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Improving performance of robots using human-inspired approaches: a survey

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Abstract Realizing high performance of ordinary robots is one of the core problems in robotic research. Improving the performance of ordinary robots usually relies on the collaborative development of multiple research fields, resulting in high costs and difficulty to complete some high-precision tasks. As a comparison, humans can realize extraordinary overall performance under the condition of limited computational-energy consumption and low absolute precision in sensing and controlling each body unit. Therefore, developing human-inspired robotic systems and algorithms is a promising avenue to improve the performance of robotic systems. In this review, the cutting-edge research work on human-inspired intelligent robots in decision-making, cognition, motion control, and system design is summarized from behavior- and neural-inspired aspects. This review aims to provide a significant insight into human-inspired intelligent robots, which may be beneficial for promoting the integration of neuroscience, machinery, and control, so as to develop a new generation of robotic systems.

Keywords human-inspired intelligent robots, brain-inspired intelligence, decision making, visual cognition, musculoskeletal robots

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1 Introduction

Robots play an increasingly significant role in the transformation process from conventional manufacturing to advanced intelligent manufacturing. With strong demands of modern manufacturing for high precision, complexity, and diversity, realizing high-performance robots in manipulation becomes an urgent problem. To complete a high-precision manipulation, a robot generally needs to have a better system precision (mainly including sensory precision and repeatable accuracy) than the manipulation task. For example, in the peg-in-hole assembly task, high-precision visual sensor is used to detect the accurate position of the hole. After calculating the assembly trajectory of the peg, high-precision encoder is adopted to calculate the position coordinates of the peg. The control torques of robot are calculated according to the error between the current and the target coordinates, which is used to adjust the movement of the robot arm and eliminate the posture error, so that the position of the peg can track the desired assembly trajectory to complete the assembly.

However, the performance of current robots in high-precision manipulation is normally limited by the perception accuracy of sensors, repeatable accuracy of robotic systems, and the performance of auxiliary mechanisms. Improving the performance of a robot in high-precision manipulation relies on the collaborative development of multiple research fields such as machinery, materials, control, chips, and information science, resulting in high cost, long development cycle, and even making it impossible to complete some high-precision tasks. This restricts the promotion of robotic applications to a great extent, especially in countries where independent robotic technologies are still in the development stage

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or even in infancy. Therefore, realizing the high performance of ordinary robots has become one of the core problems in the research field of robotics, which is also the main bottleneck of their wide application in advanced manufacturing. Under the current conditions, it will be of great significance to make full use of existing robotic systems with limited repeatable precision and limited sensor precision for achieving high-precision manipulation.

In response to this challenging research, improving a robotic system by mimicking the mechanisms of humans is a promising avenue. Human beings have been a long-term reference for the development of robots. Numerous great inspirations have been brought into the design and improvement of a robot by mimicking the biological structures, neural mechanisms, and behavioral characteristics of human beings. Compared with computers and machines, humans have limited computational-energy consumption and low absolute precision in sensing and movement control of each body unit. However, humans can realize extraordinary overall performance that is better than the independent performance of each body unit under such limited condition. It is because humans can process and fuse information from different brain regions and leverage the flexibility of their own structure. For example, in terms of perception and cognition, humans are particularly skilled in the recognition of complex objects in open environments, even if the target has interference factors such as camouflage, ambiguity, and deformation [1]. As for decision-making, the rational decision-making capacity (slow channel) of humans is good at inferring the causal relationship, and their instinctive decision-making response (fast channel) is beneficial for taking a quick action to adapt to a dynamic and complex environment [2]. In terms of motion control, humans can realize movements and manipulations with high precision and flexibility by efficiently controlling the highly-redundant and rigid-flexible coupling musculoskeletal system [3].

Therefore, integrating the internal mechanisms of humans into a robotic system by referring to the information-processing mode of the brain and structural mechanism of the movement system is promising. By mimicking the appearance, structure, behavior, intelligence, and control mechanisms of humans, research on human-inspired intelligent robots may be of great enlightening significance and promising for the development of new generation robots.

In recent years, owing to the instinct of exploring humans and the urgent demand for treating mental diseases, many countries around the world have put forward brain projects to support the research on brain science [4, 5]. It provides an important opportunity for further interdisciplinary research on brain science, information science, and robotics. Typical national brain projects are outlined as follows.

- In April 2013, the United States launched the "Brain Research through Advancing Innovative Neurotechnologies" (BRAIN) project [6]. This project aims to exploit novel technologies for brain science, including developing new tools to map the brain structure, exploiting large-scale neural network electrical activity recording technology to explore the dynamic function of the brain and promoting data processing and analysis technology for neuroscience.
- In October 2013, as one of the "European Commission Future and Emerging Technologies Flagship", "Human Brain Project" (HBP) received funding of 1 billion euros to conduct research on the brain and brain-inspired technologies [7, 8]. The primary goal of HBP is to increase human understanding of the brain and to build information, modeling and supercomputing technology platforms needed for simulating the human brain. It is expected to bring new insights for the prevention and treatment of brain diseases and form advanced computing technologies for new revolution of industry and economy.
- In September 2014, Japan launched "Brain Mapping by Integrated Neurotechnologies for Disease Studies" (Brain/MINDS) [9, 10]. The brain research of Brain/MINDS mainly focuses on marmosets. By establishing the animal models of development and disease occurrence in a marmoset brain, and constructing brain structure and functional maps of non-human primates, this project aims to accelerate the research on human brain diseases, especially for neurodegenerative diseases.
- In May 2016, the Ministry of Science, ICT and Future Planning of Korea announced the "Korea Brain Initiative" [11]. This initiative is planned to invest 300 million dollars to develop Korea into a powerhouse in brain research by 2023. The research and development goal of Korea Brain Initiative is mainly focused on four essentials: developing novel neurotechnologies for brain mapping, constructing brain maps at multiple scales, reinforcing artificial intelligence and exploiting personalized medicine for neurological disorders.
- In September 2021, the Ministry of Science and Technology of China released a major project on "Brain Science and Brain-Inspired Intelligence", marking the official launch of the China Brain Project. The project proposed a scheme of "one body, two wings", in which the basic research on the neural-circuit mechanisms of the cognitive function is the main body, and the brain-disease diagnosis/intervention and

brain-inspired intelligence technology are the two wings [12]. The research results may have important radiative effects on the treatment of mental diseases, self-exploration of human, artificial intelligence, and robotics.

Note that the brain projects of various countries have put forward the important deployment of brain-inspired intelligence, that is, promoting the artificial intelligence technology by leveraging the research results from brain science. Brain-inspired intelligence is committed to mimic the mechanisms of brain neural circuits and cognitive behavior by means of computational modeling, and integrating development of software and hardware platforms. It aims to promote the machine intelligence to realize human-level cognitive and coordinative ability in a brain-like way, and finally, reach or surpass human intelligence. Although the current level of brain-science research is still far from completely understanding the structure and function of the human brain, the research results of the brain that neuroscience has achieved could potentially address some significant problems faced in artificial-intelligence research from several perspectives.

As an important part of brain-inspired intelligence, human-inspired intelligent robots could serve as an integrating platform to integrate and verify achievements of brain-inspired research. By deeply interdisciplinary integrating robotics, artificial intelligence, brain science, and neuroscience, research on human-inspired intelligent robots can get inspiration from the mechanism of brain circuits and structural characteristics of the motor system. It is helpful to design new types of intelligent robots with robust cognition, accurate decision-making, flexible movement, and autonomous learning ability through computational modeling, and combination of software and hardware. The research direction of human-inspired intelligent robot attempts to integrate the internal mechanism of the human body into the robotic system, so as to improve the cognitive, learning, and motion control abilities of the robot and provide an experimental platform to verify new mechanisms discovered by neuroscience. Owing to the introduction of human mechanisms, human-inspired intelligent robots are promising to realize empathy with human, and generate deeper interaction and cooperation.

However, several substantial differences exist between the existing robotic systems and humans in their morphological structure, control mechanism, and functional characteristics. Therefore, modeling the structure and mechanism of a human in intelligent cognition, decision-making, dexterous operation, and fusing with robotic system is not straightforward. On the one hand, in terms of mechanism modeling, summarizing the core mechanisms from massive neural mechanisms and diverse behavioral patterns of humans is still a bottleneck problem. These mechanisms are expected to improve the performance of robots in cognitive, decision-making, motion control, and human-machine cooperation. However, it poses an urgent need for interdisciplinary cooperation of neuroscience, information science, and robotics. On the other hand, limited by the technological development of fields such as materials, machinery, and chips, simulating the neural mechanisms and compliant-motion structures of humans to form a computable and realizable software and hardware system is still the core difficulty in developing human-inspired intelligent robots.

At present, research is being conducted on human-inspired intelligent robots from two perspectives. The first perspective is based on the behavioral mechanism, and research is conducted according to the functional requirements of the robot. For the required functions, cognitive, decision-making, and control algorithms are established by observing and analyzing the appearance and behavior of humans, so that the robot can exhibit a human-like behavior. The second perspective is based on the neural mechanism, and robotic research is conducted by mimicking the neural circuits and body structures to investigate the internal mechanism of humans and improve the performance of robots. By referring to the research results of brain science, the neural mechanisms and motor properties that have been clearly elucidated in the biological domain are modeled, forming brain-inspired information-processing algorithms and rigid-flexible coupling musculoskeletal systems. This may lay the foundation for developing next-generation robots.

In this review, cutting-edge studies on human-inspired intelligent robots in decision, cognition, motion control, and system design will be summarized from behavior- and neural-inspired aspects. The remainder of this review is organized as follows. Section 2 will introduce a human-inspired decision method for robots, including the theory of "attractive region in environment (ARIE)" inspired by human operation behavior and emotion-modulated decision making inspired by neural mechanisms. Section 3 reviews the research progress of robotic cognition based on its requirement of balance between accuracy, energy efficiency, and speed. Manifold learning and cognitive models based on the visual-cortex mechanism are taken as representative work to illustrate the research progress. Section 4 summarizes the research achievements on humanoid robotic systems and movement-control methods, especially focusing on a musculoskeletal robot inspired by the human neural mechanism and musculoskeletal system. Finally, Section 5 concludes this review and presents the prospects of future work.

2 Human-inspired robotic decision making

With the wide application of robots in industrial manufacturing, medical and health care, deep space exploration, and other fields, high precision, flexibility, and generalization have become the key characteristics and important indicators of robotic manipulation.

The traditional robot mainly relies on the design of auxiliary mechanism to achieve high precision high compliant manipulation [13], and on sensor-based autonomous methods including goal-oriented movement planning and torque calculation [14]. For example, in high-precision assembly tasks, the position and attitude errors of a workpiece are corrected by the robot using visual information [15, 16]. In other operation tasks involving touching movement between the agent and external environment, the active and passive compliance can be realized by designing the auxiliary flexible mechanism [13] or a hybrid controller based on force-sensing feedback [14]. However, the structural design increases the cost of hardware, which makes it difficult to generalize for different complex scenarios. The autonomous strategy and control highly depend on the precise structure and perception.

With the rapid growth of advanced artificial intelligence technology, some studies have investigated complex robotic manipulation tasks, such as grasping irregular-shape workpieces and assembly of parts, by formulating intelligent deep reinforcement learning methods [17]. However, these methods rely on a lot of learning and iteration, and the learning process is unexplainable, which reduces the reliability of the algorithm.

