A Survey of Brain-Inspired Intelligent Robots: Integration of Vision, Decision, Motion Control, and Musculoskeletal Systems

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***Abstract*—Current robotic studies are focused on the performance of specific tasks. However, such tasks cannot be generalized, and some special tasks, such as compliant and precise manipulation, fast and flexible response, and deep collaboration between humans and robots, cannot be realized. Brain-inspired intelligent robots imitate humans and animals, from inner mechanisms to external structures, through an integration of visual cognition, decision making, motion control, and musculoskeletal systems. This kind of robot is more likely to realize the functions that current robots cannot realize and become human friends. With the focus on the development of brain-inspired intelligent robots, this article reviews cutting-edge research in the areas of brain-inspired visual cognition, decision making, musculoskeletal robots, motion control, and their integration. It aims to provide greater insight into brain-inspired intelligent robots and attracts more attention to this field from the global research community.**

***Index Terms*—Brain-inspired intelligent robots, decision making, muscle control, musculoskeletal robots, visual cognition.**

I. INTRODUCTION

WITH THE ongoing progress in robotic research, robots are playing an increasingly important role in industry, the service sector, and national defense. The efficient integration of vision, decision making, motion control, and hardware systems ensures robotic intelligence. Accurate and robust visual cognition help robots perceive and understand their environment. Based on environmental knowledge, accurate and fast decisions in complex environments are the cornerstone for robotic movements and dexterous manipulations. Furthermore, flexible and compliant robotic body, as well as motion control enable robots to realize manipulations with high precision. However, the current studies in these areas have mainly focused on the performance of particular tasks, and certain bottlenecks still exist, restricting the wider application of robots in many areas.

For visual cognition, deep-learning-based and broad-learning-based methods have been widely used in tasks, such as image classification [1]–[3] and object recognition [4]–[7], and have achieved much better performance than traditional visual models. However, such methods still have certain drawbacks. First, these methods consume a significant amount of data, but in some cases, the available data are limited. Second, they are vulnerable to disturbances, and even slight noise in the input images may cause a significant deviation in the results [8]. Third, the deep-learning-based visual model is a black box, and how the model works is unclear [9]. Furthermore, a visual model is mainly designed for specific tasks and cannot adapt to new tasks quickly.

For the decision making of robots, the key issues are acquiring environmental knowledge through autonomous learning, and making accurate and fast decisions in complex environments. The breakthrough of this technology will greatly improve the efficiency and accuracy of robotic movements and dexterous manipulations, which has a significant and profound impact on intelligent manufacturing and national life. In recent years, with the development of artificial intelligence, robotics, and neuroscience, many learning-based decision-making methods have achieved an outstanding performance in the autonomous learning of robotic knowledge and skills [10]–[14]. However, there are still some common problems in this regard, such as a low learning efficiency, poor ability to generalize, inability to develop goal-oriented strategies, and the lack of a quick adaptation to dynamic environments.

In terms of robotic body and motion control, existing joint-link robots mainly imitate the appearance and functions of humans. However, they still have limitations in realizing human-like manipulations and interactions. Compared with existing joint-link robots, musculoskeletal robots imitate the human skeletons, joints, muscles, and driving mode between muscles and joints. As these robots provide better flexibility, compliance, robustness, safety, and adaptation, they have greater potential for realizing human-like manipulations and interactions. However, the strong redundancy, coupling, and nonlinearity of musculoskeletal robots also cause difficulties in

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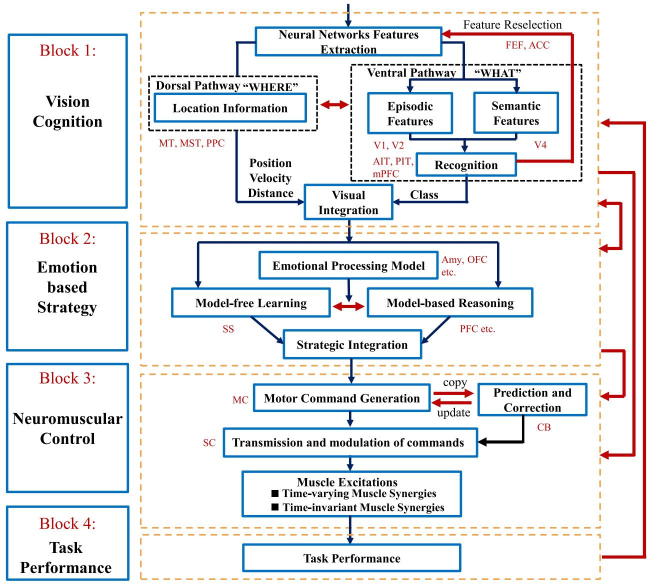

Fig. 1. Brain-inspired intelligent robot with integrated vision, decision, motion control, and musculoskeletal systems. V1, primary visual cortex; V2, V4, extrastriate cortex; AIT, anterior inferior temporal cortex; PIT, posterior inferior temporal cortex; mPFC, medial prefrontal cortex; MT, middle temporal gyrus; MST, superior medial temporal cortex; PPC, posterior parietal cortex; FEF, frontal eye fields; ACC, anterior cingulate cortex; Amy, amygdala; OFC, orbitofrontal cortex; SS, Subcortical System; PFC, prefrontal cortex; MC, motor cortex; CB, cerebellum; and SC, spinal cord.

motion control. To solve the control problem of musculoskeletal robots, many methods based on control theory and artificial intelligence have been proposed [15]–[34]. Nevertheless, the performance of musculoskeletal robots is still limited in terms of movement precision, motion generalization, and rapid response.

