Decision Making Process of Autonomous Vehicle with Intention-Aware Prediction at Unsignalized Intersections

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***Abstract*—In an environment of intelligent transportation systems, interaction with other drivers via identifying their intentions becomes a challenging and unavoidable problem for the driverless vehicles. In this paper, we propose a human-like decision model for unsignalized intersections. An intention-aware prediction for other drivers via a CNN method with multiple-object tracking and Kalman-Filter operations is considered in the developed model to construct the interaction of other drivers. A human-like decision model according to the moving intention of the obstacle was proposed to generate the strategy of an autonomous vehicle. Our approach method is validated on a real autonomous vehicle in the presence of human-driven vehicles through an on-road test.**

Keywords—CNN, intention, multiple-object tracking

I. INTRODUCTION

Traffic at intersections is quite complicated, and traffic accidents frequently occurred. The Federal Statistical Office of Germany [1] showed that 47.5% traffic accidents at intersections or junctions in 2013, and the statistics in the United States [2] showed that 40% in 2008 and up to 98% in Taiwan [3] in 2017. Unfortunately, 94% crashes are due to driver incorrect judgment, which was reported by the National Highway Traffic Safety Administration [4]. An intelligent transportation system with autonomous vehicles is one of the adopted technologies as part of the transportation infrastructure to increase driving safety. A mixed driving traffic of human driven vehicles and autonomous vehicles is unavoidable in the ITS before all vehicles are able to communicate. Autonomous vehicles are required to predict the intentions of other human drivers at intersections to take safe actions during interaction.

In [5], they proposed an autonomous intersection management model to manage traffic intersections via communication capabilities such as vehicle-to-vehicle and vehicle-to-infrastructure technology. [6] and [7] further studied optimization problem for multi-intersections and prioritizing the reservations according to their relative priorities and waiting times. [8] provided an algorithm with Partially Observable Markov Decision Process with solving continuous-state and continuous-observation and considered a specific intersection scenario in the simulation study.

[9] considered in the decision making with observation uncertainty in intersection scenarios applying a scenario-specific learned discretization of the state space by considering the exploration capabilities of the vehicles. A T-Crossing with unknown intentions of other vehicles in a discretized state space model and a simple behaviour model were proposed in [10] and [11]. However, most of the prior work on intersections based on communication capability for each driver, and/or predicting the intention with a single observation of the human driver was considered in their on-road experiment.

In this paper, we propose a human-like decision model with real-time operation for both traffic light and non-signal intersections. An intention-aware prediction for other multi-drivers via multiple-object tracking and Kalman-Filter operations based on a CNN detection result is considered in the developed model to construct the interaction of other drivers. Our approach method is validated on a real autonomous vehicle in the presence of human-driven vehicles with an on-road test. The result shows that using intention-aware decisions improves performance in comparison to the disengage rate.

The rest of the paper is organized as follows. Section II presents the overall system and formulations of the intention-aware inference model. The on-road experiment results are provided in Section III, and Section IV is the concluding remarks.

II. MODEL FORMULATION

A. System overview

In this work, we consider a human-like decision model with intention information to overcome the autonomous vehicle drives in an open-automatic-cruise environment with human drivers. The overall architecture of applied driving system is shown in Fig. 1. The sequential approach utilizes CNN-based perception including predicting the intention of multiple human drivers to generate inputs for trajectory planning based on a human-like decision model. For the intention of obstacles, the longitudinal velocity and position in vehicle coordinates of obstacles at the intersection are predicted. On the other hand, the future movements of other obstacles are considered in the human-like decision model to make a reasonable decision. Then, the controller sends the lateral commands and longitudinal commands to the host car.

