A Unified Approach Integrating Human Shared Mental Models with Intelligent Autonomous Team Formation for Crisis Management

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ABSTRACT

Autonomous systems are being exceedingly used to assist humans in various crisis responses scenarios such as earthquakes and nuclear disasters. Because they operate in highly unstructured and uncertain environments, failures are an inherent part of such autonomous systems, and, techniques for making these systems robust to failures arising from computer hardware, software or communication malfunctions are already integrated into their design. However, an important aspect while designing such systems is often times overlooked: how to better coordinate and communicate across distributed, possibly diverse human teams who are working in cooperation with autonomous systems into the design of the autonomous system itself. Unfortunately, this results in limited adoption of autonomous systems in real-life crisis scenarios. In this working paper, we describe ongoing work that attempts to address this deficit by integrating research on shared mental models between humans with techniques for autonomous agent team formation in the context of search and rescue scenarios.

Keywords

Crisis management team, intelligent autonomous system, coalition formation, shared mental model.

INTRODUCTION

Timely and effective responses to disasters are an integral part of every crises management system. Over the past decade, intelligent autonomous systems (IAS) have been employed extensively in different domains to provide efficient and rapid responses to crisis. Examples include search and rescue robots for assisting humans during relief and cleanup activities following natural calamities such as earthquakes, fire and flooding (Erdelj, Krol and Natalio, 2017; Maza *et al.*, 2011; Sable *et al.*, 2018), intelligent agents that can predict damage to infrastructure or presence of hazardous material following disasters such as chemical or nuclear accidents (Sanchez-Cuevas, 2019; Sanchez 2018), and intelligent robots that can perform preventive maintenance tasks such as infrastructure inspection of bridges and buildings or underwater inspection of structures such as ship hulls (Perrot *et al.*, 2015). However, most of these IAS have focused on two areas – 1) how to build sophisticated hardware and software algorithms that can operate autonomously in unstructured environments and uncertain, unprecedented conditions with minimal human intervention, and, 2) how to adapt the IAS' behavior and decision-making so that it can interact in a socially amiable, trustworthy and reassuring manner with the human operating or interacting with it. The design objectives of these IAS have mainly focused on improving the performance efficiency of the IAS, such as the time required and energy (battery) expended to perform its assigned task, and, in some cases, the satisfaction of the human user with using the IAS. Consequently, before deployment, the IAS are tested within simulated environments while interacting with a very limited number of humans. For example, the 2015 DARPA Robotics Challenge (DeDonato *et al.*, 2017) required a humanoid robot IAS to interact only with objects in its environment such as a door handle, fire hose, stairs, etc. Most importantly, the IAS' performance while interacting with another human or human teams was not validated as a performance criterion in the challenge.

We use this example to highlight that crisis management poses some unique challenges in the context of human-human and human-machine interaction that are usually not encountered in non-crisis or simulated-crisis tasks. Most importantly, crisis management is led by crisis management teams (CMTs) that are drawn from humans with diverse background and expertise including first responders, law enforcement, medical personnel such as doctors and nurses, legal personnel and even citizen volunteers (Yu and Khazanchi, 2015). Each of these individuals is required to work collaboratively with each other and with IAS. Unfortunately, in an unstructured and previously un-encountered scenario like a crisis, when the conventional modes of operation and interaction between human-human and human-machine are drastically altered, the performance of humans and IAS could both get severely degraded. In extreme cases, this could result in delayed or inaccurate responses, or even an inability to respond in crisis scenarios. Our research in this working paper proposes to address this deficiency by utilizing a model for human team formation drawn from coalitional game theory (Shoham and Leyton-Brown, 2009) that would enable IAS to identify and suggest ways to assimilate teams of humans based on their expertise and past performance within a team, as well as adapt the behavior of the IAS while working with an assimilated team of humans, so that the crisis management task could be handled efficiently.

RELATED WORK

Collaboration between human and agent teams has been an active research area in the field of artificial intelligence for almost two decades. Research in this area can be broadly divided into two directions – robot-based systems and multi-agent systems. Disaster robotics research (Murphy, 2014), led mainly by the robotics and engineering community, has made large advances in the past decade with robots being used in dangerous and hazardous tasks including moving concrete chunks, exploring tunnels, diffusing explosives and searching for hazardous material such as nuclear or chemical traces (Recchiuto *et al.,* 2016; Schwarz *et al.*, 2014; Haynes *et al.*, 2015; Leingartner *et al.,* 2018; Kochersberger *et al.*, 2017). However, much of this research has focused on engineering highly dexterous and robust robots that can operate either via teleoperation, or, in some cases autonomously, within adverse and unstructured environments. To the best of our knowledge, robotic disaster response systems that integrate close coordination between teams of humans and teams of robots have not been fielded or researched extensively.

