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Flexible Human-Machine Collaboration: The Concept and Case Study of Lunar Surface Exploration Task

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ABSTRACT

This paper focused on flexible human-machine collaboration in complex systems, which aims to explore all feasible or desired function allocation and collaboration solutions in the design. A three-level framework, including labour division, mutual assistance, and joint performance, is proposed to help flexible human-machine collaboration analysis. Then this study illustrates the above concept and idea with a lunar surface sampling case study, including task decomposition, analysis of human and machine capabilities for each functional unit, and determining collaboration solutions and their applicable situations. These solutions enable dynamic function allocation, enhancing system adaptability and inspiring future human-machine system designs for lunar exploration.

Keywords: Human-machine collaboration, Function allocation, Lunar surface exploration

INTRODUCTION

With the introduction of various automation or autonomous technologies into complex systems (such as aerospace, aviation, military, etc.), human-machine interaction and collaboration are receiving more and more attention (Dearden et al., 2000; Fong et al., 2013; Vaccaro et al., 2024; Yang et al., 2022). Reasonable function allocation between humans and machines is considered critical to obtain expected human-machine collaboration performance and ensure system safety (Endsley, 2015; Sun et al., 2020). The traditional human-machine function allocation is to assign functions or tasks to either humans or machines, and the allocation is often fixed during operations, which is not able to cope with various situation changes (Fitts, 1951; Price, 1985). Therefore, function allocation should adapt to the requirements of tasks and scenarios, the capabilities and states of humans and machines, and the changes of the working environment (Feigh et al., 2012; Huang et al., 2024; Pritchett et al., 2014; Wang et al., 2024), which make the human-machine system flexible when facing varied or unexpected situations. Flexible human-machine collaboration means exploration of all feasible or desired function allocation and collaboration solutions in the design phase so as to enable a human-machine team to adapt to various changes in the operation phase (Challenger et al., 2013). Human-machine system design should take the flexible human-machine collaboration as an important consideration to make the system resilient. The greater the flexibility of human-machine relationship, the greater the solution space for dynamic function allocation, the higher possibility to cope with situational changes. Flexible human-machine collaboration should be analysed in the early design stage to help to optimize human-machine relationship to improve performance and the safety, and generates requirements of technical development, human-system interface design, personnel selection and training, and so on. Thus, this paper would propose an analysis process for flexible human-machine collaboration.

In traditional function allocation, the labor division based on performers' capabilities is usually considered (Fitts, 1951). However, the development of automation or intelligent technology makes the relationship between humans and machines closer. Thus, it is not only necessary to pay attention to the coordination in the sense of traditional human-machine function allocation, but also the close cooperation between humans and machines to make a task or function possible to be performed or performed better (Cummings, 2014; Vaccaro et al., 2024). For example, the meta-analysis study found that humans can perform better with the help of the AI system (Vaccaro et al., 2024). And the researches about "Levels of Automation" propose the modes from full manual to full automation in many fields (Frohm et al., 2008; Parasuraman et al., 2000; SAE, 2021), which means the richer ways of human-machine collaboration should be taken into account for higher performance in safety and efficiency. Flexible human-machine collaboration asks to figure out all possibility in human-machine relationship. In complex human-machine systems, some tasks or functions cannot be performed by either humans or machines alone, then the combination or integration of human and machine capabilities may be considered as a feasible way which can break the boundaries by forming a close cooperation relationship between human and machine (Kolbeinsson et al., 2019; Vaccaro et al., 2024). Therefore, based on the closeness of human-machine collaboration, this paper will propose a three-level framework of human-machine collaboration to illustrates the options for human-machine collaboration.

This paper demonstrates the above concept with a case study of lunar surface sampling task with full consideration of complex situations and heterogeneous teams. Lunar surface sampling task is a typical space extravehicular activity (EVA) characterized by the low-gravity environment, limited capabilities by space suits, and distributed teams which can be composed of ground operators, astronauts in the cabin, extravehicular astronauts, and machine/automation systems. The case study would include the following parts: task decomposition to form functional units; analysis of human and machine suitability for each functional unit based on an MABA-MABA list updated by considering new technologies; determination of feasible collaboration solutions and applicable situations of each solution. The flexible collaboration solutions would support dynamic function allocation and collaboration during task performance and may inspire the new ideas of human-machine system design for future lunar exploration.

FLEXIBLE HUMAN-MACHINE COLLABORATION

In flexible human-machine collaboration, human-machine relationships are flexible so that the system can adapt to the situation by selecting the optimal collaboration solution considering the task requirements, current capabilities and state of humans and machines, and changes in environment. In addition, given the characteristics of complex human-machine systems and the safety challenges posed by automation and other new technologies, the "division of labor" relationship alone may not satisfy the needs of many complex systems. Therefore, it is necessary to fully explore potential ways for human-machine collaboration to foster effective and safe performance. For this, the concept of "levels of human-machine collaboration" in contrast to the classic concept "levels of automation" is proposed in this paper. It includes three levels: labor division, mutual assistance and joint performance. labor division refers to find the tasks/functions that humans and machines are capable to perform alone and divide the tasks/functions between them. In many cases, there is a need for "mutual assistance", i.e. although a human or machine can complete an allocated task/function independently, with the support or help (e.g., information analysis, situational assessment, etc.) from the other side, one side can perform better. What's more, due to the limited capabilities of both humans and machines, some functions/tasks are not capable of either humans or machines alone (Cummings, 2014; Fong et al., 2013; Huang et al., 2024). Then a joint performance should be considered to make human-machine system would be able to perform the task by integrating the capabilities of humans and machines.

