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SURVEY PAPER

Survey of robotic manipulation studies intending practical applications in real environments -object recognition, soft robot hand, and challenge program and benchmarking-

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ABSTRACT
Aiming at accelerating the creation of new techniques on dexterous robotic manipulations, this paper surveyed the recent results on object recognition, soft robotic hands, and benchmarks and challenge/competition programs. The former two topics construct the elemental components of the new technologies on robotic manipulations, while the last one is a key for proceeding the creation and realization of the actual robotic manipulations with the new techniques. With these surveys, we will reveal the solved and unsolved issues for the next step to realize robotic dexterous manipulation systems comparable to human being.

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Manipulation; robotics challenge; benchmark; system integration; object recgonition; softness; robotic hand

1. Introduction

Robotics, which became fully in progress in the 1960s, aimed at reproducing the human functions by artifacts from the very beginning. Of course, 'hands' had also been the target for reproducing. As a matter of fact, a pioneering work on robotic hand was done by Japanese group [1]. Since then, many robotic hands have been developed, but we have not realized robotic hands which functions are comparable to those of human hands yet.

Manipulation is 'the most central castellated wall' (or 'Honmaru' in Japanese) of robotics research to be tackled, and we cannot avoid it in order to really implement robots socially because there are many items to be manipulated around us. If we can understand the essence of hand dexterity and create next-generation manipulation techniques that are comparable to the functions of human hands, the scope of robot application will undoubtedly be wider.

Like the DRC (DARPA Robotics Challenge) conducted in 2015 and several DARPA challenges in the past, appropriately designed challenge program and benchmarking can accelerate research activities effectively. Challenge tasks also remind us that system integration is very important as well as developing elemental technologies. In the field of robot manipulation, besides individual elemental technologies such as robotic hand, sensing, object recognition, and task/motion planning, system integration is also important in order to develop systems that can work in real environment.

Another emphasized point is that robotic hand and object recognition are the key elemental technologies in the realization of real tasks, which are revealed by investigating the challenge programs. The top groups have provided new technologies for robotic hand and object recognition, and many groups imitate the technologies at the next challenge. Vacuum grippers and Deep learning in APC are typical examples. Manipulation technologies cover a broad range of topics, and it is almost impossible to survey all topics and a specified topic have been investigated as a survey [2]

With this in mind, this paper focuses on benchmarks and challenge/competition programs and their key elemental technologies of object recognition and robotic hands, and surveys them to promote the creation of novel elemental technologies for dexterous manipulation and integration of the robot manipulation systems comparable to human being. A lot of surveys for robotic hands have already existed [3–8], while real tasks in the benchmarks and challenge/competition programs require handling a wide variety of objects and an interaction with real environment, which requires high adaptability or flexibility at the endeffectors (robotic hands). So far, softness and flexibility of robotic hands have been less investigated or surveyed. Thus, on the survey of robotic hands, we mainly focus on softness.

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The subsequent section provides a survey of object recognition. After surveying robotic hands, focusing mainly on soft structures, benchmarks and challenge/competition tasks are introduced. Lastly, the summary of these surveys is provided. With these surveys, we will reveal the solved and unsolved issues for the next step to realize robotic dexterous manipulation comparable to human being.

2. Object recognition for manipulation

Recognition functions needed for robotic manipulation are not limited for knowing what the object is. To accordingly grasp target objects, estimating position, direction, perhaps shape and stiffness, are needed. In this section, we introduce object recognition methodologies focusing on three types of sensor data: image, range data, and tactile data. As there are both advantages and disadvantages to each sensor data, which sensor should be used is altered by target objects and situation. We especially focus on picking up an object from a workspace; bin picking in industrial scenes or object grasping in household environments.

2.1. Recognition methods using cameras

Image data implicitly includes rich information. Therefore, many studies employed cameras mounted on a robot, and implemented object recognition functions assuming images as input. Such a sensor system is simple, small, lightweight, and therefore suitable for intelligent robots. Toward object manipulation, the main role of recognition functions is target object detection, posture estimation, and so on.

Bin picking is a conventional task that needs object recognition. Therefore, image-based approach has been developed [9–11]. Wireframe models or 2D edge contours are given in advance, and object pose estimation is achieved based on a matching method: e.g. edge-based registration. As recent results, Harada et al. [12] achieved bin picking tasks without accurate geometrical model. Domae et al. [13] proposed a graspability evaluation method, which enables to find graspable regions from piled objects.

Most of these studies assumed to use 2D or 3D shape models given in advance. The same approach has been applied to tasks for daily assistive robots [14–16]. One advantage of this approach is its simplicity. Meanwhile, there is a burden to make individual models by manual. In addition, such approach is difficult to be applied to rich textured objects because the richness of the texture makes it difficult to extract the important edges representing the shape in image processing.

Another approach, which receives the benefits of the development of computer vision, uses image feature descriptors. Local image regions including distinctive information are extracted, and then its uniqueness is characterized as a vector. We can find famous feature descriptors: e.g. SIFT [17], SURF [18], MSER [19], and HOG [20]. As some of them are invariant to the change of translation, rotation, and scale, they are very suitable for detecting target objects in a clutter environment [21,22]. An additional advantage of using image features is that it allows to generate object models semi-automatically. On the other hand, it is difficult to work on transparent or shiny surface because the appearance of such objects is very influenced by illumination condition.

