Monte-Carlo Tree Search vs. Model-Predictive Controller: A Lane-Following Example

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Abstract

Monte-Carlo Tree Search (MCTS) has achieved remarkable success in the game of Go. However, most success of MCTS is in games where actions are discrete. For autonomous driving, the vehicle action such as throttle and steering angle is continuous. To fill the gap, we propose an MCTS algorithm for continuous actions, and used it specially for a lane-following scenario. We compared MCTS with a standard Model Predictive Controller (MPC) on the Udacity simulator. Using the same cost function and system model, this MCTS algorithm achieves a much lower cost than MPC. MCTS drives with an adaptive speed, as well as exhibits a braking behavior in sharp turns. MPC drives a nearly constant speed regardless of the curvy track.

1 Introduction

Autonomous driving aims to make cars safer. Nearly 1.3 million people die in road crashes each year, on average 3,287 deaths a day. Road crashes cost USD $518 billion globally, costing individual countries from 1-2% of their annual GDP. [1] So far there are three major avenues for autonomous driving. **The classical approach** extracts perception and localization results from sensors, summarizing into geometry relationship of the car with its environment. Based on the *geometry representation* of the world, a controller is built. This approach is so far the most popular and widely adopted by industrial leaders such as Google, Uber and Baidu. **The learning-from-demonstration approach**, started from the simple full-connected neural networks [Pomerleau, 1989] in the old days to recent deep convolution layers by NVIDIA [Bojarski et al., 2016], regresses the steer angle given the camera view. This approach leads to a simpler architecture for autonomous driving. **The affordance approach**[Chen et al., 2015] predicts relevant geometry features (called "affordances") from images. Based on the predicted features, a controller can be developed. This approach bears some similarity to Pavlovian control in which animals map predictions of events into behaviors[Modayil and Sutton, 2014].

Besides these exciting progress, it is interesting to bring reinforcement learning to autonomous driving. Reinforcement learning achieved remarkable success in Atari games [Mnih et al., 2015] and Go [Silver et al., 2016]. Recently, Mobileye proposed an interesting architecture for autonomous vehicles. Similar to the classical approach, their architecture also has two layers. In particular, their high-level path planning is implemented using a recurrent neural network over the trajectory of the car [Shalev-Shwartz et al., 2016]. The low-level control is a model-based approach that learns a model for the state transition in response to the car's action. Mobileye's efforts stand for extending model-based reinforcement learning [Sutton et al., 2008, Yao and Szepesvári, 2012, Grünewälder et al., 2012] to autonomous driving. Modeling the state that the car sees next turns out to be very

[1] http://asirt.org/initiatives/informing-road-users/road-safety-facts/road-crash-statistics

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important for cars although there has not been convincing applications published yet. However, considerable progress was made in video prediction [Zeng et al., 2017, Oh et al., 2015], which can be possibly used on cars. The reward function is also a fundamental issue to bring reinforcement learning to autonomous driving. In games, the reward signal is noise free since win or loss signals can be observed as a delayed but ground truth feedback. Although how to learn a reward function for autonomous driving is still an open problem, Hadfield-Menell et al. explored teaching a car to align with a human driver with his reward function. Brechtel et al. modeled the car's environment using an Markov Decision Process (MDP) in which the state space is equidistant cells of the coordinates on the road, and the transition probabilities are approximated using a Dynamic Bayesian Networks. Their empirical studies show that the car can coordinate well when to overtake according to oncoming traffic. Exploring in a driving environment is challenging because such exploration (normally practiced in reinforcement learning without constraint) must be safety guaranteed. Recently, Mnih et al. proposed an asynchronous reinforcement learning framework that lets a number of learning agents run in parallel aiming to explore different parts of the environment. Their algorithm on a simulated driving environment achieved near to a human driver with only 12 hours of training. It is interesting to see whether this new framework can solve the specific exploration constraint in autonomous driving.

