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Challenges and Outlook in Robotic Manipulation of Deformable Objects

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Deformable object manipulation (DOM) is an emerging research problem in robotics. The ability to manipulate deformable objects endows robots with higher autonomy and promises new applications in the industrial, services, and health-care sectors. However, compared to rigid object ma-

nipulation, the manipulation of deformable objects is considerably more complex and is still an open research problem. Addressing DOM challenges demands breakthroughs in almost all aspects of robotics: hardware design, sensing, (deformation) modeling, planning, and control. In this article, we review recent advances and highlight the main challenges when considering deformation in each subfield. A particular focus of our article lies in the discussions of these challenges and proposing future directions of research.

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Background

Until now, object rigidity has been one of the common assumptions in robotic grasping and manipulation. Strictly speaking, all objects deform upon force interaction. Rigidity is a valid assumption when object deformation can be neglected in a task. Nevertheless, many objects that need to be manipulated by robots present nonnegligible deformation: from microsurgical operation to challenging industrial assemblies.

Robots need to be capable of manipulating deformable objects to operate in human environments. This capability would benefit many application fields; however, it also poses fundamental research challenges. In this article, we consider a generalized concept of manipulation where grasping is also part of the task. We will refer to the problem as *DOM*.

The tasks involved in DOM cover a broad spectrum (see Figure 1). They include dressing assistance in elderly care, cable harnessing in industrial automation, harvesting and processing fruit and vegetables in agriculture, and surgical operations in medical services, to name a few.



Figure 1. Applications involving manipulation of deformable objects. (a) Dressing assistance [1], (b) cable harnessing [2], (c) fruit harvesting [3], and (d) suturing [4].

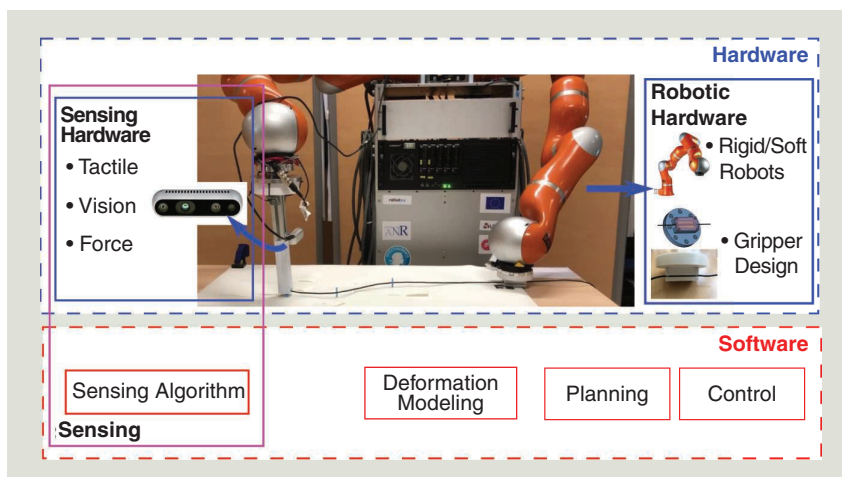


Figure 2. A typical robotic framework for handling deformable objects. In this particular example, the framework addresses a wire harness [5].

On the technical side, addressing deformation introduces the following technical challenges:

- the complication of sensing deformation
- the high number of degrees of freedom (DoF) of soft bodies
- the complexity of nonlinearity in modeling deformation.

We believe that overcoming these challenges is not only beneficial to DOM, but that it can further push toward developing autonomous robots that can operate in unstructured environments.

In recent years, there have been a few surveys on robotic manipulation of deformable objects. Some surveys focus on specific areas of DOM. The survey from Jiménez [6] focuses on model-based manipulation planning. More recently, Herguedas et al. [7] review works using multirobot systems for DOM, while the work of [8] considers multimodal sensing. The authors of [9] present the state of the art on deformable object modeling for manipulation. There are also two comprehensive surveys in the area. The survey in [10] reviews and classifies the state of the art according to the object's physical properties. Lately, [11] reported most recent advances in modeling, learning, perception, and control in DOM.

