A Survey of Methods and Strategies for High-Precision Robotic Grasping and Assembly Tasks—Some New Trends

Rui Li and Hong Qiao, *Fellow, IEEE*

***Abstract*—Grasping and assembly are essential tasks in high-precision robotic manipulation for industrial manufacturing as well as for home service applications. Many efforts have been devoted to this area in an attempt to meet the increasing precision requirement of the task. However, it remains a problematic objective to fulfill high precision, high reliability, high speed, and high flexibility all at once during one robotic manipulation task. To find answers to the above-mentioned problem, this article tries to categorize, review, and compare the recent works focusing on robotic grasping and assembly tasks to reveal some potential trends in this research area. The approaches will be divided into five groups based on the difference in the utilization of sensing or constraints. For each part, robotic grasping and assembly will be treated as practical cases to illustrate the concrete work in that area. This article could give the readers some knowledge on the current developments in robotic manipulation, and provide new thoughts on future direction in this area—inspiring new designs, structures, and systems to meet new requirements in applications in industrial manufacturing and home service.**

***Index Terms*—Assembly, environmental constraint, grasping, robotic manipulation, sensing.**

Manuscript received May 4, 2018; revised February 23, 2019 and August 14, 2019; accepted September 16, 2019. Date of publication October 2, 2019; date of current version December 31, 2019. Recommended by Technical Editor C.-C. Lan. This work was supported in part by the National Key Research and Development Program of China under Grant 2017YFB1300200 and Grant 2017YFB1300203, in part by the National Natural Science Foundation (NSFC) of China under Grant 61627808, Grant 91648205, Grant 61702516, and Grant 51705515, in part by the Strategic Priority Research Program of Chinese Academy of Science under Grant XDB32050100, and in part by the Sino-German (CSC-DAAD) Postdoc Scholarship Program under Grant 201800260080. *(Corresponding author: Hong Qiao.)*

R. Li is with the Technical University of Munich, 80333 Munich, Germany, with the Beijing Key Laboratory of Research and Application for Robotic Intelligence of "Hand-Eye-Brain" Interaction, Beijing 100190, China, and also with the Cloud Computing Center, Chinese Academy of Sciences, Dongguan 523808, China (e-mail: raysworld@outlook.com).

H. Qiao is with the State Key Lab of Management and Control for Complex Systems, Institute of Automation, Chinese Academy of Sciences, Beijing 100190, China, with the University of Chinese Academy of Sciences, Beijing 100049, China, and also with the Center for Excellence in Brain Science and Intelligence Technology, Chinese Academy of Sciences, Shanghai 200031, China (e-mail: hong.qiao@ia.ac.cn).

Color versions of one or more of the figures in this article are available online at http://ieeexplore.ieee.org.

Digital Object Identifier 10.1109/TMECH.2019.2945135

I. Introduction

How to achieve high-precision manipulation has always been a primary challenge in the robotic research area. Since the robots' extensive application in various fields, people have higher expectations and requirements for their manipulation precision.

For instance, in peg-in-hole assembly task for: 1) quartz accelerometer (a kind of linear accelerometer unit widely used in navigation and guidance systems for airplane and ships), the concentricity between the quartz reed and coil should be less than ± 20 μm; 2) automobile engine, the clearance between the piston pin and hole is around 2.5–7.5 μm. However, to date, the positioning repeatability of the most accurate 6-DoF (degree of freedom) robotic manipulator is ± 10 to ± 30 μm for lightweight applications (≤ 6 kg). Therefore, it is impossible to meet the precision requirement of many of these tasks for current robotic systems, relying on the precision of the manipulator itself. Aiming to solve this problem, methods and strategies are needed to help improve the precision of the robotic system.

In fact, to achieve high precision in robotic manipulation, the focus is on how to eliminate the uncertainty in the object, the robot, and the environment. In general, there are two solutions to this.

1) Utilize sensors to perceive the state information between the robot and the object and establish a mapping relationship between the sensing information to manipulation strategies to form robot control or learning algorithms.
2) Utilize the constraint relationship between the robot and the object, which is formed by structure, environment, etc., to compensate the uncertainty during the manipulation process.

Meanwhile, a natural problem will arise—does a solution which could integrate the sensing information and the passive constraint exist? The integration could combine the advantages from both sides. Also, it is known that humans can finish very challenging high-precision manipulation tasks [1]. Although the human musculoskeletal system suffers from signal-dependent noise, which results in relatively low repeatability of manipulation performance, it can still meet the requirement in tasks where high precision is needed. Therefore, does a solution which mimics the human structure and achieves humanlike manipulation exist? The next discussion will revolve around these issues.

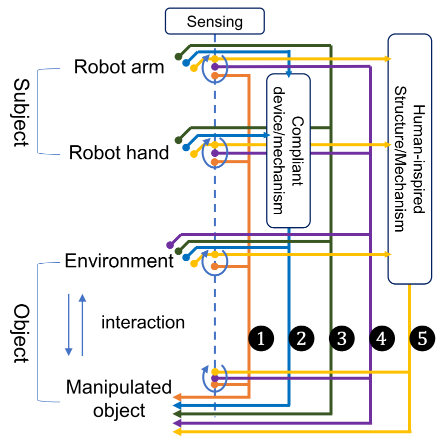


Fig. 1. Categories of methods for high-precision robotic manipulation: 1) sensing information-based methods; 2) compliant mechanism/device-based methods; 3) environmental constraint-based methods; 4) sensing-constraint-integrated methods; and 5) human-inspired methods.

Based on the above discussion, this article will provide a brief survey for high-precision robotic manipulation in five aspects:

1) sensing information-based methods;
2) compliant mechanism/device-based methods;
3) environmental constraint-based methods;
4) sensing-constraint-integrated methods;
5) human-inspired methods.

As shown in Fig. 1, a schematic illustrates the differences among the five categories of methods. In the robotic manipulation, the *subject* is the robot arm and hand, and the *object* is the environment and the manipulated object. The dashed line represents the sensing information and the loop represents an up-to-date state perceived by sensors. For sensing information-based methods, the inputs come from the sensor of every element of the system. For compliant mechanism/device-based methods, some additional parts are attached or embedded into the subject. For environmental constraint-based methods, the intrinsic knowledge of the system and its corresponding environment is used to the maximum extent. For sensing-constraint-integrated methods, the information from sensors and constraints from the environment are considered in the same framework. For human-inspired methods, every element in the system learns from humans for better performance.

Following the schematic, the rest of this article is arranged as follows. In Sections II–VI, the work on each category of methods will be presented, respectively. For each category, the following will be covered in this survey:

1) the characteristics of this category;
2) the main work in this category;
3) the existing application to robotic grasping or assembly;
4) the open questions in this category.

Discussion and conclusion will be given in Section VII.

II. Sensing Information-Based High-Precision Robotic Manipulation

A sensor is a device that can feel the detailed measurement and then, convert it to a usable output signal according to certain rules. It is a bridge for the robot to perceive the external environment. Therefore, sensing information plays an essential role in robotic manipulation. Typical sensors used in robotic manipulation tasks include the visual sensor, the range sensor, and the force/torque sensor. In this section, the research of sensing information-based high-precision robotic manipulation will be introduced.

Fig. 2. Typical sensors applied in the robotic manipulation tasks: 1) high-speed industrial camera; 2) smart industrial camera; 3) laser range sensor; 4) stereo camera; 5) structured-light sensor; 6) time-of-flight camera; 7) joint torque sensor; 8) wrist force/torque sensor; 9) finger pressure sensor; and 10) finger tactile array.

A. Visual Sensors

Vision provides the most abundant information for the human. Eyes obtain nearly 80%–90% of external data. Similarly, the visual sensor (as shown in Fig. 2, 1 and 2) could play a vital role in robotic manipulation.

First, the visual sensor can be used for target recognition and pose estimation. By installing the visual sensor in the hand of the robot (eye in hand), or fixing it in the workspace (eye to hand), the local or global scene information is extracted from images. Numerous computer vision algorithms are used for robotic manipulation tasks, especially for grasping [2]–[8]. In these works, the edge of the object is first extracted and then, the pose estimation problem is transferred to a graph-matching problem.

In recent years, deep neural networks have made remarkable progress in the field of computer vision, and have attracted the attention of some robotic manipulation researchers. Girshick *et al.* and Ren *et al.* used R-CNN and Faster R-CNN for object detection for manipulation, respectively. The recognition rates were significantly improved [9], [10].

However, for robotic manipulation, it is not only necessary to know *what* the object is, but also to know exactly *where* (position and orientation) it is. It is still difficult for the mainstream convolution neural network to *accurately* identify the position and orientation of objects. Therefore, more attention should be paid to the improvement of the detection accuracy of the object poses.

Second, the visual sensor can be used for measuring and positioning. Based on the principle of parallax of the binocular or multi-eye vision system, the position and orientation of the target object are calculated. For application in robotic manipulation, Sumi *et al.* developed a segment-based stereo vision method based on the versatile volumetric vision (VVV) system [11], which measured and tracked the position and orientation of objects with curved surfaces [12]. Agrawal *et al.* proposed a complete vision-guided robot system for three-dimensional (3-D) pose estimation for known objects, which could grasp 3-D objects effectively [13]. Chang *et al.* installed and tested a high-precision visual servo micro-assembly system, which realized micro peg-hole alignment and micro peg-hole assembly at the same time [14]. Huang *et al.* presented a visual compliance strategy for the peg-and-hole alignment. The images from high-speed camera were used in the control loop by detecting the pose error of the peg and hole [15].

For robotic manipulation, it is important to make sure the measurement is of high precision. For visual sensors, the lens, the imaging sensors, the calibration of intrinsic/extrinsic parameters, all exert a strong influence on the precision of the measurement. Around these topics, there have been many active discussions about how to correct the lens distortion, how to filter out noisy points, and how to extract the camera parameters with the least effort. The relationship between the light and the texture of the objects have also been taken into consideration, since the reflection, shadow, and occlusion may fail the extraction of the object edge.

Meanwhile, some researchers argue that more attention should be drawn on the task execution system, but not the sensors. Following this idea, they studied the approaches to lower the requirement of the sensors for the given task. A further discussion of this topic will be covered in Section III.

Third, some recent works attempt to minimize human participation during the robotic manipulation process. In this direction, visual information is taken as the raw input to train the robot for end-to-end, goal-oriented manipulation tasks. To achieve this, the researchers first tried to collect sufficient data for the robot manipulation tasks. They have studied how to effectively label and preprocess such data. Various datasets for robot task learning have appeared in recent years. For example, Bullock *et al.* provided a dataset for studying people's grasping actions. They recorded the grasping actions in home and factory environments, and manually marked different grasp types, objects, and task parameters [16]. Cai *et al.* designed the UT grasping dataset. The dataset consisted of four different subjects, who were asked to grasp a series of objects in a controllable environment (in front of the desktop) after telling them how to act [17].

Then, the researchers studied how to make a robot adapt quickly to task changes, which means that the robot should be able to promptly replan its path to fulfill the new task requirement. Krabbe *et al.* proposed an interval estimation optimization algorithm based on the fusion of support vector machine (SVM) and principal component analysis (PCA) to train the robot terminal motion parameters and plan the motion trajectory based on the experimental data [18]. Berczi *et al.* carried out the research of autonomous robot grasping based on deep learning. Through the training of grasping modes, the robot could reliably grasp different kinds of daily necessities, such as a water cup, key, eyeglass box, and book [19]. Duque *et al.* achieved the robotic assembly operation without hard coding the process in the algorithm. Using a task-parametrized Gaussian mixture model (TP-GMM), they learned the robot motion from human demonstrations [20]. Li *et al.* implemented a skill-acquisition method based on deep reinforcement learning for a low-voltage apparatus assembly [21], where they achieved a success rate of nearly 80%.

Concluding from the above-mentioned works, the existing robot learning methods need large sample data, and the coverage and size of the sample data have a high impact on the learning performance. But the process of acquiring a manipulation data is very time consuming and laborious. Currently, there are discussions on how to learn from a smaller dataset [22], [23], how to improve the learning efficiency [24], and how to train the robot in the simulation and adapt it to the real world without additional adjustments [25]. It also remains an open topic on how to improve the precision from learning-based robotic assembly tasks while preserving its ability of generalization.

