Efficiently Learning Recoveries from Failures Under Partial Observability

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Abstract—Operating under real world conditions is challenging due to the possibility of a wide range of failures induced by partial observability. In relatively benign settings, such failures can be overcome by retrying or executing one of a small number of hand-engineered recovery strategies. By contrast, contact-rich sequential manipulation tasks, like opening doors and assembling furniture, are not amenable to exhaustive hand-engineering. To address this issue, we present a general approach for robustifying manipulation strategies in a sample-efficient manner. Our approach incrementally improves robustness by first discovering the failure modes of the current strategy via exploration in simulation and then learning additional recovery skills to handle these failures. To ensure efficient learning, we propose an online algorithm Value Upper Confidence Limit (Value-UCL) that selects what failure modes to prioritize and which state to recover to such that the expected performance improves maximally in every training episode. We use our approach to learn recovery skills for door-opening and evaluate them both in simulation and on a real robot with little fine-tuning. Compared to open-loop execution, our experiments show that even a limited amount of recovery learning improves task success substantially from 71% to 92.4% in simulation and from 75% to 90% on a real robot.

I. INTRODUCTION

It is common for robots to make mistakes while attempting a task due to noise in state and actuation. For example, a robot may miss the handle or drop the key while trying to open a door due to an incorrect handle pose estimate. In practice, such mistakes are often handled with hand-engineered or heuristic behaviors and state machines. While practical for relatively simple tasks in controlled environments, this approach cannot scale easily to systems deployed in the real-world which can fail in a variety of different ways. Hence, there is a need for an algorithmic way to (1) discover potential failures and (2) continually improve the robot when new failures are discovered. Further, this improvement needs to be done as efficiently as possible to ensure that the robot is ready before the next deployment.

To this end, we propose an approach to incrementally improve a robot’s robustness to partial observability by discovering potential failures in simulation and learning recovery skills that allow the robot to recover from these failures. We assume we are given a nominal set of policies which, when executed in sequence, can complete the task under perfect state information. These could be hand-designed controllers or policies learned from human demonstrations. In reality, the state is rarely known perfectly but is estimated using an online state estimation module. Consequently, the robot may make mistakes during execution and enter a state for which it was not trained—a failure state. We discover such failures in simulation by executing the nominal policies under a simulated state estimation model. Next, we cluster similar failures and learn recovery skills for each of the clusters that allow the robot to recover to a safe state from which it can execute one of its nominal policies.

There are multiple potential recoveries from every cluster, each corresponding to a safe state, resulting in a total of \(n \times m\) potential recovery skills for \(n\) failure clusters and \(m\) safe states. Since learning all of these recoveries is computationally expensive and redundant, prior works use heuristics to choose where to recover. However, recoveries generated in such a way can be sub-optimal as these heuristics don’t reason about the quality of the recovery. For example, a common heuristic is to recover to a previous state upon detecting a failure. But, it is preferable to recover closer to the goal in terms of execution cost. On the other hand, it is not known a priori if recovering close to the goal is feasible. To this end, we propose an algorithm Value Upper Confidence Limit (Value-UCL) that monitors the progress of all the recoveries during learning and decides online what failure modes to prioritize and which state to attempt to recover to such that the overall expected performance improves maximally in every episode. Not only does Value-UCL improve performance significantly faster than round-robin in all our experiments, in 3/5 of the experiments, it achieved the best performance of round-robin using only 70% of the training budget. Additional details, experiments and videos are available at [https://sites.google.com/view/recoverylearning/home](https://sites.google.com/view/recoverylearning/home).
II. RELATED WORK

Two prior works most closely related to ours are: (a) Wang et. al. [1] discover errors due to actuation uncertainty in simulation and learn recoveries by backtracking to a previous state and skipping the successor states. By contrast, we focus on state uncertainty, learn recoveries using reinforcement learning (RL) and allow for recovering to any safe state. (b) Pacheck et. al. [2] encode the robot’s capabilities in Linear Temporal Logic (LTL) which allows them to suggest additional skills that would make an infeasible task feasible. However, they do not deal with failures due to state uncertainty.

