High Definition Map Based Motion Plan and Control of Autonomous Vehicle on Structured Road

K Zhang1, *, S J Wang2, L Ji3 and C Wang1

1E/E department, Brilliance Automobile Engineering Research Institute, shenyang 110141, China
2School of Mechanical Engineering, Shenyang University of Technology, shenyang, 110023, China
3School of Mechatronics Engineering, Shenyang Aerospace University, shenyang, 110136, China

* hit_zhangkun@126.com

Abstract. A high definition (HD) map based motion plan and control method of autonomous vehicle on structured road is proposed in this paper. The system is designed in a multi-layer structure: a motion planner and a motion controller, furthermore, the motion planner is consisted of a global path planner and a local trajectory planner. The inputs of the global path planner are HD map, start and goal state, Dynamic Program (DP) is used to plan a global path that connect these two states based on the lane-level structures and traffic rules extracted from HD map. The inputs of local motion planner are the planned global path, current host vehicle state and the surrounding dynamic object information, several candidate trajectories are generated in Frenet frame, and then the optimal one is chosen by a multi-term cost function calculation. Taking the vehicle dynamics under high speed into consideration, Model Predictive Control (MPC) is used in motion controller to track the planned target trajectory. Results of the conducted simulation tests show that the designed motion plan and control method works well in velocity keeping, vehicle following, stopping and going, and vehicle passing scenarios.

1. Introduction

Great progress has been made in autonomous driving in the past 3 decades, especially since the DARPA urban challenge which was held in 2007. It has been widely accepted that the autonomous driving software designed in a abstracted layered structure, including sensor interface layer, perception and localization layer, decision and planning layer, and vehicle interface layer. Decision and planning layer is further divided into route planner, behaviour executive layer, motion planner and motion controller. To limit the scope of this paper, we focus on the motion planner and motion controller.

Regarding the motion planner, a mass of methods have been proposed. These methods can be divided into 3 fields: variational methods, graph-search methods and incremental search methods. Variational methods represent the path as a finite-dimensional vector function, and the optimal path is found through optimizing over the parameter vector using non-linear continuous optimization techniques, this method can rapidly convergence to local minimum[1]. Graph search methods represent the configuration space of the vehicle as a graph or a multi-dimensional lattice grid, and the target path is found through a multi-term cost function, many of the popular used method like A*,
anytime A*, D* falls into this criteria[2, 3]. Incremental search methods build a reachability tree by sampling the configuration space, once the graph grows large enough that the goal is reached, the target path is found, RRT, RRT*, RRTX belongs to this criteria[4, 5].

The motion control of autonomous vehicles, depending on the vehicle models used, can be divided into 3 classes: geometric model[6, 7], kinematic model[8, 9] and dynamic model[10]. Instinctively, the lateral and longitudinal of autonomous vehicle should be coupled controlled to achieve more accurate path tracking. On the other hand, the relative high speed on structured road and rapid changing characteristic of the road users need the controller to be able to response quickly.

Thus, in this paper the whole time used for motion plan and motion control is limited to less than 100ms. Furthermore, the comfort of passenger are taken into consideration during the controller design. Based on these design requirements, an abstract layered motion plan and control method of autonomous vehicle on structured road is proposed in this paper, in which the global planner is implemented based on HD map information, local optimal lateral and longitudinal trajectory is generated and then tracked through MPC by the motion controller.

2. System structure
The designed system structure diagram is shown in figure 1, where the proposed motion plan and motion control system is designed in a multi-layered form, with a motion planner and a motion controller and the motion planner is further consisted of a global path planner and a local trajectory planner.

![System structure diagram](image)

Figure 1. System structure diagram

The inputs of the global path planner are HD map, start and goal state, and the output is a global path that connect these two states based on the HD map information. The HD map information includes the lane structure and traffic rules, such as the speed limit, traffic sign, et al., and is usually provided by the map supplier. The start and goal state are consisted of position, orientation and movement info, which is supplied by the behaviour executive layer or directly assigned by the customer through human machine interface (HMI).

The inputs of local trajectory planner are the planned global path, current host vehicle state and the surrounding dynamic objects info, and the output is a target trajectory. The current host vehicle state is provided by the GNSS/INS coupled localization system or a 3D/2D SLAM system. Several candidate trajectories are generated in Frenet frame, and then the optimal one is chosen through a predefined multi-term cost function, which should take safety, comfort and smoothness into consideration.

The target trajectory is then tracked by the MPC motion controller, whose inputs are the target trajectory and current vehicle state, and the outputs are the corresponding steering and acceleration control signal.