Besides, some researchers are trying to establish new frameworks or networks for specific tasks. Rodriguez proposed an "abort and retry" mechanism for robot grasp learning. Once a grasping failed, a new experimental process was initiated immediately, which effectively shortened the training time of the learning algorithm [26]. They also proposed an analysis method based on "force signature," which was a distance function between the new manipulation process and the successful manipulation process to quickly detect the failure that occurred in the assembly process [27]. Lin *et al.* proposed a framework to learn the movement and force of a robot from human teachers. First, they estimated the contact force and position of the fingertips based on the changes in skin color when the fingertips were under pressure. The force and motion trajectory of the manipulation process was obtained by using Gaussian mixed regression, which was further used to control the robotic hand in real time [28]. Paolini *et al.* established a general framework based on statistics for postgrasp manipulation. Instead of directly modeling the performance evaluation of action as a function of sensor observations or projecting sensor inputs into a more compact state representation, they encapsulated uncertainty through belief states. Thus, the system uncertainty caused by noisy sensors could be solved most effectively [29]. Lenz *et al.* used the RGB-D sensor to recognize the position and orientation of the daily necessities based on the deep learning method to avoid the time-consuming process of manually designing the features. They developed a two-step cascade network that followed a coarse-to-fine pattern of recognition to accelerate the recognition process [30]. Fischinger *et al.* proposed an unknown object capture method based on point cloud information. In their work, the point cloud data were used to extract the accumulative height feature of the objects in the presence of stacking and clutter, which could then be used to identify the topological structure of the object and select the grasping position [31]. Paulius *et al.* studied a graph-based model, functional object-oriented network (FOON), to model the connectivity of the functional-related objects and their motion sequences in manipulation tasks [32].

Ken Goldberg's group has recently done a series of works on robot grasping, given some prior information. They proposed Dex-Net, which is short for "dexterity network," a database and algorithm package for grasping daily objects. In Dex-Net 1.0, Mahler *et al.* designed a network which outputed optimal grasping points for a given object. First, they collected more than 10 000 3-D object models. Based on that, they extracted the grasping points for each object by analytical methods. Then, they trained the multiview convolution neural network (MV-CNN). When a new object appeared, the most similar objects in the database were found quickly, and the score of each grasping point for this object was calculated based on the most similar object in the database [33]. In Dex-Net 2.0, they trained the grasp quality convolution neural networks (GQ-CNNs). The image and point cloud data were set as input, to predict the optimal candidate points for the possible grasping points for the object by calculating the probability [34]. In their following work, they achieved a greater success rate in the universal picking problem by upgrading to an "ambidextrous" grasping system and training on synthetic datasets using domain randomization with analytic models of physics and geometry [35], [36]. The proposed policy consistently cleared bins of up to 25 novel objects with reliability greater than 95% at a rate of more than 300 mean picks per hour. It would be a favorable direction if the work could be extended to high-precision manipulation.

B. Range Sensors

A range sensor senses the distance between the target point and the sensor. Range sensors are categorized as single-dot sensors, linear sensors, and matrix array sensors, depending on how many sensing units there are and how they are arranged. Due to the difference in measurement principles, they acquire the data by divergent methods such as stereo triangulation, sheet of light triangulation, structured light, time-of-flight, interferometry, coded aperture measurement, and so on.

Several commonly used range sensors in robotic manipulation tasks are listed as follows.

1) *Laser range sensor*, which can quickly and precisely extract the distance between the sensor and the target [37], [38]. The main disadvantage is its high cost.
2) *Stereo camera*, which captures images using two cameras and calculates the distance with the matching algorithm or triangulation measurement [39]–[42]. It has moderate hardware complexity, but requires high computation complexity. Such sensors do not work appropriately in weak light or with unclear image features.
3) *Structured-light sensor*, which emits controllable structured light to objects and extracts the parameters of the object by calculating the deformation of the light [43]–[47]. The advantage of structured light is its independence from the scene, which lowers the difficulty of matching. The disadvantage is the interference of multiple sensors, and the sensor does not work in intense light.
4) *Time-of-flight camera*, which sends light pulses continuously and receives the light returned from the object to get the distance by recording the travel time of the light [48]–[52]. Similar to laser range sensors, such sensors have good precision and robustness. The high deployment price is the main obstacle for wide application.

The range sensor (as shown in Fig. 2, 3–6) is used in the robotic manipulation for object measurement and pose estimation. Jang *et al.* used stereo triangulation to realize 3-D modeling of target based on "eye-in-hand" stereo cameras. They presented an analytical method to judge the local and global reachability of a given object in real environment [53]. Based on the 3-D laser scanner, Wang *et al.* proposed a method of modeling and grasping an *a priori* unknown object [54]. Based on the linear structured light visual sensor, Xue *et al.* reported a two-step method to locate the center of the circular hole with high precision. The absolute accuracy of the sensor for measuring the radius of a circular hole in space was increased to 0.08 mm, and the relative accuracy was better than 1.6% [55].

In many cases, the range sensor is becoming a typical setup for a robotic manipulation systems. Due to the similarity between the visual sensors and range sensors, there are also many concerns on how to eliminate the side effects of the noise, how to adapt the sensor to a broader range of lighting situations, how to simplify the process of registration, and how to increase the accuracy of object pose recognition. It is also meaningful to reduce the response time for real-time control.

C. Force Sensors

In the robotic manipulation task, the force/torque information is widely used to eliminate the small pose error in the parts. Fig. 2, 7–10, shows the force sensors commonly used in robot manipulations, including a six-axis force/torque sensor and a tactile sensor. The former is typically installed at the joints and wrists of the robot. It senses the force and/or torque on the object with its rigid connection; the latter is mainly established in the mechanical fingertips or palms. It perceives the positive pressure on the corresponding mechanical part.

1) Joint Torque Sensor: These sensors are installed on the joints of the robot to obtain the torque information during the motion of the robot. On the one hand, the joint torque is used to identify the contact relationship between the robot and the object. On the other hand, the joint torque information is often used in the compliance control of the manipulator. Jakovljevic *et al.* proposed an assembly method using fuzzy inference machine (FIM), which could quickly infer the current contact state according to the contact information in the assembly process [56]. Gaz *et al.* utilized the joint torque data to identify the dynamic model of the KUKA LWR (light weight robot) for implementing force control algorithms [57]. Bicchi *et al.* proposed a method to realize the intrinsic safety of the compliant manipulator. Based on the joint torque information, a compliance controller was designed, which could adjust the compliance of the end-effector when the mechanical impedance of the joint was unknown [58]. In their subsequent work, the active compliance control algorithm and the passive compliance mechanism were fused to achieve better safety in human–robot interactions on the tendon-driven manipulator platform [59]. Santina *et al.* designed a balanced feedforward and feedback controller using joint force information to realize humanlike motion by iterative learning control [60].

The primary focus of this topic is how to design a more effective controller to achieve force control and compliant motion. Related topics include how to identify the system parameters with the sensors, and how to get the expected motion/interaction with noisy force signals. There are also efforts on extracting joint torque data from the characteristics of the mechatronic system, which will be further discussed in Section IV.

2) Wrist Force/Torque Sensor: A wrist sensor is mounted on the robot's wrist to obtain force/torque information. Similar to joint torque sensors, the wrist sensor is either used for determining the contact state between the robot and the object [61]–[63], or for identifying the inertial parameters of the robotic manipulation system [64], [65]. Such sensors have been extensively studied for a long time, and many of them have been used in high-precision manipulation tasks, such as peg-in-hole assembly. Xiao and Liu proposed a method to accurately identify the contact state under the condition of position/orientation uncertainty by using the force/torque information [66]. Kim *et al.* realized a quasi-static analysis method based on force/torque sensing information. When the robot encountered large directional error, the proposed method can adjust the force/torque effectively [67]. De Carli *et al.* designed a human–robot cooperation system which did not involve verbal interaction with the robot. Using the wrist six-axis force/torque sensor and the joint encoder information, they identified the cooperative's conscious contact with the robot, and then, changed the robot's direction in real time [68]. Shirinzadeh *et al.* synthesized the information of force and torque to effectively identify the contact state of the cylindrical hole. Basing on that, they designed a strategy to realize the minimum contact force in the process of shaft insertion [69]. Ajoudani *et al.* combined the humanlike impedance control with the minimum effort control to realize the humanlike compliant assembly task [70]. Kim *et al.* proposed an algorithm for part shape recognition and hole position detection based on a six-axis wrist force/torque sensor [71]. Luo *et al.* proposed a new method based on geometric analysis, which was suitable for a 7-DoF industrial robot with a force/torque sensor. This method could simultaneously obtain the position and orientation information of the axis by a single search. The Kalman filter with fuzzy logic was used in the controller to realize admittance control [72]. Zhang *et al.* proposed a two-phase scheme to achieve the peg-in-hole insertion. The force/torque sensor was required to detect the real-time force and torque to guide the robot motion [73]. Xu developed a discrete-time sliding mode-generalized impedance control with adaptive switching gain, which helped control the position and force of the gripper simultaneously [74]. Xu also designed a microelectromechanical systems microgripper with a dual-axis force sensor on its wrist [75], [76]. Due to the scale of the targeted system, they utilized comb-drive mechanism to realize the actuator and sensor, which provided a wide-range gripper with scale-variable precision.

Since the force/torque information is local and transient in the assembly process, it is difficult to acquire any global or absolute conclusion, without prior knowledge of the object and the system. Therefore, it is an interesting direction to investigate how the force information and other global information fuse together. There is also an interest in how to balance the contradiction between accuracy and sensitivity [77], [78], and how to achieve an efficient switch between various contact/noncontact states [79], [80].

3) Palm and Fingertip Tactile Sensors: Tactile sensors are mounted at the end of the palm or finger to obtain contact force or pressure. They are typically used for contact state identification [81]–[83], for friction estimation [84]–[86], or for slippage detection during grasping [87]–[91]. To solve the grasping problems, Cutkosky *et al.* performed a lot of fundamental work on a grasping contact model [85], [92]–[94]. Shimoga *et al.* conducted a series of research on a grasping model with soft robotic fingers [95]–[97]. Sun designed a fingerprint sensor integrated with fingertip force and torque detection. Using this sensor, high-precision contact force and contact spatial information could be obtained simultaneously [98]. Lin *et al.* realized a strategy of grasping 3-D deformable objects by a robotic hand. With the tactile sensor, a virtual traceability test algorithm was designed to detect whether the object was liftable before grasping [99]. Koval *et al.* used the contact sensor mounted on the dexterous hand to estimate the position and orientation of the plane object with high accuracy and high speed. They also studied the real-time closed-loop feedback using tactile sensors to solve the problem of planar object manipulation under uncertainty [100]. Krug *et al.* designed an algorithm to analyze the success rate of grasping using tactile information as feedback [101]. Prattichizzo *et al.* discussed the controllable internal forces and object movements for a simple gripper, the BarrettHand, and a human-inspired robotic hand. By analyzing the finger tip force and torque, they tried to develop a tool for establishing postural synergies for the given task, which could reduce the complexity of the hand design and improve the stability [102].

It is a trend to employ artificial intelligence to analyze the information obtained from tactile sensors. Particularly, extreme learning machine (ELM) has been applied to tactile sensing systems for object recognition tasks [103]–[105]. In addition, Veiga *et al.* applied supervised learning to the prediction of the future occurrence of slip during grasping [91]. Lee *et al.* designed a replacement of an existing tactile sensor through visual and electric information [106]. They combined a recurrent neural network (RNN) with a long short-term memory (LSTM) network to recognize the change pattern of deformable and undeformable objects. Eguiluz *et al.* proposed a recursive multimodal tactile material identification approach [107].

There is also work on implementing new force sensors for the palms and fingertips. And the major focus on this field also includes how to implement tactile sensors with high resolution, high sensitivity, and short response time [104], [108]–[111].

III. Compliant Mechanism/Device-Based High-Precision Robotic Manipulation

In mechanical engineering, compliant mechanisms are flexible mechanisms that transfer or transform motion, force, or energy through elastic body deformation rather than from movable joints only. Using a compliant mechanism/device can lead to a passive compliant motion of the robot arm or hand, which allows the pose error between the assembly parts to be eliminated during such movement. Compared with the sensor-based

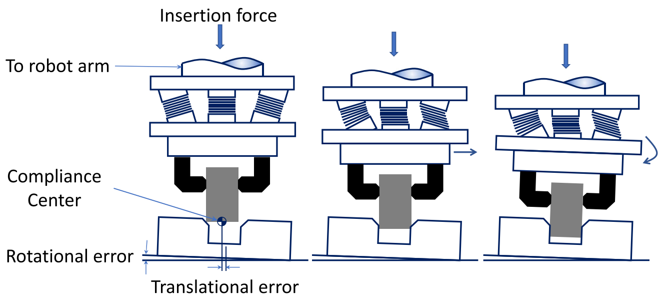


Fig. 3. General mechanical structure of an RCC device.

