3D Objects Grasps Synthesis: A Survey

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Abstract— *This survey reviews computational algorithms for generating 3D objects grasps with autonomous multi-fingered robotic hands. Over the past 20 years, grasping has been an increasingly active research area. Existing papers focus on reviewing the mechanics of grasping and the finger-object contacts interactions [21] or robot hand design and their control [4]. Robot grasp synthesis algorithms has been reviewed in [17], but since then an important progress has been made toward applying learning techniques to the grasping problem. This survey focuses on analytical as well as empirical grasp synthesis approaches.*

I. Introduction

Grasp means to seize and hold by or as if by clasping with the fingers or arms. The first goal of every grasping strategy is to ensure stability. 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 [6], [24]. Nguyen in [43] 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 [15]. In other words, the wrench or grasp matrix, noted W, which column vectors are the primitive contact wrenches, noted $\underline{w}_i$, resulted by contact forces at the contact points, should positively span the entire 6-dimensional wrench space. If r_i denotes the position vector of the $i-th$ grasp point in the object coordinate system, a wrench $\underline{w}_i$, which is the combination of the force and torque corresponding to a grasp force f_i, is given by the following equation:

$$\underline{w}_i = \left. \begin{array}{c} f_i \\ \tau_i \end{array} \right) = \left. \begin{array}{c} f_i \\ r_i \times f_i \end{array} \right) \qquad (1)$$

In the literature, force-closure condition may be confused with form-closure. The latter induces complete kinematical restraint of the object and is obtained when the positions of the fingers ensure object immobility. Bicchi in [1] describes in detail these conditions. Obviously, stability is a necessary but not a sufficient condition for a grasping

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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 objects shapes and sizes, a grasping strategy should always be prepared to grasp objects the robot sees for the first time.
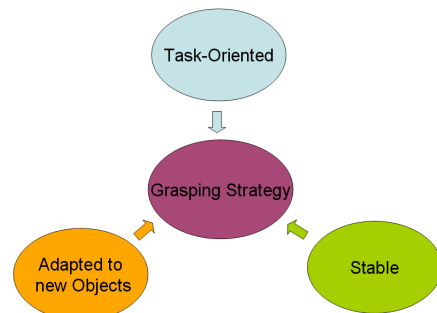

Fig. 1. Grasp strategy should satisfy three constraints: stability, task compatibility and adaptability to new objects.

Thus, a grasping strategy, as shown in figure 1, should ensure stability, task compatibility and adaptability to novel objects. In other terms, a grasp synthesis strategy should always have an answer to the following question: where to grasp a novel object in order to accomplish a task? Analytical and empirical approaches answer this question differently.

Analytical approaches choose the finger positions and the hand configuration with kinematical and dynamical formulations of the grasp stability or the task requirements. On the other hand, empirical approaches use learning algorithms to choose a grasp that depend on the task and on the object's geometry. In the following, we review these two approaches applied to 3D objects grasps synthesis. The reader should notice that many algorithms have been developed for 2D objects grasp planning [10],[13], but 3D objects grasp synthesis is still an active research area due to the high dimensional grasp space and objects complex geometry.

II. Analytical Approaches

Analytical Approaches consider kinematics and dynamics formulation in determining grasps. The complexity of this computation arises from the number of conditions that must be satisfied for a successful grasp. We previously showed that two main conditions identified in the grasping bibliography are force-closure and task compatibility. The following paragraphs present strategies developed to meet these conditions. The diagram of figure 2 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.

