Policy Learning with Continuous Memory States for Partially Observed Robotic Control

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Abstract

Policy learning for partially observed control tasks requires policies that have the ability to store information from past observations. In this paper, we present a method for learning policies with memory for high-dimensional, continuous systems. Our approach does not assume a known state representation and does not attempt to explicitly model the belief over the unobserved state. Instead, we directly learn a policy that can read and write from an internal continuous-valued memory. This type of policy can be interpreted as a type of recurrent neural network (RNN). However, our approach avoids many of the common problems that plague RNNs, such as the vanishing and exploding gradient issues, by instead representing the memory as state variables. The policy is then optimized by using a guided policy search algorithm that alternates between optimizing trajectories through state space (including both physical and memory states), and training a policy with supervised learning to match these trajectories. We evaluate our method on tasks involving continuous control in manipulation and navigation settings, and show that our method can learn complex policies that successfully complete a range of tasks that require memory.

1 Introduction

Reinforcement learning (RL) and optimal control methods have the potential to allow robots to autonomously discover complex behaviors. However, robotic control problems are often continuous, high dimensional, and partially observed. The partial observability in particular presents a major challenge. Partial observability has been tackled in the context of POMDPs by using a variety of model-based approximations [13]. However, despite recent progress [4, 6], learning the state representation, the dynamics and the observation model remains challenging.

Model-free policy search algorithms have been successfully used to sidestep the need for learning dynamics and observation models, by optimizing policies directly through system interaction [3]. However, these successes have primarily been in fully-observed domains, where reactive policies are sufficient. In contrast, partial observability often necessitates a policy with internal memory, such as a finite state machine or RNN – these types of general function approximators with internal memory, however, can be notoriously difficult to optimize. Finite state controllers have previously been applied to smaller RL tasks where value function approximation is practical [9], and policy gradient methods have been extended to RNNs [15], but an effective method for training complex, high-dimensional, general-purpose policies with internal memory is still lacking.

The contribution of this paper is an algorithm for effectively training RNN policies to solve continuous partially observed control problems under unknown dynamics. In order to handle the challenges of high dimensional policy parameterizations, we adapt the guided policy search algorithm [7] to the task of training policies with internal memory. In guided policy search, the policy is optimized using supervised learning. The supervision is provided by solving individual instances of the problem.
that each have a single initial state, which allows for efficient trajectory-centric reinforcement learning methods to be applied independently to each instance. Since the final policy is trained on data from multiple such trajectory-centric controllers, it can generalize to new initial states and provides a global policy for the task. Guided policy search has previously been applied to learn complex reactive neural networks [7], but has not previously been extended to handle policies with memory. A natural approach to extending guided policy search to handle memory would be to simply swap out the general parameterized policy, already often represented as a feed-forward neural network, with an RNN, as discussed in Section 4.1. However, training an RNN in this way is not as straightforward as training a purely feed-forward network, due to challenges in the resulting optimization problem, which include vanishing and exploding gradients, greater sensitivity to learning rates, and longer training times. Instead, we can exploit the separation between trajectory-centric controllers and neural networks induced by the guided policy search procedure and optimize the recurrent network as though it were a regular feed-forward network, with the recurrent state simply added to the state of the dynamical system. In this case, the trajectory-centric reinforcement learning algorithm used to generate the supervision for the policy optimization is responsible for setting the hidden state via a set of “store” actions, while the neural network simply attempts to match these actions at each time step. Viewed together, the final neural network policy and the hidden state dimensions of the dynamical system still form a recurrent network.

Our experimental results show that our method can be used to learn a variety of tasks involving continuous control in manipulation and navigation settings. In direct comparisons, we find that our approach outperforms a method where the neural network in guided policy search is naively replaced with a recurrent network using backpropagation through time, as well as a purely feedforward policy with no memory.

