Multiplicative Controller Fusion: A Hybrid Navigation Strategy For Deployment in Unknown Environments

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Abstract—Learning-based approaches often outperform hand-coded algorithmic solutions for many problems in robotics. However, learning long-horizon tasks on real robot hardware can be intractable, and transferring a learned policy from simulation to reality is still extremely challenging. We present a novel approach to model-free reinforcement learning that can leverage existing sub-optimal solutions as an algorithmic prior during training and deployment. During training, our gated fusion approach enables the prior to guide the initial stages of exploration, increasing sample-efficiency and enabling learning from sparse long-horizon reward signals. Importantly, the policy can learn to improve beyond the performance of the sub-optimal prior since the prior's influence is annealed gradually. During deployment, the policy's uncertainty provides a reliable strategy for transferring a simulation-trained policy to the real world by falling back to the prior controller in uncertain states. We show the efficacy of our Multiplicative Controller Fusion approach on the task of robot navigation and demonstrate safe transfer from simulation to the real world without any fine tuning. The code for this project is made publicly available at https://sites.google.com/view/mcf-nav/home

I. INTRODUCTION

Deep reinforcement learning (RL) shows immense potential for autonomous navigation agents to learn complex behaviours that are typically difficult to specify analytically via classical, hand-crafted approaches. However, they often require extensive amounts of online training data, a limiting factor for real-world robot applications. Additionally, RL policies overfit to their training environment, making them unreliable for safe deployment in new environments when transferring from simulation to the real world. On the other hand, classical approaches in reactive navigation can guarantee safety and reliably adapt to diverse environments via parameter-tuning, though they lack the capability to efficiently navigate in cluttered environments and are susceptible to oscillations [1], seizure in local minima [2] and poor path efficiency. The high level skills required to overcome these inefficiencies are difficult to hand-engineer explicitly, and tend to deteriorate in performance when extensively tuned for a particular environment.

In this work, we combine classical and learned strategies in order to address their respective limitations. We present Multiplicative Controller Fusion (MCF), an approximate Bayesian approach which utilises a classical controller (prior) for guided policy exploration during training and safe navigation during deployment (see Figure 1). This work primarily focuses on a goal-directed navigation task with sparse rewards, but can be extended to any continuous control task where a competent prior is available.

We propose a gated multiplicative fusion strategy during training which enables us to utilise a suboptimal prior to guide the exploration process during the early stages of training. We formulate the action output from the prior as a distribution around the deterministic action, allowing the agent to explore and update the surrounding state-action regions, stabilising training. As opposed to Learning from Demonstrations (LfD), MCF operates within the exploration space and hence does not require a perfect prior controller, utilising a single objective to optimise the policy. As the agent advances, the gating function gradually shifts the resulting distribution towards the policy, allowing the agent to fully exploit its behaviours, and improve beyond the prior. At deployment, MCF provides an uncertainty-aware navigation strategy for safe deployment in the real world. The multiplicative fusion of the two distributions results in a composite distribution which naturally biases towards the controller exhibiting the least uncertainty at a given state, while attaining the performance of the learned system.

To summarise, the key contributions of our paper are:

- a novel training strategy which utilises a sub-optimal controller to guide exploration for continuous control tasks involving sparse, long-horizon rewards, demonstrating significant improvements to the sample efficiency and the ability for the agent to improve beyond the performance of the controller;
- a novel deployment strategy for continuous control reactive navigation agents which leverages policy uncertainty estimates to safely fall back to a risk-averse
prior controller in states of high policy uncertainty;
- an evaluation of our approach allowing a simulation trained policy to transfer to the real world for safe navigation in cluttered environments without any fine-tuning which can outperform both the prior and end-to-end trained systems.

II. RELATED WORK

A. Classical Navigation Approaches

Classical approaches to navigation can be largely divided into two categories: deliberative and reactive systems. Deliberative systems typically rely on the availability of a globally consistent map to plan out safe trajectories [3], whereas reactive system rely on the immediate perception of their surrounding environment. This allows them to handle dynamic objects and those unaccounted for in the global map.

Vector Field Histograms (VHF) [4] is a real time motion planning algorithm that generates a polar histogram to represent the polar density of surrounding obstacles. The robot’s steering angle is then chosen based on the direction exhibiting the least density and closeness to goal. For this approach, the polar histogram has to be computed at every time step, making it suitable for dynamic obstacle avoidance.

