An Overview of 3D Object Grasp Synthesis Algorithms

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Abstract

This overview presents computational algorithms for generating 3D object grasps with autonomous multi-fingered robotic hands. Robotic grasping has been an active research subject for decades, and a great deal of effort has been spent on grasp synthesis algorithms. Existing papers focus on reviewing the mechanics of grasping and the finger-object contact interactions [7] or robot hand design and their control [1]. Robot grasp synthesis algorithms have been reviewed in [63], but since then an important progress has been made toward applying learning techniques to the grasping problem. This overview focuses on analytical as well as empirical grasp synthesis approaches.

Key words:
Grasp synthesis, force-closure, learning by demonstration, task modeling

1. Introduction

Over the past decades, research in robotic grasping has flourished. Several algorithms have been developed for synthesizing robotic grasps in order to achieve stability, force-closure, task compatibility and other properties. Different approaches have been developed to meet these goals, and substantial improvements have been claimed. Thus, the availability of large number of algorithms for our purpose has made it difficult to choose, since their approaches and assumptions are different. The primary goal of this overview is to make the task of choosing algorithms easier by providing a comparative

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view of them.

During a task execution, the grasping fingers must be controlled so that the grasp processes dexterity, equilibrium, stability and dynamic behavior. Such a control scheme, requires methods of computing the finger parameters (positions and forces of fingertips and joints). These algorithms are referred to as robotic grasp synthesis algorithms.

This paper is organized as follows. Section 2 introduces the terminology used and basics on grasp analysis. Section 3 and 4 review algorithms based respectively on analytical and empirical approaches. By analytical approaches, we mean those based on geometric, kinematic and/or dynamic formulations of grasp synthesis problems. The empirical approaches avoid the computation of the mathematical and physical models by miming or imitating human grasping strategies.

2. Background and terminology

The basic function of a gripper is to grasp objects and possibly manipulate them by means of its fingers. One of the essential properties looked for in the grasp configuration selection is the immobilization of the grasped object (its equilibrium) against the possible external disturbance. The set of fingers grasping the object by the fingertips can also be seen, from a mechanical point of view, as distributed impedances on the object surface [67].

There is a wide disparity in the terminology used in the grasping literature regarding equilibrium, stability, force closure and form closure terms [6, 42, 31, 47, 50, 68]. We adopt the terminology used in [31] and summarize in the following the corresponding definitions.

Consider an object grasped at N contact points. At each contact location, the object is subject to normal/tangential forces and torsional moment about the normal. We denote these wrenches by w_n^i, w_t^i and w_θ^i respectively, and their corresponding magnitude by c_n^i, c_t^i and c_θ^i. Each contact may be either frictionless, frictional or soft. In the case of a frictional contact, there are only normal and tangential wrenches. For a frictionless contact only the normal wrench is considered. The wrench matrix $\mathbf{W}$ is composed of the mentioned vector wrenches arranged in columns. We denote $\mathbf{c}$ the corresponding wrench magnitude vector.

Definition 1. A grasped object with an external wrench $\mathbf{g}$ is in *equilibrium* if and only if:

1. $\forall i$, $c_n^i \geq 0$, $\mid c_t^i \mid \leq \mu_t^i c_n^i$ and $\mid c_\theta^i \mid \leq \mu_\theta^i c_n^i$
2. $\mathbf{Wc} + \mathbf{g} = 0$ for $\mathbf{c} \neq 0$

Where μ_t^i and μ_θ^i correspond respectively to the coefficients of the tangential and torsional friction for each contact location given by Coulomb's law.

So, a grasped object is defined to be in equilibrium if the sum of all forces and the sum of all moments acting on it are equal to zero. An equilibrium grasp may be stable or unstable. The stability was detailed in [68] as follows:

Definition 2. A grasped object at *equilibrium*, in which all forces and moments can be derived from a potential function $V(\mathbf{q})$ is *stable* if $\forall \Delta\mathbf{q} \neq \mathbf{0}$, $\Delta V > 0$.

The first goal of every grasping strategy is to ensure stability. The Lejeune-Dirichlet's theorem gives a sufficient condition for stability analysis of a conservative system including external dissipative forces by using a direct method. General methods rely on the linearized forms of the motion system equations. These equations can be linearized around an equilibrium position in order to analyze its static stability. There is a certain A matrix whose eigenvalues characterize the behavior of the nearby points (Hartman-Grobman theorem). More precisely, if all eigenvalues are negative real numbers or complex numbers with negative real parts then the point is a stable attracting fixed point, and the nearby points converge to it at an exponential rate [29]. In addition, the local geometry of the contact could be taken into account in the grasp stability analysis [31].

Another dimension in the stability of the grasp relies on the limitations in the contact force transmissions. They are reflected by properties such as form-closure, force-closure and more generally by the "*contact stability*" [6, 42, 31, 47, 50, 68].

Moreover, a grasp is stable if a small disturbance, on the object position or finger force, generates a restoring wrench that tends to bring the system back to its original configuration [31, 12]. Nguyen in [49] introduces an algorithm for constructing stable grasps. He also proves that all 3D force-closure grasps can be made stable. A grasp is force-closure when the fingers can apply appropriate forces on the object to produce wrenches in any direction [60]. In other words, the wrench or grasp matrix, noted $\mathbf{W}$, should positively span the entire 6-dimensional wrench space.

In addition, force closed grasps are a subset of equilibrium grasps, and have the important property of being stable. However, not all stable grasps are force closed, including many common and easily obtainable grasps. Bicchi [7] observed that force closure grasp analysis is equivalent to the stability of an ordinary differential equation. Force closure property is defined as follows [31]:

Definition 3. A grasp verify the *force closure* property if and only if, for any external wrench $\hat{\mathbf{w}}$, there exists a magnitude vector λ satisfying the constraint equalities in Definition 1, such that $\mathbf{W}\lambda = \hat{\mathbf{w}}$.

Finally, *form closure* property is usually a stronger condition than force closure. The analysis of form closure is intrinsically geometric. More formally, a grasp achieves form closure if and only if it achieves force closure with frictionless point contacts. In this case, form closure and force closure are dual to each other [50, 71].

Obviously, stability is a necessary but not a sufficient condition for a grasping strategy. When we reach out to grasp an object, we have a task to accomplish. Thus, in order to successfully perform the task, the grasp should also be compatible with the task requirements. Computing task-oriented grasps is consequently crucial for a grasping strategy. Finally, because of the variety of object shapes and sizes, a grasping strategy should be prepared to grasp objects the robot sees for the first time.

