Abstract—While current autonomous navigation systems allow robots to successfully drive themselves from one point to another in specific environments, they typically require extensive manual parameter re-tuning by human robotics experts in order to function in new environments. Furthermore, even for just one complex environment, a single set of fine-tuned parameters may not work well in different regions of that environment. These problems prohibit reliable mobile robot deployment by non-expert users. As a remedy, we propose Adaptive Planner Parameter Learning (APPL), a machine learning framework that can leverage non-expert human interaction via several modalities—including teleoperated demonstrations, corrective interventions, and evaluative feedback—and also unsupervised reinforcement learning to learn a parameter policy that can dynamically adjust the parameters of classical navigation systems in response to changes in the environment. APPL inherits safety and explainability from classical navigation systems while also enjoying the benefits of machine learning, i.e., the ability to adapt and improve from experience. We present a suite of individual APPL methods and also a unifying cycle-of-learning scheme that combines all the proposed methods in a framework that can improve navigation performance through continual, iterative human interaction and simulation training.

Index Terms—Mobile Robot Navigation, Machine Learning, Motion Planning

I. INTRODUCTION

While engineered systems developed over the past several decades have enabled autonomous mobile robot navigation in certain scenarios, it is typically the case that the parameters of these systems need to be adjusted for each new deployment environment. This process is referred to as “parameter-tuning,” i.e., the process through which a human with expert knowledge of the underlying system and the role of each parameter—along with trial-and-error, experience, and intuition—manually finds the best set of system parameters for a new environment. This traditional setup (1) precludes non-expert users from optimizing the default robot system; (2) assumes a single set of parameters will work well for all regions of a specific environment; and (3) completely abandons previously fine-tuned parameters when using a new set of parameters.

In contrast, many humans—even those with little to no robotics experience—can easily teleoperate mobile robots in new environments, and even more humans are able to provide simple evaluative feedback (e.g., a numerical assessment of performance) on the robot’s behavior. These in situ end-user interactions can provide a rich source of knowledge regarding how the system should behave in deployment environments.

We hypothesize that systems that can capture and leverage these interactions will be able to quickly adapt to their deployment environments, i.e., exhibit robust and reliable navigation system performance.

In this article, we investigate this hypothesis by developing and studying a novel family of algorithms called Adaptive Planner Parameter Learning (APPL). In particular, we present an algorithm that can learn from human demonstrations (APPLD), an algorithm that can learn from human interventions (APPLI), and an algorithm that can learn from human-generated evaluative feedback (APPLE). Additionally, we present an algorithm in this family that can, if available, leverage simulation experience in an unsupervised fashion using reinforcement learning (APPLR). Importantly, the framework under which we develop APPL does not replace existing systems for autonomous navigation, but rather augments them by providing a new learned module that adjusts only certain hyperparameters of these systems (e.g., obstacle inflation radius, sampling rate, cost function coefficients, etc.). By adopting this approach, APPL systems inherit the advantages of existing navigation systems (e.g., safety and explainability), while also enjoying the benefits of machine learning methods (e.g., adaptivity and improvement from experience). Moreover, the APPL framework explicitly allows for the possibility of adjusting these hyperparameters “on-the-fly”, i.e., dynamically changing parameters at every time step to achieve robust navigation. Finally, we also present a unifying vision for how our APPL algorithms can be used in concert to enable a cycle-of-learning framework for continual system improvement through iterative interaction with simulation and end users.

We demonstrate the efficacy of the proposed algorithms in a series of experiments in which a small ground robot, accompanied by a human, must autonomously navigate in a number of complex, constrained environments. Our results show that leveraging human interaction does indeed allow the robot to quickly adapt to each new environment, learning to overcome failures and other suboptimal behavior to the point where the human is no longer necessary. Moreover, we show that combining the proposed approaches in the unified framework that can also leverage unsupervised simulated training in a series of system iterations exhibits increasing performance with each new deployment.

The remainder of this article is organized as follows. We begin by reviewing related work in terms of learning for navigation and learning from humans in Sec. II. As one of the two novel contributions of this article, we formalize the Adaptive Planner Parameter Learning (APPL) framework in Sec. III, which is an overarching paradigm that encompasses all the following more specialized methods. Specifically, in...
Sec. IV, Sec. V, Sec. VI, and Sec. VII, we present Adaptive Planner Parameter Learning from Demonstration [1], from Interventions [2], from Evaluative Feedback [3], and from Reinforcement [4], respectively. Note that APPLD and APPLE were introduced in our previous Robotics and Automation Letters articles [1], [3], so we only briefly summarize these two methods. For APPL and APPLR, which have only appeared in conference papers [2], [4], we re-formalize these two methods under the overarching APPL framework and present detailed descriptions. As the second novel contribution of this article, we introduce a cycle-of-learning scheme in Sec. VIII, which combines all four individual APPL methods in the unified framework, leveraging demonstration, interventions, evaluative feedback, and reinforcement in different deployment scenarios with different human users, and achieves cyclic and continual improvement in navigation performance. The experiments pertaining to this cycle-of-learning scheme are also new in this article. All experiment videos can be found at https://www.cs.utexas.edu/~xiao/Research/APPL/APPL.html

II. RELATED WORK

This section reviews state-of-the-art approaches that have applied machine learning to the problem of mobile robot navigation and related work in terms of using different human interaction modalities to assist machine learning.

A. Learning for Navigation

Autonomous mobile robot navigation has been a topic of interest to the robotics community for decades [5], [6]. For example, the DWA planner [6] samples feasible motion commands within a dynamic window, evaluates each sample using a forward prediction model, and selects the best sample based on a cost function that considers distance to obstacles, deviation from the global path, and progress toward the goal. While providing verifiable guarantees, these classical approaches still require extensive knowledge from robotics expert onsite during deployment, e.g., through in-situ parameter tuning, to adapt to different navigation scenarios [7], [8]. For example, max linear and angular velocities and their sampling rates determine if the DWA planner can find good motion commands with limited onboard computation, while its different optimization weights affect the final navigation behavior. All experiments reported in this article use DWA as the underlying motion planning algorithm. Furthermore, those classical systems generally do not learn with increasing navigation experience [9].

