A Hybrid Path Planning Model for Obstacle Avoidance Using Future Trajectory Prediction

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Abstract

Obstacle avoidance or collision free can be considered as one of the most crucial criteria in autonomous vehicles to enhance driving safety. In common driving scenarios, humans do not make decisions based on the current situation only but gather information from the near past to the present time, then estimate the near future to make corresponding decisions. Inspired by this observation, in this paper, we propose a hybrid path planning framework that is constructed from a conventional path planning method and a deep learning-based trajectory forecasting model for obstacle avoidance. First, the hybrid A* algorithm is applied to the global map to find out the global path. While moving toward the global destination, a bidirectional long short-term memory (BiLSTM) deep learning network takes the gray and depth images of the surrounding environment as input to predict the future occupancy grid map. If an obstacle is detected on the planned path, a new local path is generated using the hybrid A* algorithm. The framework is tested in a simulation environment and the results indicate that forecasting future trajectory helps to improve the obstacle avoidance task significantly.

I. Introduction

In recent decades, intelligent vehicles have been receiving tremendous attention with the goal of providing convenience and safety to users. As safety is one of the first priorities in autonomous vehicles, collision avoidance plays a crucial role in the autonomous vehicle system. A wide range of path planning approaches such as graph search-based, sampling-based are proposed and used for both global and local path plannings and obstacle avoidance. To assist these path planning algorithms, a variety of sensors has been utilized such as depth camera, radar, and LiDAR. With the fast growth and success of deep learning (DL), recent studies have applied deep learning to improve the way vehicles "see" and reason the surrounding environment, thus, gain better performance [1]. In this study, we propose a simple autonomous vehicle framework that utilizes the depth camera and uses the conventional hybrid A* for path planning task and a deep learning-based trajectory prediction model for obstacle avoidance.

II. Methodology

In this framework, the path planning task is divided into two stages: global and local path planning. In the former stage, in order to create a global path from the starting position to the final destination, a general map is assumed to be available. The hybrid A* algorithm is used to generate the global path. While traveling from the starting point to the ending point, a bidirectional long short-term memory (BiLSTM) model is deployed on the data collected from the depth cameras (i.e., gray image and depth information) to perceive the surrounding objects and predict the future occupancy grid map. If there is any obstacle might appear on the current path according to the output occupancy grid map, another hybrid A* algorithm is used to replan the path at a local area. The detailed architecture of the proposed framework is illustrated in Fig. 1.

A. Hybrid A for Global and Local Path Planning*

A* path planning family [2] is a graph search-based method which is an extension of Dijkstra algorithm. With the implementation of heuristics, it achieves faster performance compared to the Dijkstra algorithm. In this work, we use a variant of the A* algorithm called Hybrid A* [3] for planning the global and local paths. It automatically searches for a target point from the farthest free region. Moreover, with the hybrid structure, it is expected to take a short time for a single planning with less computational cost compared to the original A* algorithm.

B. Future Trajectory Forecasting

Humans can normally navigate smoothly through many social interaction situations which remain as challenges in autonomous vehicles, such as lane changing, yielding at roundabouts and merging in traffic. The reason is that humans do not see things and make decisions once at a time while driving but we see and gather information of the near past to the present, then reason to predict how the surrounding agents might act in the near future and make corresponding decisions. Thus, to prevent collisions, A bidirectional recurrent neural network [4] using a LSTM [5] in each forward and backward directions is applied directly to the images of five consecutive frames from past to current time stamp $\left(f_{t-4}, f_{t-3}, f_{t-2}, f_{t-1}, f_t\right)$.

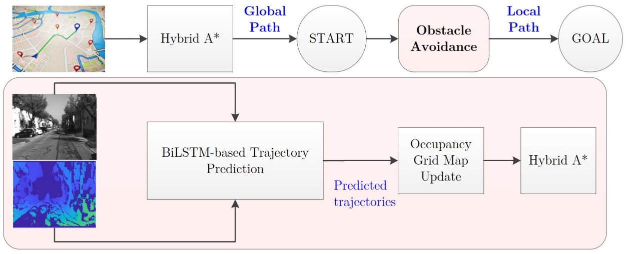

Fig. 1. Overall architecture of the hybrid path planning framework for obstacle avoidance using DL-based future trajectory prediction.

At every time stamp i, the bidirectional LSTM layer extracts the features from the input data and forward to a fully connected layer with a sigmoid activation function to predict a binary occupancy grid map $\hat{y}_i$ which includes the future trajectory information of the next frame. During training, the predicted grid maps $\left(\hat{y}_{t-4}, \hat{y}_{t-3}, \hat{y}_{t-2}, \hat{y}_{t-1}, \hat{y}_t\right)$ are compared with the corresponding ground-truth grid maps $\left(y_{t-4}, y_{t-3}, y_{t-2}, y_{t-1}, y_t\right)$ to calculate the loss. In the testing phase, the five predicted binary grid maps are added as the logic OR gate to obtain the final output. If the current planning path intersects with any occupancy area in the updated grid map, a hybrid A* algorithm is applied to replan the local path.

III. Experiments

We use the open-source robotics simulator CoppeliaSim (with a free educational license) to create the virtual environment including map, static and dynamic obstacles, robot and sensors. Data processing, path planning and deep learning-based trajectory prediction are implemented in MATLAB. The communication between the simulator CoppeliaSim and MATLAB is executed by using the ZeroMQ remote API. Four Kinect cameras are mounted on top of the vehicle in four directions (front, rear, left, and right) to capture all the surrounding information. The RGB images are converted to gray images to reduce the computational cost. At each frame, the gray and depth images of the four cameras are concatenated along the depth dimension, finally, the input f_i has a size of (244, 244, 8). There are eight maps are created with some modifications to increase the diversity of the experiment. Each map has a size of (25, 50) meters and is converted to a grid map with a resolution of (50, 100) with a cell size of (0.5, 0.5). Several cuboids, trees, indoor plants, and terrain bumps are used as static obstacles while walking people are considered as moving obstacles. The dataset contains 17 batches with more than 5000 data samples. The first 11 batches are used for training and the remaining 6 batches are used for testing. The BiLSTM model achieves an accuracy of 93% on the test set. An example of the output occupancy grid map is shown in Fig. 2. The green circles indicate the ground-truth future position of the moving obstacles while the red circles indicate the predicted trajectory.

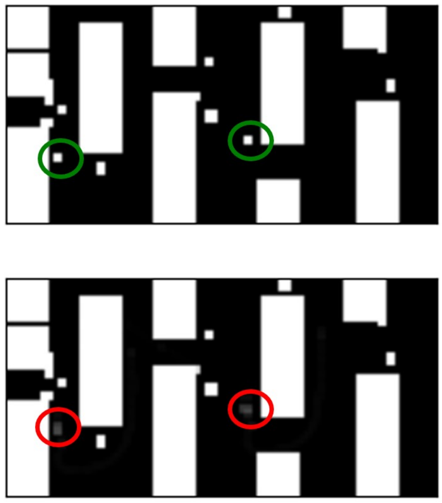

Fig. 2. Results of the future occupancy grid map prediction.

IV. Conclusion

In this study, we proposed a simple framework of path planning by combining a hybrid A* algorithm and a deep learning-based trajectory prediction module using the bidirectional long short-term memory model. With the estimated occupancy grid map, the system can find out an optimal local path which is smoother and has a lower rate of collision. Due to the requirement of exact vehicle's location in the surroundings' trajectory prediction and local path planning tasks, implementing a precise localization algorithm is considered as one of our future works.

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