Within the multi-agent systems community, a large portion of the research has focused on the problem of task allocation – how to assign tasks to agents so that the tasks can be performed effectively by the agents, such as reducing the time or effort (e.g., energy or battery) required to complete tasks and reducing the overlap or conflicts between agents while performing tasks. Much of this work has been validated within simulated agent environments closely resembling disaster scenarios (Massaguer *et al.,* 2006). In one of the earliest and seminal works in this direction (Shehory and Kraus, 1998) proposed a distributed coalition formation algorithm, where transportation-like tasks, e.g., moving blocks between locations, were allocated to teams of agents based on their capabilities. Several authors (Klein, Bradshaw, Woods, Hoffman and Feltovich, 2004; Jennings *et al.,* 2014) also laid foundation for effective cooperation between human-agent teams through a set of requirements that a human-agent collective should satisfy. These requirements included defining a mutually agreeable contract between agents and humans to perform a task jointly, being accountable to each other by revealing individual plans and intentions, being flexible to each other's requirements, having intelligent capabilities to interpret and predict each other's decisions and actions, and incentivizing each other's actions by forming coalitions, negotiating goals, managing attention and controlling costs. Future research on human-agent team formation emphasized one or more of these aspects while using a suitable computational framework to represent the interaction between agents and humans. For example, (Ramchurn *et al.,* 2015, Ramchurn *et al.,* 2016) proposed the HAC-ER (Human Agent Collective for Emergency Response) system that uses a framework called multi-agent Markov Decision Processes (MMDP) to formalize the decision making by agents to select tasks within an emergency task response scenario. A novel direction explored in this work was to include input from real-life human-in-the-loop operators to approve and selectively reassign task allocations before dispatching agents to tasks. In (Tambe, Bowring, Jung, Kaminka, Masheswaran, Marecki, *et al.*, 2005), authors observed that unifying different individual frameworks into hybrids were more effective than a single framework for performing collective tasks in disaster scenarios. For instance, integrating belief-desire-intent (BDI) and partially observable Markov Decision Processes (POMDP) frameworks enabled each framework to efficiently perform computations at different levels of information abstraction, for multi-agent task allocation and multi-agent communication in disaster scenarios. Later extensions of this concept were applied to human agent teams in security management scenarios in airports (Pita *et al.*, 2008). Recently, researchers have also focused on integrating human-agent collaboration within the context of massively multi-player online games (MMOGs) (Chan and Vonderer, 2005; Sourmeilis, Ioannou and Zaphiris, 2017). (Hafizoglu and Sen, 2018) explored the evolution of trust in human-agent team within the context of an online trust game, while (Wicke and Luke, 2017) have modeled human-agent collaboration as a treasure hunting game where each human-agent team has to select different tasks to perform. Several interesting techniques for human agent team formation in disaster response scenarios have also been proposed in the Robocup Simulation Rescue League challenge (RSRL, 2019) where teams of simulated agents representing first responders have to coordinate with each other to perform disaster response tasks. In summary, majority of these research focus on sophisticated algorithms to enable intelligent agents to plan to perform tasks, either collectively or individually, while the human's role is limited to oversight of agents' actions along with intermediate revisions of agent allocations or roles, as necessary. In other words, agents assume the role of human avatars with embedded intelligence while humans assume the role of supervising their avatars. To the best of our knowledge, a unified system, where human teams work alongside agent teams, while sharing work and responsibilities, has not been fully researched. Our proposed work attempts to address this deficit by proposing a framework where agents form coalitions while building a representation of the shared mental model (SMM) of human coalitions or teams within them. This iterated modeling enables agents to quickly identify high-performance human teams and, in parallel, adapt the agent coalitions, so that the capabilities of human-agent teams can be matched for improving task performance. To achieve this, in our proposed solution, we utilize two formalisms rooted in game theory and graph theory called coalition formation in weighted voting game and bipartite graph matching.

