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Convergence of Machine Learning and Robotics Communication in Collaborative Assembly: Mobility, Connectivity and Future Perspectives

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Abstract Collaborative assemblies of robots are promising the next generation of robot applications by ensuring that safe and reliable robots work collectively toward a common goal. To maintain this collaboration and harmony, effective wireless communication technologies are required in order to enable the robots share data and control signals amongst themselves. With the advent of artificial intelligence (AI), recent advancements in intelligent techniques for the domain of robot communications have led to improved functionality in robot assemblies, ability to take informed and coordinated decisions, and an overall improvement in efficiency of the entire swarm. This survey is targeted towards a comprehensive study of the convergence of AI and communication for collaborative assemblies of robots operating in the space, on the ground and in underwater environments. We identify the pertinent issues that arise in the case of robot swarms like preventing collisions, keeping connectivity between robots, maintaining the communication quality, and ensuring collaboration between robots. Machine Learning (ML) techniques that have been applied for improving different criteria such as mobility, connectivity, quality of service (QoS) and efficient data collection for energy efficiency are then discussed from the viewpoint of their importance in the case of collaborative robot assemblies. Lastly, the paper also identifies open issues and avenues for future research.

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1 Introduction

Artificial Intelligence (AI) has been successfully put to effective use in a plethora of real-world applications in the modern world. AI is increasingly utilized to improve the technologies in science and social domains and their applications, due to its amazing capability of dealing with big data of enormous complexities, with high accuracy and fast processing. John McCarthy, known as the father of AI, defined AI as *the science and engineering making intelligent machines.* AI can be employed in machines, robots or computers to ensure their performing various tasks effectively and in an efficient manner. Hence, AI is growing exponentially to make machines smarter and more intelligent. In light of the above, machine intelligence can be defined as the ability of a machine to perform any intelligent task in any environment efficiently, exactly or approximately similar to a skilled human operator. For example, robots are the smart machine that can effectively and efficiently perform complex tasks and safely collaborate with a human to perform any tasks collaboratively. It is expected that robots serving humans or collaborating with humans must know the human needs with minimal communication from humans. To this end, several AI techniques have been proposed [87,143]. Moreover, AI refers to the ability of robotics systems to process information and produce an outcome similarly as humans do in learning, solving problems and decision making. Therefore, AI is arguably the most exciting field in robotics. With a view to use AI approaches in robotics, many possibilities arise for automation tasks in several application areas such as domestic services [47], space explorations [78], medical procedures [34], military operations [113], collecting data [17,111], manufacturing [83], and underwater applications [74].

Recently, robots are using their abilities, along with AI, to perform tasks quickly and smartly. Therefore, robotics has capability for self-organizing [100], self-learning [39,152], and self-reconfiguring [50]. The aim of convergence of AI and robotics is to understand how can the robots be made capable of acting and thinking like humans. Therefore, communication among robots themselves and with humans is necessary. Toward that end, robotics have often been combined with advanced communication network technologies in both practice and research. In a multi-robot collaborative set-up, communication among robots is also required to ensure collision prevention by monitoring trajectories. AI may also be leveraged for Quality of Service (QoS) enhancement techniques and data collection for energy efficiency. The most commonly used metrics for robot communication systems are categorized and presented as energy metrics (related to data collection from surrounding environment), QoS metrics, mobility (related to collision prevention by assigning smooth trajectories for robots). AI techniques have been successfully applied to controlling and managing the above metrics for enhancing the effectiveness of robotic collaboration.

Convergence of AI, robotics and advanced wireless communication technologies will help robots to move autonomously and extend robotic functions to perform any given task effectively and efficiently with better (or atleast equal) skill than a human counterpart. Recently, AI and the Internet of Things (IoT) networks have made a revolution in the robotic domain applications. IoT represents the body part of robots that perform physical tasks, whereas the AI represents the brain of the robots that controls the physical entity according to the application requirements [23,115]. The difference between robotic things and IoT is that robots have intelligence concepts [93]. Pervasive robotics is closely interrelated with the Internet of Intelligent Things (IoIT) [23]. Due to the use of IoIT, the smart home and robots become the same entity. The wireless communication network plays a vital rule in transmitting and sharing data between robots over the pervasive network, communicating with each other, and also with humans. While robots will represent the middleware for data collection, AI shall be used for processing data intelligently for IoIT. The combination of robots, AI and IoT, will result in robotic systems having high capabilities to perform complex tasks autonomously. With the help of IoT, robots can connect with each other and with humans easily, facilitating high quality and high speed data exchange amongst them and with humans. Razafimandimby et al. [106] addressed the critical technology for keeping connectivity between Internet of Robotic Things (IoRT) to provide the desired QoS by using an Artificial Neural Network (ANN). The significance of using ANN was to maintain the tradeoff between global connectivity and desired QoS in the robots coverage area.

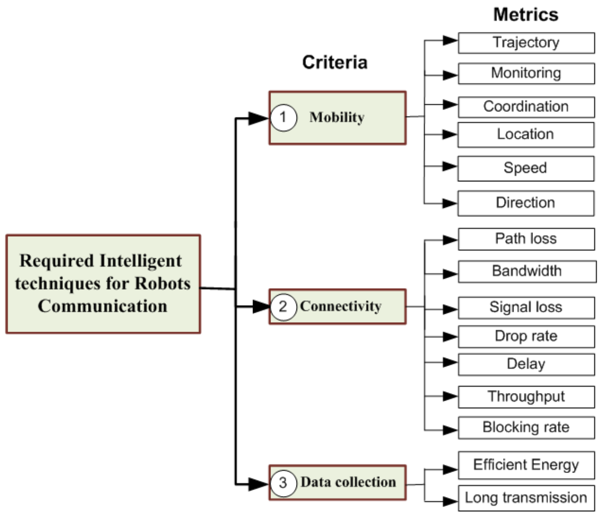

Fig. 1: Communication amongst collaborative robots

Swarm intelligence robotic communication pertains to a large group of robots that interact, control, cooperate, and coordinate with one another to solve complex tasks efficiently which is challenging to be done individual capability. Swarm robotics includes autonomous robots, local sensing, and centralized and decentralized communication capability according to the environment and performing actions. Swarm robotics has facilitated a revolution in many applications such as materials delivery, precision farming, and monitoring and performing complex tasks which a single stand-alone robot cannot do [32]. A key component of swarm intelligence is the communication between swarm robots which is usually local and guarantees QoS to be robust and scalable. Robots in the swarm can not only communicate with each other directly but are able to transmit information in a multi-robot communication network via relaying communication nodes [81]. Furthermore, swarm robotics is related to the application of swarm intelligence techniques which can be implemented to change their environment based on an intelligent decision from the sensing and collected data [144]. Also, swarm intelligence robot communication is required for maintaining a decentralized control. Swarm intelligence robots are capable of communicating with each other, capture the local information and sense the surrounding environment and make an appreciated decision dynamically based on the data sensed [24]. Swarm robots are placed in a distributed fashion to perform a common goal collaboratively. Collaborations of swarm robots are based on mutual sharing and mutual learning. Therefore, they collaborate effectively and efficiently by sensing the environment and sharing information autonomously via communication network technologies in space, ground, and underwater.

1.1 Scope of Study

AI techniques play a crucial role in enhancing accuracy of robot communication by bringing improvements in metrics like QoS, mobility, and data collection efficiency. In this survey, we present a comprehensive review of the intelligent solutions for robot communication which have been proposed in literature in recent years. The main contribution of this paper is, thus, to gather the literature and emerging researches of ML for collaborative robot communication (which includes efforts to enhance robot communication capability with each other, perform activities, take necessary and appreciated decisions, achieve independent and coordinated actions and perform their tasks efficiently). The study focuses on different criteria for keeping and evaluating connectivity between robots such as trajectory monitoring, coordination, location, speed, direction, path loss, bandwidth, Received Signal Strength (RSS), drop rate delay, energy efficiency and transmission range.

