A Survey: Robot Grasping

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Abstract

The field of autonomous robotics has made significant progress with the advent of learning methods that have been successfully applied in robotics and have achieved tremendous accuracy. Today, we can observe the successful application of classical machine learning, computer vision, and reinforcement learning in various robotic tasks like path planning, perception, locomotion, grasping, manipulation etc. But the big question remains, "Is robotics ready for the real world?" While it is true that we have now successfully deployed some robots in the real world, with some even interacting and collaborating with humans, many tasks remain difficult for robots to accomplish. In this survey paper, we focus on robot grasping, which is a significant challenge for robots and hinders their successful deployment in the real world. Our paper aims to review, categorize, and describe research in robotics focusing on robot grasping, the role of robot grippers and learning methods explored towards achieving intelligent control of robots when executing a grasping task.

1 Introduction

Robots are increasingly used in environments where grasping and manipulation of objects is required. In recent years, however, they have also found their way into homes, where objects such as books, balls, and toys need to be picked up and placed, and in production lines, where products such as packaged goods and mechanical parts need to be picked up and moved [37] [64], creating the need to improve such tasks. It is believed that research into robotic grasping and manipulation began as early as the 1970s and was popularized in various classic science fiction films. Many of these robots are indistinguishable from their human counterparts, except that they had not yet perfected their hands [14]. To date, numerous researches have been conducted in the field of robotics with various subcategories and focuses, all aimed at improving their efficiency on human processes. Among these various research areas of robotics, grasping and manipulation offers significant potential in both industrial and domestic settings. Other important applications include medical specimen collection, autonomous transportation and delivery of medical goods, rapid and autonomous manufacturing of medical and healthcare products, etc., to assist humans in jobs that require human-like dexterity. This became even more urgent with the advent of COVID-19.

In grasping and manipulation task, a robot is expected to efficiently and effectively grasp an object and then manipulate it. The goal of grasping is to ensure that the robot can fully grasp an object with its robotic hand. The key indicator of success here is the identification and firm grasping (picking) of the object, which means that the uncertainties related to the position, geometry, or nature of the object are efficiently removed and then controlling the movement of the grasped object is as simple as controlling the hand movement. On the other hand, manipulation means the application

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of force or motion to the same object to change its state and orientation in an environment [59]. In contrast to robot grasping and manipulation, robotic perception in itself grounds the use of robots in the real world. Like human sensory organs responsible for tasks such as sight, hearing, touch, taste, and smell, it is crucial for robots to be able to perceive the real world and its dynamics if they are to autonomously assist humans. Robotic perception has achieved success in tasks such as vision, haptics, tactile perception, and hearing [4]. At first glance, it is not clear how perception is related to the tasks of grasping and manipulation.

It is well known that robots have speed and strength far superior to the human hand, but they cannot reliably grasp unfamiliar objects. This limitation is due to the varying shapes, sizes, and textures of objects, which makes it difficult to build superintelligent machines for household, manufacturing, and security applications. [4] explains that this difficulty stems from the inherent uncertainty in the robot's physics, perception, and control. Virtually all applications, from manufacturing to service to security, would benefit from robots capable of grasping any object with a wide range of shapes and sizes, from rigid to deformable, and under a variety of frictional conditions. Yet despite over 40 years of research, this problem remains unsolved. One plausible reason is that robots rely on simplification of their environment, such as a specific arrangement of objects or strong backlighting that allows better perception and localization of the object or subject. Therefore, to alleviate this problem, we need to enable robots to "see" by developing robust perception systems to localise objects and plan robust grasping positions on objects [49].

The field of robot grasping, manipulation and perception is generating so much interest in the industry that e-commerce giant Amazon has challenged researchers in an annual competition for the past three years. The Amazon Robotics Challenge asks researchers to design and build a robot that can sort items from bins and assemble them into boxes for a customer's order. The items are varied, ranging from bottles and bowls to stuffed animals and sponges. They are initially jumbled, making it difficult to identify objects and grasp them mechanically.

Because of the amount of research that has been done in this area, it starts to become tedious for late entrants. Our survey aims to ease the entry of researchers into the field and to promote continuity of ongoing research. In section 2, explore various robot gripper and their applications while section 3 discusses the ways in which grasp learning has been employed.

