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Irregular Vehicle Behavior Warning Modules

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Abstract--This study develops an on-board decision module to issue appropriate warnings when the equipped vehicle's traveling track is irregular. While a vehicle is running on a road, there is a potential danger of accidents if the driver is distracted by fatigue, drowsiness, food, talk, or influenced by alcohol or drug, etc. Common types of accidents that take place on a freeway are lateral and rear-end collision. Therefore, measuring vehicle behavior is a way more relevant in terms of ensuring the security of driving behavior. This study presents two modules: one for detecting irregular tracking and the other for measuring longitudinal relationship with the preceding vehicles. According to the simulations, the proposed modules are satisfactory.

I. Introduction

In the past decade, the number of motor vehicles in developing countries is increasing a lot. Official investigation reports of traffic accidents pointed out that dangerous driving behavior, such as drunk and drowsy driving, account for a high proportion among all the accident causes. In order to avoid these kinds of unexpected accidents, it is necessary to develop an appropriate in-vehicle system with warning modules that can directly improve driving safety.

Some studies concentrated on developing a warning system that equipped with a CCD for monitoring driver's behavior, particular on the variation of driver's eyes. However, almost all drivers dislike equipping such an eye-like CCD that directly looks at their bodies all the time. Although current technologies have been improved, an on-board unit is indeed difficult directly to understand the driver's behaviors. Consequently, detecting "vehicle behavior" is used to replace monitoring driver's behavior. Developing a monitoring and warning system focusing on vehicle behavior is valid rather than driver behavior. Vehicle behavior herein means moving track and velocities (including longitudinal and lateral information), and these can reflect the prospective danger specifically.

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An important concept is that vision can provide the most sufficient and useful information. Consequently, this study develops a vision-based system for detecting the equipped vehicle behavior. In other word, image processing is selected to collect and provide the required parameters for measurement. After shooting the scene right in front of the equipped vehicle, the image processing equipment produces the data for the measurement of the equipped vehicle's moving track, including lane position and vehicle speed relative to obstacles (e.g. the preceding vehicles). In accordance with the information from image processing, the decision strategies are composed of "Fuzzy Neural Networks" which identify whether the vehicle is about to depart the lane or collide with anything ahead.

II. Unexpected Lane Departure Avoidance Module

A. Module and Practice Description

When a vehicle is traveling on a highway, unexpected lane departure caused by the driver's distraction or any irregular driving behavior might result in a lateral or rear-end collision. Unexpected lane departure incidents are relatively more abstract than rear-end collision accidents, because there is too varied to organize the phenomenon mathematically and specifically. The lateral displacement (l_v) and lateral velocity (u) are herein the only principal components utilized for the evaluation to unexpected lane departure.

This module deals with the dangerous conditions of unexpected lane departure into three levels: safety, caution, and danger. A *Radial Basis Probability Network* (RBPN) is applied to classify the three levels of warning. RBPN is a kind of universal approximator which output can approximate any continuous function. Before starting to identify the dangerous levels of lane departure, there is another issue to overcome: the distinction between lane change and unexpected lane departure. Without doubt, the turning signal must be actuated while a driver is trying to change lanes. While the equipped vehicle is approaching lane marking, this module begins to determine the warning, if the driver does not apply the turning signal. To find out the possible traveling patterns of lane change and unexpected lane departure, a series of video files captured in an equipped vehicle traveling on a freeway are conducted for the sequential training, simulation, and analysis. Neither lane change nor unexpected lane departure occurs instant-aneously. There should be a period of time before becoming the incident pattern. The data of 5 seconds (about 15 frames) before lane change or unexpected lane departure taking

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place are employed to process the decision in RBPN.

The lateral displacement and lateral velocity measures of 5 seconds before each lane change and unexpected lane departure are applied for judgment of warning. There are 7 scenarios of video for RBPN training "right lane change" (including real lane change and unexpected lane departure) and 5 scenarios for simulation. The simulating output is shown in Table I. However, scenario RULD-s3013 fails at lane change determination, since its traveling pattern is much similar to real lane change scenario RLC-s1001. In further analysis between RULD-s3013 and RLC-s1001, the statistical determination coefficient (R^2) is 0.9934 for lateral displacement and 0.9555 for lateral velocity, respectively. To avoid such confusion, drivers should activate the turning signal before lane change; otherwise, for security the module will issue a warning even if the vehicle is just changing lanes.