1.2 Related Work

The familiar tools of AI include Artificial Neural Networks (ANN), Artificial Neuro-Fuzzy Inference System (ANFIS), Genetic Algorithm (GA) clustering, Machine Learning (ML), Particle Swarm Optimization (PSO), Deep Learning (DL), etc. as shown in Fig. 2. AI has been used in several domains of sciences and technology as well as in social sciences and arts.

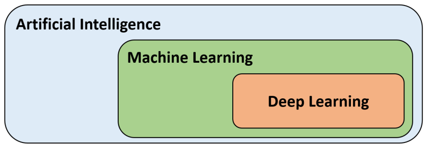

Fig. 2: AI family approaches

Consider the case of robots communicating with each other to perform complex tasks. These robots should share information to exchange amongst themselves according to the environment. To coordinate and exchange the information, the authors of [61, 134, 145] introduced the framework for empowering robots to learn cooperatively based on centralized training with decentralized execution. Therefore, communication plays a vital role in enhancing the collective intelligence of robots in their duty to perform tasks efficiently. To this end, the authors of [49, 133, 151] discussed swarm robots communication protocols based on Reinforcement Learning (RL). They applied RL to train swarm robots to learn communication protocol and have observed the communication among swarm robots achieve better reward for performing various tasks effectively. Furthermore, the authors of [49, 151] addressed the training environment of robots which has limited bandwidth due to significant exchanged information.

Robots need to share information about their status and location as well as their surrounding environment, so reliable wireless communications represent the basis for successful collaboration between robots. AI can play a vital role in improving the robot communication criteria as shown in Fig. 3. For instance, the connection between drone and ground devices such as IoT devices was discussed in [75, 127]. Meanwhile, many types of research have emerged on AI for robot communication [22, 23, 35, 36, 41, 98, 106, 130]. These researches are exciting, but they have been applied for limited applications. The studies of [22, 41] mostly restrict their scope to ML for wireless sensor networks, Machine-to-Machine (M2M) connection [98], and, hence, they do not mention the applications which ML can offer for enhancing future robot connections and networks. In addition to work of authors in [22, 41], [36] introduced the drones connectivity and predicted the number of users connected to the drone by using ML, and postulated that the complexity of algorithm may be reduced in future. However, the studies [35, 130] focus on ML for optimizing the drones location and user behavior prediction. The idea of a combination of AI, IoT, and robots is supported by the work in [106], which is highly qualitative, and the authors do not provide a quantitative description of their AI. Similarly, Arsénio et al. [23], focused on the smart robots at home for data collection and connection with processing using AI.

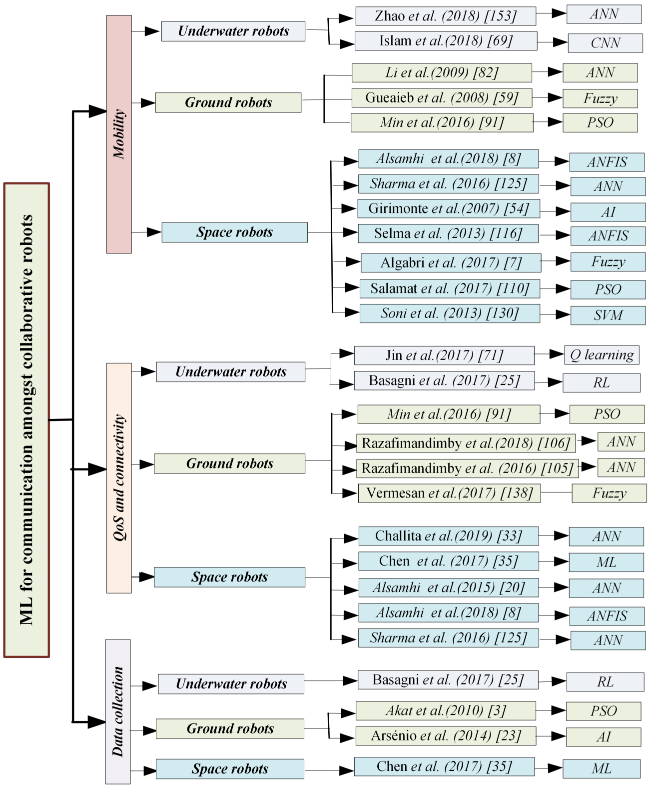

Fig. 3: Overview of current studies pertinent to ML and robotic communication

Table 1: The most recent survey related to current work

Survey	Focused
[128] (2018)	Internet of Robotic Things
[66] (2018)	Internet of Flying Robots
[37] (2018)	ML for improving IoT applications and provide IoT services
[30] (2018)	ML for networking
[45] (2017)	DL for controlling the traffic and routing of networks
[84] (2018)	DL for a wireless communication network
[136] (2019)	utilization AI to various issues of vehicles to everything
Proposed	Convergence of AI and robotics communication network based on enhancing communication criteria QoS, mobility, and data collection

Many recent and existing surveys discussed intelligent techniques for different communication networks with attention to controlling and management of traffic, such as [30,37,45,66,84,128,136]. The summary of these studies is shown in Table. 1. The authors of [128] examined how IoRT is enabling potential disruptive services, and authors of [66] focused on designing Internet of Flying Robots (IoFR) for real-world applications such as monitoring, collaborating with ground robots, wireless communication and serving a wireless sensor network (WSN).

Tong et al. [136] addressed the utilization of AI in various issues of internet of vehicles to internet of everything according to their applications domains. Furthermore, the authors of [29] explored ML techniques to solve network management in dynamic emergency environments such as military or disaster area. Furthermore, Boutaba *et al.* [30] discussed the applications of ML techniques for different communication networks include classification and routing, traffic prediction, resource, and QoS management and network security. Authors of [37] focused on providing an overview of ML application in the IoT domain. ML applications for IoT enables users to get accurate analytics for developing efficient and intelligent IoT applications. On the other hand, authors of [45] discussed DL techniques for controlling the traffic and routing aspects of networks. Also, Mao *et al.* [84] discussed the applications of DL methods for different network layers such as traffic balancing, physical layer modulation, data link layer, and routing layer. To the best of our knowledge, there does not exist a survey that is dedicated to reviewing the AI techniques applied for robotic communication.

1.3 Contribution and Structure

This survey is intended for developers and researchers working in the area of robotic communication, and engineers working on AI-based solutions for robotic communication problems. The contribution of this survey can be summarized:

(A) First, we discuss how the robots can understand the environment and take action with the help of IoT and ML.
(B) Next, a discussion is presented on how to adopt ML techniques in collaborative robot communication based on criteria such as QoS, mobility, data collection, and collaborations between robots which lead to enhance the robot communication metrics.
(C) We review the most important techniques and approaches for deploying ML for robots communication for performing tasks effectively and efficiently.
(D) Lastly, future research directions and challenges are highlighted.

