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A Quantifiable Stratification Method for Tidy-up in Service Robotics

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***Abstract*— This paper addresses the problem of tidying up a living room in a messy condition with a service robot (i.e. domestic mobile manipulator). One of the key issues in completing such a task is how to continuously select the object to grasp and take it to the delivery area, especially when the robot works in constrained and partially observable environments. In this paper, we propose a quantifiable stratification method that allows the robot to find feasible action plans according to different configurations of objects-deposits, in order to smoothly deliver the objects to the target deposits. Specifically, it leverages a finite-state machine obeying the principle of Occam's razor (called O-FSM), which is designed to integrate arbitrary user-defined action plans typically ranging from simple to complex. Instead of considering a sophisticated model for the ever-changing objects-deposits configuration in the tidy-up task, we empower the robot to make simple yet effective decisions based on its current faced configuration under a generalized framework. Through scenario planning and simulation experiments with the explicitly designed test cases based on the real robot and the real competition scene, the effectiveness of our method is illustrated.**

I. Introduction

Service robots are highly-demanded in people's daily life especially for domestic and healthcare applications. The human service robots require the capability of both mobility and manipulation. Tidying-up is a typical task for service robots (see Fig. 1), in which the robot needs to sort cluttered objects (either scattered or stacked) as required, usually by category at specified locations. This task seamlessly integrates the autonomous navigation with autonomous manipulation hence is very challenging. Specifically, it covers many aspects of robotics including semantic mapping, object detection and manipulation, decision-making, navigation and obstacle avoidance, and so forth. Admittedly, the complexity of such integration poses another level of challenge to the robustness of the robot system.

We contend that, for such a complex problem (system), an effective way is to use simple methods to minimize the impact on future uncertainties [1], and this simplicity is better to be quantifiable. To this end, as an entry point, we propose a stratification method for decision-making in tidy-up tasks, based on the finite-state machine incorporating the principle of Occam's razor, which we called O-FSM. It's designed to integrate robot action plans (similar to policies in reinforcement learning) with different levels of complexity, while these plans are quantified, independent and can switch from one to another. In contrast to model-based (such as POMDP [2], [3]) or learning-based (such as reinforcement learning [4]) methods, our proposal is based on rules which has the characteristics of process controllable, efficient and less hypothetical. Motivation for our work can be seen in World Robot Challenge 2018 - Partner Robot Challenge (Real Space), where a Toyota HSR robot [5] was asked to put ten scattered toys in order (five categories) on the toy shelf in a children room in twelve minutes.

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Fig. 1. A Toyota HSR robot is performing tidy-up task at our experimental site. Full video available here: https://youtu.be/OdHMgBkmVlk

Our approach, based on the well-known philosophical thought and the classic computer science method, has several features that make it well-suited for the tidy-up task. First, it grades the plan by explicitly counting the number of actions that the robot needs to perform, and holds a priori assumption that the uncertainty is proportional to this number. Second, it responds to changes and uncertainties in the environment through repeatable actions (model-free), i.e. facing many changes with no change. Third, it is close to human intuition (i.e. fast) rather than relying on complex models (e.g. for rational decision-making) to solve the problem, especially when the environment is constrained and partially observed. Furthermore, as the motion planning for objects and deposits is not always guaranteed, we inject the idea of active perception into the instantiation of the proposed approach, i.e. in the absence of a feasible plan, the robot can actively move objects to change the environment, thereby making future planning possible.

The contributions of this paper are two-fold. On the one hand, we categorize the tidy-up problem, propose our method for such task which allows the robot to quickly make judgments that can advance the task without the knowledge of the global environment. On the other hand, we explicitly design the test cases by taking the real competition scene into account, i.e. a robot in a messy space where objects are randomly placed, and illustrate the effectiveness of our method through scenario planning and simulation experiments. To the best of our knowledge, our work is the first to propose a system-level method with a theoretical basis for enhancing the degree of task completion.