2.2. Recognition methods using 3D measurement results

Image is a representation that a 3D scene is projected into a 2D plane. This fact makes it difficult to estimate the 3D pose of target objects. Therefore, two cameras or more have been used to obtain 3D information. Dozens of work have tried applications to robotic manipulation, e.g. [23–25]. One of them, Sumi et al. [26] developed a trinocular camera system named VVV, which enables to track the pose of an object with curvature surface.

Although the above-mentioned multi-camera system is one solution, other sensors providing 3D point cloud become typical alternative way. Such sensors allow researchers employing computer vision to participate studies on object manipulation. The combination of a camera and a pattern projector is one feasible solution. For instance, PR2 robot [27] produced by Willow Garage Inc. mounted such 3D sensor, and has been used for producing dozens of results on object manipulation [28].

Point cloud registration, e.g. the use of Iterative Closest Point (ICP) algorithm [163], is a major solution for pose estimation [29,30]. Meanwhile, like the above-mentioned image features, we can find 3D feature descriptions: for instance, Spin Image [31], Point Feature Histogram(PFH) [32], Fast Point Feature Histogram(FPFH) [28], and Normal Aligned Radial Feature(NARF) [33]. These implementations are included in Point Cloud Library(PCL) [34].

After the appearance of Microsoft Kinect in 2010, the use of point cloud becomes major approach. Many studies succeeded to implement robust object recognition for manipulation. Of course, we can find the combination of image-based method and range-based methods [21,22, 35]. These studies achieved high-level manipulation for objects placed on a table.

Meanwhile, feature description from local region is not an only way to object pose estimation; template matching is another solution. Borgefors et al. [36] and Huttenlocher et al. [37] presented progressive methods at the time, and the related methods have been developed as shown in [38,39]. LINEMOD proposed by Hinterstoisser et al. [40] introduced high-speed template matching that permits curvature surface.

2.3. Recognition method using Tactile sensor

Tactile sensing is a conventional way to know grasp quality. In addition, such sensing enables to complement the major drawbacks of cameras and range sensors: for instance, measurement capacity against transparent objects, and occlusion. From the viewpoint of the recognition focusing on this section, we attempt to present studies that employ tactile information to know object shape and pose.

Honda et al. [23] constructed object handling system composed of a multi-fingered hand and a 3D stereo vision. Tactile sensors were equipped on the tip of each finger, and helped to achieve an object grasping by estimating unseen surface from the vision sensor. Koval et al. [41] engaged the estimation of the state of an object during manipulation. Manifold Particle Filter was used to increase the accuracy of tactile information. Tanaka et al. [42] presented a tactile-based object recognition method. The proposed active learning approach enables to classify a dozen of objects having similar shapes. The same group proposed an exploratory method to know the shape of an object [43]. Bimbo et al. [44] presented an optimization method where tactile and force sensing were used to find estimate the pose of a grasped object. Zhang et al. [45] focused on 3D object classification. The proposed feature descriptor, which is generated from contact positions on an object, is invariant to object position and pose.

As mentioned above, tactile sensing becomes one possible choice for object recognition. However, temporal effectiveness on their use is still in preliminary phase. For practical application to robotic manipulation, there is room for making closer cooperation between vision and tactile sensing.

2.4. Recent trends: deep learning intending object detection and pose estimation

Deep learning becomes one major region for object recognition because deep convolutional neural network (CNN) shows remarkable results on classification problems in the field of computer vision. For robotic manipulation, however, it is insufficient to know what the object is: more detail information such as position and direction is needed. As this problem setting is rather inconsistent with recent major CNN structure, the combination with other existing methods is addressed.

To detect target objects or region, saliency map generation [46] is a conventional approach. Another representative method is Deformable Parts Model(DPM) [47,48]. In DPM, image features are extracted from image local regions, and then connection candidates are selected. These results are used for classification function enhanced by supervised learning. Recently, selective search [49] and Regionlets [50] become a novel choice to obtain salient image regions. In order to detect target objects reflected in a part of the image, these methods have been combined with deep learning. R-CNN [51] and Faster R-CNN [52] showed good results. These approach enables to enhance detection performance: for instance, [51] showed more than 15% detection rate from previous methods.

Recently object pose estimation becomes target regions for deep learning approach. We can find state-of-the-art studies. Schwarz et al. [53] employed transfer learning from pretrained network, and estimated object pose using features output from CNN. They have possibilities to be applied to robotics manipulation. Other CNN-based approach was found on recent manipulation challenge programs such as Amazon Picking Challenge [54] and DARPA ARM project [55].

2.5. Learning of manipulation: from a viewpoint of recognition

Generally, automated manipulation task is proceeded by articulated mechanical arms. One important thing here is how to define or generate motion sequence for the arms. From an engineering viewpoint, they have been defined by manual or by motion planning methods. The former is time-consuming whereas firm approach, and the latter needs explicit description of operation environment.

On the other hand, more generative and scientific approach, learning, have been developed. It can deeply be connected with automatic sensor information processing, and has high possibility to reduce the burden for programmer. Conventional one is 'Teaching by showing' proposed by Kuniyoshi et al. [56]. More developments has been proceeded [57,58]. As one pioneer work for the learning of robotic grasping, Saxena et al. [59] proposed a method to learn graspable regions from images. Support Vector Machine [60] was applied in the method. Recently, deep learning is also applied for such action learning. Lenz et al. [61] proposed a method to find graspable place as rectangular image region. It was the first time of the proposal that deep learning was applied to robotic grasping. Sasaki et al. [62] combined deep convolutional neural network with recurrent neural network. Visuomotor method [63], which directly connects sensor data with joint angles of manipulators, enables to generate motion from image streams.

