Safe Real-World Reinforcement Learning for Mobile Agent Obstacle Avoidance

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Abstract—Collision avoidance is key for mobile robots and agents to operate safely in the real world. In this work, we present an efficient and effective collision avoidance system that combines real-world reinforcement learning (RL), search-based online trajectory planning, and automatic emergency intervention, e.g., automatic emergency braking (AEB). The goal of the RL is to learn effective search heuristics that speed up the search for collision-free trajectory and reduce the frequency of triggering automatic emergency interventions. This novel setup enables RL to learn safely and directly on mobile robots in a real-world indoor environment, minimizing actual crashes even during training. Our real-world experiments show that, when compared with several baselines, our approach enjoys a higher average speed, lower crash rate, higher goals reached rate, smaller computation overhead, and smoother overall control.

I. INTRODUCTION

Due to advances in artificial intelligence and robotics, autonomous agents have more comprehensive abilities, with applications in vacuum cleaning, video recording, companionship, security, etc. Collision avoidance is key for mobile agents that operate safely in the real world and avoid damage to the agent, surrounding environment, and humans. There are numerous approaches to collision avoidance, including search-based planning methods, trajectory optimization, learning-based methods, and emergency intervention systems. Search-based trajectory planning methods are successful at finding collision-free trajectories if given good discretization, enough computation, and ideal search heuristics, however, due to the size of the search space in real-world continuous problems, the search could be too computationally heavy to yield good enough solutions [5] [17] [28] [26] [2]. Trajectory optimization is able to solve for locally optimal trajectories for collision avoidance, however, it requires very good initialization, sophisticated cost and constraint modeling to guarantee continuity and feasibility [30] [23] [4]. Learning-based methods are promising as they are data-driven and run inference on GPU or AI accelerator to achieve the fast and fixed computation, however, it is difficult to ensure safety due to distribution shift and uncertainties, especially during training [6], [11]. Another approach is automatic emergency intervention system, e.g., automatic emergency braking (AEB), which sacrifices optimality in exchange for fast computation and low false negative rate, by bringing the agent to a complete stop reactively in an emergency [14] [10] [22].

The AEB is activated when the agent has encountered an unsafe state that requires immediate takeover. Our key insight is that even though this unsafe state could be a false positive in certain situations, e.g., when the robot could avoid the head-on collision by swerving to the side, it can be treated as a conservative signal for imminent collision. Our approach treats this conservative signal as a learning signal, i.e., we want to plan ahead by learning to avoid getting into unsafe conditions, thus reducing its frequency of activation and avoiding stop-and-go behaviors. Specifically, we leverage AEB activation as a learning signal to search corrective control commands to an agent’s upstream control (could be from human control or other upstream algorithms) when detecting potential collisions. Since we want our collision avoidance search to be efficient, we focus on restricting the search space over corrective control actions, which is important to reduce the latency of our method, especially in a dynamic environment with humans.

Our collision avoidance system takes input from lidar and ultrasonic sensor scans, wheel odometry for robot state, and the upstream control commands. We fuse the lidar and ultrasonic sensor scans to detect a diverse set of obstacles, including transparent glass, reflective surfaces, furniture, humans, etc. The RL-guided search introduces additional parameters to shrink the search window in the Dynamic Window Approach (DWA) method [5], for an efficient search over control commands that avoid AEB. We design a reward function for our RL agent with three terms to accomplish this. The first term encourages the reduction of AEB activation. The second term improves collision avoidance metrics such as average speed, smoothness, distance to obstacles, etc. Finally, the third term encourages restricting the search space over possible corrective control commands. Our method learns directly in a real-world indoor office environment by using a distributed RL training setup, leveraging the Soft Actor Critic (SAC) [8] algorithm. Multiple robots collect experience through a higher-level navigation policy, and a centralized training server collects experiences and updates the RL policy that is shared by all robots. With this novel setup, we can perform real-world RL training while minimizing actual crashes throughout the learning process, avoiding potential physical damage.

Our experiments show that, when compared to both traditional and learning-based methods, our approach demonstrates a higher average speed for the robotic agents, lower collision rate, higher goal-reaching rate, lower computational overhead, and is able to perform training directly in a real world environment with minimum actual crashes. We believe this work opens up a new approach for safer learning in the real world, and thus accelerates the development of intelligent agents.
II. RELATED WORK

There’s a broad literature on the topic of real-world collision-avoidance, and in the following we discuss its related work on safety in real-world robots, learning from expert demonstration, sim-to-real learning, and learning from collisions.

