Reactive Task and Motion Planning under Temporal Logic Specifications

Shen Li†*, Daehyung Park‡*, Yoonchang Sung†*, Julie A. Shah†, and Nicholas Roy†

Abstract—We present a task-and-motion planning (TAMP) algorithm robust against a human operator’s cooperative or adversarial interventions. Interventions often invalidate the current plan and require replanning on the fly. Replanning can be computationally expensive and often interrupts seamless task execution. We introduce a dynamically reconﬁgurable planning methodology with behavior tree-based control strategies toward reactive TAMP, which takes the advantage of previous plans and incremental graph search during temporal logic-based reactive synthesis. Our algorithm also shows efﬁcient recovery functionalities that minimize the number of replanning steps. Finally, our algorithm produces a robust, efﬁcient, and complete TAMP solution. Our experimental results show the algorithm results in superior manipulation performance in both simulated and real-world tasks.

I. INTRODUCTION

Consider the problem of collaborative operation between humans and robots [1]. A central challenge is responding in real-time to changes that might render the current robot task incomplete or inefficient. For example, we might like to ask a robot to “pack up all the objects into the box” as shown in Fig. 1. To achieve this complex goal, task-and-motion planning (TAMP) has been widely used for producing a sequence of actions [2]–[5]. During execution, a human partner might help the robot by packing up some of the objects or providing tools (e.g., a tray) to the robot. However, such changes may make the current plan invalid. The robot’s plan might not have accounted for the new tool. Operating alongside human partners may require replanning-and-execution on the fly.

A popular replanning-and-execution approach is reactive synthesis that finds control strategies to react to environmental model changes including object position [6]–[8], proposition [9], and uncertainty [10] while satisfying a given task formalization [11], [12]. However, its reasoning process often requires the planner to construct a graph explicitly capturing feasible states (i.e., nodes) and edge connectivity between the states to ﬁnd solutions. A wide range of model changes due to interventions leads to computationally expensive state-graph (re-)construction and search. Further, this graph reconstruction may lower execution efﬁciency, pausing ongoing motion until a new plan is reestablished.

We propose a reactive TAMP method that hierarchically reacts to various levels of task interventions (e.g., the position changes of objects, addition/deletion of objects) by introducing complementary layers of planning and execution. The planning layer includes complete and efﬁcient reactive synthesis using linear temporal logic (LTL) suitable to formally specify complex objectives and interventions [13]–[16]. In detail, the method produces a sequence of action plans combining symbolic and (joint space) motion-cost based geometric searches over the LTL automata. Given environmental changes, our ﬁrst contribution is to show how to ﬁnd a new plan with minimal search effort by incrementally expanding the search space and leveraging experience such as previously explored paths and corresponding costs.

For the execution layer, we propose a behavior tree (BT) that conditionally activates sub-control policies (i.e., subtrees) to reactivity follow action plans from the planning layer. BTs have been widely used to handle new or partially updated policies, as well as environmental changes [17]–[19]. We use the modularity of BTs, which allows easier composition, addition, and deletion of policies on the ﬂy, to partially update policies without pausing ongoing executions. Our second contribution is to show that the recovery strategies of conditional BTs [7], [20] can minimize expensive replanning steps with LTL. By relaxing the activation conditions of trees, we maximize the recovery range and minimize replanning requests given environment changes such as object relocation.

In this work, we consider a robot that conducts a pick-and-place task of multiple objects where a human operator either cooperatively or adversarially could move the same objects. The robot can recognize the unexpected changes only by observing the location of objects. We assume that the robot does not suffer from partial and uncertain observations in this work. We do not explicitly model the human as another
agent but rather consider as a part of the environment. We show our robot is able to adaptively change its plan on the fly to complete a given task. The key contributions include:

- We present a robust TAMP method that hierarchically reacts to various environment changes or new temporal logic specifications.
- Our planning layer provides quickly replanned solutions based on past experience, online graph extension, and reconfigurable BT structures.
- Our execution layer allows seamless plan execution even with environment changes and computation delays.
- We demonstrate that our method outperforms various baselines in terms of time efficiency and motion cost-effectiveness via physics-based simulations. We also conduct proof-of-concept experiments with a UR5 robot from Universal Robots.

