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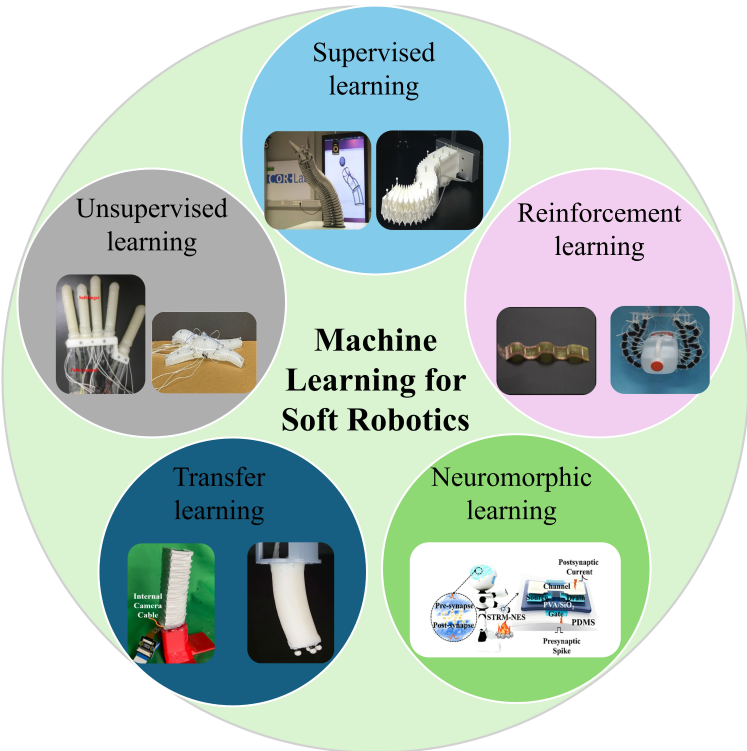
Machine Learning for Soft Robotics

Baiyu Zhang [1] Jingjing Qiu[1,*]

1 Department of Mechanical Engineering, Texas A&M University, College Station, TX, USA
** Corresponding author: jennyqiu@tamu.edu*



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ABSTRACT

Soft Robotics refers to the design, fabrication, and control of robots made from highly deformable materials that mimic biological organisms. They can perform tasks that require flexibility and soft dexterity. With the application of Machine Learning (ML) soft robots are now able to learn from data, redesign their shape, and handle various tasks with high precision. This literature review explores the integration of ML techniques in soft robotics, examining various data-driven strategies, applications, knowledge gaps, and future directions. Soft robots often require complex, nonlinear dynamics, and autonomous decision-making capability without explicit programming in order to fit in unpredictable environments. Therefore, despite the significant advances in this field, there are still a few technical challenges topical to various implementations of soft robots. In this literature review, five representative ML methods and their diverse applications for soft robots are analyzed. Lastly, the emerging bio-inspired energy-efficient neuromorphic learning is introduced, which uses far less power than traditional computing technologies and allows for a rapid adaption of soft robots to complex environmental changes. Therefore, neuromorphic learning is regarded as a promising tool for efficient event-driven sensing and adaptive locomotion control in the field of soft robotics.

Keywords: ***Machine learning, Soft robotics, Neuromorphic learning***

1. INTRODUCTION

Soft robotics represents a paradigm shift for robotics, with developments focusing on manufacturing robots out of highly flexible and compliant materials [1],[2]. These robots allow for safe interaction with humans, delicate objects, and fluids, thus finding applications from medical devices to search and rescue operations [3]. In contrast, traditional robots often rely on discrete joints with limited range of motion and low shape adaptability. In particular, recent advances in Machine Learning (ML) have significantly enhanced the functionality of soft robots, through providing learning, adaptation, and decision-making abilities based on sensory inputs [4],[5],[6].

This review covers major subcategories of ML methods used for soft robotics with a special focus on techniques, applications, and ongoing challenges. In particular, as an emerging ML technology, neuromorphic learning may reclaim a pathway of developing novel bio-inspired soft robots that are not only energy efficient but also highly intelligent and adaptable.

