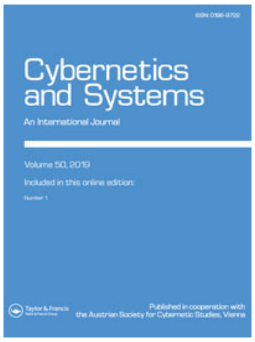

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A Panoramic Survey on Grasping Research Trends and Topics

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ABSTRACT
Grasping and object manipulation is a key element of intelligent behavior. Many innovative cyberphysical systems involve some kind of object grasp and manipulation, to the extent that grasping has been recognized as a critical technology for the next generation industrial systems. In this survey, we aim to draw a broad landscape of applications and current research trends and topics relating to grasping techniques and tools. Applications range from biomedical and surgical to industrial warehouse pick and place tasks, covering a wide range of spatial scales, from micro to macro scales. The resources involved and research lines under development include the latest computational intelligence tools as well as the research on new materials and devices for sensing and actuation.

Introduction

Grasping is such an everyday act that we are unaware of the complex cognitive and biomechanical processes involved (Xue et al. 2018). Let us illustrate in Figure 1 the main processes and elements related to grasping. The action of *grasping* is often followed by either the transportation of the object *carrying* it to a destination where it is *released* or *placed* in some specific position. Often, tools are grasped to perform some *manipulation* or operation and released afterwards in a different/same placement. Sometimes, grasping is done as a method for tactile shape sensing. Conversely, in other application instances tactile shape sensing is a mean to improve grasping and ensuing manipulation, transportation, and placement. Grasping tasks are defined by concatenation of these elementary actions. For instance, an assembly task will follow a sequence of grasping a part, carrying it to be operated and placed in the body of the item being assembled. All the elementary actions must solve localization problems regarding the object, the actuator, and/or the environment that require

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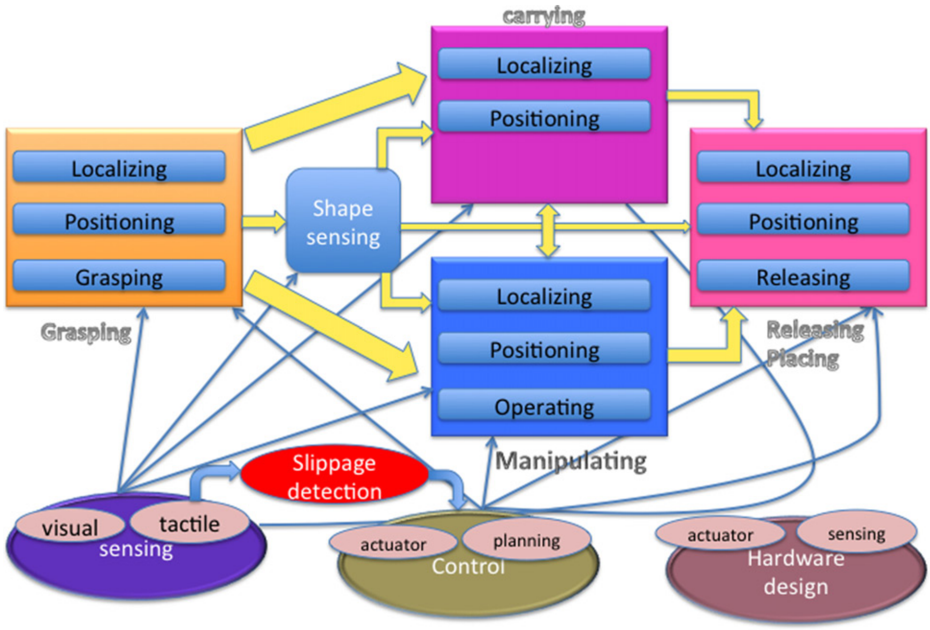

Figure 1. General layout of grasping related issues.

accurate and robust visual sensing. They also require fine control to achieve actuator positioning for grasping, releasing, or operating. Slippage (the motion of the object under the grasp) is a central issue that can either be a big problem or a desired condition when the motion provides information about the object shape. All these elements are common to human hand and automated grasping, or hybrid situations, such as assistive robotics, and are the source of a diversity of challenges such as the continuous improvement of sensing and actuation hardware, as well as computational algorithm for actuator control and sensing information processing.