In contrast with the mentioned surveys, which either focus on reporting the progress of the field or on a specific area, this article aims at identifying scientific challenges introduced by object deformations and at projecting crucial future research directions. As DOM is an emerging field of research where there is still much to be done, in this article, previous works and open problems are given equal weight. In addition, we dedicate one section to discussing practical challenges in various applications of DOM. We believe the article is the first of its kind in the field of DOM.

A robotic framework designed to handle deformable objects usually consists of five key components: *gripper and robot design, sensing, modeling, planning, and control* (Figure 2). To position the current research and identify future trends, we conducted a survey on the future perspective of DOM. We shared the survey with people working in related fields at various career stages. They were asked to rate the importance and

research maturity of each of the five identified key components, from 1 to 4, with 1 being not important/low maturity and 4 being very important/high maturity. We received 31 answers; they are summarized in Figure 3.

We consider promising directions of research as those that have the highest significance and the lowest research maturity. Based on the survey, sensing is the most promising one among all subareas. This is probably due to the current booming trend in deep learning, which has offered many new methods for processing sensory data. In addition, sensing is the prerequisite for subsequent steps, such as modeling, planning, and control.

Accordingly, the following sections of this article present these five research directions with recent works in the field and comments on the outlook and challenges ahead. We also provide a link from research to practical applications in the context of DOM and summarize key messages.

Gripper and Robot Design

Current Capability

Does the manipulation of deformable objects demand specific grippers as compared to the manipulation of rigid objects? Generally, yes (see Figure 4). Unlike rigid objects (which are mostly handled by standard grippers), deformable objects are handled with custom (and often designed ad hoc) grippers, e.g., a 3D printed gripper that enables cable sliding [5], a flat clip for holding towels [12], a cylindrical tool for pushing and tapping plastic materials [13], or a soft hand for manipulating organs [14]. Such diversity in grippers is a result of the large variety of deformable objects, which require different actions during manipulation. To avoid designing task-specific grippers for DOM, human-like dexterity and compliance is desired. Recent works in this direction consider compliant design [15], [16] and show good potential for DOM tasks.

As for the robot itself, it is rigid in most works. In some cases, as in the surgical application showcased in [17] [Figure 4(e)], both the robot and object are deformable to ensure the safety of manipulation.

Challenges and Outlook

Improving dexterity is core to robot manipulation. The improvement can come from different research domains,

such as accurate in-hand sensing or robust control, two aspects that we will detail in the sections “Sensing” and “Control,” respectively. In this section, our focus is on gripper/robot hardware aspects.

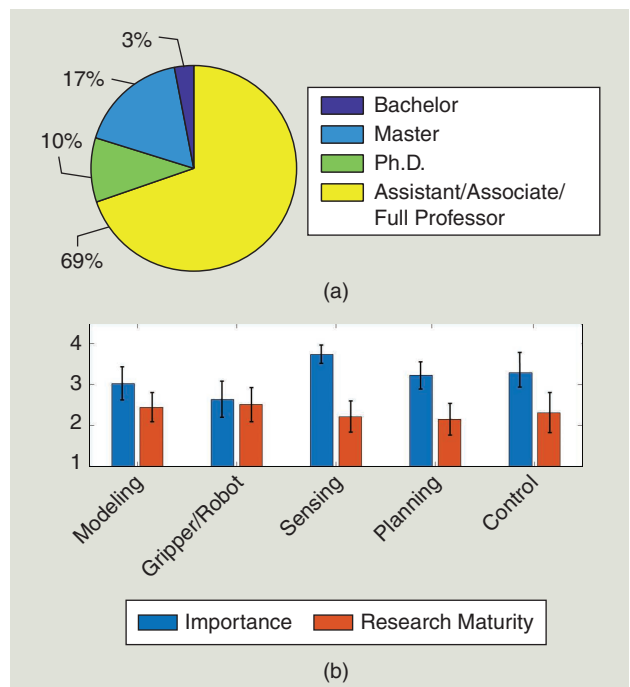


Figure 3. A summary of the outcomes of the survey on DOM. We received in total 31 answers. The respondents cover different level of qualifications, ranging from master students to full professors. (a) Highest qualifications of the respondents. (b) Means and variances of importance and research maturity ratings of each key component.

