# Search & Rescue using Multi-Robot Systems

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## Abstract

Robotic search and rescue is a challenging yet promising research area which has significant real-world application potentials. In this paper, a survey of multi-robot systems and how they can be implemented in search and rescue operations is presented. In particular, the problems of task allocation, communication, and human-robot interaction in multi-robot systems are explored.

## 1 Introduction

Search and rescue (SAR) involves locating, rescuing, and medically stabilising victims trapped in hazardous spaces. As such, SAR operations are of great importance in disaster situations like earthquakes, hurricanes, tsunamis, or terrorist attacks. Rescue workers have approximately 48 hours to find trapped survivors, otherwise the likelihood of finding victims alive drops substantially [1]. Traditionally, such missions have been performed by human teams, however, disaster environments have been known to be very difficult to access by rescue workers due to potential presence of asbestos dust, poisonous gases, hazardous materials, radiation, or extreme temperatures [2]. Robots on the other hand can bypass the danger and expedite the search for victims immediately [1]. Thus, rescue robots provide a promising solution to assist rescue workers in many aspects of SAR operations.

For instance, rescue robots can reduce the chance of injury to workers and rescue dogs by entering unstable structures, increase the speed of response, and through multiple cameras and sensor fusion, extend the reach of rescue workers to regions that would otherwise have been inaccessible [3]. In simple cases, a single tele-operated robotic solution may be able to provide mission critical reconnaissance, but as the complexity of the mission and environment increases, single robot solutions have many drawbacks. A single robot solutions presents a single point of failure. If the robot becomes trapped, damaged, or disabled, the mission is unable to be completed. Furthermore, as the number of capabilities of a robot increases, it's cost and complexity also increase and can become prohibitive to it's design, production, and acquisition [4].

In order to address the limitations of single robot systems, research has been extended to included multi-robotic systems (MRSs) into SAR tasks. The introduction of multiple robots promises faster results and increased robustness through redundancy as each individual robot becomes dispensable. Moreover, limitations in individual robot payloads can be addressed. In particular, it is more economical and easier to distribute the necessary hardware for mission completion among multiple robots rather than integrate all necessary capabilities into a single robot [5]. MRS are more flexible and fault-tolerant than single robots acting alone, and can succeed at tasks that are basically too complex for a single robot to achieve because the single robot is spatially limited [6].

While promising, the integration of multiple robots into a rescue team is a challenging task. Apart from cooperation between human operators and each individual rescue robot, robot coordination amongst the team is important too. Furthermore, task distribution amongst different rescue robots also needs to be defined so that the robots, whether homogeneous or heterogeneous, can work effectively together within the context of the team [3]. The remainder of this paper is organised as follows. Section 2 describes the types of task allocation which are currently being researched for SAR purposes. Section 3 explores the work that has been done with regards to MRS communication for SAR missions. Section 4 investigates the progress that has been made in human-robot interactions (HRI) with regards to MRS in SAR. Finally, Section 5 summarises concluding remarks and future work.

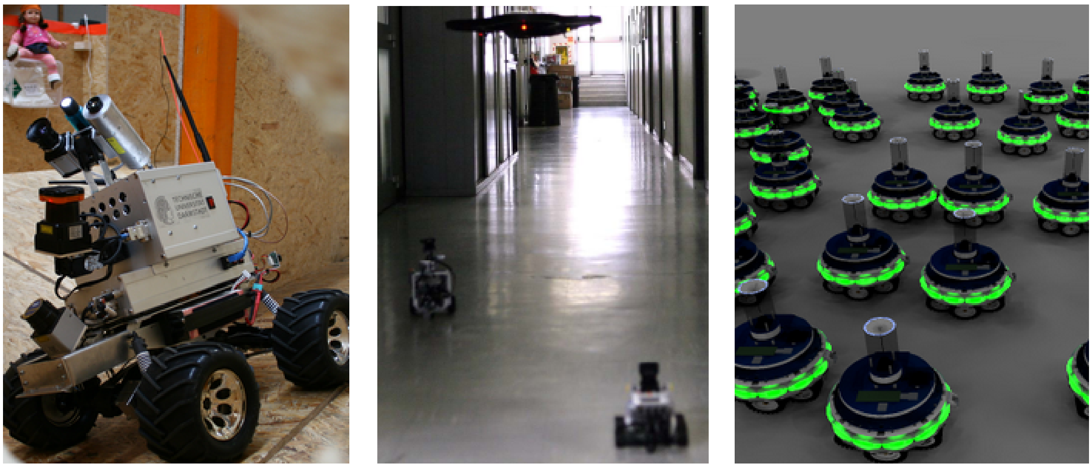

Figure 1: Different types of robots used in SAR. The first image to the left showing a single robot system, the second a heterogeneous MRS, and the third depicting a homogeneous or swarm MRS.

