Design of an Airbag Deployment Algorithm Using a Radar Sensor*

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Abstract: An airbag system has been a fundamental safety equipment for saving lives of a driver and passengers. This system has some problems even though it is very efficient for protecting drivers or passengers. After a crash is occurred, airbags must be deployed in a proper time along the crash situation. But it is tricky to deploy at the exact time depending on the situations. These tricky situations happen especially for the airbag deployment algorithm using only the post-crash signals. In general, the airbag deployment algorithm uses airbag control unit(ACU) X-Y sensor and frontal impact sensor(FIS). And it discriminates crash situations along these sensors signals. However, during the crash process, these sensors are broken, rotated or moved. That causes the malfunction of airbag deployment algorithm. In this study, a new airbag deployment algorithm is developed which is enhanced with a radar sensor signal. Using pre-crash information from the radar sensor, the algorithm can judge a crash situation before a real crash is occurred and can revise the post-crash signal.

Keywords: Vehicle dynamics; Sensor fusion; Passive safety; Airbag; Crash algorithm; Precrash algorithm; Radar.

1. INTRODUCTION

In these days, many safety systems have been developed to ensure the safety of drivers and passengers and to make more comfortable driving condition. These systems are very important because it is linked with lives of drivers and passengers directly. The safety system is divided into two classes along the operated moment excepting for integrated safety system: active and passive types. The active safety system makes the vehicle avoid from a crash when it may be occurred. Using high-technology sensors such as a radar sensor, ultrasonic sensors, and stereo-vision cameras, it gets the information about the states of a frontal object. And then it decides the crash probability and controls the brake or steering system to avoid a crash before it is occurred (Skutek et al. [2005] and Jansson et al. [2002]). On the other hand, the passive safety system operates after a crash is occurred. For example, seatbelts prevent a driver or passengers from being thrown to the windshield of a vehicle. Airbags save lives of a driver or passengers by reducing the impact from a crash in a serious car accident. However, the two systems rarely operate linked together even though it can enhance the safety performance significantly. In the passive system, only seatbelts use the information of the active safety system. They are tensioned by the pre-tensioner in advance when the crash is occurred. The combination

of active safety and passive safety systems can make a much safer vehicle for a driver and passengers. Especially, it can provide one way to solve several problems of an airbag deployment algorithm through the estimation of the frontal object trajectory using high-technology sensors (Theisen et al. [2002]).

Airbags must be deployed in a proper time for each crash situation and must never be deployed except for real crash situations. However, it is difficult to discriminate crash situation using only acceleration sensors for crash detection in the airbag deployment algorithm. These sensors are easy to be broken or rotated by impact and also the measured signal accuracy is sensitive to the mounting location (Stuetzler and Century [2000]). In case of using erroneous sensor signal, airbags may be deployed or not be deployed by misjudging crash situations in the airbag deployment algorithm. The confusion of airbag deployment algorithm in the fuzzy situation of vehicle accidents may cause inadvertent injures (Park et al. [2006]).

In this paper, a new airbag deployment algorithm is developed using a radar sensor which is originally equipped for ACC (Adaptive Cruise Control) systems. Unlike the conventional airbag deployment algorithm using only FIS and acceleration sensors in ACU, the proposed algorithm uses also a radar sensor signal and vehicle states like yaw rate, steering angle, wheel speeds and, longitudinal and lateral acceleration. The radar sensor measures the

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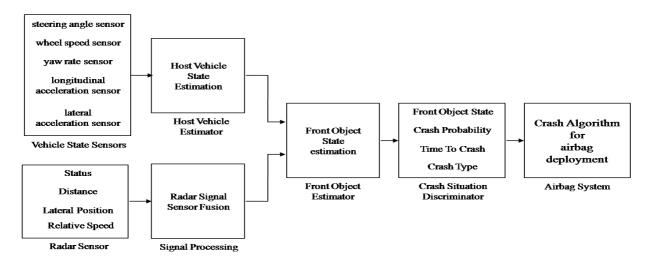


