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FULL PAPER

A Brief Review of Affordance in Robotic Manipulation Research

Natsuki Yamanobe[1], Weiwei Wan, Ixchel G. Ramirez-Alpizar, Damien Petit, Tokuo Tsuji Shuichi Akizuki, Manabu Hashimoto, Kazuyuki Nagata, and Kensuke Harada
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This paper presents a brief review of affordance research in robotics, with special concentrations on its applications in grasping and manipulation of objects. The concept of affordance could be a key to realize human-like advanced manipulation intelligence. First, we discuss the concept of affordance while associating with the applications in robotics. Then, we intensively explore the studies that utilize affordance for robotic manipulation applications, such as object recognition, grasping, and object manipulation including tool-use. They obtain and use affordance by several ways like learning from human, using simulation, and real-world execution. Moreover, we show our current work, which is a cloud database for advanced manipulation intelligence. The database accumulates various data related to manipulation task execution and will be an open platform to leverage various affordance techniques.

Keywords: Affordance, Grasping, Manipulation

1. Introduction

According to Psychologist Gibson [1], affordance was defined to be the possibility of an action on an object or environment. The definition has been very widely used in many research fields such as perceptual psychology, cognitive psychology, environmental psychology, industrial design, human-computer interaction (HCI), interaction design, artificial intelligence, and robotics. In robotics, the concept of affordance has been mainly introduced in the research on traversability of environment [2]. Although the concept of affordance plays quite an important role when a robot performs a task especially under unknown situation, it had not been clearly mentioned in the robotic manipulation field [3], but recently several works on robotic manipulation have paid attention to the concept of affordance (e.g. [4]). In the research field of robotic manipulation including interaction with objects like grasping and manipulation of objects, affordance should be a crucial factor since a robot acquires a possibility to manipulate a novel object once its affordance information can be identified.

Take a task of hitting a nail with a hammer as an example. The hammer is composed of a hammer head and a handle. The hammer head is a hard and heavy lump that is suitable for hitting objects. The handle is a long bar, it is suitable for grasping by hand and swinging down the hammer. Therefore, when hitting a nail, the hammer head affords striking something and the handle affords the action of grasping and swinging it down. The parts that express the main function of a tool are referred to as main parts, and the parts that support the main function are called subordinate parts [5]. For the hammer, the main part is the hammer head and the subordinate part is the handle. If

[1] Corresponding author. Email: n-yamanobe@aist.go.jp. Natsuki Yamanobe, Weiwei Wan, and Kazuyuki Nagata are with National Institute of Advanced Industrial Science and Technology (AIST), Japan. Ixchel Ramirez-Alpizar, Damien Petit and Kensuke Harada are with Osaka University, Japan. Kensuke Harada is also a Cross Appointment Fellow of AIST. Tokuo Tsuji is with Kanazawa University, Japan. Shuichi Akizuki is with Keio University, Japan, and Manabu Hashimoto is with Chukyo University, Japan.

there is no hammer around, you can hit the nail by using a stone, block etc., which provide the same affordance with the main part of hammers. Conversely, hammers can be utilized for other purposes. When you want to take an object existing out of your reach, you can apply the handle of hammer to dragging the object. Then, the handle provides another affordance, which is pulling something. Various affordances exist in surroundings, and human perceives some of them according to his/her intention. Recognizing various affordances and properly executing the corresponding action depending on intention must be a key to develop an intelligent autonomous robot, which is a different direction from the conventional planning method based on accurate description of environment and objects.

Sahin et al. seminally discussed the usage of affordance in robotics and formalized it towards affordance-base robot control [6]. Since the seminal formalization of affordance in robotics, related topics were investigated extensively. Several review papers have been published recently to summarize the researches of affordance in robotics [4, 7, 8]. Jamone et al. [4] presented significant evidence in psychology and neuroscience that supports the affordance theory and provided a comprehensive review of affordance researches in robotics from simple action-effect relationship to complicated affordance in human-robot interaction or developmental learning systems. Min et al. [8] reviewed and classified affordance researches from the perspective of developmental robotics focusing on the formalization and representation of affordance, and its learning methodologies. These previous review papers deal with broad area on robotics and give us structured knowledge of affordance applications in this field. However, they only briefly state about the affordance used in robotic manipulation. Bohg et al. [9] provided a comprehensive review for data-driven grasping. Although they did not mention the concept of affordance clearly, some of cited studies deal with recognition and learning of grasp affordance. However, no other affordances were included. In contrast, this paper puts stress on the review of affordance used in robotic manipulation, especially for grasping and manipulation of objects including tool-use instead of investigating every aspects of affordance in robotics to avoid repetition, and tries to show the current progress to realize advanced manipulation intelligence based on affordance.