In this paper, we study Monte-Carlo Tree Search (MCTS) for an autonomous driving setting. MCTS is especially advantageous for large and complex decision making problems, as demonstrated in the competition of AlphoGo against Mr. Lee Sedol [2]. MCTS is well practiced and relatively easy to implement. All the top Go programs have used MCTS for a decade, e.g., [Coulom, 2007, Silver, 2009, Enzenberger et al., 2010]. So far the success of MCTS is largely in board games where actions are discrete. However, in autonomous driving a car's actions like throttle, braking and steer angles are all continuous. We consider a simple motion planning setting where a car has been given a trajectory to follow, and its goal is to drive within track boundary. Our treatment of motion planing is by no means to be realistic. Practical motion planning also considering avoiding obstacle, e.g., [Kuwata et al., 2008]. We aim to have an environment that renders a simple cost function and vehicle model under which evaluating performances of algorithms is relatively easy. We propose an extension of pure MCTS to continuous actions, and compare it with an off-the-shelf Model Predictive Controller (MPC).

2 Background

The classical approach is so far the most practiced and mature. A two-level architecture for autonomous vehicle is often used: path planning at a high level and vehicle control (with a target path and speed) at a low level [Paden et al., 2016, Berntorp, 2017]. There are a spectrum of methods for each of the problems. For example, Rapid-exploring Random Trees finds feasible trajectories for robots with high degrees with freedom [Lavalle, 1998, Kuwata et al., 2008]. MPC is classical control method [Garcia et al., 1989], and has been widely used for motion planning in a short time horizon [Paden et al., 2016, Kim et al., 2014, Omar et al., 1998, Yim and Oh, 2004, Raffo et al., 2009, Ng et al., 2003, Bakker et al., 1987, Kong et al., 2015, Rajamani, 2011, Besselmann and Morari, 2009, Levinson et al., 2011, Urmson et al., 2007]. MPC is a major research field on its own and this section provides the application context of MPC for autonomous driving, especially lane following.

2.1 The Model and the Problem

The car's dynamics is represented by a practical model, often referred to as the *Kinematic model*. In this model, the two wheels of the car are connected by a rigid link. The state of the car is given by $[x, y, \psi, v]$, where x, y are the x-y coordinates of the car, ψ and v are the orientation and speed of the car, respectively. The model can be expressed by,

$$\begin{aligned}\dot{x} &= vcos(\psi)\\ \dot{y} &= vsin(\psi)\\ \dot{\psi} &= \frac{a[steer]v}{L_f}\\ \dot{v} &= a[throttle],\end{aligned} \tag{1}$$

[2] https://deepmind.com/research/alphago/

where L_f is the distance between the two front wheels. This is discretized using Euler method in practice. Without loss of generality, we denote the model by an equation: $s_{k+1} = A(s_k, a_k)$, where s is a vector of the state variables and a is a vector of action variables (steer and throttle). In our problem, at each time step, an agent (MPC or MCTS) receives a number of reference coordinate points. These points are often provided by a high-level trajectory planner. The agent is also given the a distance measures δ, the distance of the car's center to the track axis; an angle deviation measure, ω, the difference between the car's heading angle (ψ) and the track axis direction. In practice, both δ and ω are computed by first regressing a polynomial line from the reference points. The goal of the agents is to drive close a target speed v^* within the track. Specifically at each time step k, the agent selects an action a. Afterwards it receives a cost signal that is computed from the following equation:

$$\begin{aligned} r(s_k, a) = w_{tr}\delta_{k+1}(a)^2 + w_{ang}\omega_{k+1}(a)^2 + w_v(v_{k+1}(a) - v^*)^2 + w_{st}a[\text{steer}]^2 + w_{thr}a[\text{throttle}]^2 \\ + w_{steerd}(a[\text{steer}] - a_{k-1}[\text{steer}])^2 + w_{throtd}(a[\text{throttle}] - a_{k-1}[\text{throttle}])^2 \end{aligned} \quad (2)$$

2.2 Model Predictive Controller

MPC assumes to know the form of the cost function in equation 2. It defines a cost function that considers N steps ahead. This cost function is essentially the undiscounted, N-step truncated return. MPC produces a sequence of N actions to minimize the cost function

$$a_{0:N-1} = \arg\min_{a_{0:N-1}} R = \arg\min_{a_{0:N-1}} \sum_{t=0}^{N-1} r(\tilde{s}_t, a),$$

where $\tilde{s}_0$ was set to the current state s_k. Common practice of MPC is to use the interior point optimizer [Paden et al., 2016].

