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Review

# State-of-the-Art control strategies for robotic PiH assembly

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ABSTRACT

Nowadays, industrial robots have been widely applied for performing position-controlled tasks with minimum contact such as spot welding, spray painting, packing, and material handling; however, performing high-tolerance assembly tasks still poses a great challenge for robots because of various uncertainties of the parts to be assembled such as fixtures, end effector tools, or axes. From this perspective, the advancement of research and development has led to cutting-edge robotic technologies for industrial applications. To understand the technological trend of industrial robots, investigated the state-of-the-art robotic assembly technologies to identify the limitations of existing works and clarify future research directions in the field. This paper especially interested on typical peg-in-hole (PiH) assemblies, as PiH methods provide insights for further development of robot assemblies. The assembly control strategies for PiH operations is classified by based on the types and features of the assemblies, and the literature in terms of the contributions of these studies is compared to PiH assembly. Finally, the control strategies for robotic PiH assemblies are discussed in detail, and the limitations of the current robotic assembly technologies are discussed to identify the future direction of research for the control of robotic assembly.

## 1. Introduction

Towards the fourth industrial revolution or Industry 4.0, manufacturing is facing new challenges in the ever-changing dynamic and competitive environment [1–3]. During production, assembly operations account for 50% and 30% of the total time and cost of the entire production cycle, respectively [4–8]. The process is labor intensive because of the specificity of the environment and the stringent requirements for quality [9–12]. Robots form an ideal solution for assembly operations and are widely used for high-efficiency and high-quality industrial production [13–19]. However, due to the unstructured and dynamic environment of the assembly work, the assembly robot still needs many problems to be solved, such as: low sensing capability, high assembly environment requirements, poor assembly adaptability, low assembly efficiency, and inability to complete complicated assembly of complex environments [20–25]. As a result, the assembly robot is still unable to completely replace the human assembly. As one of the key technologies of assembly robots, control strategy plays a decisive role in the process of automated assembly [26,27]. Therefore, it is very meaningful to study the control strategy of assembly robots.

Various types of assembly robots have been proposed to perform different assembly tasks [28–30]. Nowadays, the assembly efficiency of robots is enhanced by integrating of machine vision [31,32], sensor technology, computer simulation technology [33–36], and artificial intelligence [37–42]. The characteristics of existing assembly robots include high precision, good flexibility, and large working range, and the manipulator end-effector of these robots is capable of performing various complicated assembly tasks.

The development of compliant control technology has created conditions for robotic assembly tasks in which the robot can adjust the posture on a specific planning trajectory to achieve compliance with the environment [43,44]. In contrast with robots that perform grinding and polishing tasks, in which they only need to control force, and robots that perform welding and handling tasks, in which they need to control the position [45,46], robots that perform assembly tasks need to control both the force and position while performing tasks [47–49]. The development of sensing detection and control technologies has also improved the intelligent sensing of assembly robots. Thus, not only the position control accuracy but also the visual and force perception of robots has been improved, thus enabling the robots to better sense and adapt to the external environment and improve the assembly process during industrial production [44]. Assembly robot technology is still rapidly developing. At present, various researchers worldwide have

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been studying assembly robot control strategies with the aim to make assembly robots more flexible, intelligent, and diversified [50–53]. This has important implications for studies on automated assembly techniques. Therefore, it is necessary to summarize the control strategies for assembly robot.

Currently, peg-in-hole (PiH) assembly is the most typical task in assembly processes, accounting for approximately 40% of the total assembly task. The shapes of the peg and hole vary [45], including simple shape [54,55], complex shape, micro PiH [56,57], ring-type, and flexural peg [38,58–60]. PiH assembly is characterized by repeatability and monotonous work tasks. Furthermore, problems of force and position control caused by surface contact of the PiH still exist, and the assembly tolerance is relatively complicated [61]. Many researchers have studied PiH assembly [45,46]. In addition, studies on PiH assembly are important for developing robot assembly technology, which is important and critical [62,64]. Therefore, the control strategies for PiH assembly in this study are reviewed and the existing problems and future development trends of robot assembly technology are discussed.

In this review, a systematic survey in PiH is conducted to identify the limitations of current studies and clarify promising research directions in this field. The rest of the paper is organized as follows. In Section 2, the robotic assembly for PiH is discussed. In Section 3, the development of robotic control strategies is surveyed, and these strategies are classified into four categories, i.e., passive compliance mechanisms, active compliance control, auxiliary technologies, and machine learning algorithms. In Section 4, the strategies for the optimization of control parameters are investigated. In Section 5, existing studies on error compensation strategies are discussed. Finally, an overview of existing theories and methods for the control of PiH assemblies is provided, and the future directions in the field of robotic assemblies are discussed.

## 2. Robotic assembly process

As shown in Fig. 1, a robotic assembly process is divided into four phases: (a) Approaching phase, (b) Searching phase, (c) Moving phase, and (d) Orientating phase. The PiH is assembled by a robot following certain control strategies [61–63]. The robot is equipped with sensors for images, forces, and contact states, and the feedback received by the sensors is processed and utilized in a closed-loop robotic control [42–46]. The robot then refines its position and orientation based on the sensor feedback until PiH assembly is completed [52–55]. However, the difficulties faced by PiH assemblies depend on the shapes of pegs and holes, which can be classified into *simple shape* [54,55], *complex shape, micro-scale shape* [56,57], *ring shape*, and *flexural shape* [38,58–60]. Fig. 1 also illustrates the geometries of these types of pegs and holes.

## 3. Peg-in-hole assembly control methods

### 3.1. Passive compliant mechanisms

In a passive compliant mechanism, the robot relies on a supplemental mechanism to generate natural compliance with external forces when the end-effector tool makes contact with an object in the environment [69–71]. However, the compliance device is passive; this means that the device is not adaptable and has no self-learning capability. Artificial intelligence (AI) algorithms can be used together with passive compliance devices to enhance the adaptable of assembly robot [72,73].

For example, Yun proposed using a gradient descent algorithm for passive compliant joints in PiH assemblies [72]. Each compliant joint in a manipulator was equipped with a series elastic actuator (SEA) so that it could passively adapt to the environment. The positional and force errors were quantified by a cost function in the gradient descent algorithm. Park et al. [69] enhanced the compliance device by Yun [72] by replacing the remote center compliance (RCC) equipment with programmable compliance equipment, in which springs and dampers could be programmed. Such an improvement addressed some issues in dual-arm PiH assemblies related to limited resolutions or precisions to detect

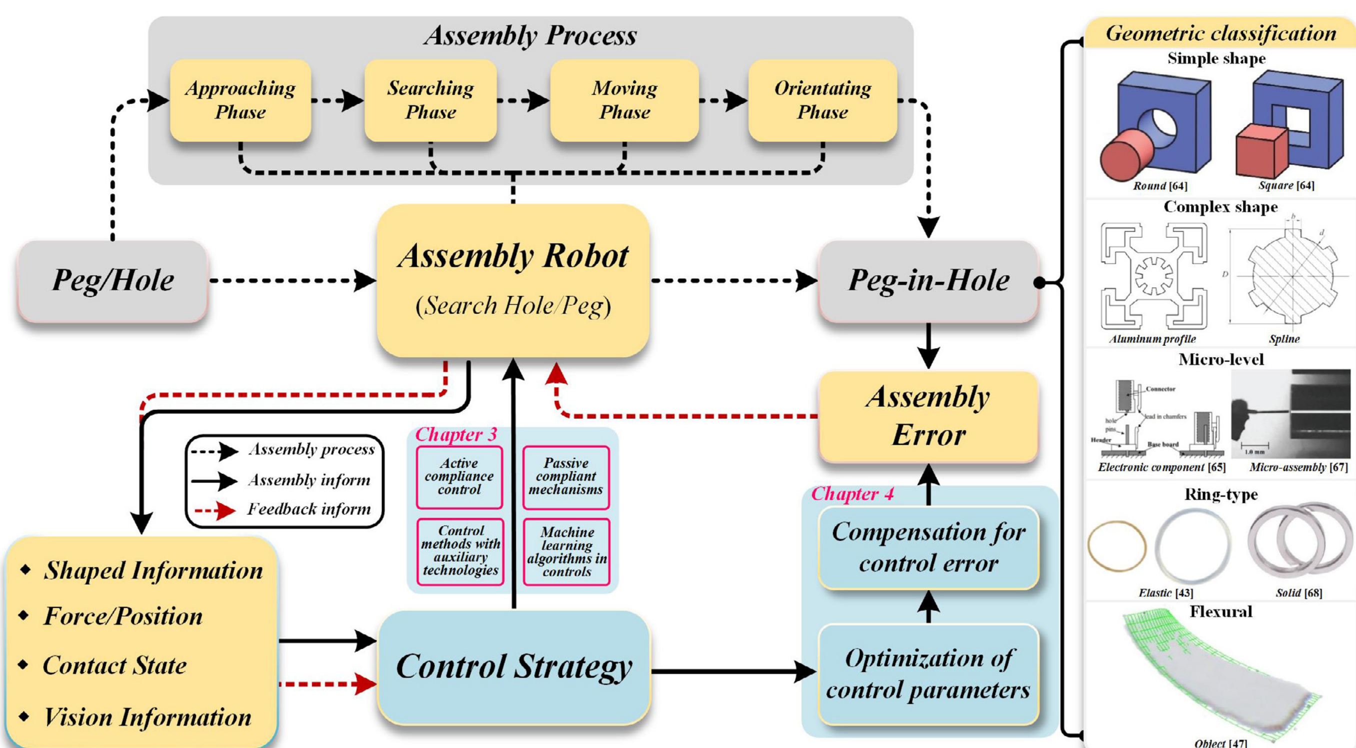



**Fig. 1.** Schematic of robotic assembly process and geometric classification.

an interference or gap in an unstructured environment. Labrecque et al. designed a low-impedance manipulator called uMan for human–robot cooperation using under-actuated redundancies [70]. The researchers proposed two specific criteria for cooperative robots, which are minimizing the impedance and eliminating nonlinear impedance. These two specific criteria enable the operator to naturally adapt to handling or assembly procedures, and the minimized impedance can improve the safety of the operator during autonomous motion of the robot. uMan involved a large radius Chebyshev parallelogram (LRCP) which was able to achieve intuitive and tiny operations. The characteristic of uMan of fast and low-impedance interactions within constrained or unconstrained environments is improved by the LRCP. The LRCP enables the operator to complete all work in the manipulative space [70].

Quek et al. designed a six degrees of freedom (DOF) haptic device; it simulated the deformation of the human finger with skin deformation modes on finger pads [71]. The force and torque of the device were delivered by translating and rotating skins. The results showed that participants can utilize tactile sensors to reduce interaction force and interaction torque. Notably, the participants utilized the tactile force cues to reduce interaction force more than they used the tactile torque cues to reduce interaction torque. The main cause of this result is that skin deformation torque cues may be less intuitive than skin deformation force cues [71].

It is difficult to simulate human touch; moreover, selecting control variables even if the touch can be simulated by a device is a difficult task. Therefore, the value and accuracy of the control variables will largely depend on the sensors and devices. An anthropomorphic robot arm without extra sensors or devices has also been designed previously [74]. An assembly robot with three fingers was proposed to perform the PiH assembly in an experiment, and the "intuitive peg-in-hole strategy" was proposed [74]. Fukukawa et al. aimed to improve the precision of assembly for ring-type parts and designed a manipulator with parallel 3-fingers to maximize the closed volume of a workspace [73]. Using the proposed control strategy, robots could complete precise assemblies of ring-type parts in an open-loop control mode. The geometry and mechanical conditions of the ring assembly were optimized for a hollow shape. Table 1 summarizes the existing work on passive compliant mechanisms studied till date.

### 3.2. Active compliance control

Active compliance control measures the contact force/torque and feeds back it to the controller to generate the desired trajectory of the robot end effector [75]. Active compliant control helps overcome the shortcomings of passive compliant control. Therefore, active compliant control has a very broad application prospect [76]. According to the characteristics of implementation, active control strategies can be divided into two categories: (1) impedance control strategies and (2) hybrid force/position control strategies.

#### 3.2.1. Impedance control

To successfully perform PiH assembly successfully, impedance control is applied on the adjustable parameters relevant to the positions, velocities, and their dynamic relationships in a real-time mode.

Tom Tsumugiwa used impedance control for a collaborative robot to help the operator locate the assembly position of the PiH [77].

The human-robot cooperative task includes a carrying task and a fitting task. The variable impedance control and compensation control, based on position control and torque control, respectively, for deadweight and friction of the robot are opposed in the paper [75]. Mol et al. developed a nested admittance/impedance control strategy that involved a force sensor to alleviate some shortcomings of pure impedance controls [75]. Fig. 2 showed the architecture of the impedance control with force sensors; the results showed that the maximum acceptable offset angle was 13 times higher and the constraints and torque were five times lower than those of pure impedance control.

Impedance control is an efficient method for handling robot force control and has been widely studied because of its low computational complexity and strong robustness [78–82]. It can be combined with algorithms and devices for assembly of parts with complex shapes. For example, Song et al. used the computer-aided design (CAD) model of complex parts to control the force and position of the robot [78]. Similarly, to deal with flexible rubber objects, Jasim et al. [79] proposed an integrated method called the model-free robust adaptive control (MFRAC) strategy, based on the adaptive fuzzy system, sliding mode control, and common Lyapunov functions. The experiments showed that the MFRAC strategy was effective for assembly of flexible pegs even when the model and impedance parameters were uncertain. Korpela et al. explored the feasibility of performing PiH assemblies for aircraft components [80]. They developed kinematic and dynamic models of robots implementing impedance control. Cho et al. developed a disturbance observer to measure and estimate the torque disturbance of a joint subjected to external forces [81]. The torque disturbance was converted to the force and torque by the Jacobi matrix in the Cartesian space. At the same time, the expectant impedance was characterized by considering both the servo position and the actual reference position. The impact of friction can be reduced by utilizing the information from the disturbance observer, which was proved by the PiH experiment [82].

