ICMIEE20-250

Learning-Based Approaches in Swarm Robotics: In A Nutshell

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ABSTRACT

Swarm robotics, as a segment of multi-robot systems, has the capability of coordinating multiple robots together to complete a complex task. The inspiration is predominated by the social instincts of insects which promote the cooperativeness of swarm robotics. In recent years, swarm robotics has advanced to its next level due to the advancements of artificial intelligence in this field. Several learning-based algorithms have been implemented on swarm robotics to address real-life problems in disaster management, transportation system, etc. These algorithms have shown promising performance towards solving various existing modeling and control problems in multi-robot systems. This paper delivers a preview of multiple researches that recently took place on learning-based swarm robotics. We provide a brief review and categorization of the existing works and their outcomes and identify some key future directions of this domain.

Keywords: Swarm robots, multi-robot system, learning-based approach, neural networks

1. Introduction

Multi-Robot Systems (MRS) is a setup of several mobile robots that can communicate with each other and work towards a predefined objective collaboratively. Such cooperation usually allows multi-robot systems to outperform large and centralized single robot setups [1]. Throughout the last two decades, extensive research on MRS has taken place resulting in various specialized subfields. Variety in these subfields can be found in group size, robot size (nanobots to large autonomous truck platoons), mobility type, group consistency (homogeneous vs heterogeneous), and through more parameters, as well as the tasks they are focused upon. The matured field of the multi-robot system has brought in success for a wide scale of setups in group size, in particular, ranging from groups of a few robots (e.g., Robocups where small robot teams can play collaboratively together but competitively against another team [2]) to over a thousand robots (e.g. Harvard's kilobots [3]), etc. Swarm Robotics (SR) is one of the derivatives of MRS which focuses on a very large group of robots, whose control algorithms are inspired by phenomena in nature such as insect colonies, flocks of birds, herds of animals, etc. Each robot in a swarm usually employs minimalistic and less computationally intensive protocols, yet together, they can perform complex functions. Swarm robotics also incorporates excellent reconfiguration capabilities in the group as a whole and hence brings in great robustness, scalability, and flexibility to the system [4]. The robustness through redundancy guides the swarm robotics system to function even if a part of the system has failed - or at a dead-end; the high levels of scalability allows the stable implementation of relatively simple control algorithms and still receive satisfactory performance at large dimensions; the flexibility ensures that changes in one part of the robot network can propagate rapidly and enable the entire system to fluidly adapt to new realities.

In addition to the above discussion, being inspired by nature, swarm robots can be considered to have two possible communication styles: explicit and implicit communication [5]. Explicit communication refers to direct communication between a sender and a receiver through an established media. On the other hand, in implicit communication, the robot can pick up information from cues and indirect signals from other robots and the environment. These instincts are certainly inspired by [6] bacteria colonies, fish schools, ant and bee colonies, locusts, primates, bird crowds and so on. Collective behavioral activities of those societies motivated the researchers to build spontaneous swarm algorithms such as Bat Algorithm, Charged System Search, Consulted Guided Search, Krill Herd Algorithm, Weightless Swarm Algorithm, Altruism Algorithm, BEECLUST Algorithm and many more [7].

Researchers have attempted learning-based algorithms on swarm robotics sparingly in earlier years but this approach has taken traction lately due to the gigantic jump in the accessibility of artificial intelligence technology and knowledge. Implementation of learning-based algorithms has opened up the possibility of even more advanced application of swarm robotics. Scientists have started seriously exploring the implication of using learning algorithms such as Deep Learning (DL) and Reinforcement Learning (RL) on SR algorithms. Application of such algorithms has turned self-organized factories [8] into a reality by creating real-time data compilers for human-like decision-making purposes. In some cases, swarm robots operate more efficiently [9] than human operators in terms of abrupt yet meticulous decision making. Deployment of those learning algorithms are also anticipated as the prompt solution for several natural disasters or pollution-related issues, such as, the Social Drone of

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Mumbai, SENEKA Project, etc. [10]. It has also been conjectured that such technological advancements would assist the military and surveillance system in a systematic manner by searching and rescuing combatants, detecting incoming threats, building maps, inspecting sites, etc. Other researchers [9] have claimed that swarm intelligence has the potentiality to upgrade the food and transportation management system as well.

This paper illustrates some recent implementation of swarm intelligence. Moreover, what issues they dealt with throughout the implementing session of such advanced algorithms have also been explored here.