Recovery from Errors Robotic systems are usually deployed with hand-designed recovery behaviors in the anticipation of failures. Common recovery strategies include retrying the previous step [3], [4] and hand-designed corrective actions [5], [6]. More recently, there has been interest in learning a policy to recover to a safe state [7], [8]. However, these works assume full observability and do not focus on the efficiency of learning. To execute a recovery, it is important to first detect [9], [10], [11] what kind of failure has happened or is about to happen. Hung et. al. [12] treat high uncertainty at a state as a sign of potential failure. Zachares et. al. [13] deal with uncertainty more directly by maintaining a belief over object types and positions which is updated based on failures. Pastor et. al. [14] propose Associative Skill Memories which associate stereotypical sensory events with robot movements. This allows them to detect failures if the observed sensory input diverges from the expected input. In all these works, the recovery behaviors are either manually designed, which limits their scalability, or are generated using a heuristic, which limits their complexity. By contrast, we learn recovery behaviors with reinforcement learning which offers the possibility of learning complex recoveries.

Hierarchical Reinforcement Learning Hierarchical reinforcement learning (HRL) [15] is a powerful approach for difficult long-horizon decision making problems. It enables autonomous decomposition of the problem into tractable sub-tasks, often building hierarchies of states and policies. This hierarchy allows decisions to be made at higher levels of abstraction without having to deal with the low-level details. Temporally extended actions, called options [16] are used as an abstraction over low level robot actions while a symbolic representation [17] of the task can be learnt from skills. A number of prior works propose algorithms for skill discovery and learning [18], [19], [20]. Our work can be viewed as an option discovery and learning approach. However, in contrast with most HRL approaches that seek options that allow them to cover the whole state space, we seek to discover and cover the part of the state space (i.e. failures) most relevant to the task. Second, we focus on resource efficiency due to practical resource constraints and the difficulty of skill learning in robotics.

III. BACKGROUND

The Options Framework We model each robot skill as an option as per the options framework [16]. Each option consists of three components: (a) a robot control policy \( \pi \) (b) an initiation set which defines the states from which the option can be executed and (c) a termination condition which defines the states in which the option must terminate. In continuous spaces, the initiation set is typically estimated using a binary precondition classifier, called the pre-condition [21]. The skill precondition \( \rho(s) : S \rightarrow [0, 1] \) is a function that returns the probability that the skill can be successfully executed at a given state.

Recovery Skill A recovery skill is an option whose goal is to bring the system to a state from which its nominal control policies can take over. Formally, let \( \Pi = \{ \pi_1, \cdots, \pi_k \} \) be the nominal set of control policies of the robot and let \( \{ \rho_1, \cdots, \rho_k \} \) be their preconditions. We say that the robot has reached a failure state if none of the preconditions \( \rho_i \) are satisfied. A recovery skill (figure 4) drives the robot to a safe state where at least one of the preconditions is satisfied so that the robot can complete the task.

Acting under Uncertainty The problem of acting under partial or uncertain state information is optimally solved by formulating it as a Partially Observable Markov Decision Process (POMDP) [22], [23]. A POMDP is defined by the tuple \( \langle S, A, T, R, \Omega, \gamma \rangle \), where \( S \) is the underlying state space and \( \Omega \) is the observation space. In this formulation, the robot acts on its state belief \( b \), which is a probability distribution over all possible current states. However, this requires learning skills in the belief space which is much larger than the state space. Further, solving this POMDP exactly is intractable in manipulation [24]. Instead, we use a common heuristic technique of using a state estimator to maintain a belief over world states based on observations and actions, while the robot acts on the most likely state (MLS) [25]. This allows us to learn control policies in the underlying state space instead of the belief space.

IV. APPROACH

We are interested in solving a manipulation task defined by a distribution of start states \( D \) and a goal indicator function \( f_{goal} : S \rightarrow \{0, 1\} \). The robot incurs a cost \( c(s, a) \) based on its actions and a penalty of \( c_{fail} \) if it finds itself in a dead-end or is unable to complete the task in \( T \) timesteps. We are given a set of nominal control policies \( \{\pi_1, \cdots, \pi_k\} \) and a high level policy \( \Pi \) which chooses among these control policies. We assume that they can reliably complete the task under perfect state information. Our goal is to improve the robustness of the system by discovering and learning additional recovery skills that can handle failures due to execution under noisy state information. Formally, we maximize the expected return of the high-level policy on the task distribution

\[
E_{r \sim D} \sum_{t=0}^{T} R(s_t, a_t) \tag{1}
\]

where \( R(s, a) = -c(s, a) - c_{fail} 1_{\text{failure}} \) and \( s_t \) is the MLS as determined by a state estimator.

