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Active Manipulation

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Synonyms

Robotic manipulation, autonomous manipulation, dexterous manipulation, object manipulation, haptic manipulation, tactile manipulation

Keywords

Tactile sensing, sense of touch, object exploration, tactile servoing, force control, motion control

Definition

An intertwined process – in which the feedback signal (perception) may affect the control input (action) and vice versa – of controlling or exploring the location and shape of an object by applying quasi-static (kinematic) and dynamic (kinetic) constraints with a robot end-effector.

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Abstract

Robotic manipulation performed by robots, both manipulator arms and robot-hands, refers to the art of controlling the location or shape of an object through force and form closure contact constraints with one or multiple robot end-effectors. These end-effectors are usually equipped with tactile sensors when the success of robotic manipulation tasks needs to be assured. For example, in a “pick and place” task a robot equipped with vibro-tactile sensors can prevent slippage of the grasped object. This section focuses on tactile aspects of autonomous manipulation.

Introduction

The nature and variety of unconscious decisions that are taken by a human hand during a manipulation task – for example, turning a key or dexterous shuffling cards – have been but slightly explored for intertwined sensory-motor actions Stuart et al (2014); Jeannerod (1984). The human hand is endowed by multiple tactile sensing modalities allowing us to perform dexterous manipulation tasks Shao et al (2016). The sensing characteristics of the human tactile sensing system depend on the mechanics of human skin, e.g, peripheral blood flow or moisture content Bowden and McNulty (2013), on the one hand. On the other hand, these characteristics depend on the type of the manipulation tasks – exploratory movements and in-hand manipulation of a known object involve different types Johansson and Flanagan (2009) of hand mechanoreceptors Kunesch et al (1989). Indeed, in human hand-oriented research, manipulation is an active intertwined process, in which motor commands and perception depend on each other Robles-De-La-Torre and Hayward (2001). In haptics-oriented research, this process refers to the action of touching, and implies self-generated movements to gather information about the properties of surfaces (texture, hardness, temperature) and objects (size, shape, weight, location) Chapman (2009). Findings in these human-centered research shed light on manipulation

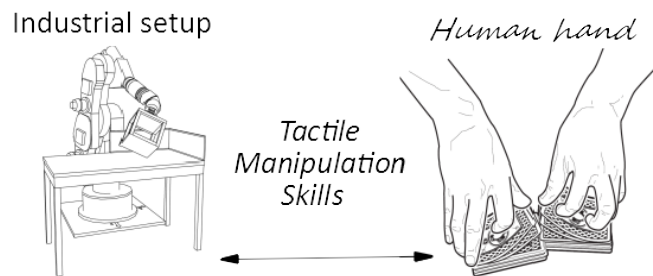


Fig. 1 Examples of human manipulation(adopted from Mason (2001)) and an industrial task(adopted from Lefebvre et al (2005))

processes and yield to novel paradigms in robotic manipulation and industrial automation (Fig. 1).

In the recent literature on robotics, there are different active control approaches:

- active manipulation for point cloud acquisition by touch Petrovskaya and Khatib (2011),
- active manipulation for optimal execution of a contact-rich task Lefebvre et al (2005),
- active motion control for the optimal movement selection in a texture identification task Fishel and Loeb (2012),
- active motion control for the exploration of the location of a physical contact Lee and Park (2014a)
- manipulation for the estimation of physical properties in object recognition tasks Mavrakis and Stolkin (2020)

These control approaches are formulated in the context of classical autonomous manipulator control Righetti et al (2014), including force control and visual servoing, or in the context of machine learning algorithms, including model-based reinforcement learning Tian et al (2019). Recently, manipulation skills of an autonomous robot were obtained by the combination of model-based reinforcement learning and an impedance controller Johannsmeier et al (2019).

These approaches are designed to be deployed on dexterous robot hands endowed with tactile sensors. In this connection, a robot hand design, tactile control and in-hand object localization are discussed in the following sections.

