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An Improved Artificial Potential Field Model Considering Vehicle Velocity for Autonomous Driving

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Abstract: Path planning is one of the most crucial technologies for autonomous driving. An improved artificial potential field method considering vehicle velocity for path planning is presented in this paper. At first, a combined artificial potential field model is proposed, which includes five components, target potential, road potential, lane potential, vehicle potential and velocity potential. Road potential and lane potential considers the road structure and traffic rules in highway driving. In addition, for vehicle potential, a potential field model is constructed with the absolute velocity and relative velocity which influences the safe distance between the host vehicle and the obstacle vehicle. The design of velocity potential is to prevent unnecessary lane changing behavior. Finally, the collision avoidance path for autonomous driving is calculated with gradient method from the superposition of disparate potential function. According to the simulation experimental validation, the results show the proposed method can achieve good performance for autonomous driving in highway.

Keywords: autonomous driving, path planning, artificial potential field, vehicle velocity

1. INTRODUCTION

In the past few decades, autonomous driving has been drawing great attention from both academia and industry. In 2016, Google Driverless Car has been tested for more than 2 million miles. In addition, Google's company Waymo announced a road test for driverless car and no human drivers or security staff inside. In 2017, the Audi A8 equipped with Traffic Jam Pilot system can achieve autonomous driving with a speed of 60 km/h or less. One of the key technologies for autonomous driving is path planning, and the main goal is focused on executing strategies to improve safety, comfort, and energy optimization.

There are many path planning algorithms applied in automated driving, such as Dijkstra Algorithm, A*, RRT and artificial potential field. Among them, the artificial potential field has the advantages of small amount of calculation and smoothness of the planned path. Artificial potential field is proposed by Khatib (2003) in 1986. The basic idea is that the host vehicle receives gravitation from the target point and repulsion from the obstacle, and avoids collision to reach the target position under the resultant force. For past few decades, the artificial potential field has been widely implemented in robot navigation and collision avoidance. Zhang et al. (2017) proposed an improved adaptive repulsive potential function, which solved the GNRON problem. Yang et al. (2016) proposed a strategy of potential field filling to escape the GNRON and local minima problems. Matoui et al. (2016) proposed the non-minimum speed algorithm to solve the problem of local minimum produced in multi-robot system. Recently, many researchers developed artificial potential field for autonomous road vehicles. Tu et al. (2017) built a PF model to describe the potential risk of traffic entities and designed a cost function based on PF model. Rasekhipour et al. (2017) introduced a model predictive path-planning controller and its objective includes potential functions along with the vehicle dynamics terms. Noto et al. (2011, 2012) presented the personalized steering assisting system based on the individual potential field. Wahid et al. (2017) presented an advanced driver assistance system using artificial potential field.

In above studies, the potential field is used to describe potential risk while driving on the road. In the traditional potential field methods, the potential function is based on the relative distance which the potential risk increases as the relative distance decreases. However, for driving on the highway, the relative distance is not enough to describe the potential risk in a dynamic environment. Studies have shown that when avoiding the same static obstacle, the driver feels more dangerous as the host vehicle velocity increases. Relative velocity between the host vehicle and obstacle vehicle also has a similar influence on the driver's perception of the risk. Therefore, we modify the potential function with absolute velocity and relative velocity in this paper. In the next section, we address a set of potential function components and later discuss simulation results.

