Pre-training of Deep RL Agents for Improved Learning under Domain Randomization

Artemij Amiranashvili¹, Max Argus¹, Lukas Hermann¹, Wolfram Burgard¹, Thomas Brox¹

Abstract—Visual domain randomization in simulated environments is a widely used method to transfer policies trained in simulation to real robots. However, domain randomization and augmentation hamper the training of a policy. As reinforcement learning struggles with a noisy training signal, this additional nuisance can drastically impede training. For difficult tasks it can even result in complete failure to learn. To overcome this problem we propose to pre-train a perception encoder that already provides an embedding invariant to the randomization. We demonstrate that this yields consistently improved results on a randomized version of DeepMind control suite tasks and a stacking environment on arbitrary backgrounds with zero-shot transfer to a physical robot.

I. INTRODUCTION

Domain randomization is a widely used and widely successful method in Deep Reinforcement Learning (DRL) in order to effectively bridge the visual gap between a simulated training environment and real world robotic applications. In visual domain-randomization, procedurally generated random textures and altered camera viewpoints are applied to simulated environments, and various image augmentations are applied to the rendered observations. This helps to learn a policy that is invariant to these shifts and is more likely to succeed on the transfer from simulated to real images or with varying backgrounds in robotic environments. It has led to many successful zero-shot sim2real transfer applications such as indoor flight [1], grasping [2], [3], stacking [4], [5] or dexterous in-hand manipulation [6], [7]. However, adding domain randomization hampers the DRL training process in simulation. Especially on harder learning tasks, randomized textures can result in an agent that does not learn at all [8].

In this paper, we propose an alternative to confronting the RL gradients, which are already weak and stochastic, with additional variance from visual randomization. We argue that the desired invariance is an issue of visual perception, which can be trained much more stably and efficiently with a self-supervised loss. Hence, we separate visual pre-training to achieve the desired visual invariance properties from RL training and call this process Domain Randomization Adjusting Pre-training (DRAP).

To this end, we use the simulation to construct paired images of randomized observations and canonical observations without randomization. We train an encoder-decoder network to reconstruct the canonical observations and predict the future canonical observations from the randomized images. The network learns to remove the textures from objects and background, and to recenter the point of view of the camera. The learned perception encoder is then used as an initialization for the neural network of a DRL algorithm. This warm-start greatly boosts DRL performance on domain randomized environments, as the encoder has already learned to ignore the visual variation and provides a much cleaner signal to the successive parts of the RL network. This is similar in spirit with the work from James et al. [9], who trained an encoder-decoder network together with an adversarial loss to map from an input image to a canonical domain. However, while they keep the encoder-decoder network as a translator network, we drop the decoder part and directly fine-tune the pretrained, invariant feature encoder during RL training. This is arguably simpler and more efficient, as we drop a whole encoder-decoder structure.

To show that the approach has the expected positive effects, we constructed randomized versions of six tasks from the DeepMind control suite [10] (shown in Figure 2). As baselines we use two state-of-the-art algorithms for continuous off-policy image-based control: DrQ [11] and RAD [12] and demonstrate that with the proposed pre-training, DrQ+DRAP is able to outperform both baselines in all six randomized tasks within the same amount of total environment interactions. We also compare the DRAP initialization to a contrastive-loss-based pre-training with paired images from different domain randomizations of the

¹ All authors are with the Department of Computer Science, University of Freiburg, Germany
the real-world observations, as proposed in previous work. Additionally, potentially slow, generative networks that transform observations in the target domain without requiring any additional ground truth data to train a perception module, which adds additional overhead for policy training and deployment. A similar approach is to condition the policy on an abstracted state representation, such as depth, a segmentation mask or optical flow [13], [14] instead of relying on image-based control. The perception system can be trained separately from the policy, mitigating the need to train a domain-invariant policy on pixels. However, these approaches rely on the abstract representation to contain sufficient information for the required task. Obtaining the abstract representation usually requires additional ground truth data to train a perception module, which adds additional overhead for policy training and deployment. A similar approach is to condition the policy on abstract measurements like depth sensors or Lidar systems, since physical depth information can be used in the auxiliary losses of [9] to address the blurriness of the reconstructed canonical images. However, the main advantage of our pre-training approach is that it does not require an additional encoder-decoder network in the pipeline to apply the policy to the target domain, making it faster for deployment or fine-tuning in the real world.