SHARED MENTAL MODELS OF CRISIS MANAGEMENT TEAMS

We have previously argued that one of the essential tasks of crisis management is to develop shared mental models (SMM) among teams and members about the crisis at hand, i.e. shared understanding of the task, process, technology and the teams (Yu and Khazanchi (2015). Developing SMM is essential for developing an effective crisis management strategy. Teams can form three types of mental models - information technology mental models, taskwork mental models, and teamwork mental models (Mathieu et al., 2000; Thomas & Bostrom, 2007; Thomas & Bostrom, 2010). A team's IT mental model is the knowledge structure and beliefs held by the team about the information technology capabilities and the usage of these capabilities (Thomas & Bostrom, 2007). A team's taskwork mental model is the knowledge structure and beliefs held by the team about the task goals, steps to accomplish the tasks, and the technologies used to accomplish the tasks (Mathieu et al., 2000). The teamwork mental models refer to the knowledge structure and beliefs held by the team about the team interaction and team members' roles, skills, and knowledge (Mathieu et al., 2000). Assessment of shared *mental models' convergence is mostly focused on measuring the degree to which knowledge structures overlap or are similar among the team members*, i.e. the SMM similarity (Yu & Khazanchi, 2015; Mohammed et al., 2010).

PROPOSED FRAMEWORK: UNIFYING SHARED MENTAL MODEL WITH COALITION FORMATION

In our proposed approach, we posit that more effective human-agent teams can be formed in crisis scenarios if, for a certain task, a team of autonomous agents is paired with a team of humans who have a high possibility of interacting and collaborating efficiently with each other. This step is challenging because, although individual humans might possess desired skills or capabilities for the task, inefficient interaction between humans in a team might degrade the performance of the task (Yu & Khazanchi, 2015). We propose to address this problem using a two-step procedure, as described below.

STEP 1: HUMAN TEAM IDENTIFICATION USING WEIGHTED VOTING GAMES

Given a task to perform in a crisis scenario, the first step in our proposed human-agent team formation technique is to identify a team of individuals with diverse set of expertise suitable for a task, such that the humans in the team can efficiently collaborate with each other to perform the task. The team should also contain only the individuals essential to perform the task, as including unnecessary or superfluous individuals could hinder and delay the task's performance due to inter-team collaboration issues. To quantify the collaboration potential of a set of individuals, we can use mental model measures for *teamwork, taskwork and information technology* to represent the suitability of an individual in a team (Yu & Khazanchi, 2015). These measures of a team's SMM convergence represent different aspects of an individual i relevant to functioning as part of a team, as described below:

- Teamwork mental model convergence (ρ_i) represents a team members knowledge structure and beliefs about team interaction and other team members' roles, skills, and knowledge;
- Taskwork mental model convergence (τ_i) represents the knowledge structure and beliefs held by the team about the task goals, steps to accomplish the tasks, and the technologies used to accomplish the

tasks;

- Information Technology mental model convergence (θ_i) represents the knowledge structure and beliefs held by the team about the information technology capabilities and the usage of these capabilities for performing the task.

The values of these suitability parameters could be solicited as input from humans in the team and conditioned with data from their past performances of in teams. In (Yu & Khazanchi, 2015), we have described case studies of using these suitability parameters for a team of individuals performing an information technology management task These parameters are aggregated into a single suitability parameter, called the individual *i*'s *weight*, w_i, and given by:

$$w_i = \alpha_1 \rho_i + \alpha_2 \tau_i + \alpha_3 \theta_i, \qquad \text{subject to, } \alpha_1 + \alpha_2 + \alpha_3 = 1$$

α_1, α_2 and α_3 are preferences over the suitability parameters and could be specified as inputs when a task is assigned to the team. With more experience of a team, these preferences could also be learned from past performances of the team in performing different types of tasks. This weight is then used in a coalition game framework called a weighted voting game (WVG) (Shoham and Leyton Brown, 2009). A weighted voting game denoted by the tuple $(N, \boldsymbol{W}, q)$ consists of the following attributes:

- N: a set of individuals, also called players
- $\boldsymbol{W}=\{w_i\}$:, a set of real-valued weights, where w_i represents the weight or suitability parameter of the *i*-th individual in the team
- q: quota, a real valued number representing a minimum threshold value that the combined weights of individuals should satisfy to be able to form a team.

