Provably Safe Deep Reinforcement Learning for Robotic Manipulation in Human Environments

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Abstract—Deep reinforcement learning (RL) has shown promising results in the motion planning of manipulators. However, no method guarantees the safety of highly dynamic obstacles, such as humans, in RL-based manipulator control. This lack of formal safety assurances prevents the application of RL for manipulators in real-world human environments. Therefore, we propose a shielding mechanism that ensures ISO-verified human safety while training and deploying RL algorithms on manipulators. We utilize a fast reachability analysis of humans and manipulators to guarantee that the manipulator comes to a complete stop before a human is within its range. Our proposed method guarantees safety and significantly improves the RL performance by preventing episode-ending collisions. We demonstrate the performance of our proposed method in simulation using human motion capture data.

I. INTRODUCTION

In recent years, researchers solved many complex manipulation tasks using deep reinforcement learning (RL), such as operating door handles [1], playing table tennis [2], stacking boxes [3], and controlling multiple robotic arms [4]. Furthermore, recent work [5]–[7] demonstrated that RL-controlled manipulators could successfully maneuver in environments with dynamic obstacles, dodging moving obstacles, and reaching the goal state consistently. Despite these promising results, one open challenge in RL is to formally guarantee the safety of surrounding humans due to their unpredictable movement and many degrees of freedom (DoF). The lack of safety assurances makes applying any vanilla RL method in human working environments irresponsible.

To overcome these restrictions, we propose a safety shield concept for RL that guarantees human safety at all times, as shown in Fig. 1. In essence, our safety concept is speed and separation monitoring (SSM) according to DIN EN ISO 10218–1 2021, 5.10.3 [8] warranting that the robot is in a completely stopped state before any collision with a human could occur. We need to verify the robot trajectory at a high frequency to achieve this strong safety criterion while still being able to maneuver close to humans. However, for the RL agent it suffices to output actions at a low frequency to make long-term decisions like moving around a human to reach its goal. Our safety shield combines the low-frequency RL agent with our high-frequency formal verification. The RL agent used in this work is a state-of-the-art soft actor-critic (SAC) [9] with hindsight experience replay (HER) [10]. However, our safety shield can be used with any online RL agent. This work presents the first provably safe robot manipulator control based on deep RL in human environments.

A. Related work

Gu et al. [1] were one of the first to show that various complex manipulation tasks can be learned using only off-policy deep RL methods. They presented a method to train multiple real robots in parallel to solve a challenging door-opening task. Shortly later, [10] proposed HER to achieve randomized manipulation goals. The combination of HER with off-policy RL contributed to many remarkable results in pushing, pick and place, and throwing tasks as presented in [10]–[12]. Recently, HER was combined with state-of-the-art RL algorithms like SAC to solve complex manipulation tasks such as controlling multiarm manipulators [4].

There have been many approaches that introduce safety constraints to the exploration process of RL agents. Simple reward shaping has shown to be insufficient to guarantee safety as it is infeasible for universally deciding between fulfilling the safety constraints and rapidly accomplishing the goal [13], [14]. Many recent works use constrained policy optimization techniques [13]–[15] to reduce the number of
safety-critical interactions with the environment. Although some of these approaches show a very low number of safety constraint violations, none can warrant safety at all times.

In many scenarios, especially when interacting with humans, a very low chance of collision is still unacceptable. Therefore, recent works [6], [16]–[18] in the field of provably safe RL (often referred to as shielding, safety layers, sandboxing, or constraining bolts) focus on provable safety guarantees. The core idea of these methods is to ensure that only safe actions are sent to the environment. As a result, unsafe actions are either replaced with safe actions, projected to the safe action space, or entirely prevented by limiting the action space. Many provably safe RL approaches have been proposed for simple environments such as Atari games [19], grid worlds [20], [21], or board games [22]. Most notably, Hunt et al. [17] exhibited how safe end-to-end learning from image data could be achieved in discrete action spaces. Unfortunately, these methods rely on a deterministic environment to assure safety, so they are not directly applicable to a complex task like human–robot collaboration or coexistence. For the use case of RL for manipulators, Pham et al. [6] proposed a differentiable safety layer (OptLayer) that projects any unsafe action to the closest safe action that satisfies the given constraints. Despite promising results, this method comes with two flaws. First, the OptLayer is only formally correct if the constraints of the underlying quadratic program are precisely fulfilled, and the optimizer finds an exact solution in the given time. Second, it is difficult to formalize the safety constraints for unknown and complex human motions. The reachable set-based safety layer of [16] provides formal safety for autonomous driving highway scenarios by masking out all nonsafe actions. Training an RL agent with this safety layer leads to faster convergence while all collisions can be avoided. This method was designed for a discrete action space and is therefore not directly transferable to the manipulator application. The approach closest to ours is the reachability-based trajectory safeguard of [18]. They use reachability analysis to predict if the agent could collide with static obstacles on the current trajectory and replan a safe trajectory if necessary. However, this approach is only designed and tested for static environments.

