Reinforcement Learning Ship Autopilot: Sample-efficient and Model Predictive Control-based Approach

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Abstract—In this research, we focus on developing a reinforcement learning system for a challenging task: real autonomous ship control, with difficulties arising from uncertainties due to the complex ocean environment and the high cost of random exploration and sampling with real ships. To this end, we explore a novel Gaussian Processes (GP) based reinforcement learning approach that combines 1) sample-efficient model-based reinforcement learning and 2) model predictive control (MPC). Our approach, Gaussian process model predictive control-based reinforcement learning (GP-MPC-RL), iteratively learns a Gaussian Process dynamics model and uses it to efficiently update control signals in real-time within the MPC closed control loop. A reinforcement learning system using GP-MPC-RL is then built to learn an autopilot task on a real ship equipped with a single engine, GPS, and sensors for detecting speed, direction, and wind.

I. INTRODUCTION

Autonomous vehicles across land, sea, and air are a rapidly expanding field that brings beneficial changes to society such as relieving labor shortages, avoiding crashes, and providing mobility to humans [1] while also enabling applications such as resource exploring [2] and search and rescue [3]. On the other hand, it is arduous to obtain good control policies for autonomous vehicles, since preparing human driving demonstrations that manually encompass all possible scenarios with different environmental settings is intractable. Such a difficulty naturally suggests the use of reinforcement learning (RL) [4] which provides a natural manner to autonomously discover optimal policies from an unknown environment via trial-and-error interactions [5].

Even though RL has been widely applied to both autonomous ground vehicles [6, 7] and autonomous aerial vehicles [8, 9], its application towards autonomous ships remains limited [10] due to:

1) The uncertainties in the complex ocean environment, e.g., the unpredictable and frequently changed disturbances like wind and current and the noise and delay of sensors on a moving ship that strongly affect the ship dynamics.

2) The extremely high cost of exploring and sampling with real ships.

Recent works in this area mainly focus upon traditional control methods including proportional integral derivative (PID) controller [11], LQR [12], model predictive controller (MPC) [13] and neural networks [14]. These approaches remain, to the best of the authors’ knowledge, insufficient to facilitate autonomous control of a real full-size ship in ocean environments without human demonstration and/or intervention.

In this research, we focus on developing a RL system specialized for autonomous ship control, specifically, automatically driving a real ship in an autopilot task. To tackle the main difficulties of the autonomous control problem mentioned above, a RL method should consider the huge uncertainties from the strong disturbances and noise in ocean environments while maintaining sample efficiency. One potential solution is the combination of the model-based RL [15] and Gaussian Processes (GP) [16]. The model-based RL methods contribute to better data efficiency than model-free ones by learning policies from a learned model instead of directly from the environment. The Gaussian Processes (GP) is a powerful tool that naturally takes the model’s uncertainties into account. PILCO [17] features good sample efficiency and model-based RL that considers system uncertainties, but is computationally demanding and sensitive to noise and disturbances. One work expanding PILCO in [18] introduced MPC to moderate the real-time disturbances within a closed control loop, although its applications were limited to toy simulations. Another work is a localized GP-MPC controller [19] applied to an unmanned quadrotor simulation. It contributes to a robust MPC controller with a relatively efficient computation. On the other hand, it requires pre-prepared data to learn the GP model without an RL framework while its GP model does not support the external

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disturbances as input state. These works naturally motivate exploration towards other approaches that can exploit the merits of these works in a unified manner.

In this light, we present a novel Gaussian Processes (GP) based reinforcement learning approach that combines 1) sample-efficient model-based reinforcement learning and 2) model predictive control. Our approach, Gaussian process model predictive control-based reinforcement learning (GP-MPC-RL), iteratively learns Gaussian Process dynamics model and uses it to efficiently updates control signals in real-time within the MPC closed control loop. To be particularly suitable for the ship autopilot purpose, i.e. to reduce the computation cost and increase the robustness of control against several unpredicted and frequently changed noises and disturbances, our method employs 1) the deterministic control signals as policy parameter, and 2) a probabilistic model predictive control framework. Then a GP-MPC-RL system is built to learn autopilot task with full size ships fitted with a single engine and sensors for GPS, speed, direction, and wind (Fig. 1). After investigating this system in an autonomous ship simulation developed from real ship driving data, we successfully applied it to an autopilot task with a real ship. Our results show the capability of the proposed approach in autonomous ships, with both robustness against disturbances and a high sample efficiency.

