Model-based Generalization under Parameter Uncertainty using Path Integral Control

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Abstract—This work addresses the problem of robot interaction in complex environments where online control and adaptation is necessary. By expanding the sample space in the free energy formulation of path integral control, we derive a natural extension to the path integral control that embeds uncertainty into action and provides robustness for model-based robot planning. Our algorithm is applied to a diverse set of tasks using different robots and validate our results in simulation and real-world experiments. We further show that our method is capable of running in real-time without loss of performance. Videos of the experiments as well as additional implementation details can be found at https://sites.google.com/view/emppi.

Index Terms—Model Learning for Control, Learning and Adaptive Systems

I. INTRODUCTION

As the complexity of tasks and environments that robots are expected to work in increases, so will the need for robots to rapidly learn from experience, adapt to sensory input, and model their environments for planning. Robots cannot solely learn from experience as this can be computationally and energetically costly, requiring many trials which can cause damage to the robot over time. Furthermore, experience-based learning may not generalize to immediate changes in the environment. Similarly, robots cannot solely spend their time modeling and planning in the environment as the interactions can be complex and difficult to model online. This work presents a method which provides a solution to these issues through optimizing and adapting an ensemble of physics simulators that capture the underlying structure and complexities of the world while adapting to physical variations in an online model-based control paradigm.

Learning robot tasks in physics simulators and applying the learned skills to the real world (also known as sim-to-real) has been studied quite extensively [1], [2], [3], [4]. All the learning occurs on detailed physics simulators which handle complex friction, contact, and multi-body interactions. These simulators often run faster than real-time, allowing for additional computation to occur. The simulated robot can explore and test skills in the simulation before attempting the task in the real world, avoiding damage to itself and the environment. A common problem with simulated learning is poor performance of learned skills when transferred into the real world. The poor performance is attributed to what is known as a reality gap [3] where imprecise physical parameters and physics interactions in the simulated world render simulated learned skills useless. Existing work tries to overcome these faults by diversifying the physical parameters of the world [2], improving the accuracy of the physics simulators [1], or updating the simulator parameters after real-world experience [5]. While currently the state of the art, these methods work in two-stages: train in simulation, then apply to real-world. Our work uses the fact that current simulators can perform faster than real time, further improving
the capabilities of sim-to-real in an online setting where we formulate stochastic model-based control with an ensemble of physics simulators with parameter variations, enabling us to synthesize a control signal for robotic systems that naturally encode parameter uncertainty and adapting the simulator parameters online.

Our approach expands upon the free energy formulation of model-predictive path integral control (MPP) \cite{dai2018, sze2017, wheeler2018, sze2019} by naturally encoding variations in physical parameters and structure in physics engine into online control synthesis. Any synthesized control signal is able to generalize to variations in the simulated worlds while adapting to the uncertainty to solve the task. The control synthesis generates actions that initially are conservative, eventually adapting and becoming more exploitative as sensory input is acquired. Thus, our contribution is an online ensemble model-based control algorithm that completes tasks while being robust and adaptive to parameter uncertainty. Simulated and real-world examples validate our approach for generalizing to model-based uncertainty.

The paper is structured as follows: Section II provides a discussion on related work, Section III formalizes and introduces problem statement, Section IV derives the algorithm used in this paper, results and conclusion are presented in Section V and VI.

II. RELATED WORK

Current state-of-the-art in simulated robot skill learning works in two stages: first learn in simulation and then apply the learned skills in the real-world \cite{levine2018, achiam2020, kumaran2017}. These methods work by using reinforcement learning techniques \cite{silver2016, mnih2013} in simulation in order to synthesize a policy for a task. These methods often fail due to a mismatch between physical parameters in the real and simulated world. The work in \cite{levine2018} tries to overcome the mismatch issue by “closing the loop” on the learning process. This loop-closure effectively allows the simulation to be updated at every attempt at a task in the real-world. Other work presents an approach for the model-mismatch problem using robust control and fine-tuning of a simulation to better predict physical phenomena \cite{levine2017} or learning policies from an ensemble of simulated environments \cite{tassa2018}. Our work combines these two stages of learning in simulation and adapting based on real-world experience. As a result, we are able to solve tasks immediately by synthesizing controls that generalize to various simulated environmental parameters.

