Long-Horizon Task and Motion Planning with Functional Object-Oriented Networks

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Abstract—Following work on joint object-action representations, functional object-oriented networks (FOON) were introduced as a knowledge graph representation for robots. Taking the form of a bipartite graph, a FOON contains symbolic (high-level) concepts useful to a robot’s understanding of tasks and its environment for object-level planning. Prior to this paper, little has been done to demonstrate how task plans acquired from FOON via task tree retrieval can be executed by a robot, as the concepts in a FOON are too abstract for immediate execution. We propose a hierarchical task planning approach that translates a FOON graph into a PDDL-based representation of domain knowledge for manipulation planning. As a result of this process, a task plan can be acquired that a robot can execute from start to end, leveraging the usage of action contexts and skills in the form of dynamic movement primitives (DMP). We demonstrate the entire pipeline from planning to execution using CoppeliaSim and show how learned action contexts can be extended to never-before-seen scenarios.

I. INTRODUCTION

An ongoing trend in robotics research is the development of robots that can jointly understand human intention and action and execute manipulations for human domains. A key component for such intelligent and autonomous robots is a knowledge representation [1] that allows a robot to understand its actions in a way that mirrors how humans communicate about action. Inspired by the theory of affordance [2] and prior work on joint object-action representation [3], [4], the functional object-oriented network (FOON) was introduced as a knowledge graph representation for service robots [5]. A FOON describes the relationship between objects and manipulation actions through its nodes and edges, and aims to be a high-level task plan abstraction that is closer to human understanding of manipulation. Ideally, FOON graphs can be formed from demonstrations of action, which can be combined into a single network from which knowledge can be retrieved as task sequences known as task trees [5]. FOON supports reusing existing knowledge to learn “new” concepts based on semantic similarity [6].

Prior to this work, however, little has been done to integrate FOON with robotic systems, as the knowledge in a FOON is too abstract for manipulation planning [7]. Rather, a FOON is ideal for object-level planning, which is agnostic to the robot and its environment, as opposed to task-level planning, which deals more with the current state of the robot and its surroundings. Doing so requires connecting the high-level semantic concepts typically found in FOON to the low-level motion and object parameters through which a robot understands its actions and world [8]. For example, cooking recipes are object-level plans, but they would require task-level plans to ground object labels to instances in the world and skills to instructional verbs.

Therefore, to address task and motion planning (TAMP) using FOON, we introduce a hierarchical task planning approach to translate a FOON graph into a manipulation plan. Our algorithm creates a domain and problem definition in PDDL (short for Planning Domain Definition Language) notation from a FOON, and they are used with an off-the-shelf planner to find a sequence of low-level actions or primitives that can be executed by a robot to achieve the intended results of executing the graph from start to end [10].

A. Contributions

Our contributions are as follows:

- We introduce an approach to translate a high-level semantic FOON graph into a low-level manipulation planning problem for classical planning (PDDL).
- We show that using FOON significantly improves the time required for manipulation planning as opposed to conventional planning methods.
- We show how our approach can derive plan for novel scenarios, which may comprise of random object configurations or ingredient sets, without having to create a new FOON for those situations.

II. BACKGROUND AND RELATED WORKS

A. Functional Object-Oriented Networks

Formally, a FOON is a bipartite graph $G = \{O, M, E\}$, where $O$ and $M$ refer to two types of nodes respectively: object nodes and motion nodes. Object nodes refer to objects that are used in activities, including tools, utensils, ingredients or components, while motion nodes refer to actions that can be performed on said objects. An object node $o \in O$ is identified by its object type, its states, and, in some cases,
Fig. 1. An example of two functional units, which describe pouring vodka and ice into a drinking glass (best viewed in colour). Object nodes are denoted by circles, while motion nodes are denoted by squares. Here, input-only nodes are depicted in green, output-only nodes are depicted in purple, and nodes that are both input and output are depicted in blue.

its make-up of ingredients or components; a motion node $m \in \mathcal{M}$ is identified by a motion or action type, which can refer to a manipulation (e.g., pouring, cutting, or shaking) or a non-manipulation action (e.g., frying or baking).