The remainder of this paper is organized as follows. Section II provides details of the proposed approach. Section III introduces the learning system of GP-MPC-RL in the context of autonomous ships. Learning results of simulation and real autonomous ship tasks are presented in Section IV. Conclusions and future work follow in Section V.

II. APPROACH

In this section, we combine MPC framework with GP model-based RL. It follows three steps: learn the system dynamics by GP, calculate the open-loop control sequence model-based RL. It follows three steps: learn the system dynamics by GP, calculate the open-loop control sequence.

A. Gaussian Processes

Consider an unknown dynamics \( f : \mathbb{R}^D \times \mathbb{R}^U \rightarrow \mathbb{R}^D \) with state \( x \in \mathbb{R}^D \), control signal \( u \in \mathbb{R}^U \) and system noise \( w \sim N(0, \Sigma_w) \):

\[
x_{t+1} = f(x_t, u_t) + w.
\]

Given the training input tuples \( \tilde{x}_t := (x_t, u_t) \), and the training target \( y_t := x_{t+1} \), for each target dimensions \( a = 1, ..., D \), a GP model is trained based on a latent function \( y_t^a = f_a(\tilde{x}_t) + w_a \) with mean function \( m_{f_a}(\cdot) \) and a covariance kernel function:

\[
k_a(\tilde{x}_t, \tilde{x}_j) = \sigma^2 f_a \exp\left(-\frac{1}{2}(\tilde{x}_t - \tilde{x}_j)^T \Lambda_a^{-1}(\tilde{x}_t - \tilde{x}_j)\right),
\]

where \( \sigma^2 f_a \) is the variance of \( f_a \), \( \Lambda_a \) is the diagonal matrix of training inputs’ length scales in kernel. They can be learned by evidence maximization [16, 20]. The prediction with new input \( \tilde{x} \) then follows:

\[
p(f_a(\tilde{x}) | \tilde{X}, Y^a) = N(f_a(\tilde{x}) | m_{f_a}(\tilde{x}), \sigma^2 f_a(\tilde{x})),
\]

\[
m_{f_a}(\tilde{x}) = k^T \alpha_a (K^a + \alpha^2 f_a \mathbf{I})^{-1} Y^a = k^T \alpha_a \beta_a,
\]

\[
\sigma^2_{f_a}(\tilde{x}) = k_{a,a} - k^T \alpha_a (K^a + \alpha^2 f_a \mathbf{I})^{-1} k_{a,a},
\]

where \( \tilde{X} = [\tilde{x}_1, ..., \tilde{x}_N] \) is the training inputs set, \( Y^a = [y^a_1, ..., y^a_N] \) is the collection of the training targets in corresponding dimension, \( k_{a,a} = k_a(X, \tilde{x}_i), k_{a,a} = k_a(\tilde{x}_i, \tilde{x}_j) \), \( k^a = k_a(\tilde{x}_i, \tilde{x}_j) \) is the corresponding element in \( K^a \) and \( \beta_a = (K^a + \alpha^2 f_a \mathbf{I})^{-1} Y^a \).