II. TEMPORAL-LOGIC PLANNING

We present a brief introduction to the LTL planning framework (more details in [21]) and show how we define variables used in the framework.

The planning problem studied in this work is to move a set of objects from initial locations to desired goal locations while overcoming environmental changes that might occur unpredictably. To enable temporal reasoning and guarantee task completion, we adopt temporal logic-based planning to synthesize a plan for the robot that achieves LTL task specifications, owing to its correct-by-design nature.

We model the robot and its workspace as a transition system (TS), which can be defined as tuples as follows:

**Definition 1. (Transition system)** $TS = (S, s_0, A, \delta_1, \Pi, \mathcal{L})$, where $S$ is a finite set of states ($s \in S$), $s_0$ is an initial state, $A$ is a set of actions, $\delta_1 : S \times A \rightarrow S$ is a deterministic transition relation, $\Pi$ is a set of atomic propositions, and $\mathcal{L} : S \rightarrow 2^\Pi$ is a labeling function that maps each state to a subset of atomic propositions that hold true.

We compose an object $o_i$ with a region $r_j$ to denote a state $s$ in $TS$, i.e., $s = o_ir_j$, implying that the object $o_i$ is located in the region $r_j$. Let $O = \{o_1, \ldots, o_n | o_i \in \mathbb{R}^3\}$ be the set of $n$ prehensile object states exist in the workspace of the robot, where $o_i$ is the 3D positional vector of the $i$-th object. The objects are placed in $m$ discrete and non-overlapping regions which we achieve by abstractly partitioning a continuous workspace. We denote the set of $m$ region states by $R = \{r_1, \ldots, r_m | r_j \in \mathbb{R}^3\}$. The robot can observe which objects belong to which region through its perception. For multiple objects we represent a state $s$ by splitting pairs of an object $o_i$ and region $r_j$ by underscore, e.g., $s = o_1r_1.o_2r_3$. The cardinality of $S$ is $|R|^{[O]}$. An element of the action set $A$ is represented by $\text{move}_{o_i}r_j$ that is to pick an object $o_i$ from its current location and place $o_i$ in region $r_j$. An atomic proposition $\pi \in \Pi$ corresponds to a state $s \in S$ that is either true or false statements that must be specified for a given task. For example, $\pi = o_ir_j$ is true if an object $o_i$ is in a region $r_j$, or false otherwise. $\mathcal{L}$ maps a state $s \in S$ to a set of true atomic propositions $\mathcal{L}(s) \subseteq \Pi$.

An LTL formula $\varphi$ is a combination of Boolean operators and temporal operators, which is involved with a set of atomic propositions $(\subseteq \Pi)$. The formula $\varphi$ can express non-Markovian temporal properties, such as temporally-extended goals. The syntax of the formula $\varphi$ over $\Pi$ is as follows:

$$\varphi = \pi \mid \neg \varphi \mid \varphi_1 \lor \varphi_2 \mid X\varphi \mid \varphi_1 \mathcal{U}\varphi_2,$$

where we denote $\pi \in \Pi$, “negation” ($\neg$), “disjunction” ($\lor$), “next” ($X$), and “until” ($\mathcal{U}$). We can additionally derive a Boolean operator “conjunction” ($\land$) and temporal operators “always” ($\mathcal{G}$) and “eventually” ($\mathcal{F}$) from the basic syntax. A detailed explanation can be found in [21].

A word is an infinite sequence of atomic propositions in $\Pi$ defined over the alphabet $2^\Pi$. There exists a union of infinite words that satisfies a given formula $\varphi$. Alternatively, the non-deterministic B"uchi automaton ($\mathcal{BA}$) constructed according to [22] is generally used to check the satisfiability of $\varphi$.

**Definition 2. (B"uchi automaton)** $\mathcal{BA} = (Q_b, q_{b,0}, \Sigma, \delta_b, F_b)$, where $Q_b$ is a finite set of states ($q_b \in Q_b$); $q_{b,0}$ is an initial state; $\Sigma = 2^\Pi$ is an alphabet from the LTL formula; $\delta_b : Q_b \times \Sigma \rightarrow 2^Q_b$ is a non-deterministic transition relation; and $F_b \subseteq Q_b$ is a set of accepting states.