By higher sampling rate and lower-pass interpolation, the data of lateral displacement and lateral velocity of the equipped vehicle are more complete and robust. This helps to build more reliable and precise criterion to distinct lane change from unexpected lane departure. Applying RBPN to process the image and data, the decision zones are illustrated in Fig.1. The white zone means "safe", not to launch any warning; "gray zone" means "cautious", to issue a blink signal to the driver; and the dark zone means "dangerous", to activate an alarm. From the white portion to the dark of the figure, it reveals that the more lateral displacement with higher lateral velocity, the more likely unexpected lane departure.

A regularized lane width is 3.6 meters, and the equipped vehicle is 2 meters wide. The lateral gap from the vehicle edge to the lane marking is 0.8m. This indicates that the vehicle will across the lane marking if the lateral displacement is approaching to +0.8m. If the equipped vehicle's traveling dynamics is dropped at the star icon in the upper right-hand corner illustrated in Fig.1, the module can immediately determine what dangerous departure level the vehicle is standing. In this case, the equipped vehicle has about 1 meter of lateral displacement and about 0.05 m/s of lateral velocity, and reveals the vehicle already in dangerous situation. Because it takes a period of time to indicate traveling pattern whether a vehicle is approaching lane change or unexpected lane departure, this study takes 5 seconds for neural traveling pattern recognition. There are three frames for processing in each second. When the equipped vehicle's lateral displacement and lateral velocity are detected dropping into the dangerous zone shown in Fig.1, the module will keep measuring the next frame. If the lateral displacement of the following frame is larger than the previous one, the equipped vehicle is tending to possible departure. When such an event is lasting to the fourteenth frame, the module is then to determine the vehicle being lane change or unexpected lane departure. If the determination output is "lane change" and the driver does not evoke the turning signal, the module immediately issues a warning for security. Also, the module will decide the warning level based on the lateral displacement and lateral velocity of the 15th frame if the output is not "lane change".

B. Result

Based on the module, the equipped vehicle's lateral displacement tracking and the corresponding warning in a certain practical case are shown in Fig.2. The upper plot shows the lateral displacement tracking, the middle plot shows the corresponding warning level detected for each collected image frames, and the bottom one shows the actual warning issued.

The module always keeps determining the danger level based on the equipped vehicle's location while traveling on the freeway. Thereby the "danger detection" keeps showing in the middle plot of Fig.2. However, it is only a threshold for the timing to activate the comprehensive departure determination, not the actually appropriate warning. Until the equipped vehicle is judged tending to depart the lane, the actual warning is issued then. From the bottom plot, it is clear that actual warning signals are more specific with less noise, and the warning levels are clarified. Even if the vehicle is detected in a danger zone initially, the module will not issue any warning if the vehicle is not judged tending to depart. This mechanism can avoid disturbing the driver with over sensitive warning.

III. Rear-end Collision Avoidance Module

A. Decision Strategy

To find out the real-time warning value for rear-end collision avoidance, there are two parameters from distance -to-collision and time-to-collision algorithms for neural networks input. On the other hand, as the vehicle is traveling, there should be a threshold to reflect the warning level by recognizing the warning value. This threshold may not be fixed all the time as traveling, fuzzy membership functions are therefore in charge of providing a series of variable threshold depending on certain environmental parameters.

1) Parameter from Distance-to-collision Algorithm: Assume the scenario of which two vehicles in a platoon are initially traveling at almost the same speed. Through image processing, the relative speed ($v_r = v - v_{preceding}$) could be obtained by the follower, the equipped vehicle. According to the sequential image data, the following vehicle can be measured approaching or leaving the preceding vehicle. Once the following vehicle is detected approaching the preceding vehicle, i.e. the relative speed is positive, the collision avoidance module will be triggered to issue warning or not. Based on distance-to-collision, the warning should be issued at a proper and necessary timing that will not cause burden to the driver. According to Mazda and Honda's algorithms [4], a warning value w was defined as $w = (d - d_{br})/(d_w - d_{br})$. Where, w is a non-dimensional warning value; d is the real-time inter- spacing (relative distance); d_{br} is the non-conservative braking critical distance; d_w is the conservative warning critical distance (in meters). A threshold defined "a=0.2" to point out the critical value of w for determining if it is necessary to issue a warning. When $w>1$ or $a<w<1$, the following vehicle is on safe traveling. Otherwise, $w<a$ means that the actual distance is very close to the braking distance, and then strong warnings is needed to issue to the driver. The main mechanism of distance-to-collision is to keep "w" updating all the time.