B. Long-term Cost Optimization

To introduce MPC into the learned GP model, the process of searching a multiple steps optimal open-loop control sequence \( u_t, u_{t+1}, ..., u_{t+H-1} \) that minimizes the expected long-term cost based on one-step cost function \( l(\cdot) \), i.e., the objective function of MPC, is required:

\[
J = \sum_{s=t}^{t+H-1} l(x_s, u_s)
\]

where the system dynamics is modeled via GP. Given an open-loop control sequence, the long-term cost \( J \) requires \( H \) steps prediction of states. One interesting issue here is to consider the variances of the GP model in MPC’s control sequence search. Conventional MPC approaches this with deterministic models are applicable only when the system error can be detected [21], while [22] applied the GP model’s prior mean to MPC while ignoring the variance. The GP model’s variance was used to reduce the periodic disturbances of MPC in [23]. In this paper, we focus on exploiting the moment matching [21, 24] to consider both the uncertain states and deterministic control signals together to predict:

\[
[\mu_{t+1}, \Sigma_{t+1}] = f(\mu_t, \Sigma_t, u_t)
\]

where \( \mu_t \) and \( \Sigma_t \) are the mean and covariance of state \( x_t \), \( u_t \) is the deterministic control signal. The prediction is the mean and covariance of next step state \( x_{t+1} \).

C. Long-term State Prediction with Deterministic Control Signal

We start by separating the kernel function in Eq. (2) by assuming the state and control signal are independent:

\[
k_a(x_t, u_t, x_j, u_j) = k_a(u_t, u_j) \times k_a(x_t, x_j).
\]

Define \( k_a(u_t, u_j) = k_a(U, u_j) \) and \( k_a(x_t, x_j) = k_a(X, x_j) \), the mean and covariance related to Eqs. (4) and (5) then follows:

\[
m_{f_a}(x_s, u_s) = (k_a(u_s) \times k_a(x_s))^T (K^a + \alpha^2 f_a \mathbf{I})^{-1} Y^a = (k_a(u_s) \times k_a(x_s))^T \beta_a,
\]

\[
\sigma^2_{f_a}(x_s, u_s) = (k_a(u_s) \times k_a(x_s)) (k_a(u_s) \times k_a(x_s))^T \Lambda_a^{-1} (k_a(u_s) \times k_a(x_s))
\]

(10)
where the element in $\mathbf{K}^a$ is $k_a(x_i, x_j) \propto k_a(u_i, u_j)$ and $\beta_a = (\mathbf{K}^a + a^2 I)^{-1} \mathbf{Y}^a$, $\mathbf{X} = [x_1, ..., x_N]$ and $\mathbf{U} = [u_1, ..., u_N]$ are the training inputs of state and action, $\mathbf{Y}^a = [y_1^a, ..., y_N^a]$ is the training target set in corresponding dimensions.

Now we turn to the moment-matching with Eq. (8). Given the uncertain state $x_i \sim \mathcal{N}(\mu_x, \Sigma_x)$ and deterministic control signal $u_i$ as inputs, the predicted mean of the moment matching becomes:

$$p(\mathbb{E}[f(x_i, u_i)] | \mu, \Sigma, u_i) \approx \mathcal{N}(\mu_{x_i}, \Sigma_{x_i}) = \int p(f(x_i, u_i) | x_i, u_i)p(x_i | \mu, \Sigma) \, dx_i,$$

$$\mu_{x_i} = \int m_{f_a}(x_i, u_i)p(x_i | \mu, \Sigma) \, dx_i = \beta_a^T \mathbf{k}_a(u_i) \mathbf{k}_a(x_i) p(x_i | \mu, \Sigma) \, dx_i = \beta_a^T \mathbf{I}_a.$$

For the target dimension $a, b = 1, ..., D$, its predicted variance $\Sigma_{ab}$ and covariance $\Sigma_{ab, \alpha}$ follow:

$$\Sigma_{x_i} = \mathbb{E}[\sigma_a^2 f_a(x_i, u_i)] + \mathbb{E}[m_{f_a}(x_i, u_i)] - \mu_{x_i}^2 = \beta_a^T L \beta_a + \alpha_a^2 \mathbf{I} - \mathbb{E}[\mathbf{f}_a^T (\Sigma + \sigma_a^2 \mathbf{I})^{-1} \mathbf{f}_a] - \mu_{x_i}^2,$$

$$\Sigma_{ab} = \mathbb{E}[m_{f_a}(x_i, u_i)m_{f_a}(x_j, u_j)] - \mu_{x_i} \mu_{x_j} = \beta_a^T Q \beta_b - \mu_{x_i} \mu_{x_j}.$$