Humans can achieve better performance than robots in terms of their current visual cognition, decision making, robotic body, and motion control. For example, humans are particularly good at dealing with difficult object recognition tasks from a variety of viewpoints and scales and under conditions involving deformation and ambiguity [35]. Humans are typically able to quickly infer the causal relationship between perceived states and actions, and rapidly adapt to a dynamic environment. Humans can also control their musculoskeletal system to achieve complex movements and manipulations with high precision and flexibility. Inspired by human intelligence, imitating the neural mechanisms of humans and animals may be a possible way to improve robotic intelligence. Therefore, a brain-inspired intelligent robot has been proposed to imitate the inner mechanisms and external structures of humans from an integration of brain-inspired vision, decision making, motion control, and musculoskeletal systems, as shown in Fig. 1, which may lead to a significant advancement in robotics.

In recent years, brain-inspired intelligent robots have made progress in terms of visual cognition, decision making, motion control, musculoskeletal systems, and their integration. For visual cognition, brain-inspired visual models have shown significant potential [36]–[38]. These models have become an important source of many recent studies on computer vision tasks [39], [40]. Brain-inspired models have numerous advantages, and the working mechanism of such models clearly improves the robustness of the cognitive process. Moreover, these models perform well on few-shot classification and transfer-learning tasks. For decision making, various factors, such as emotion [41], memory [42], and cognitive control [43], have been introduced to modulate model-based and model-free decision-making systems working together to achieve intelligent behaviors. A significant increase in emotion research is underway in a new interdisciplinary field, spanning cognitive, neuron, and computer sciences and engineering. Most of this research has simplified the complex generation of emotions and the regulation mechanisms of the biological brain, and has attempted to improve decision making by building simple mathematical models. For the motion control of musculoskeletal robots, some novel methods have been designed with the inspiration of neural mechanisms of motor systems, such as habitual planning and muscle synergy [40], [44]–[46]. These methods have improved the movements and manipulation tasks of musculoskeletal robots for rapid response and motion generalization. Furthermore, the human-like characteristics and biological plausibility of such systems have also been shown.

This article reviews the bottlenecks of existing robotic systems and summarizes the progress in brain-inspired intelligent robots. The remainder of this article is organized as follows. Sections II–V introduce the neural mechanisms and brain-inspired algorithms of visual cognition, emotion-modulated decision making, musculoskeletal robots and motion control, and their integration. Finally, some concluding remarks are given in Section VI. Some illustrations are placed in the Appendix.

II. Brain-Inspired Visual Models

A. *Conventional Visual Models*

An image is stored and presented in the form of a numerical matrix. For this high-dimensional numerical matrix, the computer cannot directly distinguish the content, and it must use low-dimensional feature descriptors to represent the visual information in the image to allow the computer to recognize such information. Feature descriptors can be divided into two categories: 1) global and 2) local. Global feature descriptors include a principal component analysis (PCA) and a linear discriminant analysis (LDA). Classic local feature descriptors are mainly divided into four categories [47]: 1) filter-based; 2) distribution-based; 3) texture-based; and 4) other types of descriptors. Other descriptor types include color-based descriptors [48], phase-based descriptors [49], and derivative-based filters [50]. Local feature descriptors usually do not require preprocessing, such as image segmentation or contour extraction, and are robust to occlusions, complex backgrounds, geometric changes, and lighting changes. Local feature descriptors are widely used in various computer vision tasks, such as image retrieval, object recognition, object positioning, image matching, and image tracking. This section focuses on the first three types of local feature descriptors.

Filter-based descriptors use filtered images. Common filters for such descriptors mainly include directional adjustable filters [51], Gabor filters [52], and complex filters [53]. Studies

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in cognitive neuroscience have found that Gabor filters have response characteristics similar to the simple cells found in the mammalian cerebral cortex [54]. Subsequently, Daugman [52] proposed a 2-D Gabor filter, which consists of a set of local spatial band-pass functions with good spatial positioning and direction and frequency selection characteristics. In addition, Lee [55] introduced a Gabor filter into an image representation and defined it as the product of an elliptic Gaussian envelope and a complex plane wave.

Traditional image descriptors are based on the experiences of researchers, and their representation capabilities can be limited. Due to the development of deep learning theories and growing GPU computational capabilities, the use of deep learning methods in visual tasks has grown in popularity. Deep convolutional neural networks (DCNNs) are classical deep learning models, and have recently found significant success in large-scale image and video recognition. Fig. A.1[1] in the supplementary material, shows a typical DCNN architecture, consisting of convolutional and pooling layers, fully connected layers, and a classification layer. A convolutional layer is primarily a layer that conducts a convolution operation. The pooling layer is used to reduce the size of the activation maps. After several convolutional and max pooling layers, the activation maps are processed by fully connected layers for classification.

Krizhevsky *et al.* [56] proposed the AlexNet model, which consists of five convolutional layers, three maximum convergence layers, three fully connected layers, and one softmax layer. The model was the winner at the ImageNet ILSVRC-2012 image classification challenge. This model has shown an unprecedented application performance as a DCNN. Szegedy applied kernels of different scales in the same convolutional layer to produce the GoogleNet model [57], which significantly reduces the number of parameters. In addition, Simonyan and Zisserman introduced the VGG model [1], proving that the addition of more layers can promote a better performance. He *et al.* [2] applied a residual connection to produce ResNet and solved the overfitting problem in deeper models. In addition, Lin designed a 1×1 convolutional kernel to reduce the number of parameters [58]. Hu *et al.* [59] introduced SENet, which considers the relationship between convolutional channels.