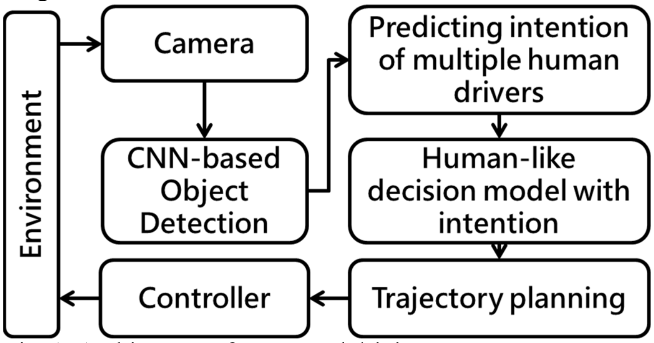

Fig. 1. Architecture of automated driving system

B. Predicting Intention Of Multiple Human Drivers

The architecture of predicting intention of multiple human drivers is shown in Fig. 2. The both position in vehicle coordinate and category of each object are recognized based on a CNN model and send the detected result to the creating ID module for assigning unique ID to every individual obstacles. Then, the Hungarian algorithm with min-cost perfect matching and unassigned track operations are applied to find the connected object and modify the tracking ID, respectively, in which the tracking assignment is based on the cost matrix, w, deciding the cost of the tracking list. Let G be a weighted bipartite graph with $|A| = |B| = n$, that is $G \coloneqq G(A, B) = G(A \cup B, A \times B)$; and let d be the cost function in terms of $d: A \times B \to R$. Let M be a set of n vertex-disjoint edges in G. Given a matching M, the cost matrix w can be defined as following,

$$w(M) = \sum_{(a,b) \in M} d(a, b).$$

Thus, the min-cost perfect matching, M^*, is approached by a matching with the smallest cost. That is,

$$w(M) \geq c \cdot w(M^*), \text{ for } c \geq 1.$$

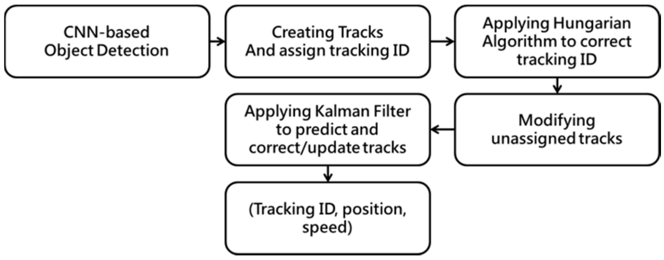

Fig. 2. Architecture of predicting intention of multiple human drivers

Moreover, the Euclidean metric is applied for the distance between the two points in Euclidean space. Then the tracking results including the both position in vehicles coordinates and their estimated speed by operation time are operated by the Kalman filter to predict and update the tracks. For the Kalman filter, the states are the longitudinal and lateral position x and y in vehicle coordinates, and longitudinal and lateral speed V_x and V_y. The longitudinal dynamic can be further described by

$$x_{k|k+1} = Ax_{k-1|k-1} + Bu_k,$$

where

$$A = \begin{bmatrix} 1 & 0 & dt & 0 \\ 0 & 1 & 0 & dt \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix},$$

with state vector x_k given by

$$x_{k-1|k-1} = \left[x, y, V_x, V_y\right]^T_{k-1|k-1},$$

and B is the control-input model which is applied to the control vector u_k. The control-input model is unconsidered in this work. Thus, the state vector can be estimated using a Kalman filter when the position of obstacles are observed. The Kalman filter equations are given by

$$x_{k|k} = x_{k|k-1} + K_k(z_k - Hx_{k|k-1}),$$
$$x_{k+1|k} = Ax_{k|k},$$

where the Kalman gain, K_k, is determined by

$$K_k = P_{k|k-1}H^T\left(HP_{k|k-1}H^T + R\right)^{-1},$$

and the updated estimate covariance, $P_{k|k}$, is

$$P_{k|k} = (I - K_kH)P_{k|k-1}.$$

For more information about the Hungarian algorithm and Kalman filter, the reader is referred to [12] and [13], respectively.

Finally, the position of participants at intersections in next t seconds can be observed in vehicle coordinate by

$$[x_t, y_t]^T = \begin{bmatrix} 1 & 0 & t & 0 \\ 0 & 1 & 0 & t \end{bmatrix} x_{k|k}.$$

C. Human-like decision model with intention

The flowchart we used for the human-like decision model with driver intention is shown in Fig. 3. Stopping at the stop line before passing though intersection once host vehicle close to a unsignalized intersection. Then, the proposed model indicates a go command to pass the intersection once other obstacles will not close to the reference path of the host car.