Overview

Many approaches – including feedforward and feedback control, optimization algorithms, e.g. satisfying multiple constraints as in Meguenani et al (2017), probabilistic algorithms, e.g. Bayesian state estimation in Petrovskaya et al (2006), and the most recent ones based on penalty-reward reinforcement approaches Rajeswaran* et al (2018) – are used to solve the problem of object manipulation. Kinematics of rigid object manipulation is described in Murray et al (1994). For the sake of the clarity, the state-of-the-art is summarized in Table 1.

There is a vast collection of industrial end-effectors, including grippers, developed for the manipulation of rigid and soft objects. These end-effectors were designed to be robust and fast during operational cycles, and to be deployed with less efforts in the industrial settings. Two-finger structure of industrial grippers was the choice that satisfied these design criteria. New challenges in consumer manufacturing include multifunctional and reconfigurable industrial line cells that operate and co-operate with human operators in close proximity. These challenges set new criteria on design of the end-effectors – in particular, the new structure of the end-effectors shall be dexterous to enable in-hand manipulation Falco et al (2014); Falco et al (2020).

Table 1 Taxonomy of robotic manipulation based on: the type of interaction – prehensile and non-prehensile, the type of tool used for object manipulation – from underactuated robot hands to redundant manipulators, the type of an object – from rigid to fabric sheet, the type of sensing modality – proprio- and extero-ceptive, and the type of a contact formation – single or multiple contact points, edge- or vertex- contact.

Type	Reference	Type	Reference	
Prehensile	Grasping	Bicchi (2000)	Rigid	Murray et al (1994)
	Pick-and-place	Romano et al (2011)	Soft	Sanchez et al (2018)
	In-hand relocation	Ramon et al (2013)	Deformable	Mazhitov et al (2019)
	Gravity-based	Viña B. et al (2015)	Fabric sheet	Mconachie et al (2018)
	In-hand rolling	Bicchi et al (1999)		
Non-prehensile	Tapping	Kumar et al (2014)	Proprioceptive	Lee and Park (2014b)
	Pushing	Meier et al (2016)	Exteroceptive	Lepora et al (2017)
	Rolling	Kappassov et al (2016)	Multimodal	Wetels et al (2008)
	Gravity-based	Bai and Liu (2014)	Vibro-tactile	Massalim et al (2019)
			Pressure array	Drimus et al (2014)
Type of Tool	Underactuated	Odhner et al (2014)	Single	Berger and Khosla (1991)
	Redundant	Meguenani et al (2017)	Multi-finger	Sommer and Billard (2016)
	Hand	Kappassov et al (2013)	Multi-link	Leboutet et al (2019)
	Gripper	Odhner et al (2014)	Point	Sommer and Billard (2016)
	Non-anthropomorphic	Yuan et al (2020)	Edge	Lepora et al (2017)

In this connection, recent research in the design of multifinger robot hands is being shifted from academic laboratories to industrial settings. Various robotic hands have been developed with different levels of anthropomorphism to reproduce the

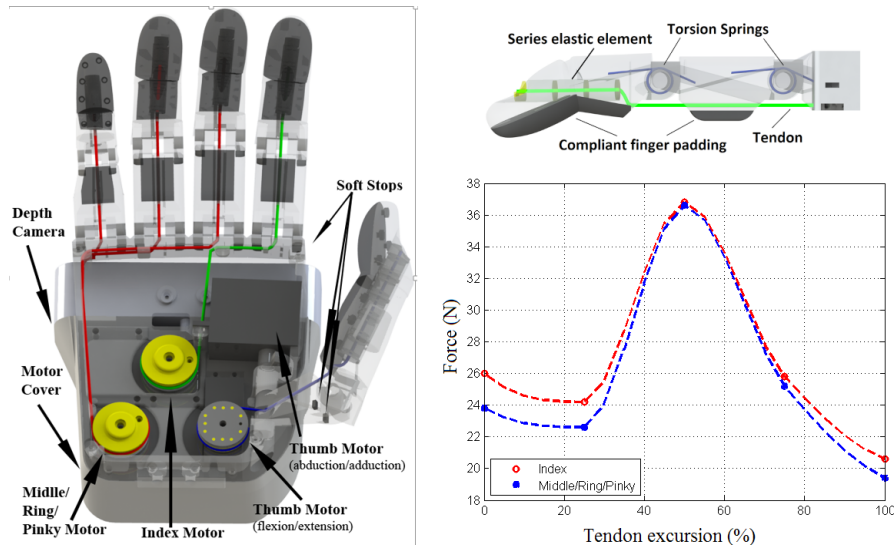


Fig. 2 Robot hand prototype. The figure is adopted from the author's paper Kappassov et al (2013)

