Received: 16 September 2022 | Accepted: 21 October 2022

DOI: 10.1049/ccs2.12073

Cognitive Computation and Systems

The Institution of Engineering and Technology WILEY

REVIEW

Review on human-like robot manipulation using dexterous hands

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Abstract

In recent years, human hand-based robotic hands or dexterous hands have gained attention due to their enormous capabilities of handling soft materials compared to traditional grippers. Back in the earlier days, the development of a hand model close to that of a human was an impossible task but with the advancements made in technology, dexterous hands with three, four or five-fingered robotic hands have been developed to mimic human hand nature. However, human-like manipulation of dexterous hands to this date remains a challenge. Thus, this review focuses on (a) the history and motivation behind the development of dexterous hands, (b) a brief overview of the available multi-fingered hands, and (c) learning-based methods such as traditional and data-driven learning methods for manipulating dexterous hands. Additionally, it discusses the challenges faced in terms of the manipulation of multi-fingered or dexterous hands.

KEYWORDS

dexterous hand, learning-based manipulation, robot manipulation

1 | INTRODUCTION

Grippers are the most essential part of a robot as it is the medium between the robot and the environment. To achieve a successful grasp, the objects must be both contacted, as well as avoid slipping and causing damage while the objects are picked and placed [1, 2]. Manipulation tasks with grippers were first used in the industrial environment and have seen tremendous success in handling, sorting, picking, and placing hard objects. Whereas in agriculture and food industries, the handling objects are fragile and damageable, [3] thus the success rate is exceptionally low. Soft fruits are prone to get damaged during robotic harvesting or food packaging, thus the development of a suitable end-effector and grasping methodology [4] is a difficult aspect of the development of an autonomous harvesting system.

Due to the lack of flexibility and adaptability of the traditional grippers in grasping soft and deformable fruits [5] the performance of the robotic system in practical application is limited [6]. Since the nature of the soft fruits, such as shape and size vary from one another, the development of various sensors and control strategies is needed. Position, force, slippage, and temperature sensors can be integrated into a gripper to be more flexible and agile. Control strategies based on the feature extraction from an image and haptic/force feedback from the sensors can be adopted to make the system more robust. Additionally, in soft fruit harvesting, the challenge also lies in identifying and picking up the underlying fruits, as they tend to grow in clusters [7]. Clustered environments limit the ability of the vision system to recognise the region of interest (ROI) to grasp the soft fruits. Additionally, strategic grasping planning for the manipulator is required to harvest specific fruit without damaging the other. The traditional grippers fail to harvest occluded fruits lying within dense clusters. Thus, there is a need to develop a robust mechanism for detecting the occluded fruits and planning the grasping/manipulating motions, and a compliant control strategy for grasping or manipulations.

Visual sensors are the most appropriate for identifying objects and obstacles, and then grasping points and approaching paths towards the objects with obstacle avoidance can be planned. The visual sensors which provide real-time data, such as the position and orientation of the object to be grasped are often mounted on a fixed base. However, it restricts the point of view once the manipulator is in action and is difficult to analyse if the object has been successfully grasped or not. Thus, it is possible to control the grasping and handling process by integrating visual sensors into or onto the grippers, also known as eye-in-hand vision. Nowadays, stereo cameras [8] are used for grasped object recognition, localisation, and 3D information acquisition [9]. However, mechanical information cannot be deduced. On the other hand, tactile sensors can provide mechanical information, such as pressure, contact forces, torques, slip, vibrations, and temperature when a gripper contacts an object [9]. The studies show that tactile information/sensors can significantly increase the accuracy of grasping in addition to visual feedback [10, 11].

Nevertheless, the traditional methods, such as tactile, visual, and visuo-tactile servoing methods consider the physical properties [12] limiting its robustness over the data-driven learning-based methods for grasping soft fruits. Supervised learning-based identification of grasp locations from an image was presented [13, 14] predicted grasp locations without severe overfitting via Convolution Neural Network (CNN). Similarly, Yu et al. [15] proposed an R-YOLO model for detecting the pose of strawberries for harvesting. Whereas Murali et al. [16] proposed a system to grasp novel objects without knowing the location and physical properties based on tactile sensing. Similarly, Dang and Allen [17] proposed the use of tactile feedback for predicting grasp stability without visual or geometric information. These studies are focussed on either perceiving visual and depth or tactile sensing information for grasping and manipulating an object.

On the other hand, the grasping strategy of the human hand relies on vision and sense of touch for object handling and manipulation. With the help of sensory feedback and foreknowledge under the control of the brain, human hands can provide stable, adaptable, and flexible grasping and other outstanding manipulation abilities. To interoperate with the variable and complex environment, all robots must use sensors, such as tactile sensors, visual sensors, hearing sensors, and so forth. With the use of multiple sensors, robotic grippers aim to perceive both tactile and visual modalities of human hands to evaluate the results of the current grasp [18]. Most of the soft fruit harvesting is still carried out manually by human hands. This shows that the human hand with both visual and tactile capabilities can adapt itself to the dynamic environment in a compliant manner to perform various grasping and manipulation tasks. Thus, with similar compliant control strategies, the robotic grippers can adapt to the dynamic environment with ease.

The haptic feedback in humans can be classified as tactile and kinaesthetic. The tactile deals with the sense one feels in the fingertips or on the surface, allowing the human brain to feel the pressure, touch, texture, and vibration while operating. While kinaesthetics refers to the sense from one's muscles, joints, and tendons to feel the weight, stretch, or joint angles of the hand. Based on this information, researchers have designed tactile sensors with various sensitivity ranges with resistive, piezoelectric capacitive and optical sensors to achieve human-like dexterous in-manipulation. Nowadays the robotic system is adopting an eye-in-hand vision system to provide the local visual information between the object contact surface and the hand to fine-tune the position and orientation while grasping. Though it is not a human-like approach, it provides better results when compared with the existing vision system mounted onto a fixed base. With the integration of depth sensors and eye-in-hand approaches, object-oriented 3D surface models can be created, thus producing better results for the dexterous grasping of 3D objects.

Additionally, with high dexterity levels [19] human hand can grasp without causing any damage [6] by adjusting the force and pressure based on the nature of the object. Also, humans can identify and pick fruits within a dense cluster without damaging the structure of the plant and the fruit. In recent years, the development of the multi-fingered hand or dexterous hand has gradually increased. The dexterous hands are available with three or five fingers [20]: More fingers can lead to more contact points, which makes it easier to form a more robust grasp. The traditional way of controlling the dexterous hand is through the opening and closing of the fingers in a binary way [21], however, these control strategies fail to adapt themselves to a dynamic environment. Thus, with the help of compliant control strategies, visual and tactile perception can be integrated with the dexterous hand to perform complex grasping and manipulation tasks.

