Multi-task Learning with Gradient Guided Policy Specialization

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Abstract—We present a method for efficient learning of control policies for multiple related robotic motor skills. Our approach consists of two stages, joint training and specialization training. During the joint training stage, a neural network policy is trained with minimal information to disambiguate the motor skills. This forces the policy to learn a common representation of the different tasks. Then, during the specialization training stage we selectively split the weights of the policy based on a per-weight metric that measures the disagreement among the multiple tasks. By splitting part of the control policy, it can be further trained to specialize to each task. To update the control policy during learning, we use Trust Region Policy Optimization with Generalized Advantage Function (TRPO-GAE). We propose a modification to the gradient update stage of TRPO to better accommodate multi-task learning scenarios. We evaluate our approach on three continuous motor skill learning problems in simulation: 1) a locomotion task where three single legged robots with considerable difference in shape and size are trained to hop forward, 2) a manipulation task where three robot manipulators with different sizes and joint types are trained to reach different locations in 3D space, and 3) locomotion of a two-legged robot, whose range of motion of one leg is constrained in different ways. We compare our training method to three baselines. The first baseline uses only joint-training for the policy, the second trains independent policies for each task, and the last randomly selects weights to split. We show that our approach learns more efficiently than each of the baseline methods.

I. INTRODUCTION

Deep reinforcement learning (DRL) has achieved considerable success in high dimensional robotic control problems [1], [2], [3]. Most of these methods have been demonstrated on single agent learning a single task. However, to obtain a truly intelligent agent, it would be desired to train the agent to perform a variety of different tasks, which is referred to as multi-task learning.

There are three general approaches to train an agent to perform multiple tasks. One can train separate agents for each task and later consolidate them together using supervised learning. However, training independently for each task can be sample inefficient. Another approach is to train multiple tasks sequentially. This approach is attractive in that it resembles how humans learn, however it is difficult to design efficient and scalable algorithms to retain the knowledge from earlier tasks. The third category is to learn multiple tasks concurrently. Existing works in this direction have been focused on learning common representations between multiple tasks and trying to achieve better data efficiency.

In this work, we study how weight sharing across multiple neural network policies can be used to improve concurrent learning of multiple tasks. We propose an algorithm that, given a set of learning problems and a fixed data budget, selects the best weights to be shared across the policies. We compute a metric for each weight in the neural network control policy that assesses the disagreement among the tasks using the variance of policy gradients.

We evaluate our methods on learning similar continuous motor control problems using reinforcement learning. We present three examples, and in each example a set of policies are trained on related tasks. We compare our result to three baseline methods, where the first one shares all the weights between policies, the second one shares no weight between policies, and the last randomly selects the weight to split. We show that by sharing part of the weights selected by our approach, the learning performance can be effectively improved.

II. RELATED WORK

In recent years, researchers have used deep reinforcement learning on continuous control problem with high-dimensional state and action spaces [2], [3], [4]. Powerful learning algorithms have been proposed to develop control policies for highly dynamic motor skills in simulation [2], [4] or for robot manipulation tasks on real hardware [3]. These algorithms typically require a large number of samples to learn a policy for a single task. Directly applying them to train a policy that is capable of multiple tasks might be possible in theory but would be data and computationally inefficient in practice.

One way to train an agent to perform multiple tasks is to first learn each individual task and later consolidate them into one policy. Rusu et al. introduced policy distillation to compress a trained policy into a smaller model or to consolidate multiple trained expert policies into a unified one [5]. They demonstrated that the distilled policy can, in some cases, perform better than the original expert policy. A similar algorithm was proposed by Parisotto et al. to learn a single agent capable of playing multiple Atari games [6]. Researchers have also applied this approach to learn parameterized robotic control tasks such as throwing darts [7] or hitting a table tennis ball [8]. These algorithms work well when the expert policies are easy to learn individually and do not present conflicting actions, but these assumptions are not always true.