II. Related Work

Service robots are expected to perform a wide range of challenging tasks [6], [7], including cleaning, storing, monitoring or tidying, to name but a few. These tasks require numerous combined skills, and as a representative example, tidying a room is often used as a case study for robotics competitions[1]. Towards the full automation of this human-beneficial application, many scientific contributions have been proposed.

For example, the use of semantic information is studied to help the robots with their decision-making process. Abdo *et al.* [8] proposed a tidying approach that integrates user preferences in terms of objects association. A database of users pairwise object preferences is computed from thousands of collected surveys and based on the user previous organization habits. When an object is not included in the created database, a mixture of experts approach is exploited to provide information about similarities between known and unknown objects. The sorting of a set of different objects constrained by the user preference expectations is modelled and solved by using a spectral clustering approach. In addition, heuristic approaches [9], [10] were proposed to sort and segregate deformable objects such as clothes piles according to the categories. In [11], a method has been proposed to represent basic human knowledge in order to improve the performance of tasks such as bringing an object or tidying a room by a robot. The idea is to structure the relationships between common activities and daily objects in a domestic environment. The data structure is automatically built from multiple sources such as children books. It consists of multiple layers in which objects and activities are associated by weighted connections. In addition to this network, answers from surveys related to the desired application (e.g. tidy-up) are used to build ontology rules that are used in the robot decision algorithm.

Action planning is also being investigated to elaborate effective tidying strategies. Yamazaki *et al.* [12] developed an integrated software system for daily assistive robots. They proposed to reduce the robot actions to two main functions including recognition and motion, and to divide the robot behaviours into three simple states including "check", "plan" and "do". This framework is used to build task structures to perform different daily assistive duties. In order to accomplish a home service task in cooperation with a human, an adaptive task planner has been proposed [13]. The authors have designed the robot episodic memory as a temporal sequence of actions to perform a specific task. When the robot receives an order, it decides how to cooperate appropriately according to perceived human behaviours and its episodic memory on the requested task. To perform a household task, service robots have to deal with a high quantity of information that may be not relevant or uncertain. Nebel *et al.* [14] have formulated a generic planning problem as an open partially-observable non-deterministic planning problem within a continual planning loop. To also deal with uncertainties, a modular approach named Interfaced Belief Space Planning (IBSP) has been developed [15]. Task and motion planning are combined in belief space through the maximum likelihood observation determinization concept.

By investigating the state-of-the-art, we noticed the gap between it and what would be required for a human-services-ready robot, that motivated us to develop a concise and robust system towards completion of the tidy-up task. In reality, domestic tasks are often accompanied by ever-changing environments and uncertainties, which are difficult to predict. In addition, the robot often has only a partial observation of the environment, and in some cases getting a global view through exploration is impossible due to non existence of feasible navigation path. An alternative is that the robot uses a basket [16] to collect the scattered objects first and then sort them one by one. However, this requires first solving the problem of loading and unloading the bucket from the hardware design level, and second, the grasping of objects from a self-occluded pile raises another level of challenge.

III. Tidy-up with a Mobile Robot

Multi-deposit multi-category tidy-up task is very challenging, as the objects can be everywhere in a room and the robot could not even reach some of them and/or target deposits smoothly due to obstacles on the ground. In order to clarify the research problem and elicit our approach, we divide the problem into four sub-categories from simple to complex including, *fully-observable-fully-reachable*, *fully-observable-partially-reachable*, *partially-observable-fully-reachable* and *partially-observable-partially-reachable*. For the sake of system-wide clarity, our prerequisites are as follows:

- The robot has a wheeled moving basis rather than legs (e.g. humanoid robot), and it is not allowed to move over any objects on the ground.
- The robot has a pre-built environment map (e.g. occupancy grid map) about the static objects such as walls and stationary furniture.
- The robot knows the 3D pose of the deposits with the corresponding categories (e.g. semantic map), and each object must has a corresponding deposit.

Moreover, the success of the object manipulation by the robot is not guaranteed, which means the *fully-reachable* may turn into *partially-reachable*, for example, an object dropped from the robot's grasper during the manipulation.