2 Robot Grippers

Design, analysis and control of grippers are essential aspects of robotic grasping and manipulation. The type of robotic gripper plays an important role in the success of gripping. For robotic grippers to be successful in small-scale manufacturing, they must have the same adaptability and sensitivity as human hands. These robots do not necessarily mimic the human hand, but it is often helpful to analyse their dynamics during grasping and manipulation to better understand the relationship between the task and the solution provided by the hand [6].

Much research has been conducted in the empirical and medical literature on the grasping abilities of the human hand. This research assumes six types of grasping: cylindrical, fingertip, hook, palmar, spherical, and lateral. The categorization led to the assignment of grips to partial shapes, which is an essential basis for the design of robotic hands [41][9][56]. Today, there are various types/designs of grippers developed and used for industrial applications. The major categories of grippers in industry today are servo electric grippers, two finger/jaw grippers, three finger/jaw grippers, adaptive or multi finger grippers, magnetic grippers, soft and flexible grippers, jamming grippers, hydraulic grippers, pneumatic grippers, vacuum grippers etc. [50]. Nevertheless, research on grippers with higher efficiency and effectiveness is still ongoing, as many use cases remain challenging for existing technologies.

2.1 Two-finger and Three-finger Grippers

Two and three-fingered grippers are typically used in manufacturing for small jobs. In **two-finger grippers**, the end effector has two parallel jaws with flat edges. They open and close, clamping onto the part and holding it steady with force. **Three-finger grippers** have three fingers or jaws that close around objects and hold them in the centre. They are usually used for round or cylindrical objects.

Two-finger grippers In 2014, students from Harvard and Yale developed the iHY robotic hand [17]. It had two fingers and an opposable thumb powered by five motors. Each finger contained proximal and distal links that connected the finger to the base to the fingertip. Heavy-duty elastic joints were used to provide flexibility and durability, which allowed for better grasping of objects. Objects ranging from small ball bearings to golf balls to heavy drills can be held by these iHY hands. Gripping force was provided by cable tendons that wrapped around the object and gripped it tightly [17]. The iHY two-finger gripper was extended to a wheeled mobile robot used in arduous, hazardous, and dirty environments. These robots have a mobile platform, robotic arm and gripper for pick-and-place tasks that can be used in any industry. To make the modifications work, the stress, deformation, and torque requirements of Von-Mises were taken into account in the computational analysis of the gripper during development [3].

A different direction for the design of a two-fingered robotic hand was taken in 2011 [26], where a robotic hand would be teleoperated by a human, focusing on the haptic properties of the robotic hand. The system would relay the reaction force measured in the robotic hand to an operator. The team developed a force feedback device that sends a reaction force to the distal segment of the operator's thumb, middle finger, and basipodite of the middle finger when the robotic hand grasps an object. While several works continues on the design of these grippers, other researchers have made efforts to optimise the dimensional synthesis and kinematic configuration of the mechanisms [5] [27].

Three-finger grippers As mentioned earlier, three-finger grippers expand the task of grasping and allow for more versatility and fixable adaptive control. Their hands adapt to a variety of part geometries and sizes, including cylindrical and circular objects [22]. [36] [22] [63] [51] [38] have done work to extend the realities and successes of two-finger grippers to three-finger grippers in terms of their design, fabrication and control.

2.2 Other Robot Grippers

In addition to robots with two and three grippers, we also have **Adaptive grippers** and **Vacuum-based grippers**.

Adaptive grippers These grippers are often made of malleable, soft materials as they are usually very flexible and have multiple fingers designed for gripping round, irregular, or delicate objects. They can be used for food production lines or for handling small, fragile objects. While adaptive grippers with 4-5 fingers have proven to be a prosthetic for the human body, it is still a challenge to use them for a robot. This is because they often lack precise repeatability and usually cannot handle heavy payloads, as they often integrate many kinematic degrees of freedom and thus complex mechanisms that must be controlled to grasp and manipulate objects [24]. For this reason, these types of grippers are not very popular; they are simply not yet ready for industry [24].