We then generate a product automaton ($\mathcal{PA}$) by applying the $TS$ and $\mathcal{BA}$ as follows:

**Definition 3. (Product automaton)** $\mathcal{PA} = TS \times BA = (Q_p, q_{p,0}, \Sigma, \delta_p, F_p)$, where $Q_p = S \times Q_b$ whose element is $q_p = (s, q_b) \in Q_p$; $q_{p,0} = (s_0, q_{b,0})$; $\Sigma = 2^\Pi$; $\delta_p : Q_p \rightarrow Q_p$; and $F_p \subseteq Q_p$. Note that $\delta_p$ satisfies $(s', q_b') \in \delta_p(s, q_b)$ iff there exist $a \in A$ and $\delta_b$ such that $s' = \delta_b(s, a)$ and $q_b' \in \delta_b(q_b, \mathcal{L}(s))$.

$\mathcal{PA}$ becomes a search graph used for finding a plan. Finding a valid path that starts from an initial state $(s_0, q_{b,0})$ to one of accepting states $(s_f, q_{b,F})$ where $q_{b,F} \in F_b$ implies computing a feasible plan $\xi = \{(s_i, q_{b,i})\}_{i=0,1,\ldots,F}$ that achieves a given formula $\varphi$.

We study a scenario where unexpected human intervention affects the state of objects. A human operator might add new objects, remove existing objects, or move an object to a different region. This is equivalent to keeping the LTL specification $\varphi$ as it is while dynamically modifying the $TS$ and $\mathcal{PA}$ to reflect the changes. Previous works also considered the same reactive approach as ours [9], [10], or relaxed the LTL specification $\varphi$ instead while keeping the $TS$ [23], [24] for handling the changes. However, they mostly focused on navigation tasks.

The objective in this work is that the robot places all objects $O$ to desired goal regions among regions $R$. Although human intervention occurs unpredictably, the robot must be able to correct $TS$ and adjust its plan to accomplish a given task. Besides robustness, we would like the proposed replanning algorithm to additionally exhibit time efficiency and completeness.
III. DYNAMICALLY RECONFIGURABLE PLANNING

We address the proposed problem by directly finding a plan over the $\mathcal{PA}$ that satisfies an LTL formula $\varphi$, i.e., placing all objects $O$ in desired goal regions $R$. We achieve this by a hierarchical architecture (Fig. 2) that disentangles the high-level planning from low-level motor control commands. We handle unexpected changes by human intervention in upper layers of the architecture.

The entire proposed hierarchical architecture consists of three layers: (1) The high-level planning layer computes a high-level plan that satisfies LTL specifications; (2) The middle-level execution layer dynamically constructs BT to make high-level plans executable for low-level controller of the robot; and (3) The low-level layer outputs control inputs used in actuators. The inputs to the architecture are a robot model, information about workspace, and LTL specifications $\varphi$ and the output is low-level control inputs. Additional inputs are environmental changes that can be detected via perception.

![Overall hierarchical architecture. The high-level layer contains the TS, BS, and PA that check the satisfiability of an LTL formula $\varphi$ as well as external databases, i.e., experience and skill library. The middle-level layer communicates between a high-level plan and a low-level controller via BT with a subtree database. The low-level layer outputs motor control commands to a robot.](image)

Fig. 2: Overall hierarchical architecture. The high-level layer contains the TS, BS, and PA that check the satisfiability of an LTL formula $\varphi$ as well as external databases, i.e., experience and skill library. The middle-level layer communicates between a high-level plan and a low-level controller via BT with a subtree database. The low-level layer outputs motor control commands to a robot.

Three desirable properties we aim at are robustness (against intervention), efficiency (in computing a plan), and completeness. We achieve robustness efficiently by (1) handling intervention without involving the expensive task planner and only calling the planner when necessary; (2) reusing partial plans from the past; (3) computing a cost-effective plan by incorporating a motion cost computed by inverse kinematics; and (4) maintaining a partial graph of $\mathcal{PA}$. We achieve completeness by employing an LTL-based planning.

In Section III-A, we present the capability of each component in our system and the pseudo-code of the framework. In Section III-B, we introduce the search algorithm with motion cost to achieve a cost-effective solution. In Section III-C, we present two ways of speeding up the search algorithms: reusing partial plans and maintaining a partial graph of $\mathcal{PA}$. In Section III-D, we explain the BT reconstruction in detail.

