Human Influence of Robotic Swarms with Bandwidth and Localization Issues

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***Abstract*—Swarm robots use simple local rules to create complex emergent behaviors. The simplicity of the local rules allows for large numbers of low-cost robots in deployment, but the same simplicity creates difficulties when deploying in many applicable environments. These complex missions sometimes require human operators to influence the swarms towards achieving the mission goals. Human swarm interaction (HSI) is a young field with few user studies exploring operator behavior. These studies all assume perfect information between the operator and the swarm, which is unrealistic in many applicable scenarios. Indoor search and rescue or underwater exploration may present environments where radio limitations restrict the bandwidth of the robots. This study explores this bandwidth restriction in a user study. Three levels of bandwidth are explored to determine what amount of information is necessary to accomplish a swarm foraging task. The lowest bandwidth condition performs poorly, but the medium and high bandwidth condition both perform well. The medium bandwidth condition does so by aggregating useful swarm information to compress the state information. Further, the study shows operators preferences that should have hindered task performance, but operator adaptation allowed for error correction.**

***Index Terms*—human-swarm interaction, bandwidth limitation**

I. Introduction

Swarm robotic systems consist of a large collection of simple robots with limited sensing, communication, actuation, and computational capabilities. Robots in a swarm robotic system act according to simple local rules and exhibit a wide range of behaviors without any centralized controller. However, because of their inherent simplicity it is difficult to deploy them for complex missions. To use swarm robotic systems in a complex mission, presence of human operators are required to guide the behaviors of the swarm towards accomplishing mission goals. Swarm behaviors that have been studied in the literature include flocking [1], [2], [3], [4], deployment [5], [6], foraging [7], [8], area clearing [9], and self-assembly [10], [11], [12]. Two key challenges in human swarm interaction is that (a) the state information of the robot available to the human may not be accurate and (b) there may be a mismatch between the intent of the operator and the robots understanding of the human intent. The error in the swarm state available to the human and the intent mismatch can happen due to bandwidth limitations in communication and localization error of individual robots.

Swarm systems may operate in a wide range of environments from indoor environments to outdoor underwater environments and their communication capabilities are limited (e.g., limited radio power). Thus, they may operate under conditions where communication bandwidth is limited. Also, the capacity of the inter-robot communication channel, the robot to human communication channel and the human to robot communication channel may all be different. Furthermore, as swarm systems are usually made of simple units, their localization capability may not be very good. The limitations on communication bandwidth and the localization error implies that the state of the swarm available to the operator may be erroneous and time delayed. Due to the localization error, any point in the reference frame of the operator will be erroneously interpreted by a robot as some other point. Thus, any effort by the operator to move the swarm towards a desired point will be misinterpreted by a robot, thus creating an intent mismatch between the human and the robot. Current human-swarm interaction (HSI) literature [13], [14], [15], [8], [16], [17], [18], [19], [20] do not consider the above aspects of HSI and assume perfect information transfer between the human and the robots. Therefore, in this paper, we conduct controlled experiments to study the effect of human-swarm intent mismatch and error in swarm state displayed to the human on human performance in controlling swarm robotic systems. To the best of our knowledge, this is the first paper that studies the effect of communication bandwidth limitations and localization errors on human performance in controlling swarm robotic systems, using controlled experiments.

In our experimental scenario, a human operator has to guide a robotic swarm to find unknown targets in a given area. The area is divided into a finite number of regions (whose boundaries are unknown to the interface) and the operator has to match the target found to the regions. The robots have a single behavior, namely achieving consensus on direction on motion. The humans can guide the swarm by giving them a point in the environment towards which the robots have to travel. The robots are assumed to have a localization error and the robot position and orientation is assumed to be a Gaussian distribution. In our experiment each subject performs the mission under three conditions (that are presented to them in a random order), namely, (a) low swarm-to-human bandwidth and low intra-swarm bandwidth (low bandwidth condition), (b) low swarm-to-human bandwidth and high intra-swarm bandwidth (medium bandwidth condition) and (c) high bandwidth between swarm and operator (high bandwidth condition). For low bandwidth condition, we assume that only one robot can send its state information at a time instant, this assumption creates displayed information that lacks temporal and spatial resolution. For the medium bandwidth condition, the swarm communicates among themselves to estimate their mean orientation and standard deviation of orientation, which is displayed on the screen creating a limited spatial resolution of the swarms state. In the high bandwidth condition, all the robots could send their position and orientation information to the operator creating high spatial and temporal resolution given the errors of the individual robots. Our experimental results indicate that, as expected, there is a degradation of performance in the low bandwidth condition compared to the high bandwidth condition. However, in the medium bandwidth condition, where the human had an understanding of the state of consensus of the robots (and thereby whether the robots were moving in the direction the human desired) from the standard deviation of orientation, they performed as well as the high bandwidth condition. These results show that temporal resolution is important for a human operator to guide the swarm to achieving this task. Also, across conditions users show preconceived notions of low frequency issuance of commands. Each command allows the swarm opportunity to lose communication with other agents, so issuing fewer commands was stressed to the operator. Results showed, however, that users issuing more commands created a more highly connected swarm showing an adaptation of operator preferences to the algorithms of the swarm and error of each robot.