Thus, this paper aims to provide an overview of human-like robot manipulation using dexterous hands. Initially, various actuated and underactuated dexterous hands with three-to-five fingers and manipulation strategies adopted for dexterous hands are reviewed, this includes traditional methods such as visual, tactile, and visuo-tactile servoing and learning-based methods, such as learning from observation (LfO), imitation learning (IL), learning from demonstration (LfD) [22], and reinforcement learning (RL) [23] are reviewed. The rest of the paper is organised as follows: Section 2—Dexterous Hands, provides an overview of various off-shelf dexterous hands with technical details and the summary is shown in Table 1. Section 3—Manipulation, provides information about control strategies: traditional and learning-based methods. In Section 4—Challenges and Discussions, challenges related to the development of a compliant model of dexterous hands and various control strategies are discussed and the summary of this paper is provided in Section 5—Conclusions and References section

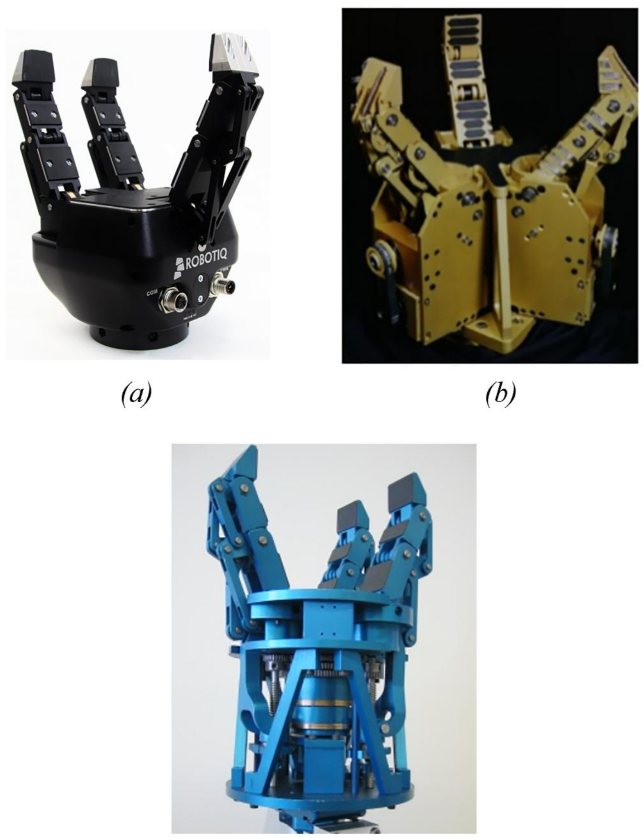
2 | DEXTEROUS HAND

2.1 | Robotiq 3-fingered adaptive robot gripper

The 3-fingered adaptive gripper shown in Figure 1a was designed at the robotics laboratory at Laval University, Canada. Initially, a single finger that could adapt itself based on the pressure points was developed which later became the base for developing their first gripper, MARS [24] Figure 1b, a gigantic, 12 degrees of freedom (DoF), fully adaptive with three independently rotating fingers. Though the gripper could grasp a lot of objects, it lacked its ability to industrial applications. Hence, in the second version of the SARAH hand [25], a 10 DoF gripper with two actuators was developed. It uses only two DC

TABLE 1 Summary of the above-reviewed dexterous hands.

Name	DoF	Fingers	Sensors	Weight (kg)	Actuation
Robotiq 3-fingered adaptive Robot Gripper	5	3	Position, force, and current sensors	2.3	DC motors
MARS Hand [23]	12	3	Force sensor	9	Brushless DC motors
SARAH Hand [24]	10	3	Force sensor	4.9	DC motors
iRobot-Harvard-Yale (iHY) Hand [25]	9	3	Pressure and optic sensors		DC motors
Shadow Hand [26]	20	5	Force/Pressure with position sensor	4.2/3.9	Electric motor/ Pneumatic
DLR Hand I [27]	16	4	Strain gauge-based torque sensors and Hall-effect sensor	1.8	DC motors
DLR Hand II [27]	13	4	Torque, force-torque, and angle sensors	1.8	DC motor
AR10 Robot Hand [28]	10	5	Torque/position sensors		Servo
DoraHand [29]	6	3	Tactile (for force and position) sensors	1.2	Motors
IH2 Azzurra [30]	11	5	Encoders, force, proximity, and current sensors	0.6	Brushed DC motors
Allegro Hand [31]	16	4	Position and force sensors	1.09	DC motors
Inspire robotics dexterous Hand [32]	6	5	Force, position, and current sensors	0.5	Micro actuators



(a) (b) (c)

FIGURE 1 (a) Robotiq three-fingered adaptive robotic gripper, (b) MARS Hand, and (c) SARAH Hand.

motors, one to control the opening and closing whereas the other to change the orientation of the fingers to grasp based on the geometry of the objects. The final version of the gripper is shown in Figure 1c. It is a 3-fingered with independent control with a programmable force of 30–70 N, a stroke of 155 mm and a payload of 10 kg. There are four grip modes, basic, wide, pinch, and scissor to handle different shapes of objects. The gripper can be integrated into any robotic platform, and it depends on Modbus RTU (Rs-485) as the primary protocol and Modbus TCP, EtherNet, PROFINET etc. as secondary. Due to the configuration, controllability and adaptability of each finger, the gripper could be used for pick and place operations, assembly, quality testing, and machine tending applications.

2.2 | iRobot-Harvard-Yale (iHY) hand

The iHY hand was developed as a part of the DARPA Autonomous Robotic Manipulation-Hardware program by both Harvard and Yale University. It has three tendon-driven fingers with five actuators, designed to be simple, durable, and inexpensive as shown in Figure 2. Also, a moderate hand can be used on mobile robots to carry out basic tool use, in-hand grasping and fingertip grasping. The authors in ref. [26] provide the list of functional activities that was decided to be performed with the hand initially at the development stage. The hand is composed of three fingers coupled by a single flexor tendon rather than differential transmission and the fingers were mounted in a triangular shape with two of them on one side and the other on the opposite. Actuators are the major components for the hand, iHY model used five actuators (EC-20 Maxon Motor AG) to control the fingers through a back driveable worn gear transmission. Three actuators control the three fingers with a single flexor throughout the finger, the adduction/abduction DoF is driven by the fourth actuator and finally, the fifth actuator allows the link angle of the thumb proximal and distal joints to operate independently. The tip of the fingers and palm consists of tactile arrays, each distal finger joint with flexure deformation sensors, magnetic encoders at the proximal and an accelerometer at distal finger links to measure the hand configuration and contact information. Overall, the iHY hand was capable of grasping, collision handling, variable stiffness and finger pivoting and pinching objects with varied shapes.

2.3 | Shadow hand

The Shadow hand is an advanced humanoid hand capable of trajectory tracking and hand movements to control its motion [27]. There are two variants, one with electric motors and the other with pneumatic muscles. Twenty DC motors are attached to the forearm for the electric motor driven and 20 pairs of air muscles for pneumatic driven. The hand has 24 joints and 20 degrees of freedom in total. Figure 3 shows the DC motor-driven Shadow hand. The thumb alone has five joints with 5 degrees of freedom whereas the fingers have four joints with 3 degrees of freedom. Force sensors were attached to each DoF for the motor-based hand while the muscle-based hand is attached with a pressure sensor for each muscle. The motor-based actuation system consists of force, position, motor drive electronics and communications, 20 of them loaded into the hand. On the other hand, the pneumatic muscle hand has pressure, position, calve driving electronics and communications for 80 valves. Both the hand models use EtherCat with a speed of 100mbps for communication and all the simulation, configuration and control of the hand is based on Robot Operating System (ROS). While all the control loops run at 1 kHz, the motor torque loop operates at 5 kHz. In the case of the muscle hand, all the control loops are operated at 1 kHz. The weight of the motor-driven hand and muscle-driven hands are 4.2 and 3.9 kg and the time response are 1 and 0.2 s respectively. The hand has degrees of freedom more than a human and has been used in various applications, such as grasping, in-hand manipulation, highly sensitive medical surgeries, bomb disposal vehicles, household works, and in highly reactive environments.

