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REVIEW PAPER

Multi-Robot Coordination Analysis, Taxonomy, Challenges and Future Scope

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Abstract
Recently, Multi-Robot Systems (MRS) have attained considerable recognition because of their efficiency and applicability in different types of real-life applications. This paper provides a comprehensive research study on MRS coordination, starting with the basic terminology, categorization, application domains, and finally, give a summary and insights on the proposed coordination approaches for each application domain. We have done an extensive study on recent contributions in this research area in order to identify the strengths, limitations, and open research issues, and also highlighted the scope for future research. Further, we have examined a series of MRS state-of-the-art parameters that affect MRS coordination and, thus, the efficiency of MRS, like communication mechanism, planning strategy, control architecture, scalability, and decision-making. We have proposed a new taxonomy to classify various coordination approaches of MRS based on the six broad dimensions. We have also analyzed that how coordination can be achieved and improved in two fundamental problems, i.e., multi-robot motion planning, and task planning, and in various application domains of MRS such as exploration, object transport, target tracking, etc.

Keywords Multi-robot system · Coordination · Cooperation · Multi-robot task planning · Multi-robot motion planning · Exploration and mapping · Object transport and manipulation · Target observation

1 Introduction

The continuous advancements in robotics technology offer the widespread deployment of autonomous robotic systems in different applications. A key specific component of this area of research is the level of autonomous behaviors of robots in MRS, unlike obsolete robotics applications. In the field of robotics, autonomy becomes an elementary requirement of the proposed system. The growing use of robotics technology and increasing levels of autonomy are encouraging the deployment of multi-robot systems (MRS) in various applications. The MRS is defined as the group of robots systematized in the form of a multi-agent architecture so that they can work towards the same or different goal. The existing Multi-Agent System (MAS) approaches of cooperation coordination are not suitable enough for dealing with uncertainty, acquiring information from the environment, and modeling incompleteness of robotics [1, 2], because of the concerns that arise while dealing with the actual physical environment. The problems can become more challenging when a cooperative situation requires to adjust the different constraints on resources, tasks, goals, and on the robots themselves. The experimental analysis of MRS becomes more challenging with this demanding need that autonomous robots should cope with acquiring information from the real environment. Therefore, to identify a common framework for developing the best solution for these different problems of MRS is a little bit complex and more challenging. Some recently developed frameworks for MRS are shown in [3–5]. It has been observed that MRS cannot be studied and evaluated by generalizing the case of a single robot. Therefore, the approaches related to the Multi-Robot system should be carefully characterized in terms of system organization, team size and composition, communication, and environmental assumptions [6, 7]. Hence, the autonomous behavior of robots in MRS, along with real-world challenges, has gained substantial interest in recent years.

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A parallel working group of mobile robots gives an abundance of benefits as compared to the single robot system. To accomplish a large variety of tasks with enough robustness, robot teams are used instead of single highly specialized robots. Researchers [8–11] agree that MRS, when works in a distributed manner to perform coordinated tasks, provides more robustness and efficiency, which is not possible with a single robot system. Although, just by increasing communication range, bandwidth, and sensor range of robots without an efficient coordination mechanism can be damaging. However, some tasks are very challenging or just not achievable with a single robot system. Therefore, systematic approaches are required to control and organize the robots in MRS. In some cases, by using a large number of robots, a multi-robot system can accomplish tasks in lesser time and more efficiently. The advantages of MRS are: better to scale, able to execute larger tasks by increasing the size of the team, have inbuilt redundancy, provide robustness (can work when some robot or communication fails). Such systems also contain some special abilities like parallel operation, cooperative behavior, etc. When multi-robot systems start working, coordination is essential during the whole process. In [12], coordination is considered as a cycle consisting of four phases: "*Definitional phase, conflict resolution phase, action phase, and adaptation phase*". Nowadays, scientists consider two opposite definitions [13] on cooperative MRS, i.e., "active and passive cooperative system" [14]. Coordination and cooperation in MRS are joint operations or actions between the group of robots [13]. In cooperation, not only robots pay attention to their own work, but they also need to know if there are more urgent tasks from other partners. Usually, problems such as bandwidth overhead, resource completion, action conflict, etc., are absent in a single robot system because these problems arise by joining multiple robots. Hence, MRS requires an effective coordination mechanism to control the robots' interactive activities. To ensure high efficiency in MRS, a major component is the ability to perform various functions optimally and maximize the system's performance. Therefore, MRS should have a proper coordination mechanism so that robots carefully select their actions and works effectively in terms of time and working space while achieving the system-wide objective. We have presented multiple dimensions of MRS that address the different facets of the MRS organization that affect coordination, such as environment, composition, team size, communication, etc. We have also analyzed the proposed solutions in relation to characteristics of organization of MRS especially aiming coordination.

1.1 Scope of Study

In this research paper, we have carried out in-depth analysis specifically, focused on MRS coordination. This research highlights the recent progress in the field of '*MRS coordination*' along with its classification and comparison (in terms of communication, scalability, validity methods, environment, robustness, control mechanism, etc.). Both homogeneous and heterogeneous MRS are considered operating in a competitive or cooperative environment. The robots can be Unmanned Aerial Vehicles (UAVs), Autonomous Underwater Vehicles (AUVs), Autonomous or Semi-autonomous Ground Robots. We have not considered robot manipulators; therefore, coordinated motion planning is studied only for the navigation of mobile robots. Coordination approaches developed for both indoor and outdoor environments are considered. The ***MRS coordination is analyzed in various application domains*** (such as Area Exploration, coverage and mapping, Object Transport, tracking, etc.) of MRS, including two fundamental problems that are present in almost all applications of MRS, i.e., motion planning and task planning. The comparison of coordination approaches is based on the parameters shown in Table 1.

1.2 Organization of the Survey

The remaining structure of the paper is as follows. Section 2 briefly describes the existing survey works related to MRS and MRS Coordination. Section 3 provides a classification of MRS. Section 4 presents the taxonomy of proposed approaches related to MRS coordination, identifies and describes the parameters related to coordination. Section 5 describes and analyses the various coordination approaches for Multi-robot task planning. The comparative analysis of coordination parameters is also discussed in Section 5. Section 6 describes and analyses the various coordination approaches for Multi-robot motion planning, along with insights on the proposed approaches. The comparative analysis of coordination parameters is also shown in tabular form. Section 7 describes and analyses the various coordination approaches related to various application domains of MRS along with their insights and comparative analysis of coordination parameters. Section 8 presents important observations based on our study and analysis of existing work in terms of open issues, strengths, challenges, and future directions.

2 Related Work

In relation to MRS classification, several research and survey papers have been presented. Authors in [15] proposed a taxonomy that categorizes MAS based on computational capacity, communication, and a few other parameters. They have also added some useful results to demonstrate the utility of the proposed taxonomy and prove that a cooperative effort can be more compelling as compared to a single entity of the collection.

Cao et al. [16] presented a review related to cooperative mobile robotics until the mid-1990s. Five research axes shown in this paper are: "group architecture, resource conflict, origin of cooperation, learning, and geometric problems". Constraints that arise because of technological limitations and research gaps in present works are also discussed in this paper. In [17], four multi-agent situations are discussed: "homogeneous non-communicating agents, heterogeneous non-communicating agents, homogeneous communicating agents, and heterogeneous communicating agents". These scenarios are discussed by means of "pursuit domain," along with a description of presented works in this field. However, their work is more inclined towards machine learning techniques. Seven key research topics related to MRS are identified in [11] which are, communication, reconfigurable robots, localization and mapping, biological inspirations, exploration, object transport and manipulation, architectures, and motion coordination. Various special issue articles are discussed in this paper, and some additional research issues are also suggested. Authors in [18] study some current trends and techniques of networked control systems, mainly focused on five control problems: event-triggered control, sampled-data control, networked control, security control, and quantization control. Survey analysis in [16] and [15] presented the classification of the research work on MRS. In [16], a few dimensions for categorizing the MRS have been proposed. It also talks about group architecture (on which cooperative behavior must rely), resource conflict, origin of cooperation, and geometric problems. In [15], the classification of MRS focused on the computation and communication facets of MRS has been discussed. The detailed description of problems associated with the synthesis and analysis of intelligent group behavior in MRS is presented in [6, 19]. The interpretation of important topics related to MRS coordination is also given in this paper that characterizes the various important attributes of the problem. Authors in [20] have classified multi-robot coordination into four approaches, i.e., reactive, deliberative, behavior-based, and hybrid approach. In a recently published work by Rizk et al. [21], special focus is given on heterogeneous MRS. They first present an overview of "multi-agent system (MAS)". The components related to the workflow for automating MRS are shown in this paper. The presented components are coalition formation, task decomposition, MAS planning and control, task allocation, and perception. The additional papers that presented a literature review on MRS are [2, 22–35].

Although several survey papers have been published in the past related to MRS, however only a few are related to MRS coordination, in spite of the abundance of research work in MRS coordination and cooperation. Work published in [28, 32, 33, 35] shows survey on MRS coordination and cooperation in recent years. A comparison of our survey with other surveys on MRS coordination is presented in Table 2.

Although some reviews on MRS also includes some details about coordination and cooperation. In [28] multi-robot environment is described as cooperative and competitive. It also describes concepts of resource conflict, explicit and implicit communication. This paper analyses the multi-robot coordination with the perspective of motion and task planning. This work remained bounded to very few approaches for task and motion planning. Farinelli et al. [33] presented a taxonomy to classify approaches to coordination in MRS. An overview of application domains of MRS is shown in this published paper along with emerging trends in the related field. In [35] problem related to robot coordination in order to avoid collisions has been discussed. They classify coordination methods as coupled and decoupled. They describe approaches proposed for solving the problem of robot coordination as well as some representative works until early 2000. In [32], three approaches proposed for multi-robot control: "leader-follower scheme, virtual structure and behavioral approach" are compared.

Table 1 Comparison parameters

Comparison parameters	Objective
Composition	To assess the capability of a coordination approach to handle heterogeneous MRS.
Control Architecture	To find how a coordination approach controls all the robots, centralized or decentralized or hybrid.
Scalability	Defines how many robots can coordinate efficiently before the performance (high computation and communication cost) degrades.
Fault Tolerance	To check the applicability of the coordination approach in case of robot or communication failure.
Reactivity	Defines how the coordination approach handles changes in the environment.
Validation	Defines how MRS is tested simulation or real-world experiment.
Communication Details	To know communication cost, one-hop or multi-hop, frequency of messages sent, information flow.
Communication Type	Defines how the robots exchange information, implicit or explicit.
Environment	Robots are cooperating or competing for executing the task.
Static/Dynamic	To find whether a coordination approach can work outside predefined scenarios or not.

Table 2 Comparison with other surveys on MRS coordination

Related survey	Topics covered	Summary	Common points with other surveys
[21]	Overview of MAS, Automation levels in MRS, Coalition formation and Task allocation in heterogeneous MRS, MAS Planning and control, Challenges	A survey of cooperative heterogeneous MRS focused on coalition formation, task decomposition, task allocation, and perception.	Task Planning, Challenges
[28]	Coordination: Static versus Dynamic, Communication: Explicit versus Implicit, Task and Motion planning	A study on MRS coordination related to multi-robot task planning and motion planning.	Explicit and Implicit communication, Task and Motion planning
[33]	Taxonomy for MRS, Task and Domains for MRS	Presents a taxonomy to classify approaches to coordination in MRS and an overview of MRS application domains.	Multi-Robot System Classification
[35]	Classification of coordination methods based on priorities, Coordination cost evaluation, Coupled and Decoupled methods	Study of approaches proposed for solving the problem of robot coordination as well as some representative works.	Multi-Robot Coordination Classification
[27]	Control Architecture, Communication, Problems and issues of cooperative multi-agent robot systems	Survey of cooperative multi-agent robot systems in terms of types of agents, communication and control architecture along with directions and future challenges for the multi-agent robot.	Open issues and challenges in coordinated MRS
Our Work	MRS Classification, Multi-robot Coordination Classification, Coordinated task and motion planning, Coordination in Multi-robot Applications such as Target observation, Exploration and Mapping, Object Transport and Manipulation, Formation Control; Open Research Issues, Challenges and Future Directions	We analyze the scalability, communication parameters such as its type topology and cost, robustness, composition, environment, validity, etc., of coordination approaches proposed for various application domains of MRS. We also present a classification of Multi-robot Coordination approaches based on adaptivity, communication, decision-making, and control architecture.	–

The closest work related to our survey is presented in [33], which is published more than a decade ago, and considerable work has been done on MRS coordination after that. The proposed work does not analyze communication cost, robustness, environment, scalability, and many other important parameters. Further, it does not include enough study on control architecture and coordination specific to various application domains of MRS. In our best knowledge, none of the work is seen yet that has analyzed MRS coordination in various application domains of MRS and compared the important parameters of coordination approaches such as communication cost, scalability, robustness, decision making.