Although the traditional method has fruitful applications in the realization of high-performance robot operation, it has several issues, which are listed as follows.

(1) The traditional method for realizing high-performance manipulation requires highly precise robotic configuration, control, and sensing. On the one hand, improving the accuracy of the configuration increases hardware cost [14–16]; on the other hand, the precision of control depends on the optimal design of related parameters and real-time feedback of system information, which increases the complexity of the algorithm [14, 18]. In terms of the accuracy of sensors, affected by zero drift and space disturbance, the reliability of sensors is difficult to be guaranteed. Therefore, formulating a new method is necessary to reduce its dependence on sensors, configuration, and control with high precision.

(2) The generalization of the traditional method is limited. It is mainly used for operation scenarios with limited types of objects, acquainted model, and structured environments, and the task-specific design makes the end-effector less adaptable to different objects and environments. Therefore, to improve the generalization and application range of the robot for different operating objects and environments, studying the common characteristics of manipulated objects is necessary.

(3) Traditional methods focus on the pursuit of single performance. For compliant operation tasks, the flexibility and compliance of the end-effector to the environment can be improved by designing auxiliary devices or force control; however, this design will reduce the position stiffness, thus degrading the accuracy of the operation [15, 19]. In addition to compliance and accuracy, the efficiency needs to be addressed in the robot operation. For example, in some streamlined assembly scenarios, robots need to complete the splicing of workpieces within a certain period of time to meet the production requirements [20]. Therefore, the robots need to achieve the balance between various performance indicators, such as accuracy, flexibility, and efficiency, as far as possible according to different requirements in the actual operation task.

With the development of brain science, the humanoid intelligent strategy has been significantly studied by scholars. To improve the robustness, autonomy, and generalization of the robot strategy, a large number of studies have formulated intelligent methods by simulating the human behavior and neural mechanism of brain [21]. For example, inspired by the accurate manipulation of assemblers that rely on environmental constraints, Qiao et al. [22, 23] proposed a robotic manipulation strategy based on the concept of ARIE, to make the robotic assembly achieve high performance while reducing the dependence on accurate configuration control and sensing. In addition to the ARIE-based strategy designed by imitating an external behavior mechanism, it is of great significance to construct a brain-like intelligent decision-making model that imitates the neural-regulation mechanism to improve the ability of the strategy and

Table 1 Overview of human-inspired robotic decision making

Human-inspired robotic decision making			Ref.
Inspired by human utilization of environments	Type of tasks	Grasping	[26, 27]
		Localization	[28, 29]
		Assembly	[30–35]
	Requirements	Low contact force requirement	[34, 35]
		Imprecise sensing requirement	[33, 34]
	Robotic systems	Fanuc	[23, 27, 28, 30]
		KUKA	[34, 35]
		YASKAWA	[33]
		Universal Robots	[26]
Inspired by human neural mechanisms	Neural mechanisms of emotion modulation	Hormone modulation	[36–38]
		Neural circuit modulation	[39–45]
	Modeling methods of emotion	Impacts of emotion on artificial agents	[46–53]
		Computational frameworks of emotion	[54–56]
		Emotion modeling by neurodynamic methods	[57–65]
		Brain-inspired emotion-modulated models	[2, 39, 40, 49, 50, 66–69]

achieve the same high performance of manipulation as that of humans. In response to this point, Qiao et al. [24, 25] have formulated an emotion-regulated multi-loop method based on the neural mechanism to achieve a balance between accuracy and efficiency. In summary, formulating an effective method is of great significance to achieving human-like high performance of manipulation with limited hardware costs, which can be achieved by integrating the mechanism of external behavior and internal neuroscience.

To sum up, the development of a novel high-performance robot-operating framework combined with humanoid operating mechanism is of great significance to improve the adaptability and implementation range of robot operation to different objects. This operating framework helps achieve the unity of high precision, flexibility, and generalization, thereby reducing the dependence on high-precision sensing and control and meeting the requirements of intelligent manufacturing in the new era.

Based on the above content, this section mainly discussed the humanoid strategy for robotic manipulation from the following two aspects. First, we introduced the ARIE-based humanoid strategy from the imitation of human behavior, which includes the proposition, development, and implementation of ARIE. Secondly, we introduced the neural decision-making mechanism of emotion regulation and its advantage in achieving the trade-off between accuracy and efficiency. The overview of human-inspired robotic decision making is shown in Table 1 [26–69].

2.1 Robotic manipulation strategy inspired by human utilization of environments

2.1.1 *Characteristics of human manipulation*

Inspired by the mechanism of human operation, research on humanoid manipulation strategy and control design has been conducted, providing new ideas and theoretical technologies to solve high-performance manipulation. In addition to other methods, ARIE is a typical method that could solve the high-precision manipulation with less requirement for accurate sensing and control. Long-term study of primate behavior has indicated that the operation of humans is characterized by flexible, accurate, compliant, and weak dependence on sophisticated perception and control. For example, while unlocking, the handler only needs to take a quick look and obtain the general position of the hole, then adjust the pose of key by using the flexibility of the hand to the environmental constraint until the key is inserted into the hole [21, 25]. In other words, humans could achieve highly precise and flexible manipulation with low perception by using the compliant organization to environmental constraints. Inspired by this, the ARIE-based strategy for robots has been developed to improve the performance of operation while reducing the dependence on sensing, configuration, and control under the environmental constraints [26, 32–35, 70–72].

2.1.2 *Proposition, existence condition and significance of ARIE*

The concept of ARIE was first proposed by Qiao et al. [22], who pointed out that the effect of ARIE can be illustrated by the "bean-bowl" system in the physical space. In the peg-in-hole assembly, the constraint of the hole forms a bowl-shaped region in the configuration space, and, using this constraint,

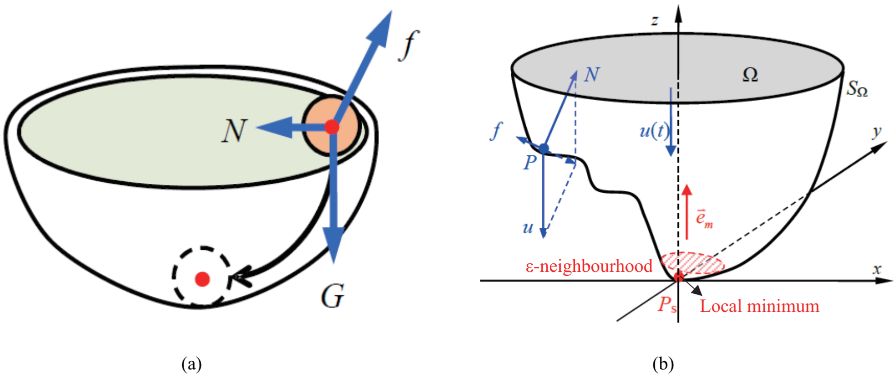

Figure 1 (Color online) (a) The "bean-bowl" system; (b) the non-strictly convex environmental constrained region [22].

the state-independent input and movement can be planned such that the pose deviation of the peg relative to the hole can be eliminated. As shown in Figure 1(a), under the effect of input (gravitational force G) and environmental constraints (frictional force f, and supporting force N), the location of the bean converges from the initial feasible range at the opening of the bowl to the target lowest point of the bowl. Meanwhile, the indeterminacy keeps decreasing throughout the assembly. Therefore, ARIE is a special constraint region existing in a high-dimensional space, and, under the action of this region, there is always a state-independent input that can make the system stable at the unique minimum point of ARIE.

According to the definition of ARIE, the state of a system could converge to a strictly unique target point under the action of this special constraint region and input force [22,23]. In other words, ARIE only has one strict stable point corresponding to one input. According to this property, and the relationship between physical and configuration states in the constraint region, it has been proved that ARIE exists extensively in the configuration space of a convex-assembly task [73]. As for the non-convex constrained region shown in Figure 1(b), if there is only one stable point corresponding to the input in a certain direction, this kind of constrained region can also be regarded as ARIE. In conclusion, ARIE could be found in the configuration space according to the existence of strict stable points.

Further, Qiao et al. concluded that ARIE exists widely in the configuration space of robot manipulation, such as the peg-in-hole assembly [32–35, 70], four-finger grasping [26, 71, 72], object localization [22, 24, 74]. If these attraction regions can be fully utilized and generalized to higher-dimensional space, a variety of high-performance operation tasks independent of high-precision sensing, configuration, and control can be realized.

The proposition of ARIE solves the industry problem of high-precision operations independent of the highly accurate sensors, configuration, and control, which provides a new theory and technology for the intelligent operation strategy, simplifies the complexity of the algorithm, and breaks through the bottleneck of achieving high-performance operations using ordinary robots [24]. First, pose uncertainties of peg and hole are unified as the uncertainty of pose to the hole to simplify the problem analysis; next, by analyzing ARIE in the subspace formed by physical constraints, a state-independent input can be planned, such that the configuration of the manipulated object could converge to a unique stable point where all relative pose errors are eliminated. Therefore, by taking full advantage of environmental constraints, the strategy for high-performance manipulation can be achieved even when the precision of sensor, configuration, and control is not as good as expected.

2.1.3 *How to achieve high precision manipulation with the ARIE*

To better realize the high-precision operations using ARIE on a practical system, a complete systemic framework including the formation of ARIE, manipulation-strategy design, compliance control design, and performance verification has been built, as shown in Figure 2.

(1) Formation of ARIE. For specific manipulation tasks, the geometric information of the workpiece is taken as the input for the formation of the ARIE module. Subsequently, the corresponding environment constraint region is formed using the projection relationship between the physical and configuration spaces. According to the definition and condition of ARIE, ARIE for guiding the high-precision assembly can be obtained in the constraint region, which is the input of the strategy-design module.

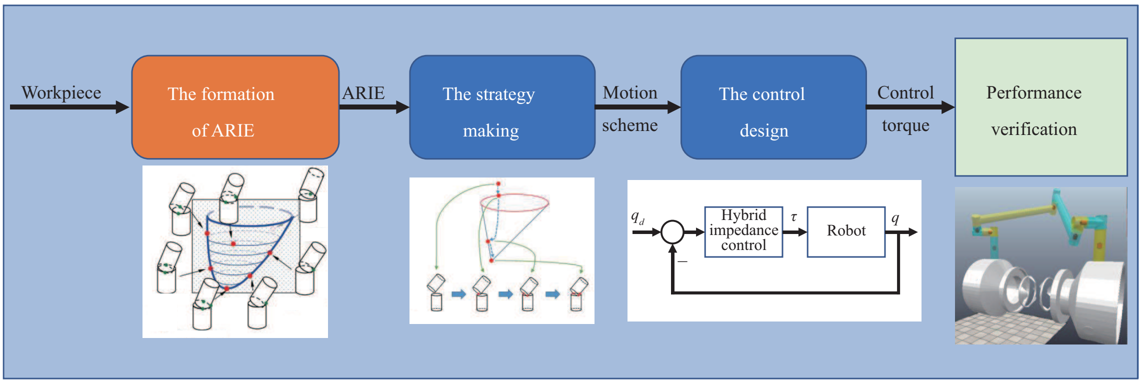

Figure 2 (Color online) The manipulation framework based on ARIE.

