Output Feedback Tube MPC-Guided Data Augmentation for Robust, Efficient Sensorimotor Policy Learning

Andrea Tagliabue, Jonathan P. How

Abstract—Imitation learning (IL) can generate computationally-efficient sensorimotor policies from demonstrations provided by computationally-expensive model-based sensing and control algorithms. However, commonly employed IL methods are often data-inefficient, requiring the collection of a large number of demonstrations and producing policies with limited robustness to uncertainties. In this work, we combine IL with an output feedback robust tube model predictive controller (RTMPC) to co-generate demonstrations and a data augmentation strategy to efficiently learn neural network-based sensorimotor policies. Thanks to the augmented data, we reduce the computation time and the number of demonstrations needed by IL, while providing robustness to sensing and process uncertainty. We tailor our approach to the task of learning a trajectory tracking visuomotor policy for an aerial robot, leveraging a 3D mesh of the environment as part of the data augmentation process. We numerically demonstrate that our method can learn a robust visuomotor policy from a single demonstration—a two-orders of magnitude improvement in demonstration efficiency compared to existing IL methods.

I. INTRODUCTION

Imitation learning [1]–[3] is increasingly employed to generate computationally-efficient policies from computationally-expensive model-based sensing [4], [5] and control [6]–[8] algorithms for onboard deployment. The key to this method is to leverage the inference speed of deep neural networks, which are trained to imitate a set of task-relevant expert demonstrations collected from the model-based algorithms. This approach has been used to generate efficient sensorimotor policies [7], [9]–[12] capable of producing control commands from raw sensory data, bypassing the computational cost of control and state estimation, while providing benefits in terms of latency and robustness. Such sensorimotor policies have demonstrated impressive performance on a variety of tasks, including agile flight [7] and driving [13].

However, one of the fundamental limitations of existing IL methods employed to produce sensorimotor policies (e.g., Behavior Cloning (BC) [1], DAgger [2]) is the overall number of demonstrations that must be collected from the model-based algorithm. This inefficiency hinders the possibility of generating policies by directly collecting data from the real robot, requiring the user to rely on accurate simulators. Furthermore, the need to repeatedly query a computationally expensive expert introduces high computational costs during training, requiring expensive training equipment. The fundamental cause of these inefficiencies is the need to achieve robustness to sensing noise, disturbances, and modeling errors encountered during deployment, which can cause deviations of the policy’s state distribution from its training distribution—an issue known as covariate shift.

Strategies based on matching the disturbances between the training and deployment domains (e.g., Domain Randomization (DR) [14]) improve the robustness of the learned policy, but do not address the demonstration and computational efficiency challenges. Data augmentation approaches based on generating synthetic sensory measurements and corresponding stabilizing actions have shown promising results [15], [16]. However, they rely on handcrafted heuristics for the augmentation procedure and have been mainly studied on lower-dimensional tasks (e.g., steering a 2D Dubins car).

In this work, we propose a new framework that leverages a model-based robust controller, an output feedback RTMPC, to provide robust demonstrations and a corresponding data augmentation strategy for efficient sensorimotor policy learning. Specifically, we extend our previous work where we show that RTMPC can be leveraged to generate augmented data that enables efficient learning of a motor control policy [6]. This new work, summarized in Figure 1, employs an output feedback variant of RTMPC and a model of the sensory observations to design a data augmentation strategy that also accounts for the uncertainty caused by sensing imperfections during the demonstration collection phase. This approach enables efficient, robust sensorimotor learning from a few demonstrations and relays our previous assumption [6] that state information is available at training and deployment time.

We tailor our method to the context of learning a visuomotor policy, capable of robustly tracking given trajectories while using images from an onboard camera to control the position of an aerial robot. Our approach leverages a 3D mesh of the environment reconstructed from images to generate the observation model needed for the proposed augmentation.
strategy. This technique is additionally well-suited to be used with photorealistic, data-driven simulation engines such as FlightMare [17] and FlightGoggles [18], or SLAM and state estimation pipelines that directly produce 3D dense/mesh reconstructions of the environment, such as Kimera [19].