2.1 Motivation and Contribution

With the increasing use of MRS in a wide variety of applications. Especially during this pandemic, a large number of MRS are being deployed in a variety of domains (warehouse [36, 37], transport [38], etc.). Moreover, MRS is going to play a key role in achieving Industry 4.0 standards. However, without efficient coordination mechanisms, the full potential of MRS cannot be realized. This inspired us to carry out this research to classify and find the state-of-the-art parameters to assess the effectiveness of proposed coordination approaches for various application domains of MRS. To meet the current and future needs in the deployment of MRS, we also analyze current challenges and future directions and technologies for MRS coordination. Consequently, this study of the coordination approaches can help the researchers to work on the current and future needs of the MRS and help developers to select an approach, which is most suitable for a given application. The main contributions of our research study are given below.

- We provide a brief overview and classification of MRS, based on five dimensions of MRS that address the different facets of the MRS organization that affect coordination.
- We have presented a novel classification of coordination approaches proposed for MRS, which categorizes the recent developments in this field.
- We have also identified and analyzed the essential parameters (communication type and cost, scalability, robustness, control architecture, validation method, environment, composition, etc.) related to MRS coordination.
- Review and analysis of the MRS coordination approach for various application domains of MRS and two fundamental problems of MRS, i.e., Motion Planning and Task Planning. In each application domain, summary and insights are also provided.

- We identify open issues, research challenges, future research directions, and potential technologies for future research to promote the deployment of MRS.

3 Multi-Robot System Classification

Although our focus is to classify the coordination approaches for MRS, however, before discussing about MRS coordination, we need to know about various aspects that are important in MRS along with how MRS is classified, what its properties are, and what are various aspects that affect the coordination of MRS. We have defined five dimensions (as shown in Fig. 1) related to MRS, with some similarities to other previous classifications. Many published research papers organize and give a taxonomy of MRS. We have added some more details in earlier classifications to incorporate recent works in MRS. The details about the proposed classification are shown below:

3.1 Coordinated and Non-Coordinated

Coordination can be defined as the mechanism used for achieving cooperation. The mechanism can be simple to complex according to the level of cooperation required. The coordination approach can be centralized or decentralized based on how decision-making is being realized in MRS to achieve cooperation. We consider that coordination may still be possible even if robots are not aware of each other by using a central system or shared memory variables, etc. Therefore, even in bio-inspired MRS, in which robots are not aware of each other can also achieve coordination. However, authors in [33] classify all of such work [39–47], in which robots are not aware of each other as non-coordinated. Although MRS does not necessarily to be coordinated, coordination for the cooperative MRS is not always an essential asset. In practice, many tasks can be completed (with efficiency) without coordination, while allowing the system to introduce more flexibility in the system by providing better access to the existing resources, such work is presented in [18] which addresses a formation maintenance task. The benefit of a non-coordinated MRS is its simple design, which has less risk of defects. However, it also results in more dissipation of resources because of the interventions arise as a result of robots performing conflicting tasks. A coordinated MRS requires complicated design; however, it can prevent or reduce these shortcomings of non-coordinated MRS. In [33], When a robot may not take into consideration the activities carried out by other robots in the system while completing the task, then it is considered as non-coordinated. It is not straightforward to determine whether the robot is accounting actions of other robots while executing its task or not.

3.2 Composition

On the basis of composition, MRS can be classified as heterogeneous and homogeneous. All the robots in a homogeneous MRS consist of the same hardware and software. In heterogeneous MRS, the team members can have dissimilarity in software control procedures or hardware or both. Heterogeneity of MRS can be of varying degrees. Sometimes when only a

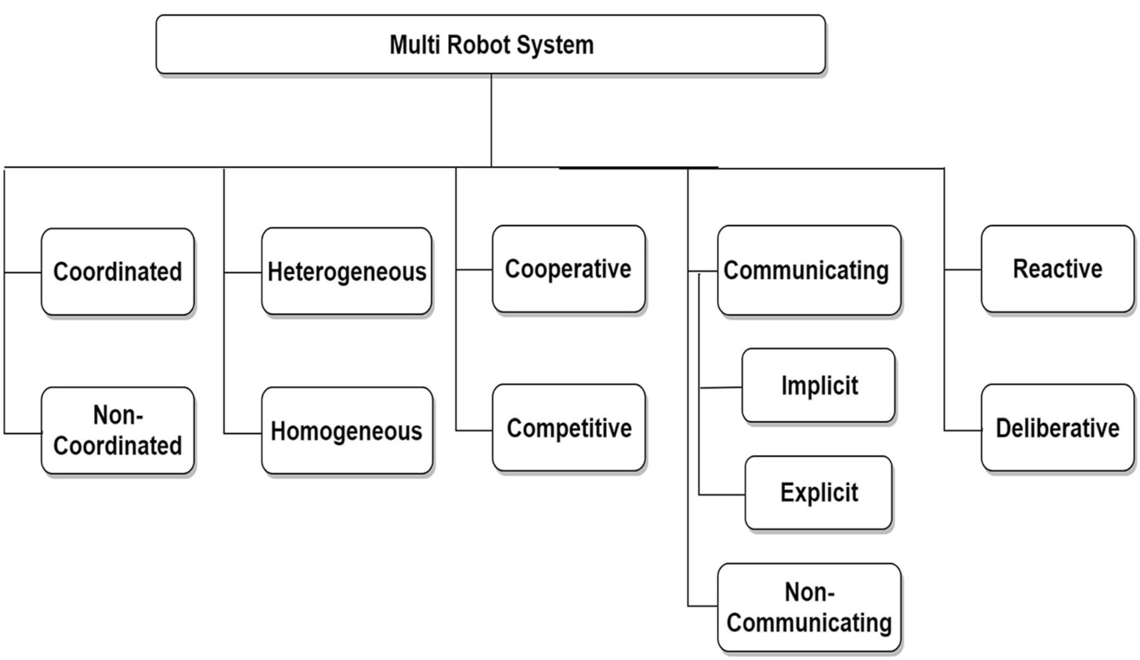

Fig. 1 Classification of MRS

leader or a specific system is different in its capabilities in terms of software or hardware or both, in this case, heterogeneity is very low. In some cases, MRS may be composed of two, three, or more different types of robots. For example, MRS deployed in a smart home scenario can have cleaning, serving, cooking robots, and security drone. More the degree of heterogeneity, more varsity application of MRS, but with that comes more complexity and difficulty in coordination and control mechanism. A large portion of research work assumes homogeneous groups of robots. However, in the recent few years, work on heterogeneous MRS has been increased significantly. Some published works on heterogeneous MRS are [48–52]. A recent survey on cooperative heterogeneous MRS is presented in [21].

The advantage of heterogeneous MRS is, it can be easily adapted to the different situations that arise in the real dynamic environment due to its better scope to deal with new and unpredictable tasks. The composition of MRS also affects its robustness and the manner in which robustness can be attained. In a homogeneous system, all robots can execute identical tasks with the same efficiency. Therefore, the failure of any robot can be adjusted by any other member; thus, robustness can be achieved. However, applicability to different situations and environment is weak due to the same hardware and software of robots. Clearly, employing heterogeneous systems need more effort in terms of developing efficient coordination approaches and software required for controlling the MRS.

3.3 Cooperative and Competitive Environment

The multi-robot environments exhibit collective behavior like human society [53]. In collective behavior, robots react to usual influence or stimulus in unstable, unpredictable, spontaneous, and unstructured circumstances [54]. Collective behavior consists of cooperative and competitive behavior. Cooperative behavior refers to interaction among robots to execute a task along with increasing the system's overall utility. Hence, all the robots in the system interact and work for a common goal or reward. The common goal of cooperative robots can also give rise to multiple sub-goals. Various illustrative examples of multi-robot cooperation are multi-robot motion planning [55–60], multi-robot exploration [61–66], multi-robot target tracking [67–71] and multi-robot transportation [72–75].

Competitive behavior, which is the opposite of cooperative behavior, refers to the case in which multiple robots compete among themselves in order to satisfy their own interest. Alternately, robots that consist of conflicting utility functions can also be considered as in competition with each other [53]. Examples of multi-robot competition are "Student Autonomous Underwater Vehicle Challenge-Europe (SAUC-E)" [76] and robot soccer leagues [77, 78].

Robots can be considered as self-centered from the sociological viewpoint because every robot gravitates to make decisions inspired by 'self-preservation'. For illustration, suppose few robots are progressing in a direction opposite to each other, and all of them want to traverse a narrow passage; however, only one of them can cross the passage at a time. If all of them try to pass that passage simultaneously, the congestion or collision may occur. In this situation, the cooperative behavior can reduce individual cognitive bias, and group thinking also requires some coordination. This required coordination can be accomplished by communication, i.e., a principle behavior used in multi-robot environments.

3.4 Communicating and Non-Communicating

Robots can cooperate via communication mechanisms that enable them to share information among them. However, without communication, weakly-coordinated and non-coordinated system can be established. By communication, we mean by any way the robots can exchange or sense some information about each other. Hence, in a non-communicating system, there is no information available about another robot to any other one. In [16], the communication framework is classified within three categories based on the way of interaction, namely: "interaction via explicit communications, interaction via sensing, and the interaction via environment". Based on the way robots' sense or share information, two types of communication are proposed, i.e., indirect and direct communication [33].

In this research paper, taxonomy established based on modes of data transmission, i.e., implicit and explicit communication is being followed. Explicit communication uses additional communication hardware, a dedicated device for signals that can be understood by other team members. The robots exchange information directly using unicast and broadcast intentional messages in explicit communication. Whereas in implicit communication, robots obtain information about other member robots through the environment. Stigmergy (both active and passive) is used in implicit communication among team members, can be obtained by utilizing specific sensors in the robot. The implicit communication is further branched into two categories by [28], which are active and passive. Interaction via environment is called active, and interaction through sensing called passive. They [28] defined active implicit communication as "the mechanism in which the robots communicate by accumulating the essential information of other robots in the environment". This form of exchanged information is linked with the area of biometrics, which is inspired by collective behavior used by ants and bees for collecting information related to other robots in the system. In passive implicit communication, robots perceive information related to change in the environment with the help of sensors in order to communicate. For example, a robot can estimate the position and altitude of other robots in the system by representing and interpreting in accordance with the acquired data in order to cooperate with other robots. Communication has great significance in MRS because various properties of the system depend on it. Direct communication is a straightforward and prominent method for exchanging information between MRS members. However, due to failures of hardware and noises, the communication becomes critical. Hence the techniques like stigmergy have been developed and utilized to deal with such communication failures [79, 80]. Higher robustness in the communication system requires more complex MRS design because every team member interprets their surrounding environment. It also needs less information exchange among the members of MRS.

Broadcast communication, a form of direct communication, which is extensively used in MRS, exhibits low scaling properties. As the number of robots increases and distributed vastly, relevant issues and techniques related to this problem covered in computer networks can be exploited.

3.5 Reactive and Deliberative

A classification of MRS is presented in [81], regarding reactive or deliberative architectures. We consider MRS is deliberative if robots can cope up with any change in the environment by some approach to restructure the overall team behaviors. However, in a reactive system, every single robot copes with the changes in the environment by giving a robust solution to re-organize its own task with the purpose of completing its initially given goal. The difference in reactivity and deliberation depends on how MRS recovers from an unpredicted situation and what are the different approaches applied by MRS. In the case of a deliberative MRS, a long-term plan to complete a global goal is provided concerning the usage of all the available resources. In a reactive MRS, plan is given directly to the robot, which is involved with the problem to deal with it. In a deliberative system, environment may be represented globally, which is common for all robots. Although, if some constraints are imposed on system behavior, then without global representation of the environment, MRS can be deliberative. Reactive MRS can speedily respond to environmental changes, without affecting other members of MRS. A required consideration for MRS to be deliberative is whether it is coordinated or not. Any MRS which is not strongly coordinated can be reactive or partially reactive, and if it is strongly coordinated, it can be deliberative or reactive. Amongst strongly coordinated, centralized MRS can be deliberative, and decentralized MRS can be reactive (distributed) or partially reactive (hierarchical). Hybrid MRS can act in both ways as deliberative and reactive, depending on a particular event or a situation of environment. In [82], reactive planning of motion and mission for MRS is presented.

