Abstract—This paper focuses on the teaming aspects and the role of heterogeneity in a multi-robot system applied to robot-aided urban search and rescue (USAR) missions. We specifically propose a needs-driven multi-robot cooperation mechanism represented through a Behavior Tree structure and evaluate the performance of the system in terms of the group utility and energy cost to achieve the rescue mission in a limited time. From the theoretical analysis, we prove that the needs-drive cooperation in a heterogeneous robot system enables higher group utility compared to a homogeneous robot system. We also perform simulation experiments to verify the proposed needs-driven cooperation and show that the heterogeneous multi-robot cooperation can achieve better performance and increase system robustness by reducing uncertainty in task execution. Finally, we discuss the application to human-robot teaming.

I. INTRODUCTION

Rescue missions can be regarded as life-saving, delivering valuable properties, and tackling crucial facilities in disaster or emergency scenarios, which involves complex, hazardous, uncertain, unstructured, dynamical changing and adversarial environments. Multi-Robot System (MRS) working in such scenarios requires to have rapid response, high adaptation, and strong robustness, which will largely help with minimizing the losses in the post-disaster scenarios. Research in robot-aided USAR aims to increase mission success rate, improve execution efficiency and minimize system cost during the rescue missions. Fig. 1 illustrates an example real-world use-case of MRS in a post-earthquake scenario, where we represent teams of three different robot types - Carrier, Supplier, and Observer - aiding the first responders in close collaboration.

Disasters are defined as a discrete meteorological, geological, or man made event, that exceeds local resources to respond and contain [1]. When robot interacts with disaster or adversarial environment, we can base the adversaries into two general categories based on their needs and motivations: intentional (such as enemy, terrorist or artificial intelligent opponent, which actively impairs the MAS needs and capabilities) and unintentional (natural obstacles and weather, which might passively threaten MAS abilities) adversary [2]. We are specifically interested in the MRS collective tackling the unintentional adversary in hazardous and disaster scenarios. So the environment models for rescue mission are grounded in two different aspects: individual perception and data sharing across the robots.

Considering individual perception, we emphasize cooperation among heterogeneous group of robots, where each robot class in the group might have different sensors and capabilities to perceive and interact with the environment and distinct actuators to execute their action. Individual robots present their observations from different angles describing the partial part in global map. Regarding system data sharing, each robot in the current group needs to update its situation awareness from other group members’ information, which can not only help in collectively building a global map [3] but also be a foundation for communicate between the agents to achieve consensus [4] or Negotiation [5].

It is important to understand how to combine a team of mobile robots to achieve a successful search and rescue mission, especially from a heterogeneity point of view and through the use of needs-driven cooperation among robots. Therefore, in this paper, we analyze the cooperation between heterogeneous robots with different capabilities and needs for MRS collaboration and cooperation. Specifically, we make the following contributions in this paper:

- We generalize the problem of rescue mission through the use of different groups of robots such as Carrier, Supplier, and Observer. And, we formalize the multi-robot cooperation through robot needs hierarchy encoded in a Behavior Tree [6] structure.
- We theoretically analyze the rescue robot teaming from two perspectives: Utility achieved by the robot group and Energy consumed by the group.
- We verify the theoretical results through simulations with different teams of homogeneous and heterogeneous
robots deployed to a rescue mission.

II. RELATED WORKS AND PROJECTS

An intelligent agent is a physical (robot) or virtual (software program) entity that can autonomously perform actions on an environment while perceiving this environment to accomplish a goal [7]. Cooperation in multiple intelligent agents (robots) working in a disaster environment is an interesting and challenging problem [1], [8]. Most research focus on the problems of environmental monitoring [9], [10], [11], structure inspection [12], [13], navigation and control [14], [15], [16] and higher-level autonomy [17], [18]. Also, there are various advancements in rescue robotics through the development of heterogeneous human-robot teaming methods in disaster response scenarios [19], [20], [21], [22], disaster detection [23], [24], disaster monitoring [25], [26], target tracking [27], [28], victims detection [29], and reinforcement learning based semi-autonomous controller for urban search and rescue missions [30].

