An Extensive Review of Research in Swarm Robotics

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***Abstract*— Swarm robotics is a new approach to the coordination of multi-robot systems which consist of large numbers of relatively simple robots which takes its inspiration from social insects. The most remarkable characteristic of swarm robots are the ability to work cooperatively to achieve a common goal. In this paper, classification of existing researches, problems and algorithms aroused in the study of swarm robotics are presented. The existing studies are classified into major areas and relevant sub-categories in the major areas.**

Keywords-swarm robotics, review, state-of-art, multi-robot

I. Introduction

The term "Swarm Intelligence" refers to sophisticated collective behavior that can emerge from the combination of many simple individuals, each operating autonomously [1]. According to Cao et al. [2], swarm intelligence is "a property of systems of non-intelligent robots exhibiting collectively intelligent behavior". Nonetheless, based on the definitions, we can see that the essential characteristics of swarm intelligence consist of a biologically inspired emphasis on decentralized local control and local communication, and on the emergence of global behavior as the result of self-organization [3]. The application of swarm intelligence principles to collective robotics can be termed "Swarm Robotics" [1].

Swarm robotics is a new approach to the coordination of large numbers of relatively simple robots [4], that are autonomous, not controlled centrally, capable of local communication and operates based on some sense of biological inspiration [1]. Swarm robotic systems have become a major research area since 1980's [5], as new solution approaches are being developed and validated, it is often possible to realize the advantages of swarm robotic systems [2, 6, 7].

The early work on classification of research areas of swarm robotic systems was done by Dudek et al. [8] in 1993. The paper classified the areas into five areas which are swarm size, communication range, communication topology, communication bandwidth, swarm reconfigurability and swarm unit processing ability. Cao et al. [2] presented the survey of cooperative robotics in a hierarchical way. They split the publications into five main axes: group architecture, resource conflicts, origins of cooperation, learning and geometric problems. Luca Iocchi et al. [9] presented an analysis of multi robot systems by looking at their cooperative aspects. They have also proposed taxonomy of multi robot systems and a characterization of reactive and social deliberative behaviors of the multi robot system as a whole. Rather than summarizing the research area of swarm robots into a taxonomy of cooperating systems [2, 8, 9], Lynne [10] have organized the areas by the principal topics that have generated significant levels of research. Open research issues within each topic area have also been identified and discussed clearly in this paper. Section II of this paper will use the classification reported in [10] as the main research axes and further classify the sub-categories in these areas.

II. Research Domains

A. Biological Inspiration

Swarm robotics and the related concept of swarm intelligence, is inspired by an understanding of the decentralized mechanisms that underlie the organization of natural swarms such as ants, bees, birds, fish, wolfs and even humans. Social insects provide one of the best-known examples of biological self organized behavior. By means of local and limited communication, they are able to accomplish impressive behavioral feats: maintaining the health of the colony, caring for their young, responding to invasion and so on [11]. Thomas et al. [12] has analyzed the behavior of a group of robots involved in an object retrieval task where the robots' control system is inspired by a model of ants' foraging behaviors. The sub-tasks assigned to the robots are extracted from simple behavior of ant swarms such as search, retrieve, deposit, return and rest. Ideas inspired from such collective behaviors have led to the use of pheromone [13], a chemical substance deposited by ants and similar social insects in order to mark the environment with information to assist other ants at a later time.

Similarly David et al. [14] and Cazangi et al. [15] used pheromones to achieve inter-robot communication mechanism in their research. A higher level of research in this area, leaded to the studies of cooperation and interaction abilities in mammals.. Bill Tomlinson et al. [16] created an interactive virtual multi-agent system based on the behavior of packs of gray wolves (Canis lupus). Their virtual wolves are able to form social relationships with each other thru the mechanism of social relationship formation involves emotion, perception, and learning. In [17], Terrence Fong et al. have reviewed on socially interactive robots. They have modeled their robots to adopt humans' social interactions. As

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research progresses in this area, more sophisticated teamwork architectures are being explored into to cater the increase in problem complexity. Such sophisticated teamwork architectures was demonstrated in [18].

B. Communication

When a task requires cooperation, there is a need for some form of communication between the participating agents. There has been much debate about the level of communication that should be allowed between such systems. Most of the open literatures have made distinctions between implicit/indirect and explicit/direct communications. Implicit communication (sometimes also called stigmergy [19, 20, 21]) is a method of communicating through the environment.

Pheromone communication is a type of implicit communication. There a many papers that have explored the use of pheromone signal to convey messages within the robots in the swarm [22]. A higher level of pheromone called "virtual pheromone" was introduced in [23-25] to employ simple communication and coordination to achieve large scale results in the areas of surveillance, reconnaissance, hazard detection, and path finding.

