

# Human Swarm Interaction for Radiation Source Search and Localization

Shishir Bashyal, Ganesh Kumar Venayagamoorthy

**Abstract - This study shows that appropriate human interaction can benefit a swarm of robots to achieve goals more efficiently. A set of desirable features for human swarm interaction is identified based on the principles of swarm robotics. Human swarm interaction architecture is then proposed that has all of the desirable features. A swarm simulation environment is created that allows simulating a swarm behavior in an indoor environment. The swarm behavior and the results of user interaction are studied by considering radiation source search and localization application of the swarm. Particle swarm optimization algorithm is slightly modified to enable the swarm to autonomously explore the indoor environment for radiation source search and localization. The emergence of intelligence is observed that enables the swarm to locate the radiation source completely on its own. Proposed human swarm interaction is then integrated in a simulation environment and user evaluation experiments are conducted. Participants are introduced to the interaction tool and asked to deploy the swarm to complete the missions. The performance comparison of the user guided swarm to that of the autonomous swarm shows that the interaction interface is fairly easy to learn and that user guided swarm is more efficient in achieving the goals. The results clearly indicate that the proposed interaction helped the swarm achieve emergence.**

## I. INTRODUCTION

Robots are no longer finding applications beyond the three RD (Dirty, Danger or Dull) environments they were traditionally confined to; they are now used for entertainment, education and elder-care among several other new applications. The wide acceptance of robots in society has accelerated robotics research and new ideas are emerging in robot deployment. Swarm robotics is one such

Manuscript received May 16, 2000. This research has been funded by two different NSF grants: i) SENSORS: Approximate Dynamic Programming for Dynamic Scheduling and Control in Sensor Networks, ECCS #0625737 and ii) NSF CAREER: Scalable Learning and Adaptation with Intelligent Techniques and Neural Networks for Reconfiguration and Survivability of Complex Systems, ECCS # 0348221.

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area that has started to gain momentum in the last decade [1].

While a number of research studies are reported each year, swarm robotics has not yet been able to go beyond laboratory research. One of the factors limiting the use of swarm robots in real-life environment is the lack of appropriate method for humans to interact with the swarm. Almost all studies in swarm robotics rely on autonomous operation of the robots. One reason for such reliance is the insect swarm metaphor that researchers often use in swarm robotics. It is uncommon for humans to collaborate, command or interact with insect swarms and hence the benefits of such an arrangement in swarm robotics have never been explored. Penders in [2] presents the idea of a human interacting with the swarm and raises some relevant questions about such interaction which the author calls assistive swarming. The author opines that the user input can prove to be useful in deploying the swarm and that the traditional swarm interaction techniques that use audio (chirping, beeping), visual (blinking, flashing) cues cease to be useful in adverse situations the swarm might be deployed in.

In swarm robotics, the individual robots are simple and have very limited planning capabilities compared to that of human beings. As with several other autonomous systems, swarm robotics can benefit by making provisions for humans to observe the performance of the system and inject knowledge in to the system where necessary. While some of the research studies (e.g. [3], [4]) have developed effective methods for observing the swarm behavior, the provision for humans to guide the swarm behavior has been least explored. Such provision for humans to affect the swarm behavior enables swarm robotics to overcome the barriers often posed by the environment. This study proposes a method for human swarm interaction (HSI) that allows users to interact with the swarm without affecting their group-intelligence. The benefit of the proposed interaction is evaluated by comparing the performance of the autonomous swarm with that of the user-guided swarm.

## II. HUMAN SWARM INTERACTION LITERATURE

The study of existing literature reveals that not much work has been done in HSI. Some of the research in human robot interaction provides inspiration and ideas for human swarm interaction. Most of the works that discuss the implementation of human interaction in a swarm of robots still call the approach human robot interaction (HRI) [3], [5] and in fact, in many cases the approach is equally applicable

to other multi-robot systems. Some of the research in multi-robot HRI [6], [7] and HCI [8] provide useful insight for HSI.