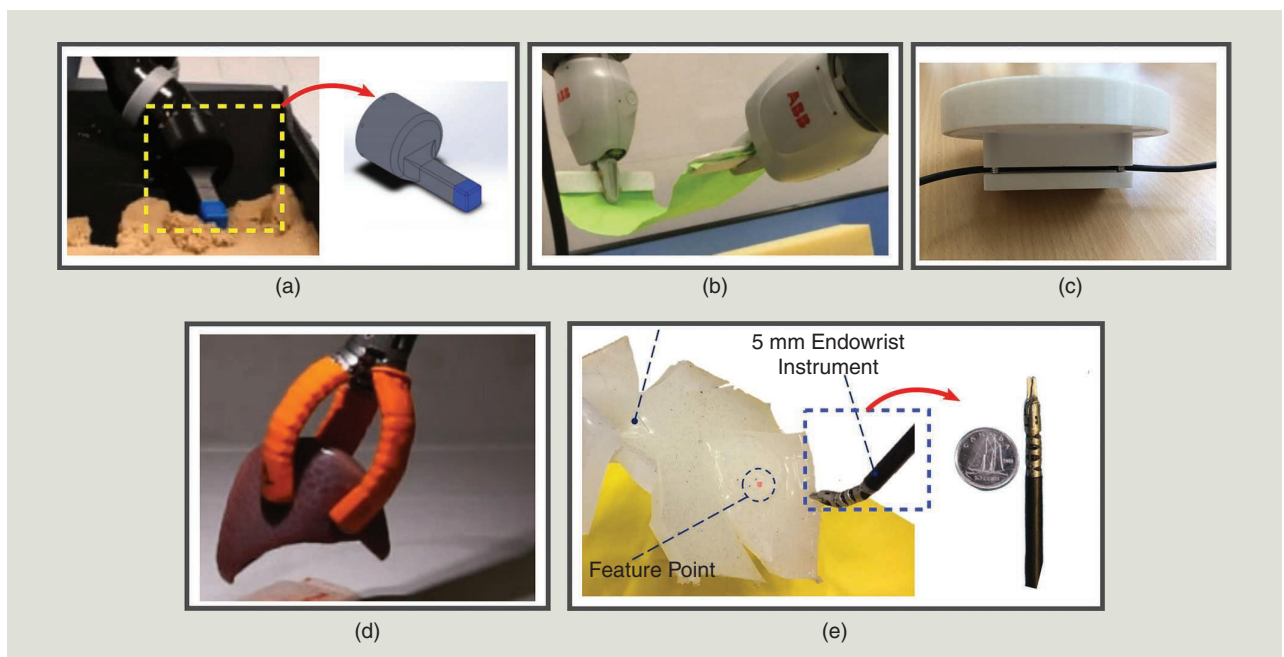


Figure 4. Various robot grippers for DOM. (a) A tool for pushing and tapping on plastic materials [13], (b) flat clips for holding a towel [12], (c) a gripper allowing a cable to slide [5], (d) a soft hand for manipulating organs [14], and (e) a soft continuum manipulator interacting with a deformable material [17].

One way of achieving such dexterity is to reproduce by design the most dexterous gripper: the human hand. An open question is whether the anthropomorphic design is in itself the optimal solution in all cases, especially in the context of DOM.

While having one dexterous gripper that can handle a variety of DOM tasks is appealing, it should be noted that additional constraints need to be considered in the design process for hygiene/safety in tasks such as food handling or surgery. For instance, for surgical applications, we are limited by the biocompatibility of the materials and actuators and by the reduced available space in minimally invasive surgery. In these cases, designing task-specific grippers is more appropriate. Nonanthropomorphic soft grippers are another emerging area of research [18]. These grippers are promising for overcoming the challenges associated with traditional fingered grippers in grasping rigid objects; yet, to date, their application to DOM has received little attention.

Otherwise, one may use a standard gripper and provide the robot with suitable tools to be grasped and used according to the type of task at stake. This demands breakthroughs on the algorithmic side to make the robot capable of reasoning about proper tools for different tasks. Training the robot to

have task-specific tool reasoning will enhance autonomy and enable the robot to realize more complex tasks.