Thus, a grasping strategy, as shown in figure 1, should ensure stability, task compatibility and adaptability to novel objects. By novel objects, we refer to ones that are being seen for the first time by the robotic system. Furthermore, a grasp synthesis strategy should have an answer to the following

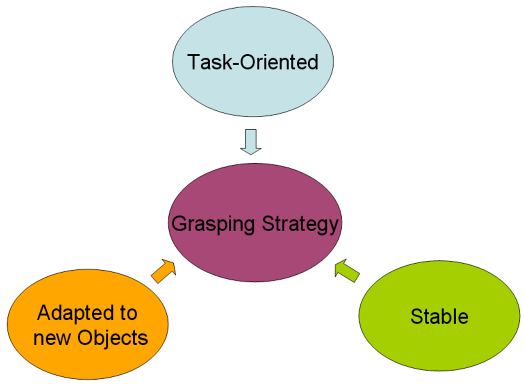

Figure 1: Grasp strategy should satisfy three constraints: stability, task compatibility and adaptability to new objects.

question: where to grasp an object in order to accomplish a task? Analytical and empirical approaches answer this question differently.

Analytical approaches determine the contact locations on the object and the hand configuration that satisfy task requirements through kinematic and dynamic formulations. Empirical approaches, on the other hand, mimic human grasping to select a grasp that best conforms to task requirements and the target object geometry. In the following, we review these two approaches applied to 3D object grasp synthesis. The reader should notice that many algorithms have been developed for 2D object grasp planning [40, 55], but 3D object grasp synthesis still an active research area due to the high dimensional grasp space and object complex geometry.

3. Analytical Approaches

Analytical approaches consider kinematics and dynamics formulations in determining grasps. The complexity of this computation arises from the number of conditions that must be satisfied for a successful grasp. Figure 2 illustrates the general strategy adopted by analytical approaches to compute grasps. Proposed algorithms in the literature do not necessarily contain all the components of the architecture presented in Figure 2. Most of them do not take into account the task constraints and/or the hand model.

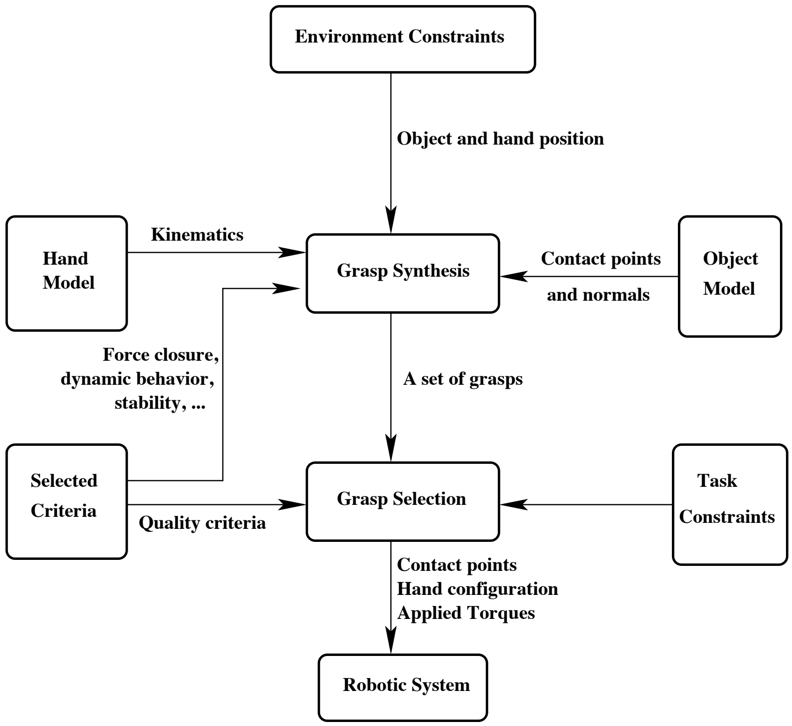

Figure 2: Strategy of grasp synthesis using analytical approaches.

The diagram of figure 3 summarizes these strategies. A quick look at this diagram shows that many works have been developed to compute force-closure grasps but only few have addressed the problem of computing task oriented ones. This shows the difficulty of the latter. In the following, we present and discuss some relevant works for generating force-closure and task-oriented grasps.

3.1. Force-Closure Grasps

The works in this section present techniques for finding force-closure grasps for 3D objects. For this purpose, two approaches may be considered: (1) analyzing whether a grasp is force-closure or not; or (2) finding fingertips locations such that the grasp is force-closure. The former considers force-closure necessary and sufficient conditions. The latter is the force-closure grasp synthesis problem, and it is the one considered here since this survey

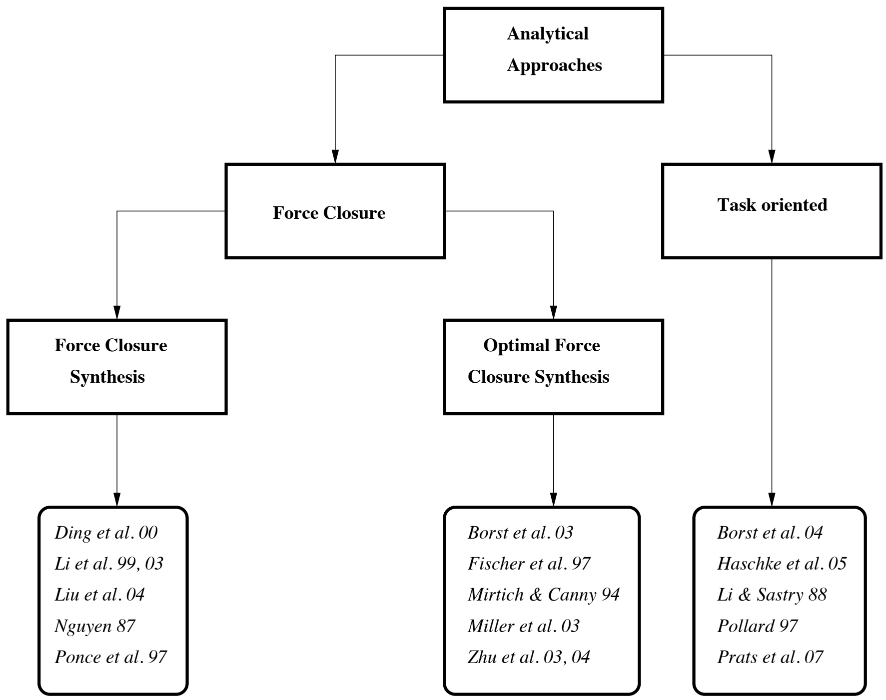

Figure 3: A synthetic view of existing analytical approaches for grasp synthesis of 3D objects. The diagram shows analytical strategies developed for satisfying force closure and task oriented conditions.

discusses grasp synthesis. Given the quantity of relevant works in this field, we divide them into the following groups: (1) force-closure grasp synthesis for 3D objects and (2) optimal force-closure grasp synthesis according to a quality criterion.