In [5], McLurkin et al. discuss how interaction with a large number of robots differs from single robot HRI and explore strategies to maintain, program and interact with swarm without having to handle them individually. While the project emphasizes on the simplicity aspect of swarm robotics by using LEDs and MIDI sounds for status revealing of individual robots, it fails to maintain the autonomy required in swarm robotics. The study uses methods to allow user to control individual robot or the entire swarm; both of which is against the notion of emergent intelligence. In [6] and [7], Bruemmer et al. discuss multi robot HRI and propose that rather than making the user exert global, centralized control from above, the interaction should allow emergence of swarm intelligence. They identify the difference between the perception of environment by a single sophisticated robot and the perception of an element in the swarm and argue that HRI for multi-robot system should be inspired from nature and should promote swarm intelligence. The research later deviates slightly from the notion of swarm intelligence: "Unlike in the insect world, the robotic system must interact with human operators. At a minimum, this interaction includes responding to operator directed tasking and status reports on task progress". This contradicts their own statement that once a system stops exploring the environment on its own and starts to follow commands from above; it ceases to promote swarm intelligence. The tasking of the robots by the human user introduced later deviates away from the notion of swarm robotics. In [9], Dudenhoeffer et al. conduct modeling and simulation for exploring HRI requirements and suggest that with high level of automation where the operator serves mainly a monitoring role; situation awareness may be negatively impacted. Their study suggests that emphasis on monitoring alone ignoring collaboration roles in multi-robot interaction poses a significant problem to the overall swarm due to degradation of situational awareness.

In [3] and [4], an augmented reality based interaction mechanism is developed for swarm robotics. The proposed approach makes monitoring of the swarm effective but the use of head-mount device makes the approach complicated and costly. The study also lacks the human-robot collaboration component that can improve the swarm performance. Casper et al. in [10] opine that the present day robotics technology is not able to operate autonomously and hence the HRI is a key component in success of the human-robot team. In [11], though the issues raised are for HRI, valuable insight for HSI is provided. The authors argue that automation is a likely way to succeed in some critical areas of technology. They find that the present day robot teleoperation is not suitable for team-centric HRI. They also point out the possibility that use of intelligent software may provide higher degree of autonomy in the robots and argue that peer-peer interaction is possibly beneficial for HRI.

Murphy in [12] emphasizes the importance of HRI in rescue-robotics. Billings [8] provides valuable insights to man-machine interface with real-life examples that prove the importance of effective interface. The author states that automation that is strong, silent and hard to direct is not a team player. The author argues that computers (robots in this context) should act as intelligent assistants; it should monitor our actions, to shield against human errors. Palmer et al. in [13] present a novel approach to swarm intelligence research. They begin with the quote "Smart things Form Teams, Stupid things Swarm" and modify the question to "What can we learn about swarms by having smart things act dumb?" They make a swarm of people act dumb and ask them to perform set of tasks so as to come up with effective algorithms for swarm intelligence. The work provides an inspiration to think out-of-the-box for solving problems in swarm robotics. Holly et al. in [14] present a detailed study of HRI taxonomy that helps to understand different modes and levels of HRI and to extend the concepts to HSI. Kartoun et al. in [15] present an intelligent approach in which a robot collaborates with a human in learning a task. Though the study is not in the context of HSI, it gives some idea on possible approach for HSI. Finally in [16], Breazeal explores HRI from the perspective of designing sociable autonomous robots. The author presents the classification of systems on the basis of HRI: robot as tool, robot as cyborg extension, robot as avatar and robot as sociable partner. Each is distinguished from the others based on the mental model a human has of the robot when interacting with it.

Literatures in human swarm interaction suggest that the systems that only offer monitoring roles to the user tend to be least useful as monitoring alone makes users less participative adversely affecting situational awareness. On the other hand, an interaction that gives a complete control to the user suffers from human errors and the user workload is very high. The ideal man-machine interaction is said to be the one that functions autonomously while providing users with a method to inject knowledge and guidance so as to improve the performance of the system.

### III. FEATURES OF HUMAN SWARM INTERACTION

In HSI, complete control of the swarm affects the emergent behavior of the swarm and thus swarm interaction methods need to limit users control over the swarm. The users should be able to inject domain knowledge without needing to manipulate the entire swarm. The degree of autonomy desired in swarm robotics is 100% and thus the swarm should be capable to work even without user input. The user input should help the swarm get better results and within a short interval.