With the recent advances in machine learning research, data-driven techniques have started being applied to the mobile robot navigation problem. Xiao, et al. [10] presented a survey on using machine learning for motion control in mobile robot navigation: in addition to some works in the emerging social [11] and terrain-based [12] navigation, most existing learning approaches for navigation adopt an end-to-end learning paradigm to address the classical collision-free navigation problem and are capable of generating navigational behaviors [13], [14]. However, those end-to-end approaches still cannot outperform classical navigation methods or are not even compared to them. More importantly, end-to-end learning is extremely data-hungry, usually requiring millions of training data or training steps, and forgoes verifiable guarantees such as safety and explainability. On the other hand, other work which targeted a specific navigational component [15], [16], [17] has achieved superior performance when being compared to their classical counterparts. Therefore, it is promising to use machine learning at the subsystem or component level and to combine it with the structure of classical approaches [10].

APPL uses machine learning at the parameter level and devises extra learning components that interact with classical navigation systems. Therefore, APPL inherits all the benefits of classical approaches, while enjoying the adaptivity and flexibility of learning methods.

B. Learning from Humans

Using interactions with humans is an effective approach to facilitate learning in general, e.g., Learning from Demonstration or Imitation Learning [18]. Of particular interest to the robotics community is learning through interactions with non-expert users, which relaxes the requirement for expert roboticists. For mobile robot navigation, it is relatively easy for most non-expert users to provide a teleoperated demonstration [19]. If a robot can successfully navigate in most scenarios, it is only necessary to teach the robot where it makes mistakes. Learning from Intervention can therefore be applied only at those trouble-some situations [20]. For non-expert users who are not able to take control of the robot, learning from evaluative feedback [21] provides another interaction modality that teaches the robot with a simple scalar feedback value. Most aforementioned approaches of learning from humans have been proposed in the learning community and applied to test domains such as Atari games or simulations, and have yet been used to tackle physical mobile robot navigation problems. We posit that this gap can be caused by the requirement for extensive training data and training time, which is prohibitive for physical mobile robots navigating in the real world.

APPL utilizes all these human interaction modalities (demonstration, interventions, and evaluative feedback), and combines them with Reinforcement Learning (RL) in a Cycle-of-Learning scheme [22] for autonomous mobile robot navigation. To alleviate the heavy dependency on huge amounts of high quality training data from the real world, APPL learns a parameter policy that interacts with an underlying navigation system, in contrast to replacing it by learning an end-to-end motion policy.

III. ADAPTIVE PLANNER PARAMETER LEARNING

In this section, we formalize the Adaptive Planner Parameter Learning (APPL) problem, which serves as the foundation for all the following APPL methods.

1) Underlying Navigation Planner: APPL assumes that a mobile robot has an underlying navigation planner \( G : \mathcal{X} \times \Theta \rightarrow \mathcal{A} \), where \( \mathcal{X} \) is the planner’s state space (e.g., robot odometry, sensory inputs, navigation goal), \( \Theta \) is the space of free parameters for \( G \) (e.g., inflation radius, sampling rate, planner optimization coefficients), and \( \mathcal{A} \) is the planner’s action space (e.g., linear and angular velocity \( v, \omega \)). Using
Fig. 1: Contrast between Conventional Agent vs. APPL Agent

$G$ and a particular set of parameters $\theta$, the robot performs navigation by repeatedly estimating its state $x$ and applying action $a = G(x; \theta) = G_\theta(x)$. Traditional learning methods for navigation replace classical navigation planner $G$ with a differentiable neural network, and use gradient descent to find thousands (or millions) of neural network weights. In contrast, APPL works within the framework of classical planner $G$, but treats it as a black box, e.g., it does not need to be differentiable, and APPL does not need to understand what each component of $\theta$ does.

2) Meta-Environment: APPL works in the context of a meta-environment $E$ composed of both the underlying navigation world $W$ (the physical, obstacle-occupied world) and the given classical planner $G$ with adjustable parameters $\theta$ and state input $x \in X$. An APPL agent interacts with this meta-environment $E$ through a meta-state $s_t \in S$, which includes both the planner’s current state $x_t \in X$ and previous parameters $\theta_{t-1} \in \Theta$, i.e., $S = X \times \Theta$. Instead of the raw action $a \in A$, APPL’s meta-action takes the form of $\theta \in \Theta$, which is the current parameters to be used by $G$.

3) Parameter Policy: We formulate the APPL problem as a meta Markov Decision Process (MDP) in this meta-environment, i.e., a tuple $(S, \Theta, T, \gamma, R)$. Note this meta-MDP differs from the conventional MDP defined by traditional learning-based motion planners, whose states are $x$ and actions are $a$ (Fig. 1 left). Based on a meta-state $s_t$, an APPL agent takes action $\theta_t$ so that the state advances to $s_{t+1}$ based on the transition function $s_{t+1} \sim T(s_t, \theta_t)$, and then receives a reward $r_t = R(s_t, \theta_t)$ (Fig. 1 right). In general, the objective of an APPL agent is to learn a parameter policy $\pi : S \rightarrow \Theta$ that can be used to select actions (as parameters $\theta$) that maximize the expected cumulative reward over time,

$$\max \pi \mathbb{E}_{s_0, \theta_0, \theta_1, \cdots} \sum_{t=0}^{\infty} \gamma^t r_t.$$  

Within the meta-environment $E$, with the selected $\theta$, $G_\theta(x)$ produces navigation action $a$ to interact with the physical world $W$. On top of this general form of parameter policy based on a general reward function, we impose additional structures on the policy and on the reward for each individual APPL method. For example, APPLR adopts this general notion of parameter policy and optimizes a reward function; an APPL policy maximizes the expected evaluative feedback from human users as an approximation of the underlying reward; APPLI and APPLD simplify the general parameter policy in terms of a pre-trained context predictor to select appropriate parameters from a parameter library.

4) Parameter Library: A specific type of APPL parameter policy $\pi : S \rightarrow \Theta$ can be instantiated by imposing two intermediate mappings, i.e. a parameterized context predictor $B_\phi : S \rightarrow C$, and a one-to-one mapping $M : C \rightarrow \Theta$, where $C$ is the space of (finite) contexts $c$ (a relatively cohesive region in the physical world $W$). Therefore, $\theta = \pi(s) = M(B_\phi(s))$. Each predefined context is associated with a set of static parameters. These parameter sets comprise a parameter library $L$. APPLD and APPLI impose such structure on the general parameter policy, and selecting an appropriate parameter set which minimizes a Behavior Cloning loss approximates maximizing the underlying reward in Eqn. 1.

