Balancing Mission and Comprehensibility in Multi-Robot Systems for Disaster Response

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Abstract— **Real-world disaster response or search and rescue operations require the seamless interaction of multiple teams and agencies. As multi-robot systems become more frequently used for disaster response due to the inherent dangerous environments, these systems must be controlled in way that balances the accomplishment of their mission with interaction with neighboring teams. In this paper, we address this problem by examining the balance of mission and comprehensibility. By mission, we refer to the overall task of the multi-robot system, which in a disaster response scenario is often searching an area and communicating results back to rescuers. By comprehensibility, we refer to a multi-robot system arranging itself in a way that a neighboring observer can understand what roles its members play, and react accordingly. When mission and comprehensibility are properly balanced, multi-robot teams will be more effective at working alongside one another. We propose a system of control laws for two robot roles, hubs and sensors, which provide communication and sensing, respectively. We propose additional control laws to maintain an understandable formation. Through extensive simulation of a variety of multi-robot system sizes and formations, we examine the effect of balancing mission and comprehensibility on concrete metrics for sensor coverage and role understanding.**

Fig. 1. We explore the effect of controlling a multi-robot system with the goal of accomplishing a *mission* (left side) such as sensor coverage, versus remaining *comprehensible* (right side). On the left side, team member roles are difficult to identify but the overall sensing area (marked by red circles) is high. On the right side, observers can comprehend the team structures as distinct central hubs emerge, but at the expense of overlapping sensing areas. When multiple multi-robot teams need to cooperate in an environment without communicating with each other, being able to understand the other teams is crucial.

I. Introduction

Multi-robot systems are being used to address a multitude of tasks for disaster response and search and rescue due to their ability to operate in hazardous environments [1]. As robots can continue to work in areas with radiation, smoke, high temperatures, risk of structural collapse, or other dangers, they are crucial to efforts to respond to disasters and search and rescue for survivors. In order to address disaster response in a large environment, robots must work together in teams, with individual robots performing distinct roles [2]. Heterogeneous multi-robot teams enable rescuers to respond to a variety of physical and technical challenges in disaster areas.

In disaster response scenarios, multiple agencies may be addressing the same problem [3]. For example, in response to a hurricane, the National Guard (NG) from the United States may be searching for survivors alongside local authorities. While both organizations may be utilizing robots to perform the search, due to the urgency of the response and the technical challenges involved in sharing data, the robot teams are unlikely to be able to communicate with one another. In a scenario like this, the multi-robot teams need to develop shared situational awareness [4] - the NG robots need to comprehend the roles of the local robots in order to determine where they might search next, and accordingly, the local robots must comprehend the roles of the NG robots in order to respond in kind. If roles are correctly understood, organizations can avoid overlapping their search areas and optimally distribute resources. Both multi-robot systems must consider the balance of their mission (searching for survivors) with maintaining comprehensibility in order to maximize the overall mission area, as illustrated in Figure 1.

The problem of controlling a heterogeneous multi-robot team in order to be understandable to observers has not been previously addressed. While applying multi-robot systems to disaster response and sensor coverage has been extensively researched [5]–[7], solutions have relied on single points of coordination, assumptions that multiple agencies use compatible tracking software, or seamless communication even in complex disaster areas. Similarly, the problem of understanding multi-robot systems has been addressed from the perspective of static formations [8], but has not been addressed to maintain this comprehensibility while accomplishing a mission. Addressing the balance of mission and comprehensibility will enable multi-robot teams to more

*This work was partially supported by ARL CA W911NF-21-2-0021.

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effectively work alongside one another.

In this paper, we propose a principled examination of balancing mission and comprehensibility in multi-robot systems, where heterogeneous multi-robot teams within the system cannot communicate with each other. We introduce a group of basic control laws that define each robot's movement in regard to accomplishing the mission or maintaining a comprehensible formation, and combine these basic control laws by parameterizing the balance of the 'mission' laws and the 'comprehensibility' laws. We then thoroughly examine the impact of this balance on a variety of multi-robot system sizes and formations.

This paper has 2 important contributions.

1) First, we introduce the problem of controlling heterogeneous multi-robot teams alongside one another without communication, where balancing accomplishing the mission and maintaining a comprehensible formation to observers are both critical.
2) Second, we describe basic control laws that enable the evaluation of balancing the competing motivations of mission and comprehensibility, enabling the study of the impact of this balance.