Another area worth investigating is that of soft robots/grippers since they have great potential for manipulating fragile materials, such as organs or food, or for collecting biological samples or fruits (see Figure 5). While traditional rigid robots need to exhibit compliant behavior when interacting with these objects, the inherent compliance of soft robots makes the task safe. This unconventional paradigm of using soft robots to manipulate soft objects will bring new challenges in modeling and control as both the robot and the object are underactuated and difficult to model. One pioneering work in this direction is [21], which adapts a finite-element-method (FEM) modeling-based inverse soft robot model with contact handling (proposed in [22]) for deformable object manipulation using soft robots.

An interesting research question to consider is whether methods can be transferred from one field to another. To be more specific, can methods for controlling/modeling soft robots be applied to manipulating deformable objects and vice versa? If so, as a community, it may be valuable to obtain a unified approach for working with both soft robots and deformable objects.

Sensing

Current Capability

In this section, we consider visual, tactile, and force sensing for DOM. Existing research relies on these three modes to estimate the state of deformable objects. In most cases, vision provides global information about shapes on a large scale, while force and tactile sensing provide local information on both shape and contact. At the end of this section, we also discuss the research in contrast to this common practice, where global deformation properties are recovered using tactile sensing. It should also be noted that force information is particularly important in industrial settings, e.g., for assembly [23], [24].

Vision is used in tasks such as rope manipulation [25], [26] or cloth unfolding [27], [28], where the object exhibits a large global deformation. In these works, configurations of deformable objects were obtained from raw image readings. Although vision offers a global perspective of the object configuration, visual data can be noisy in unstructured environments. It is then important to manage occlusions [12], [29]. Most of the aforementioned works are based on 2D vision; 3D perception of deformable objects is more challenging. Existing works employ an FEM [30] or a combination of growing neural gas and particle graph networks [31] for better tracking of the deformation. In a more recent study [32], it has been shown that a deep convolutional neural network (NN) for processing vision data can be used with small variations to process tactile data for deformable object recognition. Objects made of soft materials, such as human tissues and fruits, have a special force-displacement correlation upon contact. As a result, tactile sensing can be used to estimate the stiffness. In [33], the GelSight [34], a vision-based



Figure 5. Two examples of interactions with fragile objects that could benefit from the use of soft robots. (a) Picking tomatoes [19]. (b) A custom 3D-printed soft robotic gripper, grasping mushroom coral [20].

high-resolution tactile sensor, measures the 3D geometry of the contact surface and the normal/shear forces.

Note that the division of vision for global deformation and tactile sensing for local deformation is not absolute. The authors of [35] use vision to estimate the local deformation of objects during grasping and classify objects accordingly. In [36], high-resolution tactile sensing is used to estimate the physical properties of clothing materials through squeezing, assuming the robot can learn from the data about global properties of clothing according to a local sampling point. In [37], an example of servoing along a cable based on high-resolution tactile sensing is presented. Although vision is not used, the precise measurement of the local cable shape provides enough information to guide the robot motion on a small scale.

Challenges and Outlook

The main challenges for sensing are selecting appropriate sensors for the DOM task and using the measurements to obtain meaningful object representations. Considering the high number of DoF of the deformable bodies, a fusion of different sensing modalities (vision, force and tactile) may be a promising direction to pursue in future research. Another research question to be answered is: What yields a good representation of the object configuration? We (acknowledgedly) do not have a complete answer to this; rather, we will elaborate on considerations when designing the representation.

The representation needs to be robust to noise and useful for reconstructing the objects' configurations—even when data are partially unavailable. In vision, the most common noise is occlusion. How to generate a meaningful representation of these objects under self-occlusion is still an open problem in research. For rigid objects, one can carefully design the environment to avoid it. For deformable objects that exhibit a large global deformation, such as clothes and bed sheets, self-occlusion is inevitable during manipulation. A promising direction to deal with occlusion and noise is the use of active/interactive perception [38], [39]. With vision data from different perspectives, we might be able to reconstruct an object's configuration accurately, even under occlusion and noise.

Apart from the aforementioned challenges, choosing a good representation also involves leveraging two aspects:

- 1) the dimensionality of the representation
- 2) the accuracy of the representation.

Usually, the tradeoff depends on the task, relies on human intuition, and involves a trial-and-error process.

In end-to-end reinforcement learning settings, sensory data can be mapped directly to robot actions without explicit feature representations [40]. Human demonstrations can be used for making end-to-end learning more efficient. One example is reported in [41]. The authors use an improved version of deep deterministic policy gradients, trained with 20 demonstrations, to make robots manipulate cloth. However, since such settings often require a manually designed cost/reward function for learning, human demonstrations in this context can also be used for recovering the reward with inverse reinforcement learning.