Another approach to handle the domain shift is to continue the training of the canonical policy on the new domain, in combination with a progressive neural network architecture [23]. In this work we focus on zero-shot transfer without training in the real world, where a reward function and an automated environment reset are hard to obtain.

C. Image Reconstruction

Reconstruction of observations is often used to learn a low-dimensional state embedding for model-based DRL [24], [25], [26], [27] or as an auxiliary task in model-free DRL [28]. Instead, we reconstruct augmented images in combination with a progressive neural network architecture [23]. In this work we focus on zero-shot transfer without training in the real world, where a reward function and an automated environment reset are hard to obtain.

D. Pre-training Features

Pre-training convolutional features on a supervised datasets like ImageNet [29] is a widely used method in
Contrastive learning is an unsupervised representation learning method that has recently reached competitive results to purely supervised learning on ImageNet classification [33], [34]. The same approach has been used as an auxiliary task in DRL [35]. In this paper we also investigate whether contrastive learning can help pre-training a domain randomization invariant representation.

III. METHODS

A. Background

In Reinforcement Learning (RL) an agent interacts with an environment in discretized timesteps $t$. At each timestep it observes a state $s_t$ and has to select an action $a_t$. Thereafter the environment transitions into a next state $s_{t+1}$ and the agent receives a reward $r$ and whether a terminal state was reached. The aim of the agent, following the policy $\pi(a|s)$, is to optimize the expected return $R_t = \mathbb{E}_\pi[\sum_{i=t}^{T} \gamma^ir_i]$, given a discount factor $\gamma \in [0, 1]$ and terminal timestep $T$. In image-based RL the state is usually a concatenation of the last $n$ frames, making it a partially observable environment.

The current state-of-the-art algorithms in image-based RL with continuous control are Data-Regularized Q (DrQ) [11] and Reinforcement Learning with Augmented Data (RAD) [12]. Both algorithms are based on the Soft Actor-Critic algorithm (SAC) [36] that involves a critic network estimating the action-value function $Q(s_t, a_t)$ and an actor network $\pi(a|s)$. Both networks share a perception encoding and learn from off-policy transitions $(s_t, a_t, r_t, s_{t+1})$ which are stored in a replay memory buffer.

DrQ and RAD are concurrently published algorithms that improve the performance of SAC further by applying image augmentations to the observations in order to avoid overfitting to the images in the replay memory. RAD renders the observations in a higher resolution and crops a lower resolution image. DrQ augments the observations by padding the images by 4 pixels and randomly cropping an image of the original resolution out of the padded image. Additionally, DrQ improves its action-value function estimation by averaging the output of the critic network for multiple different augmentations of the same state. In this work, for continuous control we use the DrQ algorithm to train on the domain-randomized environments after the pre-training phase.

B. Randomised Benchmark Tasks

In order to evaluate the effectiveness of training under domain randomization we create a randomized version of different tasks from the DeepMind control suite [10]. We selected 6 tasks from the PlaNet benchmark [26], that are usually being used for continuous image-based control algorithm evaluation. We ported those environments to the mujoco_py framework [37] where we can apply procedurally generated random textures to all objects and the background. Additionally we slightly randomize the location and the perspective direction of the camera. The resulted observations for each task are shown in Figure 2. The ported environments use identical models, initial position distributions, and reward functions as the according tasks in the DeepMind control suite. We also add the action repetition values from the PlaNet benchmark as part of the environments.

The reward range of all DeepMind control suite tasks lies between 0 and 1 and each episode has a fixed length of 1000 steps. Therefore the optimal total reward is close to 1000 for each environment. We use the average performance across all 6 tasks to compare the performance of the different algorithms in the randomized setting. Since the textures are procedurally generated and the camera directions are sampled, the policies are evaluated on randomizations that were unseen during training.