In the rest of this paper, we first give a brief discussion of related work in Section II. In Section III we describe our experimental scenario in detail. We state the results of our experiments in Section IV and discuss them in Section V. Finally in Section VI we present our conclusions and outline avenues of future work.

II. Related Works

The field of human-swarm interaction is quite young [14], [15], [8], [16], [17], [18], [19], [20].

Furthermore, there has been very few user studies investigating human-swarm interaction and we will review these in detail here. In [8], the authors use particle swarm optimization in a robot swarm looking for the source of some radiation in an indoor environment. Human control is hypothesized to help because the human might have information about the environment that is unknown to the swarm but that can help their overall performance. User experiments were performed with the human operator having two types of knowledge. In the first case, the human knew the source of the radiation and simply tried to get the swarm there. In the second case, the operator knew of certain locations that, if visited, would lead to knowledge about the whole environment. In both cases, the human operator was shown to be able to help the swarm, somewhat surprisingly they were more helpful in the latter case, but the very small number of subjects make the results inconclusive.

The contribution of [16] is twofold. First the authors present a swarm control algorithm for multiple swarm tasks that adapt to battlefield conditions. The algorithm is based on a potential field that includes sub-fields for the different tasks. The swarm is controlled by adjusting various parameters of the vector field. The approach is scalable to swarms with tens of members (40 members in simulation). The authors use a scenario where the swarm performs convoy protection, reconnaissance of areas of interest and obstacle avoidance. The second contribution is the evaluation of operator displays of swarm performance. The paper reports on human experiments with displays that provide only visual information, visual and audio, visual and tactile and visual-audio-tactile. The results show that the visual-audio-tactile display performs best in terms of operator response time to messages about swarm performance (e.g. health, communication ability etc.) while at the same time the operator was performing a secondary task.

The user study of [19], compared an active and a passive selection technique to change robot's autonomous algorithm. The authors created an information foraging task to test the participant's ability to gather information in various environments from open to cluttered and unstructured. A wandering algorithm that stopped to collect information if it discovered a source showed the weakness of operator interaction for the open environments, but operators using the active selection process outperformed the autonomy as the complexity of the environment increased. The passive selection technique allowed for environmental planning and complex behaviors, but did not perform significantly better than the wandering algorithm. The results show that the active selection technique is more intuitive and allows novice users to use the swarm algorithms to perform better than a wandering algorithm in an environment that violates its assumptions.

In [20], the authors use a swarm robotic system using a bio-inspired pheromone-based strategy for patrolling. The user had to assist the robot swarm in both patrolling and response to alarms and could influence the swarm by changing the level of pheromones in a region. The user studies indicate that the human operators improved the performance of the swarm robotic system for response to alarms over an autonomous algorithm. However, for patrolling the human operator hindered performance although they believed that they are improving performance.

The above discussion shows that HSI experiments have been performed for different application areas including foraging, patrolling and firefighting. A common aspect of all these experiments is that it is always assumed that the operator knows the current state of the swarm and there is no error in robots understanding of human intent. However, in the presence of practical constraints like limited communication bandwidth and localization errors of robots, the assumption of perfect information transfer between human and swarm becomes invalid. Therefore the goal of this paper is to understand human performance for controlling robotic swarms in the presence of bandwidth constraints and localization errors.

