Recognizing human grasping strategies is an important factor in robot teaching as these strategies contain the implicit knowledge necessary to perform a series of manipulations smoothly. This study analyzed the effects of object affordance—a prior distribution of grasp types for each object—on convolutional neural network (CNN)-based grasp-type recognition. To this end, we created datasets of first-person grasping-hand images labeled with grasp types and object names, and tested a recognition pipeline leveraging object affordance. We evaluated scenarios with real and illusory objects to be grasped, to consider a teaching condition in mixed reality where the lack of visual object information can make the CNN recognition challenging. The results show that object affordance guided the CNN in both scenarios, increasing the accuracy by 1) excluding unlikely grasp types from the candidates and 2) enhancing likely grasp types. In addition, the “enhancing effect” was more pronounced with high degrees of grasp-type heterogeneity. These results indicate the effectiveness of object affordance for guiding grasp-type recognition in robot teaching applications.

1 Introduction

Robot grasping has been a major issue in robot teaching for decades [1,2]. As robot grasping determines the relationship between a robot’s hand and an object, grasping objects suitable for the given environment is critical for efficient and successful manipulations.

Recent research has trended towards learning-based end-to-end robot grasping [3–9], where contact points or motor commands are estimated from visual input. However, the desired grasp can differ depending on the manipulation to be achieved, even for the same target object. Therefore, a robot teaching framework should benefit from how a demonstrator grasps an object (i.e., their grasp type).

We recently began developing a platform to teach a robot “how-to-manipulate an object” through human demonstrations in mixed reality (MR) or the physical world [10–13] (Fig. 1). The demonstration is accompanied by verbal instructions and captured by a head-mounted device. This teaching framework is based on our assumption that verbal instructions and demonstrations can be efficiently employed by novice users to teach the name of the manipulated object and the grasping strategy, respectively. Thus, this study supposed that demonstrations are recorded by a head-mounted device, and the object name is available from verbal instructions. Here, the key issue is classifying grasp types based on the name of an object and first-person images at the time of grasping.

In most cases, an object name is associated with possible grasp types [15–18]. To further extend this association, we proposed a pipeline that leverages a prior distribution of grasp types to improve the learning-based classification with a convolutional neural network (CNN), as shown in Fig. 1[14]. We refer to the prior distribution as object affordance, a concept proposed by Gibson [19]. In the proposed pipeline, appropriate object affordance was searched from an affordance database using text matching. Although our preliminary experiments revealed the effectiveness of object affordance for grasp-type recognition, they were limited in several ways: 1) they focused on a limited number of grasp types and target objects, 2) the pipeline was tested with a small dataset (only fifty images for each grasp type), yielding possible underestimation in CNN recognition, and 3) the role of object affordance in guiding the CNN recognition was unclear.

This study aimed to investigate the role of object affordance in the above-described robot-teaching application using a large first-person grasping image dataset containing a wider range of labeled grasp types and household objects. We tested the pipeline with two types of affordance, reflecting one or both of likelihood and impossibility for each grasp type. The experiments showed that object affordance guides CNN recognition in two ways: 1) it excludes unlikely grasp types from the candidates and 2) enhances likely grasp types among the candidates. In addition, the “enhancing effect” was more pronounced with high degrees of grasp-type heterogeneity.
Fig. 1. Conceptual diagram of robot teaching. (Top) Head-mounted device provides first-person images during a demonstration with verbal instructions (modified version of image from [10]). The demonstrations are transferred to a robot in the form of a skill set, which includes grasp type. (Bottom) Proposed pipeline for grasp-type recognition leveraging object affordance. The pipeline estimates the grasp type from the pairing of an object name and an image of a hand grasping that object. Object affordance is searched from an affordance database using text matching (modified image in [14]).

pronounced for high degrees of grasp-type heterogeneity. Further, we tested the pipeline for recognizing mimed grasping images (i.e., images of a hand grasping an illusory object), assuming that a real object may be absent in some situations (e.g., teaching in MR). Similar to the experiment with real grasping images, object affordance proved to be effective for mimed grasping images. In addition, the CNN recognition for mimed images showed lower performance compared with its recognition for real grasping, indicating the importance of real objects being present for image-based recognition.

