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Comprehensive Review on Reaching and Grasping of Objects in Robotics

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SUMMARY
Interaction between a robot and its environment requires perception about the environment, which helps the robot in making a clear decision about the object type and its location. After that, the end effector will be brought to the object's location for grasping. There are many research studies on the reaching and grasping of objects using different techniques and mechanisms for increasing accuracy and robustness during grasping and reaching tasks. Thus, this paper presents an extensive review of research directions and topics of different approaches such as sensing, learning and gripping, which have been implemented within the current five years.

KEYWORDS: Cognition; Perception; Reaching and grasping task; Visual servoing; Sensing approach; Learning approach; Gripping approach.

1. Introduction

Grasping comprises actions of gripping and moving of an object from one place to another. The three basic elements that must be taken into account during a grasping task are localisation, object and its environment; all of which require visual accuracy, robust sensing and fine control with consideration of slippage detection. There are three elementary stages in which a grasping task should accomplish successfully. The initial grasping is the first stage, consisting of localisation, positioning and picking up of the object. At this stage, the vision and tactile sensing will be activated. However, the tactile sensing will be more effective at the second stage for the purpose of slippage detection and providing a fine gripping force. The second stage of grasping action is where operation and control are employed for either carrying or manipulating the object based on the perception acquired during the first stage. Lastly, the final stage is placing or releasing of the object by the gripper, manipulator, or hand at the targeted location. During interaction with the environment, grasping, or manipulating tasks is considered one of the most significant actions. Besides that, acquiring perception before grasping is important for the robot, which is called the precondition of grasping, particularly for a smart robot facing a complex surrounding with numerous objects.

Perception of the environment is one of the challenges that many researchers have devoted their effort to and thus sensing plays a significant role. The fact is that the physical properties of robots and objects can be measured by using sensors and then transform into signals that can be utilised by a robot controller. Sensors play an essential role in terms of detecting actions in the environment and the way that a robot should move so that the behaviour of the robot can be learnt as a result. By using sensors, a robotic system can be flexibly implemented in different workplaces for achieving various tasks. The purpose of using sensors such as vision and touch is to provide interaction between

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the robot's hand and object within the robot's workspace. There are global and local information that can be acquired from sensors.[1] The global information is provided by vision sensors, and it is used to determine the location of objects in the environment. The robot controller can exploit the global information for either avoiding unwanted obstacles, or moving the end effector to its target successfully. On the other hand, the local information is about the way robot interacts with objects in the environment, and it is provided by touch sensors. Local information might be used by the robot controller in terms of manipulating the contacting objects, or exploring and extracting the surface properties of the objects.[2,3] Vision sensors are mostly applied in robotics using cameras, whereas force and tactile sensors are implemented in sensing and acquiring the local information and properties of an object. There are three categories of sensory approach-based-control (i.e. visual control, force control and tactile control), which are implemented in controlling the robot's movement during reaching and grasping tasks based on the information extracted from these sensors. Under visual control, a combination of computer vision, image processing and control techniques are employed in manoeuvring the robot's end-effector or hand to reach and grasp an object (e.g. extraction of the visual information from the captured images of cameras). On the other hand, the force control is used to process the forces and torques as inputs during contacts between robot's gripper and object, while the tactile sensor is a more accurate and robust control during an interaction between robot's gripper and target objects in the environment as it has the ability to detect various physical properties such as slippage, deformation, vibrations, pressure, stress, etc.[4] Adjusting the contact of the robot's gripper with objects for a particular manipulating task is another role that tactile control provides. Therefore, these three types of controls are exploited to achieve the desired task based on the purpose of the corresponding sensors. In the last five years, robotic grasping has attracted many researchers' attention, either in developing novel techniques or improving the existing techniques that can help the robot to perform manipulation tasks successfully. However, the real challenge in the robotic grasping is in learning, sensing (e.g. controlling the force applied to the object by gripper during grasping) and gripping approaches such the methodology used for the gripping object.

Numerous reviews have been carried out based on different areas of reaching and grasping. For instance, under the learning approach, deep learning methods[5,6] and reinforcement learning[7] have been employed. Recently, ref. [8] has reviewed current and future works in deep reinforcement learning (DRL)-based grasping in clutter. A good review of recent and future works on a cognitive enabled robot for performing reaching and grasping tasks can be found in ref. [9]. In terms of sensing approach, a significant survey about visual and force/tactile control has been presented in ref. [1]. With the increasing demand for achieving high accuracy in grasping task, tactile sensing among others is becoming more important in robotic fields, whereby many studies have devoted either to the development of a sense of touch[3] or implementation of tactile sensing on robotic hands.[10,11] In terms of the gripping approach, some grasping mechanisms are inspired by geckos and spiders using dry adhesive materials,[12] or elastic inflatable actuators.[13] These are soft grippers designed based on advanced materials and soft components such as silicone elastomers, active polymers and gels, as well as shape-memory materials. Reviews on soft-robotic grippers can be found in refs. [13]–[15], whereby the researchers have mainly focused on achieving lighter, simpler and more universal grippers by using the inherent functionality of the materials. In this paper, we highlight the main difference between this review and the aforementioned, where the latter has mainly concentrated on a single topic of the grasping task. We intend to provide are view that covers techniques or approaches that have been used in reaching and grasping tasks. Thus, our contribution is in providing a comprehensive review that includes all the aforementioned review papers' topics. Figure 1 shows an overview of techniques in object reaching and grasping.

In this review, we exploit the keywords related to our research on object reaching and grasping. This includes Visual Servoing, Tactile Sensing based Robotic Grasping, Robotic Grasping with Object Pose Detection and Recognition, Robotic Manipulation, Deep Learning, Reinforcement Learning, Hand Design and Soft Robotic Grippers. We focus on a certain group of scientific sources/databases for getting the most up-to-date relevant papers, particularly IEEE Xplore, Sciencedirect, ArXiv and other specific related robotics journals. Section 2 of the paper presents a discussion on Sensing Approach. Section 3 describes the learning approach, whereas Section 4 presents a gripping approach. Assistive and Warehouse Robots can be found in Section 5. Finally, the conclusion is presented in Section 6.

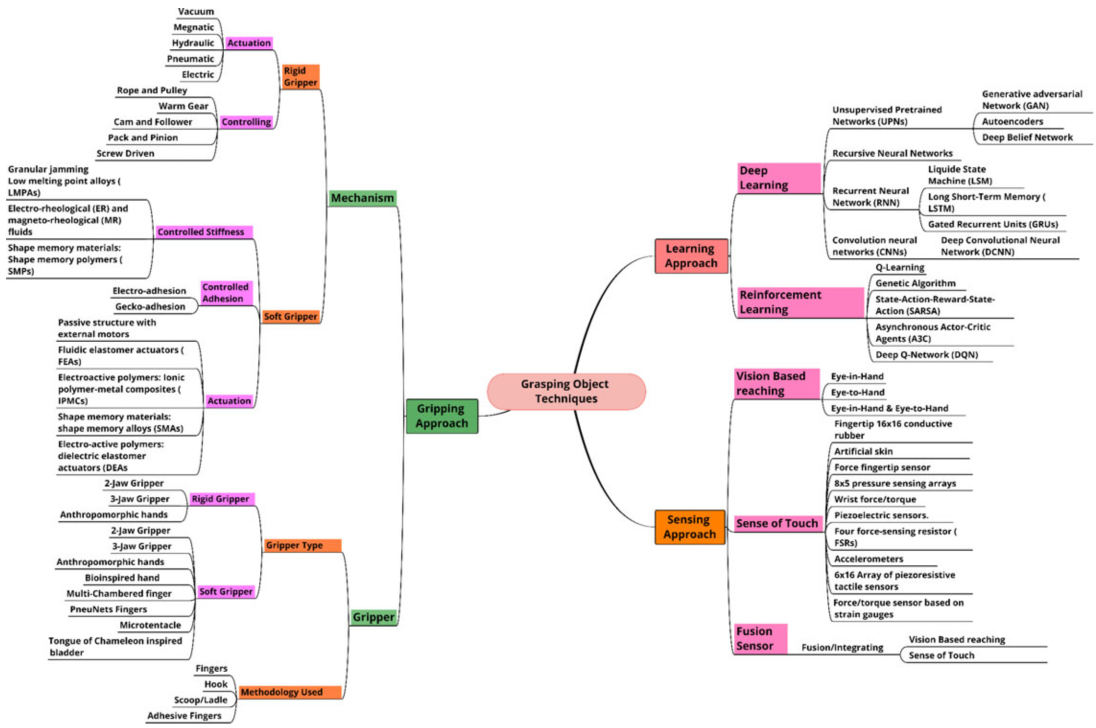

Fig. 1. Overview of techniques in reaching and grasping of objects.

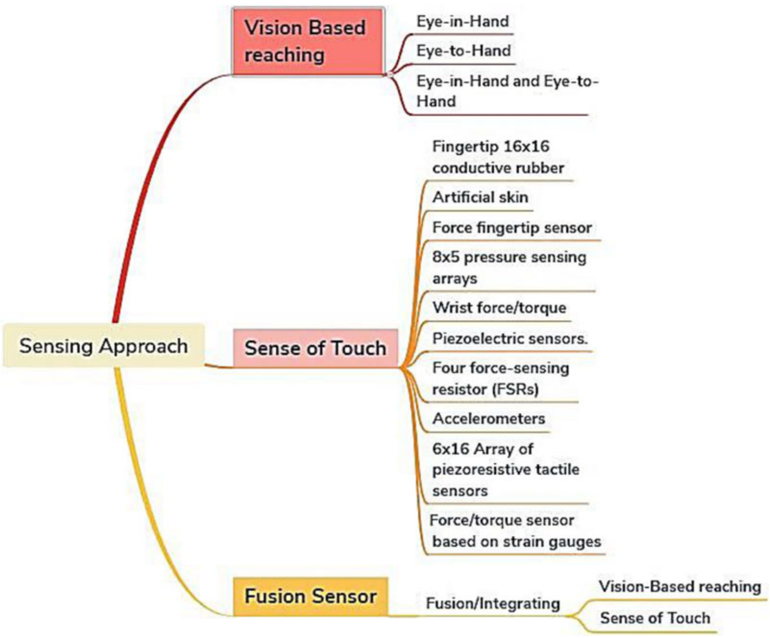

Fig. 2. Sensing approach categories.

2. Sensing Approach

In this section, there are three categories that will be explained and highlighted in this paper: (1) vision-based reaching, (2) sense of touch and (3) fusion sensor (integrating vision with touch sensors) as illustrated in Fig. 2.