The high-level algorithm of APPL is shown in Alg. 1. The subroutine $\pi = \text{LearnParameterPolicy}(I, \Theta, G)$ is instantiated differently in each APPL method, as specified in Secs. IV-VII.

Algorithm 1 APPL

1: // Training
2: Input: human interaction $I$, space of possible parameters $\Theta$, and navigation stack $G$.
3: $\pi = \text{LearnParameterPolicy}(I, \Theta, G)$.
4: // Deployment
5: Input: navigation stack $G$, parameter policy $\pi$.
6: for $t = 1 : T$ do
7: construct meta-state $s_t$ from $x_t$ and $\theta_{t-1}$.
8: $\theta_t = \pi(s_t)$.
9: Navigate with $G_{\theta_t}(x_t)$.
10: end for

IV. APPL FROM DEMONSTRATION (APPLD)

In this section, we briefly summarize Adaptive Planner Parameter Learning from Demonstration (APPLD) and reformalize it based on the APPL formulation in Sec. III. APPLD [1] utilizes a context predictor and a parameter library learned from human demonstration. A teleoperated demonstration with planner state $x$ and demonstrated action $a$ is collected, which is then segmented into different contexts using Bayesian change point detection. Within each context, we use behavior cloning to find a set of planner parameters $\theta$ to match the planner’s output with the human demonstration (Fig. 2). For full details and experiment results, please refer to our Robotics and Automation Letters (RAL) article [1].

A. Learning APPLD Policy

A human demonstration of successful navigation is recorded as time series data $I = D = \{x_i^D, a_i^D, t_i^D\}_{i=1}^N$, where $N$ is the length of the series, and $x_i^D$ and $a_i^D$ represent the planner state and demonstrated action at time $t_i^D$ (Line 2 Alg. 1). As mentioned in Sec. III, we impose additional structures on the APPLD policy, i.e. $\pi_D : S \rightarrow \Theta$ is instantiated by a parameterized context predictor $B_\phi : S \rightarrow C$, and an one-to-one mapping $M : C \rightarrow \Theta$ (Line 3 Alg. 1). Given $M$ and
$B_\phi$, our system then performs navigation by selecting actions according to $G_\phi(x) = G_{M(B_\phi(x))}(x)$ (Lines 8-9 Alg. 1).

1) Demonstration Segmentation: The key of learning $\pi_D$ is to construct the space of contexts $\mathcal{C}$, each of which corresponds to a cohesive navigation region where a single set of parameters suffices. For each specific context, we apply black-box optimization to learn a parameter set. Generally speaking, any changepoint detection method can be used to solve this segmentation problem [23]. A changepoint detection algorithm $A_{\text{segment}}$ can automatically detect how many changepoints exist in $\mathcal{D}$ and where those changepoints are within the demonstration. Denote the number of changepoints found by $A_{\text{segment}}$ as $K - 1$ and the changepoints as $\tau_1, \tau_2, \ldots, \tau_{K-1}$ with $\tau_0 = 0$ and $\tau_K = N + 1$. The demonstration $\mathcal{D}$ is then segmented into $K$ pieces $\{D_k = \{x_i^D, a_i^D, t_i^D \mid \tau_{k-1} \leq i < \tau_k\} \}_{k=1}^K$.

2) Parameter Learning: For each of the segmented contexts, $\mathcal{D}_k = \{x_i^D, a_i^D, t_i^D \mid \tau_{k-1} \leq i < \tau_k\}$, we employ behavioral cloning (BC) [24] to learn a suitable set of parameters $\theta_k^*$. More specifically, BC seeks $\theta_k^*$ which minimizes the difference between the demonstrated actions and the actions that $G_{\theta_k}$ would produce on $\{x_i^D\}$:

$$\theta_k^* = \arg \min_{\theta} \sum_{(x,a) \in D_k} ||a - G_{\theta}(x)||_H,$$  

where $||v||_H = v^T Hv$ is the induced norm by a diagonal matrix $H$ with positive real entries, which is used for weighting each dimension of the action. We solve Eqn. 2 with a black-box optimization method $A_{\text{black-box}}$. Having found each $\theta_k^*$, the parameter library $\mathcal{L}$ is formed and the mapping $M$ is simply $M(k) = \theta_k^*$.

3) Online Context Prediction: The context predictor $B_\phi$ is learned with a supervised dataset $\{x_i^D, c_i\}_{i=1}^N$, where $c_i = k$ if $x_i^D \in D_k$. To classify which segment $x_i^D$ comes from, we learn a parameterized function $f_\phi(x)$ via supervised learning:

$$\phi^* = \arg \max_{\phi} \frac{\sum_{i=1}^N \log \exp (f_\phi(x_i^D)[c_i])}{\sum_{c=1}^K \exp (f_\phi(x_i^D)[c])}.$$  

Our context predictor $B_\phi$ is then defined as:

$$B_\phi(x_i) = \text{mode} \left\{ \arg \max_{c \in \mathcal{C}} f_\phi(x_i)[c], \ t - p < i \leq t \right\}. \quad (4)$$

In other words, $B_\phi$ acts as a mode filter on the context predicted by $f_\phi$ over a sliding window of length $p$.

The LearningParameterPolicy subroutine in Alg. 1 for APPLD is shown in Alg. 2, where the above three stages are applied sequentially to learn a parameter library $\mathcal{L} = \{\theta_k^*\}_{k=1}^K$ (hence the mapping $M$) and a context predictor $B_\phi$, both of which constitute the APPLD policy $\pi_D$. During deployment, Eqn. 4 is applied online to pick the right set of parameters for $\pi_D$ as a special case of $\pi$, does not consider $\theta_{k-1}$ as part of $s_i$ (only $x_i$, line 7 Alg. 1), but consults a history of $p$ steps of $x_i$ for smoothness.

Algorithm 2 LearnParameterPolicy (APPLD)

1: Input: $\mathcal{I} = D = \{x_i^D, a_i^D, t_i^D\}_{i=1}^N$, $\Theta$, $G$.
2: Call $A_{\text{segment}}$ on $\mathcal{D}$ to detect changepoints $\tau_1, \ldots, \tau_{K-1}$ with $\tau_0 = 0$ and $\tau_K = N + 1$.
3: Segment $\mathcal{D}$ into $\{D_k = \{x_i^D, a_i^D, t_i^D \mid \tau_{k-1} \leq i < \tau_k\} \}_{k=1}^K$.
4: Train a classifier $f_\phi$ on $\{x_i^D, c_i\}_{i=1}^N$, where $c_i = k$ if $x_i^D \in D_k$.
5: for $k = 1 \rightarrow K$ do
6: Call $A_{\text{black-box}}$ with objective defined in Eqn. 2 on $D_k$ to find parameters $\theta_k^*$ for context $k$.
7: end for
8: Form the map $M(k) = \theta_k^*$, $\forall 1 \leq k \leq K$ and context predictor $B_\phi(x_i)$.