3.6 Team Size

Team size is an important parameter while deploying the MRS. Team size or number of robots in MRS can greatly affect the performance of MRS. Two or more robots can accomplish tasks that are not possible with a single robot. Almost any task requiring simultaneous or near-simultaneous actions (such as opening or closing multiple doors at the same time) is not possible with a single robot. Therefore, a number of robots can be used to obtain speed up in terms of task performance, completion time, etc. For developing an efficient coordination approach, team size is an important parameter to be considered. It is becoming a more and more relevant topic in the development of MRS. Many works explicitly address this significant issue in large scale MRS [83–86].

We analyze the scalability of the approaches proposed for MRS coordination and measure it as Low, Medium, and Good. Wherever possible, we also provide a quantitative measure of team size in terms of the number of robots in MRS.

4 Multi-Robot Coordination Classification

Coordination and cooperation in MRS are defined as: “joint operation or action amongst a group of robots” [13]. It can be said that coordination is the mechanism used for cooperation. It is also possible that the goal of robots in MRS may be different, but still, they need to coordinate. When there are many robots in a system, a mechanism for coordination between robots is essential to control the cooperative actions. Cooperation in MRS is defined as “Given some task specified by a designer, a multi-robot system displays cooperative behavior if, due to some underlying mechanism (i.e., the mechanism of coordination), there is an increase in the total utility of the system” [16]. In cooperation, not only robots pay attention to their own works but also need to know if there are more urgent tasks from the partner. A published paper on MAS [87] defined coordination as “cooperation in which the actions performed by each robotic agent takes into account the actions executed by the other robotic agents in such a way that the whole process ends up being a coherent and high-performance operation.” Hence, an effective coordination mechanism is essential to control cooperative actions between robots with the purpose of assisting each robot in selecting actions in such a way that it maximizes the efficiency of system-level objectives. These coordination approaches can be classified based on various parameters, such as communication mode, decision making, adaptivity, and protocol. One possible classification of coordination in MRS is shown in Fig. 2.

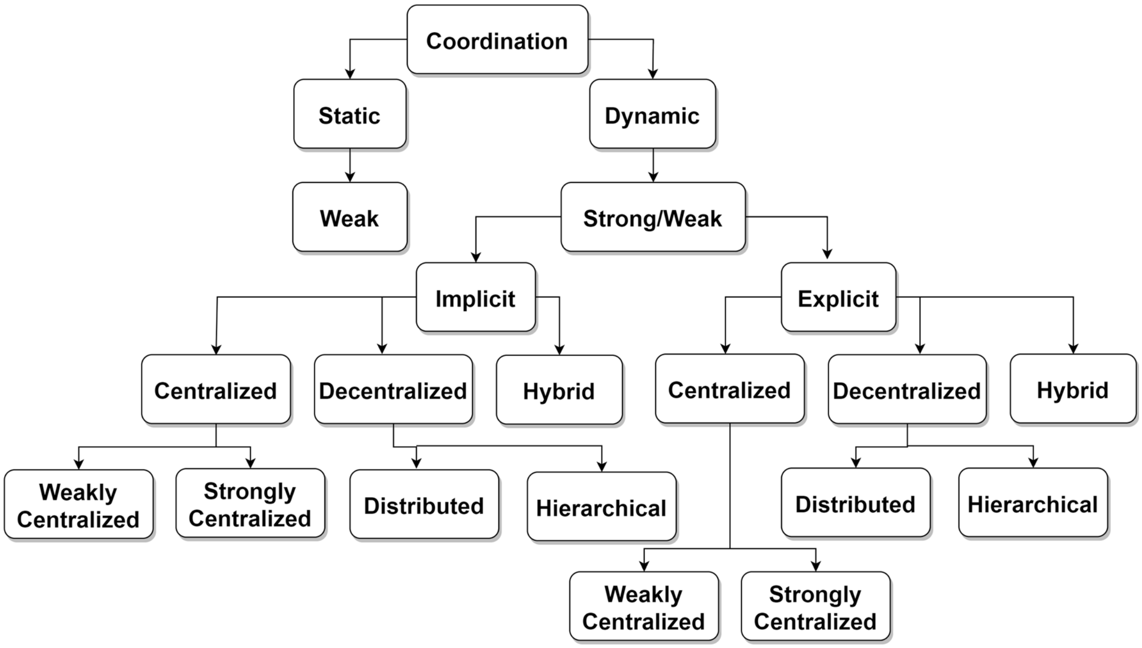

Fig. 2 Classification of Coordination in MRS

4.1 Static and Dynamic Coordination

The performance of MRS highly depends on the efficiency of the coordination and control technique of robots. One way to divide coordination is as "static and dynamic"[28]. Static coordination is based on some predefined rules or conventions. As proposed in [88], if there are two robots in the MRS and initially rules are set for one of them to keep left and another one to keep right so that they do not collide to each other while moving on the same track. These rules are decided before starting of execution of the task. Thus, static coordination is not suitable for highly dynamic environments, and it may suffer from poor real-time control. For the MRS, where coordination requirements are pre-determinable, static coordination can be suitable, and it can handle complex tasks also.

On the other hand, dynamic coordination is defined as the coordination that occurs while the task is being executed, and it depends on the present state of the system, physical location, information, and analysis of other robots. Some examples of dynamic coordination are [89–91]. Such systems make decisions according to the present state of the system. However, the behaviors can still be defined for particular states, and it also requires some method of communication. Dynamic coordination can be achieved using implicit communication or explicit communication; thus, dynamic coordination can be of two types, implicit coordination, and explicit coordination. Some works, which use both static (added prior knowledge to reduce learning) and dynamic coordination, are discussed in [52, 92].

Insights: Many times, the environment or tasks can be too complex. In that case, it can be very difficult to use only static or dynamic coordination. Depending on the nature of the task, task requirements (e.g., how frequent robots need to communicate), and the environment, using both static and dynamic coordination can be beneficial.

4.2 Implicit and Explicit Coordination

To attain desired collective performance, implicit coordination approaches [93–99] use dynamics of interactions between robots and environment (i.e., implicit communication), mostly in the form of devised emergent behaviors [100]. Different sensors or devices are used with robots to perceive environmental changes. Explicit coordination approaches [90, 101–104], use intentional communication (i.e., explicit communication) and cooperation methods, similar to those employed in MAS. Explicit coordination approaches can deal with comparatively more sophisticated robots. When using explicit coordination among robots, the differences in the methods used in MAS and MRS are few, but they are not equivalent in fundamental ways. Using both implicit and explicit information intelligently, the performance of MRS can be improved with respect to coordination. Many proposed approaches have used both implicit and explicit coordination [77, 79, 80, 105–107].

Insights: Approaches based on implicit coordination are often efficient, but the general analysis is proposed in [100]. Such approaches show great potential, especially for large scale MRS of simple robots. Presently these methods are actively studied in robotics and even in other fields. Explicit coordination ensures accuracy in exchanging information between robots; however, with the addition of more and more robots in the system, the communication load increases. Hence, it decreases the system's performance; sometimes, in extreme cases, it also leads to overall system failure. As compared to this, implicit coordination provides stability, fault tolerance, and reliability to the MRS system along with compromising the correctness of the information perceived by robots. Therefore, to achieve an efficient, robust, and reliable MRS system, implicit and explicit methods can be combined.

4.3 Weak and Strong Coordination

An MRS can be realized with "no coordination, weak or loose coordination, and strong or tight coordination". It depends on factors like required performance, task, team size, etc. to decide what level of coordination needs to be achieved, i.e., using weak or strong coordination. Many researchers have used weak coordination for various coordination applications such as foraging, box pushing, and area exploration. These tasks can be realized efficiently with weak coordination [108–119]. Weak coordination, as defined in [81], "a method of coordination that does not rely on a coordination protocol". It can also be said that weak coordination means that the system does not need complex rules, explicit protocols, and direct communication to achieve coordinated behavior. It may need implicit communication and direct communication for some basic info exchange but not for enforcing rules. As proposed in [79] leader uses explicit communication to send goal positions to robots periodically. Here, explicit protocols are those rules which outline the behavior of robots based on the information exchanged among the robots. The weakly coordinated MRS, as defined in [120], "uses a method of coordination that does not rely on a protocol," and therefore, such MRSs are more robust in terms of failures related to communication. However, as the task becomes more and more complex, environment becomes more dynamic, more efficient solutions are needed for a weakly coordinated MRS.

Strong coordination, as defined in [81] "a method of coordination that is based on a coordination protocol". It can also be said that strong coordination means to achieve coordinated behavior; the system needs complex rules, explicit protocols, and communication. Here, explicit protocols are those rules which define the behavior of robots based on exchanged information between the robots. In such systems, one robot can influence the behavior of others via signals. Signals are the means by which robots communicate information based on coordination protocols. We can also say that strong coordination is built on previously defined or learned guidelines regarding how two or more robots have to work together. Some approaches which are strongly coordinated are presented in [80, 90, 121, 122].

Insights: In the case of strong coordination, most of the literature has used explicit or direct communication, but it is also possible to use implicit or stigmergic communication to realize a strongly coordinated system. It is not necessary that strong coordination can achieve the increased efficiency of MRS. Some tasks can be completed more efficiently by using weak coordination. However, such MRS cannot have many organizational abilities that are offered by the coordination protocols used in strong coordination.

4.4 Centralized Coordination

The coordination can be achieved in a centralized or decentralized way; centralized coordination can be further divided as *strongly centralized* or *weakly centralized*. Centralized coordination is realized by a single coordinating robot, which is responsible for making decisions regarding coordination, on behalf of all other robots. This is also the way in which the decision system is defined within the MRS. In centralized MRS, it has a single robot or server (called leader) that is responsible for the work of the other robots. In the overall decision process of MRS, the leader is involved, and the other robots act as per the commands of the leader. Decentralized coordination does not need such a robot. In general, centralized approaches are not suitable for the coordination of MRS with a big team due to the high computation requirement of the leader, and the communication cost among the robots.

Weakly coordinated [123, 124] and non-coordinated MRS can be realized with or without communication. However, communication is must (with the purpose of executing the coordination protocol) for strongly coordinated systems. Strongly centralized approaches [49, 99, 125, 126] uses a fixed leader (leader can be a robot or some remote server) for the entire mission. There are approaches in which multiple robots are selected as leaders, and they can plan the actions of other robots. However, in case of strongly centralized coordination techniques, the role of a leader is assigned to a single robot at the starting of the task. The leader remains the same for the entire mission.

In a weakly centralized coordination approach [78, 97, 127], more than one robot or system is permitted to be leader, during the mission. A leader is not chosen prior. It can be selected dynamically based on some criteria, depending on the current situation of the task, environment, communication, remaining battery power, etc. There can be several policies to select a leader like some preset priorities, computation power, etc. If there are multiple leaders, and all the leaders are eventually controlled by a single one, such approaches are also categorized as centralized. If multiple leaders are working independently, means not controlled by one single leader, then it is called hierarchical.

Insights: In many cases, MRS does not follow fully centralized or decentralized coordination. Strongly centralized techniques are susceptible to failure (not robust) due to the faulty operation of the leader and due to communication failure. In such approaches, communication failure can lead to failure of the whole process of coordination. Besides, a strongly centralized technique can fail in achieving any coordination if the leader is broken. Weakly centralized techniques are more robust than strongly centralized techniques because it can select a new leader in case of leader failure.