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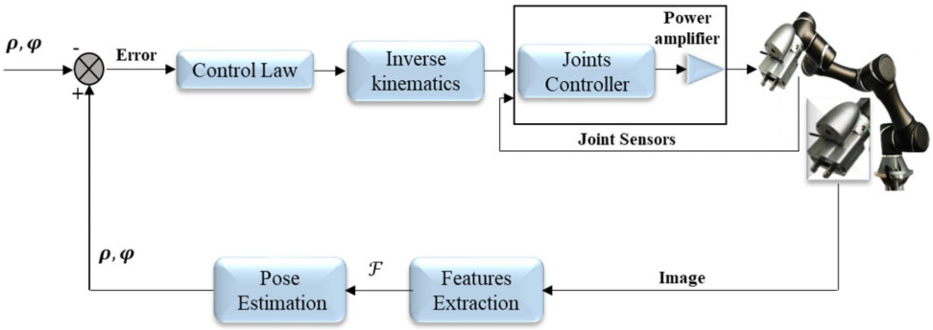

Fig. 3. Block diagram of visual servo system (adopted from ref. [1]).

2.1. *Visually guided reaching*

Implementing vision in the robotic system can significantly assist arm manipulators to accomplish different object manipulation tasks either in the structured or unstructured workspace. Using vision as feedback in controlling robot's motion is simply known as visual servoing. Ref.[16] defines visual servoing as the process of controlling the robot based on visual data that are extracted from either single or multiple cameras to perform a wanted task (see Fig. 3).

Many research studies on reaching control for manipulating tasks for various size and shape objects have been reported. For instance, reaching the desired object using gaze control has been proposed in ref. [17]. The authors exploited the learned hand–eye kinematics based on open-loop reaching. As a result, the robot has the ability to reach the object in the area of its workspace. However, learning to reach was slow, and also there was a positioning error after open-loop reaching. Gaskett et al. implemented a control system to enhance the robot to move towards the wanted object based on motor–motor mapping by implementing both closed and open loops. The aim of the work is to correct the positioning error after open-loop reaching,[18] in which open-loop controller uses only sensory data to learn. The method of hand–eye coordination system has been used to achieve reaching task using visual feedback.[18,19] However, the method suffers from the lack of error correction after the training phase with limited movement range. Algorithm to learn online kinematic parameters of the robot has also been reported[20] based on visual data. However, the algorithm is insufficient in finding the optimal set of robot configurations. Thus, joint space and sensor reading of the camera for the head has been proposed in ref. [21] to improve the learning process based on an active learning algorithm although the work has its limitation. For instance, learning has been achieved following task during an exploration phase but it did not significantly explore the robot's workspace. Jamone et al. proposed a strategy that enhances the robot to autonomously learn to reach an object through three-dimensional (3D) space based on combining both of exploration and exploitation.[22,23] The approach is heavily dependent on intuition of the designer, which is extracted from human's perception and thus not suitable for robot learning as robot sensors and end effectors vary significantly from those of human beings.

Recently, object recognition and detection have been widely achieved based on 3D laser range point clouds (LRPC). The most familiar technique in 3D LRPC is to use a bottom-up procedure based on plane and curve locations. For example, the approach is used in locating the most likely object configurations given the object's parameterisation and a point cloud by optimising relaxations of the likelihood function in ref. [24]. Also, extraction of effective features from object recognition in terms of 3D point cloud data, which is a method of keypoint extraction, has been proposed by Steder et al.[25] and Surmann et al.[26] The method has been operated on two-dimensional (2D) images generated from arbitrary 3D point clouds and has also been used to identify the borders of objects through foreground to background transition. Besides that, a laser-based indoor scene cognition has been implemented to operate a mobile robot in a structured indoor environment in ref. [26]. A bearing angle model has also been used to represent laser-point clouds, whereby a 3D laser scanner has been used to generate 2D bearing angle images for place recognition in a dynamic indoor environment.[27] Additionally, techniques of scale coordination have been proposed in ref. [28] serve as a solution to the problem of variable object scales in object detection, which can be adopted in each sub-scene segmented from the whole scene based on the spatial distribution of 3D laser points.

One of the crucial challenges in reaching and grasping tasks is the capability to reach objects based on visual feedback due to problems associated with spatial transformation, the complexity of learning spaces, redundancy and coordination. Lee et al. have presented an interesting approach in ref. [29] The approach describes the natural development of reaching in children and how the reaching developed into accumulative learning. The child's movements in reaching tasks are imitated as a model for a humanoid robot. Whereas, Chao et al. have proposed an advanced learning approach based on the hand–eye configuration which is applied in an autonomous robotic system.[30] Their method has been implemented based on building a computational structure in order to control the robot. The authors exploited the advantage of patterns in children's behaviour to construct a learning algorithm for the hand–eye approach. The work has also introduced an approach of developmental learning to robotic pointing using the interaction between client and server.[31] The approach has observed the developmental process of human infants as an inspiration to train the robot in object reaching that is out of robot's workspace. Nevertheless, the limitation of the abilities of infants restricts goal-driven learning and thus motor babbling becomes a key element in the robot's early learning. The resolution of sensor and motor abilities in infants are initially rough and gradually improve with learning over time. Subsequently, this observation reflects the developmental trajectory in robots too. For instance, a robot can master initial coarse abilities with further refinement as needed.

Brand et al. have proposed a Reachable Space Map (RSM) to control the position and posture of the robot before reaching is performed.[32] In the approach, the workspace of the robot has been expanded to reach the unreachable object using a visually guided combination of locomotion and whole-body movements. Nguyen and Kemo have employed a support vector machine (SVM) by using a vision sensor as input for predicting whether manipulation manner is successful in accomplishing a task or not at a specific 3D location.[33] Thus, the authors have enabled a mobile manipulator to autonomously learn a function by taking red-green-blue (RGB) image and a registered 3D point cloud as inputs and then returning a 3D location at which manipulation behaviour was likely to succeed. However, the approach is restricted to perform opening and closing tasks of a cupboard, as well as switching on and off lights based on active learning. The same application for opening and closing of a cupboard has also been performed in ref. [34] based on extracting kinematic background knowledge from interactions (e.g. using task-sensitive relational learning). In addition, vision-based information and Bayesian estimation techniques have been used to estimate hand position and to correct the kinematic model of a robot during movements.[35] Movement of ideal reaching begins with the open-loop phase in order to bring the robot's hand to the surrounding of the object. Once the robot's hand is observed by one of its cameras, the filter is fed through a vision-based estimation method for a 3D pose, which is used to regulate the kinematics parameter of the robot arm. The authors have devoted to control the motor directly from the images. The moment the robot's hand becomes closer to a target object, kinematic errors will be obviously minimised, so that better grasping control might be performed. Despite the fact that a human is able to acquire 3D position and orientation of a seen object, a direct map from sight-to-motor command is both inefficient and ineffective. Therefore, the same methodology has been implemented in ref. [36] by using Graphics Processing Unit (GPU). GPU improves the real-time robotic arm pose estimation and also reduces the end-effector error near the objec'svicinity.

In ref. [37], Bhattacharjee et al. have used the supplementary properties of vision and tactile sensing to acquire thick haptic maps throughout its visible environments using an algorithm. The algorithm produced two significant simplifications in the job. First, the authors used colour to identify which places were visually comparable despite extra image features such as texture features that could possibly be able to improve its performance. Secondly, the authors labelled the objects with coordinates in 2D image based on haptic labelling and then performed operations with consideration of the coordinates system of the image. As a result, the proposed algorithm has adequately labelled, almost 76.02% from all tested objects in a cluttered leafage environment. Enhancement of robotic hand–eye coordination system has been presented in ref. [38]. The proposed system has the capability of transmitting stimuli to the hand through eye and vice versa based on a stimulant delivery channel in two directions by exploiting the "Stop-to-fixate" concept.

Fantacci et al. have proposed a framework based on decoupling the control of translation and orientation by using marker-less visual servoing, which does not require prior information about the object's environment, but based on the image for predicting the unknown object's position and 3D shape to be grasped. A particle filter called Sequential Monte Carlo with visual servoing and gain scheduling method have been implemented in order to prevent the occurrence of oscillation

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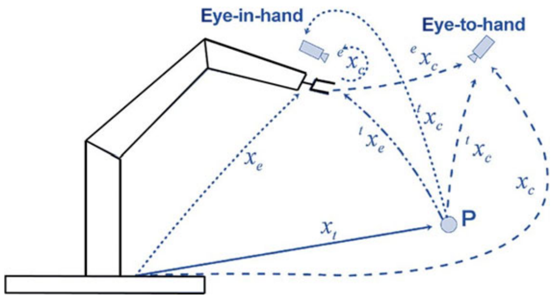

Fig. 4. Eye-in-hand and eye-to-hand configuration (adopted from ref. [49]).

and overshooting for end-effector around the desired pose. Also, extraction of the information about the shape of the end effector has been performed using the histogram of oriented gradients descriptors (HOG) based on images. Besides that, the authors have reported that grasping from the top view is better for a different small shaped object, or to be gripped from different poses that partly occludes the hand.[39] Recently, Luo et al. have proposed a mechanism for improving the reachability process as inspired by human infants. In the approach, the authors mimic the reachable mechanism of human infants based on how the infants learn the reaching for objects during their first four months for all the phases[40] using a neural network to model proprioception. In ref. [41], Sundermeyer et al. have proposed to improve the deep grasping based on using simulation and feature level based domain adaptation, which are associated with a tested data-driven and monocular vision. Also, the authors have proposed a pixel-level-based domain adaptation model, which uses synthetic images produced by the simulator as input. After that, adapted images are generated, similar to real-world images produced by a camera mounted on the shoulder of a robot. As a result, both approaches of adaptation (e.g. feature-level and pixel-level) are complementary and a new method based on a combination of these two approaches has been presented in ref. [42]. Self-supervision approach has been implemented in ref. [43], where grasp labels are automatically generated by a robot's trial and error on a large number of real-world or simulated grasp attempts. Additionally, a visual method based on a dual camera has been proposed for identifying and localising the scattered rivets for robot grasping.[44] Zhong et al. have presented a method based on combining laser-point detection and pose estimation algorithms to improve the grasping task with the application of assistive robot arm for wheelchair.[45] In the approach, a three-stage process to achieve pointing and picking up of object has to be carried out. First, a colour-depth (RGB-D) camera is used to capture an image as a pre-processing. After that, the image is processed by a convolutional neural network (CNN) for determining the coordinates of laser points and objects within the image. Lastly, centroid coordinates of the chosen object are obtained via depth information. In an indoor environment, image and depth information are usually acquired by using RGB-D sensors such as Kinect. Currently, most algorithms employ RGB images or point clouds for object detection. For example, a novel deep learning has been designed based on visual recognition of object and pose estimation.[46] The visual system proposed in the paper includes four modules: (1) visual perception, (2) pose estimation, (3) data argumentation and (4) controller of robot manipulator. Neural principles-based reaching and grasping tasks have extensively been studied in primates. However, only a few studies have developed the experimental apparatus by combining the reaching and grasping approach in 3D space. For instance, a highly flexible device has been developed by Chen et al. by combining a custom turning table with a 3D translational device. The setup enhances the robot to move to two positions at the same time and grasping of different shaped objects is easily done. While hand trajectory and grip types are recorded via optical motion tracking cameras and touch sensors, respectively in ref. [47].

