

A Potential Field Based Lateral Planning Method for Autonomous Vehicles

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ABSTRACT

As one of the key technologies in autonomous driving, the lateral planning module guides the lateral movement during the driving process. An integrated lateral planning module should consider the non-holonomic constraints of a vehicle, the optimization of the generated trajectory and the applicability to various scenarios. However, the current lateral planning methods can only meet parts of these requirements. In order to satisfy all the performance requirements above, a novel Potential Field (PF) based lateral planning method is proposed in this paper. Firstly, a PF model is built to describe the potential risk of the traffic entities, including the obstacles, road boundaries and lines. The potential fields of these traffic entities are determined by their properties and the traffic regulations. Secondly, the planning algorithm is presented, which comprises three modules: state prediction, state search and trajectory generation. The state prediction is realized through the lateral dynamics and kinematics equations of the vehicle. Then based on the PF model, a cost function is designed, which takes the potential risk and comfort requirements into consideration. With the cost function and vehicle states, a heuristic search algorithm is employed for the state search and the resulting optimal trajectory is achieved by the trajectory generation. The proposed method can escape the local-minimal effectively and meet the non-holonomic constraints. Besides, thanks to its generality of the problem formulation, this method gives the possibility to adapt to different traffic scenarios. The performance of this method is verified in the bench test.

KEYWORDS: lateral planning, autonomous vehicles, potential field, cost function, lateral dynamics, non-holonomic constraints

CITATION: Tu, Q., Chen, H., and Li, J., "A Potential Field Based Lateral Planning Method for Autonomous Vehicles," *SAE Int. J. Passeng. Cars – Electron. Electr. Syst.* 10(1):2017, doi:10.4271/2016-01-1874.

INTRODUCTION

Intelligent vehicle technologies have the potential in bringing transportation systems to a new level of safety and efficiency, and will have a positive impact on people's lives, environmental protection and so on. Current researches on this domain are mainly focus on the Advanced Driver Assistance System (ADAS), such as Adaptive Cruise Control (ACC) and Lane Keeping System (LKS). While the driver still remains responsible for control of the vehicle. Besides, autonomous driving capabilities in limited driving situations can be realized in the near future.

In the past three decades, autonomous driving has been drawing great attention from both academia and industry. The development of autonomous vehicles is pretty complicated and includes technologies in perception, planning and control. Particularly, planning allows an autonomous vehicle to determine the lateral and longitudinal movements by itself.

Planning methods for autonomous vehicles can be divided into global planning and local planning. In the global planning stage, the global route and the vehicle states are determined through information from

a digital map and a localization system. Then the local planning module works based on the global route and the surrounding information of the vehicle obtained from environment perception module. As for local planning, it includes lateral planning and longitudinal planning. In this paper, the lateral planning is specified, which generates feasible paths or trajectories for autonomous vehicles to follow.

Many studies have been conducted on lateral planning. Although lateral planning is initially studied for robotic applications, it has more recently been studied for automotive applications. As for autonomous vehicles, an integrated lateral planning method should consider the non-holonomic constraints of a vehicle, the optimization of the generated path and the applicability to various traffic scenarios. Previous research on lateral planning can primarily be separated into potential field method, grid based search method, sample based method and discrete optimization method.

The conventional potential field method virtually assigns repulsive forces to obstacles and attractive forces to the goal position. Virtual forces are used to form the gradient of a potential field. A path can

then be found along the steepest gradient of the potential field. However, the trajectory can be trapped in the local minima of the potential field in several scenarios, which cannot guarantee to find a path [1] [2] [3]. What's more, one drawback of conventional potential field method is that it is not easy to take the complex dynamic and differential constraints of the vehicle into consideration [4].