2 Related Work

While a complete survey of reinforcement learning methods for partially observed problems is outside the scope of the paper, we highlight several relevant research areas in this section. Discrete partially observed tasks have been tackled using a variety of reinforcement learning and dynamic programming methods [12, 13]. While such methods have been extended to small continuous spaces [1], they are difficult to scale to the kinds of large state spaces found in most robotic control tasks. In these domains, methods based on direct policy search are often preferred, due to their ability to scale gracefully with task dimensionality [3]. While most policy search methods are concerned with reactive policies, a number of methods have been proposed that augment the policy with internal state, including methods based on finite state controllers [9, 14] and explicit memory states that the policy can alter using memory storage actions [11]. However, these methods have been evaluated only in small or discrete settings. While our approach also supplies the policy with internal memory states and explicit actions that can be used to alter that state, our memory and storage actions are continuous, and our experiments show that our method can scale to high-dimensional problems that are representative of real-world robotic control tasks.

Taken together with their internal memory states, our policies can be regarded as a type of recurrent neural network (RNN). Previous work has proposed training RNN policies using likelihood ratio methods by using backpropagation through time [15]. However, this approach suffers from two challenges: the first is that model-free likelihood ratio methods are difficult to scale to policies with more than a few hundred parameters [5], which makes it hard to apply the method to complex tasks that require flexible, high-dimensional policy representations, and the second is that optimizing RNNs with backpropagation through time is prone to vanishing and exploding gradient problems [10]. While specialized RNN representations such as LSTMs [5] or GRUs [2] can mitigate these issues, our experiments show that our guided policy search algorithm with memory states can produce more effective policies than backpropagation through time with LSTMs.

The guided policy search algorithm used in this work is most similar to the method proposed by Levine et al. [7, 8]. This approach was proposed in the context of robotic control, and has been shown to achieve good results with complex, high-dimensional feedforward neural network policies. The central idea behind guided policy search is to decompose the policy search problem into alternating trajectory optimization and supervised learning phases, where trajectory optimization is used to find a solution to the control problem and produce training data that is then used in the super-
vised learning phase to train a nonlinear, high-dimensional policy. By training a single policy from multiple trajectories, guided policy search can produce complex policies that generalize effectively to a range of initial states. Previous work has only applied guided policy search to training reactive feedforward policies, since the algorithm assumes that the policy is Markovian. We modify the BADMM-based guided policy search method [7] to handle continuous memory states. The memory states are added to the state of the system, and the policy is tasked both with choosing the action and modifying the memory states. Although the resulting policy can be viewed as an RNN, we do not need to perform backpropagation through time to train the recurrent connections inside the policy. Instead, the memory states are optimized by the trajectory optimization algorithm, which intuitively seeks to set the memory states to values that will allow the policy to take the appropriate action at each time step, and the policy then attempts to mimic this behavior in the supervised learning phase.

3 Preliminaries

The aim of our method is to control a partially observed system in order to minimize the expectation of a cost function over the entire execution of a policy \( \pi_\theta(u_t|o_{1:T}) \), given by

\[
E_{x_o}[\sum_{t=1}^T \ell(x_t, u_t)]
\]

in the finite-horizon episodic setting. Here, \( x_t \) denotes the state of the system, \( u_t \) denotes the action, \( o_t \) denotes the observation, and \( \ell(x_t, u_t) \) is the cost function that specifies the task. For example, in the case of robotic control, \( u_t \) might correspond to the torques at the robot’s motors, \( x_t \) might be the configuration of the robot and its environment, including the positions of task-relevant objects, and \( o_t \) might be the readings from the robot’s sensors, such as joint encoders that provide the angles of the joints, or even images from a camera. The policy \( \pi_\theta(u_t|o_{1:T}) \) specifies a distribution over actions conditioned on the current observation and previous observations. This policy is parameterized by \( \theta \). We are particularly concerned with tasks where the current observation \( o_t \) by itself is not sufficient for choosing a good action \( u_t \), and the policy must integrate information from the past to succeed. Such tasks require policies with internal state, which can be used to remember past observations and act accordingly. To optimize policies with internal memory, we build on the guided policy search algorithm presented by Levine et al. [7], which we summarize briefly in this section. This algorithm optimizes reactive policies of the form \( \pi_\theta(u_t|o_t) \), and we discuss in Section 4 how it can be adapted to train policies with memory.