Eye–hand or hand–eye coordination is the controlling process of both hand and eye, which is implemented to enhance the robot for achieving reaching and grasping tasks with the use of proprioception feature either for hand to guide the eyes or for eyes to guide the hand.[48] On the one hand, the camera is nominated as eye-in-hand once the camera is located or mounted on the end effector of the robot's arm so that there is a constant relation between the position of both camera and end effecter. On the other hand, the camera is nominated as eye-to-hand once the camera is located or mounted on a fixed place to observe both robot's hand and its workspace. Hence, eye-in-hand and eye-to-hand approaches are considered as two configurations for the camera in robotic control through visual feedback as shown in Fig. 4. Thus, as an analogy, the robot manipulator behaves like

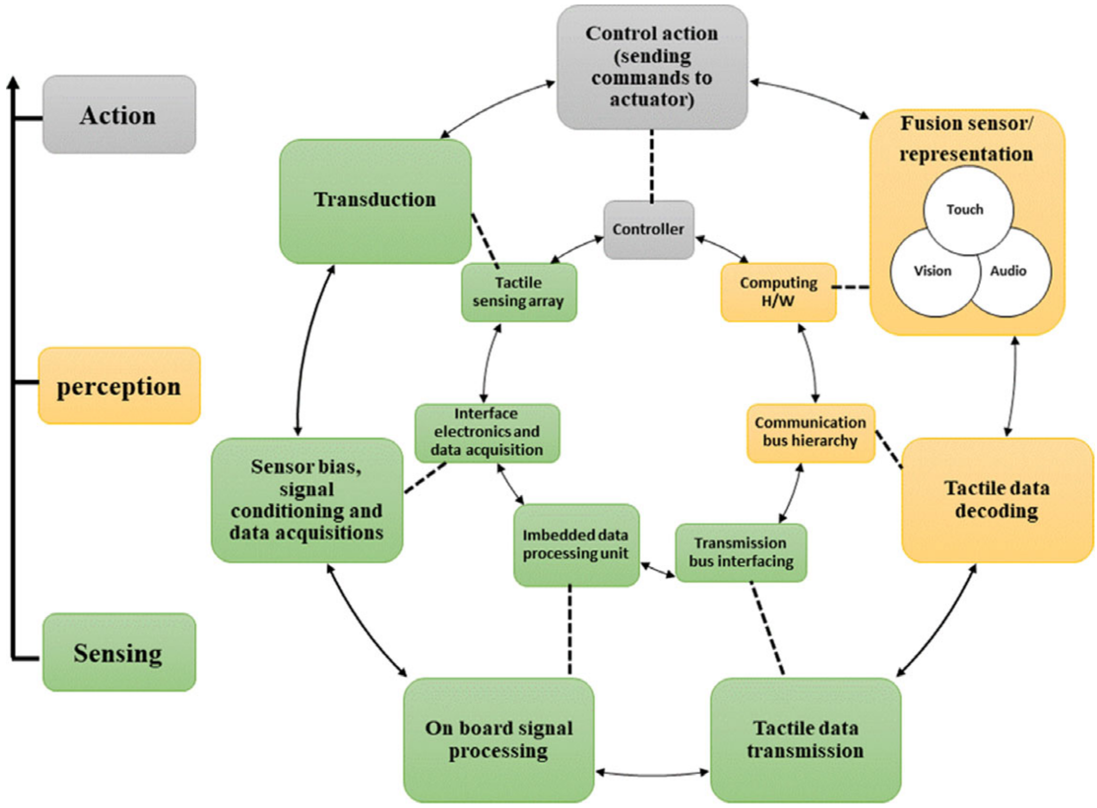

Fig. 5. Block diagrams of robotic tactile sensing system (adopted from ref. [76]).

a human hand, while the camera acts like the human eye.[49] There are a plenty of researches that have been implemented in visual guidance-based reaching and grasping tasks as summarised in Table I.

2.2. *Grasping using sense of touch*

The tactile sensor plays a sensitive role in robot's perception based on the touch concept. It helps to achieve manipulating tasks in either structured or unstructured environments, particularly in the independent exploration of robot and manipulator actions. There are six types of exploration procedures as defined by Lederman.[75] These six types of exploration are used to control the exploration action of robots and act as the foundation for performing quick identification. The sense of touch (e.g. tactile sensors) is associated with a robot that explores its surrounding stimuli through touch. Also, touch sensing is used to obtain information about the object features (e.g. shape, texture and material), which helps the robot or manipulator to give commands such as determining location and slippage detection. As shown in Fig. 5, the process of the tactile sensing passes through three stages: sensing, perception and action.[76] Figure 5 also shows the block diagram which is the structural blocks for hardware based on each corresponding functional block. Thus, transducing the external stimuli, such as vibration and pressure into changes on the elements of sensing for tactile sensors is called the sensing process. After that, these data are obtained, conditioned and processed based on an embedded data processing unit and then transmitting to the perception level to build the model as well as perceiving the properties of the desired object. At this stage, the sensing tactile can be fused with other modalities of sense (e.g. vision and auditory perception) as explained in Section 2.3. After sensing and perception stages, the actuator receives the control commands to achieve the desired actions based on the controller. The purpose of using tactile sensor for exploration is to collect information about the environment and to obtain information about objects that will be manipulated or grasped.

The relation between the force that is applied to an object and the deformation of the object has been studied based on the grasped object in ref. [77]. Object identification and extraction of features have been achieved in ref. [78] based on analysing data from tactile sensors using machine learning. In addition, sparse coding of the joint kernel has also been proposed in ref. [79] for solving the problem of interference of tactile data between dexterous hands with an object during contact. Tactile

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Table I. Summary of some visual servoing based reaching and grasping tasks.

Sensor	Technique	Application	References
Eye-in-hand	• Combination of a computed closer point (CCP) approach with an iterative closest point (ICP) with active laser projection	Roboticbin-picking	[50]
Eye-in-hand camera configuration	• Visual servoing based on image (charge-coupled device camera) • Artificial Neural Networks (ANNs)	Controlling the movements of the manipulator (the 6 DoF PUMA 560)	[51]
Eye-in-Hand stereo visual	• Feedback based on visual using a stereo head which is mounted in the wheelchair's hand of mounted robot arm on wheel chair	Assistive robotic arm to recognise and grasp textured ADL objects [ADL=activities of daily living]	[52]
Eye-hand coordination	• The vision to-kinematics mapping	Object grasping and tool based on iCub humanoid robot	[53]
Eye-in-hand stereo visual	• Image-based visual servoing algorithm	Racking and catching a moving object	[54]
Eye-in-hand	• Gaze control by integrating multiple sources of information	Predicting others' behaviour during reaching and grasping the object	[55]
Eye-in-hand and eye-to-hand configuration	• Multi-camera pose estimation • Image-based visual servoing (IBVS) controller • position-based visual servoing (PBVS) controller	Object manipulation	[56]

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Table I. Continued.

Sensor	Technique	Application	References
Eye-in-hand	• Visual servo control • Simultaneous localisation and mapping (SLAM) based on off-the-shelf libraries (Visual Servoing Platform library (ViSP) and Large Scale Direct SLAM (LSD-SLAM))	Robotics harvesting in dense vegetation	[57]
Eye-to-hand camera	• Image-based visual servoing • Combination of the Jacobian matrix with the depth-independent matrix	Regulating a 6-DOF mobile manipulator to a desired pose	[58]
Eye-to-hand camera configuration	• Adaptive artificial network-based fuzzy interference system (ANFIS) method	Controlling a robot arm for picking up and placing the targeted object	[59]
Eye-in-hand configuration	• Image-based visual servoing using a 6-DOF camera	Representing the motion of a tumbling object to be grasped	[60]
Eye-to-hand camera	• Visual feedback	Towel grasping	[61]
Hybrid visual servoing	• Reinforcement learning and finite-time adaptive Fractional-Oder Sliding-Mode Control (FOSMC)	Reaching the home location using Pioneer P3-DX robots	[62]
Eye-in-hand and eye-to-hand configuration	• Involving a single camera using marker-less model to track the desired object, as well as a pattern used to track the end-effector	Humanoid robots-based object manipulation task	[63]
Eye-in-hand camera	• Teleoperation system based on unified real-time optimisation controller	Providing robust occlusion avoidance in cluttered environments using dual-arm robot	[64]
Eye-in-hand camera	• Multi-View Picking (MVP) controller using multiple informative viewpoints	Reaching to grasp an object in clutter and occluded environment	[65]

Table I. Continued

Sensor	Technique	Application	References
Eye-in-hand	• Moment-based 2 1/2D visual servoing method based on combining image moment and relative rotation features	Grasping textureless planar parts	[66]
Eye-in-hand configuration	• Image-based visual-impedance control	Dual-arm aerial manipulator	[67]
Eye-to-hand	• Image-based position control	Controlling the motion of non-holonomic mobile robots	[68]
Eye-in-hand vision	• Vision-guided control strategy based on six image features • A behavioristic image-based look-and-move control structure • Exploiting neural-fuzzy controllers	Picking up a work-piece on the station using manipulator	[69]
Eye-in-hand visual servoing	• Online Image-Based Visual Servoing (IBVS) controller • The adaptive Neural Networks (NNs) and • The Barrier Lyapunov Function (BLF)	Usage of controlling manipulator	[70]
Hand-eye calibration	• Visual servoing using marker tracking and depth information provided by an RGB-D camera	Searching for object of interest on the scene	[71] [72]
Eye-to-hand and stereo-vision	• Position-based visual servoing method using an edge-based distance transform metric and synthetically generated images of a robot's arm-hand internal computer graphics	Reaching and grasping tasks on the iCub robot	[73]
Eye-in-hand	• Decomposing the end-to-end system into a vision module and a closed-loop controller module	Grasping a tiny sphere	[74]

sensing is closely related to the robot controller. For instance, tactile sensors are used in multiple fingers of a dexterous hand to improve stability control of an object during grasping and to decrease the possibility of the falling object during gripping tasks.[80] Using tactile sensor as feedback with Bayesian identification technique has been proposed in ref. [81] to perform identification and classification of different size and shape cylinders by using claw platform of the grasp-reposition-reorient (GR2) hand. Besides, piezoelectric polymer-based contact sensors are integrated on each finger-pad of the robot hand to improve the grasping task in an unstructured environment.[82] On the other hand, tactile sensor consisting of three thin sheets built from force-sensitive resistors has been implemented on the hand of the robot. In this approach, which has been used to trace the edge of the object during the welding process, object recognition in three dimensions is realised by considering the shape, surface and edge of the object.[83] Romano et al. presented a novel controller for the robotic grasp. In their work, the controller processes measurements extracted from pressure sensor arrays on the fingertip of the gripper. The controller then commands the jaw gripper to accurately and stably picked up and placed unknown objects based on the selected location.[84] Moreover, using a tactile sensor as the feedback has been proposed in ref. [85] to enhance the stability of the robot during the grasping process under pose uncertainty. This approach has utilised tactile sensing for estimating the grasp stability based on an algorithm of adjusting hand after pre-grasp is performed. Walker et al. have also used a tactile sensor as a feedback to improve the performance during the object manipulation.[86] In their work, a haptic system based feedback has been developed to explore the effectiveness of using the feedback of slip information from vibratory tactile because it can help to grasp objects without slipping once the visual feedback does not activate. In addition, five tactile feedback conditions (e.g. vision, pressure, slip, pressure slip and no feedback) have also been investigated in ref. [87] to explore the effectiveness of the feedback in improving the closed-loop of myoelectric control of prostheses for object grasping.