[1] https://worldrobotsummit.org/en/wrs2020/challenge/service/partner.html
https://www.robocup.org/leagues/34
http://juxi.net/challenge/tidy-up-my-room/

A. Fully-Observable-Fully-Reachable (FOFR)

The robot has a full observation of the environment, and all objects and deposits are reachable. The latter means that there exists a collision-free path to the deposit with corresponding category after the robot grasping an object. This is obviously a P-problem which can be well solved in polynomial time. For example, using the Hungarian algorithm [17] can find the optimal (e.g. in terms of time) object-deposit assignment.

B. Fully-Observable-Partially-Reachable (FOPR)

The robot still has a full observation of the environment, but not all of the objects or deposits are reachable. However, although this is a NP-hard problem, as the robot has a global view, it can still be well solved by the state-of-the-art [8], [18]. For example, the cost matrix of the Hungarian algorithm can be dynamically changed [18], with the cost for unreachable objects and deposits set to $+\infty$.

C. Partially-Observable-Fully-Reachable (POFR)

Since all objects and deposits are reachable, partial observation mainly affects the question of whether an optimal solution can be found (e.g. minimizing the overall mission time). An intuitive approach is to actively explore the entire environment in order to gain a global awareness [19]. However, this still relies on a strong assumption (prior), i.e. fully reachable of the objects and deposits.

D. Partially-Observable-Partially-Reachable (POPR)

This is a NP-complete problem, which can be formalized as a Partially observable Markov decision process (POMDP) problem [2], [3]. However, practically, difficulties emerge because of the continuous nature of the underlying state, action spaces and observation spaces, which are the core features of the tidy-up tasks. Compare to typical Bayesian-based estimation which either requires a longer of computing time or fails to ensure a feasible solution, our O-FSM method can alleviate the difficulties that exploit the structure of the elicitation problem to some extent.

IV. Methodology

A. Theoretical Basis

Different from complex modeling or high-cost reinforcement learning for the POPR problems, we believe that among competing robot action plans that face known observations equally well, one should choose the simplest one. Our approach is based on the theory of Occam's razor, which is formulated as follows inspired by the minimum description length (MDL) principle [20]:

$$A(O) = \min_{P \in \mathscr{P}} (A(P) + A(O|P)) \tag{1}$$

where A indicates the number of executable actions, O is the known observations of the robot, and P represents the motion plan in a set of considered plans $\mathscr{P}$. Specifically, $A(P)$ is related to the design of the plan and can be regarded as a priori, while $A(O|P)$ depends on the current observations of the robot and can be regarded as a posteriori. The idea is to find the plan P that requires the minimum number of actions, which is then considered as the best one, as less complicated plans are less likely to fail. Moreover, minimizing A also implies minimizing the impact on the environment, thereby minimizing the uncertainty of the future environment state.

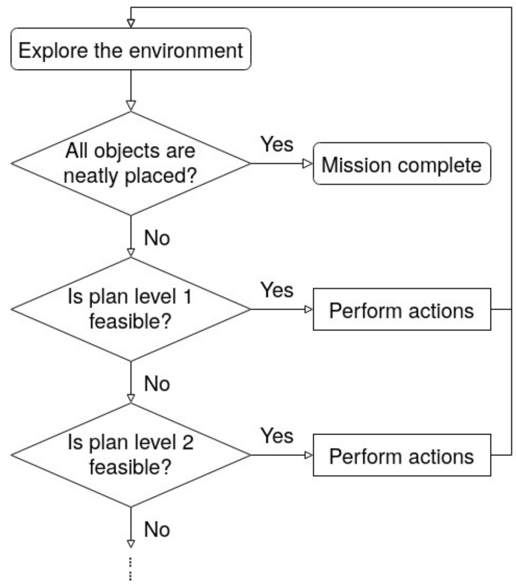

Fig. 2. Flowchart of the poposed O-FSM method for robot tidy-up tasks.