human hand functionality. These anthropomorphic robot hands on the contrary to the traditional two-finger grippers can employ multiple grasp patterns, can relocate a grasped object within the hand, and, thus, complete much wider range of tasks Bicchi (2000). Nevertheless, in terms of dexterous manipulation skills, these robot hands are still far from being deployed in the real industrial settings.

Key Research Findings

Robot hands for dexterous manipulation

Let us consider issues and limitations of multi-fingered robot hands based on the design of a laboratory prototype Kappassov et al (2013) shown in Fig. 2.

The prototype hand has an **intrinsic actuation** system – the motors are located within the hand similar to the torque controlled four-finger Allegro Robot hand. These motors could be located outside of the hand (**extrinsic**) as it was implemented in the tendon-driven five-finger Shadow Robot hand (Fig. 6). In the latter case, the robot fingers and palm are relatively closer to the human hand dimensions and smaller compare to the intrinsic approach.

The fingers of the prototype are actuated via **tendons**. This causes **non-linearities** in force control (see the plot in Fig. 2) due to the mechanical friction between a tendon (green tendon in Fig. 2) and its channels within a finger and the palm. In order to mitigate but this does not eliminate the non-linear friction, metal to plastic (self-lubrication) joints can be chosen for guiding the tendons (this is implemented in the last versions of Shadow Robot Hand). The non-linearity can be eliminated by removing the tendons and actuating the finger **within joints**, for example the four finger Allegro robot hand.

The number of **degrees of freedom** (dof) is the quantitative measure that differs the dexterous robot hands from 1 dof industrial grippers. In the prototype hand, middle, ring and little fingers are driven by one motor. Two phalanges of each finger in the prototype hand are underactuated. There are in total 10 dof and four servo-motors. Efficacy of in-hand manipulation with four actuated dof is rather limited. Dexterous manipulation can be achieved with more dof, as for example, the manipulation of Rubik cube with the tendon driven Shadow Robot hand incorporating 24 dof actuated by 20 motors.

High-speed dynamic manipulation can be achieved with high **bandwidth** actuators, e.g. the three-fingered Adamant Namiki robot hand. The majority of nowadays robot hands can operate in quasi-static regime only and inferior to industrial grippers in actuation speed. Particularly, in order to test the position tracking capability – which is equal to 3 Hz only – of the prototype hand, its fingers were commanded to track sinusoidal position signals $\pm 25\%$ of total motion range centered at the mid-flexion point. The hand requires almost a second to close and 0.85 seconds to open.

In order to improve the dynamic range grip **force control** and avoid slippage, a polyurethane rubber is incorporated on the fingers of the Shadow Robot hand. Similarly, a soft padding was added in the hand prototype (Fig. 2). It increases the coefficient of static friction between the hand and a grasped object. For the hand prototype, the average pulling force of a wooden part was 21 N.

Soft padding are also used for enabling continuous physical contact during touch-driven manipulation tasks discussed in the next sections.

Touch-driven Control

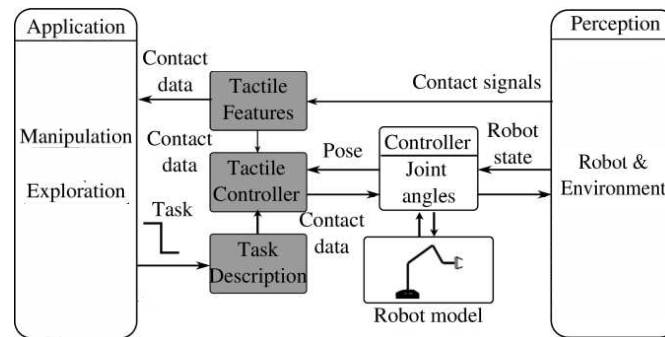


Fig. 3 Robot control block diagram for manipulation (adopted Kappassov et al (2016))