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

A.1 Force-Closure Grasps Synthesis for 3D Objects

Depending on the object model, polyhedral or complex, different grasps 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 faces normals [43] or use the linear model to derive analytical formulation for grasps characterization [46], [11], [26]. Based on the property that each point on a plane face can be parameterized linearly with two parameters, Ponce et al. [46], [14] 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. [11] 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 facet, they search locations on that facet for the nth finger that ensure force-closure. Ding et al. [26] 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 the given faces 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 facet, 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 analysis 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 modelled 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 constituting faces. Thus, new techniques are required for force-closure grasps synthesis. Such general approaches place no restrictions on the object model [7], [27]. Objects are modelled with a cloud of 3D points or a triangular mesh. The authors in [7] presented an algorithm for computing three finger force-closure grasps 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 grasps of 2D objects based on geometrical analysis. They simplify then 3D objects force-closure problem to a $2D$ problem when the three contact points constitute a plane and when this plane intersects each friction cone on a triangular area. Ding et al. [27] 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 [5] for any number of contacts with or without friction. The authors in [32] 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
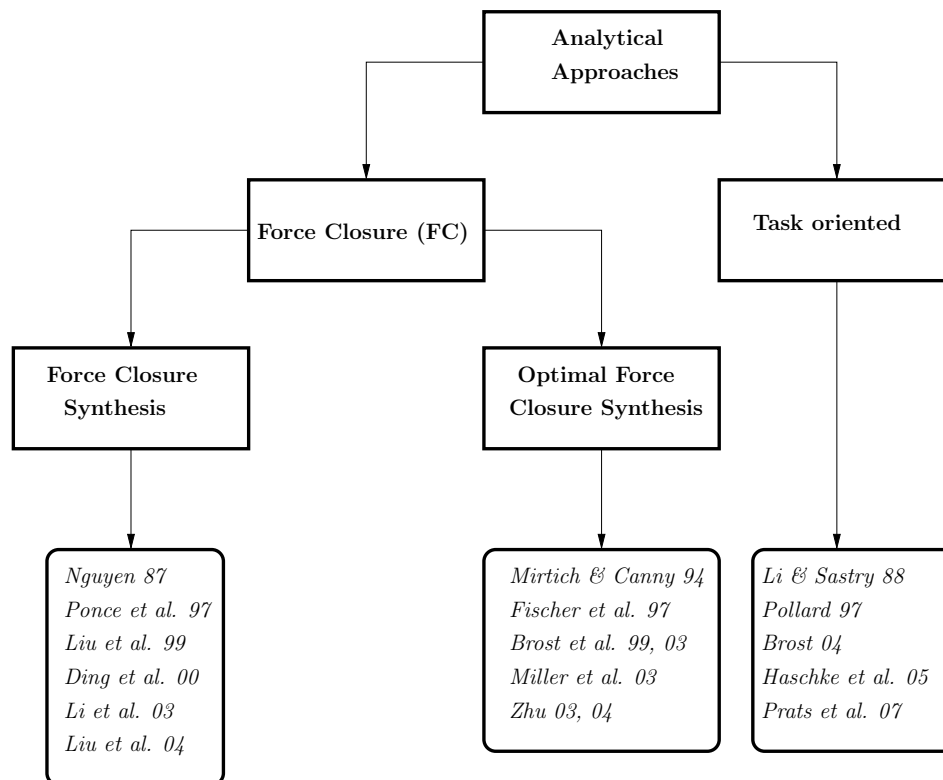
Fig. 2. A synthetic view of existing analytical approaches for grasp synthesis of 3D objects. The diagram shows analytical strategies developed for satisfying force closure and task oriented conditions.

the formulation of a new sufficient force-closure test. Their approach works with general objects, modelled 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. But what about computing good force-closure grasps? For this purpose, different quality criteria were introduced to the grasping literature. In the following, we present some relevant works on computing optimal grasps.

A.2 Optimal Force-Closure Grasps on 3D Objects

Optimal force-closure grasps synthesis concerns determining the contact points locations so that the grasp achieves the most desirable performance in resisting external wrench loads. These approaches are tackled between optimizing and heuristical techniques.

Optimizing techniques compute optimal force-closure grasps by optimizing an objective function according to a pre-defined grasp quality criterion. When objects are modelled with a set of vertices, they search all their combinations to find the optimal grasp. For example, Mirtich and

Canny [42] developed two optimality criteria and used them to derive optimum two and three finger grasps of 2D objects and optimum three fingers grasps of 3D polyhedra 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 [50] 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 [18] 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 sacle 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 corresponging 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 grasps candidates randomly [22], according to a predefined procedure [31] 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 [41],[40], filtered 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. But what really dictates the choice of a grasp? After examining a variety of human grasps, the authors in [25] 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.

B. Task Compatibility

A good grasp should be task oriented. Few grasping works take the task into account. This is due to the difficulties of modelling a task and providing criteria to compare the suitability of different grasps to the task requirements. Works that addressed task-oriented grasps computation are reviewed in this paragraph.
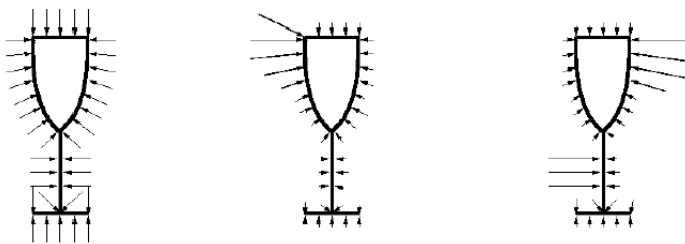

Fig. 3. Illustration of different force distributions that produce the wrench set of the OWS.

Li and Sastry [9] 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 exe-

cuted 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.

Nancy Pollard [45] designed a system that found grasps that were within 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. Assuming that the probability for every wrench direction to occur as a disturbance is equal, the task wrench space is modelled 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. 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 as presented in figure 3.

