Long-Horizon Manipulation Planning with Functional Object-Oriented Networks

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Abstract—Following work on joint object-action representation, functional object-oriented networks (FOON) were introduced as a knowledge representation for robots. 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 work, little has been done to show how plans acquired from FOON 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 manipulation plan can be acquired, which can be executed by a robot from start to end, leveraging the use of action contexts and skills as dynamic movement primitives (DMPs). 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].

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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 with the robot and the current state of its surroundings. Doing so requires connecting the high-level semantic concepts in FOON to the low-level parameters through which a robot understands its actions and world [8],[9]. For example, cooking recipes can be seen as object-level plans, but they require task-level plans to ground object names to instances in the world and skills to verbs. Therefore, to address task planning with FOON, we introduce a hierarchical task planning approach (Fig. 1) that bootstraps manipulation planning with a FOON graph. Our algorithm creates a domain and problem definition in PDDL (short for Planning Domain Definition Language) [10] notation from a FOON, and they are used with an off-the-shelf planner to find a sequence of low-level actions that can be executed by a robot to achieve the intended results of executing the graph from start to end [11]. Our contributions are as follows:

- We introduce an approach to translate a high-level FOON into a low-level manipulation planning problem for classical planning (PDDL) using an object-centered representation of geometrical changes with actions that permits generating geometrically feasible task plans.
- We show how our approach can derive plans for novel scenarios, which may comprise of random object configurations or ingredient sets, without having to create a new FOON for those situations.
- We show how long-horizon plans are executed with high rate of success by considering motion dependencies between consecutive plan actions for trajectory generation.
- We show that using FOON significantly reduces manipulation planning time over classical planning methods.
II. BACKGROUND AND RELATED WORKS

A. Functional Object-Oriented Networks (FOON)

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

As a result of executing actions, objects may take on new states. State transitions are conveyed through functional units (denoted as $FU$), which describe object nodes before and after an action takes place. Specifically, a functional unit $FU = \{O_{in}, O_{out}, m\}$ contains a set of input nodes $O_{in}$, a set of output nodes $O_{out}$, and an intermediary action node $m$, comparable to the precondition-action-effect structure of planning operators (POs) in classic planning [12]. A robot can use a FOON to identify states that determine when an action is completed. Fig. 2 shows two functional units describing a sequence of pouring vodka and ice into a driving glass. There are notably several object types with multiple node instances, as these object states will change as a result of execution. Each functional unit has the same motion node label of pour, yet the objects and effects of each action differ, thus treating them as two separate actions.

FOONs can be created by annotating manipulations from observation, such as video demonstrations, or, as we plan to explore as future work, demonstrations from a human teacher. During annotation, we note the objects, actions, and state changes required to achieve a specific goal, such as a recipe. This results in a FOON subgraph, which is simply a sequence of functional units (and their corresponding objects and actions) to fulfill the given goal. Two or more subgraphs can be merged to form a universal FOON. Presently, the FOON dataset provides 140 subgraph annotations of recipes with which a universal FOON can be created; these annotations along with helper code are publicly available for use.^[1]

B. Task Planning

We adopt the traditional approach for task planning [12] by defining a set of objects (e.g., cup or bowl) and a set of predicates, coding relations among objects or object properties (e.g., on table cup) – the cup is on the table), which are logical functions that are either true or false depending on whether these relations or properties occur in the scenario. The set of predicates describing the object configuration in a scenario defines the symbolic state $s$. Planning operators (PO) describe the changes in the symbolic state via actions and are encoded in the traditional precondition-action-effect notation using PDDL [10]. The precondition part comprises the predicates that change by the execution of the PO, as well as those predicates that are necessary for these changes to occur. The effect part, in turn, describes the changes in the symbolic state after the PO execution. Fig. 3 provides example POs written in PDDL notation. The name of a PO is a symbolic action and may contain arguments to ground the predicates in the precondition and effect parts. In task planning, a planner receives the description of the initial state ($s_{ini}$) and a goal definition ($g$) as a set of grounded predicates that should be observed after execution. With these elements, the planner carries out a heuristic search by generating causal graphs from the preconditions and effects of POs and yields a sequence of actions called a plan that would permit producing changes in $s_{ini}$ necessary to obtain $g$. In this work, we use the off-the-shelf linear planner Fast-Downward [13].

