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Flexible Robotic Grasping Strategy with Constrained Region in Environment

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Abstract: Grasping is a significant yet challenging task for the robots. In this paper, the grasping problem for a class of dexterous robotic hands is investigated based on the novel concept of constrained region in environment, which is inspired by the grasping operations of the human beings. More precisely, constrained region in environment is formed by the environment, which integrates a bio-inspired co-sensing framework. By utilizing the concept of constrained region in environment, the grasping by robots can be effectively accomplished with relatively low-precision sensors. For the grasping of dexterous robotic hands, the attractive region in environment is first established by model primitives in the configuration space to generate offline grasping planning. Then, online dynamic adjustment is implemented by integrating the visual sensory and force sensory information, such that the uncertainty can be further eliminated and certain compliance can be obtained. In the end, an experimental example of BarrettHand is provided to show the effectiveness of our proposed grasping strategy based on constrained region in environment.

Keywords: Grasping strategy, compliant grasping, dexterous robotic hands, attractive region in environment, constrained region in environment.

1 Introduction

1.1 Background

Robots are promising due to having an important role in future automation technologies for accomplishing various tasks, especially for the advanced industrial manufacturing, domestic services and other robotic areas[1−6]. As one of the most fundamental yet urgent problem, grasping and relevant manipulation are forming an active research front line. Particularly, in the complex and uncertain environments, grasping is an essential and key element for performing dexterous robotic operations[7−11]. Moreover, such a manipulation can also provide an efficient solution to human-robot interactions[12−16]. It should be pointed out that although grasping is not a difficult task for the human beings, it still remains challenging for most of the developed robots. By observing the manipulation done by human beings, our dexterous and successful grasping can express a very flexible manner. This mainly relies on our cognitive skills and interaction ability with the environment. On the other hand, grasping an object by robots is always pre-programmed and it needs considerable computational and sensory information, which is with less robustness and compliance to some extent. As a result, grasping of robots has been extensively studied in the past decades for theoretical importance and practical applications.

Generally speaking, remarkable contributions in the field of robotic grasping have been reported in the literature. Whereas in the context of grasping, the following important and basic aspects are needed:

1) Object and environment perception: Obtain feasible measurement of the object and environment by sensory information feedback.

2) Grasping planning: Determine the contact points on the object and the grasping configuration.

3) Grasping control: Motion and force control at the desired contact points.

It is noteworthy that the perception ability mainly relies on the relevant sensory precision of the robots. Obviously, one primary way is equipping the robots with high-precision sensors with rich sensor information. However, there still exist certain limitations of high-precision sensors in hardware to date[17−20]. Thus, efficient perception methods with low-precision sensors would be meaningful for the grasping problem. On the other hand, the grasping planning algorithms also affect the grasping ability of robots, especially for the cases with low-precision sensory information.

In the following, the grasping planning in robotic manipulation will be first discussed.

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1.2 Grasping planning in robotic manipulation

So far, among the vast literature available on robotic grasping, grasping planning strategies can be categorized to two main approaches: the analytical approaches and the empirical approaches[11, 21, 22].

For the analytical approaches, grasp closure analysis and synthesis are mainly established on the primitive knowledge and perception of the object, such as mathematical models or three dimensional computer aided design (CAD) models. By deriving feasible contact points or contact regions in offline conditions, the object can then be grasped according to the pre-computed results. Well-known methodologies can be found on the force closure grasps[23, 24] and the form closure grasps[25, 26]. Note that form closure can be a stronger condition than force closure. It can be found that these methodologies can prevent free motion of the grasped object by fully restraining parts of the object. Furthermore, grasping algorithms based on partial grasp closure have been studied for the scenarios without complete restraints. For instance, in [27], the partial form closure grasp is proposed and the caging grasp is introduced in [28]. In addition, the partial force closure grasps and the local force closure grasps were discussed in [29]. Readers can be referred to some recent research papers for more details[30]. However, it should be pointed out that in practical applications, the established theoretical grasping conditions are mainly based on statistical analysis which always lead to certain conservative results due to the raw sensory measurements or the uncertainties or unknown information of object.

For the empirical approaches, the robots can grasp the object based on human observations (representing human grasping gestures) or object observations (associating the object features) with existing grasping experience, which can decrease the computational complexity of analytical approaches[31, 32]. By training with desired grasp quality evaluation, the robots can analyze the object and learn to grasp. Compared with the analytical approaches, although the effectiveness of grasping can only be empirically demonstrated, it can provide a more flexible grasping solution in the real world applications. In this context, the key point of successful grasping is the sensory information acquisition and processing. In particular, the visual sensor plays a significant role in the observations of object features. However, it is worth mentioning that only online learning by empirical information could be time consuming and the offline analysis results have not been adequately utilized.

