FULL PAPER

Autonomous Planning Based on Spatial Concepts to Tidy Up Home Environments with Service Robots

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Tidy-up tasks by service robots in home environments are challenging in the application of robotics because they involve various interactions with the environment. In particular, robots are required not only to grasp, move, and release various home objects, but also plan the order and positions where to put them away. In this paper, we propose a novel planning method that can efficiently estimate the order and positions of the objects to be tidied up based on the learning of the parameters of a probabilistic generative model. The model allows the robot to learn the distributions of co-occurrence probability of objects and places to tidy up by using multimodal sensor information collected in a tidied environment. Additionally, we develop an autonomous robotic system to perform the tidy-up operation. We evaluate the effectiveness of the proposed method in an experimental simulation that reproduces the conditions of the Tidy Up Here task of the World Robot Summit international robotics competition. The simulation results showed that the proposed method enables the robot to successively tidy up several objects and achieves the best task score compared to baseline tidy-up methods.

Keywords: Autonomous robotic system; mobile manipulation; planning; semantic mapping; tidy-up task

1. Introduction

Service robots are required to perform daily-life support tasks in indoor home environments, e.g. tidying up cluttered objects, which is one of the most common tasks aimed at supporting humans at home. Indeed, tidy-up tasks performed by robots are seen as a solution to the aging and decreasing working population, which is especially true in Japan. Additionally, picking and placing various kinds of objects in the surrounding environment is still a challenging general problem in robotics applications. Therefore, tidy-up tasks have attracted attention in the field of robotics in recent years [1, 2].

This paper focuses on reproducing the conditions of the Tidy Up Here task of the World Robot Summit (WRS) international robotics competition as tidy-up evaluation experiment [3]. The tidy-up task presented in this study consists of a robot moving objects at wrong positions to their proper places in a room where several objects are scattered. In this context, wrong means that the positions are different from the usual tidied positions of the objects. In such a case, it is important to plan in which order the objects should be moved to carry out the tidy-up task efficiently. For example, it is often inefficient to tidy up first the objects discovered immediately or randomly. Rather, an object with the most defined tidied place, or an object at the farthest position from the proper place, will be tidied up first. It is also necessary for robots to properly ask the user where to tidy up an object where the place to tidy is indeterminate.

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Unsupervised learning approaches based on probabilistic models will be very effective because objects and their arrangements include uncertainty and vary depending on the home environment. General robot systems usually require to be given labeled datasets of the objects and places in advance to tidy up the specific objects of each environment, i.e. the robot should know about the relationships between a specific object and an appropriate place. However, it is difficult to prepare such kinds of knowledge in a hand-coded manner. Therefore, we consider instead that service robots need to automatically recognize specific objects and learn the places where the objects are regarded as being tidied up in the environment.

Additionally, semantic mapping-based approaches are also important for spatial recognition and semantic understanding of the environment [4, 5]. To realize the tidy-up task, the robot must recognize the environment, estimate the objects to be tidied up while moving, and determine where to put the objects in the three-dimensional space. In this case, it is also necessary to consider the case in which the objects to be tidied up, or categories of objects, change depending on the home environment constraints, e.g. the heights and levels of the shelves. Furthermore, it is necessary to deal not only with the room configurations and object arrangements that differ for each home environment, but also the place categories based on the objects and names on specific areas.

Finally, to reduce the burden on the user, robots need to be able to perform tidy-up tasks with simple user instructions like ‘Tidy up the kitchen.’ as a trigger. To enable a robot to perform tidy-up tasks, one straightforward method is to use speech utterances from a user that instructs a place where to put each object in detail, e.g. ‘Put the green cup on the left end of the first level of the shelf in the kitchen.’ However, it is then necessary for the user to give at least one detailed speech instruction for each object in a form that allows the robot to successfully carry out the tidy-up task. In this case, the burden on the user becomes heavy when there are multiple objects and places to tidy up in the environment. Therefore, our challenge is to enable robots to autonomously tidy up without processing complex language understanding.

In this study, we focus on the planning and ordering of the arrangement of objects in robotic tidy-up tasks. First, we propose a novel planning method based on the likelihood ratio maximization of object positions in the learned model for efficiently tidying up. Second, we introduce a probabilistic generative model (PGM) for spatial concept formation that autonomously learns relationships between the objects and places based on the positions of each object in a tidied environment. To realize the proposed method, we develop an automatic system that enables service robots to effectively tidy up. From a system integration perspective, a distinct feature of this study is to introduce probabilistic inference by an unsupervised learning-based PGM for spatial concept formation into an integrated robotic system for tidy-up tasks.

The main contributions of this paper are as follows:

1. Enabling robots to estimate the places where to move objects from their sensor information only, without manually being given the places to tidy up, by an unsupervised learning-based approach.
2. Enabling robots to efficiently plan tidy-up tasks by the simultaneous estimation of the objects to tidy up and their tidied positions based on the observation likelihoods in the PGM.
3. Enabling robots to perform tidy-up tasks from interaction with the user even if the objects to tidy up, and places where to put them, are not clearly instructed.

The remainder of this paper is as follows. First, we describe the related work regarding tidy-up tasks and semantic mapping by robots in Section 2. Next, we describe the proposed methods in Section 3, and the developed system in Section 4. Then, we describe the experimental conditions, evaluations, and results in Section 5. Finally, we give the conclusion and avenue for future work in Section 6.
2. Related work

We describe related work on tidy-up tasks by robots in home environments in Section 2.1, and related work on spatial recognition and semantic mapping to acquire the positional relationship between objects and places in Section 2.2.

2.1 Tidy-up tasks using robots

In recent years, international robotics competitions related to tidy-up tasks have increased, e.g., the Tidy Up Here task in the WRS 2018 [3], to relieve aging populations and accelerate the development of robotics. Fig. 1 shows an overview of the Tidy Up Here task. Details of task definition are described in Appendix A.

Some recent studies required time and physical efforts as the user ultimately tidies up [6, 7]. Fink et al. evaluated whether the robot’s behavior would affect the tidying behavior of children, from 2 to 10 years old, using a box-type robot called Ranger to urge them to tidy up toys on the floor [6]. Ogasawara & Gouko proposed a stationery holder robot to investigate its influence on human intentions for tidying up, and to improve deskwork efficiency by reducing clutter [7].

Tidy-up tasks in home environments involve diverse shapes, weights, and places of objects to be tidied up. To deal with such complexity, the above studies on Human-Robot Interaction (HRI), which encourage the user to tidy up objects, have been conducted. In our study, we overcome these above issues that users have to tidy up by proposing a planning method and a system that enables the robot to tidy up multiple objects automatically.

Alternatively, it is important for robots to autonomously learn the relationship between objects and places only from the robot’s observation. Abdo et al. developed a system to estimate object pair candidates according to the user preference by collaborative filtering [8]. In particular, a scenario of their study was a tidy-up task where groceries items had to be sorted and placed on shelves, and toys in boxes. Additionally, by grouping the object arrangements in the shelf based on the preference of the object pairs predicted by spectral clustering, it is possible to reproduce...
these object arrangements on the shelf when tidying up. However, although it is possible to arrange objects according to each home specificity, it is not realistic to investigate the preferences of object pairs for each user for every tidy-up destination, including places other than shelves and boxes. By contrast, our study proposes a model that learns the desired positions of the objects in a tidied situation only from the sensor information of the robot in each environment.

