TEST Engineering & Management

November-December 2019
ISSN: 0193-4120 Page No. 5890 - 5903

An Exploration of Swarm Behavior and Design Human-Swarm Interaction Model

[1]Mohammad Nuruzzaman, [2]Azham Hussain, [3]Omar khadeer Hussain
[1]School of Business, University of New South Wales, Canberra, ACT, Australia
[2]School of Computing, Universiti Utara Malaysia, Sintok, Kedah 06010
[3]School of Business, University of New South Wales, Canberra, ACT, Australia
[1]dr.zaman1981@gmail.com, [2]azham.h@uum.edu.my, [3]o.hussain@adfa.edu.au

Article Info
Volume 81
Page Number: 5890 - 5903
Publication Issue:
November-December 2019

Article History
Article Received: *5 March 2019*
Revised: *18 May 2019*
Accepted: *24 September 2019*
Publication: *27 December 2019*

Abstract

Developing a robotics system is one of the greatest challenges that are able to interact with unpredictable environments in real-time. A possible solution may be to use swarm robots behaving in a self-organized manner, similar to an ant colony. Efficient mechanisms of division of labour, parallel operation and share of information among group members are key components of the tremendous ecological success of ants. Inspired by the ant colony, indeed allows the design of robust, effective and flexible robotic system. A single robot is insufficient to process information and many other aspects, thus cooperation of multi-robot are needed to complete a task in an efficient way which results in the swarm robotics (SR) system. The aim of this paper is to review significant literature on collective behaviours and methods in the SR.

This paper will review recent accomplishments in SR and analyse existing literature. It begins with a brief overview of swarm robot, classification of behaviour and then a discussion of the importance of SR by explaining various tasks in swarm robotics. This paper described and identified the challenges that should be resolved in the SR system and their applications for real-world. Finally, this paper provided possible directions for future research and discussed the relevant challenges to be addressed in order to push forward the study based on our extensive analysis of the reviewed literature.

Keywords: *Swarm Robotics, Swarm Behaviour, Collective Behaviour, Autonomous System, Human-Swarm Interaction.*

1. Introduction

Swarm robotics is mostly inspired from the nature swarms. In nature, there are a set of rules, pattern can be noticed that make seemingly chaotic processes logical [1]. The research inspiration of swarm robotics comes from observing the social behaviour of insect colonies, schools of fish, flocks of birds, bacteria colonies and groups of amoeba [2]. Inspiration is taken from nature as it is shown to support the development of novel rule sets that can be used to solve difficult problems and might be impossible to solve with traditional techniques [3], [4]. For example, ants show an incredible ability to collectively transport irregularly shaped objects without prior knowledge of object shape and mass. This allows an ant colony to collectively achieve a task that is beyond the capabilities of a single individual, as well as faster transport, robustness to individual failure and better adaptability to varying object size. The central idea of this collective behaviour is to perform a complex task by dividing it into simpler tasks that are easily performed by individuals [5].

Human-Swarm Interaction (HSI) comprises understanding human interaction with the swarm of robots and an assessment of the human responses during that interaction. In such systems, human operators use the information sent by agents and issue new commands to them [6]. The presence of human operators can provide recognition, mitigation of the shortcoming of autonomy,

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failure repair, new goals changes, decision making and information for better swarm performance. Therefore, to influence the swarm of robots to be goal-directed in dynamic and complex environments human assistance is essential. It may useful in several real-world applications such as urban search and rescue, surveillance, oil spill recovery, plume tracing, autonomous construction and military operations. Additionally, human interaction provides abilities to control swarm robots. For example, a human operator can switch swarm behaviour, change overall location or inject new objectives into the agent's low-level control. However, knowledge of a limited number of robots only can be preserved by a human [7]. It is widely agreed that there is limited value in an autonomous system that cannot be controlled.

The purpose of our research on swarm robotics is to explore such mechanisms for real-life applications and design a comprehensive framework for humans interacting with swarm robots using the handheld device as shown in Fig. 1.

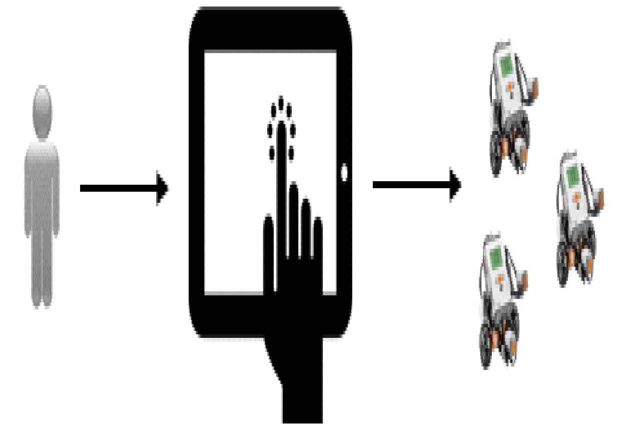

Figure 1: Human Swarm Interaction via a handheld device

2. Background of the Study

In the last few decades, there has been a considerable amount of theoretical research on swarm robotics and deployed in several scopes of applications including localization, surveillance, medical operations, sensing, and search-rescue operations [13]. These tasks are very sophisticated and hard to propose a direct solution due to collective behaviour. Behaviour control is a challenge for any swarm robotics system. Individual control rules must be found that result in the desired collective behaviour. To solve this issue, swarm robotics researchers proposed various tasks such as flocking, navigating, path planning, motion coordination, obstacle avoidance etc. Among these, flocking is the most significant task [10]. Apparently, coordinating a large number of robots with individual rules is not an easy job. Therefore, interactions of a group of robots within an environment have been the main interest of the research. In this section, several tasks for corresponding solutions using swarm intelligence approach are surveyed.

