Incorporating Recurrent Reinforcement Learning into Model Predictive Control for Adaptive Control in Autonomous Driving

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Abstract

Model Predictive Control (MPC) is attracting tremendous attention in the autonomous driving task as a powerful control technique. The success of an MPC controller strongly depends on an accurate internal dynamics model. However, the static parameters, usually learned by system identification, often fail to adapt to both internal and external perturbations in real-world scenarios. In this paper, we firstly (1) reformulate the problem as a Partially Observed Markov Decision Process (POMDP) that absorbs the uncertainties into observations and maintains Markov property into hidden states; and (2) learn a recurrent policy continually adapting the parameters of the dynamics model via Recurrent Reinforcement Learning (RRL) for optimal and adaptive control; and (3) finally evaluate the proposed algorithm (referred as MPC-RRL) in CARLA simulator and leading to robust behaviours under a wide range of perturbations.

Keywords: Autonomous Driving, Model Predictive Control, Recurrent Neural Network, Reinforcement Learning

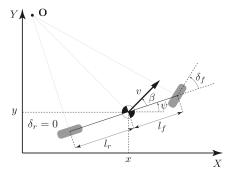
1. INTRODUCTION

Model Predictive Control (MPC) has become the primary control method for enormous fields, e.g. autonomous driving (Reiter et al.) and robotics (Song and Scaramuzza, 2020). As a model-based method, MPC largely depends on an accurate dynamics model of the system, $x_{k+1} = f(x_k, u_k; \theta)$, where x, u represent state and control respectively and θ is the parameter of the model. The parameter θ is assumed to be determined by prior knowledge or system identification method that learns the parameter from a collection of experience. However, the awareness of parameter θ consistently fails due to the perturbations emerging from all sources in the autonomous driving task. In detail, both internal (e.g. car mass, drag coefficient) and external (e.g. road friction, planning route) parameters may vary in the driving process. Also, the accurate values of the parameters are difficult to collect. Therefore, an MPC controller with a fixed parameter θ may degenerate the control performance in the autonomous driving task.

Learning-based MPC is receiving increasing attention as it focuses on automatic adaption to varying environmental parameters (Hewing et al., 2020; Spielberg et al., 2021). The standard approach is to incorporate an additional module which aims to tune the parameters of the MPC for optimal control. Bayesian Optimization (BO) and Reinforcement Learning (RL) are two significant mythologies to learn this module. BO aims at optimizing the closed-loop cost $J(\theta)$ and generates

the most suitable parameters of an MPC. However, the update of parameters is considerably slow to react in a dynamically changing environment. RL is capable of modifying the parameter at each time step. However, the perturbation in the dynamics is non-stationary, thus violating the Markov property required in RL theory.

This paper follows the RL method to boost the MPC controller's adaptability. We firstly reformulate the problem as a Partially Observed Markov Decision Process (POMDP) to ease the non-stationary property under environmental perturbations. The original state in MPC is viewed as an observation in the POMDP formulation. Meanwhile, a hidden state represents the system's actual state, including the perturbation information. We add a recurrent policy on top of the MPC and facilitate its learning with 2 objectives: cumulative reward maximization and system identification loss. The whole system achieves optimal and adaptive control in autonomous driving simulations compared with pure MPC and RL methods.





(a) The kinematic bicycle model (Kong et al., 2015).

(b) CARLA simulator.

Figure 1: Model and simulation in the autonomous driving task.

2. RELATED WORK

As mentioned in Section 1, Bayesian Optimization (BO) is a parallel approach to improve the parameters of an MPC. Marco et al. (2016) adopts an LQR formulation and learns the parameters of Q,R matrix with entropy search method. Bansal et al. (2017) also utilizes an LQR model but learns the parameters of the transition function to control a quadcopter. Both methods update the parameters θ at the end of an episode as it requires evaluating the cost $J(\theta)$, which leads to slow responses in case of environmental perturbations.

