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Vulnerable Road Users Overtaking Path Planning on Urban Road Considering Individual Driving Styles

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Abstract

In order to reduce the number of traffic accidents related to vulnerable road users (cyclists, pedestrians), recent studies show great interest in developing intelligent technologies for Advanced Driver Assistance Systems. One of the latest functions is navigating the vehicle in a reference trajectory to avoid a possible collision. However, the assistance system may be deactivated due to disagreement on ideal reference path between individuals. In this paper, we proposed the path planning method considering driving styles of drivers for overtaking a moving vulnerable road user on urban road where there is no clear risk of collision. The optimal paths which were generated based on widely studied artificial potential field method are expected to be human-like and generally accepted by drivers. An improved repulsive function was proposed for representing a vulnerable road user walking on the shoulder of the road. The parameters of potential functions for each driving style were identified using avoidance driving data. Then the potential map was created and unique reference paths were calculated with gradient descent method. The proposed method can be a useful integration to Advanced Driver Assistance Systems for gaining driver's mutual acceptance in approaching and avoiding a moving vulnerable road user.

Keywords: Advanced Driver Assistance Systems (ADAS), driving style, path planning, potential field, vulnerable road user.

1. Introduction

According to the 2020 Annual report from e-Stat [1], Statistics about Road Traffic show a high portion of urban area accidents which account for more than 80% of cases. Most of them happened at the intersection (about 58% of urban accidents), but they also took place on a straight road with high possibility (nearly 35%) [1]. In such places, driving, cycling, and walking are the most popular transportations method [2, 3]. Despite having designated roads, there are interactions between vehicles, cyclists, pedestrians every day. Although accidents between vehicle and pedestrian, cyclist account for a relatively small proportion, crashes between motor vehicles and pedestrian, pedal cyclist often results in serious injuries [1, 2]. Pedestrians, pedal cyclists who are often labelled as vulnerable road users (VRU), are at high risk of injury or death in case of collision with other road users due to unprotection [3]. From 2010, annually, traffic accidents related to cyclists and pedestrians caused about 50% of deaths in Japan [2]. Fatality rate of cyclists and pedestrians is eight times higher compared to that of motor vehicle occupants [2]. Globally, cyclists and pedestrians account for 26% of all road traffic fatalities [3].

Therefore, recent studies show great interest in developing intelligent technologies to reduce the risk of collision between vehicles and pedestrians, cyclists. The interaction between vehicle and VRU has been intensively studied with a focus on the overtaking strategy, the lateral gap between vehicle and VRU when vehicle starts avoiding, passing and the influence of various factors (road, VRU, surrounding vehicle, etc.) [2-4]. Driver behaviours were generalized to develop Advanced Driver Assistance Systems (ADAS) for collision avoidance purposes, such as Adaptive Cruise Control (ACC), Forward Collision Warning (FCW), Autonomous Emergency Braking System (AEBS) [5, 6]. ACC is designed to regulate the vehicle speed in a safe manner when approaching forward obstacle. FCW such as Pedestrian and Cyclist Collision Warning sends alerts up to 2 seconds before an imminent collision with VRU, allowing driver time to react. The alert is based on the calculation of the Time-to-Collision (TTC) with VRU. AEBS is developed to detect the crossing pedestrian and alert

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the driver to avoid collision by applying the brake, and if no action is taken by a driver and collision is likely to happen, it brakes automatically. Accordingly, the vehicle can respond to the existence of moving obstacles in driving lane. These functions reduce the change of an impact in vehicle – VRU interactions, such as VRU suddenly changes direction, crosses the road, or dashing out from the rear of a forward vehicle, etc. In summary, the ADAS provides assistance in minimizing the risk in vehicle - VRU interactions.

However, these assistances are possibly less useful in VRU overtaking situations along the road where there is no clear risk of collision. While VRU is moving on its designated place (footpath, cycling lane), the vehicle can go straight with some warnings, or slow down and even stop. In spite of effective performances, such systems may be turned off due to driver's acceptance level, which varies between individuals [4]. Analyses show the trend of VRU avoidance: drivers steer away to keep a large gap when passing VRU in most situations [2-4]. For this reason, another kind of assistance would be better suited: the ADAS should navigate the vehicle in an ideal trajectory to overtake the VRU [3]. This idea is aligned with the Lane-keeping Assistance (LKA) function. LKA was designed to prevent a vehicle from drifting into another lane by automatically employing steering and/or braking in order to bring the vehicle back to the centre of the lane.