4.5 Decentralized Coordination

Decentralized approaches can be further classified into two types: distributed approaches (for e.g. [48, 90, 91, 103, 128–131]) in which all robots are equivalent with respect to their responsibility to coordinate, and hierarchical approaches which are locally centralized. Distributed coordination requires a distributed MRS, in which the system is composed of robots that are independent to take decisions with respect to each other. This type of system does not have a single control robot. The system has all equal robots with respect to control. Every robot takes a decision in an autonomous fashion. The distributed approaches of coordination provide better robustness to the failure by allowing each robot to take decisions autonomously, but more complexity comes to achieve the coordination between robots. Many published papers have used broadcasting for communication, which leads to poor scalability of distributed approaches.

When the process of coordination is locally centralized, it is called hierarchical. Here, we consider that in hierarchical approaches [51, 96, 121, 122, 132, 133], the MRS has local leaders, but they are not eventually controlled by one single leader. Such approaches are generally used in MRS with multiple tasks where a group of robots, works on some task, other groups on other tasks or task is divided within few groups of robots by negotiation, etc., not by central system or leader. Such type of approaches are less robust than distributed, but it can be realized only with local communication or global communication with less complexity and cost.

Insights: Decentralized approaches are more robust to robot failures, malfunctions, or communication failure. In our research paper, we found that the research communities have shown their growing interest towards using decentralized approaches for MRS coordination. However, communication cost is a challenge faced by many researchers when decentralized coordination is used through explicit communication. However, using implicit communication is also possible to realize a decentralized system. Using implicit communication is more scalable. Therefore, in practice, a combination of explicit and implicit communication can be more useful and efficient.

4.6 Hybrid Coordination

When coordination is attained by using both centralized and decentralized approaches, it can be called hybrid coordination. In a coordination approaches, some degree of coordination can be achieved in a centralized manner for e.g., periodically sending goal position to all robots by a central station, and some degree of coordination can also be achieved in a decentralized manner like motion planning to reach the goal (previously sent by a central station). Such approaches are classified as hybrid coordination approaches [69, 79, 92, 134, 135].

5 Coordinated Task Planning

There are two fundamental problems of MRS, task planning and motion planning. In the large application domain of MRS, these two basic problems, i.e., task planning and motion planning, needs to be solved first. These problems may still exist even if MRS is non-coordinated but to different degrees. We consider these two problems as fundamental problems of MRS to complete any given task. However, in the case of cooperative MRS, task and motion planning are also needed for further application-specific coordination. Once coordination is achieved at the level of task and motion planning, further coordination to complete the given task is dependent on it. So, when considering domains for MRS, task and motion planning are inherent (as shown in Fig. 3) in almost all domains such as forging, exploration, target tracking, etc. Various survey works suggested on task planning and allocation are presented in [24, 136–138].

To complete any task, one or more than one robot can be needed. Some tasks can be accomplished with one robot, but its quality can be enhanced with multi robots. Tasks can vary in terms of complexity, timescale, discrete (e.g., transport an object to some room), or continuous (e.g., tracking an object). Task Planning can be separated as task decomposition (for complex tasks), task assignment, and task allocation. Task allocation in MRS can be defined as, the problem of deciding

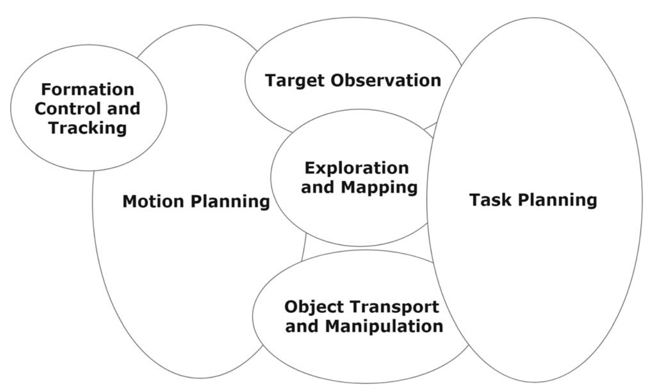

Fig. 3 Application domains of MRS

which robot is responsible for executing a task (or some part of that task) with the aim of completing the task and also achieve system objectives such as performance. It is intended to achieve coordinated team behavior. Some MRS, such as biologically inspired, local communications between robots of a team with the environment, provide coordinated team behavior. This is called implicit coordination. However, in explicit coordination, tasks are explicitly allocated, and this problem is known as "multi-robot task allocation (MRTA)". In [24] MRTA problem is categorized into three types: "First, single-task versus multi-task robots. Second, single robot versus multi-robot tasks. Third, instantaneous versus time-extended assignment".

MRTA is a problem of dynamic decision making that changes with time and environment. So, the static allocation cannot be directly applied. Therefore, another approach is to resolve the static allocation problem iteratively. Approaches based on graphical models are presented in [103]. The authors provide a solution based on "Distributed Constraint Optimization Problems (DCOP)" model for task assignment, relevant to warehouse logistics scenario. The task is to transport objects from loading to unloading bays with minimum interference. They use heuristic algorithms, precisely the "binary max-sum", which is an iterative message-passing method. It relies on explicit communication, provides robustness, and has high communication cost. In [139], a task allocation approach is presented for moving target tracking in an environment that is competitive. The problem is formulated as k-WTA [140] and solved using a two-layered Neural Network. Authors in [141] use a distributed behavior-based approach to perform tasks by the selection of behavior set. Based on impatience and accepted parameters, robots can take over the task from other one or can abandon their own task.

A work presented in [142] uses a market-based mechanism for exploration tasks in which robots are required to visit prefixed targets in the environment. They use combinatorial auctions (in place of single-item auctions) to handle in-schedule dependencies. In combinatorial auctions, more than one task can be auctioned at the same time; robots can also bid on bunches of tasks. They tested this approach with different methods that intentionally take into consideration "in-schedule dependencies" [142] by bidding a robot's surplus. For each bunch, a surplus is defined as overall profit minus overall cost. Most auction and bidding based approaches have assumed perfect communication, which is not realistic; a novel approach presented in [143] deals with communication limited environments. An algorithm known as M+ [101] proposed a decentralized approach separated into three layers: "A task allocator (based on the Contract Net Protocol [144]), a fault tolerance component, and a task execution component, which is responsible for the coordination". Task execution and allocation components have low synchronization. Though, each robot must be provided the same task description. Contract Net Protocol [144] was preliminary idea of some fruitful works like Traderbots [145], presents a distributed approach which forms coalitions which are locally centralized, and MURDOCK [146], is based on a "greedy algorithm" and uses a "time-limited contract" to offer fault tolerance. Work in [102] presented a "distributed market-based assignment algorithm", in which robots bid for tasks. This approach assumes that the task can be assigned to a single robot (at one point of time), and an individual robot can execute a single task only. It has a high communication cost $O(N3)$, where N is the number of robots in MRS. Another approach called "S + T" presented in [147]. It uses a distributed market-based algorithm to resolve "multi-robot task allocation (MRTA)" problem. It is developed for the applications in which robots need cooperation to complete all the tasks. When a task is too complex or due to any reason, it cannot be executed by a robot itself, it can ask for help. Upon receiving this request, other robots can provide needed services. Additionally, the algorithm provides flexibility to give importance to task completion time or energy consumption.

A solution presented in [138], focuses on a finite state formulation. It uses a weighted graph as an abstraction to the environment. The clusters of samples arbitrarily appear in the nodes of this graph. It is a centralized approach that uses a central unit to communicate with all the robots. The algorithm runs concurrently on each robot and the central unit. It also exchanges information between each robot and the central unit. Another "market-based" approach to MRS coordination is presented in [51], which is called Constraint-based Approach (CoBA). This proposed solution considers task and communication constraints and allows tasks to be negotiated in a complex environment between heterogeneous robots. Here complex tasks can be negotiated at variable degrees of abstraction and are "modeled with an AND/OR task tree with temporal constraints" [51]. Authors in [148] proposed an approach based on "Response Threshold Model and Learning Automata-based Probabilistic Algorithms". In this approach, each robot selects its tasks individually and autonomously so that tasks are optimally distributed and completed. Some other works are: [132] swarm intelligence (virtual pheromone-based) for adaptive and decentralized task assignment in search and surveillance tasks, [149] based on dynamic programming for task planning for the functionally heterogeneous MRS, [150] based on Incremental and distributed plan merging for Task planning and execution using requested broadcast and local communication. Authors in [151] presented algorithms to perform concurrent goal assignment and planning trajectories. A decentralized version of the algorithm is well scalable; however, it ensures high communication cost.

A scalable approach is presented in [159], for general MRS planning problems. This approach is based on "Decentralized Partially Observable Markov Decision Processes (Dec-POMDP)" [160] and facilitates asynchronous decision making using macro actions. Another approach, named as nearest-neighbor based Clustering And Routing (nCAR) presented in [155] shows good scalability (in terms of the number of tasks). Work in [161] presented task allocation algorithms for unreliable communication, which are based on auction algorithms. An algorithm is presented in [162] to minimize communication while planning for coordination. It discovers an optimal communication schedule using particle filter and describes the plan of robots as a probability distribution. Authors in [5] propose a framework to allocate the tasks automatically and plan their execution. It uses linear temporal logic (LTL) to define a high-level mission and task specifications. Some other works use LTL are [163, 164]. In [165] motion planning incremental algorithm is presented based on satisfiability modulo theories [166], robots are assigned priorities and divided into groups. The scalability of the algorithm is tested using an experiment, and it can perform motion planning of twenty-five, fifty quadrotors in compact and obstacle-free environment, respectively. This algorithm is centralized and uses explicit communication. A summary of works related to Task Planning is shown in Table 3.

Summary and Insights A number of algorithms have been used such as, "market based" [51, 147], "graph-based" [103], "Neural Networks" [139], Swarm intelligence [132], Dynamic Programming [149], Contract Net Protocol [101], biologically inspired [75], Mixed Integer Programming [167], Soft Computing based [168], Deep Learning [154, 169] etc. The applicability of these approaches depends on the application domain of MRS. Particularly, market-based approaches [51, 102, 147] are extensively used for task allocation in MRS, for many applications such as multi-robot patrolling [170], soccer [77], exploration and mapping [61, 121]. Some approaches show better performance for some particular application domain and others for other domains. Therefore, in order to decide that a solution is the best approach to allocate tasks depends on the application domain for which MRS is deployed. However, general parameters to select a good approach can be communication cost, scalability, decentralized or centralized, completeness, and computation cost. Most of the recent work uses decentralized coordination, explicit communication. However, communication cost is generally high due to broadcast, especially in bidding-based approaches broadcast is inherent, and most of the coordination approaches are dependent on global connectivity (each team member is always connected).

6 Coordinated Motion Planning

Motion planning is one of the fundamental problems of MRS. In every application domain of MRS, two basic problems (task planning and motion planning), needs to be solved first. When robots are working in the same environment then it becomes essential to coordinate with each other to generate efficient (short, deadlock free, easy to plan trajectory, collision free, etc.,) path for each robot. Therefore, it is necessary to consider the movement of other robots while developing a motion planning approach. Multi-robot motion planning (MRMP) takes into account static and dynamic obstacles in the environment, and any conceivable interference among robots, it includes the path and trajectory planning. Here in this paper, we only consider mobile robots, not manipulators. When robots perform their assigned tasks (independent task) in a given environment, they are dynamic obstacles to each other. The motion planning solution consists of creating a continuous motion from one point to another in a given environment. It should also avoid any collision with obstacles present in the environment [171].

Three types of approaches, potential field [172], roadmap, and cell decomposition, are studied in [28]. These approaches discover some recognized states and paths within the environment and then represent the continuous "motion planning problem" to a "discrete graph search" problem. Path planning approaches are also classified as decoupled and coupled. Decoupled approaches divide the problem into parts, and it can be centralized or decentralized. Such approaches can plan the path of each robot discretely and then coordinate to avoid the collision. Each robot's plan is independent, and such approaches may be fast for real-time applications; however, the completeness is not guaranteed. On the other hand, coupled approaches are capable of finding optimal or near-optimal solutions [173–175]; however, these approaches endures exponentially growing time complexity in the worst case. The complexity starts increasing with the number of robots participating in the conflict grows. Thus, coupled approaches become unrealistic for the coordination of MRS with a huge number of robots.