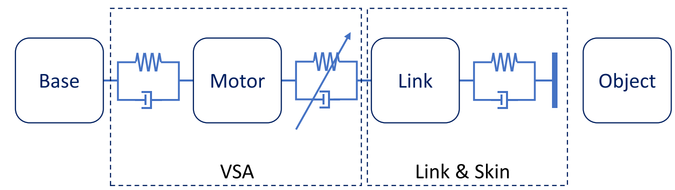


Fig. 4. Mass model of a 1-DoF VSA interacting with the environment.

methods, these methods make use of the relationship between the geometry and the mechanical structure between the object and the robot system, providing a certain degree of compliance for a specific manipulation task. Typical equipment and devices include the remote compliance center (RCC) device and the variable impedance actuator (VIA).

A. Remote Center of Compliance

RCC was invented by Whitney and Nevins to help accomplish insertion and assembly tasks [112]. In their research, they extensively discussed the robotic insertion process [113]. During the insertion process, the peg would tend to rotate about an axis in the plane of the gripper's fingers, which was called the center of compliance. As shown in Fig. 3, the RCC device was in fact an elastic mechanism with 6 DoFs, which could change the position of the center of compliance of the system.

Since the invention, there have been many variants of the RCC. Kazerooni *et al.* developed an active compliant end-effector (active RCC) with computer-adjustable impedance [114]. The structure was too complex to be widely applied to practical applications. Joo and Lee separately analyzed the limitations of RCC and proposed separate designs for variable RCC (VRCC) [115], [116], which could vary the center of compliance by adjusting some knoblike elements on the device. Dubois and Birglen designed a universal joint with a lower mobility RCC linkage [117].

There are also some efforts on integrating the vibration device with the RCC for the high-speed peg-in-hole insertion. Kilikevicius and Baksys investigated the insertion process using vibratory excitation for robotic assembly [118], [119]. Baksys *et al.* designed several vibratory alignment systems for the peg-hole insertion task [120], [121]. They further analyzed the relationship between alignment duration, initial pressing force, shape, and excitation frequency [122]. In their experimental setup, the system could realize a peg-hole insertion task with 0.05–0.10 mm clearance in 70–150 ms. However, how to find the most suitable vibratory frequency has not been reported in any work in this area.

Although the RCC is the most common solution in real applications, it has several shortcomings: 1) there has to be chamfer on the peg or the hole, which acts as the guidance for the peg to be inserted with the RCC: 2) for simplification of the design, the elastomer shear pad (ESP) was introduced by Whitney and Rourke [123]. However, with the ESP, the compliance center of the RCC is fixed so that different ESPs must be used for different lengths of the peg; and 3) the insertion direction has to be vertical since the RCC devices are made up of elastic elements. To date, combining the RCC with other devices or control methods is still a valuable topic for real applications.

B. Variable Stiffness Actuator

Besides the classic passive devices, especially the RCC and its variants, a new type of actuator, the VIA, is introduced to realize the compliant interaction with the environment (as shown in Fig. 4). Inspired by the series elastic actuators [124], the VIA has an elastic element with adjustable stiffness between the gear and the actuator output [125]. If the dedicated damping elements are omitted from the design, then it becomes a subgroup of the VIA, which is identified as the variable stiffness actuator (VSA).

Since the advent, the VSAs have been widely tested in various compliant manipulation tasks. Balletti *et al.* proposed a low-cost solution for peg-hole insertion with VIAs [126]. In the paper, VIAs were equipped to a CubeBot dual-arm platform for compliant motion during the insertion process. Due to the effect of VIAs, the platform could achieve the insertion with a small contact force (≤ 15 N) following a simple planning and control scheme. Bicchi *et al.* proposed a new design of the VSA which incorporates the possibility to vary transmission stiffness during motion execution, thus, allowing substantial motion speed up while maintaining low-injury-risk levels [127]. Currently, many prototypes of robot arms and hands with VSAs in place of stiffness motors are under development [128]–[130]. Readers are suggested to refer to [125] for a detailed review of VIA.

The VIA is especially useful for the robotic grasping and assembly, since it integrates the ability of executing compliant motion into the actuator, which greatly simplifies the difficulty of designing a compliant controller with external force/torque sensors. The current discussion about the VIA is mainly focused on how to achieve the optimal design solution for the given purpose.

IV. Environmental Constraint-Based High-Precision Robotic Manipulation

In addition to using compliant mechanisms/devices to provide the compliance required for the robot to manipulate with high precision, there is a wide range of constraints, such as configuration constraints and force constraints, between the robot and

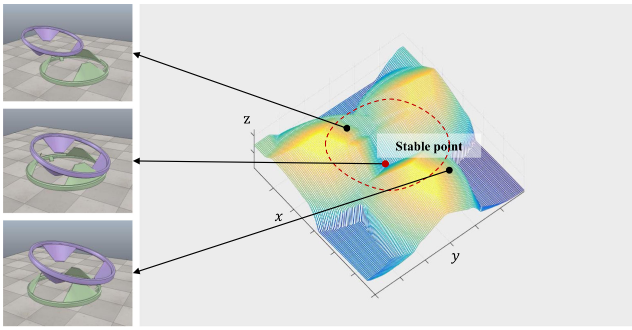


Fig. 5. Two complex parts and their corresponding ARIE in $\mathbb{R}^3$ space. *Left*: contact states of the complex parts. *Right*: the corresponding points in ARIE.

the manipulated objects. Using these constraints, it is possible to design an effective manipulation strategy for the robot, without the aid of a compliant mechanism/device, especially when the sensing information is unknown or partially known in the given system. The typical methods include the attractive region in environment (ARIE) and caging.

A. Attractive Region in Environment

The ARIE is a kind of constrained region formed by the environment, which exists in the configuration space of the robotic system.

The concept of ARIE was initially proposed by Qiao [131]. An analogous example is illustrated as follows. Imagine there are a "bean" and a "bowl" in the physical space. If the initial position of the bean is above the upper surface of the bowl, under the effect of gravity and friction, the bean will drop into the bowl, and finally, stay at the bottom of the bowl.

Inspired by such phenomena in the physical space, the concept of ARIE is delineated as follows. If the bean represents the state of the system, and the bowl represents the environmental constraint, and if there exists a state-independent input, then the state of the system can converge to stable in the "bowl." Such a "bowl" is called the "ARIE."

The concept was further discussed in [132] and [133] for achieving high-precision sensorless manipulation in production. Through a unique method of formulation and utilization of the attractive region in the configuration space, the strategy to attain high-precision assembly in physical space without a force sensor and flexible wrist was designed, and the approach to achieve 2-D and 3-D part orientation by sensorless grasping and pushing actions was also provided (see Fig. 5).

Based on this theory, several high-precision robotic manipulation tasks have been realized. For specific application areas, several methods have been developed. For example, for automobile manufacturing, Su *et al.* designed an eccentric peg-hole sensorless assembly system with ARIE-based strategy [134], [135]. They also developed a vision-based 3-D grasping planning approach with one single image [5]. Liu *et al.* composed a stable sensorless localization method for 3-D objects with a simple pushing mechanism [136]. They further created a vision-based 3-D grasping algorithm for grasping 3-D objects with a simple 2-D gripper [137]. Li and Qiao reported an ARIE-based robotic manipulation strategy for general convex peg–convex hole insertion tasks [138].

In a recent work, Qiao *et al.* discussed the definition and the generalized conditions of ARIE [139]. In this work, the general mathematical description of ARIE was presented, and the condition for the existence of the ARIE in different configuration spaces was analyzed. Notably, the relationship of the ARIE in high- and low-dimensional space was discussed. The future work includes the integration with learning algorithms and the interaction with human motion mechanisms.

B. Caging

The caging problem was originally proposed by Kuperberg as a problem of finding a set of placement of fingers that prevents a polygon from moving arbitrarily far from its given position [140]. "Let P be a polygon in the plane, and let C be a set of k points which lies in the complement of the interior of P. The points capture P if P cannot be moved arbitrarily far from its original position without at least one point of C penetrating the interior of P. Design an algorithm for finding a set of capturing points for P."

The concept and conditions for the caging problem have been growing in a series of mathematical works. Later, it was found that the theory of caging could be applied to the robotic grasping area. Rimon and Blake studied the relationship between caging configurations and grasp configurations [141]. Rodriguez *et al.* analyzed the relationship between cages and grasps of a rigid body and proposed a method to use cages as waypoints to form a stable grasp [142]. Wan *et al.* extended the work on grasping by caging where they used eigen-shapes to reduce the dimensionality of the dexterous hands. They also used space mapping to efficiently measure the robustness of caging [143]. Egawa *et al.* realized both 2-D and 3-D caging-based grasping of objects of various shapes with multifingered hands [144]. Su *et al.* discussed the relationship among caging configuration, form-closure grasp, and the ARIE. They proposed a vision-based caging grasp algorithm for a binary industrial gripper [145]–[147]. Lei and Wisse combined the advantage of caging and force closure grasping to enable different grippers to grasp unknown flat objects quickly [148]. Kwok *et al.* presented a caging grasp method inspired by the ropes, which can guarantee to generate local stable grasps [149].

The readers are suggested to refer to [150] for a recent survey of the research on caging grasp.

C. Other Methods

Other than the above-mentioned concepts, there still remain a large amount of work on environmental constraint-based manipulation. For example, Dafle *et al.* discovered that many in-hand manipulations rely on resources extrinsic to the hand, such as gravity, external contacts, or dynamic arm motions. They referred to them as "extrinsic dexterity" and demonstrated that even simple grippers were capable of ample in-hand manipulation [151], [152]. Ciocarlie and Allen discussed the concept of low-dimensional posture subspace for dexterous hand and grasping [153]. In this work, "Eigen grasp" was defined as a vector in high-dimensional hand posture space, and the goal was to find an optimal subspace where a wide range of hand postures could be represented in it. Takahashi *et al.* proposed an assembly technique based on passive alignment principle (PAP) for the deformable component, which achieved the compliance on the hand (loose grip) instead of on the wrist or joints of the robot arm (compliance control) [154], [155]. Park *et al.* presented a compliance-based peg-in-hole assembly strategy, which did not involve force/torque sensors or remote compliance mechanisms [156]. The method analyzed the contact state of the peg-hole system and provided a strategy to overcome the initial positional error of the hole incurred in the recognition process.

In contrast to the sensor-based methods, some researchers investigate sensorless methods. They attempt to be out of the trouble of the sensor noise, error, low precision, and cost [157]–[159]. Bicchi and Marigo analyzed rolling contacts for dexterous manipulation and provided a result on the analysis of controllability of rolling pairs of bodies [160]. Zhang and Goldberg studied the point-contact relationship between the gripper and planar polygons [161]. An algorithm combining toppling, accessibility, and form-closure analysis was implemented for the part alignment. Gabiccini *et al.* developed a grasp and manipulation analysis method for synergistic underactuated hands [162]. A framework to model and study the structural properties of a grasp by a general robotic hand in a quasi-static setting was established. Chen *et al.* presented an approach to recognize hand gestures accurately during an assembly task while in collaboration with a robot coworker [163]. The hidden Markov model (HMM) method was adopted to recognize patterns and assembly intentions. Xu *et al*. designed a series of mechatronic systems with compliant constant-force mechanisms for grasping and other manipulations, which did not require a force/torque sensor for safe manipulation [164]–[166].

The open problems under this topic include but are not limited to: 1) how to obtain some values in sensorless systems (modeling and control); 2) how to effectively utilize a given environment; and 3) how to intentionally design a manipulation-favorable environment (strategy investigation and planning).

V. Sensing-Constraint-Integrated High-Precision Robotic Manipulation

As discussed in Section IV, there is intrinsic knowledge (in most cases, the geometrical relationship) within the robotic manipulation system and the objects to be manipulated. If such information is used, strategies should be more easily made based on the understanding of such knowledge. Also, it should be worth a try to combine the sensor-based method with the environmental constraint-based method, which would possibly benefit from both methods. In this section, some exploratory work will be introduced to show how sensing information and environmental constraint could be integrated from different spaces into a unified framework, and how such integration could help in robotic manipulation.

