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Swarm Robotics: An Extensive Research Review

Yogeswaran M. and Ponnambalam S. G.
School of Engineering, Monash University, Sunway Campus.
46150 Petaling Jaya, Selangor,
Malaysia

1. Introduction

Swarm robotics is a new approach to the coordination of large numbers of relatively simple physically embodied robots, that are autonomous, not controlled centrally, capable of local communication and operates based on some sense of biological inspiration (Sharkey & Sharkey, 2006a). Swarm robotic systems have become a major research area since 1980's, as new solution approaches are being developed and validated, it is often possible to realize the advantages of swarm robotic systems. Table 1 shows the key advantages of swarm

BENEFITS	DESCRIPTIONS
Parallelism	In task-decomposable application domains, robots can accomplish a given task more quickly than a single robot by dividing the task into sub tasks and executing them concurrently.
Robustness	No single point of failure for the system. This is an important characteristic since many of the applications rely on continued progress even if some components in the system fail.
Scalability	As the swarm of robots becomes larger, its relative performance in comparison to a centralized system becomes better.
Heterogeneousness	Since a group of robots may be heterogeneous, it can utilize "specialists" -robots whose physical properties enable them to perform efficiently certain well defined tasks.
Flexibility	Easily adaptable for different applications as different applications will have different requirements, a general architecture will need the ability to be easily reconfigured for the different problems it proposes to solve.
Complex Tasks	Tasks may be inherently too complex (or impossible) for a single robot to accomplish or performance benefits can be gained from using a swarm of robots.
Cheap Alternative	Building and using several simple robots can be easier, cheaper, more flexible and more fault tolerant than having a single powerful robot for each separate task.

Table 1. Characteristics of swarm robotic systems.

robotic systems (Cao et al., 1997; Altshuler et al., 2006; De le Torre & Stentz, 2001; Bruemmer et al., 2002): The early work on classification of research areas of swarm robotic systems was done by Dudek et al. (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. (1997) 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. Group architecture is further divided into centralization/decentralization, differentiation (denotes the homogeneous or heterogeneous robot groups), communication structure and modeling of other agents dimensions. Modeling of other agents dimension contains studies which models the intentions, beliefs, actions, capabilities, and states of other agents to obtain more effective cooperation between robots (Bayindir & Sahin, 2007).
Iocchi et al. (2001) 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, Parker (2003) has organized the areas by the principal topics that have generated significant levels of research. The categorization done in this paper has the main structure as in the work of Parker (2003). The research axes are biological inspiration, communication, control approach, mapping and localization, object transportation and manipulation, reconfigurable robotics, motion coordination, learning and task allocation. Each of the research axes are further separated into sub-categories for in detailed discussion.

2. Research axes

2.1 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. Jung & Zelinsky (2000) described the implementation of a heterogeneous cooperative multi-robot system that was designed with a goal of engineering a grounded symbolic representation which was inspired by the communication methods employed by biological systems.
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 (Sharkey, 2006b). Labella et al. (2006) 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 pheromones (Panait & Luke, 2004), 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 Payton et al. (2003) and Cazangi et al. (2005) used pheromones to achieve inter-robot communication mechanism in their research. Pheromones in swarm robotics can be viewed as a mechanism for inter-robot communication that can help reduce the complexity of individual agents. Pheromone communication adopted from necrophoric bee behavior was introduced in (Purnamadjaja & Russell, 2004) to develop interaction between the

members of a robot swarm. The term "Necrophoric" signifies the removal of bee corpses from inside of the hive. Nevertheless, the introduction of pheromones has driven the research exploitation in communication and localization in the studies of swarm robotics.

A higher level of studies in this area leads to exploit the cooperation and interaction abilities in mammals. Unlike insects, mammals behave differently toward individual social partners, rather than interacting with all entities in the same way. Tomlinson & Blumberg (2002) created an interactive virtual multi-agent system based on the behavior of packs of gray wolves. Their virtual wolves are able to form social relationships with each other via the mechanism of social relationship formation involves emotion, perception, and learning.

Fong et al. (2003) have modeled their robots to adopt human's social interactions. As 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 by Kitano et al. (1998). Robocup is an attempt to foster intelligent robotics by including design principles of autonomous agents, multi agent collaboration, strategy acquisition, real-time reasoning, robotics and sensor fusion.