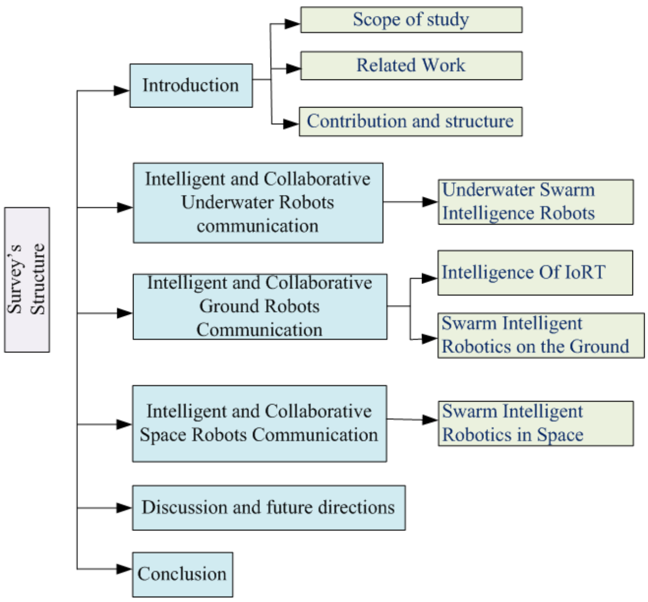

Fig. 4: Survey structure

The rest of the paper is organized as shown in Fig. 4. Section II describes intelligent and collaborative underwater robotic communication. Section III presents a review of AI approaches put forward for ground-based robot communication. Techniques which harness artificial intelligence for communication amongst robots operating above the earth (space, sky) are surveyed in Section IV. A discussion on open issues and future directions of research is presented in Section V, and the paper is concluded in Section VI.

2 Intelligent and Collaborative Underwater Robot Communication

Underwater robots play a vital role in ocean monitoring and observation of water bodies like rivers and lakes. A typical example of such an underwater robot is the Autonomous Underwater Vehicle (AUV) which has the potential capability of data collection and making intelligent decisions. With increasing interest in the development and applications of AUVs, AI can be applied for their autonomous operation. The authors of [77] investigated deep reinforcement learning for controlling underwater robots based on their tracking behavior. The proposed technique has efficiently enhanced the autonomy and control system of underwater robots operations. Furthermore, ANN has also been applied for predicting the path tracking of AUV [153]. The findings showed that the proposed ANN was efficient for predicting the path tracking of AUV. However, localization also plays a vital role in enhancing the AUVs performance. Poursheikhali et al. [99] discussed the localization based on RSS and Time of Flight (TOF). The TOF-based technique could achieve high resolution based on available bandwidth and ensured the synchronization between the transmitter and underwater receiver environments. The primary issue of the underwater robotic communication network is the limitation of the communication channel and therefore, the communication can be done up to a few meters only, offers low data rates, and presents noise and disturbances. However, Yordanova et al. [148] developed the synchronous rendezvous technique and mission planning scheme for underwater robotic communication and resource constraint environment.

The advantages of AUVs communication network include cost efficiency, time and better data gathering. Bassagni et al. [25] introduced the RL based routing protocol as a strategy for underwater robots communication network based on selecting the best communication channel and fast packet delivery to seek reliable routs to terminal robot-nodes in the network. Further, the authors of [71] applied a Q-Learning-based delay-aware routing technique to enhance the lifetime of underwater network vehicles. The authors of [69] proposed a Convolutional Neural Network (CNN) to provide accurate hand gesture recognition based on divers communicating with underwater robots. The proposed technique helped divers to communicate easily with underwater robots without using artificial tags or complex set of language rules.

2.1 Underwater Swarm Intelligence Robots

Applications of communication between robots with swarm intelligence exist not only in space and ground but also underwater. Communication network plays a critical role in swarm intelligence robots for transmitting data in a large underwater environment [139]. Swarm underwater network architecture was discussed in [107], which aimed at improving the functionalities of different vehicles underwater using smart AI techniques. Furthermore, controlling swarm underwater robots requires communication and control techniques for performing complex tasks collaboratively and efficiently [72]. Also, collected data and transmission are not enough for performing complex tasks, but the merger of AI collaboratively with underwater swarm robots and communication can efficiently make swarm underwater robots work effectively and efficiently in an optimal manner. Based on local communication and self-organized control of swarm robots underwater, the authors of [44] developed controllers for homing, dispersion, clustering and monitoring. The findings showed that the evolved

Table 2: Summary of ML techniques for collaborative underwater robots communication

Ref	AI	Highlighted	Criteria	Metrics
[153] (2018)	ANN	path tracking of AUV	– Mobility	– Location
[25] (2017)	RL	routing protocol as a strategy for underwater robot communication network	– QoS	– Delay
[71] (2017)	Q-Learning	enhance the lifetime of underwater network vehicles	– QoS – Data collection	– Delay – Energy efficiency
[69] (2018)	CNN	hand gesture recognition based on divers communicate with underwater robots	– Mobility	– Location – Coordination
[44] (2016)	Cluster	Local communication of swarm underwater robots	– Connectivity – Mobility	– Monitoring – Location
[140] (2015)	ANN	maintaining swarm underwater robots in a preferable communication coverage area	– QoS – Mobility	– RSS – Trajectory – Monitoring – Location

controllers' performance was similar to a real swarm. For maintaining the coverage area of the swarm underwater robots, the authors of [140] proposed ANN for maintaining and establishing a desirable connection of wireless communication with each robot in the whole swarm. RSS Indicator (RSSI) was used for measuring the quality of the link between swarm robots, while the ANN was used for controlling the trajectory of each robot for maintaining swarm underwater robots in the preferable communication coverage area. Table 2 shows the summary of applied AI for underwater robot communications.

3 Collaborative Ground Robots Communication

A multi-robot system is a group of robots that communicates by using advanced communication technology to perform tasks collaboratively in an efficient way. The task may be performed collaboratively and autonomously. The efficient communication of a cooperative robot team in performing common tasks is addressed in [86]. Ad hoc network is a popular communication technology used for robotics because of the ability to add autonomous nodes, and has been used for communication between robot teams [27, 119]. The authors of [142] addressed the ad hoc robots wireless network with application and protocols. Ad hoc network helps autonomous robots to perform tasks with a high degree of autonomy. They focused on the performance routing protocol for saving energy metric. However, the study does not consider the other metrics such as connectivity, accuracy, throughput, robustness and bandwidth efficiency, which should be considered in measuring the system performance. Also, a lot of research has been done in the area of robot-team communications [48, 112]. A stable communication channel between robots is dynamic and static aggregation techniques have been considered for a wireless data transmission in the intelligent and autonomous robots network [55]. While the static technique allows increasing the transfer data rate in robots network, the dynamic technique is effective for distributing load between channels. Using both techniques play a vital role in obtaining a stable communication channel between robots. The authors of [63] introduced several communication technologies for robot control. Coordinated robot teams on the ground and in the air have been investigated [126].

The use of ANN for different applications is discussed in [97]. Mechraoui *et al.* [88] utilized ANN for taking an intelligent hand-off decision based on the movements of the mobile robot out of the cell area. Also, ANN was utilized for a mobile robot communication in the same coverage area while taking into consideration velocities, orientations and positions [62]. The advantages of using ANN in this study were to ensure robot communication network stability and reduce the costs of communication. Li *et al.* [82] proposed an ANN to coordinate the movements of the robot and avoid obstacles during movement by using an intelligent planner component of the hybrid agent. Here, ANN was used to generate the desired paths automatically for multiple coordinated robots in an environment. The results showed that an intelligent planner could control a large complex robot system and achieve the required coordination among agents. In addition to the author's work of [82], Ghouti *et al.* [52,53] predicted the mobility by using a powerful, intelligent techniques. In [53], Extreme Learning Machines (ELMs) leads to a significant improvement in mobility prediction over conventional methods based on Multi-Layer Perceptrons (MLPs). The authors also improved the prediction for future location in [52]. The study leads to better prediction robustness and accuracy in designing mobility assumptions. Further, Gueaieb *et al.* demonstrated navigation algorithm for robots guidance under any Radio Frequency IDentification (RFID) tag by simple, intelligent processing of the phase difference of the signal sent by the tag and received at both antennas of the RFID reader mounted on the robot [59]. Also, the authors of [2] introduced and surveyed different AI techniques for radio navigation networks. Authors of [42] focused on improving an intelligent scheme for the autonomous indoor intelligent vehicle by using classification neural networks and Wi-Fi fingerprinting. IN that case, the ANN was able to train with the noisy WiFi signal strength smoothly. Leandro *et al.* [46] investigated smart robotic cars from the viewpoint of security and communication. They focused on design, sensing, decision making, and acting for evaluating vehicle communication security.