Behavioural Classification

Behavioural-based architectural designed are commonly used to control robots. However, flexibility often comes at the cost of difficulty in reusing existing behaviours for new application domains and unanticipated interferences among behaviours. Therefore, categorization is important for those behaviours in SR.

The classification of SR systems was introduced by [15], who identified research domain into five areas such as swarm size, communication topology, communication range, bandwidth, swarm unit processing ability and swarm reconfigurability. Luca Iocchi et al. [16] illustrated multi-robot systems by looking at their cooperative characteristics. With different perspectives, many classification criteria had been proposed successively to summarize the research area of SR into a classification of cooperating systems [2, 10, 15-22]. According to Brambilla et al. [8] analysed literature from SR engineering perspective view as shown in Fig. 2.

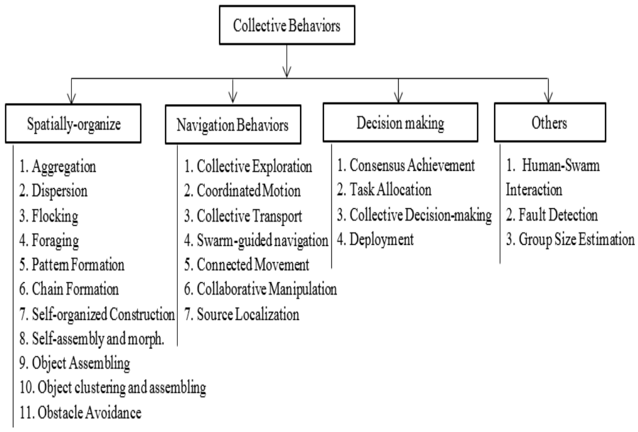

Figure 2: Classification of Collective Behaviour of Swarm Robotics

- ***Spatially-organize behaviours**:* Spatially organizing behaviours focus on how to organize and distribute robots and objects in search space. There are several possible ways robots can be organized and distributed such as aggregation, patterns and physically connected robots etc.

- ***Navigation behaviours**:* Navigation behaviours are coping with the problem of coordinating the movements of a swarm of robots such as collective exploration, coordinate motion, collective transportation etc.

- ***Decision-Making behaviours**:* Decision-making behaviour deals with how robots influence each other when making choices. It can be used to answer two opposite needs—agreement and specialization.

- ***Others**:* This described as significant works in SR that did not mention in the above categories. Such as collective fault detection, human-swarm interaction etc.

3. Literature Review

A number of studies [1, 9-13] have explored HSI with few or many agents. According to Kolling et. al [9], HSI systems can be divided into six components. These are- cognitive complexities, interaction, swarm state visualization, levels of autonomy and input timing as shown in Fig. 3.

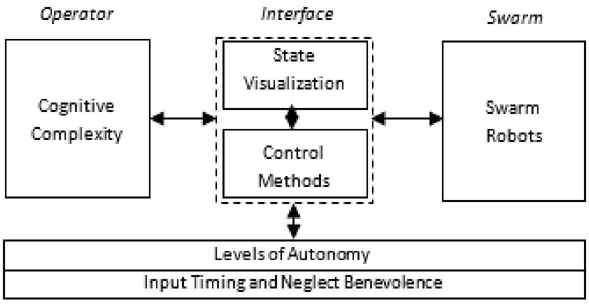

Figure 3: Key Components of Human-Swarm System

As shown in Fig. 3, an operator interacts with swarm robots through an interface that is constrained by the means of communication. It relies on control methods that visualize and estimate state information of the swarm robots. It facilitates the interaction between human and swarm robots. The entire system is influenced by levels of autonomy, input timing and neglect benevolence. Neglect benevolence is the time a human can neglect tolerance the swarm to allow for stabilization before issuing new commands [29].

There is a need for human operators to oversee swarm operations and give both goal-directed input and correct unforeseen errors in the swarm's operation. The problem is controlling the swarm system through direct teleoperation of individual agents. Before sending a command to a swarm robotics system, a human operator needs to know what state the system currently in. Therefore, swarm robotics system should provide feedback about the state of the individual agents to the human operator. Kolling et. al [9] identified two challenges when agents send state information to the human operator. The first challenge is due to the small size of agent's hardware and its simplicity. Individual agents may not be equipped with the dedicated hardware required to provide meaningful feedback to the human operator. The second challenge is due to the large swarms of robots. Even if an agent can interact with a human operator(s) meaningfully, it does not mean that each agent can do so. Hence, the state of the individual agents and composite information of swarm robots need to be delivered to the operator.

Another study [51] presents two control methods—selection and beacons for a human operator to control a foraging swarm of robots. The selection control requires an active selection of a sub-swarm of robots while the beacon control exerts an influence on nearby agents. Both methods are implemented in a testbed in which operators solve the foraging problem by utilizing a set of swarm behaviours. In addition, performance benchmarks are compared through five variations of swarms. The first variation uses random motion and agents turn into a new direction each time they collide with another agent or obstacles. The second variation uses random motion except when an agent is within sensing range. In this case, the agent moves forward to the closet object until all information is collected. The third variation uses a potential-field-based approach algorithm, in which agents are repulsed by each other. The fourth variation uses the same approach, but an agent moves forward until neighbours transmit no more messages. The fifth variation uses a pheromone-based approach for a foraging task. The result of their study [51] showed that human operators perform better with selection control. However, one of the main problems to be tackled to enable human control of swarms is scaling the controls to larger numbers of agents, larger environment and more complex tasks. In such a case, beacon control may more scalable if used to its full potential.