B. Contributions

We present a novel safety shield\(^1\) that replaces unsafe actions from the agent with provably safe actions from a high-frequency safe trajectory planner (failsafe planner). To the best of our knowledge, our method is the first safety measure for RL that provides provable safety for continuous action spaces in high-dimensional state-spaces and hard-to-predict dynamic environments. Our safety shield can easily be applied to a large variety of manipulation tasks. Compared to all previously mentioned provably safe RL approaches, we sample from the entire set of actions (instead of a safe subset) and check the safety of the current action during execution at high frequency. This allows for quick reactions to highly dynamic human motion. To summarize, our safety shield guarantees that the robot stops before a collision with a human could occur while still allowing the maximal freedom of movement under the given safety constraints.

C. Article structure

Section II summarizes our problem and presents the RL basics and notation used in the article. Next, Section III presents our proposed safety shield and RL agent. We then discuss the experimental setup and results in Section IV and present our conclusion in Section V.

II. PRELIMINARIES

A. Problem statement

In our RL setting, a six DoF modular robot, as described in [23], is mounted on a working table, where a human repeatedly performs a task. In each episode, the agent has to reach a randomized goal joint position, further referred to as episode goal $g$, from a fixed initial position and evade the human. We only consider episode goals that are collision-free with the static environment. This paper aims to provide formal safety guarantees for nearby humans with unknown motion behavior while consistently reaching the goal. Hereby, the RL agent receives the following observations: the current joint position and velocity, episode goal, current Cartesian end-effector position, and the relative Cartesian positions of the human wrists and head in relation to the end-effector. Since the only static obstacle in our scene is the table, we do not add static obstacle information to the observation space. Fig. 2 shows our setup and illustrates the observations.

B. RL

For RL, we use the notation in [9] and consider the Markov decision process defined by the tuple $(\mathcal{S}, \mathcal{A}, p, r)$ with both continuous state space $\mathcal{S}$ and action space $\mathcal{A}$. For simplicity, we assume the state to be fully observable. The transition function $p : \mathcal{S} \times \mathcal{S} \times \mathcal{A} \rightarrow \mathbb{R}$ denotes the

\(^1\)Our code and models are publicly available at https://github.com/JakobThumm/safe_RL_manipulators
probability density function of reaching the next state \( s_{i+1} \) when choosing action \( a_i \) in state \( s_i \). After each transition, the agent receives a reward from the environment according to the reward function \( r : S \times A \rightarrow \mathbb{R} \). The agent learns a stochastic policy \( \pi(a_i|s_i) \) for action \( a_i \) given state \( s_i \).

The optimal policy is learned using the online off-policy SAC algorithm first presented in [9]. Our specific implementation extends the spinningup [24] version of SAC with HER and is further described in Section II-B. The goal of SAC is to automatically balance exploration and exploitation by maximizing the accumulated reward and the information content of the policy function. Therefore, the entropy \( H \) (see e.g. [25, Eq. 4.2]) of the policy is used as part of the optimization objective (from [9, Eq. 1])

\[
J(\pi) = \sum_{t=0}^{T} E_{(s_i, a_i) \sim \rho_a} [r(s_i, a_i) + \alpha H(\pi(\cdot|s_i))].
\] (1)

In many robotic applications, one encounters the problem of sparse rewards, where the agent needs to get to a random and hard-to-reach goal. If the agent rarely reaches the goal, almost no transitions with goal encounters are added to the replay buffer. In order to create more of these goal transitions, [10] proposed HER with the idea to sample additional transitions with fictional goals, where the goal \( g \) of an episode is added to state \( s_i \), written as \( s_i || g \). The goal-conditioned transition tuples can be written as \( (s_i || g, a_i, r_i, s_{i+1} || g) \). For each transition, additional fictional episode goals \( \tilde{g}^h \), \( h = 1 \ldots k_{\text{HER}} \) are created from states that were actually reached in the episode of the transition, leading to \( k_{\text{HER}} \) (in our case \( k_{\text{HER}} = 4 \)) new transitions \( (s_i || \tilde{g}^h, a_i, \tilde{r}^h, s_{i+1} || \tilde{g}^h) \). By sampling new goals from states that have actually been reached, many successful goal transitions are added. This method enables us to use a sparse reward, where \( r_i = 0 \) if the goal was reached and \( r_i = -1 \) otherwise. Since we terminate an episode if a collision occurs, e.g., the human walks into the stationary robot, a negative reward for collisions is not strictly necessary.