3.1.1. Force-Closure Grasp Synthesis for 3D Objects

Depending on the object model, polyhedral or complex, different grasp synthesis strategies have been proposed in the literature. We present first those dealing with polyhedral objects. These objects are composed of a finite number of flat faces. Evidently, each face has a constant normal and the position of a point on a face can be parameterized linearly by two variables. Based on these properties, grasp synthesis approaches dealing with polyhedral objects reduce the force-closure condition to a test of the angles between the face normals [49], or use the linear model to derive analytical formulation for grasp characterization [54, 39, 17]. Based on the property that each point on a plane face can be parameterized linearly with two parameters, Ponce et al. [54, 56] formulated necessary linear conditions for three and four-finger force-closure grasps and implemented them as a set of linear inequalities in the contact positions. Finding all force-closure grasps is thus set as a problem of projecting a polytope onto a linear subspace. Liu et al. [39] discussed the force-closure grasp synthesis problem for n fingers when $n-1$ fingers have fixed positions and the grasp with the $n-1$ fingers is not force-closure. Using the linear parametrization of a point on an object face, they search locations on that face for the n^{th} finger that ensure force-closure. Ding et al. [17] presented an algorithm to compute the positions for n fingers to form a force-closure grasp from an initial random grasp. The algorithm first arbitrarily chooses a grasp on a given face of the polyhedral object. If the selected grasp is not form-closure or in other words if the origin O of the wrench space lies outside the primitives wrenches convex hull, the algorithm moves each fingertip position, using this linear parametrization of a point on an object face, at a fixed step on its corresponding face so that the convex hull moves towards the origin O and consequently, the form-closure property is ensured.

The previous analyses were limited to polyhedral objects such as boxes. These approaches do not consider the issue of selecting a grasping facet. An exhaustive search is performed instead. They are efficient when the number of faces of the object is low. However, commonly used objects like mugs or bottles are not necessarily polyhedral and can rarely be modeled with a limited number of faces. Hence, when polyhedral grasp synthesis approaches are applied to these objects, they need a huge computation effort to study the combinations of their large number of constituting faces. Thus, new techniques are required for force-closure grasp synthesis. Such general approaches place no restrictions on the object model [37, 18]. Objects are modeled with a cloud of 3D points or a triangular mesh. The authors in [37] presented an algorithm for computing three finger force-closure grasp for 2D and 3D objects. They assume hard-finger contacts. Based on the intersection of the corresponding three friction cones, the authors compute three-finger force-closure grasp of 2D objects based on geometrical analysis. They simplify then the 3D object force-closure problem to a 2D one when the three contact points constitute a plane and when this plane intersects each friction cone on a triangular area. Ding et al. [18] proposed an algorithm to synthesize force-closure grasps with 7 frictionless contacts. The grasped object is discretized so a large cloud of points p_i as well as their normals n_i is available. Then, a large collection of contact wrenches g_i can be obtained. The algorithm starts with an initial set of seven contacts randomly chosen among the set of points. If the selected grasp is force-closure, the algorithm finishes. Otherwise, the initial contacts are iteratively exchanged with other candidate locations until a force-closure grasp is obtained. The previous heuristic algorithm is extended in [41] for any number of contacts with or without friction. The authors in [23] demonstrate that wrenches associated to any three non-aligned contact points of 3D objects form a basis of their corresponding wrench space. This result permits the formulation of a new sufficient force-closure test. Their approach works with general objects, modeled with a set of points, and with any number n of contacts ($n \geq 4$).

Such methods find contact points on a 3D object surface that ensure force-closure. Although this criterion guarantees the stability of the grasp, it does not include any notion about the quality of the grasp generated, for example how the latter deals with the limitation of the forces that can be applied by the fingers on the object. Several quality criteria were introduced to the grasping literature and in the following some relevant works on computing optimal grasps are presented.

3.1.2. Optimal Force-Closure Grasps on 3D Objects

Given two grasps $\mathcal{G}_1$ and $\mathcal{G}_2$ described by different wrench systems, we would frequently like to be able to say how good $\mathcal{G}_1$ is as compared to $\mathcal{G}_2$. Obviously, such measure of goodness must possess some physical intuitions that correspond to how we normally view a grasp. Mishra summarizes in [46] various existing grasp metrics with extensive discussion on the trade-offs among the goodness of a grasp, the number of fingers, the geometry of the object, and the complexity of the grasp synthesis algorithm. A rich survey of grasp quality measures can also be found in [65].

Mostly, optimal force-closure grasp synthesis concerns determining the contact points locations so that the grasp achieves the most desirable performance in resisting external wrench loads. These approaches could be seen as heuristic optimization techniques. They compute optimal force-closure grasps by optimizing an objective function according to a pre-defined grasp quality criterion. When objects are modeled with a set of vertices, they search all their combinations to find the optimal grasp. For example, Mirtich and Canny [45] developed two optimality criteria and used them to derive optimum two and three finger grasps of 2D objects and optimum three finger grasps of 3D polyhedral objects. Whether the first or the second criterion is used, the maximum circumscribing or the maximum inscribing equilateral triangle defines the optimum grasp of a 3D object. The optimum grasp points must be vertices of the polyhedron. Thus, the authors test all triples of vertices of a n-vertices polyhedron in order to find its corresponding optimum three fingers grasp. This corresponds obviously to an $O(n^3)$ algorithm. On the other hand, when objects are smooth, such as ellipsoids, the primitive wrenches of the grasp are also smooth functions of the grasp configuration. If the grasp configuration that specifies the positions of the contact points is denoted by u, f(u) in [72] is a function that provides a measure on how far the grasp is from losing the closure property. Thus, a natural way to compute the force-closure grasp is to minimize f(u). The optimization problem can be solved by descent search. Zhu and Wang [71] proposed a similar algorithm based on the gradient descent minimization of the derivative of the Q distance or Q norm. The Q distance is the minimum scale factor required for a convex set to contain a given point a, i.e. it quantifies the maximum wrench that can be resisted in a predefined set of directions given by the corresponding convex set.

Searching the grasp solution space for an optimal grasp is a complex problem requiring a large amount of computing time. Fast algorithms are required to integrate grasp planners in on-line planning systems for robots. Hence, heuristic approaches were applied to the grasp synthesis problem. These approaches generate first many grasp candidates randomly [10], according to a predefined procedure [27] or by defining a set of rules to generate a set of grasp starting positions and pre-grasp shapes that can then be tested on the object model [43, 44], filter them with a simple heuristic to exclude candidates which can not lead to feasible grasps or that does not satisfy the force-closure condition and then choose the best candidate according to a quality criterion. However, such approaches suffer from the local minima problem.