In this approach, six types of objects have been studied using weights and stiffness based on a virtual environment. It has been reported that slip feedback is better than the others in terms of a quick grasping, grasping accuracy and stability. Moreover, increasing the points in contact based on haptic control has been implemented in ref. [88] to make rapid exploration for grasping unknown objects. Also, the approach of multiple points of contact has been developed based on covering the hand with tactile sensors. As a result, the experiment showed an improvement in the robustness of the grasp once the objects are enclosed by the robot hand. In addition, the approach of using a tactile sensor with kinematic information has been proposed in ref. [89] to improve the grasp quality during manipulation, and also to avoid slipping of the grasped object. In this approach, the tactile sensor is used to provide the local information of contacting between fingertip and object. Moreover, solving the effectiveness of an object's surroundings (e.g. the picking up and placing of an object in relation to other objects and surfaces) on the perception of the tactile sensor has been addressed in ref. [90] based on using multimodal tactile sensing by exploiting data-driven such as k-nearest neighbours (k-NNs), SVMs, hidden Markov models (HMMs), as well as long short-term memory networks (LSTMs). Besides, Lepora et al. have used the optical biomimetic tactile sensor to improve robustness of edge perception and contour following by exploiting the deep learning (deep CNN).[91]

Additionally, different work has been implemented based on using tactile sensors for achieving various tasks. For example, the algorithm of object exploration has been implemented in ref. [92] based on using three-axis tactile data. The three-axis tactile sensor has been applied to the two-fingered hand of a humanoid arm for object grasping. On the other hand, a robot hand with three fingers using the tactile sensor for learning and recognising objects with different shapes and sizes for various grasping applications has also been used in ref. [93]. Vezzani et al have used the tactile sensor to identify an object from a different set of known objects[94] and also to improve the perceptive capabilities of autonomous operations for the robot (e.g. the iCub humanoid robot used for experimental validation). In another work, Iterative Closest Labelled Point (ICLP) algorithm has been proposed for object recognition based on tactile data and kinaesthetic information.[95] The authors have validated their algorithm experimentally based on using a Phantom Omni device as a robotic arm where the tactile sensor is attached to robotic arm's stylus. Besides that, reducing the effort and time, that are exerted during motion and positioning of a sensor to the appropriate surface of the object, has been solved in ref. [96]. In the work, the authors simulated the data acquisition procedure in order to find the best selective data acquisition algorithm, which then allows the recognition of probed objects based on the acquired tactile data. Funabashi et al. have proposed uSkin tactile sensors (3D

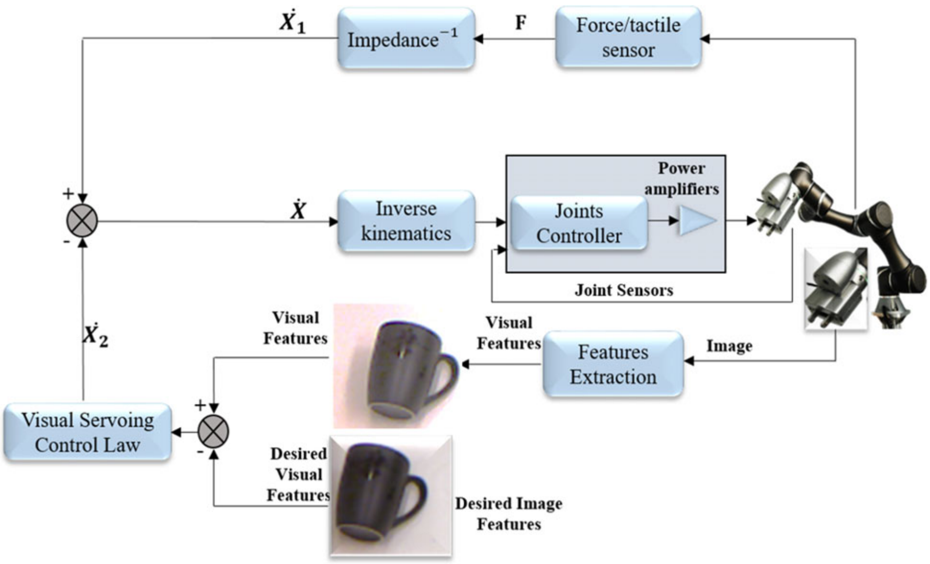

Fig. 6. Visual/force impedance control system (adopted from ref. [1]).

Tactile Sensors), which have been embedded with a two-fingered robot hand (Allegro Hand).[97] They have also concentrated on the object recognition via distributed forces with the exploitation of deep learning approach algorithms. Furthermore, the object recognition has been achieved based on using tactile to enable prosthetic fingers as well as feedback glove. It allows a human operator to control these artificial appendages while masking user's natural tactile senses[98–101] A number of literatures of dexterous grasping and object manipulation on haptic sensing, perception, manipulation and more recently for prosthetics can be found in refs. [10], [102]–[106].

2.3. Multi-sensor control

Combining local and global data, which are produced by using the sense of touch and visual sense respectively, provides a complete perception of the surrounding environment for the robot to accomplish its task successfully. Based on that, the visual data are used to feed the controller of the robotic system about object's view such as shape and pose. Whereas, data from touch sensing, such as tactile and force sensors, are used to feed the controller as specific local features of object such as texture and materials type. Therefore, both local and global data are needed to achieve a complex object manipulation task. For example, Fig. 6 shows the block diagram that uses a combine visual/force using impedance control for improving the reaching and grasping task.

Fusion sensor technique is a combination of many sensors in order to bring together the features of all sensors. Visual-tactile is the most common fusion sensor that is used and implemented in the robotic field, particularly in reaching and grasping of objects. The aim of these types of fusion sensors is to integrate the features of vision-based global information with the tactile sensor based local information of objects. The local and global data are generally combined in the literatures by applying two different strategies: neural networks or hybrid control. Many researchers have devoted their effort to come out with robust and accurate grasping. For instance, a combination of tactile data and image information has been demonstrated in ref. [107] to develop as a complementary system. In other words, in case the visual sensor could not distinguish the object, the tactile sensors in the robot's fingertips are used to capture the properties of the objects (e.g. texture, friction, roughness, or compliance). For validation, the fusion technique has been tested on practical dataset of 18 household objects. Vision-tactile fusion has been developed in ref. [108] to manipulate novel objects from known categories. Alternative approach using the RGB-D images based vision sensor has been presented to initially determine the position and shape of desired object, while tactile data are exploited to improve the planning for better grasping as a complimentary part for vision.[109] Another approach of combining has been achieved based on developing an optical multimodal-sensing skin for fingers of a robotic gripper. The sensor is built based on a combination of transparent skin made from a marked soft elastic outer layer on a hard layer and internal RGB cameras. The work's aim is to

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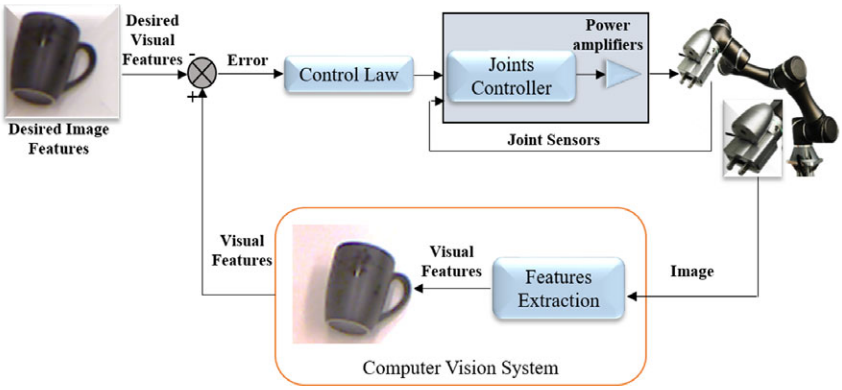

Fig. 7. Block diagram of direct visual servoing (adopted from ref. [1]).

reduce and also to handle errors while cutting vegetables.[110] In addition to that, a vision-touch fusion has been implemented to track objects using RGB-D camera as vision sensor andGelSight contact sensor as tactile sensor.[111]

Currently, fusion of vision-tactile has been achieved in building 3D shape for objects[112] by combining features of colour image-based vision (monocular vision) and small number of touch explorations. In ref. [113], estimation of tactile properties based on visual perception has been modelled, where the data are obtained based on using a webcam and uSkin tactile sensor located at the Sawyer robot's end-effector. The purpose of this modality is to increase the perception of the robot to be more aware of the contacting environment of the object while grasping. For example, the robot can move slower when in contact with a bad traction, or grasp tighter if the object looks slippery. Li et al. have used visuo-tactile modality to estimate the tool's kinematics which are attributed to robotic interactive manipulation.[114] Similarly, vision and touch sensing have been implemented in contact-rich tasks based on exploiting self-supervised learning of multimodal representations using DRL.[115] Calandra et al. have proposed using vision-tactile modalities to learn grasping and regrasping using end-to-end action-conditional model.[116] In another work, Deep Maximum Covariance Analysis (DMCA) method has been implemented to learn a joint latent space for sharing features through vision and tactile sensing as an application for texture recognition of clothes.[117]

3. Learning Approach (Computational Techniques)

Computational intelligence techniques provide a significant function in several advanced grasping mechanisms. Sorting and degradation techniques play an important role in analysing and offering semantic value to signal extracted from a range of sensors.