A. Robust Hierarchical System Design

In this subsection, we highlight which component of the hierarchical structure deals with which environmental changes. These components are in charge of different replanning queries that arrive at random time, including search graph construction and experience-based graph search in the high-level layer, and BT in the middle-level layer. In particular, we consider the following types of environmental changes: object relocation while previous plans are feasible or infeasible, and the addition and removal of objects and regions. Note again that the change in an LTL formula $\varphi$ is not considered.

The process of the system handling environmental changes is illustrated in Alg. 1. In line 5 when the object is relocated to one of existing regions, there are cases where the previous plans can be reused if the plans have been reserved as subtrees in the BT (details are explained in Section III-D). In particular, if there are still executable subtrees (line 6), the expensive task planner will not be queried. For example, as shown in Fig. 1, if the robot fails to pick up a block due to perception error, the BT will re-activate specific subtrees to attempt to grasp the block again.

Object relocation could also occur where previous plans are no longer feasible. To handle this case, our system will use the same graph (skipping line 13) and query a search algorithm to produce a new plan (line 16). Particularly, the search algorithm (Section III-B) improves its planning efficiency by reusing the planning experiences computed and cached from the previous queries and maintaining a partial graph (Section III-C). The BT will then receive the new plan and add/delete subtrees while keeping reusable subtrees for execution (line 17) (Section III-D).

B. Planning for LTL specifications

We use a weighted directed graph $G = (V, E, w)$ to represent the $\mathcal{PA}$ and deploy a graph search algorithm for planning. In particular, each $q_p \in Q_p$ corresponds to a node $v \in V$. For each $q_p$ and $q'_p$ where $q'_p \in \delta_p(q_p)$, there is an edge $e \in E$ between the nodes associated with $q_p$ and $q'_p$.

We incorporate the notion of motion cost into the $\mathcal{PA}$ as a weight $w$ on an edge $e$ of $G$. We compute the motion cost as the incremental displacement of a robot’s end effector, which can be obtained from a skill library assumed to be given. For example, when a manipulator approaches some location, the motion cost can be computed by inverse kinematics and saved as one of skills in the library. This allows for cost-effective plans with respect to a cumulative motion cost.

To increase the planning efficiency, we propose two improvements over general graph search algorithms: (1) leveraging the computations from the past to reduce the computation in motion costs for a new replanning query; and (2) constructing $G$ on the fly to avoid the overhead of generating a graph from scratch whenever the world changes.

C. Search Acceleration

We attempt to speed up the search algorithm by reusing previous plans and partially constructing a search graph. When
searching for a path in $G$, computing a motion cost on edge is costly as it requires solving an inverse kinematics problem. We cache the motion cost of edges newly explored so far as well as corresponding node names as a table data structure. When a node associated with $q_p$ is chosen to be expanded, the system will query $\delta_p$ to produce the list of next states $\{q'_p\} = \delta_p(q_p)$ and add them to $V$ and $E$ accordingly. In the worst case, if the heuristic is not effective at all, all nodes in $V$ will be expanded, and $G$ will be fully constructed. We call this approach partial graph construction. We show the efficiency of partial graph construction against the approach of fully constructing $G$ every time before the search (full graph construction) in Section V.

D. Behavior Tree & Reconfiguration

The BT is a compositional decision-making system that can group a set of behaviors, execute between groups at a fixed frequency, and change the structure on the fly. The execution starts from the root of the BT. It then gradually traverses the execution permission (the tick) from the root to child nodes. Once a node receives the tick, the node execution returns: 1) SUCCESS if the node execution was successfully completed, 2) RUNNING if the execution is not completed yet, 3) FAILURE if the execution was failed, and 4) INVALID otherwise. Fig. 3 shows the execution flow given a sequence of action plans, where $\rightarrow$ and $\Rightarrow$ represent sequence and selector behaviors, respectively (see details in [25]).