C. 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 [14] have been developed to combine knowledge bases with a query processing engine to allow robots to reason over beliefs of its world. Previously, Tenorth et al. have shown how a robot can use this knowledge base to prepare meals, such as pancakes, and form queries over object or action properties [14]. However, their main focus was on structurally defining the knowledge base and infer object locations rather than storing or retrieving recipes or task sequences in a way that can be reused like FOON. We propose that FOON can be used as a schema along with reasoning engines or knowledge bases such as KNOWROB, which are tied to low-level robotic properties. Ramirez-Amaro et al. [15] investigated how semantic knowledge can be 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 in FOON is agnostic to the robot, and it is only through planning that we obtain a robot-specific plan suited to the robot’s present environment.

Hierarchical task networks (HTN) [12] share many similarities with FOON. HTNs can be used to represent abstract tasks (referred to as methods), which may be decomposed into a sequence of sub-tasks that can be immediately executed by an agent or robot. These higher-level tasks are

\[^1\]FOONets (FOON Website) – http://www.foonets.com
similar to functional units in FOON that require a sequence of lower-level actions to achieve the 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 schematic knowledge from FOON allows us to derive manipulation plans that are tied to the state of the robot’s workspace.

Similarly, Kaelbling et al. [16] interleave hierarchical planning with execution using highly abstract behaviours for task planning to accelerate the generation of task plans but at the expense of experiencing several planning impasses at execution time. Our approach includes relevant geometrical constraints at the task planning level that permits exploiting the computational efficiency of task planners for generating feasible manipulation plans. Logic programming task planners search for solutions directly in the plan space, rather than in the state space as classic planners, which permits the inclusion of geometrical constraints for generating feasible task plans [17]. However, these approaches implement computationally demanding optimization processes on whole plans using complex dynamic models, which make them less suitable for solving long-horizon optimization problems. Other approaches incorporate semantic descriptions of geometrical constraints to evaluate motion feasibility of single actions [18] or sequences of actions [19] that are assessed during task planning using conventional state-based planners. The task planner generates candidate plans based on these constraints while a sampling-based motion planner checks actions feasibility using geometric reasoning. Instead, our object-centered predicates permit propagating geometrical constraints during task planning in terms of standard relational names that are easily mapped to object poses without using external heuristics for geometric reasoning.

Previous work explored encoding of macro planning operators into primitive operators for the execution of robotic tasks, combining macro operators and primitives into a single linear planning domain [20] or combining linear planning with reinforcement learning for executing primitives [21]. However, as with HTNs, macro operators are associated with a fixed sequence of primitive operators that are executed in a reactive manner. Manipulation action trees [22] by Yang et al. were proposed for planning and execution by representing robotic manipulation in a tree form. Similarly, Zhang and Nikolaidis proposed executable task graphs, which describe what the robot should do to replicate actions observed from cooking videos, for multi-robot collaboration [22]. However, as their focus was on imitating behaviours from demonstration, they do not show how these graphs could be adapted to novel scenarios as possible with our proposed approach.

III. MANIPULATION PLANNING WITH FOON

Up to this point, bootstrapping task execution with a FOON has not been 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 object properties and robotic skills. This is achieved by a two-level hierarchical planning approach. At the top, a macro-planning approach generates a sequence of instructions (macro-plan) for the preparation of recipes using a FOON. At the bottom, a micro-planning method defines the sequence of skills (micro-plan) for executing each instruction in a given scenario. We show an illustration of our approach as Fig. 1.