A. Constrained Region in Environment

As discussed in Section I, the integration of sensing information and environmental constraints is reasonable and should be paid more attention in the robotic manipulation area. As the first step of an attempt, the concept of "constrained region in environment" (CRIE) was proposed, which was expected to bridge environmental constraints with sensing information. Li *et al.* discussed the compliance of robotic hands by analyzing the anatomical structure of the human hand and its control mechanism [167]. Ma *et al.* proposed a flexible robotic grasping strategy with the constrained region in environment which can adjust the grasping configuration according to the approximate contact force direction [168]. A new nonphysical space was provided to combine the state space and sensing space. The definition of CRIE is described as follows.

Definition 1: For a general differential system, which can be characterized as $\mathbf{X} = f(\mathbf{x}, \mathbf{u})$, where $\mathbf{x} \in \mathbb{R}^p$ is the state of the system and $\mathbf{u} \in \mathbb{R}^q$ is the input to the system, $\mathbf{x}$ can be observed by sensors with errors, that is, $\mathbf{x}_s = \mathbf{x} + \delta\mathbf{x}$, and $\mathbf{x}$ is constrained by a region $\mathbf{\Omega} \subset \mathbb{R}^p$. If there exists an input $\mathbf{u} = \mathbf{u}_i(\mathbf{\Omega}) + \mathbf{u}_d(\mathbf{x}_s)$ and an $\mathbf{\Omega}$-related scalar function $g(\mathbf{x})$ satisfying that: 1) $g(\mathbf{x}) > g(\mathbf{x}_0)$, for all $\mathbf{x} \neq \mathbf{x}_0$, and $g(\mathbf{x}) = g(\mathbf{x}_0)$, for $\mathbf{x} = \mathbf{x}_0$; and 2) $g(\mathbf{x})$ is smooth with respect to $\mathbf{x}$, then there exists a CRIE in the system.

There are two functionalities for utilizing the CRIE: 1) it serves as an implicit sensor to detect the current state of the system since the environmental constraints refine and reveal some states and 2) it serves as an error detector since the sensing information exploits the difference of the ideal scene and the real scene.

B. Tentative Improvement of Sensing Information-Based Methods

Besides combining the sensing information and the environmental constraints in one space, there is much work on implementing tentative improvement on sensor-based methods or environmental constraint-based methods. Starting from either side, attempts are made to compensate for the other side, so as to improve the performance of the original work. For instance, Rosales *et al.* studied the solution to the grasp synthesis problem, which consisted of finding the best hand configuration to grasp a given object for a specific manipulation task while satisfying all the necessary constraints [169]. Bicchi *et al.* researched a modeling method for grasping and active touch by natural and artificial hands [170]. They also studied the hand synergy problem, which integrated robotics and neuroscience for understanding the control of biological and synthetic hands [171]. Schultz *et al.* showed a particular recruitment strategy for exploiting muscle-like actuator impedance properties [172]. Kiguchi *et al.* examined how a human being decides the grasping force necessary to manipulate an unknown object to apply a human object-grasping strategy for robotic systems [173]. Abdeetedal and Kermani designed a grasping system for picking fruits from trees [174].

Inspired by biomimetics, they introduced a method to use the gripper itself to obtain a friction model. With the knowledge of friction, the grasping system achieved the harvesting task with a better performance.

In some way, some of these works can be understood as biomimetics, but without introducing any humanlike or human-inspired structures. In the next section, a further discussion will be given on these topics.

VI. Some New Trends on Robotic Manipulation

As described in the previous section, to improve compliance in robotic manipulation, one possible method is to learn from humans—a man can utilize the dexterity of his hands to achieve high-precision manipulations [1]. Although the movement of the hand is controlled by tendons and muscles attached to the bone, its structure and control mechanism can still provide some clues for improving the design and motion planning for existing robotic systems. Inspired by human hands, two possible but essential features are listed and discussed in the following, providing some inspiration for improving the robot system to meet the requirements for the manipulation task.

1) Coupled, Redundant Structure of the Robot End-Effector: There are 41 muscles in one human arm. Some of these muscles contract and relax simultaneously as a group to control one joint; on the other hand, each muscle is usually attached to multiple joints, thus, affecting the motion of all the attached joints. Due to the complexity and redundancy of the musculoskeletal structure, the movement of a joint can be achieved by a different combination of muscles. For example, if one muscle does not work "correctly," other muscles can compensate for the loss or error caused by that muscle. At present, most of the robot arms and hands apply decoupling control. However, the motion of the hand is the superposition of each motor position in 3-D space. Therefore, the motion error is the superposition of each motor's error. If the robot end-effector can realize the coupling and redundant structure in an appropriate way, it may make the motion more compliant.

In this regard, some researchers designed new robotic hands with tendon structure, which achieve better interaction with the target in an unknown environment. Bicchi and Prattichizzo proposed a general framework for modeling a robot manipulation system with redundant tendon actuation and multilateral constraints. The optimal tendon tension was calculated by considering the force distribution in this framework [175]. Shirafuji *et al.* developed a humanlike robotic hand with tendon-driven fingers [176]. The fingers of the hand mimicked two mechanisms of human fingers: 1) the fingers consisted of an equivalent actuator and the tendon arrangement of the human LU muscle and 2) the fingers realized a kind of double pulley mechanism, which may change the moment arm in a nonlinear manner based on the joint angle values. Inouye and Valero-Cuevas proposed a tendon-driven optimization method for robotic hands, which satisfied the given anatomical and design constraints. This method could optimize the design of the tendon-driven structure to obtain the maximum force capacity [177]. Rahman *et al.* designed a dexterous four-fingered gripper, each with four degrees of freedom, for in-hand manipulation. The main feature was the ability to release objects in an appropriate manner [178]. Chen *et al.* realized a humanlike peg-in-hole assembly task with a musculoskeletal system. Combined with the muscle synergy-based iterative learning controller, the proposed system could achieve the task with a humanlike adjustment strategy [179].

2) Flexible Control Strategy: With the coupled and redundant structure of the arm and hand as mentioned above, a human learns to achieve high-precision manipulations via flexible control strategies. In the following, two main control strategies are listed and discussed.

Strategy 1: Range from large to small. To achieve flexible but precise movement, a human usually controls the arm and wrist at first to move the hand near the target position, and then, follows the movement of the fingers for later manipulation. This control strategy requires the system to have a rough idea of how precise the arm, wrist, and hand are, respectively. Moreover, the movement error of the arm and wrist could be compensated with proper control of the fingers. Inspired by such a control regime, the control of the robot hand could be adopted from a broad range to a narrow one.

Strategy 2: Experience as the basis of control. Due to the complex structure of the hands, humans learn to control their hands mainly based on experience. In childhood, people spend years trying different ways to grasp objects and manipulate them. With such a long-term learning process, one person will have his habit of control of their hands, which is mainly stored in the cerebellum and spinal cord. Later, these habits could be applied and updated for later manipulations. Thus, if the coupled redundant structure is implemented in a robot hand, such a control regime could also be employed. With the development of deep neural networks in recent years, the control strategies could be achieved via reinforcement learning and transfer learning. Based on these pretrained neural networks, it is possible to control the robot hand in the desired way to achieve compliant manipulations.

VII. Discussion and Conclusion

In the previous sections, five categories of methods for high-precision robotic manipulation have been reviewed. The characteristic of each type is concluded in Fig. 6. To quantitatively compare the recent work, peg-hole insertion is selected as a case of manipulation and papers with performances are listed in Table I. Since there are differences between the robot platforms, clearances, materials of the object, and so on in these works, it is meaningless to declare which is better or worse. However, some facts are discussed as follows.

1) For robotic assembly, most of the works are found to be sensing information based. It is most likely that the sensors provide information of the system and there are a large number of works related to sensing information processing. With the increase of precision in both the sensors and the robotic manipulation systems, which makes it easy to fulfill the requirement of the manipulation tasks, there is extensive attention on strategies to make assembly

Research Area	Categories	Typical Means	Sensor Deployment	Constraint Utilization: Additional devices / mechanisms	Constraint Utilization: Environment	Characteristics
High-precision Robotic manipulation (grasping, assembly)	Sensing information based high-precision robotic manipulation	Visual sensor-based methods	Required	Optional	Optional	• The task precision depends on the sensor precision • More efforts are focused on the sensors (e.g. noise elimination, data collection & processing) other than on the tasks
		Range sensor-based methods	Required	Optional	Optional	
		Force / torque sensor-based methods	Required	Optional	Optional	
	Compliant mechanism / device based high-precision robotic manipulation	Remote Center of Compliance (RCC)	Optional	Required	Optional	• These methods trade off the complexity of hardware against the simplification of the control scheme • For these methods, the adaptation to the change of tasks is limited
		Variable Stiffness Actuator (VSA)	Optional (External force sensor)	Required	Optional	
	Environmental constraints based high-precision robotic manipulation	Attractive Region in Environment (ARIE)	Optional	Optional	Required	• Improve the achievable precision by exploiting the environmental constraints of the system. • There is no general solution to design the system input to realize the proposed strategy
		Caging	Optional	Optional	Required	
	Sensing-constraint integrated high-precision robotic manipulation	Constrained Region in Environment (CRIE)	Required (less strict requirement for the precision)	Optional	Required (partial environmental constraint)	• Provide a promising way to achieve high precision with less strict requirement for the precision. • There is no general method to realize the integration
	Human-inspired high-precision robotic manipulation	Human-inspired structure and control	Required (less strict requirement for the precision)	Required (human-inspired structures)	Required (partial environmental constraint)	• Provide a promising way to achieve human-like dexterity in high-precision manipulation tasks • The human-inspired actuator greatly increase the complexity of the control scheme

Fig. 6. Characteristics of each type of method, in terms of the utilization of the sensors and constraints.

TABLE I
QUANTITATIVE COMPARISONS OF THE ACCURACY/PRECISION OF CURRENT WORKS

Typical work	Category	Method	Setup	Performance	Note
Kim *et al.* [71]	Sensing information based high-precision robotic manipulation	Force/moment sensor	5-axis robot	– Clearance: down to 0.1 mm (H7/g6) – Duration: 6–10s – Initial error: 8.145 mm/17.96°	– The force/torque sensor is deployed to detect the shape of the hole. – The method is limited to square peg-in-hole assembly.
Luo *et al.* [72]		Force/torque sensor	7-axis robot	– Clearance: 0.02 mm – Duration: 40 s (search phase) +6 s (insertion phase) – Initial orientation: 7.5°	– The force/torque sensor is applied for maintaining the contact force.
Zhang *et al.* [73]		Force/torque sensor (Two-phase control scheme)	7-axis robot (Baxter)	– Clearance: 0.5 mm – Duration: 55 s (single arm)/35 s (dual arm) – Initial error: 20 mm	– The force/torque sensor is used to achieve the active compliant adjustment.
Huang *et al.* [15]		Visual sensor	4-axis robot + 3-DoF high-speed active peg	– Clearance: 4 mm – Duration: 700 ms – Initial error: 2 mm	– The visual sensor is used to measure the relative pose between the peg and hole. – The pose of the hole is unknown.
Duque *et al.* [20]		Visual sensor (Learning by demonstration)	6-axis robot (ABB IRB 140)	– Clearance: Not specified – Duration: training: 30–40s, tesing: 1–3s – Initial error: Not specified	– The visual sensor is applied to acquire demonstrations and identify objects on scene. – The method has good ability of generalization, but additional sensors/high-precision sensing information are needed for higher precision.
Whitney and Rourke [123]	Compliant mechanism / device based high-precision robotic manipulation	Remote Center of Compliance (RCC)	Not specified	– Not specified	– The chamfered peg/hole is needed. – ESP can be applied for simplification of the setup, but it makes the system less flexible.
Baksys *et al.* [122]		RCC + Vibratory devices	5-axis robot (Mitsubishi RV-2AJ)	– Clearance: 0.22 mm (d_{peg} = 17.88 mm, d_{hole} = 18.10 mm) – Duration: alignment: 30 ms to 60 ms, insertion: 200 ms to 300 ms – Initial error: 3 mm	– Parameters of the vibratory system have to be determined by experiment for different targets.
Balletti *et al.* [126]		Variable Impedance Actuator (VIA)	4-axis robot × 2 (CubeBot)	– Clearance: 0.5 mm – Duration: 25 s – Initial error: ∼20 mm	– The actuator simplifies the design of the control scheme. – Compliant motion can be achieved with the position sensor instead of the force sensor.
Li and Qiao [138]	Environmental constraints based high-precision robotic manipulation	Attractive Region in Environment	6-axis robot (Fanuc M-6iB)	– Clearance: 0.05 mm – Duration: ∼13 s – Initial error: 0.5 mm/1.5°	– No external force sensor/visual sensor is needed. – Similar strategy can be designed for the shape variation of the peg.
Takahashi *et al.* [154]		Force/torque sensor (passive alignment principle)	6-axis robot (Mitsubishi RV1A)	– Clearance: 9 μm (50 H8/50 g7) – Duration: 3500 ms – Initial error: 0.5 mm/1.4°	– The force/torque sensor is for the feedback of the compliance control. – The method is applicable to ring-in-peg assembly.
Park *et al.* [156]		Visual sensor	8-axis robot arm + 2-DoF waist	– Clearance: 0.01 mm – Duration: 6.3 s – Initial error: the maximum recognition error must be less than the peg radius (translation) /must be less than 30° (orientation)	– The visual sensor is utilized to detect the pose of the hole. – The compliant contact behavior is achieved without the force/torque sensor.
Chen *et al.* [179]	Human-inspired high-precision robotic manipulation	Muscle synergy-based iterative learning controller	Tendon-driven robot (5-DoF controlled by 16 muscles)	– Clearance: 0.15 mm – Duration: ∼8 s – Initial error: 1 mm/0.2°	– The compliant motion is guaranteed by the nature of the musculoskeletal system. – Only simulation is implemented.

general and robust. Therefore, learning-based methods become a future trend to be more investigated.