II. Related Work

A. Multi-Robot Systems in Search and Rescue

Multi-robot systems have become essential for search and rescue and disaster response applications [3], [9]. While in some cases robots have been utilized to work directly alongside humans [10], [11] or are operated remotely [1], [4], increasing the autonomous capabilities of disaster response robots has seen recent work [2], motivated by benefits such as requiring fewer operators and tolerating network disconnections [12]. In order for rescue robots to operate fully autonomously, they need the capability to understand and work alongside robots that they may not be able to communicate with.

While specialized disaster response robots are still an active area of research and development [13], heterogeneous teams of simple robots have become the focus of most real world disaster response (e.g., to earthquakes [14]). Heterogeneous teams not only provide multiple options to explore an environment (i.e., ground robots can access areas aerial robots cannot, and vice versa) [15], but offer redundancy [16] and different technical capabilities [17]. Heterogeneous teams have paired ground robots and aerial robots [18] and aerial robots and underwater robots [7].

B. Multi-Robot System Sensing and Control

In this paper, we address the specific search and rescue problem of observing an area while maintaining communication with teammates, a topic that has seen extensive research as multi-robot sensor coverage [19], [20]. Sensor coverage has been approached by various methods, such as optimizing density functions [21], partitioning environments [22], or estimating information gain [23]. Additionally, many works have examined accomplishing this under communication constraints. Different forms of restrictions have been studied, such as maintaining line of sight between robots [24] or controlling movements to increase wireless connectivity [25]. Finally, sensor coverage has been evaluated with real-world sensor limitations [26] or power limitations [27]. Despite this extensive research, the problem of performing sensor coverage while following an understandable formation has not been addressed. Comprehensibility is as important a limitation in multi-robot systems as camera or power considerations.

III. Approach

We consider the specific problem of multiple heterogeneous multi-robot teams operating in a shared environment, where these teams have a shared mission of maximizing the sensor coverage of the environment, but are only able to communicate to fellow team members and not between teams. Each heterogeneous team contains two types of robots playing distinct roles, with one type acting as hubs and the second type acting as sensors. Hubs are robots with the capability to communicate over long range (e.g., back to human rescuers). All hubs, regardless of their team, follow the same control laws. Sensors are robots with the capability to provide observations of an area around their location. As with hubs, all sensors also obey identical control laws.

Each team can work to perform its mission, but needs to also anticipate the actions of neighboring allied robots as they are working towards the same overall goal. Importantly, the overall mission is maximized if allied robots do not work on the same task - e.g., it is inefficient for a sensor from team i to observe the same area as a sensor from team j. For example, if a sensor from team i believes that a robot on team j is a sensor, it should move away from it. If this belief is incorrect - if, in fact the robot on team j is a hub - then an area is now not being observed. In order to facilitate accurate role understanding, teams can also work to be comprehensible - that is, to maintain a formation that allows neighboring team to understand what roles are being played by which robots.

Overall, we consider the problem of balancing the need to make positional changes to accomplish the *mission* in a shared work environment with the need to follow a *comprehensible* formation so that allied teams can correctly anticipate robots' behavior without direct communication.

Notation. We consider a scenario with M teams, where N^m is the number of robots on the m-th team and N is the total number of robots. The i-th robot has the position $\mathbf{p}^i$ (or $\mathbf{p}^{(t),i}$ at time t), and movement updates are denoted with $\mathbf{u}^i$, with $\mathbf{u}^i_{mission}$ and $\mathbf{u}^i_{formation}$ respectively indicating movements towards the mission and towards the formation.

A. Accomplishing the Mission

In this section, we consider the control laws governing the movement updates $\mathbf{u}_{mission}$ for the hub and sensor roles. For these updates, we break the *mission* into two parts, which are specifically performing the sensing task and maintaining communication among the members of the multi-robot team.

$$\mathbf{u}^i_{mission} = \frac{\mathbf{u}^i_{task} + \mathbf{u}^i_{communication}}{2} \tag{1}$$

