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A Pre-crash Discrimination System for an Airbag Deployment Algorithm

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Abstract— **The airbag system has been a standard safety equipment for vehicles and it is efficient for enhancing the safety of a driver and passengers from crash. However, inadvertent injuries have been caused by airbag deployment in a rough and uncertain temporal interval. In this paper, a pre-crash discrimination system is proposed to prevent airbag deployment from malfunction. The system consists of a radar sensor of ACC system and vehicle state sensors of VDC system. The pre-crash information includes crash probability, time-to-crash and crash type. Using the information, the host vehicle recognizes crash situation and airbags are deployed accurately at the predefined moment for each crash situation.**

I. INTRODUCTION

In these days, the airbag system has been a standard safety equipment for vehicles. It is efficient for enhancing the safety of a driver and passengers from crash. However, inadvertent injuries also have been caused by the confusion of airbag deployment algorithm in uncertain situations of vehicle accidents. Airbags must be deployed accurately in a predefined moment for each crash situation and must never be deployed except for real crash situations. The airbags are deployed along the crash severity determined after the crash type is discriminated such as frontal, offset and oblique crash. It is difficult to discriminate crash types using acceleration sensors inside the passenger compartment alone in a timely manner. To improve the discrimination capability, the peripheral sensors are used, which are embedded in the crash zone and called "Front Impact Sensor". These sensors allow the very early discrimination of crash types.[1] But they are easy to be broken and also the measured signal accuracy is sensitive to the mounting location. In case of using erroneous sensor signal, airbags may be deployed by misjudging crash situations as shown in Fig 1. The difference of velocity between front impact sensors is one way used normally to discriminate crash types. The signals are similar to each other at the early time after a crash. But as time goes by, signal of ODB#2(offset crash) is similar to that of oblique crash and ODB#1(offset crash) is similar to frontal crashes. These situations make the judgement of crash types very ambiguously and airbags may be deployed along with misjudged crash types.[2]

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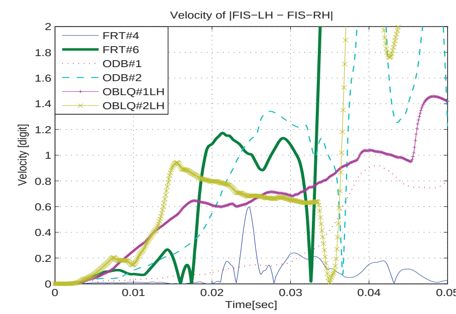

Fig. 1. Velocity difference between Front Impact Sensors

As one way to improve these situations, the information from active safety systems such as ACC (Adaptive Cruise Control), LDWS (Lane Departure Warning System), CMB (Collision Mitigation System) and Frontal Object Detector can be used. These systems use high technology sensors like a radar sensor, a stereo vision camera and ultra sonic sensors. They give a warning alarm for possible crashes and control brake pedal or steering wheel to avoid crashes.[3][4][5][6] The information used these systems has not been used after the crash although it is very useful for passive safety system such as the airbag systems.[7]

In this paper, an airbag pre-crash discrimination system is developed using the active safety system information. The pre-crash system to be presented uses the information of a radar sensor equipped for ACC. The information includes the distance, the lateral position and the relative speed to a frontal object. It is used to track the frontal object roughly. Also, VDC (Vehicle Dynamics Control) sensor signals as yaw rate, steering angle, wheel speeds, longitudinal/lateral acceleration are used to estimate the states of the host vehicle. By combining of ACC and VDC sensor information, the pre-crash information such as time-to-crash, relative speed, heading angle and lateral position for the frontal object at the crash moment is estimated. The time-to-crash information allows the activation of reversible restraint systems like seat belts. The heading angle and the lateral position at the crash moment allow to discriminate crash types such as frontal crash, offset crash and oblique crash. The aim of this study is to discriminate the possible crash and provide the crash type information to the airbag deployment algorithm before the crash is occurred in advance. This work is able to enhance the performance of the airbag deployment algorithm that the airbags are deployed along the discriminated the crash type.