III. Experimental Design

The study described below has three within subject conditions with twenty five participants. The user study explores three levels of bandwidth: low, medium, and high. Participants controlled thirty virtual robots in the robot simulator, Stage, to find targets distributed in an open environment [21]. The study used the Robot Operating System (ROS) as the controller for the robots in Stage [22].

A. Task and Environment

An open environment is divided into six heterogeneous regions, given to the participants on paper. The participants are told that each region contains exactly one target and the goal is to find all six targets. Each target is a different color so the participant can easily decipher exactly which target is in which region if all are found. Targets are placed so three are distanced from regional borders, two are near a border of two regions, and one is near a border where three regions come to a point.

B. Interface

The operator is given an interface, see Figure 1, which has a viewport of the open environment and displays the states of the swarm from a birds eye, orthographic view. The viewport does not have the regional boundaries drawn on. The participant must project the map onto the screen in their mind. A robot estimated position is displayed as a circle and a line pointing out the front of the robot. The operator can manipulate this viewport with a vertical and horizontal scroll bar and zoom in and out with two buttons in a panel to the right of the viewport. The operator can issue two commands: “head-towards” and “stop”. The “head-towards” command is given with a mouse click in the viewport. The “stop” command is issued as a button press in the panel to the left of the viewport.

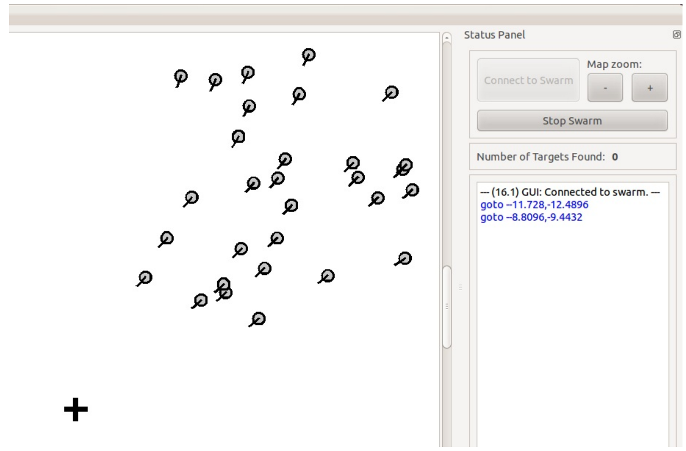

Fig. 1. The GUI used for the study. The left side shows the robots’ estimated position and the right side shows the viewport via which the study participants issued commands. The + shows the endpoint of the “head-towards” user command.

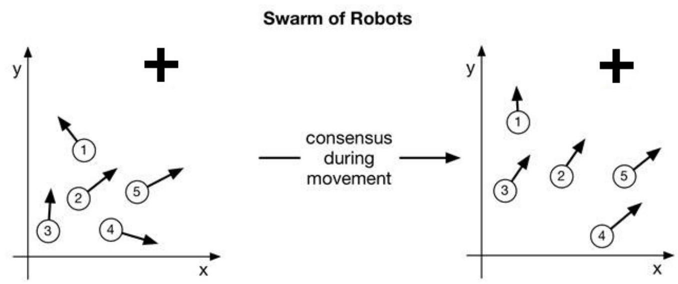

Fig. 2. Robots scatter because of orientation error, over time the swarm forms a consensus in a direction that is close to the “head-towards” point.

C. Robot Algorithms

The study includes error models for location and orientation, as well as algorithms for the effect of commands on the robots, both as individuals and a swarm. Location error is simulated with a Gaussian model, with standard deviation of 1.0 meter and mean at the ground truth. To simulate smooth transitions between sampled error values, the robots estimated position shifts in interpolated steps to the new error. Once the robot reaches the new estimated position, the error is resampled from a Gaussian distribution with mean at ground truth, so that the error remains bounded around the ground truth location. The location error should make discovery of targets near borders difficult. To place these targets in the correct region, the participant must use many robots to diminish the error or explore all possible regions until other targets are found which are clearly in one of the regions, eliminating that region from the list of possibilities. Orientation error is only calculated at the time a “head-towards” command is received. When the command is received the robot samples a Gaussian model, with standard deviation of $\pi/3$ radians and mean at the orientation vector at the “head-towards” point. The simulation of localization errors creates a more realistic scenario that considers the constraints of low-cost swarm robots.