As a first trivial note, we determine that the robots acting as *hubs* possess no direct role in the overall mission of maximizing sensing observations, so the control law to update their position here is null:

$$\mathbf{u}_{task}^{i,hub} = \mathbf{0} \tag{2}$$

However, they play a key role in maintaining communications, meaning that their control updates for communications $\mathbf{u}_{communication}^{hub}$ are crucial. In order to maintain communications, we calculate a sum of vectors to or from neighboring hubs on the same team, defining the movement update for the i-th hub in relation to the j-th hub as

$$\mathbf{u}_{communication}^{i,hub} = \sum_{j=0, j \in \text{HUBS}, \text{team}(i)=\text{team}(j)}^{N} \mathbf{v}_{ij} \tag{3}$$

where $\mathbf{v}_{ij}$ is defined as

$$\mathbf{v}_{ij} = \mathbf{p}^j - \mathbf{p}^i \text{ if } \|\mathbf{p}^j - \mathbf{p}^i\| > d \tag{4}$$

or

$$\mathbf{v}_{ij} = \mathbf{p}^i - \mathbf{p}^j \text{ if } \|\mathbf{p}^j - \mathbf{p}^i\| <= d \tag{5}$$

where d is a communications threshold.

For *sensors*, control laws are needed to both perform their task and to maintain communications. We first define a task-focused control law, in which sensors are motivated to move away from other sensors in order to increase the total area of observed by sensors. Specifically, sensors utilize a distance-weighted sum of vectors that moves sensor i away from other sensors:

$$\mathbf{u}_{task}^{i,sensor} = \sum_{j=0, j \in \text{SENSORS}}^{N} \frac{\mathbf{p}^i - \mathbf{p}^j}{\|\mathbf{p}^i - \mathbf{p}^j\|} \tag{6}$$

Importantly, we note that this control law applies to robots that the i-th robot believes are sensors, based on its understanding of neighboring multi-robot systems. This belief may or may not be correct.

In order to maintain communication between a sensor and the remainder of its team, it needs to maintain a minimum connection distance to the nearest hub robot belonging to its team. We first identify this nearest hub to the i-th sensor, located at $\mathbf{p}^h$. The i-th sensor then moves in the direction of this hub:

$$\mathbf{u}_{communication}^{i,sensor} = \frac{\mathbf{p}^h - \mathbf{p}^i}{\|\mathbf{p}^h - \mathbf{p}^i\|} \tag{7}$$

As above the movement update based on the mission is based on the values of the task update and the communications update, and is scaled to unit vector length if necessary:

$$\mathbf{u}_{mission}^{i} = \frac{\mathbf{u}_{task}^{i} + \mathbf{u}_{communication}^{i}}{2} \tag{8}$$

$$\mathbf{u}_{mission}^{i} = \frac{\mathbf{u}_{mission}^{i}}{\|\mathbf{u}_{mission}^{i}\|} \text{ if } \|\mathbf{u}_{mission}^{i}\| > 1 \tag{9}$$

B. Maintaining a Comprehensible Formation

In this section, we consider the control laws that cause a multi-robot team to maintain a comprehensible formation. Specifically, we design a formation for each variously sized multi-robot team, identify the current team's displacement and rotation from the goal, and generate a goal point for each robot.

For each hub, we generate a goal point $\mathbf{g}^i$ for the i-th robot that is either in line with other hubs (as seen with the triangle markers in Figure 2(b)) or 90° from other hubs (as in Figure 2(c)). For sensors, we identify the nearest hubs, and generate a goal position $\mathbf{g}^i$ that is a specific angle from these hubs (again, as seen in Figures 2(b) and 2(c), depicted with circular markers).

For both robot roles, the movement update is defined as

$$\mathbf{u}_{formation}^{i} = \mathbf{g}^i - \mathbf{p}^i \tag{10}$$

As with the mission-based movement update, the formation movement update is scaled to unit vector length if necessary:

$$\mathbf{u}_{formation}^{i} = \frac{\mathbf{u}_{formation}^{i}}{\|\mathbf{u}_{formation}^{i}\|} \text{ if } \|\mathbf{u}_{formation}^{i}\| > 1 \tag{11}$$

These comprehensible formations are also utilized by neighboring teams for role understanding. As all formations used are focused on hubs being centrally located and sensors being located externally, we propose a spatially-based feature for each robot dependent on its position in its team. Each robot is represented by its distance from the centroid of its multi-robot team, and a k-means clustering approach is then used to divide observed teams into two groupings. The larger set of groupings is determined to be the sensors, and the smaller set of groupings is determined to be the hubs.