Much of prior works on grid based search algorithms for path or trajectory planning have been widely conducted and these methods are widely used for autonomous driving. However, these algorithms calculate costs only through centers of cells, which produces non-smooth paths and they do not satisfy the non-holonomic constraints of vehicle motion [5] [6] [7]. To account for non-holonomic constraints, several variants of grid based search algorithms have been studied [8] [9] [10] [11]. These approaches consist two phases. In the first phase, the path planner obtains a primitive path by using discretization of state and a grid. In the second phase, further modification and optimization are conducted to improve the quality of the path.

Sample based planning methods such as probabilistic road map (PRM) and rapidly exploring random tree (RRT) have been widely used to generate paths for autonomous driving. Sample based planning algorithms use randomly generated samples to connect adjacent samples. These algorithms can guarantee kinematic feasibility by adapting a vehicle model [12]. But a randomized sampling strategy sometimes induces unnatural paths that may contain unnecessary turns or unexpected changes. Although a lot of works were proposed to smooth the trajectory planned by RRT [13], lessened meanders might still exist in the joint part of two edges. For instance, lane keeping is the most common maneuver for vehicles on road without obstacles. Using the RRT makes it difficult to plan a trajectory shaped like a straight line for the lane keeping. What's more, the optimization of the generated trajectory cannot be guaranteed.

Discrete optimization method includes two phases: path or trajectory generation and path or trajectory selection. In the generation phase, a finite set of parallel paths or trajectories is computed with the nonholonomic constraints of the vehicle. But it does not consider the obstacles in the generation process [14] [15] [16]. So in the selection phase, a cost function is built and an optimal path or trajectory that minimizes the cost is selected. This kind of method has a good performance in simple urban traffic scenarios, but it is probably unable to deal with the cluttered environments [17].

In addition to the lateral planning methods described above, most studies on autonomous driving adopt behavior based software structure. This kind of autonomous driving structure based on exiting ADAS, such as LKA, ACC, and lane change (LC) among others [18]. What all these functions have in common is that they specialize in a particular traffic situation. In the absence of these special situations, however, the assistance systems remain passive thus work

independently from each other. In this behavior based structure, it is possible to just add more and more behaviors in order to create further complex autonomous driving system. However, this architectural style reaches its limits in complex environments since the interaction among the behaviors becomes hard to arbitrate and optimize [19] [20].

As mentioned above, an integrated autonomous driving lateral planning method should consider the non-holonomic constraints of a vehicle, the optimization of the generated trajectory and the applicability to various traffic scenarios. However, the current lateral planning methods, such as the potential field, grid based search method, and sample based method and discrete optimization method, can only meet parts of these requirements.

In order to satisfy all the performance requirements above, a novel PF based lateral planning method for autonomous vehicles in urban traffic environments is proposed in this paper. Firstly, a PF model is built to describe the potential risk of the traffic entities, including the obstacles, road boundaries and lines. The potential fields of these traffic entities are determined by their properties and the traffic regulations. Secondly, based on this PF model, a cost function is designed, which takes the potential risk and comfort requirements into consideration. And the prediction of vehicle states is realized through the lateral dynamics and kinematics equations of the vehicle. Thirdly, with the cost function and vehicle states, a heuristic search algorithm is used to find the optimal trajectory. The final result consists of a sequence of sequential vehicle states that form the desired ego vehicle trajectory. Figure 1 depicts the framework of the proposed method.

The remainder of this paper is organized as follows. In the [section 2](#), the design process of the PF model is described. In [section 3](#), the improved search algorithm with a cost function is presented. The simulation and experimental results is presented in [section 4](#). Finally, conclusions and discussions are given in [section 5](#).

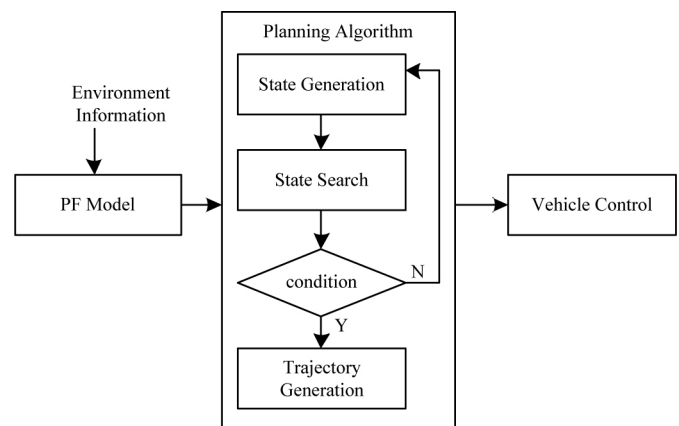


Figure 1. The framework of the lateral planning method proposed in this paper.