Another aspect in which HSI differs from HRI is the scalability of the interaction. Swarm interaction mechanism needs to be capable of supporting thousands of robots. The large number of robots necessitates that the interaction be robust; the swarm should be able to perform even without user input. With a large number of robots, it is not possible for human users to monitor the entire swarm and provide

appropriate input. It is therefore necessary for HSI methods to adopt some kind of divide-and-rule strategy allowing users to focus on a sub-group of robots at a time while the rest of the swarm operates without user interaction. Multi-robot systems often adopt a centralized command and control strategy whereas swarm robotics emphasizes on local sensing and communication. This difference suggests that the HSI methods be able to influence the swarm locally as opposed to global control in multi-robot interaction. Furthermore, individual robots in swarm robotics are far less sophisticated than those in multi-robotics. HSI architecture must therefore adhere to simplicity in design and the existing swarm robot resources should be utilized rather than requiring sophisticated equipments. The goal of multi-robot interaction is to provide methods to task and control the robots whereas in HSI the goal is to help the robots attain emergence in shorter period of time or to help them do so in cases previously not possible.

Based on the characteristics of swarm robotics, the following set of desirable features has been identified for HSI:

- i. Should promote positive emergence of intelligence
- ii. Should facilitate local rather than global interaction
- iii. Should be scalable, supporting large swarm size
- iv. The swarm should be able to perform well even without human input; the external input shall be used to speed up the mission or to achieve emergence in cases otherwise not possible
- v. Should support multiple users to interact simultaneously
- vi. Should be able to present useful information to the user(s) for situational awareness
- vii. Should use methods that utilize existing simple swarm resources rather than requiring sophisticated equipments
- viii. Should allow user(s) to adopt divide-and-conquer strategy enabling them to interact with a sub-group of robots at a time
- ix. The interaction should provide easy interface for user(s) to provide tactical input and domain knowledge to the swarm
- x. The architecture should be generic such that it could be used in a variety of applications rather than being limited to specific applications

The insect swarm metaphor is used to come up with architecture for the human swarm interaction: if user(s) were to provide strategic input to a group of ants searching for food, what could be the method to drive the ants to the food source without affecting their group intelligence. Ants are of course capable of finding food on their own; user input can help them find it sooner.

#### IV. PROPOSED ARCHITECTURE

This study proposes architecture for swarm interaction that has features suitable for swarm robotics. The architecture lets human users to represent themselves in the swarm using their avatars<sup>2</sup> which means human user(s) can select a robot and take control of it. The rest of the robots perceive the avatar as just another element in the swarm and thus the avatar (and therefore the user) does not have authority over the swarm. Their control over the swarm is only as much as that of any other member in the swarm. This provision of peer-to-peer interaction ensures that the user cannot exert external global control over the swarm. Since the swarm algorithms use a set of protocols for robot-to-robot interaction, the user input eventually is subjected to the protocol and thus the user input in helping the swarm to attain the goal is appreciated by the swarm to the extent allowed by the protocol. Usually it means that the users ability to guide the swarm is only as much as her/his ability to help the swarm obtain better results.

The user(s) use a computer (preferably a handheld device) to observe the swarm distribution and their behavior. Each user establishes a communication link to the swarm via her/his avatar. The robots in the swarm route their messages to the user via the avatars that act as base stations. The user can select any one of the robot in the swarm as her/his avatar at a time. The avatar can then be fully controlled by using the remote computational device; it can be moved by the user as desired and its status can be changed as required. Figure 1 illustrates the proposed swarm interaction architecture.

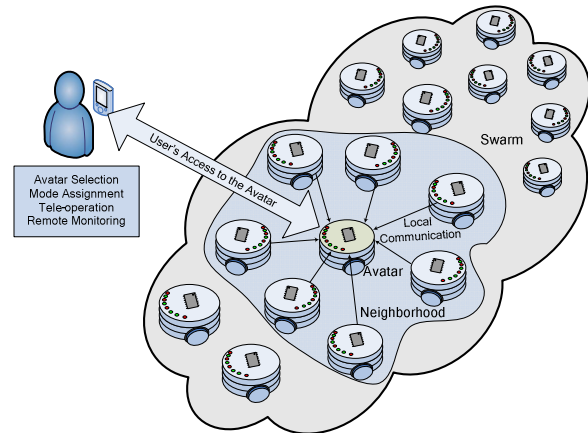


Figure 1: Proposed human swarm interaction architecture

It is evident that the users control over the swarm is very limited. However, as each user has access to one robot in the swarm, they can control it so as to lead the swarm towards the goal. For example in a swarm deployed to localize odor source, if the user drives the avatar towards the area with higher likelihood using tactical skills, other robots would start following the avatar once the odor signal detected by

