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Building a driver model using Risk Potential theory in collision avoidance situation

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Abstract

This research describes the construction and evaluation of a driver model for vehicle longitudinal control that can avoid collisions with pedestrians. While the priority for the driver model is to avoid collisions, this work also considers the potential trade-off between collision avoidance, comfort for vehicle occupants, and the effects on traffic flow. Three driver models were developed based on risk potential (RP) methods: a conservative RP model, a relative velocity RP model, and a Pedestrian Potential Position (PPP) RP model. The PPP model considers pedestrian dynamics such as position, speed, and direction of movement in its assessment of RP. The three driver models were implemented in MATLAB/Simulink and performance of the models was evaluated in simulations of nine situations involving vehicle-pedestrian interaction. The models were compared pairwise according to risk of injury to the pedestrian, comfort for vehicle occupants, and false alarms. The PPP model outperformed the other RP models in situations that have a severe risk of collision. In safe situations, the velocity model outperformed the other RP models. The PPP model was potentially over-cautious when approaching pedestrians standing near the side of the road without the intention to cross. Overall, the proposed models are expected to improve the performance of RP driver model reducing the risk of injury, occupant discomfort, and the number of false alarms.

Keywords
Self-Driving, Risk assessment, Driver assistance, Driver model, Simulation

1. Introduction
Self-driving and driver assistance systems have been developed with the intent to reduce the number of motor vehicle accidents. There were more than 2.5 million traffic accidents in the United States in 2019 in which more than 36,000 deaths occurred. Many of the traffic accidents (40%) occurred at intersections and involved pedestrians[1]. Protection of pedestrians and other vulnerable road users must be a priority for self-driving systems. To avoid collisions with pedestrians, drivers can decelerate to allow pedestrians to cross the road. However, decelerating may affect the comfort of vehicle occupants. If the driver decelerates often when it is unnecessary, it may lead to traffic jams or another collision between vehicles. In addition, if the driver brakes hard, passengers will feel uncomfortable and may be injured. Therefore, the driver must consider not only avoiding the collision, but also the potential side effects of actions on occupants and others in the environment. There is a trade-off between collision avoidance, comfort of passengers, and safety and convenience for other road users. In general, collision avoidance is a priority for safe and effective operation of autonomous ground vehicles.

In this paper, we construct a computational model of the vehicle driver and evaluate its behavior in scenarios in which a pedestrian may be crossing the road. The proposed driver model uses risk potential theory which has been used previously to describe driver's behavior. However, prior driver models developed using risk potential theory have not considered pedestrian dynamics such as position, intention, and velocity in their assessment of the risk associated with a pedestrian. Three driver models were developed and tested: 1) Conservative Risk Potential model, 2) Velocity Risk Potential model based on relative velocity of the driver's vehicle and the pedestrian, and 3) a Pedestrian Potential Position (PPP) Risk Potential model based on the maximum expected movement of a pedestrian. The models were evaluated based on their ability to achieve three objectives: 1) avoid collisions with pedestrians, 2) ensure deceleration is comfortable for vehicle occupants, and 3) avoid unnecessary deceleration that would affect traffic flow on the road.

2. Risk Potential and Its Development
Risk potential theory describes the path-planning behavior of drivers with different characteristics, such as beginners, experts, and elderly drivers. Risk potential can be used to define computational driver models that allow the evaluation

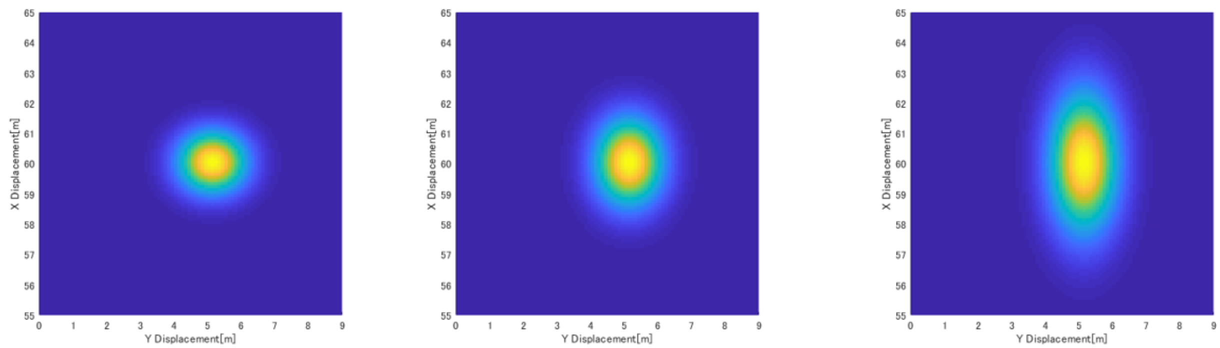

Figure 1: Risk potential map for potentially moving obstacle. The obstacle may be stopped (left), moving slowly (middle), or moving quickly (right). The risk potential map is calculated based on the state of the obstacle and the driver model will decide whether to accelerate, brake, or steer to avoid it.