C. Balancing Mission and Comprehensibility

Given the described movement updates $\mathbf{u}_{mission}$ and $\mathbf{u}_{formation}$, we can update the position of each robot according to the following equation:

$$\mathbf{p}^{(t+1),i} = \mathbf{p}^{(t),i} + \lambda \mathbf{u}_{mission}^{(t),i} + (1-\lambda)\mathbf{u}_{formation}^{(t),i} \tag{12}$$

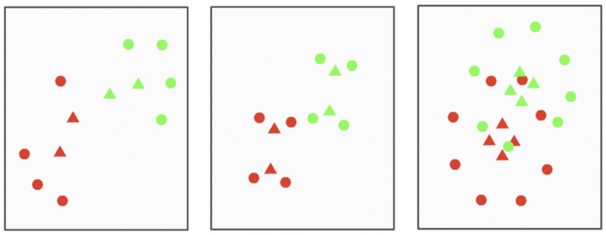
where λ is the key hyperparameter that enables the balancing of mission and comprehensibility.

By formulating movement updates in this weighted manner, we enable the evaluation of the key problem we propose - how does balancing the mission of a multi-robot team versus the coherence of a multi-robot team effect the overall accomplishment of the goal? We propose that tuning the hyperparameter λ, where higher values result in more importance towards the mission and lower values result in more importance towards the formation, will provide insight into this problem.

IV. Experimental Results

A. Experimental Setup

We consider two metrics for multi-robot systems as we evaluate the balance of *mission* and *comprehensibility*.



(a) Mission (b) Comprehensibility (c) Comprehensibility

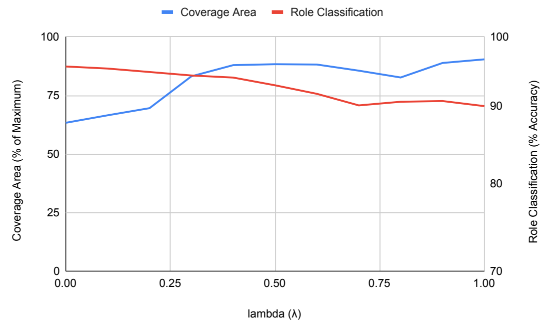
Fig. 2. Various multi-robot system configurations. Different colors depict separate teams, while hubs are represented with triangles and sensors are represented with circles. Figure 2(a) shows a multi-robot system solely valuing the sensing mission. Figure 2(b) shows the same multi-robot system when it values maintaining a comprehensible formation. Figure 2(c) shows an example of a larger multi-robot system maintaining a comprehensible formation.

- First, we consider the *coverage area* achieved by the multi-robot system. For each robot acting as a *sensor*, we consider a circular area determined by a sensing range parameter. We determine the overall area sensed by the multi-robot system by summing these areas, accounting for overlaps among sensing areas.
- Second, we consider the *role understanding* attained by each team. We consider the overall accuracy of the role classification, so if team A classifies 5 members of team B and team B classifies 5 members of team A, the accuracy is reported as a percentage of 10 multi-robot team members.

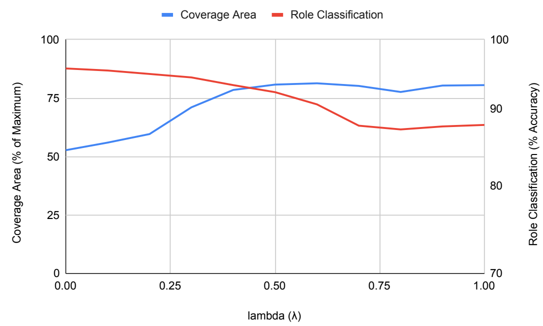
In order to understand the effects of the λ parameter, we conducted experiments on simulated multi-robot systems consisting of various numbers of teams, as well as various numbers of hubs and sensors per team. For each multi-robot system, we define a goal formation, with Figure 2 showing examples. Figure 2(a) shows a multi-robot system that is solely focused on the mission (with $\lambda = 1$). Figure 2(b) shows a multi-robot system of the same size, solely focused on its formation ($\lambda = 0$). This formation creates a backbone of hub robots, with sensors acting as spokes at the end. A comprehensible formation is shown for a larger multi-robot system in Figure 2(c), where hubs form a square backbone, and sensors again act as spokes outwards.

