ABSTRACT: This study proposes a motion planning and control system based on collision risk potential prediction characteristics of experienced drivers. Recently, automatic braking systems have been deployed in current automotive markets. However, the existing systems cannot avoid collisions in critical scenario such as a pedestrian suddenly darting out from a poor-visibility blind corner. By optimizing the potential field function in the framework of optimal control theory, the desired yaw rate and the desired longitudinal deceleration are theoretically calculated. Finally, the validity of the proposed motion planning and control system is verified by comparing the simulation results with the actual driving data by experienced drivers.

KEY WORDS: Safety, Active Safety, Vehicle Dynamics Control, Collision Avoidance, Potential Field [C1]

1. Introduction

Recently, the number of traffic accidents and traffic accident fatalities in Japan is decreasing due to development of passive and active safety technologies. However, the number of accidents remains in a high level. Particularly, accidents involving pedestrians becomes dominant. The fatalities while walking show the highest number since 2008(1). Crash energy absorbing body structures have been developed to minimize pedestrian injuries and put to practical use so far. However, to further decrease the number of pedestrian fatalities, such a passive safety device reaches its limit. Therefore, active safety devices such as autonomous braking systems have been recently introduced to the markets to realize zero fatalities. Moreover, accidents caused by elderly drivers have been increasing every year owing to their declined physical ability in terms of recognition, decision-making and operation in recent years (2). In some cases, warning devices are not effective as the reaction time to the warning devices is too long to handle crash avoidance in time. Some elderly drivers still need automobiles as a mean of mobility for active social participation as well as to improve their quality of life(2). To recover their degraded driving performance, this research project aims at improving road safety by allowing autonomous driving control intervention in advanced timing before the occurrence of accidents.

However, conventional automatic emergency braking systems (AEB) have limitations in avoiding collisions in critical scenario, e.g. a pedestrian suddenly darts out from a blind corner into driving corridor with short time margin to collision as shown in Fig. 1. In such scenario, experienced drivers reduce the risk of accidents by safe driving such as early braking based on hazard anticipation regarding occluded objects(2). Based on this fact, it is necessary to develop a risk assessment algorithm considering occluded objects based on experienced driver hazard anticipation knowledge to enhance the active safety performance.

Fig. 1 Critical scene with occluded pedestrians

Therefore, this study proposes a motion planning and control system based on situational risk assessment algorithm considering hazard anticipation of experienced drivers. This paper describes an autonomous driving intelligence system for collision avoidance. First, the potential field functions are defined for lateral and longitudinal motion control independently. The hazard potential for lateral motion control is determined considering the risk of collision with a static obstacle and lane departure. The risk
potential for longitudinal motion control is determined to express the risk of occluded objects such as pedestrians. Next, the optimal control problems are formulated based on potential field variables and the command values for lateral and longitudinal controls are determined by solving the optimization problems. Finally, the validity of the proposed control system is verified by comparing the simulation results with the actual driving data by experienced drivers.

2. Motion Planning and Control System

Conventional motion planning algorithms in static environment using potential field theory commonly calculate the desired longitudinal and lateral motions, i.e. the vehicle speed and the yaw rate, within the same potential field functions \( \text{(3)} \). In the scenario focused in this paper, the static obstacle avoidance maneuver and the vehicle speed control maneuver are calculated separately. The steering maneuver is conducted to minimize the hazard potential by changing the vehicle trajectory not to collide with the static obstacle. The braking maneuver is conducted to slow down the vehicle in order to reach the safe speed not to collide with pedestrians who might appear from behind the obstacle. Based on this design concept, Fig. 2 shows the block diagram of the autonomous driving intelligence system for obstacle avoidance. The lateral motion and the longitudinal motion control problems are formulated independently.

In the lateral motion control, the hazard potential functions with respect to the road boundaries and the obstacle are defined at first. The candidates of the desired yaw rates are defined and consequently the vehicle predicted position with respect to each yaw rate candidate value is calculated by assuming that the vehicle moves at a constant yaw rate within a finite time horizon. In addition, the performance index based on the hazard potentials of road environment is calculated with respect to a number of candidate yaw rates. The desired yaw rate is sequentially selected from the candidate yaw rate values which minimizes the performance index.