Reynolds [42] works is influenced by collective animal behaviour in nature. The paper created a virtual flock of birds to model the local rules governing flocking behaviour in animals. Couzin et. al [44] introduced leaders into a swarm and investigated how leaders within such groups can influence the overall movement of the swarm without directly telling the followers what to do. These authors also make use of swarm "leaders" and "predators" which can pull and push other members of the swarm, respectively. Although the authors found the leaders more effective, there are still cases where predators can be beneficial, such as scenarios where it is necessary to break up the swarm into separate smaller groups. In addition, the study showed that only a small number of swarm members need to be knowledgeable for this to work and it lower the control requirements for any human using this model.

A follow-up study [19] conducted a user study of swarm control with dynamically selected leaders. This paper investigates the use of a small subset of the swarm as leaders that are dynamically selected during execution using a flocking-style algorithm. The authors identified three different aspects of dynamic leader-based swarm control and interactions namely: Leader density, sensing error and method of information propagation on system performance and human control of the swarm. The leaders passively influence the consensus of the swarm similar to the Couzin model [44] as shown in Eq.1. (1)

where is the position vector at discrete-time, is the unit direction vector, is the time step length, is the constant speed and is initial direction and position. Their results show that it is possible for a human to control a simulated swarm of robots and different numbers of leaders can be selected effectively.

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4. Behaviour of Swarm Robotics

To analyse the potential capabilities of robot swarms, swarm robotics had been studied in the context of producing different collective behaviours as shown in Fig. 2. The following section will be discussed in more detail on swarm behaviours.

Aggregation

Aggregation is referred as the gathering of spatially distributed robots. It is one of the most fundamental and useful behaviours in swarm robotics. It is a crucial task due to it combines several aspects of multi-robot tasks including cooperation and precursor of collective behaviours for the accomplishment of many complex tasks that rely on local interactions [27]. For example, self-assembly, collective movement, pattern formation, exchange information and pulling heavy objects require prior aggregation.

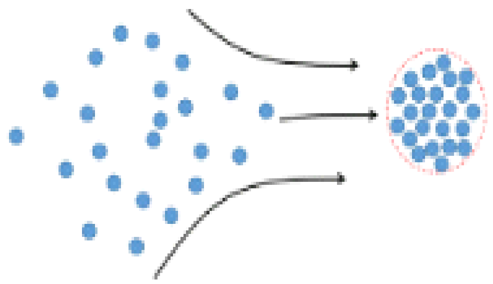

Figure 4: Aggregation of Swarm of Robots

Fig. 4 shows the aggregation of a swarm of robots. Aggregation process is not the formation of a collection of individuals in nearness of each other, but it describes in terms of density of robots in a given space. The objective of aggregation is to group individual robots into a cluster without using any environmental clues and use as a starting point of performing task [17]. Aggregation is a very useful building block; it allows swam of robots to get sufficiently close one another so that they can interact locally without central control or global information exchange.

Source of Inspiration: Aggregation behaviour can observe in almost all social insects such as ants, fishes, bees, bacteria, sheep, penguins and cockroaches etc. [28]. Aggregation helps them to avoid predators, increase chances of survival, build nests or find food. Some of the aggregation behaviours are known to be facilitated by environmental clues; flies use light and temperature, and sowbugs use humidity for aggregation. Other aggregations are self-organized. Aggregation of cockroaches, penguins and fish do not use such environmental clues but are resulting in the emergent cooperative decision [11, 29].

Challenges in this Behaviour: There are a few key challenges in aggregation. Firstly, robots use on-board sensors for robot-to-robot interaction and move forward. Whenever a robot encounters an element, sensors differentiate it from any other type of elements whether it is a robot, obstacle or target object. The main issue is that a swarm robot has limited sensing capabilities, visibility and is unable to communicate with other robots in large space due to the shorter frequency range. Cortes et al. [31] explored how to control and coordinate a team of mobile robots, sensor responsible, distributed and adaptive. Moreover, another study [32] proposed colours, luminance and relative positions can be used for sensing and are able to provide information. However, their study failed to provide evidence of different illumination conditions.

According to Arvin et al. [33] analysed BeeClust algorithm in a light distribution environment and provided evidence that aggregation relies on the interaction between individuals and the mechanism of amplification. The study indicates that individuals without global information can implement collective decision-making through dynamic interaction. Another study [34] shown that aggregating robots with limited information are challenging. This is due to the robots are not being controlled properly and maybe forming a separate cluster because of mechanical constraints such as sensor and controller complexity. The mechanical constraints determine saturation effect in robot actuators and amplitude of the control inputs which regulate robot motion. For this reason, only a limited number of studies have been considered for swarm aggregation. Additionally, authors [35] made a comprehensive investigation between hardware quality and swarm performance. Their study observed that hardware imperfection can led inaccurate movement of robots and delay to identify the target as well as decrease performance. They suggested high quality sensors, actuators, design fitness function and genetic encoding are required when constructing swarm robots.

Implementing self-organizing aggregation behaviour is crucial that relies only on local information. Typically, it requires an appropriate choice of waiting times for how long to stay in a cluster in order to avoid deadlocks. This study [34, 37] is a good example that robots achieve aggregation using finite-state characterized by "walk, approach, wait and leave", where robots continuously search for target (walk) within its sensing range, it detects other robots, it moves towards the nearest robot (approach) and stay in cluster (wait). Otherwise, robots keep moving (leave) randomly with a predefined probability. Using this approach, global aggregation is controlled by probability for robots to detect other robots after random walking. Nevertheless, authors did not consider that small aggregates prevent the formation of larger aggregate due to robots can leave their aggregate at any time.

Dispersion

Dispersion can be considered as the opposite of aggregation behaviour. Almost every application of swarms of robots requires dispersing throughout the unknown environment as a means for exploration. In dispersion, each individual robot has to maintain a predefined distance from its nearest neighbour and cover a large area while preserving the connectivity within the swarm [38]. It is one of the basic manoeuvres applicable such as planetary exploration, surveillance, nuclear decontamination after a disaster, collect samples from the unknown surface, reconnaissance in various hazardous, detect the victims or chemical leaks.