Fig. 1. Pre-crash system block diagram

distance, the lateral position and the relative speed to a frontal object. This information is used to estimate the states of the frontal object roughly. Combining the information of a frontal object and a host vehicle, the host vehicle decides the crash probability, crash time, and crash types. The information can also be used to replace frontal impact sensors which are used to discriminate crash types. It can prevent the airbag deployment algorithm from using the erroneous signal generated by frontal impact sensors which may be broken or rotated due to an impact. In section II, the pre-crash algorithm to make the pre-crash information is discussed. In section III, the airbag deployment algorithm using a radar sensor is discussed. In section IV, the proposed algorithm is verified in simulation to show the appropriateness.

2. PRE-CRASH ALGORITHM

In this section, a pre-crash algorithm for estimating the trajectory of a frontal object is discussed. The pre-crash algorithm consists of the host vehicle estimation, radar modeling, frontal object estimation and crash situation discrimination. The system block diagram is as shown in Fig. 1.

2.1 Host Vehicle Estimation

The lateral velocity and longitudinal velocity of a host vehicle are estimated using vehicle dynamics models (Farrelly and Wellstead [1996] and Kwak and Park [2000]). Car-Sim, a commercial vehicle dynamics simulation tool, is used for the vehicle dynamics simulation.

An observer is designed to estimate the lateral velocity using a modified bicycle model. The bicycle model is described in Fig. 2. The state-space representation of the lateral dynamics observer for the modified bicycle model can be described as

$$\dot{\hat{x}} = A\hat{x} + B\delta_f + K(y - \hat{y}) \tag{1}$$

where,

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

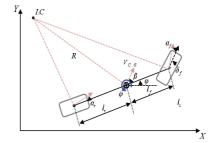


Fig. 2. Bicycle model of a vehicle

$$A = \begin{bmatrix} -\frac{2(C_f + C_r)}{mv_x} & \frac{2(C_rl_r - C_fl_f)}{mv_x^2} - 1\\ \\ \frac{2(C_rl_r - C_fl_f)}{I_z} & -\frac{2(C_fl_f^2 + C_rl_r^2)}{I_zv_x} \end{bmatrix} = \begin{bmatrix} A_{11} & A_{12}\\ A_{21} & A_{22} \end{bmatrix},$$

$$B = \begin{bmatrix} \frac{2C_f}{mv_x}\\ \\ \frac{2C_fl_f}{I_z} \end{bmatrix},$$

where, $\hat{\beta}$ is the estimated sideslip angle, \hat{r} the estimated yaw rate, r the measured yaw rate, v_x the longitudinal velocity calculated using wheel speed, δ_f the front steering angle, \hat{a}_y the estimated lateral acceleration, a_{ym} the measured lateral acceleration, and K the observer gain.

Using the kinematic model of vehicle dynamics, the lateral acceleration is estimated as follow,

$$\hat{a}_y = \dot{\hat{\beta}} v_x + \hat{r} v_x \tag{2}$$

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

$$\dot{\tilde{\beta}} = A_{11}(1 - K_{12}v_x)\tilde{\beta} + (A_{12}(1 - K_{12}v_x) - K_{11} - K_{12}v_x)\tilde{\gamma}$$
(3)

where, $\tilde{\beta} = \beta - \hat{\beta}$ and $\tilde{r} = r - \hat{r}$.

For simplicity, defining an observer gain K_{12} as $\frac{1}{v_x}$, equation (3) becomes

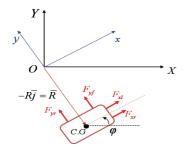


Fig. 3. Kinematic model of vehicle lateral motion

$$\dot{\tilde{\beta}} = -(1 + K_{11})\tilde{r} \tag{4}$$

Other observer gains are defined using a negative pole placement method.

With the observer gain matrix K defined as follow,

$$K = \begin{bmatrix} \frac{I_z(l_fC_f - l_rC_r)p^2}{2C_fC_r(l_f + lr)^2} - 1 & \frac{1}{v_x} \\ -2p & \frac{m(l_f^2C_f + l_r^2C_r)}{I_z(l_fC_f - l_rC_r)} \end{bmatrix}$$
$$= \begin{bmatrix} K_{11} & K_{12} \\ K_{21} & K_{22} \end{bmatrix}$$

for an arbitrary tuning parameter p, equation (1) can be proven to satisfy an asymptotically stable condition.

