Applying a Systematic Approach to Design Human-Robot Cooperation in Dynamic Environments

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Abstract: This paper introduces a framework to enhance Human-Robot Cooperation in high-risk environments by leveraging a grid-based analysis. By integrating the concepts of Know-How-to-Operate and Know-How-to-Cooperate, the framework aims to balance and streamline cooperation strategies. The framework proposes grid-based configurations to identify agent competencies, manage resources, and dynamically allocate tasks. The study details first the framework, then shows how it can be applied to a team made of one human and two robots in a search-and-rescue context.

1 INTRODUCTION

Effective cooperation between humans and robots is essential in dynamic and high-risk environments (Bravo-Arrabal et al., 2021) to ensure efficient responses to complex situations such as fires and search and rescue missions (Vera-Ortega et al., 2022). Human-Robot (H-R) cooperation takes advantage of the distinct strengths of both fields, combining human intelligence and flexibility with robotic accuracy and endurance. This mutual interaction not only increases responders' safety but also enhances overall outcomes in dangerous circumstances.

Current techniques often emphasize full autonomy (Wijayathunga et al., 2023), frequently overlooking the unique benefits that human operators bring to the cooperative framework. Indeed, Autonomous robots excel at navigating hazardous environments, but human judgments based on global knowledge and experience are vital for adapting to unforeseen events (Li et al., 2023). However, optimizing cooperation between human operators and autonomous robots in hazardous conditions raise multiple complex questions.

Designing effective H-R teams presents several challenges. One key difficulty lies in fusing human cognitive strengths with robotic functionalities to optimize task performance, efficiency, and interaction intuitiveness (Goodrich et al., 2008). This involves determining the right balance between autonomy and control sharing between humans and robots. Additionally, human factors such as cognitive limitations and potential biases need to be considered alongside technical limitations in real-time communication and coordination (Mostaani et al., 2022). Furthermore, unforeseen events in dynamic environments can disrupt established communication protocols, rendering robotic systems unusable or limiting their functioning, requiring H-R teams to adapt and react seamlessly (Nourbakhsh et al., 2005). Integrating human judgment and decision-making with robotic capabilities becomes crucial, particularly in high-risk situations where quick and accurate responses are essential (Filip, 2022).

Recent advances in human-robot cooperation architectures and frameworks, such as the use of AND/OR graphs and hierarchical models, have been developed to better integrate human flexibility with robotic precision (Murali et al., 2020). These systems aim to facilitate smoother interactions by en-

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abling robots to predict and adapt to human actions, and by validating cooperation with up-to-date information through digital twins and other virtual systems (Darvish et al., 2020).

While these digital twin systems provide important advantages, our study takes a different approach by presenting a comprehensive Human Machine Cooperation model (Pacaux-Lemoine and Vanderhaegen, 2013) adapted for human-robot cooperation and its implementation using a grid-based architecture. The HMC model analyzes the complexity of human-robot cooperation, focusing on its importance in a variety of situations, especially those requiring search and rescue missions. By exploring the design and functionality of this cooperation model grid, we intend to see its usefulness in increasing cooperation, decision-making, and communication within the H-R teams in dynamic and challenging situations. Furthermore, the purpose of this study is to uncover any possible failure situation in the model that may impact H-R cooperation.

In the following sections, we will further explain the model, exploring the frameworks that underlie human-robot cooperation and the role of the grid in facilitating the design of seamless cooperation among agents. By leveraging structured human-robot cooperation architectures and grid analysis, we aim to contribute to the development of more effective and resilient human-robot teams in critical situations.

2 BACKGROUND

Successful cooperation between human operators and autonomous robots is critical for attaining common goals in tough situations. Human-robot interaction (HRI) and human-robot teaming (HRT) involve communication, coordination, and interaction to enable successful cooperation in complicated contexts (Paliga, 2022). Understanding the complexities of this cooperation requires a comprehensive analysis on both HRI and HRT frameworks. Therefore, this section will explore the current state-of-the-art in both areas, followed by an examination of the Human-Machine System (HMS) domain, specifically focusing on the capabilities, Know-How-to-Operate (KHO) and capabilities, Know-How-to-Cooperate (KHC) model.

2.1 Cooperation in the Human-Robot Interaction Domain

While traditional HRI research focused on developing interfaces and communication protocols (Mizrahi et al., 2020), there's a growing emphasis on understanding and incorporating human cognitive aspects like situational awareness, trust, and decision-making into robot design. This shift reflects the understanding that successful human-robot teaming requires robots that can not only perform tasks but also collaborate effectively with humans in complex environments.