When it comes to grouping heterogeneous robots with various capabilities cooperating with each other to pursue certain common goals (rescue missions), the literature is thin with several gaps remaining to address the integration of organizing agents’ behaviors, solving the conflicts, optimizing system utility and boosting system adaptability and robustness for the entire group [31], [3]. On the other hand, there is little research done from agent’s needs perspective studying individual interaction and behaviours for system performance (group utility) and global behaviours in MRS, especially in disaster robotics [32], [5], [33].

In order to address those gaps, we build upon our work in [5], [32], where we represent complex relationships between different types of robots through their instantaneous needs and motivations. This helps the system to balance and optimize the utilities between individual and the whole group. We encode the individual robot needs hierarchy in the robot automated planner represented through a Behavior Tree structure [6], [34]. Then we analyze the MRS group performance by theoretically deriving and comparing their capabilities and the task requirements, they need to re-organize the group adapting current situation events like some group members run out of battery, robots assigned with new rescue tasks or encounter emergency等情况. Then through comparing their capabilities and the task requirements, they will select how to cooperate with each other in order to maximise the success rate in rescue missions and optimize or suboptimise individual and system’s utility.

In order to fulfil high level needs satisfying individual or group’s expectation utilities [2], different categories of robots consider working as one or several teams to maximise corresponding utilities or rewards efficiently. Especially, when assigned with new rescue tasks or encounter emergency events like some group members run out of battery, robots need to re-organize the group adapting current situation minimizing the cost and loss. Fig. 2 presents individual robots hierarchy of needs encoded in form of a state-of-the-art state-action planner called Behavior Trees [6].

Fig. 2: Behavior Tree representing hierarchy of robot needs at every robot. [?] - Selector Node, [-+->] - Sequence Node, Con - Conditions, Act - Actions, Pe - Perception, Sa - Safety, BN - Basic Needs, Ca - Capability, U - Utility, Pl - Plan, Ne - Negotiation, A&E - Agreement and Execution.

III. NEEDS-DRIVEN MODEL FOR ROBOT COOPERATION

In nature, from cell to human, all intelligent agents represent different kinds of hierarchical needs such as low level physiological needs (food and water) in microbe and animal, and high level needs self-actualization (creative activities) in human being [35]. Simultaneously, intelligent agents can cooperate or against with each other based on their specific needs. As an artificial intelligent agent – robot, in order to organize its behaviors and actions, we introduced the needs hierarchy of robots in [5] to help MRS building cooperative strategies considering their individual and common needs. Specifically, the robots possess the following order of needs hierarchy: Safety needs (avoid collisions, safe environment, etc.); Basic needs (Energy, time, mobility, etc.); Capability needs (task-specific such as carry or supply resources); Teaming needs (enhancing group utility and group survival); and Learning needs (self-upgrade and evolution).

Since robot needs to rescue the victims from the disaster or cooperate with people to fulfil rescue missions together, the lowest level needs of robot should guarantee human’s safety and security. This kind of condition reflex or self-reactive behaviours in robot can be represented as basic control issues like collision avoidance. After satisfying the safety needs, robot requires enough basic needs, like battery, oil, to support executing relative operations. Then through comparing their capabilities and the task requirements, they will select how to cooperate with each other in order to maximise the success rate in rescue missions and optimize or suboptimise individual and system’s utility.

In rescue missions, we consider the Group’s Utility as the number of lives (victims) or valuable properties saved and rescued as much as possible in a limited time. In the entire
process, robots need to consider exploring the uncertain area, tackling the unintentional adversaries like obstacles, wind, rain and so on, repairing crucial facilities, treating injurers, carrying victims and properties to the safety place.

IV. FORMALIZATION AND EVALUATION

In this section, we first formalize the rescue problem, and then use mathematical approaches to prove our hypothesis that heterogeneous cooperation has better performance than the homogeneous cooperation for Multi-Agent System (MAS) in rescue missions.