In the following sections, the used models and algorithms

TABLE I

PARAMETERS OF THE VEHICLE MODEL USED IN THIS STUDY

Parameter	Symbol	Value	Unit
Vehicle mass	m	1370	kg
Moment of inertia	I_z	4190	$kg \cdot m^2$
Front Cornering stiffness	C_f	2000	N/deg
Rear Cornering stiffness	C_r	1600	N/deg
Distance from CG to front	l_f	1.110	m
Distance from CG to rear	l_r	1.666	m

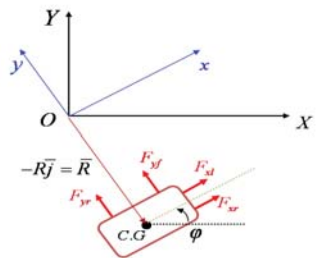

Fig. 3. Kinematic model

for the pre-crash discrimination system are introduced. In section II, the used models and the principle of operation are discussed. In section III, the pre-crash algorithm is designed. In section IV, the developed algorithm is verified in simulation to verify the appropriateness.

II. PRINCIPLE OPERATION AND SYSTEM MODELING

In this section, each part of the overall system is discussed. The pre-crash discrimination system consists of a host vehicle state estimator, a frontal object state estimator and a pre-crash information estimator. The system block diagram is as shown in Fig 2.

A. Host Vehicle State Estimator

In host vehicle state estimator, the longitudinal velocity and lateral velocity are estimated using vehicle dynamics models.[8] [9] The used parameters are as shown in TABLE I. A vehicle dynamics simulation tool, Car-Sim, is used for the vehicle dynamics simulation.

The kinematic model is as described in Fig 3, where F_{xl}, F_{xr} are the longitudinal tire forces, F_{yf}, F_{yr} the lateral tire forces. An observer is designed to estimate the longitudinal velocity. The state-space representation of the lateral dynamics observer for the kinematic model can be described as

$$\dot{\hat{x}} = [A(t) - K(t)C(t)]\hat{x} + Bu + K(t)y \tag{1}$$

where,

$$x = \begin{bmatrix} \hat{v}_x & \hat{v}_y \end{bmatrix}^T, \qquad u = \begin{bmatrix} a_{xm} & a_{ym} \end{bmatrix}^T,$$

$$A = \begin{bmatrix} 0 & r(t) \\ -r(t) & 0 \end{bmatrix}, \qquad B = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, \qquad C = \begin{bmatrix} 1 & 0 \end{bmatrix}$$

, $\hat{v}_x$ is the estimated longitudinal velocity, $\hat{v}_y$ the estimated lateral velocity, r the measured yaw rate, a_{xm} the measured longitudinal acceleration and a_{ym} the measured lateral acceleration.

The kinematic model is time varying. For a time varying system, the negative pole placement method cannot satisfy an asymptotical stable condition. In this study, the frozen-time pole placement method is adapted to prove that the observer is asymptotically stable.[10]

With the observer gain K defined as follow,

$$K(t) = \begin{bmatrix} 2\alpha|r(t)| & (\alpha^2-1)r(t) \end{bmatrix}^T \tag{2}$$

where, α is the tuning parameter. For an arbitrary tuning parameter α, (1) satisfies the asymptotically stable condition. A Lyapunov function is defined using the error dynamics of this model as follow,

$$V(v_x, v_y) = \frac{\alpha^2 \tilde{v}_x + \tilde{v}_y}{2} \geq 0, \forall x = [\tilde{v}_x, \tilde{v}_y] \in R^2 \tag{3}$$

Since,

$$\dot{\tilde{v}}_x = -2\alpha|r(t)|\tilde{v}_x + r(t)\tilde{v}_y \tag{4}$$

$$\dot{\tilde{v}}_y = -\alpha^2 r(t)\tilde{v}_x \tag{5}$$

$$\frac{dV(t,x)}{dt} = -2\alpha^3|\dot{r}(t)|\tilde{v}_x^2 < 0, \forall x = [\tilde{v}_x, \tilde{v}_y] \in R^2 \tag{6}$$

Therefore, the system is proved to be asymptotically stable applying LaSalle's theorem in (3) to (6). The lateral velocity from the kinematic model is able to be estimated, but it is not used because the model is very sensitive to the acceleration sensors.