Borst et al. combined the idea of the task ellipsoid [9] with the concept of the OWS to obtain a new description of the task wrench space (TWS). The latter is the 6D ellipsoid circumscribing the OWS [23]. 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).
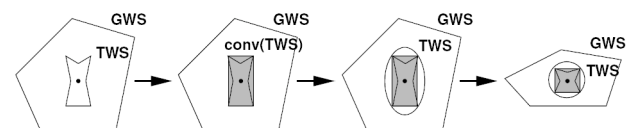

Fig. 4. Approximating the OWS with an ellipsoid. 1. The sampled OWS. 2. Convex Hull over the sampled OWS. 3. Enclosing ellipsoid. 4. Linear transformation of ellipsoid and GWS.

The authors in [38] 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 [47] 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. 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 modelled as hierarchy of boxes. This algorithm was tested for accomplishing a common task, turning a door handle.
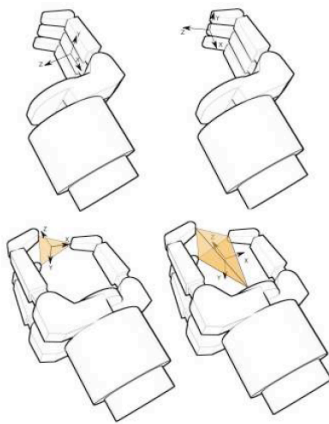

Fig. 5. Task frames for the hook power (top-left), hook precision (top-right), precision (bottom-left) and cylindrical (bottom-right) preshapes.

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's 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 adapted to new tasks nor to 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.

C. 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 to 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 problems are encountered when addressing this issue:

- The difficulty of modelling a task.

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

Different task-oriented criteria were introduced to the grasping literature and a task-oriented grasp was obtained by generating and evaluating lots of grasps according to these criteria. But all the proposed approaches could not overcome the problem of the task representation and thus are computationally unaffordable. There are also not adapted neither for new tasks nor for new objects. While the selection of task-oriented optimal grasp is very easy for a human hand, it is still a complicated process for a robot hand. Hence, there is a need to a system that takes into ac-

count aspects of naturals grasps by imitating humans rather than modelling tasks.

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 2 and figure 6, we notice that most recent works are based on empirical approaches. These techniques are detailed in the next paragraph.

III. Empirical Approaches

Empirical grasping methods avoid the computational complexity of analytical techniques by attempting to mimic human grasping strategies. Empirical strategies for grasp planning can be divided into two main kinds: (1) systems based on the observation of the object to be grasped and (2) systems based on the observation of a human performing the grasp. The former techniques generally learn to associate objects characteristics with a hand preshape, while in the latter, a robot observes a human operator performing a grasp and try then to imitate the same grasp. This technique is called in the literature learning by demonstration approach. Figure 6 summarizes the developed approaches.
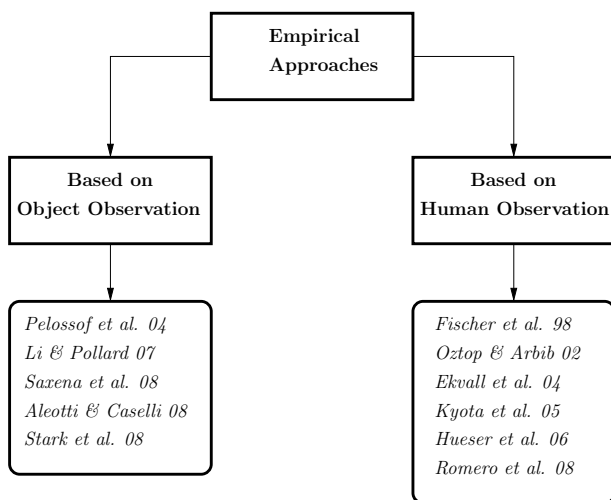

Fig. 6. A synthetic view of existing empirical approaches for grasp synthesis of 3D objects.

A. *Systems based on humans observation: Learning By Demonstration*

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. One of the problems arising in human based learning settings is the one of measuring human performance. Some researchers use datagloves, map human hand to artificial hand workspace and learn the different joint angles [35],[28], hand preshapes [39] or the

corresponding task wrench space [19] in order to perform a grasp. Others use stereoscopy to track the demonstrator's hand performing a grasp [36] or try to recognize its hand shape from a database of grasp images [48]. Mirror neurones that fire not only when grasping but also when observing an action were also introduced to the grasping problem [12]. The following paragraphs discuss these approaches.

A.1 *Magnetic trackers and datagloves based approches*

The authors in [35] presented a setup to control a four-finger anthropomorphic robot hand using a dataglove. In order to measure the finger tip 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 [28]. 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 [29], 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 [19] 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 [20].