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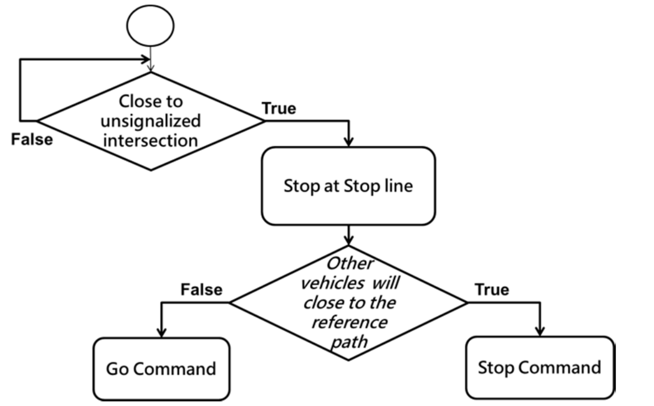

Fig. 3. Architecture of human-like decision model with intention for unsignalized intersection

Let X be the going direction of the host car. Define $X = 1$ if host car go straight; $X = 2$, if turn left; and $X = 3$ if turn right. Let Y_L be the going direction of other obstacles on the left side of Region of Interest (ROI) of host car, and $Y_L = 1, 2, 3,\ 4$ represents the obstacles go straight, turn left, turn right, and static, respectively. Define Y_R be the going direction of other obstacles on the right side of ROI, and $Y_R = 1, 2, 3$, 4 represents the obstacles go straight, turn left, turn right, and static, respectively. Therefore, the events of threatening the driving safety of the vehicle can be observed as

$$\{Y_L = 3|X = 1\}, \{Y_R = 2|X = 1\}, \{Y_L = 1|X = 2\},$$
$$\{Y_L = 3|X = 2\}, \{Y_R = 2|X = 2\}, \{Y_L = 3|X = 3\}, \text{and}$$
$$\{Y_R = 1|X = 3\}, \text{and } \{Y_R = 2|X = 3\}.$$

Let $I(\cdot)$ be an indicator function satisfying $I(\text{danger events}) = 0$. Thus, the decision function at unsignalized intersections, therefore, can be written as

$$\text{Decision} = \left\{\prod_{i=1}^{N_c} 1 - I(Y^i|X = j)\right\}\left\{\prod_{i=1}^{N_L} 1 - I(Y_L^i|X = j)\right\}\left\{\prod_{i=1}^{N_R} 1 - I(Y_R^i|X = j)\right\}$$
$$= \begin{cases} 0, & \text{safe and make host car go} \\ 1, & \text{danger and should stop} \end{cases},$$

where N, N_C, and N_R are the number of obstacles in ROI, left side of ROI, right side of ROI, respectively.

III. On-Road Experimental Study

To validate the feasibility of the proposed framework for autonomous cruise driving, the experiment is conducted in an on-road environment at the Changhua Coastal Industrial Park with a Luxgen U6 equipped with several sensors, as shown in Fig. 4. A GPS, a 32-layer 3D Lidar and a 100 horizontal angle Camera are equipped to implement the function of both localization and perception at an Nvidia PX2 computing units. The camera sensor is for detecting traffic participants in front of the host car, and the information of surrounding multi traffic participants is based on the Lidar sensor. Moreover, the proposed processing of both the sensor data and the decision-making model is also in the computing unit. In addition to the equipped units, the experiment path is constructed 15 intersections (11 unsignalized intersections with two-way intersections, t-type intersections, and four-way intersections), and the experiment vehicle stops at 3 stations. The driving speed range of human drivers is legally restricted by 50kph in the trial area.

Fig. 4. The experimental vehicle with cameras and the vehicle route at proving ground.

For the intention-aware prediction of obstacles, the position of participants at intersections in the next t=3 seconds and the decision function are applied for the experiment roads. Fig. 5 shows experimental results for autonomous vehicle passes through unsignalized intersections. The both predicting intention system and decision-making system started operation as the host vehicle stopped at assigned stop line. It turns out that the host vehicle makes yield decision to avoid the potential collision as the predicted intention of other participants is going to approach the reference path of host vehicle in which visualization of obstacles' the intention is drawn at the central coordinate of detected obstacles. The host vehicle would wait for the approaching vehicle and continue to move forward until no obstacles approach the reference path.