A. Macro-level Planning

Aside from representing knowledge in a human-readable manner, we can rely upon FOON to determine how objects can be utilized to solve more complex problems using a heuristic search. In previous work [5], we defined a heuristic search that combines breadth-first and depth-first search to find solutions directly using the FOON representation. In this work, we adopt the alternative strategy of first transforming a FOON into planning domain definition using PDDL, and then searching for solutions using a classical linear planner to generate a macro-plan. We illustrate an example of this translation as Fig. 3. The latter strategy permits the generation of sequences of functional units beyond the fixed sequences encoded in the graph representation of FOON.

We define a set of predicates that are obtained from the objects in FOON. An object \( o \in \mathcal{O} \) in a FOON is defined by a type and state attributes, for example, a drinking glass (type) is empty (attribute) (see Fig. 2). Each object is characterized by one or more predicates in the PDDL definition. First, a predicate is generated from each object by considering the object type as the object name, and by transforming the attribute into either a relational predicate in when it concerns containers (e.g., \((\text{in cup ice})\)), or by simply characterizing the attribute in PDDL notation when it refers to a physical property of the object. These latter predicates 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 [24]. These states take the form of \((\text{<rel> <obj>})\), where \(<\text{rel}>\) refers to the relation type and \(<\text{obj}>\) 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 planning perspective (Sec. III-B), and thus may not be present in micro-level problems. Finally, we define predicates encoding relations with an object label table to indicate that the object is present in the robot’s workspace (i.e., \((\text{on table <obj>})\) and \((\text{under <obj> table})\)).

These object-table relations are encoded using object-centered predicates indicating that the object is on the table and that the table is under the object. This is done to consistently map table-object relations from the effects of a macro-PO to a goal for micro-planning (see Sec. III-B).
Using these predicates, we transform each functional unit $F_i$ into a macro planning operator (macro-PO) by directly mapping the objects in $\{O_{in}, O_{out}\}$ into preconditions and effects, with its name given by the $F_i$ name $i$. For macro-planning problem definition, predicates characterizing the objects in the scenario will conform to the initial state ($g_{mic}^{ini}$), while the macro-planning goal ($g_{mic}^{mac}$) is defined by the predicates describing the desired final state of objects (e.g., $g_{mic}^{mac} = \{(\text{in drinking glass vodka}), (\text{in drinking glass ice})\}$). After the domain (macro-POs) and problem (initial state and goal) are defined, a macro-plan can be obtained using off-the-shelf planners. The translation of FOON into a PDDL macro-planning domain is performed without information loss, only adding new predicates that confirm the availability of objects in the scenario for recipe preparation. This preserves the completeness of the original FOON and guarantees finding identical solutions when using the same heuristics in both representations [5]. The generated macro-plan comprises a sequence of functional units that should be “executed” in order to prepare a recipe. To do this, each functional unit is grounded into a manipulation plan (micro-plan) for the functional unit execution.

**B. Micro-level Planning**

After a macro-plan is generated, we then perform micro-level planning for the generation of a manipulation plan, where each functional unit (as a macro-PO) is decomposed into its own domain-specific micro-level problem definition, whose goal predicates are taken directly from a macro-PO and initial state is defined using perception. For instance, a functional unit for pouring in FOON may be decomposed 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. For the generation of micro-plans, we use the same approach as in our previous works [7], [25] that characterize the object configuration space for manipulation planning using object-centered predicates. 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 ($\text{<rel> <obj}_1 \ <obj}_2$), where $\text{<rel>}$ refers to the spatial relation type, $\text{<obj}_1$ refers to the focal object, and $\text{<obj}_2$ 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 $\text{(in bowl tomato)}$ 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., (in <obj> air)). At the micro-level, we opted to segment the table into smaller cells in which objects may or may not be occupying these spaces to check geometrical feasibility in picking and placing actions. These table cells are considered further in Sec. [V].