Safety in Real-world Robots. AEB is commonly applied in real-world robots, where AEB performs maximum braking when detecting obstacles or emergency situations. Nonetheless, the AEB system could make sub-optimal decisions such as performing maximum braking too late, which can result in a head-on collision. Therefore, it’s safer to plan ahead to avoid getting into a situation where an AEB system has to take over [5]; formulating collision avoidance as one of the cost terms in an overall search or trajectory optimization problem [13][30]. With powerful computer, model simplification and heuristics, such approaches have hope for finding collision-free global optimal solutions. Yet, the computation resource on mobile robot is too limited to perform such expensive computation in additional to other essential tasks like perception [16]. Our work considers a realistic setup that we perform efficient collision avoidance using on-device compute to prevent the robot from getting into an unsafe position. Our work also relates to safe reinforcement learning (RL), such as constrained policy optimization (CPO) [1]. While there are no evidence shows that CPO works in the real world systems, our approach is demonstrated to work in real world.

Learning from Human Demonstrations. A popular way to learn to avoid collisions is to learn from human demonstrations, including imitation learning methods [20], [21], [3], [24], [7], [18], and by learning to avoid human disengagement [12]. The first class of methods (imitation learning) aim to make a robotic agent mimic human behaviors. The second class of methods (learning to avoid human disengagement) aim to make a robotic agent generate actions that avoid human disengagement, which is similar to our approach where we learn to reduce the amount of AEB activation. Although these approaches have demonstrated their effectiveness in collision avoidance, they require a lot of human demonstration data, which is expensive to collect. Our approach on the other hand, learns from AEB activation signals, which require no human demonstrations.

Sim-to-Real Transfer. Another family of collision avoidance involves learning in simulation, and then performing sim-to-real transfer [25], [19], [9], [29], [31]. Although simulation offers us a large amount of training data when compared to the real-world, the enormous sim-to-real domain gap may hinder the learning algorithms to generalize. Our approach learns directly in the real world, and evidence shows that direct real world learning is preferable to applying sim-to-real transfer [15].

Learning from Collisions. Our work also relates to learning collision avoidance by experiencing collisions [14], [6], [11], in which collision is regarded to be a valuable learning signal. However these approaches will inevitably cause physical damage to robotic agents, and the environment in which they operate in. On the other hand, our approach regards AEB activation as a valuable learning signal, which is safer in the real world.

III. METHOD

We present our collision avoidance system in Fig. 1 (a), noting that our method runs in parallel with upstream tasks, such as navigation planning and human control. Our approach takes as input the robot state from odometry, the lidar and ultrasonic scans, maximum braking signals, and the
control commands from the upstream tasks. The output is a corrective control command to the upstream reference tasks, which avoids collision and provides favorable behavior (fast speed, smooth control, etc.). There are two stages within our collision avoidance: maximum braking and collision avoidance checks (details in Sec. III-A) and RL policy and search (details in Sec. III-B). In the first stage, we determine whether the robot requires maximum braking, or a corrective control command through our learned search. In the second stage, we apply a RL-guided search to output corrective control commands with the goal of 1) reducing the frequency of emergency interventions and 2) avoiding collision efficiently. We introduce important notations in the following.

- Robot states \( x = (x, y, \theta, v, \omega) \) with \( x/y \) being 2D euclidean coordinates, \( \theta \) being the robot’s yaw, and \( v/\omega \) being the robot’s linear velocity/angular velocity.
- Reference control commands \((v_{\text{ref}}, \omega_{\text{ref}})\) are from upstream navigation planning\(^1\) or human control\(^2\).
- Corrective control commands \((v_c, \omega_c)\) are outputted by our collision avoidance module.
- Maximum linear & angular acceleration \((a_v^{\text{max}}, a_\omega^{\text{max}})\).
- Maximum and minimum linear velocity \((v_{\text{max}}, v_{\text{min}})\).
- Reaction time \( t_r \) is a hyper-parameter, representing our collision avoidance module’s latency. We set it as 50 ms.
- Plan-ahead time \( t_p \) is a hyper-parameter, representing the time horizon for trajectory planning, according to the maximum braking capability of the robot. \( t_p \) is a dynamic parameter (changing with respect to robot velocity), and depends on the collision avoidance module’s latency \( t_r \), current linear velocity \((v)\), and maximum linear acceleration \((a_v^{\text{max}})\). We set it as \( t_p = t_r + v/(2a_v^{\text{max}})\).
- Robot kinematics \( x_{i+1} := f(x_i) \) is defined as

