

# Constant-Time Motion Planning with Manipulation Behaviors

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**Abstract**—Recent progress in contact-rich robotic manipulation has been striking, yet most deployed systems remain confined to simple, scripted routines. One of the key barriers is the lack of motion planning algorithms that can provide verifiable guarantees for safety, efficiency and reliability. To address this, a family of algorithms called Constant-Time Motion Planning (CTMP) was introduced, which leverages a preprocessing phase to enable collision-free motion queries in a fixed, user-specified time budget (e.g., 10 milliseconds). However, existing CTMP methods do not explicitly incorporate the manipulation behaviors essential for object handling. To bridge this gap, we introduce the *Behavioral Constant-Time Motion Planner* (B-CTMP), an algorithm that extends CTMP to solve a broad class of two-step manipulation tasks: (1) a collision-free motion to a behavior initiation state, followed by (2) execution of a manipulation behavior (such as grasping or insertion) to reach the goal. By precomputing compact data structures, B-CTMP guarantees constant-time query in mere milliseconds while ensuring completeness and successful task execution over a specified set of states. We evaluate B-CTMP on two canonical manipulation tasks in simulation, shelf picking and plug insertion, and demonstrate its effectiveness on a real robot. Our results show that B-CTMP unifies collision-free planning and object manipulation within a single constant-time framework, providing provable guarantees of speed and success for manipulation in semi-structured environments.

## I. INTRODUCTION

Robotic arms have long been used to automate tasks in highly structured and repetitive domains, such as automotive assembly lines and electronics manufacturing. In these settings, manipulators often rely on pre-recorded and replayed motions. However, when variability is introduced, this paradigm becomes fragile: minor changes in the environment can disrupt operation, and significant human effort is required for setup and ongoing maintenance. The fundamental limitation is that real-world manipulation tasks require both collision-free motion planning and precise manipulation behaviors (e.g., grasping, insertion) to work together adaptively. For example, when objects appear in different positions or orientations, the system must dynamically coordinate these two components—something that fixed-motion approaches cannot provide.

Despite remarkable advances in robotic manipulation research, a persistent gap remains between the capabilities demonstrated in research laboratories and the requirements for real-world industrial deployment. This gap is especially pronounced in dynamic, semi-structured environments such as warehouse shelf picking (e.g., Amazon fulfillment centers [1]), bin picking in logistics, and precision assembly in

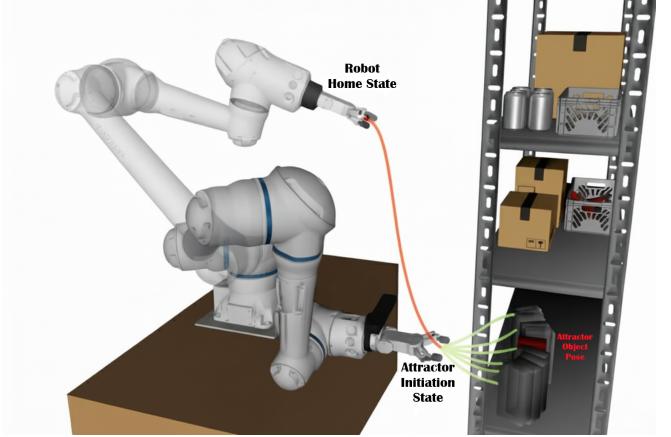


Fig. 1: Shelf-picking task commonly encountered in industrial warehouse automation. B-CTMP performs a preprocessing phase to compute compact data structures that enable finding a two-phase plan in constant time during online planning. In preprocessing, it caches a set of representative tuples, each containing a path from the robot’s home state to an attractor initiation state (red curve), from which a behavior policy can be executed to reach the target (green curves).

manufacturing. A central challenge is the lack of verifiable guarantees on system performance—particularly safety, efficiency, and predictability—which are essential for practitioners in safety-critical and high-throughput applications.

Constant-Time Motion Planning (CTMP) has been recently introduced as a promising framework for generating collision-free motion plans within strict, user-defined time bounds [2], [3], [4], [5]. By leveraging offline computation, CTMP enables online planning of collision-free motions in constant time—often mere milliseconds (e.g., 10 milliseconds)—with guarantees of completeness within a predefined region of interest. However, existing CTMP methods do not explicitly address the manipulation aspect of the task—the part that involves interaction with the environment through manipulation behaviors such as grasping, insertion, or other contact-rich actions. This is a critical limitation, as the success of many real-world tasks depends on the precise execution of these behaviors at the goal.

In this work, we bridge this gap by introducing the Behavioral Constant-Time Motion Planner (B-CTMP). Our approach incorporates manipulation behaviors directly into the preprocessing phase and computes data structures based

on the properties of these behaviors, enabling a two-step solution: (1) a collision-free motion to a behavior initiation state, and (2) execution of a manipulation behavior (e.g., grasping or insertion) to achieve the goal condition. B-CTMP guarantees constant-time online queries and ensures that the returned solution is verified to be executable for all possible poses of the manipulated object encountered during execution.