Modeling

Current Capability

For robots to perform deformation tasks using sensory data, we need a model that captures the relationship between sensor information and robot motion. A linear model characterized by Young's modulus can be employed for describing elastic deformation. The two other classes of deformation are plastic and elastoplastic deformations. This classification serves well. However, since the model should be used for control, in this section, we prefer to distinguish between local and global models—a taxonomy that has clearer implications for control. We introduce the corresponding research and—at the end of the section—discuss the limitations of these models and present works that address them.

Most local models approximate the perception/action relationship via a Jacobian matrix (called an *interaction matrix* in visual servoing). Such a model is linear and can be computed in real time with a small amount of data. However, since it is a local model, it must be continuously updated during task execution. Model-updating methods include Broyden's rule [17], receding horizon adaption [42], local gradient descent [43], QP-based optimization [44], and multiarmed bandit-based methods [45]. Another advantage of the Jacobian model is that one can design a simple controller by inverting it. However, since this controller is local, it operates via a series of intermediate target shapes [42], [44].

On the other hand, global models can be approximated with FEMs [46] and also (deep) neural networks (D)NNs. In contrast to simple linear models, (D)NN-based approaches benefit from stronger representation power in terms of accuracy and robustness [47]. Moreover, they can incorporate physics models and reason about object interaction [48]. These models can approximate highly nonlinear systems and have a larger validity range, solving (to some extent) the locality issue of the linear models. Nevertheless, these complex nonlinear representations demand large amounts of data (which might not be available in some cases).

Whether analytical or learned models are used, their predictive power will be limited. They are either specialized to some class of tasks or learned from a set of training data. Especially for the learned models, we can never hope to collect enough data to produce an accurate model in the entire state space (which is high dimensional). Thus, [49] and [50] have developed methods to reason about the validity of a (learned) model for a given state and action and have used these methods to reason about model uncertainty in planning and control. However, when the model is not precise, a replanning/recovery might be desirable. The authors of [51] introduce two NNs for learning and replanning the motion when the model is unreliable.

Challenges and Outlook

The complexity of modeling is manifested in the lack of simulators. While most existing robotic simulators are capable of producing rigid body kinematics and dynamic behaviors,

only a fraction of them can handle deformation. One recent work, Softgym [52], was proposed for benchmarking DOM based on NVIDIA Flex. In the soft robotics community, SOFA [53] and ChainQueen [54] are example simulators. In the sections “Gripper and Robot Design” and then “Challenges and Outlook,” we considered the interaction between soft robots and deformable objects. Thus, a unified simulator that is able to handle soft robots and objects and model their interaction might be desirable.

When choosing a model for control, one challenge of data-driven deformation modeling is to balance the region of validity with the amount of data required for training. One possible direction is to combine a simple model with a complex nonlinear model to form a hierarchical model. An example of such structures is exploited in [55] for robust in-hand manipulation. For DOM tasks, we can have a linear model at the lower level and a (D)NN learning the full model at a higher level. The lower-level model can be learned in a few iterations to enable instant interaction between the robot and object. The higher-level (D)NN can collect data and improve the model to enhance global convergence.

Planning

Current Capability

Planning aims at finding a sequence of valid (robot/object) configurations and contributes to solving the problem of limited validity of local models, as discussed in the section “Modeling.”

Planners can operate in the objects’ configuration space and sometimes rely heavily on physics-based simulation. While the obtained plan can be visually plausible, it may be unrealizable for a specific object. Recently, McConachie et al. presented a framework that combines global planning without physics simulation, with local control [56]. For an elastic object, considering its energy is another way to do planning; in this direction, Ramirez-Alpizar et al. [57] proposed a dual-arm manipulation planner optimizing the elastic energy, for elastic ring-shaped object manipulation. For DOM tasks involving multiple robots, planning is important for coordination. Alonso-Mora et al. employed a distributed receding horizon planner for transporting tasks that require multiple robots [58]. More recently, the work of [59] learned a latent representation for semantic soft object manipulation that enables (quasi)-shape planning with deformable objects.