Furthermore, it is important for robots to autonomously estimate the tidying positions of the objects without being instructed in advance by humans for each environment. Hatori et al. proposed a robotic system that can manipulate the object to an intended box through interactive natural dialogue [2]. However, the position to move the object is given in advance by the human hand, and the system does not consider the case of various kinds of places to tidy up in a home environment. Moreover, when moving an object, it is necessary to issue a speech command for each object, and when applied to the tidy-up task, the burden put on the user is heavy. In our study, the robot can learn the tidy-up places autonomously. Hence we consider that our proposed method can complement the shortcomings of the aforementioned work. Additionally, it is sufficient for the proposed system to request user interaction only for objects with undefined tidying positions, thanks to the learned relationships between the objects and the places.

Finally, when multiple objects are scattered around the environment, the robots must effectively determine the order in which the objects are tidied. Furuta et al. constructed a system for local-rule-aware robot task planning to tidy up a detected object with Probabilistic Object Location’s Map (POLM) generated by the long-term episodic memory related to objects [1]. The POLM for each object label is generated by Multivariate Gaussian Mixture Model (MVGMM) from a database of object labels and positions acquired in advance. The robot tidies up the objects below a certain threshold of the probability of the object position. The average value of MVGMM, which is the maximum probability location in the POLM, is given as the tidy-up target location. However, the tidy-up planning is considered only when one object is given, and not considered when a plurality of general objects is observed. Therefore, we propose a tidy-up planning method that can deal with multiple objects in an efficient order.

### 2.2 Semantic mapping and spatial concept formation

To realize the tidy-up task with robots, it is necessary to deal with the room configurations and object arrangements that differ for each home environment. Spatial recognition and semantic understanding of the three-dimensional environment are important for the robot to perform the tidy-up task [4]. Visual Simultaneous Localization and Mapping (vSLAM) [9] can simultaneously estimate the self-localization and environment construction, or mapping, using only the camera sensor. Moreover, there are studies on 3D semantic mapping that give labels of places and objects obtained by semantic segmentation and object detection methods to map information constructed from vSLAM [10–14]. McCormac et al. proposed SemanticFusion [11] that realizes 3D semantic mapping by integrating convolutional neural network (CNN)-based semantic segmentation [15] and ElasticFusion [16], which is one vSLAM method. Sunderhauf et al. proposed meaningful maps with object-oriented semantic mapping [12] that can perform semantic segmentation by combining oriented FAST and rotated BRIEF (ORB)-SLAM2 [17] and Single Shot MultiBox Detection (SSD) [18]. Tateno et al. proposed CNN-SLAM [13] by fusion of monocular SLAM and depth prediction from CNN. Additionally, semantic mapping is realized using CNN for semantic segmentation. Jeong et al. proposed a multimodal sensor-based 3D semantic mapping [14] by projecting the result obtained by CNN-based semantic segmentation to a 3D map constructed by a lidar sensor.

The effective application of these above technologies has become an important issue in recent years. Indeed, these 3D semantic mapping methods generally require a large amount of labeled training data. Additionally, in many of these methods, the pixel-level labeled data generated by semantic segmentation of observed images correspond directly to 3D pixels in a metric map. In such cases, some technical difficulties must be solved to use robots for tidy-up tasks, e.g.
misrecognition will be handled as it is, and all the 3D voxels must be stored in a large amount of memory. These are even more important issues in robot systems that must perform various internal processes in real-time with limited embedded resources.

Furthermore, it is necessary to deal with not only the room configurations and object arrangements that differ for each home environment, but also grouping of places based on the arrangement of objects and names of specific areas. Therefore, we consider that it is important to appropriately generalize and form place categories based on the object positions while dealing with the uncertainty of the observations. In an attempt to solve these issues, unsupervised learning approaches for spatial concepts were conducted in studies related to autonomous place categorization by a robot [19–24]. Taniguchi et al. proposed nonparametric Bayesian spatial concept acquisition methods, SpCoA [21] and SpCoA++ [22], that integrate self-localization and unsupervised word-segmentation from speech signals as PGMs through the latent variables of spatial concepts. In this context, spatial concepts mean place category knowledge autonomously formed based on multimodal information of spatial experience by the robot in the environment. Their methods improved the accuracy of self-localization and recognition of the place names in the spoken sentences. Moreover, SpCoSLAM [19] realized the online learning of spatial concepts, language models, and maps. Katsumata et al. proposed a Markov random field-based statistical semantic mapping method, SpCoMapping [24], for segmentation of place categories in a 2D grid map to determine the area to be cleaned by vacuum cleaner robots. Additionally, the unsupervised learning approach for the spatial concept formation was also adopted for navigational tasks at the Future Convenience Store Challenge of the WRS 2018 [25]. However, these studies are mainly focused on the place category formation and the learning of words corresponding to these places, and did not use learned knowledge for tidying up objects.

More recently, Isobe et al. proposed a model to learn the relationship between an object and a place by using the robot’s self-position, object, and word information [23]. The relationship between an object and a place means the existence probability of the object and the occurrence probability of the place name in each spatial area. This suggested the possibility to estimate the object’s existence in a specific place from ambiguous commands, e.g. ‘Tidy up this object.’. However, problems occurred when the spatial concepts were learned based on the robot’s self-position with object information including not only the objects at the place of interest but also far objects visible from the robot’s viewpoint. Moreover, the position distribution of the spatial concepts consisted of two-dimensional coordinates on the floor plane, and could not accommodate the heights of shelves and desks. Furthermore, they did not provide a concrete tidy-up planning method in an actual tidy-up task. In our study, we solve the above problem by learning the spatial concepts based on the three-dimensional position information of the object inside the tidied environment instead of the robot’s self-position. Additionally, we construct a planning formulation and algorithm based on probabilistic inference.

3. Proposed tidy-up planning based on probabilistic generative model for spatial concept formation

In this paper, we introduce a probabilistic generative model (PGM) of spatial concept formation for learning the tidied positions of objects in a tidied environment. We describe the variable definition and generative process of the PGM for spatial concept formation in Section 3.1. Additionally, we describe the inference procedure for the parameters of the spatial concept model in Section 3.2. Moreover, we propose a tidy-up planning method that can efficiently estimate the order and positions of the objects to be tidied up based on the learning results of the model parameters in the PGM. In Section 3.3, we describe the formulation of the proposed tidy-up planning. In Section 3.4, we describe the method to tidy up an unknown object by human-robot speech interaction. Algorithm 1 shows the planning algorithm used for tidying up based on the proposed method.
Figure 2. Graphical model representation of the spatial concept formation for tidying up objects. This model is a multimodal Dirichlet process mixture whose emission distributions are Gaussian distributions and multinomial distributions. Gray nodes indicate the observed variables, and white nodes the unobserved latent variables.