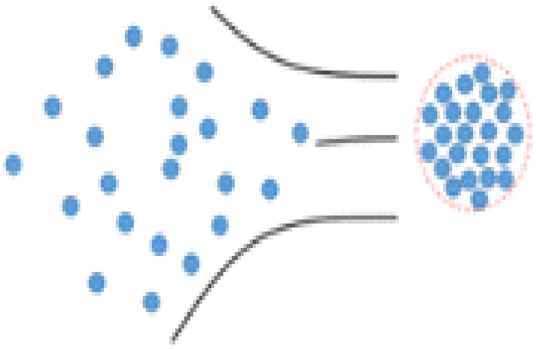

Figure 5: Dispersion of Swarm of Robots

Fig. 5 shows the dispersion behaviour of a swarm of robots. In the point of SR views, the robot moves forward in a certain direction. If sensor intensity decreases during its move, it can be assumed that the robot is moving away from other robots. However, if intensity increases, the robot is most probably towards other robots and it should change its route to enable dispersion. The objective of dispersion behaviour is not only gradually expanding in an environment maximizing the area covered, but it also stays connected at all times through some form of a communication channel.

Source of Inspiration: Dispersal behaviour is found in social insects those colonies are initiated by swarms comprising one or more queens and numerous workers such as honey bee, bacteria, amoebas. In the honey bee, quorum sensing is used for nest-site selection when a strong colony divides by swarming. The mother queen leaves parental nest, widely dispersed by a sufficient number of scouts to find future nest-site, while daughter queen and rest of the bee workers remain in parental nest. Upon departing its parental nest, scout bees search for a nest-site and recruit other honey bees to newly discovered nest-site. Once, suitable nest-site is selected, the swarm decamps in coordinate group behaviour and fly together with scouts guiding to their new place [39].

The above honey bee scenario, this study can perceive that it is a remarkable phenomenon in biological systems and effective way of communication. There are three basic behaviours that are most effective for a swarm of robot dispersion. These are random walk behaviour, find opening behaviour, and comparison behaviour [40]. In random walk behaviour, a robot moves on a slightly curved path by turning 10^0 per step. When a robot detects an obstacle, it stops, turns and then resumes moving. On the other hand, find opening behaviour uses sensors to locate openings such as doorways or halls. Finally, comparison behaviour is able to recognize another robot that is nearby and move away from it.

Challenges in this Behaviour: There are three quantitative goals in dispersion behaviour that are expected to fulfil by a swarm of robots. First, robots should move outward quickly to a maximum coverage of the area as much as possible. Second, robots need to move effectively that does not lead to any large gaps or overlap and maintain distance between them [24]. Third, while robots are moving forward, they need to stay within communication range. Due to communication range and sensing limitations, it is often necessary to execute dispersion task with little or no communication between robots.

According to Ludwig and Gini [41] cited that problems of area coverage categorized into three—blanket coverage to maximize the total detection area, barrier coverage to minimize the possibility of undetected penetration of a defined barrier, and sweep coverage where to cover an area with a moving barrier. Their study uses wireless signal intensity and through an experiment authors claim that swarm of robots can be dispersed without knowing the relative locations of neighbouring robots. It is agreed that signal intensity is proportional to the inverse square of the distance robots travel. Intensity does not depend on the distance between robots, it depends on the structure of the antenna that is used and the surrounding environment. As a result, limited distance of wireless signal intensity and environmental obstacles that causes noise in the signal may not disperse the swarm of robots effectively.

Much of prior works on swarm dispersion has been studied like uniform random walks, repulsive forces with a variety of combinations and models. For example, flocking, potential fields, diffusion-limited aggregation and springs. All of these generally perform poorly for large swarms of robots. More recently a study [24] was introduced reactive levy walks where scale-free particles motion processes formulated as models. In their study, a swarm of UAVs used to deploy over a large wilderness area and able to tolerate a transient gap during its initial deployment.

Flocking

Flocking task represents moving together as a single entity while maintaining predetermined formation or pattern and avoiding collisions with obstacle and other members of the flock. Flocking behaviour does not involve central coordination. This behaviour emerges at the collective level in a distributed manner, as a consequence of local interactions between autonomous agents. Through flocking, they gain several advantages such as higher survival rate, more precise navigation with and reduced energy consumption, exploration, object transportation

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and shepherding (guiding). In addition to aggregation, flocking has an important characteristic at the swarm level know as alignment, which allows a group to move collectively in a given direction.

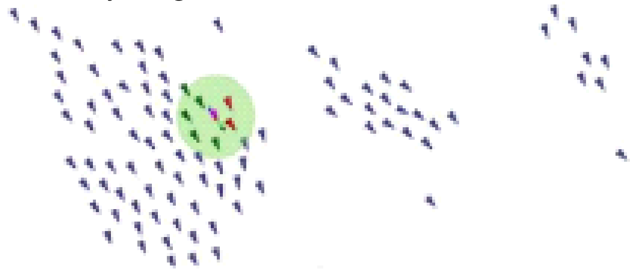

Figure 6: Flocking behavior

Fig. 6 shows that a group of a swarm of robots navigating in an arena with limited or no collisions between robots. They adjust their physical movement to avoid predators, seek food and mates, optimize environmental parameters such as temperature, etc. The objective of flocking behaviour is a swarm of robots are supposed to keep a constant distance from one another and a uniform alignment while moving using the "Boids" model proposed by [42].