In an effort to reduce the disturbance, it is important to consider how drivers envision the situation. It is suggested that there are distinguishable types of driver behaviour with regard to overtaking strategy and lateral gap when passing VRU [2, 3]. Considering the ideal trajectory as a reference path, the ADAS (ACC and LKA functions) supports the driver in controlling the car at suitable velocity and lateral gap to VRU. With assumption that drivers in each type have the same risk limit, they will easily accept the ADAS's response within their designated risk range. As a consequence, for path planning, the study of unique trajectory for vehicles considering individual driving styles is essential.

The remainder of this paper is structured as follows. Section 2 discusses related works with regard to path planning and driving style. Unique driving styles for VRU overtaking are analyzed in section 3 by controlled experiments. Section 4 illustrates the model for planning ideal path using potential field method. Section 5 shows the result of proposed method respecting individual driving styles.

2. The Related Works

2.1. Works on Path Planning

Path planning generates a safe path without collision with obstacles, which is a dynamically feasible trajectory for moving from start to goal configuration, and comfortable for passenger. A path planning for the vehicle can be a path and pre-defined velocity profile. Existing work on planning techniques includes graph search, sampling, interpolating and numerical optimization.

Graph Search Based Planners such as Dijkstra Algorithm, A-Star Algorithm, find the shortest path in a series of nodes or grids. These algorithms are suited for global planning but costly in terms of speed and memory in vast areas due to a large number of nodes. The resulting path is not continuous and not suitable for real-time applications. Applications using these families can be seen in some automated vehicles that participated in the DARPA Urban Challenge.

One of the state-of-the-art sampling-based planners is Rapidly-Exploring Random Tree, that is capable of online planning. This approach provides a fast solution in multi-dimensional systems. The algorithm is proven good enough for global and local path planning in environment with obstacles but might not converge to an optimal solution. The optimality of the path strongly depends on the time frame. The result path is not continuous and jerky.

Interpolating Curve Planners are used to generate smooth path for a given set of way-points. This approach has advantage in low computation cost and is suitable for local planning. Clothoids and Splines Curves have been used in automated vehicle. But these planners depend on global waypoints. The solution of Clothoids curve planner is continuous but not smooth. The Splines curve might not be optimal from the road fitness and curvature minimization point of view.

Numerical Optimization approach optimizes a function subject to different constrained variables, such as position, velocity, acceleration. This technique improves the potential field method in robotics for obstacle avoidance and navigating in narrow passage with continuous path [5]. The optimization takes place at each motion state for smooth computed trajectories. Despite time-consuming in theory, the method has been experimentally verified for low-speed maneuvers (i.e. urban areas). Path planning and path tracking can be done in real-time with optimal solutions [5, 6].

2.2. Works on Driving Style

Driving style can be understood as the manner of driver controlling the car in a driving situation under the influence of external factors (weather, time in the day, etc.) and internal factors (attitude, characteristics, mood, etc.) [7]. Driving style can be classified with regard to the way that driving task was accomplished: safe and unsafe, fuel consumption and excessive fuel consumption, from very bad to very good. Considering the driver aggression, there are aggressive and calm drivers. According to the mood, there is reckless, anxious, angry, and patient driving style.

Driving style takes an essential part in safety driving and is the key to ADAS development [8]. Those features support drivers during specific events. Their development is usually based on an expert's characteristics. Due to the variety of driving styles, these systems might not adapt to a specific driver. Therefore, the next generation of ADAS functions focuses on driving style which personalizes the system performance. Such ADAS features can assist in the driver's acceptance with high performance [5, 6, 9].

2.3. Research Contributions

In this paper, we propose the path planning for VRU overtaking in an urban area's straight road with VRU moving in the same direction on the shoulder. To the best of our knowledge, previous works did not mention this location of VRU due to no clear risk of collision. To generate the ideal path with regard to driving style, we use the potential field method with numerical optimization for the function of risk from driving scene and VRU. Our direction is distinguishable from other works because of its capability to handle the individual driving style while still keeping the simplicity of the algorithm. Moreover, the planning is not only suited to a static obstacle but also a moving obstacle as a result of the improved repulsive function in the potential field. By analyzing and generalizing the driving data, we propose the classification of driving style in VRU overtaking situation. The inclusion of different driving styles and the method to choose driver's behaviour is essential to increase the driver's acceptance of the reference path. The realization of path planning consists of the following steps.

- Collected and studied driving data
- Formulated potential functions (PF)
- Identified personalized parameters for PF
- Generated paths based on potential field map

3. The Related Works

This section mainly explains the controlled experiments using the Immersive Driving Simulator (DS) [2] and analysis result of driving behaviours in approaching and overtaking the VRU.