Contributions. In summary, our work presents the following contributions: a) We introduce a new data augmentation strategy, an extension of our previous work [6], enabling efficient and robust learning of a sensorimotor policy, capable of generating control actions directly from raw sensor measurements (e.g., images) instead of state estimates. Our approach is grounded in the output feedback RTMPC framework theory, unlike previous methods that rely on handcrafted heuristics, and leverages a 3D mesh of the environment to generate augmented data. b) We demonstrate our methodology in the context of visuomotor policy learning for an aerial robot, showing that it can track a trajectory from raw images with high robustness (> 90% success rate) after a single demonstration, despite sensory noise disturbances. c) We open-source our framework, available at https://github.com/andretag.

II. RELATED WORKS

Sensorimotor policy learning by imitating model-based experts. Learning a sensorimotor policy by imitating the output of a model-based expert algorithm bypasses the computational cost of planning [8], control [6] and state estimation [10], with the potential of achieving increased robustness [7], [20] and reduced latency with respect to conventional autonomy pipelines. The sensory input typically employed is based on raw images [3], [12], [21] or pre-processed representations, such as feature tracks [7], depth maps [8], or intermediate layers of a CNN [22]. Vision is often complemented with proprioceptive information, such as the one provided by IMUs [7] or wheel encoders [21]. These approaches showcase the advantages of sensorimotor policy learning but do not leverage any data augmentation strategy. Consequently, they query the expert many times during the data collection phase, increasing time, number of demonstrations and computational effort to obtain the policy.

Data augmentation for visuomotor and sensorimotor learning. Traditional data augmentation strategies for visuomotor policy learning have focused on increasing a policy’s generalization ability by applying perturbations [23] or noise [24] directly in image space, without modifying the corresponding action. These methods do not directly address covariate shift issues caused by process uncertainties. The self-driving literature has developed a second class of visuomotor data augmentation strategies [15], [16], [25] capable of compensating covariate-shift issues. This class relies instead on first generating different views from synthetic cameras [15], [16] or data-driven simulators [25] and then computing a corresponding action via a handcrafted controller. These methods, however, rely on heuristics to establish relevant augmented views and the corresponding control action. Our work provides a more general methodology for data augmentation and demonstrates it on a quadrotor system (higher-dimensional than the planar self-driving car models).

Output feedback RTMPC. Model predictive control [26] leverages a model of the system dynamics to generate actions that take into account state and actuation constraints. This is achieved by solving a constrained optimization problem along a predefined temporal horizon, using the model to predict the effects of future actions. Robust variants of MPC, such as RTMPC, usually assume that the system is subject to additive, bounded process uncertainty (e.g., disturbances, model errors). As a consequence, they modify nominal plans by either a) assuming a worst-case disturbance [27], [28], or b) employing an auxiliary (ancillary) controller. This controller maintains the system within some distance (“cross-section” of a tube) from the nominal plan regardless of the realization of the disturbances [29], [30]. Output feedback RTMPC [31]–[33] also accounts for the effects of sensing uncertainty (e.g., sensing noise, imperfect state estimation). Our work relies on an output feedback RTMPC [32], [33] to generate demonstrations and a data augmentation strategy. However, thanks to the proposed imitation learning strategy, our approach does not require solving the optimization problem online, reducing the onboard computational cost.

III. PROBLEM STATEMENT

Our goal is to generate a deep neural network sensorimotor policy $πθ$, with parameters $θ$, to control a mobile robot (e.g., multirotor). The policy needs to be capable of tracking a desired reference trajectory given high-dimensional noisy sensor measurements, and has the form

$$u_t = πθ(o_t, X_{des}^t),$$

where $t$ denotes the discrete time index, $u_t$ represents the deterministic control actions, and $o_t = (I_t, o_{other,t})$ the high-dimensional, noisy sensor measurements, comprised of an image $I_t$ captured by an onboard camera, and other noisy measurements $o_{other,t}$ (e.g., attitude, velocity). The $N + 1$ steps of the reference trajectory are written as $X_{des}^t = \{x_{des}^i, \ldots, x_{des}^{N+1}\}$, where $x_{des}^i$ indicates the desired state at the future time $t + i$, as given at the current time $t$, and $N > 0$ represents the total number of given future desired states. Our objective is to efficiently learn the policy parameters $θ$ by leveraging IL and demonstrations provided by a model-based controller (expert).