Therefore, an observer is designed to estimate the lateral velocity using a bicycle model described in Fig 4, where F_{yf} is the lateral front tire force, F_{yr} the lateral rear tire force. Assume that the longitudinal velocity is nearly constant. The state-space representation of the lateral dynamics observer for the bicycle model can be described as

$$\dot{\hat{x}} = A\hat{x} + B\delta_f + K(y - \hat{y}) \tag{7}$$

where,

$$x = \begin{bmatrix} \hat{\beta} \\ \hat{r} \end{bmatrix}, \qquad y = \begin{bmatrix} r \\ a_{ym} \end{bmatrix}, \qquad \hat{y} = \begin{bmatrix} \hat{r} \\ \hat{a}_y \end{bmatrix},$$

$$A = \begin{bmatrix} -\frac{2(C_f+C_r)}{mv_x} & \frac{2(C_r l_r - C_f l_f)}{mv_x^2} - 1 \\ \frac{2(C_r l_r - C_f l_f)}{I_z} & -\frac{2(C_f l_f^2 + C_r l_r^2)}{I_z v_x} \end{bmatrix}, \qquad B = \begin{bmatrix} \frac{2C_f}{mv_x} \\ \frac{2C_f l_f}{I_z} \end{bmatrix}$$

, $\hat{\beta}$ is the estimated sideslip angle, v_x the longitudinal velocity using wheel speed, δ_f the front steering angle, $\hat{a}_y$ the estimated lateral acceleration, a_{ym} the measured lateral acceleration, K the observer gain, C_f, C_r front, rear tire cornering stiffness, I_z moment of inertia.

From the vehicle kinematics, the lateral acceleration is estimated as follow,

$$\hat{a}_y = \dot{\hat{\beta}} \cdot v_x + \hat{r} \cdot v_x \tag{8}$$

The error dynamics of this system for a sideslip angle, β, is as follow,

$$\dot{\tilde{x}}_1 = A_{11}(1 - K_{12}v_x)\tilde{x}_1 + (A_{12}(1 - K_{12}v_x) - K_{11} - K_{12}v_x)\tilde{x}_2 \tag{9}$$

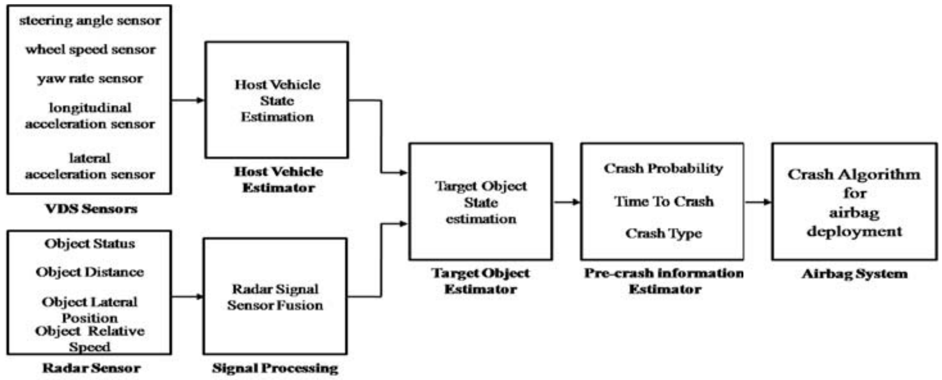

Fig. 2. System Block diagram

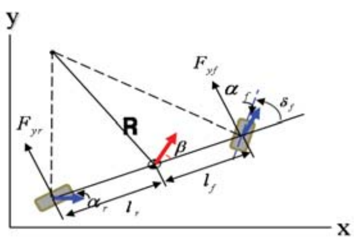

Fig. 4. Bicycle model

TABLE II
RADAR SENSOR'S SPECIFICATION

Measurement	Range	Resolution	Unit
Distance	1 - 200	0.1	[m]
Lateral Position	-20 - 20	0.1	[m]
Relative Speed	-255 - 88	1 [m/s]	[km/h]
Detection Angle	-30 - 30	0.1 - 1	[deg]