2) Parameter from Time-to-collision Algorithm: Time-to -collision concentrates on the mutual situations in terms of time orders between the following and preceding vehicles. The relative stopping dynamics begin at time t=0, when the preceding vehicle first applies its brake and starts a constant deceleration to zero speed, how immediately the velocity reaches zero is indicative of whether deceleration comes suddenly or gradually. The application of the preceding vehicle's brake determines the location of the reference for the measurement of all parameters, and this reference point is the location of the following vehicle front bumper at the instant that the preceding vehicle begins to brake. There are three given parameters for measurement, the initial speed (V_0, the same for both vehicles), the initial headway between the two vehicles ($T_h=R_0/V_0$, R_0 is the initial spacing), and the level of deceleration taken by the preceding vehicle (D_p, presumed to be a constant value). Then, the priority warning critical distance, R_w, would be obtained. As for time-to-collision, the mechanism is to keep collecting the preceding vehicle's speed, and since it begins to decelerate at time t=0, then the function starts working. Consequently, time for warning T_W is used to figure out distance for warning.

3) Fuzzy Weights for Variable Warning Threshold: Though there is a warning threshold "a=0.2" defined in distance-to-collision algorithm, it is not proper for all traveling conditions. Since many factors may influence a driver's behavior and habits to keep security conditions on a road, the warning threshold can not be fixed all the time. Two stated algorithms did not discuss about the environmental effects. To avoid rear-end collision, there are three factors used to interpret this situation: Relative distance, Rain, and Vehicle numbers in front. Drivers would adjust their awareness with these three varying factors, and the warning threshold would be variable with the varying warning weights. The shorter relative distance, heavier rain, and more vehicles ahead, the higher potential hazard exists. Fuzzy membership function is applied to figure out the weight for the warning level on different conditions [4]. The fuzzy sets are labeled with the linguistic terms of very close (VC), short distance (SD), large distance (LD), and far distance (FD). The fuzzy sets for rain (r) are no rain (NR), light rain (LR), heavy rain (HR). The fuzzy sets of the vehicle numbers (V_N) ahead are few vehicles (FV), more vehicles (MV), lots of vehicles (LV). Moreover, there is planned an output to the weight of the warning (Ww). For this non-dimensional value, the fuzzy sets are small positive (SP), medium positive (MP), large positive (LP), very large positive (VP). The fuzzy rules can be expressed by the form: {*If d=E1 and r=E2 and* V_N*=E3, Then Ww=E4*}; where *E1*, *E2*, *E3*, *E4* are fuzzy sets in the universe of discourse of d, r, V_N, and Ww, respectively. The determine values of *E1*, *E2*, *E3*, *E4* are derived from the fuzzy inference system using fuzzy and defuzzy method.

Inputting the conditions of the three factors mentioned above, there is an example about the output (warning weight) of fuzzy membership function shown in Fig.3. With the varying relative distance in the upper plot, the ordinary warning weight in the middle plot is varying as well. The shorter the relative distance (inter-spacing) is, the higher the weights will be. In the bottom plot, the rain parameter is adjusted into 0.5 (light rain), and then the weights are raised generally to reflect that the driver should enhance their awareness for traveling in rain.

B. Criteria for issuing a warning

Going through the calculations above, several referable values could be obtained to decide whether to issue a warning or not. The major reference value w is resulted from the distance-to-collision algorithm. Besides, the time-to-collision algorithm figures out R_W as an assistant reference value. In order to take more conditions in account, get more objective data, and take advantage of the merit of image processing, there should be certain additional parameters for learning and training source in the Neural Networks. Hence, the relative distance (d), the raining level (r), and the number of vehicles in the image sight (V_N) are the other parameters for input layer.