2. ML TECHNIQUES IN SOFT ROBOTICS

ML is a subset of Artificial Intelligence (AI) where algorithms and statistical models are applied, enabling a machine to perform specific tasks without explicit instructions. Through ML processes, a machine learns various patterns and makes decisions based on data. As illustrated in graphical abstract, there are several kinds of ML methods widely used in soft robotics, including supervised learning, unsupervised learning, reinforcement learning, transfer learning, and neuromorphic learning, etc. Because the learning systems are being supplied with such diverse information from the external environment, the quality of information may have a significant effect on the complexity of the learning realization. Many general principles can thus be stored in the repository that could be used to guide the implementation of a specific task when new data in the environment are provided for the machine to be dealt with. Noteworthy among them is the fact that the information from feedback can also be used to learn and guide further study, as shown in **Figure 1**.

•Supervised Learning

The supervised learning technique uses labeled datasets to train algorithms to make predictions or decisions. Supervised learning has a baseline expectation of output values. It is commonly used in those applications where historical data predicts future events successfully. Supervised learning has been applied in the field of soft robotics to provide better control, adaptability, and performance. For example, Kim has further elaborated on the review of supervised learning in soft robotics and presented supervised learning in detail within the context of different kinds of soft sensors, actuators, and wearable robots. In each case, he has talked about the present trends and limitations in the field.[8]. Besides, Mirza explored ways of making soft robot control more effective through supervised learning and how to widen the application scope[9]. This was a structure of soft grippers, as shown in **Figure 2**. Thirdly, Pandey and Windridge proposed a genetic deep learning (DL) model for electrophysiological soft robots

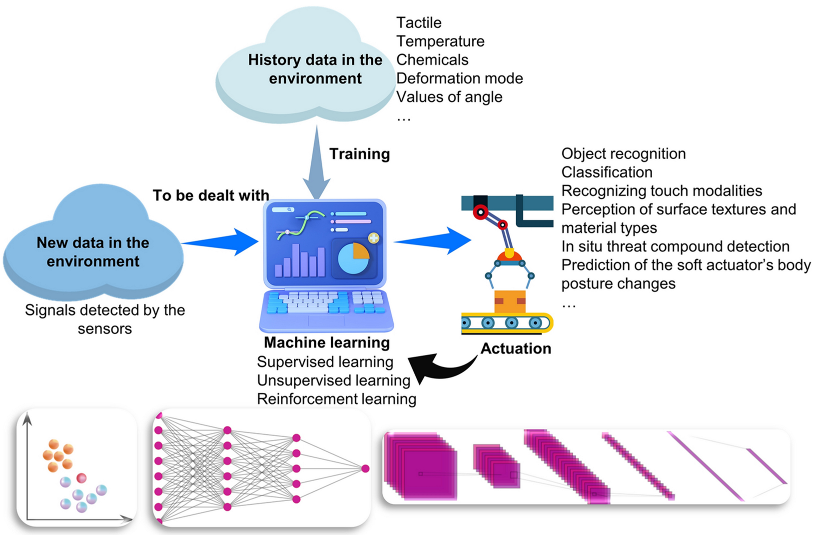

Figure 1. Schematic illustration for the basic model of machine learning in the intelligent soft robotic system [7]. The Authors, published by SpringerLink, under a Creative Commons Attribution License 4.0 (CC BY 4.0). Reprinted with permission.