FIGURE 2 iRobot-Harvard-Yale (iHY) hand.

FIGURE 3 Shadow hand.

2.4 | DLR hand I and hand II

The German Aerospace Centre also known as DLR is the national centre for aeronautics and space research with headquarters in Germany. Aeronautics, space, energy, transportation, security, and digitisation are the main fields in which extensive research and development activities are conducted. Also, on behalf of the German Federal Government, it oversees the organising and conducting of the German space programme. The space-related research and development are focussed on by the Institute of Robotics and Mechatronics at DLR. Deployment of robots to perform operations in undetermined and unpredicted structures which are remote and dangerous was the motivation behind the DLR hands as well as some autonomous grasping techniques. Below are the hands developed by the DLR for space applications.

2.4.1 | Hand I

DLR conducted several experiments called ROTEX [28] inside the Spacelab during the Spacelab-D2 Mission in 1993 to confirm the functionality of a multi-axis robot in space. Though the experiments showed the successful common operations performed with a two-fingered gripper, future space missions would need space robot assistants capable of performing tasks like humans [28]. It was found that the considerable distance between the robot tool centre point (TCP) and the palm's centre necessitates substantial elbow motions to shift the hand orientations, drastically reducing the robot's workspace. Based on these restrictions, DLR Hand I, a four modular finger with a size close to that of humans and complete actuators integration within the hand structure was developed. The four identical fingers reduced the complexity of the system and each finger had 4 degrees of freedom (DoF) (2 DoF—cardanic base with intersecting axes for extension and adduction, and two interphalangeal joints with one DoF). The hand uses three actuators with a maximum force of 150N (21 mm diameter and 33 m length) to control each of the four fingers. Dyneema tendons are used for force transmission and all the electronics and sensors are mounted into the fingers, however, the control boards which provide external communication for the host computer through an optical fibre link are mounted within the palm. The DLR Hand I model used conventional strain gauge-based torque sensors to measure the force, and the motor position and joint positions are calculated by the onboard hall-effective sensor of the brushless DC motor and in-house optical sensor, respectively as shown in Figure 4. Additionally, tactile sensors based on force-sensitive resistors (FSR) were utilised to detect contact locations. However, the fingers were unbalanced due to artificial muscle and poor opposition of the thumb due to its low placement reduces the manipulation capabilities. Due to the wear and tear of the tendon-driven linkages, the hand was less reliable, and the surface of the fingers also proved to be too stiff and slippery to make good contact with the object.

2.4.2 | Hand II

Based on the DLR Hand I limitations related to the grasping algorithms and demonstrations [28], this led to the development of DLR Hand II in 1999. To improve the performance of the DLR Hand II, a new actuation system was adopted by using a coupled actuation for both axes to enable the application of forces in the extension/flexion direction from both motors and to increase the reliability of the tendon transmission was replaced by a belt transmission. Unlike the DLR Hand I, the DLR Hand II had two configurations for fine manipulation and power grasps. With the help of an optimisation algorithm, a single actuator was used to find an optimal mapping of the end positions to the desired configurations. Additionally, reducing the length of the finger base and that of the proximal phalanx had to be reduced for fine manipulation respectively, and finger flexion must be greater than 90 (degrees) to enable power grasp. The palm uses a 12 mm diameter Maxxon brushed DC motor running a threaded rod while the other fingers use the off-the-shelf brushless DC motors (24 mm diameter at the joint base, 19 mm at the proximal phalanx). Sensors based on strain gauges were used to determine the torque of the motors in the initial version. Six DoF force torque sensors were used to measure force and magnitude at the fingertip, however, while performing grasping-related tests. It was more suitable to have a better control method and a soft fingertip rather than a rigid one to achieve a good grasp and thus object-level impedance control and soft polyurethane skin to cover the finger pads were used respectively. However, this impedance control method was not suitable for handling the transition between no-contact and contact-based tasks. The thickness and softness of the finger pads can affect the quality of grasping [28], hence, they were covered by vacuum-moulded housings with a soft polyurethane surface with a thickness of 15 mm inspired by the palmar plate of the human finger [28]. Compared to the Hand I model; the Hand II model shown in Figure 5 was able to be teleoperated with a data glove providing force and visual feedback and could play the piano autonomously.

2.5 | AR10 robot hand

Figure 6 shows the AR10 Robot Hand, a low-cost, versatile, and durable humanoid robot hand with 10 degrees of freedom (DoF) developed by Active8 Robots [29], a UK-based company. The core of the Hand is made from anodised aluminium for lightweight, robustness and durability. Additionally, Firgelli linear actuators have undergone specific modifications to offer unmatched dependability and grip power. The goal to develop the hand was to provide an innovative, affordable humanoid design for grasping and for research and academic purpose. However, it either can be mounted on a variety of off-shelf robotic arms or act as a stand-alone platform. The AR10 Hand's fingertips are interchangeable and thus can be used for a variety of applications. The hand supports various platforms, such as Windows, Linux, or any other platform. For communication purposes, the hand relies on a USB or serial interface. Utilising the given graphical user interface, whether it is the Pololu Maestro Control Centre or using Rviz, simple movements and sequences can be simply programmed. The AR10 is compatible with MoveIt and Rviz thanks to the included URDF

FIGURE 4 DLR hand I.

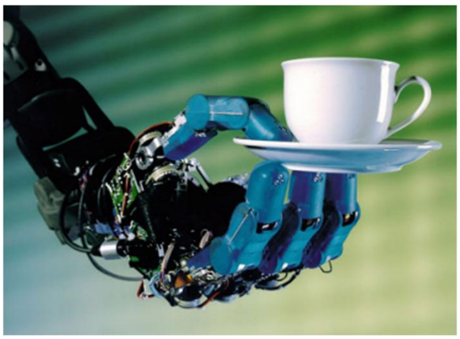


FIGURE 5 DLR hand II.

file, which is completely ROS-compliant for the hand. Complex task and motion planning are made possible by these potent visualisation tools.

2.6 | Dora hand

DoraHand [30] is a modular dexterous hand designed by Dorabot Inc., Shenzhen, China. 'The hand has two variants, three-finger and five-finger'. Figure 7 shows the three-finger DoraHand. The hand is designed with the hot-swap function, a simple plug-and-unplug action for fingers. The mechanism behind the hot swap is based on the pogo pin and locking mechanism, alongside, providing the power and signal transmission for each finger, individually. A thin, removable, asymmetric tip was designed for the hand to work with more environments and hardware. The fingertip can be utilised in some confined spaces because of its 5 mm thickness. To provide a human-like capability, the hand is equipped with a highly sensitive 0.3 mm film force sensor to act as a tactile sensor to sense the force and position simultaneously. Additionally, each force sensor is composed of two-to-four small sensors, which can identify the approximate position of the contact point on the force sensor surface. Regarding communication, there are two boards, the mainboard and the fingerboard, the main board provides the communication function and power supply to support up to six fingers and the fingerboard for controlling the fingers. The Controlled Area Network (CAN) communication protocol is used to communicate between the mainboards and fingerboards. Additionally, the hand supports USB (Universal Serial Bus) and Ethernet communication protocols operating at 60 Hz frequency between the hand and PC. The joint sensor feedback has a resolution of 0.01° and a precision of 0.1°, however, the joint motion precision is about 0.5°. The tactile sensor is highly sensitive with a precision of ±3% and can sense a minimum force of 100 mN while the position sensor has a precision of ±5%.