3. Motion planner

3.1. Global path planner
Depending on the driving scenarios, different global planning methods are used, such as A* algorithm and its variants are often used in the off-road or the parking lot conditions. These methods are able to get optimal or sub-optimal result but need much computation, and thus are not suitable for high speed structured road application.
The global path plan method proposed in this paper focus on real-time dynamic application, so DP is used to generate a feasible global path from directly from HD map, which is light weight and do not need much computation. Meanwhile, because the lane structure extracted from HD map is already smooth enough and the embedding traffic rule has been taken into consideration, this planned global path is considered to be feasible and conformed to the traffic rule.

The detailed procedure of DP based global path planner is: first, the lane centre is extracted and potential smooth work are made; second, a search tree of all the feasible path along the road is built from the start position abiding the traffic rule, meanwhile a predefined cost is calculated for every path, this step stops when the goal is reached; third, the path with the minimum cost is chosen as the optimal global path, as is shown in figure 2.

![Figure 2. DP based Global path plan](image)

3.2. Local trajectory planner

The target of local trajectory planner is to generate a safe, feasible and comfortable local trajectory along the provided global path. Based on this definition, the following requirements need to be satisfied: the planned trajectory should not collide with other dynamic and static obstacles; the planned trajectory should be smooth enough that is trackable by a non-holonomic vehicle with angular and linear velocity/acceleration constraints; the planned trajectory should be comfort enough for the passengers, thus sharp lateral and longitudinal acceleration should be avoided; planning computation needed should be small enough so as to realize real-time control. Thus, a two-step method is proposed, including a candidate trajectories generation step and an optimal calculation step.

3.2.1. Candidate trajectories generation. A jerk term that was proposed by Moritz Werling [11] is used in this paper to ensure the smooth and comfort of the generated lateral and longitudinal trajectories, which is defined as $d$ and $s$ separately. The jerk optimal solution of a start state $\begin{bmatrix} d_0 & \dot{d}_0 & \ddot{d}_0 \end{bmatrix}$ and end state $\begin{bmatrix} d_1 & \dot{d}_1 & \ddot{d}_1 \end{bmatrix}$ can be represented by a quintic-polynomials.

For lateral control, its meaningful to set the end state as $\begin{bmatrix} d_1 & 0 & 0 \end{bmatrix}$, and then $d_1$ and the prediction time is sampled with a predefined step. Given the start and sampled different end states, a set of candidate trajectories are generated, then the validation of these trajectories is checked by curvature, lateral velocity and lateral acceleration, and the invalid ones are filtered out, as is shown in figure 3.

![Figure 3. Lateral candidate trajectories generation and validation check](image)
As is shown in figure 3, the invalid trajectories are drawn in grey and the valid ones are drawn in green, and the optimal is drawn in blue.

In contrast to lateral control, longitudinal control is divided into 2 conditions, one accounts for the velocity keeping scenario and the other accounts for stop and going, vehicle following and merging scenarios. The end state of the first condition is designed as $[\dot{s}_1 \ 0]$, and $[\dot{s}_1 \ 0]$ for the second one. Then, the same sampling and validation checking step as lateral control is conducted, as is shown in figure 4.

![Figure 4. Longitudinal candidate trajectories generation and validation check](image)

3.2.2. Optimal trajectory calculation. Then for every left validated trajectory, the collision check is first made based on the Separating Axis Theorem (SAT). After this procedure, those trajectories that are in collision with other obstacles are all masked out, left the safety ones. Then, in order to decide the optimal trajectory, several cost functions are defined considering trajectory smooth, comfort and execution time.

For lateral control, the cost function $C_{lat}$ is given by

$$C_{lat} = K_{latJ}\int_{t_0}^{t_1} \ddot{d}^2 d\tau + K_{latT} (t_1 - t_0) + K_{latD} d_1^2$$  \hspace{1cm} (1)

Where $K_{latJ}$, $K_{latT}$ and $K_{latD}$ is weights for lateral jerk, execution time and end state lateral position.

For the first condition of longitudinal control, which is speed keeping, a cost function is given by

$$C_{long} = K_{longJ}\int_{t_0}^{t_1} \ddot{s}^2 d\tau + K_{longT} (t_1 - t_0) + K_{longV} (\dot{s} - \dot{s}_{target})^2$$  \hspace{1cm} (2)

Where $K_{longJ}$, $K_{longT}$ and $K_{longV}$ is weights for longitudinal jerk, planning time and end state longitudinal velocity.

For the second condition of longitudinal control, which includes stop and going, vehicle following and merging, a cost function is given by

$$C_{long} = K_{longJ}\int_{t_0}^{t_1} \ddot{s}^2 d\tau + K_{longT} (t_1 - t_0) + K_{longPos} (s - s_{target})^2$$ \hspace{1cm} (3)

Where $K_{longPos}$ is weights for the end state longitudinal position.