2) For robotic assembly, some works deploy compliant mechanisms/devices. They are very useful in some specified assembly tasks, where the assembly objects will not be frequently changed. The future works on this direction tend to either improve the existing design by combining with other effective designs to extend the flexibility of the system, or explore the new design by transferring the current control scheme into the hardware development.

3) To date, not many works are on the integration of the sensing information and the environmental constraint. The main obstacle is that there is no general technique to unify the sensing information and the environmental constraint.

4) Human-inspired method have not yet been applied to assembly tasks either. Results are only available in

simulation. The reason is possibly related to the complexity of the hardware and the corresponding control scheme. But there will be more results in this direction as our knowledge of biomimetics increases.

Currently, the primary research of the high-precision robotic manipulation is still converged on the sensing-information-based methods. Among these works, force/torque information plays a vital role in the realization of the control scheme at a low level, while the visual and range information-based methods play a significant role in recognition, measurement, and learning at a higher level. In general, the precision of these methods mainly depends on the precision of the applied sensors. Therefore, there are many works on the improvement of the sensors themselves. Meanwhile, there are also attempts to lower the precision requirement of the sensors. Some open challenges are as follows: 1) how to obtain the direct state information by the sensors; b) how to prevent the high-precision information from the noise interference; and 3) how to improve the efficiency of collecting and processing the time-consuming high-precision sensing data.

The compliant mechanism/device-based methods are classical to solve the problem of robot high-precision peg-in-hole assembly. The RCC device provides a practical solution to standard peg-in-hole insertion tasks, while the VSA implements a new possibility to achieve compliant motion by enhancing the actuation mechanisms. By increasing the complexity of the mechanical design, the complexity of the control scheme is reduced, thus, lowering the difficulty to achieve compliant motion. The open questions are as follows: 1) how to combine with other devices/mechanisms/methods to extend the flexibility and 2) how to improve the ability of generalization of these methods.

The environmental constraint-based methods provide a new thought to solve the problem. Instead of introducing additional information to the system, these works make use of intrinsic knowledge during the manipulation process, which further avoids the perturbations from the additional information. The open challenges are: 1) how to efficiently find and construct the available constraint relation and 2) how to achieve the motion from the initial state to the target state.

There is also some preliminary discovery in the sensing-constraint integration methods and the human-inspired methods. These methods provide a promising way to achieve a compliant and dexterous manipulation system as in humans. For the former, the question is how to find a rational way to integrate the sensing information with the environmental constraints. For the latter, the question is how to solve the complexity of the human musculoskeletal system and how to find the effective control law for it. Future efforts would possibly be funded to improve the performance of: 1) learning-based manipulation methods, which would enhance the intelligence of the robotic system; 2) sensing-constraint integration methods, which could reduce the dependency of high-precision sensing information for the robotic system; and 3) the human-inspired methods, which could increase compliance of the robotic system.

Acknowledgment

The authors would like to thank X. Yang for his constructive suggestions on this manuscript. The authors would also like to thank X. Li, S. Zhong, and J. Chen for their help with the revision of the article.

References

[1] X. J. Wu, "National greatest craftsmen," May 2015. [Online]. Available: http://news.cnr.cn/special/dggj/

[2] A. Morales, P. J. Sanz, A. P. del Pobil, and A. H. Fagg, "Vision-based three-finger grasp synthesis constrained by hand geometry," *Robot. Auton. Syst.*, vol. 54, no. 6, pp. 496–512, Jun. 2006.

[3] G. RecatalÁ, R. Carloni, C. Melchiorri, P. J. Sanz, E. Cervera, and Á. P. del Pobil, "Vision-based grasp tracking for planar objects," *IEEE Trans. Syst., Man, Cybern., C, Appl. Rev.*, vol. 38, no. 6, pp. 844–849, Nov. 2008.

[4] J. Speth, A. Morales, and P. Sanz, "Vision-based grasp planning of 3D objects by extending 2D contour based algorithms," in *Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst.*, Nice, France, Sep. 2008, pp. 2240–2245.

[5] J. Su, H. Qiao, and C. Liu, "A vision-based 3D grasp planning approach with one single image," in *Proc. Int. Conf. Mechatronics Autom.*, Changchun, China, Aug. 2009, pp. 3281–3286.

[6] F. Kobayashi, S. Ueno, H. Nakamoto, and F. Kojima, "Vision based grasping system with universal jamming hand," in *Proc. IEEE 10th Asian Control Conf.*, Kota Kinabalu, Malaysia, May 2015, pp. 1–4.

[7] V. Ortenzi, N. Marturi, M. Mistry, J. Kuo, and R. Stolkin, "Vision-based framework to estimate robot configuration and kinematic constraints," *IEEE/ASME Trans. Mechatronics*, vol. 23, no. 5, pp. 2402–2412, Oct. 2018.

[8] Y. Hu, L. Zhang, C. Seneci, W. Li, M. E. K. Abdelaziz, and G.-Z. Yang, "Design, fabrication and testing a semi-automatic sewing device for personalized stent graft manufacturing," *IEEE/ASME Trans. Mechatronics*, vol. 24, no. 2, pp. 517–526, Apr. 2019.

[9] R. Girshick, J. Donahue, T. Darrell, and J. Malik, "Rich feature hierarchies for accurate object detection and semantic segmentation," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, Columbus, OH, USA, Jun. 2014, pp. 580–587.

[10] S. Ren, K. He, R. B. Girshick, and J. Sun, "Faster r-CNN: Towards real-time object detection with region proposal networks," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 39, no. 6, pp. 1137–1149, Jun. 2017.

[11] F. Tomita *et al.*, "R&D of versatile 3D vision system VVV," in *Proc. IEEE Int. Conf. Syst., Man, Cybern. (Cat. No.98CH36218)*, San Diego, CA, USA, 1998, vol. 5, pp. 4510–4516.

[12] Y. Sumi, Y. Kawai, T. Yoshimi, and F. Tomita, "3D object recognition in cluttered environments by segment-based stereo vision," *Int. J. Comput. Vis.*, vol. 46, no. 1, pp. 5–23, Jan. 2002.

[13] A. Agrawal, Y. Sun, J. Barnwell, and R. Raskar, "Vision-guided robot system for picking objects by casting shadows," *Int. J. Robot. Res.*, vol. 29, no. 2/3, pp. 155–173, Nov. 2009.

[14] R. J. Chang, C. Y. Lin, and P. S. Lin, "Visual-based automation of peg-in-hole microassembly process," *J. Manuf. Sci. Eng.*, vol. 133, no. 4, 2011, Art. no. 041015.

[15] S. R. Huang, K. Murakami, Y. Yamakawa, T. Senoo, and M. Ishikawa, "Fast peg-and-hole alignment using visual compliance," in *Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst.*, Nov. 2013, pp. 286–292.

[16] I. M. Bullock, T. Feix, and A. M. Dollar, "The Yale human grasping dataset: Grasp, object, and task data in household and machine shop environments," *Int. J. Robot. Res.*, vol. 34, no. 3, pp. 251–255, 2015.

[17] M. Cai, K. M. Kitani, and Y. Sato, "A scalable approach for understanding the visual structures of hand grasps," in *Proc. IEEE Int. Conf. Robot. Autom.*, 2015, pp. 1360–1366.

[18] E. Krabbe, E. Kristiansen, L. Hansen, and D. Bourne, "Autonomous optimization of fine motions for robotic assembly," in *Proc. IEEE Int. Conf. Robot. Autom.*, Hong Kong, May 2014, pp. 4168–4175.

[19] L. P. Berczi, I. Posner, and T. D. Barfoot, "Learning to assess terrain from human demonstration using an introspective Gaussian-process classifier," in *Proc. IEEE Int. Conf. Robot. Autom.*, 2015, pp. 3178–3185.

[20] D. A. Duque, F. A. Prieto, and J. G. Hoyos, "Trajectory generation for robotic assembly operations using learning by demonstration," *Robot. Comput.-Integr. Manuf.*, vol. 57, pp. 292–302, Jun. 2019.

[21] F. Li, Q. Jiang, S. Zhang, M. Wei, and R. Song, "Robot skill acquisition in assembly process using deep reinforcement learning," *Neurocomputing*, vol. 345, pp. 92–102, Feb. 2019.

[22] D. Xu *et al.*, "Neural task programming: Learning to generalize across hierarchical tasks," in *Proc. IEEE Int. Conf. Robot. Autom.*, Brisbane, QLD, Australia, May 2018, pp. 3795–3802.

[23] Y. Duan *et al.*, "One-shot imitation learning," in *Proc. 31st Conf. Neural Inf. Process. Syst.*, 2017, pp. 1–12. [Online]. Available: http://papers.nips.cc/paper/6709-one-shot-imitation-learning.pdf

[24] S. Levine, P. Pastor, A. Krizhevsky, J. Ibarz, and D. Quillen, "Learning hand-eye coordination for robotic grasping with deep learning and large-scale data collection," *Int. J. Robot. Res.*, vol. 37, no. 4/5, pp. 421–436, Jun. 2017.

[25] Y. Chebotar *et al.*, "Closing the sim-to-real loop: Adapting simulation randomization with real world experience," in *Proc. Int. Conf. Robot. Automat. (ICRA)*, 2019.

[26] A. Rodriguez, M. T. Mason, S. S. Srinivasa, M. Bernstein, and A. Zirbel, "Abort and retry in grasping," in *Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst.*, San Francisco, CA, USA, Sep. 2011, pp. 1804–1810.

[27] A. Rodriguez, D. Bourne, M. Mason, G. F. Rossano, and J. Wang, "Failure detection in assembly: Force signature analysis," in *Proc. IEEE Int. Conf. Autom. Sci. Eng.*, Toronto, ON, Canada, Aug. 2010, pp. 210–215.

[28] Y. Lin, S. Ren, M. Clevenger, and Y. Sun, "Learning grasping force from demonstration," in *Proc. IEEE Int. Conf. Robot. Autom.*, Saint Paul, MN, USA, May 2012, pp. 1526–1531.

[29] R. Paolini, A. Rodriguez, S. S. Srinivasa, and M. T. Mason, "A data-driven statistical framework for post-grasp manipulation," *Int. J. Robot. Res.*, vol. 33, no. 4, pp. 600–615, Feb. 2014.

[30] I. Lenz, H. Lee, and A. Saxena, "Deep learning for detecting robotic grasps," *Int. J. Robot. Res.*, vol. 34, no. 4/5, pp. 705–724, Mar. 2015.

[31] D. Fischinger, A. Weiss, and M. Vincze, "Learning grasps with topographic features," *Int. J. Robot. Res.*, vol. 34, no. 9, pp. 1167–1194, May 2015.

[32] D. Paulius, Y. Huang, R. Milton, W. D. Buchanan, J. Sam, and Y. Sun, "Functional object-oriented network for manipulation learning," in *Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst.*, Daejeon, South Korea, Oct. 2016, pp. 2655–2662.