Assume that the longitudinal velocity is nearly constant. Since vehicle sideslip angle is defined as

$$\beta = \frac{v_y}{v_x},\tag{5}$$

the lateral velocity v_y can be computed from vehicle longitudinal velocity v_x and the vehicle sideslip angle β .

Also, an observer based on the kinematic model is designed to estimate the longitudinal velocity. The kinematic model is as described in Fig. 3. The state-space representation of the lateral dynamics observer can be described as

$$\dot{\hat{x}} = [A(t) - K(t)C(t)]\hat{x} + Bu + K(t)y \tag{6}$$

where,

$$\begin{aligned} x &= \left[\begin{array}{cc} \hat{v}_x \ \hat{v}_y \end{array} \right]^T, \qquad u = \left[\begin{array}{cc} a_{xm} \ a_{ym} \end{array} \right]^T, \\ A &= \left[\begin{array}{cc} 0 & r(t) \\ -r(t) & 0 \end{array} \right], \qquad B = \left[\begin{array}{cc} 1 & 0 \\ 0 & 1 \end{array} \right], \qquad C = \left[\begin{array}{cc} 1 & 0 \end{array} \right] \end{aligned}$$

where, \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.

For a time varying system as described in equation (6), the negative pole placement method cannot be applied to guarantee an asymptotical stable condition. In this study, a frozen-time pole placement method is applied to prove that the observer is asymptotically stable (LeFever [1997]).

The observer gain K defined as follow,

$$K(t) = \left[2\alpha |r(t)| \left(\alpha^2 - 1 \right) r(t) \right]^T \tag{7}$$

where, α is the tuning parameter, r the yaw rate.

Table 1. Radar sensor specifications

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]

For an arbitrary tuning parameter α , equation (6) can be made to satisfy the asymptotically stable condition.

A Lyapunov function is defined using the error dynamics of this model as follow,

$$V(v_x, v_y) = \frac{\alpha^2 \tilde{v}_x + \tilde{v}_y}{2} \ge 0, \forall x = [\tilde{v}_x, \tilde{v}_y] \in \mathbb{R}^2$$
 (8)

where, $\tilde{v}_x = v_x - \hat{v}_x$ and $\tilde{v}_y = v_y - \hat{v}_y$.

Since,

$$\dot{\tilde{v}}_x = -2\alpha |r(t)|\tilde{v}_x + r(t)\tilde{v}_y \tag{9}$$

$$\dot{\tilde{v}}_y = -\alpha^2 r(t) \tilde{v}_x \tag{10}$$

the time derivative of V is described as,

$$\frac{dV(t,x)}{dt} = -2\alpha^3 |\dot{r}(t)| \tilde{v}_x^2 < 0, \forall x = [\tilde{v}_x, \tilde{v}_y] \in R^2 \quad (11)$$

Therefore, the system is proved to be asymptotically stable by applying LaSalle's theorem in equations (8) to (11).

2.2 Radar Modeling and Signal Processing

The radar sensor is modeled using sensor specifications and the real CAN data. This information is based on a radar sensor equipped for ACC system in a luxury car. The sensor specifications are as described in Table 1. 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 distance and relative speed measured by different methods. The reliability of two signals is compared using resolution and tolerance of signals.

- (1) Resolution
 - distance: 0.1m/ 0.02s
 - relative speed: 1 m/s (=0.02 m/0.02 s)/0.02 s
- (2) Tolerance
 - distance: ± 0.25 m/ 0.02s
 - relative speed: $\pm 0.5 \text{km/h} = \pm 500 \text{m}/3600 \text{s}/0.02 \text{s}$

In this paper, the low reliability of the distance signal is improved using the high reliability of the relative speed signal. The state-space representation of the distance observer is described as follow,

$$\dot{\hat{x}} = Lv_m + K(x_m - \hat{x}) \tag{12}$$

where, x_m is the measured distance, v_m the measured relative speed, \hat{x} the estimated distance, and L, K tuning parameters.