3.1. Computer vision

Computer vision in particular has provided enormous benefits in the field of the industrial grasping mechanism. Many research studies have exploited computer vision for improving the techniques of grasping. Visual servoing control-based computer vision plays a significant role in robotics, which consists in controlling the motion of a robot from the feedback of an image as illustrated in Fig. 7. Mostly, Visual servoing control exploits to detect the objects within the workspace to perform manipulating tasks. Many different techniques of object detection for grasping or manipulation have been used to perform various tasks based on solving the problem of grasping of objects in a cluttered environment, grasping of the object in the case of physical support relation, or grasping of a single object by considering its shape and size. In this section, we will discuss two types of detection actions that researchers have deeply worked on, that are grasping in a cluttered environment and grasping when there is physical support relation between objects.

3.1.1. Grasping in cluttered environment. During grasping in a cluttered environment, a robot must be able to understand and recognise its surroundings and objects alike and perform a sequence of actions on the objects. Several studies focused on grasping or grasp-pose detection in cluttered scenes. For instance, grasping an unknown object in a cluttered scene based on a point cloud from

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a single depth camera has been introduced in ref. [118]. In ref. [119], the authors proposed an algorithm based on a CNN to improve the precision detection for grasping in a dense clutter using a depth sensor. Another equally important approach that extracts target objects from the difficult environment due to occlusion between camera and objects based on three-dimensional object segmentation has been implemented in ref. [120]. The approach comprises two steps: (1) object probabilistic prediction of the input image with convolutional networks and (2) generation of a voxel grid map designed for object segmentation. Mahler et al.[121] proposed a method to find deep-learnt policies and select objects from clutter. They achieved a grasp detection accuracy of 92.4% by using a transfer learning technique. When they tested their learnt policies on robotic grasping with five trials for each of the 20 objects of the test dataset, they achieved a success rate of 70%. The work of ref. [120] was then extended in ref. [122] by considering a multi-object manipulation. Even though the 3D object segmentation improves grasping efficiency, notably in cluttered place, there are still failures due to picking motion. In a separate work, multi-object manipulation was tackled by modelling the problem as a partially observable Markov decision process (POMDP).[123] A deep learning-based approach to eye-hand coordination for robotic grasping has been proposed in ref. [124]. Making use of monocular camera images (independent of camera calibration), the network predicted the probability of the gripper being able to accomplish the grasping tasks successfully. Some researchers have concentrated on grasping or grasp-pose detection using point clouds,[125] while others have used a template-based learning approach.[126,127] In the latter method, the target object was roughly segmented from the background, and a convex hull was constructed around the segmented points. At the same time, a template-based approach that used a bounding box around the object has also been adopted in ref. [128]. In addition, deep learning has been extensively used in detecting an object in a cluttered scene. For example, the implementation of two-stream CNNs in ref. [129] has improved the accuracy and reliability of grasping of novel objects in a cluttered environment.

3.1.2. A physical support relations between objects. To manipulate an object of interest in a clutter safely, the physical interaction between the surrounding objects in the scene must be considered. The idea of physical support relations between objects in clutter has been examined in refs. [130, 131]. The pairwise support relation between objects was inferred and used to predict the order in which these objects need to be removed for the access to the target object. The approach depends heavily on the accuracy of the structure class classifier and hand-crafted rules. In ref. [132], a 3D visual perception module was used to extract the shape and pose of the detected objects, and the support relations between objects were inferred from a configuration of geometrical computation and static equilibrium analysis, and machine learning methods depending on whether the objects were partially or fully seen. A safe manipulation strategy based on the spatial relationship between objects in the uncertain scenario has been proposed in ref. [133], in which its purpose is to avoid falling objects during grasping. The existing CNN-based techniques for objects grasping did not consider manipulation relationship between the objects on top of each other. To overcome this limitation, a new CNN architecture called Visual Manipulation Relationship Network (VMRN) has been proposed in ref. [134], which aims to ensure robot can accomplish grasping tasks in robust and accurate way. Relationships of object pairs, such as "inside" or "behind" or "on top" afford certain means-end actions such as pulling a container or tool to retrieve the desired object either inside, behind or on top of the other. In ref. [135], the concept of bootstrapping, which uses past knowledge to speed up the learning process, has been applied to the learning of relational affordances of object pairs. The work uses random forest-based affordance predictors learned from visual inputs and integrates two approaches for bootstrapping.

3.2. Deep learning

Deep learning is considered a part of the machine learning algorithms, which is also known as deep structured learning or hierarchical learning. Deep learning can be either supervised to be totally controlled by a human, sim-supervised where human or client can be part of the control process as semi-automatic learning, or unsupervised where the machine automatically learns or trains. Shallow neural networks (SNNs) are constructed with one or two hidden layers (see Fig. 8). SNNs require a perfect characteristics extractor which leads to a solution of selectivity-invariance such that the learning systems are changeless or constant to some features of an object (such as texture, shape and pose) and also not selective.[136] For achieving a high accuracy, developers exploited generic nonlinear

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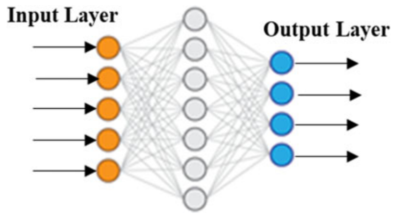

Fig. 8. Shallow neural networks.

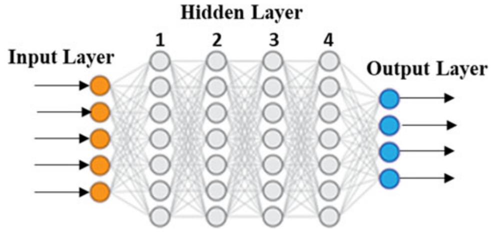

Fig. 9. Deep neural network.

features for the pose estimation of objects, which can be extracted from input image data, but generic characteristics do not help learners generalise fully from training data. Besides that, for the learning of high-level feature representation, deep learning exploits multilayer structures (see Fig. 9). There is no standard number of hidden layers used for deep structured learning, but it is generally determined based on trial and error.[137]

Deep learning is used to train large artificial neural networks. Over the last decade, deep learning has attracted many researchers and led to advanced research in the application of robotics in many fields. The various algorithm in deep learning have also been developed and implemented in object manipulation and grasping. Hundreds of millions of parameters can be included in deep neural networks (DNNs).[138,139] Deep learning continuously provides significant and technological facilities for innovative applications and techniques. In specific, a lot of researchers' efforts have been concentrated to employ the convolution neural networks (CNNs) for developing sensor interpretation and control algorithms based on actual data during grasping action. For instance, re-grasping is the ability to change the grasping attitude to improve the stability of the grasp. The idea of using large-scale data for training visuomotor controllers has been studied by Levine et al.[124] The authors have applied DRL for robotic manipulation using model-based training techniques. Meanwhile Pinto and Gupta have trained a convolutional network to predict grasp success for diverse sets of objects using a large dataset with more than 50 thousands of grasp attempts collected from multiple robots in a self-supervised setting.[140] In ref. [141], a deep learning method has also been applied to an adaptable task-performing based humanoid robot operating in an uncertain environment. In the approach, two-phase deep learning models have been utilised, one is a deep convolutional auto-encoder aimed to extract image features and reconstruct images, and the second is a deep time-delay neural network that learns task process based on features and motion angle signals of the extracted image. In addition, Hossain et al. presented teaching systems that enable non-expert operators to pick up a specific object and place it at a target location.[142] A deep belief neural network (DBNN)-based approach which uses a captured image as its input has been proposed in ref. [143]. The DBNN extracts object features from the intermediate layers. The developed system allows users to select an object via a graphical user interface in which a snapshot is captured using a USB camera and fed into the DBNN for recognition. The same authors have also proposed in a subsequent paper, a non-dominated sorting genetic algorithm (NSGA-II) to optimise DBNN for object recognition. In addition, robotic grasp detection using deep CNNs has been introduced in ref. [144]. Meanwhile, teaching a robot to accomplish picking up and placing tasks based on using Recurrent Neural Network has been proposed in ref. [145]. Another approach, an evolutionary algorithm integrated with DBNN has been implemented to optimise the structures of the network for robot grasping tasks.[146] In ref. [147], the authors have implemented DBNN for object recognition. However, there were some limitations, like limited angle orientation as well as robustness due to lighting conditions.

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The technique for multi-task learning from demonstration has been presented in ref. [148]. It is used to train the controller of a low-cost robotic arm using DBNN in order to perform several complex pick-and-place tasks and non-prehensile manipulation. The learning process consists of three stages: (1) collection of a set of demonstrations, (2) training of a single deep recurrent neural network to emulate the user's behaviour and (3) deployment of the system. Meanwhile, the trained controller converts raw camera perception into commands, which are then send to the robot to perform the tasks. Moreover, a novel deep learning-based visual recognition of object and pose estimation system has been designed based on Deep Semantic Segmentation Network.[46] On the other hand, multimodal-sensing models that learn from raw visuo-tactile data have been explored in refs. [116, 149]. The frameworks process visual and tactile data with CNNs and the extracted features are concatenated and fed into a fully connected network for the grasp outcome prediction.

CNNs have been used to predict graspable points in a cluttered environment based on using RGB-D data.[150,151] A fully convolution network (FCN) based method for robotic grasp detection has been proposed by Park et al.[152] Making use of high-resolution RGB-D images, Wang et al. have also proposed an FCN model that generates robotic grasp actions.[153] A real-time approach for multiple grasping poses prediction for a parallel-plate robotic gripper based on FCN has been proposed in ref. [154]. In ref. [155], Zhang et al. have introduced a robotic grasp detection algorithm based on the region of interest (ROI). The proposed ROI-GD method used multiple convolutional layers to generate object bounding box proposals which are the ROIs for the grasp detector. The robot then detected objects within the ROIs instead of the whole scene. On the other hand, the region-based object recognition (RBOR) method proposed in ref. [156] performed colour segmentation using a simplified pulse-coupled neural network (SPCNN). In this approach, the target must be visible and graspable. If the target is hidden or located under other things, the grasping process will be more challenging for the robot. A multi-task CNN for robotic perception, reasoning and grasping (RPRG) has been proposed in ref. [157], which can support and ease the robot in finding the target and making grasp planning. In ref. [158], a CNN has been used to extract discriminative features from RGB-D images. The framework exploited an architecture of hierarchical cascaded forests, computed and fused probabilities of object-class and grasp-pose obtained at various levels of an image hierarchy to deduce the class and the grasp of hidden objects. Another work on robotic grasp detection based on using RGB-D images implemented on a parallel-plate robotic gripper has been reported in ref. [159]. In the model, a deep convolutional neural network (DCNN) has been used to extract features from the RGB-D images. The grasp configuration of the predicted target is learned using a CNN.