A new direction in adaptive grippers is soft fingers *(related to the field of 'Soft Robotics')*, which usually have multiple fingers. An early approach using anthropomorphic hands can facilitate grasping by intrinsic compliance, allowing them to adapt to different objects. This involved embedding tubes of liquid metal in a silicone sheet wrapped around the finger. The strain on the finger is monitored using the electrical resistance of the tubes, and machine learning is used to make inferences about what is happening to the finger [7][15]. In [30] research, a new flexible hybrid pneumatic actuator (FHPA) was proposed that achieves a better balance between required flexibility and necessary stiffness with large grasping force, low cost and light weight.

Meanwhile, [12] [61] [47] proposed a non-anthropomorphic grasping method that reduces the complexity of grasping and simplifies grasping of diverse objects in different poses without detailed knowledge of the object geometry. They usually require the actuation of fewer degrees of freedom for grasping, which is possible because their deformability ensures that the contacted object dominates their shape.

Vacuum-based grippers Work with Bernoulli Principle, by creating a high-velocity flow between the vacuum cup and the object surface, creating a vacuum that lifts the object. They use the difference between the air pressure in the gripper and the external air pressure to lift, hold and move objects [18] [43]. One problem with vacuum grippers is the lack of details about the parameters that affect sealing and force transmission behaviour. Uncertainties such as leakage or the unknown force transmission behaviour of vacuum grippers make it necessary to estimate the process-specific loads and therefore overdesign the system by a certain safety margin. Therefore, it is crucial to understand the exact deformation behaviour of vacuum grippers due to a specific load condition [21]. An early approach to address these issues was to predict the maximum suction force using finite element simulations [16]. While most previous research on vacuum grippers focused on static (non-numerical) computational methods, new directions are moving towards dynamic predictive models that can be used for model-based robot trajectories and vacuum gripper design. One of these models proposed an experimental modelling method that considers the dynamic deformation behaviour of vacuum grippers in interaction with the specific gripper-object combination [10].

3 Grasping Learning Methods

The act of grasping is one of the biggest problems in robotics due to the complexity of perception, planning and execution in complex and dynamic environments. Yet, in many applications, it remains one of the most desired capabilities for a fully functional robotic system. Consequently, this is an area that has attracted and continues to attract a great deal of interest and research over the past decades, which has resulted in many advances and an active area of research and development [1]. Approaches to the grasping problem can be mainly divided into two main categories: an analytical approach and a learning-based approach.

3.1 Analytic Approach

The analytical approach to grasping involves the development of computational algorithms with low data dependence that autonomously control a robotic hand to perform tasks. It relies on the availability of a physically-based, algebraic description of an object in space, which are often approximations and sometimes simplifications of the real object or environment [48]. The method aims to achieve dexterity, balance, stability, and dynamic behaviour in the robot hand, and algorithms are used to achieve all four goals. The algorithm **dexterity** involves solving an unconstrained linear programming problem with an objective function representing one or more known dexterity measures. Simultaneously, **equilibrium** is achieved by algorithms that balance the positivity, friction, and torque constraints on the fingers of the robot hand. **Stability** algorithms aim to achieve positive definite grasp impedance matrices by solving the required fingertip impedances, while **dynamic** behaviour algorithms determine fingertip impedances that, when achieved, lead to a desired dynamic behaviour [58].

Despite these efforts to implement a reliable grasping system, analytical approaches still do not capture all aspects of the intrinsic properties of the object. The solutions do not account for the variations that arise when contact models are rich or environments are unstructured and dynamically changing. Moreover, it is difficult to derive an inverse model (inverse kinematic model of the arm) needed for forward or open-loop control, so it is implemented by a local inversion of a forward model [45].

3.2 Data-driven or Empirical approach

The data-driven approach to grasping has gained much popularity recently. This is thanks to advances and discoveries in deep learning and self-supervised methods, especially their ability to generalize to unseen objects and dynamically changing environments. Here, the robots does not employ prior knowledge of the object's features, and learning is done in an end-to-end fashion [55] [25]. They are mostly empirically evaluated and do not necessarily have to respect physical and dynamic constraints compared to analytical approaches where these constraints are manually modeled. Data-driven methods can be divided into supervised and unsupervised (reinforcement learning) learning approaches. However, there are two main pipelines applied for successful execution of grasping: model-free and model-based pipelines.