All these approaches have studied stable grasps and developed various stability criteria to find optimal grasps. After examining a variety of human grasps, the authors in [15] conclude that the choice of a grasp was dictated by the tasks to be performed with the object. Thus, finding a "good" stable grasp of an object is only a necessary but not sufficient condition. Therefore, many researchers addressed the problem of computing task-oriented grasps which will be addressed in the next paragraph.

3.2. Task Compatibility

A good grasp should be task oriented. Few grasping works take the task into account. This is due to the difficulties of modeling a task and providing criteria to compare the suitability of different grasps to the task requirements.

Manipulability ellipsoids are effective tools to perform task space analysis of robotic manipulators, in terms of their ability to perform velocities and acceleration at the end effector or to exert forces on the environment. This may be advantageous to find the best configuration to execute a given task. Shortly, a unit sphere in the joint space can be mapped into a manipulability ellipsoid in the task space by Jacobian transformation. Velocity and force manipulability ellipsoids show feasible motions and achievable forces in the task space, respectively. Yoshikawa [70] gave one of the first mathematical measures for the manipulability of any serial robot by discussing the manipulating ability of robotic mechanisms in positioning and orienting end-effectors.

Chiu [14] proposed a task compatibility index to measure the level of agreement between the optimal directions of the manipulator and the actual moving directions required by the given task. The task compatibility index is considered for both force and velocity transmissions. Despite of their popularity, ellipsoids suffer from possible inconsistency deriving from improper use of Euclidean metric and from dependency on change of scale and coordinate frame [19]. To overcome these problems, the task-space polytopes which accurately represent the maximum achievable task space capabilities with given limits in the joint space were introduced in [25]. Furthermore, Lee [35] discussed the use of manipulability ellipsoids and polytopes in measuring the dexterousness of robot manipulators. He illustrated that the manipulability ellipsoid does not transform the exact joint velocity constraints into task space and so may fail to give exact dexterousness measure and optimal direction of motion in task space. He also proposed a practical polytope method which can be applied to general 6D task space.

Li and Sastry [36] developed a grasp quality measure related to the task to be performed. They showed that the choice of a task oriented grasp should be based on the capability of the grasp to generate wrenches that are relevant to the task. Assuming a knowledge of the task to be executed and of the workpiece geometry, they planned a trajectory of the object before the grasping action in order to model the task by a six-dimensional ellipsoid in the object wrench space. The latter is then fitted to the grasp wrench space. The problem with this approach is how to model the task ellipsoid for a given task, which the authors state to be quite complicated.

Pollard [53] designed a system that found grasps having a certain percentage of the quality of a given prototype grasp. A grasp prototype is defined as an example object and a high quality grasp of that object. A task is characterized as the space of wrenches that must be applied to the object by the robot in order to complete the task objective. If one knows nothing about the grasping task and assuming that the probability for every wrench direction to occur as a disturbance is equal, the task wrench space, TWS, is modeled as a unit sphere. The grasp quality measure used is the amount the robot has to squeeze the object in order to be capable of resisting all task wrenches while maintaining the grasp. By accepting the reduced quality, the contact points of the prototype grasp can be grown into contact regions. Pollard's system can be considered one of the more general grasp synthesis tools available, but it has a few difficulties. While the prototypes allow her to greatly reduce the complexity of the search, a system to choose the closest prototype grasp is not given. Thus, the computed grasps are unlikely to be perfect for a given task or object. Modeling the TWS with a unit sphere has no physical interpretation. The forces along with their corresponding torques act on the object boundary in order to accomplish a task. Thus, the task wrench space is not uniform and varies with the object shape. Pollard introduced the Object Wrench Space (OWS) which incorporates the object geometry into the grasp evaluation. The OWS contains any wrench that can be created by disturbance forces acting anywhere on the object surface. It is a physically motivated description that takes all possible disturbances on the object into account permitting to generalize over any task.

Borst et al. combined the idea of the task ellipsoid [36] with the concept of the OWS to obtain a new description of the task wrench space (TWS). The quality of a grasp is obtained by comparing the TWS (which is no longer a sphere) with the Grasp wrench space, GWS, of the grasp that is actually evaluated. In other words, for a given TWS, the largest scaling factor is searched to fit it into a GWS (figure 4). In order to reduce the computation complexity, the authors approximate the OWS with a 6D ellipsoid which enables them afterwards to transform the problem to a sphere fitting into the GWS using a linear transformation.

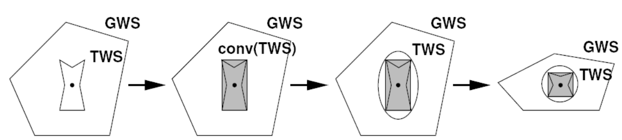

Figure 4: Approximating the OWS with an ellipsoid. 1. The sampled OWS. 2. Convex Hull over the sampled OWS. 3. Enclosing ellipsoid. 4. Linear transformation of ellipsoid and GWS [11].

The authors in [30] proposed a method for computing a task oriented quality measure. The approach is based on a linear matrix inequality formalism, treating friction cone constraints without the pyramidal approximation. It evaluates the grasp for a given task wrench along a single direction and specifies the largest applicable wrench along this direction. Thus, it allows optimization of the maximal applicable wrench for a given task wrench direction. Instead of finding a grasp and evaluating its suitability for the desired task, the authors in [57] proposed an approach that takes the task into account from the early grasp planning stages using hand-preshapes. They defined four hand preshapes along with an approximation of their grasp wrench space (figure 5). The hook power preshape is adapted for grasping handles and pushing along a known direction. The hook precision has the same preshape as the hook power one but the contact is made with fingertips. The precision preshape permit forces to be exerted along the two senses of a same direction which enables turning a tap for example. In cylindrical preshape, the fingers enclose the object and make force towards the palm. Thus, to accomplish a task, a robot has to align the appropriate hand's task frame with a target frame that is selected during task planning. The hand preshape and its corresponding target frame are selected according to the task direction and a simplified model of the manipulated object. Objects are modeled as hierarchy of boxes. This algorithm was tested for accomplishing a common task, turning a door handle.

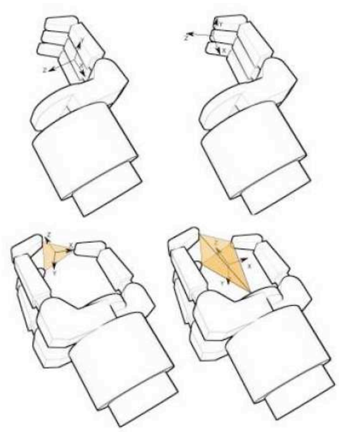

Figure 5: Task frames for the hook power (top-left), hook precision (top-right), precision (bottom-left) and cylindrical (bottom-right) preshapes [57].