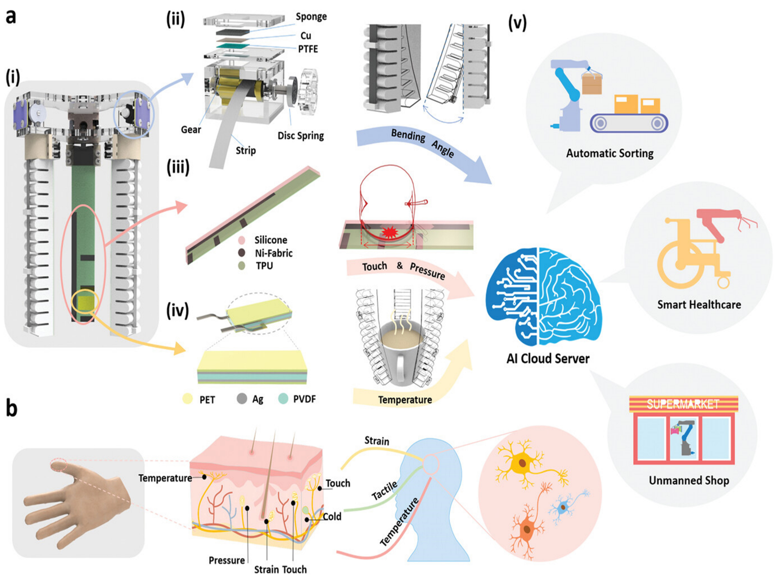

Figure 2. The structure of the sensor integrated smart soft robot grippers. The structures and functionalities of (ii) & (iii) sensors and iv) temperature sensors. (v) Various applications realized by this smart system. [11] The Authors, published by Wiley-VCH, under a Creative Commons Attribution License 4.0 (CC BY 4.0). Reprinted with permission.

implementing supervised learning tools with genetic algorithms. The combination is to effectively train the neural network for improved robotic performance [10].

•Unsupervised Learning

In contrast, unsupervised learning algorithms are trained using unlabeled data and don't take any feedback to check the accuracy of the prediction. Unsupervised learning techniques are now proving very useful in soft robotics for discovering hidden patterns and improving the behavior of robots without labeled training data. [12]. Additionally, Spielberg investigates the co-learning of sensor placement and complex tasks with an occupation task, where unsupervised learning is used to optimize sensor locations in soft robots for better performance in the completion of tasks [13]. This was a framework of sensors, as shown in **Figure 3**.

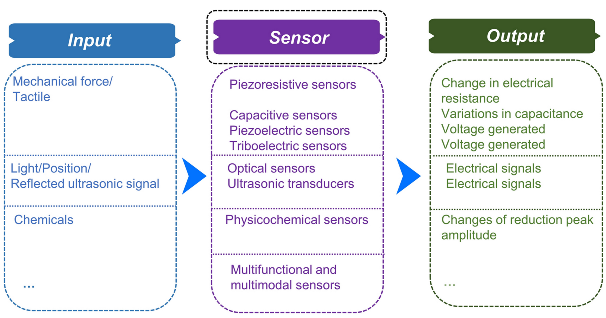

Figure 3. Schematic illustration for the working mechanism of sensors [7]. The Authors, published by SpringerLink, under a Creative Commons Attribution License 4.0 (CC BY 4.0). Reprinted with permission.

•Reinforcement Learning

Reinforcement learning (RL) is emerging as another vital ML tool in soft robotics, with promisingly resilient and effective control strategies for complex and highly adaptive systems. Unlike supervised learning, reinforcement learning is trained to perform the given task without given the correct answer key. Therefore, reinforcement learning has more advantages for scenarios requiring decision-making and policy learning. Tiboni et al. studied a domain randomization method to enhance the robustness and effectiveness of RL policies in various environments [14]. Alessi et al. showed that the generalization of RL-based controllers for soft robotic arms is very robust for various dynamic tasks [15]. An example framework of reinforcement learning is shown in **Figure 4**.

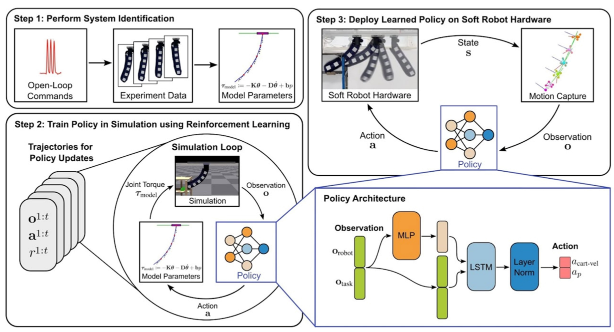

Figure 4. A reinforcement learning framework. Step 1: Fit parameters for a dynamic, physics-based model using about 30 seconds of accurate experimental data. Step 2: Train a control policy using deep reinforcement learning and a simulator that uses the dynamic model from Step 1. Step 3: Deploy the learned control policy on a physical system [16]. The Authors, published by Conference on Robot Learning (CoRL) 2023, under a Creative Commons Attribution License 4.0 (CC BY 4.0). Reprinted with permission.

