Bioinspired Embodiment for Intelligent Sensing and Dexterity in Fine Manipulation: A Survey

Yueyue Liu, Zhijun Li, *Senior Member, IEEE*, Huaping Liu, Zhen Kan, and Bugong Xu

***Abstract*—Recent advances in fine manipulation have led to increased interest in both scientific research works and engineering applications. Robot manipulation at a level approaching human skills is gaining attention in both industrial and individual services. A major challenge in fine manipulation is the unavoidable uncertainties and unpredictable conditions encountered in dynamic and unstructured application environments. The employment of biologically inspired (bioinspired) embodiments in fine manipulation shows significant advantages in tackling such problems. The aim of bioinspired embodiment is to improve fine manipulation of robotic systems utilizing the knowledge gained from natural systems with biomimetic methods. Such a method includes sensing, planning, and execution. This article provides a comprehensive survey of the current state of bioinspired technologies in fine manipulation, and outlines new challenges and some potential directions.**

***Index Terms*—Bioinspired embodiment, execution, grasping, manipulation, planning, sensing.**

I. Introduction

THERE is a growing need for robotic systems to provide assistance and services. In manufacture, robots are replacing human labor to perform tedious and repetitive works. In health care, robots are being used to facilitate surgery and rehabilitation. The success of these applications highly relies on the robot's capability of performing fine manipulation [1], i.e., the ability of performing manipulation with high precision and stability. Although many robotic systems are built to be robust and intelligent, their capabilities of performing fine manipulation are still not comparable to humans.

Inspired by the advances in biology such as neuroscience, biomechanics, animal physiology, and systems biology, bioinspired embodiment is a recent research focus in robotics [2], [3], which aims to utilize the knowledge and biomimetic methods gained from nature to improve the design and control of robots. The main idea of bioinspired embodiment is to develop technical solutions by imitating the natural models, systems, and processes [4]. Bioinspired manipulation, robot design, learning and control, and manufacturing are all typical applications of bioinspired embodiment, which integrate knowledge from physical morphology and materials [5], biology system [6], and cognitive and executive processing [7]. Recent advances in biological systems have led to new and innovative designs in a variety of domains such as sensors, materials, mechanics and mechanical systems, robotics, computers, and computing. These new designs significantly facilitate the development of robotic systems with desired properties inspired from biological organisms, such as adaptivity, robustness, versatility, and agility [2].

Because of the advantages listed above, bioinspired manipulation has attracted great research attention [8]–[11]. However, the environmental uncertainty and task complexity impose great challenges to bioinspired manipulations. To address these challenges, robots are desired to perceive external information to improve the intelligence and dexterity of manipulation. Based on bioinspired embodiment, fine manipulation has been a key breakthrough in advanced robotics.

Fine manipulation research with the goal of attaining bioinspired embodiment with intelligent sensing and dexterity is deeply connected to research in computer vision, control theory, dynamics and kinematics modeling, machine learning, etc. In [12], a feedback control was designed for a multisegmented arm to achieve lightweight/soft actuation with variable impedance. In [13], a grasping control strategy was developed for an underactuated anthropomorphic robotic hand in a synergy-based framework. In [14] and [15], based on surface electromyography (sEMG), biological signals were adopted to perceive the fine manipulation environment.

Fine manipulation requires the operation to be accurate, robust, and user friendly. To meet these requirements, a desired manipulation system needs to perceive the environment, plans the motion trajectory, and successfully executes the operation. The dexterity of fine manipulation refers to the capability of manipulating objects for various task purposes [16]. The

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robustness of fine manipulation refers to the ability of successfully manipulating an object in the presence of disturbances (unexpected forces, erroneous estimates of the object characteristics, etc.) [17]. Fine manipulation also needs to be user friendly, so that desired tasks can be easily completed by human operators [18]. It is worth pointing out that these characteristics coexist in most applications.

In this article, we summarize the challenges of bioinspired embodiment systems and different fine manipulation methods. The remainder of this article is organized as follows. Section II presents the state of the art and operating mechanism of bioinspired embodiment. Section III introduces the bioinspired robot topology and mechanical designs. Section IV reviews the recent development of sensing systems. Section V presents the existing research on grasping and manipulation, including planning and execution. Finally, Section VI concludes this article.

II. State of the Art of Bioinspired Embodiment

Typical bioinspired design methods and tools that address the principle of bioinspired embodiment in the design of bionic robots are listed in the literature of [68]–[70]. Robotic manipulation systems are often controlled to complete generic tasks by executing a series of specific motions. For example, in [19], when considering a dexterous grasping of rolling objects, the sensing information collected during manipulation was used to reconstruct the shape of the object, facilitating the planning and control of the manipulator to grasp the object. Other examples of fine manipulation can be found in [20]–[22].

In the examples of fine manipulation given above, some properties of the object, including its shape, center of mass, and other poses, need to be considered, and the external environment needs to be measured or observed with the available sensors (e.g., vision sensors and tactile sensors) to attain intelligent sensing and dexterity.

Bioinspired robots can be generally classified according to the modes of biological locomotion, such as multileg walking robots inspired by human beings and animals with feet and legs [23], crawling robots inspired by vertebrates [24], wall-climbing robots inspired by geckos [25], and swimming robots inspired by sea creatures in [26]. Essentially, these bioinspired robots are developed to replicate the human or animal motions. However, biological functionalities are hard to be replicated, mainly due to the lack of the knowledge about the mechanism of biological functions and appropriate technologies. To address this challenge, advances from mathematics, mechanics, electronics, computer science, and biomimetic technologies are adopted to enable bioinspired embodiment behaviors close to human or animal motions. In [27], the manipulation behaviors of bioinspired embodiment were generated from interactive dynamics of manipulators and continuous interactions with the environment through information processing. Fig. 1 shows the operating mechanism of bioinspired embodiment. First, the mechanical system is driven by the motors to perform manipulation tasks, which will generate mechanical feedback such as pressure, torques, and poses. In parallel, external stimuli and internal physical stimuli will be sensed by the bioinspired robot.