#### 3.2.2. Hybrid force/position control

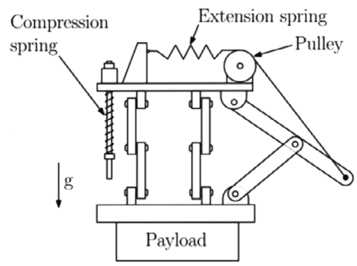
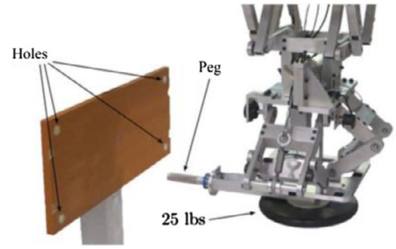
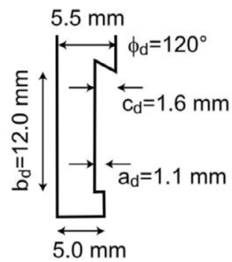
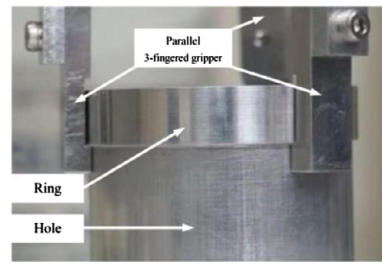
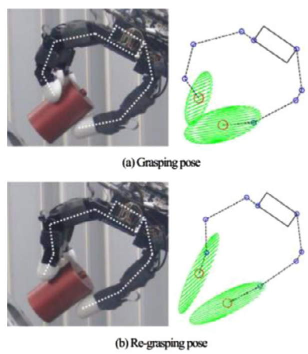
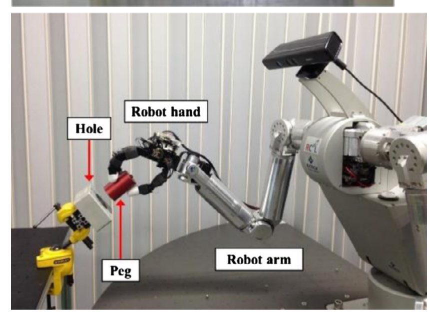
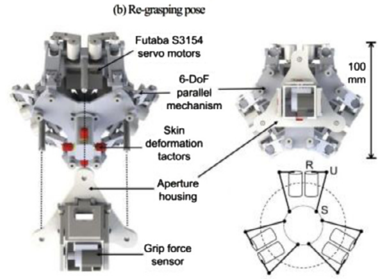
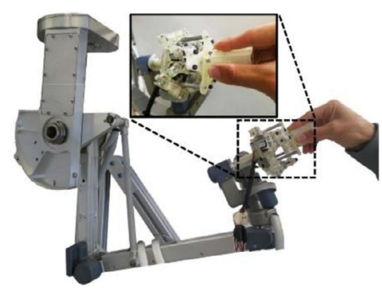
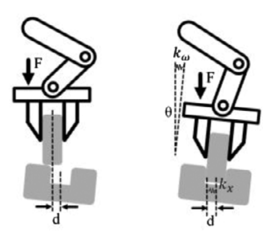
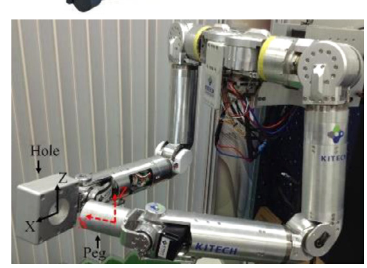
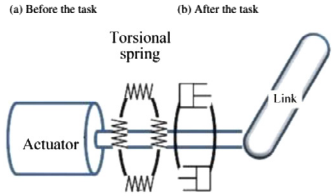
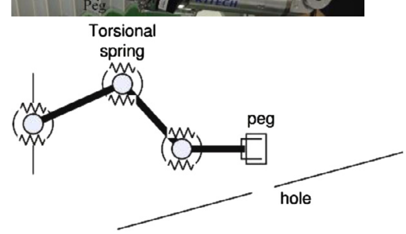
So far, hybrid force/position control has shown great potential for robotic force control; an obvious feature is that the force and position are taken into consideration simultaneously [83].

The potential of hybrid force/position control has been proven theoretically; however, its practical implications still face some difficulties [82,83]. To enhance the control outcomes, researchers have made great efforts to combine genetic algorithms, adaptive algorithms, and fuzzy controls with hybrid force/position controls [84–86].

Wang et al. proposed a hybrid force/position control strategy to replace the respective force and position controls [85]. In their implementation, a fuzzy sliding mode joint impedance controller (FSMJIC) was applied to merge the vision and force feedback to improve robotic control. Mario Farrugia also designed a generic controller for flexible assembly in which six transputers were used to build a processor network for providing generic control [84].

The software was embedded in the hardware system to perform the PiH experiment. The design of a hybrid force/position controller is not an easy task since force control has to be integrated with the algorithm of searching for the hole. Bdiwi et al. investigated a solution where a charging plug was engaged in a number of charging interfaces [87]. An infrared vision system was applied to position the robot according to the peg, and 5-hole assemblies were accomplished by force control. Hole positions were found by a spiral algorithm to improve system efficiency. Park introduced an intuitive assembly strategy (IAS) inspired by human behaviors [86], which combined position control with the passive compliance control during PiH assembly. Searching of holes was accomplished by the spiral algorithm. Korpela et al. developed the mobile manipulating unmanned aerial vehicle (MM-UAV) control system for assembly of aircraft products [80,88]. The control strategies of MM-UAV are based on visual servo and force feedbacks. The reaction forces of motors are captured and compensated to ensure the stability of the aircraft based on the kinematics and dynamic models of the aircraft. For micro-level assembly, Ravi K. Jain developed a micromanipulation system using hybrid force/position control and an ionic polymer metal composite (IPMC) [89], in which the micro-level assembly featured a large displacement, ill-defined magnitude of force, and need of offset compensation. These aspects were tackled by the proposed system. Fig. 3 shows a schematic layout of the micromanipulation system for PiH assembly. In addition, Table 2 gives a summary of existing works on active compliance control based on time sequence.

**Table 1**
Summary of literature on passive compliant mechanisms.

<table>
<tr><th>Publication, Year</th><th>Characteristics</th><th>Schematic diagram [69–74]</th><th>Assembly process diagram [69–74]</th></tr>
<tr><td>Labrecque et al. [70], 2017</td><td>❖ Underactuated redundancy macro-mini manipulator<br>❖ Large radius Chebyshev parallelogram (LRCP)<br>❖ Minimized impedance<br>❖ Elimination of nonlinear impedance<br>❖ Decoupling of human and robot dynamics</td><td>
</td><td>
</td></tr>
<tr><td>Fukukawa et al. [73], 2016</td><td>❖ Maximizes the closed area in the interference graph<br>❖ Parallel 3-finger-shaped manipulator<br>❖ Ring assembly strategy<br>❖ No sensor feedback</td><td>
</td><td>
</td></tr>
<tr><td>Park et al. [74], 2015</td><td>❖ "Intuitive peg-in-hole strategy"<br>❖ Anthropomorphic hand arm robot<br>❖ Anthropomorphic assembly process</td><td>
</td><td>
</td></tr>
<tr><td>Quek et al. [71], 2015</td><td>❖ Six degrees of freedom haptic device<br>❖ The device can simulate the deformation of the human finger<br>❖ Application of skin deformation cues</td><td>
</td><td></td></tr>
<tr><td>Park et al. [69], 2014</td><td>❖ Virtual spring programming<br>❖ Optimizes the original RCC equipment<br>❖ Can solve dual-arm PiH assembly in tiny assembly environment</td><td>
</td><td>
</td></tr>
<tr><td>Yun [72], 2008</td><td>❖ Gradient descent learning method<br>❖ Passive compliance arm manipulator (Series elastic actuators)<br>❖ Function reflects the error of the position and force<br>❖ Fast and stable learning conditions</td><td>
</td><td>
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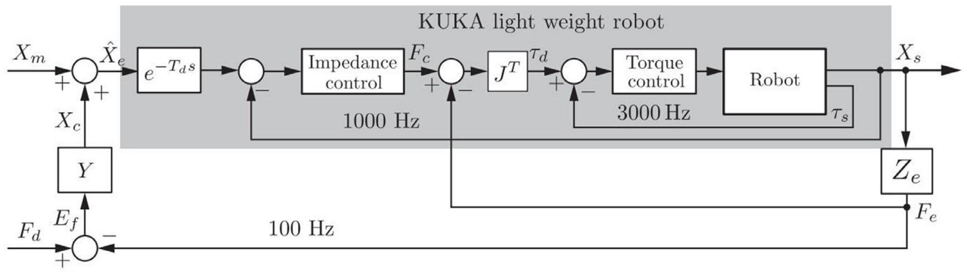



**Fig. 2.** Impedance control architecture with outer admittance control loop with delay [75]
(Here, $Z_e$ denotes the environment, $\tau_d$ represents the desired torque, $\tau_s$ is the measured torque in the inner torque control loop of the slave robot, and $X_s$ is the output position of the robot).

### 3.3. Control methods with auxiliary technologies

To increase the flexibility of a robot to deal with the complexity of assembling operations, auxiliary technologies can be integrated with an assembly robot. However, classic control strategies still play an important role in the process of robotic assembly tasks [51,81]. The existing control methods have been improved by auxiliary devices, which further expands the application range of these above control methods [51–53,90]. In this paper, *an auxiliary technology* refers to control strategies and methods used to assist PiH assemblies by introducing auxiliary devices. The auxiliary devices include leap motions [50], haptic systems [51], visions [52], trajectory planners [53] and kinesthetic guidance [91]. Correspondingly, the software must reflect the changes in control models and algorithms. The virtual assembly can be beneficial for completely utilizing auxiliary devices to improve the efficiency of assembly.

#### 3.3.1. Auxiliary devices

Numerous auxiliary devices have been introduced to improve the flexibility of assembly robots. For examples, the Leap motion was used to capture human hand postures, so that a robot could imitate hand movements [50]. The new sensor-less observer was proposed as an auxiliary device to assist a robot to perform assembly processes [81].

Takahashi et al. proposed a control method to assemble ring-type parts. To solve the problem of deformation during ring-type assembly, a novel mating technique based on the passive alignment principle (PAP) has been proposed [68]. PAP was able to correct the ring position and minimize the deformation of the ring to the nanoscale. The elasticity of ring-type parts was also analyzed by Alpizar et al. [50]. They proposed a new strategy to deal with a deformable object when it was inserted into the cylindrical peg by a dual-arm robot; a leap motion controller was used to determine the robotic trajectory based on the captured movement of the human hand. Fig. 4 showed the assembly processes and the experimental setup.

A robotic path is defined based on a number of key points. Polverini et al. proposed a trajectory generator to obtain robotic trajectory in a real-time mode for PiH assembling [53]. A sensor-less observer was developed and optimized against the specified admittance and constraints. However, this method had a limitation in dealing with geometric uncertainties, which were common in the assemblies of complex parts. Hyunchul Cho also developed an observer which was used to measure the disturbance of joint torque subjected to external forces [81]. The disturbance was converted to force and torque by the Jacobi matrix in the Cartesian space. Fig. 5 shows a schematic of such a control system.

Panzirsch et al. developed a multi-master-single slave (MMSS) tactile teleoperation system for a dual-robot [51]. This system comprised several modular subsystems; it sustained the stability of the system, which could be extended to other applications with similar requirements of stability. Jain et al. designed the M$^4$S for PiH assembly at the micro-level [90]. The system comprised micro grippers that could assemble micro-level parts by a 3-DOF mobile micromanipulation system. Accordingly, a new algorithm was proposed to assemble micro-scale parts with the satisfied productivity and accuracy. Tao et al. [52] reported a similar system with active zooming to solve the problems caused by small depth of focus and narrow field of view; the system

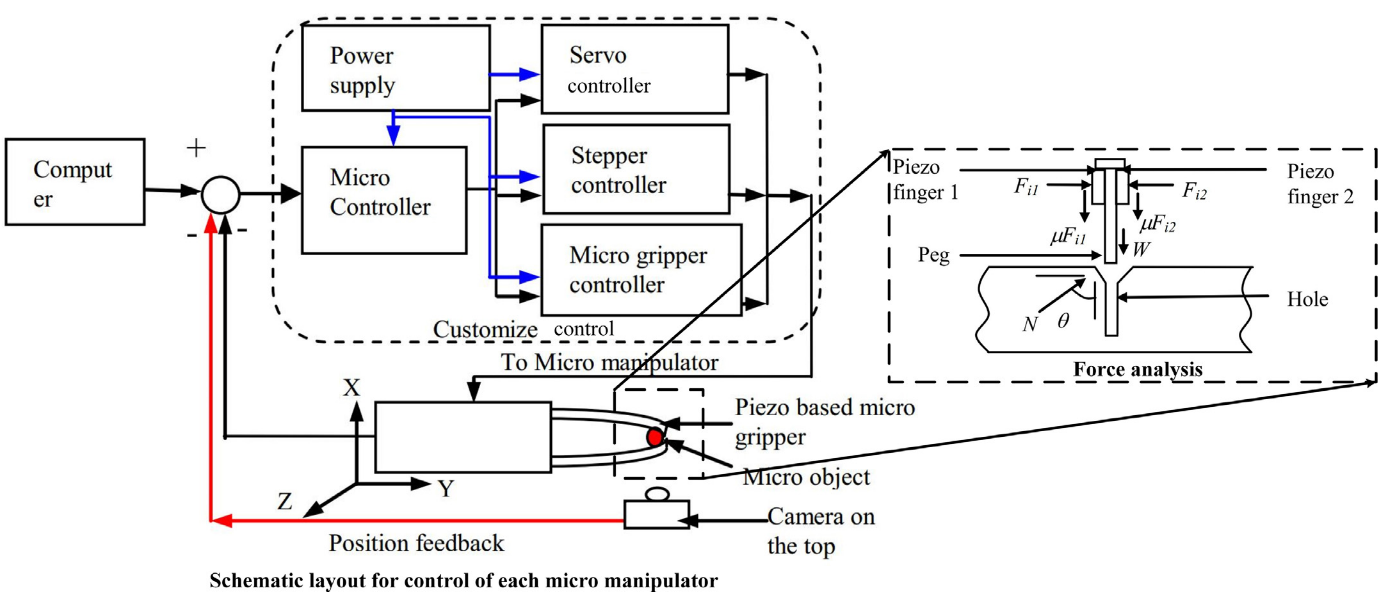



**Fig. 3.** Control schematic of micro-manipulator [89].

**Table 2**
Overview of active compliance control.

| Control Type | Publication, Year | Strategy and approach | Main Contribution | Type |
|---|---|---|---|---|
| **Impedance Control** | Mol et al. [75], **2016** | ❖ Nested admittance/impedance control strategy | ❖ Nested admittance-impedance controller<br>❖ Actively estimated and minimized the effects of geometric misalignment<br>❖ Rotational misalignment (maximal acceptable misalignment 20°) can be adjusted<br>❖ Closed-loop force sensor based nested admittance/impedance control strategy<br>❖ Improved the robustness and performance of the PiH task | *Simple* |
| | Jasim et al. [79], **2015** | ❖ Model-free robust adaptive control (MFRAC) | ❖ Flexible assembly strategy<br>❖ Could be applied for dynamic, arbitrary impedance control | *Flexural* |
| | Song et al. [78], **2014** | ❖ Force control based on visually-obtained geometric information and CAD models | ❖ Geometrically complex PiH assembly strategy<br>❖ Compensates for position and orientation errors in complex PiH | *Complex* |
| | Cho et al. [81], **2014** | ❖ Disturbance observer<br>❖ Jacobi matrix transforms into force and torque in the Cartesian space<br>❖ Impedance controller designed in Cartesian space | ❖ Reduced the friction on robotic sensitivity<br>❖ A sensor-less force control algorithm for industrial robots<br>❖ Observers measure and estimate the disturbance torque | *Simple* |
| | Korpela et al. [80], **2013** | ❖ Kinematics and dynamics modeling<br>❖ Force feedback<br>❖ Impedance control<br>❖ OpenRAVE robotics virtual environment | ❖ Exploration of aircraft assembly<br>❖ Generated kinematic solutions and robot trajectories<br>❖ Analyzed the disparity between PiH and other assemblies | *Simple* |
| | Song et al., [78] **2003** | ❖ Impedance control based on position<br>❖ Classification strategy of cooperative task | ❖ Human-computer cooperation task control method<br>❖ Compensates the robot for its own weight and friction torque based on torque control | *Simple* |
| | Wang, [85] **2016** | ❖ Force/position hybrid control with visual information<br>❖ Fuzzy sliding mode joint impedance control (FSMJIC) | ❖ Visual information enhances the ability of compliance<br>❖ Integrated visual and force information<br>❖ Effectively reduced the impact of environment constraints<br>❖ Solved the chattering problem of the drive controller | *Simple* |
| | Bdiwi et al. [87], **2015** | ❖ Position strategy based on visual and infrared information<br>❖ Force control combined with spiral algorithm | ❖ Reduced the assembly error caused by visual sensors<br>❖ Completed the assembly of the 5-pin industrial charger plug | *Simple* |
| Force/Position Hybrid Control | Farrugia, [84] **2015** | ❖ Transputer network (Six computer parallel processing performance) | ❖ Built a common force sensor<br>❖ Proposed a generic controller for flexible assembly | *Simple* |
| | Korpela et al. [88], **2014** | ❖ Visual servo system<br>❖ Force feedback<br>❖ Mobile manipulating unmanned aerial vehicle (MM-UAV) | ❖ Aircraft assembly strategy<br>❖ Captured and compensated for force<br>❖ Determined the dynamic model and controller | *Simple* |
| | Park [86], **2013** | ❖ Intuitive assembly strategy (IAS)<br>❖ Hybrid force/position control<br>❖ Passive compliance control<br>❖ Assembly strategy inspired by human behavior | ❖ Precise location of the hole is not required<br>❖ Completed PiH assembly with a multi-DOF manipulator | *Simple* |
| | Jain [89], **2013** | ❖ Ionic polymer metal composite (IPMC) micro manipulator | ❖ Developed a multi-micro operating system<br>❖ Micro PiH assembly strategy | *Micro-level* |