1.3 Dexterous robotic hands

Based on the above discussions, it should be pointed out that in order to accomplish a successful grasping for the robots, not only effective grasping planning algorithms should be designed but also the proper hardware structures of the robotic hands should be developed[33, 34]. For the grasping tasks, a gripper with fingers is utilized to grasp the objects and many efforts have been made to design different kinds of grippers. However, traditional simple gripper for a specific grasping task cannot provide enough flexibility in more general scenarios. Encouragingly, with the development of mechanics, bionics and control technologies, multi-finger or dexterous robotic hands have been receiving increasing attention, which aim to achieve the dexterity of human beings. These designs can give promise for feasible grasping as much as possible. Compared with some simple grippers or other preliminary mechanical hands, multi-finger robotic hands can provide more flexibility and increase the efficiency of a manipulator in executing grasping and manipulation tasks[35−37]. One distinguishing feature of dexterous robotic hands is its variety of sensors, such as visual, force/torque or tactile sensors, and other types of sensors. In particular, underactuated multi-finger robot hands have significant advantages due to simpler mechanical structure, lower weight, better adaptive ability, etc. Famous underactuated multi-finger robotic hands are BarrettHand hand and iCub hand[38, 39]. Recently, some bio-inspired anthropomorphic robotic hands have been reported in the literature, which can better replicate the human hand motions[40, 41].

Although some complex robotic hand designs that mimic human hands can potentially increase the flexibility and versatility compared with the simple grippers, the grasping planning and control schemes would correspondingly become sophisticated, since there are complex couplings and multiple degrees of freedom among the fingers and/or joints. Thus, it is necessary to study the grasping planning strategies of dexterous robotic hands. Some preliminary examples for the above issue can be found in the literature and the references therein[42−45].

1.4 Remaining challenges

One challenge in the robotic grasping problem is dealing with the uncertainties while making a detailed motion planning strategy. As a matter of fact, some techniques for this problem rely on the high-precision sensory information feedback to minimize the measurement errors in the grasping process. However, it is worth mentioning that a key problem seems to be that the required minimum precision of the tasks has to be lesser than the precision of the sensory systems[46]. For the grasping problems, online grasping strategies in real-time designs are very difficult for adaptation of fast motion during the execution of the grasping task. In addition, most sensors of robotic hands are with low-precision, data-drift or noise characteristics, such as common visual or tactile sensors[47, 48]. Furthermore, in some applications with high-precision requirement, certain sensors are not accurate enough, such that the obtained information may not be always valid. On the other hand, for some specific tasks, the required information for grasping may not be directly obtained, or even unavailable. One line of research in the robotic manipulation explores the sensorless methods[49, 50], which means that certain manipulations of the robots can utilize the environment constraints by the manipulated objects and the interacted environments. As a result, one of the efficient methods regarding these issues is the concept of attractive region in environment, which has been proved to be beneficial for robots to meet the desired precision requirements and to eliminate the uncertainties. This method has been adopted in the localization, assembly automation and grasping problems. It is worth mentioning that for the method of attractive region in environment, a prior knowledge of the environment constraints is often required, which may limit the real-world applications to some extent due to the tradeoff between the strategy complexity and the precision requirements.

Note that the underactuated dexterous hands can accomplish some precision grasping tasks[51, 52], since the underactuated mechanisms have the adaptive abilities with different shapes. However, another challenge lies in the fact that finding a feasible and efficient solution of grasping planning for underactuated multi-finger dexterous hands may be complicated. This is not only due to the sensory precision limitations, but also due to the complex grasp configurations of the robotic hands. Particularly, in comparison with the fully-actuated multi-fingered dexterous hands, the high-precision grasping planning and control algorithms of the underactuated multi-finger dexterous hands can be more sophisticated. The traditional motion planning in configuration space would fail due to the difficulties in describing the high dimensional hand pose and finger joints configurations. In addition, since the constraints in grasping involve the interaction between the object and the fingers, these constraints may be imposed by the kinematics or dynamics. Furthermore, to the best of the authors′ knowledge, how to deal with uncertainties in the grasping processes by simple coarse sensory information is still an open question. As a result, it is very important to choose the grasping points or regions by considering certain constraints during the grasping planning stages.

Motivated by the above discussions, in this paper, we investigate the grasping planning problems for a class of dexterous underactuated robotic hands based on a bio-inspired concept of constrained region in environment. More precisely, by observing the manipulation processes of the human beings, the framework of constrained region in environment is established by integrating the environment constraints and the multiple coarse sensory information. This concept of constrained region in environment can be considered as a more general case of attractive region in environment, which can further bridge the sensory feedback and sensor-less robotic manipulation strategies. In comparison with the existing literature, the main contributions of this paper can be summarized as follows:

1) The concept of constrained region in environment (CRIE) is introduced, based on which a theoretical strategy for robotic manipulation is proposed. This proposed concept can be considered as a further extension and more general case of attractive region in environment.

2) For the grasping problems of dexterous underactuated robotic hands, a grasping strategy based on the proposed theoretical strategy is developed for practical applications to demonstrate our obtained results. By the appropriate grasp configurations in configuration space, the high-dimensional constrained region in environment can be formed by the interaction between the fingers and object. By analyzing the constrained region in environment of the grasping process, the offline planning is first derived. Then, by integrating the coarse sensory information of visual and tactile sensors, the online adjustment can be generated, such that the desired grasping contacts can be obtained.

The rest of this paper is arranged as follows. Section 2 reviews the manipulation strategy with attractive region in environment and gives some preliminaries. In Section 3, the concept of constrained region in environment is introduced, based on which the corresponding grasping strategy is established. Section 4 provides an illustrative example with Barretthand to show the effectiveness of our theoretical results. In the end, conclusions are drawn with discussions on the future trends of neurobiologically inspired mechanisms for compliant robotic manipulation problems in Section 5.