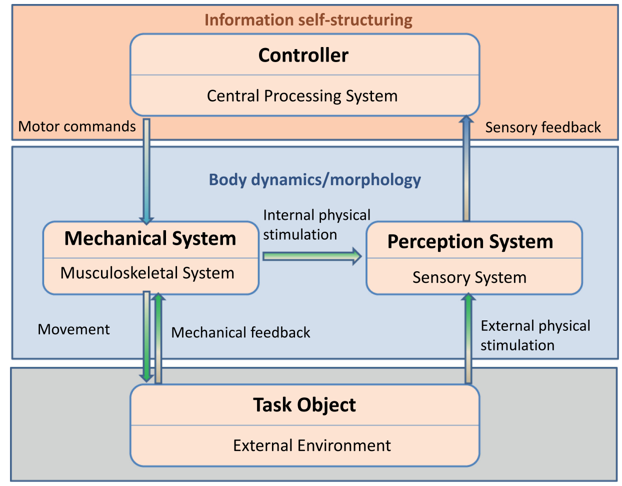

Fig. 1. Operating mechanism of bioinspired embodiment [2].

Since the behaviors of the manipulation task are sensory-motor coordinated, motor commands and compliance may be modified dynamically according to the sensed environmental information.

Bioinspired manipulations can be generally classified into the following categories.

1) Passive Mode: In this mode, the human hands are the object to a fixed manipulator. For example, a tactile perception strategy was presented in [10] that used tactile sensors in its gripper to measure tactile features of an object while safely manipulating it. In [28], a general measure of the contact stability of a two-fingered grasp was proposed, which considered the contact points of the object in the presence of disturbances. In [29], the optimization of grasping forces in handling of brittle objects based on a special three-fingered gripper was presented. In [30] and [31], the robotic hands manipulated the object blindly and performed actions such as pressing and squeezing, based on the sensing of feedback from the actions of squeeze, hold, slow slide, and fast slide. Such passive modes have been widely adopted in intelligent sensing tasks for various object materials.

2) Semiactive Mode: In this mode, objects are usually fixed, and the manipulation system detects and manipulates the object according to a specified trajectory and performs exploratory tasks. In a representative work [32], the object grasping process was divided into three steps: 1) lining up open robotic fingers with some preshape of the object; 2) planning the path trajectory and moving the fingers until the contact of the object; and 3) performing exploratory processes such as press or squeeze before the termination conditions are met. Since the exploratory procedures in such a mode are designed in advance, uncertainties in the manipulation process can lead to system instability.

3) Active Mode: In this case, the manipulator can actively perceive and manipulate the object, exhibiting more flexibility and intelligence. In [33], a bag-of-features framework was presented, which utilized tactile-image descriptors to extract the surface information of an object, enabling the developed robotic hand to autonomously grasp objects. In [34], the Bayesian inference was used to solve the intelligent identification of object texture before manipulation. In [11], by integrating the robot's manipulation and sensing capabilities, a learning algorithm was presented to detect a previously unknown object and learn its visual appearance. Among these manipulations, intelligent sensing was adopted to better extract the object features. However, efficiently integrating sensing with manipulation in a unified approach has not been largely investigated.

4) Interactive Perception (IP) Mode: The IP mode is inspired from the human perception behaviors [35], which leverages active explorations and interactions with the environment to address robust perception and guide manipulation behaviors in robotic grasping planning [36]–[38], manipulation skills learning [39]–[42], and object pose estimation [43], [44]. IP has two characteristics. First, new perceptual signals can be generated by physical interactions. Second, it makes the prediction and interpretation of the new signal more simple and robust than using the knowledge obtained from the traditional combination of perceptual data and action parameters.

III. Bioinspired Robot Topology and Mechanical Designs

Since it is challenging to replicate biological functionalities to bioinspired robotic systems, a natural question is how and which natural biological knowledge should be leveraged to facilitate the design of bioinspired robots. Motivated by this challenge, a large volume of literature seeks the joint use of the manipulator and sensors to achieve fine manipulation. For instance, in [47], bioinspired engineered systems were designed by using connecting rods, bearings, and pressurized fluid actuators to model the bones, joints, and muscles, respectively. More examples of bioinspired robots will be presented in this section.

A. Robot Hand Design Mechanisms

Aiming at enhancing the manipulation capabilities of mechanical hands, the design of anthropomorphic mechanical hands has attracted growing research interest. From the point of view of function and phylogeny, human hand grasping can be divided into precision and power grips [45]. The precision grip can be widely found in primates such as humans or marmosets for manipulating small objects through the tips of the thumb and fingers. This kind of grip generally requires stability-independent finger motion, which involves finely controlling the directions and the amount of the fingertip force. In contrast, the power grip uses all fingers in a palmar grasp and all fingers are bent around the object [46]. The design principles of bionic hands are often inspired by the aforementioned two grasps.

In [47], the Utah/MIT hand was built with tendon operated fingers with multichannel touch sensing capability. The fingers have three parallel axis joints and a proximal joint, which can be independently controlled by eight tendons and actuators per finger. The actuators were mounted in the upper arm and can be operated pneumatically to control the tendons. In [48], a three-fingered bionic hand was developed, and the fingers are actuated by 11 dc actuators. Equipped with a pair of antagonistic tendons, each finger is driven by a single motor. In [49], a biomimetic robot hand was developed based on parallel mechanisms, which has four underactuated fingers. The fingers were coupled by two linear actuators. Besides the aforementioned robotic hands, many other bionic hands are inspired by the characteristics of human hand that the tendons help bend the fingers while flexor and extensors produce the motion of the fingers.