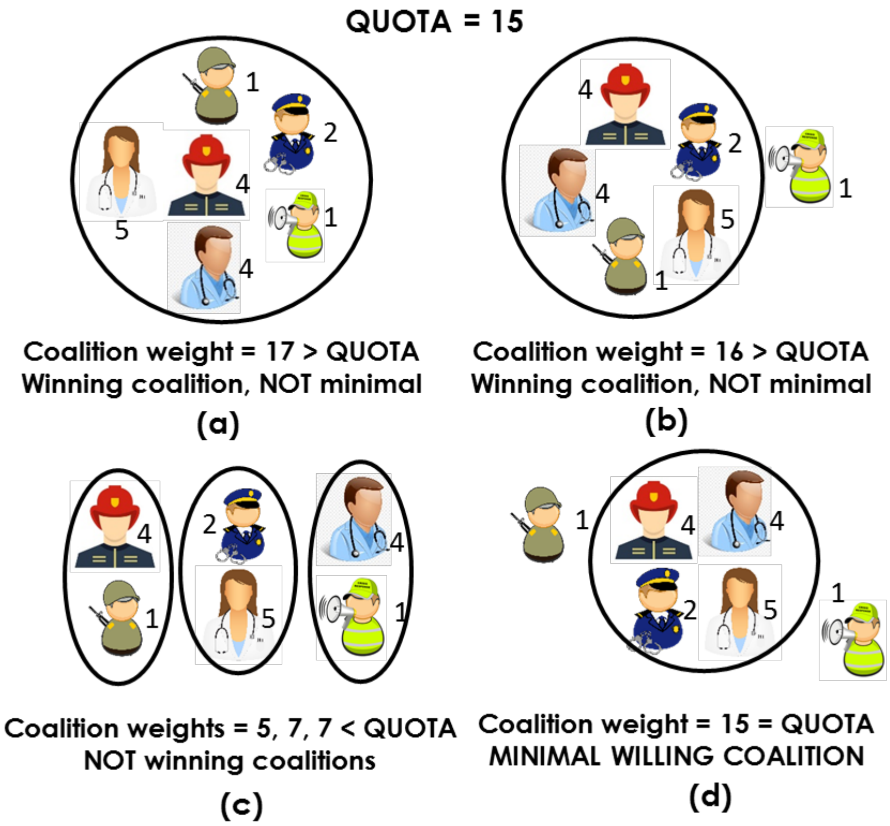

Figure 1. *A Weighted Voting Game (WVG) with quota, q = 15. (a) Grand coalition with all humans is a winning coalition as it satisfies quota, but is not minimal with 6 individuals, (b) Coalition with 5 individuals is also satisfies the quota and is a winning coalition, but is not minimal with 6 individuals, (c) None of the coalitions are winning coalitions as they do not satisfy the quota (d) A minimum winning coalition that satisfies quota and is also minimal with 4 individuals.*

To implement a voting game, all possible subsets of the players are determined. Note that for N players there can be 2^N possible subsets. For each subset S , in the 2^N possible subsets of the N players, the combined weight of the players in S is calculated as $\sum_{i \in S} w_i$. Finally, if the combined weight reaches the quota, that is, if $\sum_{i \in S} w_i \geq q$, then S is accepted as a winning coalition. The output of a WVG is a set of minimal winning coalitions (MWCs) – the smallest set(s) S out of the winning coalitions. Every WVG is guaranteed to have at least one MWC as long as $q \leq \sum_{i \in N} w_i$. An example of a weighted voting game is shown in Figure 1. Here six individuals with different weights or suitability parameter values have to form a team to perform an assigned. The objective of forming the team is to include the essential or smallest set of individuals required to perform the task. A quota value, $q=15$, is calculated for the task and given as input to the WVG. There are multiple winning coalitions in this WVG, two of which are shown in Figures 1(a) and 1(b). But there is only one MWC with four individuals, as shown in Figure 1(d). Figure 1(c) shows sets of non-winning coalitions that are not capable to perform the task as they are unable to reach the quota. Note that, in general, as the number of individuals in the scenario grows, or, as the value of quota, q, changes, the number of MWCs can become more than one. In other words, the minimal winning coalition is not unique and multiple teams or coalitions can be output by the weighted voting game. Consequently, the problem of calculating MWCs can quickly become non-trivial to solve as the number of players or individuals, N, increases.

In our earlier work (Dasgupta and Cheng, 2016), we had proposed two heuristic-based algorithms with proven performance bounds for calculating the MWC in a WVG, in the context of multi-robot team formation. These algorithms are able to calculate the MWC in polynomial and log-linear time respectively and are able to scale adequately with the number of players or individuals in the scenario. In this work, we plan to adapt those algorithms for identifying suitable human teams that are suitable for effectively performing the assigned task. Our main ongoing research questions in this direction are how to reliably elicit and combine the task suitability parameters from humans for determining the input weights of the WVG, how to address the complimentarity of individual skills or capabilities of humans while forming a team, and, how to calculate a suitable value of the WVG quota input, q, from the characteristics or features of a task that needs to be performed.