2 Related work and preliminaries

In this section, the concept of attractive region in environment is first reviewed, based on which some preliminaries on the utilization of environment constraints are introduced for subsequent analysis.

2.1 The concept of attractive region in environment

Environmental constraints can be utilized in robotic manipulations[53, 54]. In our previous work, we established a sensor-less robotic manipulation framework based on attractive region in environment, which can deal with relevant manipulation uncertainties. Before proceeding, the framework is first given to guide an intuitive understanding of the approach. Attractive region in environment (ARIE) is defined in the configuration space and the details can be explained as follows, which can also be depicted in Fig. 1:

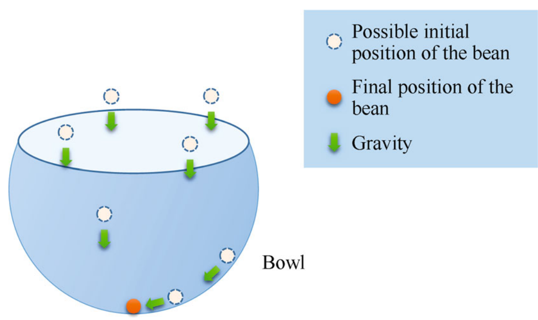

Fig. 1 The illustration of attractive region in environment

If the initial state of the system is within some range of the constrained region, and if there exists a state-independent input which will push the state of the system to a global stable point of the region, then the constrained region is an attractive region in environment.

The definition of attractive region in environment can be therefore given.

Definition 1. Assume that the state of a system can be characterized as

$$\frac{\mathrm{d}x}{\mathrm{d}t} = f\left(x, u\right) \tag{1}$$

where $x\left(t\right)$ is the state of the system. For all x in the region Ω, if there exists a state-independent input $u\left(t\right)$ and a certain function $g\left(x\right)$ satisfying that

1) $g\left(x\right) > g\left(x_0\right)$ when $x \neq x_0$,

2) $g\left(x\right) = g\left(x_0\right)$ when $x = x_0$, and

3) $g\left(x\right)$ has continuous partial derivatives with respect to all components of x, then the system will be stable in the region Ω, which is called the ARIE.

As a result, it can be found that directly searching the high-dimensional configuration space is not needed based on the ARIE, which can facilitate the planning. The theoretical framework of ARIE has been successfully applied in robotic areas related with tasks of grasping, assembly and other manufacturing processes to cope with uncertainties[46].

Remark 1. The key idea of ARIE is to deal with the uncertainties with environment constraints while considering the limitations of the sensory information. For the grasping tasks, the utilization of ARIE can lead to a stable grasp without rigorous placements of the gripper from any initial state.

3 Main results

In this section, the manipulation process of the human beings is first analyzed. Then, the concept of constrained region in environment is introduced based on the observations and the corresponding grasping strategy is further developed.

The daily manipulation of human beings may be incomprehensible for most of the robots. Note that we often use limited or coarse sensory information instead of the accurate sensory information to plan and execute appropriate motions for some tasks. Another interesting fact is that we can integrate the multiple sources of relative low-precision sensory organs in a flexible way[55]. These findings may help in investigating new robotic manipulation strategies.

3.1 General concept of constrained region in environment

As stated above, the grasps can be based on offline computation with a priori knowledge of the object in the framework of ARIE, such that corresponding feasible hand configurations can be obtained. However, this method is based on the complete information of the object, which is practically difficult to acquire in the real grasps. As a result, we will extend the above ARIE framework by incorporating an online adjustment with coarse sensory information.

Inspired by the researches of human grasping motion, we found that our grasps not only depend on various sensory information feedback but also need the interaction between the object and the environment. Moreover, recent researches in biology also suggest that human beings have the ability to deal with high-precision manipulations with relevant low-precision sensory organs. Consequently, the concept of constrained region in environment (CRIE) is introduced in the configuration space. The main idea of CRIE is the integrated framework of relaxed constraint and the coarse sensory information. The former is passive constraint which is formed by the environment, and the latter is "active constraint" which is captured by the sensing system. The passive constraint can be seen as part of the ARIE, which cannot be utilized directly. With the combination of active constraint, the constrained region is completed and the uncertainty of the system can be eliminated.

Based on the above discussion, the following definition of constrained region in environment is introduced:

Definition 2. Assume that the state of a system can be characterized as

$$\frac{\mathrm{d}x}{\mathrm{d}t} = f\left(x, u\right) \tag{2}$$

where $x\left(t\right)$ is the state of the system and u is the input to the system. The state of the system x can be divided into two parts: x_c and x_s. x_c is the set of states which are constrained by the environment:

$$x_c \in \Omega_c \subset \mathbf{R}^m$$

where Ω_c forms an ARIE, or there exists a point $x_0 \in \Omega_c$, a real number $\epsilon > 0$, and $\widetilde{\Omega}_c(x_0, \epsilon) \subset \Omega_c$ which forms an ARIE. And x_s is the set of states that is formed by the sensors:

$$x_s \in \Omega_s \subset \mathbf{R}^n.$$

In detail, x_s can be further divided into two parts: x_{sg} which represents the global information (such as in which step of a task) of the system, and x_{sl} which focuses on local information (such as pose, contact states) of the system. The relation between x_{sg} and Ω_c can be expressed as

$$h : x_{sg} \rightarrow \Omega_c.$$

On the other hand, $u = u_p + u_a$ is made up of two parts,

$$u_p = U_1(x_{sg})$$

which is the primary input to push the x_c to the stable state, and

$$u_a = U_2(x_{sl})$$

which is the secondary input to adjust x_c to speed up its convergence.