Then the total cost of lateral and longitudinal trajectories are combined by
\[ C_{\text{total}} = K_{\text{lat}}C_{\text{lat}} + K_{\text{long}}C_{\text{long}} \]  

Where \( C_{\text{total}} \) is the total cost, \( K_{\text{lat}} \) and \( K_{\text{long}} \) are weights for lateral and longitudinal cost.

4. Motion controller
The most commonly used dynamic vehicle steering model is called the bicycle model, as is shown in figure 5, is consisted of two wheels that were rigidly linked, and is made under the following assumptions: (1) Ignore the suspension system, the vehicle is only allowed travel on a plane without pitch and roll movement. (2) Ignore the steer system, the front wheel is directly controlled to rotate about an axis normal to the driving plane within some range constraints. (3) The vehicle speed at a specific time is thought to be constant. (4) The lateral acceleration of the vehicle is below 0.4g.

![Figure 5. dynamic vehicle steering model](image)

The left part of figure 5 illustrated the relationship between the force and lateral movement, where \( F_y \) and \( F_y \) denote the lateral and longitudinal force of the front wheel, \( F_y \) and \( F_y \) denote the lateral and longitudinal force of the rear wheel, \( v_f \) and \( v_r \) is the velocity of the front and rear wheel, \( v \) is the velocity at the vehicle central gravity. \( \alpha_f \) and \( \alpha_r \) denote the angle between velocity and tire heading, which are referred as lateral slip angle. The heading \( \theta \) is an angle describing the direction of the vehicle with respect to the x axis. The right part of figure 5 illustrated the dynamic vehicle steering model with respect to the reference path, which is expressed as a function of its length \( s \), and define \( \theta_p \) as the angle between the path tangent and the global x axis.

Lateral and yaw movement of the vehicle are a primary concern in steering control, given by

\[
\begin{align*}
F_y \cos \delta + F_y \sin \delta + F_y &= m(v_y + v \omega) \\
F_y \sin \delta - l_r F_y &= I \dot{\omega}
\end{align*}
\]  

Where \( m \) is the mass of the vehicle, \( \omega \) is the yaw rate, \( I \) is the inertial moment, \( l_f \) and \( l_r \) are the length of front and rear half axis. When the slip angle is small enough, the lateral force of the front and rear wheel is linearly proportional to the slip angle, which is given by

\[
\begin{align*}
F_y &= -c_f \alpha_f = -c_f \left( \frac{v_y + l_r \omega}{v_x} \right) - \delta \\
F_y &= -c_r \alpha_r = -c_r \arctan \left( \frac{v_y - l_r \omega}{v_x} \right)
\end{align*}
\]  

Where \( c_f \) and \( c_r \) is the corner stiffness of the front and rear wheels.
Define $c(s)$ as the curvature along the path, the derived yaw rate $\omega(s)$ and lateral acceleration $\dot{v}_y(s)$ under constant longitudinal velocity assumption are given by $\omega(s) = c(s)v_s$ and $\dot{v}_y(s) = c(s)v_s^2$. The lateral distance error of the vehicle central gravity and heading angle error should satisfy

$$
\begin{cases}
\dot{e}_y = v_y + v_s \sin \theta_e \\
\dot{\theta}_e = \omega - \omega(s)
\end{cases}
$$

Substitute Eqs.5 and Eqs.6 into Eqs.7, and represent it in state space form, yields

$$
\dot{x} = Ax + Bu + C\dot{\omega}(s)
$$

Where $x = \begin{bmatrix} e_{cg} & \dot{e}_{cg} & \theta_e & \dot{\theta}_e & s & \dot{s} \end{bmatrix}^T$, $u = \begin{bmatrix} \delta & a \end{bmatrix}^T$,

$$
A = \begin{bmatrix}
0 & 1 & 0 & 0 & 0 & 0 \\
0 & -\frac{c_f + c_r}{mv_s} & \frac{c_f + c_r}{m} & \frac{l_f c_f - l_r c_r}{mv_s} & 0 & 0 \\
0 & 0 & 0 & 1 & 0 & 0 \\
0 & \frac{l_f c_f - l_r c_r}{l_z} & \frac{l_f c_f - l_r c_r}{l_z} & \frac{l_f c_f - l_r c_r}{l_z} & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 1 \\
0 & 0 & 0 & 0 & 0 & 0
\end{bmatrix},
B = \begin{bmatrix}
0 & 0 \\
\frac{l_f c_f - l_r c_r}{mv_s} & 0 \\
0 & 0 \\
0 & 0 \\
0 & 0 \\
0 & 0
\end{bmatrix},
C = \begin{bmatrix}
0 & 0 \\
\frac{l_f c_f - l_r c_r}{mv_s} & -v_s \\
0 & 0 \\
0 & 0 \\
0 & 0 \\
0 & 1
\end{bmatrix}
$$

