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Internet of robotic things for mobile robots: Concepts, technologies, challenges, applications, and future directions

Homayun Kabir, Mau-Luen Tham *, Yoong Choon Chang

Department of Electrical and Electronic Engineering, Lee Kong Chian Faculty of Engineering and Science, Universiti Tunku Abdul Rahman, Selangor 43000, Malaysia

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ABSTRACT

Nowadays, Multi Robotic System (MRS) consisting of different robot shapes, sizes and capabilities has received significant attention from researchers and are being deployed in a variety of real-world applications. From sensors and actuators improved by communication technologies to powerful computing systems utilizing advanced Artificial Intelligence (AI) algorithms have rapidly driven the development of MRS, so the Internet of Things (IoT) in MRS has become a new topic, namely the Internet of Robotic Things (IoRT). This paper summarizes a comprehensive survey of state-of-the-art technologies for mobile robots, including general architecture, benefits, challenges, practical applications, and future research directions. In addition, remarkable research of i) multi-robot navigation, ii) network architecture, routing protocols and communications, and iii) coordination among robots as well as data analysis via external computing (cloud, fog, edge, edge-cloud) are merged with the IoRT architecture according to their applicability. Moreover, security is a long-term challenge for IoRT because of various attack vectors, security flaws, and vulnerabilities. Security threats, attacks, and existing solutions based on IoRT architectures are also under scrutiny. Moreover, the identification of environmental situations that are crucial for all types of IoRT applications, such as the detection of objects, human, and obstacles, is also critically reviewed. Finally, future research directions are given by analyzing the challenges of IoRT in mobile robots.

1. Introduction

A mobile robot is a machine that can sense its environment, perform computation for decision making, execute the allocated tasks autonomously, and navigate from the initial to the goal position. For the safety and security of humans, robots must comply with the three ethical laws proposed by Sir Isaac Asimov [1]:

- A robot may not injure a human being or, through inaction, allow a human being to come to harm.
- A robot must obey orders given by human beings except where such orders would conflict with the First Law.
- A robot must protect its existence as long as such protection does not conflict with the First or Second Law.

In addition, it is challenging to build a single robot to perform gigantic or complex tasks autonomously in the real-world [2]. Therefore, multiple robots with various sizes, shapes, and capabilities have been developed to accomplish the complex or gigantic or multiple tasks cooperatively termed Multi Robotic System (MRS). The key abbreviations used in this paper are listed in Table 1.

Furthermore, compared to the single robot [3–5], MRS has enormous benefits as follows:

- MRS can work concurrently on the complex task to complete it quickly.
- MRS can be homogeneous or heterogeneous, providing appropriate solutions to perform a huge task based on the capabilities of the system, with each robot cooperating to handle a specific part of the task according to its capabilities.
- MRS can be cost-effective because several simple robots can be more accessible for programming and cheaper to be manufactured than making a single powerful and complex robot for achieving the same task.
- MRS is more robust due to the capacity of data fusion, information sharing among the multiple robots, and fault-tolerance. For instance, when robots in MRS share their sensor information with

* Corresponding author.
E-mail addresses: homayunkabireee@gmail.com (H. Kabir), thamml@utar.edu.my (M.-L. Tham), ycchang@utar.edu.my (Y.C. Chang).

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Table 1
Abbreviations and definitions.

Abbreviation	Definitions	Abbreviation	Definitions
AC	Actor-critic	MITM	Man in the middle
AI	Artificial intelligence	ML	Machine Learning
AMQP	Advanced message queuing protocol	MQTT	Message queue telemetry transport
CARP	Channel-aware routing protocol	MRS	Multi Robotic System
CMPIDP	Continuous monitoring problem with inter depot routes and priorities	MR-SLAM	Multi-robot SLAM
CMRE	Centre for Maritime Research and Experimentation	NBV	Next best view
CNNs	Convolutional neural networks	NLOS	Non-line-of-sight
CoAP	Constrained application protocol	NUM	Network utility maximization
CORPL	Cognitive RPL	OSI	Open systems interconnection
CPP	Coverage path planning	PF MR SLAM	Particle filter MRSLAM
DDoS	Distributed DoS	PSO	Particle swarm optimization
DDS	Distribution service	QoS	Quality of service
Dec-MCTS	Monte Carlo tree search	R2I	Robot to infrastructure
DL	Deep learning	R2R	Robot to robot
DoS	Denial of service	REST	Representational state transfer
DQL	Deep-Q-learning	RFID	Radio frequency identification
DRL	Deep reinforcement learning	RL	Reinforcement Learning
EALC	Energy-aware link-based clustering	ROS	Robot operating system
EIF-MR-SLAM	Information filter MRSLAM	RPL	Low power and lossy networks
EKFMR SLAM	Extended Kalman filter MR-SLAM	SAR	Search and rescue
FANET	Flying ad hoc networks	SLAM	Simultaneous localization and mapping
FC-HDLF	Fog computing-based hybrid DL framework	TCP	Transmission control protocol
FIM	Fisher information matrix	TCS	Task control system
FLIRT	Fast laser interest region transform	UAV	Unmanned aerial vehicles
GA	Genetic algorithm	UDP	Datagram protocol
GMSA	Gathering multiple signatures approaches	UGV	Unmanned ground vehicles
GPS	Global positioning system	URLLC	Ultra-reliable low latency communication
GSO)	Glowworm swarm optimization	USV	Unmanned surface vehicles
HTTP	Hypertext transfer protocol	UUV	Unmanned underwater vehicles
HTTPS	HTTP Secure	UWN	Underwater wireless network
IMPF	Improved marginalized particle filter	VD	Voronoi diagrams
IoRT	Internet of robotic things	VLC)	Visible light communication
IoT	Internet of things	XMPP	Extensible message presence protocol
LOS	line-of-sight	6LoWPAN	IPv6 over low power wireless personal area networks
MANET	Mobile ad hoc network		

other robots, they can estimate their instantaneous positions more efficiently.

- MRS can display better flexibility, scalability, reliability, and versatility of the system due to its cooperative capability.

In order to properly build MRS, first, it is crucial to select hardware (sensors, such as cameras, LiDAR, Global Positioning System (GPS), etc., processing units, such as Raspberry Pi, Arduino, etc., and actuators, such as motors, mechanical parts, gears, etc.) according to the operating environment. Sequentially, researchers have concentrated on algorithms for networking and communication [6,7], estimating the robots positions and building the global maps [8] of the environment and coordinating data processing between the robot [9] and external devices [10]. Various interchangeable terms are utilized based on the different applications for characterizing the MRS, such as swarm robotics, cooperative robotics, collective robotics etc.

MRS can be classified into two major categories [9,11,12]: i) cooperative: the team of robots working cooperatively and ii) competitive: the relation among robots is competitive due to jamming robots. Cooperation is a system where robots are engaged in a common activity. Furthermore, cooperative MRS can be divided into unaware and aware MRS based on the knowledge, where aware robots have some knowledge of their teammates, but unaware robots operate without knowing who else is in the system. Coordination is the method that allows each robot to assist the other in reaching a given goal. For example, consider two robots traveling in opposite directions who wish to cross a narrow channel but can only do it one at a time. If these two robots do not synchronize their activities during the coordination process, congestion or collision can occur [13]. Based on the coordination, aware robots are classified as strongly coordinated, weakly coordinated, and uncoordinated. According to team composition, strongly/weakly coordinated MRS can be classified into i) homogeneous: each robot is identical but

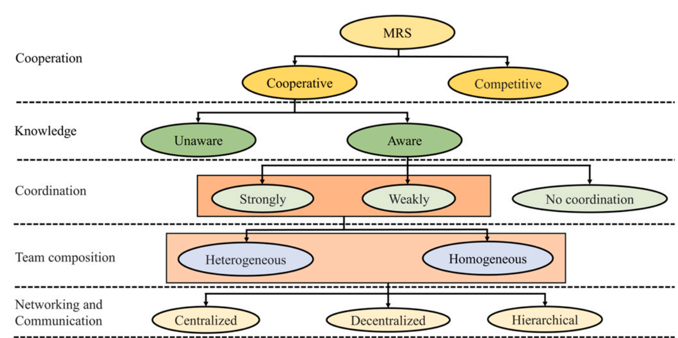

Fig. 1. The classification of MRS.

physical structures may not be similar, and ii) heterogeneous: different capabilities of robots grouped into different team sizes: big, medium and small. According to the network and communication protocol, heterogeneous/ homogeneous MRS can be classified into three categories i) centralized: all robots of MRS are controlled by a central server ii) decentralized: robots can communicate with each other iii) hierarchical: a subgroup of robots exchanges the information through a specific robot-like military structure. The whole classification is presented in Fig. 1.

The Internet of Things (IoT) has experienced an expeditious growth and attention recently for emphasizing the mission and vision of a global infrastructure that interconnects the physical objects called things, utilizing the same internet protocol, authorizing them for communicating as well as sharing the information [14]. Therefore, the concept of IoT is being implemented by more and more organizations in various fields, such as robotics, military, nanotechnology, healthcare or space, customer service, environmental monitoring, smart home, creat-

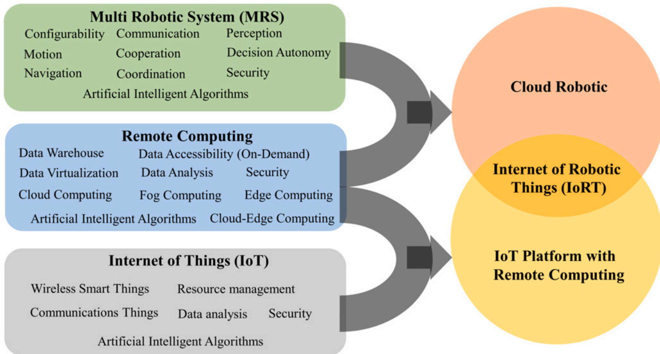

Fig. 2. The concept of IoRT for mobile robots.

ing the internet of X things, where X is the relevant area [15]. According to Gartner [16], local governments are deploying IoT technologies exponentially to monitor their assets and infrastructures more effectively, to promote the safety of their citizens as well as the living environment, for example, they endeavor to control the spread of COVID-19 and check quarantine compliance. In addition, the global IoT endpoint electronics and communications market will be 21.3 billion dollars in 2022 which is 22% more than the forecasted total of 17.5 billion dollars in 2021, where 20.6 billion things were connected to the internet. Meanwhile, cloud computing is growing rapidly, providing on-demand network access and sharing cloud computing resources such as servers, applications, storage, and services (data analytics), which are also being used for the development of IoT, robotics, industry, commerce, etc. [17,18]. Recently, the concepts of IoT and cloud computing have been applied in MRS with segregation for communicating, coordinating, navigating and analyzing, storing, sharing and updating the information among robots. Data are collected by different sensors, especially LiDAR, and cameras play an important role in autonomous navigation of robots, monitoring and controlling the entire process smoothly. This whole processing can be defined as the Internet of Robotic Things (IoRT) for mobile robots that are illustrated in Fig. 2. Furthermore, Artificial Intelligence (AI) such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Machine Learning (ML), Deep Learning (DL), Federated Learning (FL), Reinforcement Learning (RL), Deep Reinforcement Learning (DRL) is being deployed to enhance algorithmic development of IoRT due to its prodigious capacity of dealing with complexity, big data, high precision, and faster processing [19,20].

1.1. Comparison and contribution

Various research groups merged the research concepts of IoRT and robotics to illustrate the IoRT concept. Initially, the concept of IoRT was discussed in [15] emphasizing architectural principles, vital characteristics, equipment, and challenges, except for the applications of IoRT. In 2018, Simoens and Pieter presented the concept of merging robotics and IoT technologies in order to create new, potential services in human life [21] but did not discuss applications and challenges. The following year, IoRT architecture, components, data computation, various applications and challenges were briefly discussed in [22]. In 2021, it was proposed how to combine IoT and robotics to allow robotic systems to communicate over the internet with minimal cost in [23]. Additionally, cloud computing is integrated to enhance the overall performance and offload the demanding tasks in IoRT.

Researchers have gathered the published research to write the survey paper in terms of different parts of MRS. The majority of survey papers on MRS have concentrated on multi-robot coordination and communication. The succinct survey coordination and communication [24], decentralized control and coordination strategies [6], effective coordination among autonomous robots [13,25] of MRS have been reviewed. Networking and wireless communications play an important role in the coordination and cooperation of MRS due to the challenges of maintaining reliable and stable communication among robots. In [9], the authors aggregated the research, which considers the adverse electromagnetic environment including scarce spectrum, active interference, adversarial competition, etc.

Localization and mapping, referred to as Simultaneous Localization and Mapping (SLAM) and navigation, is another key issue in MRS research. In [8], the authors investigated the obstacles of map merging for multi-robot ground SLAM as well as reviewed the typical map-merging methods. Visual navigation is the fundamental technology for robots to interact with the environment for achieving advanced behaviors. Therefore, DRL-based visual navigation with high-dimensional images is extensively reviewed in [26]. In [2], the authors presented a survey of research works according to the application domain of MRS. Some research groups have conducted survey of specific applications. For example, for Search And Rescue (SAR) operations, Mobile Ad hoc Network (MANET)-based MRS communication was investigated in [7]. Additionally, the authors in [27] summarized and presented the researches by considering planning, coordination, and perception of MRS.