C. Domain Randomization Adjusting Pre-training (DRAP)

In order to pre-train a domain-randomization invariant perception encoder we first collect a dataset of the environment with paired images of randomized and canonical observations. Thereby the actions are sampled randomly $a = \cos(\phi)$ with $\phi$ uniformly sampled from $[0, \pi]$. We choose this distribution to cover the whole range of continuous actions of $[-1, 1]$ while prioritizing the actions of large magnitude to get a more diverse observation distribution in the dataset.

After the dataset collection we train a randomization removal network as shown in Figure 3. The main part of the network consists of an encoder (that will later be used as an initialization for the RL networks), a bottleneck embedding, and a decoder. The encoder receives a stack of 3 concurrent randomized observations as an input and the network tries to reconstruct the image in the canonical domain. Additionally an MLP network receives the embedding and the last action as input and outputs a vector of the same dimensionality as the embedding. Then the same decoder is applied to the MLP output, but the target frames are shifted into the future by one time step. This way the MLP indirectly trains to predict the future embedding, ensuring that the embedding contains motion information of the state.

In order to avoid overfitting during pre-training we apply the same augmentation as used in DrQ to the images sampled from the dataset.

We evaluated multiple alterations for the pre-training process and the network design. First, since using a deterministic embedding for reconstruction can lead to overfitting [27], we also evaluated using a diagonal Gaussian embedding, where the encoder outputs the means and variances for the distribution. The embedding is then sampled from the according diagonal Gaussian distribution in each forward pass. We also evaluated adding an additional regularisation term to the diagonal Gaussian embedding: $KL[N(\mu(S), \sigma(S)), N(0, I)]$ as used in Variational Autoencoders [38].

Since vision-control tasks often involve small objects we also tested replacing the conventional upconvolution-based decoder with an Spatial Broadcast Decoder (SBD) [39]. In the SBD the upconvolutions are replaced by broadcasting
For each algorithm and each environment, training is repeated three times with different random seeds.

The encoder as an initialization to train the DrQ algorithm. Thereafter we use a domain-randomization invariant encoder. Thereby we use the same similarity metric and train the same contrastive loss function as the CURL algorithm.

For the contrastive pre-training the dataset contains paired images of differently randomized observations and the DRAP the dataset contains paired images of randomized and canonical observations.

The encoder uses the same architecture as the DrQ algorithm, it consists of four convolutions with $3 \times 3$ kernel size and 32 channels. The first convolution has a stride of 2. The embedding is a fully-connected layer of size 50 followed by a LayerNorm and a $\tanh$ activation function, that provides a bottleneck for the DRAP network. We found that having a fully-connected bottleneck is crucial for the pre-training process. The decoder consists of an upconvolution with $4 \times 4$ kernel size and a stride of 2, followed by two convolutions with a $3 \times 3$ kernel. The MLP consists of two fully-connected layers of size 1024.

IV. Experiments

First we evaluate all alterations of DRAP that were introduced in Section III-C. We train the networks to construct and predict canonical observations of the randomized version of the Finger task. Then we evaluate the performance on a test set of images, unseen during training. The average mean squared errors of the reconstructions are shown in Table I. Interestingly, the simplest setup with a deterministic embedding

| Method                            | DRAP Loss |
|-----------------------------------|-----------|
| Gaussian Embedding                | $3.8 \times 10^{-3}$ |
| Variational Autoencoder           | $23.2 \times 10^{-3}$ |
| Spatial Broadcast Decoder         | $11.7 \times 10^{-3}$ |
| Deterministic Embedding +         | $1.4 \times 10^{-3}$ |
| supervised embedding prediction   | $1.4 \times 10^{-3}$ |
| Deterministic Embedding           | $1.2 \times 10^{-3}$ |
and without additional embedding training losses produced the best result. This suggests that the additional application of the DrQ augmentation to the dataset images was enough to prevent overfitting, therefore a stochastic embedding was not required. We use the deterministic embedding in all following experiments.

The result of evaluating DrQ, RAD, DRAP, and the contrastive pre-training on the 6 randomized DeepMind control suite environments is shown in Table II and the overall average performance across all 6 environments in Figure 4. Both DrQ and RAD perform significantly worse than the respective results on the DeepMind control suite tasks without the domain randomization [11], [12], showing that the training is strongly inhibited by the applied domain randomization.