FIGURE 6 AR10 robot hand.

FIGURE 7 DoraHand.

2.7 | IH2 azzurra

Figure 8 shows IH2 azzurra, a dexterous hand developed by Prensilia for multiple robotics and bio-robotics scenarios, close to human hand size with five degrees of freedom (DoF) weighing about 640 g [31]. With the help of multiple force and position sensors, the anthropomorphic hand can grasp and sense a variety of objects. The degree of activation (DoA) is different from other hands, one for the flexion/extension of the thumb, one for the index, one for the middle finger, one for ring-little fingers and adduction/abduction of the thumb. Each finger is actuated through the tendon. This architecture promotes

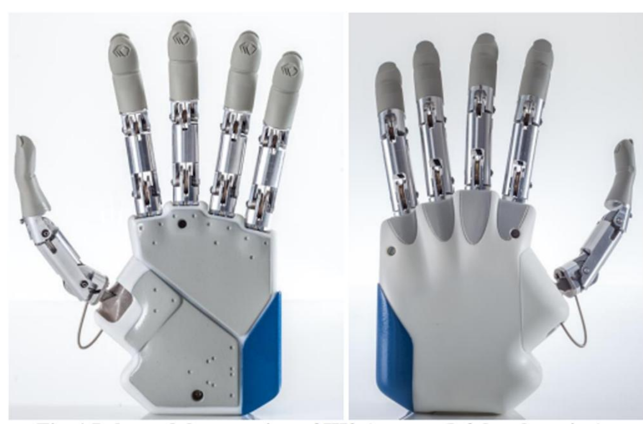


FIGURE 8 IH2 azzurra.

stability during precision or power grasps. The hand uses five motor encoders, five motor current sensors, 10 proximity sensors and four tendon-driven force sensors. IH2 Azzurra receives commands from a host PC through serial communication.

2.8 | Allegro hand

Allegro Hand shown in Figure 9 is a low-cost, highly adaptive robotic hand developed by Wonik Robotics [32], Korea. Due to its lightweight and portable anthropomorphic design, the hand has applications in research and industry to perform dexterous manipulation. However, thanks to the ready-to-use algorithms capable of grasping a variety of objects. Allegro Hand has a total of four fingers including the thumb and each finger has four independently torque-controlled joints leading it to have 16 degrees of freedom (DoF). This feature has made the hand to be an ideal platform for manipulation and grasping research. The total mass of the hand is 1.08 kg, and the payload is about 5 kg. The maximum torque and joint speeds are 0.70 Nm and 0.11 s/60° respectively. The joint angles are measured through a potentiometer with a resolution of 0.002 deg. CAN-based communication protocol with a frequency of 333 Hz is adopted to establish a connection between the user and Allegro Hand. To perform hardware testing and simulation-based algorithm prototyping, the Allegro Hand Console Application can be used.

2.9 | Inspire Robotics Dexterous hand

Figure 10 [33] shows the Dexterous Hand developed by Beijing Inspire Robots Technology, China. It has five fingers with six degrees of freedom (DoF) and flexible grasping capability and size close to that of a human hand. The thumb finger has two DoF whereas all the other fingers have only one DoF. Six Micro linear actuators with tendons attached are used to actuate the fingers. Additionally, each finger is equipped with a programmable force sensor to provide haptic feedback that is, the user can select a threshold for grip force for each finger. The position range of the fingers is 0–2000 (0—fingers fully open, 2000—fingers fully closed) while the force sensor range is 0–1000 (0–1000 g). The little, ring, middle and index fingers have an angle range of 19°–176.7° whereas the bending angle and rotating angle of the thumb are in the range of −13°–53.6° and 90°–165°. The RS232 or RS485 serial port is used to control the dexterous hand. Users may easily operate their dexterous hands thanks to the clear and effective interface control instructions. The dexterous hand is highly efficient and can be used in prosthetics, service robots, and teaching, among other things.

3 | MANIPULATION

3.1 | Traditional-based methods

3.1.1 | Visual servoing

The visual servoing of the articulated/dexterous hands is more complicated when compared to the traditional grippers. This is due to the nature of contact and mobility offered by the fingers in an articulated hand [34]. The traditional approach for dexterous hand manipulation is through planning and then controlling, yet a system without a visual feedback control loop is more susceptible to manipulation failures due to low accuracy. Thus, the visual servoing method can be utilised to increase the accuracy while estimating the object's pose. A fuzzy neural approach was put forth in ref. [35] as a technique to cope with model uncertainty, however, his approach does not include all possible manipulations. Without any input from the object posture, the Salisbury Hand, and the Karlsruhe Dexterous Hand [36–38] demonstrated a reduction in the controllers' progress. Thus, Muiioz [34] proposed a system for

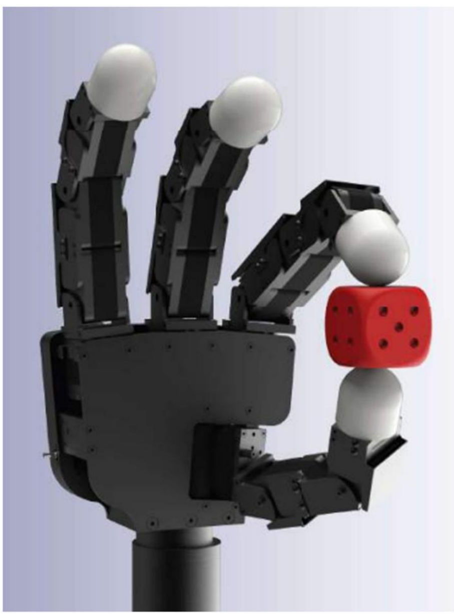


FIGURE 9 Allegro hand.

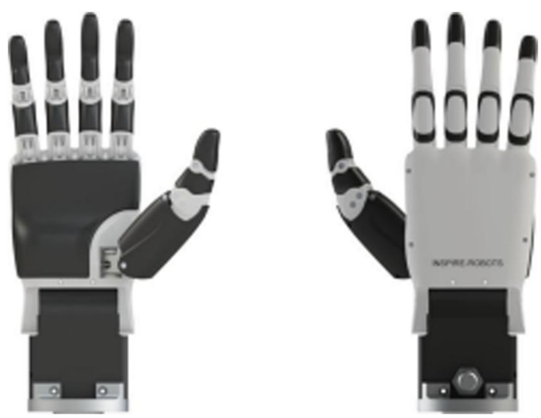


FIGURE 10 Beijing inspire robots technology dexterous hand.

robust dexterous manipulation through visual servoing techniques. Below Figure 11 shows the simple workflow of visual servoing.

Visual servoing is a technique where a robot's position and orientation are determined based on the image feedback from a vision sensor/camera concerning the target. The feedback from the vision can be obtained from two methods: eye-in-hand and eye-to-hand. The first one refers to the camera mounted on the robotic arm end-effector whereas the latter is mounted on the base or somewhere nearby as shown in Figure 12. The eye-in-hand technique is used most frequently by arm robot applications in agriculture because it is more versatile in target detection [23]. Later, by analysing the kinematics and trajectory of the arm-robot, and target position from image processing, the object can be grasped precisely. The vision servoing has a huge advantage while manipulating a robot arm, especially in agriculture as they could increase the production yields. Along with the position and orientation of the object, features such as colour, texture, ripeness, and health (in the case of fruits/vegetables) can be obtained. However, the challenge lies in synchronising the camera output used for object detection with the robot's motion.