Although deep learning-based approaches begin to open a new ocean for automated manipulation, it is rather difficult to learn complicate and accurate tasks. For this reason, it might be one future development that reinforcement learning such as Visuomotor is involved to shared autonomy [64]. Shared autonomy on intelligent robots is a framework that shares a task between human and robots. Human gives purpose and rough instruction, and then robots compensate the task by the functions of environment recognition and motion planning. It is practical because safeness and accuracy can easily be considered.

2.6. Further expectation to recognition for manipulation

Above-mentioned work has an assumption that sensors, e.g. camera or laser scanner, return sensor data including sufficient information for recognition. However, we often face difficult situations and objects for such sensors; for instance, transparent objects and shiny objects. Although there are many studies coping with such objects, we can find limited number of work that has possibilities to apply to robotic manipulation in practical environment. Fritz et al. [65] proposed a method to detect transparency object from images capturing glassed object existing in daily environment. Lysenkov et al. [66] achieved pose estimation using a 3D range image sensor. As more analytical approach, Alt et al. [67] proposed a method of 3D shape reconstruction using multi-viewpoint images. It allows relatively clutter environments: a dozen of objects are placed on a table. In [68], the same purpose was achieved by using two range images generated from a Time-of-Flight (ToF) sensor. Maeno et al. [69] detected transparent objects using the proposed Light Field Distortion (LFD) feature description. Although the above-mentioned studies are pioneer work, their results are still in a preliminary phase for robotic manipulation (for instance, the recognition success rate was under 60% in [69]). From this fact, it should be recognized that we still have huge difficulties for automatic manipulation of transparent or shiny objects.

3. Softness in robotic hands

Handling is the subsequent process after the object recognition, and robotic hand is a key for the handling. Until now, many robotic hands have been developed [7,70–75] and several robotic hands are commercially available, as shown in Table 1. Human hands are very familiar universal hand to human being. Tools and objects around ourselves are optimized for human hands. Therefore, robotic hands resembling human hands are considered to be have advantageous to work in real environment. For a few decades, many efforts have been undertaken to produce multi-fingered robotic hands resembling human hand [7,71–75] (see also Table 1(a)) so that robotic hands can have dexterity and universality. Pneumatic actuators were utilized at Shadow Hand, Festo Exohand, and so on. The other commercially available hands are manly actuated by electric motors. More than three contact points are required for force closure, which is a fundamental grasping property and defined that any external wrench in any arbitrary direction can be balanced and the motion of the grasped object can be restrained [76]. Another important feature at human hands is thumb opposition (to the other fingers). With these in mind, three fingered robotic hands with the mechanism resembling the thumb opposition have been developed, e.g. Barret Hand, Robotiq gripper, and Festo MultiChoiceGripper. Thumb opposition was also embedded at 5-fingered robotic hands, e.g. Shadow Hand, DLR Hand, Hand HIRO, Gifu Hand, D-Hand, Festo Hand.

We implicitly know how to use human hand, and have believed that planning for grasping and manipulation might be easy to produce. Although the obtained outlook was similar, materials and the internal mechanism and structure were totally different. Thus, it is hard to directly apply human methodologies to multi-fingered robotic hands for control, grasping, and manipulation. Therefore, the obtained dexterity at grasping and manipulation was not close to human being. Another aspects or viewpoints might be needed to attain dexterity. One candidate is softness.

The softness provides impact reduction at contact, safe interaction with humans and objects, and high adaptation capacity to object shape. Therefore, precise positioning of robot and accurate object recognition are not necessary for stable grasping. The allowance of the uncertainties at grasping indicates a capability of grasping a wide variety of objects. We additionally consider a lot of surveys for robotic hands [3–8], and focus on softness in robotic hands, here. There are broadly two types of softness in robotic hands. One is softness at joints, and the other is softness in surface. Here, we review the two types of softness separately.

3.1. Softness at joints

The basic design is compliant joints with stiff links, which enables a passive rotation for adapting to object shape. The complaint joints are typically constructed with spring components [88,89,101]. Recently, elastic belt-shaped components are utilized for the compliant joints [80,81,84–

Table 1. Specifications of various robotic hands; commercially availablerobotic hands and soft robotic hands.