In longitudinal control, the risk potential function with respect to the occluded pedestrian is defined using a spring model. The predicted vehicle position within a finite time horizon is calculated in accordance with the candidate longitudinal deceleration values and the performance index considering the risk potential of the occluded pedestrian is calculated with respect to a number of candidate deceleration values. The desired deceleration is sequentially selected from the candidate values which minimizes the performance index.

3. Hazard-Potential Based Lateral Control

This subsection describes the lateral motion control of the proposed system. The hazard potential used in the lateral motion control system is described by an exponential function. Under the condition that a static obstacle exists in front of the ego vehicle on a straight road, the vehicle path is determined by two factors, i.e. road boundaries and a static obstacle. Actual drivers determined the optimal path reducing the risk of collision with the static obstacle and lane departure. Therefore, artificial potential fields are formulated with respect to the two factors.

The repulsive potential field of road boundaries is defined as follows:

\[
U_r(X,Y) = w_r \left[ 1 - \exp \left( \frac{(X - X_c)^2 + (Y - Y_c)^2}{2\sigma^2} \right) \right]
\tag{1}
\]

where, \( w_r, \sigma \) are the weight and the variance of the repulsive potential field of road boundaries respectively, and \( Y_c \) is the \( Y \)-coordinate of the road center.

Fig. 3 shows the shape of the repulsive potential field of the road boundaries. This potential field has the maximum value at the position of the road boundaries to express risk of lane departure.

Next, the repulsive potential field of the obstacle is defined with respect to the vehicle position as follows:

\[
U_o(X,Y) = \begin{cases} 
  w_o \exp \left( \frac{(X - X_o)^2 + (Y - Y_o)^2}{2\sigma^2} \right) & (X \leq X_o) \\
  w_o \exp \left( \frac{(Y - Y_o)^2}{\sigma^2} \right) & (X_o < X < X_o) \\
  w_o \exp \left( \frac{(X - X_o)^2 + (Y - Y_o)^2}{2\sigma^2} \right) & (X \geq X_o) 
\end{cases}
\tag{2}
\]

where, \( w_o \) indicates the weight of the repulsive potential field of the obstacle, \( \sigma_o, \sigma \) are the variances of \( X \) direction and \( Y \) direction respectively, \( X_o, Y_o \) indicates the \( X \)-coordinate at the front end and the rear end of the obstacle respectively. As can be noticed from equation (2), the repulsive potential field of the obstacle is defined as an exponential function of \( X \) and \( Y \).

![Fig. 2 Block diagram of motion planner and controller of the autonomous driving intelligence system](image-url)

**Fig. 2** Block diagram of motion planner and controller of the autonomous driving intelligence system

![Fig. 3 Repulsive potential field of the road boundaries](image-url)

**Fig. 3** Repulsive potential field of the road boundaries
Fig. 4 shows the shape of the repulsive potential field of the obstacle. This potential field has the maximum value at the position of the obstacle to express risk of collision with the obstacle.

Next, the overall risk potential field is defined as follows:

$$U_{\text{rad}}(X,Y) = U_r(X,Y) + U_o(X,Y)$$  \hspace{1cm} (3)

As can be noticed from Equation (3), the overall risk potential field is the summation of the repulsive potential field of the road boundaries $U_r$ and the repulsive potential field of the obstacle $U_o$. $w_r$, $w_o$, $\sigma_r$, $\sigma_o$, $\sigma_{\text{rad}}$, and $\sigma_{\text{opt}}$ included in Equations (1) and (2) are the parameters to vary the shape and height of the risk potential field. These parameters are determined based on the driving data of actual experienced drivers.

In the driving situation shown in Fig. 5 (a), the combined potential hazard contour map is expressed as Fig. 5 (b).