As a result of executing actions, objects may take on new states. State transitions are conveyed in structures known as functional units (denoted as $\mathcal{FU}$), which describe object nodes before and after an action takes place. Specifically, a functional unit $\mathcal{FU} = \{O_{in}, O_{out}, n\}$ contains a set of input nodes $O_{in}$, a set of input nodes $O_{out}$, and an intermediary motion node $n$. Functional units can be linked to planning operators (PO) that are used in planning languages such as PDDL [9]. From a FOON, a robot can identify states that determine when an action is completed. Figure 1 illustrates an example of two functional units describing a sequence of pouring vodka and ice into a drinking glass for a cocktail. Without considering states, we have the objects drinking glass, cup, bottle, vodka and ice. Note, however, that there are several instances of these objects, as their states will change as a result of execution; this is analogous to Petri Nets [11], where the firing of transitions cause a change in input place nodes. Each functional unit has the same motion node label of pour, yet the objects and effects of each action are different, thus treating these as two separate actions.

1) Creating a FOON: FOONs can be created by annotating manipulations from observation, such as video demonstrations, or, as we plan to explore in the near future, demonstrations from a human teacher. During the annotation process, it is important to note the objects, actions, and state changes that have been observed for achieving a specific goal, such as preparing a meal. As a result, one can obtain a FOON subgraph for several activities or recipes, which describes a sequence of functional units (and its corresponding objects and actions) to fulfill the given goal. A combination of two or more subgraphs form a universal FOON. This merging procedure consolidates all instances of object nodes and removes duplicate functional units that are common across different subgraphs [5]. Presently, the FOON dataset provides 140 subgraph annotations from which a universal FOON can be created; these annotations along with helper code are publicly available for use.

1FOONets (FOON Website) – http://www.foonets.com

2) Planning with FOON: Aside from representing knowledge in a symbolic manner, a robot can use FOON for object-level planning. Such a problem would entail answering the question: given a set of objects (e.g., tools, ingredients, or appliances), how can a robot create an object marked as a goal node in a FOON? Given that the robot can ground object instances to FOON nodes, we can rely on FOON to determine how those objects can be utilized to solve more complex problems. This knowledge retrieval procedure is denoted as task tree retrieval [5], where a task tree is a subgraph that describes the steps for solving a given problem based on the state of the robot’s environment. Task tree retrieval combines ideas from breadth-first and depth-first search (BFS and DFS), where, starting from the goal node or sub-goal nodes, we search backwards to find the functional units needed to make them (DFS), and for each of those units, we evaluate if their input conditions are met (BFS); this requires knowledge of the initial set of objects that could be made or that are already available to the robot.

Alternatively, if we want to perform a task tree retrieval operation without immediately considering the availability of objects or to find the best course of action that a robot can successfully execute, then one can also consider building a path tree [12] to retrieve possible combinations of action sequences that achieves the final goal. This retrieval method was introduced for finding the optimal task tree based on the robot’s success rate of executing its motion primitives.

B. Related Work

There are many notable works that aim to represent knowledge for robots in a way that encourages reuse of experiences or use abstraction to improve task and manipulation planning. Frameworks such as KNOWRob [13] have been developed to combine knowledge bases with a query processing engine to allow robots to reason over beliefs of its environment. Previous work by Tenorth et al. [13] has shown how a robot can use its knowledge base for preparing meals such as pancakes and how a robot form queries over object or action properties. However, their main focus was on how to structurally define the knowledge base and infer the location of objects rather than storing or retrieving recipes or task sequences in a way that can be reused like FOON. We propose that FOON can serve as a schema that could be built upon reasoning engines or knowledge bases such as KNOWRob, which are tied to low-level robotic properties. Ramirez-Amaro et al. [14] investigated how semantic knowledge can be extracted and learned from demonstration, which can then be used by a robot to plan and reason to imitate demonstrated tasks, which included making pancakes and a sandwich. Although our work does not adopt the same degree of object and activity recognition, the recipe knowledge found in FOON is agnostic to the robot, and it is only through planning that we obtain a robot-specific plan based on the robot’s present environment.

In terms of hierarchical representations, approaches such as manipulation action trees [15] and hierarchical task networks (HTN) [16] share many similarities with FOON. In the case of HTNs, they can be used to represent abstract
tasks (referred to as methods) that may be decomposed into a sequence of sub-tasks that can be immediately executed or achieved by an agent or robot. These higher-level tasks are similar to functional units in FOON, which would require a sequence of lower-level actions to achieve the intended goal of these action units. However, one major distinction between HTNs and our hierarchical planning approach is that we pose each higher-level task as sub-problems that are liable to change based on the environment, while an HTN’s methods are typically fixed with a specific ordering of sub-tasks. Using knowledge from FOON as a schema allows us to derive domain-specific manipulation plans that are liable to change based on the configuration of the robot’s workspace.