Name	Size (mm)	Grasping force	DOF	Weight	Payload	Maximum width of graspable objects	Minimum width of graspable objects	Number of actuators	Number of fingers	Power (envelope) grasp	Pinch grasp	Softness at surface	Softness at joints	Graspable fragile objects	Graspable deformable objects
(a) Commercially available robotic hands															
Shadow Hand Lite	109 × 327 × 1020	10 N	16 (4×4)	2.4 kg	4 kg	–	–	13 (pneumatic)	4	√	√	–	√	–	–
Shadow Dexterous Hand	84 × 448 × 135	–	19 (3 × 5+4)	4.2 kg	–	– (Apple is graspable)	–	20 (pneumatic)	5	√	√	–	√	–	–
Barrett Hand BH8-282	335 × 75 × 102	–	8 (2 × 3+2)	0.98 kg	6 kg	– (About 80 mm estimated from image)	–	4	3	√	√	–	–	–	–
ROBOTIQ Adaptive Gripper 2-finger	87 × 140 × 61	20 to 235 N or 10 to 125 N	4 (2 × 2)	0.85 kg or 1.0 kg	5 kg or 2.5 kg	85 mm or 140 mm	–	1	2	√	√	–	–	–	–
ROBOTIQ Adaptive Gripper 3-finger [70]	155 × 111 × 204	15 to 60 N	12 (4 × 3)	2.3 kg	10 kg	155 mm	–	4	3	√	√	–	–	–	–
Hand HIRO	? × 241 × ?	Over 3.6 N	15 (3 × 5)	3.8 kg	–	–	–	15	5	√	√	–	–	–	–
Gifu Hand [71,72]	95 × 251.3 × 41	Over 3.6 N	15 (3 × 6)	1.4 kg	–	–	–	15	5	√	√	–	–	–	–
DLR Hand II [73,74]	–	10–40 N	12 (3 × 4)	–	–	–	–	12	4	√	√	–	–	–	–
DLR-HIT Hand II [75]	169.1 (finger length)	10 N	15 (3 × 5)	2.2 kg	–	–	–	15	5	√	√	–	–	–	–
D-Hand Ttpe A5	150 × 260 × 42	–	18 (3 × 5+3)	2 kg	–	–	–	1	5	√	√	–	–	–	–
D-Hand Ttpe A3H/A3M	? × ? × ?	–	11 (3 × 3+2)	–	–	–	–	1or 3	3	√	√	–	–	–	–
Festo ExoHand	? × ? × ?	–	18? (3? × 5+3?)	–	–	–	–	8 (pneumatic)	5	√	√	–	√	–	Soft ball
Multi Choice Gripper Festo	148? × 215 × 148?	–	5? (1? × 3+2)	0.66 kg	–	92 mm	–	3 (pneumatic)	3	√	√	√	–	–	–
VERSA BALL ® Kit [77]	ϕ89 or ϕ165	–	–	0.64 kg or 2.5 kg	4.5 kg or 9 kg	50% of head diameter	–	1 (pneumatic)	–	√	–	√	–	–	–

(*Continued*)

Table 1. (*Continued*).

(b) Robotic hands with softness at joints															
EZGripper (SAKE Robotics) Dual	? × ? × ?	–	4 (2 × 2)	0.45 kg	5 kg	170 mm	–	1	2	√	√	–	√	–	–
EZGripper (SAKE Robotics) Quad	? × ? × ?	–	8 (2 × 4)	0.87 kg	10 kg	170 mm	–	2	4	√	√	–	√	–	–
IH2 Azzurra Hand	? × ? × ?	–	11 (3 × 5+1)	0.64 kg	1.42 kg	–	–	5	5	√	√	–	√	–	–
uGRIPP [78]	? × ? × ?	–	12	–	–	–	–	10	2	√	√	–	√	–	–
FRH-4 hand [79]	93 × 149 × ?	–	11	0.216 kg	– (holding force: 110N)	120 mm	–	12	5	√	√	–	√	–	–
PISA-IIT Hand [80–83]	? × ? × ?	15 N	19	–	–	–	–	1	5	√	√	–	√	Strawberry, slice of cake	Teddy bear, paper, scarf, sponge, poster, tissue pocket
SDM hand [84–86]	? × 70 × ?	30 N	8	0.20 kg	–	125 mm	–	1	4	√	√	–	√	–	–
iHY Hand [102]	? × ? × ?	15 N	8 (2+2 × 3)	1.35 kg	22 kg	230 mm	3 mm	5	3	√	√	–	√	–	Card
Velo gripper [88]	? × 118 × ?	20 N	4 (2 × 2)	–	–	115 mm	7 mm	1	2	√	√	–	√	–	–
Adaptive prismatic gripper [89]	211.6 × ? × ?	–	6 (2 × 3)	0.766 kg	– (Gripping force: 40–60N)	211.6 mm	–	1	3	√	√	–	√	–	Rope, Chain
UC-Softhand [90]	230 × 100 × 40	–	10	280 g	740 g	–	–	3	5	√	√	–	√	–	–

(*Continued*)

Table 1. (*Continued*).

(c) Robotic hands with softness at surfaces															
Magnetorheological robot gripper [91]	? × ? × ?	–	–	–	9.5 N (Theoretical lifting force: 19 N)	–	–	–	–	√	–	√	–	Foods; Strawberry, broccoli and grapes	–
Kanazawa Hand [92]	290 × 160 × ?	7 N	12	1.5 kg	–	–	–	12	4	√	√	√	–	–	–
Safe interaction skin [93]	? × ? × ?	–	–	–	–	–	–	–	2	–	√	√	–	Tofu; Roll of paper;	Plastic cup; Aluminum can;
Inflatable rubber pockets-based gripper [94]	95 × 70 × ?	–	1	–	31 kg	64 mm	45 mm	2	2	–	√	√	–	Egg	–
Jamming gripper [95]	ϕ 43	10 N	–	–	100 N	25 mm	–	2	–	√	–	√	–	–	–
(d) Robotic hands with softness at surfaces and joints															
Starfish-like hand [96]	ϕ 100	–	–	–	0.3 kg	–	–	1	8	√	–	√	√	Egg; Mouse	–
RBO Hand [97]	? × ? × ?	–	–	0.178 kg	0.5 kg	–	–	7 (Pneumatic)	5	√	√	√	√	–	Ball
modular soft robotic grippers [98]	25 × 25 × 110 (finger)	–	–	–	–	–	–	3	3	√	√	√	√	Egg;	Paper; Paper cup; Paper box
Light weight underactuated pneumatic gripper [99]	163 mm (Finger length)	11.07 N	5 ?i3+2?j	0.137 kg (Finger)	–	–	–	1	2	√	√	√	√	Tofu; Jelly; Tomato; Banana; Egg	Meat
Variable-Grasping-Mode Underactuated Soft Gripper [100]	–	–	3	–	30 kg	80 mm	0 mm	1	2	√	√	√	√	Tofu; Sweats; Vegetables; Fruits; Balloon	Cord; Paper cup; Rope; Cards; Paper box; Stuffed