Vector $\mathbf{l}_a$ and matrices $\mathbf{L}, \mathbf{Q}$ have elements:

$$l_a = k_a(u_i, u_i) \int k_a(x_i, u_i)p(x_i | \mu, \Sigma) \, dx_i = k_a(u_i, u_i) \sigma_a^2 \Sigma A_a + I^{-\frac{1}{2}} \times \exp \left( -\frac{1}{2}(x_i - \mu)(\Sigma + A_a)^{-1}(x_i - \mu) \right).$$

$$L_{ij} = k_a(u_i, u_j)k_a(x_i, u_i) \frac{k_a(x_i, u_i)k_a(x_j, u_i)}{2 \Sigma A_a + I} \times \exp \left( (z_{ij} - \mu)^T (\Sigma + \frac{1}{2} A_a)^{-1} \Sigma A_a^{-1} (z_{ij} - \mu) \right),$$

$$Q_{ij} = \sigma_a^2 \alpha_a^2 k_a(u_i, u_i) k_h(u_i, u_j) k_a(x_i, u_j) |(A_a^{-1} + A_b^{-1}) \Sigma + I|^{-\frac{1}{2}} \times \exp \left( -\frac{1}{2}(x_i - x_j)^T (A_a + A_b)^{-1} (x_i - x_j) \right) \times \exp \left( -\frac{1}{2}(z_{ij} - \mu)^T R^{-1}(z_{ij} - \mu) \right)$$

where $\mathbf{A}_a$ is the diagonal matrix of training inputs length scales in kernel $k_a(x_i, x_j)$. $\mathbf{z}$ and $\mathbf{R}$ are given by:

$$\mathbf{z}_{ij} = \mathbf{A}_b (\mathbf{A}_a + \mathbf{A}_b)^{-1} \mathbf{x}_i + \mathbf{A}_a (\mathbf{A}_a + \mathbf{A}_b)^{-1} \mathbf{x}_j,$$

$$\mathbf{R} = (\mathbf{A}_a^{-1} + \mathbf{A}_b^{-1})^{-1} + \Sigma_t.$$

Compared with the related work [18] that exploited Pontryagin’s Maximum Principle (PMP) to search the optimal control trajectory in a reformulated optimal control problem, our approach simplifies the problem by separating the state and control in moment matching to be efficiently calculated in real autonomous ship control.

### D. Model Predictive Control Framework

Now we are able to efficiently search a $H$-step open-loop control trajectory $u_t, ..., u_{t+H-1}$ without a full planning horizon by minimizing the long-term cost in Eq. (6) (Section II-B):

$$[u_t, ..., u_{t+H-1}] = \arg \min_{u_t, ..., u_{t+H-1}} \sum_{s=t}^{t+H-1} l(x_s, u_s)$$

where the future states and the corresponding variances are predicted by learned GP model (Section II-A) using the new moment matching formulation with separates the state-control pair (Section II-C). In this research, Sequential Quadratic Programming (SQP) [25] is applied to minimize the cost. The MPC framework [26] transfers the open-loop control sequence $u_t, ..., u_{t+H-1}$ to an implicit feedback controller. As shown in the left part of Fig. 2 for each step $t$, given the current state $x_t$, a $H$-step open-loop control sequence is determined following Eq. (20) to minimize the long-term cost based on a $H$-step prediction of future states with uncertainties. The first control signal $u_t$ is then applied to get the next step state $x_{t+1}$. An implicit closed-loop controller is then obtained by re-planning the $H$-step open-loop control sequence at each coming state. For example, in applying this framework to a ship autopilot task (Fig. 2), it optimizes a control signal sequence based on a long-term prediction with uncertainties at each step via a MPC controller iteratively moderating both real-time disturbances and the errors between predicted and real performance, finally reaching the goal.