The vision servo control can be attained by two methods: position-based and image-based control. In a position-based method, the robot controller is fed with the 3D estimated position and orientation of the target and the robotic/dexterous hand-mounted arm, respectively as shown in Figure 13. This method manipulates the camera trajectory in Cartesian space, making it simple to integrate robot control with obstacle avoidance. However, stability is a concern in this kind of hybrid control system [34]. Whereas the image-based approach depicted in Figure 14 identifies a cluster of feature points on the target item and projection the signal directly on the image plane to control the hand. This method does not require any transformations and the finger dynamics, the object dynamics and the image features can be expressed. The image features help to merge the object and hand dynamics in the same entity [34].

Target detection is a huge task in the visual servoing method and can be achieved by image processing. The position of the target can be obtained using a variety of techniques, including edge detection, Euclidean [39, 40], and others, for a visual servoing control system. Lighting plays an important role in target detection and thus image segmentation based on the seeded region growing approach and colour/shape feature was considered in refs. [41–43]. However, kinematics is a part of the visual servoing method and was included by ref. [44], in fact, Wang et al. [45] proposed a more accurate model by considering a three-part visual processing system: fruit holding, stem holding and fruit separation. Furthermore, in the study [23], kinematical modelling, position-based visual servoing, and edge detection for image processing were used to design an agricultural arm-robot manipulator.

Nowadays, the visual servoing method can be adopted to achieve complex manipulation tasks by teaching the dexterous hands based on human hand movements or in other words, gesture control. In the past, different methodologies have been proposed to track hand movements. Human hand tracking based on a highly articulated hand model was introduced by refs. [46, 47]. The fingertip positions and local edges are found by projecting the axes of the truncated cylinders onto an image.

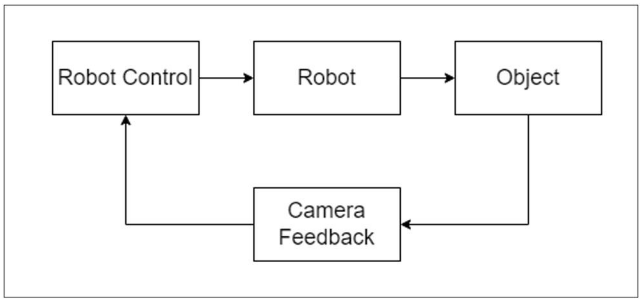


FIGURE 11 Visual servoing workflow.

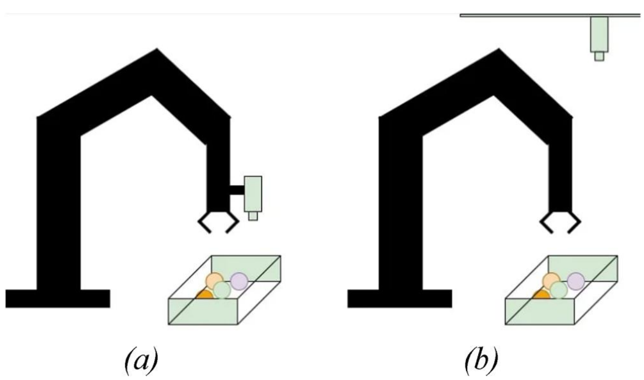


FIGURE 12 (a) Eye-in-hand and (b) eye-to-hand.

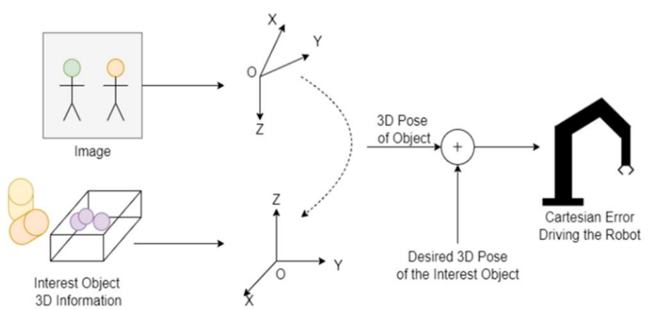


FIGURE 13 Position-based visual servo system.

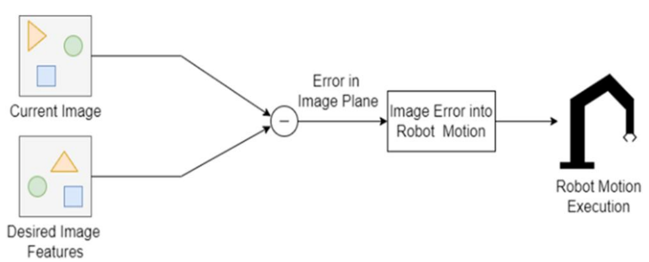


FIGURE 14 Image-based visual servo system.

To minimise the error produced between the actual and predicted locations, a non-linear least squares method was adopted. However, the model suffered due to occlusions and background clutter. [48] made advantage of a 3D changeable hand shape model with a surface mesh representing the hand created using PCA and training examples. The closest potentially deformed model that matches the image was found to enable real-time tracking. A stereo hand tracking system employing a 2D model changeable by affine transformations was proposed in ref. [49]. Wu and Huang [50] put out a two-step method to calculate the pose of the hand, first calculating the overall position and then determining the joint configuration. Their algorithm is presuming that all fingertips are visible. Infantino et al. [51] proposed a method in which the fingertip features are extracted with the assumption that all the fingers except the thumb are planar manipulators. Then computing the inverse kinematics to control the DIST-Hand based on the extracted features. However, the precision of the tracking system was lower, and the hand was not implemented fully on a robotic arm.

Features extraction in a complex environment such as clusters is a demanding task, which needs a larger sample size for processing; nevertheless, large sample size processing is challenging for traditional visual servoing methods. Thus, Convolution Neural Network (CNN) [52, 53] based visual servoing system is being adopted by many researchers. In ref. [54] an error image was obtained by explicitly subtracting the pixels from the images that represented various robot postures. They then fed this image into the CNN to predict the pose information, however, it runs a risk of losing important features due to overlapping. The study [55] proposed a neural network fed with the desired and the current image simultaneously to obtain the pose information. Since optical flow information may only be used to describe motion in images with tiny displacement, processing data involving high image feature errors may not be successful. On the other hand, [56] effectively computed the features and regress to the overall coordinate information to develop the control scheme, which is suited for simple backdrops, by applying the deep network to the image gathered by the sensor through visual servoing and processing the foreground image as the key information. The experiments in ref. [52] show that CNN can calculate better with image processing with attention mechanism in visual servoing tasks by extracting the region of interest (ROI) from the matching points of feature extraction.

3.1.2 | Tactile servoing

Along with the senses of sight, hearing, taste, and smell, the sense of touch is one of the most crucial basic sensory abilities in humans. The study [57] suggests that a tactile feedback feature for robots would be beneficial to advancing robotic manipulation as the experiments [58, 59] demonstrated that even simple manipulation tasks are difficult for people to accomplish when the tactile-driven control is compromised. Humans have always used their hands and palms to perceive the sense of touch to perform household activities. Similarly, as the name suggests, the multi-fingered (dexterous) hand consists of three to five fingers and a palm interlinked with each other [60]. It is possible to apply the necessary force and appropriately grasp delicate things if the hand is equipped with force sensors or tactile sensors. When a dexterous hand is working with an object, tactile sensing can detect its presence and measure the force needed to secure it. Tactile servoing can be broadly classified into two categories: image-based and pose-based. The image-based approach makes use of the features from the tactile image while the pose-based approach depends on task-independent Jacobian and projection matrix. Figure 15 shows a basic workflow for tactile servoing of dexterous hands.