#### **Our main contributions are:**

- We propose B-CTMP, a constant-time motion planning algorithm that explicitly integrates manipulation behaviors into the planning process.
- We demonstrate the effectiveness of B-CTMP on canonical manipulation tasks—including picking from a shelf and insertion—in both simulation and on a real robot.
- We provide theoretical analysis of completeness and constant-time performance, making B-CTMP practical for deployment in real-world, semi-structured environments.

## II. RELATED WORK

B-CTMP builds upon advances in preprocessing-based motion planning and manipulation behavior modeling to enable constant-time planning for contact-rich tasks. We organize the related work into key areas that directly inform our approach: preprocessing methods for collision-free motion planning and approaches for modeling and integrating manipulation behaviors with motion planning.

### A. Motion Planning with Preprocessing

Preprocessing (i.e., offline computations) has been a key component in the development of planning algorithms. The main purpose of preprocessing for collision-free motion planning is to efficiently compute data structures that enable fast real-time planning. The Probabilistic Roadmap (PRM) [6] algorithm and its variants pioneered the approach of reducing the configuration space to a significantly smaller subset of states through roadmap construction, enabling fast online planning. However, PRM does not guarantee solution existence, as success depends on roadmap density and only provides asymptotic completeness guarantees [7]. This leads to substantial decrease in performance as compared to our approach as we demonstrate in experiments.

To address these limitations, recent approaches focus on constructing collision-free regions in the configuration space rather than sampling discrete states, making motion within these regions computationally efficient during online planning. A prominent example of this region-based approach is Planning in Graphs of Convex Sets [8], [9], [10], [11], [12] which decomposes the configuration space offline into collision-free convex sets [13], [14], enabling fast generation of smooth motion plans. These algorithms offer several advantages: they enable smooth trajectory generation through convex optimization and can handle complex geometric constraints naturally. However, they do not guarantee time bounds on online planning duration.

Constant-Time Motion Planning (CTMP) [2] addresses the time bound limitation by providing provable guarantees for generating collision-free motion plans within user-defined time constraints. The approach preprocesses a region-of-interest into sub-regions (neighborhoods), computing compact data structures that include representative paths for each region and potential functions that, when greedily followed (e.g., steepest descent), guarantee collision-free motion to the goal. Extensions include handling dynamic goal objects [3], semi-static environments [4], and anytime planning [5]. However, unlike the work in this paper, existing CTMP methods focus solely on collision-free motion and do not incorporate manipulation behaviors, limiting their applicability to contact-rich tasks.

### B. Manipulation Behaviors

Manipulation tasks fundamentally involve physical interaction with objects to change their configuration or state through the execution of specific behaviors (i.e., skills such as grasping, pushing, or placing). A significant body of work has focused on designing [15], [16] and learning [17], [18], [19] such manipulation capabilities. However, a key question is how to integrate these behaviors with collision-free motion planning so as to provide formal, real-time guarantees on returning a valid plan within user-defined time bounds, a requirement critical for high-throughput and time-sensitive applications.

Planning with manipulation behaviors typically involves defining key attributes for each behavior, including initiation states (pre-conditions) and effects (post-conditions) [20], [21], [22], [23], [24]. The integration between collision-free motion planning and manipulation behaviors is commonly achieved through a two-step *independent* process. First, collision-free motions are planned to reach states within a behavior's initiation set. Then, the behavior is executed to achieve the desired effect. However, existing approaches rely on the collision-free motion planner's ability to find online a suitable state within the behavior's initiation set that will result in successful execution. This separation between motion planning and behavior execution can lead to suboptimal solutions and does not guarantee that the planned motion will enable successful behavior execution. For example, a robot may successfully plan a collision-free path to a grasping pose, but the approach trajectory may not be suitable for reliable grasp execution due to object geometry or environmental constraints.

While existing work has made significant progress in preprocessing-based motion planning and manipulation behavior modeling, a key gap remains in combining constant-time guarantees with explicit manipulation behavior integration. Our work addresses this gap by introducing B-CTMP, which extends CTMP to incorporate manipulation behaviors directly into the preprocessing phase. This approach enables constant-time planning for contact-rich manipulation tasks while maintaining completeness guarantees within the region of interest, going beyond existing methods that treat motion planning and manipulation as separate sequential processes.

### III. PRELIMINARY

We consider a robot  $\mathcal{R}$  with state space  $\mathcal{X}$  operating in a semi-static environment. A *manipulation behavior*  $\sigma$  is defined by the tuple  $(I_\sigma, \pi_\sigma, \text{GETINITSTATES})$ , where  $I_\sigma(w)$  is the initiation set of the behavior,  $\pi_\sigma$  is the behavior's policy, and  $\text{GETINITSTATES}$  is a behavior specific function that generates a subset of initiation states. Given a robot state  $s \in \mathcal{X}$  and a target object state  $w \in \mathcal{W} \subseteq \text{SE}(3)$  (the object to be manipulated), the *initiation set* of a behavior,  $I_\sigma(w)$ , is the set of all robot states  $s$  for which a predicate  $P_\sigma(s, w)$  evaluates to true, indicating that behavior  $\sigma$  can be attempted from that point:

$$I_\sigma(w) = \{s \mid P_\sigma(s, w) = 1\}, \quad P_\sigma : \mathcal{X} \times \mathcal{W} \rightarrow \{0, 1\}.$$

It is important to note that not all states in the initiation set will necessarily lead to successful behavior execution. As an example, consider a shelf picking scenario where the robot must grasp objects from various locations on a shelf. A valid initiation state  $s_i$  is one from which the behavior rollout (e.g., Jacobian control) can be attempted—that is, the state is not in collision and is within some controllable bound of the desired termination state. However, skill success can depend on additional factors like gripper-object alignment, approach geometry, and environmental constraints. Hence  $I_\sigma(w)$  would consist of all *valid* states for a given object state. By contrast, *feasible* initiation states are those from which  $\pi_\sigma$  will succeed for object state  $w_g$ . The behavior specific function  $\text{GETINITSTATES}$  returns a subset  $S(w_g) \subseteq I_\sigma(w_g)$  containing valid initiation states.