Disengaged rate, meaning a rate of a human safety driver had to take the wheel in total trails, is an important indicator for judging the confidence level of autonomous vehicles. To see the impact of intention information for the decision-making system omitted driving direction and future location of other obstacles, we further investigated the disengaged rate in 20 trails with random human drivers for each intersection at the Changhua Coastal Industrial Park including. That is, total

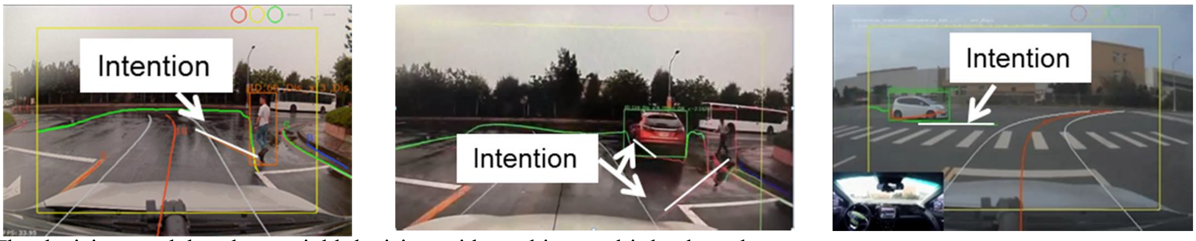

Fig. 5. The decision model makes a yield decision with tracking multiple obstacles.

moving actions of host car include 140 go straight, 40 turn left, 40 right turns. Moreover, the model without intention information makes go command as waiting four seconds at stop line if no obstacles exist in the ROI.

TABLE I. RESULT OF THE DISENGAGED RATE WITH INTENTION INFORMATION

Proposed method (Disengaged Rate =0%)				
Number of Disengagement		Host vehicle		
		Straight	Left turn	Right turn
Other Vehicles	Straight	0/45	0/12	0/7
	Left turn	0/21	0/8	0/12
	Right turn	0/51	0/6	0/14
	No existing	0/23	0/14	0/7

The performance of the proposed model with intention information is shown in Table I in a confusion matrix, and Table 2 is the results without intention information. In each table, the panels include the driving direction of the host car (straight, left turn, right turn) as well as the driving direction of the other obstacles (Straight, left turn, right turn or no existing), and the disengaged rate of all trails. The disengaged rate of the proposed model is 100 % that is calculated as the number of disengagement divided by the total trials, (0/220)*100%. It turns out that the proposed method provides high and acceptable accuracy for all intersections. In addition, we found that when it is necessary to interact with other driving scenarios (such as the action of host car if left turn), the proportion of human intervention is quite high if decision model is without considering intention information.

TABLE II. RESULT OF THE DISENGAGED RATE WITHOUT INTENTION INFORMATION

Omitted intention information (Disengaged Rate =24.5%)				
Number of Disengagement		Host vehicle		
		Straight	Left turn	Right turn
Other Vehicles	Straight	7/33	5/7	2/5
	Left turn	3/14	9/12	8/20
	Right turn	12/59	8/12	0/11
	No existing	0/34	0/9	0/4

IV. CONCLUSIONS

In this paper, we investigated a real-world interaction problem between an autonomous vehicle and human drivers of aiming to predict intentions and formulate decisions at unsignalized intersections. The Hungarian algorithm with the Kalman filter operation is applied to predict the position and speed of participants in the next few seconds for the intention problem. The human-like decision model according to the moving intention of the obstacle was proposed to generate the strategy of an autonomous vehicle. The performance of the proposed methodology is reliable and safe validated through an on-road experimental study with no disengagement. Besides, we further investigate the decision effect as the intention information is omitted, and the results showed that the proportion of human intervention is quite high as the interaction is needed. Last but not least, the detailed research we have proposed is rarely disclosed in the existing literature of the on-road test.

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