![Algorithm 1: LTL-BT System. Efficiently handling various types of interferences and updating the subtrees $\Psi$ in BT.](image)

```
Algorithm 1: LTL-BT System. Efficiently handling various types of interferences and updating the subtrees $\Psi$ in BT.

Input: $\mathbf{BA}$, $\mathbf{TS}$, $\Psi$
1 $s \leftarrow s_0$; // Initial state
2 $E \leftarrow \emptyset$; // Empty experience
3 while Environmental changes do
4     $s_{new} \leftarrow \text{GetStateFromPerception}();$
5     if Objects relocated then
6         $i \leftarrow \text{Find the subtree index of}$
7             $(A^1, C^\text{pre}_1, C^\text{post}_1) \in T$ such that $C^\text{pre}_1 \subset s_{new};$
8     if $i$ is found then
9         // Subtree $i$ can resolve this change by selecting action $A^1$. No replanning is needed
10        continue;
11     end
12     $s \leftarrow s_{new};$
13     if Objects added/removed or regions added then
14         $\text{// Search graph reconstruction}$
15         $\text{TS} \leftarrow \text{ReconstructTS}(\text{TS}, s);$  // Alg. 2
16     end
17     $q_{p,0} \leftarrow (s, q_{b,0});$ // Construct PA state
18     // Replan to find action tuples with partial graph construction, use cache experience (Sec. III-B, III-C)
19     $P, E \leftarrow \text{LTLPlanner}(q_{p,0}, \mathbf{BA}, \mathbf{TS}, E);$  // Update subtrees in BT (Sec. III-D)
20     $\Psi \leftarrow \text{BTReconfiguration}(P, \Psi);$  // Alg. 2
21 end
```

There are previous works [24], [26], [27] adopting both the LTL and BT for synthesizing controls from high-level plans. However, their methods cannot deal with environmental changes studied in this work.

We now describe how to build the internal structure of the BT given a high-level plan and reconfigure it on the fly.

1) Automatic tree construction: We convert a sequence of action plans $P$ to a sequence of subtrees $\Psi$, which can be attached to the task root of a BT. Similar to the planning domain description language (PDDL [28]), we use preconditions and effects to achieve complex sequences of behaviors similar to [20], [27]. To build the tree, we parse a plan $P$ into a sequence of action tuples $T = \{(A^1, C^\text{pre}_1, C^\text{post}_1), (A^2, C^\text{pre}_2, C^\text{post}_2), \ldots\}$, where $A^i$, $C^\text{pre}_i$, and $C^\text{post}_i$ represent an action, a pre-condition, and a post-condition, respectively. For example, given two consecutive states $(o_1 r_1, o_2 r_1, o_1 r_2, o_2 r_1)$, the action is $o_1$’s move from $r_1$ to $r_2$, where $C^\text{pre} = \{o_1 r_1, o_2 r_1\}$ and $C^\text{post} = \{o_1 r_2, o_2 r_1\}$.

We then convert the tuple to a state condition-based subtree as shown in Fig. 3a, where $C_R$ represents a set of running conditions (e.g., $o_1 r_{\text{hand}} \neg o_2 r_1$) from [7] and the State Update decorator forces the current state to be updated after the

![Fig. 3: Subtree structures. Chooser is a custom selector that does not interrupt the low priority of a child node from the higher priority of nodes.](image)
Algorithm 2: BT Reconfiguration. $P_A^i$ and $Ψ_A^i$ represent the action name of the $i$-th action tuple and subtree, respectively. Likewise, $P$ and $A$ with the subscript $C$ represent their preconditions. The superscript $-i$ accesses the $i$th element from last.

Output: $Ψ$

1. $P ← (P_A^1, ..., P_A^n)$ // A seq. of action tuples
2. $Ψ ← (Ψ_A^1, ..., Ψ_A^m)$ // A seq. of subtrees
3. for $i ← 1$ to $n$ do
   4. if $P_A^i = Ψ_A^i & |Ψ| ≥ i$ then
      5. $Ψ_C^i ← P_C^i$ // Update conditions
   6. else if $P_A^i ∉ Ψ_A^{-i}$ then
      7. $j ← \text{find the index of } P_A^{i-1} \text{ at } Ψ_A^{j-1}$
      8. $\text{Remove subtrees at } Ψ_A^{j-1}$
      9. else
         10. $\text{Add a subtree for } P_A^{i-1} \text{ at } Ψ_A^{i-1}$
   11. end
12. end
13. if $|Ψ| ≠ n$ then
   14. $\text{Remove } ∀s ∈ Ψ_A^1:|Ψ|−n$
15. end

completion of an action. Note that $C_{post}^i$ equals to $C_{pre}^{i+1}$ in this sequential plan so that we can ignore post conditions. This structure can also re-execute the previous actions if the current state satisfies the precondition. However, the state-based condition may be too conservative in that a full state specification cannot ignore unrelated environmental changes.