Several recent approaches[160–163] have employed CNNs for detection of the best grasp pose of a robotic gripper. Furthermore, a multisensor-based approach using vision and laser sensors has been proposed in ref. [164] to generate features of the image such as RGB, depth and intensity (RGB-DI). A fully convolution network (FCN) with deep layers was designed to perform semantic segmentation of RGB-DI images. A three-dimensional CNN (3D CNN) has been trained to predict optimal grasping poses and wrist orientations for soft-hands which might experience unpredictable deformations during grasping.[165] In ref. [166, 167], CNNs have also been trained to learn and generalise tool affordances based on their 3D geometry. The framework considered grasping points of tools (such as hammer, rack, hoe etc.) and predicted the effect of different actions using these tools. While most of the existing robotic grasping models were trained on large-scale datasets collected in laboratory settings, Gupta et al. collected and trained their models on a dataset of about 28K grasps in people's homes with different environmental conditions.[168] The experiment was carried out by using a low cost off-the-shelf mobile robot module. Aiming to improve robustness and reduce the training time of a CNN model for grasping, a learning strategy based on a single demonstration has also been proposed in ref. [169]. While many CNN implementations for robotic grasping have been reported in the literature, it is believed that new possibilities and innovative solutions of such models will continuously be sought.

3.3. Reinforcement learning

Reinforcement learning (RL) is an active area of machine learning that is related to how software agents should take actions in an environment such that some notion of cumulative reward is maximised. Recently, there is a surge of interest in implementing RL in robotics field, particularly in reaching and grasping of objects. In an RL framework, an agent interacts with its environment and

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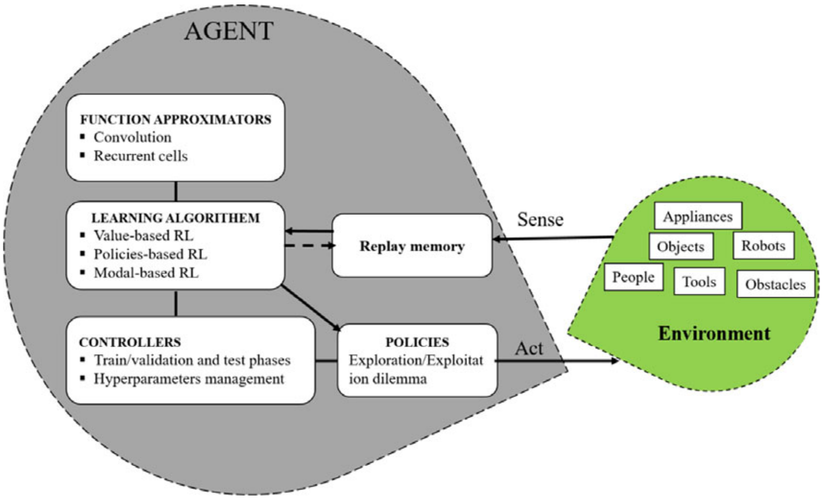

Fig. 10. General schematic of deep RL methods.[172]

learns the best policy that maximise its long-term reward via the trial-and-error strategy. In ref. [170], for instance, the RL algorithm has been implemented to perform co-operative manipulation of objects by a mobile dual-arm robot. The robot completed a pick-and-place task by dividing the tasks into a sequence of motion primitives such as reaching, grasping and co-operative manipulation of the grasped object by dual arms. To mitigate the issue of delayed reward, Krishnan et al. proposed a three-phase algorithm called sequential windowed inverse reinforcement learning (SWIRL) that learns a policy for sequential robot tasks from a series of demonstrations.[171]

Combining deep learning with reinforcement learning creates a new approach called DRL. A general schema of the various components that can be found in most deep RL algorithms is illustrated in Fig. 10. Furthermore, robot manipulation in human environments requires an additional knowledge-based reasoning component to make inferences and decisions while performing various daily tasks. DRL has been implemented to perform various robot manipulation tasks such as reaching, grasping and placing.[173–176] Soft robotic structures provide more flexibility and adaptability for accomplishing tasks and safer human-robot interaction.[177,178] Recently, the contribution of technologies of soft robotics that integrated with deep learning techniques has become a pivotal role in providing accurate and acceptable results in robot manipulation tasks.[179] With the increased advancements in grasping capacities aided by vision sensing, researchers have utilized such models in various complex intelligent robot applications. Taking advantage of the robust structure of soft robots and power the DL and DRL algorithms, different techniques have been applied in the detection of robotic grasp[6] and control for grasping of dedicated objects in various size, shape and structure.[180] To deal with the issues of complex action space, Gualtieri and Platt implemented a DRL strategy with attention focus that trained a 6-DoF robot to perform grasping and placing tasks in both cluttered and uncertain workspaces.[181] Using a hierarchical sampling process, the robot reached for the target object by learning a sequence of gazes to focus attention on the task-relevant parts of the scene. In the latest research, DRL has been developed to be a self-supervised such that robot farms can be operated autonomously for months. Striving to achieve a broad generalization to unseen objects, an off-policy DRL approach has been proposed to learn closed-loop dynamic visual grasping strategies, using self-supervised data collected from a monocular RGB camera located over the shoulder of the robot.[182] However, the method suffers some limitations that are associated with the experimental setting such as the optimal policy. Ref. [183] has presented a grasp-to-place framework that has the capability of grasping objects in sparse and cluttered environments using Q-learning that trains on fully connected DenseNet (FCN).

4. Gripping Approach (Grasping Mechanisms)

In this section, the gripping approach is classified on the basis of two categories as the main two factors in the gripping task that may be commonly involved in performing a certain task, namely, mechanism and gripper categories. The mechanism category is the way to control the gripper to

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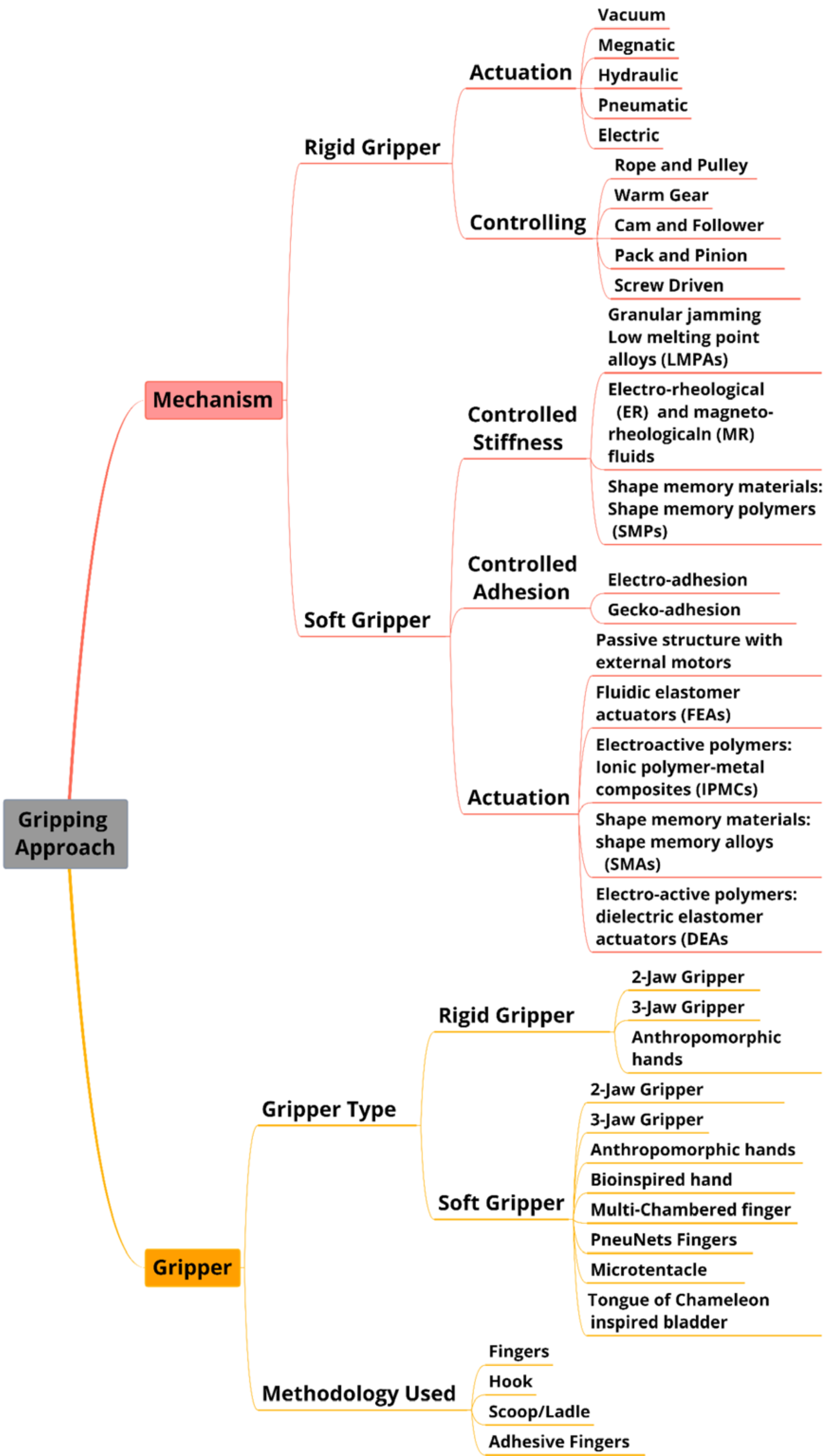

Fig. 11. Hierarchical structure of the grasping mechanism based on the gripping approach.

perform the task. The gripping mechanism can be grouped on the basis of a mechanism that involves to actuate either soft or rigid robotic grippers. Meanwhile, the gripper category is concerned about designing the gripper to be more efficient in performing a certain task. The gripper category can be grouped on the basis of designing that involves to determine the type of grippers (e.g. rigid or soft grippers) and the methodology of gripping (Fig. 11).

The mechanism is the first category grouped on the basis of soft and rigid robotic grippers. In terms of the soft gripper, three types of the mechanism are implemented in gripping an object: (1)

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controlled stiffness such as granular jamming,[184] electrorheological and magnetorheological fluid[185] and shape-memory polymers,[186] (2) controlled adhesion such as electro and gecko adhesion,[12,187–189] and (3) actuation such as a passive structure with external motors,[190] fluidic elastomer actuators[191] and electro-active polymers such as dielectric elastomer actuators.[192] In terms of rigid grippers, control and actuation are the two mechanisms being considered. The gripper is the second category that is divided into two parts: (1) gripper type, which is categorised on the basis of the types of grippers(either the number of fingers as in rigid grippers or types of fingers and hands as in soft grippers and (2) methodology used, which is the way of grasping, such as fingers, hook, scoop and adhesive or sticky fingers. Thus, manipulating an object is considered a basic fundamental function that can be accomplished by robotic systems, such as non-mobile or mobile robots, to provide beneficial roles in various workspaces for structured and unstructured environments, such as houses, industrial areas, seas and spaces. Some of the researchers focused on designing grippers according to specific actuators based on the needed task and requirements.