The policy  $\pi_\sigma$  consists of a sequence of robot commands that can be executed in either open- or closed-loop fashion. In this work, we assume a behavior  $\sigma$  is given to the planner, and we aim to find a motion plan that enables successful execution of the behavior (rather than learning or optimizing the behavior itself).

We let  $\mathcal{G} \subseteq \mathcal{W}$  denote a region-of-interest (RoI), representing the region where target object might be located. Each RoI may potentially consist of a set of disjoint regions that we call *local-RoIs* ( $\mathcal{G}_i$ )- that is,  $\mathcal{G} = \bigcup_{i=1}^n \mathcal{G}_i$ . Given object state  $w_g \in \mathcal{G}$ , our objective is to plan a full path  $p = (\tau, \pi_\sigma)$  which consists of the collision free motion plan  $\tau$ , and the successful invocation of the manipulation behavior policy  $\pi_\sigma$ . The combined plan thus ensures both safe motion of the robot and successful completion of the manipulation task.

We represent the RoI as a set of possible object states, and introduce the notion of *behavior-feasible states* as:

**Definition 1** (Behavior Feasibility). *Given a robot state  $s$ , an object state  $w_g \in \mathcal{G}$  is **behavior-feasible** from  $s$  if the robot can reach an initiation state  $s_i \in I_\sigma(w_g)$  from which executing  $\pi_\sigma$  succeeds.*

We note that for a state to be behavior-feasible, two necessary conditions must be satisfied: (1) the initiation set  $I_\sigma(w_g)$  must be non-empty and contain at least one feasible  $s_i$ , and (2) there must exist a collision-free path from the current robot state  $s$  to at least one such state. For example, if

the object is placed in a location that prevents the behavior from being performed, (like if a shelf obstructs access for grasping), then that object state is not behavior-feasible.

We require our framework to plan a path to any behavior-feasible object state  $w_g \in \mathcal{G}$  within a bounded time  $T_{\text{bound}}$ . Thus, we also define the following:

**Definition 2** (Constant-Time Feasibility). *A behavior-feasible object state  $w_g \in \mathcal{G}$  is **constant-time feasible** from a robot state  $s$  if a planner can find a path  $\tau$  to one of its corresponding feasible initiation states  $s_i \in I_\sigma(w_g)$  within  $T_{\text{bound}}$ .*

To build towards our aim, we first define the concept of *coverage* to capture behavior feasibility from specific robot states.

**Definition 3** (Initiation state Coverage). *For a given initiation state  $s_i$ , we say that it **covers** a set of object goal states  $\mathcal{G}' \subseteq \mathcal{G}$  if, starting from  $s_i$ , the behavior  $\pi_\sigma$  can be successfully rolled out to reach every  $w_g \in \mathcal{G}'$ .*

This allows us to define a modified notion of *neighborhood* similar to [5], to accommodate RoIs defined in  $\mathcal{W}$ :

**Definition 4** (Neighborhoods). *a **neighborhood**  $n_i(s_i)$  is defined as the set of all object states in the  $\mathcal{G}$  that are covered by the same  $s_i$ ; that is, they share a common feasible initiation state  $s_i$ . Neighborhoods satisfy the following:*

- $n_i(s_i) \subseteq \mathcal{W}$  for each  $n_i(s_i) \in \mathcal{N}$
- $\mathcal{G} \subseteq \bigcup_{n_i(s_i) \in \mathcal{N}} n_i(s_i)$

This establishes a *many-to-many relationship* between robot and object states: each object state  $w_g \in \mathcal{G}$  may admit multiple initiation states in  $I_\sigma(w_g)$ , while each initiation state  $s_i$  may cover multiple object states through its cover set. This coverage locality property is crucial for memory efficiency, as it allows a small number of strategically selected initiation states to cover large regions of the object-pose space.

Our aim is to exploit this relationship to avoid the memory explosion that would result from naively precomputing paths to all initiation states for every object pose. Instead, our approach strategically selects a compact set of initiation states whose neighborhoods collectively span the object-pose space, ensuring *constant-time feasibility* for all *behavior-feasible* goal states while maintaining memory efficiency.

### IV. B-CTMP: ALGORITHMIC APPROACH

In the following sections, we outline the two key phases of the algorithm—the offline preprocessing phase and the online query phase—and demonstrate how this approach provides both memory efficiency and execution guarantees.