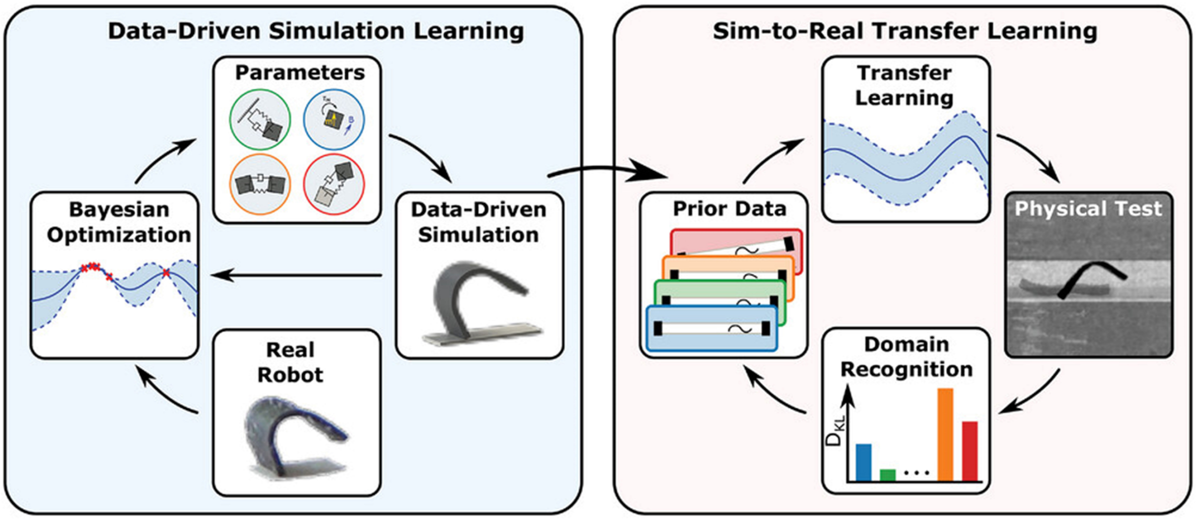

Figure 5. Data-driven magnetic soft millirobot simulation and sim-to-real transfer learning framework. The data-driven soft millirobot magnetic simulation learned the simulation parameters by running BO with GPs to maximize the JI between the simulated and experimental behavior of the sheet-shaped magnetic soft millirobot. The sim-to-real transfer learning-based previous data were generated by running an exhaustive grid search in the data-driven simulation environment for all given test environments. A domain recognition algorithm compares the observed performance values continuously to the simulated test cases through KLD and identifies the environment. The locomotion of the robot is learned using sim-to-real transfer by making use of prior knowledge with the simulated data of the identified environment. [20]The Authors, published by Wiley-VCH, under a Creative Commons Attribution License 4.0 (CC BY 4.0). Reprinted with permission.

•Transfer Learning

Transfer learning means transferring models trained on one domain to another domain, which effectively avoids the labor-intensive process of data collection in the new domain and has been emerging as a critical instrument in soft robotics for better performance. With transfer learning, a model can be built with comparatively less training data since the model is already pre-trained. Sapai et al. applied transfer learning through a semi-supervised sequential variational Bayesian-based framework, which is effective for state inference in soft robots. Effective transfer learning is demonstrated amidst missing state labels [17]. Moreover, Torkaman et al. introduced WaveLeNet, a novel transfer learning-based approach, for neural calibration in soft robots to improve sensor accuracy in noisy environments [18]. On the other hand, Fang et al. presented an efficient transfer learning-based method for solving inverse kinematics for soft robots using sim-to-real transfer to enhance practicality in practice [19]. Lastly, an adaptive magnetic soft millirobot multimodal locomotion framework enabled by sim-to-real transfer is developed [20]. Develop a data-driven magnetic soft millirobot simulation environment and learn a periodic magnetic actuation signal for a given magnetic soft millirobot in simulation as shown in **Figure 5**.