3.1 Swarm Intelligent Robotics on the Ground

Particle Swarm Optimization (PSO) is the most important technique that has been used for swarm intelligence robotics in space, ground and underwater. Regarding to swarm robots coordination, Doriya et al. [43] used PSO to coordinate swarm robot communication with the help of a cloud while cluster head gateway switch routing protocol was used forming clusters of robots. To perform the swarm robot communication and coordination, the PSO technique was efficient for making swarm robots tasks easier. Furthermore, both PSO and GA have been applied to establish an end-to-end robot wireless communication in a disaster area through finding an optimal distribution of robots. In this regard, sharing of information and transmission in real time represent the critical factors of saving people lives during a disaster. The robot allocation, propagation signals, and robots trajectory have been considered for wireless communication in a large disaster area. Asynchronous PSO based robotic search algorithm was tested in a simulation environment and implemented with real robots [3]. Therefore, integration of AI, robots, and communication technologies are slated to improve safety level for humans by making use of autonomous robots for dangerous operations and rescue missions. Stender *et al.* [131] studied a swarm of micro-robots collaborating to find a point of interest under noise and with limited communication in 2D space. The PSO technique was highly efficient to explore the solution space fitness function.

Authors of [92] proposed PSO technique for avoiding the obstacles in robot motion (and considered the robot's location, direction, and velocity) in a dynamic environment. The findings showed that the proposed technique was better than traditional statistical ones, and each robot could be manages/monitored separately because of PSO. Derr *et al.* [40] proposed PSO (to monitoring RSS) for discovering an unknown environment to get robots at a desired location. Furthermore, Pugh *et al.* [101] evaluated the performance of noise-resistant algorithms for overcoming noise, and employs PSO based on learning of obstacle avoidance of one or swarm robots Yang et al. [147] optimized the path planning by using PSO for obstacle avoidance. Authors of [65] proposed PSO for swarm robots that aimed at searching light in the room which contains many obstacles. In this case, each robot was broadcasting the information to the entire swarm. However, they considered only three robots, and therefore, it can be improved for a large number of robots with global communication to enhance the performance of the swarm.

3.2 Intelligence of IoRT

A robot represents a group of sensors, manipulators, control systems, power supplies, and software which are working together to perform a series of complex actions automatically. The IoT technologies such as cloud computing, big data, sensors, and control systems drive robotics; IoT technologies and robots connected to give birth to a new and promising technology called IoRT. IoRT is an intelligent concept which gives associated things, the ability of negotiation, reasoning, and delegation. The combination of both technologies was discussed in [38,57,108]. Furthermore, the Internet of Vehicle (IoV) was explored in [6,51] wherein the advantages, communication, intelligence, and the capability to learn and storage were discussed. Therefore, the combination of robots and IoT technology can provide efficient communication among heterogeneous network due to real-time monitoring and data gathering. The combination of IoT and robots can be used to coordinate with rescue and relief operations according to damage and risk to the environment and then deploy robot applications to perform a search [79,109]. IoT and robotics are two terms each covering a myriad of concepts and

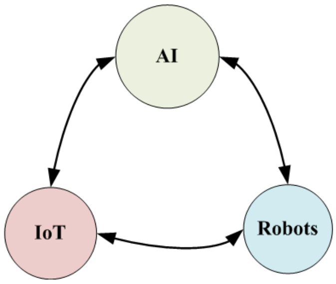

Fig. 5: Robots, IoT and AI combination

technologies [128]. To do the same, an IoT device may be connected to a drone, which performs a particular task within a specified area, where IoT is deployed to sense environmental data [115]. Therefore, IoT is considered as ears, nose, and eyes of the robotic component of IoRT, while machine learning represents the brain of robots. AI has made the combination of robots and IoT applicable for advanced applications and provide viable solutions for today's problems [138]. The combination of AI, IoT and robots is strongly linked as shown in Fig. 5. It is shown that both technologies complete each other and use all of them to perform complex tasks efficiently. Fig. 8 shows the collaboration of robots, IoT, AI and IoRT. Robots will also contribute significantly to rescue management systems, military applications, and health care. Therefore, the collaboration of robots and machine learning and big data adds to the functionalities they tend to deliver. The addition of IoT to robotics will render us to appreciate the IoT components to obtain real-time data and function accordingly.

Authors in [56] presented the analysis of robotics data (multiple views of the environment) using ML techniques. Robotic environments have been classified by the data captured using mobile robot's on-board sensors. For multi-tasking robot, the author in [1] discussed the use of AI and IoT for improving the robotics to do multiple tasks. The authors of [105] introduced the ANN technique for preserving global connectivity between IoRT robots. The advantages of applying ANN were to obtain balance between desired QoS and desired network coverage of communication domain of IoRT. ANN was used to provide the desired QoS and efficient global connectivity of multiple mobile robots. They focused on the implementation of multiple IoRT in which ANN was used for maintaining global connectivity as well as balancing the network coverage and desired communication quality. The findings showed that ANN was efficient in term of convergence, connectivity, and energy consumption.

A robot is used to gather data from the surrounding environment using IoT devices in which they help to change robots behavior as shown in Fig. 6. Combined with ML, the robot's reactions over time get more and more adequate. Furthermore, the use of IoT, cloud technology and big data analytics make the robot versatile. The capabilities include cloud computing, communication with other robotic systems and sensor inputs from the environment around them. Therefore, robots can monitor any events, collect data, process collected data intelligently to determine the best course of action, and then act to manipulate objects in the physical world. The author in [104] proposed the concept of IoRT, where intelligent robots can use ad-hoc techniques for independent communication, along with monitoring of peripheral events, and location, and transfer sensor data. The data may be acquired from a variety of sources and distributed amongst the robot group to determine the appropriate course of actions. Furthermore, IoRT acts to control static or dynamic position aware robotic things in the physical world seamlessly by providing a means for utilizing them. Table. 3 shows a summary of applied AI for ground robot communications.

4 Intelligent and Collaborative Space Robots Communication

Intelligence space describes a place where many robots are distributed and communicating with each other [67]. It aims to construct an intelligent domain for being able to monitor the environment and delivering communication services. Intelligent robots are constructed for space purposes using network distribution, actuators, sensors, cameras and processors [80]. The communication among robots, the environment, and functionalities plays a vital role in characterizing the ubiquitous robotic space. Therefore, authors of [95] discussed the distributed intelligent network robots which enable robots to move independently, and to understand the events and perform tasks quickly in an efficient manner. Then, intelligent robots in motion could deliver information about the environments to the users using advanced communication technologies. The authors of [103] introduced robot control and location in intelligent space using TCP/IP protocol for communication and coordinating. Thus, localization of the robot could be enhanced by the combined use of the multi-camera systems, sensors, and the intelligent space. Applications of AI play a critical role in the field of space engineering and space technology [54]. Skobelev et al. [129] discussed a multi-agent technique for management and solving the problem of Earth-sensing satellites. Furthermore, Stottler [132] introduced AI techniques for

