Generate and Control

Novel approaches to address data scarcity in Deep Reinforcement Learning for Robotics

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1 Introduction

The deployment of Deep Reinforcement Learning (DRL) models in robotics, particularly in high-dimensional problems and when data is scarce or costly to obtain, introduces profound challenges to the training process. This research activity is focused in designing strategies to overcome these hurdles through enhanced data utilization and synthetic data generation techniques, aiming to train DRL models without requiring extensive real-world interaction. The study bifurcates into two distinct approaches: model-based hand-engineered data augmentation techniques, based on specific domain knowledge, and data-driven counterfactual-based augmentation using generative neural networks.

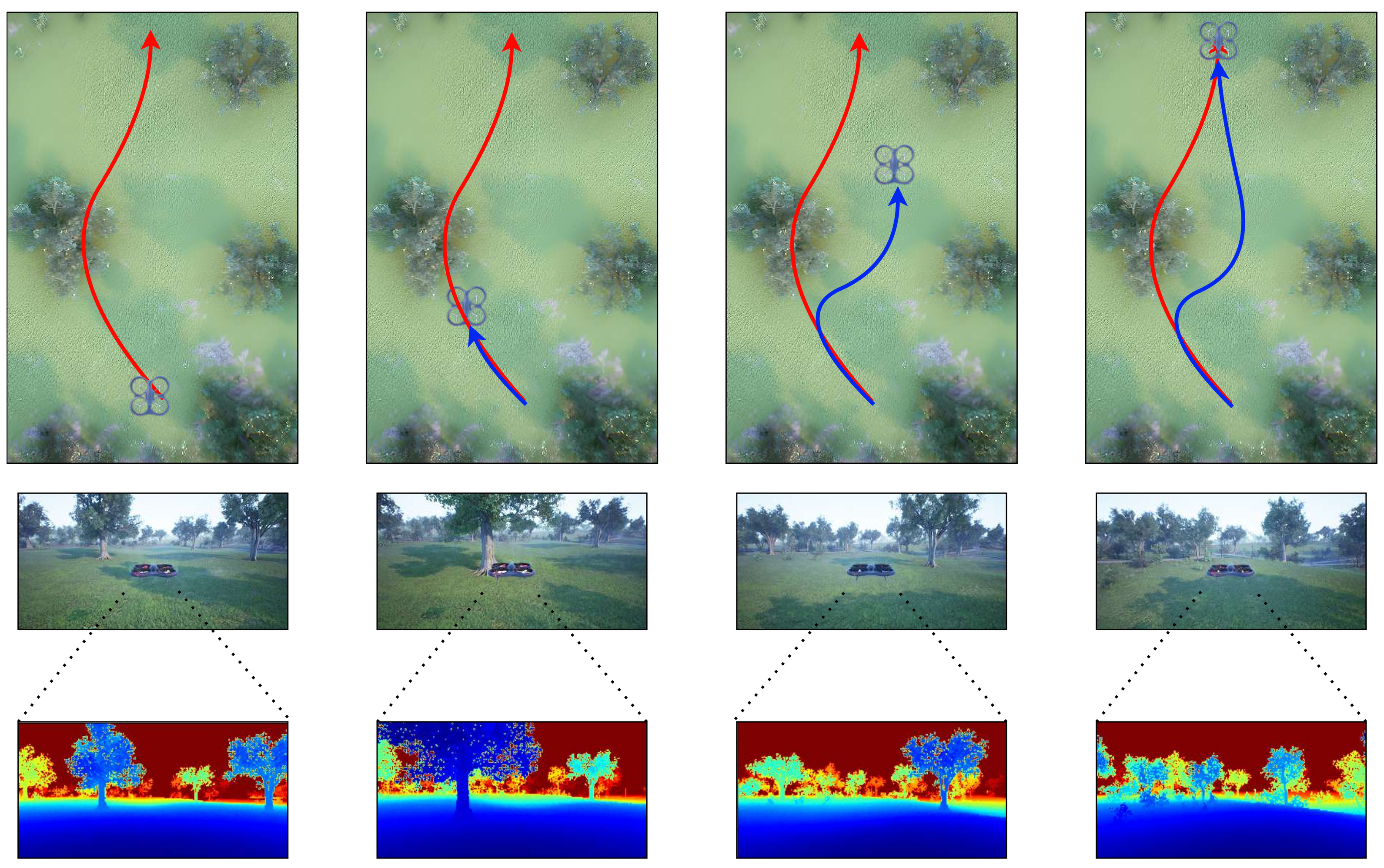
2 Contributions

The main results achieved in this research activity are:

- Improving the robustness of a Micro Aerial Vehichle (MAV) Trajectory Following and Collision Avoidance system using domain randomization and model-based data augmentation [3].
- Introducing a counterfactual-based data augmentation technique for offline reinforcement learning in vision-based problems [1].

