Path Planning and Vehicle Control Technologies for Autonomous Driving Systems

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To expand the applications of autonomous driving technologies aimed at reducing traffic accidents, technologies to recognize various surrounding environments correctly, and technologies to judge and control that ensure safety and ride comfort in such environments are important. This paper describes path planning technologies that can be applied to complicated environments and vehicle integrated control technologies that ensure highly accurate tracking of paths and comfortable ride.

1. Path Planning Technologies

1.1 Path planning technologies for autonomous driving

Conventional path planning technologies include graph search methods, such as Dijkstra(1) and A*,(2) and sampling-based planning methods such as rapidly-exploring random tree (RRT).(3) These methods enable high-speed path searching in complicated environments. However, because they do not consider the motion characteristics of the vehicle, the planned path causes jerky motion of the vehicle, which degrades the ride comfort. Many path planning technologies that use curves or combine with motion model have been proposed to overcome this problem. Mitsubishi Electric Corporation has been developing PF-RRT, which is a sampling-based path planning technology using a particle filter (PF) in order to realize smooth vehicle behavior and adaptability to complicated environments.(4), (5)

1.2 Path planning technologies using PF

PF is a state estimation method that approximates a conditional probability distribution with a group of data called particles. Target of estimation is a virtual vehicle in ideal state. Ideal observation values assumed to be obtained from the virtual vehicle are used to calculate state transition to approach the ideal state from the current state. The ideal state is equal to objectives in path planning, such as follow the center of a target lane and maintaining the target speed and safe distance from surrounding obstacles.

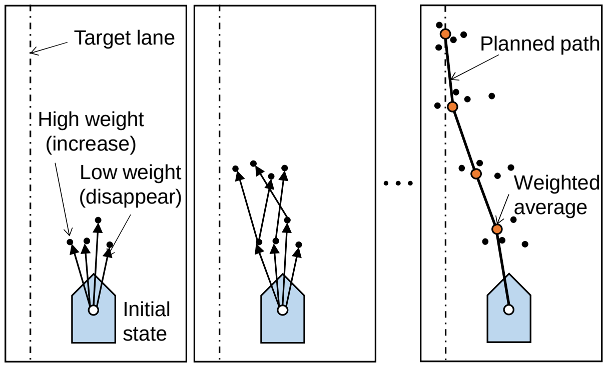

Fig. 1 Conceptual diagram of PF path planner

Figure 1 shows the flow of path planning. First, the states are predicted using a system model for all particles. Random numbers are used as input to the system model to vary the states of the particles. The weight of each particle is calculated based on the difference between the observation value obtained from the state of each particle and the ideal observation value. Resampling (increasing and decreasing of particles) is then performed based on the weight. By repeating the state prediction, weight calculation, and resampling, probability distribution of state at each time is approximately obtained by particles. The average values of the state quantities of the particles are calculated to obtain the path to the ideal state from the current state.

1.3 PF-RRT path planning

To achieve path planning in a complicated environment, Mitsubishi Electric has developed a path planning technology in which PF is combined with input-based RRT, a sampling-based planning method. RRT is a method to expand data group in a tree structure using random numbers and search a path from the data group. In input-based RRT, when a tree is expanded, nodes are randomly selected and branches are extended according to the system model. The nodes are connected based on the motion characteristics represented by the system model. Therefore, a path can be searched considering the motion characteristics of the vehicle.