The task wrench space (TWS) models wrenches applied on the grasped object in order to perform a task. Given an object and a task to be executed, Li and Sastry proposed to represent the TWS as a six-dimensional ellipsoid. The latter conforms well the task but it is difficult to obtain. The authors were conducted to pre-compute the trajectory followed by the object to accomplish the task. Obviously, this approach is not appropriate for new tasks nor for new objects, the whole computation procedure will be repeated. Pollard models the TWS with a six-dimensional unit sphere. Thus, it is assumed that the probability for every wrench direction to occur is equal. This representation has no physical interpretation since wrenches occurring at an object boundary are not uniform. Consequently, the TWS is not uniform as well. Borst approximates the OWS with an ellipsoid in order to model the TWS. This representation takes into account the object geometry and the wrenches it may encounter. But since this representation accounts for different wrenches on the whole object boundary, it does not consider task specific information. Thus, the computed grasp is not the best adapted to a specific task. Haschke optimizes the maximal applicable wrench for a given task wrench direction. However, the paper does not include any information about the corresponding task wrench direction computation. Prats' approach is adapted for tasks occurring along a specific direction such as opening a door or a drawer where it is easy to model objects with boxes in order to determine their corresponding target frame. Such approach fails to associate appropriate hand preshapes to more complex tasks.

3.3. Discussion on Analytical Approaches

The analytical methods described in the previous sections concentrate on the analysis of a particular grasp or the development of force-closure or task-oriented criteria to compare grasps. The size of the grasp solution space is the most difficult obstacle to overcome in optimizing the grasp. The presented criteria to compute force-closure grasps may yield optimal stable grasps adapted for pick and place operations (figure 1). However, physical interaction through manipulation in our daily life, even for simple and common tasks, goes beyond grasping for picking and placing. That's why many researchers addressed the problem of task-oriented grasping.

The goal of task-oriented grasp planning is to solve the following problem: given an object and a task, how to grasp the object to efficiently perform the task? Two main keypoints are encountered when addressing this issue:

- The difficulty of modeling a task.
- The computational effort to find a grasp suitable for the corresponding task.

Different task-oriented criteria were introduced in the literature. Some of the presented algorithms consider that a set of grasps has already been found, and evaluate the suitability of the given grasp for the desired task using these criteria. In practice, lots of grasps would have to be generated and evaluated, making these approaches computationally unaffordable. They often are not adapted neither for new tasks nor for new objects.

In order to avoid the computational complexity of analytical approaches, empirical techniques were introduced to the grasping problem. By taking a further look at the diagrams of figure 3 and figure 6, we notice that most recent works are based on empirical approaches. These techniques are detailed in the next paragraph.

4. Empirical Approaches

By empirical grasping approaches, we refer to the techniques based on classification and learning methods that avoid the computational complexity of analytical ones. Figure 6 summarizes the proposed algorithms in the literature. As shown in this figure, we can distinguish two broad categories: the techniques centered on the observation of a human performing the grasp and those focused on the observation of the grasped object.
In the first techniques, a robotic system observes a human operator, called also teacher or expert, performing a task and tries then to reproduce the same grasps. Such techniques represent a subset of policy learning methods and are known as Learning by (or from) Demonstration (LbD).
The second techniques are object centered methods. The robotic system learns the association between objects characteristics and different hand shapes in order to compute natural and task adapted grasps.

The general strategy adopted by the empirical approaches to compute grasps is illustrated in Figure 7. Some algorithms proposed in the literature do not meet all points of this architecture but are limited to a subpart while others incorporate the evaluation step, for example, to obtain a loop and to give the teacher an active role during learning. In fact, learning systems could be augmented to enable learner performance to improve beyond what was provided in the demonstration dataset. In the following, we detail the two introduced techniques: human and object centered methods.

4.1. Systems based on human observation

Different Learning-by-Demonstration (LbD) frameworks, where the robot observes the human performing a task and is afterwards able to perform the task itself were proposed in the literature. Regarding a categorization for these approaches, we note that many legitimate criteria could be used to

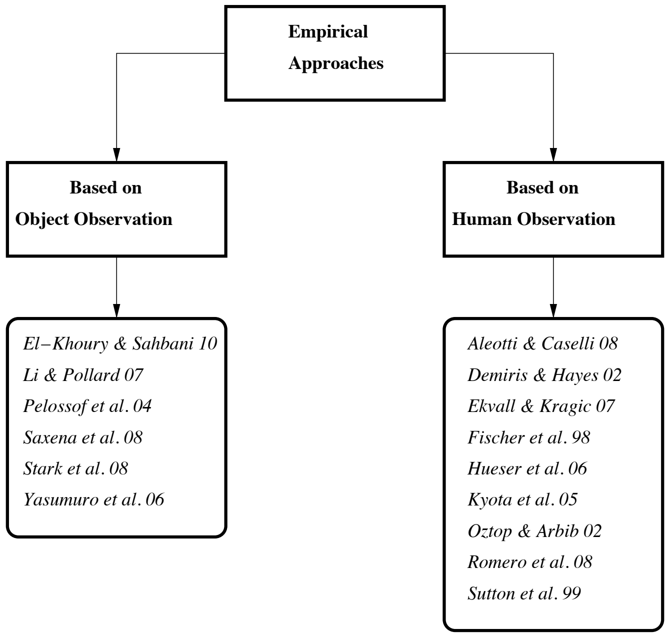

Figure 6: A synthetic view of existing empirical approaches for grasp synthesis of 3D objects.

subdivide LbD research. For example, one proposed categorization considers the questions *who, what and how* to imitate [8, 62]. Another provides a categorical structure for LbD approaches and presents the specifics of implementation [5]. Readers may find other surveys on the LbD research. In particular, the book edited by Dautenhahn and Nehaniv [48] produces a reference suitable as an introduction to the state of the art work on imitation across disciplines (psychology, linguistics, neuroscience and computer science).