The participants were given 30 robots to command. The “stop” command is trivial, as all robots halt forward motion. Once the robots are in motion they travel forward at 0.5 m/s. The “head-towards” command starts with the orientation error described above. The robots then start a standard consensus algorithm where they observe their neighbors within a communication range of 4.0 meters, average their neighbors headings, and adjust to match this average. This propagates through the swarm iterating until all robots within the communication graph are moving parallel, see Figure 2. If consensus is reached quickly enough, the robots can move beyond the communication range and break away from the main swarm group. Due to the nature of Gaussian noise models, the consensed heading will be closer to the requested “head-towards” point with a greater number of agents in the connected component of the communication graph. The participant decides whether the consensus direction is close enough.

D. Procedure

25 paid participants from the University of Pittsburgh participated in the study. The participants were familiarized with the task and the robot algorithms, and were shown how to use the GUI to issue commands. The participants were told that the goal of the study was for the robot swarm to identify all six targets. Each target was to have a different color and was placed in each region. Neither the targets nor the region divisions were shown in the GUI that the participants worked with. The participants were told that each (unknown) target had a different color and was placed in a different (not shown) region. Every time a robot member of the swarm was close to a target, the robot icon (a circle) on the display would turn the corresponding color, visible to the participants. The participants were given a hardcopy of the map showing the six regions but no targets. At the end of each session, the participants were asked to identify which region each color target existed. Participants were urged to only record a non-answer if they never saw that color target. If they were unsure which region the target was in, the participant was instructed to guess. The importance of maintaining one connected swarm of robots rather than splitting into smaller groups was stressed for error correction. Participants were told that new “head-towards” commands issued before consensus was reached could adversely affect the connectivity of the swarm, often causing robots to distance themselves from their neighbors until communication is no longer maintained. Participants were then given ten minutes to adjust to the interface and train for the task and get used to the interface.

The study had three experimental conditions: low bandwidth, medium bandwidth, and high bandwidth. Each participant performed in each of these conditions sequentially. The order of the conditions was randomized across participants. In the low bandwidth condition only one robot could update its information on the interface at a time. A token was randomly transmitted amongst the neighboring robots five times, every half second. This method used the communication network allowing for robots with a greater degree of connectivity to update more often. The interface stored the previous 21 updates. In those 21 updates, one robot could update many times and others might not update at all. If robots left the group, they would not update their data unless their path intersected with the group again. Reaching consensus could be difficult to observe since it took a few updates to see all robots moving in the same direction.

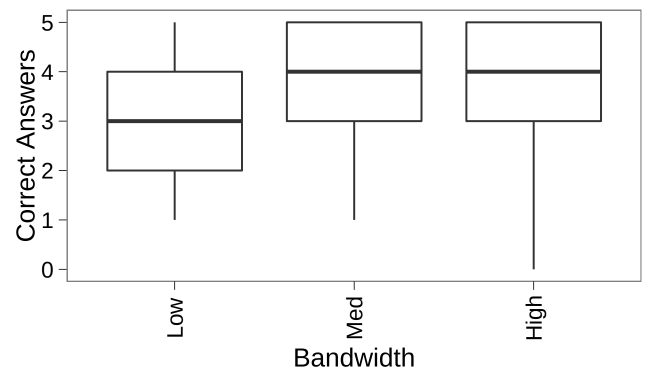

Fig. 3. Performance of the medium and high bandwidth conditions is comparable but both outperform the low bandwidth condition.

Another condition was the medium bandwidth condition. Robots could communicate between each other more and the swarm aggregated its information. The swarm determined the average location, heading, and the standard deviation of both of the robots within communication range. The standard deviation of the heading would allow the operator to determine when the swarm reached consensus and the standard deviation of the average location created the ellipsoid around the average point so the operator could interpret the general shape and density of the swarm. Up to four robots could update, which allowed smaller groups that break communication with the main swarm to update their information. Smaller groups of robot were more prone to error, but if a group happened to detect a target, the participant could use this information. Sensed targets were displayed as a colored percentage beside the aggregate display of the amount of robots in that group that could sense that color target. Finally, the third condition was the high bandwidth condition, where all robots updated their position every half second. The participant determined when consensus is reached by observing the movement of the individual robots in the swarm. As with the medium bandwidth condition, participants could see all robots so if small groups discovered a target, the participant could use that knowledge in the questionnaire.