Authors in [176] presented heuristic methods for path planning and task allocation for three robots working in a shared area. It uses "A* algorithm" and "genetic algorithm" for the path planning and task allocation, respectively. Work presented in [177] is based on Firefly Algorithm (FA) for robot navigation in a dynamic environment. The Fundamental concept of the proposed work is that with variation in brightness of firefly, there is an attraction of one firefly towards the other. Work described in [178] presented an approach, which is founded on an improved "gravitational search algorithm" for trajectory optimization of multi robots in a dynamic environment. It uses a multi-objective function, and path planning is completed in a centralized manner. The next position of the robots is computed by an iterative algorithm, which must also satisfy all restrictions forced on the multi-objective function. The path planning problem considered here is formulated by a centralized approach until all robots reach their goal position the algorithm iterates.

Table 3 Summary of research works on task planning

Reference No	Static/ Dynamic	Communication Type	Control Arch.	Composition	Scalability	Environment	Fault Tolerance	Reactive/ Deliberative	Validation	Communication details
[102]	D	E	DS	HO	Low	CO	Y	R	EXP SIM	N*N*(N-1)=O(N^3) messages
[152]	D	–	HB	HT	Medium	CO	–	R	SIM	At each planning step from all to all
[132]	D	E	HR	HO	Good	CO	Y	R	SIM	Local One Hop
[103]	D	E	DS	HO	Medium	CO	Y	R	SIM	High (all to all)
[151]	D	E	SC	HO	Low	CO	N	D	EXP SIM	With the central server
	D	D	DS	HO	Good-100	CO	Y	R	SIM	High (constantly with neighbors)
[5]	D	E	SC	HO	Low	CO	N	D	EXP SIM	Each robot accepts plan and notifies to server
[121]	D	E	HR	HO	Depends on subnetwork	CO	Y	R	SIM	Broadcast in sub-network for bidding and map sharing
[153]	D	E	DS	HO	Medium	CO	Y	R	EXP SIM	Auction and Bidding (all to all)
[48]	D	E	DS	HT	Low	CO	Y	–	SIM	Ethernet -Frequent data exchange all to all
[154]	D	B	DS	HO	Low-10	CO	Y	R	SIM	Each robot communicates with all others[d], with teammates only[e]
[80]	D	B[a]	DS	HO	Good	CO	Y	R	SIM	Bidding and Global evaluation 2*(N-1)
[155]	D	E	DS	HO	Medium	CO	Y	R	SIM	Every robot needs to communicate with all other robots
[134]	D	E	HB	HO	Good-100	CO	Y	R	EXP	Broadcast[b]- 20,000 bytes for 10 robots in 15 min
[156]	D	E	SC	HO	Good	CO	N	D	SIM	Leader needs state of all robots and tasks
[51]	D	E	HR	HT	Good	CO	Y	R	SIM	Bidding within sub-network and some multi-hop
[101]	D	E	DS	–	Low	CO	Y	R	SIM	Broadcast
[157]	D	E	HR	HT	Medium	CO	N	R	EXP SIM	With few selected robots
[128]	D	E	DS	HO	Depends on K[c]	CO	Y	R	SIM	O(N+2 K) N number of robots, K share info
[158]	D	E	DS	HT	Medium	CO	Y	R	SIM	One broadcast at each iteration by each robot and communication with neighbors

[a] Mostly explicit, [b] total messages 587, 225 for broadcasts, 87 for plans exchanged, and 95 for synchronization, [c] K <=Min (N, M), M is no of tasks, [d] for auction-based, [e] for Vacancy Chain approach

A modified version of "classical prioritized planning" [179] is presented in [49], which is called revised prioritized planning. It proposes a decentralized version of revised and classical prioritized planning that can be used in MRS without the central unit. This proposed approach is guaranteed to terminate and computes coordinated trajectories by executing a negotiation-based protocol among individual robots. The completeness of approach is also inherited from the corresponding centralized approach. Prioritized planning is a decoupled method and is commonly used for "motion planning of multiple robots". In this planning, all robots are given a distinctive priority, and algorithm progresses, beginning with topmost priority to the lowermost priority robot. At every step, one robot finalizes its trajectory in a way that it does not conflict with higher priority robots.

An event-based decentralized technique is presented in [129] to attain coordination between robots. Robots need to keep the desired formation while following a specified geometric path. It reduces the communication cost by transmitting the required data at discrete event times. The event times are calculated based on some triggering condition devised in a manner that the convergence and stability properties of the consensus controller are preserved. As compared to other distributed approaches (using broadcast, flooding), the proposed solution performs well in terms of scalability and communication cost. It shows by comparing with traditional periodic-communication; the event-based methods provide a substantial reduction in the data transmitted between robots. They decompose the problem into two parts, one-part deals with motion control of the individual robot, termed as path following. The other part (contains consensus law) called cooperative controller works for attaining coordination between robots. Authors in [180] proposed a self-triggered consensus approach for linear multi-agent systems. Self-triggered mechanism gives advantages of reduced communication cost.

A distributed approach for multi-robot route planning is proposed in [130], which is based on an "augmented Lagrangian Decomposition" method. The key idea is to increase the penalty factor whenever constraints are violated while computing a feasible solution. The algorithm is framed as an "integer programming problem". Using "augmented Lagrangian decomposition" and coordination methods, the "integer programming problem" can be split up into subproblems for each robot. This approach uses multi-hop (all to all communication) and has high communication cost and low scalability.

In [181], an approach based on "model predictive control (MPC)" is presented for following the coordinated path of multi robots. An additional penalty is integrated into MPC scheme to achieve time convergence for trajectory tracking. This approach considers whole system formation as one rigid body (i.e., virtual structure). According to the required motion of each robot and dynamics of virtual structure, control laws are optimized for virtual leader robot and real follower robots. An approach based on Distributed Model Predictive Control (DMPC) is proposed in [182]. It can re-plan the trajectories if any undesired event occurs. A geometry-based approach [183] is presented for multi-robot motion coordination. It is resolution complete and offers good scalability in practical scenarios.

Many classical techniques, such as artificial immune system, neural networks, and heuristic optimization algorithms, have been proposed for MRS path planning. In the case of meta-heuristic and classical techniques, two basic problems are, trapping in local optimum and high time complexity in the bigger problem. Therefore, in many applications, these approaches are inefficient. Probabilistic algorithms, PRM, and RRT, are developed to improve these problems. In [184], a discrete RRT algorithm is presented; it is applicable when the graph is discrete. They use an implicit representation of a composite roadmap as in [175]. Many evolutionary algorithms like PSO [185], bee colony optimization, Genetic Algorithm [186], and differential evolution algorithm are also used in "multi-robot path planning" problems.

Deadlock with other moving objects and teammates is also needed to be handled for efficient motion planning. If the robots have the option to change their path, then by replanning, the problem can be solved. However, if the robots have fixed trajectories to follow, then the way to avoid deadlock is by avoiding the robots being at the same location at the same time. That can be done by introducing initial time delays [187], stop and resume [188]. Authors in [189] have proposed a distributed algorithm for deadlock, and collision avoidance. Labeled transition system (LTS) is used to model the motion of the robots. At its core, it is based on stopping and resuming the robots at the right time and place. In [190], the classical "shunting neural network" has been adapted for path planning. This approach can dynamically (at run time) generate optimal collision-free paths even in changing environments. Other promising works for collision-free motion planning are presented in [191, 192].

Recently Deep Learning (DL) based approaches [193–195] have emerged. In [195], the authors present an Imitation Learning based approach, which does not guarantee completeness. It falls in the category of hybrid coordination because it is dependent on both global planner (centralized) and local planner (needs information of nearby robots). The summary of works related to Motion Planning is shown in Table 4.

Summary and Insights Here in "multi-robot motion planning" from a coordination point of view, most of the approaches use explicit communication with decentralized coordination. Some of them are hierarchical and weakly centralized, however very few are strongly centralized. The centralized approach requires a large amount of information and high computational resources to provide optimal solutions. For most of the proposed approaches, due to being decentralized

Table 4 Summary of research works on motion planning

Reference No	Static/ Dynamic	Communication Type	Control Arch.	Composition	Scalability	Environment	Fault Tolerance	Reactive/ Deliberative	Validation	Communication details
[129]	D	E	DS	HO	Good	CO	Y	R	EXP	Event-based transmission using Wi-Fi
[122]	D	E	HR	HO	Good- tested with 35	CO	Y	R	SIM	location and path share with all neighbors, i.e., single hop
[104]	D	E	HR[a]	HO	Good	CO	Y	R	SIM	With neighbors
[196]	D	E	HB	HO	Medium	CO	N	R	SIM	Neighborhood communication
[181]	D	E	SC	HO	Low-10	CO	N	D	SIM	–
[134]	D	E	HB	HO	Good-100	CO	Y	R	EXP	Broadcast
[182]	D	E	DS	HT	Medium-20	CO	N	R	SIM EXP	High-Each robot need to communicate with all other robots at each step.
[49]	D	E	SC	HT	Depends on network topology	CO	N	D	SIM	Robots send their start and goal to CS. CS replies with trajectory info. Broadcast or WLAN or MANET
[130]	D	E	DS	HO	Low-tested with 3, 7	CO	–	R	SIM EXP	All to All, data exchanged at each iteration
[197]	D	–	HB	HT	Medium	CO	N	R	SIM	Each robot needs information from all other robots.
[195]	D	E	HB	HT	Good	CO	N	R	SIM EXP	With nearby robots
[97]	D	I	DS	HO	Good-100	CO	Y	R	SIM	Local sensors
[49]	D	E	DS	HT	Lower than SC version	CO	Y	R	SIM	More than a centralized version

[a] Centralized shared data access

and explicit in nature, the communication cost is still a challenge. In [129], event-based information transmission is used instead of periodic transmission, which gives a significant improvement in communication cost and scalability. In [122], hierarchical coordination with one-hop neighbor to neighbor communication is used, which improves reliability, scalability, and reduces communication cost. In reactive approaches, robots try to avoid a collision as they appear while following the shortest path to their present destination. However, it cannot be promised that the robot will reach its goal, and subsequent motion will be free from deadlock because the proposed solution to resolve collisions is local. So generally, a motion planner is required, which coordinates with all robots to take into account the starting position and final destination position of each robot while planning mutually conflict-free trajectories for each of them. These planning methods are mostly based on decoupled planning or uses coupled "heuristic search" in the combined state of all the robots.

7 Coordination in Various MRS Applications

Recently, many applications have emerged as MRS is gaining popularity. Here we define some important and prominent application domains (as shown in Fig. 3) of MRS and discuss other related (similar in terms of coordination needed) applications within these domains.

7.1 Exploration and Mapping

Exploration and mapping of an area are significant topics in the study of MRS because of its widespread applications in the real world. It shows many advantages to properly utilize concurrency provided by multiple robots, for that it is necessary to have efficient coordination between robots. For such tasks, robots need to be distributed in such a manner that the part of the task accomplished by one robot should not overlap with others. Many other tasks such as foraging, searching, coverage, rescue and search operations, mine cleaning, snow removal, mowing [198], map building, waste cleaning, planetary exploration [199], reconnaissance [200] are related to exploration and mapping. Foraging task requires that the robots collect the objects spread over an area. Coverage and related tasks require all points of a given area to be processed. They require coordination so that the movement of robots should not be toward the same frontier cell to efficiently explore the area. In other related tasks, MRS needs to explore the area and perform some additional actions such as, pick up an object that generally needs additional coordination. Some important parameters for the coordination approach are its communication cost, scalability, robustness, and efficiency. Efficiency involves that the exploration task should be completed with minimum cost, such as communication bandwidth, amount of data exchanged, exploration time, overall traveling distance, etc. Zhang et al. [201] proposed multi-robot exploration approach based on RRT. Coordination between the robots is achieved using market-based task allocation approach, and the problem is formulated as a constrained optimization problem.