3.1. Experiment Configuration

The experiments took place in the DS with stereoscopic vision at Nagoya University. A realistic cockpit with all necessary equipment was placed in a square room in which floors and walls were used as a screen for 4K resolution images of driving scene. Using a head tracking system, the images were displayed from a view point that matches the position of the person. Immersive display offers binocular parallax stereoscopic vision and motion parallax stereoscopic vision, and faithfully reproduces the sense of depth and distance. The cabin was installed on the 6DOF motion platform which is capable of noticing the driver of the generation of acceleration due to the driving operation. Equipped with such unique functions, the vehicle and driving environment were quite realistic and it is more secure than real field test as shown in Fig. 1.

The overtaking scene is a straight road in urban area (Fig. 2) in which environmental factors such as buildings, houses, road's dimension, VRU's type, VRU's location, vehicle's initial speed are varied. The experiment configuration is detailed in Table 1. There is no oncoming vehicle because its high risk may result in termination of overtaking maneuver. As a result, there are 48 combinations of overtaking situation. There is an automatic phase when the vehicle was set at the centre of its driving lane with a pre-defined initial speed. The driver could change the velocity and direction in manual phase. A notification sound was played when switching between phases.

Table 1. Experiments' configuration.

Factors	Details			
Lane width [m]	3.0		3.5	
Shoulder width [m]	1.0		1.5	
Vehicle's initial speed [km/h]	30	40	50	60
VRU's type	Child	Adult	Cyclist	
VRU's location	Centre of shoulder		Near the edge	

Fig. 1. The Immersive Driving Simulator.

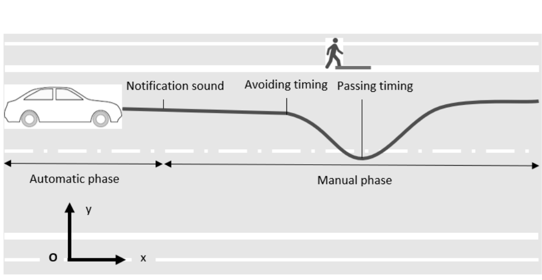

Fig. 2. Driving situation.

A group of eighteen volunteers who has valid driving license was recruited to participate in the experiment with the approval by the Ethical Review Board based on the regulation of Institute of Innovation for Future Society, Nagoya University. They had been given information about the regulation of experiment, safety precaution and consented the use of collected data. These experienced drivers (age 54.1±11.6) were assumed with stable driving behaviour. At the beginning of experiment, each participant had a trial run to get familiar with the simulator. They were told to drive freely after hearing a notification sound, without notice about the VRU. There was no guidance about how to overtake the VRU. The experiment took about one hour and 48 overtaking maneuvers per driver were collected for this study.

3.2. Analysis of Driving Styles

It is argued that in driving simulator, drivers will drive more aggressively than in reality. To our surprise, a small part (16,67%) of drivers chose to accelerate in approaching the VRU. Some of the drivers (11,11%) chose to brake to slow speed (20-30 km/h) albeit in spite of initial speeds or VRU. Moreover, even though the VRU only moved along the shoulder of the road, drivers chose to steer away in order to keep a larger lateral gap to VRU than initial gap. The largest lateral gap in approaching and overtaking phase is right before or after the vehicle passed the VRU.

As shown in data, there are three driving styles with non-identical driving behaviours among drivers, based on the overtaking strategy and the lateral gap when passing VRU. Fig. 3 shows an example of three driving styles of the overtaking maneuver in a specific situation: vehicle's initial speed is 50 km/h, VRU is a child who walked near the edge of the lane of a narrow road (lane width 3.0 m, shoulder width 1.0 m).

Driving style 1) Overcautious – drivers released throttle pedal and pressed brake pedal to reduce speed significantly, then passed the VRU with largest lateral gap in compared to other groups.

Driving style 2) Competent – drivers only released throttle pedal to reduce a little speed. They might accelerate during approaching the VRU but the maximum velocity was as high as the initial speed. Their lateral gaps were smaller than those of overcautious drivers.

Driving style 3) Reckless – these drivers almost ignored the VRU. They accelerated to a high speed of 50-70 km/h even in urban area. Their lateral gaps were the smallest, but larger than the initial lateral gap.

Two-thirds of the data were in driving style 2 while driving style 1 and 3 almost had the same amount. It suggests that a conventional ADAS may disturb drivers in one-third of situations.

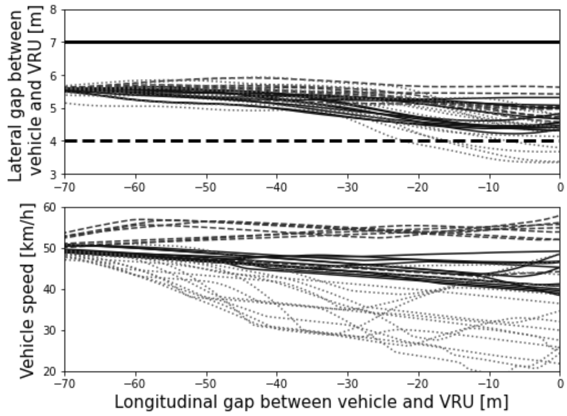

Fig. 3. Driving behaviours of different driving styles: overcautious (dots), competent (lines), reckless (dashes) in a specific situation.