A. Symbolic Skill Graph

Instead of reasoning with low-level ground states, which are high dimensional, we build a compact symbolic skill
Fig. 2: Failure Discovery: We execute the nominal skills under a simulated state estimator to induce failures (shown in red). These failure states \( s \in S \) are clustered into failure modes using a Gaussian Mixture Model (GMM). This GMM is used as a failure classifier during execution.

Graph \( G = (V, E) \). Each vertex in this graph is a symbolic state corresponding to a set of continuous states defined by its precondition \( \rho : S \to \{0, 1\} \). There exists an edge between two vertices \( u, v \in V \) if there is a skill whose precondition contains \( u \) and its effect is contained in \( v \). We initialize this graph as a chain with vertices \( V = \{\rho_1, \ldots, \rho_k, \rho_{\text{goal}}\} \) corresponding to the preconditions of the nominal skills and edges \( E \) corresponding to the nominal policies. We call these vertices safe states as they are covered by the nominal policies. Key advantages [20] of learning this symbolic representation include the ability to plan at an abstract level and to define a dense reward function based on distance from the symbol using the precondition classifier.

B. Precondition Chaining

Similar to skill chaining [18], [19], we learn the preconditions of the nominal skills backwards from the goal. The main difference is that we are not interested in discovering new skills in this step but only in learning the preconditions of the given skills. We provide the details in the appendix. Our algorithm involves two steps:

1) We collect successful trajectories by executing the nominal skills in simulation. Let \( \{s_1, \ldots, s_k, s_{\text{goal}}\} \) be one such trajectory consisting of only the start and end states of each skill and \( s_{\text{goal}} \) is a state that satisfies the goal function. For every skill \( \pi_i \), we learn a corresponding positive distribution \( D^+_i \) over its start states \( S^+_i \).

2) We train the precondition classifiers backwards from the goal. To learn the precondition \( \rho_i \), we sample states in the vicinity of \( D^+_i \) and execute \( \pi_i \) from there. We verify its success using \( \rho_{i+1} (\rho_{\text{goal}} \, \rho_k) \). This helps us gather informative negative samples \( S^-_i \) and additional positive samples which are crucial for learning a tight decision boundary. The precondition classifier \( \rho_i \) is trained using \( S^+_i \) and \( S^-_i \).

C. Failure Discovery

We procedurally generate failure states in simulation by executing the nominal skills under noisy state information. Concretely, let \( s \) be the true current state and \( o \) be a noisy observation. While the true state is known to us in simulation, we provide only the observation to the nominal skills. Because of the mismatch between \( o \) and \( s \), the skill may not work as intended and the robot may end up in a new state \( s' \) with observation \( o' \). If none of the existing skills is applicable at \( s' \), we record \( s' \) as a failure state as the robot would not be able to recover from it even if it could observe the true state. Note that we do not record \( o' \) as it may not even be a valid world state. While a recovery for \( s' \) does not allow the robot to deal with its current observation \( o' \), it will be useful when the robot observes \( o \approx s' \). We propose two failure discovery strategies:

1) Pessimistic Discovery: The robot executes its nominal policies open-loop under simulated high state uncertainty. This strategy discovers a larger and more diverse set of failures than what may actually be encountered during execution. While this makes recovery learning computationally more expensive, it doesn’t require a model of the state estimator.

2) Early Termination: The robot executes its nominal policies using observations from a simulated state estimator and terminates if none of the preconditions are satisfied. This strategy discovers a more accurate failure distribution and is preferable if a model of the state estimator is available.