Consider the following example. Supposing a group of heterogeneous robots executes the search and rescue mission in a post-disaster scenario. The robot’s categories can be generally classified as follows.

- **Carrier**: Their main function is carrying injurers and valuable properties from hazardous area to shelter.
- **Supplier**: Providing various resources for rescue missions such as medicine, food, repairing robots, rescue devices, communication supporting and so forth.
- **Observer**: They are good at surveying and acquiring real-time and dynamical rescue information from the disaster environment.

A. Problem Statement

As discussed in Sec. III, we assume that the number of Carrier, Supplier and Observer are \( x, y \) and \( z \) \((x, y, z \in \mathbb{Z}^+)\), respectively. We define the individual capability space according to the robot needs model through the below equations.

\[
\begin{align*}
\text{Carrier} &:= C_C(v_c, com_c, sen_c, eng_c, res_c, cap_c); \\
\text{Supplier} &:= C_S(v_s, com_s, sen_s, eng_s, res_s, cap_s); \\
\text{Observer} &:= C_O(v_o, com_o, sen_o, eng_o, res_o, cap_o).
\end{align*}
\]

Here,
- \( v \) represents agent’s velocity;
- \( com \) and \( sen \) represent the range of agent’s communication and sensing separately;
- \( eng \) represents agent’s energy level;
- \( res \) represents the amount of rescue resource which agent can provide;
- \( cap \) represents agent’s capacity level.

Since each type of robot specialize in different capability, we can assume Eqs. (4), (5), (8), (9), (6), (7) showing the dominance of each robot type (denoted with subscripts \( c, s, o \) to represent carrier, supplier, and observer robots, respectively) in different capabilities in terms of sensing and communication ranges, energy level capacities, etc.

**Robot Safety Needs**:

\[
\begin{align*}
\text{com}_o &> \text{com}_s > \text{com}_c; \\
\text{sen}_o &> \text{sen}_s > \text{sen}_c; \\
v_o &> v_s > v_c;
\end{align*}
\]

**Robot Basic Needs**:

\[
\text{eng}_c > \text{eng}_s > \text{eng}_o
\]

**Robot Capabilities for Rescue Mission Requirement**:

\[
\begin{align*}
\text{res}_s &> \text{res}_c > \text{res}_o; \\
\text{cap}_c &> \text{cap}_s > \text{cap}_o;
\end{align*}
\]

Supposing rescue mission \( T \) has requirement space \( TC = (C_1, C_2, ..., C_m) \), \( m \in \mathbb{Z}^+ \), where \( C_i \) represents different capabilities expected required to achieve a given global task and \( m \) is the capacity of the required to satisfy the tasks. We assume that the heterogeneous group capabilities for rescue mission requirements is \( C_G = (C_{G1}, C_{G2}, ..., C_{Gm}) \) and group members’ expected round-trips within \( t \leq t_n \) is \( m(m_1, ..., m_k) k \in \mathbb{Z}^+ \), where \( k = x + y + z \). \( U \) and \( t_n \) represent the rescue mission’s Group Utility and mission time restriction, respectively. Then, we can regard rescue problem as an optimization problem Eq. (10), which means that in the limited time, fulfilling a rescue mission maximum its Expectation Utility based on certain requirements.

\[
\begin{align*}
\arg \max_{C_G} & \quad E(U(t_n, m \cdot C_G)); \\
\text{subject to } & \quad \sum_{d=1}^{x} \sum_{e=1}^{y} \sum_{f=1}^{z} m \cdot C_G \geq TC, \ d, e, f \in \mathbb{Z}^+.
\end{align*}
\]

In order to simplify our model, we just consider one specific rescue mission and \( n \) identical obstacles distributed in an uncertain disaster environment randomly. The encountering obstacles times \( X \) for each agent follow Poisson Distribution Eq. (11) and \( \lambda \) represents as Eq. (12) \((c \text{ and } sen \text{ are corresponding coefficient and area of sensing range}).

\[
X \sim P(\lambda); \quad \lambda = \frac{cn}{sen} \quad \text{(12)}
\]

And we assume that the average time and energy cost for individual tackling each obstacle are \( t_c \) and \( e_c \) respectively, and the distance between initial group central point and rescue position is \( l \). We also assume that agent energy cost mainly consist of traveling, tackling the obstacles and fulfilling the rescue task. In there, the traveling energy cost can be regarded as constant \( e_t \) which is proportional to \( l \).