3.1 Guided Policy Search

Guided policy search is a policy optimization algorithm that transforms the policy search task into a supervised learning problem, where supervision is provided by a set of simple trajectory-centric controllers, denoted \( p_i(u_t|x_t) \), that are each optimized independently on separate instances of the task, typically corresponding to different initial states. There are two main benefits to this approach: the first is that, by requiring each trajectory-centric controller to solve the task from only a specific initial state, relatively simple controllers can be used that admit very efficient reinforcement learning methods. The second benefit is that, since the final policy is optimized with supervised learning methods, it can admit a complex, highly expressive representation without concern for the usual challenges associated with optimizing high-dimensional policies [3]. Intuitively, the purpose of the trajectory-centric controllers is to determine how to solve the task from specific states, while the purpose of the final policy is to generalize these controllers and succeed from a variety of initial states. The partially observed variant of guided policy search, which we build off of, takes this idea further, by also providing a different input to the trajectory-centric controllers compared to the policy. In this method, the trajectory-centric controllers are trained under full state observation, while the policy is trained to mimic these controllers using only the observations \( o_t \) as input. This forces the policy to handle partial observation, while keeping the task easy for the trajectory-centric controllers. This type of instrumented setup is natural for many robotic tasks, where training is done in a known laboratory setting, while the final policy must succeed under a variety of uncontrolled conditions. However, this method does not itself provide a way of handling internal memory.

The partially observed guided policy search method is summarized in Algorithm [1]. At each iteration of the algorithm, samples are generated using each of the trajectory-centric controllers \( p_i(u_t|x_t) \).

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\[1\] We will drop the subscript \( i \) from \( p_i(u_t|x_t) \) in the remainder of the paper for clarity of notation, but all of the exposition extends trivially to the case of multiple trajectory-centric controllers.
the form $p(u_i|x_i) = \mathcal{N}(K_{x_i} x_i + k, C_{x_i})$ admit a particularly efficient optimization procedure based on iterative refitting of local linear dynamics [7]. Once these dynamics are fitted, the algorithm takes $L$ inner iterations (4 in our implementation). These iterations alternate between optimizing each trajectory-centric controller $p(u_i|x_i)$ using a variant of LQR under the fitted dynamics, and optimizing the policy $\pi(\theta(u_i|o_i))$ to match the actions taken by the trajectory-centric controllers at each observation $o_i$ encountered along the sampled trajectories. The controllers are optimized to minimize their expected cost $E_p[\ell(\tau)]$, as well as minimize their deviation from the policy, measured in terms of KL-divergence. The policy is optimized to minimize the KL-divergence from the controllers. This alternating optimization ensures that the trajectory-centric controllers and the policy agree on the same actions. In general, supervised learning is not guaranteed to produce good long-term policies, since errors in fitting the action at each time step accumulate over time. Formally, the issue is that the policy will not have the same state visitation frequency as the controllers it is trained on. The alternating optimization addresses this by gradually forcing the controllers and policy to agree. To ensure agreement, guided policy search uses Lagrange multipliers on the means of the policy and the controllers, which are updated every iteration. The full details of this method, including the objectives for controller and policy optimization, are derived in previous work [7].

### 3.2 Recurrent Neural Networks

In order to avoid task-specific manual engineering of the policy class, guided policy search is often used with general-purpose function approximators such as large neural networks. In order to integrate memory into such policies, they must be converted into recurrent neural networks (RNNs). Unlike feed-forward networks, RNNs are capable of integrating past history through the activations of their hidden states, which are propagated forward in time according to the hidden state dynamics.

Figure 1 illustrates a general recurrent neural network, as well as a unit of the long short-term memory (LSTM) architecture. These networks are typically trained by viewing them as one large neural network and calculating the gradient of the parameters with respect to some loss by using backpropagation through time. Being able to integrate information over multiple time steps allows RNNs to be handle sequence processing tasks, such as speech recognition and text generation. However, learning long-term temporal dynamics is still very difficult for RNNs, since backpropagation through many time steps can lead to vanishing and exploding gradients. Many solutions have been proposed for these issues. One popular solution consists of altering the architecture of the network to make optimization easier, with the LSTM architecture being particularly popular. We therefore evaluate such an architecture as the baseline in our experiments in Section 5.