The initial state for the micro-planning problem definition ($g_{mic}^{ini}$) is automatically generated in the same manner as in our previous contribution [7], where we define functions to map object parameters (3D poses and bounding boxes) to true and false values of object-centered predicates. On the other hand, the micro-planning goal $g_{mic}^{mac}$ is generated from the predicates coding object relations in the effects of the corresponding macro-PO, also characterized using an object-centered perspective. We define micro-POs to reflect physical preconditions and expected effects of individually executing skills (e.g., pick, place, pour) in terms of changes in object-centered relations, 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 shown in Fig. [IV] and further examples can be found in previous work [7]. A manipulation plan, which is composed of micro-PO sequences for each macro-PO, can thus be acquired using an off-the-shelf planner such as Fast-Downward [13].

**IV. EXECUTION OF A MANIPULATION PLAN**

A manipulation plan comprises a sequence of basic manipulation actions that realizes the effects associated to a high-level functional unit 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 with 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 \(ac = (a_{prev}, a_{now}, a_{next}, p)\), where \(a_{now}\) corresponds to an action being executed, \(a_{prev}\) and \(a_{next}\) refer to the preceding and proceeding actions, and \(p\) corresponds to the associated motion trajectory. Each action \((a_{prev}, a_{now}, \text{ or } a_{next})\) 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 \(\mathcal{AC}\). As in prior work \(^7\), trajectories are represented as dynamic movement primitives (DMPs) \(^{26}\), which use weights as forcing terms.

B. Learning and Executing Action Contexts

When executing a micro-level plan \(P\) with \(n\) actions (i.e., \(P = \{a_1, a_2, \ldots, a_n\}\)) to achieve the goal of a macro-level plan, a robot can search its library \(\mathcal{AC}\) to derive the appropriate primitive 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 DMP parameters \(p\), we first search for \(ac \in \mathcal{AC}\) that matches the present context at some time-step \(t\), where \(a_{prev}\) is equal to \(a_{t-1}\), \(a_{now}\) is equal to \(a_t\), and \(a_{next}\) is equal to \(a_{t+1}\). In the original contribution \(^7\), action contexts are created from grounded actions observed in plan segments. Encoding action contexts in this manner prevents their use in situations where the same motion dependencies are needed for similar (but not equal) set of objects. Thus, to improve generalization, each action context is encoded using a relative coordinate-like tuple, 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 \(^{27}\), where planning operators were generalized using relative positions to targets in a grid configuration. We provide an example in Fig. 5 to show how these relative coordinates are derived. In addition, we defined a dictionary that maps each object to categories (e.g., small or large objects) to allow us to generalize across objects. For instance, the same action context can be reused on two small objects black pepper shaker and salt shaker. With this approach, we can generalize action contexts to similar but novel situations and define a suitable set of motion parameters \(p\).

Finally, if no action context matching the current micro-level plan segment can be retrieved from \(\mathcal{AC}\), a human demonstration is requested to generate a new action context using the incremental approach in \(^7\), where the associated set of DMP parameters are generated using the approach in related work \(^{28}\). Similar to prior work \(^7\), the number of demonstrations decreases to zero as learning proceeds, and the robot becomes fully autonomous in the long run.

V. Evaluation

To validate our approach, we perform cooking tasks via simulation in CoppeliaSim \(^{29}\). For this work, we created a universal FOON made of three subgraphs from the FOON dataset, from which we will perform hierarchical planning to prepare a Bloody Mary cocktail and a Greek salad. For each goal, the objective of macro-level planning is to extract a FOON-based plan (equivalent to a task tree subgraph), while that of micro-level planning is to find a manipulation plan specific to the state of the environment (viz. object locations and configurations). We thus show how this can be applied to randomly generated configurations of the scene while reliably using action contexts and motion primitives.

We evaluate our approach with a series of experiments to show that: 1) action contexts can be reused for novel scenarios, 2) FOON-based planning 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 for macro-planning allows us to significantly improve computation time over classical planning. To address 1) and 2), we measure the average success rate of plan execution for randomized scenes and/or ingredient subsets, while to address 3), we measure computation time as the overall time taken by the Fast-Downward \(^{13}\) planner to find a solution with and without a hierarchical decomposition using FOON. An image of the source universal FOON and demonstration videos are provided in supplementary materials.