Through Eqs. (11) and (12), we can easily calculate the expectation of time encountering obstacles as Eq. (13). Since without considering obstacles, individual coming to rescue position and returning to initial point energy cost is \( \frac{2l}{v} \). Then, considering the obstacles, we estimate the expectation time cost per round as Eq. (14).

\[
\begin{align*}
E(X) = & \sum_{i=0}^{+\infty} iP(X = i) = \lambda = \frac{cn}{sen}; \\
E(T) = & \frac{2l}{v} + 2t_cX = \frac{2l}{v} + \frac{2tcen}{sen}
\end{align*}
\]

B. Theoretical Evaluation

In this section, we generally classify the rescue team as two different categories: Homogeneous and Heterogeneous, and assume that each agent’s sensing range equal to its communication range, then use mathematical approaches to analyze and compare their performance as follow:
a) Homogeneous Cooperation: In this scenario, we suppose that the number of Carrier, Supplier and Observer are equal Eq. (15). According to Eq. (14), the time homogeneous group per round can be represented as Eq. (16).

\[ x = y = z = 3m, \ m \in Z^+; \]  \hspace{1cm} (15)

\[ \mathbb{E}(T_h) = \frac{2l}{v} + \frac{2t_{cn}}{3m \times sen} = \lambda_h \]  \hspace{1cm} (16)

Considering rescue mission’s tackling time equal to one unit time, the entire expectation rescue per round time is \( \mathbb{E}(T_h + 1) \). Then, we can calculate \( \mathbb{E}(\frac{1}{T_h+1}) \) as Eq. (17).

\[ \mathbb{E}(\frac{1}{T_h+1}) = \sum_{k=0}^{+\infty} \frac{1}{k+1} \mathbb{P}(T_h = k) = \sum_{k=0}^{+\infty} \frac{1}{k+1} \lambda_h^k \frac{e^{-\lambda_h}}{k!} = \frac{1}{\lambda_h} \sum_{k=0}^{+\infty} \frac{\lambda_h^{k+1} e^{-\lambda_h}}{(k+1)!} = \frac{1}{\lambda_h} \sum_{k=0}^{+\infty} \mathbb{P}(T_h = k + 1) = \frac{1}{\lambda_h} \sum_{k=1}^{+\infty} \mathbb{P}(T_h = k) = \frac{1}{\lambda_h} \sum_{k=1}^{+\infty} \mathbb{P}(T_h = 0) = \frac{1}{\lambda_h} = e^{-\lambda_h} \]  \hspace{1cm} (17)

Finally, we estimate the expectation number of rounds for this homogeneous group in the rescue mission with limited time \( t_n \) as Eq. (18).

\[ \mathbb{E}(\frac{t_n}{T_h+1}) = \frac{t_n(1 - e^{-\lambda_h})}{\lambda_h} \]  \hspace{1cm} (18)

Supposing rescuing each agent cost one point supplement, energy and space respectively. We can estimate the sum of Expectation Utility – the amount of rescued agents \( U_h \) in all rounds and the total energy cost \( E_h \) in group of Carrier, Supplier and Observer as Eq. (19) and (20) respectively.