Defining an observer gain K_{12} as $\frac{1}{v_x}$, (9) becomes

$$\dot{\tilde{x}}_1 = -(1+K_{11})\tilde{x}_2 \tag{10}$$

Other observer gains are defined similarly using the negative pole placement method.
With the observer gain defined as follow,

$$K = \begin{bmatrix} \frac{I_z(l_fC_f-l_rC_r)p^2}{2C_fC_r(l_f+lr)^2} - 1 & \frac{1}{v_x} \\ -2p & \frac{m(l_f^2C_f+l_r^2C_r)}{I_z(l_fC_f-l_rC_r)} \end{bmatrix} \tag{11}$$

for an arbitrary tuning parameter p, (7) can be proven to satisfy an asymptotically stable condition. Since vehicle sideslip angle is defined as

$$\beta = \frac{v_y}{v_x}, \tag{12}$$

the lateral velocity is computed from vehicle longitudinal velocity, v_x and the vehicle sideslip angle, β.

B. Frontal Object State Estimator

The radar sensor is modeled using the real CAN data and sensor specification. This information is based on the ACC sensor installed on a passenger vehicle. The sensor specification is as described in TABLE II. A sensor fusion method is applied to reduce the effect of phase lag and to enhance the poor resolution of the radar signals. This method uses the physical relation between velocity and distance measured by different methods. In this paper, the low resolution of the distance signal is improved using the high resolution of the velocity signal. The state space representation of the distance observer is described as follow,

$$\dot{\hat{x}} = Lv_m + K(x_m - x) \tag{13}$$

where, x_m is the measured distance, x the estimated distance, v_m the measured velocity, and L, K tuning parameters.

The radar sensor provides the information of the frontal object states to the host vehicle. The information includes

1) distance to the frontal object
2) lateral position to the frontal object
3) relative speed to the frontal object

The angle is computed using the distance and the lateral position of the frontal object.

C. Pre-crash Information Estimator

The pre-crash information is created using the frontal object information based on the host vehicle. The information includes the following information,

1) Crash Flag (Crash Probability)
2) Time-To-Crash (TTC)
3) Crash Type Information: Frontal / Offset / Oblique

The crash flag information is set if the crash is going to happen immediately, otherwise it is reset. This information is used to discriminate crash situations before an actual crash is occurred, and the airbag is deployed accurately in a predefined moment for each crash situation.