B. Neural Mechanisms of the Visual Cortex

The human visual cortex consists of eyes (including the retina), optic nerves, optic chiasma, optical cartridge, lateral geniculate nucleus (LGN), and visual cortex. When the light reflected by an external object enters the eyes of a human, it will be projected onto the central area behind the retina. The information is then intersected in the optic chiasm and arrives in the LGN through the optic nerves. Finally, the information is processed by the visual cortex. Ungerleider and Mishkin proposed a detailed dual-pathway visual model [60]. There are two parallel pathways in the visual cortex: 1) ventral and 2) dorsal. These pathways solve the two basic visual questions of what and where, respectively.

In the ventral pathway, visual information starts from V1, goes through V2 and V4, and finally arrives at the inferior temporal (IT). The IT goes through the posterior IT (PIT), central IT (CIT), and anterior IT (AIT). This pathway is related to shape information perception, object recognition, and long-term memory storage.

Visual information in the dorsal pathway starts from V1, goes through V2, V3, the middle temporal gyrus (MT), and the superior medial temporal cortex (MST), and finally reaches the posterior parietal cortex (PPC). This pathway is related to object location, spatial information decoding, motion perception, and interactive motion guidance.

As shown in Fig. A.2 in the supplementary material, due to the extensive divergence and convergence in the visual cortex, the two visual pathways are not isolated. Instead, there are many connections for achieving visual information sharing. Studies have shown that each visual cortex region has a specific function in processing visual information. By connecting multiple visual cortex regions, a balance of the visual information representation between classes and the invariance within classes is achieved.

The receptive field of the visual neuron increases layer by layer. The receptive field of the higher layer is 2.5-times larger than that of the lower layer. V1 complex cells respond to an oriented bar independent of their brightness [61]; in addition, V4 neurons maintain their selectivity for a curvature over a range of spatial positions [62]. A subset of IT cortex neurons maintains their sensitivity for objects independent of their position and size [63], [64], and another remarkable feature of such neurons is the invariance of the shape selectivity [65]. In the visual cortex, some states of an object (e.g., orientation and occlusion) can be encoded within IT. For example, cells in the IT are tuned to a certain object view or lighting condition, where their firing activities are robust to stimulus transformations, such as changes in scale and position [66], [67]. Neurons in each region can respond to and learn from visual stimuli of a specific complexity with a small number of samples, and the learned features can be shared among multiple visual tasks, ensuring a particular visual-recognition speed and generalization.

C. Biologically Inspired Visual Models

Brain-inspired models can be divided into two aspects: 1) cellular-level inspired models and 2) neural pathway inspired models, which are classified and listed in Table I.

Cellular-level inspired models simulate the coding mechanism of visual neurons. McIntosh *et al.* [68] used a CNN to construct a well-performed retina coding model, McInosh-Net, which simulated the discharge mechanism in the retina. Klindt *et al.* [69] proposed a CNN model with a sparse readout layer, Klindt-Net, from the perspective of a space-time separation. Poggio proposed the HMAX V1 cell model [70], which simulates the information mapping mechanism of simple cells and complex cells in the V1 region through a feedforward method, and initially expresses the static feature perception

[1]Fig. A.1 and Fig. A.12 in the supplementary material, are placed in the Appendix.

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capability of V1. In addition, Azzopardi *et al.* [71] proposed a texture suppression and contour enhancement model based on the antagonistic and inverse suppression properties of simple cells in the visual cortex V1. Moreover, Dura-Bernal used the loopy belief propagation to approximate the selectivity and invariance in the IT cortex [72].

Neural pathway-inspired models are based on the structure of the visual pathway. Rolls [73] proposed the Visnet model, which uses a self-organizing algorithm that can establish an invariant representation through statistical self-organized learning based on visual input. Riesenhuber and Poggio [70] Serre *et al.* [74] proposed the HMAX model for the structure of the ventral pathway of the primate cortex, which has the capability of learning from only a few training examples and competes with state-of-the-art systems, and suggested a plausibility proof for a class of feedforward models of object recognition in cortex. Dura-Bernal developed a Bayesian network similar to an HMAX structure [72]. The HMAX model has been further developed and improved in various ways [75], [76].

Despite such progress, some drawbacks to brain-inspired algorithms still exist. First, algorithms usually only focus on a part of the visual mechanism and lack the modeling of the integrity of the visual pathway. Second, because algorithms only model low-level neural mechanisms such as episodic features, this project intends to model the visual cortex from a low level. However, the modeling of a high-level visual cortex, such as semantics, memories, and conception, can reduce the redundancy of the features. Third, these algorithms are designed for specific tasks, causing it to fail to work well with approximate problems.

The following mechanisms found in human visual processing are inspired: 1) semantic extraction through interactions between the hippocampus and medial prefrontal cortex (mPFC) [77]–[79]; 2) structural learning, for example, neurons in V4 tuned for a contour fragment orientation with a specific relative object position [62]; and 3) selective attention involving the frontal eye fields (FEF), anterior cingulate, frontal cortex, etc. Yin *et al.* [35] and Green *et al.* [80] proposed a new integrated and dynamic visual cognition model consisting of six blocks, as is shown in Fig. A.3 in the supplementary material. The experimental results on four datasets show that compared with other methods, the new proposed model is more robust and achieves higher precision for visual recognition, especially when the input samples are semantically ambiguous.

Inspired by the biological evidence indicating that the memory of an object includes both episodic and semantic memories [81], that recognition memory includes familiarity and recollection components [82], [83], and that familiarity recognition is rapid and accurate and only requires a small number of neurons [84], Qiao *et al.* [85] introduced biologically inspired memory and association into the HMAX model, which is shown in Fig. A.4 in the supplementary material. Recognition is achieved through two stages of recognition memory, namely: 1) similarity discrimination and 2) recall matching. Recognition can also be achieved through cluster coding of the semantic features and the situational features of multiple feature parts. Compared with the HMAX model, the new model can output semantic descriptors for object recognition tasks with a higher recognition accuracy. This model provides a basic framework for modeling-related mechanisms.