The rest of the paper is organized as follows. After briefly reviewing the concept of affordance in Section 2, we first review the methods to recognize affordance from surroundings in Section 3. We concretely show the works that used affordance to manipulate objects in Section 4. In Section 5, we present a cloud database for advanced manipulation intelligence, which will accumulate various data related to execution of manipulation tasks. It is being developed at AIST for an open platform used for affordance research in the robotic manipulation field.

2. The Concept of Affordance

Affordance is defined as action possibilities offered to an agent (human, animal, robot, etc.) by its environments. For example, chair affords sitting, pen affords writing, etc. The concept of affordance was proposed by J.J. Gibson [1, 10]. Gibson challenged the traditional ideas on perception, which assumed that an agent internally created and reconstructed the meaning of surroundings only from simple sensory inputs with reasoning, by arguing that environments had inherent meaning and an agent could detect it directly with reference to oneself. Gibson proposed such inherent meaning as affordance and a system interacting with environment to explore and detect affordance as a perceptual system [11].

In ecological psychology, several refinements and formalizations were proposed on Gibson's affordance since the concept had wide generality and seemed to be not completely formalized by Gibson [12]. Turvey determined that affordance was a dispositional property of environment and could be actualized by the effectivity of an agent [13]. "Effectivity" was defined to be the ability of an agent to interact with environment for actualizing an affordance; affordance and effectivity complemented each other. The idea of effectivity is important to express and use affordance based on the relationship of multiple objects especially for tool manipulation. When human use a tool, his/her effectivity is expanded by the tool and different affordance of target is detected based on the expanded effectivity. Stoffregen and Chemero, on the other hand, argued that affordances did not reside in the environment. Stoffregen determined that affordances were emergent properties of the agent-environment system and behavior would occur when an affordance and corresponding intention or goal coincided [14]. Chemero suggested that affordance was relation between the abilities of agent and features of environment, which offered behavior [15]. It was similar to Stoffregen's definition but explicitly included behavior inside the definition. Therefore, the definition has been utilized to formulate affordance in robotics.

Norman introduced the concept of affordance to industrial design [16] and suggested that objects should be designed to help people easily understand how they can be used. He focused on a part of affordance that could be explicitly perceived by users and promote actions, and named such kind of affordance "perceived affordance". Although it is sometime criticized that Norman's affordance is different from what Gibson determined, his definition has important suggestion for robotics. Since everyday objects are designed by human with a purpose based on his/her experiences of affordance perception-action execution relationships, it is possible to connect a shape of everyday object and corresponding actions understandably, which will be a help to generate robot motion.

In the field of computer informatics, Steedman et al. formalized affordance based on Liner Dynamic Event Calculus [17]. In the formalization, object affordance consisted of a set of functions that were defined by actions related to the preconditions of the object and the consequences of the actions. Because the description was based on a logical language, which explicitly connects objects, actions, preconditions, and consequences, it could be used in planning of robot motion. In addition to the definition of affordance, how to learn affordance should be considered. J.J. Gibson mentioned that affordance are learned by interaction with environment in child [10]. Piaget proposed the stages of child's cognitive development and divided the progress of child's sensorimotor adaptations into two sections: (1) The elementary sensorimotor adaptations and (2) the intentional sensorimotor adaptations [18]. From the viewpoint of affordance, a child uses its inherent affordance to perceive the world and acquire adaptations in the first stage, and uses active learning to learn affordance by interacting with surroundings in the second stage. Affordances are learned by the effect-result loops as well as exploration actions are improved.

The concept of affordance, which connects environment and actions, should be a key to develop intelligent autonomous robots. In robotics, we can first find a similarity between the concept of affordance and the approach of behavior-based robotics (e.g. [19]), which relies on direct perception. In the behavior-based robotics, a robot reacts to the environment based on simple sensory-motor mappings and gradually corrects its actions according to the effects instead of using complex internal model or reasoning. Although the simple reactive behavior solves some problems of traditional model-based approach, it seems to be insufficient to realize more advanced scenarios, such as object manipulation and complicated sequenced task. How affordance is represented, accumulated and modified in a robot should be considered.

Sahin et al. proposed a formalization towards affordance-based autonomous robot control [6]. They classified affordance with respect to different viewpoints, such as agent, observer, and environmental perspectives, and argued that affordance of agent perspective should be explicitly represented in a robot for its autonomous control. Affordance of agent perspective was defined as a relation between effects, entities, and behaviors, which was based on Chemero's view of affordance [15] and was modified for applying it to robot planning. Each element, i.e. effect, entity, and behavior, was generalized as a set of instances that generated same invariants. The formalization could be represented by formal languages for the automated planning and scheduling, like STRIPS [20], and was applied to several robot planning researches.

