DOI: https://doi.org/10.52783/tojqi.v11i4.10017

Turkish Online Journal of Qualitative Inquiry (TOJQI)

Volume 11, Issue 4, December 2020: 2224-2232

Robot Learning and Adaptation for Intelligent Behavior

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Abstract. This work will offer an overview of the function that machine learning plays in the field of robotics. The relevance of machine learning in enabling robots to acquire knowledge via experience and adjust their behaviour in response to new situations is underlined. This allows robots to adapt to their surroundings and become more efficient. The article delves further into a number of different approaches to machine learning, such as reinforcement learning, imitation learning, and deep learning. These approaches are particularly well-suited for use in robots. Some of the more modern approaches, such as meta-learning, Bayesian optimisation, domain randomization, and adversarial training, are presented here. The final section of the paper discusses the topic of the future of robotics, focusing on the possibility that robots may become more powerful and capable in the future, eventually taking over jobs that are either too dangerous or too time-consuming for people to manage.

Keywords- machine learning, robotics, reinforcement learning, imitation learning, deep learning, meta-learning, Bayesian optimization, domain randomization, adversarial training, robot control, decision-making, navigation, manipulation, artificial intelligence.

I. Introduction

Robotics researchers use concepts from computer science, engineering, and mathematics to build useful robots. The body of information on this subject is expanding quickly. In many facets of human existence, including workplaces, warehouses, hospitals, and households, robots are becoming more prevalent [1]. This trend is most likely to continue. Robots will need more complicated algorithms and ways to complete difficult jobs and interact with their environments as their complexity and capabilities increase. Machine learning is one of the most important fields of research in robotics because it enables robots to learn from their own mistakes and improve over time. Robots may learn new tasks, enhance their judgement, and adapt to new surroundings with the help of machine learning. In recent years, tremendous progress has been achieved in the development of machine learning algorithms suitable for robotics applications. Deep learning, imitation learning, and reinforcement learning are a few examples of machine learning algorithms. A technique known as reinforcement learning trains an agent to interact with its surroundings by maximising a reward signal. Numerous robotics applications, including navigation, manipulation, decision-making, and control, have successfully used this approach. Robots are able to learn from their errors and enhance their performance over time and in various circumstances thanks to reinforcement learning. Another kind of machine learning is imitation learning, which includes watching people doing a job to learn how they go about it [2]. Robots have been taught a variety of skills using this method, such as manipulation, navigation, and grasping. The benefit of imitation learning is that the robot may "learn by doing" when it is difficult to construct an objective function that captures the intended behaviour of the robot.