3.3. Proposal of Driving Behaviours

As mentioned above, path planning for vehicle relies on the desired overtaking strategy and the largest lateral gap to VRU. There are three driver behaviours 1, 2, 3 which are corresponding to three driving styles, respectively. Driver behaviour 1, 2 contains: speed reduction to the desired speed $V1$, $V2$ and a reference path with largest lateral gap $D1$, $D2$, respectively. Driver behaviour 3 contains speed acceleration to the desired speed $V3$ and a reference path with largest lateral gap $D3$. The values of desired velocity and largest lateral gap must satisfy:

$$V1 < V2 < V3 \tag{1}$$

$$D1 > D2 > D3 \tag{2}$$

The vehicle velocity is monitoring from the time when VRU is within recognized range to avoiding timing. Avoiding timing can be estimated by perceptual risk index [9]. The path planning will be selected at avoiding timing based on the criteria of approaching velocity that is defined as below.

If there is a drop in velocity and the driver brakes in approaching, then driver behaviour 1 is selected.

If there is a speed deceleration but no braking action, then driver behaviour 2 is selected.

If the velocity increases without braking action around the avoiding timing, then driver behaviour 3 is selected.

4. Potential Field Method for Path Planning

This section describes the definition of potential functions to develop a risk-free reference path for approaching and overtaking the VRU based on Artificial Potential Field Method (APFM) [5] and parameter's identification method considering the driver's driving style.

4.1. APFM Functions

The basic idea of APFM treats vehicle as a point under potential force in an artificial force field that moves from starting point to the goal point. The total potential field contains the attractive field and repulsive field. PF is always considered as function of distance. The goal should be a place that is ahead of the vehicle. A force by attractive field makes the vehicle move toward the goal. There are environmental factors (infrastructure, road users) which form repulsive field. The repulsive field of such obstacle exerts repulsive force that pushes the car away and prevents collision. The synthesis of both attractive and repulsive force (or artificial force) is defined as the negative gradient of PF which is the steepest descent direction for guiding the vehicle on road to goal without making contact with other road users.

In a Cartesian coordinate system, the location of vehicle is defined by $q = (x, y)$ and the PF is defined by $U(q)$.

$$U(q) = U_a(q) + U_r(q) \tag{3}$$

$$U_a(q) = U_g(q) \tag{4}$$

$$U_r(q) = \sum_i U_{in}(q) + \sum_j U_{ru}(q) \tag{5}$$

where: $U(q)$ is the artificial potential field. $U_a(q)$ is the attractive field. $U_r(q)$ is the repulsive field. $U_g(q)$ is the goal attractive field. $U_{in}(q)$ is the infrastructure repulsive field. $U_{ru}(q)$ is the other road user repulsive field. i and j denote the ith infrastructure, jth road user, respectively. x, y are the positions of the vehicle in the x and y direction, respectively.

The goal is set at the centre of current lane, ahead of VRU. Hence, the attracting PF will be a constant gradient potential toward goal. The PF from desired goal is expressed in (6).

$$U_g(q) = -A_{goal}(x) \tag{6}$$

Infrastructure is represented by the edge and the centre of driving lane. The infrastructure potential field not only prevents the vehicle departing from the road but also guides it toward the centre of its driving lane. The PF is modelled as one-dimensional gaussian function with infinite value at the edge and minimum value at the centre of driving lane. Potential functions are expressed in (7).

$$U_{in}(q) = A_{edge} \sum_{k=l,r} e^{-\frac{(y-y_{ek})^2}{\sigma_e^2}} - A_{lc} e^{-\frac{(y-y_{lc})^2}{2\sigma_{lc}^2}} \tag{7}$$

where: A_{edge} determines the maximum amplitude of the edge of the road. σ_{el}, σ_{er} determines how quickly the potential rises. y_{el}, y_{er} are positions of the left and right edge of the road in the y direction, respectively. A_{lc} determines the minimum amplitude of the centre of the driving lane. σ_{lc} determines how quickly the potential falls. y_{lc} is position of the centre of driving lane in the y direction.

Vulnerable road user is expressed by usual two-dimensional Gaussian function in (8) with regard to its estimated position (9). Estimated time for vehicle to arrive at passing point is expressed in (10).

$$U_{vru}(q) = A_{vru} e^{\left[-\frac{\left(x-Bx_{est_{vru}}\right)^2}{\sigma_{vru}^2} - \frac{(y-y_{vru})^2}{\sigma_{vru}^2}\right]} \tag{8}$$

where: A_{vru} and σ_{vru} determine the maximum amplitude and how quickly the potential rises of the VRU. x_{estvru}, y_{vru} are the estimated position of the road user in the x, y direction, respectively. B is the compensated parameters for the road user's longitudinal position due to overtaking strategy.