Explicit communication is the type of communication in which the robots directly pass messages to each other and/or to the human operator [26]. McPartland et al. [27] has made comparison between implicit and explicit communications theory by applying it to two different swarms of robot which is assigned to explore a given environment in the shortest period of time. Paul et al. [28] introduced and explored simple communication strategies which implemented implicit and explicit communication. Hayes et al. [29] described a distributed algorithm for solving the full odor localization task, and shown that group performance can exceed that of a single robot using explicit communication.

Communication between robots can multiply their capabilities and increase the efficiency. Even though there is no clear conclusion on what type of communication is better for robot swarms, but most of the current research is aiming towards implicit communication for its robust characteristics.

C. Control Approach

Iocchi et al. [9] has clearly distinguished between distributed and centralized control as:

- Centralized: the organization of a system having a robotic agent (a leader) that is in charge of organizing the work of the other robots; the leader is involved in the decisional process for the whole team, while the other members act according to the directions of the leader.
- Distributed: the organization of a system composed by robotic agents which are completely autonomous in the decisional process with respect to each other; in this class of systems a leader does not exist.

Lynne [30] experimented on the advantages and the disadvantages of the control approaches and reported that deciding the proper balance between centralized and distributed control is the key to achieve the desired emergent group behavior in a swarm of robots. Steele et al. [31] introduced "Directed Stigmergy-Based Control" which incorporates the advantages of distributed control and centralized control. However, both distributed and centralized control approaches have contributed individually to the study of swarm robotics and have generated interesting experimental results.

D. Mapping and Localization

Mapping is a representation of the physical environments through the mobile robots sensory data into spatial models [32]. Localization is defined as finding the absolute or rational location of robot in the spatial models generated [33]. Since the development of research in mapping and localization progressed, the problems that addresses mapping and localization has been referred to as simultaneous localization and mapping (SLAM) or concurrent mapping and localization (CML). SLAM or CML is the problem of acquiring a map of an unknown environment with a moving robot, while simultaneously localizing the robot relative to this map [32]. The SLAM problem addresses situations where the robot lacks a global positioning sensor. Instead, it has to rely on a of incremental egomotion for robot position estimation (e.g., odometry). To solve the problem of odometry in SLAM, many approaches have been made thru the application of various filters introduced in [34-35].

There are two distinct mapping approaches available namely topological mapping and geometric mapping. A topological map is an abstract encoding of the structural characteristics of an environment. Often, topological maps [35-36] represent the environment as a set of distinctive places using points (e.g., rooms), connected by sequences of robot behaviors using lines (e.g., wall-following). A geometric map, on the other hand, is a representation of the precise geometric characteristics of the environment, much like a floor plan.

E. Object Transportation and Manipulation

Researches in this area of swarm robotics have drafted three types object manipulation method which are namely grasping, pushing and caging. Grasping [37-38] incorporates form closure and force closure techniques. Force closure is a condition that implies that the grasp can resist any external force applied to the object.

Pushing [39-40] on the other hand doesn't guarantee form closure or force closure, but requires external forces to be applied to the object such as gravity and friction. Pushing behaviors gives an advantage where any objects that can't be grasped to be moved and as well as to perform pushing to multiple objects.

Caging [41-42] introduces a bounded movable area for the object. Then, the contact between object and robotics mechanism need not be maintained by robot's control. This makes motion planning and control of each robotic mechanism to be simple and robust. This condition is called object closure.

F. Reconfigurable Robotics

Self-reconfiguring robots are able to deliberately change their own shape by rearranging the connectivity of their parts, in order to adapt to new circumstances, perform new tasks, or recover from damage [43].

Modular self-reconfigurable robotic systems can be generally classified into several architectural groups by the geometric arrangement of their units [44]. Lattice architectures [45-46] have units that are arranged and connected in some regular, three-dimensional pattern, such as a simple cubic or hexagonal grid. Lattice architectures usually offer simpler reconfiguration, as modules move to a discrete set of neighboring locations in which motions can be made open-loop.

Chain architectures [47-48] have units that are connected together in a string or tree topology. This chain or tree can fold up to become space filling, but the underlying architecture is serial. Through articulation, chain architectures can potentially reach any point or orientation in space, and are therefore more versatile but computationally more difficult to represent and analyze and more difficult to control.

Mobile architectures [49-50] have units that use the environment to maneuver around and can either hook up to form complex chains or lattices or form a number of smaller robots that execute coordinated movements and together form a larger “virtual” network.Self-reconfigurable robots have an advantage over fixed-shape robots in these environments because of their special abilities which include versatility, robustness, adaptability, scale extensibility and even self-repair.

G. Motion Coordination

Exploring into this domain, path-planning in swarm robotics has attracted a lot of attention in the past two decades. The problem of mobile robots path-planning is defined as follows: "for a given robot and an environment description, plan a route between two specific locations, which must be clear of obstacles and attend all the optimizations criteria" [51]. Studies in path-planning can be divided to local path-planning and global path-planning. In local path-planning, the planning is based on the information given by sensors installed on the robot, which provide details about the unknown environment [52]. In the global planning case, the environment's model is precisely defined [53-55], and the navigation is performed with the information known in priori.