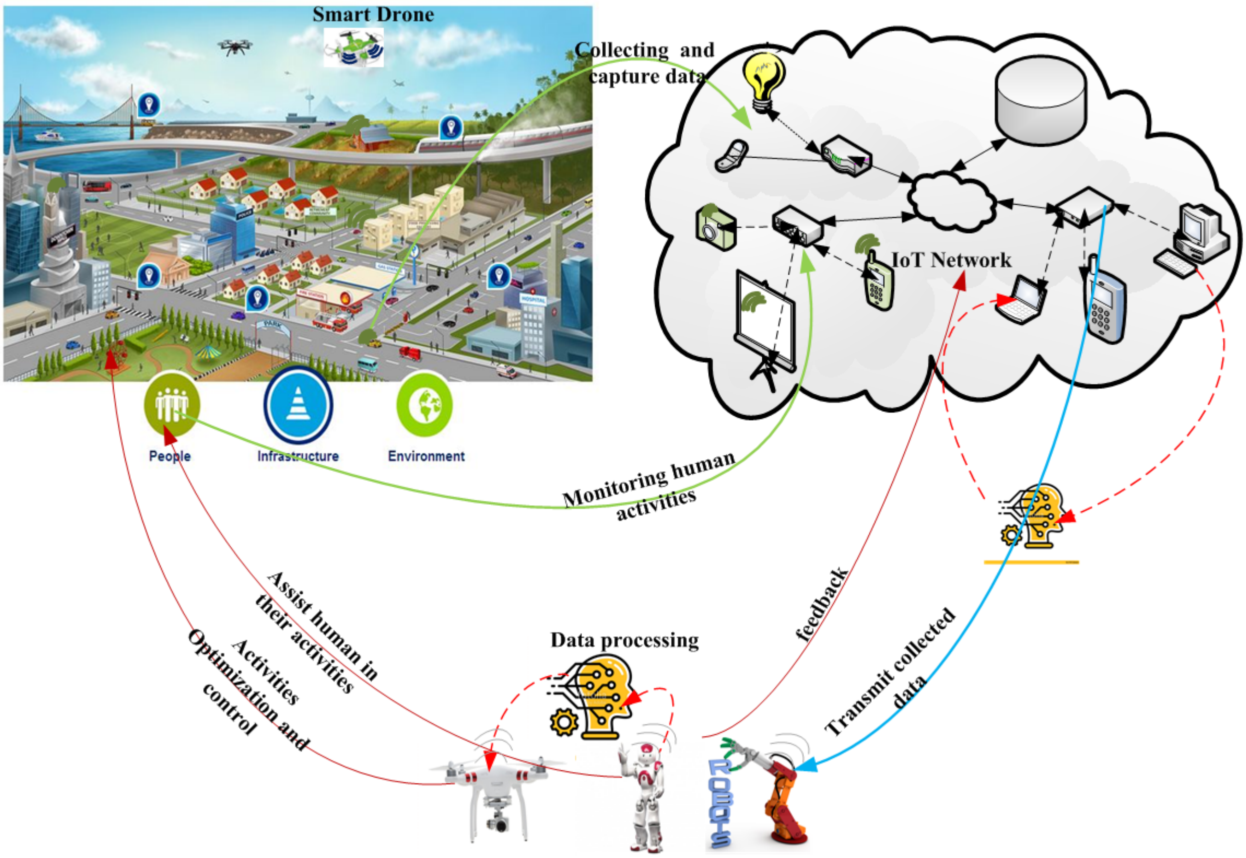

Fig. 6: Synergy among ML, robots, IoT, and environment

scheduling, automatic optimization and conflict resolution in satellite communication. The performance of loss and degradation of multi-spacecraft communication team was characterized optimally in [148], wherein it was shown that Neural network control technology enables a team of spacecraft to achieve flight formation with sustained communication and minimal supervision.

A High Altitude Platform (HAP) is an airplane or airship operated at altitude 17-21Km above the ground [18]. It was considered as a relay base station to deliver communication services to large coverage area and in shadow zones [13,19–21]. Moreover, the virtue of HAP lies in its ability to provide backup services to uncovered terrestrial areas such as mountains and/or a disaster area. Furthermore, HAP is considered a complementary system to terrestrial communication in case of limited bandwidth or severe handoff issues, and also can coexist with existing communication system efficiently [10,12,11]. A technique to recognize signal patterns of mobile subscribers using a probabilistic neural network was introduced in the Rayleigh fading channel for enhancing QoS [94]. An efficient hand-off algorithm was proposed for enhancing the capacity and QoS of an existing terrestrial communication system with the help of HAP [18]. ANN was the proposed algorithm for hand-off technique to decide when and which base station should receive the particular call, in order to prevent any service interruption [18]. Accordingly, a novel ANN for efficient hand-off between terrestrial systems and HAP in a particular coverage area was proposed. Moreover, an ANFIS has also been proposed to predict and take appreciated decision for hand-off between HAP and terrestrial systems [8], where the hand-off decision between terrestrial systems and HAP was improved significantly for enhancing QoS. Furthermore, the authors of [149] proposed an ANN to predict the user's movements and transfer user's probabilities [149]. The performance of ANN improved the hand-off rate and reduced unnecessary hand-offs. However, the authors of [137] considered adaptive parameters such as user actions, speed, RSS for pattern classification to provide a multiple-criteria hand-off algorithm [137]. Also, Zaouche *et al.* [150] introduced an intelligent technique for tracking the aerial node location in the network and video transmission. Therefore, the flying ad-

Table 3: Summary of ML techniques for collaborative ground robots communication

ref	AI	Highlighted	criteria	Metrics
[82] (2009)	ANN	coordinate the movements of the robot and avoid obstacles during moving	Prevent collision	– Trajectory – Coordination
[59] (2008)	ANN	improving an autonomous indoor intelligent vehicle	QoS	– Signal loss – Delay
[92] (2005)	PSO	Swarm robots motion in dynamics environment	Mobility	– Location – Direction
[147] (2011)	PSO	Optimal path planing	Mobility	– Trajectory – Coordination
[65] (2007)	PSO	broadcasting the information to all swarm	Mobility QoS	– Trajectory – Coordination – Connectivity
[91] (2016)	GA PSO	End-to-end robots wireless communication	QoS mobility	– Path Loss – Location – Signal Loss – Trajectory
[105] (2016)	ANN	Implemented multiple IoRT and used ANN for maintaining global connectivity.	QoS	– Balance the communication quality

hoc network (FANET) performance was enhanced, energy consumption was minimized and the delay was reduced and the throughput was increased for maintaining QoS. Furthermore, tethered balloon technology plays a vital role in supporting wireless communication and deliver broadband communication services to large coverage area and special events such as emergency and disaster recovery [9, 14–16, 76].

Smart drones play a pivotal role in enhancing the coverage of the next generation of the heterogeneous wireless network due to their capability of providing better reliability, high QoS and better connectivity to wireless communication networks. The smart drone can facilitate the end network nodes and manage user searching, gathering and tracking [68]. Smart drones were used for providing large connectivity for a large area and also used for load traffic balancing [117]. Optimal locations of drone lead to reduced delays, deliver higher data rates and achieve more extensive coverage. Sharma *et al.* explained how a smart drone could enhance the 5G wireless networks through enhancing the throughput, capacity, Signal to Interference and Noise Ratio (SINR) and reduce error and delay [125]. Furthermore, smart drone routing was proposed for delivering broadcasting services [58]. Issues pertaining to a drone's network connectivity and coverage area were discussed in [114], and also the authors of [89] considered network connectivity, coverage, and energy for mobile decision-making.

Messous et al. [90] discussed an autonomous fleet of drones and how to achieve fairness and global coverage area with maintaining desired network connectivity between drones. In addition, the authors of [85] evaluated the performance and accuracy of protocols for smart drones [85]. Al Islam *et al.* [5] explained intelligent transmission control protocol (iTCP) which could be exhibit a significant improvement in energy consumption and total network throughput over wireless mesh networks. Sharma *et al.* [119, 121] discussed the capability of drones to identify users and delivering services with high QoS.