Min et al. [8] divided the Piaget's two sections into three stages: In the first stage, a child develops "primitive affordance" like grasping, pushing, rolling, etc. In the second stage, a child develops "adaptive affordance" like using tools, manipulating multiple objects, etc. In the third stage, a child develops "social affordance" like interacting with animals and humans. Some parts of researches on object recognition (e.g. [21]), navigation (e.g. [22]), grasping and manipulation (e.g. [23]), etc., have been carried out assuming the primitive affordance. Regarding adaptive affordance, researches on tool manipulation (e.g. [24]) and learning multiple object relationship (e.g. [25]), have been done. For social affordance, for example, Shu et al. learned structural representation of human-human interactions for human-robot interaction [26].

In the following sections, we will review several works utilizing affordance for robotic manipulation depending on their purposes as object recognition, grasping, manipulation, and planning, which are mainly related to primitive affordance and adaptive affordance. Social affordance will be rarely mentioned since this paper puts stress on object manipulation.

3. Usage of Affordances for Object Recognition

For the robotics community, recognizing and classifying objects is an indispensable function to manipulate objects. This section reviews research that uses affordance for object recognition. Since affordance has the relationship of human action and object shape, it is useful to improve the accuracy of recognition, especially for daily scene. Several works has been conducted mainly in the field of computer vision and can be classified to affordance feature detection and object categorization. The supporting perception devices are usually 2D and 3D vision systems, sometimes with multi-modal techniques like tactile, force, or position sensing. Table 1 list all the studies based on the method to obtain and verify affordance.

Affordance detection: Learning from human is a popular way to obtain affordance. In [27], Hermans et al. predicted eight types of affordance such as pushable, rollable, graspable, and liftable, etc., by learning image attributes. Myers et al. [28] detected the affordance parts, such as parts providing cut, scoop, pound, contain, support, grasp, and wrap grasp functions in RGB-D images using SVM. It was trained by a dataset of RGB-D images with ground-truth annotations of affordance labels. The object of unknown category was also analyzed for detecting its function. Nguyen et al. [29] applied a deep Convolutional Neural Network (CNN) to the dataset used in [28] and evaluated the results of grasp affordance by a real robot. Chao et al. [30] introduced the new dataset of human action images. They analyzed and revealed the relations of text, visual action, and affordance. Stark et al. [31] proposed a system where affordance was learned based on the functionality and geometric features of the objects extracted during a human demonstration. Pieropan et al. [32, 33] learned pairwise relationships between objects as affordance by observing human performing activities using the objects. The results categorized objects according to their functional feature space, instead of appearance feature space. Koppula et al. [34] modeled human activities through model rich spatial-temporal relations and affordance of objects. By using the model, human motion related to an object was anticipated by a robot. Ridge et al. [35] studied object push affordance. They developed action-grounded features, which are object features in 3D point clouds defined dynamically with respect to motions acting on it based on human pushing experiments. Matsuo et al. [36] studied the interaction of a hand and an object using a CNN and estimated the interaction from a single object image. The functions such as a handle and a grip position of unknown objects were extracted as interaction images.

Besides using human knowledge to collect data, there are some simulation-based approaches for obtaining affordance of objects. Hinkle et al. used a simple physical simulation of falling spheres [37] to predict the affordance of objects such as cup-like, table-like, and sit-able. Gupta et al. [38] simulated human poses such as laying down, reaching, sitting upright, and sitting reclined to describe affordance of the furniture in a room. Grabner et al. used a sitting person model [39] to detect chairs in a room. The chairs and their sitting positions were estimated simultaneously. Erdemir et al. [40] learned affordance by simulating the outcomes of actions. The simulation was named internal rehearsal. The robot engaged in the internal rehearsal by playing out virtual scenarios grounded in yet different from actual experiences. The learned results were also examined in simulation.

Object categorization based on affordance: Varadarajan et al. [21] proposed a set of

Table 1. Research using affordance for object recognition. "A" and "C" in the column of purpose denote "affordance detection" and "object categorization" respectively.