Despite substantial progress, most existing bionic hands are either too complex or too bulky to use. The idea of designing intelligent mechanisms to simplify control has been explored in the literature. In [50] and [51], joint compliance was addressed to grasp objects of different shapes. In order to achieve intelligent sensing and dexterity, soft skin was developed to help mount embedded sensors, enabling flexible gripping [52].

Since human hand manipulation task requires proper tendon and muscle force, the forces transferred by human finger are focused on flexion. The results in [53] showed that the two distinct tendon structures can achieve a force range similar to that of human fingers. This study concluded that the design of force and moment arms of a dual tendon driven finger could achieve a similar muscle force produced by a human finger. In [54], a design principle of anthropomorphic mechanical fingers that can reproduce the grip of a human hand was proposed. The mechanism of tendon transformation works in a way that the primary motion is achieved via an actuator while the secondary motion is implemented with mechanical compliance matching statistic parameters of human motion. Moreover, the motion transmitting mechanism is embedded in the palm of the anthropomorphic hand, and the posture cooperative characteristic of the finger is reproduced by using a limited number of actuators.

B. Actuation

The motion of traditional robots mainly relies on electric motors or pneumatic/hydraulic actuators. Although they can generate large forces and precise positioning, these actuators are often of large size and do not exhibit muscle-like properties of human, due to their considerable mass, inertia, and friction. Natural muscles have high power-to-weight ratios, inherent softness and damping, fast motion, and high dynamic range. They can also generate joint displacement and force without requiring gears or extra hardware. Researchers have been working to create artificial muscles that have the desirable properties of natural muscles [55]. In order to achieve similar functions to biological muscles, many artificial muscles have been developed, such as ionic polymer-metal composites [56], dielectric elastomer actuators [57], shape memory alloy (SMA) actuators [58], shape memory polymer actuators [59], and supercoiled polymer actuators [60]. These artificial muscles materials primarily use one of three mechanisms: electroactivation, photoactivation, and chemical activation. For instance, the SMAs was used to develop mechanical devices with mini-actuators [61]. Other shape memory materials were also successfully used in the design of a variety of robots [62], [63].

Despite recent advances in artificial muscles, artificial skeletal muscles have not been largely explored. With the aim of performing close to the natural muscle-skeletal system, elastic elements are introduced to the mechanical structure of robotic systems. As indicated in [64], tendon and muscle elasticity can not only enable robust interactions with the environment but also

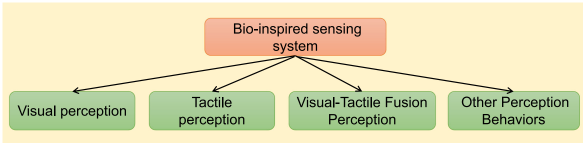

Fig. 2. Categorization of bioinspired sensing behaviors.

efficiently perform dynamic and oscillatory tasks. Elasticity can endow robots with the ability of performing tasks with increased efficiency, peak performances, and mechanical robustness. Generally, there are two main branches in terms of robot compliance. The first branch involves robots made of continuously flexible materials. Analogous to invertebrates, the compliance is distributed in the whole structure [65]. The other branch is inspired by the muscle-skeletal system of vertebrates, in which the compliance is mostly distributed on the joints [66], e.g., serial elastic actuators [71] and variable stiffness actuators [72]. Such robots are typically referred to as articulated soft robots or compliantly actuated robots.

IV. Bioinspired Sensing System

In Fig. 1, the robots need to perceive both internal (forces, torques, accelerations, etc.) and external information (pressure, temperature, position, etc.) based on the sensing system. Using the sensed movements, poses, disturbances, etc., the motor can, then, act accordingly. Intelligent sensing is a key component that allows complex robotic systems for various applications. Sensing feedback from the interactions between the manipulator and the environment provides a basis for fine manipulation.

A bioinspired robotic system usually has multiple sensors to perceive the internal and external information due to the complexity of tasks and environments. For example, for the bioinspired mobile manipulator system in [27], a binocular vision camera and two force/moment sensors were utilized to perceive the position and force information in real time. Visual and tactile perception are typical sensing for grasping or manipulation tasks. Biological signals perception is also applied for fine manipulation. Fig. 2 shows the categorization of bioinspired sensing behaviors.

A. Visual Perception

Bioinspired vision sensors are widely used in applications ranging from simple photosensitive devices to complex binocular devices. With the help of machine learning and modern computers, visual perception is essential for manipulation tasks as it provides a wealth of information necessary for fine manipulation.

Feature extraction and matching are the cores of robotic visual perception research, and early studies mainly focus on the approaches of model-based matching. In [73], perceptual organization was adopted to form features to reduce the matching dimension of the search space and the spatial correspondence. In [74], the paper presented an extended modeling and parameter solution through least squares to estimate the curve object, which utilized the Levenberg–Marquardt method to ensure the solution convergence. A more sophisticated method was developed in [75], which used color histograms to estimate the poses of objects. Although those methods could estimate the poses, there are still some limitations: the perspective distortion of the sensors and the variations of color can significantly influence the algorithm; similar objects are hard to be distinguished by using histogram-based approaches; and geometric models require a high precision for edge detection, thus restricting its application to general objects.