Indeed, grasping is one of the most difficult processes to be automated. However, there is a great effervescence of research efforts and innovative solutions due to the tremendous advances in computational resources, and data processing techonologies, as well as advances in mechatronics leading to improved actuators following a wide variety of design principles, and sensing devices, such as innovative tactile sensors, and enhanced 2D and 2.5D cameras and range sensors.

The improvement in computational solutions with the widespread application of machine learning tools, including the recent uprise of deep learning architectures, have provided enhancements in sensor data interpretation/analysis, and control algorithms, which are increasingly able to cope with the strong non-linearities, noise, and uncertainty to be faced when trying to grasp something in the wild, i.e. outside a rigidly structured scenario. Additionally, the improvement in actuators and the emergence of new robot hardware approaches, such as soft-robotics manipulators that imitate the compliance of the human hand, and the possibility to bring the actuation to the micro- and nano-scales have provided a wide front of research efforts.

One of the areas of application that first comes to mind when thinking about automated grasping is the warehouse management, where the new surge of e-commerce requires increasingly fast, robust, and secure logistics (Hodson 2018) asking for exceedingly robust, flexible, adaptive, and accurate grasping, carrying, manipulating, and placement of goods of quite shapes and mechanical properties. However, in this panoramic survey we take a broader view which includes situations where the robotic system is somehow enhancing human capabilities, such as assistive robotics, where the aim is to help the deteriorated human hand to achieve grasping, carrying, manipulating, and releasing objects safely.

Therefore, in this panoramic survey we will first dwell on several of the areas where the impact of innovations on robotic grasping is more relevant. Then we will describe the current research topics found in the most recent literature, highlighting their most significant challenges. Searching in common bibliographic sources, such as ieeexplore, sciencedirect, arxiv, and specific robotics journals, retrieves several hundreds of publications in the recent years, so we have restricted references to most recent publications, mostly in the year 2018. As we aim to provide an impression of the overall research going on instead of answering a specific research question (i.e. what is the grasping accuracy reached by reported data driven methods?), we will not follow a systematic review protocol, neither we can provide exhaustive/comprehensive references for reasons of limited space.

Areas of Application

Surgery

Automation is entering the surgical theater from several fronts, all of them are essentially ways to improve grasping and manipulating teleoperation, i.e. the surgeon controls the operation of tools and access to body tissues by a robot actuator through an *ad hoc* designed user interface. Surgical robots, such as the *daVinci* surgical system, require an exhaustive training that may be reduced with enhanced sensors and actuators. Reliable and atraumatic grasping and manipulation of biological tissue are crucial processes during Robot-Assisted Surgery (RAS). A specific challenge is the detection of the slippage of grasped tissue, often out of the surgeon field of attention. Current approaches to slippage detection include thermal-based sensors, whose integration with the da Vinci standard tools has been reported (Burkhard, Cutkosky, and Steger 2018), and force sensing in forceps instruments allowing precise control of the grasp force avoiding tissue damage (Kim et al. 2018; Yu et al. 2018). A challenge in RAS user interface design is to provide some haptic feedback about the handled tissue elastic properties in order to help the user to discriminate among tissues. Direct force sensing may provide useful haptic feedback. For standard surgical system tools lacking direct force sensors, indirect force sensing has been demonstrated using surrogate signals (O'Neill, Stephens, and Kowalewski 2018). The heterogeneous compliant tissues that are manipulated by RAS instruments may behave in unexpected ways under pressure and manipulation. Modeling and prediction of the tissue behavior is a challenging unsolved problem. Alambeigi et al. (2018) have followed a data driven approach, trying to produce an online dynamical model estimation of the tissue responses to grasping and manipulation. Currently, they have demonstrated the approach with specific phantoms for experimentation in the *da Vinci* Research Kit. In another kind of minimally invasive surgery, the Natural Orifice Transluminal Endoscopic Surgery, the challenge is to reach the target operation using natural area body conducts, hence there is a need of manipulators that can bend and adapt to their natural tortuous paths. Thermoplastic materials such as Polyethylene Terephthalate have been recently proposed to build such tools (Le et al. 2018).