(2) Strategy design for manipulation based on ARIE. In the period of strategy design, by analyzing the configuration of the attractive region, the expected initial pose, input force, and progressive relaxation strategy for pose error correction of different dimensions are planned, which are used as the basis of input and parameter design of the controller. Generally, the manipulation strategy based on the theory of ARIE comprises two steps: (1) the relaxation and correction of position under the fixed attitude and (2) the relaxation and correction of attitude.

(3) Compliance control design. By formulating the contact-dynamics analysis and compliance control method, the position and force controls can be unified, and the compliance of the manipulator end to environmental constraints can be realized. Generalized compliance control methods include impedance control and admittance control. In the control-design module, the manipulation trajectory of the control system is planned according to the above strategy, which is the input of the compliant controller and is used to generate the corresponding control torque. In the control-design module, the control parameters are designed according to the policy and task performance requirements.

(4) Performance verification. In this module, the generated control torque input and the corresponding action strategy are input to the hardware and software platforms for performance verification.

2.1.4 *Wide use of ARIE for high-performance manipulation*

At present, methods based on ARIE have been widely used in multiple types of tasks, such as grasping, assembly, and localization. Performance improvement has been achieved in different robotic systems with multiple requirements.

In grasping tasks, ARIE can be used to guide stable grasping without a strict grasping position. For example, Liu et al. [27] proposed a 3D grasping algorithm based on the decomposition of the four-dimensional ARIE into a low-dimensional sub-configuration space. By using the designed grasping strategy, a simple 2D gripper was used to grasp 3D objects. Li et al. [26] proposed a robust grasping algorithm, which was designed by analyzing ARIE during the grasping process, with form closure to obtain stable grasping points. They established a learning-based network to evaluate the grasping quality. In addition, a lightweight, three-degrees-of-freedom, four-finger gripper was designed based on the above algorithm. The effectiveness of the designed gripper and the proposed method were verified by simulation and physical experiments.

In localization tasks, the configuration space referring to the state of objects on a plane can be analyzed using ARIE. ARIE can provide guidance for robotic position from any initial state to a stable state [29]. For example, Liu et al. [28] developed a stable senseless ARIE-based localization method for three-dimensional objects using a simple pushing mechanism.

For assembly tasks, Qiao et al. used ARIE to determine the relationship among the contact force, motion of the peg, and input of the peg-hole system, which provided the basis for strategy-making of assembly operations. For example, Su et al. [30] proposed an assembly strategy independent of fixed piston rod based on ARIE for an automotive engine, whose tolerance is approximately 2–7.5 µm. In [31], ARIE has been applied to the eccentric crankshaft insertion task of the bearing hole of an automobile air conditioner. Li et al. [32] proposed a compliant human-inspired strategy based on coarse force information and environmental constraints for peg-in-hole assembly systems. In the proposed scheme, the motion is planned using the constraint region to eliminate the initial position error of the peg. Besides, the direction of the contact force is detected by a force sensor, which is regarded as an indicator for movement adjustment of the peg. Su et al. [33] proposed a dual peg-in-hole assembly strategy with yaw-angle error. High-dimensional attraction and the sub-attraction regions in the low-dimensional space are constructed in this method. This assembly strategy was applied to the dual eccentric dual-peg-in-hole assembly on the supporting flange with a clearance of approximately 0.02 mm. Liu et al. [34] designed a compliant assembly algorithm based on the ARIE theory to solve the jamming problem of a circular peg with grooves on the side. By replanning the size and direction of active input force, the system state was prevented from converging to a local optimum. Chen et al. [35] proposed a high-precision compliance assembly method for the VGA interface by utilizing low-precision robotic systems. In their proposed framework, assembly strategies were formulated based on the analysis for ARIE, and admittance control methods were designed to ensure interactive reliability in the assembly process. Finally, physical experiments were carried out to verify the effectiveness of the proposed method.

In terms of multiple requirements, the method based on ARIE has been applied to tasks with low contact force requirements and imprecise sensing. For example, in the assembly process of [34], the contact force was less than 7.6 N to satisfy the low contact force requirement, the repeatable precision of the robot was only 0.15 mm, and the clearance was 0.02 mm, which achieved the accurate assembly with low precision of the robot. In [35], the contact force was less than 8 N, which achieved the low contact force requirement. In [33], a robot with a repeatable positioning accuracy of 0.06 mm was used to achieve the dual peg-in-hole assembly task while meeting a clearance of 0.02 mm.

In multiple-robot systems, ARIE-based methods have been applied to the manipulation system of KUKA, YASKAWA, UR, and FANUC robots, which can effectively realize manipulation tasks with high precision. In [23, 27, 28, 30], ARIE-based methods have been applied to FANUC robot to realize assembly, grasping, and positioning tasks. In [26], an ARIE-based method was applied to the UR robot to realize a grasping task. In [33], an ARIE-based method has been applied to YASKAWA robot to realize an assembly task. In [34, 35], an ARIE-based method has been applied to KUKA robot to realize assembly tasks.

In summary, ARIE is inspired by the behavior mechanism of making full use of the environmental constraints in the process of manipulation, which provides a new way for the robot to complete high-precision tasks under the conditions of limited sensing accuracy and limited ontology accuracy. ARIE has been widely used in multiple types of tasks, tasks with multiple performance requirements, and multiple robot systems, which has achieved good results. ARIE is expected to help alleviate the problems of high cost and poor applicability caused by high-precision sensing and ontology, and has an important application prospect for ultra-high precision manipulation tasks in the fields of defense and industry.

2.2 Robotic decision-making models inspired by human neural mechanisms

Owing to the improvements in algorithms and software, nowadays robots can achieve high precision under hardware limits. Nevertheless, robots need to satisfy additional requirements, such as reliability, adaptability, high learning efficiency, and balance between speed and precision in decision making, to perform complicated decision-making tasks. Past few years have witnessed a lot of learning-based methods achieving great performance in self-learning of robotic skills and knowledge. However, when such methods are used in flexible decision-making tasks some problems exist, for example, unacceptable performance when generalizing, low learning efficiency, difficulty to generate goal-oriented strategies, and inability to quickly adapt to a changing environment.

Fortunately, humans have overwhelming advantages over robots in the above aspects, which promotes researchers to pay attention to mimicking the mechanism of human decision making and developing brain-inspired decision-making methods for robots. Humans are skilled in inducting the relationship between perceptual states and actions with limited experience and adapt to dynamic environments well, which reflects high learning efficiency and generalizing ability. A nonnegligible reason is that advanced cerebral cognition including emotion, memory, and cognitive control is utilized in the brain to modulate the decision-making process, which helps humans perform flexible decision making. Especially, inspired by emotion mechanisms in the brain, some studies have integrated emotion into robotic decision-making modulation, which has improved the performance in robot decision-making tasks. This part reviews some computational models of emotion in decision making based on the neural mechanism of the emotion-modulated decision-making system in the human brain.

2.2.1 *Neural mechanisms of emotion modulation in human decision-making*

The emotion mechanism is studied both in psychology and cognitive neuroscience. Generally, originating from the interaction between humans and environment, emotion provides valence guidance for human learning and decision-making [75]. On the one hand, some researchers in cognitive psychology hold opinions that emotion generates and is modulated via the interaction between two processes in human brain: bottom-up and top-down processes [76]. The former generates quick emotional evaluation to respond to low-level perceptual stimuli from urgent changes in the environment, and the latter quickly regulates rough emotion analyses by further cognitive appraisal. The cooperation of the two processes implies the balance between speed and precision. On the other hand, researchers in cognitive neuroscience have conducted further studies on emotion mechanisms, aiming to illustrate the concerning neural circuit. According to recent results, the orbitofrontal cortex (OFC), amygdala, hippocampus, striatum, insular cortex, and some other parts of the limbic system play an important role in emotion processing and modulation [39,77–79]. For instance, the amygdala is of great importance in fear learning [80]. The stimuli containing threat information is conducted to the amygdala, from which the feedforward projections are launched, terminating in the middle layers of OFC, where the meaning of the signal is decoded [81].

Similar to other cerebral cognition, hormone modulation and neural-circuit modulation are considered two main emotion-modulating approaches. In terms of hormone modulation, the change in emotion and its influence on decision making are associated with multiple neurotransmitters. According to an explanatory model, the different emotion states arise from the integrated modulation of diverse combinations of monoaminergic neurotransmitter concentrations, such as dopamine (DA), acetylcholine (5-HT), and noradrenaline (NE). The roles of the three monoamines are modeled into a cube space, where the eight basic emotions match the corresponding vertexes on behalf of different combination levels of monoamines [36]. Additionally, neurotransmitters play a significant role in modulating the learning process in decision making. Related studies show that the dopaminergic neurons in midbrain are responsible for coding the reward prediction error (RPE), which implicates the bias value between the receiving and predicting rewards [37]. 5-HT controls the refreshing speed of memory, which influences the learning efficiency in the decision-making process [38].

Regarding emotion-related neural circuits, Ref. [39] reviewed several emotional neural circuits and analyzed their effects on decision making. Especially, it emphasizes that, as a kind of subjective appraisal, emotion participates in the shift of model-free (MF) and model-based (MB) decision-making systems. Specifically, the striatal region is crucial for the shift between goal-oriented behavior and habitual behavior of human [40], in which the dorso-lateral part (DLS) is viewed as the functional region for MF learning and action (relating to habitual behavior) [41], and the dorso-medial part (DMS) mainly participates in MB ones (related to goal-oriented behavior) [42]. Meanwhile, the emotion is also modulated by emotional signals from the amygdala, which influences the value-coding process to adjust reward learning in OFC/mPFC and striatum [43]. It has been pointed out that the habitual and goal-directed systems in human brain can be arbitrated directly by signals from the amygdala [44,45], which can be considered as an important way of emotion to modulate the decision-making process.

2.2.2 *Modeling methods of emotion in robot decision-making tasks*

In terms of the vital effects of emotion on decision making, it is essential to formulate methods to integrate emotion into artificial systems, which is expected to improve the performance of robots in decision-making tasks.

A group of studies have focused on the potential impacts of emotion on artificial agents. For instance, Scheutz [46] proposed 12 potential impacts where emotion may join in artificial systems. They demonstrated that emotion can be applied to various parts of agents, from memory to strategy, from sensing to action, and from learning to decision making. Furthermore, based on an adequate survey of studies on different evaluation methods of emotion in artificial system, including emotion elicitation, type, function, and test approach, Moerland et al. [47] held the opinion that emotion modulates the decision-making process through state modification, reward modification, action selection, and meta-learning. For example, Savinov et al. [48] designed a curiosity module using episodic memory to generate novelty bonuses. The module provides abundant information on the dynamics of the environment, making it simpler for agents to learn under the circumstance of sparse external rewards. Meanwhile, some researchers suggest that emotion is suitable to modulate the mate parameters, including the learning rate, discount factor, and temporal-difference error, during the learning process [49–52]. In other studies, emotion models have

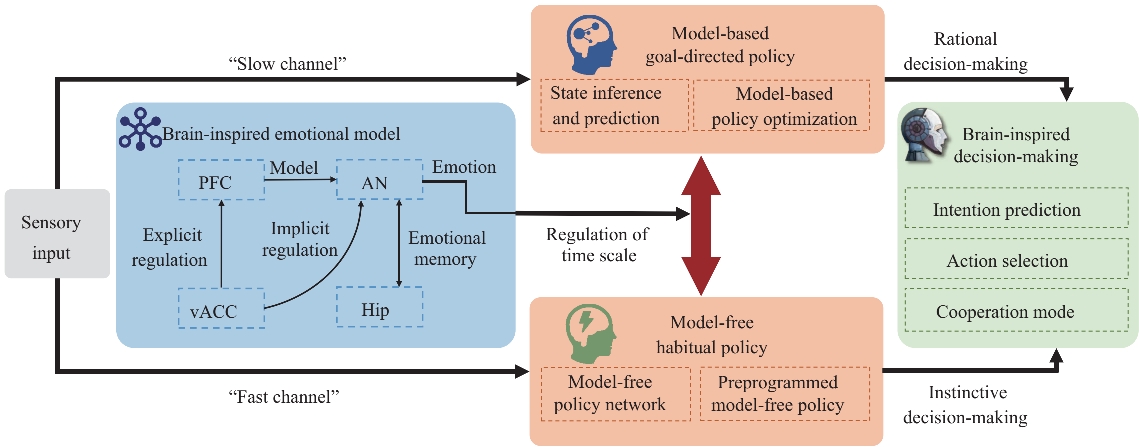

Figure 3 (Color online) Framework of robotic decision-making model inspired by emotional neural mechanisms.

been used to alter the current state to adjust action selections [53], in which emotional states are viewed as a part in the state space.