Model-based In this approach, specific physical and geometric knowledge about the object is used to solve the grasping task. Typically, this is a three-stage process involving estimation of the object pose, determination of the grasp pose, and finally path planning (which includes kinematic considerations). In the model-based approach and in the context of object pose estimation, the (visual) perception of a robot's environment and the object is of great importance for the success of the robot's grasping task. In essence, identifying objects and the recovery of their pose is crucial since the recognition must be done in real time and the texture, shape and appearance of the objects are dynamic. However, occlusions around the object, changing lighting conditions, and cluttered scenes make it even more difficult for the robot to accurately identify the pose of an object [8][46][25][52].

Model-free Here, the model directly suggests a candidate grasp and would generalize to unseen objects. The model-free process eliminates the need for object pose estimation and can understand the dynamics of an object as a result of the generalization of the models.

For each component of the pipeline (object pose estimation, grasp pose determination, and path planning), researchers have applied supervised and unsupervised algorithms that use data to execute the grasp.

3.2.1 Supervised

In the discriminative approach of supervised learning, samples from grasp candidates are collected and a neural network is trained to select the grasp with a higher probability of success. While it can be computationally intensive to train an appropriate model to support grasping, it promises generalization and good performance for unseen data. In 2017, Leitner's ACRV team won Amazon Robotics Challenge with a robot they named Cartman [29]. The robot has two tools for picking up objects: a gripper with two parallel plates (end effector) and a suction cup with a vacuum pump. For each object the robot encounters, it can specify which tool it wants to use for the task. In conjunction with an RGB-D camera, Leitner used a machine learning approach to semantic segmentation that accesses color and depth to get a good result on the challenge. Once Deep Learning segmentation is used to find a cluster of pixels that represent the object, the depth detection feature of the camera helps the robot figure out how to grasp the object. [29] [14].

As deep learning methods has progressed over the past few years and more sophisticated algorithms developed, the possibilities of grasping and manipulation with these algorithms have been further explored. One practical approach to grasping that is now being used in industry is learning by demonstration. The human provides multiple demonstrations from which a neural network learns and the robot can adapt to variations (generalization) of the same problem. This is in contrast to programming the robot to perform specific actions. Learning by demonstration is not new, but the use of deep learning and model-based reinforcement has increased the success rate [14] [35] [2] [11] [13].

A major improvement over Cartman is the software Dex-Net, which is virtually trained to grasp objects in random poses on a table using a physics simulation. The approach reduces data collection time by simulating millions of grasps very quickly (synthetic dataset). The resulting dataset is used to train a Grasp Quality Convolutional Neural Network (GQ-CNN) [53] to predict the probability of success of a grasp. The software allows an industrial robot to pick objects from a stack with a success rate of more than 90% and can be generalized to various rigid, articulated or flexible objects not seen during training. [34] [31]

The Dex-Net framework was further extended to suction grippers and a dual-arm robot where the policy infers whether to use a parallel jaw or a suction gripper for emptying a cluttered bin. The Dex-Net system continues to be one of the fastest pickers and is well above the numbers achieved by the teams at the last Amazon Robotics Challenge [32] [33]. Other algorithms that have evolved include FC-GQ-CNN [54], GraspNet [40], QT-Opt RCAN [19], Grasping in the Wild [62]. *See more details in [25]*

3.2.2 Reinforcement Learning (Unsupervised)

In recent years, Deep Reinforcement Learning has promised to improve robot learning and outperform the results of human experts in several [42], e.g. in Atari games [39], the game Go [60]. Robotics researchers have adopted the Deep Reinforcement Learning approach and applied it to various robotic tasks, including grasping and manipulation. It provides a framework and set of tools for learning dexterous manipulations from start to finish, directly from raw sensory input. The framework leverages the representational power of Deep Learning to maximize an agent's rewards in a simulated environment. Rewards are mathematical functions that are carefully crafted to drive the actions of agents in the environment.