3 Methodology

Trajectory Following and Collision Avoidance for MAVs

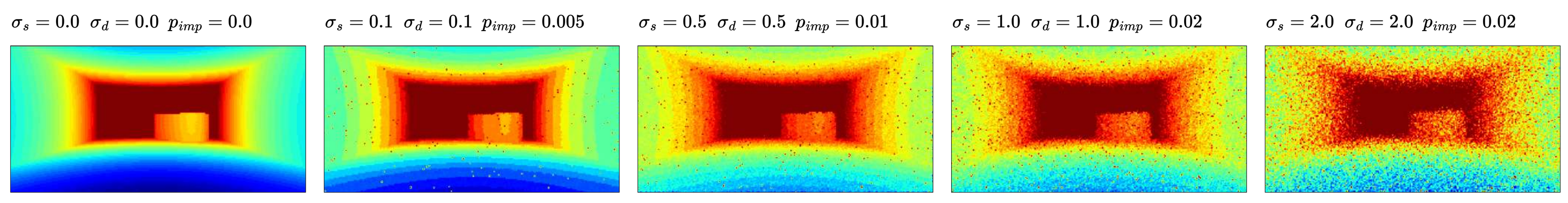


Overview of the Trajectory Tracking and Collision Avoidance task.

We consider the following problem: we want to design a DRL system which objective is to ensure that a MAV follows as accurately as possible a reference trajectory (that is planned without considering obstacles and, thus, may not be feasible), while avoiding collisions with surrounding obstacles. The task is an extension of the problem addressed in [2], where reference trajectories are constrained to have a straight-line shape. As training data was acquired using a simulator, we implemented several data augmentation techniques to mitigate the sim-to-real gap and enhance the system's robustness against elements that our simulation tools could not adequately replicate. Specifically, we performed the following augmentations on the training data:

- Depth maps were corrupted to mimic the effects of noise typically introduced by real-world cameras.
- The MAV actuation signals were perturbed with random noise to simulate real-world operational inconsistencies.