#### A. Preprocessing Phase

To guarantee plan retrieval within the desired  $T_{\text{bound}}$  online, we offload computationally expensive planning and behavior simulation to an offline preprocessing phase. During this phase, we are given a predefined robot start state  $s_{\text{home}}$  and manipulation behavior  $\sigma$ . We also assume access to a collision-free motion planner  $\mathcal{P}$ . Our goal is to find trajectories from  $s_{\text{home}}$  to a set of initiation states such

that we get full coverage of  $\mathcal{G}$  through the execution of the behavior.

The naive approach to achieve this would be to compute the corresponding feasible initiation states  $s_i$  for each possible object state  $w_i$ , and then computing and storing individual paths  $\tau_i$  from  $s_{home}$  to each  $s_i$ . However, this would be memory inefficient, since the set of all required initiation states grows significantly with the object state space dimensionality and the RoI size, making it impractical for real-world deployment.

Instead, we exploit a key insight: manipulation behaviors often exhibit *spatial locality*, where a single initiation state can cover multiple object configurations within a spatial region. For example, when grasping objects from a shelf, one pre-grasp pose (initiation state) may enable successful grasping of any object within a certain shelf region, as the behavior can adapt to the specific object pose during execution. Hence, leveraging this coverage property of initiation states, we can strategically select a reduced set of feasible initiation states  $\tilde{\mathcal{S}} \subseteq \bigcup_{w_g \in \mathcal{G}} I_\sigma(w_g)$  such that:

$$\bigcup_{s_i \in \tilde{\mathcal{S}}} n_i(s_i) \supseteq \mathcal{G},$$

which provides complete coverage over all desired goal states while requiring significantly fewer paths from  $s_{home}$ .

As seen in figure 2, we can then characterize our neighborhoods. These are defined as spatial regions of object poses in the previous section, using *attractor tuples*. Each attractor tuple consists of an object attractor state  $w_{attr}$ , an attractor initiation state  $s_{i,attr}$ , a distance  $r$ , and a collision free path  $\tau$  from  $s_{home}$ . Formally, an attractor tuple  $(w_{attr}, s_{i,attr}, r, \tau)$  supports that all object states  $w$  within distance  $r$  of  $w_{attr}$  can be successfully handled by executing the manipulation behavior  $\sigma$  from initiation state  $s_{i,attr}$ .

Given this definition, the preprocessing planning problem is finding the set of feasible attractor initiation states  $\tilde{\mathcal{S}}$ , their corresponding neighborhood size, and generating representative paths to these attractors. Algorithm 1 outlines this procedure. We begin by sampling a candidate object state  $w_i$  from an uncovered section of local region of interest  $\mathcal{G}_i^{uncover}$  and computing a set of initiation states  $\mathcal{S}(w_i)$  for that object state using the `GETINITSTATES` function (Line 8). Next, we expand candidate neighborhoods using behavior reachability analysis for each state  $s_i \in \mathcal{S}(w_i)$ . We do so by identifying the frontier of the spatial region within which the behavior executed from  $s_i$  remains successful for all object states. This frontier is determined through successive behavior rollouts, which allow us to explicitly verify behavior feasibility as the region expands.

Once the algorithm encounters an object state that cannot be reached by the behavior rollout from  $s_i$ , that state is recorded and subsequently used to seed coverage for a different local region of interest. Once all the candidate neighborhoods are expanded, the largest neighborhood (measured in terms of the maximum distance  $r$  between the attractor object state  $w_{attr}$  and the closest frontier state) is

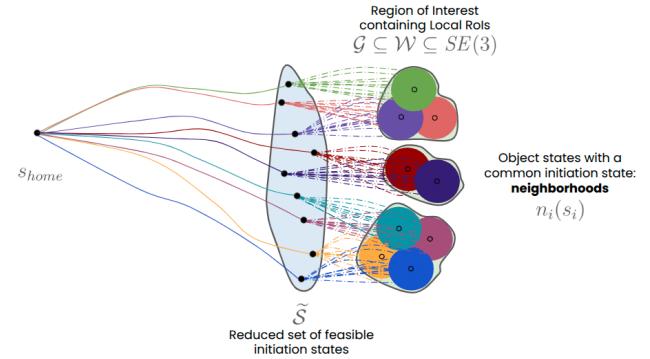


Fig. 2: Overview of the preprocessing structure. The planner computes a reduced set of feasible initiation states  $\tilde{\mathcal{S}}$ , each connected to the robot’s home state  $s_{home}$  by a precomputed path. Each  $s_i \in \tilde{\mathcal{S}}$  defines a neighborhood  $n_i(s_i)$  within the region of interest  $\mathcal{G}$  of object states  $w$  that can be reached through behavior execution. This compression is captured by attractor tuples, each representing an initiation state, its reachable neighborhood, and the stored path that enables efficient plan retrieval during online execution.

selected to get added to the stored library, and the initiation state corresponding to the neighborhood is chosen as the attractor initiation state  $s_{i,attr}$ .

### B. Online Phase

At the successful completion of the preprocessing phase, we obtain a library  $\mathcal{L}$  of stored attractor-tuples. This library enables fast online queries when a goal object state  $w_g \in \mathcal{G}$  becomes available.