System model. We assume available a model of the dynamics of the robot, described by a set of linear (e.g., via linearization), discrete and time-invariant equations:

$$x_{t+1} = Ax_t + Bu_t + w_t$$

where matrices $A \in \mathbb{R}^{n_x \times n_x}$ and $B \in \mathbb{R}^{n_x \times n_u}$ represent the system dynamics, $x_t \in \mathbb{X} \subset \mathbb{R}^{n_x}$ represents the state of the system, and $u_t \in \mathbb{U} \subset \mathbb{R}^{n_u}$ represents the control inputs. The system is subject to state and inputs constraint $\mathbb{X}$ and $\mathbb{U}$, assumed to be convex polytopes containing the origin [31]. The quantity $w_t \in \mathbb{W} \subset \mathbb{R}^{n_w}$ in (2) captures time-varying additive process uncertainties. This includes disturbances and model errors that the system may encounter.

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at deployment time, or the ones caused by the sim2real gap when collecting demonstrations using a simulator. It can additionally capture disturbances encountered at deployment time that are not present when collecting demonstrations from a real robot in a controlled environment (e.g., lab2real gap). These uncertainties are assumed to belong to a bounded set $W$, assumed to be a polytope containing the origin $[31]$. 

**Sensing model.** We assume that the model describing the measurement $\hat{o}_t \in \mathbb{R}^{n_o}$ used by the expert is:

$$\hat{o}_t = \begin{bmatrix} o_{\text{pos},t} \\ o_{\text{others},t} \end{bmatrix} = Cx_t + v_t,$$  

(3)

where $C \in \mathbb{R}^{n_x \times n_o}$, and $v_t = [v_{\text{cam},t}^T, v_{\text{others},t}^T]^T \in \mathbb{V} \subset \mathbb{R}^{n_o}$ represents additive sensing uncertainties (e.g., noise, biases), sampled from a bounded set $\mathbb{V}$. The expert has access to a vision-based position estimator $g_{\text{cam}}$ that produces a noisy estimate $o_{\text{pos}} \in \mathbb{R}^3$ of the position $p_t \in \mathbb{R}^3$ of the robot from an image:

$$o_{\text{pos},t} = g_{\text{cam}}(I_t) = p_t + v_{\text{cam},t},$$  

(4)

where $v_{\text{cam},t}$ is the associated noise/uncertainty. $\mathbb{V}$ can be obtained via system identification, and/or prior knowledge on the accuracy of $g_{\text{cam}}$.

**State estimator model.** We assume that the dynamics of the state estimator employed by the expert during the demonstration collection phase can be approximated by the linear (Luenberger) observer

$$\dot{x}_{i+1} = Ax_i + Bu_t + L(\hat{o}_t - \hat{o}_i), \quad \hat{o}_i = Cx_i,$$  

(5)

where $\hat{o}_i$ is the predicted observation, and $\hat{x}_i \in \mathbb{R}^{n_x}$ is the estimated state. $L \in \mathbb{R}^{n_x \times n_o}$ is the observer gain matrix, and is chosen so that the matrix $A - LC$ is Schur stable. The observability index of the system $(A, C)$ is assumed to be 1, meaning that full state information can be retrieved from a single noisy measurement. In this case, the observer plays the critical role of filtering out the effects of noise and sensing uncertainties. Finally, we assume that the state estimation dynamics and noise sensitivity of the learned policy will approximately match the ones of the observer.

**IV. METHODOLOGY**

The overall idea of our method is to generate trajectory tracking demonstrations from noisy sensor measurements using an output feedback RTMPC expert combined with a state estimator (5), leveraging the defined process and sensing models. The chosen output feedback RTMPC framework is based on $[33]$, with its cost function modified to track a desired trajectory $X^{\text{des}}$, while ensuring satisfaction of the state and actuation constraints $\bar{X}, \mathbb{U}$ regardless of the process noise $w$ and sensing noise $v$ in (2) and (3), respectively.

**Optimization problem.** To fulfill these requirements, the RTMPC computes at every timestep $t$ a sequence of “safe” reference states $\bar{x}_t = \{\bar{x}_{0|t}, \ldots, \bar{x}_{N|t}\}$ and actions $\bar{u}_t = \{\bar{u}_{0|t}, \ldots, \bar{u}_{N-1|t}\}$ along a planning horizon of length $N + 1$. This is achieved by solving the optimization problem:

$$\bar{U}_t, \bar{X}_t = \text{argmin}_{\bar{U}_t, \bar{X}_t} \sum_{i=0}^{N-1} \|x_{i|t}\|_Q^2 + \|u_{i|t}\|_R^2,$$

subject to $\bar{x}_{i+1|t} = A\bar{x}_{i|t} + B\bar{u}_{i|t}$, $\bar{x}_{N|t} \in X_N$, $\bar{x}_t \in \mathbb{Z} \oplus \bar{x}_{0|t}$,