Over the past decades, affine invariant local descriptors were adopted to capture the appearance of patches on the surface of objects. In [76], the descriptors of three-dimensional objects and their spatial relationships were obtained by using multiple view geometry constraints, which could achieve object recognition and pose estimation under highly cluttered scenes. In [77], scale-invariant feature transform (SIFT) descriptors were proposed for feature extraction, which were robust to rotational deformation. In [78], an RGB-D sensor-based visual-target detection for a wheelchair robot in indoors environments was developed, in which the Haar-like descriptors were extracted. These local descriptors were robust for rotation, distortion, brightness, and also can reduce computation complexity. However, these descriptors heavily rely on the texture of the objects. If an object does not have texture details, these methods can be inefficient. To address this issue, in [79] and [80], a combination of color segmentation and normal descriptors was developed, which solved object recognition problem by only using its geometric shape. The work of [81] presented an approach to learn the explicit shape model from images labeled by a bounding box. The learned model can identify the boundaries of a variety of objects, regardless of extensive clutter, scale changes, and intraclass variability.

However, the general vision-based recognition and/or estimation has not been fully solved. Typical challenges are to define the behaviors that can be captured by vision sensors, and how the visually perceived information from images and videos can be used in fine manipulation.

B. Tactile Perception

Unlike visual sensing, tactile sensing can directly perceive the physical properties of an object (e.g., softness, force, texture, and temperature), allowing humans to physically interact with their surroundings. As early as the 1980s, the experiments of local anesthesia in [9] showed that human tactile perception was important to steadily grasp objects. This study found that the grasping manipulation depends largely on the grip force applied to the object. For example, it would not generate any relative sliding between the skin and the gripped object if a proper force is applied, while a large grip force can result in deformation or damage of the gripped object.

1) Biological Tactile Sensing Systems: Microneural recordings of human peripheral neuronal signals indicate that there are four different types of tactile afferents in human hand [82]. They are fast adapting type I (FA-I), slow-adapting type I (SA-I), fast adapting type II (FA-II) and slow-adapting type II (FA-II). FA-I is sensitive to high-frequency dynamic skin deformation, while the SA-I is sensitive to low frequency dynamic skin deformation. The human afferents of type FA-I are more than that of SA-I in the fingertips. The FA-I afferent function is a response of detecting transient mechanical events. When a hand-held object touches or breaks contact with other objects, hundreds of FA-II afferents distributed throughout the hand are activated. The SA-II afferents react to the distal transverse stretching of the skin and are sensitive to the tangential shear strain of the skin when the object is manipulated.

In biological systems, properties of interest, such as contact points, pressure, torsion, normal, and abnormal forces (stress), are measured in dexterity due to the changes in strain and skin tactile element network topology. As described in [83], the FA-I and FA-II signals are the main sources to detect fingertip sliding and contact with new objects while loading process is largely regulated by SA-I. At present, most of the robot experimental systems cannot directly measure SA-II signals, which respond to tangential loading. Many of SA-II signals are obtained through expansion. The type of SA-I afferent mainly responds to low-frequency stimulation and is generally used to estimate the current fingertip force. FA-I is considered as the most important indicator of force disturbance, while FA-II is considered as the main tactile channel for human to perceive the interaction between objects and their contact surfaces, which can be used to detect hand vibration. Therefore, the three sensory channels can be used to create an advanced robot grasping manipulation to simulate human tactile operation [125].

2) Tactile Perception Applications in Fine Manipulation: In many examples of robotic manipulation, such as grasping, lifting, and safe interaction, tactile sensing plays an important role in the following two aspects: 1) The detection of action-related information, such as slipping [84]; 2) and providing control parameters in manipulation and grasping tasks, such as texture, softness, and temperature [91], [86]. The above aspects are two important components of many robots fine manipulation tasks, making the tactile perception mode crucial for the utilization of the next generation of robots.

Tactile perception in robotic manipulation is essential for the recognition and cognition of objects or environments properties. In [85], the tactile perception of objects was divided into three categories: shape, surface texture, and the deformation. These above properties are widely used for the planning of manipulation tasks. In [87], a sensor system with 64 tactile sensing modules tactile was developed to measure the distance and classify objects using dynamic time warping (DTW) and the nearest neighborhood classifier, respectively. These methods can perform well in certain circumstances, however, only the sensing information of an individual manipulator or finger is considered, without jointly considering the perception information of different manipulators. To address this issue, in [88], sparse coding and dictionary learning were applied to provide a new unified tactile perception processing approach, which can effectively improve the object recognition accuracy.

For humans, both the proprioception and touch sensing are highly utilized when performing haptic perception and fine manipulation. Inspired by the haptic perception model, in [89] and [90], a novel method, namely iterative closest labeled point, was presented to link the kinesthetic cues and tactile patterns fundamentally. Combining the proprioception and touch sensing has great potential to enhance robot perception ability.

C. Visual-Tactile Fusion Perception

Robots are often equipped with multiple types of sensors to perform manipulation tasks. Just like human manipulation, we have the experience of "touching to see" and "see to feel" [92], [93]. For example, before manipulating an object, we first see it with eyes to feel its features (e.g., shape and texture), and, then, estimate the tactile perception. When an object is grasped, the visual feedback of the object can be obscured by the hand, and, thus, the visual features become nonobservable and ineffective. The tactile perception in the hand, then, helps us to "see" the features of the object. Through the above visual and tactile mechanisms, we can "see" or "feel" objects. Neuroscience and psychophysics have studied the sharing mechanisms between visual and tactile perception [94]. It has been found that visual imagery is involved in the tactile discrimination of orientation [95]. The human brain also uses shared model with multiple sensory patterns, such as visual and tactile perception, so that the sensed knowledge can be transferred between each other [96]. This synthesis sharing is especially useful when one of the perceptions is not available. Inspired by the synthesis of vision and tactile sensing in humans, vision and touch modalities provide complementary information. Combining the two modalities could have a synergistic effect, where features in the environment can be perceived, which might not be available from a single sensing model.