A. Experimental Setup

Using CoppeliaSim, we designed simple table-top environments with objects and utensils that will be manipulated by a single KUKA LBR iiwa 7 R800 robot arm equipped with a Robotiq 2F-85 gripper. Fig. 6 shows the layout of the scene for the cocktail and salad tasks. To make it easier to replicate the recipes while preserving realism, we simplified certain steps in the recipe’s FOON for one-armed manipulation; for example, rather than squeezing a lemon for juice, we provide a cup of lemon juice in the scene. This is similar to the cooking principle of mise en place. We also fashioned objects such as the cutting board (17) for robotic manipulation. For perception (as in Sec. \(^{11}\)), objects are placed on cells that discretize the surface. Since we have objects of different sizes, we separated them into three categories, small, long and wide objects, which can be placed on appropriately sized spaces (e.g., (3), (4) and (15) in Fig. 6).

3Link to Supplementary Materials – https://bit.ly/3FaQeUS
B. Plan Generation for Variable Object Configurations

This experiment demonstrates the capability of our approach to find micro-level plans for varying object configurations and constraints for the same FOON plan. We perform these experiments on both the cocktail and salad scenarios. Fig. 7 shows various configurations for the execution of the (pour_lemon_juice) macro-PO in the cocktail scene (Figs. 7a, 7c) and (pick_and_place_tomato) in the salad scene (Figs. 7d, 7f) along with their respective micro-plans. These macro-POs are equivalent to the functional units (ignoring other ingredients) in our supplementary materials.

For pouring, the configurations are: 1) the objects are ready for pouring (Fig. 7a); 2) the drinking glass requires rotation before pouring (Fig. 7b); and 3) the drinking glass requires rotation and the ingredient (cup of lemon juice) is blocked (Fig. 7c). For the pick-and-place task, the configurations are as follows: 1) the cutting board is free of obstacles for placing the tomato on top of it (Fig. 7d); 2) the tomato is obstructed by a salt shaker between it and the cutting board (Fig. 7e); and 3) the cutting board has a stack of obstacles on it that need to be removed prior to placing the tomato (Fig. 7f). From this figure, we can observe that the planner finds different manipulation plans that account for the state of the environment for the same macro-level objective, which has the advantage over methods in HTNs that are fixed and need to be defined beforehand. We provide links to videos in our supplementary materials for each micro-plan execution.

C. Transferability to New Scenarios

To demonstrate transferability, we perform two kinds of experiments over 25 trials in variable scenarios: 1) whole recipe execution, using all ingredients in the original recipe; and 2) partial recipe execution, using random ingredient subsets. Although the same object-level plan is found across all trials, each trial will result in different manipulation plans due to the shuffling of objects (Fig. 6) in the scene (e.g., the drinking glass may be upside-down, or objects may be stacked on top of others). In addition, we show that FOON can be flexibly modified at the PDDL level to plan for novel scenarios using fewer objects without creating a new FOON via partial recipe execution. A trial is successful if all objects are manipulated with a suitable action context and motion primitive while avoiding collisions that may cause remaining steps to fail. For example, if the robot knocks a bottle out of the workspace (i.e., table cells) before pouring, then the robot is unable to complete its corresponding macro-PO. Objects stacked on top of others would be placed in a free spot after use to avoid further removing them for remaining steps.

As objects are randomly configured at the start of each trial, the robot has to rely on learned action contexts. We collected a total of 703 action contexts from demonstration (635 from the cocktail scene and an additional 168 from the salad scene), which can be generalized using the method from Sec. [LV-B]. We summarize our results in Table I. In the cocktail task, robot execution was 96% successful for whole execution and 92% for partial execution; in the salad task, robot execution was 80% successful for whole execution and 84% for partial execution. The robot failed to complete the task in certain trials due to objects being knocked out of the workspace, which occurs due to trajectories encoded by action contexts not being adapted to avoid collisions with objects lying in between manipulated ones. This is especially prevalent in the salad task, which is a longer-horizon task with an average plan length of 35 steps. Despite the lack of trajectory adaptation [69] or motion planning, however, the stored shapes were enough to avoid collisions in most cases without the need to replan. We plan to develop a fully TAMP framework bootstrapped by FOON as future work.