A diagram of the LSTM node is shown in Figure 1 and the precise details of the LSTM internal architecture used can be found in [5]. The hidden state has two components of the same size, $c_t$ and $h_t$. The sigmoid nonlinearities (pink trapezoid) followed by elementwise multiplication act as a soft memory access gate with values between 0 and 1. This set of interactions is designed so that the hidden states $c_t$ can maintain long term memory by selectively forgetting using the $f_t$ gate and to selectively add a small increment or decrement $g_t$ using the $i_t$ gate but otherwise maintaining its value. The output is gated by $o_t$ so that each hidden state $h_t$ is selectively activated. The result for one LSTM unit is that when the $f_t$ gate is close to 1, and $i_t$ close to 0, we have $c_t \approx c_{t-1}$. When $f_t$ is close to 0 and $i_t$ close to 1, we have $c_t \approx \tanh(g_t)$. When they are both close to 1, we have $c_t \approx c_{t-1} + \tanh(g_t)$. The result of gating memory access in this way is that, for most steps, we have $\frac{\partial c_t}{\partial c_{t-1}} \approx 1$ or $\frac{\partial c_t}{\partial c_{t-1}} \approx 0$. It is this property that allows the LSTM to mitigate the vanishing gradients problem, since the gradients are multiplied by either one or zero at each step.
As we discuss in the following section, we can adapt the guided policy search algorithm to directly optimize RNN policies, including LSTMs, using backpropagation through time. However, we also present a more nuanced approach that avoids backpropagation through time, and instead adds the recurrent state of the network to the state of the system, allowing it to be controlled by the trajectory-centric controllers. In our experiments, this approach achieves significantly better results.

4 Training RNNs with Guided Policy Search

In this section, we describe two methods by which RNN policies with internal memory can be trained by using the guided policy search algorithm presented in the previous section.

4.1 A Baseline Approach

A natural approach to extending guided policy search to recurrent neural networks would be to simply swap out the general parameterized policy, already often represented as a feed-forward neural network, with an RNN or LSTM network, while keeping everything else the same as detailed in Section 3.1. However, training an RNN or LSTM network this way is not as efficient as training a purely feed-forward network, the training is vulnerable to issues such as vanishing and exploding gradients, and learning rates are generally substantially harder to set. In practice, we found this approach to be more difficult to train than our method, resulting in policies that performed quite poorly. This issue is explored further in the experimental results in Section 5.

4.2 Our Approach

In our method, we treat the recurrent neural network as a standard feed-forward network, and do not backpropagate the recurrent activations through time. Instead, we add the hidden state of the network, denoted $h_t$, to the state of the dynamical system. This forces the trajectory-centric linear-Gaussian controllers to handle the optimization over the hidden state. We similarly augment the set of actions with memory storing actions $a_t$, which are added to the hidden state at each time step such that $h_{t+1} = h_t + a_t$. The feed-forward neural network policy attempts to mimic the trajectory-centric controllers and take the same memory storing actions $a_t$, in the same way that it attempts to match the regular actions $u_t$. Taken together, the hidden state, hidden state dynamics, and the feed-forward network form a recurrent network, which allows the policy to maintain memory.

Since the hidden memory states are treated simply as additional state variables, leveraging the ability of guided policy search to handle high-dimensional state spaces and policy parameterizations provides us with a simple and efficient way to incorporate memory into the policy. The full state $\bar{x}_t$ becomes $\bar{x}_t = [x_t; h_t]$. The observation also includes the hidden state, i.e. $\bar{o}_t = [o_t; h_t]$, and the action contains the “store” actions, i.e. $\bar{u}_t = [u_t; a_t]$. After every time step, the hidden state is updated by the “store” action: $h_{t+1} = h_t + a_t$. Apart from these changes, the rest of the method is the same as described in Section 3.1. Note, however, that to the guided policy search algorithm, the changes we have described here are transparent. Guided policy search treats this new modified state as a normal state vector, and knows nothing about its two separate components. Likewise, the actions
output by the policy and the linear-Gaussian controllers are treated as whole actions, and the two components of the new action vector $u_t$ are not treated separately.