Let \( S_{\text{fail}} \) be the set of failures discovered. We cluster \( S_{\text{fail}} \) using a Gaussian Mixture Model (GMM) into \( n \) failure modes \( \{\rho'_1, \ldots, \rho'_n\} \) of sizes \( \{\alpha_1, \ldots, \alpha_n\} \). Each cluster contains similar failures and is added as a state to our symbolic skill graph. For failures discovered using the early termination strategy, the size of a failure cluster corresponds to the likelihood that the robot will end up in that failure. Both of these failure discovery strategies lead to recoveries that provide significant improvement in performance over heuristic recovery strategies in our experiments.

D. Learning Recovery Skills

From every failure mode \( \rho'_i \), the robot may recover to one of the \( k+1 \) possible safe symbolic states \( \rho_1, \ldots, \rho_{\text{goal}} \). Let \( \pi_{ij} \) be the recovery skill from \( \rho'_i \) to \( \rho_j \), where \( \rho'_i \) is its precondition and \( \rho_j \) is the desired effect. Let \( q_{ij} \) be the probability that \( \pi_{ij} \) successfully recovers to \( \rho_j \) after being triggered from a state in \( \rho'_i \). If \( \pi_{ij} \) fails then we assume it ends up in an absorbing failure state \( \text{Fail} \) incurring a penalty of \( c_{\text{fail}} \). \( \pi_{ij} \) can be learnt using off-the-shelf RL algorithms where \( \rho'_i \) is the initial state distribution and \( \rho_j \) is the goal condition. While we could use \( \rho_j \) to define a binary reward function for RL, this is usually impractical for manipulation. Fortunately, \( \rho_j \) can also be used to define a dense reward, for example, by computing the distance to the decision boundary or by using the probability \( \rho_j (s) \) as the reward. Finally, let \( \Pi \) be a high level policy that chooses which robot skill to execute at every symbolic state. \( \Pi \) can be computed quickly using Value Iteration as the symbolic skill graph is compact and discrete.

Failure Value (FV): Consider the optimistic recovery learning graph in figure 3; \( \rho'_1 \) and \( \rho'_2 \) are two failure modes which are initially not connected to any of the safe states as the success probability \( q_{ij} \) of all the recoveries is 0. At the start of recovery learning, the value of a failure mode \( V(\rho'_i) = -c_{\text{fail}} \). With further training, the value of
the failure mode \( V(\rho_i^f) = \max_j q_{ij} V(\rho_j) - (1 - q_{ij}) c_{\text{fail}} \) improves. \( V(\rho_j) \) is high as nominal skills can be executed reliably from \( \rho_j \). To take into account multiple failure modes, we define the failure value as an expectation over the values of all the failure modes:

\[
FV = \sum_i \frac{\alpha_i}{\sum_j \alpha_j} V(\rho_i^f)
\]

where \( \alpha_i \) is the size of cluster \( \rho_i^f \).

Intuitively, a high failure value implies that failures during execution are less problematic as the robot is highly confident of recovering. Learning recoveries that optimize the failure value also improve our original objective of expected return under partial observability \([1]\). A good first learning strategy is to train all the recoveries in a round-robin manner as we don’t know \textit{a priori} what the best recovery from every failure mode will be. While this works well in the initial stages of learning, we observed in our experiments that it is quite inefficient as the failure value quickly saturates (figure \([3]\)).

To address this, we propose an online algorithm that tracks the progress of all the recoveries and chooses what failure modes to focus on and what safe state to recover to such that the failure value improves maximally with high probability in every training episode.

\section{Value-UCL (Upper Confidence Limit) Algorithm}

The key idea of Value-UCL is to compute and use optimistic upper bounds \( \Delta q_{ij}^U \) on the rate of improvement \( \Delta q_{ij} \) of the success probabilities \( q_{ij}^* \) of all the recoveries. This provides an optimistic estimate of how much a recovery could improve after another round of training. Let \( \theta \) be a parameter we wish to estimate. An \( \alpha \)-confidence interval \([26]\) for \( \theta \) is an interval \((l, u)\) such that \( \theta \) is contained in the interval with probability \( \alpha \), i.e., \( u \) is an upper bound on \( \theta \) at least with probability \( \alpha \). Let \( \theta_1, \ldots, \theta_w \) be a random sample of the parameter. Under the assumption that the underlying population is normally distributed, the mean \( \mu \) of the distribution lies in the following interval with probability \( \alpha \):

\[
\bar{\theta} + t_{\alpha/2, w-1} \frac{s}{\sqrt{w}} \leq \mu \leq \bar{\theta} + t_{(1-\alpha)/2, w-1} \frac{s}{\sqrt{w}}
\]

\( t \) is the student’s \( t \)-distribution and \( s \) is the standard error.