For a specific task, the region $\Omega = [\Omega_c, \Omega_s]$ forms the task space, and for each $x_{sg} \in \Omega_s$, there will be a corresponding Ω_c or $\widetilde{\Omega}_c(x_0, \epsilon)$ that forms an ARIE in the configuration space. If there exist state-independent input u_p and state-dependent input u_a, which can ensure that the system is stable in Ω_c, then region Ω is called the constrained region in environment.

It can be observed that there are two key elements of our CRIE framework: the offline grasping planning based on ARIE and the online adjustment based on sensor information feedback. Compared with some completely online grasping approaches, our proposed strategy also can reduce the computation burden and complexity of online grasping

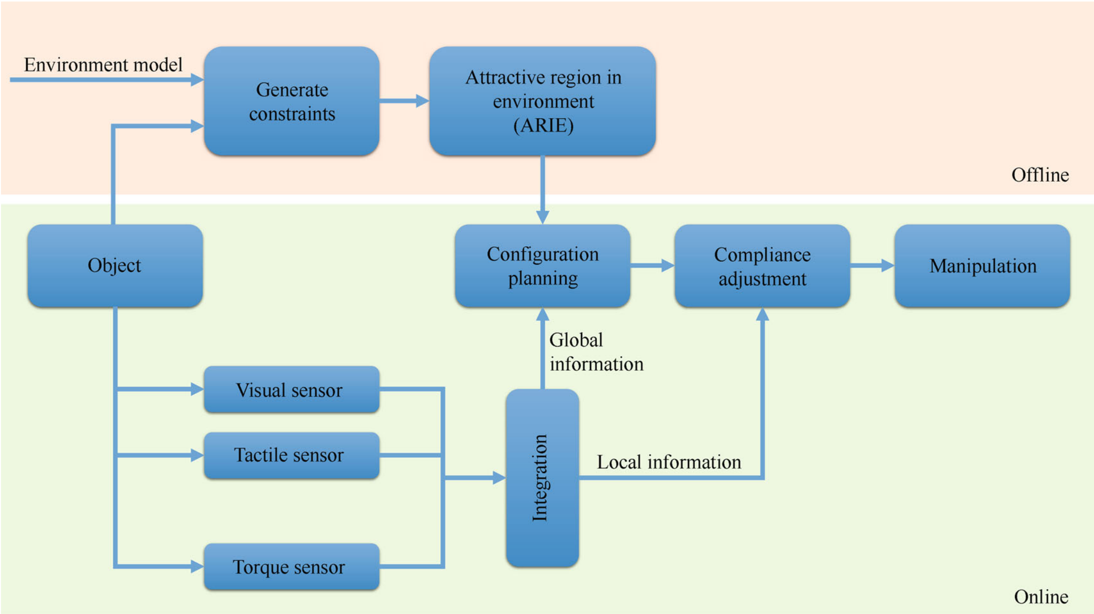

Fig. 2 Overview of the architecture of CRIE

planning, which can combine the advantages between offline planning and online planning. Fig. 2 gives an overview of the architecture of our proposed framework, which consists of offline and online parts.

As a result, the primary grasping planning is designed according to the subspace of the constrained region in environment. Then, by utilizing coarse sensory information feedback, the robotic fingers can fall into the above subspace, such that high-precision robotic grasping can be achieved by relevant low-accuracy sensory information with the desired grasping configuration. Significant advantages of this method are the improvement of robustness against the object uncertainties, and the efficiency and dexterity for grasping.

Remark 2. It is worth mentioning that the concept of CRIE is a more general case of the concept of ARIE. In the high-dimensional configuration space, only parts of the subspace with contact information formed by the environment constraints can be utilized for strategy investigation.

Remark 3. Note that in the ARIE framework, the grasping contact states are fixed such that no further adjustment can be added to the pre-designed grasping planning. As a contrast, in the CRIE framework, the coarse sensory information can be utilized to acquire the online grasping contact states. Then, based on the coarse sensory information, the robot can determine whether an appropriate adjustment should be implemented to asymptotically track the pre-designed grasping planning sequences, which can be depicted in Fig. 3. This flexible mechanism can improve the grasping stability and robustness against the uncertainties, which is a characteristic advantage of the CRIE framework.

3.2 Generating grasping planning

In accordance with the concept of CRIE, the grasping can be achieved by the following operational steps:

1) **Offline configuration design**. During the offline stage, the first step is to obtain the CAD information of the object and the environment without accurate geometrical information. Then, the specific grasping tasks for the object and the robotic hand configuration can be obtained based on ARIE, which concludes the offline operations.