A deterministic FSM (Mealy type) is then integrated, in which the output depends on both input and system state (see Fig. 2). The machine can be formally defined as a sextuple (S, s_0, O, A, T, F), where in the context of tidy-up, S is a finite set of states which represents the overall mission, $s_0 \in S$ is an initial state which can be considered as the state before the robot entered (explored) the room, O is the input which includes both known and unknown observations, A is the output which contains robot actions on the environment, T is a transition function $T : S \times O \to S \times A$, and F is the set of final states including the completion of the tidy-up task.

B. Instance Plans

For a better illustration, we give three instance plans from simple to complex in this section. The first plan (denoted by $P1$) is based on a greedy algorithm, which empowers the robot to always grasp the closest object i:

$$i = \min \|p_r - p_i\|_2,\ i \in I \tag{2}$$

subject to

$$h(p_r, p_i) \wedge h(p_i, p_d) \wedge c_i = c_d,\ d \in D,\ c \in C \tag{3}$$

where $h(x,y)$ indicates existence of a feasible path from x to y, p_r, p_i and p_d are the position of the robot, object and deposit, respectively, in the map reference frame, and c is the category. Although this is a very intuitive plan, it does not guarantee global optimality, e.g. minimum overall mission time. However, it is fast and suitable for a controlled environment, which is the one we used in the World Robot Challenge 2018.

In case no solution to Eq. (3) exists, the second plan (denoted by $P2$) attempts to find an alternative object to pick up. This typically occurs when p_d is unreachable (sometimes it also implies that p_d is unobservable). Our proposal is based on the shortest path algorithm, which means that the robot will pick the object i' and deliver it to deposit d' by obeying the following formula:

$$(i', d') = \arg \min_{i \in I, d \in D} (k(p_r, p_i) + k(p_i, p_d) | c_i = c_d) \quad (4)$$

where $k(x, y)$ is the length of a feasible path between x and y. Eq. (4) reflects the fact that the robot performs a tidy-up task from its current position p_r to the object position p_i and delivers the object to its corresponding deposit p_d. Noting that additional motions are potentially required to obtain a feasible and collision-free grasping pose for the robot.

The third plan (denoted by $P3$) is to cope with the obstruction of the system by actively changing the environment (i.e. the system state). The plan is triggered if there is no solution to Eq. (3) and Eq. (4) because no collision-free paths from p_r to p_i or p_i to p_d were found. To cope with that, the robot is expected to remove one or more objects starting from the closest one and put them in a suitable place, until getting a feasible solution. The process for the place finding is summarized in Algorithm 1. In a word, the robot should grasp the closest object and take it to the nearest waypoint and drop it in a free space nearby, while this waypoint needs to be previously reached and is neither used for grasping nor for delivery (see Fig. 3). In practice, the best area is typically near to the entrance of the room, where is designed to have the least impact on placement of objects based on human living habits.

Algorithm 1: Waypoint selection for object removal

```
Data:
W: list of waypoints
p_r: position of the robot
Result:
w: waypoint for object removal
if w = NULL then
    repeat
        w ⟵ findTheNearestWP(W, p_r);
        if isForGrasping(w) or isForDelivery(w)
        or yetReached(w) then
            w ⟵ NULL;
    until w ≠ NULL;
moveTo(w);
```

The actions taken into account for our instance plans are listed as below in order to reflect the observance of the Occam theory, i.e. the fewer the actions, the simpler the solution ($P1 \subset P2 \subset P3$):

- $P1$ (3 actions): $\{take\_object, move, deliver\_it\}$.
- $P2$ (at most 4 actions): $\{possible\_ego\_pose\_adjustment, take\_object, move, deliver\_it\}$.