		How to obtain affordance						Input information				Verification			
					Exploration			Visual data							
	Purpose	Human annotation	Demonstration	Simulation	based on simulation	based on experiments	Other	2D	3D	rgb-D	other sensors	Only recognition	Simulation	Real robot	Other
Hermans et al. [27]	A	✓						✓				✓			
Myers et al. [28]	A	✓								✓		✓			
Nguyen et al. [29]	A	✓								✓		✓		✓(grasp)	
Chao et al. [30]	A	✓						✓			texts	✓			
Start et al. [31]	A	✓							✓			✓			
Pieropan et al. [32]	A	✓								✓		✓			
Pieropan et al. [33]	A	✓								✓		✓			
Koppula et al. [34]	A	✓				✓				✓		✓			
Ridge et al. [35]	A	✓								✓		✓			
Matsuo et al. [36]	A		✓					✓				✓			
Hinkle and Sun [37]	A	✓		✓					✓			✓			
Gupta et al. [38]	A			✓					✓			✓			
Grabner et al. [39]	A			✓					✓			✓			
Erdemir et al. [40]	A				✓						simulation result		✓		
Varadarajan & Vincze [21]	C	✓								✓		✓			
Varadarajan & Vincze [41]	C	✓								✓		✓			
Castellini et al. [42]	C	✓	✓			✓		✓			data grove	✓			
Sun et al. [43]	C	✓				✓		✓				✓			
Kjellstrom et al. [44]	C	✓	✓					✓				✓			
Ren and Sun [45]	C	✓	✓					✓				✓			
Moldovan et al. [25]	C	✓				✓		✓				✓			
Schoeler & Wörgötter [46]	C	✓							✓			✓			
Akizuki et al. [47]	C	✓							✓			✓			

affordance features based on an extension of the psychophysical theory of Recognition by Components [48] for cognitive object recognition. They built a database which they call "the affordance network" to hold the affordance features of common household objects. They extended this work to also detect grasp affordance and determine grasp points and approach vector for robots in domestic environments in [49]. In the following work, they used a deep learning approach to learn a mixture of material affordance, semantic affordance, and structural affordance from depth images, and used the learned models to classify objects [41]. Castellini et al. [42] used the kinematic features of grasping hands and affordance of objects to improve object recognition. They mapped the visual features of objects (visual) to the kinematic features of hands grasping the objects (motor), and obtained significantly better recognition rate by using the mapped visualmotor feature sets. Likewise, Sun et al. [43] proposed the category-affordance model where the relationships between object categories, affordance, and appearance were saved. They applied the category-affordance model to the visual recognition and classification tasks of indoor mobile robot navigation. Kjellstrom et al. [44] presented a method to classify manipulated objects and human manipulation actions in context of each other. They could simultaneously segment and classify human hand actions, and detect and classify the objects involved in the actions. Ren and Sun [45] studied a human-object-object interaction affordance model which contained relative motions of the paired objects and human action. The interaction affordance model, which is essentially semantic affordance, was used to improve recognition reliability of the objects. Moldovan et al. [25] built relation models of objects using manually defined geometry features and used web images to learn the probabilities of the pre-built models. Then, it searched occluded objects by finding highly-related visible objects. Schoeler and W¨org¨otter [46] proposed a framework to recognize objects by using geometric similarity based on functions that each object has. The framework first segments an object into parts and then compares its geometric features with a set of geometric features of tool functionalities, which are derived from possible basic functions of the human hand. Akizuki et al. [47] proposed a novel 3D feature representation for generic object recognition. The feature represents the percentage distribution of affordance labels of tools.

This field will progress with the related area such as simulation and machine learning. The database of human motion and object shapes is important for learning process of affordance. The annotated dataset of captured motion, object category, object shapes, and object appearance etc. will be established for accurate detection of affordance. The methods of simulation on human skeleton model or particles are also useful for detecting affordance without learning process, thus such simulation based approach will be also improved and adapted to wide variety of affordance. For robotic manipulation, combining these results to robot motions is a next problem. The real-world interaction of robot is a promising way. The interaction process will be reinforced by machine learning. If the robot motion and interaction with the objects are simulated accurately in virtual world, the learning process will be accelerated.

4. Usage of Affordances in Robotic Manipulation

As we discussed in the previous section, the next goal of recognizing objects is to interact with them, which is also the main goal of affordance study in robotic manipulation. This section further reviews the research that besides defining or obtaining affordance, employs affordance to manipulate the detected objects.

4.1 *For grasping*

Various research has been done to adequately grasp new objects which are not encountered before. These works obtained simple grasp affordance according to a hand. Saxena et al. [50] proposed an algorithm for identifying good grasp locations from images. The probability of grasping points, which can be said as grasp affordance, was modeled by logistic regression using annotated synthetic images of various different objects. They demonstrated the task of unloading unknown objects from a dishwasher. The research has been succeeded by [51, 52]. In [51], grasping rectangles, which represent the location and orientation of a gripper with adequate opening width, were detected from RGB-D images for novel objects. The grasping affordance was obtained by SVM-based two-step learning process using a dataset of object images. In [52], a deep learning approach was applied to the detection of grasping rectangles. Detry et al. [23, 53] used visual features to plan the grasps for novel objects, and used real-world executions to refine the planned results. The work presented an interesting idea which used real-world execution to refine automatically planned grasps. The goal was to ensure safe grasp without considering object orientations. The obtained grasps were used to promote the performance of Barret Hands and general parallel grippers. In [54, 55], they also proposed other grasp affordance, which were prototypical object parts and learned from grasps demonstrated on a set of training objects. For a new object, a grasp candidate was predicted by similarity matching on point cloud data. Bierbaum et al. [56] also used affordance to plan grasps. Compared with other studies, the main contribution is the use of simulated tactile sensing to conduct grasp affordance searching. Levine et al. [57] used an end-to-end approach based on deep learning. 14 robots explored pick-up motion for various objects and learned grasp affordance and adequate motions based on images.