B. Experiments

We implement APPLD on a physical ClearPath Jackal robot to experimentally validate that using the learned parameter library and context predictor from a teleoperated demonstration can achieve better navigation performance in complex environments compared to that obtained by the underlying navigation system using (a) its default parameters from the robot platform manufacturer, and (b) parameters we found using behavior cloning but without context. The four-wheeled, differential-drive, unmanned ground vehicle with a top speed of 2.0 m/s is tasked to move through a custom-built maze as quickly as possible (Fig. 2). A Velodyne LiDAR provides 3D point cloud data, which is transformed into 2D laser scan data for 2D navigation. The Jackal runs Robot Operating System (ROS) onboard, and APPLD is applied to the local planner, DWA [6], in the commonly-used move_base navigation stack. Other parts of the navigation stack, e.g. global planning with Dijkstra’s algorithm, remain intact.

We use CHAMP as $A_{\text{segment}}$ (Line 2 Alg. 2), a state-of-the-art Bayesian segmentation algorithm [25]. We find each $\theta_k^*$ using CMA-ES [26] as our black-box optimizer (Line
In our experiments, APPL achieves superior performance compared to the default parameters, parameters learned without context, and even the demonstrator. For full details about the experimental setup and results, along with experimental results on a different robot with a different navigation system in a different environment, please refer to our RAL article [1].

V. APPL FROM INTERVENTIONS (APPLI)

APPLI assumes human demonstration is a good approximation for optimal navigation behavior and default parameters do not work well in most places, which are not always the case. In Adaptive Planner Parameter Learning from Interventions (APPLI) [2], instead of providing a full demonstration of the entire navigation task (such as APPLD), non-expert users can easily identify failure or suboptimal cases by watching and then provide a few teleoperated interventions to correct the failure or suboptimal behaviors (Fig. 3). APPLI utilizes this human interaction modality and learns sets of planner parameters specifically for the scenarios where failure and suboptimal behaviors take place, to create a parameter library including the default parameters. During deployment, APPLI applies those learned parameters, only when it is confident that they will benefit the current navigation based on a confidence measure of the context predictor, to the underlying navigation system in those troublesome places, while maintaining good performance in others by switching back to the default parameters. This confidence measure also enables APPLI to generalize well to unseen environments.

A. Learning APPLI Policy

APPLI assumes a default parameter set \( \theta \) is tuned by a human designer trying to achieve good performance in most environments. However, being good at everything often means being great at nothing: \( \theta \) usually exhibits suboptimal performance in some situations and may even fail (is unable to find feasible motions, or crashes into obstacles) in particularly challenging ones.

1) Interventions as Contexts: Tomitigate this problem, a human can supervise the navigation system’s performance at state \( x \) by observing its action \( a \) and judging whether she should intervene. Here, we consider two types of interventions. A Type A intervention is one in which the system performs so poorly that the human must intervene (e.g. imminent collision or a signal for help). A Type B intervention is one in which a human might intervene in order to improve otherwise suboptimal performance (e.g., driving too slowly in an open space).

For the \( i \)th intervention, we assume that the human resets the robot to the position where the failure or suboptimal behavior first occurred and then gives a short teleoperated intervention \( I_i = \{x_i, a_i\}_{i=1}^{T_i} \) of length \( T_i \), where \( x_{i-1} \) is the trajectory starting from the reset state induced by intervention actions \( a_{i-1} \). As this short demonstration naturally shows a cohesive navigation behavior in a specific segment of the environment (open space, narrow corridor, etc), it automatically forms a context \( c_i \in C \). Using human interaction composed of \( N \) interventions \( I = I_{1:N} \) instead of the full demonstration sequence \( \mathcal{D} = \{d_{i}^{1}, a_{i}^{1}, t_{i}^{1}\}_{i=1}^{N} \) (Sec. IV), APPLI finds the mapping \( M : C \rightarrow \Theta \) that determines the parameter set \( \theta_i \) for each intervention context \( c_i \), and the parameterized context predictor \( B_{\phi} : X \rightarrow C \) that determines to which context (if any) the current state \( x \) belongs. After collecting a set of \( N \) interventions \( I_{1:N} \), for each \( I_i \), we learn a set of navigation parameters \( \theta_i \) that can best imitate the demonstrated correction with the same Behavior Cloning loss (Eqn. 2) with a black-box optimizer, such as CMA-ES [26]. After identifying parameters in each context, the mapping \( M \) is simply \( M(i) = \theta_i \).

2) Confidence-Based Context Prediction: In contrast to APPLD, APPLI does not learn parameters for places where the original navigation performance is good. Therefore, it determines if the current state \( x_i \) falls into any of the collected intervention contexts \( c_i \). If so, APPLI directs the robot to use the parameter set \( \theta_i \) to avoid making the same mistake as before. If not, APPLI directs the robot to use the default parameters \( \bar{\theta} \), as they are optimized for most cases and are expected to generalize better than any parameter set learned for a specific scenario. In our system, the determination above is made using a new context predictor, \( B_{\phi} \), with confidence measure. To train this predictor, we build a similar dataset as in APPLD, \( \{(x_i, c_i)\}_{i=1}^{N} \), and train an intermediate classifier \( f_{\phi}(x) \) with parameter set \( \phi \) using the Evidential Deep Learning method (EDL) [27]. A feature of EDL is that it supplies both a predicted label and a confidence measure, \( u_i \in (0, 1] \), i.e.,

\[
f_{\phi}(x_i) = (c_i, u_i).
\]

After training \( f_{\phi} \) and during deployment, we build a confidence-based classifier \( g_{\phi} \) as

\[
g_{\phi}(x_i) = c_i \mathbb{1}(u_i \geq \epsilon_u),
\]

where \( \epsilon_u \) is a threshold on confidence and \( \mathbb{1} \) is the indicator function. For state \( x_i \), \( g_{\phi} \) determines its context from \( N + 1 \) contexts (\( N \) intervention contexts and one default context). If \( u_i \geq \epsilon_u \), it suggests the classifier \( f_{\phi} \) is confident and \( g_{\phi} \) predicts \( c_i \). Otherwise, when \( f_{\phi} \) is unsure about its prediction, \( c_i \mathbb{1}(u_i \geq \epsilon_u) = 0 \). In this case, \( g_{\phi} \) believes the current state \( x_i \) is not similar to any intervention context and instead classifies
$x_i$ as the default context. For this default context labeled as $c_i = 0$, navigation utilizes the default navigation parameters $\theta$ (i.e., we set $M(0) = \theta$). The new confidence-based context predictor $B_\phi$ is then defined as:

$$B_\phi(x_t) = \text{mode}\left\{g_\phi(x_t), t - p < i \leq t\right\}.$$  

(7)

Again, $B_\phi$ acts as a mode filter and chooses the context $c_t$ that the majority agrees with over the past $p$ time steps.