Authors in [202] present a framework for coverage of the partially known environment. They use a similar strategy as presented in [203], receding horizon reactive motion planning. Robots are divided into clusters based on proximity, to increase scalability and planning efficiency. Negotiation-based approaches are widely used for multi-robot exploration. Work proposed in [121], [204] shows that traveling distance and time required for exploration has been reduced by negotiation based approaches. The key idea is to select the best one by using a bidding mechanism from several (those who submitted their plans) robots. Authors in [121] solve the problem produced by a limited communication range in the application domain of multi-robot exploration using a distributed bidding algorithm. It is a hybrid coordination approach because it uses both local (in sub-network) information sharing and broadcast for bidding. Thus, its scalability depends on the size of the sub-network. In [80], presented a multi-robot exploration approach based on "social potential field (SPF) model" and "market-based (MD)" technique. It is a distributed approach and uses both implicit and explicit coordination. Explicit communication is based on multi-hop communication. In [98], simple random movement is used with pheromone-based implicit guidance to explore the unknown area. In [205], algorithms for exploration and mapping are presented based on Monte-Carlo tree search [206]. Monte Carlo tree search is also used by others [207, 208] for exploration and active perception. They formulate exploration problem as finite-horizon optimization and use distributed sequential greedy assignment, which enables robots to plan parallelly.

A coordination approach for MRS is presented in [98] to realize the exploration of an unknown environment. This approach uses random movements via wall avoidance along with a bias in the direction of forward movement to reduce exploration time. This algorithm uses stigmergic markers for robot to robot communication and can be used on simple robots. Authors in [52] presented a coordination approach to perform real-time exploration in disaster areas. They autonomously classify robots into two types: search and relay. Each class of robot has its behavior algorithms. Area exploration is performed by search robots using a predefined approach. Monitoring station and search robots exchange information using relay robots. The approach uses distributed coordination and wireless ad-hoc network for communication, which has high communication cost — strictly saying that communication cost and scalability depends on the number of relay nodes.

Search and rescue operations can be made greatly efficient by a suitable coordination strategy. However, first, the robots should be able to perform exploration and mapping; additionally the robots must be capable of identifying the objects, which need rescue. Therefore, the coordination approaches designed for exploration and mapping can be easily modified for search and rescue by adding the capability to identify the rescue objects (while exploring the environment) and share this information with other robots or server. In [209], authors adopt a localization and mapping approach for search and rescue. While mapping, each robot identifies the target of interest, and the target location is determined using SLAM. They use a master robot to control exploration and mapping. It uses the least square method to detect the target, and for communication, it uses an ad-hoc wireless network. Authors in [210] use UAV and UGV for search and rescue. UAV can detect the object of interest; however, the UGV must identify it. They divide the problem into two parts, coordinated search, and then jointly identify the object that needs rescuing. It uses a central coordinator for all the coordination between UAVs and UGVs. A recent survey paper [211] provides more information on cooperative multi-robot search and rescue.

Another work in [93] has proposed some coordination and control policies for a team of UAVs in environmental surveillance by using coevolving neural network controllers and assigning fitness with different evaluation functions. It relies only on implicit communication. Authors in [212] use the neural dynamics (ND) approach for complete area coverage. They use the dynamics of each neuron, and each neuron is characterized by a "shunting equation" inspired from the biological neural system [213]. An approach in [125] utilizes "occupancy grid maps" to model the environment. It makes the use of "decision-theoretic approach" to coordinate the robots for exploring an unknown environment. Work in [214] presented a multi-robot exploration and coverage algorithm for non-Euclidian environments with obstacles.

Various other approaches used for area exploration are, "Voronoi Graph-based decomposition" [63, 91]; biologically inspired [215, 216]; graph theory [217] and consensus algorithm [218]. In [219], an approach is used based on Petri Net [220] for area exploration, [221] uses partitioning of topological weighted connected graph for terrain coverage such as floor cleaning, [216] based on honey bee swarm-inspired for forging task, [222] based on finite state automata for two heterogeneous robots looking for an object in a possibly cluttered area. Recently some [223–225] Machine Learning (ML) based exploration techniques have also been proposed. These approaches are fundamentally different from other disused approaches in terms of control, perception, and theory. Authors in [226] present a novel exploration approach for constrained communication environments. They have used an auto-adaptive communication strategy to dynamically select the connectivity level between the robots. A summary of work, related to Exploration and Mapping, is shown in Table 5.

Summary and Insights Most of the recent coordination approaches on the area exploration domain are based on distributed coordination. However for search and rescue operations a central coordinator is used in most of the approaches. Both implicit and explicit communication is exploited, although a majority of work is based on explicit communication. However, when distributed coordination is achieved using explicit communication, it incurs high communication cost. Thus several attempts made to reduce the communication cost by periodic broadcast [227], auto-adaptive communication [226], local communication [91, 228], combining with implicit communication [80], and clustering [125]. In most of the proposed work, a communication link is always supposed to be present between all robots, either direct or multi-hop. However, it is not true in various real circumstances. For example, because of the limited communication range of robots, while moving robots can go out of the communication range of other robots, which can lead to a network partition. The communication channel interference can be the reason for communication link failure.

7.2 Object Transport and Manipulation

While in pushing tasks, objects are supposed to move in the same horizontal plane. Object transportation task is more complex because it involves carrying and lifting objects. Other MRS applications such as truck loading, object handling, storage, lifting objects need a similar kind of coordination mechanism. Many proposed approaches have been tested with a simple object pushing task, which needs the robots to coordinate with the purpose to reach the desired configuration.

A work in [147] describes some elementary behaviors that need to be displayed by each robot. It defines the technique of combining those behaviors that are required to accomplish the given task. As an illustration, two robots are used to push a box along a path defined by its "variable direction angle". Robots can be updated regarding any change in this angle during execution. However, in this work, robots are unaware of each other's actions. In [231], an approach is proposed for object pushing towards a fixed location using two robots. It also shows that a distributed approach based on explicit coordination of two robots achieved more efficiency than two implicitly communicating robots or a single robot. Work in [232] presented a technique for selecting an action for box-pushing in dynamic environments using multiple robots without using explicit communication.

Autonomous robots have successfully used Reinforcement Learning (RL) for behavior learning. However, applying these approaches in MRS is not so easy, because many robots demand to cooperate with other robots. Deep Learning (DL) based approaches [233, 234] are also becoming prominent in this application domain of MRS. A work in [235] solves cooperative carrying problem by using reinforcement learning

Table 5 Summary of research works on exploration and mapping

Reference No	Static/ Dynamic	Communication Type	Control Arch.	Composition	Scalability	Environment	Fault Tolerance	Reactive/ Deliberative	Validation	Communication details
[226]	D	E	DS	HO	Medium	CO	Y	R	SIM	Adaptive (None, even based, continues)
[80]	D	B	DS	HO	Good	CO	Y	R	SIM	Bidding and Global evaluation 2*(N-1)
[229]	D	E	DS	HO	Good	CO	N	R	SIM	Communication only at rendezvous.
[201]	D	E	HB	HO	Medium	CO	Y	R	SIM EXP	Local (map merging) and Global both
[125]	B	E	SC	HT	Medium[a]	CO	N	D	SIM EXP	Clustered Ad-hoc Network
[214]	D	E	DS	HT	Medium	CO	N	PR	EXP	With Neighbors
[52]	B	E	DS	HT	Depends on no of relay nodes	CO	N	R	SIM	High (Ad-hoc Network)
[134]	D	E	HB	HO	Good	CO	Y	R	EXP	Broadcast
[121]	D	E	HR	HO	Depends on sub-network size	CO	Y	R	SIM	Bidding and map sharing in sub-network
[215]	D	E	DS	HO	Good	CO	Y	R	SIM	Low
[230]	D	E	SC	HT	Low	CO	N	R	SIM	High, UAV to UGV via ground node
[98]	D	I	DS	HO	Good-implicit	CO	Y	R	SIM	–
[90]	D	E	DS	HO	Good	CO	Y	R	SIM	Small volume of data transfer to all – can use multi-hop or broadcast
[228]	D	E	DS	HO	Good[b] Low[c]	CO	Y	R	SIM	Two approaches one peer to peer and other all to all
[93]	D	I	DS	HO	Good	CO	Y	R	SIM	–
[91]	D	E	DS	HO	–	CO	Y	R	–	Share info with neighbors then transferred further in the network
[227]	D	E	DS	HO	Low-10	CO	N	R	EXP	1 KB/robot/s, uses UDP and broadcast

[a] Proportional to the range of communication link, [b] for limited communication, [c] for all to all communication

for predicting the average head direction of other robots. In [236], a bar pushing work is presented, which is based on "Rubinstein's alternate offers protocol" [237]. Authors in [238] proposed an approach for coordination between multiple robots without explicit communication using intention inference and exhibited object pushing task. The robots deduce other robot's intents from observation of the situation and behavior of other robots to remove conflicts and cooperate in completing tasks. Authors in [239] developed two solutions for the container loading problem. They define the operations and conditions essential for identifying and solving conflicts among robots. This approach uses the idea of 'Abstract Time-Windows' to represent the movement of the robots. The first one is a heuristic approach, which has low computational complexity and offers near-optimal performance. The second solution is appropriate for solving problems where requests for task execution arrive before time. It delivered optimal performance and proposed using "Mixed Integer Linear Programming (MILP)". A recent survey on collaborative robotic manipulation for robot manipulators, mobile robots, and mobile manipulators is presented in [240]. Many approaches proposed for multi-robot object transport and manipulation do not require explicit communication, such as [241, 242].

Some other works are: [99] based on virtual leaders for handling single object by multiple robots, [243] based on software agents with machine learning for object transportation task, [244] based on Reinforcement learning for cooperative carrying problem, [94] uses heartbeat signals (for leader selection and synchronization) for actions such as lifting or steering, [74] based on "Artificial Immune System" for object transport, [245] based on "biological immune system" theory and general immune network algorithm. Summary of work related to Object Transport and Manipulation is shown in Table 6.

Summary and Insights In this application domain, a large portion of work (based on explicit coordination) has used some form of broadcast communication, thus suffers from low scalability. Although many applications in this domain may not require a very large number of robots for a single object, however in some cases, it may. Both deliberative and reactive systems are used. Work presented in [246] is a deliberative system due to strongly centralized coordination others are reactive or partially reactive. Most of the work uses dynamic coordination; some use both "static and dynamic coordination". Control approaches presented in the related work mostly rely on distributed coordination [48, 75, 101, 103] and some uses centralized coordination [99], [246]. Work in [135] uses hybrid coordination because it has some communication with the central station for planning route, shipment operation, and local communication between concerning robots. Decentralized coordination is extensively used due to its invulnerability to the failure of individual robots [50, 75, 94], and the majority of them are behavior-based.

7.3 Target Observation

Applications in this domain need a team of robots to detect and track one or more objects. In the case of multiple targets, each of the targets must be observed by at least one robot. The problem of "multi-target observation" is known as: "Cooperative Multi-robot Observation of Multiple Moving Targets (CMOMMT)" [69]. This domain can also have a sensor network for helping robots such as in [253] robot-sensor network is used to track and intercept targets. Even only sensor networks [68, 70, 254] have also been used for such tasks. Other related applications in this domain are Target Tracking (Single, Multiple), Target Searching, Target Acquisition, Target Interception, etc. Target observation has a relation with surveillance [255], security, recognition, and search problems. Multi-target observation can be considered similar to the foraging task, with a greater requirement of continuous tracking of dynamic targets. In this domain, coordination is required to decide which robot should track or observe which target, how many robots should observe a single object, and trajectory planning to track that object. A social deliberative approach is used in [69] for observing multiple targets. The robotic agents in the system are homogenous and behavioral-based; however, the proposed technique is also applicable to heterogeneous MRS. The "Broadcast of Local Eligibility (BLE)" architecture is proposed in this paper, which provides coordination among robots. Every behavior of each robot is associated with a method that locally calculates the eligibility of a robot to complete the assigned task. The calculated values are shared between the "peer behaviors" of agents. The robot has the highest behavior value, inhibits the corresponding behavior on other robots in the MRS, and thus advocates the task. This approach is weakly centralized because the leader changes every time; however, the decision regarding the selection of leader is distributed. A review paper [256] classifies the approaches developed for observing moving targets. They describe five factors to categorize this problem.