A typical touch-driven robot control block diagram for tactile manipulation is shown in Fig. 3. The controller is designed to convert sensed tactile signals into robot joint movements through tactile data interpretation (tactile feature extraction) and feedback control. Similar to image features in visual servoing Chaumette (2013), there are tactile features that are fed back into a touch-driven controller that is described in this document. The robot joint control part is not considered here. An interested reader may refer to Villani (2013).

In active and semi-active manipulation, the goal is to determine a time sequence of both response actions to the changes at the contacts and control inputs to achieve the desired response, deformation or motion of an object. They involve: 1) actuation skills, i.e. ability to actuate in the environment; 2) tactile sensing skills, i.e. ability to gather signals from physical contacts; 3) precoded or learning skills, i.e. database of desired set-points or capacity to learn for achieving a goal.

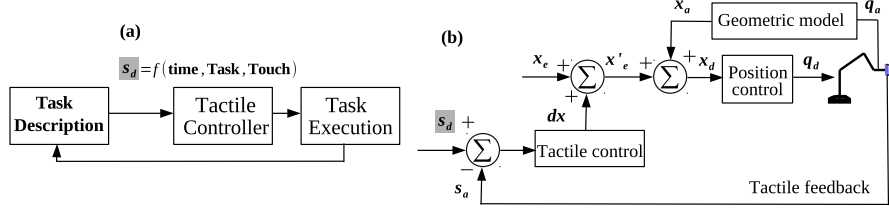


Fig. 4 Tactile control: a) task level, b) controller level.

The main idea in touch-driven control is that the pose of a single or multiple robot end-effectors can be controlled by steering contact points based on errors between the desired (s_d) and feedback (s_a) tactile feature vectors. s_d depends on both task and touch (i.e. contact and its properties). In affordance Chavez-Garcia et al (2016) and reinforcement Rajeswaran* et al (2018) learning approaches, s_d can be retrieved from robot trials in real or simulated worlds. In multiple point control, e.g. in object exploration with multi-finger robot hand Sommer and Billard (2016), this feature vector is given for each robot link. Fig. 4 a illustrates a simplified diagram of a robot controller driven with the desired set of tactile features s_d .

Depending on the response time of a tactile sensor, the error between the desired and feedback tactile features can be used as an event signal in a feedforward controller or disturbance signal for a feedback controller. In most of the cases, the tactile sensors used in the first case have a higher bandwidth than the ones used in the second case. The sensors of the first group can detect slippage Massalim et al (2019), recognize textures Fishel and Loeb (2012) or perform both Massalim et al (2020). The sensors of the second group are used in force control, object exploration and manipulation. There are mainly two types of sensors within this group: force-torque sensors installed on the fingertips of a robot hand (or end-effector) and pressure sensing tactile arrays. Force sensors can provide force and torque values in each direction in R^3 . A contact point location can be estimated from forces when the shape of the fingertip is known Liu et al (2012). Pressure sensing tactile arrays provide information about contact shape and pressure distributions Kyberd and Chappell (1992) – by measuring two-dimensional pressure profile, which is similar to a gray-scale image in computer vision Ho et al (2012). In general, the tactile feature error should be converted into the controller input disturbance, e.g. into the pose disturbance $dx \in R^6$ – so that $dx = \mathbf{Ad}_{\{g\}\mathbf{T}\{s\}}(s_d - s)\mathbf{J}^{-1}$, where \mathbf{J}^{-1} is an inverse tactile Jacobian and $\mathbf{Ad}_{\{g\}\mathbf{T}\{s\}}$ is the adjoint matrix derived from the current forward kinematics to transform the error expressed in the sensing frame $\{s\}$ to the global frame $\{g\}$ – for a robot position controller (Fig. 4) b.