This section describes the flow of the developed

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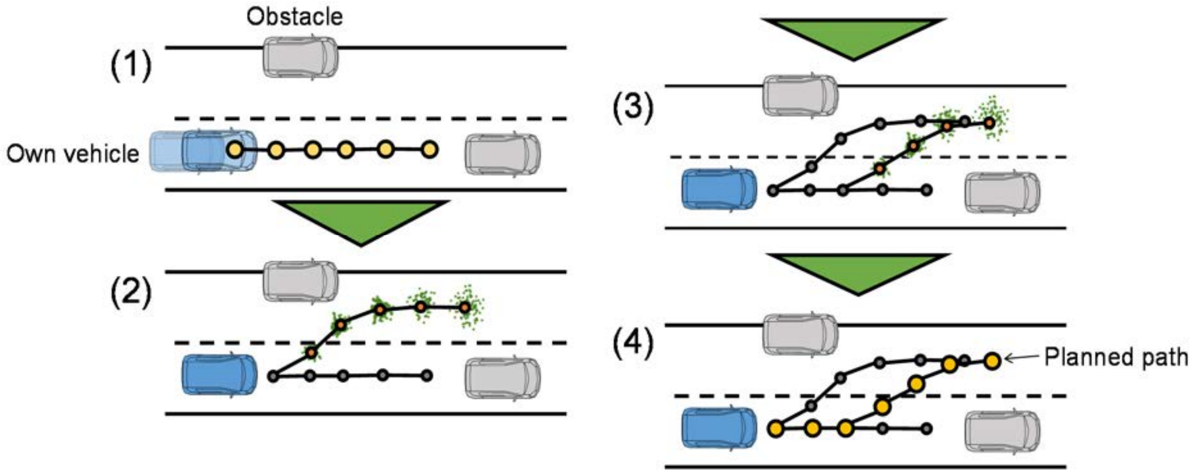

Fig. 2 PF-RRT path planner

path planning technology with reference to Fig. 2. (1) Data group including the position and velocity are held in a tree structure. (2) Randomly selected nodes are used as initial positions to create a path using PF and the created path is added to the tree as a new branch. (3) Step (2) is repeated to expand the tree. (4) The path that minimizes the reaching cost is selected from the tree and output to the controller.

In this way, by expanding a tree with randomness it is possible to search a path in a complicated environment.

2. Vehicle Integrated Control Technologies

2.1 Vehicle control technologies for autonomous driving

Recently, thanks to the improvement of computing power, nonlinear model predictive control (NMPC) has been gaining attention. NMPC is a control theory that solves an optimization problem for a finite time-horizon in the future for each sampling frequency and the initial value of the obtained solution is applied as a control input. Although the calculation loads are high, the theory has various advantages, for example, it can handle multivariable control problems and nonlinear models and constraints can be explicitly considered. Therefore, we have been developing a control system using NMPC that controls integrally the longitudinal and lateral motion of the vehicle, in order to follow the generated path with high accuracy and realize comfortable ride.(6) By using NMPC it is possible to consider the trackability of paths, ride comfort such as acceleration and jerk, and their upper limits.

2.2 Formulation of nonlinear model predictive control

In NMPC, various factors need to be set: a vehicle dynamics model that predicts the states from now to a certain point in the future; a cost function designed such that the vehicle will follow a created path while maintaining ride comfort; and upper and lower limits (constraints) for the state variables and control input. Our study used a vehicle model in which a general bicycle model(7) was combined with a nonlinear tire model using the Pacejka formula.(8) The state variables of the model are longitudinal and lateral positions, yaw angle, longitudinal velocity, lateral velocity, yaw rate, steering angle, front and rear wheel side-slip angles, and front and rear wheel angular velocity. The input variables are steering angular velocity and braking and driving torque of the front and rear wheels. As the cost functions, the trackability was considered using deviation of the self-position from the target path and that of the velocity from the target speed; the ride comfort was considered based on longitudinal acceleration, longitudinal jerk, yaw rate, and steering angular velocity. Constraints were imposed on the location deviation, which was equivalent to the lane width, steering angle, steering angular velocity, and braking and driving torque of the front and rear wheels. The solution for an NMPC controller that was designed as described above is calculated by sequential quadratic programming and the optimal solution is applied to the steering angle and speed to control the vehicle.