Given a query  $w_g \in \mathcal{G}$ , the online phase proceeds in three steps, highlighted in Alg 2. Step 1 is *region identification*, where we identify the appropriate region containing  $w_g$  by checking which attractor tuple satisfies  $d(w_g, w_{attr}) \leq r$ , where  $d(\cdot, \cdot)$  is the chosen distance metric. Next, we retrieve the stored collision-free path  $\tau$  from  $s_{home}$  to the corresponding initiation state  $s_{i,attr}$ . Finally, we execute the complete manipulation plan in two sequential parts: first, the robot follows the precomputed collision-free motion plan  $\tau$ , which terminates at the behavior initiation state. Then, we invoke the behavior rollout function, which executes the manipulation behavior policy  $\pi_\sigma$  and successfully completes the task.

Hence, the online phase reduces to simple lookup operations and direct plan execution, ensuring consistent performance within the desired time bound  $T_{bound}$ .

### C. B-CTMP Theoretical Properties

B-CTMP leverages preprocessing to provide constant-time query performance in online settings while ensuring solution existence for all valid goals within the preprocessed region of interest. During offline computation, B-CTMP constructs a finite library  $\mathcal{L}$  of attractor tuples that cover the entire region-of-interest. Online queries require only a lookup operation to identify which neighborhood contains the target object

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**Algorithm 1:** Preprocess with Behaviors

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**Input:**  $s_{home}$ : Robot home state  
 $\mathcal{P}$ : Planner  
 $\mathcal{G}$ : Set of RoIs—possible location regions of the object of interest  
 $\sigma$ : Manipulation behavior with  $(I_\sigma, P_\sigma)$