STEP 2: EFFICIENT HUMAN-AGENT COALITION FORMATION USING PREFERENCE-BASED GRAPH MATCHING

After suitable human teams have been identified in step 1 above, the next step towards forming human-robot collectives is to identify appropriate robots that could be paired with the human teams. In step 2 of our algorithm, we assume that different teams for different sub-tasks are formed by running the WVG algorithm multiple times, once for each sub-task. For example, in a post-earthquake scenario, a team comprising of medics and first responders could be formed to perform a sub-task of providing healthcare to injured persons, while another team comprising of medics and military personnel could be formed to clear debris and rescue persons trapped under rubble. For this, each human team formed from step 1, expresses its desired capabilities from robots in the form of preference values over the set of available robots. For example, a human team comprising of a medical doctor, a firefighter and a law enforcement officer might have a high preference for a group of three robots that can assist respectively with surgical assistance, with clearing and removing debris, and with detecting hazardous substances in the environment. This problem is non-trivial as there could be preference conflicts between human teams for the same set of robots, and, there could also be constraints between robots such as limited number of robots with certain specialized sensors or actuators being available, suitability of pairs of robots to work well with each other, etc. To address this problem, we adopt a framework from computational economics called *matching with preferences* (Pycia, 2012). The objective of the problem is to find a complete matching between two sets of agents such that every agent from one set is paired with exactly one agent from the other set and the preference values between the sets of agents is maximized. For our problem, the two sets of agents are the human teams and robots, and the result is a matching between a human team and a set of robots while maximizing the preference values given by human teams for the robots collectives. This would guarantee that the humans in the human team have the best match of skills and capabilities with the autonomy of the agents in the robot team. Overall, this would result in improved performance of the human-robot collective.

We plan to adapt a bipartite graph matching algorithm from our previous work on configuration formation by robot teams (Dutta and Dasgupta, 2017; Manne and Hiesling, 2007), to address our human-robot team matching problem. The algorithm takes as input a set of team of humans H and the set of robots R as two disjoint sets. Each human team i has a preference parameter p_{ij} that represents the value of a match between the autonomous assistance desired by human i and the capability of robot j. The objective of the algorithm is to find a set of matchings that maximizes the sum of preference values. Mathematically, this can be represented as $\max \sum_{i \in H, j \in 2^R} p_{ij}$ such that $| p_{ij} | = |H|$. The algorithm works by first enumerating partitions, π , of the robot set, R, such that $| \pi | = |H|$. For each partition $\pi_i \in \pi$, it then finds an initial matching where each human team $h \in H$ is matched to its highest preferred set of robots in π. These matchings are removed from the sets of human teams and robots, and the process continues sequentially until all human teams are matched with sets of robots. An example of a matching between three human teams, each with an ordered set of preferences over sets of robots is shown in Figure 2. The output of the algorithm is a set of matchings between human teams and robots that has the maximal sum of preference values, which guarantees that each human team is paired with its most preferred (but not all) set of robots. This problem is an instance of the set packing problem that is a well known NP-hard problem. Within this framework, some of the research questions we are investigating include speeding up the computation of the maximal matching using recent results from coalition game theory (Hatfield, Kominers and Westcamp, 2017), integrating dependencies or externalities between the robot sets, where the formation of one set of robots affects the preferences of other sets of robots, and, considering the matching problem with dynamically varying preferences of human teams.