## 2 Task Allocation

The basic objectives of multi-robot task allocation (MRTA) is to distribute $M$ tasks to $N$ robots with the total costs minimised, while $M$ and $N$ are integers greater than or equal to one [7]. Early research focused on centralised and homogeneous robot systems but as MRSs increase in complexity with larger team sizes and greater heterogeneity of robots and tasks, it is an NP-hard problem to find the global-optimal solution. More recent work focuses on decentralised and heterogeneous robot systems, where various kinds of algorithms have been proposed in order to extend the class of overall task performance to the multi-assignment case. Some of these decentralised algorithms have been developed by supplanting the centralised planner in order to remove the single point of failure, as well as increase the mission range [8]. In SAR missions, one must consider the real-time allocation of tasks between team members.

MRTA methods can be categorised into centralised, decentralised, and hybrid approaches. In centralised MRS, a single agent is responsible for managing all the available resources, determining and distributing tasks among the entire robot team. Decentralised methods do not need an agent and only involve local information and local communications [7]. Hybrid systems combine local control with higher-level control approaches to achieve both robustness and the ability to influence the entire team's actions through global goals and plans [9]. Table 1 gives a summary of these classifications among several algorithm types.

Table 1: Classification of several algorithms according to whether they are a Centralised, Decentralised, or Hybrid task allocation approach.

| **Centralised** | | **Decentralised** | | **Hybrid** | |
|---|---|---|---|---|---|
| Fair Subdivision | [10] | Distributed Auction-Based | [13] | Consensus-based Auction | [8] |
| Equilibrium TA | [11] | VC TA | [14] | Prim Allocation | [16] |
| Dynamic TA | [12] | Learning Automata-Based Probabilistic | [15] | SET-MASR | [17] |
| | | | | Task-Switching | [18] |
| | | | | S+T | [19] |
| | | | | RDPSO | [20] |

## 2.1 Centralised Task Allocation

In [10], fair subdivision is used for subdividing and allocating a single global coverage task between an underwater robot and a surface vehicle, deployed in an unstructured environment to accomplish a search task. It deals with the heterogeneity of the robots by letting the robots define a preference function over the task space according to it's sensing and motion capabilities. Another centralised approach, equilibrium task allocation (TA), is used in [11] where robots are randomly assigned to search regions. If more than one robot is assigned to a region, the region is divided among the robots using a gradient-descent based method in order to equalise the time-loading between all robots. Experiments were carried out at *Boeing's Vehicle Swarm Technology Lab* using two quadrotors and two tanks to complete search area coverage [3].

## 2.2 Decentralised Task Allocation

Decentralised approaches use multi-task selection instead of multi-task allocation because the agents or robots select the tasks instead of being assigned a task by a centralised planner or temporal agent. As such, decentralised algorithms are developed using different approaches of conflict resolutions instead of using a temporal agent. This allows for tasks to be selected asynchronously. In [13], each task has to be completed within it's assigned deadline to reach the almost optimal solution. In [14], vacancy chains (VCs) are used to distribute resources among agents. A typical example is a bureaucracy where the retirement of a senior employee creates a vacancy that is filled by a less senior employee. This promotion, in turn, creates a second vacancy to be filled, and so on [14]. In [15], the learning automata method tries to guide the choice of future action by past responses.

## 2.3 Hybrid Task Allocation

Hybrid methods are essentially decentralised algorithms with a temporal agent such as the consensus-based auction algorithm [8], the prim allocation algorithm [16], SET-MASR algorithm [17], task-switching algorithm [18], etc. Most of them are what are called auction-based allocation algorithms [7]. In auction-based algorithms, there are two roles, the bidders and the auctioneer that are played dynamically among the robots, identifying the winner at each round and waiting for the new bids before starting the next round. The auctioneer is the so-called "temporal agent" that is in charge of announcing the tasks and selecting the best bid from all the bids [7].

In [19], tasks can be executed by more than one robot using the S+T algorithm. The basic idea behind the S+T algorithm is that a robot can ask others for services when it cannot execute a task by itself. Thus, it is even possible to execute missions with a task involving the whole team [7]. Robot swarms are considered in [20] with the use of Robotic Darwinian Particle Swarm Optimisation (RDPSO). RSPDO allows for multiple dynamic swarms. Hence enabling a distribute approach, because the network that might have been comprised of the whole swarm of robots is divided into multiple smaller networks (one for each swarm). This makes it possible to decrease the number of robots and the information exchanged between robots on the same network. Making RDPSO scalable to large populations of robots [20].

# 3 Communication

Communication can enhance the performance of MRS from several aspects [21]. It can allow robots to share position information, the state of the environment, and sensor data with others in the system. It also works in favour of individual robots enabling them to acquire information as to the intentions, goals, and actions of other robots [22]. This information can be obtained in a number of different ways. The two most common techniques are explicit and implicit. Explicit communication is where robots directly and intentionally communicate relevant information through some active means, such as radio. Implicit communication, called stigmergy, is where robots sense the effects of team-mate's actions through their effects on the world. It is also when robots use sensors to directly observe the actions of their team-mates [9]. Table 1 classifies different communication approaches used in cited papers based on whether they are explicitly or implicitly applied.