With learning from demonstration (LfD), the robot can be trained to manipulate deformable objects by an expert (usually a human). LfD encodes the robot trajectory and interaction force from human demonstrations [60], thus avoiding explicitly planning the motion. More recently, Wu et al. have proposed a reinforcement learning scheme for DOM that does not require initial demonstrations [61].

Challenges and Outlook

A rigid object configuration can be described in space with 6 DoF, whereas a deformable object configuration has a much higher number of DoF. To address this from the

sensing algorithm side, one can find a compact representation from sensory data, as discussed in the section “Challenges and Outlook” under the section “Sensing.” An alternative that receives much less attention is the use of environmental contacts to constrain some DoF of deformable objects. Examples include the use of contact points in cable harnesses or that of flat surfaces when folding clothes. We argue that, instead of planning to avoid contacts—as most planners do—for deformable objects, we need to plan to make contact since this constrains the configuration and therefore simplifies the task.

Planning to grasp the correct point is often crucial in DOM tasks. For instance, grasping at convex vertices of the clothes guarantees stability and facilitates the task [62]. Regrasp planning is highly relevant when considering tasks that require multiple robotic arms. Additional challenges come from perception since as soon as the robot releases one or more grasp(s), the object is likely to change its configuration. We rely on sensing to track configuration changes and then plan accordingly.

Another important future work in planning is reasoning about a deformable object at a semantic level. What does it mean for a cloth to be folded? What does it mean for an object to be wrapped in a paper? We cannot manually specify all of the configurations of the deformable object to use as goals in these kinds of tasks. Instead, we need a way to learn the meaning of semantic concepts, such as *folded* or *wrapped*, so that we can determine if a given configuration of the object is a valid goal.

Control

Current Capability

Control aims at designing inputs for the robot to realize the planned motion. The type of controller is usually decided by the task. For instance, the authors employed a data-driven model predictive control [63] for cutting considering its predictive nature and the lower demand for manual tuning. For safe interaction in minimally invasive surgery, the authors of [64] used a fuzzy compensator with impedance control. For controlling large deformations, Aranda et al. proposed a shape-from-template algorithm concerning its low-dimensional representation (using the template) and robustness against occlusion [65].

Several works focus on shape control. While global models directly map sensor data to robot motion, local models must be inverted to design the robot motion controller (see the section “Modeling”). Several applications of the control scheme for robotic manipulation of deformable objects can be found in computer, communication, and consumer manufacturing [66], [67], where vision-based controllers were proposed to drive the robot to automatically grasp/contact a deformable object and then carry out the task of active deformation or separation/sorting. Other works consider the concept of diminishing rigidity to perform deformation control [68], [69].

Challenges and Outlook

Feedback control has been commonly used in most DOM works by referring to the state of the object to achieve the task. Note that this state is retrieved from the output of its deformation model and measured with sensors, and that output and state do not necessarily have the same representation and dimension. Furthermore, we can distinguish between model-based and model-free control. Because of the complexity of modeling the deformation, when using the model to derive control policies, the controller has to take into account that the model will be inaccurate or even wrong.

Model-free approaches do not require information about the deformation parameters or the structure of the deformation model. Examples include LfD or (deep) reinforcement learning, where the challenges are efficient use of data and policy generalization. To address these issues, we can combine offline and online learning methods. In the offline phase, the supervised network can be trained to estimate the model by collecting pairs of a series of predefined inputs (e.g., the velocity of the robot end effector) and the deformation of the object. The estimated model in the offline phase can be further updated online during the control task with adaption techniques (e.g., adaptive NNs), to compensate for the errors due to insufficient training in the offline phase or the changes of the deformation model. Hence, both complement each other.

When multiple features on the deformable object are controlled in parallel, the system becomes underactuated, with fewer control inputs than error outputs. Then, the robot controller should be able to deal with the conflicts between multiple features or decouple the control of multiple features in a sequential manner to guarantee controllability.

In addition, because of the deformation during control, the contact between robot end effectors and deformable objects may not always be maintained. Most existing systems require a certain level of human assistance to initiate the contact or to reestablish it, if it is lost during the task. To improve autonomy, the robot controller should automatically grasp or touch the object first, whenever physical contact is lost, laying the foundation of the subsequent manipulation task. Such a capability would allow the robot to effectively deal with the unforeseen changes due to deformation.