Next, the repulsive potential function parameters related to the road boundary are determined. By using the parameters $w_r$, $\sigma_{\text{rad}}$, $\sigma_{\text{opt}}$ determined from Eq.(4) above, the parameters $w_o$, $\sigma_o$ can be calculated by using the following expression.

$$\begin{bmatrix} w_o \\ \sigma_o \end{bmatrix} = \arg \min_{w_o,\sigma_o} \sum_{i=1}^{N_{\text{data}}} \left( \frac{\partial Y_{\text{rad}}(X_i,Y_i(i))}{\partial Y} \right)^2$$  \hspace{1cm} (4)

subject to

$$w_o = \text{constant}$$

where, $X_e$, $Y_e$ indicate the vehicle trajectory by the experienced drivers and $N_{\text{data}}$ indicates the number of trajectories used for parameter identification process.

Next, the calculation of the desired yaw rate is determined by using the above-mentioned potential field functions. Conventional path planning by the potential field method is conducted by calculating the gradient of the potential field at arbitrary vehicle position. However, the problem that the stability of the vehicle motion can be ensured in comparatively higher speed compared to mobile robot speed region and the problem that the vehicle cannot move out from at the local minimum point of the potential field may occur. Trajectory generator can be designed by using model predictive control framework, but it includes high complexity in the calculation process and it is difficult to implement for real-time vehicle control. To avoid these problems, the proposed lateral motion control system determines the vehicle yaw rate sequentially by selecting the yaw rate which results in minimum hazard potential with the application of optimal control theory.

As the calculation process, the minimum yaw rate $\gamma_{p,\text{min}}$ and maximum yaw rate $\gamma_{p,\text{max}}$ for the search range of the desired yaw rate and the resolution $\Delta \gamma_p$ of the search are given. Next, the predictive yaw rate, which is the candidate of the desired yaw rate $\gamma_p(i)$ are defined as follows:

$$\gamma_p(i) = \gamma_{p,\text{min}} + \Delta \gamma_p \cdot i_p \quad (i_p = 0, 1, 2, \ldots, M_p)$$  \hspace{1cm} (6)
where, $M_f$ indicates the number of yaw rate candidates. When the ego vehicle moves at a constant yaw rate with negligible side slip angle, the predicted vehicle positions $(X_{p-y}, Y_{p-y})$ at a time horizon $t_{p-y}$ with the command yaw rate $\gamma$ can be calculated as follows:

$$
\begin{bmatrix}
X_{p-y}(i_j, t_j) \\
Y_{p-y}(i_j, t_j)
\end{bmatrix} = 
\begin{bmatrix}
X(t) + \int_{t}^{t_{p-y}} V(t) \cos(\psi(t) + \gamma_p t) dt \\
Y(t) + \int_{t}^{t_{p-y}} V(t) \sin(\psi(t) + \gamma_p t) dt
\end{bmatrix} 
$$

(7)

where, $\psi$ indicates the yaw angle. Next, the performance index for determination of the desired yaw rate is defined as follows:

$$
J_j(i_j) = \sum_{j=1}^{N} \left[ U_j \left(X_{p-y}(i_j, t_j), Y_{p-y}(i_j, t_j)\right) + q \gamma^2 \right] 
$$

(8)

where $q$ indicates the weighting coefficient of yaw rate input. Fig. 6 shows the schematic diagram of the predictive position and the risk potential. The feature of the performance index $J_j$ is that it contains the intermediate variable as the potential field function not vehicle state variables. The performance index consists of the summation of the hazard potential field at the vehicle predicted position and the square of the command yaw rate within a finite time horizon. The performance index $J_j$ is calculated according to each command yaw rate candidate and the desired yaw rate $\gamma^*$ is determined as the value that results in the minimum value of the performance index $J_j$. This calculation process is conducted at each sampling time.

![Fig. 6 Schematic diagram of the predictive position and the risk potential](image)

Next, the calculation of the desired steering wheel angle is described. If the side slip angle at the gravity center and the risk potential. The feature of the performance index $J_j$ is that it contains the intermediate variable as the potential field function not vehicle state variables. The performance index consists of the summation of the hazard potential field at the vehicle predicted position and the square of the command yaw rate within a finite time horizon. The performance index $J_j$ is calculated according to each command yaw rate candidate and the desired yaw rate $\gamma^*$ is determined as the value that results in the minimum value of the performance index $J_j$. This calculation process is conducted at each sampling time.

$$
\delta^*_v(t) = n(1 + KV(t)^2) \frac{l}{V(t)} \gamma^*(t)
$$

(9)

where, $K$ indicates the stability factor, $n$ is the steering gear ratio. Since the frequency of the steering maneuver is low in this driving scenario, the dynamic characteristics of the yaw rate with respect to the steering wheel angle input is neglected.