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 natu-

rally 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.

A.2 Vision based approches

The authors in [36] 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 (RL) algorithm which optimizes trajectories for use by the robot. The authors, in [37], 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 [48]. 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 [25]. 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 objects 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 do not take into consideration the manipulated object properties. Consequently, these methods are not adapted to grasping previously unknown objects.

A.3 LbD approaches taking into account object features

Oztop and Arbib [12] propose a grasping strategy based on mirror neurones. 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) perform 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 an other's hand. Thus, in a biologically motivated perspective, the authors propose a very detailed model of the functioning of these neurones 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. Kyota et al. [39] 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.

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.

B. Systems based on the object observation

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 objects geometric features in order to find good grasps in terms of stability [44],[8]. Other techniques learn to identify grasping regions in an object image [16],[49]. These techniques are discussed in the following.

Pelossof et al. [44] used support vector machines to build a regression mapping between object shape, grasp parameters and grasp quality. Once trained, this regression mapping can be used efficiently to estimate the grasping parameters that obtain 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 [30], the optimal grasps computed by the algorithm are good stable grasps adapted for pick and place operations.

A learning approach for robotic grasping of novel objects is also presented by Saxena et al. [16]. By novel objects, the authors mean ones that are being seen for the first time by the robot. 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 algorithm predicts a point at which to grasp a 3D object as a function of 2D images.

In a similar approach, Stark et al. [49] propose a system for the detection of functional object classes, based on a representation of visually distinct hints on object affordances (affordance cues). Objects are classify based on their affordances in two categories: handle-graspable and sidewall-graspable. Thus, the classification itself determines how to grasp the object. When a complete 3D model of the object is available, Li and Pollard [8] 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 7 shows contact points on the hand and object, and contact normals on the object surface. 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, 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. [33],[34] 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 algorithm proposed 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 8 shows several grasps obtained using DLR hand model and GraspIT simulator on different object graspable parts.
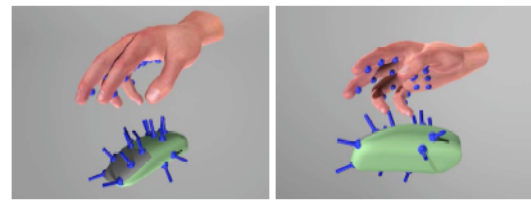

Fig. 7. A mouse grasp: matching contact points on the hand/object and contact normals on the object surface.

All these approaches learn to use objects features in order to compute a corresponding grasp. Thus, these approaches are capable to generalize to new objects. But what kind of grasps these techniques ensure? Pelossof's startegy can predict the quality of a grasp according to a stability criterion. Saxena's approach find grasping points on mugs handles or on elongated objects mid-points. Such contact points are adapted to some objects in terms of task-compatibility but when this approach encounter 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 objects classes: handle-graspable (adapted for mugs) and side-graspable (adapted for bottles). This method does not take into account the variety of objects shapes and thus the variety of possible grasps. Li and Pollard strategy determine for one object different grasps and fail to choose the one adapted to the task-requirements. El-Khoury et al. [3] proposed to imitate humans choice of unknown objects graspable components based on primitives such as objects 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.

C. Discussion on Empirical Approaches

The main difficulty of analytical task-oriented approaches was task-modelling. 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
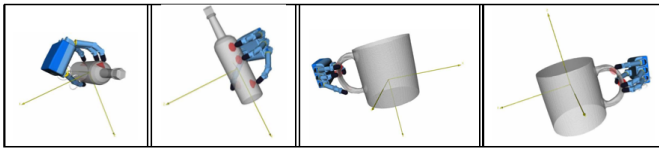
Fig. 8.   Generating 4-finger force closure grasps using DLR hand model Graspit Simulator.

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 ensure the latter ability, rather than trying to reproduce humans grasping gesture, researchers developed systems that focus on objects observation. These approaches learn to find good grasping region in an object image or associate objects 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.

IV. 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. If we summarize these works, we can conclude that: Force-closure analytical approaches can find stable but not task-oriented grasps. Task-oriented analytical approaches suffers from a major problem: computational complexity when trying to model task requirements. Empirical systems based on the observation of humans overcome task modelling difficulty by imitating humans grasping gesture. However, these systems are not fully autonomous when they face an object completely new. Empirical systems based on objects observation 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 modelling. Consequently, we are standing in front of a loop!

How to break the loop? What grasping strategy can ensure stability, task compatibility and adaptability to new objects? Obviously, adaptability to new objects is ensured by learning objects characteristics that are relevant to grasping. Stability can be obtained by computing force-

closure grasps. But what about the task requirements? On one hand, task modelling 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'll be able to autonomously identify relevant features and consequently identify the object corresponding task.

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