Practical Applications

In the previous sections, we centered our discussion from a scientific point of view. Here, we instead discuss challenges in various applications of DOM.

- *Automatic laundry*: A typical domestic application of DOM is laundry folding. A Tokyo-based company unveiled its prototype laundry-folding robot in 2015. However, the company was announced bankrupt in 2019 due to lack of funding for development and difficulties in improving the robot to reach a satisfactory level [70]. Although cloth folding has been tackled in a few previous studies [71]–[74], it remains largely a laboratory product

(limited to structured environments, certain types of clothes, and so on). Commercializing the technology seems to require substantial efforts.

- *Assistive dressing*: Robotic dressing assistance has the potential to become an important technology due to the pressing need for aging society support. Research can roughly be categorized into simulation-based learning [75], [76] and imitation learning [77] approaches. Examples are dressing support for shoes [78], shirts [79]–[81], and pants [an example of shirt dressing is shown in Figure 6(a)]. However, several technical and societal challenges have to be addressed before robot-assisted dressing will become a broadly used DOM technology: physical safety for the human; modeling and prediction of the human–robot interaction; robustness for large variations of geometric and dynamic properties of textiles; low-cost, highly reliable robot hardware; and human acceptance of such technologies.
- *Surgical robotics*: Soft tissue manipulation is mainly performed with teleoperation using solely visual feedback. Autonomous manipulation, however, still has a long way to go, and it demands developing various types of DOM hardware and software [Figure 6(c)]. The biggest concern for an autonomous solution is the safety of operation. A soft robot with intrinsic compliance will probably enhance safety.
- *Food production and retail*: Handling deformable objects is a major challenge in the whole chain from production to sales. In an agricultural setting, automated harvesting of fruits and vegetables requires interactions with deformable objects that are at the same time easy to damage, which immediately decreases their value and shelf life. Frequently, these products also undergo an intermediate processing step (e.g., filleting and packaging of meat). More generally, deformable products, e.g., with everything packaged in flexible bags [Figure 6(b)], need to be handled in warehouses, in order picking, and in restocking. Solutions for specific applications and products have been developed, but more complex objects and operations still are frequently handled by human workers.
- *Marine robotics*: Underwater grasping has been led by the oil and gas industry for decades, resulting in heavy machines with strong grippers for inspection and maintenance tasks [Figure 6(d)]. Gradually, the demands turned to more detailed tasks in marine biology, sedimentology, and archaeology [Figure 6(e)]. Another DOM application can be found in tethered robot umbilical modeling and control. A negative buoyancy cable can be modeled in real time as a simple catenary shape and tracked to control a tethered remotely operated vehicle (ROV) [82].

Summary and Key Messages

The revolution of robots from automating repetitive tasks to humanizing robot behaviors is taking place with better hardware, robust sensing capabilities, accurate modeling, increasingly versatile planning, and advanced control.