The derived input disturbance modifies the desired set points x_d of the robot controller so that $x_d = x_a + dx$, where x_a is the current pose calculated by the Forward Kinematics of the robot. Finally, corrective motions are performed by moving joints q of the robot interacting with the environment.

In-hand object localization

The number of decisions that can take nowadays robotic manipulation systems is rather limited compare to what humans do in a single manipulation task Mason (2001) (Fig. 1). In the aforementioned touch-driven control approach, a robot does not take decisions for the next action. In the following, we overview one robot control approach that is based on a point cloud acquisition via touch-driven robot arm control Petrovskaya and Khatib (2011).

Let us assume that the shape of an object is known, then its shape can be represented by a set of k points $\{p_k\}^{\mathcal{O}}$, where \mathcal{O} is the objects' frame and p_k are the coordinates of a point k on the surface of the object. These point are depicted in blue in Fig. 5a. Given the geometry of the hand and the signals from tactile sensors, there are n measurements y_1, y_2, \dots, y_n acquired from n tactile sensors at a single grasp. These detected contact points are shown in Fig. 5a (red). The Cartesian transformation from the sensor frame n to the palm frame P

$$A_n y_n + b_n = z_n, \quad (1)$$

where A_n and b_n are the rotation matrix and translational vector, respectively, and z_n is the measurement n in the palm frame. In order to localize the object we need to map the cloud of points of contact $\{y_n\}^P$ to the cloud of points in the model $\{p_k\}^{\mathcal{O}}$ by finding an optimal transformation ${}^P T^{\mathcal{O}}$.

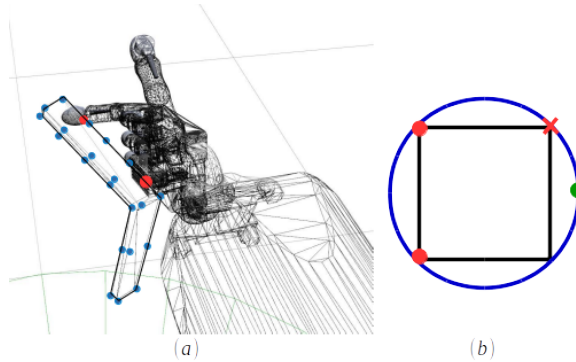


Fig. 5 In-hand object localization: (a) contact points (red) between a robot hand and an object, (b) the area to be explored with the maximum (green dot) and minimum (red cross) distinctiveness.

Let us assume that there are i solutions $[{}^P T_{(1)}^{\mathcal{O}}, {}^P T_{(2)}^{\mathcal{O}}, \dots, {}^P T_{(i)}^{\mathcal{O}}]$, then multiple point clouds similarly describe the object – the mapping between the contact points and the model – at a given grasp of an object. The robot hand will need to explore the object. Hence, a policy for the next best action, i.e. the next location for regrasping, finger gaiting, rolling, or sliding Bicchi (2000), is needed. The next manipulation action should be chosen so that it will be the most informative for localizing the

object. This problem can be solved by probabilistic **Bayes filters** with further Sequential Importance Resampling at each new manipulation action Petrovskaya et al (2006). For the sake of clarity, let us assume that the manipulation is realized via regrasping. Therefore, there can be multiple grasps denoted as G_1, G_2, \dots, G_{N_g} and Z_{G_1} represents the measurements z_1, z_2, \dots, z_n at the grasp G_1 . For a given grasp G_j (where $j = 1, 2, \dots, N_g$), each possible transformation ${}^P T_{(i)}^{\mathcal{O}}$ (where $i = 1, 2, \dots, N_s$; N_s being the number of believes/samples for the grasp G_j) will represent an hypothesis of the state $x_{G_j}^{[i]}$ of the object inside the hand. Then the posterior believe $Bel(x_{G_j}^{[i]})$ given the grasp G_j of this state will be:

$$Bel(x_{G_j}^{[i]}) = P(x_{G_j}^{[i]} | Z_{G_j}) \quad (2)$$

A possible way to calculate this posterior believe is to obtain the sum of all Euclidean distances $d_{G_j}^{[i]}$ between each measurement (or each contact point z_n) and its corresponding object model point p_k for each state i :