<sup>2</sup> The Sanskrit word *avatāra*- literally means "descent" and implies a deliberate descent (of god) into lower realms of existence (humans or animals) for special purposes.

the avatar is stronger than that of others in the swarm. The swarm is able to follow the odor gradient in the environment to localize the odor source but before the robots reach the area with odor gradient, the swarm needs to randomly explore the environment. The human navigational skills are far more superior in this regard and hence the user input not only increases the chances of detecting the odor source but also reduces the mission execution time.

The proposed architecture has all of the features identified in section III. The user does not have authority over the entire swarm and can influence only a part of the swarm at a time. The user observes a sub-group of the swarm at a time and controls the avatar so as to influence the swarm in a strategic manner. This approach makes user workload independent of the swarm size and thus scalability is achieved. When the swarm size is large, the user can still focus on a part of the swarm and act to help the swarm. Multiple users can select multiple avatars in such cases to increase the efficiency of the swarm. Furthermore, the architecture is standard in the sense that the architecture remains the same from one application to the other. The only difference would be in the protocol that the swarm uses to interact with each other and the environment.

## V. SIMULATION ENVIRONMENT AND HSI INTERFACE

This study uses MATLAB based simulation environment for simulating the swarm behavior. A two-dimensional indoor environment is created and the swarm is placed in the environment. The experiments conducted in this study use 20 robots in the swarm for experimentation. Each robot in the swarm is capable of sensing the walls and turning around to avoid collision. Inter-robot collision is not taken care of in the simulation as it does not impact the observations in this study. The robots in the swarm are programmed with different modes that they can operate in. Initially the robots are in the *normal* mode in which they wander around in straight lines deflected only by walls and obstructions. The robots can operate in a *repel* mode in which the robot becomes stationary and signals the robots in the neighborhood to move away from the robot. There are also four different *director* modes, one each for four directions up, down, left and right, in which case the robot remains stationary and signals the neighboring robots to move towards one direction.

When the simulation is launched, the robots are initialized in the *normal* mode. The user can use the mouse pointer to click on a robot to select it and then click on one of the buttons to switch it to a certain mode. The robot icon in the simulation environment changes its color and shape based on its present mode aiding the users understanding of the swarm behavior. Table I shows the different buttons and the associated modes the buttons switch the robot to. The table also presents the influence of the robot mode to its neighbors. Robots could be assigned several other

modes based on the requirement for the particular application. In this study, *repel*, *director*, *avatar* and *normal* are the only modes used.

TABLE I  
GUI BUTTONS AND THEIR FUNCTION

Button	Mode Assigned	Effect on the Neighbor	Icon
	Repel	$V_x = -V_x$ or $V_y = -V_y$	
	Up Director	$V_y = -1 * \text{abs}(V_y)$	
	Down Director	$V_y = \text{abs}(V_y)$	
	Left Director	$V_x = -1 * \text{abs}(V_x)$	
	Right Director	$V_x = \text{abs}(V_x)$	
	Select Avatar / Release Mode	None	

A graphical user interface (GUI) is provided using which a user can select robots in the swarm as the avatar and use it in different roles. Figure 2 displays GUI and simulation environment with different robots assigned to different modes. White lines are the trails of different robots.