Table 2: Classification of communication approaches used in cited papers based on whether they are explicitly or implicitly applied.

| **Explicit** | | **Implicit** | |
|---|---|---|---|
| Behaviour-Based | [23] | Virtual Pheromone | [32] |
| Principled | [24] | Ant Inspired | [35] |
| Ad-hoc Wireless | [25] | Bee Inspired | [38] |
| Robot Maintained | [26] | Sharing Search Info. | [33] |
| Ad-hoc Newtork | | Approximation Algorithm | [34] |
| Limited Communication | [27] [28] [29] | Active Environment | [37] [36] [39] |
| Wireless Constraints | [30] | | |
| Overcome Local Minima | [31] | | |

## 3.1 Explicit Communication

Existing coordination methods are mainly based on the use of explicit communication [22]. In [23], a behaviour-based formation control strategy for multi-robot teams is presented. In order to communicate with the formation's unit-center, each robot communicates it's position to the other over a wireless network. A principled approach is taken by [24] where a general framework of inter-robot communication for dynamic task allocation is presented in terms of cooperative mobile robots. Wang et al [25] demonstrate an ad-hoc robot wireless communication scheme for a large system with many mobile robots to exchange information. This is extended in [26] where an algorithm is developed that enables a group of cooperating mobile robots to establish and maintain a wireless ad-hoc network to exchange task-related data. Which could help to increase the mission range in SAR environments.

In [27], the authors aim to reduce repeat coverage, defined as any robot covering previously covered space, in an unknown setting. They exam the problem of multi-robot coverage path planning for a team of robots with limited communication, where robots operate under the restriction that communication between two robots is only available when they are within the line of sight of each other. Limited communication approaches are also examined by [29] and [28], where [28] looks at the problem of navigation of dynamically communicating robots where there is a bidirectional interaction between the robot network and continuous states. In this case, it was found that employing a mixture of deterministic and game-theoretic approaches yielded best task completion percentages.

An approach for multi-robot exploration that takes into account the constraints of wireless networking is demonstrated in [30]. A communicative exploration which takes into account the limited constraints of the transceivers is implemented. An algorithm is introduced based on a population that samples the possible moves of all robots and a utility function is used to select the best one in each time step. Explicit communication is even used to overcome the problem of local minima, particularly prevalent in homogeneous robot systems dependent on behavioural inspired coordination. In [31], a composition of gradient descent and potential fields is used to guide robots to the target while avoiding obstacles. To overcome local minima, a distribution coordination mechanism was developed based on mode switching that reallocates some robots as rescuers and sends them to help the robots that may be trapped.

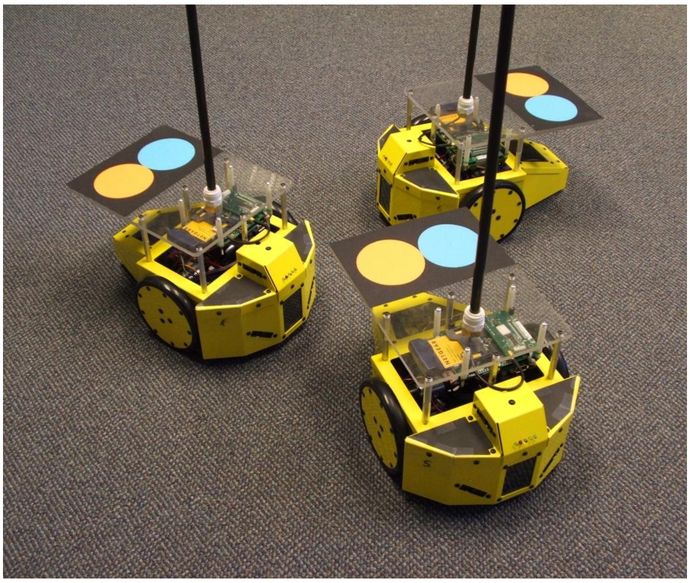

Figure 2: Group of Emulab wireless networking robots [60].

### 3.2 Implicit Communication

Implicit communication can be divided into active implicit communication and passive implicit communication. Active refers to the fact that robots can communicate by collecting the remaining information of others in the environment. The use of this is typically related to the field of biomimetrics, and is usually inspired by the collective behaviour of bees and ants. Passive refers to the fact that the robots can also communicate by perceiving a change in the environment through the use of sensors. For instance, the necessity of a robot to compute the context information, such as the position and attitude of others by modelling and reasoning based on the perceived data in order to cooperate with them.

In [32], a virtual pheromone was proposed for coordinating the actions of a robot swarm to facilitate quick survivor localisation in SAR scenes. In the proposed approach, a swarm of mini-robots can be deployed in a building. Upon detecting a survivor, a robot emits a message signalling the discovery, which is relayed locally between neighbouring robots. The message propagates along unobstructed paths, producing a "virtual pheromone" gradient, which can guide human rescuers or larger victim manipulating robots to a survivor [3]. In [35], two ant-inspired algorithms for robot foraging: VP and cardinality. Essentially, stigmergy is used as a message protocol, measuring the performance of the swarm in dynamic obstacle environments. Furthermore, the authors of [38], implement the necrophoric behaviour of bees as a way to give the robots of the swarm the capability of recognising and rescuing a disabled robot.