\[
\begin{align*}
x_{i+1} &= x_i + v_i \cos(\theta_i) t_r \\
y_{i+1} &= y_i + v_i \sin(\theta_i) t_r \\
\theta_{i+1} &= \theta_i + \omega_i t_r \\
v_{i+1} &= v_i \\
\omega_{i+1} &= \omega_i 
\end{align*}
\]

- Robot trajectory \( \text{traj}(v, \omega, \Delta t) \) is defined as

\[
\text{traj}(v, \omega, \Delta t) := [x_0, x_1, x_2, \ldots, x_{\Delta t/t_i}],
\]

where \( t_i \) is considered to be the time step and \( \Delta t \) is the total time horizon. The initial robot state \( x_0 = (0, 0, 0, v, \omega) \) since we use an ego-centric robot frame.

- 2D Lidar scan \( \{l_0, l_1, \cdots, l_{356}\} \) collects signals from 360°, representing distance in meters.
- 2D ultrasonic scans \( \{u_{-45}, u_0, u_{45}\} \) collects signals from \(-45°, 0°, 45°\), representing distance in meters. We leverage ultrasonics to detect glass surfaces.

\(^1\)The upstream navigation policy is generated from the navigation stack (i.e., we use ROS \(^2\) package), which considers a different set of inputs: the front and back rgb-d cameras, and visual odometry.

\(^2\)Our collision avoidance system also works with human control.

- Obstacles \( \mathcal{O}_s \subset \mathbb{R}^2 \) are registered using lidar and ultrasonic signals \( \{l_0, l_1, \cdots, l_{356}, u_{-45}, u_0, u_{45}\} \) within \( t_r \).
- Maximum Braking Status \( \sigma = 1 \) when maximum braking triggers; otherwise \( = 0 \).

A. Maximum Braking and Collision Avoidance Check

According to the robot’s current state and the surrounding obstacles, we perform a maximum braking and collision avoidance check, and apply corrective action to the control commands. If the maximum braking check is satisfied, we apply maximum braking to bring the robot to a complete stop. If the maximum braking check is not satisfied, but the collision avoidance is, we search for a corrective control command using our RL-guided search. If neither check is satisfied, our system maintains the upstream control. In the following, we first define collision, then discussing the maximum braking and collision avoidance check.

Collision. We define \( E(x) \in \mathbb{R}^2 \) as the set of points in 2D space by the robot’s shape at state \( x \). A collision occurs between the robot’s trajectory \( \text{traj}(v, \omega, \Delta t) \) and the set of obstacles \( \mathcal{O}_s \subset \mathbb{R}^2 \) if:

\[
\bigcup_{x \in \text{traj}(v, \omega, \Delta t)} (E(x) \cap \mathcal{O}_s) \neq \emptyset.
\]

Maximum Braking Check. We adopt maximum braking control when the robot’s trajectory along the plan-ahead time \( t_p \), denoted as \( \text{traj}(v, \omega, t_p) \), collides with obstacles, formulated as \( \bigcup_{x \in \text{traj}(v, \omega, t_p)} E(x) \cap \mathcal{O}_s \neq \emptyset \).

Collision Avoidance Check. If the maximum braking check is not satisfied, then we expand the plan-ahead time to \( \beta t_p \)\(^3\) to see if the robot collides with obstacles that are further away. It can be formulated as \( \bigcup_{x \in \text{traj}(v, \omega, \beta t_p)} E(x) \cap \mathcal{O}_s \neq \emptyset \) if there is a collision, then perform our RL-guided search for a corrective control command.