Source of Inspiration: Flocking is a behaviour observed in nature in many species. In particular, flocking in a group of birds, school of fish are impressive examples of flocking, which form large groups of individuals moving together toward a common target location. Through flocking, they gain several advantages such as higher survival rate, more precise navigation with and reduced energy consumption.

There are three fundamental rules for simulating flocking and herding behaviours. These are (i) *separation*: when the flock members get very close to each other, they must move away from each other via a repulsive force. As a result, sufficient free space around each member is guaranteed; (ii) *alignment*: each member should be moving along the general direction of its neighbouring members and (iii) *cohesion*: each member should be move towards the centre of its local neighbours so that they stay close to the group until sense repulsive forces. The logic behind these rules is that while each individual follows relatively simple rules when taken as a whole, they move as an organized group [42].

Challenges in this Behaviour: The motion of flocking robots is a result of integrated actions of all members in the group that each member acts based on a local perception of its surroundings. Any geometrical or topological shape that is used to determine the positions of flocking robots is called a formation, which consists of three elements. These are pattern generation, flocking and pattern switching. According to [43] establishing a pattern can be separated into two sub problems: (i) identification of robots in the flock, which depends on their communication ability in forming an integrated network; (ii) position of the robots in the pattern, which needs a referencing mechanism such as leader-follower.
In Boids, the behaviour is implemented through the summation of vector forces acting on each agent. As such as the number of agents in a swarm increases the amount of computation required for each time instant increase by an order of ; where is the number of agents in the Swarm. Couzin model [44] suggested a more accurate mathematical description of Reynolds model [42] in three-dimensional space referred as Couzin model. It is assumed that a group of agents are moving together under control or self-organized manner. All agents determine its next position according to the neighbours' situations, with the same constant speed but in varying directions. It is reasonable and efficient to represent a team of agents for their flocking behaviour in environment.

A self-organized flocking behaviour for a swarm of robots was presented by [45] without using the emulated sensors or the prior knowledge of the destination. The simulation shows that with only local interactions robots can share a common flocking direction in a self-organized process until the sensing noise exceeds to a certain extent. In the follow-up work, the authors studied how the swarm can be steered toward the desired direction by guiding some of the individuals externally. The results are qualitative in accordance with the ones that were predicted using in Ref. model [44].

Foraging

Foraging behaviour also is known as prey retrieval or gathering task. It can be viewed as a subset of object clustering where swarm robots cluster preys at the nest. Foraging efficiency is a key factor influencing colony productivity and mechanism of task allocation. The potential applications of foraging are demining, planetary exploration, hazardous waste clean-up, search and rescue operations.

Figure 7: Foraging behaviour

The Fig. 7 illustrated resource allocation problem. It can be decomposed into a sequence of sub-tasks of two types- (i) ants are looking for prey in the environment (ii) carrying an item to bring to the nest. Execution of each task facilitated by mechanisms of cooperation between members of the swarm. In order to achieve cooperation, communication between individuals is vital. This communication can be via shared memory, the direct exchange of information or through the environment. The objective of foraging behaviour is locating resource deposits, gathering performance and signaling to guide others.

Source of Inspiration: Foraging is most common in social insects and appears either in the form of stigmergy or direct signaling. The collective foraging task is inspired by the behaviour of ants, which search for food sources distributed around their nest. They are able to efficiently exploit food sources using local interactions between individuals. Ants utilize stigmergy and termites when they lay pheromone trails that lead to food, changing their environment such that is stores useful information that guides the behaviour of recruited conspecifics [47]. In other hand, honeybee relies on directly influencing their nestmates. They use waggle dance that communicates both food quality and location. Flexibility and sophistication are achieved by both scoutings for new food sources and re-evaluation of old foraging sites, allowing bee colonies to rapidly adapt to changing quality [48]. A number of approaches have been taken to implementing foraging in swarm robot, including random walking, bucket brigading, uniform random distribution.

Foraging strategies divided into three- Individual foraging, Behavioural matching, Recruited foraging, cooperative hunting. Individual foraging is a simple implementation where individual searches for food alone and does not receive any information about food other than what it can itself acquire. Behavioural matching, an individual follows successful foragers and thus utilises social information about where food could be located. During recruited foraging, an individual that is a part of a colony obtains food either for itself or for other colony members. Various tactile, chemical (stigmergy) or visual cues are passed between group members in order to distribute knowledge about the direction and quality of food. Bees use waggle dance in order to know the newly discovered and better food sources.

Challenges in this behaviour: In foraging, the challenge is to find the optimum search strategies that maximize the ratio of discovering a place of interests and returned to the resources committed in the arena. This paper explored and analysed different foraging strategies in terms of performance and the modelling of foraging were developed. While foraging is a task experimented with in swarm robotics, it is often the case that foraging strategies inspired by nature.

The study [49] reviews how food acquisition is solved by various biological species including ants termites, bees, dolphins, whales and humans. The authors described that the choice of how to obtain food does not depend as much on species as it depends on the niche the organisms find themselves in. on occasions when food is hard to obtain for an individual. Group foraging occurs and its benefit grows with group size until a threshold is reached when a large aggregate cannot obtain enough food and it needs to split up.

According to [50] presented that it is possible to understand swarms by studying how they behave in various environments. However, it is often difficult to intuitively predict the aggregate results of systemic properties of swarm behaviour because of the non-trivial nature of inter-robot interactions and interaction between robots and their environment. The authors implemented B-Swarm for recruitment in a foraging task. B-Swarm were not better equipped than I-Swarms to selectively forage from more energy-efficient deposits. Since B-Swarm robot was recruited to any deposit with an energy efficiency higher than the lowest known *Ee*, a larger proportion of the swarm would collect from ordinary locations instead of exploring the environment. However, it was observed that unemployed B-Swarm robots could target higher *Ee* deposits as a consequence of receiving information from a large number of returning foragers.