2) **Visual information guidance**. In this stage, the robot hand will move to the object by visual information along a desired path. In the procedure, the visual sensory feedback information taking into account uncertainties on the object location and position is utilized with simple sensing methods, such that certain finger or fingers can touch the surface of the object with a pre-grasp gesture. Once this operation is done, the robotic hands will utilize the tactile sensors for further feedback operations.

3) **Grasping contact adjustment**. Since the offline grasping planning depends on the nominal geometrical information, the real grasping process needs some adjustment due to the existence of uncertainties. An important way to deal with uncertainties of the object is to integrate tactile exploration. It should be pointed out that the tactile information about the object is always coarse, such that the lower dimensional sensory representation is adopted, and the sensory noises can be eliminated. When the tactile states with contact-level are obtained, the corresponding adjustment actions are linked to offline grasping planning to some extent and these small movements are for appropriate configurations.

4) **Grasping synthesis and execution**. Finally, by ensuring that the fingers can make contact with the objects with the desired configurations matching the generated grasping contacts and positions, the grasping operations can be executed in real time, such that no further movement occurs between the object and the hand.

Remark 4. It should be pointed out that the concept of

CRIE utilized for the grasping planning stages can be applicable for different grasping control algorithms. In relation to linking the grasping planning and control stages, many motion and force control methods can be applied, such as the well-known hybrid motion/force control algorithm or the impendence control algorithm for mechanical systems.

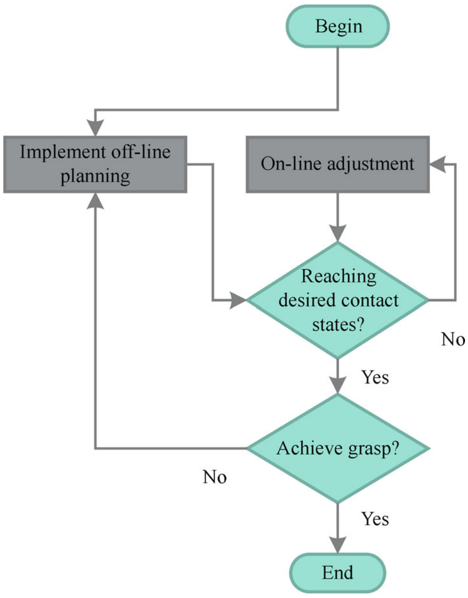

Fig. 3 Grasping planning by CRIE

The generating dynamical grasping in task space can be implemented as described in Algorithm 1.

Algorithm 1. Generating dynamical grasping based on CRIE

Require:

Prior geometry information of the object and the robotic hand

Ensure:

Grasp stability

Processure:

1) Conduct offline grasp planning based on ARIE method such that the desired grasp points and paths can be designed;

2) Find the object to be grasped by visual information such that the robot hand can move to the object;

3) Switch the grasp contact detection approach from visual sensor to the tactile sensors in the position according to the prescribed visual calculation;

4) Find the initial grasp points and grasp the object;

5) Detect whether the grasp contact states satisfy the offline planning;

6) Adjust online by moving the fingers to certain points according to the offline planning.

It is worth mentioning that in our framework, the lack of accurate geometric information of the object can be compensated by relevant coarse sensor feedback, which can provide high-precision grasping and manipulation for various grasping tasks in different environments.

4 Illustrative example

In this section, the feasibility and effectiveness of the proposed grasping planning strategy based on CRIE is demonstrated by the conducted experiments.

4.1 Experimental setting

Our experiment has been implemented with the BarrettHand with tactile sensors and the 6-DOF UR manipulator, shown in Fig. 4, where the manipulator is controlled by the inverse kinematics. Moreover, a vision system is utilized to obtain the location of the target object on the table and the task chosen for grasp is a mug in 2D cases. In addition, the mug is assumed to be stationary throughout the grasps and nominal geometric models are provided for both the BarrettHand and the mug.

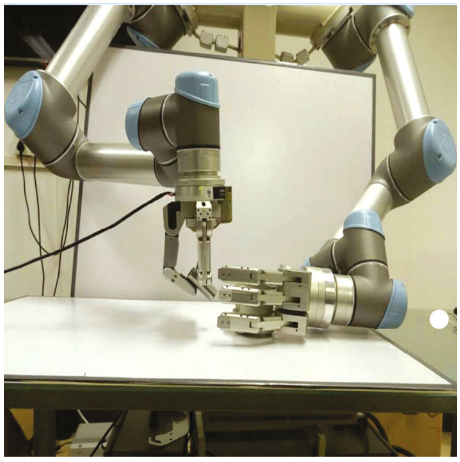

Fig. 4 UR manipulator with BarrettHand

Dexterous robotic hands have larger degrees of freedom (DoF) number and higher sensor information integration than common robot grippers. In this paper, the Barretthand with tendon-driven underactuated fingers is studied for dexterous robotic manipulations. The Barretthand is a three-fingered robotic hand with underactuated kinematic structure. The hand has total 4 DoF and each finger has two coupled joints. Since the three fingers can cooperate with different configurations, more stability and flexibility can be obtained in grasping tasks. Fig. 5 depicts the CAD model of Barretthand.