The effectiveness of a neural network (NN) for improving the delay in finding the optimal location of drone in the network was highlighted in [123]. Authors of [7] proposed fuzzy optimization to control and test drones during monitoring the crowds participating in Hajj rituals. The proposed technique can detect a differently-colored object and different shapes moving in front of the drone's camera. Furthermore, drones can detect any objects in their coverage area at different elevation angle and at different distance [25]. Selma *et al.* [116] proposed ANFIS control for navigating drones. The proposed ANFIS provided better performance than ANN and adjusted the control system effectively. Here, drones were suitable for monitoring and sending information to the network center for taking suitable action and making appreciated decisions. Also, the transmission link between drone and terminal objects on the ground plays a vital role in sharing and transmission of information. Fuzzy logic was used to enhance signal transmission between the drone team and ground-robot team with cooperation of ad hoc network [118,120]. AI was applied for maintaining the connectivity and desired QoS among drones robots and ground networks [121,126]. Also, Zhong et al. [154] proposed an ANFIS and RL to maintain the desired coverage of wireless communication and control the quality of robots connectivity while performing given tasks in an unknown environment. The strategy for controlling the motion of multi-robot was decentralized. The effectiveness of ANFIS techniques was verified via the propagation of the different wireless signals.

Lastly, ANNs techniques are essential for addressing the critical challenges in robot communication networks. For example, different types of ANNs and ANFIS are suitable for drone robots applications. ANNs techniques are superior in their effectiveness in dealing with time-dependent data in different applications. For instance, AI techniques are used for enhancing drone communication in different applications as shown in Table 4.

Table 4: AI for collaborative drone communication

AI	Uses	drones applications
RNN [31]	– Predict the users' locations – Predict traffic demand – Use for human behavior prediction	– Allow drones to optimize drone location based on the dynamics of the network
DNN [31]	– Resource management – User association – Used for data classification and path planning	– Determine the time duration that the drones need to service the ground users – Find drones optimal trajectory at any given time.
SNN [31]	– Modeling the air-to-ground channel – Dealing with continuous data – Signal detection	– Analyze the data that collected by drones from the radio environment

4.1 Swarm intelligence robotics in space

Swarm space robots are communicating among themselves using advanced communication technologies such as ad-hoc network, Long Term Evolution (LTE), and several others. AI plays a vital role in swarm space applications [54]. Swarm drones equipped with IoT devices such as sensors, camera, etc. are used for monitoring the environment, make intelligent decision autonomously to perform the tasks and send the collected information to human operators at a different location for taking action accordingly. Intelligent swarm drone cooperative search strategies in a disaster environment were introduced in [141]. The importance of using swarm robots for search and rescue operation is due to the difficulties in accessing the geographically remote and unreachable areas. For avoiding collisions between swarm drones, the estimation of optimal trajectories for all robots in the swarm represents a critical technology. The trajectory optimization of swarm drone was performed using PSO in [110], while GA was applied for finding a minimum length trajectory based on the comparison of effectiveness and execution time. Therefore, the optimal swarm trajectories were satisfied with obstacle avoidance, speed limitation, and actuator torque limitations by using PSO. The authors in [124] introduced an ad hoc network for forming swarm drones suitable for many world applications such as civil monitoring, searching areas, weather monitoring, and military uses. Here, farming swarm drone ad hoc network is dependent on collaboration for taking intelligent decisions. However, failure in any node of swarm drones will result in a decrease the performance of the swarm drones network. Therefore, Sharma et al. [122] proposed a self-healing neural model to provide stability to all nodes in a network and take actions accordingly for recovering a node back to a stable state.

Hauert et al. [64] introduced AI for swarm drones ad-hoc network relaying. Here, AI was used to identify the fittest swarm drones efficiently. Furthermore, issues related to the connectivity, location, security and predicting the number of users connected to drones were discussed in [35,36,130,33]. ANN was applied for swarm drones to control the mission, searching the obstructive areas and GA was applied to evolve the ANN weights [96]. The authors [33] focused on maintaining connectivity and guaranteeing security in real time. Furthermore, Chen at el. [36] discussed how to maximize the number of users while maintaining both stability and gain. Also, the authors of [35] introduced a technique for minimum transmit power and enhancing the quality of experience [35], and authors of Soni *et al.* discussed the mapping allocation [130]. Table 5 shows the summary of applied AI for space robot communications. Furthermore, Table 7 shows a comprehensive summary of applied AI for underwater, ground and space robot communications.

Table 5: Summary of ML techniques for collaborative space robot communication

ref	AI	Highlighted	Criteria	Metrics
[20] (2015)	ANN	To enhance handoff and communication between HAP and another device on the ground using ANN.	– QoS	– RSS – Path loss – Delay – Distance and directions
[8] (2018)	ANFIS	To predict and take an appreciate decision for handoff between terrestrial communication systems and HAP by using ANFIS.	– QoS	– RSS – Path loss – Delay – Distance and directions
[33] (2019)	ML	Drone connectivity and security	– QoS – connectivity	– Real time – Security
[36] (2017)	ML	Drone resource allocations	– Maintaining the communication link	– Channel allocation
[35] (2017)	ML	Drone for optimized quality-of-experience	– Efficient data collection	– Quality of experience – Minimum transmit power
[130] (2013)	SVM	Fast transmission data relay and simultaneous localization and mapping.	– Mobility	– Location – Mapping
[96] (2010)	ANN and GA	Swarm drones in mission searching area	– Mobility	– Direction – Location – Speed

Table 6: Convergence of ML for collaborative drones communication

Ref	Existing work	Challenge	Suggestion of future work
[31] (2017)	Position estimation	– Limit time for data collection – Error in training data	– Management of resource = DNN based RL algorithm – channel modeling for the drone to devices in the ground=SNN Prediction algorithm – Handoff for drone connection = RNN predict algorithm – design multi-hop drone network = CNN
[35] (2017)	Deployment and cashing		

5 Discussion and future directions

Over the recent past, there has been an explosive increase in the number of things being connected to the Internet. Starting from computers, the list has gone on to add smart devices, mobile phones, etc. In the not so distant future, it is envisaged that a vast variety of semi– and fully–autonomous robots shall also be connected to the Internet. AI represents the brain of robots, while IoT represents the eyes and ears of robots. Therefore, the convergence of advanced communication technologies, robotics, IoT and AI represents the promising future of the field of robotics communication. This would enable the robots to be used everywhere and help humans – anytime, anywhere, collaboratively. These technologies go further into transforming everyday objects into intelligent and smart things. To do the same, pervasive middleware is required for data transferring into actuators and also receiving data from IoT device in the robot's body which gather data from the surrounding environment of the robots. Also, middleware is required for transferring AI processing data among terminals things and cloud accordingly. Therefore, the robots can also be considered as middleware for integration of communication and data technologies, comprising the IoRT which essentially is a combination of IoT and robots.

Recently, few studies have discussed a new concept in the field of robotics communication which is called IoRT. These studies discussed the maintaining of QoS and keeping the connectivity of robots [60,138], and also the trade-off between coverage area and quality of communication by applying ANN [4,106]. The topic is still in its infancy and should be taken into consideration for its importance in many applications of our life, industries and work. IoRT will make robots share information about the environment with each other. Robots in the sky, ground, and underwater will come together to complete the IoRT for real-time applications [26].

Collaboration between ML, IoT, and robotics will make robots able to perform complex tasks autonomously or collaboratively with humans in need. Using adaptive AI for enhancing QoS will enable current and future QoS-aware network applications over networked communication for robotics, so they will be significantly and successfully integrated as a vital part of our daily life. However, many types of research are required for using AI to enhance the throughput and mitigate the signal losses and identify protocols for routing paths in order to reduce energy consumption.