Artificial Potential Field (APF) [5] [6] based approaches compute a local potential function which attracts the robot towards the goal whilst repelling it away from obstacles. Other approaches leverage short term memory [7] in order to build local maps of the surrounding environment, allowing the agent to identify potential dead-ends. The bug family of algorithms [8] can guarantee completeness when searching for a goal but lack efficiency.

A common disadvantage of all these approaches is the need of extensive tuning and hand engineering to achieve good performance with a tendency to deteriorate in performance when tuned for a particular domain. Additionally they are susceptible to oscillations, getting stuck in local minima [1]. [2] and exhibit suboptimal path efficiency.

B. Learning for Reactive Navigation

Learning navigation strategies is an attractive alternative to robot control when compared to classical analytically derived approaches. Common approaches are imitation learning [9] and deep reinforcement learning [10]. Imitation learning trains a model by mimicking a set of demonstrations provided by an expert. Such approaches have been shown to successfully teach an agent to navigate along forest trails [11], and accomplish uncertainty aware visual navigation tasks [12]. Kim et al. [13] and Pfeifer et al. [14] train a navigation agent using a global path planner as the set of labelled demonstration data. These systems are, however limited by the performance of the demonstration set. On the other hand, deep reinforcement learning based approaches do not rely on a dataset, and allow the agent to gain experience via interaction with the environment. Zhu et al. [15] train a monocular based robot for target driven navigation in a high fidelity simulation environment and fine tune it for deployment in the real world. Given the close correspondence between laser scans in simulation and the real world,

Tai et al. [16] and Xie et al. [17] show that training an agent in simulation can be transferred directly to a real robot without any fine-tuning when using laser based sensors. Despite showing reasonable performance, the robot was still shown to fail in scenarios it did not generalise to during training. Recent approaches have made attempts to improve the safety of these system when presented with unknown states. Kahn et al. [18] propose an uncertainty-aware navigation strategy using model-based learning. They rely on uncertainty estimates of a collision prediction module and utilise this as a risk term in model predictive control (MPC). Lotjens et al. [19] extend this approach to avoid dynamic obstacles in complex scenarios by utilising an ensemble of LSTM networks to estimate the uncertainty of surrounding obstacles. We extend these ideas to model-free reinforcement learning and propose a unified approach which leverages risk averse prior controllers for safe real world deployment.

C. Combining Classical and Learned Systems

Instead of assuming no prior knowledge, a better informed alternative is to leverage the large body of classical approaches to aid learning based systems. A number of recent works have taken steps towards this notion. Xie et al. [17] leverage a proportional controller to speed up the training process during exploration in navigation tasks. The idea is based on the hand-crafted controller yielding higher rewards than random exploration alone. Bansal et al. [20] train a perception module to produce obstacle-free waypoints with which an optimal controller can plan path towards. Our prior work et al. [21] proposes a tightly coupled training approach between a classical controller and reinforcement learning, based on the residual reinforcement learning framework. A residual policy is learnt to improve the performance of a suboptimal classical controller whilst leveraging the classical controller to guide the exploration. The approach however only learns a residual policy to modify the prior, limiting the expressiveness of the overall system. We formulate an alternative approach which gradually allows the policy to be independent of the classical controller enabling it to improve far beyond its performance. Iscen et al. [22] demonstrate how a learned policy can be used to modify Trajectory Generators in order to improve their base level of performance and show its applicability for real robot locomotion. Learning from Demonstrations (LfD) [23]–[25] provide a different approach to introducing prior knowledge from classical systems to aid the learning process, however heavily rely on the presence of perfect demonstrations and utilise multiple objectives to optimise the system in order to stabilise training. In our work we do not rely on a perfect controller, but instead leverage suboptimal controllers to guide the learning process and gradually allow the policy to improve beyond these inefficiencies. We additionally leverage these classical controllers as fallback controllers in cases of high policy uncertainty when deployed in the real world.
III. PROBLEM FORMULATION

We consider the reinforcement learning framework in which an agent learns an optimal controller for a given task through environment interaction. While providing an attractive solution to solve complex control tasks which are difficult to derive analytically, their application to real robots are plagued by high sample inefficiency during training and unsafe behaviour in unknown states. This hinders the overall adoption of these systems in the real world. We propose an approach which leverages the vast number of suboptimal classical controllers (priors) developed by the robotics community to address these limitations.