Besides, some studies have attempted to draw emotion into a common computational framework to improve performance. For example, the neural basis of emotional regulation can be modeled into a reinforcement-learning framework (which is widely used in decision-making tasks) as a value-based decision-making process according to the task [54], where emotion is described as a sequence of perception, valuation, and action, thus naturally integrating the emotion and decision making. Other frameworks have also been evaluated. In the Bayesian framework, emotion is mathematically represented to indicate emotional control signals throughout the interaction between agents, which enables the system to learn emotional interaction by optimizing behaviors based on previous experience [55]. Moreover, Ref. [56] succeeded to explain the emotion in free energy theory, where the negative changing rate of free energy over time is modeled as the emotional valence. By minimizing the free energy, the agent succeeds in actively inferring policies with the minimum uncertainty in changing environment.

Although the above methods focus on the realization of the emotional functions in artificial systems and have achieved significant results, some of them are short in biological plausibility, implying that it may be challenging to achieve human-like performance in decision making in similar ways. Therefore, considerable attention should be paid to biologically-inspired approaches.

Biologically inspired models of emotion mostly focus on mimicking neural information processing. Some early studies used neurodynamic methods to model emotion generation, regulation, and interaction with other cognitive functions. A series of typical studies on neural-network simulation of emotion were performed by Grossberg [57–61], who developed several computational models of interaction between emotion and cognition. The neural network (NN) models succeeded in mimicking emotional processing, motivation and reward learning. Besides, originating from the emotional learning in the amygdala-OFC interaction process of mammals, Balkenius and MorÉn's brain emotional learning (BEL) model [62] is another biologically inspired model of emotion. In the BEL model, the conditional sensory inputs are conducted directly to the amygdala, which exports emotional instructions and generates elementary emotional responses in the thalamus. Then, the advanced cognitive messages from OFC perform further emotional regulation. The model has been successfully applied to robotic control [63], motor control [64], and intelligent power system [65], improving the robustness and adaptability of control systems.

In recent years, Huang et al. [2, 49, 69] have designed a series of brain-inspired emotion-modulated models for robotic decision making, which draw ideas from the hormone regulation and neural-circuit regulation of emotion, as shown in Figure 3. On the one hand, inspired by the phenomenon that emotion modulates learning meta-parameters by influencing levels of three types of neurotransmitters [50], Ref. [49] proposed a kind of emotion-modulated Oja learning rule, in which the emotion valence is modeled as the information entropy of reward signals, adjusting the RPE, learning rate, and randomness of action selection. On the other hand, inspired by the neural mechanism of emotion arbitrating the goal-directed and habitual systems [39, 40, 66–68], Ref. [2] developed a unique decision-making framework, which can adjust the planning horizon to blend the MB- and MF-control processes. Simultaneously, it builds a biologically plausible computational model of emotion processing, which can calculate an uncertainty-

Table 2 Overview of human-inspired perception models

Human-inspired perception model			Ref.
Behavior-inspired	Theories	Intrinsic dimension	[82]
		Data distribution	[83, 84]
		Explicit mapping	[85]
		Others	[86–88]
	Applications	Image retrieval	[89]
		Human action segmentation	[90]
		Dynamic visual tracking	[91, 92]
		Pedestrian tracking	[93]
Neuro-inspired	Micro models	Two-dimensional Gabor function	[94]
		Gain control operation	[95]
		"Winner is king" model	[96, 97]
		Gaussian response model	[98]
	Macro models	Neocognitron model	[99]
		HMAX model	[100, 101]
		Three stages model	[102]
		Models based on attention mechanism	[103–105]
		Models based on multiple mechanisms	[1, 106–109]

related emotional control factor based on RPE as long as the state prediction error (SPE). Furthermore, the computational emotion model is adopted into another framework of emotion-motivated decision making for mobile robots in the environment with sparse reward [69], in which not only the interaction between amygdala and hippocampus is modeled to reflect the effect of emotional memory, but also other psychological states are mathematically introduced, including valence, novelty, and motivational relevance. These biologically plausible models are of great help to the human-like performance of robots in decision-making tasks.

3 Human-inspired perception models

To autonomously complete tasks, robots need to continuously interact with the external environment to obtain perception information. Visual perception is an important source of information in the interaction between robots and the external environment. However, unlike computer vision, robot visual perception involves the motion and control of the robots, which is an active, dynamic and continuous process. Moreover, because robots are usually used in complex and open environments, the images of objects usually have problems such as noise, occlusion, deformation, and blur. Therefore, high requirements are placed on the stability, rapidity, and robustness of the robot visual perception models, and it is necessary to achieve a balance between accuracy, energy efficiency, and speed of the robot visual algorithm.

Traditional robot visual perception models extract information from the external environment according to some fixed designed procedures. These procedures are often designed for a specific objective and can only extract specific information, that is, the perception of these procedures about the outside world is passive. However, practical working environments of robots are often dynamic and the actions of robots also change the surrounding environment. Therefore, to obtain a relatively complete perception of the surrounding information, the robot's visual perception system should be active and interactive. The brain-inspired visual perception technology can provide effective tools for enhancing the working efficiency of robots by learning from the human visual mechanisms. This section will describe two modeling approaches for the human-inspired robot visual perception technology. One is to simulate the human-perception behavioral mechanisms. The other is to simulate the human-perception neural mechanisms. The corresponding references are classified in Table 2 [1, 82–109].

3.1 Robot perception models inspired by human behavioral mechanisms

As mentioned above, robot perception has its unique features of dynamics and continuity, and seeks a balance between accuracy, energy efficiency, and speed. However, because the images obtained via visual perception lie in a high-dimensional space, the above requirements face difficulty in robotic applications. To solve the problem of computational tractability caused by high dimensionality, a class of methods dubbed dimensionality reduction (DR) has emerged, which refers to the transformation of high-dimensional data into a low-dimensional representation while preserving some properties of the original data that the user is interested in.

Manifold learning is a subfield of DR that works by discovering the low-dimensional manifold structure underlying the high-dimensional data distribution. Manifold learning is not only well-grounded on human behavioral mechanisms in terms of visual perception but also a useful tool for robot perception. For example, when a robot equipped with a camera navigates in an environment, the images captured by the camera can be assumed as high-dimensional data located on a low-dimensional manifold, and the robot's position and orientation can be represented by the intrinsic variables of that manifold. Next, we will review the biological mechanisms of manifold learning and its applications of manifold learning in robot perception.

3.1.1 *Biological mechanisms of manifold learning*

The superior ability of humans in cognitive tasks far exceeds existing computer-vision methods, which greatly inspires researchers about the potential performance improvement by mimicking human visual behavioral mechanisms. The nervous system is not only able to distinguish between different objects but also has an invariant perception of the same object, which means it can accurately recognize the object even when its physical characteristics vary greatly. For example, mammals can accurately recognize objects even when the orientation, position, pose, lighting, and background are completely different. The robustness of biological sensory systems to physical changes is impressive and has attracted extensive attention in neuroscience. Neuroscientists have proposed that the sensory system has a hierarchical architecture, and different neural circuits at different levels can transform sensory signals into distinct neural representations. Studies in high-level sensory systems, such as the inferior temporal cortex of vision, have demonstrated that neural circuits remain significantly sensitive to physical variables in the late stages of perception. Therefore, representations of objects generated at different perceptual levels can be easily decoded by downstream systems in a nearly invariant manner [110]. This phenomenon in human visual behavior is formalized as perceptual manifold, which has brought important inspiration to the development of artificial intelligence.

Perceptual manifold refers to the population structures of sensory neuron that represents identity-preserving variabilities in the input stimulus space [111]. A representative work on the biological mechanisms of perceptual manifold learning was accomplished by Seung et al. [112], which presented the biological basis of manifold learning by discussing the manifolds resulting from the continuous variability of images in visual perception. Later, Singh et al. [113] found the two-sphere topological structure of activity patterns in the primary visual cortex (V1), which is similar to those evoked by natural image stimulation. In recent years, more findings have been reported on the manifold representations of perceptual neural activities [110, 111, 114]. Meanwhile, what later became the prototypes of manifold learning algorithms also appeared, that is, the isometric feature mapping (ISOMAP) [115], which maintains the geodesic distances induced by a neighborhood graph in the transformation from high-dimensional to low-dimensional data, and the locally linear embedding (LLE) [116], which represents the data points as a linear combination of their neighbors and maintains the local properties of data in dimensionality reduction. Based on the idea of neighborhood preservation, more algorithms have been proposed, such as locality preserving projections (LPP) [117], neighborhood preserving embedding (NPE) [118], and orthogonal neighborhood preserving projections (ONPP) [119].

3.1.2 *Robot perception models based on manifold learning*

In this subsection, we will review some typical studies on robot perception based on manifold learning, from both theoretical and applied perspectives.

Although the methodology of manifold learning has witnessed great development over the years, there still exist some open issues, such as determining the intrinsic dimension, coping with the diversity of data distribution, and finding an explicit embedding. Here we review some theoretical studies that address the above issues. To determine an appropriate intrinsic dimension, Fan et al. [82] proposed a novel method to estimate the intrinsic dimension by establishing an exponential relationship between the radius of the incising ball and the amount of samples in the ball. To cope with diverse data distributions, Zhang et al. [83] developed the local tangent space alignment (ILTSA) algorithm which, by computing proper approximations to the local tangent spaces, may efficiently reconstruct the geometric structure of data manifolds. Fan et al. [84] introduced multi-manifold proximity embedding (MPE), an isometric multi-manifold learning approach that can isometrically learn data scattered across several manifolds and is highly reliable in maintaining both intra-manifold and inter-manifold geodesic distances. To construct an explicit nonlinear mapping in manifold learning, Qiao et al. [85] drew on the assumption that there exists a polynomial mapping from the high-dimensional data space and the low-dimensional embedding space. Some studies have applied manifold learning to other theoretical problems. For semi-supervised distance metric learning which finds its applications in classification and image retrieval, Ying et al. [86] deduced an intrinsic steepest descent method by exploiting the manifold topology of the positive-definite metric matrix. For online semi-supervised learning, Ding et al. [87] proposed a manifold regularized algorithm dubbed model-based online manifold regularization (MOMR), which iteratively solves a Lagrange dual problem in a reproducing kernel Hilbert space. To conclude this paragraph, we refer to a unification of various manifold learning algorithms provided by Fan et al. [88]. This work reinterpreted manifold regularization as a kernelized fitting problem regularized by one complexity term and one smoothness term, and proposed the manifold regularized kernel least squares (MR-KLS) algorithm as an example.