of each driver's behavior using computer simulation. In risk potential models, the driver calculates the risk potential for each object in their forward view. The driver then decides their behavior based on the calculated risk potential for the space around them. Figure 1 shows three examples of risk potential maps. Each map includes a potentially moving obstacle with different speeds: 1) stopped, 2) moving normally, and 3) moving quickly.

In the 20th century, Kageyama developed a driver model which included the driver's mental influence on the perception of risk from elements of the environment. Kageyama found that a driver thinks not only about their course but also about how to manipulate the vehicle's controls. In his research, he measured the driver's instantaneous heart rate to test his belief that the closer the vehicle gets to the side of the road, the driver will perceive higher risk [2, 3]. Kageyama reported that the driver's heart rate increases exponentially based on the distance from the side of the road and, thus, the risk perceived by the driver can be defined according to the driver's instantaneous heart rate. In addition, the driver of the vehicle chose a course that minimized risk suggesting that drivers decide their course based on their own risk potential field. Since Kageyama's research, many researchers have studied and constructed driver models using risk potential theory not only for collision avoidance but also for car following [4–10].

Kobayashi et al. constructed an obstacle avoidance driver model using risk potential model in which a course was selected based on a minimum point of risk potential for Double Lane Change (DLC) scenario in order to avoid an obstacle in an emergency [6, 7], a common method for evaluating vehicle performance. Raksincharoensak et al. proposed a motion planning and control system based on the prediction of potential risk of collision by experienced drivers. They applied optimal control theory to the calculated risk potential to set parameters such as yaw rate, wheel angle, deceleration, and braking torque[4]. Raksincharoensak et al. address a typical urban scenario in which a pedestrian suddenly darts into traffic from a blind corner, e.g. behind a parked car. In this scenario, the driver has limited time to avoid a collision. Raksincharoensak et al. tested their proposed control system in the scenario by comparing the computer simulation results with the actual driving data collected from experienced drivers and showed that their proposed autonomous driving system matches the actual driving of the experienced drivers. Limited research has considered the behavior of other traffic participants (i.e., pedestrians and other vehicles) in construction of risk potential models[4, 8]. Even though Raksincharoensak et al. consider the appearance of a pedestrian in their model, their model just predicts the pedestrian dynamics before passing, so the dynamics of the pedestrian are fixed. Furthermore, their research only includes one situation in which the pedestrian comes from the left and suddenly appears from behind a parking vehicle. Therefore, consideration of multiple pedestrian dynamics is needed to assess the effectiveness of risk potential models.

3. Approach

3.1 Pedestrian Dynamics

In this paper, we develop a driver model for a moving vehicle passing pedestrians that may be crossing or intend to cross the street. Whereas previous research has limited consideration of direction and speed, we vary the speed of the pedestrians as they approach and cross the street. Pinna et al. reported that pedestrian walking speed is approximately the same with the exception of those age 65 or older [11]. Tarawneh reported that the mean pedestrian walking speed

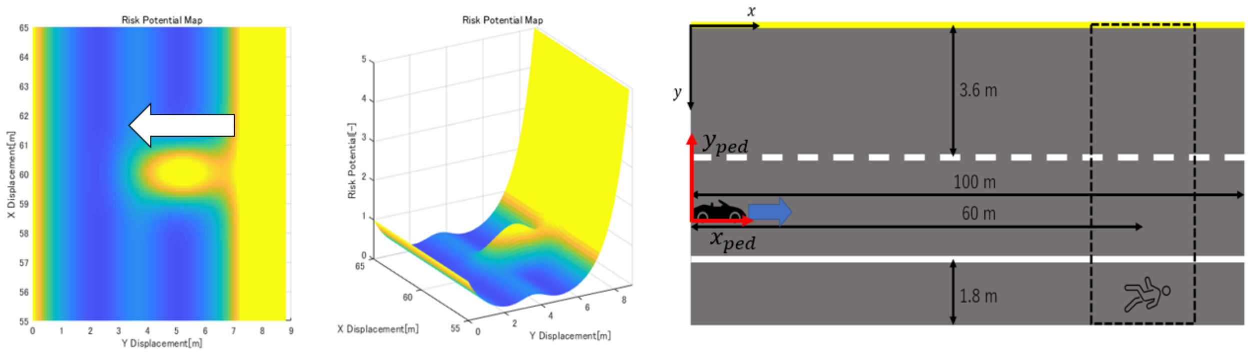

Figure 2: Road environment (right side) and its risk potential map (left side).