Alternatively, we introduce a relaxed version of subtree constructor, the action condition-based subtree (see Fig. 3B), that is designed to prevent unnecessary replanning given unrelated or minor environmental changes such as object additions, deletions, and repositions. The subtree also allows more recovery behaviors. In particular, the precondition node checks soft conditions including the location of the target object, object source, and object destination (e.g., $C_{pre} = o_{i}r_{1}$). We also use a customized selector, called chooser [25], as a root of each subtree that is to prevent interruption from higher priority of sibling subtrees. This enables BT to complete an ongoing action.

2) Online reconfiguration: We introduce how we can reconfigure a BT without interfering with running tasks (i.e., running subtrees) on the fly. Given environmental changes, the planner will produce a new plan $P'$, which may not be completely different from the previous plan $P$ so it is not necessary to reconstruct a sequence of subtrees $S$ from scratch. Alg. 2 shows how we can find sharable subtrees between $P$ and $P'$ from the back. If there is a new action in $P'$, we add a new subtree to $S$. Otherwise, we remove the unmatched subtrees. Note that if there are any running and non-interruptible subtrees, our framework postpones the change of the subtree until the return of the subtree is changed.

IV. EXPERIMENTAL SETUP

A. Statistical Evaluation

We evaluated our method with baselines on two environment settings in a physics-based simulator, GAZEBO. To show the performance of the execution layer, we compared three variations of the BT: online reconfiguration with action condition, online reconfiguration with state condition, and offline reconstruction with action condition over two scenarios. Note that the offline reconstruction stops a running node to remove all subtrees. It then constructs a new tree from scratch in an idle mode. Fig. 4 shows the online reconfiguration with action condition resulted in a smaller number of BT changes and took less completion time compared with that of offline reconstruction.
state condition. Due to the short replanning time of A* with experience, the online method with action and state conditions resulted in a similar completion time in the 3-Block scenario. On the other hand, the offline reconstruction incurred longer average completion time than online BT. Overall, the results demonstrate that the online BT reconfiguration with action condition is the most efficient among the variations.

We benchmarked three search algorithms, A*, with experience, A*, and Dijkstra, in the 3-block + tray scenario, each with three types of environmental changes (repositioning, adding, or deleting a block). We split all planning processes in each trial into (1) initial planning in the very beginning and (2) replannings, used for intervention handling. Table I highlights the robustness and efficiency of our hierarchical system. The column “# replan” presents that both means and medians of the number of replannings for object repositionings are lower than those for additions and deletions across all algorithms. This result demonstrates that the system’s efficiency in handling repositionings by using the BT alone without the expensive replanning unless necessary. The mean of the number of replannings for object repositioning is non-zero because sometimes it is necessary to replan. For example, if $o_i$ is repositioned to $r_1$ when $r_3$ is near $r_2$, since the state $o_i r_1 r_3 r_2$ is not in the optimal initial plan, no subtrees in BT can handle this case alone without replanning.

Table I highlights the efficiency of the experience-based search. A* with experience leverages the similarity between the initial plan and the plans for intervention handling. In Table I, A* with experience has a significantly lower total replanning time than A* and Dijkstra among all types of environmental changes. The initial planning time is almost the same across three algorithms due to a lack of experience in the very beginning. To demonstrate the overall efficiency, we report the completion time of each trial. Among all types of environmental changes, A* with experience achieves significantly shorter completion time due to faster replanning. The success rate is always 100% in Table I as our system guarantees task completion.