Alternatively, an agent can learn a single policy for multiple tasks sequentially [9], [10], [11]. Rusu et al. proposed to use a progressive neural network, in which each column corresponds to a task [11]. When learning a new task, the algorithm utilizes weights from the previously trained models. Fernando et al. introduced pathnet, which selects pathways from a collection of connected neural network modules.
for learning new tasks [10]. These methods can effectively retain the knowledge of previously trained policies, but the size of the network can grow extensively. Kirkpatrick et al. proposed to use a quadratic penalty on the neural network weights to prevent the old tasks from being forgotten [9]. They demonstrated sequential learning results on supervised learning problems and reinforcement learning on Atari games. However, it is unclear how well this method can perform on robotic control problems with a continuous action space.

Directly learning multiple tasks simultaneously has also been well explored [12], [13], [14], [15]. Pinto and Gupta [12] demonstrated that simultaneously training two deep neural networks with a partially shared representation achieves better performance than training only one task using the same amount of training data [12]. They manually selected the network parameters to be shared by the two policies, whereas, in our work, we attempt to identify them in an automatic way. For an agent performing multiple tasks in the same environment, Borsa et al. introduced an algorithm to learn the value function with a shared representation and used a multi-task policy iteration algorithm to search for the policy [14]. However, a new value function would need to be trained when a new environment is introduced. Teh et al. applied the idea of policy distillation to multi-task learning by learning a distilled policy that contains common information for all the individual tasks and using it to regularize the learning of task specific policies [15]. They evaluated their method on a maze navigation problem and a 3D game playing problem. However, for controlling robots with potentially different morphologies and joint types, it is unclear whether the common knowledge can be captured in one distilled policy.

Another line of research for multi-task learning incorporates the task-related information to the state input [16], [17], [18], [19]. Peng et al. duplicated the first layer of the neural network corresponding to different phases of humanoid locomotion [18]. A similar architecture was used in [19] to achieve different behaviors in a neural network. Our approach generalizes these architectures by selectively share the weights among the policies.

III. METHOD

Our method aims to integrate two important techniques in learning multiple tasks, joint learning and specialization, into one coherent algorithm. Learning multiple tasks jointly is a well-known strategy to improve learning efficiency and generalization. However, to further improve each individual task, specialized curriculum and training are often needed. We define a “task” as a particular reward function performed by a particular dynamic system. Therefore, two different tasks can mean two different robots achieving the same goal, the same robot achieving two different tasks, or both.

Our algorithm carries out two learning phases: joint training and specialization training. We first train a policy, \( \pi_\theta(a|s) : (S,A) \rightarrow [0,1] \), represented by a fully connected neural network to jointly learn the common representations across the different tasks (Section III-A). A policy is defined as a Gaussian probability distribution of action \( a \in A \) conditioned on a state \( s \in S \). The mean of the distribution is represented by the neural network and the covariance is defined as part of the policy parameters, \( \theta \), which also include the weights and the biases of the network. Based on the gradient information gathering during the joint training phase, we then select a subset of weights to be specialized to individual tasks (Section III-B). We use the Trust Region Policy Optimization (TRPO) method during the joint training phase, but modify TRPO during the specialization training phase to ensure that the trust regions are comparable across multiple tasks (Section III-C).

A. Joint training

The goal of jointly learning multiple tasks is to improve the sample efficiency of the algorithm, as well as to provide critical information to determine which weights should be shared across tasks in the specialization training phase. The training process is identical to training a single task except that the rollout pool consists of trajectories generated for performing different tasks. In addition to the observed state of the dynamic system, \( o \), the state space \( S \) of the policy also includes a one-hot vector, \( b \), to disambiguate the tasks during training. We set \( b \) to zero except for the bit that represents the task being performed. We use TRPO to search for a policy that maximizes the expected return,

\[
J(\theta) = J(\theta_{old}) + \mathbb{E}_{s \sim \rho_\theta(s), a \sim \pi_\theta(a|s)}[Q_{\theta_{old}}(s, a) - V_{\theta_{old}}(s)],
\]