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

- (1) existence of a frontal object
- (2) distance to a frontal object
- (3) lateral position of a frontal object
- (4) relative speed of a frontal object

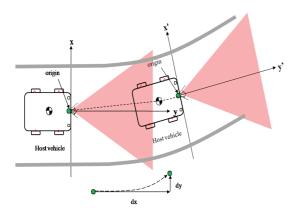


Fig. 4. Rectangular coordinate system based on a host vehicle

The angle is computed using the distance and the lateral position of the frontal object. The time-to-crash t_{TTC} can be estimated from the relation between distance and relative speed.

2.3 Frontal Object Estimation

The movement of the frontal object is tracked using the information of host vehicle and the radar signals. The new rectangular coordinate system based on the host vehicle is proposed as shown in Fig. 4. The origin of this coordinate is located at the radar sensor mounted at the center of the frontal grill. The moving distance of the host vehicle for each direction means the shifted distance of the origin in the predefined coordinate system. It is computed as follows,

$$dx = x(k) - x(k-1) = \hat{v}_x \cdot T_s$$
 (13)

$$dy = y(k) - y(k-1) = \hat{v}_y \cdot T_s \tag{14}$$

where, T_s is sampling time of CAN data, \hat{v}_x the estimated longitudinal velocity, and \hat{v}_y the estimated lateral velocity.

Since the position of the frontal object and the origin shifting are known, the heading angle and the lateral position of the frontal object at the moment of a crash can be estimated before the actual crash is occurred. Advance of the frontal object and host vehicle during the sampling time period is as described in Fig. 5. The related equations are as follows,

$$\angle a_{heading} = \arctan \left[\frac{y_t(k) - (y_t(k-1) - dy(k))}{x_t(k) - (x_t(k-1) - dx(k))} \right]$$
 (15)

$$x_t(t_{TTC}) = a_x \cdot t_{TTC} + b_x \tag{16}$$

$$y_t(t_{TTC}) = a_y \cdot t_{TTC} + b_y \tag{17}$$

where,

$$a_x = -\frac{x_t(k-1) - x_t(k) - dx(k)}{T_s},$$

$$b_x = x_t(k-1) - (dx(k) + dx(k-1)),$$

$$a_y = -\frac{y_t(k-1) - y_t(k) - dy(k)}{T_s},$$

$$b_y = y_t(k-1) - (dy(k) + dy(k-1))$$

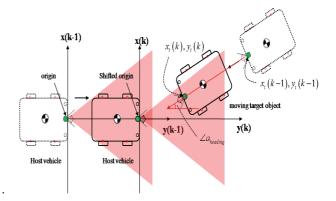


Fig. 5. Movement of the frontal object on the defined coordinate system

Table 2. Classifying crash types

	$ y_t(t_{TTC}) $		
$ \angle a_{heading} $	0 ~	$0.25 \cdot w \sim$	$0.45 \cdot w \sim$
	$0.25 \cdot w$	$0.45 \cdot w$	$0.5 \cdot w$
$0 \sim 10 \deg$	frontal	offset	oblique
$10 \sim 90 \deg$	oblique	oblique	oblique

where, index k means the present time, k-1 one sample time ago, t_{TTC} time to crash, T_s sampling time of CAN data, and x_t , y_t the frontal object positions.

2.4 Crash Situation Discrimination

The crash situation is decided using the estimated information of the frontal object based on the movement of the host vehicle. The combination of time-to-crash t_{TTC} and lateral position at the crash time $y_t(t_{TTC})$ is used to decide the crash probability. It is represented as Crash Flag which is to set in case the crash will be occurred and otherwise reset. The combination of heading angle $\angle a_{heading}$ and the lateral position at the crash time $y_t(t_{TTC})$ is used to discriminate the crash type. The crash type is divided into three cases which are frontal, offset and oblique crashes. It depends on the position and angle of the frontal object. In this study, a possible crash zone is defined to judge whether the crash is occurred. The crash flag is set if the following inequality conditions are satisfied. It means the host vehicle cannot avoid a crash.

$$t_{TTC} \le 0.1sec$$
 and $|y_t(t_{TTC})| \le 0.5 \cdot w$ (18) where, w is the width of a host vehicle.