TABLE I
OVERVIEW OF VARIOUS VISUAL MODELS

Visual models			References
Conventional models	Feature descriptors		[48–54, 56]
	Neural networks		[1, 2, 57–60, 88–93]
Brain-inspired models	Cellular level inspired models	Retina	[69, 70]
		Cortex	[71–73]
	Neural pathway inspired models	Perception	[71, 73–77]
		Cognition	[35, 86, 87]

Based on the working memory and association in [85], Qiao *et al.* [86] introduced an active attention adjustment in this model. During the recognition stage, multiple local fine-coded occlusion information of a cognitive object is used. The classification step is actively adjusted based on the initial cognitive information. The semantic and situational features of the occlusion parts are filtered out before the classification task. The experiments of this model prove the robustness of the classification task, particularly, when the samples are partly occluded.

There are several differences between brain-inspired visual models and conventional visual models. First, brain-inspired visual models are designed to imitate specific visual cortex areas. Thus, the working principle is much clearer. These models can be adjusted according to the different tasks. Second, brain-inspired visual models introduce semantic features and concept formulation. Traditional visual features only focus on extracting numerical features. Semantic and concept features are important for models to understand the samples, making the recognition result robust. Finally, conventional visual models adopt a forward structure, lacking lateral and feedback connections. With lateral and feedback connections, visual-inspired models can associate with primitive memories and make adjustments to discover more discriminative features.

III. EMOTION-MODULATED DECISION MAKING

Based on the psychological and neural mechanisms of emotion and decision-making system in the human brain, some computational models of emotion in decision making are reviewed in this section, which are classified and listed in Table II.

A. General Models of Emotion in Decision Making

Based on the functional roles of emotion, the potential roles of emotion in artificial systems have been discussed in many literature [93], [94]. For example, Scheutz [93] proposed 12 potential roles for emotions in artificial agents: 1) action selection; 2) adaptation; 3) social regulation; 4) sensory integration; 5) alarm mechanisms; 6) motivation; 7) goal management; 8) learning; 9) attentional focus; 10) memory control; 11) strategic processing; and 12) self-model. While Moerland *et al.* [94] investigated various methods of affective modeling for improving the learning efficiency of the

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agent, and compared different evaluation methods from the aspects of emotion elicitation, emotion type, emotion function, and test scenario. Specifically, emotion elicitation is divided into four categories: 1) extrinsic motivation; 2) intrinsic motivation; 3) reward; and 4) hard-wired process. Extrinsic motivation mainly derives from homeostatic dynamics that reflect the balance of the organism's internal environment, such as "energy," "sugar," and "water level" [95]. For example, a motivation of replenishing energy would come into being when resource consumption increases, or thirst leads to a motivation of searching for water [96], [97]. Intrinsic motivation is based on the appraisal theory, where different combinations of appraisal dimensions correspond to different emotions. Appraisal dimensions are often some psychological concepts, such as novelty, valence, control, motivational relevance [98], [99], and curiosity/surprise [100]. Several social dimensions, such as social fairness [101] and social cooperation [102], are also associated with intrinsic motivation. In addition, emotion elicitation is also considered as functions of value and reward. A part of works suggests that positive and negative emotions can be coded by the value function directly [99], [103], or be computed from the temporal change of reward sequence [104]. While some work connects emotion with the temporal difference error following the relationship between the dopamine and emotion [103], [105]. Hard-wired process directly maps the sensory input to some specific emotions [106], [107].

On the emotion-function basis, emotion modulates decision-making process through reward modification, state modification, metalearning, and action selection [94], as shown in Fig. A.5 in the supplementary material. Reward modification, also known as reward shaping [108], is usually formed as the sum of external reward and internally emotional reward. The internal reward is dependent on homeostatic variables [109] or appraisal variables [99]. Recently, reward modification is involved in deep reinforcement learning, which can effectively improve the ability to explore and learn in the dynamic and unpredictable environments. For example, Tang *et al.* [110] proposed a count-based exploration algorithm, where intrinsic motivation is computed by counting the occurrences of states and actions with a hash table. Some research formulates intrinsic motivation as the self-prediction error of states and actions, where the generated curiosity or surprise motivates the agent to explore more efficiently even if the external rewards are very sparse [111]–[114]. Savinov *et al.* [115] proposed a new curiosity module that uses episodic memory to form the novelty bonus. Specifically, the current state is compared with episodic memory via a comparator network, where the reachability from memory to the current state is measured for generating the intrinsic curiosity. This intrinsic motivation incorporates rich information about environment dynamics, which makes it possible for the agent to learn from the sparse external rewards.

Some work uses artificial emotion to modify the current state for impacting action selection [107], [116], where emotional variables are assigned into a part of the state space. Meanwhile, inspired by neuromodulatory effects, some research suggests that emotional systems can influence decision making by modulating the mate parameter during learning, including the learning rate, temporal difference error, discount factor, and other factors [32], [117]–[119]. Finally, emotion is also involved in the exploration/exploitation trade-off by adjusting the exploration parameter directly [117], [120] or switching different sets of value functions [106], [121].

Excepting reinforcement learning, many other machine-learning implementations incorporate emotion mechanisms to improve the performance. For instance, emotion is formulated as mathematical representations in the Bayesian framework, which models affect control during an interaction between two persons [107]. An affect control theory allows the system to generate an affective interaction by learning optimal behaviors or identities based on past interactions. In addition, the free-energy principle has recently been proposed as a unified Bayesian theory of perception, learning, and action, where emotion is a major consideration. Because the core of the free energy principle is to preclude surprise/novelty and decrease complexity so that biological systems, like ourselves, maintain their homeostasis [122]. In this theory, agents actively infer a policy by minimizing the free energy so that they can not only pursue the goal state with highest expected utility but also predict the environment with the minimum uncertainty. Decision making is drawn in a variational Bayesian framework, where perception, learning, and action are governed by an expected utility of future states and relative entropy between likely and desired outcomes. When minimizing surprise, more different goal states are visited, which leads naturally to concepts such as novelty seeking and satisfying curiosity [123]. Based on this theory, emotional valence [124] is recently proposed as the negative rate of change of free energy over time. The dynamics of basic forms of emotion, such as happiness, unhappiness, hope, and fear are explained as a result of conjunctive adjusting and control between the first and second time derivative of free-energy.