$$d_{G_j}^{[i]} = \sum_{\forall n \in G_j} \|z_n - {}^P T_{(i)}^{\mathcal{O}} \cdot p_k\| \quad (3)$$

and later obtain the probability of this state (i.e. sample) as the ratio of its inverse distance to the sum of all the inverse distances in all the states (samples) of a given grasp G_j :

$$Bel(x_{G_j}^{[i]}) = \frac{1/(d_{G_j}^{[i]})}{\sum_{i=1}^{N_s} 1/(d_{G_j}^{[i]})} \quad (4)$$

A more complex – presumably, more reliable – way would include the mapping between tactile features (for instance, the orientation of an edge in the tactile image) and not contact points only. At any next grasp G_{j+1} , probabilities of some of the states will increase or decrease. Then those states that will have higher probabilities will be **resampled** and the ones with lower probabilities will be dropped out.

Defining the policy for the next grasp is a rather challenging task. One of the simplest solution is to find for each finger such a new contact point on the surface that would give the maximum differentiation between all the considered states of the object. An example is shown in Fig. 5 b: the current points of contact are depicted as the red dots; in order to classify the shape whether it is a circle or square, the next contact point to test should be at the location of the green dot rather than at the location of the red cross, which would provide a higher distinctiveness (i.e. discrimination).

Future Directions and Challenges in robotic manipulation

In this section we discussed the robot hand design on one hand, and its control on the other hand. Particularly, we have reviewed the foundation of touch-driven robot control for active manipulation. There is an intersection with the literature covered in classical motion and force control, e.g. Siciliano and Khatib (2008).

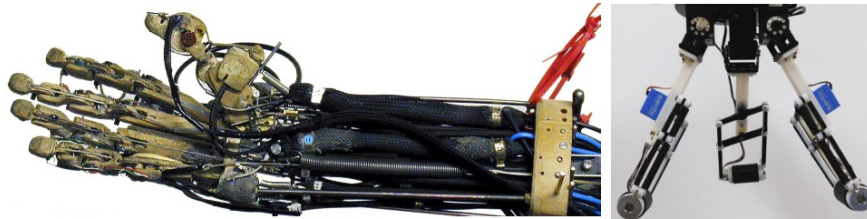


Fig. 6 Biomimetic (left, provided by Richard Greenhill) and non-biomimetic (right, Yuan et al (2020)) hands.

The problem of robotic manipulation remains a key challenge in robotics due to both the lack of reliable dexterous robot hands and durable tactile sensors. In this connection, in the manipulation-oriented literature, there are no approaches with the ability to finely and dynamically manipulate an object within a multi-fingered robot hand. Indeed, these capabilities shall be considered during both the manufacturing of robot hands and design process of touch driven controllers. Non-linearity of tendon-driven mechanisms, trade-off between the bandwidth of actuators and the dynamic range of force control, number of dof, and the life time of the robot hands are some but not all issues that set constraints on truly dexterous manipulation.

In the past century, one of the first dexterous robot hands was made from wood (Fig. 6). With injection molding and rapid prototyping technologies, robot hand mechanisms have been improved in terms of backlash, lubrication, durability. Nevertheless, the computational power of the current processing units and advances in control theory, e.g. reinforcement learning algorithms, are ahead of the capabilities of both the robot hands and tactile sensors. In the future, these sensors and robot hands will need to catch up with the computational power to let the future robots be capable of dexterous manipulation of objects used in manufacturing environments by human operators.

One of the potential solutions for in-hand robot manipulation is based on development of non-anthropomorphic end-effectors Yuan et al (2020). These non-anthropomorphic robot hands incorporate fingertips with active contact surfaces, e.g. gecko skin Hashizume et al (2019) or a DC motor actuated fingertip Yuan et al (2020) as shown in Fig. 6. The active surfaces allow robots to perform robust pick-and-place tasks of tiny objects.

Cross-References

Haptics and Haptic Interfaces, 19; Physical Human-Robot Interaction, 26; Tactile Sensors, 115.

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