Collective Transport

Collective or cooperative transport/movement of an object by two or more individuals is an impressive example of collaboration among individuals. However, this behavioural mechanism that leads to cooperation in social insects are often unknown or poorly understood. Cooperative transport is one of the more distinctive collective behaviours in which a group of individuals has to cooperate in order to collect and retrieve an object that is too heavy to be transported by an individual. For example, carry large food items by groups of ants from one location to another. This technique is also known as group prey retrieval. Cooperative transport does not include behaviour where individuals separately move an object, which known as foraging.

One major benefit of cooperative transport appears to be that it allows a colony to utilize large food items in an environment with aggressive or dominant competitors by quickly moving the item to the nest rather than having to cut it up or consume it on the spot [60]. Additionally, it increases the speed of transportation or efficiency. Swarm robotics aims to mimic the behaviour of the natural swarm by looking for the individual rule that generates robust group-level response.

Source of Inspiration: Social insects such as ant show incredible and remarkable cooperation in diverse tasks. A small prey or food item is easily carried by a single ant. When an ant finds a prey item, physically attaches to it and then tries to pull or push it alone. When successful, the ant moves the prey item back to the nest. If an item does not perceive any movement after a while, the ant changes the orientation of the body, re-attach at a different point and try again. Finally, even not able to move the prey item because of its weight or size; ant recruits nestmates through direct contact, trail laying and pheromone [25, 61]. Other ants sensing the presence of pheromone move along this trail, going towards the item to be transported. On the other hand, ants may not synchronise their pulling efforts and pulled in opposite directions. This task often accomplished without a leader.

From the above scenario, cooperative transport in ants could be categorized into three general syndromes. The first syndrome is uncoordinated transport, in which individuals push or pull the object in multiple directions. In [61] noted that uncoordinated efforts are interrupted by deadlocks where ants pull in opposite directions. Each attempting drags the food item backwards from its current position, meaning that no forward motion. The second syndrome is encircling coordinated transport, ants are recruited to a food item, encircle it and quickly transport the item back to the nest once a sufficient number of ants have assembled to move it. The third syndrome is forward-facing coordinated transport without deadlocks and all individual ants face the direction of travel to the nest.

Challenges in this Behaviour: According to [62], there are four major techniques to produce cooperative transport behaviour in swarm robotic systems such as grasping, pushing, caging and tool-using. Initially, in grasping, multiple robots grasp an object using manipulators and then transport it to a goal. This technique enables robust transportation as the authors claim. However, a large or irregular-shaped object cannot be transported because of robots should tightly grasp an object in advance. Secondly, pushing behaviour enables swarm robots to transport irregular-shaped objects that cannot be grasped. However, a drawback with pushing is that it is hard to predict the movement of the robots and object being pushed over uneven terrain. Thirdly, robots wrap and transport an object to a goal by maintaining a regular formation known as caging. This technique allows for transporting an object without having to maintain direct contact with the object. However, this requires caging identification, positions of the object and its shape in real-time. In contrast to grasping, pure caging does not enable objects to be lifted. Finally, there are diverse tools that can be used for transportation such as a stick or a rope.

A complementary approach has been pursued by SR research, where decentralized transport strategies have been developed using evolutionary computation algorithm [56]. This algorithm relies on simple local sensing by individual robots, with no explicit knowledge of the object's shape or coordination between robots. A disadvantage of the decentralized method is that it has not been theoretically analysed and evaluation is done only in simulation or through limited robot experiments. In one interesting exception, cooperative behaviour is analysed but requires a leader-follower strategy [63]. The lack of analysis makes it unclear whether the ant-inspired decentralized approaches generalize to more complex object geometries or larger numbers of robots.

5. Human-Swarm Interaction

Human-Swarm Interaction (HSI) is defined as collaboration between human operators and semi-autonomous teams of robots. It involves understanding how humans interact with swarm robots and an assessment of the human responses during that interaction. In such a system, a human operator uses the information sent by the swarm and issue new commands to the swarm [65]. It is useful in several real-world applications such as urban search and rescue, surveillance, oil spill recovery, plume tracing, autonomous construction and military operations.

Swarm robotics systems are considered to be autonomous and to make decisions in a distributed way. Most autonomous systems required some degree of interaction with human operators to achieve a desired behaviour. It is an essential component in the successful operation of a system for the cooperation of swarm robots in an unstructured environment. The presence of human operator provides recognition and mitigation shortcoming of the autonomy, repair failures, impart a new goal to the system, convey changes in intent as mission, decision making and inaccessible information can be utilized to increase performance. Therefore, these real-world applications require a need for human assistance to influence the swarm to become more goal-directed in complex and changing environment.

Challenges in HSI: A number of studies [65, 67-71] focused on supporting autonomous HSI with one or few robots. However, autonomous technology to permit such systems to work on their own is lacking. While good progress is being made in swarm autonomy, a little attention has been paid to swarm interaction with human operators and how to issue commands and get feedback from individuals. The problem arises when an operator trying to interact with a swarm. Individual robot in a swarm system interacts with its neighbours only which is low-level dynamics. By contrast, the human operator is not aware of it and they only can see global behaviours that emerge through self-organised interaction between individual robot [26]. This is an extremely challenging task of decoding low-level swarm dynamics and need to be resolved programmatically. Human operators are not capable to understand this. In addition, such system interfaces could be complex, unusable or less effective when then number of robots involved in the task grows larger.