2.3 Monte-Carlo Tree Search

MCTS is a special policy search algorithm. Comparing to other reinforcement learning methods, policy search algorithms can find global optima [Valko et al., 2013, Munos, 2014]. MCTS algorithms are designed for discrete actions. In the Upper Confidence Tree (UCT) algorithm [Kocsis and Szepesvári, 2006], the actions are treated as the arms in a multi-armed bandit problem and the frequency of actions is used to measure the knowledge of the actions according to which the exploration term in selecting the action is determined. Practice and theory of MCTS for continuous actions is largely a gap. A number of recent advances aim to generalize across actions. In particular, [Couetoux et al., 2011, Yee et al., 2016] explored generalizing in actions from already exploited actions. HOOT replaces the UCB algorithm in UCT with a continuous action selection procedure [Mansley et al., 2011]. In this paper, we aimed to first extend pure MCTS for autonomous driving.

3 A New MCTS Algorithm

Besides UCT and its variants, there is a basic MCTS algorithm which works by playing a number of random games to the end; and the moves that achieves the best game scores are chosen. This algorithm is often referred to as the pure MCTS. This algorithm by definition can be extended to continuous actions in a straight forward way. However, it is very inefficient to sample the actions in a random fashion especially in real time.

Based on the observation that in everyday driving our steering and throttle control is continuous, we propose the following tree search algorithm. Similar to the pure MCTS, at each depth of the tree we only sample one node. This essentially searches over paths instead of trees. We will generate a number of paths expanded from continuous actions. Specifically, in expanding the path from a state, we enforce the continuity in the actions going down the path. This small trick reduces the search space significantly. The algorithm is shown in Algorithm 1. The sampling distribution $u(a')$ for the current time step is incrementally adjusted according to the last action a'. In the experiment, we used a uniform distribution over a neighborhood of a'. In general u is not limited to the uniform distribution but it can incorporate knowledge we gained through exploitation and be learned automatically.

input : A system model A and a cost function that considers N steps of future costs.
output : A policy that minimize the cost function.
Initialize the state s_0 and the action a_0.
for $t = 0, 1, \ldots$ **do**
    Observe state s_t
    Receive a number of reference points, and fit a polynomial line
    /* Search over N_p paths */
    for $p = 0, \ldots, N_p$ **do**
        Set $\tilde{s}_0 = s_t, a' = a_{t-1}$ /* each path starts with the current state and last action */
        Set $R(p) = 0$
        /* planning into future N steps */
        for *k = 0,..., N* **do**
            Sample a from a distribution $u(a')$
            Predict the next state, $\tilde{s}_{k+1} = A(\tilde{s}_k, a)$
            Compute the cost r according to $\tilde{s}_{k+1}$, a, a', and deviation from the reference line
            Update $R(p) = \gamma R(p) + r$
            Set $a' = a$
        end
    end
    Select the best path with lowest cost R
    Set a_t to the first action in the best path.
    Take action a_t
end

Algorithm 1: Continuity-preserved (Monte-Carlo) Tree Search for following lane.

4 Experiments

In the experiment, we used the Udacity simulator [3]. The simulator is developed by Unity to support self-driving car development. Both algorithms used the same model in equation 1 and the same cost function in equation 2. Simulation for both algorithms was run with lookahead depth of 8. The weights for the cost function are, $w_{tr} = 10.0, w_{ang} = 50.0, w_v = 1.0, w_{st} = 10.0, w_{thr} = 3000.0, w_{steerd} = 10.0, w_{throtd} = 3000.0$.

For both MPC and MCTS, only the first action a_0 was used although N actions were produced at a single time step. In the experiment, the target speed was set to 70 km/h.