We assume no change in lateral position of a road user during VRU overtaking process. Estimated longitudinal position of the road user at passing timing is defined as follows:

$$x_{est_{vru}} = \Delta D + V_{vru} t_{est_{vru}} + 0.5 a_{vru} t_{est_{vru}}^2 \tag{9}$$

$$t_{est_{vru}} = \frac{-\Delta V + \sqrt{\Delta V^2 + 2\Delta D \Delta a}}{\Delta a} \tag{10}$$

$$\Delta V = V - \alpha V_{vru} \tag{11}$$

$$\Delta D = x_{vru} - x \tag{12}$$

$$\Delta a = a - \alpha a_{vru} \tag{13}$$

where: x_{est_ruj}, t_{est_ruj} is estimated position when vehicle passes road user and estimated travelling time; ΔD, ΔV, Δa are the relative longitudinal gap, relative velocity and relative acceleration between vehicle and the road user, respectively; x, V, a are the longitudinal position, velocity and acceleration of vehicle, respectively; x_{vru}, V_{vru}, a_{vru} are the longitudinal position, velocity and acceleration of the road user, respectively; the effect of road user directions is modelled by parameter α.

The PF is illustrated in Fig. 4. Then, the desired motion from any given position q can be determined by the negative gradient ($-\nabla U(q)$) of PF, as in (14). At every point in the field, the car moves along the direction of the PF vector at that point.

$$-\nabla U(q) = -\left[\frac{\partial U(x,y)}{\partial x} \; \frac{\partial U(x,y)}{\partial y}\right]^T \tag{14}$$

4.2. Identified Personalized Parameters for Potential Functions

The reference path is designed based on the total artificial potential field. In conventional APFM, the potential functions were designed based on only the geometrical information, no optimization process is involved in. So, the reference path will be safe but not optimal. In this study, personalized PF is designed to accurately reflect the driving behaviour of unique driver. Evolutionary algorithm is used to optimize the PF, i.e., find the fittest parameters of PF for each driving style. The study focuses on the VRU's perception and assumes the parameters of infrastructure are identical across drivers. The optimal trajectory is not the shortest trajectory, but it is the safest and accepted by drivers.

The identification problem is formulated by the following optimization problem.

Given:
Infrastructure information: y_{el}, y_{er},
Vulnerable road user position: x_{vru}, y_{vru}.
Vehicle position, velocity: $q\left(x_k^l, y_k^l\right), \dot{q}\left(x_k^l, y_k^l\right)$
Find: $A_{goal}, A_{edge}, \sigma_{el}, \sigma_{er}, A_{lc}, \sigma lc, A_{vru}, \sigma_{vrux}, \sigma_{vruy}$.
which minimize:

$$J = -\sum_{l}^{L}\sum_{k}^{K} E\left(\dot{q}\left(x_k^l, y_k^l\right), grad\left(x_k^l, y_k^l\right)\right) \quad (15)$$

Subject to:

$$E(\dot{q}, grad) = \frac{\dot{q}.grad}{|\dot{q}||grad|} \quad (16)$$

$$grad(q) = -\nabla U(q) \quad (17)$$

where: $k \in \{1, 2, 3\ldots, K\}$ and $l \in \{1, 2, 3\ldots, L\}$ denotes the number of the data in sequence of one trial and number of trials in the experiment, respectively. $q\left(x_k^l, y_k^l\right), \dot{q}\left(x_k^l, y_k^l\right)$ are the position and velocity of vehicle at point k in trial l, respectively.