To the best of our knowledge, there are a few related works focusing on the concept of IoRT [15,22,23], but none of them reviewed its concept, securities, technologies, and challenges for mobile robots. Due to the mobility of robots, it is very challenging to ensure the stable communication, coordination, computation, sharing and updating of the generated data in MRS. This article presents a comprehensive description of IoRT for mobile robots where its general architecture, benefits and challenges, security issues, real-time applications, and future research directions are discussed. In addition, the comparison of this paper with other survey papers is presented in Table 2. The main contributions of this paper are listed below:

- Remarkable research such as i) multi-robot localization, mapping, and path planning, ii) network architecture, routing protocols and communications for Robot to Robot (R2R) and Robot to Infrastructure (R2I), iii) coordination among robots to accomplish the assigned task or tasks as well as data analysis via external devices (cloud, fog, edge, edge-cloud) are merged with IoRT architecture according to their applicability.
- When devices, such as robots, sensors, actuators, etc., are connected through the internet, security is a complex problem. Hence, various security threats, attacks, and their existing solutions based on IoRT architecture are critically reviewed.
- For the real-time application of IoRT, identification of the environmental situations, e.g. detection of the object, human, obstacles, etc., is vital and critically reviewed.
- Challenges of the framework, security, real-time applications of IoRT for mobile robots are summarized.
- After critically analyzing the challenges, the most suitable algorithms (DRL-based algorithms) for autonomous decision making and extensive data handling are recommended as future directions of the IoRT framework for mobile robots.

1.2. Survey organization

The rest of this paper is organized as follows. In Section 2, the IoRT architecture for mobile robots and its hardware and software are described and discussed according to the layers of the IoRT architecture. In each layer, general concepts, technologies, and existing research on robots suitable for that layer are reviewed. In Section 3, the concepts and technologies of the physical layer in IoRT are discussed as well as the existing state-of-the-art research work on navigation of multiple mobile robots. In Section 4, the concepts, network architecture, routing protocols, and communication protocols that can be related to the network and control layers of IoRT with R2R and R2I are discussed. In Section 5, the concepts and technologies for services and applications of IoRT are described, which include existing research on robot coordina-

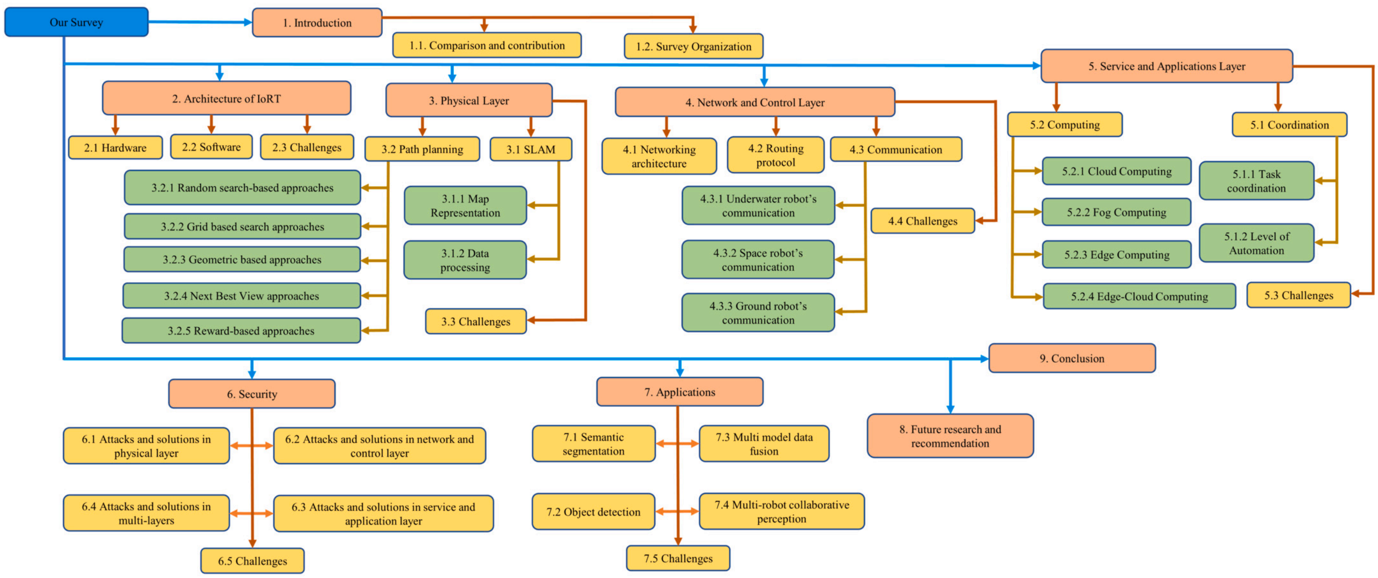

Fig. 3. Summary of paper organization.

tion and data processing by external devices. In Section 6, the security of the IoRT architecture is described. In Section 7, various applications of mobile robots through IoRT and identification of objects, which is an important issue for any application, are explained. In addition to the introduction, each section points out the existing challenges. In Section 8, the existing challenges and future research directions of mobile robotics based IoRT framework are discussed. Finally, in Section 9, the paper is summarized. In addition, the organization of the paper is summarized in Fig. 3.

2. Architecture of IoRT

The concept of the IoRT was coined by Dan Kara in ABI Research in 2014 [28], where intelligent robots can monitor tasks, collect sensor data from various sources, utilize AI to determine the best way of action, and finally take action to control the object in the real world. In general, the Open Systems Interconnection (OSI) model of IoT has seven layers, which are i) physical, ii) data link, iii) network, iv) transport, v) session, vi) presentation and vii) application layers. In [15], the architecture of IoRT has been divided into five layers that are (i) the hardware/robotic things layer, (ii) the network layer, (iii) the internet layer, (iv) infrastructure layer, and (v) the application layer. It is portrayed by three layers such as i) physical, ii) network and control, and iii) service and application layers in [22,23], which is the most suitable architecture of IoRT in mobile robots as shown in Fig. 4. Each of these is illustrated in the following section.

- The physical layer of IoRT has been built by various mobile robots such as Unmanned Ground Vehicles (UGV), Unmanned Surface Vehicles (USV), Unmanned Aerial Vehicles (UAV), Unmanned Underwater Vehicles (UUV), military mobile robots, industrial mobile robots, etc. These robots are described as intelligent and smart agents that can autonomously communicate and navigate from an initial location to a desired target location and establish MRS. According to the standard of OSI model, the purpose of the physical layer is to summarize all of the technical data and supply a set of services about its periphery towards the network and control layer.
- The network and control layer consists of various routers, controllers, and servers that efficiently integrate all robots in MRS of the physical layer by utilizing communication and control protocols. In addition, robots are capable of sending data to other robots as well as to local and cloud storage by exploiting the distance

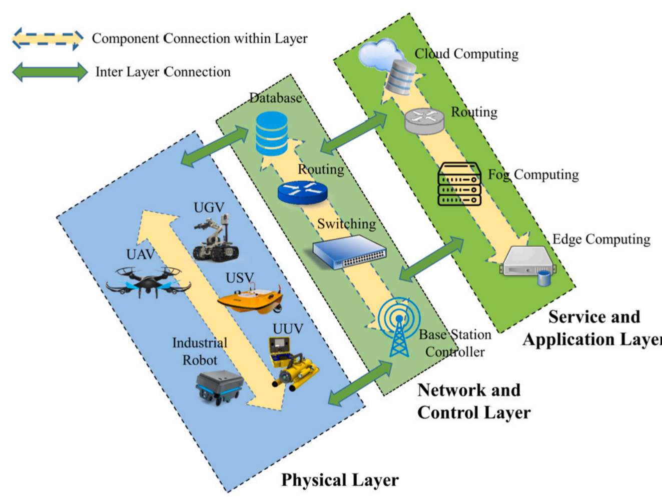

Fig. 4. The architecture of IoRT for mobile robots.

between receiver and sender robot. For mobile robots' communication via IoRT, two categories of communication/data links are identified: R2R and R2I communications. Both links play a pivotal role in accomplishing the assigned tasks cooperatively. In R2R communication link, the shorter to medium range IoT protocol such as ZigBee (IEEE 802.15.4), BlueTooth (IEEE 802.15.1), threads, and Wi-Fi (IEEE 802.11 a/b/g/n/ac) are generally used. In contrast, the medium to more extended range protocols including Wi-Fi (IEEE 802.11 a/b/g/n/ac), LoRa, NB-IOT, and WiMAX (IEEE 802.16) LTE-M, cellular, and satellite, etc. are deployed in R2I [23,29]. The network layer can be classified into two sub-layers, i) the routing layer, which manages the data packets transmitted from the source robot to the destination robot, and ii) the encapsulation layer, which forms the data packets. Routing Protocol for low power and lossy networks (RPL), Cognitive RPL (CORPL), Channel-Aware Routing Protocol (CARP), and IPv6 over low power wireless personal area networks (6LoWPAN) are generally used protocols in IoT and also applicable in IoRT [15,23]. For end-to-end robot communications which demand reliability and congestion avoidance, Transmission Control Protocol (TCP) and User Datagram Protocol (UDP) are commonly used at the transport layer of IoRT

Table 2
The comparison of review papers with our survey.

Year	Authors	Contributions	Navigation	Communication	Coordination	Hardware/ Software	Object Detection	IoRT	Computing	Security	Application
2016	P. P. Ray [15]	The architectural principles, essential aspects, research problems, and future research prospects were highlighted to better understand the IoRT framework.	✗	✓	✗	✓	✗	✓	✓	✗	✗
2018	Pieter Simoens [21]	The capability of both existing IoT and robotic systems has grown due to the combination of robotic and IoT technologies, enabling the creation of new, potentially disruptive services.	✗	✓	✗	✓	✗	✓	✓	✗	✗
2019	I. Afanasyev [22]	The framework, issues and possible solutions of the IoRT architecture and robotic applications in smart environments have been discussed.	✗	✓	✗	✓	✗	✓	✓	✓	✓
2021	D. Villa [23]	How to merge the IoT and robotics for IoRT are presented that Allow robotic systems to communicate over the internet at a minimal cost and cloud robotics to improve the overall performance and offload demanding tasks.	✗	✓	✓	✗	✗	✓	✓	✗	✓
2013	Z. Yan [13]	The present study on MRS coordination has been illustrated, particularly the communication technique, a planning method, and a decision-making framework.	✗	✓	✓	✗	✗	✗	✗	✗	✗
2015	Rajesh Doriya [24]	A brief overview of current research on MRS coordination and communication and a framework for MRS coordination and communication using cloud computing is presented.	✓	✓	✓	✗	✗	✗	✓	✗	✗
2017	R. N. Darmanin [2]	The current research works on MRS applications according to the various categories has been figured out.	✗	✓	✓	✗	✗	✗	✗	✗	✓
2017	S. S. Anjum [7]	The taxonomy for routing protocol, network design, and MRS communication mechanisms via MANETs in disasters and emergencies has been thoroughly examined.	✗	✓	✓	✗	✗	✗	✗	✗	✓
2017	J. Cortés [6]	The research on decentralized control and coordination techniques of MRS has been discussed .	✗	✓	✓	✗	✗	✗	✗	✗	✗
2018	Z. H. Ismail [25]	The current research, problem and future direction on cooperation and coordination of MRS, mainly control architecture and communications, have been discussed.	✗	✓	✓	✗	✗	✗	✗	✗	✗
2020	Y. Wu, [9]	A framework for efficient management of challenges of MRS in the electromagnetic adversarial environment, including autonomous control, intelligent communication etc., has been presented.	✗	✓	✓	✓	✗	✗	✗	✗	✗
2020	S. Yu [8]	The recent research, challenges, and future research on map-merging for MRS (ground robots) via SLAM have been summarized	✓	✓	✓	✗	✗	✗	✗	✗	✗
2020	F. Zeng, [26]	A comprehensive study , current challenges and opportunities on visual DRL navigation for mobile robots has been presented.	✓	✗	✓	✗	✗	✗	✗	✗	✗
2020	J. P. Queralta, [27]	The entry aspects of MRS, including navigation, coordination, perception, computer vision, etc., have been reviewed for SAR operations in the maritime, wilderness, urban or other post-disaster scenarios.	✓	✓	✓	✗	✓	✗	✗	✗	✓
	Our Servey	We have surveyed state-of-the-art technologies of IoRT for mobile robots, including general architecture, benefits, challenges, practical applications, and future research directions. In addition, MRS navigation, communication, coordination, data computing, security threats, security solutions, applications, and computer vision for goal recognition have been critically reviewed.	✓	✓	✓	✓	✓	✓	✓	✓	✓

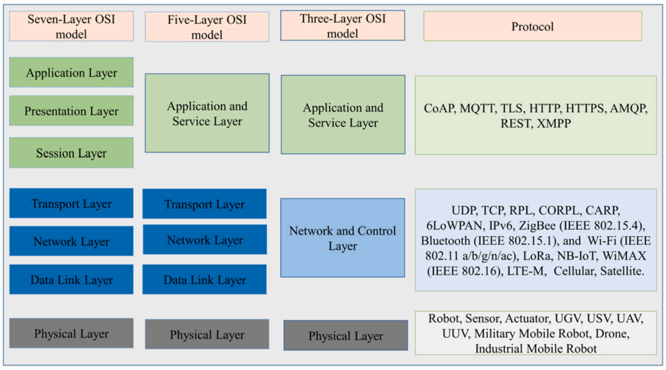

Fig. 5. The OSI model and protocols of IoRT.

[15,22,23,29]. The combination of data links, network, and transport layer is called network and control layer of IoRT.

- The service and application layer refers to the top layer of architecture and depends on the implementation of programs successfully to monitor, process, control, and coordinate both environment parameters and mobile robots. In addition, AI algorithms can be exploited to enhance the performance of IoRT. Several protocols in this layer are available, e.g. the Constrained Application Protocol (CoAP) that utilizes UDP for resource-constrained devices on lossy, low-power networks. The most commonly used protocols are Hypertext Transfer Protocol (HTTP), HTTP Secure (HTTPS), Data Distribution Service (DDS), Advanced Message Queuing Protocol (AMQP), Representational State Transfer (REST), EXtensible Message Presence Protocol (XMPP), and Message Queue Telemetry Transport (MQTT) [15,23,30].