2. IMPROVED POTENTIAL FIELD MODEL

Different from collision-free robotic navigation using artificial potential field, there are many factors need to be considered while driving a vehicle on the road. Firstly, the host vehicle should stay in lanes, preferably in the middle of a lane. Secondly, the lateral speed of the host vehicle when changing lanes is generally small relative to the longitudinal speed. Therefore, the lateral and longitudinal safety distances of the vehicle are different. Thirdly, the dynamic characteristics of the host vehicle and other traffic targets play a significant role in maintaining safe distance. The

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velocities of the host vehicle and other traffic targets are key factors to determine safe distance while driving on the road. Thus, the total proposed potential U_{total} can be derived from a few potential functions combination, including target potential U_{target}, road edge potential U_{edge}, lane potential U_{lane}, vehicle potential U_{car} and velocity potential U_{vel}. It can be defined as equation (1). We address each component respectively below and discuss their function.

$$U_{total} = U_{target} + U_{edge} + U_{lane} + U_{car} + U_{vel} \quad (1)$$

2.1 Target Potential

The target in the environment is expressed as the attractive potential which leads the host vehicle to the desired target location. The equation (2) represents the potential function of the target. In equation (2), the k_{target} is the weight of the attractive potential function, and the x_{target} is the position of the target in the x direction. The minimum value of potential energy is formulated at the target position. The target potential is illustrated in Fig.1.

$$U_{target}(x, y) = -k_{target}(x - x_{target}) \quad (2)$$

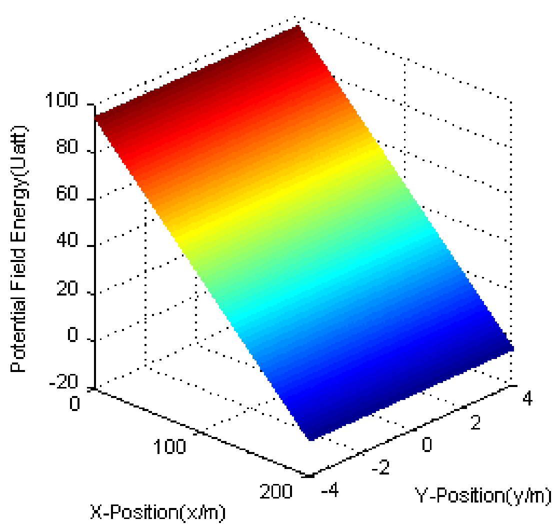


Fig. 1. Potential function of target destination

2.2 Road Potential

The road edge potential prevents the host vehicle from lane departure by employing the repulsive potential function on the left and right of the road. The repulsive potential function of road edges can be written as equation (3).

In equation (3), the k_{edge} is the weight of potential function of road edges, and $y_{0,j}$ is the j^{th} road edge coordinate, j$\epsilon\{1,2\}$. As illustrated in Fig.2, the potential field energy is highest at each side of road edges.

$$U_{edge,j}(x, y) = k_{edge}[-exp(y - y_{0,j}) + 1] \quad (3)$$

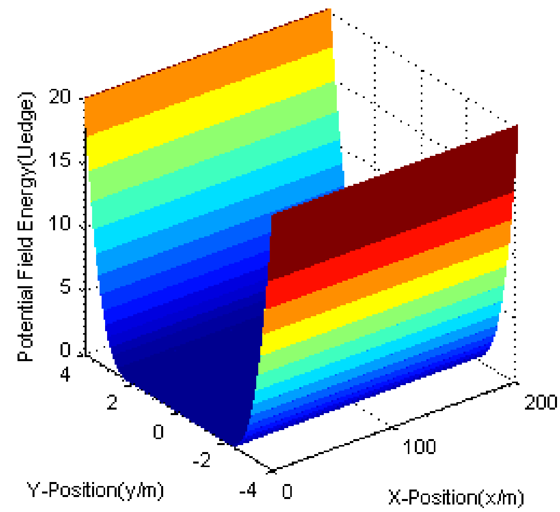


Fig. 2. Potential function of road edge

2.3 Lane Potential

The lane potential generates a barrier for lane changing and guides the host vehicle driving along the centre line of its lane. But it also should be small enough to be overcome in the case that a lane changing is necessary (or preferred) for collision avoidance or other situations. To avoid mutations, it is necessary to require that the derivative of the potential function is continuous. The lane potential function is calculated by a cubic polynomial and can be defined as equation (4). In equation (4), a, b, c and d are the polynomial coefficients. The lane potential function is illustrated in Fig.3.