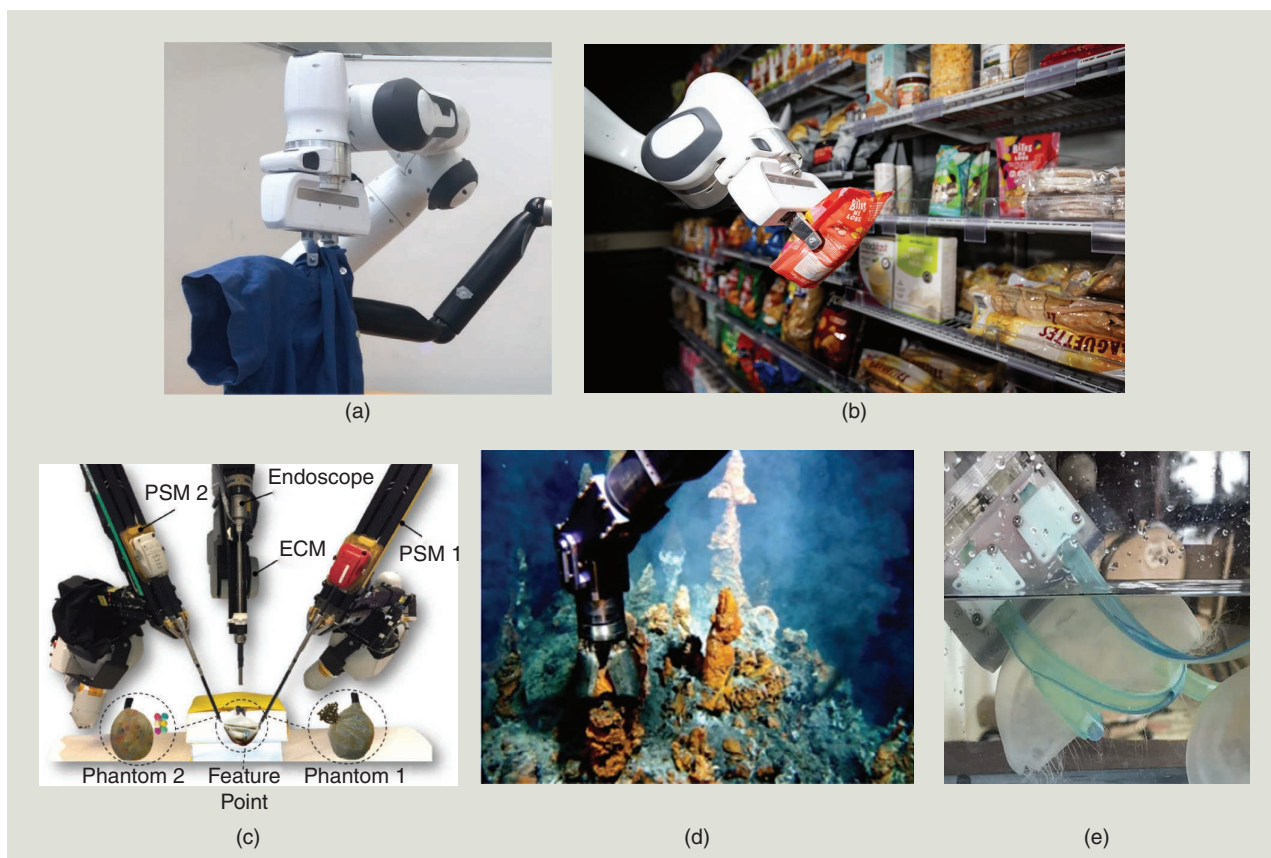


Figure 6. Various applications of DOM. (a) A mockup for robotics dressing assistance [83]. (b) A robot picking a flexible bag of goods on the shelf (courtesy AIRLab, Delft University of Technology, photo by Guus Schoonewille). (c) Autonomous surgical manipulation by the da Vinci Research Kit system [84]. PCM: patient side manipulator; ECM: endoscopic camera manipulator. (d) The remotely operated vehicle (ROV) Victor 6000 sampling black smokers (IFREMER/GENAVIR) (courtesy D. Desbruyères). (e) Ultrasoft underwater gripper for jellyfish. (Source: [85]; reprinted with permission from AAAS.)

Manipulation of deformable objects breaks fundamental assumptions in robotics, such as rigidity, known dynamics models, and low-dimensional state space. It, therefore, requires breakthroughs in all of the areas mentioned previously and serves as a great testbench for novel ideas in both robotic hardware and software.

In terms of hardware, recently, the community has been increasingly shifting from rigid to soft robots. Robotic manipulation is also gradually shifting from rigid to deformable objects. One open question is: Are some of the algorithms in one field transferable to the other? We believe the interaction between a soft robot and a deformable object will bring more challenges to the robotic community.

Sensing plays a vital part in the robotics manipulation of deformable objects. Depending on the nature and complexity of the task, one or multiple fused sensing modes may be needed. Machine learning will facilitate the development of robust algorithms to process data from different sensors to generate meaningful representations of deformation.

All models are wrong; some are useful. We do not believe there exists a “best” model for deformation. While models increasingly tend to be data driven, we would like to draw the readers’ attention to the importance of physical models for studying interactions.

For planning, current research lacks the high-level semantic reasoning of the DOM task. Furthermore, while often the purpose of planning is to avoid contact and collision, we argue that, for DOM, it can be very useful to plan for contact.

Underactuation is a key challenge of DOM because of the deformable bodies’ high DoF. Another practical issue introduced with deformation is contact loss during manipulation. Future controllers should be able to detect contact loss and react accordingly.

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