Comparatively, Reinforcement Learning (RL) can modify MPC parameters at each time step to quickly adapt to dynamic environments. Zarrouki et al. (2021) and Song and Scaramuzza (2020) both learn a policy that can improve parameters of MPC's cost function, while Gros and Zanon (2020); Amos et al. (2018) aim to modify both transition and cost function's parameters. Nevertheless, none of these methods consider the non-stationary scenario in an autonomous driving system, which violates the essential Markov property in RL.

There are other research directions to combine RL with MPC. Brito et al. (2021) utilizes RL to learn a sub-goal so as to reduce the optimization horizon of the MPC. Farshidian et al. (2019);

Zhong et al. (2013) replace the terminal cost in MPC by the value function in RL to avoid inaccurate human-designed objectives. While previous works focus on improving the efficiency of MPC with the aid of RL, in our work we are more interested in ensuring adaption to perturbed environments.

3. PRELIMINARIES

3.1. Vehicle Dynamics Modelling

The kinematic bicycle model (Kong et al., 2015) is a simplified vehicle model targeted for autonomous vehicles, whose continuous time equation is

$$\begin{bmatrix} \dot{p} \\ \dot{q} \\ \dot{\psi} \\ \dot{v} \\ \beta \end{bmatrix} = \begin{bmatrix} v\cos(\psi + \beta) \\ v\sin(\psi + \beta) \\ \frac{v}{l_r}\sin\beta \\ a \\ \tan^{-1}\left(\frac{l_r}{l_f + l_r}\tan\delta_f\right) \end{bmatrix}$$
(1)

where state $x=[a,b,\psi,v,\beta]$ includes a,b: the coordinates of the mass center, ψ : the heading angle of the vehicle, v: the speed at the mass center and β : the angle of the current velocity w.r.t. the longitudinal axis of the vehicle; control $u=[a,\delta_f]$ consists of a: the acceleration at the mass center and δ_f : the steering angle of the front wheel. Other than that, l_r and l_f are the vehicle's inertial parameters. An intuitive illustration of the kinematic bicycle model can be seen in Figure 1(a) subfigure.

However, such a model cannot be directly adopted in existing autonomous driving platform (e.g. CARLA (Dosovitskiy) and APOLLO (Gao et al., 2022)) where the output control u normally consists of steering st, throttle th, brake br instead of acceleration a and angle δ_f . Xia (2019) suggests utilizing a neural network to represent the dynamics, which has the following form

$$\dot{x} = \begin{bmatrix} \dot{p} \\ \dot{q} \\ \dot{\psi} \\ \dot{v} \end{bmatrix} = \begin{bmatrix} v\cos(\psi + \beta) \\ v\sin(\psi + \beta) \\ f_0(v, \beta; \theta) \\ f_1(v, \beta, st, th, br; \theta) \\ f_2(v, \beta, st, th, br; \theta) \end{bmatrix} = f(x, u; \theta), \tag{2}$$

where f_0, f_1, f_2 are neural networks parameterized with θ , which can be approximated by system identification methods. Furthermore, the discrete dynamic function becomes $x_{t+1} = x_t + f(x_t, u_t; \theta) \Delta t$, with the state $x_t = [p_t, q_t, \psi_t, v_t, \beta_t]^T$ and the control $u_t = [st_t, th_t, br_t]^T$. The control interval Δt equals 0.1 seconds in the experiments.

3.2. Model Predictive Control Formulation

Model Predictive Control (MPC) is an advanced optimization method for non-linear optimal control problems with constraints. To control an autonomous vehicle moving along a reference trajectory $\mathbf{G} = (g_1, g_2, ..., g_{|G|})$ (g_i are waypoints on the trajectory) with a target speed \mathbf{V} , an MPC problem can be formulated as follows:

$$\min_{\mathbf{x},\mathbf{u}} \quad l_{H}(x_{H},\mathbf{G}) + \sum_{t=0}^{H-1} l(x_{t}, u_{t}, \mathbf{G}, \mathbf{V})$$
s.t. $\forall t, \quad x_{t+1} = x_{t} + f(x_{t}, u_{t}; \theta) \Delta t$