Finally, the OSI model for IoRT and protocols for various layers are summarized in Fig. 5.

2.1. Hardware

The five components needed to build a complete IoRT framework for a mobile robot are: i) manipulator (like a human arm, consisting of several joints and links); ii) end effector (like a hand performing a task); iii) the locomotive devices (motors); iv) the controller and v) sensor. Apart from the mechanical parts, the most common hardware utilized for building MRS are Raspberry Pi [45], and Arduino [46,47] which are used as processing unit. Both Raspberry Pi and Arduino constitute open-source hardware and electronic prototyping platforms. Robots were made using various sensors, such as Radio Frequency Identification (RFID), smoke sensors, infrared and light sensors, video cameras, temperature, humidity and light sensors, temperature and gas and accelerometers, and gyros. GPS receivers were also installed in many robots for localization and navigation. Details of sensors are presented in Table 3.

2.2. Software

The current trend of MRS research is to solve the complex problem in a complex environment by utilizing IoRT. Consequently, MRS needs more intelligent, autonomous, and faster processing units that have the ability to understand the surroundings for accomplishing the tasks in complex, dynamic, and uncontrolled environments. The complexity of software architecture is increasing day by day due to the increasing requirements for computation, interfaces, reusability, scalability, fault tolerance and efficiency. Furthermore, an appropriate MRS middleware software has to be a strong infrastructure for distributed systems where robots communicate with other robots independently. In this subsection, middleware software of MRS [48–50] for IoRT has been analyzed in Table 4.

2.3. Challenges

The development of sensors, actuators, hardware of networking, communication, and data processing have been vital drivers for IoRT. In this section, the concept of mobile robotics IoRT is introduced and its hardware and software are reviewed. Still now, MRS faces a plethora of challenges due to hardware issues, especially the sensor and communication hardware. The camera is the primary sensor to make the perception. In the typical environment, the maximum range between the two is around 200 m [51]: however, it depends on the intensity of light in the operational environment. This is because the visibility is very low for completely dark environments, especially underwater. Fading is another issue that hinders the overalls performance of sensors, especially in Non-Line-of-Sight (NLOS) environments. As a result, the latest communication technology struggles to provide stable communication in dense urban areas, forests, underwater, and caves, etc. Finally, various software for MRS is also reviewed. Robot Operating System (ROS) is the most suitable software framework for hardware thanks to its user-friendliness and graphical user interface, it also provides tools like Gazebo for robot simulations and Rviz for maps and navigation simulations.

3. Physical layer

The physical layer is the lowest layer of the IoRT architecture, where several mobile robots cooperatively work as MRS. Such MRS technology can advance and upgrade the innovative applications regarding robotic systems, remotely manage distributed activities, and increase fault tolerance, to attain an improvement of the overall system performances [52]. Additionally, various sensors and actuators can be integrated into robotic applications to optimize, monitor, and control multiple processes such as calibration, tuning, and navigation. Navigation is an

Table 3
Typical sensors in MRS of IoRT.

Sensor	Intended Use
Microphone [31]	Recognition of voice by converting sound into a small electrical
Gyrometer, accelerometer [32,33]	Observation linear and angular motion
RFID, infrared sensor [34,35]	Proximity sensing by measuring infrared light radiating from objects
Occupancy sensor [36]	Indoor motion detector to identify the presence of a person
Video camera [37]	Human remote vision, computer vision etc.
Pressure sensor [38]	Measurement of experimental environment pressure
Medical sensors [39]	Measurement of the health condition of humans, animals etc.
GPS receiver [40]	Position estimation
Gas/chemical sensor [41]	Hazardous materials sensing
Smoke sensor [42]	Detection of fire or smoke
Temperature/humidity sensor [43]	Weather conditions sensing, and surveillance etc.
Light sensor [44]	Measurement of the illumination, and surveillance

Table 4
List of middleware software for MRS in IoRT.

Name	Operating software	Programming language	Distributed architecture	Node communication mechanisms	Message transport
JADE	JVM Platforms: J2EE, J2SE, J2ME	Java JVM languages, NET languages	Hybrid peer to peer (P2P)	Simple-messages, topics, complex interactions	RMI, CORBA, HTTP, JICP
Mobile-C	Windows, Linux, OSX, QNX, other UNIX System	C/C++	Hybrid P2P	Simple-messages	HTTP
OpenRDK	Linux, OSX	C++	Hybrid P2P	Ports, properties	TCP, UDP, shared memory (locally)
OpenRTM	Linux, Windows	C++, Java, Python	Hybrid P2P	Ports, services, properties	CORBA (OmniORB, ACE/TAO, MICO) (TCP, UDP, SSL, UNIX)
OROCOS	Linux/RTAI/ Xenomay, OSX, Windows	C++, Python, Simulink Orocos Scripting Language	Hybrid P2P	Ports, services, events, properties	CORBA (OmniORB, ACE/TAO), (TCP, UDP, SSL, UNIX), MQueue, EtherCAT, CanOPEN
ORCA	Linux, Windows, OSX, QNX	C++, experimental (Java, Python, PHP)	Hybrid P2P	Services	ICE (TCP, UDP, SSL)
ROS	Linux, OSX and Windows (limited)	C++, Python, Java, Lisp, Octave	Hybrid P2P/ Pure P2P (planned)	Topics, properties, services	TCP, serial (proprietary), UDP (experimental)
YARP	Windows, Linux, OSX, QNX4	C/C++, SWIG languages (Python, Java, Octave)	Hybrid/Pure P2P	Ports, topics	ACE, TCP, UDP, shared memory (locally), multicast

important paradigm in order to allow mobile robots to accomplish specified tasks in IoRT. For appropriate navigation of mobile robots, localization, mapping, and path planning have to be done sequentially. The whole process can be divided into i) SLAM and ii) path planning, which is explained below.

3.1. SLAM

Localization (where are the robots?) and Mapping (what is around the robots?) are two indispensable prerequisites to achieve the goal in any applications of mobile robots in IoRT. In this paper, localization defines the ability to obtain the internal system states of robot motion, including instantaneous positions, directions, and velocities relative to the environment. Mapping, on the other hand, refers to the ability to perceive the conditions of the external environment and to capture the environment, including the appearance and geometry of two or three-dimensional scenes. In practice, it is challenging to solve positioning and mapping problems independently. Robots need to know the environment as well as the location. The accurate location of the robot is essential to build a good mapping of the environment. In contrast, a good map plays a pivotal role in estimating the position of the robot. It is a bit like the chicken and egg problem. Researchers have solved this problem at the same time and defined it as SLAM.

Different types of SLAM are available based on different perspectives [53] (i) online SLAM vs full SLAM (ii) any-space SLAM vs any-time SLAM, (iii) active SLAM vs passive SLAM, (v) visual SLAM vs laser SLAM. Online SLAM only estimates the current time and the most updated pose of the robot. In comparison, full SLAM deals with the complete information of map of environment and location and path trajectory of the robot from starting time and location. The robot moves autonomously for acquiring information about the environment and pose of its self, and the robot is manually derived in passive SLAM. Any space and any time algorithms operate based on the availability of the resource. Any space SLAM algorithm works depending on the availability of memory size. In contrast, the any-time SLAM algorithm returns the best possible map generated based on the sensor observations in a specified amount of time. SLAM algorithm that deals with the information of laser is called laser SLAM. The visual SLAM algorithm uses the information collected from the visual camera.

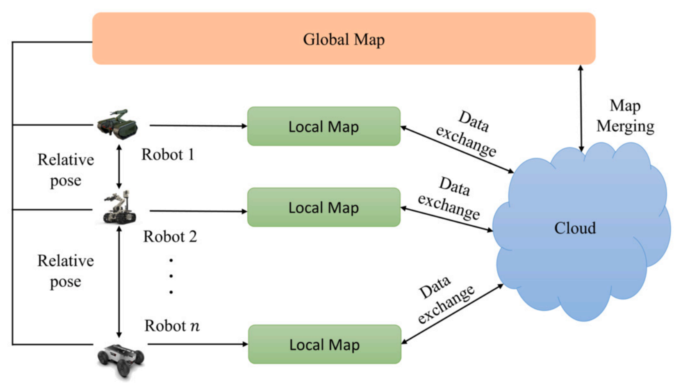

Fig. 6. Global map generation from local maps.

SLAM plays an indispensable role in navigating mobile robots autonomously in any complex environment. As a result, over the past two decades, researchers have developed a large number of effective methods to solve SLAM problems, mainly for single mobile robots. In contrast, there has been little research on estimating the locations of multiple robots based on a complied global map of the whole environment as illustrated in Fig. 6. A reliable map and the instantaneous position of robots within the map are the output of the SLAM problem. A concise review of the principal building blocks of SLAM techniques is depicted in this subsection. For achieving the realistic outcomes of any SLAM technique, three indispensable blocks illustrated as sensors, data processing, and map representation have to be considered. Details of sensors that collect the information from the environment embedded with underground, aerial, and ground robots are described in Section 2. After capturing the information through appropriate sensors, on-board/off-board data processing algorithms including smoothing, filtering and artificial intelligence, taking into account various uncertainties, e.g., modeling, algorithms and computational latency, start the process. In the end, the environmental model called a map with the trajectory of the robot is produced. In addition, mapping and data processing work simultaneously to achieve the realistic and reliable outcome of SLAM. A concise overview of mapping is unraveled below, while data processing will be discussed later.

3.1.1. Map representation

Various types of map representation are commonly classified into four types: metrical, topological, hybrid, and semantic.

- A metrical map illustrates the indoor or outdoor environment as a feature or grid or geometric map [54]. A feature map presents the real environment by determining a single frame's plausible metric location of the credible features, landmarks, etc. Generally, features, such as lines or corners, are deployed for range sensors. More complex features, for instance, Fast Laser Interest Region Transform (FLIRT) [55] is also utilized. Additionally, scale invariant feature transform [56] is used for vision feature while radio signal strength [57] is utilized for producing the feature map. In some specific environments, such as disaster and mines areas, RFID technology [58] is deployed for artificial landmarks for mitigating the correspondence problem in the process of mapping [59]. A grid map visualizes the environment with the grid of equal cells that represent the sample of the real environment. For 2D SLAM, the most useful map is the occupancy grid map. Every cell illustrates a tiny rectangular part of the environment. The maximum utilized value for the grid cell is considered as the probability of the presence of an obstacle in the grid cell [54]. In addition, the occupancy grid map deals with moving objects and dynamic environment effectively [60]. It can also be extended to 3D mapping, what is known as volumetric pixel maps. In the geometric map, the objects of the environment are depicted as geometric shapes, such as ellipses, circle, etc. It requires less memory of storage rather than feature and grid map.
- Topological maps illustrate the environment as a graph where the graph's nodes depict positions, obstacles, connected paths, intersections, etc. Generally, insects and humans utilize the topological maps for navigating, to estimate routes and locations, and to avoid obstacles [61]. For example, pigeons use topological maps for long-distance flights. Topological maps are utilized for metro rail maps or subway maps, or building maps. Although topological maps produce more compact maps but it does not provide metric information. Hence, it needs lower memory of storage. A metric-free topological map is introduced in [62]. Topological maps are useful for high-level planning activities where metrical information is not required.
- Semantic maps consist of semantic data, including elements of the map, markers of objects such as saucers, cups, tables, bottles, buildings, trees, lampposts, etc.; also relationships between environment and object attributes such as color, shape, walls, windows, doors, chairs, people, etc.; contributing to the realization of high-level and goal-oriented behaviors that are essential for reasoning about spatial and perspective ambiguities in real time.
- Hybrid map is created by combining various mapping methods. For example, the metric topological hybrid map combines the metrical and topological information based on the user demand.

3.1.2. Data processing

This subsection critically reviews filtering, smoothing, and AI-based existing solutions for Multi-Robot SLAM (MR-SLAM) problems.