Traditionally in RL, an agent begins by randomly exploring its environment, arriving at any given state \(s\), the agent performs an action \(a\) and arrives in state \(s'\), receiving a reward \(r(s,a,s') \in \mathbb{R}\). In order to learn an optimal policy, the goal of the agent is to maximise the expectation of the sum of discounted rewards, known as the return \(R_t = \sum_{i=t+1}^{\infty} \gamma^i r(s_i,a_i,s_{i+1})\), which weighs rewards according to the discount factor \(\gamma\). In this work, we leverage existing classical controllers to both guide exploration during training as well as provide safety guarantees during deployment. We make the assumption that a suboptimal classical controller is present for this task and that its explicit analytical derivation can provide such performance guarantees, which generally are not provided by learnt policies. We refer to this as risk-averse behaviour.

IV. MULTIPLICATIVE CONTROLLER FUSION

We introduce Multiplicative Controller Fusion (MCF), which takes a step towards unifying classical controllers and learned system in order to attain the best of both worlds during training and deployment. Our approach focuses on continuous control tasks, a staple in robotics. We formulate the action outputs from both the prior controller and policy as distributions over actions where a composite policy is obtained via a multiplicative composition of these distributions. The general form of our approach is given by:

\[
\pi'(a|s) = \frac{1}{Z} (\pi_\theta(a|s) \cdot \pi_{prior}(a|s))
\]  

(1)

where \(\pi_\theta(a|s)\) and \(\pi_{prior}(a|s)\) represents the distribution over actions from the policy network and prior controller respectively. \(Z\) is a normalisation coefficient which ensures that the composite distribution \(\pi'(a|s)\) is normalised.

A. Components

MCF consists of two components: a reinforcement learning policy and a classical controller which we refer to as the prior. We describe each of these systems below.

**Policy:** We leverage stochastic RL algorithms that output each action as an independent Gaussian \(\pi_\theta(a|s) = \mathcal{N}(\mu, \Sigma)\) with \(\mu\) containing the component wise means \(\mu_c\) for the linear velocity and \(\mu_\omega\) for angular velocity. The diagonal covariance matrix \(\Sigma\) contains the corresponding variances \(\sigma_\nu^2\) for the linear velocity and \(\sigma_\omega^2\) for the angular velocity. This output distribution is suitable for use during training, however since the distribution is trained to maximise entropy over the actions, its variance does not reflect the model’s uncertainty. At deployment it is particularly important that the distribution provides a representation of the policy’s state uncertainty, known as epistemic uncertainty. In order to attain such a distribution at deployment, we follow approaches for uncertainty estimation from the deep learning literature based on training ensembles [26]. \(N\) randomly initialised policies are trained and at inference the agreement between them at a given state indicates the level of uncertainty. We employ this idea at the deployment phase on a real robot.

**Prior Controller:** We utilise the large body of work developed by the robotics community consisting of analytically derived controllers. These hand-crafted controllers demonstrate competent levels of performance across various domains but are inefficient in unstructured environments and are limited to the behaviours defined at design stage. For uncertainty-aware deployment, MCF relies on a distribution over the actions. However, most classical methods do not produce principled and calibrated uncertainty estimates. Therefore, we construct an approximate distribution based on the sensor noise, which is the main source of uncertainty in these systems. We do this by propagating the sensor uncertainty using Monte Carlo sampling to extract an uncertainty estimate over the action space. For guided exploration, the training distribution primarily serves as a medium for Gaussian exploration, allowing the policy to explore the surrounding state-action pairs for potential improvements.

B. Guided Exploration

Exploration is difficult in sparse long horizon settings for standard reinforcement learning techniques, requiring large amounts of environment interaction. To this end, we leverage the prior controller during training to guide exploration. We utilise a gated variant of Equation 1 for Gaussian exploration using the composite distribution. The gating function biases the composite distribution \(\pi'(a|s)\) towards the prior early on during training, exposing it to the most relevant parts of the state-action space. As the policy becomes more capable, the gating function gradually shifts \(\pi'(a|s)\) towards the policy distribution by the end of training. This allows the system to fully exploit its learned policy and improve beyond the prior. The multiplicative fusion constrains the exploration such that the policy does not deviate far off from the prior, exploiting unwanted behaviours.