We validated the efficiency of the partial graph construction over the full graph construction through simulations. We measured the time taken for both constructing the PA and replanning when an object was added as environmental changes for efficiency comparison. We fixed the number of regions to be five while varying the number of objects from two to six, resulting in the number of states in the PA to vary from 50 to 31,250. We randomly generated locations of regions ten times. Fig. 5 shows the mean and the standard deviation of a total time measured over ten random interventions scenarios. Given the same LTL specification, we finally demonstrated the proposed TAMP method with a real UR5 robot. Fig. 5 shows captures of two representative intervention scenarios. Given the same LTL specification,
our robot successfully initiated a complete task and motion plan to transfer all objects to another storage by visually recognizing the environment. When an operator added and relocated objects, the online BT enabled the robot to continue seamless task execution while replanning the new setup. The proposed graph construction and experience-based planning enabled the robot quickly to transition to a new plan. Given a new transfer tool (see Fig. 5d), our system could also show cost-effective behaviors by utilizing the tray as we humans do. These demonstrations show our framework enables the robot to achieve robust and efficient high-level planning and middle-level execution in human–robot operation scenarios.

VI. DISCUSSION & CONCLUSION

We introduce a hierarchically reactive TAMP method, which generates a complete and semi-optimal task plan by using LTL and approximated motion costs. Our framework provides an efficient replanning approach leveraging experience-based graph search and node modification algorithms. In addition, to minimize the replanning and also maximize the recovery control capability, we combine it with a dynamically reconfigurable BT with the action condition subtree structure. Our statistical evaluation shows the superial efficiency compared to other baseline methods. We also demonstrate the robustness in real world with a UR5 robot.