One additional detail in this approach is that the dynamics of the hidden state do not need to be fitted to data in order to optimize the trajectory-centric controllers, since these dynamics are known. We therefore still only fit the time-varying linear dynamics to the original state $x_t$ and action $u_t$ at each iteration, and then fill in the known hidden state dynamics. Aside from this, the method is identical to the one described in Algorithm 4.1.

4.3 Representational Power and Connections to LSTMs

In order to optimize the memory states as part of the linear-Gaussian controller optimization, the dynamics of the memory states $h_t$ must be fixed, in contrast to general RNN architectures, where the dynamics are learned. However, since the memory action $a_t$ can be an arbitrary nonlinear function of the input at time step $t$, any arbitrary RNN can be embedded in this structure. Let $h_{t+1} = f(x_t, h_t)$ represent the RNN dynamics and $u_t = g(x_t, h_t)$ represent its output at step $t$. In general, the functions $f$ and $g$ might be part of the same neural network and might share some connections.

Furthermore, our hidden state dynamics behave much like the dynamics of the LSTM hidden state $c_t$, since $\frac{\partial h_t}{\partial h_{t-1}} = 1$ and $\frac{\partial h_t}{\partial o_t} = 1$. This makes the memory states easy to optimize for the linear-Gaussian controllers and more likely to be used to communicate information forward in time, as opposed to embedding ad-hoc memory into the physical state of the system. While we do not include any gates in our policy architecture that are similar to the LSTM gates, one could easily multiply the output of the memory actions $a_t$ with a sigmoid gate before outputting it in order to smoothly restrict write access to the memory states. The corresponding RNN dynamics would then be $h_{t+1} = h_t + \sigma(\mu_t(o_t, h_t)) \circ a_t$ where $\sigma$ is the sigmoid function, $\circ$ is elementwise multiplication, and $\mu_t$ is the mean output by the feedforward neural network that composes the policy. There is a clear analogy between this architecture and the input gate $i_t$ in the LSTM, since we would have $h_{t+1} \approx h_t$ if the gate is closed (near 0), or the normal $h_{t+1} \approx h_t + a_t$ if it is open (near 1).

One difference between the architecture produced by our algorithm and LSTM-like neural networks, however, is that our policy is stochastic. In our experiments, it is represented by a Gaussian with a learned variance that is independent of the input, and a mean $\mu_t(o_t, h_t)$ determined by the feedforward neural network based on the observation $o_t$ and memory state $h_t$. This means that, taken together with the memory states, the policy forms a stochastic recurrent network. For a low-variance policy, this is not particularly significant, but exploring the benefits of training stochastic RNNs in this way is an interesting avenue for future work.

5 Experimental Results

The need to use memory arises frequently in more complex robotic tasks, so we tested our approach on a number of simulated robotic control problems that require remembering some aspect of prior observations. We compare our method to two baselines. The first baseline trains a reactive policy corresponding to a feedforward neural network, without memory, while the second trains a recurrent network with LSTM units using the naive method described in Section 4.1.

All of our tasks are evaluated in a partially observed setting, where the policy receives an observation $o_t$ which does not contain all of the information necessary to accomplish the task, in contrast to the full state $x_t$ that is provided to the trajectory-centric controllers during training. We evaluated our method on two manipulation tasks and a simple 2D navigation and retrieval task. All tasks were performed in a physical simulation, with the robot in the manipulation tasks modeled roughly on the right arm of a PR2 robot, while the 2D task used simple double integrator dynamics.

In the first manipulation task, the robot was required to sort a peg into one of two holes. The hole position is provided to the policy on the first time step, and the policy must remember this position and move to the correct target. To prevent the policy from applying a large force in the direction of the target immediately when the target is presented, the robot is not allowed to move until the
For the peg sorting task, the dotted black line shows the depth of the hole. Policies that do not bring the object successfully.

Both our method and the feedforward policy used neural networks with two hidden layers and rectifying nonlinearities, with 40 hidden units for the manipulation tasks and 10 for the retrieval task. The LSTM network was identical, except that the second layer consisted of LSTM recurrent units.