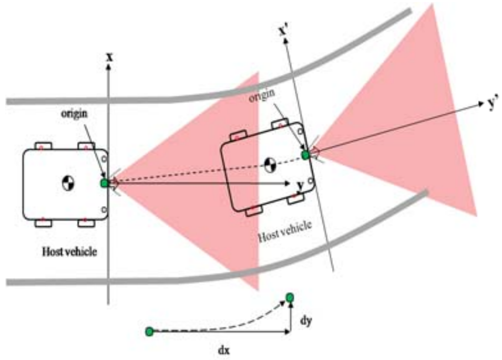

Fig. 5. Rectangular coordinate system based on the host vehicle

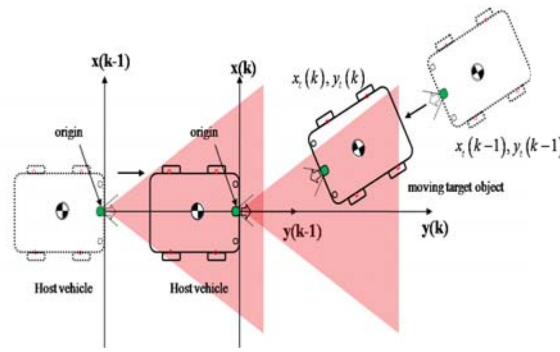

Fig. 6. Moving frontal object on the defined coordinate system

III. PRE-CRASH ALGORITHM

In this section, the pre-crash discrimination algorithm is discussed for each sub-system. The estimated states of the host vehicle and the frontal object are used as input variables for creating the pre-crash information. The used dynamics models are simplified in general motion of the vehicle. To keep the validity for the used models in crash situation, the pre-crash algorithm predicts the motion of the frontal object using both the present information and the past information. It is valid for the cases such as very aggressive driving maneuvers or loss of vehicle control in crash situations.

A. Host Vehicle State Estimation

The new rectangular coordinate system based on the host vehicle is defined as shown in Fig 5. The origin of the coordinates is located at the radar sensor mounted on the center of the front bumper or grill. The moving distance of the host vehicle in each direction per sampling time is computed as

$$dx(k) = dx(k-1) + T_s \cdot \hat{v}_x(k) \tag{14}$$

$$dy(k) = dy(k-1) + T_s \cdot \hat{v}_y(k) \tag{15}$$

where, dx is the longitudinal moving distant, dy the lateral moving distant, T_s sampling time, $\hat{v}_x$ the estimated longitudinal velocity, $\hat{v}_y$ the estimated lateral velocity, k the present time, $k-1$ the one sample time ago.
The variations, dx and dy, represent the movement of the host vehicle. It means not only the shifted origin of the predefined coordinate system, but also the movement of the defined coordinate system.

B. Frontal Object State Estimation

Since the position of the frontal object and the origin shifting in the defined coordinate system are known, the movement of the frontal object is predicted. Also, the time-to-crash, t_{TTC}, is estimated from the relation between distance and relative speed of the frontal object. Using the information, the heading angle and the lateral position of the frontal object at the moment of the crash are estimated before the actual crash is occurred. The related equations are as follows,

$$\angle a_{heading} = \arctan\left[\frac{y_t(k) - (y_t(k-1) - dy(k))}{x_t(k) - (x_t(k-1) - dx(k))}\right] \tag{16}$$

$$x_t(t_{TTC}) = a_x \cdot t_{TTC} + b_x \tag{17}$$

$$y_t(t_{TTC}) = a_y \cdot t_{TTC} + b_y \tag{18}$$

where,

$$a_x = -\frac{x_t(k-1) - x_t(k) - dx(k)}{T_r},$$
$$b_x = x_t(k-1) - (dx(k) + dx(k-1)),$$
$$a_y = -\frac{y_t(k-1) - y_t(k) - dy(k)}{T_r},$$
$$b_y = y_t(k-1) - (dy(k) + dy(k-1))$$

The index k means the present time, $k-1$ one sample time ago, t_{TTC} time to crash, T_r sampling time of a radar sensor and x_t, y_t the frontal object x-y positions, $y_t(t_{TTC})$ the predicted lateral position at the crash moment.

Advance of the vehicles during the time period is as described in Fig 6. The heading angle, $\angle a_{heading}$, and the lateral position at the crash time, $y_t(t_{TTC})$, are used to discriminate the crash types.

C. Pre-crash Information Estimation

The crash situation is discriminated using the estimated information of the frontal object with respect to the host vehicle. The combination of time-to-crash and estimated lateral position is used to decide whether the crash will occur or not. The combination of estimated lateral position and heading angle of the frontal object is used to decide the crash type.

In this paper, the crash zone is defined to judge the crash possibility. The crash is declared to be unavoidable if the following inequality conditions are satisfied.

$$t_{TTC} \leq 0.1sec \qquad and \qquad |y_t(t_{TTC})| \leq 0.5 \cdot w \tag{19}$$

where, w is the width of host vehicle, $y_t(t_{TTC})$ the predicted lateral position at the crash moment.