\[
\pi'(a|s) = \frac{1}{Z} (\pi_\theta(a|s)^{1-\alpha} \cdot \pi_{prior}(a|s)^\alpha)
\]  

(2)

Equation 2 defines the gated form of our multiplicative fusion strategy used during training, where \(\alpha\) represents the gating term that shifts the resulting distribution. By formulating the action outputs of the prior as a unimodal Gaussian we allow the surrounding state-action regions of the Q-value network to be correctly updated reducing the chances of overestimation bias, stabilising training. The gating formulation is reminiscent of the epsilon-greedy
strategy used in Q-learning [10], however, as opposed to totally random action we utilise a distribution around a competent controller. The complete MCF Training algorithm is shown in Algorithm 1.

Algorithm 1: MCF Training

1. Given: Given Policy Network \( \pi_\theta \), Prior Controller \( \pi_{prior} \)
2. Input: State \( s_t \), Gating Function, \( \alpha \)
3. Output: Trained Policy, \( \pi_\theta \)
4. for \( t = 1 \) to \( T \) do
5. Compute the composite distribution
6. \[ \pi'(a|s_t) \sim \mathcal{N}(\mu', \sigma'^2) \]
7. \[ \pi'(a|s_t) = \frac{1}{2}(\pi_\theta(a|s_t)(1-\alpha) \cdot \pi_{prior}(a|s_t)^\alpha) \]
8. Sample action \( a \) from the new distribution \( \pi'(a|s_t) \) and step in environment.
9. Store \( (s_t, a, r, s_{t+1}) \)
10. Update \( \pi_\theta \)
11. Compute \( \alpha \)
12. end
13. return \( \pi_\theta \)

The mean \( \mu' \) and variance \( \sigma'^2 \) defining the composite Gaussian \( \pi'(a|s_t) \) can be expressed as follows,

\[ \mu' = \frac{\mu_\theta \sigma_{prior}^2(1-\alpha) + \mu_{prior} \sigma_\theta^2 \alpha}{\sigma_{prior}^2(1-\alpha) + \sigma_\theta^2 \alpha} \quad (3) \]

\[ \sigma'^2 = \frac{\sigma_\theta^2 \sigma_{prior}^2}{\sigma_{prior}^2(1-\alpha) + \sigma_\theta^2 \alpha} \quad (4) \]

This expansion implicitly handles the normalisation term \( \frac{1}{2} \). The multiplicative formulation constrains the exploration process, allowing the agent to focus on the most relevant regions in the environment, reducing the overall training time. The gating parameter, \( \alpha \) initially begins at 1, indicating complete shift towards the prior distribution and gradually shifts entirely towards the policy distribution when its value is 0. The gating function should ideally be a function of the policy’s performance during training however we leave the exploration of this idea to future work. In this work we represent the gating function as a reverse logistic function which is a function of the training steps taken.

An advantage of using this type of fusion during exploration is that the policy distribution is biased towards the state-action trajectories followed by the prior. This mitigates the exploitation of unwanted behaviours commonly seen during random exploration. It also makes the policy suitable for multiplicative combination with the prior during deployment, as we will describe in the following section.

C. Uncertainty-Aware Deployment

At deployment we directly use Equation 1 to derive a composite policy, \( \pi'(a|s) \) which demonstrates the complex navigational skills attained by the learned system whilst exhibiting the risk averse behaviours of the prior in states of high policy uncertainty. This allows for efficient and safe real-world deployment. In order to attain this behaviour in the fusion process, we require the policy distribution to represent its state uncertainty. Given that all training is completed in a non-exhaustive simulation environment, the policy is bound to encounter states it not generalise well to when transferred to the real world. We encapsulate this uncertainty by training an ensemble using Algorithm 1 and computing the mean and variance of the action produced by the ensemble at a given state during inference. This allows the distribution to indicate a higher standard deviation in unknown states and lower values when all policies agree at familiar states. The complete MCF Deployment algorithm is described in Algorithm 2.