The contributions of this study are as follows: 1) it demonstrates the effectiveness of object affordance in guiding grasp-type recognition as well as the conditions under which the merits of object affordance are pronounced, 2) demonstrates the importance of real objects being present in grasp-type recognition, and 3) provides a dataset of first-person grasping images labeled with possible grasp types for each object.

The remainder of this paper is organized as follows. Section 2 gives an overview of the proposed pipeline alongside some related works. Section 3 describes the experiments conducted with and without real objects. Finally, Section 4 summarizes the results of the study and describes future work.

2 System overview

2.1 Grasp taxonomy and dataset

There are two main approaches to analyzing human grasping from a single image: 1) using hand poses of grasping [20, 22] and 2) using a specific grasp taxonomy [16, 23–28]. Each approach has its own advantages. Hand pose analysis in 3D space enables the state of an object, such as posture [21] and grasping area [20], to be measured. Meanwhile, taxonomy analysis enables human grasps to be represented as discrete intermediate states that focus on the pattern of fingers in contact.

This study aimed to recognize grasp types from human behavior as an extension of taxonomy-based studies. We employed the taxonomy by Feix et al., which contains 33 grasp types [29].

Building a realistic dataset of human hand shapes while manipulating objects will contribute to the study of human grasping. Some studies collected joint positions using wired sensors [30], a data glove [31], and model fittings [22, 32]. Another study created a dataset of hand–object contact maps obtained using thermography [33]. Taxonomy-based studies have also created datasets annotated with grasp types [23, 24, 27, 34]. For example, Bullock et al. collected a dataset containing first-person images of four workers [34].

Despite the variety of datasets available for grasp-type recognition, they could not be directly applied to our study because they do not aim to cover possible grasp types associated with an object. Although there exists a pseudo-image
dataset focusing on object-specific affordance [18], there exists no dataset that provides actual grasping images. The dataset created in this study covers several common household objects and provides RGB images of real human grasps, considering possible grasp types for each object (see Section 3.1.1 for details).

2.2 Object affordance

We introduce object affordance obtained by searching a database by object name (Fig. 1). Although several studies have reported the effectiveness of using multi-modal cues for grasp-type recognition [24,35], the effectiveness of linguistically-driven object affordance is still poorly understood in the context of learning-based recognition.

Predicting affordance has become an active research topic in the cross-domain of robotics and computer vision. Affordance, which is generally regarded as an opportunity for interaction in a scene, has been defined in different ways depending on the problem to be solved. For example, in computer vision research using deep learning, affordances have been formulated as a type of label in semantic segmentation tasks [33,36,39]. In robotics research, affordance prediction is a factor in the task-dependent object grasping problem of task-oriented grasping (TOG) [20]. In the context of TOG, affordance is defined as possible tasks (e.g., cut and poke) allowed for an object [40,43]. Similarly, this study considered affordances as object-specific entities and defined them as possible grasp types for an object.

The experiments in Section 3 evaluated the role of object affordance using sub-datasets that were sampled from the created dataset, which was labeled with possible grasp types for each object (see Section 3.1.1 for details). In testing the proposed pipeline (Fig. 1), an affordance database was created for each sub-dataset by referring to the grasp-type labels found in the sub-dataset. We prepared two types of affordances for each object (Fig. 2):

- **Varied affordance** was calculated as a normalized histogram of the labeled grasp types for each object.
- **Uniform affordance** was calculated by flattening the non-zero values in the histogram.

While the varied affordance contains information about the likeliness and unlikeliness of grasping, the uniform affordance only contains information about the unlikeliness of grasping.