In equation (18), a threshold of time-to-crash is determined by the response characteristic of a host vehicle. The fastest yaw rate responding time of the host vehicle to a step steering input is measured to be 0.1sec. The driver cannot avoid the crash even if any actions are taken in this time period. The crash types are classified into three cases as shown in Table 2.

3. INTEGRATED AIRBAG DEPLOYMENT ALGORITHM

In this section, a new airbag deployment algorithm is discussed. Unlike the conventional airbag deployment algorithm, this algorithm uses not only the acceleration signals

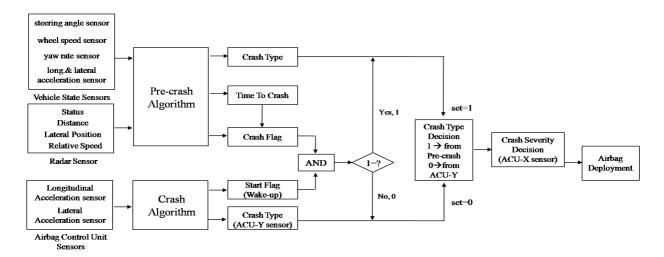


Fig. 6. Integrated airbag deployment algorithm

in ACU, but also the pre-crash information like crash flag, time-to-crash, and crash type. The integrated algorithm is as described in Fig. 6.

The pre-crash information is activated when the start flag in the crash algorithm and the crash flag in the pre-crash algorithm are all set. Airbags are deployed according to the crash type discriminated by the precrash algorithm. In case of the crash when the crash flag is not activated, the airbag deployment algorithm is operated as a stand-alone system using the sensors in ACU. It prevents the malfunction of the airbag deployment due to the fault of the radar sensor. Using the pre-crash algorithm, the misjudgment of the crash situation owing to the erroneous signals of the broken or rotated frontal impact sensors can be prevented. It is as described in Fig. 7. Even though the signals of FIS(Front Impact Sensors) must be nearly identical in case of the frontal crash as shown in FRT#5(FRonT Crash), the signal can be faulty as the case of FRT#6. This causes the misjudgment of the airbag deployment algorithm; the crash type is determined as oblique crash. As a result, the time of airbag deployment is delayed and it cannot satisfy the required-time-to-fire (RTTF) condition. However, using the pre-crash information this problem can be solved easily because the crash type is defined in advance before the real crash is occurred.

4. SIMULATION RESULTS

Series of simulations are carried on to verify the performance of the developed integrated airbag deployment algorithm. Car-Sim, a commercial vehicle dynamics simulation tool is used for this work. Twelve difference crash cases are simulated. They are standard crash test modes including the test modes of NHTSA and Euro NCAP. The integrated airbag deployment algorithm is compared with one of the conventional algorithm using only acceleration sensors in ACU. The simulation results are as shown in Fig. 8, 9, 10 and 11.

In the lower region of the diagonal line, airbags are deployed faster than RTTF. In the upper region, airbags are deployed slower than RTTF. This case is especially dangerous because airbags can strike a drooping down

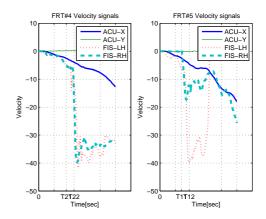


Fig. 7. Normal (FRT#4) and faulty (FRT#5) crash sensor signals during frontal crashes

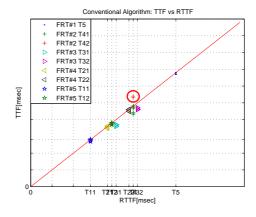


Fig. 8. Conventional algorithm: frontal(FRT) collisions

head. As the case of FRT#2 in Fig. 8 shows, airbags of the conventional algorithm are deployed twice even though they must be deployed only once. Also the airbags can be deployed too fast in case of the oblique crash as shown in Fig. 10. As Fig. 9 and 11 show, the integrated algorithm satisfies RTTF more precisely than the conventional algorithm do. It shows that the pre-crash information is very useful to improve the accuracy of the airbag deployment algorithm.