B. Biologically Inspired Models of Emotion in Decision Making

Biologically inspired approaches focus on simulating the neural information processing, where neurodynamic methods are usually used to model the generation and regulation of emotion and the interaction between emotion and cognition. In the 1970s and 1980s, Professor Grossberg built a great deal of biologically inspired neural networks to simulate conditional and unconditional stimulus experiments, and later developed a series of computational models of cognitive-emotional interactions [125]–[129]. Levine [125] reviewed a range of neural-network modeling approaches and development history of emotion-modulated cognitive and decision-making processing, including computational models of emotional influences on attention, models of emotionally influenced decision making, and models of specific emotions. Therein, many algorithms are based on neural-network models proposed by Grossberg. For example, Grossberg and Gutowski [128] proposed an opponent processing network called a gated dipole to model the neural dynamics of decision making under risk, which can also simulate the emotional processing, motivation, and reinforcement

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learning well. After that, Leven and Levine [129] extended this gated dipole model further to implement multiattribute decision making. Taylor and Fragopanagos [130] integrated functions of emotionally related brain regions to the model of attentional control, which achieved a selective attention with emotion modulation. In addition, some research focuses on the influence of emotions on long-term social behavior and emotional disorders [131]–[133].

Another prevalent framework is the brain emotional learning (BEL) model proposed by Balkenius and Moren [134], which is based on the mammalian emotional learning during the amygdala-orbitofrontal cortex (OFC) interaction. The flow of information is shown in Fig. A.6 in the supplementary material. The conditional sensory stimuli first enter the amygdala to generate primary emotional response through the thalamus part, which is a rough and fast representation of conditional response. In another pathway, the sensory stimuli are processed finely by the amygdala and OFC through the sensory cortex, where the high-level cognitive information from the OFC inhibits the primary emotion. The learning of the amygdala and OFC is dependent on the mismatches between the actual activations and received reinforcer. Based on BEL, a range of new models has been developed. For example, the brain-emotional-learning-based intelligent controller (BELBIC) is applied for intelligent robotic control [135], intelligent power system [136], and motor control [137]. This model can improve the adaptive ability and robustness of the control system. Lotfi and Akbarzadeht [138] proposed a supervised BEL-based pattern recognizer (BELPR) for addressing multi-input and multioutput classification problems. Milad *et al.* [139] proposed a neo-fuzzy-integrated adaptive decayed BEL network for online time-series prediction.

In recent years, Huang *et al.* [32], [140], [141] have also proposed some brain-inspired models of emotion-modulated decision making. Inspired by the fact that emotion can modulate the process of decision making by adjusting the metaparameters of learning [117], a novel emotion-modulated Oja learning rule has been proposed [32]. Therein, the Oja reinforcement learning rule is used to update the weights of a multilayer dynamic recurrent neural network. The information entropy of reward signals is used to generate the emotional valence for adjusting the decision parameters online. The proposed method is able to control some complex robotic systems to perform the goal-directed and delayed-reinforcement tasks with higher accuracy and a faster learning rate.

Inspired by the neural mechanism of emotion modulation on the goal-directed and habitual behaviors [41], [142]–[145], a new approach to connect model-based and model-free control with emotion modulation has been proposed [140], as shown in Fig. A.7 in the supplementary material. This decision-making framework bridges a gap between model-based and model-free control processes by only adjusting the planning horizon. If the planning horizon decreases to zero, the model-based control will transform into the model-free control smoothly. Meanwhile, that work built a biologically plausible computational model of emotion processing. This model can generate an uncertainty-related emotional response on the basis of the state prediction error and reward prediction error, and then dynamically modulate the planning horizon in the tasks. The proposed decision-making framework can not only improve the learning efficiency and the accuracy of decision making but also gradually accelerate the decision-making with continuous learning.

TABLE II
OVERVIEW OF EMOTION IN DIFFERENT DECISION ARCHITECTURES

Decision architecture	Emotion function	References
Reinforcement learning	Reward modification	[111–116]
	State modification	[108, 117]
	Meta-learning	[118–121]
	Action selection	[107, 118, 122, 123]
Bayesian decision	Affect control theory	[108, 148, 149]
	Free-energy principle	[124–126]

In addition, emotional reactions are usually incorporated into the computation of subjective value during decision making in humans [41]. Based on it, an emotion-motivated decision-making framework has been proposed [141]. In that work, a brain-inspired computational model of amygdala-hippocampus interaction was first built to generate emotional reactions. The intrinsic emotion derives from the external reward and episodic memory, and represents three psychological states: 1) valence; 2) novelty; and 3) motivational relevance. Then, a model-based decision-making approach with emotional intrinsic rewards was proposed to solve the continuous control problem of mobile robots. This method executes an online model-based planning based on a learned environmental model and a model-free guiding policy. The proposed approach has higher learning efficiency and maintains a higher level of exploration, especially in some very sparse-reward environments.