**Output:** Library  $\mathcal{L}$  containing attractor tuples and representative paths to each tuple.

```

1 Procedure Preprocess ( $s_{home}, \mathcal{P}, \mathcal{G}, \sigma$ ):
2    $\mathcal{L} \leftarrow \text{InitHashMap}()$ 
3   foreach  $\mathcal{G}_i \in \mathcal{G}$  do
4      $\mathcal{G}_i^{covered} \leftarrow \emptyset$ 
5      $\mathcal{G}_i^{uncov} \leftarrow \mathcal{G}_i \setminus \mathcal{G}_i^{covered}$ 
6     while  $\mathcal{G}_i^{uncov} \neq \emptyset$  do
7        $w_i \leftarrow \text{SampleValidPlacement}(\mathcal{G}_i^{uncov})$ 
8        $\mathcal{S}(w_i) \leftarrow \text{GetInitStates}(w_i, P_\sigma)$ 
9        $\triangleright$  use behavior predicate and sampled object state to get feasible initiation state set
10      if  $\mathcal{S}(w_i) = \emptyset$  then
11        continue
12         $(n_i(s_i), r_i, s_i, \tau_i) \leftarrow$ 
13        ConstructNeighborhood ( $s_{home}, w_i, \mathcal{S}(w_i), \mathcal{P}, \sigma$ )
14         $\triangleright$  Returns a neighborhood  $n_i$ , its size  $r_i$ , representative attractor initiation state  $s_i$ , and path to  $s_i$ 
15         $\mathcal{G}_i^{covered} \leftarrow \mathcal{G}_i^{covered} \cup n_i$ 
16         $\mathcal{L} \leftarrow \mathcal{L} \cup (w_i, s_i, r_i, \tau_i)$ 
17   return  $\mathcal{L}$ 

18 Procedure ConstructNeighborhood ( $s_{home}, w_i, \mathcal{S}(w_i), \mathcal{P}, \sigma$ ):
19    $s_{i,attr} \triangleright$  attractor initiation state
20    $r_{max} \leftarrow 0 \triangleright$  largest neighborhood size
21    $n_{max} \leftarrow \emptyset \triangleright$  largest neighborhood
22    $\tau_{i,attr} \triangleright$  path to attractor initiation state
23   foreach  $s_i \in \mathcal{S}(w_i)$  do
24      $\tau_i \leftarrow \mathcal{P}.PlanPath(s_{home}, s_i)$ 
25     if  $\tau_i = \emptyset$  then
26       continue
27      $success \leftarrow \text{BehaviorRollout}(s_i, w_i, \sigma) \triangleright$  simulate manipulation
28     if  $success$  then
29        $n_i(s_i) \leftarrow \text{ExpandNeighborhood}(w_i, s_i)$ 
30        $r \leftarrow \text{SIZE}(n_i(s_i))$ 
31       if  $r > r_{max}$  then
32          $s_{i,attr} \leftarrow s_i$ 
33          $r_{max} \leftarrow r$ 
34          $n_{max} \leftarrow n_i(s_i)$ 
35          $\tau_{i,attr} \leftarrow \tau_i$ 
36   return  $(n_{max}, r_{max}, s_{i,attr}, \tau_{i,attr})$ 

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**Algorithm 2:** Query

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**Input :**  $\mathcal{R}$ : Robot  
 $s_{home}$ : robot start state ( $s \in \mathcal{X}$ )  
 $w_g$ : object state ( $w_g \in \mathcal{G}$ )  
 $\mathcal{L}$ : The preprocessed library  
 $\sigma$ : Manipulation Behavior

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1 Procedure Query ( $\mathcal{R}, s_{home}, w_g, \mathcal{L}, \sigma$ )
2   if  $\tau \leftarrow \text{FindRepPath}(w_g, \mathcal{L}) \neq \emptyset$   $\triangleright$  Find the representative path from the containing neighborhood
3     then
4        $\mathcal{R}.Execute(\tau)$ 
5        $\mathcal{R}.Rollout(w_i, \sigma) \triangleright$  Execute behavior
6     else
7       return failure  $\triangleright$  No valid path

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state, resulting in worst-case complexity of  $O(|\mathcal{L}|)$  where  $|\mathcal{L}|$  is the number of precomputed neighborhoods. Since  $|\mathcal{L}|$  is determined during preprocessing and independent of the specific query, B-CTMP achieves constant-time performance.

To characterize B-CTMP’s solution guarantees, we introduce a notion of completeness tailored to behavior-based manipulation planning.

**Definition 5** (PR-Completeness). *Given a behavior, we say that an algorithm is **PR-complete** (predicate-complete) if for all behavior-feasible object states  $w \in \mathcal{W}$  with at least one feasible robot initiation state  $s_i$  that is discoverable via GETINITSTATE, the algorithm returns a valid plan. Otherwise, it reports that no plan exists for the given behavior and goal.*

**Theorem 1** (B-CTMP PR-Completeness). *B-CTMP is PR-complete within the preprocessed region-of-interest (RoI)  $\mathcal{G}$ .*

*Proof sketch.* Consider any object state  $w_g \in \mathcal{G}$  such that there exists at least one feasible robot state  $s_i \in I_\sigma(w_g)$  discoverable by GETINITSTATE. During the preprocessing phase (Algorithm 1), B-CTMP loops through local-RoIs until  $\mathcal{G}_i \setminus \mathcal{G}_i^{covered} = \emptyset$  and constructs a library  $\mathcal{L}$  of attractor tuples that covers the entire ROI  $\mathcal{G}$ . This means that for every such state  $w_g$ , the preprocessing phase guarantees the existence of an attractor tuple  $(w_{attr}, s_{i,attr}, r_{max}, \tilde{\tau}) \in \mathcal{L}$  such that  $d(w_g, w_{attr}) \leq r_{max}$ , the behavior  $\sigma$  executed from  $s_{i,attr}$  successfully handles  $w_g$  (verified through behavior rollout during preprocessing), and a collision-free path  $\tilde{\tau}$  exists from  $s_{home}$  to  $s_{i,attr}$ .

B-CTMP also guarantees that object states that are *infeasible* with respect to the behavior are handled appropriately during preprocessing. Specifically, during neighborhood expansion, object states that cannot be reached by behavior rollout are maintained in a frontier queue. Each such state then becomes a candidate attractor state, due to which the algorithm attempts to find a valid initiation set  $\mathcal{S}(w_g)$  for it via the GETINITSTATES function. Thus, B-CTMP is PR-complete within  $\mathcal{G}$ .  $\square$

## V. EXPERIMENTS

We evaluate our B-CTMP on two canonical manipulation tasks across distinct simulation environments—shelf picking and plug insertion, and demonstrate its effectiveness on a physical UR10e robot in the accompanying video.

### A. Manipulation Tasks

1) *Shelf Grasping*: For our first task, we consider a shelf-picking scenario commonly encountered in industrial warehouse automation, where a robotic manipulator must retrieve objects from structured storage environments. The manipulation task involves grasping a target object whose pose is specified in the world coordinate frame by  $w_g \in \text{SE}(3)$ .