The prominent areas of exploration within HRI are HRT or Human–Autonomy Teaming (O'Neill et al., 2022). HRT research focuses on developing robots that can act as teammates, understanding human intentions, anticipating needs, and adapting to changing situations (Li et al., 2023). This cooperative approach has the potential to significantly enhance efficiency and performance in various applications.

However, current research focuses predominantly on physical human-robot cooperation (Aronson et al., 2018), leaving a significant gap in addressing the cognitive elements of human-robot interaction (Jiang and Arkin, 2015). Identifying the limitations of current methodologies, three key challenges emerge (Tula et al., 2024):

Lack of Swift Human Decisions: Autonomous robots often struggle with rapid decision-making in dynamic situations. Human operators, with their cognitive abilities and field knowledge, can respond quickly to unexpected events (Chella et al., 2018).

Complex Sensor Data Interpretation: Autonomous robots may face difficulties analyzing and interpreting complex sensor data. Human operators excel in understanding global information at a cognitive level, making their presence essential in navigating complex scenarios where sensor data alone is insufficient (Mizrahi et al., 2020).

Communication Weakness between Humans and Robots: Effective communication between humans and robots is essential for successful cooperation. Current approaches often exhibit weaknesses in establishing robust communication channels, hindering the seamless exchange of critical data necessary for cooperative decision-making (Grislin-Le Strugeon et al., 2022).

2.2 Cooperation in the Human-Machine System Domain

More generally, the concept of cooperation between humans and machines has evolved greatly throughout time, owing to technological improvements and a better knowledge of human factors. Early techniques focused on automating specific tasks with robots acting as machines controlled by humans. As technology evolved, the emphasis switched to developing more interactive systems in which robots could help people with real-time data and analysis (Alirezazadeh and Alexandre, 2022). This growth resulted in the creation of collaborative systems in which humans and robots operate smoothly together, using each other's competencies. Modern HMS research focuses on the integration of cognitive and autonomous capacities in robots (Hoc, 2001), allowing for more complex interactions and cooperation.

The state of the art in Human-Machine Systems (HMS) (Pacaux-Lemoine, 2020) focuses on diverse ways to improve human-machine interaction, highlighting both technology developments and human-centered design principles. Researchers created models to better understand the dynamics of these interactions. One such principle in this field is the Know-How-to-Operate (KHO) and Know-How-to-Cooperate (KHC) model developed by (Pacaux-Lemoine et al., 2023). This framework analyzes human-machine cooperation by dividing it into two key categories: i) KHO focuses on an agent's (human or machine) ability to perform individual tasks. It involves a four-step process: Information Gathering (IG), Information Analysis (IA), Decision Selection (DS), and Action Implementation (AI); ii) KHC tackles how agents interact and coordinate actions. Similarly to KHO, it involves four steps: Information Gathering on Other Agents (IGO) to understand their capabilities, Interference Detection (ID) to identify potential conflicts, Interference Management (IM) to resolve conflicts and optimize cooperation, and finally, Function Allocation (FA) to assign tasks to the most suitable agent (human or machine).

The KHO-KHC structured approach offers a platform for organizing agent roles, accelerating information flow, and optimizing task allocation within Human-Robot Cooperation. By defining individual and cooperative functionalities, this approach provides a framework to enhance cooperation between humans and robots.

3 GRID-BASED ANALYSIS

This section describes a systematic approach to establishing cooperation-related characteristics for Human-Robot (H-R) teams that employs a grid architecture. The goal is to aid the designer in analysis by thoroughly understanding each agent's role, interactions, and capabilities within the cooperative environment. The subsections that follow detail the contents of the grid, the grid filling process, the organization's dynamic adaptability, and the potential benefits of the grid support.

3.1 Grid Description

The grid framework is divided into four quadrants, each reflecting a different facet of cooperation between the human operator and the robots. The reason for specifically mentioning robots is that the abilities of two robots are generally similar, making it simpler to consider them together (in Table 1). The top left quadrant handles cooperation based on each agent's ability to interact with the environment or process, such as individual task accomplishment and environmental interaction. The top right quadrant, known as KHC-human, enables the human operator to access the robots' behavior or condition depending on the situations, determining the human agent's capabilities. The lower left quadrant, known as KHC-robot, allows robots to interact with human operator depending on the specific situation in a scenario, establishing the robot agent's competencies. Finally, the bottom right quadrant focuses on cooperation between both agents in terms of abilities like information sharing, task sharing, allocation and, coordination, using the common workspace to communicate and store essential information or cooperation needed for a situation in an aftermath scenario such as a fire accident. A Common Workspace acts as the hub for all interactions, ensuring that all agents have access to shared information and can coordinate their efforts efficiently.