IV. RESULTS

Analysis of the experimental data reveals differences between conditions as well as general differences of the control strategies between operators using ANOVA testing with a 0.05 p-value threshold indicating significance. Participants identify fewer targets correctly when in the low bandwidth condition than in the medium bandwidth condition. ($p<0.03$), see Figure 3. The difference between the medium bandwidth condition and the high bandwidth condition is statistically insignificant.

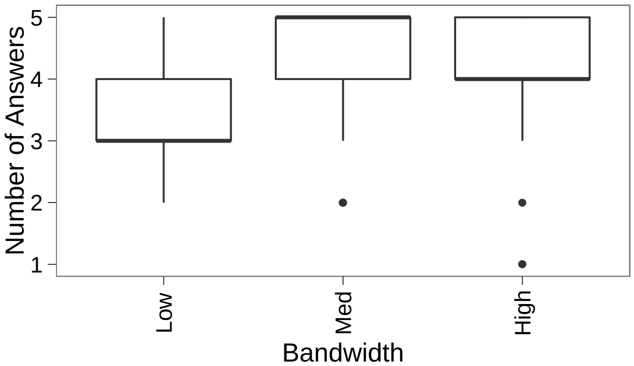

Fig. 4. The lack of performance for the low bandwidth condition is due to a lack of target discovery, not incorrect answers.

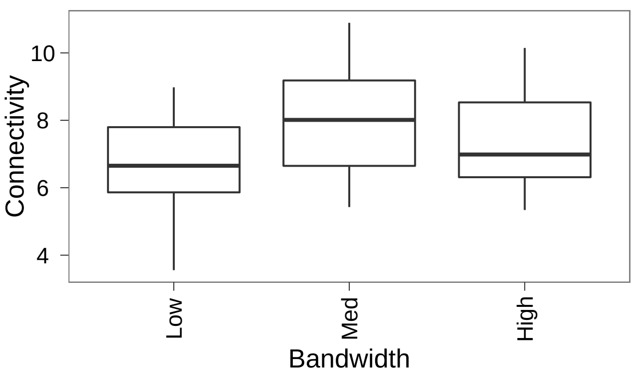

Fig. 5. Connectivity is highest in the medium bandwidth condition.

The difference in correct answers is explained by the difference in the total number of answers which corresponds to the total number of targets an operator finds, see Figure 4. Incorrect answers are statistically insignificant between all conditions.

The average degree of nodes in the communication graph between the swarm members is used to measure connectivity of the swarm. The low bandwidth condition is significantly less connected than the medium bandwidth condition ($p<0.003$), creating sparse communication graphs or possibly many smaller groups apart from the main swarm group, see Figure 5. The connectivity of the medium bandwidth shows that participants can maintain a denser swarm despite lacking information about the individual robots.

Operator behavior also differs regardless of condition. Operators that maintain a connected swarm differ by distance from swarm of “head-towards” commands and number of commands given. A comparison between the number of commands given and the average degree of nodes in the communication graph shows a positive correlation ($p<0.001$). This trend is counter-intuitive since commands should give swarm members opportunity to leave their neighbors decreasing swarm connectivity. Figure 6 shows a negative correlation between number of commands and mean distance to each command ($p<0.001$) explaining the counter-intuitive results since “head-towards”

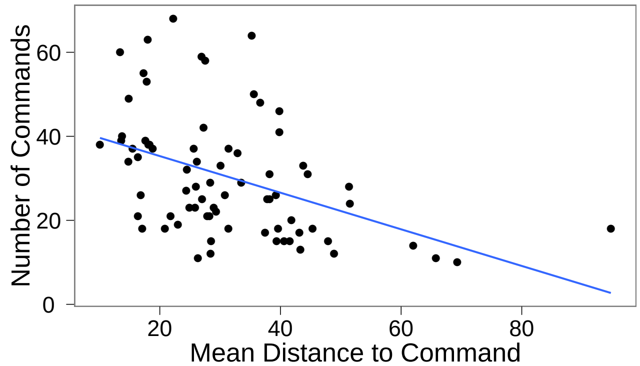

Fig. 6. Each point represents a participant during one condition. This compares the mean distance to a given “head-towards” point from the centroid of the swarm throughout each trial to the number of commands issued during the trial. Participants who give more commands do so closer, improving the connectivity counter-intuitively.

points selected closer will create more overlap between the agents’ Gaussian error models making it more likely that individual robots will turn towards others.