From our point of view and as illustrated in figure 7, sensors and signal processing are key points in the proposed techniques. Some researchers use datagloves, map human hand to artificial hand workspace and learn the different joint angles [28, 20], hand preshapes [34] or the corresponding task wrench space [3] in order to perform a grasp. Others use stereoscopy to track the demonstrator's hand performing a grasp [32] or try to recognize its

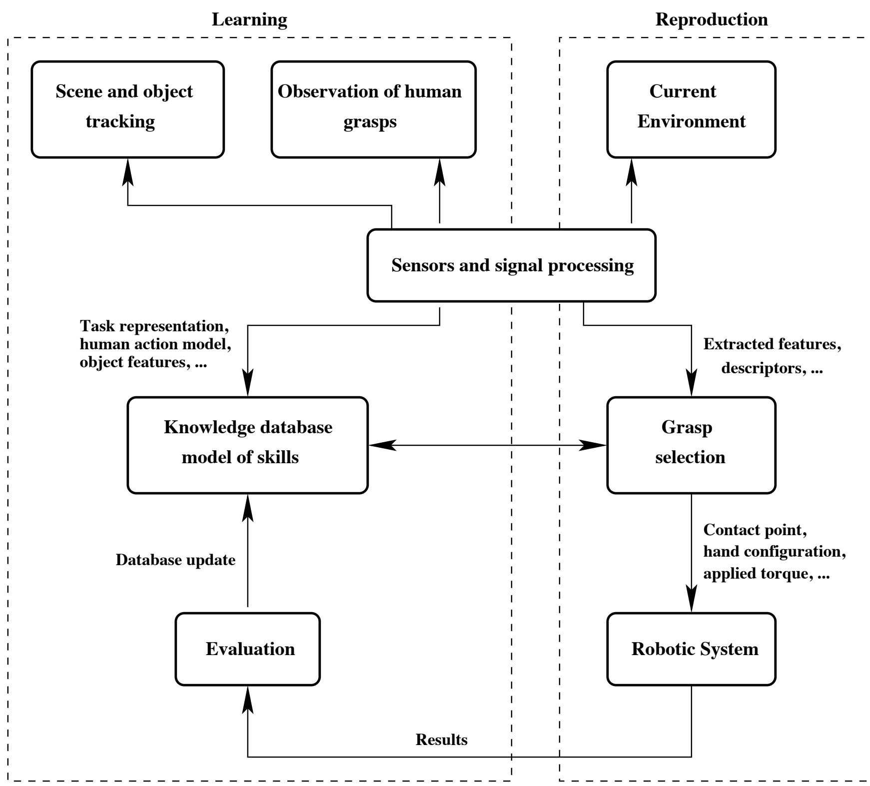

Figure 7: Strategy of grasp synthesis using empirical approaches.

hand shape from a database of grasp images [58]. Moreover, mirror neurons that fire not only when grasping but also when observing an action were also introduced to the grasping problem [51]. Our LbD review aims to focus on the specifics of used sensors. The extracted features from sensors, used as inputs for learning, are crucial for learning policy and for the choice of the demonstration technique (the strategy for providing data to the learner). The following two paragraphs present respectively techniques using dataglove and vision systems. Finally, other human centered approaches incorporate object descriptors. This is the topic of the last paragraph of this section.

4.1.1. Magnetic tracker and dataglove based descriptors

A dataglove is used to control a four-finger anthropomorphic robot hand in [28]. In order to measure the fingertip positions of an operator wearing a dataglove, the fingertips were marked with round colored pins. A calibrated stereo camera setup was used to track the four color markers in real time. To be able to accurately use the dataglove a nonlinear learning calibration using a neural network technique was implemented. Based on the dataglove calibration, a mapping for human and artificial hand workspace can be realized enabling an operator to intuitively and easily telemanipulate objects with the artificial hand. A similar framework is proposed in [20]. The human and the robot are both standing in front of a table, on which a set of objects are placed. The human demonstrates a task to the robot by moving objects on the table. The robot is then able to reproduce the task performed by the human, using magnetic trackers and Hidden Markov Models (HMM). Since objects may not be placed at the same location as during the demonstration, more recently [21], the authors addressed the problem of grasp generation and planning when the exact pose of the object is not available. Thus a method for learning and evaluating the grasp approach vector was proposed so that it can be used in the above scenario. Aleotti and Caselli [3] also proposed a method for programming task-oriented grasps by means of user-supplied demonstrations. The procedure is based on the generation of a functional wrench space which is built by demonstration and interactive teaching. The idea is to let an expert user demonstrate a set of task-appropriate example grasps on a given target object, and to generate the associated functional wrench space as the convex union of the single wrenches. The grasp evaluation is obtained by computing a quality metric Q, defined as the largest factor by which the grasp wrench space (GWS) of the grasp to be evaluated can be scaled to fit in the demonstrated functional wrench space (FWS). Functional wrench space Grasp demonstration is performed in virtual reality by exploiting a haptic interface including a dataglove and a motion tracker for sensing the configuration of human hand [2].

Although magnetic trackers and datagloves deliver exact values of hand joints, it is desirable from a usability point of view that the user demonstrates tasks to the robot as naturally as possible; the use of gloves or other types of sensors may prevent a natural grasp. This motivates the use of systems with visual input.

4.1.2. Vision based descriptors

The authors in [32] proposed a vision and audio based approach. The user demonstrates a grasping skill. The robot stereoscopically tracks the demonstrator's hand several times to collect sufficient data. The accuracy of the visual tracking is limited by the camera's resolution and the quality of the calibration procedure. Additionally, every time a grasp is demonstrated, the user performs it differently. To compensate for these inaccuracies, the measured trajectories are used to train a Self-Organizing-Map (SOM). The SOMs give a spatial description of the collected data and serve as data structures for a reinforcement learning algorithm which optimizes trajectories for use by the robot. The authors, in [33], applied a second learning stage to the SOM, the Q-Learning algorithm. This stage accounts for changes in the robot's environment and makes the learned grasping skill adaptive to new workspace configurations.

Another vision based Programming by Demonstration (PbD) system is proposed in [58]. The system consists of three main parts: The human grasp classification, the extraction of hand position relative to the grasped object, and finally the compilation of a robot grasp strategy. The hand shape is classified as one of six grasp classes, labelled according to Cutkosky's grasp taxonomy [15]. Instead of 3D tracking of the demonstrator hand over time, the input data consists of a single image and the hand shape is classified as one of the six grasps by finding similar hand shapes in a large database of grasp images. From the database, the hand orientation is also estimated. The recognized grasp is then mapped to one of three predefined Barrett hand grasps. Depending on the type of robot grasp, a precomputed grasp strategy is selected. The strategy is further parameterized by the orientation of the hand relative to the object.

These approaches enable object telemanipulation or grasp type recognition. However, their learning data is based on the hand observation, i.e. the joint angles, the hand trajectory or the hand shape. Thus the learning algorithm does not take into consideration the manipulated object properties. Consequently, these methods are not adapted to grasping previously unknown objects.