Assistive Robotics

The aging society requires increasingly assistive robotic tools that help the elderly to carry out independent lives (Bemelmans et al. 2012). Assistive robotic graspers promise to help safe grasping and manipulation in daily life. A critical challenge is the stable control of the assistive hand, so that it follows smoothly the natural hand motions, filtering out motion noise such as essential tremor. Such enhanced control of robotized exoskeleton hands has been demonstrated (Ruiz Maymo, Shafti, and Aldo Faisal 2018) using computer vision. However, achieving natural motion and response is still challenging. In this endeavor, research on soft-hand systems holds the best promise. Examples of current approaches are a soft-hand powered by pneumatic muscles (Al-Fahaam, Davis, and Nefti-Meziani 2018), and soft gloves with cable driven flexion and extension that can be custom 3D printed (Yi, Chen, and Wang 2018). Alternatively, research into supernumerary hand design aims to minimize stress on the upper limbs while providing additional grasping force (Ciullo et al. 2018).

Rehabilitation Robotics

Though rehabilitation robotics may be considered some kind of assistive robotics, its goal is somehow different, and so are the raised challenges. Specifically hand rehabilitation requires grasping robot aids. Hand rehabilitation patients aim to recover mobility, strength, and dexterity in their hands after some trauma. Therefore, the exoskeleton must sense/predict the intended motion of the human hand guiding it to the completion of the motion without stressing it. Sensing the object grasping quality and the hand state, and achieving control that avoids hand stress are challenging in grasping rehabilitation robotics. The use of conductive elastometer sensors allows for low cost rehabilitation exoskeleton gloves that also have capabilities to detect object slippage (Lee, Williams, and Ben-Tzvi 2018). Force sensing at the tip of the fingers allow intelligent grasping that is able to distinguish between rigid and flexible objects. For rehabilitation purposes, it is important to provide the user with sensory feedback, allowing to perceive the completion of the rehabilitation exercise (Schoepp et al. 2018) while avoiding excessive stress on the damaged hand. A different kind of challenge is that of hand exoskeleton weight and size, which is critical for its usability. The use of novel elastic actuators (Bianchi et al. 2018) holds the promise of compact and lightweight hand exoskeletons for grasping rehabilitation.

Prosthetics

Losing a hand compromises the daily activities of a person, hence the high social and economical value of hand prosthetics. Besides the direct control command of the grasping device, the user needs some kind of sensorial feedback in order to have a natural grasping experience. Vibro-tactile feedback (Aggravi et al. 2018) has been proposed to overcome the sensorial feedback challenge. It has been demonstrated to help preventing slippage (Aboseria et al. 2018). Regarding the control challenge, there is extensive research on the transformation of limb mioelectrographic (MEG) signals into prosthetic hand control commands to achieve multiple grasp poses (Kanitz, Cipriani, and Edin 2018), sometimes combined in hybrid systems with computer vision (Madusanka et al. 2017). Fine MEG pattern recognition is required for the control of so called myolectric hands, which may achieve individual finger control (Zhang, Jiang, and Liu 2018). An active line of research combines underactuation (less motors than degrees of freedom) and underlying soft-energies (encoding first principal component of hand postures) (Gailey et al. 2017). Underactuated hands that achieve multiple grip patterns with a single actuator have been already demonstrated (Wattanasiri, Tangpornprasert, and Virulsri 2018).

Warehousing

Many of the industrial applications of grasping are related to warehousing and transportation of products and tools. The interest of the big stakeholders is well represented by the Amazon Picking Challenge (http://www.robocup2016.org/en/events/amazonpickingchallenge), consisting in picking objects from toters under very unstructured conditions, i.e. high clutter. The Amazon Robotics Challenge also included a Stowing challenge, consisting in placing the objects in cluttered shelves. Some lessons learned from this challenge (Corbato et al. 2018) are the following: (1) solution choice must be guided by the task conditions, (2) integration requires good knowledge of individual solutions, and (3) a hierarchical structure of levels of automation should be used to attack the problem. It seems that the grasping technology is mature to solve the specific problem, using Convolutional Neural Networks for visual camera-in-hand recognition of objects, and conventional grippers, such as the hybrid pinch and suction gripper used by the challenge winners. However, according to reported experiment results measured in picks-*per*-hour, it seems that the robotic solutions lag behind the human hands (Hodson 2018). A hot challenge is navigating the gripper in highly cluttered scenarios (Kimmel et al. 2018). Similar to stowing, kitting is the task of preparing kits of products or tools to be used afterwards. Kitting requires grasping/placing objects in/from cluttered environments applying online real-time planning able to overcome object model complexity and collision detection issues (Shi and Koonjul 2017).