Table 1. Description of the random variables in the graphical model.

| Symbol | Definition |
|--------|------------|
| $x_i$  | Position of an object |
| $o_i$  | Detected object information |
| $w_i$  | Words representing place names |
| $C_i$  | Index of spatial concepts |
| $\mu_k, \Sigma_k$ | Parameters of the Gaussian distribution for the position of object $x_i$ |
| $\varphi_k, \eta_k$ | Parameters of the multinomial distribution for the observations $o_i, w_i$ |
| $\pi$  | Parameter of the multinomial distribution for the index $C_i$ of spatial concepts |
| $\mu_0, \kappa_0, \psi_0, \nu_0$ | Hyperparameters of the Gaussian–inverse–Wishart prior distribution |
| $\alpha, \beta, \gamma$ | Hyperparameters of the Dirichlet prior distribution |

3.1 Probabilistic generative model of spatial concepts for tidying up objects

We introduce a PGM of spatial concepts for tidying up objects. The model can estimate places to tidy up a three-dimensional space, and the occurrence probability of objects and words for each place based on position, image, and word information related to the objects in a tidied environment. In other words, the model can perform the place categorization in an unsupervised manner from multimodal data obtained by the robot autonomously, which means generalizing the place where an object should be tidied up from the observations regarding the objects. Furthermore, the model can deal with the uncertainty of the observations and the estimation error, e.g. sensor noise, object misrecognition, or self-localization error.

Fig. 2 shows the graphical model, and Table 1 shows the description of the random variables in the model. We describe the generative process of the model as follows:

\[
\pi \sim \text{GEM} (\gamma) \tag{1}\\
C_i \sim \text{Mult} (\pi) \tag{2}\\
\Sigma_k \sim \text{IW} (\psi_0, \nu_0) \tag{3}\\
\mu_k \sim \mathcal{N} (\mu_0, \Sigma_k / \kappa_0) \tag{4}\\
\varphi_k \sim \text{Dir} (\alpha) \tag{5}\\
\eta_k \sim \text{Dir} (\beta) \tag{6}\\
\gamma_i \sim \mathcal{N} (\mu_{C_i}, \Sigma_{C_i}) \tag{7}\\
o_i \sim \text{Mult} (\varphi_{C_i}) \tag{8}
\]
\[ w_i \sim \text{Mult}(\eta_{C_i}) \]  

where the Stick-Breaking Process (SBP) [26, 27], a type of Dirichlet process, is denoted as GEM(·), the multinomial distribution as Mult(·), the Dirichlet distribution as Dir(·), the inverse-Wishart distribution as IW(·), and the multivariate Gaussian distribution as N(·). See [28] for the specific formulas of the above probability distributions.

In the previous method [23], the position distribution was represented by two-dimensional coordinates. In contrast, the proposed method learns the relationship between objects and places in the three-dimensional space, and can deal with cases where objects to be tidied change depending on the height, e.g. on shelves and tables. The position information of the object is denoted as \( L \)-positions when given the set of the object information as \( \{d_i\} \). Additionally, we only deal with positions other than the position \( x_d \) of the object to be tidied up do not change.

### 3.2 Learning of parameters for the spatial concept model

During the learning of spatial concepts, the robot estimates the set of all of the latent variables \( C = \{C_i\}_{i=1}^L \) and the set of model parameters \( \Theta = \{\mu_k, \Sigma_k, \varphi_k, \eta_k, \pi\} \) from the set of multimodal observations \( O = \{x_i, a_i, w_i\}_{i=1}^I \) by Gibbs sampling which is a type of Markov Chain Monte-Carlo. The total number of training data is \( I \). The sampling values are given by the iteration of Gibbs sampling from the joint posterior distribution as:

\[
C, \Theta \sim p(C, \Theta \mid O, h) \tag{10}
\]

where the set of hyperparameters is denoted as \( h = \{\alpha, \beta, \gamma, \mu_0, \kappa_0, \psi_0, \nu_0\} \). We provide the details of Gibbs sampling in Appendix B.

### 3.3 Formulation for planning the tidying of an object based on spatial concepts

The proposed tidy-up planning method is formulated to first select an object whose tidied place is the most defined. In the spatial concept model learned in the tidied environment, the likelihood is the highest when each object position is tidied. Therefore, when tidying up one object from scattered objects, the object with the highest likelihood is selected first. In this study, tidying up means moving the positions of the observed objects to increase the likelihood of the spatial concept model. The object \( d^* \) and the position \( x_d^* \) to tidy up are estimated among the detected \( D \) objects, as shown in the following equation:

\[
d^*, x_d^* = \underset{d, x_d}{\text{argmax}} \, \mathcal{L}(\{x_j\}_j \setminus d, x_d') - \underbrace{\mathcal{L}(\{x_j\})}_{\text{const.}} \tag{11}
\]

where the tidied position of the object \( d \) is represented as \( x_d' \), the likelihood function on the object positions when given the set of the object information as \( \mathcal{L}(\{x_j\}) = p(\{x_j\} \mid \{o_j\}, \Theta) \), the set of parameters learned by the spatial concept model as \( \Theta \), and the set of position information of the detected objects excluding position information of the object \( d \) is denoted as \( \{x_j\}_j \setminus d \). Additionally, we only deal with \( \mathcal{L}(\{x_j\}_j \setminus d, x_d') \) because \( \mathcal{L}(\{x_j\}) \) is constant in Equation (11).

The positions \( x_j \) of each object are conditionally independent of each other. It is assumed that the positions of objects other than the position \( x_d' \) of the object to be tidied up do not change.
Therefore, \( L(\{x_j\}_{j:d'}, x'_d) \) is developed as follows:

\[
L(\{x_j\}_{j:d'}, x'_d) = p(\{x_j\}_{j:d'} | \{o_j\}_{j:d'}, \Theta) p(x'_d | o_d, \Theta) \\
= \prod_j \sum_{C_j} p(x_j | \mu_{C_j}, \Sigma_{C_j}) p(o_j | \varphi_{C_j}) p(C_j | \pi) \\
\times \sum_{C_{d'}} p(x'_d | \mu_{C_{d'}}, \Sigma_{C_{d'}}) p(o_d | \varphi_{C_d}) p(C_d | \pi) \tag{12}
\]

where \( D\setminus d \) indicates that the object \( d \) is excluded among the \( D \) detected objects.