For multi-robot system sizes, we specifically evaluate on:

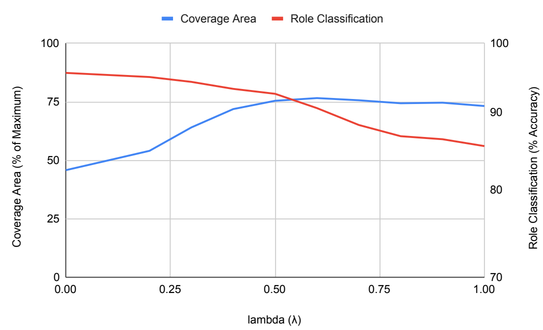
- *Small Multi-Robot Systems*: These systems have each team consist of two hubs and four sensors. Their formation is based on a straight axis between the two hubs.
- *Large Multi-Robot Systems - Line Formation*: These systems consist of teams which each employ four hub robots and eight sensor robots. Their formation is again based on a straight axis connecting the four hubs (the hubs form a line).
- *Large Multi-Robot Systems - Square Formation*: These systems again consist of teams which each employ four hub robots and eight sensor robots. However, their formation is based on a square formation of the hubs, with sensors acting as spokes outwards.



(a) 2 Teams (2 Hubs, 4 Sensors Each)



(b) 3 Teams (2 Hubs, 4 Sensors Each)



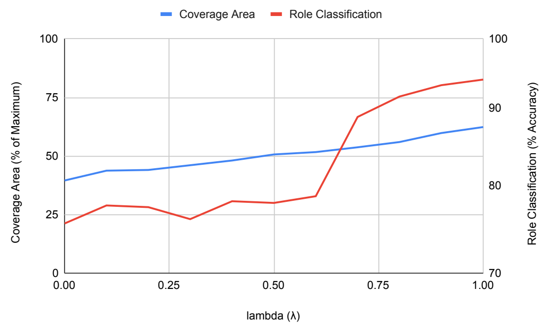
(c) 4 Teams (2 Hubs, 4 Sensors Each)

Fig. 3. Coverage and role understanding as λ increases from 0 to 1. Results shown for small multi-robot systems, with each team consisting of two hubs and four sensors. Figures 3(a)-3(c) show results from two to four teams, respectively.

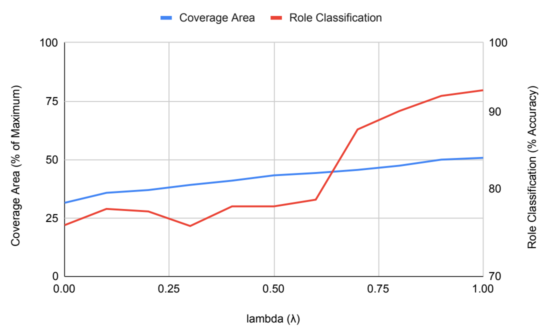
B. Small Multi-Robot Systems

We first consider small multi-robot systems, with each team consisting of two hubs and four sensors. We consider systems of two to four teams, with quantitative results seen in Figure 3. For these systems, the set formation consists of two central hubs in a line, with sensors positioned outwards as spokes (with Figure 2(b) as an example).

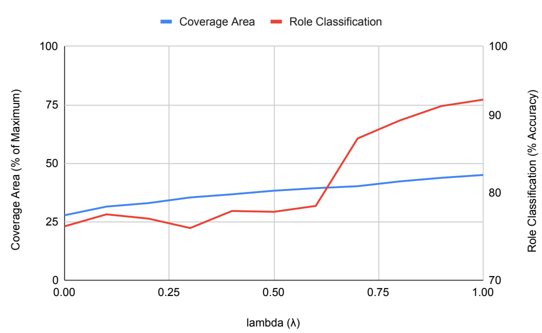
For each set of systems across the two to four teams, we can see a consistent pattern of coverage area increasing with the value of λ while the role understanding decreases accordingly. While the crossover points vary slightly on the exact value of λ where they occur, we can see that the highest value area for both coverage area and role understanding occurs