The LearningParameterPolicy subroutine in Alg. 1 for APPLI is shown in Alg. 3. APPLI learns a confidence-based classifier (Line 2) and navigation parameters $\theta_{1:N}$ for each context (Lines 3-5). During deployment, we use $\theta_t = \pi_I(x_t) = \overline{M(B_\phi(x_t))}$ to select the parameters for the navigation system at time $t$. Similar to $\pi_D$, $\pi_I$ does not consider $\theta_{t-1}$ as part of $s_t$ (only $x_t$, line 7 Alg. 1), but consults a history of $p$ steps of $x_t$ for smoothness.

Algorithm 3 LearningParameterPolicy (APPLI)

1. **Input:** $I = I_{1:N} = \{(x_t, a_t)\}_{t=1}^T \quad \forall i \in \{1, \ldots, N\}$, $\Theta$, $G$.
2. **Train a confidence-based classifier $f_\phi$ on:** 
   \[
   \{x_t, c_{t=1}^T\}_{i=1}^N.
   \]
3. **for** $i = 1, \ldots, N$ **do**
4. **Find parameter $\theta_i$ for context $i$ using Eqn. 2 on** $I_i$.
5. **end for**
6. **Form the map $M(i) = \theta_i$, $\forall 1 \leq i \leq N$, and confidence-based context predictor $B_\phi(x_t)$.

B. Experiments

In our experiments, we aim to show that APPLI can improve navigation performance by learning from only a few interventions and, with the confidence measurement, that the overall system can generalize well to unseen environments. We apply APPLI on the same ClearPath Jackal ground robot with the same setup as in APPLD (Section IV-B) in a physical obstacle course. Navigation performance learned through APPLI is then tested both in the same training environment, and also in another unseen physical test course, which is qualitatively similar to the training environment (i.e., similar contexts were created in a different ordering). Furthermore, to investigate generalizability, we test the learned systems on a benchmark suite of 300 unseen simulated navigation environments [28].

During data collection, one of the authors (the intervener) followed the robot through the test course and intervenes when necessary, reporting if the intervention is to drive the robot out of a failure case (Type A) or to correct a suboptimal behavior (Type B). The four interventions are shown in Fig. 3: before the two Type A interventions (shown in red), the default system (DWA with $\overline{\theta}$) fails to plan feasible motions and starts recovery behaviors (rotates in place and moves backward); before the two Type B interventions (shown in yellow), the robot drives unnecessarily slowly in a relatively open space and enters the narrow corridor with unsmooth motions. For every intervention, the intervener stops the robot, drives it back to where they deem the failure or suboptimal behavior to have begun, and then provides recorded teleoperation $I$ that avoids the problematic behavior. To compare the performance learned from interventions and learned from a full demonstration, we also collect extra demonstrations for those places where the default planner already works well (shown in green in Fig. 3).

1) Physical Experiments: After training, we deploy $\pi_I$ with learned mapping $M$ and context predictor $B_\phi$ on the move_base navigation stack $G$ with threshold $\epsilon_u = 0.8$.

We first deploy APPLI in the same training physical environment (Fig. 3). We compare the performance of the DWA planner with default parameters, APPLI learned only with Type A interventions, APPLI learned with Type A and Type B interventions, and APPLI learned with a full demonstration (which is basically APPLD enhanced by manual context segmentation and the confidence measure). The motivation for the variation of APPLI learned only with Type A interventions is to study the effect of an unfocused or inexperienced human intervener. In this case, the human would still conduct all Type A interventions, as those mistakes are severe and easy to identify—some robots may even actively ask for help (e.g., by starting recovery behaviors). However, the human may fail to conduct Type B interventions as she is not paying attention, or isn’t equipped with the knowledge to identify suboptimal behaviors. For each method, we run five trials and report the mean and standard deviation of the traversal time in Tab. 1 1st row. If the robot gets stuck, we introduce a penalty value of 200 seconds. We also deploy the same sets of variants in an unseen physical environments (Fig. 4 and Tab. 1 2nd row).

For both the training and unseen environments, Type A interventions alone significantly improve upon the default parameters, by correcting all recovery behaviors such as rotating in place or driving backwards, and eliminating all failure cases. Adding Type B interventions further reduces traversal time, since the robot learns to speed up in relatively open spaces and to execute smooth motion when the tightness of the surrounding obstacles changes. All the interventions are able to improve navigation in both training and unseen environments, suggesting APPLI’s generalizability. Surprisingly, in both environments, APPLI learned from only Type A and Type B interventions can even outperform APPLI learned from an entire demonstration. One possible reason

TABLE I: APPLI Traversal Time

<table>
<thead>
<tr>
<th></th>
<th>Default</th>
<th>Type A</th>
<th>Type A+B</th>
<th>Full Demo</th>
</tr>
</thead>
<tbody>
<tr>
<td>Training</td>
<td>134.0±60.6s</td>
<td>77.4±2.8s</td>
<td>70.6±3.2s</td>
<td>78.0±2.7s</td>
</tr>
<tr>
<td>Unseen</td>
<td>109.2±50.8s</td>
<td>71±0.7s</td>
<td>59±0.7s</td>
<td>62±2.0s</td>
</tr>
</tbody>
</table>

Fig. 4: APPLI Running in an Unseen Physical Environment

For both the training and unseen environments, Type A interventions alone significantly improve upon the default parameters, by correcting all recovery behaviors such as rotating in place or driving backwards, and eliminating all failure cases. Adding Type B interventions further reduces traversal time, since the robot learns to speed up in relatively open spaces and to execute smooth motion when the tightness of the surrounding obstacles changes. All the interventions are able to improve navigation in both training and unseen environments, suggesting APPLI’s generalizability. Surprisingly, in both environments, APPLI learned from only Type A and Type B interventions can even outperform APPLI learned from an entire demonstration. One possible reason
for this better performance from fewer human interactions is the additional human demonstrations may be suboptimal, especially since they are collected in places where the default navigation system was already deemed to have performed well. For example, in the full demonstration, we find the human interventional is more conservative than the default navigation system and drives slowly in some places. Hence, learning from these suboptimal behaviors introduces suboptimal parameters and consequently worse performance in contexts similar to that intervention.