The rest of the paper is ordered as follows: Section 2 briefly discusses the methodology of the project, Section 3 provides the findings of the reviews and illustrates a discussion, Section 4 notifies about the challenges and future scopes of learning-based swarm robotics, and finally, Section 5 draws the conclusion.

2. Methodology

For this literature review project, all the papers have been curated through Google Scholar. We performed a thematic search focusing on only the learning-based approaches in swarm robotics. While choosing papers, we mainly prioritized three types of problems related to swarm: control, modeling, and application; that were addressed and solved by the researchers using learning algorithms. Finally, we were able to gather seventeen recent papers (published between 2017 and 2020) in total for our review purpose where six of them focused on utilizing learning-based approaches on the control aspect, four of them implemented learning towards the modeling of the system, three used data-driven approaches during application and the remaining four were on some other important problems in the swarm system.

3. Findings and Discussion

It is clear that learning-based approaches can help researchers design swarm robotic systems to perform better, especially for a set of preexisting problems. This section summarizes the problems focused upon the researchers, the methods they followed and the experiment environment they used while solving those problems.

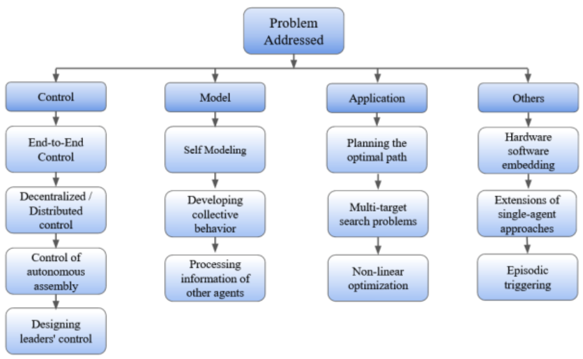

Fig. 1 Categorization of Addressed Problems

3.1 Addressed Problems

A wide range of problems can be solved using a learning-based approach as it updates the action of the system by acknowledging the current performance as well as the new environment. Recently, scientists had admitted this fact and applied the learning-based techniques in the swarm robotics domain. In Fig. 1, the problems are divided into four categories: control-based problems, model-based problems, application-based problems, and other problems.

By adopting the learning techniques, researchers tried to solve different problems related to control of swarms such as control of autonomous assembly [11], decentralized control [12], control of the leaders of a swarm [13], distributed control [14], designing shepherds' control [15], end-to-end control [16], and so on. Some scientists also solved swarm model-based problems including self-modeling [25], processing information of other agents [19, 21], developing collective behavior [20], etc. Others focused on application-based problems e.g. non-linear optimization [18], planning the optimal path [23], and multi-target search problems [26] as well. Witnessing the effectiveness of this approach, researchers also applied the learning technique to solve hardware-software embedding problems [17], to extend single-agent approaches to multi-agent problems [22], to handle episodic triggering issues [24], and to visualize the behavior of swarm system [27].

3.2 Methods

Researchers explored multiple learning-based algorithms to address the problems mentioned in the tables. The most popular were neural network-based approaches. They adopted some popular types of networks like basic Neural Network [21], Deep Neural Network [12, 20, 26], Convolutional Neural Network [16, 22], Feedforward Neural Network [15, 19, 26] in their models to make them more efficient. Q-Learning [23, 24, 25] and Reinforcement Learning [21] are also popular among them. Some have preferred Deep Q-Learning [16, 19] and Deep Reinforcement Learning [15, 19, 20] models for learning-based approaches. There are some other techniques such as Particle Swarm Optimization [23, 25], Evolutionary Algorithms [13, 23, 26], Histogram-based embedding [14, 21], etc. which researchers found very helpful for their models.

