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A simulation based method for vehicle motion prediction

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ABSTRACT

The movement of a vehicle is much affected by surrounding environments such as road shapes and other traffic participants. This paper proposes a new vehicle motion prediction method to predict future motion of an on-road vehicle which is observed by a stereo camera system mounted on a moving vehicle. Our proposed algorithm considers not only the history movement of the observed vehicle, but also the environment configuration around the vehicle. To find feasible paths under a dynamic road environment, the Rapidly-Exploring Random Tree (RRT) is used. A simulation based method is then applied to generate future trajectories by combining results from RRT and a motion prediction algorithm modelled as a Gaussian Mixture Model (GMM). Our experiments show that our approach can predict future motion of a vehicle accurately, and outperforms previous works where only motion history is considered for motion prediction.

1. Introduction

Being able to predict the future motions of vehicles is important especially in Advanced Driver Assistance Systems (ADAS) [1] and autonomous car systems [2]. Unique in a vehicle system, the motions of vehicles are constrained by a road network, steering geometry as well as their momentum in speed. Using the information as constraints, we are able to predict the future motions of a vehicle.

In current state-of-the-art technologies in vehicle motion prediction, a number of algorithms have been developed to predict the motions of vehicles captured by surveillance cameras in a static environment [3]. Besides, more and more researches are interested in predicting the motions of vehicles under dynamic environment where input video is captured by a car-mounted camera on a moving car [2,4]. By predicting the motions of surrounding vehicles around a moving car, better safety precaution can be installed in the ADAS and autonomous car.

In this paper, we propose a motion planning based algorithm to predict the motion of a vehicle observed by a stereo camera rig mounted on a moving vehicle under dynamic environments. In particular, the Rapidly-Exploring Random Tree (RRT) [5] is applied to incrementally sample the future motion of the observed vehicle based on its motion history and road configuration. Different from conventional RRT where the objective is just to find routes to a goal, we use the routes as reference paths to simulate future movement. This allows us to achieve a more accurate motion prediction, and a longer range of prediction.

In our setting, we use road networks from the Open Street Map (OSM) [6] to set possible goal points for RRT. In addition, we use the satellite map from the Google Earth [7] to configure road environments that include information about boundaries and lanes of roads. To detect and localize positions of vehicles by the camera system, we use the Deformable Part Model detector [8]. Since our focus is to predict the future motion of a vehicle, we assume the information about the road network and the surrounding environment is accurate.

We tested our algorithm using real road data sequences from the KITTI vision benchmark suite data set [9] with ground truth evaluation to estimate prediction accuracy. We have also compared our results with prior methods for vehicle motion prediction. The results show that using motion planning helps to enhance accuracy of prediction of future trajectories.

The remainder of this paper follows this outline. Section 2 reviews related works in vehicle motion prediction and motion planning. Section 3 defines our problem. Section 4 describes the configuration of our environment data. Section 5 presents our method to model motion history. Section 6 details our proposed motion prediction algorithm. Section 7 evaluates the performance of our algorithm. Finally, our paper is concluded in Section 8.

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2. Related work

2.1. Vehicle motion prediction

We review vision based approaches for vehicle motion prediction. The majority of previous works in vehicle motion prediction focus on a static setting of a surveillance camera installed at intersections of roads or highways [10–13].

In [10], Hu et al. use a chain of Gaussian distribution to represent motion patterns, and moving objects of a scene are clustered according to the estimated motion patterns. In [11], a Hidden Markov Model (HMM) is used to represent temporal sequences of sub-trajectories of moving objects. This work is later extended by Vasquez et al. [12] who proposed the growing HMM which incrementally learns and predicts the motions of moving objects. Recently, Atev et al. [13] have also presented a clustering based algorithm to estimate and predict vehicle trajectories.

There are also works that can be applied to car-mounted camera where background environments are dynamically changing. Using driving state information, such as velocity, acceleration and yaw rate, Barth and Franke [14] present a short time motion prediction algorithm based on motion extrapolation. Hermes et al. [15,16] and Wiest et al. [17] introduce methods which classify trajectory data that are represented as sequences of velocity and yaw rate. In [15,16], the quaternion-based rotationally invariant longest common subsequence (QRLCS) metric is proposed to measure similarity between motion trajectories. The QRLCS metric is then combined with a radial basis function classifier to track and predict motion hypotheses. In their method, the particle filter is applied to estimate the velocity and yaw rate of vehicles in a video. In [17], motion trajectories are approximated by the Chebyshev polynomials, and are modelled as a variational Gaussian Mixture Model. Ref. [18] introduced a threat assessment system based on the Monte Carlo Sampling.