- Generally, three filtering methods are particle, Kalman, and information filters for MR-SLAM, derived from the bayesian filter and deployed for estimating the instantaneous pose of the robots or optimizing the whole trajectory of the robots. The most popular MR-SLAM algorithms in regards to filtering are extended Kalman filter MR-SLAM (EKF-MR SLAM), extended information filter MR-SLAM (EIF-MR-SLAM), and particle filter MR-SLAM (PF-MR-SLAM). Recently, colossal development has been done in this research field, such as modified distributed PF-MR-SLAM algorithms [63,64]. For MR-SLAM, EKF is one of the most widely used filtering techniques due to its simplicity and low computational power requirement. As a result, researcher proposed numerous solutions in regards to the EKF, such as the cooperative EKF estimator [65], map evaluation in [66], performance prediction [67], distributed MR-SLAM [68] and distributed EKF [69]. In [70], the authors implemented the combination of the EKF and other techniques for heterogeneous sub map matching. In 2001, Thrun [71] proposed the MR-SLAM algorithm by deploying the particle filter. They concentrated on updating pose and map by combining the maximum likelihood mapping with Monte-Carlo localization. However, it has two main limitations: i) the starting poses of the robots have to be approximately known and ii) mapping of robots must begin in approximate locations for overlaps of their starting maps. Howard [72] improved Thrun's research utilizing Rao-Blackwellised particle filter by solving relative poses of robots and updating maps and poses issues, which are crucial for generating a global map. In their work, this issue has been solved by unitizing the Line-of-Sight (LOS) observation using cameras mounted on the robots. In 2010, Carlone et al. [73] applied a modified particle filter to solve the MR-SLAM problem by extending Howard's method [72]. His contribution considered the uncertainty of relative poses in mappings using grid map and the mild assumption on wireless communication. In the following year, Carlone et al. [74] improved his work by adding short-range communication technologies (Bluetooth, RFID, etc.). As a result, a small amount of data is shared with robots considering the relative pose of measurements. In 2016, Peiliang Wu et al. [75] proposed an Improved Marginalized Particle Filter (IMPF) for MR-SLAM by addressing robot localization and sensor network localization issues. In 2019, Peiliang Wu et al. [63] proposed an M-posterior estimation-based MR-SLAM algorithm. In their work, the accuracy and estimation error are superior to the traditional FastSLAM 2.0 algorithm.
- Smoothing methods determine the entire trajectory of each robot by optimizing the observation and process constraints. Generally, two smoothing techniques are available i) GraphSLAM and ii) submap matching. GraphSLAM is a method that employs least square method to estimate the location and map of each robot. GraphSLAM has been deployed for multiple robots such as C-SAM for feature-based map merging [76] and decentralized SLAM [77,78]. In [79], the authors introduced software to collaborate SLAM of multiple real-time robots. That software framework combined the local pose graphs of each robot into a global pose graph. This global pose graph is then sent each robot to estimate their location and mapping effectively. In [80], the authors proposed a low-cost and high-efficiency framework for active pose-graph SLAM for multiple robots in the 3D environment. In their research, the proposed method found better trajectories for optimal information exchange. Based on tree-connectivity, which is considerably related to the D-optimality metric of the Fisher Information Matrix (FIM), they explored the relationship among edge selection and node edge selection, which often occurred in active SLAM, in terms of information increment. Submap matching is an effective method for mapping, in which local maps produced from each robot are aggregated into one global map. It prevents global error due to odometry and measurement inaccuracies and is therefore an effective solution, especially for outdoor environments. In [81], the authors proposed feature-based submap matching solution for MR-SLAM.
- AI has been utilized for solving many complex problem such as MR-SLAM. Nowadays, filtering and smoothing are using AI algorithms for optimization. For example, a fuzzy logic based solution was proposed in [82] to tune the covariance values of the measure-

ment model. An algorithm based on the neural network technique called ratSLAM is proposed in [83]. The DL algorithm is a part of AI that has multiple levels of representation with nonlinear modules [84]. Researchers have applied DL for SLAM in three aspects, namely semantic mapping [85], loop closure detection [86] and inter-frame estimation [87]. The authors proposed a DL based visual SLAM, where dense scene flow is proposed to improve traditional algorithms in highly dynamic and large-scale environments [88]. In addition, researchers have applied DRL due to its decision-making feature [89]. DRL methods have been implemented to solve complex problems, such as estimating robot motion primitives in unknown environments [90]. For SAR applications, DRL has been deployed to the robot visual serving issues based on the detection of a target object [91].

3.2. Path planning

In general, a robot creates a local path to reach the goal by avoiding obstacles and collisions within a small area allocated to that particular robot. The global path is created by combining all the local paths. Consequently, the global/optimized path planning of all robots that are deployed covers all experimental areas. Therefore, path planning and area coverage are crucial research areas for mobile robots via IoRT to achieve the desired tasks called Coverage Path Planning (CPP). The main goal of CPP is to provide a collision-free path that covers the entire area of the predefined region. These CPP approaches that can be classified into random search, grid-based search, geometric, Next Best View (NBV), and reward approaches based on path planning methodology are briefly discussed below:

3.2.1. Random search based approaches

The rapidly exploring Random Tree (RRT) algorithm is a model-free and random sampling path-planning algorithm invented by LaValle [92] which is used for path planning of mobile robots. Its operation entails growing a tree-shaped data structure from the path's initial location (root node) to one of its tree branches reaching the final/goal place (last leaf node). Each branch represents a connection between two nodes, and its length is an algorithm input parameter. A node is any collision-free place in a search space that is discovered through a random sampling method. In [93], an RRT-based path planning algorithm was developed for small dog robots. Improved RRT was used for mobile robot [94] and intelligent vehicle [95]. Furthermore, multi-agent RRT algorithm has been developed for path planning and cooperation of MRS [96].

3.2.2. Grid based search approaches

For global path planning of MRS, one of the vital methods is the grid-based search method created from the cell decomposition method and tree-based method. Initially, the boustrophedon cell decomposition method has been extended from a single robot to MRS to fulfill the complete coverage of unknown environment in [97]. In their research, two algorithms named distributed coverage and team-based coverage were illustrated considering the communication restrictions in an unknown environment where those algorithms have optimally minimized the repeated coverage area among the cooperative team of robots. Furthermore, two stages CPP approach have been depicted in [98]. In the first stage, a complete grid map is constructed by decomposing the entire area into line sweep rows, and in the second stage, the generated grid map is assigned to teams of robots. It was demonstrated that the solution was fast to deploy the minimum number of robots to complete the entire area. In [99], the authors have proposed two approximation heuristic approaches to solve the multi-robot coverage problem, dealing with optimal communication and maximum coverage. The first solution was the extended version of cell decomposition, while the second was a greedy approach. Furthermore, multi-objective genetic algorithms were proposed in [100], where non-intersecting trees were used to solve the coverage problem within time constraints. They resulted in covering the entire region in a predefined time using a minimum number of robots.

3.2.3. Geometric based approaches

The geometric-based methods such as Voronoi Diagrams (VD) use the visibility graphs to generate robots' paths. The visibility graph is created by a set of nodes and obstacles where nodes represent the locations, and the edges are line segments that do not go through hinders. In many applications of MRS, geometric approaches have been employed to find the optimally minimum paths and maximum coverage polygonal area. In 2013, a dynamic path planning technique by deploying generalized VD was proposed in [101] to solve the heterogeneous multi-robot coverage issues considering the energy capacity of the robots. The proposed approach commenced with a unidirectional graph followed by generating subgraphs that were utilized to generate every robot's optimal shortest path. Furthermore, simultaneous area partitioning and allocation method based on VD partitioning technique was proposed in [102] that covered the entire experimental with minimum processing time.

In addition, Fotios et al. [103] proposed an approach by combining the graph search strategies and computation algorithms for geometry according to partitioning the area of coastal. At first, the whole area was decomposed utilizing a growing region's approach. Then, the holes and area were identified by forced edge constraints performing a constrained delaunay triangulation. This algorithm started from the initial position of each UAV, propagating towards the other UAVs or the borders of the area. In [104], the authors presented an exact geometric-based algorithm for solving the path planning issues in MRS where the proposed algorithm found the shortest path by avoiding any collision in MRS. According to their result, it can create safe, smooth, and hinders free paths for multiple robots at a time in the populated sparsely with convex and nonconvex polygonal obstacles environment.

3.2.4. Next best view (NBV) approaches

When no data about the environment is available, researchers developed a method to plan the paths of robots to cover all areas of that environment; this method is called NBV. It is generally applied complex real-world applications and estimates the information by using different probability theories. One of the recently developed NBV CPP approaches has been presented in [105]. A heterogeneous MRS for collecting the physical water samples has been proposed to solve the two subproblems, including an exploration algorithm for generating the map that collects the actual physical samples concurrently by deploying sampling algorithms. The exploration was accomplished by employing a gaussian process frontier-based procedure, in which it anticipated variables for suggesting the sample utility. The vital part of the method was to aggregate the effective real-time anticipation of a variable upon that their phenomenon of interest was partially dependent on the subsequent gathering of information. The authors in [106] developed a variation of vehicle routing problem with an insertion heuristic and a negotiation mechanism for energy resources and a heuristic for the Continuous Monitoring Problem with Inter Depot Routes and Priorities (CMPIDP) which utilized all available information and was fast enough to react to dynamic environmental variations. Furthermore, a two-layer exploration method, including a coarse exploration layer performed by UGVs and a fine mapping layer performed by UAVs in an environment where GPS data is not available, is described in [107]. The 3D laser mounted on the UGV starts the exploration of the area of interest to create a 2.5D volumetric map, where the UAV uses the 2D tilting laser mounted on the UGV to update the occupancy data of the gaps. In addition, a frontier CPP approach was followed to generate the set of viewpoints that were then utilized to determine the path utilizing the fixed start open traveling salesman problem.

3.2.5. Reward-based approaches

In recent years, reward-based algorithms have been utilized to solve the multi-robot path planning issues to cover the whole area of interest due to colossal advantages such as learning ability, nonlinear mapping, parallel processing, etc. One of the basic reward-based algorithms is RL, a subdivision of ML algorithms concerned with how intelligent robots ought to take actions in an obscure environment by maximizing the cumulative sum of penalty and reward for the actions taken by the robot. RL can be divided into i) value-based method: It is intended to account for the expected return value of being in a provided state and the optimal policy corresponds to the action with the optimal action-value function, ii) policy-based method: it is different from value-based methods, that directly find an optimal policy. One of the most foremost methods is policy gradient, which enumerates an estimator of the agent's policy gradient by utilizing the stochastic gradient ascent algorithm, and iii) Actor-Critic (AC) approach is the hybrid method that combines the benefits of the policy and value-based methods. The actor is a policy network to select an action. The critic, a value network, is deployed to evaluate the benefits of the action made by the actor. The primary advantage of RL lies in its inherent power of automatic decision-making, even with minor variations in real-world applications. There exists extensive research on multi-robot navigation on RL that has been evaluated in many simulated environments [108] but on a limited basis in real-world scenarios. Recently, learning-based methods have been applied to address online planning in dynamic environments [109–111]. Thus, the effectiveness, generalizability, and scalability of recently developed RL-based planners still do not satisfy the requirements of many real-time applications. For overcoming those challenges, a globally guided-based RL algorithm has been proposed in [112]. Still now, it has a low-dimensional state space problem. For solving the issues, RL is integrated with Deep Convolutional Neural Networks (CNNs) [113] to constitute DRL. Some researchers have already applied DRL to estimate the real-time path planning of MRS, which is applied in various applications such as surveillance by UAVs [114], indoor navigation [115], unknown complex environments [116], SAR [27,117], cleaning and maintenance [118], and maritime SAR [119].

3.3. Challenges

In the physical layer of IoRT, recent research on mobile robots navigation is summarized. In this paper, SLAM and path planning problems that have to be solved by appropriate algorithms for mobile robot navigation were reviewed and various recent proposed studies related to CPP using MRS were reviewed. Based on the critical review, the challenges of the physical layer of IoRT are listed and explained briefly.

- Relative poses of robots: Each robot in the IoRT creates a map to generate path planning for robot navigation by evaluating data acquired from its sensors, such as lasers and cameras, about its surroundings, referred to as the local map. Each robot takes the necessary steps to incorporate the local maps generated by others to produce the environment's global map. Different relative pose of different robots hampers to produce the global map and the navigating path in multi-robot. The uncertainty of the relative poses and which relative poses are more critical emerges when robots carry out their tasks with incomplete state information. Thus, the uncertainties and the search for the critical poses hinder the production of the global map from the local maps as well as the appropriate path planning.
- Update of pose and maps: After selecting the appropriate relative information from various mobile robots of IoRT, the fusing process of local maps has been done by integrating all plausible information of local maps to generate the global map. Then, the recent updated global map and instantaneous poses of robots are updated via IoRT within the mobile robots. Due to environmental noise, limitations of multi-robot networks and communication, and uncertainty in the relative locations of the robots, plausible information of the local map and the locations of different robots may be missed. As a result, updating the current map production and instantaneous poses of robots within multiple robots is not an easy task.
- Heterogeneous sensors and robots: In the real-time application of mobile robots, almost all sensors and robots are connected with a heterogeneous network that has crucial advantages. This type of network can build better global maps; e.g. aerial robots collect the data from the top of the environment while the ground robots gather environmental information. Consequently, a better 3D global map can be generated by utilizing the appropriate information from the ground and aerial robots. Despite the advantages of a heterogeneous network of robots, the most challenging part is merging different types of maps, such as feature maps and occupancy grid maps produced by aerial and ground robots. Due to the heterogeneity of sensors, maps and information, different forms of problems, e.g. augmentation of feature maps and topological maps, combination of laser scanners and visual sensors, integration of satellite views and ground views, and the appropriate path planning, have emerged and presented in [120].
- Complexity: The robot is deployed to achieve any real-time application. Robots always experience context-aware interaction with the environment and other robots in real-life applications. Still, it is a complex task to develop the appropriate algorithms to generate local and global maps, estimate the robot's position and predict the appropriate navigation path is a complex task. In addition, time and space complexity in mobile robots are two pivotal issues.
- Synchronization: Synchronization, such as clock synchronization, data synchronization, etc., is also a key challenge for IoRT due to latency issues. Synchronization is divided into two levels that are local and global synchronization. Local synchronization means the different sensors of every robot have to be synchronized. In contrast, global synchronization means all robots within a team have to be synchronized with the robot's clocks. Additionally, the clocks of robots and ROS must be synchronized through Network Time Protocol (NTP). In each acquired data set, the synchronization of time has inserted a label in the header [121].

4. Network and control layer

The IoRT technology involves the application of a fully distributed system that extends to various levels, such as smart buildings, factories, environments and cities, robots, sensors, and actuators. They can be prepared with controllers that collect, analyze and transfer data through gateway routers to other networks, computing devices, clouds, or autonomous agents for onboard decision-making [22]. In addition, inter-robot communication plays a key role due to the need for coordination and information sharing to accomplish the predefined collaborative tasks of mobile robots via IoRT. Robots have to be connected with a network that the performance of the network has a direct impact on most other solutions such as SLAM, coordination of MRS, data processing and computing, etc. In this section, network architectures, routing protocols, and communication among robots, and infrastructure of IoRT for mobile robots are presented.

4.1. Networking architecture

Several networking architectures have been identified, such as centralized, hierarchical, decentralized, and hybrid, which greatly predicts the reliability, scalability, and robustness of the system as well as the interactions among the robots [122–124].

- In centralized networking architecture, the whole team of robots is controlled and coordinated from a single server [125]. This architecture is easy to maintain, but is prone to limitations in practical applications due to the vulnerability to single point of failure and scalability limitations. Furthermore, the primary server must be continuously stable to ensure stable communication among robots.