Algorithm 2: MCF Deployment

1. Given: Ensemble of N Trained Policies \((\{\pi_{\theta_1}, \pi_{\theta_2}, ..., \pi_{\theta_N}\})\), Prior Controller \( \pi_{prior} \)
2. Input: State \( s_t \)
3. Output: Action \( a \)
4. Approximate ensemble predictions as a unimodal Gaussian \( \pi_{\theta_n}^*(a|s_t) = \mathcal{N}(\mu_{n}, \sigma_{n}^2) \), where:
5. \[ \mu_{n} = \frac{1}{N} \sum_{n=1}^{N} \mu_{\theta_n} \]
6. \[ \sigma_{n}^2 = \text{Var}[\mu_{\theta_n}] \]
7. Compute the composite distribution
8. \[ \pi'(a|s_t) \sim \mathcal{N}(\mu', \sigma'^2) \]
9. \[ \pi'(a|s_t) = \frac{1}{2}(\pi_{\theta_n}^*(a|s_t) \cdot \pi_{prior}(a|s_t)) \]
10. Sample action \( a \) from the distribution \( \pi'(a|s_t) \)
11. return \( a \)

The mean \( \mu' \) and variance \( \sigma'^2 \) representing this composite Gaussian can be expressed as follows,

\[ \mu' = \frac{\mu_{\theta} \sigma_{prior}^2 + \mu_{prior} \sigma_{\theta}^2}{\sigma_{prior}^2 + \sigma_{\theta}^2} \quad (5) \]

\[ \sigma'^2 = \frac{\sigma_{prior}^2 \sigma_{\theta}^2}{\sigma_{prior}^2 + \sigma_{\theta}^2} \quad (6) \]

where this expansion implicitly handles the normalisation term \( \frac{1}{2} \).

V. EXPERIMENTS

In this work we focus on the goal directed navigation task presented by Anderson et al. [27] which requires the agent to efficiently navigate to a desired goal whilst avoiding obstacles and dead-ends.

A. Experimental Setup

Training Environment: All policy training was conducted in simulation and deployed in the real world without any additional fine tuning. We utilise the laser-based navigation simulation environment provided in [21] to train all agents and transfer the trained policy to an identical robot in the real world. The training environment consists of 5 arenas.
with different configurations of obstacles. The goal and start location of the robot are randomised at the start of each episode each placed on the extreme opposite ends of the arena (see Figure 3). This sets the long horizon nature of the task. As we focus on the sparse reward setting, we define \( r(s, a, s') = 1 \) if \( d_{target} < d_{threshold} \) and \( r(s, a, s') = 0 \) otherwise, where \( d_{target} \) is the distance between the agent and the goal and \( d_{threshold} \) is a set threshold. The length of each episode is set to a maximum of 500 steps. The action space consists of two continuous values: linear velocity \( v \in [-1, 1] \) and angular velocity \( \omega \in [-1, 1] \). We assume that the robot can localise itself within a global map in order to determine its relative position to a goal location. The 180° laser scan range data is divided into 15 bins and concatenated to the robots angle and distance to goal and the previously executed linear and angular velocity. This 19 dimensional tensor represents the state input \( s_t \) to the policy. The prior controller takes as input the entire 180° laser scan data and angle-to-goal data in order to build its local potential field.

**Prior Controller:** For the prior controller, we utilise a variant of the Artificial Potential Fields controller introduced by Warren et al. [5]. It demonstrates a competent level of obstacle avoidance capabilities whilst exhibiting the same limitations faced by most reactive planners. As the standard form of this prior produces a deterministic action for the linear and angular velocities \([v, \omega]\), we approximate the distribution over these actions using Monte Carlo sampling. Given a known noise model of the laser scan range values \( \mathcal{N}(0, \sigma^2) \), we sample a 180 dimensional noise vector and add it to the laser scan value at a given state. This is passed through the controller producing the resulting linear and angular velocity. This is repeated \( N \) times and the mean and variance of these values are computed to represent the distribution over the prior actions. At training, the distribution over the prior action space primarily serves as a medium for Gaussian exploration, allowing the policy to explore the surrounding state-action pairs for potential improvements, which we found important to stabilise training. We set this to a value of 0.3 throughout training.

**Policy:** For training, we utilise Soft Actor-Critic (SAC) [28], an off-policy RL algorithm which naturally expresses its output as a distribution over its action space. SAC is known for its stability and robustness to hyper-parameters during training when compared to other off-policy algorithms. It incorporates an entropy regularisation term during training and is optimised to maximise a trade-off between expected return and entropy. This encourages exploration and prevents the policy from prematurely converging to a bad local optimum. The outputs from this policy follow the same same convention outlined in section IV.