Our approach mirrors model-based optimal control method (in particular ensemble model-based control \cite{park2016, park2017, tong2019, park2018}) which have existed for some time. Specifically, we use an ensemble \cite{park2016, park2017} of physics simulators in receding horizon to generate an optimal control sequence which we apply to the robot. Prior work uses motion primitives and policies \cite{park2016, tong2019}, or standard trajectory optimization with PD control feedback to handle the ensemble models \cite{park2017}. The main difference is that we utilize the free energy formulation for a stochastic control problem to directly incorporate the uncertainty in the ensemble into synthesis of the control. This enables us to handle the uncertainty as a natural extension to stochastic model-based control. Furthermore, utilizing stochastic control allows us to handle discontinuous events without concern which is often difficult to handle for common model-based controllers \cite{park2016, park2017, tong2019}. Last, our approach is able to adapt to real-world experience through online adaptation of the parameters and receding horizon control which allows for reactive planning while generalizing to local variations in the physical parameters of the simulated world.

The work in \cite{amos2019, mitrovic2020} first introduced the idea of using simulators with system identification to improve the performance of sim-to-real transfer. The mention work shows that the reality gap can be overcome when a policy is trained to be invariant to the variations found in the physical parameters. The main difference between this work and our own is that we apply this approach online and illustrate that complex systems can be modeled and controlled in real-time in a receding horizon controller formulation that can generalize to the variations in the physics simulators. In contrast, \cite{amos2019} uses a series of learned policies using reinforcement learning and an online system identification function to counteract the reality gap. Similarly, \cite{mitrovic2020} learns a family of policies and then searches for the best policy. These methods require the need to learn the policies a-priori from data which is a rigid process and difficult to adapt online. We extend these ideas to online model-based receding horizon control where we weigh in the variations in the simulated physical worlds and update them online to provide informed and reactive control.

III. PROBLEM STATEMENT

Let us first consider the partially unknown dynamics \footnote{We assume we at least know the type of robot and how it is articulated.} of a robot and the objects in the environment as a stochastic dynamical system of the form

\[
x_{t+1} = f(x_t, u_t + \delta u_t; \theta)
\]

where \(x_t \in \mathbb{R}^n\) is the state of the system at time \(t\), \(u_t \in \mathbb{R}^m\) is the control input to the system, \(\delta u_t \sim \mathcal{N}(0, \Sigma)\) is normally distributed noise with variance \(\Sigma \in \mathbb{R}^{m \times m}\), \(f : \mathbb{R}^n \times \mathbb{R}^m \times \mathbb{R}^p \to \mathbb{R}^n\) is the transition model, and \(\theta \sim p(\theta)\) is a set of physical parameters sampled from a distribution \(p(\hat{\theta})\) with mean \(\hat{\theta} \in \mathbb{R}^p\). Let us assume that we can sample a set of \(N\) parameters \(\{\theta_n\}_{n=1}^N\), such that each parameter describes a candidate transition model. The problem is to find the sequence of controls \(u_t\forall t \in \{0, \ldots, T-1\}\) for a robotic system such that it solves a task specified by the cost function

\[
S(x_0, x_1, \ldots, x_T) = S(v) = m(x_T) + \sum_{t=0}^{T} \ell(x_t)
\]

subject to uncertainty in the transition model parameters \(\theta\). Here, \(\ell(x) : \mathbb{R}^n \to \mathbb{R}\) and \(m(x) : \mathbb{R}^b \to \mathbb{R}\) are the state dependent running cost and terminal cost respectively for the value function \(S(v)\), and \(v = \{v_0, v_1, \ldots, v_{T-1}\}\) is the sequence of stochastic controls \(v_t = u_t + \delta u_t\) that generate the states \(x_t\). The specified problem is equivalent to the stochastic optimal control problem."
Using our method, all tasks are successful regardless of uncertainty in the parameters of the simulated environments. For example, (top) half-cheetah backflip where the link masses and joint damping values are unknown, (middle) in-hand manipulation of the dice while the mass of the dice is unknown, and (bottom) opening a door where the articulation of the door is unknown.

where $E$ is the expectation operator with respect to the distribution $p(\theta)$ and the open-loop control distribution $Q$, i.e., the distribution of admissible control sequences.