- In the hierarchy approach, the robots are embodied as leader-follower formation, which is generally shown in the military [126]. Here, a robot governs a small team of other robots, each team member controls other teams of robots, and so forth. It is better than the centralized category due to its scalability; however, it has raised the issue of reliability because of the considerable vulnerability in handling failures of robots at the higher levels in the hierarchy [127,128].
- The most common networking approach of mobile robots in IoRT is decentralized. In this approach, robots are governed based on their local situation by considering specific guidelines and goals [129,130]. It is a highly robust method due to its ability to overcome the failures of any team members and non-centralizing control. The major challenge of this approach is to maintain synchronization and coherence between the robots.
- In mesh networking, robots are constituted by mesh clients and mesh routers. Each robot functions as a client and as a router that forwards data as a gateway. It is dynamically self-organizing and self-configuring and can be automatically established and maintained between nodes [131].
- Hybrid combines decentralized and hierarchical networking approaches that provide robustness to achieve the global synchronization and coordination of actions, goals, and tasks. In many real-world applications, it is deployed due to the higher scalability and the ability to take quick decisions on the local level.
- MANET is an alternative approach to MRS network architecture, defined as a distributed system of multiple similar mobile nodes with the ability to move robotically arbitrarily and dynamically. MANET has no specific infrastructure and is subjected to rapid changes, with each node communicating with other hosts within transmission range via packet radio. Due to its bandwidth and constrained propagation range, the majority of the routes in MANETs are multihop. In a nutshell, MANETs are dynamic, self-adaptive, and unpredictable wireless networks [7,132].

4.2. Routing protocol

Routing protocols of IoRT define the rules utilized by the routers to communicate between source and destination and do not move the information from the source to a destination but only update the routing table that contains the information. Network router protocols help robots to specify the way routers communicate with each other and allow the network to select the routes between any two robots through IoRT. Such routing protocols can be categorized into the following: [133,134].

- The static protocol is used when a router utilizes a manually configured routing table, which has mobility issues; therefore, it can be useful only for some special missions where predefined and relatively fixed routing can be used in IoRT.
- In the proactive category of protocols, routing information of the entire network has been maintained, even if all information is not required at a time. Furthermore, each robot sends routing information to all and exchanges and updates all information among robots. Consequently, the scalability of the IoRT network is reduced and it can be applied in cases where the application cannot tolerate large and unpredictable route discovery delays, such as IoRT networks with high real-time coordination involving most nodes.
- In reactive routing protocols, an end-to-end path from source to destination is only disclosed when the demand is indispensable. It has two primary components: route discovery when a robot wants to communicate with other specific robots, and the use of route maintenance to manage the path failure due to the mobility of the robots. It is suitable for such applications with a relatively large number of robots and low traffic, for instance, SAR, surveillance, etc.

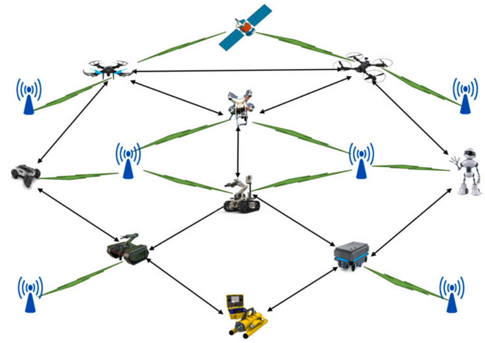

Fig. 7. Mobile robots communication links of IoRT.

- In hybrid categories, proactive and reactive routing strategies are deployed to generate the new routing protocol called hybrid routing protocols that harness the complementary benefits of both proactive and reactive protocols. For applying this strategy, the whole IoRT network has to be divided into multiple clusters by selecting a cluster head robot in each robot's cluster. Consequently, the proactive routing protocol is deployed for intracluster communication. Reactive protocols, on the other hand, are used to control inter-cluster communication between nodes in different clusters and are routed to the cluster head of the source cluster to transmit data to the cluster head of the destination cluster, solving the scalability problem for a broader range of IoRT networks.
- In geographic routing, each robot must be mounted with a GPS sensor or must be supplied the position data of other robots from a location service. Here, the data is moved from source robot to destination robot deploying different routing protocols. The main intention is to keep forwarding the information to the closer robots considering the geographical position for reaching the data to the final destination. Hence, transferring time and overhead are reduced. This type of routing can be useful for IoRT networks stretching over larger geographic areas, and the nodes are highly mobile, leading to constant topology changes.

4.3. Communication

Mobile robots are employed in various environments such as maritime, urban, wilderness, etc., to perform cooperative tasks. Based on the operating environment, communication is varied due to the limitation of communication equipment and protocols. In the following, mobile robots communicate in underwater, ground, and air by R2R and R2I communication links named Bluetooth, ZigBee, UWB, WIfi, LoRA, Wimax, LTE-M, NBIoT etc. has shown in Fig. 7. For R2R communication, a most common low-cost and low-power consumed wireless standard known as Bluetooth operates in 2.4 GHz, which maximum range is 100 m with 0.27 Mbps throughput. Furthermore, ZigBee is a straightforward, inexpensive, and power-efficient wireless alternative. It is based on IEEE 802 standard and has a network capacity of 65000 nodes. Its range can be increased by deploying the repeaters in the mesh topology; however, this will soar the deployment cost. Additionally, UWB is a radio technology that utilizes the low energy level for short-range and provides high-bandwidth communications. Wi-Fi is a wireless technology that runs in the 2.4 GHz or 5 GHz range and utilizes radio waves for communication. Its range is 70-250 m with 600 Mbps and less than 20 ms latency. Due to the limitations of the current Wi-Fi standards 802.11 a/b/g/n/ac, IEEE has developed two new protocols called 802.11ah and 802.11ax, which can provide a stable connection among thousands of devices with low power consumption. For long-range (2-5 km) and low-power communication, LoRa is also important wireless technology in IoT/IoRT developed by Semtech based on IEEE

Table 5
The comparison of communication links based on performance parameters.

Performance parameters	Bluetooth	ZigBee	UWB	Wi-Fi	LoRA	Wimax	LTE-M	NBIoT
Range	<100 m	75-100 m	102 m	70-250 m	2-5 km	0.3-49 km	11 km	10-15 km
Bandwidth	1 MHz	2 MHz	0.5-0.75 MHz	20-25 MHz	<500 kHz	1.25-20 MHz	1.08 MHz	180 kHz
Operating band	2.4 GHz	915 MHz	10.6 GHz	2.4, 5 GHz	868, 915 MHz	2-11 GHz	1800, 1900, 2100 MHz	700, 800, 900 MHz
Signal rate	1 Mbps	250 kbps	110 Mbps	600 Mbps	50 kbps	70 Mbps	375 kbps	200 kbps
Throughput	0.27 Mbps	250 kbps	100 Mbps	600 Mbps	50 kbps	50 Mbps	1 Mbps	150 kbps
Latency	3-10 ms	15 ms	<3 ms	<20 ms	1-10 ms	25-40 ms	10-15 ms	<10 s
Transmitted power	10 dBm	-25 to 0 dBm	-41.3 dBm	20 dBm	14-20 dBm	23 dBm	20-23 dBm	20-23 dBm
Mobility	Limited	Yes, but low	Yes	Yes	Yes	Yes	Yes	Nomadic

802.15.4 g standard. It provides 50 kbps throughput with low latency (1-10 ms). In addition, WiMax is a wireless technology for long-range (0.3-49 km) with high-speed connectivity (50 Mbps) of IoT/IoRT devices utilizing the radio waves while latency is from 25 ms to 40 ms. Due to low cost, data rates and transmitted power, LTE-M and NB-IoT based on 3GPP cellular standards are famous IoT/IoRT communication technologies in recent years. LET-M provides the 1 Mbps throughput while NBIoT gives 150 kbps. In addition, the latency of NBIoT is higher compared to LTE-M [135–137]. The comparison of technical specifications of above mentioned wireless technologies is presented in Table 5.

4.3.1. Underwater robots communication

Application of underwater robots, such as prediction of natural disasters [138], data collection, maritime surveillance [139], assisted navigation, oil, and the gas industries [140] etc., has soared recently. Consequently, Underwater Wireless Network (UWN) has played a pivotal role in accomplishing the task by Unmanned Underwater Vehicles (UUVs). Due to the high attenuation of underwater electromagnetic signals, UWN applications are not as straightforward as typical wireless networks applied on Earth. Although acoustic signals that can reach several kilometers have been used for communication between UUVs, ambient acoustic noises, limited bandwidth, high latency for low speed of sound propagation in water, high variability due to multipath [141–143]. Generally, commercial acoustic modems have only a few kbps transmission rate [144]. Recently, Visible Light Communication (VLC) has been utilized due to comparatively high transmission rates. However, it only applies to a range of a few tens of meters [145]. Another alternative of acoustic signals is the utilization of radio frequency by deploying the larger antennas, which can communicate up to 12 meters [146]. Recently, research in underwater communication has been directed towards software-defined and cognitive, adaptable solutions using a connectivity stack, as it is capable of calibrating all communication parameters, such as frequencies, waveform, and encoding according to the demand of the acoustic channel [147]. Recent research [148] has shown the implementation of this modem according to the requirement network. Accordingly, the Centre for Maritime Research and Experimentation (CMRE) communication stack is evolving into a fully cognitive-communication architecture to establish an intelligent, adaptable, and safe underwater network [149].

In addition, AI has been deployed to mitigate the challenges of underwater communication. Yordanova et al. proposed the synchronous rendezvous technique and mission planning scheme to communicate among UUVs autonomously by applying AI [150]. In [151], the authors applied RL-based routing protocol to select the optimal communication channel for faster packet delivery to ensure reliable routs for UUVs communication. Q-learning based algorithms are also applied in [152] to optimize delay-aware routing. Furthermore, the authors have proposed CNN based algorithm for providing accurate hand gesture recognition underwater.

4.3.2. Space robots communication

Multiple UAVs have been deployed in commercial applications such as border surveillance, disaster monitoring, emergency rescue, etc., because of their size, capacities, limited payload, and flying time [153]. In order to accomplish assigned tasks, networking and communications are indispensable to monitor team behavior and coordinate and communicate the autonomous behavior of multiple UAVs. Consequently, a high-capacity wireless network and connectivity is essential to ensure Quality of Service (QoS) requirements. This network technology must maintain two communication links: i) air-to-ground to ensure R2I connectivity, and ii) air-to-air to establish R2R connectivity. Several wireless technologies such as IEEE 802.15.4 [154], IEEE 802.11x, 3G/LTE etc. have been exploited for UAVs networks [155,156]. However, they did not analyze whether the existing protocols ensure the communication requirements for all UAV applications or not. The special characteristics of Flying Ad Hoc Networks (FANETs) such as radio propagation model, network lifetime, computational and power limitations due to size and weight, flight path updates, bandwidth, and latency prerequisites are comprehensively discussed in [157]. In [158], the authors addressed research problems of routing protocols, networking, and communication in terms of robots mobility, connectivity, message routing, QoS, application areas, etc. in FANETs, which are different from traditional MANETs. In addition, the authors proposed the Energy-Aware Link-based Clustering (EALC) model by applying the K-Means density clustering algorithm to select the best cluster head, which improved the lifetime of the cluster and mitigated the overhead of routing [159]. In [160], the authors have presented a hybrid clustering method by combining Glowworm Swarm Optimization (GSO) and krill herd algorithm for upgrading the routing protocol of FANETs and reducing the energy consumption in three steps. First GSO algorithm is exploited to form the cluster in terms of energy and location. After that, cluster management has been set up, and finally, clusters are maintained by performing staged routing using the path detection function.

Daniela and Dario analyzed the implementation of AI in the research field of space engineering, and technology [161]. In [162], multi-agent technology has been discussed to manage and solve the scheduling problem of the earth sensing satellites. The authors in [163] proposed a Deep-Q-Learning (DQL) based control algorithm for the unmanned vehicle to manage its data collection considering the minimum power supply. The system state included the data about the sample priority of each sub-region, the location of the charging point, and the moving trace of the UAV and unmanned vehicle, and the UAV and unmanned vehicle can choose the moving direction. The DQL algorithm employed the concept of CNN to extract correlations of adjacent sub-regions, thus increasing the convergence speed of training, and thrives during the exploration process by deploying feasible control methods as a baseline. Furthermore, the authors in [164] investigated energy saving as well as the secure transmission for air-to-ground link, taking into accounts the impact of UAV jitter. Notably, in order to minimize the total transmit power of the base station installed on the UAV, a joint beamforming optimization of the confidential and artificially noisy signals was developed under the constraints of the DRL algorithm on the worst-case confidentiality performance.

4.3.3. Ground robots communication

A ground MRS is the combination of multiple ground mobile robots that communicate with each other by utilizing advanced communication technology to perform the assigned task collaboratively and autonomously. The effective communication among robots in MRS for completing the task is discussed in [165]. In addition, famous communication technology for communicating robots on the ground is MANETs due to the ability to add nodes autonomously [166]. A stable communication channel among robots is the combination of dynamic as well as static techniques that have been proposed to transfer data in wireless network [167]. In their proposal, the static approach thrived data rate in robots network, while the dynamic technique efficiently distributed the load among channels. DL based algorithm was also deployed to ensure stable communication by considering the velocities and pose of mobile robots [168]. In [169], the authors applied the Monte Carlo Tree Search (Dec-MCTS) algorithm to select the prerequisites of communication resources for MRS, and predicted the demand by applying particle filters. In the automated manufacturing industry, Ultra-reliable Low Latency Communication (URLLC) is indispensable. In [170], an ML-based framework named Rely was proposed, which was implemented in the physical layer and was able to transmit data within 5 ms latency. In [171], DRL-based algorithms have been proposed for performing the material handling considering the maximum throughput as well as safety in an intelligent manufacturing factory.