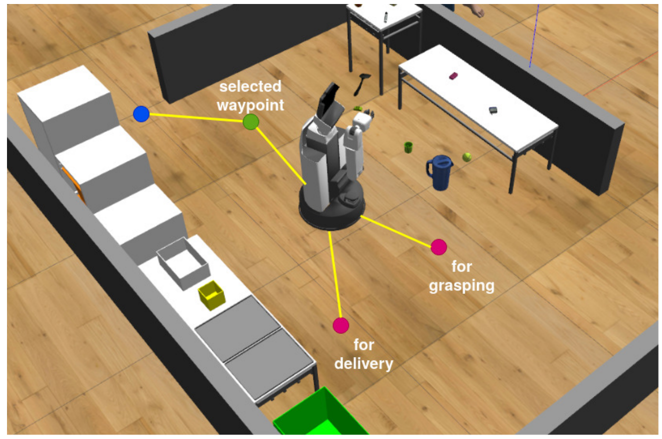

Fig. 3. Selection of waypoint for object removal.

- $P3$ (at least 7 actions): $\{take\_object, move, drop\_object, move\_back, take\_object, move, deliver\_it\}$.

The state-transition table of the instance plans is shown in Table I.

TABLE I
AN EXAMPLE OF THE STATE-TRANSITION TABLE WITHIN O-FSM

	P1	**P2**	**P3**
P1	object delivered	p_d unreachable	-
P2	object delivered	-	p_i unreachable
P3	object delivered	-	-

V. EVALUATION

To illustrate the effectiveness of our method, we explicitly designed three test cases, with the real robot and the competition scenario kept in mind. As tidy-up is a complex and multi-module coordination and integration demand task, we first explain the relevant premises, assumptions, and system parameters [21], that can be severed for future benchmarking on the specific module, then conduct scenario planning and Gazebo-based simulation experiments to evaluate the proposed method.

A. Settings

The robot has a pre-built 2D occupancy grid map of the static environment, and maintains it dynamically according to the position of the objects detected by a built-in RGB-D camera (see Fig. 4). It knows the position of the deposits in the map, and performs map-based localization and navigation with a 2D laser rangefinder. The mission starting point of the robot is at the entrance of a room while the door is open. The robot enters the room and explores it to obtain positions of the objects to pick up. The exploration could be done either with the frontier-based method [21], [22] or the waypoint-based topological exploration [23], [24], both could be managed by a layered map. Since we are interested in the POPR problem as described in Section III-D, at least one object or deposit is unobservable and one object or

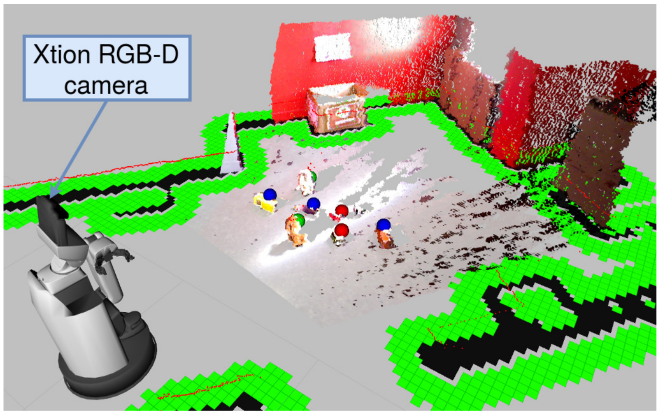

Fig. 4. An Xtion RGB-D camera on top of the robot is used for object detection. Due to its effective working distance (between 0.8m and 3.5m) and field of view (about 58° horizontally and 45° vertically), it is tricky to get the knowledge of the entire environment for the robot.

deposit is unreachable. The robot performs object grasping when the environment can no longer be explored.

In addition to the above execution conditions, other components used in our test cases include:

- Inputs: 12 objects (3×4 categories) are randomly placed on the floor and table in the room.
- Testing method: O-FSM, greedy algorithm (i.e. $P1$).
- Expected results: tidy up the room within a limited actions (for scenario planning) and time (for simulation).

Two halting criteria can be defined: either the robot completed the overall mission, or the number of actions performed (or the runtime) reached a predetermined threshold.