In addition to the simple grasp affordance, research on how to grasp an object according to its category or task achieved by the object has been studied. Granville et al. [58] used the affordance obtained from visual perception to do the preparatory grasping [59] of various tools.

Table 2. Research on learning and using grasp affordance. “Sg” and “Tg” in the column of category denote “simple grasp affordance” and “task-oriented grasp affordance” respectively.

		How to obtain affordance						Input information				Verification			
					Exploration			Visual data							
	Category	Human annotation	Demonstration	Simulation	based on simulation	based on experiments	Other	2D	3D	rgb-D	other sensors	Only recognition	Simulation	Real robot	Other
Saxena et al. [50]	Sg	✓						✓						✓	
Jiang et al. [51]	Sg	✓								✓		✓		✓	
Lenz et al. [52]	Sg	✓								✓		✓		✓	
Detry et al. [23]	Sg			✓					✓					✓	
Detry et al. [53]	Sg			✓					✓					✓	
Detry et al. [54]	Sg		✓						✓					✓	
Detry et al. [55]	Sg		✓						✓					✓	
Bierbaum et al. [56]	Sg				✓				✓		tactile sensors		✓		
Levine et al.[57]	Sg					✓		✓						✓	
Granville et al. [58]	Tg			✓					✓					✓	
Chang et al. [59]	Tg		✓								motion capture			✓	
Sahbani et al. [60]	Tg	✓							✓				✓		
Barck-Holst et al. [61]	Tg	✓							✓				✓		
Zhu et al. [63]	Tg		✓							✓		✓			human demonstration
Abelha et al. [64]	Tg		✓							✓		✓			compare with ground truth

The affordances were used by a Robonaut robot to do tool clustering. Sahbani and El-Khoury [60] segmented the mesh models of objects and identified the object graspable part by learning from human choices as well as geometric analysis. The relationship between the features of an object and its functions was considered. Barck-Holst et al. [61] used a mixture of simulated planning and post inference to learn grasp affordances. The initial grasps were automatically planned using the Graspit! Simulator [62]. The authors used predefined features (probabilistic approaches) and predefined rules (ontological approaches) to learn which object afford which types of grasps. Zhu et al. [63] proposed a task-oriented affordance model to select and use tools. The methods defined two types of attribute, the affordance basis which indicated the location should be grasped for performing the assigned task, and the functional basis which indicated the location to act on a target object. They successfully used the affordances to select tools and grasp locations for different tasks. Abelha et al. [64] proposed a similar application which used affordances to find substitute tools. Their essential technique was to fit superquadrics of the query tool to the input point cloud data.

In Table 2, all the studied in this sub-section are listed based on the method to obtain and recognize affordance, and how to verify the proposed approach.

The results of learning and using simple grasp affordance seem to be promising. Task-based grasp is indispensable for a robot working like human. Although several studies provide task-based grasp locations as shown here, it is not considered whether a corresponding motion can be executed for achieving the target task by the grasp. For dealing with that, grasp and motion should be learned together. In the following sub-section, we will review the research which tackles object manipulation.

4.2 *For manipulation*

Many research have been done towards object manipulation using different methodologies for different types of manipulation tasks. Table 3 lists all the studied for manipulation based on the method to obtain and recognize affordance, and how to verify the proposed approach.

The ontology-based [65] method is a manual way to define affordances (The term ontology is from cognitive psychology which studies high level mental processes occurring in the brain. From the viewpoint of robotic engineering, it is equal to predefined things). In this work, the perception of the environment is processed semantically to obtain an appropriate affordance for a specific robot and determine which of the available robots is able to execute a specific task, like pushing a refrigerator door. Reich et al. [66] used affordance to plan task-level motion sequences. They obtained affordance by considering semantics like relations with obstacles and supporting surfaces in the environment. The afforded actions were associated to objects considering their surrounding objects. For example, robot might push an object if it was on a table, and could only pick it if the object was laying against a wall. The obtained affordance was used by a dual-arm KUKA LWR to perform pick and place tasks. The concept of relational affordance was initially proposed in [67], which models the interactions and relations between multiple objects and is also essentially semantic affordance. Hart et al. [68] developed the affordance template ROS package to quickly plan and adjust robot grasps and goal poses in the ROS environment. The template saved the geometric relationship between robot hands and target objects, and trajectories of the hands to perform specific tasks. The template was defined manually but could be scaled to similar objects interactively. The ROS package was used to support various robots to manipulate objects and tools. Romay et al. [69] also designed an object template that contains physical properties and affordance of the object. The affordance is defined as motion constraints like a set of poses that can generate constrained motion paths to achieve a task. The templates were applied to an Atlas robot and used to execute several tasks in the DARPA Robotics Challenge (DRC). Using ontology and semantics, a wide range of objects can be processed, however these have to be programed manually and store in a database and the resulting affordance depends on how accurate an object was recognized by the perception system.