a. Carrier/Supplier/Observer expectation amount of rescued agents

\[ \mathbb{E}(U_{hc/s/o}) = \frac{t_n(1 - e^{-\lambda_{hc/s/o}})}{\lambda_{hc/s/o}} 3m \times res_e/cap_s/cap_o, \]

\[ \lambda_{hc/s/o} = \frac{2l}{v_{c/s/o}} + \frac{2t_{cn}}{3m \times sen_{c/s/o}} \]  \hspace{1cm} (19)

b. Carrier/Supplier/Observer expectation energy cost

\[ \mathbb{E}(E_{hc/s/o}) = e_t + \frac{2cn}{3m \times sen_{c/s/o}} e_{e+c} + \frac{t_n(1 - e^{-\lambda_{hc/s/o}})}{\lambda_{hc/s/o}} 3m \times res_e/cap_s/cap_o \]  \hspace{1cm} (20)

b) Heterogeneous Cooperation: For heterogeneous cooperation, we consider four different combinations as follow:

- \((x \text{ Carriers, } y \text{ Suppliers, } z \text{ Observers})\), \(x + y + z = 3m\);
- \((x \text{ Carriers, } z \text{ Observers})\), \(x + z = 3m\);
- \((y \text{ Suppliers, } z \text{ Observers})\), \(y + z = 3m\);
- \((x \text{ Carriers, } y \text{ Suppliers, } z \text{ Observers})\), \(x + y + z = 3m\);

Then, we estimate the expectation amount of rescued agents \( U_e \) and energy cost \( E_e \) for each group.

a. \((x \text{ Carriers, } y \text{ Suppliers})\)

In this scenario, we consider Carrier and Supplier have the similar sensing range, and they both have enough energy (Basic Needs) to support the entire rescue mission. So we can present \( \mathbb{E}(U_{e1}) \) and \( \mathbb{E}(E_{e1}) \) as Eq. (21) and (22).

\[ \mathbb{E}(U_{e1}) = \frac{t_n(1 - e^{-\lambda_{e1}})}{\lambda_{e1}} \times ((x \times cap_s + y \times cap_o) \cap (x \times res_e + y \times res_o)), \]

\[ \lambda_{e1} = \frac{2l}{v_{e}} + \frac{2t_{cn}}{3m \times sen_{e}} \]  \hspace{1cm} (21)

\[ \mathbb{E}(E_{e1}) = e_t + \frac{2cn}{3m \times sen_{e}} e_{e+c} + \frac{t_n(1 - e^{-\lambda_{e1}})}{\lambda_{e1}} \times ((x \times cap_s + y \times cap_o) \cap (x \times res_e + y \times res_o)) \]  \hspace{1cm} (22)

b. \((x \text{ Carriers, } z \text{ Observers})\)

Here, we assume the entire group’s velocity adapt Carriers’ speed. Similarly, we can express \( \mathbb{E}(U_{e2}) \) and \( \mathbb{E}(E_{e2}) \) as Eq. (23) and (24).

\[ \mathbb{E}(U_{e2}) = \frac{t_n(1 - e^{-\lambda_{e2}})}{\lambda_{e2}} \times ((x \times cap_s + z \times cap_o) \cap (x \times res_e + z \times res_o)), \]

\[ \lambda_{e2} = \frac{2l}{v_{e}} + \frac{2t_{cn}}{x \times sen_{e} + z \times sen_{o}} \]  \hspace{1cm} (23)

\[ \mathbb{E}(E_{e2}) = e_t + \frac{2cn}{x \times sen_{e} + z \times sen_{o}} e_{e+c} + \frac{t_n(1 - e^{-\lambda_{e2}})}{\lambda_{e2}} \times ((x \times cap_s + z \times cap_o) \cap (x \times res_e + z \times res_o)) \]  \hspace{1cm} (24)

c. \((y \text{ Suppliers, } z \text{ Observers})\)

\( \mathbb{E}(U_{e3}) \) and \( \mathbb{E}(E_{e3}) \) as Eq. (25) and (26).