$$U_{lane} = ay^3 + by^2 + cy + d \quad (4)$$

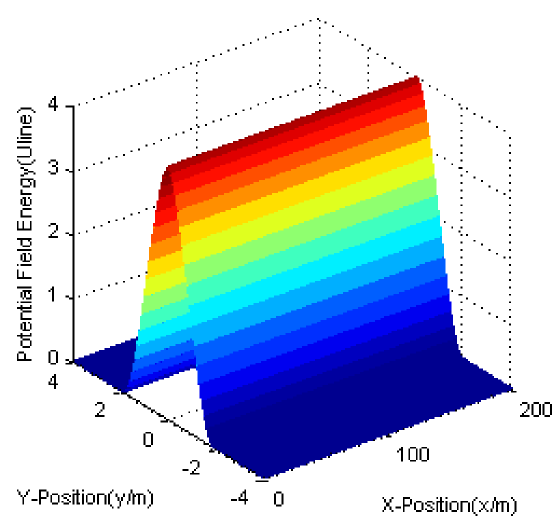


Fig. 3. Potential function of lane

2.4 Vehicle Potential

The potential field of obstacle vehicles are formulated to keep the host vehicle a safe distance from other obstacle vehicles.

The potential function should be formulated in shape to encourage the lane changing in the case that the host vehicle approached the obstacle vehicles. A two-dimensional Gaussian distribution function is used to generate the repulsive potential of obstacle vehicles, and it can be expressed as equation (5).

$$U_{car,i} = k_{obs} exp\left\{-\left[\frac{(x-x_{obs,i})^2}{\sigma_x^2} + \frac{(y-y_{obs,i})^2}{\sigma_y^2}\right] + \gamma\left(k_1 v + k_2\left(v - v_{obs,i}\right)\right)\frac{(x-x_{obs,i})^2}{\sigma_x^2}\right\} \quad (5)$$

$$\gamma = \begin{cases} 1, & x \le x_{obs,i} \\ 0, & x > x_{obs,i} \end{cases} \quad (6)$$

In equation (5), k_{obs} is the weight of potential function of obstacle vehicles which represents the maximum potential field value of the obstacle. $(x_{obs,i}, y_{obs,i})$ represents the nearest point from the host vehicle to the obstacle $vehicle_i$. σ_x and σ_y stand for the convergence coefficient of the repulsive potential field which decides the horizontal influence scope of the potential field. v is the host vehicle's velocity and $v_{obs,i}$ is the velocity of the obstacle car_i. k_1 and k_2 are weight coefficients of velocities.

The level of danger associated with obstacle vehicles depends upon several factors. The relative distance of vehicles plays a significant role. The host vehicle should keep an appropriate longitudinal distance from the leading car in its lane. But a relatively short lateral distance is allowed, to the vehicles on the side lanes. Another factor affecting safe distances is the velocity, including relative velocity and absolute velocity. For a higher relative velocity, the repulsive potential would generate a longer distance. The host vehicle will take longer time to slow down or speed up to follow a leading vehicle. Furthermore, a higher absolute velocity increases the level of danger. As the absolute velocity of the host vehicle increases, more space is required for evasive maneuvering, as well as the time for emergency operations. Therefore, we use absolute velocity v and relative velocity $v - v_{obs,i}$ to improve vehicle potential function. As shown in equation (5), the higher the absolute velocity is, the lager influence distance should be along the X position which parallels to the lane line. The change of relative velocity also has similar effects. We introduce the coefficient γ only to change the repulsive potential in the rear part of the obstacle vehicle, as the impact of vehicle velocity on the repulsive potential is based on the obstacles in the current lane. Fig.4 and Fig.5 shows the improved repulsive potential function and it's isopotential contours.