(a) 2 Teams (4 Hubs, 8 Sensors Each) - Line

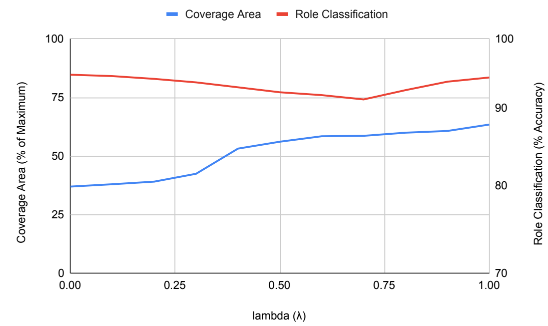


(b) 3 Teams (4 Hubs, 8 Sensors Each) - Line

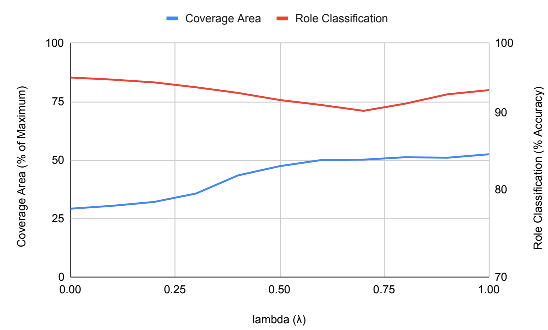


(c) 4 Teams (4 Hubs, 8 Sensors Each) - Line

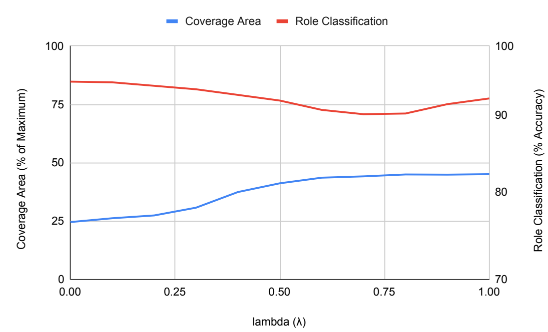
Fig. 4. Coverage and role understanding as λ increases from 0 to 1. Results shown for large multi-robot systems in line formation, with each team consisting of four hubs and eight sensors. Figures 4(a)-4(c) show results from two to four teams, respectively.



(a) 2 Teams (4 Hubs, 8 Sensors Each) - Square



(b) 3 Teams (4 Hubs, 8 Sensors Each) - Square



(c) 4 Teams (4 Hubs, 8 Sensors Each) - Square

Fig. 5. Coverage and role understanding on large multi-robot systems in square formation, with each team consisting of four hubs and eight sensors. Figures 5(a)-5(c) show results from two to four teams, respectively.

when $0.25 < \lambda < 0.5$. When λ decreases below this range, we see only small increases in role understanding, while risking large drop offs in coverage area. When λ increases above this range, we see decreases in role understanding, while coverage area stagnates. Based on these results, trending multi-robot control towards comprehensibility in systems of this size maximizes role understanding without sacrificing the mission of sensor coverage.

C. Large Multi-Robot Systems - Line Formation

Next, we consider large multi-robot systems, with each team consisting of four hubs and eight sensors. We consider systems of two to four teams. We first consider the 'line' formation, which is shaped similarly to the smaller system seen in Figure 2(b), where hubs form a line and sensors act as spokes. Quantitative results for this set of systems is reported in Figure 4.

For multi-robot teams of this size, we see slightly different results than previously. Across all three numbers of teams, we see a steady increase in coverage area as λ increases, as we would expect. However, in all three cases we see almost no change in the system's role understanding until $\lambda > 0.6$. This is counter intuitive, as logically lower values of λ would indicate higher coherence. This is likely due to the long line of the four hub robots causing some sensors to be closer to the centroid than the end hubs, resulting in classification errors. For systems of this size and formation, maximizing λ results in both the highest amount of area covered and the highest role understanding.

D. Large Multi-Robot Systems - Square Formation

Finally, we again consider large multi-robot systems, with each team consisting of 4 hubs and 8 sensors. Here, we consider systems of two to four teams in the 'square' formation, where hubs maintain 90° angles from each other (an example can be seen in Figure 2(c)). Quantitative results for this set of systems are reported in Figure 5.

Here, we return to seeing role understanding results consistent with the expectation of the λ parameter. Specifically, we see the maximum role understanding when $\lambda = 0$, indicating the multi-robot system is solely motivated on moving to a coherent formation. However, this is also the point with the lowest coverage area. For this set of systems, we see that when $\lambda = 1$ we can maximize the coverage area with only a small decrease from the highest level of role understanding.

V. Conclusion

Multi-robot systems are crucial for effective disaster response and efficient search and rescue. In order for teams of robots to work alongside neighboring teams with the same objective, they must behave in understandable ways while working towards their mission. We introduce the problem of controlling a multi-robot system in order to balance accomplishing a mission with maintaining a comprehensible formation that neighboring teams can understand. We propose a system of control laws for a heterogeneous multi-robot system that generate movements either to increase the sensor coverage area or follow a predefined formation. Through simulation on a variety of multi-robot system sizes and formations, we show the effects of different weightings on both coverage area and role understanding.

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