IV. Brain-Inspired Motion Control of Musculoskeletal Robots

Although existing joint-link robots have imitated the partial functions of humans, they still have certain limitations. First, the precision of a movement and manipulation depends excessively on the precision of the sensors and robotic body. Second, these robots are relatively rigid and are not conducive to realizing a safe interaction with people. Moreover, the breakdown of a single actuator will affect the overall performance of the robots. In contrast, humans can utilize a flexible body to achieve a safe interaction, robust movement, and high-precision manipulation tasks. Therefore, a musculoskeletal robot with a human-like skeleton, joints, and muscles has been proposed as a new generation of robot.

One of the bottlenecks slowing down musculoskeletal robot research is the control of such robots. Current studies on the control of musculoskeletal robots have mainly been based on control theory and artificial intelligence. However, human-like movements with both a high level of performance and biological plausibility have not been achieved. In order to break the bottleneck, some brain-inspired control algorithms have been proposed from imitating how humans control a musculoskeletal system and achieved some great results.

A. Musculoskeletal Robots

Some musculoskeletal robots have been established to imitate the skeletons, joints, muscles, and tendons of

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humans [15], [148]–[166]. Traditional industrial robots mainly use motors to drive the joints directly. Musculoskeletal robots use muscular modules to imitate the manner in which muscles contract and drive the joints. The skeletons and joints of musculoskeletal robots are mainly made of light resin, carbon fiber, and mental materials. Muscular modules mainly use a DC motor, a pneumatic actuator, or an intelligent material as the power source. Some muscular actuators use a DC motor as a power source and are fabricated through a combination of DC motors, pulleys, chemical fibers, springs, and numerous sensors [15], [148]–[154]. In these muscular modules, a motor drives the skeleton indirectly using kite lines or wires. These muscular modules have better controllability but fewer characteristics similar to those of actual biological muscles. Furthermore, pneumatic actuators [155]–[162] and new materials [163]–[166] have also been adopted as power sources in musculoskeletal robots. Muscular modules with pneumatic actuators and intelligent materials have better characteristics of biological muscles but less controllability. These musculoskeletal robots have preliminarily demonstrated human-like free motion, climbing, walking, jumping, and running capabilities. They also show the characteristics of flexibility, robustness, and variable stiffness to a certain extent. A typical musculoskeletal robot with pneumatic actuators [167] is shown in Fig. A.8 in the supplementary material.

Compared with joint-link robots, musculoskeletal robots have several advantages. First, musculoskeletal robots are more flexible with more degrees of freedom (DOF) and can realize a specific task with more postures. Second, musculoskeletal robots have better compliance and variable stiffness through regulating the co-activation patterns of many agonist and antagonist muscles. Furthermore, musculoskeletal robots have better robustness. Because muscular actuators are redundant and arranged in parallel, the fatigue or failure of a muscle can be compensated by other muscles with similar functions.

However, the sophisticated structure of a musculoskeletal robot also brings about numerous control challenges. First, because a musculoskeletal robot has strong redundancy in the joints and muscles, the muscle activations of a specific movement have infinite solutions. Second, musculoskeletal robots also exhibit a strong coupling. Each muscle will actuate numerous joints, and each joint is also affected by many different muscles, which increases the complexity of the solutions to muscle activations. In addition, muscular modular dynamics have a strong nonlinearity, and the arrangement of muscles is complex. Therefore, constructing an explicit mathematical model of a sophisticated musculoskeletal system is almost impossible, which further enhances the difficulty of control.

B. Algorithms Based on Control Theory and Artificial Intelligence

To solve the control problem of musculoskeletal robots, many approaches have been proposed in this area, which are classified and listed in Table III. Some control methods have been applied in physical musculoskeletal robots and can accomplish simple and imprecise movements [15]–[20]. Other methods can realize more human-like and complex movements. However, they have only been realized in simulated musculoskeletal systems as a proof-of-principle and may be further applied to physical musculoskeletal robots in the future [21]–[34].

Because musculoskeletal robots have a complex relationship between muscles and joints, many control methods have been proposed for the utilization of explicit muscle-joint state mapping [15]–[27]. With these methods, muscle-joint state mapping is first established, and the controller is then designed. On the one hand, muscle-joint state mapping can be derived based on the geometric relationship between the muscles and joints [15]–[17], [21]–[27]. On the other hand, it can also be approximated using data collected from musculoskeletal robots [18]–[20]. A feedback controller [16], [17], [19], [21], iterative learning controller [22], adaptive controller [23], neuro-fuzzy controller [24], sliding-mode controller [25], antagonist inhibition controller [20], and static optimization [26], [27] can then be applied to compute the force, length, or excitation of the muscles. However, the above methods are not applicable for musculoskeletal robots with a sophisticated relationship between muscles and joints. These robots have complex skeleton structures, winding muscular paths, and strongly nonlinear muscular dynamics. Therefore, it is difficult to derive a mapping based on a geometric relationship. Furthermore, a mapping approximated using collected data also has modeling errors and cannot be applied to realize precise movements and manipulation.

To control sophisticated musculoskeletal robots, some model-free methods have been proposed to control robots directly without establishing muscle-joint mapping [28]–[34], [168]. Using these methods, deep neural networks (DNNs) are trained to compute muscle excitations based on movement targets and robotic states directly with supervised [28], [29] and reinforcement [30]–[34] learning. Based on these methods, human-like reaching and running tasks can be realized with sophisticated musculoskeletal systems during a simulation. Nevertheless, they still have certain limitations. First, supervised learning methods [28], [29] require a large number of training data for muscle excitations in the workspace. Because musculoskeletal robots have many redundant muscles and joints, each movement has numerous redundant solutions to muscle excitations. Therefore, it is difficult to collect training data in simulated and physical environments. Second, some reinforcement learning methods have been proposed to realize muscle control in reaching tasks [32], [33]. However, the precision and generalization of motion learning still need to be improved. Furthermore, deep reinforcement learning based on algorithms, such as a deep deterministic policy gradient, proximal policy optimization, and trust region policy optimization, are proposed to allow the musculoskeletal system to be controlled as quickly as possible and avoid obstacles [30], [31], [34]. Although these methods are effective while running and avoiding obstacles, the effectiveness is mainly a benefit from the huge computational power and are still lacking in biological plausibility.