### 4. Risk-Potential Based Longitudinal Control

This subsection describes the longitudinal motion control of the proposed system. The risk potential function used in the longitudinal motion control system is described as a spring model. Under the condition that a poor visibility corner caused by occlusions such as a parking vehicle exists, actual drivers reduce the collision risk with respect to a darting-out pedestrian by early braking based on hazard anticipation knowledge. Although road infrastructure such as X2X communication can be effectively used to know the existence of pedestrians and then prevent collisions, this study aims to apply experienced driver hazard anticipatory characteristics to the design of intelligent driving system without requiring communication systems. To further decrease the number of pedestrian fatalities, the risk assessment algorithm which considers the collision risk including such occluded objects is essential. Based on this fact, an artificial potential field regarding the occluded pedestrian is also introduced in the motion planning computation algorithm. The repulsive potential field of the occluded pedestrian $U_{ped}$ is defined as follows:

$$
U_{ped} = \frac{1}{2} k_{ped} \left[ x_{max} - l(t) \right]^2 \text{ if } X^* < l(t) < l_{max}
$$

(10)

where, $k_{ped}$ indicates the spring constant of the repulsive potential of the occluded pedestrian, $l$ indicates the relative distance between the pedestrian moving axis and the ego vehicle. In addition, $l_{max}$ and $X^*$ indicate the maximum and minimum distances with respect to the occluded pedestrian which causes risk potential, respectively. $l_{max}$ refers to the braking start distance and $X^*$ refers to the braking finish distance.

Next, Eq.(11) is obtained based on the law of energy conservation between the potential energy and the kinetic energy of the vehicle. In other words, the kinetic energy must be reduced as the potential energy increases in the artificial risks potential field.

$$
\frac{1}{2} mV(t)^2 + \frac{1}{2} k_{ped} \left[ x_{max} - l(t) \right]^2 = \frac{1}{2} mV_{min}^2 + \frac{1}{2} k_{ped} \left[ x_{max} - X^* \right]^2
$$

(11)

where, $m$ indicates the vehicle mass and $V_{min}$ indicates the desired minimum velocity which is determined based on the driving data of experienced drivers.

Based on Eq.(11), the spring constant is determined as follows:

$$
k_{ped} = \frac{m(V_{min}^2 - V(t)^2)}{\left[ x_{max} - l(t) \right]^2 - \left[ x_{max} - X^* \right]^2}
$$

(12)

The spring constant varies sequentially based on the velocity and the relative distance. Fig. 7 shows the shape of the repulsive risk potential field of the occluded pedestrian. To calculate the value of the spring constant, the terminal vehicle velocity $V_{min}$ must be given. The terminal vehicle velocity $V_{min}$ can be theoretically determined from the stopping distance equation and the geometrical relationship of the vehicle and the pedestrian as follows:
where, \( a_{\text{max}} \) denotes the maximum deceleration applied for stopping, \( \tau \) the braking reaction time with respect to the pedestrian recognition and \( X^* \) the position where the velocity is lowest. The position where the velocity is lowest is dependent on the distance to the parked vehicle \( Y_{\text{pass}} \) by solving the following equations.

\[
\frac{\ddot{Y}_{\text{ped}} - d}{V_{\text{ped}}^2} = \frac{\dot{X}^*}{V_{\text{min}}} \tag{15}
\]

\[
\ddot{Y}_{\text{ped}} = \frac{\ddot{X}_{\text{ped}} - X_{\text{fin}}}{X_{\text{of}} - X_{\text{fin}}} Y_{\text{pass}} \tag{16}
\]

Eq.(16) is obtained by using the similarity of triangles in the pictorial diagram of Fig.7. By substituting Eq.(16) into Eq.(15), \( X^* \) can be expressed as a function of the distance to the parked vehicle \( Y_{\text{pass}} \). In Eq.(15), \( V_{\text{ped}} \) is defined as the average walking speed of pedestrian in crash-relevant events, using the pedestrian motion analysis in the reference (12).