We compute the upper confidence limit of \( \Delta q_{ij} \) using only the \( w \) most recent forward differences of \( q_{ij} \) as the rate of improvement is a non-stationary quantity \((w \text{ is a domain-dependent hyper-parameter})\). For every recovery with current success probability \( q_{ij}^* \), \( q_{ij}^* = q_{ij} + \Delta q_{ij}^U \) is then an optimistic bound on its success probability after an additional round of training. Let \( \Delta q_{ij}^U \) be the failure value computed by replacing \( q_{ij} \) with \( q_{ij}^* \) in the transition matrix of the optimistic recovery learning graph \([3]\). \( \Delta q_{ij}^U \) then provides an optimistic upper bound on the failure value if we were to train \( \pi_{ij}^* \) for another round. Our algorithm picks a recovery for training that promisses the highest failure value in the next round. We initialize Value-UCL with \( K \) rounds of round-robin to estimate the UCL. Priors on \( \Delta q_{ij} \), if available, can further speed up learning.

\section{Experiments}

We evaluate our approach on the task of door opening under noisy handle position information both in simulation and in the real world. The goal is to open a door by at least 0.3 rad with the Franka Panda robot under high initial state uncertainty.

\textbf{Simulation Environment:} We adapt the door environment from the MuJoCo-based robosuite \([27]\), [28] framework to match our real door. The world state is 18 dimensional and includes the robot’s joint angles and poses of the door and the handle. The initial state uncertainty is sampled from
where $f_{D^+}$ is the probability density function of the corresponding $D^+$.

**Evaluation: Recovering Skills**

We first evaluate the effectiveness of our overall approach by assuming that the standard deviation of the noise distribution halves after every robot action. As we show in table I, learnt recoveries are significantly better than heuristic recovery strategies in improving success rate. Recovering from failures during door opening often requires the robot to (1) carefully move the handle so as not to weaken the grasp and (2) avoid collision with the environment. Heuristic recoveries are unable to account for this and hence perform poorly. Compared to open-loop execution, our approach substantially improves task success rate from 71% to 92.4%. This indicates that (1) the failures discovered using our pessimistic failure discovery strategy we described earlier. We execute the nominal skills 1000 times for failure discovery to collect a total of 1400 failure states which we group into 6 clusters using the Gaussian Mixture Model (GMM) [31]. Common failure modes include the robot missing the handle and the robot slipping while pulling the handle due to an improper grasp. We learn recovery skills in simulation using a budget of just 150 REPS queries. With 24 potential recovery skills, this means that each recovery policy can get only 6 data-points on average.

**Evaluation in Simulation:** We simulate a state estimator and a limit of 10 skills per evaluation. The statistics are averaged over 5 sets of recovery skills learnt with different seeds, each evaluated 200 times using a simulated state estimator and a limit of 10 skills per evaluation.

**Symbolic Skill Graph:** We train the preconditions of the nominal skills by precondition chaining using a total of 1223 positive and negative samples. Each precondition is a generative classifier with the positive distribution $D^+$ learnt as a Gaussian distribution and the negative distribution $D^-$ learnt as a Gaussian Mixture Model. The 3 nominal skills result in 4 symbols for the start, subgoals, and the goal.

**Recovery Skill:** Each recovery skill $\pi_{ij}$ is a parameterized skill [29] that uses a regression model to predict robot actions $\theta \in \Theta$ based on the start state $s$. We use k-nearest neighbours regression to predict a 21D vector, a sequence of three 6D poses with respect to the initial end-effector pose and gripper open/close states, as robot actions. Collecting data of the form $(s, \theta)$ for training this regression model involves sampling a start state $s$ from the failure mode $\rho_{ij}^f$ and computing the robot action parameters $\theta$ for recovery to $\rho_{ij}$ using Relative Entropy Policy Search (REPS) [30]. For learning a recovery to precondition $\rho$, REPS uses the reward function

$$R(s) = 0.1 \log f_{D^+}(s) + 10\rho(s)$$

where $f_{D^+}$ is the probability density function of the corresponding $D^+$. Each REPS query takes about 2 minutes to solve on our Intel® Core™ i7-9700K CPU.