2.3 Convolutional neural network with object affordance

We formulated grasp detection by fusing a CNN with object affordance (Fig. 1) as follows. The image, object name, and grasp type are denoted as \( i \), \( o \), and \( g \), respectively. We can assume that the output of a CNN and an affordance reflect conditional probability distributions \( p(g|i) \) and \( p(g|o) \), respectively (Fig. 1). Further, assuming that \( p(i) \) and \( p(o) \) are independent, the following equation holds:

\[
p(g|i) p(g|o) = \frac{p(i|g) p(o|g) p(g)^2}{p(i) p(o)} = p(g|i,o) p(g).
\]

Hence, the conditional probability distribution \( p(g|i,o) \) can be estimated from the available distributions \( p(g|i) \), \( p(g|o) \), and \( p(g) \). Finally, the grasp type can be determined as the one that maximizes \( p(g|i,o) \).

A CNN network was obtained by fine-tuning ResNet-101 [44]. To avoid overfitting, we applied random reflection and translation to images, and randomly shifted the image color in the HSV (hue, saturation, value) space after every training epoch. The learning was conducted using the Adam optimizer [45] and continued until the validation accuracy stopped increasing. The number of training images was changed for each experiment.

3 Experiments

3.1 Scenario 1: with real objects

In this scenario, the demonstration of grasping a real object was given as a first-person image using a head-mounted device. We assumed that the system could retrieve object affordance from the affordance database using the name of the object mentioned through verbal instructions (e.g., “Pick up the apple”). This section evaluates the performance of the pipeline under Scenario 1, i.e., first-person images with object affordance.
3.1.1 Data preparation

Demonstrations are often recorded by a head-mounted device in MR-based robot teaching. Even for robot teaching in the physical world, first-person images given by the demonstrator are preferred over third-person images due to the ability to avoid self-occlusion. Therefore, we required a dataset of first-person images of possible grasp types for each object. Because we were not able to find any existing dataset meeting these requirements, we created one.

The images were captured by a HoloLens2 sensor [46]. We used this sensor because it is a commercially-available sensor that can capture first-person images without the use of hand-made attachments. The type of target object was chosen from the Yale-CMU-Berkeley (YCB) object set [47], which covers common household items. We used this object set because it has been used as a benchmark for many robotic studies. We selected eight items from the food category and 13 items from the kitchen category: chip can, cracker box, gelatin box, potted meat can, apple, banana, peach, and pear; and pitcher, bleach cleanser, glass cleaner, wine glass, metal bowl, mug, abrasive sponge, cooking skillet, plate, fork, spoon, knife, and spatula, respectively. We selected these items to cover a variety of sizes. We prepared two datasets to avoid the overestimation of the performance of the network due to CNN overfitting:

- **YCB dataset**: Training dataset containing exactly the same items as the YCB object set.
- **YCB-mimic dataset**: Testing dataset containing objects that are the same as those in the YCB dataset but different in color, texture, or shape (e.g., a cracker box from another manufacturer).
The datasets were prepared through the following pipeline. Before collecting the images, we manually assigned a set of plausible grasps according to the taxonomy in [29] (Fig. 3). Based on a previous study [48], we focused on 13 grasp types that we believed were possible for common robot hands. For each object and grasp type, we captured images of a human grasping the object with their right hand. We captured more than 1500 grasp images by varying the arm orientation and rotation as much as possible. A third-party hand detector [49] was then applied offline to crop the hand regions from the captured images. After manually filtering out detection errors, 1000 images were randomly collected for each object and grasp type. The following experiments were conducted with sub-datasets that were sampled from the YCB or YCB-mimic dataset.

### 3.1.2 Evaluation of dataset size

Because small datasets lead to underestimation in CNN recognition, we validated the performances of CNNs trained with different sized sub-datasets of the YCB dataset. We prepared five sub-datasets containing 10, 50, 100, 500, and 1000 images per grasp type. The images were randomly sampled such that a sub-dataset included all images from the other smaller sub-datasets. The CNNs were tested with sub-datasets of the YCB-mimic dataset. We refer to these sub-datasets as the test datasets. The test datasets were created by randomly sampling 100 images per grasp type. The performances of the CNNs were validated ten times using different test datasets.