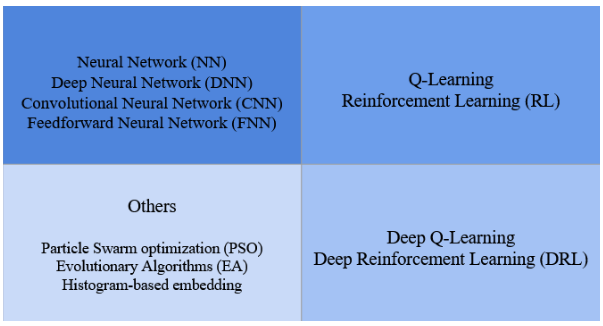

Fig. 2 Methods used in the learning-based approaches

Table 1 Recent work on control of swarm robots using learning-based approach

Author	Category	Year	Addressed Problem	Proposed Solution	Contribution
Gebhardt, G. H. [11]	Extended Abstract	2017	Control of autonomous assembly	Proposed reinforcement learning for assembling objects using a swarm of robots.	A stable policy of object movement and learning process has been assured here.
Li, Q. [12]	Conference Paper	2017	Distributed control for Large-scale robotic swarms	Developed a deep learning model to learn the policies of distributed coordination from centralized strategy.	For systems having different numbers of agents, the model outperforms some well-known control laws of distributed systems.
Tuzel, O. [13]	Conference Paper	2018	Designing leaders' controller	Used a control method based on neuro-evolutionary learning for training leaders to manipulate motion behaviors of follower agents.	With a minimum of 4% leadership, leaders successfully guided the agents to their goal.
Hüttenrauch, M. [14]	Conference Paper	2018	Decentralized control	Proposed histogram-based communication protocols to find policies of decentralized control for swarm settings.	A potential way for information processing in the swarm environment has been demonstrated here.
Nguyen, H. T. [15]	Conference Paper	2019	Designing shepherd' control	Proposed a deep hierarchical reinforcement learning approach by decomposing tasks into sub-tasks.	A stable, scalable and accurate method has been presented here.
Wei, Y. [16]	Journal	2019	End-to-End Control	Explored deep Q-learning algorithm while developing policies of end-to-end control of robotic swarms.	With appropriate reward design, control policies can be achieved successfully using raw inputs from a high-dimensional camera.

Some researchers have found that a combination of a few algorithms works better than using them individually. Interestingly, while solving the optimal path problem, researchers found that using the combination of the Q-learning algorithm and particle swarm optimization performs faster than these algorithm's individual performance [23]. The Q-table is initialized with zeros and the swarm particles by random trajectory. According to the current state, the system selects an action and the best position of all particles is settled using q-values. After that, particle swarm optimization is applied to all the particles and the system calculates a new trajectory. The architecture of the system can be seen in Fig. 3. Similarly, dealing with the multi-target search tasks, researchers used a deep neural network with four hidden layers to train the model and then applied evolutionary algorithms to fine-tune the parameters and improve the performance of the network [26].

An interesting work has been presented in [27] which focused on *visualizing* the decision-making process by a deep Q-Learning algorithm as it is a black box to many people. They merged Deconvolutional Network with Gradient Class Activation Mapping and successfully illustrated the policies gained by the model. By creating a heat map to highlight the relevant parts in the input frame, they identified the important parts of the frame that drive the model to its final decision.

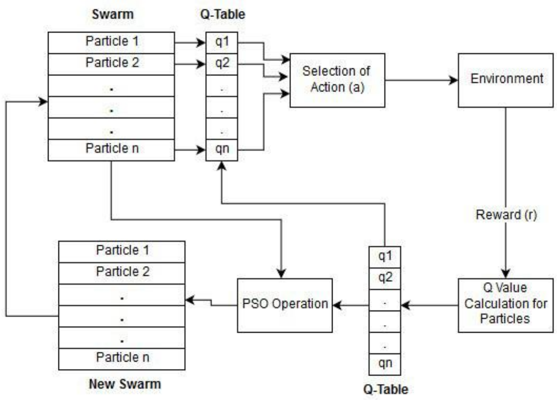

Fig. 3 Q-Learning-Based PSO Algorithm reproduced from [23].

Table 2 Recent work on some popular problems of swarm robotics using learning-based approach