at signalized intersections is 1.34 m/s [12]. Knoblauch et al. reported that the overall mean speed at signal-controlled intersections in four urban areas for younger pedestrians is 1.46 m/s while for older pedestrians it is 1.21 m/s [13]. Based on these observations, we assume that a pedestrian's walking speed is approximately 1.3 m/s. The starting velocity of the vehicle in the scenarios is set to 18 m/s (64.8 kph, 40.3 mph). We define multiple scenarios in which there is a significant risk of collision (unsafe) and no risk of collision (safe). For instance, in one scenario, a pedestrian crosses the road ahead of the vehicle at 1.3 m/s and, if the driver doesn't brake, the vehicle will collide with the pedestrian. In a safe scenario, the pedestrian approaches the road from a sidewalk at 1.3 m/s, but stops at the center of the sidewalk without entering the road. In this scenario, the risk changes dynamically with some risk of collision at first but the risk suddenly diminishes when the pedestrian stops moving.

3.2 Risk Potential Function

In this section, we describe the risk potential functions that are used in the models. According to Kageyama's research, perception of risk can be described by exponential functions. Because of this, we use an exponential function for calculating the risk potential field for each of the obstacles [2]. Equation 1 to 4 indicate each risk potential function.

$$R_{L_{road}}(Y) = A \times e^{\frac{1}{L} \times (Y - Y_{end})} \tag{1}$$

$$R_{R_{road}}(Y) = A \times e^{-\frac{1}{L} \times (Y - Y_{end})} \tag{2}$$

$$R_{center}(Y) = \frac{1}{4} \times e^{-B \times (X - X_{ped})^2} \tag{3}$$

$$R_{Ped}(X,Y) = e^{-C \times (X - X_{ped})^2 - D \times (Y - Y_{ped})^2} \tag{4}$$

$R_{L_{road}}$ and $R_{R_{road}}$ indicate the risk potential associated with each shoulder of the road. The coefficient A indicates the risk potential at the shoulder and L is the relaxation length of the risk potential. L is equal to the time constant and can be used to adjust the sensitivity of the driver model. For instance, as L increases, the derivative value of risk potential also increases. In other words, if L is large, the driver is more 'scared' of risk than other drivers. R_{center} is the risk potential from the center line of the road and the coefficient B indicates the risk potential at the center line. R_{ped} is the risk potential associated with the pedestrian. The coefficients C and D indicate derivative values of R_{ped} and depend on a pedestrian's dynamics and the vehicle position. If the vehicle has passed the pedestrian (i.e., the vehicle's longitudinal position is higher than the pedestrian's longitudinal position), the driver should not consider the pedestrian to be a risk. In that condition, R_{ped} would be zero. In addition, we define three models for R_{ped} by changing the coefficients C and D. In the first model, R_{ped} is affected by only the distance between the pedestrian and the vehicle. This model is a conservative model (C and D are set to 1) and matches models used by previous researchers [4]. In the second model, R_{ped} is affected by the relative velocity between the pedestrian and the vehicle. This model is similar to the risk potential model proposed by Li et al [8]. As the relative velocity increases, the risk potential gets higher. In the third model, R_{ped} is affected by the Pedestrian Potential Position (PPP) and the Time to Collision (TTC). For instance, if TTC is 3.0 s, the pedestrian can move up to 9.0 m based on their estimated maximum speed. We refer to this as the potential position and it is calculated by TTC times the maximum speed of the pedestrian. This model accounts for maximum potential change in speed and direction and therefore position, but likely overestimates the risk associated with the pedestrian.