B. Analysis

We use three test cases (see Fig. 5) to illustrate the effectiveness of our method. The scenario is abstracted from the competition arena specifications of the World Robot Challenge 2020 [25]. Specifically, as shown in Fig. 6, a $3.5m \times 4m$ room contains a variety of furniture, and one side of the room is set as the delivery area, while the rest of the area is for scattered objects. A Toyota HSR robot is then asked to perform the tidy-up task at the entrance through which the robot enters the arena.

The scenario planning was carried out according to the designed test cases, and the results are given in Table II. As shown in Fig. 5, there is an unobservable and unreachable object (in green) in Case I, an unobservable and unreachable deposit (in rose) in Case II, and both in Case III. We count the number of times each plan is used and the total actions required to complete the entire task. For the convenience of calculation, we count four actions if the robot completes $P2$. Empirically, fewer actions usually mean faster completion of tasks. It can be seen that by using our method, the tidy-up task can be completed within a limited number of actions, while without the need for complete and global awareness of the environment. Moreover, from our experience, the best practice would be use the proposed method to ensure first that all the deposits are reachable, then the whole tidy-up problem can be solved smoothly.

TABLE II

O-FSM-BASED SCENARIO PLANNING RESULTS

Case	P1	P2	P3	Total actions
I	12	0	0	36
II	10	1	1	45
III	11	0	1	52

Table III shows the simulation experiment results (the simulation scenario is shown in Fig. 3) including the time required for the robot to complete the task and the total distance traveled. We omit the process of object recognition, grasping and release in order to focus more on the evaluation of decision-making methods. In Case I, using greedy algorithm and using O-FSM get the same result as only $P1$ was performed in O-FSM. In Cases II and III, only using greedy algorithm caused the task to fail.

TABLE III

SIMULATION EXPERIMENT RESULTS WITH DIFFERENT METHODS

Case	Method	Time	Distance
I	O-FSM Greedy	661s 661s	56.87m 56.87m
II	O-FSM Greedy	822s fail	80,69m fail
III	O-FSM Greedy	919s fail	91.36m fail

VI. CONCLUSIONS

In this paper, we proposed a quantifiable stratification method for tidy-up task with service robots that are typically domestic mobile manipulators. Called O-FSM, it reintegrates traditional approaches into modern applications, includes a series of independent plans, from simple to complex, to cope with ever-changing object-deposit configurations. Different from the existing work, the core idea of our proposal is to always prioritize the simplest method that inherently has the least impact on future uncertainty, while the effectiveness has been illustrated with well designed test cases.

Our method is based on the assumption that the robot has incomplete observation and the task is characterized by high complexity. In the case of that the robot has a complete observation of the entire environment during the execution of the mission, the traditional global planning method can be applied. The future work will take dynamic objects such as humans and other robots into account in the task planning, for human-aware navigation [26], [27] or manipulation. Moreover, we will consider integrating the lifelong learning of spatio-temporal representations [28], [29], that allows the robot perform the right action at the right time through active navigation.

REFERENCES

[1] A. Blumer, A. Ehrenfeucht, D. Haussler, and M. K. Warmuth, "Occam's razor," *Information processing letters*, vol. 24, no. 6, pp. 377–380, 1987.

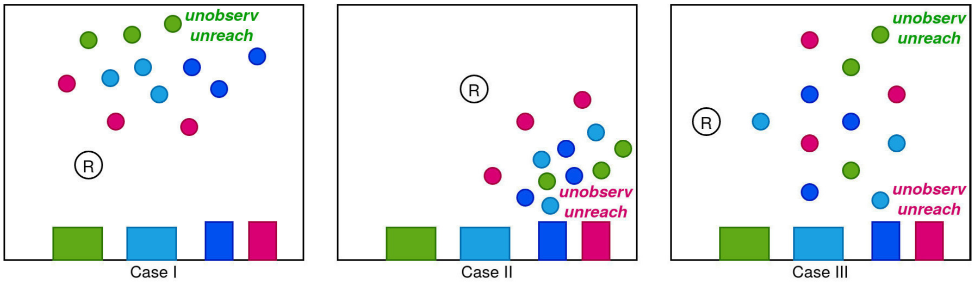

Fig. 5. Three test cases. The square colored areas represent the deposit location, while the colored circles represent different objects. Different colors indicate different categories. R stands for robot.