Assembly

There is a host of industrial applications for grasping robots besides warehousing, such as item assembly. For instance, smartphone assembly using eye-in-hand configuration for visual guidance has been recently demonstrated (Chang 2018), but the problem is far from solved in the general case. Peg-in-hole is a general part insertion problem encountered in many assembly processes. It is an open problem offering several challenging aspects, such as optimal grasping of the part and the search for the part insertion placement. Current peg-in-hole solutions are force-based manipulation by compliant robot manipulators (the part is pressed to the surface and moved until the insertion placement is found). Authors agree that there is a broad avenue for research looking for optimal solutions to the problem, but that good benchmarking methodology is needed to evaluate proposals fairly (Wyk et al. 2018).

Miscelanea

Another quite frequent operation that requires specific grasping techniques whose current solutions from the point of view of navigation and object picking are under-optimal is tabletop arrangement (Han et al. 2018). In agriculture robotics, grasping is a critical action for picking fruits in harvesting robots. For instance, picking tomatoes (Abdeetedal and Kermani 2018) involve inserting wrench into the fruit stems in order to fracture them and liberate the fruits to be picked. Manipulation of deformable objects, such as ropes (Wang and Balkcom 2018), is another challenging research area that often involves cooperating robots, modeling of the deformable parts, and carefully optimized grasping control. An example application is cleaning of deformable parts (Langsfeld et al. 2018). Space robotics is an emerging area of challenging applications of grasping instruments and techniques. A big difference between the robots in space and those on the ground is the apparition of new kinematics and dynamics coupling between the manipulator and the base. Modeling these dynamics coupling, and learning by differential evolution the soft grasp control trying to minimize the angular momentum has been tackled by Chu and Wu (2018), while Lampariello et al. (2018) dealt with tracking by extended Kalmar filter a tumbling satellite prior to grasping it.

Current Research Topics and Trends

Most current research efforts are in line with the three basic technologies identified in Figure 1, i.e. innovative gripper hardware design, sensing capabilities, and computational resources for improved sensor information interpretation and actuator control. In this section, we give some indications on the most active lines of development.

Specific Actuators

General-purpose grippers provide solutions to a large variety of problem instances, but there is always need of new gripper designs for specific tasks. For instance, the task of picking small and flat objects (e.g. coins, paper sheets) from surfaces is rather difficult for conventional grippers. Suction cup grippers that can be used in many practical cases fail to perform when objects are lightweight and fragile. A recent line of research proposes to use passive and epicyclic mechanisms (i.e. rolling joints), which imitate the way that the humans use their hands for such tasks (Babin, St-Onge, and Gosselin 2019), sliding the thumb below the object. This scooping strategy is also implemented by Lévesque et al. (2018) but with different gripper finger design.

A completely different realm appears at micro- and nano-scales where the challenge is to built, operate, control, and sense micro- and nano-grippers, which are at very early stage of development. For instance, Shi et al.

(2018) present experimental micro-grippers with a jaw thickness of 300 micrometers able to pick and place micro-objects whose size scale ranges from hundreds of microns to almost nothing. The positioning and jaw grasp control is carried out under microscope. In experiments, they have achieved picking frequency of the order of 1 kHz, and they have show online multiple size (from tens to hundreds of micrometers) object calibration and manipulation. Asymmetric designs, with piezoelectric actuators where one of the jaws is fixed, have been also proposed (Liang et al. 2018) claiming more robust gripping under a discrete time sliding model control. This kind of micromanipulation is limited to rotations of objects with simple regular shapes. To overcome this limitation, Seon, Dahmouche, and Gauthier (2018) give a proposal for developing in-hand micromanipulation using dexterous micro-hands benefitting from the adhesion forces in order to manipulate arbitrary shaped objects. Experiments at the millimeter scale show the feasibility of the approach that is yet to be scaled down to the micrometer scales. Another kind of micro-grippers proposed for biomedical applications, are articulated microbots built from special materials, such as hidrogel, that will be star-like shaped and able to perform dexterous postures to grasp organic living tissues. Their localization can be achieved by image processing, applying an optimization process such as the particle swarm optimization to estimate the current gripper configuration from the image segmentation (Scheggi et al. 2018).