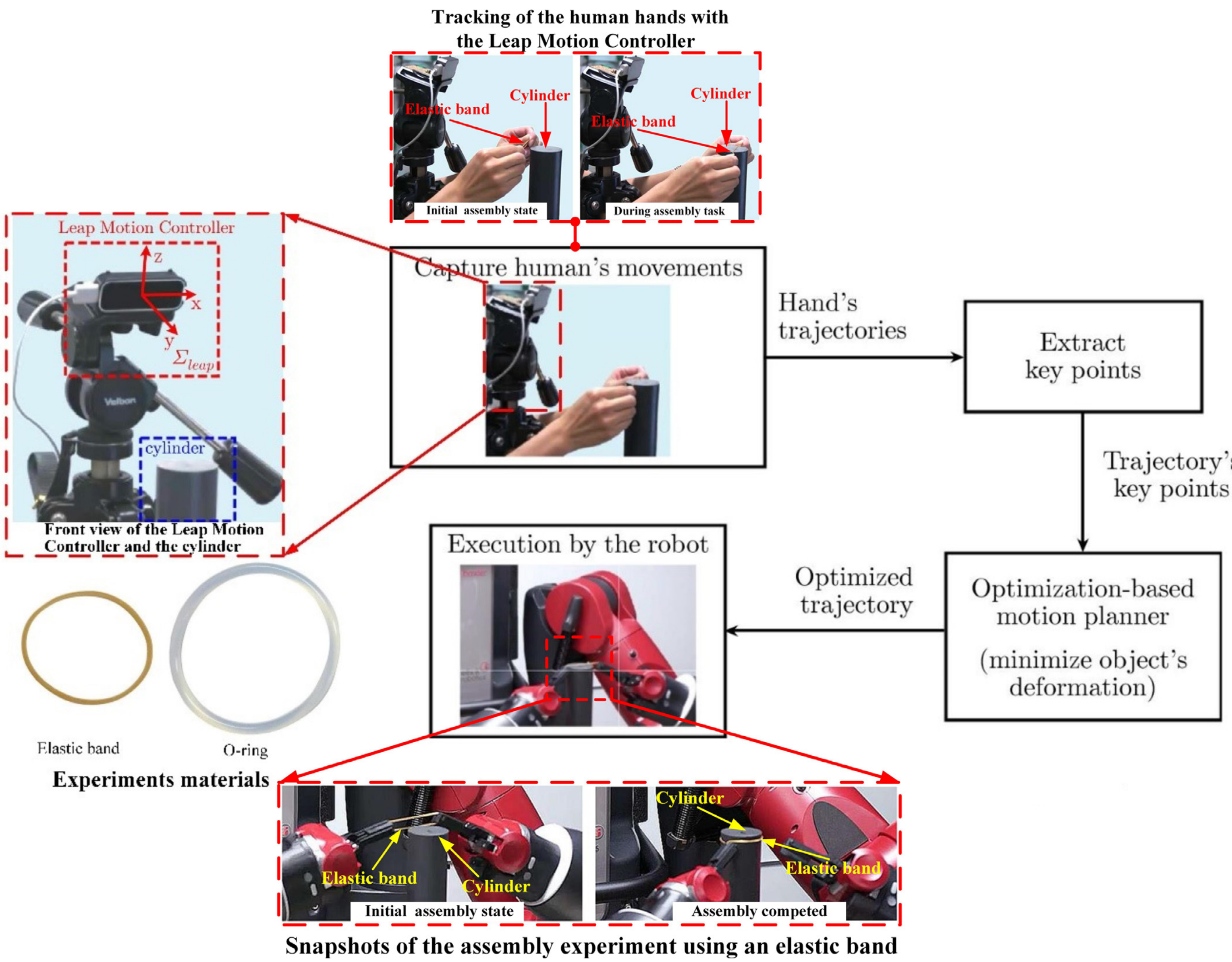



**Fig. 4.** Assembly processes and experimental setup [50].

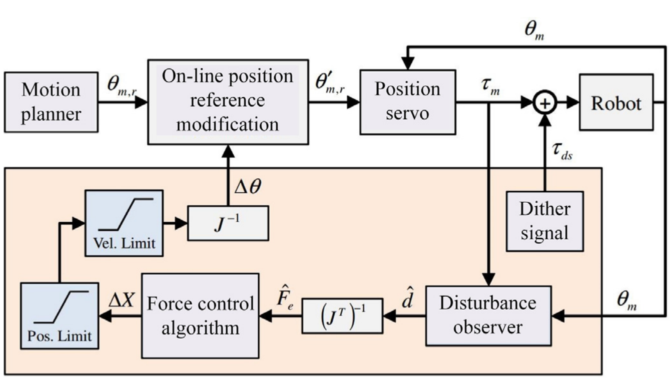



**Fig. 5.** Block diagram of the force-control system proposed by Cho [81] (Here, $\theta_{m,r}$ stands for desired trajectory using the on-line position reference modification block, $\theta'_{m,r}$ stands for the updated position reference, $\tau_m$ denotes motor input torque, $\theta_m$ is the link angle of the '$m$' motor the environment, $\tau_{ds}$ is a dither signal to reduce the effect of friction on the control performance, $\hat{d}$ is the estimated disturbance, $\hat{F}_e$ is external force, $\Delta X$ stands for incremental position reference, $\Delta\theta$ stands for incremental joint angle).

supported the zooming lens for fuzzy measurement of moving targets so that the robot was able to acquire a clear view of the image. Fischer et al. [91] compared robotic programming techniques using teleoperation, control panels, and kinesthetic guidance based on the criteria of efficiency, effectiveness, and usability; they concluded that kinesthetic guidance provided the best control for users, but the level of difficulty of the operations was increased when complex or large assembly was involved.

Savarimuthu et al. also utilized a teleoperated approach to perform PiH assembly experiments with different starting configurations to obtain the grasping data in an assembly environment. According to analysis of the grasping data generated by operators, an assembly strategy was proposed with the aim to derive a strategy for performing operators' actions by a robot [92,93]. A six-DOF robotic arm and a flexible 3 finger SDH-2 gripper are installed in the robot (Fig. 6).

### 3.3.2. Models auxiliary technologies

Bodenhagen et al. presented a control model for the assembly of flexural objects [58]. The trajectory was parameterized to a 1-D function with respect to length, and a physical model was developed to represent the elastic behaviors of the object. Furthermore, Bodenhagen et al. extended the control model to make their assembly system adaptable by combining visual tracking, model reconstruction, and deformable physical modeling in planning of PiH and lay-down operations [59]. The manipulation system and four modular components are shown in Fig. 7.

Yanchun et al. investigated the control approach for the assembly of deformable objects [60] based on analysis of the deformation field, geometrics, and dynamic constraints. To simplify the analysis, a

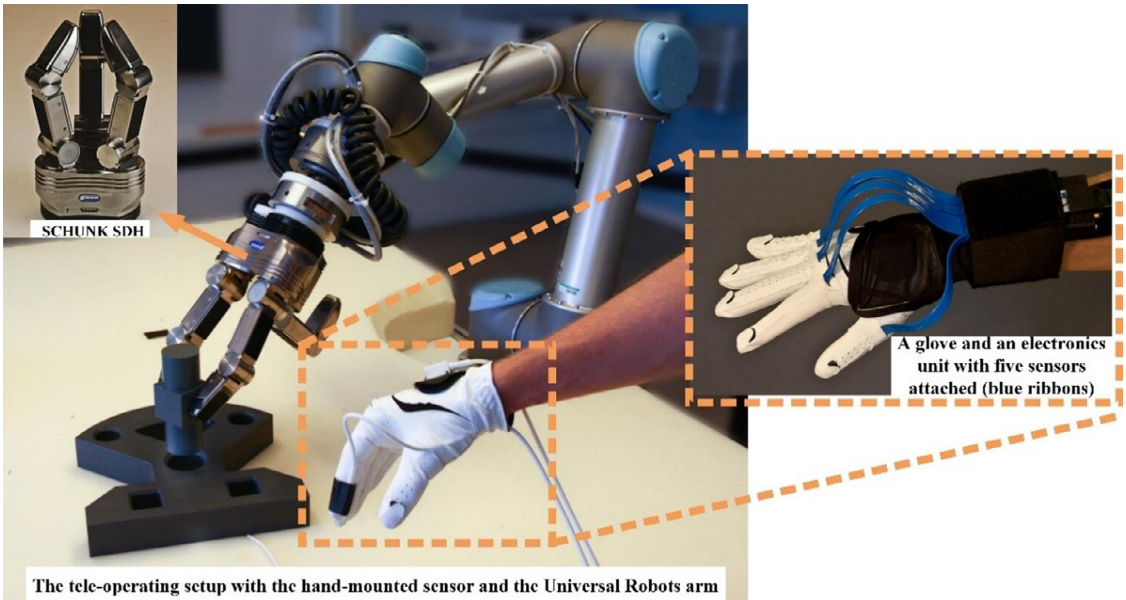



**Fig. 6.** Assembly process and glove [92, 93].

flexural peg was considered as the beam. Vision information and CAD models were used to define robotic paths for the assembly of complex parts [53]. The profile of complex objects was represented by a number of key points. The geometric uncertainties of a peg or hole might increase the difficulty of control even if their shapes are simple. To tackle the shape uncertainty while assembling, Chung et al. proposed the use of force feedback in the absence of fixtures [61]. The assembly process was modelled as a petri net, which was then used to identify conditions and relations of contacts. Yong Lee et al. also applied the petri net to describe the contact states of objects in the PiH assemblies of L-shaped parts [38]. The proposed petri net was augmented and could be generated automatically for an assembly frame [38]. This proposed control also allowed the online adaptation of assembly models to accommodate new conditions. Fig. 8(a) shows a schematic diagram of the online model adaptation. The petri net of the assembly model was initialized automatically by merging and extending two original models from initial contact and targeted contact. The reachability graph saved the latest assembly sequence and searched for an optimal sequence. Fig. 8(b) shows an expansion of the reachability graph. This model could be evolved into a robust model with respect to time. Table 4 summarizes the major studied on auxiliary technologies in robotic assemblies ordered by dates.

### 3.3.3. Virtual assembly technologies

Virtual assembly is an integrated technology that combines CAD, visualization, modeling and simulation, virtual reality (VR), decision support systems, and assembly modeling [33,34]. In virtual assembly, a virtual environment (VE) is used to represent the real-world assembly environment, and assembly is simulated interactively by the assembler by the means of VR [35,36,94]. The feasibility of virtual PiH assemblies with a focus on contact relations of pegs and holes has been studied. The limitations of virtual assembles, which are mainly related to human factors, have also been discussed. Leu et al. discussed the technical gap of virtual assembly based on CAD models [95]; their emphasis was on the data exchange between CAD system and VR system.

Due to superior versatility and interactivity, haptic devices are widely used in virtual assembly. Lim et al. verified the performance of virtual assembly using haptic devices with force feedbacks [96]. To improve the interaction between haptic device and users, Tching et al. defined kinematic constraints in the virtual assemblies of PiH

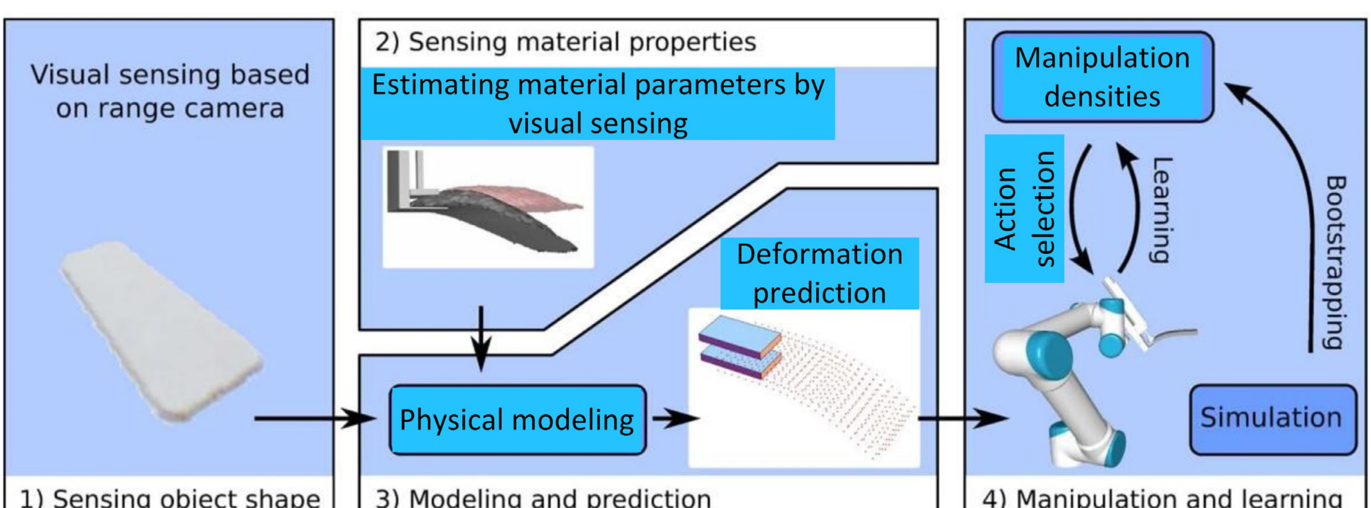



**Fig. 7.** Manipulation system and four modular components by Bodenhagen et al. [58].

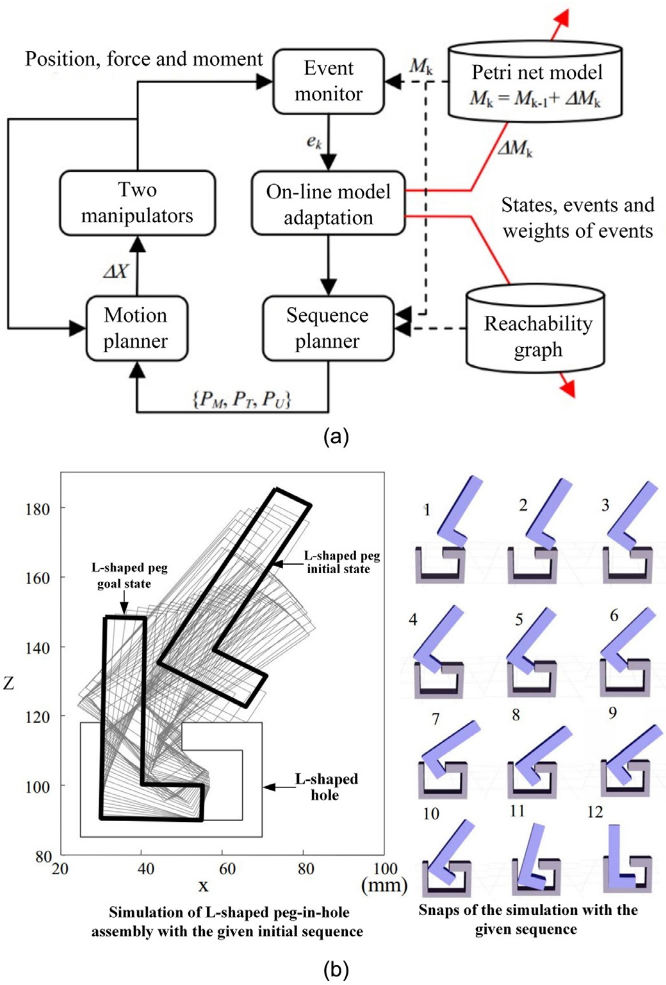



**Fig. 8.** Augmented petri net for modeling of robotic assemblies by Lee et al. (a) Online model adaptation; (b) simulation: automatic generation of the petri-net assembly model with a given initial sequence [38]. (Three sets of primitive contacts $\{P_M, P_T, \text{and } P_U\}$ that are primitive contacts to be maintained, primitive contacts to be acquired, and primitive contacts to be avoided, respectively; model $M_k$ is updated using $\Delta M_k$ whenever new states and events are generated; $k$ stands for step).