Next, we consider the issue of estimating \( x^*_d \) based on the object \( d \). The argmax operation in Equation (11) is approximated as:

\[
\arg\max_{x'_d} \sum_{C_d} p(x'_d | \mu_{C_d}, \Sigma_{C_d}) p(o_d | \varphi_{C_d}) p(C_d | \pi) \\
\approx \sum_{C_{d'}} \int_{x'_d \mid \mu_{C_d}} x'_d p(x'_d | \mu_{C_{d'}}, \Sigma_{C_{d'}}) dx'_d p(o_d | \varphi_{C_d}) p(C_d | \pi). \tag{13}
\]

Furthermore, the operation of the marginalization of \( C_d \) is approximated as the value with the highest probability as follows:

\[
C^*_{d'} = \arg\max_{C_{d'}} p(o_d | \varphi_{C_{d'}}) p(C_{d'} | \pi), \tag{14}
\]

\[
x^*_d = \mu_{C^*_{d'}}. \tag{15}
\]

Moreover, because \( x^*_d \) in Equation (11) is obtained by Equation (15), the object \( d \) is obtained when \( L(\{x_j\}_{j:d}, x'_d = \mu_{C^*_{d'}}) \) takes the maximum value as follows:

\[
L(\{x_j\}_{j:d}, x'_d = \mu_{C^*_{d'}}) \\
= p(\{x_j\}_{j:d} | \{o_j\}_{j:d'}, \Theta) p(x'_d = \mu_{C^*_{d'}} | o_d, \Theta) \\
\times \prod_j \sum_{C_j} p(x_j | \mu_{C_j}, \Sigma_{C_j}) p(o_j | \varphi_{C_j}) p(C_j | \pi) \\
\times \sum_{C_{d'}} p(x'_d = \mu_{C_{d'}} | \mu_{C_{d'}}, \Sigma_{C_{d'}}) p(o_d | \varphi_{C_d}) p(C_d | \pi). \tag{16}
\]

Additionally, we consider the case of selecting the \( n \)-th object to be tidied up when \( n-1 \) objects have been tidied already. We introduce the likelihood ratio between the likelihoods before and after tidying up concerning the detected object \( d \) when tidying up the \( n \)-th object as follows:

\[
R_n(x_d, x'_d) = \frac{L(\{x_j\}_{j:d'}, x'_d)}{L(\{x_j\})} / \frac{L(\{x_j\})}{L(\{x_j\}_{j:d}, x'_d = \mu_{C^*_{d'}})} = \frac{\sum_{C_{d'}} p(x'_d | \mu_{C_{d'}}, \Sigma_{C_{d'}}) p(o_d | \varphi_{C_d}) p(C_d | \pi)}{\sum_{C_{d'}} p(x'_d = \mu_{C_{d'}} | \mu_{C_{d'}}, \Sigma_{C_{d'}}) p(o_d | \varphi_{C_d}) p(C_d | \pi)}. \tag{17}
\]
Note that $1 \leq n$.

Finally, solving Equation (11) is equivalent as estimating the object $d$ and the position $x'_d$ with the maximum likelihood ratio as follows:

$$\arg\max_{d,x'_d} L \left( \{x_j\}_{j \neq d}, x'_d \right) = \arg\max_{d,x'_d} R_n(x_d, x'_d). \quad (18)$$

The formulation for the simultaneous estimation of $N$ objects and their positions for tidying up is described in Appendix C.

### 3.4 How to tidy up unknown objects by speech interaction with a user

When an object is determined as being unknown in Stage 2, as described in Appendix A.2.2, the robot can ask the user the target place to tidy up, e.g. ‘Where should I put this object?’.

Additionally, the user can give the robot the word $w_d$ representing the correct place when asked. The robot then determines an object $d$ with the probability value $P_d$ below the threshold $\lambda$ as an object whose target place is unknown by finding the maximum of Equation (14) as follows:

$$P_d = \max_{C_d} p(o_d | \varphi_{C_d}) p(C_d | \pi), \quad (19)$$

$$C^*_d = \arg\max_{C_d} \left\{ \begin{array}{ll} p(o_d | \varphi_{C_d}) p(C_d | \pi) & (\lambda \leq P_d) \\
 p(w_d | \eta_{C_d}) p(C_d | \pi) & (\lambda > P_d) \end{array} \right. \quad (20)$$

This means that the tidied position of the object $d$ is ambiguous if the existence probability of the object $d$ is extremely low at each tidied position. Finally, the robot updates the tidied position of an object that is determined to be an unknown object from the given words using Equations (20) and (15).

Algorithm 1 is obtained as described in Section 3.3 and 3.4. In the proposed planning method, the robot usually tidies up, in order, from an object whose the target place is the most defined. Finally, the robot tidies up the unknown objects at the end to postpone the time-consuming act of asking the user for the target place.

**Algorithm 1** Planning algorithm.

1. Gather object observations $\{o_j\}$ by object detection from image data
2. for $n = 1$ to $N$ do ▶ Number of objects to tidy up
3. for $d = 1$ to $D$ do ▶ Number of detected objects
4. Estimate $C^*_d$ ▶ Eq. (14)
5. Decide $x'_d$ as $\mu_{C^*_d}$ ▶ Eq. (15)
6. Calculate the likelihood ratio $R_n(x_d, x'_d)$ ▶ Eq. (17)
7. end for
8. Select the $d^*$-th object and $x^*_d$ ▶ Eq. (18)
9. Calculate the probability value $P_d$. ▶ Eq. (19)
10. if $\lambda > P_d$ then ▶ Judge whether the object is unknown
11. Observe word information $w_d$ from the user
12. Update $C^*_d$ ▶ Eq. (20)
13. Update $x^*_d$ ▶ Eq. (15)
14. end if
15. Tidy up the selected $d^*$-th object to the estimated position $x^*_d$ ▶ Section 4.2
16. end for
4. **Autonomous robotic system for tidying up multiple objects**

In this paper, we develop an autonomous robotic system that can recognize and tidy up the environment automatically. Our system is implemented with Robot Operating System (ROS) [30] middleware. An overview of the proposed autonomous robotic system is shown in Fig. 3. The training phase is described in the Section 4.1, and the planning phase is described in the Section 4.2.

4.1 **Training phase**

The training phase consists of collecting the data and learning the spatial concepts, as shown in Fig. 3 (a) – (d).

We describe the process of data collection of Fig. 3 (a) – (c) as following. First, the robot obtains multimodal data related to the objects, i.e. positions, images, and words, in the tidied environment. The input data in Fig. 3 are RGB and depth images, which are acquired by the RGB-D camera mounted on the robot. The robot generates a two-dimensional occupancy grid map of the environment beforehand by Hector SLAM [31], and performs self-localization by Adaptive Monte-Carlo Localization (AMCL) [32].

In particular, the robot moves around the environment and acquires the following data:

(a) The object information that is a one-hot vector representation of the object class corresponding to each bounding box obtained from an RGB image using a CNN-based object detection method [33].

(b) The position information of the objects that are three-dimensional coordinate points of each detected object obtained with depth information from the RGB-D camera. Here, we use the average of the depth values of an area within 10% of the detected bounding box center.

(c) Word information that is a Bag-of-Words (BoW) representation of a place name. We assume that the user’s speech gives the place name as one or a few isolated words representing
the tidied position of an object.

In Fig. 3 (d) of the training phase, the spatial concept model learns the occurrence probability of objects and words in each place based on multimodal sensor information gathered by the robot in a tidied environment, as described in Section 3.2.

4.2 Planning phase

In the planning phase, the robot tidies up detected objects using the learned spatial concepts, as shown in Fig. 3 (e) – (g).