B. RL Policy and Search

Our RL-guided search is inspired by the Dynamic Window Approach (DWA)\(^5\). The DWA approach defines a dynamic window \( W = [v_{\text{lower}}, v_{\text{upper}}] \times [\omega_{\text{lower}}, \omega_{\text{upper}}] \) identifying the set formed by the Cartesian product of values in the range between lower and upper linear velocity, and angular velocity values. DWA then searches for a corrective control command \( (v_c, \omega_c) \in W \). Alternatively, our approach introduces additional parameters to shrink the dynamic window \( W \) via a RL policy, then searching inside of the smaller \( W \). In the following, we define the dynamic window, discuss the RL policy and reward, and lastly discuss the search.

Dynamic Window. In the DWA approach\(^5\), the standard dynamic window \( W_{\text{standard}} \) is defined using the current robot velocity \((v, \omega)\), the maximum linear and angular acceleration \((a_v^{\text{max}}, a_\omega^{\text{max}})\), and the robot reaction-time \( t_r \):

\[
[a_v^{\text{max}} t_r, v + a_v^{\text{max}} t_r] \times [\omega - a_\omega^{\text{max}} t_r, \omega + a_\omega^{\text{max}} t_r].
\]

However, searching in \( W_{\text{standard}} \) can be inefficient since the ranges between the lower and upper velocities can be large. Hence, we propose to reduce the search space and shrink

\(^3\)\( \beta > 1 \) as a hyper-parameter, we use \( \beta = 2 \).
We consider a distributed RL training setup with the soft actor critic (SAC) [8] approach. The training server sends training setup with the soft actor critic (SAC) [8] approach. The critic network consists of lidar and ultrasound scans, robot’s linear and angular velocity, and the control commands from the upstream task: $s_t = [b_0, b_1, \ldots, b_{359}, u_{-45}, u_{45}, v, \omega, v_{ref}, \omega_{ref}]$. The learned window $W_{learned}$ becomes:

$$W = [v - b_0 a_{max, t_r}, v + b_1 a_{max, t_r}] \times [\omega - b_2 a_{max, t_r}, \omega + b_3 a_{max, t_r}].$$

(1)

Note that $[b_0, b_1, b_2, b_3]$ are the output of our RL policy. We see that the search space of $W_{learned}$ compared to $W_{standard}$ gets reduced by $b_0b_1b_2b_3$.

RL Policy and Reward. We consider a distributed RL training setup with the soft actor critic (SAC) [8] approach. Our robots collect experiences and send them to a central training server, and the training server uses these experiences to train and update the actor’s policy network, as well as the critic and critic target networks. The training server sends all robots the updated actor network after a fixed number of training steps. The following figures present the overall setup and network specifications:

For each time step, $s_t$ represents the input to the policy and the critic network, consisting of lidar and ultrasound scans, robot’s linear and angular velocity, and the control commands from the upstream task: $s_t = [b_0, b_1, \ldots, b_{359}, u_{-45}, u_{45}, v, \omega, v_{ref}, \omega_{ref}]$.

### Procedure 1 Training Algorithm

1. Initialize upstream navigation ($v_{ref}, \omega_{ref}$)
2. Initialize experience buffer $D \leftarrow \emptyset$
3. Randomly initialize RL network parameters $\theta$
4. RL policy action $a_t$, observation $s_t$, reward $r_t$.
5. for learning epochs do
   6. $(v_{ref}, \omega_{ref}) \leftarrow$ upstream control command
   7. $s_t \leftarrow \{\text{sensor scans, } v, w, v_{ref}, \omega_{ref}\}$
   8. if maximum braking check satisfied then
      9. $\sigma_t \leftarrow 1$, perform maximum braking
     10. $a_t, (v_c, \omega_c) \leftarrow \text{Null, } (v_{max}, 0)$
   else
      12. $\sigma_t \leftarrow 0$, do not perform maximum braking
     13. if collision avoidance check satisfied then
        14. $a_t \leftarrow [b_0, b_1, b_2, b_3] \leftarrow$ RL policy network
     15. $(v_c, \omega_c) \leftarrow \text{eq. (4)}$ with $\{s_t, a_t\}$
   else
      17. $a_t, (v_c, \omega_c) \leftarrow \text{Null, } (v_{ref}, \omega_{ref})$
   18. if $a_{t-1}$ not Null then
      19. $r_{t-1} \leftarrow \text{eq. (2)}$ with $\{s_{t-1}, a_{t-1}, \sigma_{t-1}\}$
     20. $D \leftarrow \{s_{t-1}, a_{t-1}, r_{t-1}, \sigma_t\}$
   21. command robot with $(v_c, \omega_c)$
   22. use $D$ to update $\theta$ using RL