Implicit cooperation is also enabled through the sharing of search progress information [33], using an approximate algorithm for multi-robot path-planning [34], and through the robots' perception of their surroundings [37], enabling robots to make decisions through stigmergy. In [36], the authors use a swarm of robots for checking emergency infrastructure in order to anticipate the restoration of this infrastructure as well as the community functions. They propose that a decision support system can receive feedback of a swarm of robots specialised in inspecting infrastructure in a disaster scenario using stigemergy. In [39], a swarm of robots serves as guidance to human fire-fighters in large critical scenarios where visibility is poor due to the smoke. The purpose is to give support when the navigation of the human being is compromised to some degree.

### 3.3 Hybrid Communication

Selecting the appropriate use of communication in a MRS is a design choice dependent upon the tasks to be achieved by the MRS. The challenge in MRSs is to discover the "optimal" pieces of information to exchange that yield these performance improvements without saturating the communications bandwidth [9]. The use of explicit communication can ensure the accuracy of the exchange of information between robots. However, the communication load of a system will increase as the number of robots increases. This may cause a decrease in system performance or else lead to an overall system failure in extreme cases. In using implicit communication, although the information obtained by a robot is not completely reliable, the stability, reliability and fault tolerance of the whole MRS are better than in using an explicit pattern. Thus, applying both explicit and implicit methods in practice can make the two methods complement each other [22]. Hybrid communication approaches have been implemented in [40], [41], [21], and [42].

In [40], experiments were conducted at the *McKenna Military Operation on Urban Terrain site*, where a team of aerial and ground robots was deployed to patrol an urban village and search for and localise human targets. A hybrid framework for a single operator to deploy the team of heterogeneous robots was presented. The robots autonomously deployed themselves to search for a target of interest after receiving a universal commence signal from the base station. Local controllers implemented on each robotic sensor platform were used to direct the robots as well as their sensors according to a mutual information gradient approach, allowing individual robots to drive in directions that maximise their information gain locally. Aerial robots conducted an initial coarse search of the region, determined potential target locations and generated maps that were used to design navigation controllers an plan missions for the team. The UGVs were deployed to conduct a more localised search and identify the targets on the basis of the aerial robots' initial assessment [3].

# 4 Human-Robot Interaction

The HRI problem can be defined as understanding and shaping the interactions between one or more humans and one or more robots. Interactions between humans and robots are inherently present in all of robotics, including autonomous robots. Humans can play a variety of roles while participating in given tasks with MRS [43]. Such roles include: Planning and instructing the MRS to perform a task in a particular manner. Monitoring the MRS's implementation of given instructions. Intervening, when necessary, to adjust or correct robots. Learning from the performance and outcomes of the MRS in order to improve planning for future interactions [44].

In SAR, teamwork is essential. However, the integration of multiple robots and humans into a rescue team is a challenging task. Regarded as one of the major bottle-necks in rescue robotics [45]. One of the main considerations in devising a team is to determine the ratio of human operators to robots [3]. How many remote robots can a single human manage? In general, the answer is dependent on factors such as the level of autonomy (LOA) of the robots, the task at hand, and the available modes of communication [46]. More autonomy in robots means that the human managing the robot may have available free time. Free time which could be used to manage multiple robots [47]. Figure 1 illustrates levels of autonomy with emphasis on human interaction.

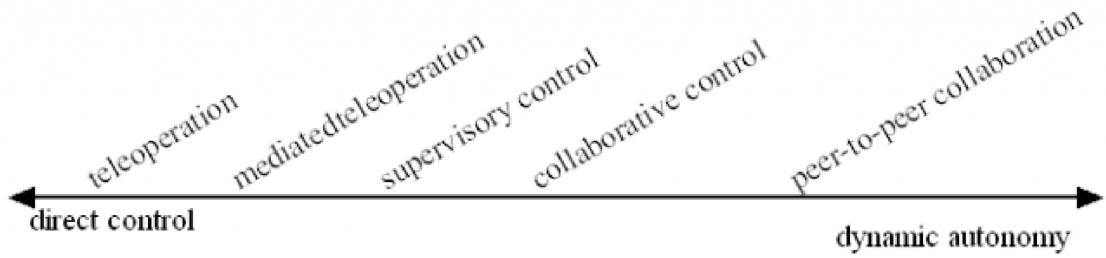


Figure 3: Levels of autonomy with emphasis on human interaction [52].

## 4.1 Human-Robot Teams

A key factor in constructing human-robot teams is the ratio of robots to humans and visa-versa. The effects of the number of robots controlled by an operator on the performance of a SAR task were investigated in simulations with 4 to 12 simulated UGVs in [48]. Participants were asked to search for victims while controlling varying numbers of robots. The results showed that task performance increased when going from 4 to 8 robots but decreased when going from 8 to 12 robots. The human-robot ration was also investigated in [49] within the context of the RoboCup Rescue Real Robot League[1]. It was found that the success rate of cooperative tasks increased when the number of robots to be controlled was increased. An operator made faster decisions with less hesitation while controlling more than one robot.