First, the robot detects cluttered objects while moving. The object detection method in the planning phase, Fig. 3 (e), is the same as in the training phase, Fig. 3 (a). We assume that the robot knows the places of the cluttered objects in advance, based on the task setting described in Appendix A.

Next, if multiple scattered objects are detected, the robot decides on an object and a place to be tidied up, as shown in Fig. 3 (f). The robot estimates simultaneously the order and the positions of the objects to tidy up from the multiple objects observed by the robot in the cluttered environment, using the parameters learned by the spatial concept model, as described in Section 3.3. Moreover, if the tidy-up position of an object is unknown, the robot can ask where to move the object, as described in Section 3.4.

We describe the methods used for motion planning in the developed system, as shown in Fig. 3 (g). After both estimating the tidied positions and planning the object order by Equation (18), the robot is required to accurately manipulate the objects to tidy up. In this study, the developed system uses the integrated MoveIt! [34] framework that relies on the Open Motion Planning Library (OMPL) [35] for planning the motion of the robot arm when grasping an object. The motion planning algorithm used by MoveIt! adopts RRT-Connect [36] which is an extension of Rapidly-exploring Random Trees (RRT) [37]. The system uses Octomap [38] as obstacle information so that motion planning can be performed safely without collision. Octomap is generated using 3D map information generated in advance by Real-Time Appearance-Based Mapping (RTAB-Map) [39], which is a vSLAM method. Furthermore, the robot moves to appropriate search positions while performing self-localization based on its map and observations. When the robot cannot directly observe the position to tidy up the object from its current self-position, Octomap is used to navigate toward that position.

Additionally, we developed the system using high-level behavior state-machines implemented with FlexBE [40] because it provides various functional modules to realize the tidy-up task. Using FlexBE allows to reuse code and states in various systems and scenarios, and thus increases abstraction during the development. Part of this system implementing the planning phase was also adopted by a team, OIT Challenger and Duckers, at the Partner Robot Challenge (Real Space) of WRS 2018.

When the robot finishes tidying an object, the state of the other objects may have changed due to external factors. In order to deal with such situations, it is possible to sequentially plan the tidy-up task by redoing object detection after tidying each object.

5. Experiments

In this paper, we perform the experiments based on the conditions and evaluation of Stage 1 and 2 of the Tidy Up Here task, as previously described in Appendix A. By the quantitative evaluation of the achievement of the tidy-up task, we aim to show the validity and viability of the proposed planning method for tidying up objects. The successfulness of the tidy-up task is measured based on the same score criteria as the Tidy Up Here task. Furthermore, in Stage 2, we conduct experiments not only exclusively with known objects that have already been learned (Stage 2-1), but also including objects with unknown target positions (Stage 2-2). Herewith, we
show that the robot can adequately tidy up by asking the user for the desired target place for objects without known tidied positions.

5.1 **Condition and environmental setting**

In this experiment, we use a simulator environment with a virtual Toyota Human Support Robot (HSR)\(^1\) [41]. The HSR has been adopted as a standard platform for RoboCup@Home and WRS [42]. The simulations are performed on a laptop computer with the following specifications: Intel Corei7-7820HK CPU, 32 GB of DDR4 memory, Nvidia GeForce GTX 1080 GPU. The WRS rulebook defines these specifications. The robot is operated by ROS Kinetic Kame running on Ubuntu 16.04 LTS. The simulator environments constructed using Gazebo [43] are shown in Fig. 4 and 5. We describe the pre-training for object detection and the pre-evaluation of objects to tidy up in Appendix D and E.
Table 2. 3D models and names of the known objects (Stage 1 and 2). All of them are known and do not deform.

| Category | Plush doll                      | Toy car                          |
|----------|---------------------------------|----------------------------------|
| Object   | Bear plush toy (doll_bear)      | Green toy car (toy_car)          |
|          | Sheep plush toy (doll_sheep)    | Truck toy car (toy_truck)        |
|          | Pig plush toy (doll_pig)        | Toy airplane (toy_airplane)      |

| Category | Sound toy                      | Block                           |
|----------|--------------------------------|---------------------------------|
| Object   | Whistle sound toy (sound_whistle) | Cube block (block_cube_rits) |
|          | Shaker sound toy (sound_maracas) | Star-shaped block (block_star) |
|          | Piano sound toy (sound_keyboard) | Cylinder block (block_cylind_wood) |

Table 3. 3D models and names of the objects with unknown tidied positions (Stage 2-2).

| Category | Plush doll |
|----------|------------|
|          | Penguin plush toy (doll_penguin) |
|          | Monkey plush toy (doll_monkey)   |
|          | Rabbit plush toy (doll_rabbit)   |

5.1.1 Stage 1

In the environment of Stage 1 (Fig. 4), toy boxes are lined up at the back of the children room, and the cluttered objects must be moved into them. Table 2 shows the objects used in Stage 1. The number of training data is 227. The hyperparameters of the spatial concept model are \( \alpha = 0.5, \beta = 10, \gamma = 15, \mu_0 = (2.719, -0.394, 0.655), \kappa_0 = 0.1, \psi_0 = \text{diag}(0.01, 0.01, 0.01), \) and \( \nu_0 = 1000. \) \( \mu_0 \) is set as the average positions of the observed objects. The number of Gibbs sampling iterations is 100. In the planning phase, 10 objects from the 12 objects of Table 2 are selected for each trial. Excepted the number of objects, all other conditions remain identical to the Tidy Up Here task.

5.1.2 Stage 2

In the environment of Stage 2 (Fig. 5), there are multiple target places, e.g. desks and shelves, for tidying up the cluttered objects. In Stage 2, we perform two experiments: Stage 2-1 using the same objects as in Stage 1, and Stage 2-2 in which objects from the plush doll category used in Stage 1 were replaced by other objects whose desired tidied positions are unknown. Table 3 shows unknown objects.

In Stage 2-2, the word information representing the place names to be tidied is given by the user. The word list is \{shelf, work_desk, nakamura_desk, white_table, low_table, sofa\}. The number of training data is 225. Among these, the number of word information is 11, i.e. 5% of the data. In Stage 2-1, the hyperparameters of the spatial concept model are \( \alpha = 0.5, \beta = 10, \gamma = 10, \mu_0 = (1.611, 0.841, 0.628), \kappa_0 = 0.1, \psi_0 = \text{diag}(0.01, 0.01, 0.01), \) and \( \nu_0 = 1000. \) In Stage 2-2, the hyperparameters of the spatial concept model are \( \alpha = 0.3, \beta = 0.3, \gamma = 10, \)

\(^1\)Toyota Human Support Robot (HSR): http://www.toyota-global.com/innovation/partner_robot/robot/#link02
\( \mu_0 = (1.611, 0.841, 0.628), \kappa_0 = 0.1, \psi_0 = \text{diag} (0.01, 0.01, 0.01), \) and \( \nu_0 = 1000. \) \( \mu_0 \) is set as the average positions of the observed objects. The number of Gibbs sampling iterations is 100. The threshold for identifying an unknown object is \( \lambda = 0.003. \)

5.2 Comparison methods

We used the following three comparison methods:

1. **Proposed method.**
2. **Baseline method 1**: Selection criteria for tidying object: nearest, tidying position candidates: database. The nearest object is selected from the robot position as an object to be tidied up. The position of the object in the list of the training data matching the selected object is determined as the desired tidy-up position. This method is assumed as one of the typical conventional methods used even in actual competitions. Actually, a similar method was adopted by our team during WRS 2018.
3. **Baseline method 2**: Selection criteria for tidying object: random, tidying position candidates: random. An object to be tidied up and its position are selected from the list of the training data randomly.