[33] J. Mahler *et al.*, "Dex-Net 1.0: A cloud-based network of 3D objects for robust grasp planning using a multi-armed bandit model with correlated rewards," in *Proc. IEEE Int. Conf. Robot. Autom.*, Stockholm, Sweden, May 2016, pp. 1957–1964.

[34] J. Mahler *et al.*, "Dex-Net 2.0: Deep learning to plan robust grasps with synthetic point clouds and analytic grasp metrics," in *Proc. Robot., Sci. Syst.*, Cambridge, MA, USA, Jul. 2017, pp. 1–10.

[35] J. Mahler, M. Matl, X. Liu, A. Li, D. Gealy, and K. Goldberg, "Dex-Net 3.0: Computing robust vacuum suction grasp targets in point clouds using a new analytic model and deep learning," in *Proc. IEEE Int. Conf. Robot. Autom.*, Brisbane, QLD, Australia, May 2018, pp. 5620–5627.

[36] J. Mahler *et al.*, "Learning ambidextrous robot grasping policies," *Sci. Robot.*, vol. 4, no. 26, Jan. 2019, Art. no. eaau4984.

[37] J. Aleotti, D. L. Rizzini, and S. Caselli, "Perception and grasping of object parts from active robot exploration," *J. Intell. Robot. Syst.*, vol. 76, no. 3/4, pp. 401–425, Mar. 2014.

[38] S. Fur, A. Verl, and A. Pott, "Simulation of industrial bin picking: An application of laser range finder simulation," in *Proc. IEEE Int. Conf. Comput. Intell. Virtual Environ. Meas. Syst. Appl.*, Ottawa, ON, Canada, Jun. 2018, pp. 1–6.

[39] Y. Hu, Z. Li, G. Li, P. Yuan, C. Yang, and R. Song, "Development of sensory-motor fusion-based manipulation and grasping control for a robotic hand-eye system," *IEEE Trans. Syst., Man, and Cybern., Syst.*, vol. 47, no. 7, pp. 1169–1180, Jul. 2017.

[40] X. Zhang, Y. Song, Y. Yang, and H. Pan, "Stereo vision based autonomous robot calibration," *Robot. Auton. Syst.*, vol. 93, pp. 43–51, Jul. 2017.

[41] K. Pachtrachai *et al.*, "Adjoint transformation algorithm for hand–eye calibration with applications in robotic assisted surgery," *Ann. Biomed. Eng.*, vol. 46, no. 10, pp. 1606–1620, Jul. 2018.

[42] C. Deniz and M. Cakir, "In-line stereo-camera assisted robotic spot welding quality control system," *Ind. Robot, Int. J.*, vol. 45, no. 1, pp. 54–63, Jan. 2018.

[43] J. Yang, X. Gao, Z. Li, S. Li, and B. Liang, "Pose measurement for capture of large satellite docking ring based on double-line structured light vision," in *Proc. 2nd Int. Conf. Mater. Sci., Machinery Energy Eng.*, 2017, pp. 1336–1345.

[44] V.-L. Tran and H.-Y. Lin, "Accurate RGB-d camera based on structured light techniques," in *Proc. Int. Conf. Syst. Sci. Eng.*, Ho Chi Minh City, Vietnam, Jul. 2017, pp. 235–238.

[45] C. S. Wieghardt and B. Wagner, "Self-calibration of a mobile manipulator using structured light," in *Proc. 18th Int. Conf. Adv. Robot.*, Hong Kong, Jul. 2017, pp. 197–203.

[46] I. Anwar and S. Lee, "High performance stand-alone structured light 3D camera for smart manipulators," in *Proc. 14th Int. Conf. Ubiquitous Robots Ambient Intell.*, Jeju, South Korea, Jun. 2017, pp. 192–195.

[47] Y. Yu, Z. Sun, X. Zhao, J. Bian, and X. Hui, "Design and implementation of an automatic peach-harvesting robot system," in *Proc. 10th Int. Conf. Adv. Comput. Intell.*, Xiamen, China, Mar. 2018, pp. 700–705.

[48] W. Pan, F. Zhu, and Y. Hao, "Combining depth and gray images for fast 3D object recognition," *Proc. SPIE*, vol. 10155, Oct. 2016, Art. no. 101553C.

[49] L. Santos and R. Cortesao, "Computed-torque control for robotic-assisted tele-echography based on perceived stiffness estimation," *IEEE Trans. Autom. Sci. Eng.*, vol. 15, no. 3, pp. 1337–1354, Jul. 2018.

[50] G. Du, M. Chen, C. Liu, B. Zhang, and P. Zhang, "Online robot teaching with natural human–robot interaction," *IEEE Trans. Ind. Electron.*, vol. 65, no. 12, pp. 9571–9581, Dec. 2018.

[51] Y. Lin, H. Min, H. Zhou, and F. Pei, "A human–robot-environment interactive reasoning mechanism for object sorting robot," *IEEE Trans. Cogn. Develop. Syst.*, vol. 10, no. 3, pp. 611–623, Sep. 2018.

[52] D. Han, H. Nie, J. Chen, and M. Chen, "Dynamic obstacle avoidance for manipulators using distance calculation and discrete detection," *Robot. Comput.-Integr. Manuf.*, vol. 49, pp. 98–104, Feb. 2018.

[53] H.-Y. Jang, H. Moradi, S. Lee, and J. Han, "A visibility-based accessibility analysis of the grasp points for real-time manipulation," in *Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst.*, Edmonton, AB, Canada, 2005, pp. 3111–3116.

[54] B. Wang, L. Jiang, J. W. Li, and H. G. Cai, "Grasping unknown objects based on 3D model reconstruction," in *Proc. IEEE/ASME Int. Conf. Adv. Intell. Mechatronics*, Monterey, CA, USA, 2005, pp. 461–466.

[55] T. Xue, B. Wu, T. Zhang, and S. Ye, "Analysis on round-hole orientation error based on structured light stripe vision sensor," *Opt. Precis. Eng.*, vol. 16, no. 4, pp. 624–629, Apr. 2008.

[56] Z. Jakovljevic, P. B. Petrovic, V. D. Mikovic, and M. Pajic, "Fuzzy inference mechanism for recognition of contact states in intelligent robotic assembly," *J. Intell. Manuf.*, vol. 25, no. 3, pp. 571–587, Oct. 2012.

[57] C. Gaz, F. Flacco, and A. D. Luca, "Identifying the dynamic model used by the KUKA LWR: A reverse engineering approach," in *Proc. IEEE Int. Conf. Robot. Autom.*, Hong Kong, May 2014, pp. 1386–1392.

[58] A. Bicchi, S. L. Rizzini, and G. Tonietti, "Compliant design for intrinsic safety: General issues and preliminary design," in *Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst.*, Maui, HI, USA, 2001, pp. 1864–1869.

[59] R. Schiavi, A. Bicchi, and F. Flacco, "Integration of active and passive compliance control for safe human– robot coexistence," in *Proc. IEEE Int. Conf. Robot. Autom.*, Kobe, Japan, May 2009, pp. 259–64.

[60] C. D. Santina *et al.*, "Controlling soft robots: Balancing feedback and feedforward elements," *IEEE Robot. Autom. Mag.*, vol. 24, no. 3, pp. 75–83, Sep. 2017.

[61] J. G. Garcia, A. Robertsson, J. G. Ortega, and R. Johansson, "Self-calibrated robotic manipulator force observer," *Robot. Comput.-Integr. Manuf.*, vol. 25, no. 2, pp. 366–378, Apr. 2009.

[62] J. Garcia, A. Robertsson, J. G. Ortega, and R. Johansson, "Generalized contact force estimator for a robot manipulator," in *Proc. IEEE Int. Conf. Robot. Autom.*, Orlando, FL, USA, 2006, pp. 4019–4024.

[63] H.-R. Choi, D.-H. Lee, U. Kim, T. Gulrez, W. J. Yoon, and B. Hannaford, "A laparoscopic grasping tool with force sensing capability," *IEEE/ASME Trans. Mechatronics*, vol. 21, no. 1, pp. 130–141, Feb. 2016.

[64] L. Villani, C. Natale, B. Siciliano, and C. de Wit, "An experimental study of adaptive force/position control algorithms for an industrial robot," *IEEE Trans. Control Syst. Technol.*, vol. 8, no. 5, pp. 777–786, Sep. 2000.

[65] Y. Du and Q. Zhu, "Decentralized adaptive force/position control of reconfigurable manipulator based on soft sensors," *Proc. Inst. Mech. Eng., Part I, J. Syst. Control Eng.*, vol. 232, no. 9, pp. 1260–1271, Jun. 2018.

[66] J. Xiao and L. Liu, "Contact states: Representation and recognizability in the presence of uncertainties," in *Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst.*, Victoria, BC, Canada, 1998, pp. 1151–1156.

[67] I.-W. Kim, D.-J. Lim, and K.-I. Kim, "Active peg-in-hole of chamferless parts using force/moment sensor," in *Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst.*, Kyongju, South Korea, 1999, vol. 2, pp. 948–953.