The above scenarios refer to single-human multiple-robot cooperation tasks. In [50], the challenge of controlling multiple robots with multiple humans was investigated. Twenty-four simulated mobile robots were used to explore and search for victims in a large SAR virtual environment. The group of robots was controlled by teams of two people, in either a joint control capacity or an assigned (twelve robots each) control approach. It was found that there was a substantial advantage for autonomous exploration over manual exploration in joint/shared control, whilst the difference was negligible in the assigned case [50]. Indicating that the level of autonomy required by robots in a MRS is dependent on the number of human operators involved.

In addition to teams with human operators and robots, there has also been some work that has focused on devising teams where human rescue workers work in a peer-to-peer fashion with robots. In [51], the problem of jointly performing RFID-based[2] SLAM by robots and fire-fighters was explored. Human poses were tracked by analysing acceleration patterns to determine footsteps, and robot poses were tracked using wheel odometry and IMU data. Then both the humans and robots estimated the distances between RFID tags by pose tracking and this information was sent to a central station, where a joint global graph was constructed. Human-robot team experiments conducted on the campus of the *University of Freiburg* showed that information sharing between humans and robots allows for the correction of their individual paths globally [51].

## 4.2 Information Exchange

A second component which is important in HRI is the manner in which information is exchanged between humans and robots. Measures of the efficiency of an interaction include the interaction time required for an intent and/or instructions to be communicated to the robot [47], the cognitive or mental workload of an interaction [54], the amount of situational awareness (SA) produced by the interaction [55], and the amount of shared understanding between humans and robots [56] [57]. Information exchange in HRI can happen through an array of mediums, the primary forms being seeing, hearing, and touch which manifest in HRI as follows:

- Visual displays, typically presented as graphical user interfaces or augmented reality interfaces [58] [53].
- Gestures, including hand and facial movements and by movement-based signalling of intent [53].
- Sounds for alerting.
- Speech and natural language, which include both auditory speech and text-based responses [59].
- Physical interaction and haptics, frequently used remotely in augmented reality or in tele-operation to invoke a sense of presence especially in tele-manipulation tasks.

[1]The RoboCup Rescue Robot League is an international competition for urban search and rescue robots, in which robots compete to find victims in a simulated earthquake environment.

[2]RFID is radio-frequency identification.

Many human-robot interfaces for mobile robots are often hard to use, confusing, and suffer from both information overload and poor situational awareness. In [58], a human-robot interface for the tele-operated SAR research robot, CASTER, is presented. Experiments conducted evaluated the designed interface as quick to learn, easy to use, and effective. In [53], a novel interface *Pose and Paste (P%P)* was conceived to facilitate interaction between a single user and a number of robots equipped with cameras. The user of the (P&P) interface is able to cycle through the visual perspective of each robot, acquire control of a robot, and map the user's body movements into robot motion. In experiments, operators at MIT in the USA successfully controlled two aerial robots flying in a lab at DLR in Germany.

## 5 Conclusions

In this paper, a search and rescue focused survey of task allocation, communication, and human-robot interaction methodologies in multi-robot systems has been presented. The main conclusions drawn from this review are as follows.

In SAR missions time is of the essence, thus, in [13], each task has to be completed within it's assigned deadline. Time constraints in TA can be beneficial to SAR where robots need to move objects from one place to another so that the paths become usable by other robots that have to reach potential victims. In such cases, there may be a deadline for the robots to clear paths because victims should be found and reached within some time [13]. In [15], the learning automata TA method tries to guide the choice of future action by past responses. As such, this algorithm can be applied to a broad range of modelling and control problems without the complete knowledge of the environment [7]. The S+T algorithm [19], could be used in scenarios where transmitting images in real-time could require another robot to act as a communication relay. If a robot cannot execute a task by itself, it asks for help. Other possible scenarios, where this approach is useful, is in the box-pushing problem [19]. Future SAR robotics could use this for developing robots that can help manoeuvre and transport trapped victims out of the rubble [9].

With regards to robot coordination, researchers generally agree that communication can have a strong positive impact on the performance of a robot team. However, more information does not necessarily continue to improve performance, as it can quickly overload the communications bandwidth without providing an application benefit. The challenge in MRSs is to discover the "optimal" pieces of information to exchange that yield these performance improvements without saturating the communications bandwidth [9]. So far a mixture of explicit and implicit methods have been demonstrated in SAR experiments each demonstrating strengths in different areas. Explicit can ensure accuracy but does not scale well, unlike implicit, when more robots are introduced. Thus, hybrid methods, applying both explicit and implicit communication, appear to best approach in practice that should be further researched in the context of MRS in SAR [22].