2.2 Communication

The role of communication among mobile robots remains one of the most important research issues in swarm robotics system design. When a task requires cooperation, there is a need for some form of communication between the participating agents. Cooperation work requires communication whenever one agent's actions depend critically on knowledge that is accessible only from other 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 (also referred to as stigmergy (Trianni et al., 2004)) is a method of communicating through the environment.

Mir & Amavasai (2007) have modeled an autonomous swarm which is able to make decentralized decisions and demonstrate implicit communication. The paper also stressed that the swarm exhibits behavior based cooperation in the absence of explicit communication. White & Pagurek (1998) presented a new architectural description for an agent that is based on ants' stigmergy behavior for inter-swarm communication is introduced. Ramos et al. (2005) discusses several concepts related to self-organization, stigmergy and social foraging in animals. The paper also suggested and stressed the role played not only by the environmental media as a driving force for societal learning, as well as by positive and negative feedbacks produced by the many interactions among agents.

Pheromone signal plays an important role in communication domain as its capability of establishing communication between a sender and a receiver when there is no direct clear path between them. Pheromone communication is a type of implicit communication. There a many papers that have explored the use of pheromone signal to convey messages to other robots in a swarm such as the work by Purnamadjaja & Russell (2004) and Purnamadjaja et al. (2007). An improved form of pheromone communication method called "virtual pheromone" was used by (Payton et al., 2003; Meng et al., 2007) to employ simple communication and coordination to achieve large scale results in the areas of surveillance, reconnaissance, hazard detection, and path finding. More implementations of implicit communication in robots swarm has been reported by D'Angelo & Pagello (2005) and Bruemmer et al. (2004).

Explicit communication is the type of communication in which the robots directly pass messages to each other and/or to the human operator. McPartland et al. (2005) 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. Rybski et al. (2007) introduced and explored simple communication strategies which implemented implicit and explicit communication.

Trianni et al. (2004) studied the use of direct communication in order to achieve a reaction to the detection of a hole. Hayes et al. (2003) 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. Christodoulopoulos et al. (2007) implemented an ad hoc wireless network communication to exchange information between all its individual agents within the swarm. Ad-hoc mode is a method for wireless devices to directly communicate with each other. Operating in ad-hoc mode allows all wireless devices within range of each other to discover and communicate in peer-to-peer fashion without involving central access points.

Communication between robots can multiply their capabilities and increase the efficiency. This has been shown in simulation and on real robots. The amount of communication has also been studied. Sometimes even little communication will enhance the performance of the system (Adolfsson, 2001). 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.

2.3 Control approach

In general, swarm robot coordination strategies assume either a centralized approach, where a single robot plans for the group, or a distributed approach, where each robot is responsible for its own planning (De le Torre & Stentz, 2001). Iocchi et al. (2001) has clearly distinguished between centralized and distributed 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.

Table 2 shows the advantages and disadvantages of centralized and distributed control approach. Parker (1993) 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 Jr & Thomas (2007) introduced "Directed Stigmergy-Based Control" which incorporates the advantages of distributed control and centralized control. The aim of the paper is to stress the need of a supervisor in useful tasks that require searching large areas such as planetary science exploration, urban search and rescue, or land mine remediation.

However, both distributed and centralized control approaches have contributed individually to the study of swarm robotics and have generated interesting experimental results. Extensive studies in distributed control approaches (Spaan et al., 2006; Shen et al., 2002) lead to implementation of control laws or force laws (Gazi & Passino, 2002;

Dimarogonas & Kyriakopoulos, 2007) incorporating both attraction and repulsion features. On the other hand, centralized control approach (Li et al., 2007) has contributed in supporting several capabilities of swarm robotic systems such as hierarchical planning, concurrent planning, execution and perception, reactivity to environmental changes, error recovery, and coordination of multiple tasks.