In [67], the cooperation approach depends on "Voronoi Graph," which is used to compute feasible trajectories based on different targets. After that, every vehicle is assigned to some target in order to intercept the group of pre-allocated targets. A "distributed cooperative target intercept strategy" to solve the problem of cooperative target intercept using multiple unicycles is proposed in [96]. Each pursuer is dynamically allocated to the target autonomously with the help of local coordination. This approach uses "minimal weighted distance," which is similar to the maximum intercept chance. The group of

Table 6 Summary of research works on object transport and manipulation

Reference No	Static/ Dynamic	Communication Type	Control Arch.	Composition	Scalability	Environment	Fault Tolerance	Reactive/ Deliberative	Validation	Communication details
[99]	B	I	SC	HO	Low	CO	N	PR	EXP	Implicit only
[247]	D	E	SC	HO	Low	CO	N	D	SIM EXP	High- Central master communicates with all robots very frequently
[103]	D	E	DS	HO	Medium-20	CO	Y	R	SIM	High (All to All)
[135]	D	E	HB	HO	Low-Tested with 3	CO	Y	PR	EXP	Local communication between concerned robots and some with the central station
[248]	D	B	HB	HO	Low-Tested with 3	CO	N	PR	SIM	Communication with neighbors and some communication with leader robot
[101]	D	E	DS	–	Low	CO	Y	R	SIM	Broadcast, TCP/IP
[249]	D	E	HR	HT	Medium	CO	Y	R	SIM	Two categories of robots one can communicate with all leaders while others only with neighbors.
[50]	D	E	DS	HT	Low	CO	Y	R	SIM	Very high- Too many broadcasts
[246]	D	E	SC	HO	Low	CO	N	D	SIM EXP	Broadcast (ZigBee)
[250]	D	E	DS	HO	Medium-10	CO	Y	R	SIM	One-hop only
[48]	D	E	DS	HT	Low	CO	Y	–	SIM	High-frequent data exchange between all robots
[251]	D	E	DS	HO	Low	CO	N	R	EXP	Each robot need to communicate with all others
[94]	D	I	DS	HO	Good	CO	Y	R	EXP	Broadcasting RF signals in the environment
[252]	D	E	DS	HO	Low	CO	N	R	SIM	At each instance to all others

pursuit cycles is used for dividing the targets in a distributed manner with the help of local coordination without any negotiation, unlike in [67]. In [71], an approach is proposed for target acquisition, which is based on "Multiple Objective Behavior Coordination (MOBC)"[257].

In [258], two solutions are proposed to solve target allocation in a team of the robot. In the first approach, Hungarian algorithm is used by each robot for centralized team allocation. In the second solution, this allocation problem is expressed as the "relaxed integer problem," which is further solved with the help of decentralized optimization. The robots learn incrementally, the impact of each robot on team utility, and accordingly make globally coordinated decisions. A mechanism is also proposed in this paper where robots can switch between negotiating and using the "learnt utility model (LUM)," which decreases the communication demands for coordination and also maintains tracking performance similar to the explicitly coordinated MRS. The results show that total communication is reduced by 19%. Authors in [259] presented a decentralized information gathering algorithm and show its applicability for target tracking. If robots are in communication range, they perform collective estimation; otherwise, each robot has its own estimation of the target. This work releases some assumptions about their previous work [260]. In [261], coordination approach (based on explicit communication) for mobile target tracking is presented, where robots are restricted to move within their mutually exclusive bounded regions. Authors in [262] proposed a decentralized target tracking approach. They use a self-triggered communication approach to reduce communication cost. Some work [90, 139], have also used PSO (nature-inspired algorithms) and Neural Network for target searching and target tracking, respectively.

Summary and Insights The summary of related work is shown in Table 7. Most of the work presented uses one or more robots to track a single target. A few research papers have presented, tracking more targets with less number of robots, as in [258]. The algorithm is tested with twenty instances of three robots tracking four targets. Both implicit and explicit coordination can be used for such domain of applications. Most of the early work is decentralized and reactive. Some decentralized [69, 263] work have very high communication cost therefore scalability of such approaches is also poor. However, distributed coordination approaches using local or one-hop communication are better to scale. Recently (in [264, 139]) some scalable and distributed approaches have been proposed with low communication cost. The efficiency of such coordination approaches can be further improved by incorporating some triggering mechanism or heuristic to decide when the information should be exchanged between two are more robots.

7.4 Formation Control

In the recent few years, the problem of "multi-robot formation control" has been widely studied. Formation control can be described as: robots are required to maintain some specific pattern, relative position, converge towards given structure, etc. Other areas, such as coalition formation, containment control [272], can be considered related to this domain. One way to classify the proposed approaches for formation control in MRS can be behavior based approach [273], leader-follower approach [67, 115, 274–276], and virtual structure approach [277, 278]. Applications in this domain need coordination to control the velocity, trajectory following, and relative distance of the robots.

Neural network and consensus-based algorithms are extensively used to achieve formation control in recent years. In [279] distributed neural network is used, where each robot of swarm contains few neurons and wirelessly communicates with nearby robots. This distributed artificial neural network is trained at runtime, and the swarm can show a variety of behaviors. In [280], the authors proposed a solution for multiple mobile robots (nonholonomic) based on a distributed consensus-based approach with unknown dynamics. It uses an adaptive neural network and translates the formation control problem as a state consensus problem. In [281], an approach is presented for multi-robot formation control using state-space model; this can also be used for trajectory tracking. In [133], an extended "consensus-based" estimation algorithm and "consensus-based" formation control algorithm are presented. It needs only local neighbor to neighbor communication. It requires multiple leaders, thus comes in the category of hierarchical coordination. It is not fully robust; however, robustness can be improved with the help of large number of group leaders in the formation for a single point of failure. Authors in [282], proposed solution for containment control problem for a semi-markovian multi-agent systems. They use static and dynamic containment control approaches to solve this problem. Another solution for nonlinear multi-agent systems using fuzzy-logic is presented in [283].

In [127], the problem is formulated into two parts: Intra and intergroup formation. In the "intragroup formation", the formation of each robot in every group has been determined, and in the "intergroup formation", the coordination of groups in the team is determined. A key idea, "adaptive interactive force," is proposed to handle intergroup interactions. It is weakly centralized coordination because it uses multiple leaders, one global, and several local leaders. Work in [79] can maintain given proximity and able to converge to a given destination by using Lyapunov-like barrier function. It uses hybrid coordination architecture, i.e., the goal is periodically sent by the leader, and the decision taken to reach the goal is decentralized. [276] presented a consensus-based

Table 7 Summary of research works on target observation

Reference No	Static/ Dynamic	Communication Type	Control Arch.	Composition	Scalability	Environment	Fault Tolerance	Reactive/ Deliberative	Validation	Communication details
[96]	B	I	HR	HO	Good	CO	Y	R	SIM	Local coordination by observing
[264]	D	E	DS	HO	Good	CO	Y	R	SIM	With neighbors (can define the number of communication rounds), a tradeoff between communication rounds and performance
[265]	D	E	SC	HO	Low	CO	N	R	SIM	Each robot communicates with all other
[132]	D	E	HR	HO	Good	CO	Y	R	SIM	Local single hop One hop
[90]	D	E	DS	HO	Good	CO	Y	R	SIM	Small volume of data transfer to all can use multi-hop or broadcast
[258]	B	E	DS	HT	Good	CO	Y	R	SIM EXP	Broadcast (less than normal[a])
[266]	D	B	DS	HO	Medium	CO	Y	R	SIM EXP	With all other robots but not dependent on others, if no communication, it can still work.
[267]	D	E	DS	HO	Low	CO	Y	R	SIM	Each UAV need to share its state and target information at each step
[228]	D	E	DS	HO	Good	CO	Y	R	SIM	Peer to peer (one-hop)
[268]	D	E	HB	HO	Low	CO	Y	R	SIM	High-Each robot need to share with all other robot and with central server
[263]	D	E	DS	HT	Low	CO	Y	–	SIM EXP	O(M*N) [b] communication steps, M-task, N-robot, WLAN, UDP
[269]	D	E	SC	HO	Low	CO	N	R	EXP	A central server used to communicate with all robots at each step
[69]	D	E	HB	HO	Low	CO	Y	D	EXP	High-Broadcast
[270]	D	E	DS	HO	Good	CO	Y	R	SIM EXP	Only with neighbors
[139]	D	E	DS	HO	Good	CM	Y	R	SIM	With Neighbors
[228]	D	E	DS	HO	Low	CO	Y	R	SIM	Peer to peer (multi-hop)
[271]	D	E	DS	HO	Good	CO	Y	R	SIM	Local broadcast (for neighbors)

[a] By using learnt utility model, total communication was reduced by 19%, [b] This is for negotiation only. Other cost at the time of task execution

approach for formation control with a specified reference trajectory, [275] uses a bio-inspired neurodynamics based approach for formation control. Authors in [55] solve the problem of "task-oriented motion planning" for formation control using representation space model. Work in [284], proposed algorithms to automatically create controller and synchronization mechanism for MRS, based on swarm behavior (taken as input). The summary of works related to Formation control is shown in Table 8.

Summary and Insights This domain is well studied for both heterogeneous and homogenous robots. Some research work [97] uses only implicit coordination and achieves high scalability compared to explicit coordination. However, using both (broadcast and local sensing) [79] creates a balanced approach in terms of accuracy, communication cost, and scalability. Fully distributed coordination is not suitable for this domain of problems. Advantages of approaches in [129, 285] are that they are robust and fully reactive; however, have high communication cost. Work in [129] presents an excellent approach to minimize communication cost by using an event-based transmission.

7.5 Other Applications

Applications of MRS are widely broad. All of that cannot be grouped in the above domains. In this section, we present some other coordination approaches used for other prominent applications of MRS. Such as, [95] based on State transition automata for construction task, [92] for fixed-obstacle avoidance, goal-seeking, and mobile-robot avoidance, [290, 291] for Multi-robot SLAM, [292] based on "game-theoretic learning algorithms" using "fictitious play" and extended Kalman filter for cooperation among patrolling and material handling robots in a warehouses, [77, 105] soccer, [202] collective construction, [259] cooperatively carrying mass by multiple UAV, [293] presents approach for coordination with limited communication ranges and communication failures i.e., rendezvous algorithm via proximity graph, [294] cooperatively performs a few of servicing tasks in a hospital environment, [89] can send information related to task in minimum time with a local communication scheme, [295] based on "mixed-integer linear programming" for Autonomous Intersection Management, [107] Localization and navigation of salve robots, [78] based on idea of setplay, i.e., to organize a robotic soccer team behavior for any "RoboCup cooperative league" and similar domains. Authors in [296] present a decentralized approach for coordination where robots use explicit communication during planning. It is used for tasks that require active perception using multiple robots. This algorithm is a variation of the 'Monte Carlo tree search (MCTS)'. In [297], a multi-robot coordination algorithm using Voronoi partitioning is presented for underwater environment sampling. Table 9 presents a summary of such work.

8 Open Research Issues, Challenges and Future Directions

Till now, we presented a systematic study and analysis of the existing approaches to MRS coordination. Now, we discuss insight on the presented works, open issues, challenges, and future directions for developing MRS.