V. Discussion

The variation in task performance shows that bandwidth limitations primarily affect the ability to explore more of the regions rather than the ability to associate a target to a region, since incorrect answers are insignificant. The medium bandwidth is sufficient for this task since the difference to the high bandwidth condition is insignificant. The low bandwidth condition compares poorly to the medium bandwidth in both task performance and connectivity, showing a bias of the stated task towards temporal resolution over spatial resolution since this is the main difference between these two conditions. The medium bandwidth shows a diminished spatial resolution of the swarm since the information of the individual robots is aggregated into important information about the group and information about individual robots is not available. The results show that this decrease in spatial resolution does not adversely affect the performance or the participant’s ability to maintain a dense, connected swarm because of the lack of significant difference between the high and medium condition. The low bandwidth condition shows diminished temporal resolutions as well as a slightly diminished spatial resolution since most displayed locations of robots are over five seconds old and not all robots update their states. The decrease in performance of the low bandwidth condition could suffer from the temporal resolution or the in ability to see updates from individual robots exploring the environment apart from the main swarm group. It is possible that enough smaller, separated groups in the medium and high bandwidth conditions happened upon targets that the participants were not actively looking for increasing the average performance. The inability of the participant to maintain a dense swarm in the low bandwidth condition should be attributed to the lack of temporal resolution, however, because this is the only variable different between the other conditions that might affect connectivity of the swarm.

The results on operator behavior show trends of interest to user studies in HSI. The participants all have different styles when influencing the swarm to accomplish the given task. Some click with a greater frequency then others, but interestingly these participants do not diminish the connectivity of the swarm as expected due to the damaging effects of resetting the consensus algorithm often. This suggests that participants adapted to the given system and chose points closer to the swarm to maintain swarm cohesion when using a high frequency of commands, as shown in Figure 6. The participant's used intuition to adapt to a strategy that was not explicit in the instructions.

VI. Conclusions and Future Works

Two interesting results are observed. First, the medium bandwidth condition is sufficient for the given task. The lack of spatial information did not diminish the participants ability to accomplish the goal of the study. The low bandwidth condition suffered from temporal resolution and lack of information from the individual robots that separated from the group. The medium bandwidth condition could suffice as long as the operator can receive the information as in this study. Second, the operator behavior showed great adaptability to each participant's preferences even in the short time the participant used the system. This adaptability supports the hypothesis that an operator can interact with a swarm of robots in a way that can accomplish tasks. Operators learn and adapt to swarm dynamics and adapt their instructions to improve the swarm's behavior and state.

The limitations of this study include some task issues, environment simplification, and areas requiring further exploration. The difference between the medium and high condition could be significant, but the mean performance for both was too close to the maximum value. Future studies should increase the number of regions and target, increase environment size, or decrease the time for each condition so that the task is impossible to accomplish so variance in the data is available. In future work we will conduct studies to determine what information is necessary to maintain connectedness to exploring the connectivity observation between the low and medium bandwidth conditions. Future studies should also search for the role of the human operator in HSI by comparing different levels of control and varying types of control. This study shows a supervisory control with intermittent interaction. Other possibilities include varying level of control and continuous interactions.

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References

[1] C. Reynolds, "Flocks, herds and schools: A distributed behavioral model," in *ACM SIGGRAPH Computer Graphics*, vol. 21, no. 4. ACM, 1987, pp. 25–34.

[2] I. Couzin, J. Krause, R. James, G. Ruxton, and N. Franks, "Collective memory and spatial sorting in animal groups," *Journal of theoretical biology*, vol. 218, no. 1, pp. 1–11, 2002.

[3] W. Spears and D. Spears, *Physicomimetics: Physics-Based Swarm Intelligence*. Springer-Verlag New York Inc, 2012.

[4] D. Bruemmer, "A robotic swarm for spill finding and perimeter formation," DTIC Document, Tech. Rep., 2002.