In recent years, research has been carried out to attain human-like manipulation and interaction with the environment [61]. The authors in refs. [62, 63] provided an overview of how mechanical design and tactile sensing capabilities are prominent for dexterous hand manipulation. A RIBA robot system was proposed by Mukai et al. [64] for lifting and transferring a patient from a bed to a wheelchair with twin robot arms. The robot's tactile guidance system and the monitoring of the pressure distribution between the robot arms and the patient both made use of the smart rubber sensor which was mounted on the RIBA for monitoring the pressure distribution in the arms. However, this mechanism did not regulate the pressure distribution in and of itself. The study [65, 66] proposed a robot system for massage therapy based on a unified motion-force control on the forearm and an impedance control-based tapping system respectively. Also, a system based on the pressure feedback from the internal soft fluid actuators was proposed to shave a human's beard via teleoperation [67].

On the other hand, Lepora and Lloyd [68] proposed a controller based on pose-based tactile servoing. The tactile feature-contact edge in their controller is represented as a vector in Cartesian space and is learnt from a collection of images that were gathered and captured by the TacTip camera. Similarly, a three-axis tactile sensor was developed by Ohka et al. [69]. Similarly, Berger and Khosla [70] proposed a real-time control of a manipulator based on the tracked edges using the Hough Transform from the threshold tactile image. Pavan et al. [71] proposed a system whose control strategy was based on the features obtained from the tactile images and was utilised to perform the rolling task of a cylindrical pin on a planar surface. Later, refs. [72–75], expanded on the strategy in ref. [71] to create a more comprehensive design for a tactile servo that can make point and edge interactions with curved

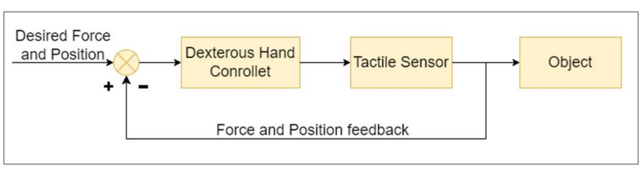


FIGURE 15 Basic tactile servoing workflow.

and flat sensing surfaces. For a broad range of tactile servoing activities with task-specific tactile interaction patterns, Li et al. [76] developed a control architecture utilising a task-dependent projector matrix. To implement more general tasks, Kappassov et al. [77] presented an external hybrid tactile position controller. However, these above tactile servoing methodologies were specifically designed for either a planar surface [76] or a spherical surface [78].

To make the tactile servoing more robust, Wen et al. [61] proposed a control framework that proposed a tactile servoing control system based on CNN representing the non-linear relationships (error) between the current and desired pressure and robot motion [79]. A CNN deep touch model was combined with the low-cost tactile sensor on a multi-DoF soft robotic gripper for fruit harvesting. The developed tactile-enabled gripper could detect and avoid the obstacles such as leaves or branches while harvesting. The study [57], showed that tactile servoing can be attained on any surface based on learning-based methods which will be discussed in the later sections.

Figure 16 depicts a simple illustration of a tactile servoing control system [80]. The intended contact state, S_d, is specified by the motion planner. When an inverse sensor model is provided, extracted tactile sensor characteristics, F_a, are converted to the actual contact state, S_a, and then S_a and S_d are compared to determine the inaccuracy. If an inverse sensor model is not available, the Tactile Jacobian must be used to connect changes in the tactile feature vector to changes in the contact state. The planner is informed about the modification of the intended contact state by the tactile servo solver through the generation of the error dS. To translate changes in the contact feature state to the location of the robot's end-effector dX in the task space, the contact model block is used. To determine the robot's joint values d from the error of the end-effector location in Cartesian space, the Robot Inverse Jacobian is then employed. The following is how the robot joint angles determined by tactile feedback are expressed [80]:

$$\theta(t+1) = \theta(t) + d(\theta) \tag{1}$$

$$d(\theta) = J_\theta^{-1} dX \tag{2}$$

$$dX = \frac{X_f - X_a(t)}{T_{seg} - t} \quad (t < T_{seg}) \tag{3}$$

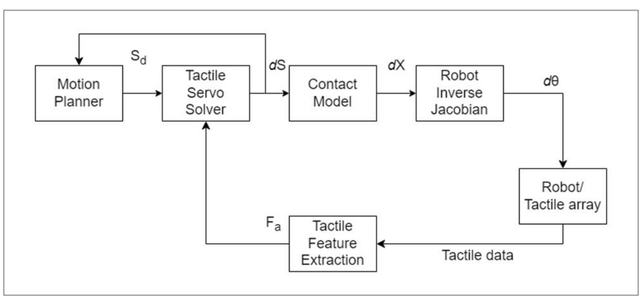


FIGURE 16 Illustration of tactile servoing control system [80].

$$X_a(t) = f_s^{-1}(F_a(t)) \tag{4}$$

where $\theta(t)$ and $\theta(t+1)$ are the actual and calculated joint angles, $d\theta$ is the error in joint angles, f_s^{-1} is the inverse tactile model, J_θ^{-1} is the robot inverse kinematics, X_a is the actual Cartesian position of the robot end-effector, X_f is the desired final position, T_{seg} and t are the periods within which the robot reaches its final position and time.

3.1.3 | Visuo-tactile servoing

Robots need multisensory inputs to operate in an unstructured environment capable of grasping an object and making decisions such as humans. In recent years, vision sensors have shown a prominent result in terms of controlling and artificial intelligence in the robotics field. The robots can adapt to the environment by making decisions and taking corresponding actions for complex manipulation tasks. This is due to the huge amount of data provided by the global dynamic image sequence. The received data is fed to the controller running a deep neural network. However, as a downside, modelling the physical contact and predicting information in the force domain cannot be relied entirely on the vision sensor and is a challenging task respectively.

On the other hand, tactile sensors can obtain the physical interaction data between the objects and the robot end-effector, and they are not affected by external environmental changes [81]. Information such as collision, geometry, and slip detection can be obtained from tactile sensors. In terms of dexterous hands, manipulating an object is a crucial task and the relevant information such as softness, geometry and grasping status of the object is needed to perform successful manipulation. However, to reach the object, the tactile sensors lack vision capabilities. We find that both visual and tactile sensing capabilities are needed for dexterous grasping and manipulation tasks. Thus, by combining both visual and tactile sensors, information such as initial estimation and trajectory planning can be obtained from the visual system, later, the dexterous hand can use this data to move close to the object and then the tactile system can refine those estimates and perform in-hand dexterous manipulation [82–84].

A study [84], proposed a vision-guided tactile crack perception system establishing coordination between tactile and visual perception. Before applying a high-resolution optical tactile sensor, a camera vision is utilised to quickly investigate the candidate crack regions. The collected tactile pictures are then used to recreate a refined shape. Cao and Luo [85] discussed a multimodal perception for dexterous manipulation through visuo-tactile cross-modal learning and attention-based spatiotemporal tactile texture recognition. A visuo-tactile servoing control framework in ref. [86] realise a full set of visuo-tactile interaction primitives on unknown objects, ranging from aligned approach through gripping, optimal object contacts and in-hand manipulation, and finally surface exploration. They used direct visual servoing to guide the robotic manipulation system and perform visual tracking of the object being manipulated. Because of this, the suggested approach differs from prior control schemes for dexterous manipulation [87] in that it considers the dynamics model of the robot hand's use of tactile and visual sensory data.