And the analysis for flexible human-machine collaboration can be broken down into the following steps.

The first step is to perform task decomposition. It refers to the process of splitting a series of activities need to be performed in order to achieve the task goals. For most complex human-machine systems, the two generic goals are to achieve the task goal and to ensure safety. But more information about the specific task objectives and the difficulties and danger when performing task should be done by field survey and subject-matter expert interview. If the activity should be allocated to one performer, either one of humans and machines or any of their combinations, then it is regard as a functional unit for latter analysis (Huang et al., 2024). In addition, the requirements of performing functional unit should be analysed, such as what are the capabilities involved in the functional unit, or what are the specific demands or limitations on these capabilities of the performer (can be obtained from the objectives, difficulties and danger of task), or what level of performance is desired and so on.

The next step is suitability matching. It is conducted to find out whether the actual capabilities of humans and machines can match with the requirement of performing functional unit, and the following questions should be considered: Are humans and machines has the capabilities for performing the unit? Is a human or machine capable for performing the unit alone? If performing the task alone is not enough to achieve the desired requirements of performance, what limitations or problems there may have when performing? Can humans compensate for the limitations of machines? What support can machines provide to humans? These considerations are the key foundation for function allocation between and capability integration of humans and machines. In this step, an updated MABA-MABA list may be used to analyse the relative strengths and weaknesses of humans and machines, which has been developed based on the original MABA-MABA list (Fitts, 1951) but incorporates new items reflecting the development of new technologies and new knowledge from relevant literature, as shown in Table 1 (Hu, 2022).

Table 1: The updated MABA-MABA list (Hu, 2022).

Machines are Better at Usually	Human are Better at Usually
- Better at detecting signal (with high accuracy, high resolution and high reliability) - Better at stable and long-term signal monitoring - Better at locating position over long distances (with high precision) - Better at transmitting data and responding to request - Better at remote, high-speed communication and control between machines, as well as between humans and machines - Better at storing, generating, integrating, and filtering information - Better at performing rapid and reliable reasoning and judgment in situations with low level of informational interference when rules, algorithms or logic are known. - Ability to visualize both the reasoning process and the outcomes when the reasoning has good interpretability. - Better at handling large volumes of data, requiring high precision, and operating under well-defined processing rules - Better at long-hour work in harsh environments if under proper maintenance - Ability to perform consistently, unaffected by beliefs, motivations, or emotions - Better at repetitive tasks (with constant performance) - Better at applying and withstanding forces stably and accurately especially when the required force is beyond the limits of human strength - Ability to handle multiple parallel tasks at the same time	- Ability to detect small amount visual and auditory signals - May be better at detecting useful signals from noise (not susceptible to interference, able to eliminate interference based on experience and knowledge) - Better at obtaining and outputting incidental information about major activities - Better at retrieving memory under fuzzy conditions - May be better at comprehending and integrating information, and making judgements and decisions - Better at tasks that require creativity, flexibility and improvisation - Ability to complete tasks with acceptable precision after adequate training

The last step is feasible allocation, i.e. to find all feasible collaboration solutions for each functional unit. The three-level framework of human-machine collaboration discussed before is used to conduct the analysis. For the case where a single performer's capabilities can meet the requirements of functional unit, the labor division would be applied, i.e. a person or a machine work independently is considered a feasible solution. Then for the case where a single performer can complete functional unit alone but with suboptimal performance, mutual assistance can be a feasible solution, including Human with Machine-assisted, or Machine with Human-assisted. In addition, for the case where none of the performers can complete functional unit independently, joint performance is the way to go, emphasizing the need for close collaboration between humans and machines without detailing how they should cooperate. For a given function unit, all feasible solutions will be listed. Meanwhile, the applicable situations for each collaboration solution should be determined so that in operation stage the reasonable solution can be selected for the current situation.

CASE STUDY: LUNAR SURFACE EXPLORATION TASK

The lunar surface exploration task requires astronauts get soil or rock samples using a lunar rover with a robotic arm. The specific dangers include turnover when moving on the lunar surface and collisions during the process of sampling (such as impacts caused by splashing objects); in addition, it is possible that the task is interrupted due to equipment failure or astronaut injury. The performers for lunar surface exploration task would involve multiple humans and multiple machines, including two astronauts on the lunar surface, support staff team outside the lunar (on Earth or in the space station), an auxiliary robotic arm and its system, a lunar rover and a computer system, among others. However, in this case study, performers are simplified into two categories (human and system) without further distinction.