$a_t$ is the output of the policy network and also part of the input to the critic network: $a_t = [b_0, b_1, b_2, b_3]$. $r_t$ is our reward function. Since we aim to learn corrective control commands that can 1) reduce the number of maximum braking interventions and 2) avoid collision efficiently, we compose $r_t$ to be

$$r_t = -\lambda_1 \sigma_{t+1} - \lambda_2 (b_0b_1b_2b_3) - \lambda_3 J(v_c, \omega_c),$$

(2)

where $\lambda_1, \lambda_2, \lambda_3$ are hyper-parameters, $\sigma_{t+1}$ is the maximum braking status of the next time step, $(b_0b_1b_2b_3)$ represents the size of the search space, and $J(v_c, \omega_c)$ measures the distance between the planned trajectory and the obstacles given control command $(v_c, \omega_c)$. Precisely, we define $J(v_c, \omega_c)$ as

$$J(v_c, \omega_c) = c_1 (v_{max} - v_{c}) + c_2 (|v_c - v_{ref}| + |\omega_c - \omega_{ref}|) + \frac{1}{\text{dist}(O_s, \text{traj})},$$

(3)

where $c_1, c_2, c_3$ are hyper-parameters, $(v_{max} - v_{c})$ encourages the corrective linear velocity to be fast, $(|v_c - v_{ref}| + |\omega_c - \omega_{ref}|)$ minimizes the deviation of corrective control commands from upstream control commands, and $\frac{1}{\text{dist}(\cdot)}$ encourages the robot to stay away from obstacles with $\text{dist}(O_s, \text{traj})$ distance between the robot’s trajectory and the obstacles:

$$\text{dist}(O_s, \text{traj}) = \min_{\forall(x, y) \in O_s} \{(x, y) \in \text{traj} \mid d((x, y)) \leq d(x, y)\}.$$

### Footnotes:

4 In our design, $\lambda_1 = 35$, $\lambda_2 = 10$, $\lambda_3 = 10$.
5 In our settings, $c_1 = 0.4$, $c_2 = 0.2$, $c_3 = 0.4$. 
TABLE I
QUANTITATIVE COMPARISONS IN THE TRAINING ENVIRONMENT.

| Methods   | Search | Learning from AEB | average speed (\(\uparrow\)) | collision rate (\(\downarrow\)) | time between collision (\(\uparrow\)) | goals reached rate (\(\uparrow\)) | search size (\(\downarrow\)) | unsmoothness (\(\downarrow\)) |
|-----------|--------|-------------------|-----------------------------|-------------------------------|-----------------------------------|-------------------------------|-----------------------------|-----------------------------|
| NoSafety  | no     | no                | 0.57 m/s                    | 26.0 %                        | 1.9 min.                          | 70.0 %                        | n/a                         | 0.26                        |
| PureAEB   | no     | no                | 0.39 m/s                    | 8.0 %                         | 6.2 min.                          | 82.0 %                        | n/a                         | 0.41                        |
| PureRL    | no     | yes               | 0.58 m/s                    | 12.0 %                        | 4.1 min.                          | 72.0 %                        | n/a                         | 0.61                        |
| StandardSearch | yes  | no                | 0.49 m/s                    | 4.0 %                         | 10.5 min.                         | 86.0 %                        | 100.0 %                     | 0.31                        |
| Ours      | yes    | yes               | 0.68 m/s                    | 2.0 %                         | 23.5 min.                         | 92.0 %                        | 32.0 %                      | 0.17                        |

TABLE II
QUANTITATIVE COMPARISONS IN THE EVALUATION ENVIRONMENT.