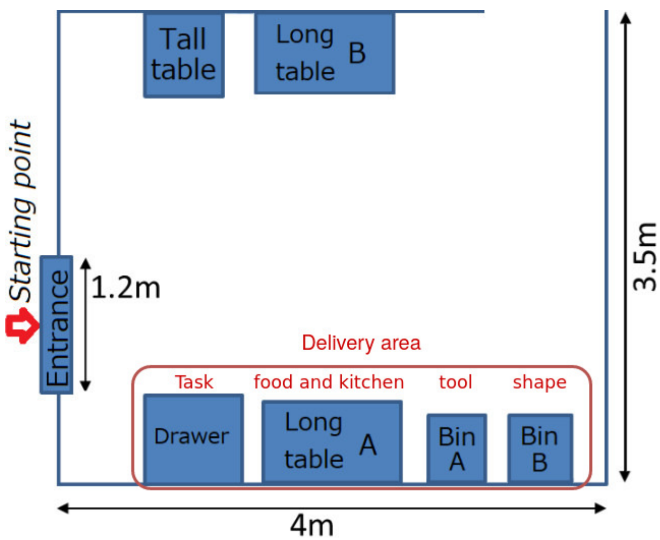

Fig. 6. Room (competition arena) layout [25].

[2] J. Pajarinen and V. Kyrki, "Robotic manipulation of multiple objects as a POMDP," *Artificial Intelligence*, vol. 247, pp. 213–228, 2017.

[3] D. Hadfield-Menell, E. Groshev, R. Chitnis, and P. Abbeel, "Modular task and motion planning in belief space," in *Proceedings of IROS*, 2015, pp. 4991–4998.

[4] T. Hester, M. Quinlan, and P. Stone, "Generalized model learning for reinforcement learning on a humanoid robot," in *Proceedings of ICRA*, 2010, pp. 2369–2374.

[5] T. Yamamoto, K. Terada, A. Ochiai, F. Saito, Y. Asahara, and K. Murase, "Development of human support robot as the research platform of a domestic mobile manipulator," *ROBOMECH Journal*, vol. 6, no. 4, 2019.

[6] K. Doelling, J. Shin, and D. O. Popa, "Service robotics for the home: a state of the art review," in *Proceedings of PETRA*, 2014.

[7] A. Hornung, S. Böttcher, J. Schlagenhauf, C. Dornhege, A. Hertle, and M. Bennewitz, "Mobile manipulation in cluttered environments with humanoids: Integrated perception, task planning, and action execution," in *Proceedings of the IEEE-RAS International Conference on Humanoid Robots (Humanoids)*, pp. 773–778.

[8] N. Abdo, C. Stachniss, L. Spinello, and W. Burgard, "Robot, organize my shelves! tidying up objects by predicting user preferences," in *Proceedings of ICRA*, 2015, pp. 1557–1564.

[9] L. Sun, S. Rogers, G. Aragon-Camarasa, and J. P. Siebert, "Recognising the clothing categories from free-configuration using gaussian-process-based interactive perception," in *Proceedings of ICRA*. IEEE, 2016, pp. 2464–2470.

[10] L. Sun, G. Aragon-Camarasa, S. Rogers, R. Stolkin, and J. P. Siebert, "Single-shot clothing category recognition in free-configurations with application to autonomous clothes sorting," in *Proceedings of IROS*. IEEE, 2017, pp. 6699–6706.

[11] W. Skulkittiyut, H. Lee, T. N. Lam, and M. Mizukawa, "Building of commonsense knowledge for home robotic services: 'bring something' and 'tidy things up'," *International Journal of Mechatronics and Automation*, vol. 4, no. 1, pp. 1–16, 2014.