(7)

where $e_{i|t} = x_{i|t} - x_{i|t}^{\text{des}}$ represents the trajectory tracking error. The positive definite matrices $Q$ (size $n_x \times n_x$) and $R$ (size $n_u \times n_u$) are tuning parameters, and define the trade-off between deviations from the desired trajectory and actuation usage. A terminal cost $\|x_{N|t}\|_Q^2$ and terminal state constraint $\bar{x}_{N|t} \in X_N$ are introduced to ensure stability $[33]$, where $P$ (size $n_x \times n_x$) is a positive definite matrix, obtained by solving the infinite horizon optimal control LQR problem, using the system dynamics $A, B$ in (2) and the weights $Q$ and $R$. The “safe” references $\bar{x}_t, \bar{U}_t$ are generated based on the nominal (e.g., not perturbed) dynamics, via the constraints $\bar{x}_{i+1|t} = A\bar{x}_{i|t} + B\bar{u}_{i|t}$.

**Auxiliary controller.** The control input for the real system is obtained via a feedback controller, called auxiliary controller:

$$u_t = \bar{u}_t + K(\bar{x}_t - x^*_t),$$  

(8)

where $\bar{u}_{i|t} = \bar{u}_t$ and $x^*_{i|t} = x^*_t$. The matrix $K$ is computed by solving the LQR problem with $A, B, Q, R$. This controller ensures that the system remains inside a set $\mathbb{Z}$ (“cross-section” of a tube) centered around $x^*_t$ regardless of the realization of process and sensing uncertainty, provided that the state of the system starts in such tube (constraint $\hat{x}_t \in \mathbb{Z} \oplus \bar{x}_{0|t}$).
Tube and robust constraint satisfaction. Process and sensing uncertainties are taken into account by tightening the constraints $X$, $U$ by an amount which depends on $Z$, obtaining $\bar{X}$ and $\bar{U}$.

We start by describing how to compute the set $Z$, which depends on the errors caused by uncertainties when employing the ancillary controller (8) and the state estimator (5). The system considered in (2) and (3) is subject to sensing $V$ and process $W$ uncertainties, sources of two errors: a) the state estimation error $\xi^e_t = x_t - \tilde{x}_t$, which captures the deviations of the state estimate $\tilde{x}_t$ from the true state $x_t$ of the system; b) the control error $\xi^c_t = \tilde{x}_t - \tilde{x}^*_t$, which captures instead deviations of $\tilde{x}_t$ from the reference plan $\tilde{x}^*_t$. These errors can be combined in a vector $\xi_t = [\xi^e_t, \xi^c_t]^T$ whose dynamics evolve according to (see [32], [33]):

$$\xi_{t+1} = A_\xi \xi_t + \delta_t, \quad \delta_t \in \mathbb{D}$$

$$A_\xi = \begin{bmatrix} A - LC & 0_{n_x} \\ LC & A + BK \end{bmatrix}, \quad \mathbb{D} = \begin{bmatrix} I_{n_x} & -L \\ 0_{n_x} & L \end{bmatrix} \begin{bmatrix} W \\ V \end{bmatrix}.$$ (9)

We observe that, by design, $A_\xi$ is Schur-stable, and $\mathbb{D}$ is a convex polytope. Then, the possible set of state estimation and control errors correspond to the minimal RPI set $S$ associated with the system $A_\xi$ under the uncertainty set $\mathbb{D}$.

We now introduce the error between the true state $x_t$ and the reference state $\tilde{x}^*_t$: $\xi^0_t = x_t - \tilde{x}^*_t = \xi^c_t + \xi^e_t$. As a consequence, the set (tube) $Z$ that describes the possible deviations of the true state $x_t$ from the reference $\tilde{x}^*_t$ is:

$$Z = \begin{bmatrix} I_{n_x} & 0_{n_x} \end{bmatrix} S.$$ (10)

Finally, the effects of noise and uncertainties can be taken into account by tightening the constraints of an amount:

$$\bar{X} := X \ominus Z, \quad \bar{U} := U \ominus \begin{bmatrix} 0_{n_x} \\ K \end{bmatrix} S.$$ (11)