Next, the calculation of the desired deceleration is described. The maximum deceleration \( a_{\text{max}} \) and the resolution \( \Delta a \) for the search of the desired deceleration are given and a number of decelerations which are the candidates of the desired deceleration \( a(i_*) \) are defined as follows:

\[
a(i_*) = \Delta a_i \cdot i_*, \quad (i_* = 0, 1, 2, \cdots, M_i) \tag{17}
\]

where, \( M_i \) indicates the number of acceleration candidates. When the ego vehicle moves only the longitudinal direction, the predicted vehicle position \( X_{p}(i_*, j_*) \) at a time horizon \( t_p(j_*) \) with respect to the deceleration \( a(i_*) \) are calculated as follows:

\[
X_{p}(i_*, j_*) = X(t) + V(t) \cdot t_{p}(j_*) + \frac{1}{2} a(i_*) \cdot t_{p}(j_*)^2 \tag{18}
\]

Next, the performance index \( J_r \) for the determination of the desired deceleration is defined as follows:

\[
J_r(M_i) = \sum_{i_*=1}^{N} (U_{\text{ped}}(X_{p}(i_*, j_*))) + r a_{\text{max}}^2 \tag{19}
\]

where, \( r \) indicates the weight of the command longitudinal deceleration input. This performance index \( J_r \) is expressed as the summation of the risk potential at the predictive position and the square of the predictive deceleration. The performance index \( J_r \) is calculated at the several predictive decelerations and the desired deceleration \( a_{\text{des}} \) is determined as the value which minimizes the performance index \( J_r \). This calculation process is sequentially conducted at each sampling time as same as the lateral motion control.

The braking torque command of the vehicle \( T_m \) in order to achieve the desired longitudinal deceleration \( a_{\text{des}} \) is determined by using the inverse dynamics of the vehicle longitudinal motion combined with the one-wheel rotational motion model. The longitudinal slip ratio is assumed to be zero.

\[
T_m = \frac{1}{2} \left( \frac{J + m r_v^2}{r_v} a_{\text{des}}^2 + F_r r_v \cdot \text{sgn}(V) \right) \tag{20}
\]

where, \( J \) denotes the moment of inertia of the tire-wheel, \( r_v \) the effective radius of the tire, and \( F_r \) the driving resistance.

5. Validation of the Proposed Motion Planning and Control

5.1. Driving scenario

The simulation was conducted to verify the effectiveness of the proposed motion planning and control system. The simulation scenario is shown in Fig. 8. The simulation was conducted on the straight road in which the parking vehicle existed. The front end and the rear end of the parking vehicle were set as far as 53.6 m and 48.1 m from the start point respectively. Additionally, the parking vehicle was located at a lateral distance of 0.9 m from the road center. The ego vehicle was running at a speed of 40 km/h at
first. As a vehicle model in the simulation, the 4-wheel vehicle model was used. The simulation result was compared with the driving data of the selected experienced drivers. Additionally, the control parameters of the longitudinal motion and the lateral motion control are shown in Table 1 and Table 2.

Table 1 Parameters of the lateral vehicle control

| Symbol | Value    | Unit |
|--------|----------|------|
| \( w_c \) | 7.41 × 10^4 | -    |
| \( \sigma_l \) | 2.40 | -    |
| \( w_o \) | 8.99 × 10^4 | -    |
| \( \Delta \sigma_r \) | 27.8 | -    |
| \( \sigma_{\Delta r} \) | 3.05 | -    |
| \( \gamma_{\Delta r} \) | -0.50 | rad/s |
| \( \gamma_{\Delta r} \) | 0.50 | rad/s |
| \( \Delta \gamma_{\Delta r} \) | 0.01 | rad/s |
| \( q \) | 200 | -    |