2) Simulated Experiments: To further test APPLI’s generalizability to unseen environments, we test our method and compare it with two baselines on the Benchmark for Autonomous Robot Navigation (BARN) dataset [28]. The benchmark dataset consists of 300 simulated navigation environments randomly generated using Cellular Automata, ranging from easy ones with a lot of open spaces to challenging ones where the robot needs to get through dense obstacles. Using the same training data collected from the physical environment shown in Fig. 3, we test the following seven variants: (1) APPLI (A+B+c); APPLI learned from Type A and B inventions with confidence measure, (2) APPLI (A+B): APPLI learned from Type A and B inventions without confidence measure, (3) APPLI (A+c): APPLI learned from only Type A interventions with confidence measure, (4) APPLI (A): APPLI learned from only Type A interventions without confidence measure, (5) APPLI (A+B+D+c): APPLI learned from full demonstration with confidence measure, (6) APPLI (A+B+D): APPLI learned from full demonstration without confidence measure, (7) the DWA planner with default parameters.

Testing these variations aims at studying the effect of learning from different modes of interventions caused by different degrees of human attention and experience levels, i.e., imperative interventions (A), optional interventions (A + B), and a full demonstration (A + B + D). They also provide an ablation study for the confidence measure in the EDL context classifier $f_\phi$: when deployed without the confidence measure, the robot has to choose among the parameters learned from interventions and never uses the default parameters.

For each method in each simulation environment, we measure the traversal time for 12 different runs, resulting in 25200 total navigation trials. The average traversal time for each method in all simulation environments is normalized by DWA and is shown in order of increasing performance in Fig. 5.

APPLI (A+B+c) and APPLI (A+B+D+c) outperform DWA: their average traversal time is shorter than that of DWA by 8% and 17% respectively. However, for APPLI (A+c), its traversal time is only 1% better than DWA, which suggests that even though type B inventions only correct suboptimal performances, they are crucial for performance improvement.

In terms of the effect of confidence, APPLI (A) only selects parameters learned from 2 Type A inventions and never uses the default parameters even when they are more appropriate. Removing confidence greatly harms its performance, making its traversal time even longer than DWA by 31%. However, APPLI (A+B+c) and APPLI (A+B+D+c), which use more interventions or even the full demonstration to train the parameter mapping $\theta$ and context predictor $B_\phi$, are more confident about their predictions most of the time. As a result, removing confidence in the context predictor doesn’t result in a significant difference.

Lastly, a counterintuitive, but similar result as in the physical experiments is that APPLI (A+B+c) learned from only Type A and B interventions achieves shorter traversal time than APPLI (A+B+D+c) and APPLI (A+B+D) by 9.2% and 6.1%, respectively. Similar to the discussions about physical experiments, unnecessary human demonstrations are most likely suboptimal. In this sense, APPLI not only reduces the required human interactions from a full demonstration to only a few interventions, but also reduces the chance of performance degradation caused by suboptimal demonstrations.

VI. APPLI FROM EVALUATIVE FEEDBACK (APPLI)

APPLI and APPLI require non-expert users to take full control of the moving robot with a joystick, which some non-expert users may not feel comfortable with, e.g., due to perceived risk of human error and causing collisions. For these users, we introduce Adaptive Planner Parameter Learning from Evaluative Feedback (APPLI) [3], where they only need to observe the robot navigating and provide real-time positive or negative assessments of the observed navigation behavior through evaluative feedback. This more-accessible modality provides a new interaction channel for a larger community of non-expert users with mobile robots (Fig. 6). In this section, we briefly summarize APPLI and reformalize it based on the APPLI formulation in Sec. III. For full details and experiment results, please refer to our RAL article [3].

A. Learning APPLI Policy

APPLI learns a parameter policy from human evaluative feedback in order to select the appropriate parameter set $\theta$ for the current deployment scenario. The parameter set can be selected from either a discrete parameter set library or from a continuous full parameter space. To be specific, a human observes the underlying planner taking action $a$ at state $x$, and then provides evaluative feedback $e$. The human can provide either discrete (e.g., “good job”/“bad job”) or
For continuous APPLE policy, the parameter policy $\pi_\psi$ and the feedback predictor $F_\phi$ are parameterized in the actor-critic style [30]. Similar to the discrete APPLE policy, we also train $F_\phi$ by minimizing the difference between predicted and collected feedback using the collected dataset $\mathcal{F} = \{x_j, \theta_j, e_j\}_{j=1}^N$ (Eqn. 8). The parameter policy $\pi_\psi$ is trained to not only choose the action that maximizes expected feedback, but also to maximize the entropy of policy $\mathcal{H}(\pi_\psi(x|\theta))$ at state $x$. We use the same entropy regularization as Soft Actor Critic (SAC) [30], so that $\pi_\psi$ favors more stochastic policies for better exploration during training:

$$
\psi^* = \arg \min_\psi \sum_{x_j \in \mathcal{F}} \mathbb{E}_{\theta_j \sim \pi_\psi(\cdot|x_j)} \left[-F_\phi(x_j, \tilde{\theta}_j) + \alpha \log \pi_\psi(\tilde{\theta}_j|x_j)\right],
$$

where $\alpha$ is the temperature controlling the importance of the entropy bonus and is automatically tuned as in SAC [30].

The LearningParameterPolicy subroutine in Alg. 1 for APPLE to learn $\pi_\psi$ is simply learning $F_\phi^*$ with Eqn. 8 and learning $\psi^*$ with SAC [30] for the discrete and continuous parameter policy, respectively.

B. EXPERIMENTS

In our experiments, we find that APPLE can improve navigation performance by learning from evaluative feedback, in contrast to a teleoperated demonstration or a few corrective interventions, both of which require the non-expert user to take control of the moving robot. We also show APPLE’s generalizability to unseen environments. We implement APPLE on the same ClearPath Jackal ground robot in BARN [28], and in two physical obstacle courses. For full details about the experimental setup and results, please refer to our RAL article [3].