[68] D. De Carli *et al.*, "Measuring intent in human–robot cooperative manipulation," in *Proc. IEEE Int. Workshop Haptic Audio Vis. Environ. Games*, Lecco, Italy, Nov. 2009, pp. 159–163.
[69] B. Shirinzadeh, Y. M. Zhong, P. D. W. Tilakaratna, Y. L. Tian, and M. M. Dalvand, "A hybrid contact state analysis methodology for robotic-based adjustment of cylindrical pair," *Int. J. Adv. Manuf. Technol.*, vol. 52, no. 1/4, pp. 329–342, May 2011.
[70] A. Ajoudani, M. Gabiccini, N. G. Tsagarakis, and A. Bicchi, "Human-like impedance and minimum effort control for natural and efficient manipulation," in *Proc. IEEE Int. Conf. Robot. Autom.*, Karlsruhe, Germany, May 2013, pp. 4499–4505.
[71] Y. L. Kim, H. C. Song, and J. S. Song, "Hole detection algorithm for chamferless square peg-in-hole based on shape recognition using F/T sensor," *Int. J. Precis. Eng. Manuf.*, vol. 15, no. 3, pp. 425–432, Mar. 2014.
[72] R. C. Luo, A. Chang, and L. Cheng, "A novel peg-in-hole approach based on geometrical analysis for inclined uncertainty," in *Proc. IEEE Int. Conf. Adv. Intell. Mechatronics*, Munich, Germany, Jul. 2017, pp. 891–896.
[73] X. Zhang, Y. Zheng, J. Ota, and Y. Huang, "Peg-in-hole assembly based on two-phase scheme and F/T sensor for dual-arm robot," *Sensors*, vol. 17, no. 9, Sep. 2017, Art. no. 2004.
[74] Q. Xu, "Adaptive discrete-time sliding mode impedance control of a piezoelectric microgripper," *IEEE Trans. Robot.*, vol. 29, no. 3, pp. 663–673, Jun. 2013.
[75] Q. Xu, "Design, fabrication, and testing of an MEMS microgripper with dual-axis force sensor," *IEEE Sensors J.*, vol. 15, no. 10, pp. 6017–6026, Oct. 2015.
[76] Q. Xu, "Design and development of a novel compliant gripper with integrated position and grasping/interaction force sensing," *IEEE Trans. Autom. Sci. Eng.*, vol. 14, no. 3, pp. 1415–1428, Jul. 2017.
[77] Y. Sun, Y. Liu, T. Zou, M. Jin, and H. Liu, "Design and optimization of a novel six-axis force/torque sensor for space robot," *Measurement*, vol. 65, pp. 135–148, Apr. 2015.
[78] K. Miyashita, T. O. Vrielink, and G. Mylonas, "A cable-driven parallel manipulator with force sensing capabilities for high-accuracy tissue endomicroscopy," *Int. J. Comput. Assisted Radiol. Surg.*, vol. 13, no. 5, pp. 659–669, Mar. 2018.
[79] H. Zhang, Y. Liu, and G. Liu, "Multiple mode control of a compact wrist with application to door opening," *Mechatronics*, vol. 23, no. 1, pp. 10–20, Feb. 2013.
[80] L. Gracia, J. E. Solanes, P. Muñoz-Benavent, A. Esparza, J. V. Miro, and J. Tornero, "Cooperative transport tasks with robots using adaptive non-conventional sliding mode control," *Control Eng. Pract.*, vol. 78, pp. 35–55, Sep. 2018.
[81] Z.-Y. Chu, S.-B. Yan, J. Hu, and S. Lu, "Impedance identification using tactile sensing and its adaptation for an underactuated gripper manipulation," *Int. J. Control, Autom. Syst.*, vol. 16, no. 2, pp. 875–886, Apr. 2018.
[82] S. Pirozzi and C. Natale, "Tactile-based manipulation of wires for switchgear assembly," *IEEE/ASME Trans. Mechatronics*, vol. 23, no. 6, pp. 2650–2661, Dec. 2018.
[83] M. Abdeetedal and M. R. Kermani, "Grasp and stress analysis of an underactuated finger for proprioceptive tactile sensing," *IEEE/ASME Trans. Mechatronics*, vol. 23, no. 4, pp. 1619–1629, Aug. 2018.
[84] R. Howe, N. Popp, P. Akella, I. Kao, and M. Cutkosky, "Grasping, manipulation, and control with tactile sensing," in *Proc. IEEE Int. Conf. Robot. Autom.*, 1990, vol. 2, pp. 1258–1263.
[85] M. R. Cutkosky and P. K. Wright, "Friction, stability and the design of robotic fingers," *Int. J. Robot. Res.*, vol. 5, no. 4, pp. 20–37, Dec. 1986.
[86] A. Montaño and R. Suárez, "Manipulation of unknown objects to improve the grasp quality using tactile information," *Sensors*, vol. 18, no. 5, May 2018, Art. no. 1412.
[87] C. Schürmann, M. Schöpfer, R. Haschke, and H. Ritter, "A high-speed tactile sensor for slip detection," in *Towards Service Robots for Everyday Environments (Springer Tracts in Advanced Robotics, vol. 76)*, E. Prassler *et al.*, Eds., Berlin, Germany: Springer, 2012, pp. 403–415.
[88] T. Wong, P. Bigras, V. Duchaîne, and J.-P. Roberge, "Empirical comparison of differential evolution variants for industrial controller design," *Int. J. Comput. Intell. Syst.*, vol. 9, no. 5, pp. 957–970, Sep. 2016.
[89] A. Rana, J.-P. Roberge, and V. Duchaine, "An improved soft dielectric for a highly sensitive capacitive tactile sensor," *IEEE Sensors J.*, vol. 16, no. 22, pp. 7853–7863, Nov. 2016.
[90] M. R. Motamedi, J.-P. Roberge, and V. Duchaine, "The use of vibrotactile feedback to restore texture recognition capabilities, and the effect of subject training," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 25, no. 8, pp. 1230–1239, Aug. 2017.
[91] F. Veiga, J. Peters, and T. Hermans, "Grip stabilization of novel objects using slip prediction," *IEEE Trans. Haptics*, vol. 11, no. 4, pp. 531–542, Oct.-Dec. 2018.
[92] M. Cutkosky, "On grasp choice, grasp models, and the design of hands for manufacturing tasks," *IEEE Trans. Robot. Autom.*, vol. 5, no. 3, pp. 269–279, Jun. 1989.
[93] M. Cutkosky and I. Kao, "Computing and controlling compliance of a robotic hand," *IEEE Trans. Robot. Autom.*, vol. 5, no. 2, pp. 151–165, Apr. 1989.
[94] R. Howe and M. Cutkosky, "Dynamic tactile sensing: Perception of fine surface features with stress rate sensing," *IEEE Trans. Robot. Autom.*, vol. 9, no. 2, pp. 140–151, Apr. 1993.
[95] K. Shimoga and A. Goldenberg, "Soft materials for robotic fingers," in *Proc. IEEE Int. Conf. Robot. Autom.*, 1992, vol. 2, pp. 1300–1305.
[96] K. Shimoga and A. Goldenberg, "Soft robotic fingertips: Part I: A comparison of construction materials," *Int. J. Robot. Res.*, vol. 15, no. 4, pp. 320–334, Aug. 1996.
[97] K. Shimoga and A. Goldenberg, "Soft robotic fingertips: Part II: Modeling and impedance regulation," *Int. J. Robot. Res.*, vol. 15, no. 4, pp. 335–350, Aug. 1996.
[98] Y. Sun, "Fingertip force and contact position and orientation sensor," in *Proc. IEEE Int. Conf. Robot. Autom.*, Shanghai, China, May 2011, pp. 1114–1119.
[99] H. Lin, F. Guo, F. F. Wang, and Y. B. Jia, "Picking up a soft 3D object by "feeling" the grip," *Int. J. Robot. Res.*, vol. 34, no. 11, pp. 1361–1384, Apr. 2015.
[100] M. C. Koval, N. S. Pollard, and S. S. Srinivasa,"Pose estimation for planar contact manipulation with manifold particle filters," *Int. J. Robot. Res.*, vol. 34, no. 7, pp. 922–945, May 2015.
[101] R. Krug, A. J. Lilienthal, D. Kragic, and Y. Bekiroglu, "Analytic grasp success prediction with tactile feedback," in *Proc. IEEE Int. Conf. Robot. Autom.*, Stockholm, Sweden, May 2016, pp. 165–171.
[102] D. Prattichizzo, M. Malvezzi, M. Gabiccini, and A. Bicchi, "On motion and force controllability of precision grasps with hands actuated by soft synergies," *IEEE Trans. Robot.*, vol. 29, no. 6, pp. 1440–1456, Dec. 2013.
[103] H. Liu, J. Qin, F. Sun, and D. Guo, "Extreme kernel sparse learning for tactile object recognition," *IEEE Trans. Cybern.*, vol. 47, no. 12, pp. 4509–4520, Dec. 2017.
[104] B. Zhang, B. Wang, Y. Li, W. Huang, and L. Weng, "Detection and identification of object based on a magnetostrictive tactile sensing system," *IEEE Trans. Magn.*, vol. 54, no. 11, pp. 1–5, Nov. 2018.
[105] C. Liu, W. Huang, F. Sun, M. Luo, and C. Tan, "LDS-FCM: A linear dynamical system based fuzzy C-means method for tactile recognition," *IEEE Trans. Fuzzy Syst.*, vol. 27, no. 1, pp. 72–83, Jan. 2019.
[106] D.-H. Lee, W. Hwang, and S.-C. Lim, "Interaction force estimation using camera and electrical current without force/torque sensor," *IEEE Sensors J.*, vol. 18, no. 21, pp. 8863–8872, Nov. 2018.
[107] A. G. Eguíluz, I. Rañó, S. Coleman, and T. McGinnity, "Multimodal material identification through recursive tactile sensing," *Robot. Auton. Syst.*, vol. 106, pp. 130–139, Aug. 2018.
[108] J. Yin, P. Aspinall, V. J. Santos, and J. D. Posner, "Measuring dynamic shear force and vibration with a bioinspired tactile sensor skin," *IEEE Sensors J.*, vol. 18, no. 9, pp. 3544–3553, May 2018.
[109] R. Patel, R. Cox, and N. Correll, "Integrated proximity, contact and force sensing using elastomer-embedded commodity proximity sensors," *Auton. Robots*, vol. 42, no. 7, pp. 1443–1458, Apr. 2018.
[110] C. M. Boutry *et al.*, "A hierarchically patterned, bioinspired e-skin able to detect the direction of applied pressure for robotics," *Sci. Robot.*, vol. 3, no. 24, Nov. 2018, Art. no. eaau6914.
[111] J. Hughes and F. Iida, "Tactile sensing applied to the universal gripper using conductive thermoplastic elastomer," *Soft Robot.*, vol. 5, no. 5, pp. 512–526, Oct. 2018.
[112] D. E. Whitney and J. L. Nevins, "What is the remote center compliance (RCC) and what can it do?," in *Proc. 9th Int. Symp. Ind. Robots*, Washington, DC, USA, 1986, pp. 135–152.
[113] D. E. Whitney, "Historical perspective and state of the art in robot force control," *Int. J. Robot. Res.*, vol. 6, no. 1, pp. 3–14, Mar. 1987.
[114] H. Kazerooni, "Direct-drive active compliant end effector (active RCC)," *IEEE J. Robot. and Autom.*, vol. 4, no. 3, pp. 324–333, Jun. 1988.
[115] S. Joo and F. Miyazaki, "Development of variable RCC and its application," in *Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst.*, Victoria, BC, Canada, 1998, pp. 1326–1332.
[116] S. Lee, "Development of a new variable remote center compliance (VRCC) with modified elastomer shear pad (ESP) for robot assembly," *IEEE Trans. Autom. Sci. Eng.*, vol. 2, no. 2, pp. 193–197, Apr. 2005.

[117] P.-O. Dubois and L. Birglen, "Analysis and design of a remote center compliance universal joint," in *Proc. Int. Des. Eng. Tech. Conf. Comput. Inf. Eng. Conf.*, Boston, MA, USA, Aug. 2015, Paper V05BT08A019.

[118] S. Kilikevicius and B. Baksys, "Analysis of insertion process for robotic assembly," *J. Vibroeng.*, vol. 9, no. 4, pp. 35–40, 2007.

[119] S. Kilikevicius and B. Baksys, "Dynamic analysis of vibratory insertion process," *Assem. Autom.*, vol. 31, no. 3, pp. 275–283, 2011.

[120] B. Baksys and J. Baskutiene, "Vibratory alignment of parts during robotized assembly," *J. Vibroeng.*, vol. 10, no. 1, pp. 69–73, 2008.

[121] B. Baksys, S. Kilikevicius, and A. Chadarovicius, "Experimental investigation of vibratory assembly with passive compliance," *Mechanika*, no. 6, pp. 608–614, 2011.

[122] B. Baksys, J. Baskutiene, A. B. Povilionis, and K. Ramanuskyte, "Sensorless vibratory manipulation of the automatically assembled parts," *Solid State Phenom.*, vol. 164, pp. 265–270, 2010.

[123] D. E. Whitney and J. M. Rourke, "Mechanical behavior and design equations for elastomer shear pad remote center compliances," *J. Dyn. Syst., Meas., Control*, vol. 108, no. 3, pp. 223–232, 1986.

[124] G. A. Pratt and M. M. Williamson, "Series elastic actuators," in *Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst.*, Pittsburgh, PA, USA, Aug. 1995, vol. 1, pp. 399–406.

[125] S. Wolf *et al.*, "Variable stiffness actuators: Review on design and components," *IEEE/ASME Trans. Mechatronics*, vol. 21, no. 5, pp. 2418–2430, Oct. 2016.

[126] L. Balletti *et al.*, "Towards variable impedance assembly: The VSA peg-in-hole," in *Proc. 12th IEEE-RAS Int. Conf. Humanoid Robots*, Osaka, Japan, Nov. 2012, pp. 402–408.

[127] A. Bicchi, G. Tonietti, M. Bavaro, and M. Piccigallo, "Variable stiffness actuators for fast and safe motion control," in *Proc. 11th Int. Symp. Robot. Res.*, in Springer Tracts in Advanced Robotics, vol. 15, P. Dario and R. Chatila, Eds., Berlin, Germany: Springer, 2005, pp. 527–536.

[128] H. Zheng, M. Wu, and X. Shen, "Pneumatic variable series elastic actuator," *J. Dyn. Syst., Meas., Control*, vol. 138, no. 8, Jun. 2016, Art. no. 081011.

[129] J. J. Rice and J. M. Schimmels, "Passive compliance control of redundant serial manipulators," *J. Mechanisms Robot.*, vol. 10, no. 4, May 2018, Art. no. 044507.

[130] M. Haas, W. Friedl, G. Stillfried, and H. Höppner, "Human-robotic variable-stiffness grasps of small-fruit containers are successful even under severely impaired sensory feedback," *Frontiers Neurorobot.*, vol. 12, pp. 1–15, Oct. 2018.

[131] H. Qiao, "Attractive regions in the environment [motion planning]," in *Proc. IEEE Int. Conf. Robot. Autom. Symp. Proc. (Cat. No.00CH37065)*, San Francisco, CA, USA, 2000, pp. 1420–1427.

[132] H. Qiao, "Attractive regions formed by the environment in configuration space: The possibility of achieving high precision sensorless manipulation in production," *Int. J. Prod. Res.*, vol. 40, no. 4, pp. 975–1002, Jan. 2002.

[133] H. Qiao, "Two- and three-dimensional part orientation by sensor-less grasping and pushing actions: Use of the concept of 'attractive region in environment'," *Int. J. Prod. Res.*, vol. 41, no. 14, pp. 3159–3184, Jan. 2003.