87,90,102,103]. The main difference is the compliant direction. The spring-based compliant joints provide unique compliant direction whereas the elastic belt-typed compliant joints provide arbitrary complaint directions, although the flexibility for the main direction is large and that for the other direction is small. Functional requirements for robotic hands determine which component is better. The compliant joints can work as underactuated joints, and tendon systems are popularly utilized for the joint actuations. Cable and wire are popular for constructing the tendon systems [80,81,84–86,88–90,101–106]. The pulling direction of cable and wire can change, and then there could be a number of mechanisms to construct the compliant joints with cables or wires, although the magnitude of the pulling force is limited. One solution for realizing heavy object grasping is an utilization of both tendon and belt type compliant flexure joints introduced at i-HY hand [87] that is capable of grasping an object with a weight of 22 kg. Meanwhile, uGripp [78] utilized a linkage mechanism. Another interesting system is air-based complaint joint [79,97–99,107–109]. Special flexible pneumatic actuators provide a rotational joint which works both passively and actively.

3.2. Softness at surfaces

Shimoga and Goldenberg firstly pointed out the importance of softness at contact area [110]. Since them, soft fingertips have been investigated from many kinds of viewpoints including (frictional) modeling [111–121], controlling [122,123], and so on. However, large deformation was not assumed. As shown in [120,121], large deformation decreases the magnitude of applicable or generable forces. Deformable soft fingertips decrease the weight of graspable objects while provide high adaptation to object (shape). This drawback can be resolved by solidifying the soft fingertips after the contact. Typical examples are the magnetic fields-based gripper [91, 124], agar impression material-based robotic hand [92], and robotic fingertip with the two layer structure of inner rigid and outer soft components [118,125–129]. The two layer structure resembles human finger structure, and provides the softness at surfaces while large grasping forces at the internal rigid layer. The mechanism of air inflation is effective for constructing deformable soft surface and for controlling the softness or stiffness; e.g. soft elastomer quadrupedal robots [130], safe interaction hand [93], inflatable rubber pockets-based gripper [94], and puncture resistant soft gripper [109]. Jamming phenomenon is also powerful for producing versatile grasping, and several grippers based on the jamming were presented [77,95,131,132].

3.3. Combined types

As described the above, pneumatic actuation facilitates robotic hands have the softness. Both the above-mentioned two types of softness can be easily embedded, for example, in ROBO hand [97,108], Starfish-like hand [96], lightweight underactuated pneumatic fingers [99], puncture resistant soft gripper [109], and modular soft robotic grippers [98].

The air-based combination of the two types cannot resolve the drawback that the weight of graspable objects is small. The coexistence of hard and soft components is a solution [118,125–129]. The installation of soft surfaces and fixing mechanism such as ratchet mechanism at underactuated joints is also effective to increase the weight of graspable objects while receiving the benefits of softness [100].

3.4. Functions of soft robotic hands

There are several benefits at soft robotic hands, which the conventional hard robotic hands do not have. Here, we discuss the benefits.

One of the effective functions for versatile grasping is adaptation to object shape. Soft surface deforms according to the object shape, and contact uncertainties such as shape recognition error and positioning error are absorbed. Even poor controller or planner can realize stable grasping. The high adaptation to the object shape indicates large contact area or contact at concave points on object, which increases friction leading to stable grasping. Large friction indicates grasping can be realized by small contact forces. Therefore, softness at surfaces is preferable for delicate grasping of fragile objects.

As shown in Table 1(c) and (d), robotic hands with soft surfaces realized grasping of several fragile objects. The impact reduction at contact and safe interaction with humans and objects, which are also benefits on soft softness, are investigated by Kim et al. [93]. They showed the soft skin reduces the impact or peak forces drastically. The damping effect was also observed. However, the deformability of the surface indicates the low stiffness at fingers, and the weight of graspable objects is limited to be small as shown in Table 1(c) and (d). The exceptions are inflatable rubber pockets-based gripper [94], Variable-Grasping-Mode Underactuated Soft Gripper [100], and jamming gripper [77,95,131,132]. At [94], the rubber pocket was located at the tip of stiff finger, and the stiff finger enables to grasp an object with a weight of 31 kg. At [100], underactuated joint-fixing mechanism enables heavy object grasping. Jamming originally provides large fixing force enabling to hold heavy weight, different from the other robotic hands with soft surfaces. Instead, the jamming gripper is not preferable for grasping fragile objects. With this feature of jamming in mind, the combined actuator of pneumatically driven finger and jamming actuator was proposed [133].