Similarly, previous work investigated how to encode macro planning operators into primitive operators for the execution of robotic tasks, combining macro operators and primitives into a single linear planning domain \[17\] or combining linear planning with reinforcement learning for the execution of primitives \[18\]. However, similar to HTN, macro operators are associated with a fixed sequence of primitive operators that are executed in a reactive manner. Manipulation action trees \[14\] and grammar \[19\] by Yang et al. have been shown to facilitate robotic planning and execution by representing robotic manipulation in a tree form. Similarly, Zhang and Nikolaidis aimed to construct executable task graphs for multi-robot collaboration, where graphs are used to describe what the robot should do to replicate actions observed from cooking videos \[20\]. However, when compared to FOON, the aforementioned task graphs are very domain-specific and do not show the same degree of flexibility, where they can be used in symbolic or object-level planning across various scenarios, as possible with FOON.

III. MANIPULATION PLANNING WITH FOON

Up to this point, task execution with FOON as a robot’s primary source of knowledge has not been thoroughly investigated. To achieve this, we need to consider how the knowledge in FOON can be connected to how the robot views or interacts with its surroundings. FOON can be viewed as a domain-independent representation, while our objective is to translate it to a domain-specific representation, where abstracted concepts in a FOON are grounded to the physical world and to relevant robotic properties and skills. In the following subsections, we introduce our pipeline to connect a FOON to a manipulation planning framework. We provide an illustration of our approach as Figure 2.

A. FOON to PDDL Translation

To facilitate manipulation planning, we translate FOON graphs into PDDL \[9\], which is a language used for classical AI planning. PDDL-based planning requires two basic components: a domain definition and a problem definition. In the domain definition, we define the types of objects that may exist, object attributes or relations as predicates, and the types of actions that can be executed to change the state of the scenario as planning operators. In the problem definition, we instantiate the state of the world and specify a goal as that needs to be achieved using concepts (objects and/or relations) from the domain definition defined as predicates.

A FOON graph (either a task tree or a universal FOON) is hierarchically decomposed into two stages of translation and planning: macro-level and micro-level planning. The translation process is done as follows: first, a macro-level domain definition is created by parsing a FOON graph and translating each functional unit \(FU\) into planning operators referred to as macro-PO, where input object nodes \(O_{in}\) form preconditions and output object nodes \(O_{out}\) form effects. We illustrate an example of this translation as Figure 3.

With a task tree, we can then perform micro-level planning for completing a manipulation task, where each functional unit (as a macro-level planning operator) is decomposed into its own micro-level problem definition. If a universal FOON is provided as input to the framework, macro-level planning is intended to find a task tree, in lieu of the algorithm briefly described in Section II-A.2 where a macro-level problem definition is created for the intended goal in FOON. In the case where we may already have a task tree, we may simply use it as a solution for determining the
sequence of macro-PO solving. Using each macro-PO of the task tree, we define a micro-level problem definition, where preconditions and effects of a macro-PO form its initial state and intended goal. A micro-level domain definition is also provided, in which we predefine several planning operators (referred to as micro-PO) that are associated with skills as motion primitives. A manipulation plan, which is composed of micro-PO sequences for each macro-PO, can be acquired using an off-the-shelf planner such as Fast-Downward [21], which we use in our experiments.

B. Translating FOON Objects to Predicates

An object $o \in \mathcal{O}$ in a FOON is defined by a type and state attributes. When considering objects in PDDL, each object will be symbolically represented by one or more predicates, which are logical statements for facts used for planning. Objects in PDDL are described using two kinds of predicates: 1) spatial or geometrical relations, which are described using object-centered predicates [7], [22], and 2) predicates corresponding to physical states of matter.

1) Geometrical relations: Object-centered predicates are used to describe poses or locations of objects from each individual object perspective, as they relate to other objects within the robot’s environment. The object-centered approach permits consistently representing and propagating geometrical constraints during the heuristic search, rendering geometrically feasible plans. These predicates have the form of $\langle \text{rel} \rangle \langle \text{obj}_1 \rangle \langle \text{obj}_2 \rangle$, where $\text{rel}$ refers to the spatial relation type, $\langle \text{obj}_1 \rangle$ refers to the focal object, and $\langle \text{obj}_2 \rangle$ refers to the relative object. We use the relations in, on, and under, as these are typically attributed to object nodes in FOON. For instance, the predicate $\langle \text{in \ bowl \ tomato} \rangle$ means that a tomato is inside of a bowl. Additionally, we adopt the convention from prior work [7] to describe an empty object as it containing air (i.e., $\langle \text{in \ object \ air} \rangle$).