4.2 Grasping planning

Offline grasping planning:

Firstly, the grasp configuration is determined and the offline grasping planning is implemented in the ARIE framework. Moreover, it is assumed that the mug is initially set statically on a horizontal table and there is no further movement between the mug and the table. The grasp is carried out with a horizontal attitude and all the fingers can move simultaneously, which is depicted in Fig. 6.

As illustrated in Fig. 6, the BarrettHand and the mug are projected on 2-D plane. The essential definitions are introduced in Table 1. Based on the established reference frame, the attractive function can be defined as $S = f(rx, \theta)$, where rx denotes the projection coordinate for the center of the mug and θ represents the angle between the handle of mug and the X-axis. We choose the 2-D area S formed by the final position of the BarrettHand when the fingers touch the mug. The coordinates $A_1(0, d/2)$, $A_2(l_1 \sin\alpha_1, -l_1\cos\alpha_1 + d/2)$, $A_3(l_1\sin\alpha_1 - l_2\sin(\alpha_1 + \alpha_2), -l_1\cos\alpha_1 + d/2 + l_2\cos(\alpha_1+\alpha_2))$ can be calculated as well as B_1, B_2, B_3. Note that l_1, l_2 and d are constant. Thus, by ARIE, the area of polygon formed by the BarrettHand fingers when the fingers touch the mug can be calculated as

$$S = g(\alpha_1, \alpha_2, \alpha_3, \alpha_4).$$

Since the parameters are all relative to rx and θ, S can also be represented as

$$S = g(\alpha_1, \alpha_2, \alpha_3, \alpha_4) = f(rx, \theta)$$

Fig. 5 Structure of BarrettHand

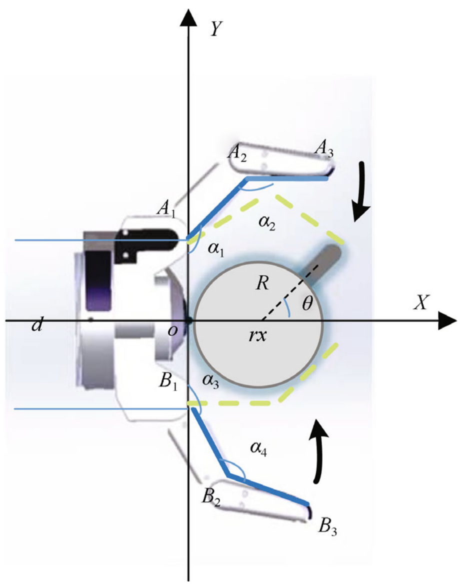

Fig. 6 Grasping configuration

Table 1 Notations

Symbols	Definitions
OXY	Coordinate frame fixed to the BarrettHand, while O is defined as the center of the BarrettHand palm, the axis X is defined as the line from O which is orthogonal to the plane of the BarrettHand palm, and OY is perpendicular to OX and satisfies the right-hand rule.
d	The length of the projection of BarrettHand palm.
l_1	The length of finger line A_1A_2 and the length of finger line B_1B_2.
l_2	The length of finger line A_2A_3 and the length of finger line B_2B_3.
α_1	The angle between finger line A_1A_2 and the Y-axis.
α_2	The angle between finger line A_1A_2 and the finger line A_2A_3.
α_3	The angle between finger line B_1B_2 and the Y-axis.
α_4	The angle between finger line B_1B_2 and the finger line B_2B_3.
x_c	The projection center of the mug.
R	The radius of the center of the projection of the mug.
θ	The angle between the handle of mug and the X-axis.
S	The area of polygon formed by the BarrettHand fingers when the fingers touch the mug and prepare to grasp.
rx	The coordinate of the projection center of the mug.

where S denotes the area of polygon $A_1A_2A_3B_3B_2B_1$. As a result, by denoting the system state as (rx, θ), the attractive region can be provided as shown in Fig. 7, where every point on the attractive region denotes a grasping configuration. Then, since the grasping configuration is located on the attractive region, the mug can be grasped under the squeezing force of the fingers. It should be pointed out that the above grasping planning is based on the nominal geometric models, such that online grasping adjustments should be further carried out.

Online grasping adjustment:

As discussed in the previous section, there always exist uncertainties of the hand and the mug in the real world application scenarios. In order to establish a stable grasp with the uncertainties, once the offline grasping planning is completed, the online adjustments for pre-computed contact points would be implemented.

As illustrated in Fig. 8, an image analysis with coarse visual sensory information is given to aid the initial grasping guidance, such that the BarrettHand can move to the initial contact regions with desired grasping configurations according to the ARIE results.

After the initial touch with visual guidance, the grasping will be switched to the tactile sensor based mode. According to the offline grasping planning, when a contact is not detected by the tactile sensors situated in each finger at the desired configuration, the appropriate adjustment is then implemented to asymptotically track the pre-designed grasping planning sequence. Finally, the fingers would keep closing until the desired contact points can be reached and the uncertainties can be eliminated significantly. Fig. 9 shows the corresponding grasping procedures by the nominal models and the practical applications.