The softness at joints also has the similar function of the adaptation; the passive joints rotate according to object shape. However, its ability of the adaptation is lower than that at soft surfaces. As shown in Table 1(b), only few robotic hands such as PISA-IIT hand [80–83] realized grasping of fragile objects. Note that at PISA-IIT hand, the length of stiff links is short, and its ability of the adaptation is then relatively high. In contrast, stiff links can resist large external disturbing forces, and robotic hands with underactuated or passive joints can grasp relatively heavy objects.

Another interesting feature of soft robotic hands is the small number of actuators. The deformability of the softness on robotic hand produces passive and adaptive motion to object shape. Therefore, a wide variety of grasping style can be achieved with a small number of actuators. It leads to low cost, which is also a benefit of softness on robotic hand.

3.5. Sensor technologies on soft robotic hands

The deformability or flexibility of soft robotic hands makes a state estimation difficult. The information from the conventional internal sensors such as encoder does not provide enough information when the fingertip surface is deformable. We cannot estimate the fingertip position and orientation from the joint angles estimated by the encoders or internal sensors. Note that if softness is only at joints, the encoders could provide accurate information. Instead of the encoders, soft or flexible sensors are preferable. Morrow et al. [134] presented a methodology for estimating the pose for deformable finger by utilizing a microfluidic soft sensors utilizing eGaIn fluid [135]. Homberg et al. utilized resistive flex sensor for estimating the bending [98]. Zhao utilized optoelectronic sensor for estimating finger motion [136]. Basically, it is difficult to estimate the deformable or flexible finger pose by internal sensors, and external sensors such as camera or radar are then effective for the estimation.

There are several methods to obtain tactile information. One of the most popular methods is based on the pressure measurement of a fluid installed in finger [93,94,99,108,118,125–129]. Another method is to embed micro force sensors on (soft) surfaces [87,137–139]. Optical-based methods are also effective [140–144]. Flexible optical fibers can transfer the tactile information from the tip to the root with less noises even when the fibers are flexed by external forces.

3.6. Future expectation to soft robotic hands

There are a lot of unclear issues on constructing soft robotic hands. As mentioned above, there are a lot of methodologies for embedding softness in robotic hand. The target tasks, and the related target objects and environments would proceed the development of a number of new soft robotic hands. Moreover, the selection of materials and shapes for the soft components have been less investigated. Air is popular material for constructing the soft robotic hands, and its features are compressible and a constant contact stiffness if the air pressure is kept constant. Other fluids such as oil and water are incompressible and the contact stiffness increase with an increase in contact deformation. The selection of fluid should be conducted while keeping the features in mind. Both types of fluid provides uniform contact pressure profile which is preferable for grasping fragile objects. Fracture is not in force domain but in the domain of stress or pressure. The control of contact pressure is important for grasping fragile objects. Few researches [118,125] focused on this point. Granular materials are also a candidate for soft surface. They are stiffer than fluids while having the ability of high adaptation to object shape. Moreover, jamming phenomenon is expected to be utilized [133].

Softness is powerful for grasping a wide variety of objects, but makes manipulation difficult. The absorbing uncertainties in object information indicates that it is difficult to obtain precise object information. Then, motion planner has to allow the uncertainties. One solution will be deep learning [145]. But, the research has just begun and the obtained results are limited.

The fingernail is an effective function for soft robotic hands, and provides a hard component to increase an applicable or grasping force and a function of scooping (for example, [87,100]). However, the optimization of its structure have been less investigated.

Biomimetics is an important concept for developing soft robotic hands because animals have soft structure and effectively utilize the structure at manipulation or motion. One example is flip-and-pinch motion which is effective to pick up a thin object on a table [146]. As mentioned above, the two layer structure of soft outer and hard inter components [118,125–129] resembles human fingertip. The motion and structure of animals could include hidden resources leading to novel approaches for robots, and then biomimetic approach would be useful in the development of structure for soft robotic hands.

4. Benchmark tasks and challenge programs for manipulation

4.1. Benchmark tasks

In 1984, Collins et al. proposed Cranfield benchmark for comparing robot programming for assembly [147]. Although this benchmark was designed to examine the robot programing systems, the benchmark was designed by considering (i) compactness and portability, (ii) ability to test a variety of basic assembly operations such as picking, placing, and inserting, and (iii) universal applications, i.e. the benchmark must be capable of being assembled by majority of assembly robots.

Recently, researchers at Yale University, CMU, and the University of California Berkeley jointly proposed YCB Object and Model Set (hereinafter referred to as YCB) [148], which is a set of objects and their 3D models to promote the manipulation research. The objects are selected considering not only the diversity of characteristics, such as shape, texture (including transparency), and flexibility, but also availability, persistence, and portability. The items for an existing benchmark in the rehabilitation field have also been adopted. YCB is unique in that it proposes not only a diverse set of objects but also accompanied benchmarks using these items.

YCB objects are divided into food items, kitchen items, tool items, shape items, and task items. The proposed object set gives an impression (at least for the authors) that it is a collection of items necessary for the tasks chosen as benchmarks rather than selected in an exhaustive manner considering their diversity. Most of the benchmarks shown as examples also seem to aim at evaluating a specific function rather than the total evaluation of an integrated manipulation system. In fact, Backus et al. [149] used a part of YCB in order to evaluate the grasping function of their developed hand. Interestingly, one can see LEGO blocks in the task items of YCB. Regarding LEGO, Yokokohji et al. [150] has already proposed the assembly of the LEGO block as a benchmark of the teleoperation system.