In contrast, instead of manually defining affordances, a human demonstrates a given task and the robot learns the affordance related to an object. Montesano et al. [70, 71] and Lopes et al. [72] developed a probabilistic model based on a Bayesian Network which enables the learning of different affordance by both observing human demonstration and robot-object interaction, to allow the prediction of an action on an object and provide both task interpretation and planning capabilities. Their results were exercised by a humanoid robot on simple imitation games of object selection with people. Ek et al. [73] developed algorithms to obtain the affordance for object handover. The goal was to handover objects from a robot to human, where a robot needs to prepare graspable features for a human during the handover motion. The work used automatically generated training data in simulation and posterior observation of human motions in the real world to learn affordance. Ugur et al. [74] used “parental scaffolding” and “motionese” to teach affordance of objects, which have been shown as useful support from caregivers for child’s skill acquisition in developmental psychology. Parents (Human teachers) were supposed to hold a robot (scaffolding) and teach the robot to grasp and move objects using short and long pauses (motionese). The robot obtained adequate affordance from the parental scaffolding teaching and then used the obtained affordance to do integrated grasping and motion planning. They demonstrated simple motions like pushing and pick and place. Using human demonstration to teach a robot how to manipulate a certain object reduces the burden of manually defining each object affordance, however the range of objects used is limited.

Uyanik et al. learned “social” affordances, which they referred to as the affordance that only exists in the presence of humans, to assist robot manipulation to create multi-step plans [75]. Wang et al. [76] used the affordance obtained from real-world interaction to support navigation and stacking objects. A NAO robot was asked to perform predefined actions on some objects and learn the affordance of these objects using the results of the actions. It was demonstrated that after several interaction cycles, the robot was able to obtain affordance and use it to perform the navigation and manipulation tasks. In some later work [77, 78], they continued the research by using active exploration to change robot motions for household products composed of several parts and demonstrated several kinds of lid opening tasks. Compared with [76] which used random exploration, active exploration made learning affordance faster and more accurate. Ugur et al. [79] proposed a bootstrapping system to learn complex affordance between objects by using obtained affordance of single objects and realized object stacking tasks. Vina et al. [80] used force sensors to sense contact forces. They developed a robot that can autonomously learn force and torque bounds and use them to infer the motions that the object can afford, and then execute actions on objects such as sliding and pushing. Jain et al. [81] proposed a tool affordance concept, which is functional features of tools, and used a Bayesian Network to learn bi-directional causal relationships between actions, functional features and the effect of tools based on exploration in simulation environment. Goncalves et al. [82] used robot motions and execution results in simulation environments to learn both the affordance of objects and the affordance of tools. Stick-like tools were adopted for experiments. They defined distinctive features and learned which features are afforded with hand or tool motions. Mar et al. [24, 83] obtained the affordance of multiple stick-like tools using self-supervised motion and execution results. Different grasp configurations and geometry features of the tools were compared. The obtained affordances of these studies were used to assist an iCub robot to generalize grasps and motions among tools considering their geometry features, and help the robot to choose different tools to manipulate different objects. In their later work [84], their system was improved based on parallel SOM mapping and SOM to SOM regression to avoid the loss of information by clustering and predefined categorization. In these works, the robot explores its surroundings to learn affordance, thus a human demonstrator is not needed. However, the exploration domain is limited to few objects and it heavily relies on sensor data, which will in turn limit the exploration capabilities of the robot. A generalized exploration strategy is required to cope with different objects and a robust pipeline to deal with sensor data noise, etc.

Kaiser et al. [85] proposed a hierarchical system for affordance extraction where a high level affordance is a combination of a low level affordance, e.g. a bi-manual affordance is based on unimanual affordances. This hierarchical scheme is a promising method for generating complex affordances based on simpler ones. At the moment it has been implemented for some manipulation tasks like pushing and also for some whole-body tasks such as climbing a staircase and a ladder.