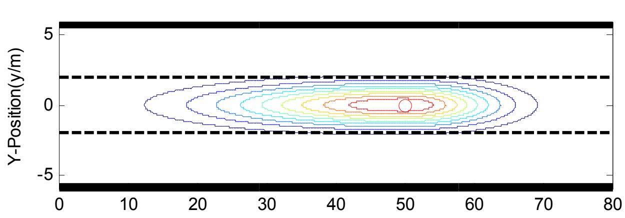


Fig. 4. Isopotential contours of an obstacle vehicle

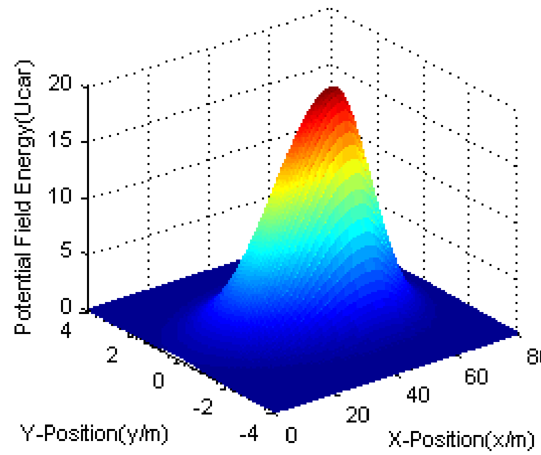


Fig. 5. Potential function of an obstacle vehicle

2.5 Velocity Potential

When a leading vehicle's speed is larger than the host vehicle's or the host vehicle is running in heavy traffic, the host vehicle should stay in the current lane and follow the leading vehicle. Therefore, we design velocity potential to prevent unnecessary lane changing behaviour. In this case, the target position temporarily becomes a position behind the front vehicle. Thus, we introduce an attractive potential calculated by equation (7). In equation (7), (x_{safe}, y_{safe}) represents temporary target position which is calculated by 'three second rule' as shown in equation (8).

$$U_{vel} = -k_{vel} exp\left\{-\left[\frac{(x-x_{safe})^2}{\sigma_x^2} + \frac{(y-y_{safe})^2}{\sigma_y^2}\right]\right\} \quad (7)$$

$$x_{safe} = x_{obs} - vt \quad (8)$$

3. SIMULATION AND DISCUSSION

3.1 Simulation Scenario and Parameters Design

In order to test the validity of proposed method, a driving scenario of a highway with two-lane is constructed, as illustrated in Fig. 6. We assume the highway is straight and each vehicle on the road should drive with a constant speed along the centre line of lane. When there is a lower speed vehicle in front of the host vehicle, the host vehicle will seek to change lanes with a consideration of the safety condition. And if there is a higher speed vehicle in front of the host vehicle, the host vehicle will seek to follow.

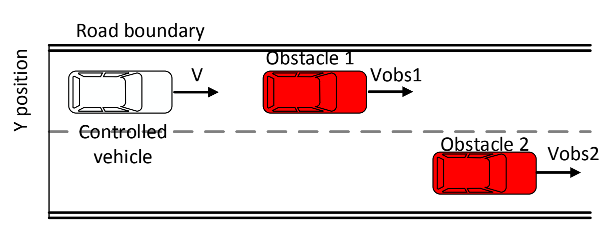


Fig.6. The simulation scenario with the host vehicle and two obstacle vehicles

The host vehicle drives at an absolute velocity v and two obstacle vehicles drive at $v_{obs1} = 50km/h$ and $v_{obs2} = 20m/h$. The scenario and parameter values used are shown in Table 1.

Table 1 Potential function parameters

Potential	Parameter	Definition	Value
Target potential	k_{target}	weight	0.25
Road edges potential	k_{edge} $y_{0,j}$	Weight j^{th} road edge coordinate	1 2, -2
Vehicle potential	k_{obs} σ_x σ_y k_1 k_2	Weight convergence coefficient convergence coefficient coefficient of velocity coefficient of velocity	10 10 1.4 0.005 0.005
Lane potential	a, b c, d	polynomial coefficients polynomial coefficients	1, -3 0, 4
Velocities potential	k_{vel}	weight	10

3.2 Discussion of Results

Fig. 7, Fig. 8 and Fig. 9 show the results of the path planning for avoiding obstacles and the host vehicle's velocity equals to 30km/h, 60km/h and 90km/h respectively.