Finally, a lot more progress needs to be made in the way of HRI with respect to MRS in SAR tasks. At the moment, the current level of autonomy in robots allows a single human operator to effectively control approximately 8 robots in SAR simulations [48]. However, in most real world SAR missions the ration of human to robots is in fact 2:1 [45]. Future improvements in SAR robot infrastructure and communication interfaces need to focus on correcting this. Human-robot communication interfaces in particular requiring a lot of attention. Multi-agent software exists [61] but it needs to be adapted for the SAR task. The user should be able to give high level commands to a team of robots and the robots should be able to plan and coordinate their task. Unfortunately, unfamiliar and unstructured environments, unreliable communications and many sensors combine to make the job of a human operator, and hence the job of the interface designer, challenging. However, the work of [58] and [53] have proved this to not be impossible.

## References

[1] Shah, B., & Choset, H. Survey on Urban Search and Rescue Robotics.

[2] Casper, J., & Murphy, R. R. (2003). Human-robot interactions during the robot-assisted urban search and rescue response at the world trade center. *Systems, Man, and Cybernetics, Part B: Cybernetics, IEEE Transactions on, 33*(3), 367-385.

[3] Liu, Y., & Nejat, G. (2013). Robotic urban search and rescue: A survey from the control perspective. *Journal of Intelligent & Robotic Systems, 72*(2), 147-165.

[4] Drenner, A., Janssen, M., Kottas, A., Kossett, A., Carlson, C., Lloyd, R., & Papanikolopoulos, N. (2013). Coordination and Longevity in Multi-Robot Teams Involving Miniature Robots. *Journal of Intelligent & Robotic Systems, 72*(2), 263-284.

[5] Wong, C. Y., Seet, G., & Sim, S. K. (2011). Multiple-Robot Systems for USAR: Key Design Attributes and Deployment Issues. *International Journal of Advanced Robotic Systems, 8*(1).

[6] El Zoghby, N., Loscri, V., Natalizio, E., & Cherfaoui, V. (2014). Robot Cooperation and Swarm Intelligence. *Wireless Sensor and Robot Networks: From Topology Control to Communication Aspects.*

[7] Jia, X., & Meng, M. Q. H. (2013, December). A survey and analysis of task allocation algorithms in multi-robot systems. In *Robotics and Biomimetics (ROBIO), 2013 IEEE International Conference on* (pp. 2280-2285). IEEE.

[8] Choi, H. L., Brunet, L., & How, J. P. (2009). Consensus-based decentralized auctions for robust task allocation. *Robotics, IEEE Transactions on, 25*(4), 912-926.

[9] Parker, L. E. (2008). Multiple mobile robot systems. *Springer Handbook of Robotics*, 921-941.

[10] Higuera, J. C. G., & Dudek, G. (2013, May). Fair subdivision of multi-robot tasks. In *Robotics and Automation (ICRA), 2013 IEEE International Conference on* (pp. 3014-3019). IEEE.

[11] Meuth, R., Saad, E. W., Wunsch, D. C., & Vian, J. (2009, November). Adaptive task allocation for search area coverage. In *Technologies for Practical Robot Applications, 2009. TePRA 2009. IEEE International Conference on* (pp. 67-74). IEEE.

[12] Tsalatsanis, A., Yalcin, A., & Valavanis, K. P. (2009). Dynamic Task Allocation in Cooperative Robot Teams. *International Journal of Advanced Robotic Systems, 6*(4).

[13] Luo, L., Chakraborty, N., & Sycara, K. (2013, May). Distributed algorithm design for multi-robot task assignment with deadlines for tasks. In *Robotics and Automation (ICRA), 2013 IEEE International Conference on* (pp. 3007-3013). IEEE.

[14] Dahl, T. S., Mataric, M. J., & Sukhatme, G. (2003, September). Multi-robot task-allocation through vacancy chains. In *Robotics and Automation, 2003. Proceedings. ICRA'03. IEEE International Conference on* (Vol. 2, pp. 2293-2298). IEEE.

[15] de Lope, J., Maravall, D., & Quiñonez, Y. (2013). Response threshold models and stochastic learning automata for self-coordination of heterogeneous multi-task distribution in multi-robot systems. *Robotics and Autonomous Systems, 61*(7), 714-720.

[16] Lagoudakis, M. G., Berhault, M., Koenig, S., Keskinocak, P., & Kleywegt, A. J. (2004, October). Simple auctions with performance guarantees for multi-robot task allocation. In *Intelligent Robots and Systems, 2004.(IROS 2004). Proceedings. 2004 IEEE/RSJ International Conference on* (Vol. 1, pp. 698-705). IEEE.

[17] Viguria, A., Maza, I., & Ollero, A. (2007, April). SET: An algorithm for distributed multirobot task allocation with dynamic negotiation based on task subsets. In *Robotics and Automation, 2007 IEEE International Conference on* (pp. 3339-3344). IEEE.

[18] Sung, C., Ayanian, N., & Rus, D. (2013, May). Improving the performance of multi-robot systems by task switching. In *Robotics and Automation (ICRA), 2013 IEEE International Conference on* (pp. 2999-3006). IEEE.

[19] Viguria, A., Maza, I., & Ollero, A. (2008, May). S+ T: an algorithm for distributed multirobot task allocation based on services for improving robot cooperation. In *Robotics and Automation, 2008. ICRA 2008. IEEE International Conference on* (pp. 3163-3168). IEEE.