APPROACH	CRITERIA	DESCRIPTION
Centralized	Advantages	Optimal plans can be produced. The leader can take into account all the relevant information conveyed by the members of the team and generate an optimal plan for the team.
	Disadvantages	Strongly rely on communication. Thus, when a communication failure takes place, it results in a failure of the entire system.
		A strongly centralized system can fail in accomplishing its task when its leader goes out of order.
		System response to changes in the environment is sluggish since all relevant information must be conveyed to the leader before any action can be taken.
Distributed	Advantages	Do not have a single point of failure. The loss of a single agent will not cripple the system, as can be the case in single-agent or centrally controlled systems.
		Can achieve complex results with relatively simple system design. The designer need only create simple, low level behaviors, instead of a single, computationally intense control system to govern all possible situations.
		Are inherently parallel, which allows for extremely scalable systems and faster task completion.
	Disadvantages	Often result in highly sub-optimal solutions because all plans are based solely on local information.
		Independent task execution by the system components causes problems in the area of coordination between the system agents.

Table 2. Advantages and disadvantages of control approaches (Iocchi et al., 2001; Steele Jr & Thomas, 2007).

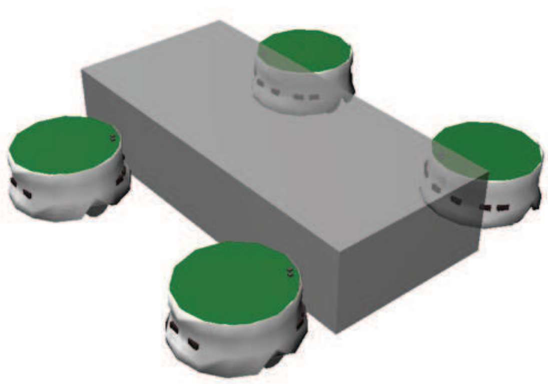
2.4 Mapping and localization

Mapping and localization is an exceedingly well-studied problem in swarm robotics which gathered a lot of research papers the last two decades. Mapping is a representation of the physical environments through the mobile robots sensory data into spatial models (Thrun, 2002). Localization is defined as finding the absolute or rational location of robot in the spatial models generated. 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).

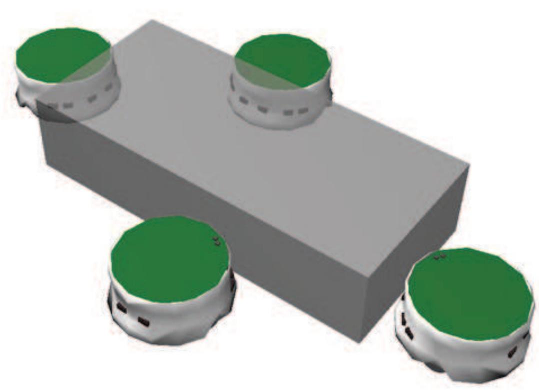
SLAM or CML is the problem of acquiring a map of an unknown environment with a moving robot, while simultaneously localizing the robot relative to this map (Thrun, 2002). The SLAM problem addresses situations where the robot lacks a global positioning sensor. Instead, it has to rely on a sensor (e.g., laser scanner, sonar and vision) 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 (Thrun, 2001; Se et al., 2002; Thrun et al., 2004; Howard, 2006).

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 (Kuipers & Byun, 1991; Fabrizi & Saffiotti, 2000; Choset & Nagatani, 2001) 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 (Wolter et al., 2004). This area also covers the studies in the type of terrains (Seraji, 1999; Triebel et al., 2006) and dynamic environments (Wolf & Sukhatme, 2004).

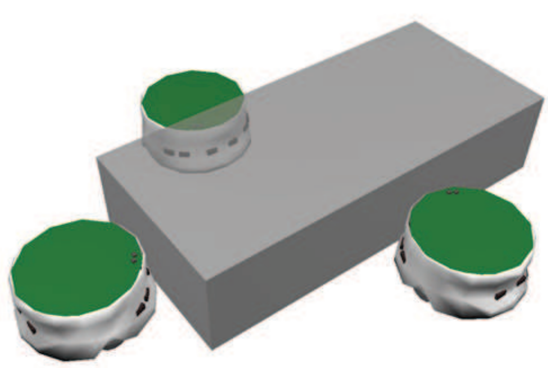
2.5 Object transportation and manipulation