4.3 *For planning alternative solutions*

Usage of affordance is a powerful way to modify planned motion or task sequences when a robot meets unforeseen objects or situations. Awaad et al. [86, 87] proposed a planning framework based on ontology, which can modify a generated plan when it will fail because of unexpected situations, like missing or unavailable objects. They adopted functional affordance, which represents for what objects are meant to be used, and conceptual similarity as key concepts and realized the replanning by substituting objects to achieve a goal. The framework was evaluated in some case studies, such as tea-making task and plant-watering task. Romay et al. [88] utilized their object template, which is proposed in [69], to unknown objects or new task situations. A human operator selected an adequate object template and adjusted it to the corresponding sensory data of the robot; and the robot then executed motions replanned by the template. It was shown that the templates can be transferred between different objects with same manipulation classes classified based on motion constraints in [89], or to a new task situation requiring a intermediate object to achieve a task. These belong to a manually defining affordance approach; thus, these have a same burden to develop adequate predefined knowledge. Understanding the semantic similarity of objects or tasks to achieve a goal should be one of future research directions.

Table 3. Research using affordance for object manipulation

	How to obtain affordance						Input information				Verification			
				Exploration			Visual data							
	Human annotation	Demonstration	Simulation	based on simulation	based on experiments	Other	2D	3D	rgb-D	other sensors	Only recognition	Simulation	Real robot	Other
Hidayat et al. [65]	✓				✓		✓						✓	
Reich et al. [66]	✓						✓		✓				✓	
Hart et al. [68]	✓											✓	✓	
Romay et al. [69]	✓								✓			✓	✓	
Montesano et al. [70]	✓	✓					✓						✓	
Montesano et al. [71]		✓					✓						✓	
Lopes et al. [72]		✓					✓						✓	
Ek et al. [73]		✓	✓				✓				✓			
Ugur et al. [74]		✓							✓				✓	
Uyanik et al. [75]					✓				✓	motion capture			✓	
Wang et al. [76]		✓			✓		✓			sonar sensor			✓	
Wang et al. [77, 78]					✓		✓						✓	
Ugur et al. [79]					✓			✓					✓	
Vina et al. [80]					✓					tactile sensor			✓	
Jain and Inamura [81]				✓			✓				✓			
Goncalves et al. [82]				✓	✓		✓					✓	✓	
Mar et al. [83]				✓			✓						✓	
Mar et al. [24, 84]				✓				✓				✓		
Kaiser et al. [85]						primitive shapes			✓				✓	

5. Cloud Database for Advanced Manipulation Intelligence

As shown so far, various researches have been conducted for recognizing, grasping, and manipulating objects adequately based on the concept of affordance. However, it is still not clearly shown how affordance should be expressed, how a robot learns and perceives the affordance, and how the robot executes adequate motion according to the detected affordance, which are exactly the work being advanced in several research fields. Especially for object manipulation, research has just started for some individual tasks as shown in Section 4.2. Several good database of object image, 3D, and rgb-D data (e.g. listed in [90] as examples) have impressively advanced object recognition and grasping research field and provided an opportunity to compare each proposed methodologies. However, there is no database for manipulation. The Yale dataset [91] includes only videos where a human operates several daily tasks or manufacturing work. Existing human motion databases (e.g. [92]) mainly focus on whole-body motions like walking and have few manipulation motions like wiping a table. In order to accelerate the affordance research for object manipulation, various motion data should be accumulated and can be utilized in the research community as a first step.

Therefore, the authors are now building a cloud database for human-like advanced manipulation intelligence as a part of a national project of Japan. Human can flexibly perform diverse tasks. This is presumably because human can conceptualize the experience of performing varied tasks and can also apply skills and knowledge accumulated through the experience to a new task. Namely, it is the way how human learns affordance and corresponding behavior, and perceives affordance and realizes adequate motion for new situation. Figure 1 shows a schematic view of the database. The database consists of object database, task database, and motion database. To build the database, it is important to first accumulate a variety of information about specific