### III. METHODOLOGY

#### A. Safety shield

Our proposed safety shield is based on the provably safe trajectory planner, called failsafe planner in [26]. The shield functionality is illustrated in Fig. 1 and further elaborated in this subsection. Please refer to [23], [26]–[28] for a more detailed description of the trajectory planning and verification process.

In our application, the actions of the RL agent are intermediate goal joint positions \( \tilde{g}_i \). These intermediate goals \( \tilde{g}_i \) are not to be confused with the episode goal \( g \) or the fictional episode goals for HER \( \tilde{g}^h \). In each episode, the agent outputs multiple intermediate goals \( \tilde{g}_i \) to reach the single episode goal \( g \). The HER goals \( \tilde{g}^h \) are only relevant for training the agent. Furthermore, we would like to emphasize that the RL agent outputs the intermediate goals at a lower frequency than our safety shield is operated. Each RL action is executed for a user-defined time interval \( \Delta T \), or until all joints are within a small \( \epsilon \)-range of the intermediate goal. We refer to this as one RL step and use the index \( i \). The user-defined time between two safety shield verification steps is \( \Delta t \) with \( \Delta t < \Delta T \) and the index \( k \) is used.

#### a) Long-term and failsafe planning

This paragraph describes the trajectory planning in our safety shield and is accompanied by a simplified example in Fig. 3. To reach the intermediate goal \( \tilde{g}_i \), we calculate an intended trajectory from the current joint state \( x_0 \) to \( \tilde{g}_i \) using a long-term planner. We guarantee that a failsafe trajectory always exists, which brings the robot to an inherently safe state, i.e., a full stop, because a dynamic obstacle can block the robot’s path during the execution of this intended trajectory. Formal safety can now be guaranteed by induction, where it is assumed that the robot starts in a safe state (stopped). The first intended trajectory is executed starting from \( t_0 \) if no collision with
a human is possible between \( t_0 \) and \( t_1 \) and if a collision-free failsafe trajectory exists starting from \( t_1 \). During the execution of a trajectory between \( t_k \) and \( t_{k+1} \), we calculate a failsafe trajectory starting from \( t_{k+2} \). If this failsafe trajectory cannot be verified as safe, we execute the previously verified failsafe trajectory starting from \( t_{k+1} \). Since each failsafe trajectory ends in a safe state, we can guarantee safety for an infinite time horizon. Similarly, one time step of the intended trajectory between \( t_k \) and \( t_{k+1} \) is only executed if it is verified as safe; otherwise, the failsafe trajectory is executed. In each time step, a new intended and failsafe trajectory is planned.

In our RL scenario, the agent repeatedly updates the intermediate goal. If there is a new intermediate goal \( g_{k+1} \) at time step \( t_k \), the intended trajectory is calculated from the state at time \( t_k+1 \) to \( g_{k+1} \), and a new failsafe trajectory is calculated from the new intended trajectory starting at time \( t_{k+2} \). If the new intended and failsafe trajectories can be verified as safe, the robot changes to the new intended trajectory. Otherwise, it follows the last verified failsafe trajectory at \( t_{k+1} \).

b) Adaption to manipulator control: In our use case, the 3D trajectory planning can become computationally expensive, especially in regards to the high-frequency requirement. Therefore, we do not recompute the intended trajectory in every time step. Instead, we only compute intended trajectories for every new intermediate goal \( g_{k+1} \) until an executable one is found and use velocity scaling for the failsafe trajectory as described in [26]. In short, a failsafe trajectory is path-consistent with the intended trajectory and ends in the complete stop of the robot. We use the synchronous Type IV online trajectory planner of [29] for the intended and the failsafe planner. Thus, the intended trajectory planning adheres to velocity, acceleration, and jerk limits \((v_{\text{max}}, a_{\text{max}}, j_{\text{max}})\), which are gentle for the manipulator joints. To achieve fast-braking, we increase the acceleration and jerk limits for the failsafe planning \((v_{\text{max}}^{\text{failsafe}}, a_{\text{max}}^{\text{failsafe}}, j_{\text{max}}^{\text{failsafe}})\) to the physical limits given by the robot manufacturer.

c) Verification: The trajectory verification is based on collision checking of the reachable sets of all possible human motions and the intended robot trajectory. It is assumed that no human joint moves faster than \( 2 \text{ m/s} \) as defined in DIN EN ISO 13855:2010 [30], and all human joint positions are reliably measurable within a specified error bound, e.g., by using a motion capture system. The safety verification also works with other perception methods like light curtains, as presented in [31], but the robot’s movement would become more conservative. The entire space a human can occupy within the time interval \([t_k, t_{k+b}]\) is defined as the reachable occupancy \( \Gamma([t_k, t_{k+b}]) \), where \( b \) is the number of time steps needed to bring the robot to a complete stop, and is calculated using the task space approach presented in [23], [27].