C. Neural Mechanisms of Muscle Control

In the field of motor neuroscience, how to control the musculoskeletal system to achieve a movement and manipulation

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is a long-term and open problem. It was found that the movements of people and animals can be achieved through a combination of motion primitives [169]–[171]. As Mussa-Ivaldi *et al.* [169] found, when two different parts of a spinal cord of a frog are stimulated concurrently, the force field generated at the end of the limb is the vector superposition of the force fields generated by stimulating the two parts separately.

Based on an analysis of electromyographic signals, it was found that muscles with strong structural and functional correlations are always co-activated. These groups of co-activated muscles are defined as muscle synergies [172]–[174], which can be regarded as a specific movement primitive.

Furthermore, muscles are regulated by motoneurons and interneurons in the spinal cord and are primarily affected by the response of neurons in the motor cortex. However, how the motor cortex encodes the movement information and muscle excitations is controversial. Some neuroscientists have proposed that the motor cortex encodes muscle-like commands and controls the muscles directly [175], [176]. Other neuroscientists believe that the motor cortex mainly encodes abstract movement information, such as direction and speed [177]–[179]. Based on the above study, Churchland *et al.* [180], [181] and Russo *et al.* [182] further proposed that the motor cortex is a dynamic system, and that the major response of neurons reflects the fundamental dynamic characteristics of the system. Muscle-like commands are regulated based on movements and are embedded in such an untangled population response.

TABLE III
OVERVIEW OF MOTION CONTROL AND LEARNING METHODS OF MUSCULOSKELETAL ROBOTS

Control of musculoskeletal robots			References
Model-based methods		Control methods using inverse model	[15–25]
		Optimization methods using forward model	[26, 27]
Model-free methods	Artificial intelligence methods	Supervised learning	[28, 29]
		Reinforcement learning	[30–34]
	Biologically inspired methods	Muscle-synergies-inspired methods	[44–47]
		Motor-cortex-inspired methods	[183, 185]

D. Brain-Inspired Muscle Control Algorithms

Based on the above neural mechanisms of muscle control, some inspirations to the control of musculoskeletal robots can be obtained and some brain-inspired algorithms have been proposed. With these inspirations, the performance of control and biological plausibility is improved. First, better performance on motion precision, generalization, and multitask learning is obtained. Furthermore, the generation of muscle commands and how muscle commands are affected by movements can be better explained.

Inspired by the hypothesis of motor primitives, redundant muscles can be controlled by the combination of motor primitives. Qiao *et al.* [40] proposed a new control method for musculoskeletal robots. With this method, the muscle excitations of a new target are computed through a linear combination of movement patterns, as shown in Fig. A.9 in the supplementary material. The movement patterns are selected as the muscle excitations of certain targets. These targets are near the new target and can form a convex polygon surrounding the new target. With this method, the computation of muscle excitations is reduced, and a fast response and a certain generalization are achieved.

Inspired by the hypothesis of muscle synergy, co-activation muscle patterns can be used as specific motor primitives to characterize the intrinsic features of muscles. Rückert and d'Avella [44] introduced time-varying muscle synergies to realize the motion learning of a musculoskeletal system. Using this method, time-varying muscle synergies are constructed and can be modulated with different targets in terms of amplitude and time shift. For new targets, muscle synergies learned on training targets are shared but the amplitude and time shifts of muscle synergies should still be relearned. This method realizes a certain generalization and accelerates the motion learning of new targets. Furthermore, Chen and Qiao [45] proposed a novel muscle-synergy-based neuromuscular control method. With this method, a new computational model of time-varying muscle synergies is constructed. This model utilizes both phasic and tonic muscle synergies to characterize the coupling relationship among muscles in terms of their structure and function. Muscle excitations are computed using the combination of phasic and tonic muscle synergies, which is illustrated in Fig. A.10 in the supplementary material. With a neural modulation between movement targets and muscle synergies, the acquired knowledge from the training targets can be directly transferred to new targets. Based on this method, better precision and generalization of motion learning are realized. For manipulation tasks, Chen *et al.* [46] also proposed a muscle-synergy-based control scheme. In this control scheme, the strategy based on the attractive region of the environment is applied to motion planning in the task space. A learning controller is then designed to compute muscle excitations based on motion planning. With the introduction of time-invariant muscle synergies, muscle excitations can be computed through a combination of low-dimensional muscle synergies, which is shown in Fig. A.11 in the supplementary material. The control problem is effectively simplified by transforming high-dimensional muscle excitations into a relatively low-dimensional space. Based on this control scheme, the musculoskeletal system can realize manipulations with robustness, flexibility, and high precision under relatively low-precision sensor information and control.

Inspired by the hypothesis of dynamic encoding in motor cortex, the dynamic system like RNN can be used to realize implicit motor primitives with the motor-cortex-like dynamic characteristics. Sussillo *et al.* [181] realized the computation of muscle activations with a regularized RNN and supervised learning, and demonstrated the motor-cortex-like consistent population response. Chen and Qiao [183] further defined a specific pattern of consistent population response in RNN and derived the condition based on the Lyapunov analysis. With the combination of reinforcement learning, the motion learning and multitask learning of a musculoskeletal system was realized. With the motor-cortex-like RNN, the performance of motion precision and multitask learning was improved.

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V. Integration of Brain-Inspired Intelligent Robot

The above sections discuss the visual cognition, emotion-modulated decision making, motion control, and musculoskeletal system of a brain-inspired intelligent robot individually. For a complete robotic system, the integration of these parts is necessary to realize great performance.