A bio-inspired approach to develop enhanced grippers is the gecko-like grippers, which use diverse methods to control the friction forces at the hand contact points. For instance, Roberge et al. (2018) propose to cover the gripper with gecko inspired directional adhesives, that need low pressure to sustain large shear forces, which is appropriate to manipulate fragile objects. Moreover, if tactile sensors provide estimates of the contact surface area, it is possible to achieve fine tuning of the gripper exerted pressure, because the shear force is proportional to the contact area. Releasing pressure, the object is liberated without residual adhesion. Another gecko inspired approach uses the shear force to increase the grip pressure in an approach that is quite appropriate for objects that are much larger than the gripper (Hawkes et al. 2018). Spiky contact surfaces built of shape memory alloys produce the gecko shear-induced adhesive effect allowing to design specific planar grippers that are able to pick flat surface objects from flat surfaces (Modabberifar and Spenko 2018).

Soft robots are pneumatically actuated robots. They have been considered for flexibility and safety reasons, they can be used in close interaction with humans (Wang, Torigoe, and Hirai 2017). Contrary to motor actuated robots, they have natural smooth pose deformation and recovery upon contact so that interaction is quite comfortable. Also they are robust in front of the interactions, not losing part alignment or suffering motor tearing. Flexible pneumatic actuators have been proposed for the construction of underactuated multi-jointed, multi-fingered soft robotic prosthetic hand (Devi, Udupa, and Sreedharan 2018; Piazza et al. 2017), because they have the additional advantage of light weight. Food handling is a future application of soft robots (Wang, Torigoe, and Hirai 2017) where they can comply easily to diverse shapes and object consistency. Another line of research tests oblique design of air chambers that have been proven to produce bending and twisting motion mimicking natural hand motions (Wang, Ge, and Gu 2018) for grasping actions.

Collaborative Robotics

The innovation push of Industry 4.0 has set the goal of having robots side by side with humans. Collaborative robotics combines the accuracy, speed and repeatability of robots, with the adaptability and cognitive skills of human workers (Villani et al. 2018). This kind of collaborative work imposes new constraints to the robot design, robustness and flexibility (Maeda et al. 2017), and opens new opportunities of control design, such as teaching by demonstration (Ghalamzan and Ragaglia 2018), i.e. guiding the robot to carry out the grasping task step by step, often in an incremental process.

Tactile Sensing

Tactile sensing is a critical aspect of grasping. It is key to assess the completion of the grasp, to avoid slippage, and to apply the correct pressure without damaging the object, as well as to obtain information from the object that may be used for cognitive processes. Moving the robot effectors from highly structured to highly unstructured environments, the tactile sensory capabilities acquire a greater value. Bioinspired sensors and signal processing, such as spike train processing (Yi, Zhang, and Peters 2018), offer a great promise to reproduce human hand tactile abilities: texture recognition, slip detection, grip force perception, shape modeling and recognition, and hardness perception. In the recent past, Piezoresistive sensors (Fiorillo, Critello, and Pullano 2018) have played a key role in the development of tactile sensors. Despite being known for long time, they are still evolving to new and more compact forms offering more sensitive readings with greater spatial resolution. Tactile sensor designs are becoming more sophisticated. There is currently a frantic design race where modalities are combined and intelligent pattern recognition plays a central role. Many sensor design approaches use friction estimation for the detection of incipient and/or gross slippage (Chen et al. 2018). An example of gross slip detection sensor is the TacTip sensor (James, Pestell, and Lepora 2018), which measures the optical deformation field of internal pins embedded in a compliant skin. Detection is achieved by a support vector machine (SVM) classifier trained on the experimental data. These sensors are designed for the fingers, but there is also work in progress trying to imitate the sensing capabilities of the human hand palm. A super-resolution tactile dome (Piacenza, Sherman, and Ciocarlie 2018) consisting of a soft material embedded with pressure sensors is able to detect specific contact patterns with great accuracy. Soft skins capable of distributed tactile sensing over both fingers and palm are also current research hot topics. Some approaches are embedding magnetic sensors in silicone skins (Tomo et al. 2018) which allow for 3 axis force sensing, other approaches embed capacitive sensors (Tavakoli et al. 2017) which are capable of detecting both conductive and non conductive elements, even achieving hand close posture without supervisory control. A quite different approach to tactile sensing is based on the propagation of ultrasounds waves in polyvinylidene fluoride thin film generated by piezoelectric transductors, these waves are converted into a grayscale image by a Thin-Film Transistor array (Chuang et al. 2018). Fusion of vision and touch allows robust 3D shape perception with the aid of given shape priors (Wang et al. 2018), and to develop re-grasping control to improve the grasp already acquired of an object (Calandra et al. 2018).