Assuming that the true physical system parameters reside within a local minimum of the set of parameters $\{\theta_n\}$, a solution to (3) will be a sequence of controls that can generalize amongst the variations in the physical parameters. As an aside, we treat each of these parameters as a particle (similar to a particle filter) that describes the simulated world. Then $p(\theta_n)$ is viewed as the weight of the particle and how likely the particle is in representing the real world. The optimal sequence of controls would then be a sample from an optimal control distribution $Q^*$ which is used in the following Section IV in developing the proposed algorithm.

IV. Ensemble Model-Predictive Path Integral Control (EMPII)

In this section, we present ensemble model-predictive path integral control (EMPII) as a natural extension to the information theoretic approach to the path integral control problem [6]. The concept behind path integrals is to indirectly solve for (3) by minimizing the free energy of the control system [22]. For a full derivation of model predictive path integral control, we refer the reader to [6]. We start with the definition of the free energy formulation that is introduced in [6]. Here, the sample space of the free energy formulation of the control system is expanded in order to incorporate model uncertainty into the control problem. This enables us to derive the controller that best generalizes to the parameter uncertainty as well as synthesize actions that encourage robustness given the uncertainty. Using Jensen’s inequality and importance sampling, the free energy of the stochastic control system in question is defined as

$$F(v) = -\lambda \log \left( E_{p(\theta),P} \left[ \exp \left( -\frac{1}{\lambda} S(v) \right) \right] \right) \leq -\lambda E_{p(\theta),Q} \left[ \log \left( \frac{p(v)}{q(v)} \exp \left( \frac{1}{\lambda} S(v) \right) \right) \right] \leq E_{p(\theta)} \left[ E_Q[S(v)] - \lambda E_Q \left[ \log \left( \frac{p(v)}{q(v)} \right) \right] \right] \leq E_{p(\theta)} \left[ E_Q[S(v)] + \lambda D_{KL}(Q||P) \right]$$

where $P$ and $Q$ are the control noise of the uncontrolled system distribution and the open loop control distribution defined by the probability density functions

$$p(v) = \prod_{t=0}^{T-1} \left( \frac{(2\pi)^m |\Sigma|}{2} \right)^{-\frac{1}{2}} \exp \left( -\frac{1}{2} v_t^T \Sigma^{-1} v_t \right)$$

$$q(v) = \prod_{t=0}^{T-1} \left( \frac{(2\pi)^m |\Sigma|}{2} \right)^{-\frac{1}{2}} \exp \left( -\frac{1}{2} (v_t - u_t)^T \Sigma^{-1} (v_t - u_t) \right)$$

respectively. Here, $\Sigma \in \mathbb{R}^{m \times m}$ is the covariance of the control signal, $\lambda$ is a positive scalar variable known as the temperature [6], [23], and $D_{KL}(Q||P)$ is the Kullback-Leibler (KL) divergence measure between $Q$ and $P$. From (4), it can be seen that choosing $\frac{p(v)}{q(v)} \propto 1/\exp \left( -\frac{1}{\lambda} S(v) \right)$ reduces the KL-divergence to $-E[S(v)]$ which converts the free energy into a constant and an equality which corresponds to the control objective in (3). This suggests we can solve the

Local minima refers to the, often common, coupling between physical parameters that result in similar or apparent behavior of rigid bodies given another set of distinct parameters.

This expression is used as short hand for the likelihood $p(\theta_n | \theta)$.

We refer the reader to the work in [6], [22] for more information on path integral control and free energy formulations.
Using importance sampling by multiplying by corresponding sample-based optimization:
\[ N \]

The variables
\[ \mathbf{x}_t \]

of the parts does not depend on \( u_t \), and \( \Omega \) is the sample space of \( \mathbb{R}^m \times T - 1 \). Using iterated expectations and the change of variable \( u_t = u_t + \delta u_t, \) we write Eq.(8) as
\[ u_t^* = \arg \min_{u_t} \mathbb{E}_{p(u)} \left[ D_{KL}(Q^* || Q) \right] \]

which is equivalent to solving for the control problems specified in (3) and (4) where \( Q \) is replaced with the optimal distribution \( Q^* \) and the uncontrolled system noise distribution \( P \) becomes the open-loop control distribution \( Q \).