If an object in FOON does not have spatial state attributes, it is defaulted to being located on the robot’s working surface. At the macro-level, this is represented by an object label table, and thus certain objects will by default be on a table (i.e., $\langle \text{on \ table \ object} \rangle$) and (under $\langle \text{object \ table} \rangle$). At the micro-level, we opted to segment the table into smaller cells in which objects may or may not be occupying these spaces. These table cells are described further in Section V.

A table with no object on top of it is simply described as containing air (e.g., $\langle \text{on \ table \ air} \rangle$). As these details are not known ahead of time, a FOON will not have information on where each object is found or how they are oriented in the scene. Therefore, we defined functions to map object parameters (e.g., poses) to true and false values of predicates to instantiate the state for each micro-level problem definition.

2) Physical features: We also define predicates that correspond to physical features of matter and are temporally relevant for cooking. For instance, an object may naturally be raw, but it can then become cooked as a recipe progresses. Several states in FOON have been identified in related work on state recognition for cooking [23]. These states take the form of $\langle \text{attribute} \rangle \langle \text{object} \rangle$, where $\langle \text{attribute} \rangle$ refers to the relation type and $\langle \text{object} \rangle$ refers to the focal object. Examples of these states and their respective predicates include is-whole for the whole state, is-sliced for the sliced state, and is-mixed for the mixed state.

It is also important to note that some of these features become irrelevant from the micro-level manipulation planning perspective, and thus may not be present in micro-level problems. However, there may be other state predicates that are used to decide if a specific action is complete, thus narrowing the scope of attributes. For instance, it is important to know when an object is completely chopped so that it can be further processed or cooked. These object-states would require computer vision approaches to distinguish an object’s state from all other possible states it can take. For the time-being, these states in micro-level actions are always assumed to be true when their corresponding action is completed.

C. Defining Micro-POs for Manipulation Planning

As mentioned before, each functional unit ($FU \in \mathcal{G}$) is translated to macro-PO definitions, whose preconditions and effects directly map to input and output object nodes ($O_{in}$ and $O_{out}$ respectively). Each macro-PO obtained from a FOON graph is used to define a series of micro-level problems, where the goal is to achieve the effects of the macro-PO using a sequence of lower-level manipulation actions defined as micro-PO. Some of these actions refer to skills or primitives that are commonly defined as atomic skills, which can then be used consecutively with others. For instance, a functional unit for pouring in FOON can be broken down into a sequence of simpler actions: pick a source container, pour from source to target container, and place the source container to free the robot’s gripper. We defined micro-PO actions to characterize physical pre-conditions and expected effects of executing these skills, considering aspects such as the state of the robot’s gripper (being empty or not empty), the position and orientation of objects, and the available surfaces for robot-object and object-object interactions through the virtual object air.

Examples of micro-PO definitions are provided as Figure 4. Further examples of planning operators can be found in previous work [7]. We also provide an example of how
macro-PO in a macro-level plan can be broken down into micro-PO steps as Figure 5

IV. EXECUTION OF A MANIPULATION PLAN

A manipulation plan comprises a sequence of basic manipulation actions that permits reaching the intended effect associated to a high-level functional units in a FOON. These low-level steps are automatically generated using the micro-level problem and domain definition, and they can be linked to motion primitives corresponding to skills. Motion primitives are associated to tuples known as action contexts [7] that encode motion dependencies between consecutive actions in a plan for appropriate usage and successful execution.

A. Action Contexts

An action context is a data structure that is used to associate a motion trajectory to a sequence of low-level actions. Formally, an action context ac is represented as a tuple in the form of ac = (ac.prev,  ac.now,  ac.next, m), where ac.now corresponds to an action being executed, ac.prev and ac.next refer to the preceding and proceeding actions, and m corresponds to the associated motion trajectory. Each action (ac.prev, ac.now, or ac.next) is made up of the PO name and its object arguments (as found by the planner), and a set or library of action contexts is denoted as AC. As in prior work [7], trajectories are represented as dynamic movement primitives (DMP) [24], which use weights as forcing terms to preserve the shape of the original trajectory while allowing different initial and end positions for the robot’s gripper.