•Neuromorphic Learning

Neuromorphic learning is inspired by the structure and function of biological neural networks, and thus naturally suited for adaptive control schemes that mimic biological nervous systems. Unlike conventional computing systems that operate on a continuous clock cycle, neuromorphic learning systems are event-driven and process information only when necessary. Therefore, it is considered highly energy and data-efficient, reducing the need for extensive data transfer and central processing, as shown in **Figure 6**.

For instance, in coupling the support of spiking neural networks with electronic neuromorphic hardware, researchers have accomplished working prototypes in a development that includes not only bio-inspired soft robotic policing systems that can be programmed to recognize real-time tasks within a visual-based target-tracking and smooth-pursuit movement mimicking human eye movements. [22]. Further, Park et al. showed that the sequential generation raised neuromorphic electronic systems optimized the biological neuronal systems. Their research resulted in new-generation devices such as wearable computing, soft robotics, and neuroprosthetics that emulate learning and memory features—relevant leadership to highly intelligent soft robots [23].

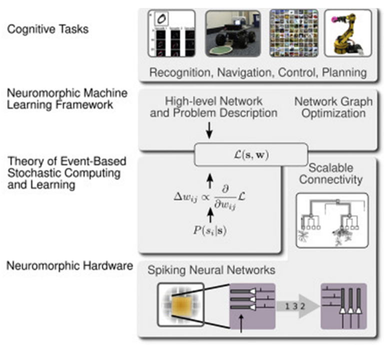

Figure 6. Neuromorphic learning framework [21]. Copyright 2018, Elsevier

3.APPLICATIONS OF ML IN SOFT ROBOTICS

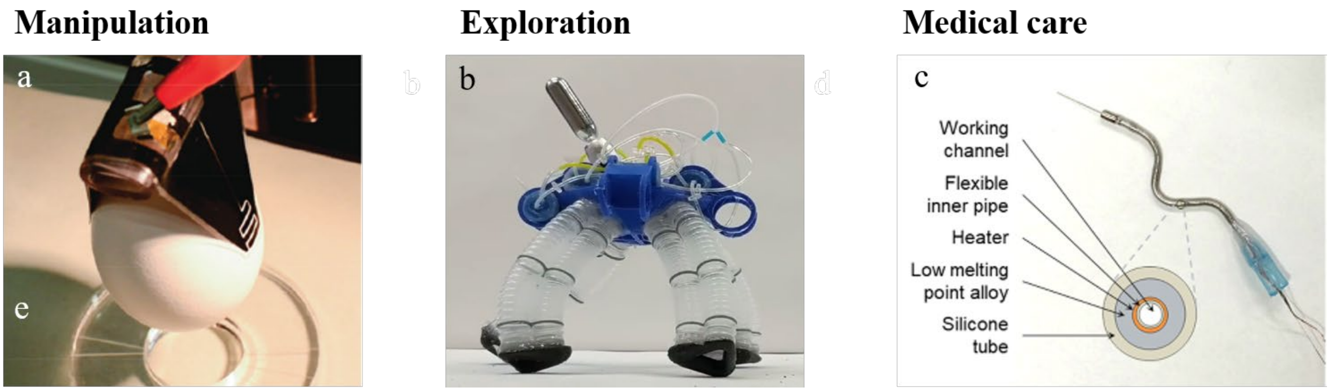

Figure 7. Soft robot applications in manipulation [24], exploration [25], and medical care [26]. (a) Copyright 2016, EPFL. (b) Adapted from Yasa, O., et al [27]. The Authors, published by Annual Reviews, under a Creative Commons Attribution License 4.0 (CC BY 4.0). Reprinted with permission. (c) Adapted from Chautems, C., et al [26]. The Authors, published by Wiley-VCH, under a Creative Commons Attribution License 4.0 (CC BY 4.0). Reprinted with permission.