**Grasp Behavior:** The grasp behavior  $\sigma_{grasp}$  depends on two key points, the pre-grasp pose (an initiate state) from which we execute the policy to reach the second key point, and the grasp pose, where we activate a closure sequence to grasp the object. The behavior policy  $\pi_{\sigma_{grasp}}$  uses Jacobian control to gradually and smoothly move the end-effector pose through differential kinematics between these points, enabling grasp execution.

**Behavior Implementation:** The GETINITSTATES function for the grasp behavior outputs a subset of valid pre-grasp poses (initiation states), which are computed as follows. First, we compute candidate grasp poses with valid IK solutions using the target object’s point cloud. Then, Local surface normals are used to calculate antipodal scores that quantify grasp stability by measuring alignment between gripper fingers and object surface. The top  $K$  grasps ranked by antipodal score are selected, and the corresponding pre-grasp poses are computed by applying a fixed retraction transformation along each grasp’s approach direction.

**B-CTMP Integration:** B-CTMP leverages the behavior during offline preprocessing to compute a compact set of representative initiation states with their corresponding neighborhoods. During this process, the system discovers candidate states and selects those with the largest coverage areas to serve as tuple-attractors in the final library, creating a small set of representative pre-grasp poses capable of handling many different target object configurations.

2) *Charger Insertion:* The second task we consider is precision charger insertion with perception, commonly required in automated charging systems and electronic assembly. This task requires inserting a charger connector into a target port located at  $w_g \in SE(3)$ , and represents dual challenges due to strict geometric constraints for successful insertion and uncertainty from perception.

**Insertion Behavior:** In this case, since the geometry of the port uniquely dictates a single insertion pose, all the behavior needs is the initiation state from which to rollout the policy. However, due to the high-precision required in the task and the perception uncertainty, we rely on visual-based Jacobian control for our policy  $\pi_{\sigma_{insert}}$ .

**Behavior Implementation:** We directly compute the insertion pose for each port location and apply a predefined transformation to obtain the corresponding pre-insert initiation state, which is output by the GETINITSTATES function. To ensure robust execution under perception uncertainty, we impose a manipulability constraint during policy execution. We define the minimum manipulability radius as  $r_{\min}(q) = \min_i \sqrt{\lambda_i(J(q)J(q)^T)}$  where the manipulability ellipsoid radii are derived from the Jacobian eigenvalues.

**B-CTMP Integration:** B-CTMP’s offline preprocessing step creates a compact set of initiation states that can cover multiple port locations while maintaining the ability to handle the perception uncertainty.

It does so by imposing the manipulability constraint during behavior rollouts during preprocessing, marking the rollout as infeasible if  $r_{\min}(q) < \epsilon$ , where  $\epsilon$  represents the perception noise. This ensures that selected attractor pre-insert poses can maintain adequate dexterity for corrective motions across their neighborhoods.

B-CTMP performs all pose discovery processes (grasp pose computation and pre-insertion pose calculation) offline to maximize region coverage. Each attractor initiation state is validated to handle all goal object poses within its neighborhood. Online execution retrieves the precomputed path to

the appropriate representative state and executes the behavior rollout, hence enabling fast online planning.

### B. Baseline Methods

We compare our method against two baseline families:

**Online Planning Baseline:** The fully online baseline represents the common approach for behavior-based manipulation planning. For each query with target object pose  $w_g$ , it first samples initiation states for the specified behavior  $\sigma$  using the GETINITSTATES function, then attempts to generate collision-free motion plans to these states. Upon successful plan generation, it executes the behavior policy  $\pi_\sigma$ . This approach incurs expensive online computation as it performs sampling, motion planning, and behavior rollout for every query. Additionally, finding an initiation state does not mean that the policy execution will succeed. We implement this baseline using the BiTRRT [25] planner from OMPL.

**Preprocessing-based Baselines:** We implement two variants that leverage offline computation to accelerate online planning. The first utilizes an offline PRM graph that seeds the planner with a precomputed roadmap. The second employs prior CTMP methods [5] to store a library of paths to a manually defined initiation region  $S_{\text{init}}$ , estimated to at least partially overlap with the  $I_\sigma(w_g)$  for different target poses  $w_g$ .

Both preprocessing-based baselines follow the same online protocol: they compute initiation states using the GETINITSTATES function, then leverage their preprocessed structures to obtain collision-free motion plans to valid initiation states. The PRM baseline uses the roadmap to seed planning, while vanilla CTMP directly queries the path library for trajectories terminating in  $S_{\text{init}}$ . Finally, both baselines execute  $\pi_\sigma$  from the computed path’s terminal state.

### C. Experimental Setup

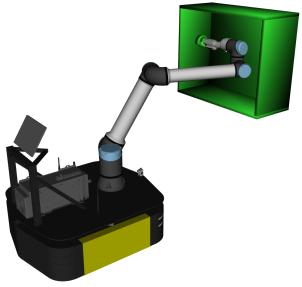
We conducted 100 trials for the grasping domain and 60 trials for the insertion domain, with all plans starting from the robot home state  $s_{\text{home}}$ . The chosen goal states cover diverse regions of the task space to capture varying spatial localities and manipulation complexities, enabling comprehensive evaluation across different planning and behavior execution scenarios. A timeout of 5 seconds was set for all planners.

### D. Results and Analysis

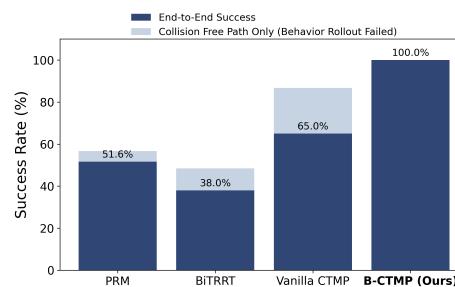
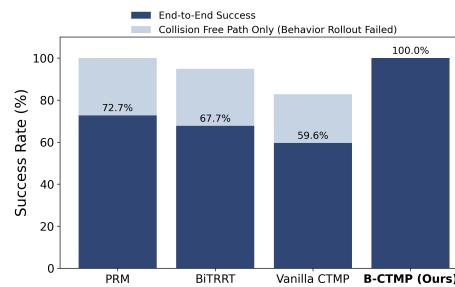
1) *Performance Comparison:* Figure 3 presents the success rate and planning time for B-CTMP compared to the baseline methods. In both experiments, our planner maintained a 100% end-to-end success rate, whereas the baselines failed either at finding valid collision-free paths to initiation states or during behavior execution from the path terminal states. Our approach also demonstrates sub-millisecond online query performance through fast lookup operations, compared to expensive online computation required by baseline methods. Additionally, B-CTMP achieves significant memory efficiency, with its offline storage requiring up to 21x less memory than Vanilla CTMP. This efficiency stems from B-CTMP’s decomposition strategy.