B. Executing Action Contexts

When executing a micro-level plan P with n actions (i.e., P = {a1, a2, ..., an}) to achieve the intended goal of a macro-level plan, a robot can search its library AC to derive the appropriate primitive needed for a current action a_t, given that a robot has executed a prior action a_t−1 and that it will then execute another action a_t+1 (if available). To select the appropriate set of DMP parameters m, we first search for ac ∈ AC that matches the present context at some time-step t, where ac.prev is equal to a_t−1, ac.now is equal to a_t, and ac.next is equal to a_t+1. In the likely case that an exact context match has not been found, we can use an approximate action context ac in AC. To elaborate, each action context can be generalized using a coordinate-like tuple from the robot’s point of reference, where a_t is considered as the origin point (target), while a_t−1 and a_t+1 are treated as points relative to the origin. This draws inspiration from previous work [25], where planning operators were generalized using relative positions to targets in a grid configuration for the game of Sokoban. By generalizing each ac into this form, we can easily find ac and reuse its associated motion primitive m with similar objects. For instance, an action context for a black pepper shaker can be extended to a similar object such as a salt shaker. We provide an example in Figure 6 to show how these relative coordinates are derived.
For this work, we selected the which will be performed via simulation in CoppeliaSim [27].

This is similar to the cooking principle of lemon juice, we provide a cup of lemon juice in the scene. simplified certain steps in the recipe’s FOON for one-armed replicate the cocktail recipe while preserving realism, we layout of the scene as Figure 7. To make it easier to manipulated by a single KUKA LBR4+ robot arm with a two-fingered Baxter gripper. We provide an image of the table-top environment with objects and tools to be ma-

A. Experimental Setup

Using the CoppeliaSim platform, we designed a simple table-top environment with objects and tools to be manipulated by a single KUKA LBR4+ robot arm with a two-fingered Baxter gripper. We provide an image of the layout of the scene as Figure 7. To make it easier to replicate the cocktail recipe while preserving realism, we simplified certain steps in the recipe’s FOON for one-armed manipulation; for example, rather than squeezing a lemon for lemon juice, we provide a cup of lemon juice in the scene. This is similar to the cooking principle of mise en place. As mentioned in Section III to facilitate perception, objects are placed on table cells that discretize the table surface. Since we have objects of different sizes, we separated them into two categories, small objects and large objects, which can be placed on small or large table cells respectively (examples labeled as (2) and (3) in Figure [7]. In the scene, there are a total of 21 cells, where large table cells are used for placing large objects (marked as (12) to (14) in Figure [7].

V. Evaluation

To validate our approach, we use a cooking scenario, which will be performed via simulation in CoppeliaSim [27]. For this work, we selected the Bloody Mary cocktail recipe from the FOON dataset. Although the knowledge in this graph is fixed, the manipulation plan obtained from macro- and micro-level planning can change based on the state of the environment (viz., object locations and configurations). Therefore, we show how this source of knowledge can be applied to randomly generated configurations of the scene while flexibly and appropriately reusing action contexts. A visualization of the original recipe graph and demonstration videos are provided as supplementary materials [26].

We evaluate our approach with a series of experiments to show that: 1) low-level task plans tied to motion primitives can be demonstrated and appropriately reused in novel scenarios, 2) a hierarchical task planning framework using FOON allows us to flexibly obtain plans for low-level situations that may not fully match that of the schema proposed by a FOON, and 3) task planning using FOON functional units as a basis for sub-problems allows us to significantly improve computation time over conventional planning. To address 1) and 2), we will measure the average success rate of manipulation plan execution for scenarios with randomized configurations and/or ingredient subsets, while to address 3), we measure computation time as the overall time taken by the Fast-Downward [21] planner to find a solution.

B. Experiment: Transferability of Action Contexts

To illustrate the transferability of learned action contexts to new scenarios, we perform two kinds of experiments: 1) whole recipe execution, which follows the original recipe by using all ingredients, and 2) random ingredient subsets, which we refer to as partial recipe execution. Although the same object-level plan is found across all trials, the task-level plan for each trial will differ due to the objects in Figure [7] being randomly configured (e.g., the drinking glass may be upside-down, or objects may be stacked on top of others). As a result, manipulation plans can range between 26 and 28 micro-level steps. For each round, 25 trials of planning and execution are conducted via simulation. We deem a trial as a success if all objects are manipulated correctly with the appropriate motion primitive and action context while avoiding any collisions that would cause any remaining steps to fail. For example, if the robot knocks the bottle out of the workspace (i.e., table cells) before it gets the chance to pour its contents in the drinking glass, then the robot is unable to complete the vodka pouring macro-level action. From demonstration, we collected a total of 516 action contexts, which can be generalized using the approach from Section IV-B. Results are summarized in Table I.