$$-1 \leq st_{t} = u_{t}[0] \leq 1$$

$$0 \leq th_{t} = u_{t}[1] \leq 1$$

$$0 \leq br_{t} = u_{t}[2] \leq 1$$

$$x_{0} = x_{init}$$
(3)

where $\mathbf{x}=(x_0,...,x_H)$ and $\mathbf{u}=(u_0,...,u_{H-1})$ represent the state and control sequences to be optimized respectively, and x_{init} is the initial state of the autonomous vehicle. The stage cost function $l(x_t,u_t,\mathbf{G},\mathbf{V})=c_{position}\times D(x_t,\mathbf{G})+c_{speed}\times (x_t[3]-\mathbf{V})^2+c_{control}\times (u_t[0]^2+u_t[1]^2+u_t[2]^2+u_t[1]\times u_t[2])$, where $D(x_t,\mathbf{G})=\min_{k\in\{1,2,...,|G|\}}\|x_t[:2]-g_k)\|_2$ is the distance function to the nearest waypoint. The terminal cost function $l_H(x_H,\mathbf{G})=\|x_H[:2]-g_{|G|})\|_2$. Among them, $c_{position},c_{speed},c_{control}$ are coefficients to balance different parts in the cost function and set to 0.04,0.002,0.0005 in the experiments. To solve this non-linear MPC problem efficiently, the iLQR method (Li, 2004) can be applied accordingly.

3.3. Partially Observed Markov Decision Process (POMDP)

A Partially Observable Markov Decision Process (POMDP) is a generalized mathematical framework of an MDP to deal with the unobserved state issue. It is formulated as a 7-tuple $\langle S,A,P,r,\Omega,O,\gamma\rangle$, where S,A and Ω stand for the state, action and observation space respectively, and $r(s_t,a_t):S\times A\to\mathbb{R}$ is the reward function at time step t. Define $\Delta_{|S|}$, $\Delta_{|A|}$, $\Delta_{|\Omega|}$ be the probability measure on S,A and Ω respectively, then $P(s_{t+1}|s_t,a_t):S\times A\to\Delta_{|S|}$ is the transition function, and the future rewards are discounted by the discount factor $\gamma\in[0,1]$. The most crucial concept in POMDP is that agents can only obtain the observation o_t with probability $O(o_t|s_t,a_{t-1}):S\times A\to\Delta_{|\Omega|}$, instead of receiving the entire state s_t .

The received partial observation is not sufficient for agents to make decisions. Instead, the agent needs to maintain a belief state $b_t(s_t):\Delta_{|S|}$ (b_t for short) to estimate a complete knowledge of the system. There exists an update equation for the belief state given previous belief state b_{t-1} , action a_{t-1} and new observation o_t : $b_t = \eta O(o_t|s_t,a_{t-1})\sum_{s_{t-1}}P(s_t|s_{t-1},a_{t-1})b_{t-1}$, where η is a normalization factor to ensure probability measure. The policy function in a POMDP is usually defined as $\Pi = \left\{\pi(a_t|b_t):\Delta_{|S|} \to \Delta_{|A|}\right\}$ and the objective of this agent can be formulated as an optimization problem,

$$J^* = \max_{\pi \in \Pi} \mathbb{E}_{\pi, P, O} \left[\sum_{t=0}^{+\infty} \gamma^t r(s_t, a_t) | b_0 \right]. \tag{4}$$

where b_0 is an initial guess on the belief state. The expectation is on policy π , transition function P and observation function O. The belief state b_t can be iteratively calculated.

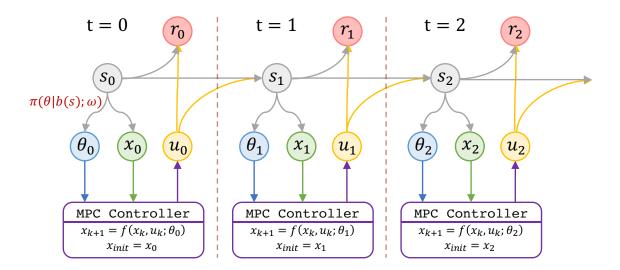


Figure 2: A POMDP Formulation of autonomous driving with an MPC controller

4. MPC-RRL Framework

In this section, we will firstly reformulate the autonomous driving task with an MPC controller as a POMDP problem. Furthermore, within this formulation, we learn a recurrent policy with RL to pursue optimal and adaptive control, thus called *MPC-RRL* for short.