| Methods   | Search | Learning from AEB | average speed (\(\uparrow\)) | collision rate (\(\downarrow\)) | time between collision (\(\uparrow\)) | goals reached rate (\(\uparrow\)) | search size (\(\downarrow\)) | unsmoothness (\(\downarrow\)) |
|-----------|--------|-------------------|-----------------------------|-------------------------------|-----------------------------------|-------------------------------|-----------------------------|-----------------------------|
| NoSafety  | no     | no                | 0.48 m/s                    | 33.3 %                        | 1.5 min.                          | 66.7 %                        | n/a                         | 0.32                        |
| PureAEB   | no     | no                | 0.37 m/s                    | 10.0 %                        | 5 min.                            | 76.7 %                        | n/a                         | 0.44                        |
| PureRL    | no     | yes               | 0.46 m/s                    | 16.7 %                        | 2.8 min.                          | 70.0 %                        | n/a                         | 0.64                        |
| StandardSearch | yes  | no                | 0.52 m/s                    | 6.7 %                         | 7.2 min.                          | 80.0 %                        | 100.0 %                     | 0.35                        |
| Ours      | yes    | yes               | 0.66 m/s                    | 3.3 %                         | 13.7 min.                         | 86.7 %                        | 37.0 %                      | 0.19                        |

Search. After we obtain \([b_0, b_1, b_2, b_3]\) from the RL policy network, we perform search for the corrective control command. In particular, we consider a search with granularity of \(n_v\) linear and \(n_\omega\) angular velocity control commands from \(W_{\text{learned}}\) (eq. (1)) that minimizes \(J(v_c, \omega_c)\) (eq. (3)):

\[
(v_c, \omega_c) = \arg \min_{(v_c, \omega_c)} J(v_c, \omega_c)
\]

s.t. \(v_c \in \{v - b_0a_{\text{max}}^v, v - b_0a_{\text{max}}^v + s_v, \ldots, v + b_1a_{\text{max}}^v\}\)

\[
\omega_c \in \{\omega - b_2a_{\text{max}}^\omega, \omega - b_2a_{\text{max}}^\omega + s_\omega, \ldots, \omega + b_3a_{\text{max}}^\omega\},
\]

where \(s_v = (b_0 + b_1)a_{\text{max}}^v/n_v\) and \(s_\omega = (b_2 + b_3)a_{\text{max}}^\omega/n_\omega\). We note that our learned window \(W_{\text{learned}}\) provides a more granular search in comparison to \(W_{\text{standard}}\), when \((n_v, n_\omega)\) are fixed in both cases (we follow this in our work).

IV. EXPERIMENTS

In this section, we perform real-world robot experiments in indoor office environments. Given a goal location, the robots leverage the ROS navigation stack [27] to provide navigation as the upstream task. Our indoor environment contains many different obstacles including glass, humans, office chairs, other robots, etc. We consider 50 random location goals in the training and 30 random goals in the evaluation environments.

Methods of Comparison. We consider four baselines to demonstrate the effectiveness of our method. The first baseline only considers an upstream reference navigation policy, in which the robots have the ability to map, localize, and navigate in a static environment given goal locations, but there is no collision avoidance system. Building upon the first baseline, the second, third, and fourth baselines add a collision avoidance component to correct the reference navigation policy. For the second baseline, its safety system comes from a pure reinforcement learning setting: the reinforcement learning algorithm learns to directly output corrective actions for the robot, when it is triggered by a collision avoidance check according to time horizon \(\beta t_p\). We use the reward function described in Equation (2), and set the window size \(b_0b_1b_2b_3 = 0\) because no search is performed. For the third baseline, its safety system only utilizes a maximum braking mechanism. The second and third baselines do not perform collision avoidance search, and are triggered when a maximum braking condition is detected. The fourth baseline is the most similar to our approach, but we use the standard dynamic window in [5] (DWA) for performing collision avoidance search. We shorthand the first baseline as NoSafety, the second baseline as PureRL, the third baseline as PureAEB, the fourth baseline as StandardSearch, and our method as Ours. Note that PureRL and Ours both learn with maximum braking signals.

Metrics. We report metrics on maximizing 1) average speed: the mean of the linear speed across all control decisions in \((m/s)\); minimizing 2) collision rate: the ratio of the number of goals resulting in a collision compared to all goals; maximizing 3) time between collision: average number of minutes between collisions; maximizing 4) goals reached rate: the percentage of goals reached out of the total; minimizing 5) searchsize: the relative search window size compared to that in dynamic window approach [5]; and minimizing 6) unsmoothness: the mean of the linear and lateral accelerations between control decisions. As an example, given two sequential control decisions \((v_0, w_0)\) and \((v_1, w_1)\), and elapsed time of \(t\) we calculate unsmoothness for this step to be \(|v_1 - v_0 + w_1 - w_0|/t\). Note that unsmoothness reflects the frequency of maximum braking performed: frequent maximum braking leads to high unsmoothness.