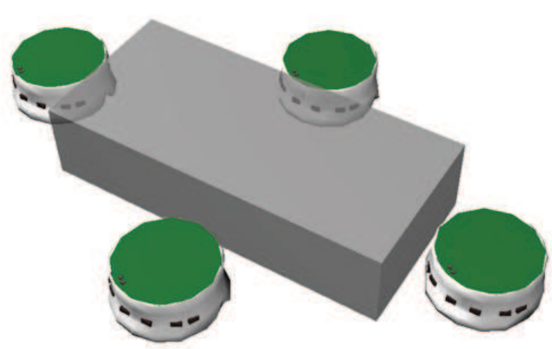
(a) Force closure.



(b) Form closure.



(c) Conditional closure.



(d) Object closure.

Fig. 1. Closure techniques for object manipulation.

Researches in this area of swarm robotics have drafted three types object manipulation method which are namely grasping, pushing and caging. In grasping, all robots are arranged so that the total robots system is grasping the object (Wang et al., 2007; Agassounon, 2004). Grasping incorporates form closure (refer to Fig.1(b)) and force closure (refer to Fig.1(a)) techniques. Force closure is a condition that implies that the grasp can resist any external force applied to the object. Form closure can be viewed as the condition guaranteeing force closure, without requiring the contacts to be frictional. In general, robots are the agents that induce contacts with the object, and are the only source of grasp forces. Pushing (Miyata et al., 1997; Yamada & Saito, 2001) 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. For this type of object manipulation, conditional closure (refer to Fig.1(c)) is introduced. Pushing behaviors gives an advantage where any objects that can't be grasped to be moved and to perform pushing to multiple objects as well. The main difficulty on object manipulation via pushing is that the robots cannot pull the object directly when it needs to slow down or move back the object.

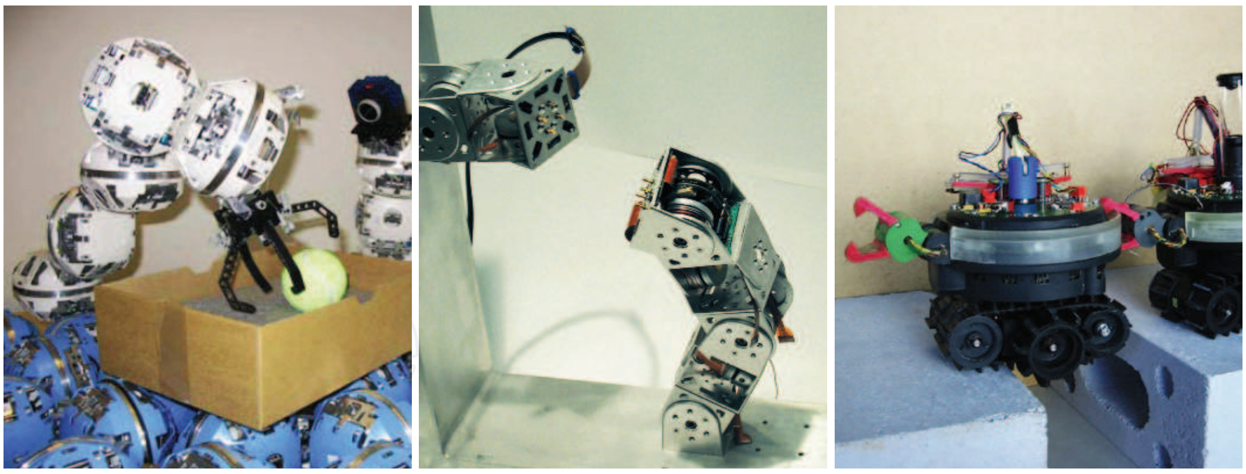
Caging (Pereira et al., 2003; Wang & Kumar, 2002; Wang et al., 2004) introduces a bounded movable area for the object. Then, the contact between object and robotics mechanism need not be maintained by robot's control. This makes motion planning and control of each robotic mechanism become simple and robust. This condition is called object closure (refer to Fig.1(d)). Caging has been widely used in manipulation of swarm robotics because this makes motion planning and control of each robotic mechanism simple and robust.