Soft robots can carry out complex operations that call for the capability of navigation through unstructured environments and safe interaction with delicate objects, as illustrated in **Figure 7**.

The integration of ML techniques into soft robotics enables enhanced performance, adaptability, and intelligence. ML improvements in Soft Robotics are shown in **Table 1**.

Table 1: Machine Learning Improvements in Soft Robotics

Evaluation Parameter	Pre-ML Results	Post-ML Integration Results	Specific ML Techniques Used	Examples
Adaptability	Limited; reliant on pre-programmed instructions	Highly adaptable to real-time changes	Reinforcement Learning, Deep Learning	Adjusting behavior based on real-time sensor data
Efficiency	Lower due to rigid programming	Improved through optimized algorithms	Neuromorphic Learning	Energy-efficient data processing and decision-making
Controllability	Basic, with minimal autonomous adjustments	Enhanced precision and autonomy in control	Deep Learning, Reinforcement Learning	Precise control in unpredictable environments
Precision in Task Execution	Often imprecise in complex tasks	High precision, especially in handling delicate tasks	Deep Learning	Accurate task execution in medical robotics
Energy Consumption	Generally high	Reduced, more sustainable operations	Neuromorphic Learning	Lower power consumption during operations

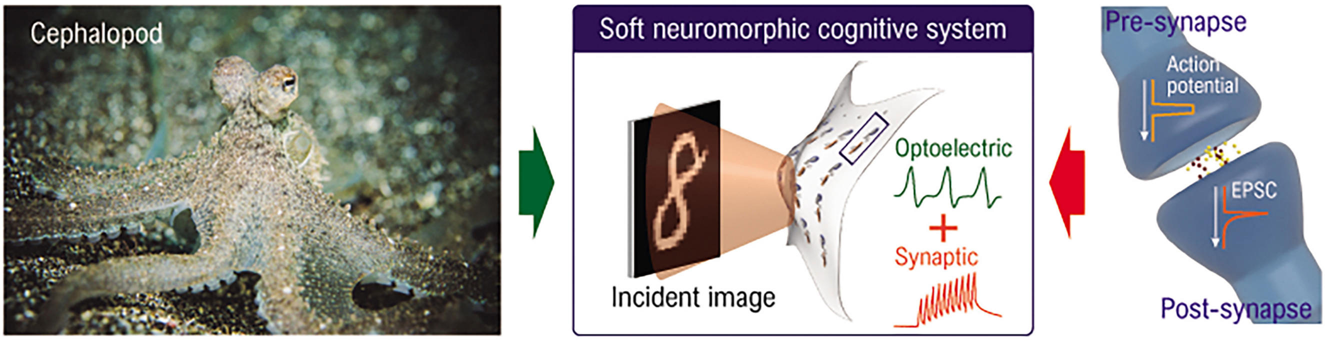

Figure 8. Soft neuromorphic cognitive system: Schematic illustrations of the soft neuromorphic cognitive system by combining the functions of cephalopod skin and biological synapse [39]. Copyright 2022, PNAS

3.1 Soft Grippers

ML has found diverse and impactful applications in the field of soft robotics. ML methods have been initially applied in precise grasping and handling of different objects with delicate, fragile, or irregular shapes. Ling et al. developed a novel approach of shape-invariant, indirect hardness estimation for an onboard depth camera using the convolutional neural network. The method is non-obtrusive and can predict hardness values with great accuracy [28]. Similarly, Ménager et al. demonstrated a technique for direct and inverse modeling of soft robotic kinematics through learning a reduced-order finite element method (FEM) model [29]. Furthermore, Huang et al. proposed a Bayesian modeling-based convolutional neural networks (CNNs) for object recognition with variable stiffness and uncertain size. Applying reinforcement learning in soft robot locomotion control can improve the soft robot gripper's holding and clamping performance, also these collected ML data can reduce the simulation displacement error. In this application, the CNNs method offers enhanced reliability of the soft grippers [30]. Currently, the accuracy of soft grippers still needs to be improved. More efforts need to be carried out by simplifying neural networks while retaining accuracy.