For neural networks training, firstly, the fuzzy membership functions will figure out the warning weight corresponding to the inputs of d, r and V_N . Next, in fact, the relative distance is the most concerned factor among all the inputs. Thereby the warning value (w) resulted from distance-to-collision is employed as the networks training targets. If the relative speed (v_r) is negative, the module won't give any warning value. Conversely, the networks provide simulated new warning value (w_n). Finally, a new weighted threshold (W_T) for warning level determination comes from fuzzy membership functions

In addition, time-to-collision algorithm is originally based on the assumption that the preceding and following vehicles are traveling with the same speed, and started to get R_W instantly while the preceding vehicle's deceleration is detected. Indeed, two vehicles seldom travel with the same speed on roads. Hence, to apply R_W in this study, the warning distance from time-to-collision (R_W) is outputted continuously once the relative speed ($v_r=v-v_{preceding}$) is greater than zero.

C. Result

With the decreasing of relative distance and the increasing of relative speed, plus environmental parameters, the module could issue a warning if the warning value is greater than the threshold. In the bottom plot of Fig.4, the dotted line is the variable threshold for warning and the other line is the actual warning value. From the 10th to 15th second, the module keeps issuing warnings as the warning value is over the threshold. Both the threshold and warning value become zero while the relative speed is negative, i.e., it's not necessary to issue any warning when the following equipped vehicle is slower than the preceding one. Because the warning threshold is not a constant, thus 60% of the threshold is regarded as a critical boundary of "caution level" to be the secondary warning level.

IV. Scenario Analyses

A. *Unexpected Lane Departure Avoidance Module*

In order to assure the reliability of the modules, for ordinary traveling on the freeway, there is certain prerecorded video to proceed with scenario analyses. Some of the prerecorded information has been already taken for Neural Networks training and simulating, the others are about to be tested and analyzed below. Table 2 describes the training scenarios in advance. The experiments on the other scenarios, traveling conditions, and the analyses results are shown in Table 3.

In accordance with the module determining the unexpected lane departure and danger level frame by frame, Table 4 shows the success rate of the image frames which are needed to be determined while the equipped vehicle is traveling on a freeway. There were a few failed frames in scenarios-3009, 3010, and 3019 that made the possible lane departure was regarded as lane change. However, the next frame of the failed one made the right determination immediately, so it still came out successfully. Scenario-3013, unfortunately, there were sequential four frames failed to determine the lane departure but regarded them as lane change. As stated above, this must be solved by whether the turn signal is employed. Assuming that all the image processing works well, the accurate successful rate in these scenario analyses is 85.71%. With the turn signal employing, the module can overcome the failed determination to make successful results.

B. *Rear-end Collision Avoidance Module*

Table 5 shows the simulation scenarios for the rear-end collision avoidance module. During the following processing, the equipped vehicle might be overtaken, thus the spacing had decreased suddenly and a warning was needed, as shown in scenario-3009. Besides, the rain condition would affect the driver's awareness about the traffic as scenario-4009. As mentioned in last section, all the scenarios are picked with successful image processing. Table 6 shows the results of rear-end collision avoidance scenario analyses. All the warnings were issued before the actual braking. In scenario-3005, the timing gap is 6 seconds. Actually, for video recording, the equipped vehicle braked while it was very close to the preceding vehicle, as shown in Fig.4. It should slow down at the 10th second; the warning was not issued too early. The accurate successful rate in these scenario analyses is approximately 100%.

V. Conclusion

In this study, two security modules about intelligent vehicles are developed. The unexpected lane departure avoidance module is applied to prevent lateral collision. The rear-end collision avoidance module, as implied in the name, can prevent colliding with a preceding vehicle or an obstacle ahead.

As the states, the module for Unexpected Lane Departure Avoidance, the accurate successful rate is about 85.71%. If with turning signal consideration, the module can have higher successful results. The module for Rear-end Collision Avoidance has 100% successful rate. These conclude that the proposed modules are satisfactory.