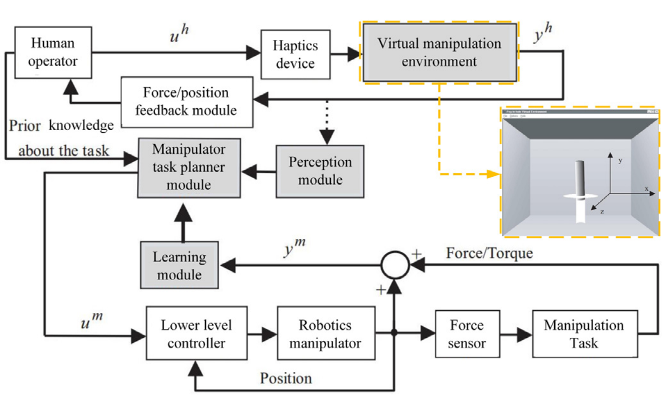



**Fig. 9.** Overall system model by Chen et al. [94].

operations and presented the virtual constraint guidance (VCG) to operate haptic devices [97]. VCG treated peg and hole geometries as virtual fixtures to guide robotic motion. The experiment proved the feasibility of using virtual assembly to implement robotic assembly; using active kinematic constraints relevant to objects geometries assisted users to perform insertion tasks. Chen et al. proposed a skill acquisition algorithm to transfer human manipulation skills into a robotic system [94]. The assembly robot could acquire the data regarding positions and contact forces/torques in the virtual environment, and the collected data could be converted to actual robotic trajectories during implementation. Fig. 9 illustrated the overall model of the system.

Dong et al. demonstrated virtual assemblies using the haptic device [98]. The competitive agglomeration (CA) algorithm and fuzzy maximum likelihood estimation (FMLE) algorithm were used to detect the states of the pegs and holes during operation. The clusters in the optimum cluster set were tuned using locally weighted regression (LWR), which was used to predict the outcomes of robotic trajectory based on the force/position feedback from the rig. Sagardia and Hulin discussed some technical bottlenecks while investigating visual, haptic, and audio feedback modalities of the virtual assembly process [56]. The experiments showed that the discrepancies between virtual and actual contact forces were a critical challenge while utilizing haptic feedback. Fig. 10 shows the generic setup of the virtual assembly model.

Lee et al. evaluated the performance of the haptic guidance and emphasized on the impact of inaccuracy of haptic guidance on the teleoperation system in a nuclear power plant [99]. Haptic guidance within the tolerance of inaccuracy was able to reduce operation time, contact force, and total force since the operator was guided to an optimal path, whereas an increase in inaccuracy affects the outcome of haptic guidance. Ullah et al. invited ten volunteers to form five groups, and volunteers in each group controlled a robot to perform PiH assembly cooperatively [100]; their results revealed that haptic guides improved the sense of co-presence and awareness of users significantly. Gromov et al. also investigated virtual assemblies using a dual-arm robot [101]. As shown in Fig. 11(a), they studied the multiple-master/multiple-slave setup using two 7-DOF Schunk LWA-3 robots for PiH assemblies. Two SensAble PHANToMs were utilized to capture the information regarding forces of the operator, and the Gazebo simulator and the robot operating system (ROS) were integrated to realize PiH virtual assembly (Fig. 11(b)).

For the purpose of multi-part assemblies, Wei Gao simulated assembly operations in a virtual environment, and human factors including the visibility of an assembling part, posture, reachability, and fatigue of an operator were quantified [102]. The results showed that this assembly method that considers human factors provides a realistic simulation of assembly operations in the virtual space and can help realize a high consistency between virtual and real assembly processes. To make the assembly simulation more realistic, Gao et al. developed a novel approach to analyze and evaluate the assemblability and assembly sequence [103]. Quantitative evaluation of component assemblability (CA) was performed according to the assembly time and assembly trial time. A product assemblability (PA) evaluation system was established based on the assemblability of each component, and the assembly sequence was optimized according to the PA evaluation results. At each step, the position, attitude, and motion parameters of the assembling part were obtained through calculated dynamic equations, so that it could accurately simulate real-world interactions with virtual parts, along with their physical behavior and properties.

To solve the PiH assembly of an MM-UAV, Korpela et al. explored a rotorcraft emulation environment using a seven-DOF manipulator [104]. To reduce the significant setup time of UAVs and avoid potential crashes, the gantry system is modeled after the systems integrated sensor test rig (SISTR) and is called mobile manipulating -SISTR (MM-SISTR). The researcher proposed solutions to deal with the control precision and equipment requirements of micro PiH assembly; however, virtual assembly provides a novel solution for micro assembly [104]. J. Cecil and James Jones developed the virtual reality based environment for micro assembly (VREM) to realize rapid assembly of micro PiH and an interface with physical micro assembly environments [39]. It comprised a collaborative cyber-physical integrator, an assembly plan generator, a manual planning module, an assembly analysis module, and a command generator module. The collaborative

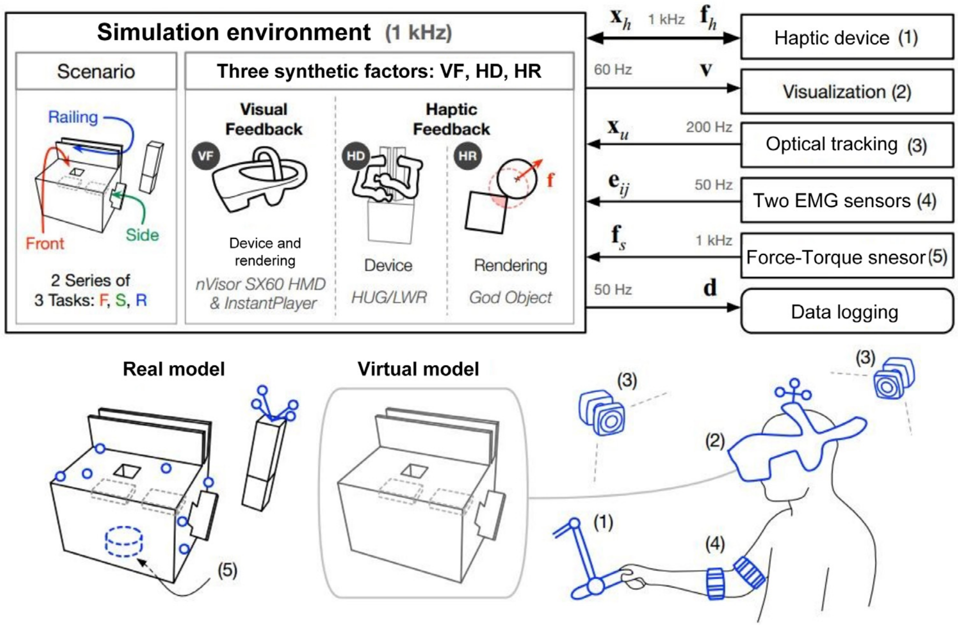



**Fig. 10.** Setup of generic virtual assembly model by Sagardia et al. [56].

cyber-physical integrator and the assembly plan generator formed key parts of the VREM.

Along with the development of VR systems, similar technologies called augmented reality (AR) and mixed reality (MR) have been applied to robotic micro PiH assemblies. The National Cheng Kung University combined AR with VR to solve problems associated with micro PiH assembly [57]. By utilizing the image from the AR system, the performances of manual and automatic assembly were compared. In the manual micro assembly test, AR was used to enable the human operator to perform the micro assembly operation with a success rate of 80%. In the automatic PiH micro assembly, the localization of the micro peg and assembly hole was performed by employing CCD1 (CCD, charge coupled device) and CCD2 in the AR system, which reduces the time spent by utilizing CCD3 in the visual servo and improved the automatic assembly efficiency. Fig. 12 shows the alignment operations of image-based AR micro-assembly. Table 3 provides a summary of existing works on virtual assembly strategies based year of publication.

### 3.4. Machine learning algorithms in controls

Machine learning specializes on how computers simulate or implement human learning behaviors to acquire new knowledge or skills and reorganize existing knowledge structures to continuously improve their performance [31, 42]. In the case of PiH assembly tasks, the corresponding models were trained by machine learning algorithms and data, and then the assembly capabilities of the robot were enhanced using this model. Machine learning can be divided into supervised and unsupervised learning, and learning by demonstration (LbD) is the most typical form of supervised learning [105,106].

LbD has gradually shifted from service-oriented robots to industrial robots [107–109], and the robots can learn new behaviors through demonstration instead of machine command programming. Motion capture is an important part of LbD [105]. Verner et al. developed a system to add additional grip freedom to the three-DOF phantom haptic device master. A four-DOF telemanipulator comprises two Phantom

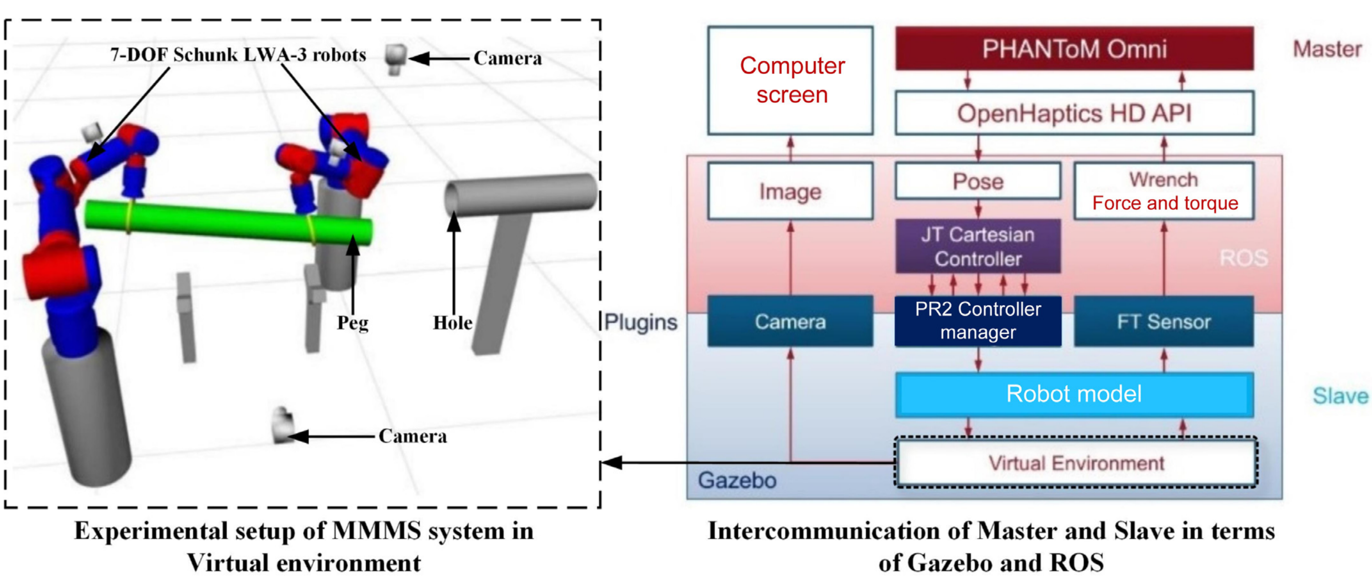



**Fig. 11.** Setup of virtual assembly system by Gromov et al. [101].

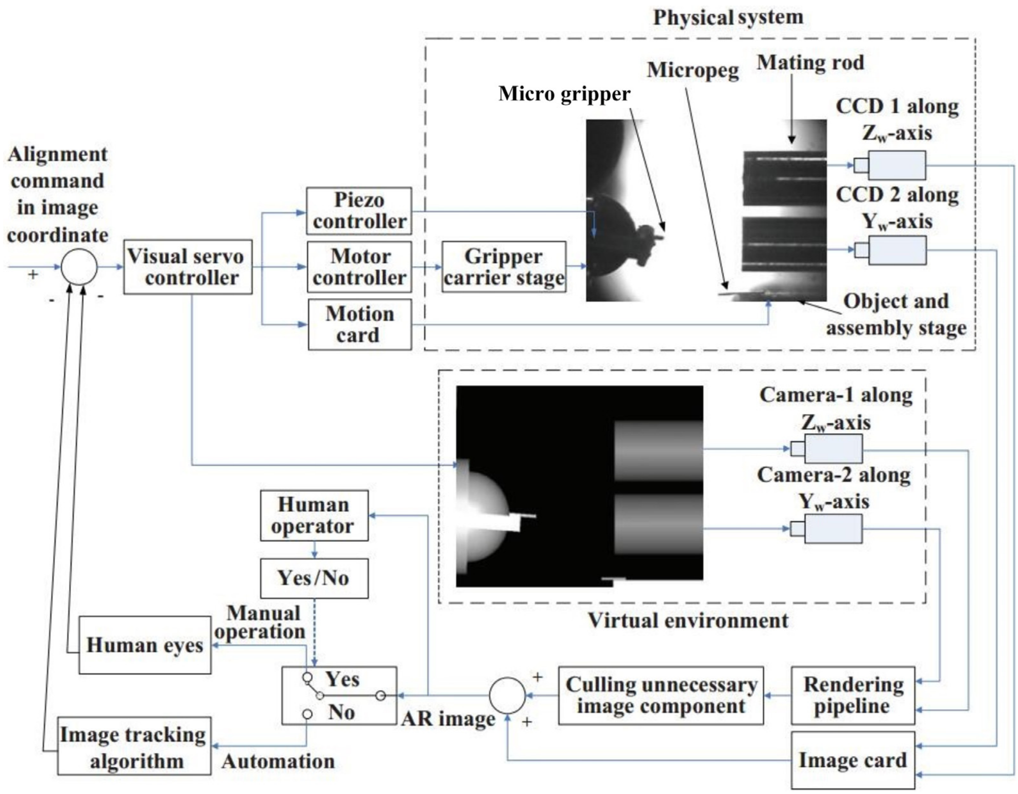



**Fig. 12.** Alignment operation of image-based AR micro-assembly [57].

haptic devices and an attachable clamping mechanism to realize force feedback [110]. In this paper, the experiment task is to grasp a rectangular foam “peg” and insert it into rectangular holes in a foam block. Researcher set four feedback conditions: 1) Full force feedback, 2) Translational force feedback only, 3) Gripping force feedback only, and 4) No force feedback. The purpose of this experiment is to evaluate how partial force feedback influences user performance during assembly tasks. Experiment result show that force feedback does significantly affect the average applied translational force and the average applied gripping force, but does not significantly affect the assembly time.

A novel policy learning and adaptation algorithm was developed by Nemec et al. for robots to adapt the trajectory in automated assembly tasks [41]. This algorithm uses the dynamic movement primitives (DMP) framework as the underlying representation of peg-in-hole insertion trajectories. Initial trajectories and force/torque were replicated by human demonstration, thus leading to the robot repeatedly adapting to the environment configurations. Admittance or impedance control was used to adapt to the required force, and the algorithm reduced the error of force/torque during the assembly process. Ajoudani et al. proposed a novel concept of Tele-impedance, which inspired by human's neuro-motor strategies for impedance control. Tele-Impedance algorithm that replicates the human's arm endpoint stiffness in robot by controlling the common-mode and confguration-dependant stiffness. Efficiency of proposed approach to cope with contact stability issues is evaluated in a Peg-in-Hole task. The impedance algorithm used common-mode and configuration-dependent stiffness control to replicate the stiffness of the robotic arm joints, which is adjusted according to the human joint and robot assembly errors [111, 112]. Fig. 13 shows the experiment equipment.