3.2 Steps to Fill the Grid

Filling the quadrants involves a detailed process. The grid is meant to be filled by the system designer and to support the identification of the task that the human operator will complete according to the situation.

To begin, the roles and competencies of the agents must be determined. The Human Operator is in charge of decision-making, task distribution, and interfacing with other agents. Sensors, actuators, and autonomous capabilities enable the robots to collect information, maneuver, and complete tasks.

Step 1: In the top left quadrant, focusing on Know-How-to-Operate (KHO) aspects, tasks include information gathering IG, where both the human operator and robots could gather relevant data from the environment; information analysis IA, where both agents' process and interpret the gathered information to make informed decisions specific to their own tasks; decision selection DS, choosing the most suitable course of action based on analyzed information about their own area of authority; and Action implementation AI, executing the chosen actions effectively to complete their parts of the overall task.

Table 1: KHO & KHC grid for a team of 1 Human operator, and 2 Robots agents'.

			Human Operator							
			Know-How-to-Operate				Know-How-to-Cooperate			
			IG	IA	DM	AI	IGO	ID	IM	FA
ROBOTS(R1,R2)	Know-How-to-Operate	IG	HO/R1,R2: some info on the environment like bluprint of the building	HO: Analyse the situation of the environments	HO: Decision selection according to the observed analysis	HO is not able to act in the environment but robots	HO: sensor's information	HO: sensors breakdown or improper readings	HO: Modify the sensors based on the analysis.	HO: Decide who will perform the IG function
		IA	R1,R2: Analyzes the environment with the available sensors.	HO/R1,R2: Analysis of the environment to classify or identify the objects and the specific areas.	HO: Desision selection according to robots analysis		HO: perception of robot's analysis	HO: check if the robot's analysis is good or not	HO: if any differences HO will midfy	HO: Decide who will perform the IA function
		DM	R1,R2: Desision selection according to the robots analysis in the previous step	R1,R2: Desision selection based on Human Operator analysis	HO/R1,R2: Decision making of robot's movement or classifing the area based on HO and Robots analysis		HO: perception of robots decision making	HO: check if the decision by robots is good or bad.	HO: moify or follow the instructions by HO	HO: Decide who will perform the DM function
		AI	R1,R2: Robots implement an action based on their desision making	R1,R2: Robots implement an action based on their desision making	R1,R2: Robots implement an action based on HO desision making	R1,R2: robots move by following HO or their own decisions	HO: Perception of robots actions	HO: check if the actions made by robots is good or bad.	HO: will modify the action according to robot's actions	HO: Decide if AI is the right one
	Know-How-to-Cooperate	IGO	We decide that R1,R2 are not able to perceive human cognition or to predict it thanks to model they have about human		R1,R2:Through Joystick or Interface use	There's no action to evaluate	Cooperation between HO and Rx on the way they can perceive each other	HO has the ability to detect a problem about the way Rx can communicate about themselve (or perceive HO)	HO has the ability to manage the way Rx can communicate about themselve (or perceive HO)	HO has the authority to impose the function allocation
		ID			R1,R2:HO intention could be wrong		Rx have no ability to detect a problem about the way to communicate	Cooperation between HO and Rx on the way they can detect interference	HO has the ability to adapt the way Rx can detect interference	HO has the authority to impose the function allocation
		IM			R1,R2:Visual, audio, haptic alert if necessary		Rx have no ability to manage a problem about the way to communicate	Rx have no ability to manage a problem about the way to detect interference	Cooperation between H and Rx on the way they can manage interference	HO has the authority to impose the function allocation
		FA			R1,R2: Decide to not take into account HO decision if necessary		Rx have the authority to impose the function allocation in case of obstacle	Rx have the authority to impose the function allocation in case of obstacle	Rx have the authority to impose the function allocation in case of obstacle	Cooperation between H and Rx to decide authority for function allocation