The results of these experiments are presented in Figure 2. The graphs show the distance to each of the targets in terms of the number of samples. Note that although the graphs show multiple lines for each method (e.g. red lines with square or triangular markers), these lines represent the same policy, just tested on different target locations. This shows, for example, that the feedforward baseline succeeds well on one of the positions for the peg sorting task, but fails completely on the other one. Each method was provided with 5 samples per target per iteration, and the distance was measured from the bottom of the peg, bottle, or plate to the target for the manipulation tasks, and from the target object to the agent’s starting position for the navigation and retrieval task. Traces of the trajectories attained by each method are shown under the corresponding plots.

For the peg sorting task, the dotted black line shows the depth of the hole. Policies that do not bring the peg closer to the target than this amount do not insert the peg successfully. On this task, only our method was able to learn a successful policy that sorts the peg correctly each time. The feedforward network was unable to complete this task due to lack of memory, and simply chose the same hole each time. Surprisingly, the LSTM network did not learn to remember the target, and instead found a sort of “middle ground” action where it moved to the center rather than choosing a hole. Despite
the fact that in theory this network could complete this task, in practice we found the LSTM network to be more difficult to train than our method, which required substantially less tuning.

On the bottle and plate task, the feedforward policy generally achieved good accuracy, succeeding on three of the four conditions. However, as the trajectory plots underneath the graph show, the resulting paths were significantly more circuitous, as the feedforward policy attempted to use the physical state of the robot as its “memory”. Our method could instead use its internal memory to store its knowledge about which task it was performing, resulting in a much cleaner trajectory and success under all four conditions. This task neatly illustrates one of the motivating factors for our method: even without explicit memory states, feedforward policies can adopt strategies that “off-load” memory onto the physical state of the system, by utilizing subtly different joint angles and velocities depending on their past experience. However, with internal memory, this type of physical “offloading” is unnecessary. The LSTM network also successfully completed the task in most cases, but resulted in motions that were less clean and sometimes drifted away from the target location, resulting in substantially higher cost. This again is indicative of the difficulty of training recurrent policies using this baseline method.

For the 2D navigation and retrieval task, our method was able to succeed on three of the four starting positions. The feedforward network could not return the object back to the initial state due to lack of memory, while the LSTM policy could not be optimized successfully and did not produce a coherent behavior. We hypothesize that this is because even small deviations in the state of the double integrator can lead to compounding errors, and that the LSTM network did not learn the feedbacks necessary to perform the task stably and successfully.

The project website contains supplementary videos that illustrate the behavior of these policies.

6 Discussion and Future Work

We presented a method for training policies for continuous control tasks that require memory. Our method consists of augmenting the state space with memory states, which the policy can choose to read and write as necessary. The resulting augmented control problem is solved using guided policy search, which uses simple trajectory-centric reinforcement learning algorithms to optimize trajectories from several initial states, and then uses these trajectories to generate a training set that can be used to optimize the policy with supervised learning. In the augmented state space, the policy is purely reactive, which means that policy training does not require backpropagating the gradient through time. However, when viewed together with the memory states, the policy is endowed with memory, and can be regarded as a recurrent neural network. Our experimental results show that our method can be used to learn policies for a variety of simulated robotic tasks that require maintaining internal memory to succeed.

Part of the motivation for our approach came from the observation that even fully feed-forward neural network policies could often complete tricky tasks that seemed to require memory by using the physical state of the robot to “store” information, similarly to how a person might “remember” a number while counting by using their fingers. In our approach, we exploit this capability of reactive feedforward policies by providing extra state variables that do not have a physical analog, and exist only for the sake of memory.

One interesting direction for follow-up work is to apply our approach for training recurrent networks for general supervised learning tasks, rather than just robotic control. In this case, the memory state comprises the entire state of the system, and the cost function is simply the supervised learning loss. Since the hidden memory state activations are optimized separately from the network weights, such an approach could in principle be more effective at training networks that perform complex reasoning over temporally extended intervals. Furthermore, since our method trains stochastic policies, it would also be able to train stochastic recurrent neural networks, where the transition dynamics are non-deterministic. These types of networks are typically quite challenging to train, and exploring this further is an exciting direction for future work.

\footnote{We tested a variety of hyperparameters for the LSTM baseline and chose the best-performing policy.}

\footnote{http://rll.berkeley.edu/gpsrnn}
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