Training with the DRAP initialization outperforms both RL baselines on all 6 tasks. The contrastive pre-training reaches a higher average score than the RL baselines, but performs worse than DRAP in most environments.

We only compare to pre-training baselines since the focus of our work is on training domain invariant policies without the overhead of additional encoder-decoder translator networks. Additionally no official code is available for the approach of James et al. [9].

In addition to training DrQ on the DRAP initialization we also tested other possible training procedures like freezing the pre-trained encoder, decreasing the encoder learning rate or keeping the DRAP loss as an auxiliary task during the RL training. However, any of those changes resulted in an overall worse performance of the algorithm.

V. APPLICATION TO ROBOTIC SETTING

We further evaluate our method in the robotics domain on a block stacking task, both in simulation and as zero-shot sim2real transfer. Stacking is widely used as a benchmark task for robotics RL since it comprises important sub-skills like reaching, grasping and placing. We build upon a PyBullet [41] simulation environment for block stacking described in [4], where a 7-DOF Kuka iiwa robot with a parallel gripper has to pick up a small cube and place it on top of another cube.

The agent receives image observations from a gripper-mounted camera and additionally the gripper height and rotation. For the actions we use discretized position control in end-effector space of the robot arm, allowing movement along all translation axes and the rotation along the z-axis. Each degree of freedom is discretized to 3 values.

The environment yields a sparse reward upon task completion. Since exploration for long horizon sparse reward tasks is challenging for RL algorithms, we follow [4] and use Adaptive Curriculum Generation from Demonstrations (ACGD) to guide exploration with a handful of demonstrations.

ACGD generates a reverse curriculum of initial states from ten task demonstrations, but in contrast to naive linear curriculum learning implementations it adapts the curriculum on the fly depending on the experienced success rates during training, such that the agent always learns at its appropriate level of difficulty. As in [4] we learn the policy by applying ACGD to the PPO algorithm [42].

Originally ACGD was already able to achieve a 90% stacking success rate in simulation and successfully transfer the policy to the real world robot. In order to increase the difficulty of the task we extend the environment to feature arbitrarily colored backgrounds. This change resulted in a performance drop to 48% success rate in simulation.

We test the performance of the DRAP initialization by applying it to the given task. During the pre-training the network learns to reconstruct the canonical observations with a uniformly colored background and removed augmentations including: camera position and orientation, contrast saturation brightness sharpness hue and blur randomization, and light location. The difference between the randomized and the canonical domain is shown in Figure 5.

We use the same pre-training procedure as for DrQ algorithm, except that the encoder is replaced by the encoder architecture from the ACGD algorithm, which in turn uses the DQN perception network [43]. Since the fully-connected
layer after the convolutions has a size of 512, which is too large for a bottleneck, we attach a second fully-connected layer of size 64 and a tanh activation to the encoder and use the output as the embedding. The additional layer is discarded after the pre-training process.

Compared to the tasks from the DeepMind control suite, obtaining a dataset for pre-training that sufficiently covers the state space of the task is not possible through a random policy alone. Therefore we make use of the same demonstrations that are used in the ACGD algorithm. During the dataset collection we randomly sample a state from one of the demonstrations and use it as the initial point for the data collection. Thereafter random action are applied. Also since the stack task is a 3-dimensional environment we collect a larger dataset for the pre-training, containing 250,000 environment interactions. However this number is very small compared to the $10^7$ environment interactions required to train the staking task.

Originally ACGD also used curriculum learning to slowly increase the degree of domain randomization during training. Since the DRAP initialization already provides an encoder that is invariant to those augmentations we do not use the visual curriculum and directly start the training with the highest degree of randomization. Other than the removal of the visual curriculum and the usage of the DRAP initialization, the ACGD algorithm remains unchanged.

The resulting stacking performance in simulation are shown in Figure 6. The DRAP initialization improves over the visual-curriculum-free baseline with a success rate difference of 60%. It also outperforms the full ACGD curriculum setup with a success rate difference of 29%.