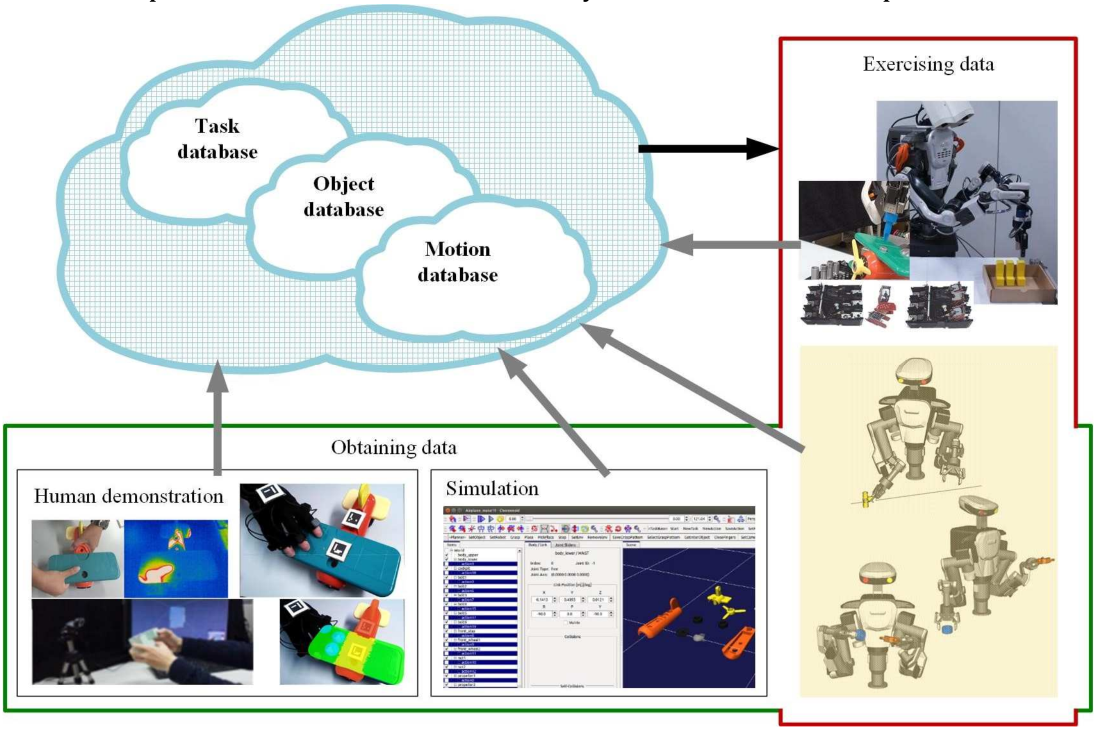

Figure 1. Cloud database for advanced manipulation intelligence

tasks. A task consists of many sub-tasks, and each sub-task consists of related objects and the multiple motions necessary to perform the sub-task. It is not clear at the first trial what kind of information is important, thus we are trying to leave all information that is as concrete as possible and in a form usable by different robots. Because there can be multiple objects during object manipulation tasks, an object that a robot will grasp to operate is defined as a manipulated object, and an object worked on using the manipulated object is defined as an environmental object. When two objects are grasped and operated by dual arms, for convenience, one is defined as the manipulated object and the other as the environmental object. We focus on tool manipulation and assembly tasks. Because tools are good target since it is relatively clear how they are used. Regarding assembly, there is demand even at manufacturing since conventional model-based method is getting difficult to apply due to multiproduct variable quantity production. The following is a list of information that is being accumulated to the database:
[Task information]

- Task procedure (order of sub-tasks, order of motions in a sub-task)
- Operator information (human/robot/teaching, etc.)
- Robot information (identifier, type, constituent part information such as hand information)

[Object information]

- Object identifier (proper noun that distinguishes individuals)
- Category name (name that distinguishes type of object, JICFS code, etc.)
- Shape information (3D shape file)
- Physical information (weight, center of mass, material, stiffness, etc.)

[Motion information]

- Grasping point, grasp configuration (manipulated object)
- Grasping point, grasp/fixed configuration (environmental object)
- Time sequence of position/orientation of the manipulated object as reference to the environmental object
- Time sequence of force information
- Control method and control parameters for the motion
- Visual information during the motion

These types of information are collected from human operations or robot teaching data. A framework to efficiently save and share robot teaching information has been developed [93], as well as a system has been constructed for easily collecting human operation data with less constraints [94]. We defined a YAML-based template to accumulate the data in a same format from these system.

First use-case of the database could be as follows. When a new task is assigned to a robot, an inquiry will be sent to the database to obtain the relevant information. If it contains the information about the identical task, it can be used directly. It will also be possible to obtain guidelines for motion design from information about similar task. After executing the task, the motion information or results of the task actually performed will be uploaded to accumulate or update the information. The second use-case, which is the main purpose of the database, is that the database becomes a open platform to leverage various affordance frameworks and provide supports to accelerate affordance research dealing with a variety of manipulation tasks for various robots.

6. Conclusions

In this paper, we gave a brief review of affordance research with special emphasis on robotic manipulation. We first summarized the methods for object recognition based on affordance, and then made an overview of studies that learned and applied affordance in manipulation applications. The fields of object recognition and grasping are being accelerated based on the progress of machine learning and several good databases. Towards object manipulation, many studies have been done using different methodologies and frameworks for different types of manipulation tasks. However, it is still not clearly shown how affordance should be expressed and how a robot appropriately executes actions based on detected affordance. Based on the discussion, we presented a cloud database system, which is being developed at AIST to advance the affordance research in robotic manipulation. The database accumulates various data related to manipulation task execution and will be an open platform to leverage various affordance techniques. We hope this review could provide insights on affordance especially in robotic manipulation and promote future studies.

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