Since we do not have access to \( Q^* \) and thus can not directly sample from the optimal distribution, \( Q^* \) is defined through its probability density function
\[ q^*(v) = \frac{1}{\eta} \exp \left( -\frac{1}{\lambda} S(v) \right) p(v). \]

Using importance sampling by multiplying by \( p(s)/p(s) \), we can decoupling the expectation over the parameter distribution and separate (6) into two parts. The resulting optimization in (6) using the density functions in (5) is defined as the closed form solution
\[ u_t^* = \mathbb{E}_{p(u)} \left[ \arg \min_{u_t} \int q^*(v) \log \left( \frac{q^*(v) p(v)}{p(v) q(v)} \right) dv \right] = \mathbb{E}_{p(u)} \left[ \arg \max_{u_t} \int q^*(v) \log \left( \frac{q(v)}{p(v)} \right) dv \right] = \mathbb{E}_{p(u)} \left[ \int q^*(v) u_t dv \right] \]

where going from the first step to the second step in (8) is a result of separating the inner integral into two parts where one

\[ \Sigma = 0.51 \]

\[ \Sigma = 0.81 \]

\[ \Sigma = 0.1 \]

\[ \Sigma = 1.01 \]

\[ \Sigma = 0.081 \]

\[ \Sigma = 0.081 \]

\[ \Sigma = 0.01 \]

This is possible as the optimization is not over the parameters \( \theta \).
Algorithm 1: Ensemble Model-Predictive Path Integral Control (EMMPI)

1: initialize: sim \( f(x,u;\theta) \), parameter distribution \( p(\theta) \) with \( N \) parameter samples, \( K \) number of trajectory samples, time horizon \( T \), objective \( \ell \), terminal cost \( m \), control noise \( \Sigma \), temperature parameter \( \lambda \), \( u_t = 0 \) \( \forall t \in [0, T-1] \), real world time \( \tau = 0 \)
2: while task not done do
3:   sample state \( \tilde{x}_\tau \) from robot environment
4:   set each sim \( f \) with sampled state \( x_{0,k,n} \leftarrow \tilde{x}_\tau \)
5:   for \( \theta_n \in \{\theta_1, \ldots, \theta_N\} \) do
6:     for \( k \in \{1, \ldots, K\} \) do
7:       for \( t \in \{0, \ldots, T-1\} \) do
8:         sample \( \delta u_{t,k,n} \sim \mathcal{N}(0, \Sigma) \)
9:         set local cost variable \( s_{t,k,n} \) using \( x_{t}, u_{t} \)
10:        update state with transition model \( x_{t+1,k,n} = f(x_{t,k,n}, u_{t} + \delta u_{t,k,n}; \theta_n) \)
11:        add terminal cost \( s_{T,k,n} = m(x_{T,k,n}) \)
12:     for \( t \in \{0, \ldots, T-1\} \) do
13:       \( S(t,k,n) \leftarrow S(t,k,n) + s_{t,k,n} \)
14:       \( u_t \leftarrow u_t + \sum_{n=1}^{N} \sum_{k=1}^{K} \omega(v_{t,k,n}) \delta u_{t,k,n} \)
15:     update parameter distribution from past state \( x_{-1} \) and control \( u_{-1} \)
16:     \( p(\theta_n) \leftarrow p(x_0 | x_{-1}, u_{-1}, \theta_n) p(\theta_n) / \eta \)
17:     resample \( p(\theta) \) if \( 1/ \sum_n p(\theta_n)^2 < N_{\text{eff}} \)
18:     optional apply filter to \( u_t \)
19:     apply \( u_0 \) to robot and shift control sequence

V. RESULTS

In this section, we evaluate our method against a diverse set of robotic systems and tasks (both in simulation and in

Fig. 3: Online improvement of half-cheetah body masses (kg) and joint damping (kg/s) values during backflip maneuver. Each line corresponds to the squared error of the individual estimate of the half-cheetah’s joint damping values and body masses.
We initialize $p$ using a uniform distribution (see Table I) without dropping the dice. The state space includes the joint poses and velocities of the robot and the position and orientation of the objects in the simulation using the Adroit hand door environment \cite{27,28}. The state space includes the joint poses and velocities of the Adroit hand and arm as well as the hinge rotation (the location of the hinge is unknown). The control space includes the desired joint positions and the arm position in the world.