However, it remains a challenge for models to understand the relationship between different visual-tactile perspectives of objects and data structures. To achieve the integrated visual-tactile perception, visual-tactile fusion perception mainly focuses on data, features, and decision-making [97]. In [98], researches have shown that the receptive areas of the human visual cortex are sparsely coded to extract meaningful information. Inspired by this observation, sparse coding algorithms applied in visual-tactile perception have also been developed rapidly in recent years. In [101], the joint sparse coding approach was proposed as a valid method to deal with multimodality information fusion. In [102], the idea of combining visual information with tactile information was proposed to classify the surface material using a novel deep learning method. These methods benefit from the sparse coding technique and can characterize the intrinsic relationship among different modalities to share the common sparse patterns. There exist various methods to solve multitask or multimode fusion problems by utilizing joint or structured sparse representation. These methods can achieve good robustness and accuracy because sparse coding can characterize the intrinsic relationship among different modalities to share the common sparse patterns. Recently, cross-modal perception has also been investigated in visual-tactile fusion perception. In [99], a transfer learning method was proposed to improve the accuracy of cross-modal recognition. This approach was proposed to address the problems of common representation and descriptors selections for visual and tactile sensing. In addition, for the exploration tasks in fine manipulation, it is important to combine vision and tactile sensing to localize the object contact through matching tactile features with visual map. In [100], the integration of vision and tactile sensing by localizing tactile readings in a visual object map was proposed. Prominent features bridge the vision and tactile sensing, facilitating the fine manipulation.

D. Other Perception Behaviors

Although a variety of sensors are available, there still exist perceptions that cannot be easily sensed. Recently, biological signals have been used to perceive human's motion intention and assist the estimated motion in real time. In [103] and [104], sEMG was used to manipulate a series of tasks consisting of tracking/recognitioning/grasping of an object. In [105], the electroencephalogram was applied to enable the robot to perform manipulation tasks guided by the human operator's mind. To better classify the sensing behaviors, in [14], a method based on the Bayesian theory patterns classification was proposed. However, the biological perceptions face a common challenge including latency, low-dimensional user commands, and asymmetric control inputs due to the difficulty of decoding biological activity. To address these problems, the combination of visual or tactile perception and biological signals were proposed. In [106], the visual sensing and brain machine reference commands were effectively integrated. In [111], a tradeoff between the computer vision and the user intent inference schemes were proposed. This system can perform quality-of-life fine manipulation tasks such as opening a door, pouring liquids from containers, and manipulating objects previously unknown to the system in densely cluttered environments.

E. Deep Learning for Perception

Robotic sensing is paramount for fine manipulation. Traditional sensing methods are through signal processing and feature extraction (e.g., DTW [87], Sparse Coding [33], principal component analysis [142]). However, those methods have weak generalization ability and poor robustness to disturbances. Recently, deep learning [143] has been widely applied in robotic vision and tactile perception from object shape recognition, pose estimation, and hardness estimation to sharing features with vision [148]. Deep learning is derived from neural network, which is inspired by the central nervous system (CNS) (especially the brain) of primates and humans. It has been widely used in computer vision for visual perception, such as object classification [107], detection [108], localization [109], and segmentation [110]. Recently, the deep learning has also been gradually applied to the fields of tactile and visual-tactile perception. In [112]– [115], the deep learning was used for shape recognizing, hardness estimation, material classification, and grasp slip detection. Most of these works use a convolutional neural network (CNN) trained by thousands of examples, or use long short-term Memory (LSTM) layer for sequential information, which has been proven to be able to overcome the limitations of traditional sensing approaches.

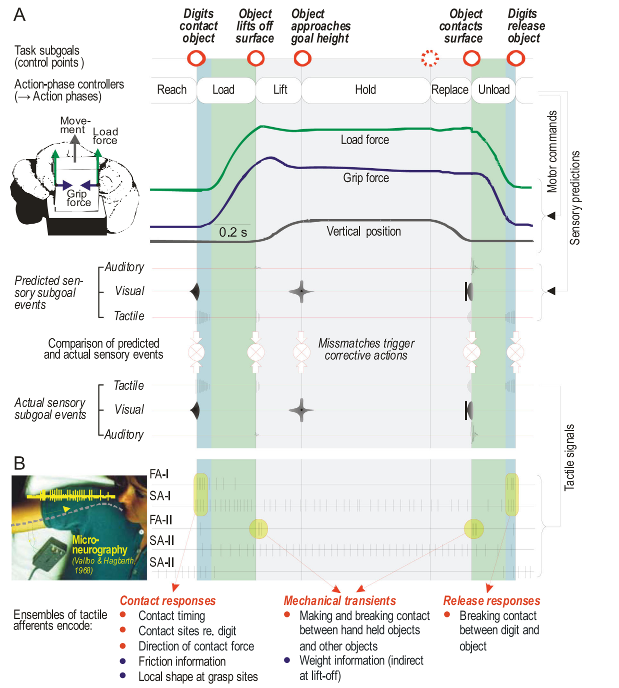

Fig. 3. Human sensorimotor control in an object manipulation task [119].