Li et al. [88] focus on study, the modelling of the tool using the robot as a new manipulator and the use of geometry-based parameter estimation will be the main topics. Their approach used a visuo-tactile controller to estimate the kinematic characteristics of an articulated tool with a flap. A visuo-tactile controller was used to interactively manipulate the tool utilising a robotic dual arm setup. A robotic hand on one arm is used to grab the tool's handle while the tactile sensor mounted on the other delicately flips the flap. The tactile servoing is used to ensure that the normal direction of the contact point is orthogonal to the normal direction of the flap, while the visual, guides the fingertip to follow along the contact point. The experimental results showed positive results for the proposed method.

To manipulate a soft deformable object using a dexterous hand, visual data such as position, orientation, and texture, as tactile data such as stiffness and actual contact forces acting on the object are essential. Thus, a visual-tactile-based control strategy was proposed in ref. [89] for in-hand soft object recognition and manipulation. The proposed method utilises a vision system for locating the object in the environment, and the tactile data with a Shadow Hand on a robotic arm kinematic information for manipulation and recognition. Once the object is recognised, the object's softness is estimated and then the tactile-servo controller is used to achieve a secure grasp and object deformation control. Initially, when the grasping points are analysed through a 'grasp planner' based on the visual data, a tactile position-based adjustment algorithm is executed to perform a secure grasp and if it fails to do so then a tactile-based force readjustment algorithm is executed on each finger for in-hand manipulation.

Similarly, Li et al. [86], proposed a visuo-tactile control framework to achieve robust grasping, in-hand manipulation, and exploration of objects without prior knowledge [90]. Two KUKA LWR robots fitted with a 16 x 16 tactile sensor array are used to demonstrate the approach. Initially, tactile sensors are deployed to align and approach based on the visual feedback on the object's pose. Later, the grasp is adjusted and maintained based on tactile feedback, performs in-hand manipulation, and then explores the surface object by acquiring a tactile point cloud. Furthermore, an action-conditional deep-learning-based CNN model was proposed [11]. The model constantly received the data from the visual and tactile sensors to re-plan actions to achieve the best grasp. The model was trained on over 6000 trials from 65 training objects and could grasp a wide range of unknown objects with a high success rate. However, the approach had some limitations:

- The action-conditional model could make only single-step predictions,
- Relatively coarse actions were considered rather than fine-grained actions, and
- The experiments were not conducted in cluttered environments.

3.2 | Learning-based methods

From the above section, we can conclude that the traditional based methods include visual, tactile, and visuo-tactile methods that rely on position, orientation, and physical properties of an object such as stiffness and texture to attain dexterity, robustness, and dynamic behaviours [91], however, it lacks the ability to adapt to the dynamic environment close to that of a human. Learning-based methods, on the other hand, not only have good adaptability but also have less reliance on accurate information and may take advantage of human experience to adapt to the dynamic and challenging environment. The manipulation of autonomous vehicles has been successful by adopting learning-based methods [92] and thus can be used for dexterous manipulation. Yet there exists a series of challenges for directly adopting the learning-based methods for dexterous or multi-fingered hands: first, due to high action spaces and state dimensions, second, variety of complex tasks and environments and finally, differences in kinematic modelling (includes actuators, structures and DoF).

In this section, current studies on dexterous hand manipulation based on learning-based methods are discussed such as Learning from Observation (LfO), Imitation Learning (IL) – focussed more on Learning from Demonstration (LfD), and Reinforcement Learning (RL) and no in-depth information about the implementation is provided.

3.2.1 | Learning from observation (LfO)

Learning from Observation (LfO) is a technique where the dexterous hand learns the task based on the observation made from the vision system as depicted in Figure 17. LfO is likely to be a direct approach for dexterous manipulation due to the high dimensionality of states and action spaces. However, the challenge lies in object pose detection, extraction of human-hand skeletal data, hand pose and grasping techniques, object and hand interactions, and manipulation learning. In ref. [93], a multi-stage pipeline was proposed comprising PointNet++-based human pose detection and refinement, hand skeletal and pose from the glove and MLP-based joint angle mapping. The proposed model was able to obtain 20 joint angles for the Allegro hand (four-fingered).

A novel human-inspired architecture for autonomous grasping of various objects using a soft hand was proposed in ref. [94]. The architecture comprised of a deep neural network algorithm to predict the human performable grasps on target objects based on the visuals obtained from the RGB sensor. These predicted values are then used to select suitable reactive primitives to produce human grasp operations. Finally, these primitives were executed and validated using a seven DoF KUKA arm and soft hand. The proposed approach had an

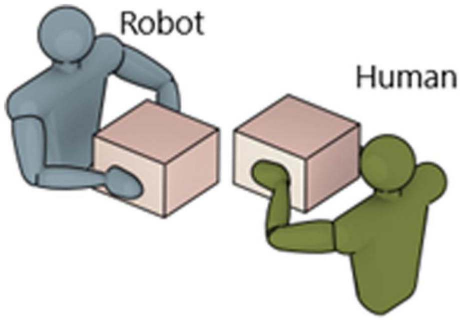


FIGURE 17 Learning from observation.

81.1% success rate for 111 autonomous grasps. Similarly, human hand skeletal was extracted by applying the hand pose estimator (HPE) to the depth images of the human hand. The hand skeletal data was then combined with inverse kinematics algorithms to teleoperate a robotic arm to do basic household tasks proposed in ref. [95].

Furthermore, Li et al. [96] create a dataset with 400 K paired depth pictures of the human hand, the Shadow Hand, and its joint angles first using a BioIK solver. Later, the Shadow Hand was manipulated through a network based on teacher-student with joint angle, consistency, and physical loss solely relying on human hand depth input. To accomplish real-time control of an under-actuated bionic hand in accordance with the bending angles of human fingers, Su et al. [97] propose multi-leap motion controllers and a Kalman filter-based adaptive fusion architecture.

3.2.2 | Imitation learning (IL)

Imitation learning is a promising strategy for achieving effective learning in complex, sequential multi-fingered manipulation tasks with high-dimensional and limited state-action spaces. Imitation learning techniques aim to mimic human behaviour in each task. An agent (a learning machine) is trained to perform a task from demonstrations by learning a mapping between observations and actions [98]. By using a single RGB image input, a model with a genuine human grab method for each object in a congested environment was provided by Corona et al. [99]. The method included the predictions for each of the 3D models and possible hand grasp types for 51 DoF hand models.

Learning from Demonstration (LfD) also known as Programming by Demonstration (PbD) replaces the time-consuming process of hard programming with automatic programming based on human demonstrations without any prior knowledge of the object [100]. LfD can be achieved either from kinaesthetic teaching or by immersive teleoperation. In kinaesthetic teaching, the human operates with the dexterous hand or robot's body to teach certain tasks while the immersive teleoperation approach uses external control devices, such as a joystick or any wearable trackers or sensors. A detailed survey on teleoperation-based LfD can be found in refs. [101, 102]. Li and Fritz [103] proposed an LfD method to teach the robotic arm with two fingers non-dexterous gripper to use the human tools.