In our risk potential map, R_{Lroad}, R_{Rroad} and R_{center} do not depend on dynamics (speed). Because of this, we can calculate the total risk potential using equation 5. From these equations, we construct a risk potential map in our simulation and apply it to our collision avoidance driver model as discussed in the driver model section.

$$R_{sum} = R_{L_{road}} + R_{R_{road}} + R_{center} \tag{5}$$

3.3 Road Environment and Its Risk Potential Map

In this paper, we discuss the validity of our risk potential model in a road environment that has a sidewalk, center line, a pedestrian, and a road boundary in simulation. This section shows the road environment of our research. Figure 2 shows the risk potential map for our road environment that includes a one-way road with two lanes, one sidewalk, and a pedestrian. Each lane is 3.6 m wide and the sidewalk is 1.8 m wide. The vehicle's initial x position is 0 m, y position is 5.4 m, and speed is 18 m/s. The pedestrian's initial x position is 60 m. The pedestrian's y position and speed depend on the scenario. The ellipse at the center of the map represents the risk potential of the pedestrian as the pedestrian tries to cross from the right sidewalk to the left sidewalk. The maximum risk potential is usually 1.0. For example, the risk potential from the pedestrian would be 1.0 at the center of the pedestrian's current position and the risk potential from the sidewalk would be 1.0 at its boundary. The risk potential associated with the center line separating the two lanes is set at 0.25 based on Li et al [8]. However, the risk potential for the right sidewalk is set beyond 1.0. In general, vehicles seldom enter the sidewalk so we set the right-side road boundary at 7.2 m. Therefore, the risk potential is 1.0 at 7.2 m and increases exponentially beyond that point.

3.4 Velocity model and PPP model

As mentioned in the last section mentioned, the second model (Velocity model) is affected by the relative velocity between the pedestrian and the vehicle such that the coefficients C and D are related to velocity. We define the coefficients C and D as equation 6 shown. The third risk potential model (PPP model) is affected by Pedestrian Potential Position (PPP). The PPP is the distance that pedestrian might move before the vehicle reaches the crosswalk. Therefore, PPP can be described using Time to Collision (TTC) and the coefficients C and D are defined by equation 7.

$$C, D = \frac{G_C}{Vx_{Vehicle} - V_{x_{ped}}}, \frac{G_D}{Vy_{Vehicle} - V_{y_{ped}}} \tag{6}$$

$$C, D = \frac{G_C}{PPP}, \frac{G_C}{PPP} (PPP = \frac{x_R}{Vx_{Vehicle}} \times V_{ped_{max}}) \tag{7}$$

In equation 7, $\frac{x_R}{V_{x_{Vehicle}}}$ indicates TTC, x_R is the longitudinal distance between the pedestrian and the vehicle, and $V_{Vehicle}$ is the velocity of the vehicle (set to 18 m/s). $V_{ped_{max}}$ is the maximum velocity of the pedestrian which is set to 3.0 m/s. We apply this in the PPP model to our risk potential function to define the coefficients C and D. If PPP is lower than x_R, it means that, moving at maximum speed, the pedestrian cannot collide with the vehicle. Therefore, the risk potential R_{ped} would be zero. So the coefficient C and D should diverge to infinity when PPP is lower than y_R. In this research, G_C and G_D are set at the minimum value with which the model can avoid a collision in an unsafe scenario.

3.5 Driver model

In this research, we construct a novel driver model using risk potential theory and consideration of pedestrian dynamics. The model has two inputs: 1) an action threshold for risk potential, R_{th}, and 2) calculated risk potential. The action threshold for risk potential defines the point at which, when risk potential exceeds the threshold, the driver will take action and apply the brakes to reduce risk. In the current study, the action threshold is equivalent to the minimum risk potential of the map (center of an empty lane, 0.15). The calculated risk potential is calculated instantaneously by the driver based on the circumstances of the road environment. The risk potential is the sum of the risk potential fields of the pedestrian and the road elements. Based on the total risk potential and the risk potential threshold, we define the deviation as in Equation 8 and the model calculates the deceleration rate according to Equation 9. K indicates a maximum deceleration rate such that if the gain K is 5.0, the maximum deceleration would be 5.0 m/s^2. We assume that a comfortable deceleration is below 3.0 m/s^2, therefore, the gain K is set to 3.0.