The human and robot occupancies are modeled with capsules, as shown in Fig. 4 to achieve fast computation times. A capsule comprises a cylinder with half-spheres at both ends and is defined by a line segment \( l(p_1, p_2) \) with endpoints \( p_1 \) and \( p_2 \) and a radius \( r \). The robot occupancy is described as a set of capsules enclosing each robot link’s movement between time \( t_k \) and \( t_{k+b} \). Hereby, we follow the approach described in [26] to guarantee overapproximation of the link occupancies. This approach assumes that the controller follows the desired trajectory exactly. If additionally deviation occurring due to low-level control should be considered, the approach presented in [31] can be used. A robot motion is verified as safe if no robot capsule intersects with any human capsule for all times before reaching the resting position.

B. Safe RL

Our policy network has a tanh activation function for the output layer and thus outputs actions \( a_i = [a_{i1}, a_{i2}, \ldots, a_{in}], a_{in} \in [-1; 1] \forall n \in 1 \ldots N \) with \( N \) being the number of joints. We convert these actions to intermediate goal joint positions with \( q^n_{g,i+1} = q^n_i + a_{in} \Delta q^n_{\text{max}} \), where \( q^n_i \) is the current position of joint \( n \) and \( \Delta q^n_{\text{max}} \) is the maximum joint position difference per RL step. In recent literature, it is more common to use the relative change in 3D position of the robot end-effector as action space and calculate \( q^n_{g,i+1} \) using inverse kinematics (e.g. in [3]) since it leads to a lower dimensional action space. However, we use joint positions as actions to have full control over each joint. Nevertheless, both approaches are equally compatible with our proposed safety shield. The choice of \( \Delta q^n_{\text{max}} \) depends on the maximum velocity of the robot \( v^n_{\text{max}} \) and the execution time of each RL step \( \Delta T \). Choosing \( \Delta q^n_{\text{max}} \geq v^n_{\text{max}} \Delta T \) allows the agent to output a new action before the current action is finished. This is desirable because each trajectory ends in a stopped state and we do not want the robot to stop after each action. If the robot collides with the static environment in its intermediate goal, a new action is generated randomly with a uniform distribution over the entire action space until a collision-free intermediate goal is determined. An alternative to this method is to project the unsafe action to the safe action space with respect to the static environment. However, this is nontrivial in the case of a high-dimensional manipulator.

In our training procedure, which is described in Algorithm 1 an episode is done if the episode goal is reached, the robot is in collision, or by timeout when the maximum number of RL steps \( T_{\text{max}} \cdot \text{max} \) is reached. We consider the episode goal as reached, if \( |q^n_{g,i+1} - q^n_g| < \epsilon_g, \forall n \in 1 \ldots N \), where \( q^n_{g,i+1} \) is the position of joint \( n \) after the environment step, \( q^n_g \) is the episode goal.
Algorithm 1: Training procedure

1. Initialize:
   - soft actor-critic agent \( A \)
   - environment \( E \)
   - replay buffer \( R \) and local buffer \( L \)
   - \( T_{\text{total}} \leftarrow 0 \), \( T_{\text{last_update}} \leftarrow 0 \)
   - randomly initialize weights of \( \pi_b \)