PF MODEL

There are many factors need to be considered while the vehicle driving on the road. And these factors, including traffic regulations and properties of the traffic entities, will influence the decision making of the autonomous driving. As mentioned in the introduction, in real traffic scenarios, it is pretty complex to consider the entire possible situations in a state flow chart to make the behavior decisions. So it is essential to achieve a uniform environment description to simplify the decision making process.

In order to build up a uniform description for surrounding environment of the ego vehicle, in this paper, the surrounding information is mapped onto a potential field, taking the traffic regulations and the properties of surrounding traffic entities into consideration. In fact, Actual drivers determine the optimal path by reducing the risk of collision with the obstacles and lane departure. Therefore, the resulting potential field consists of the potential fields of obstacles, road lines and road boundaries.

It needs to point out that, the potential field is a particular kind of hazard map. Obstacles are represented as potential hills. The potential field of the road rises on the road border and has its minimum along the middle of the lane. To some extent, the PF value reflects the risk of each position on the road environment. So the vehicle is relatively safer in the region where PF value is lower. The potential field functions with respect to the road boundaries, road lines and obstacles are defined at first.

Obstacle Potential Field Function

There are many kinds of obstacles exist in real traffic situations, including vehicles, bicycles and pedestrians and so on. The goal of building the surrounding obstacle potential field is to describe the collision risk of the surrounding obstacles around the host vehicle, which is necessary to keep the safe distance between the host vehicle and the surrounding obstacles. Considering the vehicle dynamics and road driving rules, the levels of danger distribution on the lateral and longitudinal of the vehicle is not uniform. For example a vehicle should stay far behind the preceding vehicle in its lane, but is allowed relatively near the obstacle to its side. The obstacle potential field distribution can be roughly described as shown in [Figure 2](#).

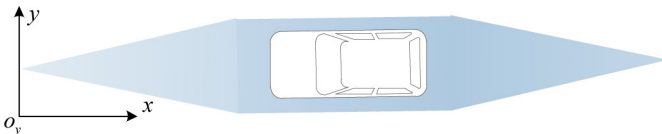


Figure 2. A rough description of the obstacle potential field.

Considering a point $P(x,y)$, the potential field value contributing by the obstacle i is calculated by:

$$P_{obs(i)}(x,y) = A_{obs} \cdot e^{-\left\{ \frac{(x-x_{obs(i)})^2}{2\sigma_x^2} + \frac{(y-y_{obs(i)})^2}{2\sigma_y^2} \right\}^c} \quad (1)$$

where the constant A_{obs} represents the maximum potential field value of the obstacle. $(x_{obs(i)}, y_{obs(i)})$ represents the nearest point from ego vehicle to the obstacle. σ_x, σ_y stand for the convergence coefficient of the obstacle potential field which decides the horizontal influence scope of the potential field. c is the coefficient to adjust the shape of the obstacle potential field hill. The overview of the obstacle potential field is shown in [Figure 3](#).