\[ \mathbb{E}(U_{e3}) = \frac{t_n(1 - e^{-\lambda_{e3}})}{\lambda_{e3}} \times ((y \times cap_s + z \times cap_o) \cap (y \times res_e + z \times res_o)), \]

\[ \lambda_{e3} = \frac{2l}{v_{e}} + \frac{2t_{cn}}{y \times sen_{e} + z \times sen_{o}} \]  \hspace{1cm} (25)

\[ \mathbb{E}(E_{e3}) = e_t + \frac{2cn}{y \times sen_{e} + z \times sen_{o}} e_{e+c} + \frac{t_n(1 - e^{-\lambda_{e3}})}{\lambda_{e3}} \times ((y \times cap_s + z \times cap_o) \cap (y \times res_e + z \times res_o)) \]  \hspace{1cm} (26)
C. Comparative Analysis

After above discussion, in this section, we first compare the performances between (Homogeneous vs Homogeneous), (Heterogeneous vs Heterogeneous) and (Homogeneous vs Heterogeneous), then analyze the exiting of optimal or suboptimal solution for heterogeneous cooperation system in rescue mission. In order to simplify calculation, we assume Eq. (29) and also regard Carrier and Supplier have the similar sensing range, and the sensing range of group Observer approaches infinity.

\[ \text{res}_c = \text{cap}_s = \text{cap}_o = \text{res}_o = k, \quad k \in Z^+ \]  

a. Homogeneous vs Homogeneous

The comparison of the expectation amount of rescued agents between those groups can be represented as Eq. (30).

\[ \mathbb{E}(U_{hc}) : \mathbb{E}(U_{hs}) : \mathbb{E}(U_{ho}) = 1 : 1 : \frac{\lambda_{hc}(1 - e^{-\lambda_{ho}})}{\lambda_{ho}(1 - e^{-\lambda_{ho}})} \]  

(30)

Also, we can compare the group expectation energy cost of Carrier and Supplier, Carrier and Observer and Supplier and Observer as Eq. (31) and (32) respectively.

\[ \mathbb{E}(E_{hc}) - \mathbb{E}(E_{hs}) = 0 \]  

(31)

\[ \mathbb{E}(E_{hc}) - \mathbb{E}(E_{ho}) = \mathbb{E}(E_{hs}) - \mathbb{E}(E_{ho}) = \frac{2cn}{3m \times \text{sen}_c} e_c + \frac{3mkt_n}{\lambda_{hc}} \left(1 - e^{-\lambda_{hc}}\right) - \frac{1 - e^{-\lambda_{ho}}}{\lambda_{ho}} \]  

(32)

Through above discussion, if we assume that Observers also does not concern about their energy cost (Basic Needs) in the entire rescue mission, they will have best performance comparing with other groups. Actually, in the reality, the energy level and consumption rate of Observer, like drone, are much lower and faster than Carrier and Supplier correspondingly, which means that Observer need to waste lots of time to charge. Considering this issue, in order to simplify our calculation, we assume that these three groups have the similar performance generally.

b. Heterogeneous vs Heterogeneous

Similarly, considering involving Observers in the group, the entire group sensing range approach infinity. And according to the assumption Eq. (4), (5), (8) and (9), we can estimate the heterogeneous comparison of the expectation amount of rescued agents as Eq. (33).

\[ \mathbb{E}(U_{c1}) : \mathbb{E}(U_{c2}) : \mathbb{E}(U_{c3}) : \mathbb{E}(U_{c4}) \approx \frac{\lambda_{c1}(1 - e^{-\lambda_{c1}})}{\lambda_{c2}(1 - e^{-\lambda_{c2}})} : \frac{x \times \text{cap}_c + z \times \text{cap}_o}{x \times \text{cap}_c \cap y \times \text{res}_s} : 1, \quad \lambda_{c0} = \frac{2l}{v_c} \]  

(33)

The corresponding group expectation energy cost comparison show as follow Eq. (34), (35) and (36).

\[ \mathbb{E}(E_{c1}) - \mathbb{E}(E_{c2}) \approx \frac{2cn}{3m \times \text{sen}_c} e_c + \frac{t_n}{3m \times \text{sen}_c} \left(1 - e^{-\lambda_{c1}}\right) - 3mk \left(\frac{1 - e^{-\lambda_{c0}}}{\lambda_{c0}}\right) > 0 \]  