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TABLE I

"Right Lane Change" determination output from RBPN

Scenario	Componen	Result Outpu	Comment
RLC-s3015	*Lv, u*	LC	correct
RULD-s100	*Lv, u*	ULD	correct
RULD-s301	*Lv, u*	ULD	correct
RULD-s301	*Lv, u*	LC (failed)	Similar to lane change RLC-s1001
RULD-s301	*Lv, u*	ULD	correct

LC: lane change; ULD: unexpected lane departure; RLC: right lane change; RULD: right unexpected lane departure; l_v and u :lateral displacement and lateral velocity of the equipped vehicle

TABLE II DESCRIPTION OF TRAINING SCENARIOS FOR UNEXPECTED LANE DEPARTURE

Scenario	Time	Field	Climate	Traffic Condition	Incidents
1001	day	freeway	sunny	free flow	right lane change
1002	day	freeway	sunny	in a platoon	right lane departure
1003	day	freeway	sunny	in a platoon	right lane change
1004	day	freeway	sunny	in a platoon	Right/left lane departure
1005	day	freeway ramp	sunny	in a platoon	right lane departure
3001	day	expressway	cloudy	in a platoon	left lane change
3003	day	freeway	cloudy	in a platoon	right lane departure
3004	day	freeway	cloudy	in a platoon	right lane departure
3006	day	freeway	cloudy	free flow	right lane change
3012	night	freeway	--	free flow	left lane departure
3013	night	freeway	--	free flow	left lane departure

TABLE III DESCRIPTION OF TESTING SCENARIOS FOR UNEXPECTED LANE DEPARTURE

Scenario	Time	Field	Climate	Traffic Condition	Unexpected lane departure direction	Warning Result
1002	day	freeway	sunny	in a platoon	right	successful
1008	night	freeway	--	in a platoon	Left, right	successful
3009	day	freeway	cloudy	in a platoon	approaching left	successful
3010	day	freeway	cloudy	free flow	right	successful
3013	night	freeway	--	free flow	right	failed
3014	night	freeway	--	in a platoon	approaching left	successful
3019	night	freeway	--	in a platoon	right	successful

TABLE IV SUCCESSFUL RATE OF EXPERIMENTAL SCENARIOS TESTS

Scenario	Time	Traffic Condition	Total Times (sec)	Frames Need to Be Determined	Failed (frame)	Success (%)	Comment
1002	day	in a platoon	28	13	0	100.00	
1008	night	in a platoon	30	16	0	100.00	
3009	day	in a platoon	36	15	1	93.33	success
3010	day	free flow	34	10	1	90.00	success
3013	night	free flow	33	10	4	60.00	failed to warn
3014	night	in a platoon	32	18	0	100.00	
3019	night	in a platoon	34	12	1	91.67	success

TABLE V DESCRIPTION OF SCENARIOS FOR REAR-END COLLISION AVOIDANCE

Scenario	Time	Field	Climate	Traffic Condition	Incidents
3005	day	freeway	cloudy	in a platoon	following
3008	day	freeway	cloudy	in a platoon	following
3009	day	freeway	cloudy	in a platoon	interrupted
4009	day	freeway	rainy	in a platoon	following

TABLE VI RESULTS OF REAR-END COLLISION AVOIDANCE SCENARIOS ANALYSES

Scenario	Time	Climate	Incidents	Actual Timing for Brake (sec)	Timing for Warning (sec)
3005	day	cloudy	following	16th	10th
3008	day	cloudy	following	15th	14.2th
3009	day	cloudy	interrupted	19th	18th
4009	day	rain		1.5th, 29.5th	0.4th, 28.3th