Fig. 4 shows the results. The CNN performance tended to increase with the dataset size and converged above 500 images per grasp type. This indicates that the YCB dataset is sufficiently large to avoid underestimation due to insufficient images.

### 3.1.3 Effect of affordance on recognition

We evaluated the effectiveness of the proposed pipeline by comparing five methods: the proposed pipeline using varied affordance \( p(g|i, o) \), using uniform affordance, only varied affordance \( p(g|o) \), only uniform affordance, and only the CNN \( p(g|i) \). For a fair comparison, the same CNN was used for each method. The grasp type that maximizes the probability distribution was chosen. In the case of using only uniform affordance, the grasp type was randomly selected from the possible grasp types.

The CNN was trained with a sub-dataset of the YCB dataset. Based on the evaluation of dataset size in Section 3.1.2, the sub-dataset was prepared by randomly sampling 1000 images per grasp type. The comparison was tested 100 times using different test datasets from the YCB-mimic dataset. Each test dataset was created by randomly sampling 100 images per object.

Fig. 5 shows the result. The pipelines combining the CNN and affordance performed better than the CNN-only and affordance-only pipelines. While the proposed pipeline using varied affordance performed best, the proposed pipeline using uniform affordance was comparable. This indicates the effectiveness of using affordance for guiding grasp-type recognition.

To elucidate the role of affordance, we examined cases where the CNN failed, such as in Fig. 6. In these cases, the correct grasping was not the best candidate for the CNN, possibly due to finger occlusion, but it had a small affordance value, resulting in a small likelihood to be the output of the proposed method. As a result, the correct grasping was chosen as the final output. Therefore, it seems that object affordance contributed to excluding unlikely grasp types from the candidates of the CNN.

To investigate the advantage of varied affordance over uniform affordance, we examined cases where the proposed pipeline using uniform affordance failed, as shown in Fig. 7. In these cases, the pipeline outputted the correct grasping by employing varied affordance. Therefore, it seems that varied affordance contributed to enhancing the grasps that were likely for an object.

### 3.1.4 Enhancing effect of varied affordance

After observing the enhancing effect of affordance, based on information theory, we hypothesized that the effect would be stronger with higher grasp-type heterogeneity. To test this hypothesis, we evaluated the effect of grasp-type heterogeneity on recognition.

We used the same 100 test datasets that were prepared for the comparison experiment. The degree of grasp-type heterogeneity, \( h \), was defined for each test dataset by the following equation:

\[
    h = \frac{1}{N} \sum_{i=1}^{N} \text{std} \left( a_i \right),
\]

where \( N \), \( a_i \), and \text{std} represent the number of object classes, vector of varied affordance of an object (i.e., each column in Fig. 2(b)), and an operation to calculate the standard deviation of non-zero values of a vector, respectively.
The sub-datasets were tested with the proposed pipeline using varied affordance and uniform affordance. The same CNN as in the comparison experiments was used. Fig. 8 shows the performance difference of the pipelines plotted against the grasp-type heterogeneity. As hypothesized, the improvement when using varied affordance increased as the grasp-type heterogeneity increased. This indicates that the enhancing effect is more pronounced when the degree of grasp-type heterogeneity is higher.

3.2 Scenario 2: without real objects

In the previous section, we evaluated the pipeline for images of grasping real objects. However, robot teaching may not require real objects to be grasped in some situations (e.g., teaching in MR). In such situations, captured images do not include real objects; however, a user can interact with an illusory object in MR (i.e., an MR object). Because such “mimed” images lack visual object information, image-based grasp-type recognition can become challenging. This section evaluates the performance of the proposed pipeline when mimed images and object affordance are available.