(34)

\[ \mathbb{E}(E_{c2}) - \mathbb{E}(E_{c3}) = 0 \]  

(35)

\[ \mathbb{E}(E_{c2}) - \mathbb{E}(E_{c4}) \approx \frac{1 - e^{-\lambda_{c0}}}{\lambda_{c0}} (3mk - (x \times \text{cap}_c \cap y \times \text{res}_s)) > 0 \]  

(36)

According to Eq. (33), (34), (35) and (36), we can notice that the performance of the low bound and the high bound in those groups are the combination of (Carrier & Supplier) and (Carrier & Supplier & Observer) respectively.

c. Homogeneous vs Heterogeneous

As above discussion, at this stage, we compare the performance between low bound of heterogeneous cooperation system and homogeneous cooperation system as Eq. (37) and (38).

\[ \mathbb{E}(U_{c1}) : \mathbb{E}(U_{c2}) \approx \frac{x \times \text{cap}_c \cap y \times \text{res}_s}{3mk \times \text{cap}_c} > 1 \]  

(37)

\[ \mathbb{E}(E_{c1}) - \mathbb{E}(E_{c2}) \approx \frac{t_n}{3m \times \text{sen}_c} \left((x \times \text{cap}_c \cap y \times \text{res}_s) \times \text{sen}_c\right) - 3mk \left(\frac{1 - e^{-\lambda_{c1}}}{\lambda_{c1}}\right) < 0 \]  

(38)

According to Eq. (37), we can notice that the Expectation Utility of heterogeneous cooperation system is larger than homogeneous cooperation system, also Eq. (38) shows that the energy cost of homogeneous cooperation system is higher than the heterogeneous system.

V. NUMERICAL EVALUATION

To simulate the above problem, we use "Unity" game engine and build a simple scenario (see Fig. 3) to verify our results. We design two kinds of experiments – Homogeneous and Heterogeneous MRS Cooperation and consider two categories of robots – Carrier and Observer implemented in the specific experiments. Video demonstration of
Fig. 3: Illustration of the four scenarios with homogeneous and heterogeneous team of Carrier (UGV) and Observer (UAV) in a rescue mission simulation. Scenario 3 is non-cooperative (NC) between the UGVs and UAVs and Sc. 4 is cooperative (C) between the different type of robots.

Fig. 4: The analysis of experiments’ results on homogeneous and heterogeneous MRS cooperation in simulation.

the experiments is available at http://hero.uga.edu/research/heterogeneous-cooperation/.

We suppose the common category has the same battery level in the initial state, and in every moving step, carrier and observer will cost 0.045% and 0.015% energy separately. To simplify the visualization of the group utility, we do not consider any obstacles, rescue resource requirement Eq. (8) and communication energy cost. We design four scenarios – homogeneous part simulates six carriers (Car) and six observers (Obs) fulfilling rescue mission correspondingly, and considering three carriers and three observers cooperation (C) and non-cooperation (NC) for heterogeneous MRS. We also implement a simple Negotiation-Agreement Mechanism [5], [32] to avoid collision in the whole process.

To compare the performance of Homogeneous and Heterogeneous MRS in the experiments, we calculate the amount rescuers (Group Utility) and the average energy cost per rescuing unit in five minutes Eq. (10). Considering observer limited energy store (basic needs) Eq. (7), we assume that if individual energy level is below 30%, it needs to go to rest place charging 10 seconds then back to work. Also, since we assume the observer can perceive the whole map, in the homogeneous scenarios, due to working in uncertain environment with limited perception range, carrier’s velocity is equal to a tenth of observer’s for avoiding uncertainty risks and satisfying its safety needs Eq. (6). But with the observers’ assist in heterogeneous MRS cooperation, carriers can share information with observer, enlarge their perception range and double their velocity. And observers will decrease a half of speed to adapt carriers’ involving. Each carrier and observer can rescue eight and one units respectively in each round Eq. (9). For non-cooperation heterogeneous system, the two groups do not have any interaction and fulfil the mission separately.