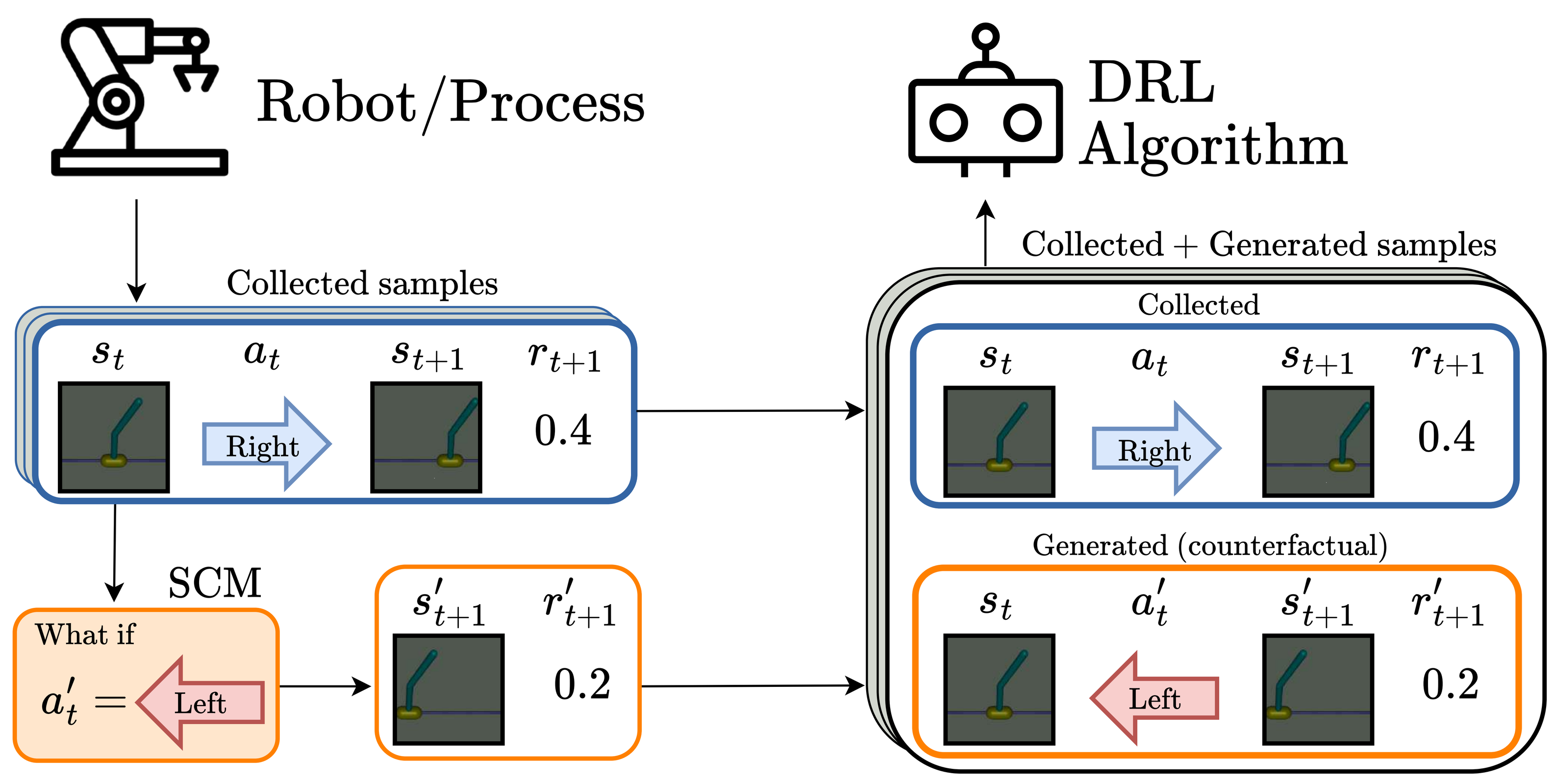
Our experimental campaign demonstrated that a model trained with these augmentation techniques significantly outperforms a model trained solely on the original, unmodified training data, both in terms of tracking effectiveness and generalization to environment settings not seen during training.



Qualitative view of the introduction of noise on the depth maps appearance.

Counterfactual Data Generation for Vision-Based Control

Despite its validity, the DRL approach is burdened by the issue of sample inefficiency, particularly with high-dimensional data, such as images, making it less effective for vision-based tasks. Counterfactual-based data augmentation emerges as a powerful solution to mitigate the sample inefficiency problem, expanding the pre-collected training dataset by generating additional plausible data. However, its potential in vision-based control has been scarcely explored. In this study, we introduced a novel counterfactual-based data augmentation technique tailored for vision-based tasks, leveraging the Generative Adversarial Networks paradigm and Convolutional AutoEncoders to estimate the Structural Causal Model (SCM) describing the process considered and the associated reward model. The learned SCM is then used to augment the training dataset and optimize the DRL agents. We show the effectiveness of our method compared to existing state-of-the-art approaches on a series of control problems, both with discrete and continuous action spaces.



Proposed solution that aims to learn the SCM from the available data and then leverage it to perform counterfactual-based data augmentation for Offline DRL policy learning.

References

[1] Raffaele Brilli, Alberto Dionigi e Gabriele Costante. "Enhancing Counterfactual-Based Data Augmentation for Offline Reinforcement Learning in Vision-Based Control". In: *submitted at 2024 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS 2024)*. 2024.

[2] Raffaele Brilli et al. "Monocular Reactive Collision Avoidance Based on Force Fields for Enhancing the Teleoperation of MAVs". In: *2021 20th International Conference on Advanced Robotics (ICAR)*. 2021, pp. 91–98. DOI: 10.1109/ICAR53236.2021.9659337.

[3] Raffaele Brilli et al. "Towards Trajectory Following and Vision-Based Collision Avoidance for MAVs with Deep Reinforcement Learning". In: *submitted at IEEE Transactions on Robotics (T-RO)*. 2023.