C. Tube-guided data augmentation for visuomotor learning

Imitation learning objective. We assume that the given output feedback RTMPC controller in (7), (8) and the state observer in (3) can be represented via a policy $\pi_\theta$, [34], where $\pi$ is of the form in (1), with parameters $\theta^*$. Our objective is to design an IL and data augmentation strategy to efficiently learn the parameters $\theta^*$ for the sensorimotor policy (1), collecting demonstrations from the expert. Using IL, this objective is achieved by minimizing the expected value of a distance metric $J(\theta, \theta^*|\tau)$ over a distribution of trajectories $\tau:

$$\hat{\theta}^* = \arg \min_{\theta} \mathbb{E}_{\mu(\tau|\pi_\theta, K_{\text{aux}})}[J(\theta, \theta^*|\tau)],$$ (12)

where $J(\theta, \theta^*|\tau)$ captures the differences between the trajectories generated by the expert $\pi_\theta$ and the trajectories produced by the learner $\pi_\theta$. The variable $\tau := ((o_0, u_0, x^*_0), \ldots, (o_T, u_T, x^*_T))$ denotes a $T + 1$ step (observation, action, reference) trajectory sampled from the distribution $p(\tau|\pi_\theta, K_{\text{target}})$. Such distribution represents all the possible trajectories induced by the learner policy $\pi_\theta$ in the deployment environment $K_{\text{target}}$, under all the possible instances of the process and sensing uncertainties. In this work, the chosen distance metric is the MSE loss:

$$J(\theta, \theta^*|\tau) = \frac{1}{T} \sum_{t=0}^{T-1} \|\pi_\theta(o_t, x^*_t) - \pi_{\theta^*}(o_t, x^*_t)\|^2_2.$$ (13)

As observed in [6], the presence of uncertainties in the deployment domain $K_{\text{target}}$ makes the setup challenging, as demonstrations are usually collected in a training environment $K_{\text{source}}$ that presents only a subset of all the possible uncertainty realizations. At deployment time, uncertainties may drive the learned policy towards the region of the input space for which no demonstrations have been provided (covariate shift), with potentially catastrophic consequences.

Tube and ancillary controller for data augmentation. To overcome these limitations, we design a data augmentation strategy that takes into account and compensates for the effects of process and sensing uncertainties encountered in $K_{\text{target}}$, and that it is capable of producing the augmented input-output data needed to learn the sensorimotor policy (1). We do so by extending our previous approach [6], named Sampling Augmentation (SA), which provides a strategy to efficiently learn a policy robust to process uncertainty. SA relies on recognizing that the tube $Z$, as computed via a RTMPC, represents a model of the states that the system may visit when subject to process uncertainties. The ancillary controller (8) provides a computationally efficient way to generate the actions to take inside the tube, as it guarantees that the system remains inside the tube for every possible realization of the process uncertainty.

Our new approach, named Visuomotor Sampling Augmentation (VSA), employs the output feedback variant of RTMPC in Section IV-B, as its tube represents a model of the states that might be visited by the system when subject to process and sensing uncertainty, and its ancillary controller provides a way to efficiently compute corresponding actions, guaranteeing that the system remains inside the tube $Z \oplus \tilde{x}^*_t$ in (10) for every possible realization of $w_t \in \mathbb{W}$ and $v_t \in \mathbb{V}$. These properties can be leveraged to design a data augmentation strategy while collecting demonstrations in the source domain $K_{\text{source}}$.

More specifically, let $\tau_{\text{aux}}$ be a $T + 1$ step demonstration generated by the output feedback RTMPC in Section IV-B, collected in the training domain $K_{\text{source}}$:

$$\tau_{\text{aux}} = (((o_0, u_0, \tilde{x}^*_0, x^*_0), \ldots, (o_T, u_T, \tilde{x}^*_T, x^*_T))), (\bar{u}_0, \bar{u}_1, \ldots, (\bar{u}_T, \bar{u}_T, \tilde{x}^*_T, x^*_T))).$$ (14)

Then, at every timestep $t$ in the collected demonstration $\tau_{\text{aux}}$, we can compute extra (state, action) pairs $(x^+_t, u^+_t)$ by sampling extra states from inside the tube $\tilde{x}^*_t + \tilde{X}$ and the corresponding robust control action $u^+_t$:

$$u^+_t = \tilde{u}^*_t + K(x^+_t - \tilde{x}^*_t).$$ (15)