A leader-follower type multiple robot system was addressed by Wang et al. (2007) where the proposed system consists of a pushing leader, a robot without grasping mechanisms, and multiple follower robots. During the object transportation, a desired trajectory is given to the leader robot only, and follower robots estimate the trajectory of the leader based on force/moment from the object. In Behavior-based Multiple Robot System with Host for Object Manipulation (BeRoSH) (Wang et al., 1996), the unit which processes all common tasks is named the host. The host is incorporated into one of the robots, by giving the robot the ability to organize other robots and generate motivations/goals for the other robots. More papers reporting leader-follower implementations can be found in (GroB et al., 2006; Song & Kumar, 2002).

2.6 Reconfigurable robotics

Modular self-reconfiguring robotic systems or self-reconfigurable modular robots are autonomous kinematic machines with variable morphology. Beyond conventional actuation, sensing and control typically found in fixed-morphology robots, self-reconfiguring robots are also 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. Modular self-reconfigurable robotic systems can be generally classified into several architectural groups by the geometric arrangement of their units (Mark et al., 2007; Østergaard et al., 2006; Tuci et al., 2006).

- Lattice Architectures (refer to Fig.2(a)): have units that are arranged and connected in some regular, three-dimensional pattern, such as a simple cubic or hexagonal grid. Control and motion can be executed in parallel. Lattice architectures usually offer simpler reconfiguration, as modules move to a discrete set of neighboring locations in which motions can be made open-loop. The computational representation can also be more easily scaled to more complex systems.



(a) Lattice type. (Brandt et al., 2007)

(b) Chain type. (Yim et al., 2007)

(c) Mobile type. (Mondada et al., 2003)

Fig. 2. Architectural group.

- Chain Architectures (refer to Fig.2(b)): 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 (refer to Fig.2(c)): 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.

The types of modular self-reconfigurable robotic systems reported in the gathered literatures have been classified into their architectural groups and is presented in Table 3. Self-reconfigurable robots hold potential to be able to move robotics into new areas of application. In addition to traditional mass production environments, self-reconfigurable robots may become useful in real-world environments. These environments are characterized by being unstructured, complex, dynamic, and unknown. 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.

2.7 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" (Langer et al., 2007). 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 (Lei et al., 2006; Lei & Li, 2007). In the global planning case, the environment's model is precisely defined (Kang et al., 2007), and the navigation is performed with the information known in priori.

SYSTEM	CLASS	DOF	REFERENCE(s)
CEBOT	Mobile	various	Fukuda et al. (1989)
Polypod	Chain	2	Yim (1993)
Metamorphic	Lattice	3	Chirikjian et al. (1996)
3d Fracta	Lattice	6	Murata et al. (1998)
Molecule	Lattice	4	Kotay & Rus (1998)
CONRO	Chain	2	Castano et al. (2002)
Polybot	Chain	1	Golovinsky et al. (2004)
Telecube	Lattice	6	Suh et al. (2002)
Vertical	Lattice	2	Hosokawa et al. (1999)
Crystal	Lattice	4	Rus & Vona (2000)
I-Cube	Lattice	3	Unsal & Khosla (2001)
Pneumatic	Lattice	2	Inou et al. (2002)
Uni Rover	Mobile	2	Damoto et al. (2001)
M-TRAN	Hybrid	2	Murata et al. (2002)
Atron	Lattice	1	Brandt et al. (2007)
Swarm-bot	Mobile	3	Groß et al. (2006)
Superbot	Hybrid	3	Shen et al. (2006)
Catom	Lattice	0	Kirby et al. (2005)
Molecube	Chain	1	Studer & Lipson (2006)
YaMoR	Chain	1	Upegui et al. (2005)
Miche	Lattice	0	Gilpin et al. (2008)
Proteo	Hybrid	0	Bojinov et al. (2000)
ACM	Chain	various	Hirose & Mori (2004)
Fractum	Hybrid	0	Tomita et al. (1999)
Miniturized	Lattice	2	Yoshida et al. (1999)
Semi-Cylindrical	Hybrid	2	Murata et al. (2000)
M-TRAN II	Hybrid	2	Kurokawa et al. (2003)
RIKEN Vertical	Lattice	2	Hosokawa et al. (1999)