Manifold learning has various applications in robot perception, such as the segmentation of objects, the recognition of human actions, the tracking of dynamic objects, etc. Here we list some examples. For image retrieval, Liu et al. [89] proposed a novel image descriptor based on Gestalt psychology named perceptual uniform descriptor (PUD), which was combined with manifold learning to solve the incompatibility between image descriptors and ranking. For human action segmentation, Liu et al. [90] proposed a novel physical-based human action descriptor with the manifold learning algorithm named curvature sequence warp space alignment (CSWSA). For dynamic visual tracking, Qiao et al. [91] constructed a manifold in training by maintaining the continuity of intrinsic variables, for tracking a human who can move and rotate freely. Qiao et al. [92] tackled tracking feature extraction from the manifold learning perspective and applied the proposed method to several real-world robotic systems. For pedestrian tracking, Wang et al. [93] introduced a new class of manifold subspaces, which can best preserve the intrinsic variables of the target motion while having a very low dimensionality of features. By using manifold learning, the high-dimensional tensor of features is reduced to the low-dimensional tensor of intrinsic variables, achieving the purpose of high-speed robot perception.

3.2 Robot perception models inspired by human neural mechanisms

To make robots have brain-like visual cognitive ability, in addition to modeling the behavioral mechanisms of human visual cognition as described in Subsection 3.1, many researchers have analyzed and modeled the neural working mechanisms of the human visual system. By the cooperation of multiple visual cortex regions, the human visual system can achieve the complete perception of visual information. By analyzing and modeling neural mechanisms in different visual cortex regions, a robot can simulate the balance of accuracy, energy efficiency, and speed of the human visual perception system to a certain extent.

3.2.1 *Neural mechanisms of human visual perception*

Among many perception organs of the human body, the visual organ has fast perception speed and high accuracy. In the human body, this organ gathers maximum external information. For most primates, visual perception is the basis of all advanced behaviors. Structurally, the human visual perception system mainly includes the eyeball, ocular adnexal, visual conducting pathway, and visual center. The area of the cerebral cortex responsible for visual information processing is located in the occipital lobe, including the striate cortex, extrastriate cortex, inferior temporal (IT) gyrus, and prefrontal cortex (PFC). Neurobiologists have unraveled many working mechanisms of the human visual neural circuits through various experiments. These neural mechanisms ensure that the human visual perception system can maintain good performance in complex environments and achieve a balance between perception accuracy, energy efficiency, and speed.

First, the human visual system can map the image information of the same object in different environments into some essential features and hence has high recognition accuracy for objects in different environments. Many areas of the visual cortex have the capacity for this kind of cognitive invariance. For example, the V4 cells only respond to certain curvature of an object and are not affected by their spatial position [120]. Features such as shape, size, and location of an object stimulate different neurons in the IT cortex [121–123]. Moreover, the human visual system can perceive key information through attention mechanism, thereby achieving high recognition accuracy. Experimental studies have demonstrated that the frontal eye fields (FEF), the lateral intraparietal cortex (LIP), and the superior colliculus (SC) are the areas where attention mechanisms may arise. Direct mapping from the FEF and the LIP to the extrastriate cortex has both been observed experimentally [124, 125].

Second, the human visual perception system represents rich information as a low-dimensional representation by perceiving and memorizing semantic features, thereby reducing storage capacity and improving perception energy efficiency. The objects' orientation, location, and color provide important information for feature learning in visual perceptual processes. For example, the neurons in area V1 can discriminate small differences in orientation and spatial frequency, and can preserve the information about the spatial location. The neurons in area V2 can distinguish between foreground and background stimuli, and their responses can be affected by the illusion contours [126]. Area V4 is sensitive to the objects' simple geometric shapes that are intermediate-level features. Complex object features are achieved in area IT. The color neurons in LGN and V1 are sensitive to color in two axial directions, namely red-cyan and blue-yellow [127, 128]. In area V1, pairs of opposing neurons compute local color's contrast and agreement [129, 130]. The color information in the IT layer may help shape perception [131].

Third, the human visual perception system can achieve fast learning and recognition through similarity discrimination and population coding. Recognition memory used to identify, judge and recall whether an object or event has been consciously seen or experienced is a type of declarative memory [132, 133]. It consists of two parts: similarity discrimination and recall matching. Compared with deep recall matching, which takes a long time, a simplified visual system based on similarity discrimination can serve for quick decision-making and speed up the response in emergencies [134, 135]. The population coding theory [136] believes that the objects are defined by using a group of feature units that are simultaneously activated. Hence, the population coding theory supports distributed feature learning and memory storage. This theory can explain human's ability about recognizing novel objects. When novel objects have some similarity with familiar objects, the units that represent similar features will be activated. Then, the recognition of novel objects through associative learning with semantic memory can be rapidly realized.

The above biological evidence indicates that the human visual system can form a balance between the accuracy, energy efficiency, and speed of perception through the cooperation of various neural mechanisms among different brain areas. These visual neural mechanisms have important significance for promoting the study on robot dynamic vision.

3.2.2 *Brain-inspired visual models*

The design of a visual perception model inspired by human neural mechanisms can provide tools for neuroscientists to analyze the working mechanisms of brain's visual perception and can provide ideas for information scientists to solve the shortcomings of traditional visual computing algorithms. The designs of these brain-inspired computing models fall into two main categories: micro-modeling methods and macro-modeling methods.

(1) The micro-modeling method mainly simulates the electrophysiological characteristics of visual neurons. Hubel and Wiesel [137] used electrodes to stimulate the V1 neurons of cats and observed the characteristics of their responses. They proposed a qualitative description model including simple and complex neurons. Daugman [94] used a two-dimensional Gabor function to simulate the spatial characteristics of the visual neural cortical receptive field. Adelson and Bergen [138] used paired orthogonal filters with the same direction to simulate simple neurons and designed the energy model of complex neurons through summation calculation. Carandini et al. [95] proposed gain control operation, which uses shunting inhibition to describe the response characteristics of V1 neurons. A "winner is king" visual computing method which selects and transmits the strongest response in neural inputs was proposed in [96, 97]. Poggio and Bizzi [98] found that the response of visual cortical neurons to their most sensitive patterns was similar to Gaussian response.

(2) The macro-modeling method mainly simulates the transmission of visual neural signals. Marko and Giebel [139] proposed the earliest feedforward homogeneous multilayer cognitive model. Subsequently, Fukushima [99] proposed the Neocognitron model. Riesenhuber and Poggio proposed the HMAX model [100, 101]. The basic idea of these models is to gradually improve the invariance representation ability of high-level output to complex objects and scenes by integrating low-level inputs. Marr and Poggio used three independent layers to describe visual-information processing: computing, algorithm representation and hardware layers. A visual computing framework including three stages: primal sketch, 2.5D sketch, and 3D model, is proposed in the algorithm layer [102]. Marr's visual computing model integrates

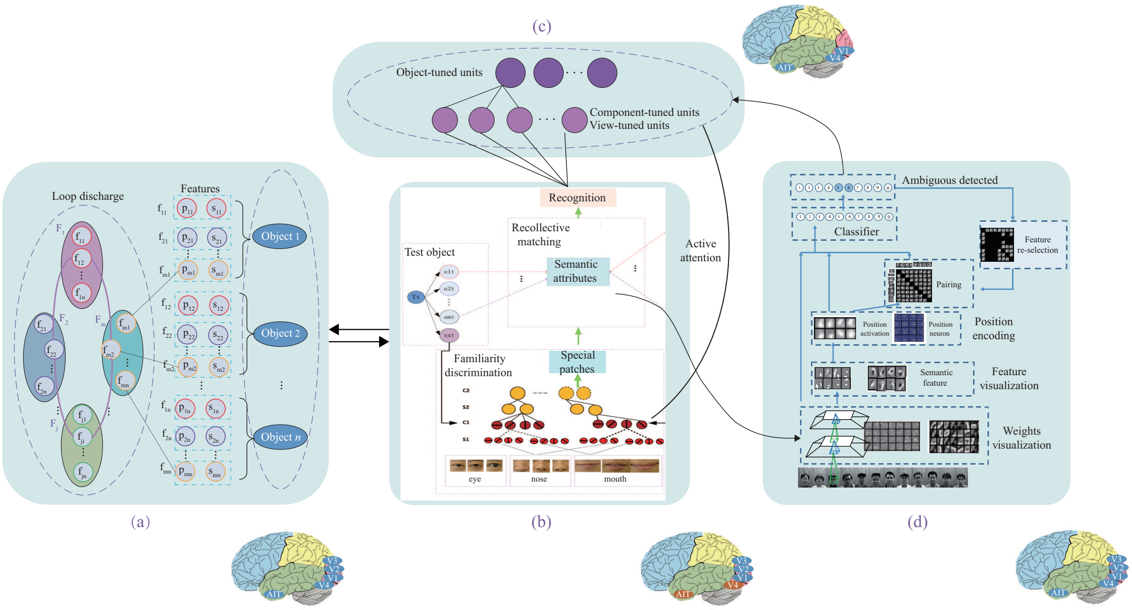

Figure 4 (Color online) Perception model of robot inspired by neural mechanisms. (a) Model of distributed storage (V1–V4) and AIT; (b) recognition model based on semantic and situational memory (V1–V3 and V4-AIT); (c) preliminary cognitive and active regulation model for hierarchical robust recognition (V1, V4 and AIT); (d) computational model of dynamic semantic learning and conceptual integration (V1–V4 and AIT).

multiple independent research contents, including feature analysis [137, 140], receptive field [141], spatial frequency analysis [142], Gestalt psychology [143], and random point stereo vision [144]. This model has a great impact on neuroscience and information science. Itti et al. [103–105] added the attention mechanism to the object recognition model based on the saliency mapping theory.

Although the above models simulate some aspects of the working mechanisms of human visual perception, they are still unable to match the real human visual perceptual ability in many characteristics. First, these models do not consider the particularity of the recognition process when recognizing a type of special object, resulting in their poor effect under some specific scenes. Second, these models do not consider complex neural mechanisms that can efficiently process visual information such as semantics, memory, and concepts. Third, these models cannot well complete the perception of the objects with occlusion, deformation, and blur. Furthermore, the outputs of these models can be affected by even small disturbances [145]. At present, some studies on robot vision have analyzed and utilized these complex mechanisms, as shown in Figure 4.

The visual cortex of the human brain has a particularity in the perception of specific objects. For example, the process of facial perception is two-stage. The first stage processes the structural information of the face. Then, the second stage uses two interacting functional pathways to perceive more specific facial information. These two pathways have different functions, dealing with the invariable and variable features of the face, respectively. In addition, encoding, storage, and recall constitute the three parts of memory in brain. Recall begins with retrieval, followed by identification and decision making. Based on the above mechanisms, Xi et al. [109] proposed a neural-inspired face-perception model. To recognize facial expressions, this model uses convolutional deep belief networks (CDBNs) to automatically find highly discriminative regions, and simultaneously implements feature learning and feature selection. This model uses HMAX to encode salient features and proposes a new memory model including initial decision making, expression modulation, and expression recognition for the recognition of facial identity perception.