For more information about vehicle motion prediction including non-vision based techniques, there is a recent survey paper [19] which introduces diverse motion prediction and risk assessment methods.

2.2. Motion planning

The Rapidly-Exploring Random Tree (RRT) [5] is one of the most representative sampling based motion planning algorithms. To plan a motion path, RRT incrementally expands a tree by randomly sampling a new path in a short time interval in a free space until a feasible path to a goal position is detected. The incremental nature of RRT facilitates fast on-line exploration under dynamic environments. From the original RRT, many variants have been emerged for various purposes. In [20,21], the availability of RRT is extended to a non-linear system with dynamic constraints. [22] proves that solutions of the original RRT are not optimal, and introduces RRT$*$ which guarantees asymptotic optimality of their solutions. There are also many works which applied RRT in real platforms [23–25].

2.3. Our work

Our work provides a unique approach for vehicle motion prediction by combining motion planning in the motion prediction problem. The motion planning algorithm allows us to predict longer motion trajectories, and improves the performance of a previous algorithm by taking environment configurations into account during the motion prediction. In order to combine these two algorithms elegantly, we suggest a simulation-based method which takes into account kinematic constraints of a vehicle and environmental configurations. Using the reference paths generated by RRT, and the motion model based on the Gaussian Mixture Model (GMM), we simulate the future motion of a vehicle. Since multiple trajectories can be simulated, we evaluate the simulated trajectories by several criteria such as environment cost and distance with the reference path. The most likely trajectory is returned as our predicted vehicle motion.

3. Definitions

3.1. Problem definition

We first define the vehicle motion prediction problem. In our work, we use a car-mounted camera on a moving vehicle (ego vehicle) to capture other vehicles on a road. Without loss of generality, we consider the problem to predict the future movement of a single target vehicle. Traffic participants except the target vehicle are considered as dynamic obstacles.

The input data for our problem are a history trajectory T_h of the target vehicle and environment data. The history trajectory T_h consists of velocities and yaw rates (details will be given in Section 3.2) of the target vehicle in past few seconds, and the environment data contains information of a road network which describes locations of roads and the connectivity among them, and a cost map which describes static and dynamic obstacles around the target vehicle. More specific definitions about the environment data will be given in Section 4. Our goal is to predict the future trajectory T_f of the target vehicle in terms of velocities and yaw rates a few seconds into the future.

3.2. Motion trajectory

The trajectory of a vehicle is represented as follow

$$T = \{(v(t_0), \omega(t_0)), \ldots, (v(t_{N-1}), \omega(t_{N-1}))\} \tag{1}$$

where v and ω are velocity and yaw rate at each timestamp t_i. The physical time interval between the timestamps depends on a sampling rate of data capturing. In our case, data are collected at 10 timestamps per second.

3.3. Coordinate system

Since our data are captured on a moving vehicle, they are influenced by the ego motion of the cameras mounted on the ego vehicle. In order to avoid this problem, we transfer the observed data into fixed coordinates with respect to the environment data. In this section, we will define two coordinates, absolute coordinate and relative coordinate. Fig. 1 shows the relation between the absolute coordinate (super-script a) and the relative (ego) coordinate (super-script r).

Note that, because the ground is usually flat, we drop y-direction information (height information) for simplicity and use only x- and z-information, i.e. geolocation, for the remaining part of the paper.

3.3.1. Relative coordinate to absolute coordinate

To transform from the relative coordinate to the absolute coordinate, homogeneous transformation matrix $G_a(t)$ is used which is cumulatively calculated at each frame that contains translation and rotation information of the prior motion of the ego vehicle.

$$G_a(t) = G_a(t-1) \times \begin{bmatrix} \cos(d\theta) & \sin(-d\theta) & dx \\ \sin(d\theta) & \cos(d\theta) & dz \\ 0 & 0 & 1 \end{bmatrix} \tag{2}$$

where dx, dz and $d\theta$ are translational and rotational changes during 1 timestamp period on the relative coordinate at time t. In this paper, dx, dz and $d\theta$ are obtained from a high-precision IMU installed on the ego vehicle (OXTS RT 3003 used in KITTI data set – velocity accuracy: 0.05 km/h RMS, bias of angular rate: 0.01°/s 1σ [26]).