**B. Evaluation of Training Performance**

We provide an evaluation of the training performance of our approach when compared to 3 learned baseline alternatives described below:

**End-to-end:** We train an agent using the standard Gaussian exploration provided in the SAC implementation.

**Baseline:** This method illustrates the naive use of demonstrations in the replay buffer. The replay buffer is filled with 50% demonstrations from our prior and 50% experience gathered by sampling the agent’s policy.

**MCF (no-gating):** A variant of our proposed approach which does not rely on a gating function.

![Fig. 2. Learning curves showing average path length during training. MCF achieved the best performance compared to all alternatives with the least variance across 10 seeds.](image)

After every 5 episodes, we evaluated the policies’ performance and the results are shown in Figure 2. All agents were trained across 10 different seeds. We additionally overlay the performance of the prior controller for comparison. Our approach shows the fastest convergence and the least variance across all seeds. The end-to-end based approach is shown to exhibit the worst performance with very high variance. The baseline approach also shows very high variance and is shown to converge to a suboptimal policy. We note that the no-gating variant of MCF, whilst showing lower variance, quickly converges towards a suboptimal policy with similar performance to the prior. This is a result of it not being able to fully exploit its own policy and identify improvements beyond that of the prior, highlighting the importance of the gating parameter.

Figure 3 shows the state space coverage during exploration by standard Gaussian exploration, the baseline approach and our MCF in an environment with a fixed start and goal location. This illustrates the poor performance of standard Gaussian exploration in sparse long horizon reward settings incapable of moving far beyond its initial position. The baseline whilst benefiting from the demonstrations is seen to spend time exploring unnecessary regions of the state space. MCF on the other hand illustrates structured exploration around the deterministic path of the prior controller (indicated by the dashed line) allowing it to focus on parts of the start space most relevant to the task whilst exploring the surrounding state-action regions for potential improvements.

Figure 4 shows the progression of the MCF training distribution used for exploration and the impact of the gating function. Without gating, the standard multiplicative
Gaussian Exploration (a) Baseline (b) MCF (Ours) (c)

Fig. 3. State space coverage during exploration. The dotted line in (c) illustrates the deterministic path taken by the prior controller. Note how our formulation explores immediate surrounding regions.

Policy Only: An individual policy trained end-to-end using SAC. Given that the standard Gaussian exploration used in the algorithm was insufficient to learn in the sparse reward setting, this algorithm was trained using Algorithm 1.

Prior: This represents the analytically derived reactive navigation controller based on the Artificial Potential Fields approach [5].

ROS Move-Base: For the real world experiments, we compare to the state of the art classical local planner provided in the ROS navigation stack.

Random: Actions are randomly sampled from a uniform distribution between -1 and 1.

To evaluate the performance of these systems, we report the average Success weighted by (normalised inverse) Path Length (SPL), a specific metric for PointGoal navigation tasks presented by Anderson et al. [27] and the episodic actuation time as a measure of efficiency. The SPL ratio requires a measure of the shortest path to goal which we approximate using the path found by an A-Star search across a $2000 \times 1000$ grid. An episode is deemed successful when the robot arrives within 0.2m of the goal. The episode is timed out after 500 steps and is considered unsuccessful thereafter. This is captured by the SPL metric which additionally indicates how close the agent’s determined path came to an optimal path. We do not report this value on the real robot experiments as we did not have access to an optimal path. We however, provide distance travelled along each path and compare them to the distance travelled by a fine-tuned ROS movebase planner. In most states, we found that the prior controller utilised in this work exhibited very little variance to the magnitude of laser noise present in the robot’s laser scanner. As a result, we set the variance of the distribution to $\sigma_{mc}^2$, where $\sigma_{mc}^2$ represents the variance computed by the Monte Carlo sampling approach. This prevented the prior distribution from collapsing to a very small value, limiting the impact of the policy on the overall system.