The human brain has selectivity in memorizing visual information, and the storage of features is distributed in the brain. According to some physiological studies on the cerebral cortex, researchers have found that memory includes two parts: episodic and semantic. Information is first processed into semantic memory and then into episodic memory. Specific cortical areas have specific features to address. Recognition memory includes recall matching and familiarity discrimination, which is fast and accurate, and requires few neurons. Based on the above evidence, Qiao et al. [106] modeled the memory and association mechanism of the human brain and added them to the HMAX model, obtaining a visual perception model that can actively filter key features. If the semantic description of an object exceeds the predefined threshold in the memory process, the feature corresponding to this semantic is considered salient, and then the feature is stored and learned. The features of different key components (semantic and situational features) are stored in separate brain areas. Similar features about different objects are clustered together to facilitate fast feature matching and recognition through association comparison. The recognition is realized in two ways: recognition memory and population coding. The results of their experiments indicated that the new model requires less storage and has a better recognition effect than the HMAX model. In addition, Qiao et al. [107] established an active and dynamic visual learning model by imitating the perception process of the infant visual cortex about unseen objects. The experimental results indicated that the model is effective in the learning semantic descriptions.

Humans can recognize and understand objects well under complex conditions, such as occlusion, deformation, and blur. Inspired by the findings in neurophysiology and psychophysics of the human abilities above, Qiao et al. [108] proposed a general visual perception model, which consists of three processes: encoding, storage, and recall. In the encoding phase, a deeply improved HMAX model is proposed by simulating the modulation ability of the anterior inferotemporal cortex (AIT) to view angles, components, and object categories. The storage phase simulates the characteristics of the brain's distributed storage, which supports the model implementation of the encoding and recall phases. In the recall phase, a recognition framework based on the fusion of similarity probability was proposed. The validity and generality of the model are proved experimentally, especially the robust recognition performance in the case of occlusion reflects that the model has a deep understanding and simulation of the human visual cognitive process. This model can provide a reference for the structured modeling of visual cognition and facilitate the effective fusion between biological mechanisms and information models. By simulating semantic-information extraction, concept formation and feature reselection in the visual signal processing of cerebral cortex, Yin et al. [1] designed an integrated and dynamic visual recognition framework to realize perception under highly complex conditions. The experimental results on four different datasets indicate that the model has stronger robustness than the traditional models in visual-perception tasks. Especially, if the training data is small or the test samples have semantic confusion, the model can still maintain good performance.

The particularity of perception about specific objects, selective memory, distributed storage of features, and robust recognition can help humans realize better recognition and understanding of objects in complex scenarios. The above studies applied these mechanisms to the robots' visual recognition and achieved good results, providing an idea for the robot researchers to reproduce or even surpass the human visual perception ability.

4 Human-inspired robotic systems and control

Continually investigating the nature of human beings and trying to understand what it means to be human have always been a fascinating topic in science. No matter in scientific fiction or reality, robots are often thought to be the potential candidate for mimicking and producing humanity. At present, although articulated robots composed of rigid links and motor joints have been widely applied in plenty of fields, such as industry and medical treatment, they have certain limitations and are far from approaching people's expectations. For example, articulated robots are considerably different from human beings in their shape, structure, and movement characteristics, which makes it difficult for human cooperator to understand and predict their movement, thus bringing challenges to realize safe cooperation. Meanwhile, sophisticated structure, highly accurate sensors, and well-designed controllers are all necessary for an articulated robot to achieve high-precision movement.

As a comparison, humans can naturally realize compliant interaction, robust movement, and accurate manipulation by leveraging their flexible body and abundant neural modulation. Therefore, developing humanoid robots that not only resemble humans but also can think, act, and cooperate like humans has been an attractive area in robotics. In this section, the advances in human-inspired robotic systems and control will be summarized, including robots with human-like appearance (from outside-in) and those inspired by neural mechanisms (from inside-out). Typical references to these two types of robots are listed in Table 3 [3, 146–207].

Table 3 Overview of human-inspired systems and control

Human-inspired systems and control			Ref.
Systems with human-like appearance and function	Bipedal locomotion	Zero mement point	[146–150]
		Capture point	[151–153]
		Central pattern generator	[154–156]
		Behavior-based	[157–159]
	Autonomous manipulation	Model-based	[160, 161]
		Learning-based	[162–169]
Systems inspired by neural mechanisms	Brain	Cerebral cortex	[170–181]
		Cerebellum	[182, 183]
	Body	Spinal cord	[184–188]
		Muscle model	[3, 189–207]

4.1 Humanoid robots with human-like appearance and function

Making robots increasingly similar to humans in appearance, function, and intelligence for them to be real assistants and friends of humans, has been a long-term dream of roboticists. In general, humanoid robots have human-like appearance and adopt bipedal locomotion. The first humanoid robot, WABOT, was created in 1972 by Ichiro Kato of Waseda University. WABOT can realize stable walking, recognize and manipulate objects, and synthesize voice [208]. Afterwards, many scientists and engineers dedicated themselves to the research on humanoid robots and designed plenty of remarkable robots [209–213], as shown in Figure 5.

• Honda Motor Company developed and announced their first humanoid robot Humanoid P2 in 1997. Based on Humanoid P2, they further developed the famous humanoid robot ASIMO. Owing to its favorable human-like appearance, natural gait, ability to walk up and down stairs, and friendly interaction with humans, ASIMO has drawn considerable attention of public [214, 215].

• Since 2000, the Beijing Institute of Technology has been developing a series of humanoid robots called BHR [216]. These research projects have continually made breakthroughs in plenty of core technologies such as bionic-mechanism design, bipedal stable walking, complex motion design, human expression simulation, dexterous motion generation, and rigid-flexible coupling motion control. The latest released humanoid robot in the series, BHR-T, is approximately of human size. It weighs 43.2 kg and has one degree of freedom in each arm and six in each leg. BHR-T has significant resistance to environmental interference to achieve stable and compliant walking [157].

• In 2007, the National Aeronautics and Space Administration (NASA) teamed up with General Motors Company (GM), and jointly developed the second-generation astronaut robot Robonaut-2 [217]. The robot is equipped with a tendon-driven 5-finger dexterous hand, which has 12 degrees of freedom and controls the movement of fingers and wrist using 18 actuators. Robonaut-2 can complete a variety of extra-vehicular operations in the international space station.

• A child-like humanoid robot named iCub was developed by the Italian Institute of Technology to advance research on cognitive development and embodied artificial intelligence [218]. iCub is capable of cognitive and behavioral interaction with the world through head movements, eye contact, hand manipulation, and bipedal locomotion, providing a physical body for neuroscientists and roboticists to investigate how a human cooperates with the robot and how the robot fits into the real world.

• Boston Dynamics has released a series of brilliant videos to demonstrate the high mobility of the humanoid robots called Atlas in recent years, including backflips, gymnastics and parkour. Atlas is a full-sized hydraulic humanoid robot. It stands 150 cm tall, weighs 75 kg, and has 28 degrees of freedom [209, 219]. The high mobility of Atlas, including stable walking in uneven terrain and force interaction with the environment, is of great significance for its further application to complex tasks such as disaster relief.

Different from the human motor system, which uses muscle traction to complete the target movement, the humanoid robots reviewed above normally leverage high-performance servo motor as their power source. In extreme cases, such as running and jumping, hydraulic actuators are adopted to provide high torque; however, this incurs a high cost. To generate sufficient joint torque for a low-cost electric motor, two common methods are used [209]. One approach is to use harmonic drive, in which multiple motors operate simultaneously to provide high torque for each joint [209]. The other approach is to guarantee

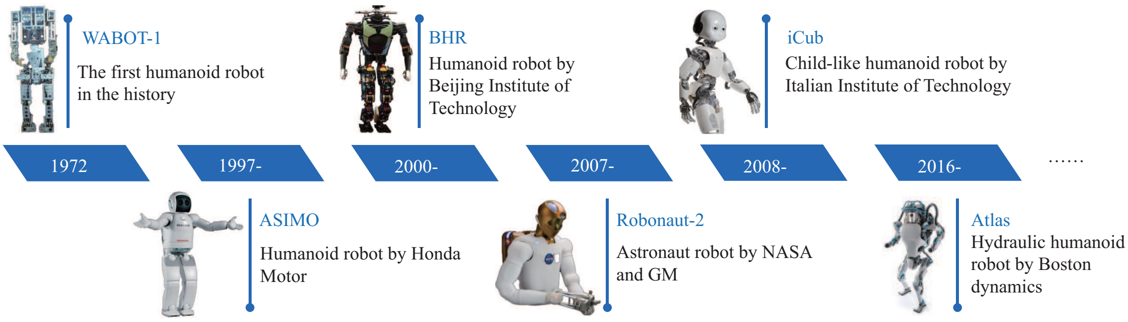

Figure 5 (Color online) Representative achievements in the development of humanoid robots.

sufficient heat dissipation by water- [220–222] or air-cooling [213] so that the electric motor can work in the optimal temperature range for a long time.

By deploying highly redundant actuators, humanoid robots can achieve high flexibility similar to humans while increasing the barrier of system control. In general, the challenges for controlling humanoid robot mainly come from two aspects: (i) realizing stable bipedal locomotion and (ii) developing planning and control algorithm to complete diverse manipulation.

Bipedal walking ability is the main difference between humanoid robots and most existing robots. The primary research goal of bipedal locomotion is to enable humanoid robots to achieve robust and flexible movement on different terrain and irregular surfaces. The control methods of bipedal walking can be categorized into model-based and bio-inspired algorithms. Based on the dynamic model of the humanoid robot, the model-based algorithms leverage stability criteria to plan the trajectories of the center of mass and legs and then calculate the time sequence of each joint angle by inverse kinematics and further solve the joint torques for realizing stable bipedal locomotion.

The stability criteria that are widely applied mainly include zero moment point (ZMP) [146–150] and capture point (CP) [151–153]. The ZMP method was first proposed by Vukobratović et al. [146, 147] and has been widely used in the balance control of biped robots. Kim et al. [148] designed an online controller that can maintain stability during the walking cycle for KHR-2 robot using force/torque sensors and an inertial sensor. Urata et al. [149] proposed an online walking trajectory generalization algorithm using the ZMP method with nondivergence conditions of center of mass, so that a biped robot can change its walking direction and speed under an unknown external force. Fu et al. [150] realized humanoid stair climbing using the sensory feedback controller which is composed of the torso attitude controller, ZMP compensator, and impact reducer. Pratt et al. [151–153] defined the concept of CP and the capture region, and proposed an algorithm to compute the exact solutions of the capture region which a humanoid robot must step into to avoid a fall due to an unexpected push.

Bio-inspired walking algorithms are normally designed by analyzing human walking data or biological movement mechanisms. Control methods based on central pattern generator (CPG) are representative studies on bio-inspired walking algorithms. CPG is a neural control mechanism which has been verified in the spinal cord of vertebrates and the thoracic ganglion of invertebrates. It plays a pivotal role in completing rhythmic movements of organisms, such as walking and swimming. By adopting the CPG-based algorithm, the active joints of biped robots are designed as neuronal oscillators so that stable gaits can be generated by adjusting the parameters of oscillators [154–156]. Miguel-Blanco et al. [154] leveraged a CPG-based fast learning method for online sensory adaptation. It allows robots with different number of legs to perform self-organized walking and deal with damage within a few walking steps. Thor et al. [155] proposed a generic walking control framework by combining a CPG and radial basis function network. Huang et al. [156] extended the concepts of controlled passive walking using structured control parameters and a CPG-based method.