Augmented sensory data generation. The output feedback RTMPC-based augmentation strategy described so far provides a way to generate extra (state, action) samples for data augmentation, but not the sensor observations $o^+ = \theta^* - \tilde{u}^*_t, \tilde{x}^*_t$. To address this gap, we propose an approach that takes advantage of the fact that the learner $\pi_{\theta^*}$ is trained online on $\tau_{\text{aux}}$ and generates a trajectory $\tilde{x}^*_t$. The process is completed by simulating the trajectories $\tau_{\text{aux}}$ in parallel, running the learner $\pi_{\theta^*}$ on top of the sensor observations $o^+ = \theta^* - \tilde{u}^*_t, \tilde{x}^*_t$, to generate extra sensory data $o^+$. This way, the sensor observations $o^+ = \theta^* - \tilde{u}^*_t, \tilde{x}^*_t$ can be collected and added to the training set, providing a way to augment the data with not only external states but also sensory observations, as required for the baseline policy $\pi_{\theta^*}$.
(\mathcal{I}^+, o_{\text{other}}^+) required as input of the sensorimotor policy (1). We overcome this issue by employing observation models (3) available for the expert, obtaining a way to generate extra observations $o^+$, given extra states $x^+$.

In the context of learning the visuomotor policy (1), we generate synthetic camera images $\mathcal{I}^+$ via an inverse pose estimator $g_{\text{cam}}^{-1}$, mapping camera poses $T_{IC}$ to image observations $\mathcal{I}$

$$\mathcal{I}^+ = g_{\text{cam}}^{-1}(T_{IC}^+)$$

where $T_{IC}$ denotes a homogeneous transformation matrix [35] from a world (inertial) frame $I$ to a camera frame $C$. The inverse camera model $g_{\text{cam}}^{-1}$ can be obtained by generating a 3D reconstruction of the environment from the sequence of observations obtained in the collected demonstrations, and by modeling the intrinsic and extrinsic parameters of the onboard camera used by the robot [35]. Extra camera poses $T_{IC}^+$ can be obtained from the extra state vector $x^+$, assuming that the state contains position and orientation information

$$T_{IC}^+ = T_{IB}(x^+)T_{BC},$$

where $T_{IB}$ represents the homogeneous transformation expressing the pose of a robot-fixed body frame $B$ with respect to $I$. $T_{BC}$ describes a known rigid transformation between the body of the robot $B$ and the optical frame of the camera $C$. The full extra observation $o^+$ can be obtained by additionally computing $o_{\text{other}}^+$ via the measurement model (3), assuming zero noise:

$$o^+ = (\mathcal{I}^+, o_{\text{other}}^+), \quad o_{\text{other}}^+ = SCx^+, \quad (18)$$

where $S$ is a selection matrix.

V. EVALUATION

A. Visuomotor trajectory tracking on a multirotor

Task setup. We consider the task of learning a visuomotor trajectory tracking policy for a multirotor, starting from slightly different initial states. The chosen trajectory is an eight-shape (lemniscate), with a velocity of up to 3.5 m/s and a total duration of 30.0 s. We assume that the robot is equipped with a downward-facing monocular camera, and it has available onboard noisy velocity $i v \in \mathbb{R}^3$ and roll $i \phi$, pitch $i \vartheta$ information, corrupted by measurement noise $v_{\text{other},i}$:

$$o_{\text{other},i} = [i v_{\text{vel},i} \varphi_{\text{roll},i} \vartheta_{\text{pitch},i}]^T + v_{\text{other},i}. \quad (19)$$

$I$ denotes a yaw-fixed, gravity aligned inertial reference frame in which the quantities are expressed, and $v_{\text{other}}$ is zero-mean, Gaussian noise with three standard deviations $3\sigma_{\text{other}} = [0.2, 0.2, 0.2, 0.05, 0.05]^T$ (units in $m/s$ for velocity, and $rad$ for tilt). Information on the position $i p \in \mathbb{R}^3$ of the robot is not provided to the learned policy, and it must be inferred from the onboard camera. The output feedback RTMPC has instead additionally access to noisy position information corrupted by additive, zero mean Gaussian noise $v_{\text{cam}}$ with three standard deviations $3\sigma_{\text{cam}} = [0.2, 0.2, 0.4]^T (m)$. Demonstrations are collected from the output feedback RTMPC expert in a nominal domain $\mathcal{K}_{\text{source}}$ that presents sensing noise and model uncertainties (e.g., due to drag, unmodeled attitude dynamics). We consider two deployment environments $\mathcal{K}_{\text{target}}$, one with sensing noise, matching $\mathcal{K}_{\text{source}}$, and one that additionally presents wind-like force disturbances $f_{\text{wind}}$, with magnitude corresponding to 15% - 20% of the weight of the multirotor (12.75 N). During training and deployment, the robot should not collide with the walls/ceiling nor violate additional safety limits (maximum velocity, roll, pitch).