where \( \theta_{old} \) is a reference policy, typically the policy from previous learning iteration, \( \rho_\theta(s) \) is the state visitation function, \( Q(s_t, a_t) = \mathbb{E}_{s_{t+1}, a_{t+1}, ..., \infty} \sum_{t=0}^\infty r(s_{t+1}, a_{t+1}) \) is the state-action value function and \( V(s_t) = \mathbb{E}_{a_t, s_{t+1}, a_{t+1}, ..., \infty} \sum_{t=0}^\infty r(s_{t+1}, a_{t+1}) \) is the state value function. The difference between the Q-function and the value function is also known as the advantage function, i.e. \( A(s, a) = Q(s, a) - V(s) \). The accuracy of the estimation of advantage function is crucial to the stability of the learning process. We use Generalized Advantage Function (GAE) [20] to estimate the advantage function because GAE has been shown to effectively reduce the variance in the policy gradient estimation with controllable bias. We manually determine the iteration number for joint training by assessing the similarity among the tasks.

B. Specialization training

In specialization training phase, we first analyze the policy after the joint training phase and select a subset of the weights to be shared across the policies. We compute a per-weight specialization metric to estimate whether a particular weight in the neural network should be shared or specialized to each task. They key idea of our approach is, for each weight in the network, to estimate the disagreement among different tasks.

Algorithm [1] begins by collecting rollouts \( R_i \) for each task \( i \) using the current policy. We then approximate the gradient of the expected return (Equation [1]) with respect to the policy parameters \( \theta \), using rollouts \( R_i \):

\[
\mathbf{g}_i = \frac{\partial J}{\partial \theta} = \mathbb{E}_{s \sim \rho_\theta(s), a \sim \pi_\theta(a|s)}[\nabla \log(\pi_\theta(a|s))A(s, a)].
\]
We refer each subnet as an individual policy $\pi$. Gradient-guided weight selection

TRPO updates before selecting the weights to be shared or how TRPO updates the policy in each iteration. The divergence constraint in TRPO. To see this, we briefly review diminished because every task is subject to the same KL-divergence constraint (Line 7), we perform the final line search for the aggregated $d$ to guarantee that the KL-divergence constraint is satisfied. We denote $f^{kl}$ as the scaling and line search operations and refer as KL-line-search. The final change in the policy parameters is $\Delta d = f^{kl}(d)$.

In the multiple task scenarios, directly applying the original TRPO update results in the following change between the new policy and the old policy:

$$
\Delta d = f^{kl}(H^{-1}(\sum_{i=1}^{N} g_i)).
$$

This formulation might lead to unbalanced updates among tasks for two reasons. First, TRPO sums up the gradient before applying Fisher information matrix and performing KL-line-search. A task with a large gradient can potentially dominate other tasks with small gradients because it will hit the KL-divergence constraint before other tasks. Second, TRPO imposes the same KL-divergence on every task, despite that each task has its own policy during specialization training. To fix these issues, we propose a new update to enable TRPO for multiple task learning:

$$
\Delta d = \sum_{i=1}^{N} f^{kl}(H_i^{-1} g_i). \tag{5}
$$

Note that the Fisher information matrix $H_i$ and the KL-line-search $f^{kl}$ are now different for every task, derived from each individual KL-divergence constraint, $D_{KL}(\pi^{old}_{\theta_i}||\pi_{\theta_i})$. To ensure that the final policy change lies within the trust region of the aggregate policy, we perform another line search to enforce the overall KL-divergence constraint $D_{KL}(\pi^{old}||\pi_{\theta})$.