Table 3. List of self reconfigurable modular systems (Mark et al., 2007; Jantapremjit & Austin, 2001; Østergaard et al., 2006)

The basic path-planning problem deals with static environments (Garro et al., 2007; Li et al., 2007), 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 (Van Den Berg et al., 2006; Tian et al., 2007), in which besides stationary obstacles, also moving obstacles are present. Planning in such environment is challenging as in many cases the motions of the moving obstacles are not known beforehand, so often their future trajectories are estimated by extrapolating current speed in order to plan a path. This path may become invalid when some obstacle changes its speed, so then a new path should be planned. However, there is actually no time for planning; as the world is continuously changing, the computation would already be outdated even before it is finished (Smierzchalski & Michalewicz, 2007).

Various algorithms has been introduced to tackle the problems in path-planning for example fuzzy-logics (Lei & Li, 2007), particle-swarm optimization (PSO) (Rigatos, 2008), distributed gradient (Rigatos, 2008), ant-colony optimization (ACO) (Garro et al., 2007), genetic algorithm (GA) (Lei et al., 2006), D*(Van Den Berg et al., 2006) and K-Bug(Langer et al., 2007). Most of the algorithms aim to solve the shortest path (Garro et al., 2007) 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 Kitamura et al. (1995) and Yamashita et al. (2000).

Nonholonomic path-planning is also covered in this category. Nonholonomic systems are characterized by constraint equations involving the time derivatives of the system configuration variables. These equations are non integrable; they typically arise when the system has less controls than configuration variables. For instance a car-like robot has two controls (linear and angular velocities) while it moves in a 3-dimensional configuration space (Laumond et al., 1998). Nonholonomic constraint generally exists in wheeled system. Under the nonholonomic constraint, the vehicles and wheeled mobile robots can only run along the tangential direction of trajectory within the steering angle limit, and the motion is non-slipping and pure rolling (Liu et al., 2007). In another word, the robot can instantly move forward and backward, but cannot move sideward.

Formation or pattern generation is another area in motion coordination that received a lot of author's attention. 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 (Defago & Konagaya, 2002), line (Arkin & Balch, 1999) or even arbitrary shapes (Sahin et al., 2002). Current application areas of pattern formation include search and rescue operations, landmine removal, remote terrain and space exploration, control of arrays of satellites and unmanned aerial vehicles (UAVs). Bahceci et al. (2003) has divided formation generation into two groups. The first group includes studies where the coordination is done by a centralized (Belta & Kumar, 2002) unit that can oversee the whole group and command the individual robots accordingly. The second group contains distributed (Pavone & Frazzoli, 2007) strategies for achieving the coordination. Chen & Wang (2005) discussed various control strategies in formation generation such as behavior-based approach (Arkin & Balch, 1999), potential field approach (Bruemmer et al., 2002), leader-follower approach (Desai et al., 2001) and more.

2.8 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 (Alpaydin, 2004). This method allows for automated design of efficient, robust controllers, which saves much design time and effort. Furthermore, it is useful for allowing robots to adapt to situations where the task/environment is unknown beforehand or is constantly changing (Pugh & Martinoli, 2006).

There are many paradigms in supervised learning that have been identified in the open literatures. 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 (Mitchell & Mitchell, 1997). Decision tree learning (Quinlan, 1986), neural network learning (Pomerleau, 1990) and inductive logic programming (Konik & Laird, 2002) are all examples of inductive methods that operate in this fashion. Another well studied paradigm would be explanation-based learning (EBL) (Mitchell & Thrun, 1993) 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 (Mitchell & Mitchell, 1997). EBL studies how domain knowledge about the function being learned can be used to speed up learning (Mahadevan, 1996). Other common paradigms that have been applied to robot learning are case-based learning (CBL) and memory-based learning (MBL) which were reported by Sim et al. (2003).

Similarly, in unsupervised learning, paradigms such as evolutionary learning and reinforcement learning (RL) received massive attention from the researchers recently. Genetic algorithms (Ram et al., 1994) and genetic programming (Koza, 1994) are the most prominent computational techniques for evolutionary learning. Evolutionary learning starts with a population of policies, and combines them to produce better policies till an optimal policy is found. The evolutionary learning paradigm is normally set with a good set of policies to start which helps to accelerate the learning process.