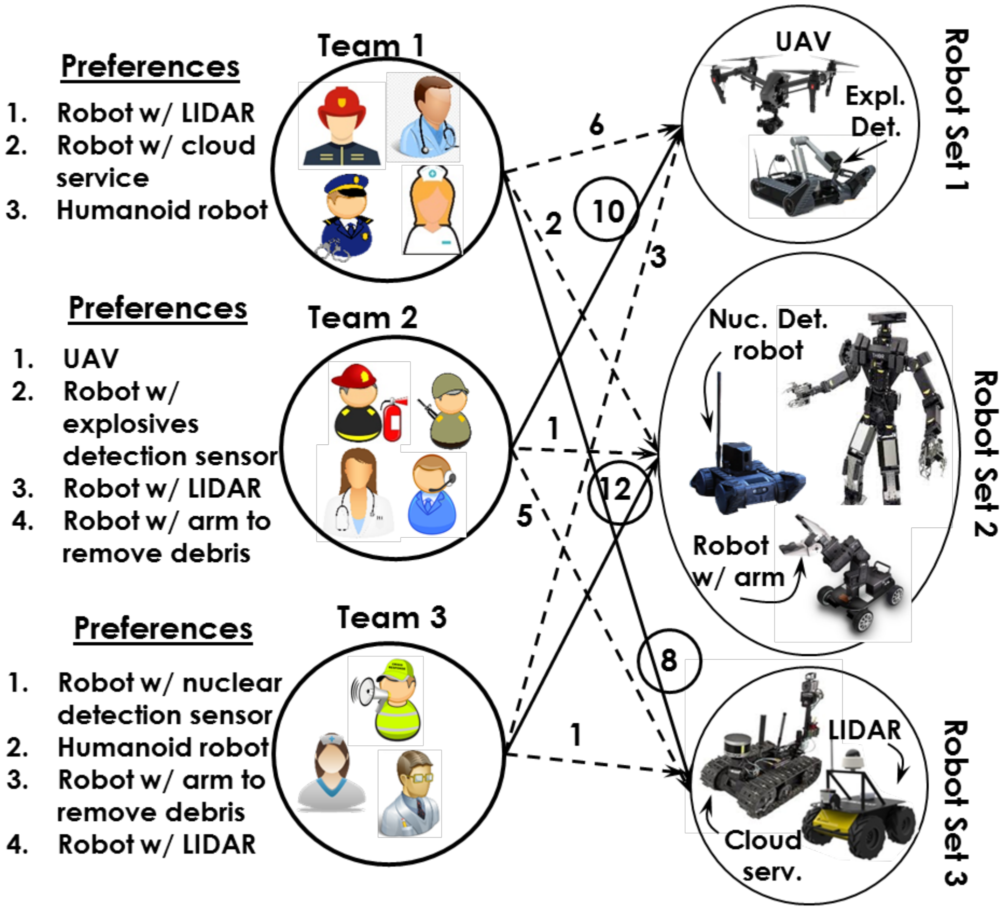

Figure 2. Matching between three human teams (formed in step 1) with different sets of robots. The values of the different matches to each team are specified by the individuals in the team and shown as edge weights between teams and corresponding robot sets. The matching algorithm returns the maximal matching (shown as solid edges, circled edge weights) between the human team and robot sets that gives the highest combination of preference values. Non-maximal matches, shown with dashed lines, are not selected.

ONGOING WORK AND CONCLUSIONS

Currently, we are working on formalizing the different research questions and implementing software algorithms in the two-step process for integrating shared mental model (SMM)-based human team formation with human-robot collective formation in the context of crisis management scenario. We plan to evaluate our software algorithms on the Repast multi-agent simulation environment within simulated disaster scenarios, while drawing inspiration from situations and environments featured in the Robocup Rescue Simulation League (Robocup Rescue Simulation League, 2019). In the future, we plan to integrate machine learning-based techniques into our proposed algorithms towards speeding up the computations and making them robust to errors in individuals' reporting of their capabilities and preference for robot assistance. Machine learning algorithms usually require training the model being learned with data from team formation in disaster scenarios. Real-life data for such scenarios will most likely be difficult to obtain. To address this data scarcity problem, we plan to generate virtual, game-like setups that model disaster scenarios, and engage humans to form teams to perform simulated tasks within the game setup. The data generated during these games could then be used to train the machine learning-based models required by our algorithms. Another direction worth investigating in the future is to form teams with a specified number of humans with certain expertise, e.g., a team with at least five firefighters and two paramedics. Such constraints on team formation could be handled by richer representations of coalition games beyond weighted voting games in step 1 of our algorithm, such as marginal contribution nets (MC-nets). Awareness theory, eliciting human and agent preferences, and dependencies between formed coalitions are additional future directions that we plan to investigate.

Our proposed work investigates a novel direction by integrating human cognitive processes through shared mental models into team formation with autonomous agents. In the future, we envisage that this work will lead to many interesting problems and solutions towards making systems requiring tight coordination and close interactions between human and AI more efficient, reliable and trustworthy in crisis management scenarios.