Finally we test the block stacking policy trained with ACGD + DRAP on a zero-shot sim2real transfer. Since the DRAP pre-training ensured invariance to changing backgrounds, our policy is able to perform successfully in the real world on a variety of different background colors and textures (see supplementary video). However, on red, blue, and black backgrounds, with coloring similar to the cubes or the gripper, the policy failed to work. Across other 6 tested backgrounds the policy had a success-rate of 60%, while ACGD with visual randomization curriculum only reached 15% on these backgrounds. Examples of different backgrounds are shown in Figure 7.

VI. CONCLUSION

The pre-training setup presented in this paper improves policy training with deep reinforcement learning under domain randomization. Strong randomization is desired to enable zero-shot sim2real transfer of RL policies. Our results demonstrate that performing domain randomization in a self-supervised pre-training step and separating it from the more brittle reinforcement learning part is beneficial. It greatly
increases the convergence speed of RL and improves zero-shot transfer to a physical robot. We did not observe any drawbacks using the approach.

REFERENCES

[1] F. Sadeghi and S. Levine, “Cad2rl: Real single-image flight without a single real image,” arXiv preprint arXiv:1611.04201, 2016.

[2] J. Tobin, R. Fong, A. Ray, J. Schneider, W. Zaremba, and P. Abbeel, “Domain randomization for transferring deep neural networks from simulation to real world,” in 2017 IEEE/RAS International Conference on Intelligent Robots and Systems (IROS). IEEE, 2017.

[3] L. Pinto, M. Andrychowicz, P. Welinder, W. Zaremba, and P. Abbeel, “Symmetric actor critic for image-based robot learning,” arXiv preprint arXiv:1710.06542, 2017.

[4] L. Hermann, M. Argus, A. Eitel, A. Amirnashvili, W. Burgard, and T. Brox, “Adaptive curriculum generation from demonstrations for sim-to-real visuomotor control,” in 2020 IEEE International Conference on Robotics and Automation (ICRA), 2020.

[5] Y. Zhu, Z. Wang, J. Merel, A. Rusu, T. Erez, S. Cabi, S. Tunyasuvunakool, J. Kramár, R. Hadsell, N. de Freitas, et al., “Reinforcement and imitation learning for diverse visuomotor skills,” arXiv preprint arXiv:1802.09564, 2018.

[6] OpenAI, M. Andrychowicz, B. Baker, M. Chociej, R. Józefowicz, B. McGrew, P. Welinder, W. Burgard, and I. Fischer, “Vr-goggles for robots: Real-to-sim domain adaptation for visual control,” IEEE Robotics and Automation Letters, vol. 4, no. 2, pp. 1148–1155, 2019.

[7] A. Pinto, P. Isola, and A. A. Efros, “Unpaired image-to-image translation using cycle-consistent adversarial networks,” in Proceedings of the IEEE international conference on computer vision, 2017, pp. 2223–2232.

[8] K. Boussalis, A. Irpan, P. Wohlhart, Y. Bai, M. Kelcey, M. Kalakrishnan, L. Downs, J. Ibarz, P. Pastor, K. Konolige, et al., “Using simulation and domain adaptation to improve efficiency of deep robotic grasping,” in 2018 IEEE international conference on robotics and automation (ICRA). IEEE, 2018, pp. 4243–4250.

[9] K. Ruo, C. Harris, A. Irpan, S. Levine, J. Ibarz, and M. Khansari, “Rl-cyclegan: Reinforcement learning aware simulation-to-real,” in Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2020, pp. 11157–11166.

[10] J. Zhang, L. Tai, P. Yun, Y. Xiong, M. Liu, J. Boedecker, and W. Burgard, “Vr-goggles for robots: Real-to-sim domain adaptation for visual control,” IEEE Robotics and Automation Letters, vol. 4, no. 2, pp. 1148–1155, 2019.

[11] A. A. Rusu, M. Véciér, T. Rothörl, N. Heess, R. Pascanu, and R. Hadsell, “Sim-to-real robot learning from pixels with progressive nets,” in Conference on Robot Learning. PMLR, 2017, pp. 262–270.

[12] M. Watter, J. Springenberg, J. Boedecker, and M. Riedmiller, “Embed to control: A locally linear latent dynamics model for control from raw images,” in Advances in neural information processing systems, 2015, pp. 2746–2754.