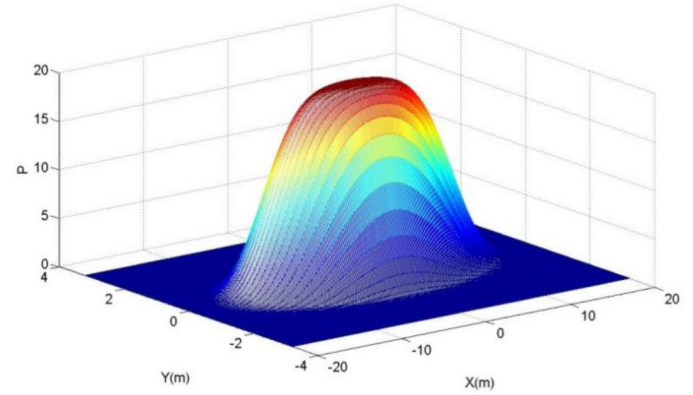


Figure 3. The three dimensional stereogram of the obstacle potential field in this paper.

Road Potential Field Function

During the autonomous driving process, the ego vehicle needs to take the constraints of the lane lines and road boundaries into consideration and avoid the risk of lane departure. Generally speaking, Lane lines should be classified into two categories, which include one category that can be crossed and another category that cannot be crossed separately, depending on the traffic regulations.

In the implementation, each lane line is fitted into a cubic polynomial, which can be expressed in vehicle coordinate system as:

$$y = a_3 \cdot x^3 + a_2 \cdot x^2 + a_0 \quad (2)$$

where a_3, a_2 , and a_0 are the polynomial coefficients.

The potential field value generated by each lane line for a same point $P(x,y)$, is calculated by:

$$P_{line(i)}(x,y) = e^{(-d_i + d_c + \frac{b}{2})h_i} \quad (3)$$

where d_i is the minimum distance from the point $P(x,y)$ to the lane line i . b denotes the vehicle width. d_c is the safety margin. The potential field caused by the lane lines that can be overcome creates a barrier to guide the vehicle into the center of the lane. But it also should be small enough to be easily overcome in the case that a lane change is necessary (or preferred) for collision avoidance or other situations. While as for lane lines and road boundaries that cannot be overcome, the magnitude of the potential field value should be as high as enough to keep the vehicle in the safe area. So in [Equation \(3\)](#), the coefficient h_i is used to adjust the magnitude of the potential field value. The overview of the road potential field is shown as [Figure 4](#).

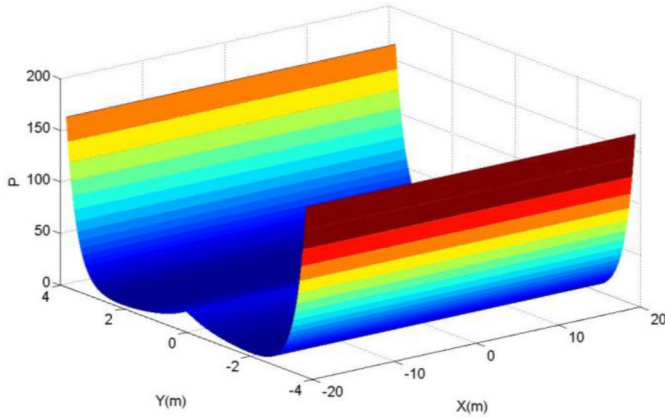


Figure 4. The three dimensional stereogram of the road potential field in this paper.

As discussed above, the PF model needs to reflect various factors and build up a uniform description of the surrounding environment of the ego vehicle. And the resulting PF model is a combination of the obstacle potential fields and the road potential fields, which is given as:

$$P(x, y) = \sum_{i=1}^m A_{obs} \cdot e^{-\left\{ \frac{(x-x_{obs(i)})^2}{2\sigma_x^2} + \frac{(y-y_{obs(i)})^2}{2\sigma_y^2} \right\}^c} + \sum_{j=1}^n e^{(-d_j+d_c+\frac{b}{2}) \cdot h_c} + \sum_{q=1}^q e^{(-d_j+d_c+\frac{b}{2}) \cdot h_{nc}} \quad (4)$$

where the constant m denotes the number of the obstacles in the current surrounding environment. n is the total number of the lines that can be overcome. And q is the number of the boundaries or lines that cannot be overcome. h_c and h_{nc} are the selected magnitude coefficients for two kinds of lane lines or boundaries. A respective example of a potential field with two obstacles is shown in Figure 5.