Step 2 & 3: The Know-How-to-Cooperate (KHC) components are addressed from both the human and robot perspectives to ensure effective coordination. From the human perspective (Step 2), tasks involve information gathering (IGO) on the robots' actions and intentions, interference detection (ID) to identify potential conflicts arising from the combined actions of multiple agents, interference management (IM) to resolve these conflicts for smooth and coordinated task execution, and function allocation (FA) to assign tasks and responsibilities among the agents for optimal team performance. Similarly, from the robot perspective (Step 3), tasks include gathering information on the human operator's actions and intentions, detecting potential conflicts due to the human operator's actions, managing these interferences to ensure seamless task execution, and allocating functions to optimize overall team performance. The key difference between these steps lies in the perspective: Step 2 emphasizes the human operator's view of understanding and managing robot interactions, while Step 3 focuses on the robot's view of understanding and human interactions.

Step 4. The bottom right quadrant focuses on the control of the cooperation between human operator and robots. Tasks include shared information gathering, where both agents gather and share information relevant to the overall task; shared decision making, a cooperative decision-making process considering inputs from both agents; and shared action implementation, executing tasks cooperatively to ensure coordinated efforts and mutual support.

3.3 Dynamic Adaptation

Dynamic adaptability is critical for maintaining effective teamwork in changing circumstances. This includes real-time monitoring of the environment and agent status, as well as continuous feedback loops to alter actions and tactics in response to new information. Adaptive task allocation enables the dynamic redistribution of tasks depending on the current situation and agent capabilities. Situation-based adjustments employ predetermined cases to guide initial task allocation and cooperation, which may be modified based on real-time data. Regular training sessions for human operators and robots will enhance teamwork abilities and enable the assessment of the cooperation model using the grid in various circumstances.

The grid provides a unique viewpoint on dynamic adaptation. By examining the capabilities and capacities of human and robot agents inside the KHC-human and KHC-robot quadrants (see Table 1), the grid makes it easier to identify strengths and weaknesses for appropriate work allocation. This approach promotes a better knowledge of human-robot capabilities, allowing designers to strategically assign tasks based on real-time data. Furthermore, the grid promotes flexible and responsive cooperation by allowing for dynamic allocation of workload based on predetermined situations and real-time modifications. It's also a useful tool for designers and developers. Designers can define approaches to cooperation inside the grid to create specific parameters for interaction between humans and robots. Furthermore, the grid may be utilized to develop the needed functions for agent capabilities and incorporate these abilities towards cooperation.

3.4 Implementation and Evaluation

Proof-of-concept experiments in crisis scenarios, such as fires or post-earthquake settings, should be conducted to evaluate agent cooperation under various configurations. Tasks will range from simple navigation to complex pick-and-place actions, supporting both human and robot agents. Evaluation metrics will include reaction time, event detection precision, navigation accuracy, and task management, alongside subjective feedback from Human-Robot Interaction surveys to assess cooperation and system usefulness. Comparative analyses between scenarios with and without the cooperative model will highlight its benefits, focusing on agent skills, responsibilities, and results.

The grid framework is crucial in these evaluations, structuring interactions and task assignments based on agent roles and capabilities. Metrics such as reaction time and navigation accuracy directly correlate with the grid's efficacy. Feedback from these evaluations will refine the grid, creating a feedback loop that enhances overall system performance.

3.5 Grid Analysis Aids Cooperation

The grid analysis enables the identification of agent competencies. Typically, the system designer creates the grid to identify, manage, and allocate the roles and actions of the agents. Each cell represents a distinct interaction between agents, simplifying the identification of their competencies. For example, in a search and rescue effort, a human operator might examine blueprints to identify areas of interest, while robots use sensors to detect objects and navigate effectively.

Resource management is another important feature of the grid design. The grid structure promotes optimal resource utilization by allocating particular functions and authorities to each agent depending on their capabilities and the situation's requirements with the help of human operator. For example,in a rescue operation, the human operator will assign roles to himself, such as analyzing blueprints and making educated judgments, while robots are given tasks such as navigation and data gathering.

The grid analysis facilitates allocation of tasks based on the situation, allowing operations to be dynamically assigned in response to changing environments or objectives. This might ensure that resources are allocated efficiently. For example, if the environment gets more dangerous or complicated, the human operator may assign additional tasks to the robots in order to reduce risk and increase efficiency. The grid helps to manage this assignment operation by clearly defining roles and competencies. In contrast, if comprehensive analysis or complicated decision-making is necessary, the human operator may take on a more active role to process information and recommend best plan of action based on the agents' competencies.