3.2 Soft Crawlers

In robotics, soft crawlers are a type of soft robot designed to move across surfaces by crawling. Some soft crawlers are designed to navigate through complex internal pathways within the human body, such as the gastrointestinal tract and blood vessels, to deliver medication, perform internal diagnosis, or assist with minimally invasive surgery. With the help of ML, researchers have been able to find a solution for enhanced controllability, adaptability, and effectiveness of soft crawler robots. Shu et al. integrated ML into the design and development of electronic skins to better recognize surface conformations and identify different terrains with improved autonomous capabilities [31]. Asawalertsak and Manoonpong et al. also developed a soft-bodied crawling robot with electromagnetic legs and a neural control system based on the central pattern generator (CPG), showing its applicability in different metal terrains [32]. Recently, Yang and Wu et al. reviewed diverse ML techniques for sensor material optimization and signal analysis in order to enhance the automation and decision-making capability of strain sensor-integrated soft robots [33]. It was also reported that a predictive control system for hydraulically amplified, self-healing, electrostatic (HASEL) actuators with high accuracy was achieved through the use of ML techniques: Recurrent Neural Networks (RNNs) and (multilayer perceptron) MLP [34]. However, the soft crawler has limited sensory feedback. For example, the soft crawler cannot continuously crawl from horizontal to vertical paths by itself.

3.3 Soft Swimmers

Soft swimmers are a type of soft robot designed to move through water. For example, Li et al. reported the development of novel soft-bodied, undulatory, swimming soft robots with the help of an energy-efficient deep reinforcement learning technique. As-fabricated soft robots demonstrated significantly saved energy compared to traditional robots [35]. Null et al. developed a modular, submersible soft robotic arm actuated with hydraulic actuators, featuring a kinematics model embedded with deep neural networks for easy configuration and control [36]. In 2021, Li et al. reviewed a deep reinforcement learning (DRL) framework for underwater locomotion of soft robots, emphasizing the use of neural network controllers in enhancing the swimming capabilities of the robot under real-world conditions [37]. Rajendran & Zhang et al. also developed a soft robotic fish driven by super-coiled polymers, with the underlying mechanism of driving for yaw control and path following, controlled by deep deterministic policy gradient reinforcement learning method. [38]. Nevertheless, at present, reinforcement learning-based controllers for soft swimmers using visual learning-based controllers are only used to mimic anatomical functions. In the future, the mimicking of the cognitive phases in locomotion still needs to be developed, as shown in **Figure 8**.

4. PROSPECTS

In summary, the integration of ML techniques into soft robotics has stimulated significant advances in versatile intelligent, adaptive, and high-precision soft robotic systems by enabling robots to learn from data. However, current soft robots are still limited by low propulsion speed, low energy efficiency, and long response time. The major challenge in this field hinges on (1) the design of complex geometries and multiple materials for desirable flexibility and adaptability, (2) requirement of novel flexible sensors that can accurately perceive the information of environment and its kinematics, (3) precise control of the complex, nonlinear dynamics for deformable robots with intricate soft actuation, (4) further development and simplification of ML-based controller, and (5) requirement of more compact, lightweight, portable, and endurable power sources and remote operation capability. More efficient ML techniques are in urgent demand to improve their autonomous capability and environmental adaptability.

However, in the majority of cases, soft robotics applications focus mainly on supervised and unsupervised learning training models to simultaneously optimize structure/morphology and the ML algorithms [40]. This is because RL requires much time in training models, and high operational limitations make learning often unsuccessful [41]. More efforts are anticipated to address the adaptability of RL models so that the trained models are capable of generalizing and performing well across a variety of datasets, tasks, or environments [42].

Meanwhile, polymer-based soft robots indicate a complicated non-linear nature and further confound the control strategy due to its numerous additional degrees of movement freedom [43]. Novel energy-efficient neuromorphic learning techniques are highly promising to help overcome these challenges. Most important of all, neuromorphic learning is expected to offer a variety of advantages relevant to soft robotics, such as fast locomotion, agile actuation, safer human-robot interaction, and real-time autonomous operation through various complex and dynamic environments.

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COMPETING INTERESTS

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