The purpose of the gripper is to provide a solution for a variety of grasping problems. Various approaches have been presented to improve the grasp gripper with objects of different shapes and sizes. The algorithm for computing the forced closure on 2D and 3D objects with three hard fingers and a point contact with friction is developed.[193] An alternative approach to find the forced closure without friction has been presented.[194] A solution has been provided to lift objects even in the absence of the form closure,[195] where the proposed solution has depended on using microscopic hair-like features to exploit van der Waals forces. Furthermore, lateral grasping has been proposed[196] and inspired by the human grasping of flat-shaped objects, such as dishes and plates, by considering hooked fingers to increase the robustness of grasping. However, it is restrictive to the thickness of the object. The end effector of the gripper for handling specific food industry tasks, such as grasping sliced fruits and vegetables, has been designed on the basis of the Bernoulli principle.[197] Some researchers developed a gripper by using a spatula-like device (e.g. designing end effectors with spatula-like devices to slide under the object and lift from the ground).[198] The approach is also restricted in terms of the size and shape of an object by considering the spatula-like device space. Another approach has used push grasping techniques, such as a push grasping mechanism based on generating a trajectory of the object, to select an object from the floor and take advantage of its dynamics.[199] Conversely, a pushing grasp based on sliding adjusts the object in the environment before grasping,[200] which depends on the environment more than the designing of the fingers (e.g. sliding the object to the edge of the table to grasp). Furthermore, a flip-and-pinch task has been presented on the basis of the under-actuated finger design for grasping a small object from a flat surface.[201,202] They used a flip-and-pinch task where the hand picks up thin objects from the surface of a table by flipping them into a stable configuration, but this approach is almost limited by the type and size of objects. Suction cup grasping is a common approach that has been utilised to pick up various types of objects. In ref. [203], a universal jamming gripper has been proposed on the basis of vacuum with a combination of the positive and negative pressure consisting of a membrane containing granular materials. Although the approach proposed a grasping mechanism that involves using a suction cup, it is restrictive to some objects that are not flat and nonfragile. Kessens and Jaydev[204] designed a self-sealing suction cup array grasp; however, the suction force is only exerted when suction cups are physically in contact with another object.

Catalano et al.[205] designed Pisa-IIT Soft Hand by using adaptive synergy. The idea is adopted from an under-actuated hand design, so the approach uses pattern recognition tools. Another hand design (iRobot-Harvard-Yale [iHY] hand) has been introduced,[206] and it is an under-actuated hand-driven on the basis of five actuators to increase the wide of grasping for objects with different shapes and sizes. As reported, the approach shows the capability of power and fingertip grasping based on the compliant mechanics of the fingers. The design is activated on the basis of the electric motor inside the gripper. Additionally, Valois et al.[207] developed a simple closed-loop hybrid grasping controller that mimics an interactive contact-rich strategy based on position-force, pre-grasp and landing strategies for finger placement. Although the approach involves a compliant control of the hand during the grasping and releasing of objects to preserve the safety of target objects, it has been implemented to grasp a specific small object by generating the trajectory of that object and taking the advantages of its dynamic and adjacent features, such as a hard surface or a table, to achieve grasps. Furthermore, a gripper that consists of two fingers has been developed;[208] in this gripper, each finger consists of two links actuated by a single actuator. Even though the approach varies in the grasping type, including parallel grasping, enveloping and fingertip grasping of objects with different shapes, it suffers from

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picking up a flat object from a flat surface. A robotic hand with inherent abilities has been designed by exploiting environmental constraints.[209] The author focused on cases in which the gripper can utilise environmental constraints to bring an object to its target place.

In the area of micro- and nano-grippers, studies have focused on the gripper design to perform a specific task. For instance, picking micro- and nano-objects needs an appropriate gripper to deal with a task. Shi et al.[210] designed micro- and nano-grippers to pickup and place down micro-objects with size scales of 100 microns and less. For grasping micro-objects, the author also proposed a different gripper design by using piezoelectric actuators.[211] Ref. [212] has presented piezoelectric (PZT) actuated micro-grippers, however it has focused on the independent control of position and grasping force, which cannot meet the requirements of the precision operation. Another gripper design for micro-object grasping in biomedical applications has been proposed.[213] These kinds of micro-grippers are designed from specific materials, such as hydrogel. Micro-grippers have a star-like shape and can perform dexterous postures to grasp living tissues. An image processing-based optimisation process has been applied to determine localisation. For example, particle swarm optimisation has been implemented to estimate the current gripper configuration from image segmentation. Hence, studies on micro-grippers have offered many opportunities for improvement in terms of accuracy and robustness in micro-gripper controllers.[214] Because of the advantages of fast response, large output force and small size, piezoelectric actuator is widely adopted as the micro-grippers' actuators. Generally, micro-grippers as the manipulator of the micromanipulation system are adopted to contact the tiny objects directly and achieve grasp-transmit-release micromanipulation. Hence, the micro-grippers' performance has a direct influence on the quality and precision of micromanipulation. In addition, taking the small and easily broken characteristics of micro-objects into account, therefore, a high-performance control algorithm needs to be introduced to precisely control the entire manipulation process of grasping-transfer-release.

Using conventional grippers to pick up small and flat objects (e.g. coins and sheets of paper) from a surface is a difficult task to accomplish. Thus, different types of gripper designs have been developed to improve grasping tasks, such as using a suction cup. Although suction cups have been used in various practical tasks, they fail to deal with lightweight and fragile objects.[215] Hasegawa et al.[216] proposed suction with a pinching hand, which is used to grasp objects in a cluttered narrow space. It has two under-actuated fingers with one extendable and foldable suction finger whose fingertip has a suction cup.[216] Thus, some researchers employed suction and pinch grasp motions in which an end-effector grasps an object with a pinching system to fix the pose while suctioning the object with a vacuum gripper. However, during suctioning, the object may change its pose because the suction cup is too soft to stably fix the pose of the object. The unstableness of a vacuum gripper increases the probability of dropping the object as air can leak from an open space between the suction cup and the object. A three-fingered hand-based approach has been developed[217] on the basis of the suction mechanism at each fingertip. The hand with GRIPP 4, which has three fingers and two servomotors, is designed to grasp objects by using power and precision grasps. In this approach, the combination of the grasp mechanism and vacuum pads allows iGRIPP 4 to grasp objects steadily. Even though the suction mechanism at the fingertips enhances grasp stability and enables the hand to hold large objects, iGRIPP 4 has a robot hand with low degrees of freedom because a vacuum pad is present at each fingertip and the hand is too big to enter a narrow place. Lévesque et al.[218] proposed a scooping grasp with two fingers; in the design, one finger is bent from the tip finger to function as a spatula-like grasp. The same strategy has been implemented[219] with different finger designs; in particular, a quasistatic method is proposed to design a gripper by considering a passive thumb to compensate the manipulator positioning error. They aimed to grasp thin and small objects from hard surfaces. Babin et al.[220] proposed a passive and epicycle mechanism to pick up a flat object from a smooth hard surface by sliding the thumb finger under the object. Soft pneumatic grippers have also been proposed to achieve successful grasps for a flat and flexible object.[221] They are built on the basis of the combination of the benefits of electro-adhesive and soft pneumatic grippers.

A bio-inspired approach (e.g. a gecko-like gripper) has been developed to enhance grippers for grasping a wide range of objects with various shapes and sizes and control friction force at the contact points of the hand. For instance, an under-actuated Gecko Adhesive Gripper has been presented in ref. [222] for simple and versatile grasping. In the approach, their purpose is to grasp a wide range of curved surfaces using a single actuator through a simple tendon-driven mechanism that attaches and adheres in one step. Therefore, with the tactile sensor, the contact area can be estimated, where a force/torque sensor provides the overall measurement of the force and moment. However, during the release of the object from the end effector, a shaking operation is needed in the approach to detach the adhered object. Ngo et al.[223] modelled a gripper with an embedded compliant bistable mechanism (BM) to detach the adhered object from the end effector during the picking and releasing of objects and avoid the issue of a shaking operation or detaching the object from the end effector. The adhered object is released from the gripper by inducing the vibration of the end effector by an impact pestle adjacent to the shuttle mass of the BM. In addition, Huh et al.[224] introduced an active sensing based on inspired gecko adhesives to offer good contact on the surface that can be useful for grasping an object in space. Their active sensing approach involves Lamb waves in thin bilayers, which are excited and detected by piezoelectric strips. In another study,[225] sensing has been proposed to grasp an object of various shapes and textures based on a capacity sensor by using a thin film of gecko-inspired adhesives. This type of sensor is useful because films adhere more tightly to the surfaces of an object when the weight of the object increases as the capacitance locally increases at contact areas. With high weighted objects, adhesion force might be failed to tightly hold the object during grasping that causes the object to fall down due to an insufficient adhesion force, so that gecko-based a gripper design is presented using shear force.[226] The aim of the work is to increase the pressure of the gripper for grasping an object that is larger than that of the gripper.

Most studies have focused on designing robot hands, which have been considered one of the hottest research topics since the early beginning of the robotics field because of its fundamental role as a complementary task in different control robotic systems. Thus, it is the way to accomplish grasping and manipulating in various industrial tasks.[227] In ref. [228], a pneumatic tactile sensor is used with different robot hand designs, which are constructed and applied to the robot hand's fingertip to recognise some features associated with grasping, such as force, slippage and vibration as the pressure of the air bladder changes. As such, the design of fingers of the hand resembles the shape of an arched curve, and a pressure tactile sensor is attached to the curved surface to increase the ability of the hand to grasp and handle fragile objects because of the inherent compliance of the air bladder. In ref. [229], a novel tendon-driven bio-inspired robotic hand has been designed for in-hand manipulation. A soft hand has been developed and implemented to grasp unknown objects by using a 3D deep CNN.[165] Integrating actuators and sensors in a pneumatic gripper design has been proposed[230] to improve adaptive grasping and size recognition. The control system of the soft pneumatic gripper is built on the basis of the two types of sensors: one is a pressure sensor, which is used to detect the force grasp, and the other is a bending sensor implemented to recognise the grasping position. In ref. [231], a grasping mechanism is proposed on the basis of a multi-fingered robot hand to solve the problem of uncertainty of an object pose. This mechanism is attributed to the uncertainty of the object pose that leads to a great impact on the stability of grasping. Thus, the control method is dependent on the function of a finger state. In ref. [232], modifying the configuration of hands and joints (because the fingertip is considered spherical, which restricts the grasping task in a certain shape of objects) has been proposed to achieve a desired grasp based on the stiffness features by considering stability during a grasping task. The modification is accomplished by using a novel controller and tested on two shapes of objects, such as cuboids and spheres. However, the lack of sensory data in the method leads to finding the intersection between the spherical fingertip and the new cylindrical object. The approach of using a human-inspired robotic grasping has been studied and implemented;[233] in this approach, a hand with two fingers can be beneficial to grasping flat objects. Based on the mechanism, the work aims to exploit environmental constraints for supporting the surface, such as setting a complaint contact with the support surface. In this work, the authors intended to increase the robustness against geometrical uncertainties of the object and estimate the pose error based on the perception system. For example, different mechanisms have been used (Table II).