[13] J. Oh, X. Guo, H. Lee, R. L. Lewis, and S. Singh, “Action-conditional video prediction using deep networks in atari games,” in NIPS, 2015.

[14] D. Hafner, T. Lillicrap, I. Fischer, R. Villegas, D. Ha, H. Lee, and J. Davidson, “Learning latent dynamics for planning from pixels,” in International Conference on Machine Learning. PMLR, 2019, pp. 2555–2565.

[15] D. Hafner, T. Lillicrap, J. Ba, and M. Norouzi, “Dream to control: Learning behaviors by latent imagination,” arXiv preprint arXiv:1912.01603, 2019.

[16] D. Yarats, A. Zhang, I. Kostrikov, B. Amos, J. Pineau, and R. Fergus, “Improving sample efficiency in model-free reinforcement learning from images,” arXiv preprint arXiv:1910.07141, 2019.

[17] O. Russakovsky, S. Deng, H. Su, J. Krause, S. Satheesh, S. Ma, Z. Huang, A. Karpathy, A. Khosla, M. Bernstein, et al., “Imagenet large scale visual recognition challenge,” International journal of computer vision, vol. 115, no. 3, pp. 211–252, 2015.

[18] K. He, G. Gkioxari, P. Dollár, and R. B. Girshick, “Mask r-cnn,” 2017 IEEE International Conference on Computer Vision (ICCV), pp. 2980–2988, 2017.

[19] S. Xie, R. B. Girshick, P. Dollár, Z. Tu, and K. He, “Aggregated residual transformations for deep neural networks,” 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2017.

[20] J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova, “Bert: Pre-training of deep bidirectional transformers for language understanding,” in NAACL-HLT, 2019.

[21] K. He, H. Fan, Y. Wu, S. Xie, and R. Girshick, “Momentum contrast for unsupervised visual representation learning,” in Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2020, pp. 9729–9738.

[22] T. Chen, S. Kornblith, M. Norouzi, and G. Hinton, “A simple framework for contrastive learning of visual representations,” arXiv preprint arXiv:2002.05790, 2020.

[23] M. Müller, A. Dosovitskiy, B. Ghanem, and V. Koltun, “Driving policy transfer via modularity and abstraction,” arXiv preprint arXiv:1804.09364, 2018.

[24] B. Zhou, P. Krähenbühl, and V. Koltun, “Does computer vision matter for action?” arXiv preprint arXiv:1905.12887, 2019.

[25] U. Vieravecz, A. Bas, K. Saenko, and R. Platt, “Learning a visuomotor controller for real world robotic grasping using simulated depth images,” arXiv preprint arXiv:1706.04652, 2017.

[26] J. Mahler and K. Goldberg, “Learning deep policies for robot bin picking by simulating robust grasping sequences,” in Conference on robot learning, 2017, pp. 515–524.

[27] J. Mahler, J. Liang, S. Niyaz, M. Laskey, R. Doan, X. Liu, J. A. Ojea, and K. Goldberg, “Dex-net 2.0: Deep learning to plan robust grasps with synthetic point clouds and analytic grasp metrics,” arXiv preprint arXiv:1703.09312, 2017.

[28] L. Tai, J. Zhang, M. Liu, and W. Burgard, “Socially compliant navigation through raw depth inputs with generative adversarial imitation learning,” in 2018 IEEE International Conference on Robotics and Automation (ICRA). IEEE, 2018, pp. 1111–1117.

[29] Y.-Y. Zhu, T. Park, P. Isola, and A. A. Efros, “Unpaired image-to-image translation using cycle-consistent adversarial networks,” in Proceedings of the IEEE international conference on computer vision, 2017, pp. 2223–2232.
[43] V. Mnih, K. Kavukcuoglu, D. Silver, A. A. Rusu, J. Veness, M. G. Bellemare, A. Graves, M. Riedmiller, A. K. Fidjeland, G. Ostrovski, et al., “Human-level control through deep reinforcement learning,” 
nature, vol. 518, no. 7540, pp. 529–533, 2015.