4.1. POMDP Formulation

As mentioned in Section 1, it is challenging for the original dynamic of the MPC (Equation 2) to react to both internal and external variations of the system, thus decreasing the performance in real-life scenarios. Comparatively, a POMDP Formulation can ease this problem. Viewing the state x_t in MPC's dynamic function as an observation o_t in a POMDP, one can maintain a hidden state s_t in a POMDP that can reflect the perturbations in the current system. The observation distribution $O(x_t|s_t)$ represents the probability of the MPC controller receiving state x_t given hidden state s_t .

Furthermore, we model MPC's system parameters θ_t as the output action in this POMDP. The MPC controller calculates the control action u_t given the state x_t and the system parameters θ_t , referred as $u_t = MPC(x_t, \theta_t)$. After executing u_t on the environment, the hidden state transfers to s_{t+1} with probability $P(s_{t+1}|s_t, u_t) = P(s_{t+1}|s_t, MPC(x_t, \theta_t))$ and reward $r_t = r(s_t, u_t)$ is returned.

The optimal action aims to modify the parameters θ_t at each time step so that MPC can achieve an optimal control u_t even under perturbed environments. As mentioned in Section 3.3, an agent needs to maintain a belief state b_t on the current hidden state s_t so that it can generate the action θ_t to influence the MPC results by following the policy $\pi(\theta_t|b_t)$. This whole POMDP formulation allows the MPC controller to dynamically change the dynamics' parameters, leading to an optimal and adaptive control if the belief state b_t and the action θ_t is appropriately generated. The overall framework is illustrated in Figure 2.

4.2. Recurrent Policy

In this section, we will focus on the most essential sub-modules in the framework, belief state b_t and neural policy $\pi(\theta_t|b_t)$, on how they are represented, learned and deployed. In general, these two modules are combined in one single recurrent neural network and learned with 2 objectives for optimality and adaptability respectively. The combination is referred as recurrent policy for simplicity.

4.2.1. POLICY REPRESENTATION

We leverage neural networks to represent both belief state and neural policy, with parameters τ and ω respectively. A belief tracker $b_t = F(b_{t-1}, x_t; \tau)$ is designed to update the belief state given new observation x_t at each time step, while the neural policy is represented by $\pi(\theta_t|b_t;\omega)$. Following the general practice in POMDP problem (Wang et al., 2017; Hausknecht and Stone, 2017), these two networks can be combined into one recurrent neural network. Recurrent neural network (Hochreiter and Schmidhuber, 1997) possess a general representation of b_t , $\theta_t = R(x_t, b_{t-1}; \lambda)$, which perfectly absorbs F and π in one network R with parameter λ . The whole network can be optimized and utilized altogether (Young et al., 2012).

4.2.2. TRAINING DETAILS

As introduced in last section, the recurrent policy R with parameters λ is the only module to be learned. We design two learning objectives focusing on (i) encouraging MPC to generate optimal control sequences; (ii) adapting the transition model to realities separately.

The first objective is to maximize the discounted cumulative reward, as introduced in Equation 4,

$$J_1 = \max_{\lambda} \mathbb{E}_{\pi, P, O} \left[\sum_{t=0}^{+\infty} \gamma^t r(s_t, \theta_t) | b_0 \right]. \tag{5}$$

This objective encourages the neural policy to output the parameters beneficial to the control behaviours with respect to a higher return.

The second objective is inspired by the system identification loss in control theory,

$$J_2 = \min_{\lambda} \mathbb{E} \left[\sum_{t=0}^{+\infty} [x_t + f(x_t, u_t; \theta_t) \Delta t - x_{t+1}]^2 \right]. \tag{6}$$

This objective pushes the policy to imitate the realistic dynamics' parameters when it deviates from the previous approximations.