Figure 2 illustrates a successful execution of the Adroit hand opening the door over a distribution of possible articulations depicted by the arrows. Each candidate joint in $p(\theta)$ has a joint axis and joint pose for the door where the value of $p(\theta_a)$ is illustrated using the transparency of the arrow. For the purpose of illustration we chose to sample each joint axis and pose from a uniform distribution over vertical and horizon poses, and a binomial distribution of axes spread away from the handle position. In Fig. 2, we see that our method controls the Adroit hand toward the handle of the door, forcing an interaction with the door. This interaction provides state feedback through the actuator forces, the hand joint poses, and the handle position. The state feedback is then used to update the estimated door articulation as shown in the time series images in Fig. 2 where the hand is shown to successfully open the door.

### B. Experiments

In this section, we provide three real-world experiments using EMPPI with the Franka Panda robot arm. The first experiment is planar pushing on a block with unknown mass and sliding friction towards a target location, second is object reconfiguration where the mass and the sliding friction of the object is unknown, and last is opening a cabinet drawer with uncertain articulation. Note that here, collisions are handled through a partial model of the objects in the simulation environment. We refer the reader to the videos of each result in \url{https://sites.google.com/view/emppi}, Table IX for parameters and Fig. 6 for the time series images of the experimental results.

**Object Manipulation:** In this task, the goal is for the Panda robot to push an object towards a target where the mass and sliding friction of the object is unknown. The geometry of the object is loaded into the simulation where contacts are resolved. Therefore the state space includes the joint position and velocities of the robot and the position and orientation of the object. The object position and orientation are calculated using tracking tags. The generated control signal directly controls the joint velocities of the Panda robot. During the experimental trial, we found that the Panda arm would initially contact the object in a conservative manner, making light taps at the object to move it towards the target. As the state of the object and the robot are collected, the certainty in the sliding articulation of objects is improved.

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**Shadow Hand Manipulation for EMPPI Comparison:** The following example uses the Shadow Dexterous robot hand for inhand manipulation of a dice \cite{26}. The goal is for the robot to move the dice to the target orientation ($< 0.15 \ell_2$ error in quaternions) without dropping the dice. The state space includes the joint poses and velocities of the hand as well as the pose of the dice. The control space includes the target joint poses which is wrapped in a proportional controller.

This example is used to compare the performance of EMPPI against MPPI with perfect knowledge and MPPI with imperfect model information. Here, the uncertainty resides in the finger joint proportional actuator gains of the Shadow hand. We initialize $p(\theta)$ using a uniform distribution (see Table I) where we sample the actuator gains. Figure 4 illustrates the performance of our method against MPPI with perfect model parameters and MPPI with imperfect model parameters. Our method is shown to perform comparably to MPPI with perfect knowledge even when the physical parameters are still incorrect. It takes around 4 seconds for the estimate of the actuator gains to converge to the true value. During the time, the controller is still able to provide a robust signal that utilizes the ensemble of physics simulators with the variations in the actuator gain to improve the overall performance of the task.

**Opening Doors with Adroit Hand** In this example, we deal with generalizing uncertainty of articulated objects in the environment. Specifically, we test our method against uncertainty in the articulation of doors and drawers. The task of the robot is to grab onto a handle and open the door when the robot does not know how the door will open. This is an important task as often robots do not have full knowledge of how doors are articulated in the world. We first test this in simulation using the Adroit hand door environment \cite{27,28}. The state space includes the joint poses and velocities of the Adroit hand and arm as well as the hinge rotation (the location of the hinge is unknown). The control space includes the desired joint positions and the arm position in the world.

Figure 2 illustrates a successful execution of the Adroit hand opening the door over a distribution of possible articulations depicted by the arrows. Each candidate joint in $p(\theta)$ has a joint axis and joint pose for the door where the value of $p(\theta_a)$ is illustrated using the transparency of the arrow. For the purpose of illustration we chose to sample each joint axis and pose from a uniform distribution over vertical and horizon poses, and a binomial distribution of axes spread away from the handle position. In Fig. 2, we see that our method controls the Adroit hand toward the handle of the door, forcing an interaction with the door. This interaction provides state feedback through the actuator forces, the hand joint poses, and the handle position. The state feedback is then used to update the estimated door articulation as shown in the time series images in Fig. 2 where the hand is shown to successfully open the door.