VII. APPL FROM REINFORCEMENT (APPLR)

Adaptive Planner Parameter Learning from Reinforcement (APPLR) [4] adopts the general notion of parameter policy (Sec. III Fig. 1). One disadvantage of learning planner parameters from different human interaction modalities is that the learner’s performance is limited by the human’s (most likely suboptimal) teleoperated demonstration, corrective interventions, and evaluative feedback. With reinforcement learning in a wide variety of simulation environments, APPLR does not need access to any human interaction, and learns to make planner parameter decisions in such a way that allows the system to take suboptimal actions at one state in order to perform even better in the future.

A. Learning APPLR Policy

APPLR uses an existing RL algorithm and a reward function to learn a parameter policy $\pi_R$.

1) Reward Function: In general, we encourage three types of behaviors: (1) behaviors that lead to the global goal faster; (2) behaviors that make more local progress; and (3) behaviors that avoid collisions and danger. Correspondingly, the designed reward function can be summarized as

$$
R_t(s_t, a_t, s_{t+1}) = c_f R_f + c_p R_p + c_c R_c.
$$
Here, \( c_f, c_p, c_c \) are coefficients for the three types of reward functions \( R_f, R_p, R_c \). Specifically, \( R_f(s_t, a_t) = 1(s_t \text{ is terminal}) - 1 \) applies a \(-1\) penalty to every step before reaching the global goal. To encourage the local progress of the robot, we add a dense shaping reward \( R_p \). Assume \( \beta = (\beta_x, \beta_y) \in \mathbb{R}^2 \) is the global goal and at time \( t \), the absolute coordinates of the robot are \( p_t = (p_t^x, p_t^y) \), we define

\[
R_p = \frac{(p_{t+1} - p_t) \cdot (\beta - p_t)}{|\beta - p_t|},
\]  

(12)

In other words, \( R_p \) denotes the robot’s local progress \((p_{t+1} - p_t)\) projected on the direction toward the global goal \((\beta - p_t)\). Finally, a penalty for the robot colliding with or coming too close to obstacles is defined as \( R_c = -1/d(p_{t+1}) \), where \( d(p_{t+1}) \) is a distance function measuring how close the robot is to obstacles based on sensor observations (e.g., using LiDAR).

2) Reinforcement Learning Algorithm: For continuous actions and high sample efficiency, we use the Twin Delayed Deep Deterministic policy gradient algorithm (TD3) [31], an actor-critic algorithm that keeps an estimate for both the policy and two state-action value functions.

B. Experiments

Again, we use the same ClearPath Jackal and the same setup to validate that APPLR can enable adaptive autonomous navigation without access to expert tuning or human demonstrations and is generalizable to many deployment environments, both in simulation and in the real-world. The results of APPLR are compared with those obtained by the underlying navigation system using its default parameters from the robot platform manufacturer. For the physical experiments, we also compare to parameters learned from APPLD.

1) Training: \( x_t \) is composed of 720-dimensional laser scan (capped to 2m) and a relative goal angle, computed from a local goal taken from the global path 1m away from the robot. The meta-state \( s_t \) is composed of \( x_t \) and \( \theta_{t-1} \). APPLR learns a parameter policy \( \pi_R \) to select the same DWA parameters \( \theta_t \) as other APPL methods. \( \pi_R \) is trained in simulation using 250 randomly selected training environments from the BARN dataset [28]. In each of the environments, the robot aims to navigate from a fixed start to a fixed goal location in a safe and fast manner. For the reward function, while \( R_f \) penalizes each time step before reaching the global goal, we simplified \( R_f \) by replacing it with its projection along the \( y \)-axis (longitudinal direction) of all BARN environments. The distance function in \( d(p_{t+1}) \) in \( R_c \) is the minimal value among the 720 laser beams. \( \pi_R \) produces a new set of planner parameters every two seconds.

This simulated navigation task is implemented in a Singularity container, which enables easy parallelization on a computer cluster. TD3 [31] is implemented to learn the parameter policy \( \pi_R \) in simulation. The policy network and the two target Q-networks are represented as multilayer perceptrons with three 512-unit hidden layers. The policy is learned under the distributed architecture Gorila [32]. The acting processes are distributed over 500 CPUs with each CPU running one individual navigation task. On average, two actors work on a given navigation task. A single central learner periodically collects samples from the actors’ local buffers and supplies the updated policy to each actor. Gaussian exploration noise with 0.5 standard deviation is applied to the actions at the beginning of the training. Afterward the standard deviation linearly decays at a rate of 0.125 per million steps and stays at 0.02 after 4 million steps. The entire training process takes about 6 hours and requires 5 million transition samples in total.

2) Simulated Experiments: After training, we deploy the learned parameter policy \( \pi_R \) on both the 250 training and 50 test environments. We also use traversal time to evaluate the performance of the policy. A maximum traversal time of 50s is used, and the failing trials are set to be 50s plus a 20s penalty. We average over the traversal time of 40 trials for DWA and APPLR in each environment. We also perform t-tests for each pair of APPLR and DWA performance to check statistical significance. The results over the 250 training environments and 50 test environments are shown in Fig. 7. For the majority of the environments (green bars), APPLR shows statistically significantly better navigation performance. Tab. II shows the average traversal time of APPLR and DWA, and relative improvement. APPLR yields an improvement of 11.8% in the training environments, and 11.2% in the test environments. In addition, Tab. III compares the number of environments that show significant improvement and deterioration. In both training and test set, APPLR achieves statistically significantly better navigation performance in over 40% of environments than DWA does, while DWA is only better in 4.8% and 8% of environments in the training and test set, respectively.

3) Physical Experiments: To validate the sim-to-real transfer of APPLR, we also test the learned parameter policy \( \pi_R \) on a physical Jackal robot. The learned policy is deployed in a real-world obstacle course (Fig. 8). This physical environment...
TABLE III: Number and Percentage of All Environments in which One Method is Better Compared to the Other

<table>
<thead>
<tr>
<th></th>
<th>APPLR better</th>
<th>DWA better</th>
</tr>
</thead>
<tbody>
<tr>
<td>Training</td>
<td>106 (42.4%)</td>
<td>12 (4.8%)</td>
</tr>
<tr>
<td>Test</td>
<td>20 (40%)</td>
<td>4 (8%)</td>
</tr>
</tbody>
</table>

is different from any of the navigation environments in BARN. Therefore, both generalizability and sim-to-real transfer of APPLR can be tested with this unseen real-world environment. Note that the use of LiDAR input also reduces the difference between simulation and the real-world.