3. Verification Using Actual Vehicles

3.1 Configuration of the autonomous driving system

Figure 3 shows the configuration of the autonomous driving system. The system uses a Global Navigation Satellite System (GNSS) and high-definition map. The high-definition map has point cloud information on the latitude and longitude of the center of lanes. The system also has sensors that measure the position and speed of obstacles. The sensor and map information are used to create a target path and speed with PF-RRT. To follow

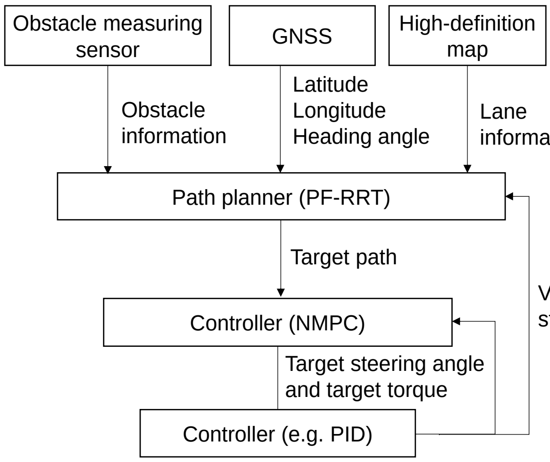

Fig. 3 System configuration

the target path, the NMPC controller calculates the target steering angle and target braking and driving torque. The vehicle controller controls the steering angle and speed so as to follow the calculated target values by the PID control of the like.

3.2 Verification results using an actual vehicle

The effectiveness of this autonomous driving system was checked in a test using an actual vehicle. In the test, the vehicle traveled at the target speed of 80 km/h on a straight two-lane road while avoiding stationary obstacles. Figure 4 shows the vehicle trajectory in the test, and Figure 5 shows the lateral position error, steering angle, and vehicle velocity. Figure 5 shows that the vehicle followed the path with smooth steering while maintaining the target speed of 80 km/h. These results confirm that the autonomous driving system can control the steering and vehicle velocity and can drive a vehicle while changing lanes to avoid obstacles.

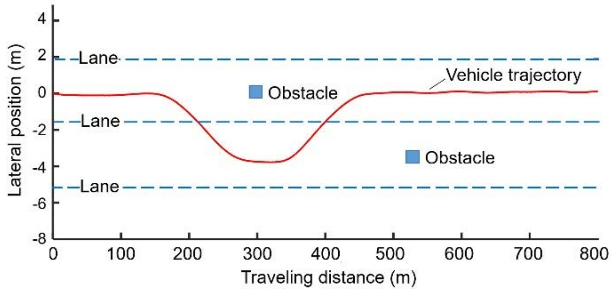

Fig. 4 Vehicle trajectory to avoid obstacles

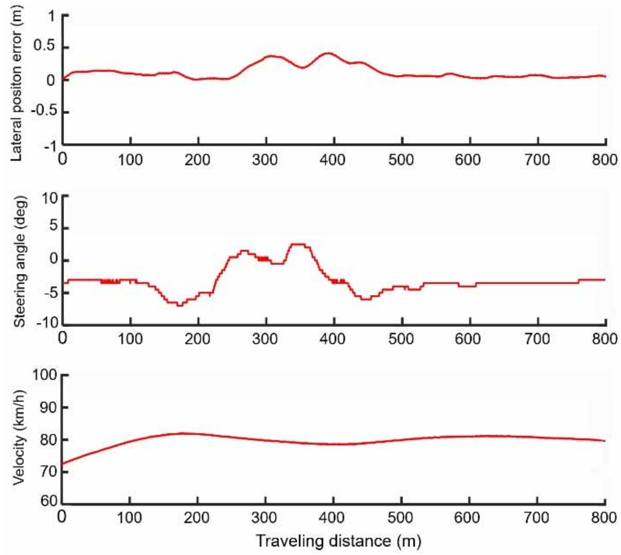

Fig. 5 Vehicle states when avoiding obstacles

4. Conclusion

To popularize the path planning and vehicle control technologies described in this paper, it is important to enhance the robustness and reduce the calculation cost, in addition to applying them to more complicated cases. Mitsubishi Electric has been working to solve these issues, aiming to establish practical autonomous driving technologies.

5. References

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