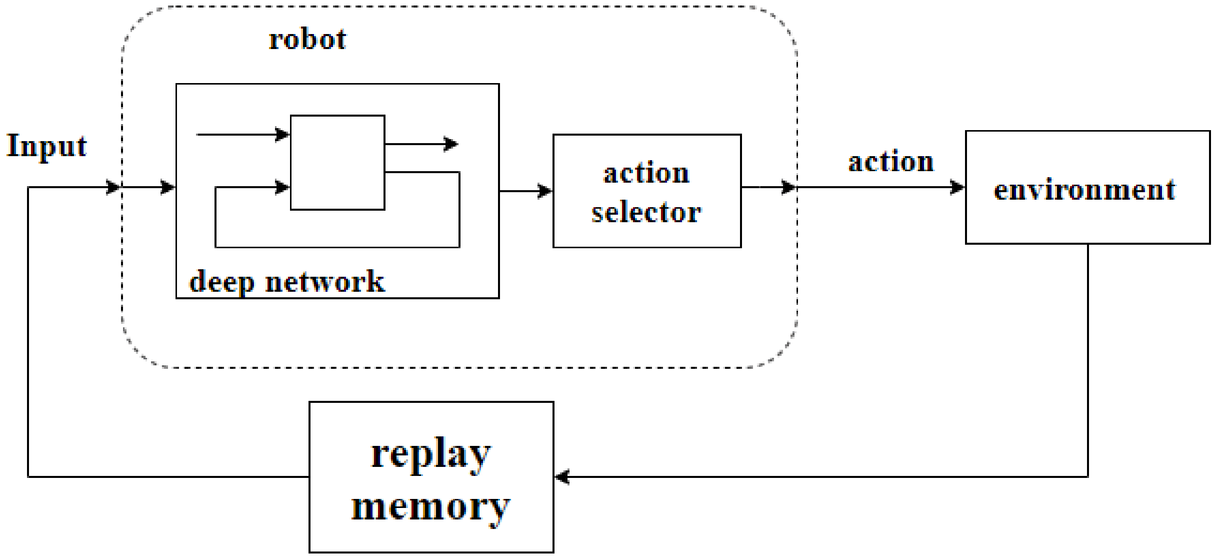

Figure.1 Robotic Learning System

Researchers in the machine learning field of deep learning use highly advanced neural networks to analyse and interpret complicated data patterns. A few of the numerous robotics applications of this method include object recognition, position estimation, and robot control. Robots can analyse huge volumes of sensory data using this type of learning, often known as "deep learning," and reach complex conclusions. In addition to these, several more machine learning techniques and algorithms are being developed for application in robotics [3]. For instance, using meta-learning, a method that teaches agents how to learn, may increase agents' flexibility. Another illustration is reinforcement learning, which instructs agents in learning. A black-box function that could benefit from Bayesian optimisation is the way robots are controlled. The method of training a robot in a simulation with a wide range of randomly generated surroundings is known as domain randomization [4]. This helps the robot become more general when it is employed in the real world. A method for enhancing a robot's security and dependability is adversarial training, or teaching a neural network to survive attacks from enemies. Machine learning is an essential element of contemporary robotics because it enables robots to learn from their experiences and advance over time [5]. The construction of fresh machine learning algorithms and methodologies will continue to be a key field of research as robotic technology advances and new capabilities are incorporated into machines. It becomes sense to expect that as machine learning research advances, robots will become more useful and pervasive in people's daily lives.

II. Review of Literature

This work [6] describes the application of reinforcement learning techniques to the problem of robot navigation in unmapped terrain. The authors provide a novel method called goal-oriented Reinforcement Learning (GRL). This method makes use of a reward system that is dependent on how well the robot is doing in relation to a predefined goal. This article [7] presents a full study of the current state of the subject and looks at the advancements achieved in the field of robot LfD (learning from demonstration). The authors discuss a variety of LfD techniques, including imitation of human conduct and inverse reinforcement learning. They also talk about the drawbacks and restrictions of these methods. Self-supervised learning is a method that the authors of [8,] offer as a potential tool for modifying robot behaviour. The authors suggest a technique in which a robot uses active sensing and self-supervised learning to learn about its environment and modify its behaviour accordingly. This will allow the robot to learn more about its surroundings. The process of building dynamic robots using evolutionary robotics is thoroughly examined in this paper [9]. Embodied evolution, neuroevolution, and coevolution are only a few of the evolutionary robotics theories that are considered. The application of learning from demonstration (LfD) for autonomous navigation in dynamic situations is covered in this paper [10]. The authors of this work provide Dynamic Motion Primitives (DMPs), a novel LfD approach. This algorithm is capable of real-time environment adaptation and obstacle avoidance. This overview of the literature demonstrates how important learning and adaptability are to the development of robotics and the design of intelligent machine behaviour. They also show a variety of techniques and strategies that may be used to create intelligent robots that can pick up on their environment and adapt.