2. for \( j \leftarrow 0 \) to \( n_{\text{epochs}} \) do
   3. for \( l \leftarrow 0 \) to \( n_{\text{episodes per epoch}} \) do
      4. reset \( E \) and clear \( L \)
      5. for \( i \leftarrow 0 \) to \( l_{\text{max episode}} - 1 \) do
          6. if \( T_{\text{total}} \geq l_{\text{start steps}} \) then
              7. \( a_i \leftarrow \pi_b \big(s_i \big| g\big) \)
          8. else
              9. \( a_i \leftarrow \text{random action} \)
              10. \( \langle s_{i+1}, r_i, \text{done} \rangle \leftarrow \text{E.step}(a_i) \); \( L[i] \leftarrow \langle s_i \big| g, a_i, r_i, s_{i+1} \big| g \rangle \)
              11. \( T_{\text{total}} \leftarrow T_{\text{total}} + 1 \)
          12. if done then break;
      13. \( l_{\text{episode}} \leftarrow i \)
      14. for \( i \leftarrow 0 \) to \( l_{\text{episode}} - 1 \) do
          15. \( \langle s_i \big| g, a_i, r_i, s_{i+1} \big| g \rangle \leftarrow L[i] \);
          16. \( R.\text{store}(s_i \big| g, a_i, r_i, s_{i+1} \big| g) \);
          17. remaining_ids \leftarrow \{ i + 1 \} . \ldots . (l_{\text{episode}} - 1) \)
          18. randomly select \( k_{\text{HER}} \) random_ids from remaining_ids;
          19. for \( \text{id in remaining_ids} \) do
              20. \( \langle s_{\text{id}} \big| g, \ldots \rangle \leftarrow L[\text{id}] \);
              21. \( \tilde{g} \leftarrow s_{\text{id}} \);
              22. \( \tilde{r}_i \leftarrow \text{E.ComputeReward}(s_{i+1} \big| \tilde{g}) \);
              23. \( R.\text{store}(s_i \big| \tilde{g}, a_i, \tilde{r}_i, s_{i+1} \big| \tilde{g}) \);
          24. if \( T_{\text{total}} \geq T_{\text{update after}} \) and
             \( T_{\text{total}} \geq T_{\text{update every}} \) then
             25. for \( m \leftarrow 0 \) to \( T_{\text{total}} - T_{\text{last update}} \) do
                 26. \( \text{A.Update}(R.\text{sample batch}) \);
             27. \( T_{\text{last update}} \leftarrow T_{\text{total}} \);

TABLE I

| Parameter                | Value   |
|-------------------------|---------|
| \( \Delta T \)          | 4 ms    |
| \( \Delta t \)          | 0.2 ms  |
| \( v_{\text{max}} \)    | 2 rad/s |
| \( a_{\text{max}} \)    | 2 rad/s |
| \( v_{\text{max}} \)    | 10 rad/s|
| \( a_{\text{max}} \)    | 400 rad/s|
| \( \Delta q_{\text{max}} \) | 0.4 rad |

C. Software structure

Our software framework is based on Gazebo and ROS Noetic. The robot simulation uses the Open Dynamics Engine (ODE) solver with a step size of 1 ms. We choose the ODE QuickStep method with 10 solver iterations. The safety shield is implemented in C++ to achieve fast calculation times with an average of 0.5 ms per verification step. With the safety shield operating at 250 Hz, our simulation runs roughly five times faster than real-time.

IV. RESULTS

A. Experimental setup

We conduct two different experiments. In the first randomized-goal experiment, the episode goal is randomly and uniformly sampled over the entire joint space, and the start state is fixed with all joints at their zero position. Notably, the human may block the episode goal. For the second human-evasion experiment, we manually define the start and episode goal position so that the robot collides with the human if it takes the shortest path. The agent must learn to evade the human by taking a longer path or waiting until the human moves away from the table. In this scenario, the episode goal is only slightly randomized so that the human never blocks the goal state. The two experiments are also shown in our accompanying video.

For the simulation, the human motion is taken from real-world motion capture data provided by CMU. Currently, we are using animation 62_01, containing a human walking to the working table, where they perform a wrenching action. This motion pattern is diverse and complex and can effectively validate our concept. To prevent overfitting to the motion data, we randomize the \( x \)- and \( y \)-position and start time of the human animation in each episode uniformly in the range of \([-0.2 \text{ m}, 0.2 \text{ m}] \) and \( [0 \text{ s}, 1 \text{ s}] \).

In all experiments, the maximum episode length is set to 100 RL steps per episode to give the robot adequate

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Fig. 5. Evaluation of the randomized-goal (upper row) and human-evasion (lower row) experiment. Figures (a) and (d) compare the rate of safety-critical collisions per episode of the baseline and the safe agent. The success rate of both experiments is displayed in (b) and (e). The reason for episode endings using the safe agent are displayed in (c) and (f). Hereby, a safe collision occurs when the human touches the stopped robot.

V. CONCLUSIONS

Our results clearly show that our proposed safety shield is an effective method to avoid collisions with humans in the working environment. Contrary to existing RL methods for safe manipulator control, our safety shield provides formal safety guarantees in highly dynamic and prior unknown human environments. The human-evasion experiment also demonstrated that our safety shield could significantly impact the training success in scenarios with a high likelihood of a collision. We believe that our method enables the high-level control of manipulators with RL agents in real-world human environments while providing the necessary safety guarantees to any human operator. Our subsequent goals are to refine the RL agent further and train it on a more complex set of real-world human motions. Finally, we plan to test our safe RL agent on actual robots and perform tasks in a human working environment.
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