A. Integration of Vision, Decision, and Motion Control

In this section, we focus on the integration of visual cognition, decision making, and motion control. For biological creatures, the coordination of multiple brain regions and functions is essential to realize intelligent behaviors and deal with various sophisticated situations, which is also critical for intelligent robots. Sensorimotor coordination is a classical coordination of multiple brain regions and is the coupling between sensing and acting [184]. For example, when trying to catch a baseball, the eyes focus on the moving direction of the target, the future location of the ball is predicted, and the hand moves to that location.

1) Neural Mechanisms in Sensorimotor Coordination: The generation and consolidation of sensorimotor commands and skills in animals depend on the cortex, basal ganglia, and cerebellum, which contribute to different learning processes of sensorimotor coordination. Here, we only discuss the PPC and cerebellum.

The PPC has long been studied due to its essential contributions to spatial attention and multisensory integration for generating a unified perceptual representation, which plays an important role in behavior guidance [185], [186]. Researchers have also reported that PPC contributes to movement planning in different contexts [187], [188], which might be related to different types of movement for a particular body part [189], [190]. It has recently been reported that such individual movement-related regions are organized hierarchically among different subareas for the same effector, which might indicate that the PPC contributes to sensorimotor integration at different levels [191], [192].

The cerebellum also plays an important role in sensorimotor coordination tasks in animals. For example, when rodents process sensory information from their vibrissae and control the whisker movement, the cerebellum receives the information from the trigeminal nucleus and sensory cortex through the pontine nucleus [193], [194] and synchronization of the neuronal firing activities with the sensory cortex during whisker movements [195]. It has also been reported that the olivocerebellar system contributes to the modulation of vibrissal movements [196].

2) Computational models of Sensorimotor Coordination: Humans can solve sensorimotor coordination during various tasks. For example, a basketball player can control his or her entire body to throw a ball into a basket, which requires visual information to meet the required movements. However, it is still difficult for a robot to finish such tasks because it needs to collect all sensory information, carry out motion planning, make the corresponding movements, evaluate the effects, and tune the entire process accordingly. Meanwhile, the information flow between vision and motion is not straightforward, and how to create a proper plan from visual information under many DOF of the actuators under various situations is a challenge.

However, some basic principles observed in biological creatures can be applied to robotics. First, sensory information is combined and processed for motion planning. Second, motor commands satisfy the requirements of coordination of multiple DOF actuators. Third, the sensory monitoring and movement adjustment work together to ensure the accuracy of the movements [197]. These three principles are essential in sensorimotor coordination in biological systems, which partly ensures the learning abilities [197]–[202].

In recent years, researchers have made some progress in the development of sensorimotor coordination in robots. For example, Xiong *et al.* [203] proposed a neuromechanical control and sensorimotor learning in a hexapod robot, where the feedforward and feedback pathways are implemented. The sensorimotor learning in this hexapod robot aims to predict the force on the feet and tune the stiff parameters accordingly. Some studies have focused on models of sensorimotor coordination of reaching-and-grasping tasks [204]–[207], where the main concern lies in the learning architecture inspired by the cerebral cortex and its connectivity. For instance, Zollo *et al.* [208] proposed a robotic platform for reaching-and-grasping tasks with adaptive sensorimotor learning. Training and offline learning were implemented in a multinetwork control regime in the simulation, which produced the inputs for low-level position control.

B. Integration of Brain-Inspired Algorithms and Musculoskeletal Robots

The above section discusses the integration of brain-inspired vision, decision, and motion control. However, realizing tasks, such as compliant and precise manipulation, a fast and flexible response, and deep collaboration between humans and robots, requires not only efficient vision, decision making, and motion control but also a flexible and compliant robotic body. Therefore, brain-inspired intelligent robots imitating humans from inner mechanisms to external structures should integrate both efficient brain-inspired algorithms and musculoskeletal robots with the advantages of flexibility, compliance, and robustness. As shown in Fig. A.12 in the supplementary material, brain-inspired intelligent robots can realize accurate and robust visual cognition, make fast and accurate decisions, and compute motion commands with brain-inspired algorithms in the master chip. A flexible, compliant, and robust musculoskeletal robot is then driven by the master chip to realize tasks, such as assembling, grasping, and catching objects. With the feedback of the task performance, brain-inspired algorithms can be further adjusted to improve the performance. With the integration of visual cognition, emotion-modulated decision making, motion control, and musculoskeletal systems, the brain-inspired intelligent robot has potential to achieve high speed (e.g., different circuits of vision, decision, and control can be formed to deal with normal or urgent situations), high robustness (e.g., the failure of part muscular actuators

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can be compensated by appropriate modulation of other muscles), and high precision in manipulation (e.g., higher precision can be achieved using compliant musculoskeletal robots and environmental constraints).

VI. Conclusion

Cutting-edge research into brain-inspired intelligent robots was reviewed herein in terms of vision cognition, decision making, musculoskeletal robots and control, and integration. Although brain-inspired intelligent robots are still at the laboratory stage, significant progress has been made in recent years in the mimicking of both biological structures and functions. In the future, we think this direction also has great development potential. First, with a new understanding of biological creatures, particularly, their brain mechanisms and functional circuits, new brain-inspired computational models closer to human intelligence will be proposed. Second, tighter integration of the vision, decision making, and motion control will significantly improve the entire performance of robots. Furthermore, with the development of material and mechanical sciences, better stability, flexibility, and controllability of musculoskeletal robots will be achieved. We believe that brain-inspired intelligent robots can shed light on the development of novel types of robots with human-like intelligence and behavioral characteristics and lead to a significant leap in robotics.

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