Combining these two objectives by $J=J_1+\alpha J_2$ (α is a coefficient to balance these 2 objectives), we can successfully learn a policy aiming optimal and robust MPC control. In Section 5 we will further illustrate the effectiveness of this method and the different roles of these 2 objectives. Since the expectation in Equation 5 and Equation 6 is expensive to calculate directly, the RL area usually interacts with the environments and learns from the sampling experience. In this paper, we adopt PPO (Schulman et al., 2017) as the basic RL algorithm as it is one of the best performing on-policy RL algorithms suitable to the training of dynamics belief states.

4.2.3. Inference Details

The parameters λ are fixed during inference. Given an observation of the vehicle x_t and the belief state of last step b_{t-1} , the agent directly generates the dynamics parameter θ_t and updates the belief state b_t by executing b_t , $\theta_t = R(x_t, b_{t-1}; \lambda)$. The MPC controller utilizes the dynamics parameter θ and initial state x_t to generate the control value u_t , which is further sent to the autonomous driving environment.

5. Experiments

In this section, we evaluate our proposed *MPC-RRL* framework on the CARLA simulator. We first show the superior performance with respect to goal error and route error in the main results and further analyze the controller's behaviours in the ablation study and policy study.

5.1. CARLA Simulator

We utilize CARLA simulator (Dosovitskiy) (See Figure 1(b)subfigure for a rendering example) to evaluate autonomous driving performances of all baselines. CARLA simulator is a popular simulation platform to train and evaluate different components of an autonomous driving system (perception, planning, control, etc.). CARLA is grounded on Unreal Engine to run the simulation with changeable configurations. Thus it is convenient to modify both internal (car mass, tire friction) and external (planning route, road friction) factors of the system, which facilitates our evaluation. We run CARLA in a synchronous mode, which ensures the reproducibility of the experiments but may fail to simulate some real-world situations, e.g. missing observations and delayed control, which will be studied in further research.

5.1.1. TASK SETUP

For each episode of the autonomous driving task, a starting and goal point is generated. The aim of a control method is to reach the goal point following a reference trajectory. The episode ends if the vehicle reaches the goal or experiences a collision. The performance is evaluated by the goal error and the route error together. The goal error is defined by the distance between the vehicle's final position and the goal point, while the route error is calculated by the cumulative displacement between the vehicle's actual trajectory and the reference trajectory during the driving process.

We divide the self-driving task into training and testing phase. We first train the RL policy described in Section 4.2.2 and freeze the policy's parameters in the testing phase. To evaluate the adaptability of each controller, we modify a system parameter (e.g. car's final ratio, tire's friction) to a different value. A decent controller should be able to adapt to such model mismatches between training and testing environments. The specific parameters for evaluation and their value during the training and testing phase are in Table 1. Notably, for each parameter, we testify on 3 perturbed values, with one value slightly different from the training value and the other two deviating largely.

5.1.2. BASELINES

MPC Controller The *MPC* controller strictly follows the MPC formulation as described in Section 3.2. Some practical implementation details should be considered to apply MPC on the CARLA simulator, which will be further clarified in Section 5.1.3.

D		77.1	Explanation		
Parameter	Training Value	Testing Value			
final_ratio	4.0	2.0, 5.0, 10.0	Transmission ratio from engine to wheels		
moi	1.0	0.4, 1.3, 1.9	Moment of inertia of the vehicle		
tire_friction	3.5	0.5, 2.25, 4.0	Friction factor of all wheels		
damping_rate	0.25	5e-3, 5e-1, 5e1	Damping rate of all wheels		
drag_coefficient	0.15	1e-4, 2e-1, 100	Drag coefficient of the vehicle's car body		
town	Town01	Town04, Town02, Town06	Carla's default town maps		

Table 1: Verified parameters and their values during training and testing phase.

MPC-RRL Controller The *MPC-RRL* controller is precisely the framework introduced in Section 4. For a fair comparison, we adopt the same MPC controller as Paragraph 5.1.2 as the based controller in the framework.