Reinforcement leaning (RL) (Fernandez et al., 2005) 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 (Sutton & Barto, 1998). Trial-and-error search and delayed reward are two most important distinguishing features of RL.

Among RL algorithms, Q-learning has attracted a great deal of attention in research. Q-learning (Yang et al., 2007; Ahmadabadi & Asadpour, 2002) is a recently explored RL algorithm that stores the expected reinforcement values associated with each state-action pair usually in a lookup table. In a survey conducted by Yang & Gu (2004) on multi-agent reinforcement learning, they have highlighted that traditional Q-learning is not directly applicable in swarm robots application as involvement of multiple robots in the environment makes the environment dynamic. Due to that reason, many researchers have put efforts to modify the Q-learning framework to suit dynamic environment involving multiple robots. Algorithms such as Minimax-Q learning (Littman, 1994), Nash-Q learning (Hu&Wellman, 2003), Friend-or-Foe Q-learning (Littman, 2001), rQ-learning (Suh et al., 1997), Fictitious Play (Claus & Boutilier, 1998), SARSA learning (Sutton & Barto, 1998) and Policy Hill Climbing (Ng & Jordan, 2000) were gathered and reported by Yang & Gu (2004).

As far as robot learning is concern, it is still at the infant stage of research and is one of the interesting and difficult machine learning problems. This domain can be further explored by exploiting more paradigms and scaling the algorithms to solve more problems related to robot learning.

2.9 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 (Baghaei & Agah, 2002). Task refers to a sub-goal that is necessary for achieving the overall goal of the system. Tasks can be discrete or continuous and also can vary in a number of other ways, including time scale, complexity and specificity (Gerkey & Mataric, 2004).

Often in task allocation problems, the comparison between heterogeneous system and homogeneous systems are made. Heterogeneous system consists of a team of robots whose members have a difference either in the hardware devices or in the software control procedures. Homogeneous system consists of a team of robots whose members are exactly the same both in the hardware and in the control software (Iocchi et al., 2001). Such comparison results can be found in papers presented by Goldberg & Mataric (2002).

The problem of multi-robot task allocation (MRTA) has been investigated using different techniques such as physical modeling (Parker, 2002), distributed planning (Ortiz et al., 2005), market-based techniques (Dias et al., 2006), auction based techniques (Bertsekas & Castanon, 1991) and ALLIANCE (Parker, 2001). One of the first algorithms for market based solutions for the MRTA problem was described in the MURDOCH system developed by Gerkey & Mataric (2002). The implemented methodologies served as design guidelines to allow swarm robot systems to gain more efficiency.

3. Conclusion

A state of the art survey of swarm robotic research is presented in this paper. The research in the area of swarm in these nine research axes are critically reviewed and reported for the benefit of researchers in this field. Swarm robotic systems have a very high potential in solving highly complex tasks as they are competent of parallelism, robustness, scalability and low cost. It is clear that since the initiation of the field of swarm robotics, significant progress has been made on domains such as biological inspiration, communication, control approach, mapping and localization, object transportation and manipulation, reconfigurable robotics, motion coordination, learning, and task allocation. 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 homogeneous systems are widely discussed. This domain has contributed in development of various techniques as listed in the paper.

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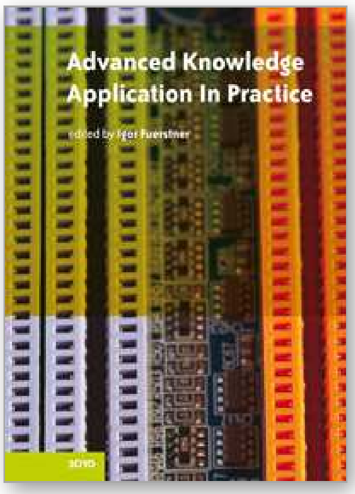

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The integration and interdependency of the world economy leads towards the creation of a global market that offers more opportunities, but is also more complex and competitive than ever before. Therefore widespread research activity is necessary if one is to remain successful on the market. This book is the result of research and development activities from a number of researchers worldwide, covering concrete fields of research.