4.1.3. Biologically oriented learning and object feature extraction

Oztop and Arbib [51] propose a grasping strategy based on mirror neurons. The latter were identified within a monkey's premotor area F5 and they fire not only when the monkey performs a certain class of actions but also when the monkey observes another monkey (or the experimenter) performing a similar action. It has been argued that these neurons are crucial for understanding of actions by others. In a grasping context, the role of the mirror system may be seen as a generalization from one's own hand to another hand. Thus, in a biologically motivated perspective, the authors propose a very detailed model of the functioning of these neurons in grasp learning. They present a hand-object state association schema that combines the hand related information as well as the object information available. This method is capable of grasp recognition and execution (pinch, precision or power grasp) of simple geometric object models. The only object features used are the object size and location.

A grasping task could be also described as a succession of "action units". Such movement primitives, proposed in [4, 66], are sequences of actions that accomplish a complete goal-directed behavior. Nevertheless, as discussed in [48], such low-level representations do not scale well to learning in systems with many dofs. It is useful for a motion primitive to code complete temporal behaviors [16].

Kyota et al. [34] proposed a method for detection and evaluation of grasping positions. Their technique detects appropriate portions to be grasped on the surface of a 3D object and then solves the problem of generating the grasping postures. Thus, points are generated at random locations on the whole surface of the object. At each point, the cylinder-likeness, that is the similarity with the surface of a cylinder, is computed. Then, the detected cylindrical points are evaluated to determine whether they are in a graspable portion or not. Once the graspable portions are identified, candidate hand shapes are generated using a neural network, which is trained using a data glove. Grasps are then evaluated using the standard wrench space stability criterion. Figure 8 shows several solutions for grasping a frying pan with different hand shapes.

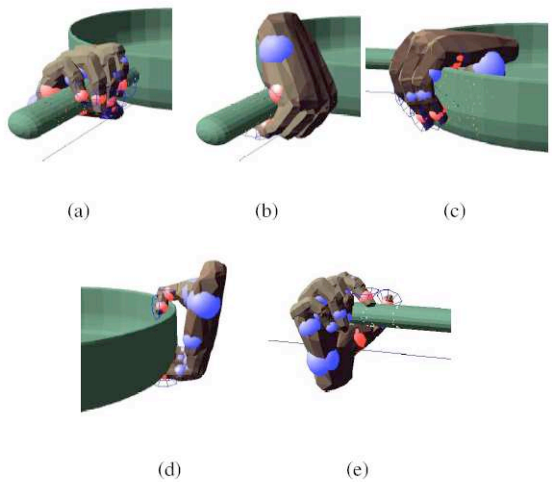

Figure 8: Grasping postures for a frying pan [34].

Oztop and Arbib's approach can determine the grasp type of simple geometric objects. When facing new objects, it will roughly estimate their sizes and locations in order to identify the corresponding hand parameters and thus the grasp type in order to pick them up. Kyota's method finds different possible grasping regions on the object surface. However, it does not take into account object usage. Thus, these approaches can find stable grasps for pick and place operations but are unable to determine a suitable grasp for object manipulation.

4.2. Systems based on the object observation

Some authors consider that hand motion has a variety of expressions (or configurations) with its high degrees of freedom. It is then roughly divided into gesture type and functional one. Patterns in gesture type motion have advantages to be reused in the generation of new movement. While a functional motion varies depending on the target objects' features such as sizes and shapes [69].

Grasping strategies based on the object observation analyze its properties and learn to associate them with different grasps. Some approaches associate grasp parameters or hand shapes to object geometric features in order to find good grasps in terms of stability [52, 38]. Other techniques learn to identify grasping regions in an object image [61, 64]. These techniques are discussed in the following.

Pelossof et al. [52] used support vector machines to build a regression mapping between object shape, grasp parameters and grasp quality (Figure 9). Once trained, this regression mapping can be used efficiently to estimate the grasping parameters that obtain the highest grasp quality for a new query set of shape parameters. The authors use simple object representation in their learning algorithm, such as spheres, cylinders etc. Since the grasp quality metric used, determines the magnitude of the largest worst-case disturbance wrench that can be resisted by a grasp of unit strength [26], the optimal grasps computed by the algorithm are "good" stable grasps adapted for pick and place operations.

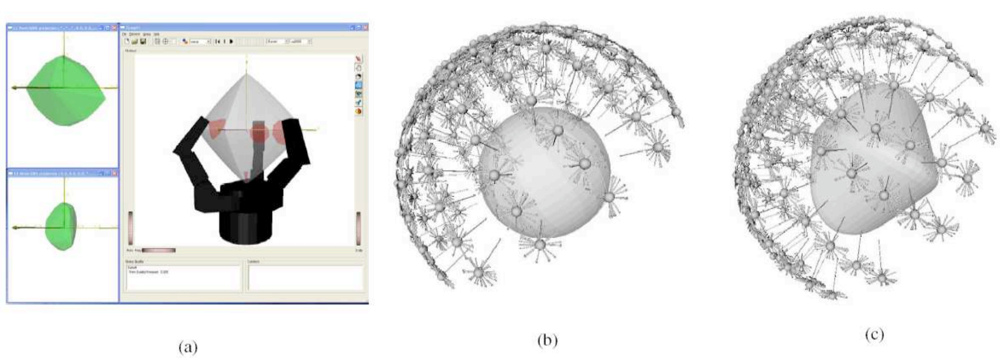

Figure 9: The GraspIt! simulator allows to import a robot hand model (here a Barrett hand) and an object model. (a) This image shows one successful grasp of the object. (b) and (c) For each object in the training set, 1600 grasp starting poses are generated and evaluated [52].

A learning approach for robotic grasping of novel objects is also presented by Saxena et al. [61]. Based on the idea that there are certain visual features that indicate "good" grasps, and that remain consistent across many different objects (such as coffee mugs handles or long objects such as pens that can be grasped at their mid-point), a learning approach that uses these visual features was proposed to predict "good" grasping points. The approach is based on training a logistic regression model on annotated synthetic images, combining a 2D filter responses with 3D range data in a dense, multi-scale image representation. The algorithm predicts a grasping point as a function of 2D images. The supervised learning is used to identify images patches that contain grasping points. The method starts by dividing the image into small rectangular patches. For each patch, it computes local image features and predict if it is a projection of a grasping point onto the image plane. The chosen features represent three types of local cues: edges, textures, and color. Thus given two (or more) images of an object, the algorithm identify a few points in each image corresponding to "good" grasp locations of the object. This set of points is then triangulated to obtain a 3D location of the grasp.