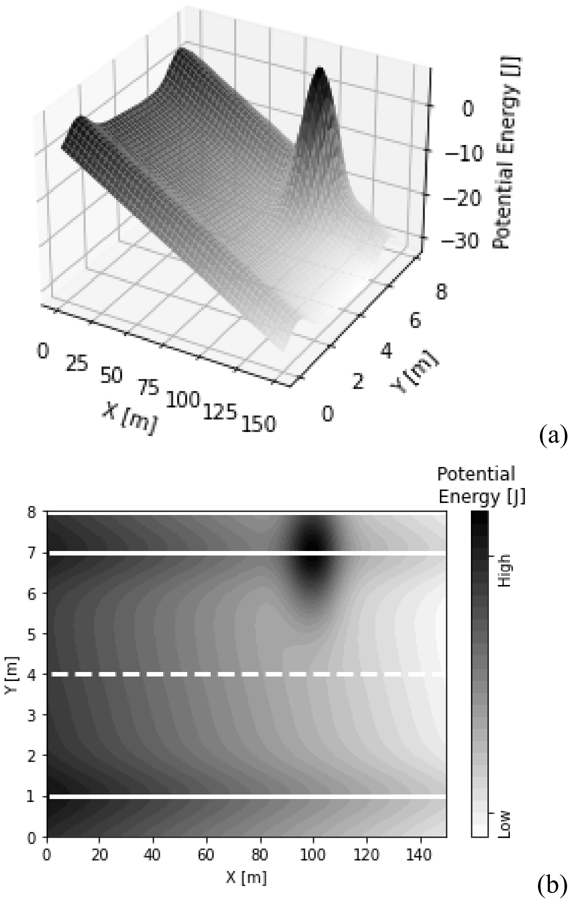

Fig. 4. Example of total potential field map in 3D view (a) and contour view (b)

Using the driving data, parameters in those functions are identified by genetic algorithm [10]. The workflow is shown in Fig. 5. For generating initial population, the floating-point coding method is used for large range of variables, high accuracy and continuous. Data is generated by the random Halton sequence [11]. Roulette Wheel Selection is used to determine how to select those individuals from the parent population in combination with the optimal preservation strategy [12]. As a consequence, the probability of each individual being selected is proportional to its fitness size and the most adapted individuals in the current population directly into the next generation. Since a small number of genes, a single point crossover is used to set a random crossover point in the coding strings of individuals and then parts of the chromosomes of two paired individuals are exchanged with each other at that point. After crossover, there is a possibility that some replication errors may occur in their cell division due to some accidental factors, which may lead to some mutations in some genes. For individuals encoded by floating-point numbers, the gene value at a variation point will be taken from a defined range. The variation operation is to replace the original gene value with a random number in that range. There are three termination conditions: (1) when an upper limit on the number of the generations is reached, or (2) when there has been no improvement in the population after defined iterations, or (3) when the objective function value has reached a certain pre-defined value.

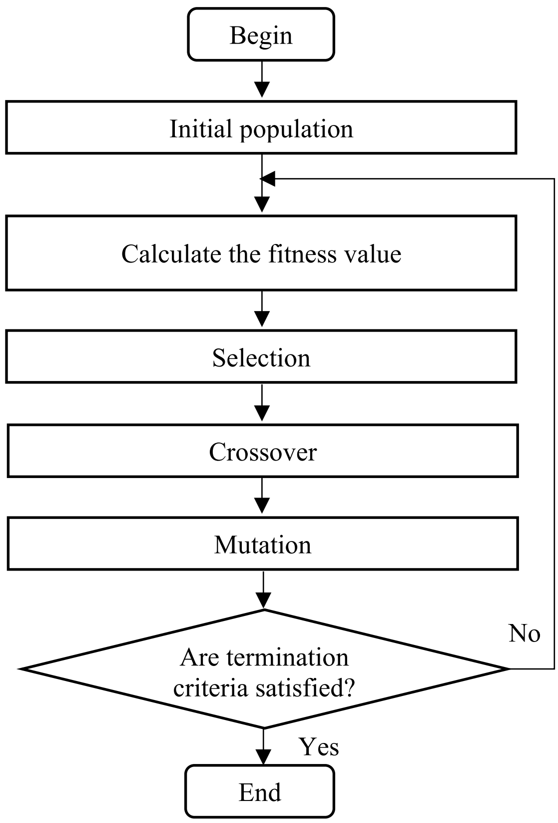

Fig. 5. Genetic Algorithm workflow

Table 2. Parameters of potential functions.

Parameters	A_{goal}	A_{edge}	σ_{el}	σ_{er}	A_{lc}	σ_{lc}	A_{vru}	σ_{vrux}	σ_{vruy}
Driving style 1	1	5	0.8	0.8	2.5	2	3.8	30.3	3.2
Driving style 2	1	5	0.8	0.8	2.5	2	2.0	48.6	3.1
Driving style 3	1	5	0.8	0.8	2.5	2	1.0	22.5	3.2

After series of processes (selection, mating, and mutation), the new generation of individuals differs from the initial generation, toward increasing overall fitness. The reason is the best individuals are always more often selected to produce the next generation, and the less adapted individuals are gradually eliminated. This process is repeated over and over again: each individual is evaluated, fitness is calculated, two individuals are mated, and then mutation occurs to produce a third generation. The process was repeated until the termination conditions are met.

The identified parameters of participants are shown in Table 2. The values of driving style 3's parameters for VRU are the smallest in comparison with others. Driving style 1's parameters' values are the biggest. It suggests that reckless driver did not feel as much pressure as overcautious one. Therefore, the overcautious driver started their avoiding behaviour earlier and kept bigger lateral distance to VRU than others. Competent driver had an intermediate driving behaviour. These characteristics can also be seen in the driving data shown in Fig. 3. Hence, this method can be used to estimate the personalized parameters which express the driving style.