For efficient data collection and processing, the formation of a *drone cloud* with enhancement of the capacity is one of the challenges as shown in Table 6. Drones can be used in large formation to support a massive number of users in the large coverage area. Furthermore, using AI will help to process big data and deal with different drones formation, protocols, and mobility in varied environments.

Nowadays, power consumption has become an important issue, which should be actively considered for saving the environment. In the case of multi-robot systems, the robots require energy. AUVs and drones carry a multitude of devices onboard, either for communication or for capturing data during performing the designated tasks. These devices consume energy during collection/sensing of data, transmission/sharing of information, and data processing. Therefore, energy consumption still represents one of the limitation of AUV and drone operations. We believe that the use of suitable intelligent techniques and fog computing will reduce energy consumption and enhance AUV and drone operations. Furthermore, prediction techniques will also help to predict routing tables, which would reduce the data exchange.

Cloud robotics communication represents the collaboration between IoT and robotics for performing common tasks efficiently in the workspace, due to the ability of IoT devices in a robot's body to gather data of the workspace environment [23,138]. DL plays a vital role in robotics due to its ability to train big data in real time. Training data locally leads to consuming time and energy and expense. Therefore, cloud robotics represents promising technology for crowdsourcing training data. Therefore, local parallel processing and training time issues are discussed in [28] for increasing processing speed and are shown to lead to significant improvements, but it can be limited by communication speeds [73]. Thus, DL may be the way of making the training process more efficient, and can be applied in the cloud robotics for processing data collected from robots body in the workspace (using IoT devices).

Lastly, considering the mobility of the robots, the aim is that the robotic mobile intelligence should navigate, localize itself and understand the workplace environments [70]. IoT devices in the robotic mobile intelligence help robots to learn and understand their environments, collaborate to perform complex tasks anywhere independently and interaction with human collaboratively. Several studies have been done based on the robot's mobility and navigation, exploration and obstacle avoidance [70,135]. Avoiding collision and maintaining movement in a fixed speed and navigation of robotic mobile intelligent devices in the real world have been discussed in [102,146]. However, navigation of robotic mobile intelligence has immense challenges in an outdoor environment with obstacles. Therefore, self-supervised techniques will play a vital role in robotic mobile intelligence in dynamic obstacle avoidance in outdoor environments. We believe that DL techniques such as CNN and Recurrent Neural Networks (RNN) will help robots to learn about the outdoor environment and the real world.

6 Conclusion

In this survey, we have provided a comprehensive overview on the use of variety of ML techniques in robotics communication. This survey is different from the previously published work in term of scope and focus, we have reviewed the ML techniques which are recently being used to improve robots communication based on connectivity, QoS, mobility and efficient data collection criteria for enhancing robots performance of complex tasks in a collaborative assembly. This paper has attempted to cover the most of ML techniques for robots communication underwater, on the ground and in space, with a view on energy consumption, coordinating individual robot's duties, keeping connectivity, protecting collisions, fast data processing and taking action accordingly, enhancing the QoS, collaborating to perform complex tasks. From this survey, we concluded that ML plays a vital role in enhancing robot communication criteria for making the robots smarter to perform tasks anywhere effectively and efficiently, as well as collaboratively with humans. We have presented concise research challenges, directions and open issues, along with an analysis to enhance robots communication criteria.

Table 7: A comprehensive analysis of different techniques for enhancing the intelligence in collaborative robot communication

Category	Criteria	Metrics	Ref.	Work	ML	Focus	Findings	Application	Advantages	Future Improvement
Underwater	Mobility	Location	[153] (2018)	Practical	ANN	To compensate for the time-delay to realizing the purpose of path tracking and in control system of AUV. AUV can realize tracking control smoothly and converge to the desired trajectory.	ANN was efficient for predicting the path tracking of AUV	Path tracking of AUV	The effectiveness of the proposed control strategy.	DL can be used for more efficient prediction of path tracking.
Underwater	Mobility	Location, Coordination	[69] (2018)	Practical	CNN	To design, a hand gesture recognition based on divers communicate with underwater robots	CNN trained to perform accurate hand gesture recognition	Human-robots communication and controlling	Efficient gesture to-instruction mapping using a Finite-State machine. Divers communicate with underwater robots efficiently.	Extend the work may focus on larger vocabulary for control-flow tokens.
Underwater	QoS, collect data	Delay, Energy consumption	[25] (2017)	Practical	RL	To find routing protocol for underwater robots' communication network based on select the best communication channel and fast packet delivery to seek reliable routs to terminal robots in the network	RL was a smart, learned selection of relay to obtain a packet delivery ratio while maintaining low latencies and energy consumption.	Exploiting multi-modal communications	Reliable and low-latency underwater networking	Prediction the throughput may be considered to enhance robot communication

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Category	**Criteria**	**Metrics**	**Ref.**	**Work**	**ML**	**Focus**	**Findings**	**Application**	**Advantages**	**Future Improvement**
Underwater	QoS	Delay, Energy efficiency	[71] (2017)	Practical	Q-Learning	To enhance the lifetime of underwater network vehicles, Q-Learning was proposed.	Q-learn was more efficient for reducing the total energy consumption and decreasing delay significantly	Suitable for time-critical applications	Tradeoff between residual the energy of nodes and delay	PSO may be used for shortness and smooth path and save energy
Ground	Data collection	Transmit data	[23] (2014)	Survey	AI	To improve smart home due to the using of IoIT to become the same entity. Furthermore, robots will represent the middleware for data collection while AI used for processing data intelligently for IoIT.	Creating intelligence and network to exploit the benefits brought by AI.	Appliance robots	Communicate the appliance robots with each other intelligently through the internet. IoT becoming the robot's body Robots and smart home become the same entity	Energy efficiency may be enhanced.
Ground	Data collection	Real-time data	[3] (2010)	Practical	PSO	To show the performance of asynchronous PSO in the sense that the robots can move towards an aggregate in areas with a high gas concentration around the maximum points of the gas concentration.	PSO variant performs satisfactorily in an experimentally obtained smoothed virtual gas profile.	Search for a Multi-robot System	Satisfactory in an experimentally obtained smoothed virtual gas profile.	implementing the technique for possibly dynamically changing environments with gas and using robots equipped with a real chemical gas sensing hardware.

Table 7: A comprehensive analysis of different techniques for enhancing the intelligence in collaborative robot communication

Category	Criteria	Metrics	Ref.	Work	ML	Focus	Findings	Application	Advantages	Future Improvement
Ground	mobility	Trajectory, Coordination	[82] (2009)	Practical	ANN	To coordinate the movements of the multiple robots path and avoid obstacles during moving to coordinate with others to achieve a common goal	ANN could control the path of multiple robots intelligently so that coordination among robots significantly achieved	Path planning of multiple robots	Coordinate multiple robots to achieve common goal efficiently. Generate paths for multiple robots in an environment with moving obstacles. Automatically generate desired actions for multiple robots in an environment with moving obstacles.	DL may Apply to develop behaviors and high-level navigation control in a different environment
Ground	Mobility	Trajectory, Location	[59] (2008)	Practical	Fuzzy	To exploit the ability of a mobile robot to navigate a priori unknown environments without building an approximate map of the robot workspace	The proposed technique was quite promising in tracking the rectilinear-desired trajectories of various complexities at unknown locations of robots workspace	desired trajectory and the target position	Reaching a target point in its a priori unknown workspace Tacking the desired trajectory with a high precision	The proposed technique might be used for the navigation solution for many robotic applications where vision might not be necessary. Although it might be applied to the navigation of unmanned vehicles

Table 7: A comprehensive analysis of different techniques for enhancing the intelligence in collaborative robot communication