- *Communication Model:* In the case of explicit coordination, it is important to decide the proper communication model. Most of the work, especially based on distributed coordination approach, incurs high communication cost. Although, using a distributed approach provides better scalability and robustness but on the cost of increased communication. Some work like [129] reduces communication cost; however, such works are very limited. Therefore, it can be an efficient way to use hybrid coordination in terms of communication cost, robustness, real-time requirements, etc., for a particular form of cooperation as and when which one is more efficient.
- *Scalability:* To operate in the application domains where a large number of robots are required, such as smart cities, MRS needs to be scalable. However, work done on large scale of robots is not sufficient; many of the MRS coordination approaches do not scale well. Although every MRS application does not require a large number of robots, however, a large number of robots can be efficient for cooperative localization and long-term autonomy. Hierarchical approaches [51, 122] can be a good option for scalable solutions. Simultaneously taking care of both scalability and heterogeneity is needed in areas like smart cities, which is more challenging. So special attention is needed to develop largely scalable coordination approaches.
- *Explicit and Implicit Communication:* Communication has two extremes, first is only using explicit communication, in which the robots communicate directly among themselves. Second is only using implicit communication, in which each robot perceives the actions of other robots or changes (due to other robot's activity) in the environment. Most of the presented work has used either one of the two. The efficiency of the MRS is affected by communication cost and design of elementary behavior for explicit and implicit coordination, respectively. However, a hybrid system using both explicit and implicit communication can enhance the efficiency of

Table 8 Summary of research work on formation control

Reference No	Static/ Dynamic	Communication Type	Control Arch.	Composition	Scalability	Environment	Fault Tolerance	Reactive/ Deliberative	Validation	Communication Details
[79]	D	B	HB	HO[a]	Medium	CO	N	PR	SIM	Local sensing and Broadcast by leader
[49]	D	E	SC	HT	Depends on communication	CO	N	D	SIM	Broadcast or WLAN or Ad-hoc Network
[286]	D	E	DS	–	Good	CO	Y	R	SIM	With neighbors
[97]	D	I	WC[b]	HO	Good-100	CO	Y	R	SIM	Local sensing
[287]	D	E	SC	HO	Medium	CO	N	R	SIM EXP	Central server communicates with all robots
[91]	D	E	DS	HO	–	CO	Y	R	–	Shared info floods from neighbors to others
[288]	D	E	DS	–	Medium	CO	Y	R	SIM	With neighbors
[133]	D	E	HR	HO	Medium	CO	N	R	EXP	Local information exchange with neighbors Ethernet TCP/IP
[289]	D	E	DS	HO	Good	CO	Y	R	SIM EXP	With neighbors
[127]	D	B[c]	WC	HT[d]	Good	CO	Y	PR	SIM	With local leader (if radio) and between same level leaders
[129]	D	E	DS	HO	Better than periodic transmission	CO	Y	R	EXP	Event-based transmission using Wi-Fi
[285]	D	E	DS	HO	Low	CO	Y	R	SIM EXP	Flooding in Wireless Ad-hoc Network

[a] Only Leader is different, [b] decentralized motion planning, [c] vision or radio, [d] only software is different

Table 9 Summary of research works on other applications

Reference No	Static/ Dynamic	Communication Type	Control Arch.	Composition	Scalability	Environment	Fault Tolerance	Reactive/ Deliberative	Validation	Communication details
[77]	D	B	DS	HO	Low-10	CM	Y	R	–	Bidding, sharing location and ball position using broadcast
[279]	D	E	DS	HT	Good-316	CO	Y	R	EXP SIM	Wireless communication with nearby robots
[105]	D	B	DS[a]	HT	Low-seems broadcast or flooding	Both	Y	R	EXP	Local observations and sharing of own position, velocity, ball position to all teammates.
[298]	D	B	DS	HO	Good	CO	Y	R	EXP	Mostly implicit, object and robot using NFC
[95]	D	I	DS	HO	–	CO	Y	R	SIM	Local sensing
[291]	D	E	SC	HO	Low	CO	N	R	SIM	High- Centralized master sends and receives from all robots at each sensing cycle
[292]	D	E	DS	HO	–	CO	Y	R	SIM	50 msg by each in a group of two.
[106]	D	B	DS	HO	–	CO	Y	R	SIM	Period of communication can be set, first uses implicit, if not then explicit using WLAN
[293]	D	E	HR	–	Medium-Tested with 10	CO	Y[b]	R	SIM	With all neighbors
[290]	D	E	DS	HO	Good	CO	Y	R	SIM	Peer to peer (depending on relative position)
[126]	D	E	SC	HT	Low	CO	N	R	EXP	High- Images and messages, ROS (publish-subscribe)
[181]	D	E	SC	HO	Low-10	CO	N	D	SIM	–
[89]	D	E	HR	HO	Good	CO	Y	R	SIM EXP	Local communication with few robots using infrared led (2400 bps)
[107]	D	B	SC	HT	Low	CO	N	D	EXP	Depends on task (how frequent master sends commands)
[299]	D	E	DS	HO	Medium	CO	Y	R	SIM	All to all
[220]	D	E	DS	HO	Better than only broadcast	CO	Y	R	SIM	Peer to peer bidding and broadcast for local map sharing
[78]	B	E	WC	HO	Low	CM	N	R	SIM	A Start msg at each step and then other updates by lead player uses IEEE 802.11

[a] Assignment algorithm runs on base station [b] only for communication failure

coordination in many applications. It will also enhance the scalability of the system (for both centralized explicit and decentralized explicit) because implicit communication will reduce overall communication complexity. How much to exploit implicit coordination (i.e., how much to rely on autonomous behavior for individual robot), and explicit coordination is a critical decision.

- *Human Interaction:* In many MRS, it is important to allow humans to interact with MRS easily. Human can work alongside robots or only provide instructions to the system whenever needed. Presently, many tasks are very complicated for robots, which requires coordination among humans and robots. Sometimes human wants to control the system in certain safety situations such as overriding the automatic decisions of a self-driving car in case of emergency. However, introducing humans in the loop reduces the responsiveness of the system because of uncertainty in human performance and increased communication overhead. Human intervention can make the system more error-prone and slow. Therefore, the key to select the appropriate system architecture that can successfully complete the tasks is to figure out whether the human-in-the-loop can be considered as an asset or liability for a given scenario. Interactions can be through a graphical interface, or text or speech or visual, or a combination of two or more. However, the issue is to decide how humans and robots should communicate so that interaction is easy, smooth, and accurate (reduces faults). This interaction should also have minimum delay on responsiveness and minimal increment in the computation complexity of MRS. Recently a human-aware (considers unpredicted human behavior) task allocation approach is proposed in [300].
- *Internet of Robotic Things:* The idea of "Internet of Robotic Things (IoRT)" [301] is based on using cloud services and global connectivity via the internet. Robotic systems can be greatly benefited by the information gathered from IoT devices. In IoRT heterogeneous devices (including robots) can be integrated into a distributed manner, and devices can communicate with the local network, cloud, and edge devices. The challenges in the implementation of IoRT are: handling high degree of heterogeneity, security, sensor fusion, interoperability, self-adaptivity, etc. Further details about IoRT and its challenges can be found in [302, 303]. In [304], the authors attempted to solve the problem of maintaining global connectivity between robots using neural networks.
- *Heterogeneity:* Presented approaches for MRS coordination are mostly homogenous. Although considerable work has been done on heterogeneous MRS in recent years, still, the diversity of robots is very limited (some are only heterogeneous in terms of software). For achieving autonomy at the level of the smart house, smart hotels, smart cities, etc. we require very diverse robots for good efficiency, autonomy, and ubiquitous computing. Heterogeneity is also needed to be handled at the level of communication architecture, information exchange protocols. So, there is a need to develop approaches for highly diverse heterogeneous MRS.
- *Resource Limitations for Machine learning:* Machine learning capabilities for individual robots, and for overall system needs to be developed and applied. So that future systems would be able to incorporate machine learning models in various applications of MRS, even for MRS with limited computational and communication capabilities. Presently, heavy ML algorithms are used on the cloud. However, it leads to high latency, increased communication cost, and cannot be used for real-time applications. Therefore, present ML algorithms need to be customized in order to be used with resource-constrained robots. In some cases, edge devices can also be used for running ML algorithms. Other solutions are to use cooperative learning [305] and distributed machine learning [306].
- *Autonomous and Transfer Learning:* Autonomous learning is less explored for MRS as compared to MAS. In some applications such as foraging, box pushing, soccer, etc., autonomous learning has been applied to a certain extent. However, learning becomes more challenging for domains where the action of one robot depends on the current activity of other robots. One solution is to develop autonomous machine learning algorithms (AutoML) [307, 308], that do not need human intervention to select training data for tuning algorithmic parameters, etc. AutoML algorithms developed for mobile devices can also be used in MRS. Transfer learning [309] can improve the performance of MRS because there are many MRS applications that have similar scenarios. It is like using the experience of robots or MRS as an input for future decisions of other robots or MRS. This type of learning is especially useful for robots that learn by reinforcement learning. However, there are many challenges to be addressed before using it in real-world MRS.
- *Energy Efficiency:* This is also an important parameter to be considered while deploying MRS. Therefore, energy consumption needs more attention, which is highly neglected in the presented works. Special attention in terms of energy consumption is needed for small robots used in the internet of things applications. One way to minimize energy consumption can be by developing proper coordination approaches. The properties required for a coordination approach to be energy efficient are: minimizing overall distance traveled by robots, efficient communication type (having less cost and complexity), reduce computation requirements. To enhance the life span of

MRS, energy consumption by each member of MRS should be approximately equal (unless members are heterogeneous like the central server is on ac power) in a given time period. It can be achieved by developing load balancing coordination approaches such as different leader for each time period, multiple changing leaders, considering energy status in task allocation.

- *Performance Evaluation and Benchmarking:* To compare the performance of MRS evaluation standards are required to be developed to effectively compare them because this field is still in the developing phase. This is one of the major issues to be addressed defining suitable evaluation methodologies, in order to assess the adequacy and effectiveness of various forms of cooperation in MRS. One such attempt is made in [310].
- *Communication Network:* Extensive research on computer network algorithms, protocols, along with their performance modeling and analysis, is required in order to improve explicit communication and coordination. To deal with the network limitations (such as network unreachable, slow, and intermittent) delay tolerant, software-defined, networks can be designed. Moreover, protocols and algorithms should be interoperable so that robots can communicate with other, heterogeneous robots and IoT devices.
- *Robustness:* There can be situations like network partitioning; robots may move out of communication range, on-robot sensors failure, leader failure, etc. Therefore, to ensure robustness, there has to be some failsafe or preventive mechanism in place. For example, if a leader fails, then a mechanism to select a new leader should trigger or have multiple leaders with some priority, predict and restrict the movement of robots if it is going out of communication range. Robustness in terms of communication needs to be addressed like communication range, communication failure, network partition recovery, and low bandwidth because most of the work has assumed a reliable communication medium.
- For robots, with limited hardware resources. Efficient algorithms for task allocation, motion planning, decision making, etc., are required, which can work with less computation, communication, and power requirements.
- Coordination approaches that are strongly centralized tend to be deliberative, less flexible, have high computing load on a single system, and have a single failure point. Distributed approaches are generally more flexible, robust, high communication demanding, and less computational demanding. To balance resource consumption and QoS hybrid approach is a good option. However, it is also a challenge to decide how much centralization and decentralization is required.
- Exploiting cloud resources such as computational power can be useful for increasing the performance of MRS. Although connecting with the cloud can have some additional parameters to be taken care of. Such as how frequently robots should communicate with the cloud, which services to be deployed on edge, how much processing to be performed locally, how to improve response time for time-sensitive tasks, etc.
- Collision, congestion, and deadlock are other issues to be dealt with while developing a coordination approach. Deadlock is easily possible in implicit coordination because others cannot foresee global goals.

9 Conclusion

In our research paper, we first presented an overview of MRS and its classification with respect to various dimensions, such as communication, coordination, composition, etc. Then, we analyzed various coordination approaches proposed for Multi-Robot System and categorized them according to various dimensions such as static or dynamic, implicit or explicit, and centralized or decentralized. We presented a comprehensive, diverse aspect of MRS coordination which will help newcomers to grasp the basic concepts of MRS and how coordination can be achieved in MRS. Further, we studied various existing application domains of MRS in multiple disciplines. Finally, we analyzed MRS coordination work focusing on various application domains of MRS, including Task Allocation, Motion Planning, Area exploration, Object transport, etc. We discussed the outcome of our analysis in terms of prominently used techniques, their drawbacks, and strengths, along with the challenges faced in each domain and in the overall coordination of MRS. We also analyzed the efficiency of MRS coordination approaches in terms of parameters such as communication cost, scalability, robustness, etc. and presented them in tabulated form to easily understand the insight and decide the effectiveness of a specific approach in a given MRS application domain. Our study concludes that coordination is an important and challenging factor in designing efficient MRS. We have also presented some open research issues and future directions such as autonomous learning, development of approaches for resource-constrained robots in IoT scenarios, exploiting cloud resources, balanced use of implicit and explicit communication, etc. to develop efficient coordination approaches. We expect this article will serve as an insightful and comprehensive resource on MRS coordination for researchers and practitioners in the area.

Abbreviations S, Static; D, Dynamic; B, Both; I, Implicit; E, Explicit; SC, Strongly Centralized; WC, Weakly Centralized; HR, Hierarchical; HB, Hybrid; HO, Homogeneous; HT, Heterogeneous; CO, Cooperative; CM, Competitive; Y, Yes; N, No; R, Reactive; PR, Partially Reactive; D, Deliberative; SIM, Simulation; EXP, Experiment

Availability of Data and Material No such data.

Code Availability No software application and custom code is used.

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Declarations

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