5. Risk-Free Path Planning Using Potential Field Method Considering Driving Style

5.1. Risk-Free Path Planning Based on Potential Field Map

This trajectory is designed based on the total artificial potential field by calculating the steepest descent direction at any position in the potential field. This can be achieved by solving optimization problem to find the vehicle position that minimizes the potential of the field using gradient descent optimization method.

The path planning problem is formulated as the following optimization problem.

Given:

PF parameters

Vehicle state at avoiding timing ($t = 0$): $q, \dot{q}$

Find: q at time $k+1$ until vehicle passes VRU

Which minimizes: $U(x_{k+1}, y_{k+1})$

The workflow to generate the reference path is shown in Fig. 6.

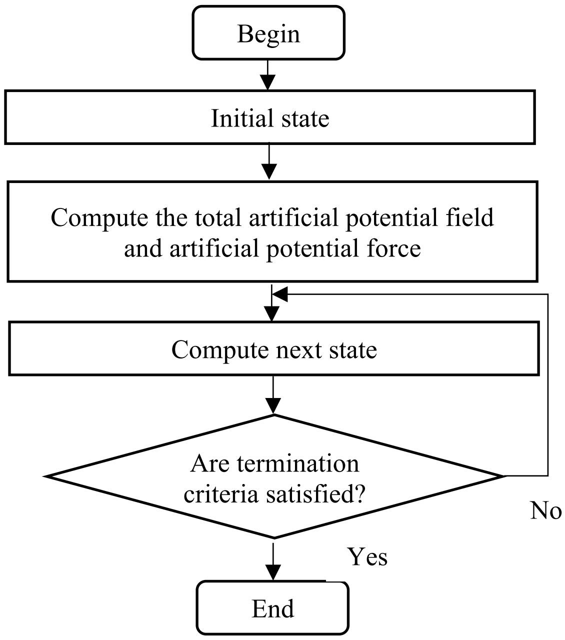

Fig. 6. Workflow for path generating

5.2. Path Planning Results

Based on the potential functions above, we simulated the overtaking scenarios on a two-lane, urban straight road with shoulder, employing the gradient-descent method described earlier. To investigate the validity of the potential functions, we modelled the vehicle as simple omnidirectional point forced toward goal by negative gradient. In this study, the personalized paths for three driving styles to approaching and overtaking a VRU are generated using the identified parameters from DS experiments.

Scenario 1: When there is no vulnerable road user on the road, the reference paths (bold line) are coincident with the centre line of lane (Fig. 7). This is the desired path for the vehicle's movement. The dash lines are road markings. It is verified that the infrastructure potential successfully guides the vehicle in an optimal trajectory.

Scenario 2: When there is a VRU on the shoulder of the road, the reference path is unique for each driving style (Fig. 8, 9, 10) and non-identical to the centre of lane. The dash lines are road markings. The dots are the driving data observed from simulation experiments. The bold lines are the reference paths for driver behaviour 1, 2, 3, respectively. The background contours demonstrate the estimation of potential energy from VRU and infrastructure. The ellipses are the contour of the VRU potential field. Dark contour is the place where potential energy is at highest value. Bright one is the lowest potential energy place. The addition of VRU in shoulder effectively changed the optimal trajectory of the vehicle. The vehicle was forced out of the lane's centre line before passing the VRU. The lateral distance to VRU is non-identical between drivers in different driving styles. From the illustration, the risk-free paths are in good agreement with experimental data sets.

Different reference paths for each driving style toward a pre-defined VRU are demonstrated in Fig. 11. Using these reference paths, ADAS such as LKA can provide assistance that fits the desired of the driver. Such function may help to convey trust and gain acceptance in daily driving.

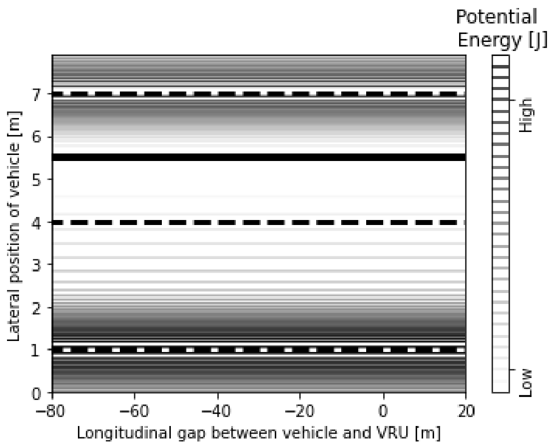

Fig. 7. Reference path (bold line) when there is no vulnerable road user.