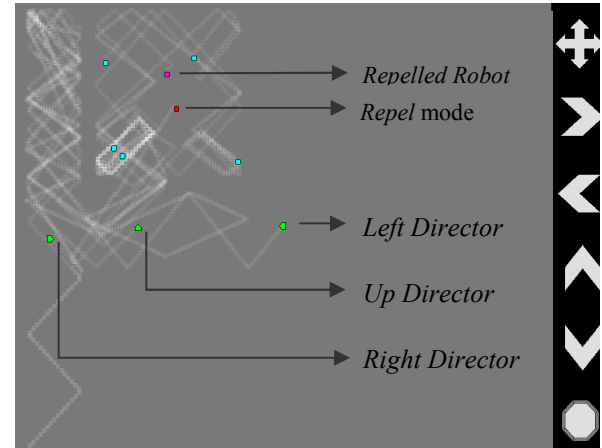


Figure 2: Effect of Director and Repel robots on neighbors

When the user selects a robot and clicks either the *repel* button or one of the *director* buttons, the user has selected the robot as the avatar and changed its mode to that corresponding to the button. Therefore the robot remains stationary and signals the neighbors as per the mode. Once user changes the mode of a robot, it remains to be so even after the user releases it as the avatar. This allows the user to select multiple robots one by one and change their mode over time and the robots once assigned remain in the mode until the user does not select it again and release it by using the *Select Avatar / Release Mode* button. Selecting a robot in the *normal* mode and clicking on the *Select Avatar / Release Mode* button makes the robot the user's avatar without any impact on the neighbors. In any of the modes, the robot last selected by the user can be moved by using the number pad

in the keyboard. The *director* robots direct neighbors in their respective direction whereas *repel* mode repels robots approaching from all directions.

## VI. RADIATION SOURCE LOCALIZATION

In order to evaluate the effectiveness of the proposed interaction, the swarm of robots is used for radiation source search and localization. The goal for the swarm is to search an indoor environment to detect presence of radiation sources in the environment and if radiation is detected, the radiation source needs to be localized. The robots are programmed to move randomly through the environment until the radiation source is detected. Particle swarm optimization (PSO) algorithm is used in the robots that enable them to locate the source of radiation once at least one robot detects the radiation.

PSO has been used in a number of studies in swarm robotics. Doctor et al. in [17] propose a PSO based collective robotic search application where a number of robots distributed over a search space collaborate to locate the target. The work uses a PSO to do the target search and another PSO to tune the parameters of the search PSO for better convergence. The tuned PSO leads to better convergence in single as well as multiple target searches. Marques et al. in [18] present a particle swarm based olfactory guided search where robots with odor sensors collaborate to localize the source of the odor. In absence of the odor signal, robots in the swarm repel each other achieving explorative behavior. Pugh et al. recently reported their work [19] in PSO based multi-robot search in which they modified standard PSO algorithm to better suit their problem.

Particle swarm optimization proposed in [20] is an optimization tool inspired by the foraging behavior of a flock of birds. Particle swarm optimization algorithm, since its proposition in 1995, has been used in solving a wide variety of problems and has recently been used in multi-robot search applications.

In particle swarm optimization, a particle is an  $n$ -dimensional vector that encodes the  $n$ -dimensional solution to the optimization problem. A swarm of such particles are randomly initialized in the problem space. Each particle has some memory that stores (i) the best position (called *pbest*) the particle has achieved so far, (ii) the present position of the particle in the problem space and (iii) the velocity with which the particle ‘flies’ in the problem space. In addition to that, the particles communicate with each other to share the best solution discovered by the entire swarm (called *gbest*). Based on this two information, *pbest* and *gbest*, the position and velocity of each particle is updated which eventually leads to the convergence of the swarm to the best solution in the search space. The standard particle swarm optimization algorithm is presented below:

- i. Initialize a population of particles with random positions and velocities in  $n$  dimensions of the problem space and fly them.

- ii. Evaluate the fitness of each particle in the swarm. In each iteration, compare each particle's present fitness with its *pbest*. If the current value is better than *pbest*, then set *pbest* equal to the current value and the *pbest* location equal to the current location in the  $n$ -dimensional space.
- iii. Compare *pbest* of particles with each other and update the *gbest*
- iv. Change the velocity and position of the particle according to equations (1) and (2) respectively.
$$V_{k+1} = w V_k + c_1 \text{rand}_1(pbest_k - P_k) + c_2 \text{rand}_2(gbest - P_k) \quad (1)$$

$$P_{k+1} = P_k + V_k \quad (2)$$
- v. Repeat steps (ii) to (v) until desired convergence is reached.

When a number of robots with sensing, positioning and communication capability are put together and treated as the particles in the particle swarm optimization algorithm, the swarm is capable of locating the source of signal (radiation, odor, heat or light source that the sensors in the robot are capable of sensing) given that the robots are evenly distributed in the search space such that at least some of the robots sense the signal from the source. Studies [18], [19] and [20] use PSO based approach to localize the source that creates a gradient in the environment (e.g. light, odor, vapor etc) using a swarm of robots. The studies assume that the swarm is already dispersed in the environment. Usually, a swarm of robots are brought to the search space in a container and need to be deployed from there. The random initial distribution is in itself a problem in swarm robotics.