Computational Algorithms

Computational intelligence techniques play a role in many of the advances and innovations in grasping technology. Classification and regression techniques help to analyze and give semantic value to the signals obtained from a variety of sensors. Specifically, computer vision has had a significant role in most industrial grasping methods since their very early installations, and it is still a constant source of challenges for new research avenues. Some recent instances of computer vision challenges: (a) discovering the physical support relations between objects in a cluttered scenario for picking (Kartmann et al. 2018) in order to avoid undesired falls of the objects, (b) guiding the cooperative work of multiarm robots in the task of grasp an place objects (Zhao et al. 2018), and (c) predicting contact forces from visual information (RGB-D data), tackled with recurrent neural networks with long short term memory (LSTM) neurons by Pham et al. (2018) after a quite careful experimental design involving specific sensors and 3D printed objects. Predicting the actual in-hand pose of the object can be done combining visual and propioceptive information of the dexterous hand (i.e. the actual position of the finger joints) (Pfanne et al. 2018).

Almost all brands of computational intelligence techniques have been tested for grasping sensing and actuation. Interpretation of tactile information is one of the hot computational intelligence challenges. Compressed learning has been demonstrated in the classification of tactile signals from arrays of tactile sensors embedded in a robotic skin working on the natural low dimension data obtained directly from the sensors (Hollis, Patterson, and Trinkle 2018). Another recent proposal encodes the signals using a linear dynamic system approach applying a fuzzy c-means clustering algorithm to the signal features, the resulting signal encodings are used for recognition in a bag-of-words approach (Liu et al. 2018). Combining particle filters and unscented Kalman filter (Vezzani et al. 2017) are able to overcome the strong non-linearities and multimodal distributions of tactile measurements in time achieving localization of objects in 6 degrees of freedom and accurate geometrical modeling with a commercial iCub robot endowed with capacitive fingertip sensors. Random forests have been used to classify tactile information predicting slippage in order to achieve grasp stabilization in a collaborative experiment with a human and robot endowed with a novel tactile sensor (Veiga, Peters, and Hermans 2018). The publication of rich datasets, such as the so-called YCB dataset (Calli et al. 2017), has fostered research from many fronts that serve both to validate published approaches and to try new approximations to grasping control issues.