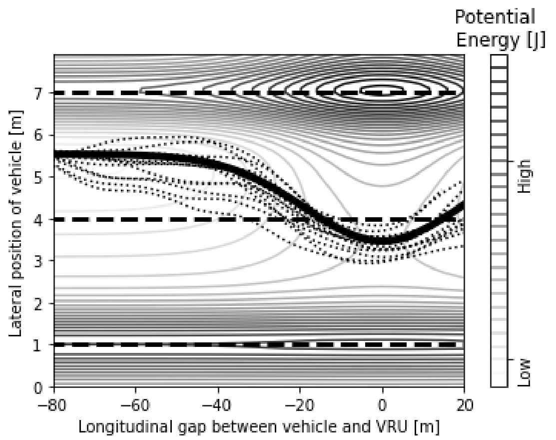

Fig. 8. Reference path (bold line) of driving behaviour 1 to approach and overtake a vulnerable road user on the shoulder

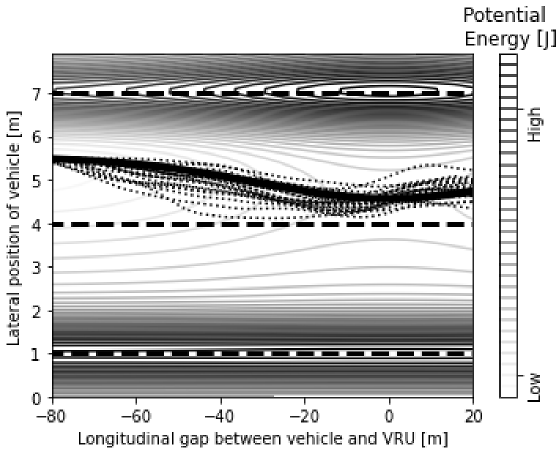

Fig. 9. Reference path (bold line) of driving behaviour 2 to approach and overtake a vulnerable road user on the shoulder.

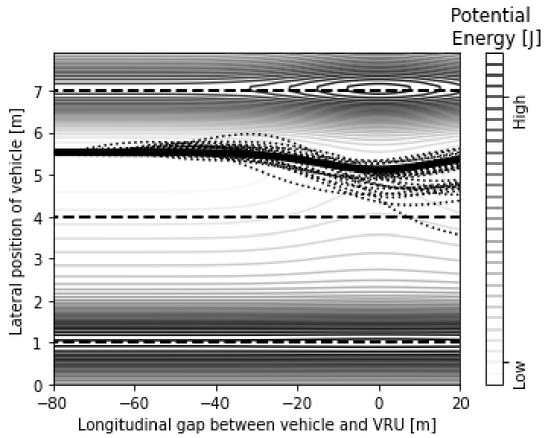

Fig. 10. Reference path (bold line) of driving behaviour 3 to approach and overtake a vulnerable road user on the shoulder.

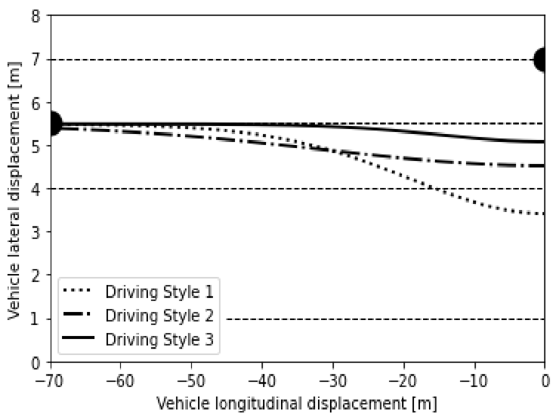

Fig. 11. Reference paths for a vehicle to approach and overtake a VRU considering driver's driving style.

6. Conclusion

For modelling the ideal path in vulnerable road user overtaking process, a set of potential functions is presented. The infrastructure potential keeps the vehicle moving forward on the roadway, and follows the centre of lane. A barrier prevents vehicle's lateral movement. The vulnerable road user potential results in appropriate avoidance behaviour. Corresponding set of potential functions' parameters is identified by genetic algorithm using driving data collected from experiments for each driving style. The proposed path planning can generate a continuous, risk-free path successfully at avoiding timing. This reference path can be applied to ADAS system, such as Lane-keeping Assistance to navigate the vehicle in the overtaking process. Moreover, this finding is useful in designing ADAS systems in order to improve mutual understanding and mutual control with drivers.

The reference paths with regard to driving styles are not only continuous and optimal for vehicle to follow, but also encourage the driver's acceptance of ADAS system. Despite the positive results in path planning, it is argued that the potential functions should be different with the presence of other road users, and different setups of infrastructure. They would be the motivation for scholars to open directions for further investigations.

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