3.2.1 Data preparation

To obtain the CNN for recognizing grasp types, we prepared a dataset of mimed images captured by a HoloLens2 sensor [46]. We used the texture-mapped 3D mesh models of the YCB objects described in Section 3.1.1 as MR objects. Grasp achievement was determined by the type and number of fingers in contact, following the definition in [29]. The positions of the hand joints were estimated via the HoloLens2 API. When collecting the images, a user grasped one of the rendered MR objects guided by visual cues that represent the contact state between the user’s hand and the MR object [10]. Although
we captured images based on the grasp-type mapping in Fig. 3, the glass cleaner and the wine glass were ignored because corresponding 3D models were not available among those provided by [47], and the abrasive sponge was ignored owing to the inability to express soft materials in MR. Further, “small diameter” grasping was ignored because of the difficulty in measuring the joint positions with corresponding accuracy (i.e., within 1 cm [29]). We also excluded objects with only one type of grasp (i.e., the pitcher and cooking skillet).

Following the same recording and post-processing protocol as described in Section 3.1.1, we collected a dataset containing 1000 mimed images for each object and grasp type (note that the MR objects were not captured in the images). We created two datasets under different lighting conditions and used one for training the CNN and the other for testing the pipeline. Fig. 9 shows examples of the images.

### 3.2.2 Effect of affordance on recognition

We compared the same five methods as in Section 3.1. The protocols to obtain the CNN and affordance database were the same as described in Section 2.3. Fig. 10 shows the comparison results. Similar to the results in Section 3.1, the proposed pipeline showed the highest performance. Although the CNN recognition for mimed images was worse than that for real grasping images (see Fig. 5), the use of affordance proved to be effective.

We also observed the two functions of object affordance (i.e., excluding unlikely grasp types from the candidates and enhancing likely grasp types among the candidates), similar to Section 3.1. For example, Fig. 11 shows cases where the CNN failed to discriminate between “power sphere” and “precision sphere,” which appeared similarly in mimed grasping. Despite such similarity, the proposed pipeline using varied affordance succeeded by excluding either of them as candidates.
4 Conclusion, discussion, and future studies

This study investigated the role of object affordance for guiding grasp-type recognition. To this end, we created two first-person image datasets containing images with and without grasped objects, respectively. The results revealed the effects of object affordance in guiding CNN recognition: 1) it excludes unlikely grasp types from the candidates and 2) enhances likely grasp types among the candidates. The enhancing effect was stronger when there was more heterogeneity between grasp types. These findings suggest that object affordance can be effective in improving grasp-type recognition.

The advantage of our proposed pipeline (Fig. 1) is that it can be updated independently of the CNN. For example, if a user experiences a grasp type that is not assigned for an object, the pipeline can be updated by simply modifying the object affordance according to the user’s feedback. As another example, if a user wants to deal with objects that are not registered in the affordance database, the pipeline can be updated by adding object affordances manually. In the case of using uniform affordances, which showed promising results (Fig. 5), object affordances can be readily added by manually
assigning possible grasp types. Such an approach is less expensive than updating a CNN by collecting a large number of grasp images depending on the use case.

This study assumed that the pipeline could access the name of the grasped object and retrieve the affordance using the object name. For practical robot teaching applications, separate solutions to these requirements are needed. To access the name of the grasped object, general object recognition or user input information can be used. For example, our robot teaching platform is designed to extract the name of the grasped object from human instructions [12]. While this study used text matching to retrieve affordance using object names, we could also employ a thesaurus or word embedding methods to cover word variations.

Recognition from mimed images seems to be more difficult than that from images of grasping real objects (Fig. 5 and 10), indicating the importance of real objects being present for image-based recognition. Although this result is reasonable considering the lack of visual information about the objects, the use of real objects may limit the advantage of MR in representing a wide variety of objects. To overcome the difficulty of recognizing grasp types in MR, a previous study has proposed combining other information, such as contact points and contact normals, which can be easily calculated for MR objects [50]. As explained in Section 2.3, the proposed pipeline can be applied to an arbitrary learning-based classification technique beyond an image-based CNN as long as the output can be considered as a probability distribution. Therefore, we believe that our research will benefit studies based on MR objects as well as real objects.

As future research, the proposed pipeline could be employed in a learning-from-observation (LfO) framework, where object names can be estimated from verbal instructions. We are currently testing this hypothesis by integrating the pipeline with an LfO system that we developed in-house [11, 12].

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