As shown in Figure 1 (left plot), MCTS achieved a much smaller cost than MPC. The cost function is a linear combination of seven cost components. MCTS achieved both a smaller speed cost and a smaller "trackPos" cost (deviation from the track center) than MPC most of the time as shown in the second plot.

The third plot in Figure 1 is the speeds of the agents on the track, which shows that (a) MCTS accelerates faster in the beginning (the ascending curves from bottom); (b) MCTS drives closer to the target speed (70 km/h) than MPC most of the time; (c) MCTS's control is more adaptive to curvature in the track. In particular, at sharp turns we see speed dip in the orange line while MPC drives at almost a constant speed. After the beginning acceleration period, MPC drove between 57.8 km/h and 58.6 km/h with an average speed of 58.4 km/h. MCTS drove between 42.8 km/h and 67.5 km/h, averaging at 62.3 km/h.

Interestingly, in the experiment we observed that MCTS showed braking behavior (continually negative throttles) ahead of sharp turns (Figure 2) although it was never explicitly trained to do so. In contrast, MPC never braked. For MCTS, $10,000$ paths were generated. The $u(a')$ is a uniform distribution over a close neighborhood of last steer angle and last throttle. In particular, the steer angle and throttle were independently drawn uniformly from the intervals, $(a'[steer] - 0.02, a'[steer] + 0.02)$ and $(a'[throttle] - 0.2, a'[throttle] + 0.2)$, respectively.

We produced videos of MCTS driving

`https://youtu.be/YP7qPJSJAVU`

[3] `https://github.com/udacity/self-driving-car-sim`

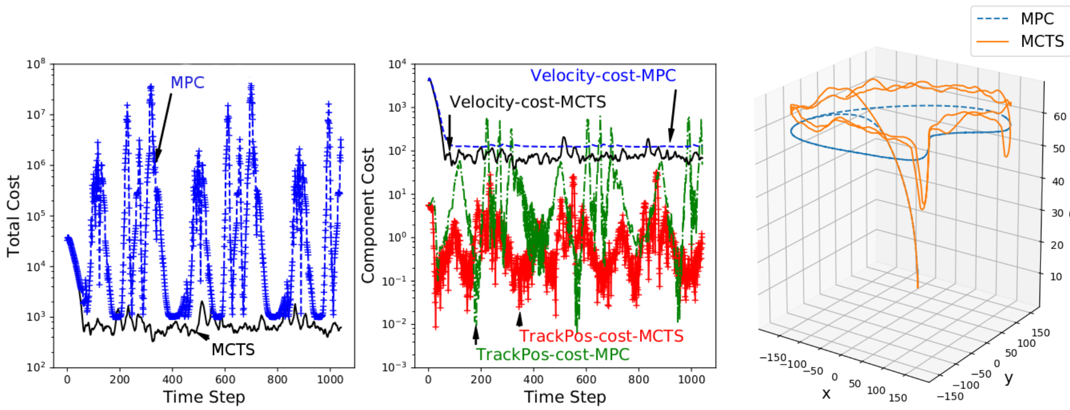

Figure 1: MCTS vs. MPC. The left plot compares the total cost over the next 8 time steps of the two algorithms. The middle plot compares the cost of the speed component and the "trackPos" (distance to the center of the lane) component. The right plot compares the speeds of the two agents driving on the track.

Figure 2: MCTS braking in front of a sharp turn. MPC never shows braking behavior in the experiment.

and MPC driving:

`https://youtu.be/SL150wMenyY`

5 Conclusion

In this paper, we proposed a primitive Monte-Carlo Tree Search algorithm for following lane in autonomous driving. The algorithm is inspired by that in driving action change is smooth: the next steering or throttle is a small modification to the existing values. In a simulated driving environment, the algorithm achieves much smaller cost than a standard off-the-shelf Model Predictive Controller under the same setting. We hope this incremental step could help the efforts of bringing reinforcement learning to autonomous driving. We plan to do a more comprehensive study of Monte-Carlo Tree Search algorithms for continuous actions and use it for autonomous driving.

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