Pervez et al. proposed a novel learning from demonstration approach based on dynamic movement primitives (DMPs) to handle less consistent, asynchronized and incomplete demonstrations with large spatial and temporal variations, demonstration with different starting/ending phases and partial demonstrations of the task [40]. A new expectation maximization (EM) algorithm was proposed, which estimates the parameters and phase variables of the Gaussian mixture model (GMM) based on EM. The algorithm was tested and validated using multiple peg-in-hole assembly experiments on remote control systems with discrepancies in DOF.Kramberger et al. compared three LbD methods including kinesthetic guiding, haptic device, and magnetic tracker [105]. In this paper, the assembly trajectory of the three methods is calculated, and PiH assembly task is divided into the following five steps: a) Start configuration; b) initial contact; c) alignment of the peg and base; d) applying force to ensure, and e) the final contact; applying final rotation. While performing the assembly task arising $F_x$, $F_y$, and $F_z$ were recorded. The result shows that not all methods are suitable for a certain task like the PiH task. The experiment assembly involved a simple shaped PiH, and the result demonstrate that kinesthetic guiding is the best method among these three learning methods.

Robot teaching and robot learning are necessary processes for application of industrial robots, but work stations have to be stopped when robots perform teaching and learning, thus reducing manufacturing efficiency [113]. To solve this problem, Cheng et al. proposed a method involving ‘adult’ robots and ‘children’ robots, wherein the ‘adult’ robot could learn, was mobile, and was equipped with a calibration visual system [113]. The ‘children’ robots were supervised by the ‘adult’ robots and could complete assembly tasks without pausing the work process. The whole assembly process contains four subtasks: primitive motion learning, offline robot learning, online robot teaching and compliant assembly, which accomplish a successful robot teaching and assembly process. A partial observable Markov decision process was established using the successive approximation of the reachable space under optimal policies algorithm and was introduced to increase system flexibility and complete calibration without human operation. Fig. 14 illustrates the overall assembly process.

Okodi et al. proposed a method that could generate high-speed constrained compliance robots using controlled kinematics [114]. Using a non-structured teaching environment, the PiH task in the captured demonstration force and position data is estimated and reconstructed from three sets of complimentary models, including

**Table 3**
Overview of auxiliary technologies.

| Auxiliary type | Publication, year | Principle and approach | Main contribution | Type |
|---|---|---|---|---|
| **Auxiliary Devices** | Jain et al. [90], **2017** | ❖ Multi-mobile micromanipulation systems<br>❖ Bimorph piezoelectric actuator | ❖ Multiple robotic assembly strategies<br>❖ Complete multiple robotic assemblies in a limited space | *Simple* |
| | Ramirez Alpizar et al. [50], **2017** | ❖ Leap motion<br>❖ Human demonstration<br>❖ Capture hand motion to generate key points | ❖ Assembly strategy of ring-shaped deformable objects<br>❖ Reduce the deformation of ring according to generated key points | *Ring-Type* |
| | Fischer et al. [91], **2016** | ❖ Comparison of three-type programming by demonstration (teleoperation, control panel and kinesthetic guidance) | ❖ Experiment results:<br>1.Long teleoperation operation time;<br>2.Control panel is intuitive, the best sense of control;<br>3.Speed of kinesthetic guidance is fast, error low | *Complex* |
| | Polverini et al. [53], **2016** | ❖ Admittance control strategy<br>❖ Real-time trajectory generator | ❖ Robot assembly speed is close to human assembly speed<br>❖ Force/torque sensors not required in assembly process | *Simple* |
| | Takahashi et al. [97], **2016** | ❖ Passive alignment principle (RAP)<br>❖ Close tolerances fit<br>❖ Hertz contact stress | ❖ Ring assembly strategy<br>❖ RAP corrects the position at nanoscale level and removes ring deformation | *Ring-Type* |
| | Panzirsch et al. [51], **2015** | ❖ Multi-master-single-slave haptic teleoperation system<br>❖ Creates virtual crawling points in the Cartesian framework | ❖ Dual-arm robot assembly strategy<br>❖ Divides system into several subsystems | *Simple* |
| | Cho et al. [81], **2014** | ❖ Disturbance observer<br>❖ Force and torque in Jacobi matrix are transformed into Cartesian space<br>❖ Utilizes high frequency dither signal | ❖ Reduces the friction on robotic sensitivity<br>❖ Observers measure and estimate the disturbance torque | *Simple* |
| | Savarimuthu et al. [92, 93], **2013, 2015** | ❖ A glove unit with five sensors<br>❖ Six-DOF robotic arm and 3 fingers SDH-2 gripper<br>❖ Robot operating system<br>❖ Trajectory of grasped object | ❖ A standing peg and a down peg are analyzed<br>❖ According to the posture of peg, feasible grasp strategy is determined | *Simple* |
| | Tao [52], **2005** | ❖ Active zoom microassembly strategy<br>❖ Control zoom lens based on ambiguous measurement of moving targets<br>❖ Visual servoing | ❖ Solves the depth of focus and the small field of view<br>❖ The rough visual servo and fine visual servo are discussed to prove that the strategy is feasible | *Micro-Scale* |
| **Auxiliary Model** | Song et al. [78], **2014** | ❖ Impedance control combined with vision and CAD models<br>❖ Guidance algorithm based on geometric information | ❖ Complex PiH assembly strategy<br>❖ Compensates for position and orientation errors<br>❖ Assembly strategy is simpler than existing methods | *Complex* |
| | Bodenhagen et al. [59], **2014** | ❖ Visual tracking<br>❖ Shape reconstruction<br>❖ Physical modeling of the materials and model deformation | ❖ Adaptable and flexible PiH assembly strategy<br>❖ Completes large deformation of flexible peg | *Flexural* |
| | Bodenhagen et al. [58], **2012** | ❖ Established physical elasticity model<br>❖ Kernel density estimation | ❖ Parameterizes trajectory of flexible peg<br>❖ Performs assembly process by learning mechanism | *Flexural* |
| | Yanchun et al. [60], **2010** | ❖ Elastic long peg is considered as a beam<br>❖ Based on hypothesis of material, mechanism, and deformation of the elastic long peg | ❖ Analyzes geometrical deformation of peg<br>❖ Simplification and assumption of flexible peg<br>❖ Flexible assembly strategy | *Flexural* |
| | Lee et al. [48], **2007** | ❖ Augmented petri net assembly model<br>❖ Reachability graph of assembly model | ❖ Petri net will be expanded to a strong model based on the initial contact state<br>❖ Searches the best sequence of assembly<br>❖ Complex PiH assembly strategy | *Complex* |
| | Chung et.al. [38], **2001** | ❖ Force feedback of the active assembly strategy<br>❖ Petri net model<br>❖ Discrete event system | ❖ Recognizes the contact and contact relationships by the petri net, and the robot predicts the next step of PiH | *Simple* |

(*continued on next page*)

**Table 3** (*continued*)

| Auxiliary type | Publication, year | Principle and approach | Main contribution | Type |
|---|---|---|---|---|
| **Virtual Assembly Technologies** | Lee et al. [99], **2017** | ❖ Haptic guidance<br>❖ Haptic teleoperation | ❖ Nuclear power environment<br>❖ Evaluates the effectiveness of tactile guidance<br>❖ Measures assembly time and guidance performance | *Simple* |
| | Sagardia and Hulin [56], **2017** | ❖ Visual feedback<br>❖ Haptic device<br>❖ Haptic rendering<br>❖ Virtual manipulations | ❖ Discusses the bottleneck of tactile feedback virtual assembly simulation<br>❖ Assembly feedback sources are replaced with 5 aspects (haptic device, visualization, optical tracking, two EMG sensors, and force torque sensors) | *Simple* |
| | Gao et al. [102], **2016** | ❖ Real world model<br>❖ Desktop virtual assembly prototype system<br>❖ Physics-based assembly | ❖ Human factors, human posture, and other behaviors are quantified<br>❖ Solves the impact of human factors in virtual assembly | *Simple* |
| | Chang [57], **2016** | ❖ Static augmented reality (AR) and dynamic AR system<br>❖ Features are reconstructed by computer aided design (CAD) | ❖ Reconstructed the hidden feature of the mating hole in the peg<br>❖ Solves the speed differences between the virtual environment and the actual system<br>❖ Save the time of micro PiH assembly | *Micro-level* |
| | Korpela et al., [104] **2014** | ❖ Mobile manipulating systems integrated sensor test rig<br>❖ Mobile manipulating unmanned aerial vehicle | ❖ Solve aircraft assembly problems<br>❖ Captures and compensates reaction force on the rotor<br>❖ Simulation of seven-DOF arm assembly in virtual assembly | *Simple* |
| | Cecil and Jones [49], **2014** | ❖ Virtual reality based environment for micro assembly<br>❖ Genetic algorithm | ❖ Complete the analysis of micro PiH before the assembly process in virtual environment<br>❖ Increase the speed assembly of micro devices | *Simple* |
| | Gao et al. [103], **2014** | ❖ Force-guided motion navigation<br>❖ Component assemblability and Product assemblability | ❖ Evaluate CA based on assembly time<br>❖ Simulate the interaction between real parts and virtual parts<br>❖ Quantitative measurements of CA and PA | *Simple* |
| | Gromov [101], **2012** | ❖ Two seven-DOF Schunk LWA-3 robots<br>❖ SensAble PHANToM<br>❖ Robot operating system (ROS) | ❖ Achieve dual robots' collaborative assembly<br>❖ The information of force can be displayed to the operator<br>❖ Combined with ROS in the process of virtual operation | *Simple* |
| | Tching et al. [97], **2010** | ❖ Haptic simulation and haptic guidance<br>❖ Virtual constraint guidance (VCG) | ❖ Virtual assembly through haptic control<br>❖ Proves the feasibility of VCG with operator assembly | *Simple* |
| | Ullah et al. [100], **2010** | ❖ Virtual environment technology<br>❖ Two parallel robot cooperation | ❖ Two volunteers collaboratively operate the robot to complete the PiH assembly task<br>❖ Simple force feedback for the best operator performance<br>❖ Increases the sense of collaboration and awareness | *Simple* |
| | Chen et al. [94], **2007** | ❖ Virtual manipulation environment<br>❖ Manipulator task planner module<br>❖ Skill acquisition algorithm | ❖ Obtain the robot assembly parameters through the virtual environment and proposed algorithm<br>❖ Developed perception models in virtual environment | *Micro-level* |
| | Lim et al. [96], **2007** | ❖ Force feedback tactile devices based on quantitative data | ❖ PiH assembly is divided into pick, place, movement in the virtual environment for simplification of the assembly process<br>❖ Evaluate PiH assembly performance under geometry and force | *Simple* |
| | Dong et al. [98], **2006** | ❖ Competitive agglomeration (CA)<br>❖ Fuzzy maximum likelihood estimation algorithm<br>❖ Locally Weighted Regression (LWR) | ❖ Proposed a robot controller programming demonstration method<br>❖ The data are used to classifier train CA in virtual environment<br>❖ LWR adjusts the optimal parameters based on weight | *Simple* |

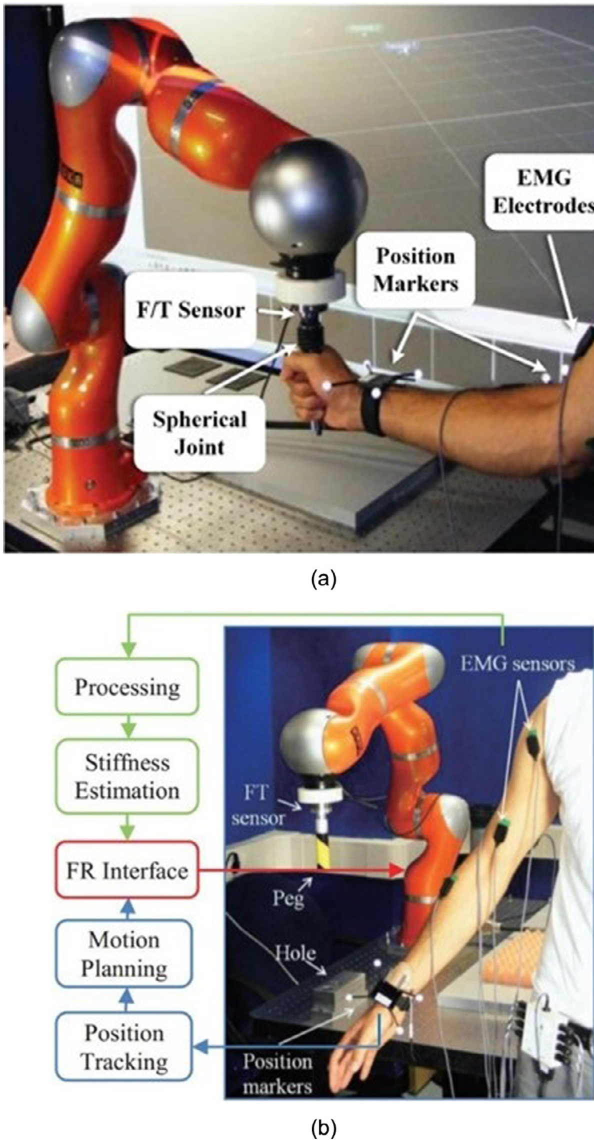



**Fig. 13.** (a) Experimental setup (b) Experimental setup used for calibration experiments [111, 112].

analytical mathematical modeling, empirical modeling and human skill demonstration modeling. The demonstration force and location data were estimated and reconstructed by mathematical modeling, empirical modeling, and human skill modeling in an unstructured teaching environment. To help the robot imitate human skills, the effect of human skill was studied through the analysis of contact forces.

However, the ability of deep learning is also required in unsupervised robot assemblies. Neural networks are the most widely applied machine learning algorithms. Cortesão et al. proposed the data fusion architecture of robot assembly tasks based on human sensory motor skills [37]. Artificial neural networks (ANNs) were introduced in the learning process, which consisted of two separate modules for optimal blending and filtering. The data fusion architecture was combined with Kalman techniques related to the evolution of stochastic signals. Experimental setup includes three subtasks: a) PiH assembly task done by a human; b) Human use a teach device to complete PiH assembly, and force, velocity, and pose are recorded, representing the human skill, and c) assembly robot perform the PiH assembly task after the human–robot skill transfer. The assembly motion signals obtained from the visual and postural sense are fused into the data fusion architecture to enhance the performance of the PiH assembly.

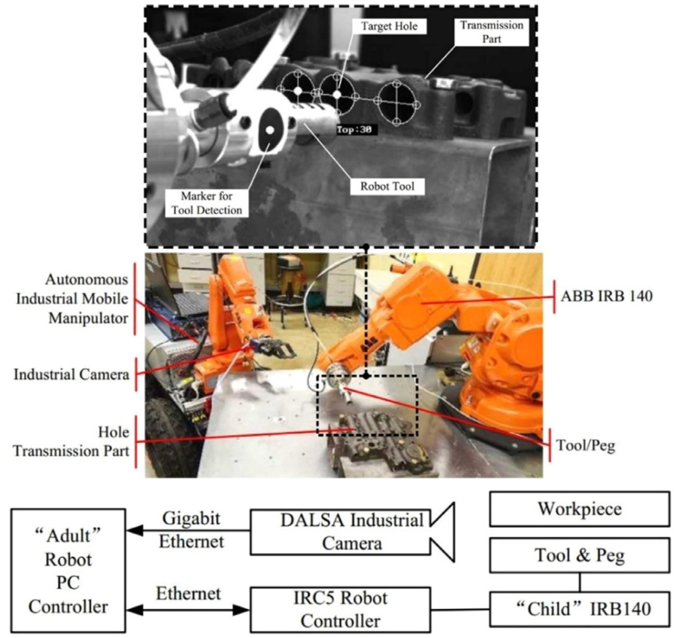



**Fig. 14.** The ‘child’ robot performs precise assembly tasks [113].

In the same manner, Luis et al. proposed an online incremental learning technique based on Fuzzy ARTMAP and mode selection criteria [42]. In this incremental learning method, online update can be performed based on the weights of the ANN, and the necessity of the new learning mode can be defined. Researchers use a KUKA KR16 industrial robot carrying out the PiH operation in conjunction with data coming from a robotic wrist Force/Torque sensor. The PiH assembly experiment proved that incremental learning reduces the amount of movement by 27.86% for the completion of the same task, and the force error is significantly reduced. In addition to the application of neural networks in PiH assembly, support vector machines (SVM) have also been applied to solve the segmentation problem of the assembly system by not only maintaining computational efficiency but also obtaining good segmentation results. Castellani et al. established a model that combined Hidden Markov Models (HMM) and SVM [115], in which the PiH teleoperation assembly tasks were described by the HMM and SVM was introduced as a probability generator to provide limitations of the distribution probabilities and to accelerate the classification for splitting task information. Researchers use SVM as “probability generators” to overcome limitations of the HMM emission distribution probability. Therefore, the force/torque signals of a complex teleoperation task can be analyzed and segmented by HMM/SVM hybrid model. Table 4 provides a summary of the major studies on machine learning strategies in robotic assemblies.