RRL Controller To fairly illustrate the power of combing RRL and MPC, we also add a baseline with the recurrent policy only and trained with reinforcement learning methods. In this baseline, the input of the policy is observation x, and the output is direct control action u, including steering, throttle, and brake instead of MPC's parameters in comparison with MPC-RRL.

5.1.3. PRACTICAL IMPLEMENTATION DETAILS

To apply the proposed *MPC-RRL* framework on the CARLA simulator, we explain some practical implementations on both MPC and RL parts in this section.

Vehicle Dynamics Model (i) Regarding the dynamics model in MPC, we utilize 3 neural networks f_0, f_1, f_2 parameterized with a 65-dim variable θ to represent it. $f_0(v, \beta; \theta) = \frac{v \sin \beta}{\theta[0]}$ following the original format of the vehicle model (Equation 1) can predict the heading angle ψ . For f_1, f_2 , we require them to have such properties: $f_1(v, \beta, st, th, br; \theta) = f_1(v, -\beta, -st, th, br; \theta), f_2(v, \beta, st, th, br; \theta) = -f_2(v, -\beta, -st, th, br; \theta)$ so that the symmetry of velocity angle β and steering control st maintain. To achieve that, we rewrite f_1 as $[f_1'(v, \beta, st, th, br; \theta) + f_1'(v, -\beta, -st, th, br; \theta)]/2$ and f_2 as $[f_2'(v, \beta, st, th, br; \theta) - f_2'(v, -\beta, -st, th, br; \theta)]/2$. Currently, only f_1' and f_2' are represented with parameters θ , which is a 2-layer feed-forward neural network in our experiment; (ii) Notably, the prediction of the velocity v should always be positive, for which we further rewrite f_1 as $[f_1'(v, \beta, st, th, br; \theta) \times (2\sqrt{v} + f_1'(v, \beta, st, th, br; \theta)) + f_1'(v, -\beta, -st, th, br; \theta) \times (2\sqrt{v} + f_1'(v, -\beta, -st, th, br; \theta))]/(2\Delta t)$ so that $v + \Delta t \times f_1(v, \beta, st, th, br; \theta) \ge 0$ is always true; (iii) For system identification, we manually control the vehicles running in the CARLA simulator and collect 19000 transitions to train the f_0, f_1, f_2 models. The mean-squared-error loss and Adam optimizer (Kingma and Ba, 2017) are used to learn the parameters θ .

Model Predictive Control (i) As mentioned in Section 3.2, the stage cost function $l(x_t, u_t, \mathbf{G}, \mathbf{V})$ is written as $c_{position} \times \min_{k \in \{1,2,\dots,|G|\}} \|x_t[:2] - g_k)\|_2 + c_{speed} \times (x_t[3] - \mathbf{V})^2 + c_{control} \times (u_t[0]^2 + u_t[1]^2 + u_t[2]^2 + u_t[1] \times u_t[2])$. The minimization term is not a perfect choice for gradient-based optimization methods. Instead, we utilize a differential function $D(x_t, \mathbf{G}) = -\log\left(\sum_{k=1}^{|G|} \exp{-\|x_t[:2] - g_k)\|_2}\right)$ as the distance function, which can be viewed as an approxi-

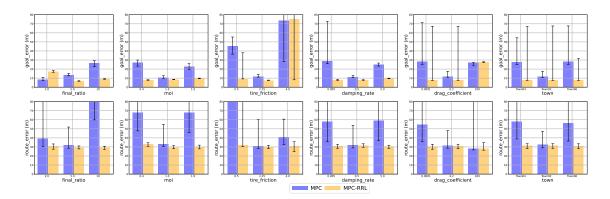


Figure 3: The average goal error and route error of the autonomous vehicle under perturbed testing environments. The x-axis is the modified parameter value during testing. The y-axis shows the corresponding goal error and route error respectively.

mation to the minimization calculation (Chen et al., 2017); (ii) In this experiment, we incorporate the constraints on the controls as a sine activation function on the original controls.