Another important approach for designing a bio-inspired walking control algorithm is to extract mechanisms from human movement data. Inspired by the behavioral mechanism of human resistance to external forces by posture adjustment, Huang et al. [157] proposed a resistant compliance strategy for biped robots to handle long-term external disturbances, which effectively improves the stability and safety of the humanoid robot in environmental interaction. Srinivasan et al. [158] proposed an energetically optimal gait pattern of a biped system for low-speed walking and high-speed running by analyzing the experimental data on human walking and running. Sinnet et al. [159] formulated a black-box model to generate a human-like gait for a biped robot using measured human kinematics data.

Developing control algorithms for humanoid robots to fulfill complex manipulation tasks is another core challenge. Manipulation is a fundamental way by which robots can interact with and affect the real world. When designing and building working and living environments, humans naturally take their physical size, behavior customs, and convenience requirement into consideration, such as the height of doorknobs, weight of tools, and width of stairs. Humanoid robots are similar to humans in size, structure, and movement mode, which lays the foundation for utilizing tools and adapting to the environment of human life, so as to complete different manipulation tasks like humans.

To complete human-like tasks, some researchers tried to establish the dynamic model of humanoid robots. He et al. [160] used the recursive Newton-Euler formula and particle swarm optimization to estimate and optimize the manipulator dynamic model of the HUBO humanoid robot, and they proposed an adaptive control algorithm to improve its tracking performance. Vaz et al. [161] modeled the slosh dynamics of a liquid-filled container and proposed model-based suppression control of a humanoid robot to complete liquid vessels carried task during stair-climbing.

However, owing to the redundancy and nonlinearity of humanoid robots, as well as the disturbance and uncertainty caused by environmental contact during their operation, it is difficult to establish an accurate dynamic model to represent the process of humanoid robots in manipulation. Therefore, learning-based algorithms have attracted wide attention in recent years. Typical learning-based algorithms include model-free reinforcement learning [162, 163], imitation learning based on demonstration [164, 165] and the control method inspired by human behavior [166–168]. Although the study of humanoid robotic manipulation with learning-based methods is still in its infancy, it is expected to be a promising avenue for further improving the adaptability of robots in unstructured environments [169].

The technological progress of the two challenges, walking and manipulation, will be of great significance in promoting the application of humanoid robots in complex and unstructured real world. In 2015, Defense Advanced Research Project Agency (DARPA) Robotic Challenge was held for seeking potential solutions to high-risk disaster relief using humanoid robots. However, the practical effects are still far from expectations [214, 223]. Achieving high performance of humanoid robots by integrating perception, decision making, control, and mechanical system still has a long way ahead.

4.2 Humanoid robots inspired by neural mechanisms

Traditional articulated robots have partially imitated the function and structure of humans, thus obtaining particular performance. The precision of motion control with designed controllers in certain and structured environments can be of micron level. However, the precision of movements and manipulations depends excessively on the precision of sensors and the mechanical body. With the growing requirements of compliant multi-task operations in industrial manufacturing and flexibility in human-machine interaction, existing joint-link robots have some limitations and bottlenecks. Their relatively rigid bodies are not suitable for realizing a safe interaction with humans. Furthermore, their overall performance is affected by their every single actuator.

Compared with articulated robots, bio-inspired musculoskeletal robots have considerable advantages [224–226]. First, with more degrees of freedom, musculoskeletal robots are sufficiently flexible to complete a task with multiple postures. Second, owing to the non-linear muscle driven and variable-stiffness joints, musculoskeletal robots have better compliance for interacting with environments and humans. By adjusting the activation patterns of agonist and antagonist muscles, continuous stiffness variation can be realized. Furthermore, system robustness is improved because of the parallel and redundant muscular actuators. The fatigue or damage of a muscle can be compensated by recruiting other neighboring muscles with similar functions.

However, two main challenges slow down the development of musculoskeletal robotics: muscle actuator imitation and control-system design. On the one hand, muscle tissue is able to contract, thus producing a pulling force to generate movements. The mathematic model established by bio-mechanical research suggests that muscle dynamics is highly non-linear and highly coupled with the skeletal system [227, 228]. Moreover, the cooperation of redundant muscles is hard to be realized using existing drive-mode like motors. The mode changing between motor and generator when simulating the active and passive working states of muscles extremely reduces the control performance. New drive modes such as pneumatic muscle [229] and electromagnetic drive [230, 231] have been investigated and obtained exciting achievements. On the other hand, the controller design for such a multi-input multi-output, nonlinear, and highly coupled system is difficult, thus increasing the barrier of developing musculoskeletal robots. Because neural mechanisms of motion control and learning have not been clearly investigated, current research on the control of musculoskeletal systems are mainly based on control theory and artificial intelligence. However, human-like manipulations with high precision and biologically plausible algorithms require further development. Considering the core problem mentioned above, some bio-inspired control algorithms have been investigated to imitate humanoid control mechanism and have yielded some exciting results.

4.2.1 *Neural mechanisms of movements*

Humans can robustly complete intricate tasks in a flexible manner under a variable unstructured environment; therefore, the musculoskeletal and central neural systems are two key parts that can be further studied and imitated.

Human musculoskeletal structure and dynamics play an important role in adaptive and flexible locomotion. To understand its driving mechanism, researchers in the biomechanical field have proposed mathematical models of muscle dynamics by testing the changes in muscle heat during different movements [189–192]. These mathematical models express the relationship between muscle force, muscle states, and muscle active signal. To improve the bioaccuracy and computational speed, many modified models based on the Hill-type muscle model have been proposed and developed [193–201]. The most widely used muscle model in system analysis and simulations was proposed by Thelen in 2003 [197, 202], which used relatively fewer parameters to realize higher bio-accuracy and generalization.

Neural-circuit research on motion control in brain and spinal cord has always been a hotspot in neuroscience. Neuroscientists have proposed a concept in humanoid motion control called motor primitives, which might be the component of the movements of people and animals [98, 184, 232]. The equilibrium-point hypothesis is an important example of a motor primitive [185, 186]. This hypothesis suggests that the electric stimulation in a particular part of spinal cord elicits muscle contraction and limb motion. The direction and magnitude depend on the position of the limb in space. The force vector converges to a particular point, called the equilibrium point, where the force elicited is zero [187].

Mussa-Ivaldi et al. [184] found that the force-field vector generated by simultaneously stimulating two different positions of a spinal cord is the vector superposition of the force fields generated by separately stimulating the two positions. This observation by analyzing electromyography signals indicated that muscles with strong structural and functional correlations are always co-activated. These groups of co-activated muscles can be regarded as a specific movement primitive, which are defined as muscle synergies [203–205].

Furthermore, besides the regulation of motoneurons and interneurons in the spinal cord, the motor cortex is the primary center of motion control and has an important role in generating motion instructions. However, the encoding mechanisms of movement information and muscle excitations in motor cortex are controversial. Some neuroscientists proposed that the muscle commands are directly encoded and generated by motor cortex [170,171], whereas others believe that the motor cortex mainly encodes abstract movement information [172–174]. Churchland et al. [175,176] and Russo et al. [177] further proposed that the motor cortex is a dynamic system, and the population response of neurons reflects the fundamental dynamic characteristics of the system. Muscle-like commands are regulated and embedded in such a chaotic and dynamic system. Neuroscientists have also found some sufficient evidence to support the movement-preparation phase of the movement-execution process in the motor cortex [178]. Churchland et al. [179, 180] proposed an optimal subspace hypothesis to explain the neural activity about movement preparation.

4.2.2 *Bio-inspired control algorithms of musculoskeletal systems*

Inspired by the high performance of humanoid motion control and manipulations, the interdisciplinary research between control science and neuroscience has been developed for decades. To improve the control performance of musculoskeletal robots, numerous model-based and model-free approaches have been proposed in this area. Because the musculoskeletal system has a sophisticated relationship between muscles and joints, plenty of control algorithms have been proposed using explicit muscle-joint state mapping [233–235]. Based on computed torque control, Jäntsch et al. [233] proposed a scalable joint-space control scheme for a musculoskeletal robot. The control scheme employs the hierarchical control architecture formed by the inner-loop muscle force control and outer-loop joint torque control in series. A neural network is used for mapping the muscle force to joint torque. In another work, Jäntsch et al. [234]

proposed a general control framework for a musculoskeletal robot. High-dimensional dynamic surface control was applied to settle the computational-complexity problem of solving continuous differential equations of system state. Inspired by the neural mechanism of reciprocal innervation, Kawaharazuka et al. [235] proposed antagonist inhibition control for a musculoskeletal humanoid to complete wide range limb motion. Based on these algorithms, the function of state mapping was established, and thus the controller was developed. However, the modeling errors inevitably reduced the performance when it was applied to a real system. Various model-free methods, such as deep learning [236, 237], reinforcement learning [49, 238–241] have been proposed to control sophisticated musculoskeletal systems without establishing realistic models. These data-driven methods perform relatively better than model-based control on complex robotic models; however, their effectiveness and generalization need to be further studied.

Based on the biological structure and neural mechanisms mentioned above, some inspirations can be drawn for the control of musculoskeletal robots, and bio-inspired algorithms can be proposed correspondingly. With these inspirations, the muscle dynamics was analyzed to ameliorate the system's robustness and the recurrent dynamics of motor cortex was analyzed, then utilized to realize generalization and sparse control. The operational performance and biological plausibility were further improved in these studies. First, the performances of motion, generalization, and, multi-task learning were improved. Furthermore, the muscle command generation and muscle control mechanism of movements can be better explained.

Inspired by the humanoid advantages in flexible and robust operations, Wu and Qiao [206] mathematically and experimentally analyzed the nonlinear and highly coupled muscle dynamics. In this study, the anti-interference ability of structure and dynamics were analyzed and proved. Then, the low control frequency and robust controllers inspired by the equilibrium-point hypothesis were proposed to utilize muscular properties to complete target-reaching tasks. Zhong et al. [188] combined ARIE and equilibrium point hypothesis for musculoskeletal-robot control, and proposed constraint force field (CFF) to guide robot movements. This method constructs the CFF through a structure transforming optimization algorithm to guarantee the target point being the convergence point of the CFF; then, the control signal can be constant. The target point can be reached using musculoskeletal recurrent dynamics. This method reduces the cost of computational effort of control signal, and its precision can also be guaranteed.

The motor primitives theory suggests that redundant muscles can be controlled by a combination of motor primitives. Qiao et al. [182] introduced a novel musculoskeletal robot control approach. The muscle excitations of a new target are calculated using this approach, which uses a linear combination of movement patterns. The muscle excitations of specific targets are used to select movement patterns. These targets are close to the new target and can create a convex polygon around it. The calculation of muscle excitations is minimized using this approach, and a quick reaction and some generalization are accomplished.

According to the concept of muscle synergy, the intrinsic properties of muscles can be identified by taking the coactivated muscle patterns as specific motor primitives.