Category	**Criteria**	**Metrics**	**Ref.**	**Work**	**ML**	**Focus**	**Findings**	**Application**	**Advantages**	**Future Improvement**
Ground	QoS	Position, RSS	[106] (2018)	Practical	ANN	To enhance IoRT working in the desired coverage area, provisioning desired QoS and reducing energy consumption.	The efficient trade-off between network coverage and communication quality	IoRT and desired QoS	Maintaining and improving the trade-off between global robots' connectivity Desired QoS in the robots coverage area.	The capacity may be taken into consideration for improving QoS
Ground	QoS	RSSI, Distance	[105] (2016)	Practical	ANN	To Trade of between collective coverage area and desired QoS. The efficient IoRT robots used ANN for maintaining connectivity, convergence and energy consumption.	Maintaining global connectivity of IoRT	Desired QoS and global connectivity	Desired QoS for efficient global connectivity of multi mobile robots.	ML and DL may use to enhancing QoS, connectivity, convergence and energy consumption.
Ground	QoS	Signal Loss, Drop rate	[138] (2017)	Survey	AI	To overview the IoRT technologies, concept, application and architectures to provide comprehensive coverage of applications, challenges, and applications	point out the combination of Robotics, IoT, and AI, which result in robots with a higher capability to perform more complex tasks.	Concept of IoRT	Provided the IoRT concept, architectures, technologies and applications	ML for IoRT is the future scope of robotics communication.

Table 7: A comprehensive analysis of different techniques for enhancing the intelligence in collaborative robot communication

Category	Criteria	Metrics	Ref.	Work	ML	Focus	Findings	Application	Advantages	Future Improvement
Ground	QoS, Mobility	Path for deployment of robot network	[91] (2016)	Practical	PSO	To optimize the path of robots and find the acceptable and efficient solution for relay robots allocation and the intersection between robots path.	Minimizing the path required for the deployment of robots' network in order to create an end-to-end communication network.	The application that required for long-distance communications such as rescue, disaster, and emergency	It applies to rescue, disaster, and emergency scenarios. Minimizing the path required for the deployment of networked robots. Enable the formation of the long-distance coverage network	Maximize the received signal strength indication (RSSI) may be taken into consideration.
Space	QoS	Real-time connection	[33] (2019)	Survey	ANN	To enable the drone for exploiting the wireless connection with high security in real time.	Introducing intelligent solutions drone connectivity and security for use cases	drones Connectivity and security	Guarantee the connectivity and security in real time	Using quantum key distribution with Ml may lead to enhance security.
Space	QoS	Resource allocation	[36] (2017)	Practical	ML	To investigate the joint cashing and resource for enabling drone to deliver service over LTE licensed and LTE unlicensed. The proposed techniques enabled drone to choose the optimal resource allocation strategies to depend on network status.	LMS enhanced the performance gains and improved convergence time significantly.	Predict the user content request from drone	Maximize the number of stable queue users Significant performance gain	The complexity of the algorithm may be reduced.

Table 7: A comprehensive analysis of different techniques for enhancing the intelligence in collaborative robot communication

Category	Criteria	Metrics	Ref.	Work	ML	Focus	Findings	Application	Advantages	Future Improvement
Space	Data collection	Energy efficiency	[35] (2017)	Practical	ML	To develop a novel framework that uses drones to provide service for the users. The proposed methods enable the ML to separate the users' behavior into several patterns and learn these patterns with various non-linear systems and also yields significant performance gains regarding the minimum transmit power.	Proposed technique yielded significantly to reduce transmits power.	deployments of drone and user behaviors prediction	Minimum transmit power guarantee the quality of experience	The complexity of the algorithm may be reduced.
Space	mobility	Location	[7] (2017)	Practical	Fuzzy	To detect a moving of any color moving in front of drone camera. The proposed work was applied for surveillance applications such as crowd monitoring during Hajj.	Detecting any object with different shapes and color	monitoring crowds participating in Hajj rituals	Crowd monitoring during Hajj. Detecting any object with different colors and shapes. Suitable for object-following tasks.	Increasing the distance may lead to detect things in the large area
Space	QoS	RSS, Path loss, Drop rate	[20] (2015)	Practical	ANN	To enhance the hand-off rate and blocking rate. Hand-off decision between HAP and the terrestrial system for enhancing the QoS was significantly improved.	The block rate and hand-off rate was significantly enhanced by using the proposed technique.	Intelligent Hand-off for enhancing QoS	Efficient handoff techniques between HAP and terrestrial systems. Enhanced the QoS.	It may be improved if the throughput is taken into consideration for enhancing the QoS.

Table 7: A comprehensive analysis of different techniques for enhancing the intelligence in collaborative robot communication

Category	Criteria	Metrics	Ref.	Work	ML	Focus	Findings	Application	Advantages	Future Improvement
Space	QoS, Mobility	Delay, Location	[123] (2016)	Practical	ANN	To enhance the drone positioning and reduce the delay in heterogeneous networks. The approach was capable of optimizing the allocation delays.	The proposed technique was capable of optimizing the drone allocation delays in the heterogeneous networks. It did not affect the capacity and coverage of networks.	drones assisted delay	Enhancing the drone positioning with reduced delay It does not affect its capacity and coverage.	Checking the capacity and throughput may be enhanced because they may get affected by the change in the location of drone.
Space	Mobility	Coordination, Trajectory	[54] (2007)	Survey	AI	To review the applications of AI in the field of space engineering and space technology.	Opening the issue regarding the effective use of artificial intelligence for space technologies	Intelligent space	Enhanced situation self-awareness, and decision support for spacecraft system design	It may be better also to use AI for drone self-awareness.

Table 7: A comprehensive analysis of different techniques for enhancing the intelligence in collaborative robot communication

Category	**Criteria**	**Metrics**	**Ref.**	**Work**	**ML**	**Focus**	**Findings**	**Application**	**Advantages**	**Future Improvement**
Space	Mobility	Trajectory	[116] (2013)	Practical	ANFIS	To improve the control system adjusted in comparison to the ANN.	Improvement the control system adjusted by using the proposed technique and it was a powerful tool for controlling nonlinear dynamical systems.	Navigation an unmanned vehicle	A powerful tool for controlling nonlinear dynamical systems. Suitable for controlling system adjusted. Reduce errors and effect fast response to obstacles	It may be improved by using the techniques for swarm drones.
Space	Mobility	Trajectory, Location, Speed	[110] (2017)	Practical	PSO	To provide minimum length trajectory for Drones efficiently by using	Proposed technique verified the smoothness of trajectory and fulfillment of practical constraints introduced by the drone dynamics	Optimal Trajectory for drone	Dynamic feasibility and smoothness trajectory	ML may be used for improving the drone trajectory.

Table 7: A comprehensive analysis of different techniques for enhancing the intelligence in collaborative robot communication

Category	Criteria	Metrics	Ref.	Work	ML	Focus	Findings	Application	Advantages	Future Improvement
Space	Mobility	Coordination, Location	[130] (2013)	Practical	SVM	To transmit relayed data about the trapped victim in the disaster toward the rescue team receiver using robots	Using the proposed technique helped rescue robot correctly to identify the victims and presented an accurate map of the disaster area.	Disaster recovery	SVM classification Fast simultaneous localization and mapping	RSS may be considered for enhancing robots allocation during a disaster
Space	QoS, Mobility	Drop rate, RSS, Distance, Location	[8] (2018)	Practical	ANFIS	To predict and take appreciate decision making of handoff between terrestrial communication systems and HAP.	The decision for making hand-off was efficient and unnecessary hand-off was avoided, thereby increasing the overall effectiveness of the technique.	Adaptive handoff prediction	Reduce the drop call rate, Enhance the QoS	Taken delay into consideration may lead to better prediction.

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