REFERENCES

Billah, M. M., Ahmed, M., & Farhana, S. (2008, June). Walking hexapod robot in disaster recovery: developing algorithm for terrain negotiation and navigation. In Proceedings of World Academy of Science, Engineering and Technology (Vol. 42, pp. 328-333).

Chan, E., & Vorderer, P. (2006). Massively multiplayer online games. In Playing Computer Games: Motives, responses and consequences. P. Vorderer and J. Bryant (Eds.) Lawrence Erlbaum Associates Publishers, Mahwah, NJ, US 77-88

Dasgupta, P., & Cheng, K. (2016). Dynamic multi-robot team reconfiguration using weighted voting games. Journal of Experimental & Theoretical Artificial Intelligence, 28(4), 607-628.

DeDonato, M., Dimitrov, V., Du, R., Giovacchini, R., Knoedler, K., Long, X., ... & Moriguchi, H. (2015). Human-in-the-loop control of a humanoid robot for disaster response: A report from the DARPA Robotics Challenge Trials. Journal of Field Robotics, 32(2), 275-292.

Erdelj, M., Król, M., & Natalizio, E. (2017). Wireless sensor networks and multi-UAV systems for natural disaster management. Computer Networks, 124, 72-86..

Hafizoglu, F. & Sen, S. (2018, July). The Effects of Past Experience on Trust in Repeated Human-Agent Teamwork. In Proceedings of the 17th International Conference on Autonomous Agents and MultiAgent Systems (pp. 514-522). International Foundation for Autonomous Agents and Multiagent Systems.

Hatfield, J. W., Kominers, S. D., & Westkamp, A. (2017, June). Stability, strategy-proofness, and cumulative offer mechanisms. In Proceedings of the 2017 ACM Conference on Economics and Computation (pp. 673-674). ACM.

Haynes, G. C., Stager, D., Stentz, A., Vande Weghe, J. M., Zajac, B., Herman, H., ... & Brindza, J. (2017). Developing a robust disaster response robot: CHIMP and the robotics challenge. Journal of Field Robotics, 34(2), 281-304.

Jennings, N. R., Moreau, L., Nicholson, D., Ramchurn, S., Roberts, S., Rodden, T., & Rogers, A. (2014). Human-agent collectives. Communications of the ACM, 57(12), 80-88.

Klien, G., Woods, D. D., Bradshaw, J. M., Hoffman, R. R., & Feltovich, P. J. (2004). Ten challenges for making automation a "team player" in joint human-agent activity. IEEE Intelligent Systems, 19(6), 91-95.

Kochersberger, K., Kroeger, K., Krawiec, B., Brewer, E., & Weber, T. (2014). Post-disaster remote sensing and sampling via an autonomous helicopter. Journal of Field Robotics, 31(4), 510-521.

Leingartner, M., Maurer, J., Ferrein, A., & Steinbauer, G. (2016). Evaluation of sensors and mapping approaches for disasters in tunnels. Journal of field robotics, 33(8), 1037-1057.

Manne, F., & Bisseling, R. H. (2007, September). A parallel approximation algorithm for the weighted maximum matching problem. In International Conference on Parallel Processing and Applied Mathematics (pp. 708-717). Springer, Berlin, Heidelberg..

Massaguer, D., Balasubramanian, V., Mehrotra, S., & Venkatasubramanian, N. (2006, May). Multi-agent simulation of disaster response. In Proceedings of the First International Workshop on Agent Technology for Disaster Management (pp. 124-130).

Mathieu, J.E., Heffner, T.S., Goodwin, G.F., Salas, E., & Cannon-Bowers, J.A. (2000). The influence of shared mental models on team process and performance. *Journal of Applied Psychology,* 85, 2, 273-283.

Maza, I., Caballero, F., Capitán, J., Martínez-de-Dios, J. R., & Ollero, A. (2011). Experimental results in multi-UAV coordination for disaster management and civil security applications. Journal of intelligent & robotic systems, 61(1-4), 563-585.

Mohammed, S., Ferzandi, L., & Hamilton, K. (2010). Metaphor no more: A 15-year review of the team mental model construct. *Journal of Management,* 36, 4, 876-910.

Murphy, R. R. (2014). Disaster robotics. MIT press.

Perrot, Y., Gargiulo, L., Houry, M., Kammerer, N., Keller, D., Measson, Y., ... & Verney, A. (2012). Long-reach articulated robots for inspection and mini-invasive interventions in hazardous environments: Recent robotics research, qualification testing, and tool developments. Journal of Field Robotics, 29(1), 175-185.