5.3 Evaluation metrics

We measure the level of achievement of the tidy-up with the score criteria of the Tidy Up Here task described in Appendix A. Stage 1 is evaluated by Performance 1 and 2 of Table A1, and Stage 2 is evaluated by Performance 1 and 3 of Table A2. When evaluating the tidy-up task, we execute the whole planning system including the sub-processes developed for the object grasping and release, as described in Section 4. Additionally, we isolatedly evaluate the tidy-up planning using the spatial concept model, which is the main contribution of this study, while omitting object manipulation.

5.4 Results

We describe the experimental results of the training phase in Section 5.4.1, and the planning phase in Section 5.4.2.

5.4.1 Result of spatial concept formation in during the training phase

Fig. 6 and 7 shows the results of spatial concepts learned in the environments of Stage 1 and 2, respectively. These results qualitatively show that the object classes learned at each place coincide with the objects present in the properly tidied environment.

5.4.2 Result of tidying up objects during the planning phase

Fig. 8 shows an example of the tidy-up process flow by the robot in Stage 1. The robot operates for the number of objects determined in advance by repeating 1. – 7. sequentially. Even if grasping and release fail during the process, the robot can continue to operate continuously.

Fig. 9 – 11 show the average values and standard deviations of the log-likelihood values of the spatial concept model for each tidy-up planning in 10 trials of Stage 1, 2-1, and 2-2, respectively. The log-likelihood indicates a high value if the robot could bring the object to the correct place, starting with an object where the place to tidy up is the most defined. In all stages, the proposed method returned the highest values at any time. Welch’s t-test was performed to confirm that the log-likelihoods between the proposed method and each baseline are statistically significant. A p-value less than 0.05 was considered statistically significant. The t-test showed that the changes for each step were statistically significant, except for the last step of baseline 1 in Fig. 9. Additionally, t-tests on the mean of log-likelihoods across steps showed statistical significance in
all results. As a result, the proposed planning method based on the spatial concept model has proven more efficient and accurate for selecting the objects to tidy up.

Table 4 shows the score result for each method in Stage 1 and 2 in which the proposed method shows the highest scores for both. Because the baseline 1 operates by taking the nearest object, the robot repeatedly failed to grasp the same nearest object, and the score was lower than the proposed method for both Stage 1 and 2. In Stage 1, we consider that baseline 1 and 2 showed similar score values because the robot could get a score by simply moving an object anywhere in the toy boxes, even if the desired tidied position was incorrect. In Stage 2-1, the score of baseline 2 was significantly lower because no point was obtained if the desired tidied position was incorrect. Additionally, since Stage 2-2 contains objects with unknown tidied positions, the difference between the scores of the proposed method and baseline 1 was even more significant compared to that of Stage 2-1. In the proposed method, the robot can judge if the tidied position of an object is unknown from Equation (20). Because the robot could estimate the target tidied position of unknown objects by directly asking the user, the proposed method obtained a score higher than all other methods in Stage 2-2.

Finally, Table 5 shows the score of the planning without object grasping and release in 10 trials. The proposed method showed again the highest scores for both Stage 1 and 2. In baseline 1, the position where to tidy up an object was selected from the list of the training data of the spatial concept model. Therefore, we consider that it was easily influenced by object position and detection errors during data acquisition. We also consider that the proposed method led to a higher score because it was less likely to be affected by data uncertainty by generalizing the target places to tidy up from the positions of the objects observed multiple times in the training data. Additionally, the proposed method achieved a much higher score than baselines in Stage 2-2 when objects with unknown tidied positions were included, as shown in Table 4.
Figure 7. Top: object placement in the tidied situation. Middle: learning result of spatial concepts (Stage 2-1). Bottom: learning result of spatial concepts (Stage 2-2). The 3 best words and probabilities for each spatial concept are displayed.

Table 4. Score values of Tidy Up Here for each stage.

| Method   | Stage 1 | Stage 2-1 | Stage 2-2 |
|----------|---------|-----------|-----------|
| (1) Proposed | 35 /50  | 28 /50    | 23 /59    |
| (2) Baseline 1 | 14 /50  | 20 /50    | 10 /59    |
| (3) Baseline 2 | 13 /50  | 8 /50     | 4 /59     |

Table 5. Score values of Tidy Up Here (without object grasping and release).

| Method   | Stage 1 | Stage 2-1 | Stage 2-2 |
|----------|---------|-----------|-----------|
| (1) Proposed | 50 /50  | 50 /50    | 59 /59    |
| (2) Baseline 1 | 49 /50  | 47 /50    | 38 /59    |
| (3) Baseline 2 | 35 /50  | 14 /50    | 15 /59    |
6. Conclusion

We proposed an autonomous tidy-up planning method based on an unsupervised PGM for spatial concept formation using multimodal observations. We also developed an autonomous robotic system that can tidy up home environments with several scattered objects. The proposed method can learn co-occurrence probability between objects and target places where objects should be tidied up from observation information gathered by the robot. Additionally, the robot can plan the tidy-up in order, from an object whose target place is the most defined among the objects cluttered in the environment by using the parameters of the learned model. In the experiment, we reproduced the Tidy Up Here task of the WRS international robotics competition using simulation environments constructed with Gazebo. The results showed that the proposed method achieves efficient and accurate planning to tidy up scattered objects compared to other baseline methods. Therefore, we consider that the proposed method is effective to tidy up various indoor environments, as reproduced by the WRS tasks.

Furthermore, the proposed method is easily extendable by, for example, adding to the objective function of the tidy-up planning the cost of the positional movement from the robot to the object. Moreover, although we experimented with virtual simulations in this paper, the proposed method is by nature environment-agnostic and can work effectively in real environments as well. Therefore, we consider the applicable scope of the proposed method to be broad. In particular, the transfer of knowledge from a virtual environment to a real environment would also be possible when the spatial concepts are learned in a simulator environment that imitates the real one, as illustrated by Stage 2 and shown in Fig. 5. These two ideas will be investigated as future work.

Figure 8. Process flow of tidying up objects performed by the proposed method. A video example in which the robot tidies up the objects in Stage 1 can be found online at: https://youtu.be/inm1FHcubw.
Figure 9. Log-likelihood values for each tidied object (Stage 1).

Figure 10. Log-likelihood values for each tidied object (Stage 2-1).