**Evaluation on a Real Robot**

We transfer the precon-
conditions, failure classifier, nominal skills and recovery skills learnt in simulation to a real Franka Panda robot and run experiments with (a) 5 different lever latch handles on a small door and (b) a full-sized door in our building with a cylindrical handle (figure 4). We fine-tune only the gains of the impedance controller on the real robot by increasing their values for better tracking. As in simulation, the robot is controlled by a Cartesian-space impedance controller that executes each skill open-loop. We evaluate the recovery skills learnt in simulation under an idealized state estimator. The ground-truth handle position is known to us but at $T = 0$, we only provide a noisy handle position estimate to the robot, where, noise $\sim N(0, \sigma = 2cm)$. The robot executes its nominal skill using this noisy state information. At $T = 1$, by the time the robot finishes executing the first skill, we assume that the state estimator has converged to the ground-truth. Hence, the robot has access to the accurate handle position at this point. The robot uses its preconditions to check if any of its nominal skills can be executed. If so, it executes the remaining nominal skills. If not, it uses the failure classifier to identify the failure mode and execute the best recovery from that mode.

We compare our approach (RECOVERY) with open-loop execution (OPEN-LOOP) of nominal skills (table 1). The success rate of OPEN-LOOP is sensitive to the handle and varies from $50 - 80\%$. By contrast, RECOVERY improves the success rate to $80 - 90\%$ consistently across all of the 5 handles even though it was trained only for handle 1. Both OPEN-LOOP and RECOVERY struggle at the full-sized door due to the slippery cylindrical handle. However, our approach still does significantly better than OPEN-LOOP which only succeeded in $3/10$ attempts. We expect recovery performance to improve with further training and by the use of a good state estimator which will enable closed-loop behavior. Importantly, our approach did not induce any additional failures which indicates good transfer of the preconditions and failure classifier learnt in simulation.

B. Evaluation of Value-UCL

In this evaluation, we assume that we have access to an accurate model of the state estimator so that we can estimate the failure distribution accurately. We discover failures using our early termination discovery strategy along with a simulated state estimator that halves the standard deviation of the noise distribution after every robot action. We discover a total of 2000 failure states which we group into 5 clusters using the GMM. These failures are less diverse than the failures discovered by pessimistic discovery and are more concentrated near the handle door. We compare round-robin learning of recoveries with our proposed Value-UCL algorithm in figure 6 on 5 different seeds. We use $\alpha = 0.95$ to compute the confidence interval, window size $w$ of 3 and query REPS for a new data-point in every round, i.e. $\eta = 1$. We initialize the UCL estimates by training every recovery twice in a round-robin order. Value-UCL is used to select which recoveries to learn from episodes 41 to 100. It not only improves significantly faster than round-robin, but it also converges to a better Failure Value (FV) in all the trials. In 3/5 trials, Value-UCL used only 70% of the training budget to achieve the best FV achieved by round-robin, i.e., 1 hour earlier. This shows that it can make better use of training resources to improve robustness.

VI. CONCLUSION

We propose a scalable algorithmic framework to efficiently robustify a given manipulation strategy against failures due to state uncertainty. Our method consists of discovering failures in simulation by evaluating the given strategy under simulated partial observability and then learning recoveries using reinforcement learning. We also propose an efficient recovery learning algorithm Value-UCL that chooses which recoveries to learn such that the expected value of failure states improves the most, in turn, improving the expected return on the task. Our experiments on door opening show that compared to open-loop, the learnt recovery skills improve task success from 75% to 90% in the real world and Value-UCL learns significantly better recoveries than round-robin. In our future work, we would like to combine failure discovery in the real world with discovery in simulation to further improve robustness. Finally, we are also interested in investigating if we can provide theoretical bounds on the performance of Value-UCL.
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