Table 2 Parameters of the longitudinal vehicle control

| Symbol | Value    | Unit |
|--------|----------|------|
| \( l_{\text{max}} \) | 50 | m    |
| \( a_{p,x,\text{max}} \) | -3.0 | m/s^2 |
| \( \Delta a_{p,x} \) | 0.1 | m/s^2 |
| \( r_x \) | 60 | -    |

5.3. Simulation results and discussions

The desired vehicle motion calculated by the motion planning algorithm is shown in Fig. 10 and the velocities and the vehicle trajectories of the simulation and experienced drivers are shown in Fig. 11. Fig. 12 shows the braking distances with and without the risk prediction. The braking distance in Fig. 12 is calculated assuming that the maximum jerk and the response time are 12 m/s^3 and 0.1 s considering the recognition time of the pedestrian detection sensor. The drawn lines indicate the required braking distance with respect to the velocity, at the time instant that the pedestrian darts out from the space behind the parked vehicle, in order to avoid collision when the maximum deceleration for stopping is given (0.2G, 0.4G, 0.6G and 0.8G). The distance of the pedestrian appearance is set at 8.0 m, 10.0 m, 12.0 m and 14.0 m. The marks plotted in the graph indicate the vehicle velocity at each condition in the case that the risk prediction is conducted (circles) and not conducted (squares). The vehicle velocity becomes lower when the risk prediction is considered in the vehicle motion planning. The position of each mark also indicates the magnitude of the required maximum deceleration in order to avoid collision. The mark below the line of 0.8 G means that the required deceleration is higher than 0.8G which exceeds the braking capability of the vehicle on dry road friction condition. In other words, the collision is unavoidable. In this paper, the simulation finish point was defined as \( X = 60 \) m as the proposed system focused on the parking-vehicle overtaking and the collision avoidance with occluded objects.

As can be noticed from Fig. 10 and Fig. 11, the ego vehicle was able to avoid the parking vehicle with the stable behavior. Moreover, the simulation results about both the vehicle velocity and trajectory closely match the driving data of the experienced drivers. Therefore, the proposed autonomous driving system with combination of risk potential field and optimal control theories are feasible to express the actual anticipatory driving characteristics of the experienced drivers. In addition, as can be noticed from Fig. 12, the ego vehicle equipped with an autonomous emergency braking (AEB) without pedestrian risk potential prediction cannot avoid the collision even with 0.8G if a pedestrian dart out at the distance between the ego vehicle and the front end of the obstacle of 12 m. On the other hand, the ego vehicle with the risk-potential based motion planning and control can avoid the collision with 0.4G in the same situation. Moreover, the ego vehicle with the control can avoid the collision with 0.8G even if a pedestrian darts out at the distance between the ego vehicle and the front end of the obstacle of 8 m. In this fact, the proposed risk-potential based control system can effectively enhance pedestrian crossing collision avoidance performance.
6. Conclusions

This paper has described an autonomous driving intelligence system by embedding the risk potential prediction knowledge of experienced drivers for enhancing the obstacle avoidance performance. A typical dangerous scenario in urban environment that a pedestrian suddenly darts out from a blind corner, i.e. behind a parked car, with short time margin to collision is focused. First, the potential field functions of the static road environment and the virtual pedestrian are defined for the lateral and the longitudinal motion control respectively. The hazard potential field for the lateral motion control is determined considering the risk of collision with an obstacle and the risk of lane departure. The risk potential for the longitudinal motion control is determined to express the collision risk with an occluded object such as a pedestrian. Next, the optimal control problem is formulated by taking the potential field functions into the account. The command values for the lateral and the longitudinal control are sequentially determined by solving the formulated optimization problems. Finally, the validity of the proposed control system is verified by comparing the computer simulation results with the actual driving data by experienced drivers. As the result, it has been shown that the proposed autonomous driving system with the combination of potential field theory and the optimal control theory are feasible to express the actual driving of the experienced drivers. From the theoretical collision avoidance analysis, the proposed motion planning and control with risk potential prediction shows superior collision avoidance performance to the conventional automatic emergency braking (AEB) system.

As a future plan, the effectiveness of the proposed motion planning and control will be verified by using a prototype experimental vehicle equipped with sensors and the vehicle control system. Driver acceptance issues will be also studied.
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