Output feedback RTMPC design. To design the output feedback RTMPC, we employ a hover-linearized model of a multirotor [36]. The state of the robot ($n_x = 8$) is:

$$x = [p^T, i v^T, i \varphi, i \vartheta]^T, \quad (20)$$

while the output ($n_u = 3$) $u_i$ corresponds to roll, pitch and thrust commands, which a cascaded attitude controller executes. Safety limits and position limits are encoded as state constraints. The sampling period for the controller and prediction model is set to $T_s = 0.1$ s, and the prediction horizon is $N = 30, (3.0)$ s. The tube $\mathcal{Z}$ is computed assuming the observation model in (3) to be: $\bar{o}_i = x_i + v_i$, where the bounded measurement uncertainty matches the three standard deviations of the noise encountered in the environment: $\mathcal{V} = \{v \mid \|v\| \leq 3\sigma_{\text{cam}}, \sigma_{\text{other}}^T \}$. The observer gain matrix $L$ is computed by assuming fast state estimation dynamics, by placing the poles of the estimation error dynamics $A - LC$ at 30.0 rad/s. The process uncertainty $\mathcal{W}$ is set to correspond to a bounded force-like disturbance of magnitude equal to 25% of the weight of the multirotor, capturing the physical limits of the platform. Using these priors on uncertainties, sensing noise and the system (9), we compute an approximation of the tube $\mathcal{Z}$ via Monte Carlo simulations, randomly sampling instances of the uncertainties. The RPI set $\mathcal{S}$ is obtained by computing an axis-aligned bounding box approximation of the error trajectories.

Policy architecture. The architecture of the learned policy (1) is represented in Figure 3. The policy takes as input the raw image produced by the onboard camera, the desired trajectory, and noisy attitude and velocity information $o_{\text{other}}$. It employs three convolutional layers, which map the raw images into a lower-dimensional feature space; these features
are then combined with the additional velocity and attitude inputs, and passed through a series of fully connected layers. The generated action \( \mathbf{u}_t \) is then clipped such that \( \mathbf{u}_t \in \mathbb{U} \). To promote learning of internal features relevant to estimating the robot’s state, the output of the policy is augmented to predict the current state \( \hat{x} \) (or \( x^\pi \) for the augmented data), modifying (13) accordingly. This output is not used at deployment time, but it was found to improve the performance.

**B. Dense reconstruction of the environment**

We generate a 3D mesh of the environment needed for data augmentation via VSA from a sequence of real images collected by the onboard downward-facing camera of the Qualcomm Snapdragon Flight Pro [37] board mounted on a multirotor. The images are obtained by executing the trajectory that we intend to learn, which helps us validate the assumption that it is possible to collect a quantity and quality of images sufficient to create an accurate 3D mesh from a single demonstration. Overall we employ 145 black and white images of size \( 640 \times 480 \) pixels. The 3D reconstruction of the considered indoor flight space and the resulting mesh, shown in Figure 2 (left), are generated via the 3D photogrammetry pipeline provided by Meshroom [38]. The scale of the generated reconstruction, which is unobservable from the monocular images, is set manually via prior knowledge of the dimensions of the environment. The obtained mesh is then integrated with our multirotor simulator. We additionally simulate a pinhole camera, whose extrinsic and intrinsic are set to approximately match the parameters of the real onboard camera. Figure 2 (right) shows examples of synthetic images from our simulator.