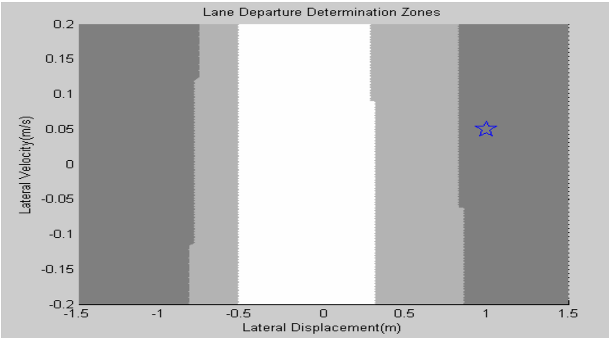

Fig. 1 Lane determination zones resulted from RBPN

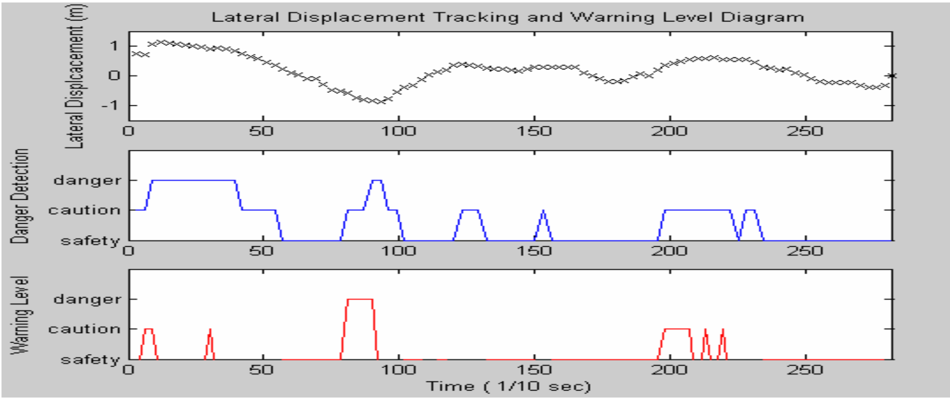

Fig. 2 Vehicle's lateral displacement vs. dangerous detection and actual warning

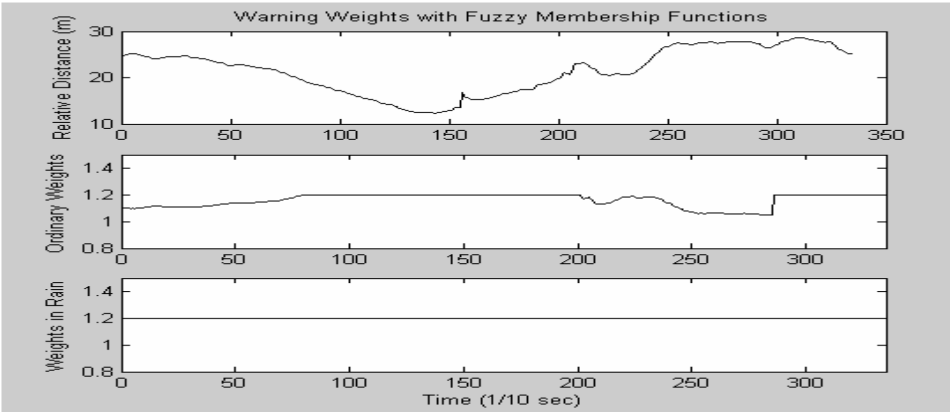

Fig. 3 Warning weights with fuzzy membership function

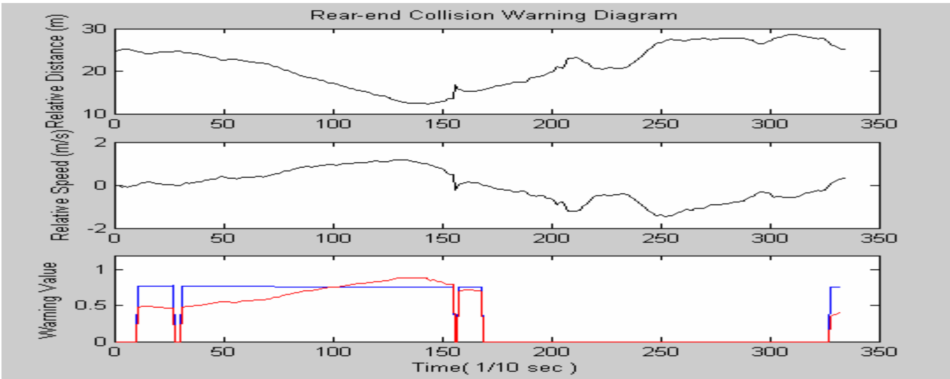

Fig.4 Warning result of rear-end collision avoidance module