V. BIOINSPIRED ROBOT GRASPING AND MANIPULATION

The task of human grasping and manipulation has been studied by a large number of neurophysiological and behavioral research works. In order to manipulate the object, human should have the abilities of action understanding to achieve the internal description of the action and utilize it for appropriate future behavior [116]. Two types of hypotheses are proposed for the action understanding. One is "visual hypothesis," which states that action understanding is based on a visual analysis of different elements that form an action without considering motor involvement [117]. The other is "direct-matching hypothesis," in which the visual representation of the observed action can be mapped onto human motor representation of the same action [118]. Both of these hypotheses suggest that the process of grasping and manipulation can be seen as a series of sequential phases. Each phase is characterized by a specific sensorimotor behavior and parallel activation of various muscle groups. Fig. 3 shows an example of a human manipulation task including lifting, holding, and replacing a box on a tabletop. In Fig. 3, the manipulation task involves several action phases, which consist of a series of contact events. The first stage of the task is the initial reaching phase, which is marked by the fingers contacting the object. When a finger touches the object, the grasping force increases while the tangential force applied on the object increases synchronously to overcome gravity. If the load force exceeds the gravity, the object will rise and loose contact with the desktop. The grasp and load force would decline until the object releases. These contact events depend on the corresponding sensing events, which are characterized by specific afferent neural signals in tactile or visual morphology (sometimes include auditory sensing). Such sensing signals provide guidance for subsequent control of continuous manipulation phases, which produce the motor command. In addition, each action phase controller plans the sensory events to realize subgoals.

It is necessary to keep the object stable during manipulation without slipping, rolling, or losing contact with the manipulator even in the presence of uncertain disturbances. The manipulation force should also be regulated properly to enforce safety for both manipulators and environment. Inspired by the humans grasp and manipulation, the vision system and the mounted sensing arrays are used to mimic human visual and tactile signals, respectively [125]. Based on the theories of human sensorimotor control [119], [82], two key points should be addressed: planning and execution. More details and examples can be found in the surveys of [1] and [120].

A. Planning of Grasping and Manipulation

According to Fig. 3, the object manipulation task consists of a serious of subgoals. One of the most important issues is to predict sensory subgoal events and the desired sensing behaviors. As reviewed in [121], the grasping properties include contact surface, texture, and weight. All of these factors determine the kinematics of grasping. For example, heavier objects require greater grasping force. Compared to grasping objects with rough surfaces, grasping smooth objects demands greater grasping force. In [16], [29], [84], [122], and [123], these early planning efforts focused on the optimization of the grasping force of robotic hands, in which the planning problem was formulated to minimize a cost function with a set of constraints, such as friction constraints and force balancing constraints. The main purpose is to get the grasping matrix, which describes the relationships between the velocities and forces at the contact points, and those mapped at the center of the object mass. However, those approaches usually require the knowledge of the object properties in advance while the hand-object system is often assumed as quasi-static.

Since planning the grasping force only is not sufficient for complex environment, sometimes it is necessary to plan the contact positions on the objects as well. Planning the grasping configuration is important. The contact points of the robot hand should perfectly match the local geometry of the object, so that the contact areas between the manipulator and the object can be maximized to improve the grip stability. In [124], the developed fingertips can match the local geometry of the object by adopting soft materials to optimize the residuals, while other methods define the task frame with respect to the available sensors. In [18], [21], and [27], the manipulations were performed under a vision-based manipulation system, in which the task frame is considered as fixed to a point on the object that can be observed by the vision system. However, many object properties may change [125], e.g., the weight of a cup changes as it is being gradually filled up. The environment can affect friction coefficients to cause potential rolling or slipping. Due to the environmental influence, it is prohibitive to know the system properties *a priori*. Therefore, the grasping manipulation needs to perform more proper adjustments to modulate the planning.

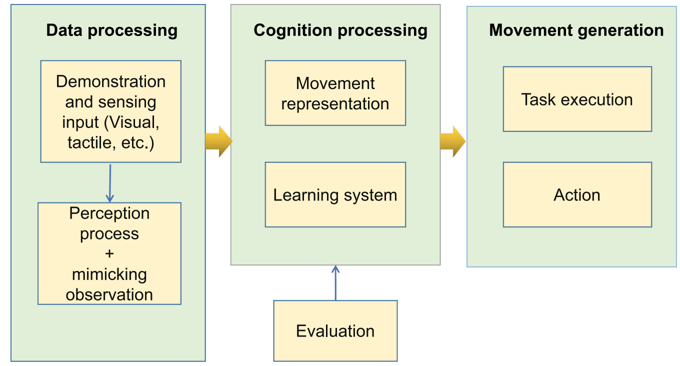

Fig. 4. Architecture of imitation learning in robot manipulation.

Recent neurophysiological evidence suggests that observers can reproduce action effects by mapping visual information into their previously learned knowledge, thus achieving the goal of understanding [116]– [118]. Such observation indicates that learning from previous knowledge is important to grasp a previously unknown object. To plan an effective robotic movement to achieve fine manipulation, like human manipulation in complex environments, the "learning by demonstration," which is also referred to as imitation learning was introduced. Fig. 4 shows an architecture of imitation learning in robot manipulation. A typical example of imitation learning is shown in [152], where the system perceives a sequence of high-level operations from human operations and transforms them into a serious of commands for modeling. In imitation learning, the movement demonstrated through human guiding can adapt to the robot kinematics and dynamics. Imitation learning has been widely applied to not only replicate the human demonstration, but also learn from the representative knowledge of the robot and generate the "skill" for different tasks. A number of special methods are summarized in Table I.

B. Execution of Grasping and Manipulation

The research on manipulation execution mainly focuses on the design of control algorithms, aiming to compensate for external disturbances and achieve desired planning configurations. Various control algorithms have been proposed for bioinspired robots including multifinger hand, bionic arm and biped robot. These control algorithms can be roughly classified into two groups: the hybrid position/force control [126] and impedance control [131].