Figure 11. Log-likelihood values for each tidied object (Stage 2-2).
The one-hot vector of the object recognition results detected by YOLO was used as object information in the experiment. As prospects, we plan to experiment with more complex tidy-up planning tasks considering environments where different objects classified into the same class exist in the recognition results at multiple separate places to tidy up. Finally, the proposed method can also use the image features extracted by CNN in the detected object area [2]. In such a case, additional computational resources and time are required to calculate the object features, but we believe they can make it possible to autonomously determine the positions where to move the objects based on the similarity of features even for unknown new objects.

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Appendix A. Task definition

We describe the overview of the tidy-up task in Appendix A.1, and the definition of Tidy Up Here, Stage 1 and 2, in Appendix A.2.

A.1 Task overview

In recent years, international robotics competitions related to tidy-up tasks have increased. The Tidy Up My Room Challenge\textsuperscript{1} was held at the IEEE International Conference on Robotics and Automation (ICRA) 2018. Additionally, the Tidy Up Here\textsuperscript{2} task was conducted as one of the tasks of the Partner Robot Challenge (Real Space) at the World Robot Summit (WRS) 2018 [3]. Hence pick-and-place tasks with many kinds of objects in home environments are becoming a common problem in robotics applications, and competitions, e.g. the Tidy Up My Room Challenge are held to invite the community to develop novel solutions. Moreover, by setting challenging tasks that include various techniques and problems considered to be difficult, various robotics systems can be compared and benchmarked with scoring criteria that take into consideration the technical difficulties of the task. Another aspect of these competitions is to envision solutions to social issues due to the decreasing and aging working population. In the Partner Robot Challenge (Real Space) of WRS, the Tidy Up Here task provides a benchmark for robot assistance, not only for disabled people but also for elderly people and healthy people, by supporting daily housekeeping tasks. Therefore, tidy-up tasks are seen as an important issue to be addressed for the improvement of social welfare as well as the development of robotics in general.

A.2 Partner Robot Challenge: Tidy Up Here task evaluation in WRS

The WRS Tidy Up Here task consists of moving objects from incorrect positions to predetermined spaces, i.e. their original positions in the room, to consider them as tidied up. It includes two separate sub-tasks of increasing challenge, designated as Stage 1 and Stage 2 (See Fig. 1). As for the environment, the layout of the room furniture is announced in advance and contains four rooms, e.g. a children room, a dining room, a kitchen, and a living room, with the names of the rooms known in the environment. Additionally, there are two types of objects: known and

\textsuperscript{1}Tidy Up My Room Challenge (ICRA 2018): https://icra2018.org/tidy-up-my-room-challenge/

\textsuperscript{2}Tidy Up Here (WRS 2018): http://worldrobotsummit.org/en/wrc2018/service/
Table A1. Score table of Tidy Up Here at WRS (Stage 1).

| Performance | Score |
|-------------|-------|
| 1. Tidy up an object into the toy storage | $3 \times 10$ |
| 2. Tidy up an object into the correct box within the toy storage | $2 \times 10$ |
| 3. Report back to the kitchen within the time limit | 2 |

| Special Bonus | Score |
|---------------|-------|
| 1. Complete the task on time | $3 \times \text{minutes remaining}$ |
| 2. Open the house door | 20 |

unknown. Known objects are given with pre-announced recognition data and consist of about 45 units, without deformable objects, of frequently used daily goods and toys with information on their desired tidy up spaces, e.g. toys are on toy storage, foods are in refrigerator. Unknown objects are not given with pre-announced recognition data and place information. They consist of about 10 units of daily items, including deformable objects, e.g. clothing, food, paper. For unknown objects, the robot can, from its own judgment, inquire the operator to get information on the desired tidy up space by voice or QR code, e.g. ‘Where should I put this object up?’.

Each stage starts with an instruction by the operator in the kitchen. The robot then enters the rooms in a messy condition, and tidy up each stage in 12 minutes per trial. The number of trials is 2 for each stage.

As described above, various information on objects and places are provided beforehand to the participants. However, in reality, it is necessary to have the robot acquire additional information about the real world from object recognition and place recognition in order to translate them into a form that can be understood and used by the robot. For that reason, participating teams of the competition are given a setup time to create/adjust the map data in the actual environment, and memorize unknown objects if necessary.

A.2.1 Tidy Up Here: Stage 1

Stage 1 consists of tidying objects scattered on the floor after a child played. The task starts with the robot being instructed to ‘Tidy up the children room.’ by the operator. In this simulated children room, there are 10 objects randomly selected from 15 known objects included in 5 categories, each of which containing 3 units. The storage places are toy boxes.

Table A1 shows the evaluation criteria and the score table of Stage 1. The robot gets 3 points for each object moved to a toy box. If the object is placed in the correct box, the robot gets 2 additional points. Additionally, the robot can get 2 points if it finishes the tidy-up task within the time limit and reports to the operator. The objects scattered on the floor may become problematic obstacles when the robot moves. Therefore, Stage 1 evaluates the basic and comprehensive ability of the robot’s autonomous tidy-up system.

A.2.2 Tidy Up Here: Stage 2

Stage 2 reproduces the conditions found when tidying a messy home environment. The task starts with the robot being instructed to ‘Tidy up the living and dining rooms.’ by the operator. In Stage 2, 10 objects, consisting of 5 known objects and 5 unknown objects, are randomly selected from 32 known objects and 8 unknown objects. The storage places are a coffee table, a wall shelf, a food cabinet, a kitchen unit, and so on. The robot can ask the operator where is the desired tidy-up space.

Table A2 shows the evaluation criteria and the score table of Stage 2. The robot gets 5 points for each object moved back to its correct original place. If an unknown object is moved to the correct place, the robot gets 3 additional points. Additionally, the robot can get 3 points if it finishes the tidy-up task within the time limit and reports to the operator. Compared to Stage 1, the robot needs to deal with a larger range of objects and places. It is difficult to finish the searching, moving, and tidying up of all objects within the time limit. Therefore, the task
Table A2. Score table of Tidy Up Here at WRS (Stage 2).

| Performance                                                                 | Score |
|-----------------------------------------------------------------------------|-------|
| 1. Tidy up an object to the correct place                                   | $5 \times 10$ |
| 2. Inquire the human operator whether to discard or the tidy up space of the objects | $6 \times 5$ |
| 3. Tidy up an unknown undeformable object                                  | $3 \times 3$ |
| 4. Tidy up an unknown deformable object                                     | $3 \times 2$ |
| 5. Report back to the kitchen within the time limit                         | 3     |

Special Bonus

| Performance                                                                 | Score                          |
|-----------------------------------------------------------------------------|--------------------------------|
| 1. Complete the task on time                                                | $3 \times$ minutes remaining   |
| 2. Open the cabinet drawer                                                  | 20                             |
| 3. Open the refrigerator door                                                | 20                             |

Conditions in Stage 2 are more advanced and difficult than in Stage 1.