POMDP Setup (i) Reward function is a combination of goal error e_g and route error e_r , informed as $r_t = e^{-e_g/steps} * e^{-e_r}$; (ii) State function can be acquired from the CARLA simulator. Among them, position p, q, heading angle ϕ and v is returned directly, while velocity angle β is calculated by $\arctan v_-y/v_-x$ and smoothed closed to 0; (iii) Action space of the recurrent policy is 65-dim, including 1 parameter in f_0 , 32 parameters in f_1' and f_2' respectively.

Recurrent Policy (i) Recurrent policy adopts a LSTM-based neural network (Hochreiter and Schmidhuber, 1997) with one 256-dim recurrent layer; (ii) Hyperparameters are set equally among all baselines for a fair comparison. The roll-out step of the PPO is a small value of 32 for the stationary hidden state of the recurrent policy, and the system identification coefficient equals 0.01. The detailed hyperparameters are exhibited in the open-sourced code base ¹ due to the page limit.

5.2. Main Results

We firstly train MPC-RRL and RRL controllers in training environments until convergence and then include MPC controller into the testing phase. However, we find that the RRL controller fails to learn proper driving behaviours even in the training scenario (i.e. The mean episode goal error exceeds 100), which implies the difficulties and inefficiencies of pure RL algorithms in such a complex control task. We therefore exclude RRL in the testing phase and only compare MPC and MPC-RRL. From Figure 3, both MPC-based methods MPC and MPC-RRL present an acceptable adaptive performance under minor perturbations of environments. However, when the perturbed value significantly deviates from the training setup, MPC controller fails to control vehicles towards the goal (a large goal error) or following the reference trajectory while MPC-RRL can still adapt to the changes in most cases, except 2.0 in final_ratio 4.0 in tire_friction and 100 in drag_coefficient.

^{1.} Code base for this work: https://github.com/mikezhang95/mpc_rl

5.3. Ablation Study

In this section we execute an ablation study on the two most essential designs in the framework: RNN structure (RNN for short) and system identification loss (SI Loss for short). "- RNN" replaces recurrent policy with a feed-forward policy, and "- SI Loss" trains with cumulative reward maximization alone. As Table 2 shows, RNN plays a more fundamental role in terms of the goal error. Incorporating both designs leads to the best performance.

Table 2: The median goal error and average rank of all ablation settings. Less goal error turns to lower rank.

Ablatio RNN	on Settings SI Loss	final ratio	moi	tire friction	damping rate	drag coefficient	town	AVG RANK
+	+	9.09	8.44	9.13	8.33	23.50	8.03	1.3
+	-	10.44	9.43	9.97	9.19	10.68	8.83	2.5
-	+	10.82	9.40	9.94	9.28	10.74	8.94	3.0
-	-	10.65	9.40	9.98	9.12	23.89	8.80	2.8

5.4. Study on Recurrent Policy

In this section, we further analyze the learned recurrent policy to find out why it successfully resists perturbations in the environment. We plot a graph on the average absolute value of the vehicle's acceleration and how it varies by the recurrent neural policy. Figure 4 clearly explains that acceleration goes up with the rise of **final_ratio** and goes down with the rise of **drag_coefficient** and **tire_friction**. These trends all show that our *MCP-RRL* framework can adapt well to environmental perturbations, thus leading to better control performance.

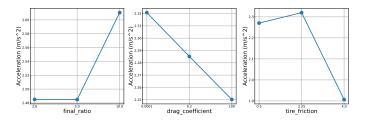


Figure 4: The average absolute value of the autonomous vehicle's acceleration under perturbed testing environments.

6. CONCLUSION

In this paper, we propose an *MPC-RRL* algorithm to handle the problem of perturbed parameters in the autonomous driving task, which is proven to be effective theoretically and empirically. This is the first work to combine RRL and MPC under a POMDP Formulation, which could be potentially beneficial to develop more robust control methods.

In future work, we will combine this work with domain randomization to better generalize the algorithm on unseen environments. Furthermore, *MPC-RRL* is expected to reveal a more robust performance than vanilla MPC on real-world cars, which will be evaluated in further experiments.

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