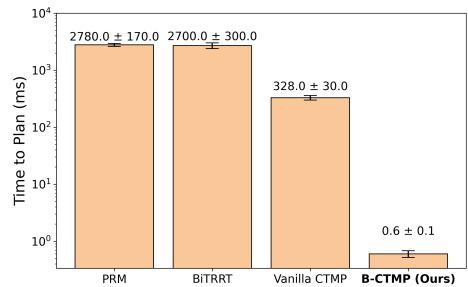
(a) Shelf Grasping Environment



(b) Charger Insertion Environment



(c) Success Rate



(d) Planning Time(ms)

Fig. 3: Experimental comparison of B-CTMP against baseline methods on the two tasks. (3a) The shelf grasping environment, where a fixed-base robot must grasp a known target object at any location on the shelf. (3b) The charger insertion environment, where the robot must precisely insert a charger into a port located anywhere within the confined box, with pose uncertainty due to perception noise. (3c) Success rates for collision-free motion planning and subsequent behavior execution show that baseline methods exhibit 10-30% failure rates due to unsuccessful behavior rollouts, while B-CTMP maintains consistently high performance. (3d) Planning times demonstrate B-CTMP’s sub-millisecond online query performance through fast lookup operations, compared to expensive online computation required by baseline methods.

Rather than storing neighborhoods in robot configuration or end-effector space like Vanilla CTMP, where physically proximate configurations may be partitioned into separate regions due to greedy unreachability, B-CTMP organizes neighborhoods in the object space using high coverage behavior initiation states. This object-centric representation enables more coherent neighborhood structures that better reflect the underlying task geometry.

2) *Failure Mode Analysis:* The results reveal three critical limitations of the baselines that B-CTMP addresses. First, discovering or specifying  $\tilde{\mathcal{S}}$  (a set of feasible initiation states with high coverage) is computationally expensive online and error-prone. This challenge is especially evident in the Vanilla CTMP baseline, which requires practitioners to manually tune preprocessed regions by estimating regions in task space  $\mathcal{S}_{\text{init}}$  which contain good initiation states with high target pose coverage. This leads to frequent planning failures, since estimating this set is non-trivial and is behavior-dependent. In contrast, B-CTMP automatically discovers and selects a curated subset of initiation states during preprocessing, ensuring that stored states are both memory-efficient and support valid behavior rollouts. Second, the experiments expose the fundamental inadequacy of treating behavior validation as an afterthought. Baseline methods decouple motion planning from behavior execution, leading to failures from initiation states that are kinemat-

ically reachable but behaviorally invalid. For the insertion domain, regions such as shelf corners and side walls proved particularly challenging, as these locations often yield initiation states with poor manipulability or suboptimal approach angles for successful behavior execution. Since B-CTMP explicitly simulates behavior rollouts during preprocessing, it selects appropriate paths and initiations that promote success. Third, B-CTMP demonstrates flexibility in handling domain-specific constraints such as uncertainty requirements. While baselines cannot account for the requirements needed for corrective motions under perception noise, B-CTMP actively integrates manipulability constraints during preprocessing, ensuring selected initiation states maintain adequate dexterity throughout behavior execution.

These results demonstrate that planning to kinematically feasible, collision-free initiation states alone is insufficient for reliable behavior-based manipulation. B-CTMP’s integrated approach of coupling motion planning with behavior validation during preprocessing achieves PR-Completeness by ensuring all stored states will result in successful behavior execution. This establishes both theoretical guarantees and practical advantages over existing methods that treat motion planning and behavior execution as separate, sequential processes.

## VI. CONCLUSION AND FUTURE WORK

This work introduces B-CTMP, a constant-time algorithm that extends existing CTMP methods to incorporate manipulation behaviors directly into the preprocessing phase. Instead of treating collision-free motion planning and behavior execution as separate sequential processes, B-CTMP integrates behavior validation during offline computation to improve the reliability of manipulation tasks in semi-structured environments. The method addresses a practical limitation in current constant-time planning approaches: the tendency to plan paths to kinematically feasible states that may prove unsuitable for successful behavior execution. A key insight is that by defining the region of interest in object space rather than robot configuration or task space, B-CTMP can automatically discover the relevant initiation states for the manipulation task. This eliminates the need for manual specification of robot configuration or task-space initiation regions, which requires human intuition and domain expertise. Through behavior validation during preprocessing and selection of initiation states based on their coverage properties, B-CTMP reduces the likelihood of execution failures that commonly occur when motion planning and behavior execution are decoupled. The experimental results demonstrate that B-CTMP maintains consistent success rates while achieving fast online query performance. Baseline methods exhibit higher failure rates, particularly in challenging regions where kinematically reachable states prove behaviorally invalid. The approach also demonstrates improved memory efficiency by organizing neighborhoods in object space. We introduce PR-completeness as a framework for reasoning about solution guarantees in behavior-based manipulation tasks within predefined regions of interest. Several directions for future work emerge from this work. The approach could be extended to handle sequences of multiple behaviors. The preprocessing framework may also provide a foundation for learning-based methods where behavior policies are refined or analyzed during offline computation to increase the probability of successful execution online. B-CTMP provides a practical step toward more reliable preprocessing-based manipulation planning by demonstrating that behavior validation can be effectively integrated into constant-time frameworks. While the approach focuses on specific classes of two-step manipulation tasks, it offers a useful building block for developing more robust robotic automation systems that can provide predictable performance.

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