[20] Couceiro, M. S., Rocha, R. P., & Ferreira, N. M. (2011, November). A novel multi-robot exploration approach based on particle swarm optimization algorithms. In *Safety, Security, and Rescue Robotics (SSRR), 2011 IEEE International Symposium on* (pp. 327-332). IEEE.

[21] Cayrpunar, O., Tavl, B., & Gazi, V. (2008). Dynamic robot networks for search and rescue operations.

[22] Yan, Z., Jouandeau, N., & Cherif, A. A. (2013). A Survey and Analysis of Multi-Robot Coordination. *INTERNATIONAL JOURNAL OF ADVANCED ROBOTIC SYSTEMS, 10.*

[23] Balch, T., & Arkin, R. C. (1998). Behavior-based formation control for multirobot teams. *Robotics and Automation, IEEE Transactions on, 14*(6), 926-939.

[24] Gerkey, B. P., & Matarić, M. J. (2001). Principled communication for dynamic multi-robot task allocation. In *Experimental Robotics VII* (pp. 353-362). Springer Berlin Heidelberg.

[25] Wang, Z., Zhou, M., & Ansari, N. (2003, October). Ad-hoc robot wireless communication. In *Systems, Man and Cybernetics, 2003. IEEE International Conference on* (Vol. 4, pp. 4045-4050). IEEE.

[26] Pimentel, B. S., & Campos, M. F. M. (2003, October). Cooperative communication in ad hoc networked mobile robots. In Intelligent Robots and Systems, 2003.(IROS 2003). Proceedings. *2003 IEEE/RSJ International Conference on* (Vol. 3, pp. 2876-2881). IEEE.

[27] Rekleitis, I., Lee-Shue, V., New, A. P., & Choset, H. (2004, April). Limited communication, multi-robot team based coverage. In *Robotics and Automation, 2004. Proceedings. ICRA'04. 2004 IEEE International Conference on*(Vol. 4, pp. 3462-3468). IEEE.

[28] Bayram, H., & Bozma, H. I. (2010, October). Multi-robot navigation with limited communication-deterministic vs game-theoretic networks. In *Intelligent Robots and Systems (IROS), 2010 IEEE/RSJ International Conference on (pp. 1825-1830). IEEE.*

[29] Li, S., & Guo, Y. (2012, May). Distributed source seeking by cooperative robots: all-to-all and limited communications. In *Robotics and Automation (ICRA), 2012 IEEE International Conference on* (pp. 1107-1112). IEEE.

[30] Rooker, M. N., & Birk, A. (2007). Multi-robot exploration under the constraints of wireless networking. *Control Engineering Practice, 15*(4), 435-445.

[31] Marcolino, L. S., & Chaimowicz, L. (2008, May). No robot left behind: Coordination to overcome local minima in swarm navigation. In *Robotics and Automation, 2008. ICRA 2008. IEEE International Conference on* (pp. 1904-1909). IEEE.

[32] Payton, D., Estkowski, R., & Howard, M. (2005). Pheromone robotics and the logic of virtual pheromones. In *Swarm Robotics* (pp. 45-57). Springer Berlin Heidelberg.

[33] Anderson, M., & Papanikolopoulos, N. (2008). Implicit cooperation strategies for multi-robot search of unknown areas. *Journal of Intelligent and Robotic Systems, 53*(4), 381-397.

[34] Hollinger, G., Singh, S., Djugash, J., & Kehagias, A. (2009). Efficient multi-robot search for a moving target. *The International Journal of Robotics Research, 28*(2), 201-219.

[35] Hoff, N. R., Sagoff, A., Wood, R. J., & Nagpal, R. (2010, December). Two foraging algorithms for robot swarms using only local communication. In *Robotics and Biomimetics (ROBIO), 2010 IEEE International Conference on* (pp. 123-130). IEEE.

[36] Plevris, V., Karlaftis, M. G., & Lagaros, N. D. (2010). A swarm intelligence approach for emergency infrastructure inspection scheduling. In *Sustainable and Resilient Critical Infrastructure Systems* (pp. 201-230). Springer Berlin Heidelberg.

[37] Simonin, O., & Charpillet, F. (2010, May). Indirect cooperation between mobile robots through an active environment. In *5th National Conference on Control Architecture of Robots* (pp. 71-80).

[38] Purnamadjaja, A. H., & Russell, R. A. (2004, December). Pheromone communication: implementation of necrophoric bee behaviour in a robot swarm. In *Robotics, Automation and Mechatronics, 2004 IEEE Conference on* (Vol. 2, pp. 638-643). IEEE.

[39] Marjovi, A., Marques, L., & Penders, J. (2009, October). Guardians robot swarm exploration and firefighter assistance. In *Workshop on NRS in IEEE/RSJ international conference on Intelligent Robots and Systems (IROS), St Louis, USA*.

[40] Hsieh, M. A., Cowley, A., Keller, J. F., Chaimowicz, L., Grocholsky, B., Kumar, V., ... & MacKenzie, D. C. (2007). Adaptive teams of autonomous aerial and ground robots for situational awareness. *Journal of Field Robotics, 24*(1112), 991-1014.