Falco et al. [151] shows a framework for robotic hand performance benchmarking. The performance benchmarking can be divided into three levels, i.e. component level, system level, and functional level. They proposed a set of component-level and system-level test methods together with the experimental results from a subset of these tests for three robotic hand configurations.

4.2. Challenge programs

At the conference site of ICRA 2015 in Seattle, Amazon Picking Challenge (APC), a robot competition of picking operation, was held [54]. This competition was started because picking operation is still difficult to be automated and has been a bottleneck in logistics.

Although the condition is rather simplified compared to the real picking field, APC is challenging enough for robot systems with the currently available technologies, because they have to recognize the target items with various shapes and appearance (they could be partially occluded) and pick them up reliably without damaging (they could be deformable, fragile, or very heavy).

In the second APC held in Leipzig, Germany in 2016, some target items were added and the difficulty level was increased. In this year, stowing task, where the robot had to pick up a target item from a tote bag and stow it in the shelf, was also newly introduced.

From the third competition held in July, 2017, Amazon Picking Challenge has been renamed as Amazon Robotics Challenge, since the challenge no longer focuses only on picking. From 2017, the teams are allowed to design their original shelf so that their robot can easily pick up and stow the items. This is an interesting rule revision so that the teams have to design a total logistic system including the shelf. Although the Amazon Robotics Challenge become more system integration-oriented competition for picking and stowing together with object recognition and task environment (shelf) design, the task is still rather simple from the view point of manipulation because with the current rule the robots are not required complex manipulations such as in-hand manipulation.

The ARM project of DARPA was also a challenge program on manipulation [55]. The ARM project was actually consisted with two sub-projects, ARM-S and ARM-H. ARM-S was a software project where several softwares were developed on the provided robot platform having a camera head, dual arms, and hands. In phase 1 of the ARM-S, six teams who participated in the program had to perform several grasping and manipulation tasks using the same platform. The top three teams moved to phase 2 where they had to perform more complex task using dual arms. Using the same platform is very important to compare and benchmark different softwares. However, it is also very important to prepare appropriate hardware platform. It would also be challenging to make the software portable so that it can be easily ported to different hardwares.

In contrast, ARM-H was a hardware project where several low-cost and robust multi-fingered robot hands were developed with the aim of future commercialization. Three teams participated in ARM-H program, and they had to perform grasping and manipulation tasks which were almost similar to those for ARM-S. It is interesting that the teams were allowed to teleoperate their hand, meaning that this program only focuses on hardware capabilities of the developed hands. The primary purpose of ARM-H was to develop dexterous but solid and low-cost hands, aiming at their commercialization. Actually, ReFlex Hand by Righthandrobotics [152], which has been commercialized as a research platform, is originated from ARM-H.

In RoboCup, RoboCup@Work [153] has been held from 2012 as a competition of advanced manipulation in industrial applications. The competition consists of some basic elementally tasks (called 'Test') including 'Basic Manipulation Test (BMT)' and application-oriented tasks that need the advanced manipulation (called 'Technical Challenges'). Teams have to prepare at least one mobile robot and one manipulator (the manipulator can be mounted on the mobile robot).

Manipulation objects in RoboCup@Work include aluminum profiles in different size and color, screws, nuts, and bearings. BMT tested the robot's manipulation capabilities such as grasping, turning, and placing objects of different size and shape. When placing objects, the robot may have to transport them in a small distance using mobile platform but placing task itself is rather simple. In 'Precision Placement Task (PPT),' however, the robot has to grasp and place objects into object-specific cavities, meaning that PPT requires more advanced recognition and manipulation capabilities than BMT.

There are three Technical Challenges in RoboCup@Work 2017 and only 'Basic Assembly Test (BAT)' is relevant to grasping and manipulation. As an example of BAT, assembling a tire to the axle of a model car is shown but it seems still preliminary. From the viewpoint of grasping manipulation, tasks in RoboCup@Work are still simple but controlling a manipulator mounted on a mobile platform is challenging because one can no longer use a stationary world coordinates.

In EU, a challenge program called EuRoC (Europian Robotics Challenge) has been started recently [154]. Three industry-relevant challenges, Challenge 1: Reconfigurable Interactive manufacturing Cell, Challenge 2: Shop Floor Logistics and Manipulation, and Challenge 3: Plant Inspection and Servicing, launched in April 2014. The challenges relevant to manipulation and grasping are Challenges 1 and 2. To encourage the collaboration between industrial and research, EuRoc introduces a unique call for challenger teams consisting of research teams, end users, technology developers, and system integrators. The challenger teams have to pass through several steps, such as qualification, realistic lab stage, and field test stage, and the limited number of teams are selected and can proceed to the next stage. In EuRoc, challenge tasks are also unique in a sense that challenger teams, who proceeded to the realistic lab stage, have to perform not only benchmark task provided by the organizer but also free-style user-case driven task as well as a show-case which is completely end-user driven. In the filed test stage, the selected teams have to perform the pilot experiment in the real environment at the end-user site.