Some existing studies have investigated on haptic interfaces. According to [67] suggests that to enable effective HSI, interfaces must be designed systematically. Authors focus on leader-follower networks. In their experiment, the human operator controls one robot (the leader) and that robot influences the swarm locally. The leader robot controlled by a haptic device such as joystick. Whereas the remaining robots maintaining distances

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between one another. But feedback generated and responded to human operator was not scaled well. This is due to the inflexibility of the formation and the rigid structure of robots. Additionally, not all team-level properties may be particularly well-suited for haptic feedback. Therefore, it is essential to discover SR systems using haptic feedback where a human can supervise a large team of robots and receive feedback from it. Besides that, multimodal feedback to human operators using potential field approach has been examined. It enables controlling and designing the swarm system's interface that provides feedback regarding the swarm speed, strength, capability and dispersion.

Another problem is controlling the swarm system. Before sending a command to an SR system, human operator needs to know what state the system currently in. Therefore, swarm robotics system should provide feedback about the state of the individual robot to the human operator. In [66] indicates that inappropriate timing of control input could lead to swarm fragmentation. The author provides evidence of a simple target-searching task using neglect benevolence in a swarm. The result shows that frequently issue commands lead to lower levels of performance. Furthermore, to decide optimal timing of control input, it is essential to incorporate human operator decision. According to [67] identified two challenges when robots send state information to the human operator. The first challenge is due to small size of robot's hardware and its simplicity. An individual robot may not be equipped with the dedicated hardware required to provide meaningful feedback to the human operator. The second challenge is due to the large swarm of robots. If a robot can interact with human operator meaningfully, it does not mean that each robot can do so. Hence, the state of the individual robot and composite information of team of robot need to deliver to the operator.

A recent study [37] introduce a pheromone-based human-swarm interaction called the autonomy spectrum. The author emphasis on the assignment of a level of autonomy (LOA) to analysis, decision selection, information acquisition and implementation. Moreover, their model includes a predefined pathway between different LOA. This pathway combination of methods of operation. But the author was not concerned with a systematic comparison of human-swarm interactions. The primary conclusion is that human operators had some positive impact on system performance but further work remains to be done to better integrate human and swarm technology. In a similar work in [29] authors use two switchable modes of operation for a swarm to allow the human operator to switch between high and low autonomy. High autonomy mode was captured via a dispersion algorithm whereby the swarm members spread to cover the open space in the environment. Besides the low autonomy mode allowed the user to select subsections of the swarm to direct via waypoints. Here, the author perceived that operators found most success when using a mix of two modes. Nevertheless, further research work needed before properly say whether flexible LOA are beneficial in HSI. Moreover, properties of swarms are often unpredictable and human operators has little knowledge for understanding the swarm.

Another study [22] motivated on supporting the interaction through gesture recognition using proximal swarm interaction. This enables human operator to monitor part of or whole swarm directly as well as interact with each other locally through the environment. This can control and influence the swarm of robots in a distributed manner. This open possibility of control robots by having multiple human operators via speech commands, gestures and face engagement. Though, such experiment has not been carried out yet. Proximal interactions treat operators as a special or ordinary swarm member which usually not found in other human-robot systems. However, it is not clear how one would utilize them for controlling large team of swarm.

A touch-based input may allow users to perform complex tasks in an intuitive manner. Fong [20] presented a portable vehicle teleoperation interface using a personal digital assistant (PDA) with collaborative control. The authors discussed the use of collaboration, human-robot dialogue and waypoint-based driving that can enable an operator to effectively control a team of robots. A similar study [12] proposed an intuitive interface using a touch screen to control multiple robots simultaneously. Their interest is to discover how a human operator's behaviours differ when using a robot control interface to send commands to humans, in order to adapt those guidelines and allow us to build interfaces that provides better simultaneous human and robot command and localization capabilities.

6. Comparison

Existing HSI work has focused on developing mathematical models that allow humans to control swarm behaviours and have generally been evaluated on fixed computers with large screens, mouse and keyboard, as shown in Table 1. However, swarms have a mobile aspect and a human who is part of a swarm may move with the swarm. This calls for mobile interfaces, which in turn have novel interaction capabilities such as touch screens, but limited screen real estate. Table 2 shows that significantly less work has been done in this area. This project will thus focus on the unique challenges of HSI via a mobile device.

Table 1: Computer-based Swarm Interaction

Source	1	2	3	4	5	6	8	9	10	11	12	14	16
CS 1	Y	Y	Y	Y	N	?	?	Y	?	Y	?	?	N
CS 2	Y	Y	Y	Y	N	N	Y	Y	?	Y	?	?	N
CS 3	Y	Y	Y	Y	N	N	Y	Y	N	?	?	?	N
CS 4	Y	Y	Y	Y	Y	?	Y	Y	Y	Y	Y	Y	N
CS 5	Y	Y	Y	Y	N	?	Y	Y	?	Y	?	N	N

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Table 2: Mobile-based Swarm Interaction

Source	1	2	3	4	5	6	8	9	10	11	12	14	16
MS 1	Y	N	N	N	N	N	N	Y	N	N	N	N	N
MS 2	Y	N	N	N	N	N	N	Y	N	N	N	N	N
MS 3	Y	N	N	N	N	N	N	Y	N	N	N	N	N
MS 4	Y	N	N	N	N	N	N	Y	N	N	N	N	N
MS 5	Y	N	N	N	N	N	N	Y	N	N	N	N	N
MS 6	Y	Y	Y	Y	N	Y	Y	Y	N	Y	N	N	N

1-Move around; 2-Aggregation; 3-Dispersion; 4-Flocking; 5-Foraging; 6-Formation; 8-Obstacle Avoidance; 9-Exploration; 10-Transport; 11-Coordinated Motion; 12-Source Localization; 14-Decision Making; 16-Human Swarm Interaction; ?-Not mentioned.