Scenario 1: As shown in Fig. 7, the velocity of the leading vehicle in the current lane is higher than the host vehicle. Therefore, the desired behaviour is to stay in the current lane and drive with a cruise speed of 30km/h. In this scenario, the velocity potential function generates a local minimum behind the leading vehicle, so that the host vehicle can stay in lane and follow the leading vehicle.

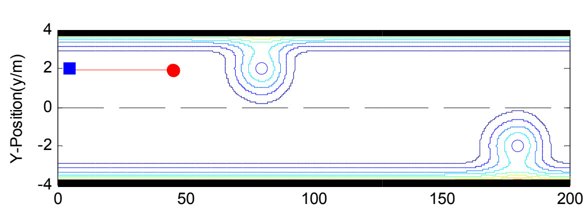
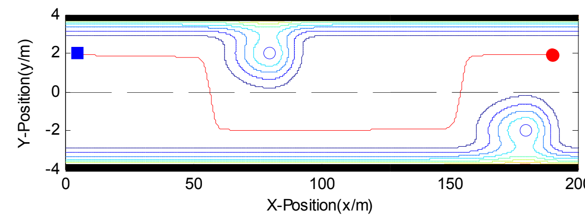


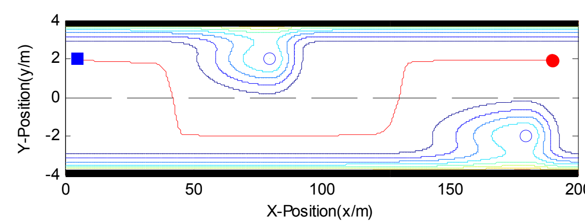
Fig.7. The host vehicle drives with an initial velocity of 30km/h

Scenario 2: As shown in Fig. 8, the speed of obstacle vehicle is lower than the host vehicle, thus the desired behaviour is to changing lanes to avoid collision. In this scenario, the local minimum generated by velocities potential is not present, and the host vehicle changes lanes through the vehicle potential. Because of the difference in velocity, the potential fields generated by the two obstacle vehicles are also different. The greater the relative speed, the larger the influence distance of the repulsive field. Thus, lane changing occurs earlier when approaching the second obstacle vehicle.



Fg.8. The host vehicle drives with an initial velocity of 60km/h

Scenario 3: As shown in Fig. 9, similar behaviour occurs compared with scenario 2. And we can see the influence of relative velocity on the vehicle potential more obviously. In this scenario, the relative speed of the host vehicle and the first obstacle vehicle is 40 km/h, which is equal to the second obstacle vehicle in scenario 2. As the absolute velocity of the host vehicle increases, the influence distance of vehicle potential field increases accordingly. Therefore, the host vehicle changes lane earlier to avoid collision which is consistent with the actual traffic scene.



Fg.9.The host vehicle drives with an initial velocity of 90km/h

4. CONCLUSIONS

In this paper, an improved artificial potential field model with a set of potential function components is presented for autonomous driving. At first, the target potential bring the vehicle to the target destination, while the road edge potential and lane potential prevent the vehicle from leaving the highway and guide the vehicle into the centre of the current lane. And then, the vehicle potential results in appropriate collision avoidance behaviour and velocity potential for following the leading vehicle. In vehicle potential, we both consider the absolute and relative velocity which influences the safe distance. Simulation results show that the presented the improved artificial potential field model has a stable and robust performance for avoiding the collision with different velocity conditions. Besides, the effectiveness of presented potential function components can be validated with actual vehicle experiment in the future.

5. ACKNOWLEDGEMENTS

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