PSO implementation in this study is slightly different from the standard PSO. Initially, when the robots are brought to the environment, none of the robots can detect the radiation as they are away from the region. The robots therefore start moving with randomly initialized velocity changing directions only when they come across walls and obstructions. This process of exploration continues unless the radiation strength detected by a robot is higher than that of others. The robot detecting the highest radiation shares its position to others in the neighborhood (as opposed to sharing it to the entire swarm in the standard PSO) and thus the algorithm is a localized version of PSO. The best position of the robot then becomes the local best (*lbest*) for its neighbors and the neighbors use equation (1) (replacing *gbest* with *lbest*) for velocity update. Position update equation remains the same as in equation (2). The local sharing of the behavior allows other elements in the swarm to continue exploring other areas in the environment therefore enabling the swarm to search and localize multiple radiation sources in the environment. Figure 3 shows flow-chart of the PSO implementation.

In order to evaluate the proposed interaction architecture and the interaction interface, two user-evaluation experiments are conducted for radiation source search and localization. The first experiment is designed to familiarize the participants with the interaction tool and to observe their learning behavior during the process. The second experiment is meant to compare the performance of the user-guided swarm to that of the autonomous swarm.

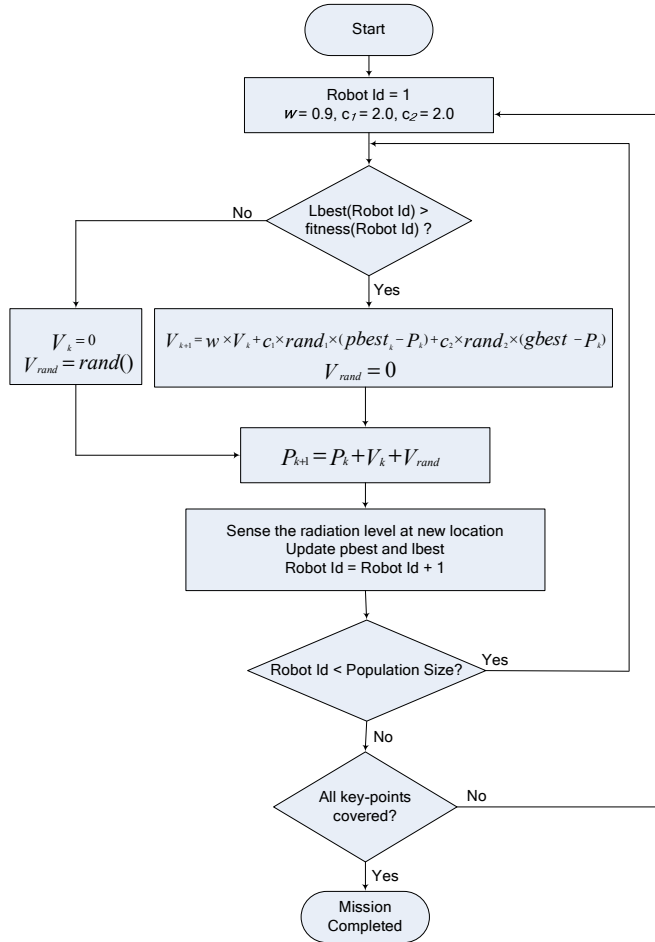


Figure 3: PSO implementation flowchart

#### A. User Familiarization Experiment

The swarm application used in the experiment is to deploy the swarm to detect and localize the radiation source in the environment. To make things easy for the participants, the radiation is displayed in the map and therefore searching for the radiation is not necessary. The robots have the ability to navigate through the environment sensing the radiation signal. If at least one robot reaches the region where the radiation can be detected, it collaborates with other robots using PSO algorithm to navigate to the source. Participant's goal is therefore to help robots reach the region with detectable radiation within a minimum time. Figure 3 shows the scenario with the higher radiation area appearing white. The radiation field is created using graphics editing tool and placed in the simulation environment. The goal of the swarm is to reach the centre of the white gradient.

A brief introduction of the HSI research was provided to each participant at the beginning of the experiment. Some participants requested for a demonstration in addition to the instructions provided in the documentation which was provided to them. The participants are allowed to repeat the sample application up to 5 times and their mission completion time for each run is noted.