In order to make a more comprehensive comparison and elaboration of the assembly control method, the advantage and disadvantage of assembly control method are summarized into Table 5.

## 4. Optimization of control strategies

### *4.1. Optimization of control parameters*

To improve the success rate of assembly, several parameters have been considered in control strategies, such as environment information, impedance factor, force, and position. These parameters play a crucial role in the speedy assembly using industrial robots. Therefore, it is important to find optimal assembly parameters to improve the success rate and efficiency of the assembly [116,117].

Kenneth and Milgram from University of Toronto applied stereo graphic (SG) and stereo video (SV) systems to PiH assembly systems.

**Table 4**
Overview of machine learning strategies.

| Learning strategy | Learning method | Characteristic | Application result |
|---|---|---|---|
| **Learning mode** | **LbD** [28, 41, 105, 114, 110–112] (*Learning by Demonstration*) | ❖ Direct demonstration is a direct mapping function from state to action | ❖ Initial trajectories and force are replicated by demonstration |
| | | ❖ Indirect demonstration is to learn the environmental parameters by observing the behavior, and obtain the optimal strategy through the controller. | ❖ Adjusts assembly trajectories in real time |
| | | ❖ Focus on a single task and depend on robot kinematics | ❖ Overcomes larger errors preceding contact |
| | | ❖ Demonstration process is complicated and time consuming | ❖ Geometric optimization of task movement |
| | | ❖ Adjust the robot movement repeatedly, the timeliness is poor | |
| | **Offline learning/online teaching** [42,113] | ❖ All data involved in training | ❖ Integrated online robot teaching and compliant assembly subtasks |
| | | ❖ Each training instance in offline learning is considered to be extracted independently from the instance space by a certain probability distribution. | ❖ Increase the flexibility of PiH assembly strategy |
| | | ❖ Online learning makes random searches in multidimensional weight space | ❖ Solve partial observable Markov decision process<br>❖ Integrated online robot teaching and compliant assembly subtasks |
| **Learning algorithm** | **Increment learning + Fuzzy ARTMAP** [42] | ❖ No need to save historical data to reduce storage space | ❖ Assembly process in unknown environment |
| | | ❖ Learn new knowledge from new data while saving most of the pervious knowledge | ❖ Increases assembly efficiency |
| | | ❖ Applied to large databases | |
| | **HMM + SVM** [115] (*Hidden Markov Models + Support Vector Machines*) | ❖ Support vector is the training result of SVM | ❖ SVM provides the limitations of distribution probabilities |
| | | ❖ Small sample learning method, unable to train large samples | ❖ HMM describes a typical sequential teleoperation task |
| | | ❖ Adding or deleting non-support vector samples has no effect on the model and it has certain robustness. | ❖ Split complex PiH assembly tasks into simple tasks |
| | **EM** [40] (*Expectation Maximization*) | ❖ Iterative algorithm for maximum likelihood estimation or maximal posterior probability estimation of probability parameter models with latent variables | ❖ Multi PiH assembly strategy |
| | | ❖ EM algorithm is widely used to process missing data | ❖ Inconsistent teleoperation demonstrations are resolved (e.g., large spatial and temporal variabilities, demonstrations with different starting/ending phases, partial task executions) |
| | | ❖ Sensitive to the initial value: The EM algorithm needs to initialize the parameter $\theta$, and the choice of the parameter $\theta$ directly affects the convergence efficiency and whether the global optimal solution can be obtained | |
| | **ANN** [37, 42] (*Artificial Neural Network*) | ❖ Nonlinear: artificial neurons are in either active or suppressed state | ❖ Data fusion architecture for robotic assembly tasks based on human sensory-motor skills |
| | | ❖ Non-limiting: a neural network is usually made up of multiple neurons | ❖ Fusion of visual cues and posture |
| | | ❖ Non-convexity: The function has multiple extreme values, so the system has multiple stable equilibrium states, which will lead to the diversity of system evolution | ❖ Enhances PiH performance |
| | | ❖ Adaptive, self-organizing, self-learning | |

SG + SV offers an effective method for displaying and enhancing spatial information for the operator [118]. SV is used to augment the SG to improve the error-tolerance rate of the teleoperation assembly system. However, the impedance coefficient was not studied from the algorithm aspect. Itabashi et al. proposed a realization method for human skill for the PiH task and identified task impedance, which was obtained by human demonstration [119]. The hybrid architecture was adopted by considering the disturbances and vibrations in the PiH assembly system. This architecture helps robots adapt to each task situation by using the most suitable impedance coefficients. The skill controller was constructed based on hybrid architecture. Optimal constraint conditions were added to obtain the optimal impedance coefficients. Yamanobe et al. presented a method to design impedance coefficients to decrease the cycle time and obtain the optimal impedance parameters in fewer assembly experiments [120]. Similarly, Wiemer et al. obtained the best admittance and the associated maximum friction coefficient by considering the contact type and force condition of a variety of polygon shaped pegs and holes [121]. The impedance coefficients were optimized with respect to contact state. With the gradual maturity of the optimization algorithm, Cheng et al. developed Gaussian process regression and Bayesian optimization algorithm (GPRBOA) to realize the online optimization of parameters and reduce the computational complexity of the PiH assembly system [116]. Meanwhile, random variation factors were added to the lower confidence bound acquisition function to reduce the risk of converging to a local minimum and perfecting the GPRBOA, which was called GPRBOA variation random (GPRBOA-VR). Wu et al. further improved the GPRBOA [117] by adding constraint conditions to the GPRBOA; therefore, the online robotic assembly parameter optimization method Gaussian Process Regression surrogated Bayesian Optimization Algorithm based on the orthogonal exploration (OE-GPRBOA) was proposed to deal with low efficiency, low success rate, and low robustness of GPRBOA. Fig. 15 shows the OE-GPRBOA optimization algorithm. Results showed that the assembly time of OE-GPRBA is 9 s and the assembly success rate is 99%; therefore, the assembly effective of OE-GPRBA is higher than more than design-of-experiment (DOE) and GPRBOA.

To optimize the position, velocity, and environment information of the assembly system, Li et al. [122] and Wei et al. [67] also an optimization algorithm with the advantage of low impedance force and vibration. Li et al. analyzed the general relation between the physical space and the configuration space of the robotic assembly system and optimized the environment information of PiH assembly [122]. Attractive region in environment (ARIE) was proposed based on the constraints formed by the environment. The coarse sensing information was integrated in the ARIE to increase the generality and robustness of the assembly system. Wei et al. contrasted and optimized the

**Table 5**
Overview of advantage and disadvantage of assembly control method.

| Assembly control method | | Advantage | Disadvantage |
|---|---|---|---|
| Passive compliant mechanisms [69–74] | | ❖ The passive compliant mechanisms is specifically designed for specific assembly tasks<br>❖ Simple structure and fast response<br>❖ Low cost, no need for expensive force sensors | ❖ There is a contradiction between the high stiffness and high flexibility of the robot because of the spring constant and the geometrical direction.<br>❖ Poor adaptability and limited use<br>❖ Low assembly accuracy<br>❖ Low assembly success rate<br>❖ Without the ability to feel the external force information |
| **Active compliance control** | **Impedance control** [75,77–81] | ❖ No need for accurate offline mission planning, and it is highly adaptable to the transition between free motion and constrained motion<br>❖ Strongly robustness to system uncertainties and disturbances<br>❖ Less task planning and real-time calculations, and it no need to switch control modes | ❖ Control accuracy is directly controlled by the robot itself and its control<br>❖ Force tracking accuracy depends on the operator's understanding of environmental knowledge<br>❖ Small estimation errors lead to large force errors when the actual application environment is inaccurate<br>❖ Poor trajectory tracking capability occurs when the constraint environment is uncertain or unknown |
| | **Hybrid force/position control** [84–89] | ❖ The introduction of compliance matrix enables robots to independently control position and contact force<br>❖ Overcome robot kinematics and dynamic uncertainty<br>❖ Guarantee the stability of the robot end effector | ❖ Compliance matrix depends on the environment and specific assembly tasks<br>❖ Robust adaptability of the control is poor once the assembly task is changed because of the position control and force control requirements are completely different for the stiffness parameters |
| **Control methods with auxiliary technologies** [38,49–53,56–60,90–104] | | ❖ Improve the flexibility of assembly robots<br>❖ Deal with the complexity of assembling operations<br>❖ Combine visions, haptic systems, kinesthetic guidance, complexity model reconstruction and simulation<br>❖ Developed assembling perception models in virtual environment | ❖ Auxiliary devices are sophisticated and costly<br>❖ Development cycles of Auxiliary algorithms and software tools are time consuming<br>❖ Virtual assemblies efficiency depend on the advancement of VR devices<br>❖ Difference between the virtual environment and the actual system |
| **Machine learning algorithms in controls** [37,40–42,105,110–115] | | ❖ Learning by demonstration<br>❖ Demonstrates human assembly skill motion on constrained control<br>❖ Adjusts assembly trajectories in real time<br>❖ Overcomes the limitations of impedance regulation mechanism in the case of multiple joints | ❖ Few algorithms are mature enough to be applied in actual assembly processes<br>❖ Machine learning training model takes a long time<br>❖ The increasing number of trainings has a negative impact on the robot structure |

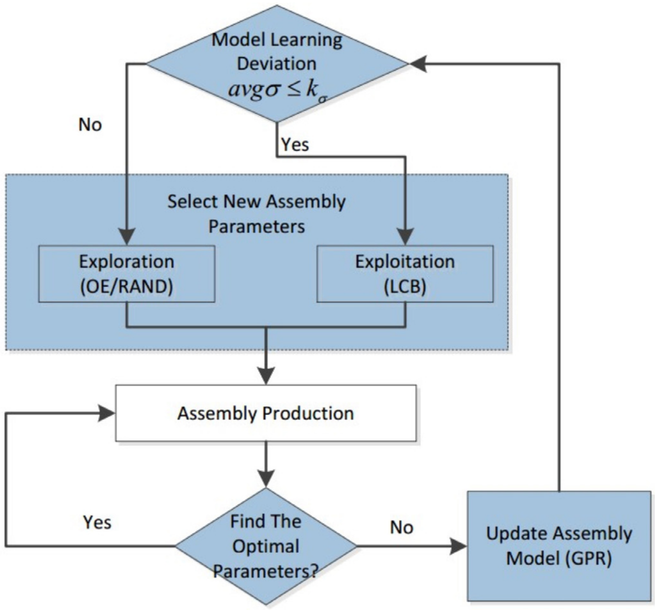
information of the impact of position, speed, and moment information, which may influence the PiH assembly system [67]. A prediction method based on the forgetting factor function is presented to reduce the impact of the spring term in impedance control on the complex multi-peg-in-hole docking. This optimization strategy predicted and adjusted assembly control system parameters during the whole docking process and could effectively decrease the impedance force and vibration caused by the spring term.

Optimization approach type, advantage, optimized object and optimized result are listed in Table 6. According to the results summarized in Table 6, it can be concluded that the current mainstream optimization approaches are divided into algorithm and experiment. Algorithm is more efficient in obtaining the optimal control parameters, and the optimization result is better than the experimental approach [67]. As summarized in Table 6, the number of optimized experimental groups and the optimization time will be significantly reduced, however, the development cycle of the algorithm is long, the specificity is strong, and the universality is poor [116]. In particular, the intelligent algorithm that introduces deep learning has a long training period. On the contrary, the optimization process of experiment is simple through simulation and multiple groups of experiments, but the optimization results and efficiency are inferior to algorithm [122]. Experiment usually depend on external experimental devices or a large amount of experimental data, so there will be device accuracy and data sampling accuracy. In summary, the optimization process of algorithm is complex, the development cycle is long, but the optimization result and efficiency are better than experiment. The advantage of experiment is that the optimization process is simpler than algorithm. Table 7 provides a summary of existing studies on optimization of control parameter strategies ordered by dates of publication.

### 4.2. Compensation for control error

Error compensation of PiH assembly is mainly generated from two aspects: error compensation from auxiliary devices [113] and from the algorithm [65]. Auxiliary devices include high-speed visual servo systems [113], laser trackers [123], and IPMC [124]. Based on remote center compliance (RCC) mechanisms, Jain et al. proposed a new active four-DOF using two segmented IPMCs for robotic micro PiH assembly to compensate the position and orientation errors between two parts [124]. The test setup for robotic micro assembly and the lateral view of the mechanism are shown in Fig. 16. The PiH assembly task was modeled analytically where the misalignment of the peg was corrected by the IPMC tip force. The RCC is controlled by applying a voltage (0–3 V) to discrepant IPMC segments through a proportional-derivative (PD) controller. The schematic diagram of the robotic micro assembly system is shown in Fig. 16.

The wide application of the RCC wrist enables the robot to have certain flexibility. To complete the assembly task, the RCC wrist adjusts the relative posture actively or passively between the assembly parts to compensate the assembly error [125]. However, the RCC wrist of the assembly robot is usually designed depending on the actual demand. The design cost for RCC wrists of large-scale industrial robots is especially high. Therefore, Liu et al. presented a large-scale PiH robotic assembly system based on a laser tracker and its corresponding error compensation strategy [123]. To eliminate the impact of orientation and position error of the robot on hole and peg alignment, a laser tracker was used as the feedback sensor. Multiple spherically mounted




**The OE-GPRBOA online robotic assembly parameter optimization algorithm**

**The success rate of different method**

| Method | Assembly Times | Success rate |
|---|---|---|
| *DOE* | 270S | 100% |
| *GPRBOA* | 20S | 67% |
| | 14S | 48% |
| | 9S | 25% |
| *OE-GPRBOA* | 9S | 99% |

**Fig. 15.** OE-GPRBOA online robotic assembly parameter optimization algorithm [117]. .

reflectors (SMR) were used to track the position and orientation of the peg. The laser tracker identified the posture of the SMR in the assembly process and gave feedback regarding the location to the control system, which adjusted the posture of assembly robot and compensated the orientation error. Similarly, Andre et al. proposed a method for reliable and error tolerant assembly for impedance-controlled robots by using a particle filter-based approach [126]. By generating voxmaps (modeling the passive part) and pointshells (modeling the passive part) from CAD models, the relative objects pose implemented as particles can be evaluated (Fig. 18). The advantage of this strategy is that the voxmaps and pointshells of large-scale parts can also be generated for comparing the real-world force/torque sensor values, thus correcting pose uncertainties during the assembly process. The position and joint torque representing the real-world state were measured by the KUKA LBR iiwa's intrinsic sensors. This method calculated expected forces and torques on-line allowing flexible and fast adaption to new assembly tasks. Fig. 17 illustrates the overall model of the system and the presented results.