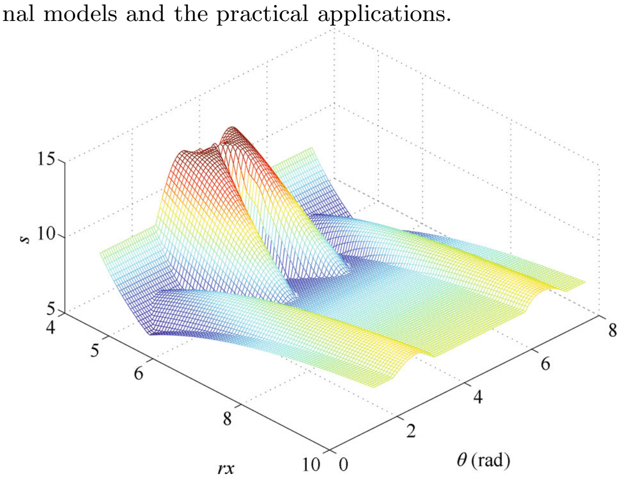

Fig. 7 Attractive regions corresponding to the grasping configuration

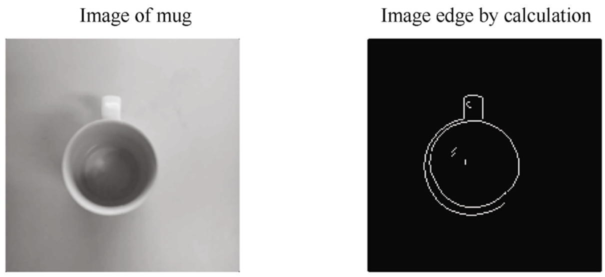

Fig. 8 Calculated edge position of the mug

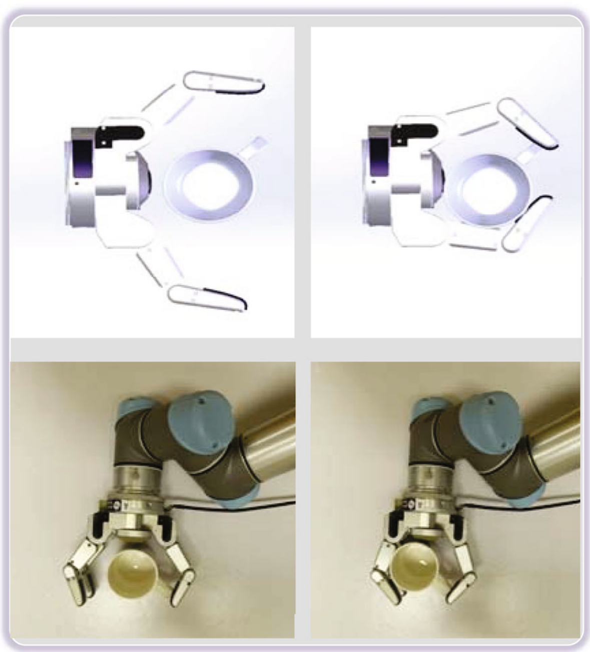

Fig. 9 Grasping procedures by the nominal models and the practical applications

Following similar analysis, other grasp experiments with different mug configurations are also employed, which can be seen from Figs. 10 and 11. These results illustrate that by integrating information of tactile sensors and utilizing the environment constraints, the desired grasping of the dexterous robot hands can be guaranteed.

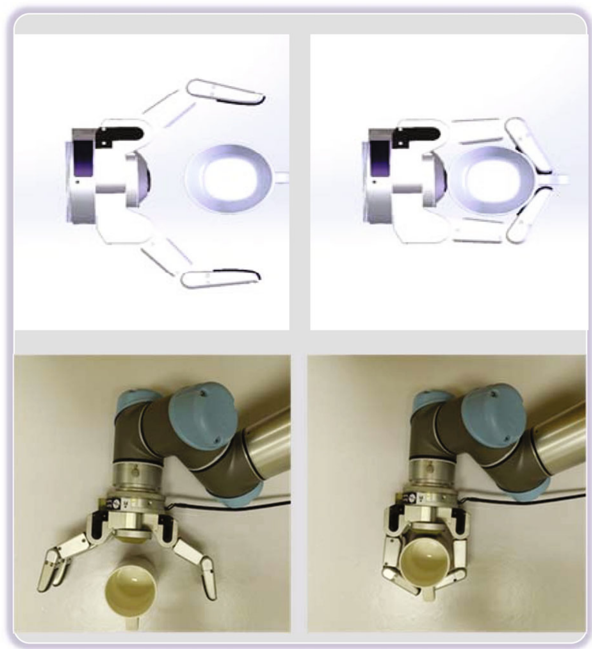

Fig. 10 Grasping procedures with a different mug configuration by the nominal models and the practical applications