4.4. Challenges

Here, the published research of network architecture, routing protocols, and communication protocols for R2R and R2I in underwater, air, and ground operational environments has been critically reviewed, amalgamated with the network and control layer of IoRT. Additionally, challenges that are found in the review of network architecture, routing protocols, and communication are listed down:

- Network selection: Unstable communication channel in a complex environment can significantly degrade the system's overall performance because wireless networks and communications are the backbones of IoRT. Hence, choosing a network for communication is a big challenge. In industrial manufacturing, IoVs scenarios, intelligent services must be ultra-reliable, providing the necessary data and functionality even when the network connection is weak.
- Traffic management and routing: Traffic management in communication networks is often modeled as Network Utility Maximization (NUM) by optimizing a path to forward the information traffic, given a set of network flows from source to destination nodes. In general, NUM problems are mostly model-based, because in advanced WSN technologies, the network environment becomes more complex and dynamic and is difficult to model, predict, and control. Optimization of traffic routing is a challenging task due to improper traffic management algorithms, high latency, etc.
- Constrained resources: The essential resources of WSN are bandwidth, transmission power, and antennas. The frequency spectrum is limited, as well as licensing fees soar with the increment of bandwidth. Since the size of the robot should not be too large, the size of the battery and antenna must be within the limited size, and the transmission power is also limited, while at the same time multiple antennas are needed to handle the complex space-time signals to ensure stable communication. When signal propagates through wireless channels, it distorts due to path loss, shadowing and multipath fading, which depend on the operational environment.
- Cost: Generally, significant network bandwidth and huge computing capacities in IoRT architecture are indispensable to stream and process the generated colossal data. For example, a group of surveillance, SAR robots may be required to send various acoustic and visual information during their operation. For completing the possible action by appointed MRS, faster data processing and rapid response are mandatory.
- Resource management: The demand for reliability and low latency communication channel has soared drastically in various MRS applications. The traffic carried over WSN is diversified in type, data rate, service duration, and quality of service requirement. To accommodate such a diverse set of requirements, systems have to provide high data rates at very low latency in stable ways which may be possible after the massive development of physical and network layers hardware. Still now, it is almost impossible to achieve the goals by utilizing limited resources. As a consequence, resource management has to be done with efficient utilization. Resource management in WSN is defined as a series of processes that considers the timing, ordering, procedures, and the number of resources to share and schedule among robots.

5. Service and applications layer

At the service and application layer of IoRT, the standard and user programs are implemented to monitor, process, and control both environmental parameters and robots in the smart environment. Meanwhile, AI algorithms can be used for optimizing the overall performance of IoRT. In order to monitor and control mobile robots, MRS must be coordinated, and data computation in external resources is also important for smooth processing, so there are two factors that can improve the performance of IoRT.

5.1. Coordination

In order to achieve the collective optimization goals of IoRT, collaborative interactions between robots must be properly considered. Both the design of MRS coordination and the implementation of multi-robot task assignment for MRS coordination are important challenges, especially when these questions arise in heterogeneous robot networks installed with various sensors, actuators, on-board processing systems, etc., to optimally accomplish the prerequisite tasks. Cooperative MRS has to be designed to design a wide range of tasks depending on the task's degrees of complexity, calculated by considering the difficulty of the assigned task, which stimulates an estimate of a reasonable number of robots to complete that assigned task. The assigned task can also be decomposed into different subgroups of robots [172,173].

5.1.1. Task coordination

For accomplishing the complex task systematically and autonomously by mobile robots via IoRT, four main sequential blocks have been identified in [174,175]. There are task decomposition, coalition formation, task allocation, and task planning/execution, as depicted in Fig. 8 and discussed below:

- Task decomposition is a process that segments the complex task into sub-tasks [176–178], which are either totally independent or sequentially attached; for instance, building a megacity map can be segregated into small area maps that a single robot can do. It is an immensely challenging process because various issues such as the incomplete information of the environment, the dynamism of environmental conditions, the risk of external entities collision, etc., have to be considered. In [178], the authors proposed a task decomposition algorithm to divide the soccer court and gravitational

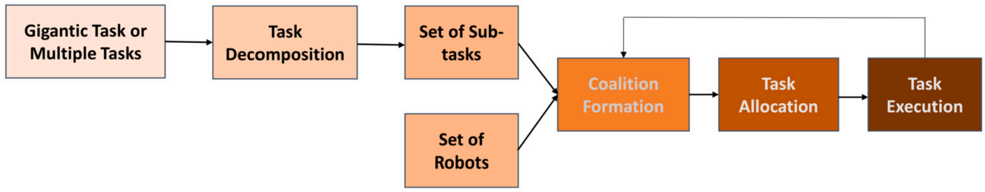

Fig. 8. Task coordination and execution by IoRT.

field. In their paper, accomplishing the whole soccer match, the whole task decomposed among all robots considering the dynamical adjustment by avoiding the conflict among players (robots). Furthermore, the extra robot was prepared to replace the position if any robot faced a malfunction. In [179], the authors introduced an algorithm to decompose the exploration tasks in the marine area among the multiple USVs. For compelling exploration, dynamic workload balance among USVs has been incorporated by taking into account the surface current of the port area, the risk of collision among the civilian traffic, and the variation of weather and tides port area. In [180], the authors applied the task decomposition process for sustainable clearing of the large area such as airports, libraries, modern big bus terminals, train terminals, etc., for saving maintenance time and cost.

- Coalition formation is to form different teams by dividing the total number of robots assigned to fulfill the large task and multi-task autonomously. The team formation can either be cooperative [181] or non-cooperative [182]. The cooperative coalition formation can be dynamic also in the heterogeneous multi-robot network [183].
- Task allocation is the distribution of sub-tasks decided during task decomposition to the assigned robots to perform the whole task. The complexities and approximation of task allocation among multiple robots are illustrated in [184]. In MRS, task allocation algorithm such as swarm intelligence [185], PSO [181], DRL [186] have been deployed. In [187], the authors reviewed the task allocation issues and challenges by considering market-based task allocation, behavior-based task allocation, dynamic task allocation, task clustering, and heuristic task allocation. Their work analyzes objective function, time of task allocation, task completion time, robustness, and the task reallocation feature.
- Task planning/execution and control is a decision-making process to complete the allocated task to the specific robot or team of robots in a smart environment. It decides policy for robots to accomplish their allocated work within the complex experimental tasks categorized into subtasks. In robotics, decision-making algorithms are normally evaluated in terms of policy optimization, estimated time, and space complexity [188].

5.1.2. Level of automation

Recently, various robots such as mobile, humanoid, and vehicles have been utilized in real-world applications, as discussed in section 7, to accomplish tasks. In general, the complexity of the task is estimated by finding solutions to some problems, for example, 1) how smoothly decompose the large task into sub-tasks? 2) how many teams are formed effectively? 3) how to easily distribute decomposed sub-tasks in the created robot groups? and 4) how can tasks allocated to a specific group of robots or individual robots be performed efficiently and effectively? In [189], the authors proposed four levels of automation from most to least automation to complete the assigned task. According to their paper, only task execution (only the 4th question has to be solved) is fulfilled automatically in the first level. Task allocation (question no. 3) or robot team formation (question no. 2) with question no. 1 has to be done automatically in the second level. When task allocation and team formation have to be accomplished simultaneously, it is called the third level of automation. In the fourth level, the entire process from questions 1 to 4 has to be done automatically. In this article, MRS task allocation has been reviewed from least to top-level below:

- This is the least automated level in IoRT where except task execution, all (task decomposition, collation formation, and task allocation) have been performed by human experts. In [190], the authors proposed a cooperative MRS system that consisted of UAVs, high-speed robots, and mobile stations for assisting in humanitarian relief actions. Additionally, Q learning-based data processing algorithms have been proposed for transporting a hose by deploying multiple UGVs in [191]. An MRS built by Unmanned Aerial System (UAS) and UGV has been designed and implemented towards radiation source localization as well as mapping [192]. For accomplishing their research goal, data processing approaches have also been developed to build trajectory planning of UGV based on obstacle map and source localization. In addition, the authors developed cooperative MRS for litter cleaning in [193], where a multi-robot path planning algorithm was proposed to efficiently clean the entire space with better performance than a single robot with the same battery power and cleaning area.
- The second level of automation is separated into two classifications: (1) human experts execute the task decomposition and coalitions, while task allocation and execution are accomplished autonomously by MRS, or (2) human experts do the task decomposition and allocation while coalition formation, as well as task execution, are completed by MRS. Automated method of task allocation as well as execution by MRS has been applied in different applications including but not limited to health care sectors [194–196], surveillance [197], SAR [198], warehouses management [199,200], exploration and destruction [201] etc. Some research has performed autonomously coalition formation as well as task execution in different implementations, including SAR, search and prosecute [202,203].
- In the third level of automation, team formation of robots and allocation and accomplishment of the task has been performed autonomously. Making coalition formation, task allocation, and execution without human involvement is a challenging problem. In [204], the authors proposed an algorithm by modifying ant colony optimization to solve the challenges of the third level of automation for the application of surveillance in the surveyed environment within the stipulated time. In [205], the authors proposed dynamic algorithms to overcome the challenges of third-level automation in a disaster environment. Furthermore, those challenges are considered in a collision-free UGV navigation [206]. These algorithms were evaluated in small-scale experiments. In [207], the authors proposed immigrant-based novel genetic algorithms for simultaneously find the robot's coalitions and task allocation.
- Fourth level of automation: Very little research has been done to fulfill the solutions of four questions related to task decomposition, task allocation, and task accomplishment in MRS. In [208], the authors proposed a solution to construct a well with the predefined model by a heterogeneous robotic network that consisted of one mobile robot and up to three UAVs. In their work, the wall was built with different sizes and weights of bricks, some large and heavy. Therefore, multiple robots made the number of teams neces-

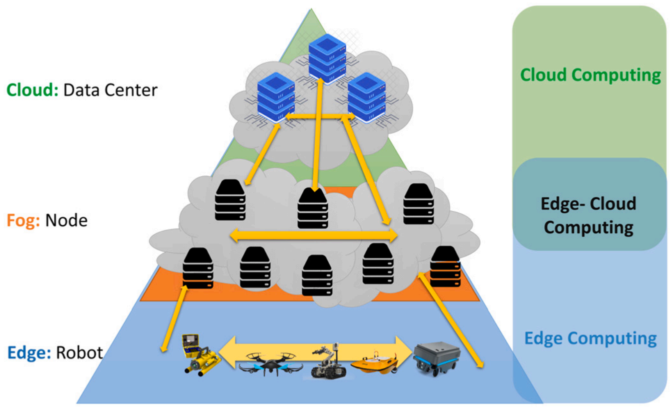

Fig. 9. Data computing of IoRT.

sary to locate, pick, transport and place the bricks to automatically build the wall.

5.2. Computing

In general, IoRT has to generate and process an enormous quantity of information to successfully operate all connected devices that may not have the same data storage and computing system capacity. Even a large size IoRT device can have a small quantity of place and energy for computing and storing data [209]. Consequently, it is indispensable to augment external resources for calculation and storage with IoRT network. These resources are generally provided by cloud computing and cloud-related architectures as shown in Fig. 9.

5.2.1. Cloud computing

Recently, cloud IoRT has arisen as a collaborative technology among service robots, IoRT devices, and cloud computing by adopting the WSN, gigantic storage, advanced communication technologies, and AI algorithms. Cloud computing provides quicker and more powerful computational capabilities by handling the colossal parallel computation and massive data storage system to enhance the ability of robots. For instance, robots can offload the data such as video, audio, text, gesture etc., to the cloud for processing and storage. Amazon web services, microsoft azure, google compute engine etc. are some of the commercial cloud computing service providers available today. Based on the cloud computing paradigm, the authors proposed a real-time MRS visual SLAM approach in [210]. Google's self-driving cars utilize google maps data and images that are stored in the cloud to identify their environment (such as road conditions), gather data regarding traffic conditions using LiDAR cameras etc. In [10], the authors discussed the recent works of cloud robotics technologies and their applications.

5.2.2. Fog computing

Fog computing is the extended concept of cloud computing to the network edge where IoT and other applications can easily interact in real-time. It is a decentralized computing system in which information, computation, storage system, and applications are embodied somewhere between the source of information and the cloud. It exploits the local computer resources rather than accessing remote computer resources. As a result, the latency issues are solved and the performance efficiency is improved [211,212]. In [213], the authors investigated the potential benefits of fog computing for MRS applications and explored the many challenges of fog computing for MRS. The authors developed an effective fog computing-based technique for mobile robot object detection in the IoT. In order to process the video data from the robot, they used YOLOv3 as the main algorithm in the Graphics Processing Unit (GPU) [214]. Furthermore, a fog computing framework named Phone + Embedded board + Neural compute stick (PEN) has been proposed for developing the guide dog robot for visually impaired people [215].

5.2.3. Edge computing

Edge computing generally processes the data where data is generated around the network in replacement of a centralized data processing system, which enhances the IoRT performance by exploiting the AI algorithms to ensure security. In IoRT, many smart devices are connected with a core network; Therefore, smart and intelligent devices are able to process their collected data and share it with other devices to perform specific tasks. As a result, the edge computing model can overcome the latency and bandwidth challenges and ensure efficient connectivity and data process. Edge computing can provide more benefits in some special cases; for example, a self-driving car needs to make a decision within a short time, so edge computing is the best solution. For autonomous driving of mobile robots, the authors in [216,217], used to reduce latency and increase reliability. In addition, the car can communicate with the infrastructure and can also use its on-board processing system to talk to other vehicles around it [218].