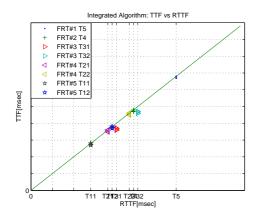


Fig. 9. Integrated algorithm: frontal(FRT) collisions

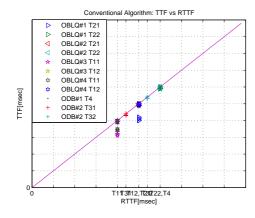


Fig. 10. Conventional algorithm: offset(ODB) and oblique(OBLQ) collisions

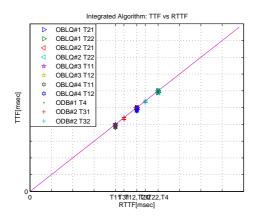


Fig. 11. Integrated algorithm: offset(ODB) and oblique(OBLQ) collisions

5. CONCLUSION

In the airbag system, the most serious problem is occurred when the erroneous frontal sensors are used. It makes the airbag deployment algorithm misjudge the crash situation. It can even cause a number of inadvertent injuries if the airbags are deployed in no-fire conditions or not deployed in fire conditions. The conventional airbag deployment algorithm has limits like this because they use only acceleration signals measured after a real crash is occurred.

In this study, the radar sensor in ACC system and other vehicle state sensors are used as one way to solve this problem. It allows the judgment of the crash situation before the real crash is occurred and airbags are deployed in a proper time. The performance of the integrated airbag deployment algorithm has been verified through computer simulation for standard crash test modes using real airbag sensor data. The simulation results show that the precrash information obtained and processed using a radar sensor and vehicle state sensors is very useful to enhance the accuracy of the airbag deployment algorithm. The discrimination of the crash situation is very important in the airbag deployment algorithm since it is linked directly with RTTF. The integrated airbag deployment algorithm satisfies RTTF for all crash types. Therefore, the performance of airbags improved significantly. In conclusion, this study shows that the integrated algorithm can play a prominent role in enhancing the accuracy of the airbag deployment algorithm using only the vehicle sensors existing for other control purposes.

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REFERENCES

- M. Skutek, DT. Linzmeier, N. Appenrodt, and G. Wanielik. A PreCrash System based on Sensor Data Fusion of Laser Scanner and Short Range Radars. 2005 8th International Conference on Information Fusion (FUSION), volume 2, pages 1287–1294, 2005.
- J. Jansson, F. Gustafsson, and J. Ekmark. Decision making for collision avoidance systems. *Citeseer*, 2002.
- M. Theisen, S. Eisele, and M. Rolleke. The computation of airbag deployment times with the help of precrash information. *SAE International*, 2002.
- F.J. Stuetzler, and K. Century. Advanced frontal crash sensing with peripheral sensors. SAE International, 2000.
- T-W Park,H-Y Jeong, and S-W Park. A crash severity algorithm for all frontal crash modes using compensation factors. *Proc.IMechE Vol.220 Part D:J. Automobile Engineering*, volume 220, pages 531–541, Prof Eng Publishing, 2006.
- J. Farrelly, and P. Wellstead. Estimation of Vehicle Lateral Velocity. *Proceedings of the 1996 IEEE International Conference on Control Applications*, pages 552–557, 1996.
- B-M Kwak, and Y-J. Park. Design of Observer for Vehicle Stability Control. Seoul 2000 FISITA World Automotive Congress, 2000
- VC. LeFever. Design and Implementation of a Time-Varying Observer and an EMA Controller for Linear Systems. Southeastern symposium on system theory, volume 29, pages 297–301, IEEE Computer Society Press, 1997.