Pita, J., Jain, M., Marecki, J., Ordóñez, F., Portway, C., Tambe, M., ... & Kraus, S. (2008, May). Deployed ARMOR protection: the application of a game theoretic model for security at the Los Angeles International Airport. In Proceedings of the 7th international joint conference on Autonomous agents and multiagent systems: industrial track (pp. 125-132). International Foundation for Autonomous Agents and Multiagent Systems.

Pycia, M. (2012). Stability and preference alignment in matching and coalition formation. Econometrica, 80(1), 323-362.

Ramchurn, S. D., Wu, F., Jiang, W., Fischer, J. E., Reece, S., Roberts, S., ... & Jennings, N. R. (2016). Human–agent collaboration for disaster response. Autonomous Agents and Multi-Agent Systems, 30(1), 82-111..

Ramchurn, S. D., Huynh, T. D., Ikuno, Y., Flann, J., Wu, F., Moreau, L., ... & Simpson, E. (2015, May). HAC-ER: A disaster response system based on human-agent collectives. In Proceedings of the 2015 International Conference on Autonomous Agents and Multiagent Systems (pp. 533-541). International Foundation for Autonomous Agents and Multiagent Systems.

Recchiuto, C. T., & Sgorbissa, A. (2018). Post-disaster assessment with unmanned aerial vehicles: A survey on practical implementations and research approaches. Journal of Field Robotics, 35(4), 459-490.

Robocup Rescue Simulation League. Online: https://rescuesim.robocup.org/; Last Retrieved January 31, 2019

Sable, A., Wankhede, S., Jadhav, V., & Chavan, S. D. (2017). Fire Fighting Robot for Disaster Management. International Journal of Engineering Science, 12278.

Sanchez, J. M., Cordero, J., Chaudhary, H. M., Sheers, B., & Riobó, Y. (2017). Tactical Communications for Cooperative SAR Robot Missions. In Search and Rescue Robotics-From Theory to Practice. InTech.

Sanchez-Cuevas, P. J., Ramon-Soria, P., Arrue, B., Ollero, A., & Heredia, G. (2019). Robotic System for Inspection by Contact of Bridge Beams Using UAVs. Sensors, 19(2), 305.

Schwarz, M., Rodehutskors, T., Droeschel, D., Beul, M., Schreiber, M., Araslanov, N., ... & Schwarz, D. (2017). NimbRo rescue: Solving disaster-response tasks with the mobile manipulation robot momaro. Journal of Field Robotics, 34(2), 400-425.

Shehory, O., & Kraus, S. (1998). Methods for task allocation via agent coalition formation. Artificial intelligence, 101(1), 165-200.

Shoham, Y and Leyton-Brown, K. “Mutli-Agent Systems: Mathematical, Logical and Game Theoretic Foundations.” MIT Press, 2008.

Sourmelis, T., Ioannou, A., & Zaphiris, P. (2017). Massively Multiplayer Online Role Playing Games (MMORPGs) and the 21st century skills: A comprehensive research review from 2010 to 2016. Computers in Human Behavior, 67, 41-48.

Tambe, M., Bowring, E., Jung, H., Kaminka, G., Maheswaran, R., Marecki, J., ... & Paruchuri, P. (2005, July). Conflicts in teamwork: Hybrids to the rescue. In Proceedings of the fourth international joint conference on Autonomous agents and multiagent systems (pp. 3-10). ACM.

Thomas, D.M., & Bostrom, R.P. (2010). Team leader strategies for enabling collaboration technology adaptation: team technology knowledge to improve globally distributed systems development work. *European Journal of Information Systems,* 19, 2, 223-237.

Thomas, D.M., & Bostrom, R.P. (2010). Vital signs for virtual teams: An empirically developed trigger model for technology adaptation interventions. *MIS Quarterly,* 34, 1, 115-142.

Touati, M., El-Azouzi, R., Coupechoux, M., Altman, E., & Kelif, J. M. (2017). A Controlled Matching Game for WLANs. IEEE Journal on Selected Areas in Communications, 35(3), 707-720.

Wicke, D., & Luke, S. (2017, October). Bounty Hunting and Human-Agent Group Task Allocation. In 2017 AAAI Fall Symposium Series.

Yu, X & Khazanchi, D. (2015). Patterns of Information Technology (IT) Adaption in Building Shared Mental Models for Crisis Management Teams. In Proceedings of the ISCRAM 2015 Conference – Palen, Buscher, Comes & Huges, eds.