TABLE III

SIMULATION METHODS

	Radar signals	Sensor fusion	Frontal+Host estimation
Simulation 1	○	·	·
Simulation 2	○	○	·
Simulation 3	○	·	○
Simulation 4	○	○	○

Inequality (19) means the time-to-crash is less than 0.1sec and the frontal object exists within the width of the host vehicle at the crash moment. A threshold of time-to-crash is determined by the host vehicle's response characteristic. The fastest time for a host vehicle to respond to a step steer is assumed to be 0.1sec, which is based on the experiment data of step steers. The driver is not able to avoid the crash even if any actions are taken in this time period. If this condition is satisfied by the frontal object, the crash flag is set and the crash type is decided.

The crash type is determined using the predicted lateral position and the heading angle of the frontal object.

- Frontal: $|\angle a_{heading}| \leq 2$ deg & $|y_t(t_{TTC})| \leq 0.1 \cdot$w
- Offset : $|\angle a_{heading}| \leq 2$ deg & $|y_t(t_{TTC})| > 0.1 \cdot$w
- Oblique: $|\angle a_{heading}| > 2$ deg

These thresholds to discriminate each crash type are determined by simulations for each crash situation. In simulations, the frontal and offset crashes have the range of heading angle within ± 2 degrees and the oblique crashes have larger angles than ± 2 degrees. In case of the predicted lateral position, the frontal crashes have the range of the position within $\pm 0.1 \cdot w$ from the center point. The range of the offset crashes is out of this. The oblique crash is not affected the predicted lateral position because of the dominant characteristic of the heading angle. When the crash is occurred, airbags are deployed along the crash type discriminated by the pre-crash estimator.

IV. SIMULATION AND RESULTS

The simulation is carried on to verify the appropriateness of the pre-crash discrimination algorithm. Car-Sim, a commercial vehicle dynamics simulation tool, is used for this work. The simulation is performed for the conditions classified as shown in TABLE III. Twelve different crash cases are simulated, which are standard crash test modes. In the case of offset crashes, simulation is carried along the amount of overlaps between a host vehicle and a frontal object. The overlapped range of offset is from -10% to 100%. Also, oblique crashes with eight different heading angles are simulated. The range of the heading angle for the frontal object is from 17 to 26 degrees. The results of simulations are shown in TABLE IV, V and VI. In those tables, the frontal crash (FRT) is represented as 1, the offset deformable barrier crash (ODB) as 2, the oblique crash (OBLQ) as 3 and no crash as 0.

TABLE IV

CRASH TEST MODES

	Sim 1	Sim 2	Sim 3	Sim 4	Defined Type
FRT#1	1	1	1	1	1
FRT#2	1	1	1	1	1
FRT#3	1	1	1	1	1
FRT#4	1	1	1	1	1
FRT#5	1	1	1	1	1
FRT#6	1	1	1	1	1
ODB#1	3	3	2	2	2
ODB#2	3	3	2	2	2
OBLQ#1LH	3	3	3	3	3
OBLQ#1RH	3	3	3	3	3
OBLQ#2LH	1	2	3	3	3
OBLQ#2RH	1	2	3	3	3

TABLE V

OFFSET CRASH TEST MODES

ODB #2	Sim 1	Sim 2	Sim 3	Sim 4	Defined Type
-10%	0	0	0	0	0
0%	0	0	2	0	0
10%	0	0	2	3	3
20%	3	3	2	2	2
30%	3	3	1	2	2
40%	3	3	2	2	2
50%	3	3	2	2	2
60%	3	3	1	2	2
70%	2	2	1	1	1
80%	1	2	1	1	1
90%	1	2	1	1	1
100%	1	1	1	1	1

TABLE IV shows that sim3 and sim4 are better than sim1 and sim2 to discriminate the crash types. It proves that the accuracy of discrimination is more improved significantly by adding the combination of information of the host and frontal vehicle than using radar information alone.