D. Planning with and without FOON

An advantage of using a FOON’s functional units to define PDDL problems is that it simplifies planning, where, rather than composing a single problem definition, our approach transforms each functional unit into smaller problem definitions, which benefits in a significantly reduced time complexity. To support this claim, we compared the average computation time over 10 configurations of the cocktail task for two flavours of planning: (1) FOON-based planning, where we translate each functional unit into macro-level problems (our approach in this work); and (2) classical planning, where a single problem file is defined with goals of \( n \) functional units (where \( n \) ranges from 1 to the full plan length \( N \)). We use A* search as provided by Fast-Downward and two heuristics: landmark cut (LMCUT) and Fast Forward

![Fig. 6. Layouts for the cocktail and salad tasks in CoppeliaSim.](image)

| Task      | Execution Type | Avg. Plan Length | No. Successful Trials | % Success |
|-----------|----------------|------------------|-----------------------|-----------|
| Cocktail  | Whole          | 27.9 ± 1.35      | 24/25                 | 96%       |
|           | Partial        | 19.8 ± 3.57      | 23/25                 | 92%       |
| Salad     | Whole          | 34.6 ± 1.78      | 20/25                 | 80%       |
|           | Partial        | 24.9 ± 5.33      | 21/25                 | 84%       |
LMCUT is an admissible heuristic that finds optimal plans, while FF is non-admissible yet it can be used to find acceptable plans. Running times were measured on a machine running Ubuntu 20.04 with 16 GBs of RAM and an Intel Core i5-8300H processor. A maximum allotted time of 20 minutes was set for each trial. We plot our findings as Fig. 8 using a logarithmic scale to highlight the difference in computation time between the two approaches and heuristics. From the plot, we can observe that FOON-based planning finds plans in significantly less time than classical planning, as the planner operates with a much smaller search space. Using LMCUT for classical planning took a significantly longer time to find a solution, so much that plans were not found for problems larger than 5 functional units. In addition, despite non-admissibility of FF, classical planning could not perform as well as FOON-based planning. The advantage of using FOON-based planning is that we can use optimal heuristics on smaller problem sets, which would allow the robot to find and execute a plan in real-time. Furthermore, perception can be used between macro- and micro-actions to keep monitoring the state of the environment. Finally, FOON can be used schematically to enforce a high-level ordering of actions. One example we observed in this experiment from using classical planning is the mixing action. At the macro-level, mixing requires ingredients in a container, but at the micro-level, the only requirement is that the container is free of obstacles on top of it. Mixing at the micro-level results in the container being mixed (\[is-mixed \langle \text{obj} \rangle\]) rather than the ingredients being mixed. As a result, without a macro-level plan, a robot may acquire a plan to execute the mixing action before adding all ingredients.

4 More details on these heuristics can be found here: [https://www.fast-downward.org/doc/Evaluator](https://www.fast-downward.org/doc/Evaluator)
VI. CONCLUSIONS

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. This is done through a hierarchical task planning approach with the objective of translating functional units of 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 an object-level representation such as FOON.

A. Limitations and Future Work

Despite the exceptional performance of our approach to transform FOON into long-horizon manipulation plans, there are several limitations that we plan to address. One of them is the open-loop nature of the robotic executions that do not permit coping with unexpected contingencies inherent to real-robot, unstructured scenarios. As future work, we plan to explore re-planning options if actions fail, in the same vein of the prior work [27], and to include geometric feedback at the motion planning level in real-world settings. In addition, even though DMPs associated to action contexts permit reproducing the shape and orientation of trajectories of demonstrated actions in similar scenarios, they do not warranty collision-free executions. We plan to incorporate mechanisms to adapt motion primitives for obstacle avoidance using a similar strategy as in [50]. Finally, we will review methods to generalize knowledge and action contexts using semantic similarity [31] 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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