1) Whole recipe execution: In the first round, the entire Bloody Mary cocktail recipe was performed. As objects are randomly configured at the start of each trial, the robot will have to rely on primitives from learned action contexts. Objects that are stacked on top of others would be placed in a free spot after they are used for pouring or sprinkling to avoid the need for removing it for remaining steps. We observed that the entire robot execution was 96% successful (24 out of 25 trials). The reason for failure was due to some objects being tipped or knocked out of the scene, which prevented the robot from completing some of the macro-level actions.

2) Partial recipe execution: In the second round, the Bloody Mary cocktail recipe was modified by planning over a subset of ingredients, where a plan would be generated that omits a random subset of ingredients. The objective is to further support FOON as a schema that can be flexibly
modified in PDDL while planning for novel scenarios at the PDDL level without creating a new FOON. In this task, we observed that execution was 88% successful (22 out of 25 trials). As with the whole recipe scenario, the reason for failure was mainly due to stacked objects being tipped over that prevented further execution. In the case of whole recipe execution, all objects would be manipulated, resulting in objects being placed into individual locations safe from collision of other objects. However, in the case of partial recipe execution, certain objects would remain in stacked locations, and thus the likelihood of object collision from executing certain motion primitives was higher.

Overall, our findings show that action contexts can be reused for novel situations with high rates of success, granted that objects are of the same category or type, due to the generalization process from Section IV-B.

C. Experiment: Planning with or without FOON

An advantage of using FOON and its notion of functional units to define problems in PDDL is that it simplifies planning. Rather than composing a single planning problem definition, our approach is to decompose each functional unit into smaller problem definitions, which has the benefit of a significantly reduced time complexity. To support this, we compared the average computation time over 10 trials in two flavours of planning: (1) creating FOON-based macro-level problems, where we translate each functional unit into macro-level problems (as done by our framework); and (2) creating a single, comprehensive problem definition. Specifically, in (2), rather than treating each functional unit as its own problem, we will create one problem file that captures the goals of $n$ functional units from the retrieved task tree (where $n$ ranges from 1 to the tree length $N$).

To compare, we perform A* search as provided by Fast-Downward \cite{fast-downward} using two heuristics: landmark cut (LMCUT) and Fast Forward (FF). Being an admissible heuristic, LMCUT allows A* to find an optimal solution, while FF is non-admissible yet it can be used to find acceptable solutions. Running times were measured on a machine running Ubuntu 20.04 equipped with 16 GBs of RAM and an Intel Core i5-8300H processor. We plot our findings as Figure 8 using a logarithmic scale to better highlight timing differences. Times for LMCUT beyond 6 functional units could not be recorded due to memory limitations.

![Fig. 8. Graph showing average computation times over all trials for FOON-based planning (using macro-level problems) and non-FOON-based planning (single problem) with A* search using two kinds of heuristics: landmark cut (LMCUT) and Fast Forward (FF). This graph uses a logarithmic scale to better highlight timing differences. Times for LMCUT beyond 6 functional units could not be recorded due to memory limitations.](image)

To summarize, we introduce an approach to combine domain knowledge from the functional object-oriented network (FOON) representation and classical planning via PDDL to perform manipulation planning for robotic execution, which

\begin{table}[h]
\centering
\caption{Success rates with randomized configurations of scene objects for whole recipe and partial recipe execution.}
\begin{tabular}{|l|c|c|}
\hline
Execution Type & Total Successful Trials & Percentage Success \\
\hline
Whole Recipe & 24/25 & 96\% \\
Partial Recipe & 22/25 & 88\% \\
\hline
\end{tabular}
\end{table}

3More details on these heuristics can be found here: \url{https://www.fast-downward.org/doc/Evaluator}
has not been investigated in prior work with FOON. This is
done through a hierarchical task planning approach with the
objective of translating functional units in a FOON graph to
planning operators and predicates in PDDL. Using FOON
to bootstrap lower-level task planning allows us to quickly
obtain flexible solutions that correspond to the state of the
robot’s environment, which are not necessary to be present in
a high-level abstraction such as FOON.

A. Future Work

As future work, to avoid having to learn every single
context, we will explore how a robot could use a smaller
action context library and break down trajectories into avail-
able action context parts. Related to this idea, we will also
explore re-planning approaches if we encounter action failure
or if action contexts have not been experienced before in the
same vein of previous work [25]. Finally, we will also review
methods to generalize knowledge and action contexts using
semantic similarity [6], [28] to creatively extend concepts at
the symbolic level or trajectories at the execution level to
new object instances in the physical world.

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