Appendix B. The details of formulation for Gibbs sampling

We describe the sampling procedure of each parameter by Gibbs sampling as follows:

$$C_i \sim p\left(C_i = k \mid x_i, \mu, \Sigma, \pi, \varphi, \eta\right)$$
$$\propto \mathcal{N}\left(x_i \mid \mu_{C_i}, \Sigma_{C_i}\right) \text{Mult} \left(o_i \mid \varphi_{C_i}\right) \times \text{Mult} \left(w_i \mid \eta_{C_i}\right) \text{Mult} \left(C_i \mid \pi\right),$$  \hspace{1cm} (B1)

$$\mu_k, \Sigma_k \sim \prod_{i=1}^{I} \mathcal{N}\left(x_i \mid \mu_{C_i}, \Sigma_{C_i}\right) \mathcal{NIW}\left(\mu_k, \Sigma_k \mid \mu_0, \kappa_0, \psi_0, \nu_0\right)$$
$$\propto \mathcal{NIW}\left(\mu_k, \Sigma_k \mid \mu'_k, \kappa'_k, \psi'_k, \nu'_k\right),$$  \hspace{1cm} (B2)

$$\varphi_k \sim \prod_{i=1}^{I} \text{Mult} \left(o_i \mid \varphi_{C_i}\right) \text{Dir} \left(\varphi_k \mid \alpha\right)$$
$$\propto \text{Dir} \left(\varphi_k \mid \alpha'_k\right),$$  \hspace{1cm} (B3)

$$\eta_k \sim \prod_{i=1}^{I} \text{Mult} \left(w_i \mid \eta_{C_i}\right) \text{Dir} \left(\eta_k \mid \beta\right)$$
$$\propto \text{Dir} \left(\eta_k \mid \beta'_k\right),$$  \hspace{1cm} (B4)

$$\pi \sim \prod_{i=1}^{I} \text{Mult} \left(C_i \mid \pi\right) \text{Dir} \left(\pi \mid \gamma\right)$$
$$\propto \text{Dir} \left(\pi \mid \gamma'\right),$$  \hspace{1cm} (B5)

where the Gaussian-inverse-Wishart distribution is denoted as $\mathcal{NIW}(\cdot)$. The hyperparameters of the posterior distribution $\alpha'_k, \beta'_k, \gamma', \mu'_k, \kappa'_k, \psi'_k, \nu'_k$ are calculated by the conjugate distributions between prior and likelihood.
Appendix C. Formulation for simultaneous estimation of \(N\) objects and their positions for tidying up

The Tidy Up Here task has a time limit. In other words, among the number of scattered objects in the environment, the number of objects to be tidied up is finite. In this case, the problem of simultaneously finding \(N\) objects and positions to be tidied up from the total number \(D\) of detected objects is as follows:

\[
D, \{x'_{d}\} = \arg\max_{D, \{x'_{d}\}} L(\{x_{j}\}_{j \notin D}, \{x'_{d}\}_{d \in D}) - L(\{x_{j}\}), \tag{C1}
\]

\[
L(\{x_{j}\}_{j \notin D}, \{x'_{d}\}_{d \in D}) = p(\{x_{j}\}_{j \notin D} | \{o_{j}\}_{j \notin D}, \Theta) p(\{x'_{d}\}_{d \in D} | \{o_{d}\}_{d \in D}, \Theta) \\
\propto \prod_{j \notin D} \sum_{C_{j}} p(x_{j} | \mu_{C_{j}}, \Sigma_{C_{j}}) p(o_{j} | \phi_{C_{j}}) p(C_{j} | \pi) \\
\times \prod_{d \in D} \sum_{C_{d}} p(x'_{d} | \mu_{C_{d}}, \Sigma_{C_{d}}) p(o_{d} | \phi_{C_{d}}) p(C_{d} | \pi) \tag{C2}
\]

where the set of indexes \(d\) of the selected objects to be tidied is denoted as \(D\). Note that \(1 \leq N \leq D\).

In the same way, considering the case of tidying \(N\) objects at a time from the initial situation, the changing terms of the two equations of the likelihoods of before and after tidying up are:

\[
\arg\max_{D, \{x'_{d}\}} \prod_{d \in D} \sum_{C_{d}} p(x'_{d} | \mu_{C_{d}}, \Sigma_{C_{d}}) p(o_{d} | \phi_{C_{d}}) p(C_{d} | \pi) \\
= \prod_{n=1}^{N} \arg\max_{d_{n}, x'_{d_{n}}} R_{n}(x_{d_{n}}, x'_{d_{n}}). \tag{C3}
\]

The tidy-up method consisting of estimating combinations of \(N\) objects at once shown in this section is equivalent to tidying object one by one using a greedy method \(N\) times, as described in Section 3.3, because the object positions \(x_{j}\) are conditionally independent from each other. Finally, the robot can perform the tidy-up task by recursively selecting the object \(d\) to be tidied up, one at a time, i.e. sequentially calculating Equation (18).

Appendix D. Pre-training for object detection

To detect the objects used in the experiment, we prepared a training dataset using the RGB-D camera mounted on the HSR and trained a YOLOv3 model. The image size used for object detection was \(640 \times 480\) pixels. A total of 10,000 images containing multiple objects were generated by augmentation using 20 images of different poses for each object and 25 background images of Stage 1 and Stage 2 environments. Annotation files, including bounding box information of the objects in the augmented images, were generated and divided into two datasets of 90% training data and 10% test data. The training and parameter tuning of YOLOv3 was performed by using convolutional layer weights\(^1\) pre-trained with ImageNet [44]. Object classes were prepared individually for each object.

\(^1\)YOLO: https://pjreddie.com/darknet/yolo/
Table E1. Results of the pre-evaluation for the tidying up tasks.

| Accuracy          | Stage 1 | Stage 2-1 | Stage 2-2 |
|-------------------|---------|-----------|-----------|
| Object detection  | 1.00    | 0.96      | 0.95      |
| Object grasping   | 0.64    | 0.69      | 0.76      |
| Object release    | 0.84    | 0.79      | 0.68      |

Appendix E. Pre-evaluation on objects to tidy up

In this paper, we evaluate the achievement of the tidy-up task regarding the successful estimations of tidying objects and positions. As a pre-evaluation, we evaluate the accuracy of object detection, grasping, and release through all of the trials in the experiments. The YOLOv3 object detection model used in the experiments was trained using the dataset created by ourselves, as described in Appendix D. Additionally, various object shapes are included in the experiments. After considering the effects of these above factors, we examine the superiority of the proposed planning method in Section 5.4. The accuracy of object detection is defined as the ratio of the number of bounding boxes in which the object class is correctly detected to the number of bounding boxes detected and the number of objects not detected in the image. The accuracy of object grasping and release are defined as the ratio of the number of successful actions to the total number of planned actions.

Table E1 shows the resulted accuracy of the object detection, grasping, and release. The object detection was highly accurate. Additionally, the accuracy values of the object grasping and release were around 70% although objects of various shapes were used. In the case of grasping failure, either the grasp position coordinates of the detected object were inaccurately estimated, or the object shapes were complex to grasp in the first place, e.g. cylinders or stars.

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