Designing simpler and universal grippers is increasingly studied on the basis of advanced soft materials and components regarding the soft-robotic gripper. The advantage of using a soft gripper is to avoid making damage on the target object that possibly happens once the rigid gripper uses to grasp fragile objects. Thus, compliant materials as a partial solution in a robotic end effector are commonly added to create a simpler and lighter gripper that can safely grip objects. Many studies have been devoted to designing a soft-robotic gripper. Table III shows different grasping mechanisms based on different soft-robotic hands and grippers that have been developed to perform a specific grasping task.

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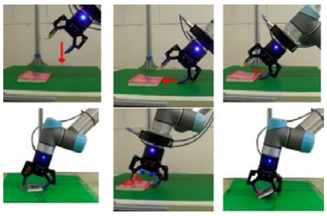
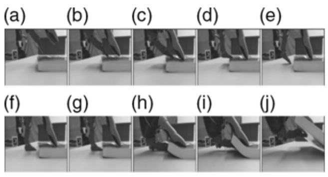
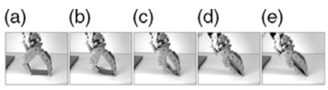
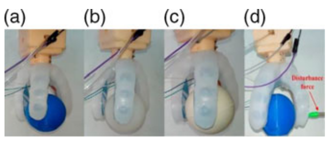
Table II. Grasping mechanism of picking up an object.

Technology of Mechanism	**Gripper**	**Application**	**References**
Behaviour of a tendon-driven robotic gripper performing parallel, enveloping and grasping with fingertips. The gripper consists of two fingers, and each has two links and is actuated using a single active tendon		Enveloping grasps of a large range of objects and applying it to a set of common household objects	[208]
The scooping grasp with two fingers by using a commercial gripper; in the design, one finger is bent from the tip finger to function a spatula-like grasp		Picking thin objects on a flat surface	[218]
Using passive and epicyclic mechanisms based on the consideration of a finger making a contact with the top of the object while the thumb of the gripper is being forced between the object and the surface		Picking up large thin objects lying on smooth hard surfaces	[219]
Using quasistatic methods, such as scooping with a passive thumb. Considering a finger standing behind the object while the thumb of the gripper is being forced between the object and the surface		Picking, grasping or scooping small objects lying on flat surfaces	[220]
Integration of actuating and sensing the soft pneumatic gripper		Grasping a large range of objects	[230]
Human-inspired framework for grasping		Grasping domestic flat objects on support surfaces	[233]

5. Assistive and Warehouse Robots

The needs of assistive robotic purposely designed and controlled for helping the elderly carry out everyday tasks are increasing.[244] Assistive robots are used to allow grasping safely in daily tasks. The most crucial challenge faced by researchers is how to make the robot's hand more stable and robust during the grasping of an object. Some studies have focused on controlling the stability and robustness of hand motion while it is grasping. For example, a computer vision has been used to enhance the wrist control by using the robotised exoskeleton hands in achieving an assistive robotic grasp.[245] Although an improvement has been made in terms of control, natural reaching and grasping

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Table III. Some types of soft-robotic grippers.

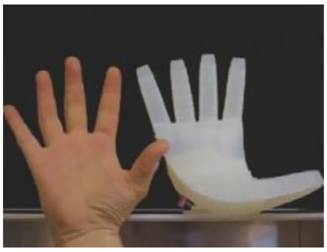
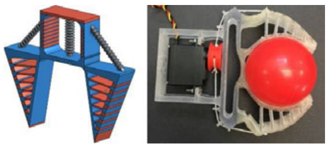
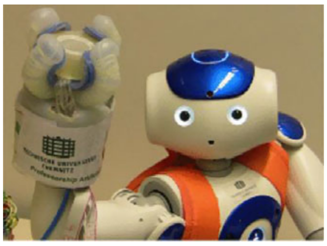
Technology of mechanism	**Gripper**	**Application**	**References**
Bio–inspired hand (the RBO Hand 2) which is • pneumatically actuated and • made of a silicone rubber, polyester fibers and a polyamide scaffold		For dexterous grasping capabilities based on achieving 31 grasp postures from a state-of-the-art human grasp taxonomy	[234]
Actuated using a passive structure with external motors		Picking up a wide range of objects, including tissues, cups, needles and pins	[235]–[237]
Jamming gripper-based control by means of pressure		Picking up familiar and unfamiliar objects of widely varying shapes and surface properties	[184]
Actuated based on combining air-pump actuation with superimposed curvatures and pressure sensors		Grasping different objects	[238] [239]
Controller adhesion inspired by gecko (fluidic elastomer actuators) combination of fluidic elastomer actuators and gecko-inspired adhesives		Grasping large objects and achieving high-strength grasps	[240] [189]
Fluidic elastomer actuators (self–healing polymers)		Picking up a wide range of objects	[241]

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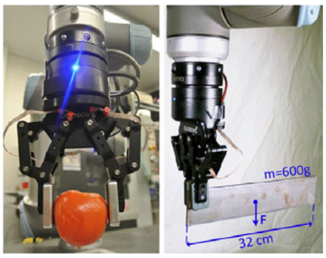
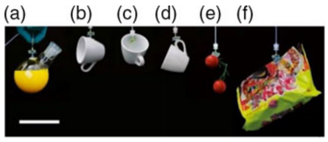
Table III. Continued.

Technology of mechanism	**Gripper**	**Application**	**References**
Controller adhesion inspired by a gecko. A UR-5 robot arm was equipped with • an FT-300 force/torque sensing in the wrist. • each finger having a 7-by-4 tactile sensor array and a patterned skin of directional adhesive		Improving the ability of robots to grasp delicate objects, such as rotten tomatoes and acrylic sheets	[242]
Gecko adhesion dry multi-fingered gripper in which each finger is made of a liquid crystal polymer (LCP), with a gecko-adhesive pad placed on the fingertip		Grasping different items by an elastomer membrane with mushroom—shaped microfibers	[243]

motion is yet to be achieved. In the same field of assistive robots, some studies have been performed to design soft hands. For instance, a soft hand with pneumatically enhanced muscles[246] and soft gloves[247] has been designed to be driven with a custom 3D-printed cable that can perform flexion and extension. A supernumerary hand with an additional force has been designed for grasping to decrease the stress on the upper limbs.[248]

An assistive robot is a warehouse robot that is yet to be able to pick up and place objects in cluttered areas or shelves. Grasping techniques can provide a solution for particular problems, such as using CNNs based on an eye-in-hand approach for object recognition and conventional grippers (for example, hybrid pinch and suction gripper). On the basis of the challenge of amazon robotics, Corbato et al.[249] discussed some lessons learned from such challenges; for instance, task conditions must be the basis for choosing a solution, and an individual solution is required for integration and problem solving based on using the hierarchical structure of automation levels. As such, some robotic solutions for grasping tasks are associated with human hands.[250] Thus, the real challenge in robots is when a robot gripper needs to plan and navigate extremely cluttered environments.[251] For instance, in contrast to storing, kitting needs to prepare products or tools quickly, and it needs to pick up an object from a cluttered place and to put down an object in cluttered environments via real-time planning, which can exceed the complexity of objects and detect the issues of collision.[252]

6. Conclusion

This paper presents a comprehensive review devoted to the techniques related to reaching and grasping of objects in different workplaces. In this paper, different robotic techniques are highlighted to provide a clear view on how the researchers dedicated their efforts through time for the robotic development of either mobile, non-mobile robots or industrial manipulators. There is no doubt that in this fast-paced world, advanced novel robotic techniques are needed to achieve high accuracy and precision for reaching and grasping tasks. This motivation has thus spurred many research studies in the field of robotic reaching and grasping using various techniques and approaches.

By using a vision sensor to guide the robotic arm to the target, many research studies have concentrated on developing and improving the techniques that help the arm in target detection (e.g. exploration) and path generation to reach and grasp. Using vision only as a technique for object recognition and pose estimation is prone to error that will definitely affect the robotic arm and target object alike during grasping and manipulating task. Alternatively, object localisation based on using tactile sensors will be a significant and advanced approach that helps to ease object grasping. However, in the same vein, using a tactile sensor only is also prone to error. Thus, the tactile sensor can be fused with a vision sensor to complement each other. Over the last five years, tactile sensors

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have taken over a wide area in robotic applications. Advanced development in tactile sensors such as meticulous devices and skins has brought about the huge benefits and opportunities to be applied in numerous robotics applications such as object recognition, object localisation, slippage detection, perception and so on. Meanwhile, it has also brought about many challenges due to its effectiveness in implementing haptic data in robotic applications. For example, the properties of objects in object recognition tasks such as texture, shape and material can be known through haptic feedback; and estimation of object localisation has become a crucial challenge for successful robotic applications in reaching, manipulating and grasping tasks. Recently, localisation based on haptic using single point contact sensor has attracted a lot of attention and interest from researchers. However, using single point contact sensor is associated with a limited information as the single point contact sensor needs a multi-contact. Thus, using a tactile array sensor is a solution for identifying contact patterns. As a result, there are many challenges that are open to further investigations such as (1) the mapping of the points of contact on the sensor pad into 3D space; (2) the technique of combining data points observed from a sense of vision and touch alike; (3) the determination of the priority structure once the data of various sensors are in conflict. As a consequent, computational solutions have been proposed for the development of either control or sensing systems that are extremely flexible and universal such that conversion from one application to another can be done with less effort. While the development time can also be reduced to accomplish fast implementation. Different solutions have been implemented to perform a quick implementation. However, the recent solutions that researchers dedicate their efforts and attention on are deep learning approaches, which require a significant amount of training and tuning.

One of the most important challenges in grasping task is the gripper's design. However, to really achieve a flexible, robust and adaptive hand or gripper is still subject to further studies and development. Until then, soft gripper design is currently one of the hot topics that captivate some of researchers' attention. A well-designed gripper could significantly be implemented in industrial applications as well as assistive robotics for achieving specific tasks. The gripper is the basis for the mechanism and grasping approach especially when robots serve as intelligent autonomous agents. Thus, in the future, gripper design can be more focused on the type of materials, architectures, distribution of the sensors, control techniques and the processing of local information. All of these are still big pending challenges, which can smoothen the way for achieving wide and tremendous applications based on either hard or soft-robotic grippers such as in manufacturing workplace, haptics and object manipulation within robot's workspace. We hope that this comprehensive review will encourage more new researchers to be interested in the field of robotics as well as stimulate more research studies, not only limited to reaching and grasping of objects.

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