1) Simulation Environment Evaluation: We deploy the agent in both it’s training environment and an unseen environment to evaluate its performance when presented with unknown states. Table I summarises the results. As expected, both our approach and the Policy Only systems show superior performance in the training environment given that the policies have generalised well to all given states present as indicated by the high SPL values. Additionally we

| Method          | Training Environment | Unseen Environment |
|-----------------|----------------------|--------------------|
|                 | SPL                  | Actuation Time     |
|                 | (Steps)              | SPL                |
|                 |                      | (Steps)            |
| Prior           | 0.793                | 207                |
| Policy Only     | 0.946                | 126                |
| MCF (Ours)      | 0.965                | 119                |
| Random          | 0                    | 500                |
|                 |                      | 0.666              |
|                 |                      | 305                |
|                 |                      | 0.608              |
|                 |                      | 247                |
|                 | 0.728                | 227                |
|                 | 0.148                | 478                |
We utilise a PatrolBot mobile base shown in Figure 1 which is equipped with a 180° laser scanner. All velocity outputs are scaled to a maximum of 0.25 m/s before execution on the robot. The environment in which the system was deployed was a cluttered indoor office space which had been previously mapped using the laser scanner. We utilise the ROS ACML package to localise the robot within this map inorder to extract the necessary system inputs for the policy network and prior. Despite having a global map, the agent is only provided with global pose information with no additional information about its operational space. The environment also contained clutter which was unaccounted for in the mapping process. To enable large traversals through the office space, we utilise a global planner to generate target locations, 3 meters apart for our reactive agents to navigate towards.

We evaluate the performance of the system on two different trajectories indicated as Trajectory 1 and Trajectory 2 in Table II and Figure 5. Trajectory 1 consisted of a lab space with multiple obstacles, tight turns, and dynamic human subjects along the trajectory, whilst Trajectory 2 consisted of narrow corridors never seen by the robot during training. As a comparative baseline, we include the performance achieved by a fine-tuned ROS move-base planner. We summarise the results in Table II. In all cases, the Policy only approach failed to complete the task without any collisions, exhibiting random reversing behaviours. We attribute this to its poor generalisation to certain states given the limited simulation training environment. The prior was capable of completing all trajectories however had the largest execution times as a result of its inefficient oscillatory behaviour. MCF was successful in all cases and showed significant improvements in efficiency when compared to the prior. We attribute this to the impact the policy has on the system. It also demonstrates competitive results with a fine tuned move-base planner with similar distance coverage.

To gain a better understanding into the reasons for MCF’s success when compared to the prior and policy only alternatives, we overlay the trajectories taken by these systems as shown in Figure 5. The trajectory taken by MCF is colour-coded to illustrated the policy uncertainty in the linear velocity as given by the standard deviation of the policy ensemble outputs. We draw the readers attention to the region marked A which exhibits higher values of policy uncertainty. The multiplicative combination of the distributions at this region are shown within the orange ring. As expected, given the higher uncertainty at this point, the resulting distribution was biased more towards the prior which displayed greater certainty, allowing the robot to progress beyond this point safely. We note here that this is the particular region that the Policy Only system failed as shown in Figure 5. The purple ring at region C, illustrates regions of lower uncertainty and show that both the policy and prior significantly overlap. Comparing the performance benefit over the prior, we draw the readers attention to regions B and D which show the path profile taken by the agents. The dense darker path shown by the prior indicate regions of high oscillatory behaviour and significant time spent at a given location. On the other hand, we see that MCF does not exhibit this and represents a smoother trajectory which we can attribute to the policy having higher precedence in these regions, stabilising the oscillatory effects of the prior. We provide a video illustrating these behaviours with the real robot on our project page1.

VI. Conclusions

In this paper, we propose Multiplicative Controller Fusion (MCF), a stochastic fusion strategy for continuous control tasks. It provides a means to leverage the large body of work from the robotics community into learning based approaches.

1https://sites.google.com/view/mcf-nav/home
MCF operates both during training and deployment. At training, we show that our gated formulation allows for low variance sample efficient learning from sparse, long-horizon reward tasks. At deployment, we demonstrate how MCF attains the efficiencies of learned policies in familiar states, whilst falling back to a classical controller in cases of high policy uncertainty. This allows for superior performance when transferring a policy from simulation to the real world when compared to both the policy and classical systems individually. A limitation of our approach is when both the prior and policy are confident on totally different actions, which stagnates the resulting distribution. This may occur if the policy exploits an unwanted behaviour during training and hence acts considerably different from the prior. One way to mitigate this stagnation is to always fall back to the reliable classical controller in cases of total disagreement. Additionally, the gating function could be defined to directly relate to the policy’s performance. We leave the exploration of these ideas to future work.

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