Liu et al. [123] and Andre et al. [126] also studied the error compensation strategy of large-scale assemblies using the auxiliary device. In addition to the error compensation strategy of large-scale PiH assembly, that of micro PiH assembly is a research hotspot. Niklas Bergstrom proposed a robotic system based on high-speed camera for auxiliary human-robot micromanipulation [127]. The feedback element was a 1-kHz high-speed camera. The robot tracked the workpiece held by the human operator and aligned the workpiece to the target which is mounted to the robot's actuator. The accuracy of the system track and error compensation is less than one micrometer. The results showed that the proposed system outperforms the operator performing the same task with magnified visual feedback in terms of both completion time and number of successful insertions. Similarly, Chen et al. presented error recovery strategies of electronic connector mating for robotic fault-tolerant assembly [66]. The assembly objects are 4-pin electronic connectors. They discussed four search strategies for electronic connector mating with an initial position error (Fig. 19). For each method, the relationship between the force sensor signal and relative position within the connector pair, the search space requirements, and error probability are studied. The experimental results show that the proposed strategies can diagnose the position errors in the assembly process correctly and can realize error recovery effectively. Fig. 18 illustrates the connectors and presents the recovery method for each error condition.

Pac et al. investigated the effect of parametric uncertainties on robot precision using interval analysis [128]. Two types of errors are considered: geometric errors generated by the link and joint parameter uncertainties and sensing errors generated by the inaccurate measurement of joint positions. They proposed a novel method to estimate uncertainty bounds for manipulator end-effector positions due to uncertainties in the kinematic model using both analytical and computational tools of interval analysis. Simulation results predicted the required tolerances in a PiH micro assembly operation. It is illustrated that the presented approach can replace the more computationally expensive Monte-Carlo simulations to estimate the effect of uncertainties. Hu et al. developed a compliance control integration robotic assembly system as well as a human-computer interaction interface based on visual and force sensors [129]. The system can automatically perceive and control assembly errors through sensor information. The experiment was performed more than 100 times and was successful at each attempt. The error of the identification of position of the hole is less than 1 mm. The active compliance robotic assembly system deals with a variety of assembly error types mainly from self-perception and control; moreover, it can take the initiative to control the assembly as well as reduce damage of the components caused by passive compliant devices. Force guided assembly is an attractive alternative. However, its implementation is challenging. Dietrich et al. modeled force-torque maps (FTM) based on the forces, torques, and relative displacement of peg and hole contact, which is measured by attempting the assembly [130]. To improve the assembly efficiency for multi-peg-hole components, Luo et al. proposed a force/stiffness compensation method to control positioning accuracy [131]. Based on the force and displacement information in the assembly process, the position errors were acquired, and the stiffness of the assembly system under the exerted assembly force was calculated. According to the stiffness, the deviation from the target position is calculated and compensated.

Jaesung Oh and Jun-Ho Oh proposed the modified perturbation/correlation method (MPCM) for force-guided PiH assembly [132]. Performance index R (the correlation value of the resulting reaction force/moment) was used to calculate and correct the position/orientation errors between the connectors. This method can be applied to automatically perform the assembly task without human intervention. On the basis of force feedback and dynamic movement primitives (DMP), Abu-Dakka et al. proposed a new methodology for learning and adaption of manipulation skills that involve physical contact with the environment [133]. The proposed algorithm takes a reference Cartesian trajectory and force/torque profile as input and adapts the movement so that the resulting forces and torques match the reference profiles. It is suitable both for robots with admittance and impedance control. In addition to the error compensation strategy based on force feedback, Huang et al. modeled possible faults as “trap regions” in the configuration space (C-space) of the assembly and presented a reliable error recovery strategy based on the fault models [65]. Fig. 19 shows the devices used in these experiments and presents a flowchart of the fault-tolerant connector mating strategy.

Owan et al. proposed the use of contingency procedures for mixed-initiative traded control [134]. The proposed consensus-based approach facilitated traded control that led to improved overall performance of

**Table 6**
Overview of optimization of control parameters.

| Optimization approach type | Optimization approach | Advantage | Optimized object | Optimized result |
|---|---|---|---|---|
| **Algorithm** | **ARIE** [122] (*Attractive Region in Environment*) | ❖ Build relation between ARIE in configuration space and assembly parts in physical space<br>❖ Low-precision robotic system achieves high-precision PiH assembly | ❖ Environment information | ❖ Assembly success rate is increased **from 62% to 100%** |
| | **Forgetting factor function** [67] | ❖ Adjusts the balance position of the virtual spring | ❖ Position | ❖ The X-direction contact force variance is decreased from 1.3 to 0.53 |
| | | ❖ Decreases the impedance force and vibration caused by spring term effectively | ❖ Speed<br>❖ Torque | ❖ The Y direction contact force variance is decreased from 2.72 to 0.96 |
| | **GPRBOA-VR** [116] (*Gaussian process regression surrogated Bayesian optimization algorithm-Variation Random*) | ❖ Online parameter optimization | ❖ Process parameters | ❖ The optimization time is decreased from 1254s to 54.26s |
| | | ❖ Reduces the computational complexity for coordinate optimization process and production process | | ❖ The number of experiments is decreased from 270 to 8 groups |
| | **OE-GPRBOA** [117] (*Gaussian process regression surrogated Bayesian optimization algorithm based on the orthogonal exploration*) | ❖ Improved GPBOA | ❖ Search speed | ❖ The assembly rate is increased from 67% to 100% |
| | | ❖ Based on orthogonal exploration | ❖ Search force | ❖ The assembly times is decreased from 20 to 9 groups |
| | | ❖ High efficiency, high success rate and high robustness | ❖ Insertion force | |
| Experiment | Geometric variation of peg [121] | ❖ Suitable for some geometries<br>❖ Reduce the impact of friction on assembly | ❖ Admittance matrix | ❖ The PiH is assembled when the contact friction coefficient is greater than 5 |
| | Human demonstration [119] | ❖ Improves robustness of skill in time domain by symbolic feedback loop<br>❖ Comprehensive system considers interference and vibration of system | ❖ Impedance control parameters | ❖ The robustness of skill in time domain is improved |
| | Simulation [120] | ❖ Non-linear optimization<br>❖ Shorten optimization cycle time<br>❖ Develop simulator based on MATLAB Simulink | ❖ Damping control parameters | ❖ Assembly cycle time is decreased by 35% |

**Table 7**
Overview of optimization of control strategies.

| Optimized type | Publication, year | Principles and approach | Optimized objective and contribution |
|---|---|---|---|
| **Optimization of control parameters** | Li et al. [122], **2017** | ❖ Attractive region in environment formed by the environment<br>❖ Physical space and configuration space | ❖ Optimizes the environment information<br>❖ Robotic flexible assembly system<br>❖ Low-precision system achieves high-precision PiH assembly<br>❖ Two-step assembly strategy (step 1: push peg to constant force; step 2: keep force and rotate peg) |
| | Wei et al. [67], **2016** | ❖ Prediction method based on the forgetting factor function<br>❖ Considering the impact of the spring term in impedance control | ❖ Optimizes position, speed, and torque information<br>❖ Balances position of the virtual spring adaptively adjusted by three input parameters (average, summit, and variance)<br>❖ Optimized strategy decreases the impedance force and vibration caused by spring term effectively |
| | Wu et al. [117], **2015** | ❖ Gaussian process regression surrogated Bayesian optimization algorithm based on the orthogonal exploration (OE-GPRBOA) | ❖ Online robotic assembly parameter optimization method<br>❖ Reduces the number of experiments to obtain the best impedance coefficient<br>❖ Improved GPBOA |
| | Cheng et al. [116], **2014** | ❖ Gaussian process regression and Bayesian optimization algorithm (GPRBOA)<br>❖ A random variation factor is added to the lower confidence bound | ❖ Achieves online optimization parameters<br>❖ Reduces the computational complexity for coordinate optimization process and production process |
| | Wiemer and Schimmels [121], **2012** | ❖ Contact mode of different polygons<br>❖ Analysis of geometric variation | ❖ Optimizes and obtains the best passive admittance<br>❖ Maximum friction coefficient |
| | Yamanobe et al., [120], **2004** | ❖ Non-linear optimization<br>❖ Develop simulators to increase optimization constraints | ❖ Reduces the experimental period for the best damping parameters<br>❖ Obtains the optimization parameters under various errors |
| | Itabshi et al. [119], **1998** | ❖ According to human demonstration<br>❖ Hybrid architecture (controller switching module, environmental testing device, the overall monitoring device) | ❖ Obtains hard impedance parameters<br>❖ Comprehensive system considers interference and vibration of system<br>❖ Improves robustness of skill in time domain by symbolic feedback loop |
| | Kenneth et al. [118], **1992** | ❖ Stereo graphic (SG) and stereo video (SV) | ❖ Utilizes SV to enhance SG for improved fault tolerance of system |

(*continued on next page*)

**Table 7** (*continued*)

| Optimized type | Publication, year | Principles and approach | Optimized objective and contribution |
|---|---|---|---|
| **Compensation for control error** | Owan et al. [134], **2017** | ❖ Mixed active transaction emergency procedures | ❖ Proposed a consensus approach to control trading<br>❖ Increases the assembly success rate in condition of assembly error<br>❖ Reduces baseline operation time |
| | Andre et al. [126], **2016** | ❖ Compensation strategy based on particle filter<br>❖ Voxmaps-pointshells generated by CAD data | ❖ The collisions of PiH are checked by voxmap-pointshells<br>❖ Increased system flexibility<br>❖ Online calculation of expected forces and torques |
| | Chen, [66] **2016** | ❖ Search strategy of electronic connector based on force/torque sensor<br>❖ Compensation of force sensor signal and connector relative position | ❖ Proposed four kinds of errors situations and compensates them<br>❖ Diagnoses the assembly position error and effectively compensates for the error |
| | Bergstrom, [127] **2016** | ❖ Assistive device (high-speed camera and one-dimensional actuator)<br>❖ High-speed visual feedback | ❖ Robot system assists human micromanipulation<br>❖ Compensates for errors of less than 1 micron |
| | Hu et al. [129], **2016** | ❖ Vision sensor system (camera maximum resolution is 1280 × 720) and force sensor<br>❖ Sensing information | ❖ Automatic perception of control error<br>❖ Develop compliance control integration system<br>❖ Identification errors are less than 1 mm |
| | Abu-Dakka et al. [133], **2015** | ❖ Cartesian trajectory and force/torque profile<br>❖ Learning and adaption of manipulation skills<br>❖ Based on dynamic movement primitives and quaternion representation of orientation | ❖ Forces and torques match the reference profiles<br>❖ Suitable for robot with admittance and impedance control<br>❖ Different geometries and number of holes |
| | Oh, [132] **2015** | ❖ Modified perturbation/correlation method<br>❖ Performance index R (the correlation value of the resulting reaction force/moment) | ❖ Compensates position/posture error between connectors<br>❖ Robots complete assembly in a limited margin of error<br>❖ Corrects the directionality error |
| | Liu et al. [123], **2014** | ❖ Compensation strategy based on laser tracker | ❖ Eliminates the positioning error and its impact<br>❖ Laser tracker as a feedback sensor |
| | Luo, [131], **2013** | ❖ Acquired position error based on force and displacement information | ❖ Multi-PiH interference assembly<br>❖ Compensation algorithm based on force and stiffness |
| | Jain, [124], **2013** | ❖ Remote center compliance wrist<br>❖ Two ionic polymer metal composite (IPMC)<br>❖ Proportional-derivative controller | ❖ Compensates PiH position error<br>❖ Controls potential balance contact friction through the reaction force of IPMC |
| | Pac et al. [128], **2012** | ❖ Considers two types of errors (geometric errors; sensing errors)<br>❖ Interval analysis of manipulator kinematics | ❖ Estimates uncertainty bounds for manipulator end-effector position<br>❖ Predicts the required tolerances in a PiH micro assembly operation |
| | Dietrich et al. [130], **2010** | ❖ Based on pre-calculated force/torque<br>❖ Based on relative displacement of force and torque contact part | ❖ Builds a force/torque map<br>❖ Posture errors are identified based on force/moment vectors |
| | Huang et al. [65], **2008** | ❖ Fault-tolerant assembly strategy based on the proposed trap area<br>❖ Based on configuration space | ❖ Trap area is established by analysis of the error situation<br>❖ Compensates for a variety of error conditions |

PiH assembly in terms of task time and success rate. Table 7 summarizes the major studies on PiH assembly error compensation strategies in robotic assembly systems ordered by dates.

## 5. Conclusions and future trends

### 5.1. Conclusions

Compared with manual or collaborative assemblies, robotic assemblies have a variety of advantages, and the control strategies

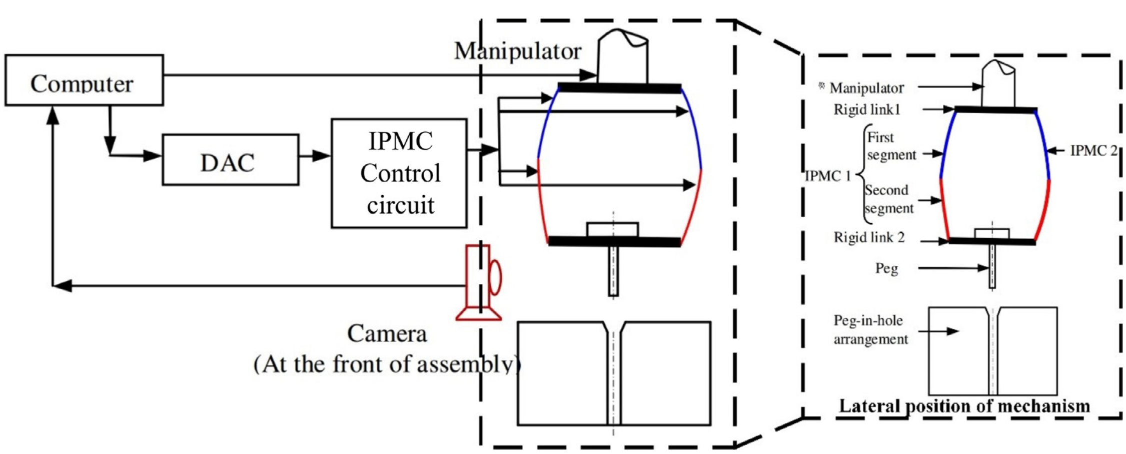



**Fig. 16.** Schematic diagram of test setup for robotic micro assembly and lateral view of mechanism [124].

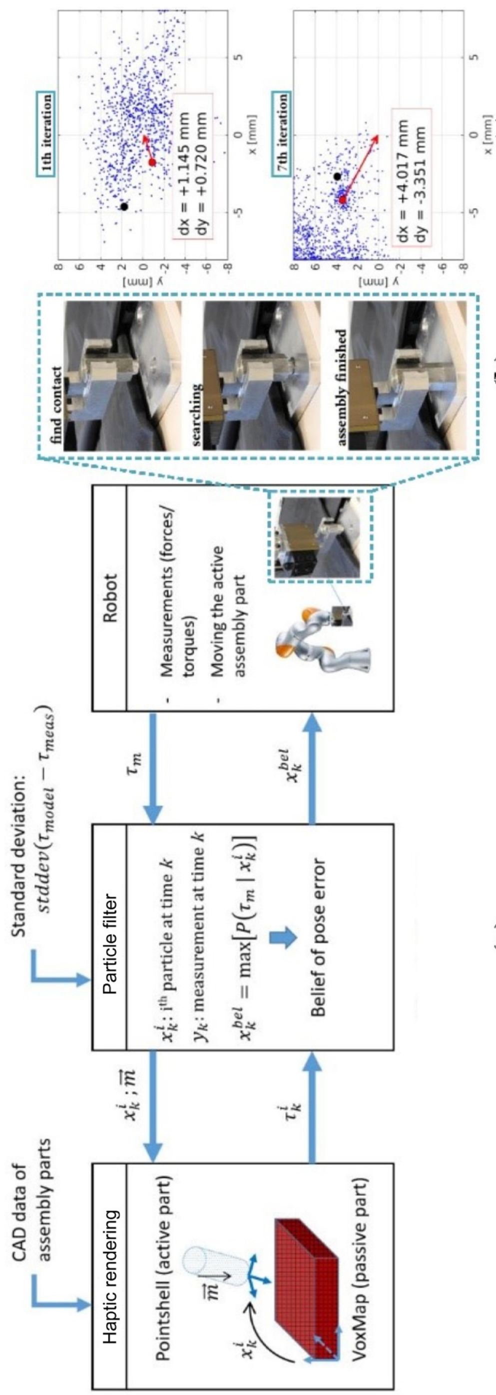



**Fig. 17.** (a) The overall system (b) Assembly progress (c) The upper right image shows all particles (blue) and the most probable one (red) with the resulting motion vector of the robot for 1st iteration. For comparison the actual robot position is indicated by the black dot. The lower right image shows the same for 7th (here final) iteration [126]. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

showed their potential in substituting human operators for full automation of assembly processes. In the presented work, the recent studies, main methodologies, and limitations are classified and summarized. This comprehensive survey provides a useful guide to gain understanding of the state of the art research on robotic assemblies and control strategies. The conclusion on robotic assemblies and control strategies should mainly focus on four aspects mentioned in this paper.