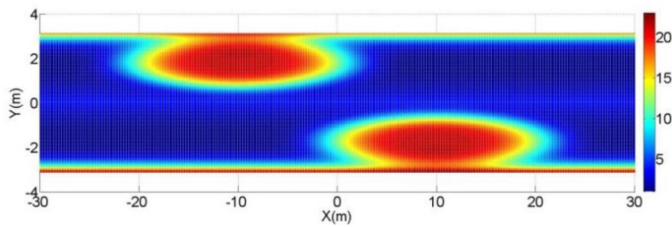


Figure 5. A respective example of a potential field with two obstacles.

PLANNING ALGORITHM

As described in the introduction, an integrated lateral planning method should consider the non-holonomic constraints of a vehicle and the optimization of the generated trajectory. So in this section, an implementation is presented in detail. As shown in Figure 1, the lateral planning algorithm includes three parts: state generation, state search and trajectory generation, where the former two parts play a pivotal role in the planning algorithm.

State Generation

Traditional grid-based search method generally finds the globally sub-optimal path connecting each cell of the grid map from an initial position to the goal while avoiding obstacles in the environment and it ignores the non-holonomic constraints of the vehicular system. In this paper, the non-holonomic constraints of a vehicle are satisfied by employing the vehicle dynamic model to predict the vehicle states rather than the center of grid cells.

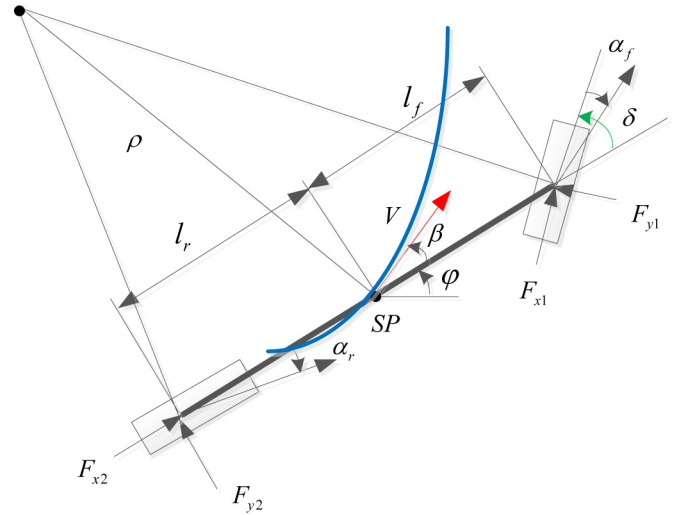


Figure 6. The linear single track vehicle model.

Vehicle Model

To predict the vehicle state, a precise model is needed on the one hand. On the other hand, the model complexity needs to be low in order to reduce the computational effort. In order to fulfill both requirements, a nonlinear single track model combined with the vehicle kinematic equation is used as a compromise. The top view on the single track model is shown schematically in Figure 6. So the lateral vehicle dynamics is given as:

$$x(t) = \begin{bmatrix} \beta(t) \\ \omega_r(t) \end{bmatrix} \quad u(t) = \frac{\delta_h(t)}{i_s} \quad (5)$$

$$\begin{cases} \dot{x}(t) = Ax(t) + Bu(t) \\ y(t) = Cx(t) + Du(t) \end{cases} \quad (6)$$

$$A = \begin{bmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{bmatrix} \quad B = \begin{bmatrix} B_{11} \\ B_{21} \end{bmatrix} \quad (7)$$

$$A_{11} = -\frac{k_f + k_r}{mv}; A_{12} = -\frac{l_f k_f - l_r k_r}{mv^2} - 1;$$

$$A_{21} = -\frac{l_f k_f - l_r k_r}{I_z}; A_{22} = -\frac{l_f^2 k_f + l_r^2 k_r}{v I_z}$$

$$B_{11} = \frac{k_f}{mv}; B_{12} = \frac{l_f k_f}{I_z}$$