In addition to EuRoC, Airbus Shopfloor Challenge [155], which was held at ICRA 2016, and RoCKIn@Work [156–158] are other challenge programs related to EU. In the Airbus Shopfloor Challenge, which was held at ICRA 2016, the participating teams were required to design and develop a lightweight robot system that can drill on a panel, mimicking the part of aircraft body, accurately and quickly. Therefore, there is no element of grasping and manipulation in this challenge. RoCKIn@Work was competition designed by the RoCKIn project founded by FP7 (7th Framework Programme, European Commission) together with RoCKIn@Home. The aim of the RoCKIn project was to develop competitions for benchmarking, ensuring reproducibility and repeatability. It was also an unique feature of the RoCKIn project that competitions were designed to include both functionality and task benchmarks that evaluate elemental technologies and system integration, respectively.

The RoCKIn project was successfully completed in 2015 and has been inherited by the European Robotics League (ERL) founded by Horizon 2020 framework of EU. Among ERL, ERL Industrial Robots (ERL-IR) is a successor of the RoCKIn@Work [159]. Meanwhile, some of the outcomes and insights obtained from the RoCKIn project have been introduced to RoboCup@Work and RoboCup@Home.

At the IROS 2016 conference site in Korea, IROS Robotic Grasping and Manipulation Competition [160] was held. The competition consists of three tracks, hand-in-hand grasping, fully autonomous, and simulation. Track 1 (hand-in-hand grasping) includes two stages, Stage 1: Pick-and-place and Stage 2: Manipulation. In Stage 1, 10 objects, such as a mineral water PET bottle and a bag of potato chips, must be picked up from a shopping baskets and place on the designated locations, while in Stage 2, 10 manipulation tasks, such as using a spoon to pick up peas and hanging towel on rack, must be performed. Track 2 (fully autonomous) also includes two stages exactly the same as those in Stage 1 but the robots must perform the tasks autonomously. Track 3 was the competition in a simulation environment. Among these tracks, hand-in-hand grasping was an interesting competition where the hands developed by the teams were manipulated manually by the competition staffs so that only hardware performance can be evaluated (just like ARM-H). It can also reduce the burden of the teams because they need not bring the robot arm but only their hand to the competition site. The hand was operated by the competition staffs in order to avoid any cheating by team members. Interestingly, asking the competition staffs, who have no background, to operate the hands happened to be a good usability test of the hand.

The objects in Stage 1 (pick-and-place) and the tasks in Stage 2 (manipulation) were selected mainly from daily living. This means that this competition mainly aimed at service robots. In April, 2017, however, official announcement of the second IROS Robotic Grasping and Manipulation Competition has been released and they have announced that there will be two tracks, Service Robot Track and Manufacturing Track in the second competition [161]. In the second IROS Robotic Grasping and Manipulation Competition, hand-in-hand grasping will be discontinued and every task must be performed autonomously.

As a movement on challenge programs in Japan, World Robot Challenge (WRC) is being planned as a part of World Robot Summit (WRS) [162]. WRS is a robotic international convention held in 2020 which aims at an opportunity to accelerate the research and development of robots and social implementation based on the 'Robotic New Strategy' formulated by Japanese government in 2015. The World Robot Challenge will feature competitions in four categories: Industrial Robotics Category, Service Robotics Category, Disaster Robotics Category, and Junior Category. Specific competition rules in each category are currently under consideration.

In summary, there have been many robotic challenges relevant to grasping and manipulation. However, none of them requires sophisticated grasping and manipulation which would be necessary in, for example, assembly tasks. Probably Manufacturing Track in the second IROS Robotic Grasping and Manipulation Competition would be the first attempt for such a robotic challenge aiming at sophisticated grasping and manipulation. For example, gear-unit assembly, which is one of the tasks of Manufacturing Track and also serves as a trial task for Industrial Robotics Category of WRC, requires the capability of grasping parts in different shape (including part recognition with vision), reorienting the grasping pose for assembly, and precise insertion of parts, preferably, without using jigs or any other peripheral devices.

5. Conclusion

Aiming at the creation of advanced technologies for dexterous robotic manipulations comparable to human being, this paper surveyed the recent results about the following three topics; object recognition, soft robotic hands, and benchmarks and challenge/competition programs. The former two topics construct the fundamental components of the advanced robotic manipulations, while the last one is a key for proceeding the creation and realization of the actual advanced robotic manipulation systems.

Firstly, we have examined the recent methodologies for object recognition utilizing the 2D and 3D image-based information and tactile information, and showed the difficulty in recognizing transparent and shiny objects, and the difficulty in integration of multiple information such as image and tactile data. How and how many sensors are appropriate for object recognition? How information should be acquired through sensors? How the sensor information should be processed? These issues are deeply connected to and implicitly provided by targets, and then many of the issues have not been solved yet.

Second, we have presented the survey of softness of robotic hands, which is a key for stably grasping objects even under uncertain conditions. However, there are still a lot of unclear issues. First of all, it is still unclear how to embed softness in robotic hands. For example, appropriate material, shape, structure, and mechanism are unclear. Although soft robotic hands can deal with a wide variety of objects, the range of the graspable objects is not comparable to human hand yet. The softness enhances the stability of grasping while it makes the manipulation difficult. Very few researchers have tried this issue, and the obtained methodologies are limited. Further examination and development of soft robotic hands are required to enhance the dexterity and versatility in robotic manipulations.

Third, we have shown the recent benchmarks and challenge/competition programs which have proceeded the creation of new technologies on robotic manipulation. However, a number of human tasks are still impossible to be conducted by robots. The appropriate definition of benchmarks and challenge/competition programs is a key for accelerating the next step for robotic manipulation.

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