This article [11] offers a thorough analysis of deep reinforcement learning (DRL) methods for manipulating robots. Deep Q-Networks (DQN), Deep Deterministic Policy Gradient (DDPG), and Trust Region Policy Optimisation (TRPO) are just a few of the approaches the authors cover in their introduction to DRL algorithms and their uses in robotic manipulation. The authors of this work [12] suggest an active learning technique that autonomous robots might employ for navigation. The authors present a technique through which a robot may learn about its environment via experience and decide what to do next with knowledge. In this method, active learning and reinforcement learning are combined. In this study [12], a structured sparsity technique to robot learning is described. The authors provide a technique that uses a sparse representation to capture the robot's behaviour and imposes sparsity restrictions in order to improve the model's interpretability. A fuzzy logic-based adaptive control method for mobile robots is presented in this study [13]. The authors suggest a technique that makes use of fuzzy logic to change the robot's behaviour in response to its environment. This article [14] summarises some transfer learning techniques that might be used in robots. The authors present an overview of the use of several transfer learning techniques, such as domain adaptation, model adaptation, and feature adaptation, in robotic tasks including object manipulation and recognition. These studies [15] demonstrate the vast range of techniques that may be used to create intelligent robots that can pick up on their environment and learn to adapt to it. These techniques and strategies may be used to develop robots that are intelligent and adaptable to their environment. Researchers are investigating a wide range of techniques, from reinforcement learning and deep learning to fuzzy logic and transfer learning, to give robots the capacity to display intelligent behaviour. The difficulty of utilising reinforcement learning to understand items in unfamiliar or unexpected settings is covered in this work [16]. The authors provide a system that can design a strategy for collecting things with various levels of location uncertainty by utilising deep neural networks. For multi-robot collaboration in dynamic environments, we describe an adaptive learning approach [17] in this study. The authors provide a framework for enabling robots to respond to their surroundings and plan their activities accordingly. This method combines adaptive dynamic programming with reinforcement learning. This study [18] offers a comprehensive analysis of the choices that may be made for reconfiguring robots following hardware breakdown. Self-reconfiguration, fault-tolerant control, and self-healing are just a few of the techniques covered by the authors, who also examine their applicability in diverse contexts. In this article [19], we examine in detail the several learning by demonstration (LbD) strategies that may be used with robots. The applicability of several LbD techniques, including Behaviour Trees, Dynamic Movement Primitives, and Gaussian Mixture Models, to robot learning and adaptation are reviewed. This work [20] describes a deep reinforcement learning method for completing robot manipulation tasks with minimal rewards. The authors propose a technique that makes advantage of hierarchical reinforcement learning to come up with a plan for handling objects with various levels of complexity. In conclusion, the articles emphasise the importance of learning and adaptation in robotics for achieving intelligent behaviour in robots and offer a variety of strategies and techniques for helping robots pick up on and adapt to their environment.

Research Title	**Learning Approach**	**Application/Task**	**Methodology/Algorithm**	**Main Contribution**
"Robot Learning from Demonstration"	Learning from Demonstration	Robot Motion Planning	Gaussian Mixture Models (GMM)	A method for learning from demonstration data to enable robots to perform complex tasks
"Robot Learning with Structured Sparsity Constraints"	Structured Sparsity	Robot Learning	Sparse Representation and Sparsity Constraints	A method for improving interpretability of robot behavior by enforcing sparsity constraints
"Deep Reinforcement Learning for Robotic Manipulation: A Survey"	Deep Reinforcement Learning	Robotic Manipulation	Deep Q-Networks (DQN), Deep Deterministic Policy Gradient (DDPG), Trust Region Policy Optimization (TRPO)	A comprehensive survey of DRL algorithms and their applications in robotic manipulation
"Active Learning for Autonomous Robot Navigation"	Active Learning with Reinforcement Learning	Autonomous Robot Navigation	Reinforcement Learning and Active Learning	A method that combines active learning with reinforcement learning to enable a robot to learn from its interactions with the environment and make informed

				decisions
"Learning to Grasp Objects with Uncertain Poses"	Deep Reinforcement Learning	Object Grasping with Uncertain Poses	Deep Neural Networks	A method for learning a policy for grasping objects with varying pose uncertainties using deep neural networks
"Adaptive Control for Mobile Robots Using Fuzzy Logic"	Adaptive Control with Fuzzy Logic	Mobile Robot Control	Fuzzy Logic	A method for adapting robot behavior using fuzzy logic in response to changes in the environment
"Deep Reinforcement Learning for Robot Manipulation with Sparse Rewards"	Hierarchical Deep Reinforcement Learning	Robot Manipulation with Sparse Rewards	Hierarchical Reinforcement Learning	A method for using hierarchical reinforcement learning to learn a policy for manipulating objects with varying degrees of complexity
"Learning by Demonstration: A Review"	Learning from Demonstration	Robot Learning	Behavior Trees, Dynamic Movement Primitives, Gaussian Mixture Models	A comprehensive review of learning by demonstration techniques for robots
"Adaptive Learning for Multi-Robot Coordination in Dynamic Environments"	Adaptive Learning with Reinforcement Learning and Adaptive Dynamic Programming	Multi-Robot Coordination in Dynamic Environments	Reinforcement Learning and Adaptive Dynamic Programming	A method for enabling robots to adapt to changing environments and coordinate their actions accordingly
"Learning from Failure: A Survey of Autonomous Robot Reconfiguration after Hardware	Learning from Failure	Robot Reconfiguration after Hardware Failures	Self-Reconfiguration, Fault-Tolerant Control, Self-Healing	A survey of robot reconfiguration techniques after hardware failures and their