REFERENCES

[1] A. Ajoudani, A. M. Zanchettin, S. Ivaldi, A. Albu-Schäffer, K. Kosuge, and O. Khatib, “Progress and prospects of the human–robot collaboration,” Autonomous Robots, vol. 42, no. 5, pp. 957–975, 2018.
[2] N. T. Dantam, Z. K. Kingston, S. Chaudhuri, and L. E. Kavraki, “Incremental task and motion planning: A constraint-based approach,” in Proceedings of Robotics: Science and Systems (RSS), vol. 12, p. 000052, Ann Arbor, MI, USA, 2016.
[3] C. R. Garrett, T. Lozano-Pérez, and L. P. Kaelbling, “Sampling-based methods for factored task and motion planning,” International Journal of Robotics Research, vol. 37, no. 13-14, pp. 1796–1825, 2018.
[4] W. Vega-Brown and N. Roy, “Asymptotically optimal planning under piecewise-analytic constraints,” in Algorithmic Foundations of Robotics XII, pp. 528–543, Springer, 2020.
[5] S. Srivastava, E. Fang, L. Riano, R. Chitnis, S. Russell, and P. Abbeel, “Combined task and motion planning through an extensible planner-independent interface layer,” in Proceedings of the IEEE International Conference on Robotics and Automation (ICRA), pp. 639–646, IEEE, 2014.
[6] K. He, A. M. Wells, L. E. Kavraki, and M. Y. Vardi, “Efficient symbolic reactive synthesis for finite-horizon tasks,” in Proceedings of the IEEE International Conference on Robotics and Automation (ICRA), pp. 8993–8999, IEEE, 2019.
[7] C. Paxton, N. Ratliff, C. Eppner, and D. Fox, “Representing robot task plans as robust logical-dynamical systems,” in Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), pp. 5588–5595, IEEE, 2019.
[8] T. Migimatsu and J. Bohg, “Object-centric task and motion planning in dynamic environments;” IEEE Robotics and Automation Letters, vol. 5, no. 2, pp. 844–851, 2020.
[9] M. Guo, K. H. Johansson, and D. V. Dimarogonas, “Revising motion planning under linear temporal logic specifications in partially known workspaces;” in Proceedings of the IEEE International Conference on Robotics and Automation (ICRA), pp. 5025–5032, IEEE, 2013.
[10] S. C. Livingston, R. M. Murray, and J. W. Burdick, “Backtracking temporal logic synthesis for uncertain environments,” in Proceedings of the IEEE International Conference on Robotics and Automation (ICRA), pp. 5163–5170, IEEE, 2012.
[11] H. Kress-Gazit, G. E. Fainekos, and G. J. Pappas, “Temporal-logic-based reactive mission and motion planning,” Transactions on Robotics, vol. 25, no. 6, pp. 1370–1381, 2009.
[12] E. M. Wolff, U. Topcu, and R. M. Murray, “Efficient reactive controller synthesis for a fragment of linear temporal logic;” in Proceedings of the IEEE International Conference on Robotics and Automation (ICRA), pp. 5033–5040, IEEE, 2013.
[13] S. Chinchali, S. C. Livingston, U. Topcu, J. W. Burdick, and R. M. Murray, “Towards formal synthesis of reactive controllers for dexterous robotic manipulation,” in Proceedings of the IEEE International Conference on Robotics and Automation (ICRA), pp. 5183–5189, IEEE, 2012.
[14] K. He, M. Lahijanian, L. E. Kavraki, and M. Y. Vardi, “Towards manipulation planning with temporal logic specifications,” in Proceedings of the IEEE International Conference on Robotics and Automation (ICRA), pp. 346–352, IEEE, 2015.
[15] E. Plaku and S. Karaman, “Motion planning with temporal-logic specifications: Progress and challenges,” AI Communications, vol. 29, no. 1, pp. 151–162, 2016.
[16] C. K. Verigin and D. V. Dimarogonas, “Timed abstractions for distributed cooperative manipulation,” Autonomous Robots, vol. 42, no. 4, pp. 781–799, 2018.
[17] I. Millington and J. Funge, Artificial intelligence for games. CRC Press, 2009.
[18] A. Marzinotto, M. Colledanchise, C. Smith, and P. Ögren, “Towards a unified behavior trees framework for robot control,” in Proceedings of the IEEE International Conference on Robotics and Automation (ICRA), pp. 5420–5427, IEEE, 2014.
[19] M. Colledanchise and P. Ögren, Behavior trees in robotics and AI: An introduction. CRC Press, 2018.
[20] E. Giunchiglia, M. Colledanchise, L. Natale, and A. Tacchella, “Conditional behavior trees: Definition, executability, and applications,” in Proceedings of the IEEE International Conference on Systems, Man and Cybernetics (SMC), pp. 1899–1906, IEEE, 2019.
[21] H. Kress-Gazit, M. Lahijanian, and V. Raman, “Synthesis for robots: Guarantees and feedback for robot behavior;” Annual Review of Control, Robotics, and Autonomous Systems, 2018.
[22] C. Baier and J.-P. Katoen, Principles of model checking. MIT press, 2008.
[23] M. Guo and D. V. Dimarogonas, “Reconfiguration in motion planning of single-and multi-agent systems under infeasible local ltl specifications,” in Proceedings of the IEEE Conference on Decision and Control, pp. 2758–2763, IEEE, 2013.
[24] J. Tumova, A. Marzinotto, D. V. Dimarogonas, and D. Kragic, “Maximally satisfying ltl action planning,” in Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), pp. 1503–1510, IEEE, 2014.
[25] “Py trees.” http://py-trees.readthedocs.io. Accessed: 2020-07-10.
[26] M. Colledanchise, R. M. Murray, and P. Ögren, “Synthesis of correct-by-construction behavior trees,” in Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), pp. 6039–6046, IEEE, 2017.
[27] M. Lan, S. Lai, T. H. Lee, and B. M. Chen, “Autonomous task planning and acting for micro aerial vehicles,” in Proceedings of the IEEE International Conference on Control and Automation (ICCA), pp. 738–745, IEEE, 2019.
[28] M. Fox and D. Long, “Pddl2.1: An extension to pddl for expressing temporal planning domains,” Journal of artificial intelligence research, vol. 20, pp. 61–124, 2003.
[29] N. Koenig and A. Howard, “Design and use paradigms for gazebo, an open-source multi-robot simulator;” in 2004 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS) (IEEE Cat. No. 04CH37566), vol. 3, pp. 2149–2154, IEEE, 2004.
[30] Y. Wu, A. Kirillov, F. Massa, W.-Y. Lo, and R. Girshick, “Detectron2;” https://github.com/facebookresearch/detectron2, 2019.
[31] K. He, G. Gkioxari, P. Dollár, and R. Girshick, “Mask r-cnn,” in Proceedings of the International Conference on Computer Vision (ICCV), pp. 2961–2969, 2017.
[32] J. Brooks, “COCO Annotator;” https://github.com/jsbrooks/coco-annotator, 2019.