Chen and Qiao [207] proposed a neuromuscular control method based on the concept of muscle synergy. The coupling relationship among muscles in terms of their structure and function was represented by phasic and tonic muscle synergies. Muscle excitations for fulfilling target movement can be generated by leveraging the combination of phasic and tonic muscle synergies. Experiences learned from the training targets are able to directly transfer to new targets through brain modulation between movement objectives and muscle synergies. This strategy allows for more precision and generalization in motion learning. Chen et al. [3] developed a muscle-synergy-based control scheme for manipulation tasks. The motion planning for the assembly task was completed by applying an algorithm based on the ARIE. Based on path planning, muscle excitations were computed by combining time-invariant muscle synergies in a low-dimensional space using an iterative learning controller. Thus, the control problem can be effectively simplified from a high-dimensional muscle-excitation space to a relatively low-dimensional space. The robustness, flexibility, and high-precision manipulation can be realized under relatively low-precision sensor information.

Inspired by the movement-preparation mechanism of motor cortex, Wang et al. [181] proposed a motion-learning framework with two recurrent neural networks (RNN). In this study, the preparation network provides initial states to the modulated-execution network, which can generate time-varying motor commands for movement. With this learning framework, the initial states of unlearned movements can be computed through searching for the latent space constructed by the learned initial states. Then, the en-

No.	Muscle name
#1	Pectoralis Major 1
#2	Pectoralis Major 2
#3	Deltoid 1
#4	Deltoid 2
#5	Deltoid 3
#6	Deltoid 4
#7	Latissimus dorsi
#8	Biceps long/ brachialis
#9	Triceps long
#10	Pronator teres
#11	Brachioradialis
#12	Extensor carpi ulnaris
#13	Flexor carpi ulnaris
#14	Extensor carpi radialis longus 1
#15	Extensor carpi radialis longus 2

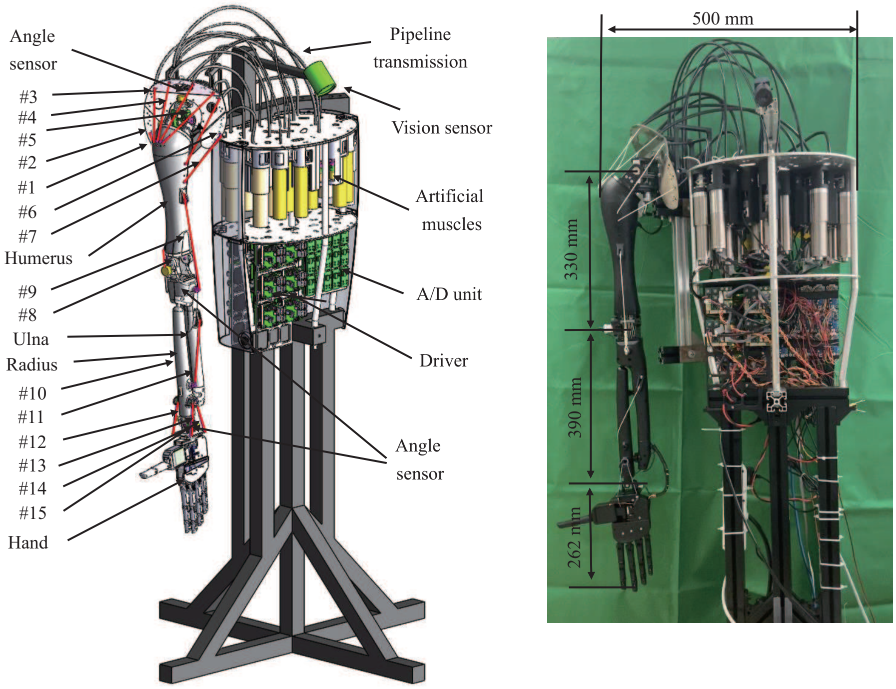

Figure 6 (Color online) The hardware platform of bio-inspired musculoskeletal robotic system.

tire neural space can be established through transformation. Using the proposed method, target-reaching movements of the musculoskeletal system with high generalization efficiency and precision can be realized.

Inspired by the forecast and correction mechanisms of the cerebellar internal model, Capolei et al. [183] proposed a novel methodology to replicate the learning and adaptive principles into robotic feedback controllers. Owing to its neural network-based nature, this architecture can be applied to different robots. The combination of models and structural, learnable features of this network benefit the adaptation mechanism, and system response to nonlinearities, noise, and external forces.

Although neural mechanisms of motion control are sophisticated and have not been sufficiently studied, the important role of related organs has been found in high-performance operations of human. The mentioned algorithms and models inspired by the function of these organs have significantly improved the anti-interference ability and sparse control of robotic systems. High-precision operation with low-accuracy body and low-accuracy sensors can be further enhanced using bio-inspired robotic systems.

4.2.3 *Integration of bio-inspired robots*

To realize human-like motion control and high performance of manipulations, not only efficient motion-control algorithms but a flexible and compliant robotic body are required. Based on the muscular-dynamic analysis and mechanical-structure design, we built a software and hardware bio-inspired musculoskeletal robotic system, as shown in Figure 6. Its muscle distribution and dynamic features are the same as that of the musculoskeletal system, which provides the robot flexibility, robustness, and high-performance potential. Considering improving the accuracy of this robot, a software system which has the same parameters was also established. Owing to the virtual-real simulations, the brain-inspired algorithms can be used to complete high-performance manipulations. The calculation of perception, decision making, and motion control of the musculoskeletal robot is completed by the master chip, so that the robot can realize complicated tasks, such as grasping, assembly, and catching tasks. According to the feedback information, the performance of the brain-inspired algorithms can be further improved. Therefore, with the integration of visual cognition, emotion-modulated decision making, motion control, and musculoskeletal systems, the brain-inspired intelligent robot has the potential to achieve high speed, robustness, and precision in manipulation.

5 Conclusion

This review reviewed the cutting-edge progress of human-inspired intelligent robots in decision making, cognition, motion control, and system design from behavior- and neural-inspired aspects. Based on the characteristics of humans that their overall performance is significantly better than the independent performance of each body component, research on human-inspired intelligent robots can get inspiration from the internal mechanisms to external structures of humans, by integrating robotics, artificial intelligence, brain science, and neuroscience. As reviewed in this review, studies along this route have primarily demonstrated the effectiveness of improving the performance of robots with limited system and sensor precision.

In the future, human-inspired intelligent robots will attract more attention and greater developmental opportunities. On the one hand, the progress of brain science and neuroscience will continuously promote the understanding of the human body, providing significant research evidence to reveal the essence of biological intelligence, including the principle of multimodal integration and generation mechanism of autonomous behavior. This will be the source of fundamental theories for continuously improving the performance of human-inspired intelligent robots. On the other hand, in terms of the practical requirement that autonomous systems need to be upgraded from the static enclosed environment to a dynamic open environment, and from independent operation to group and human-machine collaboration, human-inspired intelligent robots will provide a firm basis for better understanding and predicting the requirements of the human collaborator, efficient experience sharing, and friendly responses, owing to its similarity to humans in its intrinsic mechanism and external structures. It will be a promising avenue for realizing tacit human-robot collaboration in unstructured environments and for realizing new tasks.

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Profile of Hong QIAO

Prof. Hong QIAO received her B.E. and M.E. degrees from Xi'an Jiaotong University in 1986 and 1989, respectively. She received her M.S. degree in robotic control from Strathclyde University in 1992 and her Ph.D. in artificial intelligence and robotics from De Montfort University in 1995. She worked at the City University of Hong Kong (1997–2002) and the University of Manchester (2002–2004) and is currently working with the Institute of Automation, Chinese Academy of Sciences since 2004. She is a member of the Chinese Academy of Sciences, a fellow of the IEEE and China Computer Federation (CCF), the deputy director of the State Key Laboratory of Management and Control for Complex Systems, and the group leader of Robotic Theory and Application (with more than 100 researchers) in the Institute of Automation, Chinese Academy of Sciences.

She has made significant contributions to interdisciplinary research in robotics and other areas, as well as to robotics research in different directions. She is a pioneer researcher in high-precision robotic manipulation and biologically-inspired robotic cognition and manipulation, whose work is widely recognized and highly acknowledged. She was the first to discover and propose the theory of "Attractive Region in Environment (ARIE)" — reported as "Qiao's Concept" — which has been widely applied to industrial robots in China and has been cited and effectively used by eminent scholars from different countries. Prof. Qiao's research contributions are proven by 320 academic papers (179 SCI indexed), with over 5600 total citations, an H-Index of 39, and 50 patents. Her research findings won the Second Prize in the National Natural Science Award, the First Prize in the Beijing Science and Technology Award, and the First Prize in the Chinese Association of Automation Technical Invention Award.

As the first scholar from Chinese mainland, she was elected and re-elected as an Administrative Committee member of the IEEE Robotics and Automation Society (IEEE RAS). She served as a member of the IEEE Awards Board, IEEE RAS Pioneer Award Nomination Committee, and World Economic Forum Global Future Councils — The Future of Artificial Intelligence and Robotics. She is currently a member of the IEEE Fellow Committee and the IEEE RAS George Saridis Leadership Award Selection Committee. She has made significant contributions to promoting cooperation in robotics and multidisciplinary fields and is a highly recognized and influential expert in robotics theory and applications worldwide.

One of the fundamental problems in robotic research is realizing the high performance of ordinary robots, which is also the major barrier to their wide application in advanced manufacturing. Based on the fact that humans can achieve extraordinary overall performance under the condition of limited body unit performance, Prof. Qiao has made significant contributions in proposing the theory of high-dimensional ARIE and mimicking mechanisms of human behavior, the musculoskeletal system, and neural circuits, forming a new avenue to realize high-performance robotic manipulation.

High-precision robotic manipulation

High-precision and high-robustness robotic manipulation is one of the most important tasks in robotics and has wide applications in industry. Prof. Qiao pioneered ARIE in high-dimensional space by modeling constraints between the robot body, manipulated object, and environment (Qiao, 2002). This theory is groundbreaking for high-precision robotic manipulation without the requirements of a high-precision mechatronic system (Qiao et al., 2014). She also found an exceptional solution to connect the switching of ARIEs with the switching process in control theory. This innovative idea has led to several high-impact papers (Li et al., 2019). Moreover, she expanded ARIE with partial visual sensing to an integrated robotic hand–eye framework (Liu et al., 2014) to achieve high-speed and high-robustness robotic vision tasks. As the first participant, her research work won the Second Prize in the National Natural Science Award (the highest fundamental award in China) in 2014.

Biologically-inspired robotic cognition and manipulation

Biologically-inspired robotic cognition and manipulation is an emerging research direction in robotics. Focusing on the human-inspired robotic system, Prof. Qiao established an integrated robotic framework, including vision (Qiao et al., 2014), motion (Chen et al., 2019), emotion (Huang et al., 2019), energy, and interaction (Qiao et al., 2021), which could provide more reliable cognition and flexible manipulation using limited muscle-like control. Since 2009, Prof. Qiao has proposed a series of elegant algorithms that learn intrinsic features for robust recognition and tracking (Qiao et al., 2009) and further established novel brain-inspired frameworks that simultaneously achieve high speed and high precision. For bioinspired manipulation, she proposed a bioinspired musculoskeletal robot with redundancy, Multi-DOF, and a tendon-like structure based on the mechanism and inner structure of human arms (Zhong et al., 2020). In 2013, her research work won the First Prize in the Beijing Science and Technology Award for fundamental research and, in 2018, the First Prize in the Chinese Association of Automation Technical Invention Award.

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