Given that manned lunar surface exploration task are infrequent in practice, this case study would use the Apollo program as a point of reference, integrating our own insights and analysis to decompose the task procedures. The astronauts first select a sampling site and move safely to it, then observe and analyse the sampling site, and use tools to collect, store and transport samples. During the process, it is necessary to monitor the status of astronauts and machines, and make emergency stop when safety issues arise. Due to the large amount of information that needs to be comprehensively considered when planning the moving path, there are high requirements in integrating, calculating and analysing data. For safety reasons, the astronauts should retain the ultimate decision-making authority. Due to the limitations of communication between lunar and Earth, some tasks with a heavy workload can be delegated to the support team in non-emergency situations, while emergencies must rely on the immediate response of astronauts and system on the lunar. Sampling is a delicate and challenging operation for astronauts wearing space suits, especially if the sampling tools are not designed for ease of use. In uncertain sampling environments, the use of a robotic arm for sampling would impose significant demands on its control algorithms. Regardless of whether the task is performed by human or system, there is always the potential for errors or failures, making monitoring an essential component. To provide warnings of danger and enable emergency stops, additional technical support or enhanced human-machine collaboration may be required.

The system is incapable of predicting the intent behind sampling and requires human input to specify the start and end points for path planning. While system excels at detecting over long distances and integrating vast amount of information, it may fail to handle situations that fall outside its database or algorithmic framework. In such cases, human can make the judgment but with the assistance of system. The system can automatically calculate intermediate path points between the start and end points to generate a path plan. It can also evaluate the proposed path by integrating observational data. However, it can't guarantee the safety of all path points. Therefore, human must designate critical path points to avoid obstacles or achieve specific objectives, as well as select the optimal path. Given the inconvenience of operating in space suits, priority is given to system for controlling the lunar rover and performing other operational tasks. Process monitoring and risk response require prolonged information detection and real-time analysis, making close collaboration between human and system ideal. This solution leverages the strengths of both parties: the system's capability to collect and integrate information, and the human's capability for judgment and decision-making. Certain physical activities—such as clearing obstacles, collecting and transporting samples—are better assigned to system due to their heavy lifting requirements and operational safety risks. Nevertheless, human may need to assist in handling unforeseen challenges during these processes.

Through the analysis above, the flexible human-machine collaboration of lunar surface exploration task is shown in Table 2, which includes the functional units and its allocation solution with applicable situations.

Table 2: Flexible human-machine collaboration of lunar surface exploration task.

Functional Units	Function Allocation	Applicable Situations
Select sampling destination	Human	
Observe the environment and gather information	System	Large detection range, Lots of data processed
	Human with System-assisted	Information is difficult to recognize or integrate
Propose moving path	System	Algorithms can reliably
	Human with System-assisted	The path plan given by the machine is unsafe
Evaluate moving path	System	Lots of data processed
Determine moving path	Human	
Control rover's movement	System	Algorithms can reliably
	Human with System-assisted	Control system is down, or change path temporarily

Continued

Table 2: Continued

Functional Units	Function Allocation	Applicable Situations
Monitor during movement	Joint performance	
Response to the risk	Joint performance	
Investigate the sampling site	Joint performance	
Record in videos and pictures	System	
Analyse the sampling position	Human with System-assisted	Requires constant judgment based on information
Deployment sampling flag	Joint performance	
Identify obstacles	System	Lots of data processed, algorithms can reliably
	Human with System-assisted	Obstacles is difficult to recognize
Clear obstacles	System with Human-assisted	Some danger in operation, more physical operation
	Human	System is down
Monitor during clearing	Joint performance	
Identify sample morphology	System	Lots of data processed, algorithms can reliably
	Human with Machine-assisted	Samples is difficult to recognize
Collect samples	System Human-assisted	Some danger in operation, more physical operation
	Human	System is down
Seal/store samples	System with Human-assisted	Delicate and physical operation
	Human	System is down
Transport samples	System	Heavy physical activity
	Human	System is down
Monitor during collecting	Joint performance	

CONCLUSION

This study focused on the concept of flexible human-machine collaboration and proposed a three-level framework of human-machine collaboration, including labour division, mutual assistance, and joint performance. And further, a process for forming the flexible human-machine collaboration is proposed to support dynamics function allocation, including task decomposition, suitability matching, and feasible allocation. Finally, the analysis process is applied to the context of a lunar surface exploration task for the flexible human-machine collaboration. The results could inspire thinking about the needs of humans and systems in lunar exploration, thus contributing to the design of human-machine systems for safety and flexibility.

The lunar exploration task analysed in this paper contains elements of imagination and is not entirely based on real-world data, due to limitations in the information available. The methodology used to analyse the strengths and weaknesses of humans and machines capabilities is relatively general. Although applicable rules can be identified to support the capability analysis process, it remains necessary to seek specific guidelines that address the unique characteristics of humans and machines involved in lunar exploration. Therefore, it is crucial to pay continuous attention to real lunar exploration activities and to conduct interviews with experts to gather more detailed information. This additional data will help refine the analysis process and improve its accuracy and relevance.

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