This designed dynamic model is then transferred into discrete form, meanwhile the reference local trajectory generated by the motion planner can be represented by as sequence of reference states $x^\star$. MPC is then used to utilize path tracking, within a prediction horizon $H$, define the cost function as

$$
J = \sum_{i=1}^{H} \left( (x_i - x_i^\star)^T Q (x_i - x_i^\star) + u_i^T R u_i \right)
$$

Where $Q$ and $R$ is the weight matrix, furthermore, $Q$ is designed as a semi-definite diagnose matrix, $R$ is designed as a definite diagnose matrix. Then given a set of constraints on $u$, some of which are derived from the vehicle dynamic constraints, others directly from the HD map, the optimal control during the prediction horizon can be solved by

$$
u^\star_i = \arg \min (J)
$$

5. Simulation and results
In order to test the effect of this work, a set of simulation tests are conducted. The simulation results show that the designed motion plan and control method works well on structured road, which can handle common driving scenarios like velocity keeping, vehicle following, stop and going, passing, etc., some of these scenarios are shown in figure 6.
As is shown in figure 6: (a) when there is no other central in-path vehicles (CIPV), the host vehicle will keep a predefined target speed; (b) when there exist a lower speed CIPV, the host vehicle will follow it with a self-adaptive space gap; (c) when approaching a turning corner or a stopping line, the host vehicle will stop at the defined position and waiting for the signal and then start moving again; (d-f) when there exist a slow moving CIPV and the speed gap is less than a predefined threshold, the host vehicle will passing it and then merging back to the original lane. Limited by the space of this paper, only a few representable common driving tasks are illustrated here.

6. Conclusion
A HD map based autonomous driving motion plan and control method for structured road condition is proposed in this paper, which is consisted of a motion planner and a motion controller, and the motion planner is further divided into a global planner and a local planner. DP is used to generate a global path based on HD map information. Several candidate trajectories are generated in Frenet frame, and the optimal is chosen through a predefined cost function. Then MPC is used in motion controller to track the reference trajectory. Simulation results show that the designed motion plan and control method is able to handle common scenarios occurred on structured road.

Acknowledgments
This work is supported by the China National key research and development plan key special project of intergovernmental international science and technology innovation cooperation development project “automotive passive and active collaborative protection technology for pedestrian safety” (No. 2018YFE0192900).

References
[1] Darby C L, Hager W W and Rao A V 2011 An hp-adaptive pseudo spectral method for solving optimal control problems Optimal Control Applications & Methods vol 32(4) pp 476-502.
[2] Likhachev M, Ferguson D, Gordon G, Stentz A and Thrun S 2005 Anytime Dynamic A*: An Anytime, Replanning Algorithm Proceedings of the International Conference on Automated Planning and Scheduling (ICAPS) pp 262-71.
[3] Ferguson D and Stentz A 2006 Using interpolation to improve path planning: The Field D* algorithm Journal of Field Robotics vol 23(2) pp 79-101.
[4] Karaman S and Frazzoli E 2010 Optimal Kinodynamic Motion Planning using Incremental Sampling-based Methods Proceedings of the 49th IEEE Conference on Decision and Control, CDC 2010 pp 7681-87.

[5] Webb D J and Berg J V D 2013 Kinodynamic RRT*: Asymptotically optimal motion planning for robots with linear dynamics IEEE International Conference on Robotics & Automation. IEEE pp 5054-61.

[6] Thrun S, Montemerlo M and Palatucci M 2009 Stanley: The Robot that Won the DARPA Grand Challenge Journal of Field Robotics vol 23(9) pp 661-92.

[7] Urmson C, Anhalt J, Bagnell D, et al 2008 Autonomous Driving in Urban Environments: Boss and the Urban Challenge Journal of Field Robotics vol 25(8) pp 425–66.

[8] Luca A D, Oriolo G and Samson C 1998 Feedback control of a nonholonomic car-like robot In Robot Motion Planning and Control pp 171–249.

[9] Campbell S F 2007 Steering control of an autonomous ground vehicle with application to the DARPA Urban Challenge Massachusetts Institute of Technology pp 25-42.

[10] Guo J H, Hu P, Li L H, et al 2012 Automatic steering controller design for vision-based unmanned vehicle J Dalian Univ of Tech vol 52(3) pp 437-42.

[11] Moritz W, Julius Z, Sören K and Sebastian T 2010 Optimal Trajectory Generation for Dynamic Street Scenarios in a Frenet Frame Proceedings - IEEE International Conference on Robotics and Automation pp 987-93.