5.2.4. Edge-cloud computing

The Edge-Cloud Computing (ECC) approach, which combines cloud computing with edge computing, can overcome the limitations of cloud and edge computing. At first, workloads in the ECC framework can be split into edge nodes and clouds using more efficient workloads division algorithms to balance edge nodes and cloud centers. As a result, the optimization of the edge node's power consumption and cost will be further refined. Furthermore, edge nodes upload pivotal data to the cloud to store but only partially cache the raw data locally, enhancing data security. The majority of existing ECC approaches may be divided into privacy-first and efficiency-first collaboration. The cloud often does not access edge-specific private data in privacy-first collaboration and relies on a simple edge model aggregation method. In contrast, the cloud can utilize high computation capacity as well as all edge data in efficiency-first collaboration. An ECC framework to allocate the computing resources for the MRS workflow of the smart factory was proposed [219]. For autonomous navigation of mobile robots, a real-time edge-cloud collaborative computing framework has been constructed [220]. In [221], the authors proposed Runespoor by enabling ECC to analyze the video data that were collected from robots. Nowadays, FL [222] has been proposed as a way to train the shared model, in which massive data from various IoT devices are used by avoiding data loss. In [223], ECC framework based on personalized FL for intelligent IoT applications has been proposed. Furthermore, a novel algorithm based on FL has been proposed to detect Covid-19 by utilizing the ECC [224].

5.3. Challenges

In this sub-section, we have presented the overview of the coordination of MRS that consists of multi-robot task coordination and summarized the main elements of the workflow, which aims to minimize the human efforts with MRS team formation, task decomposition, task allocation, task execution. After that, existing research in mobile robots has been surveyed according to the level of automation. Since multiple mobile robots are deployed for gigantic tasks, ample data are generated from sensors and actuators, which has to be analyzed anyhow. For mobile robots' limited memory and power, data has to be stored and analyzed in external resources that can call external computing, which is reviewed. Furthermore, the main challenges summarized from the reviewed research of service and application layer are given below:

- Task complexity: The complexity of tasks is a big challenge and decision algorithms face difficulties in properly identifying the complexity of tasks and decomposing them into sub-tasks. Therefore, in order to accomplish complex tasks in any environment, the tasks must be automatically decomposed.
- Tradeoff between scalability and heterogeneity: MRS has to be scalable, generalizable, and adaptable to cope with dynamic and com-

plex environments such as smart cities. The uncertainty of MRS has increased because a large number of robots work simultaneously in that environment. Many decentralized and distributed algorithms for MRS planning and control have been developed. However, researchers face a plethora of hinders when handling the balance between scalability and robot heterogeneity in complex and dynamic environments.

- Big data: Due to the dual cyber-physical characteristics and heterogeneous devices of IoRT, enormous data are generated in different forms from various sources such as sensors, transducers, etc. This information must be processed at the edge or transferred from the robot to a remote computing system for remote processing. Due to the continuous generation of heterogeneous data, the problem of efficiently storing, managing and transmitting data arises. MySQL and NoSQL databases are utilized to handle the big data [225] in IoT real-time applications. However, researchers are still trying to efficiently develop a database system to handle big heterogeneous data of IoT/ IoRT.
- Latency: In the real-time application of MRS through IoT, transmission delays significantly impact transmitting and processing information. Especially for autonomous vehicles, hundreds of millisecond delays can not be allowed due to the safety issues [226].
- Optimization: System optimization has a significant impact on achieving a better performance of MRS. Generally, data can be processed in edge or fog or cloud server or combination. When the resources such as bandwidth and memory of edge devices are limited, edge computing is perfect for IoT/IoRT. Hence, which computing gives the optimized results is a big challenge.

6. Security

The employment of robots through IoT has been tremendously shored recently. Almost all applications of IoRT have extreme demands on security and safety for ensuring their stable operations. Besides, enormous heterogeneous data is generated in the IoRT that needs to be shared among external computing deceives and robots, which increases the possibility to take attempts for compromising the IoRT safety due to its values. In IoRT architecture, layers are placed on top of one another. As a result, if one layer of the IoRT architecture is attacked, other layers are also affected. As a consequence, security compromise can be categorized as i) physical, ii) network and control, iii) service and application, and iv) multiple layers attacks, which are discussed with solutions below.

6.1. Attacks and solutions in physical layer

The essential equipment in the physical layer is various types of mobile robots which consist of multiple sensors, actuators, and communication equipments. Due to the various wired and wireless components in the physical layer, many security threats and attacks can occur. Attacker removes or deactivates IoRT devices physically that is called physical damage attacks [227]. Tampering is another kind of physical layer attack where the attacker modifies, adds, or deletes the information of robots physically or virtually [228]. RFID tags are frequently used in IoT devices for tracking. Sometimes, the hacker uses reverse engineering means cloned RFID tags to take over the access of end devices, and this attack system is known as tag cloning [229]. One of the most common physical layer attacks is Radio Frequency (RF) jamming which is created from ineffectual wireless bandwidth sharing for connected devices and interrupts RF resources by interference, and saturated noise signals [230]. Node injection attack is not the most common but most potent attack where the attacker compromises the security system of the physical layer as well as deploys additional nodes which are utilized to control the communications and traffic in the IoT/IoRT network [231].

For ensuring the security of the physical layer in the IoT framework, dynamic watermarking [232] is an algorithm that can detect as well as prevent cyber-physical attacks, for example, injection, eavesdropping, etc. Additionally, the authors proposed an RL-based Q learning algorithm to detect the physical layer spoofing [233]. In [234], the authors developed a DL-based algorithm for providing security across jamming attacks. Furthermore, RL-based algorithms are better to provide security against jamming problems [235,236]. However, the traditional RL learning-based algorithms face challenges when handling continuous or high-dimensional inputs. To overcome these challenges, a double DQN algorithm with frequency hopping strategy against RF jamming attack has been proposed in [237].

6.2. Attacks and solutions in network and control layer

The network and control layer ensures universal access to each robot of the physical layer. It collects the data from the physical layer and transfers the assembled information to a specific data framework through access systems or the internet. Hence, many protocols for managing routing and communication have been developed, discussed in section 3. As a consequence, an attacker tries to make attempts for compromising the security of IoT/IoRT through the network and control layer [233]. The critical security threats to network and control layer [238–240] are i) the hello flood attack (an attacker tries to exhaust network or devices resources by misleading routing path), ii) sinkhole (an attacker compromises a central device of IoT/IoRT network for eliminating the original node from the network) iii) clone Id (an attacker clones the legitimate identity of the node for gaining the access of user traffic), iv) selective forwarding attack (an attacker penetrates within the network and pushes selective packets for depriving the communication resources) v) blackhole attack (a hacker drops all the packets in a node to affect the network operation) and vi) replay attack (during the synchronization, an attacker misleads the destination node to exhaust the network).

For identifying various attacks in the network and control layer of IoT, an artificial immune system-based model has been developed [241], in which immunology theory, complex adaptive system theory, and computational experiment technology are integrated. According to their research, if a new attack affects one layer, the online identification and learning process activates the dynamic extension automatically. Furthermore, a DL-based detection model against network layer attacks is proposed in [242]. They generated a dataset in the Cooja simulator that was trained to identify the sinkhole attack, Blackhole, and Wormhole attacks.

6.3. Attacks and solutions in service and application layer

The application layer has a greater possibility of suffering security attacks than other layers because users primarily use various applications by this layer in IoRT architecture. Applications that analyze the data generated in IoRT can be overhead due to security attacks, as well as service unavailability [243]. One of the foremost security threats is malware such as worms, backdoors, viruses, spywares, trojans, and other malicious programs, which attacks the confidentiality of applications, steals user credentials as well as shutdowns of system [244,245]. When hackers impersonate authorized nodes or user accounts to steal data, spread malware, or bypass access control, known as spoofing attacks, it may occur at every layer of IoRT and impede authentication as well as user privacy [246]. In addition, IoRT can be affected due to code injection attacks. A hacker targets to compromise the entry nodes and inject harmful scripts or code into authorized nodes and databases. A successful attempt can take over the user accounts and destroy the entire network [247].

In [248], the authors introduced significant permission identification, which utilized ML-based classification methods to classify different families of malware and benign apps in IoT. In addition, a DL-based algorithm has been developed to defend against malware in real-world android applications [249]. According to their results, the developed algorithm achieved the highest accuracy at 93.4% and 80.3% for static and dynamic layers, respectively. For spoofing attacks counterparts, a ML-based algorithm has been proposed in [250,251]. Yongxin Liu, et at. proposed DL-based jointed solution for identity verification and spoofing detection in air traffic control or other safety-critical systems [252]. In [253] the authors developed a tool called the Gathering Multiple Signatures Approaches (GMSA) for counterparts against code injection attacks. It presented an accuracy of 99.45% against code junction attacks in the service and application layer.

6.4. Attacks and solutions in multi-layers

Some cyberattacks are defined as multilayers attacks because they can compromise more than one layer of IoRT architecture. For example, Denial of Service (DoS) and cryptanalysis attacks may happen in physical, network and control, and service and application layers in IoRT. Man-In-The-Middle (MITM) attack is the most common hacking attempt. The cryptanalyst stays between two IoT nodes and is used to monitor, control and obtain encrypted data and interfaces for communication between IoT devices. As a result, an attacker can attack in all layers of IoRT [254]. DoS or Distributed DoS (DDoS) attack is an endeavor to completely or partially shut down any IoRT node, network device, or application for disrupting the accessibility and services to its users. Moreover, DDoS attack is more threatening than that of the DoS attack, which consists of several hacking platforms to haunt one or more layers [255]. In a cryptanalysis attack, a hacker endeavors to access the encrypted message without the encryption key. A brute-force attack is one of the cryptanalysis attacks in which the attacker attempts and anticipates every possible combination of encryption keys [231].

In order to mitigate the security issues caused by MITM attacks, a hybrid routing mechanism was proposed in [256], where dedicated nodes were appointed to enforce routing between IoT nodes and users with minimal intervention and workload on the network. In [257], the authors proposed real-time MITM detection and mitigation algorithm, which has been implemented on WiFi-enabled IoT gateways. For detecting DoS / DDoS attacks, principal component analysis-recurrent neural network [258], DL [259], DRL [260] based algorithms have been proposed. In [261], the authors designed a novel algorithm to detect and classify the DDoS attacks based on FL, in which only model gradient parameters were shared from various terminals to the central server for maintaining data privacy. In [262], the authors proposed a differential linear cryptanalysis model for evaluating and mitigating cryptanalysis attacks in IoT framework, and also deploying complete security systems, such as Intrusion Detection System (IDS) may be deployed for protecting the IoT/IoRT from the security attacks. Furthermore, DRL [263], FL [264], multi-view FL [265], segmented FL [266] for IDS has been developed.

6.5. Challenges

In this sub-section, the security issues directly related to the IoRT architecture have been critically reviewed. Various types of attacks according to IoT layers have been merged with IoRT layers. Different solutions to multiple attacks have been discussed here. The direct use of existing security methods is not candid to IoRT devices with limited resources. In addition, the security approaches of the traditional network are developed in terms of the users' perspective, which may not always be apt for R2R or R2I communication. Researchers in [22,23,267] have found a few specific reasons for cyber safety and security issues in IoRT thus are: i) insecure communication among end-users and robotic devices, ii) authentication issues that have been failed to guard against unauthorized access, iii) lack of appropriate encryption at vendor and iv) weakness of default program configuration of the robot. The significant challenges to ensure IoRT security are listed below:

- Physical layer challenges: The resources in the IP-based IoRT devices are constrained, which can make them more vulnerable to security threats and attacks. The traditional security approaches are heavyweight and not suitable for use in IoRT devices because mobile robots' power, processing unit, and memory are not sufficient.
- Network and control layer challenges: The main functionalities of this layer are communication and information routing among various robots across the IoRT network. Attackers can strike quickly due to the i) diverse communication medium (robots can be connected to private, public, global, and local networks through wireless communication medium), ii) multi-protocol network iii) scalability of IoRT network, and iv) mobility of robots.
- Service and application layer challenges: The generated big data from physical layers are processed and stored inside the robot or in external devices in this layer. The safety of this big heterogeneous data is the most challenging issue in this layer.

7. Applications

Integration of robotics can be deployed to build smart environments which can upgrade our daily life in various areas such as home automation, smart city, transportation, health, logistics, etc. Over the past decades, mobile robots have been proposed by prominent research groups and companies in different environments and frameworks, and have been successfully applied in many fields. In [12,122], the authors have addressed many application domains of MRS. Later, Rachael Darmanin, et al. wrote a review on MRS in terms of application domains in [2]. The concept of IoT has been applied to the study of MRS and recently a new dimension of MRS applications called IoRT has been applied to develop healthcare, education, surveillance, military, domestic support, SAR, agriculture, autonomous vehicles, etc. Some categories are overlapping, for instance, health with domestic support, surveillance with the military, emergency/disaster response with rescue operations. In this subsection, applications of IoRT have been reviewed as well as have shown in Table 6.

For all types of IoRT applications, It is essential to quickly identify the environmental situations, such as detection of objects, people, obstacles, etc. The overview of computer vision has been addressed for emergency situations [289], agricultural automation [290], obstacle detection by UAVs [291], civil infrastructure inspection and monitoring [292] and military operation of UGVs [293]. Compared to traditional computer vision techniques, DL algorithms are becoming famous in research due to their higher accuracy in tasks such as semantic segmentation, image classification, object detection, etc. [294]. In this section, computer vision for real-time perception in MRS via IoT has been illustrated. In addition, cameras and LiDAR are the most common sensors for the perception of sensors for MRS in any application. Two methods are commonly used for camera information analysis: i) semantic segmentation and ii) object detection. Robots label everything perceived in semantic segmentation, while the only object has been labeled in the object detection method. In addition, multi-modal sensor fusion has combined data from other sensors and cameras in the same robot. In multi-agent perception, data from multiple robots have been aggregated.