$$R_{dev} = |R_{th} - (R_{sum} + R_{ped})| \tag{8}$$

$$a = K \times R_{dev} \tag{9}$$

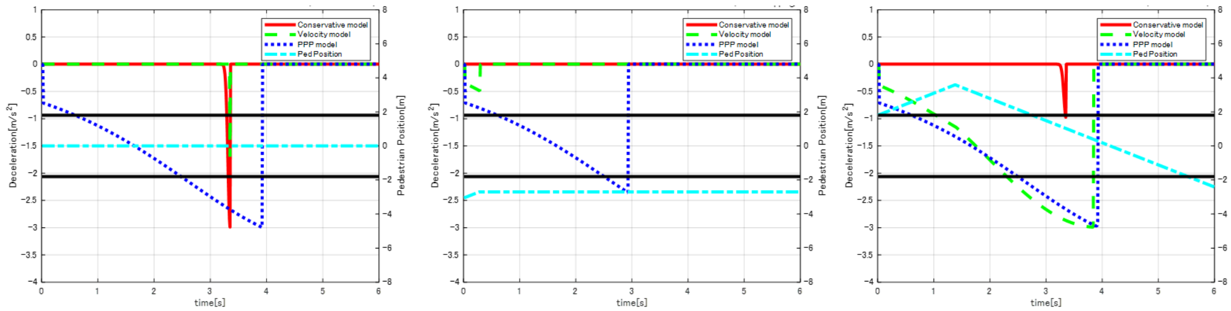

Figure 3: Simulation results in deceleration for the conservative model (solid red), the velocity model (dashed green), and PPP model (dotted blue).

4. Results and Discussion

The proposed driver models were tested in multiple scenarios in simulation. The three risk potential models were tested in each scenario. The performance of the vehicle was evaluated relative to three objectives: minimize occupant discomfort, avoid false alarms (unnecessary braking), and reduce the risk of collision or injury from the collision. Figure 3 shows the deceleration data for each model in three scenarios (left: the pedestrian stops at the center of the lane, center: the pedestrian is initially crossing but stops at the edge of the sidewalk, right: the pedestrian crosses the lane before the vehicle approaches, but turns back leading to a collision if the driver does not brake). The black lines indicate the boundaries of the lane in which the vehicle is traveling. If the pedestrian (light blue dashed line) is between the black lines, it is an unsafe situation. Therefore, the left and right figures are considered to be unsafe scenarios, and the center scenario is safe.

In the first scenario (left figure), all models result in a collision, but the PPP model decelerates the most (down to 11 m/s). According to the Foundation of Traffic Safety, the speed at which a vehicle impacts a pedestrian is highly related to the risk of severe injury and death[14]. According to the report, the risk of injury at 18 m/s is 75% and 25% at 11 m/s. Based on the observed deceleration, the PPP driver model may reduce the risk of injury and death by one-third compared with the other two models.

In the second scenario (center figure), both the velocity and the PPP models brake even though there is no risk of collision. The PPP model brakes until the model perceives that it is safe (until PPP $< y_R$). This is because the PPP model still perceives some potential risk from the pedestrian as the pedestrian could cross the road suddenly. When the pedestrian cannot reach the road before the vehicle passes, the PPP model perceives the situation as safe and stops braking. This result shows that both the velocity and the PPP model respond to a false alarm, and the conservative model can minimize occupant discomfort in this situation.

In the third scenario (right figure), all models collide with a pedestrian as in the first result. Both the velocity model and the PPP model reduce the risk of injury from 75% to 25%. Therefore, even though our two proposed models cannot avoid collision in a suddenly unsafe situation, it may reduce risk of severe injury and death as the model does decelerate more than previous research models. However, the PPP model tends to have false alarms as the model considers the possibility of collision with a pedestrian because of the possibility of the pedestrian changing their behavior. False alarms may discomfit the occupants and affect traffic flow, but reducing the risk of injury is more important. Therefore, the PPP model shows better results than the previous research models considering the weight of the risk of injury against road occupant discomfort due to false alarms.

5. CONCLUSIONS

In this research, we proposed novel driver models using risk potential theory and evaluated three approaches for assessing risk potential in our driver model. The resulting PPP model shows better results than the other two models in unsafe scenarios even though it cannot fully avoid a collision. Based on the parameters set to minimize deceleration, the PPP model was able to decelerate its velocity to 11 m/s and reduce the risk of injury from 75% to 25%. Despite the PPP model outperforming the other models with respect to risk of injury, the PPP model does decelerate for pedestrians that are stopped at the side of the road (a potential false alarm). While there is some potential for a stopped pedestrian to begin to cross, the PPP model reacts to every stopped pedestrian as a threat. It may be possible to determine whether the pedestrian intends to cross. Incorporating input from a classification system that determines pedestrian intent to cross could further reduce unnecessary deceleration. In addition, the proposed models presented here are not derived from observation of human drivers as is typical of risk potential research. Observing human drivers in these scenarios may reveal adjustments to the risk potential model that improves the trade-offs made between deceleration to maximize pedestrian safety and avoiding unnecessary deceleration that affects comfort for occupants and slows the flow of traffic.

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