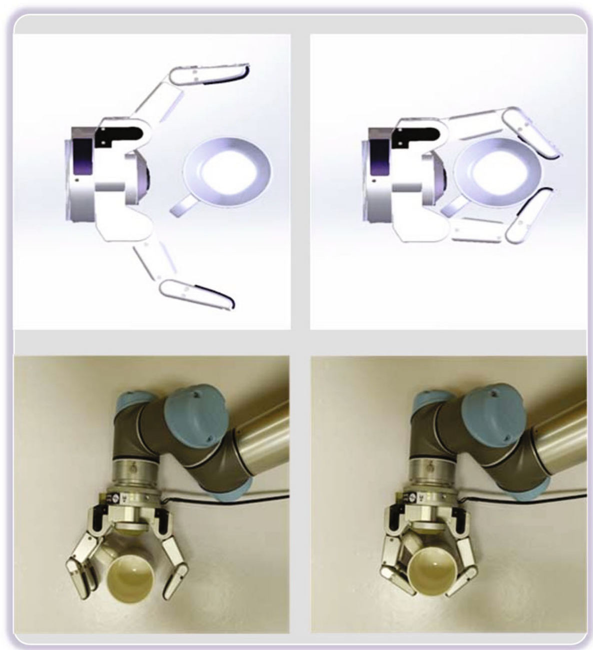

Fig. 11 Grasping procedures with another different mug configuration by the nominal models and the practical applications

4.3 Results and discussions

Based on these experimental results, it can be concluded that our proposed CRIE can demonstrate robust grasping against the uncertainties.

Since an offline planning could not be sufficient for the implementation of the pre-computed grasps, there is a need for relevant adjustment for the fingers.

On the other hand, real tactile sensors are not accurate enough, such that the precise online grasping planning may not be guaranteed. Therefore, various sensory information and environment constraints should be properly integrated to achieve the dexterous grasping tasks. Another point worth mentioning is that there is a trade-off between the adjustment complexity and the model uncertainties, which implies that if there exist relatively large uncertainties of the nominal models, the pre-designed grasping planning sequences may be more difficult to dynamically track, even in some cases the offline grasping planning sequences may fail.

In addition, it should be pointed out that our proposed CRIE can be applied to other high-precision robotic manipulations with low-precision sensory information, such as robotic assembly manipulations, etc.

5 Conclusions and future work

5.1 Conclusions

Biological evidences have revealed the manipulations of the human beings, which can promise to support and investigate the robotic manipulations. In this paper, the bio-inspired framework of constrained region in environment is introduced to deal with the flexible robotic grasping problems for a class of underactuated multi-finger dexterous hands. The primarily key feature of constrained region in environment is the integration of the coarse sensory information feedback and the environment constraints. An effective grasping planning strategy is designed under the framework of CRIE, where offline and online stages are combined for dynamic adjustments to eliminate the uncertainties. With the help of environment constraints, the pre-computed grasping planning can be carried out on the basis of the attractive region in environment. Then, the dynamic adjustment can be implemented to reach the desired contact configurations by coarse visual and tactile sensory information integration, such that the stable grasping can be achieved against uncertainties. In order to verify the effectiveness of our corresponding grasping algorithm, an experiment is provided where the grasping task is with the BarrettHand. The experimental results have shown that the proposed grasping strategy can reach the stable grasp without utilizing high-precision sensory information. At last, it should be noted that the concept of constrained region in environment can be further extended to other robotic manipulations with uncertainties.

5.2 Future perspective

Researches on the flexible robotic manipulations mimicking the human beings never cease. Despite diverse results, there are still numerous points that could be further considered in future work. From a practical point of view, the flexible manipulation of the dexterous robotic hands can be considered as a kind of compliance. As we have successfully performed numerous sophisticated and compliant operations, with this premise, one of the attempts to bridge the existing gaps of the compliant manipulations between the robots and the human beings may be investigating the intrinsic manipulation mechanism of the human beings and developing the corresponding bio-inspired compliant robotic designs. As a final remark for the grasping problem of robots, advanced and intelligent compliant manipulation framework should be employed. In order to achieve this goal, the following points may be addressed to deal with these problems:

1) It is worth mentioning that the dexterity is highly dependent on the hardware designs of the robotic hands. Although simple grippers can be utilized to accomplish specific tasks, there remain considerable difficulties to meet the more general tasks in unstructured environments. Thus, how to design the anthropomorphic robotic hands is quite a challenging problem. Meanwhile, note that the complexity of the robotic hands would also make the corresponding manipulation strategies more complicated. Encouragingly, some remarkable dexterous robotic hands have been reported in the area, which can grasp and manipulate the object with certain compliance. However, it is still far from a satisfying method that could achieve the human hand functionalities.

2) On the other hand, it would also be interesting to implement an appropriate manipulation strategy for the dexterous robotic hands. Since the execution of the manipulation should be robust to the uncertainties, a more intelligent manipulation strategy with perception, planning and control may be a key factor. Moreover, the ability to learn is also required to deal with the scenarios of unknown or partly unknown objects. Although some effective learning algorithms have been developed, yet there remain certain gaps compared with the human beings. With the rapid development of neuroscience, brain sciences and the related cross-discipline science, the corresponding theoretical and practical results of the robotic researches would yield promising results.

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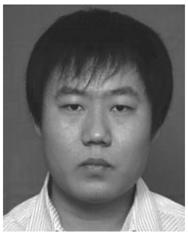

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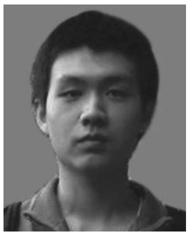

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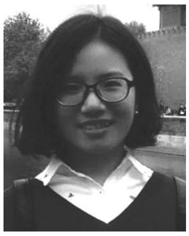

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