**C. Choice of baselines, training setup and hyperparameters**

Demonstration collection, training and evaluation is performed in simulation, employing a realistic full nonlinear multirotor model (e.g., [36]). We apply our data augmentation strategy, VSA, to BC and DAgger, comparing their performance without any data augmentation. We additionally combine BC and DAgger with Domain Randomization (DR); in this case, during demonstration collection, we apply random wind disturbances with magnitude in \([0.1, 1.1]|f_{\text{wind}}|\). We set \( \beta \), hyperparameter of DAgger controlling the probability of using actions from the expert instead of the learner policy, to be \( \beta = 1 \) for the first set of demonstrations, and \( \beta = 0 \) otherwise. For every method, we perform our analysis in \( M \) iterations, where at every \( m \)th iteration we: (i) collect \( K \) new demonstrations via the output feedback RTMPC expert; (ii) train a policy with randomly initialized weights using all the demonstrations collected so far, and (iii) evaluate the obtained policy for 20 times, under different realizations of the uncertainty and initial states of the robot. We record the time taken to perform phase (i)-(ii) at the \( m \)th iteration, denoted as \( T_{\text{iter}}^m \). The entire analysis is repeated across 10 random seeds. We use \( M = 2, K = 1 \) for methods using VSA, while \( M = 15, K = 10 \) for all the other methods, in order to speed up their computation. When using VSA, we additionally train the policy incrementally, i.e., we only use the newly collected demonstrations and the corresponding augmented data to update the previously trained policy. All the policies are trained for 50 epochs using the ADAM optimizer, with a learning rate of 0.001 and a batch size of 32. When using VSA, we augment the training data by generating a number \( S = \{50, 100, 200\} \) of observation-action samples, for every timestep, by uniformly sampling states inside the tube. We denote the corresponding method as VSA\( -S \).

**D. Efficiency, robustness and performance**

**Robustness and efficiency.** We evaluate the robustness of the considered methods by monitoring the *success rate*, as
TABLE I: Properties of the considered visuomotor policy learning approaches, including robustness, performance, and demonstration efficiency. We define an approach easy if it does not require applying disturbances during the demonstration collection phase, and it is safe if it does not violate state constraints (e.g., wall collision) during training. Performance captures the relative error between the trajectory generated by output feedback RTMPC (expert) and the learned policy. Demonstration efficiency indicates the number of demonstrations required for one approach to achieve at least 90% success rate. The baseline approaches are evaluated after 150 demonstrations, while VSA methods are evaluated after only 2 demonstrations.

| Method     | Noise | Vel. | VSA-50 | VSA-100 | VSA-200 |
|------------|-------|------|--------|---------|---------|
| DAgger     | No    | No   | Yes    | Yes     | Yes     |
| DAgger     | No    | No   | Yes    | Yes     | Yes     |
| VSA-50     | Yes   | No   | Yes    | No      | No      |
| VSA-100    | Yes   | No   | Yes    | No      | No      |
| VSA-200    | Yes   | No   | Yes    | No      | No      |

TABLE II: Trajectory tracking errors. The position error is expressed in m², while velocity error in m²/s².

| Method     | Noise | Vel. | VSA-50 | VSA-100 | VSA-200 |
|------------|-------|------|--------|---------|---------|
| DAgger     | No    | No   | Yes    | Yes     | Yes     |
| DAgger     | No    | No   | Yes    | Yes     | Yes     |
| VSA-50     | Yes   | No   | Yes    | No      | No      |
| VSA-100    | Yes   | No   | Yes    | No      | No      |
| VSA-200    | Yes   | No   | Yes    | No      | No      |

TABLE III: Computation time required to generated a new action for the output feedback RTMPC (Expert) and the proposed learned visuomotor neural network policy (Policy), given a sensory observation. The learned neural network policy is 17.6 times faster than the optimization-based expert.

VI. CONCLUSIONS

We have presented a strategy for efficient and robust sensorimotor policy learning. Our key idea relies on the co-design of controller and data augmentation strategy with IL methods. Such controller and data augmentation approach leverage the theory of output feedback RTMPC to compute relevant observations and actions for data augmentation—considering the effects of sensing noise, domain uncertainties, and disturbances. We have tailored our approach to the context of visuomotor policy learning, relying on a mesh of the
considered environment to generate tube-guided augmented views. Our numerical evaluation has shown that the proposed method can learn a robust visuomotor policy from a few demonstrations, outperforming IL baselines in demonstration and computational efficiency. Future works will focus on robustifying the policy to uncertainties/imperfections in the 3D mesh of the environment \(q_{\text{pol}}\), accounting for state estimation dynamics in the data augmentation procedure, and performing hardware experiments.

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