### E. Bias Compensation for MPC

A significant issue for real-world application is the bias caused by the MPC controller. As shown to the right of Fig. 2 in autonomous ship control the initial input state $x_t$ in Eq. 6 will be biased because of both the control signal (e.g., the engine throttle) being operated and the disturbances like current and wind during long-term cost optimization (biases are shown in purple arrow). This bias will result in a worse control performance, especially when the optimization time is long. Therefore, a bias compensation is required to moderate this bias by predicting the ship state after optimization. The details of this compensation in autonomous ship control will be introduced in Section II-B.

### III. REINFORCEMENT LEARNING SYSTEM FOR AUTONOMOUS SHIP CONTROL

In this section, the details of building the GP-MPC-RL system specialized for full size autonomous ship control using the approach proposed in Section II is introduced.
TABLE I: The observed states and control parameters of autonomous ship system

| Name   | Description               | From                  |
|--------|---------------------------|-----------------------|
| X      | The position in X axis    | GPS sensor            |
| Y      | The position in Y axis    | GPS sensor            |
| ss     | Ship speed                | Direction sensor      |
| sd     | Ship direction            | Direction sensor      |
| rws    | Relative wind speed       | Wind sensor           |
| rwd    | Relative wind direction   | Wind sensor           |

Control Signal

| Name | Description               | Range            |
|------|---------------------------|------------------|
| RR   | The steering angle        | $[-30, 30]$°     |
| Throttle | The throttle value of engine | $[-8000, 8000]$ |

A. Ship System

As shown in Fig. 1, the proposed system was applied to a Nissan JoyFish 25 (length: 7.93 m, width: 2.63 m, height: 2.54 m) with a Honda BF130 single engine and two sensors: a Furuno SC-30 GPS/speed/direction sensor and a Furuno WS200 wind sensor. As listed in Table I the observed states include the current ship position from the GPS sensor, the ship speed, and direction from the direction sensor, the relative wind speed, and direction from the wind sensor. The control parameters are defined as the steering angle and engine throttle that control the ship’s direction and velocity respectively. Note that there is no sensor to detect ocean currents that strongly affect the ship’s movements, as the authors believe these disturbances can be handled by the proposed approach.

B. GP-MPC-RL System

The autonomous system that applies GP-MPC-RL to autonomous ship control has three parts for training GP model, predicting long-term states and running MPC framework, respectively. To train a GP model following Section II-A we define the input state as $x_t = [X_t, Y_t, ss_t, sd_t, rws_t \times \sin(rwd_t), rws_t \times \cos(rwd_t)]$ where the relative wind speed and direction are translated to a 2D vector, the control signal as $u_t = [RR_t, \text{throttle}_t]$ and the training target as $y_t = [X_{t+1}, Y_{t+1}, ss_{t+1}, sd_{t+1}]$. Since the wind is an unpredictable disturbance in ocean environment, the GP model will not learn to predict corresponding states. Therefore, in the minimizing of the long-term cost in Eq. (6) the wind states in $x_a$ should be fixed to the initial one, i.e., we assume the wind does not change in the long-term cost optimization.

Define the optimization time as $t_{opt}$, we implement the bias compensation for MPC in Section II-E to predict position after $t_{opt}$ according to the current ship speed $ss$ and direction $sd$:

$$X_{bias} = X + ss \times \sin sd \times t_{opt}$$
$$Y_{bias} = Y + ss \times \cos sd \times t_{opt}$$

(21)

The working flow of both autonomous system and ship system are shown in Fig. 3. There is one node to communicate between the autonomous system and the ship system as shown in Fig. 3. At each step $t$, this node first transfers the sensor readings from the ship system to the autonomous system as the initial state following Section III-B. After processing the bias compensation, the autonomous system searches an $H$-step control signal sequence that minimizes the long-term cost based on the $H$-step state prediction with fixed wind states. The first control signals $u_t$ in the...
output sequence is then sent to the ship system to control the steering and engine.