The basic path-planning problem deals with static environments [53-54], in which the workspaces solely containing stationary obstacles of which the geometry is known. A natural extension to the basic path planning problem is planning in dynamic environments [56-57], in which besides stationary obstacles, also moving obstacles are present.

Various algorithms has been introduced to tackle the problems in path-planning for example fuzzy-logics [52], particle-swarm optimization (PSO) [58], ant-colony optimization (ACO) [53], D*[56] and K-Bug [51]. Most of the algorithms aim to solve the shortest path [53-54] problem in path-planning. Nearly all the previous work has been aimed at 2D environment; only some papers considered 3D environments such as the work presented by Yoshifumi et al [59] and Atsushi et al. [60].

The formation generation problem is defined as the coordination of a group of robots to get into and maintain a formation with a certain shape, such as circle [61], line [62-63] or even arbitrary shapes [64]. Erkin et al. [65] has divided formation generation into two groups. The first group includes studies where the coordination is done by a centralized [66] unit that can oversee the whole group and command the individual robots accordingly. The second group contains distributed [62] strategies for achieving the coordination. Various control strategies in formation generation such as behavior-based approach [63], potential field approach [67] and leader-follower approach [68] can be adopted to achieve coordination.

H. Learning

At present most learning algorithms can be classified as supervised and unsupervised learning. Supervised learning requires the use of an external supervisor. With supervised learning the robot knows what the best output is in a certain situation as the supervisor provides the corrective information to the learner. Unsupervised learning is a method of learning with minor or without any external corrective feedback from the environment [69]. This method is useful for allowing robots to adapt to situations where the task/environment is unknown beforehand or is constantly changing [70].

Inductive learning is one of the supervised learning paradigms which is a method that generalize from observed training examples by identifying features that empirically distinguish positive from negative training examples [71]. Decision tree learning [72], neural network learning [73] and inductive logic programming [74] are all examples of inductive methods that operate in this fashion. Another well studied paradigm would be explanation-based learning (EBL) [75-76] where prior knowledge is used to analyze, or explain, how each observed training examples satisfies the target concept. This explanation is then used to distinguish the relevant features of the training example from the irrelevant, so that examples can be generalized based on logical reasoning [71]. Other common paradigms that have been applied to robot learning are case-based learning (CBL) and memory-based learning (MBL) which are reported in [77].

Similarly, in unsupervised learning, paradigms such as evolutionary learning and reinforcement learning (RL) received major attention from the researchers recently. Genetic algorithms [78-79] and genetic programming [80-81] are the most prominent computational techniques for evolutionary learning. Reinforcement leaning (RL) is defined as learning what to do, how to map situations to actions so as to maximize a numerical reward signal. The learner is not told which actions to take, as in most forms of machine learning, but instead must discover which actions yield the most reward by trying them. Actions may affect not only the immediate reward but also the next situation and, through that, all subsequent rewards [82]. Examples of implementation of reinforcement learning can be viewed in [83-84].

I. Task Allocation

Task allocation means assigning tasks among the robots in swarm in a productive and efficient manner. Task allocation must ensure that not only the global mission is achieved, but also the tasks are well distributed among the robots. An effective task allocation approach considers the available resources, the entities to optimize (time energy, quality and etc.), the capabilities of the deployable robots and appropriately allocates the tasks accordingly [85]. Tasks can be discrete or continuous and also can vary in a number of other ways, including time scale, complexity and specificity [86].

Often in task allocation problems, the comparison between heterogeneous system and homogeneous systems are made. Such comparison results can be found in papers presented by Goldberg and Mataric [87-88].

The problem of multi-robot task allocation (MRTA) has been investigated using different techniques such as physical modeling [89], distributed planning [90], market-based techniques [91], auction based techniques [92] and ALLIANCE [93-94]. One of the first algorithms for market based solutions for the MRTA problem was described in the MURDOCH system developed by Gerkey et al. [95, 96].

III. Conclusion

Most of the research conducted was based on the biological inspirations adopted from the behaviors of ants, bees and birds. Implicit communication seems to give more robustness in the communication architecture of swarm robotics. Distributed control architecture was preferred compared to centralized architecture to prevent single point failures. As far as mapping and localization is concerned, work is still being carried out to fine tune the problems faced in this domain. In object transportation and manipulation, caging is preferred over the available methods as the constraints in the domain can be reduced and kept simple. In last two decades, research in reconfigurable robotics has taken a good progress. Even so, this domain is still at its infant stage. Path-planning and formation generation is one of the main domains that received a lot of attention from the authors. A lot of new heuristics and algorithms were introduced to solve the problems in this domain. In the learning domain, reinforcement learning (RL) was given much interest by the researchers. In task allocation domain, heterogeneous and homogenous systems are widely discussed. This domain has contributed in development of various techniques as listed in the paper.

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