The grid also acts as a paradigm for developing and deploying agent skills including programming and training. Designers can analyze what could be the best plan of action and decision required for good cooperation by mapping out how the grid's agents interact. For example, the grid might emphasize the need for robots to traverse barriers autonomously or convey crucial information to human operators, motivating designers to include suitable capabilities. By outlining these interactions, the grid aids in the systematic development of cooperation strategies and skills.

By linking the dynamic adaptation of the organization, implementation, and evaluation processes back to the grid framework, we underscore its importance in enhancing cooperation. This integral approach not only optimizes the performance of H-R teams but might also improve their adaptability and effectiveness in dynamic and hazardous environments.

To summarise, the grid framework provides a systematic way to define agents' role, resources, and objectives, for cooperation among the agents, shared task, allocation and execution to complete a goal. Its simplicity and versatility make it appropriate for a variety of circumstances, opening the path for wider adoption in crisis management and other cooperative contexts. Designers may use the grid framework as a tool to program and apply the cooperative model based on unique situational needs, resulting in resilient and successful real-world solutions.

In the next section, we explore the application of the grid analysis in a real-world situation and show how the human operator and robots communicate and coordinate their actions.

4 APPLICATION

Based on the grid analysis between the human operator and robots, we apply the method explained in Section 3 to a simple Search and Rescue operation. We will use examples of cells in each quadrant of the grid to illustrate the use of the grid analysis, highlighting benefits, difficulties, and remaining gaps. The section concludes with the need for an intermediary agent.

Consider a situation where the goal is to locate and rescue a vital object trapped within a collapsed structure. The grid arranges the roles and interactions of each agent as follows:

4.1 Human Operator (HO)

The human operator has authority for analyzing blueprints or visualizing the surroundings to uncover prospective areas of interest, assessing information provided by the robots to make educated decisions, and using situational analysis to direct the robots' movements and behaviors. The human operator's resources and objectives include collecting data on the environment (Information Gathering - IG), interpreting data from the robot's sensors to evaluate the situation (Information Analysis - IA), determining the best course of action (Decision Seclection - DS), and sending orders to the robots to perform search and rescue tasks such as removing debris or accessing difficult areas (Action Implementation - AI).

4.2 Robots (R1, R2)

The robots are responsible for navigating through the environment to locate the necessary object, using sensors to detect the presence of an object and structural irregularities, and reporting findings to the human operator and following their directions. The robots' resources and objectives include acquiring data on the building's layout, structural stability, and potential hazards (Information Gathering - IG), analyzing sensor data to identify areas with the highest likelihood of locating the vital object (Information Analysis - IA), making decision on the best course of action based on gathered information (Decision Selection - DS), and performing tasks such as moving debris, entering restricted areas, and sending real-time updates to the human operator (Action Implementation - AI).

4.3 Dynamic Grid Use: Example

The dynamic use of the grid (as mentioned in Section 3.3) not only facilitates the identification of agent competencies but also assists in resource management, task allocation according to the situation, and system implementation to design the abilities of the agents can be illustrated through various situations:

Situation 1: Initial Assessment. In the initial assessment phase, the human operator uses IG and IA to analyze initial data and directs robots to high-priority areas (top left quadrant - KHO). Robots gather detailed structural data but await further instructions before proceeding as seen in the top left quadrant KHO.

Situation 2: Encountering an Obstacle. When robots encounter debris, the human operator assesses the situation and decides to direct the robots to remove it (top right and bottom right quadrant). Both robots and the human operator pause to reassess the organization of cooperation, possibly seeking additional data (bottom right quadrant - KHC).

Situation 3: Locating the Object. As robots identify potential locations of the trapped object, the human operator uses IA to interpret sensor data and confirm the findings (top left and top right quadrant). The robots then proceed to the identified locations to begin the rescue operation (top left quadrant), while continuously providing real-time updates to the human operator(bottom left quadrant).

Situation 4: Structural Instability. If the robots discover any physical unpredictability in the environment, the human operator must swiftly analyze the dangers and determine whether to proceed, change the robots' direction, or evacuate the area (top left, right left and bottom right quadrant). The human operator may request further data or relevant information to better grasp the consequences (top right and bottom right quadrant).