C. Reinforcement Learning Process

In this section, we introduce the learning process of the GP-MPC-RL system for autonomous ship control following Algorithm 1. The first step is to get several samples to learn an initial GP model \(dyModel\). Without any human demonstration, we run \(N_{rollouts}\) rollouts with random control signals. At each time step \(t\), the system first observes the \(x_t\), then applies the random action signals \(u_t\) and then observes the training target \(y_t\). The next step is the RL process. Defining a cost function specialized for a task, e.g., the distance to the target via GPS sensor, the system runs \(N_{trial}\) rollouts where the MPC framework searches optimal control sequences that minimize the cost function predicted for \(H\) steps. The corresponding data will be used to update the learned GP model at the end of each rollout.

IV. EXPERIMENTS

A. Simulation Experiments

The GP-MPC-RL system is first investigated in an autonomous ship simulation developed by FURUNO ELECTRIC CO., LTD which approximated the responses of speed, rudder, and wind based on the real driving data of the Nissan Joy Fisher 25. In the simulation, we set an autopilot task in a \(500 \times 500\ m^2\) ocean area with random wind and current. The target is to drive the ship from its initial position \([0, 0]\) to the target position \([400, 250]\) and remain as close as possible. The states and actions of the proposed method are defined in Table I. The experiment starts with \(N_{rollout} = 10\) rollouts with random actions to train a GP model, then \(N_{trial} = 10\) rollouts to iteratively update the GP model with new samples as an RL process. Finally, the learned GP model is tested with another 20 rollouts. At each step, the control signal will be operated 3.5 s including 2.5 s operation time and 1 s optimization time \(t_{opt}\). The cost function is defined as the squared distance between the current position and target position. Sparse Gaussian processes [27] with 50 pseudo-inputs is utilized to efficiently calculate the GP model. In order to evaluate: 1) whether the longer horizon contributes to a better control result; 2) whether considering the uncertainties of predicted state in MPC, i.e., the ship position, velocity, and direction, improve the performance in complex environments; 3) whether the bias compensation contributes to better control results, four different settings of GP-MPC-RL system are compared in this experiment:

1) 1 step prediction, with variance and bias compensation
2) 5 step prediction, no variance, with bias compensation
3) 5 step prediction, with variance, no bias compensation
4) 5 step prediction, with variance, and bias compensation

For each rollout during experiments, the wind is randomly generated from \([-180, 180]\)° with max speed 10 m/s. The current is randomly generated from \([-180, 180]\)° with four different max speeds 0, 1, 2, 3 and 4 m/s as a parameter of environmental uncertainty since the ship has no current sensor. The average distances to the target position in the last 20 steps and the corresponding standard deviation are recorded and compared in Fig. 4. According to the result in Fig. 4, all four settings worked well when the current speed is small. On the other hand, only setting 4 (five step prediction, support variance, and bias compensation) kept its good performance with the increase of current speed. These results also suggest that the long prediction horizon contributes to good performance in complex environments while considering variance, and bias compensation also results in better control performance. One comparison of ten test rollouts with different prediction horizons under the same
random wind and current disturbance is showed in Fig. 5. Clearly, with longer prediction horizon ($H = 5$), the test trajectories all converged to the targets with larger current $0 \sim 3 \text{ m/s}$ while the controller with shorter prediction horizon ($H = 1$) could not.

According to these results, with the optimization process taking 1 s per step, GP-MPC-RL system was able to drive the ship to reach the target position with a GP model learned from 1000 samples. It shows great efficiency in both sampling and calculation, and robust control against a complex environment (detectable wind from $0 \sim 10 \text{ m/s}$ and undetectable current $0 \sim 3 \text{ m/s}$).

**B. Real Ship Experiment**

In this section, we implemented GP-MPC-RL system to a real autonomous ship reaching task following Section II. Hardware items were provided by FURUNO ELECTRIC CO., LTD. following Section II-A. The states and actions are again defined in Table I. In the real system (Fig. 3), our algorithm ran on a laptop with Intel Core i7 8700K CPU and 32GB RAM, while a firmware communication node ran on a laptop with Intel Core i7 6600U CPU and 16GB RAM. The experimental area is Ashiya-hama, Ashiya, Hyogo, Japan ($34^\circ42'15.9''N 135^\circ18'55.4''E$, top left of Fig. 7) with the following weather conditions: cloudy, current speed $0.0 \sim 0.2 \text{ m/s}$, current direction $45^\circ$, wave height $0.3 \sim 0.5 \text{ m}$, wind speed $2 \text{ m/s}$, wind direction $135^\circ$.