A novel architecture and framework to teach the Shadow hand the manipulation tasks demonstrated by humans wearing a data glove was proposed in ref. [104]. The data received is fed to the artificial neural network with trajectory optimisation to perform various manipulation tasks. Various tasks such as picking and placing, turning the lid, and opening a bottle using UR10e and LBR4+ arms with Shadow Hand C5 were conducted. The model could learn the control policies with minimal demonstration data provided. Kumar et al. [102] proposed an approach for dexterous manipulation using object-centric demonstrations. This method does not rely on any wearable devices but is purely based on the human desired demonstrations using their hand. The model uses Reinforcement Learning (RL) to optimise the control strategy for corresponding grasping tasks.

Relative Entropy Q-Learning (REQ), a universal policy iteration approach, is developed to make use of the heterogeneous data distribution of the suboptimal experts and existing policies and generates suboptimal experts via waypoint tracking controllers for 7-DoF bimanual robotic arms and learn primitives for 20-DoF robotic hands [105]. As part of their development of a hierarchical RL method for dexterous grasp using point cloud inputs, Osa et al. [106] adopted initialised policies, created a dataset with contact information by human demonstration in simulation and adopted initialised policies. The upper-level policies select the grasp types and locations, and based on these, the lower-level policies generate the final grasp motions. A state-only imitation learning technique that does policy gradient analysis and interactively learns an inverse dynamics model is proposed by Radosavovic et al. [107].

3.2.3 | Reinforcement learning (RL)

Reinforcement Learning (RL) is a type of machine learning algorithm that learns how to translate environment state to action while maximising cumulative rewards throughout interactions with the environment. RL can be divided into two methods: model-based and model-free RL. The model-based methods require a model to train the system based on the data while the model-free-based method does not rely on any model but performs numerous trials to learn the task from scratch. To monitor the location of a hand's fingertip and estimate an object's pose using Multiview CNN, Andrychowicz et al. [108] proposed a model-free hardware setup with 16 tracking cameras and three RGB cameras. Proximal Policy Optimisation (PPO) and Long Short-Term Memory (LSTM) were the foundations of the proposed distributed RL system. The learnt discrete rules could be applied to the Shadow Hand for in-hand manipulation tasks by varying physical parameters in numerous simulated scenarios.

Model-Predictive Control (MPC), an offline learning approach, and online planning, which may be thought of as a model-based RL method, are combined to create MPC-SAC

[109]. Similarly, model-based methods such as time-varying linear-Gaussian [102] and deep neural networks [110]. Q-learning, a traditional solution for RL, however, Srinivasan et al. [111] proposed a safety Q function for RL (SQRL) where the policies are learnt in the pre-training phase while fine-tuning. On the other hand, Nagabandi et al. [110] proposed a model-based method of iteratively training the dynamic model with MPC. Lowrey et al. [112] offered a plan online and learn offline technique (POLO), which uses local MPC to help speed and stabilise global value function learning and accomplish direct and effective exploration based on the assumption that the dynamics model is known to be valid.

Furthermore, the above-mentioned architectures for dexterous manipulation rely on RL from scratch, whereas some researchers have combined RL with LfD which is also known as imitation learning (IL). However, the architecture does rely on a huge amount of data. The study [113], segregated the LfD approach into two types: prior and online knowledge. Figure 18 shows the workflow of these approaches. As the name suggests, in the prior knowledge method, the model had the demonstration data stored previously and acted as a source of knowledge before applying RL. In the case of online knowledge, the knowledge is provided when it is required, such as during trajectory.

4 | CHALLENGES AND DISCUSSIONS

Though advancements have been made in terms of dexterous hand development as mentioned in the dexterous hand section, the challenge still exists in developing a cost-effective, relatively small size with multimodal sensory fusions, such as vision, haptic, force etc. and the adaptability of the hand to perform various tasks. Artificial muscles with coiling-and-pulling capabilities and soft fingers with specialised actuators, such as shape memory alloys (SMA's) should be further researched from the structural perspective for compliant and safe handling. Sense of touch is one of the main aspects of dexterous hand manipulation and thus a thin layer of soft material with tactile ad force feedback capabilities strategically placed on the fingers and palm regions could increase the interactions between the object and the hand. In terms of simulation, platforms such as Gazebo, Mujoco, and Webots provide a safe, low-cost, and

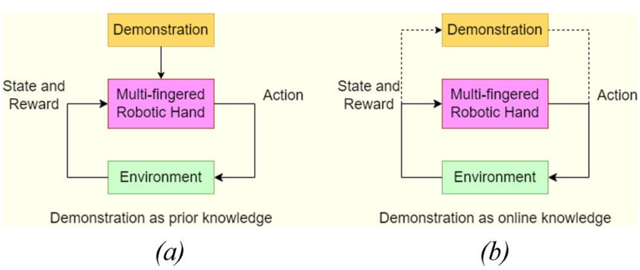


FIGURE 18 (a) Demonstration as prior knowledge and (b) Demonstration as online knowledge.

effective platform for data collection and testing out the theories. However, modelling a new system and maintaining the gap between the simulation and the real-time environment is a challenging task.

As discussed, due to the high dimensional state and action spaces, the manipulation control and learning of a dexterous hand is a challenge. Perceiving data from the multi-modal sensory inputs such as vision, force, haptic, position, velocity, acceleration etc. from the arm-hand system has been studied before but lacks a general framework to acquire data. When applying learning-based methods, the generation of data is a crucial task because the more data the better the system's efficiency and performance. The joints of each finger of the hand are considered an independent component, in that case, learning those policies is difficult. On the other hand, considering the grasping taxonomy and muscle synergies could help to achieve fast, robust, and efficient manipulation.

With imitation learning (IL) and learning from demonstration (LfD), the collection of demonstrated data is a key challenge. A suitable retargeting method needs to be developed to transfer the skills either from the human hand or through wearable haptic devices to the dexterous hand and the robotic arm to carry out specific tasks. While transferring, mapping and pose recognition from the human hand with occlusions is a demanding task as slight variation can cause maximum damage given the dynamic and sensitivity of the environment. Therefore, the design and development of a robust and retargeting methodology and the ability to make use of distorted or noisy data to effectively perform the manipulation tasks are required.

5 | CONCLUSION

In this paper, a brief overview of human-like robot manipulation using dexterous hands is provided. The development and technical details of various actuated and underactuated dexterous hands with three-to-five fingers are reviewed. Under the manipulation section, various manipulation strategies broadly classified into traditional and learning-based methods were studied. The traditional methods using visual, tactile, and visuo-tactile servoing architectures were reviewed with their pros and cons. Later, under learning-based methods, learning from observation (LfO), imitation learning (IL), learning from demonstration (LfD), and reinforcement learning (RL) were discussed. Despite the effectiveness of LfD in transferring human skills to the robotic arm-hand system, RL turns out to be a better solution for dexterous hand manipulation. However, RL needs more data to train the model, this issue could be resolved by adopting multiple (fusion) learning-based methods such as LfD to teach the robot arm-hand the specific task and then introduce RL for robust adaptiveness and efficient human-like dexterous manipulation.

CONFLICTS OF INTEREST STATEMENT

Authors declare that they have no competing interests.

DATA AVAILABILITY STATEMENT

Data sharing is not applicable to this article as no datasets were generated or analysed during the study.

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How to cite this article: Kadalagere Sampath, S., et al.: Review on human-like robot manipulation using dexterous hands. Cogn. Comput. Syst. 5(1), 14–29 (2023). https://doi.org/10.1049/ccs2.12073