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With this formulation, each synthesized action is robust to the uncertainty of the physical parameters while exploiting the dynamic structure provided by the physics engine.

Fig. 4: Comparison of our method (EMPPI) on the Shadow hand dice manipulation task when there is uncertainty in the proportional actuator gains of the finger of the Shadow hand. Success rate is calculated as the sum of total successful attempts at manipulating the dice divided by the total attempts made within the allotted time (variance derived from testing over 5 trials). (a) Our method is shown to maintain similar success rates compared to MPPI with perfect information. Initializing MPPI with a model with incorrect parameters results in significant performance loss. (b) EMPPI is able to achieve an accurate estimate the uncertain parameters within 4 seconds.
friction and the object mass continued enabling the robot arm to push the object towards the target location below the tag on the table. We found that there was significant coupling between the mass of the object and the sliding friction where the estimated mass was predicted to be 0.256 kg where the actual mass was 0.164 kg. This results in an apparent added mass due to the friction between the object and the table due to the coupling between mass and friction in rigid body movement. Regardless of the inaccuracies, having an ensemble of these models where the variations in the parameters is part of the control synthesis allows a robotic system to adapt to uncertain parameters and achieve the task in real-time. Furthermore, having physics simulations render the behavior of the object allows for a more structured approach to model-based control and is shown to be capable of online use without a loss of performance.

Object Reconfiguration: In this example, the goal is for the Panda robot to rotate the object into a target configuration. The state and control spaces remain the same as with the prior experiment. As in the previous example, the uncertainty resides in the mass of the object and the friction between the object and the table. The goal is to rotate the object 90 degrees on its side (chicken side up). This required EMPPI to generate actions for the Panda arm to compensate for uncertainty in the sliding of the object while not losing control of the object due to uncertainty in the mass. We found that the solution that EMPPI had come up with was to quickly brush across the top of the object and then tip the object on its side so that the object would naturally rotate over. This is an interesting solution for two reasons: the first is that EMPPI avoided actions which would unnecessarily slide the object, and the second is that the task had occurred quickly enough that the uncertainty in the parameters were unable to converge. Suggesting that EMPPI was able to plan for the uncertainty and generate actions which would have the best outcome despite the worse-case set of parameters which would cause an unsuccessful trial of the task. We recommend the reader see the results in the attached multimedia and in [https://sites.google.com/view/emppi](https://sites.google.com/view/emppi).

Opening Drawer: In this last example, the task is to open the drawer where there is uncertainty in how the drawer is articulated. The state space is the same as the prior experiment except the position and orientation of the handle is measured. The control space is converted to joint position control of the robot to ensure safe planning when interacting with the cabinet. We initialize the distribution of simulations using a normal distribution biased towards outward prismatic motion with a wide variance (see Table I). We found that this
encourages pulling motions that do not damage the cabinet nor the robot while still providing a sufficient amount of samples. In Figure 6, we illustrate a depiction of the model simulations of the candidate joint axis. Note that axes whose largest unit value points upward or horizontally are specified as revolute joints where the unit values pointing outward perpendicular to the drawer are prismatic. In addition, the shown cabinet model is used as illustration, but does not exist in the models used for EMPI. Instead, only the geometry of the handle is used for handling contacts where the position is handled through object tracking. During execution of the task, the uncertainty of the articulation does not change until the robot measures the movement of the drawer. At that time, the set of candidate parameters \( \{ \theta_n \}^N_{n=1} \) collapses into a distribution of prismatic joints (which reflects the real-world articulation).

VI. CONCLUSION

In conclusion, we present a method that can synthesize control signals to complete a task while under parameter uncertainty. Our method utilizes the structure and complexity provided by physics engines to create a model-based controller that can generalize to parameter uncertainty. We show that our method is a natural extension to path integral control and is robust to various forms of uncertainty. We illustrate its effectiveness using a series of tasks with high dimensional robots. Last, our approach is experimentally validated our approach and provide some future work for improvements to the method.

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