[5] R. Morlok and M. Gini, "Dispersing robots in an unknown environment," *Distributed Autonomous Robotic Systems 6*, pp. 253–262, 2007.

[6] H. Choset, "Coverage for robotics–a survey of recent results," *Annals of Mathematics and Artificial Intelligence*, vol. 31, no. 1, pp. 113–126, 2001.

[7] F. Ducatelle, G. Di Caro, and L. Gambardella, "Cooperative self-organization in a heterogeneous swarm robotic system," in *Proceedings of the 12th annual conference on Genetic and evolutionary computation*. ACM, 2010, pp. 87–94.

[8] S. Bashyal and G. Venayagamoorthy, "Human swarm interaction for radiation source search and localization," in *Swarm Intelligence Symposium, 2008. SIS 2008. IEEE*. IEEE, 2008, pp. 1–8.

[9] C. Parker, H. Zhang, and C. Kube, "Blind bulldozing: multiple robot nest construction," in *Intelligent Robots and Systems, 2003.(IROS 2003). Proceedings. 2003 IEEE/RSJ International Conference on*, vol. 2. IEEE, 2003, pp. 2010–2015.

[10] R. Groß, M. Bonani, F. Mondada, and M. Dorigo, "Autonomous self-assembly in swarm-bots," *Robotics, IEEE Transactions on*, vol. 22, no. 6, pp. 1115–1130, 2006.

[11] R. Groß, R., F. Mondada, and M. Dorigo, "Transport of an object by six pre-attached robots interacting via physical links," in *Robotics and Automation, 2006. ICRA 2006. Proceedings 2006 IEEE International Conference on*. IEEE, 2006, pp. 1317–1323.

[12] F. Mondada, L. Gambardella, D. Floreano, S. Nolfi, J. Deneuborg, and M. Dorigo, "The cooperation of swarm-bots: Physical interactions in collective robotics," *Robotics & Automation Magazine, IEEE*, vol. 12, no. 2, pp. 21–28, 2005.

[13] M. Cummings, "Human supervisory control of swarming networks," in *2nd Annual Swarming: Autonomous Intelligent Networked Systems Conference*, 2004.

[14] P. Klarer, "Flocking small smart machines: An experiment in cooperative, multi-machine control," Sandia National Labs., Albuquerque, NM (United States), Tech. Rep., 1998.

[15] Z. Kira and M. Potter, "Exerting human control over decentralized robot swarms," in *Autonomous Robots and Agents, 2009. ICARA 2009. 4th International Conference on*. IEEE, 2009, pp. 566–571.

[16] M. Fields, E. Haas, S. Hill, C. Stachowiak, and L. Barnes, "Effective robot team control methodologies for battlefield applications," in *Intelligent Robots and Systems, 2009. IROS 2009. IEEE/RSJ International Conference on*. IEEE, 2009, pp. 5862–5867.

[17] A. Naghsh, J. Gancet, A. Tanoto, and C. Roast, "Analysis and design of human-robot swarm interaction in firefighting," in *Robot and Human Interactive Communication, 2008. RO-MAN 2008. The 17th IEEE International Symposium on*. IEEE, 2008, pp. 255–260.

[18] M. Goodrich, B. Pendleton, P. Sujit, and J. Pinto, "Toward human interaction with bio-inspired robot teams," in *Systems, Man, and Cybernetics (SMC), 2011 IEEE International Conference on*. IEEE, 2011, pp. 2859–2864.

[19] A. Kolling, S. Nunnally, and M. Lewis, "Towards human control of robot swarms," in *Proceedings of the 7th international conference on Human-robot interaction*. ACM, 2012.

[20] G. Coppin and F. Legras, "Autonomy spectrum and performance perception issues in swarm supervisory control," *Proceedings of the IEEE*, no. 99, pp. 590–603, 2012.

[21] B. P. Gerkey, R. T. Vaughan, and A. Howard, "The player/stage project: Tools for multi-robot and distributed sensor systems," in *International Conference on Advanced Robotics*, Coimbra, Portugal, 2003, pp. 317–323.

[22] M. Quigley, B. Gerkey, K. Conley, J. Faust, T. Foote, J. Leibs, E. Berger, R. Wheeler, and A. Ng, "Ros: an -open source robot operating system," in *International Conference on Robotics and Automation*, Kobe, Japan, 2009.