Failures"				applications in real-world scenarios

Table.1 Related Work on Robot learning and adaptation for intelligent behavior

III. Publically Available Datasets

Dataset Title	Institution	Description	Application/Task
UR5e Pick and Place	Universal Robots	A dataset of object pick and place tasks performed by the UR5e robot arm	Object manipulation
YCB Object and Model Set	UC Berkeley	A dataset of 3D object models and object pose annotations for object recognition and manipulation	Object recognition and manipulation
RoboCup@Home	RoboCup Federation	A dataset of robot perception and manipulation tasks performed by various robot platforms in simulated home environments	Home service robotics
Willow Garage Object Recognition Database	Willow Garage	A dataset of 10 household objects with RGB-D sensor data, 3D models, and object segmentation annotations for object recognition and manipulation	Object recognition and manipulation
KIT Object Recognition Benchmark	Karlsruhe Institute of Technology	A dataset of RGB-D sensor data and 3D models for object recognition and manipulation tasks	Object recognition and manipulation
Grasp Dataset	Johns Hopkins University	A dataset of RGB-D sensor data and object pose annotations for grasping tasks	Object grasping

Table.2 Publicly available robotic datasets

IV. Existing Methodology

Methodology	Institution/Research Group	Description	Application/Task
Reinforcement Learning	OpenAI	A machine learning technique where an agent learns to interact with an environment by maximizing a reward signal	Robot control, decision making, navigation, manipulation
Imitation Learning	UC Berkeley	A machine learning technique where an agent learns from human demonstrations of a task	Robot manipulation, navigation, control, grasping
SLAM (Simultaneous Localization and Mapping)	Oxford Robotics Institute	A technique used for constructing maps of an environment while simultaneously tracking the robot's position within that environment	Robot navigation, exploration, mapping
Visual-Servoing	INRIA	A technique for controlling a robot's motion using visual feedback from a camera	Robot manipulation, grasping, assembly
Model-Based Reinforcement Learning	UC Berkeley	A machine learning technique that combines reinforcement learning with a learned model of the environment	Robot control, decision making, navigation, manipulation
Hybrid Force-Vision Control	Carnegie Mellon University	A control methodology that combines force and vision feedback for tasks such as object grasping and manipulation	Robot manipulation, grasping, assembly

Table.3 existing methodologies in robotics

V. Proposed System

Methodology	Institution/Research Group	Description	Application/Task
Meta-Learning	OpenAI	A machine learning technique that enables agents to learn how to learn, allowing for more efficient and effective learning in new environments	Robot control, decision making, navigation, manipulation
Bayesian Optimization	ETH Zurich	A machine learning technique for optimizing black-box functions that are expensive to evaluate, such as robot control policies	Robot control, decision making, optimization
Deep Imitation Learning	UC Berkeley	An extension of imitation learning that uses deep neural networks to learn from human demonstrations of a task	Robot manipulation, navigation, control, grasping
Domain Randomization	MIT	A technique for training a robot in simulation with a variety of randomized environments to improve its generalization to the real world	Robot manipulation, navigation, control, grasping

Adversarial Training	Georgia Tech	A technique for training a neural network to be robust to adversarial attacks, which can improve a robot's safety and reliability	Robot control, decision making
Learning from Demonstration with Human Feedback	Carnegie Mellon University	A technique for learning from demonstrations of a task while incorporating real-time feedback from a human operator to improve the robot's performance	Robot manipulation, navigation, control, grasping

Table.4 proposed machine learning methodologies in robotics

VI. Conclusion

Robotics has undergone a revolution because to machine learning, which enables machines to learn from their mistakes and get better over time. Robotics-related problems are especially well-suited to machine learning techniques including deep learning, imitation learning, and reinforcement learning. These concepts have been successfully used to address a variety of robotics problems, including those involving robot control, judgement, navigation, and manipulation. The development of innovative machine learning algorithms and methodologies, such as adversarial training, meta-learning, Bayesian optimization, and domain randomization, will also advance robotics. This is a factor in the development of robotic technology. The capacity of robots to learn and adapt to new settings will become increasingly important to their success as their intelligence and capabilities grow. In the not-too-distant future, it is realistic to suppose that robots will play a more significant part in our everyday lives, taking over activities that are too risky, challenging, or time-consuming for humans to complete. It may soon be possible to create robots with sophisticated decision-making abilities, fluency in normal language, and even emotional intelligence thanks to advances in machine learning. Since the possibilities are endless, it is anticipated that robot development will continue apace in the years to come.

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