### 5.1.1. Compliance control strategies

Compliant control strategies have been classified into active and passive compliance mechanisms. Passive compliance mechanisms are less attractive, but a few recent studies have made some improvement for better adaptability of robotic assembly. The improvements were mainly on (1) the integration of tactile characteristics of human hands [43] and (2) the optimization of robotic design for better efficiency of assembly processes. Active compliant mechanisms can be used to overcome the shortcomings of the passive compliant mechanisms, and studies on active complaint mechanisms have attracted a lot of attention. Active control strategies are expected to solve most of the problems faced during robotic assemblies. While not all active compliant mechanisms have achieved expected outcomes, further efforts are needed to improve the adaptability and robustness of existing compliant assembly strategies. Vision systems, CAD technologies [78], Petri nets [37], fuzzy algorithms [85], and remote impedance algorithms can be utilized to enhance active compliance control strategies.

With the diversification of the PiH assembly, intelligent compliance assembly strategies have become increasingly important. Especially for PiH assemblies with complex shapes, an assembly control strategy should consider more assembly parameters related to the environment. Thus, an assembly-modeling tool must define robotic paths for PiH assemblies with the consideration of all constraints. This is not a trivial task, and the compliance control strategies will play a crucial role in PiH assembly. The passive compliance mechanisms will be integrated with intelligent active control to deal with the assemblies of complex parts.

### 5.1.2. Auxiliary assembly technologies

Auxiliary assembly strategies use auxiliary devices, software, and algorithms to assist assembly processes. Auxiliary devices are sophisticated that are costly, and their development cycles are time consuming. Efforts have been made to utilize some common devices such as leap motion [50] and visioning systems; no sophisticated assembly equipment is available for robotic assembly. In contrast, algorithms and software tools for auxiliary devices have been developed. To assemble parts with complex, flexural, or micro-scale shapes, robotic assembly can be assisted by capturing real-time data to reconstruct and simplify the assembly models. Auxiliary algorithms have laid a solid foundation for assembly of complex parts. The efforts on the development of auxiliary devices, control algorithms, and software tools should be integrated to assist assembly robots to perform assemblies of complex parts in unstructured environments.

Virtual assembly is an important branch of virtual manufacturing, combines various technologies such as virtual reality, computer vision, computer network, and human-computer interaction. Virtual assemblies can be used to verify the feasibility of assembly processes before they are executed in the physical world, so that users can identify potential issues in assembly processes. The virtual assembly provides a human–computer interface for users to demonstrate assembly processes, and the capacities can be enhanced by integrating them with interactive devices such as haptic devices [33] and force feedback devices [96]. The users stay in the operating environment as self-participations. Virtual assemblies depend relatively on the advancement of VR devices; the assembly plans from existing virtual assemblies expose the limitations for reliable assembly plans. The typical PiH assembly has been widely studied in the virtual environment and provides some insights of practical assembly. However, additional studies are needed

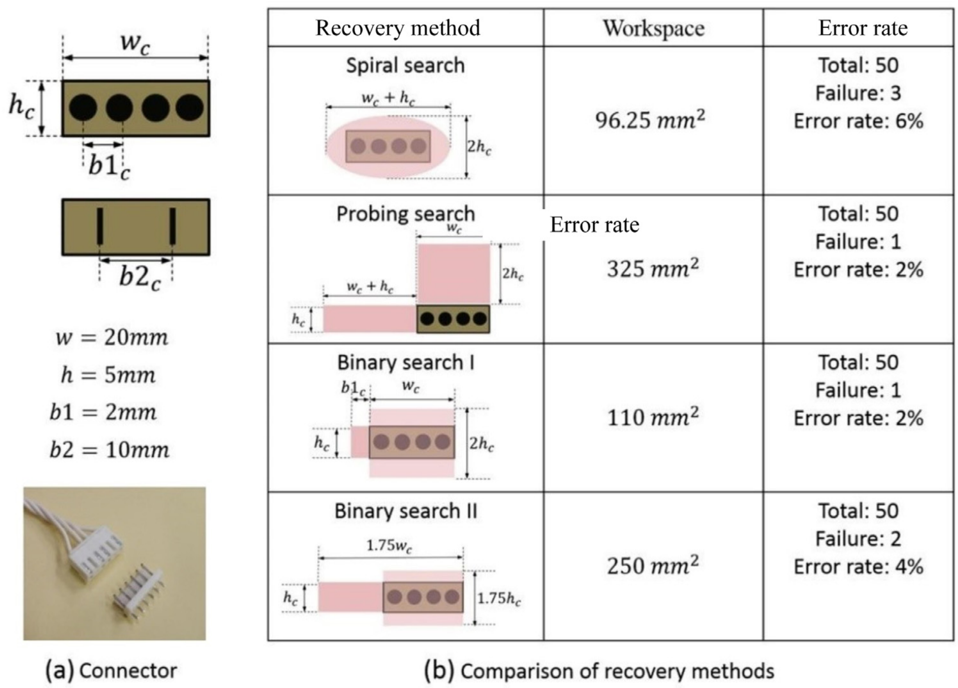



**Fig. 18.** Work space of the error recovery method using force/toque sensors (a) Connector (b) Comparison of recovery methods [66].

to minimize the discrepancies of assembly variables between virtual and actual assemblies.

### 5.1.3. Machine learning algorithms

Machine learning algorithms have demonstrated their advantages in supporting PiH assemblies; however, few algorithms are mature enough to be applied in actual assembly processes [32]. Recently, researchers focused on the customization of mechanical grippers based on the characteristics of human assembly processes; this represents the trend of future developments on this subject. To this end, developing advanced machine learning algorithms is essential. The controllability of a robot assembly process should be improved through a remote control and machine learning during the assembly process. The assembly robots in the next-generation will be combined with advanced machine-learning algorithms to break through traditional assembly modes; the potential applications should be extended to assembly of complex parts, multiple-holes assemblies, and micro-scale assemblies.

### 5.1.4. Optimization of control strategies

In assembly planning, the assembly parameters must be optimized to achieve better outcomes of robotic assemblies. The system performance can be improved by the deployment of optimization algorithms in assembly modeling. Existing algorithms for assembly modeling have identified limited number of assembly parameters related to kinematic

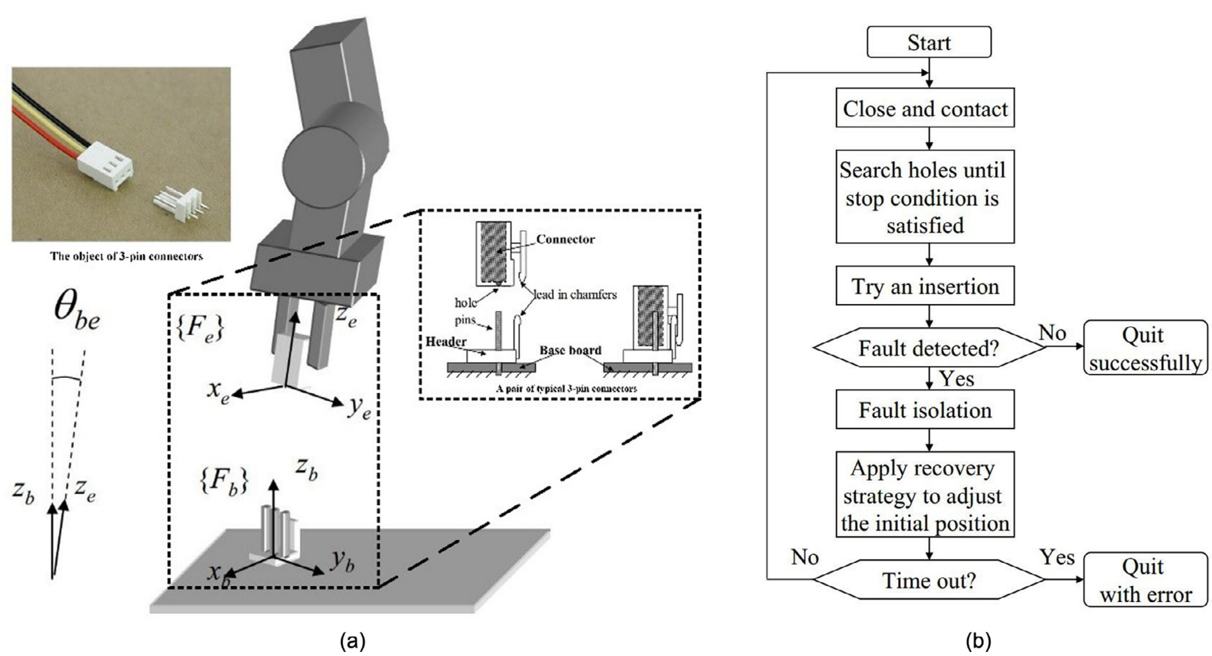



**Fig. 19.** Experiments devices (a) The tilt error between the end effector and the base board (b) Flowchart of the fault-tolerant connector mating strategy [65].

Table 8
Overview of abbreviations in the paper.

| Abbreviations | Full name (A-L) | Abbreviations | Full name (L-V) |
|---|---|---|---|
| AFS | Adaptive Fuzzy System [89] | **LRCP** | Large Radius Chebyshev Parallelogram [70] |
| AI | Artificial Intelligence | **LWR** | Locally Weighted Regression [98] |
| ANN | Artificial Neural Network [37,42] | **M$^4$S** | Multimobile Micromanipulation Systems [90] |
| AR | Augmented Reality [52] | **MFRAC** | Model-Free Robust Adaptive Control [79] |
| ARIE | Attractive Region in Environment [122] | **MMS** | Mobile Micromanipulation System [90] |
| CA | Competitive Agglomeration [98] | **MM-SISTR** | Mobile Manipulating-Systems Integrated Sensor Test Rig [104] |
| CA | Component Assemblability [103] | **MMSS** | Multi-Master-Single Slave [51] |
| CAD | Computer-Aided Design | **MM-UAV** | Mobile Manipulating Unmanned Aerial Vehicle [79,88] |
| CCD | Charge Coupled Device [57] | **MPCM** | Modified Perturbation/Correlation Method [132] |
| CLF | Common Lyapunov Functions [79] | **OE-GPRBOA** | Gaussian Process Regression surrogated Bayesian Optimization Algorithm based on the Orthogonal Exploration [117] |
| C-space | Configure space [100] | **PA** | Product Assemblability [103] |
| DMPs | Dynamic Movement Primitives [40, 133] | **PAP** | Passive Alignment Principle [68] |
| DOF | Degree of Freedom | **PD** | Proportional-Derivative [124] |
| DOE | Design of experiments | **PiH** | Peg-in-Hole |
| EM | Expectation Maximization [40] | **POMDP** | Partial Observable Markov Decision Process [113] |
| EMG | A German Company [51] | **RCC** | Remote Center Compliance [72, 124] |
| FMLE | Fuzzy Maximum Likelihood Estimation [98] | **ROS** | Robot Operating System [101] |
| FSMJIC | Fuzzy Sliding Mode Joint Impedance Controller [85] | **SARSOP** | Reachable Space Under Optimal Policies [113] |
| FTM | Force-Torque Maps [130] | **SEA** | Series Elastic Actuators [72] |
| GPRBOA | Gaussian Process Regression and Bayesian Optimization Algorithm [116] | **SG** | Stereo Graphic [118] |
| GPRBOA-VR | Gaussian Process Regression and Bayesian Optimization Algorithm Variation Random [117] | **SISTR** | Systems Integrated Sensor Test Rig [104] |
| HD | Haptic Device [56] | **SMC** | Sliding Mode Control [79] |
| HMM | Hidden Markov Models [115] | **SMR** | Spherically Mounted Reflectors [126] |
| HR | Haptic Rendering [56] | **SV** | Stereo Video [118] |
| IAS | Intuitive Assembly Strategy [86] | **SVM** | Support Vector Machines [115] |
| IPMC | Ionic Polymer Metal Composite [86,124] | **VCG** | Virtual Constraint Guidance [97] |
| IT | Information Technologies | **VE** | Virtual Environment |
| KUKA LBR iiwa's | Lightweight Robotic Arm [126] | **VF** | Visual Feedback [56] |
| LbD | Learning by Demonstration [107,108,109] | **VR** | Virtual Reality |
| LCB | Lower Confidence Bound [116] | **VREM** | Virtual Reality based Environment for Micro Assembly [39] |

constraints and operating forces. In recent years, researchers have focused on the optimization algorithms themselves, for example, online optimizations and nonlinear optimizations [121]. In the future, the current optimized methods need to be combined with mature algorithms, which will intuitively and greatly enhance the effect of optimization parameters for the control system. It will be desirable to take into consideration more assembly parameters such as joint velocities and accelerations so that the assembly performances can be dynamically optimized.

Error compensation is an indispensable step in the process of PiH assembly, and the strategy for error compensation is critical to predict and optimize errors occurring to the end-effector tool of an assembly robot. A compensation method optimization for the positional and orientational error based on the information of forces, geometries, and deflections of objects. At present, effective error-optimization strategies are lacking; in existing methods, the collected information is not fully utilized to estimate and optimize errors efficiently in real-time models. As the next step, existing error compensation methods should be combined with optimization algorithms and hardwired compensation. Meanwhile, error compensation strategies should be tailored to assembly robots, for example, it is promising to develop error compensation strategies for dual-arm robots.

### 5.2. Future trends

The market share of assembly robots worldwide is expected to expand further, and its assembly performance and price will be more adaptive to the development needs of the manufacturing industry. Robotic PiH assembly involves multiple scientific fields and relies on advances in many related technologies. At present, the field of robotics is stepping up scientific research, conducting research on common technology and key technologies of assembly robots, and moving towards intelligent and diversified directions. In the future, intelligent direction is mainly involved in the multi-sensor fusion control strategy, intelligent compliance control strategy and intelligent optimization algorithms. Robotic PiH assembly have the ability to think logically and actively learn to deal with unstructured complex environments and assembly tasks, and to find the optimal solution independently. Diversification is mainly involved in the development of compliant wrists, computer simulation technology and collaborative assembly robots. The development of a compliant wrist makes the robot's structure more flexible and versatile, and it will be suitable for a variety of assembly tasks. With the combination of computer simulation technology, the programming method is diversified, the human-computer interaction mode is novel, and the assembly efficiency is improved. The introduction of multi-robot collaboration and human-machine collaboration is essential for the completion of precision assembly.

## Abbreviations

Overview of abbreviations are shown in Table 8. It is convenient for readers to check the existing abbreviations in the text.

## Declaration of Competing Interest

None.

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