TABLE V shows that the crash type of the offset crashes is classified along the overlapped portion. The 40% offset crash is a standard offset crash test mode. Normally, it is determined as the front crash if the range of the overlapped portion is over than 65%. The oblique crash is declared if the range of the overlapped portion is less than 15%. Otherwise, it is determined as the offset crash. The results of sim4 show the best performance of classifying offset crashes.

TABLE VI shows that the oblique crashes are classified along the measured angle or estimated heading angle. The heading angle information is very useful to distinguish the oblique crashes from all crash types. The sim1 and sim2 is not able to discriminate the oblique crashes because it is used only the radar information. These cases use the measured angle, which is computated by relation bewteen the distance and the lateral position. It means the angle of the relative postion of the frontal object. On the other hand, the sim3 and sim4 use the pre-crash information including the estimated heading angle. The estimated heading angle means the one for the direction that the frontal object is coming. In TABLE VI, the case 8 shows the effect of the sensor fusion. This

TABLE VI
OBLIQUE CRASH TEST MODES

OBLQ #2	Sim 1	Sim 2	Sim 3	Sim 4	Defined Type
case 1	1	1	3	3	3
case 2	1	1	3	3	3
case 3	2	3	3	3	3
case 4	3	3	3	3	3
case 5	3	3	3	3	3
case 6	3	3	3	3	3
case 7	0	0	3	3	3
case 8	0	0	3	0	0

TABLE VII
MEASURED AND ESTIMATED HEADING ANGLE

ODB #2	Measured angle	Estimated angle	OBLQ #2	Measured angle	Estimated angle
0%	25	-0.170	case1	-1	30.38
10%	25	0.439	case2	-6	23.37
20%	22	1.150	case3	-12	25.84
30%	19	0.144	case4	-16	22.61
40%	18	-0.141	case5	-19	17.50
50%	15	0.118	case6	24	35.20
60%	13	0.058	case7	27	31.08
70%	10	0.066	case8	28	24.12
80%	7	-0.058	.	.	.
90%	4	0	.	.	.
100%	0	0	.	.	.

case is the situation that the frontal object disappears in the crash zone after it is coming to the host vehicle, which means the crash is not occurred. The sim3 is not able to detect the disppearance of the frontal object because it has the lagged distance information. The sim4 detects that the crash is not occurred using the distance information leaded by sensor fusion obsever.

TABLE VII shows the difference between the measured and estimated heading angle. The measured angles do not have the characteristics to discriminate oblique crashes from all crash types because it is the relative postion. On the other hand, it shows that the estimated angles have the distinct values clearly. Therefore, the estimation of the heading angle for the frontal object is crucial to enhance the accuracy of the pre-crash discrimination system.

V. CONCLUSIONS

The most serious problem can happen to the airbag system if the airbags are deployed in a no-fire condition or not deployed in fire condition by misjudging crash situations. A number of inadvertent injuries have been caused by this problem. The judgment of the crash situation is very important. However, existing production airbag systems cannot judge the crash situation accurately because they use only the acceleration signal measured after a crash. If the crash situation is known before an actual crash is occurred, the performance of the airbag system can be improved significantly.

In this paper, the pre-crash discrimination system has been proposed as a solution to this problem. It exploits the information from VDC and ACC systems. From these information, valuable pre-crash knowledges are derived such as crash probability, time-to-crash, and crash type. After the crash is occurred , airbags are deployed along the predetermined schedule depending on the crash type information provided by the pre-crash discrimination system in advance. The robustness of the pre-crash discrimination system has been verified through computer simulations for a variety of crash cases. The simulation results show that it is not enough to discriminate the crash situation using a radar sensor alone. In case of adding the combination of the information of the host and frontal vehicles, it shows the best performance to discriminate the crash situation. In conclusion, the judgement of crash type as well as a crash itself is very important and the proposed pre-crash discrimination system is able to play a prominent role in enhancing the performance of the airbag deployment algorithm.

VI. ACKNOWLEDGMENTS

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