A. Results in Training Environment

We report the results in Table I. First, we compare the methods with and without safety systems. We find that methods with a safety system come with a lower collision rate, larger time between collisions, and a higher goals reached rate (a goal is considered as not reached as soon as a collision occurs). For instance, the collision rate drops from 26.0% to 8.0% from NoSafety to PureAEB, and time between collisions nearly triples. Nonetheless, we also find
that the methods with a safety system (except our approach Ours) have lower average speed and higher unsmoothness. We find that there may be a compromise between safety (i.e., collision rate) and user experience (i.e., average speed and unsmoothness) when adding safety systems into the robot.

Next, we focus on evaluating the effects of performing collision avoidance search in the safety system. We find that methods that have collision avoidance search can reduce collision rate, increase time between collisions, improve goals reached rate, and reduce unsmoothness. For instance, the collision rate drops from 8.0% to 4.0%, the goals reached rate increases from 82.0% to 86.0%, and the unsmoothness drops from 0.41 to 0.31 from PureAEB to StandardSearch. Nonetheless, the average speed can be a compromise of adding search: we observe a reduction of average speed from 0.58 m/s to 0.49 m/s from PureRL to StandardSearch. A possible explanation is that search introduces turns and speed reduction for the robots.

Third, we compare StandardSearch and Ours, which Ours additionally leverages maximum braking signals to 1) reduce the frequency of maximum braking and 2) search more efficiently. We observe that all metrics improved significantly from StandardSearch to Ours, which suggests that maximum braking provides a good signal for collision avoidance learning.

Comparisons in the Evaluation Environment. Now, we evaluate the generalization capability of our method in the evaluation environment in Table II. Note that the experiments are performed post-training (we do not re-train the networks in the evaluation environment) and the training and the evaluation environments contain different layout and obstacles. When compared to the training environment, the overall trend is similar in the evaluation environment: our approach Ours achieves the best performance on all metrics.

Conclusion. Our experiments suggest that maximum braking can serve as a good learning signal for the robotic agent to learn to avoid collision. Nonetheless, learning to avoid maximum braking in a pure RL setting was not sufficient to provide safety (the PureRL approach). Alternatively, our method Ours leverages maximum braking signals to improve trajectory search, which provided better search efficiency, quality, and lower collision rates.

B. Qualitative Results

In this section, we provide qualitative results for our method against obstacles that are static and non-transparent (walls and furniture), static and transparent (glass), and moving (human). The comparisons are made between methods with safety system and with search in the safety system: StandardSearch and Ours.

Static, Non-transparent Obstacles. We present the results in the left figure of Fig. 2. First, we find our approach (Ours) explores far fewer trajectories in a much more confined search window. Next we observe that the bounded search space contains little to no trajectories that cause collision, and includes trajectories that take the robot closer to the goal. The results provide insight into how our method improves the efficiency of search by leveraging maximum braking signals.

Static, Transparent Obstacles (glass). We present the results in the middle figure of Fig. 2. Note that in this setup, the goal location is on the other side of a glass surface. When compared to the traditional search (StandardSearch), we find our method (Ours) effectively learns to leverage sparse ultrasonic sensory input to avoid glass surfaces.

Moving Obstacles (Human). We present the results in the right figure of Fig. 2. We find our approach (Ours) can also avoid collisions with humans. Note that our system does not treat moving obstacles differently than static obstacles, and hence having a low latency between control cycles for collision avoidance is important. The result suggests that Ours can perform an efficient collision avoidance, and for future work we plan to explore more complex methods for obstacle avoidance against dynamic objects.

V. CONCLUSION

In this work, we leverage the activation of emergency interventions as a learning signal for a real-world reinforcement learning guided search method that 1) reduces the frequency of triggering emergency interventions and 2) reduces the search space with learned search heuristics. Our approach enables direct and safe real-world learning without human intervention or overtake. In our real-world experiments, we show our method outperforms other collision avoidance baselines. For future work, we plan to extend our setting to non-stationary multi-agent environments with potentially diverse dynamic obstacles.
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