For the autopilot task, one rollout is defined as $L_{\text{rollout}} = 30$ steps autonomous driving started from initial position $[0, 0]$ with direction close to $0^\circ$. The target is to reach $[100, 100]$ and remain as close as possible. For one step, the control signal is operated for around 7 s, comprised of 5 s operation time and a 2 s optimization period $t_{\text{opt}}$. $N_{\text{rollout}} = 10$ rollouts with random actions were first conducted to train an initial GP model, then $N_{\text{trial}} = 10$ rollouts with MPC controller based on learned GP model were applied to the
RL process. The setting of GP-MPC-RL is $H = 5$ steps prediction with both variance and bias compensation. The settings of the cost function and sparse Gaussian Processes followed the simulation experiments. During the reinforcement learning process across 10 rollouts, the GP-MPC-RL system successfully reduced the cost to reach the target position within 20 steps and tried to stay near that position against disturbances from the ocean environment. Several route maps during learnings are shown in Fig. 6 where the ship explored the area and updated its GP model. One example of GP-MPC-RL with 10 rollouts learning is shown in Fig. 7. With totally 600 steps data as samples (50% from random sampling and 50% from RL), the ship was able to reach the target position and then try to stay at the area within 30 steps (about 3.5 minutes).

These results indicate the proposed system is able to achieve the autopilot task in a real ocean environment with a full-size ship. Without any human demonstration, the reinforcement learning process iteratively learned a robust MPC controller against strong disturbances such as the wind which could be detected, and the undetectable current within great sample efficiency and reasonable calculation (only 2 s for optimizing 5-step cost at each step).

V. CONCLUSIONS AND FUTURE WORKS

This work presents an RL system specialized for autonomous ship control which is challenging due to the strong and unpredictable disturbances in the ocean environment and the extremely high cost of getting learning samples with real ships. We explore a novel GP based RL approach to combine model-based RL, GP modeling and MPC framework together to naturally handle real-time system uncertainties with efficiency in both calculation and sampling. Then we developed an RL system based on the proposed algorithm for application in autonomous ship control. After investing

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1 The video of real experiment is available in [https://youtu.be/38fyzEWrnSg](https://youtu.be/38fyzEWrnSg)
its capability in an autonomous ship simulation developed from real driving data, we successfully applied it to an autopilot task in a real ocean environment with a full size ship. The experimental results show that our system could achieve the autopilot task with not only robustness against strong disturbances from wind and ocean currents, but also great sample efficiency and quick calculation with a limited computational resource.

Compared with other works [18] that introduced the Pontryagin’s maximum principle (PMP) to PILCO to search the optimal control sequence under an MPC framework, our work focuses on challenging application in the real world with efficient long-term optimization. While a GP-MPC controller was proposed in [19] to control the unmanned quadrotor simulation with a GO model learned from pre-prepared samples, the proposed approach iteratively learned the MPC controller using an RL framework without pre-prepared samples or human demonstrations and was successfully applied to a real ship in a complex ocean environment. Compared with other MPC based RL approaches applied to autonomous ground vehicles and autonomous aerial vehicles [6, 28] where models are learned via neural networks, GP-MPC-RL naturally considers system uncertainties through the moment-matching with GP model in order to tackle the strong disturbances and noises in the complicated ocean environment.

For future work, the potential of GP-MPC-RL system can be further investigated in different challenging autonomous ship tasks which can be specialized by cost function. For example reaching one target position with minimized energy cost, while keeping the current position with a fixed ship direction. Since the current real ship experiment does not utilize any sensor to detect ocean currents but considers their effect as a component of system noise to its MPC controller, we believe that the performance of our system should be improved with the addition of a dedicated current sensor. Furthermore our system could also directly learn expert driving skills by building a GP model based on human demonstrations, to achieve a more human-like autonomous driving.

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