The trend of the mission completion time reflects the learning curve of the interface. If the mission time decreases with repetitions, it reflects that the interface is easy to learn. If the users do not find it necessary to repeat up to the maximum allowed number of times, it reflects that the interface is very easy to learn and that users are confident of the interaction within a short period of time. Of the five participants that participated in the experiment, four participants repeated the sample application 5 times, the maximum allowed number of repetitions. One participant repeated it 4 times before moving on to the next experiment. This indicates that the interaction is fairly easy to get familiar with; had it been too easy, all participants would have repeated it less number of times. If it had been too difficult, the participant who did it only for four times would have continued it for the fifth time as well.

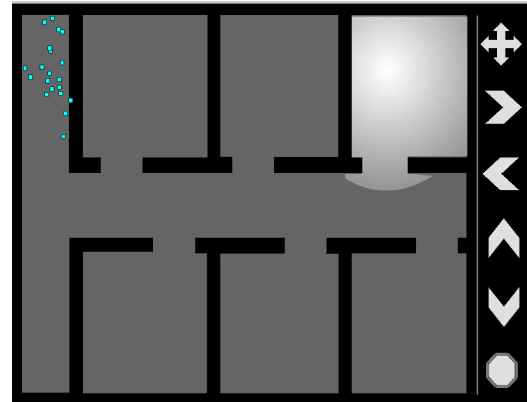


Figure 3: Sample radiation source localization application scenario

Almost all participants' sample mission completion time decreased with the number of repetitions except for some fluctuations due to the random initialization of the swarm. Figure 4 presents the learning curve for all five participants.

When the swarm operated without user input, the average and standard deviation of the mission completion time is found to be  $69.64 \pm 8.91$  seconds. In the first try, the mission completion time of the participants was higher than the swarm performing on its own. The reason is that the users experimented with the different modes of the robots rather than focusing on the goal of the mission. In later runs, their performance improved and three users achieved mission completion time shorter than the average completion time of the autonomous swarm. Participants 2 and 5 demonstrated ideal learning behavior whereas other participant's performance fluctuated. All but participant 3 performed better in repetitions than in the first attempt. Only participant



4 did not achieve mission completion time as good as the average completion time for the autonomous swarm displayed in blue line in the figure.

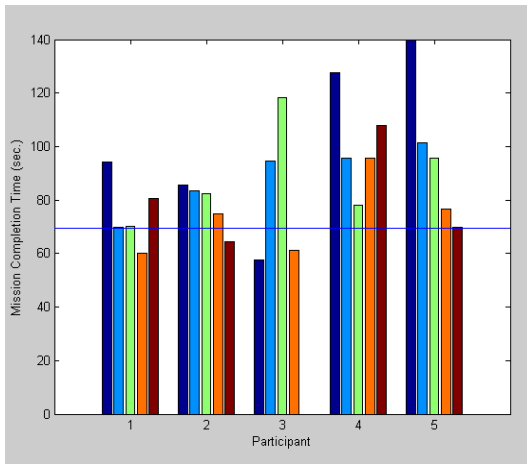


Figure 4: Comparison of completion time of participant guided swarm (bars) with that of the autonomous swarm (horizontal line) for sample mission

#### B. B. User Evaluation Experiment

After the users are familiar with the simulation environment and the interaction interface, the users are asked to deploy the swarm for searching an indoor environment to decide whether any sources of radiation are present in the environment. If there are any radiation sources, the swarm also needs to localize them. Radiation source, if present, would radiate over an entire region and thus it is not necessary that the entire space be scanned thoroughly. Furthermore, there is a gradient of the radiation signal around the source which the swarm can use to converge to the source using computational intelligence techniques. PSO is used in this study to enable the swarm to converge to the radiation source. The details of the algorithm are presented in the next section.

In a practical radiation source search scenario, human user can plan the mission by identifying a set of key-points in the map that can be searched to decide whether a radiation source is present in the environment or not. By taking into account the area covered by radiation sources; the presence or absence of radiation sources can be determined just by searching a number of key-points. The user planning, absent in the autonomous swarm, can therefore help in completing the mission earlier as searching only the key-points can be completed in a short time as compared to the through search of the entire search space. The mission completion time achieved by the participants is compared with that of the autonomous swarm to evaluate the benefit of proposed HSI.