7.1. Semantic segmentation

Semantic segmentation is a computer vision technique where the probability of semantic label, for example, sky, road, forest, vehicles, human, etc., for each image pixel has been analyzed and labeled to recognize. In [295], the authors briefly discussed and provided an extensive view of DL-based semantic segmentation. For the self-driving car, a distance estimation network has been proposed that uses an encoder based on self-attention coupled with robust semantic feature guidance to the decoder, which can be trained in a one-step manner

Table 6
Application of multiple robots via IoRT.

Application Area	Application
Surveillance	Under water surveillance [139], marine environments [179], IoT based surveillance robot [46], and drones as a service [268]
SAR operations	Maritime SAR [119], and UAVs in SAR missions [198]
Emergency/disaster response	Post disaster observation [269], and UAVs in disaster response tasks [270]
Military	Multi-purpose field surveillance [38], and autonomous weapon system [271]
Agriculture	Soil crop monitoring [272], and monitoring and mapping of crop fields [273,274]
Transportation	Self driving cars [275], and autonomous parking system [276]
Health	Remote treatment [277], diabetes management [278], tele echography [279], tele-surgery [280], and measuring reflexes [281]
Environment	Smoke detection [42], space exploration [282], and water quality monitoring [47]
Education	Assist for learning computer programming, robotic programming in institutes [283,284], and social awareness [285]
Domestic support	Medical and health care [286], support to human with dementia [287], support of elderly as well as disabled people [288]

[296]. In [297], the authors have addressed the comparison of such semantic segmentation methods and proposed a real-time benchmarking framework for autonomous driving. The application of semantic segmentation is less common in the marine environment. However, well-known state-of-the-art DL semantic: U-Net [298], DeepLab [299] and PSP-Net [300] have been applied to the marine environment in [301]. For autonomous USVs operation, it is necessary to observe the environment using visual information. For example, water segmentation is a major work where the surface of the water is recognized and segregated from everything else. In [302], the authors applied a DL algorithm for water segmentation which was previously utilized for road segmentation. In [303], the authors proposed semantic segmentation to analyze the robustness of different color spaces (e.g., RGB and HSV) to segment the water.

7.2. Object detection

In computer vision, object detection is the process of determining semantic objects of a given class from images and videos. Detecting the single instance of the class from the given image is termed single class object detection. In contrast, detecting all instances of classes present in the given image is called multi-class object detection. Various challenges, such as partial/full occlusion, variation of illumination conditions, scale, pose, etc., have to be overcome to successfully perform the object detection, which is the most important for the recognition of any visual activity [304]. The object detection technique has been categorized into two classifications: two-stage and one-stage detector. In the two-stage detector, candidate bounding boxes of the object are determined, followed by extraction of various features from every candidate box. In comparison, one stage detection technique estimated the boxes from given images without the region proposal step. one-stage detectors have high inference speed, while the two-stage technique has high accuracy ability to localize and recognize the object. Recently, a review of DL-based object detection has been published [305]. According to their survey observation, high computing power and memory are indispensable for real-world object detection applications. In addition, detecting objects by CNN's requires extreme computational power making it almost impossible to apply in the lightweight and low-cost drone. As a consequence, recently developed IoRT has brought more remarkable improvements in object detection. In [306], CNNs algorithm, which is deployed in cloud computing, has been applied for real-time object detection in UAVs. However, the major challenge in cloud computing is to maintain stable communication and low latency. In fog computing, both issues can be optimized due to the location of the devices. In [307], the authors proposed a Fog Computing-based hybrid DL framework (FC-HDLF) for smart manufacturing, which improved its performance considerably.

7.3. Multi model data fusion

Multi-model data fusion is a process that combines the information which is collected from multiple sources such as cameras, LiDAR, etc. Various methods are available to fuse the information, so they can be separated based on raw data/input level, on feature/ intermediate level, or decision/output level, as discussed in [308]. In multi-model-data fusion, some unique challenges have emerged due to the heterogeneous information from different sources, which are i) representation: how to depict multi-modal information by considering the complementarity and redundancy of multiple modalities, ii) translation: how to translate the information from one form to another, iii) alignment: how to identify the relationships between sub-elements from two or more different modalities, iv) fusion: how to merge data from two or more modalities to perform the prediction, and v) co-learning: how to transfer knowledge between the modalities [309]. The colossal quantity of information with features of high volume, variety, velocity, and veracity are currently being generated from heterogeneous networks. Hence, multi-model big data fusing is a big challenge. In [310], the authors reviewed some prominent DL methods for fusing these multi-modal big data. In MRS applications, an important role in continuously building and updating the maps. In [269], the authors applied multi-model fusion to erect a dense 3D map from RGB-D data using EKF. In addition, a standard probabilistic approach for solving the SLAM issues by utilizing the multi-sensor data fusion has been presented [311]. In agriculture, UAVs have shown great potential for plant protection. In order to improve the intelligence of UAVs and to minimize the adverse effects of obstacles on operational safety and efficiency, a comprehensive solution consisting of DL based object detection, image processing, RGB-D information fusion, and task control system (TCS) has been proposed [312]. According to the author, the proposed comprehensive approach has extensive capacity to enhance the UAV's perception of the environment and the ability of autonomous obstacle avoidance.

7.4. Multi-robot collaborative perception

Much progress has already been made in single robot perception, where single or multiple sensors are used to detect obstacles. To take full advantage of MRS, where robots are distributed in different positions in the environment to accomplish any specific task, multi-robot collaborative perception must be performed appropriately. For example, if an object has been seen from multiple angles, the accuracy of detecting that object will be improved. However, one major challenge for multi-robot collaborative perception is the transmission bandwidth limitation. To overcome this issue, a communication framework for doing multi-agent perception has been proposed in [313]. Little research is published taking into account the target tracking by utilizing the multi-robot collaborative perception [314,315].

7.5. Challenges

In this section, we have summarized the various applications of mobile robots via IoRT and critically analyzed the critical point for identifying robots' surroundings. Furthermore, the main challenges for the perception of MRS are:

- Noisy data: Various information sources face different types and amplitude of noise. In general, a heterogeneous set of information from heterogeneous sources of noise ranging from calibration errors to thermal noise.
- Unbalanced data: Normally various sensors generate the data with various features in terms of quality and reliability, and spatial and temporal resolution.
- Conflict data: Data from various sensors can be conflicted. For example, in autonomous robots, multiple sensors such as cameras, LiDAR or radar may identify the object at different distances. Missing information over a specific time interval from one of the sources can also affect the data fusion.

8. Future research and recommendation

In this paper, we have discussed the architecture of IoRT in mobile robots where three basic layers are included: i) physical layer consisting of different mobile robots, ii) network and control layer involving different routers, controllers and servers, and iii) the service and application layer dealing with different programs are included. In addition, security and safety have been critically reviewed to ensure the stable operation of IoRT. Finally, the application of IoRT, including object detection in various sectors, is summarized. Although the development and implementation of IoRT have been growing expeditiously, it is still in the preliminary stage of development. Consequently, which are discussed according to each layer of IoRT.

In the physical layer, the basic goal is to navigate multiple robots. Researchers have identified some obstacles that need to be overcome to optimize robot path planning. These obstacles are 1) uncertainty of the relative poses of robots, 2) nonlinearity problem of updating and sharing the pose and other information among all devices, 3) complexity of context-aware interaction with environment and robots in real applications, 4) heterogeneous data generated from heterogeneous sensors of robots and 5) synchronization of the clock as well as data among robots and other devices of IoRT. Decision-making algorithms may be suitable to address the above challenges may be suitable algorithms.

In the network and control layers, basic resources such as bandwidth, transmission power, etc., are limited. Optimization of these resources is therefore the key issue. In addition, all traffic must be optimally managed by finding the best routing policy for each traffic. The algorithm is indispensable to overcome the discussed limitations, which has autonomous decision-making capacity as human beings for compatible optimization of network resources, total traffic, and routing policy. Consequently, latency problems are also solved by proper management of communication resources.

At the service and application level, the question of what type of task requires what level of automation is still very much open. The algorithms which have optimal decision-making capacity are more compatible. In addition, due to the cyber-physical characteristics and heterogeneous devices of IoRT, huge amounts of data are generated from various sources such as sensors, transducers, etc. These data need to be either processed on-board or transmitted from the robot to the distance

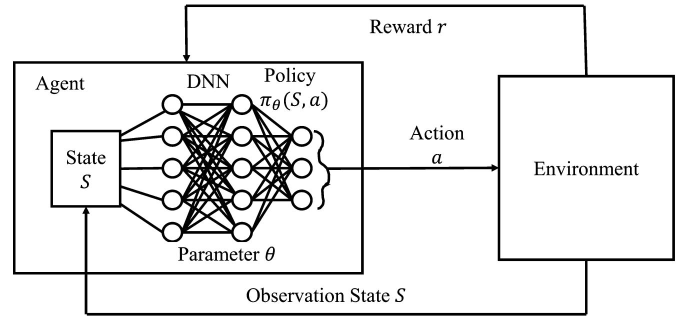

Fig. 10. The architecture of DRL [316].

computing system for remote processes. Consequently, making sensible decisions about whether to offload the computational data to the cloud/fog/edge servers or compute it locally is a major challenge that needs to be addressed at the application layer of IoRT.

Ensuring the safety and security of IoRT framework have to be done due to its values. Hence, researchers have developed a plethora of IoT security solutions. Most of the researchers utilized the concept of supervised and unsupervised machine learning to develop security algorithms, which are generally heavyweight. Whether attacks are attempted or not is a big decision making question. As a result, RL-based security algorithms are being more popular due to their decision-making capacity. However, the management of big heterogeneous data is a mammoth issue for the security and safety of IoT/IoRT. In [317], the authors have reviewed DRL-based algorithms against various attacks on the IoT framework.

For the applications of MRS via IoRT, it is essential that the environment around the robot is perceived as quickly as possible, with data collected mainly from cameras or LiDAR or both. In general, DL-based algorithms are used to identify the features of the environment. The DL model is updated according to the output loss/error, and there is no technique to recover the correct value when it is incorrect. On the other hand, DRL-based techniques are designed to handle sequential decision problems where feedback is available after each system action. As a result, executing the sequence of action in an uncertain environment with the feedback system to reach some defined aims can improve DRL results in each step. Hence, DRL-based algorithms are going to be popular for object detection [318].

Although few algorithms such as GA, PSO, etc., have decision-making capacity, RL based algorithms are most suitable in robotic as well as IoT research because RL has the decision making capacity as human beings [319,320]. However, the storage of value functions / Q-functions in RL generally requires a huge amount of memory. In most real-world issues, the state sets are large, sometimes infinite, making it almost impossible to reserve the value functions / Q functions in tables. As a result, the trial and error interaction with the environment is hard to learn due to the incredible computational complexity and storage requirements. This is where DL comes into the context where the value/Q-functions or policy functions can be approximated with a minimum set of parameters by the implementation of DL. The combination of RL and DL, known as DRL, gives more powerful results. Therefore, we will propose the concept of the DRL algorithm for the development of the novel algorithms for IoRT frameworks mainly due to the capability of autonomous decision-making and high dimension data handling [318,321–323]. In the standard DRL setting presented in Fig. 10, an artificial agent interacts with an environment over several discrete time steps according to Markov Decision Process (MDP). At each time step, the agent receives a state from the environment and generates an action according to its learned policy. In return, the environment provides the agent the next state and the reward (positive or negative value) generated from a suitable reward function for a specific problem, where, Deep Neural Network (DNN) is utilized to approximate the value/policy function and model (state transition function and reward function).

Consequently, formulating the effective reward function considering the appropriate parameters of then problem is a challenging issue.

Most DRL-based mobile robot navigation studies have formulated the reward function by considering: i) goal rewards: positive rewards for reaching goals and moving close to these goals, ii) collision penalty: negative reward for colliding with an obstacle or driving too close to an obstacle, and iii) time step penalty: negative rewards given for encouraging the robot to move faster on its way to the goal [116,206]. Various researchers have formulated the challenges of network and control layer to solve with DRL in various ways by satisfying the QoS. Most of the researches have defined the reward function based on i) optimizing the radio resource utilization, ii) minimizing the latency iii) minimizing the error probability and iv) minimizing the power consumption [324–326]. To monitor and control the mobile robots via IoRT, two factors (coordination and computation) have to be improved. For generated data computation based on DRL, the processing delay, task drop rate, computation cost, load balance etc. are considered the potential points for formulating the reward function of data computing [327–329]. To ensure the security of IoRT devices from various attacks via DRL approaches, researchers have considered the utility of the signal, the cost of frequency switching SINR, the time taken by the jammer to interfere etc. to formulate the reward function [317]. For object detection, intersection-over union with any ground-truth instances, lower image patches with the coarse level detector image, image acquisition cost, runtime performance etc. have been considered to formulated the reward function [330,331].

9. Conclusion

The rapid advancements of IoT and MRS have paved the way for a new paradigm of robotic systems known as IoRT. In this paper, we have provided a comprehensive survey of the state-of-the-art works that lies at the intersection between IoT and MRS. First, we have introduced the general concept and architecture of IoRT from the perspective of three layers namely physical, network and control, and application and service layers. Second, in each layer, we have summarized the hardware/software, followed by an in-depth analysis on how to tailor relevant technologies such as navigation, networking protocols and communications, and robot coordination and data computing to mobile robot domain, an aspect overlooked by previous surveys. Third, for each layer, we have critically discussed the research challenges, security issues and potential solutions with respect to the unique mobility characteristics of IoRT. Then, we have classified four main techniques for the use of IoRT applications and identified their relevance in the AI/DL context. Finally, we have presented several promising directions, where we believe that DRL shall be evaluated as a key enabler to realize the full potential of IoRT. Armed with the capability of autonomous decision-making and high dimension data handling, it is expected that DRL can optimize the resources in all three layers while ensuring the safety and security of IoRT frameworks.

Declaration of competing interest

None.

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