According to above assumption, we conduct 10 simulation trials for each scenario. Fig. 4 shows the amount rescuers and average energy cost per rescuing unit respectively. For the homogeneous MRS cooperation, comparing with the performance of group carrier and observer separately, although observer can achieve higher group utility (the amount rescuers) than carrier 4(a1) in a limited time Eq. (30), the average energy cost per rescuing unit represents more consumption 4(a2). On the other hand, for the heterogeneous MRS, the non-cooperation system represents a medial performance comparing with the other three scenarios, which does not show distinguished advantages. But for the heterogeneous MRS cooperation, it not only shows greater group utility Eq. (37) and less system cost Eq. (38) comparing with the homogeneous ones and non-cooperation heterogeneous system from system perspective, but also saves more cost per rescuing unit from individual angle.

More importantly, from the statistical analysis (Fig. 4), we can notice that comparing with the rest of scenarios, heterogeneous cooperation system decreases performance uncertainty (deviation between trials) and provides more stability and robustness for the whole system, which means that it can help the system adapting more complex and uncertainty environment efficiently and presents stronger viability.

VI. APPLICATION TO HUMAN-ROBOT TEAMING
As higher level intelligent creature in the world, human represents more complex and diversified needs such as per-
sonal security, health, friendship, love, respect, recognition and so forth. When we consider human and robots work as a team, how to organize their needs and get a common ground is the precondition for human-robot collaboration in rescue missions.

From robot needs perspective, it first needs to guarantee human’s security and health, such as avoiding collision with human, protecting them from radiation and so forth. But in the higher level teaming needs, robots should consider human team member’s speciality and capability to form corresponding heterogeneous Human-Robot team adapting specific rescue mission automatically.

From human needs perspective, human expects that robots provide safety and stable working environment in aiding rescue missions. Also, efficient and reliable assistance play an essential element for the entire rescue missions. More importantly, design of an Interruption Mechanism can help human interrupt robots’ current actions and re-organize them to fulfill some certain emergency tasks or execute some crucial operations manually.

Individual robot learning model can be regarded as constructing models of the other agents which takes as input some portion of the observed interaction history, and returns a prediction of some property of interest regarding the modelled agent [36]. In our future work, we enable robots to learn and adapt to the human needs and keep up trust and rapport between humans and robots, which are critical for increased task efficiency and safety [22]. Here, the adaptation learning of Human-Robot Interaction will be pursued along the following lines:

- Adopting suitable formation to perceive and survey environments predicting threats (and warn human team members) and explore new rescue tasks.
- Reasonable path planning adaptation in various scenarios avoid collision guaranteeing human security and decreasing the interference for human working environment.
- Combining the specific capabilities and needs of robots and human, calculating sensible strategies to organize the entire group collaboration fulfilling corresponding rescue mission efficiently.

VII. CONCLUSION

We presented an overview of the needs-driven cooperation model for heterogeneous multi-robot systems and theoretically analyzed the importance of heterogeneity in increasing rescue mission performance. We advanced the use of the robot needs hierarchy established in our earlier work and formalized the general rescue mission and categorized the robots in USAR missions as carrier, supplier, observers. We theoretically evaluated the performance of the system in terms of the group utility and energy cost to achieve the rescue mission in a limited time and proved that the needs-drive cooperation in a heterogeneous robot system enabled higher group utility compared to a homogeneous robot system. We also demonstrated the advantages of needs-driven heterogeneous cooperation through simulation experiments involving two groups of robots (carriers - UGVs and observers - UAVs). The results verified that heterogeneous multi-robot cooperation increased group utility and robustness, and decreased energy costs and performance uncertainties compared to the homogeneous multi-robot grouping for the same task execution. Future work will focus on extending this work to human-robot teaming and how the system as a whole can enable self-learning at the robot-level.

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