Given this target environment, we further collect a teleoperated demonstration provided by one of the authors and learn a parameter tuning policy based on the notion of navigational context (APPLD). The author aims at driving the robot to traverse the entire obstacle course in a safe and fast manner. APPLD identifies three contexts using the human demonstration and learns three sets of navigation parameters.

We compare the performance of APPLR with that of APPLD and the DWA planner using a set of hand-tuned default parameters. For each trial, the robot navigates from the fixed start point to a fixed goal point. Each trial is repeated five times and we report the mean and standard deviation in Table IV. In all DWA trials, the robot gets stuck in many places, especially where the surrounding obstacles are very tight. It has to engage in many recovery behaviors, i.e. rotating in place or driving backwards, to “get unstuck”. Furthermore, in relatively open space, the robot drives unnecessarily slowly. All these behaviors contribute to the large traversal time and high variance (plus an additional failure trial). Unlike many simulation environments in BARN [28], where obstacles are generated by cellular automata and therefore very cluttered, the relatively open space in the physical environment (Fig. 8) allows faster speed and gives APPLR a greater advantage. Surprisingly, APPLR even achieves better navigation performance than APPLD, which has access to a human demonstration in the same environment. One of the reasons we observe this result in the physical experiments is that the human demonstrator is relatively conservative in some places; the parameters learned by APPLD are upper-bounded by this suboptimal human performance. Another reason is that APPLR is given the flexibility to continually change parameters, and RL is able to utilize the sequential aspect of the parameter selection problem, in contrast to APPLD’s three sets of static parameters.

TABLE IV: Traversal Time in Physical Experiments

<table>
<thead>
<tr>
<th></th>
<th>DWA</th>
<th>APPLD</th>
<th>APPLR</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>72.8±10.1s*</td>
<td>43.2±4.1s</td>
<td>34.4±4.8s</td>
</tr>
</tbody>
</table>

VIII. CYCLE-OF-LEARNING

The four individual APPL methods are combined to form a cycle-of-learning scheme [22], in which a mobile robot can interact with different users in different deployment environments and continually improve its navigation in a cyclic fashion. We present our cycle-of-learning algorithm in Alg. 4. We provide detailed explanation of Alg. 4 using one full cycle (Fig. 9) as an example, which starts from APPLR, goes through APPLD, APPLI, and APPLE, and comes back to APPLR.

To distinguish the start and end of the cycle, we name them APPLR1 and APPLR2.

We assume a mobile robot is given an underlying navigation system $G$ (e.g., DWA planner [6]) and a space of possible parameters $\Theta$ (e.g., DWA parameters). We also assume there is a set of simulation environments, where the robot can learn through trial and error, e.g., the BARN dataset [28] (line 1 Alg. 4). Before any real-world deployment, we first train the APPLR1 policy $\pi_R^1$ in the BARN dataset $E$ (line 3 Alg. 4). Then the cycle-of-learning starts (lines 5-28 Alg. 4). With only one parameter policy $\pi_R^1$ in the policy set $\Pi$ (line 7 Alg. 4), the first deployment environment in our example cycle is a relatively open space, where default DWA slowly drives at the default 0.5m/s max velocity and APPLR1 is able to accelerate to 2.0m/s (line 9 Alg. 4). Therefore user 0 is satisfied with the navigation performance and does not choose to interact with the robot (skipping lines 10-15 Alg. 4). Moving on to the second environment (line 9 Alg. 4), APPLR1 produces unsmoothing motion at the narrow gap (line 10 Alg. 4). User 1 provides a full demonstration for environment 2 (line 11 Alg. 4), from which APPLD learns two contexts and corresponding parameters (line 12 Alg. 4). The navigation therefore improves (line 13 Alg. 4). When deployed in the third environment (line 9 Alg. 4), APPLD gets stuck multiple times in the narrow corridor (line 10 Alg. 4), where User 2 intervenes (line 11 Alg. 4) and uses APPLI to learn an extra context (line 12 Alg. 4). In environment 4 (line 9 Alg. 4), APPLI suffers from suboptimal behaviors in the obstacle field (line 10 Alg. 4). User 3 provides evaluative feedback (line 11 Alg. 4) and uses APPLE to improve the context predictor of APPLI (line 12 Alg. 4). The performance of different APPL variants in the four environments is shown in Tab. V (averaged over 5 trials). The method which directly utilizes human interaction in the particular environment achieves the best results in the corresponding environment (bold).

After deploying in Environment 4 with APPLE, we finish all physical deployment in this cycle (line 16 Alg. 4) and then train APPLR2 on the BARN dataset (lines 18-27 Alg. 4). For each policy learned from different human interactions in the current policy set $\Pi$ (line 19 Alg. 4), we identify the BARN environments where the APPL variants perform better than APPLR1 (line 21 Alg. 4), and use the learned APPLD, APPLI,
or APPLE policies for exploration (line 22 Alg. 4) with a probability which decreases from 1 to 0 in those environments. APPLR2 achieves significantly better performance in these environments due to the better exploration policy learned within the cycle from different human interaction modalities. We further test APPLR2’s performance against APPL1’s in all BARN environments and do not observe significant deterioration in other environments. In fact, APPLR2’s average traversal time in BARN improves from APPL1’s 24.7s to 24.0s. We also deploy APPLR2 in Environment 4 in Fig. 9. Although the training experience in BARN slightly increases traversal time compared to APPL, APPLR2 significantly outperforms APPL1 by incorporating all human interactions, including the learned context predictor and parameters, into a stand-alone parameter policy.

IX. CONCLUSIONS

We present APPL, a learning paradigm that leverages different human interaction modalities, including demonstration, interventions, evaluative feedback, and unsupervised reinforcement learning, to dynamically fine-tune classical navigation planner parameters to achieve better navigation performance. In addition to the individual APPL methods and experiments, we also introduce a cycle-of-learning scheme, in which different human interaction modalities can be utilized to continually improve future navigation performance in a cyclic fashion. One interesting direction for future work is to investigate other methods to incorporate human interaction to RL training in simulation, e.g., using inverse reinforcement learning to infer an underlying reward function, or creating high fidelity simulations similar to real-world deployment environments.

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REFERENCES