4.4 Addressing Gaps

To address the gaps as discussed in background section 2, the cooperation model should leverage the cognitive strengths of human operators and the advanced data processing capabilities of robots. By dynamically updating the grid analysis, the system can help at ensuring that human operators can make swift decisions in fast-changing situations, thereby compensating for the autonomous robots' slower and sometimes the decision-making processes bad. The human operators excel at interpreting complex sensor data, providing critical insights that robots alone may miss. Effective communication channels within the grid can facilitate seamless data exchange between humans and robots, ensuring robust cooperation and timely responses to dynamic rescue scenarios. However, gaps remain in efficiently integrating data processing and communication within the grid framework. Real-time data interpretation and synchronization are crucial for improving the cooperation model.

4.5 Benefits and Difficulties

Benefits. A key benefit of the proposed model is its capacity to support organized interactions between human and robot agents', which closely resemble the designer's planned cooperation designs. This is accomplished by a systematic analysis of the grid. This organized procedure enables seamless interaction and task execution resulting in simplified task completion. Real-time data analysis and communication enable informed decision-making, allowing for swift adaptation to changing situations. Additionally, the grid framework facilitates resource allocation by dynamically assigning tasks based on the capabilities of each agent, maximizing the utilization of available resources.

Difficulties. While the proposed method offers significant benefits, there are also challenges associated with its usage. Real-time data exchange between human operators and robots, while crucial for collaboration, can be hindered by communication delays, which impact the scenario's speed and the robot's abilities. Highly dynamic situations with fast-moving robots may necessitate immediate action without waiting for human input, especially when encountering potentially dangerous unknowns. This highlights the need for a step back preventative action, where the robot takes a pre-programmed, safe pause to allow for human analysis. Additionally, sensor data from robots may contain inaccuracies or disturbances, affecting decision-making. Integrating advanced data processing systems with existing human-robot interaction frameworks can be complex, requiring careful planning and implementation. Addressing these challenges will be crucial for the implementation of the cooperation.

4.6 Need for an Intermediary Agent

The grid analysis between the Human operator and robots highlights the critical need for an intermediary agent to bridge gaps in coordination, lack of swift human decisions, communication weakness and complex sensor data (refer to Section 2) and enhance overall efficiency. In this context, the Intelligent Assistance System (IAS) serves as the ideal intermediary agent. The IAS can process information from both human operators and robots, creating an integrated action plan that optimizes the use of available resources.

The IAS empowers rapid interpretation of complex sensor data. By leveraging advanced algorithms and machine learning, the IAS can swiftly analyze vast amounts of data, identify patterns, and extract actionable insights. This comprehensive understanding, in contrast to a robot's limited local view, allows the IAS to maintain a crucial overview of the situation. This capability is crucial for making swift and informed decision in dynamic S&R scenarios. The IAS can also facilitate robust communication channels by acting as a central hub for data exchange, ensuring that critical information is seamlessly shared between human operators and robots. For example, it can synchronize real-time updates from robots and relay important information to the human operator, ensuring that both agents are informed and can coordinate their actions as needed.

Additionally, the IAS can dynamically adjust strategies in response to real-time changes in the environment. By continuously monitoring the situation and analyzing incoming data, it can recommend action plan adjustments to ensure efficient and effective operations as conditions evolve. The inclusion of an IAS as an intermediary agent addresses research gaps by leveraging advanced data processing and communication capabilities, thereby enhancing coordination and efficiency in rescue operations and highlighting the importance of integrating such agents for successful human-robot cooperation.

5 CONCLUSION

The integration of human operators, robots, and an intermediate agent within a grid-based framework can enhance cooperation in complex scenarios such as search and rescue operations. By defining roles and interactions, the grid framework facilitates a structured approach to identifying competencies, managing resources, and dynamically allocating tasks based on the situations. Human operators use their analytical skills to guide decisions, while robots autonomously navigate and collect data with advanced sensors. The intermediate agent, though still under development, is crucial for coordinating actions and processing information, optimizing mission performance and safety. Further practical implementation, such as a proof-of-concept experiment, is required to show the framework's effectiveness, dependability, and workload management. The intermediate agent's ability to implement adaptive algorithms and real-time monitoring can have the potential to reduce the cognitive workload on human operators.

In conclusion, the grid-based analysis offers a structured approach for cooperative tasks in disaster management and other domains requiring coordinated multi-agent systems. The clarity, organization, and adaptability of the grid structure promote efficient cooperation in diverse environments. Future research should focus on refining the intermediate agent and exploring new dimensions of the human-robot interaction to meet emerging challenges.

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