In a similar approach, Stark et al. [64] developed a functional approach to affordance learning in which subcategories of the graspable affordance (such as handle-graspable and sidewall-graspable) are learned by observation of human-object interactions. Interaction with specific object parts leads to the development of detectors for specific affordance cues (such as handles). An object is represented by a composition of prehensile parts. The affordance cues are obtained by observing the interaction of a person with a specific object. The authors determine the interaction region as the set of object pixels that has been occluded by the human tutor in the course of an interaction. Affordance cues representation is based on geometric features extracted from a local neighborhood around that region. Grasp hypotheses for new stimuli are inferred by matching features of that object against a codebook of learnt affordance cues that are stored along with relative object position and scale. An extension of this approach, where the global shape of the object is used instead of local appearance, was proposed in [9].

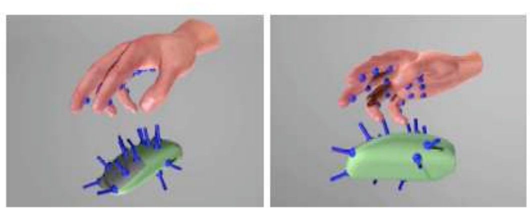

Figure 10: Matching contact points on the hand/object and contact normals on the object surface [38].

When a complete 3D model of the object is available, Li and Pollard [38] treated grasping as a shape matching problem. Based on the idea that many grasps have similar hand shapes, they construct a database of grasp examples. Thus, given a model of a new object to be grasped, shape features of the object are compared to shape features of hand poses in the database in order to identify candidate grasps. These shape features capture information about the relative configurations of contact positions and contact normals in the grasp. Figure 10 shows contact points and normals on the hand and on the object. Note that the inside surface of the hand contains a great deal of information about the shape of the mouse. If similar features can be found on a new object, it may be possible to use the same grasp for the new object. After shape matching, a number of grasps is obtained. Some of these grasps may be inappropriate to the task. They may fail to support the object securely or the main power of the grasp may be aligned in the wrong direction for the task. Thus, the authors used a grasp quality that takes into account both the hand and the task requirements to evaluate the computed grasps. By applying such a grasp quality measure, many grasps are pruned. Even though, the authors stated that the user should select manually the desired grasp from among the possibilities presented by the system because some of the grasps are unintuitive. Thus a fully autonomous system that generates natural grasps should take into account aspects other than ability to apply forces.

El-Khoury et al. [22, 59] consider the problem of grasping unknown objects in the same manner as humans. Based on the idea that the human brain represents objects as volumetric primitives in order to recognize them, the proposed algorithm predicts grasp as a function of the object's parts assembly. Beginning with a complete 3D model of the object, a segmentation step decomposes it into single parts. Each single part is fitted with a simple geometric model. A learning step is then employed to find the object component that humans choose to grasp this object with. Figure 11 shows several grasps obtained using DLR hand model and GraspIT simulator on different object graspable parts.

All these approaches learn to use object features in order to compute a corresponding grasp. Thus, they are capable to generalize to new objects. But what kind of grasps these techniques ensure? Pelossof's strategy can predict the quality of a grasp according to a stability criterion. Saxena's

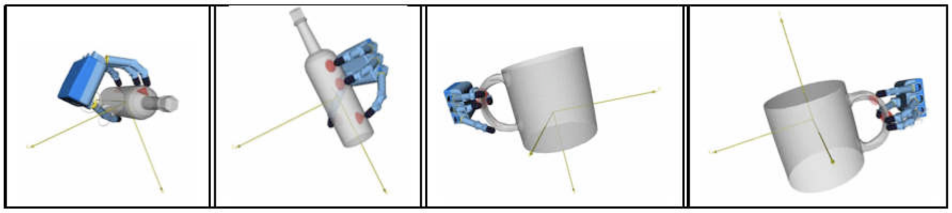

Figure 11: Generating 4-finger force closure grasps using DLR hand model Graspit Simulator in [24].

approach finds grasping points on mugs handles or on elongated object midpoints. Such contact points are adapted to some objects in terms of task-compatibility but when this approach encounters elongated objects such as screw-drivers or bottles, it will also identify a grasping region situated at these objects middles. Such grasps are not necessarily adapted to such kinds of objects. Stark's grasping strategy can only distinguish between two object classes: handle-graspable (adapted for mugs) and side-graspable (adapted for bottles). This method does not take into account the variety of object shapes and thus the variety of possible grasps. Li and Pollard's strategy determine for one object different grasps and fail to choose the one adapted to the task-requirements. El-Khoury et al. [24] proposed to imitate humans choice of unknown object graspable components based on primitives such as object sub-parts shapes and sizes. But does the selected graspable part convey any information about the object corresponding task? In the following, we discuss in details the limitations of the empirical approaches.

4.3. Discussion on Empirical Approaches

The main difficulty of analytical task-oriented approaches was task modeling. Empirical approaches based on a human demonstration can overcome this difficulty by learning the task. For such approaches, when given an object and a task, the teacher shows how the grasp should be exactly performed. The robot is able afterwards to perform the task for the given object by itself. However, these systems are not fully autonomous when they face a new object or a new task. To overcome this problem, rather than trying to reproduce human grasping gestures, researchers developed systems that focus on object observations. These approaches learn to find good grasping region in an object image or associate object local features to different hand shapes. These systems can generalize to new objects but they find either stable grasps or generate for one object different grasps and fail to select automatically the one that best suits the task.

This selection is done manually or use a task-oriented quality criterion which is complicated to compute. Thus, much research remains to be done to better understand human grasping and to develop algorithms that achieve natural grasps.

5. Conclusion

Autonomous grasping strategies aim to achieve stability and task compatibility when grasping new objects. In the literature, grasp synthesis, has been tackled with two different approaches: analytical or empirical. By reviewing these works, we may conclude that force-closure analytical approaches find stable but not task-oriented grasps. Task-oriented analytical approaches suffer from the computational complexity of the task requirement modeling. Empirical systems based on the observation of humans overcome task modeling difficulty by imitating human grasping gestures. However, these systems are not fully autonomous when they face new objects. Empirical systems based on object observations are adapted to new objects but generate a lot of possible grasping positions and fail to select the one that best suits the task. When trying to do this autonomously, they encounter the same problem of analytical task-oriented methods, which is task modeling.

Thus, what grasping strategy is able to ensure stability, task compatibility and adaptability to new objects? Adaptability to new objects is ensured by learning object characteristics that are relevant to grasping. Stability can be obtained by computing force-closure grasps. In order to deal with the task requirements, on one hand, modeling the task is difficult; analytical approaches fail to find a general mathematical formulation compatible with different tasks. On the other hand, learning specific task/hand performance works only on a particular object to perform a particular task. Finding a task compatible grasp for a new object is still an open problem. A possible solution may be to learn tasks/features mapping, i.e. learn to identify object features that are immediately related to the object corresponding task. Thus, when a robot encounters a new object, it will be able to autonomously identify relevant features and consequently identify the object corresponding task.

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