1) Hybrid Position/Force Control: As shown in Fig. 3, the human grasping process consists of six action phases (e.g., reach, load, lift, hold, replace, and unload). The switching of position and contact force exists in two adjacent phases. From a simplified mechanical viewpoint, it is similar to hybrid position/force control that regulates position and forces explicitly to control the interaction between the manipulator and the object [82]. One of the most typical examples is presented in [125], where a simple

TABLE I
METHODS OF PLANNING/PROGRAMMING TRAJECTORIES

Approach	References	Characteristic
Spline or wavelets fitting	[149], [150], [151], [153], [152], etc.	Easy for imitation learning, can autonomously scale the splines in space and time for generalization but not easy online modulation when the execution is perturbed by noise.
Gaussian mixture models (GMM), Gaussian Mixture Regression(GMR), hidden Markov models(HMM)	[156], [154], [155], [157], [158], etc.	Can learn a skill manifoldly and provide fast on-line replanning of the motion in case of of spatio-temporal perturbations, can generalize a novel nonlinear motion dynamics.
Dynamical movement primitives (DMP)	[130], [159], [160], [161], [162], [27], etc.	Encoding the desired trajectories robustly for nonlinear dynamical systems, can learn techniques from nonparametric regression for shaping the attractor landscapes based on the demonstration, can represent and generate new motion sequences by reinforcement learning and statistical methods, and can be combined in a dynamic way according to the demonstrated trajectories.

proportional derivative controller was developed for position control and a force controller was used to produce the desired position and velocity. In [127], a feedback force controller was designed for Dynamical movement primitives (DMP) trajectories tracking. The proposed hybrid position/force control was developed for compliant movement primitives without requiring explicit models of task dynamics. In [128], a bionic arm robot was used to manipulate a rigid object for vibration suppression through hybrid position/force control. Hybrid position/force control employs a position controller for approaching. However, once the end-effector contacts the object, then it will switch to a force controller. Such a switch is necessary, since the controller relies on the dynamic characteristics of the robot and the contact environment, which can change between the noncontact and contact states.

In order to solve the transition problem between position and force control, in [129], a parallel position/force controller with a tradeoff was adopted to enable smooth transitions between the position controller and the force controller. Recently, in [22], a parallel position/force controller based switching approach was proposed. In this approach, the switching process learned by a probabilistic model can be obtained according to the distance between the target and the hand poses. Although the parallel position/force controller could deal with transitions between the position control and the force control, only limited uncertainties are considered during the manipulation execution. In addition, the constraints are imposed on the grasped object rather than on the robot's configuration.

2) Impedance Control: It has been suggested that the sensorimotor system could control the impedance of the neuromuscular system [132], [133]. In the presence of unmodeled dynamics, (e.g., sudden perturbations) the neural feedback pathways may be insufficient to maintain stability [134]. In the normal grasping process, the grasping stiffness is almost entirely derived from the natural impedance-like behavior of the muscle, which is utilized by the CNS to produce a strong response to rapid interference. Therefore, humans can perform dexterous manipulation, even if there are significant feedback delays between the CNS and the muscles [135]. Drawing inspiration from the human impedance behavior, impedance control has been widely used in fine manipulation. In [136] and [137], impedance control modulated the interaction force implicitly by specifying the impedance of the object. Generally, the impedance control works better when the stiffness and damping characteristics against external forces are known, i.e., the impedance for a given task is specified. Such approach does not require precise offline planning and has strong adaptability to the transition between free motion and constrained motion. Usually, impedance control in manipulation can be divided into a joint space and an object space, and the latter is more suitable for robust grasping and dexterous manipulation. In [138], a global compliant manipulation for a dual-arm 7-DOF cooperative manipulators was achieved using impedance at three levels, i.e., object, end-effector and body level. All of them could converge to the desired position in free motion until a stable equilibrium position is reached when interacting with the environment.

However, when the specification of impedance is uncertain, impedance control shows poor force tracking ability, which may limit its potential applications. To specify the proper impedance for a given task, in [17] and [139], the approaches of analytical impedance specification and impedance learning were proposed. In [67], the manipulator was treated as an uncentralized impedance controller while the object was treated as a centralized impedance controller. This method can obtain a desired impedance, which includes not only the motion of the object with respect to its environment but also the motion of its manipulator with respect to the object (indirect internal force control). For low-stiffness actuation manipulation, for example, in [140] and [141], variable impedance control was adopted. In such manipulation processes, the proposed methods first assumed an imperfect manipulation dynamical model, and then learned the stiffness setting trajectories based on gain scheduling. The impedance control could achieve desired dynamic behaviors by adjusting feedback gains.

3) Summary: In general, the hybrid position/force control approach divides the task space into two separate spaces in which the force and position can be individually controlled. To handle the grasping or manipulation transition between position and force control, parallel position/force controller was proposed. While impedance control approach does not require precise offline planning, it has strong adaptability to the transition between free motion and constrained motion. To deal with the model uncertainties, recently many intelligent control methods have been applied in bioinspired robot manipulation. Such approaches mainly deal with nonlinear and uncertain dynamic models, but they depend on the choice of parameters in terms of system convergence, stability, and robustness.

VI. Discussion and Conclusion

Intelligent sensing and dexterity in fine manipulation have been widely developed for bioinspired robots. This survey reviewed recent research about sensing and manipulation, and discussed the advantages and disadvantage of existing methods. The bioinspired dexterous hands and sensing systems were driven by artificial muscles and controlled by advanced cognitive technologies. In this section, the existing open issues and potential future research directions are discussed.