Algorithm 2 summarizes the modified TRPO update for learning multiple tasks. Starting from the split network, for each learning iteration, we first collect rollouts for each task $i$ by setting the input layer of the network to zero except for the subnet that corresponds to task $i$ (Line 4). We then compute the gradient of the objective function and the Fisher information matrix using the rollouts of task $i$ (Line 5). The change of policy for each individual task $i$ is then computed using KL-line-search: $\Delta d_i = f^{kl}(H_i^{-1} g_i)$ (Line 6). Summing up the changes in policy from all the tasks (Line 7), we perform the final line search for the aggregated policy (Line 8–10). Our modified TRPO update is reminiscent of mini-batch updates in the supervised learning paradigm.
Algorithm 2 Modified TRPO update

1: Split and initialize policy
2: for $k = 1 : K$ do
3:   for $i = 1 : N$ do
4:     Collect rollouts $\mathcal{R}_i$ from task $i$
5:     Compute $g_i$, $H_i$ using $\mathcal{R}_i$
6:     $\Delta d_i = f_i^k(H_i^{-1}g_i)$
7:     $\Delta d = \sum_{i=1}^N \Delta d_i$
8:     Initialize line search step $\delta = 1$.
9:     while $D_{KL}(\pi_\theta || \pi_{\theta+\delta\Delta d}) > \sigma$ do
10:        $\delta = 0.9\delta$
11:     $\theta = \theta + \delta\Delta d$
12:     return $\pi_\theta$

IV. RESULTS

We evaluate our approach on three continuous motor control problems. In each problem, we define a set of related learning tasks and use our approach to learn them concurrently. We compare our method $\pi_{our}$ to three baseline methods. The first is to use only jointly trained policy without specialization, which we denote $\pi_{joint}$. The second baseline is training individual policies from the beginning, which we denote $\pi_{ind}$, and the last baseline is to randomly select the weights to be specialized instead of using our approach, which we name $\pi_{rand}$.

We use the implementation of TRPO in rllab[21]. The batch size and the of iterations for joint training vary by the difficulty and similarity of the tasks. To represent the control policy, we use a neural network with two hidden layers, composed of 64 and 32 hidden units respectively. All other hyper-parameters are set to the default value in rllab. For all examples presented using $\pi_{our}$ and $\pi_{rand}$, we choose the threshold $M$ such that $50\%$ of the neural network weights will be shared. We found that this works well empirically for all tasks presented. We also evaluate the effect of modified TRPO update scheme by comparing it to the training result with vanilla TRPO.

All simulation results demonstrated in this work are produced using DartEnv [22], a fork of the OpenAI Gym [23] library that uses Dart [24] as the underlying rigid body simulator. The simulation timestep is set to 0.002s. We run each example three times and report the average learning curves. We choose the total iteration numbers empirically so that the policies can be sufficiently trained to learn the motor skills.

A. Single Legged Robot Locomotion

We begin with an example of hopping locomotion by a single legged robot. We design three single legged robots that are constructed with capsules, boxes and ellipsoids respectively, as shown in Figure 2. In addition, we scale them to have different total heights. These variations lead to considerable difference in the inertia and contacts of the robots, while the similarity in the configuration should lead to similar locomotion gaits, which we expect the joint-training to capture. We use a batch size of 30,000 for the training. The initial policy is jointly trained for 100 iterations.

![Fig. 2: Three single legged robots with different shapes and sizes. All of them are trained to hop forward.](image)

The result of this example can be found in Figure 3. Our approach noticeably outperforms the other baselines. Since the hopping gait is similar between the different robots, it can benefit from joint-training, as indicated by the slower learning of $\pi_{ind}$. Furthermore, randomly split weights achieves a similar performance to joint training, showing the importance of selecting the right weights to split.

