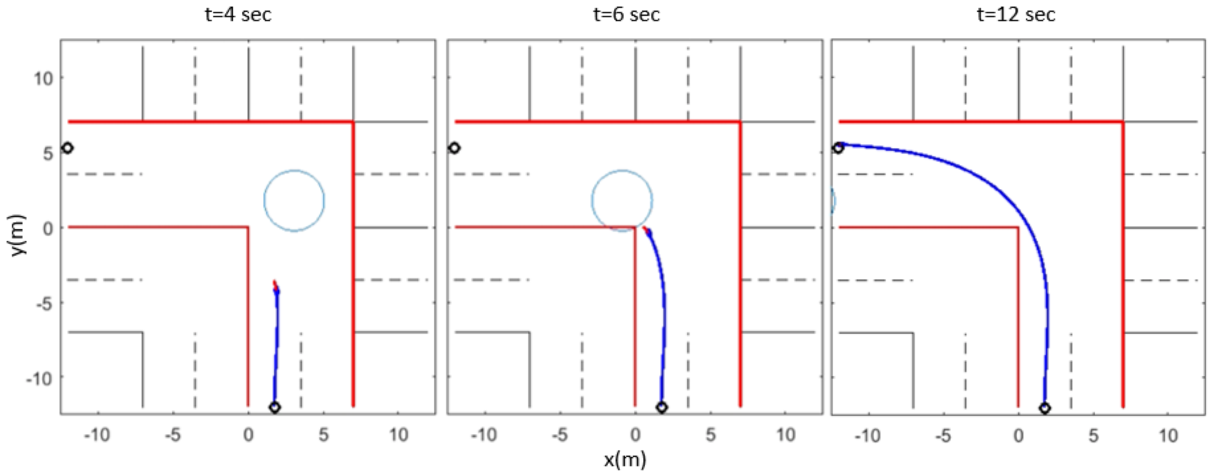

Figure12: The spatio-temporal trajectory for the obstacle which moves slower with longer ETA

4 Conclusions

In this paper, the perception navigation and the intersection decision making technique are presented. Before doing the intersection decision making, the constraints in the road must be considered and most of constraint informations are obtained from P-Navi. The main sensor module P-Navi in the proposed system corrects the GPS positioning by the stop line information captured by camera and the computer vision program. Before driving close to the intersection, the positioning result is fused by GPS result and INS which is the integration result of inertia measurement unit (IMU). When the vehicle is passing through the intersection, there is no any other ground truth information for P-Navi to correct the GPS positioning error because the stop line is behind the vehicle. In this scenario, P-Navi fails to help fixing the positioning results but the decision making algorithm is already done at the entrance of the intersection. This situation makes the vehicle cannot follow the planning spatio-temporal route given by decision making algorithm exactly. The only thing might be expected is the GPS/INS function work well that the positioning error holds after passing the stop line. However, it just plays the dice with very unreliable result. To improve the result form P-Navi, the rear camera can be added but the truth is that the stop line is still easy to be blocked by the other vehicles. Thus, the more ground truth resources are needed. Actually, our on-going research now focuses on the non-easy blocked target in the intersection – the traffic light.

The decision making technique is formulated as a convex optimization problem with the constraints referred to the result of P-Navi. Although some constraints are simplified by some assumptions, the optimization process still needs to be solved with multi-nonlinear constraints. It will increase the computational complexity during solving this optimization problem by the iteration method. The reason for applying the optimization based method here is that it is easy to combine any kind of constraint like vehicle dynamics, the road boundary, or the obstacle size and its position. For real-time application, there is method which should combine multi-nonlinear constraints with low computational complexity. For the next stage of this research, we try to develop a method which is combined with rule base method and traditional control theory and can give similar solution patterns to the optimization based method.

Acknowledgments

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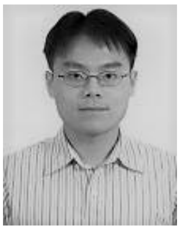

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