A. Design of the Bioinspired Robot

The design of bioinspired robots should consider various factors that may implicitly or explicitly influence the robot behaviors. For instance, the performance of manipulation system can be affected by its morphology (i.e., the shape of its body and limbs, as well as the type and placement of sensors). Simply applying methods from control engineering may not yield desired performance. Compared with human hand, many existing designs of manipulators are still inefficient and lack of adaptability. Most of the bioinspired robots have complex hardware structures, but they can only perform under certain circumstances due to the limitation of the mechanical materials and structures. This is because biological systems are more capable than most engineered systems [68]. Although the dexterous manipulation has been well understood and well documented in the literature, few existing robotic hand systems can have full dexterous manipulation abilities as humans.

As animals exploit the deformability of soft structures to move efficiently in complex natural environments, soft bioinspired robots could be the next generation of advanced robots. These soft structures may have soft bodies and actuators (e.g., tendons, muscles, and ligaments), sensing systems (deformable tactile sensors such as electronic skin), and will be able to perform soft movements or soft interaction with people. However, there are still many challenges in developing soft bioinspired robots, including materials, design, and system integration. Although the engineering principles of conventional robots are well studied, new challenges arise when considering soft bioinspired robots. First, it demands advances in sensors, actuators, energy, and propulsion technologies. Second, the designed modular systems need to be well integrated to enable full cooperation and functionalities. Advances in soft materials are also demanding for bioinspired robotic technology.

B. Bioinspired Manipulation

From the control perspective, robot is a time-varying nonlinear and strongly coupled system with many internal or external constraints. The following problems need to be handed.

1) Most tasks cannot be planned in advance due to the changing manipulation tasks and unmodeled disturbances.
2) The exact dynamical model of robots is often not available.
3) The incurred noise and delays in information exchange when integrated complex sensors and multilayer software are considered.

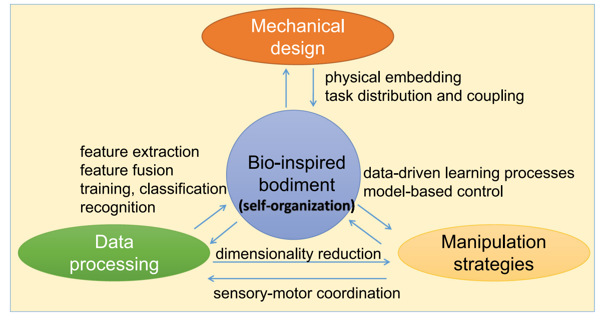

Fig. 5. Implication of bioinspired embodiment in fine manipulation.

Since traditional control theories may not be applicable, specialized control methods are desired to address these issues.

With the development of artificial intelligence and bioneuroscience, machine cognitive methodologies can be extended to improve the capabilities of bioinspired robotics. Deep learning, reinforcement learning [144], deep reinforcement learning [145], and other machine learning methods have been adopted to allow robots to learn complex manipulation skills from the interactions with the environment and human operators.

In [146], a grasping approach based on instance segmentation and self-supervised learning pose estimation network was proposed. The implementation of the proposed grasping approach shows a high success rate. In [147], an approach to hand-eye coordination for robotic grasping from continuous servoing mechanism based on CNN was presented, which can effectively grasp a wide range of different objects, including objects previously unknown during training. Unlike traditional manipulation methods, this kind of grasping considers the model of the robot and the object, without requiring any force analysis of the grasping process.

However, practical real-world applications of machine learning have limitations. Reinforcement learning often requires long interaction with the system to learn complex skills—typically weeks or months of real-time execution, and in the process of training, the controller may exhibit sudden and chaotic behavior, leading to logistical complications and safety concerns. There are also limitations on the robotic execution environment, the training data collection, and the generation for other tasks and platforms. The learning methods remain unclear whether such approaches could be adapted to real systems given their sample complexity. The most important issue is that there is no stability guarantee in theory. Since many manipulation tasks require real-time operation, combining traditional perception and manipulation methods with machine learning is a promising direction to pursue.

C. How to Implement the Bioinspired Embodiment

As shown in Fig. 5, the operating mechanism of bioinspired embodiment includes three parts: mechanical design, data processing, and manipulation strategies. For the mechanical design, the behavior of a system is not only the result of some internal control structures, but it is also affected by the physical environment, morphology, and material properties of the system. In addition, the mechanical design of body morphology and material properties are mutually affected. Because all components of the system are coupled (e.g., movement capabilities have to match those of the sensory systems), the task distribution and coupling should be considered. The process of the data is mainly involved with the information processing, which consists of the sensory information and motor commands self-structuring. Many fine manipulation tasks often have highly sophisticated sensory-motor coordination, which means that the problems of processing potentially large amounts of information in real time should be addressed. For example, feature extraction, fusion, training, classification, and recognition are needed in sensing process. As for the manipulation, there are mainly two kinds of solutions. One is data-driven learning method and the other is model-based strategy. Based on the neuroscience and biology, understanding and analyzing biological systems across diverse scales is becoming more and more important. Therefore, dimensionality reduction plays a key instrument to implicate the bioinspired embodiment in fine manipulation.

D. Conclusion

In conclusion, a review of bioinspired embodiment intelligent sensing and dexterity in fine manipulation has been provided. Due to the space limitation, many other issues were not discussed, such as the bioinspired material, and the design of a friendly interface with human or other manipulators. In the end, we also discuss the future trends and potential guidelines about the bioinspired embodiment intelligent sensing and dexterity in fine manipulation.

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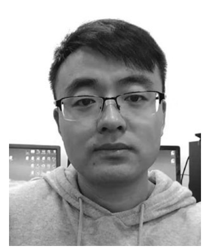

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