B. Robot Manipulator Reaching

Accurately controlling a robot end-effector to reach different locations is an important motor skill in many robot applications. In this example, we apply our approach to learn reaching skills for three different three-link robotic manipulators. The lengths of links are different across the manipulators, but the total length is the same (Figure 4). We also assign different degrees of freedom and rotation axes to some of the joints of the manipulators while maintaining the same total degrees of freedom. Specific joint types can be seen in Table I. The goal of learning is to be able to reach six different locations lying on the three axes with different distances to the origin as shown in Figure 5(b). We use a batch size of 30,000 for the training, and the initial policy is jointly trained for 50 iterations.

| Manipulator | Joint 1 | Joint 2 | Joint 3 |
|-------------|---------|---------|---------|
| 1           | XZ      | Z       | XZ      |
| 2           | XZ      | X       | XZ      |
| 3           | XZ      | XZ      | Z       |

![Fig. 3: Learning curves for the three hoppers example.](image)
Fig. 4: (a) Three robotic manipulators with different configurations. (b) The six target locations the manipulators are trained to reach.

Fig. 5: Learning curves for the three robotic manipulators example.

The results of this example can be found in Figure 5. We see a similar trend as in the first example, where $\pi_{\text{our}}$ outperforms the other baselines, and $\pi_{\text{ind}}$ has worse data efficiency.

C. 2D Bipedal Walk in Two Styles

In the previous examples we have shown cases where we train different dynamic systems to learn the same reward function. In this example, we vary the other parameter of the tasks, where we train one robot to optimize different reward functions. Specifically, we train a bipedal robot to move forward in two distinct styles: with one foot lifted up or with one foot kept low to ground. The bipedal robot is constructed similar to the 2D Walker example in OpenAI Gym [23] and is constrained to move in 2D space. To learn different styles, we modify the termination criteria of the environment. We terminate the rollout when the foot touches the ground to force the policy to learn moving with one leg lifted, and we terminate the rollout when the foot reaches 0.5m in height to make it stay close to the ground. An illustration of the two styles can be found in Figure 6 and Figure 7.

The learning result of this example is shown in Figure 8. Again, we observe similar trend in this case. This shows that our approach could also handle training of one robot to perform different tasks.

D. Evaluation of Multi-task TRPO Update

To evaluate the effect of Multi-task TRPO Update scheme, we run both our method and the vanilla TRPO on the robot manipulator example and measure the KL-divergence for each task at every iteration. The result is shown in Figure 9. We can see that the task-wise KL-divergence value for vanilla TRPO has considerably higher variance compared to Multi-task TRPO update. Note that the average KL-divergence for both cases satisfies the pre-defined step size, which in this work we set to 0.02.

V. DISCUSSION

We have shown that by combining joint training, policy specialization and Multi-task TRPO update, we can improve the performance and efficiency of concurrent learning of multiple robotic motor skills of different types. However, we recognize a few limitations that require further investigations.
Our approach works best for tasks that benefit from joint training, however, for tasks that are significantly different from each other, e.g. training two single legged robot to hop forward and backward respectively, we found that directly training individual policies achieved the best performance overall. One direction to solve this issue is to identify the number of weights to be specialized based on the similarities between tasks.

In this work we use joint-training to learn the common representations in the multiple tasks and then rely on policy specialization to fine tune each individual task. We currently determine the amount of joint-training for each task empirically based on our prior knowledge about the similarities among the multiple tasks. It would be desirable to have an automatic way to determine the joint-training iteration number that leads to the optimal learning performance.

We demonstrated that Multi-task TRPO update can effectively reduce the variance in the KL-divergence of each learning task, leading to more balanced learning. However, due to the summation of TRPO updates, the KL-divergence constraint for each individual task is not guaranteed to be satisfied. A future direction to investigate is to mathematically formulate this problem as a multi-dimensional constrained problem with one KL-divergence constraint for each task and solve it directly.

VI. CONCLUSION

We have introduced a method for learning multiple related robotic motor skills concurrently with improved data efficiency. The key stages of our approach consist of a joint-training phase and a specialization phase. We propose a metric using the variance of the task-based policy gradient to selectively split the neural network policy for specialization. Furthermore, we modify the TRPO update stage to achieve more balanced learning of multiple tasks. For continuous motor control problems we demonstrate that our approach improves the learning performance compared to joint-training alone, independent training, and random policy specialization.

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