Observe from Fig. 10 that when a machine offers no assistance and is fully influenced by a human, there is minimal machine autonomy. However, when a machine has the ability to make decisions on its own, executes automatically and does not need to ask a human for approval/suggestions, we have maximal machine autonomy. On the other hand, between these extremes, machines can execute automatically, request human approval and permit humans to suggests alternatives. Additionally, semi-autonomy may allow the human to veto the machine decision or suggest a completely different set of alternatives.

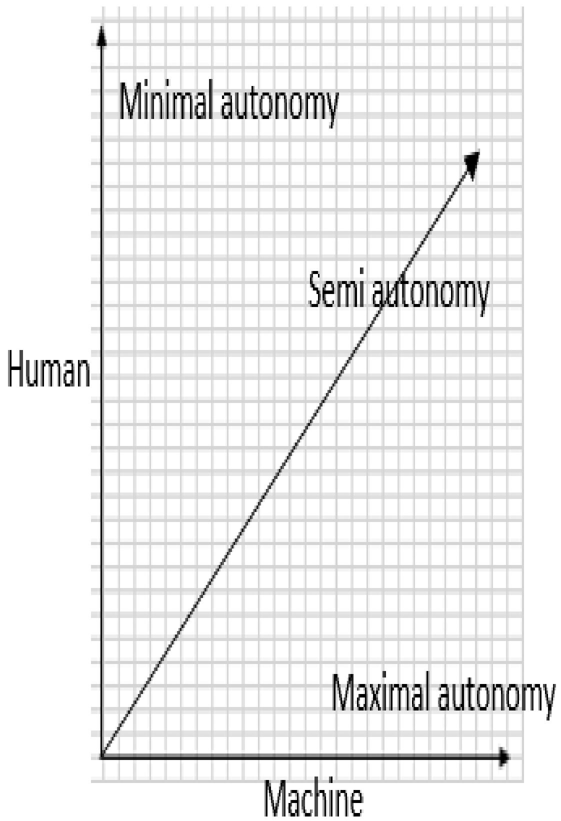

Figure 8: Human vs Machine Autonomy

Fig. 10 suggests that human will gradually decrease their interactions or lose the ability to decide or have less involvement when machine autonomy increases. However, there is a problem as the decision, priority of tasks become more important and human has less or no involvement. Thus, human intervention is necessary and we argue that higher robot autonomy requires higher levels or more sophisticated forms of interaction [68]. This project will focus on the area of semi-autonomy where the swarming agents undertake low-level control autonomously but respond to high-level goals from the human.

7. IntelliBot Framework

Research Problem and Solution Overview

Human control of swarms is a complex problem, as there is no ready correspondence between human goals, swarm behaviours and actions an operator might take to influence the swarm. Additionally, the current state of the art has significant limitations including unreliability of automation [29], inability to fully capture operator's intent [18] and lack of flexibility to deal with situations [21]. To overcome uncertainties in the environment or execute complex tasks; human supervisory control is essential. However, as the number of agents increases, bandwidth and constraints make it difficult for a human to interact with individual agents. Human operators need to coordinate and control the actions of large numbers of agents. This requires sequences of decisions, commands to control swarm behaviours and division of operator's attention between agents, which is limited by the number of agents that operator can reasonably control. Thus, a system designed named IntelliBot that allows human operators to influence swarm robots at a high-level while the swarm continues their operations and low-level control.

Individual agents in swarm systems interact with their neighbours only, which is low-level dynamics. By contrast, the human operator may only see global behaviours that emerge through self-organised interaction between individual agents [26]. The challenging task of decoding low-level swarm dynamics needs to be resolved programmatically. It is not clear human operators are capable of understanding this. The operator must be able to obtain a clear understanding of the present robots' status and environment in order to effectively supervise swarm robots. It is currently not always possible for such systems to ensure that swarm robots will act in a desirable way or complete a particular objective. For this reason, mathematical models of control laws.

IntelliBot's interaction technique takes advantage of both swarm robots and human capabilities is a way to push the capabilities of robotics systems that lack of intelligence. In order to take advantage of both swarm robots and human operators, a graphical user interface (GUI) designed to allow operators to give commands that accomplish high-level decision-making and complex tasks.

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Figure 9: Prototype Design of HIS: IntelliBot

Experimental Setup

Experiments using real robots/agents provide realistic results for the robotic study. However, this study will perform android smartphone simulations prior to investigations with real agents. In the initial stage, we will design experimental scenarios and conduct a pilot study before going for user studies. During user studies, all participants will be trained and asked to perform a range of interface-related tasks covering types of human-swarm interaction. Upon training completion, all participants will have the same set of instruction to assign agents to tasks. Tasks execution time, estimated travel time for each agent and task completion time will be captured by the system for further analysis. Following the completion of each scenario, all participants will respond to a questionnaire to obtain each user's satisfaction, ease of use and performance.

Significance of the research

This research is significant due to—Firstly, it can expose whether human can control swarm robots and improve system performance. Secondly, data that will be collected can be used for further studies for measuring performance. Thirdly, large scale swarming robots (drones) could be used in situations too dangerous or impractical for humans such as search and rescue operations, or help farmers to monitor the quality of crop growth, apply fertilizer, or tasks in urban environments such as temperature monitoring. Furthermore, drones have socio-economic impacts on other areas such as telecommunication, transportation, humanitarian, firefighting, surveillance and airspace safety.

8. Conclusion

Developing a swarm robotics system is one of the greatest challenges. However, this study implemented HSI systems to overcome the limitations of traditional supervisory control. The field of robot swarm systems or multi-agent dynamic systems is still an active research field. Although there are many solved problems, there also many potentially fruitful new directions. Moreover, developing models and strategies for HSI, intelligent learning strategies and various levels of autonomy/intelligence for individual agents and the swarms as a whole are important topics of future research.

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