[41] Wang, T., Dang, Q., & Pan, P. (2013). A Multi-Robot System Based on A Hybrid Communication Approach. *Studies in Media and Communication, 1*(1), 91-100.

[42] Mi, Z., Yang, Y., & Liu, G. (2011, May). HERO: A hybrid connectivity restoration framework for mobile multi-agent networks. In *Robotics and Automation (ICRA), 2011 IEEE International Conference on* (pp. 1702-1707). IEEE.

[43] Mi, Z. Q., & Yang, Y. (2013). Human-Robot Interaction in UVs Swarming: A Survey. *International Journal of Computer Science Issues (IJCSI)*, 10(2).

[44] Sheridan, T. B., & Parasuraman, R. (2005). Human-automation interaction. *Reviews of human factors and ergonomics, 1*(1), 89-129.

[45] Murphy, R. R. (2004). Human-robot interaction in rescue robotics. *Systems, Man, and Cybernetics, Part C: Applications and Reviews, IEEE Transactions on, 34*(2), 138-153.

[46] Goodrich, M. A., & Schultz, A. C. (2007). Human-robot interaction: a survey. *Foundations and trends in human-computer interaction, 1*(3), 203-275.

[47] Crandall, J. W., Goodrich, M. A., Olsen Jr, D. R., & Nielsen, C. W. (2005). Validating human-robot interaction schemes in multitasking environments. *Systems, Man and Cybernetics, Part A: Systems and Humans, IEEE Transactions on, 35*(4), 438-449.

[48] Velagapudi, P., Scerri, P., Sycara, K., Wang, H., Lewis, M., & Wang, J. (2008, September). Scaling effects in multi-robot control. In *Intelligent Robots and Systems, 2008. IROS 2008. IEEE/RSJ International Conference on* (pp. 2121-2126). IEEE.

[49] Sato, N., Matsuno, F., Yamasaki, T., Kamegawa, T., Shiroma, N., & Igarashi, H. (2004, October). Cooperative task execution by a multiple robot team and its operators in search and rescue operations. In *Intelligent Robots and Systems, 2004.(IROS 2004). Proceedings. 2004 IEEE/RSJ International Conference on* (Vol. 2, pp. 1083-1088). IEEE.

[50] Lewis, M., Wang, H., Chien, S. Y., Scerri, P., Velagapudi, P., Sycara, K., & Kane, B. (2010, October). Teams organization and performance in multi-human/multi-robot teams. In *Systems Man and Cybernetics (SMC), 2010 IEEE International Conference on* (pp. 1617-1623). IEEE.

[51] Kleiner, A., Dornhege, C., & Dali, S. (2007, September). Mapping disaster areas jointly: RFID-Coordinated SLAM by Hurnans and Robots. In *Safety, Security and Rescue Robotics, 2007. SSRR 2007. IEEE International Workshop on* (pp. 1-6). IEEE.

[52] Human-Robot Interaction. (n.d.). *HumanRobot Interaction RSS*. Retrieved May 7, 2014, from http://humanrobotinteraction.org/autonomy/

[53] Lichtenstern, M., Angermann, M., Frassl, M., Berthold, G., Julian, B. J., & Rus, D. (2013, November). Pose and pasteAn intuitive interface for remote navigation of a multi-robot system. In *Intelligent Robots and Systems (IROS), 2013 IEEE/RSJ International Conference on* (pp. 1632-1639). IEEE.

[54] Sheridan, T. B. (2002). *Humans and automation: System design and research issues.* John Wiley & Sons, Inc..

[55] Endsley, M. R. (2012). *Designing for situation awareness: An approach to user-centered design.* CRC Press.

[56] Johnston, J. H., Fiore, S. M., Paris, C., & Smith, C. A. (2002). *Application of cognitive load theory to developing a measure of team decision efficiency.* NAVAL AIR WARFARE CENTER TRAINING SYSTEMS DIV ORLANDO FL.

[57] Klein, G., Feltovich, P. J., Bradshaw, J. M., & Woods, D. D. (2005). Common ground and coordination in joint activity. *Organizational simulation, 53.*

[58] Kadous, M. W., Sheh, R. K. M., & Sammut, C. (2006, March). Effective user interface design for rescue robotics. In *Proceedings of the 1st ACM SIGCHI/SIGART conference on Human-robot interaction* (pp. 250-257). ACM.

[59] Hong, J. H., Song, Y. S., & Cho, S. B. (2005, April). A hierarchical bayesian network for mixed-initiative human-robot interaction. In *Robotics and Automation, 2005. ICRA 2005. Proceedings of the 2005 IEEE International Conference on* (pp. 3808-3813). IEEE.

[60] *Emulab.Net - Emulab Tutorial - Mobile Wireless Networking.* (n.d.). Retrieved from http://www.emulab.net/tutorial/mobilewireless.php3.

[61] Giampapa, J. A., & Sycara-Cyranski, K. (2002). *Team-oriented agent coordination in the RETSINA multi-agent system.* Carnegie Mellon University, The Robotics Institute.