[12] K. Yamazaki, R. Ueda, S. Nozawa, Y. Mori, T. Maki, N. Hatao, K. Okada, and M. Inaba, "System integration of a daily assistive robot and its application to tidying and cleaning rooms," in *Proceedings of IROS*, 2010, pp. 1365–1371.

[13] S. Lee, J. Park, D. Kim, and J. Kim, "Adaptive task planner for performing home service tasks in cooperation with a human," in *Proceedings of IROS*, 2018, pp. 2857–2864.

[14] B. Nebel, C. Dornhege, and A. Hertle, "How much does a household robot need to know in order to tidy up," in *Proceedings of the AAAI Workshop on Intelligent Robotic Systems*, 2013.

[15] D. Hadfield-Menell, E. Groshev, R. Chitnis, and P. Abbeel, "Modular task and motion planning in belief space," in *Proceedings of IROS*, 2015, pp. 4991–4998.

[16] Y. Iwamura, M. Shiomi, T. Kanda, H. Ishiguro, and N. Hagita, "Do elderly people prefer a conversational humanoid as a shopping assistant partner in supermarkets?" in *Proceedings of HRI*, A. Billard, P. H. K. Jr., J. A. Adams, and J. G. Trafton, Eds., 2011, pp. 449–456.

[17] H. W. Kuhn, "The hungarian method for the assignment problem," *Naval research logistics quarterly*, vol. 2, no. 1-2, pp. 83–97, 1955.

[18] G. A. Mills-Tettey, A. Stentz, and M. B. Dias, "The dynamic hungarian algorithm for the assignment problem with changing costs," *Carnegie Mellon University*, 2007.

[19] T. Gedicke, M. Günther, and J. Hertzberg, "Flap for caos: Forward-looking active perception for clutter-aware object search," *IFAC-PapersOnLine*, vol. 49, no. 15, pp. 114–119, 2016.

[20] J. Rissanen, "Modeling by shortest data description," *Automatica*, vol. 14, no. 5, pp. 465–471, 1978.

[21] Z. Yan, L. Fabresse, J. Laval, and N. Bouraqadi, "Metrics for performance benchmarking of multi-robot exploration," in *Proceedings of IROS*, 2015, pp. 3407–3414.

[22] B. Yamauchi, "A frontier-based approach for autonomous exploration," in *Proceedings of CIRA*, 1997, pp. 146–151.

[23] Z. Yan, N. Jouandeau, and A. Ali Cherif, "Sampling-based multi-robot exploration," in *Proceedings of ISR/ROBOTIK*, 2010, pp. 44–49.

[24] S. Oßwald, M. Bennewitz, W. Burgard, and C. Stachniss, "Speeding-up robot exploration by exploiting background information," *IEEE Robotics and Automation Letters*, vol. 1, no. 2, pp. 716–723, 2016.

[25] S. C. T. Committee, *Partner Robot Challenge (Real Space) Rule Book*. World Robot Summit, 2020. [Online]. Available: https://worldrobotsummit.org/wrs2020/challenge/download/Rules/DetailedRules_Partner_EN.pdf

[26] L. Sun, Z. Yan, S. M. Mellado, M. Hanheide, and T. Duckett, "3dof pedestrian trajectory prediction learned from long-term autonomous mobile robot deployment data," in *Proceedings of ICRA*, 2018, pp. 5942–5948.

[27] Z. Yan, L. Sun, T. Duckett, and N. Bellotto, "Multisensor online transfer learning for 3d lidar-based human detection with a mobile robot," in *Proceedings of IROS*, 2018, pp. 7635–7640.

[28] T. Vintr, Z. Yan, T. Duckett, and T. Krajnik, "Spatio-temporal representation for long-term anticipation of human presence in service robotics," in *Proceedings of ICRA*, 2019, pp. 2620–2626.

[29] T. Krajník, J. P. Fentanes, J. M. Santos, and T. Duckett, "Fremen: Frequency map enhancement for long-term mobile robot autonomy in changing environments," *IEEE Transactions on Robotics*, vol. 33, no. 4, pp. 964–977, 2017.