[134] J. H. Su, H. Qiao, C. K. Liu, and Z. C. Ou, "A new insertion strategy for a peg in an unfixed hole of the piston rod assembly," *Int. J. Adv. Manuf. Technol.*, vol. 59, no. 9/12, pp. 1211–1225, 2012.

[135] J. H. Su, H. Qiao, Z. C. Ou, and Y. R. Zhang, "Sensor-less insertion strategy for an eccentric peg in a hole of the crankshaft and bearing assembly," *Assem. Autom.*, vol. 32, no. 1, pp. 86–99, 2012.

[136] C. K. Liu, H. Qiao, and B. Zhang, "Stable sensorless localization of 3-D objects," *IEEE Trans. Syst., Man, Cybern., C, Appl. Rev.*, vol. 41, no. 6, pp. 923–941, Nov. 2011.

[137] C. K. Liu, H. Qiao, J. H. Su, and P. Zhang, "Vision-based 3-D grasping of 3-D objects with a simple 2-D gripper," *IEEE Trans. Syst., Man, Cybern., Syst.*, vol. 44, no. 5, pp. 605–620, May 2014.

[138] R. Li and H. Qiao, "Condition and strategy analysis for assembly based on attractive region in environment," *IEEE/ASME Trans. Mechatronics*, vol. 22, no. 5, pp. 2218–2228, Oct. 2017.

[139] H. Qiao, M. Wang, J. Su, S. Jia, and R. Li, "The concept of "attractive region in environment" and its application in high-precision tasks with low-precision systems," *IEEE/ASME Trans. Mechatronics*, vol. 20, no. 5, pp. 2311–2327, Oct. 2015.

[140] W. Kuperberg, "Problems on polytopes and convex sets," in *Proc. DIMACS Workshop Polytopes*, 1990, pp. 584–589.

[141] E. Rimon and A. Blake, "Caging planar bodies by one-parameter two-fingered gripping systems," *Int. J. Robot. Res.*, vol. 18, no. 3, pp. 299–318, 1999.

[142] A. Rodriguez, M. T. Mason, and S. Ferry, "From caging to grasping," *Int. J. Robot. Res.*, vol. 31, no. 7, pp. 886–900, Apr. 2012.

[143] W. Wan, R. Fukui, M. Shimosaka, T. Sato, and Y. Kuniyoshi, "A new "grasping by caging" solution by using eigen-shapes and space mapping," in *Proc. IEEE Int. Conf. Robot. Autom.*, Karlsruhe, Germany, 2013, pp. 1566–1573.

[144] T. Egawa, Y. Maeda, and H. Tsuruga, "Two- and three-dimensional caging-based grasping of objects of various shapes with circular robots and multi-fingered hands," in *Proc. 41st Annu. Conf. IEEE Ind. Electron. Soc.*, Yokohama, Japan, Nov. 2015, pp. 643–648.

[145] J. Su, Z. Ou, and H. Qiao, "Form-closure caging grasps of polygons with a parallel-jaw gripper," *Robotica*, vol. 33, no. 6, pp. 1375–1392, 2015.

[146] J. Su, H. Qiao, Z. Ou, and Z.-Y. Liu, "Vision-based caging grasps of polyhedron-like workpieces with a binary industrial gripper," *IEEE Trans. Autom. Sci. Eng.*, vol. 12, no. 3, pp. 1033–1046, Jul. 2015.

[147] J. Su, H. Qiao, C. Liu, Y. Song, and A. Yang, "Grasping objects: The relationship between the cage and the form-closure grasp," *IEEE Robot. Autom. Mag.*, vol. 24, no. 3, pp. 84–96, Sep. 2017.

[148] Q. Lei and M. Wisse, "Object grasping by combining caging and force closure," in *Proc. 14th Int. Conf. Control, Autom., Robot. Vis.*, Phuket, Thailand, Nov. 2016, pp. 1–8.

[149] T.-H. Kwok *et al.*, "Rope caging and grasping," in *Proc. IEEE Int. Conf. Robot. Autom.*, Stockholm, Sweden, May 2016, pp. 1980–1986.

[150] S. Makita and W. Wan, "A survey of robotic caging and its applications," *Adv. Robot.*, vol. 31, no. 19/20, pp. 1071–1085, 2017.

[151] N. C. Dafle *et al.*, "Extrinsic dexterity: In-hand manipulation with external forces," in *Proc. IEEE Int. Conf. Robot. Autom.*, Hong Kong, May 2014, pp. 1578–1585.

[152] N. C. Dafle, "Regrasping objects using extrinsic dexterity," in *Proc. IEEE Int. Conf. Robot. Autom.*, Hong Kong, May 2014, pp. 2560–2560.

[153] M. T. Ciocarlie and P. K. Allen, "Hand posture subspaces for dexterous robotic grasping," *Int. J. Robot. Res.*, vol. 28, no. 7, pp. 851–867, Jun. 2009.

[154] J. Takahashi, T. Fukukawa, and T. Fukuda, "Passive alignment principle for robotic assembly between a ring and a shaft with extremely narrow clearance," *IEEE/ASME Trans. Mechatronics*, vol. 21, no. 1, pp. 196–204, Jun. 2016.

[155] T. Fukukawa, J. Takahashi, and T. Fukuda, "Precise assembly of ring part with optimized hollowed finger," *ROBOMECH J.*, vol. 3, no. 1, 2016, Art. no. 16.

[156] H. Park, J. Park, D. H. Lee, J. H. Park, M. H. Baeg, and J. H. Bae, "Compliance-based robotic peg-in-hole assembly strategy without force feedback," *IEEE Trans. Ind. Electron.*, vol. 64, no. 8, pp. 6299–6309, Aug. 2017.

[157] M. Erden and T. Tomiyama, "Human-intent detection and physically interactive control of a robot without force sensors," *IEEE Trans. Robot.*, vol. 26, no. 2, pp. 370–382, Apr. 2010.

[158] A. Pistillo, S. Calinon, and D. G. Caldwell, "Bilateral physical interaction with a robot manipulator through a weighted combination of flow fields," in *Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst.*, San Francisco, CA, USA, Sep. 2011, pp. 3047–3052.

[159] B. Yao, Z. Zhou, L. Wang, W. Xu, and Q. Liu, "Sensor-less external force detection for industrial manipulators to facilitate physical human–robot interaction," *J. Mech. Sci. Technol.*, vol. 32, no. 10, pp. 4909–4923, Oct. 2018.

[160] A. Bicchi and A. Marigo, "Rolling contacts and dexterous manipulation," in *Proc. IEEE Int. Conf. Robot. Autom. Symp. Proc. (Cat. No.00CH37065)*, San Francisco, CA, USA, 2000, vol. 1, pp. 282–287.

[161] M. T. Zhang and K. Goldberg, "Gripper point contacts for part alignment," *IEEE Trans. Robot. Autom.*, vol. 18, no. 6, pp. 902–910, Dec. 2002.

[162] M. Gabiccini, E. Farnioli, and A. Bicchi, "Grasp and manipulation analysis for synergistic underactuated hands under general loading conditions," in *Proc. IEEE Int. Conf. Robot. Autom.*, Tokyo, Japan, 2012, pp. 2836–2842.

[163] F. Chen, L. Carbonari, C. Canali, M. Dimperio, and F. Cannella, "Design of a novel dexterous robotic gripper for in-hand twisting and positioning within assembly automation," *Assem. Autom.*, vol. 35, no. 3, pp. 259–268, 2015.

[164] Q. Xu, *Micromachines for Biological Micromanipulation*. Basel, Switzerland: Springer, 2018.

[165] P. Wang, S. Yang, and Q. Xu, "Design and optimization of a new compliant rotary positioning stage with constant output torque," *Int. J. Precis. Eng. Manuf.*, vol. 19, no. 12, pp. 1843–1850, Nov. 2018.

[166] X. Zhang and Q. Xu, "Design and testing of a novel 2-DOF compound constant-force parallel gripper," *Precis. Eng.*, vol. 56, pp. 53–61, Mar. 2019.

[167] R. Li, W. Wu, and H. Qiao, "The compliance of robotic hands—From functionality to mechanism," *Assem. Autom.*, vol. 35, no. 3, pp. 281–286, 2015.

[168] C. Ma, H. Qiao, R. Li, and X.-Q. Li, "Flexible robotic grasping strategy with constrained region in environment," *Int. J. Autom. Comput.*, vol. 14, no. 5, pp. 552–563, Jul. 2017.

[169] C. Rosales, R. Suarez, M. Gabiccini, and A. Bicchi, "On the synthesis of feasible and prehensile robotic grasps," in *Proc. IEEE Int. Conf. Robot. Autom.*, Saint Paul, MN, USA, May 2012, pp. 550–556.

[170] A. Bicchi, M. Gabiccini, and M. Santello, "Modelling natural and artificial hands with synergies," *Philos. Trans. Roy. Soc. B, Biol. Sci.*, vol. 366, no. 1581, pp. 3153–3161, 2011.

[171] M. Santello *et al.*, "Hand synergies: Integration of robotics and neuroscience for understanding the control of biological and artificial hands," *Phys. Life Rev.*, vol. 17, pp. 1–23, 2016.

[172] J. Schultz, G. Mathijssen, B. Vanderborght, and A. Bicchi, "A selective recruitment strategy for exploiting muscle-like actuator impedance properties," in *Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst.*, Hamburg, Germany, 2015, pp. 2231–2237.

[173] K. Kiguchi, K. Watanabe, K. Izumi, and T. Fukuda, "A humanlike grasping force planner for object manipulation by robot manipulators," *Cybern. Syst.*, vol. 34, no. 8, pp. 645–662, 2003.

[174] M. Abdeetedal and M. R. Kermani, "Grasp synthesis for purposeful fracturing of object," *Robot. Auton. Syst.*, vol. 105, pp. 47–58, Jul. 2018.

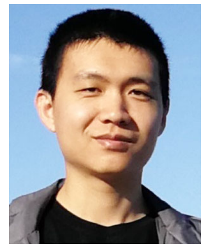
[175] A. Bicchi and D. Prattichizzo, "Analysis and optimization of tendinous actuation for biomorphically designed robotic systems," *Robotica*, vol. 18, pp. 23–31, 2000.

[176] S. Shirafuji, S. Ikemoto, and K. Hosoda, "Development of a tendon-driven robotic finger for an anthropomorphic robotic hand," *Int. J. Robot. Res.*, vol. 33, no. 5, pp. 677–693, Feb. 2014.

[177] J. M. Inouye and F. J. Valero-Cuevas, "Anthropomorphic tendon-driven robotic hands can exceed human grasping capabilities following optimization," *Int. J. Robot. Res.*, vol. 33, no. 5, pp. 694–705, 2014.

[178] N. Rahman, L. Carbonari, M. Dimperio, C. Canali, D. G. Caldwell, and F. Cannella, "A dexterous gripper for in-hand manipulation," in *Proc. IEEE Int. Conf. Adv. Intell. Mechatronics*, Banff, AB, Canada, 2016, pp. 377–382.

[179] J. Chen, S. Zhong, E. Kang, and H. Qiao, "Realizing human-like manipulation with a musculoskeletal system and biologically inspired control scheme," *Neurocomputing*, vol. 339, pp. 116–129, Apr. 2019.



Rui Li received the B.Eng. degree in automation engineering from the University of Electronic Science and Technology of China (UESTC), Chengdu, China, in 2013, and the Ph.D. degree from the Institute of Automation, Chinese Academy of Science (CASIA), Beijing, China, in 2018.

He is currently a Postdoctoral Researcher with Informatics 6, Technical University of Munich, Munich, Germany. His research interests include intelligent robot system and high-precision assembly.

Hong Qiao (SM'06–F'18) received the B.Eng. and M.Eng. degrees from Xi'an Jiaotong University, Xi'an, China, in 1986 and 1989, respectively, the M.Phil. degree from the University of Strathclyde, Strathclyde, U.K., in 1997, and the Ph.D. degree from De Montfort University, Leicester, U.K., in 1995.

She is currently a "100-Talents Project" Professor with the State Key Laboratory of Management and Control for Complex Systems, Institute of Automation, Chinese Academy of Sciences (CASIA), Beijing, China. She proposed the concept of the attractive region in environment (ARIE) in strategy investigation, which was reported in *Advanced Manufacturing Alert*. Her current research interests include robotic manipulation, robotic vision, bioinspired intelligent robot, brainlike intelligence, etc.