Deep learning has been a disruptive technology facilitating innovative applications and techniques. Specifically, a lot of effort is devoted to apply Convolution Neural Networks (CNN) in their diverse flavors to develop sensor interpretation and control algorithms from actual data in specific grasping challenges. For instance, regrasping is the ability to change the grasping attitude improving the stability of the grasp. Some research teams (Calandra et al. 2018) have been developing a CCN model predicting grasping outcomes from visuo-tactile information. Another classical grasping problem is the identification of object grasping properties, such as graspable points, affordances, and grasping pose. Using RGB-D data, a CNN can be trained to predict graspable points of the objects (Chu, Xu and Vela 2018, Chen and Guhl 2018) in cluttered scenes. CNN can also be engineered to extract high level grasping-related features which are used by cascades of Random Forests to predict optimal grasp poses for large collections of objects (Asif, Bennamoun, and Sohel 2017). Three-dimensional CNN (3DCNN) can be trained on images from multiple points of view to predict optimal grasping poses of softhands, which are inherently uncertain due to the deformations suffered by the fingers at grasping time (Choi et al. 2018). CNNs have been also trained to detect object affordances (i.e. specific grasping poses with some functional value, like the arm of a hammer) (Mar, Tikhanoff, and Natale 2018), which provides usability to the grasp. Some authors emphasize the need for robustness of the sensor and actuator system. As a demonstration, they have carried extensive experimentation in different homes using of-the-shelf inexpensive robot arm and gripper and cameras (Gupta et al. 2018). CNNs have been critical to achieve high performance grasping under these wildly changing environmental conditions. They have been also applied to collaborative robotics in a learn-by-demonstration process where the CNN is trained on positive images obtained from the human demonstration and negative images generated by random transformations of the positive images (Van Molle et al. 2018). By no means the application of CNNs has been fully exploited, they are a continuous source of innovative solutions.

A very active research track is the use of reinforcement learning (RL) to look for the optimal grasping control algorithms. The main appeal of RL is its minimalistic supervision requirements. On the other side, training process is very slow and tricky, very sensitive to the action-value space representation. For instance, RL has been applied to find the optimal collaborative manipulation of objects by a dual arm robot (Zhao et al. 2018) based on a collection of motion primitives which allow for efficient encoding of motion and compact formulation of the search space for the Markovian decision process. RL is quite sensitive to long delays in receiving the reward to the actions, because until receiving some reward the system behavior is purely random. An approach to tackle this problem is a temporal decomposition of the learning process. Windowing the learning process has been proposed in Krishnan et al. (2019) to learn manipulation of deformable objects by the medical da Vinci robot. Deep reinforcement learning (DRL) refers to the use of deep learning architectures, often CNNs, to model the state-action space navigated in the RL process. For instance, DRL has been applied in Gualtieri and Platt (2018) to achieve optimal grasping and placing in cluttered and uncertain scenarios allowing six degrees of freedom localization of the gripper endowed with a RGBD camera under a hierarchical sampling process that effectively guides the robot through a sequence of relevant gazes. In the latest advances, DRL has been upgraded to self-supervised learning consisting of robot farms that operate autonomously for months carrying out RL epoch experiments. In this setting, high generalization of grasping strategies has been reported using only a shoulder RGB camera (Kalashnikov et al. 2018). Though this experiment has limited general value, because the optimal policies learnt are highly dependent of the specific experimental setting, it shows the way for empirical research on the development of innovative grasping control.

Conclusions

We have presented a panorama of the research actually going on about automated grasping which is a central issue in the development of innovative cyberphysical systems. We have described the main areas of application with significant economical impact, namely medical applications such as surgery, rehabilitation and assistive robotics, and prosthetics, and industrial applications centered about material handling. Summarizing, we identify the following as the most important open problems and research directions:

- Computational solutions to achieve sensing/control systems that are highly adaptable and universal, i.e. that can be translated from one application to another with minimal effort. This flexibility is desirable to reduce development times to achieve quick implementation. Current solutions, such as recent deep learning based approaches, require a great deal of engineering and tuning before being operable, even if they are labeled as industry-ready. Ideally, the computational architecture would be portable event between large shifts in domain involving physical scales (space, weight, forces), sensing devices, and actuator designs.
- Universal gripper design is always the big pending challenge. Achieving human hand flexibility, robustness of operation, and adaptability is a goal that it is still far in the future. A gripper design that could be used for industrial labor as well as in assistive robotics, for instance, would be a basic block for pervasive deployment of intelligent autonomous agents.
- Tactile sensing is still in its infancy. Development of tactile sensing will improve grasping quality by several orders of magnitude in any grasping performance measure. Its development depends on computational intelligence as well as mechatronic advances already on the way.

We hope that this survey will stimulate new researchers to enter the field. Research teams in this topic are naturally multidisciplinary, encompassing disciplines as different as cognitive science, cybernetic engineering, and physical and computational sciences.

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