To evaluate the usefulness of the HSI for this application, participants are provided with a map of the environment. Seven key-points are previously marked in the map so as to standardize the experiment among different participants. The goal of each participant therefore reduces to sending at least one robot each to all seven of the key-points. If there is a radiation source in the environment, it would be detected by the time all seven key-points are explored. The robot that

first detects the radiation source then collaborates with others in the neighborhood to localize the source of radiation. Figure 5 shows the map of the environment with the key-points marked with blue 'x' signs.

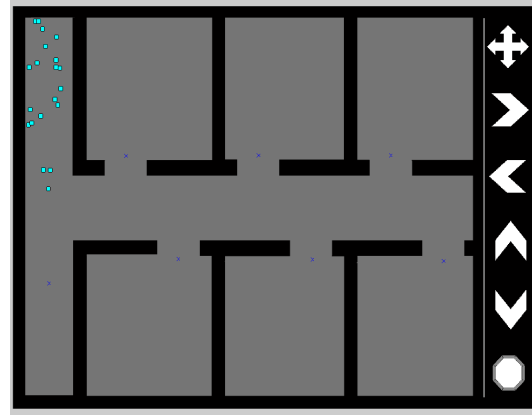


Figure 5: Map of the environment with key-points marked with blue 'x' markers

The simulation is run for 5 times (equal to the number of participants) without user input to obtain the mean and standard deviation of the mission completion time for the autonomous swarm which is found to be  $637.02 \pm 343.75$  whereas that for the human guided swarm is  $314.19 \pm 155.40$ . This is a reduction in mission completion time by 50.68%. All participants completed the mission before the average time for the autonomous swarm. Four of the participants completed the mission in less than half of the mean time required by the autonomous swarm. This result shows that the human's ability to develop strategies can be used to guide the swarm to the desired areas much faster therefore improving the efficiency of the swarm. In this experiment no radiation sources were placed in the environment and the mission is complete when the user drives at least one robot each to the seven areas identified by the markers. If there was a radiation source, at least one robot would detect the radiation signal and the PSO algorithm would come into effect and localize the swarm, just like in the previous mission. Figure 6 shows the completion time for the users and the average mission completion time for the autonomous swarm.

As evident from the result, the user guided swarm is able to complete the mission much earlier by visiting all seven key-points within a short period of time. Users were able to convert their tactical knowledge to appropriate input for the swarm enabling the swarm to achieve the goal in a shorter period of time.

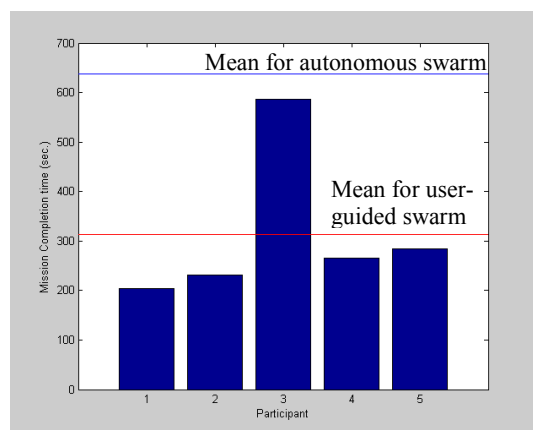


Figure 6: Comparison of completion time of the participant guided swarm (bars) to that of the autonomous swarm

## VII. VI. CONCLUSION

Methods and benefit of user guided swarm has been least explored in literatures. This study proposes swarm interaction architecture that has scalability, robustness and emergent features suitable for swarm robotics. User-interaction interface is developed based on the proposed architecture and user evaluation experiments are conducted to evaluate the interaction interface. The results of the experiments show that the interface is fairly easy to use and that user guided swarms achieve goals much faster. Faster completion of the mission is critical in applications like radiation source search and localization and hence the proposed user interaction makes the swarm much more preferable.

Energy consumption of robots is another major constraint that severely limits the mission lengths. Elements of the swarm are miniature in size and thus the battery life is very short due to small size of the batteries. As the result obtained in this experiment shows that the use of proposed user interaction helps the swarm search the area more efficiently, it is possible to search a larger area by deploying user-guided swarm. The proposed interaction can therefore improve the performance of swarm deployment for search and localization tasks.

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