Author	Category	Year	Addressed Problem	Proposed Solution	Contribution
Chamanbaz, M. [17]	Technology Report	2017	Hardware-software embedding	Proposed a design that integrated both software and hardware for different tasks of robotic swarms.	Newly designed cooperative and collective behaviors models can be simulated onto this platform.
Bakhshipour, M. [18]	Conference Paper	2017	Non-linear optimization	Proposed an optimization algorithm based on collective search to find a victim in a disaster.	The application of this optimization algorithm can be extended to other fields of science.
Hüttenrauch, M. [19]	Conference Paper	2017	Processing information from other agents	Followed a data-driven learning process on local information of agents to solve cooperative tasks.	With limited capabilities of sensing, the agents could learn control policies.
Yasuda, T., [20]	Conference Paper	2018	Developing collective behavior	Conducted experiments on real swarm robots and analyzed learning performance.	In learning behavior, robots that have experience sharing capability in multi-robot systems were successful.
Hüttenrauch, M. [21]	Journal	2019	Processing information of other agents for large-scale robotic swarms	Proposed a representation of deep reinforcement learning for multi-agent-based on empirical mean embeddings.	The richest exchange of information among agents has been found by the model that uses features of neural networks.
Sartoretti, G. [22]	Conference Paper	2019	Extensions of single-agent approaches	Proposed a scalable, distributed learning framework, where all agents learn a general collaborative policy.	Around 90% accuracy was achieved by most of the structures tested in the framework.
Meerza, S. I. A. [23]	Conference Paper	2019	Planning the optimal path	Proposed Q-learning-based particle swarm optimization approach for finding an optimal path in a foreign environment.	The algorithm outperforms other traditional algorithms by accuracy and speed.
Matta, M. [24]	Electronics Letter	2019	Episodic triggering	Proposed a modified Q-learning algorithm by considering iteration-based knowledge sharing.	The algorithm requires fewer iterations to solve a task and achieves better performance with larger state-spaces.
Meerza, S. I. A. [25]	Conference Paper	2019	Self-Modeling	Proposed Q-learning-based particle swarm optimization to learn its own gait configuration.	Parametric identification has been demonstrated to obtain standing pose without data on gaits and legs.
Li, J. [26]	Journal	2019	Multi-target search problems	Proposed a framework that has a deep neural network followed by evolutionary algorithm.	An efficient, stable and effective framework has been validated in this paper.
Nie, X. [27]	Conference Paper	2019	Visualizing Behavior of Swarm Robotic System	Proposed a method by merging Deconvolutional Network with Gradient Class Activation Mapping.	In illustrating the policies gained by the deep Q-learning, the method was successful.

Tables 1 and 2 illustrate some recent work on this field; the addressed problems, proposed solutions, and the main contribution of the approaches undertaken. We have already discussed the addressed problems and proposed solutions in this section. In terms of the contribution, in most of the cases researchers offered models or methods to solve specific problems using learning-based approaches [11-16, 18-21, 23-25, 27], few of them delivered frameworks [22, 26] and in one case, researchers presented a whole platform [17] where other models can be tested.

3.3 Experiment Environment

For implementing and testing the proposed models, simulated environments were chosen most of the time. Among different environments, Robotic Operating System (ROS) is the most popular among the researchers where processing, Microsoft XNA, and other programming language-based modules are also used by many analysts. For faster calculation, many researchers used high-performance computers as well.

4. Open challenges

Although there are some outstanding works on learning-based swarm systems, there are still a lot of challenges to overcome. First of all, most of the algorithms were tested in the simulated environment. Even though the outcomes of those experiments were remarkable, there are still some possibilities that the algorithms might face some challenges in real-life scenarios. Secondly, the experiments were done under several assumptions. Hence robustness is still not confirmed by many of the proposed algorithms. Thirdly, scalability seems like an issue. In some cases, the algorithm loses its peak performance when the size of the swarms' increases [11, 19]. With a higher number of agents, a model in the swarm system should perform better but in most of the cases the models failed to achieve that quality [11, 19]. Finally, in some cases, the model needs a vast number of iterations [23] and a huge computational cost to learn the policy properly [19]. So, further research should be done to reduce the cost and the number of iterations.

5. Conclusion

This paper provides dimensional research on swarm robotics systems. A study on swarm robotics, precisely on learning-based swarm robotics, has been illuminated here for a better understanding of this field. A total of seventeen papers based on learning algorithms have been analyzed here in order to get a clearer vision of this topic. After summarizing all the research, we have stated that among the mentioned methods, different neural network-based approaches have been the most popular ones whereas histogram-based approaches were less popular. However, there are still some issues to deal with in terms of stimulation, backgrounds, etc. and deeper systematic exploration in this field is needed as this was not an exhaustive list of papers. Also, further research is needed to address the common open problems so that learning-based swarm intelligence can have more practical and efficient applications. In the future, we would like to establish formal categorizations and paradigms based on a more exhaustive literature review. We would also simulate and experiment with various approaches and protocols and provide a comparative analysis of their performance.

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