[57] presented in their research a deep deterministic policy gradient approach that can be applied to a robotic arm with numerous degrees of freedom to autonomously grasp objects according to their classification and a given task. They used 'Only Look Once v5' for object detection while detecting a 3D position of the target object with a backward projection. After calculating the angles of the joints at the detected position using inverse kinematics, the robot arm is moved to the position of the target object using RL algorithm. Grasping in the Wild, another reinforcement learning approach for grasping, proposes a new low-cost hardware interface to collect grasping demonstrations from humans in different environments. It enables closed-loop 6DoF grasping and works in dynamic scenes with moving objects up to some speed limit [62]. QT-Opt in [20] demonstrates a variety of manipulation strategies through a scalable, self-supervised, image-based reinforcement learning. It uses real-world grasping trials to train a deep neural network Q-function that performs closed-loop grasping in the real world and generalizes grasping success to 96% for novel objects. An impressive experiment by OpenAI used automatic domain randomization (ADR) and a custom robotic platform to solve a Rubik's Cube of unprecedented complexity with a humanoid robotic hand [44].

3.2.3 Human-in-the-loop Grasping and Manipulation

Another popular research direction in robotic grasping and manipulation that should not be overlooked is skill transfer, where the skills of a human operator can be used to gain autonomous control. There is also shared control, where the robot and the human control the same body, tool, or mechanism. While the idea of shared control is brilliant, it also raises the issue of co-adaptation between humans and robots, where the two agents can benefit from each other's capabilities or must adapt to each other's behaviour to achieve effective cooperative task performance [23].

The so-called human-in-the-loop (HitL) framework enables autonomous capabilities that can reduce the burden on the operator and increase the overall efficiency of the task. While a robot may not be able to perform some tasks autonomously in a robust and generalizable way, HitL suggests that we can use autonomy for subtasks that can be performed reliably or require relatively effortless operator input. Identifying and developing such techniques, investigating their interplay with operator-controlled subtasks, and analyzing overall efficiency gains are all steps on the path to deployable HitL systems [28]. Some challenges with this method arise from the use of non-anthropomorphic arms with many degrees of freedom (DOFs) or limited sensor data about the robot's environment. However, there are research works that address this problem. In one of the HitL strategies, the operator directly controls the 6D pose of a PR2 gripper in real time by clicking and dragging a series of rings and arrows. Dragging the arrows causes linear motion along the three orthogonal axes, and dragging the rings causes rotation about the same axes. As the action is performed on the rings and arrows, the real gripper attempts to track the motion in real time. This is achieved with a J-transposed control law for the Cartesian position and orientation of the gripper [28].

4 Conclusion

In this survey paper, we have presented various aspects of robot grasping, we have summarized Robot Grippers in detail, and we have described the various grasp learning methods used in previous works. Robot grasping is a very interesting and broad area of research and we have tried to summarize the previous research works in this field. We must emphasize that this is an actively evolving research area that encompasses the specifics of robotic grippers and the execution of grasping, aiming at a fully autonomous and safe robotic system. Therefore, we do not claim to cover all relevant research in this area.

Robot Gripper Great success has already been achieved in the development of robotic grippers for specific types of objects. However, much work has been put into developing robotic grippers that adapt to objects of different shapes. Grippers with multiple fingers promise dexterity equal to that of humans, but there is the problem of increasing complexity due to the greater degrees of freedom that must be controlled. Also, the resilience of the gripper and the ability to grasp delicate objects with dexterity and safety remains a challenge for robots.

Grasp Execution Data-driven learning approaches have shown impressive success rates in grasping. Compared to the analytical approach, the ability of learning-based models to generalize to new objects and environments shows that the gap to human accuracy is closing. However, the determination to capture a wider variety of objects poses a problem caused by increasing complexity. The reinforcement learning approach to object sensing solves much of this problem, but the use of a black box model in the real world poses a safety risk.

While more work needs to be done to improve the applicability of robot grasping in the real world, significant progress has already been made to achieve this goal. In future work, we intend to we aim to delve deeper into the research works in robot manipulation. As state in earlier, manipulation of objects by a robot arm involves application of particular forces to the object and a lot of work has been done in this area.

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